# Soft Computing Techniques applied to Tool Condition Monitoring in Drilling - A Review

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**Abstract**

Supervision of tool wear is the most difficult task in tool condition monitoring. Without the proper diagnosis of tool condition, the full automation can not be realized in the industry. Despite more than one decade of intensive research on the intelligent tool condition monitoring, the development of tool wear monitoring systems is an on-going attempt. This paper presents a summary of the soft computing techniques used for the diagnosis of the condition of a drill bit during drilling. Only limited attempts have been made to apply artificial neural networks, fuzzy logic systems, hybrid systems for monitoring and controlling of the drill wear.

***Key words:*** Tool condition monitoring, drill wear, neural networks, fuzzy logic, hybrid system

## 1 Introduction

Drilling is one of the most common manufacturing processes. The worn drill produces a poor-quality hole and in extreme case, the drill may be broken which results a complete halt to the production. In order to ensure the high quality product, and at the same time to avoid loss of production time, drill wear must be monitored effectively. The drill wear can be measured directly with optical methods (e.g. CCD camera or fibre optic sensor) during intervals of the cutting process. Although direct methods can accurately measure the drill wear, but these methods are not suitable for automated manufacturing process where cutting process is continuous. The present trends in the area of tool condition monitoring are to measure different process parameters through sensor signals, which are indirectly correlated to drill wear. An indirect method of tool condition monitoring allows the estimation of tool wear online; thus does not interrupt the cutting process, and is very much suitable for fully automated manufacturing systems. Effective tool condition monitoring (TCM) is still a great challenge to the manufacturing society due to the complexity of the cutting process and complex tool wear pattern. Without the effective TCM, the full automation of a manufacturing process can not be realized. It is very often difficult to obtain a mathematical model which can accurately predict the tool wear state. Artificial neural network, Fuzzy logic System, Genetic algorithm, Simulated annealing, and combination of any two or more of these soft computing tools can effectively map the nonlinear relationship of the sensors signals and wear state, and control the process parameters for maximizing the utilization of the cutting tool. This paper presents a summary of the different soft computing techniques applied to drill wear and failure monitoring systems. Only limited attempts have been made on the application of soft computing techniques for tool wear and fracture monitoring in drilling compared to other machining processes like turning, milling, etc.

## 2 Application of Artificial Neural Networks (ANN) in TCM

Artificial neural network is a collection of simple, interconnected nodes which operate in parallel, and store knowledge through the connection weights between nodes of adjacent layers. The types of neural networks which were already applied to drill wear monitoring successfully are presented in the following sections.

### 2.1 Multilayer Neural Network

Drill wear was predicted with the help of a multilayer neural network trained with signals from four sensors namely thrust force, torque and strains in two orthogonal directions to the drill axis [2]. Different architectures of multilayer feed forward neural network with back propagation training were compared, and the best architecture was determined for predicting drill wear [7]. Mean values of thrust force and torque signals were used along with the cutting conditions as inputs to the network. Eight features extracted from the thrust force and torque signals and three cutting conditions (speed, feed, and drill diameter) were used as input to the back propagation neural network to predict drill wear state in [9]. Several architectures of multilayer neural network with a back propagation training algorithm were compared for drill wear monitoring [13]. Training data set was extracted from the acquired vibration signal from an accelerometer attached to the work piece. It was shown that the frequency domain features such as average harmonic wavelet coefficients, and the maximum entropy spectrum peaks were more efficient in training the network than the time-domain statistical moments. Average thrust force, average torque, peak thrust force, peak torque, RMS thrust force, RMS torque, area under the thrust force versus time and the area under torque versus time were used as the input to the modified back propagation neural network with adaptive activation function slopes for the classification of the drill wear [5]. Modified neural network converged much faster than the conventional feed forward neural network. A multilayer neural network with back propagation training algorithm was developed and tested for drill wear prediction at different cutting conditions [15]. The network was trained and tested by experimental data containing thrust force, torque, spindle speed, feed rate, drill diameter and maximum flank wear. Network architecture 5-4-1 with learning rate 0.3 and momentum coefficient 0.3 has lowest error in predicting the flank wear for the testing case used in the analysis.

## 2.2 Self Organizing Neural Network

This type of neural network is based on competitive learning and the output neurons of the network compete among themselves to be activated or fired for any applied input pattern. The synaptic weights of the neurons are initialized randomly; and once the network has been initialized, the unsupervised learning of the network is performed through competition, cooperation and synaptic weight updation processes. A diagnosis system based on a self- organizing neural network was developed [4]. The input patterns applied to the network was consisting of 33 components; 30 components extracted from FFT analysis of feed-force and torque signals, 3 components are three drill wear states. The proposed network operated in two phases: an adaptation and a classification. During adaptation phase, $Q = (Q_s, Q_d)$ of set $K$ optimally represent the empirical distribution of input vector $\mathbf{X} = (X_s, X_d)$ of set $N$, where $K << N$.

$X_s$ : represents 30 FFT based component of sensor signal

$X_d$ : represents 3 descriptor (three drill wear state)

$Q_s$ : sensory feature part of the prototype vector $Q$

$Q_d$ : descriptor part of the prototype vector $Q$

During classification phase, new sensory signal components $X_s$ were applied to the network. The prototype $Q$ having the sensory feature part most similar to the input pattern was selected from minimum Euclidian distance

$$d(X_s, Q_{s,j}) = \text{minimum, where } j = 1,\ldots\ldots,K.$$

The descriptor part $Q_d$ of the selected prototype was the estimated drill wear class for the input pattern whose wear state was unknown. The classification error was studied with different numbers of features and considering both adaptation and without adaptation of the prototype vector $Q$. The network was trained, and tested for one particular cutting condition. The effect of cutting conditions was not considered.

## 2.3 Adaptive Resonance Theory (ART) Networks

According to adaptive resonance theory (ART), adaptive resonance occurs when the input to a network and the feedback expectancies match. ART2-type neural networks have been developed to realize the self organized stable pattern recognition capability in real time. If the input pattern to the network is found similar to any of the previously encountered patterns, it will be then kept in the same category of similar patterns. Otherwise, the input pattern will form a new category. In this way all the input patterns are categorized. Total number of categories will depend on a factor known as vigilance. High vigilance will increase sensitivity, reduce error and generate large number of categories. An optimum value must be created for reasonable number of categories and minimum error. ART2-type network has been used for the detection of severe micro-drill damage just before a complete tip breakage occurs [3]. Wavelet coefficients of the thrust force signals were used to train the ART2-type neural network. Two approaches were tested. In the first one, called as direct encoding, 22 wavelet coefficients out of total 24 original wavelet coefficients from the thrust force signal were presented to the network; and in the second, called as secondary encoding, six most significant coefficients were presented to the network. The direct encoding method was found to be slower but more accurate. There was only one classification error in 61 cases. The ART2 with secondary encoding method was much faster but there were at least three classification errors in any of the two studied case.

## 2.4 The Learning Vector Quantization (LVQ) Neural Network

Drill wear was estimated by the supervised vector quantization neural networks, which were trained by the extracted features from vibration signals [14]. The network is trained with training patterns having 47 input features; 6 Power Spectrum Density (PSD) peak values and their respective 6 locations (a total of 12 PSD indices), 32 averaged Continuous Wavelet Transform (CWT) scales, 2 inputs for cutting conditions (speed and feed), and 1 input for the drilling lengths, and their corresponding output target nodes (11 classes) which state the measured flank-land wear size. Fig. 1 shows a schematic diagram of a LVQ used in [14], where $x=(x_1,x_2,\ldots\ldots x_N)$ is input feature vector $y=(y_1,y_2\ldots\ldots y_N{}^m)$ is the synaptic weight of the m[th] neuron in the neural layer, $y=(y_1,y_2\ldots\ldots y_m)$ is the output vector, and $t=(t_1,t_2\ldots\ldots t_m)$ is the target vector. The network was trained through LVQ algorithm using 53 training patterns and tested with unseen data for different cutting condition (speed and feed). The same drill was used throughout the training and testing phase, the effect of drill diameter was not tested in the analysis.

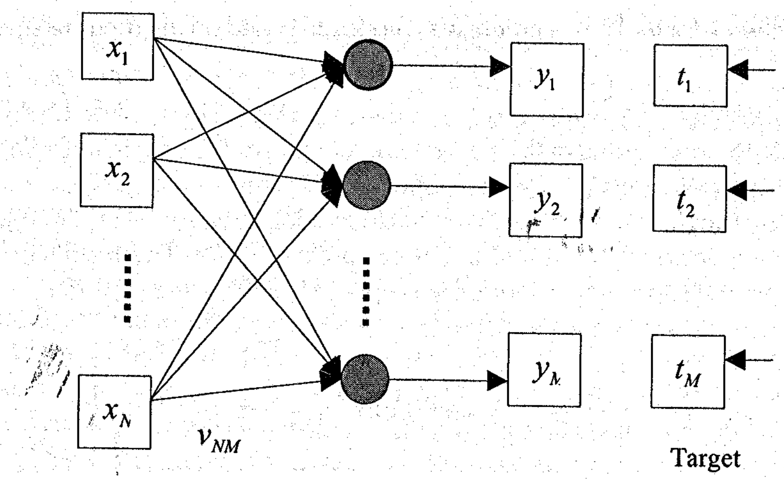


Fig.1. Learning vector quantization network [14]

## 2.5 Recurrent Neural Networks

Recurrent networks are neural networks with one or more feedback loops. The basic building block of this type of network is multilayer perceptron. In [8], two recurrent neural networks were used as neural identifier and neural controller with a recursive least square training algorithm. This training algorithm improved the performance of the network by avoiding the long training time associated with the commonly used feed forward networks. The neural identifier was used to model the drilling dynamics by correlating feed-rate with thrust force, where current feed-rate, previous values of feed-rate and thrust force were used as input and current thrust force used as output. The output of the trained identifier was then used to train the neural controller. The feed-rate was controlled through this controller to maintain the thrust force at desired limit for minimizing the delamination while drilling a graphite-epoxy laminate. The effect of speed parameter on the thrust force was not considered in this analysis.

### 2.6 Abductive Network

These networks are composed of a number of polynomial functional nodes, and are organized into several layers. The best network structure, number of layers and node types are determined automatically by using a Predicted Squared Error (PSE) criterion. Tool life, metal removal rate, thrust force and torque were predicted under varying drill diameter, cutting speed and feed rate by an abductive network [10]. Simulated annealing was applied to the network in determining the best combination of speed and feed-rate for optimum tool life and metal removing rate.

## 3 Application of Fuzzy Logic System in TCM

Drill wear classifications in previously mentioned papers were based on the predefined crisp limits. A different approach have been considered in paper [1, 6, 11] to classify drill wear states, which are fuzzy in nature i.e., states are not exactly defined and limits overlap.

The features of the drill wear monitoring system used in [1] were graded by four fuzzy parameters 'initial', 'small', 'normal', and 'severe'. The input features were measured thrust force and torque values. The drill wear states were monitored by a fuzzy C-means algorithm which consisting of three parts: feature selection, clustering and classification. Two test cases used for the development of the fuzzy system worked well. However, the approach did not take into account the effect of different cutting conditions, i.e. the user would need to define new fuzzy limit for different types of work piece materials, drills, speeds and feed-rates.

A fuzzy classification method was used to classify the drill wear states in [11]. A regression analysis was used to model the spindle motor current and feed motor current as functions of spindle speed, feed rate, drill diameter and drill wear. A control scheme for tool replacement was proposed based on the membership grade for the drill wear state.

A real time fuzzy logic control scheme, shown in fig. 2 was developed in [6] to monitor the drill wear conditions, and to control the feed rate for maximizing drill life and for preventing drill failure in automated small diameter drilling operation. The membership functions for three input variables (thrust force, torque and radial force), drill wear states and output variable (feed-rate) were taken as sinusoidal, trapezoidal and triangular, respectively. Diagnosis of drill wear state was performed by fuzzy min-max algorithm. The results from drill wear state diagnosis was used as input to the fuzzy logic controller to optimally control the feed-rate.

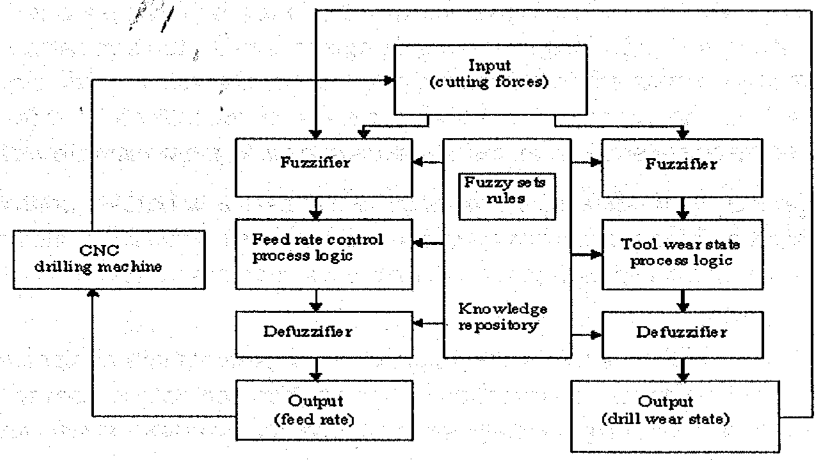


Fig. 2. A schematic diagram of fuzzy logic control system used in [6]

## 4 Application of Hybrid System

In order to overcome the drawbacks and to utilize the strong features of Neural Network (NN) and Fuzzy Logic system (FLS), a hybrid model (here the combination of both NN and FLS) was developed for drill wear monitoring [12]. The R.M.S. values of the vibration signal in five frequency bands were taken as input **X** $(x_1,\dots\dots, x_n)$ to the Fuzzy Neural Network (FNN), shown in fig. 3. The drill wear state which was the output **Y**$(y_1, y_2,\dots\dots,y_n)$ of the FNN, was classified into five fuzzy membership grades. The FNN would recognize the air cutting and failure of the drill perfectly, but the recognition rates of initial, acceptable and severe tool condition were not satisfactory (less than 75%). The effect of drill wear on the vibration signal was only considered in the development of the FNN model. The effects of cutting conditions were not considered.

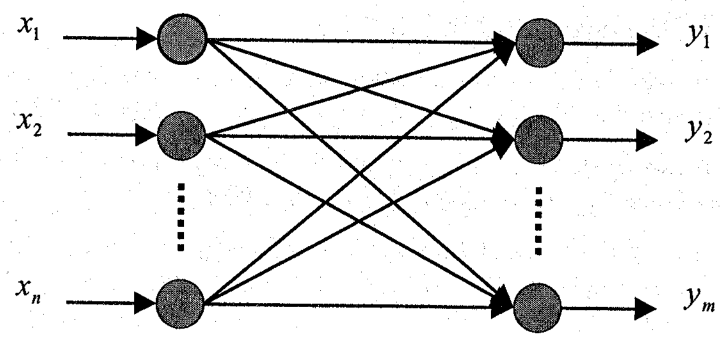


Fig. 3. FNN architecture used in [12]

A fuzzy learning vector quantization (FLVQ) neural network was also trained and tested with the same data sets used by a simple learning vector quantization (LVQ) network mentioned earlier in [14]. It was reported that the misclassification rate in classification of flank wear was less for FLVQ compared to LVQ network.

## 5 Conclusion

A summary of different soft computing techniques used for drill wear and failure monitoring and control has been presented in this work. Only a limited number of automatic diagnostic tools have been developed for tool condition monitoring in drilling. A large number of diagnostic tools used are multilayer neural network and these were tested for limited cutting conditions. Other soft computing tools were tested in very few cases. There is no generalized diagnostic tool developed which will work for all cutting conditions i.e., variation of work piece material, tool material, speed, feed rate.

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