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Flank wear prediction in drilling using back propagation neural network and radial basis function network

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Abstract

In the present work, two different types of artificial neural network (ANN) architectures viz. back propagation neural network (BPNN) and radial basis function network (RBFN) have been used in an attempt to predict flank wear in drills. Flank wear in drill depends upon speed, feed rate, drill diameter and hence these parameters along with other derived parameters such as thrust force, torque and vibration have been used to predict flank wear using ANN. Effect of using increasing number of sensors in the efficacy of predicting drill wear by using ANN has been studied. It has been observed that inclusion of vibration signal along with thrust force and torque leads to better prediction of drill wear. The results obtained from the two different ANN architectures have been compared and some useful conclusions have been made.

Keywords: Neuron; Cluster; Centre vector; Euclidian distance; Sensor signal; Flank wear

1. Introduction

Manufacturing industries are trying to reduce the operation cost as well as better quality of product. So, automation with online monitoring in metal cutting operation is a new approach toward improvement of the quality of the product as well as reduction of the overall cost of the product. Monitoring of drill wear is an important issue since wear on drill affect the hole quality and tool life of the drill. Direct visual inspection of cutting edge is not feasible and hence indirect methods using sensory feed back during machining has been is use to assess the wear of the drill. For improving the performance of decision-making in tool condition monitoring, different type of intelligent systems has been put forwarded by many authors. Following paragraph describes some of the relevant researches in this direction.

Lin and Ting [1] used the neural network model to study the drill wear and observed that the training error in case of sample mode converges faster than that in case of batch mode. Li and Tso [2] monitored the tool wear based on current signals of spindle motor and feed motor using regression model. Tsao [3] used the radial basis function network (RBFN) and adaptive based radial basis function network (ARBFN) to predict the flank wear, and compared their results with experimental observation. Lin and Ting [4] in a work used thrust force and torque signal to monitor the drill flank wear using regression model. Abbu-Mahfouz [5] predicted wear rate in drilling using Fast Fourier Transformation (FFT) of vibration signature as an input to ANN. Multiple objectives linear programming models for optimizing drill hole quality with different cutting conditions such as speed and feed rate was proposed by Kim and Ramulu [6]. Singh et al. [7] used back propagation neural network for prediction of flank wear of high-speed steel (HSS) drill in a copper work piece using spindle speed, feed rate, drill diameter, thrust force and torque as input parameters and maximum flank wear as output parameter in a neural network. Panda et al. [8] used back propagation neural network for prediction of flank wear of HSS drill in a mild steel work piece using the spindle speed, feed rate, drill diameter, thrust force, torque and chip thickness as input parameters and maximum flank wear as output parameter to neural network and concluded that inclusion of chip thickness as an input parameter to network leads to better prediction of flank wear. Li et al. [9] proposed hybrid learning for monitoring of drill wear using a combination of fuzzy system and neural network. Kuo and

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Kohen [10] applied a modified fuzzy neural network for detecting the defective sensor signal using membership function at the input node and fuzzy rule base. Lo [11] described the tool state in turning operation using artificial neuro fuzzy inference system (ANFIS) architecture, and concluded that higher accuracy could be achieved in the case of triangular and bell shape membership function. Hashmi et al. [12] proposed a fuzzy model for correlating the drilling speed with hardness of work material. They have used triangular membership function with fuzzy rule base in there analysis. Chung-Chen Tsao [13] used radial basis function network to forecast the flank wear of different coated drill using hybrid learning rule, i.e. combination of least square method and gradient descent method. Lim [14] in his work correlated the flank wear of tool with the acceleration amplitude of vibration signature in turning operation and he concluded that vibration acceleration produces two-peak amplitudes just before tool failure. Marek Balazinski et al. [15] used three artificial intelligence (AI) methods: feed forward back propagation neural network, fuzzy decisions support system and an artificial neural network based fuzzy inference system to monitor the flank wear in turning operation. Toshiyuki Obikawa and Jun Shinozuka [16] used unsupervised and self-organizing neural network adaptive resonance theory (ART2) for monitoring of flank wear in high-speed machining operation. Chungchoo and Saini [17] used fuzzy neural network model for online tool wear estimation in CNC turning. Panda et al. [18] in another work fused the fuzzy rule into the BPNN model for predicting the flank wear of drill in a drilling operation. In the literature [19,20] authors concluded that single hidden layer of feed forward neural network could able to classify the pattern well.

The present paper aims at studying the efficacy of ANN in predicting drill wear when trained with different combination of sensor signals. Comparison has also been made between standard BPNN model and RBFN in predicting drill wear on cast iron work piece.

2. Back propagation neural network

2.1. Back propagation neural network architecture

Back propagation neural network is a three-layered feed forward architecture. The three layers are input layer, hidden layer and output layer. Functioning of back propagation proceeds in three stages, namely learning or training, testing or inferences and validation.

Fig. 1 shows the *l–m–n* (*l* input neurons, *m* hidden neurons, and *n* output neurons) architecture of a back propagation neural network model. Input layer receives information from the external sources and passes this information to the network for processing. Hidden layer receives information from the input layer, and does all the information processing, and output layer receives processed information from the network, and sends the results out to an external receptor. The input signals are modified by interconnection weight, known as weight factor w_{ji}, which represents the interconnection of *i*th node of the first layer to *j*th node of the second layer. The sum of modified signals (total activation) is then modified by a sigmoid transfer function (f). Similarly, outputs signal of hidden layer are modified by interconnection weight (w_{kj}) of *k*th node of output layer to *j*th node of hidden layer. The sum of the modified signal is then modified by sigmoid transfer (f) function and output is collected at output layer.

Let $I_p = (I_{p1}, I_{p2}, \ldots I_{pl})$, $p = 1,2 \ldots N$ be the *p*th pattern among N input patterns. Where W_{ji} and W_{kj} are connection weights between *i*th input neuron to *j*th hidden neuron, and *j*th hidden neuron to *k*th output neuron, respectively.

Output from a neuron in the input layer is,

$$O_{pi} = I_{pi}, i = 1,2\ldots l \tag{1}$$

Output from a neuron in the hidden layer is,

$$O_{pj} = f(\mathrm{NET}_{pj}) = f\left(\sum_{i=0}^{l} W_{ji} O_{pi}\right), j = 1,2\ldots m \tag{2}$$

Output from a neuron in the output layer is,

$$O_{pk} = f(\mathrm{NET}_{pk}) = f\left(\sum_{j=0}^{m} W_{kj} O_{pj}\right), k = 1,2\ldots n \tag{3}$$

where $f()$ is the sigmoid transfer function given by $f(x) = 1/(1 + e^{-x})$.

2.2. Learning or training in back propagation neural network

Batch mode type of supervised learning has been used in the present case, where, interconnection weights are adjusted using delta rule algorithm after sending the entire training sample to the network. During training, the predicted output is compared with the desired output, and the mean square error is calculated. If the mean square error is more than a prescribed limiting value, it is back propagated from output to input, and weights are further modified till the error or number of iterations is within a prescribed limit.

Mean square error, E_p for pattern p is defined as

$$E_p = \sum_{i=1}^{n} \frac{1}{2} (D_{pi} - O_{pi})^2 \tag{4}$$

where D_{pi} is the target output, and O_{pi} is the computed output for the *i*th pattern.

Weight change at any time t, is given by

$$\Delta W(t) = -\eta \frac{\partial E_p(t)}{\partial W} + \alpha \times \Delta W(t-1) \tag{5}$$

η is the learning rate, i.e. $0 < \eta < 1$. α is the momentum coefficient, i.e. $0 < \alpha < 1$.

2.3. Testing and validation of back propagation neural network

Entire experimental data set is divided into training set, testing set and validation set. The error on the testing set is monitored during the training process. The testing error will