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Prediction of Cutting Force Model by Using Neural Network

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Abstract: This study describes application of neural network methods to predict the cutting force model in milling 618 stainless steel. Cutting force was taken as response and the variables (cutting speed, feed rate, axial depth and radial depth). Design of experiments was used to reduce the number of the experiments and provide the optimum experiments condition. The predictive result between experimental result and neural network were compared. The error from the neural network prediction result was acceptable since the value of the prediction was closer to the experimental result.

Key words: Cutting force, neural network, milling design of experiments

INTRODUCTION

Recently, Artificial Neural Networks (ANN) and neuro-fuzzy techniques have been intensively studied and are the most frequently chosen methods of Artificial Intelligence (AI) for feature fusion[1-4]. Artificial Neural Networks (ANNs) are excellent tools for complex manufacturing processes that have many variables and complex interactions. Neural networks have provided a means of successfully controlling complex processes[5]. In the past, a large number of researchers reported application of neural network models in tool condition monitoring and predictions of tool wear and tool life. An exclusive review of the current literature is presented by Dan and Mathew[6].

A neural network is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to 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[7-9].

In the current application, the objective was to use the network to learn mapping between input and output patterns. 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 (cutting force). The nodes in the hidden layer were necessary to implement the nonlinear mapping between the input and output patterns.

In the present study a method known as the active learning has been used. 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. 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. Figure 1 shows the example of the neural network computational model.

The patterns were suitably normalized between 0 and 1[10] 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

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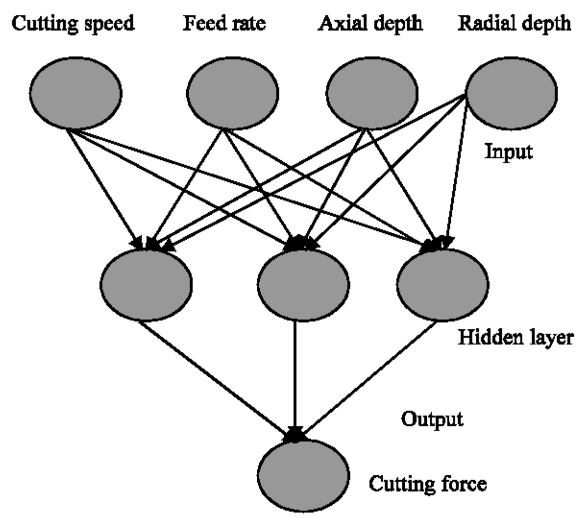

Fig. 1: Neural network computational model

10,000 iterations rms, error appeared to be minimum for the learning rate and momentum. After the training of the network, the Neural Network model can be used to assess the force with the set of data of the input parameters.

MATERIALS AND METHODS

The 618 stainless steel workpieces were provided in fully annealed condition in sizes of 65x170 mm and produce by Sanyo Special Steel Co. Ltd. The tools used in this study are carbide inserts PVD coated with one layer of TiN. The inserts are manufactured by Kennametal with ISO designation of KC 735M. They are specially developed for milling applications where stainless steel is the major machined material.

The end-milling tests were conducted on Okuma CNC machining centre MX-45VA. The cutting tests were carried out according to ISO standard. Dynamometer used to measure the force. Every one passes (one pass is equal to 85 mm), the cutting test was stopped. The same experiment has been repeated for 3 times to get more accurate result.

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 do not have axial points, thus can be sure 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[11,12]. Preliminary tests were carried out to find the suitable cutting speed, feed rate, axial depth and radial depth as shown in Table 1.

Table 1: Levels of independent variables

Levels	Low	Medium	High
Coding	-1.0	0.0	1.0
Speed v (m s^{-1})	100.0	140.0	180.0
Feed f (mm rev^{-1})	0.1	0.2	0.3
Axial depth d_a (mm)	1.0	1.5	2.0
Radial depth d_r (mm)	2.0	3.5	5.0

RESULTS AND DISCUSSION

Table 2 show the predictive result of neural network and experimental result. The error shows that the value of the prediction result of neural network can be acceptable. The range of the error is round 12%. From the result, the cutting force increase at low speed and increase at high feed rate, axial depth and radial depth. The accuracy of the prediction value of neural network is very closer to the experimental result. Figure 2 shows the force comparison between Neural Network and experimental. Error between prediction value and experimental is shown in Fig. 3

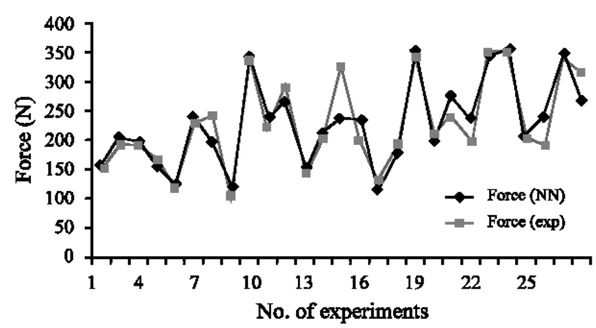

Fig. 2: Force comparison between experimental data and prediction force by NN

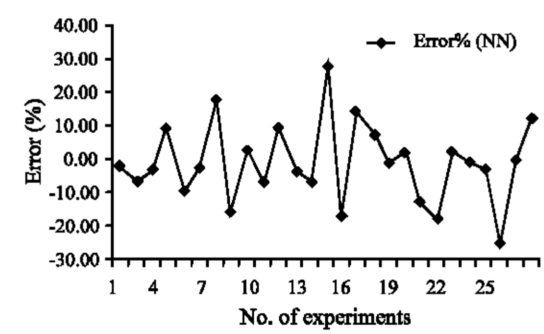

Fig. 3: Error between prediction and experimental values

Table 2: Experimental force and prediction force by neural network

Run	Cutting speed (m s^{-1})	Feed (mm rev^{-1})	Axial depth (mm)	Radial depth (mm)	Force form experimental	Force pre. (NN)	Error (%)
1	140	0.15	1	2	146.67	150.49	-2.61
2	140	0.2	1	3.5	190	203.07	-6.88
3	100	0.15	1	3.5	190	197.01	-3.69
4	180	0.15	1	3.5	170	154.69	9.01
5	140	0.1	1	3.5	110	120.27	-9.34
6	140	0.15	1	5	225	232.79	-3.46
7	100	0.15	1.5	2	240	200.01	16.66
8	140	0.1	1.5	2	100	115.69	-15.69
9	100	0.2	1.5	3.5	340	334.22	1.70
10	140	0.15	1.5	3.5	220	235.51	-7.05
11	180	0.2	1.5	3.5	293.33	266.22	9.24
12	180	0.15	1.5	2	145	149.74	-3.27
13	140	0.2	1.5	2	200	212.65	-6.32
14	140	0.15	1.5	3.5	325	235.51	27.54
15	140	0.15	1.5	3.5	200	235.51	-17.75
16	180	0.1	1.5	3.5	130	113.49	12.70
17	100	0.1	1.5	3.5	190	175.70	7.53
18	100	0.15	1.5	5	340	343.23	-0.95
19	140	0.1	1.5	5	210	205.30	2.24
20	180	0.15	1.5	5	240	270.98	-12.91
21	140	0.15	1.5	3.5	200	235.51	-17.75
22	140	0.15	2	5	350	345.75	1.21
23	140	0.2	2	3.5	350	352.57	-0.73
24	140	0.1	2	3.5	200	207.68	-3.84
25	140	0.15	2	2	190	237.76	-25.14
26	100	0.15	2	3.5	340	342.97	-0.87
27	180	0.15	2	3.5	313.33	272.30	13.09

CONCLUSIONS

The number of neurons in the hidden layer of the neural network and the number of iteration can be selected arbitrarily as they have very little influence on system influence. The most important difference is learning time. The experimental data of measured surface cutting force was utilized to train the neural network models. Trained neural network models were used in predicting cutting forces for various different cutting conditions. The developed prediction system was found to be capable of accurate cutting force prediction for the range it has been trained. In the design of neural networks, our major concern was to obtain a good generalization capability. In this study, Bayesian regularization with Levenberg-Marquardt training algorithm was used. As described earlier, this method was also utilized to overcome the problem of determining optimum number of neurons in hidden layer. The results obtained after simulations proved the efficiency of this methodology.

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