Proceedings of the Estonian Academy of Sciences,
2020, **69**, 2, 109–115
https://doi.org/10.3176/proc.2020.2.02
Available online at www.eap.ee/proceedings

MANUFACTURING ENGINEERING

Evaluation of surface roughness in the turning of mild steel under different cutting conditions using backpropagation neural network

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Received 26 November 2019, accepted 23 January 2020, available online 8 April 2020

Abstract. This paper exhibits a model of feed-forward backpropagation neural network system for estimating surface roughness in the turning operation. The workpiece of mild steel (carbon content 0.2%; hardness125 BHN) has been taken for turning operation under different cutting conditions with high-speed steel (HSS) tool (carbon content 0.75%; vanadium content 1.1%, molybdenum content 0.65%, chromium content 4.3%, tungsten content 18%, cobalt content 5%, hardness 290 BHN). Experiments have been executed on lathe machine HMT LB20. In the neural network model, the speed, feed and depth of cut have been considered as process parameters and surface roughness was taken as a response parameter. The neural network was developed based on initial experimental data. The developed neural network model during testing and validation was found to be within acceptable limits. The estimated maximum error was expected to be 10.77%. Error below 20% was considered reasonable, taking into account the fact that there is an intrinsic irregularity in metal cutting procedure.

Key words: backpropagation neural network, mild steel, neural network, surface roughness, turning.

1. INTRODUCTION

The researchers' attraction towards versatile computer numerical control (CNC) machine tools has been considerably increased. Tremendous efforts have been made by the researchers to develop a system that behaves like a man-made brain known as Artificial Intelligence (AI) machine tools. The artificial brilliant machine tool can evaluate the tool's conditions and response quality based on the feedback sensor system. Moreover, it also takes remedial actions at an ideal time. However, it was concluded that the existing study is still far from the desired objectives. The reliable prediction strategy for the development of work quality requires an unmanned turning centre or artificially-intelligent system. These days, the manufacturing corporations are worried about the clients' high expectations for product quality and manufacturers are always focused on the production of good quality products in minimum time at minimum cost. The surface roughness as response parameter is dependent on various parameters such as feed rate, speed rate and depth of cut. This paper proposes a strategy for the surface unpleasantness estimation based on the process parameters like feed rate, speed rate and depth of cut in cylindrical turning operation. The neural network was used to forecast surface finish for the tool-workpiece combination for various operating parameters during the machining operation.

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2. LITERATURE REVIEW

Abouelatta and Mádl [1] established an interrelationship between turning and cutting oscillations and surface roughness. Chien and Tsai [2] worked on tool damage and determined the optimal cutting situations in the turning process by adopting the backpropagation neural network. Das et al. [3] measured flank damage of the carbide tool in the turning process by using the backpropagation algorithm. Dixit et al. [4] measured the cutting forces and vibrations to develop the network-based model to foresee dimensional accuracy and surface roughness. Senthilkumar et al. [5] used an artificial neural network (ANN) approach to predict the cutting inserts' performances of different geometries in hard turning. Kohli and Dixit [6] forecasted the surface roughness for the turning process-by-process parameters to the neural chain model by an acceleration of the radial vibration of the holder for the tool. Lee and Tarng [7] made the surface images of the workpiece by the digital camera to investigate surface roughness for turning operations using a computer vision technique. Lee and Chen [8] analysed the model of turning operation at a constant nose radius using an artificial neural network. The vibration signatures in three directions had been utilized by the online surface roughness prediction.

Rangwala and Dornfeld [9] carried out a comprehensive study, compared the theoretical model with neural network models and also discussed the limitations of theoretical models. Selvam [10] studied the impact of tool vibrations and surface irregularities by measuring the frequency spectra of tool vibration.

Ugrasen et al. [11] have created a model to optimize wire electrical discharge machining (EDM) and estimation. Examination of outcomes were finished by using backpropagation neural network (BPNN) and Levenberg–Marquardt algorithm (LMA). It was seen that a neural system prepared with 70% of the information in the training set gave high expectation for the results compared to the half and 60% of the information in the training set. Therefore, anticipated response factors of 70% training set associate well with the deliberate response factors.

Paturi et al. [12] exhibited a methodology for foreseeing the surface roughness during hard turning of AISI 52100 steel utilizing regression analysis and artificial neural system. Simunovic et al. [13] assessed surface roughness using digital image features.

Based on the above described information, it may be concluded that regression analysis and artificial neural network models can be considered to be successful technique for the present research. It can also help to minimize the time and cost of experimental runs.

3. METHODOLOGY

In the present research, backpropagation neural network (BPNN) methodology was applied to predict the surface roughness. The BPNN includes an input layer, hidden layer and output layer as presented in Fig. 1. The information was received by the input layer from an external source and was further delivered to the networks for processing. Further information was received and

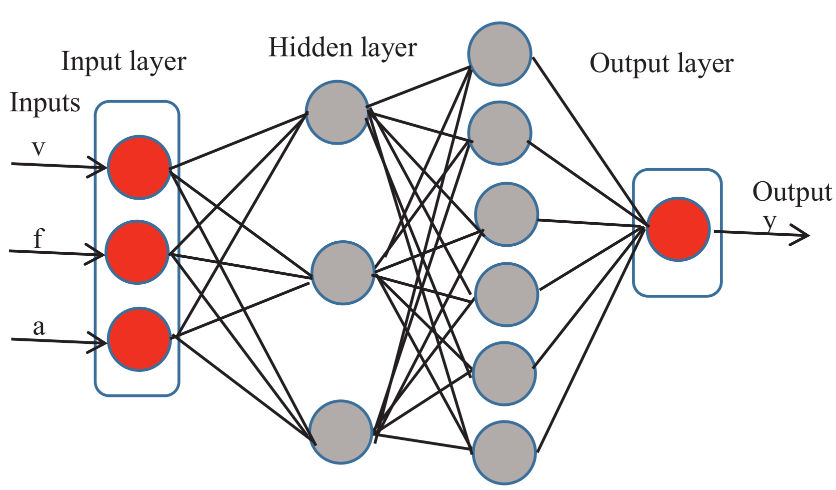

Fig. 1. A backpropagation neural network.

processed by the hidden layer. The output layer received the processed information. The interconnection weight, also known as weight factor *ijw*, was modified by input signals which speak about the linkage between *i*-th node (for the first layer) to *j*-th node (for the second layer) [14–16]. Total activation i.e. the modified signal was modified using log sigmoid activation function [16–18]. During training process, the determined output was compared with the objective output, the mean square, error (E) was estimated [19] by the Eq. (1), and error was calculated. While preparing the system, the determined output was correlated with the objective yield. Later on the mean square, the mean square error (E) was determined [19] by the accompanying Eq. (1). During initial modelling, the Error (E) is calculated [19] by condition (1). During the development of the model, the predicted output was compared with target output and mean squared error (MSE) was evaluated [19]:

$$E = \frac{1}{p}\left(\sum_{1}^{p}\sum_{k=1}^{n}\left(d_k^p - c_k^p\right)^2\right). \qquad (1)$$

4. DESIGN OF EXPERIMENTS

The cutting conditions were maintained the same for several number of experiments. The lathe machine (HMT LB20) was used for the turning operation. The workpiece of mild steel (carbon content 0.2%; hardness 125 BHN) was used for turning operation with high-speed steel (HSS) tool (carbon content 0.75%; vanadium content 1%; molybdenum content 0.65%; chromium content 4.3%; tungsten content 18%; cobalt content 5%; hardness 290 BHN) under different cutting conditions. Portable surface roughness tester (Surftest SJ-201P/M) was used to quantify surface irregularity of the machined surface.

5. OBSERVATIONS

Table 1 illustrates various experimental trial runs performed on mild steel (MS) workpiece using high speed steel (HSS) cutting tool.

6. RESULTS AND DISCUSSIONS

Different levels of speed, cut depth and feed rate were taken as process parameters for the turning process for the measurement of surface irregularity in a neural network. Error below 20% was considered to be reasonable, taking into account that there is an intrinsic irregularity in metal cutting procedure. The present feedforward neural networks (backpropagation) gives precise outcomes. On the other hand, this requires extra time for training and testing. The Levenberg-Marquardt algorithm based network training function (trainlm) of MATLAB Version 9.7 was used for faster convergence. The backpropagation based on the Levenberg-Marquardt method is well known heuristic method. To meet a performance goal of 0.001 neural networks with different combinations of several number of hidden neurons in the hidden layer were trained. This optimum neural network architecture was selected based on minimum mean squared error (MSE) and number of epochs.

Comparison between experimental surface roughness and simulated surface roughness (estimated by a neural network) was also carried out. The trained neural network prediction coincides closely with the obtained experimental results. Thirteen designed data (nearly 20% of data) were used as testing data. The neural network with various algorithms and transfer functions were tested and validated. Table 2 shows the testing data for the neural network. The three neurons such as depth of cut, feed rate and speed were selected. Input and output parameters were standardized to remain between 0.10 and 0.90 using Eq. (2):

$$y = 0.1 + 0.8 \times \left(\frac{x - x_{min}}{x_{min} - x_{max}}\right), \qquad (2)$$

where y = standardized value, corresponding to x, $x_{\max}$ = maximum value of x, $x_{\min}$ = minimum value of x, x = actual value.

The trial and error method was used to decide the several number of nodes in the hidden layer. To meet an objective of 0.001 neural systems with various mixes, several number of concealed neurons in the hidden layer were prepared. Table 3 exhibits errors during training for various neural network structures. The hidden neuron in neural network relies on the calculated mean square error, convergence rate, and optimized network architecture. In this study, the optimum network was found to be 3-6-1 as presented in Table 3. The training error variety with the quantity of iteration for the structure is shown in Fig. 3.

Table 4 shows the actual surface roughness values of the neural network and predicted surface roughness for 13 test data with percentage error. The maximum error was found to be 10.77 %. It was found that 20% error is reasonable, due to the intrinsic irregularity in the metal cutting procedure [6]. Figures 2 to 4 show the comparison of the surface roughness of experimental and simulated values given by 3-6-1 neural network for the test data as given in Table 4.

Table 1. Experimental data during turning MS using HSS tool

Test No.	Turning speed (rpm)	Cut depth (mm)	Feed speed (mm/rev)	Surface irregularity (μm)
1	320	0.8	0.2	8.57
2	320	0.8	0.1	7.56
3	320	0.8	0.075	5.03
4	320	0.8	0.066	4.13
5	320	0.5	0.2	7.72
6	320	0.5	0.1	6.67
7	320	0.5	0.075	4.28
8	320	0.5	0.066	3.15
9	320	0.2	0.2	6.28
10	320	0.2	0.1	5.02
11	320	0.2	0.075	3.63
12	320	0.2	0.066	2.95
13	320	0.1	0.2	7.02
14	320	0.1	0.1	5.90
15	320	0.1	0.075	3.77
16	320	0.1	0.066	2.99
17	500	0.8	0.2	8.13
18	500	0.8	0.1	7.24
19	500	0.8	0.075	5.59
20	500	0.8	0.066	4.59
21	500	0.5	0.2	6.72
22	500	0.5	0.1	5.58
23	500	0.5	0.075	3.58
24	500	0.5	0.066	3.05
25	500	0.2	0.2	7.42
26	500	0.2	0.1	5.17
27	500	0.2	0.075	3.73
28	500	0.2	0.066	2.85
29	500	0.1	0.2	7.70
30	500	0.1	0.1	6.42
31	500	0.1	0.075	4.84
32	500	0.1	0.066	3.95
33	800	0.8	0.2	7.20
34	800	0.8	0.1	6.81
35	800	0.8	0.075	4.98
36	800	0.8	0.066	3.85
37	800	0.5	0.2	7.74
38	800	0.5	0.1	6.26
39	800	0.5	0.075	4.36
40	800	0.5	0.066	3.75
41	800	0.2	0.2	7.40
42	800	0.2	0.1	5.87
43	800	0.2	0.075	4.29
44	800	0.2	0.066	3.65
45	800	0.1	0.2	6.90
46	800	0.1	0.1	6.40
47	800	0.1	0.075	4.60
48	800	0.1	0.066	3.71
49	1000	0.8	0.2	8.90
50	1000	0.8	0.1	6.44

Continued on the next page

Table 1. *Continued*

Test No.	Turning speed (rpm)	Cut depth (mm)	Feed speed (mm/rev)	Surface irregularity (μm)
51	1000	0.8	0.075	4.07
52	1000	0.8	0.066	3.15
53	1000	0.5	0.2	9.14
54	1000	0.5	0.1	8.26
55	1000	0.5	0.075	5.50
56	1000	0.5	0.066	4.12
57	1000	0.2	0.2	7.50
58	1000	0.2	0.1	6.21
59	1000	0.2	0.075	4.27
60	1000	0.2	0.066	3.50
61	1000	0.1	0.2	3.53
62	1000	0.1	0.1	3.03
63	1000	0.1	0.075	2.95
64	1000	0.1	0.066	2.02

Table 2. Testing data for the neural network

Test No.	Turning speed (RPM)	Cut depth (mm)	Feed rate (mm/rev)	Surface irregularity (μm)
1	320	0.8	0.2	8.57
2	320	0.5	0.1	6.67
3	320	0.2	0.075	3.63
4	320	0.1	0.066	2.99
5	500	0.5	0.2	6.72
6	500	0.2	0.1	5.17
7	500	0.1	0.075	4.84
8	800	0.8	0.066	3.85
9	800	0.2	0.2	7.40
10	800	0.1	0.1	6.40
11	1000	0.8	0.075	4.07
12	1000	0.5	0.066	4.12
13	1000	0.1	0.2	3.53

Table 3. The error of training for various neural structures

Neural network architecture	Mean square error in training	Number of epochs	Remarks
3-4-1	0.002323	1000	Performance goal not met
3-5-1	0.002313	1000	Performance goal not met
3-6-1	0.000995	48	Performance goal met

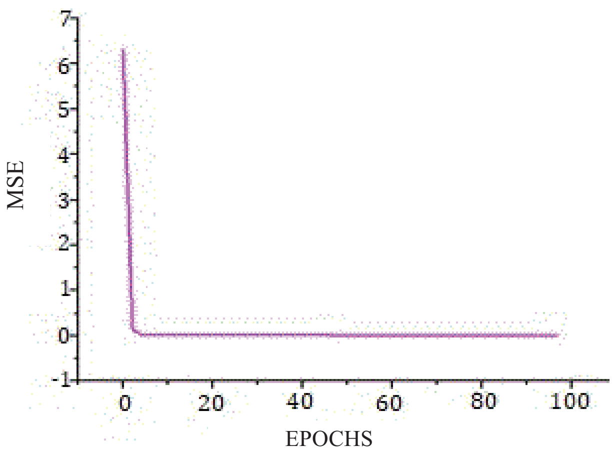

Fig. 2. Deviation of MSE in training with number of emphases for 3-6-1 neural system.

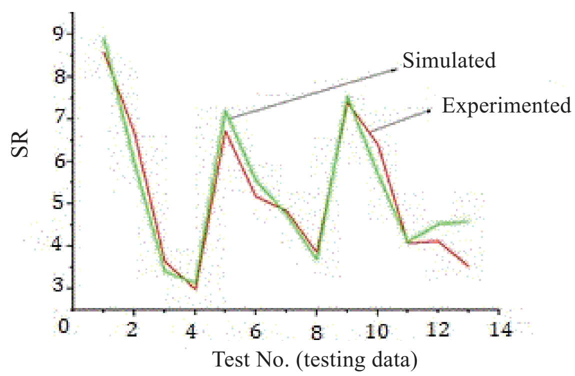

Fig. 3. A simulated and experimental surface roughness in testing data.

Table 4. The percentage error in testing data

Test No.	Actual surface roughness (μm)	Predicted surface roughness (μm)	% error
1	8.57	8.89	–3.74
2	6.67	5.98	10.31
3	3.63	3.41	5.84
4	2.99	3.12	–4.38
5	6.72	7.19	–7.06
6	5.17	5.59	–7.58
7	4.84	4.76	1.61
8	3.85	3.68	4.38
9	7.40	7.52	–1.71
10	6.40	5.71	10.77
11	4.07	4.10	–0.90
12	4.12	4.53	–10.19
13	3.53	4.59	–30.29

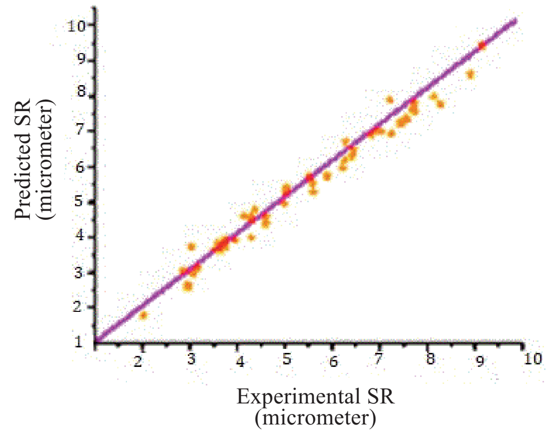

Fig. 4. The actual and predicted values of surface irregularity by 3-6-1 neural system.

7. CONCLUSIONS

The BPNN methodology was implemented to estimate the surface roughness in the turning process. The experiments were conducted on mild steel as a workpiece and high-speed steel as a tool. All tests were carried out on a lathe machine (HMT, LB-20). In this neural model, three process parameters were used: feed, speed and depth of cut. In this optimal network structure, mean square error and the convergence rate were calculated to investigate the response. The predicted surface roughness was very close to the values measured during experiments, showing the efficiency of the backpropagation neural network. The maximum presumptive error was 10.77 %. Also, error below 20% was considered reasonable, taking into account the fact that there is an intrinsic irregularity in metal cutting procedure. Further, software solution based on Artificial Intelligence (AI) and Internet of Things (IoT) is useful in building intelligent CNC machines to manage the production efficiently. Future research in this area can enable to open up a new revenue stream by imbibing such production solution into an enterprise resource planning (ERP) system.

ACKNOWLEDGEMENTS

The authors acknowledge the support from the Deanship of Scientific Research at King Khalid University, Kingdom of Saudi Arabia for funding this research under grant award number R.G.P.1/138/40. The publication costs of this article were partially covered by the Estonian Academy of Sciences.

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