Sudan University of Science & Technology College of Engineering
School of Mechanical Engineering
Department of Production

PREDICTING AND OPTIMIZING OF SURFACE ROUGHNESS IN METAL CUTTING PARAMETERS

تنبؤ وتحسين خشونة السطح بالنسبة لمتغيرات قطع المعادن

A Project Submitted in Partial Fulfilment for the Requirements of B.Sc. Degree in Mechanical Engineering (Production)

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قال تعالى

آية الكرسي سورة البقرة آية ٢٥٥

صدق الله العظيم

DEDICATION

To our parents

Who educated us and enabled us to reach this level

To our families

Who supported us

To people who paved our way toward the pursuit of science and knowledge

To all colleagues and friends

ACKNOWLEDGEMENT

This research would not have been possible without ***ALLAH***, and then the help of many people.

First of all, we would like to deeply thank our supervisor***, Dr. El Sawi,*** who improved our experience, knowledge and skills. We have to say that we have been lucky to work with him, and we wish to him all the best. Also we would like to take this opportunity to thank ***the Deanship of Scientific Research,*** **University of Science and Technology**, who fully sponsored this work.

We would like to convey our sincere thanks and appreciation to all peoples that share the knowledge and any kind of information with us that help us or at least guide us to accomplish this project

These are the last words we write for our graduation project. We wish they would also be the best words, to acknowledge all those who directly and indirectly contributed to the support of this project.

ABSTRACT

This study aimed to predict and optimize the surface roughness for work piece type (St 42crmo4) in straight turning process, the study will focus on three cutting parameters that effect on the surface roughness which is the cutting speed feed rate and depth of cut while maintaining the other parameter constant, to predict and optimize the response two models are developed, the first is mathematical second order model by using response surface methodology to analyze the cutting parameter effects on surface roughness , and the second is artificial Neural Networks model to predict and optimize the response, the experiments were conducted by three level full factorial design methodology in (CNC) lathe machine type (TB−15Z ~ NL635SCZ), the response variable namely the surface roughness was measured using Portable surface roughness tester (Surf−test SJ−210 SERIES), the effect of process parameters with the output variable were predicted which indicates that the cutting speed has significant role in producing least surface roughness followed by feed and at least depth of cut, and the optimized parameters which give the optimal response value are gained by utilizing (ANN) model.

مستخلص

الدراسة تهدف للتنبؤ وتحسين خشونة السطح لقطعة من نوع (St 42crmo4) وذلك عند التشغيل بعملية الخراطة الطولية ، الدراسة تركز على ثلاث متغيرات لعملية القطع تؤثر على خشونة السطح مع إبقاء باقي المتغيرات ثابتة وهي سرعة القطع ، التغذية و عمق القطع ، لتحسن خشونة السطح يتم إنشاء نموذجين ، الأول عبارة عن نموذج رياضي من الدرجة الثانية تم تطويره بإستخدام منهجية إستجابة السطح لتحليل تأثير متغيرات القطع على خشونة السطح ، والنموذج الثاني عبارة عن نموذج من الشبكات العصبية الإصطناعية للتنبؤ وتحسين خشونة السطح ، التجارب تم تصميمها عن طريق "Three level full factorial design methodology " في مخرطة CNC من نوع (TB-15Z ~ NL635SCZ)، متغير الإستجابة الذي هو خشونة السطح يتم قياسه عن طريق جهاز قياس خشونة السطح (Surf-test SJ-210 SERIES) تأثير متغيرات القطع على خشونة السطح تم التنبؤ بها و أظهرت التحليلات أن سرعة القطع لديها دور مهم في تقليل خشونة السطح تتبعها التغذية ثم أخيرا عمق القطع ، والمتغيرات الأمثل التي تعطي الإستجابة المثلى تم الحصول عليها من نمودج الشبكات العصبية.

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MMW	men’s material welfare
NR	natural resource
HE	human effort
Ra	Arithmetic average roughness
Ry	Maximum Height
Rz	Ten Spot Average Roughness
S	Cutting speed
D	Depth of cut
S	Number of the transfer functions in the neural network
b	Biases of the neural network
W	Weight of the activation function in the neural network
DoE	Design of Experiment
CVD	Chemical Vapor Deposition
C	Carbon
Si	Silicon
Mn	Manganese
P	Phosphorus
S	Sulfur
Cr	Chromium
Mo	Molybdenum
RSM	Response Surface Methodology
ANOVA	Analysis of variance
ANN	Artificial Neural Network
CNC	Computer numerical control
R	Coefficient of regression
R^2 or R-s	Coefficient of determination
MSE	Main squire errors
DF	Degree of freedom
Seq SS	Sum Squire
Seq MS	Mean Squire

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CHAPTER I

INTRODUCTION

1.1 General overview

Surface quality is playing a great role in manufacturing processes, which is one of important key critical factors in customer's satisfaction and economic consideration.

As the machining industry welcomes the introduction of new materials and cutting tools, it finds itself undergoing a rapid development which is giving rise to processes of highly complex and nonlinear phenomena. Executing such processes, Singh and Rao [1] point out, constitutes an additional challenge for planning and optimization [2].

An important advantage in meeting this new challenge is being able to quickly acquire information on specific machining operations. When a key role in such operations is economy, Reddy and Rao [3] maintain that knowing the optimum machining parameters is vital. Researchers wanting to gather such knowledge have proposed using machinability models. For Paiva et al. [4], these models may be used as objective functions in optimization, simulation, control, and planning [2].

One area where machinability models have been extensively investigated is surface quality. Because of its impact on product performance [5, 6], surface quality in machining is an essential consumer requirement. Basheer et al. [7] affirm that characteristics of machined surfaces significantly influence its physical properties. According to Sharma et al. [8], new applications in various manufacturing fields like aerospace, automobile, and die and mold have fueled a rapid increase in the demand for products with high-quality finishes [2].

A surface quality indicator widely used is surface roughness [9, 10]. It plays a critical role, according to Öktem [11], in evaluating and measuring the quality of a machined product. For Öktem, the ability of a product to withstand stresses, temperature, friction, and corrosion is greatly affected by its roughness. In addition, roughness has an impact on properties like wear resistance, light reflection, and coating. Karayel [12] contends that the difficulty in controlling roughness is due to the intrinsic complexity of the phenomena that generates its formation. For these reasons, roughness modeling has become not just an especially defying business but an area of great interest for research [2].

Surface quality influenced by the process parameters such as tool geometry (i.e. nose radius, edge geometry, rake angle, tool tip radius, chamfer thickness, etc.), cutting conditions (feed rate, cutting speed, depth of cut, etc.) and work-piece properties. Cutting speed, depth of cut & feed rate are the cutting parameters that are carried at in this study, the study focus in finding the significant level of each parameter, and optimize the values of these parameters to achieve the desired values of surface roughness through predictor model.

1.2. Project background

The progress and the prosperity of human civilization are governed and judged mainly by improvement and maintenance of standard of living through availability or production of ample and quality goods and services for men’s material welfare (MMW) in all respects covering housing, clothing, medicine, education, transport, communication and also entertainment.

Machining are one of the manufacturing processes, it play importance role in industries, because most of the engineering components such as gears, bearings, clutches, tools, screws and nuts etc. need dimensional and form accuracy and good surface finish for serving their purposes. Preforming like casting, forging etc. generally cannot provide the desired accuracy and finish. For that such preformed parts, there is necessity to semi-finishing and finishing and it is done by one of machining processes like turning.

In turning process we must use science and technology to manufacturing products effectively, efficiently, economically and environment-friendly through:

a. Application of any existing manufacturing process and system.

b. Proper selection of input materials, tools, machines and environments.

c. Improvement of the existing materials and processes.

d. Development of new materials, systems, processes and techniques.

All such manufacturing processes, systems, techniques have to be:

a. Technologically acceptable.

b. Technically feasible.

c. Economically viable.

d. Eco-friendly.

From the above presentation the study of turning parameters (improvement of processes and techniques) has necessary role in improving turning process, most of researcher are focused on variation of cutting parameter values.

1.3. Problem Statement

The commercial success of a new product is strongly influenced by time factor. Shorter product lead-times are importance for industry in a competitive market. This can be achieved only if the product development process can be realized in a relatively shorter time frame. However, the development of new cutting inserts involve time consuming trial and error iterations, which mainly due to limited empirical knowledge of the mechanical cutting process . The study of cutting process (surface roughness) is further complicated by the fact that material removal occurs in a hostile environment with high temperature and pressure involved in the cutting zone.

1.4. Project Goals and Aims

The aim of this study is to predict surface roughness under multiple cutting conditions of the spindle speed, feed rate & depth of cut, and also optimize the response using full factorial approach (design of experiment).

1.5. Specific Objectives of this study

1. Develop second order model by use the Response Surface Methodology for analyze the response.
2. Check the model Adequacy and which of the parameter is more Significant by using Analysis of Variance (ANOVA).
3. Develop automated technique model to predicted and optimize the response by using artificial neural network.

1.6 Project significance

The Project will have a great value in increasing the understanding of the cutting process and in reducing the number of experiments which are traditionally used for tool design, process selection, and machinability evaluation, also by reducing the number of experiments we reduce material consumption which leads to reduce the economic cost.

1.7 Project Layout

This research is divided into five chapters. Chapter one addresses the general background, declaration of the problem statement and discussion of the objectives. Chapter two presents the literature review; with focus on turning process, and its technologies, application, parameters and analytical tool for parameters. This chapter also reviews the previously published works of researchers related to this study. Chapter three explains the methodology in detail for experimental procedure and instrumentation. Chapter four is showing the results obtained from the experimental work discussion and analysis of the findings and comparing the existing results. Chapter five is the Conclusion, which contains the theoretical and practical contribution of this research, and recommendations.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

Literature review shows the cumulative past work related to this research which collected from international journals applications, conference publication, report and book. It provides strong base for understanding subject related to research topic.

This chapter presents a detailed literature review with aim to present a general overview of the opportunity of optimizing turning process. It also includes a detailed review of turning parameters (feed rate, spindle speed and depth of cut). Moreover, it also reviews the analytical tool used to study the machining parameters of the lathe.

2.2 Lathe machine

Lathe is one of the most versatile and widely used machine tools all over the world. It is commonly known as the mother of all other machine tool. The main function of a lathe is to remove metal from a job to give it the required shape and size. The job is securely and rigidly held in the chuck or in between centers on the lathe machine and then turn it against a single point cutting tool which will remove metal from the job in the form of chips [13]. Fig.2.1 shows the working principle of lathe.

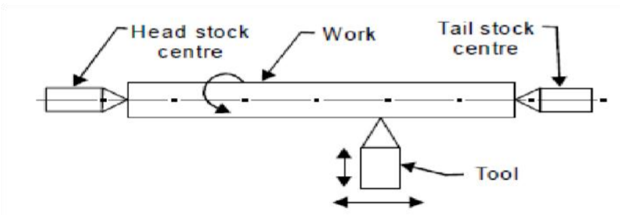


Fig 2.1: Principal Components of a central lathe

The first screw cutting lathe was developed by an Englishman named Henry Maudslay in the year 1797. Modern high speed, heavy duty lathes are developed based on this machine [14].

2.3 Surface Roughness

The surface roughness of machined components is an important design specification which has greater influence on properties such as wear resistance and fatigue strength [15]. Surface with high roughness wear more quickly and have higher friction coefficients than smooth surfaces [16].

Surface roughness is referred to the deviation from the nominal surface of the third up to sixth order. The order of deviation is defined in international standards. First and second order deviations are related to form, i.e. flatness, circularity etc. and to waviness, respectively. They occur due to machine tool errors, deformation of the work-piece, erroneous setups and clamping, vibration and work-piece material inhomogeneity's. Third and fourth order deviations are referred to periodic grooves, and to cracks and dilapidations, which are connected to the shape and condition of the cutting edges, chip formation and process kinematics. Fifth and sixth order deviations take place due to work-piece material structure, which is connected to physical-chemical mechanism acting on a grain and lattice scale (slip, diffusion, oxidation, residual stress, etc.). Different order deviations are superimposed and form the surface roughness profile.

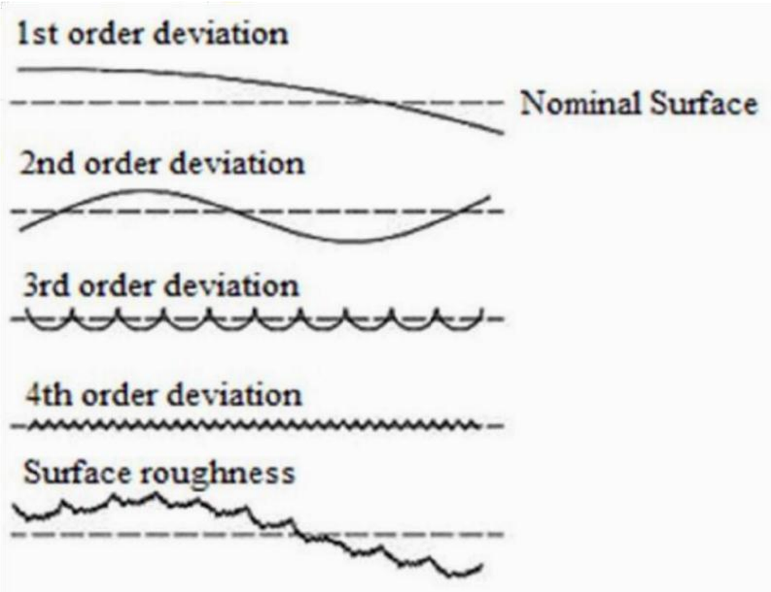


Fig 2.2: Different form of deviations of surfaces

To achieve high dimensional accuracy, the machining process must produce a surface with lesser deviations from the nominal surface, i.e. the surface roughness must be as small as possible. Lower surface roughness leads to improve the surface finish, better contact between mating surfaces, increased bearing surface, lesser friction etc. In a totality, the less the surface roughness is, better the quality of the surface [17].

2.3.1 Types of measuring the surface roughness

2.3.1.1 Arithmetic average roughness (Ra)

The arithmetic average value of filtered roughness profile determined from deviations about the center line within the evaluation length, it's the most popular parameter for a machining process and product quality control. This parameter is easy to define, easy to measure even in the least sophisticated profilometers and gives a general description of surface amplitude. Though it lacks physical significance, it is established in almost every national standard for measuring roughness. It is very common type surface roughness parameter and widely used for the surface roughness measurement [17].

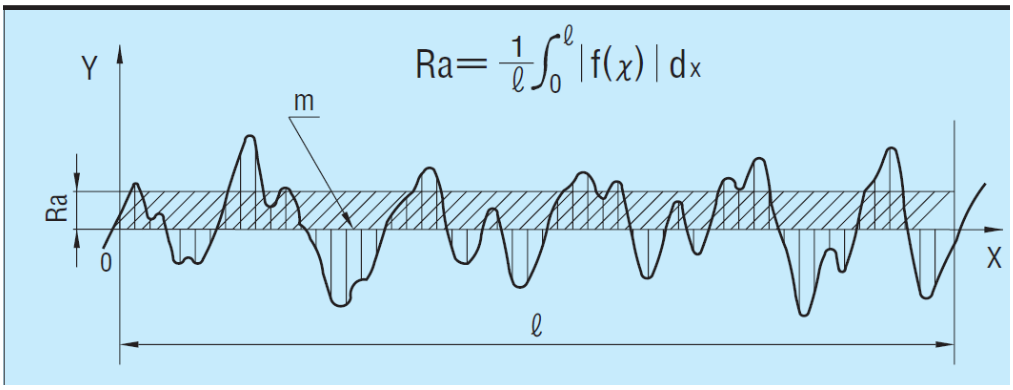


Fig 2.3: Illustration of arithmetic average roughness

2.3.1.2 Maximum Height (Ry)

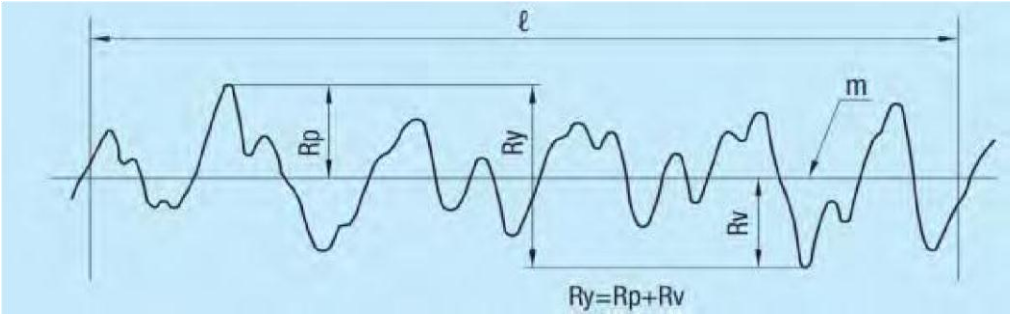


Fig 2.4: Illustration of Maximum Height (Ry)

The figure above indicates the portion stretching over a reference length in the direction in which the average line extends is cut out from the roughness curve. The gap between the peak line and the trough line is measured in the direction in which the magnitude axis extends, in (μm) [16].

2.3.1.3 Ten Spot Average Roughness (Rz)

Portion stretching over a reference length in the direction in which the average line extends is cut out from the roughness curve. The average of the levels (Yp) of the highest peak to the fifth highest peak as measured from the average line and the average of the levels (Yv) of the lowest trough to the fifth lowest trough similarly measured in the said portion are added together. Rz is this sum, in microns (μm) [16].

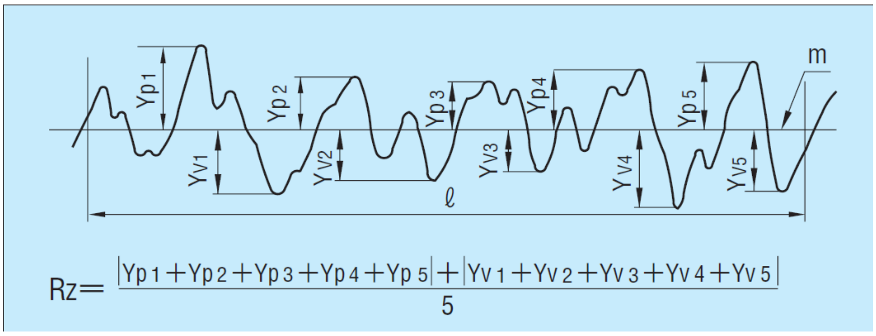


Fig 2.5 Illustration of ten spot average roughness

2.4 Important parameters of cutting process

The process of cutting parts in turning machine has many affecting parameter such as; tool material, tool geometry, work material's, … etc. In this research we will focus our attention in three factors which are cutting speed, feed rate and depth of cut.

2.4.1 Cutting speed

The cutting speed is the distance travelled by a point on the outer surface of the work-piece in one minute**.** It is expressed in meters per minute [13].

Cutting speed = $\frac{\pi DN}{\mathbf{1,000}}$ m/min. *(2.1)*

Where:

'D' = is the diameter of the work-piece in mm.

'N' = is the r.p.m. of the work.

2.4.2 Feed

The feed of a cutting tool in a lathe work-piece is the distance the tool advances for each revolution of the work. Feed is expressed in millimeters per revolution [13].

2.4.3 Depth of cut

The depth of cut is the perpendicular distance measured from the machined surface to the uncut surface of the work-piece. It is expressed in millimeters [13].

Depth of cut = $\frac{d1 - d2}{2}$. *(2.2)*

Where:

'd1' = diameter of the work surface before machining.

'd2' = diameter of the machined surface.

2.5 Artificial neural network

2.5.1 Introduction of the neural network

Work on artificial neural networks, commonly referred to as neural networks, has been motivated right from its inception by the recognition that the brain computes in an entirely different way from the conventional digital computer. Typically, neurons are five to six orders of magnitude slower than silicon logic gates; events in a silicon chip happen in the nanosecond (10^{-9} s) range, whereas neural events happen in the millisecond (10^{-3} s) range. However, the brain makes up for the relatively slow rate of operation of a neuron by having a truly staggering number of neurons (nerve cells) with massive interconnections between them. Specifically, the energetic efficiency of the brain is approximately 10^{-16} joules (J) per operation, whereas the corresponding value for the best computers (in 1994) is about 10^{-6} joules per operation [18].

Table 2.1: Parameters of biological and artificial neural networks [18].

Attributes	Biological NN	Artificial NN
Number of neurons	10^{10}	‘000
Number of synapses	60×10^{12}	‘000
Speed [s/op]	10^{-3}	10^{-9}
Energy [J/op]	10^{-16}	10^{-6}

The brain is a highly complex, nonlinear, and parallel information processing system. It has the capability of organizing neurons so as to perform certain computations (e.g. pattern recognition, perception, and motion control) many times faster than the fastest digital computer [18].

A neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented using electronic components or simulated in software on a digital computer. Our interest will be confined largely to neural networks that perform useful computations through a process of learning. To achieve good performance, neural networks employ a massive interconnection of simple computing cells referred to as neurons or processing units. We may thus offer the following definition of a neural network viewed as an adaptive machine:

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects [18]:

1. Knowledge is acquired by the network through a learning process.

2. Interneuron connection strengths known as synaptic weights are used to store the knowledge.

2.5.2 Benefits of neural networks

It is apparent from the above discussion that a neural network derives its computing power through, first, its massively parallel distributed structure and, second, its ability to learn and, therefore, generalize. Generalization refers to the neural network producing reasonable outputs for inputs not encountered during training (learning). These two information-processing capabilities make it possible for neural networks to solve complex (large-scale) problems that are currently intractable [18].

2.5.3 Network Architectures

There are two common types of Network Architectures.

2.5.3.1 The one-layer network with R input elements and S neurons

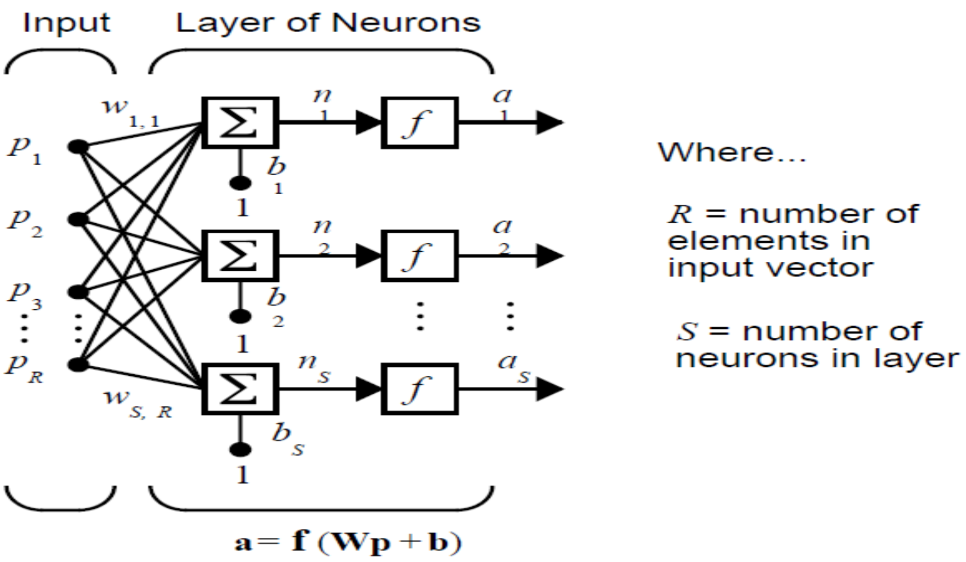


Fig 2.6: The one-layer network

In this network, each element of the input vector **p** is connected to each neuron input through the weight matrix **W**. The ith neuron has a summer that gathers its weighted inputs and bias to form its own scalar output n(i). The various n(i) taken together form an S-element net input vector **n**. Finally, the neuron layer outputs form a column vector **a**. The expression for **a** at the bottom of the figure.

The input vector elements enter the network through the weight matrix **W**.

$$\mathbf{W} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,R} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,R} \\ & & & \\ w_{S,1} & w_{S,2} & \cdots & w_{S,R} \end{bmatrix} \qquad (2.3)$$

The row indices on the elements of matrix **W** indicate the destination neuron of the weight, and the column indices indicate which source is the input for that weight [19].

The transfer function block $\boxed{f}$ is used for limiting the amplitude of the output of a neuron [18],

The S neuron R input one-layer network also can be drawn in abbreviated notation as in Fig.2.8.

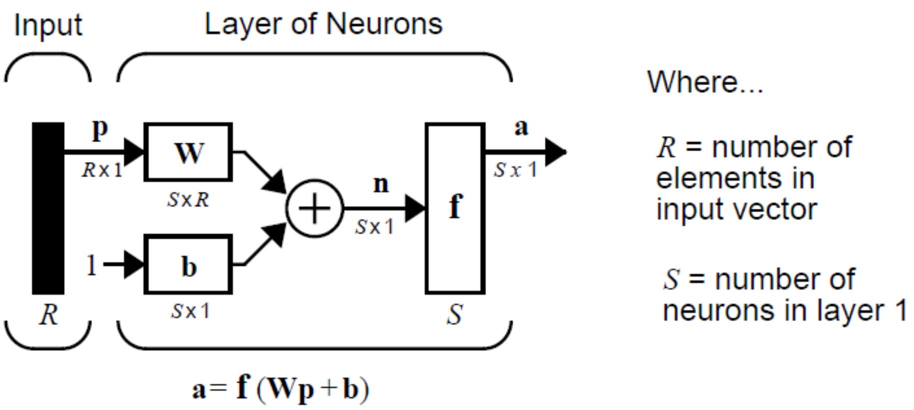
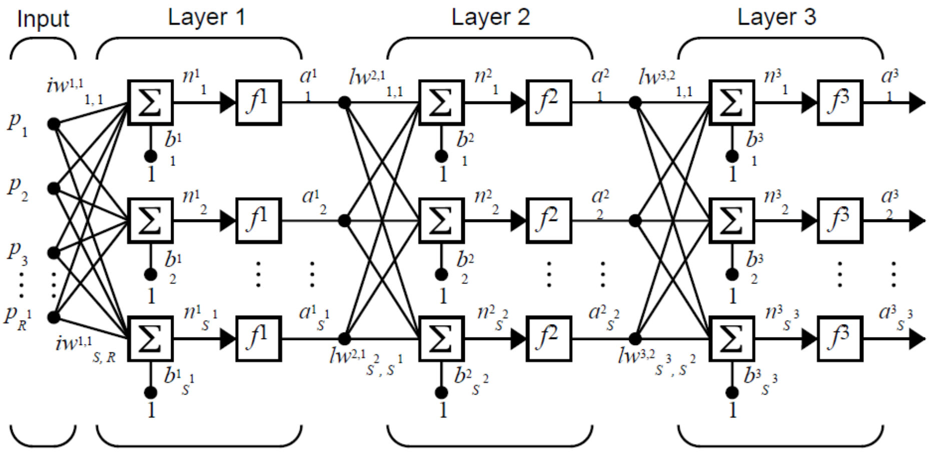


Fig 2.7: Abbreviated notation of one-layer of neurons

2.5.3.2 Multiple Layers of Neurons

The network shown below has R^1 inputs, S^1 neurons in the first layer, S^2 neurons in the second layer, etc. It is common for different layers to have different numbers of neurons. A constant input 1 is fed to the biases for each neuron. That the outputs of each intermediate layer are the inputs to the following layer. Thus layer 2 can be analyzed as a one-layer network with S^1 inputs, S^2 neurons, and an S^2x S^1 weight matrix. The input to layer 2 is $\mathbf{a}^1$ the output is $\mathbf{a}^2$ [19].



$$a^1 = f^1(IW^{1,1}p + b^1) \qquad a^2 = f^2(LW^{2,1}a^1 + b^2) \qquad a^3 = f^3(LW^{3,2}a^2 + b^3)$$

$$a^3 = f^3(LW^{3,2} f^2(LW^{2,1} f^1(IW^{1,1}p + b^1) + b^2) + b^3)$$

Fig 2.8: Multiple Layers of Neurons

A layer that produces the network output is called an output layer. All other layers are called hidden layers [19].

The same three-layer network discussed previously also can be drawn using our abbreviated notation [19].

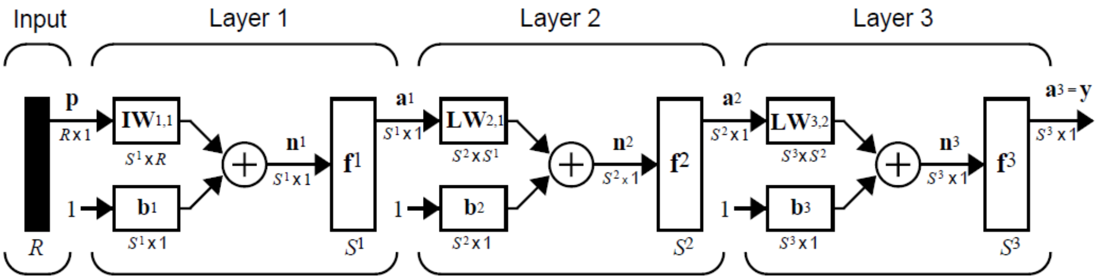


Fig 2.9: three-layer network drawn by abbreviated notation

2.5.4 The come types of transfer functions

2.5.4.1 Hard-Limit Transfer Function

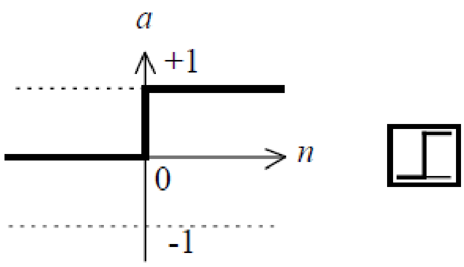


Fig 2.10: Hard-Limit Transfer Function

The hard-limit transfer function shown above limits the output of the neuron to either 0, if the net input argument n is less than 0; or 1, if n is greater than or equal to 0 [19].

2.5.4.2 Linear Transfer Function

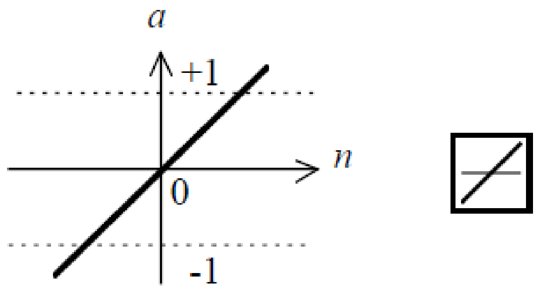


Fig 2.11: Linear Transfer Function

Neurons of this type are used as linear approximations and give the same value of the input n [19].

2.5.4.3 Log-Sigmoid Transfer Function

This transfer function squashes the output into the range (0, +1) [19].

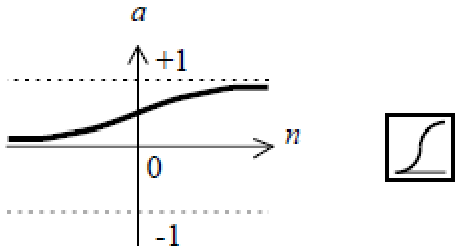


Fig 2.12: Log-Sigmoid Transfer Function

2.6 Response Surface Methodology

As an important subject in the statistical design of experiments, the Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response If the response can be defined by a linear function of independent variables, then the approximating function is a **first-order model**. A first-order model with two independent variables can be expressed as;

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \qquad (2.3)$$

If there is a curvature in the response surface, then a higher degree polynomial should be used, then the approximating function with two variables is called a second-order model it expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_{11}^2 + \beta_{22} x_{22}^2 + \beta_{12} x_1 x_2 + \varepsilon \qquad (2.4)$$

In general all RSM problems use either one or the mixture of the both of these models. In each model, the levels of each factor are independent of the levels of other factors. In order to get the most efficient result in the approximation of polynomials the proper experimental design must be used to collect data. Once the data are collected, the Method of Least Square is used to estimate the parameters in the polynomials [20].

2.6.1 Theory of RSM

RSM defines the effect of the independent variables, alone or in combination, on the processes. In addition to analyzing the effects of the independent variables, this experimental methodology also generates a mathematical model. The graphical perspective of the mathematical model has led to the term Response Surface Methodology. The relationship between the response and the input is given below

$$\eta = f(x_1, x_2, \ldots, x_n) + \varepsilon \qquad (2.5)$$

Where η is the response, f is the unknown function of response, $x_1, x_2, \ldots, x_n$ denote the independent variables, also called natural variables, n is the number of the independent variables and finally ε is the statistical error that represents other sources of variability not accounted for by f. These sources include the effects such as the measurement error .It is generally assumed that has a normal distribution with mean zero and variance [21].

2.6.2 Response Surface Methods and Designs

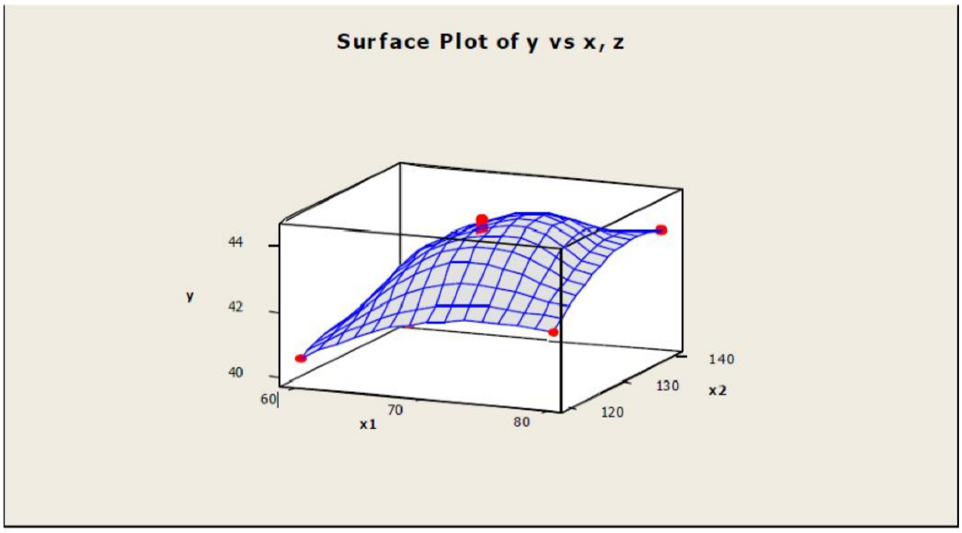


Fig 2.13: Response surface plot

Response Surface Methods are designs and models for working with continuous treatments when finding the optimal or describing the response is the goal [22]. The first goal for Response Surface Method is to find the optimum response. When there is more than one response then it is important to find the compromise optimum that does not optimize only one response [22]. When there are constraints on the design data, then the experimental design has to meet requirements of the constraints. The second goal is to understand how the response changes in a given direction by adjusting the design variables. In general, the response surface can be visualized graphically. The graph is helpful to see the shape of a response surface; hills, valleys, and ridge lines. Hence, the function f (x1, x2) can be plotted versus the levels of x1 and x2 as shown as in Fig 2.13.

$$y= f (x1, x2) + \varepsilon \qquad (2.6)$$

In this graph, each value of x_1 and x_2 generates a y-value. This three-dimensional graph shows the response surface from the side and it is called a response surface plot.

Sometimes, it is less complicated to view the response surface in two dimensional graphs. The contour plots can show contour lines of x_1 and x_2 pairs that have the same response value y. An example of contour plot is as shown in Fig 2.14.

In order to understand the surface of a response, graphs are helpful tools. But, when there are more than two independent variables, graphs are difficult or almost impossible to use to illustrate the response surface, since it is beyond 3-dimension. For this reason, response surface models are essential for analyzing the unknown function f [20].

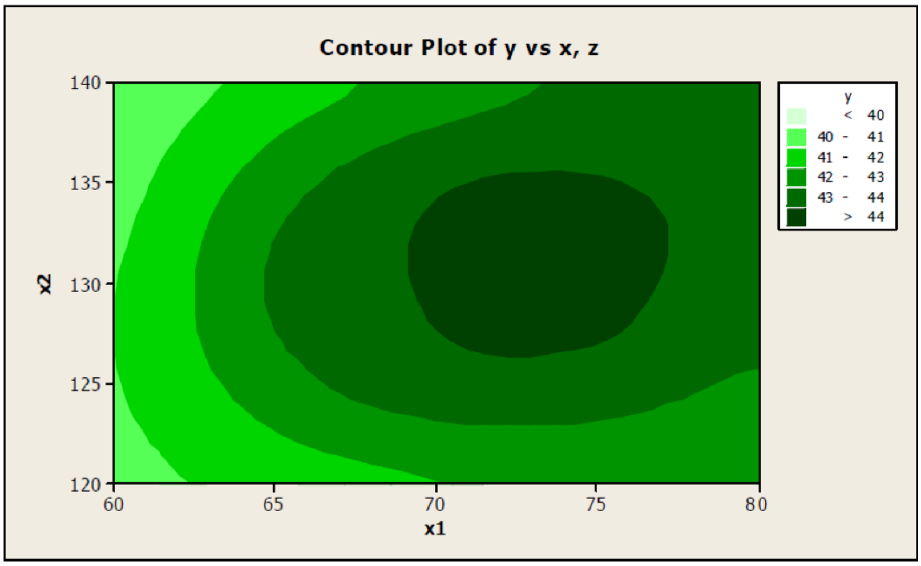


Fig 2.14: Contour plot

2.6.3 First-Order Model

A first-order model with N experimental runs carrying out on q design variables and a single response y can be expressed as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots\dots\dots + \beta_q x_{iq} + \varepsilon_i \qquad (i = 1, 2, \dots\dots, N) \tag{2.7}$$

The response y is a function of the design variables x_1, x_2, …, x_q, denoted as f, plus the experimental error. A first-order model is a multiple-regression model and the b_j's are regression coefficients [20].

Lack of fit of the first-order model happens when the response surface is not a plane. If there is a significant lack of fit of the first-order model, then a more highly structured model, such as second-order model, may be studied in order to locate the optimum [20].

2.6.4 Second-Order Model

When there is a curvature in the response surface the first-order model is insufficient. The second order model includes all the terms in the first-order model, plus all quadratic terms like $\beta_{11} x_{1i}^2$ and all cross product terms like $\beta_{13} x_{1i} x_{3j}$. It is usually expressed as;

$$y = \beta_0 + \sum_{j=1}^{q} \beta_j x_j + \sum_{i=1}^{q} \beta_{jj} x_j^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{2.8}$$

The second-order model is flexible, because it can take a variety of functional forms and approximates the response surface locally. Therefore, this model is usually a good estimation of the true response surface [20].

2.7 Highlight about some reviewed papers

After viewing fife papers which have the same searching area of this work, we summarize the following point.

2.7.1 Studying object

Bheem Singh Rajpoot investigate the effect of turning parameters on surface roughness and metal removal rate in turning of Metal Matrix Composite steel to produce desired finish on the machined surface while using the cutting resources like cutting tool and machine tool to the full limit possible [23]. **Taquiuddin Quazi, Pratik gajanan** Utilize Taguchi method to optimize the surface roughness in turning EN8, EM31 and mild steels and compare the results in terms of effectiveness of the performance of different grades of Tools by varying process parameters [24]. **Brajesh Kumar Lodhi, Rahul Shukla** investigate the setting of turning parameters (Spindle speed, Feed rate and Depth of Cut) in order to obtain an optimal value of Surface Roughness and (MRR) while machining AISI 1018 steel alloy with Titanium coated Carbide Inserts (TN4000) [25]. **Rony Mohan, Josephkunju Paul C, George Mathew** there work is to optimize the process parameters such as speed, feed and depth of cut and to investigate the effect of these input parameters on surface roughness. Then to achieve the surface roughness within the rejection criteria (1.6μm) when grinding operation is replaced by (CNC) high speed hard turning operation [26]. **Shunmugesh K., Panneerselvam K., Pramod M. and Amal George** study (CNC) Turning Parameters with value

Carbide Tool in order to find out optimal machining parameter for optimal of Ra and Rz [27].

2.7.2 Analyzing methods

Bheem Singh Rajpoot utilize Response Surface Methodology to determine and simultaneously solve the multivariate equation and the Design of experiments based on face centered design [23]. **Taquiuddin Quazi, Pratik gajanan** use Minitab Statistical 16 for analysis and the Design of experiment based on Taguchi’s L9 orthogonal array [24]. **Brajesh Kumar Lodhi, Rahul Shukla** use (S/N) ratios and Analysis of variance (ANOVA) for analyzing data and the design of experiment based on Taguchi’s Methodology [25]. **Rony Mohan, Josehphkunju Paul C, George Mathew** utilize Taguchi’s concepts of orthogonal arrays, signal to noise (S/N) ratio and (ANOVA) to optimize the surface roughness for high speed (CNC) turning process [26]. **Shunmugesh K., Panneerselvam K., Pramod M. and Amal George** use MINITAB (version17) software for statistical analysis (signal to noise ratios) and the experiment is planned according to Taguchi’s L9 orthogonal array [27].

Table 2.2 Summary of review papers

Author's Name	Work-piece Material	Cutting Tool	Cutting Parameters	Method Used	Highest Affecting Factors
Bheem Singh Rajpoot.	Metal Matrix Composite steel.	Single point Tungsten Carbide tool (TCT).	Cutting speed (m/min) Feed (mm/rev) Depth of cut (mm).	Response Surface Methodology.	Feed rate.
Taquiuddin Quazi, Pratik gajanan.	EN8, EM31 and mild steels.	TN60, TP0500 and TT8020.	Speed rate and Feed Rate.	Taguchi method.	Feed rate.
Brajesh Kumar Lodhi, Rahul Shukla.	(AISI 1018) steel alloy.	Titanium coated Carbide Inserts (TN4000).	Spindle speed, Feed rate and Depth of Cut.	(S/N) ratios, Taguchi method and Analysis of variance.	Spindle speed.
Rony Mohan, Josephkunju Paul C, George Mathew.	(AISI 52100) bearing steel alloy.	Tungsten carbide tool.	Cutting speed (m/min) Feed (mm/rev) Depth of cut (mm).	(S/N) ratios, Taguchi method and Analysis of variance.	Feed rate.
Shunmugesh K.,Panneerselvam K., Pramod M. and Amal George.	(11SMn30) alloy of mild steel and magnesium rod.	(WIDIA CNMG 120408-49-TN 2000) was used as tool tip.	Cutting speed (m/min) Feed (mm/rev) Depth of cut (mm).	Taguchi method and signal to noise ratio.	Feed rate.

CHAPTER III

METHODOLOGY

3.1 Introduction

This chapter describes the approaches employed in this project. The aims and the objective of this project rounds around the optimizing and predicting surface roughness, in order to achieve the above target we simulates the turning process by applying the following steps:

1. Problem definition.

2. Data collection.

3. Data analysis.

4. Model selection, fitting and validation.

The frame work of project which determined the sequence of steps is represented by the following flaw chart (Methodology flaw chart).

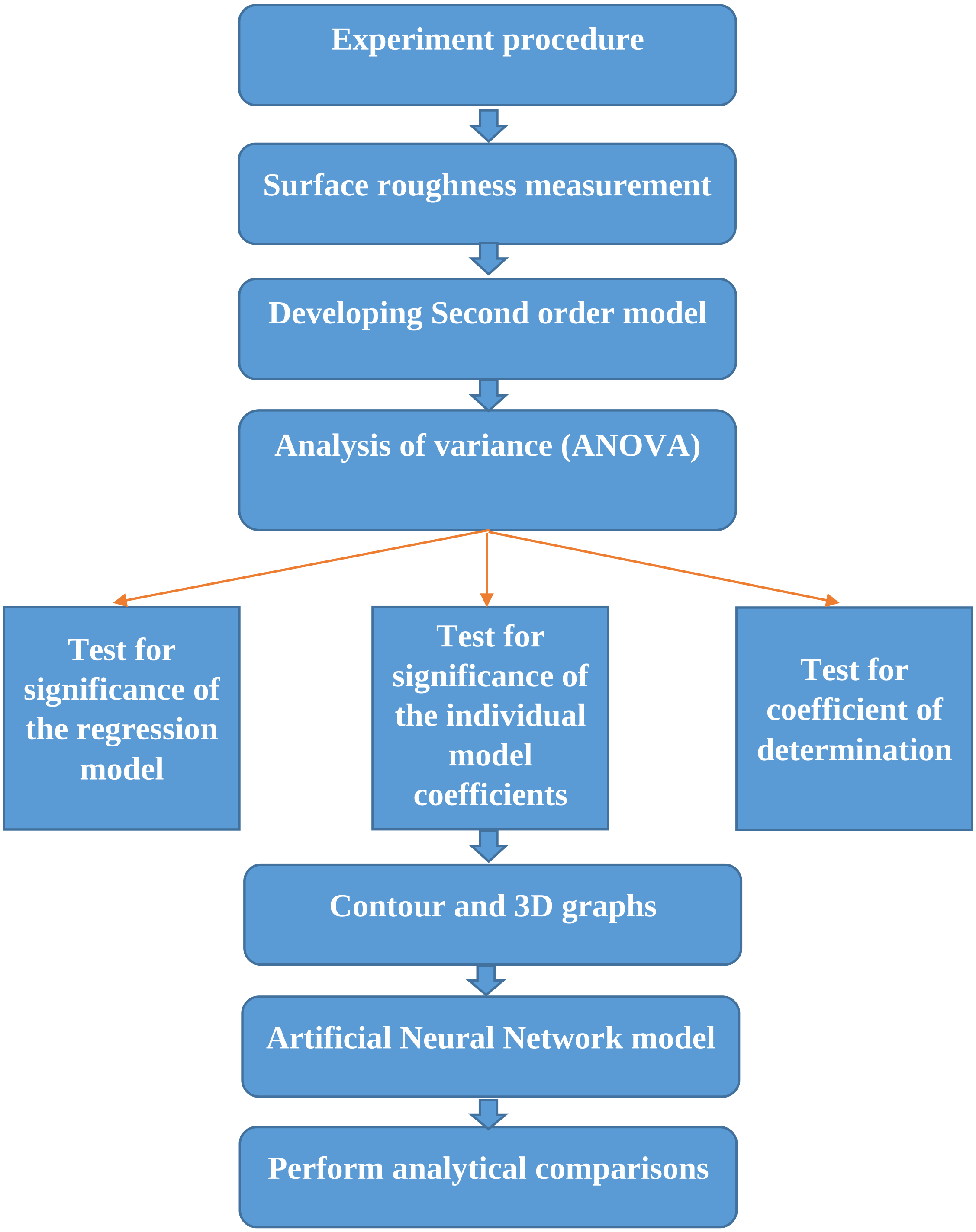


Fig 3.1: Methodology flaw chart

3.2 Design of Experiment

Design of Experiment (DoE) is a structured, organized method for determining the relationship between a number of factors affecting a process and the output of that process or strategies developed for the model fitting of physical experiments. Regardless of the domain of application, this methodology is useful for two objectives, they are screening and optimization. Screening experiments are commonly designed to explore many factors, in order to evaluate their effects on the responses.

In this project three levels full factorial design will employed to determine the optimal average surface roughness, a factorial experiment is an experimental strategy in which design variables are varied together, instead of one at a time. Before to use three levels full factorial design methodology, we first have to determine the maximum and minimum levels of each factor, the possible settings of each independent variable in the n-dimensional space are called levels. This step is important because we have to define the field of variation of each factor, inside whose analysis and response of the modeling will be valid. In this study the three levels full factorial Design methodology is used to evaluate the respective impacts of parameters model which are the cutting speed, feed rate and depth of cut, as mention before there is three levels for each factor coded by -1,0,+1 to represent the minimum, mean and maximum data respectively. Three levels full factorial design consist of 3^k experiment where k=3 is number of factors, which means 27 experiments will be done.

3.2.1 Design of parameters levels

First must been determined the three levels for each factor which are -1, 0 and+1, they are represented in table 3.1.

Table 3.1: Process parameters with different operating levels

Factor	-1	0	+1
Speed (rpm)	700	800	900
Feed (mm/r)	0.05	0.10	0.15
Depth of cut (mm)	0.3	0.6	0.9

And then 27 experiment will been done in work-piece that we want to test it, also the response for each experiment will collected which is the surface roughness, the selection of each experiment according to the cubic shape in figure. 3.2. There are 27 circle distributed in the cubic shape in which the coordinate of each circle represent the three levels of the experiment, and selection of the each circle is random.

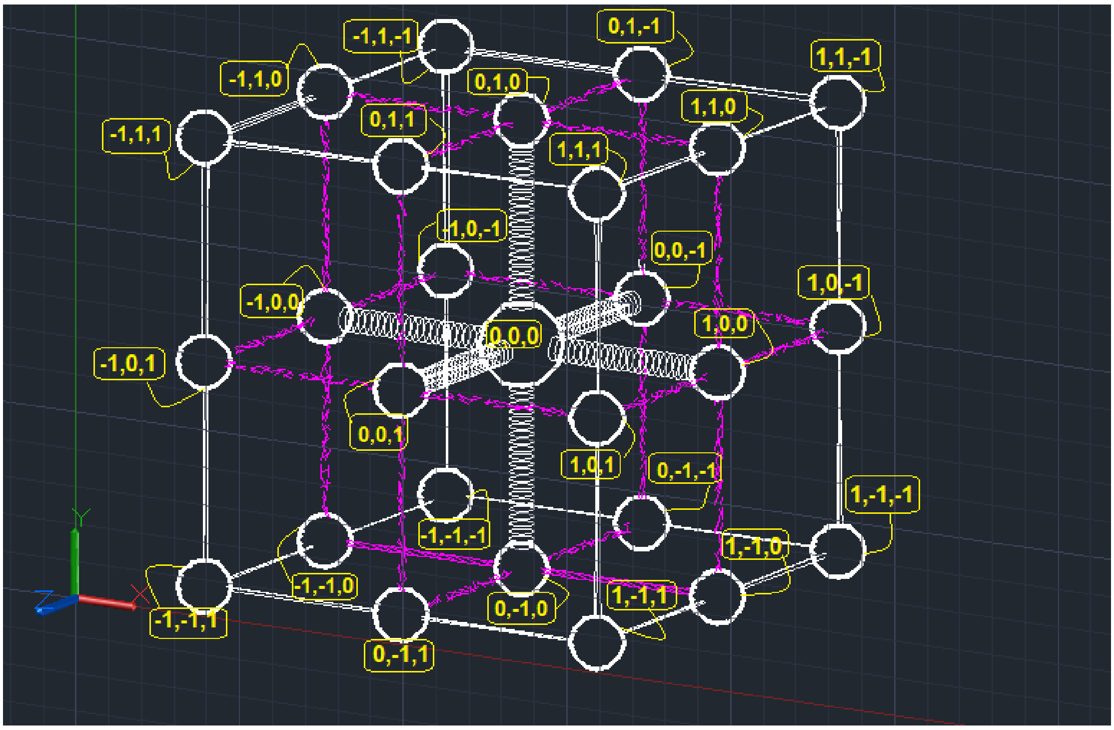


Fig 3.2: Dimensional representation for the parameters levels

3.2.2 Experiment's tool & device

3.2.2.1 Cutting tool

- Manufacture: sandvik.
- Metric code: D-N-M-G-15-06-08- -L-PM.
- Material: CVD-coated carbide grade.

For a detailed information about cutting tool you can return to reference [28].

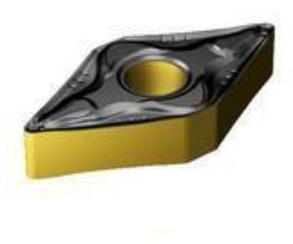


Fig 3.3: Cutting tool

3.2.2.2 Measuring device

PORTABLE SURFACE ROUGHNESS TESTER SURFTEST (SJ-210) SERIES.

For a detailed information about measuring device you can return to reference [29].

Fig 3.4: Tester surftest (SJ-210) series

3.2.2.3 (CNC) lathe machine

- Name: TB-15Z ~ NL635SCZ.
- Manufacture: NEWAY.

For a detailed information about this machine you can return to reference [30].

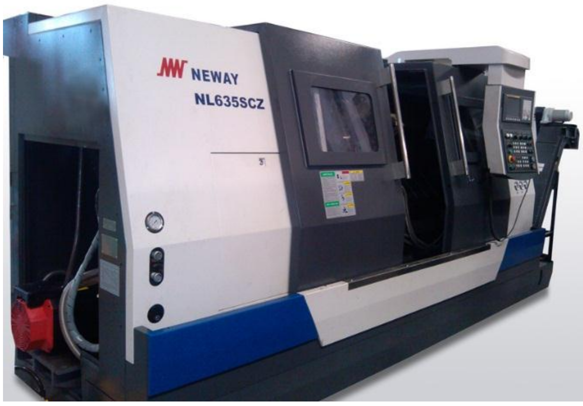


Fig 3.5: CNC lathe machine

3.2.2.4 Work-piece

Table 3.2: Work-piece specification [31]

Type of Work-piece material			St 42crmo4				
Hardness			35-38 HRC				
Chemical composition							
C%	**Si% Max**	**Mn%**	**P% max**	**S% max**	**Cr%**	**Mo%**	
0.83-0.45	0.4	0.6-0.9	0.025	0.035	0.9-1.2	0.15-0.3	Product deviation are allowed
±0.02	+0.03	±0.04	+0.005	+0.005	±0.05	±0.03	

3.3 Experiment procedure

The experiment was conducted using three work-piece material (St 42crmo4) which machined in (CNC) lathe machine (straight turning), the work piece is cylindrical have Diameter of 60 mm (machined diameter

58 mm) and total length of 162 mm (machined length 135 mm), the experiment was performed with a coolant (ECOCOOL MK 3), and the parameter included for study are cutting speed, feed rate and depth of cut with three levels for each parameter, all the other parameters that effect on the experiments will assumed to be constant. Each work-piece is divided to nine sections one experiment is done in each section, and so until all experiments are completed, the length of section is 15 mm, the tool bit using for turning is (CVD)-coated carbide insert.

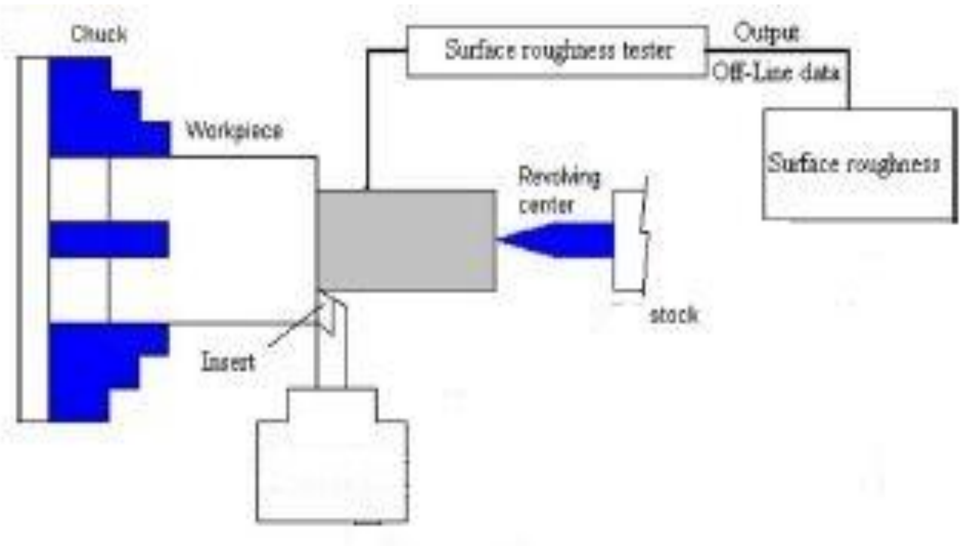


Fig 3.6: Experimental setup

3.4 Surface roughness measurement

Measuring process accomplished by utilizing portable surface roughness tester device which has detector attached to drive unit, this detector is moved along the surface to be measured by speed of 0.5 mm/s and returned back by speed of 1mm/s approximately and then the reading is taken. This device has capability to give various evaluation parameters for surface roughness but in this study our interest is limited to Ra.

3.5 Second order model

Second order model is developed using response surface methodology for analyze the effect of the parameters and their interaction in the response of the surface roughness. Response surface methodology (RSM) aims at building a regression model (approximation) that is closest to the true regression model. The true regression model is usually never known. The model to be built is based on observation data. The mathematical equation developed for second order model in (RSM) consists of 10 terms arrived from (k+1)(k+2) / 2 where k = 3 is the number of factors, second order model equation expressed as:

$$y=\beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_{11}x_1^2+\beta_{22}x_2^2+\beta_{33}x_3^2+\beta_{12}x_1x_2+\beta_{13}x_1x_3+\beta_{23}x_2x_3 \quad (3.1)$$

Where y is the predicted response (surface roughness) and x_1, x_2, x_3 are the design variables represent cutting speed, feed rate and depth of cut respectively, and β_0 model constant, β_1, β_2 and β_3 are linear coefficients, β_{12}, β_{13} and β_{23} are cross product coefficients, β_{11}, β_{22} and β_{33} are the quadratic coefficients, the model coefficient have been estimated from the experimental results by computer software using Minitab.

3.6 Analysis of variance (ANOVA)

After developing the model it is important to examine the fitted model if the model provides an adequate approximation of the true response surface, and how much each factor influence in response surface, in **(ANOVA**) the flowing test will be performed.

3.6.1 Test for significance of the regression model

This test is performed as an ANOVA procedure by calculating the *F*-ratio, which is the ratio between the regression mean square and the mean square error. The *F*-ratio, also called the variance ratio, is the ratio of variance due to the effect of the model and variance due to the error term. If the variances are close to the same, the ratio will be close to one and it is less likely that any of the factors have a significant effect on the response, from the F-ratio the P-value can be found [32], a significance level α equals to 0.05 is used which is the probability of making the wrong decision when the null hypothesis is true [33].

3.6.2 Test for significance of individual model coefficients

It is just like the Test for significance of the regression model but F-ratio will be the ratio of variance due to the effect of factor and variance due to the error term, this test provide information of which factor or model coefficient is more significant or no significant at all [32].

3.6.3 Test for coefficient of determination

The coefficient of determination (R^2) is defined as the ratio of the explained variation to the total variation, and is a measure of the degree of fit [34], the (R^2) coefficient have values between 0 and 1 [32], Joglekar etal [35] suggested that a good model fit should yield an (R^2) of at least 0.8. All the tests above are done by Minitab software.

3.7 Second order model graphs

3.7.1 Contour and 3D graphs

This graphs are used after check adequacy of the model, they give us the whole change in the response between two parameter in 3D form and contour plot form. The contour and 3D graphs are generated using matlab software. In this project three parameters are being studied, so two parameters are selected while the other will assumed to be constant, the range of the two selected parameters is divided to 30 elements uniformly in the form that first element is the low level of data and the last element is high level, a mesh will be created for the two selected parameters which will make it a matrix 30x30 and this data entered in equation of second order model to give the contour and 3D plot.

3.7.2 Main effects plot

A main effects plot is a plot of the means of the response variable for each level of a factor, which allows to obtain a general idea of the effect of each independent variable in the surface roughness, and how much it’s significant [20].

3.8 Artificial Neural Network model (ANN)

(ANN) is as a computational model consists of three layers containing different neurons in each layer. The three layers are input layer, hidden layers and output layer. These layers are further interconnected to each other in such a way so that each neuron in one layer is connected to all neurons in the next layer. The diagram for a network with a single neuron is shown in figure 3.7.

Where j is the member of inputs and k is the number of neural in the layer. The input layer does not perform any information processing. Each of its neuron takes the input from the actual environment. The input vector (i_j) is transmitted using a connection that multiplies its strength by a weight (w) to make the product (WI). This neuron has a bias (b_j). The output is produced by a summation function and an activation function according to the equation:

$$Y = f\,(WI + b) \qquad (3.2)$$

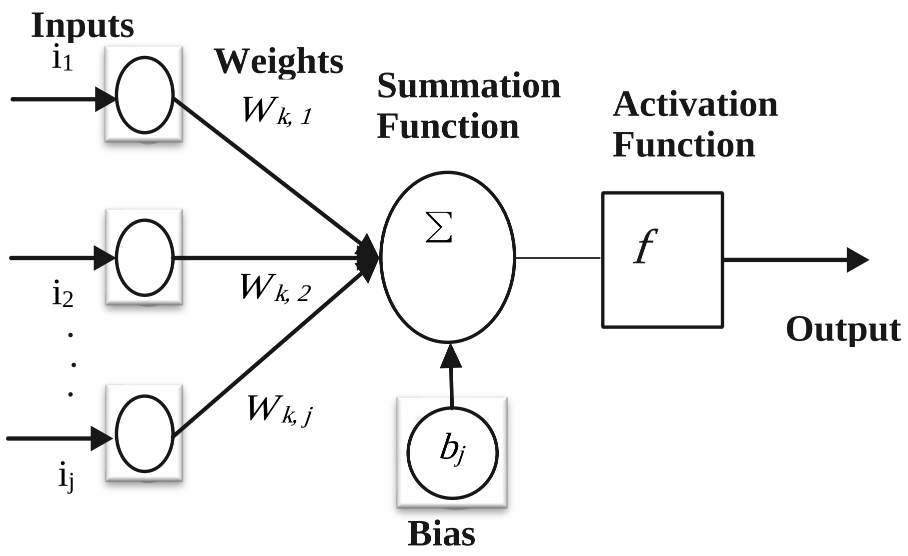


Fig. 3.7: Mathematical principal of a neuron

Summation function calculates the net input to the processing neurons. The activation function converts the neuron's weighted input to its output activation. An activation function consists of linear and nonlinear algebraic equations which make a neural network capable of storing nonlinear relationships between the input and the output. After being weighted and transformed by an activation function, neurons are then passed to other neurons. Output accepts the results of the activation function and presents them either to the relevant processing neuron or to the outside of the network. As each input is applied to the network, the network output is compared to the target. The difference between the target output and the network output is known as error.

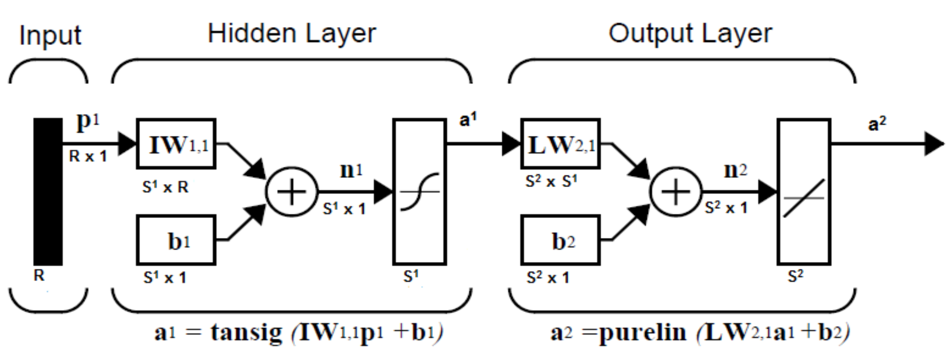


Fig 3.8: Design of the network

The neural network used in this project is Feedforward Backpropagation Network**,** develop by matlab software, the design of this network in the figure above.

Where:

R = number of inputs

S^1 = number of neurons in the hidden layer

n^1 = the output of the summation function in the hidden layer

a^1 = the output of the activation function in the hidden layer

S^2 = number of neurons in the output layer

n^2 = the output of the summation function in the output layer

a^2 = the output of the activation function in the output layer

$IW^{1,1}$= the weight of the hidden layer

$LW^{2,1}$= the weight of the output layer

b_1 = the biases in the hidden layer

b_2 = the biases in the output layer

The activation function used in the hidden layer is (Tan-Sigmoid), it's used to limit the input in range between -1 to +1, and in the output layer linear activation function is used, the output of linear activation function is the same as the input of it [19].

3.8.1 Training the network

Training the network is a process of iteratively adjusting weights and biases until least possible network performance function is reached. The default performance function for Feedforward networks is mean square error (MSE) which is average squared error between the network outputs and the target outputs (responses) [19].

3.8.2 Training groups

3.8.2.1 Training group

These are presented to the network during training, and the network is adjusted according to its error, and it will be 70% of the experiments data.

3.8.2.2 Validation group

These are used to measure network generalization, and to halt training when generalization stops improving, and it will be 20% of the experiments data.

3.8.2.3 Testing group

These have no effect on training and so provide an independent measure of network performance during and after training, and it will be 10% of the experiments data.

The target in this project is the surface roughness which represent the responses of the 27 experiments, so the number of neurons in the output layer is one, but the number of neurons in the hidden layer will be changing until the best fitting and minimum (MSE) is achieved, after that the error of each of the three groups is approximately identified by the Error histogram plot.

3.9 Analytical comparisons

3.9.1 Comparison of actual and predicted value

The comparison between the actual and predicted values for both the (ANN) and (RSM) models is accomplished by comparing the fitting for the two models.

3.9.2 Comparison of ANN and RSM models

The comparison between the two models is in accordance to the statistical methods by comparing the R which is the correlation between outputs and targets [19]. An R value of 1 means a close relationship, 0 a random relationship, and the mean sum square error (MSE), lower values of RSM is better.

CHAPTER IV

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the experimental results obtained using the method and equipment described in chapter 3. The result of (RSM) model is illustrated in section two followed by the analysis of variance in section three. Section four and section five shows 3D & contour plot and main effect plot respectively. Moreover section six describe the result of (ANN) model, and recently comparison of actual & predicted values of surface roughness and (ANN) & (RSM) model illustrated in section seven and eight respectively.

4.2 Result of response surface methodology

The second order response surface equations have been fitted using Minitab software for the response variable (Ra) .The regression coefficients for the roughness parameters are shown in Table 4.1. The equations can be given in terms of the coded values of the independent variables as the following:

$$Ra = 3.61 - 0.00302*X_1 - 5.08*X_2 - 1.644*X_3 - 0.00550*X_1*X_2 + 0.001444*X_1*X_3 - 0.78*X_2*X_3 - 0.000000*X_1^2 + 70.0*X_2^2 + 0.296*X_3^2 \qquad (4.1)$$

Where:

X1= Depth of cut.

X_2= feed rate.

X_1= cutting speed.

Table 4.1: Regression coefficients for the roughness parameters

Coefficient	value
β_0	3.61
β_1	-0.00302
β_2	- 5.08
β_3	- 1.644
β_{12}	- 0.00550
β_{13}	0.001444
β_{23}	- 0.78
β_{11}	- 0.000000
β_{22}	70.0
β_{33}	0.296

4.3 Results of analysis of variance

Table 4.2: ANOVA resul

Source	DF	Seq SS	Seq MS	F-Value	P-Value
Regression	9	2.3458	0.2606	41.72	0.000*
X_1 (rpm)	1	1.3122	1.3122	210.05	0.000*
X_2 (mm/rev)	1	0.7404	0.7401	118.47	0.000*
X_3 (mm)	1	0.0722	0.0722	11.56	0.003*
X_1* X_2	1	0.0091	0.0091	1.45	0.245
X_1* X_3	1	0.0225	0.0225	3.61	0.075
X_2 * X_3	1	0.0016	0.0016	0.26	0.616
X_1^2	1	0.0000	0.0000	0.00	1.000
X_2 ^2	1	0.1838	0.1838	29.41	0.000*
X_3 ^2	1	0.0043	0.0043	0.68	0.420
Error	17	0.1062	0.0063		
Total	26	2.4520			
R-s	95.67%				

- **Hint:** symbol (*) means that source is significance.

The analysis of variance (ANOVA) and the *F*-ratio test have been performed to check the adequacy of the models as well as the significance of the individual model coefficients. For brevity, the (ANOVA) table for (*Ra*), is shown here. Table 4.1 presents the (ANOVA) table for the second order model proposed for (*Ra*) given in equation *(4.1)*.

4.4 3D surface plot and Contour plot

The 3D surface graphs for surface roughness between the two independent variables cutting speed and feed rate shown in Fig 4.1 (A), between the cutting speed and depth of cut shown in Fig 4.1 (B), finally between feed rate and depth of cut shown in Fig 4.1 (C), from the figures below it seem all have curvilinear profile in accordance to the quadratic model fitted.

The contour for the response surface for surface roughness between the two independent variables cutting speed and feed rate shown in Fig 4.2 (A) , between the cutting speed and depth of cut shown in Fig 4.2 (B), and finally between feed rate and depth of cut shown in Fig 4.2 (C).

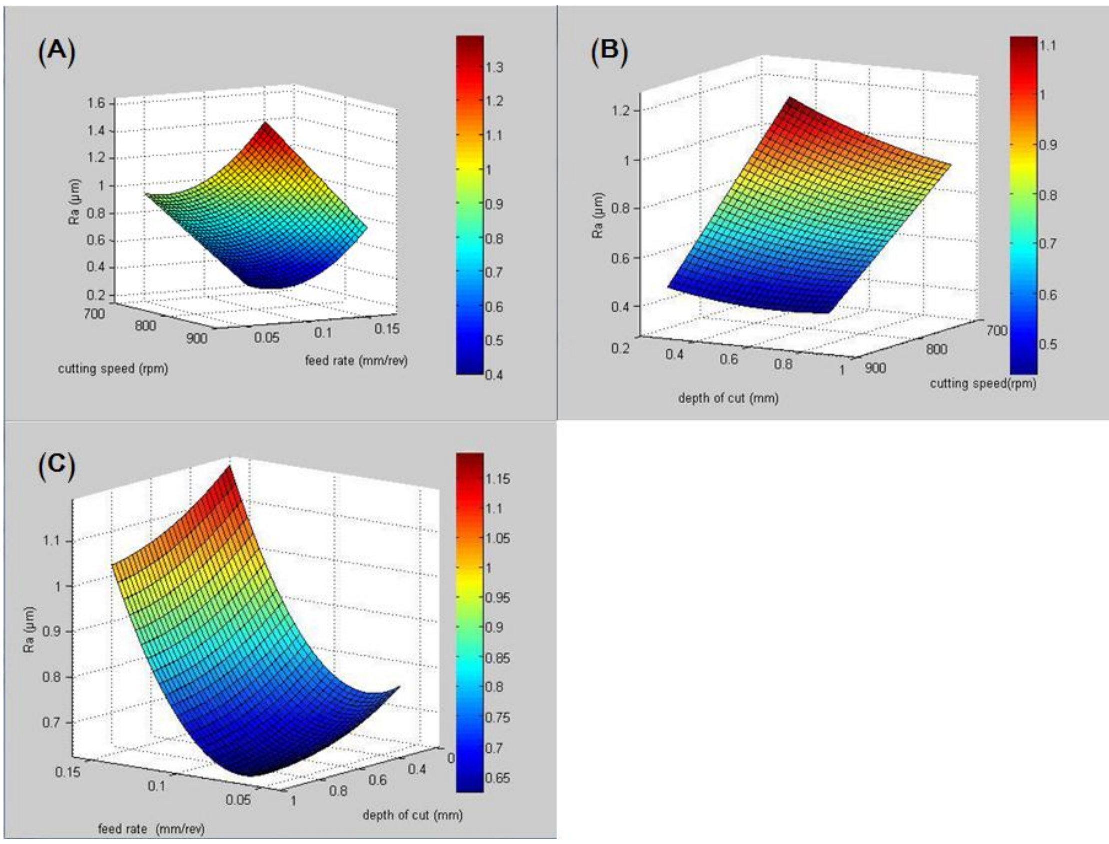


Fig 4.1: 3D surface graphs for surface roughness

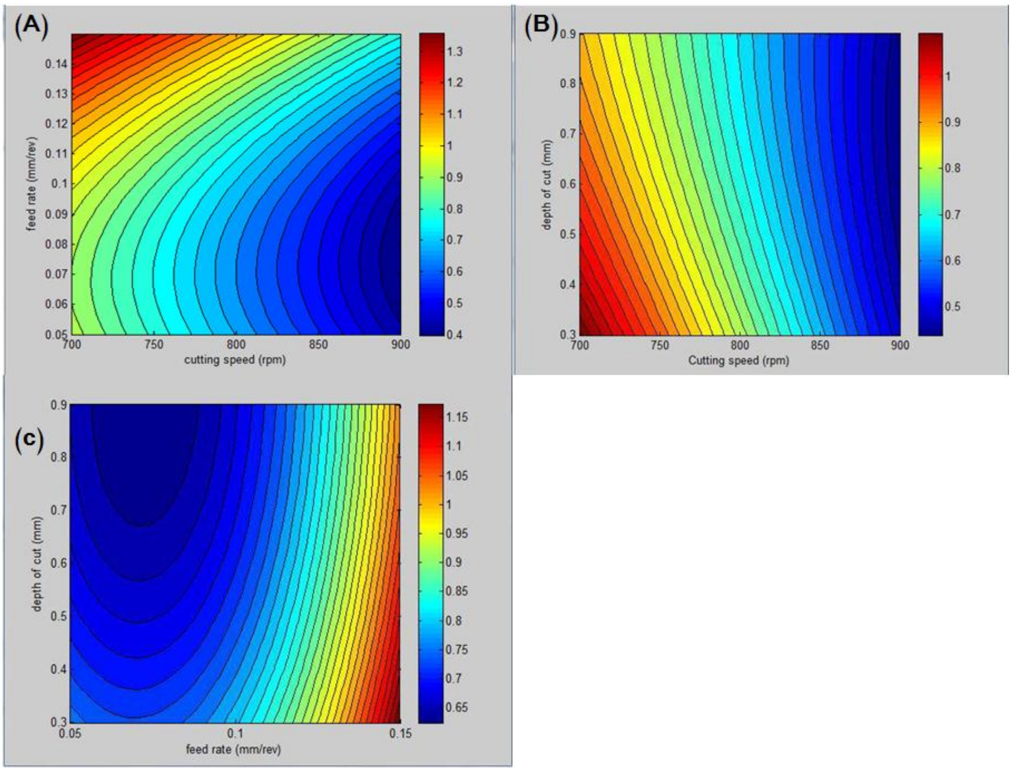


Fig 4.2: contour graphs for surface roughness

4.5 Main effects plot

Figure 4.3 presents the main effect plots for surface roughness parameters with cutting process variables. In these main effect plots if a line for a particular parameter is near horizontal, then the parameter has no significant effect. On the other hand, a parameter for which the line has the highest inclination will have the most significant effect.

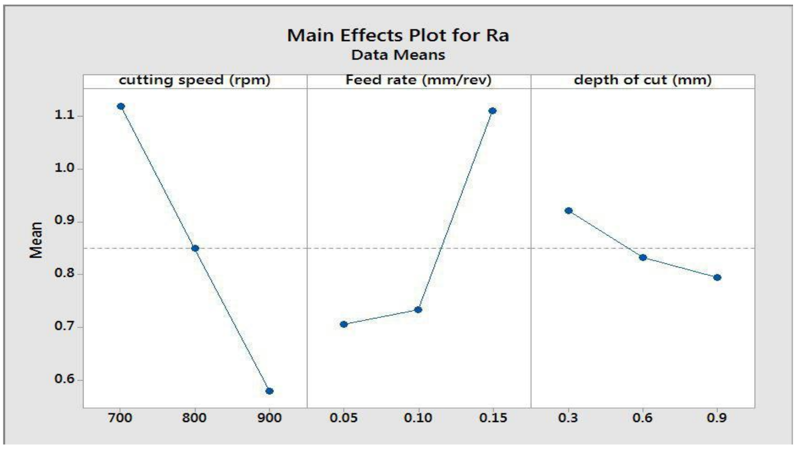


Fig 4.3: Main effects plot for (Ra) cutting parameters

4.6 (ANN) Model

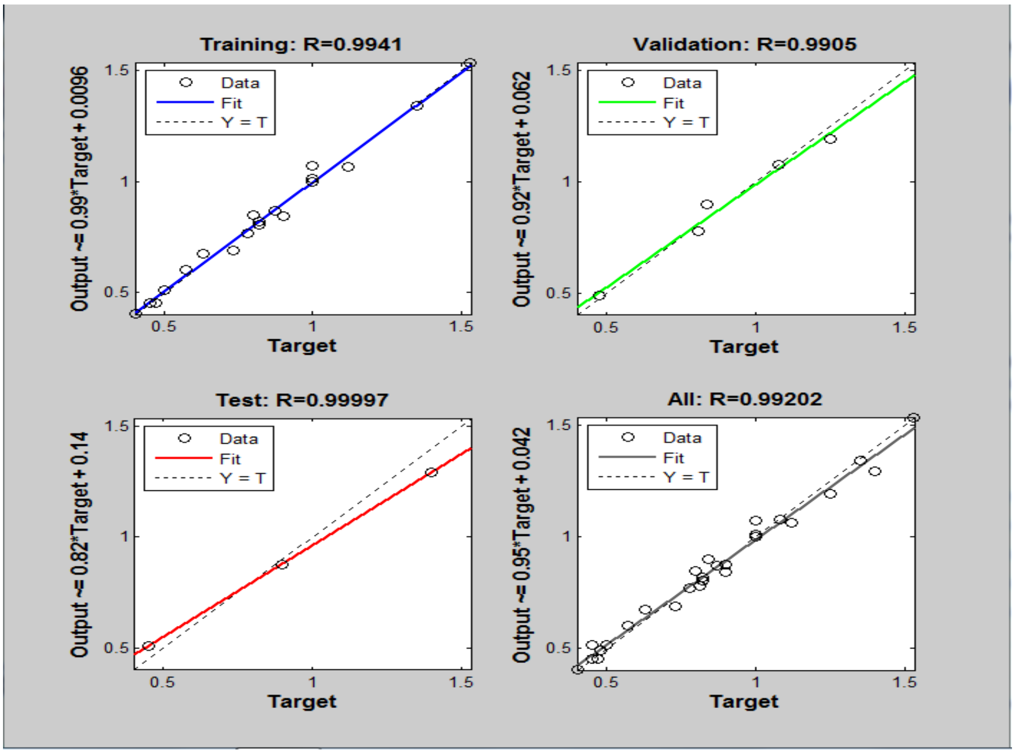


Fig 4.4: Target vs output of the (ANN) model

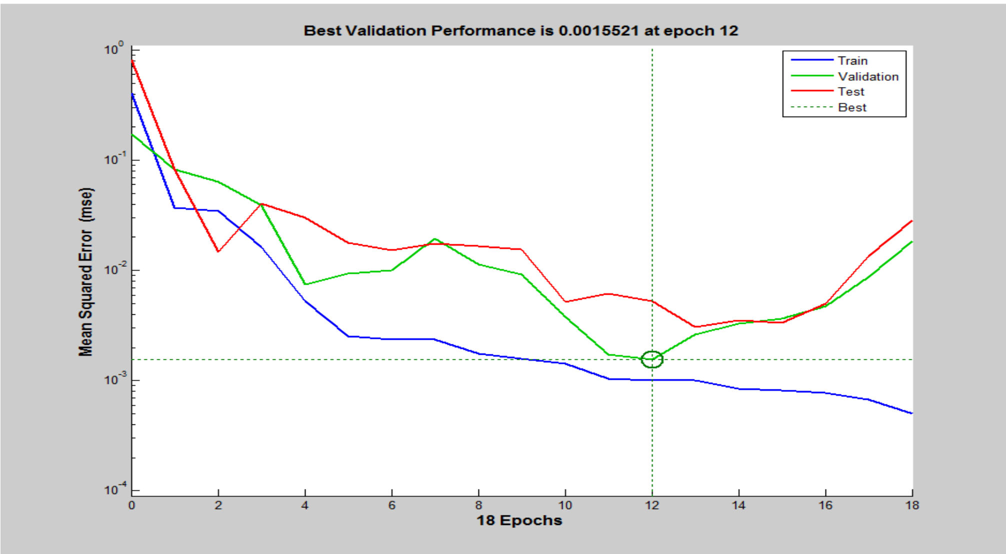


Fig 4.5: The relationship between the MSE and the maximum iterations

In order to develop the (ANN) model, the network was trained by a set of 19 values out of 27 experimental values and validated by a set of 5 values out of 27 experimental values. After successful training and validation, the network was used to predict the surface roughness for testing. The network was tested for 3 experimental values. From figure 4.4, it is clear that during training relative position of all the experimental and predicted values in the regression line make R=0.9941. This indicates that the network was satisfactorily trained. At the next stage, R was found to be equal to 0. 9905 for validation and followed by 0.99997 for testing. During testing and validation of the network, a few experimental values are slightly away from the regression line. Consequently, the value of R becomes slightly less than 0.9941. The training was stopped and all the 27 experimental values were used to predict the surface roughness from the (ANN) model which make R = 0.99202 for the ANN model, training process was performed by Matlab software. Figure 4.5 indicates the comparison of the (MSE) with the maximum number of iterations through training process.

Parameters of the developed ANN model are given in table 4.3, and figure 4.6 illustrate the construction of the ANN model**.**

Table 4.3: ANN Parameters Settings

Network type	Feed Forward Back Propagation
Training function	Levenberg Mrquardt (LM)
Performance function	MSE
Transfer function of the hidden layer	TANSIGMOID
Transfer function of the output layer	LINEAR
Number of hidden layer	1
Number of neurons in hidden layer	7

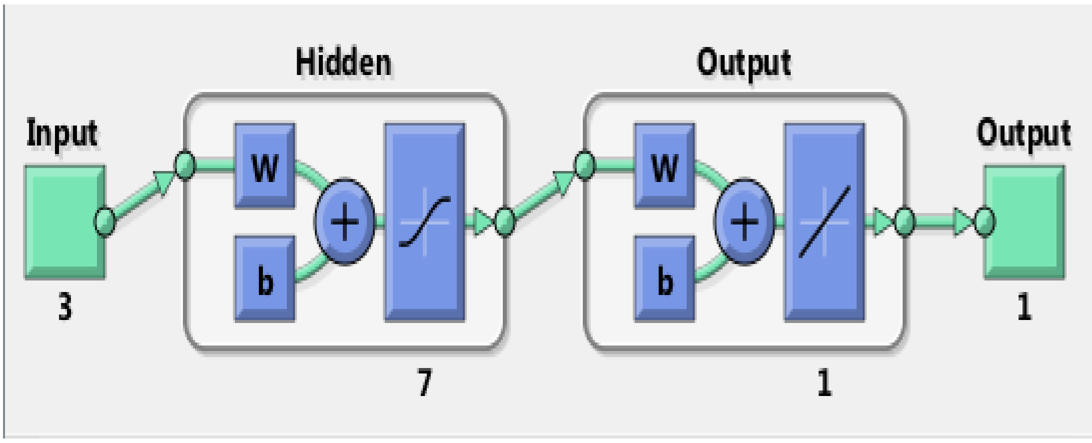


Fig 4.6: Schematic diagram of ANN

Error histogram is depicted in Fig 4.7. It is based on [actual output-predicted output]. Zero point is the minimum point in which the possibility of error lies. The large peak at zero point means small difference between experimental outputs and predicted values; however, small peak shows incorrect values.

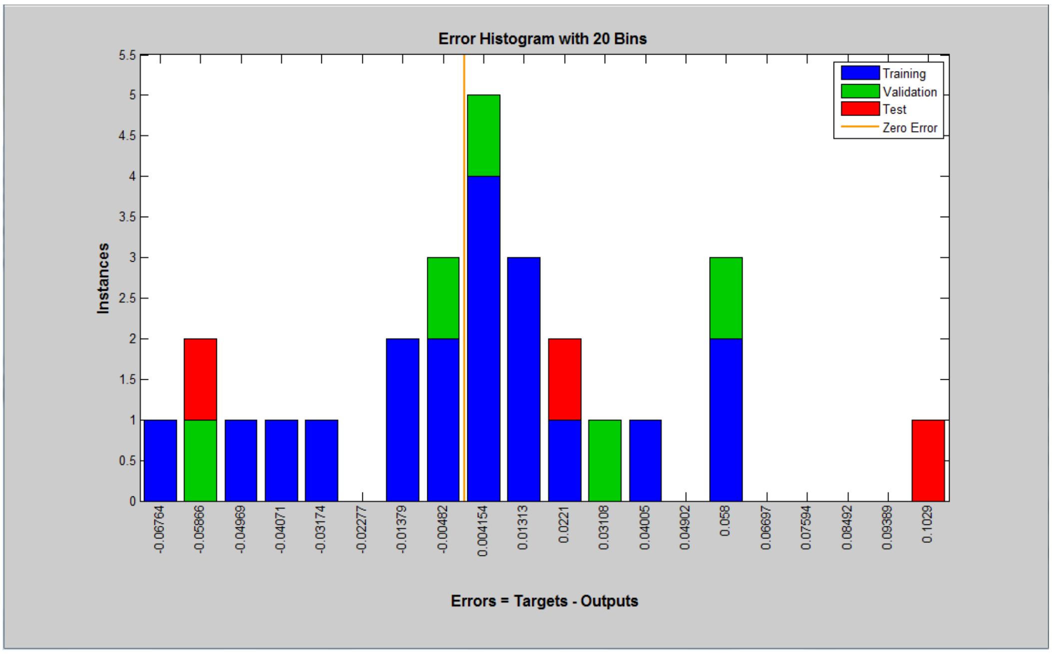


Fig 4.7: Error Histogram results simulation

4.7 Comparison of actual and predicted values

The comparison of the experimental values against the Predicted values by the (ANN) and (RSM) is shown in Figure 4.8 It is obvious that the ANN model profile has more accuracy than that of the (RSM) model. The mean square error in the (ANN) model was found to be 0.0016.

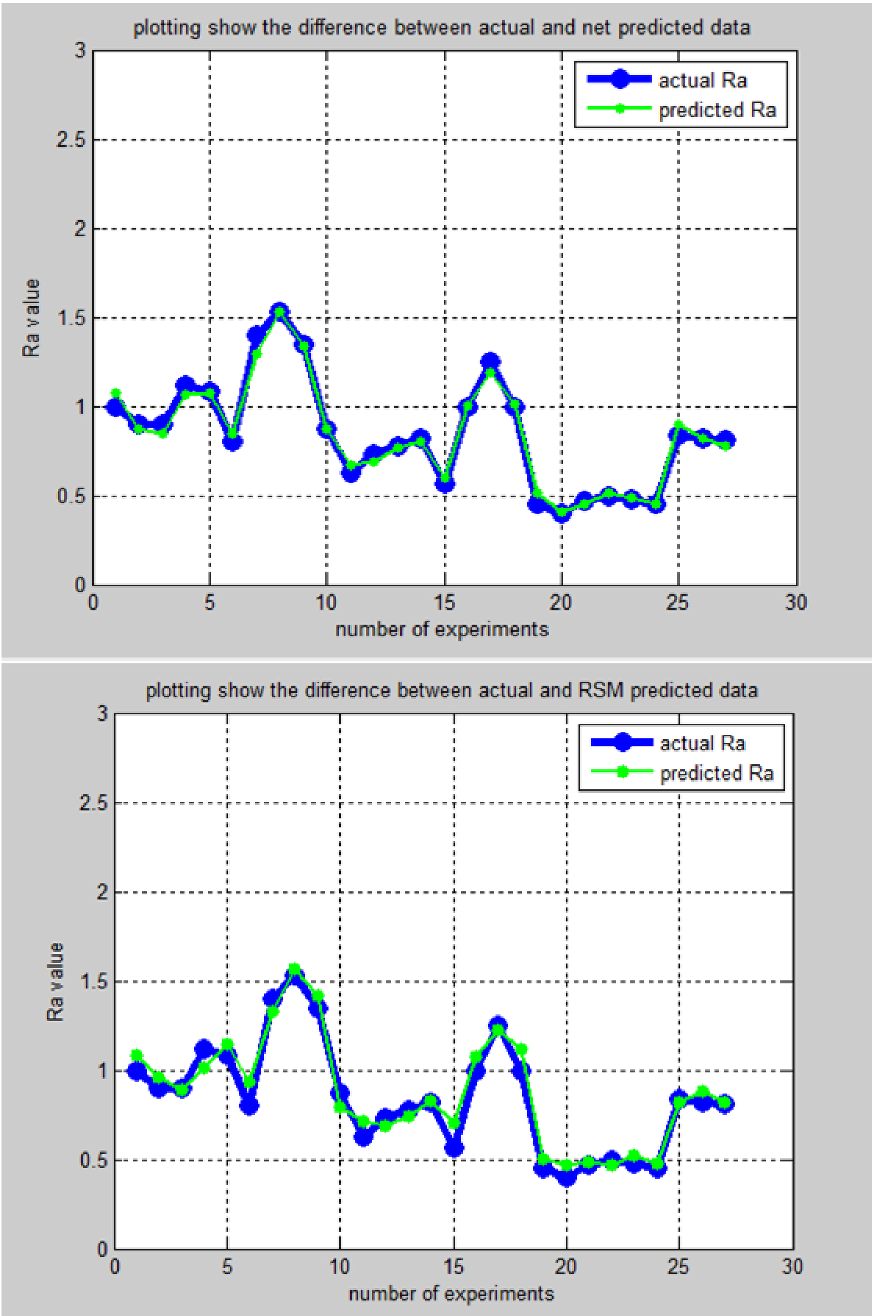


Fig 4.8: The comparison of predicted and actual values of surface roughness

4.8 Comparison of ANN and RSM model

Table 4.4 shows the comparison of resulting model from (ANN) and (RSM) using statistical methods (R and MSE which are calculated by software).The graphical representation for the errors of the (ANN) and (RSM) models is presented in figure 4.9 it is clear from figure 4.9 that the maximum error in the (ANN) and the (RSM) model is 0.107 and 0.136 respectively. Also, from figure 4.9 the minimum errors in the (ANN) and (RSM) model are 0.000324 and 0.0107 respectively. On the basis of the (R) and errors evaluated, it can be stated that the (ANN) model gives more accurate results than the (RSM) model but (RSM) can give opportunity to perform statistical tests (*i.e.* ANOVA) which determine whether the studying parameters are represent the physical phenomena well or else.

Table 4.4: Comparison of ANN and RSM model

Method	R	MSE
ANN model	0.992	0.0016
RSM model	0.978	0.0047

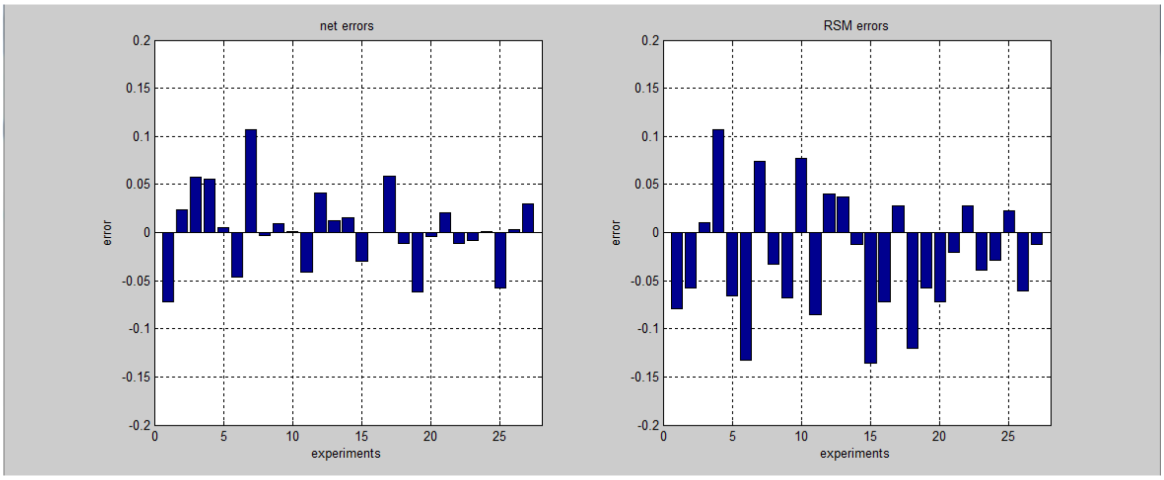


Fig 4.9: Graphical representation for the errors of ANN and RSM model

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

1. The three level full factorial designs are employed for developing mathematical models for predicting surface roughness in (CNC) turning of (St 42crmo4) high grade steel.
2. (RSM) is applied successfully in analyzing the effect of process parameters on different levels of parameters.
3. The experimentation is carried out considering three machining parameters which are cutting speed, feed rate and depth of cut to predict the average surface roughness.
4. (ANOVA) analysis shown that the P-value of second order model is less than 0.05 which mean the model is significant, also the cutting speed, feed rate, depth of cut and quadratic effect of feed are significant, because they have P-value less than 0.05.
5. (ANOVA) analysis shown the coefficient of determination of the second order model is equal to 95.67% which means 95.67% of the variation occurred in the response the model can explained
6. Main effects plot for Ra cutting parameters shown that cutting speed is the most significant factor and the depth of cut is the least significant, it also notice that with the increase of cutting speed and depth of cut the surface roughness decrease, but with increase of feed rate the surface roughness increases.
7. From the contour and 3D surface plots the Ra between the cutting speed vs feed rate shown that the minimum value of Ra is when the cutting speed in maximum level and feed rate is almost at minimum level, between the cutting speed vs depth of cut the Ra is minimum when the cutting speed is maximum and depth of cut lies between the middle and maximum level, and finally between the feed rate vs the depth of cut the Ra is minimum when depth of cut is almost maximum but the feed rate is almost minimum.

8. The (ANN) model was developed with good predicting capability to give surface roughness values.
9. The developed models were evaluated for their capability to predict surface roughness on the basis of (R) and MSE. The (R) was 99.202% for the (ANN) and 97.81% for the (RSM) model. It was concluded that the proposed models can be used effectively to predict surface roughness. Based on the error of the (ANN) and (RSM) model, the (ANN) was found to be more accurate than the (RSM) model.
10. The optimal cutting parameters that optimize the value of surface roughness was developed by (ANN) model, and are 0.549 mm (depth of cut), 900 rpm (cutting speed) and 0.0601 mm/r (feed rate), which correspond to 0. 39 µm (Ra).

5.2 Recommendations

There are several issues can receive more attention in the future researches which are:

1. The number of experiments required to build a model of certain precision.
2. The influence of the technique adopted to collect data.
3. In this work the studied variables are limited to feed rate, depth of cut and spindle speed, but for better results enlarging the number of studied variables are recommended (*i.e.* nose radius, …etc.), and so for response.

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Appendix (A)

Experiment result

	studing parameters			
experiment number	cutting speed(rpm)	feed rate (mm/rev)	depth of cut(mm)	actual Ra (μm)
1	700	0.05	0.3	1.00
2	700	0.05	0.6	0.90
3	700	0.05	0.9	0.90
4	700	0.10	0.6	1.12
5	700	0.10	0.3	1.08
6	700	0.10	0.9	0.80
7	700	0.15	0.9	1.40
8	700	0.15	0.3	1.53
9	700	0.15	0.6	1.35
10	800	0.05	0.3	0.87
11	800	0.05	0.6	0.63
12	800	0.05	0.9	0.73
13	800	0.10	0.6	0.78
14	800	0.10	0.3	0.82
15	800	0.10	0.9	0.57
16	800	0.15	0.9	1.00
17	800	0.15	0.3	1.25
18	800	0.15	0.6	1.00
19	900	0.05	0.3	0.45
20	900	0.05	0.6	0.40
21	900	0.05	0.9	0.47
22	900	0.10	0.6	0.50
23	900	0.10	0.3	0.48
24	900	0.10	0.9	0.45
25	900	0.15	0.9	0.84
26	900	0.15	0.3	0.82
27	900	0.15	0.6	0.81

Appendix (B)

RSM model result and errors

	studing parameters			predicted output	
experiment number	cutting speed(rpm)	feed rate (mm/rev)	depth of cut(mm)	RSM Ra (µm)	Erorr of RSM
1	700	0.05	0.3	1.08	0.0795
2	700	0.05	0.6	0.96	0.0577
3	700	0.05	0.9	0.89	0.0107
4	700	0.10	0.6	1.01	0.1072
5	700	0.10	0.3	1.15	0.0663
6	700	0.10	0.9	0.93	0.1327
7	700	0.15	0.9	1.33	0.0739
8	700	0.15	0.3	1.56	0.0331
9	700	0.15	0.6	1.42	0.0679
10	800	0.05	0.3	0.79	0.0767
11	800	0.05	0.6	0.71	0.0849
12	800	0.05	0.9	0.69	0.0403
13	800	0.10	0.6	0.74	0.0375
14	800	0.10	0.3	0.83	0.0126
15	800	0.10	0.9	0.71	0.1356
16	800	0.15	0.9	1.07	0.0715
17	800	0.15	0.3	1.22	0.0281
18	800	0.15	0.6	1.12	0.1201
19	900	0.05	0.3	0.51	0.0571
20	900	0.05	0.6	0.47	0.0720
21	900	0.05	0.9	0.49	0.0202
22	900	0.10	0.6	0.47	0.0279
23	900	0.10	0.3	0.52	0.0389
24	900	0.10	0.9	0.48	0.0286
25	900	0.15	0.9	0.82	0.0230
26	900	0.15	0.3	0.88	0.0607
27	900	0.15	0.6	0.82	0.0122

Hint: mean minimum error **mean maximum error**

Appendix (C)

ANN model result errors

	studing parameters			predicted output	
experiment number	cutting speed(rpm)	feed rate (mm/rev)	depth of cut(mm)	ANN Ra (μm)	Erorr of ANN
1	700	0.05	0.3	1.07	0.0721
2	700	0.05	0.6	0.88	0.0238
3	700	0.05	0.9	0.84	0.0575
4	700	0.10	0.6	1.06	0.0552
5	700	0.10	0.3	1.08	0.0047
6	700	0.10	0.9	0.85	0.0462
7	700	0.15	0.9	1.29	0.1074
8	700	0.15	0.3	1.53	0.0030
9	700	0.15	0.6	1.34	0.0091
10	800	0.05	0.3	0.87	0.0011
11	800	0.05	0.6	0.67	0.0416
12	800	0.05	0.9	0.69	0.0414
13	800	0.10	0.6	0.77	0.0128
14	800	0.10	0.3	0.80	0.0150
15	800	0.10	0.9	0.60	0.0294
16	800	0.15	0.9	1.00	0.0003
17	800	0.15	0.3	1.19	0.0587
18	800	0.15	0.6	1.01	0.0110
19	900	0.05	0.3	0.51	0.0616
20	900	0.05	0.6	0.40	0.0039
21	900	0.05	0.9	0.45	0.0201
22	900	0.10	0.6	0.51	0.0109
23	900	0.10	0.3	0.49	0.0086
24	900	0.10	0.9	0.45	0.0009
25	900	0.15	0.9	0.90	0.0574
26	900	0.15	0.3	0.82	0.0032
27	900	0.15	0.6	0.78	0.0303

Hint: **mean minimum error** **mean maximum error**