Modeling and Prediction of Surface Roughness During Dry Turning Process

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Abstract--Surface roughness (R_a) prediction model using artificial neural network (ANN) is developed in this work for dry turning of mild steel (St. 42) using carbide inserts. Cutting parameters (cutting speed, feed rate, and depth of cut) are used as network inputs. Also, investigations of the effect of cutting parameters are presented. The analysis reveals that increasing the cutting speed will decrease surface roughness, and increasing feed rate will increase surface roughness. The results show that the developed ANN model can predict surface roughness with regression value 98.641 % between measured and predicted values and average error 5.4%. Detailed experimentation and ANN network structure are presented in the paper.

Keywords: Surface roughness, artificial neural network, dry turning, cutting parameters

1. INTRODUCTION

Turning is the primary operation in most of the production processes. Components, with critical features usually require specific surface finish. Selection of the proper cutting parameters in turning operation is a critical task and greatly affects surface roughness.

So achieving the desired surface roughness greatly affects the functional behavior of the mechanical parts. Surface roughness has influence on several properties such as wear resistant, fatigue strength, coefficient of friction, wear rate, and corrosion resistance of machined parts [1].

The surface roughness can be defined by (R_a) which is the arithmetical average roughness. Theoretical equation was presented [2] to estimate this parameter:

$$R_a = \frac{1000\ f^2}{32r}$$

Where R_a is the average surface roughness (μm), f is the feed rate (mm/rev) and r is the tool nose radius (mm).

However, the above theoretical equation does not take into consideration many parameters that can affect surface roughness as cutting speed, depth of cut, and others. It will be shown that all of these parameters play an important role on surface roughness of the finished components.

2. LITERATURE REVIEW

Standard roughness measurement procedures depend on stylus instruments which have only limited flexibility in handling. Furthermore, this procedure is not suitable for automation and relatively slow. In recent years several researchers developed many models to predict surface roughness in terms of various process parameters during turning of different materials to overcome the disadvantages of standard roughness measurement.

2.1. Artificial neural network model

J. Paulo et al. [2] developed a surface roughness prediction model using artificial neural network to investigate the effect of cutting conditions during turning of free machining steel. It is found that the maximum absolute error between the predicted values and the measured values are 28.29% and 8.19% for R_a and R_t respectively, K. A. Risbood et al. [3] developed three artificial neural network models to predict surface roughness for dry and wet turning of commercially available steel using high cobalt-HSS and TiN coated carbide tools. It is found that the maximum absolute error between the predicted values and the measured values are 38.55%, 31.9%, and 22.93% for first model, second model, and third model respectively, Ilhan Asilturk et al. [4] developed artificial neural network and multiple regression (second order) approaches to predict surface roughness of AISI 1040 steel, using carbide inserts and they found that artificial neural network produces better results compared to multiple regression, C. Natarajan et al. [5] developed an artificial neural network to predict surface roughness for dry turning of brass C26000 using CNMG 120408 insert. The percentage deviation between actual roughness values and predicted roughness values is 24.4%, and the model could achieve an accuracy of 75.6%.

2.2. Adaptive fuzzy network model

Yue Jiao et al. [6] developed a fuzzy adaptive network to model surface roughness in turning operations, during turning of cold rolled steel using coated carbide tool, the results of the adaptive fuzzy model are compared with the results obtained from a regression model and they found that the adaptive fuzzy model outperforms the regression model. Shinn-Ying Ho et al. [7] proposed a method using an adaptive neuro-fuzzy inference system to accurately establish the relationship between the features of surface image and the actual surface roughness of S45C steel bars using tungsten carbide tool. The errors of the developed model are smaller than 4.6%.

2.3. Regression model

I.A. Choudhury et al. [8] developed a first order prediction model, and a second order prediction model to predict surface roughness for turning EN 24T steel using uncoated carbide inserts. It indicated that the second order model is more adequate, Yusuf Sahin et al. [9] developed a first order and second order model to predict surface roughness for turning of mild steel using coated carbide tool. It is found that only the first order model for prediction is important. Vikas Upadhyay et al. [10] developed two regression models (first-order and second-order) to predict surface roughness of turning Ti-6Al-4V alloy using uncoated cemented carbide. The best R^2 value of the models is 93.2% and the average error of this model found to be 3.5%. Sudhansu Ranjan Das et al. [11] developed multiple regression analysis to predict surface roughness of turning AISI 4340 steel using multilayer coated carbide inserts. It is observed that feed rate is the most significant parameters followed by cutting speed and it is found that the depth of cut did not impact the surface roughness in the studied range. Zahia Hessainia et al. [12] developed two multiple regression models to predict surface roughness when turning of 42CrMo4 hardened steel using Al_2O_3/TiC mixed ceramic tool. The results indicate that the feed rate is dominant factor affecting the surface roughness.

2.4. Abductive network model

W. S. Lin et al. [13] developed two models: the first one is an abductive network model, the second model is regression analysis, for the surface roughness and cutting force for turning high carbon steel using carbide inserts. It is found that the percentage error under various cutting conditions is generally 10%, while it is 59.44% for regression model. B. Y. Lee et al. [14] developed a polynomial network using a self organizing adaptive modeling method to construct the relationships between the feature of the surface image and the actual surface roughness under a variation of turning operations of S45C steel bars using tungsten carbide tool. The developed model can predict surface roughness with reasonable accuracy (average percentage error is 6.2%), B. Y. Lee et al. [15] developed a system for measuring surface roughness of turned parts through computer vision system, the model use an adaptive network to predict surface roughness for turning of S45C steel bars using tungsten carbide tool. It is found that the maximum absolute error between the surface roughness measured by vision system and that measured by the stylus instrument is 14.96%,

2.5. Experimental studies

Thomas M. et al. [16] study and analyze of surface roughness and tool vibration data generated by lathe during dry turning of mild carbon steels using cemented carbide tool, Hasan Gokkaya [17] study and analyze cutting force, surface roughness, built-up edge, and built-up layer during turning of AA2014 (T4) alloy by uncoated carbide tool, and N. Satheesh Kumar et al. [18] investigate the effect of process parameters in wet turning of carbon alloy steel using a carbide tip tool.

The aim of this study is to:

- analyze the effect of feed rate (*f*), cutting speed (*v*), and depth of cut (*d*) on surface roughness parameter such as average roughness (R_a).
- Develop a model using artificial neural network (ANN) to predict surface roughness using cutting parameters as network inputs.

3. EXPERIMENTAL SETUP

Data sets are from experiments conducted on a conventional lathe in the workshop of Ain Shams University, Faculty of Engineering, Cairo, Egypt. The details of the machining experiments are given in table 1. Carbide insert was used for machining a mild steel bar of length 300 mm. After each experiment the surface roughness (R_a) is measured using surface roughness tester (TAYLOR-HOBSON, surtronic 3). Roughness measurements are taken five times for each work piece then the average value is calculated and used. In order to avoid the effect of cutting tool wear and tool nose radius, each experiment was conducted with new, identical cutting edge. The cutting experiments were performed without coolant, and totally 27 experiments were performed according to full factorial design. Table 2 shows the experimental cutting parameters and the resulted surface roughness.

Table – 1: Cutting parameters details

Parameter	Level 1	Level 2	Level 3
Depth of cut (mm)	0.50	1.00	2.00
Cutting speed (rpm)	765	955	1200
Feed rate (mm/rev)	0.20	0.40	0.60
Initial work piece diameter (mm)	25	26	28

Table - 2: detailed experimental data

Test No.	*v* (m/min)	*f* (mm/rev)	*d* (mm)	R_a (μm)
1	98.06	0.2	2	2.93
2	98.06	0.4	2	4.29
3	98.06	0.6	2	8.09
4	78.04	0.2	2	4.05
5	78.04	0.4	2	5.61
6	78.04	0.6	2	10.31
7	62.51	0.2	2	4.95
8	62.51	0.4	2	7.85
9	62.51	0.6	2	10.91
10	94.29	0.2	1	1.27
11	94.29	0.4	1	4.25
12	94.29	0.6	1	8.39
13	75.04	0.2	1	3.09
14	75.04	0.4	1	4.13
15	75.04	0.6	1	8.97
16	60.11	0.2	1	4.47
17	60.11	0.4	1	8.47
18	60.11	0.6	1	10.87
19	92.40	0.2	0.5	3.05
20	92.40	0.4	0.5	4.33
21	92.40	0.6	0.5	7.57
22	73.54	0.2	0.5	4.29
23	73.54	0.4	0.5	4.59
24	73.54	0.6	0.5	8.97
25	58.91	0.2	0.5	4.09
26	58.91	0.4	0.5	7.13
27	58.91	0.6	0.5	10.45

4. ARTIFICIAL NEURAL NETWORK (ANN)

In this study, ANN structure shown in figure 1 is used for modeling and predicting surface roughness (R_a) in turning process. Many neural network structures with different

number of neurons in each layer and different processing functions are tested and it is found that the network with the best results has 3 layers, the first layer is the input layer and it consists of 3 neurons for the 3 inputs of the network, the

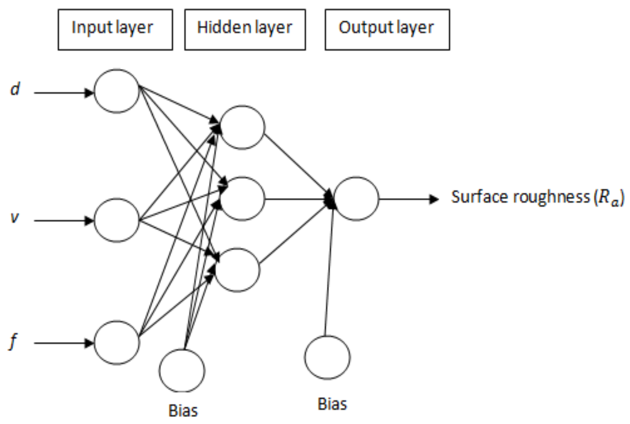

Figure - 1: ANN structure

second layer is the hidden layer and it consist of 3 neurons, and the third layer is the output layer and it consists of 1 neuron.

The processing function for the hidden layer is logsig, and for the output layer is tansig. Feed-forward back propagation ANN is used, Leven berg-Marquardt back propagation (TRAINLM) algorithm is used for network training and mean square error (MSE) is used as performance function, many neural network structures with different number of neurons in each layer and different processing functions are tested and it is found that this one has the best results

5. RESULTS AND DISCUSSION

In this section, the results obtained from the ANN and the developed model are presented and discussed. Finally, the effect of different cutting parameters on surface roughness (R_a) are explained.

5.1. *Artificial neural network results*

The experimental data set consists of 27 experiments of which 19 experiments are used for training the network and 8 experiments are selected randomly for validation and testing the performance of the trained network.

Table 3 shows the results obtained from the trained ANN for the 27 experiments; also it shows the error percentage between the measured value of surface roughness and the predicted value. Figure 2 shows the difference between the measured value and the predicted value of surface roughness.

Table – 3: ANN results

Test No.	*v* (m/min)	*f* (mm/rev)	*d* (mm)	R_a(µm)	$\boldsymbol{R_{an}}$**(µm)**	**% error**
1	98.06	0.2	2	2.93	2.73	6.72
2	98.06	0.4	2	4.29	4.22	1.70
3	98.06	0.6	2	8.09	8.12	0.32
4	78.04	0.2	2	4.05	3.30	18.48
5	78.04	0.4	2	5.61	5.95	6.11
6	78.04	0.6	2	10.31	10.07	2.33
7	62.51	0.2	2	4.95	4.95	0.01
8	62.51	0.4	2	7.85	7.85	0.01
9	62.51	0.6	2	10.91	10.73	1.65
10	94.29	0.2	1	1.27	1.67	31.88
11	94.29	0.4	1	4.25	4.03	5.09
12	94.29	0.6	1	8.39	7.76	7.52
13	75.04	0.2	1	3.09	3.18	2.87
14	75.04	0.4	1	4.13	4.14	0.14
15	75.04	0.6	1	8.97	8.97	0.00
16	60.11	0.2	1	4.47	4.03	9.77
17	60.11	0.4	1	8.47	7.54	10.96
18	60.11	0.6	1	10.87	10.63	2.19
19	92.40	0.2	0.5	3.05	2.65	13.20
20	92.40	0.4	0.5	4.33	3.95	8.82
21	92.40	0.6	0.5	7.57	7.58	0.14
22	73.54	0.2	0.5	4.29	4.28	0.21
23	73.54	0.4	0.5	4.59	4.59	0.03
24	73.54	0.6	0.5	8.97	9.78	9.05
25	58.91	0.2	0.5	4.09	3.93	3.84
26	58.91	0.4	0.5	7.13	7.29	2.20
27	58.91	0.6	0.5	10.45	10.57	1.12

***$\boldsymbol{R_{an}}$: surface roughness predicted by ANN**

The results show that the error percentage is less than 5% for the majority of experiments, also it shows that error percentage is near zero in many experiments, also it shows that the correlation coefficient between the measured values and predicted values is 0.98641, and the average error percentage is 5.4%.

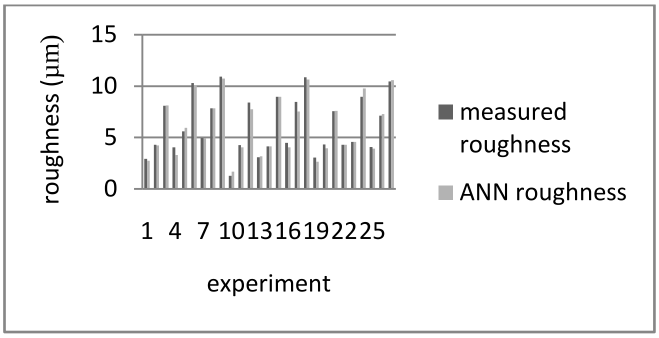

Figure -2: Measured and predicted data for surface roughness

5.2. *Effect of cutting parameters*

Now the effect of each cutting parameter (*f*, *v*, *d*) on surface roughness (R_a) will be discussed. Figures 3, 4, and 5 show the relation between feed rate and surface roughness (R_a) for different cutting speed and different depth of cuts.

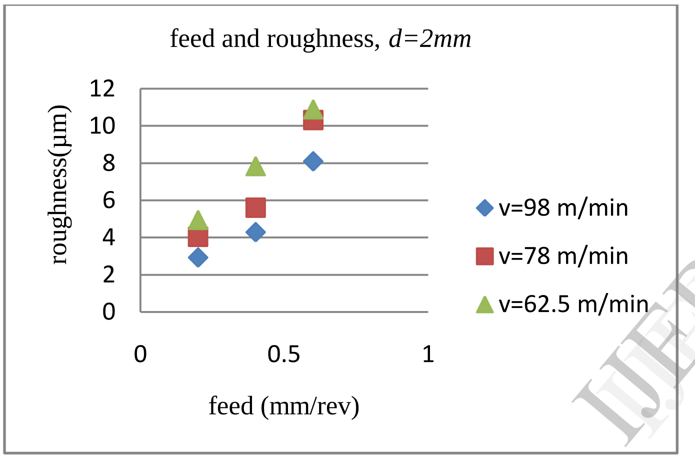

Figure – 3: Relation between feed and roughness for *d*= 2 mm

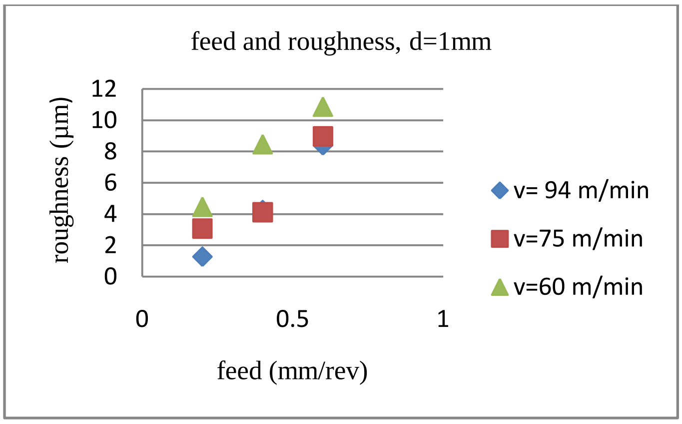

Figure - 4: Relation between feed and roughness for *d*= 1 mm

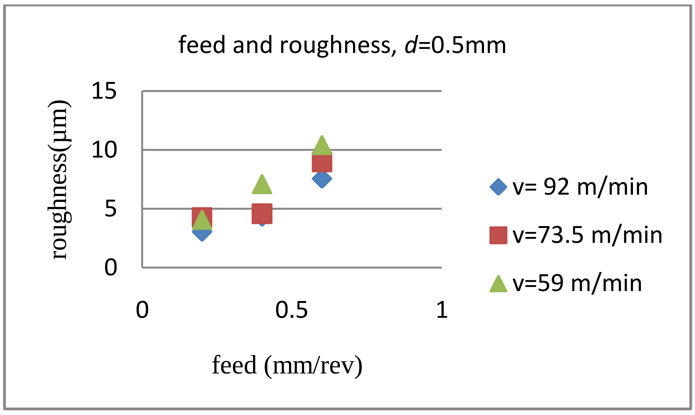

Figure - 5: Relation between feed and roughness for *d*= 0.5mm mm

5.2.1. *Effect of feed rate*

From the experiments it is shown that increasing feed rate will increase surface roughness for different cutting speeds and different depth of cuts. The reason for that is increasing the feed rate during machining causes the cutting forces to increase due to high frictional forces on the tool rake face.

5.2.2. *Effect of cutting speed*

From the experiments it is shown that increasing cutting speed will decrease surface roughness for different depth of cuts and different feed rates. The reason for that is increasing the cutting speed during machining causes the cutting forces to decrease due to low frictional forces on the tool rake face at high cutting speeds.

5.2.3. *Effect of depth of cut*

From the experiments it is shown that increasing depth of cut from 0.5 mm to 1 mm for small and medium feed rate (0.2 and 0.4 mm/rev) will decrease surface roughness for different speeds. But further increasing of depth of cut will cause increasing in surface roughness; also it is shown that increasing depth of cut at high feed rate (0.6 mm/rev) will not have remarkable effect on surface roughness and this may be because that the feed rate become the dominant factor affecting the surface roughness.

6. CONCLUSIONS

In this study experiments are done on conventional lathe using different cutting parameters and the results of the experiments are used to build artificial neural network (ANN) model to predict surface roughness(R_a). The following conclusions are extracted from this study:

- The surface roughness (R_a) could be effectively predicted by using depth of cut, cutting speed, and feed rate as the inputs variables.
- The developed artificial neural network prediction model can predict surface roughness (R_a) accurately as correlation coefficient between the

measured values and predicted values is 0.98641, and the average error percentage is 5.4%.

- Artificial neural network can predict non-linear relationships accurately.
- Increasing feed rate will cause increasing of surface roughness for different cutting speeds and different depth of cuts.
- Increasing cutting speed will cause decreasing of surface roughness for different feed rates and different depth of cuts.
- Increasing depth of cut from for small and medium feed rate (0.2 and 0.4 mm/rev) will decrease surface roughness for different speeds. But further increasing of depth of cut will cause increasing in surface roughness. Also it is shown that increasing depth of cut at high feed rate will not have remarkable effect on surface roughness and this may be because that the feed rate becomes the dominant factor affecting the surface roughness.

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