PREDICTION OF TORQUE IN MILLING BY RESPONSE SURFACE METHOD AND NEURAL NETWORK

K. Kadirgama* and K.A. Abou-El-Hossein**

Abstract

The present paper discusses the development of the first-order model for predicting the cutting torque in the milling operation of ASSAB 618 stainless steel using coated carbide cutting tools. The first-order equation was developed using response surface method (RSM). The input cutting parameters were the cutting speed, feed rate, radial depth and axial depth of cut. The study found that the predictive model was able to predict torque values close to those readings recorded experimentally with a 95% confident interval. The results obtained from the predictive model were also compared by using multilayer perceptron with back-propagation learning rule artificial neural network. The first-order equation revealed that the feed rate was the most dominant factor which was followed by axial depth, radial depth and cutting speed. The cutting torque value predicted by using Neural Network was in good agreement with that obtained by RSM. This observation indicates the potential use of RSM in predicting cutting parameters thus eliminating the need for exhaustive cutting experiments to obtain the optimum cutting conditions in terms of torque.

Key Words

Torque, response surface method, milling, neural network

1. Introduction

Response surface method (RSM) is a collection of mathematical and statistical techniques for empirical model building [1, 2]. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables to identify the reasons for changes in the output response. Originally, RSM was developed to model experimental responses and then migrated into the modelling of numerical experiments. In RSM, the errors are assumed to be random [1, 2].

Mead and Pike [3] and Hill and Hunter [4] reviewed the earliest work on RSM. To establish an adequate functional relationship between the surface roughness and the cutting parameters (speed, depth of cut and feeds), a large number of tests are required, requiring a separate set of tests for each and every combination of cutting tool and workpiece material. Alauddin *et al.* [5] developed surface roughness models and determined the cutting conditions for 190 BHN steel and Inconel 718. They found that the variations of both tool angles have important effects on surface roughness. To model and analyze the effect of each variable and minimize the cutting tests, surface roughness models utilizing RSM and the experimental design were carried out in this investigation. Boothroyd [6] and Baradie [7] investigated the effect of speed, feed and depth of cut on steel and grey cast iron, and then emphasized the use of RSM in developing a surface roughness prediction model.

Artificial neural networks (ANNs) are excellent tools for complex manufacturing processes that have many variables and complex interactions. Neural networks (NN) have provided a means of successfully controlling complex processes [8]. Koren *et al.* [9] proposed a model-based approach to online tool wear and the breakage sensing. Algorithms and online training of the model-based approach by using artificial intelligence methods were suggested by them. Tarng and Lee [10] proposed using the average and median force of each tooth in the milling operation. Measured by sensors, the average and median forces of each tooth were used as input values. An appropriate threshold was built to analyze information and detect tool conditions. Koren *et al.* [9] introduced an unsupervised self-organized NN combined with an adaptive time-series AR modelling algorithm to monitor tool breakage in milling operations. Lee and Lee [11] used a NN-based approach to show that by using force ratio, flank wear could be predicted within 8–11.9% error and by using force increment the prediction error could be kept within 10.3% of the actual wear, whereas Choudhury *et al.* [12] used an optical fibre to sense the dimensional changes of the work piece and correlated it to the tool wear using a NN approach. Dimla and Lister [13] acquired cutting force and vibration data and

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measured wear during turning, and a NN was trained to distinguish the tool state. Tsai Yu-Hsuan *et al.* [14] used NNs to predict surface roughness in milling operations including machining parameters such as spindle speed, feed, depth of cut and vibration "intensity" per revolution.

2. Torque Model

The proposed relationship between the machining responses (torque) and machining independent variables can be represented by the following [1]:

$$\tau = C(V^m F^n A_x^q A_r^z)\varepsilon' \tag{1}$$

where τ is the torque in Nm, V, F, A_x and A_r are the cutting speed (m/s), feed rate (mm/rev), axial depth (mm) and radial depth (mm). C, m, n, q and z are the constants. (1) can be written in the following logarithmic form:

$$\ln\tau = \ln C + m\ln V + n\ln F + q\ln A_x + z\ln A_r + \ln\varepsilon' \tag{2}$$

(1) can be written as a linear form:

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \varepsilon \tag{3}$$

where y is the torque, $x_0 = 1$ (dummy variables), $x_1 = \ln V$, $x_2 = \ln F$, $x_3 = \ln A_x$, $x_4 = \ln A_r$ and $\varepsilon = \ln\varepsilon$, where ε is assumed to be normally distributed uncorrelated random error with zero mean and constant variance, $\beta_0 = \ln C$ and β_1, β_2, β_3 and β_4 are the model parameters. The values of β_1, β_2, β_3 and β_4 are to be estimated by the method of least squares using the following basic formula:

$$\beta = (x^T x)^{-1} x^T y \tag{4}$$

where x^T is the transpose of the matrix x and $(x^T x)^{-1}$ is the inverse of the matrix $(x^T x)$. The details of the solution by this matrix approach are explained in [1, 2]. The parameters were estimated by the method of least square using Matlab package.

2.1 Neural Network

A neural network (NN) is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing new, previously unseen data. Some networks are supervised, in that a human determines what the network should learn from the data. In this case, you give the network a set of inputs and corresponding desired outputs, and the network tries to learn the input–output relationship by adapting its free parameters. Other networks are unsupervised, in that the way they organize information is hard-coded into their architecture [15–17]. In addition to batch gradient descent, there is another batch algorithm for feedforward networks that often provides faster convergence, i.e. steepest descent with momentum [18]. Momentum allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Acting like a low-pass filter, momentum allows the network to ignore small features in the error surface. Without momentum, a network may get stuck in a shallow local minimum [19].

In the current application, the objective was to use the supervised network with multilayer perceptrons and trained with back-propagation algorithm with momentum. The components of the input pattern consisted of the control variables of the machining operation (the cutting speed, feed rate, axial depth and radial depth), whereas the output pattern components represented the response from sensors (torque). The nodes in the hidden layer were necessary to implement the non-linear mapping between the input and output patterns.

During the training process, initially all patterns in the training set were presented to the network and the corresponding error parameter (sum of squared errors over the neurons in the output layer) was found for each of them. Then the pattern with the maximum error was found which was used for changing the synaptic weights. Once the weights were changed, all the training patterns were again fed to the network and the pattern with the maximum error was then found. This process was continued till the maximum error in the training set became less than the allowable error specified by the user. In the mean time, the consistency of sum of squared errors and sum of network weights is maintained. Network structure 4-3-1 is chosen after the observation of consistent number of effective parameters and error terms. Torque RMS errors on the test data confirm the reliability of this approach.

This method has the advantage of avoiding a large number of computations, as only the pattern with the maximum error was used for changing the weights. The patterns were suitably normalized between 0 and 1 [20] to fit the sigmoid function model. First, a set of training data consisting of the normalized values of the input patterns and the corresponding output data was used for training the network, that is, to determine the connection weights. Optimization of associated parameters of the networks was carried out for achieving the minimum training error. It was observed that after 10,000 iterations RMS error appeared to be minimum for the learning rate and momentum. After the training of the network, the NN model can be used to assess the torque with the set of data of the input parameters.

2.2 Design of Experiments using RSM

To develop the first-order, a design consisting 27 experiments was conducted. Box–Behnken design is normally used when performing non-sequential experiments. That is, performing the experiment only once. These designs allow efficient estimation of the first- and second-order coefficients. Because Box–Behnken design has fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box–Behnken design does not have axial points so that all design points fall within the safe operating. Box–Behnken design also ensures that all factors are never set at their high levels simultaneously [21–23]. After the preliminary investigation, the suitable levels of the factors were determined as

Table 1
Levels of Independent Variables

Levels	Low	Medium	High
Cutting speed V (m/s)	100	140	180
Feed rate F (mm/rev)	0.1	0.15	0.2
Axial depth A_x (mm)	1	1.5	2
Radial depth A_r (mm)	2	3.5	5

shown in Table 1, and the necessary order and combinations of cutting experiments were generated using Minitab as shown in Table 2.

2.3 Experimental Details

The 27 experiments were carried out in a random manner on Okuma CNC machining centre MX-45 VA using a standard coolant. Each experiment was stopped after 85 mm cutting length. Meanwhile, the data about torque was acquired with the aid of a piezoelectric dynamometer provided by Kistler. Each experiment was repeated three times using a new cutting edge every time to obtain an accurate reading of the cutting force. A cutting pass was conducted in such a way that a shoulder, of depth ranging from 1 to 2 mm, and width of 2 to 5 mm, was produced. Fig. 1 shows the experimental setup employed in this study.

3. Results and Discussion

3.1 First-Order Model by RSM

The first-order linear equation for predicting the torque is expressed as:

$$y = 2.6215 - 0.1308x_1 + 0.2292x_2 + 0.1408x_3 + 0.2142x_4 \quad (5)$$

The levels of independent variables and coding identifications used in this design are presented in Table 1. Table 3 shows the experimental conditions and results obtained from experiments.

(5) can be transformed into the following form:

$$T = 315.23(V^{-0.5204}F^{0.796719}A_x^{0.489432}A_r^{0.60055}) \quad (6)$$

From this linear equation, it can be observed that the response y (torque) is affected significantly by the feed rate followed by axial depth of cut, then by radial depth of cut and lastly, by the cutting speed. Generally, the increase in feed rate, axial and radial depths of cut will cause the torque to become larger. On the other hand, the decrease in cutting speed will slightly cause a reduction in cutting torque. Table 3 compares the torque values obtained experimentally with those predicted by the first-order model (5) and NN. It is clear that the predicted values are in good agreement with the experimental values. This indicates that the obtained linear model is able to predict the values of torque.

Table 2
Design Values Obtained from the Minitab

Run	Cutting Speed (m/s)	Feed Rate (mm/rev)	Axial Depth (mm)	Radial Depth (mm)
1	140	0.15	1	2
2	140	0.2	1	3.5
3	100	0.15	1	3.5
4	180	0.15	1	3.5
5	140	0.1	1	3.5
6	140	0.15	1	5
7	100	0.15	1.5	2
8	140	0.1	1.5	2
9	100	0.2	1.5	3.5
10	140	0.15	1.5	3.5
11	180	0.2	1.5	3.5
12	180	0.15	1.5	2
13	140	0.2	1.5	2
14	140	0.15	1.5	3.5
15	140	0.15	1.5	3.5
16	180	0.1	1.5	3.5
17	100	0.1	1.5	3.5
18	100	0.15	1.5	5
19	140	0.1	1.5	5
20	180	0.15	1.5	5
21	140	0.15	1.5	3.5
22	140	0.15	2	5
23	140	0.2	2	3.5
24	140	0.1	2	3.5
25	140	0.15	2	2
26	100	0.15	2	3.5
27	180	0.15	2	3.5

The adequacy of the first-order model was also verified using the analysis of variance (ANOVA). At a level of confidence of 95%, the model was checked for its adequacy and the results are presented in Table 4. The model is adequate as the P values of the lack-of-fit are not significant. This implies that the model could fit and it is adequate.

The developed linear model (5) was used to plot contours of the torque at different values of cutting speed and radial depth. Fig. 2(a–c) shows the torque contours at three different combinations of cutting speed and feed rate.

Figure 1. Tool holder and Okuma CNC machine.

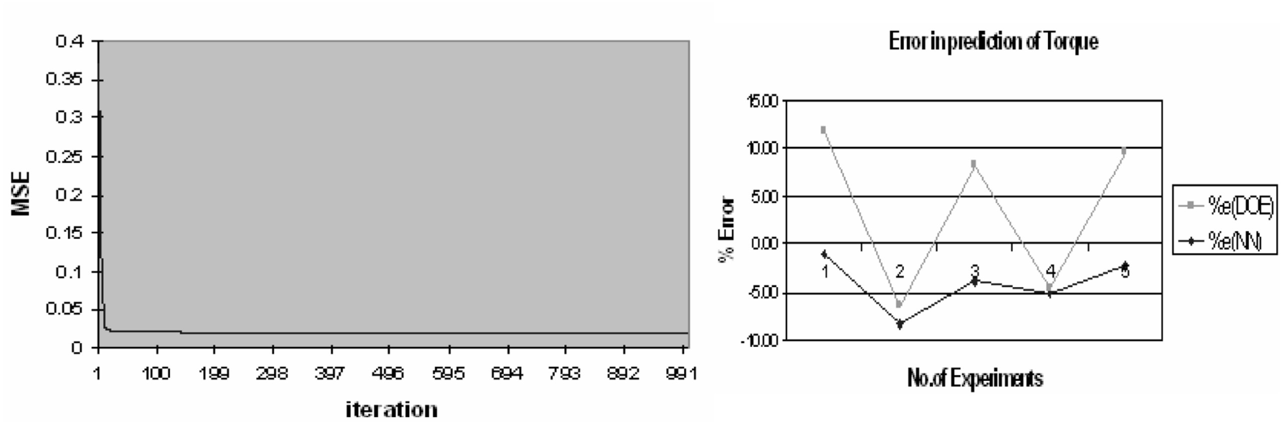
Table 3
Torque Experimental Results, Prediction Values by RSM

Run	Cutting Speed (m/s)	Feed Rate (mm/rev)	Axial Depth (mm)	Radial Depth (mm)	Experimental Torque (Nm)	Prediction of Torque by RSM (Nm)
2	140	0.15	1	2	10	8.06
7	140	0.2	1	3.5	13	14.18
11	100	0.15	1	3.5	16	13.43
14	180	0.15	1	3.5	13	9.89
19	140	0.1	1	3.5	8	8.16
21	140	0.15	1	5	16	13.97
4	100	0.15	1.5	2	16	11.71
5	140	0.1	1.5	2	7	7.11
6	100	0.2	1.5	3.5	17	20.6
9	140	0.15	1.5	3.5	14	13.75
10	180	0.2	1.5	3.5	18	15.17
12	180	0.15	1.5	2	12	8.62
15	140	0.2	1.5	2	13	12.36
22	140	0.2	1.5	5	18	21.42
24	140	0.15	1.5	3.5	13	13.75
25	180	0.1	1.5	3.5	8	8.73
26	100	0.1	1.5	3.5	14	11.86
8	100	0.15	1.5	5	22	20.29
17	140	0.1	1.5	5	14	12.33
18	180	0.15	1.5	5	15	14.95
22	140	0.15	1.5	3.5	18	13.75
1	140	0.15	2	5	20	19.61
3	140	0.2	2	3.5	23	19.91
13	140	0.1	2	3.5	13	11.46
16	140	0.15	2	2	11	11.31
20	100	0.15	2	3.5	23	18.86
27	180	0.15	2	3.5	16	13.89

Table 4
Analysis of Variance of RSM First-Order Equation

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	434.746	434.746	108.687	186.37	0
Linear	4	434.746	434.746	108.687	186.37	0
Residual error	22	12.830	12.830	0.583		
Lack-of-fit	20	12.830	12.830	0.642	5.1033	0.196
Pure error	2	0.000	0.000	0.1258		
Total	26	447.576				

Figure 2. Torque contours in the axial depth–radial depth plane: (a) cutting speed 100 m/s and feed rate 0.1 mm/rev; (b) cutting speed 140 m/s and feed rate 0.15 mm/rev; and (c) cutting speed 180 m/s and feed rate 0.2 mm/rev.



(a) (b)

Figure 3. (a) MSE of the torque predicted by ANN and (b) prediction error by ANN and RSM.

Table 5
Prediction Results of Torque by ANN and RSM

No. Exp.	Experimental Torque (Nm)	Prediction of Torque by RSM (Nm)	Prediction of Torque by ANN (Nm)
1	10	8.06	11.41
2	13	14.18	16.63
3	16	13.43	15.61
4	13	9.89	12.11
5	8	8.16	10.80
6	16	13.97	16.16
7	16	11.71	14.47
8	7	7.11	9.80
9	17	20.6	18.42
10	14	13.75	15.16
11	18	15.17	16.29
12	12	8.62	10.93
13	13	12.36	15.72
14	18	21.42	18.63
15	13	13.75	15.16
16	8	8.73	10.34
17	14	11.86	13.83
18	22	20.29	18.14
19	14	12.33	14.53
20	15	14.95	15.75
21	18	13.75	15.16
22	20	19.61	17.92
23	23	19.91	18.25
24	13	11.46	13.29
25	11	11.31	13.96
26	23	18.86	17.57
27	16	13.89	14.68

It is clear that the reduction in cutting speed and increase in feed rate will cause the torque to increase dramatically.

From the contour shown in Fig. 2(c) the torque reaches its highest value when the cutting speed is at its lowest value and feed rate, axial depth and radial depth are at their maximum values. In this case, the torque can reach more than 20 N. The lowest torque occurs when the cutting speed is at its maximum value and the other factors at its minimum value (Fig. 2(a)).

3.2 Comparison between Two Techniques

After determining the ANN programme and RSM equations for predicting the torque values, the two techniques will be compared. It is clear that the two groups of values are close to each other (Table 5). Fig. 3(a) shows the MSE (mean square error) of the NN for predicting torque and Fig. 3(b) shows the prediction error of both methods. It is clear that the error percentage of RSM and ANN techniques is relatively small and can be neglected. Fig. 4 shows the experimental results and the ANN prediction results.

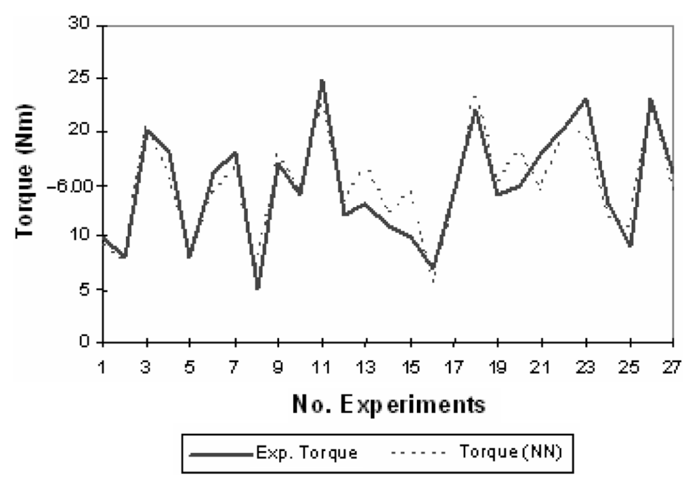


Figure 4. Prediction of torque by NN and experimental data.

4. Conclusion

In the present research, the first mathematic model was developed to predict cutting torque when milling of ASSAB

618 stainless steel using coated carbide RSM. The predicted results by RSM were compared by experimentation and further confirmed by using artificial intelligent.

In general, the results obtained from the mathematical model are quite close to those found experimentally as well as those predicted by NN. The results showed that the torque increases with increasing feed rate, cutting speed, axial depth and radial depth. With feed rate having the most dominant effect on the cutting torque.

The use of ANN in predicting the cutting torque was found to be effective. The results obtained by ANN were in good agreement with those predicted by RSM. In conclusion, the two techniques are considered potential to conduct optimization tasks in machining operations. The current study can be utilized successfully in similar experimentations as far as the same range of cutting parameters are used when end milling ASSAB 618 steel with coated carbide inserts.

Acknowledgement

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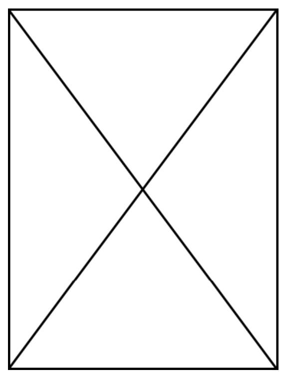
Biographies



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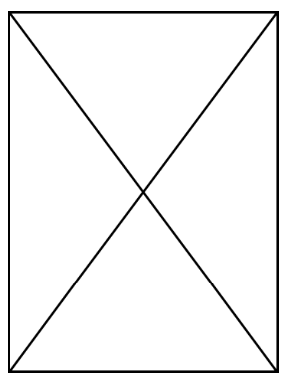

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