**Engineering and Technology Journal**
**Journal homepage:** engtechjournal.org

# Prediction the Influence of Machining Parameters for CNC Turning of Aluminum Alloy Using RSM and ANN

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Submitted: 30/09/2019 Accepted: 19/11/2019 Published: 25/06/2020

K E Y W O R D S

Response Surface Methodology (RSM), Surface Roughness (Ra), Artificial Neural Network (ANN).

A B S T R A C T

*The main objective of this paper is to develop a prediction model using Response Surface Methodology (RSM) and Artificial Neural Network (ANN) for the turning process of Aluminum alloy 6061 round rod. The turning experiments carried out based on the Central Composite Design (CCD) of Response Surface Methodology. The influence of three independent variables such as Cutting speed (150, 175 and 200 mm/ min), depth of cut (0.5, 1 and 1.5 mm) and feed rate (0.1, 0.2 and 0.3 mm/rev) on the Surface Roughness (Ra) were analyzed through analysis of variance (ANOVA). The response graphs from the Analysis of Variance (ANOVA) present that feed-rate has the strongest influence on Ra dependent on cutting speed and depth of cut. Surface response methodology developed between the machining parameters and response and confirmation experiments reveals that the good agreement with the regression models. The coefficient of determination value for RSM model is found to be high (R2 = 0.961). It indicates the goodness of fit for the model and high significance of the model. From the result, the maximum error between the experimental value and ANN model is less than the RSM model significantly. However, if the test patterns number will be increased then this error can be further minimized. The proposed RSM and ANN prediction model sufficiently predict Ra accurately. However, ANN prediction model is found to be better compared to RSM model. The artificial neutral network is applied to experimental results to find prediction results for two response parameters. The predicted results taken from ANN show a good agreement between experimental and predicted values with the mean squared error of training indices equal to (0.000) which produces flexibility to the manufacturing industries to select the best setting based on applications.*

**How to cite this article**: H.H. Abdulridha, A.J. Helael and A.A. Al-duroobi, "Predicted the influence of machining parameters for

CNC turning of aluminum alloy using RSM and ANN," Engineering and Technology Journal, Vol. 38, No. 06, pp. 887-895, 2020.
DOI: https://doi.org/10.30684/etj.v38i6A.705



## 1. Introduction

Today, Surface finish plays a significant role during machining of any of the components. The surface finish is the vital quality characteristic that affects the performance of the mechanical parts in addition to manufacturing cost. A high surface finish improves fatigue strength, creep failure, corrosion resistance and better-finished components increase also the productivity & economics of any industry. In actual practice, there are a lot of factors that have an effect on Ra i.e. cutting conditions, work-piece variables, and tool variables. Out of the various parameters we select surface roughness for study in the present work. These two factors directly affect the machining hourly-rate and machining cost. The machining conditions like depth of cut, feed rate, and cutting speed were considered. The main aim is to predict the optimized values for achieving good surface finish [1, 2].
Response Surface Methodology (RSM) which is defined as a specialized DOE technique that utilizes quantitative data from suitable experiments for determining and solving multi-variable equations simultaneously correlating the response like (power consumption, tool life, cutting force, surface roughness) with input parameters (depth of cut, feed rate and cutting speed in a turning process). The graphical representations of these equations are called response surfaces, which can be utilized to determine the reciprocal interactions between the input conditions and their effect on the output and to describe the cumulative and individual effect of the input variables on the response. It has many applications in the design and improvement of products and processes [3, 4].
The machining operation complexity implementing optimization of a machining process is more difficult. Thus Artificial Neural Network (ANN) is used for mapping relationships between the input and the output and also performs computing. ANN works like a human brain to implement functions like self-organization, generalization, and association. Any functions can approximate more efficiently by ANN, thus it is appropriate for non-linear process modeling. ANN can capture complex relationships between input/output and possess good generalization ability, learning ability [5].
Several pieces of research have also utilized several methods, static methods for modeling Ra. Also, several methods or techniques have been employed to optimize process parameters. Recently, various scientific studies according to ANN have been carried out because of its good predictive ability. [6]
Alagarsamy and Rajakumar presented an effective method for the optimization of turning conditions according to Taguchi's approach with RSM. This work examines the employ of Taguchi's method to minimize desired Ra and maximize MRR during machining Al-7075 alloy using tungsten carbide (TNMG 115 100) insert. Signal to Noise (S/N) ratio and Analysis of Variance (ANOVA) are used for studying the performance features in CNC Turning process. Additionally, a second-order mathematical model in terms of input conditions is improved utilizing RSM [7]. Batwara and Verma established the new process model to predict the surface roughness and MRR in different practical applications. Model equations for response MRR and surface roughness were accurately predicted with Minitab software and present good prediction 90% for output. MRR and surface roughness also was predicted by ANN approach. Model equations produce cutting conditions values for controlling process models in a better way if they are used in various industrial applications [1]. Devkumar et al. utilized RSM to improve an effective model for predicting the optimum levels. A comparison was done between experimental values and tabulated values for Ra using ANOVA. The model has shown statistically fit for 95% confidence level [8]. P. Jayaraman et al. (2015) response surface methodology and the genetic algorithm have been applied to determine the optimum cutting conditions leading to minimum surface roughness (Ra), minimum machining force (Fm), minimum power of cutting (Pc) and maximum (MRR) in turning operation on AA6351with different cutting condition. RSM was employed to develop (Ra, MRR Pc, and Fm) quadratic model. The established RSM model was further coupled with an established genetic algorithm to improve the optimum cutting parameter combination to get optimized response values [2]. Rudrapati et al. analyzed the significance of turning parameters on surface roughness in computer numerically controlled (CNC) turning operation while machining of aluminum alloy material [9]. Sahoo et al. studied the development of prediction model utilizing RSM and ANN and optimizes cutting parameters utilizing 3-D surface plot. Experiments were implemented by a coated carbide tool during machining steel (AISI 1040) through a dry medium. The value of the determination coefficient for RSM model was ($R2$ = 0.99 close to unity). It shows more importance of the model and quality of fit for the model. So

that, both of the proposed ANN and RSM model predicted Ra accurately but, ANN prediction model was better as compared with RSM model [10]. Zerti et al. studied the impact of the machining parameters on Ra criteria and the components of cutting force through dry turning of (AISI 420) treated at 59 hardness Rockwell cone. Experiments were executed utilizing cutting-tool (CC6050) based on Taguchi design method (L25). RSM and ANN approach was utilized for modeling the output. Finally, process parameters optimization was done utilizing desirability function (DF) minimizing Ra and cutting forces simultaneously. An output result was present that Ra is robustly affected by feed-rate (f), and that cutting forces is influenced by the depth of cut (ap) [6].
In this paper, the influence of machining parameters (Cutting speed (mm/ min), feed rate (mm/rev) and depth of cut (mm)) was studied to determine the influence of them on the Surface Roughness (Ra) values based on Response Surface Methodology (RSM) with (3 factors, 3 levels) and Artificial Neural Network (ANN).

## 2. Experimental Work

*I. Workpiece material and machine tool*

The experimental work was implemented on a CNC Turning Machine. A carbide insert was used to Machine Aluminum alloy 6061 round rod using to determine optimum values of machining parameters. The chemical composition of Al-6061 alloy is listed in Table 1.

**Table 1: chemical composition of Al-6061 alloy**

| | |
|---|---|
| Fe | 0.195 |
| Mn | 0.068 |
| Si | 0.49 |
| Cu | 0.388 |
| Zn | 0.003 |
| Mg | 1.07 |
| Cr | 0.243 |
| Ti | 0.019 |
| Al | Balance |

Al-6061 alloy round rod with has 25mm diameter and 300mm length is cut into five workpieces. Each shaft of this workpiece was divided into four sections with dimensions as shown in Figure 1, which illustrates the workpiece after machining.

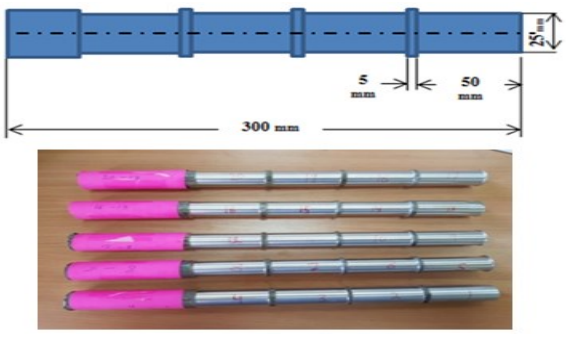


**Figure 1: Work piece after machining**

*II. Selection parameters and their levels*

Depth of Cut (mm), feed rate (mm/rev), and Cutting Speed (m/min) were taken as process parameters. The process parameters and their levels are given from Table 2.

**Table 2: Process parameters and their levels**

| Process Parameters | Cutting Speed (v) (m/min) | Feed-rate (f) (mm/rev) | Depth of cut (d) (mm) |
|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| Levels | Low | 150 | 0.1 | 0.5 |
| | Medium | 175 | 0.2 | 1 |
| | High | 200 | 0.3 | 1.5 |

*III. Calculation of Surface Roughness (Ra)*

Ra calculations were repeated three times after machining at various positions and then the average value was taken. The calculated average values were utilized to represent the machined surface roughness (Ra) [10].

## 3. Experimental Design and Analysis

*I. Response Surface Methodology (RSM)*

Response surface method (RSM) adopts both statistical and mathematical methods which are beneficial for the modeling and analysis of problems to find the input parameters that produce the best output and recognize new input parameters that give developed qualities of the part over the achieved qualities [11,8]. The most common method for creating a quadratic model of a response surface is the central composite design (CCD) [8].

RSM with Central Composite Design (CCD) matrix was employed for experimentation. Planning of experiments is a significant step in the generation of response surface models through RSM in MINITAB software [8]. After experimentation, surface roughness is measured by a surface roughness tester (Pocket Surf) as shown in Figure 2. The experimental values of surface roughness and material removal rate are given from Table 3 and Figure 3.


**Figure 2: The surface roughness tester (Pocket Surf)**

**Table 3: Experimental results of Surface Roughness (Ra)**

| No. | Cutting speed (m/min) | Feed rate (mm/rev) | Depth of cut (mm) | Average Ra (μm) |
|---|---|---|---|---|
| 1 | 150.000 | 0.100000 | 0.50000 | 2.387 |
| 2 | 200.000 | 0.100000 | 0.50000 | 1.827 |
| 3 | 150.000 | 0.300000 | 0.50000 | 3.650 |
| 4 | 200.000 | 0.300000 | 0.50000 | 3.583 |
| 5 | 150.000 | 0.100000 | 1.50000 | 1.243 |
| 6 | 200.000 | 0.100000 | 1.50000 | 1.497 |
| 7 | 150.000 | 0.300000 | 1.50000 | 3.660 |
| 8 | 200.000 | 0.300000 | 1.50000 | 3.773 |
| 9 | 132.955 | 0.200000 | 1.00000 | 1.947 |
| 10 | 217.045 | 0.200000 | 1.00000 | 2.303 |
| 11 | 175.000 | 0.031821 | 1.00000 | 3.067 |
| 12 | 175.000 | 0.368179 | 1.00000 | 5.093 |
| 13 | 175.000 | 0.200000 | 0.15910 | 2.350 |
| 14 | 175.000 | 0.200000 | 1.84090 | 1.953 |
| 15 | 175.000 | 0.200000 | 1.00000 | 1.897 |
| 16 | 175.000 | 0.200000 | 1.00000 | 2.040 |
| 17 | 175.000 | 0.200000 | 1.00000 | 1.977 |
| 18 | 175.000 | 0.200000 | 1.00000 | 1.930 |
| 19 | 175.000 | 0.200000 | 1.00000 | 2.043 |
| 20 | 175.000 | 0.200000 | 1.00000 | 1.660 |

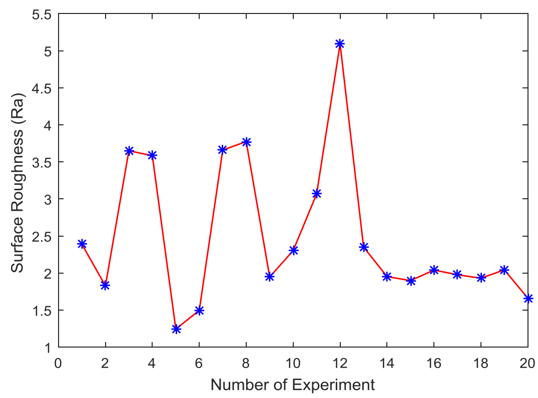


**Figure 3: Experimental results of Surface Roughness (Ra)**

The mathematical model commonly used for the machining response Y is represented as in Eq. (1) :

$$Y = f(A, B, C) \quad (1)$$

Where: $(A, B, C)$: Input variables

$Y$ : Response (output variables)

The statistical model of surface roughness (Ra) will be designed as in Eq. (2):

$$\mathrm{Y} = \mathrm{b}_0 + \mathrm{b}_1(\mathrm{A}) + \mathrm{b}_2(\mathrm{B}) + \mathrm{b}_3(\mathrm{C}) + \mathrm{b}_{11}(\mathrm{A}^2) + \mathrm{b}_{22}(\mathrm{B}^2) + \mathrm{b}_{33}(\mathrm{C}^2) + \mathrm{b}_{12}(\mathrm{AB}) + \mathrm{b}_{13}(\mathrm{AC}) + \mathrm{b}_{23} \quad (2)$$

Where: b0: intercept term

b1, b2, b3: liner terms

b11, b22, b33: squared terms

b12, b13, b23: interactions between independent variables. [2,9]

*II. Development of ANN Modelling*

The Artificial Neural Network can be defined as a computational model that inspired its design schematically from the actual neuron (human, animal) functioning. Statistical learning methods are utilized to optimize neural networks so that they are positioned with statistical applications group on one hand, which they enriched with a group of models allowing generating large functional spaces that are flexible and partially structured [6].

In this paper, Hebbian learning rule in Neural Network model consists of three input neurons and one output corresponding to (tool diameter (d), feed–rate (f), cutting speed (v)), and (Ra) respectively. The number of the hidden layer and the number of neurons equal to (2) and (10) respectively. The number of input parameters is equal to 3. Figure 4 shows the schematic view of the neural network used.

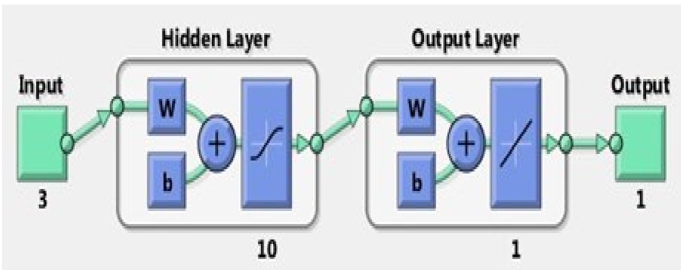


**Figure 4: Schematic view of the neural network used**

## 4. Result and Discussion

*I. Analysis Of Variance (ANOVA)*

Based on the experimental results obtained from Table 3, the influence of the input parameters (v), (f), and (d) on the two responses namely Ra were analyzed by analyses of variance (ANOVA) from RSM approach using MINITAB 17 software. (ANOVA) was conducted to test the significance of the model when the P-value is less than 0.05 (95 % of confidence interval), then the model terms are statistically significant. Table 4 and Figure 5 illustrate the results of ANOVA for Ra respectively.

**Table 4: Analysis of Variance of Ra**

| Source | DF | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|
| Model | 9 | 17.6001 | 1.95556 | 27.46 | 0.000 |
| Linear | 3 | 9.3377 | 3.11257 | 43.71 | 0.000 |
| V | 1 | 0.0084 | 0.00840 | 0.12 | 0.738 |
| F | 1 | 9.0533 | 9.05326 | 127.15 | 0.000 |
| D | 1 | 0.2761 | 0.27606 | 3.88 | 0.077 |
| Square | 3 | 7.7731 | 2.59103 | 36.39 | 0.000 |
| v*v | 1 | 0.0258 | 0.02585 | 0.36 | 0.560 |
| f*f | 1 | 7.7546 | 7.75461 | 108.91 | 0.000 |
| d*d | 1 | 0.0385 | 0.03855 | 0.54 | 0.479 |
| 2-Way Interaction | 3 | 0.4893 | 0.16309 | 2.29 | 0.140 |
| v*f | 1 | 0.0155 | 0.01549 | 0.22 | 0.651 |
| v*d | 1 | 0.1235 | 0.12350 | 1.73 | 0.217 |
| f*d | 1 | 0.3503 | 0.35028 | 4.92 | 0.051 |
| R-sq = 96.11% | R-sq(adj)= 92.61% | | | | |

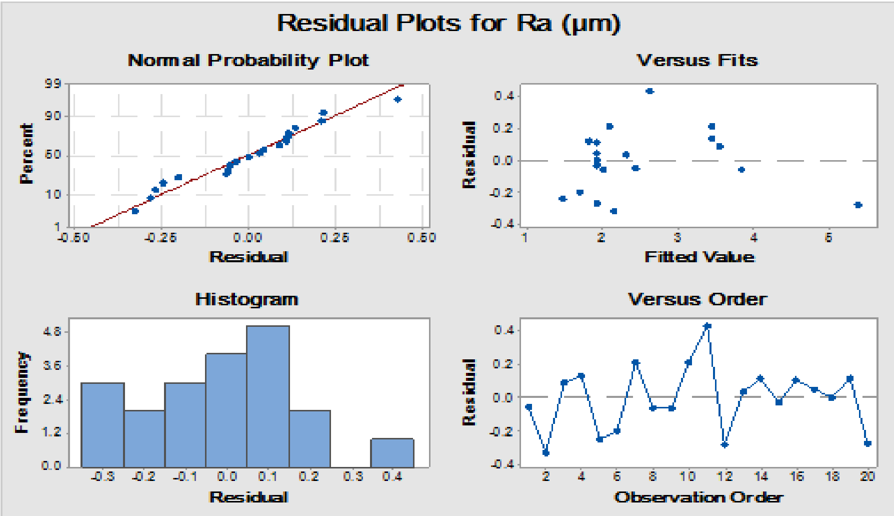


**Figure 5: Residual plot of Ra**

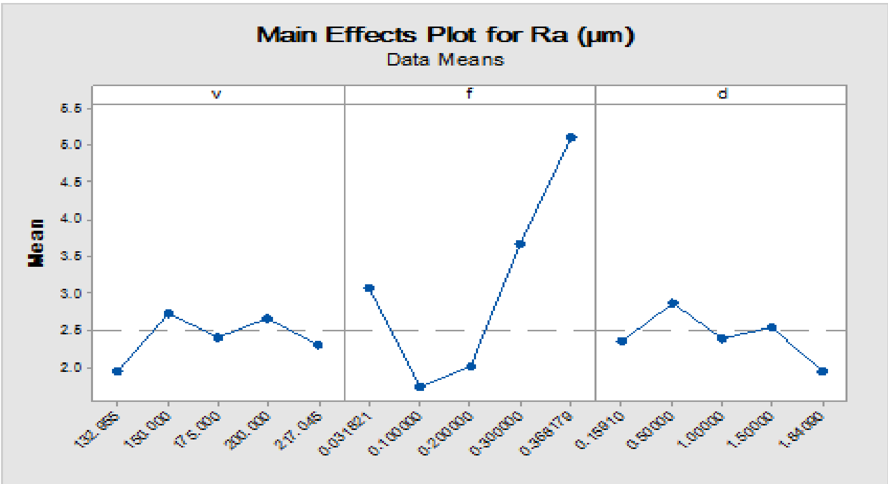


**Figure 6: Main Effects Plot for Ra (μm)**

The mathematical model for surface roughness is developed below as in Eq. (3) to represent the relationship between the input parameters (v, f, and d) and the response (Ra).

$$\mathrm{Ra}\ (\mu m) = 8.82 - 0.0362(v) - 28.46(f) - 3.27(d) + 0.000068(v*v) + 73.35(f*f) + 0.207(d*d) + 0.0176(v*f) + 0.00994(v*d) + 4.18(f*d) \quad (3)$$

The overall significance of mathematical model can be seen in Table 4, where (R-Sq) determines the fit value between the predicted and experimental results. (R-Sq(adj)) value means that the independent variable (v, f, and d) explain (92.61%) from the dependent variable (Y), and the remaining lead to another factor like a random error. Figures 5-6 illustrate the residual plot of Ra and Main Effects Plot for Ra (μm) respectively.

*II. Artificial Neural Network*

Artificial neural network (ANN) is employed to create another predictive model and compare it with experimental and RSM model results.

The experimental database is utilized to construct the neural network. About 15% of data are utilized for model testing, whereas 70% of data are utilized for model training. The typical observation of the response of the output has been presented in Table 5. Figure 7 shows the graphical representation of the proposed network.

**Table 5: Observation of the output response**

| | |
|---|---|
| Network Configuration | 3 – 10 – 1 – 1 |
| Type of transfer function | Trainlm |
| Epoches number | 1000 |
| Factor of learning rate (α) | 0.1 |
| Hidden neuron size | 10 |
| Hidden layer size | 2 |
| Number of trails for training | 14 |
| Number of trails for testing | 3 |

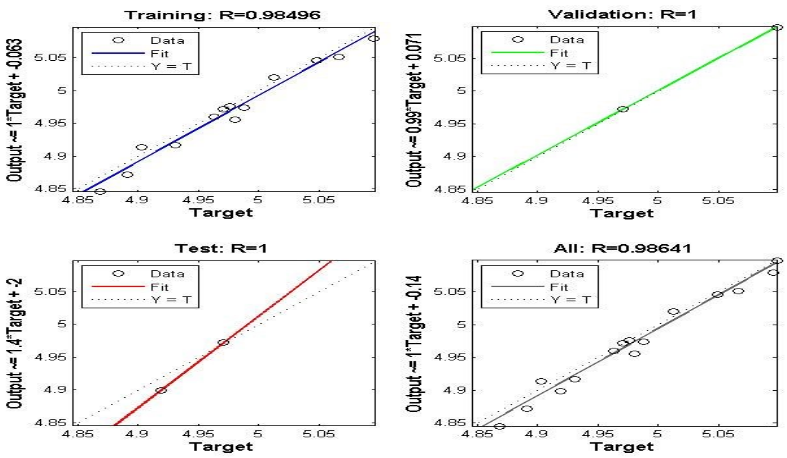


**Figure 7: Graphical representation of the proposed**

Table 6 presents the comparison between RSM and ANN results with experimental results for surface roughness (Ra). The value of Mean Square Error is calculated based on using Eq. (4) as shown below [12]:

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \quad (4)$$

Figure 8 shows the real output and net output of Ra with the number of experiments.

**Table 6: Comparison between RSM and ANN vs. experimental values for Ra**

| No. | Average Ra (μm) | Predicted Ra (μm) by RSM | RSM Error | Predicted Ra (μm) by ANN | ANN Error |
|---|---|---|---|---|---|
| 1 | 2.387 | 2.437 | -0.050 | 2.387 | 0.0 |
| 2 | 1.827 | 2.150 | -0.323 | 1.827 | 0.0 |
| 3 | 3.650 | 3.559 | 0.091 | 3.650 | 0.0 |
| 4 | 3.583 | 3.448 | 0.135 | 3.583 | 0.0 |
| 5 | 1.243 | 1.486 | -0.243 | 1.243 | 0.0 |
| 6 | 1.497 | 1.696 | -0.199 | 1.497 | 0.0 |
| 7 | 3.660 | 3.445 | 0.215 | 3.660 | 0.0 |
| 8 | 3.773 | 3.831 | -0.058 | 3.773 | 0.0 |
| 9 | 1.947 | 2.007 | -0.060 | 1.619 | 0.328 |
| 10 | 2.303 | 2.090 | 0.213 | 2.173 | 0.139 |
| 11 | 3.067 | 2.634 | 0.433 | 3.067 | 0.0 |
| 12 | 5.093 | 5.373 | -0.280 | 5.093 | 0.0 |
| 13 | 2.350 | 2.314 | 0.036 | 2.350 | 0.0 |
| 14 | 1.953 | 1.836 | 0.117 | 1.953 | 0.0 |
| 15 | 1.897 | 1.929 | -0.032 | 1.985 | -0.088 |
| 16 | 2.040 | 1.929 | 0.111 | 1.985 | 0.055 |
| 17 | 1.977 | 1.929 | 0.048 | 1.985 | -0.008 |
| 18 | 1.930 | 1.929 | 0.001 | 1.985 | -0.055 |
| 19 | 2.043 | 1.929 | 0.114 | 1.985 | 0.058 |
| 20 | 1.660 | 1.929 | -0.269 | 1.985 | -0.325 |

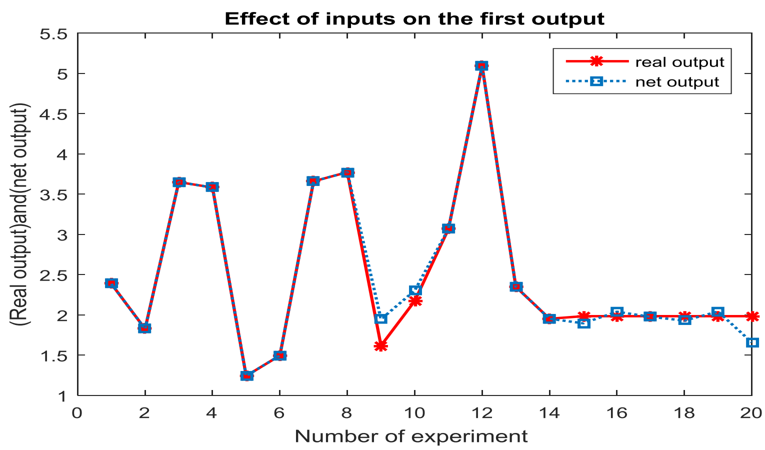


**Figure 8: The Real output and net output of Ra**

## 5. Conclusions

i. It is concluded from the investigations mentioned above that the central composite design produces a prediction that comparatively accurate surface roughness averages (Ra).
ii. The lower surface roughness value can be obtained when v = 150 (m/min), f = 0.1 (mm/r), and d = 1.5 (mm).
iii. From RSM model, feed is the considerable factor that affecting on Ra followed by the depth of cut and cutting speed.
iv.It is clear that the maximum error between the experimental value and ANN model lies between (0.3277 to -0.325) for Ra, which is less than the RSM model significantly. However, if the test patterns number will be increased then this error can be further minimized. RSM model residual error for Ra is found to be (0.433 to -0.323).

v. The proposed RSM and ANN prediction model sufficiently predict Ra accurately. However, ANN prediction model is found to be better compared to RSM model.

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