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Modelling of Surface Roughness Performance of Coated Cemented Carbide Groove Cutting Tool Via Artificial Neural Networks

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ABSTRACT

The objective of the presented study is to model the effects of cutting speed, feed rate and depth of cut on the surface roughness (roughness average, Ra) in the turning process carried out by the grooving cutting tool by using Artificial Neural Network (ANN). To realize this aim, twenty seven specimens are machined at the cutting speeds of 100, 140 and 180m/min, feed rates of 0.05, 0.15 and 0.25mm/rev, and cutting depth of 0.6, 1.3 and 2mm in wet conditions. Data from these experiments are used in the training of ANN. When we compare the experimental results with the ANN ones, it is observed that proposed method is applied with an error rate of 8.14% successfully.

Key Words: S*urface roughness, ANN, turning, modelling, groove cutting tool.*

1. INTRODUCTION

The prediction and modelling of surface roughness, which constitutes an important part of machinability studies, are very complicated. For this reason, ANN and statistical experimental design methods play an important role in solving this problem.

RSM and Taguchi, two of the statistical methods, stand one step further than others. Researchers [1-10] widely prefer RSM as it can model the factors' main, interaction and quadratic effects at high correlation coefficients with less number of tests and realize the optimisation of the system. The main limitation of this method is that it can only examine the effects of quantitative process parameters on the quality characteristic. Taguchi has perhaps been the most widely used method in the last decade [11-19]. The main reason for this is that it can determine the effects of factors and their interactions on the quality characteristic without the need for complex mathematical calculations with the least number of tests and realize the system optimization. Its main disadvantage, compared to other methods, is that it cannot provide a predictive model.

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On the contrary, ANNs are the data-based systems that are created by connecting the artificial nerve cells in the form of layers. The method intends to be used to solve complex problems with the help of simplified models by imitating human brain skills such as learning and very quick decision-making under different conditions. The most important advantage of ANN applications, which are used in the fields such as classification, clustering, regression and prediction of time series, is to find solutions to the problems by training the network without the need to use complex models. Therefore, it can be said that techniques of artificial intelligence have the advantages that classical methods cannot provide when the uncertainties are taken into consideration [20].

Surface roughness modelling studies carried out via neural networks approach are evaluated below:

Sarma and Dixid [21] investigated the performance of mixed oxide ceramic tool in the turning of grey cast iron in dry and air cooled conditions in terms of surface roughness and tool life criteria. As a result of the analysis using neural networks, it is observed that air cooling decreased the tool wear significantly at high cutting speeds.

Özel and Karpat [22] modelled the surface roughness and tool wear with neural networks by using experimental data in the finish turning of hardened steels of AISI H13 and 52100 with CBN. Cutting edge geometry, work piece hardness, feed rate and cutting speed factors were chosen as independent variables. Also, proposed model was compared with regression model, and it was observed that the proposed method better estimates the roughness and wear behaviour. It was obtained that the decrease in feed rate slightly accelerated the occurrence of tool wear with better surface roughness. On the other hand, it was observed that tool wear went up with the increase of cutting speed whereas better surface roughness was obtained. Similarly, the increase in the work piece hardness resulted in better surface roughness and increasing tool wear.

Risbood et al [23] studied the machinability of low-carbon steel with HSS and carbide tools in wet and dry conditions according to the criteria of surface roughness and dimensional accuracy. Surface roughness was modelled in the experiments conducted at the different levels of cutting speed, feed rate and cutting depth through obtaining radial vibration of the tool holder and acceleration of cutting force as feedback via neural networks method. Accordingly, in the experiments performed with carbide cutting tools, it was observed that up to a specific feed rate, surface roughness improved with the increase of feed rate; however, same situation did not take place in HSS tool. Dimensional error was only observed in the turning of small diameter parts. While the measuring of radial component of cutting force via a dynamometer was needed in the dimensional deviation, the use of radial vibration acceleration as feedback element was sufficient in surface roughness

Karayel [24] carried out a software that predicts the effects of cutting speed, feed rate and dept of cut on the surface quality in the turning of St50.2 steel with cemented carbide cutting tool. Roughness average (Ra), maximum profile height (Rt) and root mean square roughness (Rq) as roughness parameters were modelled by using multi-layer feed forward neural networks. As a result of the analyses, it was obtained that feed rate parameter was more dominant than the others and roughness went up dramatically with its increase, and cutting speed had a critical value in the achievement of the best surface roughness.

Abburi and Dixit [25] developed a knowledge-based system by using neural networks and fuzzy set theory in the turning of low-carbon steel with HSS and carbide cutting tool. The effects of cutting speed, feed rate and depth of cut parameters on surface roughness were modelled for dry and wet conditions and prediction results were compared with the neural networks method. Accordingly, two methods were compared with a specified accuracy determined with the criteria of root mean squared error and percentage of prediction. It was observed that the performance of proposed method was slightly worse than neural networks, however the extrapolation skill of the system was better than neural networks when some parameters were outside a certain range.

Ahmari [26] examined the tool life, cutting force and surface roughness quality characteristics in the turning of AISI 302 austenitic steel with carbide cutting tool. The results of twenty eight experiments conducted in different levels of cutting speed, feed rate, depth of cut and tool nose radius factors were evaluated by using neural networks, response surface and regression analysis methods. Consequently, it was reported that Neural network method could predict the quality characteristics better than regression and response surface methodology, and tool life and cutting force were predicted better than regression analysis in the response surface method.

Ho et al. [27] determined the relation between surface image and surface roughness, and modelled the effect of cutting parameters on surface roughness via adaptive neuron-fuzzy inference system. The effects of Cutting speed, feed rate and dept of cut on the surface roughness were predicted by using grey level of surface image in the machining of S45 steel material with tungsten carbide tool.

Davim et al. [28] investigated the machining of free machining steel with cemented carbide cutting tool in terms of R_a and R_t. They modelled the results of experiments conducted in the different levels of feed rate, cutting speed and cutting depth based on Taguchi's L27 orthogonal array via ANN. Accordingly, a high nonlinearity between surface roughness and cutting conditions was obtained. It was determined that cutting speed and feed rate factors were more effective on the change of surface roughness than depth of cut, and roughness tended to go down with the increase of cutting speed and decrease of feed rate as expected.

Nearly all machinability studies evaluate the surface roughness performance in the machining of the specimens with different materials via left hand side cutting tool of different material and geometries in longitudinal turning motion. In contrast, in this study, surface roughness performance of groove cutting tool, which allows grooving, cutting and profile turning with only one tool and brings big flexibility to turning operations, has been investigated for the first time. This will allow the manufacturing of a whole workpiece with one cutting tool so that the tool change and tool setting time can be reduced dramatically. In other words, machining time can also be reduced by the proposed system especially in mass production manufacturing systems. AISI 1040 steel, one of the reference materials in the machinability studies, was chosen in particular as work piece. For this purpose, the effects of cutting speed, feed rate and depth of cutting parameters on the surface roughness have been investigated via ANN.

2. EXPERIMENTAL STUDY

In this study, AISI 1040 steel bar with a dimension of Ø65x60mm is employed as test specimen, and its chemical content is given in Table 1.

Table 1. Chemical composition of AISI 1040 steel (W%).

C	Mn	Si	S	P	Cr	Ni	Cu
0.40	0.70	0.22	0.006	0.008	-	-	-

Specimens are machined in the Goodway GLS 150 CNC turning centre which is programmed according to Fanuc control unit (Oi Tc), and has a maximum spindle speed and spindle power of 6000rev/min and 5.5kw, respectively (Figure 1).

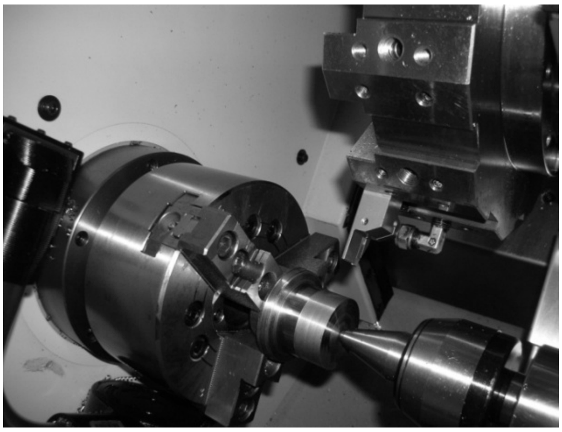
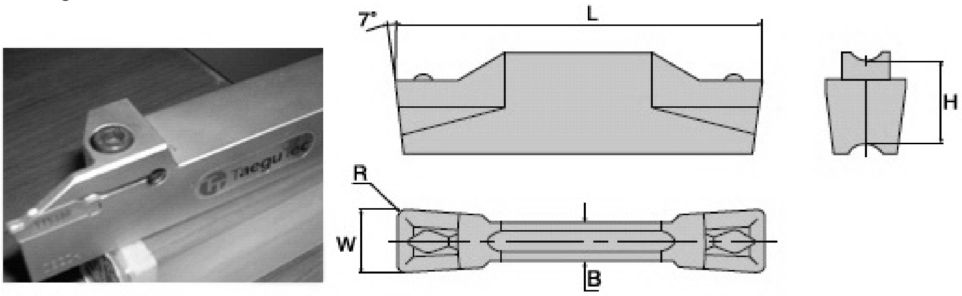


Figure 1. Image of specimen during the turning process.

TiAlN coated cemented carbide cutting tool (Tool holder order code: TCLAMP TTER 2020-3T20 and insert order code: TDT3E-0.4TT5100) with CVD method from Teagutec inc. is selected. Tool's approach angle, front clearance angle and nose radius are 90°, 7° ve 0.4mm, respectively. Image and detailed dimensions of the cutting tool are given in Figure 2. In the experiment, cutting speeds of 100, 140 and 180m/min, feed rates of 0.05, 0.15 and 0.25mm/rev and cutting depths of 0.6, 1.3 and 2mm are used as factor levels in wet conditions.



Insert Seat Size	W±0.05	R	B	L	H
3	3.0	0.4	2.2	20.0	4.7

Figure 2. Image and detailed dimensions of the cutting tool.

Specimen is turned to diameter of Ø64mm with TiN coated cemented carbide left hand side cutting tool through longitudinal turning before the machinability test with groove cutting tool (region 1 in Figure 3). Groove cutting tool machines region 2 in Figure 3 with plunge motion to the desired diameter and later with longitudinal turning based on the experiment plan appropriate to its nature of use. Surface roughness measurements are carried out in this region. In order to facilitate measuring process, left hand side cutting tool is recalled in the CNC part program and region 3 is machined.

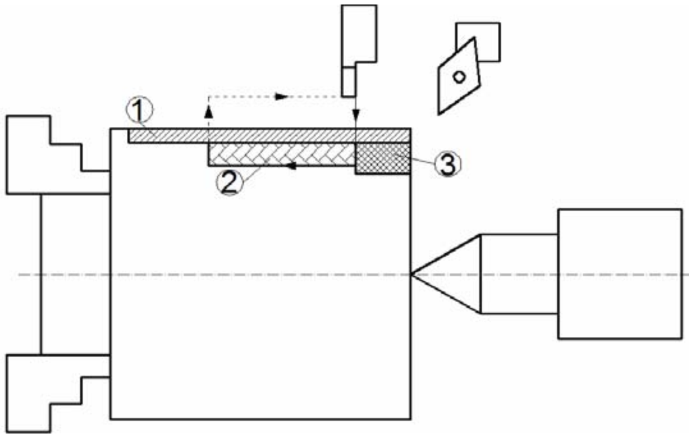


Figure 3. The machined parts of the specimen.

Surface roughness measurements are carried out using a stylus type Mitutoyo Surftest SJ-301 with the sampling and cut off length of 5 and 0.8 mm, respectively. Measurements (R_a, µm) are repeated three times and their mean values (Ra_{mean}) are used in the analyses.

3. ANN MODEL

ANN has been finding a wide application area in different fields in recent years. In the literature, many neural network architectures are used. In this study, the feed-forward back-propagation algorithm, suitable for engineering applications, is employed. The advantage of this algorithm is its high learning capacity and simplicity. These algorithms are named as back propagation as they reduce the errors to the back and from output to input.

Back propagation learning rule is used to recalculate the weights in each layer according to the existing error level in network output [29]. While there are three layers, input, hidden and output, in a back propagation network model, it is possible to increase the number of hidden layers according to the characteristics of the problem (Figure 4)

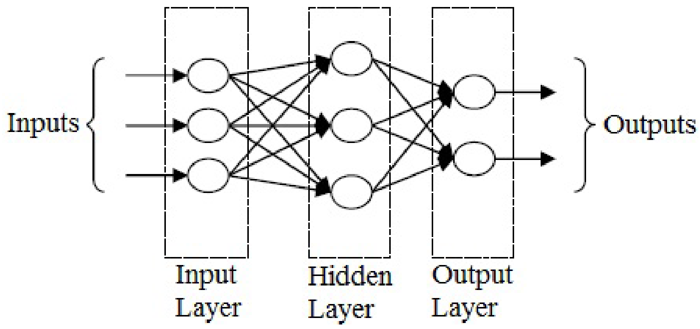


Figure 4. Architecture of multi-layer back propagation ANN [30].

For a multi layered network given in Figure 4, input value of any unit is expressed as a weighted sum of the values coming from other layers (one hidden and one input layer)

$$y_j = \sum_{i}^{N} x_i w_{ij} \tag{1}$$

Where w_{ij} is the weight between the j_{th} neuron and the i_{th} neuron in the preceding layer and x_i is the output of the i_{th} neuron in the preceding layer. The output of the unit is calculated by using a nonlinear function as below.

$$y_j = f(y_j) \tag{2}$$

The output of the unit is calculated as in Eq. 3 using the activation function [30].

$$y_j = \frac{1}{1 + e^{-[\sum_i^N x_i w_{ij}]}} \tag{3}$$

In this study, the input and output values obtained from the experimental results (Table 2) are initially normalized within 0-1. The values to be used are tried in order to find the proper network. The most appropriate network architecture is chosen as the network where the lowest error value is obtained in the training and testing phases as seen in Figure 5. The mean square error graph is given in Figure 6 according to the iteration number. There are two hidden layers and a neuron in each of them. There are three neurons (cutting speed, feed rate and dept of the cut) in the input layer and one value (surface roughness) in the output layer (Figure 7). Twenty two values are chosen to be used in training phase and five as test phase. As shown in Figure 10, results of trial no 4, 9, 12, 18 and 27 are used in the test phase, and the rest are in the training phase.

Table 2. Experimental parameters and results.

Trial no	Cutting speed	Feed rate	Depth of cut	R_{a1}	R_{a2}	R_{a3}	Ra_{mean}
1	100	0.05	0.6	0.4	0.4	0.38	0.393
2	100	0.05	1.3	0.45	0.39	0.35	0.397
3	100	0.05	2	0.55	0.59	0.57	0.57
4	100	0.15	0.6	0.78	0.78	0.83	0.797
5	100	0.15	1.3	1.16	0.92	0.9	0.993
6	100	0.15	2	0.74	0.8	0.77	0.77
7	100	0.25	0.6	1.2	1.18	1.16	1.18
8	100	0.25	1.3	1.28	1.3	1.3	1.293
9	100	0.25	2	1.5	1.49	1.46	1.483
10	140	0.05	0.6	0.39	0.34	0.39	0.373
11	140	0.05	1.3	0.42	0.32	0.41	0.383
12	140	0.05	2	0.5	0.54	0.46	0.5
13	140	0.15	0.6	0.55	0.59	0.58	0.573
14	140	0.15	1.3	0.63	0.68	0.69	0.667
15	140	0.15	2	0.84	0.8	0.78	0.807
16	140	0.25	0.6	1.08	1.05	1.05	1.06
17	140	0.25	1.3	1.06	1.08	1.06	1.067
18	140	0.25	2	1.4	1.42	1.39	1.403
19	180	0.05	0.6	0.32	0.33	0.31	0.32
20	180	0.05	1.3	0.33	0.34	0.34	0.337
21	180	0.05	2	0.4	0.42	0.41	0.41
22	180	0.15	0.6	0.49	0.47	0.4	0.453
23	180	0.15	1.3	0.58	0.59	0.59	0.587
24	180	0.15	2	0.89	0.92	0.8	0.87
25	180	0.25	0.6	0.9	0.9	0.9	0.9
26	180	0.25	1.3	1.01	1.02	1.01	1.0133
27	180	0.25	2	1.3	1.27	1.14	1.236

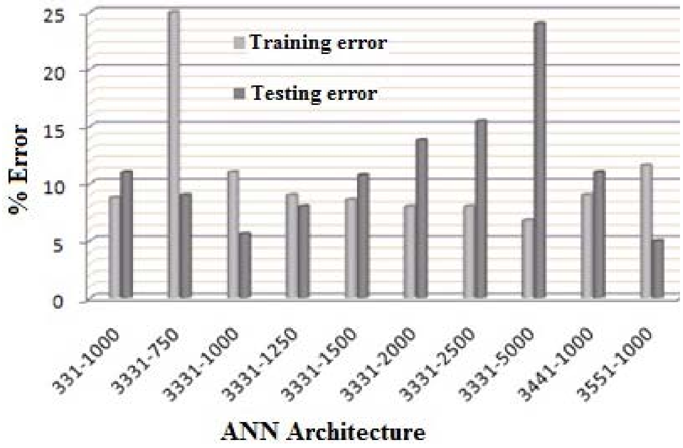


Figure 5. % Error values of the different ANN models.

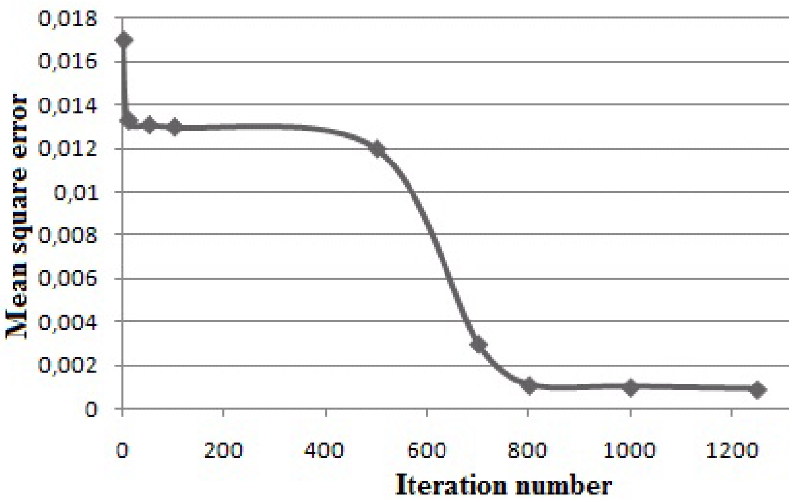


Figure 6. The graph of mean square error based on iteration number.

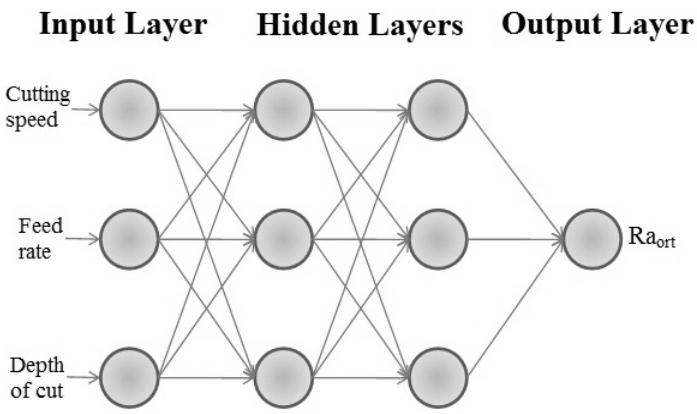


Figure 7. Architecture of ANN.

Iteration number, training rate and momentum values are chosen as 1250, 0.7 and 0.6, respectively. Training phase is created before testing phase and while the average error of training phase is 8.97%, testing phase's one is 8.14%.

Surface roughness values obtained from the testing phase are compared with experimental results in the Figure 8 and 9, and it is obtained that predicted values show good agreement with observed ones.

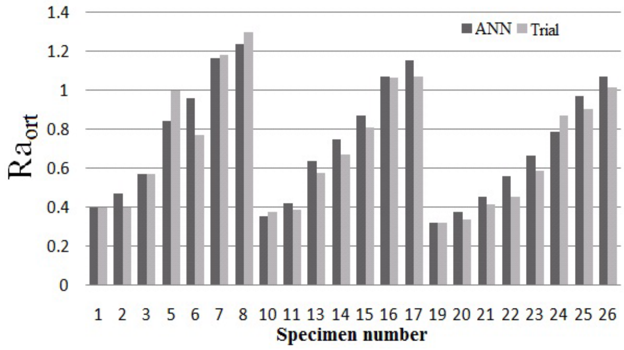


Figure 8. Comparison of the experimental and ANN results at the training phase.

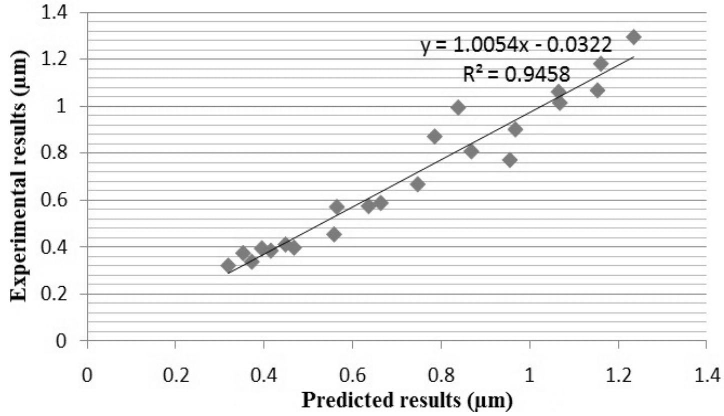


Figure 9. Comparative diagram of the experimental and ANN roughness results.

As a result of the testing phase, it is seen that surface roughness values in all desired cutting parameters can be predicted with small error rates (Figure 10). In this manner, thanks to proposed method, the effects of basic cutting parameters, cutting speed, feed rate and depth of cut on the change of surface roughness are predicted with an error rate of 8.14%.

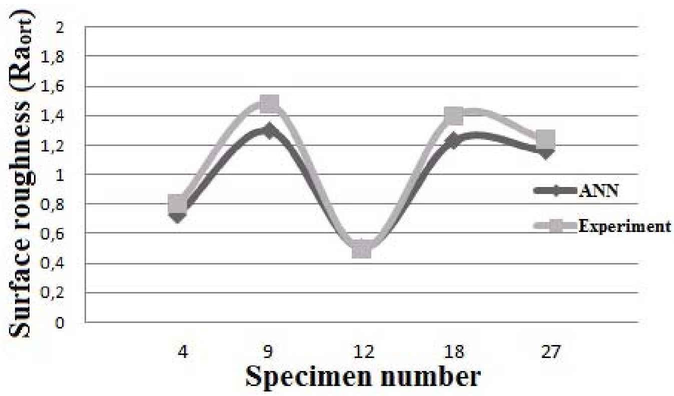


Figure 10. Comparison of experimental and ANN results of the specimens at test phase.

In addition to modelling, main effects of each factor based on experiment results in Table 2 are given graphically in Figure 11. It is observed that surface roughness correlates negatively with cutting speed and positively with feed rate and depth of cut. It is evident from the graph slope that feed rate is more significant in roughness change than the others.

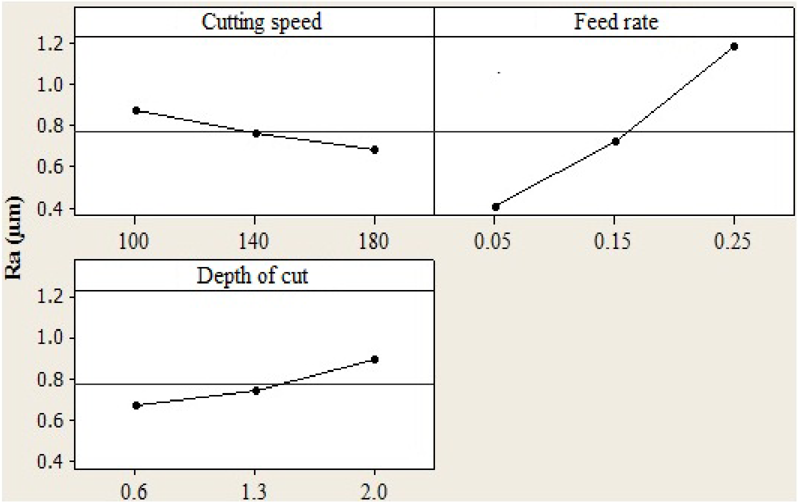


Figure 11. Main effects graph of factors.

4. CONCLUSIONS

In the study, the effects of cutting speed, feed rate and depth of cut factors on the surface roughness in the machining of AISI 1040 steel with groove cutting tool in the turning operation with plunging and longitudinal turning motions are investigated via ANN method. Accordingly, following conclusions are drawn:

- When main effects graph of factors is taken into account, it is observed that surface roughness correlates negatively with cutting speed and positively with feed rate and depth of cut, and feed rate has more significant effect than cutting speed and depth of cut.
- It is obtained that effective results can be obtained through modelling surface roughness with ANN, and surface roughness can be predicted for desired cutting conditions.
- Minimum surface roughness is obtained in the nineteenth trial (Cutting speed: 180m/min, feed rate: 0.05mm/rev and depth of cut: 0.6mm) according to both ANN and experimental results as 0.32µm.
- The proposed tool can be used in low and medium carbon steels both in rough and finish machining so that it can provide flexibility and time save in manufacturing. Furthermore, it has been observed that the roughness values obtained in high cutting speed, low feed rate and depth of the cut are of grinding quality.
- Thanks to proposed method, the effects of basic cutting parameters, cutting speed, feed rate and depth of cut on the change of surface roughness are predicted with an error rate of 8.14%.
- Surface roughness performance of groove cutting tool is examined for the first time in this study. As a further work, we aim to compare the proposed cutting tool with classical left hand side cutting tool in terms of surface roughness, tool life, cutting force and power consumption quality characteristics in the turning of different materials.

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