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# Modern Optimization Techniques for Advanced Machining

Heuristic and Metaheuristic Techniques

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# Preface

Advanced manufacturing via computer numerical machining is the art of producing mechanical components employed in aerospace, automobile and industrial applications where a high level of accuracy is needed. This book focuses on the machining of some selected alloys and its optimization. The application of aluminium alloy and titanium alloys in the manufacturing industry has increased tremendously due to its lightweight-to-high strength ratio and high-level resistance to corrosion. However, aluminium alloy and titanium alloys have some challenges during the machining and manufacturing stage such as material adhesion and titanium alloy is very difficult to cut, in order to solve real-life manufacturing challenges in advanced machining operation for sustainable production processes. There is a need for the implementation of a general algebraic modelling system (GAMS) and other heuristic and metaheuristic techniques for problem-solving and to effectively develop mathematical models for high accuracy prediction and optimization under nano-lubrication machining conditions. This book will discuss majorly on the three responses in machining such as surface roughness, cutting force and material removal rate, which will give an excellent guide to undergraduate and postgraduate students, senior research fellows in academia, operational and strategic staff in manufacturing industries, the theoretical and practical skills for implementing a sustainable and biodegradable nano-lubricant in machining processes. The structure of this book is as follows: Chap. 1: “Overview of Advanced Machining Process” that cut across the major four advanced machining process such as computer numerical control machining (CNCM), wire electro-discharge machining (WEDM), abrasive water jet machining (AWJM) and electro-discharge machining (EDM) and discusses their working principles, advantages and disadvantages. Chapter 2: “Cutting Fluid and Its Application with Different Delivering Machining Techniques” is presented in this chapter cut across the cryogenic cooling, flood cooling, solid lubrication, compressed air vapour gas as coolant, high-pressure lubrication and MQL. Chapter 3: “Development and Application of Nano-lubricant in Machining: A Review”. Chapter 4: “Global Machining Prediction and Optimization”—This chapter discusses the Importance of prediction and optimization in machining via heuristic and metaheuristic techniques such as artificial neural network (ANN), adaptive neuro-fuzzy inference

system, particle swarm optimization, genetic algorithm, whale optimization algorithm (WOA), ant lion optimization algorithm, grasshopper optimization algorithm. Chapter 5: “Multi-objective Grey Wolf Optimizer for Improved Machining Performance”. Chapter 6: “Multi-objective Ant Lion Optimizer for Improved Machining Performance”. Chapter 7: “Multi-objective Grasshopper Optimizer for Improved Machining Performance”. Chapter 8: “A Multi-objective Optimization Approach for Improving Machining Performance Using the General Algebraic Modelling System (GAMS)”. Chapter 9: “ANN and QRCCD Prediction of Surface Roughness Under Biodegradable Nano-lubricant”. Chapter 10: “Cutting Force Optimization Under ANN and QRCCD”. Chapter 11: “Material Removal Rate Optimization Under ANN and QRCCD”. Chapter 12: “Application of Hybrid ANN and PSO for Prediction of Surface Roughness Under Biodegradable Nano-lubricant”. Chapter 13: “Adaptive Neuro-Fuzzy Inference System for Prediction of Surface Roughness Under Biodegradable Nano-lubricant”.

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# Chapter 1

## Overview of Advanced Machining Process



**Abstract** Sustainable development depends on the dynamics of the manufacturing process. This chapter discusses an overview of the advanced machining processes that are currently in use in the manufacturing industry. In order to study the heuristic and metaheuristic techniques for advanced nanolubricant machining optimization. The need for an overview of modern techniques in machining was carried out, which cut across the application, working principle, advantages, and disadvantages of computer numerical control machining (CNCM), wire electro-discharge machining (WEDM), abrasive water jet machining (AWJM), and electro-discharge machining (EDM). From the study, CNCM is one of the best techniques until now in the machining industry, so the different aspects of CNCM such as the lathe, drilling, grinding, and milling processes were discussed. This will help researchers, students, and manufacturers understand the sustainable aspects of advanced machining processes. Also, from the study, it is seen that the application of cutting fluid is a significant aspect of all machining processes, so this study will recommend that manufacturers employ eco-friendly cutting fluid for sustainable machining. Therefore, chapter two of this book will be on the study of cutting fluid and its applications via different delivery techniques, abrasive water jet machining.

**Keywords** Machining · Computer numerical control · Wire electro-discharge machining · Milling process · Lathe

### 1.1 Introduction of Overview of the Advanced Machining Process

Non-conventional machining techniques are another name for modern machining techniques. These procedures comprise a collection of techniques that use mechanical, electrical, chemical, thermal, or a mix of these energy to remove extra material [1, 2]. The significance of this type of machining process is on the application in the monolithic metals, such as metals and alloys, can be machined using a method that is

well-known and widely used in a variety such as aerospace, biomedical, and automotive industries [3–6]. However, due to the disparity between the chemical and physical properties of the metal matrix and the hard reinforcement, metal matrix composites (MMCs) provide a unique set of difficulties [7]. The current metalworking sector has a number of difficulties, including cost management, product quality enhancement, a shorter preparation time from design to manufacturing, and product finishing [8]. A useful tool for processing sophisticated materials like MMC is non-conventional machining (NCM) [9], Modern machining process cut across Computer Numerical Control Machining, Wire Electro Discharge Machining (WEDM), Abrasive Water Jet Machining (AWJM), Electro Discharge Machining (EDM), Electro Discharge Machining (EDM). This chapter one will give brief over view of this method under types of modern machining operations. The types of advanced machining operations are analysed in the subsections.

## 1.2 Computer Numerical Control Machining

The automated use of a computer to manage machining equipment is known as numerical control. Without a manual intervention directly overseeing the milling cutter [10]. A computer numerical control CNC machine follows coded, programmed commands to process a piece of material in accordance with standards of the manufacturer [11–13]. This Sect. 1.2.1 discusses the working principles of CNC, advantages and disadvantages. Also, types of CNC operation such as milling, lathe, drilling and grinding.

### 1.2.1 Working Principle of CNC Machining Operations

All-automatic CNC machines are available nowadays. They only need digital data with details on the tools and cutting trajectories. Numerous tools are required for design or machining procedures to produce a certain product. Digital tool libraries that are connected to the machine itself can be made by machinists [14].

- (a) The first stage of CNC manufacturing is the component design using CAD software. The 3D model is used to establish the required size and attributes for the finished product.
- (b) Since some of these programs are a part of CAD-CAM packages, the flow can continue in the same programs. Otherwise, CAD models are employed with CAM software.
- (c) If the CAD and CAM systems are integrated into the same item, file conversion is not necessary. The model is ready for the entire production process thanks to CAM (computer-aided manufacturing) software. It first looks for mistakes in the model. The physical portion is then created using a CNC software.

- (d) The program is primarily a set of directives that controls the cutting head during the production process.
- (e) The third stage involves choosing the suitable parameters. These include parameters like voltage, RPMs, and cutting speed. The configuration is influenced by the part's geometry as well as the equipment and tooling that are available.
- (f) The software ultimately determines the nesting. The term “nesting” describes how parts are arranged and oriented in relation to raw materials. The objective is to make the most of the resources.
- (g) From all of this data, M-code and G-code are formed, which the machinery can understand. M-Code versus G-Code is a language used to instruct a machine on how to move is referred to as G-code. It is essentially the geometric code. Cutting head motion and speed are controlled via G-code.
- (h) An industrial computer known as a machine controller is provided the instructions. This then determines how the motors should operate. The path that will be taken is, of course, decided by the motors.
- (i) On the other side, the M-code provides all the information that the G-code omits. It is referred to as machine code or miscellaneous code for this reason.

The instructions in M-code cover topics like changing tools, using coolant, stopping programs, and more. Therefore, while not identical, both are equally vital [15].

### ***1.2.2 Advantages and Disadvantage of CNC***

Table 1.1 shows the advantages and disadvantages of CNC machining operation. It clearly shown that CNC machining is viable and sufficients in manufacturing component.

There are several operating procedures of the CNC during manufacturing process such as, milling, lathe, drilling, grinding and shaping machining process. These processes are the manufacturing powerhouses because they can switch tooling automatically based on the digital instructions.

### ***1.2.3 Milling Machining***

With the use of a spinning cutter that revolves at a very high speed for effective metal removal, milling machines are used to remove metal pieces. Cutting edges on a rotating cutter aid in material cutting. Milling machines have the capacity to accommodate one or more cutters at once. On milling machines, operations can be carried out with a very high degree of accuracy [16]. Milling machines remove metal at a high rate as compared to other metal-removal equipment [1–18]. They are known

**Table 1.1** Advantages and disadvantage of CNC machining processes

| S/<br>No. | Advantages of CNC machining                                                                        | Disadvantage of CNC machining                                                                                                                                                        |
|-----------|----------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1         | The precision and accuracy of machining are very high                                              | Despite costs gradually declining, Machineries are costlier than manually controlled equipment                                                                                       |
| 2         | It takes extremely little time to complete a task                                                  | The CNC machine operator just needs rudimentary training and abilities, which are sufficient to oversee multiple machines. The loss of many traditional talents is indicated by this |
| 3         | Operational safety and there is a reduction in the number of operators needed to operate a machine | CNC machines require minimal operators comparing to machinery that is operated manually. Investment in CNC machines could lead to employment loss                                    |
| 4         | There is no chance for human error                                                                 | In many countries, students and children are not taught how to operate manually controlled lathes and other machinery any more                                                       |
| 5         | Reliable<br>Even extremely complicated designs can be created                                      | The complex skills required by engineers in the past are no longer acquired by students or teachers. Engineering and math expertise are a couple of these                            |
| 6         | Minimum maintenance is necessary                                                                   |                                                                                                                                                                                      |

for their superior precision and superior surface finishing, milling machines can be applied with four different milling techniques, they are:

- (a) Plain milling: This milling procedure, often referred to as surface milling, uses a cutting tool to remove material from the workpiece's surface. The rotation axis in plain milling is perpendicular to the workpiece.
- (b) Face milling: makes use of a rotary axis that is parallel to the surface of the material. To remove material, the cutting or grinding tool is pressed firmly on the workpiece surface.
- (c) Peripheral milling: a machining technique known as peripheral milling involves aligning the milling cutter parallel to the workpiece. To put it another way, the milling cutter is set up so that its sides grind away at the top of the workpiece.
- (d) End milling: A cylindrical cutter used in the end milling process contains several cutting blades on both its periphery and its tip, allowing for both end and peripheral cutting. To lessen the impact that occurs when each flute engages the workpiece, these cutting edges or flutes are typically designed with helical spirals.

In milling machining process there are four major parameters involves in the operation that are very significant, such as spindle speed, radial depth of cut, feed rate and axial depth of cut [19]. These parameters are presented in Fig. 1.1.

This machining parameters can be calculated theatrically using the formula from Eqs. (1.1)–(1.4) for milling process

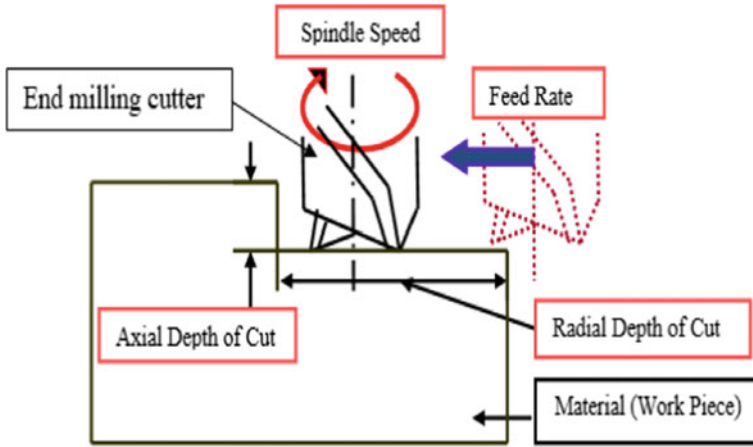


**Fig. 1.1** The four most influential parameters and cutting tools in milling machining

$$\text{Cutting speed } (Cs) = \frac{\pi \times D \times n}{1000} \quad (1.1)$$

$$\text{Spindle speed } (Ss) = Cs \div \pi \div D \times 1000 \quad (1.2)$$

$$\text{Feed rate } (Fr) = Ss \times f \times Z \quad (1.3)$$

$$\text{Depth of cut } (DOC) = \frac{d_1 - d_2}{2} \quad (1.4)$$

where  $Cs$  is cutting speed in m/min,  $Ss$  is spindle speed in  $\text{min}^{-1}$ ,  $D$  is diameter in mm,  $\pi$  is 3.14 in radius,  $z$  is number of flutes,  $ft$  is feed per tooth in mm/tooth, and  $Fr$  is feed rate in mm/min. Also, the  $d_1$  is the workpiece diameter before machining and  $d_2$  is the surface diameter of the machined workpiece.

Due to its extreme versatility, CNC milling machines can be utilized for a wide range of cuts and machining processes. In order to remove material and actualize the design. The cutting tool often moves and rotates while the workpiece generally stays still [20]. Different spindle configurations on CNC milling machines retain and move the workpiece in various ways.

- Vertical milling: To remove material from a still workpiece, a vertically oriented spindle drives a spinning cutting tool up and down. The spindle and table of the turret-style milling machine can move both perpendicularly and parallel to the axis.
- Horizontal milling: When pressing on the workpiece, a spindle with a mounted cutting tool is horizontally orientated. Use of larger and shorter cutting tools allows for deeper, heavier cuts during horizontal milling.



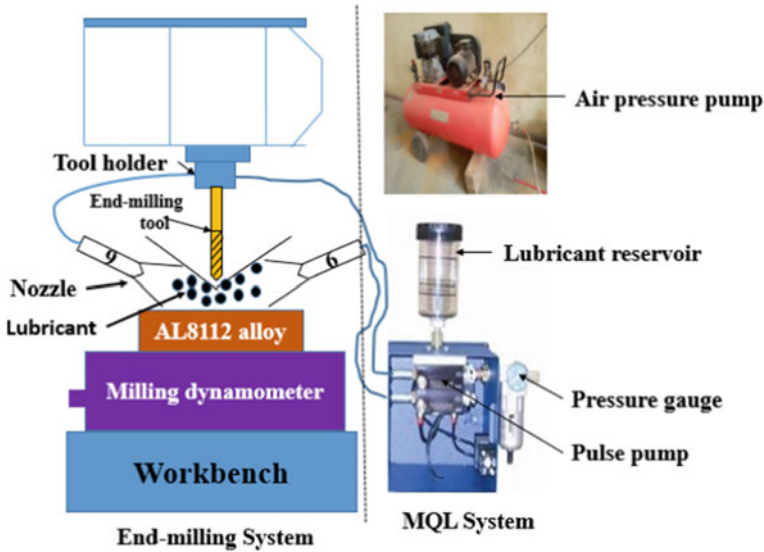


Fig. 1.2 Schematic illustration milling machining and MQL system [21]

- **Multi-axis milling:** CNC mills with 4 and 5 axes enable intricate or difficult machine operations. In addition to rotating on the A and B axes, multi-axis milling machines can also move along the X, Y, and Z axes. This makes it possible to approach the workpiece from any angle, frequently allowing numerous processes at once [21].

A typical illustration of a milling machining process with the minimum quantity lubricant process is presented in Fig. 1.2.

#### 1.2.4 Lathes Machining

A lathe machine removes undesired material from a rotating workpiece in the form of chips by using a tool that may be fed deeply into the work and is traversed through it [22]. One of the most versatile and widely used machine tools in the world. Numerous objects, including nuts, bolts, piston, ram, pump parts, electric motor sleeves, airframe components, rifle barrels, candlesticks, railway spikes, cue sticks, wooden bowls, baseball bats, and crankshafts, can be produced using the lathe machine. There are various types of CNC lathe machining. Different types of CNC lathes can be identified based on the quantity of movement axes [23], and these are:

- 2-axis—can be used for drilling, tapping, facing, and machining of the outer and inner diameters. Adds a live tool system for milling, boring, etc.
- 3-axis—A second tool carrier or turret is frequently added in a 4-axis machine.

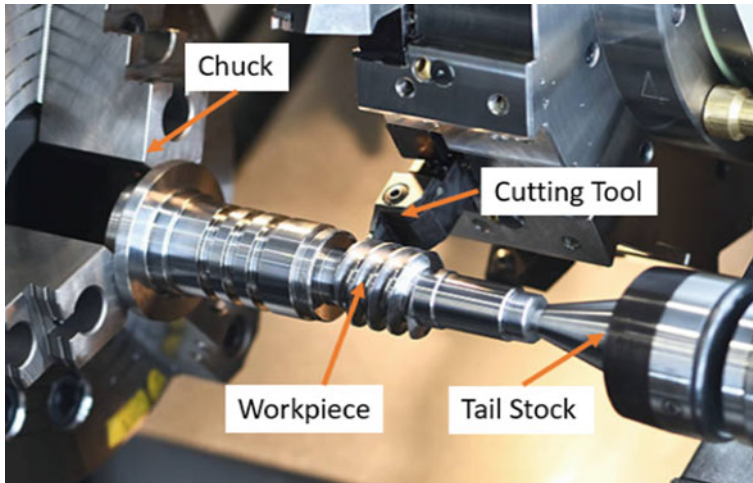


**Fig. 1.3** Illustration of lathe machining process

- (iii) 5 and 6-axis—adds an extra Y axis and, on occasion, a B axis to one or both tool carriers.
- (iv) Multi-Spindle Machines—often known as specialized CNC lathes with more than six axes, are also offered with cutting-edge capabilities and versatility.

Furthermore, there are several methods for lathe machining, but the turning process is the most commonly used method in most industrial manufacturing. The most frequent machining operation on a lathe is turning as shown in Fig. 1.3. During the turning process, a cutting tool removes material from the outside diameter of a spinning object. The main objective of turning is to reduce the workpiece's diameter to a suitable size. There are two categories for turning operations: rough and finish [24].

### ***1.2.5 Grinding Machining***

A grinding wheel is employed in the machining process of grinding to remove material from a workpiece. The workpiece is chopped off by the grinding wheel as it rotates, producing a smooth surface characteristic [25]. In a nutshell, the grinding machine works by feeding the workpiece against a rotating abrasive wheel. The material is removed as a result of the friction that is created between the workpiece and the tool. The following step can be followed to achieve a sustainable grinding process.

- Start by using a fresh brush to clean the machine.

- In the worktable, the workpiece is fixed. The grinding wheel tool is likewise placed in the portion with the tool holders.
- As the machine has not yet begun, we now adjust the tool and workpiece with the aid of the traversing wheel, bring them into contact, and check that there is only a small gap.
- After all, be sure to fill the space between the tool and the workpiece by inspecting the coolant supply nozzle.

Grinding machining has various types for manufacturing mechanical component. The various types of grinding machines [26] are as follows:

- The bench grinder. These grinding devices are mounted to a table or workbench.
- Hand chopper. Additionally, this grinder is mounted to a workbench or table
- Grinder on a platform
- Pedestal Grinder,
- Compact Grinder,
- Adjustable Grinder,
- Precision Grinder

These are a few examples of the different types of grinding machines, Fig. 1.4 illustrate grinding machining process.

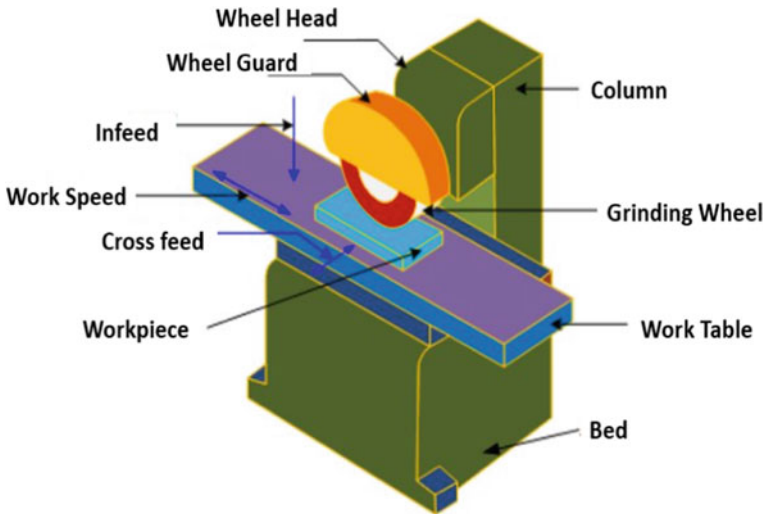


**Fig. 1.4** Illustration of grinding machining process

### 1.2.6 Drilling Machining

The drilling machine, commonly referred to as the drill press, is a cutting procedure that creates circular holes in solid materials such as metal, plastic, wood, rocks, etc. by using drill bits of various diameters. The multi-point drill bit spins with the cutting tool [27]. The drill is firmly pressed on the workpiece as it turns at speeds between hundreds and thousands of revolutions per minute and illustration of drilling machining process is presented in Fig. 1.5. The cutting edge removes chips from the workpiece by cutting them off with the given force. Small hand-held power drills, bench-mounted models, and lastly floor-mounted models are all distinct sizes and types of drilling machines. They are used to do tasks including tapping both large and tiny holes as well as countersinking, counter boring, reaming, and spot facing. The principles and drill bits used to accomplish the activities vary greatly since drilling machines are capable of performing them. To accomplish different hole sizes on the tasks outlined above, drilling machines are utilized in conjunction with drill bits that have sharp cutting edges. To get a good hole, the operator needs to know how to set up the work, adjust speed and feed, as well as coolant.



**Fig. 1.5** Illustration of drilling machining process

Maintenance and Safety drilling process is very important in machining process. The following can be applied to maintain and provide safety are:

- (a) Lubricating the interface between the drill bit and the workpiece as it is being used is one of the essential maintenance procedures for a drilling machine. By doing so, the temperature and friction produced by the moving parts are reduced. Some manufacturers include instructions for the appropriate cleaning and lubrication techniques [28, 29].
- (b) To prevent damage to the moving parts, it is expected that the drilling machine will be cleaned up after each usage and cleared of chips.
- (c) To prevent harming the precision fit, make sure the spindles and sleeves are free of grit. Oil should be sparingly covered on the surfaces of the machine parts, particularly the bed, to avoid rust.

There are various drilling machines used in manufacturing include the following:

- Portable Drilling
- Sensitive Drilling
- Standing Drilling
- Radial Drilling
- Gang Drilling
- Multi-Spindle Drilling Equipment
- Machine for Deep Mole Drilling.

In summary of the different machining method of CNC lies in the way and method of the machine and the component spin is the primary. For example, milling machines entail revolving a multi-bladed or tipped cutting tool against a fixed workpiece, while lathes involve rotating a workpiece against a single-bladed cutting tool.

### **1.3 Wire Electro Discharge Machining (WEDM)**

Wire electro discharge machining is an unconventional machining technique that is frequently applied to hard materials. This technique is well-liked since EDM can work with all materials, regardless of how hard they are. Modern engineering materials used in harsh environments are frequently molded or created via the EDM technique [30].

#### ***1.3.1 Working Principle of Wire Electro Discharge Machining Operations***

- (a) The EDM wire-cut machine is a type of electro discharge machining in which an electrode is made of a thin electrically conducting wire, typically brass.

- (b) The workpiece and the wire (electrode) in the EDM-wire cut machine are both connected to the terminals of the DC pulse generator, and they are both submerged in a dielectric fluid and separated by a little gap (spark-gap). The EDM-wire cut machine's dielectric fluid is deionized water.
- (c) The metallic wire used in the EDM-wire cut machine moves slowly and has a variable speed. The top and bottom diamond wire guides allow the metallic wire to move continuously from the top spool (roller) to the bottom spool. Additionally, a tensioner is included to guarantee proper tension in the moving wire.
- (d) The deionized water becomes conductive (ionized) as the EDM wire is moved along the specified path towards the workpiece, enabling spark discharge to happen at a specific spark gap and discharge voltage between the wire and the workpiece surface.
- (e) The DC pulse current is briefly disrupted, and continuously flowing deionized water from the EDM-wire cut machine flushes away the small chips, cools the workpiece, and fills the spark-gap area with new deionized water.
- (f) The material from the surface of the workpiece is melted and annihilated into tiny chips due to the intense electro-thermal heat produced by the spark discharge.
- (g) The EDM-wire cut machine cuts material between the moving wire and the workpiece surface using continuous spark discharges. The sparks have a square wave, and the CNC controls the spark-on and spark-off periods.
- (h) Since the wire weakens after spark discharge, the wire (electrode) in the EDM-wire cut machine is only used once. The used wire is then spooled at the bottom and cut into little pieces for scrap.
- (i) Any complex profile or shape can be programmed and cut using the EDM-wire cut machine, and the profile can run the entire thickness of the workpiece. The movement of the wire is controlled by the CNC program. And cannot machine blind cavities with an EDM-wire cut machine; it is only used to cut through cavities.
- (j) The EDM-wire cut machine's top and bottom wire guides are crucial for correct wire movement and, consequently, accurate wire cutting;
- (k) The wire must be threaded through the through-hole on the workpiece of the EDM-wire cut machine before cutting can begin. Threading is the act of placing the wire through the hole from the top guide to the bottom guide. Either an automatic threading system is available on the EDM-wire cut machine, or threading must be done manually [31].
- (l) During the EDM-wire cut procedure, a sensor will be used to detect wire breakage or running out of wire (Fig. 1.6).

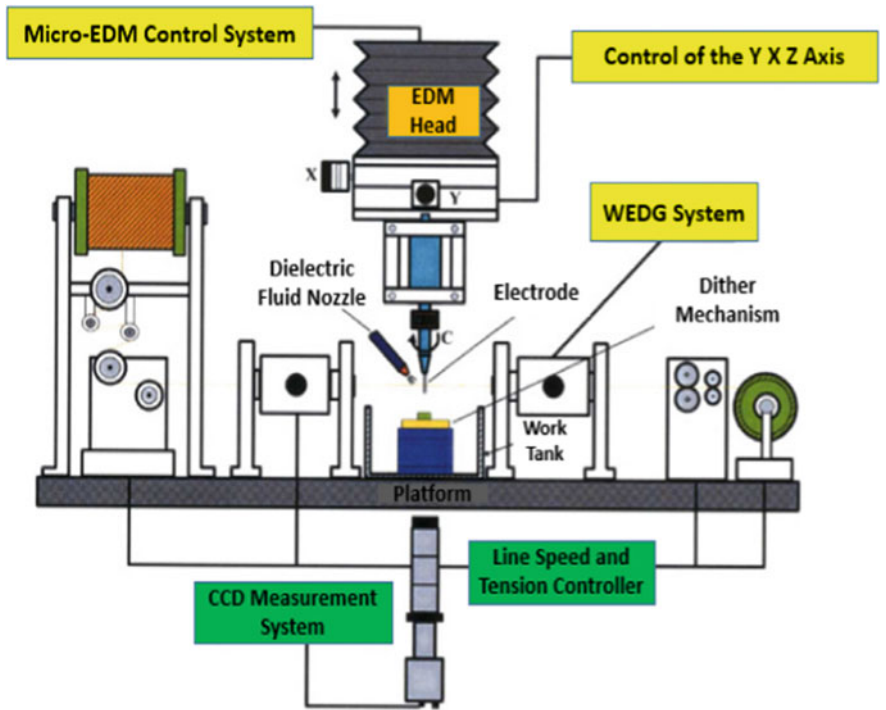


**Fig. 1.6** Shows the setup for a method that combines coax cable grinding and micro-electrical discharge machining

**1.3.2 Advantages and Disadvantage of WEDM**

Table 1.2 depict the several advantages and disadvantages of the AWJM, this tabulated analysis is to give a clear picture of the benefit and limitation of the wire electro discharge machining operations.

**Table 1.2** Advantages and disadvantages of WEDM machining operations

| S/ No. | Advantages of WEDM machining                                                                                                                                   | Disadvantage of WEDM machining                                                    |
|--------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|
| 1      | Even on small workpieces, wire EDM can be used to cut challenging profiles with precise tolerances, which is not achievable with traditional machining methods | Only materials that are electrically conductive can be cut using EDM-wire cutting |

(continued)

**Table 1.2** (continued)

| S/<br>No. | Advantages of WEDM machining                                                                                                                                                                          | Disadvantage of WEDM machining                                                                                                                                                                                                                         |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2         | The wire EDM machine works equally well to cut brittle materials like graphite, strong materials like carbide and Inconel, and soft metals like brass and copper                                      | EDM-wire cutting's low cutting speed or material removal rate makes it uneconomical; as a result, its employment is restricted to the machining of extremely hard materials or challenging profiles that cannot be achieved with conventional machines |
| 3         | Sharp corners can be cut with a wire cut machine (with negligible radius). And EDM wire cutting has a problem with wire breaking, which results in some time loss and a small amount of wire material | Since the wire (electrode) in EDM-wire cutting can only be used once, the cost is increased                                                                                                                                                            |
| 4         | Burrs and tool marks are not left after an EDM-wire cut operation                                                                                                                                     | EDM-wire cutting may leave a recast layer on the surface of the workpiece that requires a follow-up procedure like polishing to remove                                                                                                                 |
| 5         | Since the electrode in the EDM-wire cut machine is only a simple wire, the tool's cost is extremely low because it doesn't need to be manufactured                                                    |                                                                                                                                                                                                                                                        |

## 1.4 Laser Beam Machining (LBM)

The machining procedure known as “laser beam machining” removes material from the surface of the workpiece by heating it up with a laser. It is a specific kind of non-traditional machining method. The laser used in laser beam machining is created by a ruby crystal [32]. When the surface of the workpiece is exposed to the laser. The material surface is then melted and turned to vapor by the heat energy this laser produces. Use of laser beam machining. Currently, it has been determined that the laser machining process is only appropriate in extraordinary circumstances, such as when creating extremely small holes and cutting intricate features in thin, hard materials like ceramics. In partial cutting or engraving, it is also utilized. Other uses include resistor trimming, blanking, and steel metal trimming. Despite the fact that LBM is not a mass material removal technique, it can be used to produce microparts in large quantities.

### 1.4.1 The Operation of Laser Beam Machining

Let's assume that the atoms in a material are in their ground state, like those in a rod of ruby crystal. The atoms in this medium absorb radiation when a quantum of energy from a light source is made to fall on them [33]. As a result, an electron from



one of the medium's atoms jumps to a higher energy level. The following procedure are employed:

- (a) The workpiece that has to be cut is placed on the metal work table during operation (which is resistant to being cut by laser beam).
- (b) While manually adjusting the control panel, the operator moves the laser head over the workpiece and visually examines the cut.
- (c) The associated machine, which was built to duplicate the master drawing or actual profile and was set up on a nearby bench, provided the actual profile.
- (d) The power output of the laser in brief bursts is almost 10 kW/cm of the beam cross-section.
- (e) A laser beam can be focused in a brief burst to a power density of 100,000 kW/cm and energy of several joules lasting for a minute by focusing on a point that is 1/100 of a square mm in size.
- (f) A laser beam can be focused in a brief flash to a power density of 100,000 kW/cm and energy of many joules lasting for a minute fraction of a second by focusing it on a point that is 1/100 of a square mm in size.
- (g) Short pulses with, let's say, 100 J of energy are needed for machining.
- (h) Therefore, the laser may generate enough heat to melt and evaporate any known substance (Fig. 1.7).

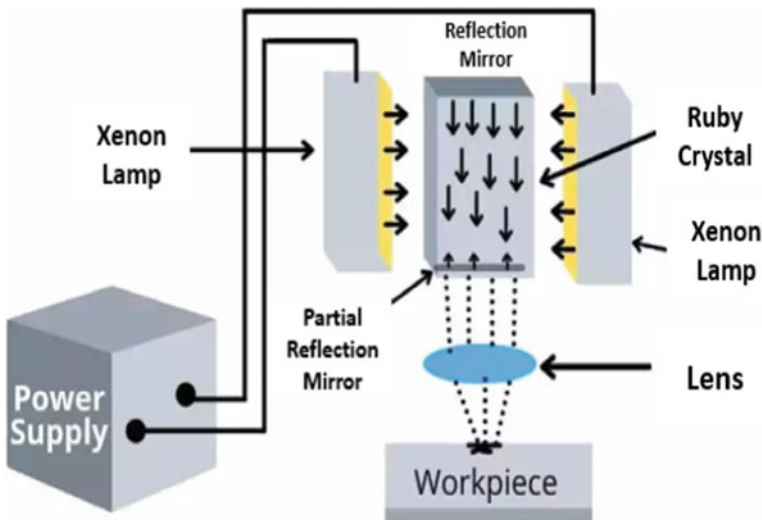


**Fig. 1.7** Illustration of the setup of the laser beam machining process

**1.4.2 Advantages and Disadvantage of Laser Beam Manufacturing**

The following are some of the main benefits and limitation of laser beam machining: The laser’s inability to cut metals with high heat conductivity or high reflectivity, such as aluminum, copper, and their alloys, is one of its fundamental drawbacks [34]. The procedure also has the following drawbacks presented in Table 1.3.

**1.5 Abrasive Water Jet Machining (AWJM)**

A high-velocity water jet powered by water is utilized in the unconventional machining method known as “water jet machining” (WJM) to cut the material. Abrasive Water Jet Machining (AWJM) is the name of the technique in which abrasive particles are added to a rising water jet to enhance trimming and machining [35]. High air velocity (between 180 and 200 m per second) propels the particulate. Because the surface fracture occurs more quickly when an abrasive jet strikes brittle materials like glass and ceramic, the impact of waterjet is more noticeable when cutting those materials. It is additionally more effective when cutting and machining components like tungsten and tungsten-carbide, which are challenging to machine using conventional techniques. There are two categories of water jets are involved kind and type suspended, the working principle during machining operation is presented in Fig. 1.8.

**Table 1.3** Advantages and disadvantage of LBM machining operations

| S/<br>No. | Advantages of laser beam machining                                                   | Disadvantage of laser beam machining                                          |
|-----------|--------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| 1         | The tool and the workpiece are in close proximity                                    | Its overall effectiveness (10–15%) is rather modest                           |
| 2         | Any material, including nonmetals, can be machined                                   | It has a remarkably low rate of material removal                              |
| 3         | There is a possibility of drilling and cutting in inaccessible locations             | The technique is just for thin sheets                                         |
| 4         | Because of the collimated beam, the heat-affected zone is quite tiny                 | Not all of the machined holes are square and straight                         |
| 5         | No tool wear exists                                                                  | The short lifespan of the lash lamp makes the laser system rather ineffective |
| 6         | It is possible to machine very tiny holes and soft materials like rubber and plastic | It is expensive                                                               |

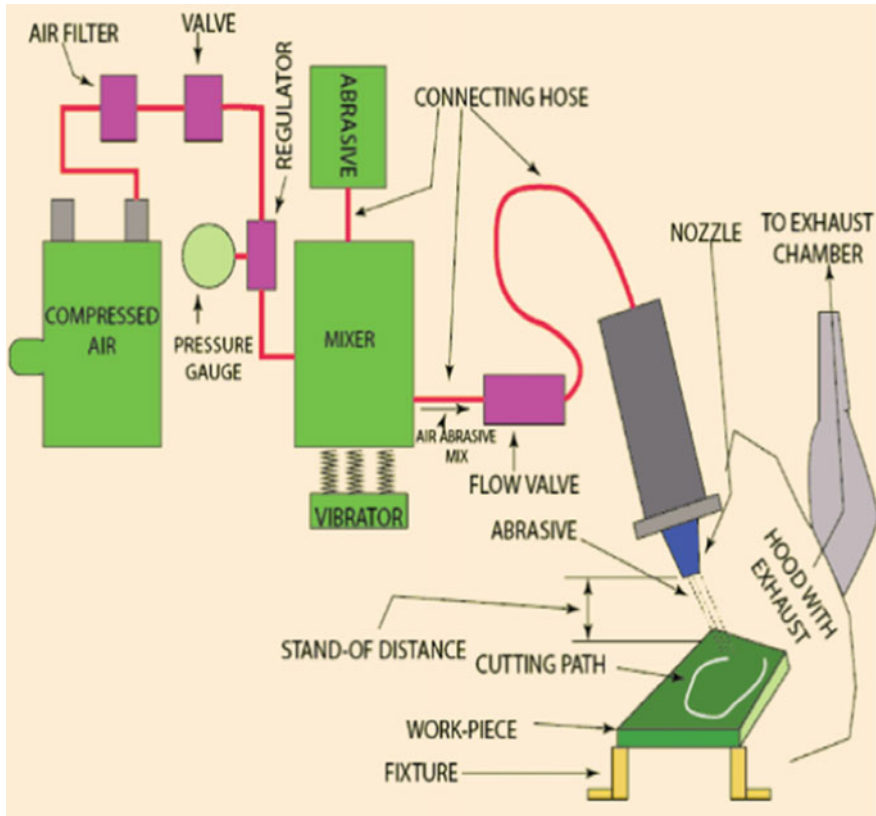


**Fig. 1.8** Illustration of the abrasive jet machining in operations

### **1.5.1 Working Principle of Abrasive Jet Machining Operations**

- (a) The Water Jet Machine (WJM) employs a high-pressure water stream that has been transformed into a high-velocity water jet as a cutting tool to machine and cut the materials; the water jet leaves the nozzle at an extremely high velocity and impacts the point of cutting on the work-piece.
- (b) The high-velocity water jet from the WJM strikes the workpiece and causes a crack in the material, which causes material failure and material particles to break off from the workpiece surface. In the WJM, the metal continues to fail, crack, and separate from the workpiece while being cut to the appropriate profile.
- (c) The WJM process involves high pressure water that enters the nozzle and high velocity water that exits the nozzle aperture (0.2–0.5 mm) at 800–1000 m per

second. This is the recommended approach for cutting hard, brittle, and rubber-like materials. The WJM process can machine and cut any material, from rubber to metals.

- (d) A water mist may be formed around the cutting region, and the tools in this area need to be covered. The water jet of the WJM removes the metal particles (chips) and sends them out through the drain system for further filtering and recycling.
- (e) Abrasive water jet (AWJ) cutting is the technique of adding particulate to a rising water spray to increase the cutting efficiency of the WJM process is called AWJM [36].

### 1.5.2 Advantages and Disadvantage of AWJM

The benefits of the WJM and AWJM processes are listed in Table 1.4.

**Table 1.4** Advantages and disadvantage of AWJM machining operations

| S/<br>No. | Advantages of AWJM machining                                                                                                                                                         | Disadvantage of AWJM machining                                                                                                                                                                              |
|-----------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1         | The WJM or AWJM technique can safely cut materials like tool steels where the extra heat produced during the cutting modifies the material's properties                              | Materials that are damaged or deteriorate when exposed to water cannot be cut with AWJM or WJM                                                                                                              |
| 2         | A heat-affected zone is not created by WJM or AWJM (HAZ).and Materials cut with a WJM or AWJM typically don't need extra steps like deburring                                        | Surface finish suffers when cutting at higher speeds                                                                                                                                                        |
| 3         | Reduced material waste as a result of narrower cutting (kerf)                                                                                                                        | As they cut the material, AWJM and WJM cause cracks to form and spread (due to the impact of a high-velocity jet of water and abrasive)                                                                     |
| 4         | Since there is no tool wear, there is no need to re-sharpen the tool                                                                                                                 | The AWJM/WJM equipment has a higher initial cost, therefore the operators must carefully consider its utility and returns before making a choice                                                            |
| 5         | Cutting forces produced by the WJM and AWJM processes are minimal and the amount of tooling needed is minimal. Ra (surface finish) values between 150 and 250 microns are achievable | Brittle materials should be cut with particular care and attention since the cracks may extend beyond the cutting path                                                                                      |
| 6         | AWJM and WJM can cut brittle and hard materials like porcelain as well as soft materials like rubber and metals                                                                      | Given that it cuts taper; the waterjet method is inaccurate for cutting thicker materials. Because of this, waterjet cutters are often only able to cut materials and sheet metals up to a 4-inch thickness |

(continued)

**Table 1.4** (continued)

| S/<br>No. | Advantages of AWJM machining                                                                                            | Disadvantage of AWJM machining                                                                              |
|-----------|-------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|
| 7         | For cutting reflective metals like copper and aluminum, which are challenging for lasers, the AWJM technique is perfect | The WJM/use AWJM’s of high pressure and high velocity water raises safety issues as well as the noise level |

**1.6 Electro Discharge Machining (EDM)**

EDM is a non-traditional machining method that is specifically intended to cut metals that cannot be cut using standard techniques. Only materials that are electrically conductive can be used for EDM. Electrical Discharge Machining, also known as EDM, can be used to create delicate holes and complicated curves that are challenging to make with a grinder or other tools [37]. EDM cutting tools can be manufactured of titanium carbide, Inconel, toughened too metal, or kovar. Another name for EDM is “Spark Machining.” This name was given because the metal is removed using a quick succession of recurrent electrical discharges. These electrical discharges use the work piece and an electrode as their conducting paths. A fluid that is always flowing is used to flush away the minimal amount of removed material. The workpiece is given the desired shape through repeated discharge. Ram EDM and Wire EDM are the two main EDM techniques. The electrodes are where these two methods differ most from one another. Graphite electrodes are utilized in ram EDM. Traditional techniques are used to mill these electrodes, and a unique shape is created that connects to the power supply. Additionally, a ram is linked to the electrodes. The electrodes are introduced into the workpiece once all the setups are complete. The entire procedure is carried out in a fluid bath that is submerged. The electrode in wire electrode manufacturing is a thin wire. Brass wires that have undergone special processing are utilized to feed the substance. The workpiece is sliced using electrical discharges to achieve the required shape. Typically, wire EDM is carried out in a water bath. Figure 1.9 present a schematic illustration of an EDM.

Principle: The fundamental tenet of electrical discharge machining is the removal of metal via spark erosion. EDM spark erosion is the same as an electric spark, both of which leave a small hole in the metal they impact [38]. As a result of the spark created by this action, heat is created, which erodes and evaporates metal. Both the work piece and the tool used in this machining technique must be made of conductive material.

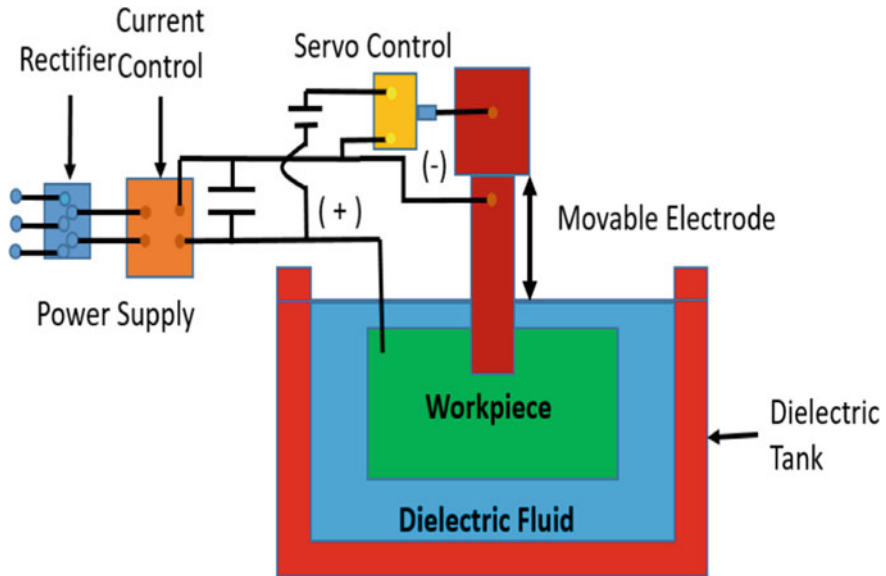


**Fig. 1.9** Schematic illustration of an EDM during operation

### ***1.6.1 Working Principles of Electrical Discharge Machining***

The work piece in this procedure needs to have good electrical conductivity. This technique can only be used to machine electric conductive materials. The following is how EDM functions.

- (a) First, dielectric fluid is applied to both the work piece and the tool. The dielectric fluid aids in arc discharge management. Additionally, this clears the work cavity of any dangling tools and material from the work piece.
- (b) The work piece and the tool are separated by a very small distance thanks to a servomechanism. In order for an arc to form properly, this spacing is ideal. It is comparable to the width of a human hair.
- (c) The tool is made to resemble the work piece's opposite shape.
- (d) A spark is created between the tool and work piece by a high frequency current applied to an electrode. This spark produces a lot of energy in the work cavity.
- (e) Due to erosion and evaporate ion, the metal was taken out of the work piece.
- (f) To avoid them forming a bridge that would create a short circuit, the chips or suspended particles between the tool and work piece should be removed. Dielectric fluid is continuously supplied to accomplish this.
- (g) Due to overcut, the EDM creates a cavity that is slightly larger than the electrode [39].

**Table 1.5** Advantages and disadvantage of EDM machining operations

| S/<br>No. | Advantages of EDM                                                                                                                                                                      | Disadvantage of EDM                                                                                                                                                               |
|-----------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1         | Hardened dies can be machined and Replicating intricate shapes is possible                                                                                                             | In comparison to conventional machining, the power needed for machining is significantly higher. ( $120 \text{ J/mm}^2$ ) that is it consume more energy during machining process |
| 2         | Harder materials that are utilized for molding and other non-conventional machining techniques like forging and press tools, like steel alloys or tungsten carbides, can be replicated | The steel workpieces, a thin coating typically ranging from 0.01 to 0.10 mm thick and containing 4% carbon may be deposited                                                       |
| 3         | Workpieces created using EDM feature micro-craters that may efficiently hold lubricants, wear-resistant surfaces can be created                                                        | Surface cracking is a possibility when materials fragile at room temperature                                                                                                      |
| 4         | It is possible to accurately drill very small holes and tThe precision is quite high. It is possible to attain a 0.005 mm tolerance                                                    | The Material Removal Rate (MRR) is just $75 \text{ mm}^3/\text{sec}$ , which is quite low                                                                                         |
| 5         | The tool and workpiece avoid making physical touch with one another. Other than blasting pressure, no cutting force is applied                                                         | When the microstructures are deformed, etching often follows                                                                                                                      |
| 6         | Therefore, delicate tasks and cylinders can be machined without suffering any harm Compared to the standard machining method, harder metals can be processed relatively quickly        | In EDM, sharp corners are challenging to reproduce                                                                                                                                |

### 1.6.2 Advantages and Disadvantage of EDM

The EDM techniques has been discusses extensively in this chapter, therefore, the advantages and disadvantages of this techniques are depicted in Table 1.5.

## 1.7 Conclusion

Advanced machining processes such as computer numerical control machining (CNCM), wire electro discharge machining (WEDM), abrasive water jet machining (AWJM), electro-discharge machining (EDM), and electro-discharge machining (EDM) are introduced in chapter one of this book. The chapters discuss their working principles, advantages, and disadvantages as they relate to machining operations. From the analysis carried out on the different advanced machining processes, it can be seen that CNCM is viable for the production of different mechanical components

and is one of the major processes currently employed by manufacturing companies. Therefore, this book is primarily focused on the computer numerical control optimization process. The chapter discusses the different types of CNC machining processes, such as lathe, milling, drilling, and grinding; however, from the application of these methods, milling machining processes have wider operation techniques.

From the working principles of the various types of advanced machining, it is stated that there is significance in the application of cutting fluid for the safety of the machining process. Therefore, Chap. 2 of this book will discuss the implementation of cutting fluid and the different techniques of lubrication delivery systems.

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## Chapter 2

# Cutting Fluid and Its Application with Different Delivering Machining Techniques



**Abstract** Cutting fluid is a major aspect of the machining process when machining metals with material adhesion challenges, as the fluid assists in the flushing of the chips from the cutting region and reduces the temperature generation and friction during the process. This chapter focuses on the cutting fluid and its application with various delivery mechanisms for machining. Because the quality of the cutting fluid applied at the cutting region is what drives the current trend in sustainable machining processes, the classifications of cutting fluid—straight machining oils, soluble oils, semi-synthetic cutting fluids, and synthetic fluids—are covered in this chapter. Also, the chapter analyzed the six various machining lubrication supply methods, including the solid lubrication process, flood cooling (a traditional process), cryogenic cooling, high pressure cooling, and compressed air vapour gas (CAVG) as coolant. The advantages and disadvantages of the lubricant delivery systems were carried out to further bring out the sustainability factors of the techniques in the manufacturing process. The findings show that the MQL is a sustainable and efficient process for machining, and the study recommended that the trend of producing a hybrid delivery system that can cryogenically MQL-deliver with high pressure continue.

**Keywords** Cutting fluid · Cryogenic cooling · CAVG · Machining · MQL · Machining optimization

## 2.1 Introduction

A cutting lubricant is one of the essential parameters used in the manufacturing industry; the method has been in use for decades [1–3]. The primary reasons for adopting cutting oil in machining operations are to enhance the performance of the machining operations, reduce thermal deformations of working materials, help flush the chips away from the cutting region, and help reduce surface roughness, which in return will minimize the wear rate of the materials, protect and enhance the cutting tool life, reduce cutting force, friction, and vibration, and increase the rate

of material removal [4–6]. Cutting lubricants employed in machining have different classifications, including straight machining oils, soluble oils, semi-synthetic cutting fluids, and synthetic fluids [6].

- (i) **Straight machining oils** are non-emulsifiable and are used in machining processes without dilution with water or any other solvent. The machinist applied straight oil in its original state without mixing the oil with any chemical substance. Manufacturers obtain straight oils from animal fat, vegetable, petroleum, or mineral sources and typically include high-pressure additives such as sulphur and chlorine [8]. They have the advantages of excellent lubricity, good resistance to corrosion, and good constancy. Straight-machining oil helps in reducing cutting force and friction during the machining operation. The primary issue with straight-machining oil is its insufficient cooling property coupled with its inability to function during the machining process without producing smoke. Straight oil cannot dissipate heat efficiently in the cutting region during machining [9].
- (ii) **Soluble oils** are types of cutting fluids widely used in machining operations. They have little or no odor and are designed as lubricants and coolants for metal cutting processes. Industries develop soluble oils from hydro-treated mineral oils containing a mixture of inhibitors and emulsifiers [10]. From the literature, soluble oils have been established as machining lubricants with excellent cooling effects. Therefore, soluble oil is a suitable replacement for straight oil during a machining operation. It can be applied to metals with differing compositions. It is friendly to the environment, reduces thermal failure, accommodates water rigidity, and sustains pH stability between 9 and 10. It is worthy of note that including water in the mixture will increase the corrosion rate of the cutting fluid on the metal during machining and after machining [11].
- (iii) **Synthetic fluids** are man-made cutting fluids that are extracted from metallic and non-metallic compounds. Manufacturers produce this lubricant from crude oil and synthetic raw materials. Synthetic cutting fluid is a replacement for refined petroleum cutting oil [12]. The advantages of synthetic cutting fluid are enormous. They have excellent cooling effects, good lubricating properties, high corrosion resistance, safe handling, hard water stability, neatness, ease of maintenance, and are effective in high-temperature machining operations. The major disadvantages are that they are relatively costly, toxic, and easily polluted by external lubricants [13].
- (iv) **Semi-synthetic cutting fluids** are a combination of synthetic metal cutting liquid and soluble oil. The fat content in cutting solutions and synthetic liquids is minimal, at around 30% [14]. Semi-synthetic fluids combine the physical and chemical lubricity, cleanliness, and cooling characteristics of soluble oil and synthetic fluid, and they form a translucent liquid when mixed with water. They have excellent stability as lubricants and have cooling properties. The major disadvantage is that semi-synthetic oil has a high water content, which will aid in corrosion because of surface interactions [15].

The primary purpose of cutting fluids includes the following aspects: flushing of the chips, cooling, lubrication, and corrosion protection. The cooling effect of cutting fluids is to remove the excessive heat generated during the machining operation. Much heat is generated during the metal-to-metal machining process due to deformation and frictional sliding. This high heat generated can shorten the cutting tool life, affect production time, increase friction, increase vibrations, and cause unattractive surface quality [14].

Lubricants are employed in machining operations to reduce the friction generated by the contact between metal to metal during cutting or shaping operations. Oils also reduce the cutting force, moving unwanted chips from the cutting zone. A suitable lubricant should possess a useful viscosity index, excellent thermal stability, high boiling point, and low freezing point for the fluid to withstand high temperature [16]. An adequate cutting fluid provides excellent corrosion protection for the cutting tool and the workpieces. It also reduces rust during operation, minimises wear rate, and improves the life span of the cutting tool and workpiece alongside other machining parameters, during its application at the machining region [17]. Also, the flushing of the chips from the machining region needs the implementation of cutting fluids during machining without damaging the surface of the workpiece. This removal of the chips from the cutting region assists in preventing the occurrence of chips discontinuity that can lead to high vibration and reduce the cutting tool life [18]. The characteristics of cutting liquids include: good thermal conductivity for heat reduction, high-quality lubrication, high flash point to avoid fire threat, oxidation stability, high corrosion resistance, the cutting fluid must not be quickly rancid, cutting fluid must be free from unpleasant odour during machining operations, should be environmentally friendly to both the working materials and the operators, suitable viscosity and the ability to reduce friction, must be able to reduce heat generation at the cutting zone, the ability to recycle and should be economically viable, to lengthen the lifespan of the cutting tool, reduce workpiece thermal deformation and to enhance surface finishing.

Cutting fluid and machining parameter characteristics are the essential aspect of machining operation that either strengthen the mechanical component or cause it to fail during the process [19–21]. According to Joshua et al. [22], there is a need to develop and optimise a biodegradable cutting fluid for the machining process, to enable the manufacturers to produce quality mechanical components with a good quality machined surface. This biodegradable cutting fluid will assist in reducing the energy consumption, wear rate, and corrosion on the cutting tool and the workpiece material during operation. Osama et al. [23] in their review work, recommended the use of corrosion-free cutting fluid in machining operations. Phuoc et al. [24] studied the viscosity and thermal conductivity of nano-lubricant, and the result shows that nanoparticles have good thermal conductivity. The authors concluded and recommended that nano-lubricants should be efficiently-utilised in machining operation. Pervaiz et al. [25] affirm that cutting fluid is one of the parameters that can lead to good quality machining.

Sani et al. [26] concluded that the thermo-mechanical loads in machining operations have significant effects on the surface finish of the material and the cutting tool.

The result proved that the thermo-mechanical load leads to high surface roughness and breakage of the cutting tool during the machining. The authors also recommended that the use of vegetable oil is highly needed. This is due to the significant effects vegetable oil have on the microstructural characteristics of the metals after machining. Furthermore, when vegetable oil is disposed of, it is eco-friendly without causing any environmental pollutions. The authors carried out an experimental study on *Jatropha*-based cutting fluid and the synthetic Esther-based MQL machining fluid. The result shows that this vegetable oil-based machining fluid performs excellently in reducing friction between the cutting tool and the working materials during operations. Finally, the authors also recommended that the additions of nanoparticles in the base vegetable oil should be utilised to improve the thermal resistance of the vegetable oil in machining operations. According to Okonkwo et al. [27], the study of machining parameters in end milling, turning, and grinding cannot be overemphasised. These machining parameters, if not adequately studied before any experimental analysis, can lead to vibrations and friction that can damage the workpiece. Nwoke et al. [28] carried out a study on vibration analysis and discovered that the machining parameters have much influence on CNC machining. Onoroh et al. [29] studied the effects of machining parameters on the cutting tool. From the conclusion of the study, the authors stated that machining parameters could easily damage or reduce the tool life during the machining process. The authors also recommended that subsequent machining operations should involve an eco-friendly lubricant to minimise the vibration occurrences during machining. However, apart eco-friendly lubricant, the method of lubrication delivery still has significant effects in the manufacturing process, which is needed to be discussed in the Sect. 2.2 delivery techniques of machining process.

## 2.2 Lubricant Delivery Techniques for Machining Operations

The movement of globalization has made it possible for most nations to produce things. As a result of increased rivalry among manufacturing firms, the quality of the items produced has varied [30]. Therefore, each manufacturing industry want to produce quality product at low cost, reduce material waist, and increase machining accuracy. In order to achieve this desire and to overcome the challenges of vibration, friction, rough surface, high cutting force that led to high energy consumption have led to the development of different techniques of fluid delivery in machining operations [31]. This section of the chapter two discusses the application of different delivery system of fluid in machining process such as minimum quality lubrication, CAVG cooling, high pressure cooling, Compressed Air Vapour Gas as Coolant (CAVG), Flood cooling (Conventional process), cryogenic cooling, and solid lubrication process. These different machining techniques are thus adopted to obtain good quality products at a low cost as illustrated in Fig. 2.1.

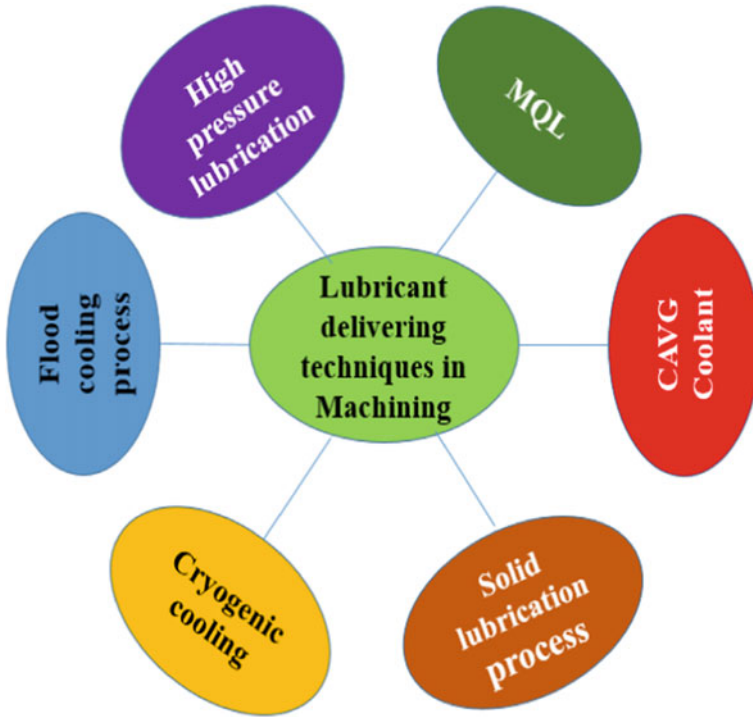


**Fig. 2.1** Lubricant delivery techniques in manufacturing

### ***2.2.1 Flood Cooling Techniques Machining Operations***

Various techniques can administer the lubrication process, and the most well-known type is flood cooling. This strategy provides a continuous lubricant flow to the tool work area. It requires a few apparatuses in the framework, primarily filters, a recirculation setup, nozzles, pipes, and the lubricant reservoir [7].

Flood cooling, which is best represented as a continuous stream of a controlled amount of coolant, evacuates chips through a blushing activity [32]. This technique is more often than not a yardstick for various experiments because of its extensive use in regular machining operations. Unfortunately, it is inadequate in a couple of instances. Flood cooling does not depend on the precise amount; it is applied straight to the cutting region. In some extraordinary cases, where titanium alloy is used, the chip blocks the coolant or lubricant from being administered to the area between the cutting tool and the workpiece. Figure 2.2 shows the typical flood cooling process in machining. Along these lines, the cutting edge encounters a substantial thermal load, resulting in reduced tool life [33].

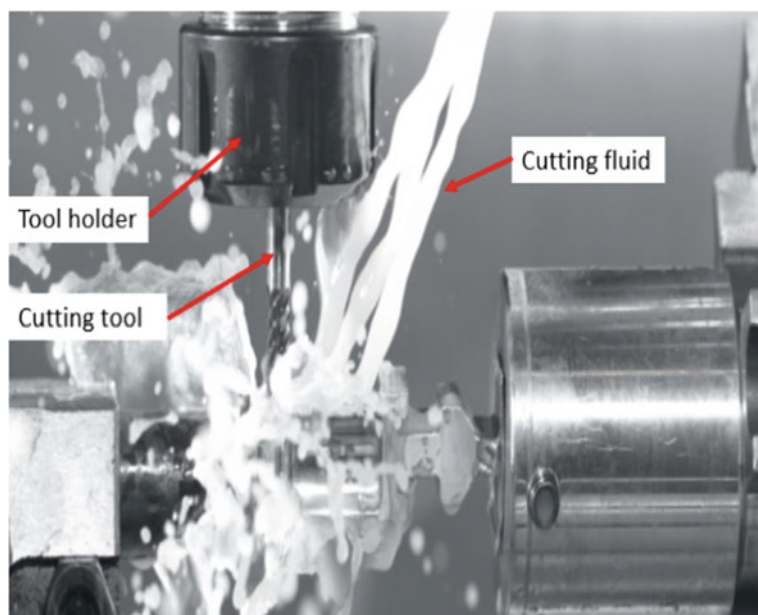


**Fig. 2.2** Illustration of flood cooling process during machining operations

### ***2.2.2 Solid Coolants/Lubricants Operation***

Solid lubricants and coolants are elements in the solid state, for example, graphite, carbon nanotubes, diamond, molybdenum disulfide, and tungsten disulfide. They have uniform heat distribution, high conductivity, and perform better than conventional cutting liquids. In milling or lathe machining that works unevenly under high pressure and high machining speed, solid coolants or lubricants should be implemented for better performance [34].

Solid lubricants are free of the history of pathogens and don't provide any health risks to workers as a result. They are also easily accessible. A few illustrations are given to support the use of solid lubricants in machining. When grinding moderate and hard materials, lubricating like graphite and calcium fluoride ( $\text{CaF}_2$ ) are used in a variety of ways. Use techniques include supplying fine powder at the grinding zone, blending it with paraffin, and supplying it there in paste form [35].

### ***2.2.3 Cryogenic Cooling in Machining Operation***

Cryogenic machining (using either  $\text{CO}_2$  snow or  $\text{LN}_2$ , at  $85^\circ\text{C}$  and  $195.8^\circ\text{C}$ , respectively) is considered lethal-free and ecologically friendly when contrasted to traditional metalworking liquids [36]. Additionally, it has been demonstrated



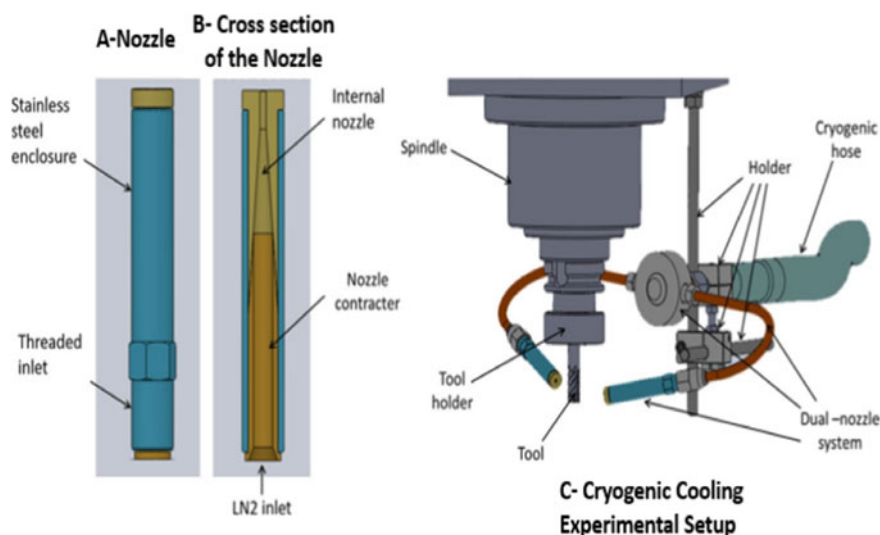


**Fig. 2.3** Cryogenic cooling method for machining

that cryogenic chilling with LN<sub>2</sub> increases tool life and creates exceptional surface finish characteristics, such as residual compressive stresses, extremely hard nano-crystalline outer layer, and increased rust resistance [37]. Figure 2.3 illustrates cryogenic machining setup operations. The advantages of machining under a cryogenic condition when contrasted with customary cutting fluid, according to Aggarwal et al. [38], are as follows: Cryogenic cooling is a nature-friendly and clean innovation compared with traditional coolants; it is harmless and stable; it increases tool life and decreases tool wear primarily because of the decrease in tooltip temperature; Cryogenic cooling also has innovative advantage in terms of enlightening the product quality, reducing power consumption, and cutting force. However, the disadvantages of the application of cryogenic cooling are that the process incurs a high cost during the machining process.

### 2.2.4 MQL Machining Operations

Minimum quantity lubrication (MQL) is a technique developed in recent times whereby a minimal amount of cutting liquid, in aerosol form, is splashed into the cutting zone. The use of MQL minimizes the dangers related to job-related wellbeing and security [39]. A few investigations on MQL notice the constructive outcomes of the strategy on occupational well-being and safety [40]. MQL is administered in the form of micron-sized beads and droplets. The system can be balanced so that the drops are consumed and dried up by the heat generated during the machining. Any surplus quantity could be cleaned or flushed off as soon as the machining is done [41].

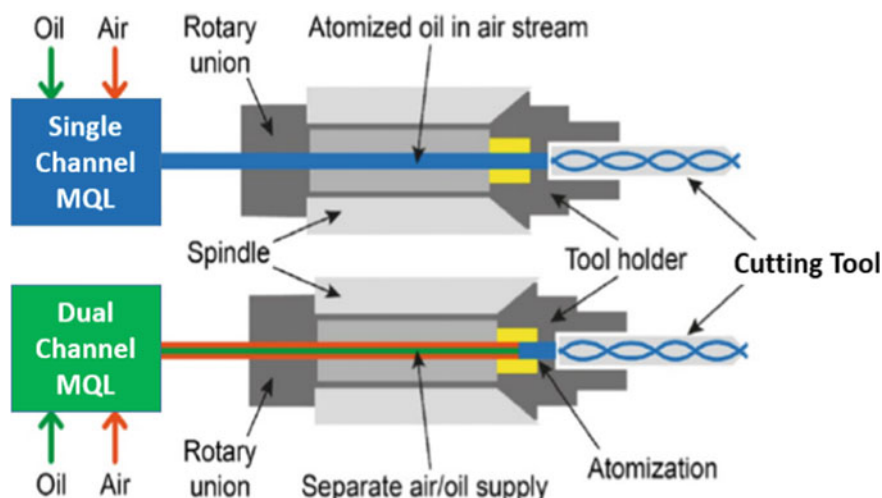


Fig. 2.4 MQL delivery procedure for both single and dual channel

Traditional methods of applying cutting fluids, such as wet and dry machining, have given rise to several environmental problems as well as safety and health hazards in the machining sector. Hence, numerous studies of the MQL fluid distribution method have been conducted over the years to ensure that cutting fluids are supplied optimally during machining in order to significantly lower production costs and increase machinability [42]. The MQL cutting fluid delivery technology, also known as microlubrications or near-dry lubrications, utilizes compressed air as the supply medium to significantly minimize the amount of lubricant or coolant that is applied from the spray nozzle to the cutting region, as presented in Fig. 2.4.

Superior lubrication, corrosion prevention, high spark and boiling temperatures, are frequent use [43], non-natural ester (usually vegetable oil), is frequently utilized. However, in contrast to the synthetic ester, fatty alcohols perform better in terms of heat transmission and produce less waste when they evaporate. When lubrication is a crucial requirement for the machining operation, the synthetic ester is used in certain operations. Fatty alcohol lubricant is also used in situations that call for cutting fluid to facilitate heat transmission throughout machining.

### 2.2.5 Compressed Air Vapour Gas as Coolant

Another attractive green method to make cooling and lubrication available during machining depends on the use of ice air as a coolant. The use of chilled, compressed air for cooling purposes is environmentally friendly, and it gives better tool life preservation than conventional cooling. However, various literature reveals that surface completion is delicate if chilled packed air cooling occurs [44]. The delicate surface

finishing operation is linked to the interaction of the thermo-mechanics of distortion, which adjusts the microstructure of the developed surface produced by the machining tool. The application of the conventional cooling process and the MQL on the machined surface is superior to the ice air-cooling strategy. Although machining industries developed mist lubrication using vegetable oil and cryogenics to replace mineral oil-based flooding, its insufficient lubrication and cooling property at high speeds prompted a search for a new hybrid (compressed air vapour gas as coolant) solution that provides appropriate cooling and lubrication (C/L), according to Ross et al. [45]. Furthermore, there is currently no information available on the impacts of hybrid cooling on the milling of Nimonic-80A. To assess the viability of using cryogenics with a hybrid cooling strategy, the machining of Nimonic-80A under hybrid C/L was compared to various cooling approaches (flood, cryogenic and MQL). The best cutting circumstances were chosen using the Complex Proportional Assessment (COPRAS) technique to obtain the perfect surface trait. Along with enhancing surface superiority, the hybrid state is regarded as a pioneer in line with the most recent worldwide movement toward viable means of manufacturing. The optimization result showed that the best value, which regulates the energy consumption, is produced by machining with a feed rate of 0.04 mm/rev and a cutting speed of 60 m/min while using a hybrid cooling method. To develop the sustainability assessment among the various cooling settings, the Pugh matrix approach has been used. The study's conclusion demonstrates the viability of the hybrid cooling technique and outlines how turning green works. Besides that, there is a need to investigate the capability of this strategy for cutting hard-to-cut workpieces under a consistent machining approach.

### ***2.2.6 High-Pressure Lubrication in Machining Operations***

High-pressure lubrication techniques emerged during the 1980s and 1990s. The research account describes accurately adjusted coolant jets with exceptionally high pressures (100–1000 bar) as a part of the cutting parameter [46]. The preparation of hard-to-machine materials (for example, titanium) ran smoothly. Under this cooling technique, the coolant is injected under high pressure precisely in the cutting region between the workpiece and the rake of the cutting tool. As long as the parameters are in line with the machining process, there will be successful cooling and a decrease in the tool wear rate when compared with conventional cooling techniques. The cutting rate and thrust force will increase productivity. The high-pressure system will prolong the cutting tool in operation with a much lower load demand during the cooling process when contrasted with the conventional cooling method [47].

The important goal of HPC machining is to fundamentally reduce the temperature produced at the machining region between the cutting tool and the workpiece. Furthermore, when machining at a higher cutting speed with the HPC assist at tool-chip interfaces, the chip discontinuity at the machining region is reduced [48]. This

is accomplished by applying coolant with high pressure at the cutting zone interface [49]. This procedure can likewise achieve high chip brittleness and control the expulsion rate of the chips with compressive pressure. Flood cooling at the machining region can reduce the machining temperature while machining at a lower speed. The coolant additionally acts as a lubricant in this manner, limiting friction and reducing the cutting forces and, subsequently, tool wear [50]. Kramar and Kopac [51] carried out a study on the use of high-pressure cooling when performing turning operations on materials that are difficult to cut during machining operations. In the experiments, the lubrication pressure was adjusted while the cutting feed, breadth of cut, and cutting speeds remained unchanged. It was found that the breakability of the chips increased with increased lubricant pressure, which had a major impact on washing out the chips at the cutting region throughout operations.

### **2.3 Advantages and Disadvantages of the Lubricant Delivery Techniques**

The advantages and disadvantages of the six techniques of lubricant delivery in machining operations discussed in this chapter are presented in the following sections.

#### ***2.3.1 Advantages of Lubrication Delivery System***

- (i) When applied during delivery, the lubricant in the cutting region enhances the tribological procedures that take place at the tool-workpiece contact to increase the machinability of metals.
- (ii) eliminate adverse effects on the environment and lessen some issues relating to the employees' well-being and safety.
- (iii) Improve the machining surface of the product.
- (iv) Reduce vibration and friction by using high pressure to flush out the chips at the cutting region.
- (v) Reduce the contact between the cutting tool and the workpiece in operation by converting the sliding friction into a rolling mechanism.

The advantages are generally analyzed over flood cooling and dry machining processes. It is worthy of note that, from the literature, MQL, known as the minimum quantity lubrication process, is viable and highly efficient. All the experiments and the experimental data employed for the modeling, prediction, and optimization discussed in this book are under the MQL machining operations.

### 2.3.2 *Disadvantages of Lubrication Delivery System*

- (i) The delivery system is very expensive, and as a result, only large industry companies can afford it.
- (ii) High-quality and knowledgeable operators are required.
- (iii) Heavy lubricant mixtures, extremely cold temperatures, and extremely long supply line runs between the pump and nozzles are not ideal for it.

However, with the use of lubricant delivery systems in machining operations, manufacturers are still faced with the challenge of producing a high-quality product at a low cost. This is due to other factors like the machining parameters during the cutting process, types of lubricants, measurement of lubricant, and having an idea of the precise surface finishing of the product. This challenge leads to the study of prediction and optimization in machining processes, which will be briefly discussed in Sect. 2.4. Also, this is what this book is all about: the application of heuristic and metaheuristic techniques for advanced nano-lubricant machining optimization.

## 2.4 Machining Optimization

The machining optimization techniques are powerful statistical instruments employed for obtaining the optimal parameters for a sustainable manufacturing process. This book discusses the design of experimental optimization techniques in Chap. 3 and also the heuristic and metaheuristic techniques for advanced nano-lubricant machining optimization in the other chapters. The current trend in manufacturing lies in the ability to optimize the machining process, which has led to the study of machining optimizations. Davoudinejad et al. [52] developed a mathematical model to predict the performance of the machining parameters in end-milling machining with the finite element method. In the experiment, three machining parameters with three levels were considered to study the surface roughness of the material. The authors discovered that there are lots of machining parameters that lead to low performance in manufacturing mechanical components using computerized numerical control (CNC) machines. Furthermore, they recommended that more research be done on machining parameters to study the influential parameters. Okokpuije et al. [53] also developed a model with response surface methodology to predict the surface roughness under four-factor, five-level experiments. From the result, the model was able to predict the surface roughness with 96% accuracy. The authors recommend the need to develop more mathematical models using different numerical tools, increasing the factors and levels, to study the potential influence of the machining parameters. Masmiati et al. [54] worked on the optimization of machining parameters during end-milling machining. The study confirmed that for proper optimization to be done, there is a need for mathematical models to be developed.

## 2.5 Conclusion

This chapter focuses on the cutting fluid and its application with different delivery machining techniques. Due to the fact that the current trend in sustainable machining processes lies in the quality of the application of cutting fluid at the cutting region, this chapter discusses the classifications of cutting fluid, which are straight machining oils, soluble oils, semi-synthetic cutting fluids, and synthetic fluids. Furthermore, the study looked into six different machining lubrication delivery techniques: MQL, high pressure cooling, compressed air vapour gas as coolant (CAVG), flood cooling (a traditional process), cryogenic cooling, and the solid lubrication process. These various techniques have their uniqueness as well as their disadvantages. This chapter's conclusion and recommendation are as follows:

- (i) MQL delivery techniques are highly efficient in the machining process as well as the cryogenic cooling process. However, a current trend delivery system that can be cryogenic and deliver a minimum amount of lubricant at high pressure is required.
- (ii) The manufacturing industry should consider studying the optimization of the MQL cryogenic machining process with precise amounts of lubricants at a specific time during the cutting process.

However, even with the application of MQL in machining operation there are still changelings due to the lack of cooling properties of the cutting fluid, which has led to the study of Nanolubricant in machining operations by several researchers. Therefore, chapter three of this book will discuss the development and application of nano-lubricant in machining.

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# Chapter 3

## Development and Application of Nano-lubricant in Machining: A Review



**Abstract** The development and the implementation of nano-lubricants together with the use of numerical approach for prediction and optimization in the machining process is state of the art in the manufacturing of engineering and structural component. This study has reviewed the application of the development of nano lubricants, and the implementation of various optimization techniques for advanced manufacturing systems. Numeral approaches in machining process is a viable process that manufacturers use to produce different parts employed to develop machines. However, the challenge of the CNC system is cutting fluid application due to excess heat generation during the cutting process. Therefore, the review of various nano lubricants development and implementation in the milling, turning, and grinding processes were studied in this chapter. Also, the chapter discusses the modern optimization techniques via design experts such as response surface methodology, Taguchi method, Full Factorial design and Plackett–Burman Design.

**Keywords** Machining · Nano-Lubricant · Cutting fluid classification · Modern Multi-Objective Optimization · Response surface methodology

### 3.1 Introduction

Nano-lubricants are state of the art in manufacturing mechanical components for sustainable development. Since the inception of the application of nano-lubricant, there has been a sustainable improvement in the manufacturing sector via numerical approaches applied to the machining process. The implementation of nanoparticles in the base fluid to form Nano-lubricant for the machining process improved the efficiency of the manufacturer output of the CNC machining process [1]. The global CNC machine market was projected to grow from \$83.99 billion in 2021 to \$128.41 billion in 2028 at a Compound annual growth rate (CAGR) of 6.3% due to the high efficiency growing demand for precision products [2].

Machining with nano-lubricants is mainly formed with a base fluid called lubricant, oil, and water before the application during the cutting operation. Figure 3.1

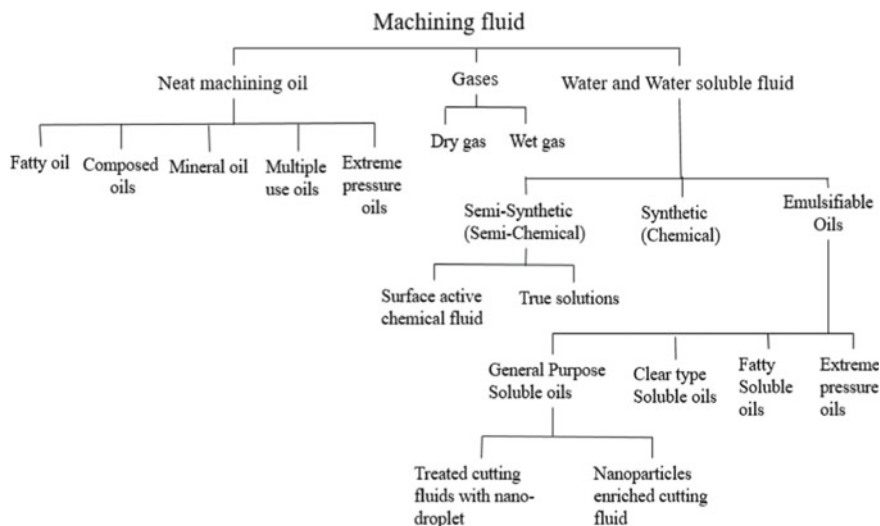


**Fig. 3.1** Machining fluid classification during the manufacturing process

shows the various machining lubricants that can be applied in the turning, milling, and grinding operations. These cutting fluids are classified according to their function in the manufacturing process. Nano-lubricant is implemented in different ways to improve cutting fluid performance. Cutting fluids, Spreaders, and Nanoparticles are combined to make nano lubricants. Thermal destruction to work units and tools happens because of the vital forces of friction. The machining costs rely directly on the rate at which metals are removed. Including nano-particulate matter in the lubricants increases structural stability, lubrication properties, and how effective it is in transmitting heat. The NFMQL technique is being developed, in comparison with other lubrication techniques, to significantly increase machining performance, minimize tool wear, and boost the quality of surfaces [3].

The application of current optimization techniques for machining is highly needed to protect the sustainability of the manufacturing process globally. Researchers have critically carried out machining various metals and non-metals with various optimization techniques from the experiment design. Including the response surface methodology (which entails Central Composite Design, Box-Behnken Design, and 3-Level Factorial Design), Taguchi method, full factorial, and Two-Level Factorial Design. However, this chapter focuses on the review process of the development of nano-lubrication and its application in machining operations. This chapter further discusses some selected optimization techniques used for machining.

## 3.2 Different Methods of Nano-lubricant Preparations

A nano-cutting fluid is developed by immersing a distinctive size of 0–100 nm of organic or non-organic nano-element in base oil [4]. The preparation of nano-liquid is a significant step to enhance the thermal conductivity of the fluids. There are two significant ways of preparing nano lubricants: single-step and dual-step techniques [5]. Nanoparticles (the additives of nano-lubricant) play a significant part in varying the thermal transfer properties of nano-liquids. Recently, different types of nanoparticles, such as organic and non-organic nanoparticles, have been employed in nano-liquid development. The nanoparticles are put into base oil by applying a stirring device and ultrasonic vibration cleaning machine to break down the aggregation of the nanoparticles. The addition of dispersants to regulate the pH value of the mixture will ensure that the re-aggregation of nano-elements is avoided, thereby leading to stable nano-liquid [6].

The dual-step techniques are commonly used to prepare nanotubes, nanofibers, nano-lubricants with various nanomaterials. The process starts by developing the nanoparticles in dry powder form through physical and chemical processes. The characterization of the powder is to identify the percentage of purity and determine the specific side of the nanoparticles. The nanoparticles are dispersed into the base fluid [7]. The mixtures of the base fluid and the nanoparticles are stirred using a rigorous magnetic force with a mechanical stirrer. After that, the ultrasonic vibrator is used to homogenize the nano-lubricant.

This dual-step technique is the most economical process for developing nano-lubricant at low cost and in large quantities. The nanoparticle synthesis method was established at the nano-industrial manufacturing level. As a result, there is a high tendency that the nanoparticle will aggregate with high surface area activity. The required method to improve the stability of nanopowder in the base fluid is the implementation of surfactants. However, the surfactants have some challenges in operating in an environment of high-temperature applications [8].

The one-step technique involves the preparation and suspension of the nanopowder mixed with the base oil; in this case, both the base oil and the nanopowder are produced simultaneously. In the one-step method, the drying of the nanoparticles, storing, transportation, and dispersion of the nanoparticles into the base oil is prevented from eliminating or reducing particle agglomeration. Many techniques are used in this one-step method, such as vapor deposition, pulsed wire evaporation (PWE), Laser Ablation Method, and Submerged Arc Method [9].

The most employed method is the vapour deposition technique which is a process where a tinny film is produced due to the rotating disc acting creating a centrifugal force at the boundary of the vessel. The mixture of the base oil and the nanoparticles are heated and evaporated in the vessel containing inert gas at low pressure. The nano-lubricant is formed at the interaction of the tinny film with the raw materials due to condensation. The nanoparticles are mixed with the base oil. The different methods of nano-lubricant preparation and characterization are presented in Fig. 3.2.

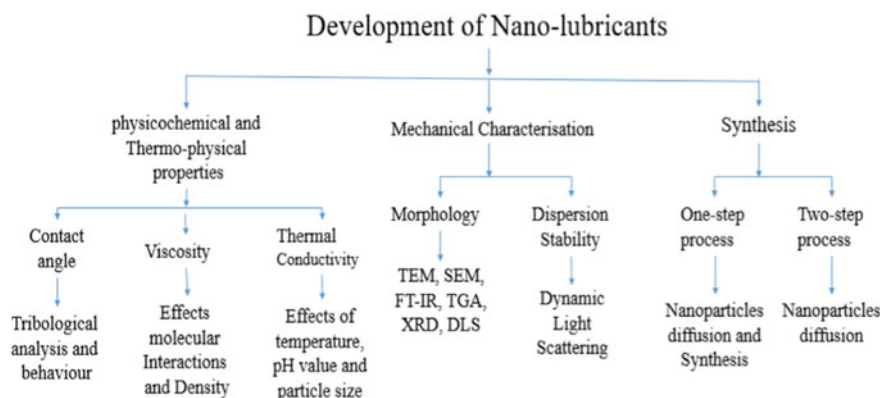


**Fig. 3.2** Flow chart for nano-lubricant development, characterization and physiochemical properties

Also, Table 3.1 summarizes the nano-lubricant preparation technique used by several researchers [10].

### 3.3 Application of Nano-lubricant in Milling Machining

Nano-oointments are the recent trend of lubricant for machining that have been found to improve rheological and tribological properties during the machining process widely [24]. Scientists have, as of late, used nanoparticles in regular oil because of the noticed change in thermo-physical and temperature trade capacities. To diminish the coefficient of crushing and wear sway, work on the usefulness and constancy of mechanical devices.

Different nanoparticles have been widely used to study machining performance in milling machines, such as fullerene, diamond, silicon dioxide, graphite, etc. Due to the outstanding lubricity performance, molybdenum disulphide ( $\text{MoS}_2$ ) is generally used in lubrication. A combination of two different materials and oil [25]. Wang et al. [26] the nano-size of molybdenum disulphide ( $\text{MoS}_2$ ) exhibits excellent tribological properties when compared with the bulksize.  $\text{MoS}_2$  and graphite are found among the conventional lubricants because of their morphology and crystalline structure. They are available in the market in a wide variety of sizes. Rahmati et al. [27] studied the effects of different concentrations between 0.5 and 1 wt% of  $\text{MoS}_2$  mixed in ECOCUT HSG 905S as a base oil on the surface morphology of AL6061-T6. The study applied the MQL system to minimize lubricant consumption while delivering the nano-lubricant to the cutting region. The result shows that the  $\text{MoS}_2$  during the machining operations generally has better surface roughness. At 0.5 wt% concentration of the  $\text{MoS}_2$ , the minimum surface roughness of  $0.223 \mu\text{m}$  was achieved.

**Table 3.1** Summary of different preparation techniques of nano-lubricant employed in the manufacturing industry

| Researchers | Nano-liquid                                                                         | Mixing apparatus                                                                                                                        |
|-------------|-------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| [11]        | TiO <sub>2</sub> and MWCNTs + Copra oil                                             | The mixture was stirred for 2 h at room temperature and ultra-sonicated for 5 h before implementation                                   |
| [12]        | Nitric acid–MWCNT                                                                   | The solution was ultra-sonicated in an ultrasonic water bath for 4 h at 60 °C                                                           |
| [13]        | MWNTs + H <sub>2</sub> O                                                            | Magnetic stirrer for about 3 h and ultrasonic tub for 60 min                                                                            |
| [14]        | MWNTs + H <sub>2</sub> O                                                            | The magnetic stirrer was used for 20 min and 10 min. Ultrasonic vibration continues for 1 h                                             |
| [15]        | The mixture of MWNTs + H <sub>2</sub> O – ethylene glycol                           | Magnetic stirrer for 30 and 90 min ultra-sonication                                                                                     |
| [16]        | Carbon + H <sub>2</sub> O                                                           | Mixed for 30 min with Magnetic stirrer and ultrasonic liquid processor for 30 min (repeated five times)                                 |
| [17]        | Cu + R113 (refrigerant-based)                                                       | 1 h ultra sonication workstation                                                                                                        |
| [18]        | MWCNTs + H <sub>2</sub> O                                                           | 30 min ultrasonication vibration process                                                                                                |
| [19]        | Al <sub>2</sub> O <sub>3</sub> + H <sub>2</sub> O – Egg mixture                     | The mixtures were stirred for five (5) h with a magnetic stirrer and also Ultrasonic for four (4) h for the proper mix of the lubricant |
| [20]        | CuO + H <sub>2</sub> O                                                              | Homogenizer with an ultrasonic cleaner for a 1 h                                                                                        |
| [21]        | Al <sub>2</sub> O <sub>3</sub> and TiO <sub>2</sub> + H <sub>2</sub> O – EG mixture | The magnetic stirrer was employed for 2 h, homogenizer for 30 min, and ultrasonic liquid processor for 30 min                           |
| [22]        | Cu + H <sub>2</sub> O                                                               | An ultrasonic bath was employed to sonicate for about 10 h                                                                              |
| [23]        | Al <sub>2</sub> O <sub>3</sub> + H <sub>2</sub> O                                   | An ultrasonic disruptor was employed for 30 min to sonicate the mixture                                                                 |

Sayuti et al. [28] applied silicon dioxide (SiO<sub>2</sub>) nano-lubricant in the machining of AL6061-T6 to study the surface morphology of the material. The authors discovered that during machining of the said workpiece using conventional oil, the function of the oil is negligible at high pressure and temperature. Because the oil evaporates at high temperatures and pressure when applied to the machining region between the cutting tool and the workpiece. However, introducing SiO<sub>2</sub> nanoparticles mixed with the base oil could withstand several conditions, such as flushing chips from the cutting region. Also, it reduced cutting force and prolonged the cutting tool life from quick damage. The nano-lubricant applied in this work was prepared by mixing the ECOCUT SSN 322 as base oil with 40.2 CST at 40 °C from FUCHS with SiO<sub>2</sub> and then homogenizing the solution for 48 h. With nanoparticles sizes of 5–15 nm with different concentrations such as 0, 0.2, 0.5, and 1 wt%. The lubricant is free from chlorine, phenol, or any other additive. The grease was delivered to the cutting zone with the help of a developed thin jet pulsed nozzle having a 1 mm diameter

with a delivering rate of 2 ml/min. The result shows thin protective films formed in the cutting region between the cutting tool and the workpiece containing a large  $\text{SiO}_2$ . During the machining process, which helps reduce friction and cutting tool deformation, the surface roughness of the workpiece is reduced.

Ooi et al. [29] developed a model for the nano-lubricant delivery system to predict the machine's performance on the workpiece during milling operation under  $\text{SiO}_2$  nano-lubrication conditions. The parameters considered as the input parameters are the concentration of the nano-lubrication, air pressure, and nozzle location, with the responses, such as surface roughness, cutting force, and cutting temperature. However, huge amounts of  $\text{SiO}_2$  would lead to a poor machining environment due to crashes and impedance within the elements and asperities of the material. The fuzzy mathematical model displayed the accuracy of predicting the cutting force with about 95.39%, surface finish with 93.78%, and cutting temperature with 98.27%. Also, Paturi et al. [30] worked on the artificial neural network and Taguchi L27 ( $3^{13}$ ) experimental design to develop a scientific model for predicting surface roughness during the machining of AISI 52100 under three experimental factors. ANOVA and MATLAB toolbox was employed to check the effect of the machining factors on the surface finishing result. The findings show that the Taguchi L27 ( $3^{13}$ ) and the ANN models are in good agreement with the experimental results when compared.

Singh et al. [31] studied the effects of graphene nano additive found in olive, canola, and sunflower oils on grinding planes of titanium at a grade of 23 compared to the conventional cutting fluid. The research has its limitations in terms of how rough the plane surfaces were ( $R_z$ ,  $R_a$ ), the amount of force needed to grind ( $F_n$ ,  $F_t$ ), the friction coefficient, and the exact energy needed to grind ( $U$ ). Low tocopherol levels have been used to improve oxidation stability in vegetable oils in additives. In order to have an equal graphene-nanoplatelet dispersion in oils, nanofluids were put under sonication for probing, using a stirrer for an hour and thirty minutes at 20 kHz followed by an ultrasonication at the same time but 40 kHz. In order to make further enhancements, an addition of a surfactant known as Sodium Laurel Sulphate was used by adding a ten percent graphene weight concentration. Using a technique that has proven to show a stable development experimentally, by comparing, was analyzed in the study. Tests were carried out repeatedly, and the averaged values were considered. A grinding process that is technologically sustainable and benign to the surroundings was proposed. Canola, olive, and sunflower oils with graphene were researched using the Minimum Quantity Lubrication method. Comparing and measuring how effectively they worked with these inclusive and exclusive prerequisites, testing the grind using the standard method of flooding water-soluble synthetic fluids at a twenty-to-one ratio was done. The results obtained using this method were used as a standard throughout the research.

Setti et al. [32] studied nano-lubricants impact during MQL machining of solidified AISI 52100 steel. The result shows that nanofluid with higher complex nanoparticles reduces granulating power, crushing temperature, and surface unpleasantness. The authors also found that the utilization of nanoparticles with a bigger width disintegrated the surface wrap-up. Molybdenum disulphide ( $\text{MoS}_2$ ) nanoparticle has been

utilized as a heavy grease in metal cutting for a long time.  $\text{MoS}_2$  is one of the suitable grease materials that reduce the coefficient of harshness up to 0.05 with the end goal to enhance the execution of ointment and decrease warm bending. Sridharan and Malkin [33] included CNT and  $\text{MoS}_2$  nanopowder to ester grease for the MQL environment. Zhang et al. [34] also carried out an experimental study on the grinding operation of hard-to-cut Ni-based amalgam. The result affirmed that the  $\text{MoS}_2$ -CNT nano-cutting fluid employed in the cutting process enhanced the materials' cutting accuracy and surface nature.

Diamonds (precious stones) have sizes under 1 ml with paramount consideration due to their incredible automated physical possessions. It has proper surface zones, an excellent composition area, and low cytotoxicity. Nano-diamonds have risen as a standout amongst the most encouraging carbon nanoparticles devoid of health hazards during the machining operation [35, 36]. To justify nanofluid utilization, Sharma et al. [37] spread nano-diamond particles with distance across 30 nm, separately in petroleum jelly and vegetable lubricants, for a smaller-scale penetrating procedure of aluminum 6061 alloys. The result shows that the paraffin mixed with vegetable oils nanofluid decreases penetrating torques and increases the number of boring gaps.

Furthermore, the authors confirmed that the paraffin nanofluid was more viable than the vegetable nanofluid. Lee et al. [38] furthered the examination by testing nano-diamond particles in a based fluid known as paraffin oil for the micro-grinding process. The authors discovered the nano-diamond with paraffin performed better than the base oil. In Abbasi et al. [39] the utilization of nano-diamond particles as nanofluid was not viable for boring with massive width. Similar findings were confirmed in the work of Kim et al. [40] for small-scale end-processing of titanium composite (Ti-6AL-4 V) that is diamond-nano-fluid performed better in end milling machining.

### 3.4 Turning Operations

The base oil or water mixture with non-metallic or metallic nanoparticles is called a nano-lubricant (NL). Sharma et al. [41] carried out a study on  $\text{TiO}_2$  nano-lubricant thermal conductivity, viscosity, and the performance during turning of AISI1040 steel. The nano-lubricant was developed by mixing 5% volume of vegetable oil containing water with different volume percentages of  $\text{TiO}_2$  from 0 to 3% in the mixture to achieve the nano lubricants stability. The solution was kept for 6 h on the ultrasonic vibrator. The MQL technique was used to deliver the lubricant to the machining zone. This process was also compared with the wet/MQL and dry machining. The result shows that the nano-lubricant improved the efficiency of the machining process by decreasing the cutting tool wear, cutting force, and surface roughness.

Mahadi et al. [42] carried out research that employed boric acid as a nanoparticle mixed with palm kernel oil to form a machining cutting fluid for turning operations



of AISI 431 steel under MQL operations to study surface roughness. A full factorial experimental design of  $2^4$  factorials was applied with three factors, two experiment levels, which amount to 16 experimental runs. The factors considered are depth of cut varying from 0.5 to 1 mm, feed rate of 0.16 to 0.24 mm/rev, and cutting speed of 150 to 200 m/min. From the comparison result, the palm kernel oil mixed with the boric acid performed better than the flood cooling process, and feed rate was the most significant parameter of the surface roughness. The nano-lubricant developed with the boric acid has a performance difference with a surface roughness of about 7.21%. The developed model predicted the experimental result with 99.15% from the ANOVA analysis.

Rapeti et al. [43] experimented using L27 Taguchi's orthogonal array with four-factor three-level experiment consideration parameters. In the study, various cutting fluids such as coconut oil, canola oil, and sesame oil were mixed with molybdenum disulphide ( $\text{MoS}_2$ ) of 0.25%, 0.5%, and 1% during lathe machining of AISI 1040 steel. The multi unbiased optimization was carried out with the Taguchi grey relational-based analysis, which was employed to determine the best machining environment. The authors discovered that 0.5%  $\text{MoS}_2$ -coconut oil with the machining parameters of spindle speed of 40 m/min and 0.14 mm/rev reduces the heat generated, surface finish, cutting force, and wear rate of the cutting tool. The authors performed the cost analysis to determine the economic advantage of the MQL when compared with the conventional way of fluid supply to the machining zone. The study revealed that there were cost savings of up to 22,422 INR.

Gutnichenko et al. [44] developed a nano-lubricant using graphene nanoparticles and rapeseed oil. The rapeseed oil was obtained from Accu-Svenska AB in Sweden. The graphene nanoparticles formed from the thermally expanded graphite (TEG). In 1 g of 10% (vol.) alcohol media and was ultra-sonicated for 24 h, the ultra-sonication machine operates with 350 W power. The nanoparticle size was 1  $\mu\text{m}$  and had a thickness of 50 nm. The authors dispensed a 0.2% volume of graphene nanoparticles in rapeseed oil obtained from vegetables. They studied the effects of the nano-lubricant in the lathe machining of tempered ~60 HRC alloy steel with cemented carbide cutting tool under the cooling technics of MQL and dry turning operations. The surface roughness was determined using a portable roughness tester of Mahr MarSurf PS10. It was measured 5 times after each machining operation, and the average is taken as the surface roughness result. The investigation concluded that the implementation of GnP in the rapeseed oil helped reduce the friction during the turning operation. This led to an improvement in the cutting tool life and reduced the surface roughness. The dry turning process had a high adhesiveness in the machining region, which led to excess heat generation and increased surface roughness.

Sharma et al. [45] studied the effects of  $\text{Al}_2\text{O}_3$  on different conventional cooling fluids employed during the turning operation of AISI 1040 steel. The materials considered are AISI 1040 of 70 mm long and having a diameter of 300 mm, uncoated cemented carbide insert,  $\text{Al}_2\text{O}_3$  nanoparticles (1 and 5%) mixed with water, Olympus BX51M microscope. In order to analyze the surface roughness, the Mitutoyo SurfTest SJ-210 were employed to measure the surface roughness of the machined face after turning operations. The parameters are cutting feed of 0.1 mm/rev, depth of cut of

1 mm, and a spindle speed of 96.7 m/min. The nano-lubricant was ministers with a 50 ml/min flow rate with a pressure of 4 bar. The researchers experimented with dry turning, MQL, and wet machining processes. However, the result shows that nano-lubricant significantly lessens the cutting force than dry and wet turning operations with about 59.1% and 29.2%. Also, it reduces the wear rate and the surface roughness by about 47.8% and 29.1%, respectively. Finally, it was concluded that the increase of the nanoparticles on the base lubricant enhances the viscosity of the base fluid's grease, density, and thermal conductivity. Also, the specific heat analysis shows that the increase of the  $\text{Al}_2\text{O}_3$  nanoparticles will decrease the specific heat capacity.

### 3.5 Grinding Operations

The role of lubricants in grinding operations is very significant because of their need for environmental protection. To prevent the increase of health risks in the operators' lives, the issue of traditional cutting fluid is progressively fading away. Nano-lubricant has the potential to serve as a green lubricant because of the effects of the nanoparticles in the grease. Various researchers have discovered that nano-lubricant in grinding operation enhanced the heat transfer ability and the lubricant properties. During grinding operation, friction between the abrasive grains and the work materials can rightly impact the wear rate of the grinding wheel, the quality of the material's surface, and the grinding force. Therefore, using nano-lubricant will help improve the grinding performance [46].

Wang et al. [47] carried out a study on the tribological performance of  $\text{Al}_2\text{O}_3$  during grinding operations. The authors developed a Nano-cutting fluid, using palm oil as the base fluid and 0.5 to 4% volume concentration of  $\text{Al}_2\text{O}_3$  as the additives, during the grinding operations of Ni-base alloy, under the MQL method. The study was carried out on the macro factors (G-ratio, force ratio, and specific energy) and micro factors (surface superiority, the microstructure of coarse grains and grinding fragments, viscosity, and angle contact). Results show that the nano-cutting fluid runs through the grinding wheel, work material at the grinding zone, and developed a lubricating oil film that significantly decreases friction. The best concentration of nano-lubricant was obtained. At the 1.5% volume concentration, the minimum grinding force ratio of 0.281 was achieved. In contrast, the minimum coarseness of 0.301 mm, tiny grinding fragments, and maximum drop moistening zone was obtained at the volume concentration of 2.0%.

Huang et al. [48] study the effects of multi-wall carbon nanotubes (MWCNTs) nano cutting fluid, using ultrasonic-assisted MQL, and dry in grinding NAK80 mold steel. The oscillator agitation ultrasonic MQL is to maintain the nano-lubricant stability during the grinding process. The three grinding environments were conducted experimentally, and the grinding performance analysis was determined. The result shows that MWCNT's nano-lubricant using the MQL could reduce the temperature generated at the grinding zone, the surface finish, and the cutting force compared with dry machining. This is credited to the ultrasonic oscillator

applied to the MQL techniques, which reduced the particle agglomeration to the minimum lubricant. According to Zhang et al. [49] the sustainability of manufacturing quality products during the application of computer numerical control (CNC) in the grinding process depends strongly on the employment of lubricant delivery systems. The authors employed three lubrication techniques in their research work: the nano-lubricant MQL, nano-lubricant cryogenic air minimum quantity lubrication (CNMQL), and cryogenic air with  $\text{Al}_2\text{O}_3$  as the nano-lubricant during the grinding operation of Ti-6Al-4V. In order to study the specific energy consumption and the coefficient of friction during the machining process. The study shows that the minimum specific energy and the resistance ratio were achieved at  $51.96 \text{ J/mm}^3$  and 0.60, respectively, in the grinding environment of CNMQL. From the comparative analysis, it is seen that the CNMQL is superior. Its performance was better than the CA and the NMQL in terms of energy-saving, economic efficiency, use of low carbon, outstanding cooling, and lubrication influences on the grinding process.

### 3.6 Current Modern Optimization Techniques for Advanced Machining Processes

The current modern optimization techniques in the advanced machining process are borne out of experiment design, such as response surface methodology, Central Composite Design, Box-Behnken Design, Taguchi method, full factorial, and Two-Level Factorial Design employed for machining optimizations [50]. This section will discuss this method in other to introduce a new research method for machining optimization. Most of the multi-optimization techniques are classified under the experiment design, which enables the study of input parameters interaction as it affects the responses during the machining.

#### 3.6.1 Response Surface Methodology

Response surface technique (R. S. M) is an assortment of numerical and measurable strategies for planning, creating, improving, and streamlining item plans. The numerous variables affect the characteristics of the products [51]. First, the estimation function is generated among the output and then input. A first-order model is in place [52]. The following illustrates the most accessible model based upon a first-order polynomial that can be used for RSM in Eqs. (3.1) and (3.2).

$$y = \beta_0 + \sum_i^k \beta_i x_i + \varepsilon \quad (3.1)$$

In comparison, a polynomial in Eq. (3.1) can be expressed in the following manner.

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \sum_{j \geq i}^k \beta_{ij} x_i x_j + \varepsilon \quad (3.2)$$

**i**: linear-coefficient, **j**: quadratic-coefficient **k**: factor quantity.

$x_i$  and  $x_j$ : independent variables **y**: expected response.

$\beta_0$ : constant,  $\beta_i$ : linear-coefficient constant  $\beta_{ij}$ : interactive-coefficient constant  $\varepsilon$ : noise error.

### 3.6.2 Box-Behnken Design

A three-level fragmentary factorial arrangement created by Box and Behnken [53] is the Box-Behnken technique for the plan. For each block factorial plan, numerous variables are obtained through all mixes. At the same time, various components are retained at the focal levels. Some focal plans are normally included in contrast to the central composite layout. It has fewer composite design factor levels and does not have exceptionally high or insufficient levels. For example, Singh et al. [54] employed Box-Behnken design to developed a model that predict the performance of the material removal rate and optimised the machining factors during the computer numerical machining process of AL6061. The factors employed are feed rate, the cutting tool speed, depth of cut at three levels. The results show that the Box-Behnken design was capable to predict the response MRR and the optimised factor achieved was cutting speed of 1800 rpm, feed rate of 0.15 mm/rev and depth of cut 1.5 mm.

### 3.6.3 Central Composite Design

Olawaye [55] states that the Central Composite design and Box-Behnken design are the two classifications of surface response theory. A focal Composite design is a response surface design with a hub or star point separated from the 3 level variables. The hub or star point, usually signified as ( $\alpha$ ), expands the number of levels to 5 levels, giving the trial design adaptability. Its points of interest over Box-Behnken are that it permits the exploratory designer to realize what impact the variables had on response. The test designer goes past or beneath the picked factors. Notwithstanding, in Central Composite Design, the base number of elements it can oblige is two (i.e., mathematical or consistent components). The recipe gives the quantity tentatively acquired at each number of elements in Eq. (3.3):

$$N = 2^n + 2n + n_c \quad (3.3)$$

N is the number of runs, n is the number of factors,  $n_c$  is the number of center points the designer desires.

### 3.6.4 Taguchi Method

This is a factual technique, additionally called vigorous plan strategies, created by Genichi Taguchi to work on the nature of produced products. More recently, this statistical method has found application in the engineering discipline [56].

Taguchi identified three situations seen in Eqs. (3.4)–(3.10):

- (i) Larger the better (e.g., agricultural yield);

$$\frac{S}{N} = -10 * \log \left( \frac{\sum \left( \frac{1}{Y^2} \right)}{N} \right) \quad (3.4)$$

Y = reactions for the element level blend; n = the number of reactions in the variable level mix.

- (ii) Smaller the better (e.g., carbon dioxide emissions) Eq. (3.5);

$$\frac{S}{N} = -10 * \log \left( \frac{\sum (Y^2)}{N} \right) \quad (3.5)$$

- (iii) Nominal is best.

- (a) Nominal is best (i):

$$\frac{S}{N} = 10 * \log(s^2) \quad (3.6)$$

- (b) Nominal is best (ii):

$$\frac{S}{N} = 10 * \log \left( \frac{\sum \left( \bar{Y}^2 - \frac{s^2}{n} \right)}{N} \right) \quad (3.7)$$

$\bar{Y}$  = mean of responses for the given factor level combination.

For dynamic designs, the Signal-to-noise ratio can be calculated using Eqs. (3.8)–(3.10):

$$\frac{S}{N} = 10 * \log \left( \frac{\sum \text{slope}^2}{\text{MSE}} \right) \quad (3.8)$$

Or

$$\frac{S}{N} = 10 * \log \left( \frac{\sum \text{slope}^2}{\text{MSE}} - \left( \frac{1}{r} \right) \right) \quad (3.9)$$

MSE = Mean square error

$$r = \sum (\text{signal} - \text{reference signal or mean signal})^2 \quad (3.10)$$

This process involves three stages:

- System design: This is design at the conceptual level
- Boundary (measure) plan: The different aspects and configuration boundaries' qualities should be set when the idea has been perceived. The selection of boundaries limits the consequences for execution brought about by variety in the assembling, climate, and aggregate harm, additionally called robustification.
- Resilience plan: The boundary plans are credited, the different boundaries' impact on execution is perceived. The assets can be placed into limiting and directing variety in the primary few aspects.

Khare et al. [57] used titanium (grade 5) as a work material with a copper electrode for conducting experiments to minimize surface roughness. L-9 Taguchi array was employed in carrying out this experiment. Kumar and Kulkarni [58] Obtained optimum surface roughness and tool wear by using the Taguchi L-9 orthogonal array for analysing the results from the turning operations of Ti-6Al-4V titanium alloy with carbide insert tools. Cetin et al. [59] in an assessment of vegetable-based cutting fluid (VBCF) in the turning of AISI 304L, employed the use of Taguchi's lower-the-better quality characteristic of S/N ratio. For the analysis of surface roughness, cutting force, and feed force. The S/N ratio was calculated with the Eq. (3.11):

$$\frac{S}{N} = -10 \log \left[ \frac{1}{n} \left( \sum_{i=1}^n y_i^2 \right) \right] \quad (3.11)$$

where n represents the number of measurements in a row, and  $y_i$  is the measured value in a run.

The Taguchi method for experimental design is anything but difficult to apply to many design issues as it permits the investigation of numerous boundaries without a high measure of experimentation. It distinguishes essential boundaries that influence the performance, and the boundaries that have a negligible impact are disregarded. Taguchi's strategy makes a standard symmetrical cluster to assess the impacts of design boundaries on the response esteem in an impartial way. The utilization of symmetrical clusters limits the quantity of all-out exploratory runs. Little-scope tests' results are legitimate over a whole exploratory locale traversed by the control factors and their settings [60]. In this way, Azadeh et al. [61] detailed that the Taguchi strategy has developed into a setup approach for breaking down cooperation impacts

when positioning and screening different controllable components. Also, this strategy applies to tackle different issues, including consistent, discrete, and subjective design factors. The Taguchi technique for test design has been generally used to locate the fundamental factors in accomplishing practical assembling measures.

Also, Rajesh et al. [62] announced that Taguchi's method utilizes a remarkable symmetrical exhibit to look at the quality attributes through a base number of analyses. The trial results dependent on the symmetrical cluster are then changed into S/N proportions to assess the exhibition qualities. Taguchi's Design of examinations is utilized to design the symmetrical exhibit for three boundaries shifted through three levels. Examinations have been completed utilizing Taguchi's L9 Orthogonal Array, comprising eight blends of cutting side rake point, back rake point, and nose sweep. As indicated by Taguchi's design inventory, three-cycle boundaries (without association) are to have fluctuated in three limited levels.

The Taguchi L9 symmetrical exhibit boundary design and response improvement approach were used by Venkatesan et al. [63]. The Taguchi signal-to-noise ratio chart and the 3D surface graph showed that a 0.14 mm/fi feed rate and cutting speed of 60 mm/min are accountable for minimum surface hardness. And the device wears with the greatness of 0.58 and 158  $\mu\text{m}$  at 0.25% (device wear) and 1.00% (surface unpleasantness). For cutting power, 169 N is seen at 0.14 mm/fire up, 100 m/min, next to 0.25%. From the effects of Signal-to-response and ANOVA, it is more likely that cutting pace takes care of rate emphasis to restrict deliberate responses. The developers effectively recognized the ideal environment for prevailing machining performance using the research model Taguchi.

### ***3.6.5 The Grey-Taguchi Multi-objective Optimization Method***

The conflicting nature of objective functions makes the use of mono-objective formulation unsuitable. Therefore, it is advised to use multi-objective optimization [64]. A renowned scientist Prakash et al. [65] developed a grey system that can solve problems with multiple quality characteristics of a re-enforce aluminium metal composite. These equations and procedures prove instrumental in optimizing multiple responses, and optimum input factors can be determined [66]. Optimization is divided into 'Maximization,' 'Minimization,' and 'Reach a Target.'

### ***3.6.6 Factorial Design***

Factorial design can be used at different levels (two or more to analyze the effects of factors on the response parameters. Compared to the one-factor-at-a-time design, experimentation demonstrates interactions between factors that combine different factors and makes it more effective in handling more factors. There are two (2) categories of factorial design: full-factorial design and fractional factorial design.

**Table 3.2** Design for a  $2^2$  factorial design of experiment [67]

|     | A   | B   | AB  |
|-----|-----|-----|-----|
| – 1 | – 1 | – 1 | + 1 |
| A   | + 1 | – 1 | – 1 |
| B   | – 1 | + 1 | – 1 |
| AB  | + 1 | + 1 | + 1 |

### 3.6.7 Full Factorial Design

Complete factorial design is effective for a smaller number of factors that assume resources are available. Two  $2^2$  and three  $2^3$  factors and  $2k$  factorial design explain the theoretical method about the design of experiment (DOE), where  $k$  signifies different factors. At the same time, the number of levels is characterized by the number 2. Factor designation is used for upper case letters, and lowercase letters are treatments. Each combination is called treatment and is marked with a small letter [67]. The design matrix is provided in Table 3.2 for a  $2^2$  factorial design.

Arif et al. [68] carried out experiments using a full-factorial design, and wear losses were discovered from the experiments. It was specified that ANOVA is a statistical means that displays percentage contributions used to distinguish the control of independent variables. Also, their respective percentage contributions to the results from experiments of the wear loss for this situation was analysed. Minitab was used to perform calculations, as shown in Table 3.2.

The analysis was taken for a 5% significance level. ANOVA calculates the F-ratio, which gives each independent variable the significance level by considering the variance of all terms discovered from the error term at the ideal significance level.

Although factorial DoEs have attractive highlights, they have a few drawbacks, including (i) they are appropriate for creating observational models or direct relapse but do not take into account the structure of main nonlinear models; (ii) the research does not take into account the earlier boundary data proportionately when planning new investigations; (iii) they require a fixed number of exploratory runs.

### 3.6.8 Fractional Factorial Design

The expectations of this method are at the stage at which the number of runs is moderately high for a complete factorial schedule. The experiment may use the fractional factorial method to streamline the ideal data, also referred to as a fractional factorial plan, to distinguish it from the complete factorial plan [69]. The fractional factorial approach offers an optional method where the number of runs for a complete factorial plan is too high ever to be feasible. Certain variables' impacts on a reaction can be concentrated with a fractional factorial design under a reasonable and efficient condition.



### 3.6.9 Plackett–Burman Design

A two-tier fractional factorial system is the Plackett–Burman model developed by Plackett and Burman. It has been commonly used for screening basic components for further study. Karlapudi et al. [70] express that Plackett–Burman’s design is commonly used and is now valuable in considering during machining of mechanical parts. It is a two-factorial design (i.e.,  $-1$  and  $+1$ ) that finds distinct variables as “ $n + 1$ ” tests. All elements picked in the analysis were tried at these two levels depending on the Plackett–Burman network plan. The principle impact was determined to distinguish between every factor’s normal estimations at a significant level ( $+1$ ) and a low level ( $-1$ ). This planning technique is a basic apparatus for screening the impacts of cycle factors on yield and can reduce the number of redundant trials directed in a further streamlining study utilizing a reaction surface system [71–76].

## 3.7 Conclusion

The development and application of nano-lubricant in machining is the current trend in the manufacturing process. This is one of the unique contribution of this book because this chapter has reviewed the various methods of developing nano-lubricants with a base oil. The application of the lubricants in milling, turning, and grinding operations in advanced machining processes. Also, it discusses the existing method of optimization. Knowing the existing method used for machining optimization via experimental design techniques. From the review of various articles on the application of Nano-lubricant this study will have the following conclusion:

- (i) The nano-lubricants significantly improve the machining process during the milling, turning, and grinding operations.
- (ii) It has been justified that the development of nanoparticles with base oil is majorly prepared in two ways techniques.
- (iii) Optimization study is the most significant aspect of the machining process.

This will lead the authors to introduce global optimization techniques to improve the machining and manufacturing process for the sustainable development of engineering components in Chap. 4.

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# Chapter 4

## Global Machining Prediction and Optimization



**Abstract** Optimization in the manufacturing process enhances the quality and productivity of the industry. This chapter is aimed at discussing and reviewing global optimization and prediction techniques in the machining process. This study covered the review of heuristic and metaheuristic techniques for advanced manufacturing optimization, such as the artificial neural network, adaptive neuro-fuzzy inference system, particle swarm optimization (PSO), genetic algorithm (GA), whale optimization algorithm (WOA), ant lion optimization algorithm (ALOA), and grasshopper optimization algorithm (GOA). The various procedures and steps for implementing these techniques were also covered. Also, a review of related literature on optimization techniques in the machining process was carried out to enable a concrete study to significantly improve the machining process. According to the findings, global optimization techniques are viable, sustainable, and can be used to optimize machining parameters and responses during the manufacturing process. However, several studies have implemented the techniques for only multi-objective optimization; therefore, this study will recommend that studies of multi-response-objective optimization be carried out.

**Keywords** Global optimization and prediction · ANN · ANFIS · ALOA · GOA · Machining

### 4.1 Introduction to Optimization in Machining

Optimization is the process of finding solutions that maximize or decrease certain research criteria, such as minimizing expenses associated with producing a thing or service, maximizing profits, minimizing the amount of raw materials needed to make a good, or maximizing output, optimization techniques are often used [1]. Optimization techniques has been applied in various field of engineering application such as Program optimization, coding, or software optimization are all terms used to describe the process of changing a software system such that some component of it operates more effectively or consumes less resources [2]. Global optimization techniques are

applied in machining process to optimized parameters values employed during the manufacturing process of mechanical component [3]. In order to reduced energy consumption, surface roughness, tool wear, cutting force and increases the material removal rate in machining process sustainable production of quality products these techniques are employed. There are several optimization and prediction techniques that has been employed in different area of research [4–7]. However, the current trend is the hybrid formulation and application which this book will be applying. Figure 4.1 depict a flow chart of global optimization tool and prediction techniques in the modelling world. The Conventional prediction and optimization techniques has been discussed in Chap. 3 of this book under the Sect. 3.6 current modern optimization techniques for advanced machining processes. The Non-conventional and the global prediction techniques will be discussed in this chapter in subsections.

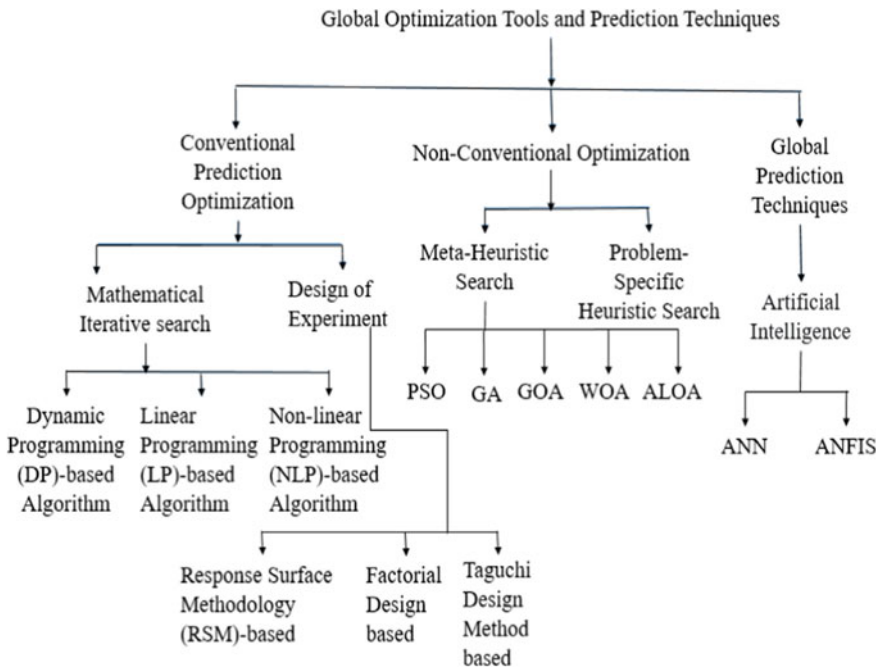


**Fig. 4.1** Global optimization tool and prediction techniques

## 4.2 Artificial Neural Network (ANN) as a Global Prediction Technique

Artificial neural network (ANN) is a nonlinear computational based model that comprises artificial neurons likened to brain cells. This neural system can learn to execute tasks such as classification, visualisation, decision making, and prediction [8–10]. The neurons have three interconnected layers, namely input, hidden, and output layers. The input layer sends the information to the hidden layer; at the hidden layer, inputs interact with the assigned weight of each hidden layer, and this weighted inputs produce the activated signal and sent it to the transfer function. This activated signal interacts with the transfer function to define the output from the neuron [11]. There are seven major types of ANN used for prediction analysis they are as follows:

- (i) Radial basis function Neural Network,
- (ii) Recurrent Neural Network (RNN),
- (iii) Convolutional Neural Network,
- (iv) Kohonen Self Organizing Neural Network,
- (v) Long/Short Term Memory,
- (vi) Modular Neural Networks,
- (vii) Feedforward Neural Network—Artificial Neuron.

There are seven step to train a model via ANN they as follows.

- Model an approximate solution.
- Set up the data.
- Decide on a network architecture.
- Neural network training.
- Boost generalization abilities.
- Test outcomes.
- Create a model.

Also, there are different ways of determining the percentage error of the neurons. The one considered in this study is the backpropagation feed-forward method. The backpropagation feed-forward method is a supervised learning technique used in the domain of artificial neural networks for multilayer feed-forward networks [11–13]. The information processing of one or more neurons, also known as neural cells, serves as the model for feed-forward neural networks. Artificial neural network (ANN) is a novel method used in building scientific models to predict and improve engineering systems [14]. Asiltürk and Çunkaş [15] developed an experimental model to predict the turning operation of AISI 1040 steel using an artificial neural network (ANN) and the full factorial design of the experiment. The three-factor applied as input data are: cutting velocity, machining rate, and width of cut, with a response known as surface finishing. The result showed that the ANN back-propagation training algorithms used to train the system could predict the experimental outcome with 98.9% certainty. From the analysis, the feed rate has more influence on cutting when compared to the other factors (Fig. 4.2).



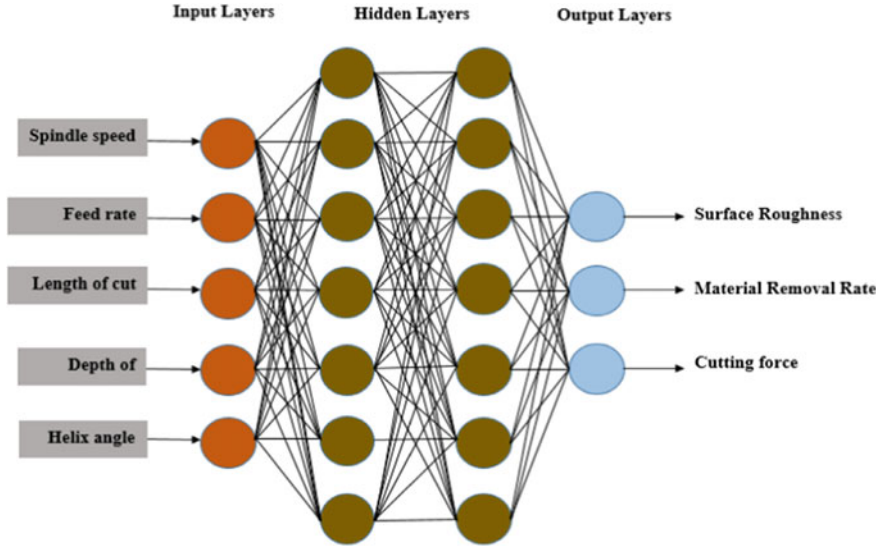


**Fig. 4.2** The standard ANN structure for modelling and prediction analysis

Input, hidden, and output are the three layers that make up the network. The hidden layer provides the link between the input and output layers using various numbers of neurons, and the input and output layers are defined as nodes or neurons [16]. The output layer's neurons get the processed data from the hidden layer's processing neurons via the input layer's neurons. The generic form, for instance, can be used to describe the input data to the neurons in the hidden layer as seen in Eqs. (4.1) and (4.2).

$$x_{hidden,j} = \sum_{i=1}^n w_{ij}u_i + \theta_j \quad (4.1)$$

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \quad (4.2)$$

where  $u_i$  is the value of the input,  $W_{ij}$  is the weight coefficient between the input neurons and hidden neurons, and  $j$  stands for the biases of the hidden neurons. Neural network models' performance depends on a number of factors, including network architecture, activation functions, and training procedures. In this study, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method, conjugate gradient, and the steepest descent training algorithm were all used to train the MLP network.

Additionally, during learning, testing, and validation, the error function was employed to identify discrepancies between actual values and computed values, which is defined as in Eq. (4.3):

$$Errors\ analysis = \sum_{i=1}^n (y_i - t_i)^2 \quad (4.3)$$

The root mean square error (RMSE), determination coefficient (R), and mean absolute percentage error (MAPE) were used to assess the efficacy of the regression models and selected neural networks (MAPE) [17], as presented in Eqs. (4.4) to (4.6).

$$RMSE = \left( \left( \frac{1}{N} \right) \left( \sum_{i=1}^N |t_i - y_i|^2 \right) \right)^{1/2} \quad (4.4)$$

$$R^2 = 1 - \left( \frac{\sum_{i=1}^N |t_i - y_i|^2}{\sum_{i=1}^N (y_i)^2} \right) \quad (4.5)$$

$$MAPE = \frac{\sum_{i=1}^N ((t_i - y_i)/t_i) \times 100}{N} \quad (4.6)$$

where N is the number of samples used in the analysis, y is the predicted value, and t is the target value.

### 4.3 Adaptive Neuro-fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the benefits of Fuzzy Logic (FL) and Artificial Neural Networks (ANNs) into a single framework. In order to model complicated patterns and comprehend nonlinear interactions [18]. It offers rapid learning capacity and adaptive interpretation skills. System for Adaptive Neuro-Fuzzy Inference. The Takagi–Sugeno Fuzzy System, also known as adaptive neuro-fuzzy inference systems, was created in 1993 by J. S. Roger Jang and is commonly recognized as a universal estimator. The Takagi–Sugeno Fuzzy Model is a Type 3 Fuzzy Inference System, where the final output is the weighted average of the outputs of all the rules, and the rule outputs are a linear combination of the input variables and a constant [19].

IF–THEN the rules for 3-input Takagi–Sugeno System are described as follows:

- (i) Rule 1: IF  $X = A_1$ ,  $Y = B_1$ ,  $Z = C_1$ , THEN

$$f_1 = P_1 X + q_1 y + r_1 Z + S_1$$

- (ii) Rule 2: IF  $X = A_2$ ,  $Y = B_2$ ,  $Z = C_2$ , THEN

$$f_1 = P_2 X + q_2 y + r_2 Z + S_2$$

(iii) Rule 2: IF  $X = A_3$ ,  $Y = B_3$ ,  $Z = C_3$ , THEN

$$f_1 = P_3X + q_3y + r_3Z + S_3$$

where the inputs in the crisp set are  $x, y$ , and  $z$ ; the linguistic labels are  $A_i, B_i$ , and  $C_i$ ; the consequent parameters are  $p_i, q_i$ , and  $r_i$ ; and the output fuzzy membership functions are  $f_1, f_2$ , and  $f_3$ . The five layers of interconnected neurons of the typical ANFIS architecture, shown in Fig. 4.3, provide evidence of artificial neural networks with similar functionality. The following is a basic explanation of the architecture.

Layer 1: Each neuron in this layer is an adaptive node that stores the fuzzy value of the crisp inputs.

The formula for calculating the node output is given in Eq. (4.7):

$$O_i^1 = \begin{cases} \mu_{A_i}(x), & \forall i = 1, 2, \\ \mu_{B_{i-2}}(x), & \forall i = 3, 4, \\ \mu_{C_{i-4}}(x), & \forall i = 5, 6, \end{cases} \quad (4.7)$$

where the fuzzy sets  $A_i, B_i$ , and  $C_i$  membership function is.

There are many membership functions, including Gaussian, Trapezoidal, Triangular, and others. In ANFIS, we favour a bell-shaped function. As a result, the

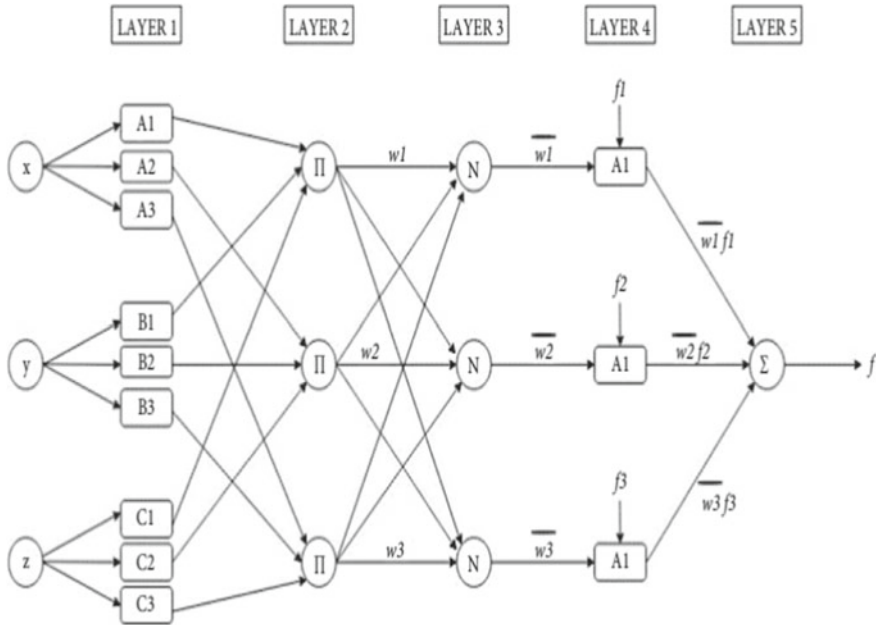


**Fig. 4.3** The ANFIS standard structure for modelling and prediction analysis

Gaussian function is the best option. The Gaussian function's formula expressed in Eq. (4.8).

$$f(x) = a \cdot \exp \left\{ \frac{(x - b)^2}{(2C^2)} \right\} \quad (4.8)$$

Fuzzification Layer 2: This is an Implication Layer where the weight of the premise parameters is stored in the neurons as the product of the inputs. The formula for calculating the node output expressed in Eq. (4.9):

$$O_i^2 = w_i = \mu_{Ai}(x) * \mu_{Bi}(x) * \mu_{Ci}(x), \quad \forall i = 1, 2, 3 \quad (4.9)$$

where  $w_i$  is the neuron's weight

Layer 3: The neurons in the normalizing layer are fixed and are normalized using the weights of all the neurons in this layer. The formula for determining the node output is:

$$O_i^3 = \bar{w}_i \quad f_i = \frac{w_i}{\sum w_i} \quad \forall i = 1, 2, 3 \quad (4.10)$$

where  $\bar{w}_i$  is the normalized weight of the neuron

Layer 4: In the defuzzification layer, each neuron serves as an adaptable node and stores the architecture's ensuing parameters. This is how the node output is determined as shown in Eqs. (4.10) to (4.11):

$$O_i^4 = \bar{w}_i \quad f_i = \bar{w}_i * (p_i x + q_i y + r_i z + s_i) \quad \forall i = 1, 2, 3 \quad (4.11)$$

Layer 5: There is only one neuron in the output layer, which is the sum of all the input layers. The formula for calculating the node output expressed in Eq. (4.12):

$$O_i^5 = \bar{w}_i \quad f_i = f(x, y, z) = \sum_i \bar{w}_i \quad f_i = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i} \quad \forall i = 1, 2, 3 \quad (4.12)$$

The hybrid learning method, where parameters are updated over two passes and use two separate optimization algorithms, is preferred by traditional ANFIS. This five layers are employed for the modelling and prediction analysis of ANFIS [20].

#### 4.4 Particle Swarm Optimization (PSO)

One of the bio-inspired algorithms, particle swarm optimization (PSO), is straightforward in its search for the best solution in the problem area. It differs from other optimization techniques in that it does not depend on the gradient or any differential form of the objective and simply requires the objective function. There are also not many hyperparameters [21]. PSO can be applied in various area of engineering process such as energy storage, renewable energy system, machining process optimisation such electrochemical, Micro-EDM optimization [22]. In order to maximize the measures of process performance, it is crucial to choose the ideal values for key electrochemical machining process parameters such the tool feed rate, electrolyte flow velocity, and applied voltage. Dimensional accuracy, tool life, material removal rate, and machining cost are examples of these performance indicators. For the purpose of determining the ideal set of process parameters for an electrochemical machining process, a particle swarm optimization approach is proposed in this research. Dimensional accuracy, tool life, and material removal rate are the goals taken into account. These goals are subject to temperature, choking, and passivity restrictions [23]. Aspects of both single- and multi-objective optimization are taken into account. The suggested algorithm's outcomes are contrasted with those of existing optimization methods that have already been published.

In the current study of Quarto et al. [24] a methodology for choosing the ideal process parameters for the EDM process was established up using an artificial neural network (ANN) and a heuristic algorithm known as particle swarm optimization (PSO). The created methodology has a dual direction feature that adapts to various industry needs. Typically, in an industrial setting, the operators are constrained by the requirements of the project or by the time constraints. Because of this, a methodology that has only been tried on a single type of workpiece material, has a small number of input variables, or was created to optimize a single performance is constrained. The created 2-step model gives operators the freedom to decide which criteria to include in the optimization and helps them to determine the optimum production option.

#### 4.5 Genetic Algorithm (GA)

The genetic algorithm, which is based on natural selection, the mechanism that propels biological evolution, is a metaheuristic algorithm technique for resolving both limited and unconstrained optimization issues [25]. A search-based technique known as a genetic algorithm is used to address optimization issues in machine learning. This method is crucial because it resolves challenging issues that would require a lot of time to resolve. Data centers, electronic circuit design, code-breaking, picture processing, and artificial creativity are just a few of the real-world uses for it. The Generational GA (GGA), Steady-State (SSGA), Steady-Generational (SGGA), and (+)-GA are the four different forms of Genetic Algorithms (GA) that are described

[26]. Each crossover method for each type of GA is split into its comparable classes based on 30 runs of the top 12 EC variants. A heuristic search algorithm called a genetic algorithm (GA) is used to tackle search and optimization issues. A subset of evolutionary algorithms, which are utilized in computation, includes this algorithm. Genetic algorithms employ the concept of genetics and natural selection to provide solutions to problems.

These algorithms are more intelligent than random search algorithms because they direct the search to the best performing area of the solution space using historical data [27]. GAs are also based on chromosomal behavior and genetic structure. Every chromosome plays a part in offering a potential answer. The fitness function assists in supplying the traits of each person inside the population [7]. The solution is better the larger the function. In the 1960s and 1970s, Holland [76] developed the concept of GA, which he adapted from natural genetics and evolution. To get the best solution, randomly combined solutions are examined and their information is shared. GA can be used by functions with one or more objectives. By maximizing radial rake angle, speed, and feed rate throughout the end milling machining process, a single-objective function minimizes SR for Ti–6Al4V [28].

A process for optimizing genetic algorithms is as follows:

1. Select a coding scheme, a crossover operator, a mutation operator, and a selection operator to describe the problem parameters. Select the n-fold crossover probability,  $p_c$ , and the p-fold mutation probability. Create a random population of strings with a length of  $l$ . Select the  $t_{max}$  generation number as the most permitted. Set  $t = 0$ .
2. Assess each string in the sample.
3. Terminate if  $t = t_{max}$  or other termination requirements are met.
4. Encourage population reproduction.
5. Use probability  $PC$  to do a crossover on a pair of strings.
6. Apply  $PM$  probability to string mutations.
7. Assess the new population's strings. Go to Step 3 after setting  $* = t + 1$ .

## 4.6 Whale Optimization Algorithm

Whale optimization algorithm (WOA) is a meta-heuristic optimization algorithm inspired by nature that imitates the behavior of humpback whales when hunting. The bubble-net searching tactic served as the basis for the algorithm. Bubble-net feeding is the term used to describe the humpback whales' foraging activity [29]. An optimization algorithm is a methodical process used to find the highest or minimum value of an objective function [30]. Engineering applications are increasingly using meta-heuristic optimization techniques because they:

- (i) rely on relatively simple ideas and are straightforward to put into practice.
- (ii) They do not need gradient information to avoid local optima and
- (iii) can be used to a wide range of issues from many academic fields.



**Fig. 4.4** How humpback whales feed while using bubble-nets

Bubble-net feeding is the term used to describe the humpback whales' foraging activity. Hunting krill or small fish in schools near the surface is preferred by humpback whales [31]. This foraging has been seen to involve the formation of characteristic bubbles along a circular or '9'-shaped path, as depicted in Fig. 4.4. Only humpback whales have been documented to engage in bubble-net feeding, which is a distinctive behavior. The spiral bubble-net feeding movement is mathematically described in the whale optimization algorithm (WOA) in order to accomplish optimization.

- WOA mimicked hunting behavior by using the best search agent or a random search agent to pursue the prey.
- To mimic humpback whales' bubble-net attacking technique, WOA employs a spiral.

In the machining industrial sector, choosing the right cutting parameters is crucial for enhancing product quality. The use of optimization techniques in metal cutting operations is therefore essential for a high-quality end result [32, 33]. Because multiple conflicting objectives must be optimized at once due to the complexity of the machining operations, single objective optimization techniques have drawbacks [34]. In order to resolve this conundrum, the multi-objective optimization method is introduced [35]. Tanvir et al. [36] this paper's primary goal is to create a multi-objective optimization method using a hybrid version of the Whale Optimization Algorithm (WOA). The WOA algorithm incorporates grey analysis to complete the multi-objective optimization. This study examines the impact of machining parameters such as cutting speed, feed rate, and depth of cut on surface roughness, cutting forces, power, peak tool temperature, material removal rate, and heat rate when turning stainless steel 304. Through a number of simulations and experiments, the output parameters are acquired. Then, by taking into account unit cost and production

quality, the hybrid optimization algorithm achieves the best machining conditions for a turning operation. It is also discovered that the ideal cutting condition changes when the output parameter weight varies. The effects of various cutting parameters on surface roughness and power consumption are also examined. This study has shown that the application of Whale optimization algorithm is a viable tool for machining process to optimized the machining parameters during production process.

## 4.7 Ant Lion Optimization Algorithm (ALOA)

A more recent meta-heuristic, the Ant Lion Optimizer (sometimes called Antlion Optimizer), describes mathematically how ants and antlions interact in the natural world [37]. In order to resolve optimization issues with ant random walks, trap building, ant entrapment in traps, prey capture, and trap re-building are applied, an optimization algorithm has been created to address engineering. The ALO algorithm imitates the way ant lions hunt, that is, how the ant lions engage with their prey (ant) [38]. The several processes that outline the interaction between antlions and ants are shown in Fig. 4.5.

The mathematical models are shown in the sections and Eqs. (4.13)–(4.14) [39]:

$$X(t) = [0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1), \dots, \text{cumsum}(2r(t_n) - 1)] \quad (4.13)$$

$$r(t) = \begin{cases} 1 & \text{rand} > 0.5 \\ 0 & \text{rand} \leq 0.5 \end{cases} \quad (4.14)$$

where  $r(t)$  is a stochastic function,  $\text{rand}$  is a random integer generated with uniform distribution in the range  $[0, 1]$ ,  $\text{cumsum}$  calculates the cumulative sum,  $n$  is the maximum number of iterations,  $t$  shows the step of the random walk (iteration in this research), and  $r(t)$  is a stochastic function.

The five primary phases of the ant lions' hunting strategy are described in the following steps.

### 4.7.1 Random Walks of Ants

Ants adjust their placements according to a random walk search at each stage of optimization as presented in Eq. (4.13) [40]. The ant positions are normalized using the following expression to make sure that all of them fall inside the search space's perimeter as given in Eq. (4.15):

$$X_i^t = \frac{(X_i^t - a_i)(d_i - c_i^t)}{(d_i^t - a_i)} + c_i \quad (4.15)$$



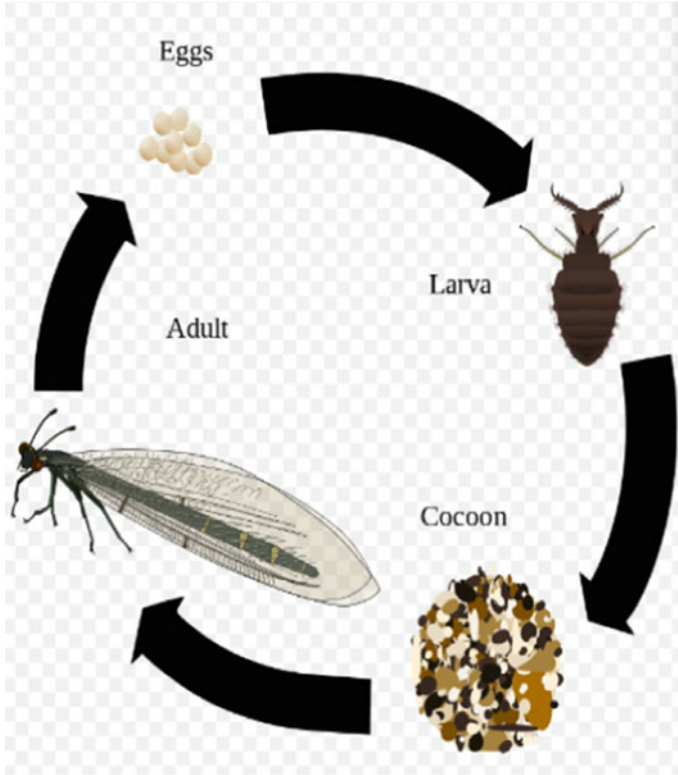


**Fig. 4.5** The structural formulation of the interaction between antlions and ants

where display style  $a_i$  presents the minimum random walk in the  $i$ -th variable, displaystyle  $b_i$  represents the maximum random walk in the  $i$ -th variable, displaystyle  $c_i^t$  it represents the minimum of the  $i$ -th variable at the  $t$ -th iteration, and displaystyle  $d_i^t$  it represents the maximum of the  $i$ -th variable at the  $t$ -th iteration.

### 4.7.2 Trapping in the Pits of Antlions

According to a model, antlions have the following effects on ant movement as presented in Eqs. (4.16) and (4.17):

$$c_i^t = Antlion_j^t + c^t \quad (4.16)$$

$$d_i^t = Antlion_j^t + d^t \quad (4.17)$$

where display style  $c^t$  represents the minimum value for all variables at iteration  $t$  and display style  $d^t$  is the vector containing the maximum value for all variables at iteration  $t$ . The  $i$ -th ant's minimum set of variables is View the MathML code. The sum of all the variables for the  $i$ -th ant is View the MathML code, and The position of the chosen  $j$ -th antlion at the  $t$ -th iteration can be seen by viewing the MathML source.

### 4.7.3 Building Traps

Using a roulette wheel, traps are constructed. During optimization, the operator of the roulette wheel chooses the lions based on their fitness. The fitter antlions have a greater probability of catching ants thanks to this technique.

### 4.7.4 Ants Sliding Toward the Antlion

The aforementioned methods explain how antlions can build traps in proportion to their fitness and how ants travel toward the center of the pit [41]. Equations (4.18) and (4.19) is the mathematical representation of this step of the hut. The hyper-radius sphere's for ants' random movements is reduced, as can be seen in the equation.

$$adaptive.C^t = \frac{C^t}{I} \quad (4.18)$$

$$d^t = \frac{d^t}{I} \quad (4.19)$$

Knowing  $I$  is a ratio,  $c^t$  is the minimum value for all variables at iteration  $t$ , and  $d^t$  denotes the vector containing its maximum value for all variables.

### 4.7.5 Re-building the Pit and Catching Prey

When ants become more physically fit (dives deeper into the sand than their linked antlion), they can grab prey in ALO [42]. In order to increase its chances of snagging fresh prey, an antlion must then adjust its position to match the most recent location of the chased ant. This behavior is simulated by the Eq. (4.20):

$$Antlion_j^t = Ant_i^t \quad iff (Ant_i^t) > f(Antlin_j^t) \quad (4.20)$$

where the present iteration is shown by  $t$ , the placement of the chosen  $j$ -th antlion at the  $t$ -th iteration can be seen in the MathML source. The position of the  $i$ -th ant at the  $t$ -th iteration is shown in the MathML source.

#### 4.7.6 Elitism

The ability of evolutionary algorithms to keep the best solution(s) found at any step of the optimization process is known as elitism [43]. The top antlion from each iteration is preserved and treated as an elite in this study. Since the elite is the strongest antlion, it ought to be able to have an impact on how the ants move over iterations. As a result, it is supposed that each ant simultaneously moves around an antlion chosen by the elite and the roulette wheel this expression is shown in Eq. (4.21):

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (4.21)$$

where  $Ant_i^t$  denotes the position of the  $i$ -th ant at the  $t$ -th iteration and  $R_A$  denotes the random walk around the antlion chosen by the roulette wheel at the  $t$ -th iteration. Ant Lion Optimizer can be applied as a single (ALO), Binary ALO (\*BALO), and Multi-objective ALO (MOALO) in all world applications [44]. However, since the study of optimization in machining operation is very complex, due to several responses (cutting force, materials removal rate, surface roughness, temperature distribution, friction, and vibration). Machining parameters (cutting speed, depth of cut, feed rate, and length of cut), and environment of the cutting such as nanolubricants and vegetable oil, a multi-objective ALO is preferable. According to Kalita et al. [45] the multi-objective antlion optimization (MOALO) and the multi-objective dragonfly algorithm (MODA) are two nature-inspired optimization algorithms that are used in this research to optimize a variety of process parameters during the machining of MMCs. An ensemble strategy merging MOALO and MODA techniques is proposed here to reduce uncertainty in the global optimality of the anticipated Pareto optimal fronts resulting from the stochastic character of the metaheuristics. Two case studies are used to show how the MOALO-MODA ensemble is significantly better than its separate equivalents and may be used to create solid and trustworthy Pareto optimum fronts. Therefore, this book applied the MOALO in optimizing the cutting force and surface roughness in Chap. 7.

## 4.8 Grasshopper Optimization Algorithm (GOA)

Saremi, Mirjalili, and Lewis introduced the Grasshopper Optimization Algorithm (GOA) as an optimization method in 2017. It comprises both the attraction of the most desirable individual and social interaction between common agents (grasshoppers). In the course of our research, these intriguing exploratory skills of the GOA will be further studied, as evidenced by the authors' initial tests [46]. The objective of this contribution is to assess the machining response, optimizing the machining parameters, using the GOA as the optimization strategy. Figure 4.6 depicts how grasshoppers behave. Some search agents locally fly the search space during implementation. While this is happening, these relationships are driving a dramatic change in the other phase. Equation (4.22) describes the swarming behavior of grasshoppers using  $X_i$  as the position of the  $i$ -th insect:

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \quad (4.22)$$

While  $S_i$  represents a social connection,  $G_i$  stands for gravity, and  $A_i$  represents wind advection. Additionally, the random values for  $r_1$ ,  $r_2$ , and  $r_3$  range from 0 to 1 [34, 47] provide additional mathematical details concerning the approach.

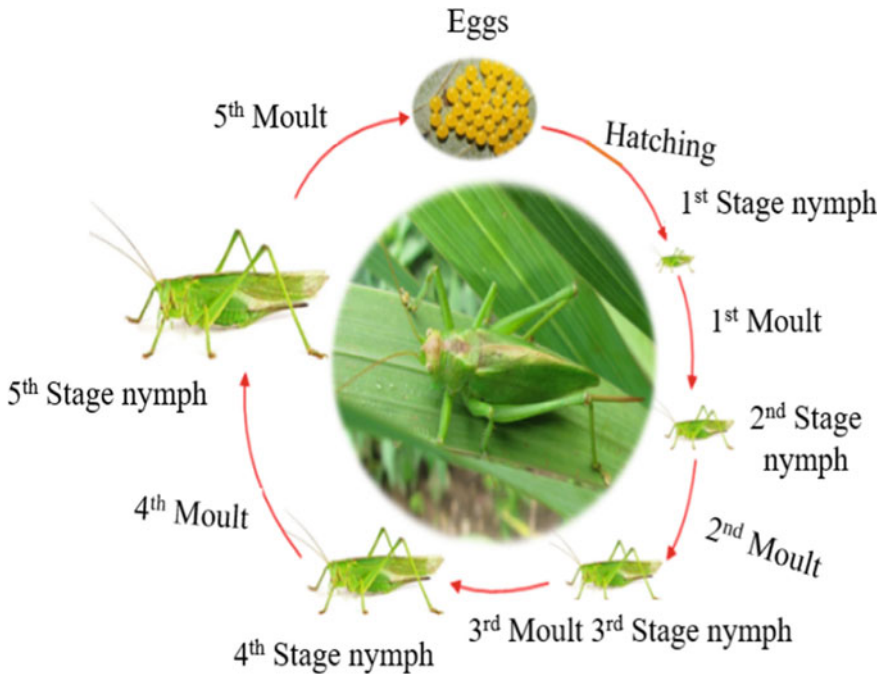


**Fig. 4.6** The implementation of grasshopper optimization algorithm life cycle for machining operations

One of the most frequently referenced case cases in the literature is this structural design issue [48], which lead to the formulation of the measures for GOA as presented in the following steps of implementation:

- (i) Initialization
- (ii) first population and assessment
- (iii) The entire beat solution is assigned
- (iv) updating the parameter for the decreasing coefficient
- (v) measuring grasshopper distances
- (vi) updating the answer
- (vii) Limitations of the solution
- (viii) visiting all of the population's solutions
- (ix) assessments of solutions
- (x) Termination standards
- (xi) delivering the top response

Figure 4.7 show the different step of the GOA flowchart for performance evaluation. The following are the Benefits of the application of GOA in manufacturing process:

- (a) Even though grasshoppers can seriously harm a farmer's crops, the ecology wouldn't be the same without them [49].
- (b) They have a significant impact on the ecosystem, enhancing its capacity to support the growth of plants and other creatures.

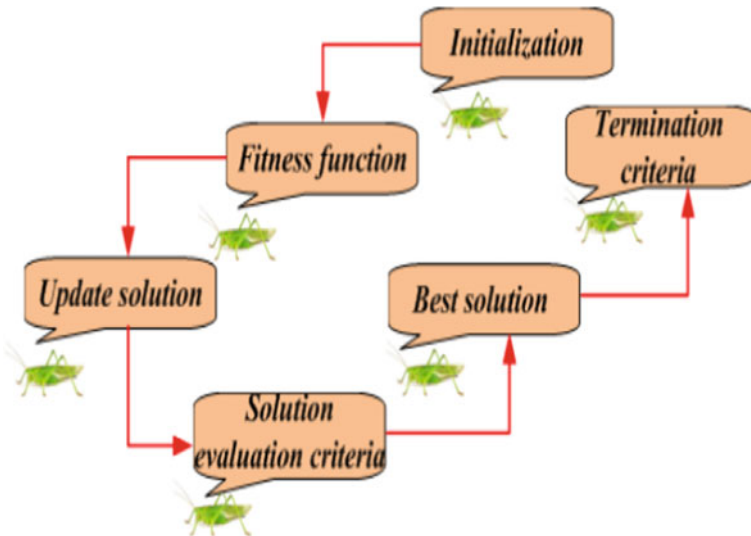


**Fig. 4.7** GOA analysis flowchart for implementation

- (c) The grasshopper facilitates plant decay and regrowth, maintaining a balance between the varieties of plants that survive, which helps people and the ecosystem as a whole.
- (d) The ability of the grasshopper to dramatically alter the kinds of plants that flourish in his surroundings is proof that he benefits the ecology by promoting plant growth [50].
- (e) Because the waste is smaller, bacteria can break it down more quickly and fertilize the soil more quickly.
- (f) The grasshopper may not be aware of this particular function he performs in the ecosystem, but in the wild, he serves as a crucial source of food for predators.
- (g) The insect's appetite can generally cause havoc on farm crops, but it also helps the ecosystem by ensuring that plant development is kept at its ideal levels [51].

Adapa et al. [52] in this study, the milling capabilities of polymer nanocomposite materials modified with glass fiber and multiwall carbon nanotube are examined (MWCNT). Spindle speed (S), Feed rate (F), Depth of Cut (D), and weight% MWCNT (wt.%), which are among the variables taken into consideration, have successfully controlled to obtain the desired value. Planning for the experiment used the Taguchi L9 Orthogonal array (OA). Using the Technique for Order of Preference by Similarity to Ideal Solution, the responses Material removal rate (MRR), cutting force (Fc), and surface roughness (Ra) were combined (TOPSIS). The Grasshopper optimization algorithm achieves the ideal combination of machining constraints (GOA). To choose the optimal target among the many possible solutions, GOA mitigates the bionic-inspired concepts. The larval phase of the GOA is characterized by the grasshopper's sluggish movement and little movements.

## 4.9 Review of Related Literature of the Optimization Techniques in Machining Process

This section gives details of research's that as implemented the global optimization tool and prediction techniques for machining process via various machining environment (Table 4.1).

According to Jawade et al. [68] the optimization of processing variables for the surface roughness of AISI316 austenitic stainless steel is discussed in this paper. Experimental parameters such feed rate (fd), speed (vc), and depth of cut (DoC) were utilized to examine the effects on the workpiece's surface roughness (Ra). The experiment was conducted on a computer numerical control (CNC) lathe utilizing the design of experiments (DOE). Following the turning process, the surface roughness is evaluated under three different conditions: dry, wet, and cryogenic. With a set of experiments planned, samples are step turned on a CNC lathe for each of the three circumstances. For all three scenarios, the response surface methodology is used, and mathematical models are created. It is best to use the algorithm that was inspired by nature to the optimal values for the machining parameters. In

**Table 4.1** Summary of selected optimization techniques and their analysis in machining operations

| Authors details           | Optimization tools                                          | Factors                                                                                   | Responses                                                                              | Machining types    | Findings                                                                                                                                                                                                                                                                                                                                                                                                     |
|---------------------------|-------------------------------------------------------------|-------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|--------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Han et al. [53]           | Particle swarm algorithm in milling                         | Spindle speed (rpm), width of cutting (mm), feed rate (mm/min), and depth of cutting (mm) | Material removal rate (MRR) and cutting power (P)                                      | Milling            | The optimization model and technique given here address the trade-off issue involving P and MRR. The findings show that the compared to not, the weighting optimization is more thorough just improving the empirical cutting power P and MRR not only guaranteeing the minimum P and the highest MRR. Research demonstrates the process and results. It is legitimate and practical to optimize objectively |
| Osorio-Pinzon et al. [54] | Multi-objective particle swarm optimization (PSO) algorithm | Rake angle ( $\alpha$ ), velocity ( $V$ ), and cutting feed ( $f$ )                       | Reduce cutting force, improve microstructure, and increase material removal rate (MRR) | Turning of AI-6063 | Through the incorporation of the multi-objective PSO (MOPSO) algorithm during the machining of Aluminum 6063, the optimization models may be able to help meet the intended objectives for optimizing the cutting force and materials removal rate                                                                                                                                                           |

(continued)

Table 4.1 (continued)

| Authors details   | Optimization tools                                 | Factors                                                      | Responses                                                             | Machining types  | Findings                                                                                                                                                                                                                                                                                                                                                      |
|-------------------|----------------------------------------------------|--------------------------------------------------------------|-----------------------------------------------------------------------|------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Kahya et al. [55] | Reconfigured particle swarm optimization algorithm | Depth of cut, Stepover, feed per tooth, and cutting velocity | Specific cutting energy, material removal rate, and surface roughness | Ball-end milling | PSO was a successful and simple to use multi-objective optimization technique. It was successful in producing a 3D Pareto front of the three-objective finish ball-end milling process. It was possible to recommend and validate three different machining scenarios based on a company's strategies in an industrial context using the created Pareto front |

(continued)



Table 4.1 (continued)

| Authors details | Optimization tools                                           | Factors                                                                    | Responses                                                                         | Machining types                                          | Findings                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        |
|-----------------|--------------------------------------------------------------|----------------------------------------------------------------------------|-----------------------------------------------------------------------------------|----------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Das et al. [56] | Particle Swarm optimisation technique, and Taguchi technique | Depth of cut, d (mm),<br>Cutting speed, V (m/min),<br>and Feed, f (mm/rev) | Average surface roughness (Ra), cutting tool temperature (T), and tool flank wear | Turning operation of reinforced Al 7075 matrix composite | Compared to the outcomes of the traditional Taguchi technique, the multi-objective PSO produced better results for the answers. It successfully produced a set of non-dominated answers. For T, Ra, and VBc, Pareto optimum fronts were assembled and plotted; these could be chosen based on production needs. When comparing the experimental and PSO results, the confirmation experiments revealed errors of 2.12%, 2.76%, and 3% for T, Ra, and VBc, respectively. These findings suggested that this strategy was incredibly realistic and can be thought of as a workable substitute for resolving various objective optimisation issues |

(continued)

Table 4.1 (continued)

| Authors details     | Optimization tools                                                     | Factors                                                                        | Responses                           | Machining types             | Findings                                                                                                                                                                                                                                                                                                                                                                                                                   |
|---------------------|------------------------------------------------------------------------|--------------------------------------------------------------------------------|-------------------------------------|-----------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Balonji et al. [57] | Particles swarm optimisation (PSO) and artificial neural network (ANN) | Rotational speed, feed rate, radial depth cut, and axial depth cut of the tool | Surface roughness (SR)              | End milling of Al6061 alloy | With respect to this investigation, the highest trained regression value (R <sup>2</sup> ) was reported to be 0.9938, and the lowest mean square error was reported to be 0.00044. These values correspond to nine (9) neurons, a 200-person swarm, and acceleration factors of 1.5 and 2.25. This work demonstrates the hybrid ANN-potential PSO's for surface roughness prediction, which may improve aluminum machining |
| Imani et al. [58]   | Hybrid ANN and GA                                                      | Cutting depth, feed rate, coolant, and speed of cutting                        | Cutting force and surface roughness | Turning of Inconel 738      | For both wet and dry milling of Inconel 738, the optimal artificial network developed in this study is beneficial for predicting the machining force and surface roughness of milling based on the values of cutting speed, feed rate, and axial depth of cutting                                                                                                                                                          |

(continued)

Table 4.1 (continued)

| Authors details         | Optimization tools                                           | Factors                                           | Responses                                              | Machining types                               | Findings                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        |
|-------------------------|--------------------------------------------------------------|---------------------------------------------------|--------------------------------------------------------|-----------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Karthikeyan et al. [59] | Genetic algorithm and feed forward artificial neural network | Voltage, input power, pulse on and off, and pulse | Material removal rate (MRR) and surface roughness (SR) | Wire cut electric discharge machining (WCEDM) | An artificial neural network was used to build the model between the process factors and output values. While the root mean square error for the MRR model was found to be as low as 0.0059386 and the determination coefficient to be 1, the root mean square error for the SR model was found to be as low as 0.0033068 and the determination coefficient to be 0.99991. The evolutionary computational methods of genetic algorithms for optimization were properly combined with the model developed by ANN |

(continued)

**Table 4.1** (continued)

| Authors details         | Optimization tools                                              | Factors                                     | Responses                                                            | Machining types                             | Findings                                                                                                                                                                                                          |
|-------------------------|-----------------------------------------------------------------|---------------------------------------------|----------------------------------------------------------------------|---------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Nguyen et al.<br>[60]   | Genetic algorithms                                              | Feed rate, cutting speed, cutting depth     | Surface roughness and the maximum value of the material removal rate | Grinding process of 9CrSi alloy             | To obtain the least amount of surface roughness and the highest amount of material removal rate, the genetic algorithms (GAs) were used to calculate the ideal values of external cylindrical grinding conditions |
| Santhosh et al.<br>[61] | RSM and ANN-genetic algorithms using a face-centered CCD method | Depth of cut, rotating speed, and feed rate | <i>Surface roughness</i>                                             | Turning operation for AISI 4340 alloy steel | To find the best machining process parameters and get a satisfactory output response in real-world settings, a combination of artificial neural network and genetic algorithm technique is advised                |
| Sahoo et al.<br>[62]    | Taguchi-Whale optimization algorithm                            | Feed rate, spindle speed and tool condition | Surface roughness, maximizing power and torque                       | CNC-drilling of Inconel 718                 | To decrease surface roughness and maximize torque and thrust force during drilling operations, the process parameters are optimized using the Whale optimization method                                           |

(continued)

Table 4.1 (continued)

| Authors details    | Optimization tools                                                                                                                                         | Factors                                                 | Responses                                                                                   | Machining types             | Findings                                                                                                                                                                                                                                                                                                                                                                                                                                   |
|--------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------|---------------------------------------------------------------------------------------------|-----------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Tanvir et al. [36] | Hybrid Whale optimization algorithm                                                                                                                        | Cutting speed, feed rate and depth of cut               | Cutting pressures, power, maximum tool temperature, rate of material removal, and heat rate | Turning stainless steel 304 | Numerous simulations and tests are used to acquire the output parameters. The best machining conditions for turning operations are therefore attained by employing this hybrid optimization technique while taking unit cost and production quality into account. Additionally, it has been discovered that the ideal cutting condition changes when the weight of the output parameter changes                                            |
| Joshi et al. [63]  | The multi-objective ant lion optimization (MOALO), non-dominated sorting genetic algorithm II (NSGA-II), and multi-objective dragonfly optimization (MODA) | Cutting depth (D), feed rate (f), and cutting speed (N) | Material removal rate (MRR) and surface roughness (SR)                                      | Micro-machining processes   | According to a comparison of the metaheuristics for multi-objective optimization, MOALO is faster at solving these kinds of problems than MODA or NSGA-II. Additionally, it is discovered that MOALO and MODA have considerably superior Pareto front recognition and generating skills than NSGA-II. Both of the COPRAS solutions for MODA performed significantly better than NSGA-II, with MOALO being only slightly superior to COPRAS |

(continued)

**Table 4.1** (continued)

| Authors details       | Optimization tools                                | Factors                                                                                   | Responses                                                                   | Machining types                                        | Findings                                                                                                                                                                                                                                    |
|-----------------------|---------------------------------------------------|-------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Laouissi et al. [64]  | ANN-MOALO                                         | Cutting depth, feed rate and cutting speed                                                | Surface roughness                                                           | Turning of EN-GJL-250 cast iron                        | Future industrial applications for accurately predicting part quality and power consumption as well as optimizing cutting parameters to obtain the greatest production control have been discovered to benefit from the ANN-MOALO technique |
| Sinha et al. [65]     | Multi-objective grasshopper optimization          | Servo voltage, peak current, spark-on time, spark-off time                                | Material removal rate (MRR) and Surface Roughness (SR)                      | Wire electro discharge machining (WEDM) of Inconel 625 | Multiple objective particle swarm optimization (MOPSO) and non-dominated sorting genetic algorithm II (NSGA-II) were compared with MOGOA, and MOGOA was determined to be superior to both                                                   |
| Kumar and Verma [66]  | Grasshopper-inspired optimization algorithm (GOA) | Feed rate (F), depth of cut (D), weight percentage of MWCNT (wt.%), and spindle speed (S) | Cutting force (Fc), material removal rate (MRR), and surface roughness (Ra) | Milling of polymer nanocomposite                       | The Grasshopper optimization algorithm achieves the ideal combination of machining constraints (GOA). To choose the optimal target among the many possible solutions, GOA mitigates the bionic-inspired concepts                            |
| Nagarajan et al. [67] | Grey wolf optimizer (GWO)                         | Applied voltage, flow rate, and electrolyte concentration                                 | Material removal rate (MRR)                                                 | Electrochemical machining                              | This proves that the GWO metaheuristic algorithms are more suited for determining the ideal process variables for milling Monel 400 alloys using ECM                                                                                        |

**Table 4.2** Present the grasshopper optimization algorithm’s optimal settings for the machining parameters

| Surface roughness | Cutting speed (Vc) | Feed rate (fd) | Depth of cut (D.O.C.) | Optimal values |
|-------------------|--------------------|----------------|-----------------------|----------------|
| Ra (dry)          | 160                | 0.3            | 1.01                  | 0.4535         |
| Ra (wet)          | 200                | 0.3            | 0.5                   | 0.7916         |
| Ra (cryogenic)    | 165.58             | 0.1            | 1.5                   | 0.3895         |

order to get the best parameter values for the problem being presented in the study, which involves minimizing surface roughness under all predetermined conditions, naturalistic methodologies are applied. The approach that works well for practical applications is the Grasshopper optimization algorithm (GOA). In this study, GOA is employed to obtain the best surface roughness (Ra) values under dry, wet, and cryogenic circumstances as shown in Table 4.2. Finally, findings are contrasted, and it is found that GOA values have the lowest surface roughness values.

However, it can be seen from the optimal results from Table 4.1 that for each machining environments there are different optimal machining values. This is the challenge and limitation of most studies done in the area of optimization with modern optimization tools. This study book will address this challenges in the different chapters employing the multi-optimization tools such as multi-objective grasshopper optimizer, multi-objective grey wolf optimizer and multi-objective ant lion optimizer.

4.10 Conclusion

This chapter has successfully discussed Global optimization tool and prediction techniques as it pertained to machining process. The optimization and prediction tools discussed in this chapter cut across the Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System, particle swarm optimization, genetic algorithm, Whale optimization algorithm, Ant Lion Optimization Algorithm (ALOA), and Grasshopper Optimization Algorithm (GOA). From the results obtained from the review and discussion of the various techniques this chapter has the following conclusion such as:

- (i) It has been proven that the GOA and ALOA is a viable optimization tools for machining operations.
- (ii) The global prediction tool employed such as Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System has also proven viable, which assist the predictions of the future works in the response surface parameters during machining.

- (iii) Due to the complexity in studying the optimizations parameters of the factors and the responses in machining, single optimization tool will not be satisfactory, however, it can give optimal value but not as sustainable as the multi-optimization tools.

Therefore, the application of Multi-Heuristic and Metaheuristic Techniques for Advanced Machining Optimization is high needed to improve the manufacturing production system. Chapter 5 of this book discusses the multi-objective Grey Wolf Optimizer for improved machinability performance employing various factors and studying various responses.

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## Chapter 5

# Multi-objective Grey Wolf Optimizer for Improved Machining Performance



**Abstract** Real engineering difficulties come in a variety of forms, each requiring a unique set of tools to solve. Multi-objectivity is one of the key elements of real situations that makes them difficult to solve. In this section, the machinability performance problem is studied using two indicators namely the cutting force and the surface roughness. The speed of cutting, the feed rate and the depth of cut are the parameters, describing the setting of the CNC lathe machine, to optimize. In this study, titanium alloy (Ti–6Al–4V) was chosen as the turning work material. Quadratic equations of the cutting force and the surface roughness were extracted from an existing study to illustrate the approach. A single objective optimization problem was developed to optimize the cutting force and the surface roughness separately using the grey wolf optimizer. Details showing the formulation of the problem and the results have been disclosed. The Multi-objective grey wolf optimizer (MOGWO) was the metaheuristic-based approach proposed for the formulation of the problem and the computation of the non-dominated or Pareto optimal solutions. The best compromise was obtained by optimizing these two objectives simultaneously. The optimal settings corresponding to the optimal values of cutting force and surface roughness were computed and reported in this section.

**Keywords** Grey Wolf Optimizer · Multi-objective optimisation · Machining · Cutting force · Surface roughness

## 5.1 Introduction

One of the earliest and most common techniques for cutting metal has been turning operations utilizing single-point cutting tools. With shorter lead times, it has even taken the position of grinding in some applications without sacrificing surface quality. Cutting forces and workpiece surface roughness are two significant factors that are

extensively researched in turning operations [1, 2]. When examining the process capabilities of any machining operation, process parameter optimization is quite important. In order to understand cutting forces in turning operations, Shaw and Cookson [3] have underlined their significance. Surface precision, tool wear, tool breakage, cutting temperature, self-excited and forced vibrations, etc. are only a few of the aspects that are influenced by cutting forces. Özel and Karpat [4] among other studies, discovered that the surface quality of machined components is directly influenced by the cutting parameters (Feed rate, Cutting Speed, Depth of Cut, Tool Geometry, and Material Properties of Tool). The cutting force, thrust, and feed forces all have different effects on power consumption, however only the cutting force is taken into account as an endogenous element in this study.

Another crucial parameter is surface roughness, which can affect the wear resistance, fatigue strength, or creep life of machined components. A better surface finish (low surface roughness) is crucial for turned components as it can minimize or even totally eliminate the need for additional machining [2]. Many researchers have discovered that surface roughness affects a variety of factors, including heat transmission, lubricant retention, surface friction, wearing, etc. The machining process does not have perfect control over the surface finish obtained, despite the fact that surface roughness plays a significant role in the usefulness and lifespan of a machined component due to its dependence on several process parameters and numerous uncontrollable factors. Therefore, the ongoing process of adjusting process parameters to create the optimal surface finish involves a variety of material-to-tool combinations and machining circumstances [5].

Because turning is crucial for metal cutting, there is a wealth of literature on the subject. Speed, feed, and cut depth are the three key process variables in this study. To create a prediction model for surface roughness and cutting force, Lin et al. [6] used an abdicative network. This network can forecast the surface roughness and cutting force given the process parameters namely the cutting speed, the feed rate, and the depth of cut. It is essential to design the components in a way that can boost productivity, lengthen tool life, and lower overall machining costs. The machining process is optimized to increase productivity and product quality in order to reach the aim. The selection of variable parameters is regarded as a crucial task in machining optimization since it aids in assessing the effectiveness of the machining process. Typically, human (machinist) judgment and experience are used to determine the machining parameters. The optimum machining procedure, however, might not have been produced by the given parameters. In order to increase the efficiency of the machining process, optimization must be used [7].

As shown in Fig. 5.1, there are two main groups of optimization tools and techniques: traditional approaches and advanced methods. The majority of traditional optimization methods are gradient search based. Depending on the level of nonlinearity in the objective function and the initial assumption about the starting point, the standard optimisation technique has the potential to converge in a local optimum. Thus, the global optimum promised by the traditional optimisation technique was not achieved. In recent years, researchers have had a tendency to optimize machining operations using new techniques. Unlike the traditional approach, the advanced

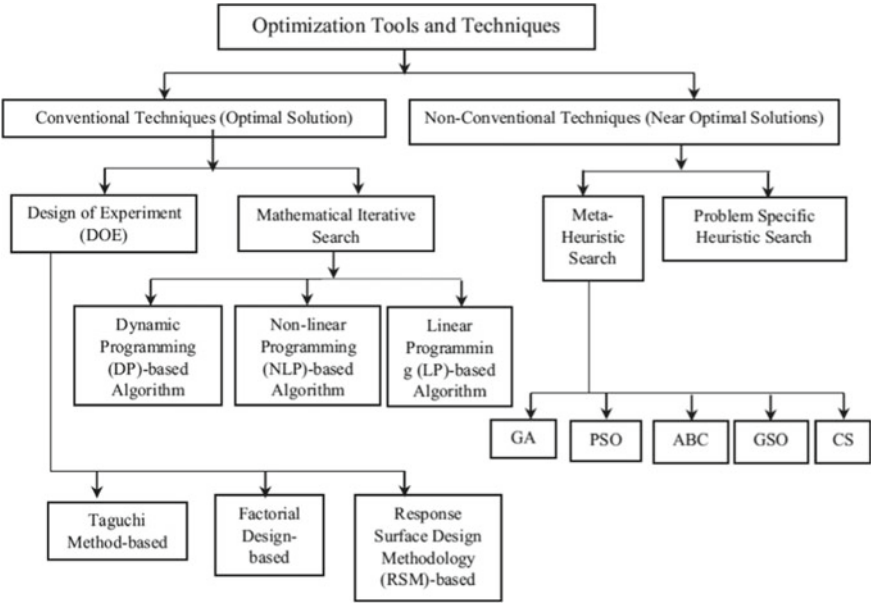


**Fig. 5.1** Typical optimisation tools and techniques in the machining process [7]

approach, particularly metaheuristic search, is based on an evolutionary algorithm (EA) [such as genetic algorithm (GA), particle swarm optimisation (PSO), artificial bee colony (ABC), simulated annealing (SA), cuckoo search algorithm (CSA), firefly algorithm (FA), and glow worm swarm (GWS)] that imitates biological processes like natural selection, recombination, and mutation to identify the best design possible given a set of constraints. These evolutionary algorithms (EA) can be implemented to optimize machining parameters. An illustration of the formulation and the implementation of some evolutionary algorithms to solve classical mathematical problems is provided in the study of Okwu and Tartibu [8].

The foundation of bio-inspired algorithms (BIA) is the concept of the orderly, natural movement of organisms and a phenomenon that is frequently seen in various animal species. Amazing examples of self-organized coordination are flocks of birds and schools of fish. Particle Swarm Optimization (PSO), for instance, mimics the social behavior of birds. The system begins with a population of randomly distributed particles, or “swarm,” and it continuously iterates through new generations in order to find the best value. Each particle in the swarm makes an effort to find a potential solution, and the group then makes an effort to achieve its overall goal based on feedback from the other members. Swarm intelligence-based algorithms (SIA) take advantage of the notion that a swarm’s aggregate intelligence exceeds the sum of its constituent parts. The swarm’s agents are all thought to be less than intelligent, but because they adhere to a few simple principles, the swarm as a whole can exhibit self-organizing behavior and act as though it had some form of collective intelligence.

These algorithms were developed by first studying the common habits of several animal species, such as wolves. This work aims to develop a new approach to optimize the machining performance of a CNC lathe machine. This approach seeks to optimize the cutting force and the surface roughness which are a function of the speed of cutting, the feed rate and the depth of cut using the grey wolf optimizer (GWO) algorithm.

The processing of a single objective function in optimization is known as a single objective, and the simultaneous handling of many objective functions is known as multi-objective optimization [9]. Through the discovery of a group of workable solutions known as non-dominated or Pareto optimal solutions, multi-objective optimization attempts to optimize a specific problem. The need for more effective methods is growing as a result of the abundance of multi-objective optimization issues in various study areas. One study has suggested using and adapting various metaheuristic-based approaches in research fields like engineering [10]. Based on the behavior of the method searching, the metaheuristic-based approaches are divided into three primary classes: trajectory, evolutionary, and swarm-based approaches [11]. The ability of the swarm-based approaches to approximate the entire Pareto front made them the most effective at addressing multi-objective optimization problems. To address the multi-objective optimization problem, several multi-objective optimization swarm-based techniques have been developed. This includes multi-objective optimization salp swarm optimizer [12], MO moth-flame optimization [13], multi-objective optimization ant lion optimizer [14] and multi-objective optimization grey wolf optimizer (MOGWO) [15].

The Multi-objective grey wolf optimizer (MOGWO) draws inspiration from grey wolves and their natural habitat (such as their leadership hierarchy and hunting mechanism) and has been effectively used to address a variety of issues [11]. Due to the fact that the grey wolf optimizer (GWO) is gradually being implemented in many engineering fields, there are no studies about the use of this method for the optimization of problems involving the cutting force and the surface roughness in order to enhance machinability performance.

## 5.2 Grey Wolf Optimization (GWO) Background

The grey wolves typically coexist in packs of between 5 and 12 individuals. These wolves are divided into four groups based on their prevailing strategies: alpha ( $\alpha$ ), beta ( $\beta$ ), delta ( $\delta$ ), and omega ( $\omega$ ) wolves.  $\alpha$  wolves are the most dominating, and the dominance progressively declines to  $\omega$  wolves. Important decisions are made by the  $\alpha$  wolves regarding hunting, sleeping arrangements, and walking schedules. The group is informed of these choices.  $\alpha$  wolves may also choose to follow other wolves in the pack, creating a democratic system. Despite not always being the group's strongest member, the  $\alpha$  wolves serve as its leader [16]. The second degree of authority in the pack is represented by the  $\beta$  wolves, who aid  $\alpha$  wolves in decision-making and other activities. In the event that  $\alpha$  wolves pass away or get very old, they are nominated

to replace those  $\alpha$  wolves. The  $\beta$  wolves serve as the remainder of the pack's leaders and counselors. The group's lowest dominance is the  $\omega$  wolves. These wolves are permitted to eat last. They could give birth to group members. The  $\delta$  wolves rule over the  $\omega$  wolves and provide information to the  $\alpha$  and  $\beta$  wolves. There are three primary steps in the grey wolf hunt, which are as follows [17]:

- 1 Looking for, pursuing, and getting close to the prey.
- 2 Surrounding and agitating the prey until it stops moving (Fig. 5.2).
- 3 Taking the prey by force.

The following can be used to model the GWO algorithm:

(a) Social Strategy

The fittest solution in the GWO algorithm is referred to as  $\alpha$  wolf. Consequently, the  $\beta$  and  $\delta$  wolves are referred to as the second and third best options. The remaining potential solutions are the  $\omega$  wolves. In general, the optimization process is guided by  $\alpha$ ,  $\beta$ , and  $\delta$  wolves which are followed by  $\omega$  wolves.

(b) Surrounding the prey

The following equations describe how grey wolves circle their prey:

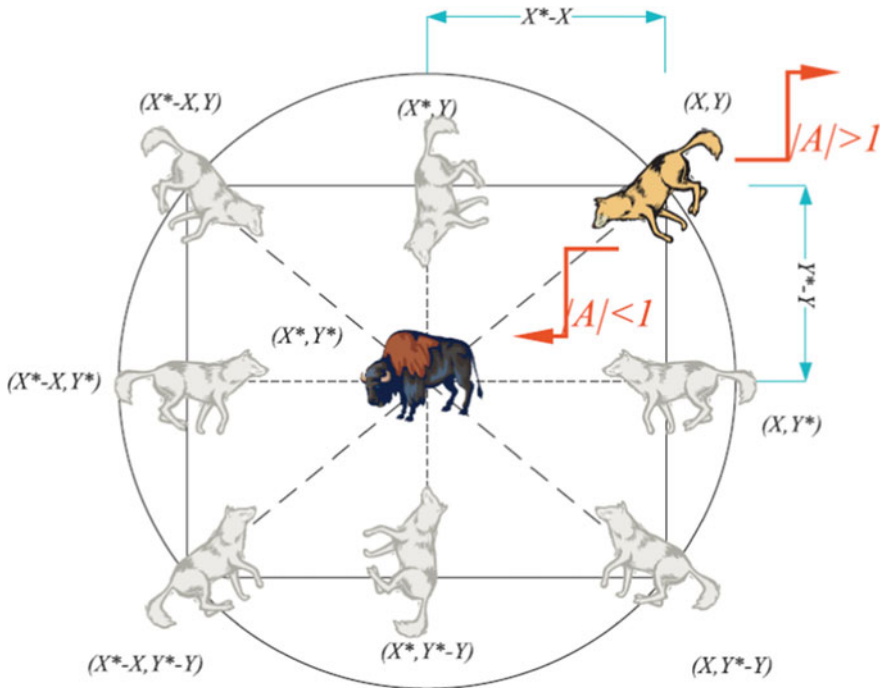


**Fig. 5.2** Illustration of grey wolves surrounding a prey



$$D = |C.X_p(t) - X(t)| \quad (5.1)$$

$$X(t+1) = X_p(t) - A.D \quad (5.2)$$

where  $X_p(t)$  represents the position vector of the prey,  $D$  is the problem dimension,  $A$  and  $C$  are the coefficient vectors given as follows:

$$A = 2a.r_1 - a \quad (5.3)$$

$$C = 2.r_2 \quad (5.4)$$

With each iteration, the components of the vector  $a$  linearly drop from 2 to 0;  $r_1$  and  $r_2$  are random vectors  $[0, 1]$ .

#### (c) Hunting

It is assumed that  $\alpha$  (best candidate solution),  $\beta$  and  $\delta$  wolves have adequate knowledge of the prey position to replicate the hunting behavior of the grey wolves. In order to update their positions based on the positions of the top search agents, the first three best solutions are saved. The hunting behavior is described by the following equations:

$$D_\alpha = |C_1.X_\alpha - X|, D_\beta = |C_2.X_\beta - X|, D_\delta = |C_3.X_\delta - X| \quad (5.5)$$

$$X_1 = X_\alpha - A_1.D_\alpha, X_2 = X_\beta - A_2.D_\beta, X_3 = X_\delta - A_3.D_\delta \quad (5.6)$$

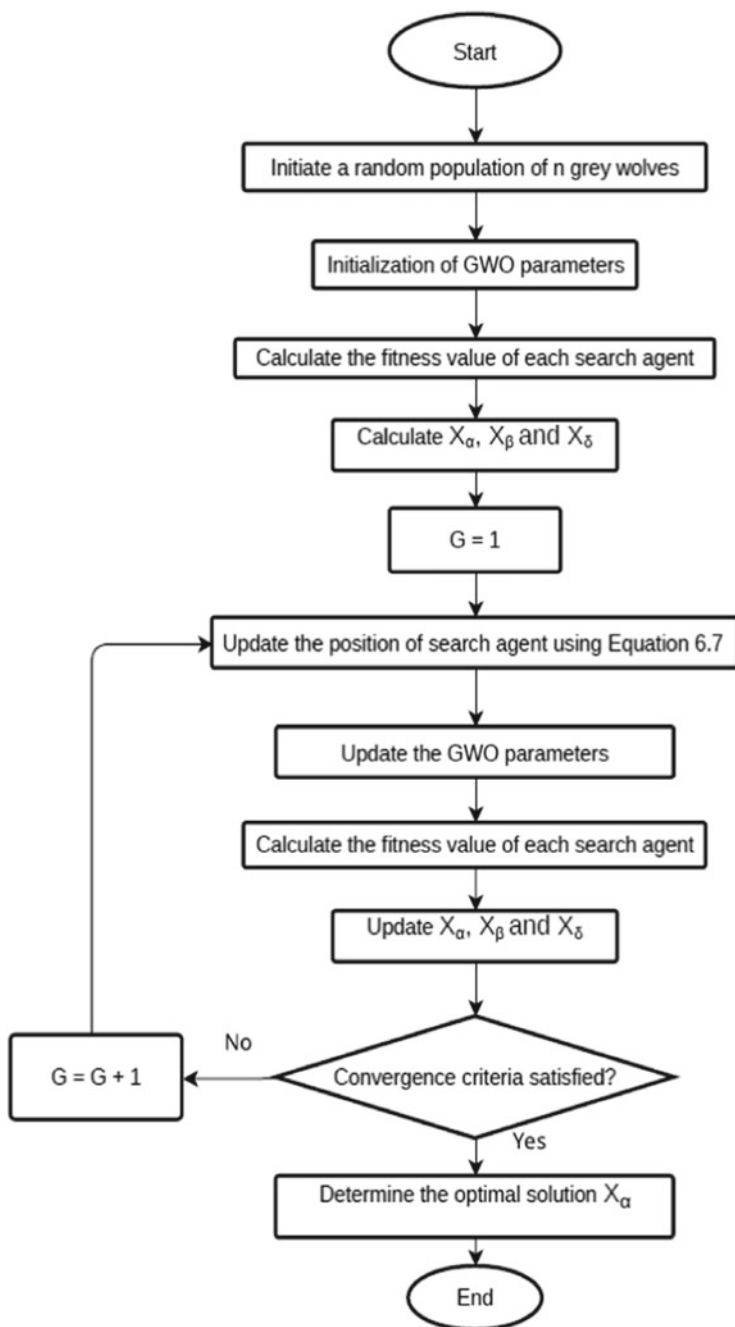
$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (5.7)$$

#### (d) Attacking the prey

When the target stops moving, an attack is launched to end the hunting process. Mathematically, this can be accomplished by repeatedly decreasing the value of vector  $a$  from 2 to 0. It has been discovered that  $|A| < 1$  can make the wolves charge their prey. The GWO algorithm is being exploited by this malicious action.

#### (e) Searching for the prey

The grey wolves look for the prey based on where the three other  $\alpha$ ,  $\beta$ , and  $\delta$  wolves are. They split off from one another to look for the prey and then come together to attack it. It has been noted that  $|A| > 1$  can compel wolves to look for more advantageous prey. This divergence behavior relates to the GWO algorithm's global search. Figure 5.3 shows a thorough flowchart of the GWO algorithm. The best candidate solution ( $X_\alpha$ ) is reached at the end of the suggested process, which begins with a random population of grey wolves.

**Fig. 5.3** Flowchart of the GWO algorithm

### 5.3 Brief Description of Data Extraction and Processing

In order to illustrate the approach proposed in this study, quadratic equations were extracted from the study conducted by Sahu and Andhare [18]. In the reported study, titanium alloy (Ti–6Al–4V) was chosen as the turning work material. The bar size for turning was determined to be 32 mm in diameter, 100 mm in length, and 35 mm in length cut. The turning operations were carried out on a CNC lathe machine with a 5.5 kW power capacity. The machine's controller provided fine motion and spindle speed control with 0.005 mm position precision and 0.004 mm repeatability during cutting. During turning operations, the cutting force was measured using a dynamometer that was interfaced with a control unit.

The design of experiment was performed with a central composite design (CCD) based on Response Surface Methodology (RSM). The speed of cutting, the feed rate and the depth of cut were the input factors. The regression coefficient and subsequently the quadratic equation of the cutting force were generated based on the experimental design and the response measured. The model adequacy was checked using the analysis of variance (ANOVA) and non-significant parameters were discarded. A similar approach was adopted to develop the quadratic equation describing the surface roughness [19]. The roughness of the machined surface and the force of cutting were the two responses. In the formulation of the multi-objective optimization models described in the following sections, the speed of cutting, the feed rate and the depth of cut are the variables to be optimized while the surface roughness and the cutting force are the two objective functions to minimize.

### 5.4 Formulation of Quadratic Equations and Mathematical Formulation

#### 5.4.1 Design Variables and Objectives Functions

Three different variables namely the cutting speed (S), the feed rate (F) and the depth of cut (D) have been considered. These three variables are closely related to the setting of the CNC lathe machine used for data extraction and processing described in the previous section. The lowest and the highest level of cutting parameters used for central composite design reported in the study of [18] were taken into account to illustrate the approach proposed in this study.

$$\begin{aligned} S_{\min} &= 69.9 < S < S_{\max} = 150 \\ F_{\min} &= 55.6 < F < F_{\max} = 120.6 \\ D_{\min} &= 0.66 < D < D_{\max} = 2 \end{aligned} \tag{5.8}$$

S, F and D  $\in \mathbb{R}^+$ .

In this study, the machinability of Ti–6Al–4V alloy is measured with the cutting force (CF) and the surface roughness (SR). The two objective functions in the formulation of the mathematical programming problem are these indicators. They are given by the following quadratic Equations:

$$\begin{aligned} \text{CF} = & 513.915 - 0.2466 \times S + 5.3773 \times F + 64.92 \\ & \times D - 2.594e - 4 \times S^2 - 0.055 \times F^2 + 0.0052 \times S \times F \end{aligned} \quad (5.9)$$

$$\begin{aligned} \text{SR} = & 1.27686 - 0.000897964 \times S + 0.0008937 \\ & \times F + 0.036303 \times D + 1.69203e - 7 \times S^2 \end{aligned} \quad (5.10)$$

These equations suggest that the three variables (S, F and D) have a significant effect on the cutting force and the surface roughness of Ti–6Al–4V alloy. The optimum values of the parameters describing the setting of the CNC lathe machine can be obtained by solving Eqs. 5.9 and 5.10.

### 5.4.2 Multi-objective Optimization

The following Equation is a formulation of the general multi-objective optimization problem with equality and inequality constraints [20]:

$$\begin{aligned} & \text{Minimize } \left\{ \overrightarrow{F_i(x)} \right\}, \forall_i \in N_{oj}, \\ & \text{Subject to: } \begin{cases} \overrightarrow{g_m(x)}, \forall_m \in N_{EQ} \\ \overrightarrow{h_k(x)}, \forall_k \in N_{INQ} \end{cases} \end{aligned} \quad (5.11)$$

where  $F_i$  is the  $i$ th objective function,  $g_m(x)$  and  $h_k(x)$  are the constraints,  $N_{EQ}$  and  $N_{INQ}$  are respectively the numbers of equality and inequality constraints, and  $N_{oj}$  is the number of objective functions.

If the following criteria are met, the solution  $\overrightarrow{x_1}$  prevails over  $\overrightarrow{x_2}$  in the multi-objective minimization problem:

$$F_i(\overrightarrow{x_1}) \leq F_i(\overrightarrow{x_2}), \quad \forall_i \in N_{oj} \quad (5.12)$$

Pareto optimum solutions are the prevailing options across the whole search space.

A fuzzy membership function  $\mu_i$  can be used to represent the  $i$ th objective function  $F_i$  as follows:

$$\mu_i = \frac{F_i - F_i^{\min}}{F_i^{\max} - F_i^{\min}} \quad (5.13)$$

where the parameters  $F_i^{\min}$  and  $F_i^{\max}$  are respectively the minimum and the maximum values of the  $i$ th objective function among all Pareto solutions.

The normalized membership function  $\mu^k$  is calculated as follows for each Pareto solution:

$$\mu^k = \frac{\sum_{i=1}^{N_{oj}} \mu_i^k}{\sum_{k=1}^M \sum_{i=1}^{N_{oj}} \mu_i^k}, \quad \forall k \in M \tag{5.14}$$

The minimal value of  $\mu^k$  is the best compromise option.  $M$  is the number of Pareto solutions.

5.5 Results and Discussion

The optimization of the CNC lathe machine problem to improve machining performance is solved in this section using the GWO algorithms. The proposed algorithm is applied to solve the single-objective optimization problem described by the objective function 1 (OF1) corresponding to Eq. 5.9. The proposed approach was implemented in a MATLAB environment. Details of the mathematical programming model are provided in Appendix B. Additional details of the formulation of the single objective optimization using the GWO algorithm are provided in the work of Okwu and Tartibu [8]. The simulation results are carried out using an 11th Gen Intel(R) Core (TM) i5-1135G7 @ 2.40 GHz Processor, 8 GB RAM, 64-bit operating system, PC. Table 5.1 provides details showing how the parameters of the suggested algorithm are configured.

The optimal solutions that minimise the cutting force (CF) are shown in Fig. 5.4 and presented graphically in Fig. 5.5. These results suggest that the cutting force can be optimised by setting the cutting speed to a minimum of 69.9, setting the feed rate to a maximum of 120.6 and ensuring that the depth of cut is set to a minimum of 0.66. The corresponding value of the minimum cutting force is 430.6557.

The optimal solutions that minimise the surface roughness (SR) are shown in Fig. 5.6 and presented graphically in Fig. 5.7. These results suggest that the surface roughness can be optimised by setting the cutting speed to a maximum of 150, setting the feed rate to a minimum of 55.6 and ensuring that the depth of cut is a minimum of 0.66.

Table 5.1 GWO parameters

|                                                 |
|-------------------------------------------------|
| Number of wolves: 100                           |
| Maximum iteration: 1000                         |
| Grid inflation parameter $\alpha$ : 0.1         |
| Number of grids per each dimension: 10          |
| Leader selection pressure parameter $\beta$ : 4 |

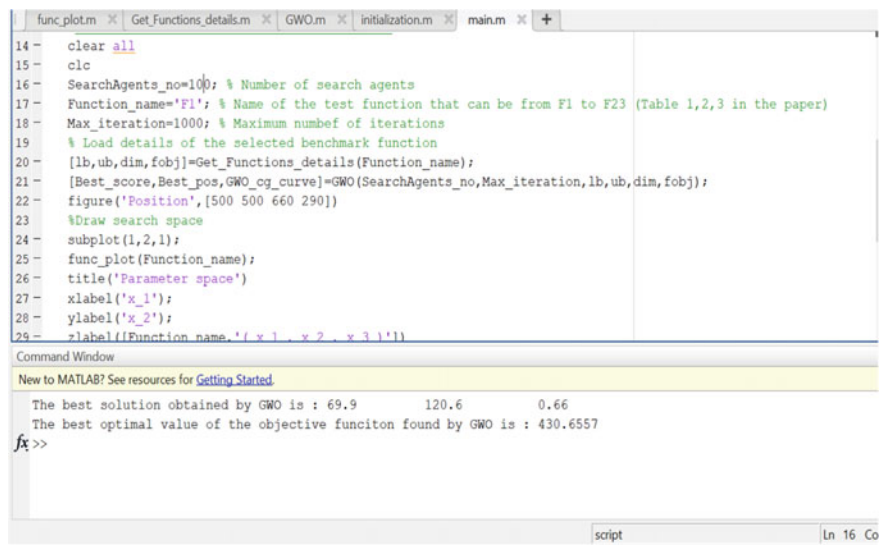


**Fig. 5.4** Screenshot of MATLAB main code and corresponding results considering minimization of the cutting force

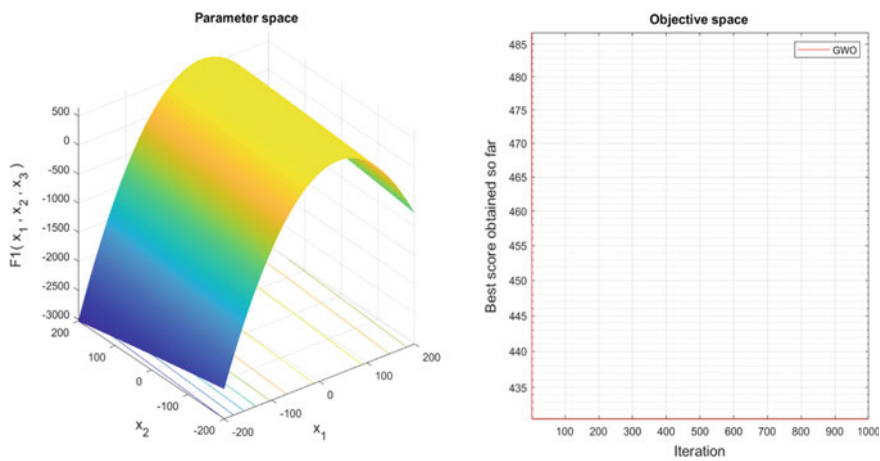


**Fig. 5.5** Graphical representation of the parameter space and objective space considering the minimization of the cutting force

func\_plot.m

Get\_Functions\_details.m

GWO.m

initialization.m

main.m

+

```
14 - clear all
15 - clc
16 - SearchAgents_no=100; % Number of search agents
17 - Function_name='F1'; % Name of the test function that can be from F1 to F23 (Table 1,2,3 in the paper)
18 - Max_iteration=1000; % Maximum numbef of iterations
19 - % Load details of the selected benchmark function
20 - [lb,ub,dim,fobj]=Get_Functions_details(Function_name);
21 - [Best_score,Best_pos,GWO_cg_curve]=GWO(SearchAgents_no,Max_iteration,lb,ub,dim,fobj);
22 - figure('Position',[500 500 660 290])
23 - %Draw search space
24 - subplot(1,2,1);
25 - func_plot(Function_name);
```

Command Window

New to MATLAB? See resources for [Getting Started](#).

The best solution obtained by GWO is : 150                      55.6                      0.66

The best optimal value of the objective funciton found by GWO is : 1.2196

**fx**>>

Ln 1 Col

**Fig. 5.6** Screenshot of MATLAB main code and corresponding results considering minimization of the surface roughness

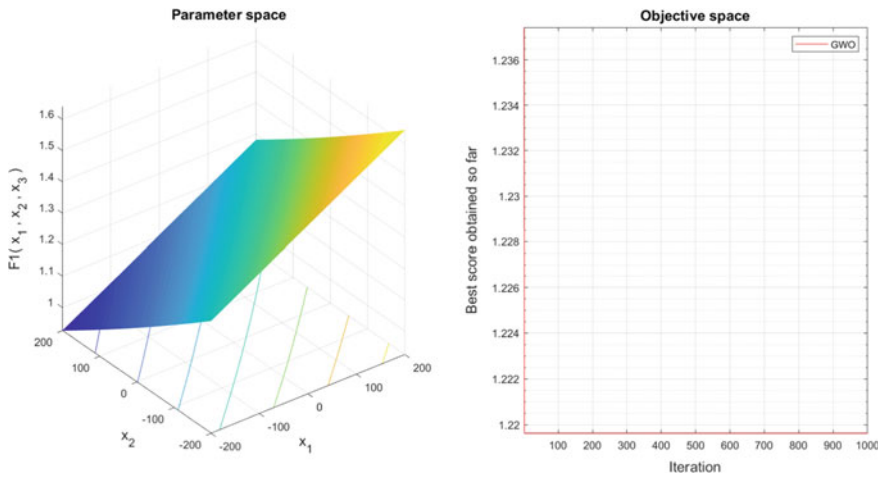


**Fig. 5.7** Graphical representation of the parameter space and objective space considering minimization of the surface roughness

The proposed algorithm is applied to solve the multi-objective problem described by the objective function 1 (OF1) and objective function 2 (OF2) corresponding to Eqs. 5.9 and 5.10 respectively. As described in the previous sections, the cutting force and the surface roughness are conflicting in nature. Therefore, the best compromise was obtained by optimizing these two objectives simultaneously. The optimal settings corresponding to the optimal values of cutting force and surface roughness are described in Table 5.2 by values of OF1 and OF2 respectively. Figure 5.8 shows two-dimensional Pareto optimal solutions that achieved the best compromise solution. Details of the main MATLAB code are provided in Appendix C.

**Table 5.2** Pareto optimal solutions

| Index | OF1      | OF2      | Index | OF1      | OF2      |
|-------|----------|----------|-------|----------|----------|
| 1     | 635.7987 | 1.247029 | 51    | 516.6977 | 1.270052 |
| 2     | 441.5449 | 1.318489 | 52    | 643.3    | 1.244936 |
| 3     | 518.6081 | 1.2693   | 53    | 666.8548 | 1.238423 |
| 4     | 438.7592 | 1.325797 | 54    | 657.0877 | 1.2412   |
| 5     | 439.8855 | 1.322851 | 55    | 659.9708 | 1.239524 |
| 6     | 537.2843 | 1.266471 | 56    | 586.3027 | 1.258123 |
| 7     | 437.6217 | 1.328761 | 57    | 445.5637 | 1.307814 |
| 8     | 432.4052 | 1.342203 | 58    | 443.6822 | 1.312832 |
| 9     | 597.33   | 1.25601  | 59    | 442.3123 | 1.316463 |
| 10    | 499.6039 | 1.272167 | 60    | 654.1663 | 1.241704 |
| 11    | 490.027  | 1.273971 | 61    | 455.9888 | 1.279327 |
| 12    | 514.4365 | 1.270059 | 62    | 442.5006 | 1.315965 |
| 13    | 448.4277 | 1.300106 | 63    | 596.7871 | 1.256329 |
| 14    | 445.6978 | 1.307455 | 64    | 441.4369 | 1.320452 |
| 15    | 682.7093 | 1.227418 | 65    | 441.3214 | 1.321388 |
| 16    | 684.1928 | 1.22613  | 66    | 684.6534 | 1.22532  |
| 17    | 686.3116 | 1.22199  | 67    | 657.4318 | 1.24075  |
| 18    | 663.5179 | 1.238618 | 68    | 595.0838 | 1.256944 |
| 19    | 454.3478 | 1.285381 | 69    | 613.6401 | 1.252846 |
| 20    | 455.2681 | 1.281336 | 70    | 618.3204 | 1.251461 |
| 21    | 475.3236 | 1.275596 | 71    | 648.755  | 1.243432 |
| 22    | 455.6825 | 1.280181 | 72    | 606.3711 | 1.254722 |
| 23    | 452.3699 | 1.289851 | 73    | 610.4124 | 1.253348 |
| 24    | 652.3743 | 1.242647 | 74    | 614.7563 | 1.252182 |
| 25    | 595.875  | 1.256442 | 75    | 612.8183 | 1.253072 |
| 26    | 554.7898 | 1.263973 | 76    | 440.6746 | 1.321644 |

(continued)



**Table 5.2** (continued)

| Index | OF1      | OF2      | Index | OF1      | OF2      |
|-------|----------|----------|-------|----------|----------|
| 27    | 673.7655 | 1.23343  | 77    | 447.8408 | 1.301954 |
| 28    | 675.2952 | 1.232579 | 78    | 612.8872 | 1.252889 |
| 29    | 531.4623 | 1.267371 | 79    | 585.3317 | 1.258493 |
| 30    | 670.7082 | 1.234988 | 80    | 583.7969 | 1.258533 |
| 31    | 557.1943 | 1.263251 | 81    | 585.4353 | 1.258223 |
| 32    | 677.2935 | 1.231497 | 82    | 587.7068 | 1.257806 |
| 33    | 644.8196 | 1.244673 | 83    | 589.0514 | 1.257628 |
| 34    | 538.176  | 1.266331 | 84    | 637.3647 | 1.246963 |
| 35    | 562.5508 | 1.262373 | 85    | 445.265  | 1.309514 |
| 36    | 544.9744 | 1.265254 | 86    | 448.894  | 1.299503 |
| 37    | 547.3097 | 1.264878 | 87    | 448.1362 | 1.3019   |
| 38    | 541.7005 | 1.265776 | 88    | 587.1483 | 1.258068 |
| 39    | 546.6957 | 1.264978 | 89    | 659.0943 | 1.239881 |
| 40    | 540.1496 | 1.266021 | 90    | 535.8299 | 1.266923 |
| 41    | 528.1256 | 1.267898 | 91    | 443.2242 | 1.314084 |
| 42    | 608.7939 | 1.25398  | 92    | 439.4763 | 1.323923 |
| 43    | 497.5352 | 1.27286  | 93    | 613.6645 | 1.252653 |
| 44    | 527.4849 | 1.267976 | 94    | 530.8407 | 1.267668 |
| 45    | 673.5649 | 1.233872 | 95    | 439.4374 | 1.324792 |
| 46    | 676.9673 | 1.2322   | 96    | 444.2782 | 1.311246 |
| 47    | 621.3261 | 1.251199 | 97    | 587.4205 | 1.258062 |
| 48    | 533.7528 | 1.267019 | 98    | 614.2238 | 1.252414 |
| 49    | 521.5029 | 1.268872 | 99    | 448.3293 | 1.300372 |
| 50    | 447.6523 | 1.304206 | 100   | 446.9346 | 1.304298 |

### 5.6 Conclusion

In this section, a Multi-Objective Grey Wolf Optimizer (MOGWO) is proposed to enhance the machining performance during the turning of a titanium alloy. This advanced approach has been described in detail to demonstrate the applicability of metaheuristic optimization methods in manufacturing. The cutting force and the surface roughness were the two objective functions to optimize. This study reveals that setting the cutting speed to the minimum, setting the feed rate to the maximum and ensuring that the depth of cut is set to a minimum would minimise the cutting force. However, setting the cutting speed to the maximum, setting the feed rate to the minimum and ensuring that the depth of cut is minimum would minimise the surface roughness. The proposed Multi-Objective Grey Wolf Optimizer (MOGWO) was applied to solve the multi-objective problem and the best compromise between

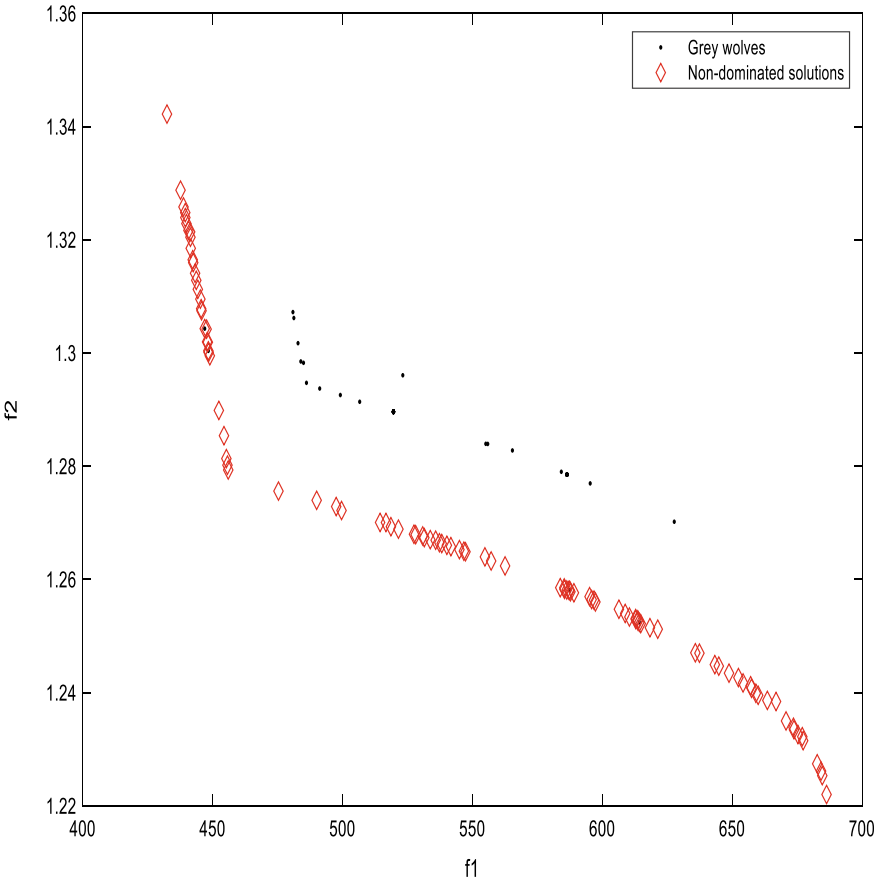


**Fig. 5.8** Graphical representation of the Pareto optimal solutions

the two objective functions was computed to assist the decision-maker in the selection of the best setting that could potentially improve machinability performance.

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# Chapter 6

## Multi-objective Ant Lion Optimizer for Improved Machining Performance



**Abstract** Titanium alloys are challenging to cut due to low thermal conductivity and excessive tool wear. This work seeks to address poor machinability through optimization. In this section, titanium alloy (Ti–6Al–4V) was chosen as the turning work material. The cutting force and the surface roughness were considered indicators of the machining performance. The speed of cutting, the feed rate and the depth of cut are the variables to optimize. Quadratic equations of the cutting force and the surface roughness were extracted from an existing study to illustrate the approach. A single objective optimization problem was developed to optimize the cutting force and the surface roughness separately using the Antlion optimizer. Details showing the formulation of the problem and the results have been disclosed. The Multi-objective antlion optimizer (MALO) was the metaheuristic-based approach proposed for the formulation of the problem and the computation of the non-dominated or Pareto optimal solutions. The best compromise was obtained by optimizing these two objectives simultaneously. The optimal settings corresponding to the optimal values of cutting force and surface roughness were computed and reported in this section.

**Keywords** Ant lion optimization · Machining · Titanium alloy · Metaheuristic techniques

### 6.1 Introduction

Due to its desirable and advantageous mechanical qualities, titanium alloys are a fantastic substitute for materials used in marine, biomedical, and aerospace applications. enhanced corrosion resistance, high strength-to-weight ratio, and superior longevity. The fracture toughness of titanium alloys is one of their attractive qualities. Although having beneficial properties, titanium alloys are challenging to cut due to low thermal conductivity and excessive tool wear. Because they result in poor machinability, high cutting temperatures are a major issue that requires rapid treatment [1]. One of the most important industrial processes is turning, which involves rotating a cylindrical workpiece while a single-point cutting tool removes material

from it. Three cutting forces are generated while turning: a thrust force acting in the cutting speed's direction, a feed force operating in the feed direction, and a radial force acting in the direction perpendicular to the cutting speed. Many parameters' effects on cutting power have been studied [2]. Several researchers have worked to increase the machinability of titanium alloys by enhancing process variables. The impact of cutting parameters on titanium alloys and surface roughness were studied in relation to the effects of cutting settings [3]. The outcomes showed that surface roughness is significantly influenced by feed rate and cutting speed. The tool nose radius has an impact on the product's surface quality as well [4]. Cutting temperature has been discovered to be more affected by cutting speed and feed [5]. A multi-objective optimization approach was proposed by Shah et al. [6] to optimize the cutting force, the cutting temperature and the surface roughness using a genetic algorithm. This study demonstrates the potential of the proposed approach to achieve a desirable combination of machining performance.

One of the finest methods to enhance the machining of titanium alloys is the use of optimization techniques. The primary flaw of conventional optimization methods, local optima stagnation, has led to their general depreciation [7]. Stochastic optimization techniques are the primary possibilities for designers. These methods approximate the ideal designs while treating difficulties as black boxes. They begin the optimization process by refining a set of arbitrary potential solutions to a particular problem over a predetermined number of iterations. Notwithstanding these methods' benefits, real-world optimization requires dealing with several challenges, including numerous objectives [8, 9], limitations [10], uncertainties [11], local solutions [12], deceptive global solutions [13], etc. Different operators should be included in optimization techniques to overcome these problems [14].

Finding solutions for issues with many objectives is the major goal of this effort, which is multi-objective optimization. Due to the nature of such problems, there are multiple solutions for a multi-objective problem [15]. A single-objective issue, however, only has one global optimum. The major issue in multi-objective optimization is addressing numerous objectives, which are frequently at odds with one another. A stochastic multi-objective optimization algorithm's job is to identify the set of best trade-offs among the objectives, or the Pareto optimal set.

In the research on multi-objective optimization employing stochastic optimization techniques, a posteriori versus a priori are the two basic approaches [16]. Using a priori methods, aggregating the objectives reduces a multi-objective optimization problem to a single-objective problem. An expert in the problem domain typically provides a set of weights that describe the importance of the objectives. A single-objective optimization approach can quickly resolve the issue following the objective aggregation. The primary flaw with these approaches is that in order to find the Pareto optimal set, an algorithm needs to be performed numerous times. Moreover, seeking professional advice is necessary, and using this method makes it impossible to find some particular Pareto optimal fronts [17]. The advantages of posterior techniques include keeping the multiobjective formulation of the problem and locating the Pareto optimal set in a single run. Another benefit is that these techniques can be used to

find any type of Pareto front. Yet, they cost more to compute and must simultaneously handle several goals. According to the literature, these techniques have been successfully applied to real-world issues ever since they were created [18].

This study proposes the antlion technique to improve machining performance namely minimising the cutting force and the surface roughness. Therefore, it is critical to determine the optimal parameters corresponding to the setting of the CNC machine. In this study, the machining parameters are made of the cutting speed, the feed rate and the depth of cut. This issue can be resolved using the ant lion optimization technique with a global minimum convergence outcome [18]. The uniqueness and contribution of this research is the ability to appropriately enhance the machining performance during the turning of a titanium alloy using a relatively recent MALO technique. Due to the following benefits, the optimization results generated with MALO can result in a worldwide optimal solution for optimization issues.

- In machining optimization, the MALO technique is a population-based approach that increases the possibility of reaching global minima and prevents local minima.
- Due to the random selection of ants and ant pathways and the adaptively reducing border of the ant lion trap, convergence may be assured when exploring the search space.
- The MALO technique uses a small number of gradient-free parameters, which facilitates convergence and results in less computational work.

## 6.2 Ant Lion Optimization (ALO) Background

The Multiobjective Ant Lion Optimization (MALO) method belongs to a group of artificial intelligence-based methods. Mirjalili was the one who first suggested this method [18]. The Multiobjective Ant Lion Optimization approach takes its cues from a common occurrence in nature: ant lion creatures seek food by hunting prey [19]. Ant lions hunt prey by setting up traps to grab ants that cross a path, catching captured ants, and then setting up new traps to catch more ants. Ant lions go through two stages of development: the 35-week-long larval stage and the 3-year-long adult stage. Similar to butterflies, ant lions go through a transformation known as a cocoon in order to mature and reach adulthood. During the larval stages, hunting for food takes place. Additionally, the cocoons go through reproductive procedures during the adult stage.

The ant lions use their powerful jaws to dig holes in sandy soil to trap their food. A cone-shaped crater is created by the hole that was dug in the sandy soil. As seen in Fig. 6.1, the ant lion successfully makes a cone-shaped crater and then conceals itself by exactly descending into the center of the cone's tip. The ant lion's position is concealed by the sand covering it, but its powerful jaw is facing upward in readiness to receive the small ant prey that landed. Such a crater's design allows for the trapping of little ants, which then fall to the cavity's bottom where the ant lion can easily capture them. During the adult cocoons' growth period, this technique is repeated until there is enough food available [18].

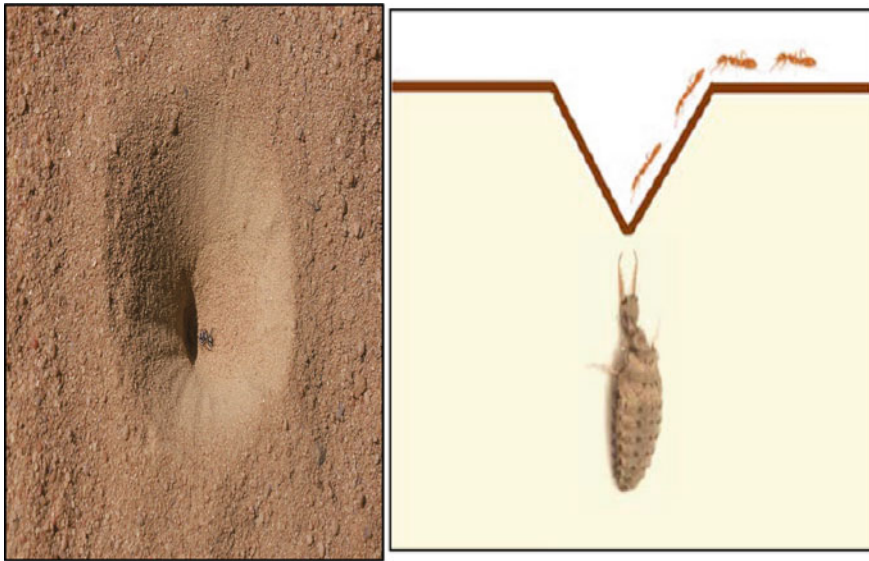


**Fig. 6.1** Illustration of an ant lion's method of trapping prey

To describe the interaction of ants with their predators, it is assumed that the ants move in a search space since the ants that become victims to the ant lion travel randomly in quest of food. The following equation explains the random walk model as ant movement in this situation, where ants move stochastically in search of food.

$$V(s) = [0, cs(2w(s_1) - 1), cs(2w(s_2) - 1), \dots, cs(2w(s_n) - 1)] \quad (6.1)$$

The symbols in Eq. (6.1) have the following meanings. The cumulative counter operator (cs) is used in addition operations. The greatest number of times this method can be repeated is  $n$ . The  $s$  is a random ant step; in the ant lion approach, iteration is compared to the ant step. In this instance, the  $w(s)$  is a stochastic function. The following definition applies to the stochastic function  $w(s)$ .

$$w(s) = \begin{cases} 0 & \text{if } \text{gen} < 0.5 \\ 1 & \text{if } \text{gen} > 0.5 \end{cases} \quad (6.2)$$

where  $\text{gen}$  is a random number created at a predetermined interval of  $[0, 1]$  and  $s$  is a random ant step, which is similar to the iteration process.

The ants' positions are updated with each action they take to complete the optimization. Since each ant food search space for the optimization step has a changeable range, updating the ant's role directly using an equation is not possible (6.2). The min-max normalization equation must therefore be used to normalize in order to retain random pathways in the search space.

$$W_i^s = \frac{(W_i^s - a_i) \times (d_i^s - c_i^s)}{(b_i - a_i)} \quad (6.3)$$

Here is an explanation of the notation used in Eq. (6.3). The notation  $a_i$  represents the random ant's minimum step for the  $i$ -th variable,  $b_i$  represents its top step,  $c_i^s$  represents its minimum value in the  $s$ -th iteration, and  $d_i^s$  represents its maximum value in the  $s$ -th iteration. The construction of an optimization matrix based on the ant's position is represented by Eq. (6.4) as follows.

$$T_{\text{ant}} = \begin{bmatrix} T_{1,1} & \cdots & T_{1,d} \\ \vdots & \ddots & \vdots \\ T_{n,1} & \cdots & T_{n,d} \end{bmatrix} \quad (6.4)$$

Based on Eq. (6.4),  $T_{\text{ant}}$  is a matrix that states the location of each ant.  $T_{i,j}$  is the value of the variable, where  $j$  is the  $j$ -th order of variables and  $i$  is the  $i$ -th order of ants. Notation of  $n$  is the total number of ants, and  $d$  is the real variable. Let us consider other AI-based optimization methods. The ants in the ant lion method are similar to individuals in the genetic algorithm or particles in the PSO method [20]. In the antlion method, the ant position states the parameters used to represent the variables in a particular solution. Matrix  $T_{\text{ant}}$  was made to fit all possible ant places that may be saved after optimization. By analyzing each ant stored in the following matrix, objective functions are also used in the optimization process.

$$T_{\text{Oant}} = \begin{bmatrix} f([T_{1,1} \cdots T_{1,d}]) \\ \vdots & \ddots & \vdots \\ f([T_{n,1} \cdots T_{n,d}]) \end{bmatrix} \quad (6.5)$$

It is clear from Eq. (6.5) that  $T_{\text{Oant}}$  is a matrix that is utilized to store each ant's fitness. The  $i$ -th ants in the  $j$ -th dimension are represented in the matrix  $T_{\text{Oant}}$  by the elements of the matrix  $T_{i,j}$ . The cost function is represented by the letter  $f$ , whereas  $n$  stands for the overall number of ants.

The ant lion technique makes the assumption that ants can use the search space to conceal themselves. The positions and fitness values of the ants are also stored in a matrix, as illustrated in the following section.

$$T_{\text{AL}} = \begin{bmatrix} TL_{1,1} & \cdots & TL_{1,d} \\ \vdots & \ddots & \vdots \\ TL_{n,1} & \cdots & TL_{n,d} \end{bmatrix} \quad (6.6)$$

According to Eq. (6.6),  $T_{\text{AL}}$  is the matrix that is utilized to store each ant lion's position. The elements of the  $TL_{i,j}$  matrix are stated by the matrix  $T_{\text{AL}}$ , which consists of the  $i$ -th ant lion with the  $j$ -th dimension value. The notation  $n$  represents the overall number of ant lions, and  $d$  represents all dimensions taken into account in a case.



$$T_{OAL} = \begin{bmatrix} f([TL_{1,1} \cdots TL_{1,d}] \\ \vdots & \ddots & \vdots \\ f([TL_{n,1} \cdots TL_{n,d}] \end{bmatrix} \quad (6.7)$$

Equation (6.7) indicates that  $T_{OAL}$  is the fitness-storing matrix. The elements of the  $TL_{i,j}$  matrix are stated in the matrix  $T_{OAL}$ , which consists of the  $i$ -th ant lion with the  $j$ -th dimension value. The cost function is denoted by the letter  $f$ , and  $n$  is the total number of ant lions.

As shown in Fig. 6.2, the ant lion's capacity for hunting can be replicated using a roulette wheel to further explain how the ant lion approach operates. One ant lion was thought to contain all of the ants in the roulette wheel area. The selection of ant lions based on fitness was done using a roulette wheel operator.

The following two equations are used to model this process.

$$c_j^s = AL_j^s + c^s \quad (6.8)$$

$$d_j^s = AL_j^s + d^s \quad (6.9)$$

This section provides an explanation of the notations used in Eqs. (6.8) and (6.9). The variables  $AL_j^s$  represents the position of the  $j$ -th ant lion at the  $s$ -th iteration,  $c^s$  represents the smallest value of the  $s$ -th iteration variable,  $c_j^s$  represents the smallest

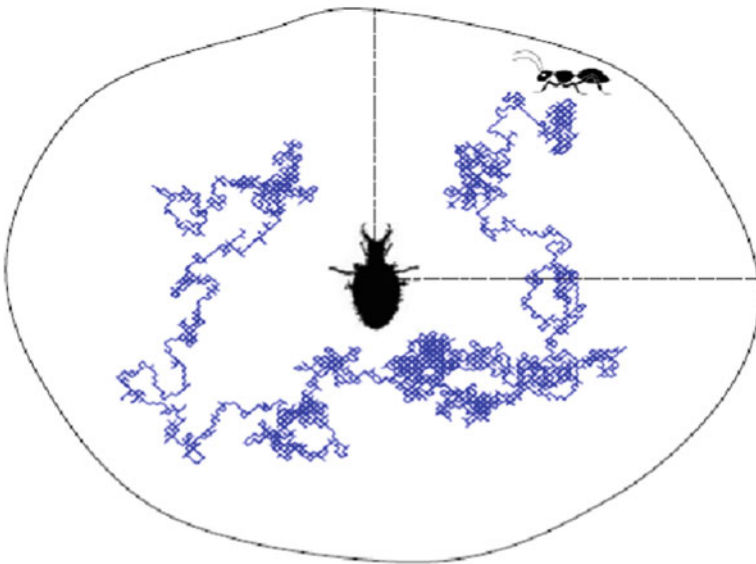


**Fig. 6.2** Search space boundary of antlion

value of the  $j$ -th ant,  $d^s$  represents the vector containing the maximum values of the  $s$ -th iteration variable, and  $d_j^s$  represents the maximum value of the  $j$ -th ant.

The reaction of the ant when it discovers it has been caught in the ant lion's trap is another mechanism of this strategy. The ant typically doesn't become aware that there is an ant lion waiting to pounce at the bottom of the sandpit until after it has entered the cone-shaped sand device and has sunk to the bottom. The ants attempt to flee under the supposition that they are in excellent condition by sprinkling sand around the hole in order to diminish the radius of the hole that forms their trail. The following two mathematical equations can be used to model this mechanism.

$$c^s = \frac{c^s}{R} \quad (6.10)$$

$$d^s = \frac{d^s}{R} \quad (6.11)$$

Equations (6.10) and (6.11)'s notations can be understood using the following information. The ratio factor is  $R$ . The variable with the smallest value in the  $s$ -th iteration is called  $c^s$ , while the vector with the highest value in the  $s$ -th iteration is called  $d^s$ .

The ant lion technique's final mechanism is elitism. The best ant lion is stored at each iteration to be regarded as an elite; elitism is the most potent ant lion in the computational process. The mathematical representation of elitism is shown in the following equation.

$$Ant_i^s = \frac{R_{AL}^s + R_{Elite}^s}{2} \quad (6.12)$$

In Eq. (6.12),  $R_{AL}^s$  is a random walk around the ant lion, and  $Ant_i^s$  is the position of the  $i$ -th ant at the  $s$ -th iteration. The choice was made using a roulette wheel. A random walk-around elite at the  $s$ -th iteration is known as  $R_{Elite}^s$ . The optimization process of ant lion algorithm is summarized in Fig. 6.3.

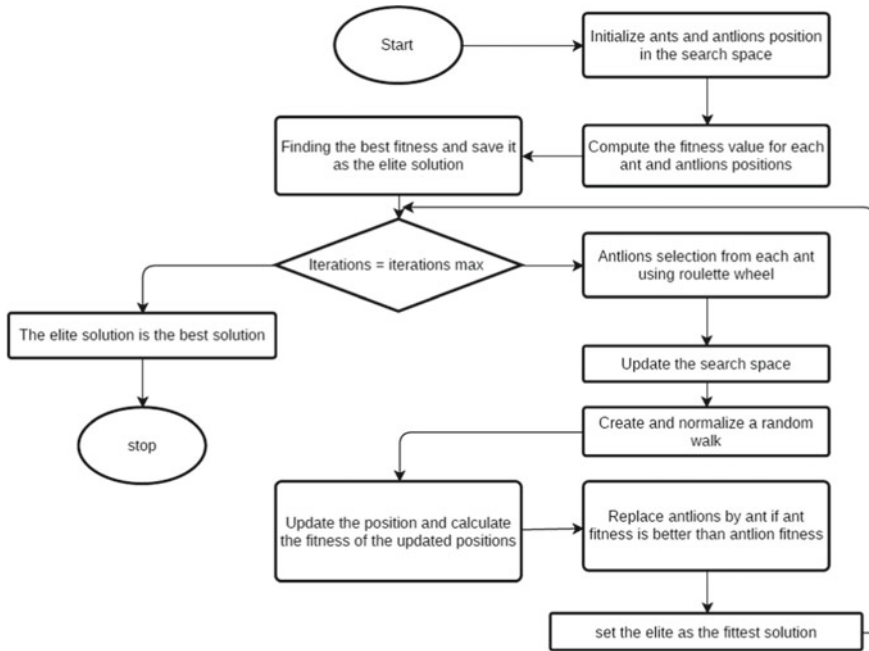


**Fig. 6.3** Flowchart of ant lion optimizer

### 6.3 Brief Description of Data Extraction and Processing

In order to illustrate the approach proposed in this study, quadratic equations were extracted from the study conducted by Sahu and Andhare [21]. In the reported study, titanium alloy (Ti-6Al-4 V) was chosen as the turning work material. The bar size for turning was determined to be 32 mm in diameter, 100 mm in length, and 35 mm in length cut. The turning operations were carried out on a CNC lathe machine with a 5.5 kW power capacity. The machine's controller provided fine motion and spindle speed control with 0.005 mm position precision and 0.004 mm repeatability during cutting. During turning operations, the cutting force was measured using a dynamometer that was interfaced with a control unit.

The design of experiment was performed with a central composite design (CCD) based on Response Surface Methodology (RSM). The speed of cutting, the feed rate and the depth of cut were the input factors. The regression coefficient and subsequently the quadratic equation of the cutting force were generated based on the experimental design and the response measured. The model adequacy was checked using the analysis of variance (ANOVA) and non-significant parameters were discarded. A similar approach was adopted to develop the quadratic equation describing the surface roughness [22]. The roughness of the machined surface and the force of cutting were the two responses. In the formulation of the multi-objective optimization models described in the following sections, the speed of cutting, the feed rate

and the depth of cut are the variables to be optimized while the surface roughness and the cutting force are the two objective functions to minimize.

## 6.4 Formulation of Quadratic Equations and Mathematical Formulation

### 6.4.1 Design Variables and Objectives Functions

Three different variables namely the cutting speed (S), the feed rate (F) and the depth of cut (D) have been considered. These three variables are closely related to the setting of the CNC lathe machine used for data extraction and processing described in the previous section. The lowest and the highest level of cutting parameters used for central composite design reported in the study of Sahu and Andhare [21] were taken into account to illustrate the approach proposed in this study.

$$\begin{aligned} S_{\min} &= 69.9 < S < S_{\max} = 150 \\ F_{\min} &= 55.6 < F < F_{\max} = 120.6 \\ D_{\min} &= 0.66 < D < D_{\max} = 2 \end{aligned} \quad (6.13)$$

S, F and D  $\in \mathbb{R}^+$

In this study, the machinability of Ti-6Al-4V alloy is measured with the cutting force (CF) and the surface roughness (SR). The two objective functions in the formulation of the mathematical programming problem are these indicators. They are given by the following quadratic Equations [21].

$$\begin{aligned} CF &= 513.915 - 0.2466 \times S + 5.3773 \times F + 64.92 \\ &\times D - 2.594e - 4 \times S^2 - 0.055 \times F^2 + 0.0052 \times S \times F \end{aligned} \quad (6.14)$$

$$\begin{aligned} SR &= 1.27686 - 0.000897964 \times S + 0.0008937 \\ &\times F + 0.036303 \times D + 1.69203e - 7 \times S^2 \end{aligned} \quad (6.15)$$

These equations suggest that the three variables (S, F and D) have a significant effect on the cutting force and the surface roughness of Ti-6Al-4V alloy. The optimum values of the parameters describing the setting of the CNC lathe machine can be obtained by solving Eqs. 6.13 and 6.14.

### 6.4.2 Multi-objective Optimization

The following Equation is a formulation of the general multi-objective optimization problem with equality and inequality constraints [23];

$$\begin{aligned} & \text{Minimize } \left\{ \overrightarrow{F_i(x)} \right\}, \forall_i \in N_{oj}, \\ & \text{Subject to: } \begin{cases} \overrightarrow{g_m(x)}, \forall_m \in N_{EQ} \\ \overrightarrow{h_k(x)}, \forall_k \in N_{INQ} \end{cases} \end{aligned} \quad (6.16)$$

where  $F_i$  is the  $i$ th objective function,  $g_m(x)$  and  $h_k(x)$  are the constraints,  $N_{EQ}$  and  $N_{INQ}$  are respectively the numbers of equality and inequality constraints, and  $N_{oj}$  is the number of objective functions.

If the following criteria are met, the solution  $\overrightarrow{x_1}$  prevails over  $\overrightarrow{x_2}$  in the multi-objective minimization problem:

$$F_i(\overrightarrow{x_1}) \leq F_i(\overrightarrow{x_2}), \quad \forall_i \in N_{oj} \quad (6.17)$$

Pareto optimum solutions are the prevailing options across the whole search space.

A fuzzy membership function  $\mu_i$  can be used to represent the  $i$ th objective function  $F_i$  as follows:

$$\mu_i = \frac{F_i - F_i^{\min}}{F_i^{\max} - F_i^{\min}} \quad (6.18)$$

where the parameters  $F_i^{\min}$  and  $F_i^{\max}$  are respectively the minimum and the maximum values of the  $i$ th objective function among all Pareto solutions.

The normalized membership function  $\mu^k$  is calculated as follows for each Pareto solution:

$$\mu^k = \frac{\sum_{i=1}^{N_{oj}} \mu_i^k}{\sum_{k=1}^M \sum_{i=1}^{N_{oj}} \mu_i^k}, \quad \forall k \in M \quad (6.19)$$

The minimal value of  $\mu^k$  is the best compromise option.  $M$  is the number of Pareto solutions.

## 6.5 Results and Discussion

The optimization of the CNC lathe machine problem to improve machining performance is solved in this section using the ALO algorithms. The proposed algorithm is applied to solve the single-objective optimization problem described by the objective

**Table 6.1** ALO parameters

|                        |
|------------------------|
| Number of antlions: 40 |
| Maximum iteration: 500 |

**Table 6.2** Optimal solutions considering an emphasis on CF

| S*   | F*    | D*   | SR*      |
|------|-------|------|----------|
| 69.9 | 120.6 | 0.66 | 430.6557 |

**Table 6.3** Optimal solutions considering an emphasis on SR

| S*  | F*   | D*   | SR*    |
|-----|------|------|--------|
| 150 | 55.6 | 0.66 | 1.2196 |

function 1 (OF1) corresponding to Eq. 6.2. The proposed approach was implemented in a MATLAB environment. Details of the mathematical programming model are provided in Appendix D. Additional details of the formulation of the single objective optimization using the GWO algorithm are provided in the work of Okwu and Tartibu [20]. The simulation results are carried out using an 11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40 GHz Processor, 8 GB RAM, 64-bit operating system, PC. Table 6.1 provides details showing how the parameters of the suggested algorithm are configured.

The optimal solutions that minimise the cutting force (CF) are shown in Table 6.2. These results suggest that the cutting force can be optimised by setting the cutting speed to a minimum of 69.9, setting the feed rate to a maximum of 120.6 and ensuring that the depth of cut is set to a minimum of 0.66. The corresponding value of the minimum cutting force is 430.6557.

The optimal solutions that minimise the surface roughness (SR) are shown in Table 6.3. These results suggest that the surface roughness can be optimised by setting the cutting speed to a maximum of 150, setting the feed rate to a minimum of 55.6 and ensuring that the depth of cut is a minimum of 0.66.

The proposed algorithm is applied to solve the multi-objective problem described by the objective function 1 (OF1) and objective function 2 (OF2) corresponding to Eqs. 6.2 and 6.3 respectively. As described in the previous sections, the cutting force and the surface roughness are conflicting in nature. Therefore, the best compromise was obtained by optimizing these two objectives simultaneously. The optimal settings corresponding to the optimal values of cutting force and surface roughness are described in Table 6.4 by values of OF1 and OF2 respectively. Figure 6.4 shows two-dimensional Pareto optimal solutions that achieved the best compromise solution. Details of the main MATLAB code are provided in Appendix D and E.

**Table 6.4** Pareto optimal solutions

| Index | OF1      | OF2      | Index | OF1      | OF2      |
|-------|----------|----------|-------|----------|----------|
| 1     | 682.8249 | 1.227025 | 51    | 561.6548 | 1.262498 |
| 2     | 456.1512 | 1.278873 | 52    | 561.6222 | 1.262505 |
| 3     | 683.2253 | 1.226601 | 53    | 561.6537 | 1.262499 |
| 4     | 479.2329 | 1.274789 | 54    | 561.6421 | 1.262499 |
| 5     | 684.9679 | 1.224297 | 55    | 561.6842 | 1.262492 |
| 6     | 662.807  | 1.239083 | 56    | 561.673  | 1.262494 |
| 7     | 451.2938 | 1.292305 | 57    | 561.628  | 1.262505 |
| 8     | 451.0648 | 1.292932 | 58    | 561.6786 | 1.262493 |
| 9     | 618.3685 | 1.251486 | 59    | 600.6687 | 1.255215 |
| 10    | 455.4038 | 1.280958 | 60    | 600.7076 | 1.255206 |
| 11    | 495.3195 | 1.27263  | 61    | 600.6885 | 1.25521  |
| 12    | 526.4183 | 1.268333 | 62    | 600.7352 | 1.2552   |
| 13    | 572.7151 | 1.260565 | 63    | 600.7027 | 1.255208 |
| 14    | 575.7213 | 1.260076 | 64    | 600.697  | 1.255209 |
| 15    | 578.1053 | 1.259711 | 65    | 600.6641 | 1.255222 |
| 16    | 448.2942 | 1.300467 | 66    | 600.6725 | 1.255214 |
| 17    | 512.3523 | 1.270764 | 67    | 660.7904 | 1.239255 |
| 18    | 473.8894 | 1.275492 | 68    | 666.5354 | 1.236884 |
| 19    | 460.9717 | 1.278422 | 69    | 666.5325 | 1.236886 |
| 20    | 435.4067 | 1.334498 | 70    | 666.5336 | 1.236885 |
| 21    | 442.0974 | 1.317031 | 71    | 666.5344 | 1.236885 |
| 22    | 438.7703 | 1.325768 | 72    | 666.5337 | 1.236885 |
| 23    | 445.8303 | 1.311738 | 73    | 666.5347 | 1.236884 |
| 24    | 434.9602 | 1.335649 | 74    | 666.5331 | 1.236885 |
| 25    | 434.994  | 1.335581 | 75    | 666.5341 | 1.236885 |
| 26    | 434.9437 | 1.335692 | 76    | 666.5332 | 1.236885 |
| 27    | 444.0201 | 1.311933 | 77    | 643.9034 | 1.24476  |
| 28    | 444.0086 | 1.311964 | 78    | 643.8996 | 1.244762 |
| 29    | 441.437  | 1.318774 | 79    | 643.9011 | 1.244761 |
| 30    | 441.4609 | 1.318711 | 80    | 643.9008 | 1.244761 |
| 31    | 441.4964 | 1.318641 | 81    | 643.8988 | 1.244762 |
| 32    | 431.0774 | 1.345587 | 82    | 643.9006 | 1.244761 |
| 33    | 431.0779 | 1.345586 | 83    | 643.9005 | 1.244761 |
| 34    | 431.0738 | 1.345597 | 84    | 684.0245 | 1.225661 |
| 35    | 431.0768 | 1.345589 | 85    | 684.0245 | 1.225661 |
| 36    | 431.0779 | 1.345586 | 86    | 684.0245 | 1.225661 |

(continued)

**Table 6.4** (continued)

| Index | OF1      | OF2      | Index | OF1      | OF2      |
|-------|----------|----------|-------|----------|----------|
| 37    | 431.0765 | 1.34559  | 87    | 684.0245 | 1.225661 |
| 38    | 641.1141 | 1.245565 | 88    | 684.0245 | 1.225661 |
| 39    | 641.1149 | 1.245563 | 89    | 684.0245 | 1.225661 |
| 40    | 593.0178 | 1.2572   | 90    | 684.0245 | 1.225661 |
| 41    | 593.0378 | 1.257194 | 91    | 684.0246 | 1.225661 |
| 42    | 593.0974 | 1.257185 | 92    | 684.0245 | 1.225661 |
| 43    | 665.1326 | 1.237478 | 93    | 684.0245 | 1.225661 |
| 44    | 665.1654 | 1.237465 | 94    | 684.0246 | 1.225661 |
| 45    | 665.121  | 1.23748  | 95    | 684.0245 | 1.225661 |
| 46    | 665.1495 | 1.237469 | 96    | 613.6276 | 1.253991 |
| 47    | 665.1408 | 1.237472 | 97    | 613.6278 | 1.253991 |
| 48    | 636.8775 | 1.246738 | 98    | 613.6277 | 1.253991 |
| 49    | 636.8951 | 1.246733 | 99    | 613.6279 | 1.253991 |
| 50    | 561.7064 | 1.262489 | 100   | 613.6276 | 1.253991 |

## 6.6 Conclusion

In this section, a Multi-objective Ant Lion Optimizer (MALO) is proposed to enhance the machining performance during the turning of a titanium alloy. This advanced approach has been described in detail to demonstrate the applicability of meta-heuristic optimization methods in manufacturing. The cutting force and the surface roughness were the two objective functions to optimize. This study reveals that setting the cutting speed to the minimum, setting the feed rate to the maximum and ensuring that the depth of cut is set to a minimum would minimise the cutting force. However, setting the cutting speed to the maximum, setting the feed rate to the minimum and ensuring that the depth of cut is minimum would minimise the surface roughness. The proposed Multi-objective Ant Lion Optimizer (MALO) was applied to solve the multi-objective problem and the best compromise between the two objective functions was computed to assist the decision-maker in the selection of the best setting that could potentially improve machinability performance.



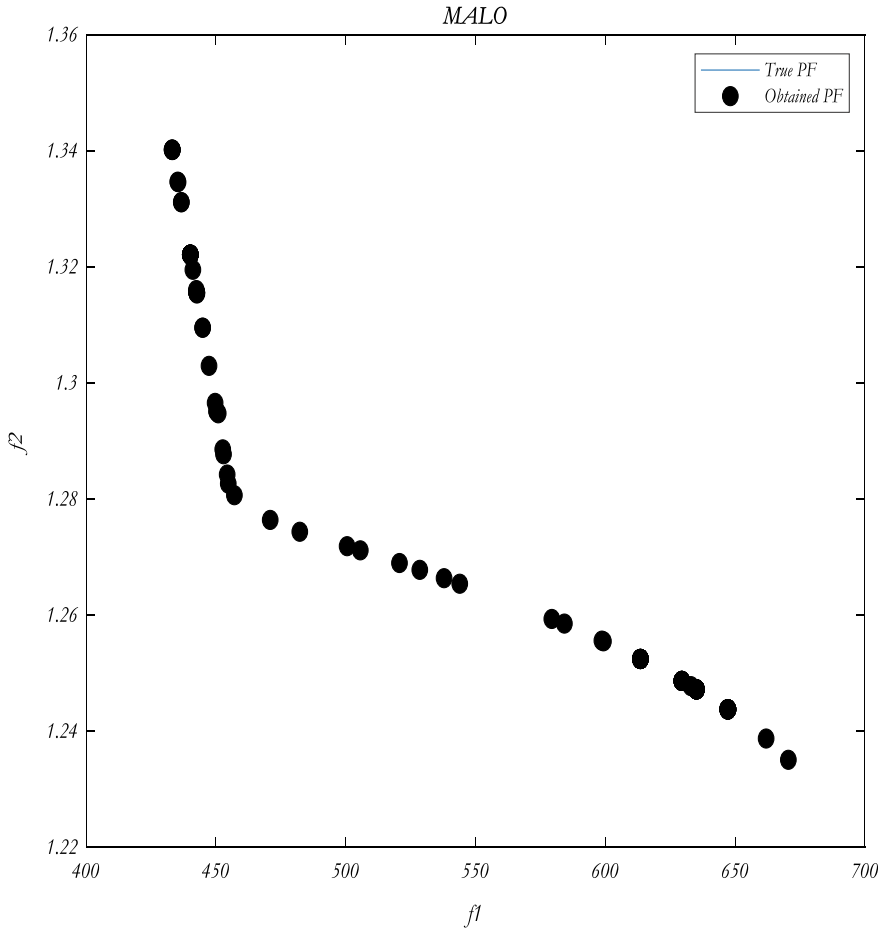


**Fig. 6.4** Graphical representation of the Pareto optimal solutions

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# Chapter 7

## Multi-objective Grasshopper Optimizer for Improved Machining Performance



**Abstract** One of the most popular meta-heuristic optimization algorithms today is the grasshopper algorithm. Several industries, including engineering design, wireless networking, machine learning and control of power systems have effectively used it to solve a variety of optimization challenges. Despite its potential for optimization, grasshopper optimizer algorithm has not been used for machining performance. Therefore, the present work is the first study that utilized grasshopper algorithm to optimize the cutting force and the surface roughness simultaneously in a multi-objective approach. In order to illustrate the approach proposed in this study, quadratic equations were extracted from an existing study. The speed of cutting, the feed rate and the depth of cut were the input factors. Details showing the formulation of the problem and the results have been disclosed. The Multi-objective grasshopper optimizer (MOGOA) was the metaheuristic-based approach proposed for the formulation of the problem and the computation of the non-dominated or Pareto optimal solutions. The best compromise was obtained by optimizing these two objectives simultaneously. The optimal settings corresponding to the optimal values of cutting force and surface roughness were computed and reported in this section.

**Keywords** Multi-objective optimisation · Grasshopper optimizer · Machining · Cutting force · Surface roughness

### 7.1 Introduction

In the aerospace industry, high-speed turning is becoming a crucial industrial technology. High-speed turning is typically done at a pace that is five to ten times faster than usual cutting. It has several benefits, including decreased cutting forces and temperatures, low power usage, improved surface polish, low-stress components, burr-free surfaces, improved dimensional accuracy, and higher part quality. Higher tool life results from reduced temperature effects on the workpiece and the tool [1].

The process, workpiece, and tool-related factors used while machining has a significant impact on the efficiency and quality of the completed component in high-speed turning.

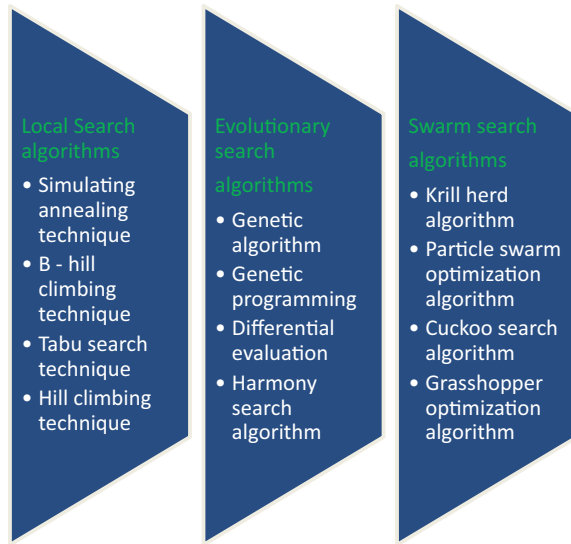
Turning characteristics including cutting speed, feed rate, depth of cut, and edge geometry have a big impact on performance indicators like surface roughness and cutting forces [2]. Typically, the manufacturers' recommendations or their experience are used to choose the machining parameters. The quality of the surface produced and the optimal and economical usage of the machines are not the results of this selection process. Scientific techniques based on Taguchi orthogonal arrays are occasionally employed [3]. A given set of independent parameters and a response variable can be analyzed using this method, and the best parameters can be provided. The methodology offers a different set of optimum operating conditions for each response variable if there are numerous response variables for a given set of independent factors. For instance, in machining, the ideal conditions for decreasing surface roughness and cutting forces need not be the same. Under these circumstances, it may be required to find a solution that provides the finest surface finish at the least amount of cutting force. The Taguchi approach may not offer a suitable answer in such cases [4].

In many different fields, including data mining, engineering applications, machine learning, energy, networks, economics, text mining, medicine, and others, a variety of optimization approaches have been used to solve diverse complicated problems. In order to fully solve the underlying problem, it is mostly used to achieve the optimal solution by obtaining numerous optimal values (decisions). In order to make better decisions, meta-heuristic optimization algorithms often run based on taking into account the optimal value by minimizing or maximizing the objective function. Finding the best selection from a variety of accessible possibilities is the primary goal of decision-making. Finding the best choice value from all provided alternatives as a single unit is the ultimate goal of optimization processes (solution). A sufficiently obtained solution that is the best alternative so far to address the underlying issue is referred to as the best expression. Also, the best solution that was found through several development cycles is regarded as a satisfactory solution [5].

Many research problems in the optimization fields are still interesting today. Due to their nature and reality, they require positive results (i.e., mathematical problems, industrial-type problems, real-world problems, and other problems). Hard optimization problems, or NP-hard problems, are what these issues fall under [6]. By optimizing (minimizing or maximizing) a problem's objective function or fitness function, the main goal of using the various optimization techniques is to obtain optimal decisions (problem solutions). Many optimization issues can be broken down into four broad groups: the first group examines limited and unconstrained issues, while the second group examines continuous and discrete issues. There are either single- or multi-objective tasks in the third class. Problems that are static or dynamic are covered in class 4.

Lately, several biological or naturalistic-inspired algorithms have been developed to locate nearly optimal solutions to several types of challenging optimization problems. These techniques have been successfully utilized to resolve similar optimization issues in practical situations. They are superior to other approaches

**Fig. 7.1** Optimization algorithms



due to their excellent searchability and ability to handle high-dimensional instances (such as calculus-based methods). Optimization algorithms typically examine natural phenomena, such as animal foraging behaviour [7]. The most common varieties of these optimization methods can be broken down into local, evolutionary, and swarm search algorithms (Fig. 7.1).

- **Local Search algorithms:** Simulated tabu search [8], annealing [9], B-hill climbing, and hill-climbing [10] are examples of local search algorithms that operate with a single solution and enhance it (raise its fitness function) over a predetermined number of rounds.
- **Evolutionary search Algorithms:** These algorithms include the genetic algorithm [11], genetic programming [12], salp swarm algorithm [13], firefly algorithm [11], harmony search algorithm [14], and ant colony optimization which operate with a population design (a set of initial solutions) that will be improved iteratively through a specific number of iterations in order to get the best solution.
- **Swarm search,** the third class of algorithms, eventually uses a population mechanism for each iteration. These algorithms are created using data on the past evolution of several potential solutions. Particle swarm optimization method [15], biogeographical-based optimization algorithm [16], artificial bee colony algorithm [17], krill herd algorithm, bacterial foraging algorithm [18], flower pollination algorithm [19], and more related algorithms can be found in Abualigah and Diabat [5].

Despite its potential for optimization, the grasshopper optimizer algorithm has not been used for machining performance. Therefore, the present work is the first study that utilized the grasshopper algorithm to optimize the cutting force and the surface

roughness simultaneously in a multi-objective approach. This study aims to assess the extent to which this multi-objective optimizer could be applied to machining performance. In this study, quadratic equations extracted from an existing work were used to illustrate how the grasshopper optimization algorithm could be employed for multi objective-optimization related to machining performance.

## 7.2 Grasshopper Optimisation Algorithm (GOA) Background

The foundation of mathematical optimization techniques is the gradient search. Local Optima is one of the disadvantages of these techniques. Stochastic approaches make use of random operators to avoid local optima. The nature-inspired stochastic approaches have gained the most traction during the past few decades. Grasshopper Optimisation Algorithm GOA was created by Saremi et al. [20]. It is a potent optimization tool that makes use of a swarm-based metaheuristic optimization algorithm that takes inspiration from nature.

GOA imitates grasshopper swarms' organic behaviours. Millions of these insects jump and move around the crops in a manner similar to rolling cylinders. The search procedure is logically divided into two sections by algorithms with natural inspiration namely exploration and exploitation. During the exploration stage, the search agents of the optimization algorithm move quickly. However, they frequently stay put during the exploitation phase. The following mathematical equations combine the natural behaviour of grasshoppers with the logic of optimization search [20].

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \quad (7.1)$$

The social interaction, gravitational pull, and wind advection of the  $i$ th grasshopper, respectively, define  $X_i$ ,  $S_i$ ,  $G_i$ , and  $A_i$ , which determine the  $i$ th grasshopper's position. The  $[0, 1]$  range of random numbers makes up the  $r$  parameters. The social interaction (attraction and repulsion of grasshoppers) is calculated by the following equation and illustrated in Fig. 7.2 [20]:

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^N s(d_{ij}) \widehat{d}_{ij} \quad (7.2)$$

Thus,  $f$  stands for the intensity of attraction,  $l$  for the attractive length scale, and  $s$  is the function that represents the strength of social forces.  $N$  is the grasshoppers' total number.  $\widehat{d}_{ij}$  ( $\widehat{d}_{ij} = \frac{(x_j - x_i)}{d_{ij}}$ ) is a vector between two grasshoppers and  $d_{ij}$  ( $d_{ij} = |x_j - x_i|$ ) represents the distance between the  $i$ th and  $j$ th grasshopper.  $S$

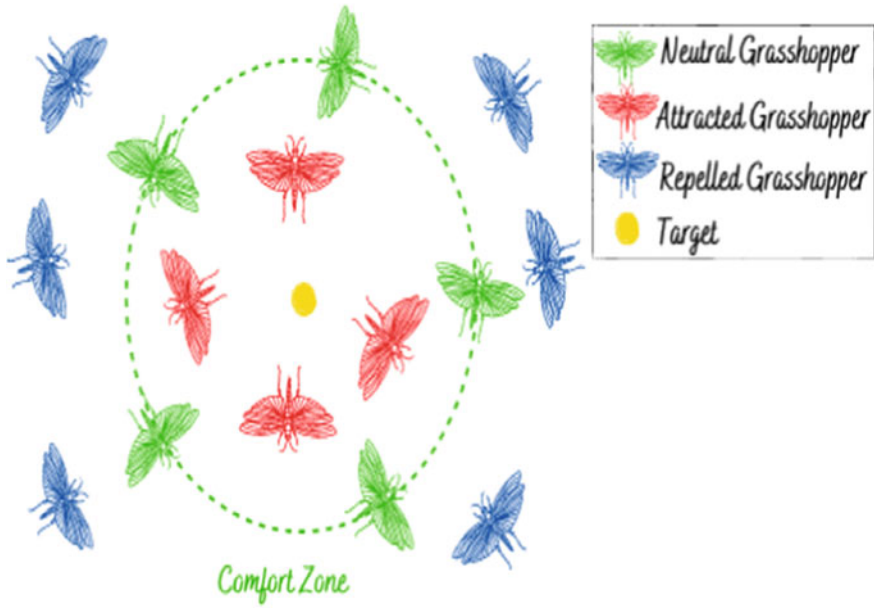


**Fig. 7.2** Grasshoppers' social interactions

function affects the social behaviour (attraction and repulsion) of artificial grasshoppers. Three parts are created using this function to divide the space between two grasshoppers (repulsion region, comfort zone, and attraction region). Saremi et al. [20] investigated distances from 0 to 15 and found out that the repulsion happened between  $[0, 2.079]$ . They suggested defining the comfort distance as the separation of two artificial grasshoppers at a distance of 2.079 units (there is no attraction or repulsion in this comfort zone). The  $l$  and  $f$  settings modify this comfort zone. Unfortunately, the  $s$  function resets to zero when the distance exceeds 10. Hence, large forces cannot be applied between grasshoppers across great distances using this function.  $G_i$ , also known as the gravitational force on the  $i$ th grasshopper, is a part of  $X_i$  that may be determined using Eq. (7.3).

$$G_i = -g\hat{e}_g \quad (7.3)$$

$g$  stands for the gravitational constant, while  $\hat{e}_g$  is a unit vector pointing at the earth's center. The component  $A_i$  is given by the following Equation:

$$A_i = u\hat{e}_w \quad (7.4)$$

where  $\hat{e}_w$  is a unit vector pointing in the direction of the wind and  $u$  is a continuous drift. In conventional swarm-based algorithms, the swarm is modelled as searching and taking advantage of the search space surrounding a solution. The

swarm's mathematical model, the grasshopper algorithm, is in free space. As a result, the  $X_i$  model mimics the behaviour of a swarm of grasshoppers. Equation (7.5) replicates grasshopper behaviour in two-dimensional, three-dimensional, and hyperdimensional areas. It is an enlarged version of Eq. (7.1).

$$X_i^d = c \left( \sum_{\substack{j=1 \\ j \neq i}}^N c \frac{ub_d - lb_d}{2} s \left( \left| X_j^d - X_i^d \right| \right) \frac{X_j - X_i}{d_{ij}} \right) + \hat{T}_d \quad (7.5)$$

In the  $D$ th dimension  $sr$ , the upper ( $ub$ ) and lower bounds ( $lb$ ) are represented by  $ub_d$  and  $lb_d$ , respectively. The third component,  $c$ , is a decreasing coefficient that causes the comfort, repellency, and attraction zones to contract.  $\hat{T}_d$  is the target value (optimal solution). Each search agent only has one location vector, according to GOA. To determine each search agent's subsequent position in GOA, all search agents are used. The first term of Eq. (7.5) (the summation) simulates grasshopper interaction in nature by taking into consideration the positions of other grasshoppers. The second term  $\hat{T}_d$  simulates their propensity to travel in the direction of the sources of food. Last but not least, Eq. 7.6 uses parameter  $c$  to implement the slowdown of grasshoppers approaching the food source.

$$c = c_{\max} - l \frac{c_{\max} - c_{\min}}{L} \quad (7.6)$$

where  $l$  denotes the current iteration and  $L$  is the maximum number of iterations, and  $c_{\max}$  and  $c_{\min}$  stand for the highest and lowest values, respectively. In this section, values of  $c_{\max} = 1$  and  $c_{\min} = 0.00001$  were used as recommended by Saremi et al. [20]. In summary, the swarm gradually moves towards a stationary target by reducing its comfort zone by the  $c$  parameter. Also, the swarm correctly pursues a moving object by  $\hat{T}_d$ . Throughout iterations, the grasshoppers will flock together toward the objective. The optimization process of ant lion algorithm is summarized in Fig. 7.3.

### 7.3 Brief Description of Data Extraction and Processing

In order to illustrate the approach proposed in this study, quadratic equations were extracted from the study conducted by Sahu and Andhare [21]. In the reported study, titanium alloy (Ti-6Al-4V) was chosen as the turning work material. The bar size for turning was determined to be 32 mm in diameter, 100 mm in length, and 35 mm in length cut. The turning operations were carried out on a CNC lathe machine with a 5.5 kW power capacity. The machine's controller provided fine motion and spindle speed control with 0.005 mm position precision and 0.004 mm repeatability



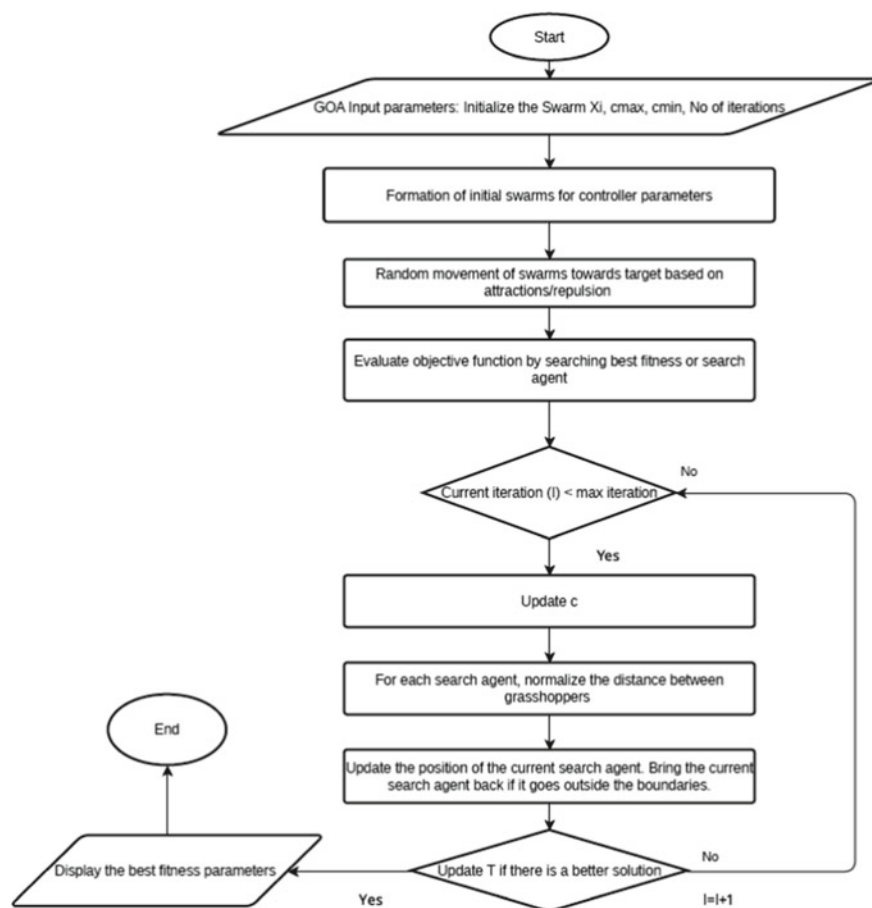


**Fig. 7.3** Flowchart of grasshopper optimizer algorithm

during cutting. During turning operations, the cutting force was measured using a dynamometer that was interfaced with a control unit.

The design of experiment was performed with a central composite design (CCD) based on Response Surface Methodology (RSM). The speed of cutting, the feed rate and the depth of cut were the input factors. The regression coefficient and subsequently the quadratic equation of the cutting force were generated based on the experimental design and the response measured. The model adequacy was checked using the analysis of variance (ANOVA) and non-significant parameters were discarded. A similar approach was adopted to develop the quadratic equation describing the surface roughness [22]. The roughness of the machined surface and the force of cutting were the two responses. In the formulation of the multi-objective optimization models described in the following sections, the speed of cutting, the feed rate

and the depth of cut are the variables to be optimized while the surface roughness and the cutting force are the two objective functions to minimize.

## 7.4 Formulation of Quadratic Equations and Mathematical Formulation

### 7.4.1 Design Variables and Objectives Functions

Three different variables namely the cutting speed (S), the feed rate (F) and the depth of cut (D) have been considered. These three variables are closely related to the setting of the CNC lathe machine used for data extraction and processing described in the previous section. The lowest and the highest level of cutting parameters used for central composite design reported in the study of Sahu and Andhare [21] were taken into account to illustrate the approach proposed in this study.

$$\begin{aligned} S_{\min} &= 69.9 < S < S_{\max} = 150 \\ F_{\min} &= 55.6 < F < F_{\max} = 120.6 \\ D_{\min} &= 0.66 < D < D_{\max} = 2 \end{aligned} \quad (7.7)$$

$S, F \text{ and } D \in \mathbb{R}^+$

In this study, the machinability of Ti-6Al-4V alloy is measured with the cutting force (CF) and the surface roughness (SR). The two objective functions in the formulation of the mathematical programming problem are these indicators. They are given by the following quadratic Eqs. (7.8–7.10) [21]:

$$\begin{aligned} CF &= 513.915 - 0.2466 \times S + 5.3773 \times F + 64.92 \\ &\times D - 2.594e - 4 \times S^2 - 0.055 \times F^2 + 0.0052 \times S \times F \end{aligned} \quad (7.8)$$

$$\begin{aligned} SR &= 1.27686 - 0.000897964 \times S + 0.0008937 \\ &\times F + 0.036303 \times D + 1.69203e - 7 \times S^2 \end{aligned} \quad (7.9)$$

These equations suggest that the three variables (S, F and D) have a significant effect on the cutting force and the surface roughness of Ti-6Al-4V alloy. The optimum values of the parameters describing the setting of the CNC lathe machine can be obtained by solving Eqs. 7.7 and 7.9.

### 7.4.2 Multi-objective Optimization

The following Equation is a formulation of the general multi-objective optimization problem with equality and inequality constraints [23]:

$$\begin{aligned} & \text{Minimize } \left\{ \overrightarrow{F_i(x)} \right\}, \quad \forall_i \in N_{oj}, \\ & \text{Subject to: } \begin{cases} \overrightarrow{g_m(x)}, \forall_m \in N_{EQ} \\ \overrightarrow{h_k(x)}, \forall_k \in N_{INQ} \end{cases} \end{aligned} \quad (7.10)$$

where  $F_i$  is the  $i$ th objective function,  $g_m(x)$  and  $h_k(x)$  are the constraints,  $N_{EQ}$  and  $N_{INQ}$  are respectively the numbers of equality and inequality constraints, and  $N_{oj}$  is the number of objective functions.

If the following criteria are met, the solution  $\overrightarrow{x_1}$  prevails over  $\overrightarrow{x_2}$  in the multi-objective minimization problem:

$$F_i(\overrightarrow{x_1}) \leq F_i(\overrightarrow{x_2}), \quad \forall_i \in N_{oj} \quad (7.11)$$

Pareto optimum solutions are the prevailing options across the whole search space.

A fuzzy membership function  $\mu_i$  can be used to represent the  $i$ th objective function  $F_i$  as follows:

$$\mu_i = \frac{F_i - F_i^{\min}}{F_i^{\max} - F_i^{\min}} \quad (7.12)$$

where the parameters  $F_i^{\min}$  and  $F_i^{\max}$  are respectively the minimum and the maximum values of the  $i$ th objective function among all Pareto solutions.

The normalized membership function  $\mu^k$  is calculated as follows for each Pareto solution:

$$\mu^k = \frac{\sum_{i=1}^{N_{oj}} \mu_i^k}{\sum_{k=1}^M \sum_{i=1}^{N_{oj}} \mu_i^k}, \quad \forall k \in M \quad (7.13)$$

The minimal value of  $\mu^k$  is the best compromise option.  $M$  is the number of Pareto solutions.

## 7.5 Results and Discussion

The optimization of the CNC lathe machine problem to improve machining performance is solved in this section using the ALO algorithms. The proposed algorithm is applied to solve the multi-objective optimization problem described by the objective

**Table 7.1** MOGOA parameters

|                             |
|-----------------------------|
| Number of Grasshoppers: 200 |
| Maximum iteration: 100      |
| cMax = 1                    |
| cMin = 0.00004              |

functions 1 OF1 and OF2 corresponding to Eqs. 7.7 and 7.9. The proposed approach was implemented in a MATLAB environment. Details of the mathematical programming model are provided in Appendix F. The simulation results are carried out using an 11th Gen Intel(R) Core (TM) i5-1135G7 @ 2.40 GHz Processor, 8 GB RAM, 64-bit operating system, PC. Table 7.1 provides details showing how the parameters of the suggested algorithm are configured.

The proposed algorithm is applied to solve the multi-objective problem described by the objective function 1 (OF1) and objective function 2 (OF2) corresponding to Eqs. 7.2 and 8.3 respectively. As described in the previous sections, the cutting force and the surface roughness are conflicting in nature. Therefore, the best compromise was obtained by optimizing these two objectives simultaneously. The optimal

**Table 7.2** Pareto optimal solutions

| Index | OF1      | OF2    | Index | OF1      | OF2    |
|-------|----------|--------|-------|----------|--------|
| 1     | 513.9150 | 1.2769 | 51    | 513.7916 | 1.2764 |
| 2     | 513.9125 | 1.2769 | 52    | 513.7892 | 1.2764 |
| 3     | 513.9101 | 1.2768 | 53    | 513.7867 | 1.2764 |
| 4     | 513.9076 | 1.2768 | 54    | 513.7842 | 1.2764 |
| 5     | 513.9051 | 1.2768 | 55    | 513.7818 | 1.2764 |
| 6     | 513.9027 | 1.2768 | 56    | 513.7793 | 1.2764 |
| 7     | 513.9002 | 1.2768 | 57    | 513.7768 | 1.2764 |
| 8     | 513.8977 | 1.2768 | 58    | 513.7744 | 1.2763 |
| 9     | 513.8953 | 1.2768 | 59    | 513.7719 | 1.2763 |
| 10    | 513.8928 | 1.2768 | 60    | 513.7694 | 1.2763 |
| 11    | 513.8903 | 1.2768 | 61    | 513.7669 | 1.2763 |
| 12    | 513.8879 | 1.2768 | 62    | 513.7645 | 1.2763 |
| 13    | 513.8854 | 1.2768 | 63    | 513.7620 | 1.2763 |
| 14    | 513.8829 | 1.2767 | 64    | 513.7595 | 1.2763 |
| 15    | 513.8805 | 1.2767 | 65    | 513.7571 | 1.2763 |
| 16    | 513.8780 | 1.2767 | 66    | 513.7546 | 1.2763 |
| 17    | 513.8755 | 1.2767 | 67    | 513.7521 | 1.2763 |
| 18    | 513.8731 | 1.2767 | 68    | 513.7497 | 1.2763 |
| 19    | 513.8706 | 1.2767 | 69    | 513.7472 | 1.2762 |

(continued)

**Table 7.2** (continued)

| Index | OF1      | OF2    | Index | OF1      | OF2    |
|-------|----------|--------|-------|----------|--------|
| 20    | 513.8681 | 1.2767 | 70    | 513.7447 | 1.2762 |
| 21    | 513.8657 | 1.2767 | 71    | 513.7423 | 1.2762 |
| 22    | 513.8632 | 1.2767 | 72    | 513.7398 | 1.2762 |
| 23    | 513.8607 | 1.2767 | 73    | 513.7373 | 1.2762 |
| 24    | 513.8583 | 1.2767 | 74    | 513.7348 | 1.2762 |
| 25    | 513.8558 | 1.2766 | 75    | 513.7324 | 1.2762 |
| 26    | 513.8533 | 1.2766 | 76    | 513.7299 | 1.2762 |
| 27    | 513.8509 | 1.2766 | 77    | 513.7274 | 1.2762 |
| 28    | 513.8484 | 1.2766 | 78    | 513.7250 | 1.2762 |
| 29    | 513.8459 | 1.2766 | 79    | 513.7225 | 1.2762 |
| 30    | 513.8435 | 1.2766 | 80    | 513.7200 | 1.2762 |
| 31    | 513.8410 | 1.2766 | 81    | 513.7176 | 1.2761 |
| 32    | 513.8385 | 1.2766 | 82    | 513.7151 | 1.2761 |
| 33    | 513.8361 | 1.2766 | 83    | 513.7126 | 1.2761 |
| 34    | 513.8336 | 1.2766 | 84    | 513.7101 | 1.2761 |
| 35    | 513.8311 | 1.2766 | 85    | 513.7077 | 1.2761 |
| 36    | 513.8287 | 1.2765 | 86    | 513.7052 | 1.2761 |
| 37    | 513.8262 | 1.2765 | 87    | 513.7027 | 1.2761 |
| 38    | 513.8237 | 1.2765 | 88    | 513.7003 | 1.2761 |
| 39    | 513.8213 | 1.2765 | 89    | 513.6978 | 1.2761 |
| 40    | 513.8188 | 1.2765 | 90    | 513.6953 | 1.2761 |
| 41    | 513.8163 | 1.2765 | 91    | 513.6928 | 1.2761 |
| 42    | 513.8139 | 1.2765 | 92    | 513.6904 | 1.2760 |
| 43    | 513.8114 | 1.2765 | 93    | 513.6879 | 1.2760 |
| 44    | 513.8089 | 1.2765 | 94    | 513.6854 | 1.2760 |
| 45    | 513.8064 | 1.2765 | 95    | 513.6830 | 1.2760 |
| 46    | 513.8040 | 1.2765 | 96    | 513.6805 | 1.2760 |
| 47    | 513.8015 | 1.2764 | 97    | 513.6780 | 1.2760 |
| 48    | 513.7990 | 1.2764 | 98    | 513.6756 | 1.2760 |
| 49    | 513.7966 | 1.2764 | 99    | 513.6731 | 1.2760 |
| 50    | 513.7941 | 1.2764 | 100   | 513.6706 | 1.2760 |

settings corresponding to the optimal values of cutting force and surface roughness are described in Table 7.2 by values of OF1 and OF2 respectively. Figure 7.4 shows two-dimensional Pareto optimal solutions that achieved the best compromise solution. Details of the main MATLAB codes are provided in Appendices F and G.

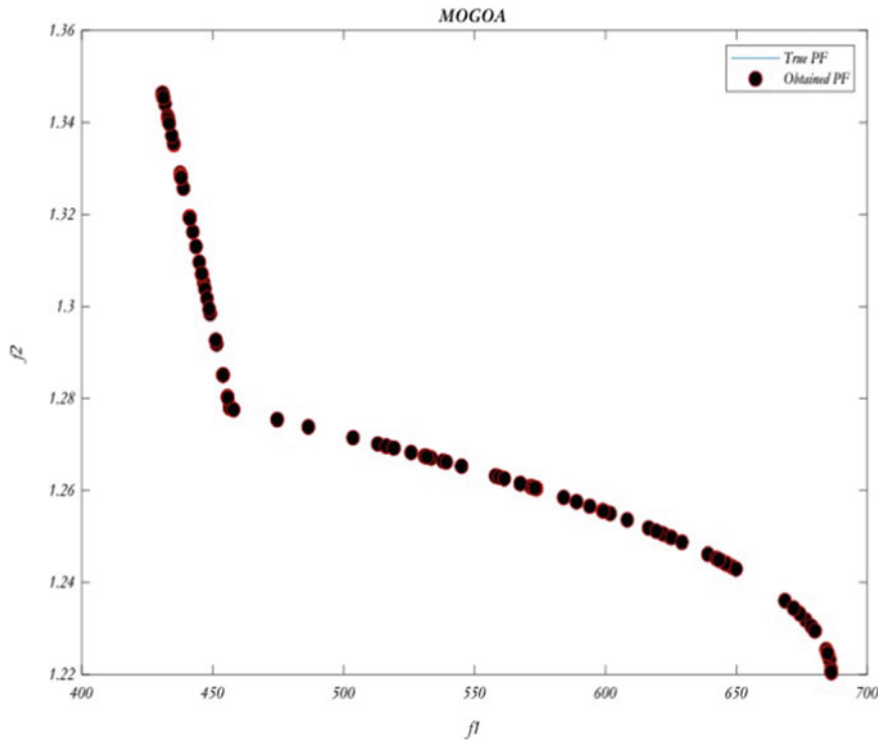


Fig. 7.4 Graphical representation of the Pareto optimal solutions

7.6 Conclusion

In this section, a Multi-objective Grasshopper Optimizer (MOGOA) is proposed to enhance the machining performance during the turning of a titanium alloy. This advanced approach has been described in detail to demonstrate the applicability of metaheuristic optimization methods in manufacturing. The cutting force and the surface roughness were the two objective functions to optimize. Details describing the proposed optimization approach are provided. The approach was implemented in software MATLAB. The proposed Multi-objective Grasshopper Optimizer (MOGOA) was applied to solve the multi-objective problem and the best compromise between the two objective functions was computed to assist the decision-maker in the selection of the best setting that could potentially improve machinability performance.

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## Chapter 8

# A Multi-objective Optimization Approach for Improving Machining Performance Using the General Algebraic Modelling System (GAMS)



**Abstract** Machining performance can be assessed through indicators such as cutting force and surface roughness. These indicators can be predicted and optimized by adjusting parameters such as the cutting speed, the feed rate and the depth of cut. Several studies have pointed out the conflicting nature of cutting force and surface roughness when attempting to optimize them simultaneously. Unlike previous studies, the machinability performance is analysed in this work using an improved version of the augmented  $\epsilon$ -constraint approach that takes cutting force and surface roughness into account as objective functions. In order to illustrate the approach proposed in this study, quadratic equations were extracted from an existing study related to a CNC lathe machine. These equations relate variables such as cutting speed, the feed rate and the depth of cut to the cutting force and surface roughness considered as objective functions in the mathematical programming formulation. The General Algebraic Modeling System (or GAMS) was used to construct and implement the Non-Linear Problem. The proposed new multi-objective approach provides accurate Pareto sets that correspond to the optimal setting of the CNC lathe machine. In addition, this study provide clarity on the implication of an adjustment of machining parameters to optimize machining performance.

**Keywords** General algebraic modeling system • Machining • Cutting force and surface roughness • Optimization

## 8.1 Introduction

Due to the exceptional qualities indicated in the literature, titanium alloys are widely used in the aviation and biomedical industries [1, 2]. However, the literature also reports challenges in machining titanium alloys [2–4]. Cutting force and surface roughness, which serve as indicators of surface integrity, are frequently utilized as response parameters for assessing machining performance [5]. This is due to the explanations provided in the paragraphs that follow.

After machining, surface integrity is a crucial indicator of reliability, as are fatigue life and end-part quality [6, 7]. A widely used technique for determining the integrity of a machined surface is to quantify the surface roughness [8]. In past studies, traditional machining was used to determine the influence of machining input parameters on the roughness of machined surfaces in operations like turning and milling [9, 10]. According to Sahu and Andhare [11], although cutting speed and feed rate are important elements for turning and facing operations, feed rate and radial depth of cut are key factors for surface roughness for milling operations. In the past, researchers have conducted experiments to create empirical models with variables like cutting parameters to identify the ideal circumstances for minimal surface roughness [12–14].

As it relates to the power needed for machining, cutting force is a crucial machinability evaluation criterion. Because cutting pressures rise with tool wear, surface quality depends on cutting force. In order to find the best cutting parameters for machining a challenging titanium alloy under minimal quantity lubrication (MQL) conditions, Liu et al. [15] suggested a new approach referring to coupling response surface methodology (CRSM). As a result, cutting forces were minimized when the feed rate and depth of cut were set to the lowest levels while the cutting speed was set to the greatest levels. From the previous studies, it appears that, while cutting Ti–6Al–4V, cutting force reduces with increasing cutting speed for constant feed rate, depth of cut, and given rake angle [16]. According to the literature, it is possible to create models that predict and optimize cutting forces and surface roughness based on cutting parameters.

Rao and Kalyankar [17] propose the use of a multi-objective optimization approach to determine the variables that optimize multiple objectives while taking restrictions into account. Many studies discuss the theory of optimization for single- and multi-objective optimizations [18, 19]. Advanced optimization algorithms, such as the Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO) etc. are described by Okwu and Tartibu [20] to illustrate how optimization problems could be formulated and resolved. Although most of these algorithms yield robust solutions, improper tuning of algorithm-specific parameters either increases the computational effort or yields a locally optimal solution. In addition to the tuning of algorithm-specific parameters, the common control parameters also need to be tuned which further enhances the effort. There is no universal rule for the choice of these parameters. Improper selection of these parameters leads to a local optimum solution. The repeatability of results obtained with the same design variables and initial conditions is not guaranteed with these non-traditional optimization techniques.

Sahu and Andhare [16] proposed the use of Teaching Learning Based Optimization (TLBO), “JAYA,” and Genetic Algorithm (GA) to show how the turning of titanium alloys (Ti–6Al–4V) can be optimized to reduce surface roughness and the resulting cutting forces. The results show that when cutting Ti–6Al–4V, a greater cutting speed combined with a lower feed rate can result in better surface roughness and less cutting force. Unlike previous studies, the machinability performance is analysed in this work using an improved version of the augmented  $\varepsilon$ -constraint approach

(AUGMENCON2) that takes cutting force and surface roughness into account as objective functions. Mavrotas and Florios [21] created the proposed AUGMENCON2 technique. A high-level modeling system for mathematical programming and optimization called the General Algebraic Modeling System (or GAMS) is used to construct and implement Non-Linear Problems. With a fair level of precision and quick computation times, this new multi-objective approach aims to provide accurate Pareto sets that correspond to the optimal setting of the CNC lathe machine.

## 8.2 Modelling with GAMS

GAMS stands for General Algebraic Modeling System. It is an optimization and programming modeling. This chapter illustrates how problems related to machining processing could be formulated in GAMS in order to compute optimal solutions. The GAMS technology is made to make it easier for modelers to build mathematical representations of the world around us. It frees modelers from having to create model algorithms in addition to developing models. Consequently, creating algorithms for mathematical models is the primary functional goal of GAMS.

Though the acronym of GAMS incorporates the word “Algebraic”, this does not imply that this system is limited to algebraic equation-based mathematical models. Those who are familiar with the techniques for solving partial differential equations know that they are always converted to a system of algebraic equations. An iteration approach is used to solve these algebraic equations. That is to say, GAMS has a considerably larger range of applications.

Each GAMS model is composed mostly of the following components [22]:

- **Sets:** The indices in the algebraic representations of models are defined by sets.
- **Data:** Each GAMS model’s input data are expressed as parameters, tables, or scalars.
- **Variables:** Prior to solving the model, the variables are uncertain decision sets.
- **Equations:** The relationships between the variables and data are described by the equations.
- **Model and Solve Statements:** An objective function-containing set of equations is referred to as the model. GAMS is commanded to solve the model in the solve sentence.
- **Output:** The results of the solved model can be seen in a variety of ways, including by displaying them or saving them in an XLS file.

Figure 8.1 depicts the general GAMS code structure and its components.

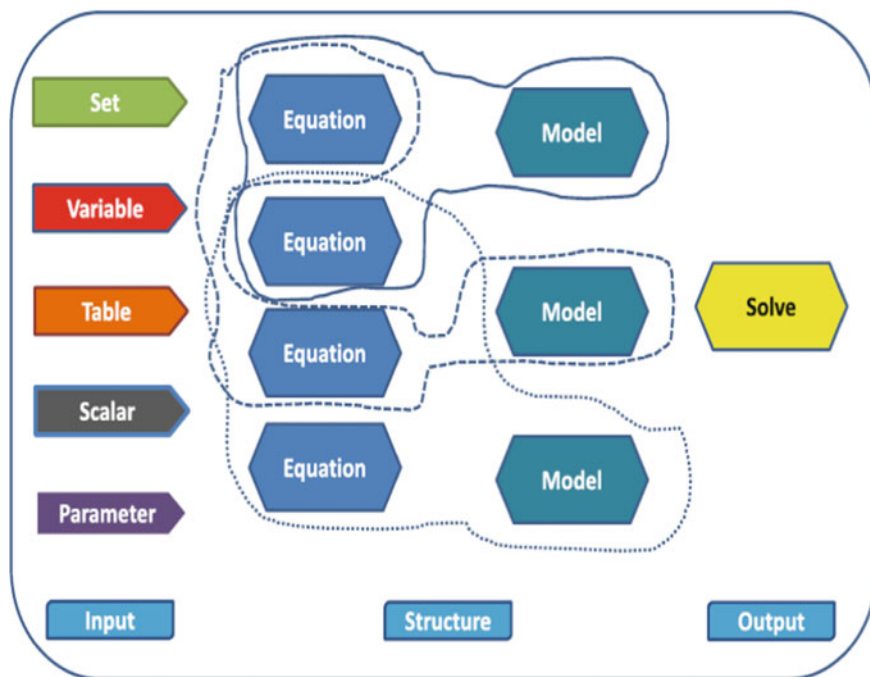


**Fig. 8.1** GAMS code structure and its components

### 8.3 Brief Description of Data Extraction and Processing

In order to illustrate the approach proposed in this study, quadratic equations were extracted from the study conducted by Sahu and Andhare [16]. In the reported study, titanium alloy (Ti–6Al–4V) was chosen as the turning work material. The bar size for turning was determined to be 32 mm in diameter, 100 mm in length, and 35 mm in length cut. The turning operations were carried out on a CNC lathe machine with a 5.5 kW power capacity. The machine's controller provided fine motion and spindle speed control with 0.005 mm position precision and 0.004 mm repeatability during cutting. During turning operations, the cutting force was measured using a dynamometer that was interfaced with a control unit.

The design of experiment was performed with a central composite design (CCD) based on Response Surface Methodology (RSM). The speed of cutting, the feed rate and the depth of cut were the input factors [23]. The regression coefficient and subsequently the quadratic equation of the cutting force were generated based on the experimental design and the response measured. The model adequacy was checked using the analysis of variance (ANOVA) and non-significant parameters were discarded. A similar approach was adopted to develop the quadratic equation describing the surface roughness [11]. The roughness of the machined surface and the force of cutting were the two responses. In the formulation of the multi-objective

optimization models described in the following sections, the speed of cutting, the feed rate and the depth of cut are the variables to be optimized while the surface roughness and the cutting force are the two objective functions to minimize.

## 8.4 Formulation of Quadratic Equations and Mathematical Programming Models

### 8.4.1 Design Variables and Objectives Functions

Three different variables namely the cutting speed (S), the feed rate (F) and the depth of cut (D) have been considered. These three variables are closely related to the setting of the CNC lathe machine used for data extraction and processing described in the previous section. The lowest and the highest level of cutting parameters used for central composite design reported in the study of Sahu and Andhare [16] were taken into account to illustrate the approach proposed in this study.

$$\begin{aligned} S_{\min} &= 69.9 < S < S_{\max} = 150 \\ F_{\min} &= 55.6 < F < F_{\max} = 120.6 \\ D_{\min} &= 0.66 < D < D_{\max} = 2 \\ S, F \text{ and } D &\in \mathbb{R}^+ \end{aligned} \quad (8.1)$$

In this study, the machinability of Ti-6Al-4V alloy is measured with the cutting force (CF) and the surface roughness (SR). The two objective functions in the formulation of the mathematical programming problem are these indicators. They are given by the following quadratic Eqs. (8.1–8.6):

$$\begin{aligned} CF &= 513.915 - 0.2466 \times S + 5.3773 \times F + 64.92 \times D \\ &\quad - 2.594e - 4 \times S^2 - 0.055 \times F^2 + 0.0052 \times S \times F \end{aligned} \quad (8.2)$$

$$\begin{aligned} SR &= 1.27686 - 0.000897964 \times D + 0.0008937 \times F \\ &\quad + 0.036303 \times D + 1.69203e - 7 \times S^2 \end{aligned} \quad (8.3)$$

These equations suggest that the three variables (S, F and D) have a significant effect on the cutting force and the surface roughness of Ti-6Al-4V alloy. The optimum values of the parameters describing the setting of the CNC lathe machine can be obtained by solving Eqs. 8.2 and 8.3.

### 8.4.2 Single Objective Optimization

In the preceding section, descriptions of each phrase used in the Mathematical Problem Formulation (MPF) are provided. They are the basis of the Non-Linear Programming Problem (NLP) that is represented by the following equation:

$$(\text{MPF}) \min_{S,F,D} \xi = w_1(\text{CF}) + w_2(\text{SR}) \quad (8.4)$$

This mathematical model captures the main elements that describe the machinability of Ti-6Al-4V alloy. The analysis of restricted cases of objectives and the identification of geometric parameter trends with respect to each objective function are covered in the discussion that follows.

#### 8.4.2.1 Emphasising Cutting Force

All proposed NLPs developed in this study were solved by GAMS 23.8 on a personal computer Intel Core i5, 2.4 GHz with 8 GB RAM. Although there are several optimization solvers incorporated in GAMS, the solver LINDOGLOBAL was adopted for this study (Fig. 8.2). This is because LINDOGLOBAL identifies solutions that are guaranteed to be globally optimal for nonlinear problems involving continuous and/or discrete variables [24]. This study includes information on the input file and the GAMS compilation models used for the analysis and optimization of machining processes, with the GAMS process shown in Fig. 8.3.

In order to emphasise the cutting force, the objective function weight  $w_2 = 0$ . Hence, the problem would be reduced to Eq. 8.2 and the variable restrictions described in Eq. 8.1. The objective function (Eq. 8.4) becomes:

$$(\text{MPF}) \min_{S,F,D} \xi_{\text{CF}} = \text{CF} \quad (8.5)$$

A screenshot showing the mathematical programming model and the compilation process is shown in Fig. 8.4. Details of the GAMS code are provided in Fig. 8.4.

The optimal solutions that minimise  $\xi_{\text{CF}}$  are represented in a tabulated format with letters subscripted with an asterisk (Table 8.1). Practically, this optimal solution suggests that the cutting force can be optimised by:

- Setting the cutting speed to the minimum.
- Setting the feed rate to the maximum.
- Ensuring that the depth of cut is minimum.

The minimum and the maximum cutting force are respectively 430.656 and 774.451.

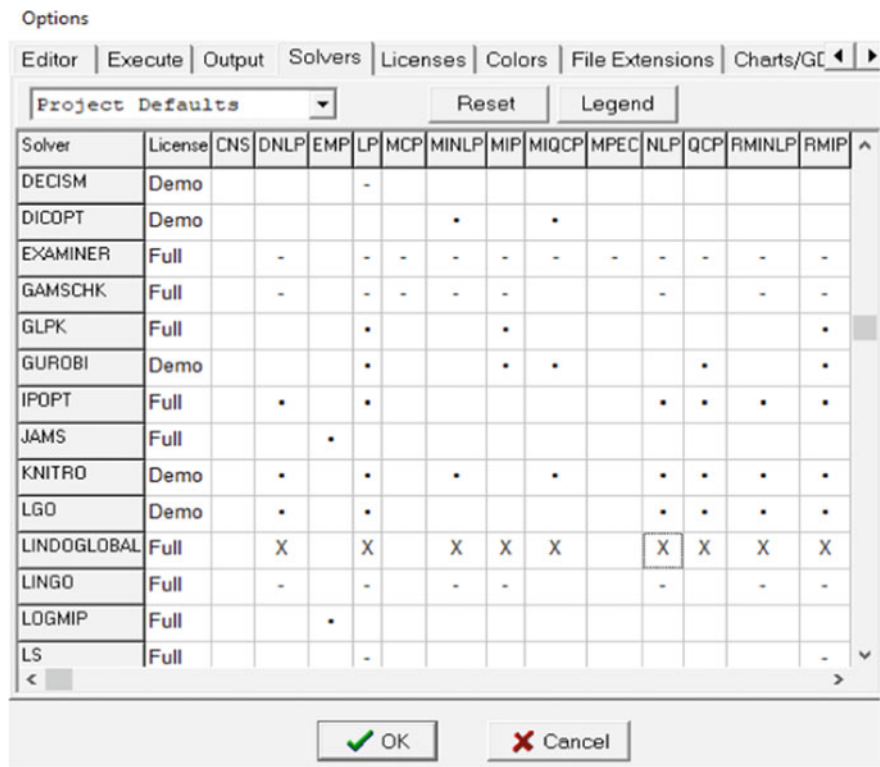


Fig. 8.2 GAMS solvers

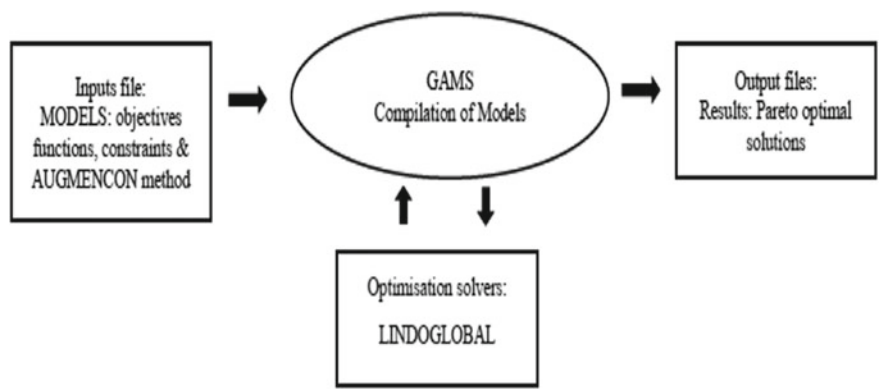


Fig. 8.3 Process illustration using GAMS

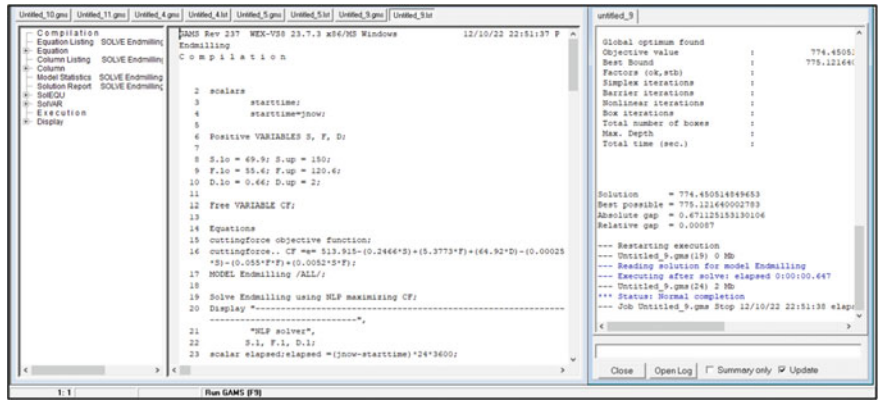


Fig. 8.4 GAMS model formulation with an emphasis on the cutting force

Table 8.1 Optimal solutions minimising the cutting force

|    | S*     | F*      | D*    | $\xi_{CF}^*$ | CPU time (s) |
|----|--------|---------|-------|--------------|--------------|
| x* | 69.900 | 120.600 | 0.660 | 430.656      | 0.616        |

8.4.2.2 Emphasising Surface Roughness

In order to emphasise the surface roughness, the objective function weight  $w_1 = 0$ . Hence, the problem would be reduced to Eq. 8.3 and the variable restrictions described in Eq. 8.1. The objective function (Eq. 8.4) becomes:

$$(MPF) \min_{S,F,D} \xi_{SR} = SR \tag{8.6}$$

A screenshot showing the mathematical programming model and the compilation process is shown in Fig. 8.5. Details of the GAMS code are provided in Fig. 8.5.

The optimal solutions that minimise  $\xi_{SR}$  are represented in a tabulated format with letters subscripted with an asterisk (Table 8.2). Practically, this optimal solution suggests that the cutting force can be optimised by:

- Setting the cutting speed to the minimum.
- Setting the feed rate to the minimum.
- Ensuring that the depth of cut is minimum.

The minimum surface roughness is 1.289.



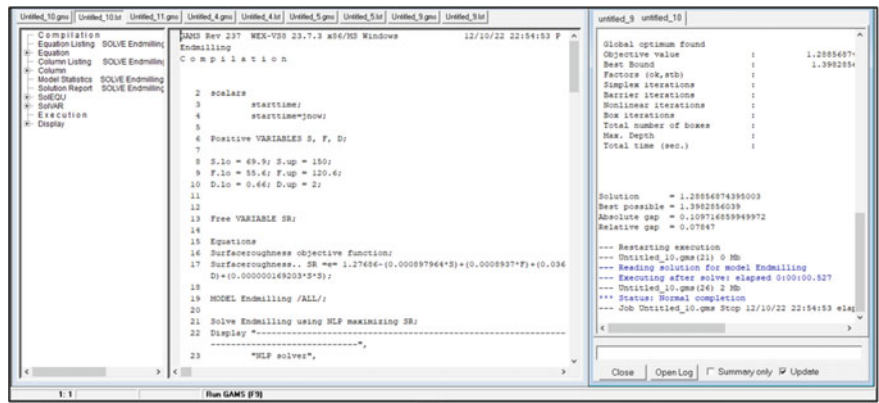


Fig. 8.5 GAMS model formulation with an emphasis on the surface roughness

Table 8.2 Optimal solutions minimising surface roughness

|    | S*     | F*     | D*    | $\xi_{SR}^*$ | CPU time (s) |
|----|--------|--------|-------|--------------|--------------|
| x* | 69.900 | 55.600 | 0.660 | 1.289        | 1.929        |

Table 8.3 Tendencies of parameters considering an individual objective function

|   | CF | SR  |
|---|----|-----|
| S | ↓  | ↓   |
| F | ↑  | ↓ ≠ |
| D | ↓  | ↓   |

8.4.2.3 Single Objective Optima: Variable Analysis

Table 8.3 summarises the results of the two previous sections, highlighting the trends of parameters. In this analysis, ↑ indicates an increasing tendency, ↓ indicates a decreasing tendency and ≠ indicates conflicting tension between parameters.

The conflicting nature of objective functions is observed when considering the trends of the feed rate in Table 8.3. Therefore, the use of adoption of a multi-objective optimization approach would be suitable to compute the optimal solutions that would optimize the two objective functions simultaneously.

8.4.3 Emphasising All Objective Components

An enhanced version of the augmented  $\epsilon$ -constraint approach is suggested in this study. As a result, a summary of the original augmented  $\epsilon$ -constraint approach

is given. Mavrotas [25] provide information on how the  $\epsilon$ -constraint technique is implemented as compared to the augmented  $\epsilon$ -constraint approach.

(a) Augmented  $\epsilon$ -constraint method (AUGMENCON)

Numerous studies on thermal systems by Tartibu et al. [26] and [27] have successfully used the original augmented  $\epsilon$ -constraint approach (AUGMENCON), which was proposed by Mavrotas [25]. The AUGMENCON is a modification of the conventional  $\epsilon$ -constraint approach that addresses many of its shortcomings. (1) Unlike the traditional  $\epsilon$ -constraint method, the AUGMENCON uses a lexicographic optimization method to calculate the ranges of the objective functions; (2) the efficiency of the returned solutions is demonstrated, and (3) the AUGMENCON significantly reduces the computational time by utilizing several acceleration techniques. It is possible to formulate the increased  $\epsilon$ -constraint approach as follows:

$$\max \left( f_1(x) + \text{eps} \times \left( \frac{s_2}{r_2} + \frac{s_3}{r_3} + \dots + \frac{s_p}{r_p} \right) \right) \quad (8.7)$$

Subject to

$$\begin{aligned} f_2(x) - s_2 &= \varepsilon_2; f_3(x) - s_3 = \varepsilon_3, \dots; f_p(x) - s_p = \varepsilon_p \\ x &\in s \text{ and } s_i \in \mathbb{R}^+ \end{aligned}$$

where  $\varepsilon_2, \varepsilon_3, \dots, \varepsilon_p$  are the right-hand side parameters corresponding to the objective functions 2, 3, ..., p. The ranges are denoted with  $r_2, r_3, \dots, r_p$ , the surplus variables are described as  $s_2, s_3, \dots, s_p$  while eps represent a small number whose value is in-between  $10^{-3}$  and  $10^{-6}$  [25]. Figure 8.6 shows the flowchart of the AUGMENCON method for optimizing several objective functions.

(b) Improved version of the augmented  $\epsilon$ -constraint method (AUGMENCON2)

According to Mavrotas and Florios [21], the enhanced version of the  $\epsilon$ -constraint approach (AUGMENCON2) is used in the following ways:

- To locate any additional optima (unlike AUGMENCON), the lexicographic optimization is applied to the primary objective and the remaining objective functions.
- The payout table is used to compute the objective function range.
- Ranges are divided into equidistant grid points.

The Mathematical Formulation Problem (MPF) established by Eq. 8.7 is somewhat altered in AUGMENCON2 as follows:

$$\max \left( f_1(x) + \text{eps} \times \left( \frac{s_2}{r_2} + 10^{-1} \frac{s_3}{r_3} + \dots + 10^{-(p-2)} \frac{s_p}{r_p} \right) \right) \quad (8.8)$$

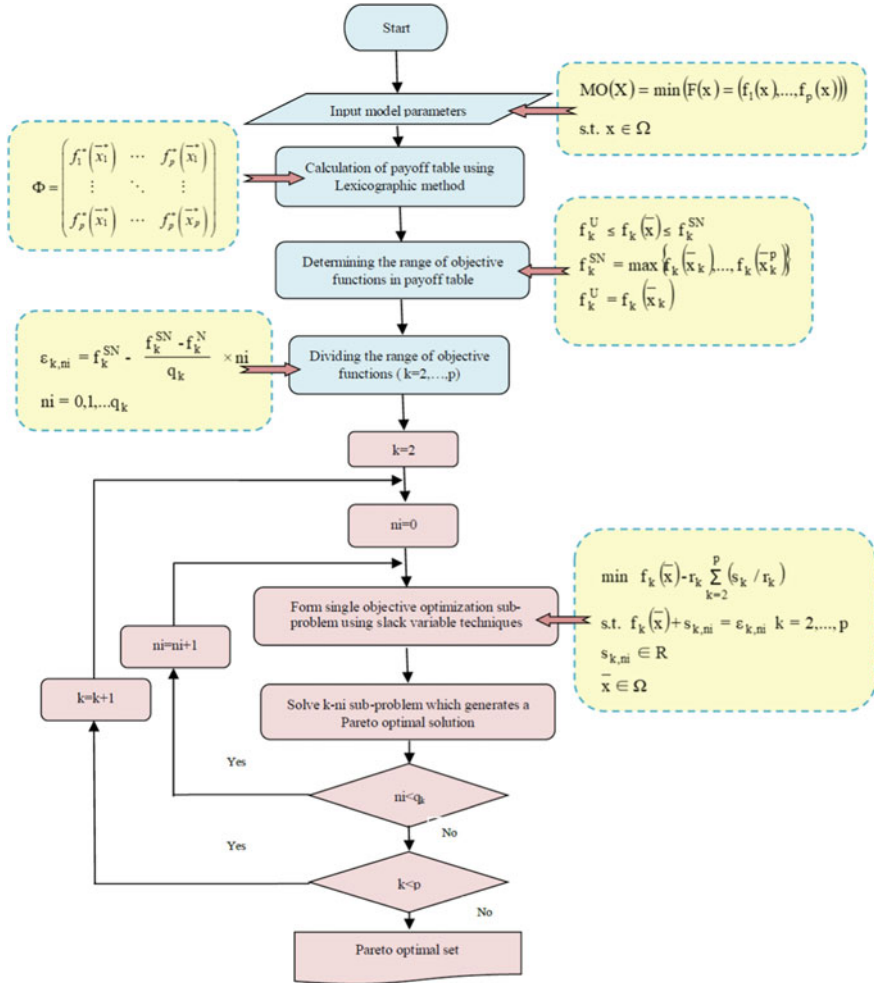


**Fig. 8.6** Flowchart of AUGMENCON method. Adapted from Tartibu et al. [19]

This change is made to do lexicographic optimization on all objective functions, not just the main one, in order to find any potential alternate optima. Therefore, in contrast to the preceding formulation, the solver is compelled to carry out the sequential optimization of the restricted objectives and discover sequentially their optimum. The potential improvement of this approach was demonstrated in the two studies related to a microchannel heat sink [28, 29]. Figure 8.7 gives a flowchart of AUGMENCON 2.

#### (c) GAMS Model implementation

The two objective components (cutting force and surface roughness) are taken into account simultaneously in this section. The previous section provided descriptions

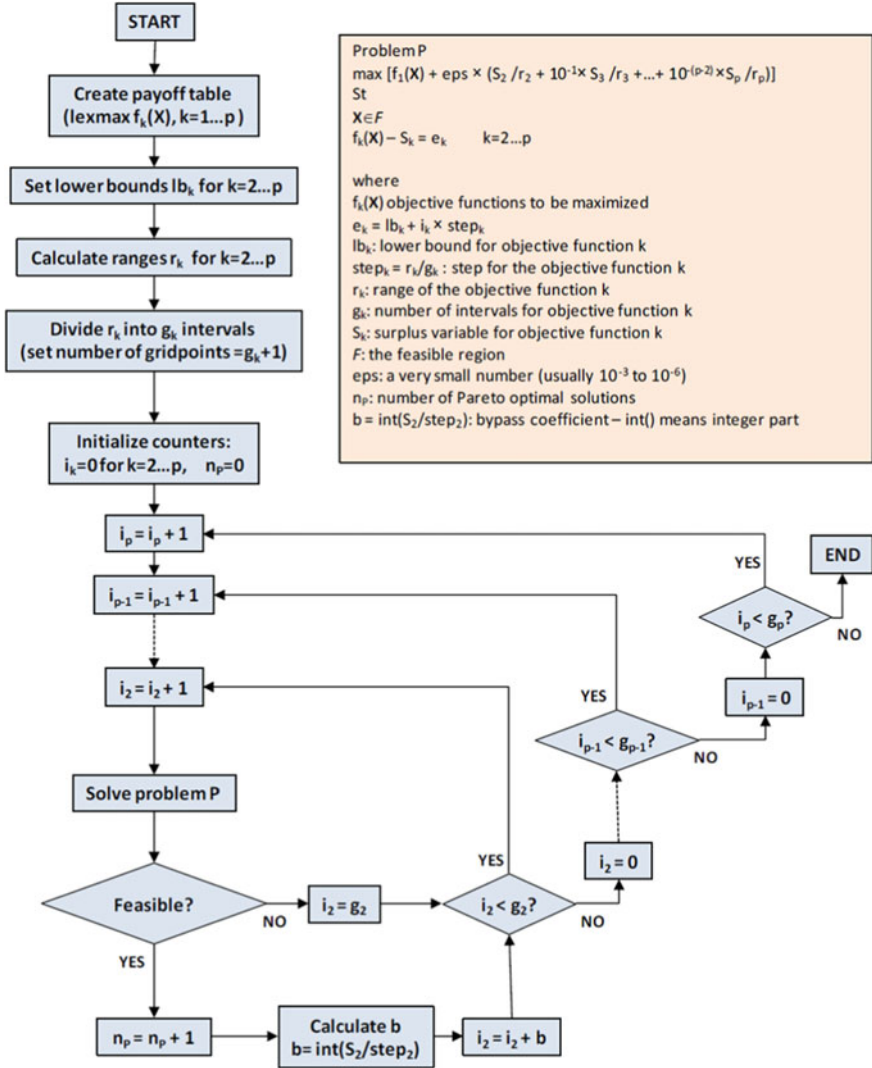


Fig. 8.7 Flowchart of AUGMENCON2 method. Adapted from Mavrotas and Florios [21]

of the majority of the equations used in the formulation of the Multi-objective mathematical Programming Formulation (MPF). The two-criteria NLP used to formulate the optimization problem minimizes both the cutting force (CF) and the surface roughness (SR).

$$(\text{MPF}) \min \xi = \{CF_{S,F,D}; SR_{S,F,D}\} \quad (8.9)$$

Subject to bound limits detailed in Eq. 8.1.

In the formulation (Eq. 8.9), S, F, and D denote the parameters describing the setting of the CNC lathe machine. The two objective functions cannot be optimized simultaneously by a single optimal solution. However, in these circumstances, the decision-makers look for the “most favoured” solutions. The improved augmented  $\epsilon$ -constraint method (AUGMENCON2) is used to locate these solutions. The GAMS code for the AUGMENCON2 technique has been developed. The GAMS library includes an example that uses a multi-objective integer programming problem to demonstrate the method and adapt it to diverse optimization problems ([https://www.gams.com/latest/gamslib\\_ml/libhtml/gamslib\\_epscmmip.html](https://www.gams.com/latest/gamslib_ml/libhtml/gamslib_epscmmip.html)). The portion of the code that deals with the example (specific objective functions, constraints, and variables) has been altered to take into account the machining processes problem, even though the parts of the code that perform the calculation of the payoff table with lexicographic optimization and the generation of Pareto optimal solutions are fully parameterized and almost ready to use.

Only Pareto optimum solutions are produced when the payoff table for the MPF is constructed using the lexicographic optimization for each objective function [30]. Weakly efficient solutions are avoided. The model can be solved using the enhanced  $\epsilon$ -constraint technique (Eq. 8.10), which can be written as follows:

$$\min \left( CF_{S,F,D} + \text{eps} \times \left( \frac{s_2}{r_2} \right) \right) \quad (8.10)$$

Subject to

$$SR_{S,F,D} - s_2 = \varepsilon_2$$

and variable restrictions described by Eq. 8.1.

$$s_i \in \mathbb{R}^+$$

where  $\text{eps}$ ,  $s_2$ ,  $r_2$  and  $\varepsilon_2$  represents, respectively a small number (between  $10^{-3}$  and  $10^{-6}$ ), the surplus variables of the respective constraints, the range of objective function  $SR_{S,F,D}$ , and the parameters of the right-hand side of  $CF_{S,F,D}$ . Equation 8.10 is known as the “augmented  $\epsilon$ -constraint approach” because the second term augments the objective function  $CF_{S,F,D}$ . With this approach, each objective function is subjected to lexicographic optimization in order to find any other optima and steer clear of any suboptimal Pareto solutions. A screenshot showing the mathematical programming model and the compilation process is shown in Fig. 8.8. Details of the GAMS code are provided in Appendix H. The maximum CPU time taken to compute the results was 68.734 s.

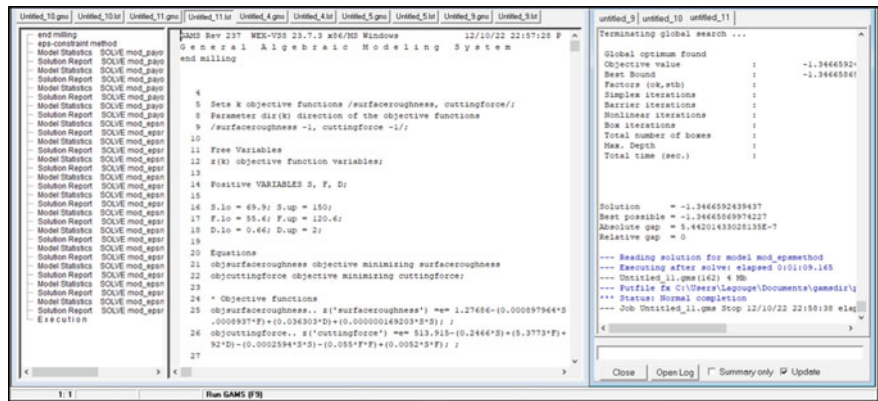


Fig. 8.8 GAMS model formulation with an emphasis on all objective functions

## 8.5 Results and Discussion

### 8.5.1 Pareto Optimal Solutions

The objective function optimization is carried out using the AUGMENCON2 algorithm. To analyze the trade-off between cutting force and surface roughness, the Pareto optimal solutions were calculated, and the Pareto optimal front was built. Table 8.4 provides the details of the 11 Pareto optimal solutions obtained by considering the optimization of the surface roughness and the cutting force simultaneously. As indicated in the previous section, there is no unique solution that optimizes the problem. The first two columns give the magnitude of the surface roughness and the cutting force. The third column provides details of the three variables namely the cutting speed (S.L), the feed rate (F.L) and the depth of cut (D.L). These results suggest that to improve the machinability of Ti–6Al–4V alloy, multiple settings yield the best performance with respect to the surface roughness and the cutting force. A decision maker would be able to get an insight into the implication of his decision and set the CNC lathe machine accordingly.

Figure 8.9 shows the magnitude of the optimal objective functions plotted against one another. This graph shows that the relation between the two objective functions is nonlinear. However, each set of results would potentially enhance the machinability of the Ti–6Al–4V alloy. There are trade-offs to consider depending on the preference of a decision maker which could include a strong emphasis on the reduction of the cutting force or the surface roughness.

Figure 8.10 shows a graphical representation of the Pareto optimal solutions corresponding to the three variables. The graph shows higher machinability performance could be achieved through adjustment of the setting of the CNC lathe machine. It points out that several settings could be determined using the proposed AUGMENCON2 method. It appears that the three variables considered namely the

**Table 8.4** Optimal objective functions and variables

|   | Surface roughness | Cutting force | Pareto optimal solutions                                                          |
|---|-------------------|---------------|-----------------------------------------------------------------------------------|
| 1 | 1.22              | 686.26        | Variable S.L.:<br>150.000<br>Variable F.L.:<br>55.600<br>Variable D.L.:<br>0.660  |
| 2 | 1.24              | 660.70        | Variable S.L.:<br>150.000<br>Variable F.L.:<br>77.536<br>Variable D.L.:<br>0.660  |
| 3 | 1.25              | 635.14        | Variable S.L.:<br>150.000<br>Variable F.L.:<br>86.465<br>Variable D.L.:<br>0.660  |
| 4 | 1.25              | 609.58        | Variable S.L.:<br>150.000<br>Variable F.L.:<br>93.316<br>Variable D.L.:<br>0.660  |
| 5 | 1.26              | 584.02        | Variable S.L.:<br>150.000<br>Variable F.L.:<br>99.092<br>Variable D.L.:<br>0.660  |
| 6 | 1.27              | 558.46        | Variable S.L.:<br>150.000<br>Variable F.L.:<br>104.181<br>Variable D.L.:<br>0.660 |
| 7 | 1.27              | 532.90        | Variable S.L.:<br>150.000<br>Variable F.L.:<br>108.782<br>Variable D.L.:<br>0.660 |

(continued)

Table 8.4 (continued)

|    | Surface roughness | Cutting force | Pareto optimal solutions                                                       |
|----|-------------------|---------------|--------------------------------------------------------------------------------|
| 8  | 1.27              | 507.34        | Variable S.L:<br>150.000<br>Variable F.L:<br>113.013<br>Variable D.L:<br>0.660 |
| 9  | 1.27              | 481.78        | Variable S.L:<br>150.000<br>Variable F.L:<br>116.951<br>Variable D.L:<br>0.660 |
| 10 | 1.28              | 456.22        | Variable S.L:<br>148.843<br>Variable F.L:<br>120.600<br>Variable D.L:<br>0.660 |
| 11 | 1.35              | 430.66        | Variable S.L:<br>69.900<br>Variable F.L:<br>120.600<br>Variable D.L:<br>0.660  |

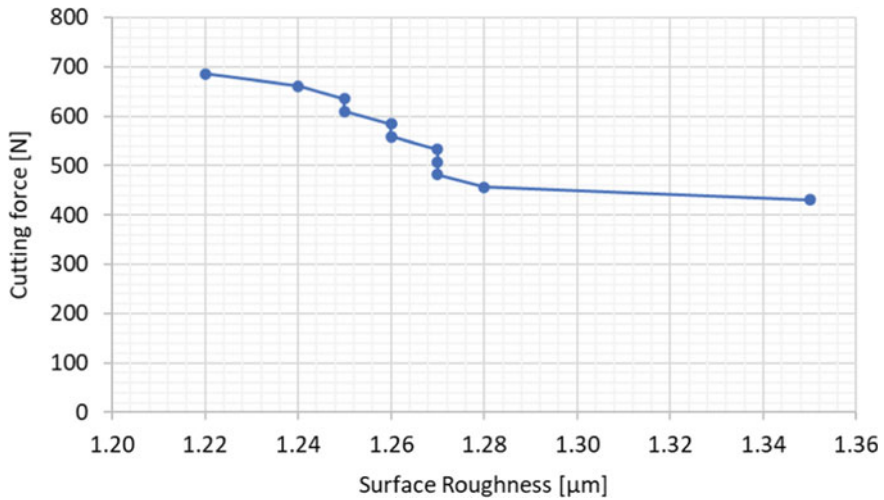


Fig. 8.9 Global optimal Pareto solutions showing the two objective functions



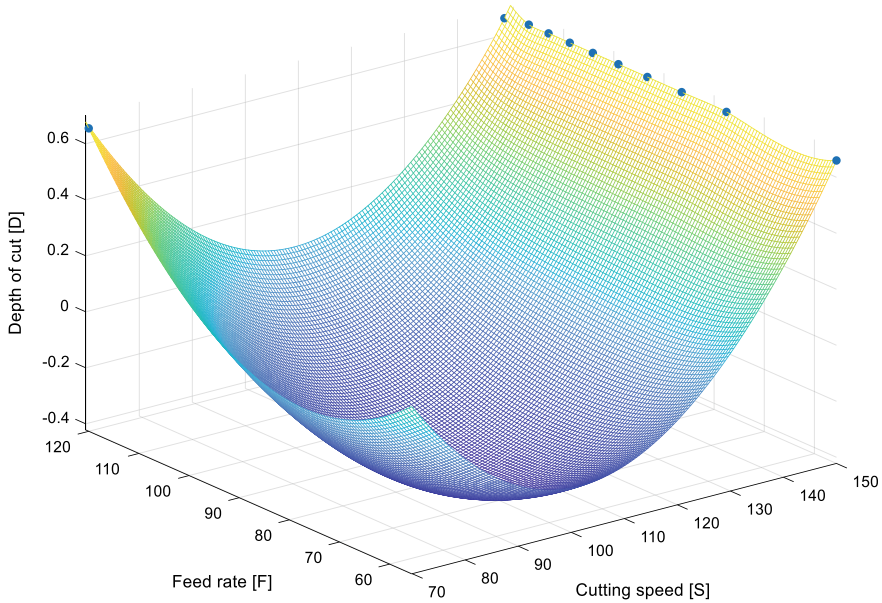


**Fig. 8.10** Plot showing the profile of Pareto optimal solutions

cutting speed, the feed rate and the depth of cut are interdependent meaning that there is a specific cutting speed corresponding to a specific feed rate and depth of cut to improve the machinability of Ti-6Al-4V alloy.

### 8.5.2 Parametric Analysis of the Solutions

#### (a) Analysis of the cutting speed [S]

The impact of the variation of each variable, corresponding to the setting of the lathe machine, has been examined in order to gain a further understanding of the Pareto optimal solutions. Tables 8.5, 8.6 and 8.7 shows the optimal objective function and variables corresponding to a cutting speed of 70, 110 and 150 respectively. This study shows that an adjustment of the cutting speed would affect the surface roughness and the cutting speed. It was interesting to note that the lowest surface roughness is achieved with the highest cutting speed (Table 8.7). Conversely, the lowest cutting force is achieved at a lower cutting speed (Table 8.5).

The results reported in Tables 8.5, 8.6 and 8.7 have been summarised graphically in Fig. 8.11. It is interesting to note how an increase in the cutting speed results in a relative decrease in surface roughness in general. This finding is similar to the result reported by Sahu and Andhare [16].

**Table 8.5** Optimal objective functions and variables [S = 70]

|    | Surface roughness | Cutting force | Pareto optimal solutions                           |
|----|-------------------|---------------|----------------------------------------------------|
| 1  | 1.29              | 687.42        | Variable F.L:<br>55.600<br>Variable D.L:<br>0.660  |
| 2  | 1.3               | 661.75        | Variable F.L:<br>74.066<br>Variable D.L:<br>0.660  |
| 3  | 1.31              | 636.07        | Variable F.L:<br>82.937<br>Variable D.L:<br>0.660  |
| 4  | 1.32              | 610.4         | Variable F.L:<br>89.770<br>Variable D.L:<br>0.660  |
| 5  | 1.32              | 584.73        | Variable F.L:<br>95.538<br>Variable D.L:<br>0.660  |
| 6  | 1.33              | 559.06        | Variable F.L:<br>100.624<br>Variable D.L:<br>0.660 |
| 7  | 1.33              | 533.38        | Variable F.L:<br>105.225<br>Variable D.L:<br>0.660 |
| 8  | 1.34              | 507.71        | Variable F.L:<br>109.457<br>Variable D.L:<br>0.660 |
| 9  | 1.34              | 482.04        | Variable F.L:<br>113.397<br>Variable D.L:<br>0.660 |
| 10 | 1.34              | 456.36        | Variable F.L:<br>117.099<br>Variable D.L:<br>0.660 |
| 11 | 1.35              | 430.69        | Variable F.L:<br>120.600<br>Variable D.L:<br>0.660 |

**Table 8.6** Optimal objective functions and variables [S = 110]

|    | Surface roughness | Cutting force | Pareto optimal solutions                           |
|----|-------------------|---------------|----------------------------------------------------|
| 1  | 1.25              | 687.25        | Variable F.L:<br>55.600<br>Variable D.L:<br>0.660  |
| 2  | 1.27              | 662.93        | Variable F.L:<br>75.168<br>Variable D.L:<br>0.660  |
| 3  | 1.28              | 638.61        | Variable F.L:<br>83.862<br>Variable D.L:<br>0.660  |
| 4  | 1.29              | 614.29        | Variable F.L:<br>90.539<br>Variable D.L:<br>0.660  |
| 5  | 1.29              | 589.97        | Variable F.L:<br>96.169<br>Variable D.L:<br>0.660  |
| 6  | 1.29              | 565.65        | Variable F.L:<br>101.130<br>Variable D.L:<br>0.660 |
| 7  | 1.3               | 541.33        | Variable F.L:<br>105.616<br>Variable D.L:<br>0.660 |
| 8  | 1.3               | 517.01        | Variable F.L:<br>109.742<br>Variable D.L:<br>0.660 |
| 9  | 1.31              | 492.69        | Variable F.L:<br>113.582<br>Variable D.L:<br>0.660 |
| 10 | 1.31              | 468.36        | Variable F.L:<br>117.188<br>Variable D.L:<br>0.660 |
| 11 | 1.31              | 444.04        | Variable F.L:<br>120.600<br>Variable D.L:<br>0.660 |

**Table 8.7** Optimal objective functions and variables [S = 150]

|    | Surface roughness | Cutting force | Pareto optimal solutions                           |
|----|-------------------|---------------|----------------------------------------------------|
| 1  | 1.22              | 686.26        | Variable F.L:<br>55.600<br>Variable D.L:<br>0.660  |
| 2  | 1.24              | 663.29        | Variable F.L:<br>76.415<br>Variable D.L:<br>0.660  |
| 3  | 1.25              | 640.32        | Variable F.L:<br>84.878<br>Variable D.L:<br>0.660  |
| 4  | 1.25              | 617.35        | Variable F.L:<br>91.373<br>Variable D.L:<br>0.660  |
| 5  | 1.26              | 594.38        | Variable F.L:<br>96.849<br>Variable D.L:<br>0.660  |
| 6  | 1.26              | 571.41        | Variable F.L:<br>101.673<br>Variable D.L:<br>0.660 |
| 7  | 1.26              | 548.44        | Variable F.L:<br>106.034<br>Variable D.L:<br>0.660 |
| 8  | 1.27              | 525.47        | Variable F.L:<br>110.045<br>Variable D.L:<br>0.660 |
| 9  | 1.27              | 502.5         | Variable F.L:<br>113.778<br>Variable D.L:<br>0.660 |
| 10 | 1.27              | 479.54        | Variable F.L:<br>117.284<br>Variable D.L:<br>0.660 |
| 11 | 1.28              | 456.57        | Variable F.L:<br>120.600<br>Variable D.L:<br>0.660 |

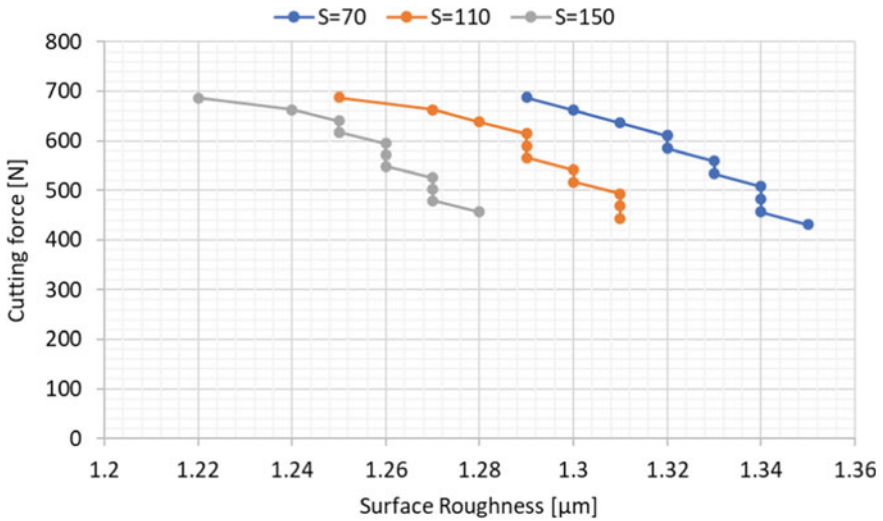


**Fig. 8.11** Effect of the cutting speed [S]

(b) Analysis of the feed rate [F]

Tables 8.8, 8.9 and 8.10 shows the optimal objective function and variables corresponding to feed rates of 60, 88 and 120 respectively. This study shows that an adjustment of the feed rate would affect the surface roughness and the cutting speed. It was interesting to note that the lowest surface roughness would be achieved at a lower feed rate (Table 8.8). Conversely, the lowest cutting force is achieved at a relatively higher feed rate (Table 8.10).

The results reported in Tables 8.8, 8.9 and 8.10 have been summarised graphically in Fig. 8.12. It is interesting to note that a lower feed rate improves surface roughness. This finding is similar to the result reported by Sahu and Andhare [16]. It appears that a relatively higher feed rate results in a decrease in the cutting force.

(c) Analysis of the depth of cut [D]

Tables 8.11, 8.12 and 8.13 show the optimal objective function and variables corresponding to the depth of cut of 0.8, 1.4 and 2 respectively. This study shows that an adjustment of the depth of cut affects the surface roughness and the cutting speed. It was interesting to note that the lowest surface roughness would be achieved at a lower depth of cut (Table 8.11). Similarly, the lowest cutting force is achieved at a relatively lower depth of cut as well (Table 8.11).

The results reported in Tables 8.11, 8.12 and 8.13 have been summarised graphically in Fig. 8.13. It is interesting to note that a relatively lower feed rate improves the surface roughness and the cutting force.

**Table 8.8** Optimal objective functions and variables [F = 60]

|    | Surface roughness | Cutting force | Pareto optimal solutions                             |
|----|-------------------|---------------|------------------------------------------------------|
| 1  | 1.22              | 685.37        | Variable S.L.:<br>150.000<br>Variable D.L.:<br>0.660 |
| 2  | 1.27              | 685.31        | Variable S.L.:<br>97.230<br>Variable D.L.:<br>0.660  |
| 3  | 1.27              | 685.24        | Variable S.L.:<br>93.056<br>Variable D.L.:<br>0.660  |
| 4  | 1.28              | 685.17        | Variable S.L.:<br>89.354<br>Variable D.L.:<br>0.660  |
| 5  | 1.28              | 685.11        | Variable S.L.:<br>85.992<br>Variable D.L.:<br>0.660  |
| 6  | 1.28              | 685.04        | Variable S.L.:<br>82.891<br>Variable D.L.:<br>0.660  |
| 7  | 1.28              | 684.97        | Variable S.L.:<br>79.999<br>Variable D.L.:<br>0.660  |
| 8  | 1.29              | 684.91        | Variable S.L.:<br>77.278<br>Variable D.L.:<br>0.660  |
| 9  | 1.29              | 684.84        | Variable S.L.:<br>74.701<br>Variable D.L.:<br>0.660  |
| 10 | 1.29              | 684.77        | Variable S.L.:<br>72.247<br>Variable D.L.:<br>0.660  |
| 11 | 1.29              | 684.7         | Variable S.L.:<br>69.900<br>Variable D.L.:<br>0.660  |

**Table 8.9** Optimal objective functions and variables [F = 88]

|    | Surface roughness | Cutting force | Pareto optimal solutions                             |
|----|-------------------|---------------|------------------------------------------------------|
| 1  | 1.25              | 629.86        | Variable S.L.:<br>150.000<br>Variable D.L.:<br>0.660 |
| 2  | 1.26              | 628.62        | Variable S.L.:<br>140.902<br>Variable D.L.:<br>0.660 |
| 3  | 1.26              | 627.39        | Variable S.L.:<br>132.104<br>Variable D.L.:<br>0.660 |
| 4  | 1.27              | 626.16        | Variable S.L.:<br>123.580<br>Variable D.L.:<br>0.660 |
| 5  | 1.28              | 624.93        | Variable S.L.:<br>115.306<br>Variable D.L.:<br>0.660 |
| 6  | 1.29              | 623.69        | Variable S.L.:<br>107.260<br>Variable D.L.:<br>0.660 |
| 7  | 1.29              | 622.46        | Variable S.L.:<br>99.424<br>Variable D.L.:<br>0.660  |
| 8  | 1.3               | 621.23        | Variable S.L.:<br>91.784<br>Variable D.L.:<br>0.660  |
| 9  | 1.3               | 619.99        | Variable S.L.:<br>84.324<br>Variable D.L.:<br>0.660  |
| 10 | 1.31              | 618.76        | Variable S.L.:<br>77.033<br>Variable D.L.:<br>0.660  |
| 11 | 1.32              | 617.53        | Variable S.L.:<br>69.900<br>Variable D.L.:<br>0.660  |

**Table 8.10** Optimal objective functions and variables [F = 120]

|    | Surface roughness | Cutting force | Pareto optimal solutions                           |
|----|-------------------|---------------|----------------------------------------------------|
| 1  | 1.28              | 460.81        | Variable S.L:<br>150.000<br>Variable D.L:<br>0.660 |
| 2  | 1.28              | 458.25        | Variable S.L:<br>141.497<br>Variable D.L:<br>0.660 |
| 3  | 1.29              | 455.68        | Variable S.L:<br>133.116<br>Variable D.L:<br>0.660 |
| 4  | 1.3               | 453.11        | Variable S.L:<br>124.851<br>Variable D.L:<br>0.660 |
| 5  | 1.31              | 450.55        | Variable S.L:<br>116.698<br>Variable D.L:<br>0.660 |
| 6  | 1.31              | 447.98        | Variable S.L:<br>108.653<br>Variable D.L:<br>0.660 |
| 7  | 1.32              | 445.42        | Variable S.L:<br>100.710<br>Variable D.L:<br>0.660 |
| 8  | 1.33              | 442.85        | Variable S.L:<br>92.867<br>Variable D.L:<br>0.660  |
| 9  | 1.33              | 440.28        | Variable S.L:<br>85.120<br>Variable D.L:<br>0.660  |
| 10 | 1.34              | 437.72        | Variable S.L:<br>77.466<br>Variable D.L:<br>0.660  |
| 11 | 1.35              | 435.15        | Variable S.L:<br>69.900<br>Variable D.L:<br>0.660  |



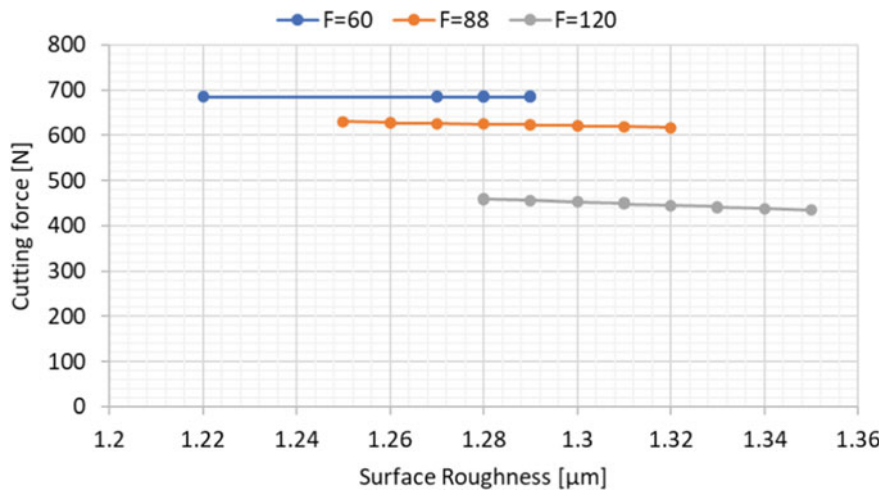


**Fig. 8.12** Effect of the feed rate [F]

**Table 8.11** Optimal objective functions and variables [D = 0.8]

| S/N | Surface roughness | Cutting force | Pareto optimal solutions                       |
|-----|-------------------|---------------|------------------------------------------------|
| 1   | 1.22              | 695.35        | Variable S.L: 150.000<br>Variable F.L: 55.600  |
| 2   | 1.24              | 669.79        | Variable S.L: 150.000<br>Variable F.L: 77.536  |
| 3   | 1.25              | 644.23        | Variable S.L: 150.000<br>Variable F.L: 86.465  |
| 4   | 1.26              | 618.67        | Variable S.L: 150.000<br>Variable F.L: 93.316  |
| 5   | 1.26              | 593.11        | Variable S.L: 150.000<br>Variable F.L: 99.092  |
| 6   | 1.27              | 567.55        | Variable S.L: 150.000<br>Variable F.L: 104.181 |

(continued)

**Table 8.11** (continued)

| S/N | Surface roughness | Cutting force | Pareto optimal solutions                             |
|-----|-------------------|---------------|------------------------------------------------------|
| 7   | 1.27              | 541.98        | Variable S.L:<br>150.000<br>Variable F.L:<br>108.782 |
| 8   | 1.28              | 516.42        | Variable S.L:<br>150.000<br>Variable F.L:<br>113.013 |
| 9   | 1.28              | 490.86        | Variable S.L:<br>150.000<br>Variable F.L:<br>116.951 |
| 10  | 1.28              | 465.3         | Variable S.L:<br>148.843<br>Variable F.L:<br>120.600 |
| 11  | 1.35              | 439.74        | Variable S.L:<br>69.900<br>Variable F.L:<br>120.600  |

**Table 8.12** Optimal  
objective functions and  
variables [D = 1.4]

|   | Surface roughness | Cutting force | Pareto optimal solutions                            |
|---|-------------------|---------------|-----------------------------------------------------|
| 1 | 1.25              | 734.3         | Variable S.L:<br>150.000<br>Variable F.L:<br>55.600 |
| 2 | 1.27              | 708.74        | Variable S.L:<br>150.000<br>Variable F.L:<br>77.536 |
| 3 | 1.27              | 683.18        | Variable S.L:<br>150.000<br>Variable F.L:<br>86.465 |
| 4 | 1.28              | 657.62        | Variable S.L:<br>150.000<br>Variable F.L:<br>93.316 |
| 5 | 1.29              | 632.06        | Variable S.L:<br>150.000<br>Variable F.L:<br>99.092 |

(continued)

**Table 8.12** (continued)

|    | Surface roughness | Cutting force | Pareto optimal solutions                             |
|----|-------------------|---------------|------------------------------------------------------|
| 6  | 1.29              | 606.5         | Variable S.L:<br>150.000<br>Variable F.L:<br>104.181 |
| 7  | 1.29              | 580.94        | Variable S.L:<br>150.000<br>Variable F.L:<br>108.782 |
| 8  | 1.3               | 555.38        | Variable S.L:<br>150.000<br>Variable F.L:<br>113.013 |
| 9  | 1.3               | 529.82        | Variable S.L:<br>150.000<br>Variable F.L:<br>116.951 |
| 10 | 1.31              | 504.26        | Variable S.L:<br>148.843<br>Variable F.L:<br>120.600 |
| 11 | 1.37              | 478.7         | Variable S.L:<br>69.900<br>Variable F.L:<br>120.600  |

**Table 8.13** Optimal objective functions and variables [D = 2]

|   | Surface roughness | Cutting force | Pareto optimal solutions                       |
|---|-------------------|---------------|------------------------------------------------|
| 1 | 1.27              | 773.25        | Variable S.L: 150.000<br>Variable F.L: 55.600  |
| 2 | 1.29              | 747.69        | Variable S.L: 150.000<br>Variable F.L: 77.536  |
| 3 | 1.3               | 722.13        | Variable S.L: 150.000<br>Variable F.L: 86.465  |
| 4 | 1.3               | 696.57        | Variable S.L: 150.000<br>Variable F.L: 93.316  |
| 5 | 1.31              | 671.01        | Variable S.L: 150.000<br>Variable F.L: 99.092  |
| 6 | 1.31              | 645.45        | Variable S.L: 150.000<br>Variable F.L: 104.181 |
| 7 | 1.32              | 619.89        | Variable S.L: 150.000<br>Variable F.L: 108.782 |

(continued)

**Table 8.13** (continued)

|    | Surface roughness | Cutting force | Pareto optimal solutions                       |
|----|-------------------|---------------|------------------------------------------------|
| 8  | 1.32              | 594.33        | Variable S.L: 150.000<br>Variable F.L: 113.013 |
| 9  | 1.32              | 568.77        | Variable S.L: 150.000<br>Variable F.L: 116.951 |
| 10 | 1.33              | 543.21        | Variable S.L: 148.843<br>Variable F.L: 120.600 |
| 11 | 1.4               | 517.65        | Variable S.L: 69.900<br>Variable F.L: 120.600  |

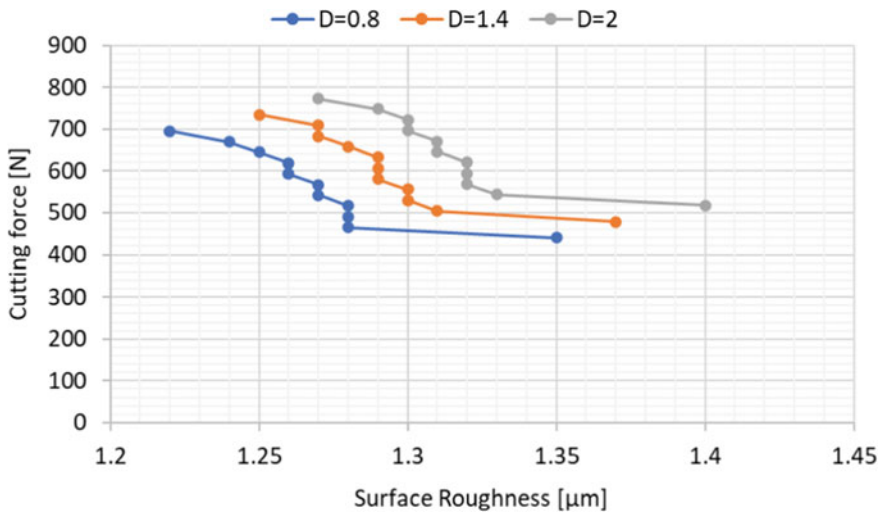


**Fig. 8.13** Effect of the depth of cut [D]

8.6 Conclusion

Many existing studies point out the possibility to create models that predict and optimize cutting forces and surface roughness based on cutting parameters. In this chapter, the machinability performance of a titanium alloy is analysed using an improved version of the augmented  $\epsilon$ -constraint approach (AUGMENCON2) that takes cutting force and surface roughness into account as objective functions. Unlike many existing multi-objective optimization approach, the augmented  $\epsilon$ -constraint approach (AUGMENCON2) yield Pareto optimum solutions only and avoid weakly efficient solutions. The problem was formulated in implemented in the software GAMS. In order to illustrate the approach proposed in this study, quadratic equations were taken from an existing study. The speed of cutting, the feed rate and

the depth of cut were the variables to optimize. The quadratic equations of the cutting force and surface roughness were the two objective functions to optimize. The conflicting nature of these objective functions was demonstrated through the tendencies of variables after performing single objective optimization. Details of the modelling development and implementations have been provided. The graph shows higher machinability performance could be achieved through adjustment of the setting of the CNC lathe machine. It points out that several settings could be determined using the proposed AUGMENCON2 method. This study reveals that the three variables considered namely the cutting speed, the feed rate and the depth of cut are interdependent meaning that there is a specific cutting speed corresponding to a specific feed rate and depth of cut to improve the machinability of Ti-6Al-4V alloy. The results show that an increase in the cutting speed results in a relative decrease in surface roughness in general. A lower feed rate could potentially improve surface roughness but a relatively higher feed rate results in a decrease in the cutting force. A relatively lower feed rate improves the surface roughness and the cutting force. The comprehensive machining optimization proposed in this study provides clarity about the handling of conflicting criteria involved in setting a CNC lathe machine and improves the understanding of the relative sensitivity of variables affecting the outcome. This contribution would potentially help decision makers to handle CNC lathe machines and improve the machinability performance taking several design constraints into account.

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## Chapter 9

# ANN and QRCCD Prediction of Surface Roughness Under Biodegradable Nano-lubricant



**Abstract** Sustainable manufacturing of machine parts lies in predicting and optimizing the machining parameters for the machining operations. The optimized parameters will produce sustainable products with reduced corrosion and fatigue problems because the roughness of the surface of the product will lead to the failure of the component or part during the production process. This investigation focuses on the prediction and optimization of the **experimental data** of surface roughness of AA8112 alloys obtained during the end-milling process with a biodegradable nano-lubricant. The study employed vegetable oil as the base cutting fluid (copra oil) and MWCNTs nanoparticles as an additive. This study prediction analysis was carried out with an artificial neural network (ANN) and quadratic rotatable central composite design (QRCCD). The results show that the ANN and QRCCD predicted the **experimental data** with 95.50% and 99.50%, respectively. Both prediction analyses' error percentages are 5.5% from the ANN and 0.5% from the QRCCD. The QRCCD optimized parameters for the minimum surface roughness are spindle speed of 3366 rpm, 101 mm/min feed rate, 1 mm depth of cut, 20 mm length-of-cut, and 39.6° helix angle. These parameters achieved the minimum surface roughness of 1.16  $\mu\text{m}$ , which is closely related to the optimized value from the **experimental data**. Therefore, the study in this chapter will recommend manufacturers employ the optimized machining parameters for product production.

**Keywords** ANN · QRCCD · Surface roughness · Biodegradable nano-lubricant · Machining

## 9.1 Introduction

The application of intelligent systems during the manufacturing process is a significant way to follow when advanced manufacturing of mass production of mechanical or parts via computer numerical control (CNC) with good quality [1]. Many



researchers have employed several intelligent methods in prediction and optimization during the machining process [2]. However, there is a great need to look into the manufacturing process with multiple prediction techniques to predict surface roughness end-milling machining, which will be considered in this Chap. 10 of this book. A nanoparticle material's ability to produce Nano-lubricant for manufacturing creates progress in developing mechanical parts utilizing machining, which can't be overemphasized [3, 4]. At the same time, creating mechanical parts for aviation, car, and underlying application through the end-processing aluminum alloy composites. Notwithstanding, end-milling creates intensity and grating because of the machining boundary that starts the contact between the cutting instrument and the workpiece. This overabundance of heat prompts high surface harshness, low material evacuation rate, and high cutting power. Okokpujie et al. [5] study meant to determine the machining boundaries and the material bond via a trial assessment with multi-objective streamlining of the machining factors on end-processing of AL8112 combination utilizing copra oil-based multi-walled carbon nanotube as a nano-ointment. The nano-ointment arrangement was finished utilizing the two-venture technique, and nano-greases were carried out through the base amount oil strategy with the five machining factors.

Moreover, the multi-objective streamlining and expectation study was accomplished utilizing the incline and allure bar plot for the three reactions, i.e., surface roughness, MRR, and cutting force under the quadratic rotatable focal composite plan. The multi-objective enhancement result shows that the surface roughness of  $1.2\text{ }\mu\text{m}$ , the highest material removal rate of  $52\text{ mm}^3/\text{min}$ , and the least cutting force of  $34\text{ N}$  were acquired at the improved machining factors. Besides, the models anticipated the exploratory outcomes precisely. Overall, the multi-objective advancement with copra oil-based MWCNT'S-nano-grease improved machine parts' creation for practical added substance production.

Dubey et al. [6] The cutting liquid is improved with alumina nanoparticles of two standard molecule sizes of 30 and 40 nm. The info boundaries picked for examination are cutting velocity, the profundity of cut, feed rate, and nanoparticle fixation. The reaction surface methodology is utilized in the plan of the trial. To assess the surface harshness at the trial worth to the anticipated qualities, AI-based models, including direct relapse, irregular backwoods, and backing vector machine, are likewise used. The motivation behind assessing the precision of the anticipated qualities is the coefficient of assurance, mean outright rate blunder, and mean square error. Irregular backwoods outflanked the other two models in both the molecule sizes of 30 and 40 nm, with an R-squared of 0.818 and 0.723, individually.

Consequently, this study gives an original methodology in foreseeing the surface unpleasantness by differing the molecule size in the cutting liquid utilizing AI, which can save time and wastage of material and energy [7]. However, this study considered only three factors at three levels, limiting the experimental runs 27. There is a need for a good number of experimental runs to have a reasonable prediction rate using artificial intelligence. Alharthi et al. [8] The authors carried out surface roughness prediction analysis under ANN and regression analysis. The study developed Five models of neural networks best fit with investigational results with six neurons in

the hidden layer. Also, the study used regression analysis to build a precise model on behalf of the surface roughness as a meaning of the process parameters. The coefficient of prediction originated at 95 and 94% for the perfect ANN prediction and regression investigation, respectively. The evaluation of the models with 13 experimental authentication test optical microscopy was directed on the workpiece surfaces with two unique upsides of feed rates while keeping up with the axle speed and profundity of cut at similar qualities. Analyzing the surface geography and surface harshness profile for the two surfaces uncovered that a higher feed rate generally brings about thick harshness markings that are remotely dispersed. While low upsides of feed rate bring about slim surface unpleasantness markings firmly separated, giving better surface completion.

However, this chapter considered the prediction and optimization of surface roughness under the multi-walled carbon nano-lubricant machining operation via ANN and QRCCD with five factors five-level experimental analysis. The machining factors considered are helix angle, depth of cut, cutting length, feed rate, and spindle speed.

## 9.2 Methodology

In this study, the authors conducted an empirical examination to study the effect of the nano-lubricants and machining factors on surface roughness. Furthermore, mathematical models were developed to predict surface roughness by an end milling operation. SIEG 3/10/0016 CNC machine with high-speed-steel-cutting-tool inserts was used for the experimental study of the machining process with machining cutting conditions via MWCNTs-nano-lubricant. The authors created the part programs code G and M to instruct each of the experimental coordinates to mill the AL8112 alloy workpiece used for this study. The M42-high-speed-steel cutting tool of 13 mm diameter was employed in this study, having molybdenum of 9.5%, Cobalt of 8.25%, Chromium of 3.9%, Carbon of 1.1%, Tungsten of 1.6%, and Vanadium 1.2%. With explicit orders, the CNC part programs were created for the machining activity. The various lengths of cut, feed rate, cutting depth, helix angle, and cutting speed were carried out with reference to the Y-hub and Z-hub. This reference of the Y and Z-hub is finished for every 50 examples. Figure 9.1 represents the exploratory arrangement of the end-processing of the AL8112 combination.

After each trial, the surface roughness of the workpiece was additionally estimated utilizing the Mitutoyo surface analyzer. The workpiece is permitted to dry correctly, and afterward, the surface roughness analyzer is locked in to gauge the outer layer of the workpiece. The test is put on the AL8112 composite with an estimating range: Ra, Rq: 0.05 ~ 10.00  $\mu\text{m}$ /1.000 ~ 400.0, Rz, Rt: 0.020 ~ 100.0  $\mu\text{m}$ /0.780 ~ 4000 unit in inch. The roughness is estimated in three distinct places of the workpiece. And its normal was recorded as the surface unpleasantness of the workpiece. Figure 9.2 shows the trial arrangement of the SRT-6210S surface severity analyzer utilized for this evaluation (Table 9.1).

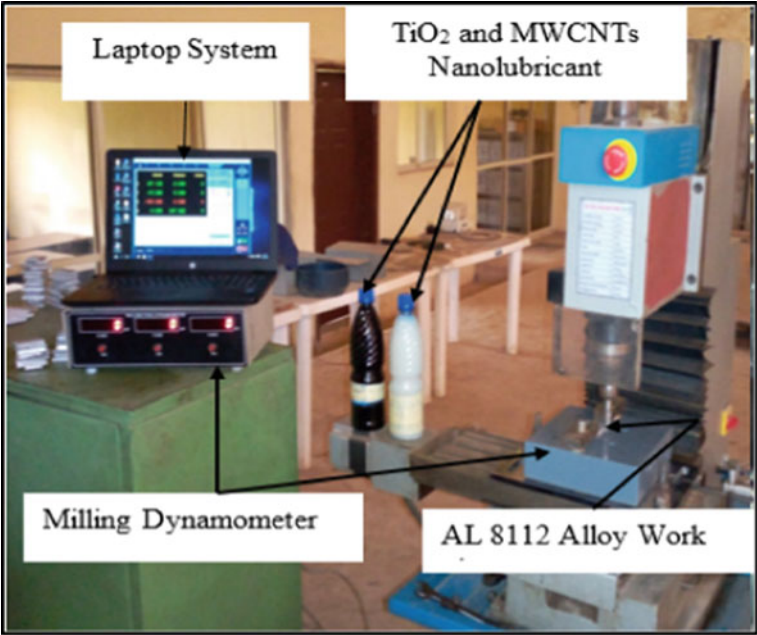


Fig. 9.1 The CNC milling experimental setup

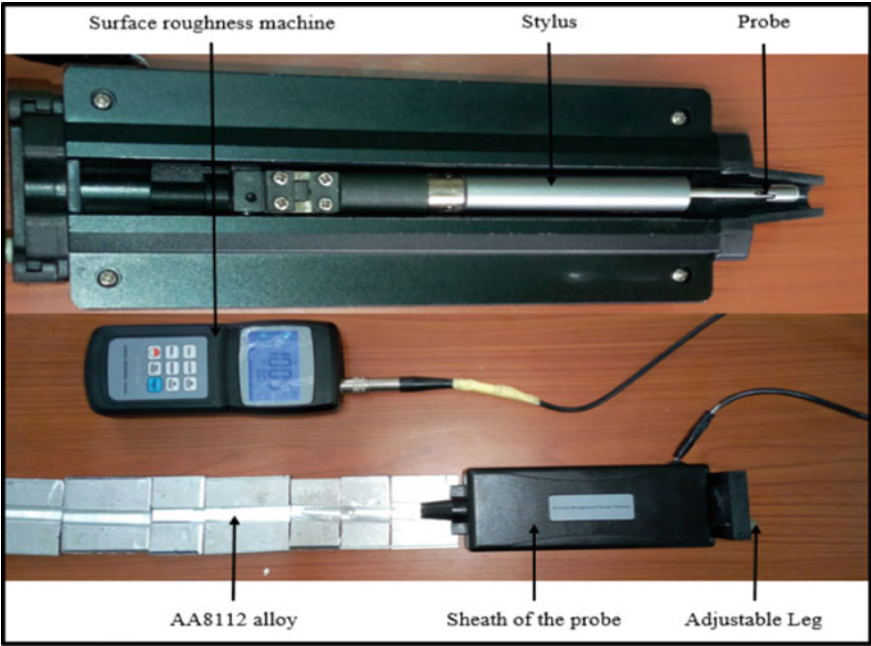


Fig. 9.2 Experimental setup of the Mitutoyo surface roughness tester and the AA8112 alloy

**Table 9.1** Machining conditions for the study of the surface roughness using MWCNTs nano-lubricant

| Name          | Units  | Low  | High | – alpha    | + alpha |
|---------------|--------|------|------|------------|---------|
| Spindle speed | rpm    | 2000 | 4000 | 621.586    | 5378.41 |
| Feed rate     | mm/min | 100  | 300  | – 37.8414  | 437.841 |
| Length of cut | mm     | 20   | 60   | – 7.56828  | 87.5683 |
| Depth of cut  | mm     | 1    | 3    | – 0.378414 | 4.37841 |
| Helix angle   | o      | 0    | 60   | – 41.3524  | 101.352 |

**9.2.1 Experimental Procedures for the Preparation of the Nano-lubricant and Machining Process**

Multi-walled carbon nano-lubricants are synthesized using the two-step techniques. It is the most inexpensive technique used in current times to develop nano-lubricant in large amounts. In this Chapter, the nanoparticles (MWCNTs) were in a dry powder form using the chemical methods by Sigma-Aldrich Corporation. The SEM and EDS of the nanoparticles are shown in Fig. 9.3. The proportion concentration of 0.6 g of MWCNTs nanoparticles was mixed with a liter of copra oil made from the local production process. Furthermore, the authors used the Stuart magnetic stirrer for 2 h to stir the particles and the based fluid with a speed of 1400 rpm and also employed the Branson 2800 ultrasonic cleaner machine for 5 h to homogenize the nanoparticles with the copra oil, as shown in the experimental setup in Fig. 9.4.

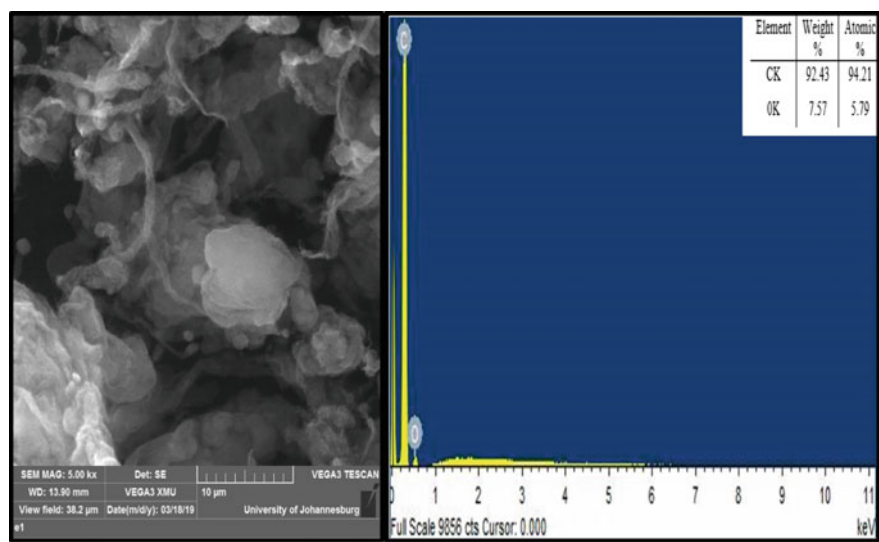


**Fig. 9.3** The SEM of MWCNTs nanoparticles used in preparing the nano-lubricant

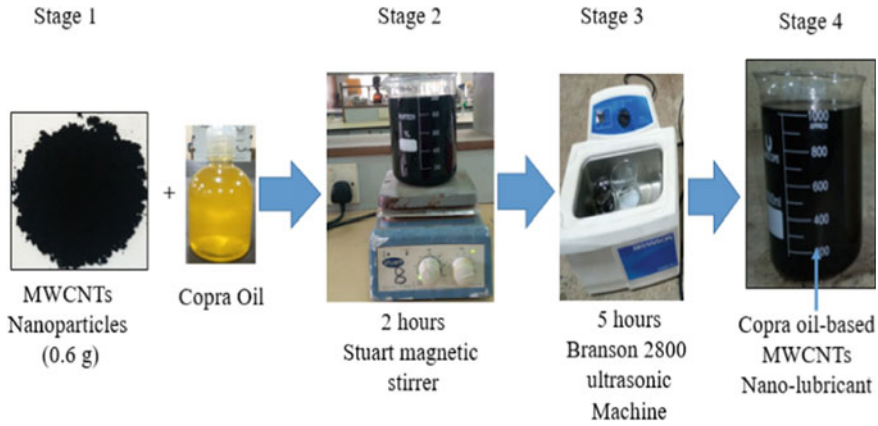


**Fig. 9.4** Stages 1–5 shows the different processes used to synthesise the nano-lubricant

### 9.2.2 Mathematical Modelling Using Artificial Neural Network

Artificial Neural Network (ANN) is a data handling procedure that emulates the natural nervous system using workstations. ANN comprises the number of basic units known as a neuron that uses a precise model with simple workstations that receive one or more input variables and process them to produce the correct output. These neurons are a group of data for information processing using connected links. Every neuron has an associated load based on the strength of the input variables used to determine the output responses.

A layer is a group of neurons arranged in parallel without having any interaction with each other. The workstation consists of three processes: the input layer, hidden layer, and output layer. Variables are presented to the workstation via the input layer and transferred to hidden layers where the work is done through a weight connections process; the hidden layers determine the output responses layer. After the experiment has been carried out, the values of the responses are recorded. The neuron has a bias  $\emptyset$ , which is added with the weighted sum  $W_n$  and input variables ( $U_n$ ) to determine the total net input ( $T_n$ ), as presented in Eq. (9.1) [9].

$$T_n = \sum_{i=1}^n (W_n * U_n) + \emptyset \quad (9.1)$$

The neuron for this Back Propagation feed-forward Neural Network (BPNN) has five (5) inputs, with five (5) weights; this weight is randomized during the training period of the BPNN. The transformation process is carried out through the sigmoid non-linear transfer function ( $Z$ ), which is given in Eq. (9.2).

$$Z = U_1 * W_1 + U_2 * W_2 + \dots + U_n * W_n + \emptyset * 1 \quad (9.2)$$

where the total net input ( $T_n$ ), is transposed as given in Eq. (9.3)

$$\hat{T} = Y_{out} = \text{sigmoid}(Z) \quad (9.3)$$

The sigmoid transfer function ( $Z_i$ ) is given in Eq. (9.4) as:

$$\text{Sigmoid}(Z_i) = \frac{1}{1 + e^{-Z_i}} \quad (9.4)$$

The output ( $Y_{out}$ ) is determined by multiplying the activated transfer function with the weight  $W_{ni}$  between the inner last layer of the hidden neuron and the output layer, which becomes Eq. (9.5).

$$Y_{out} = W_{ni} * Z_i \quad (9.5)$$

The error is  $e_i$ , and is obtained by subtracting the experimental values from the predicted values. The equation is given in Eq. (9.6), and the total error (SSE) is computed using Eq. (9.7).

$$e_i = SR_e - SR_p \quad (9.6)$$

$$SSE = \frac{1}{2} \sum_{i=1}^n e_i^2 \quad (9.7)$$

Depending on the problem to be solved, ANN has numerous techniques for training a neural system. In this work, the BPNN was adopted to build and train the system for the prediction of output parameters. The structure of the ANN employed for this study is presented in Fig. 9.5. The inputs ( $U_n$ ) correspond to feed rate, spindle speed, length of cut, helix angle, and depth of cut. The signal ( $\emptyset$ ) is the interior threshold of a neuron, i.e., the bias, and  $Z_i$  is the nonlinear transfer function. The neuron is trained with 70% input data, 15% of the input data for testing, while the remaining 15% input data is used for the validation process.

### 9.2.3 Mathematical Modelling Using Quadratic Rotatable Central Composite Design

Quadratic rotatable central composite design (QRCCD) is a design tool employed to analyze engineering problems. QRCCD is one of the packages in response surface methodology in Design expert software, mainly used for factors above four and five-level to study the relationship's effects on the response parameters. QRCCD is

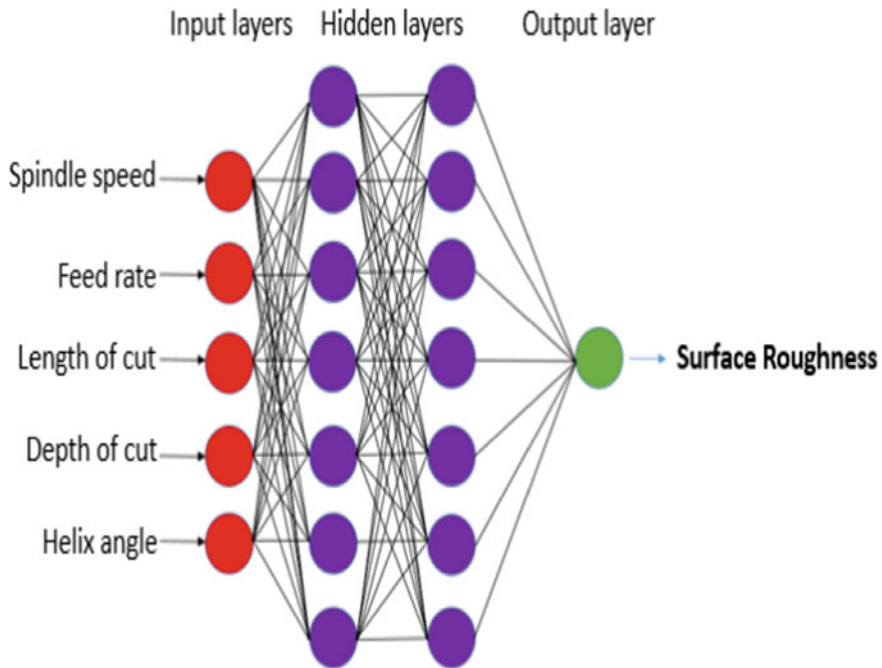


**Fig. 9.5** The surface roughness system structure for the ANN

suitable for prediction, optimization, and model developments in the manufacturing of mechanical components. In this study, the relationship between surface roughness (the response parameters) and the cutting parameters under multi-walled carbon nano-lubricant cutting conditions is given in Eq. (9.8) [10–12].

$$Y_i = \theta(S_s, F_r, L_c, D_c, \alpha) \quad (9.8)$$

The desired machinability feature is  $Y_i$  and the response function is  $\theta$ . However, the evaluation  $Y_i$  They are projected using a nonlinear scientific model, which is suitable for evaluating the effects of cutting parameters interface on machinability features. The interactions become Eq. (9.9).

$$Y_i = \theta\left(S_s^{X_x}, F_r^{Y_y}, L_c^{Z_z}, D_c^{Z_r}, \alpha^{Z_i}\right) \quad (9.9)$$

$$\begin{aligned} \log(Y_i) = & \log(\theta) + X_x \cdot \log(S_s) + Y_y \cdot \log(F_r) + Z_z \cdot \log(L_c) \\ & + Z_r \cdot \log(D_c) + Z_i \cdot \log(\alpha) \end{aligned} \quad (9.10)$$



where,

$$\begin{aligned} Y_i &= \log(Y_i) \quad \beta_0 = \log(\theta) \quad x_1 = \log(S_s) \quad x_2 = \log(F_r) \\ x_3 &= \log(L_c) \quad x_4 = \log(D_c) \quad x_5 = \log(\alpha) \end{aligned}$$

and

$$x = \beta_1, y = \beta_2, z = \beta_3, zr = \beta_4, zi = \beta_5.$$

The overview of a replacement gets the following expression in Eq. (9.10), where the constant and exponents  $\theta$ ,  $X_x$ ,  $Y_y$ ,  $Z_z$ ,  $Z_r$ , and  $Z_i$  are determined by the least-squares regression procedure. This research work, the Quadratic rotatable central composite design-based regression model second-order, is implemented and given in Eq. (9.11) as:

$$Y_i = \beta_0 + \sum \beta_i x_i + \sum \beta_{ii} x_i^2 + \sum \beta_{ij} x_i x_j + e \quad (9.11)$$

The regression constant is  $\beta_0$ , and the coefficients are  $\beta_1$  to  $\beta_5$ , and the logarithmic alteration of parameters are  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_4$ , and  $x_5$ . i.e.,  $S_s$ ,  $F_r$ ,  $L_c$ ,  $D_c$ ,  $\alpha$ , and  $e$  represent the spindle speed, feed rate, length-of-cut, depth-of-cut, helix angle, and the error term, respectively. The input variables and levels were undoubtedly within the interludes recommended by the computer numerical control manufacturer. Equation (9.11) is the regression model employed to develop the prediction model from the response surface method from the design experts. The flow chart of the research method is presented in Fig. 9.6.

#### 9.2.4 Validation of the Surface Roughness Results

In order to ascertain the accuracy of the developed model from the **experimental data**, both the percentage deviation  $\varphi_i$ , and the average deviation  $\bar{\varphi}$  was used. After the prediction of the surface roughness, the percentage deviation was utilized to validate the rate of prediction of the surface roughness. The general equation to determine the validation accuracy is presented in Eq. (9.12) [13].

$$\varphi_i = \left( \frac{R_{(m)} - R_{(e)}}{R_{(e)}} \right) \times 100\% \quad (9.12)$$

where,  $\varphi_i$ : percentage deviation of single variables,  $R(m)$  measure results,  $R(e)$  experimental results.



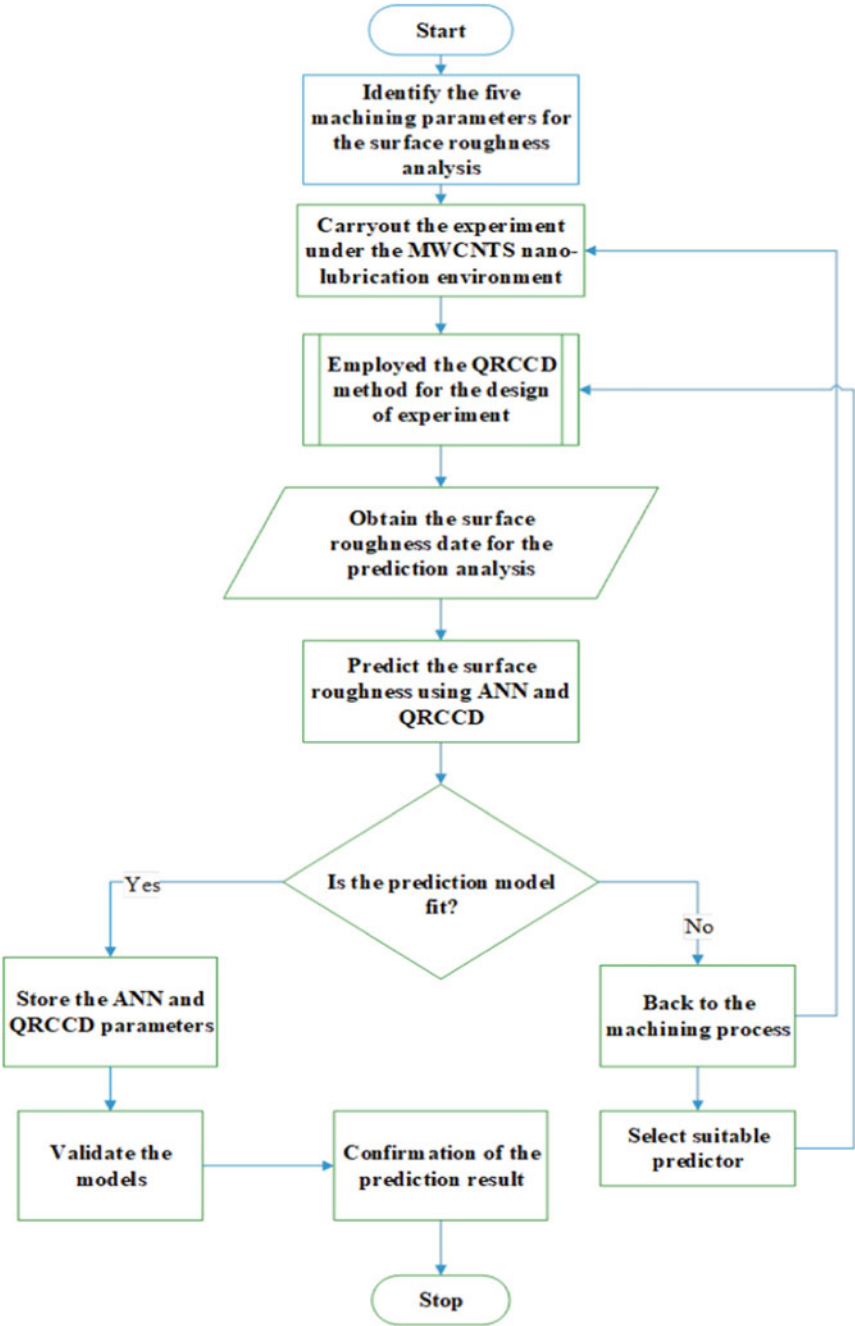


**Fig. 9.6** The flow chart showing the research design employed in this study

### 9.3 The Experimental Data and Mathematical Model for Surface Roughness

This section explains the nano-lubrication machining environments, i.e., multi-walled carbon nanolubricant. The experiment is carried out to study the effects of the machining parameters on the end-milling machining surface of AA8112 alloy and to develop predictive models using ANN and QRCCD for sustainable manufacturing processes.

#### 9.3.1 *The Results of Surface Roughness Obtained in Machining Operation*

The investigation of surface roughness (SR) was analyzed using a five-factor, five-level experiment during the end-milling of AA8112 alloy in machining environments under multi-walled carbon nano-lubricant. Table 9.2 presents the evaluation of the multi-walled carbon nano-lubricant used in the end-milling machining of AA8112 alloy, this data is used for the prediction analysis using ANN and QRCCD.

#### 9.3.2 *The QRCCD Model and the Prediction of the Surface Roughness*

This section explains the process of development of the quadratic model and the importance of individual machining parameters involved in the end-milling machining of AA8112 alloy.

The response surface methodology used QRCCD, it was observed that the model developed was significant, having a 52.64 F-value, entailing that the alteration of sound (error) rate is 0.01%. The important factors were gotten using the *P*-value. The factors with a *P*-value < 0.05 demonstrate that it is substantial in the predictive prototypical. However, factors with *P*-value > 0.1% are not important in the generated model. Hence, the important factors for surface roughness with the biodegradable nano-lubricant (MWCNTs) as presented in Table 9.3. The lack-of-fit of 0.46 designates is not significant when associated with the error value. Table 9.4 shows that an **acceptable adequate precision** value of 39.188 was obtained during this analysis. It entails that the signal-to-noise ratio has a good correlation, and the model can be engaged to direct the design universe.

The estimation of the ANOVA coefficient is a significant aspect of this analysis. It represents the expected transformation of the surface roughness per unit alteration of each value of machining factors. However, the intercept of the orthogonal plan for the average surface roughness experiment and coefficients are used to adjust the settings of the machining factors. The value of variance inflation factors (VIFs) is used to determine the existence between the predictor model and the variable factors used for

**Table 9.2** Surface roughness experimental data

| Runs | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle ( $\alpha$ ) (°) | SR (MWCNTs) ( $\mu\text{m}$ ) |
|------|---------------------|--------------------|--------------------|-------------------|------------------------------|-------------------------------|
| 1    | 2500                | 150                | 30                 | 2.5               | 45                           | 2.04                          |
| 2    | 2500                | 250                | 50                 | 2.5               | 15                           | 2.06                          |
| 3    | 2500                | 250                | 30                 | 1.5               | 15                           | 1.98                          |
| 4    | 3500                | 250                | 50                 | 1.5               | 45                           | 1.46                          |
| 5    | 2500                | 250                | 30                 | 1.5               | 45                           | 1.75                          |
| 6    | 2500                | 150                | 50                 | 1.5               | 45                           | 1.68                          |
| 7    | 3000                | 200                | 40                 | 2                 | 30                           | 1.53                          |
| 8    | 3500                | 250                | 30                 | 2.5               | 45                           | 1.51                          |
| 9    | 2500                | 150                | 50                 | 2.5               | 45                           | 1.66                          |
| 10   | 3500                | 150                | 30                 | 1.5               | 15                           | 1.44                          |
| 11   | 2500                | 250                | 50                 | 2.5               | 45                           | 1.69                          |
| 12   | 3000                | 200                | 40                 | 2                 | 30                           | 1.54                          |
| 13   | 2500                | 150                | 30                 | 2.5               | 15                           | 1.71                          |
| 14   | 3500                | 150                | 50                 | 2.5               | 45                           | 1.52                          |
| 15   | 3500                | 150                | 30                 | 2.5               | 15                           | 1.65                          |
| 16   | 2500                | 250                | 30                 | 2.5               | 15                           | 1.76                          |
| 17   | 2500                | 250                | 50                 | 1.5               | 45                           | 1.74                          |
| 18   | 3000                | 200                | 40                 | 2                 | 60                           | 1.59                          |
| 19   | 3000                | 200                | 40                 | 2                 | 30                           | 1.58                          |
| 20   | 4000                | 200                | 40                 | 2                 | 30                           | 1.16                          |
| 21   | 3000                | 200                | 40                 | 2                 | 30                           | 1.58                          |
| 22   | 3000                | 300                | 40                 | 2                 | 30                           | 2.51                          |
| 23   | 3500                | 150                | 50                 | 1.5               | 45                           | 1.49                          |
| 24   | 3000                | 200                | 60                 | 2                 | 30                           | 1.61                          |
| 25   | 3000                | 200                | 40                 | 1                 | 30                           | 1.56                          |
| 26   | 3500                | 150                | 30                 | 1.5               | 45                           | 1.36                          |
| 27   | 3500                | 250                | 30                 | 1.5               | 45                           | 1.51                          |
| 28   | 3500                | 250                | 50                 | 2.5               | 45                           | 1.61                          |
| 29   | 3500                | 150                | 30                 | 2.5               | 45                           | 1.59                          |
| 30   | 2500                | 150                | 50                 | 1.5               | 15                           | 1.92                          |
| 31   | 2500                | 250                | 50                 | 1.5               | 15                           | 2                             |
| 32   | 3000                | 200                | 40                 | 2                 | 30                           | 1.66                          |
| 33   | 3500                | 250                | 50                 | 2.5               | 15                           | 1.52                          |
| 34   | 3000                | 200                | 40                 | 3                 | 30                           | 2.2                           |
| 35   | 3500                | 150                | 50                 | 1.5               | 15                           | 1.54                          |

(continued)

**Table 9.2** (continued)

| Runs | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle ( $\alpha$ ) (o) | SR (MWCNTs) ( $\mu\text{m}$ ) |
|------|---------------------|--------------------|--------------------|-------------------|------------------------------|-------------------------------|
| 36   | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 37   | 3500                | 150                | 50                 | 2.5               | 15                           | 1.52                          |
| 38   | 3000                | 100                | 40                 | 2                 | 30                           | 1.21                          |
| 39   | 3500                | 250                | 50                 | 1.5               | 15                           | 1.5                           |
| 40   | 2000                | 200                | 40                 | 2                 | 30                           | 2.3                           |
| 41   | 3000                | 200                | 20                 | 2                 | 30                           | 1.51                          |
| 42   | 3500                | 250                | 30                 | 2.5               | 15                           | 1.49                          |
| 43   | 2500                | 150                | 30                 | 1.5               | 45                           | 1.74                          |
| 44   | 3500                | 250                | 30                 | 1.5               | 15                           | 1.45                          |
| 45   | 3000                | 200                | 40                 | 2                 | 0                            | 1.61                          |
| 46   | 2500                | 150                | 50                 | 2.5               | 15                           | 1.76                          |
| 47   | 2500                | 250                | 30                 | 2.5               | 45                           | 1.77                          |
| 48   | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 49   | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 50   | 2500                | 150                | 30                 | 1.5               | 15                           | 1.77                          |

the prediction. The VIFs pace of one (1) implies the elements are symmetrical, while a worth higher than one (1) suggests multi-collinearity of the variables, as displayed in Table 9.5. The more noteworthy the VIFs, the more the multi-collinearity of the machining elements.

The developed mathematical model for the surface roughness analysis under the machining environment with multi-walled carbon nano-lubricant using QRCCD is presented in two forms as coded and actual. Equation (9.13) gives the model in the coded form and Fig. 9.7 shows the predicted analysis of the QRCCD.

$$\begin{aligned}
\text{SR}_{\text{coded}} = & +1.59 - 0.5700S_c + 0.6500F_c - 0.0042L_c - 0.0625D_c \\
& - 0.0100\alpha_c - 0.0663SF_c + 0.0212SL_c + 0.0988SD_c \\
& + 0.1037S\alpha_c + 0.0712FL_c - 0.0612FD_c - 0.0613F\alpha_c \\
& - 0.0637LD_c - 0.1238L\alpha_c + 0.0988D\alpha_c + 0.1400S_c^2 \\
& + 0.2700F_c^2 - 0.0300L_c^2 + 0.2900D_c^2 + 0.0100\alpha_c^2 \\
& - 0.0925SFL_c + 0.0025SFD_c + 0.2825SF\alpha_c \\
& - 0.0225SLD_c + 0.2775SL\alpha_c - 0.1175SD\alpha_c \\
& + 0.2975FLD_c + 0.0275FL\alpha_c - 0.0875FD\alpha_c \\
& - 0.0925LD\alpha_c - 2.50S^2F_c - 0.1975S^2\alpha_c + 1.06SF_c^2 \\
& + 0.0542L_c^3 + 0.3825D_c^3 - 0.1750SFL\alpha_c \\
& + 0.1950SFD\alpha_c + 0.3850SLD\alpha_c - 1.57S^2F_c^2
\end{aligned} \tag{9.13}$$

**Table 9.3** ANOVA of surface roughness under QRCCD

| Source                          | Sum of squares | Degree of freedom | Mean square | F-value | p-value  | % Concentration |             |
|---------------------------------|----------------|-------------------|-------------|---------|----------|-----------------|-------------|
| <b>Model</b>                    | 3.05           | 39                | 0.078       | 52.64   | < 0.0001 | 99.52           | Significant |
| S <sub>s</sub> -(spindle speed) | 0.649          | 1                 | 0.649       | 438.04  | < 0.0001 | 21.24           |             |
| F <sub>r</sub> -(feed rate)     | 0.845          | 1                 | 0.845       | 569.62  | < 0.0001 | 27.61           |             |
| L <sub>c</sub> -(length of cut) | 0.0001         | 1                 | 0.0001      | 0.0421  | 0.8415   | 0.003           |             |
| D <sub>c</sub> -(depth of cut)  | 0.0141         | 1                 | 0.0141      | 9.48    | 0.0117   | 0.461           |             |
| α-(helix angle)                 | 0.0002         | 1                 | 0.0002      | 0.1348  | 0.7211   | 0.007           |             |
| S <sub>s</sub> F <sub>r</sub>   | 0.0088         | 1                 | 0.0088      | 5.92    | 0.0353   | 0.288           |             |
| S <sub>s</sub> L <sub>c</sub>   | 0.0009         | 1                 | 0.0009      | 0.6088  | 0.4533   | 0.029           |             |
| S <sub>s</sub> D <sub>c</sub>   | 0.0195         | 1                 | 0.0195      | 13.15   | 0.0046   | 0.637           |             |
| S <sub>s</sub> α                | 0.0215         | 1                 | 0.0215      | 14.51   | 0.0034   | 0.703           |             |
| F <sub>r</sub> L <sub>c</sub>   | 0.0102         | 1                 | 0.0102      | 6.84    | 0.0258   | 0.333           |             |
| F <sub>r</sub> D <sub>c</sub>   | 0.0075         | 1                 | 0.0075      | 5.06    | 0.0483   | 0.245           |             |
| F <sub>r</sub> α                | 0.0075         | 1                 | 0.0075      | 5.06    | 0.0483   | 0.245           |             |
| L <sub>c</sub> D <sub>c</sub>   | 0.0081         | 1                 | 0.0081      | 5.48    | 0.0413   | 0.265           |             |
| L <sub>c</sub> α                | 0.0306         | 1                 | 0.0306      | 20.65   | 0.0011   | 1               |             |
| D <sub>c</sub> α                | 0.0195         | 1                 | 0.0195      | 13.15   | 0.0046   | 0.637           |             |
| S <sub>s</sub> <sup>2</sup>     | 0.0314         | 1                 | 0.0314      | 21.14   | 0.001    | 1.026           |             |
| F <sub>r</sub> <sup>2</sup>     | 0.1166         | 1                 | 0.1166      | 78.63   | < 0.0001 | 3.81            |             |
| L <sub>c</sub> <sup>2</sup>     | 0.0014         | 1                 | 0.0014      | 0.9707  | 0.3477   | 0.046           |             |
| D <sub>c</sub> <sup>2</sup>     | 0.1346         | 1                 | 0.1346      | 90.71   | < 0.0001 | 4.399           |             |
| α <sup>2</sup>                  | 0.0002         | 1                 | 0.0002      | 0.1079  | 0.7494   | 0.007           |             |
| SFL                             | 0.0043         | 1                 | 0.0043      | 2.88    | 0.1203   | 0.141           |             |
| SFD                             | 3.13E-06       | 1                 | 3.13E-06    | 0.0021  | 0.9643   | 0               |             |
| SFα                             | 0.0399         | 1                 | 0.0399      | 26.9    | 0.0004   | 1.304           |             |
| SLD                             | 0.0003         | 1                 | 0.0003      | 0.1706  | 0.6883   | 0.009           |             |
| SLα                             | 0.0385         | 1                 | 0.0385      | 25.96   | 0.0005   | 1.258           |             |
| SDα                             | 0.0069         | 1                 | 0.0069      | 4.65    | 0.0564   | 0.225           |             |
| FLD                             | 0.0443         | 1                 | 0.0443      | 29.83   | 0.0003   | 1.448           |             |
| FLα                             | 0.0004         | 1                 | 0.0004      | 0.2549  | 0.6246   | 0.013           |             |
| FDα                             | 0.0038         | 1                 | 0.0038      | 2.58    | 0.1393   | 0.124           |             |
| LDα                             | 0.0043         | 1                 | 0.0043      | 2.88    | 0.1203   | 0.141           |             |
| S <sup>2</sup> F                | 0.6238         | 1                 | 0.6238      | 420.48  | < 0.0001 | 20.386          |             |

(continued)

**Table 9.3** (continued)

| Source                        | Sum of squares | Degree of freedom | Mean square | F-value | p-value  | % Concentration |                 |
|-------------------------------|----------------|-------------------|-------------|---------|----------|-----------------|-----------------|
| S <sup>2</sup> L              | 0.0039         | 1                 | 0.0039      | 2.63    | 0.136    | 0.127           |                 |
| SF <sup>2</sup>               | 0.1129         | 1                 | 0.1129      | 76.1    | < 0.0001 | 3.689           |                 |
| L <sup>3</sup>                | 0.0026         | 1                 | 0.0026      | 1.78    | 0.2117   | 0.085           |                 |
| D <sup>3</sup>                | 0.1317         | 1                 | 0.1317      | 88.76   | < 0.0001 | 4.304           |                 |
| SFL $\alpha$                  | 0.0038         | 1                 | 0.0038      | 2.58    | 0.1393   | 0.124           |                 |
| SFD $\alpha$                  | 0.0048         | 1                 | 0.0048      | 3.2     | 0.1037   | 0.157           |                 |
| SLD $\alpha$                  | 0.0185         | 1                 | 0.0185      | 12.49   | 0.0054   | 0.605           |                 |
| S <sup>2</sup> F <sup>2</sup> | 0.049          | 1                 | 0.049       | 33.02   | 0.0002   | 1.601           |                 |
| <b>Residual</b>               | 0.015          | 10                | 0.002       |         |          | 0.484           |                 |
| Lack-of-fit                   | 0.002          | 3                 | 0.001       | 0.458   | 0.7201   | 0.078           | Not significant |
| Pure error                    | 0.012          | 7                 |             |         |          | 0.41            |                 |
| <b>Corrected total</b>        | 3.06           | 49                |             |         |          | 100             |                 |

**Table 9.4** The ANOVA statistics justification of the **experimental data** of surface roughness

|                                   |        |                         |         |
|-----------------------------------|--------|-------------------------|---------|
| Standard deviation                | 0.0385 | R <sup>2</sup>          | 0.9952  |
| Mean                              | 1.66   | Adjusted R <sup>2</sup> | 0.9762  |
| Coefficient of variation (C.V.) % | 2.32   | Adequate. Precision     | 39.1881 |

In Eq. (9.13), the model is in the state of coded form for proper identification of the comparative effect of the machining factors or parameters when comparing the coefficients. The equation developed for the prediction of surface roughness in the coded parameters can be employed to validate the model with a given level of the original unit of the machining parameters, to predict the response. However, this model should not be employed to study the interactions of the machining parameters because the estimated coefficient of the parameters is embedded to accommodate each parameter. It should be known that the intercept is not at the midpoint of the design space. The actual parameters model can be employed to predict the response in a given level of controlled parameters. The actual factors of the model are presented in Eq. (9.14).

$$\begin{aligned}
 SR_{\text{actual}} = & -18.29 + 0.008S + 0.477F + 0.037L + 0.100D - 0.158\alpha \\
 & - 0.0003SF + 0.00002SL + 0.0014SD + 0.00067S\alpha \\
 & - 0.0004FL + 0.00009FD - 0.0002F\alpha + 0.033LD \\
 & + 0.001L\alpha + 0.143D\alpha - 9.275E - 07S^2 - 0.002F^2 \\
 & - 0.001L^2 - 2.005D^2 + 0.00001\alpha^2 + 4.125E - 08SF \\
 & - 1.925E - 06SFD + 8.083E - 08SF\alpha - 0.00002SLD
 \end{aligned}$$

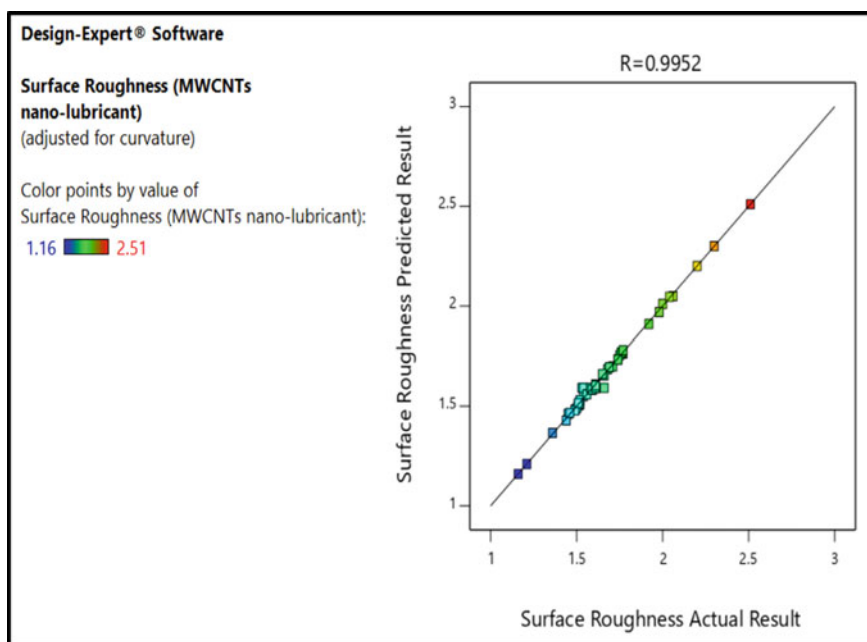
**Table 9.5** ANOVA coefficients of surface roughness for the QRCCD

| Factor                  | Coefficient estimate | Df | Standard error | 95% CI low | 95% CI high | VIF    |
|-------------------------|----------------------|----|----------------|------------|-------------|--------|
| Intercept               | 1.59                 | 1  | 0.0136         | 1.56       | 1.62        |        |
| $S_s$ -(spindle speed)  | - 0.5700             | 1  | 0.0272         | - 0.6307   | - 0.5093    | 5.00   |
| $F_r$ -(feed rate)      | 0.6500               | 1  | 0.0272         | 0.5893     | 0.7107      | 5.00   |
| $L_c$ -(length of cut)  | - 0.0042             | 1  | 0.0203         | - 0.0494   | 0.0411      | 2.78   |
| $D_c$ -(depth of cut)   | - 0.0625             | 1  | 0.0203         | - 0.1077   | - 0.0173    | 2.78   |
| $\alpha$ -(helix angle) | - 0.0100             | 1  | 0.0272         | - 0.0707   | 0.0507      | 5.00   |
| SF                      | - 0.0663             | 1  | 0.0272         | - 0.1269   | - 0.0056    | 1.0000 |
| SL                      | 0.0212               | 1  | 0.0272         | - 0.0394   | 0.0819      | 1.0000 |
| SD                      | 0.0988               | 1  | 0.0272         | 0.0381     | 0.1594      | 1.0000 |
| $S\alpha$               | 0.1037               | 1  | 0.0272         | 0.0431     | 0.1644      | 1.0000 |
| FL                      | 0.0712               | 1  | 0.0272         | 0.0106     | 0.1319      | 1.0000 |
| FD                      | - 0.0612             | 1  | 0.0272         | - 0.1219   | - 0.0006    | 1.0000 |
| $F\alpha$               | - 0.0613             | 1  | 0.0272         | - 0.1219   | - 0.0006    | 1.0000 |
| LD                      | - 0.0637             | 1  | 0.0272         | - 0.1244   | - 0.0031    | 1.0000 |
| $L\alpha$               | - 0.1238             | 1  | 0.0272         | - 0.1844   | - 0.0631    | 1.0000 |
| $D\alpha$               | 0.0988               | 1  | 0.0272         | 0.0381     | 0.1594      | 1.0000 |
| $S^2$                   | 0.1400               | 1  | 0.0304         | 0.0722     | 0.2078      | 1.25   |
| $F^2$                   | 0.2700               | 1  | 0.0304         | 0.2022     | 0.3378      | 1.25   |
| $L^2$                   | - 0.0300             | 1  | 0.0304         | - 0.0978   | 0.0378      | 1.25   |
| $D^2$                   | 0.2900               | 1  | 0.0304         | 0.2222     | 0.3578      | 1.25   |
| $\alpha^2$              | 0.0100               | 1  | 0.0304         | - 0.0578   | 0.0778      | 1.25   |
| SFL                     | - 0.0925             | 1  | 0.0545         | - 0.2139   | 0.0289      | 1.0000 |
| SFD                     | 0.0025               | 1  | 0.0545         | - 0.1189   | 0.1239      | 1.0000 |
| SF $\alpha$             | 0.2825               | 1  | 0.0545         | 0.1611     | 0.4039      | 1.0000 |
| SLD                     | - 0.0225             | 1  | 0.0545         | - 0.1439   | 0.0989      | 1.0000 |
| SL $\alpha$             | 0.2775               | 1  | 0.0545         | 0.1561     | 0.3989      | 1.0000 |
| SD $\alpha$             | - 0.1175             | 1  | 0.0545         | - 0.2389   | 0.0039      | 1.0000 |
| FLD                     | 0.2975               | 1  | 0.0545         | 0.1761     | 0.4189      | 1.0000 |
| FL $\alpha$             | 0.0275               | 1  | 0.0545         | - 0.0939   | 0.1489      | 1.0000 |
| FD $\alpha$             | - 0.0875             | 1  | 0.0545         | - 0.2089   | 0.0339      | 1.0000 |
| LD $\alpha$             | - 0.0925             | 1  | 0.0545         | - 0.2139   | 0.0289      | 1.0000 |
| $S^2F$                  | - 2.50               | 1  | 0.1218         | - 2.77     | - 2.23      | 5.00   |

(continued)

**Table 9.5** (continued)

| Factor      | Coefficient estimate | Df | Standard error | 95% CI low | 95% CI high | VIF    |
|-------------|----------------------|----|----------------|------------|-------------|--------|
| $S^2L$      | − 0.1975             | 1  | 0.1218         | − 0.4689   | 0.0739      | 5.00   |
| $SF^2$      | 1.06                 | 1  | 0.1218         | 0.7911     | 1.33        | 5.00   |
| $L^3$       | 0.0542               | 1  | 0.0406         | − 0.0363   | 0.1446      | 2.78   |
| $D^3$       | 0.3825               | 1  | 0.0406         | 0.2920     | 0.4730      | 2.78   |
| $SFL\alpha$ | − 0.1750             | 1  | 0.1089         | − 0.4177   | 0.0677      | 1.0000 |
| $SFD\alpha$ | 0.1950               | 1  | 0.1089         | − 0.0477   | 0.4377      | 1.0000 |
| $SLD\alpha$ | 0.3850               | 1  | 0.1089         | 0.1423     | 0.6277      | 1.0000 |
| $S^2F^2$    | − 1.57               | 1  | 0.2723         | − 2.17     | − 0.9582    | 2.25   |

**Fig. 9.7** Experimental data and predicted data of surface roughness

$$\begin{aligned}
& - 2.375E - 07SL\alpha - 0.00004SD\alpha + 0.0002FLD \\
& + 9.208E - 06FL\alpha - 0.002FD\alpha - 0.002LD\alpha + 3.763E \\
& - 08S^2F - 6.583E - 09S^2F + 1.045E - 06SF^2 \\
& + 6.771E - 06L^3 + 0.383D^3 - 2.916E - 09SFL\alpha \\
& + 6.500E - 08SFD\alpha + 6.4167E - 07SLD\alpha - 1.565E \\
& - 10S^2F^2
\end{aligned} \tag{9.14}$$



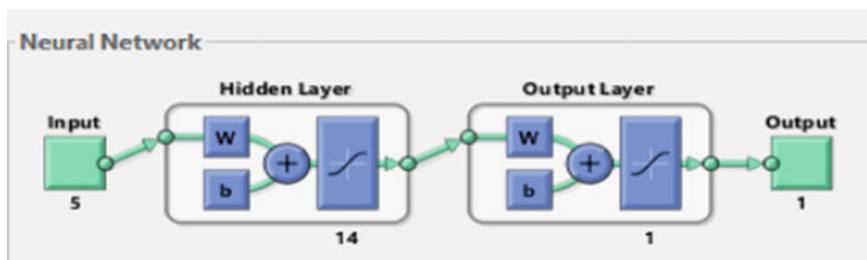


**Fig. 9.8** The ANN model used for the prediction analysis of the surface roughness

### 9.3.3 The Prediction of Surface Roughness Using ANN

This section presents the ANN prediction of surface roughness during the end-milling operation of AA8112 alloy under the MWCNT's nano-lubricant machining environment. Figure 9.8 shows the performance of the ANN model under the multi-walled carbon nano-lubricant. From the analysis, the R-value for the data training set, data validation, and data testing is 0.90919, 0.95479, and 0.98872, respectively. The overall performance of the training, validation and testing is 0.91959, as shown in Fig. 9.9a–b.

From the ANN model, the best validation performance is 0.10917 as measured using the SSE; this occurs at epoch 0 and iteration 6 (Fig. 9.10). From the analysis, the SSE gradually increased from zero epoch to the peak point. Figure 9.11 shows the gradient constant of 0.15668, Marquardt unit parameter (Mu) of  $1e-09$ , total validation checks, and the iterations value at epoch 6.

## 9.4 The Comparison of Predicted Results Between ANN and QRCCD and the Machining Optimization

The predicted models developed from the experimental data using ANN and QRCCD under machining operation of AA8112 alloy using multi-walled carbon nano-lubricant machining environment, the experimental data predicted result for ANN, and QRCCD is depicted in Fig. 9.12. The ANN and QRCCD models predicted the experimental data of surface roughness by 95% and 99%, respectively. Hence, both the ANN and the QRCCD are useful innovative design tools for the prediction process [14–17].

Figures 9.13, 9.14 and 9.15 shows the factors of objective optimization of the machining parameters obtained from the quadratic rotatable central composite design (QRCCD). The result shows that the spindle speed of 3366 rpm, 101 mm/min feed rate, 1 mm depth of cut, 20 mm length of cut, and  $39.6^\circ$  helix angle achieved the minimum surface roughness of  $1.16 \mu\text{m}$  with the desirability of 0.926. This result is closely related to the experimental data from the machining operations, this result

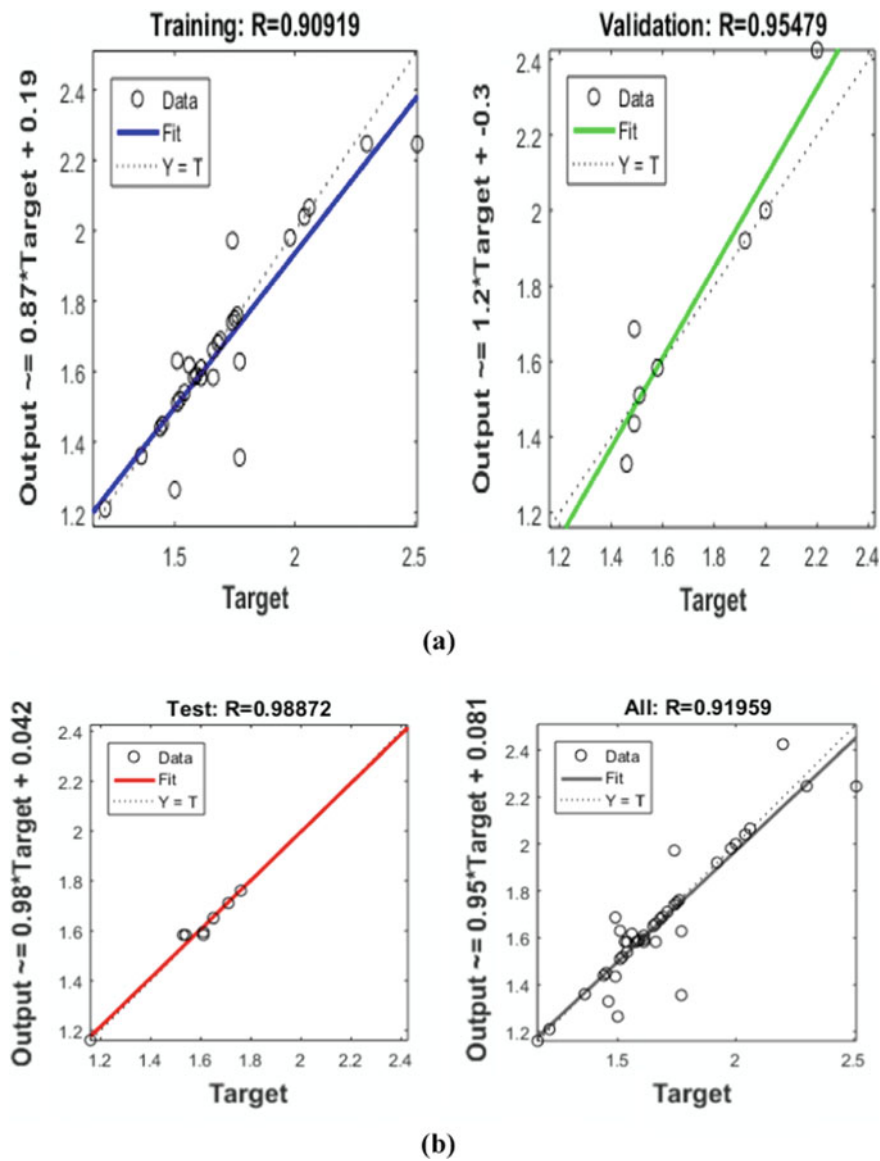


**Fig. 9.9** **a** The ANN regression plot for surface roughness. **b** The ANN regression plot for surface roughness

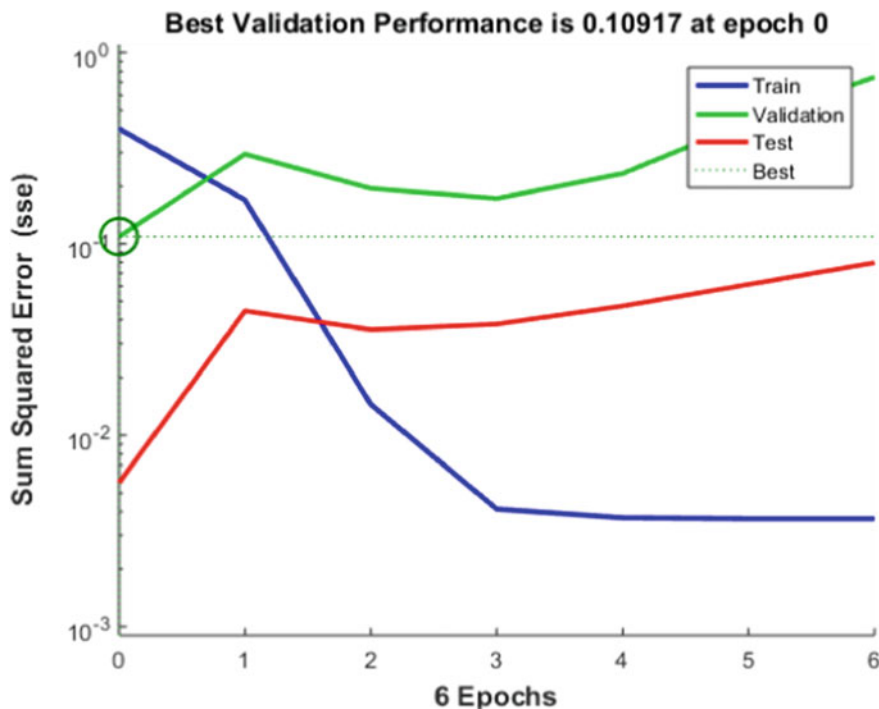


**Fig. 9.10** ANN validation plot for surface roughness

is supported by Refs. [18, 19]. Also, Fig. 9.16 depict the overlay plot showing the influence factors on the surface roughness values at low and high surface areas are depicted with the colour variations.

## 9.5 Study of the Machining Parameters Interaction for Optimal Performance

Interaction study of machining parameters during machining process leads to high performance operation with quality product. As the optimal interactions parameters assist to improve the surface finishing of the workpiece. Surface roughness is a significant response in machining operations, because it prolongs the work life of the product, reduces the rate of corrosion activity of the workpiece during operations [20]. Therefore, the five machining parameters in this study is analyses using QRCCD to study the interactions between them. From Figs. 9.17, 9.18, 9.19, 9.20, 9.21, 9.22, 9.23, 9.24, 9.25 and 9.26 present the interactions plots. Figure 9.17 shows that the depth of cut and the helix angle has good interactions, however, the two parameters when increased it increases the surface roughness. Figure 9.18 depict the relation

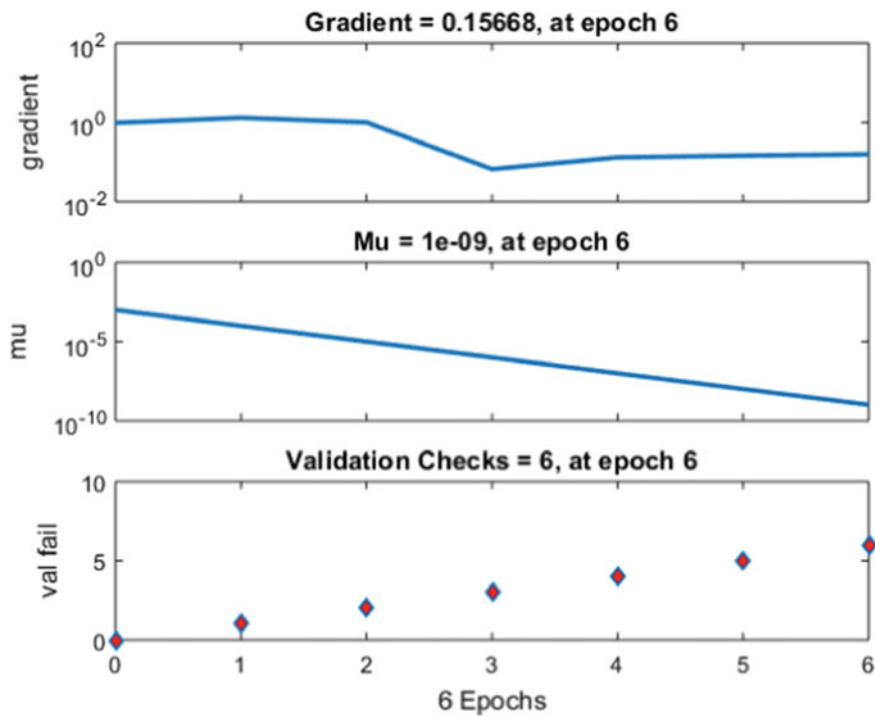


Fig. 9.11 ANN performance training state for surface roughness

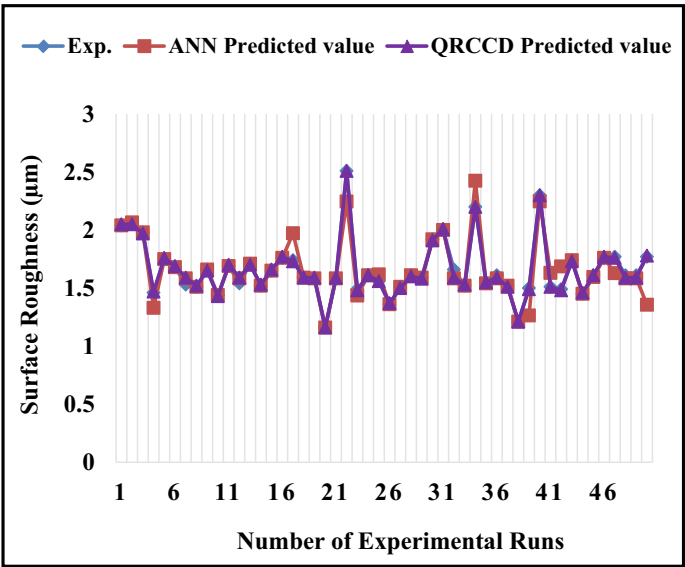


Fig. 9.12 Experimental data, ANN, and QRCCD predictions of the surface roughness

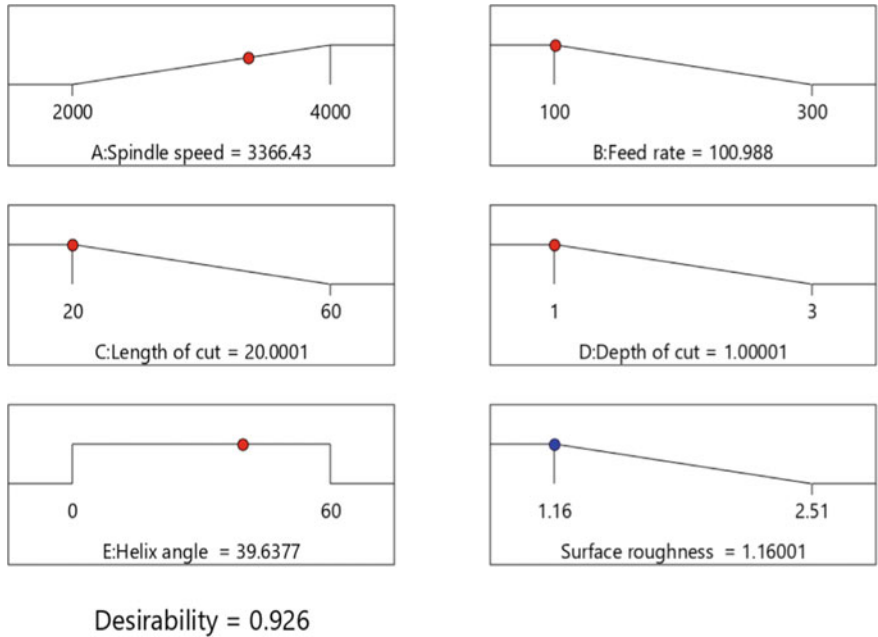


**Fig. 9.13** The ramps plots for the objective five factors five levels of optimization of the surface roughness

**Design-Expert® Software**  
Factor Coding: Actual

**Desirability**  
0.000 1.000

X1 = A: Spindle speed  
X2 = B: Feed rate

**Actual Factors**  
C: Length of cut = 20.0001  
D: Depth of cut = 1.00001  
E: Helix angle = 39.6377

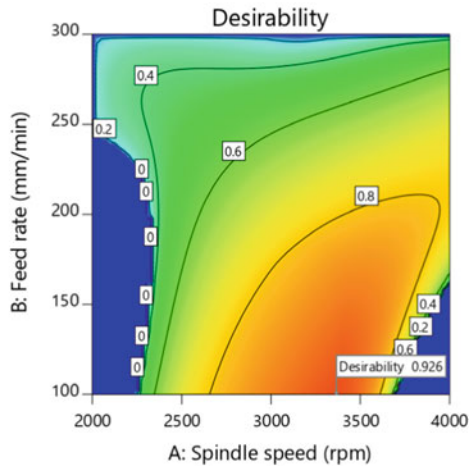


**Fig. 9.14** The desirability plots for the surface roughness

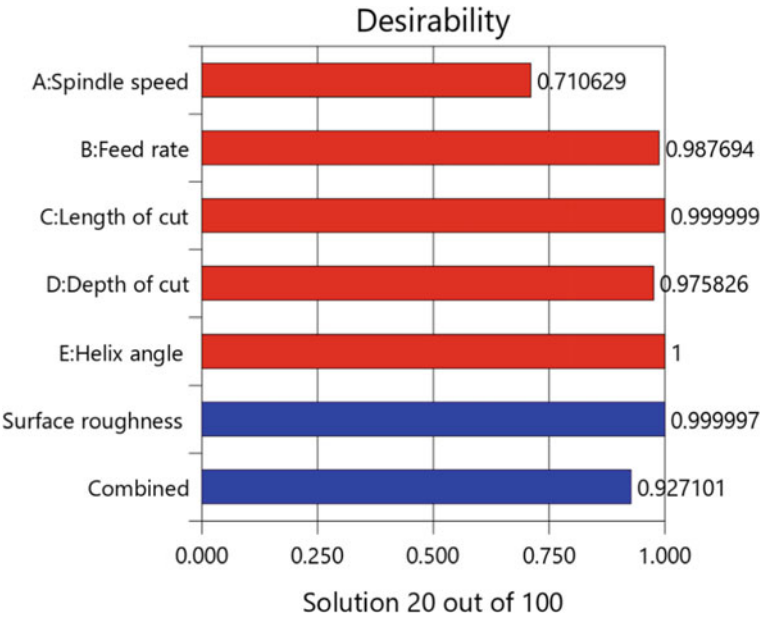


**Fig. 9.15** The desirability bar plots for the multi-objective optimization parameters and the combine function

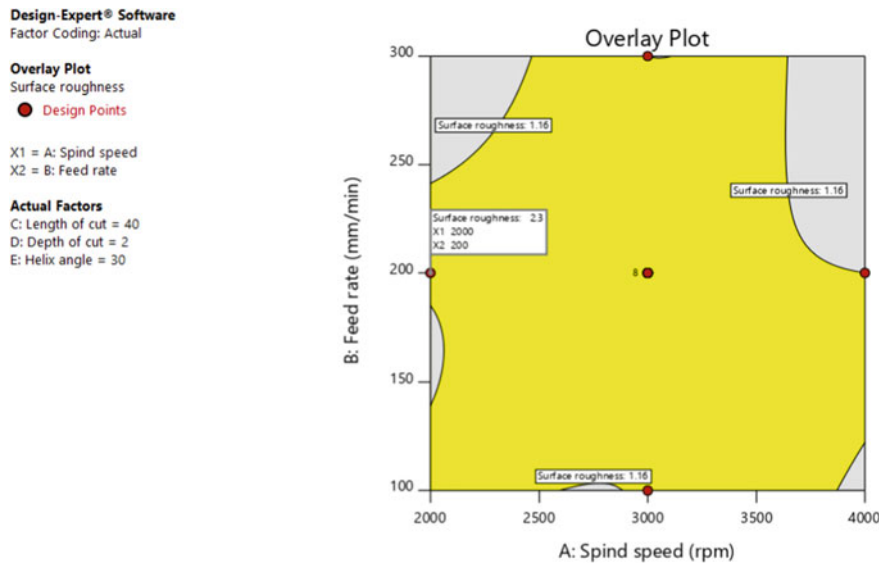


**Fig. 9.16** The overlay plots showing the different surface area concentration for the multi-objective optimization parameters

between the helix angle and the length of cut, the helix angle when increased it allows the intake of lubricant into the cutting region to reduce the heat generated during operations, sot therefore, it relatively reduces the surface roughness when increased. However, length of cut when increase it increases the surface roughness, increases the material removal rate, and increases the cutting force. Figure 9.19 shows the interaction study of the length of cut and depth of cut, these two machining parameters is very significant because for any machining process to occur there must be an analysis of the estimated materials that is needed to be removed for the manufacturer to obtain the desired shape. However, these two parameters when increase, it led to increase in the surface roughness, due to high vibration occurrence during the machining. Also, when the chips are been relatively removal in high volume, some of the chip’s falls back on the surface of the workpiece which increases material adhesion.

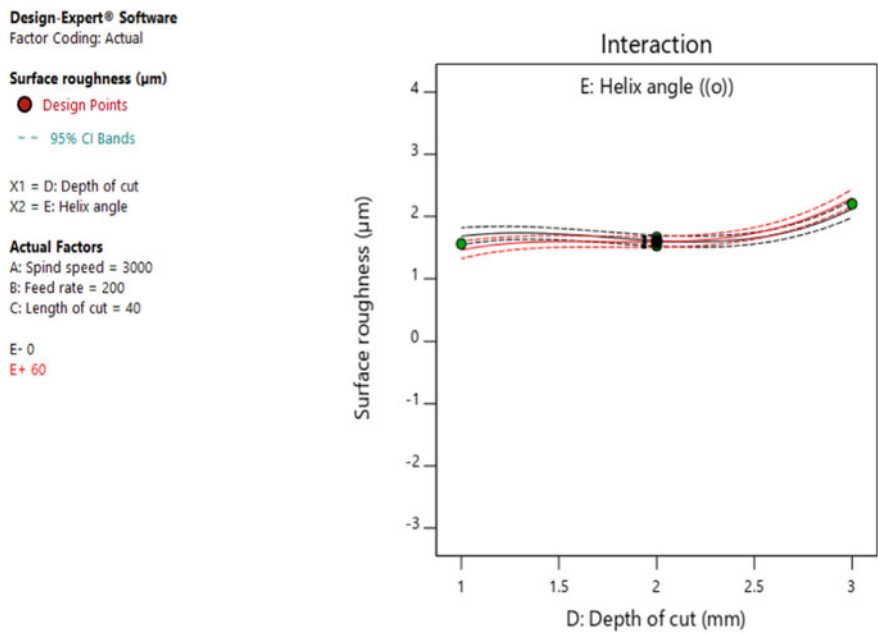


**Fig. 9.17** Interactions study of the machining parameters between depth of cut and helix angle for surface roughness analysis

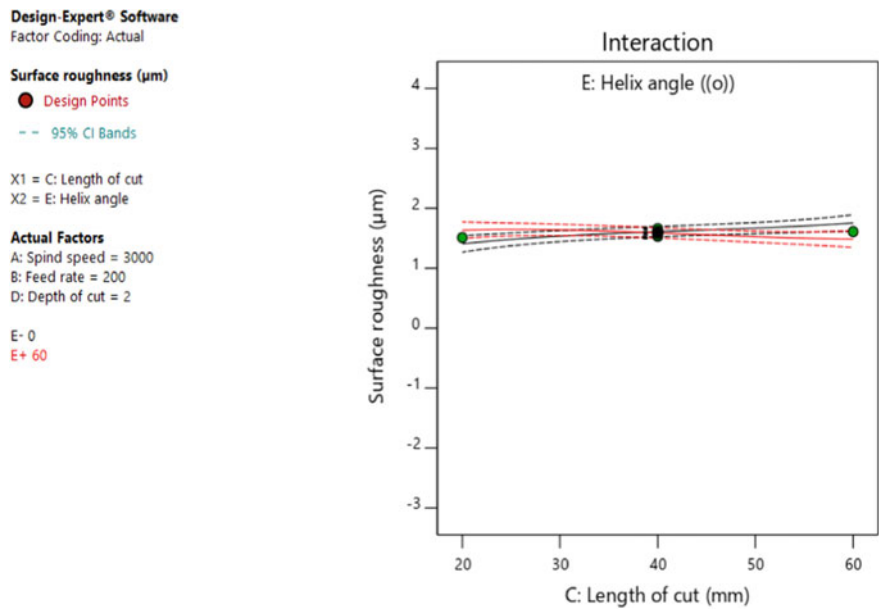


**Fig. 9.18** Interactions study of the machining parameters between length of cut and helix angle for surface roughness analysis

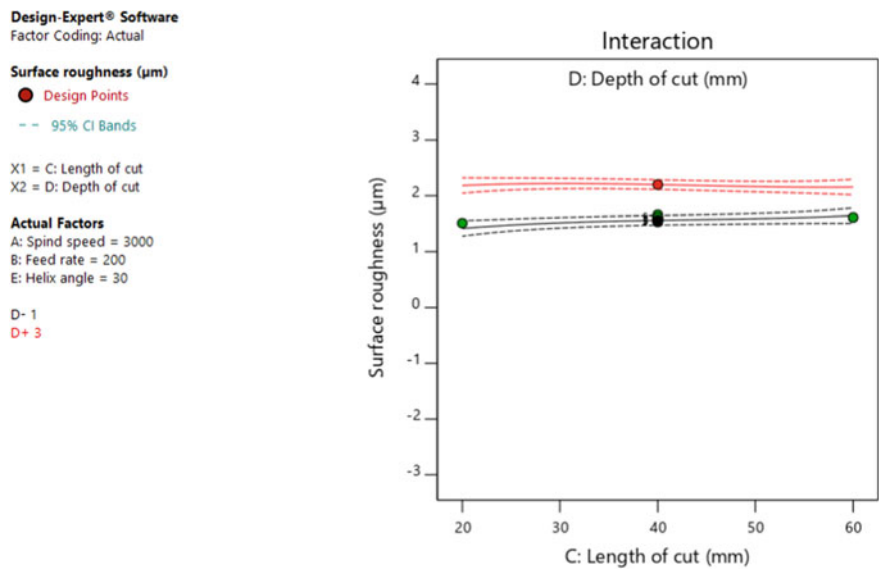


**Fig. 9.19** Interactions study of the machining parameters between length of cut and depth of cut for surface roughness analysis



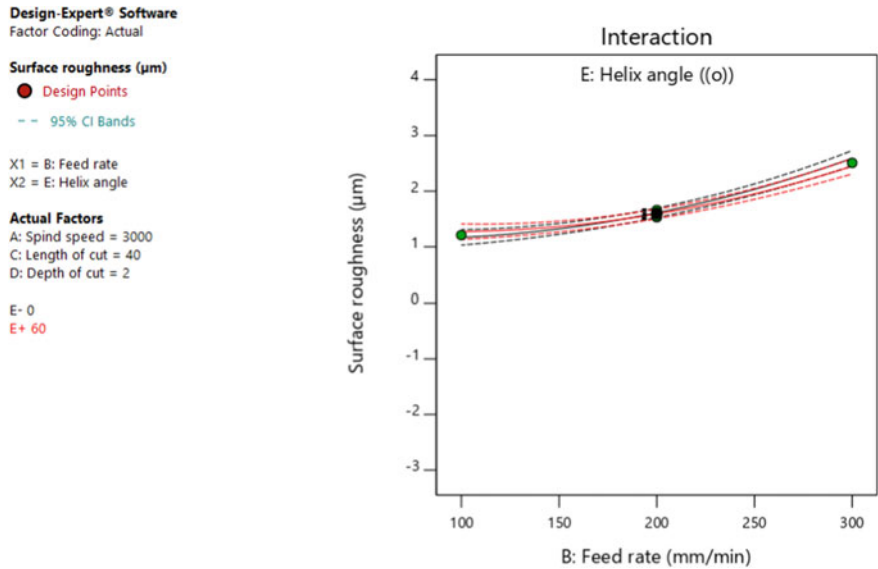


Fig. 9.20 Interactions study of the machining parameters between feed rate and helix angle for surface roughness analysis

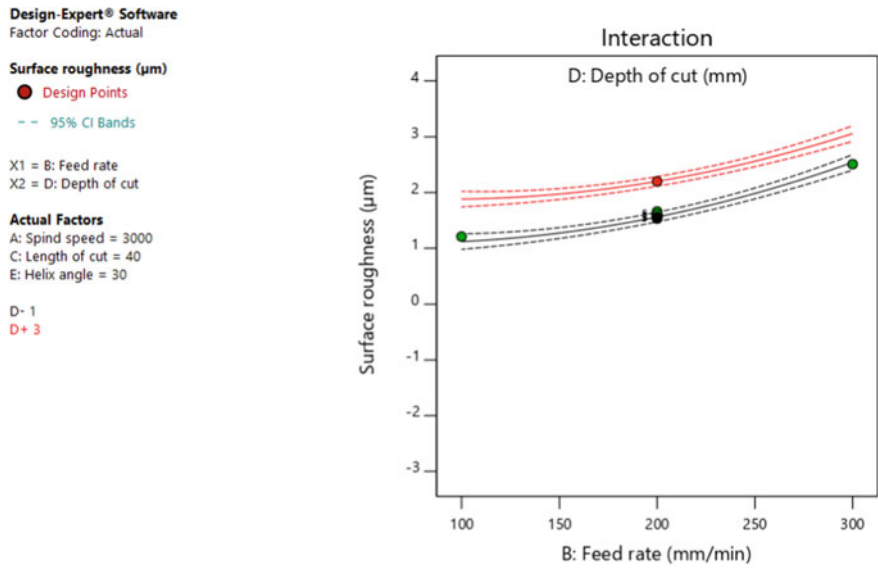


Fig. 9.21 Interactions study of the machining parameters between depth of cut and feed rate for surface roughness analysis

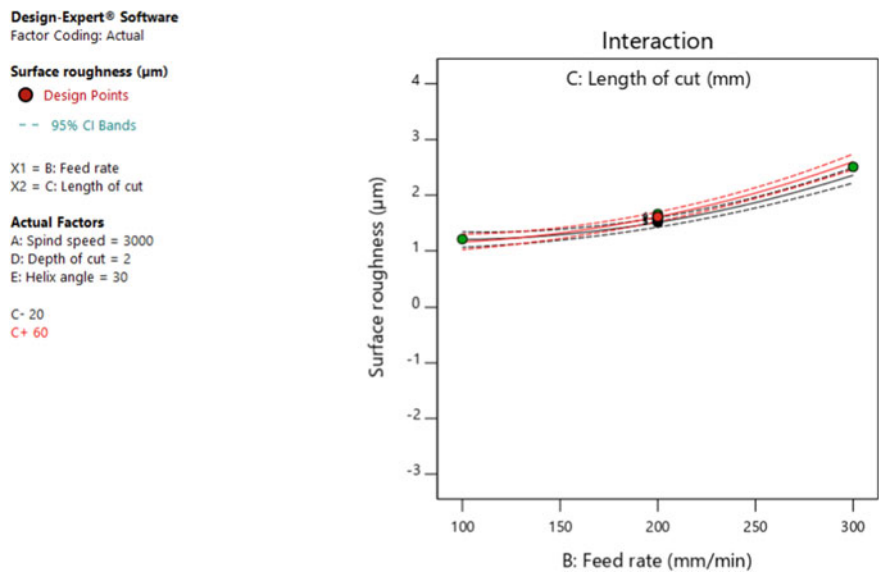


Fig. 9.22 Interactions study of the machining parameters between feed rate and length of cut for surface roughness analysis

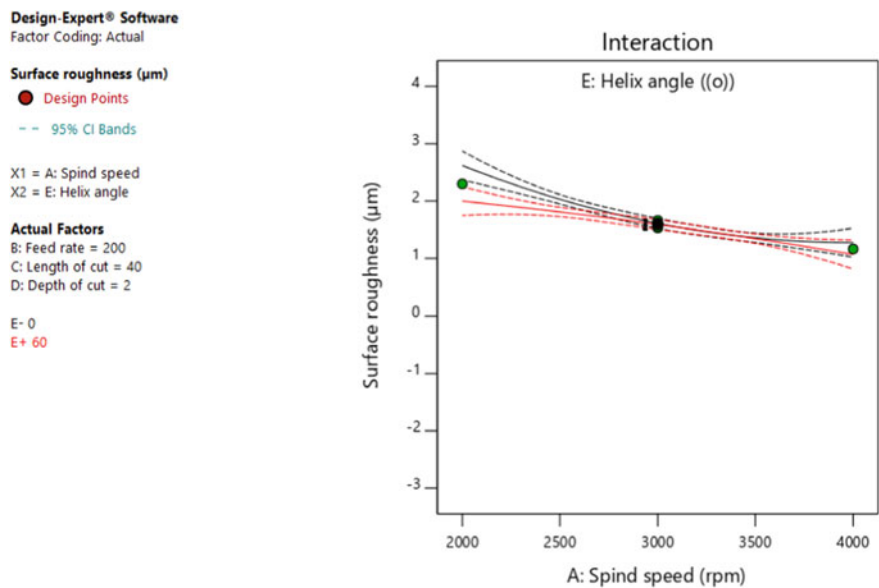


Fig. 9.23 Interactions study of the machining parameters between spindle speed and helix angle for surface roughness analysis

Design-Expert® Software  
Factor Coding: Actual

Surface roughness ( $\mu\text{m}$ )

● Design Points  
-- 95% CI Bands

X1 = A: Spind speed  
X2 = D: Depth of cut

Actual Factors

B: Feed rate = 200  
C: Length of cut = 40  
E: Helix angle = 30

D- 1

D+ 3

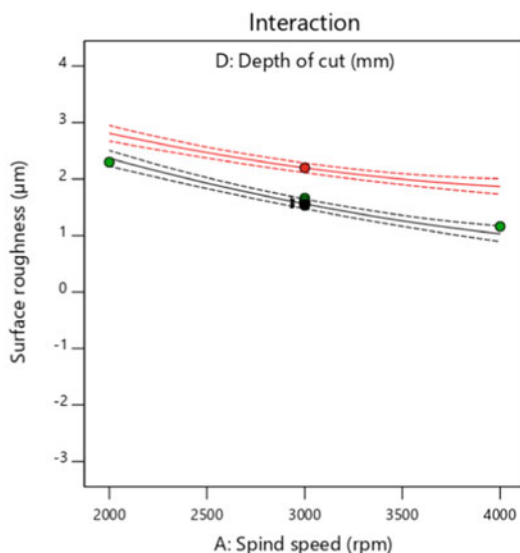


**Fig. 9.24** Interactions study of the machining parameters between spindle speed and depth of cut for surface roughness analysis

Design-Expert® Software  
Factor Coding: Actual

Surface roughness ( $\mu\text{m}$ )

● Design Points  
-- 95% CI Bands

X1 = A: Spind speed  
X2 = C: Length of cut

Actual Factors

B: Feed rate = 200  
D: Depth of cut = 2  
E: Helix angle = 30

C- 20

C+ 60

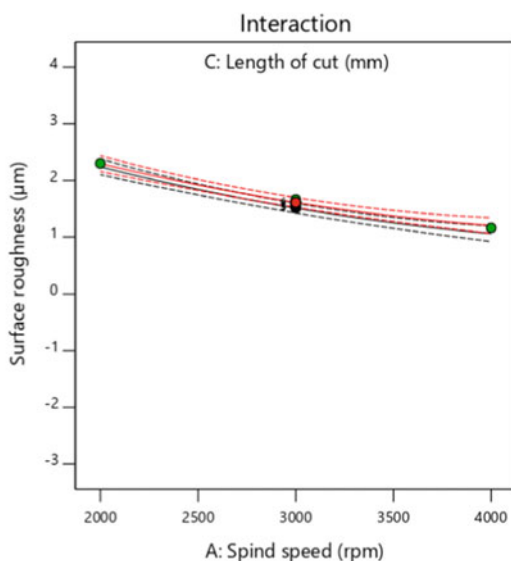


**Fig. 9.25** Interactions study of the machining parameters between spindle speed and length of cut for surface roughness analysis

Design-Expert® Software  
Factor Coding: Actual

Surface roughness ( $\mu\text{m}$ )

● Design Points

-- 95% CI Bands

X1 = A: Spind speed

X2 = B: Feed rate

Actual Factors

C: Length of cut = 40

D: Depth of cut = 2

E: Helix angle = 30

B- 100

B+ 300

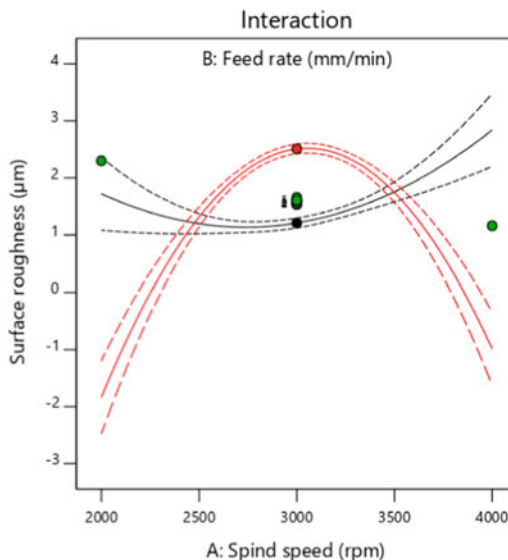


**Fig. 9.26** Interactions study of the machining parameters between spindle speed and feed rate for surface roughness analysis

## 9.6 Conclusion

In this chapter, the conclusion drawn from the surface roughness prediction analysis using ANN and QRCCD with five-factors five-levels of cutting parameters. The machining parameters considered are spindle speed ( $S_s$ ), feed rate ( $F_r$ ), cutting length ( $L_c$ ), cutting depth ( $D_c$ ) and helix angle ( $\alpha$ ) as the following conclusion:

- (i) Feed rate  $F_r$  was found to have the most significant effects on the surface roughness. The percentage contribution shows that  $F_r$  contributed 27.13% and 27.60%, followed by  $S_s$  with 23.70% and 21.24%, respectively.
- (ii) From the experimental data, the optimized machining parameter for the five-factor, five-level experiment for the surface roughness was achieved at a  $S_s$  of 4000 rpm, a  $F_r$  of 200 mm/min,  $L_c$  of 40 mm,  $D_c$  of 2 mm, and helix angle of  $30^\circ$  to attain a minimum surface roughness values of  $1.16 \mu\text{m}$ . However, the QRCCD optimized parameters for the minimum surface roughness are  $S_s$  of 3366 rpm, 101 mm/min  $F_r$ , 1 mm  $D_c$ , 20 mm  $L_c$ , and  $39.6^\circ$  helix angle achieved the lowest surface roughness of  $1.16 \mu\text{m}$ .
- (iii) The models developed using ANN and QRCCD predicted the experimental data with predicted values are 95.50% and 99.50%, respectively.

From the results of this research, the prediction and optimization of surface roughness under biodegradable Nano-lubricant via ANN and QRCCD is a sustainable tool to increase manufacturing processes.

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# Chapter 10

## Cutting Force Optimization Under ANN and QRCCD



**Abstract** The prediction analysis of cutting force in the cutting process is very significant in the manufacturing of products for industrial use. Cutting force is one of the responses in machining operations that affect energy consumption via computer numerical control of the manufacturing process. The focus of this chapter is to employ artificial neural network (ANN) and quadratic rotatable central composite design (QRCCD) to carry out prediction and optimisation to study the cutting force to minimised the energy consumption. The data employed in this study is obtained from experimental machining operation of AA 8012 alloy under vegetable oil TiO<sub>2</sub> biodegradable nano-lubricant for sustainable machining process. The result obtained showed that the minimum cutting force occurs at the optimal machining parameter of spindle speed of 2351 rpm, 101 mm/min feed rate, 1 mm depth of cut, 20 mm length of cut, and 60° helix angle and the minimum cutting force of 31 N with the desirability of 0.968. Also, the generated models developed for the cutting force using ANN and QRCCD predicted the experimental results with 97.5% and 95.56% accuracy under the biodegradable TiO<sub>2</sub> nano-lubricant. This result has proven that the implementation of Heuristic and Metaheuristic Techniques for Advanced Nano-lubricant Machining Optimization is a sustainable manufacturing process.

**Keywords** Cutting force · Artificial neural network · QRCCD · Nano-lubricant

### 10.1 Introduction

A high rate of energy consumption affects the economical aspect of the production of goods products of mechanical parts. This challenge of most mechanical processes use consume high energy during production as a result of the contact of the materials and the machining parameters, as lead to implementation of nano-lubrication system and optimisation techniques for sustainable production process with less energy consumption. Yeganefar et al. [1] the study predicted the cutting force of aluminium 7075-T6 alloy using artificial neural network (ANN), regression analysis

(RA) and support vector regression (SVR). Also the authors carried out optimisation of the cutting factors such as tool types, cutting depth, feed per tool and the machining speed via desirability and ANOVA. In order to validate the predictive models the Grid search and cross-validation approaches were employed to find the best fit of the ANN and SVR models. The analysis of this researcher was trained using Levenberg–Marquardt and RMSprop algorithms for the cutting force. The findings show that Hyper-parameter tuning is totally urgent to choose legitimate ANN and SVR models. Since ANN models own numerous hyperparameters, tuning is tedious, yet all at once the significance of this undertaking can't be overemphasized. Also, the RMSprop could anticipate  $F_z$  all the more definitively interestingly, with LMA. Hence, preparing calculations with versatile learning rate might prompt better reaction expectation.

Imani et al. [2] the current review uses man-made brainpower as a successful technique for anticipating processing powers and surface unpleasantness in view of exploratory outcomes. To examine the way of behaving of this combination, four levels for the two previous info boundaries and two levels for the two other, absolutely 64 trials, were satisfied and considered. In view of the trial results, the impact of information boundaries on the results, or at least, cutting power and surface unpleasantness, was researched, and afterward, brain network for displaying and anticipating and hereditary calculation for the streamlining of the results have been used. The improved counterfeit organization, which was gotten in this exploration, is helpful for expectation of machining power and surface unpleasantness of processing in view of the benefits of cutting pace, feed rate, and the hub profundity of cutting, for wet and dry processing of Inconel 738.

Wang et al. [3] as of late, the developing prominence of counterfeit brain networks has encouraged an ever increasing number of scientists to attempt acquaint these techniques with the machining field, with some of them really delivering great outcomes. The obtaining of reducing information frequently implies higher expense and time, restricting the use of brain network in the machining area, somewhat. In this paper, for the errand of cutting power expectation, a “move organization” was laid out, in light of information got by reproduction, joined with the hypothesis and strategy in the field of move learning. Contrasted with “common organization”, that is, conventional back-engendering brain network in light of exploratory examples alone, move network shows clear execution benefits. On one hand, this intends that, utilizing similar exploratory examples, the expectation blunder of move organization will be controlled; while then again, when a similar forecast mistake is accomplished, the quantity of trial tests expected by the exchange organization will be less.

Daniel et al. [4] this study plans to enhance the info boundaries, for example, mass portion and molecule size of SiC alongside profundity of cut, feed and cutting pace in the processing of Al5059/SiC/MoS2. The cross breed metal network composites are by and large created by building up of various sizes (10, 20 and 40 mm) of SiC with aluminum at an alternate level (5, 10 and 15%) though the MoS2 expansion is fixed as 2%. The impact of each control factor on reaction factors are examined through Taguchi S/N proportion technique. Likewise, the main technique for expectation of reaction boundaries is fulfilled by ANN model than the relapse model. Examination



of difference (ANOVA) results conceive that mass part of SiC, feed rate is the most oppressive component on reaction variable.

Kilickap et al. [5] in this paper, an exploratory review was led to decide the impact of various cutting boundaries, for example, cutting speed, feed rate, and profundity of cut on cutting power, surface harshness, and device wear in the processing of Ti-6242S combination utilizing the established carbide (WC) end factories with a 10 mm measurement. Test results were described using both Response Surface Methodology and Artificial Neural Networks (ANN). Utilizing Levenberg–Marquardt (LM), ANN prepared a network and loads. On the other hand, the Box Behnken plan was used to create the numerical models in RSM. Values obtained from the ANN and RSM were thought to be quite close to the knowledge obtained through trial research. High cutting velocities, low feed rates, and deep cuts produced the least cutting power and surface discomfort. Low cutting velocity, feed rate, and cut depth resulted in the base instrument wear. The difficulty with this study is that it did not take into account the helix angle and length of cut, which are important factors in the cutting process. However, this chapter has address this and as created a sustainable optimisation. Several studies have been done to predict cutting force, but the implementation of Heuristic and Metaheuristic Techniques for Advanced Nano-lubricant Machining Optimization for cutting force has not been done. The novelty of this chapter is the prediction and optimisation of cutting force during machining operations via ANN and QRCCD.

10.2 Materials and Method

The procedure for conducting an experimental examination of the effects of milling settings on the cutting force for alloys AA 8112 is described in this section. The experiment was done using a CNC milling SIEG 3/10/0016 and an HSS cutting tool. Tables 10.1 and 10.2 provide a detailed breakdown of the chemical composition of the tool and the alloy made of aluminum 8112. Table 10.3 also includes the levels and cutting settings.

Type: 

Full

 Blocks: 

1

Points

Non-center points: 42

Center points: 8

alpha = 2.37841

Options...

50 Runs

**Table 10.1** Machining factors and response parameters

| Exp. runs | Workpiece    | Machining tool                                                                                                                                                                                                                  | Variable parameters                                                | Response parameters |
|-----------|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------|---------------------|
| 1–50      | AA8112 alloy | Coated high-speed steel (the M42-high-speed-steel cutting tool of 13 mm diameter was employed in this study, having molybdenum of 9.5%, cobalt of 8.25%, chromium of 3.9%, carbon of 1.1%, tungsten of 1.6%, and vanadium 1.2%) | Spindle speed, feed rate, length of cut, depth of cut, helix angle | Cutting force       |

**Table 10.2** Chemical properties of AA8112 alloy

| Elemental composition | Weight % |
|-----------------------|----------|
| Aluminium (AL)        | 94.7     |
| Magnesium (Mg)        | 0.8      |
| Silicon (Si)          | 1.2      |
| Iron (Fe)             | 1.2      |
| Copper (Cu)           | 0.45     |
| Chromium (Cr)         | 0.25     |
| Zinc (Zn)             | 0.3      |
| Manganese (Mn)        | 0.6      |
| Titanium (Ti)         | 0.3      |
| Others                | 0.05     |
| Residuals             | 0.15     |

**Table 10.3** Variables and their levels in the experiment

| Name                     | Units  | Low  | High | – alpha    | + alpha |
|--------------------------|--------|------|------|------------|---------|
| Spindle speed ( $S_s$ )  | rpm    | 2000 | 4000 | 621.586    | 5378.41 |
| Feed rate ( $F_r$ )      | mm/min | 100  | 300  | – 37.8414  | 437.841 |
| Length of cut ( $L_c$ )  | mm     | 20   | 60   | – 7.56828  | 87.5683 |
| Depth of cut ( $D_c$ )   | mm     | 1    | 3    | – 0.378414 | 4.37841 |
| Helix angle ( $\alpha$ ) | 0      | 0    | 60   | – 41.3524  | 101.352 |

A 4 arms strain gauge dynamometer having bridge resistance of  $350\ \Omega$ ,  $5\text{ V}$  maximum with a wide range of  $0\text{--}300\text{ KGF}$  was employed in the machining process to measure the cutting force. The three (3) phases dynamometer measures the x-axis, y-axis, and z-axis during the cutting operations and the Eq. (10.1) shows the formulae used to calculate the final cutting force [6, 7].

$$C_f = \sqrt{C_{fx}^2 + C_{fy}^2 + C_{fz}^2} \quad (10.1)$$

where  $C_f$  is the consequential force,  $C_{fx}$ ,  $C_{fy}$  and  $C_{fz}$  are the machining cutting forces along the x-axis, y-axis, and z-axis, respectively as shown in the experimental setup in Fig. 10.1.

The scanning electron microscopy (SEM) and energy dispersive spectroscopy (EDS) analysis of the  $\text{TiO}_2$  nano-powder used in preparing the nano-lubricant are shown in Figs. 10.2. The EDS analysis confirmed that the chemical composition of the nano-powders is 99.7% titanium-oxide ( $\text{TiO}_2$ ). The morphology of the  $\text{TiO}_2$  on the SEM analysis is stable, with a specific area of  $240\text{ m/g}$  and particle size of  $15\text{ nm}$ . The stability of the nanoparticle size is very significant for the development of the nano-lubricant because the homogenisation process of nano-particles and the base oil needs uniform nanoparticle sizes.

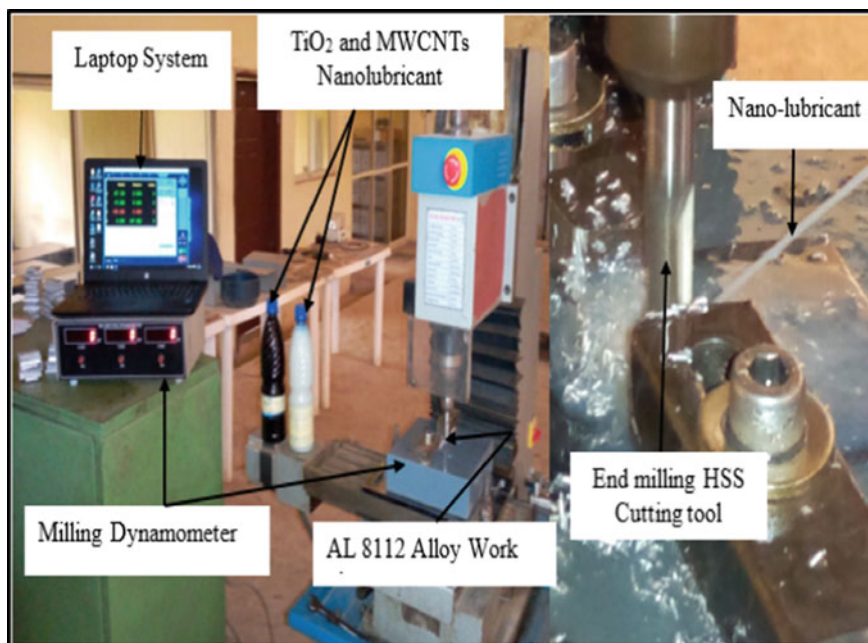


**Fig. 10.1** The experimental setup of the CNC milling machine

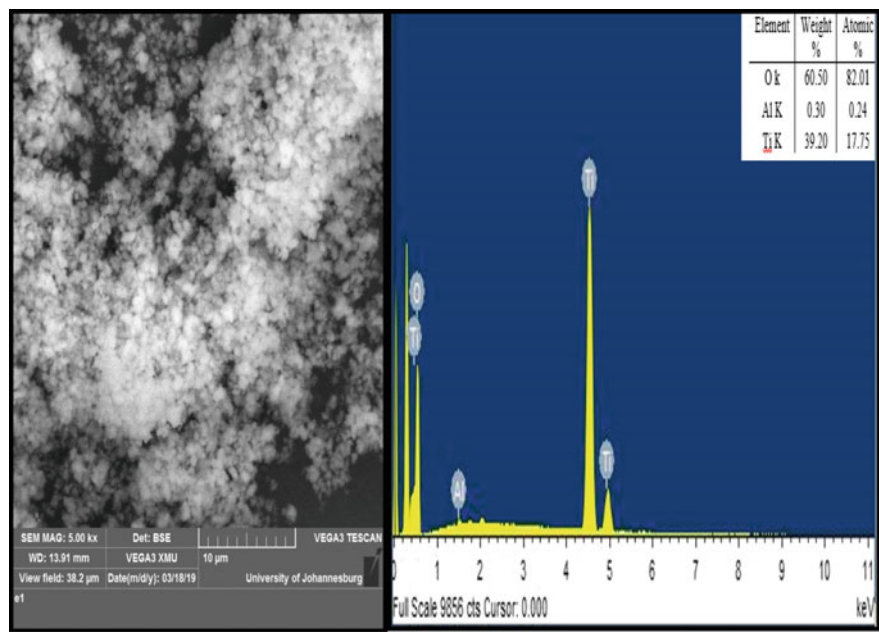


**Fig. 10.2** The SEM and EDS micrograph of  $\text{TiO}_2$  nano-powder used for the study

The Nanolubricant were developed with five different stages, the first stage is the weighing of the nanoparticles and the base oil. The second stage is the application of magnetic stirrer via mechanical process of mixing the nanopowder and the copra oil which is the cutting fluid for 2 h. The third stage is the used of ultrasonic machine to homogenised the Nanolubricant for 5 h, after the 5 h process the nano-lubricant is then formed as shown in Fig. 10.3. After developing the Nanolubricant the results show an excellent crystalline structure of the copra oil. This characteristic is in line with findings in the work of [8, 9] on the effects of coconut oil lubricant on the carbide cutting tool during turning operations. The EDS analysis shows the percentage chemical composition of the copra oil, by weight. The copra oil contains seven elements with a reasonable amount of carbon, oxygen, and silicon. The procedure followed during the experiment and the optimisation of the cutting force is presented in Fig. 10.4.

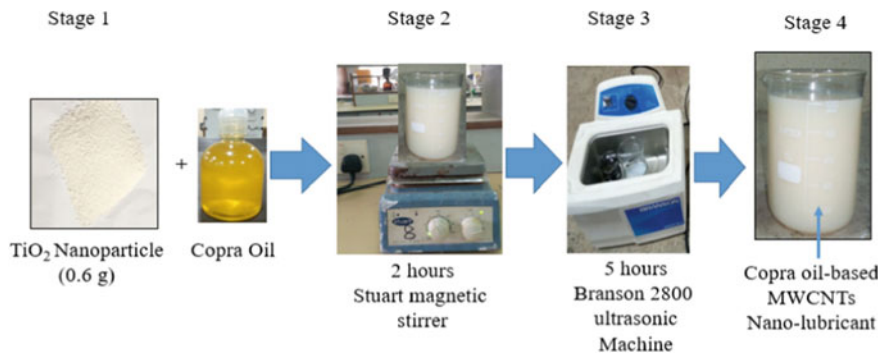
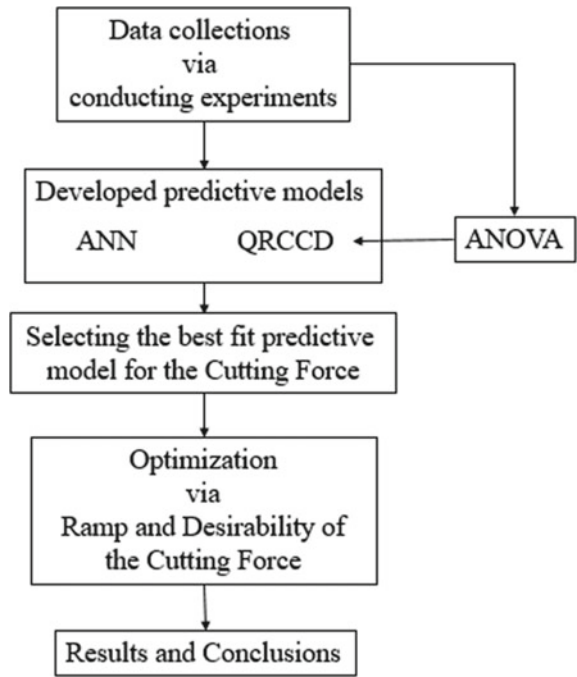


**Fig. 10.3** Experimental set-up for the preparation of the nano-lubricant used for the study

**Fig. 10.4** Procedure of the research design



**10.2.1 Mathematical Modelling Using Artificial Neural Network**

The design of ANN is roused by the natural brain organization to copy the mind execution to settle complex issues. The fake neurons are associated with one another to build the ANN. Every neuron’s information vector is boosted by the weight vector,

which is combined with a predisposition term to include the contribution of an initiation capacity. A neuron's output is the consequence of the enactment capability.

One of the most well-known networks for capability estimate is the feedforward brain network (Fig. 10.5), which includes one or more secret layers in addition to the information and result layers. The information layer does not handle data; instead, it has the ability to locate the information's noteworthy features. Layer by layer, input signal is distributed across the organization's neurons. While the synaptic loads are fixed. The result layer presents the measures of reaction factors.

A layer is a group of neurons arranged in parallel without having any interaction with each other. The workstation consists of three processes that are: the input layer, hidden layer, and output layer. Variables are presented to the workstation via the input layer and transferred to hidden layers where the actual work is done through a weight connections process; the hidden layers determine the output responses layer. After the experiment has been carried out, the values of the responses are recorded. The neuron has a bias  $\emptyset$ , which is added with the weighted sum  $W_n$  and input variables ( $U_n$ ) to determine the total net input ( $T_n$ ), as presented in Eq. (10.2) [10].

$$T_n = \sum_{i=1}^n (W_n * U_n) + \emptyset \quad (10.2)$$

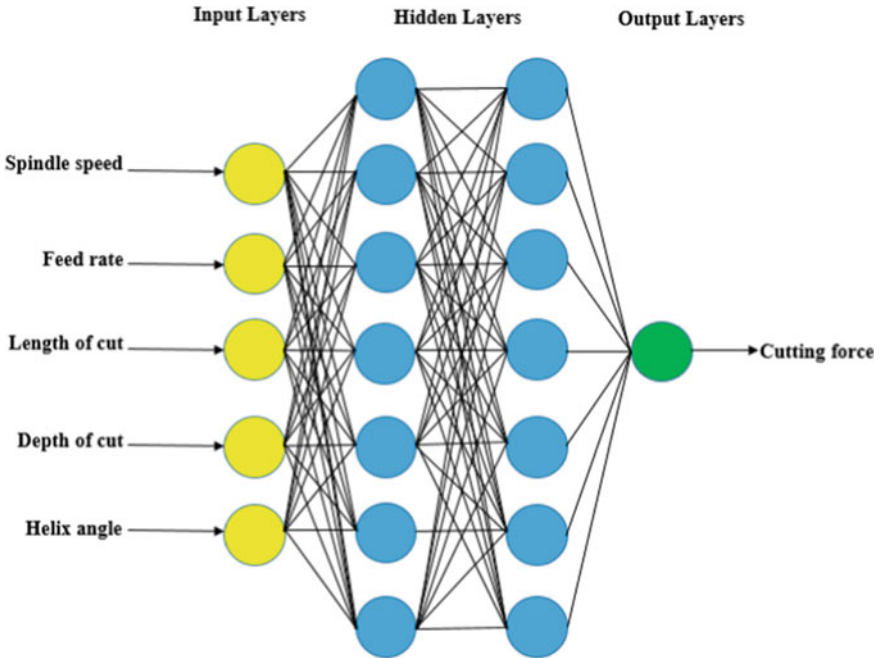


**Fig. 10.5** The neural network system for the end-milling operation of AA8112 alloy

The neuron for this Back Propagation feed-forward Neural Network (BPNN) has five (5) inputs, with five (5) weights; this weight is randomised during the training period of the BPNN. The transformation process is carried out through the sigmoid non-linear transfer function ( $Z$ ), which is given in Eq. (10.3).

$$Z = U_1 * W_1 + U_2 * W_2 + \dots + U_n * W_n + \emptyset * 1 \quad (10.3)$$

where the total net input ( $T_n$ ), is transposed as given in Eq. (10.4)

$$\hat{T} = Y_{out} = \text{sigmoid}(Z) \quad (10.4)$$

The sigmoid transfer function ( $Z_i$ ) is given in Eq. (10.5) as:

$$\text{Sigmoid}(Z_i) = \frac{1}{1 + e^{-Z_i}} \quad (10.5)$$

The output ( $Y_{out}$ ) is determined by multiplying the activated transfer function with the weight  $W_{ni}$  between the inner last layer of the hidden neuron and the output layer, becomes Eq. (10.6).

$$Y_{out} = W_{ni} * Z_i \quad (10.6)$$

The error is  $e_i$ , and is obtained by subtracting the experimental values from the predicted values. The equation is given in Eq. (10.7), and the total error (SSE) is computed using Eq. (10.8).

$$e_i = SR_e - SR_p \quad (10.7)$$

$$SSE = \frac{1}{2} \sum_{i=1}^n e_i^2 \quad (10.8)$$

Depending on the problem to be solved, ANN has numerous techniques for training a neural system. In this work, the BPNN was adopted to build and train the system for the prediction of output parameters. The structure of the ANN employed for this study is presented in Fig. 10.5. The inputs ( $U_n$ ) correspond to feed rate, spindle speed, length of cut, helix angle, and depth of cut are built in the ANN structure. The signal ( $\emptyset$ ) is the interior threshold of a neuron, i.e., the bias, and  $Z_i$  is the nonlinear transfer function. The neuron is trained with 70% input data, 15% of the input data for testing, while the remaining 15% input data is used for the validation process.

### 10.2.2 Mathematical Modelling Using Quadratic Rotatable Central Composite Design

Quadratic rotatable central composite design (QRCCD) is a design tool employed to analyze engineering problems. QRCCD is one of the packages in response surface methodology in Design expert software, mainly used for factors above four and five-level to study the relationship's effects on the response parameters. QRCCD is suitable for prediction, optimization, and model developments in the manufacturing of mechanical components. In this study, the relationship between surface roughness (the response parameters) and the cutting parameters under multi-walled carbon nano-lubricant cutting conditions is given in Eq. (10.9) [11–13].

$$C_f = \theta(S_s, F_r, L_c, D_c, \alpha) \quad (10.9)$$

The desired machinability feature is  $C_f$  and the response function is  $\theta$ . However, the evaluation  $C_f$  They are projected using a scientific model, which is suitable for evaluating the effects of cutting parameters interface on machinability features. The interactions become Eq. (10.10–10.11).

$$C_f = \theta\left(S_s^{X_x}, F_r^{Y_y}, L_c^{Z_z}, D_c^{Z_r}, \alpha^{Z_i}\right) \quad (10.10)$$

$$\begin{aligned} \log(C_f) &= \log(\theta) + X_x \cdot \log(S_s) + Y_y \cdot \log(F_r) + Z_z \cdot \log(L_c) \\ &+ Z_r \cdot \log(D_c) + Z_i \cdot \log(\alpha) \end{aligned} \quad (10.11)$$

where,

$$\begin{aligned} C_f &= \log(Y_i)\beta_0 = \log(\theta)x_1 = \log(S_s)x_2 = \log(F_r) \\ x_3 &= \log(L_c)x_4 = \log(D_c)x_5 = \log(\alpha) \end{aligned}$$

and

$$x = \beta_1, y = \beta_2, z = \beta_3, z_r = \beta_4, z_i = \beta_5.$$

The overview of a replacement gets the following expression in Eq. (10.10), where the constant and exponents  $\theta$ ,  $X_x$ ,  $Y_y$ ,  $Z_z$ ,  $Z_r$ , and  $Z_i$  are determined by the least-squares regression procedure. This research work, the Quadratic rotatable central composite design-based regression model second-order, is implemented and given in Eq. (10.12) as:

$$Y_i = \beta_0 + \sum \beta_i x_i + \sum \beta_{ii} x_i^2 + \sum \beta_{ij} x_i x_j + e \quad (10.12)$$



The regression constant is  $\beta_0$ , and the coefficients are  $\beta_1$  to  $\beta_5$ , and the logarithmic alteration of parameters are  $x_1, x_2, x_3, x_4$ , and  $x_5$ . i.e.,  $S_s, F_r, L_c, D_c, \alpha$ , and  $e$  represent the spindle speed, feed rate, length-of-cut, depth-of-cut, helix angle, and the error term, respectively. The input variables and levels were undoubtedly within the interludes recommended by the computer numerical control manufacturer. Equation (10.12) is the regression model employed to develop the prediction model from the response surface method from the design experts.

### 10.2.3 Validation of the Surface Roughness Results

In order to ascertain the accuracy of the developed model from the **experimental data**, both the percentage deviation  $\varphi_i$ , and the average deviation  $\bar{\varphi}$  was used. After the prediction of the surface roughness, the percentage deviation was utilized to validate the rate of prediction of the surface roughness. The general equation to determine the validation accuracy is presented in Eq. (10.13) [14].

$$\varphi_i = \left( \frac{C_{f(m)} - C_{f(e)}}{C_{f(e)}} \right) \times 100\% \quad (10.13)$$

where,  $\varphi_i$  : percentage deviation of single variables,  $C_f$  (m) measure results,  $C_f$  (e) experimental results.

## 10.3 Results and Discussion

The result used in the ANN and QRCCD prediction analysis was obtained from the experimental results from the study of cutting force during the end-milling machining of AA8112 alloy with a biodegradable TiO<sub>2</sub>-nano-lubricants. This data is applied for the development of the mathematical models. The total experimental number of fifty (50) is derived from the trial runs, which is based on the quadratic rotatable central composite design (QRCCD) for five factors-five levels of machining parameters. The results gotten from the experiment is presented in Table 10.4.

**Table 10.4** Data for the cutting force prediction and optimization

|     |     | Factor 1              | Factor 2          | Factor 3              | Factor 4             | Factor 5                    | Response 1         |
|-----|-----|-----------------------|-------------------|-----------------------|----------------------|-----------------------------|--------------------|
| Std | Run | A: spindle speed (Ss) | B: feed rate (Fr) | C: length of cut (Lc) | D: depth of cut (Dc) | E: helix angle ( $\alpha$ ) | Cutting force (Cf) |
|     |     | rpm                   | mm/min            | mm                    | mm                   | 0                           | N                  |
| 27  | 1   | 2500                  | 150               | 30                    | 2.5                  | 45                          | 74.34              |
| 6   | 2   | 2500                  | 250               | 50                    | 2.5                  | 15                          | 102.62             |
| 44  | 3   | 2500                  | 250               | 30                    | 1.5                  | 15                          | 99.62              |
| 42  | 4   | 3500                  | 250               | 50                    | 1.5                  | 45                          | 84.29              |
| 20  | 5   | 2500                  | 250               | 30                    | 1.5                  | 45                          | 88.24              |
| 37  | 6   | 2500                  | 150               | 50                    | 1.5                  | 45                          | 86.27              |
| 14  | 7   | 3000                  | 200               | 40                    | 2                    | 30                          | 89.39              |
| 12  | 8   | 3500                  | 250               | 30                    | 2.5                  | 45                          | 94.68              |
| 30  | 9   | 2500                  | 150               | 50                    | 2.5                  | 45                          | 93.58              |
| 16  | 10  | 3500                  | 150               | 30                    | 1.5                  | 15                          | 78.76              |
| 38  | 11  | 2500                  | 250               | 50                    | 2.5                  | 45                          | 94.23              |
| 1   | 12  | 3000                  | 200               | 40                    | 2                    | 30                          | 59.78              |
| 22  | 13  | 2500                  | 150               | 30                    | 2.5                  | 15                          | 68.67              |
| 10  | 14  | 3500                  | 150               | 50                    | 2.5                  | 45                          | 59.23              |
| 23  | 15  | 3500                  | 150               | 30                    | 2.5                  | 15                          | 58.52              |
| 19  | 16  | 2500                  | 250               | 30                    | 2.5                  | 15                          | 86.11              |
| 28  | 17  | 2500                  | 250               | 50                    | 1.5                  | 45                          | 67.11              |
| 24  | 18  | 3000                  | 200               | 40                    | 2                    | 60                          | 55.67              |
| 25  | 19  | 3000                  | 200               | 40                    | 2                    | 30                          | 59.29              |
| 48  | 20  | 4000                  | 200               | 40                    | 2                    | 30                          | 32.56              |
| 40  | 21  | 3000                  | 200               | 40                    | 2                    | 30                          | 59.47              |
| 13  | 22  | 3000                  | 300               | 40                    | 2                    | 30                          | 105.11             |
| 5   | 23  | 3500                  | 150               | 50                    | 1.5                  | 45                          | 98.51              |
| 26  | 24  | 3000                  | 200               | 60                    | 2                    | 30                          | 102.53             |
| 41  | 25  | 3000                  | 200               | 40                    | 1                    | 30                          | 50.24              |
| 8   | 26  | 3500                  | 150               | 30                    | 1.5                  | 45                          | 78.59              |
| 15  | 27  | 3500                  | 250               | 30                    | 1.5                  | 45                          | 91.34              |
| 2   | 28  | 3500                  | 250               | 50                    | 2.5                  | 45                          | 89.56              |
| 35  | 29  | 3500                  | 150               | 30                    | 2.5                  | 45                          | 60.57              |
| 36  | 30  | 2500                  | 150               | 50                    | 1.5                  | 15                          | 61.12              |
| 49  | 31  | 2500                  | 250               | 50                    | 1.5                  | 15                          | 68.45              |
| 21  | 32  | 3000                  | 200               | 40                    | 2                    | 30                          | 59.46              |
| 11  | 33  | 3500                  | 250               | 50                    | 2.5                  | 15                          | 85.56              |

(continued)

**Table 10.4** (continued)

|     |     | Factor 1              | Factor 2          | Factor 3              | Factor 4             | Factor 5                    | Response 1         |
|-----|-----|-----------------------|-------------------|-----------------------|----------------------|-----------------------------|--------------------|
| Std | Run | A: spindle speed (Ss) | B: feed rate (Fr) | C: length of cut (Lc) | D: depth of cut (Dc) | E: helix angle ( $\alpha$ ) | Cutting force (Cf) |
| 4   | 34  | 3000                  | 200               | 40                    | 3                    | 30                          | 110.23             |
| 46  | 35  | 3500                  | 150               | 50                    | 1.5                  | 15                          | 76.86              |
| 33  | 36  | 3000                  | 200               | 40                    | 2                    | 30                          | 59.48              |
| 50  | 37  | 3500                  | 150               | 50                    | 2.5                  | 15                          | 65.12              |
| 47  | 38  | 3000                  | 100               | 40                    | 2                    | 30                          | 33.59              |
| 34  | 39  | 3500                  | 250               | 50                    | 1.5                  | 15                          | 58.58              |
| 45  | 40  | 2000                  | 200               | 40                    | 2                    | 30                          | 108.56             |
| 17  | 41  | 3000                  | 200               | 20                    | 2                    | 30                          | 59.55              |
| 29  | 42  | 3500                  | 250               | 30                    | 2.5                  | 15                          | 59.11              |
| 18  | 43  | 2500                  | 150               | 30                    | 1.5                  | 45                          | 64.15              |
| 39  | 44  | 3500                  | 250               | 30                    | 1.5                  | 15                          | 65.11              |
| 32  | 45  | 3000                  | 200               | 40                    | 2                    | 0                           | 60.23              |
| 31  | 46  | 2500                  | 150               | 50                    | 2.5                  | 15                          | 52.55              |
| 43  | 47  | 2500                  | 250               | 30                    | 2.5                  | 45                          | 63.12              |
| 7   | 48  | 3000                  | 200               | 40                    | 2                    | 30                          | 59.25              |
| 3   | 49  | 3000                  | 200               | 40                    | 2                    | 30                          | 59.25              |
| 9   | 50  | 2500                  | 150               | 30                    | 1.5                  | 15                          | 54.53              |

### 10.3.1 The Cutting Force Models Prediction via QRCCD

The model uses factor coding. A partial Type III sum is the square sum. The Model F-value of 4.20 suggests that the model is significant. Only 1.89% of the time could noise account for an F-value this high. When the  $P$ -value is less 0.0500, model terms are deemed significant. Important model terms in this case include A, B, C, D, ABE, BCD, A2B, A2D, and AB2. If the value is higher than 0.1000, model terms are not significant. If your model has a lot of extraneous terms, model reduction may improve it. When compared to the pure error at 0.05, the F-value for the lack of fit suggests that it is not significant. A “Lack of Fit F-value” this significant has an 82.22% possibility of being caused by noise, per Table 10.5. We prefer a non-significant lack of fit since we want the model to fit. Adeq Precision measures the signal-to-noise ratio. The ideal ratio is at least 4. Your ratio of 8.517 indicates a suitable signal, according to Table 10.6. Use this model to navigate the design area.

The coefficient estimate displays the anticipated change in reaction per unit change in factor value when all other factors remain constant. In an orthogonal design, the intercept is the mean response over all runs. The coefficients alter the average in the vicinity of it depending on the factor values. When the factors are orthogonal, the

**Table 10.5** ANOVA analysis of the cutting force

| Source                     | Sum of squares | df | Mean square | F-value | p-value |             |
|----------------------------|----------------|----|-------------|---------|---------|-------------|
| <i>Model</i>               | 17,038.81      | 41 | 415.58      | 4.20    | 0.0189  | Significant |
| A-spindle speed ( $S_s$ )  | 2888.00        | 1  | 2888.00     | 29.17   | 0.0006  |             |
| B-feed rate ( $F_r$ )      | 2557.56        | 1  | 2557.56     | 25.84   | 0.0009  |             |
| C-length of cut ( $L_c$ )  | 923.64         | 1  | 923.64      | 9.33    | 0.0157  |             |
| D-depth of cut ( $D_c$ )   | 1799.40        | 1  | 1799.40     | 18.18   | 0.0027  |             |
| E-helix angle ( $\alpha$ ) | 10.40          | 1  | 10.40       | 0.1050  | 0.7542  |             |
| AB                         | 120.98         | 1  | 120.98      | 1.22    | 0.3011  |             |
| AC                         | 0.4705         | 1  | 0.4705      | 0.0048  | 0.9467  |             |
| AD                         | 347.29         | 1  | 347.29      | 3.51    | 0.0979  |             |
| AE                         | 161.01         | 1  | 161.01      | 1.63    | 0.2380  |             |
| BC                         | 84.63          | 1  | 84.63       | 0.8549  | 0.3822  |             |
| BD                         | 438.52         | 1  | 438.52      | 4.43    | 0.0684  |             |
| BE                         | 83.53          | 1  | 83.53       | 0.8438  | 0.3852  |             |
| CD                         | 290.89         | 1  | 290.89      | 2.94    | 0.1248  |             |
| CE                         | 102.67         | 1  | 102.67      | 1.04    | 0.3383  |             |
| DE                         | 61.66          | 1  | 61.66       | 0.6229  | 0.4527  |             |
| A <sup>2</sup>             | 87.35          | 1  | 87.35       | 0.8824  | 0.3750  |             |
| B <sup>2</sup>             | 61.08          | 1  | 61.08       | 0.6170  | 0.4548  |             |
| C <sup>2</sup>             | 510.87         | 1  | 510.87      | 5.16    | 0.0528  |             |
| D <sup>2</sup>             | 465.87         | 1  | 465.87      | 4.71    | 0.0619  |             |
| E <sup>2</sup>             | 43.62          | 1  | 43.62       | 0.4406  | 0.5255  |             |
| ABC                        | 13.76          | 1  | 13.76       | 0.1389  | 0.7190  |             |
| ABD                        | 444.62         | 1  | 444.62      | 4.49    | 0.0669  |             |
| ABE                        | 1243.01        | 1  | 1243.01     | 12.56   | 0.0076  |             |
| ACD                        | 85.09          | 1  | 85.09       | 0.8595  | 0.3810  |             |
| ACE                        | 274.60         | 1  | 274.60      | 2.77    | 0.1344  |             |
| ADE                        | 29.95          | 1  | 29.95       | 0.3026  | 0.5973  |             |
| BCD                        | 937.23         | 1  | 937.23      | 9.47    | 0.0152  |             |
| BCE                        | 162.99         | 1  | 162.99      | 1.65    | 0.2354  |             |
| BDE                        | 9.72           | 1  | 9.72        | 0.0982  | 0.7620  |             |
| CDE                        | 41.45          | 1  | 41.45       | 0.4187  | 0.5357  |             |
| A <sup>2</sup> B           | 1029.21        | 1  | 1029.21     | 10.40   | 0.0122  |             |
| A <sup>2</sup> C           | 510.01         | 1  | 510.01      | 5.15    | 0.0529  |             |
| A <sup>2</sup> D           | 1524.48        | 1  | 1524.48     | 15.40   | 0.0044  |             |

(continued)

**Table 10.5** (continued)

| Source                        | Sum of squares | df | Mean square | F-value | p-value |                 |
|-------------------------------|----------------|----|-------------|---------|---------|-----------------|
| A <sup>2</sup> E              | 209.31         | 1  | 209.31      | 2.11    | 0.1840  |                 |
| AB <sup>2</sup>               | 2158.55        | 1  | 2158.55     | 21.81   | 0.0016  |                 |
| ABCD                          | 189.35         | 1  | 189.35      | 1.91    | 0.2040  |                 |
| ABCE                          | 12.15          | 1  | 12.15       | 0.1228  | 0.7351  |                 |
| ABDE                          | 59.24          | 1  | 59.24       | 0.5984  | 0.4614  |                 |
| ACDE                          | 226.85         | 1  | 226.85      | 2.29    | 0.1685  |                 |
| BCDE                          | 8.57           | 1  | 8.57        | 0.0866  | 0.7761  |                 |
| A <sup>2</sup> B <sup>2</sup> | 18.84          | 1  | 18.84       | 0.1904  | 0.6742  |                 |
| Residual                      | 791.95         | 8  | 98.99       |         |         |                 |
| Lack of fit                   | 6.11           | 1  | 6.11        | 0.0544  | 0.8222  | Not significant |
| Pure error                    | 785.84         | 7  | 112.26      |         |         |                 |
| Cor Total                     | 17,830.76      | 49 |             |         |         |                 |

**Table 10.6** Fit statistics validation of cutting force

|          |       |                         |        |
|----------|-------|-------------------------|--------|
| Std. Dev | 9.95  | R <sup>2</sup>          | 0.9556 |
| Mean     | 73.05 | Adjusted R <sup>2</sup> | 0.7280 |
| C.V. %   | 13.62 | Adeq Precision          | 8.5175 |

VIFs are 1, multi-collinearity is indicated by VIFs more than 1, and Table 10.7 demonstrates that the higher the VIF, the more severe the correlation of the components is. VIFs under 10 are generally considered tolerable.

$$\begin{aligned} \text{Cutting force (Cf)} = & +63.17 - 38.00A + 35.76B + 21.49C \\ & + 30.00D - 2.28E - 7.78AB + 0.4850AC \\ & - 13.18AD + 8.97AE - 6.50BC + 14.81BD \\ & - 6.46BE + 12.06CD + 7.17CE - 5.55DE \\ & + 7.39A^2 + 6.18B^2 + 17.87C^2 + 17.06C^2 \\ & + 17.06D^2 - 5.22E^2 + 5.24ABC + 29.82ABD \\ & + 49.86ABE - 13.05ACD - 23.44ACE \\ & - 7.74ADE + 43.29BCD - 18.06BCE \\ & - 4.41BDE - 9.11CDE - 101.45A^2B \\ & - 71.42A^2C - 123.47A^2D + 45.75A^2E \\ & + 146.92AB^2 \end{aligned}$$

(10.14)

**Table 10.7** ANOVA coefficients of the cutting force under TiO<sub>2</sub> nano-lubricant

| Factor                            | Coefficient estimate | df | Standard error | 95% CI low | 95% CI high | VIF    |
|-----------------------------------|----------------------|----|----------------|------------|-------------|--------|
| Intercept                         | 63.17                | 1  | 3.52           | 55.06      | 71.28       |        |
| A-spindle speed (S <sub>s</sub> ) | − 38.00              | 1  | 7.04           | − 54.22    | − 21.78     | 5.00   |
| B-Feed rate (F <sub>r</sub> )     | 35.76                | 1  | 7.04           | 19.54      | 51.98       | 5.00   |
| C-length of cut (L <sub>c</sub> ) | 21.49                | 1  | 7.04           | 5.27       | 37.71       | 5.00   |
| D-depth of cut (D <sub>c</sub> )  | 30.00                | 1  | 7.04           | 13.77      | 46.22       | 5.00   |
| E-helix angle (α)                 | − 2.28               | 1  | 7.04           | − 18.50    | 13.94       | 5.00   |
| AB                                | − 7.78               | 1  | 7.04           | − 24.00    | 8.45        | 1.0000 |
| AC                                | 0.4850               | 1  | 7.04           | − 15.74    | 16.71       | 1.0000 |
| AD                                | − 13.18              | 1  | 7.04           | − 29.40    | 3.05        | 1.0000 |
| AE                                | 8.97                 | 1  | 7.04           | − 7.25     | 25.20       | 1.0000 |
| BC                                | − 6.50               | 1  | 7.04           | − 22.73    | 9.72        | 1.0000 |
| BD                                | 14.81                | 1  | 7.04           | − 1.42     | 31.03       | 1.0000 |
| BE                                | − 6.46               | 1  | 7.04           | − 22.69    | 9.76        | 1.0000 |
| CD                                | 12.06                | 1  | 7.04           | − 4.16     | 28.28       | 1.0000 |
| CE                                | 7.17                 | 1  | 7.04           | − 9.06     | 23.39       | 1.0000 |
| DE                                | − 5.55               | 1  | 7.04           | − 21.78    | 10.67       | 1.0000 |
| A <sup>2</sup>                    | 7.39                 | 1  | 7.87           | − 10.75    | 25.53       | 1.25   |
| B <sup>2</sup>                    | 6.18                 | 1  | 7.87           | − 11.96    | 24.32       | 1.25   |
| C <sup>2</sup>                    | 17.87                | 1  | 7.87           | − 0.2698   | 36.01       | 1.25   |
| D <sup>2</sup>                    | 17.06                | 1  | 7.87           | − 1.07     | 35.20       | 1.25   |
| E <sup>2</sup>                    | − 5.22               | 1  | 7.87           | − 23.36    | 12.92       | 1.25   |
| ABC                               | 5.24                 | 1  | 14.07          | − 27.20    | 37.69       | 1.0000 |
| ABD                               | 29.82                | 1  | 14.07          | − 2.63     | 62.27       | 1.0000 |
| ABE                               | 49.86                | 1  | 14.07          | 17.41      | 82.31       | 1.0000 |
| ACD                               | − 13.05              | 1  | 14.07          | − 45.49    | 19.40       | 1.0000 |
| ACE                               | − 23.44              | 1  | 14.07          | − 55.88    | 9.01        | 1.0000 |
| ADE                               | − 7.74               | 1  | 14.07          | − 40.19    | 24.71       | 1.0000 |
| BCD                               | 43.29                | 1  | 14.07          | 10.85      | 75.74       | 1.0000 |
| BCE                               | − 18.06              | 1  | 14.07          | − 50.50    | 14.39       | 1.0000 |
| BDE                               | − 4.41               | 1  | 14.07          | − 36.86    | 28.04       | 1.0000 |
| CDE                               | − 9.11               | 1  | 14.07          | − 41.55    | 23.34       | 1.0000 |

(continued)

**Table 10.7** (continued)

| Factor                        | Coefficient estimate | df | Standard error | 95% CI low | 95% CI high | VIF    |
|-------------------------------|----------------------|----|----------------|------------|-------------|--------|
| A <sup>2</sup> B              | − 101.45             | 1  | 31.46          | − 174.00   | − 28.90     | 5.00   |
| A <sup>2</sup> C              | − 71.42              | 1  | 31.46          | − 143.97   | 1.14        | 5.00   |
| A <sup>2</sup> D              | − 123.47             | 1  | 31.46          | − 196.02   | − 50.92     | 5.00   |
| A <sup>2</sup> E              | 45.75                | 1  | 31.46          | − 26.80    | 118.30      | 5.00   |
| AB <sup>2</sup>               | 146.92               | 1  | 31.46          | 74.37      | 219.47      | 5.00   |
| ABCD                          | − 38.92              | 1  | 28.14          | − 103.81   | 25.97       | 1.0000 |
| ABCE                          | − 9.86               | 1  | 28.14          | − 74.75    | 55.03       | 1.0000 |
| ABDE                          | 21.77                | 1  | 28.14          | − 43.12    | 86.66       | 1.0000 |
| ACDE                          | − 42.60              | 1  | 28.14          | − 107.49   | 22.29       | 1.0000 |
| BCDE                          | − 8.28               | 1  | 28.14          | − 73.17    | 56.61       | 1.0000 |
| A <sup>2</sup> B <sup>2</sup> | 30.69                | 1  | 70.35          | − 131.54   | 192.93      | 2.25   |

Using the equation stated in terms of coded factors, it is possible to predict the reaction for given concentrations of each element. The high values of the factors are by default recorded as + 1 and the low levels as − 1. The coded equation is helpful for determining the elements’ relative importance. By comparing the factor coefficients given in Eq. (10.14). Figure 10.6 shows the prediction analysis of the cutting force graph done with QRCCD and also, Table 10.8 present the detail analysis of the predicted, actual, residual and influence on fitted value.

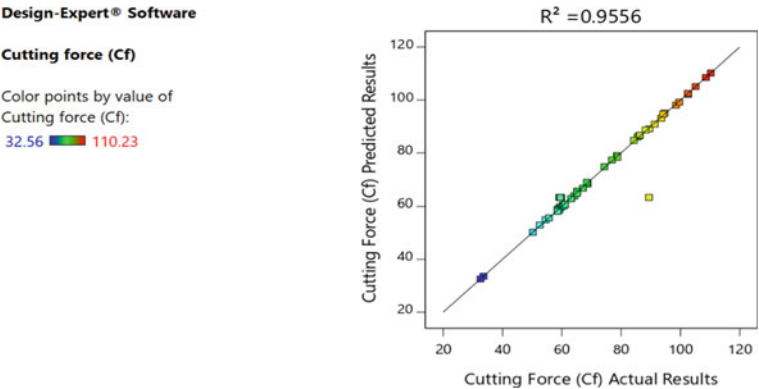


**Fig. 10.6** The plot of the **Experimental data** and predicted data of cutting force

**Table 10.8** The actual, predicted, internal and external residual analysis of the cutting force

| Run Order | Actual value | Predicted value | Residual | Leverage | Internally studentized residuals | Externally studentized residuals | Cook's distance | Influence on fitted value DFFITS |
|-----------|--------------|-----------------|----------|----------|----------------------------------|----------------------------------|-----------------|----------------------------------|
| 1         | 74.34        | 75.55           | − 1.21   | 0.581    | − 0.202                          | − 0.198                          | 0.002           | − 0.233                          |
| 2         | 102.62       | 96.83           | 5.79     | 0.581    | 0.973                            | 0.971                            | 0.049           | 1.144                            |
| 3         | 99.62        | 100.48          | − 0.8642 | 0.581    | − 0.145                          | − 0.142                          | 0.001           | − 0.167                          |
| 4         | 84.29        | 75.75           | 8.54     | 0.581    | 1.434                            | 1.470                            | 0.106           | 1.732                            |
| 5         | 88.24        | 77.69           | 10.55    | 0.581    | 1.772                            | 1.865                            | 0.161           | 2.197                            |
| 6         | 86.27        | 85.89           | 0.3817   | 0.581    | 0.064                            | 0.063                            | 0.000           | 0.074                            |
| 7         | 89.39        | 62.13           | 27.26    | 0.100    | 3.122                            | 4.022 <sup>(1)</sup>             | 0.040           | 1.341                            |
| 8         | 94.68        | 84.79           | 9.89     | 0.581    | 1.661                            | 1.731                            | 0.142           | 2.040                            |
| 9         | 93.58        | 86.86           | 6.72     | 0.581    | 1.128                            | 1.135                            | 0.065           | 1.337                            |
| 10        | 78.76        | 74.90           | 3.86     | 0.581    | 0.648                            | 0.640                            | 0.022           | 0.754                            |
| 11        | 94.23        | 92.94           | 1.29     | 0.581    | 0.216                            | 0.212                            | 0.002           | 0.249                            |
| 12        | 59.78        | 62.13           | − 2.35   | 0.100    | − 0.269                          | − 0.263                          | 0.000           | − 0.088                          |
| 13        | 68.67        | 66.92           | 1.75     | 0.581    | 0.294                            | 0.288                            | 0.004           | 0.339                            |
| 14        | 59.23        | 61.83           | − 2.60   | 0.581    | − 0.436                          | − 0.428                          | 0.010           | − 0.504                          |
| 15        | 58.52        | 57.37           | 1.15     | 0.581    | 0.193                            | 0.188                            | 0.002           | 0.222                            |
| 16        | 86.11        | 89.25           | − 3.14   | 0.581    | − 0.527                          | − 0.519                          | 0.014           | − 0.611                          |
| 17        | 67.11        | 70.44           | − 3.33   | 0.581    | − 0.559                          | − 0.550                          | 0.016           | − 0.648                          |
| 18        | 55.67        | 68.99           | − 13.32  | 0.200    | − 1.618                          | − 1.681                          | 0.024           | − 0.840                          |
| 19        | 59.29        | 62.13           | − 2.84   | 0.100    | − 0.325                          | − 0.318                          | 0.000           | − 0.106                          |
| 20        | 32.56        | 33.05           | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |
| 21        | 59.47        | 62.13           | − 2.66   | 0.100    | − 0.304                          | − 0.298                          | 0.000           | − 0.099                          |
| 22        | 105.11       | 105.60          | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |
| 23        | 98.51        | 88.94           | 9.57     | 0.581    | 1.606                            | 1.667                            | 0.133           | 1.965                            |
| 24        | 102.53       | 103.02          | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |
| 25        | 50.24        | 50.73           | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |
| 26        | 78.59        | 79.30           | − 0.7095 | 0.581    | − 0.119                          | − 0.117                          | 0.001           | − 0.137                          |
| 27        | 91.34        | 94.26           | − 2.92   | 0.581    | − 0.490                          | − 0.482                          | 0.012           | − 0.568                          |
| 28        | 89.56        | 100.01          | − 10.45  | 0.581    | − 1.755                          | − 1.844                          | 0.158           | − 2.173                          |
| 29        | 60.57        | 61.77           | − 1.20   | 0.581    | − 0.202                          | − 0.198                          | 0.002           | − 0.233                          |
| 30        | 61.12        | 58.35           | 2.77     | 0.581    | 0.465                            | 0.457                            | 0.011           | 0.538                            |
| 31        | 68.45        | 74.32           | − 5.87   | 0.581    | − 0.986                          | − 0.985                          | 0.050           | − 1.161                          |
| 32        | 59.46        | 62.13           | − 2.67   | 0.100    | − 0.305                          | − 0.299                          | 0.000           | − 0.100                          |
| 33        | 85.56        | 81.70           | 3.86     | 0.581    | 0.648                            | 0.640                            | 0.022           | 0.754                            |
| 34        | 110.23       | 110.72          | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |

(continued)



**Table 10.8** (continued)

| Run Order | Actual value | Predicted value | Residual | Leverage | Internally studentized residuals | Externally studentized residuals | Cook's distance | Influence on fitted value DFFITS |
|-----------|--------------|-----------------|----------|----------|----------------------------------|----------------------------------|-----------------|----------------------------------|
| 35        | 76.86        | 89.09           | − 12.23  | 0.581    | − 2.054                          | − 2.223                          | 0.217           | − 2.619 <sup>(2)</sup>           |
| 36        | 59.48        | 62.13           | − 2.65   | 0.100    | − 0.303                          | − 0.297                          | 0.000           | − 0.099                          |
| 37        | 65.12        | 61.98           | 3.14     | 0.581    | 0.527                            | 0.519                            | 0.014           | 0.611                            |
| 38        | 33.59        | 34.08           | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |
| 39        | 58.58        | 57.43           | 1.15     | 0.581    | 0.193                            | 0.188                            | 0.002           | 0.222                            |
| 40        | 108.56       | 109.05          | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |
| 41        | 59.55        | 60.04           | − 0.4875 | 0.900    | − 0.167                          | − 0.164                          | 0.009           | − 0.492                          |
| 42        | 59.11        | 61.92           | − 2.81   | 0.581    | − 0.472                          | − 0.464                          | 0.011           | − 0.546                          |
| 43        | 64.15        | 64.98           | − 0.8345 | 0.581    | − 0.140                          | − 0.137                          | 0.001           | − 0.161                          |
| 44        | 65.11        | 71.39           | − 6.28   | 0.581    | − 1.055                          | − 1.057                          | 0.057           | − 1.246                          |
| 45        | 60.23        | 55.26           | 4.97     | 0.200    | 0.603                            | 0.595                            | 0.003           | 0.297                            |
| 46        | 52.55        | 59.32           | − 6.77   | 0.581    | − 1.137                          | − 1.145                          | 0.066           | − 1.349                          |
| 47        | 63.00        | 66.45           | − 3.45   | 0.581    | − 0.580                          | − 0.571                          | 0.017           | − 0.673                          |
| 48        | 59.25        | 62.13           | − 2.88   | 0.100    | − 0.329                          | − 0.323                          | 0.000           | − 0.108                          |
| 49        | 59.25        | 62.13           | − 2.88   | 0.100    | − 0.329                          | − 0.323                          | 0.000           | − 0.108                          |
| 50        | 54.53        | 56.36           | − 1.83   | 0.581    | − 0.307                          | − 0.301                          | 0.005           | − 0.355                          |

The superscript values 1 and 2, shows that there are wide variations between the actual and predicted value, which can because by several factors during machining

### ***10.3.2 The Prediction of the Cutting Force Using ANN for TiO<sub>2</sub> Nano-lubricant***

This section presents the result of the prediction of cutting force experimental results with the TiO<sub>2</sub> nano-lubricant during the end milling of AA8112 alloy using ANN. The Back Propagation feed-forward Neural Network (BPNN) was used to predict the experimental outcome and Levenberg–Marquardt (trainlm) to train the neuron for better performance. The BPNN employed the sigmoid non-linear transfer function (Z) and the total sum of squared error (SSE) to determine the error performance. The statistical formulation is presented in Eqs. (10.2)–(10.8). Figure 9.8 shows the neuron network used for the cutting force (that is the pattern for surface roughness prediction).

From the analysis, the R-value for the data training set, data validation, and data testing are 0.93394, 0.97481, and 0.93984, respectively. The overall performance of the training, validation, testing is 0.93751, as depicted in Fig. 10.7a–d. The solid line shows the level of performance of the regression model. While the dashed line is the perfect line of the regression, both lines help to show the relationship between the

target and the predicted cutting force under  $\text{TiO}_2$  nano-lubricant machining environment. From the ANN model, the best validation performance as measured applying the SSE occurs at epoch 0 and iteration 6, as presented in Fig. 10.7a–d. From the analysis, the SSE gradually decreased from the zero epoch to the peak point. Figure 10.8 shows the performance analysis of the ANN model for the  $\text{TiO}_2$  nano-lubricant machining environment using SSE with the coefficient relationship (R-value) of the regression model. The R-value explains the nearness of the ANN model predicted output target (cutting force) with the experimental result obtained from the machining operation. Figure 10.9 shows the gradient constant of the Marquardt unit parameter ( $\mu$ ), total validation checks, and the iterations value.

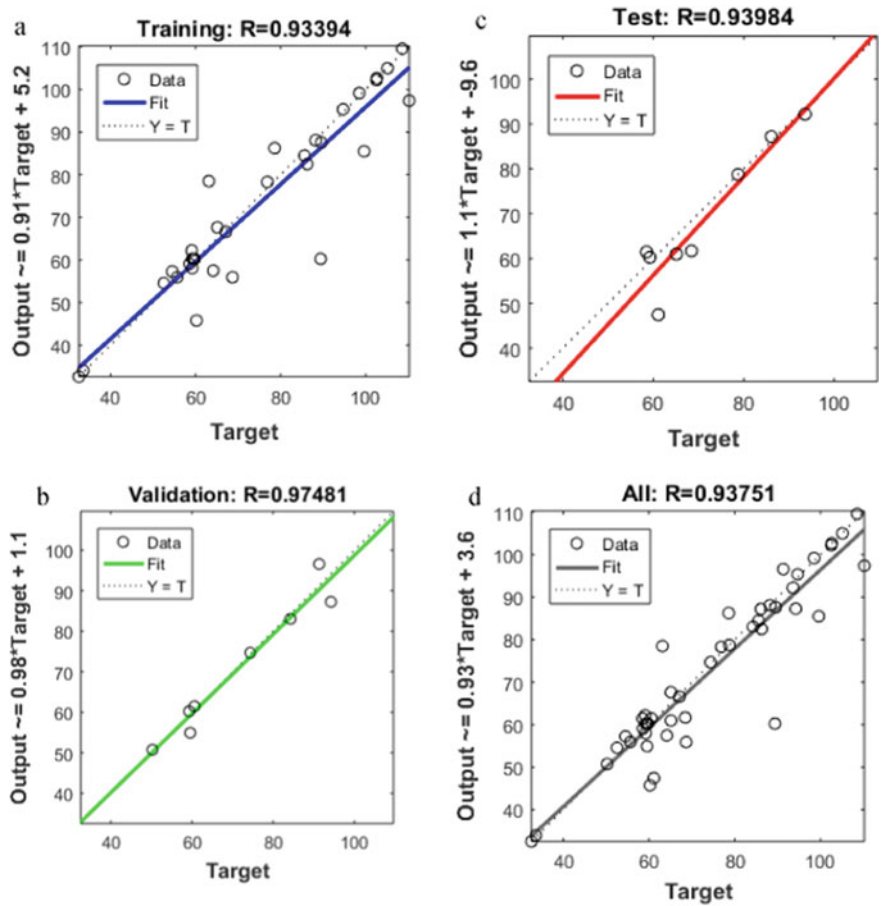


**Fig. 10.7** The ANN regression plot for cutting force under  $\text{TiO}_2$  nano-lubricant, **a** training, **b** validation analysis, **c** testing analysis and **d** all prediction

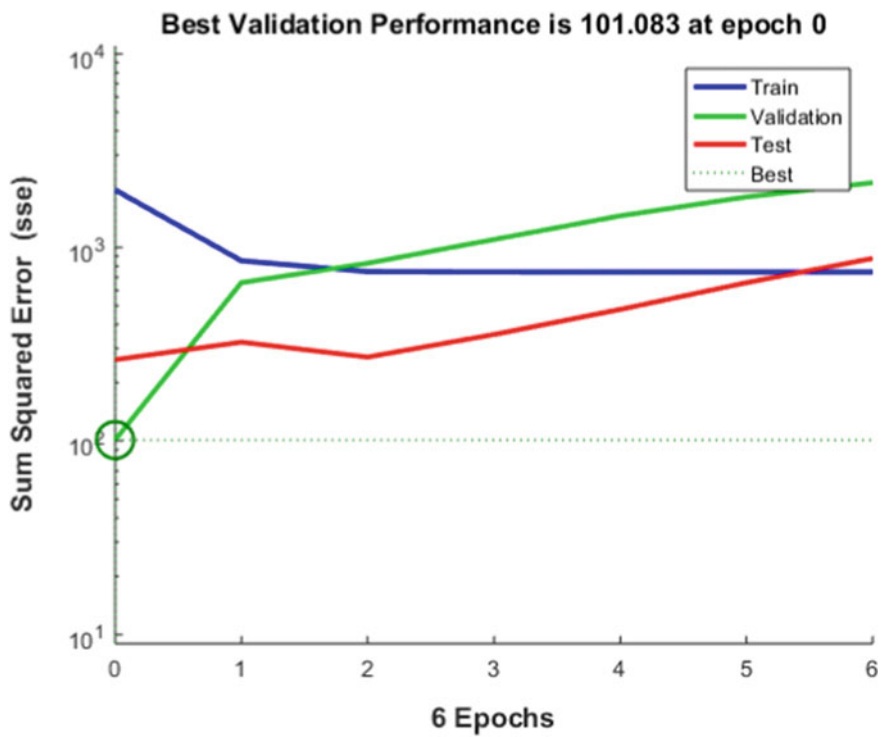


Fig. 10.8 ANN validation plot of the cutting force under the  $\text{TiO}_2$  nano-lubricant

**10.3.3 Validation and Comparison of the Predicted Result for Cutting Force from ANN and QRCCD Model**

The predicted outcome from the developed models from ANN, QRCCD, and the experimental data under  $\text{TiO}_2$  nano-lubricant machining of AA8112 alloy is shown in Fig. 10.10. Applying the percentage deviation method presented in Eq. (10.13) and the ANN and the QRCCD model predicted the cutting force experimental result with 97.5% and 89.1%, respectively. Figure 10.10 show that the ANN and QRCCD employed for the prediction of the cutting force have performed reasonably well with the standard of machining operations when compared with other related work from Chabbi et al. [15].

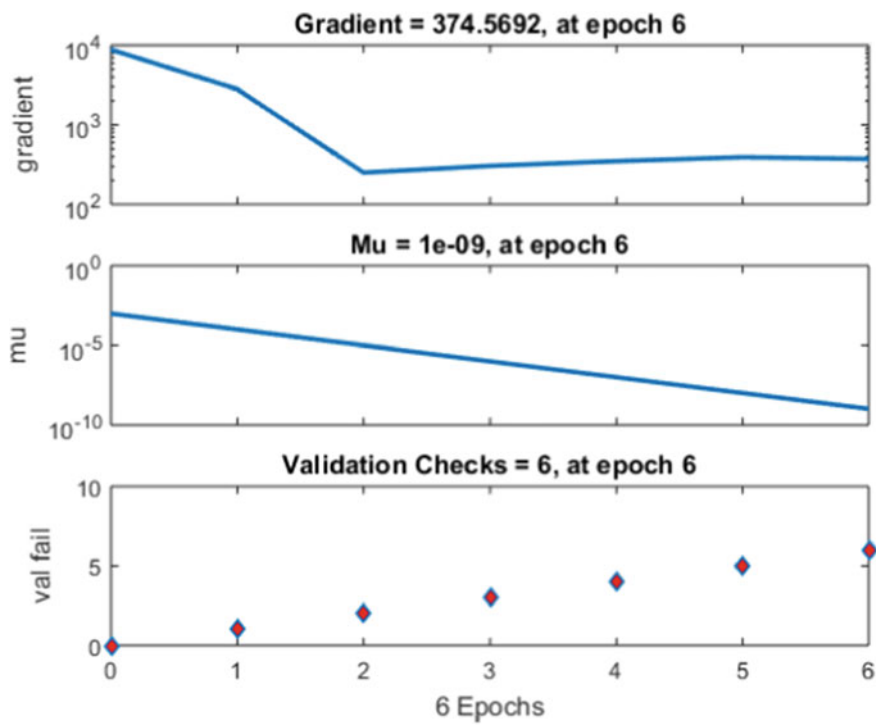
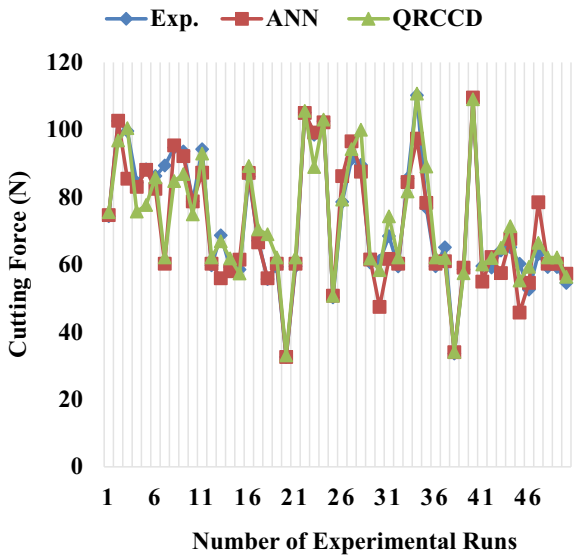


Fig. 10.9 ANN performance training state of the cutting force under the TiO<sub>2</sub> nano-lubricant

Fig. 10.10 Experimental result, predicted values of ANN, and QRCCD of the cutting force



Figures 10.11, 10.12 and 10.13 shows the factors of the cutting force objective optimization of the machining parameters obtained from the Quadratic rotatable central composite design (QRCCD). The result shows that the spindle speed of 2351 rpm, 101 mm/min feed rate, 1 mm depth of cut, 20 mm length of cut, and 60° helix angle achieved the minimum cutting force of 31 N with the desirability of 0.968. This result is closely related to the experimental data from the machining operations, this result is supported by Refs. [16, 17]. The desirability value of 0.968 shows that the prediction rate of the cutting force is satisfactory in the manufacturing industry. The ANN and QRCCD prediction of cutting force is significant when it comes to energy consumption during manufacturing via CNC. The prediction parameters is slightly different from the experimental result, this can be as a result of human error during the experimental analysis during the machining process [18–20].

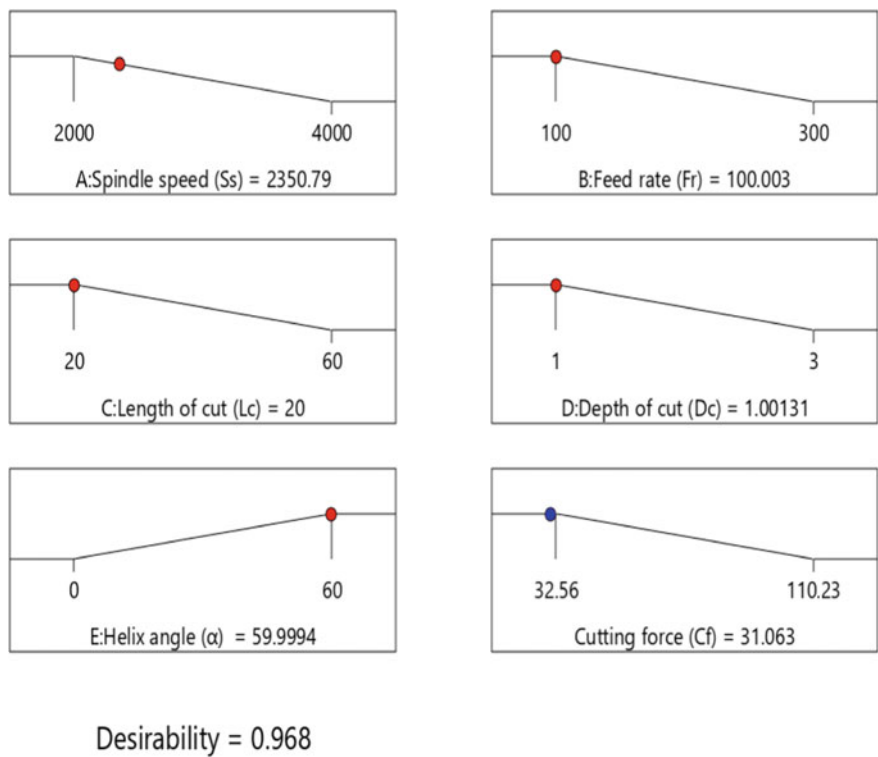


**Fig. 10.11** The ramps plots for the objective five factors five levels of optimization of the cutting force

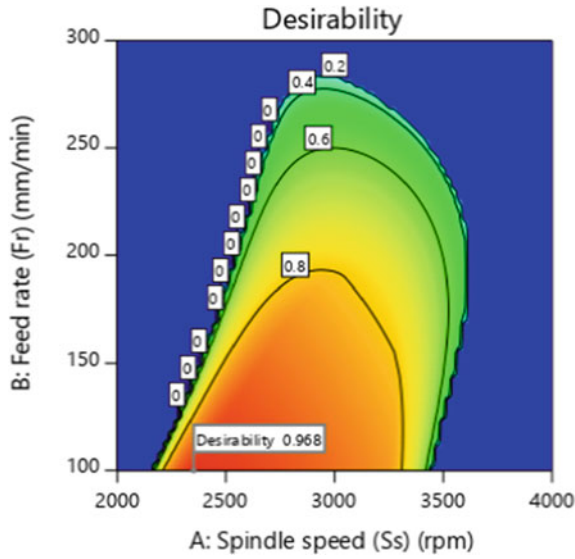


Fig. 10.12 The desirability plots for the cutting force

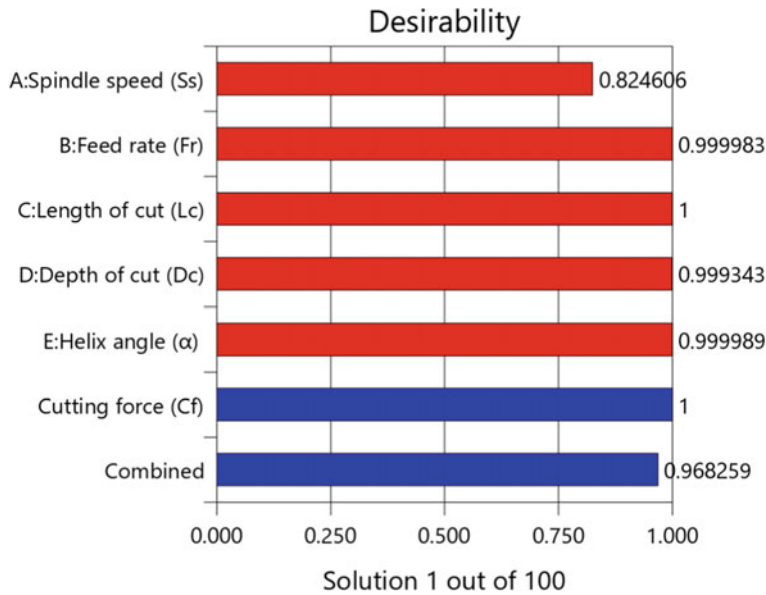


Fig. 10.13 The desirability bar plots for the multi-objective optimization parameters and the combine function for the cutting force

10.4 Parameters Interactions Study for Cutting Force

The study of the machining parameters for cutting force optimization during machining has been carried out with five (5) machining parameters such depth of cut, helix angle, feed rate, length of cut and spindle speed. Cutting force is a significant response parameter that affect the energy consumption during machining process. Therefore, to reduce the high amount of energy consumption during machining process the need to study the cutting force is needed. The major ways are to look into the parameters interaction to understand the formulation between to parameter to be able to predict the cutting force during manufacturing [21]. From Figs. 10.14, 10.15, 10.16, 10.17, 10.18, 10.19, 10.20, 10.21 and 10.22 shows the interaction study of the five machining parameters considered in this study. The most significant machining interactions parameters for the cutting force prediction and optimizations are spindle speed and length of cut as shown in Fig. 10.15. The analysis shows that the spindle speed was at 4000 rpm and the length of cut is 40 mm, why other parameters were held constant at depth of cut of 2 mm, feed rate of 200 mm/min, and helix angle of 30°, which produces a cutting force of 32.56 N. The second most interaction parameters are helix angle and length of cut. Furthermore, at the high spindle speed with a moderate length of cut, the machining process has a relatively low cutting force [22]. This has proven that the inclusion of helix angle can be implemented and still have a relatively low cutting force during machining operations, as presented in Fig. 10.17.

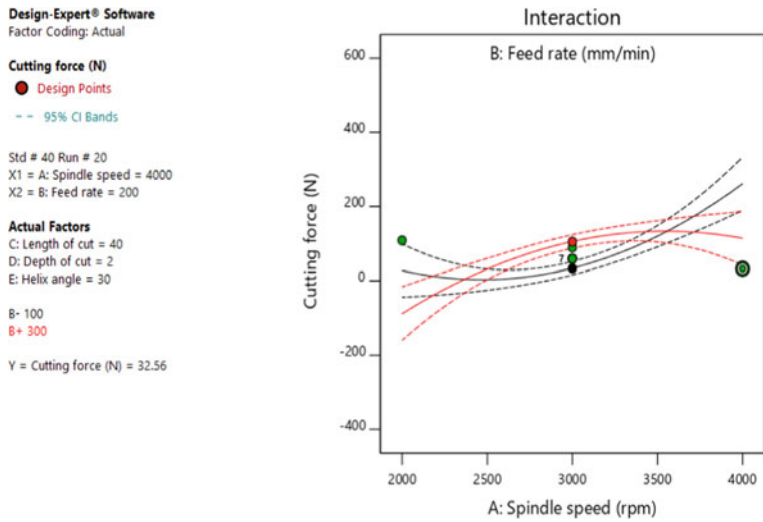


Fig. 10.14 Study of the parameters interactions between feed rate and spindle speed for cutting force optimization

Design-Expert® Software  
Factor Coding: Actual

**Cutting force (N)**  
● Design Points  
-- 95% CI Bands

Std # 40 Run # 20  
X1 = A: Spindle speed = 4000  
X2 = C: Length of cut = 40

**Actual Factors**  
B: Feed rate = 200  
D: Depth of cut = 2  
E: Helix angle = 30

C: 20  
C+ 60

Y = Cutting force (N) = 32.56

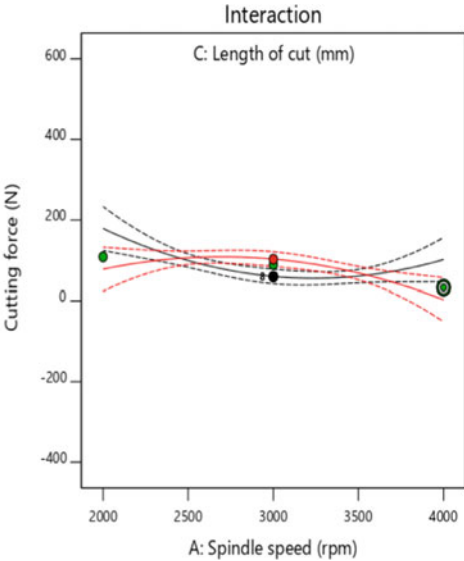


**Fig. 10.15** Study of the parameters interactions between length of cut and spindle speed for cutting force optimization

Design-Expert® Software  
Factor Coding: Actual

**Cutting force (N)**  
● Design Points  
-- 95% CI Bands

Std # 40 Run # 20  
X1 = A: Spindle speed = 4000  
X2 = D: Depth of cut = 2

**Actual Factors**  
B: Feed rate = 200  
C: Length of cut = 40  
E: Helix angle = 30

D: 1  
D+ 3

Y = Cutting force (N) = 32.56

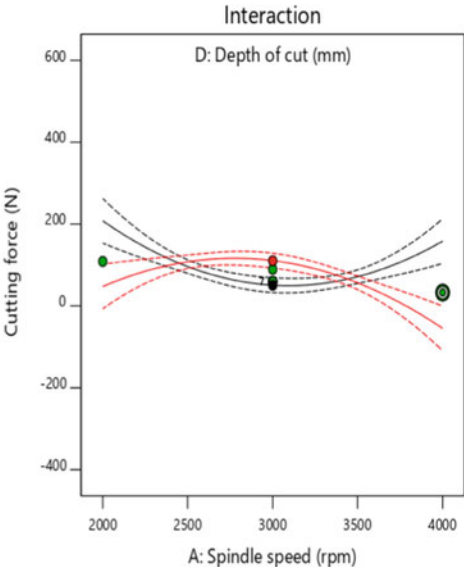


**Fig. 10.16** Study of the parameters interactions between depth of cut and spindle speed for cutting force optimization



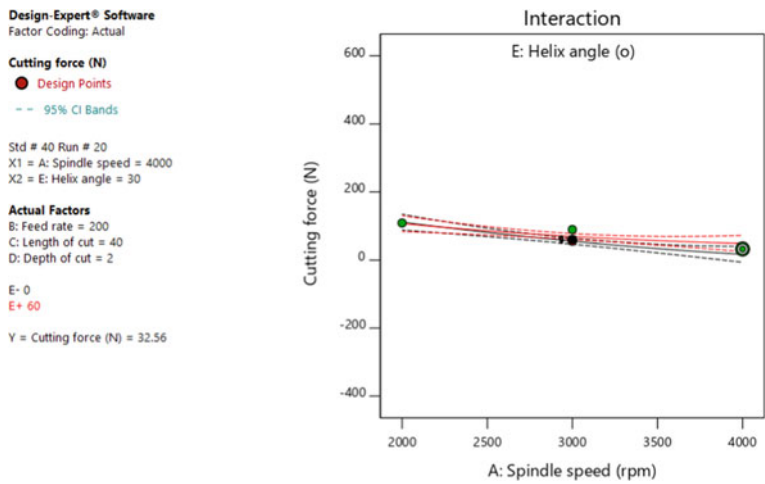


**Fig. 10.17** Study of the parameter’s interactions between spindle speed and helix angle for cutting force optimization

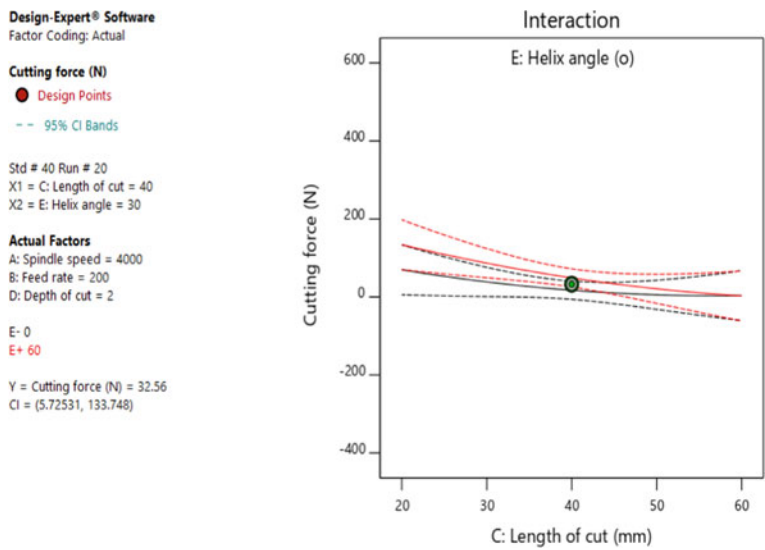


**Fig. 10.18** Study of the parameter’s interactions between helix angle and length of cut for cutting force optimization

Design-Expert® Software  
Factor Coding: Actual

Cutting force (N)

● Design Points  
-- 95% CI Bands

Std # 40 Run # 20  
X1 = B: Feed rate = 200  
X2 = C: Length of cut = 40

Actual Factors

A: Spindle speed = 4000  
D: Depth of cut = 2  
E: Helix angle = 30

C- 20  
C+ 60

Y = Cutting force (N) = 32.56  
CI = (234.21, 412.842)

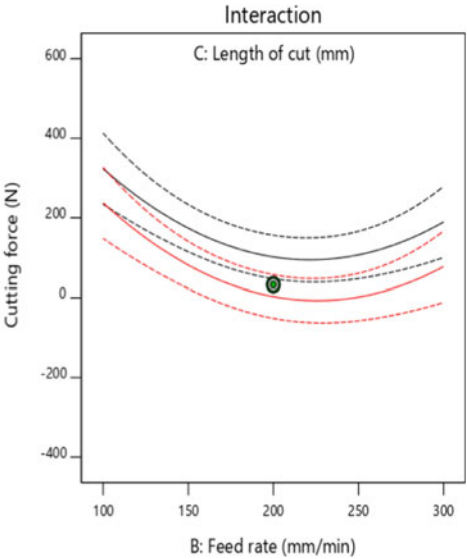


**Fig. 10.19** Study of the parameters interactions between feed rate and length of cut for cutting force optimization

Design-Expert® Software  
Factor Coding: Actual

Cutting force (N)

● Design Points  
-- 95% CI Bands

Std # 40 Run # 20  
X1 = B: Feed rate = 200  
X2 = D: Depth of cut = 2

Actual Factors

A: Spindle speed = 4000  
C: Length of cut = 40  
E: Helix angle = 30

D- 1  
D+ 3

Y = Cutting force (N) = 32.56  
CI = (337.809, 524.383)

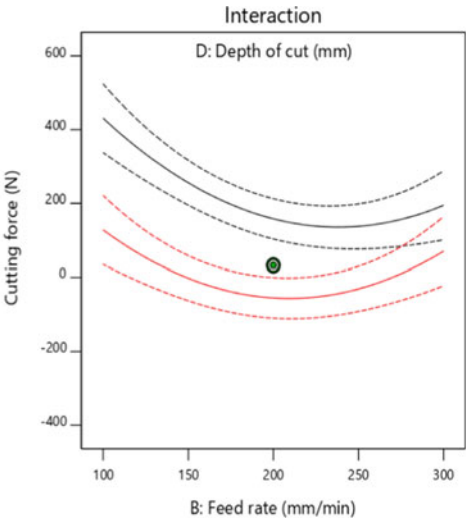


**Fig. 10.20** Study of the parameters interactions between feed rate and depth of cut for cutting force optimization

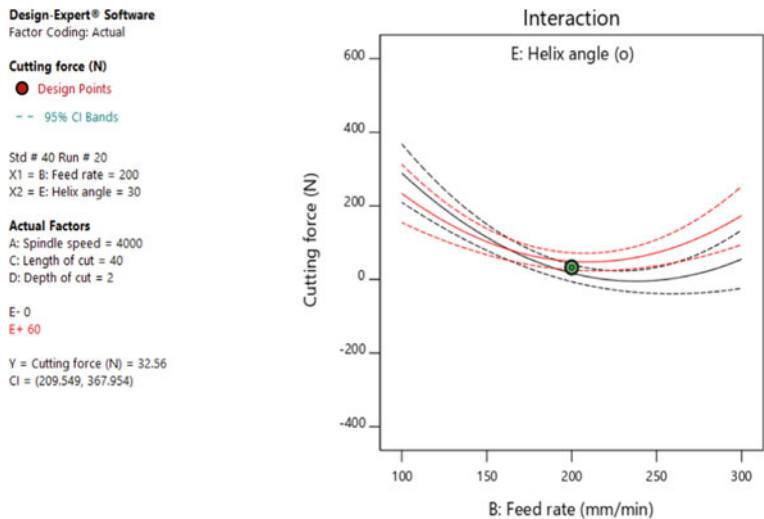


**Fig. 10.21** Study of the parameters interactions between feed rate and helix angle for cutting force optimization

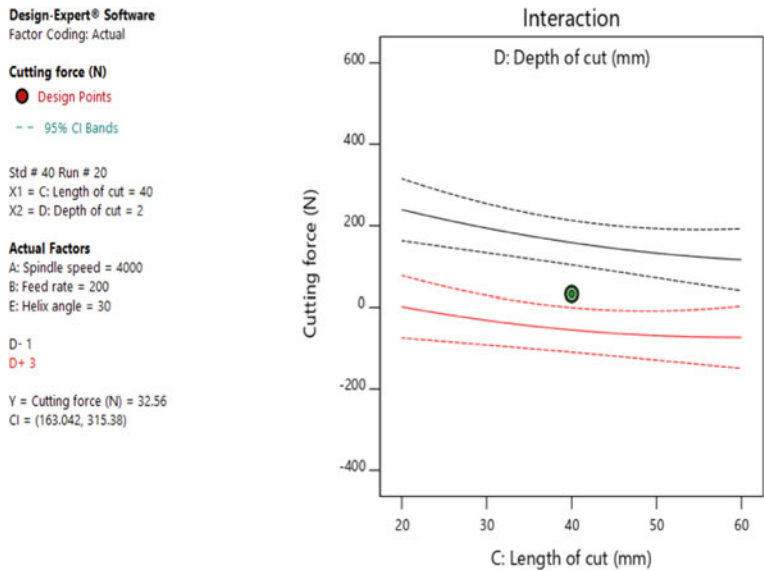


**Fig. 10.22** Study of the parameters interactions between length of cut and depth of cut for cutting force optimization

## 10.5 Conclusion

This chapter entails the study of cutting force both in experimental study, prediction and optimization via ANN and QRCCD to achieve a sustainable machining process with less cutting force. The study employed the five machining parameters varies in five different stages such as cutting speed, helix angle, feed rate, cutting depth and length of cut.

- Spindle speed has the most significant effect on cutting force, having a percentage contribution of 16.19%, followed by feed rate with 14.34%, depth of cut with 10.09%, length of cut with 5.18%, and helix angle with 2.64%.
- The most significant interactions between the machining parameters are feed rate and depth of cut as it pertains to the cutting force analysis.
- The prediction and optimization of the cutting force at its minimum was achieved with spindle speed of 2351 rpm, 101 mm/min feed rate, 1 mm depth of cut, 20 mm length of cut, and 60° helix angle and the minimum cutting force of 31 N with the desirability of 0.968 was obtained.
- The models developed for the cutting force using ANN and QRCCD predicted the experimental results with 97.5 and 95.56% accuracy under the biodegradable TiO<sub>2</sub> nano-lubricant.

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# Chapter 11

## Material Removal Rate Optimization Under ANN and QRCCD



**Abstract** Numerical analysis is a significant aspect of the manufacturing process. This process is used to study the performance of lubricants and cutting parameters during machining operations. Material removal rate (MRR) is an important factor to consider to enhance the machining and production processes of manufacturing components. Using an artificial neural network (ANN) and a quadratic rotatable central composite design (QRCCD), this study focuses on the numerical analysis of the copra oil-based  $\text{TiO}_2$  nano-lubricant performance with the machining parameters on the material removal rate during the end-milling machining operation. This study considered five machining parameters that are the control factors, such as spindle speed, feed rate, length-of-cut, cutting depth, and helix angle, on the response known as MRR under end-milling of AA8112 alloy. The measured experimental result from the end-milling machining operation is used to develop a model for the MRR to predict the performance of the nano-lubricant with the machining parameters. The ANN model developed could predict the surface roughness with 99.85% accuracy and the MRR with 98.7%. The results also show that increasing the spindle speed reduced surface roughness, which increased the material removal rate slightly during the machining process.

**Keywords** Material removal rate · Nano-lubricant · Copra oil · Artificial neural network · QRCCD

### 11.1 Introduction

An artificial neural network is a nonlinear computational based model that comprises artificial neurons derived from brain cells. This neuron can learn to execute tasks such as classification, visualization, decision making, and prediction [1]. It is a novel method used in building scientific models to predict and improve engineering systems [2]. Using ANN and the full factorial design of the experiment, Asiltürk and Unkaş [3] created an experimental model to predict the turning operation of AISI 1040 steel. The three factors applied as input data are: cutting velocity, machining rate,

and width of cut, with a response known as surface finishing. The result showed that the ANN back-propagation training algorithms used to train the system could predict the experimental outcome with 98.9% certainty. From the analysis, the feed rate has more influence on cutting when compared to the other factors. A quadratic rotatable central composite design from RSM is an essential tool used to study the effect of various parameters in machining operations. This process aids in the optimization and forecasting of the response function for optimal performance of the end milling system. Prajina [4] concentrated on a superficial level of completion and material removal rate (MRR) in processing machining utilizing second-request quadratic models. The model that was created was used to advance the machining boundaries. Also, Okokpujie and Okonkwo [5] created a model using RSM. The result shows that the RSM predicted the experimental date with 96% accuracy. Reddy et al. [6] applied RSM in their exploration to evaluate the exhibition of the machining boundaries on surface completion in the processing activities of pre-solidified steel (P20). In the examination, the RSM and the hereditary technique utilized achieved the ideal machining factor values to convey superb surface completion.

Cutting fluid and machining parameter characteristics are the essential aspect of machining operation that either strengthen the mechanical component or cause it to fail during the process [7–9]. According to Joshua et al. [10], there is a need to develop and optimize a biodegradable cutting fluid for the machining process, to enable the manufacturers to produce quality mechanical components with a good quality machined surface. This biodegradable cutting fluid will assist in reducing the energy consumption, wear rate, and corrosion on the cutting tool and the workpiece material during operation. Saini et al. [11] in their review work, recommended the use of corrosion-free cutting fluid in machining operations. Phuoc et al. [12] studied the viscosity and thermal conductivity of nano-lubricant, and the result shows that nanoparticles have good thermal conductivity. The authors concluded and recommended that nano-lubricants should be efficiently-utilised in machining operation. Pervaiz et al. [13] affirm that cutting fluid is one of the parameters that can lead to good quality machining.

Sani et al. [14] concluded that the thermo-mechanical loads in machining operations have significant effects on the surface finish of the material and the cutting tool. The result proved that the thermo-mechanical load leads to high surface roughness and breakage of the cutting tool during the machining. The authors also recommended that the use of vegetable oil is highly needed. This is due to the significant effects vegetable oil have on the microstructural characteristics of the metals after machining. Furthermore, when vegetable oil is disposed of, it is eco-friendly without causing any environmental pollutions. The authors carried out an experimental study on Jatropa-based cutting fluid and the synthetic Esther-based MQL machining fluid. The result shows that this vegetable oil-based machining fluid performs excellently in reducing friction between the cutting tool and the working materials during operations. Finally, the authors also recommended that the additions of nanoparticles in the base vegetable oil should be utilised to improve the thermal resistance of the vegetable oil in machining operations. According to Okonkwo et al. [15], the study

of machining parameters in end milling, turning, and grinding cannot be overemphasized. These machining parameters, if not adequately studied before any experimental analysis, can lead to vibrations and friction that can damage the workpiece. Nwoke et al. [16] carried out a study on vibration analysis and discovered that the machining parameters have much influence on CNC machining. Onoroh et al. [17] studied the effects of machining parameters on the cutting tool. From the conclusion of the study, the authors stated that machining parameters could easily damage or reduce the tool life during the machining process. The authors also recommended that subsequent machining operations should involve an eco-friendly lubricant to minimize the vibration occurrences during machining.

Davoudinejad et al. [18] developed a mathematical model to predict the performance of the machining parameters in end-milling machining with the finite element method. In the experiment, three machining parameters with three-levels were considered to study the surface roughness of the material. The authors discovered that there are lots of machining parameters that lead to low performance in manufacturing mechanical components using computerized numerical control (CNC) machines. Furthermore, they recommended that more research work on machining parameters should be looked into to study the influential parameters. Masmiahi et al. [19] worked on the optimization of machining parameters during end-milling machining. The study confirmed that for proper optimization to be done, there is a need for mathematical models to be developed.

However, this Chap. 12 has address this and as created a sustainable optimization. Several studies have been done to predict material removal rate, but the implementation of Heuristic and Metaheuristic Techniques for Advanced Nano-lubricant Machining Optimization for material removal rate has not been done. The novelty of this chapter is the prediction and optimization of material removal rate with five machining factors during machining operations via ANN and QRCCD.

## 11.2 Materials and Method

The study of the material removal rate (MRR) was carried out via SIEG 3/10/0016 CNC machine with high-speed steel-cutting-tool inserts. The workpiece was dimensions in different lengths of the cut with the specification to machining with other machining parameters as shown in Tables 11.1 and 11.2. Chapter 10 of this book in Sect. 10.2 entails the workpiece chemical composite and also the cutting tool. In this machining operation, TiO<sub>2</sub> copra-based nano-lubricant was employed as a sustainable lubrication process for this Chap. 12. Figure 11.1 shows the experimental set-up for the MRR study, the cutting speed, the helix angles, cutting depth, cutting length, and feed rate were varying during the machining process via the design template from the quadratic rotatable center composite design to enable the study to carry out prediction and optimization of the machining factors on the MRR. Figure 11.2



illustrate the procedure employed for the development of the TiO<sub>2</sub> copra-based nano-lubricant employed to study the MRR for sustainable removal of chips at the cutting region during the machining of aluminium alloys. Also, Fig. 11.3 shows the QRCCD method employed to carry out the optimization and prediction for this study.

**Table 11.1** Details of materials, factors and responses parameters used for the experiment

| Exp. runs | Workpiece     | Machining tool          | Variable parameters | Response parameters   | Lubricant        |
|-----------|---------------|-------------------------|---------------------|-----------------------|------------------|
| 1 to 50   | AL 8112 alloy | Coated high-speed steel | Spindle speed       | Material removal rate | TiO <sub>2</sub> |
|           |               |                         | Feed rate           |                       |                  |
|           |               |                         | Length of cut       |                       |                  |
|           |               |                         | Depth of cut        |                       |                  |
|           |               |                         | Helix angle         |                       |                  |

**Table 11.2** Machining conditions for the study MRR

| Name          | Units  | Low  | High | − α        | + α     |
|---------------|--------|------|------|------------|---------|
| Spindle speed | rpm    | 2000 | 4000 | 621.586    | 5378.41 |
| Feed rate     | mm/min | 100  | 300  | − 37.8414  | 437.841 |
| Length of cut | mm     | 20   | 60   | − 7.56828  | 87.5683 |
| Depth of cut  | mm     | 1    | 3    | − 0.378414 | 4.37841 |
| Helix angle   | o      | 0    | 60   | − 41.3524  | 101.352 |

Copra oil- based TiO<sub>2</sub>  
Nano-lubricant

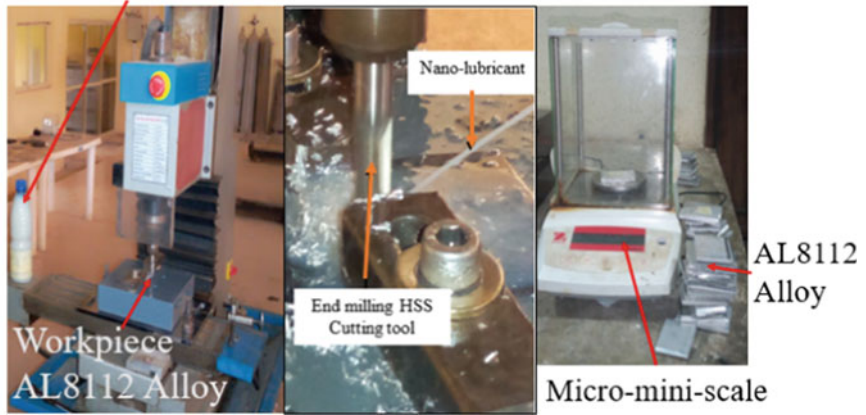


**Fig. 11.1** Experimental set-up for the MRR

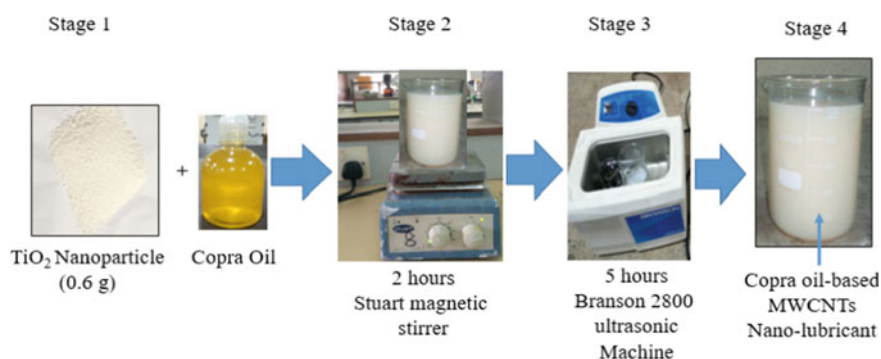


**Fig. 11.2** Experimental set-up for the preparation of the nano-lubricant used for the study

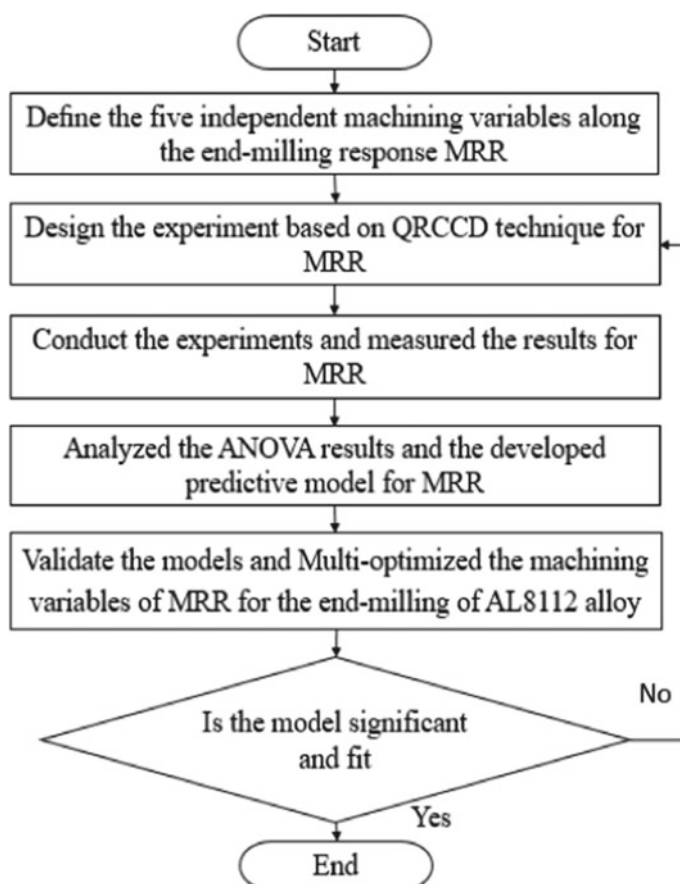


**Fig. 11.3** The experimental flow chart design

A mini normal scaling machine was utilized to gauge every one of the cut examples when the end processing machining activity, to decide the first and the last weight of the workpiece. During machining, the machining time is estimated, and with the thickness of the workpiece, the MRR is figured utilizing Eq. (11.1) [19].

$$\text{MRR} = (P_1 - P_2) / \rho * t \quad (11.1)$$

where  $P_1$  = initial weight (in grams),  $P_2$  = final weight of the AL8112 alloy (in grams),  $\rho$  = density of the AL8112 alloy workpiece (in g/mm<sup>3</sup>), and  $t$  = machining time (minutes).

### ***11.2.1 Artificial Neural Network (ANN) and Quadratic Rotatable Central Composite Design (QRCCD)***

ANN is a simple workstation that receives one or more input variables and process them to produce corrected output. These neurons are a group of data for information processing using connected links; every neuron has an associated load bases on the strength of the input variables that will be used to determine the output responses. The mathematical expression are presented in Chap. 10 of this book from Eqs. (10.1) to (10.7).

Quadratic rotatable central composite design (QRCCD) employed for the MRR is given in Eqs. (10.8)–(10.12). The study used it for the experimental design and also for the prediction analysis of the MRR due to its important in the prediction and optimization system in manufacturing industry (Fig. 11.4).

## **11.3 Results and Discussion**

The investigate of material removal rate was carried out with five factors; five levels experiment during end milling of AL-8112 alloy under the TiO<sub>2</sub> nano-lubricant machining environment is presented in Table 11.3. Fifty (50) runs of the experiment were carried out according to the quartic rotatable central composite design (QRCCD) for five factors, five levels of machining parameters. The need to predict and optimized machining parameters in terms of MRR is significant because the rate at which the unwanted materials is removed determined the performance of the production of the mechanical components [20, 21].

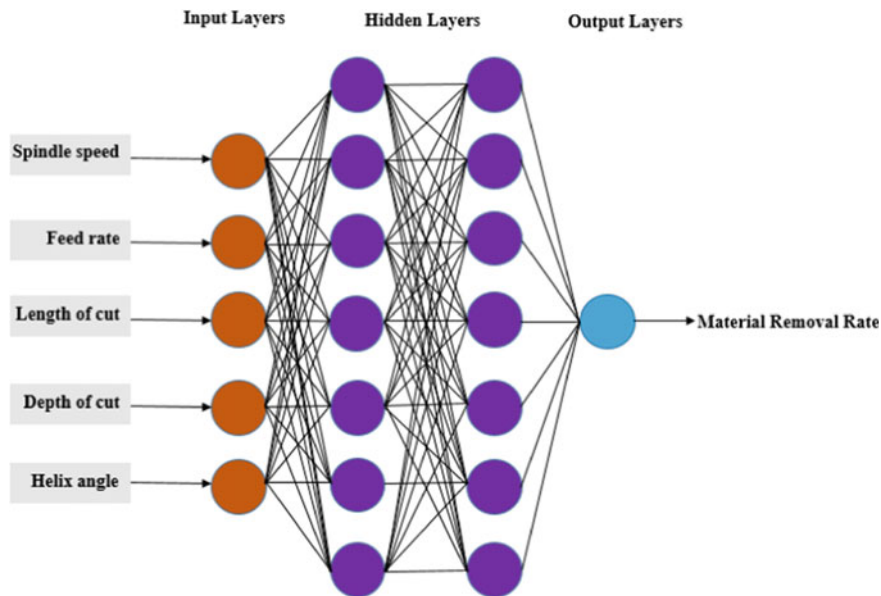


**Fig. 11.4** The ANN mathematical structure employed for the prediction of the material removal rate (MRR)

### 11.3.1 *The Models and Prediction Analysis for MRR Using QRCCD*

The experimental result obtained from the study of MRR during the end-milling of AL8112 alloy under  $\text{TiO}_2$ -nano-lubricants was employed to develop a mathematical model to predict and ascertain the accuracy of the experiments. The experimental results were made up of 50 experimental runs, which is according to the quadratic rotatable central composite design (QRCCD) for five factors-five levels of machining parameters. This section explains the generated of the QRCCD model, and the significance of the individual machining parameters involve in studying the MRR in the end-milling of AL8112 alloy under the  $\text{TiO}_2$  nano-lubricant machining environment. From the response surface methodology carried out for the MRR using QRCCD, the model developed was significant, having an F-value of 19.36, which implies that the change of noise (experimental error) occurrence is 0.01%. The significant parameters are determined using the P-value. Parameter having a P-value less than 0.05 shows that the parameter in the model is significant, why the parameters higher than 0.1 are not significant in the model. Furthermore, the significant parameters for the  $\text{TiO}_2$  nano-lubricant machining environment are F, L, D,  $S\alpha$ , FD, as present in Table 11.4. The F-value of the lack of fit is 1.80 indicate that the lack of fit is not significant when compared with the error value.

Table 11.3 Material removal rate experimental results

| Run | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle (α) (°) | Time of cut TiO <sub>2</sub> (min) | Total weight (g) | Density g/mm <sup>3</sup> | TiO <sub>2</sub> MRR mm <sup>3</sup> /min |
|-----|---------------------|--------------------|--------------------|-------------------|---------------------|------------------------------------|------------------|---------------------------|-------------------------------------------|
| 1   | 2500                | 150                | 30                 | 2.5               | 45                  | 0.33                               | 2.56             | 0.275                     | 27.98                                     |
| 2   | 2500                | 250                | 50                 | 2.5               | 15                  | 0.3                                | 4.33             | 0.275                     | 52.42                                     |
| 3   | 2500                | 250                | 30                 | 1.5               | 15                  | 0.2                                | 1.43             | 0.275                     | 25.96                                     |
| 4   | 3500                | 250                | 50                 | 1.5               | 45                  | 0.28                               | 2.57             | 0.275                     | 32.97                                     |
| 5   | 2500                | 250                | 30                 | 1.5               | 45                  | 0.18                               | 1.54             | 0.275                     | 30.68                                     |
| 6   | 2500                | 150                | 50                 | 1.5               | 45                  | 0.45                               | 2.52             | 0.275                     | 20.39                                     |
| 7   | 3000                | 200                | 40                 | 2                 | 30                  | 0.3                                | 3.25             | 0.275                     | 39.36                                     |
| 8   | 3500                | 250                | 30                 | 2.5               | 45                  | 0.2                                | 2.56             | 0.275                     | 46.63                                     |
| 9   | 2500                | 150                | 50                 | 2.5               | 45                  | 0.47                               | 4.32             | 0.275                     | 33.6                                      |
| 10  | 3500                | 150                | 30                 | 1.5               | 15                  | 0.33                               | 1.5              | 0.275                     | 16.42                                     |
| 11  | 2500                | 250                | 50                 | 2.5               | 45                  | 0.3                                | 4.24             | 0.275                     | 51.41                                     |
| 12  | 3000                | 200                | 40                 | 2                 | 30                  | 0.3                                | 3.25             | 0.275                     | 39.36                                     |
| 13  | 2500                | 150                | 30                 | 2.5               | 15                  | 0.35                               | 2.5              | 0.275                     | 26.01                                     |
| 14  | 3500                | 150                | 50                 | 2.5               | 45                  | 0.45                               | 4.27             | 0.275                     | 34.48                                     |
| 15  | 3500                | 150                | 30                 | 2.5               | 15                  | 0.35                               | 2.96             | 0.275                     | 30.74                                     |
| 16  | 2500                | 250                | 30                 | 2.5               | 15                  | 0.2                                | 2.54             | 0.275                     | 46.15                                     |
| 17  | 2500                | 250                | 50                 | 1.5               | 45                  | 0.27                               | 2.6              | 0.275                     | 35.41                                     |
| 18  | 3000                | 200                | 40                 | 2                 | 60                  | 0.28                               | 3.25             | 0.275                     | 41.67                                     |
| 19  | 3000                | 200                | 40                 | 2                 | 30                  | 0.3                                | 3.25             | 0.275                     | 39.36                                     |
| 20  | 4000                | 200                | 40                 | 2                 | 30                  | 0.32                               | 2.74             | 0.275                     | 31.41                                     |
| 21  | 3000                | 200                | 40                 | 2                 | 30                  | 0.3                                | 3.25             | 0.275                     | 39.36                                     |

(continued)

Table 11.3 (continued)

| Run | Spindle speed<br>(rpm) | Feed rate<br>(mm/min) | Length of cut<br>(mm) | Depth of cut<br>(mm) | Helix angle<br>( $\alpha$ ) ( $^{\circ}$ ) | Time of cut TiO <sub>2</sub><br>(min) | Total<br>weight (g) | Density g/<br>mm <sup>3</sup> | TiO <sub>2</sub> MRR mm <sup>3</sup> /<br>min |
|-----|------------------------|-----------------------|-----------------------|----------------------|--------------------------------------------|---------------------------------------|---------------------|-------------------------------|-----------------------------------------------|
| 22  | 3000                   | 300                   | 40                    | 2                    | 30                                         | 0.22                                  | 2.87                | 0.275                         | 48.18                                         |
| 23  | 3500                   | 150                   | 50                    | 1.5                  | 45                                         | 0.47                                  | 2.6                 | 0.275                         | 20.22                                         |
| 24  | 3000                   | 200                   | 60                    | 2                    | 30                                         | 0.42                                  | 4.13                | 0.275                         | 36.06                                         |
| 25  | 3000                   | 200                   | 40                    | 1                    | 30                                         | 0.32                                  | 1.33                | 0.275                         | 15.28                                         |
| 26  | 3500                   | 150                   | 30                    | 1.5                  | 45                                         | 0.33                                  | 1.5                 | 0.275                         | 16.38                                         |
| 27  | 3500                   | 250                   | 30                    | 1.5                  | 45                                         | 0.22                                  | 1.48                | 0.275                         | 24.95                                         |
| 28  | 3500                   | 250                   | 50                    | 2.5                  | 45                                         | 0.3                                   | 4.21                | 0.275                         | 51                                            |
| 29  | 3500                   | 150                   | 30                    | 2.5                  | 45                                         | 0.33                                  | 2.52                | 0.275                         | 27.48                                         |
| 30  | 2500                   | 150                   | 50                    | 1.5                  | 15                                         | 0.45                                  | 2.54                | 0.275                         | 20.56                                         |
| 31  | 2500                   | 250                   | 50                    | 1.5                  | 15                                         | 0.28                                  | 2.55                | 0.275                         | 32.68                                         |
| 32  | 3000                   | 200                   | 40                    | 2                    | 30                                         | 0.3                                   | 2.71                | 0.275                         | 32.82                                         |
| 33  | 3500                   | 250                   | 50                    | 2.5                  | 15                                         | 0.28                                  | 4.25                | 0.275                         | 54.54                                         |
| 34  | 3000                   | 200                   | 40                    | 3                    | 30                                         | 0.32                                  | 4.29                | 0.275                         | 49.19                                         |
| 35  | 3500                   | 150                   | 50                    | 1.5                  | 15                                         | 0.45                                  | 2.67                | 0.275                         | 21.6                                          |
| 36  | 3000                   | 200                   | 40                    | 2                    | 30                                         | 0.3                                   | 2.79                | 0.275                         | 33.79                                         |
| 37  | 3500                   | 150                   | 50                    | 2.5                  | 15                                         | 0.48                                  | 4.2                 | 0.275                         | 31.59                                         |
| 38  | 3000                   | 100                   | 40                    | 2                    | 30                                         | 0.6                                   | 2.81                | 0.275                         | 17.05                                         |
| 39  | 3500                   | 250                   | 50                    | 1.5                  | 15                                         | 0.2                                   | 2.52                | 0.275                         | 45.89                                         |
| 40  | 2000                   | 200                   | 40                    | 2                    | 30                                         | 0.32                                  | 2.81                | 0.275                         | 32.27                                         |
| 41  | 3000                   | 200                   | 20                    | 2                    | 30                                         | 0.22                                  | 1.42                | 0.275                         | 23.79                                         |
| 42  | 3500                   | 250                   | 30                    | 2.5                  | 15                                         | 0.17                                  | 1.72                | 0.275                         | 37.62                                         |

(continued)

Table 11.3 (continued)

| Run | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle ( $\alpha$ ) ( $^{\circ}$ ) | Time of cut TiO <sub>2</sub> (min) | Total weight (g) | Density g/mm <sup>3</sup> | TiO <sub>2</sub> MRR mm <sup>3</sup> /min |
|-----|---------------------|--------------------|--------------------|-------------------|-----------------------------------------|------------------------------------|------------------|---------------------------|-------------------------------------------|
| 43  | 2500                | 150                | 30                 | 1.5               | 45                                      | 0.33                               | 2.99             | 0.275                     | 32.57                                     |
| 44  | 3500                | 250                | 30                 | 1.5               | 15                                      | 0.2                                | 1.86             | 0.275                     | 33.89                                     |
| 45  | 3000                | 200                | 40                 | 2                 | 0                                       | 0.28                               | 2.64             | 0.275                     | 33.93                                     |
| 46  | 2500                | 150                | 50                 | 2.5               | 15                                      | 0.43                               | 3.64             | 0.275                     | 30.56                                     |
| 47  | 2500                | 250                | 30                 | 2.5               | 45                                      | 0.2                                | 3                | 0.275                     | 54.57                                     |
| 48  | 3000                | 200                | 40                 | 2                 | 30                                      | 0.28                               | 2.59             | 0.275                     | 33.31                                     |
| 49  | 3000                | 200                | 40                 | 2                 | 30                                      | 0.28                               | 2.61             | 0.275                     | 33.54                                     |
| 50  | 2500                | 150                | 30                 | 1.5               | 15                                      | 0.33                               | 1.73             | 0.275                     | 18.94                                     |

**Table 11.4** ANOVA analysis of the MRR

| Source                  | Sum of squares | Df | Mean square | F-value | p-value  | %C    |                 |
|-------------------------|----------------|----|-------------|---------|----------|-------|-----------------|
| Model                   | 4913.88        | 1  | 327.59      | 19.36   | < 0.0001 | 89.52 | Significant     |
| S-(Spindle speed)       | 5.78           | 15 | 5.78        | 0.3418  | 0.5627   | 0.11  |                 |
| F-(Feed rate)           | 2394.91        | 1  | 2394.91     | 141.52  | < 0.0001 | 43.63 |                 |
| L-(Length of cut)       | 234.69         | 1  | 234.69      | 13.87   | 0.0007   | 4.28  |                 |
| D-(Depth of cut)        | 1891.86        | 1  | 1891.86     | 111.8   | < 0.0001 | 34.46 |                 |
| $\alpha$ -(Helix angle) | 23.45          | 1  | 23.45       | 1.39    | 0.2473   | 0.43  |                 |
| SF                      | 3.07           | 1  | 3.07        | 0.1814  | 0.6729   | 0.06  |                 |
| SL                      | 60.53          | 1  | 60.53       | 3.58    | 0.0671   | 1.1   |                 |
| SD                      | 0.4395         | 1  | 0.4395      | 0.026   | 0.8729   | 0.01  |                 |
| S $\alpha$              | 82.92          | 1  | 82.92       | 4.9     | 0.0337   | 1.51  |                 |
| FL                      | 48.49          | 1  | 48.49       | 2.87    | 0.0997   | 0.88  |                 |
| FD                      | 99.93          | 1  | 99.93       | 5.91    | 0.0205   | 1.82  |                 |
| F $\alpha$              | 10.36          | 1  | 10.36       | 0.6124  | 0.4393   | 0.189 |                 |
| LD                      | 4.88           | 1  | 4.88        | 0.2881  | 0.5949   | 0.09  |                 |
| L $\alpha$              | 40.21          | 1  | 40.21       | 2.38    | 0.1325   | 0.73  |                 |
| D $\alpha$              | 12.36          | 1  | 12.36       | 0.7306  | 0.3987   | 0.23  |                 |
| Residual                | 575.36         | 34 | 16.92       |         |          | 10.48 | Not significant |
| Lack of fit             | 502.97         | 27 | 18.63       | 1.8     | 0.215    | 9.16  |                 |
| Pure error              | 72.39          | 7  | 10.34       |         |          | 1.32  |                 |
| Cor. total              | 5489.25        | 49 |             |         |          | 100   |                 |

Table 11.5 shows the adequate precision value of 16.909 measured during this analysis. With the value of 16.909, the adequate precision is satisfactory, which implies that the signal to noise ratio has a good relationship, and the model can be employed to predict the design space. Table 11.6 shows the ANOVA coefficient estimation, which is a significant aspect of the analysis that represents the expected transformation in the MRR per unit alteration of each machining factor value when other factor’s values are kept constant. The intercept of the orthogonal plan is the whole MRR experimental runs. The coefficients are to adjust the machining factors settings. The variance inflation factors (VIFs) value is to determine the existence between the predictor model and the variable parameter factors used for the prediction.



**Table 11.5** Statistical validation of the MRR

|                                         |       |                               |         |
|-----------------------------------------|-------|-------------------------------|---------|
| <b>Standard deviation</b>               | 4.11  | <b>R<sup>2</sup></b>          | 0.8952  |
| <b>Mean</b>                             | 33.72 | <b>Adjusted R<sup>2</sup></b> | 0.8489  |
| <b>Coefficient of variation (C.V.)%</b> | 12.20 | <b>Adequate precision</b>     | 16.9085 |

**Table 11.6** ANOVA coefficients analysis of the MRR

| Factor            | Coefficient estimate | df | Standard error | 95% CI low | 95% CI high | VIF    |
|-------------------|----------------------|----|----------------|------------|-------------|--------|
| Intercept         | 33.72                | 1  | 0.5818         | 32.54      | 34.90       |        |
| S-(Spindle speed) | − 0.7605             | 1  | 1.30           | − 3.40     | 1.88        | 1.0000 |
| F-(Feed rate)     | 15.48                | 1  | 1.30           | 12.83      | 18.12       | 1.0000 |
| L-(Length of cut) | 4.84                 | 1  | 1.30           | 2.20       | 7.49        | 1.0000 |
| D-(Depth of cut)  | 13.75                | 1  | 1.30           | 11.11      | 16.40       | 1.0000 |
| α-(Helix angle)   | 1.53                 | 1  | 1.30           | − 1.11     | 4.18        | 1.0000 |
| SF                | 1.24                 | 1  | 2.91           | − 4.67     | 7.15        | 1.0000 |
| SL                | 5.50                 | 1  | 2.91           | − 0.4102   | 11.41       | 1.0000 |
| SD                | − 0.4687             | 1  | 2.91           | − 6.38     | 5.44        | 1.0000 |
| Sα                | − 6.44               | 1  | 2.91           | − 12.35    | − 0.5273    | 1.0000 |
| FL                | 4.92                 | 1  | 2.91           | − 0.9877   | 10.84       | 1.0000 |
| FD                | 7.07                 | 1  | 2.91           | 1.16       | 12.98       | 1.0000 |
| Fα                | − 2.28               | 1  | 2.91           | − 8.19     | 3.64        | 1.0000 |
| LD                | 1.56                 | 1  | 2.91           | − 4.35     | 7.47        | 1.0000 |
| Lα                | − 4.48               | 1  | 2.91           | − 10.40    | 1.43        | 1.0000 |
| Dα                | 2.49                 | 1  | 2.91           | − 3.43     | 8.40        | 1.0000 |

The VIFs value of one (1) means the factors are orthogonal, and the VIFs values greater than one (1) implies the factors are multi-collinearity [22]. The greater the VIFs, the higher the multi-collinearity of the connection of the factors. The model developed for the MRR analysis under the TiO<sub>2</sub> nano-lubricant machining environment from the quartic rotatable central composite design (QRCCD) of the experiment is presented in two forms the coded and actual form. Equation (11.2) gives the model in the coded form for the MRR.

$$\begin{aligned} \text{MRR}_{\text{coded}} = & +33.72 - 0.7605S_c + 15.48F_c + 4.84L_c + 13.75D_c + 1.53\alpha_c \\ & + 1.24SF_c + 5.50SL_c - 0.4687SD_c - 6.44S\alpha_c + 4.92FL_c \\ & + 7.07FD_c - 2.28F\alpha_c + 1.56LD_c - 4.48L\alpha_c + 2.49D\alpha_c \end{aligned} \quad (11.2)$$

The Eq. (11.2) is the model in the state of coded form for proper identification of the comparative effect of the machining factors or parameters when comparing the coefficients.

The model, in terms of the actual factors, is presented in Eq. (11.3).

$$\begin{aligned} \text{MRR}_{\text{actual}} = & +30.30 - 0.007S - 0.099F - 1.007L - 4.586D + 0.979\alpha \\ & + 0.00001\text{SF} + 0.0003\text{SL} - 0.0005\text{SD} - 0.0002\text{S}\alpha \\ & + 0.0025\text{FL} + 0.071\text{FD} - 0.0008\text{F}\alpha + 0.078063\text{LD} \\ & - 0.0075\text{L}\alpha - 0.0075\text{L}\alpha + 0.083\text{D}\alpha \end{aligned} \quad (11.3)$$

Therefore, the final model for prediction of the MRR for TiO<sub>2</sub> nano-lubricant end milling of AA8112 alloy machining environment given in Eq. (11.3), was used to predict the MRR under the TiO<sub>2</sub> nano-lubricant environment, and Fig. 11.5 shows the prediction plot and Table 11.7 present the prediction results, residual, leverage, externally and internal studentized residuals.

Design-Expert® Software

MRR

(adjusted for curvature)

Color points by value of

MRR:

15.28 54.57

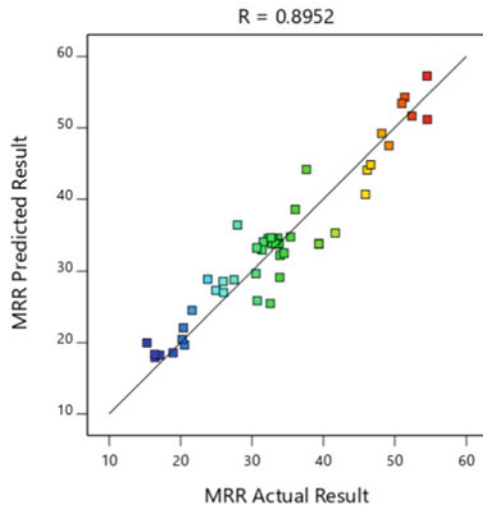


Fig. 11.5 The experimental result and predicted result of the MRR under TiO<sub>2</sub> nano-lubricant

**Table 11.7** The analysis of the predicted values with the internal and external residual

| Run order | Actual value | Predicted value | Residual | Leverage | Internally studentized residuals | Externally studentized residuals | Cook's distance | Influence on fitted value DFFITS |
|-----------|--------------|-----------------|----------|----------|----------------------------------|----------------------------------|-----------------|----------------------------------|
| 1         | 27.98        | 36.38           | − 8.40   | 0.458    | − 2.773                          | − 3.105                          | 0.405           | − 2.851                          |
| 2         | 52.42        | 51.65           | 0.7685   | 0.458    | 0.254                            | 0.250                            | 0.003           | 0.230                            |
| 3         | 25.96        | 28.57           | − 2.61   | 0.458    | − 0.863                          | − 0.859                          | 0.039           | − 0.789                          |
| 4         | 32.97        | 34.34           | − 1.37   | 0.458    | − 0.453                          | − 0.448                          | 0.011           | − 0.411                          |
| 5         | 30.68        | 33.19           | − 2.51   | 0.458    | − 0.827                          | − 0.823                          | 0.036           | − 0.756                          |
| 6         | 20.39        | 22.07           | − 1.68   | 0.458    | − 0.555                          | − 0.550                          | 0.016           | − 0.505                          |
| 7         | 39.36        | 33.72           | 5.64     | 0.020    | 1.385                            | 1.405                            | 0.002           | 0.201                            |
| 8         | 46.63        | 44.83           | 1.80     | 0.458    | 0.596                            | 0.590                            | 0.019           | 0.542                            |
| 9         | 33.60        | 34.55           | − 0.9513 | 0.458    | − 0.314                          | − 0.310                          | 0.005           | − 0.284                          |
| 10        | 16.42        | 17.90           | − 1.48   | 0.458    | − 0.488                          | − 0.483                          | 0.013           | − 0.443                          |
| 11        | 51.41        | 54.27           | − 2.86   | 0.458    | − 0.942                          | − 0.941                          | 0.047           | − 0.864                          |
| 12        | 39.36        | 33.72           | 5.64     | 0.020    | 1.385                            | 1.405                            | 0.002           | 0.201                            |
| 13        | 26.01        | 27.01           | − 0.9965 | 0.458    | − 0.329                          | − 0.325                          | 0.006           | − 0.298                          |
| 14        | 34.48        | 32.47           | 2.01     | 0.458    | 0.664                            | 0.658                            | 0.023           | 0.605                            |
| 15        | 30.74        | 25.86           | 4.88     | 0.458    | 1.610                            | 1.651                            | 0.137           | 1.516                            |
| 16        | 46.15        | 44.07           | 2.08     | 0.458    | 0.685                            | 0.680                            | 0.025           | 0.624                            |
| 17        | 35.41        | 34.72           | 0.6915   | 0.458    | 0.228                            | 0.225                            | 0.003           | 0.207                            |
| 18        | 41.67        | 35.25           | 6.42     | 0.120    | 1.663                            | 1.710                            | 0.024           | 0.631                            |
| 19        | 39.36        | 33.72           | 5.64     | 0.020    | 1.385                            | 1.405                            | 0.002           | 0.201                            |
| 20        | 31.41        | 32.96           | − 1.55   | 0.120    | − 0.402                          | − 0.397                          | 0.001           | − 0.146                          |
| 21        | 39.36        | 33.72           | 5.64     | 0.020    | 1.385                            | 1.405                            | 0.002           | 0.201                            |
| 22        | 48.18        | 49.20           | − 1.02   | 0.120    | − 0.263                          | − 0.260                          | 0.001           | − 0.096                          |
| 23        | 20.22        | 20.46           | − 0.2388 | 0.458    | − 0.079                          | − 0.078                          | 0.000           | − 0.071                          |
| 24        | 36.06        | 38.56           | − 2.50   | 0.120    | − 0.649                          | − 0.643                          | 0.004           | − 0.238                          |
| 25        | 15.28        | 19.97           | − 4.69   | 0.120    | − 1.214                          | − 1.223                          | 0.013           | − 0.452                          |
| 26        | 16.38        | 18.35           | − 1.97   | 0.458    | − 0.650                          | − 0.644                          | 0.022           | − 0.591                          |
| 27        | 24.95        | 27.31           | − 2.36   | 0.458    | − 0.778                          | − 0.774                          | 0.032           | − 0.711                          |
| 28        | 51.00        | 53.42           | − 2.42   | 0.458    | − 0.799                          | − 0.795                          | 0.034           | − 0.730                          |
| 29        | 27.48        | 28.80           | − 1.32   | 0.458    | − 0.434                          | − 0.429                          | 0.010           | − 0.394                          |
| 30        | 20.56        | 19.67           | 0.8910   | 0.458    | 0.294                            | 0.290                            | 0.005           | 0.266                            |
| 31        | 32.68        | 34.59           | − 1.91   | 0.458    | − 0.631                          | − 0.625                          | 0.021           | − 0.574                          |
| 32        | 32.82        | 33.72           | − 0.9004 | 0.020    | − 0.221                          | − 0.218                          | 0.000           | − 0.031                          |
| 33        | 54.54        | 57.25           | − 2.71   | 0.458    | − 0.893                          | − 0.890                          | 0.042           | − 0.818                          |

(continued)

**Table 11.7** (continued)

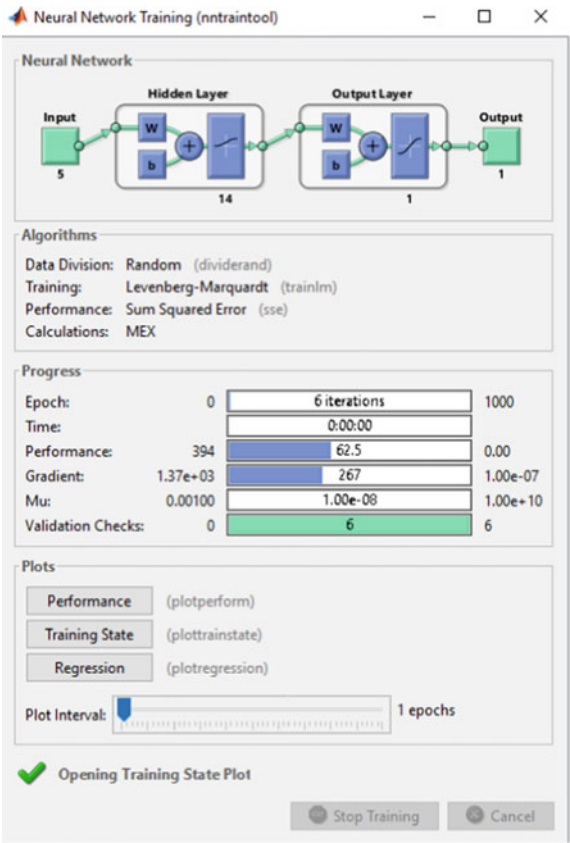
| Run order | Actual value | Predicted value | Residual | Leverage | Internally studentized residuals | Externally studentized residuals | Cook's distance | Influence on fitted value DFFITS |
|-----------|--------------|-----------------|----------|----------|----------------------------------|----------------------------------|-----------------|----------------------------------|
| 34        | 49.19        | 47.47           | 1.72     | 0.120    | 0.444                            | 0.439                            | 0.002           | 0.162                            |
| 35        | 21.60        | 24.49           | − 2.89   | 0.458    | − 0.955                          | − 0.954                          | 0.048           | − 0.876                          |
| 36        | 33.79        | 33.72           | 0.0696   | 0.020    | 0.017                            | 0.017                            | 0.000           | 0.002                            |
| 37        | 31.59        | 34.02           | − 2.43   | 0.458    | − 0.801                          | − 0.797                          | 0.034           | − 0.732                          |
| 38        | 17.05        | 18.24           | − 1.19   | 0.120    | − 0.310                          | − 0.305                          | 0.001           | − 0.113                          |
| 39        | 45.89        | 40.65           | 5.24     | 0.458    | 1.728                            | 1.783                            | 0.157           | 1.637                            |
| 40        | 32.27        | 34.48           | − 2.21   | 0.120    | − 0.573                          | − 0.567                          | 0.003           | − 0.209                          |
| 41        | 23.79        | 28.88           | − 5.09   | 0.120    | − 1.318                          | − 1.333                          | 0.015           | − 0.492                          |
| 42        | 37.62        | 44.17           | − 6.55   | 0.458    | − 2.161                          | − 2.292                          | 0.246           | − 2.105                          |
| 43        | 32.57        | 25.46           | 7.11     | 0.458    | 2.345                            | 2.524                            | 0.290           | 2.318                            |
| 44        | 33.89        | 29.14           | 4.75     | 0.458    | 1.569                            | 1.605                            | 0.130           | 1.474                            |
| 45        | 33.93        | 32.19           | 1.74     | 0.120    | 0.451                            | 0.446                            | 0.002           | 0.165                            |
| 46        | 30.56        | 29.66           | 0.8990   | 0.458    | 0.297                            | 0.293                            | 0.005           | 0.269                            |
| 47        | 54.57        | 51.17           | 3.40     | 0.458    | 1.122                            | 1.126                            | 0.066           | 1.034                            |
| 48        | 33.31        | 33.72           | − 0.4104 | 0.020    | − 0.101                          | − 0.099                          | 0.000           | − 0.014                          |
| 49        | 33.54        | 33.72           | − 0.1804 | 0.020    | − 0.044                          | − 0.044                          | 0.000           | − 0.006                          |
| 50        | 18.94        | 18.58           | 0.3642   | 0.458    | 0.120                            | 0.118                            | 0.001           | 0.109                            |

### 11.3.2 Material Removal Rate Prediction Using ANN

This section presents the predicting result of the MRR during the end-milling of AA8112 alloy under the TiO<sub>2</sub> nano-lubricant using ANN. The Back Propagation feed-forward Neural Network (BPNN) was used to predict the experimental result obtained from experimental data by employing Levenberg–Marquardt (trainlm) to train the neuron for better performance. Furthermore, the best validation performance is analysed by the sigmoid non-linear transfer function (Z) and the total sum of squared error (SSE). The statistical formulation is presented in Eqs. (3.7)–(3.13). Figure 11.6 shows the neuron network pattern used for the prediction of the MRR under the machining environment of the TiO<sub>2</sub> nano-lubricant.

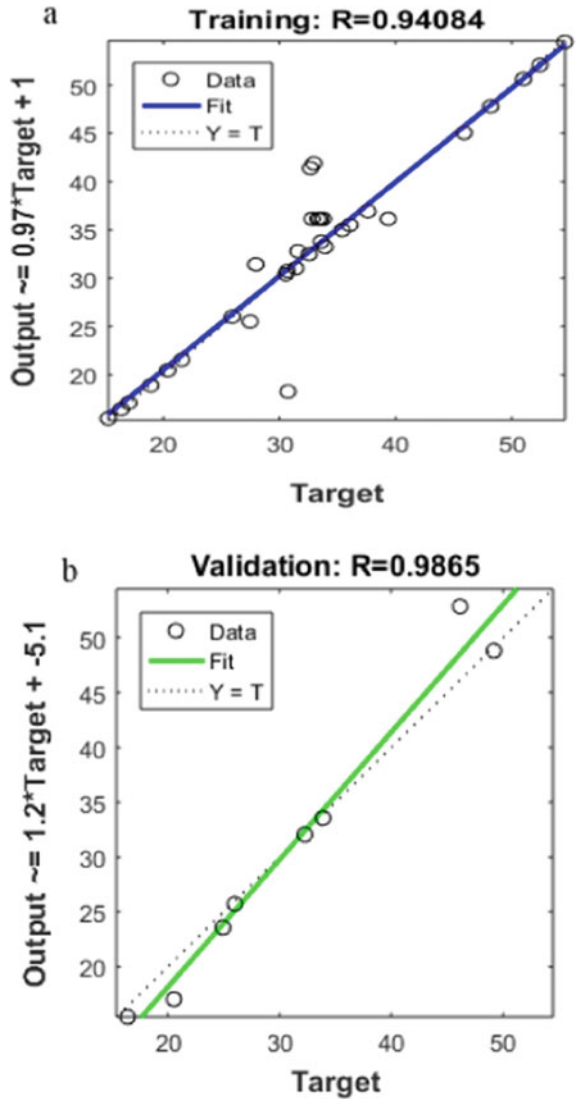
Figure 11.7a, b shows the performance analysis of the ANN model for the TiO<sub>2</sub> nano-lubricant machining environment using SSE with the coefficient relationship (R-value) of the regression model. The R-value shows the nearness of the ANN model predicted output target (MRR) with the experimental result obtained from the machining operation. From the analysis, the R-value for the data training set and data validation, 0.9865, and 0.9926, respectively. The overall performance and testing are 0.94084 and 0.95872, as depicted in Fig. 11.8a, b.

**Fig. 11.6** The Model structure of the ANN for the MRR



The solid line shows the level of performance of the regression model. In contrast, the dashed line is the perfect line of the regression, and both lines help to show the relationship between the target and the predicted MRR under TiO<sub>2</sub> nano-lubricant machining environment. From the ANN model, the best validation performance, as measured by applying the SSE, occurs at epoch 0 and iteration 6, as presented in Fig. 11.9. The analysis depicts that the SSE decreased gradually from the zero epoch to the peak point. Figure 11.10 shows the gradient constant of the Marquardt unit parameter (Mu), total validation checks, and the iterations value.

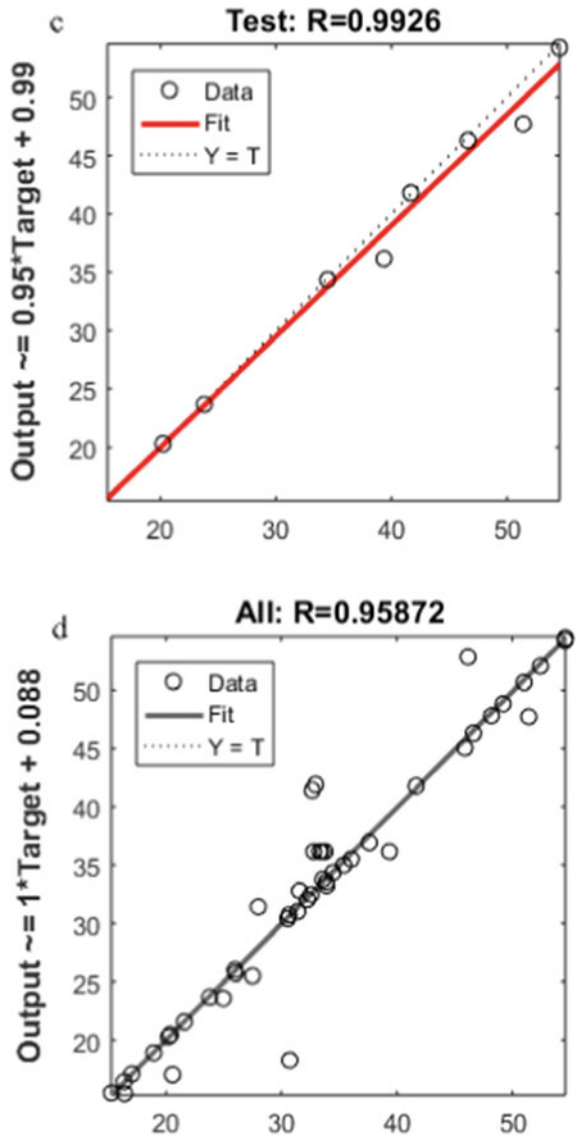
**Fig. 11.7** ANN regression plot of MRR under the TiO<sub>2</sub> nano-lubricant **a** Training process, and **b** the validation analysis



**11.4 Comparative Analysis Between the ANN and QRCCD and Machining Optimization**

The models developed used in training of the experimental data for the ANN and the RSM under TiO<sub>2</sub> nano-lubricant machining of AL 8112 alloy is depicted in Fig. 11.11. Applying the percentage deviation method presented and equation of the ANN and the QCCD model could predict the MRR experimental result with about 98.7% and 89.5%, respectively. Figure 11.11 it can be noted that the two

**Fig. 11.8** ANN regression plot of MRR under the TiO<sub>2</sub> nano-lubricant **a** Testing process, and **d** overall prediction of the MRR



techniques employed for the prediction of the MRR for performance and productivity improvement have performed reasonably well within the standard of machining operations when compared with other previous work of Gjeldum et al. [23], Hadad and Ramezani [24], and Basar et al. [25]. The high rate of the model prediction has proven that the experiment carried out has a high level of accuracy and can be implemented in the manufacturing company.

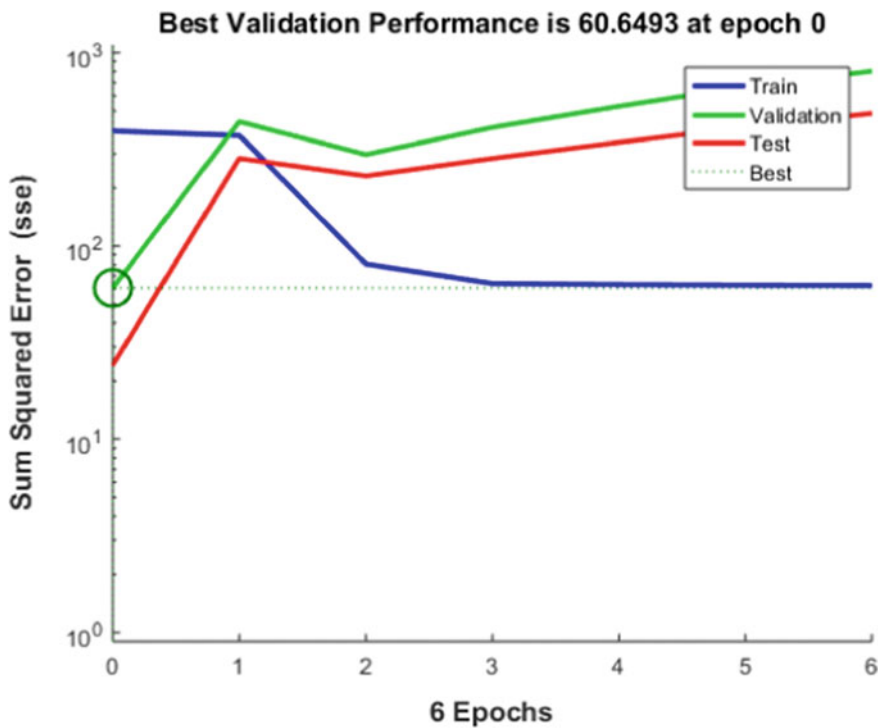


Fig. 11.9 ANN validation performance plot for MRR

Figures 11.12, 11.13, and 11.14 shows the factors of objective optimization of the machining parameters obtained from the Quadratic rotatable central composite design (QRCCD) for the MRR. The result shows that the spindle speed of 2000 rpm, a feed rate of 192 mm/min, length of cut of 59 mm, depth of cut of 2.99 mm, and helix angle of 60° to have the maximum MRR of 53.87 with the desirability of 0.895.



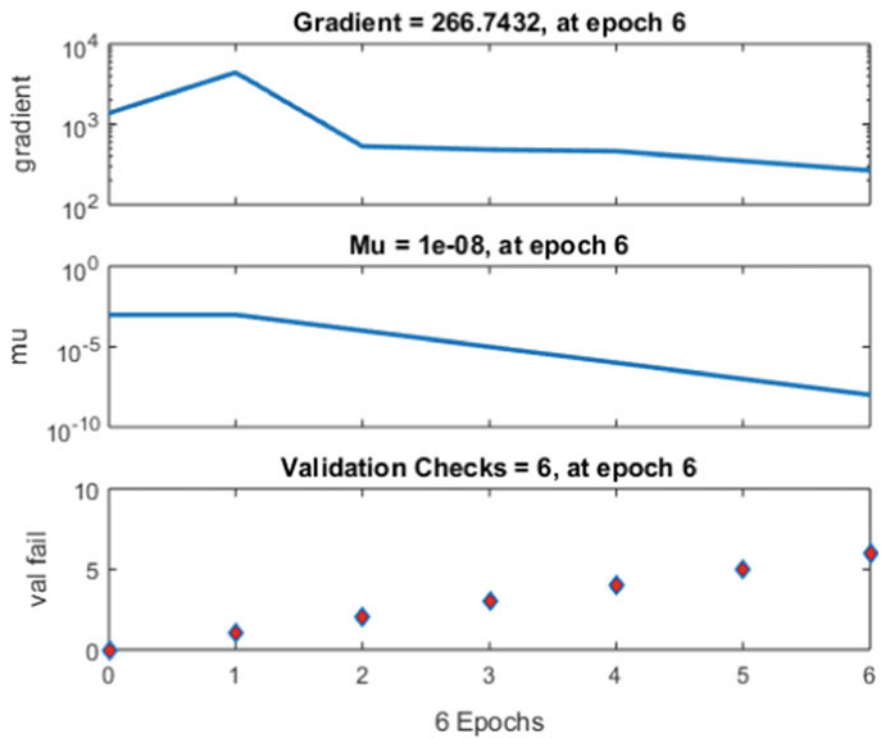
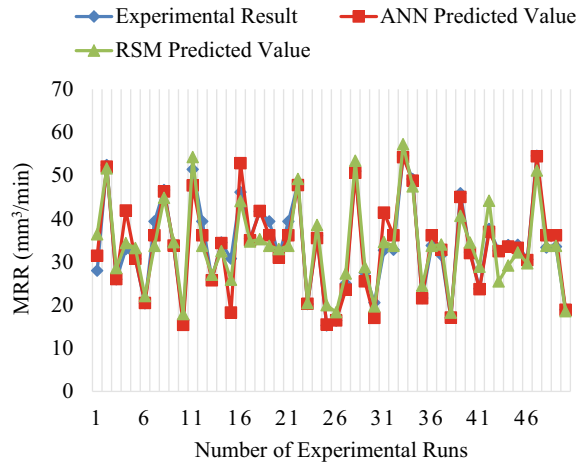
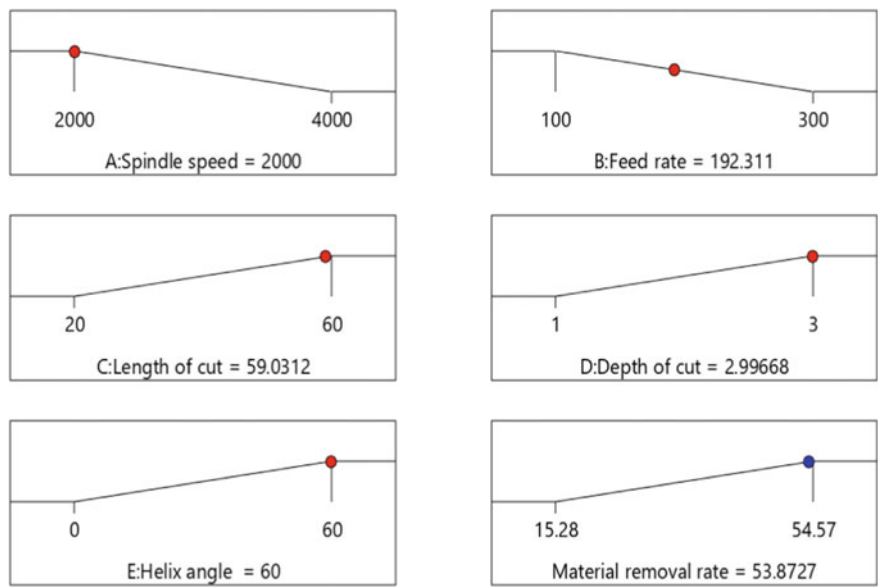


**Fig. 11.10** ANN performance training state for the MRR

**Fig. 11.11** Experimental result, predicted values (ANN) and predicted values (RSM) of the MRR under  $\text{TiO}_2$  nano-lubricant machining environment

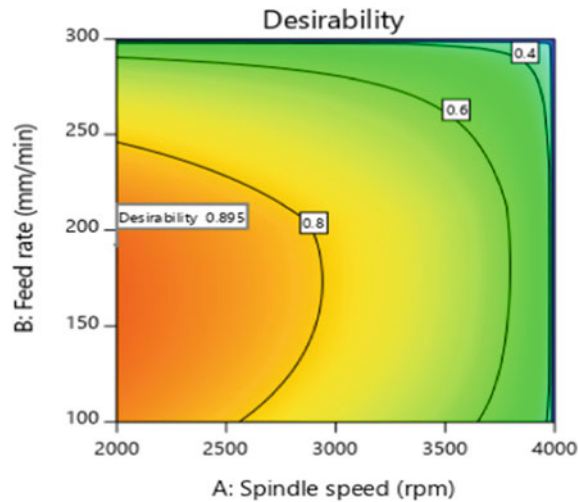




Desirability = 0.895

**Fig. 11.12** The MRR ramps plots for the optimisation of the five factors five levels parameters

**Fig. 11.13** The desirability plots for the MRR



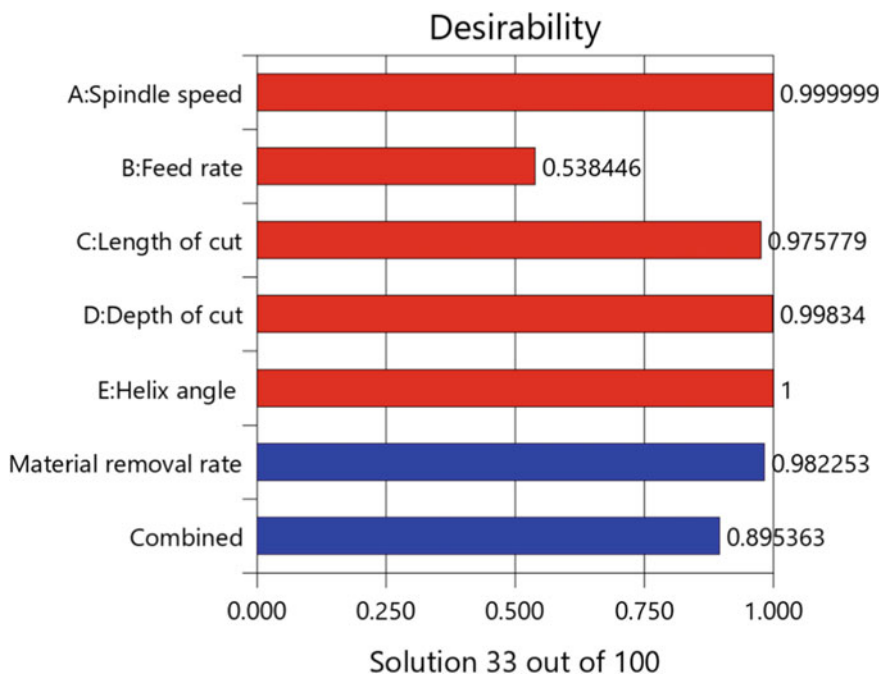


Fig. 11.14 The desirability bar plots for the multi-objective optimization parameters for MRR

11.5 Interactions Study Between the Machining Parameters for MRR

This section explains the significant of carrying out the interaction study of the machining parameters when discussing the materials removal rate during end-milling under biodegradable nano-lubricants. From Figs. 11.15, 11.16, 11.17, 11.18, 11.19, 11.20, 11.21, 11.22, 11.23 and 11.24 present the interaction study for the five (5) machining parameters cutting across the spindle speed, depth of cut, helix angle, length of cut and feed rate. From Fig. 11.18, it can be seen that the most interaction parameters are feed rate and helix angle, followed by spindle speed and helix angle depicted in Fig. 11.21. This interaction study is very important and it gives the correlations on how machining parameters function together during machining process [26]. However, in this case the study is on materials removal rate and in machining the easier and high the chips have been removed from the workpieces the better the MRR. Therefore, the helix angle interactions with the spindle speed, feed rate and length of cut is very significant because it assists to increase the MRR [27].

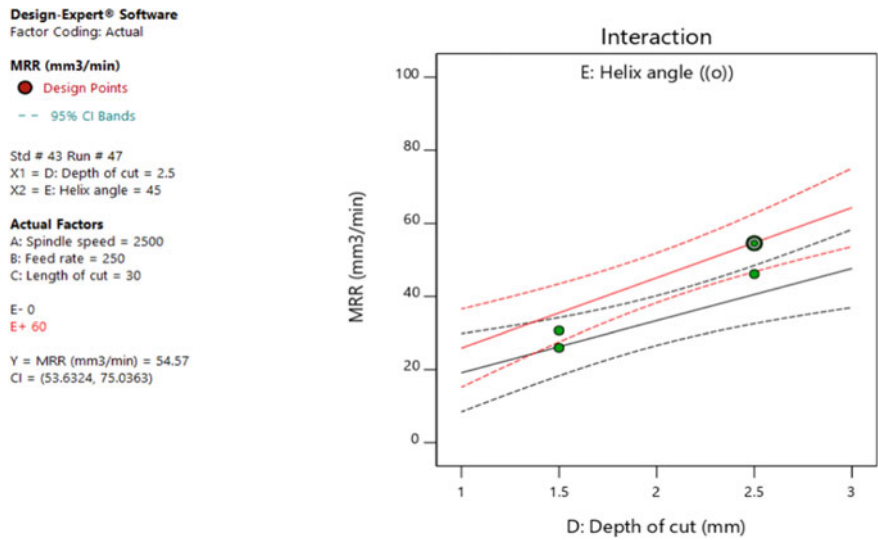


Fig. 11.15 MRR machining parameters interactions between depth of cut and helix angle

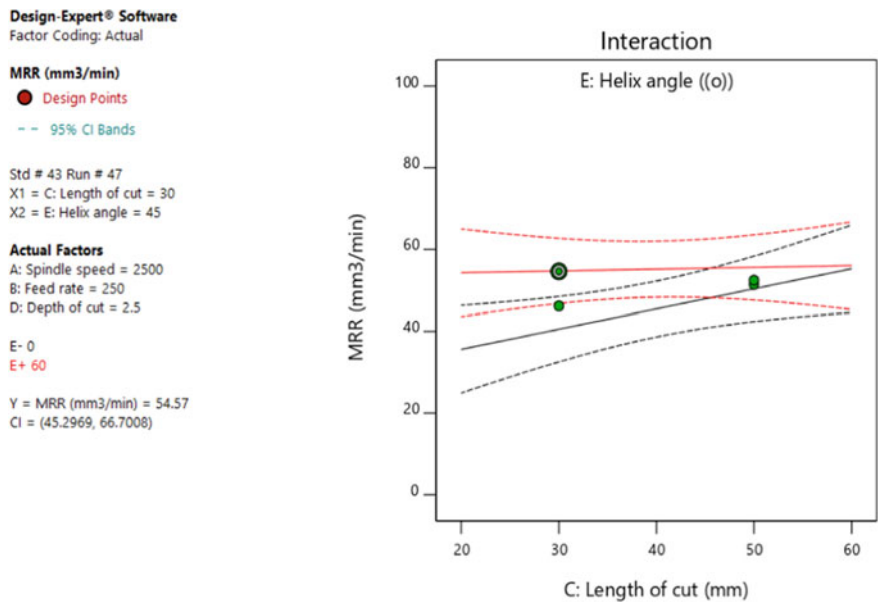


Fig. 11.16 MRR machining parameters interactions between length of cut and helix angle

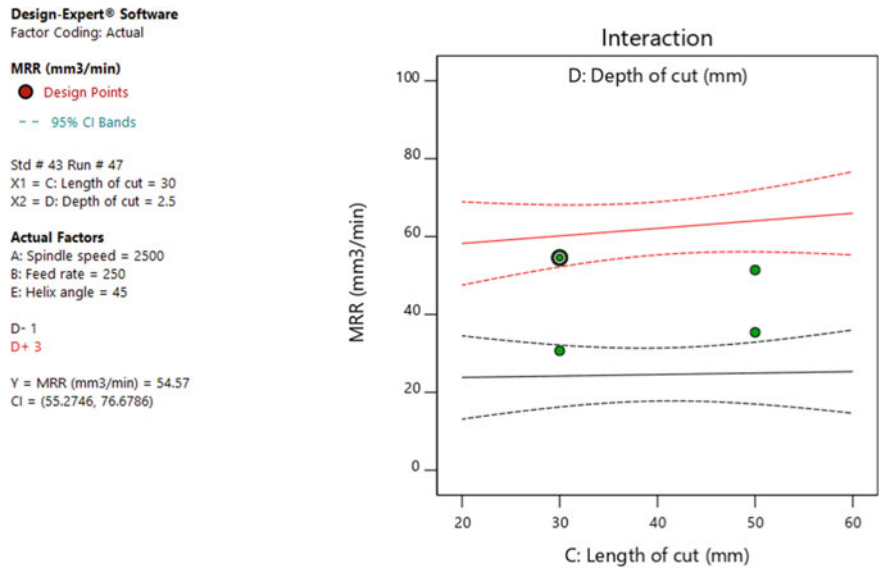


Fig. 11.17 MRR machining parameters interactions between length of cut and depth of cut

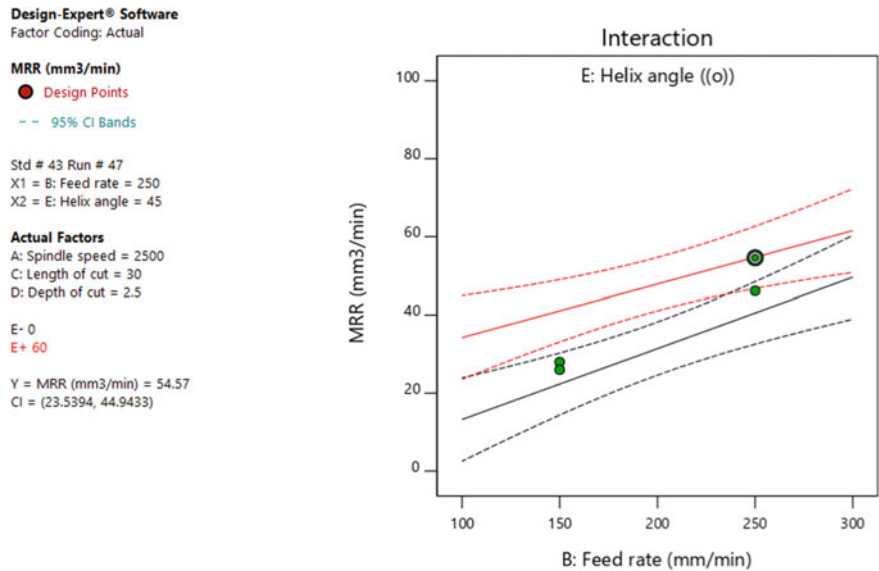


Fig. 11.18 MRR machining parameters interactions between feed rate and helix angle

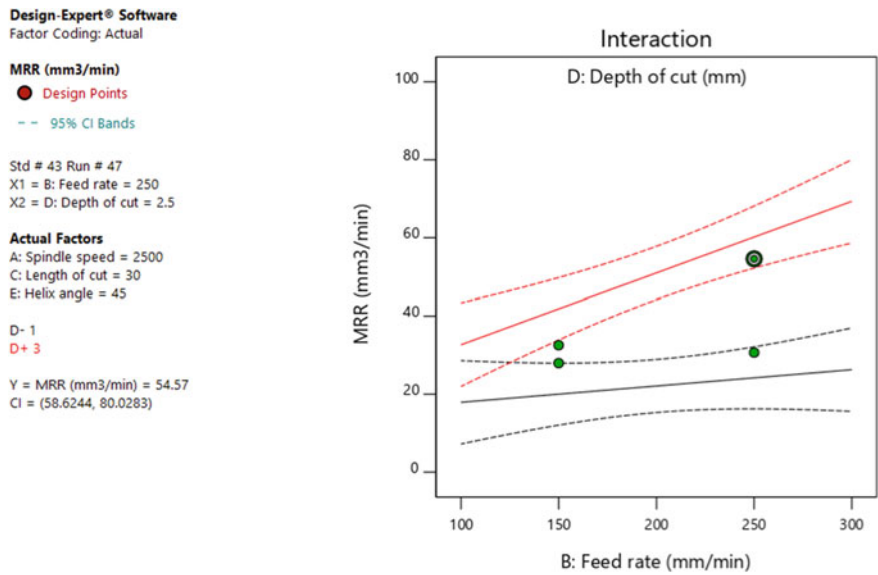


Fig. 11.19 MRR machining parameters interactions between feed rate and depth of cut

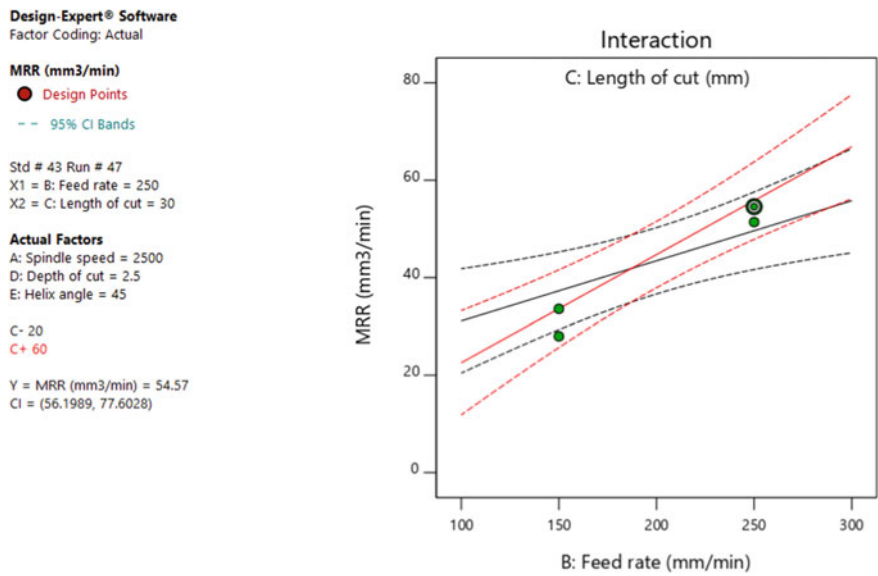


Fig. 11.20 MRR machining parameters interactions between feed rate and length of cut

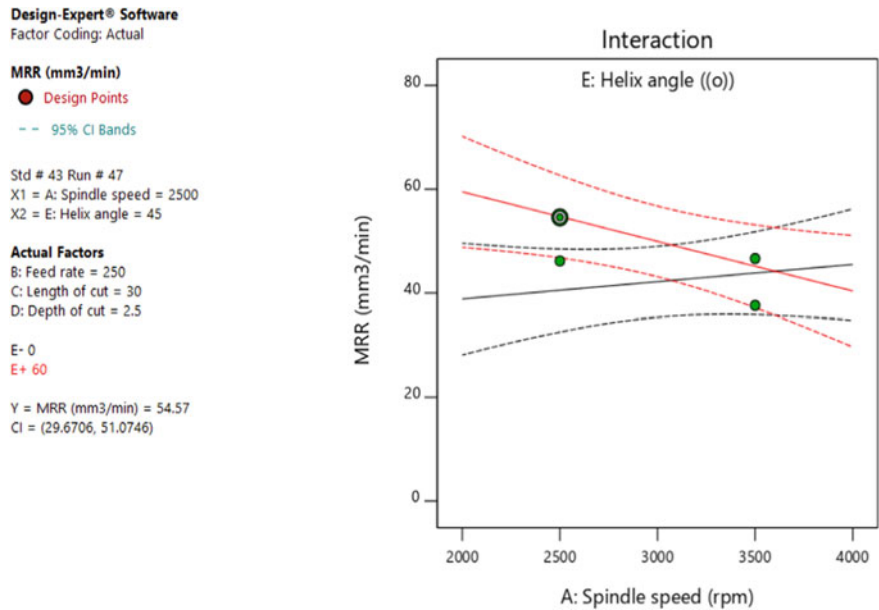


Fig. 11.21 MRR machining parameters interactions between spindle speed and helix angle

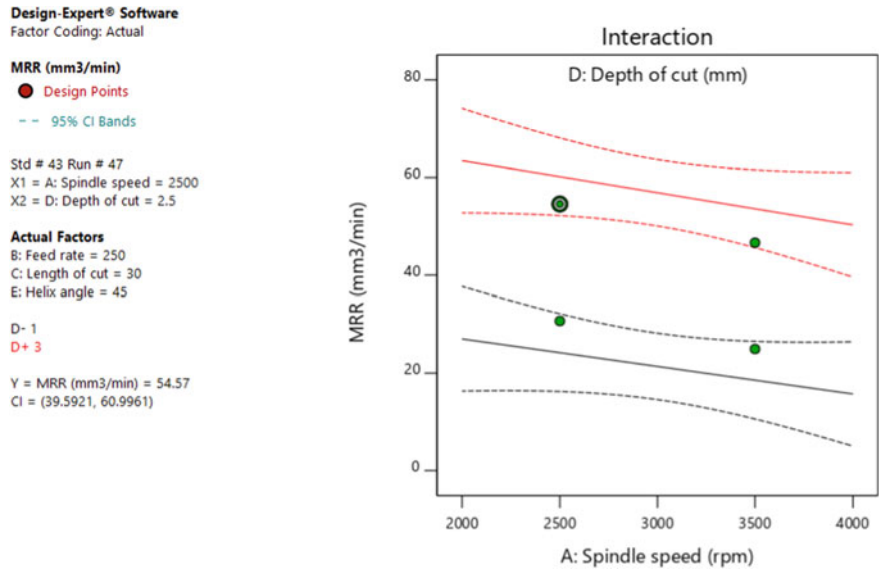


Fig. 11.22 MRR machining parameters interactions between spindle speed and depth of cut

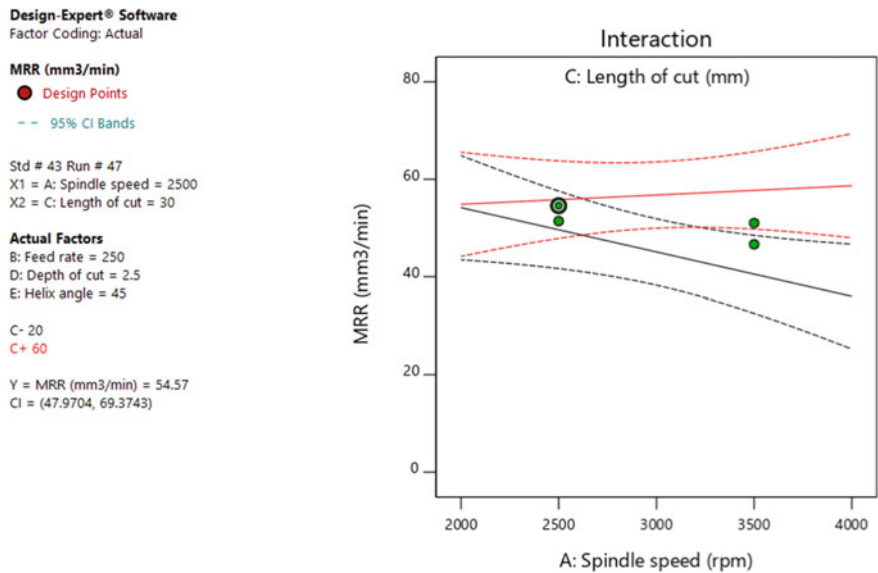


Fig. 11.23 MRR machining parameters interactions between length of cut and spindle speed

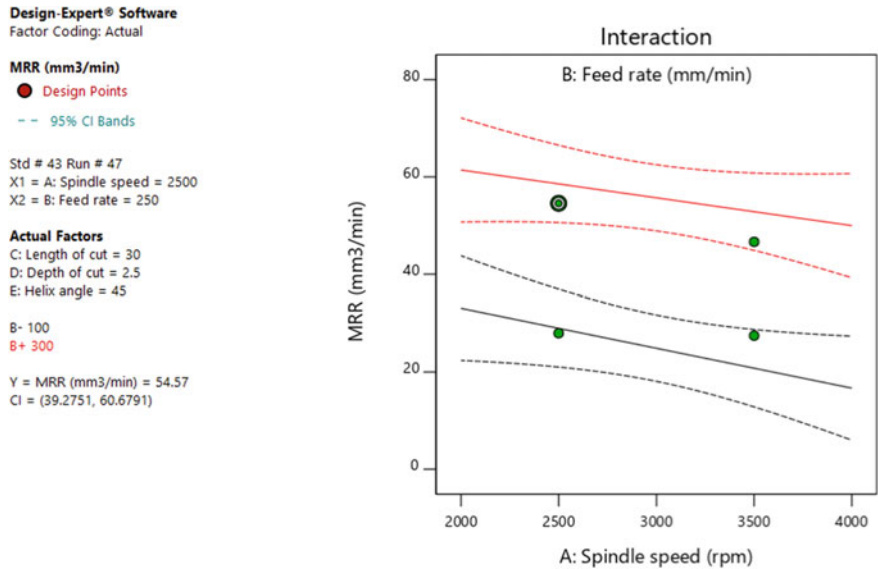


Fig. 11.24 MRR machining parameters interactions between spindle speed and feed rate



## 11.6 Conclusion

In this paper, a numerical analysis of the performance of copra oil-based TiO<sub>2</sub> nano-lubricant on end-milling of AL 8112 alloy using ANN and QCCD was carried out. The developed copra oil-based TiO<sub>2</sub> nano-lubricant was implemented to study the surface roughness and the material removal rate with the five-factors, five-levels (such as spindle speed, feed rate, length of cut, depth of cut and helix angle) of experiment. From the analysis, the following conclusion depicted as follows:

- (i) Feed rate has the most significant effect on MRR because of its percentage contribution of 43.63%, followed by the depth of cut with 34.46%, length of cut with 4.28% under machining environment with TiO<sub>2</sub> nano-lubricant.
- (ii) The feed rate and length of cut are the most interacted machining parameters, followed by the length of cut and helix angle in MRR analysis.
- (iii) The optimised machining parameters from QRCCD are spindle speed of 2000 rpm, a feed rate of 192 mm/min, length of cut of 59 mm, depth of cut of 2.99 mm, and helix angle of 60° to have the maximum MRR of 53.87 with the desirability of 0.895.
- (iv) The ANN and QRCCD models could predict the experimental results with 98.7% and 89.5% accuracy.

Finally, the most accurate model is the artificial neural network which were able to predict the surface roughness and the material removal rate with a significant difference when compared with and quadratic rotatable central composite design.

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## Chapter 12

# Application of Hybrid ANN and PSO for Prediction of Surface Roughness Under Biodegradable Nano-lubricant



**Abstract** Modelling of surface roughness is challenging because machining conditions cannot be well covered by theoretical models. In this section, 50 configurations corresponding to various spindle speed, feed rate, length of cut, depth of cut, helix angle were considered to predict the surface roughness of the end milling machining of an AA8112 alloy. In this study, an ANN-PSO approach has been considered for the development of a suitable prediction model for surface roughness. The sensitivity analysis of numerous Particle Swarm Optimization (PSO) parameters, including the population size of the swarm, the number of neurons in the hidden layer, and the magnitude of the acceleration factors, was carried out. This study reveals that the prediction performance metric is closely related to the model configuration or parameters. The best configurations of the ANN-PSO models were identified. This study shows that the hybrid ANN-PSO enhances the performance of ANN. The proposed approach would address time-consuming and expensive experiment required to identify a configuration that yield the minimum surface roughness.

**Keywords** ANN-PSO models · ANN · Particle swarm optimization · Surface roughness · Machining

## 12.1 Background

The surface roughness plays a major role in the performance of mechanical parts. It can affect their performance during operations [1]. Hence, several studies are focusing on minimizing surface roughness through the adjustment of machining parameters and the implementation of lubricant during manufacturing. Shivanna et al. [2] analyse the impacts of machining parameters on the surface roughness of machined surfaces. Surface roughness parameters were measured using a computer vision system. This study shows that surface quality depends on the speed, the feed, and the depth of cut in a CNC milling machine. A critical assessment of lubrication techniques in machining processes was performed by Lawal et al. [3]. This study points out that irrespective of the lubrication techniques, workpiece material,

tool material and machining conditions were vital to the performance of machining processes. Any modification to a process variable or the state of the cutting tool affects the surface geometry and texture.

Manufacturers have investigated several methods for applying cutting fluid during environmentally friendly machining operations. Minimum quantity lubrication (MQL) strategies are potentially more suitable to save manufacturing costs and environmental pollutants. The need for cleaner and greener machining cannot be met by using MQL for lubricants with low thermal conductivity [4]. Therefore, adding nanoparticles to the base oil (which is created) improves its rheological characteristics, thermal conductivity, and stability [5]. According to Lee et al. [6], adding graphite nanoparticles to conventional fluid improved its lubricating properties.

Because roughness is nonlinear, modelling it analytically is difficult. The wide range of machining conditions cannot be well covered by the proposed theoretical models, necessitating the development of additional novel techniques to identify the ideal machining settings and forecast the roughness of machined surfaces [7, 8]. Studies on the effects of the variables that could reduce surface roughness were done, but the findings were not very gratifying in light of the complex interactions of so many contributing variables. For instance, contrary to what was expected, a strong tendency for surface roughness to grow as the depth of the cut rose was not seen [9]. To tackle the challenges, researchers used artificial intelligence techniques like genetic algorithms (GAs) and artificial neural networks (ANNs).

The advantages of ANNs include input–output mapping, handling nonlinearity, managing incomplete data, processing data in parallel, and improving computing power [10, 11]. The optimization of the ANN design, however, is a problem with ANNs [12]. They also lack a warranty for application performance as result, which is a drawback [10]. The design of the ANN architecture frequently used the process of trial and error [12]. The determination of the number of layers and neurons in an ANN needed for an application lacks a general and ideal solution [13]. It was difficult to choose appropriate (but not necessarily optimal) process parameters like feed rate and depth of cut when any permissible surface roughness may be one of an ANN's inputs. Additionally, the competing goals of product quality, cost, and production rate present optimization issues [14].

In order to estimate the degree of roughness on sample surfaces turned using diamond and carbide tools, Zhong et al. [9] used neural networks with seven inputs. The activation function and network design were optimized for good prediction accuracy to produce the optimal network. Additionally, this study showed that the constructed ANN could accurately forecast the roughness of the sample surfaces turned on a different machine. Sofuoglu [15] showed that the ANN technique could simulate the roughness of the machined wood surfaces by predicting the surface roughness using an ANN. Additionally, Tiryaki et al. [16] revealed that they could forecast the roughness of their machined wood surfaces by utilizing ANNs.

Several studies suggest that ANN training parameters (bias and weight) could be enhanced using Particle Swarm Optimization (PSO). The Stirling engine performance was improved using a hybrid ANN-PSO in comparison with a typical ANN model in a study reported by Machesa et al. [17]. Seguini et al. [18] indicated that ANN combined with PSO was more accurate in the prediction of the crack in the pipeline. The prediction of the transverse vibration peak, the vertical vibration peak, and the longitudinal vibration peak, as a result of the blast, was improved using ANN-PSO compared to ANN in a study conducted by Tartibu et al. [19]. The clad characteristics in the laser metal deposition process were predicted by Pant and Chatterjee [20] using ANN and combined PSO-ANN algorithms. This study revealed that better-clad properties can be predicted by the combined PSO-ANN based supervised learning model. This is by no means all the existing works that indicate the enhancement of ANN parameters when combined with PSO but it justifies the rationale behind the selection of ANN-PSO as a potential modelling approach for the analysis of Surface Roughness.

Therefore, in this work, a readily available dataset was used to build ANN and ANN-PSO models. A parametric analysis was performed to analyse how parameters involved in the building of the ANN-PSO model affect its prediction accuracy.

## 12.2 Modelling Approaches

In this study, an ANN-PSO approach has been considered for the development of a suitable prediction model for surface roughness. Prior to the description of the proposed approach, ANN is described. This ANN model was used as a benchmark to analyse the performance indicators considered for the prediction of surface roughness. ANN is one of the most common intelligent systems created by imitating the human brain. ANN draws inspiration from the complex operation of human brains where hundreds of billions of linked neurons process information in parallel [21].

An artificial neural network, often known as a “neural network,” is made up of three layers of neurons: an input layer of neurons (or nodes, units), one to three hidden layers of neurons, and a layer of output neurons as shown in Fig. 12.1. Backpropagation is a popular technique for neural network training [22]. Numerous data-intensive applications have seen success in implementing neural networks. The ANN strategy has been used in this study despite the fact that the ANN technique tends to become stuck in local minima, which is one potential drawback of this approach. Successful implementation of neural networks has been documented in various data-driven applications.

The equation describing the ANN backpropagation approach can be described as follows [23]:

$$f(net_k) = \frac{1}{1 + e^{-net_k}} \quad (12.1)$$

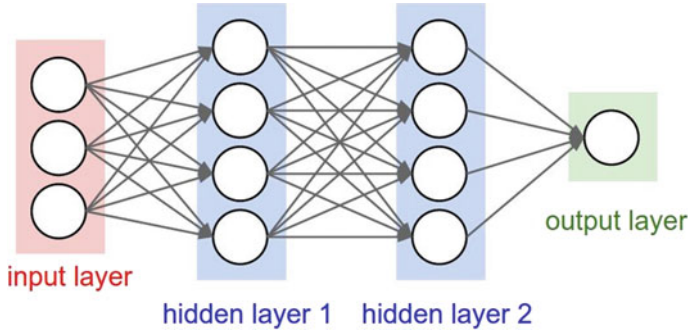


**Fig. 12.1** Typical architecture of an ANN model

$$\begin{aligned}
 x_j &= \text{normalized } X_d \quad 1 < d \leq m \\
 net_k &= \sum_{j=1}^{k-1} W_{kj} x_j + b_j \quad m+1 \leq k \leq N+n \\
 x_k &= f(net_k) \quad m+1 \leq k \leq N+n \\
 O_s &= x_{N+s} \quad 1 \leq s \leq n
 \end{aligned}$$

where,

|            |                                           |
|------------|-------------------------------------------|
| $m$        | The number of inputs to the network       |
| $n$        | Number of outputs of the ANN              |
| $X_d$      | The actual inputs of the ANN              |
| $f(net_k)$ | Log-sigmoid function                      |
| $N$        | Number of intermediate neurons in the ANN |
| $W$        | The weight matrix in each layer           |
| $W_{kj}$   | The elements of the matrix weight         |
| $x_j$      | The activation level of the neuron        |
| $O_s$      | The output from ANN.                      |

One metaheuristic optimization technique, known as particle swarm optimization, is based on the social and cooperative cooperation of several species in a multidimensional search space. Numerous research has demonstrated that hybridizing ANN and PSO considerably enhances the network's performance [24]. Neurons are the building blocks of an ANN. Through weights and biases, these units are interconnected. To determine the network's ideal weights and biases, training using inputs and outputs that are known must be done after the ANN model has been created. Particle Swarm Optimization (PSO) was used in this paper even though there are other ways to obtain appropriate weights and biases. Once training is effective, ANN will be able to link complex input and output datasets.

The beginning position Pbest, the initial best particle position Gbest, and the particle's location in the search spaces serve as identifiers for each particle. To determine the Gbest and Pbest values and to update the optimized weights and biases of the ANN, each particle's fitness is evaluated throughout training. The flowchart in Fig. 12.2 provides an overview of this procedure. Eberhart and Kennedy [25] go into detail on how PSO was put into practice. Using Eqs. (12.2) and (12.3), the updating of particle position and velocity is condensed. In these Equations,  $c_1$  and  $c_2$  are the acceleration constants and  $r_1$  and  $r_2$  are referred to as random integers. The weight of inertia (Pbest), which includes  $x$ ,  $v$ ,  $P^t$ , and  $G^t$ .

$$V_{ij}^t = \chi \left[ \omega v_{ij}^{t-1} + c_1 r_1 (p_{ij}^{t-1} - x_{ij}^{t-1}) + c_2 r_2 (G_j^{t-1} - x_{ij}^{t-1}) \right] \quad (12.2)$$

$$x_{ij}^t = x_{ij}^{t-1} + v_{ij}^t \quad (12.3)$$

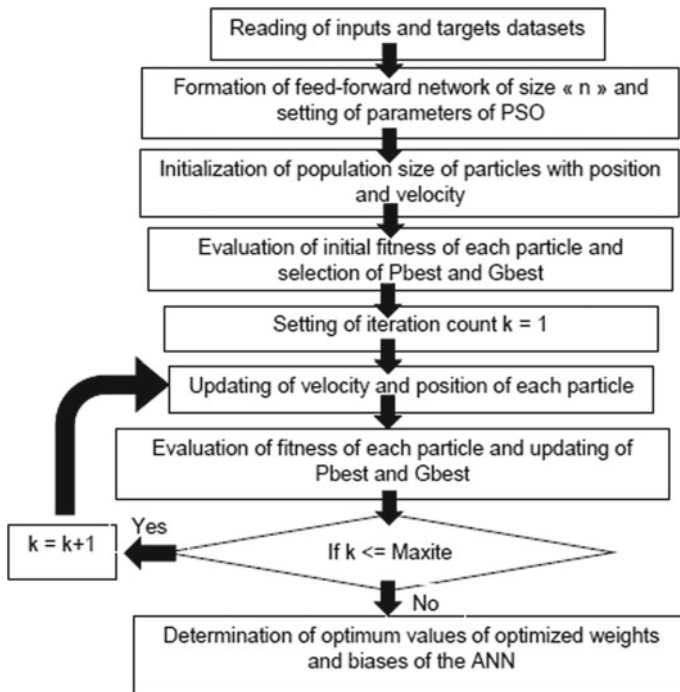


**Fig. 12.2** Training flowchart describing the ANN-PSO approach (Adapted from [24])



## 12.3 Description of Dataset Extraction

In this study, the end milling machining of an AA8112 alloy was performed on a SIEG 3/10/0016 CNC machine. Details describing the experimental setup and the variables (spindle speed, feed rate, length of cut, depth of cut, helix angle) are available in Okokpujie et al. [26]. The machining parameters were derived using a quadratic rotatable central composite design. In order to develop nano-lubricant in large quantities, a two-step method was used. The first step consisted of synthesizing nanomaterials in dry powder. The second step consisted of dispersing them into base oil by mixing techniques.

Titanium dioxide ( $\text{TiO}_2$ ) and multi-walled carbon nanotube (MWCNTs) nano-lubricants mixed with copra oil were used as the cutting fluid [27]. The rectangular plate of the AA8112 alloy was cut into 20, 30-, 40-, 50- and 60-mm lengths. The 150 pieces were divided equally namely 50 pieces of  $\text{TiO}_2$ , 50 pieces of MWCNTs and 50 pieces of copra oil. The CNC machine was programmed for the length of cut to be adjusted between 20 and 60 mm, the spindle speed was adjusted between 2000 to 4000 RPM, the feed rate was adjusted between 100 to 300 mm/min, the depth cut was adjusted between 1 and 3 mm, and the helix angle was adjusted between 0 and 60°. The 50 experimental runs considered as a dataset in this study are provided in Table 12.1.

## 12.4 Methodology

The dataset considered to build the ANN model is provided in Table 12.1. These data relate the outputs (targets), namely the Surface Roughness (SR) to the inputs described by the spindle speed, feed rate, length of the cut, depth of cut, and helix angle. The dataset is then split into the appropriate places to clearly distinguish between the training and testing phases. 80% of the data, or 40 data, were used for training the ANN model in order to forecast the values of Surface Roughness. The remaining 10% of the data (or five data) were utilized for testing, and the remaining 10% was used for validation. The capabilities of the ANN model were assessed using the validation and testing data. The MATLAB environment was used to implement this process (Appendix I). Figure 12.3 depicts the neural network's structure.

The prediction performance of the Surface Roughness taken into consideration in this study was examined using a hybrid ANN-PSO model. A total of 50 data points were divided in half; of these, 42 were utilized to train the hybrid ANN-PSO model and 8 were used to test it. The MATLAB environment was used to implement the model (Appendix J). The sensitivity analysis of numerous PSO parameters, including the population size of the swarm ( $N$ ), the number of neurons in the hidden layer ( $n$ ), and the magnitude of the acceleration factors ( $c_1$  and  $c_2$ ), must be carried out, according to Momeni et al. [28]. It is required to perform numerous runs and take into account various parameter combinations in order to construct a robust network.

**Table 12.1** Dataset

| Index | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle ( $\alpha$ ) (o) | SR (MWCNTs) ( $\mu\text{m}$ ) |
|-------|---------------------|--------------------|--------------------|-------------------|------------------------------|-------------------------------|
| 1     | 2500                | 150                | 30                 | 2.5               | 45                           | 2.04                          |
| 2     | 2500                | 250                | 50                 | 2.5               | 15                           | 2.06                          |
| 3     | 2500                | 250                | 30                 | 1.5               | 15                           | 1.98                          |
| 4     | 3500                | 250                | 50                 | 1.5               | 45                           | 1.46                          |
| 5     | 2500                | 150                | 50                 | 1.5               | 45                           | 1.68                          |
| 6     | 3000                | 200                | 40                 | 2                 | 30                           | 1.53                          |
| 7     | 3500                | 250                | 30                 | 2.5               | 45                           | 1.51                          |
| 8     | 2500                | 150                | 50                 | 2.5               | 45                           | 1.66                          |
| 9     | 3000                | 200                | 40                 | 2                 | 30                           | 1.54                          |
| 10    | 3500                | 150                | 50                 | 2.5               | 45                           | 1.52                          |
| 11    | 3500                | 150                | 30                 | 2.5               | 15                           | 1.65                          |
| 12    | 2500                | 250                | 30                 | 2.5               | 15                           | 1.76                          |
| 13    | 2500                | 250                | 50                 | 1.5               | 45                           | 1.74                          |
| 14    | 3000                | 200                | 40                 | 2                 | 60                           | 1.59                          |
| 15    | 3000                | 200                | 40                 | 2                 | 30                           | 1.58                          |
| 16    | 4000                | 200                | 40                 | 2                 | 30                           | 1.16                          |
| 17    | 3000                | 300                | 40                 | 2                 | 30                           | 2.51                          |
| 18    | 3500                | 150                | 50                 | 1.5               | 45                           | 1.49                          |
| 19    | 3000                | 200                | 60                 | 2                 | 30                           | 1.61                          |
| 20    | 3000                | 200                | 40                 | 1                 | 30                           | 1.56                          |
| 21    | 3500                | 150                | 30                 | 1.5               | 45                           | 1.36                          |
| 22    | 3500                | 250                | 30                 | 1.5               | 45                           | 1.51                          |
| 23    | 3500                | 250                | 50                 | 2.5               | 45                           | 1.61                          |
| 24    | 3500                | 150                | 30                 | 2.5               | 45                           | 1.59                          |
| 25    | 2500                | 150                | 50                 | 1.5               | 15                           | 1.92                          |
| 26    | 2500                | 250                | 50                 | 1.5               | 15                           | 2                             |
| 27    | 3000                | 200                | 40                 | 2                 | 30                           | 1.66                          |
| 28    | 3500                | 250                | 50                 | 2.5               | 15                           | 1.52                          |
| 29    | 3000                | 200                | 40                 | 3                 | 30                           | 2.2                           |
| 30    | 3500                | 150                | 50                 | 1.5               | 15                           | 1.54                          |
| 31    | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 32    | 3000                | 100                | 40                 | 2                 | 30                           | 1.21                          |
| 33    | 3500                | 250                | 50                 | 1.5               | 15                           | 1.5                           |
| 34    | 2000                | 200                | 40                 | 2                 | 30                           | 2.3                           |
| 35    | 3000                | 200                | 20                 | 2                 | 30                           | 1.51                          |

(continued)

**Table 12.1** (continued)

| Index | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle ( $\alpha$ ) (o) | SR (MWCNTs) ( $\mu\text{m}$ ) |
|-------|---------------------|--------------------|--------------------|-------------------|------------------------------|-------------------------------|
| 36    | 2500                | 150                | 30                 | 1.5               | 45                           | 1.74                          |
| 37    | 3500                | 250                | 30                 | 1.5               | 15                           | 1.45                          |
| 38    | 3000                | 200                | 40                 | 2                 | 0                            | 1.61                          |
| 39    | 2500                | 150                | 50                 | 2.5               | 15                           | 1.76                          |
| 40    | 2500                | 250                | 30                 | 2.5               | 45                           | 1.77                          |
| 41    | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 42    | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 43    | 2500                | 250                | 30                 | 1.5               | 45                           | 1.75                          |
| 44    | 3500                | 150                | 30                 | 1.5               | 15                           | 1.44                          |
| 45    | 2500                | 250                | 50                 | 2.5               | 45                           | 1.69                          |
| 46    | 2500                | 150                | 30                 | 2.5               | 15                           | 1.71                          |
| 47    | 3000                | 200                | 40                 | 2                 | 30                           | 1.58                          |
| 48    | 3500                | 150                | 50                 | 2.5               | 15                           | 1.52                          |
| 49    | 3500                | 250                | 30                 | 2.5               | 15                           | 1.49                          |
| 50    | 2500                | 150                | 30                 | 1.5               | 15                           | 1.77                          |

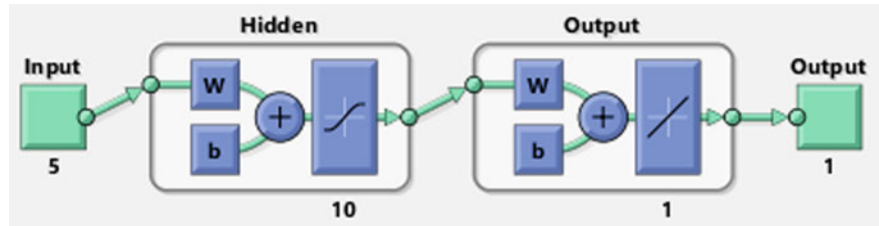


**Fig. 12.3** Neural network’s structure

According to Alam et al. [29], the present investigation took into account six different values of neurons (5–6–7–8–9–10), six different swarm size populations (10–20–50–100–200–400), and acceleration factors  $c_1$  and  $c_2$  that fell within the range of 1–2.5 and 2–3, respectively. One thousand iterations have been specified as the maximum. If after 100 iterations the improvement in the objective function did not surpass  $10^{-8}$ , the run was stopped.

Assessment indices were used to examine the model’s error rates and prediction accuracy. The Mean Square Error (MSE) and Coefficient of determination ( $R^2$ ) are the statistical measurements utilized. The system of Eqs. 12.4 and 12.5 is used to compute the statistical measurements.

$$R^2 = 1 - \frac{\sum_k (y_k - \hat{y}_k)^2}{\sum_k (y_k - \bar{y}_k)^2} \quad (12.4)$$

$$MSE = \frac{1}{2} \sum_{k=1}^n (y_k - \hat{y}_k)^2 \quad (12.5)$$

where the details of  $y_k$ ,  $\hat{y}_k$ ,  $\bar{y}_k$   $n$  and  $k$  are given. The symbols  $y_k$ ,  $\hat{y}_k$  and  $\bar{y}_k$  stand for the experimental data sample, the algorithm's projected values and the mean value of the experimental data samples, respectively.  $N$  stands for the number of data samples, and  $K$  stands for the set of all source points indexed by  $k$ .

## 12.5 Results and Discussions

### 12.5.1 ANN Results

Figure 12.4 allow an easy visual comparison between the predicted Surface Roughness against the actual values respectively. The regression value  $R^2$  of 0.91272 suggests that the output tracks the targets effectively.

Figure 12.5 the ANN predictions versus the actual data of the Surface Roughness considering the 50 data. The anticipated outputs frequently match the desired values very nearly. The average percentage of the deviation was approximately 5.49%. A discrepancy exceeding 12% was observed for 5 data while most of the deviation of the predicted value was under 10%.

### 12.5.2 ANN-PSO Results

A parametric analysis was performed to identify the configuration of the ANN-PSO model that yields the highest performance metrics. It has been determined which acceleration factors ( $c_1$  and  $c_2$ ) are most effective given the population size and the number of neurons in the hidden layer. For the training and testing dataset, the Mean Squared Error (MSE) and R squared value ( $R^2$ ) was used to assess the model's prediction accuracy. The best training outcome was obtained with 10 neurons, a 200-swarm population, and acceleration factors  $c_1$  and  $c_2$  of 1 and 2.75, respectively, according to Table 12.2. This corresponds to configuration 35. The training regression value  $R^2$  and MSE were 0.99671 and 4.5886e-04 respectively. Conversely, the best result considering training and testing was obtained when the number of neurons is 8, swarm population size is 10, and acceleration factors  $c_1$  and  $c_2$  are 1 and 2.75. This corresponds to configuration 19. The training regression value  $R^2$  and MSE

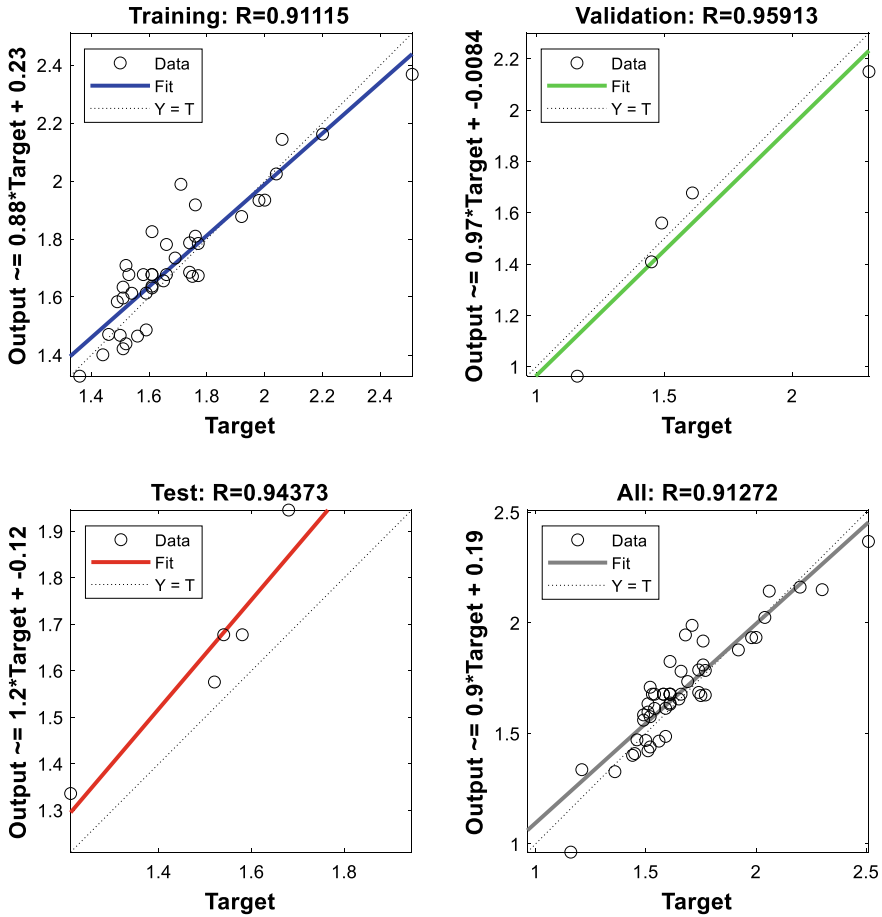


**Fig. 12.4** Performance indicators of ANN models considering training, testing and validation

were 0.91641 and 0.0112 respectively. Interestingly, the best model configuration considering training performance only exhibits a poor testing performance of 0.1997 while the best model configuration considering training and testing yields 0.8567. Nevertheless, these results show that the ANN performance metric was enhanced from 0.91115 (Fig. 12.4) to 0.99671 (Fig. 12.6-configuration 35), using ANN-PSO.

The network's training responses of all the 36-configuration considered are shown in Fig. 12.6, and their testing responses are shown in Fig. 12.7.

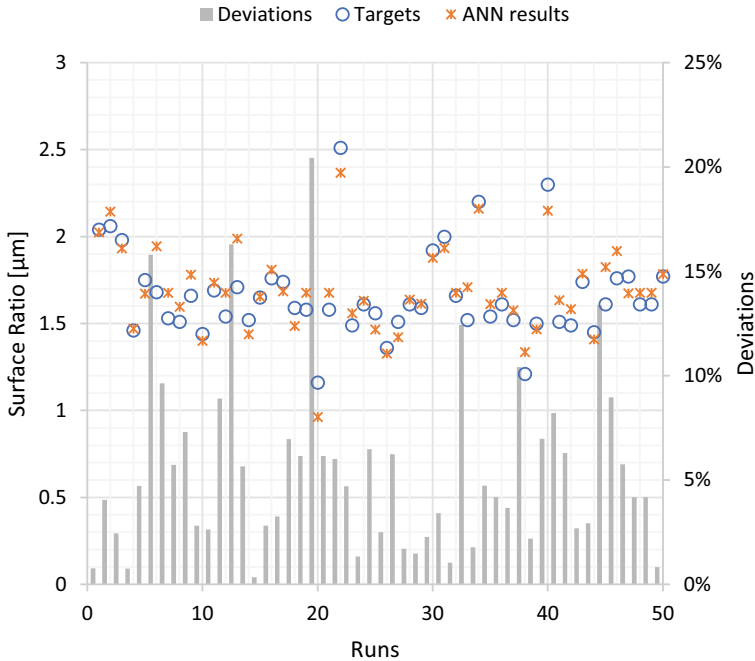


**Fig. 12.5** Performance of ANN predictions

A crucial finding from the data is that the parameters of the PSO have an impact on performance prediction. Additionally, the outcomes of the finest testing and training were not the same. As a result, the most ideal network found was ANN-PSO 10-200-1-2.75 considering the training performance (configuration 35). However, considering training and testing performance, the best model configuration was ANN-PSO 8-10-1-2.75 (configuration 19). A comparison between these two best configurations was done. Figure 12.8 shows that the performance prediction of these two configurations was very close. The average deviations of the ANN-PSO 10-200-1-2.75 (configuration 35) and ANN-PSO 8-10-1-2.75 (configuration 19) were 15.14% and 14.06% respectively.

The ANN-PSO 8-10-1-2.75 model (configuration 19) was considered for further analysis. As mentioned in the previous part, the 50 data were divided into two groups: 42 data were used for the hybrid ANN-PSO model's training, and 8 data were utilized for the model's testing. The testing performance  $R^2$  was 0.8567. Compared to the testing performance of 0.94373 exhibited by the ANN model, the proposed ANN-PSO model was less robust. Figure 12.9 shows clearly that most targets were hit (or were closer to) by ANN results. However, several reasons could justify these findings:

**Table 12.2** Summarized training and testing performance for all ANN-PSO configurations

|    |                   |                       | Acceleration factors |                |                         |        |                        |
|----|-------------------|-----------------------|----------------------|----------------|-------------------------|--------|------------------------|
|    | Number of neurons | Swarm population size | c <sub>1</sub>       | c <sub>2</sub> | Training R <sup>2</sup> | MSE    | Testing R <sup>2</sup> |
| 1  | 5                 | 10                    | 2.25                 | 2              | 0.87886                 | 0.0159 | 0.3411                 |
| 2  | 5                 | 20                    | 2.25                 | 2              | 0.84861                 | 0.0195 | 0.6002                 |
| 3  | 5                 | 50                    | 1.5                  | 2.25           | 0.87277                 | 0.0166 | 0.5472                 |
| 4  | 5                 | 100                   | 1                    | 2.75           | 0.88137                 | 0.0156 | 0.2904                 |
| 5  | 5                 | 200                   | 1.5                  | 2              | 0.91317                 | 0.0116 | 0.6768                 |
| 6  | 5                 | 400                   | 1.5                  | 2              | 0.96013                 | 0.0055 | 0.6972                 |
| 7  | 6                 | 10                    | 1                    | 3              | 0.90203                 | 0.0130 | 0.5419                 |
| 8  | 6                 | 20                    | 2                    | 2.25           | 0.84777                 | 0.0196 | 0.5927                 |
| 9  | 6                 | 50                    | 1                    | 2.5            | 0.87693                 | 0.0161 | 0.5835                 |
| 10 | 6                 | 100                   | 1                    | 2.5            | 0.94649                 | 0.0073 | 0.0959                 |
| 11 | 6                 | 200                   | 1                    | 2.75           | 0.9086                  | 0.0122 | 0.56                   |
| 12 | 6                 | 400                   | 1                    | 2.25           | 0.86753                 | 0.0173 | 0.0336                 |
| 13 | 7                 | 10                    | 1.5                  | 2.5            | 0.95834                 | 0.0057 | 0.5098                 |
| 14 | 7                 | 20                    | 1                    | 2.75           | 0.96653                 | 0.0046 | 0.3564                 |
| 15 | 7                 | 50                    | 1                    | 2.5            | 0.96475                 | 0.0048 | 0.2747                 |
| 16 | 7                 | 100                   | 1                    | 2.5            | 0.92512                 | 0.0102 | 0.3592                 |
| 17 | 7                 | 200                   | 1.5                  | 2.25           | 0.96838                 | 0.0044 | 0.6541                 |
| 18 | 7                 | 400                   | 2                    | 2              | 0.89297                 | 0.0143 | 0.0339                 |
| 19 | 8                 | 10                    | 1                    | 2.75           | 0.91641                 | 0.0112 | 0.8567                 |
| 20 | 8                 | 20                    | 1                    | 2.5            | 0.93957                 | 0.0082 | 0.4328                 |
| 21 | 8                 | 50                    | 1.5                  | 2.25           | 0.89193                 | 0.0143 | 0.3082                 |
| 22 | 8                 | 100                   | 1                    | 2.5            | 0.97414                 | 0.0036 | 0.2846                 |
| 23 | 8                 | 200                   | 1                    | 2.75           | 0.86246                 | 0.0179 | 0.8557                 |
| 24 | 8                 | 400                   | 1                    | 2.25           | 0.92936                 | 0.0095 | 0.135                  |
| 25 | 9                 | 10                    | 1                    | 2.75           | 0.90869                 | 0.0122 | 0.535                  |
| 26 | 9                 | 20                    | 1                    | 3              | 0.89998                 | 0.0133 | 0.174                  |
| 27 | 9                 | 50                    | 1.5                  | 2.25           | 0.95093                 | 0.0067 | 0.4457                 |
| 28 | 9                 | 100                   | 2                    | 2              | 0.96381                 | 0.0050 | 0.6959                 |
| 29 | 9                 | 200                   | 1.5                  | 2.25           | 0.9754                  | 0.0034 | 0.0744                 |

(continued)

**Table 12.2** (continued)

|    |                   |                       | Acceleration factors |                |                         |            |                        |
|----|-------------------|-----------------------|----------------------|----------------|-------------------------|------------|------------------------|
|    | Number of neurons | Swarm population size | c <sub>1</sub>       | c <sub>2</sub> | Training R <sup>2</sup> | MSE        | Testing R <sup>2</sup> |
| 30 | 9                 | 400                   | 1                    | 2.5            | 0.94264                 | 0.0078     | 0.0439                 |
| 31 | 10                | 10                    | 1                    | 2.75           | 0.9286                  | 0.0096     | 0.3589                 |
| 32 | 10                | 20                    | 1.5                  | 2.5            | 0.90495                 | 0.0127     | 0.3903                 |
| 33 | 10                | 50                    | 1.5                  | 2.5            | 0.92313                 | 0.0103     | 0.7149                 |
| 34 | 10                | 100                   | 1                    | 2.75           | 0.93147                 | 0.0092     | 0.6535                 |
| 35 | 10                | 200                   | 1                    | 2.75           | 0.99671                 | 4.5886e-04 | 0.1997                 |
| 36 | 10                | 400                   | 1.5                  | 2.5            | 0.98866                 | 0.0016     | 0.3323                 |

- The split of data: While building the ANN model, the split between training, testing and validation data is done within MATLAB. When retraining an ANN model, the testing data are reallocated to enhance the prediction performance. This is in contrast with the ANN-PSO model. In this latter approach, the testing data must be picked randomly within the parameter’s domain.
- The performance of the ANN-PSO model: This performance depends on the values attributed to the number of neurons, the swarm population size and the acceleration factors. This study shows that an adjustment of these parameters could improve or deteriorates the prediction performance. Therefore, performing an optimization to identify the best configuration of the ANN-PSO model would potentially improve its prediction performance.
- The limitations of the data available: This study was based on 50 data. It is expected that performance could be enhanced with a larger dataset.



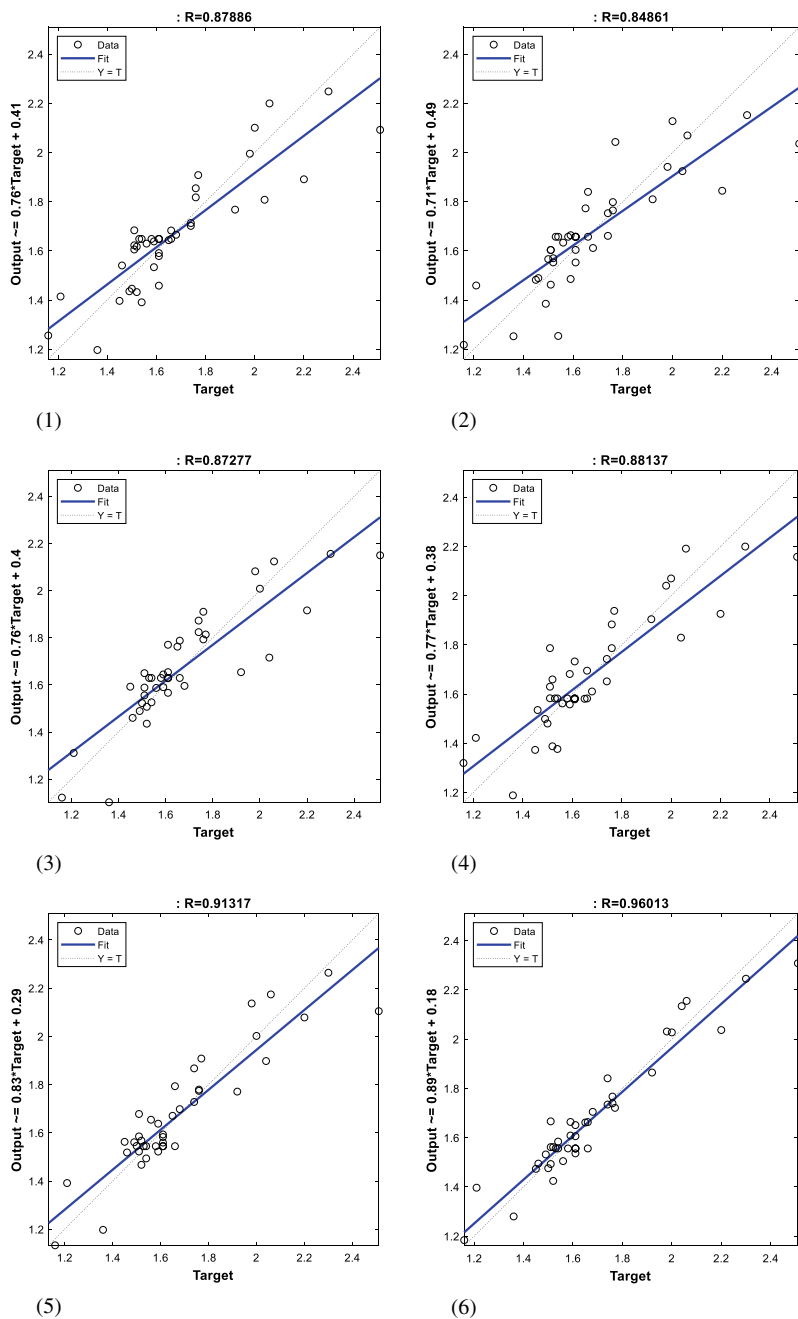
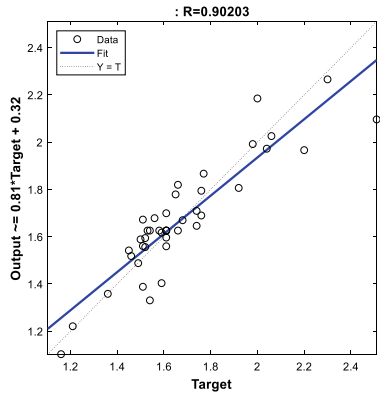
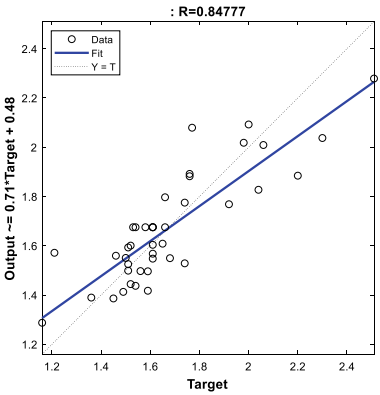


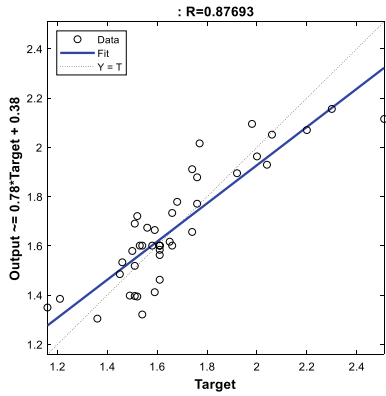
**Fig. 12.6** ANN-PSO training results per configuration number (1–36)



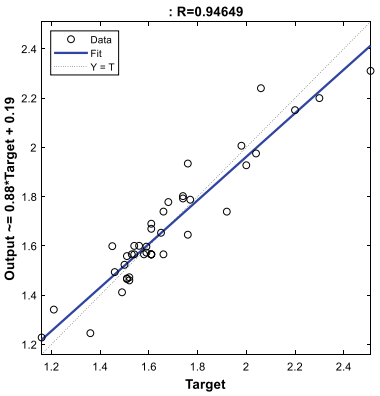
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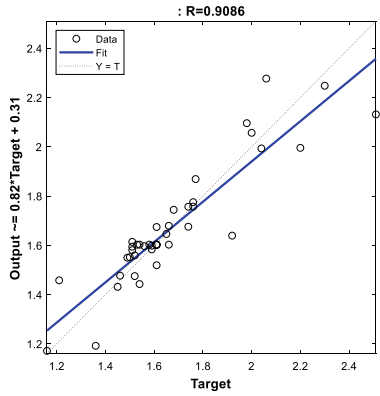
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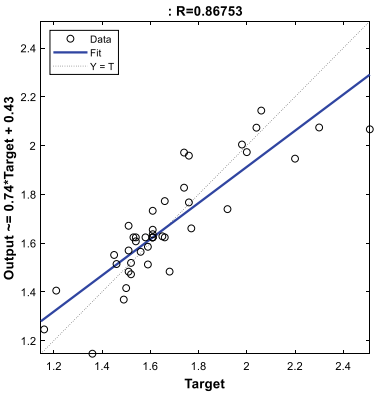
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(10)

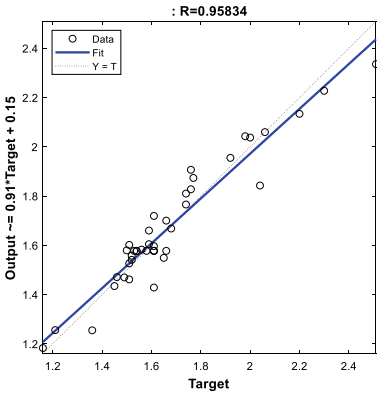


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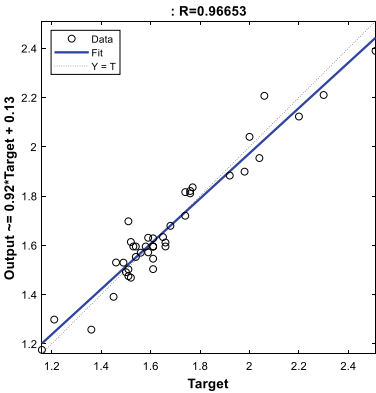


(12)

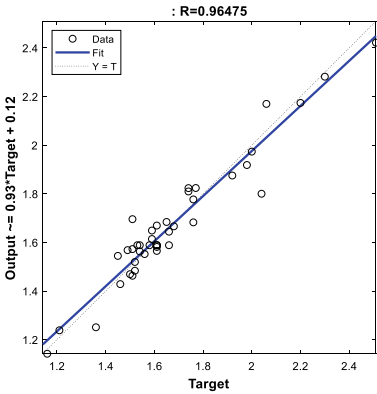
Fig.12.6 (continued)



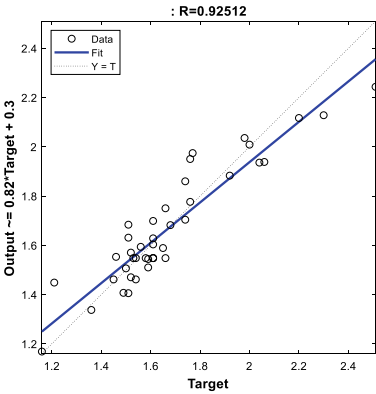
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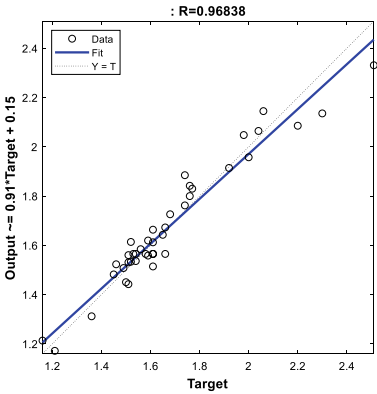
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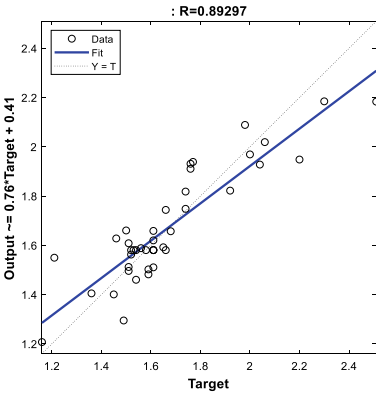
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(16)

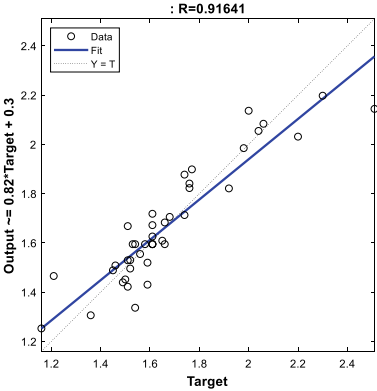


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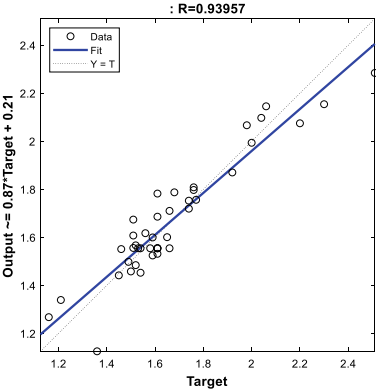


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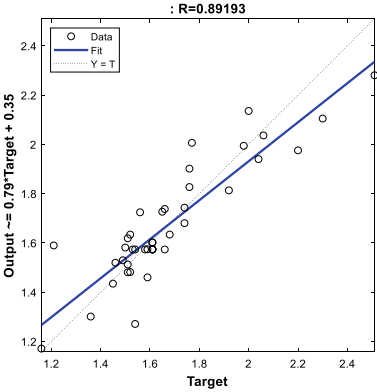
Fig. 12.6 (continued)



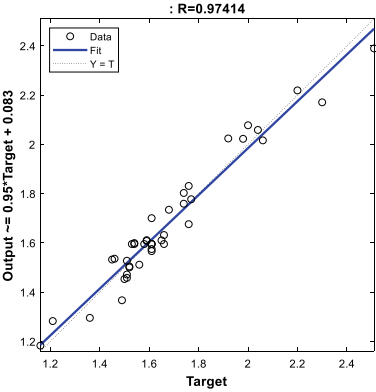
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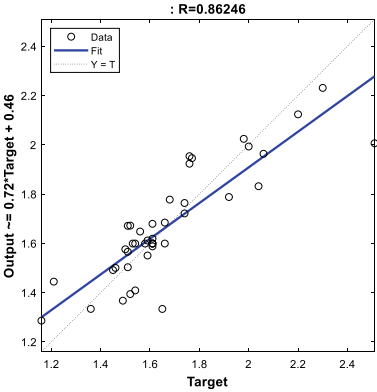
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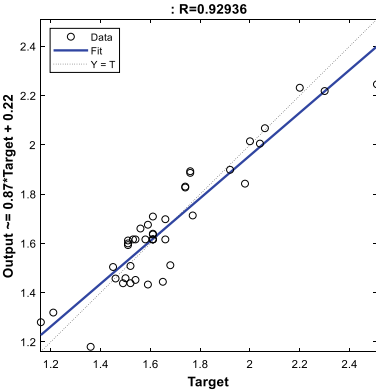
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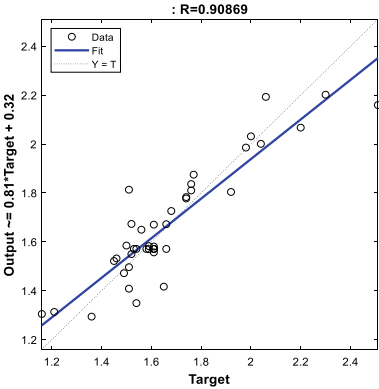


(23)

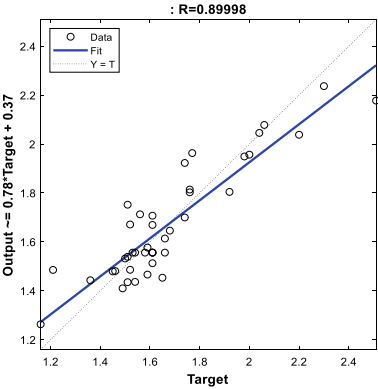


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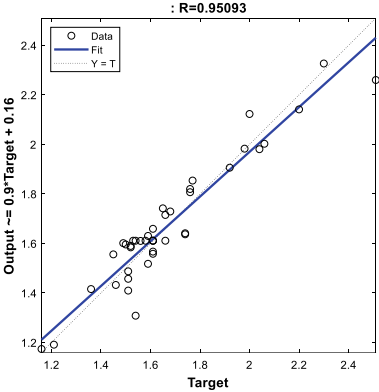
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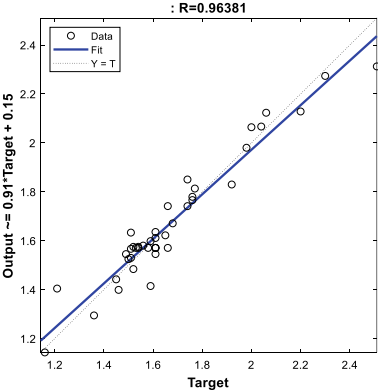
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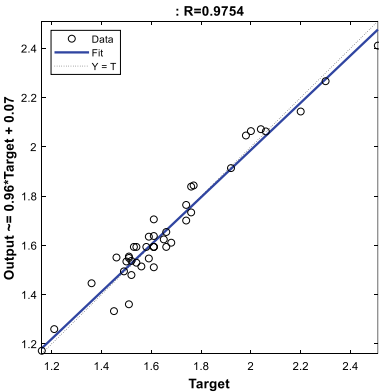
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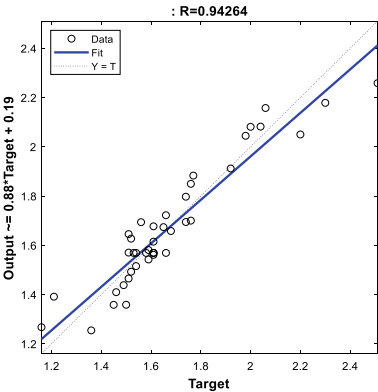
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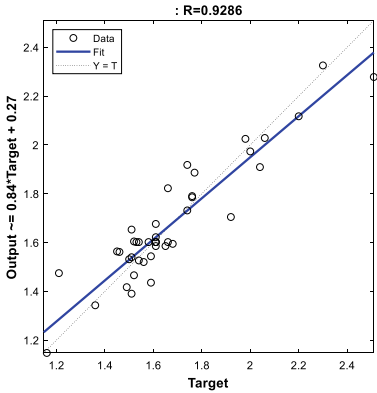


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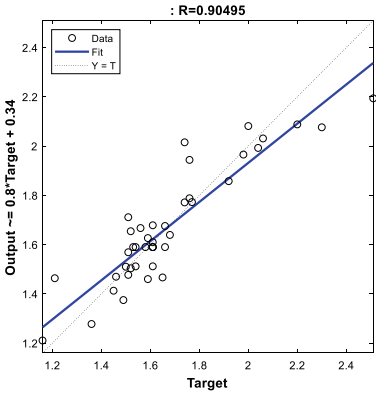


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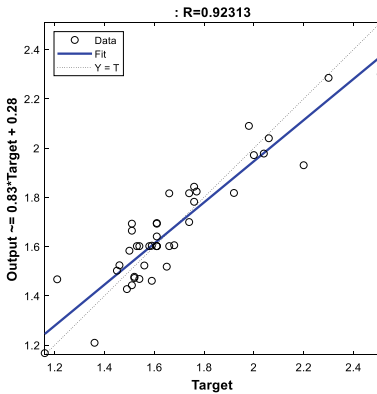
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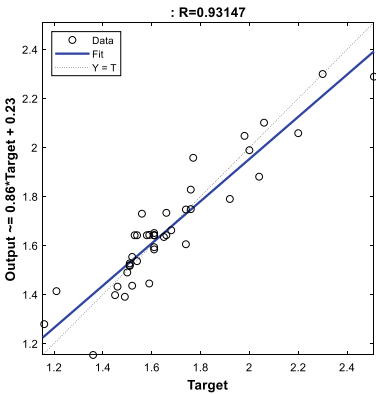
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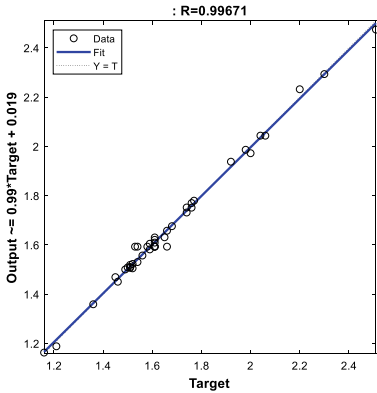
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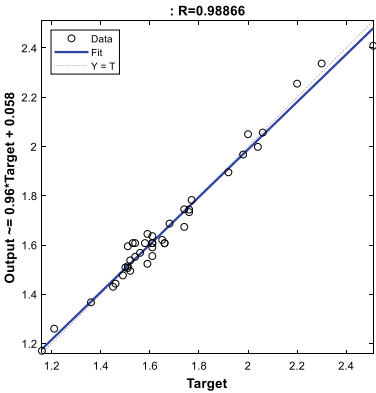
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Fig. 12.6 (continued)

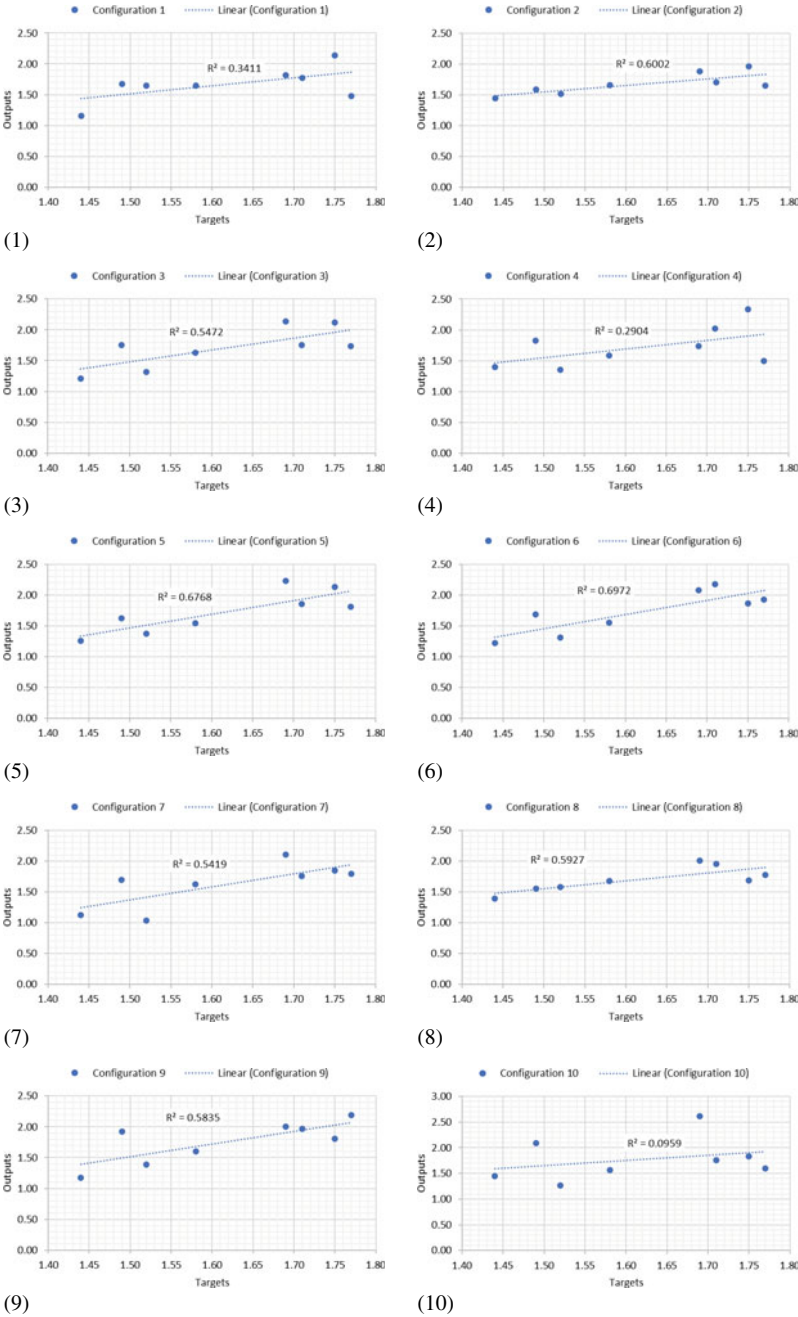
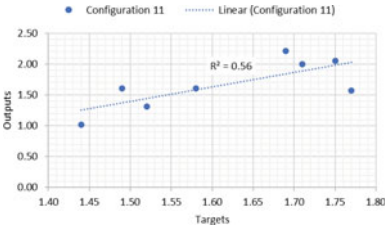
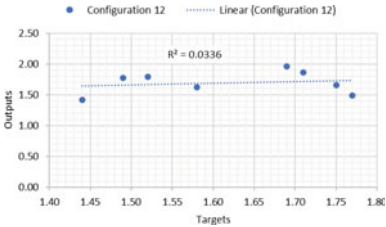


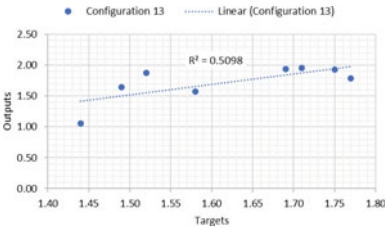
Fig. 12.7 ANN-PSO testing results per configuration number (1–36)



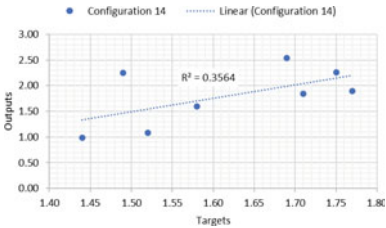
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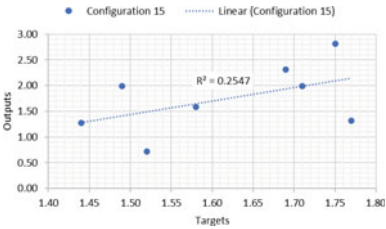
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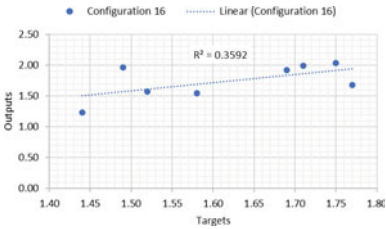
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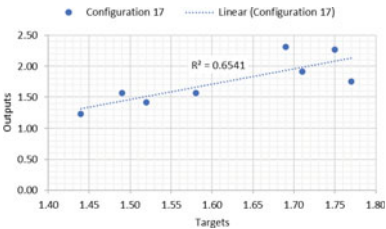
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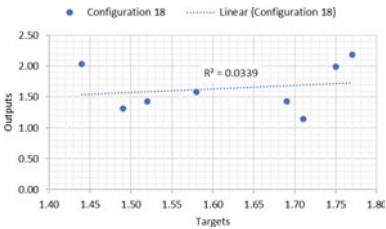
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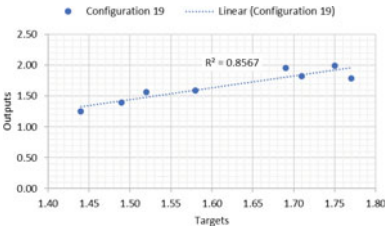
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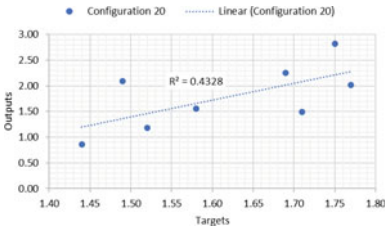
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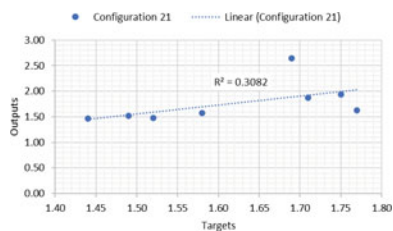
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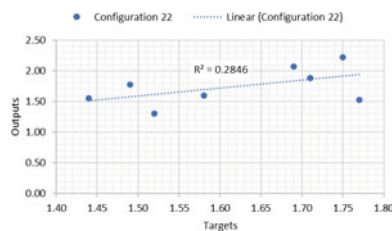
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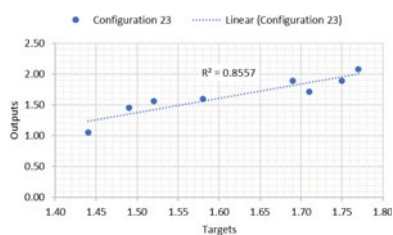




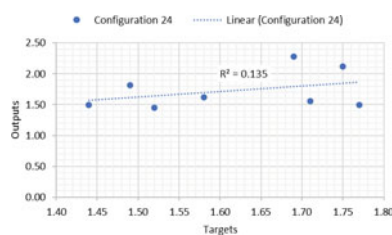
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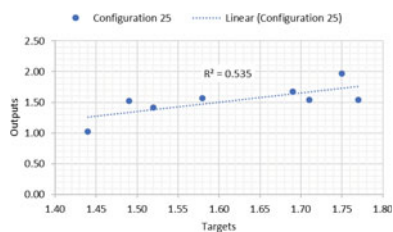
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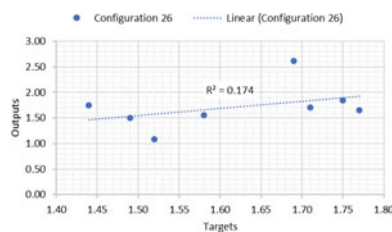
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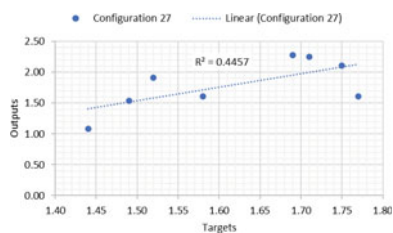
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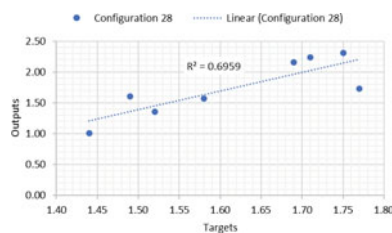
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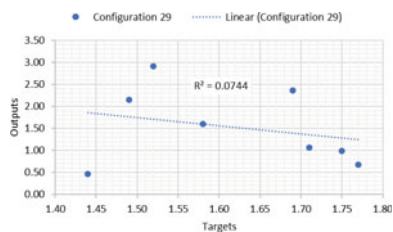
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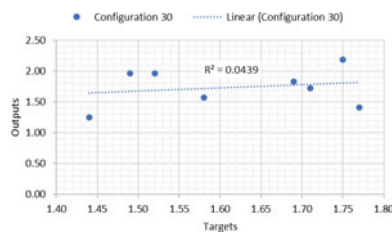
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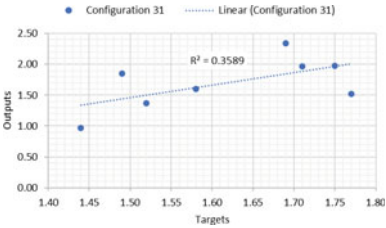


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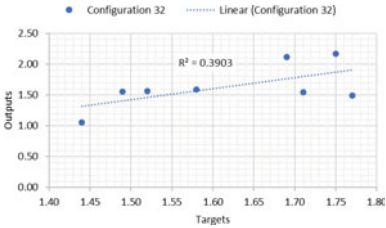


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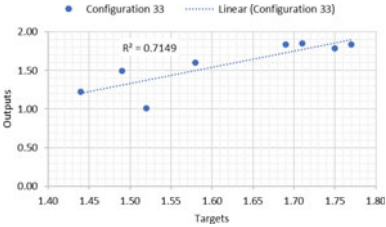
Fig. 12.7 (continued)



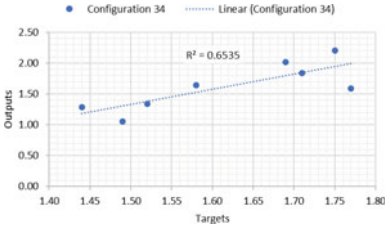
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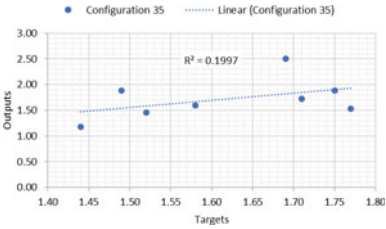
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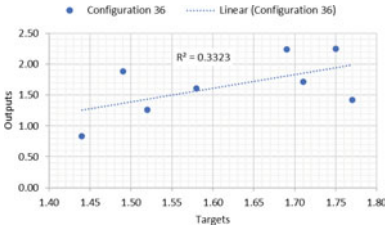
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Fig. 12.7 (continued)

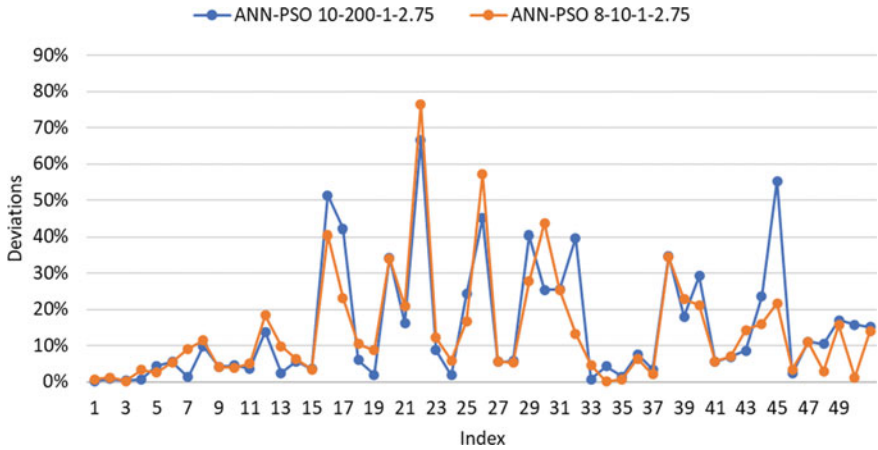


Fig. 12.8 Comparison of ANN-PSO results

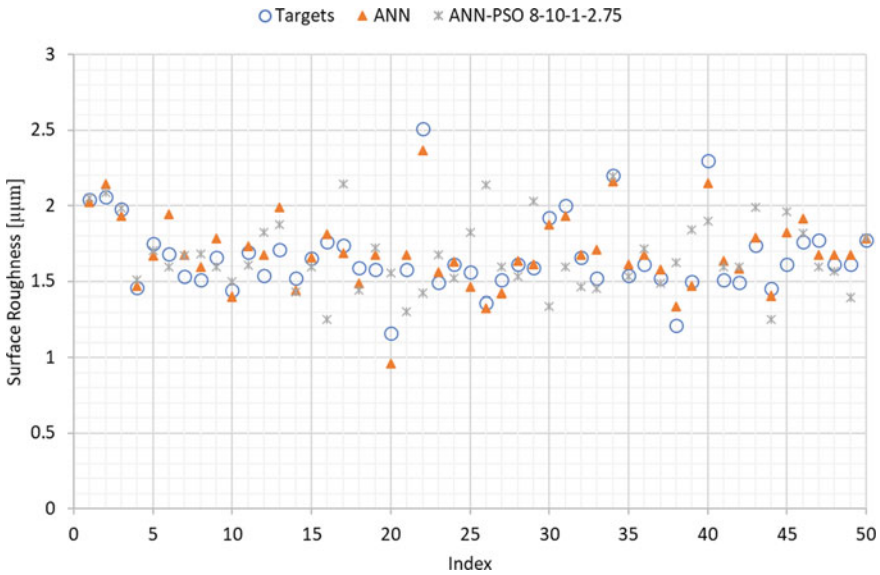


**Fig. 12.9** ANN and ANN-PSO 8-10-1-2.75 results comparison

## 12.6 Conclusion

In this paper, a readily available dataset extracted from an end milling machining of an AA8112 alloy performed on a SIEG 3/10/0016 CNC machine was considered. Titanium dioxide ( $\text{TiO}_2$ ) and multi-walled carbon nanotube (MWCNTs) nano-lubricants mixed with copra oil were used as the cutting fluid. 50 experimental runs were conducted to obtain the parameters used in this study. The Surface Roughness (SR) was considered as output parameters while the spindle speed, the feed rate, the length of the cut, the depth of cut, and the helix angle were considered as input parameters. An ANN-PSO model was built. Details describing the building of the model were disclosed. A parametric analysis was performed to identify the configuration (parameters) of the ANN-PSO that yield the highest prediction performance. The number of neurons, the swarm population size and the acceleration factors were given random values. The results reveal the potential of ANN-PSO to accurately predict the performance of the Surface Roughness. The prediction performance metric is closely linked to the model configuration or parameters. The best configurations of the ANN-PSO models were identified. A comparison between the results obtained with ANN-PSO and ANN models was done. This study shows that the ANN performance metric was enhanced from 0.91115 to 0.99671 using ANN-PSO. Further studies would be required to analyse the performance of the proposed model with test data. The lower performance, with respect to test data reported in this study, can be attributed to the selection of test data, the limited number of data

and the need to optimize the parameters of the ANN-PSO model. Nevertheless, this study gives an insight into possible strategies that will cut down on time-consuming and expensive experimentation and help decision-makers find the configuration that maximizes efficiency during machining operations.

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## Chapter 13

# Adaptive Neuro-Fuzzy Inference System for Prediction of Surface Roughness Under Biodegradable Nano-lubricant



**Abstract** Machining processes involve many nonlinear parameters which make them complex. Setting of machines is generally relying on decision-making skills based on intuition and common sense learned through experience. In this work, five variables namely the spindle speed, the feed rate, the length of the cut, the depth of cut and the helix angle were considered to predict the surface roughness during the end-milling machining of AA8112 alloy. The adaptive neuro-fuzzy inference system (ANFIS) is proposed in this study. A dataset made of 50 data was used. Each data corresponds to a specific configuration of the end-milling machine and the corresponding surface roughness. In order to assess the prediction performance of ANFIS, various types of membership functions. This includes  $\pi$ -shaped (PIMF), generalized bell shape (GBELLMF), triangular shape (TRIMF), trapezoidal shape (TRAPMF), and Gaussian curve (GAUSSMF). This study shows that the various outputs track the targets effectively irrespective of the membership functions adopted the deviations between the predicted results and the targets were within 7%. This study demonstrates the potential of ANFIS models for the prediction of surface roughness.

**Keywords** Adaptive neuro-fuzzy inference system • Surface roughness • Nano-lubricant • Machining

## 13.1 Background

Surface roughness during manufacture is important because the surface of the element influences its performance throughout operations [1]. The product can be produced with the least amount of surface roughness by optimizing the machining settings and the lubricant used during the machining operations [2]. The lubricant's lubricity and cooling actions aid to lower the temperature and friction at the cutting region [3]. The thermal, rheological, and tribological properties of lubricants can be improved by new types of lubricants called nano-cutting fluids [4]. Because of the newly noticed change in thermo-physical and temperature exchange capacities, researchers have started utilizing nanoparticles in conventional oil [5]. Okokpuije et al. [6] proposed

the use of vegetable oil consisting of copra oil lubricant, titanium dioxide ( $\text{TiO}_2$ ) and multi-walled carbon nanotube (MWCNTs) nano-lubricants during end-milling of AA8112 alloy. Their study reports an improvement in surface roughness.

Machining processes are generally complex. They involve many nonlinear parameters. In addition, the process takes place amid external disturbances. A proficient operator often completes a machining operation using decision-making skills based on intuition and common sense learned through experience. This method is not precise enough, and product flaws frequently occur. This is why intelligent machining—a dependable, automated machining system with cognitive functions—is required to achieve extremely productive and adaptable machining [7].

In an end milling operation, the cutting force is utilized to forecast surface quality during cutting. Milled surfaces benefit greatly from surface quality because it increases fatigue strength, corrosion resistance, and creep life. Additionally, the quality of a part's surface influences a number of its functional characteristics, including contact that results in surface friction, wear, light reflection, heat transmission, the capacity to distribute and hold lubricant, coating, and fatigue resistance [8].

The association between cutting force and surface roughness must be modelled in order to obtain greater levels of surface quality. Soft computing technologies enable modeling based on cutting force and surface roughness data [9]. Soft computing technologies enable modeling based on cutting force and surface roughness data [10]. When exact mathematical knowledge is unavailable, soft computing techniques can be helpful. These techniques differ from conventional computing in that they accommodate imprecision, uncertainty, approximation, and other heuristics [11]. One of the soft computing methods that are important in describing the relationship between the input–output matrix and the output is ANFIS. It is employed for defining the objective function and decision variables when expert advice and subjective knowledge are important. Because of the nonlinear nature of the machining process, ANFIS is the best tool for predicting surface roughness based on input data [12].

The adaptive neuro-fuzzy inference system (ANFIS) blends fuzzy logic theory and artificial neural networks, two well-known machine learning techniques [13]. Similar to an ANN, the ANFIS method can learn from training data and then map out the results onto a fuzzy inference system (FIS) [14]. As a result, a FIS in the ANFIS network precisely determines the hidden layers. By doing so, the ANN model's infamously difficult problem of identifying the hidden layer is solved, enhancing prediction accuracy overall [15]. As a result, ANFIS is taken into consideration since it can quickly and adaptively create the prediction model of surface roughness without requiring a complicated mathematical model. Previously, the ANFIS technique was used to estimate surface roughness and cutting zone temperature in dry turning processes of AISI304 stainless steel [16] and surface roughness in ball end milling processes [17].

In this study, ANFIS is proposed for the prediction of surface roughness using data collected during the end-milling machining of AA8112 alloy.

## 13.2 Modelling Approach

Classification jobs, rule-based process controls, pattern recognition issues, and function approximation issues have all benefited from the application of ANFIS [18]. The ideal distribution of membership functions is determined by the mapping relation between the input and output data in the ANFIS architecture, which combines fuzzy logic and artificial neural networks. It incorporates fuzzy logic (FL) theory and adaptive neural network (ANN) principles into adaptive network frameworks. The fuzzy inference system (FIS) application has been derived from FL theory, and by trial and error, the membership functions (MF) in FIS have been enhanced. In the ANFIS technique, the FIS model is developed using the ANN procedure, which also enables the learning of the neural network training data from the supplied data. The factors in the Sugeno category IF–THEN rule arrangement have simultaneously mapped the results.

Figure 13.1 depicts the overall architecture of the ANFIS framework. This inference system is fundamentally composed of five separate layers. They are the following: (i) layer fuzzy, (ii) product layer, (iii) normalized layer, (iv) de-fuzzy layer and, (v) total output layer. Each layer is made up of unique nodes, where the adaptive nodes are represented by squares and the factors could change. The fixed nodes, however, where the factors are fixed, are represented by circles.

The nodes in the preceding layers serve as the inputs for the current layers. For the sake of simplicity, it is assumed that this system has two inputs ( $a$ ,  $b$ ) and one output ( $S_i$ ) in order to demonstrate the ANFIS operations [20]. Sugeno-type IF–THEN fuzzy rules are present in the ANFIS rule base. The two IF–THEN rules for a first-order

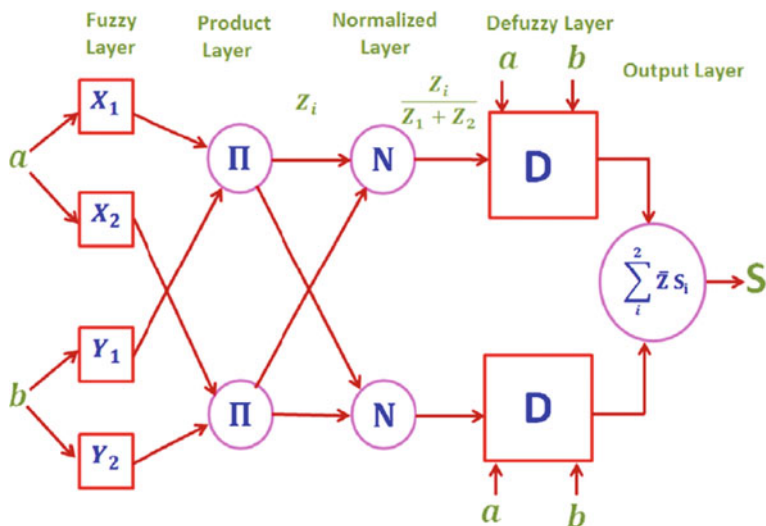


Fig. 13.1 Typical architecture of ANFIS [19]



Sugeno-fuzzy inference system (FIS) can be written as follows in Eqs. (13.1) and (13.2).

$$\text{Rule 1} \rightarrow \text{IF } a \text{ is } X_1 \text{ and } b \text{ is } Y_1; \text{ THEN } c \text{ is } S_1(a, b) \quad (13.1)$$

$$\text{Rule 2} \rightarrow \text{IF } a \text{ is } X_2 \text{ and } b \text{ is } Y_2; \text{ THEN } c \text{ is } S_2(a, b) \quad (13.2)$$

$P_i$  and  $Q_i$  stand for fuzzy sets, where  $a$  and  $b$  are the ANFIS inputs.  $S_i(a, b)$  is a Sugeno-FIS of first order.

(a) Fuzzy layer

The adaptive nodes with node functions make up the fuzzy layer. The inputs ( $a, b$ ) are transformed into the linguistic labels ( $X_1, X_2, Y_1$  and  $Y_2$ ) that are utilized to divide the membership functions. Each node's output is governed by Eqs. (13.3) and (13.4) [19].

$$O_{1,i} = u_{X_i}(a) \quad \text{for } = 1, 2 \quad (13.3)$$

$$O_{1,i} = u_{Y_{i-2}}(b) \quad \text{for } = 3, 4 \quad (13.4)$$

where  $u_{X_i}$  and  $u_{Y_{i-2}}$  are the membership functions,  $O_{1,i}$  is the output function.

Typically, several membership functions are accessible, including the  $\pi$ -shaped membership function (PIMF), the generalized bell shape membership function (GBELLMF), the triangular shape membership function (TRIMF), the trapezoidal shape membership function (TRAPMF), and the Gaussian curve membership function (GAUSSMF).

The  $\pi$ -shaped curve membership function (PIMF), which is another name for the spline-based curve, is a function of the vector  $a$  and depends on the four parameters  $p, q, r$ , and  $s$  as given in the expression in Eq. (13.5) [21].

$$u_{X_i}(a, p, q, r, s) = \begin{cases} 0, & a \leq p \\ 2\left(\frac{a-p}{q-r}\right)^2, & p \leq a \leq \frac{p+q}{2} \\ 1 - 2\left(\frac{a-q}{q-p}\right)^2, & \frac{p+q}{2} \leq a \leq q \\ 1, & q \leq a \leq r \\ 1 - 2\left(\frac{a-r}{s-r}\right)^2, & r \leq a \leq \frac{r+s}{2} \\ 2\left(\frac{a-s}{s-r}\right)^2, & \frac{r+s}{2} \leq a \leq s \\ 0, & a \geq s \end{cases} \quad (13.5)$$

The generalized bell-shaped curve in GBELLMF depends on three parameters  $p, q$ , and  $r$ , and is a function of a vector  $a$ . The Eq. (13.6) is presented as [21]:

$$u_{x_i}(a, p, q, r) = \frac{1}{1 + \left| \frac{a-r}{p} \right|^{2q}} \quad (13.6)$$

The generalized bell-shaped curve's foot, where the parameter  $q$  is often positive, are located by the parameters  $p$  and  $r$ . The center of the curve is represented by the parameter  $r$ .

The triangular curve in TRIMF depends on three scalar parameters,  $p$ ,  $q$ , and  $r$ , and is a function of a vector,  $a$ . The Eq. (13.7) is given as follows.

$$u_{x_i}(a, p, q, r, s) = \begin{cases} 0, & a \leq p \\ \frac{a-p}{q-p}, & p \leq a \leq q \\ \frac{r-a}{r-q}, & q \leq a \leq r \\ 0, & r \leq a \end{cases} \quad (13.7)$$

The triangle's feet are located by the parameters  $p$  and  $r$ , while the peak is located by the parameter  $q$ .

As illustrated in the following expression in the Eq. (13.8), the trapezoidal curve in TRAPMF depends on four scalar parameters:  $p$ ,  $q$ ,  $r$ , and  $s$ .

$$u_{x_i}(a, p, q, r, s) = \begin{cases} 0, & a \leq p \\ \frac{a-p}{q-p}, & p \leq a \leq q \\ 1, & q \leq a \leq r \\ \frac{s-a}{s-r}, & r \leq a \leq s \\ 0, & s \leq a \end{cases} \quad (13.8)$$

The trapezoid's feet are located by the parameters  $p$  and  $s$ , while its shoulders are located by the parameters  $q$  and  $r$ .

As shown in Eq. (13.9), curves in GAUSSMF are a function of a vector  $a$  and depend on two parameters  $\sigma$  and  $r$  [22].

$$u_{x_i}(a; \sigma, c) = e^{-\frac{(a-c)^2}{2\sigma^2}} \quad (13.9)$$

#### (b) Product layer

This layer, denoted by a circle and the letter P, employs fixed nodes. Each node's output is the sum of all the signals it has received from the layer before. The output of this layer is shown in the following Eq. (13.10).

$$O_{2,i} = Z_i = u_{x_i}(a) \cdot u_{y_i}(b) \quad \text{for } I = 1, 2 \quad (13.10)$$

The firing strength of a rule is shown by the output  $Z_i$  of each node.

(c) Normalized layer

A fixed node with a circle and the letter N are used to symbolize each node in a normalized layer. It is defined as the ratio of the firing power of the  $i$ th node ( $Z_i$ ) to the total firing power of the rules, as given in Eq. (13.11) [22].

$$O_{3,i} = \bar{Z} = \frac{Z_i}{Z_1 + Z_2} \quad \text{for } i = 1, 2 \quad (13.11)$$

where  $O_{3,i}$  and  $Z$  stand for the normalized layer's and firing strength's respective outputs. Only within a range of 0 to 1 are the output of the normalized layer and normalized firing strength acceptable.

(d) Defuzzy layer

The defuzzification layer, which is the fourth layer and is identified by the square and the letter D, is made up of adaptive nature nodes. It calculates the multiplication of the first-order polynomial and the normalized firing strength. Consequently, the following Eq. (13.12) defines this defuzzy layer's output [23].

$$O_{4,i} = \bar{Z}.S_i = \bar{Z}(e_i a + f_i b + g_i) \quad \text{for } i = 1, 2 \quad (13.12)$$

where the ensuing parameters are  $e_i$ ,  $f_i$ , and  $g_i$ .

(e) Output layer

The output layer, which is the fifth layer, contains one fixed node and is identified by a circle. Here, the node function must calculate the overall output according to the Eq. (13.13) below [23].

$$O_{5,i} = \sum_i \bar{Z}.S_i = \sum_i \bar{Z}(e_i a + f_i b + g_i) = \text{Overall output for } i = 1, 2 \quad (13.13)$$

To increase the convergence rate, an algorithm used for this present work is a hybrid learning algorithm. This algorithm is used to integrate the least square and gradient descent methods in order to update the premise parameters. The least square method is utilized to optimize the consequent parameters. The gradient descent approach is used to regulate the premise parameters optimally after obtaining the best consequent parameters. Indirect parameters are used to determine ANFIS' output. The following Eq. (13.14) provides the entire output

$$\begin{aligned} \text{Total output} &= \bar{Z}S_1 + \bar{Z}S_2 = \frac{Z_1}{Z_1 + Z_2}S_1 + \frac{Z_2}{Z_1 + Z_2}S_2 \\ &= \frac{Z_1}{Z_1 + Z_2}(e_1 F_1 + f_1 F_2 + g_1) + \frac{Z_2}{Z_1 + Z_2}(e_2 F_1 + f_2 F_2 + g_2) \end{aligned} \quad (13.14)$$

### 13.3 Description of Dataset Extraction

The end-milling machining of AA8112 was done in this investigation using the SIEG 3/10/0016 CNC machine [24]. Three (3) planes x, y, and z planes make up the CNC milling machine. Five variables (namely the spindle speed, the feed rate, the length of the cut, the depth of cut and the helix angle) and five levels of the experiment make up the end-milling process, and the cutting fluid is a nano-lubricant made of multi-walled carbon Nanotube (MWCNTs) and titanium dioxide ( $TiO_2$ ) combined with copra oil. This section is broken down into several steps. The experimental inquiry used the following techniques:

- Aluminum 8112 alloy rectangular plate was divided into several lengths, including 20, 30, 40, 50, and 60 mm, respectively. 150 pieces overall, 50 pieces for  $TiO_2$ , 50 pieces for MWCNTs nano-lubrications, and 50 pieces for copra oil machining were considered in a cut-off machine environment.
- $TiO_2$  and MWCNTs nano-lubricants are set up for end-milling machining while the vertical CNC milling machine is being cleaned.
- The spindle head of the end-milling tool was mounted with a 13 mm diameter High-Speed Steel (HSS) cutting tool.
- Mounting the AA8112 alloy and dynamometer on the machine's table bed and securing them with a vibration-reducing device.
- The Y-axis and Z-axis were used as references while developing the CNC part programming, which included particular commands for implementing various cut lengths, feed rates, axial depths of cuts, helix angles, and spindle speeds.
- After each sample has been machined, the surface roughness of the workpiece is measured using the SRT-6210S surface roughness tester.
- Following all of the experimental analyses, Okokpujie et al. [24] investigated the surface interaction between the nano-lubricant and the AA8112 alloy using the linear polarization resistance method.

The 50 experimental runs considered as a dataset in this study are provided in Table 13.1.

### 13.4 Methodology

The dataset considered to build the ANN model is provided in Table 13.1. These data relate the outputs (targets), namely the Surface Roughness (SR) to the inputs described by the spindle speed, feed rate, length of the cut, depth of cut, and helix angle. The dataset is then split into the appropriate places to clearly distinguish between the training and testing phases. 80% of the data, or 40 data, were used for training the ANN model in order to forecast the values of Surface Roughness. The remaining 10% of the data (or five data) were utilized for testing, and the remaining 10% was used for validation. The capabilities of the ANN model were assessed using

**Table 13.1** Dataset

| Index | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle ( $\alpha$ ) (o) | SR (MWCNTs) ( $\mu\text{m}$ ) |
|-------|---------------------|--------------------|--------------------|-------------------|------------------------------|-------------------------------|
| 1     | 2500                | 150                | 30                 | 2.5               | 45                           | 2.04                          |
| 2     | 2500                | 250                | 50                 | 2.5               | 15                           | 2.06                          |
| 3     | 2500                | 250                | 30                 | 1.5               | 15                           | 1.98                          |
| 4     | 3500                | 250                | 50                 | 1.5               | 45                           | 1.46                          |
| 5     | 2500                | 150                | 50                 | 1.5               | 45                           | 1.68                          |
| 6     | 3000                | 200                | 40                 | 2                 | 30                           | 1.53                          |
| 7     | 3500                | 250                | 30                 | 2.5               | 45                           | 1.51                          |
| 8     | 2500                | 150                | 50                 | 2.5               | 45                           | 1.66                          |
| 9     | 3000                | 200                | 40                 | 2                 | 30                           | 1.54                          |
| 10    | 3500                | 150                | 50                 | 2.5               | 45                           | 1.52                          |
| 11    | 3500                | 150                | 30                 | 2.5               | 15                           | 1.65                          |
| 12    | 2500                | 250                | 30                 | 2.5               | 15                           | 1.76                          |
| 13    | 2500                | 250                | 50                 | 1.5               | 45                           | 1.74                          |
| 14    | 3000                | 200                | 40                 | 2                 | 60                           | 1.59                          |
| 15    | 3000                | 200                | 40                 | 2                 | 30                           | 1.58                          |
| 16    | 4000                | 200                | 40                 | 2                 | 30                           | 1.16                          |
| 17    | 3000                | 300                | 40                 | 2                 | 30                           | 2.51                          |
| 18    | 3500                | 150                | 50                 | 1.5               | 45                           | 1.49                          |
| 19    | 3000                | 200                | 60                 | 2                 | 30                           | 1.61                          |
| 20    | 3000                | 200                | 40                 | 1                 | 30                           | 1.56                          |
| 21    | 3500                | 150                | 30                 | 1.5               | 45                           | 1.36                          |
| 22    | 3500                | 250                | 30                 | 1.5               | 45                           | 1.51                          |
| 23    | 3500                | 250                | 50                 | 2.5               | 45                           | 1.61                          |
| 24    | 3500                | 150                | 30                 | 2.5               | 45                           | 1.59                          |
| 25    | 2500                | 150                | 50                 | 1.5               | 15                           | 1.92                          |
| 26    | 2500                | 250                | 50                 | 1.5               | 15                           | 2                             |
| 27    | 3000                | 200                | 40                 | 2                 | 30                           | 1.66                          |
| 28    | 3500                | 250                | 50                 | 2.5               | 15                           | 1.52                          |
| 29    | 3000                | 200                | 40                 | 3                 | 30                           | 2.2                           |
| 30    | 3500                | 150                | 50                 | 1.5               | 15                           | 1.54                          |
| 31    | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 32    | 3000                | 100                | 40                 | 2                 | 30                           | 1.21                          |
| 33    | 3500                | 250                | 50                 | 1.5               | 15                           | 1.5                           |
| 34    | 2000                | 200                | 40                 | 2                 | 30                           | 2.3                           |
| 35    | 3000                | 200                | 20                 | 2                 | 30                           | 1.51                          |

(continued)

**Table 13.1** (continued)

| Index | Spindle speed (rpm) | Feed rate (mm/min) | Length of cut (mm) | Depth of cut (mm) | Helix angle ( $\alpha$ ) (o) | SR (MWCNTs) ( $\mu\text{m}$ ) |
|-------|---------------------|--------------------|--------------------|-------------------|------------------------------|-------------------------------|
| 36    | 2500                | 150                | 30                 | 1.5               | 45                           | 1.74                          |
| 37    | 3500                | 250                | 30                 | 1.5               | 15                           | 1.45                          |
| 38    | 3000                | 200                | 40                 | 2                 | 0                            | 1.61                          |
| 39    | 2500                | 150                | 50                 | 2.5               | 15                           | 1.76                          |
| 40    | 2500                | 250                | 30                 | 2.5               | 45                           | 1.77                          |
| 41    | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 42    | 3000                | 200                | 40                 | 2                 | 30                           | 1.61                          |
| 43    | 2500                | 250                | 30                 | 1.5               | 45                           | 1.75                          |
| 44    | 3500                | 150                | 30                 | 1.5               | 15                           | 1.44                          |
| 45    | 2500                | 250                | 50                 | 2.5               | 45                           | 1.69                          |
| 46    | 2500                | 150                | 30                 | 2.5               | 15                           | 1.71                          |
| 47    | 3000                | 200                | 40                 | 2                 | 30                           | 1.58                          |
| 48    | 3500                | 150                | 50                 | 2.5               | 15                           | 1.52                          |
| 49    | 3500                | 250                | 30                 | 2.5               | 15                           | 1.49                          |
| 50    | 2500                | 150                | 30                 | 1.5               | 15                           | 1.77                          |

the validation and testing data. The MATLAB environment was used to implement this process (Appendix J). Figure 13.2 depicts the neural network’s structure.

The prediction performance of the Surface Roughness taken into consideration in this study was examined using a hybrid ANFIS model. A total of 50 data points were divided in half; of these, 42 were utilized to train the hybrid ANFIS model and 8 were used to test it. This study used the ANFIS structure and network model to forecast the Surface Roughness, as seen in Figs. 13.3 and 13.4. It carries out Sugeno-type FIS systems, and the membership function is used to carry out the training process. In this study, the FIS takes into account five machining inputs, including spindle speed (X1), feed rate (X2), length of the cut (X3), depth of cut (X4), and helix angle (X5). The Surface Roughness (Y) is the only output.

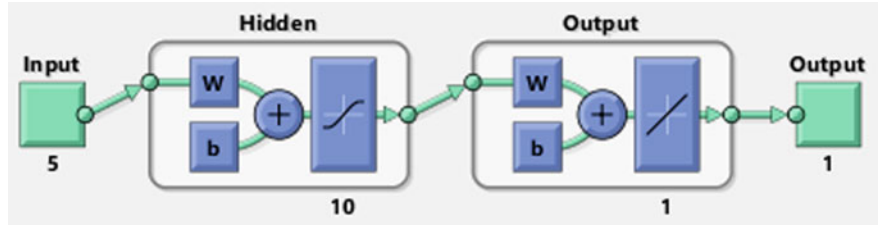


**Fig. 13.2** Neural network’s structure

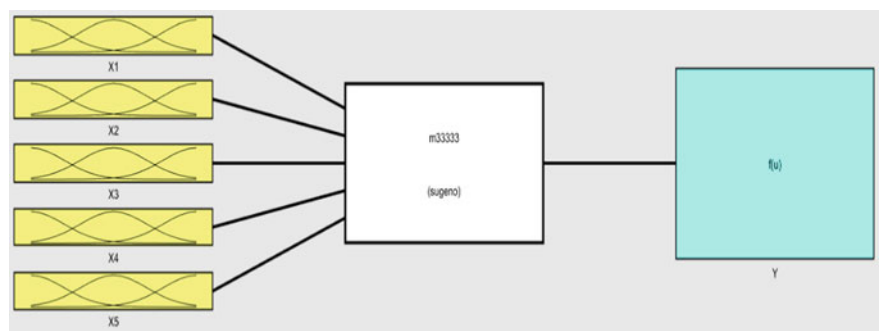


**Fig. 13.3** ANFIS structure

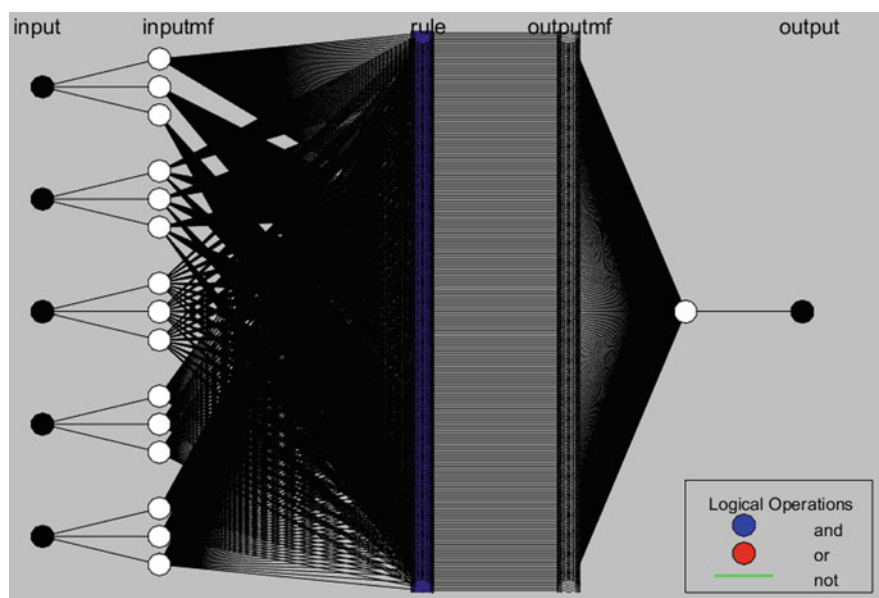


**Fig. 13.4** Neural network model for surface roughness

To produce the optimum rules for a given dataset, the grid partition technique is employed. The first 42 data in Table 13.1 were used to train the ANFIS model, while the remaining 8 data were used to assess the model’s ability to predict outcomes. The loading of training data and testing data into the ANFIS model are depicted in Figs. 13.5 and 13.6 respectively.

The ANFIS model underwent training before testing the outcomes using test data. The input dataset is plotted multiple times throughout the ANFIS model’s training to lower the prediction error. Epochs are the units used to express the number of iterations necessary for mapping. It can be seen from Figs. 13.5 and 13.6 that the

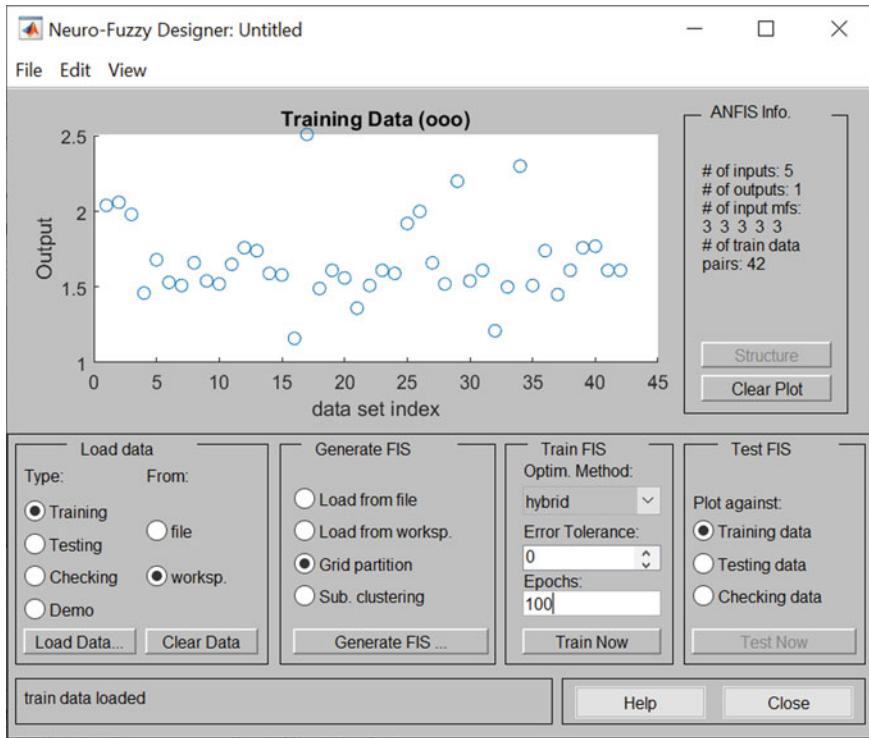


**Fig. 13.5** Loading of training data

100 epochs (number of iterations) are necessary to complete the training process on 42 data.

Assessment indices were used to examine the model's error rates and prediction accuracy. The Coefficient of determination ( $R^2$ ) is the statistical measurement utilized. Equation 13.15 is used to compute the statistical measurements.

$$R^2 = 1 - \frac{\sum_k (y_k - \hat{y}_k)^2}{\sum_k (y_k - \bar{y}_k)^2}. \quad (13.15)$$

where the details of  $y_k$ ,  $\hat{y}_k$ ,  $\bar{y}_k$   $n$  and  $k$  are given. The symbols  $y_k$ ,  $\hat{y}_k$  and  $\bar{y}_k$  stand for the experimental data sample, the algorithm's projected values and the mean value of the experimental data samples, respectively.  $N$  stands for the number of data samples, and  $K$  stands for the set of all source points indexed by  $k$ .



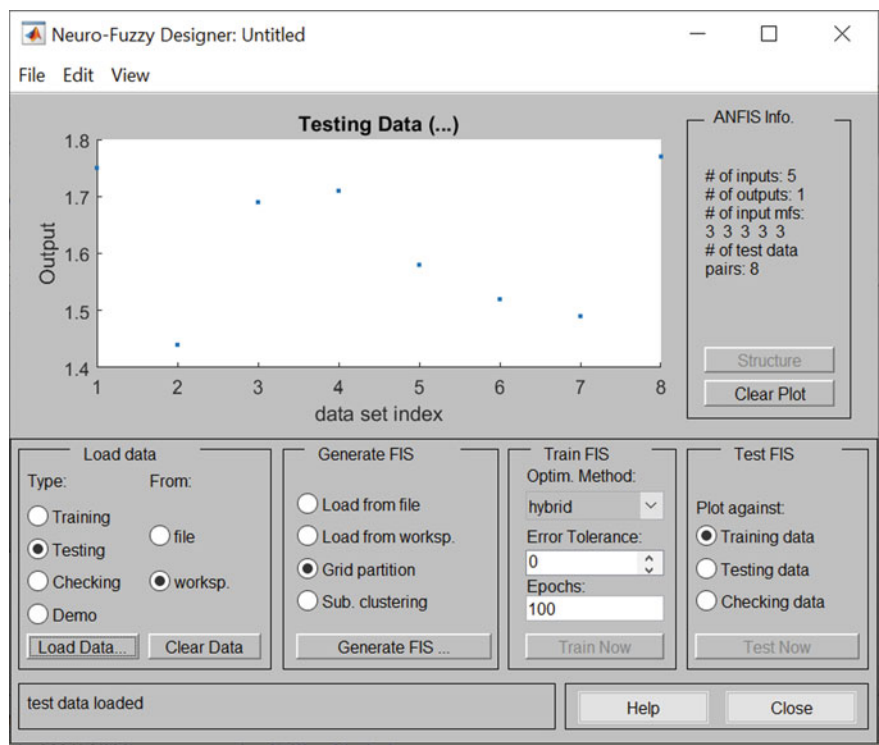


Fig. 13.6 Loading of testing data

### 13.5 Results and Discussions

The outcomes of the ANFIS model’s training and testing process were assessed using various types of membership functions described in Sect. 13.2. Considering a Triangular membership function (TRIMF), Fig. 13.7a, b allow easy visual comparison between the predicted Surface Roughness against the actual values. The training and testing regression value  $R^2$  of 0.9958 and 0.8921, respectively, suggests that the output tracks the targets effectively. Figure 13.7 (c) shows the surface plot of Surface Roughness (Y) of sample values at the different spindle speeds (X1) and feed rates (X2). This Figure shows that when the spindle speed is decreased from 4000 to 2000 rpm and the feed rate is set to 100 or 300 mm/min, the Surface Roughness will be relatively high, resulting in a lower surface quality finishing.

Considering a Trapezoidal membership function (TRAPMF), Fig. 13.8a, b allow easy visual comparison between the predicted Surface Roughness against the actual values. The training and testing regression value  $R^2$  of 0.9958 and 0.8921, respectively, suggests that the output tracks the targets effectively. Interestingly, these results suggest that the adoption of a trapezoidal membership function doesn’t affect the results. The surface plot of Surface Roughness (Y) of samples values at the different

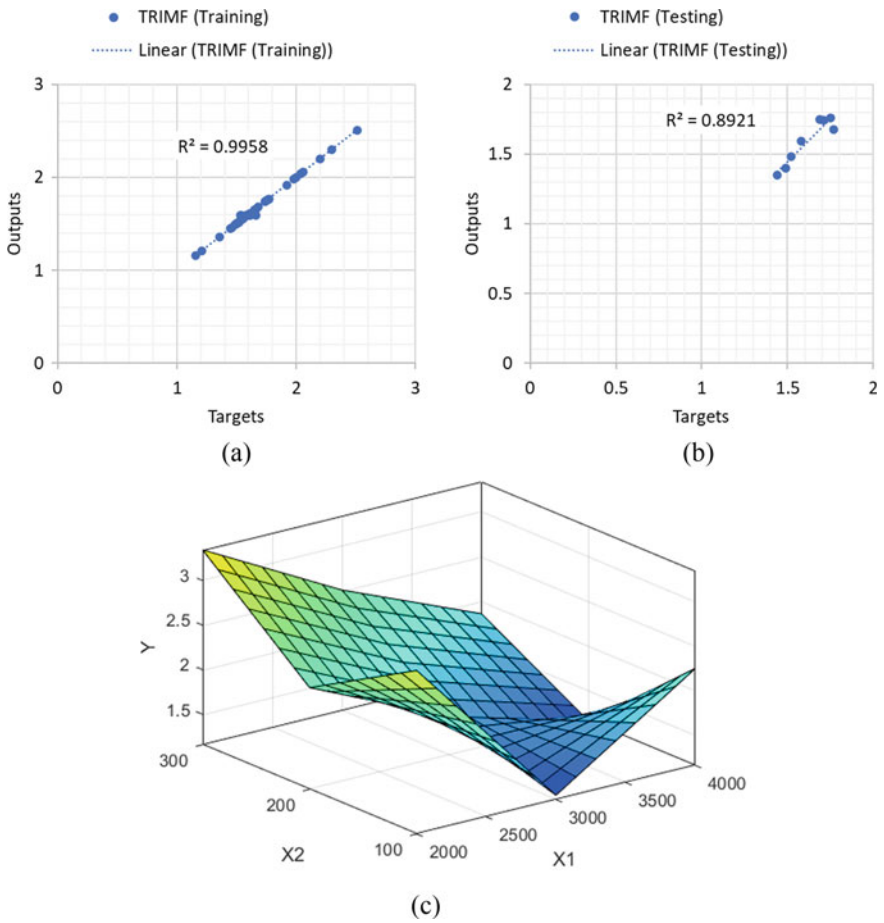


**Fig. 13.7** TRIMF results

spindle speeds (X1) and feed rate (X2) is shown in Fig. 13.8c. This Figure shows that when the spindle speed is decreased from 4000 to 2000 rpm and the feed rate is set to 100 or 300 mm/min, the Surface Roughness will be relatively high, similar to the conclusion reported previously.

Considering a generalized bell-shaped curve membership function (GBELLMF), Fig. 13.9a, b allow easy visual comparison between the predicted Surface Roughness against the actual values. The training and testing regression value  $R^2$  of 0.9958 and 0.8959, respectively, suggests that the output tracks the targets effectively. These results suggest that the adoption of a generalized bell-shaped curve membership function improves the prediction slightly. The surface plot of Surface Roughness (Y) of samples values at the different spindle speeds (X1) and feed rates (X2) is shown in Fig. 13.9c. This Figure shows that when the spindle speed is decreased from 4000

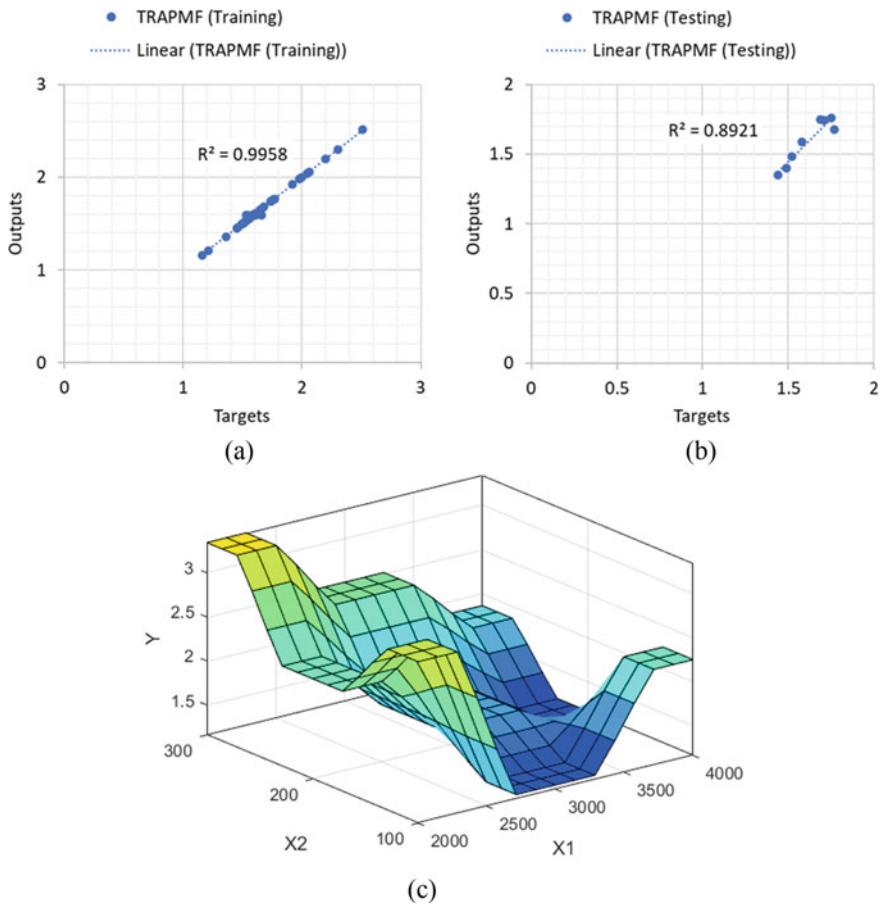


**Fig. 13.8** TRAPMF results

to 2000 rpm and the feed rate is set to 100 or 300 mm/min, the Surface Roughness will be relatively high, similar to the conclusion reported previously.

Considering a Gaussian curve membership function (GAUSSMF), Fig. 13.10a, b allow easy visual comparison between the predicted Surface Roughness against the actual values. The training and testing regression value  $R^2$  of 0.9958 and 0.847, respectively, suggests that the output tracks the targets effectively. However, the testing regression value was poorer. These results suggest that the adoption of a Gaussian curve membership function results in a poorer prediction. The surface plot of Surface Roughness (Y) of samples values at the different spindle speeds (X1) and feed rates (X2) is shown in Fig. 13.10c. This Figure shows that when the spindle speed is decreased from 4000 to 2000 rpm and the feed rate is set to 100 or 300 mm/min, the Surface Roughness will be relatively high, similar to the conclusion reported previously.

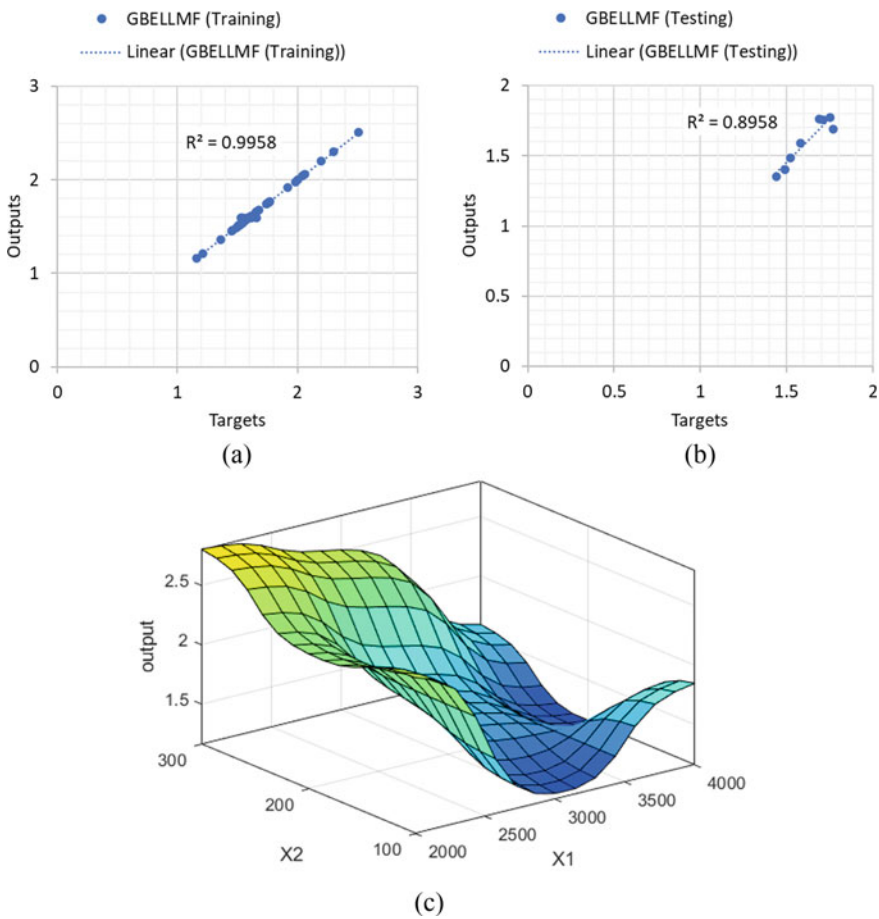


**Fig. 13.9** GBELLMF results

Considering a  $\pi$ -shaped curve membership function (PIMF), Fig. 13.11a, b allow easy visual comparison between the predicted Surface Roughness against the actual values. The training and testing regression value  $R^2$  of 0.9958 and 0.8921, respectively, suggests that the output tracks the targets effectively. These results suggest that the adoption of a generalized bell-shaped curve membership function improves the prediction slightly. The surface plot of Surface Roughness (Y) of samples values at the different spindle speeds (X1) and feed rates (X2) is shown in Fig. 13.11c. This Figure shows that when the spindle speed is decreased from 4000 to 2000 rpm and the feed rate is set to 100 or 300 mm/min, the Surface Roughness will be relatively high, similar to the conclusion reported previously.

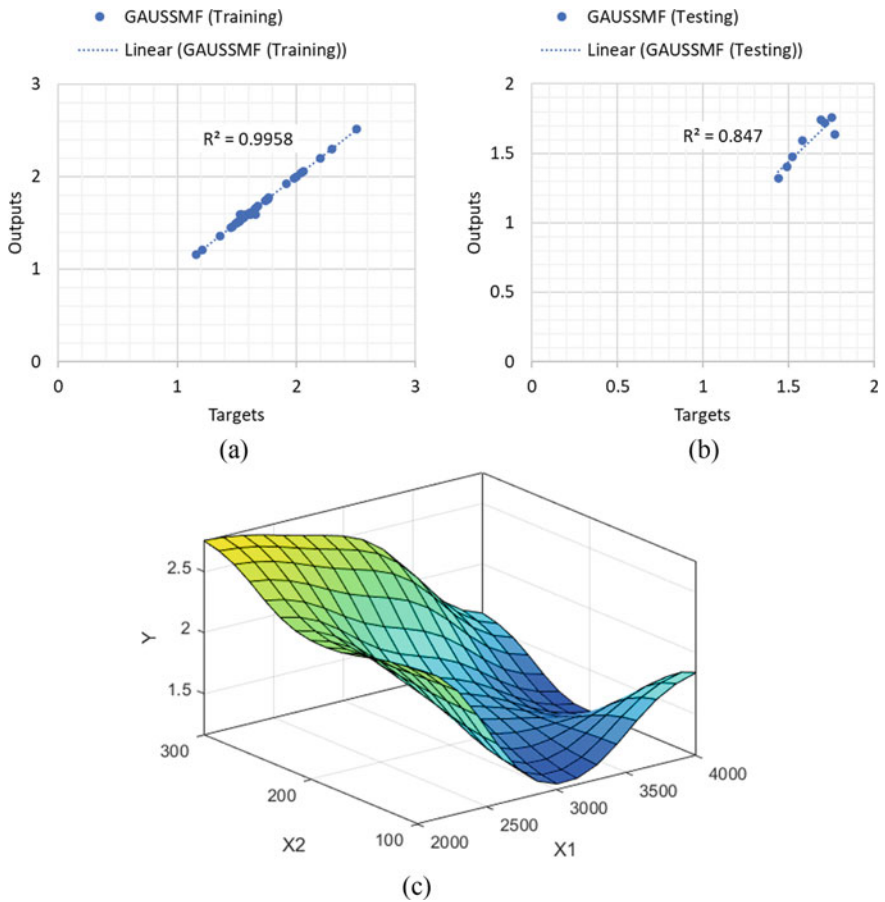


**Fig. 13.10** GAUSSMF results

A comparison between the results reported in the previous section was made. The performance metrics of the various membership function is presented in a tabulated format (Table 13.2). The results reported suggest that the training of the ANFIS model is not affected by the selection of the membership function. However, the highest testing performance was achieved with a generalized bell-shaped curve membership function (GBELLMF) while the lowest performance was obtained with a Gaussian curve membership function (GAUSSMF).

The predicted results were compared to the experimental results to assess visually how the predictions match the targets. Considering a Triangular membership function (TRIMF), the anticipated outputs and target values match in more than 50% of cases. The average deviations between results were approximately 3.47%. All deviations were under 10% as shown in Fig. 13.12.

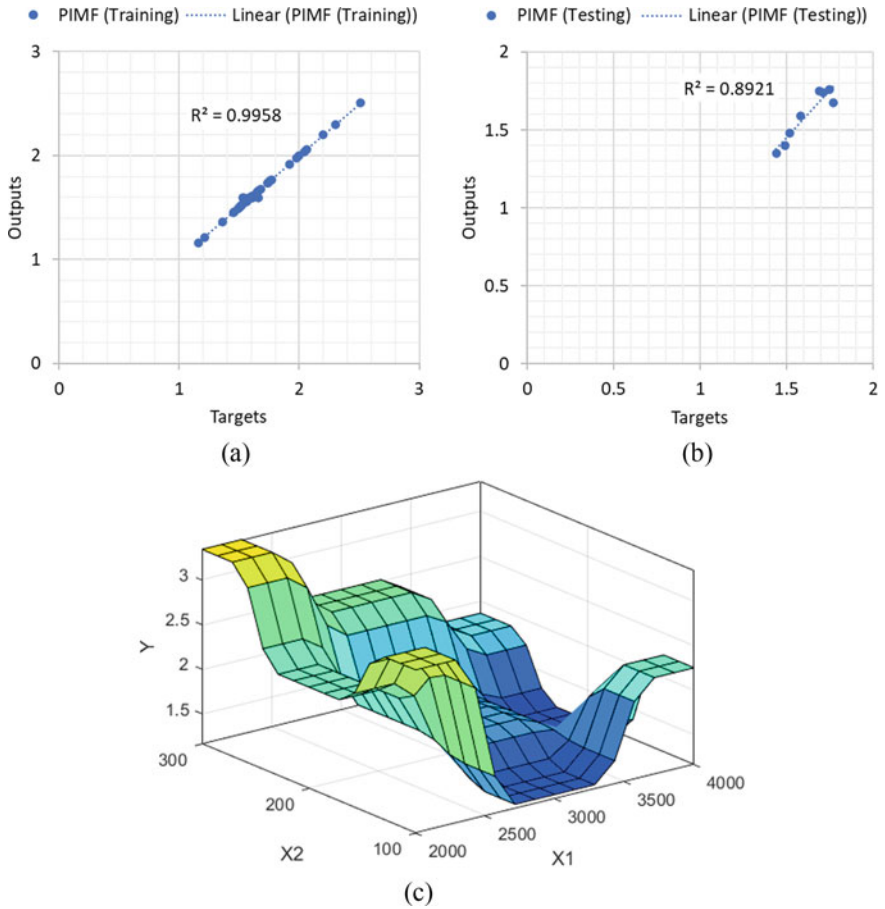


Fig. 13.11 PIMF results

Table 13.2 Comparison of the result of different membership functions

|   | Number of membership function | Function type | Output function | $R^2$ training | $R^2$ testing |
|---|-------------------------------|---------------|-----------------|----------------|---------------|
| 1 | 33,333                        | TRIMF         | Constant        | 0.9958         | 0.8921        |
| 2 | 33,333                        | TRAPMF        | Constant        | 0.9958         | 0.8921        |
| 3 | 33,333                        | GBELLMF       | Constant        | 0.9958         | 0.8958        |
| 4 | 33,333                        | GAUSSMF       | Constant        | 0.9958         | 0.847         |
| 5 | 33,333                        | PIMF          | Constant        | 0.9958         | 0.8921        |

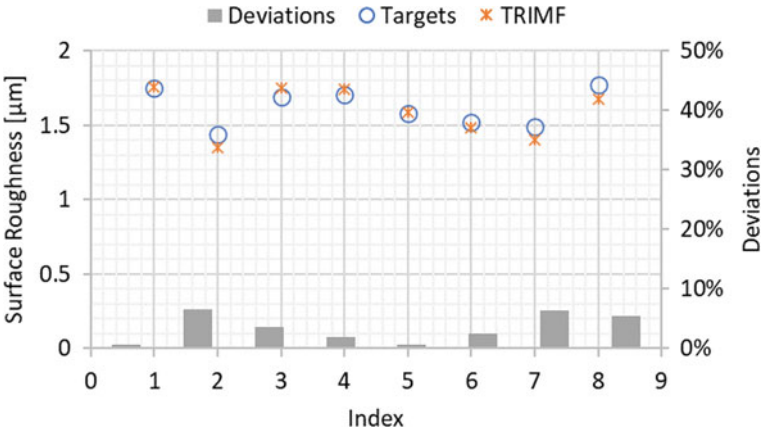


Fig. 13.12 Comparison between the “targets” and “outputs” → TRIMF

Considering a Triangular membership function (TRAPMF), the anticipated outputs and target values match in more than 50% of cases. The average deviations between results were approximately 3.47%. All deviations were under 10% as shown in Fig. 13.13.

Considering a generalized bell-shaped curve membership function (GBELLMF), the anticipated outputs and target values match in more than 50% of cases. The average deviations between results were approximately 3.62%. All deviations were under 10% as shown in Fig. 13.14.

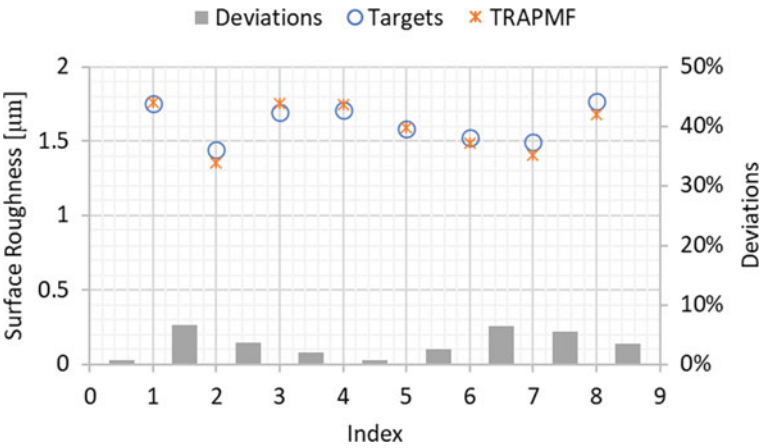


Fig. 13.13 Comparison between the “targets” and “outputs” → TRAPMF

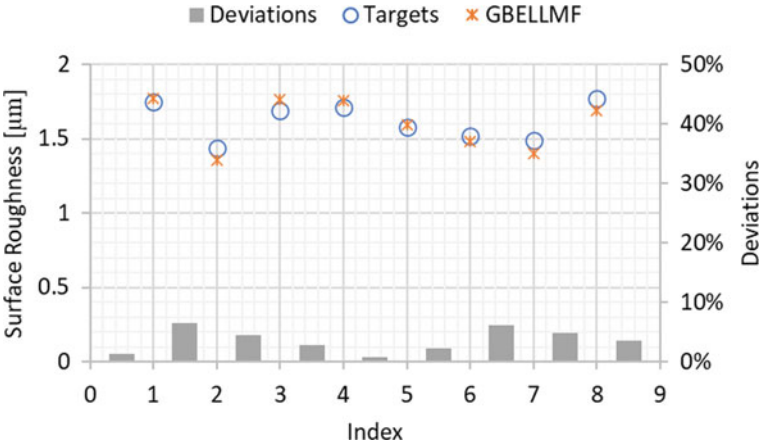


**Fig. 13.14** Comparison between the “targets” and “outputs” → GBELLMF

Considering a Gaussian curve membership function (GAUSSMF), the anticipated outputs and target values match in more than 50% of cases. The average deviations between results were approximately 3.88%. All deviations were under 10% as shown in Fig. 13.15.

Considering the  $\pi$ -shaped curve membership function (PIMF), the anticipated outputs and target values match in more than 50% of cases. The average deviations between results were approximately 3.47%. All deviations were under 10% as shown in Fig. 13.16.

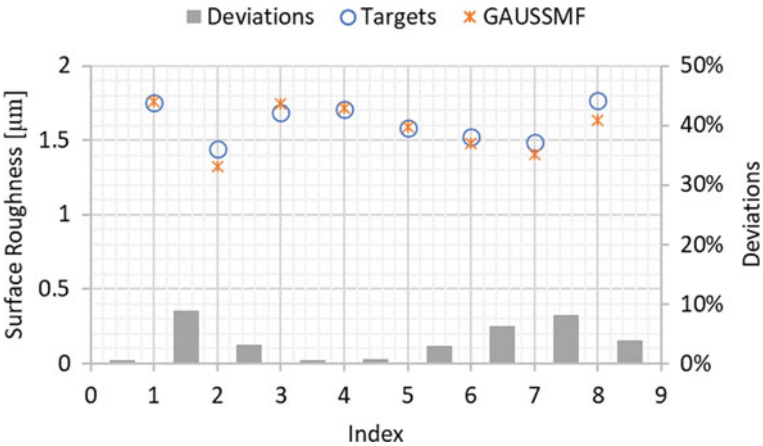


**Fig. 13.15** Comparison between the “targets” and “outputs” → GAUSSMF



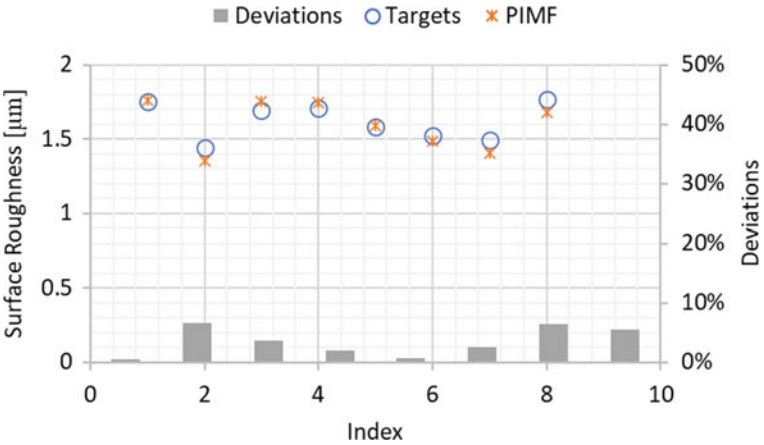


**Fig. 13.16** Comparison between the “targets” and “outputs” → PIMF

In this section, the results obtained with ANFIS were compared to those obtained using ANN models. Figure 13.17 shows the various predictions against the targets. The graph clearly shows the superiority of ANFIS models in comparison to the ANN model. While the highest deviations of ANN models were beyond 12%, all ANFIS deviations were under 7%.

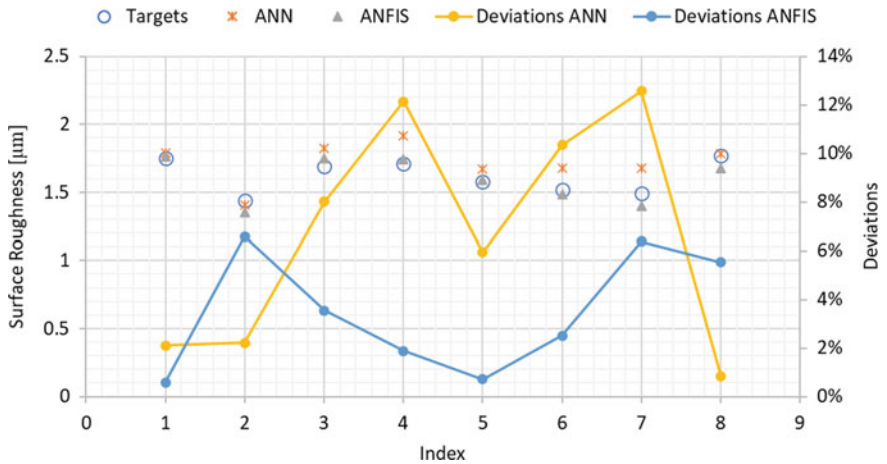


**Fig. 13.17** Comparison between ANN and ANFIS model

## 13.6 Conclusion

In this section, an Adaptive Neuro-Fuzzy Inference System is proposed for the Prediction of Surface Roughness Under Biodegradable Nano-Lubricant. Fifty data were extracted experimentally from the end-milling machining of AA8112. Five machining input parameters including the spindle speed, the feed rate, the length of the cut, the depth of cut, and the helix angle were adjusted to extract the configurations that made up the data. The Surface Roughness was the only output. The outcomes of the ANFIS model's training and testing process were assessed using various types of membership functions. The study is limited to the following membership functions:  $\pi$ -shaped (PIMF), generalized bell shape (GBELLMF), triangular shape (TRIMF), trapezoidal shape (TRAPMF), and Gaussian curve (GAUSSMF). Through this parametric analysis, this study shows that the various outputs track the targets effectively irrespective of the membership functions adopted. In general, the training and the testing performance indicators were relatively higher. This demonstrates that ANFIS models are suitable for the modelling and the prediction of Surface Roughness. However, the highest testing performance was achieved with a generalized bell-shaped curve membership function (GBELLMF) while the lowest performance was obtained with a Gaussian curve membership function (GAUSSMF). The results obtained with ANFIS were compared to those obtained using ANN models. While the highest deviations of ANN models were beyond 12%, all ANFIS deviations were under 7%. These results demonstrate that ANFIS models would be more suitable for the predictions and the analysis of surface roughness in order to make adjustments to the machining parameters and improve surface finishing.

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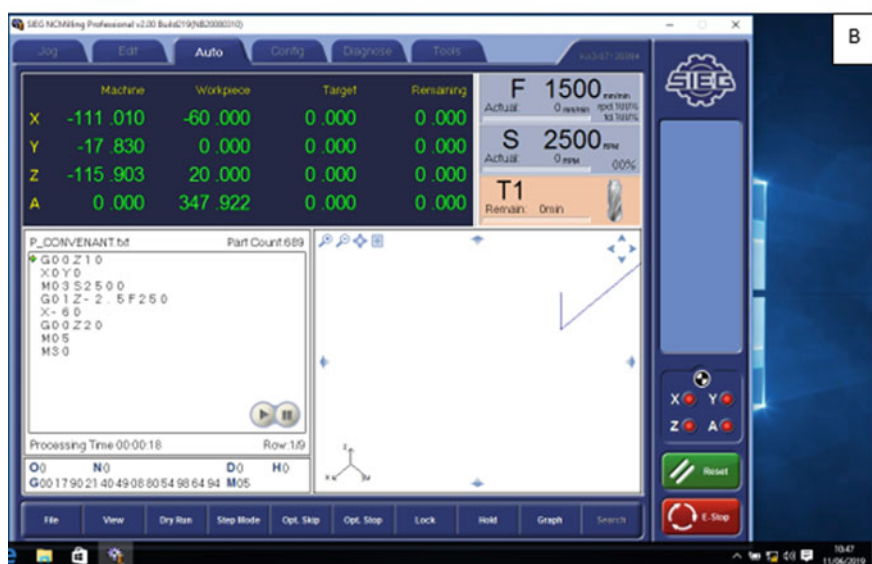
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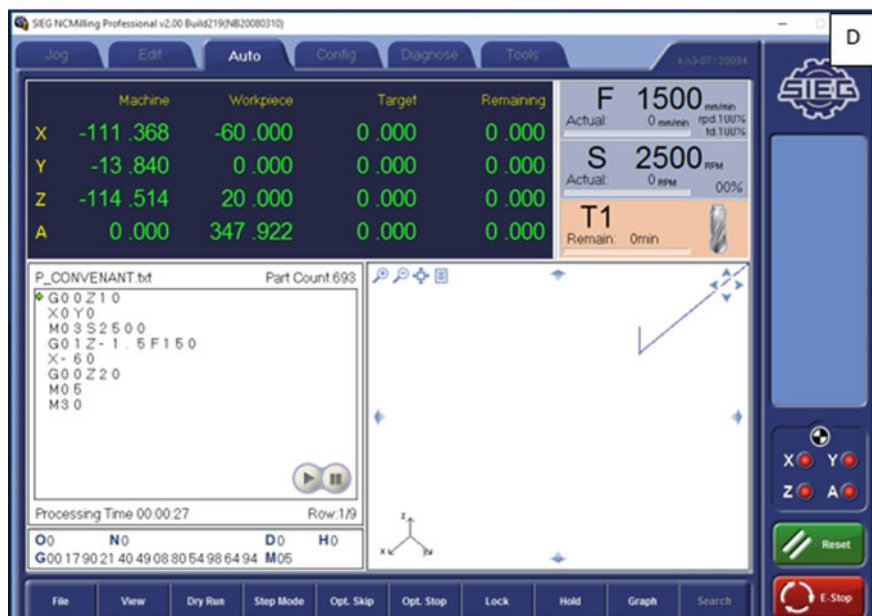
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# Appendix A

The computer numerical control (CNC) programming language employed in the machining operation.







Appendix A–E: The CNC programming language software employed for various machining parameters during operations



# Appendix B

## MATLAB Codes Grey Wolf Optimizer

Supplementary codes can be found on the following link: <https://es.mathworks.com/matlabcentral/fileexchange/44974-grey-wolf-optimizer-gwo>

```
% Cutting force
function [lb,ub,dim,fobj] = Get_Functions_details(F)
switch F
case 'F1'
    fobj = @F1;
    lb=[69.9 55.6 0.66];
    ub=[150 120.6 2];
    dim=3;
end
end
% F1
function o = F1(x)
o=513.915-(0.2466*x(1))+5.3773*x(2)+64.92*x(3)-0.0002594*(x(1)^2)-
0.055*(x(2)^2)+0.0052*x(1)*x(2);
end
```

```
% Surface roughness
function [lb,ub,dim,fobj] = Get_Functions_details(F)
switch F
case 'F1'
    fobj = @F1;
    lb=[69.9 55.6 0.66];
    ub=[150 120.6 2];
    dim=3;
end
end
% F1
function o = F1(x)
o=1.27686-
0.000897964*x(1)+0.0008937*x(2)+0.036303*x(3)+0.000000169203*(x(1)^2);
end
```

```
% Grey Wolf Optimizer
function [Alpha_score,Alpha_pos,Convergence_curve]=GWO(SearchAgents_no,Max_iter,lb,
ub,dim,fobj)
% initialize alpha, beta, and delta_pos
Alpha_pos=zeros(1,dim);
Alpha_score=inf; %change this to -inf for maximization problems
```

```

Beta_pos=zeros(1,dim);
Beta_score=inf; %change this to -inf for maximization problems
Delta_pos=zeros(1,dim);
Delta_score=inf; %change this to -inf for maximization problems
%Initialize the positions of search agents
Positions=initialization(SearchAgents_no,dim,ub,lb);
Convergence_curve=zeros(1,Max_iter);
l=0;% Loop counter
% Main loop
while l<Max_iter
    for i=1:size(Positions,1)

        % Return back the search agents that go beyond the boundaries of the search
space
        Flag4ub=Positions(i,:)>ub;
        Flag4lb=Positions(i,:)<lb;
        Posi-
tions(i,:)=(Positions(i,:).*(~(Flag4ub+Flag4lb)))+ub.*Flag4ub+lb.*Flag4lb;

        % Calculate objective function for each search agent
        fitness=fobj(Positions(i,:));

        % Update Alpha, Beta, and Delta
        if fitness<Alpha_score
            Alpha_score=fitness; % Update alpha
            Alpha_pos=Positions(i,:);
        end

        if fitness>Alpha_score && fitness<Beta_score
            Beta_score=fitness; % Update beta
            Beta_pos=Positions(i,:);
        end

        if fitness>Alpha_score && fitness>Beta_score && fitness<Delta_score
            Delta_score=fitness; % Update delta
            Delta_pos=Positions(i,:);
        end
    end

    a=2-l*((2)/Max_iter); % a decreases linearly from 2 to 0

    % Update the Position of search agents including omegas
    for i=1:size(Positions,1)
        for j=1:size(Positions,2)

```

```

r1=rand(); % r1 is a random number in [0,1]
r2=rand(); % r2 is a random number in [0,1]

A1=2*a*r1-a;
C1=2*r2;

D_alpha=abs(C1*Alpha_pos(j)-Positions(i,j));
X1=Alpha_pos(j)-A1*D_alpha;

r1=rand();
r2=rand();

A2=2*a*r1-a;
C2=2*r2;

D_beta=abs(C2*Beta_pos(j)-Positions(i,j));
X2=Beta_pos(j)-A2*D_beta;

r1=rand();
r2=rand();

A3=2*a*r1-a;
C3=2*r2;

D_delta=abs(C3*Delta_pos(j)-Positions(i,j));
X3=Delta_pos(j)-A3*D_delta;

Positions(i,j)=(X1+X2+X3)/3;

end
end
l=l+1;
Convergence_curve(l)=Alpha_score;
end

```

# Appendix C

## MATLAB Codes Multi-Objective Grey Wolf Optimizer

Supplementary codes can be found on the following link: <https://es.mathworks.com/matlabcentral/fileexchange/55979-multi-objective-grey-wolf-optimizer-mogwo>

```

%% Objective functions
function fobj = cec09(name)
    switch name
        case 'UF1'
            fobj = @UF1;
        end
    end
end
%% UF1
% x and y are columnwise, the input x must be inside the search space and
% it could be a matrix
function y = UF1(x)
y = [0, 0];
y(1) = 513.915-(0.2466*x(1))+5.3773*x(2)+64.92*x(3)-0.0002594*(x(1)^2)-
0.055*(x(2)^2)+0.0052*x(1)*x(2);
y(2) = 1.27686-
0.000897964*x(1)+0.0008937*x(2)+0.036303*x(3)+0.000000169203*(x(1)^2);
end

```

```

% MOGWO
clear all
clc
drawing_flag = 1;
TestProblem='UF1';
nVar=3;
fobj = cec09(TestProblem);
xrange = xboundary(TestProblem, nVar);
% Lower bound and upper bound
lb=[69.9 55.6 0.66];
ub=[150 120.6 2];
VarSize=[1 nVar];
GreyWolves_num=100;
MaxIt=1000; % Maximum Number of Iterations
Archive_size=100; % Repository Size
alpha=0.1; % Grid Inflation Parameter
nGrid=10; % Number of Grids per each Dimension
beta=4; % Leader Selection Pressure Parameter
gamma=2; % Extra (to be deleted) Repository Member Selection Pressure
% Initialization

```

```

GreyWolves=CreateEmptyParticle(GreyWolves_num);
for i=1:GreyWolves_num
    GreyWolves(i).Velocity=0;
    GreyWolves(i).Position=zeros(1,nVar);
    for j=1:nVar
        GreyWolves(i).Position(1,j)=unifrnd(lb(j),ub(j),1);
    end
    GreyWolves(i).Cost=fobj(GreyWolves(i).Position');
    GreyWolves(i).Best.Position=GreyWolves(i).Position;
    GreyWolves(i).Best.Cost=GreyWolves(i).Cost;
end
GreyWolves=DetermineDomination(GreyWolves);
Archive=GetNonDominatedParticles(GreyWolves);
Archive_costs=GetCosts(Archive);
G=CreateHypercubes(Archive_costs,nGrid,alpha);
for i=1: numel(Archive)
    [Archive(i).GridIndex Archive(i).GridSubIndex]=GetGridIndex(Archive(i),G);
end
% MOGWO main loop
for it=1:MaxIt
    a=2-it*((2)/MaxIt);
    for i=1:GreyWolves_num

        clear rep2
        clear rep3

        % Choose the alpha, beta, and delta grey wolves
        Delta=SelectLeader(Archive,beta);
        Beta=SelectLeader(Archive,beta);
        Alpha=SelectLeader(Archive,beta);

        % If there are less than three solutions in the least crowded
        % hypercube, the second least crowded hypercube is also found
        % to choose other leaders from.
        if size(Archive,1)>1
            counter=0;
            for newi=1:size(Archive,1)
                if sum(Delta.Position~=Archive(newi).Position)~=0
                    counter=counter+1;
                    rep2(counter,1)=Archive(newi);
                end
            end
            Beta=SelectLeader(rep2,beta);
        end
    end
end

```

```

% This scenario is the same if the second least crowded hypercube
% has one solution, so the delta leader should be chosen from the
% third least crowded hypercube.
if size(Archive,1)>2
    counter=0;
    for newi=1:size(rep2,1)
        if sum(Beta.Position~=rep2(newi).Position)~=0
            counter=counter+1;
            rep3(counter,1)=rep2(newi);
        end
    end
    Alpha=SelectLeader(rep3,beta);
end

c=2.*rand(1, nVar);

D=abs(c.*Delta.Position-GreyWolves(i).Position);

A=2.*a.*rand(1, nVar)-a;

X1=Delta.Position-A.*abs(D);

c=2.*rand(1, nVar);

D=abs(c.*Beta.Position-GreyWolves(i).Position);

A=2.*a.*rand()-a;

X2=Beta.Position-A.*abs(D);

c=2.*rand(1, nVar);

D=abs(c.*Alpha.Position-GreyWolves(i).Position);

A=2.*a.*rand()-a;

X3=Alpha.Position-A.*abs(D);

GreyWolves(i).Position=(X1+X2+X3)./3;
% Boundary checking
GreyWolves(i).Position=min(max(GreyWolves(i).Position,lb),ub);

GreyWolves(i).Cost=fobj(GreyWolves(i).Position)';
end

```



```

GreyWolves=DetermineDomination(GreyWolves);
non_dominated_wolves=GetNonDominatedParticles(GreyWolves);

Archive=[Archive
        non_dominated_wolves];

Archive=DetermineDomination(Archive);
Archive=GetNonDominatedParticles(Archive);

for i=1:numel(Archive)
    [Archive(i).GridIndex Archive(i).GridSubIndex]=GetGridIndex(Archive(i),G);
end

if numel(Archive)>Archive_size
    EXTRA=numel(Archive)-Archive_size;
    Archive=DeleteFromRep(Archive,EXTRA,gamma);

    Archive_costs=GetCosts(Archive);
    G=CreateHypercubes(Archive_costs,nGrid,alpha);

end

disp(['In iteration ' num2str(it) ': Number of solutions in the archive = '
num2str(numel(Archive))]);

% Results

costs=GetCosts(GreyWolves);
Archive_costs=GetCosts(Archive);

if drawing_flag==1
    hold off
    plot(costs(1,:),costs(2,:), 'k. ');
    hold on
    plot(Archive_costs(1,:),Archive_costs(2,:), 'rd');
    legend('Grey wolves','Non-dominated solutions');
    drawnow
end
end

```

# Appendix D

## MATLAB Codes Ant Lion Optimizer

Supplementary codes can be found on the following link: <https://es.mathworks.com/matlabcentral/fileexchange/49920-ant-lion-optimizer-alo>

```
% Cutting force
function [lb,ub,dim,fobj] = Get_Functions_details(F)
switch F
case 'F1'
    fobj = @F1;
    lb=[69.9 55.6 0.66];
    ub=[150 120.6 2];
    dim=3;
end
end
% F1
function o = F1(x)
o=513.915-(0.2466*x(1))+5.3773*x(2)+64.92*x(3)-0.0002594*(x(1)^2)-
0.055*(x(2)^2)+0.0052*x(1)*x(2);
end
```

```
% Surface roughness

function [lb,ub,dim,fobj] = Get_Functions_details(F)
switch F
case 'F1'
    fobj = @F1;
    lb=[69.9 55.6 0.66];
    ub=[150 120.6 2];
    dim=3;
end
end
% F1
function o = F1(x)
o=1.27686-
0.000897964*x(1)+0.0008937*x(2)+0.036303*x(3)+0.000000169203*(x(1)^2);
end
```

```
% Antlion optimizer
function
[Elite_antlion_fitness,Elite_antlion_position,Convergence_curve]=ALO(N,Max_it
er,lb,ub,dim,fobj)
% Initialize the positions of antlions and ants
```

```

antlion_position=initialization(N,dim,ub,lb);
ant_position=initialization(N,dim,ub,lb);
% Initialize variables to save the position of elite, sorted antlions,
% convergence curve, antlions fitness, and ants fitness
Sorted_antlions=zeros(N,dim);
Elite_antlion_position=zeros(1,dim);
Elite_antlion_fitness=inf;
Convergence_curve=zeros(1,Max_iter);
antlions_fitness=zeros(1,N);
ants_fitness=zeros(1,N);
% Calculate the fitness of initial antlions and sort them
for i=1:size(antlion_position,1)
    antlions_fitness(1,i)=fobj(antlion_position(i,:));
end
[sorted_antlion_fitness,sorted_indexes]=sort(antlions_fitness);

for newindex=1:N
    Sorted_antlions(newindex,:)=antlion_position(sorted_indexes(newindex),:);
end

Elite_antlion_position=Sorted_antlions(1,:);
Elite_antlion_fitness=sorted_antlion_fitness(1);
% Main loop start from the second iteration since the first iteration
% was dedicated to calculating the fitness of antlions
Current_iter=2;
while Current_iter<Max_iter+1

    % This for loop simulate random walks
    for i=1:size(ant_position,1)
        % Select ant lions based on their fitness (the better antlion the higher chance
of catching ant)
        Rolette_index=RouletteWheelSelection(1./sorted_antlion_fitness);
        if Rolette_index==1
            Rolette_index=1;
        end

        % RA is the random walk around the selected antlion by rolette wheel
        RA=Random_walk_around_antlion(dim,Max_iter,lb,ub, Sorted_
ed_antlions(Rolette_index,:),Current_iter);

        % RA is the random walk around the elite (best antlion so far)
        [RE]=Random_walk_around_antlion(dim,Max_iter,lb,ub,
Elite_antlion_position(1,:),Current_iter);

        ant_position(i,:)= (RA(Current_iter,:)+RE(Current_iter,:))/2;

```

```

end
for i=1:size(ant_position,1)

    % Boundary checking (bring back the antlions of ants inside search
    % space if they go beyond the boundaries
    Flag4ub=ant_position(i,:)>ub;
    Flag4lb=ant_position(i,:)<lb;

ant_position(i,:)=(ant_position(i,:).*(~(Flag4ub+Flag4lb)))+ub.*Flag4ub+lb.*Flag
4lb;

    ants_fitness(1,i)=fobj(ant_position(i,:));
end

% Update antlion positions and fitnesses based of the ants (if an ant
% becomes fitter than an antlion we assume it was caught by the antlion
% and the antlion update goes to its position to build the trap)
double_population=[Sorted_antlions;ant_position];
double_fitness=[sorted_antlion_fitness ants_fitness];

[double_fitness_sorted I]=sort(double_fitness);
double_sorted_population=double_population(I,:);

antlions_fitness=double_fitness_sorted(1:N);
Sorted_antlions=double_sorted_population(1:N,:);

% Update the position of elite if any antlions becomes fitter than it
if antlions_fitness(1)<Elite_antlion_fitness
    Elite_antlion_position=Sorted_antlions(1,:);
    Elite_antlion_fitness=antlions_fitness(1);
end

% Keep the elite in the population
Sorted_antlions(1,:)=Elite_antlion_position;
antlions_fitness(1)=Elite_antlion_fitness;

% Update the convergence curve
Convergence_curve(Current_iter)=Elite_antlion_fitness;
% Display the iteration and best optimum obtained so far
if mod(Current_iter,50)==0
    display(['At iteration ', num2str(Current_iter), ' the elite fitness is ',
num2str(Elite_antlion_fitness)]);
end
    Current_iter=Current_iter+1;
end

```

# Appendix E

## MATLAB Codes Multi-Objective Ant Lion Optimizer (MALO)

Supplementary codes can be found on the following link: <https://es.mathworks.com/matlabcentral/fileexchange/58460-multi-objective-ant-lion-optimizer-moalo>

```
% Objective functions to optimize
function o = ZDT1(x)
o = [0, 0];
o(1) = 513.915-(0.2466*x(1))+5.3773*x(2)+64.92*x(3)-0.0002594*(x(1)^2)-
0.055*(x(2)^2)+0.0052*x(1)*x(2);
o(2) = 1.27686-
0.000897964*x(1)+0.0008937*x(2)+0.036303*x(3)+0.000000169203*(x(1)^2);
```

```
% MALO
clc;
clear;
close all;
% Change these details with respect to your problem%%%%%%%%%
ObjectiveFunction=@ZDT1;
dim=3;
lb=[69.9 55.6 0.66];
ub=[150 120.6 2];
obj_no=2;
if size(ub,2)==1
    ub=ones(1,dim)*ub;
    lb=ones(1,dim)*lb;
end
%%%%%%%%%
%%%%%%%%%
% Initial parameters of the MALO algorithm
max_iter=100;
N=100;
ArchiveMaxSize=100;
Archive_X=zeros(100,dim);
Archive_F=ones(100,obj_no)*inf;
Archive_member_no=0;
r=(ub-lb)/2;
V_max=(ub(1)-lb(1))/10;
Elite_fitness=inf*ones(1,obj_no);
Elite_position=zeros(dim,1);
Ant_Position=initialization(N,dim,ub,lb);
fitness=zeros(N,2);
V=initialization(N,dim,ub,lb);
```

```

iter=0;
position_history=zeros(N,max_iter,dim);
for iter=1:max_iter

    for i=1:N %Calculate all the objective values first
        Particles_F(i,:)=ObjectiveFunction(Ant_Position(:,i));
        if dominates(Particles_F(i,:),Elite_fitness)
            Elite_fitness=Particles_F(i,:);
            Elite_position=Ant_Position(:,i);
        end
    end

    [Archive_X, Archive_F, Archive_member_no]=UpdateArchive(Archive_X,
    Archive_F, Ant_Position, Particles_F, Archive_member_no);

    if Archive_member_no>ArchiveMaxSize
        Archive_mem_ranks=RankingProcess(Archive_F, ArchiveMaxSize,
obj_no);
        [Archive_X, Archive_F, Archive_mem_ranks, Ar-
chive_member_no]=HandleFullArchive(Archive_X, Archive_F, Ar-
chive_member_no, Archive_mem_ranks, ArchiveMaxSize);
    else
        Archive_mem_ranks=RankingProcess(Archive_F, ArchiveMaxSize,
obj_no);
    end

    Archive_mem_ranks=RankingProcess(Archive_F, ArchiveMaxSize, obj_no);

    % Chose the archive member in the least population area as arrtactor
    % to improve coverage
    index=RouletteWheelSelection(1./Archive_mem_ranks);
    if index== -1
        index=1;
    end
    Elite_fitness=Archive_F(index,:);
    Elite_position=Archive_X(index,:);

    Random_antlion_fitness=Archive_F(1,:);
    Random_antlion_position=Archive_X(1,:);

    for i=1:N

        index=0;
        neighbours_no=0;

```



```

    RA=Random_walk_around_antlion(dim,max_iter,lb,ub, Random_antlion_position',iter);

    [RE]=Random_walk_around_antlion(dim,max_iter,lb,ub, Elite_position',iter);

    Ant_Position(:,i)=(RE(iter,:)+RA(iter,:))/2;

    Flag4ub=Ant_Position(:,i)>ub';
    Flag4lb=Ant_Position(:,i)<lb';

    Ant_Position(:,i)=(Ant_Position(:,i).*(~(Flag4ub+Flag4lb)))+ub'.*Flag4ub+lb'.*Flag4lb;

    end
    display(['At the iteration ', num2str(iter), ' there are ',
num2str(Archive_member_no), ' non-dominated solutions in the archive']);
end
figure
Draw_ZDT1();
hold on
plot(Archive_F(:,1),Archive_F(:,2),'ko','MarkerSize',8,'markerfacecolor','k');
legend('True PF','Obtained PF');
title('MALO');
set(gcf, 'pos', [403 466 230 200])

```

# Appendix F

## MATLAB Codes Grasshopper Optimisation Algorithm (GOA)

Supplementary codes can be found on the following link: <https://es.mathworks.com/matlabcentral/fileexchange/61421-grasshopper-optimisation-algorithm-go>

```
% Cutting force
function [lb,ub,dim,fobj] = Get_Functions_details(F)
switch F
case 'F1'
    fobj = @F1;
    lb=[69.9 55.6 0.66];
    ub=[150 120.6 2];
    dim=3;
end
end
% F1
function o = F1(x)
o=513.915-(0.2466*x(1))+5.3773*x(2)+64.92*x(3)-0.0002594*(x(1)^2)-
0.055*(x(2)^2)+0.0052*x(1)*x(2);
end
```

```
% Surface roughness

function [lb,ub,dim,fobj] = Get_Functions_details(F)
switch F
case 'F1'
    fobj = @F1;
    lb=[69.9 55.6 0.66];
    ub=[150 120.6 2];
    dim=3;
end
end
% F1
function o = F1(x)
o=1.27686-
0.000897964*x(1)+0.0008937*x(2)+0.036303*x(3)+0.000000169203*(x(1)^2);
end
```

```
% The Grasshopper Optimization Algorithm
function [TargetFit-
ness,TargetPosition,Convergence_curve,Trajectories,fitness_history, posi-
tion_history]=GOA(N, Max_iter, lb,ub, dim, fobj)
disp('GOA is now estimating the global optimum for your problem....')
```

```

flag=0;
if size(ub,1)==1
    ub=ones(dim,1)*ub;
    lb=ones(dim,1)*lb;
end
if (rem(dim,2)~=0) % this algorithm should be run with a even number of variables. This line is to handle odd number of variables

    ub = [150 120.6 2];
    lb = [69.9 55.6 0.66];
    flag=1;
end
%Initialize the population of grasshoppers
GrassHopperPositions=initialization(N,dim,ub,lb);
GrassHopperFitness = zeros(1,N);
fitness_history=zeros(N,Max_iter);
position_history=zeros(N,Max_iter,dim);
Convergence_curve=zeros(1,Max_iter);
Trajectories=zeros(N,Max_iter);
cMax=1;
cMin=0.00004;
%Calculate the fitness of initial grasshoppers
for i=1:size(GrassHopperPositions,1)
    if flag == 1
        GrassHopperFitness(1,i)=fobj(GrassHopperPositions(i,1:end-1));
    else
        GrassHopperFitness(1,i)=fobj(GrassHopperPositions(i,:));
    end
    fitness_history(i,1)=GrassHopperFitness(1,i);
    position_history(i,1,:)=GrassHopperPositions(i,:);
    Trajectories(:,1)=GrassHopperPositions(:,1);
end
[sorted_fitness,sorted_indexes]=sort(GrassHopperFitness);
% Find the best grasshopper (target) in the first population
for newindex=1:N
    Sort-
    ed_grasshopper(newindex,:)=GrassHopperPositions(sorted_indexes(newindex),:);
end
TargetPosition=Sorted_grasshopper(1,:);
TargetFitness=sorted_fitness(1);
% Main loop
l=2; % Start from the second iteration since the first iteration was dedicated to calculating the fitness of antlions
while l<Max_iter+1

```

```

c=cMax-1*((cMax-cMin)/Max_iter);

for i=1:size(GrassHopperPositions,1)
    temp= GrassHopperPositions';
    for k=1:2:dim
        S_i=zeros(2,1);
        for j=1:N
            if i~j
                Dist=distance(temp(k:k+1,j), temp(k:k+1,i)); % Calculate the distance
between two grasshoppers

                r_ij_vec=(temp(k:k+1,j)-temp(k:k+1,i))/(Dist+eps);
                xj_xi=2+rem(Dist,2); % |xjd - xid| in Eq. (2.7)

                s_ij=((ub(k:k+1) - lb(k:k+1))*c/2)*S_func(xj_xi).*r_ij_vec;
                S_i=S_i+s_ij;
            end
        end
        S_i_total(k:k+1, :) = S_i;

    end

    X_new = c * S_i_total' + (TargetPosition);
    GrassHopperPositions_temp(i,:)=X_new';
end
% GrassHopperPositions
GrassHopperPositions=GrassHopperPositions_temp;

for i=1:size(GrassHopperPositions,1)
    % Relocate grasshoppers that go outside the search space

Tp=GrassHopperPositions(i,:)>ub';Tm=GrassHopperPositions(i,:)<lb';GrassHopp
erPositions(i,:)=(GrassHopperPositions(i,:).*(~(Tp+Tm)))+ub'.*Tp+lb'.*Tm;

    % Calculating the objective values for all grasshoppers
    if flag == 1
        GrassHopperFitness(1,i)=fobj(GrassHopperPositions(i,1:end-1));
    else
        GrassHopperFitness(1,i)=fobj(GrassHopperPositions(i,:));
    end
    fitness_history(i,1)=GrassHopperFitness(1,i);
    position_history(i,1,:)=GrassHopperPositions(i,:);

    Trajectories(:,1)=GrassHopperPositions(:,1);

```

```
% Update the target
if GrassHopperFitness(1,i)<TargetFitness
    TargetPosition=GrassHopperPositions(i,:);
    TargetFitness=GrassHopperFitness(1,i);
end
end

Convergence_curve(l)=TargetFitness;
disp(['In iteration #', num2str(l), ' , target"s objective = ',
num2str(TargetFitness)])

l = l + 1;
end
if (flag==1)
    TargetPosition = TargetPosition(1:dim-1);
end
```

# Appendix G

## **MATLAB Codes Multi-Objective Grasshopper Optimization Algorithm (MOGOA)**

Supplementary codes can be found on the following link: <https://es.mathworks.com/matlabcentral/fileexchange/63786-mogoa-multi-objective-grasshopper-optimization-algorithm>

```
% Objective functions to optimize
function o = ZDT1(x)
o = [0, 0];
o(1) = 513.915-(0.2466*x(1))+5.3773*x(2)+64.92*x(3)-0.0002594*(x(1)^2)-
0.055*(x(2)^2)+0.0052*x(1)*x(2);
o(2) = 1.27686-
0.000897964*x(1)+0.0008937*x(2)+0.036303*x(3)+0.000000169203*(x(1)^2);
```

```
% MOGOA
clc;
clear;
close all;
% Change these details with respect to your problem%%%%%%%%%%
ObjectiveFunction=@ZDT1;
dim=3;
lb=[69.9 55.6 0.66];
ub=[150 120.6 2];
obj_no=2;
if size(ub,2)==1
    ub=ones(1,dim)*ub;
    lb=ones(1,dim)*lb;
end
%%%%%%%%%%
%%%%%%%%%%
flag=0;
if (rem(dim,2)~=0)
    dim = dim+1;
    ub = [ub, 1];
    lb = [lb, 0];
    flag=1;
end
max_iter=100;
N=200;
ArchiveMaxSize=100;
Archive_X=zeros(100,dim);
Archive_F=ones(100,obj_no)*inf;
Archive_member_no=0;
%Initialize the positions of artificial whales
```



```

GrassHopperPositions=initialization(N,dim,ub,lb);
TargetPosition=zeros(dim,1);
TargetFitness=inf*ones(1,obj_no);
cMax=1;
cMin=0.00004;
%calculate the fitness of initial grasshoppers
for iter=1:max_iter
    for i=1:N

        Flag4ub=GrassHopperPositions(:,i)>ub';
        Flag4lb=GrassHopperPositions(:,i)<lb';
        GrassHopperPosi-
tions(:,i)=(GrassHopperPositions(:,i).*(~(Flag4ub+Flag4lb)))+ub'.*Flag4ub+lb'.*
Flag4lb;

        GrassHopperFitness(i,:)=ObjectiveFunction(GrassHopperPositions(:,i));
        if dominates(GrassHopperFitness(i,:),TargetFitness)
            TargetFitness=GrassHopperFitness(i,:);
            TargetPosition=GrassHopperPositions(:,i);
        end

    end

    [Archive_X, Archive_F, Archive_member_no]=UpdateArchive(Archive_X,
Archive_F, GrassHopperPositions, GrassHopperFitness, Archive_member_no);

    if Archive_member_no>ArchiveMaxSize
        Archive_mem_ranks=RankingProcess(Archive_F, ArchiveMaxSize,
obj_no);
        [Archive_X, Archive_F, Archive_mem_ranks, Ar-
chive_member_no]=HandleFullArchive(Archive_X, Archive_F, Ar-
chive_member_no, Archive_mem_ranks, ArchiveMaxSize);
    else
        Archive_mem_ranks=RankingProcess(Archive_F, ArchiveMaxSize,
obj_no);
    end

    Archive_mem_ranks=RankingProcess(Archive_F, ArchiveMaxSize, obj_no);
    index=RouletteWheelSelection(1./Archive_mem_ranks);
    if index==-1
        index=1;
    end
    TargetFitness=Archive_F(index,:);
    TargetPosition=Archive_X(index,:);

```

```

c=cMax-iter*((cMax-cMin)/max_iter);

for i=1:N
    temp= GrassHopperPositions;
    for k=1:2:dim
        S_i=zeros(2,1);
        for j=1:N
            if i~=j
                Dist=distance(temp(k:k+1,j), temp(k:k+1,i));
                r_ij_vec=(temp(k:k+1,j)-temp(k:k+1,i))/(Dist+eps);
                xj_xi=2+rem(Dist,2);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% %
                s_ij=((ub(k:k+1)' - lb(k:k+1))' .*c/2)*S_func(xj_xi).*r_ij_vec;
                S_i=S_i+s_ij;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% %
            end
        end
        S_i_total(k:k+1, :) = S_i;

    end

    X_new=c*S_i_total'+(TargetPosition)';
    GrassHopperPositions_temp(i,:)=X_new';
end
% GrassHopperPositions
GrassHopperPositions=GrassHopperPositions_temp';

display(['At the iteration ', num2str(iter), ' there are ',
num2str(Archive_member_no), ' non-dominated solutions in the archive']);
end
if (flag==1)
    TargetPosition = TargetPosition(1:dim-1);
end
figure
Draw_ZDT1();
hold on
plot(Archive_F(:,1),Archive_F(:,2),'ro','MarkerSize',8,'markerfacecolor','k');
legend('True PF','Obtained PF');
title('MOGOA');
set(gcf, 'pos', [403 466 230 200])

```

# Appendix H

## GAMS Code: AUGMENCON2

```
$inlinecom [ ]
$eolcom //
$title end milling

Sets k objective functions /surfaceroughness, cutting-
force/;
$set min -1
$set max +1
Parameter dir(k) direction of the objective functions
/surfaceroughness %min%, cuttingforce %min%/;

Free Variables
z(k) objective function variables;

Positive VARIABLES S, F, D;

S.lo = 69.9; S.up = 150;
F.lo = 55.6; F.up = 120.6;
D.lo = 0.66; D.up = 2;
```

**Equations**

objsurfaceroughness objective minimizing surfaceroughness

objcuttingforce objective minimizing cuttingforce;

*\* Objective functions*

```
objsurfaceroughness.. z('surfaceroughness') =e=
1.27686-
(0.000897964*S)+(0.0008937*F)+(0.036303*D)+(0.000000169
203*S*S); ;
```

```
objcuttingforce.. z('cuttingforce') =e= 513.915-
(0.2466*S)+(5.3773*F)+(64.92*D)-(0.0002594*S*S)-
(0.055*F*F)+(0.0052*S*F); ;
```

```
z.lo('surfaceroughness')=0; z.up('surfaceroughness')=
5;
```

```
z.lo('cuttingforce')=430.655;
```

```
z.up('cuttingforce')=774.45;
```

**Model** Endmilling / all /;

```
Endmilling.optfile =1;
```

```
$STitle eps-constraint method
```

**Set** k1(k) the first element of k,

km1(k) all but the first elements of k

kk(k) active objective function in constraint allobj;

k1(k)\$**(ord(k)=1) = yes**; km1(k)=**yes**; km1(k1) = **no**;

**Parameter**

rhs(k) right hand side of the constrained obj functions  
 in epsconstraint  
 maxobj(k) maximum value from the payoff table  
 minobj(k) minimum value from the payoff table  
 numk(k) ordinal value of k starting with 1

**Scalar**

iter total number of iterations  
 infeas total number of infeasibilities  
 elapsed\_time elapsed time for payoff and e-sonstraint  
 start start time  
 finish finish time

**Variables**

a\_objval auxiliary variable for the objective function  
 obj auxiliary variable during the construction of the  
 payoff table  
 sl(k) slack or surplus variables for the eps-  
 constraints

**Positive Variables** sl**Equations**

con\_obj(k) constrained objective functions  
 augm\_obj augmented objective function to avoid weakly  
 efficient  
 solutions  
 allobj all the objective functions in one expression;  
 con\_obj(km1).. z(km1) - dir(km1)\*sl(km1) =e= rhs(km1);  
*\* We optimize the first objective function and put the  
 others as constraints*

```

* the second term is for avoiding weakly efficient
points
augm_obj.. a_objval =e= sum(k1,dir(k1)*z(k1))
+ 1e-3*sum(km1,power(10,-(numk(km1)-
1))*s1(km1)/(maxobj(km1)-
minobj(km1))));
allobj.. sum(kk, dir(kk)*z(kk)) =e= obj;

Model mod_payoff / Endmilling, allobj / ;

Model mod_epsmethod / Endmilling, con_obj, augm_obj / ;

Parameter
payoff(k,k) payoff tables entries;
Alias (k,kp);

option optcr=0, limrow=0, limcol=0, solprint=off,
solvelink=%SolveLink.LoadLibrary%;
* Generate payoff table applying lexicographic optimi-
zation
loop (kp,
kk(kp)=yes;
repeat

solve mod_payoff using nlp maximizing obj;
payoff(kp,kk) = z.l(kk);
z.fx(kk) = z.l(kk); // freeze the value of the last ob-
jective optimized
kk(k+1) = kk(k); // cycle through the objective func-
tions
until kk(kp); kk(kp) = no;
* release the fixed values of the objective functions
for the new iteration
z.up(k) = inf; z.lo(k) = -inf;
);
if (mod_payoff.modelstat<>%ModelStat.Optimal% and
mod_payoff.modelstat<>%ModelStat.integer Solution%,
abort 'no optimal solution for mod_payoff');
file fx / 2kp50_augmecon2_results.txt /;
put fx ' PAYOFF TABLE' / ;

loop (kp,
loop (k, put payoff(kp,k):12:2);

```

```

put /);
minobj(k)=smin(kp,payoff(kp,k));
maxobj(k)=smax(kp,payoff(kp,k));
* gridpoints are calculated as the range (difference
between max and min) of
* the 2nd objective function from the payoff table
$if not set gridpoints $set gridpoints 10
Set g grid points /g0*g%gridpoints%/
grid(k,g) grid

```

### Parameter

```

gridrhs(k,g) rhs of eps-constraint at grid point
maxg(k) maximum point in grid for objective
posg(k) grid position of objective
firstOffMax, lastZero some counters
* numk(k) ordinal value of k starting with 1
numg(g) ordinal value of g starting with 0
step(k) step of grid points in objective functions
jump(k) jumps in the grid points traversing;
lastZero=1; loop(kml, numk(kml)=lastZero;
lastZero=lastZero+1); numg(g) =
ord(g)-1;
grid(kml,g) = yes; // Here we could define different
grid intervals for different objectives
maxg(kml) = smax(grid(kml,g), numg(g));
step(kml) = (maxobj(kml)- minobj(kml))/maxg(kml);
gridrhs(grid(kml,g))$(dir(kml)=-1) = maxobj(kml) -
numg(g)/maxg(kml)*(maxobj(kml)- minobj(kml));
gridrhs(grid(kml,g))$(dir(kml)= 1) = minobj(kml) +
numg(g)/maxg(kml)*(maxobj(kml)- minobj(kml));
put / ' Grid points' /;
loop (g,
loop(kml, put gridrhs(kml,g):12:2);
put /);
put / 'Efficient solutions' /;
* Walk the grid points and take shortcuts if the model
becomes infeasible or
* if the calculated slack variables are greater than
the step size
posg(kml) = 0; iter=0; infeas=0; start=jnow;
repeat
rhs(kml) = sum(grid(kml,g)$(numg(g)=posg(kml)),
gridrhs(kml,g));

```

```

solve mod_epsmethod maximizing a_objval using nlp;

Display "-----"
-----",
        "NLP solver",
        S.l, F.l, D.l;

iter=iter+1;
if (mod_epsmethod.modelstat<>%ModelStat.Optimal% and
mod_epsmethod.modelstat<>%ModelStat.integer Solution%,
infeas=infeas+1; // not optimal is in this case infeasible
put iter:5:0, ' infeasible' /;
lastZero = 0; loop(km1$(posg(km1)>0 and lastZero=0),
lastZero=numk(km1));
posg(km1)$(numk(km1)<=lastZero) = maxg(km1); // skip all solves for more demanding values of rhs(km1)
else
put iter:5:0;
loop(k, put z.l(k):12:2);
jump(km1)=1;
* find the first off max (obj function that hasn't reach the final grid point).
* If this obj.fun is k then assign jump for the 1..k-th objective functions
* The jump is calculated for the innermost objective function (km=1)
jump(km1)$(numk(km1)=1)=1+floor(sl.L(km1)/step(km1));
loop(km1$(jump(km1)>1), put ' jump');
put /;
);
* Proceed forward in the grid
firstOffMax = 0;
loop(km1$(posg(km1)<maxg(km1) and firstOffMax=0),
posg(km1)=min((posg(km1)+jump(km1)),maxg(km1));
firstOffMax=numk(km1));
posg(km1)$(numk(km1)<firstOffMax) = 0;
abort$(iter>1000) 'more than 1000 iterations, something seems to go wrong'
until sum(km1$(posg(km1)=maxg(km1)),1)= card(km1) and
firstOffMax=0;
finish=jnow; elapsed_time=(finish-start)*60*60*24;
put /;
put 'Infeasibilities = ', infeas:5:0 /;
put 'Elapsed time: ',elapsed_time:10:2, ' seconds' / ;

```



# Appendix I

## ANN Model

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
%
% This script assumes these variables are defined:
%
% Inputs - input data.
% Output - target data.

x = Inputs';
t = Output';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation.

% Create a Fitting Network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};
```

```

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 80/100;
net.divideParam.valRatio = 10/100;
net.divideParam.testRatio = 10/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse'; % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

```

```
% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
    % Generate MATLAB function for neural network for application
    % deployment in MATLAB scripts or with MATLAB Compiler and Builder
    % tools, or simply to examine the calculations your trained neural
    % network performs.
    genFunction(net,'myNeuralNetworkFunction');
    y = myNeuralNetworkFunction(x);
end
if (false)
    % Generate a matrix-only MATLAB function for neural network code
    % generation with MATLAB Coder tools.
    genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunction(x);
end
if (false)
    % Generate a Simulink diagram for simulation or deployment with.
    % Simulink Coder tools.
    gensim(net);
end
```

# Appendix J

## ANN-PSO Model

```
% myfunc.m
%The myfunc.m file and the nn_pso.m files must be put
in the same directory %as an excel spreadsheet contain-
ing the data (sheet 1: Inputs; sheet 2: %output)
%Run the code nn_pso
function [f] = myfunc(x,n,m,o,net,inputs,targets)
k=0;
for i=1:n
    for j=1:m
        k=k+1;
        xi(i,j)=x(k);
    end
end
for i=1:n
    k=k+1;
    x1(i)=x(k);
    xb1(i,1)=x(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=x(k);
end
net.iw{1,1}=xi;
net.lw{2,1}=x1;
net.b{1,1}=xb1;
net.b{2,1}=xb2;
f=sum((net(inputs)-targets).^2)/length(inputs);
```

```
% nn_pso.m
clc
tic
close all
clear all
rng default
filename = 'datafile.xlsx';
sheetname1 = 'Sheet1';
sheetname2 = 'Sheet2';
input = xlsread(filename,sheetname1,'A1:Z10000');
target = xlsread(filename,sheetname2,'A1:Z10000');
inputs=input';
targets=target';
m=length(inputs(:,1));
o=length(targets(:,1));
```

```

% Number of neurons
n=8;
net=feedforwardnet(n);
net=configure(net,inputs,targets);
kk=m*n+n+n+o;
for j=1:kk
    LB(1,j)=-1.5;
    UB(1,j)=1.5;
End
% Swarm population size
pop=10;
for i=1:pop
    for j=1:kk
        xx(i,j)=LB(1,j)+rand*(UB(1,j)-LB(1,j));
    end
end
maxrun=1;
for run=1:maxrun
    fun=@(x) myfunc(x,n,m,o,net,inputs,targets);
    x0=xx;
    % pso initialization-----
    -----start
    x=x0; % initial population
    v=0.1*x0; % initial velocity
    for i=1:pop
        f0(i,1)=fun(x0(i,:));
    end
    [fmin0,index0]=min(f0);
    pbest=x0; % initial pbest
    gbest=x0(index0,:); % initial gbest
    % pso initialization-----
    -----end
    % pso algorithm-----
    -----start
% Acceleration factors
    c1=1; c2=2.75;
    ite=1; maxite=1000; tolerance=1;
    while ite<=maxite && tolerance>10^-8
        w=0.1+rand*0.4;
        % pso velocity updates
        for i=1:pop
            for j=1:kk
                v(i,j)=w*v(i,j)+c1*rand*(pbest(i,j)-
x(i,j))+c2*rand*(gbest(1,j)-x(i,j));
            end
        end
    end
end

```

```

% pso position update
for i=1:pop
    for j=1:kk
        x(i,j)=x(i,j)+v(i,j);
    end
end
% handling boundary violations
for i=1:pop
    for j=1:kk
        if x(i,j)<LB(j)
            x(i,j)=LB(j);
        elseif x(i,j)>UB(j)
            x(i,j)=UB(j);
        end
    end
end
% evaluating fitness
for i=1:pop
    f(i,1)=fun(x(i,:));
end
% updating pbest and fitness
for i=1:pop
    if f(i,1)<f0(i,1)
        pbest(i,:)=x(i,:);
        f0(i,1)=f(i,1);
    end
end
[fmin,index]=min(f0); % finding out the best
particle
ffmin(ite,run)=fmin; % storing best fitness
ffite(run)=ite; % storing iteration count
% updating gbest and best fitness
if fmin<fmin0
    gbest=pbest(index,:);
    fmin0=fmin;
end
% calculating tolerance
if ite>100;
    tolerance=abs(ffmin(ite-100,run)-fmin0);
end
% displaying iterative results
if ite==1
    disp(sprintf('Iteration Best particle Ob-
jective fun'));
end
disp(sprintf('%8g %8g %8.4f',ite,index,fmin0));

```

```

        ite=ite+1;
    end
    % pso algorithm-----
    -----end
    xo=gbest;
    fval=fun(xo);
    xbest(run,:)=xo;
    ybest(run,1)=fun(xo);
disp(sprintf('*****'
));
    disp(sprintf(' RUN fval ObFuVa'));
    disp(sprintf('%6g %6g %8.4f
%8.4f',run,fval,ybest(run,1)));
end
toc
% Final neural network model
disp('Final nn model is net_f')
net_f = feedforwardnet(n);
net_f=configure(net_f,inputs,targets);
[a b]=min(ybest);
xo=xbest(b,:);
k=0;
for i=1:n
    for j=1:m
        k=k+1;
        xi(i,j)=xo(k);
    end
end
for i=1:n
    k=k+1;
    x1(i)=xo(k);
    xb1(i,1)=xo(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=xo(k);
end
net_f.iw{1,1}=xi;
net_f.lw{2,1}=x1;
net_f.b{1,1}=xb1;
net_f.b{2,1}=xb2;
%Calculation of MSE
err=sum((net_f(inputs)-
targets).^2)/length(net_f(inputs))
%Regression plot
plotregression(targets,net_f(inputs))
disp('Trained ANN net_f is ready for the use');
%Trained ANN net_f is ready for the use

```