Modelling, prediction and analysis of surface roughness in turning process with carbide tool when cutting steel C38 using artificial neural network

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Abstract: Surface roughness is a very important measurement in machining process and a determining factor describing the quality of machined surface. This research aims to analyse the effect of cutting parameters [cutting speed (*v*), feed rate (*f*) and depth of cut (*d*)] on the surface roughness in turning process. For that purpose, an artificial neural network (ANN) model was built to predict and simulate the surface roughness. The ANN model shows a good correlation between the predicted and the experimental surface roughness values, which indicates its validity and accuracy. A set of 27 experimental data on steel C38 using carbide P20 tool have been conducted in this study.

Keywords: prediction; surface roughness; artificial neural network; turning; cutting parameters; artificial neural network; ANN; modelling; simulation.

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1 Introduction

Surface quality is one of the most important product quality characteristics in manufacturing, and it is one of the most frequent consumer requirements in machining process because of its impact on product performance (Al-Zubaidi et al., 2011; Zain et al., 2012). Surface quality is often expressed by the measurement of surface roughness (R_a), which is mostly used as an index to determine the surface finish (Ståhl et al., 2011). The R_a greatly affects the functional performance of mechanical parts such as wear resistance, fatigue strength, ability of distributing and holding a lubricant, heat generation and transmission, and corrosion resistance (Moghri et al., 2014).

The formation of R_a is a complex process, affecting by many factors like tool variables, workpiece material and cutting parameters (Acayaba and de Escalona, 2015). To reduce machining costs and to obtain required surface quality of the machined parts, much effort has been developed in understanding the effects of cutting conditions on R_a through the creation of adequate models (Davim et al., 2008). The most frequently used models for prediction of machining performance are mathematical modelling, the regression technique and artificial intelligence (AI) technique (Cica et al., 2013). Recently, (AI)-based models, such as ANN approaches, have become the preferred trend as they are applied by most researchers to develop optimal machining conditions to predict performance measure (Hossain and Ahmad, 2014).

The difference between the models lies mainly in the nonlinear regions (Ozen and Bayhan, 2013). Although the regression method may work well for modelling, this technique may not describe precisely the underlying nonlinear complex relationship between machining parameters and performance measures (Ahilan et al., 2013). Meanwhile, ANN models provide better prediction capabilities since they offer the ability to model more complex nonlinearities and interactions between input and output variables without the need to go deep into the mathematical formulation complexity (Phate and Tatwawadi, 2015).

Among various cutting processes, turning is one of the most applied metal removal operations and one of the widely used machining processes in engineering industries (Velibor and Milos, 2011). In turning, the cutting conditions affect the process efficiency and performance characteristics (Acayaba and de Escalona, 2015). Due to inadequate knowledge of the complexity of the process and factors affecting the surface integrity in turning operation, an improper decision may cause high production costs and low machining quality (Basheer et al., 2008; Xavior and Adithan, 2012). The proper selection of the operator, the cutting tools machine, the process parameters and the suitable environment for achieving a higher cutting performance in a turning operation is a critical task (Vaxevanidis et al., 2014). Hence, an accurate evaluation of R_a has been the purpose of study for many years and it is the focus of the present study.

The present investigation first builds an ANN prediction model of the (R_a) from the cutting speed (v), feed rate (f) and depth of cut (d). Then, an analysis of the variation of the R_a according to the variation of those cutting parameters is performed after making some simulations' operations, during finish turning of steel C38 using a carbide P20 tool.

2 Literature review

Ra plays an important role in determining the quality of machined surface. It is often a good estimator of the performance of a mechanical component. Among the strategies used for predicting R_a from different input parameters, (AI)-based methods and ANN in particular, are the most accurate, since they offer better prediction capabilities.

In turning process: Pontes et al. (2012) proposed an RBF neural network method to predict R_a using v, f and d as input variables of SAE 52100 hardened steel. Vaxevanidis et al. (2014) investigated the influence of the main cutting parameters on R_a and cutting forces using three materials AISI D6 tool steel, Ti6A14V ELI and CuZn39Pb3 brass. Davim et al. (2008) developed a model to study the influence of cutting conditions on R_a parameters (R_a and R_t) using free machining steel 9SMnPb28k (DIN). Asiltürk and Çunkas (2011) stated that ANN produces better results comparing to multiple regression when predicting R_a of AISI 1040 steel. Nalbant et al. (2009) showed that ANN may be used as a good alternative in analysing the effects of cutting tool geometry and processing parameters on the average R_a.

In other machining processes: Topal (2009) proposed a backpropagation algorithm discovering the role of stepover besides the standard cutting conditions on R_a prediction in flat end milling operation of AISI1040 steel. Al Hazza and Adesta (2013) built up an ANN model to predict best cutting parameters for minimum values of R_a in end milling machining of AISI H13. Basheer et al. (2008) found the ANN model to be in a very good agreement with experimental dataset when modelling R_a in precision machining of metal matrix composites Al/SiCp. Murthy and Rajendran (2012) proposed an ANN approach in drilling to predict R_a and tool wear with chip thickness inputs and cutting power in addition to cutting parameters and confirmed the accuracy of the model in term of prediction of the output parameter. Shandilya et al. (2012) stated that ANN model is close to the experimental values than RSM approach when predicting of R_a during wire electrical discharge machining of SiCp/6061 Al metal matrix composite.

From the literature survey, it is observed that ANN is a good alternative in terms of predicting R_a from several input parameters using different machining processes. This research presents an investigation of the effect of cutting condition parameters on the R_a during finish turning through ANN modelling. For this purpose, a set of 27 experimental data on steel C38 using carbide P20 tool have been conducted in this study.

3 Experimental work

The machining process was conducted using a copying lathe with a 7.5 KW power. This machine has a rotational speed range between 45 and 2,000 rev/min; *f* range between 0.05 and 0.07 mm/rev.

This study was carried out at the mechanical engineering department of Ecole Nationale Polytechnique d'Oran (ENPO) school. The experiments were done with values of *v* from 210 up to 310 m/min, low *f* from to 0.05 to 0.2 mm/rev and *d* between 0.3–0.7 mm. They were performed on heat-treated steel C38 workpieces, using a carbide P20 tool material. The dimensions of each workpiece are 100 mm in diameter and 150 mm in length. Machining consists of a finish straight turning operation. The geometric characteristics of the P20 tool used in the experiment were as follows:

- Clearance angle: 6°.
- Rake angle: 8°.
- Nose radius: 0.5 mm.

In this work, experimental design involves variations of three factors (*v*, *f* and *d*) at three levels as shown in Table 1.

Table 1 Cutting parameters and their levels

Parameters	*Units*	*Levels*		
		1	*2*	*3*
Cutting speed (*v*)	m/min	210	250	310
Feed rate (*f*)	mm/rev	0.05	0.1	0.2
Depth of cut (*d*)	mm	0.3	0.5	0.7

Hence, 27 experiments were performed according to a 3^3 full factorial design in order to estimate the R_a and a matrix were constructed Table 2.

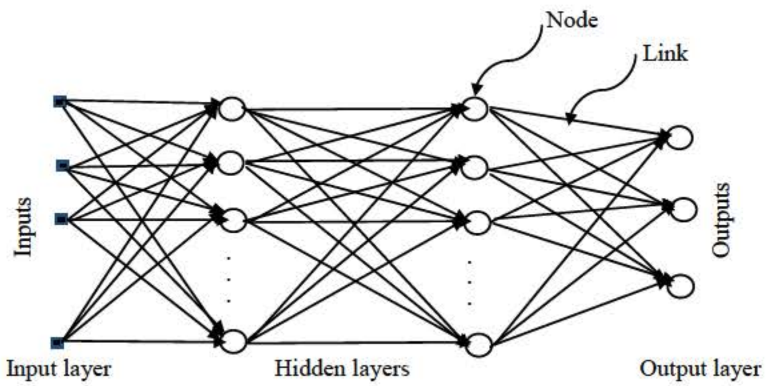
Table 2 Experimental data and surface roughness values

N	*Cutting speed v(m/min)*	*Feed rate f(mm/rev)*	*Depth of cut d(mm)*	*Surface roughness R_a(μm)*
1	210	0.05	0.3	1.6
2	210	0.05	0.5	1.6
3	210	0.05	0.7	1.7
4	210	0.1	0.3	2.1
5	210	0.1	0.5	3.3
6	210	0.1	0.7	2
7	210	0.2	0.3	3.3
8	210	0.2	0.5	3.6
9	210	0.2	0.7	2.9
10	250	0.05	0.3	2.1
11	250	0.05	0.5	1.2
12	250	0.05	0.7	2
13	250	0.1	0.3	1.6
14	250	0.1	0.5	1.4
15	250	0.1	0.7	1.9
16	250	0.2	0.3	3
17	250	0.2	0.5	2.5
18	250	0.2	0.7	3
19	310	0.05	0.3	1.8
20	310	0.05	0.5	1.1
21	310	0.05	0.7	1.8
22	310	0.1	0.3	1.5
23	310	0.1	0.5	1.5
24	310	0.1	0.7	3.8
25	310	0.2	0.3	2.7
26	310	0.2	0.5	2.1
27	310	0.2	0.7	3.2

4 Neural network models

An ANN structure principally consists of layers (input, hidden, output) and nodes also known as neurons Figure 1. The neurons between the layers are connected by links having synaptic weights (Sunder and Yadava, 2014; Xavior and Adithan, 2012).

Figure 1 Structure of a network



Artificial neural networks are nonlinear mapping systems that perform specific mathematic functions such as nonlinear function approximation between input and output variables (Pontes et al., 2012). They are composed of fully interconnected multilayers consisting of neurons as the basic element (Murthy and Rajendran, 2012). There are many types of neural networks such as backpropagation neural network (BPNN), counter propagation neural network, radial basis function neural network, etc. (Vaxevanidis et al., 2014). The standard feedforward (FF) BPNN is the most widely used by researchers and it was found that this technique gave the more accurate results in term of prediction of the R_a response variable (Shandilya et al., 2012), but it required more time for training and testing (Madić and Radovanović, 2013). To escape the slowness of the process, Levenberg-Marquardt (LM) algorithm is used since it converges very fast with less danger from entrapment in local minimum, while at the same time, it can provide high accuracy of prediction (Upadhyay et al., 2013,). Therefore, this problem is treated with FF BPNN type using LM algorithm for the training part.

4.1 FF BPNN model

Training a network by backpropagation involves three stages: the FF of the input training pattern, the backpropagation of the associated error, and the adjustment of the weights (Fausett, 1994; Kialashaki and Reisel, 2014). Its learning procedure is based on gradient descent search to satisfy the condition of minimising the mean squared error (MSE) $MSE = \frac{1}{2p}\sum_{p=1}^{p}\sum_{k=1}^{m}\left(t_k(p) - o_k(p)\right)^2$ (Ahilan et al., 2013) over all training samples. Where p is the number of the training patterns, $t_k(p)$ is the experimental (desired) output for the p^{th} pattern, $o_k(p)$ is the predicted value.

For a network with one hidden layer (Fausett, 1994; Freeman and Skapura, 1991; Zain et al., 2012), the net-input values to the j^{th}-hidden unit are given by the expression:

$$net_j = \sum_{i=1}^{N} w_{ji}\, x_i + \theta_j \tag{1}$$

where i is the number of the node in the input layer, w_{ij} is the weight between the input nodes and the hidden nodes, x_i is the input value, which represents the cutting conditions and θ_j is the biases on the hidden nodes.

The net-input values to the k^{th}-output unit are done by the equation:

$$net'_k = \sum_{j=1}^{L} w'_{k\,j}\, i_j + \theta'_k \tag{2}$$

where j is the number of the node in the hidden layer, $w'_{k\,j}$ is the weight between hidden and output nodes, i_j is the value of the output from the hidden nodes and θ'_k is the biases on the output nodes.

From equations (1) and (2), the output values from the hidden layer and the output values from the output layer, can be done using equations (3) and (4) respectively:

$$i_j = f_j\left(net_j\right) \tag{3}$$

$$o_k = f'_k\left(net'_k\right) \tag{4}$$

where f_j and f'_k are the transfer functions used for the model prediction.

5 Architecture of the proposed ANN model

The training of ANN for 27 input-output patterns has been carried out using MATLAB (R2013 a) neural network toolbox NNTOOL. 70% for the training data, 15% to validate the model and 15% for the test part. The simulated multi-layer ANN architecture consists of three neurons in the input layer (corresponding to three process inputs: v, f, d), one neuron in the output layer (corresponding to R_a). One hidden layer with 10 neurons was used between the input and output layers Figure 2.

Figure 2 Topology of the trained network

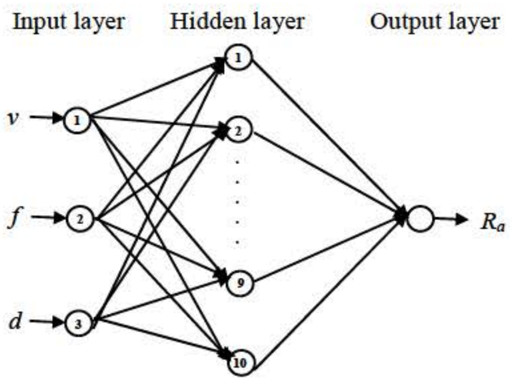


Table 3 summarises the neural network model specifications.

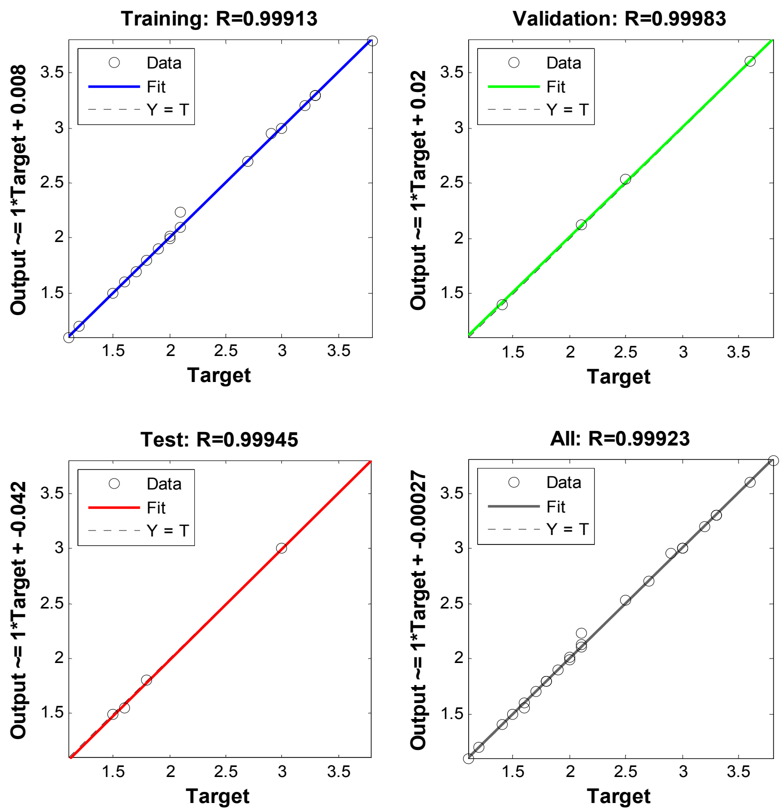
Table 3 Specification of the trained neural network

Tool	MATLAB R2013a
Toolbox	NNTOOL
Type	Feedforward backpropagation
Learning system	Supervised learning
Algorithm	Levenberg-Marquardt algorithm
Training function	Trainlm
Adoption learning function	Learngdm
Transfer function	Tansing for layer1, Purelin for layer2
Number of layers, data ratio	3 layers (input, hidden and output), 70:15:15
Number of hidden layer neurons	10
Performance function	Mean squared error (MSE)

The validity of any designed model is mainly given by the following parameters and plots generated by MATLAB NNTOOL toolbox (Al Hazza and Adesta, 2013; Beale et al., 2010).

MSE, regression plots that show the network output with respect to target and the error histogram plot which displays the difference between target and output values.

Figure 3 Regression plot (see online version for colours)



6 Results and discussion

6.1 *Regression plot*

The regression plot for all patterns, training, validation and testing the model are summarised in Figure 3. The plots display the network output (corresponding to the predicted values of R_a) with respect to target (corresponding to the experimental values of R_a) for all patterns, training, validation and testing sets. For a perfect fit, the data should fall along a 45-degree line (dash line), where the network outputs are equal to the targets. In our case, the fit is quite good for all datasets, with R-value higher than 0.999 and the outputs track the targets very well. It can be observed that prediction is quite accurate, since (R_a) predicted points lie very close to the original experimental results.

6.2 *Error histogram*

The error histogram Figure 4 can give us an additional verification of the network performance. In this case, while most errors fall between –0.047 and 0.047, there is only one training point with an error of –0.13, and it cannot even be considered as an outlier point. Hence, the outputs fit the target points accurately. That can be confirmed too with the graph on Figure 5 showing the shape of the predicted and experimental R_a curves. As it can be seen, both of the curves are very close to each other and that the predicted values follow the same trend of the experimental ones.

Figure 4 Error histogram (see online version for colours)

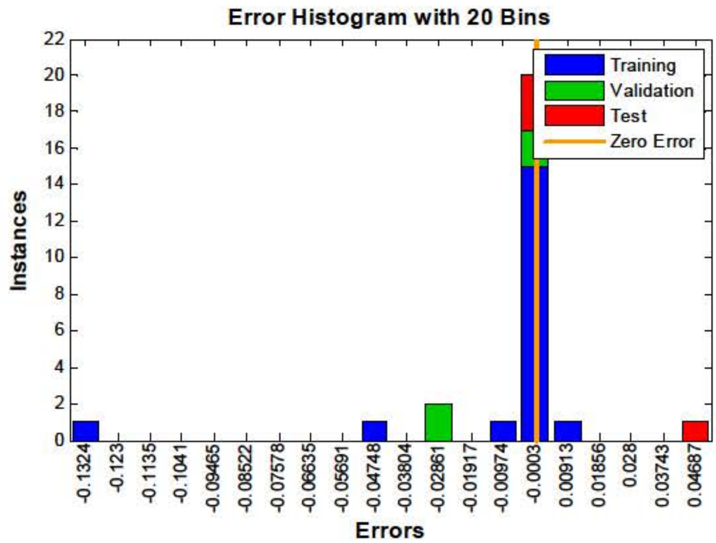
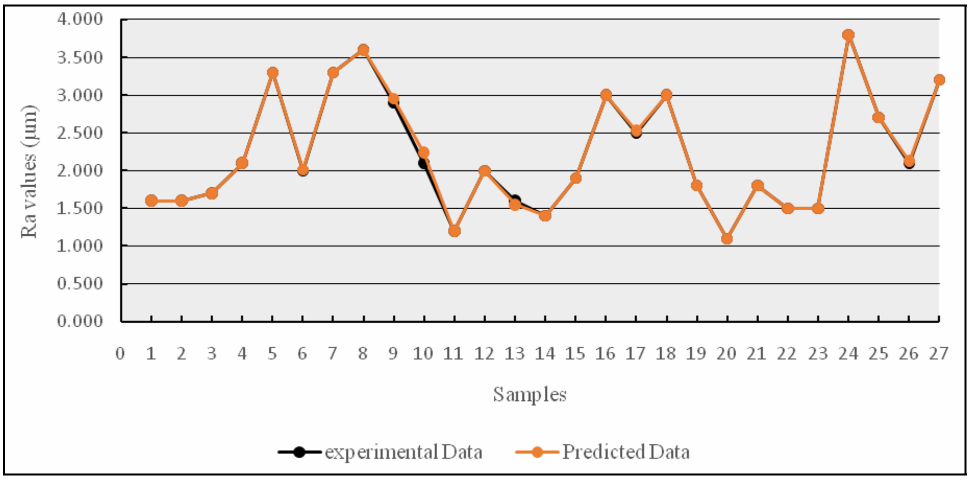


Figure 5 Comparison between the experimentally measured and ANN predicted values (see online version for colours)



Finally, *MSE* obtained have values of 0.096% for all patterns, but specifically, 0.114% for training data, 0.043% for validation data and 0.067% for test data.

Hence, the obtained results are very reasonable and quite accurate in this experiment. Therefore, the average R_a value (R_a) could be accurately predicted by the developed ANN model, using the three input parameters (v, d, f).

6.3 *Weights and biases*

The weights and biases of the final model are shown on Tables 4 and 5.

Table 4 Weights of input layer to hidden layer

Hidden layer	*Cutting speed*	*Feed rate*	*Depth of cut*	*Bias*
1	1.4615	–2.4515	0.7979	–4.3189
2	3.9434	0.3584	–0.6710	–2.5551
3	–3.0736	0.6691	1.3308	2.4384
4	1.4752	–0.9420	1.7394	–2.7400
5	0.3722	3.8340	–0.0029	–1.0852
6	–1.5586	–3.6355	0.6554	–2.4624
7	–2.8812	1.8520	3.7498	–0.8693
8	0.7589	3.6328	–1.0381	2.9322
9	3.5199	2.0897	3.6084	1.0718
10	3.4669	0.1046	–3.7812	1.5407

Table 5 Weights of hidden layer to output layer

Layer	R_a
1	–1.1094
2	–0.2769
3	–0.5356
4	1.6783
5	0.6260
6	0.8108
7	0.1445
8	1.0430
9	–0.3677
10	–0.1753
Bias	0.3944

7 Simulations

7.1 Effects of cutting parameters on R_a

To study the effect of the cutting parameters on R_a, simulations have been performed. Three groups of measurements were implemented according to three different depths of cut: $d = 0.3$ mm, $d = 0.5$ mm and $d = 0.7$ mm. For each d value, three different feed rates have been considered: $f = 0.05$ mm/rev, $f = 0.1$ mm/rev and $f = 0.2$ mm/rev. The curves are plotted according to the v parameter and the results have been concluded in Figures 6 to 8.

Figure 6 The effect of v and f on the R_a with $d = 0.3$ mm (see online version for colours)

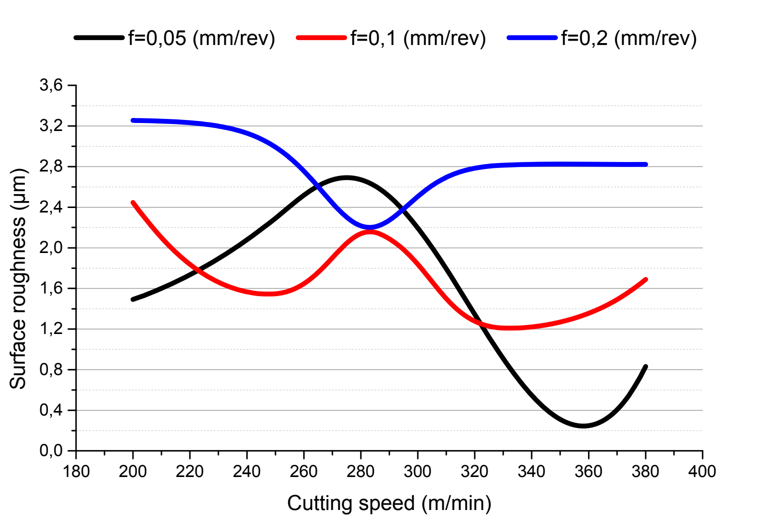


Figure 7 The effect of v and f on the R_a with $d = 0.5$ mm (see online version for colours)

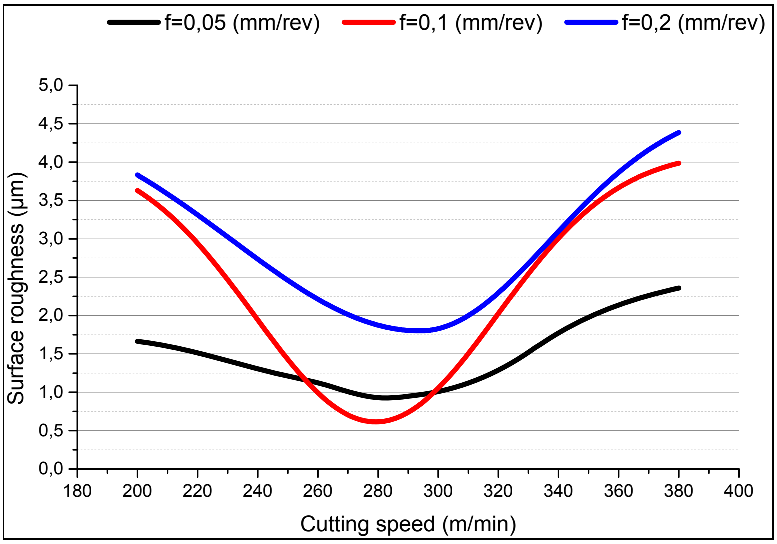
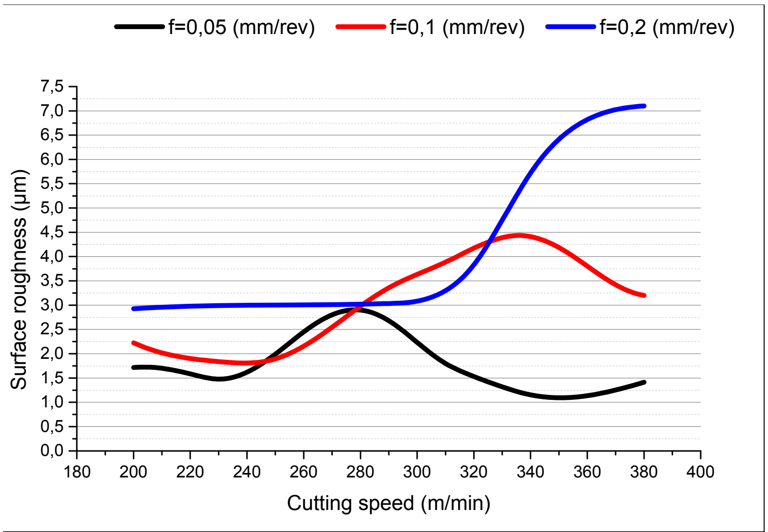


Figure 8 The effect of v and f on the R_a with $d = 0.7$ mm (see online version for colours)



On Figure 6, it can be observed that best R_a values are obtained using v higher than 320 m/min with a feed rate f = 0.05 mm/rev, where the minimum value of R_a is R_a = 0.25 µm corresponds to a cutting speed v = 360 m/min. f = 0.2 mm/rev gives high values of R_a all above 2.2 µm. Intermediate values of R_a are obtained with f = 0.1 mm/rev.

Figure 7 is showing the same shape for all curves. Higher values of R_a are obtained with f = 0.2 mm/rev. The curve represented by f = 0.05 mm/rev holds the lowest R_a values. The minimum value of R_a is R_a = 0.66 µm corresponds to v = 280 m/min and can be depicted on f = 0.1 mm/rev curve which contains the intermediate R_a values.

With d = 0.07 mm on Figure 8, best R_a values are obtained with f = 0.05 mm/rev, where R_a = 1.09 µm represents a minimum corresponding to v = 350 m/min. Intermediate values of R_a are obtained with a value of f = 0.1 mm/rev. Always a feed rate value of f = 0.2 mm/rev leads to high values of R_a.

From the statements above it can be said that:

- In general, f = 0.2 mm/rev gives the highest R_a values. Intermediate R_a values can be obtained with f = 0.1 mm/rev and the lowest R_a values with a feed rate f = 0.05 mm/rev.
- The increase in v does not always lead to an improved R_a, that depends on both the d and f.
- Good R_a values are obtained with d = 0.5 mm but the best ones with the association of f = 0.1 mm/rev and the v interval of [250 m/min, 300 m/min].
- For the same value of d, an increase in f leads to a considerable increase in R_a for high values of v. However, for a given value of f, an increase in d does not lead to such big variation of R_a when the v gets big values. So, there is a major dependence of R_a on f than on d.
- The lowest R_a values are obtained with the lowest d and f values (d = 0.3 mm and f = 0.05 m/min) associated to high values of v.

7.2 Combined effects of cutting conditions on R_a

In order to give a general view of the combined effects of turning parameters on R_a, the three-dimensional surface plots were built considering two parameters at a time. These combined effects are shown in Figures 9 to 11.

Figure 9 Effects of the couple (f, v) on R_a (see online version for colours)

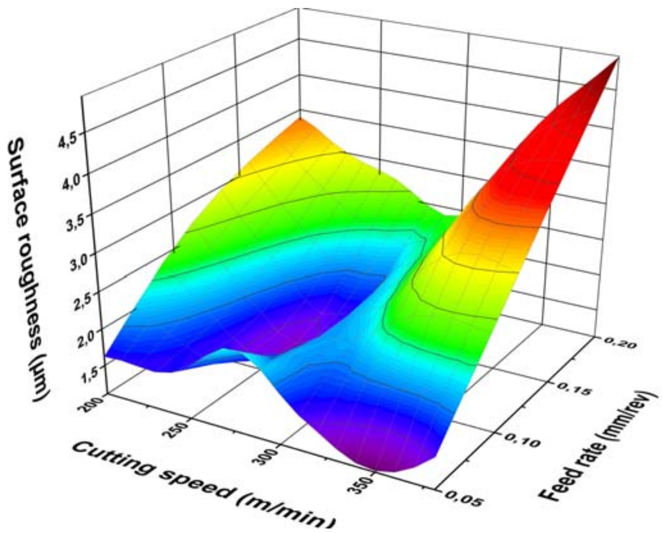


Figure 10 Effects of the couple (d, v) on R_a (see online version for colours)

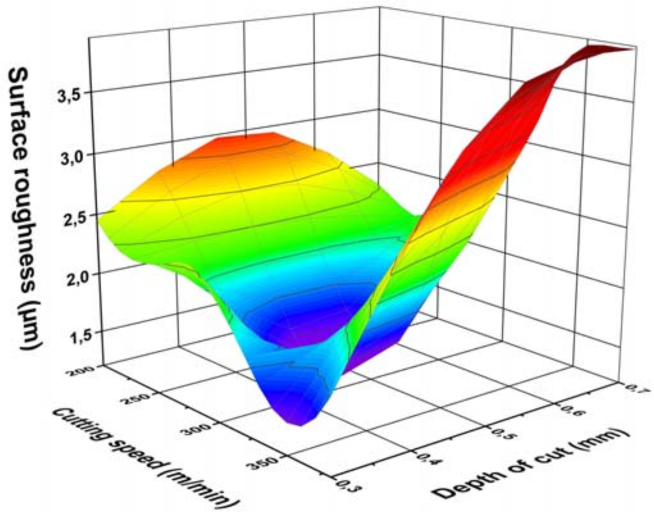
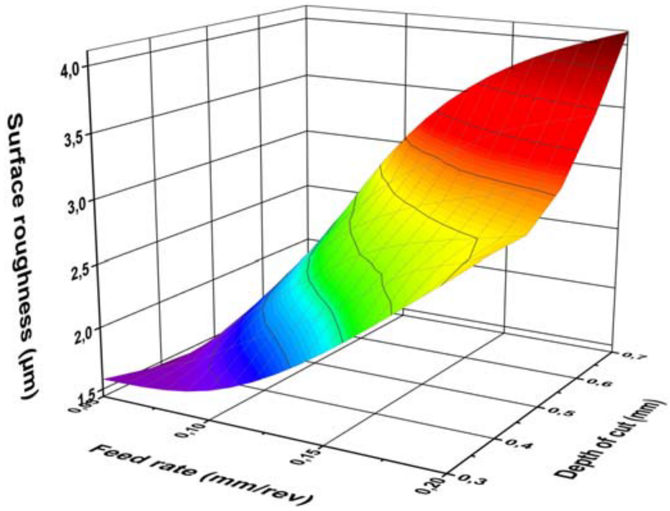


Figure 11 Effects of the couple (f, d) on R_a (see online version for colours)



Based on Figures 6 to 8, and considering the combined effects of different couples of parameters influencing R_a (Figures 9 to 11), the following conclusions may be drawn:

- For small values of feed rate ($f < 0.1$ min/rev) Figure 9, an increase in v reduces considerably the R_a. This situation is due to the rise of temperature caused by the v increase, which soften the material leading to an improvement of the cutting performance giving better surface finish, as was also stated by Davim et al. (2008) and Ståhl et al. (2011).

- With small d values ($d < 0.4$ mm) (Figure 10), R_a decreases with the increase of cutting speed ($v > 280$ m/min). However, for a given superior d value, R_a has a tendency to decrease to a minimum value around $v = 280$ m/min then starts increasing with the increase of v. That can be explained by the fact that the increase in depth increases the chip volume per unit time. Thus, the resulting increased cutting forces lead to an increase in vibrations giving high R_a values, as was also reported by Eki̇ci̇ et al. (2014).
- Figure 11 is showing that R_a increases with the increase in f for the majority of d values. At the beginning, for low values of depth of cut ($d < 0.4$ mm) and feed rate ($f < 0.1$ mm/rev), R_a gets low values. However, for a given superior d value, R_a keeps increasing with the increase in f.
- Generally, for any v or d value from Figures 9 or 11 respectively, it can be observed that R_a sharply increases with the increase in f. Particularly, in Figure 11, we have high R_a values with an interaction of high values of feed rate ($f > 0.1$ mm/rev) and depth of cut ($d > 0.4$ mm). When f is (0.1 mm/rev $< f <$ 0.15 mm/rev) (Figure 9), low cutting speed ($v < 250$ m/min) leads to big R_a values, however, an increase in v to around ($v = 280$ m/min) reduces to a great extent the R_a due to the rise of temperature that leads to better surface finish as mentioned above. The increase in R_a values with cutting speed ($v = 280$ m/min) is due to the possible tool wear caused by higher cutting speeds as mentioned by Eki̇ci̇ et al. (2014). Finally, greater f values gives big R_a values, since increased f leads to increased thrust force involving more vibrations and hence, altering surface finish as was reported also by Davim et al. (2008) and Cica et al. (2013).
- Among the interaction effects, it can be seen that the couple (v, f) (Figure 9) has more influence on R_a than the couple (v, d) (Figure 10). Figure 9 shows a more pronounced increase of R_a than in Figure 10 and the highest values of it. Hence, it can be confirmed that f has more influence on R_a than d.

8 Conclusions

This study has been involved with the ANN technique to develop a model to predict the values of R_a from input cutting parameters (v, f and d). A three layers' neural network was used (ten neurons in the hidden one) using MATLAB (R2013a) NNTOOL toolbox. The results show that the model is valid and can be used for prediction of R_a values R_a.

In the field of R_a, ANN deals with any degree of linearity that exists between a process response and input parameters and shows good generalisation. The advantages of the ANN compared to classical methods are speed, simplicity and capacity to learn from examples without the need of additional experimental study.

The model analysis was performed by generating 2D and 3D plots after simulation of the model and hence, we can say that:

The relationship between R_a and the cutting parameters is considerably nonlinear. In particular, R_a is very sensitive to f and v and less sensitive to d. R_a has a tendency to get small values with the increase in v and decrease in f. A minimal R_a can be obtained with low f and high v.

Since we are dealing with a finish turning process, a depth of cut value $d = 0.7$ mm is showing R_a values not corresponding to this context. Even though best R_a values are obtained with a depth of cut $d = 0.3$ mm, but a depth of cut $d = 0.5$ mm is recommended since productivity improvement also matters in industrial context. For the same reason, the feed rate value $f = 0.1$ mm/rev is rather chosen than $f = 0.05$ mm/rev. Taking these two values $d = 0.5$ mm and $f = 0.1$ mm/rev in account, minimum R_a values can be easily depicted from Figure 6 and tell they correspond to the v interval of [250 m/min, 300 m/min]. Particularly, minimum $R_a = 0.66$ μm can be obtained with a combination of $f = 0.1$ mm/rev, $d = 0.5$ mm and $v = 280$ m/min.

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