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Prediction of Surface Roughness for Aluminium 6053 alloyusing Soft Computing Techniques

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Abstract –Artificial Neural Network and Response Surface Methodology are used to develop predicted values and are verified using regression coefficient. The machining depends on the three fundamental parameters i.e. Speed, Feed and the Depth of cut made, so here an array is obtained using the Minitab software. In this paper an attempt is made to compare various methods to predict the surface roughness of al 6053 alloy. The ANN model is modelled using Multilayer Perceptron Network for nonlinear mapping between the input and output parameters..From the results it is seen that ANN predicted values are close to the experimental values indicates that the developed model can be effectively used to predict the Material Removal Rate and Surface Roughness of 6053 alloy.

Index terms- Material Removal Rate; Artificial Neural Network; Response Surface Methodology; Aluminium Alloy

1 Introduction

Machining is the most wide spread metal machining process in mechanical manufacturing industry. The goal of changing the geometry of raw material in order to form mechanical parts can be met by putting material together. Conventional machining is the one of the most important material method. Machining is a part of the manufacturing all most all metals products. In order to perform cutting operations, different machining tools such as lathes, drilling machine, horizontal and vertical milling machines etc. are utilizing. Out of this machining process, turning still remains most important operation used to shape metal, because in turning the condition of operation are most varied. Increasing productivity and reducing manufacturing cost has always been the primary object of successful business. In turning, higher values of cutting parameter offered opportunities for increasing productivity but it also involves greater risk of deterioration in surface quality and tool life. Turning operation is very important material removal process in modern industry.

The turning test of aluminium alloy was carried out by using central composite surface design of RSM . The influence of cutting parameters (cutting speed , feed rate and cutting depth) on the surface roughness was analysed . The surface roughness prediction model was established based on second order RSM. According to test results, regression coefficient was estimate by least square method and the regression equation was curve fitted.

1.1.Turning Operation-

Turning is the removal of metal from the outer diameter of a rotating cylindrical workpiece. Turning is used to reduce the

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diameter of the workpiece, usually to a specified dimension, and to produce a smooth finish on the metal. Often the workpiece will be turned sothat adjacent sections have different diameters.

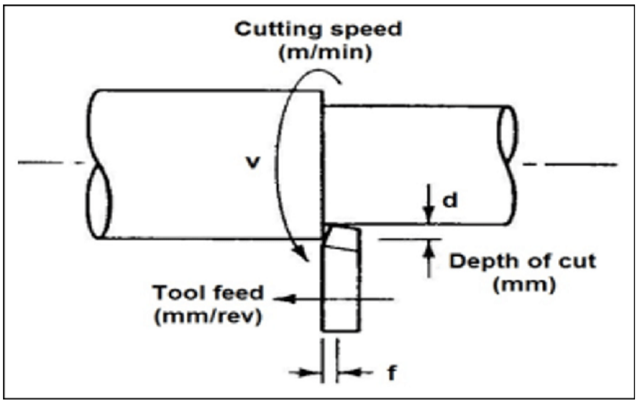

fig-1.1

1.2 Tool Geometry-

- **Cutting Angle-**

The angle between the cutting face of a cutting tool and the surface of the work back of the tool

- **Rake Angle-**

Angle of inclination of rake surface from reference plane. It is provided for ease of chip flow and over all machining. It can be positive, negative or zero.

- **Chip –**

If the metal chips formed during machining is without segments i.e. without breakage, than it is called as continuous types of chips. Continuous chips are formed when the ductile material is machined with high cutting speed and minimum friction between the chip and tool face.

- **Chip Thickness-**

Equivalent chip thickness is a kinematic parameter that combines real depth of cut, work speed, and wheel speed. It can be considered as a modified depth of cut. The real depth of cut is the thickness of the layer of material removed in one pass or revolution of the workpiece.

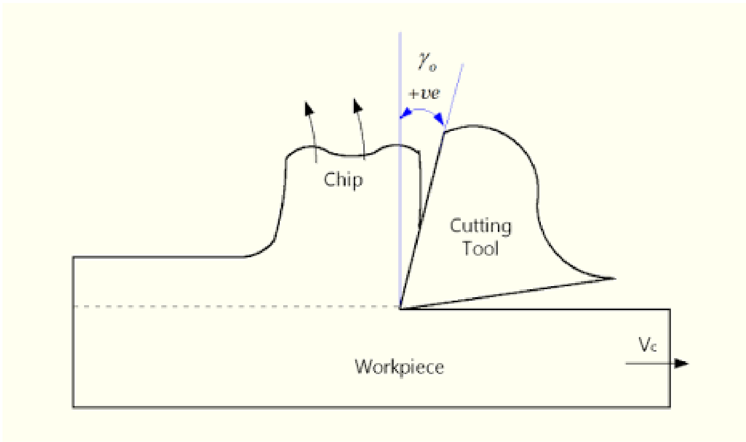

fig-1.2.1turning process

- **Chip Velocity-**

Chip velocity is a crucial parameter in metal cutting. The continuous variation of chip velocity in primary shear zone cannot be obtained from conventional shear plane model. The velocity of chip material was calculated from the mathematical expression of streamline model.

- **Clearance angle-**

The angle between machined surface and the flank surface , it is provided to avoid rubbing of tool with machined surface.

1.3 Input & Output Parameters needed for machining process-

- **Input Parameters-**

1. **Cutting Speed-**

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The cutting speed of a shaper is the speed at which the metal is removed by the cutting tool in one minute. In other words, only the forward cutting stroke is considered. The speed is expressed in metre per minute.

2. Feed-

Feed is the relative movement of the work or tool in a direction perpendicular to the axis of reciprocation of the ram per double stroke. It is expressed in mm per stroke.

3. Depth of Cut-

Depth of cut is the thickness of metal that is removed during machining. The perpendicular distance measured between the machined surface and the uncut surface of the workpiece is taken. It is expressed in mm or in inches.

- **Output Parameters-**

1. Surface Roughness –

Surface roughness often shortened to roughness, is a component of surface vector. It is quantified by the deviations in the direction of the normal vector of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small, the surface is smooth. In surface metrology, roughness is typically considered to be the high-frequency, short-wavelength component of a measured surface. However, in practice it is often necessary to know both the amplitude and frequency to ensure that a surface is fit for a purpose.

1.4 Response Surface Methodology

A response surface design is a set of advanced design of experiments (DOE) techniques that help you better understand and optimize your response. Response surface design methodology is often used to refine models after you have determined important factors using screening designs or factorial designs; especially if you suspect curvature in the response surface. RSM explores the relationships between several explanatory variables and one or more response variables. The method was introduced by George E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. Box and Wilson suggest using a second degree polynomial model to do this. They acknowledge that this model is only an approximation, but they use it because such a model is easy to estimate and apply, even when little is known about the process. There are two main types of response surface designs Central Composite designs & Box- Behnken designs.

1.5 Central Composite Design

A CCD spans a set of quantitative factors with fewer points than a standard Fractional multilevel design, without a large loss in efficiency. It uses central points, extreme (corner) points and either face points or extended points. Central composite designs with face points require three levels; with extended axial points, five levels are required.

These three-level designs are often used for response surface analysis to map out the shapes of the quadratic surfaces. The centre and axial points allow estimates of quadratic terms. (Recall that two-level designs only can be used to estimate linear surfaces.) Repeat centre points provide an estimate of pure error.

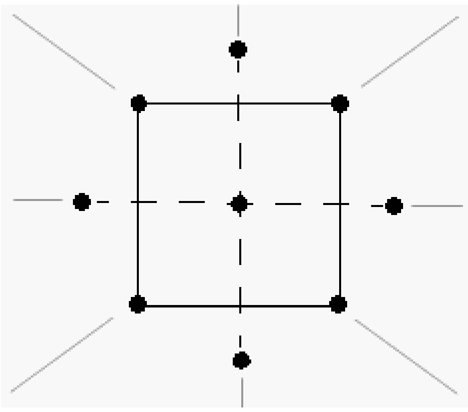

Fig1.5.1

A central composite design is the most commonly used response surface designed experiment. Central composite designs are a factorial or fractional factorial design with centre points, augmented with a group of axial points (also called star points) that let you estimate curvature. You can use a central composite design to:

- Efficiently estimate first- and second-order terms.
- Model a response variable with curvature by adding centre and axial points to a previously-done factorial design.
- Central composite designs are especially useful in sequential experiments because you can often build on previous factorial experiments by adding axial and centre points.

1.6 Response Surface Methodology based predictive model-

The experiments were designed and conducted by employing response surface methodology. Second-order non-linear mathematical models have been developed to predict the surface roughness, which are of the following form

Y=b0+b1x1+b2x2+b3x3+b4x4+b11x12+b22x22+ b33x32+b44x42+b12x1x2+b13x1x3+b14x1x4+b23x2x3+b24x2x4+b34x3x4

(1)Where: Y Response

xi Coded values for i=A1, A2, A3 and A4

b0,..., b34 Regression coefficients

The regression equation for the surface roughness as a function of four input process variables is developed using the regression coefficients of the second order equation are obtained by using the experimental data .The coefficients of some terms of the quadratic equation have been omitted.

1.7 Artificial Neural Network (ANN)

The Artificial Neural network (ANN) is made up of a series of interconnected nodes that simulate individual neurons like a biological neural system. The ANN can be used for classification, pattern recognition and forecasting problem in situations of complex processes characterized by chaotic features such as trends and seasonality observed in parking ticket data, nonlinear and non-stationary in stock market data, chaotic features in ozone concentration measurements and weather related problems with non-linear relationships between inputs and the outputs.

An ANN is based on a collection of connected units or nodes called An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it.

In ANN implementations, the "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections

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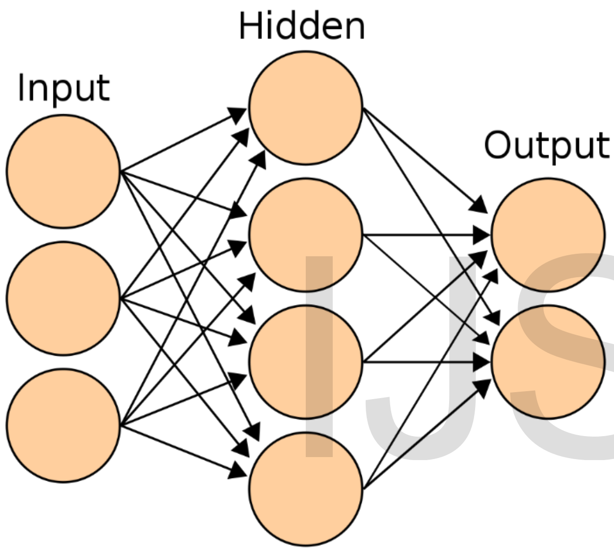
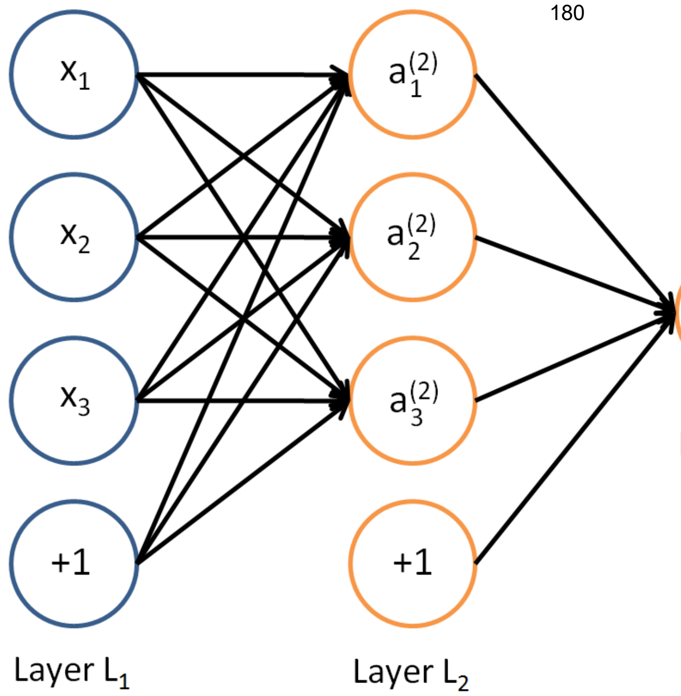
are called *edges*. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.



An artificial neural network.



2Literature survey

Ch. Sateesh Kumar *et al.*[1] has studied the important factors for the performance cutting tool in which coating is provided. Coating thickness and structure of coating on a tool is an important factor on coated cutting tool performance. Coating technology variation could affect the structure and its thermal and mechanical properties.

Ahmed A. D. Surhan [2] has worked over developing an accurate modal for predicting tool wear. ANFIS modelling is an adept technique for tool wear prediction with low error and high accuracy level of 6.91 and 94.8% respectively.

Ph.D. IlijaSvalina*et al.*[3] has studied to obtain the optimal cutting parameter along with the required quality of product demonstrated by surface roughness for the sequence of machining process.

Satish Chinchanikar*et al.*[4] has studied comparative evaluation of surface roughness produced by considering the effect of different cooling medium and cutting parameters using mathematical modelling using response surface methodology. Highly significant parameters on surface roughness were determined by performing and analysis of variance (ANAVO).

Kuldeep Singh Sangwal*et al*.[5] has studied multi objective optimization model to maximize the material removal rate and minimize the consumption at the targeted value of surface roughness during machining. It is reported that power consumption can be reduced and M.R.R can be improved if the surface roughness is targeted for a desired value instead of minimizing it.

Pankaj Kumar Sahu*et al*.[6] has studied the different process of machining for optimization by varying different parameters including cutting speed, feed, depth of cut.

Chithajalu Kiran Sagar *et al*.[7] has studied cutting force model for orthogonal model comparing the predicted cutting force and thrust force components with corresponding experimental data. Optimization using RSM shows the optimal combination of machining parameters.

Ojolo Sunday Joshua *et al*.[8]has concluded that the surface roughness could be predicted by combining the two parameters (i.e feed rate, spindle speed and depth of cut) and keeping one of them constant at a time and their interactions in the multiple regression model. Surface roughness values were affected mostly by cutting feed, followed by spindle speed and depth of cut has the least impact on surface roughness valuescryogenic coolant. The surface roughness of machined sample under cryogenic environment was around 20% lesser when compared with conventional coolant.

G.J. Pavan Kumar *et al*. [9] has concluded that regression techniques are used to predict the workpiece surface roughness after the turning process and to analyse the effect of three turning parameters including speed, feed and depth of cut on surface roughness.

Kunwar Singh Vaisla*et al*. [10] has a method to forecast the daily stock price using neural networks and the result of the Neural Network forecast is compared with the Statistical forecasting result. Stock price prediction is one of the emerging field in neural network forecasting area. This paper also presents the Neural Networks ability to forecast the daily Stock Market Prices.

M. Vishnu Vardhan*et al*. [11] has made an attempt is made to predict Material Removal Rate and Surface roughness in CNC milling of P20 steel using Artificial Neural Networks (ANN). Taguchi's L50 orthogonal array is used to design the experiments.

2.1Salient Points Of Literature Review:-

1. There are different methods of predictthesurface roughness for turning operations.
2. By using RSM method and ANN method we can precisely predict the surface roughness of the material.

3. The predicted values using RSM are in close agreement with the experimental values when compared.
4. The surface roughness depends upon the parameters like speed, depth of cut and feed.

2.2Problem Statement –

Prediction of surface roughness by using RSM and Artificial Neural Network method,the surface roughness is one of the important properties of workpiece quality in the turning operation . A good surface roughness and hence poor surface roughness improves the tribological properties,fatigue strength,corrosion resistance and esthetical appeal of the product so to develop an effective approach based on RSM method to predict the surface roughness of aluminium alloy 6053 and investigating the following parameters such as feed, speed, depth of cut and surface roughness.

2.3Objective-

1. To predict the surface roughness of Al 6053 material using RSM method.
2. To compare the predicted values obtained by using RSM method with the experimental values.

3 Methodology

1. Selection of material Aluminium alloy 6053on which machining can be done easily.
2. By using Minitab, generation of the parameters for machining.
3. To generate the optimized equation with RSM method& ANN method and predicted the surface roughness.
4. Performed the turning process on Aluminium 6053 in CNC machine.
5. Checked the surface roughness using surface roughness tester after the job is obtained from machining.
6. Comparing the experimentally obtained surface roughness values with the predicted values of surface.

3.1Properties of Aluminium 6053-

The following table shows the **chemical composition** of the Aluminium 6053 –

Table no.- 3.1.1

Element	**Content(%)**
Aluminium	97.5 - 98.8
Magnesium	1.1 – 1.4
Iron	<= 0.35
Chromium	0.15 - 0.35
Copper	<= 0.10
Zinc	<= 0.10
Remainder	<= 0.15

Mechanical Properties–

Table no-3.1.2

Properties	**Metric**
Tensile strength	110 MPa
Yield strength	55 MPa
Elastic modulus	69 GPa
Shear modulus	26 GPa
Poisson’s ratio	0.33
Hardness	26 BHN

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3.2 List ofInput Parameters for Turning of Aluminium

Table-3.2.1

Sr no.	Parameters	Low	High
1	Cutting depth (mm)	0.25	0.75
2	Feed (mm/rev)	50	100
3	Speed (rpm)	1500	2000

Measurement of all three parameters for experimental run

Central composite design for 3 parameters at two level gives 20 numbers of experiment is carried by using MINITAB 17 statistical software

Table -3.1.2

Sr no.	Cutting depth (mm)	Feed (mm/rev)	Speed (rpm)
1	0.920448	75.000	1750.00
2	0.750000	100.000	1500.00
3	0.750000	50.000	2000.00
4	0.750000	50.000	1500.00
5	0.750000	100.000	2000.00
6	0.500000	75.000	1750.00
7	0.500000	75.000	1750.00
8	0.500000	75.000	1750.00
9	0.500000	75.000	1750.00
10	0.500000	75.000	2170.45
11	0.500000	117.045	1750.00
12	0.500000	75.000	1750.00
13	0.500000	32.955	1750.00
14	0.500000	75.000	1750.00
15	0.500000	75.000	1329.55
16	0.250000	100.000	1500.00
17	0.250000	50.000	1500.00
18	0.250000	100.000	2000.00
19	0.250000	50.000	2000.00
20	0.079552	75.000	1750.00

3.3 Insert Materials-

Inserts are removable cutting tips, which means they are not brazed or welded to the tool body. They are usually indexable, meaning that they can be exchanged, and often also rotated or flipped, without disturbing the overall geometry of the tool (effective diameter, tool length offset, etc.).

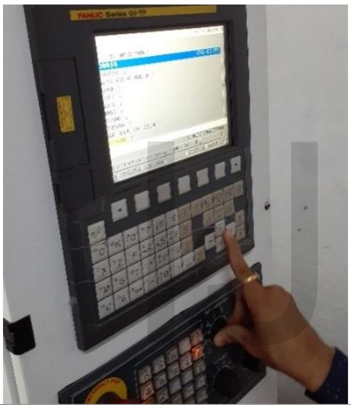
Carbide Insert tool-

Carbide inserts are replaceable and usually indexable bits of cemented carbide used in machining steels, cast iron, high temperature alloys, and nonferrous materials. Carbide inserts allow faster machining and leave better finishes on metal parts.

The powder is transported in 100-kg barrels to the pressing machines where the inserts are made. The inserts are heated to approximately 1,500 degrees Celsius in a process that takes some 13 hours and fuses the pressed powder into cemented carbide, an extremely hard material.

3.4Experimental Setup-

CNC Machine fig-3.4.1



CNC controller Panel (fig 3.4.2)Aluminium 6053 bars (Work piece Material) (fig-3.4.3)

Surface Roughness Tester (fig- 3.4.4)

The values obtained from experimental run and using surface roughness tester-

Table no- 3.4.1

Sr No.	Surface Roughness Values obtained from experimentation (μm)
1	1.27
2	1.491333
3	0.858
4	0.471333
5	2.393333
6	1.234
7	1.234
8	1.234
9	1.234
10	1.682333
11	2.444333
12	1.207333
13	0.285667
14	1.207333
15	0.732333
16	1.523333
17	0.451667
18	2.365333
19	0.819667
20	0.795667

Artificial Neural Network Method-

Equations for solving Artificial Neural Network using Matlab version 19.1-

The hidden layer includes several processing units connected with variable weights called neurons. Each neuron connected to another neuron with several weight in the network and input signal Xj connected to neuron K is multiplied by the weight Wkj. The processing of neural network has been mathematically expressed as follows.

$$u_k = \sum_{j=1}^{m} (w_{kj} \times x_j)$$

$$y_k = f(u_k + b_k)$$

Carried out with the help of where X1 , X2 , …. Xm are input signals Wk1,Wk2,…Wkm are the weight of neuron k,Uk is linear combiner due to the input signal, Bk is bias, F is the activation function and Yk is output signal for neuron.

During the learning stage predicted output is connected with the target output and the connected weight inside the network are adjust to minimize the differences. The network forecasts the output according to the knowledge it has gained. The training of the network is completed when validation error starts to increase in order to avoid overlearning of networks and corresponding mean square error (MSE) value was noted. The performance of the neural network is evaluated by MSE and coefficient of correlation are. The correlation is said to be the strong if the predicted and the targeted values are very close to the line of the entire data sets. The good ANN architecture is selected based on lower MSE and higher R values. The minimization of MSE are carried out by updating the weights through the gradient descent method. The MSE value can found out by the equation.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_{pi} - y_{ti})^2$$

Where Ypi and Yti are the network predictions and target values.

N is the total number of observations.

R is used to show relation between predicted and the random values. If the value is 1, then the relationship is said to be close and if R value is 0 then the relation is said to be random.

4 Result & Discussion-

4.1 Equation for prediction of surface roughness by RSM method on MINITAB version 19.1Regression Equation in Uncoded Units -

$$\begin{aligned} Ra = {} & -6.84 + 0.00513\,v - 0.0123\,f + 15.30\,d \\ & + 0.000000\,v*v + 0.000163\,f*f - 0.70\,d*d \\ & - 0.000020\,v*f - 0.01035\,v*d + 0.0500\,f*d \end{aligned}$$

The table below shows the values obtained from predicted by the formula generated using CCD (Central Composite Design) method from RSM (Response Surface Methodology) approach.

Table- 4.1.1

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Sr No.	Predicted values of Surface hardness from RSM method
1	1.169698
2	1.478294
3	0.947383
4	0.64154
5	2.478803
6	1.187782
7	1.273613
8	1.258342
9	1.187782
10	1.584874
11	1.187782
12	1.187782
13	1.187782
14	1.368748
15	1.187782
16	1.49115
17	0.636237
18	2.23464
19	0.685061
20	0.959923

4.2 The error value obtained in predicted value from the values of surface roughness obtained from the experimentation-

Error between surface roughness values obtained from RSM and experimental values

Table- 4.2.1

Sr no.	Surface Roughness Values obtained from experimentation (μm)	Predicted values of Surface hardness from RSM method	Error
1	1.27	1.169698	0.100302
2	1.491333	1.478294	0.01304
3	0.858	0.947383	-0.08938

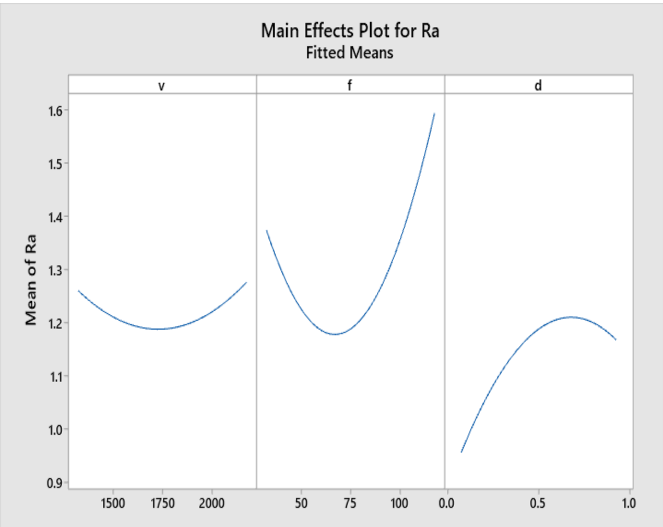
When the values were predicted by RSM method, it was found that some error was seen in the predicted values. The error observed is calculated as the difference between values of surface roughness obtained from experimental values and the surface roughness values obtained from the predicted

4	0.471333	0.64154	0.029793
5	2.393333	2.478803	-0.08547
6	1.234	1.187782	0.046218
7	1.234	1.273613	-0.03961
8	1.234	1.258342	-0.02434
9	1.234	1.187782	0.046218
10	1.682333	1.584874	0.097459
11	2.444333	1.187782	1.256551
12	1.207333	1.187782	0.019551
13	0.285667	1.187782	-0.90212
14	1.207333	1.368748	-0.16141
15	0.732333	1.187782	-0.45545
16	1.523333	1.49115	0.032183
17	0.451667	0.636237	0.01543
18	2.365333	2.23464	0.130693
19	0.819667	0.685061	0.134606
20	0.795667	0.959923	-0.16426

4.3 Studying the values obtained by RSM approach and plotting various graphs-

Further studying the values of surface roughness obtained from RSM approach and compare the values obtained with the input parameters and the surface roughness values obtained from the experimental run we can see some specific pattern that can be plotted in the graph as follows

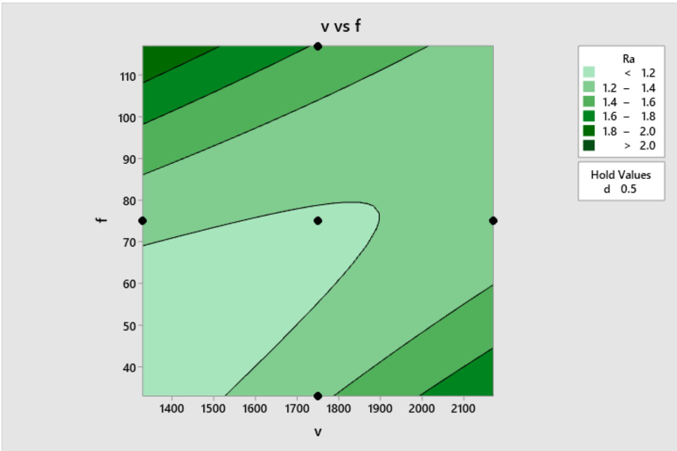
4.3.1 Factorial Plots for Ra



Graph – 4.3.1

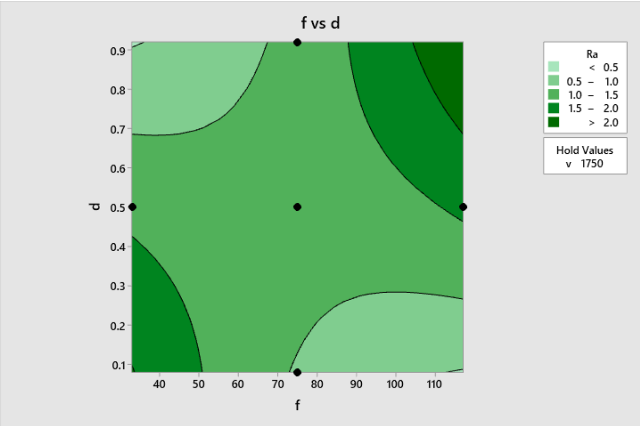
This is the graph between the parameters, speed, feed and depth of cut with the mean surface surface roughness from RSM prediction. The graph shows the variation of surface roughness with varying of three parameters.

4.3.2 Contour Plot of Rs vs f, v



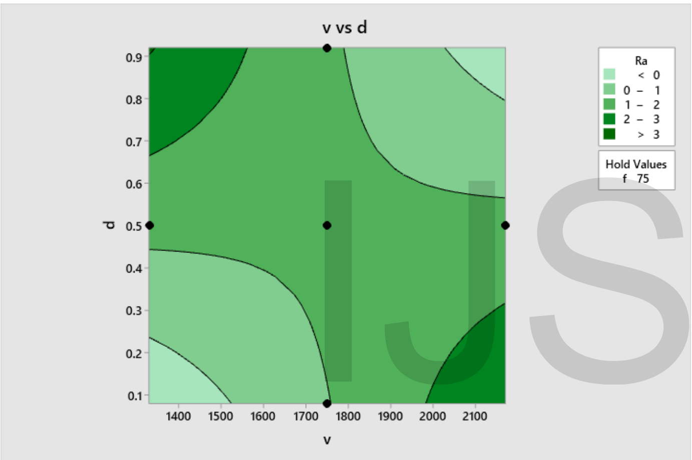
Graph- 4.3.2

4.3.3 ContourPlot of Ra vs d, f



Graph-4.3.3

4.3.4 Contour Plot of Ra vs d, v

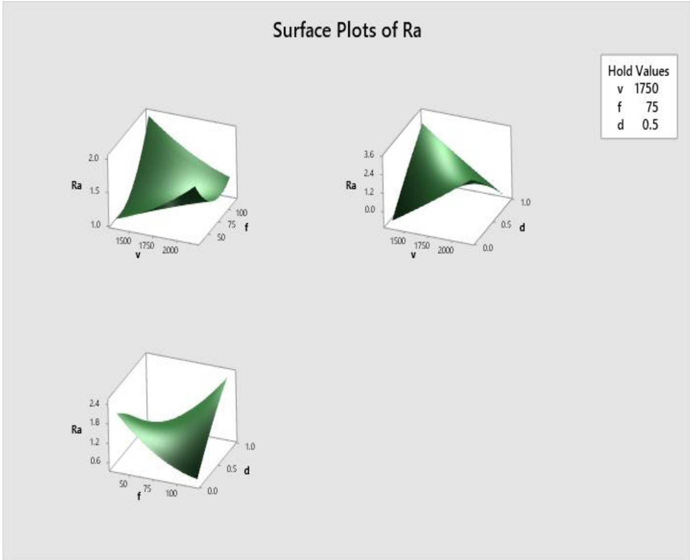


Graph-4.3.4

These are the graphs between Ra vs f,v , Ra vs d,f& Ra vs d,v. These graph shows the closeness of the prediction with the different shade of green colour. The chart given adjacent shows the closest predicted value of surface roughness.

4.3.5 Surface Plots of Ra

This is graph considering of all the parameters including speed, depth of cut and feed. This graph shows the surface plots of the surface roughness. This is the 3D graph.



Graph-4.3.5

Values predicted by Artificial Neural Network method–

Table no.- 4.2.2

Sr No.	Predicted values of Surface hardness from ANN method
1	1.20910000000000
2	1.34810000000000
3	1.21470000000000
4	0.665670000000000
5	1.50540000000000
6	1.14410000000000
7	1.14410000000000
8	1.14410000000000
9	1.14410000000000
10	1.92720000000000
11	1.53640000000000
12	1.14410000000000
13	1.04290000000000
14	1.14410000000000
15	0.689270000000000
16	1.29860000000000
17	0.540650000000000
18	2.22000000000000
19	0.904770000000000
20	0.938040000000000

The error value obtained in predicted value from the values of surface roughness obtained from the experimentation-

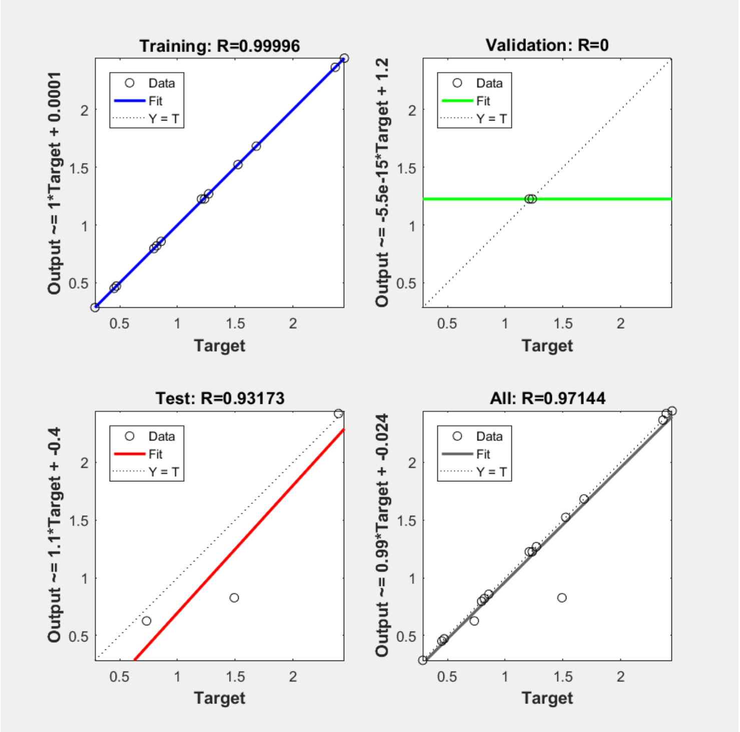
Table no.- 4.2.3

Sr no.	**Surface Roughness Values obtained from experimentation (μm)**	**Predicted values of Surface hardness from ANN method**	**Error**
1	1.27	1.20910000000000	0.0609
2	1.491333	1.34810000000000	0.143233
3	0.858	1.21470000000000	-0.3567
4	0.471333	0.665670000000000	-0.194337
5	2.393333	1.5054000000000	0.887933
6	1.234	1.1441000000000	0.0899
7	1.234	1.1441000000000	0.0899
8	1.234	1.1441000000000	0.0899
9	1.234	1.1441000000000	0.0899
10	1.682333	1.92720000000000	-0.244867
11	2.444333	1.53640000000000	0.907933
12	1.207333	1.14410000000000	0.063233
13	0.285667	1.04290000000000	-0.757233
14	1.207333	1.14410000000000	0.063233
15	0.732333	0.689270000000000	0.043063
16	1.523333	1.29860000000000	0.224733
17	0.451667	0.540650000000000	-0.088983
18	2.365333	2.22000000000000	0.145333
19	0.819667	0.904770000000000	-0.085103
20	0.795667	0.938040000000000	-0.142373

Comparision between the values predicted by RSM method and ANN method–

Table no. – 4.2.4.

Sr no.	Values obtained from RSM method	Values obtained from ANN method
1	1.169698	1.2700000000000
2	1.478294	0.827100000000000
3	0.947383	0.85800000000000
4	0.64154	0.47133000000000
5	2.478803	2.42180000000000
6	1.187782	1.22510000000000
7	1.273613	1.22510000000000
8	1.258342	1.22510000000000
9	1.187782	1.22510000000000
10	1.584874	1.68230000000000
11	1.187782	2.4443000000000
12	1.187782	1.2251000000000
13	1.187782	0.2856700000000
14	1.368748	1.2251000000000
15	1.187782	0.62617000000000
16	1.49115	1.52330000000000
17	0.636237	0.45167000000000
18	2.23464	2.36530000000000
1920	0.685061	0.81967000000000
	0.959923	0.795600000000000



5 Conclusion-

In this work twenty experiments conducted according to proposed design of experiments with two levels of cutting parameters such as cutting parameters feed, depth of cut, spindle speed. We have studied and compared the various methods for prediction of surface roughness which includes RSM and ANN which was used to learn the collected experimental data.

From the results it can be concluded that values predicted by ANN are closer to experimental values. This indicates that the model can be effectively used to predict the surface roughness. It has been inferred that the responses of this study were effectively predicted by ANN.

The huge economical benefits, higher predictability, short simulation time make ANN to be a promising model tool as demonstrated here. This could benefit to a forming industry, particulary research and development phase where cost and time reduction is a major objective.

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