Proceedings of the International Conference on Recent Advances in Material Processing Technology
(RAMPT '05) 23- 25 February 2005
Department of Mechanical Engg., National Engineering College, K.R. Nagar, Kovilpatti – 628 503. Tamil Nadu, India.

SENSING TOOL BREAKAGE IN FACE MILLING OPERATIONS USING NEURAL NETWORK APPROACH

S.Madhava Reddy[1] and Dr.A.Chennakesava Reddy[2]

[1]Associate Professor, Dept. of Mechanical Engineering, MGIT, Gandipet, Hyderabad-500 075.
E-mail: Deepak_madhav2003@yahoo.co.in
[2] Associate Professor, Dept. of Mechanical Engineering, JNTU College of Engineering, Kukatpally, Hyderabad-500 075.

ABSTRACT
A neural network is a new approach using to process the features of the cutting force signal for the recognition of tool breakage in face milling is proposed. The cutting force signal is first compressed by averaging the cutting force signal per tooth. The average cutting force signal is passed through a medium filter to extract the features of the getting force signal due to tool breakage. With the back propagation training process, the neural network memorizes the feature difference of the cutting force signal between with and without tool breakage. As a result the neural network can be used to classify the cutting force signal with or without tool breakage. Experiments show this new approach can sense tool breakage in a wide range of face milling operations.

Keywords: Neural network, Cutting force, back-propagation and milling operation

1. INTRODUCTION
The cutting force variation characteristics of normal and broken tools are different. It is possible to train neural networks with the normal and broken tool cutting force variation signals. An automatic on-line sensing of tool breakage is a crucial step toward the full automation of machine tools in an unmanned factory [1]. A number of researchers reported application of neural network systems in tool condition monitoring. Applying sensors to monitor tool state condition and representing it with neural networks is a reliable and attractive alternative as opposed to previously employed empirical methods with senior fusion, vibrations, ultrasonic, torque, power, and speed and temperature sensors. Then, the cutting signals are further processed through the signal processing algorithms to extract the signal patterns from the recognition of tool breakage [2]. Developments in computer technology have made faster computation possible and economically viable for common users. Neural networks with these faster computations are a part of decision-making about the occurrence of tool breakage is greatly dependent on how the cutting signal patterns are classified and interpreted. However, it has been found that the classification and interpretation of the cutting signal patterns in face milling operations is not straightforward due to variation of cutting conditions, the measurement error of the cutting signals, and the unavoidably noisy cutting environment, etc., As a result, the rate used in the recognition of tool breakage in milling is usually not high enough, especially under the varying cutting conditions [5].

Artificial neural system (ANS) technology has demonstrated a great potential application in intelligent manufacturing systems. Therefore tool condition monitoring systems via neural networks used in turning have been proposed. However, most of the work has focused on turning operations only. In the present paper, a tool breakage monitoring system using a neural network in face milling is presented. The cutting force signal is utilized to detect tool breakage in face milling.

The cutting force signal is compressed by averaging the cutting force signal per tooth in order to increase the response time of the monitoring system and then passed through a median filter [6]. As a result, the features of the cutting force signal due to tool breakage still remain in the condensed cutting force signal. Later, the different features of the cutting force signal are fed into a back-propagation feed-forward neural network in order to teach the neural network to classify the cutting force signal as being with or without tool breakage. Through the back-propagation teaching process, finally, the neural network continuously modifies its weights so that the output of the neural network can be used to indicate the occurrence of tool breakage [7]. Experiments show the neural network has fine robustness for sensing tool breakage even with variations in cutting speed, redials depth of cut, axial depth of cut, feed rate and work piece material. Therefore, a vary promising approach for the automatic sensing of tool breakage by the use of neural network in face milling operations has been developed in this study.

2. THE NEURAL NETWORK AND BACK-PROPAGATION TRAINING ALGORITHM

A neural network is a massively parallel-distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge on the strength of connections between the individual nodes. Such a parallel computing network inspired by the computational architecture of the human brain has been successfully applied to intelligent take such as earning and pattern recognition, generally, there one three kinds of processing units in the neural network, i.e., input layer node, output layer mode and hidden layer node. However, the role of the hidden layer nodes is to intervene between the external input and the network output. As shown in fig, the input to a node can be expressed as:

$$net_j = \sum w_{ji} O_i \qquad (1)$$

Where net_j is the summation of all the inputs of the jth neuron; w^k_{ji} is the weight from the ith neuron; O_i is the output of the ith neuron.

The result of the summation function can be treated as an input to a transfer function from which the output of the neuron will be determined. In the paper, a sigmoidal, transfer function, f (neti), with a bias, b_j is used. The input-output behaviour is described by a sigmoidal function, that is.

$$O_j = f(net_j) = 1/(1 + e^{-(net_j + b_j)}) \quad \text{-----} \quad (2)$$

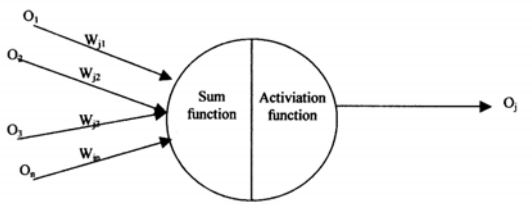

Fig 1. Schematic diagram of a neuron

Then, a learning process wing the back-propagation algorithm is applied to obtain the proper weights in the neural network. If the response of neural networks is correct, no weights need to be changed. However, if there is an error in the output response of neural networks, the difference between the derived output and the actual outputs is used to guide the modification of connection weights appropriately. Since it is a supervised learning procedure, examples of input and output patterns are necessary for training the network. Therefore, the error between the desired output. T_j and the actual output, O_j is computed. The summation of the square of the error, E can be expressed as :

$$E = 1/2 \sum (T_j - O_j)^2 \quad \text{-------------------}(3)$$

where T_j is the desired output of the J-th node. An iterative error reduction performed in a back ward direction from the output layer to the input layer of the network. In order to minimize the error, the gradient of the error with respect to the weights of the nodes is used to modify the weights of the nodes that is

$$\Delta w_{ji} = -\eta \, \partial E/\partial w_{ji} ,$$

where Δw_{ji} is the incremental change of weight from the j-th node to the j-th node and η is the learning rate[13].

3. STRUCTURE OF THE NEURAL NETWORK FOR SENSING TOOL BREAKAGE

The neural network requires nine nodes in the input layer which are allocated to the eight components of the variable cutting force in one revolution and one component of the moving average of the cutting force. As to the output layer, one node is enough to describe, the cutter with or without tool breakage. The output value of the node is in the range of between zero and one. This represents the grading of the cutter without and with tool breakage. An output value closer to one represents a higher possibility of having a cutter with tool breakage. By using the root mean square error between the actual output pattern and the desired output pattern with different numbers of nodes in the hidden layer during the training process. The training patterns were, in effect, extracted from experimental cutting tests with an eight-tooth cutter, rotating 600 rpm, and machining gray cast iron. As a result, a neural network with a 9-10-1 type (see fig 2) is adopted here for sensing tool breakage in face milling. The process diagram for sensing tool breakage with a neural network in face milling is shown in Fig.3. First, the cutting force signal is preprocessed by averaging per tooth**.**

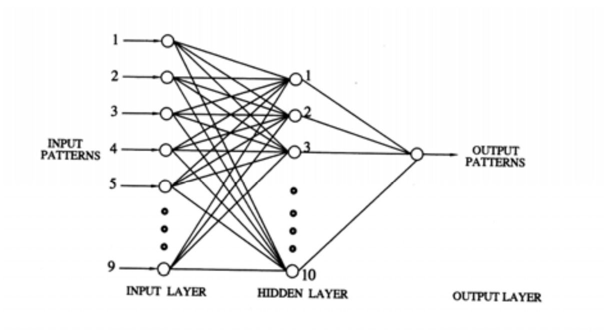

Fig.2 Configuration of the neural network for sensing tool breakage

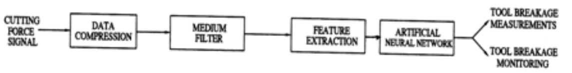

Fig 3. Process diagram for sensing tool breakage with the neural network.

4. RESULTS AND DISCUSSION

A case of face milling with tool breakage occurs at 2.85s as shown in fig.4. The output values of the neural network are displaced in fig.4. It is shown that the output value remains about zero for the cutter without tool breakage. However, the output value immediately jumps almost to one as tool breakage suddenly occurs. The use of neural network to sense tool breakage in face milling operations is feasible. The applicability of this new approach still needs to be verified under various cutting conditions. Therefore, a number of experiments have been conducted and a part of the result of the experiments is shown in the following.

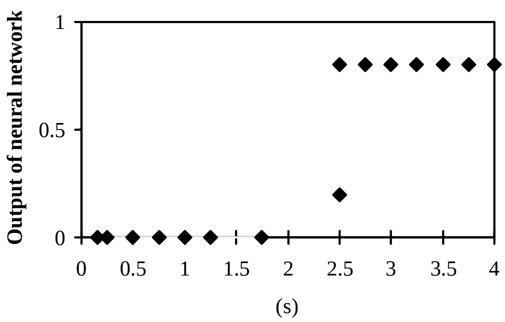

Fig 4. output value of the neural network (axial depth of cut = 1.27 mm; radial depth of cut = 50.8 mm; feed per tooth = 0.25 mm; spindle speed=600 rpm; cutter diameter = 101.6 mm; 8 teeth; up milling; work piece material: gray cast iron).

4.1 Effect of spindle speed

Figure 5 shows the output value of the neural network for the undamaged and damaged cutters with a change of spindle speed to 2250 rpm. It is observed that the neural network can recognize tool breakage even using different spindle speeds. This is because the features of the cutting force signal in one revolution are almost invariant with change of spindle speed [6].

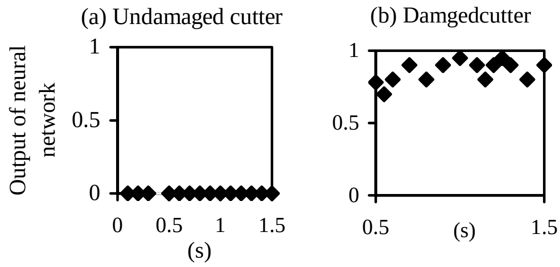

Fig 5. output value of the neural network (see fig.4. for the cutting parameters, but spindle speed = 2250 rpm)

4.2 Effect of radial depth of cut

Fig 6 shows the cutting force signal and the output value of the neural network with varying radial depth of cut. Even though the cutting force varies greatly for both the undamaged and damaged cutters, the output value of the neural network stays at zero for the undamaged cutter and jumps almost to one for the damaged cutter. However, it is also found that the neural network is insensitive to tool breakage when there is a small radial depth of cut. This is because the signal to noise ratio is very small with the small radial depth of cut.

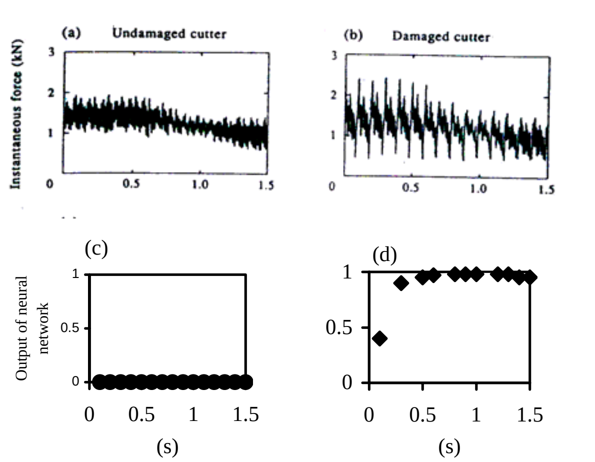

Fig 6. measured force and output value of the neural network with varying radial depth of cut (see fig4 for the cutting parameters, but the radial depth of cut gradually changes from o to 50.8 mm).

4.3 Effect of feed rate

Fig.7 shows the cutting force signal and the output value of the neural network with a sudden decrease of feed rate. Basically, the cutting force signal is proportional to the feed rate [6]. However, after the cutting force features are normalized and fed into the neural network, the influence of the feed rate on the cutting force features will be greatly reduced. Therefore, a clear destination in the output value of the neural network between Fig 7 (a) and (b) is shown.

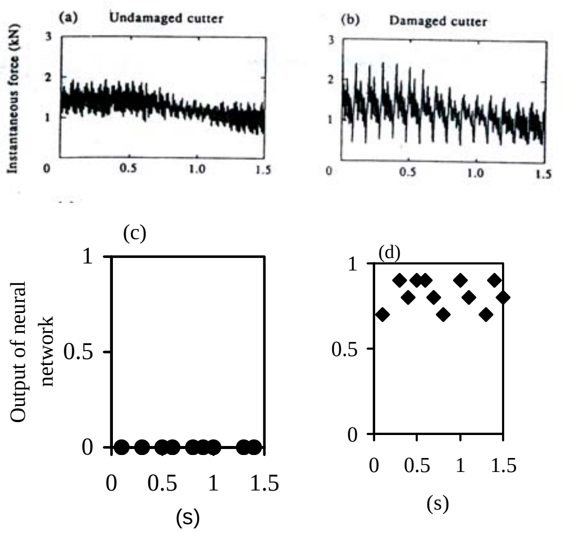

Fig 7. Measured force and out put value of the neural network with sudden decrease of feed rate (See fig 4. for the cutting parameters, but the feed per tooth changes from 0.38 to 0.2 mm).

4.4. Effect of axial depth of cut

The cutting force signal and the output value of the neural network with a sudden increase of the axial depth of cut are shown in Fig.8. It has been shown that the cutting force signal is proportional to the axial depth of cut [6]. The influence of the axial depth of cut on the cutting force features is also removed when the cutting force features are normalized. Therefore, a clear destination in the output value of the neural network between the undamaged and damaged cutters is shown again fig 8 (c) and (d).

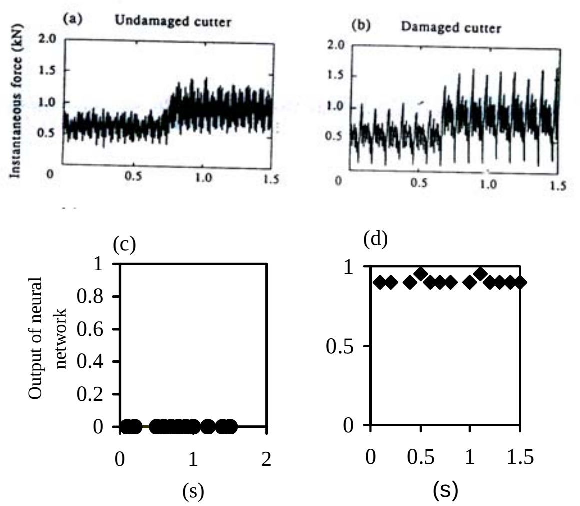

Fig 8. Measured force and output value of the neural network with sudden increase of axial depth of cut (see fig.4 for the cutting parameters but the axial depth of cut changes from 1.0 to 2.54 mm).

4.5. Effect of change of work piece material

The work piece material is changed to 7075 Al. The cutting force signal and the output value of the neural network are shown in fig.9. The cutting force signal is proportional to the specific cutting force, a mechanical parameter of the work piece material. Once, the cutting force features are normalized, the effect of the specific cutting force on the input patterns of the neural network will almost be removed. As a result, the neural network can distinguish the undamaged cutter from the damaged cutter with a change of work piece material (see fig.9 (c) and (d).

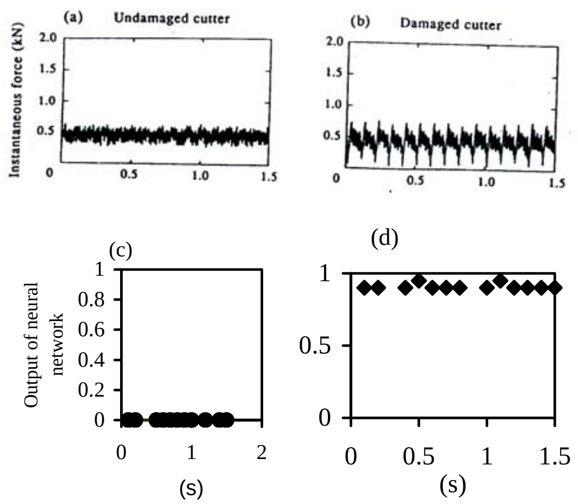

Fig 9. Measured force and output value of the neural network with different work piece material (see fig.4 for the cutting parameters but work piece material: 7075 Al)

5. CONCLUSIONS

A new approach using a neural network to recognize the patterns of the milling cutting force with and without tool breakage is proposed. Based on the present study, several conclusions can be drawn.

- Artificial neural networks are a suitable tool for the design of a tool breakage monitoring system in face milling operations.
- The appropriate selection of the input patterns of the neural network has a decisive influence on the level of success in applying the neural network to sensing tool breakage.
- The number of training sets for the neural network is not required to be very large for sensing tool, breakage, with variations in cutting conditions if the input patterns of the neural network are normalized**.**

6. REFERENCES

1) Ibrahim Nur tnasel and Charles. Mc.Laughlin, 1993, "*Detection of tool breakage in Milling*", Int. Jnl. Machine Tools Manufacture, vol.33. No.4, pp.545-558.
2) Abhijit Nadgir and Tugrucl Ozel, " Neural network modeling of Flan wear for tool condition monitoring", *4th International conference on Engineering Design and Automation, July 3—Aug 2000, Florida, USA*
3) Sridhar Sastry, Shiv G.Kappor, 2002, "Floquet Theory based approach for stability analysis of the variable speed Face-Milling Process", Transactions of ASME, vol.124, pp.10-30.
4) Zeki Yazur and Karl-Fridrich, 1994 ,"Feed rate optimization based on cutting force calculations

in 3 –Axis Milling", Intl. Jnl. Machine Tools Manufacturing, vol.34, No.3, pp.365-377.

5) Yusuf Attintas, 1994, "*Direct adaptive control of end milling process*", Intl. Jnl. of Machine Tools Manufacturing, vol.34, No.4, pp.461-472.
6) Y.S.Tarng, Y.W.Hseih and S.T.Hwang, 1994, "*Tool breakage in face milling with a neural network*", Intl. Jnl. of Machine Tools Manufacturing, vol.34, No.3, pp.341-350.
7) Myon-Woong Park and Hyung-Min Rho, 1996, "*Generation of modified cutting condition using neural network*", Annals of the CIRP, vol.45, pp.475-478.
8) Kuang-Hom Hscieh and C.Alec Chang, 2003, "*Process-Monitoring using past shape-scales with neural networks*", Intl. Jnl. of Appl. Sci. Engg, pp.30-44.
9) Ibrahim N.Tansel, 1992, "*Modeling 3-D cutting dynamics with neural networks*", Intl. Jnl. of Machine Tools Manufacturing, vol.32, No.6, pp.829-853.
10) Choongyun Sim and Minyang Yang, 1993, "*The prediction of the cutting force in Ball –end Milling with a flexible cutter*", Intl. Jnl. Machine Tools Manufacturing, vol.33, No.2, pp.267-284.
11) K.Hans Raj, P.Mangla and P.Bharadwaj, 1998, " *Cutting force estimation with artificial neural network models*", The Institution of Engineers (India), vol.79, pp.21-25.
12) K.Niranjan Prasad and Ramamoorthy.B, 2002, "Estimation of tool using artificial neural network in turning operation", Proc. Of *International Conference on Manufacturing Techniques*, pp.632-639.
13) Jacek M. Zurada, 2003, *Introduction to Artificial Neural Systems*, Jaico Publishing House.
14) Yegnanarayana.B, 2001, *Artificial Neural Network*, PHI Publishers,.
15) Haykin, 2003, *Neural Networks*, EEE Publications.
16) James A. Freeman and David M.Skapura, 2002, *Neural Networks, Algorithms, Application and Programming Techniques*, Pearson Education Asia.