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Prediction of Tool Life in End Milling of Ti-6Al-4V Alloy Using Artificial Neural Network and Multiple Regression Models

(Ramalan Hayat Mata Alat dalam Kisar Hujung Aloi Ti-6Al-4V Menggunakan Rangkaian Neural Tiruan dan Model Regresi Pelbagai)

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ABSTRACT

Tool life of the cutting tools is considered as one of the factors which has effects on machining costs and the quality of machined parts. The topic of tool life prediction has been an interesting and important research topic attracting the attention of a wide number of researchers in this particular area. In terms of the suitable methods used in this research topic, it is stated that both statistical and artificial intelligence (AI) approaches can be employed to model tool life. For further justifying the capability of the ANN model in predicting tool life, the current study was based on conducting experimental work for collecting the experimental data. After carrying out the experiment, 17 data sets were collected and they were divided into two subsets; the first one for training and the second for testing. Since the data sets seemed to be lower than the number of data sets used in previous studies, we attempted to make verification of the ability of the ANN model in learning and adapting with low training and testing data. Diverse topologies accompanied with single and two hidden layers were created for modeling the tool life. For choosing the best and most effective network, the study adopted the mean square error function as criteria for the evaluation of the network selection. Thus, based on the data generated from the same experiment, a regression model (RM) was constructed employing the SPSS software. A comparison between the ANN model and RMs in terms of their accuracy was carried out and the findings revealed that the accuracy of the ANN was higher than that of the RM.

Keywords: Artificial neural network; prediction; tool life; uncoated carbide

ABSTRAK

Hayat mata alat merupakan salah satu faktor yang memberi kesan terhadap kos pemesinan dan kualiti produk yang dimesin. Topik mengenai ramalan hayat mata alat sangat menarik dan merupakan kajian yang penting dan menarik perhatian sebahagian jumlah penyelidik dalam bidang ini. Kaedah yang sesuai digunakan dalam kajian ini ialah statistik dan pintar buatan bagi memodelkan hayat mata alat. Bagi justifikasi keupayaan model ANN dalam ramalan hayat mata alat, kajian ini berdasarkan kepada membuat kerja eksperimen untuk pengumpulan data. Selepas menjalankan eksperimen, 17 set data telah dikumpulkan dan dibahagikan kepada dua subset data; pertama untuk latihan dan kedua untuk ujian. Disebabkan set data agak rendah berbanding kajian sebelum ini, keupayaan model ANN dikaji dalam pembelajaran dan adaptasi dengan data latihan dan ujian yang rendah. Topologi yang besar berserta satu dan dua lapis tersorok telah direka bagi memodelkan hayat mata alat. Bagi memilih rangkaian terbaik dan paling berkesan, kajian ini menggunakan fungsi min ralat kuasa dua sebagai kriteria untuk penilaian rangkaian yang dipilih. Oleh itu, berdasarkan data yang dijana daripada eksperimen, model regresi (RM) telah dibangunkan menggunakan perisian SPSS. Perbandingan kejituan antara model ANN dan RMS telah dibuat dan hasil kajian menunjukkan kejituan model ANN lebih tinggi berbanding dengan RM.

Kata kunci: Hayat mata alat; karbida tak bersalut; ramalan; rangkaian neural tiruan

INTRODUCTION

The process of machining has been proven to be a complex or sophisticated process in previous studies. This indicates that it is characterized as a non linear problem. It is stated that any approach employed or applied for the purpose of modeling such processes shows a relation between inputs parameters and response (Zain et al. 2010). Modeling of machining processes is possible to be carried out either through conventional methods or artificial techniques. However, the problem in using the conventional approaches is that they cannot be representatives of the nonlinearity of these kinds of problems. Here, at this particular point, the importance of artificial intelligence (AI) methods is emphasized as they are more capable of doing this specific function, thus, meeting the need and achieving this purpose. Generally pointing out the features of all AI methods, it is stated that they are considered as a mimic and simulation of nervous cell (Graupe 2007). Moreover, the literature has proven that the artificial neural network (ANN) method is regarded as the most well-known method among all AI methods. This is because it is the most frequently used technique which has been used by researchers for modelling linear and non-linear problems. Furthermore, AI methods are more capable of mapping non-linear input-output relation than statistical techniques. Due to the evidence of the importance of artificial neural network (ANN) as an artificial intelligence approach, the current utilized AI in predicting tool life as one of the uncoated carbide cutting tools and its role in ending milling of Ti-6Al-4V alloy under dry cutting conditions.

It was pointed out that tool wear leads to degradation of the quality of machined part being cut, so it can be modeled employing or making a use of the ANN. The majority of the previous studies and investigations have been conducted on surface roughness in comparison to those studies on tool wear and life especially in milling process (Al-Zubaidi et al. 2011). For instance, Dutta et al. (2000) conducted a study examining the convergence speed and prediction accuracy of modified back propagation in comparison to normal back propagation in monitoring the tool conditions. The findings of the study showed that the momentum factor significantly affects the convergence speed more than the learning rate does. In a study by Chen and Chen (2004), an online tool wear prediction system was presented and the ANN was used. Moreover, 100 and 9 experimental data sets were applied in training and testing the feed forward back propagation. In this study, input parameters were average peak force in Y axis, feed rate and depth cut. The findings obtained good results by using this system.

Another study by Palanisamy et al. (2007) investigated the application of both of regression model (RM) and the ANN model for tool wear prediction in end milling AISI 1020 steel with carbide inserts. The design of the experiments was carried out based on three full factorials which have five levels namely; cutting speed, feed rate and depth of cut which constituted the input parameters whereas the output was flank wear. The findings obtained from the experiments revealed that the ANN model generated accurate results than those results obtained through the RM. In addition, Bruni et al. (2008) enhanced ANN and multiple regression models to be used or adopted by studies on surface roughness and tool wear prediction in end milling AISI 420B stainless steel under different cutting and lubricant conditions (dry, wet and minimum lubricant quantity MQL). It was found that under high cutting speed with MQL, minimum surface roughness and wear can be obtained. Therefore, for the current study, the ANN method was applied for the purpose of predicting tool life of uncoated carbide cutting tools in end milling of Ti-6Al-4V alloy.

ARTIFICIAL NEURAL NETWORK (ANN)

ANN is defined as a neural network mimic nervous system which is made up of processing units working in parallel. Such units are connected in terms of their weights, a connection which is usually updated through training so that the minimum error between the targets and desired output can be reached in the experiment. The process of tuning the weight values is pursued till the ANN output becomes almost equal or approaches the targets.

This type of ANN known as back propagation is used in machining in comparison to other algorithms. This is because of its efficiency and accuracy. The architecture of the back propagation neural network is depicted in Figure 1. The architecture consists of input, hidden and output layers. Each layer has a number of processing elements called neurons. The number of neurons at the input and output are determined by the problem parameters. However, researchers are free to select the number of hidden layers and their neurons, as there is no clear-cut method in selecting network parameters. Feed forward back propagation neural networks are considered as

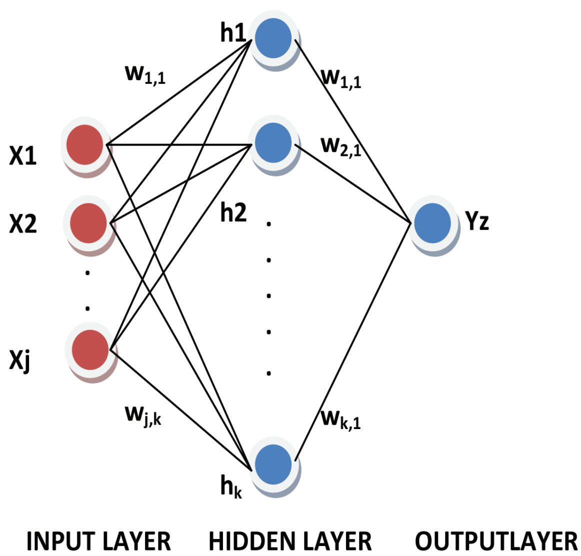

FIGURE 1. Back propagation neural network architecture

supervised network which both the inputs and outputs are being provided. Depending on the complexity of the problems, this neural network is more probable to contain one or more hidden layers. The ANN allows the existences of multi-nonlinear transfer functions so that the nonlinear input-output relationships can be mapped. As described in the Neural Network Tool Box User Guide (Beale et al. 2010; Hagan et al. 1996), the design steps of neural networks are shown in Figure 2.

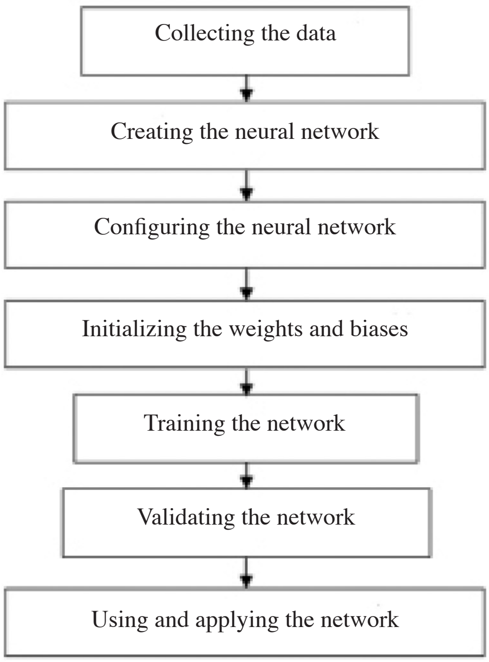

FIGURE 2. Design steps of neural networks

Based on this guide, it is stated that after conducting the initial four points, the neural network becomes ready for training. In the training phase, determining the mean square error between the output and target is conducted using the following equation:

$$\text{MSE} = \frac{1}{N}\sum_{i=0}^{N}\left(\text{Target - Output}\right)2, \quad (1)$$

where N symbolizes the number of input sets.

The weights and biases in back propagation are adjusted using gradient decent algorithms so that a rapid decrease in MSE can be achieved and it is described as follows:

$$wi + 1 = wi + \alpha gi, \quad (2)$$

$$bi + 1 = bi + \alpha gi, \quad (3)$$

where w and b represent the weight and the bias and α stands for the learning rate and g for the current gradient, respectively.

THE MULTIPLE LINEAR RM

The RM for analysis is defined as a statistical technique used for the purpose of modeling and examining the relationship between two or more variables. It is stated that a simple linear RM is used when there is only a single independent variable. However, there are cases when a multiple RM is applied especially when there are two or more than two independent variables affecting the outcome of a process (Magrab et al. 2000). For the current study, this type of analysis was carried out as follows:

$$y = \beta_0 + \sum_{j=1}^{k}\beta_j x_j, \quad (4)$$

where K is a symbol representing the independent variables and the parameters β_j, j=0, 1, 2 and k are the regression coefficients.

EXPERIMENTAL DETAILS

In this study, Nagi's work (Elmagrabi 2009) is a dependent case study carried out in the ANN modeling. In this study, Ti-6Al-4V alloy was machined with uncoated carbide using a CNC Milling machine. The cutting speed, depth of cut and axial depth of cut were used as the input parameters whereas the tool life was used as the output. Below are the mechanical properties of Ti-6Al-4V alloy and information concerning the cutting tool insert geometry:

Ultimate tensile strength [MPa]:950
Yield strength [MPa]:880
Rockwell Hardness HRC:36
Modulus of elasticity [GPa]:113.8
Poisson's ratio:0.342
ISO grade K20: (S20)-XOMX090308TR ME06, H25 (Uncoated Carbide) with chamfer of 0.06 width at 4°
Insert cutting rake angle: 24°
Insert side clearance angle: 11°
Insert helix angle: 15°
Insert radius: 8 mm

ANN MODELING

As previously discussed, it is evident that the back propagation neural network is more advantageous than other neural networks. Therefore, it was applied in the present study. Table 1 shows the 17 sets of the experimental data used in the study and such experiments were designed based on the factorial design of experiment. Furthermore, creating 110 different topologies was conducted for later evaluation of the data in the current study and single and two hidden layers were employed along with a number of neurons ranging from 1 to 10. For tansigmoid and purline transfer functions, they were only used in hidden and output layers, respectively. Then, training the neural network was done by using Levenberg-Marquard algorithm.

TABLE 1. Experimental data

No.	Cutting speed (mm\min)	Feed rate(mm/tooth)	Depth of cut (mm)	Tool life (min.)
1	77.5	0.1	1	5.8
2	105	0.1	1.5	3.65
3	77.5	0.15	1.5	3.8
4	77.5	0.15	1.5	3.5
5	50	0.15	1	5.74
6	77.5	0.2	1	3.735
7	105	0.15	2	1.098
8	105	0.2	1.5	0.82
9	50	0.15	2	4.208
10	105	0.15	1	2.451
11	77.5	0.15	1.5	3.7
12	50	0.2	1.5	4.6
13	77.5	0.2	2	3
14	77.5	0.1	2	5
15	50	0.1	1.5	6
16	77.5	0.15	1.5	3.7
17	77.5	0.15	1.5	3.5

Furthermore, 1000 max epochs were used in the current study. Normalization of all the input and output: These sets were divided into two subsets; 14 sets were used for training the network and the other three sets were used for testing the network. The data sets were conducted for the purpose of avoiding computing problems in this study. As previously stated, the first 14 data sets were used for training and the last three were used for testing. Summing up this, the neural networks was designed, configured, trained and tested using Matlab neural network.

RESULTS AND DISCUSSION

After we completely carried out the processes of training and testing the 110 configurations, we used only 4 configurations for evaluating the model, but the remaining configurations were discarded. Table 2 presents the results regarding the real and predicted values of the fourth ANN models.

The absolute mean square error (AMSE) was used as criteria for evaluating the selection of the best ANN model. Based on the results of such evaluation, as displayed in Table 2, it was found that networks numbered (3-7-1) are the best network in the training phase and some identical values can be evidently seen in network in the training phase and some identical values can be evidently seen in the same above table. An additional evidence of the previously stated best selected networks (3-7-1) is the best results in the testing phase generated from them in comparison to the results of others with minimum AMSE 0.1967 as displayed:

AMSE (3-7-1): 0.1967.
AMSE (3-7-5-1): 1.55167.

TABLE 2. Training phase results

No.	Real tool life [min.]	3-7-1	3-7-5-1	3-8-5-1	3-8-8-1
1	5.8	5.586869	4.576413	5.800038	5.804433
2	3.65	3.649999	3.65	3.65	5.501951
3	3.8	3.5	3.65	3.800085	3.655642
4	3.5	3.5	3.65	3.800085	3.655642
5	5.74	5.74	5.74	5.74009	5.713932
6	3.735	3.734999	3.735	3.73491	3.812408
7	1.098	2.03089	1.098	1.098024	1.092142
8	0.82	0.820001	1.762881	0.819953	0.957487
9	4.208	4.208	4.208	4.297046	4.350178
10	2.451	2.451	2.451	3.109888	2.461321
11	3.7	3.5	3.65	3.800085	3.655642
12	4.6	4.599999	4.626785	4.60001	4.600945
13	3	3.000001	3	2.999999	2.965786
14	5	4.999993	5	5	5.002285

AMSE (3-8-5-1): 0.83417.
AMSE (3-8-8-1): 0.88387.

Moreover, Figure 3 shows the actual and predicted values of the best network selection and it is evident that the results revealed a good level of agreement or consistence between agreement, the targets and the output of the ANN model.

For developing RM for the purpose of evaluating the tool life values, the mathematical model given in (4) was used and the following equation reflects this:

$$Y = \beta 0 + \beta 1x1 + \beta 2x2 + \beta 3x3, \qquad (5)$$

where y stands for the predicted value of tool life and the symbols ×1, ×2, ×3 represent the cutting speed, feed rate and depth of cut, respectively, whereas βo, β1, β2 and β3 stand for the coefficients of these cutting parameters. Thus, based on the data for the real machining experiments as presented in Table 1, the RMs for each cutting tool presented in (5) were developed by using the SPSS software.

Table 3 shows the results concerning the values of coefficients for the model parameters of uncoated cutting tools.

Having the values of coefficients for uncoated cutting tool transferred from Table 3 into (5), the equations of the RM can be expressed as follows:

$$Y = 12.964 - 0.057x1 - 20.737x2 - 1.105x3, \qquad (6)$$

where Y is the predicted tool life, ×1, ×2, ×3, represent cutting speed, feed rate and depth of cut, respectively.

Consequently, the scores of tool life values of the experimental data (Table 1) and the tool life predicted values of the RM (6) were compared as displayed in Table 4.

The results showed that in both training and testing phases, the accuracy of the ANN model was higher than that of the RM. In other words, we found that the accuracy of the ANN model reached more than 92% whereas the accuracy of the RM was 86.53%. This indicates that using the ANN model can generate results which are much better than the results obtained through the RM. This is due to the fact that the ANN

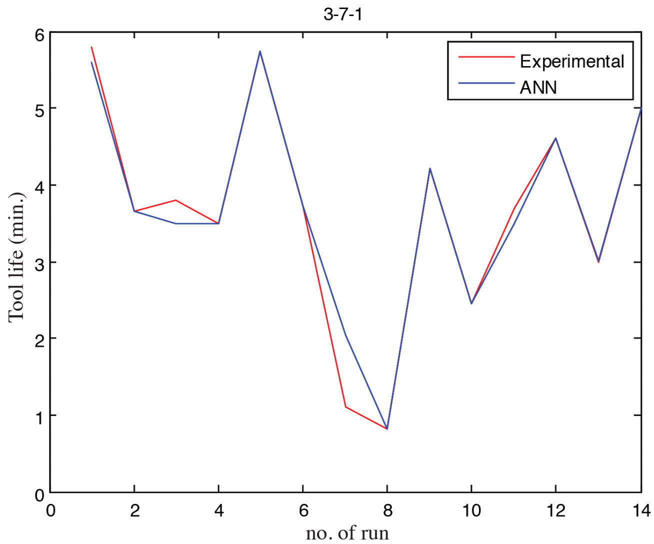

FIGURE 3. Actual and predicted values of model 3-7-1 in training phase

TABLE 3. Coefficients values for uncoated cutting tool

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% Confidence interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	8.196	.994		8.246	.000	6.078	10.315
Cutting speed	-.057	.012	-.763	-4.570	.000	-.084	-.030
(Constant)	11.307	.924		12.239	.000	9.325	13.288
Cutting speed	-.057	.008	-.763	-7.074	.000	-.074	-.040
Federate	-20.737	4.428	-.505	-4.683	.000	-30.234	-11.241
(Constant)	12.964	.880		14.736	.000	11.064	14.865
Cutting speed	-.057	.006	-.763	-9.149	.000	-.070	-.044
Federate	-20.737	3.424	-.505	-6.057	.000	-28.134	-13.341
Depth of cut	-1.105	.342	-.269	-3.227	.007	-1.845	-.365

Dependent Variable: tool life

TABLE 4. Comparison between ANN and RM models

No.	Actual tool life (min.)	Predicted tool life (3-7-1 ANN model)	Error %	Predicted tool life (RM model	Error %
1	5.8	5.586869	3.674672	5.3678	7.451724
2	3.65	3.649999	2.74E-05	3.2478	11.01918
3	3.8	3.5	7.894737	3.77845	0.567105
4	3.5	3.5	0	3.77845	7.955714
5	5.74	5.74	0	5.89845	2.760453
6	3.735	3.734999	2.68E-05	3.2941	11.80455
7	1.098	2.03089	84.96266	1.65845	51.04281
8	0.82	0.820001	0.000122	1.1741	43.18293
9	4.208	4.208	0	4.79345	13.91279
10	2.451	2.451	0	2.76345	12.74786
11	3.7	3.5	5.405405	3.77845	2.12027
12	4.6	4.599999	2.17E-05	4.3091	6.323913
13	3	3.000001	3.33E-05	2.1891	27.03
14	5	4.999993	0.00014	4.2628	14.744
15	6	5.3	11.66667	6.3828	6.38
16	3.7	3.4	8.108108	3.77845	2.12027
17	3.5	3.4	2.857143	3.77845	7.955714
Average error% in training Average error% in testing			7.281275 7.543973	Average error%	13.4776

model is capable of modeling the nonlinear problems much more effective than other conventional techniques.

CONCLUSION

It is evident that the ability of the ANN model to model and map the non linear input-output relations is better than that of other traditional models. The results of the current study also revealed that the best neural network topologies selected were (3-7-1); which represents a single hidden layer with seven hidden neurons, respectively. In addition, it was found that the minimum absolute MSE for this model in the testing phase was 0.1967 and this means that good generalization was obtained. The results showed evidence of obtaining a high level of accuracy by using this model and this was proved as it reached more than 92% in the training and testing phases. However, the study proved that the accuracy of the RM was 86.53% which is less than that of the ANN model. Although the experiment was based on low training and testing data, the ANN model was more effective and more capable of predicting the tool life of uncoated carbide when end milling of Ti-6Al-4V under dry conditions in a good accuracy. The ANN proved its ability to learn through training with low data sets and can give good predictive accuracy and efficiency. So, large data sets do not guarantee network generalization, but at the same time, large training data sets cover the conditions of the problems and they are better than low training data sets.

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