Roughness Assessment for Machined Surfaces in Turning Operation Using Neural Network

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ABSTRACT

Feed forward artificial neural network has been applied to predict the quality of turned surfaces for two types of coated carbide inserts. Four networks were proposed for each insert. The networks have been trained and tested using a former experimental data. The input data, represented by cutting parameter values, and output data, represented by surface roughness, were fed into the network model. Each network has three layers adopted for prediction. The first one is the input layer which involves cutting parameters: cutting speed, feed rate, and depth of cut; the second layer is hidden layer consisting of two hidden layers. The third layer of the network is the output layer which gives the surface roughness value. Levenberg - Marquardt algorithm is used in the back-propagation algorithm to train these networks. The best result was obtained for networks which have (12) neurons in the first hidden layer and (9) neurons in the second hidden layer. These networks had given $R^2 = 0.9902$ and mean square error = 0.0033 for the first insert, whereas, for the second insert, $R^2 = 0.9892$ and mean square error = 0.0023. These networks were used to predict the optimum cutting parameters which give minimum surface roughness.

Keywords: neural networks, machining, turning operation, cutting parameters and surface roughness.

تخمين خشونة السطوح المشغلة في عملية الخراطة باستخدام الشبكة العصبية

الخلاصة

استخدمت الشبكة العصبية للتنبؤ بخشونة السطح المشغل بعملية الخراطة و لنوعين من عدد القطع الكاربيدية المطلية. اقترحت اربع شبكات بكل عدة. دربت هذه الشبكات واختبرت باستخدام بيانات تجارب سابقة. البيانات المدخلة للشبكة هي متغيرات عملية القطع (سرعة القطع و التغذية وعمق القطع) اما المخرجات هي خشونة السطح. كل شبكة تتكون من ثلاث طبقات دربت لتعطي قيمة الخشونة. الطبقة الأولى تعتبر طبقة الأدخال و تتضمن متغيرات عملية القطع(سرعة القطع والتغذية وعمق القطع)، أما الطبقة الثانية تتكون من طبقتين مخفيتيين. الطبقة الثالثة هي طبقة الأخراج و التي تعطي قيمة الخشونة السطحية. استخدمت خوارزمية لفنبرغ – ماركوارت ضمن خوارزمية التغذية العكسية لتدريب الشبكات. افضل نتيجة كانت من الشبكة العصبية التي تحوي على طبقة مخفية أولى بعدد 12 خلية عصبية وطبقة مخفية ثانية بعدد 9 خلايا عصبية. اعطت هذه الشبكات$R^2 = 0.9902$ ومعدل الخطأ التربيعي =0.0033 للعدة الأولى، بينما $R^2 = 0.9892$ ومعدل الخطأ التربيعي =0.0023 للعدة الثانية. استخدمت هذه الشبكات للتنبؤ بأفضل ظروف قطع للحصول على اقل خشونة سطحية.

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INTRODUCTION

Surface quality is an important requirement for many machine parts. The surface quality is affected by machining process and parameters such as the geometry of selected cutting tool, coating method, the type of material, machine and cutting parameters [1, 2]. The machining process is more complex, and therefore, it is difficult to develop a comprehensive model involving all cutting parameters [3]. The optimization of cutting parameters is required for efficient use of machine tools. So it is necessary to find a suitable optimization method in which the optimum values of cutting parameters for minimizing surface roughness can be found [4].

Many researches were conducted to consider the surface roughness using different approaches. Nalbant et al. [1]had used both uncoated PVD and CVD coated cemented carbide insert to machine AISI 1030 steel with different cutting parameters by developing artificial neural network (ANN) using back-propagation scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) algorithms. The actual and predicted data were compared by statistical error analyzing methods. Their network model has one hidden layer with 9 neurons, and it has produced $R^2 = 0.9998$ and root mean square error = 0.00265.

IlhanAsiltürk and Mehmet Çunkas[3] had developed an effective approach based on artificial neural networks and multiple regression to predict the surface roughness for AISI 1040 steel. Full factorial experimental design (27 trails) is implemented to investigate the effect of the cutting parameters, i.e. cutting speed, feed rate, and depth of cut on the surface roughness.

Predictive neural network modeling is used by TugrulÖzel and YigitKarpat[5] to predict surface roughness and tool wear in finish hard turning. Also, an exponential model has been developed. These two models were compared, and the neural network model was better than the exponential regression model for prediction. They concluded that decreasing the feed rate resulted in better surface roughness, but increasing both cutting speed and workpiece hardness resulted in better surface roughness. Vishal S. Sharma et al [6] had used a different turning cutting parameters such as approaching angle, speed, feed and depth of cut to construct model using neural networks. This model is used for estimation the surface roughness and cutting forces for hard turning.

MilošMadic and MiroslavRadovanovic[7] applied an artificial intelligence (AI) approach to predict the surface roughness in CO_2 laser cutting. The experimental results that were used to develop ANN model, had been obtained from Taguchi's L25 orthogonal array. Statistical results indicate that the ANN model can predict the surface roughness with good accuracy. Chinnasamy Natarajan et al [4] has designed an artificial neural network (ANN) model to predict the surface roughness, through feed forward back-propagation network using Matlab (2009a) software for the data obtained. Comparison of the experimental data and ANN results show that there is no significant difference and ANN has been used confidently.

Cemal et al. [8]developed three mathematical models (linear, second order and exponential) to examine the effects of cutting parameters (cutting speed, feed rate and depth of cut) onto the surface roughness. In additional, they investigated the influence of two well-known coating layers onto the surface roughness.

In the present work, feed-forward neural networks were proposed to predict the surface roughness from the cutting parameters (cutting speed, feed rate and depth of cut). The neural models are trained and tested using experimental data obtained from reference [8].

Neural networks

A neural network is a parameterized non-linear model which can be used to perform regression, in which case, a very flexible, non-linear function is fitted to experimental data. The details of this method have been reviewed in [9, 10].

Neural networks are basically connectionist system, in which various nodes called neurons are interconnected. A typical neuron receives one or more input signals and provides an output signal depending on the processing function of the neuron. This output is transferred to connected neurons in varying intensities, the signal intensity being decided by the weights. Feed forward networks are commonly used. A feed forward network has a sequence of layers consisting of a number of neurons in each layer. The output of neurons of one layer becomes input to neurons of the succeeding layer. The first layer, called an input layer, receives data from the outside world. The last layer is the output layer, which sends information out to users. Layers that lie between the input and output layers are called hidden layers and have no direct contact with the environment. Their presence is needed in order to provide complexity to network architecture for modeling non-linear functional relationship. After choosing the network architecture, the network is trained by using back propagation algorithm, where back propagation algorithm is the efficient optimization method used for minimizing the error through weight adjustment [10]. The trained neural network has to be tested by supplying testing data.

Experimental work and results

The experiments data were taken from reference paper[8]. All the experiments were applied in dry conditions on a conventional lathe machine with cutting speed range of120-200 m/min and feed rate range of 0.12–0.22 mm/min. Cold-work tool steel AISI P20has been used as wrokpiece material, with diameter of 70 mm and length of 300 mm. This material has good machinability even if it was hardened and tempered. Table (1 gives the chemical composition of the used material. Two cutting tools, CNMG 120408 (with an ISO designation) carbideinserts, used in the experiments with completely same geometry and substratebut different coating layers [8].

Table (1)Wrokpiece material chemical composition

ISO/DIN	AISI	C	Mn	Cr	Mo	V	Si
1.2738	P20	0.37	1.40	2.00	0.20	–	0.30

The first insert has been coated with three layers, a TiCN underlayer,an intermediate layer of Al_2O_3 and aTiN outlayer, all deposited by chemical vapor deposition (CVD).The second insert hasan extremely hard submicron substrate having high fracture toughness. It was coated using the physical vapor deposition (PVD) method with a thin TiAlN layer (3 ± 1 μm). Because the PVD coating process can be applied at considerably lowtemperatures, the substrate toughness doesn't decrease if it is compared to that in CVD coating technique.

The experiments for the two inserts were applied individually using different cutting parameters (cutting speed, feed rate and depth of cut). Table (2shows the experimental data.

Table (2)The experimental data for insert 1 and insert 2

cutting speed (v)	feed (f) $\frac{mm}{rev}$	depth of cut (a)mm	surface roughness (Ra) μm (insert 1)	surface roughness (Ra) μm (insert 2)
120	0.12	1	0.869	0.824
120	0.12	1.5	1.091	0.860
120	0.12	2	1.104	0.984
120	0.18	1	1.620	1.112
120	0.18	1.5	1.628	1.270
120	0.18	2	1.632	1.379
120	0.22	1	2.576	1.845
120	0.22	1.5	2.582	1.981
120	0.22	2	2.629	2.232
160	0.12	1	0.816	0.802
160	0.12	1.5	0.859	0.888
160	0.12	2	0.873	0.939
160	0.18	1	1.391	1.287
160	0.18	1.5	1.420	1.546
160	0.18	2	1.452	1.560
160	0.22	1	1.998	1.681
160	0.22	1.5	2.029	1.722
160	0.22	2	2.086	1.901
200	0.12	1	0.766	0.692
200	0.12	1.5	0.785	0.786
200	0.12	2	0.864	0.834
200	0.18	1	1.284	1.284
200	0.18	1.5	1.371	1.324
200	0.18	2	1.428	1.509
200	0.22	1	1.766	1.572
200	0.22	1.5	1.929	1.783
200	0.22	2	1.973	1.883

To model the relation between the dependent variable, surface roughness, and the independent variables, predictors, cutting parameters, the neural network model has been proposed to develop this relation. Four feed-forward neural networks have been proposed for each insert under MATLAB® environment.

All the proposed networks have the same structure. They have one input layer, two hidden layers and one output layer. The input layer consists of three neurons and taking the cutting speed, feed rate and depth of cut as inputs. The output layer has one neuron to give the corresponding surface roughness, whereas the hidden layer specifies the difference between the proposed networks. In other word, the differences between these networks are the number of neurons in the first and second hidden layers. The symbol m has been used to represent the number of neurons for the first hidden layer and the symbol n for the number of neuron in the second hidden layer. For the first network, m=28 neurons are used in the first hidden layer and n=7 neurons for the second hidden layer, whereas for the three other networks the first hidden layers have 12, 17 and 9 neurons, respectively. Finally, the second hidden layers for the last three networks have 9, 18 and 18 neurons, respectively. Figure (1shows the proposed neural network model of this work. The hyperbolic tangent function (tanh) was used as an activation function for all neurons. The back-propagation training algorithm based on Levenberg-Marquardt algorithm is used to train these networks. The Levenberg-Marquardt algorithm is seems to be the fastest training method for training feed-forward neural network. In addition, it has efficient implementation in MATLAB® software, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment [12]. The training algorithm parameters used in this work are given in Table .

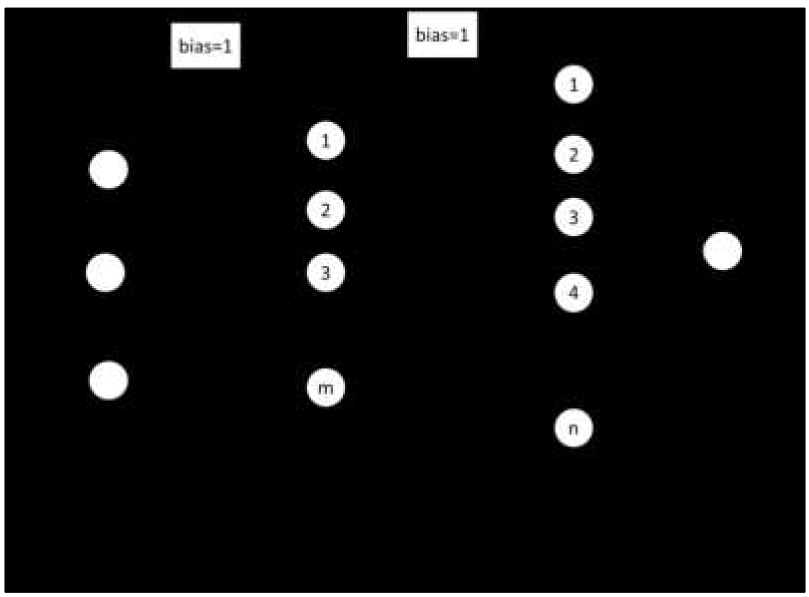

Figure (1) The proposed neural network model

These networks have been trained using the experimental data shown in Table (2. The shaded cells shown in the table are excluded from the training and they were used to verify the trained networks.

Table lists the correlation coefficient and the mean square error of the networks outputs and the associated experimental surface roughness for the data used in the training.

Table (3)Levenberg-Marquardt training algorithm parameters

Parameter Name	Parameter value
Epochs	5000
Goal	1.00E-08

Parameter Name	Parameter value
max fail	1000
memory reduction	1
minimum gradient	1.00E-08
adaptive value μ	0.001
adaptive value decrement μ_{dec}	0.1
adaptive value increment μ_{inc}	10
maximum of the adaptive value μ_{max}	10000000000
Learning rate	0.0005
learning rate increment	1.005

Table (4)Networks correlation coefficient and the mean square error for the training data

insert no	m	n	R^2	mse
1	28	7	0.9994	0.0002
1	**12**	**9**	**0.9988**	**0.0005**
1	17	18	0.9994	0.0002
1	9	18	0.9926	0.0026
2	28	7	0.9996	0.0001
2	**12**	**9**	**0.9994**	**0.0001**
2	17	18	0.9837	0.0030
2	9	18	0.9982	0.0003

After finishing the training phase, the networks are considered ready to be used to predict the surface roughness. The data in the shaded cells of Table (2 are involved and used to compute the correlation coefficients and the mean square error along with the data used in the training phase. Table liststhe correlation coefficient and the mean square error of the networks outputs and the associated experimental surface roughness for all data. It is obvious from the two tables (

Table and Table) that the network which has first hidden layer of 12 neurons and second hidden layer of 9 neurons is the best one for the two types of inserts. These two networks are represented in the two tables by the shaded cells. Figure (2)The network response with respect to experimental training sets for m=12 and n=9 network of insert 1. and Figure (4 shows the network response with respect to experimental training sets for m=12 and n=9 network of insert one and two, respectively. Figure (3 and Figure (5 show the linear regression and correlation coefficient (R-value) between the network response (m=12 and n=9) and the experimental data for training sets of insert one and two, respectively. Figure (6 and Figure (8the network response with respect to all experimental sets for m=12 and n=9 network of insert one and two, respectively. Figure (7 and Figure (9) The linear regression and correlation coefficient (R-value) between the network response (m=12 and n=9) and the experimental data for all sets of insert 2.the linear regression and correlation coefficient (R-value) between the network response (m=12 and n=9) and the experimental data for all sets of insert 2show the linear regression and correlation coefficient (R-value) between the network response (m=12 and n=9) and the experimental data for all sets of insert one and two, respectively.

It can be mentioned that the correlation coefficients of reference[8] which are given through three mathematical models (linear, second order and exponential) are lower than those given by the network of (m=12 and n=9) for the two inserts,

Table shows those values. From

Table it is shown that the best R^2 obtained from the mathematical models were0.98 and 0.95 for insert 1 and insert 2, respectively. Where as, Table shows that R^2values were 0.99 and 0.98 for insert1 and insert 2, respectively. This means that the neural network gave a better regression model than the mathematical models used in reference [8].

Table (5)networks correlation coefficient and the mean square error for all data

insert no	M	n	R^2	mse
1	28	7	0.9272	0.0267
1	**12**	**9**	**0.9902**	**0.0033**
1	17	18	0.9752	0.0085
1	9	18	0.9906	0.0030
2	28	7	0.9180	0.0158
2	**12**	**9**	**0.9892**	**0.0023**
2	17	18	0.7877	0.0411
2	9	18	0.9392	0.0157

Table (6)The correlation coefficients of reference [8]

Model type	R^2	
	Insert 1	Insert 2
Liner	0.93	0.94
Second order	0.98	0.95
Exponential	0.98	0.95

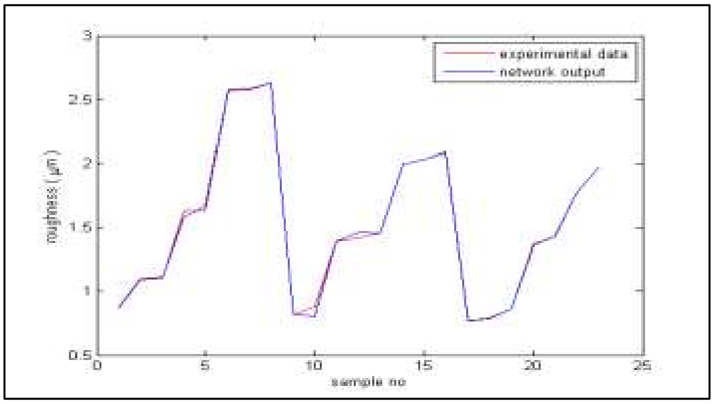

Figure (2)The network response with respect to experimental training sets for m=12 and n=9 network of insert 1.

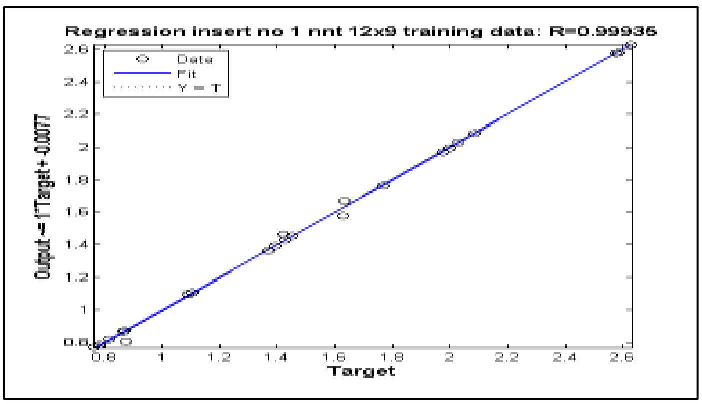

Figure (3)The linear regression and correlation coefficient (R-value) between the network response(m=12 and n=9) and the experimental data for training sets of insert 1.

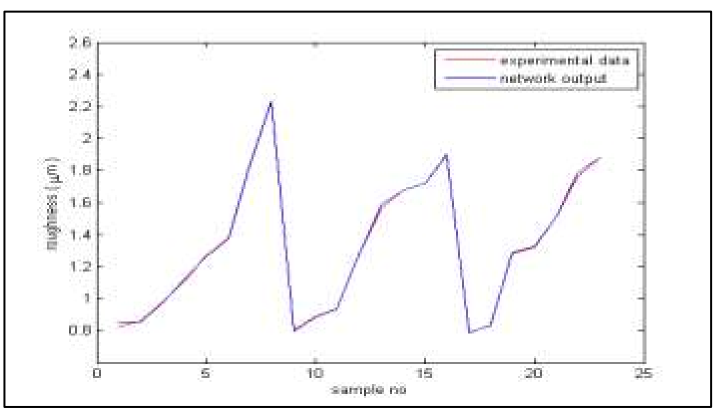

Figure (4)The network response with respect to experimental training sets for m=12 and n=9 network of insert 2.

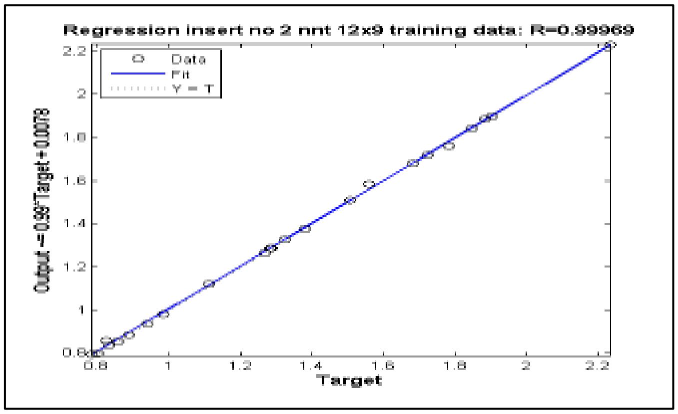

Figure (5)The linear regression and correlation coefficient (R-value) between the network response (m=12 and n=9) and the experimental data for training sets of insert 2.

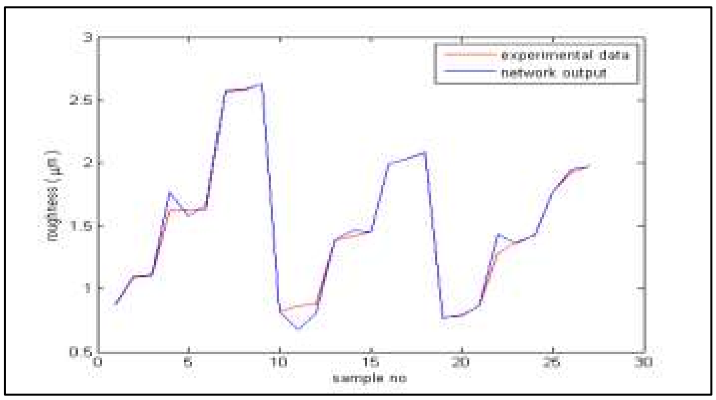

Figure (6) The network response with respect to all experimental sets for m=12 and n=9 network of insert 1

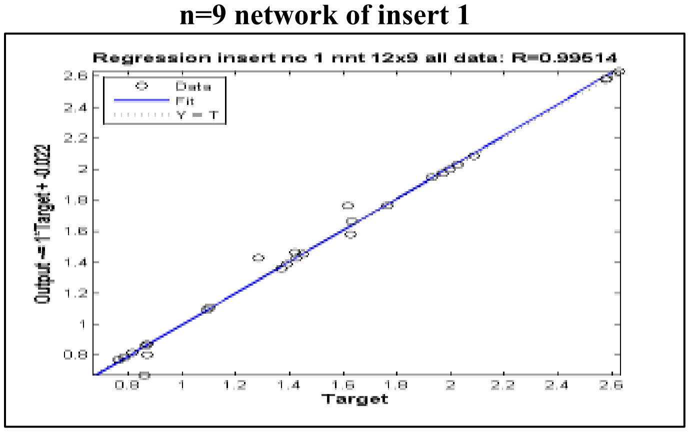

Figure (7) The linear regression and correlation coefficient (R-value) between the network response (m=12 and n=9) and the experimental data for all sets of insert 1

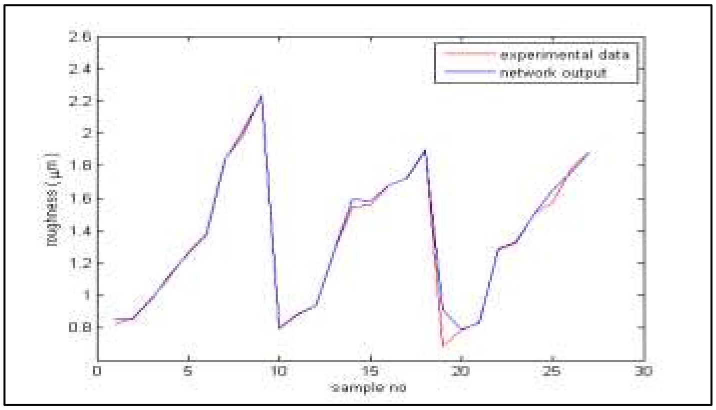

Figure (8) Network response with respect to all experimental sets for m=12 and n=9 network of insert 2

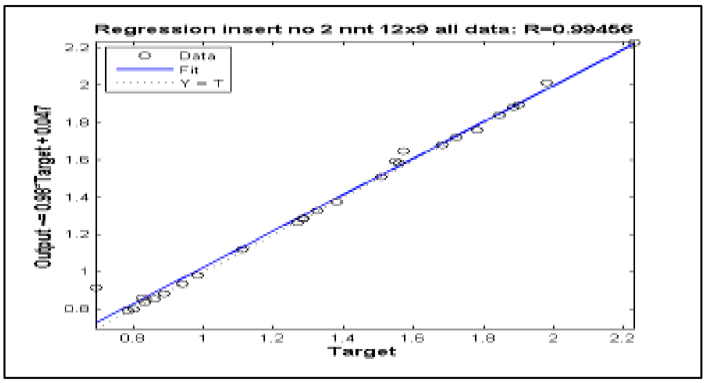

Figure (9) The linear regression and correlation coefficient (R-value) between the network response (m=12 and n=9) and the experimental data for all sets of insert 2.

The network in which the first hidden layer has 12 neurons and the second hidden layer has 9 neurons has been used to find the optimum cutting conditions for the two inserts to get the lowest surface roughness. As mentioned in advance that the cutting speed has three values(120, 160 and 200 m/min) in this work. For each cutting speed,20 points of depth of cut and 20 points of feed rate have been generated to represent the x and y coordinates which hare used to compute the surface roughness using the mentioned network. These coordinates, x and y, along with the computed surface roughness which represents the z coordinate were drawn to generate a surface as shown in the Figure (10 to Figure (15. Figure (10 to Figure (12 show the surface roughness produced by insert 1 with cutting speed 120, 160 and 200 m/min, respectively. The lower points of drawn surfaces of Figure (10 to Figure (12 represent the optimum cutting conditions, feed rate and depth of cut; with respect to the specified cutting speed as given in Table (. It can be concluded from Table (that the minimum surface roughness is 0.5309 μm which has been gotten from the cutting speed 160 $\frac{\mathrm{m}}{\mathrm{min}}$, feed rate 0.12 $\frac{\mathrm{mm}}{\mathrm{rev}}$ and depth of cut 1.3158 mm. These cutting parameters can be considered as the optimum cutting conditions for manufacturing products with minimum roughness values when using insert 1.Figure (13 to Figure (15show the surface roughness by using insert 2 with cutting speed 120, 160 and 200 m/min, respectively.

Table gives the lowest surface roughness for the optimum combination of the cutting parameters for the cutting speed 120, 160 and 200 m/min. From the

Table optimum surface roughness is 0.6387 μmwhich is generated from the cutting parameters combination, cutting speed $200 \frac{\mathrm{m}}{\mathrm{min}}$, feed rate $0.12 \frac{\mathrm{mm}}{\mathrm{rev}}$ and depth of cut 1.8421 mm.

From the results, it can be seen that the lowest value of surface roughness can be obtained by using insert 1 from the surface quality vantage point. If the production time is considered, the insert 2 is recommended to use. As mentioned the optimum cutting parameters of insert 2 is higher than those of insert 1. Also, there is no significant difference between roughness generated using insert 1 and insert 2.

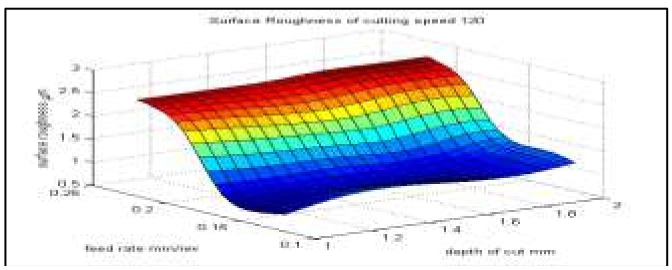

Figure (10) Surface roughness of insert 1 with cutting speed of 120 m/min

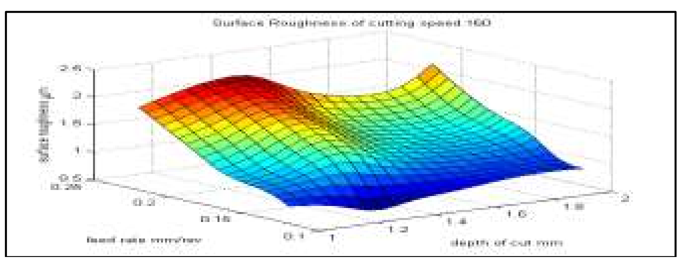

Figure (11) Surface roughness of insert 1 with cutting speed of 160 m/min

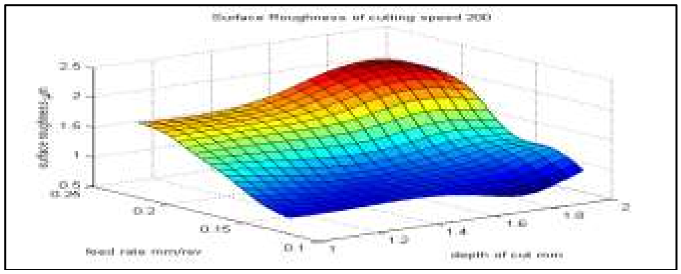

Figure (12)Surface roughness of insert 1 with cutting speed of 200 m/min

Table (7) Optimum feed rate and depth of cut which give minimum surface roughness of each cutting speed for insert 1

Cutting speed m/min	Feed rate mm/rev	Depth of cut mm	Surface roughnessμm
120	0.1463	1.0000	0.7684
160	0.1200	1.3158	0.5309
200	0.1200	1.7895	0.5860

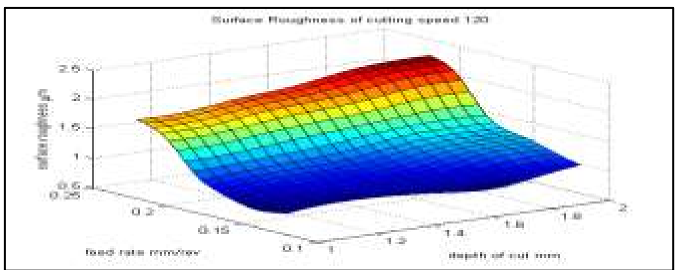

Figure (13) Surface roughness of insert 2 with cutting speed of 120 m/min

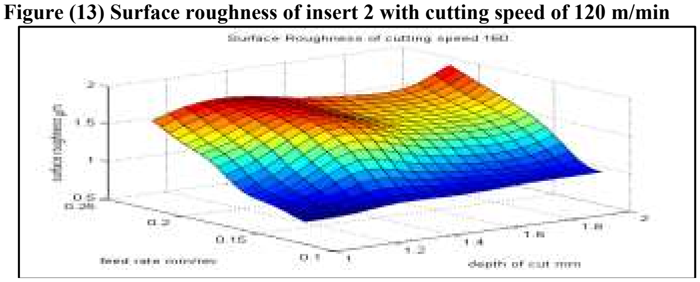

Figure (14) Surface roughness of insert 2 with cutting speed of 160 m/min

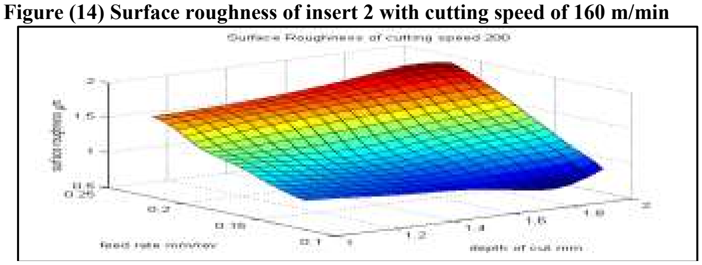

Figure (15) Surface roughness of insert 2 with cutting speed of 200 m/min.

Table (8) Optimum feed rate and depth of cut which give minimum surface roughness of each cutting speed for insert 2.

Cutting speed m/min	Feed rate mm/rev	Depth of cut mm	Surface roughnessμm

120	0.1200	1.6842	0.7820
160	0.1200	1.0000	0.7983
200	0.1200	1.8421	0.6387

CONCLUSION

In this study, artificial neural network has been used to predict the surface roughness. Two different coated inserts data were used to train and test neural network models. The parameters such as cutting speed, feed, and depth of cut were considered as input to the network. From this work the following conclusions can be presented.

1- The best result having the minimum error was obtained in networks which have m=12 neurons and n= 9 neurons.

2-The neural networks have showed good surface roughness fitting with $R^2 = 0.9902$ andmean square error = 0.0033 for the first insert, whereas, with $R^2 = 0.9892$ andmean square error = 0.0023 for the second insert. These correlation coefficients were compared with those obtained by mathematical model (liner, second order and exponential), giving better results.

3-The neural models have showed a good reliability to predict the surface roughness, so they have been used to optimize the cutting parameters to produce minimum surface roughness.

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