Case Report

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Abstract: Real time condition monitoring and precision health assessment system is a mandatory need for effective maintenance program in industrial sector. Rapid advancement in the information technology and other engineering technologies have invited more proactive attention from research and development in industrial sectors and particularly in condition monitoring of machines and related Industrial processes. In this work, drill bit condition monitoring techniques have been developed based on wavelet analysis and artificial neural networks (ANN) for automatic drill bit fault detection and classification. An experimental work has been conducted to capture the vibration signals for analysis. In this experiment, the CNC drill machine is used with high carbon steel drill bit and mild steel material as work piece. The cutting condition parameters are kept constant and the wear level is varied from 0.2 to 0.6 mm. The Data Acquisition system (DAQ) with Lab VIEW software is used to capture the vibration signals for drill bit with different wear conditions using accelerometer. The captured vibrations data are analyzed using continuous wavelet transform (CWT) with Morlet wavelet and Daubechies wavelet as a prime function. In general, the CWT coefficient is used to generate the inputs features to ANN for automatic tool condition classification, with two outputs (0, 1) for healthy and (1, 0) for faulty. The outcome of ANN showed 98% of accuracy in the wear prediction and this results show the effectiveness of the combed WT and ANN for automatic classification of tool wear conditions with high success rate.

Keywords: condition monitoring; wavelets transform analysis; artificial neural network; lab VIEW software

1. Introduction

In manufacturing, increasing productivity and product quality is very important for customers. In this' condition monitoring plays a vital role to ensure product quality. So, preventive maintenance and condition monitoring are required to achieve greater machinery availability, improve the quality of the manufacturing process, enhance the machine reliability, maximize profit and productivity and reduce maintenance costs. Normally, an industrial investor will concern more about the profit and also to save cost of production due to heavy competition of the market. To increase productivity, condition monitoring is capable of providing warning based on fault detection in the early stage of production.

In drilling operations, If the condition of the drill tool is not monitored properly, drill tool will stick inside the work piece and possibility of breaks if operation is not stopped. Normally, the condition of the tools are analyzed based on mathematical models, physic-based models and data driven models which use the data using sensors and data acquisition systems. Since the mathematical model analysis is having more complexity and physics-based models require in-depth knowledge of

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physics involved in the process, there is an increasing trend of applying machine learning model-based analysis to predict the tool conditions more accurately. Drill tool condition monitoring is slightly complex in nature due to production tolerances and asymmetric profile of the drilling tool.

In this work, the predictive or condition-based maintenance is applied based on the wear condition of drill bit. This type is useful to monitor the condition of the drilling tool of a bench type CNC drilling machine which uses a specific technique which is drilling tool's vibration signal. It can be used to detect the signal of the drill bit faults and analyses by using the time domain statistics and wavelet analysis as feature extraction. The extracted WT analyzed parameter to be fed as inputs features to an artificial neural network (ANN) for fault detection and classification.

The drilling fault detection techniques have been developed based on the wavelet analysis and ANN as automatic drill bit fault detection and classification. An experimental work has been employed to capture the vibration signals for analysis with different measuring intervals. The bench type CNC drill is used with high carbon steel tip drill bit and mild steel material as work piece. The drilling condition has been set to 12mm/min federate and the rpm of 800. The drill bit has drill dia 8 mm, Overall length 92 mm, the angle point is 135. Using accelerometers, vibration data has been collected and analyzed in the life cycle of the drill bit. In this experiment, The direction of sensor is vertical and the wear levels (0.0mm, 0.2mm, 0.4mm and 0.6mm) are changed.

Several methods of drill bit condition monitoring are investigated by researchers which includes both direct and indirect methods. The direct methods like visual inspection, machine vision and infra-red methodology are used to monitor the drill bit which will give less accuracy compared to indirect methods [1]. Indirect methods include use of signals like force, vibrations, acoustic emission etc., in which the signal features have a relationship with wear condition / parameters Indirect methods include use of signals like force, vibrations, acoustic emission etc., in which the signal features have a relationship with wear condition / parameters [2]. Acoustic Emission (AE) and vibration based drill bit monitoring are the most popular indirect methods which are used for assessing the condition with more accuracy for micro level measurements. Acoustic emission is a phenomenon which occurs when, for different reasons, a small surface displacement of a material surface is produced. This occurs due to stress waves generated when there is a rapid release of energy in a material, or on its surface which has frequency range from 10 to 70 kHz with non-linear frequency response. In some advanced testing, we can use 200 kHz sensor for tool wear and the 800 kHz sensor for tool breakage detection which will come under the broad band acoustic sensor. AE has been widely used for monitoring wear in the laboratory as well as at the industrial level for monitoring failures like scuffing, fretting, rolling contact fatigue etc.,[1].

Furthermore, indirect methods are widely used in drill bit condition monitoring and as fault detection. They are used in different techniques such as cutting forces, acoustic emission, temperature, vibration, motor current and torque [3]. However, vibration measurement for machinery condition monitoring is easy, less costly and yields a great deal of information that can be used to monitor the relative motion between the tool tip and the work piece for precision of the cutting operation [4]. Waleed Abdulkarem et al., have reported that vibration analysis is widely accepted as a tool to monitor the operating conditions of a machine as it is nondestructive, reliable and permits continuous monitoring without intervening with the process. This study has demonstrated drill bit condition monitoring approach in drilling operation based on the vibration signal collected using sensor and data acquisition system. Advantages of this approach include availability, low cost, large information data, nondestructive, reliable and facilitating continuous on-line monitoring. This method allows substitution of another sensor (e.g., an acoustic sensor) or very cost-effective accelerometer [5].

The novelty of this work is the proposal of WPT and ANN in drill condition monitoring. Many researchers have applied this kind of techniques to predict the faults in turning machine. But condition monitoring in drill bit is still under research since the drill bit having complex features. So, this attempt will open a path to do research to identify the drill bit faults which will useful in many fields. Particularly, Stone drilling process is very important process for oil and gas industries, so that, there is a huge demand for high level condition monitoring system for drill bit in oil and gas sector.

We believe that the proposed methodology will play a significant role in stone drilling operations. The innovation in the research is to apply accelerometer/ acoustic emission sensor, Artificial neural network (deep learning based analysis), comparison of the results and to keep the error in below 3% which is not obtained in the previous researches.

2. Literature Review

AI algorithms such as ANN, fuzzy based techniques, Genetic Algorithms, Support Vector Machines etc are highly useful in fault diagnosis. So, AI is the future of condition monitoring to have preventive maintenance [6]. Internet of Things and AI have many advantages in the prediction of the health of the machine which improve the productivity and profit of an industry [7,8].In the research paper by Miho Klaic et al., decision tree algorithm has been applied to predict tool wear. The research paper concluded that the methodology assured that 90% success rate and more reliable. The researcher has not compared the decision tree with deep learning algorithms which is a big research gap in this paper[9]. Rui Zhao et al., surveyed related to deep learning and its application for machine health monitoring. He has concluded in this way in their research article as "It is believed that deep learning will have a more and more prospective future impacting machine health monitoring, especially in the age of big machinery data". So, this paper reveals that deep learning can be used in a precise way to monitor tool wear and also the research concluded that deep learning is a promising technique to assess any kind of tool wear[10]. P.Krishnakumar et al., used acoustic emission signal for tool condition monitoring during high-speed milling of Ti-6Al-4V. Discrete wavelet transform (DWT) was used to extract coefficients from vibration and acoustic emission signals. Machine learning algorithms like decision tree, Naïve Bayes, SVM, and ANN are used to predict the tool condition. The authors concluded that SVM based vibration analysis predicts tool condition effectively and assure that prediction accuracy is more than 99% [11]. Yaochen Shi identified the wear in the drill bit based on the Local Mean Decomposition (LMD) and Back Propagation (BP) neural network. The research team used a multi-signal platform to acquire different parameters from the drilling machine. Then the feature parameter is predicted by the combination of noise-assisted LMD method and BP neural network. The accuracy of monitoring drill bit wear with multi-signal fusion is 95.8%[12]. Lang Dai developed a new Deep Learning Model for Online Tool Condition Monitoring Using Output Power Signals. The output power from the sensor which is mounted on the cutting tool holder during its operation is used for further analysis. The date were analyzed using wider first-layer kernels (WCONV), and long short-term memory (LSTM) which is available in the deep learning algorithms. This paper concerns about the output power signals and its analysis on deep learning algorithms [13]. Wang et al., have done a survey on tool Wear Monitoring Methods Based on Convolutional Neural Networks. The autho concluded that application convolution neural networks in tool wear and condition monitoring is more reliable. They added that the convolution neural network can improve accuracy, which is a great significance of the CNN [14]. Chacon et al., used multi-threshold count-based feature extraction at multi-resolution level based on wavelet packet transform for extracting a redundant and non-optimal feature map from the AE signal. Recursive feature elimination is used to reduce and optimize the number of features and the random forest regression is used to estimate the tool wear; The performance is compared with other ML techniques like RF, SVM, ANN, KNN, and DT, to obtain the lowest RMSE for predicting tool flank wear [15].

Kolar , P et al., dealt about indirect drill condition monitoring based on machine tool control system data. In this work, work piece vibration has been monitored and correlation of various features of signals are evaluated. As a result of this paper, researchers concluded that root mean square of the vibration and spindle torque signals strongly correlate with flank wear near bottom of the hole. In this paper, spindle current torque and Z slide drive current torque have been analyzed for flank wear [16].

Reeber,T et al., demonstrated two anomaly detection approaches for drill condition monitoring. The XG Boost approach provide the timely detection near end of tool life. Machine learning models have been used to predict tool wear before any risk in drilling process. An another method called

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unsupervised autoencoder is also used by authors for anomaly detection from reconstruction errors [17].

Anomaly detection using auto encoder or other neural networks are used to supervise equipment failure and predict the intervals for maintenance. These are unsupervised algorithms which is easy to apply in condition monitoring. Pores and blow holes in the work piece and potential dimensional inaccuracies (or) monitoring anomalies related to progressive tool wear for tool condition monitoring in CNC machines has been dealt by Netzer,M.,Palenga,Y and Fleischer [18].

Anomaly detection algorithms for tool wear detection using sensors can be done using convolutional neural network (or) auto encoder which is supported by the papers of sun,s et al., Li,G et al., Ahmad et al., and Vonhahn,T and Mechefske,C.K [19–22].

Karri,V and Kiatcharoenpol,T used artificial neural network in drilling machine condition monitoring. In this paper, feed forward network is applied to predict tool life in terms of number of holes' failure. By benchmarking root mean square (RMS) the results were obtained from thirty-two cutting condition inputs to predict failure in drilling [23].

3. Wavelet Analysis and Kurtosis

A wavelet is a wave-like short oscillating function which begins at zero amplitude and will increase or decrease and then returns to zero one or more times. Wavelets are applied to transform the signal under examination into another representation which presents the signal information in a more amenable form for further analysis using AI techniques like machine learning/deep learning. This transformation is known as Wavelet Transform (WT) is a technique for converting a function or signal into another form, making certain features of the original signal more useful for analysis. There are five stages of wavelet transform in condition monitoring time–frequency analysis of machining signal,

1. feature extraction,
2. signals de-noising,
3. singularity analysis of the tool state
4. density estimation for tool wear classification according to its multi-resolution, sparsity and localization properties [24,25]

The wavelet method overcomes the limitation of Fourier Transform such as inability to check continuity, fixed resolution , poor time frequency localization and limited time frequency resolution trade-off , by using a multi-resolution technique (time & frequency) [26]. It has the ability to examine a signal simultaneously in time and frequency with a flexible mathematical foundation. Time information is obtained by shifting the wavelet over the signal. The frequencies are changed by contraction and dilatation of the wavelet function. Wavelet analysis is more sensitive and trustable than Fourier analysis for recognizing the tool wear states in turning [22]. Wavelets were first mentioned by Alfred Haar in 1909. It can be moved at various locations on the signal and also it can be squeezed to different scales.

There are some requirements for the wavelet, which are: it must have finite energy, based on Fourier transform, the wavelet must have zero mean and for complex wavelets the Fourier transform must be both real and vanish for negative frequencies. To make the wavelet of chosen mother wavelet(original wavelet) more flexible, two basic manipulations are applied which are stretch or squeeze it (dilation) and move it (translation). The dilation of the wavelet is governed by the dilation parameter a. The movement of the wavelet along the time axis is governed by the translation parameter b. These shifted and dilated versions of the mother wavelet Ψ (t) are denoted by Ψ [(t – b)/a]. The wavelet represented by Maamar Al Tobi is [27] :

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \quad (1)$$

Where, the factor $\frac{1}{\sqrt{a}}$ is used to ensure energy preservation.

The sum over all time of the signal multiplied by scaled and shifted versions of the wavelet function Ψ is called the continuous wavelet transform (CWT). Continuous wavelet transforms are

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recognized as effective tools for both stationary and non-stationary signals. Based on the equation (3 – 9) the CWT given as:

$$T(a,b) = \int_{-\infty}^{\infty} x(t)\, \Psi_{a,b}^{*}(t)\, dt \quad (2)$$

Where, $T(a,b)$ is the continuous wavelet transform (CWT), X (t) is the signal and the superscript asterisk '*' stands for the complex conjugate.

It can be expressed in more compact form as an inner product:

$$T_{a,b} = \langle x, \Psi_{a,b} \rangle \quad (3)$$

The windowing techniques with variable-size regions in wavelet analysis can be overcome the limitations of the Short-Term Fourier Transform (STFT). Wavelet analysis allows the use of shorter time intervals where more precise high frequency information is desirable and long regions for low frequency information. Sometimes the wavelet is irregular and asymmetric waveform of effectively limited duration (average value zero), so the varieties of wavelets (Wavelet Families) are exist, and an analyst can choose from the wavelet families that suits his application best.

This project focuses on Daubechies wavelets (db10) and Morlet wavelet (morl) as basis function based on the role of features extraction, because they are more similar characteristics to the extracted signals. The morl wavelet is known by the following Equation(Eqn4) . Figure 1 shows the morl wavelet.

$$\Psi(x) = e^{-t^2} \cos\left(\pi \sqrt{\frac{2}{\ln 2}}\, t\right) \quad (4)$$

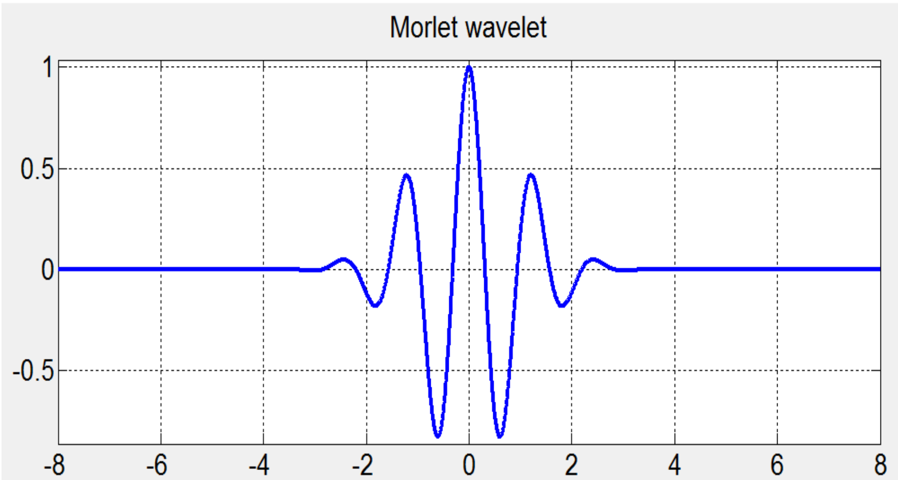

Figure 1. Morlet wavelet.

The names of Daubechies family wavelets are signed db N (N is the order) as Figure 2 shows the db 10 wavelet. The Daubechies wavelet is defined as given in equation (5) .

$$\Psi(t) = \sum_{k=-\infty}^{\infty} \beta_k \sqrt{2}\, \Phi(2t-k) \quad (5)$$

Where, Φ(t) is scaling function and $\beta_k = (-1)^k \alpha_{-k+1}$, If N= 1, then $\alpha_0 = \alpha = 1$

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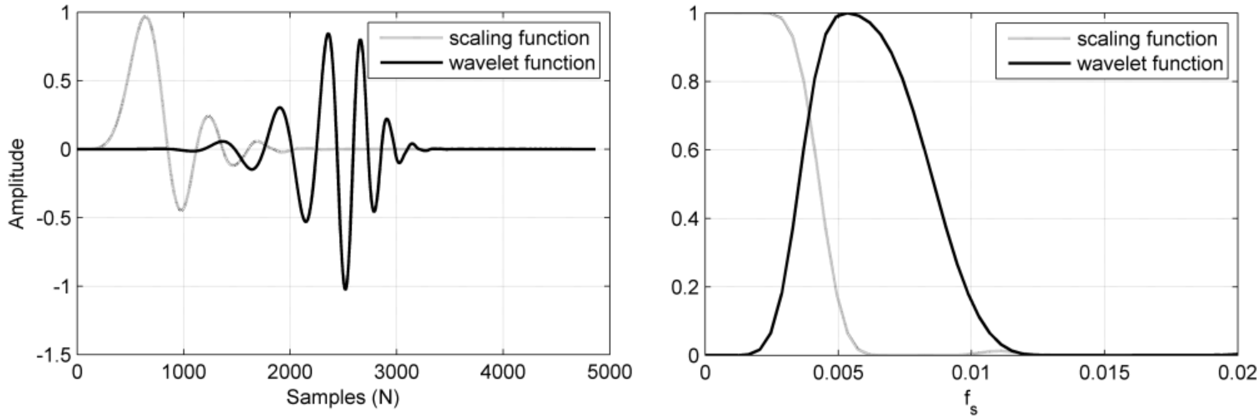

Figure 2. Daubechies wavelet db 10.

In the wavelet transform, kurtosis prediction of vibration signal will help to find out the faulty as soon as possible. Normally, the wavelet transform is an important tool for nonlinear and non-stationary signal analysis which contains discreate wavelet transform (DWT) and wavelet packet transform (WPT). The next step in WPT is to decompose the detailed information of the signal in high frequency region. Thus WPT is used to decompose the kurtosis of the vibration signal into several sub signals with different frequency ranges [27].

Kurtosis is a measure of peakedness and hence it is a fine indicator of signal impulsiveness in fault detection for rotating components expecially for drill bits.

Kurtosis is expressed

Askurtosis $(x) = (E\{(x-\mu)/\ \sigma^{4}) - 3$ (6)

Where μ = mean of time series x

σ = standard deviation of time series x

E{.} is the expectation operation

The minus 3 is to make kurtosis of the normal distribution of the normal distribution equal to zero.

Kurtosis have three measures which are called as mesokurtic, leptokurtic and platykurtic. when the kurtosis statistic of a distribution is similar to normal distribution or bell curve, then it is called as mesokurtic distribution. If the kurtosis value is greater than mesokurtic and then it is called as leptokurtic distribution. If the kurtosis value id smaller than mesokurtic , then it is called as platykurtic distribution. The Figure 3 shows the various kurtosis distribution.

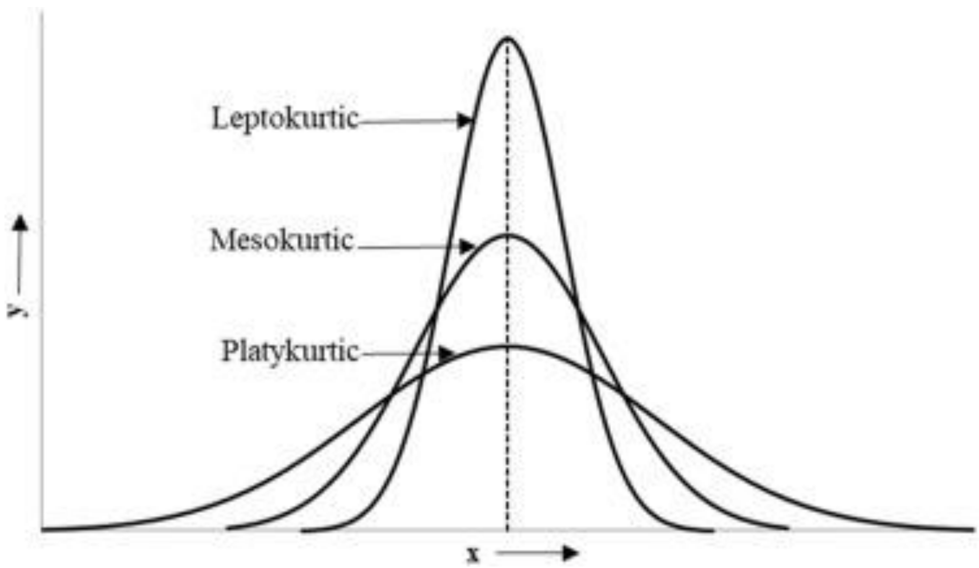

Figure 3. Kurtosis distribution [28,29].

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4. Modelling of Condition-Based Maintenance Using Artificial Intelligence

Traditional type monitoring involves a measurement system that contains sensors/wireless sensor and then the sensor data will undergo signal condition to process the signal. Then, the processed signal will be converted from analog to digital and then feature extraction is performed. Finally, the signal has been extracted for further analysis in AI techniques to predict the faults in a machine [30,31].

A block diagram of machine condition monitoring integrating with AI is given in Figure 4.

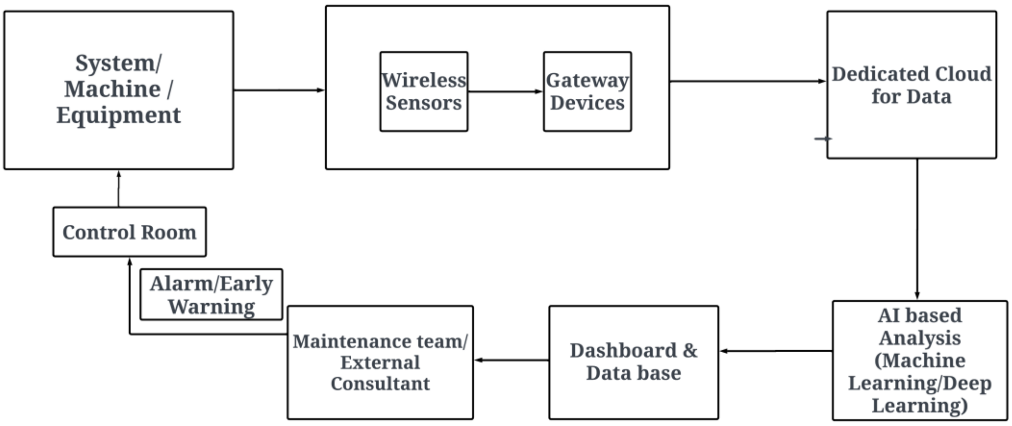

Figure 4. Machine condition monitoring model integrating with AI techniques [32].

Tool wear condition monitoring (TCM) is an important part of machining automation. In recent years, Machine learning (ML) and deep learning (DL) based TCM methods have been widely researched [33].

As per Surucu , O et al., machine learning (ML) techniques are selected as an intelligent model for Predictive maintenance (PdM) or condition monitoring of a machine. They added that the efficacy of the predictive maintenance strategy relies on selecting the appropriate data processing method and ML model. Existing surveys do not comprehensively inform users or evaluate the quality of the monitoring systems proposed [34]. The authors have given a machine condition monitoring model integrating with machine learning algorithms is given in Figure 5.

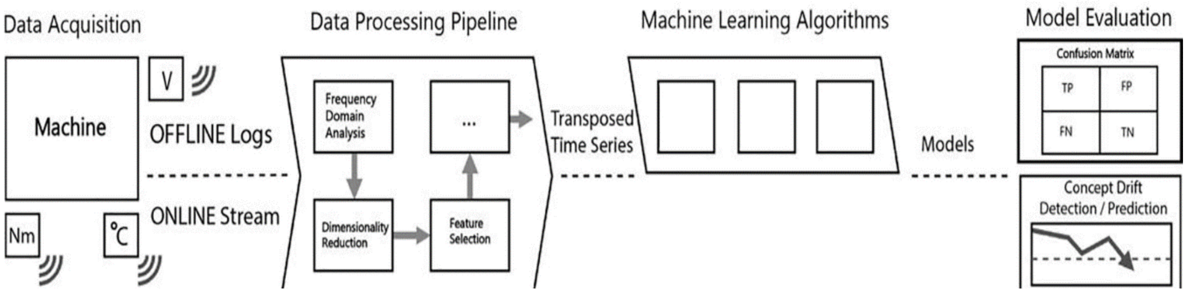

Figure 5. Machine condition monitoring model integrating with Machine learning algorithms [34].

The idea of Artificial Neural Network (ANN) is creating a computing system that simulates the biological neural systems of the human brain. The artificial neural network is particularly useful in the modeling of nonlinear mapping, and also in the recognition of distinctive features from chaotic input data even if it is not complete. The behavior of ANN modifies in response to its environment. The inputs will self-adjust while a set of them are given to the network to produce consistent responses through a process called learning. The learning process can change the weights systematically in order to achieve some desired results for a given set of inputs. The types of learning are, supervised and unsupervised; the supervised has been selected based on the environment knowing. The popular algorithm related to the supervised learning is known as the Back-Propagation. The construction of ANN involves the determination of the network properties

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depending on the network topology (connectivity), the type of connections, the order of connections, and the weight range. Moreover, it determines the node properties like the activation range and the activation function. Also, in dynamic system the ANN determines weight initialization scheme, the activation calculating formula and the learning rule.

A large number of researchers presented application of neural network models in Tool Condition Monitoring (TCM) and classification of tool wear. Artificial neural network (ANN) is useful as online prediction of tool wear based on back propagation network [35]. The multi-layer feed-forward neural network with a back propagation (FFBP) training algorithm is successful in TCM as tool fault detection and classification [36]. In this project the ANN is used as fault detection and wear condition classification based on Multi-layer feed-forward with back propagation.

Artificial neural network contains many connected neurons, which work as receiver for the impulses from input or other neurons. These neurons transform the input by giving the outcome to the output or other neurons. Also, ANN consists of different layers of connected neurons, which receive the input from the previous layer and transfer the output to the succeeding layer. Figure 6 shows the model of a neuron, where the inputs are forwarded to the neuron and multiplied by their synaptic weights. Then, the outcome is forwarded to sum in summing junction and it is activated by the activation function. The inputs of the activation function are affected by the bias (bi), so it will increase if positive and decrease in the case of negative. Finally, the output will be given. The learning and storing of the knowledge will be possible by this model of the ANN.

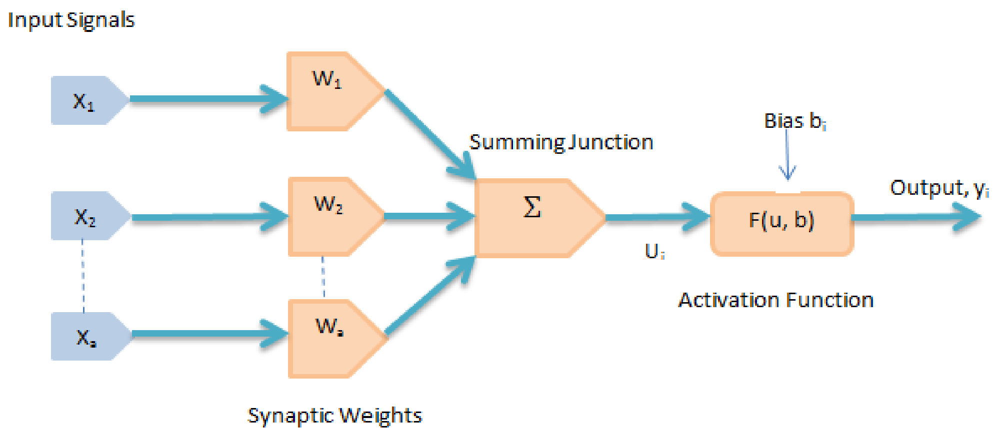

Figure 6. The model of a neuron.

Typically, in neural network architectures two types of layers are organized in the shape of a layered neural network. There are the signal-layer feed-forward perceptron (SLP) neural network and the feed-forward multilayer perceptron (MLP) ANN. The arrangement of neurons in each of the layers is entirely dependent on the user, hence they have the ability to represent a large range of output and input patterns. The Figure 7 shows the limitations in the range of functions or processes that they can represent in signal-layer feed-forward (SLP) neural network. However, the feed-forward multilayer perceptron (MLP) neural network is selected in this study; because it has a wide range of processes and more powerful representation capacity which can be achieved by using more than one layer, as shown in Figure 7 .

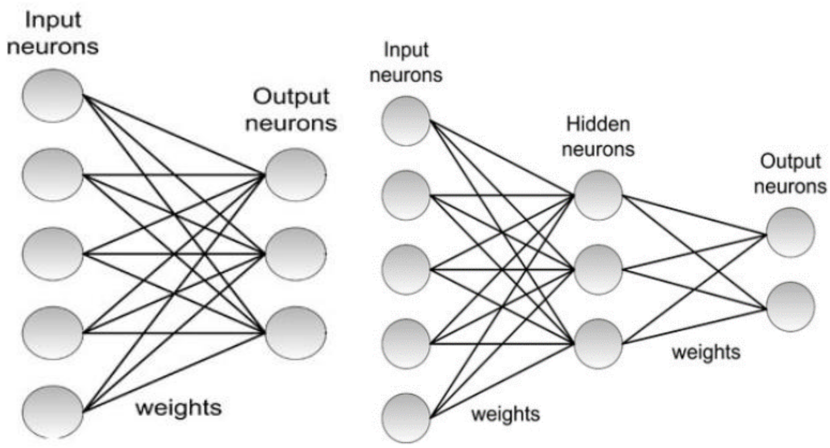

Figure 7. Typical diagram of a single-layer perceptron and multi-layered feed-forward ANN [37] .

5. Experiment Setup

In this experimental work, four healthy drill bits were taken and wear was intentionally introduced in three of the drill bits using a grinding machine, leaving one as healthy drill bit. A grinding machine was operated in the speed of 450 rpm to create wear with the levels of 0.2mm, 0.4mm and 0.6mm at the tip of the carbide tool. The wear at carbide insert tips was measured using a microscope. Figure 8 shows the process of creating wear levels. The work piece used in this experiment is mild steel in which the hole has been made using the healthy tool and wearied tools to collect the vibration data.

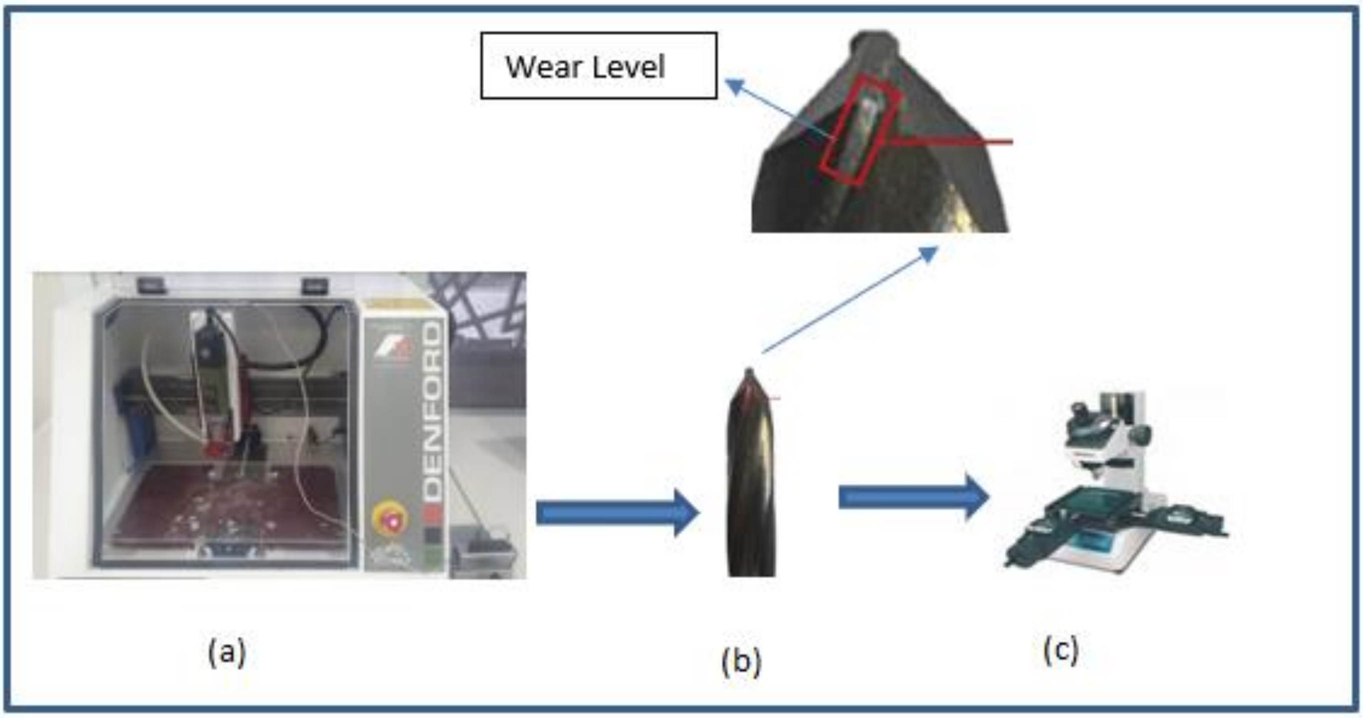

Figure 8. The process of creating wear levels, (a) use of drill bit in a bench CNC (b) the wear created in the tip of drill bit (c) the microscope.

In the experimental work, the speed of the drilling condition has been set to 12mm/min feed rate and the rpm of 800. The drill bit has drill diameter of 8 mm, Overall length 92 mm, the angle point is 135. Using accelerometers, vibration data has been collected and analyzed in the life cycle of the drill bit. In this experiment, the direction of sensor is vertical and the wear levels (0.0mm, 0.2mm, 0.4mm and 0.6mm) are changed. vibration signals are captured by data acquisition card from National Instruments (DAQ Card) with Lab VIEW software. The output of the signal conditioning device is directly connected to a PC with a data acquisition card (DAQ card- NI C- DAQ- 9174) and LabVIEW software and this experimental works have been done with 16000 sampling rate. The signal conditioning device used for the signal processing is Type NI – 9234. In this experiment , the work piece and drill bit is fixed at the drilling machine and the distance between the work piece and the drill bit is adjusted with 50 mm. The drill bit with different wear is employed with the work piece and the direction of the accelerometer sensor (coated by aluminum coil for safety) is vertical which was placed on the tool head as shown in the Figure 9.

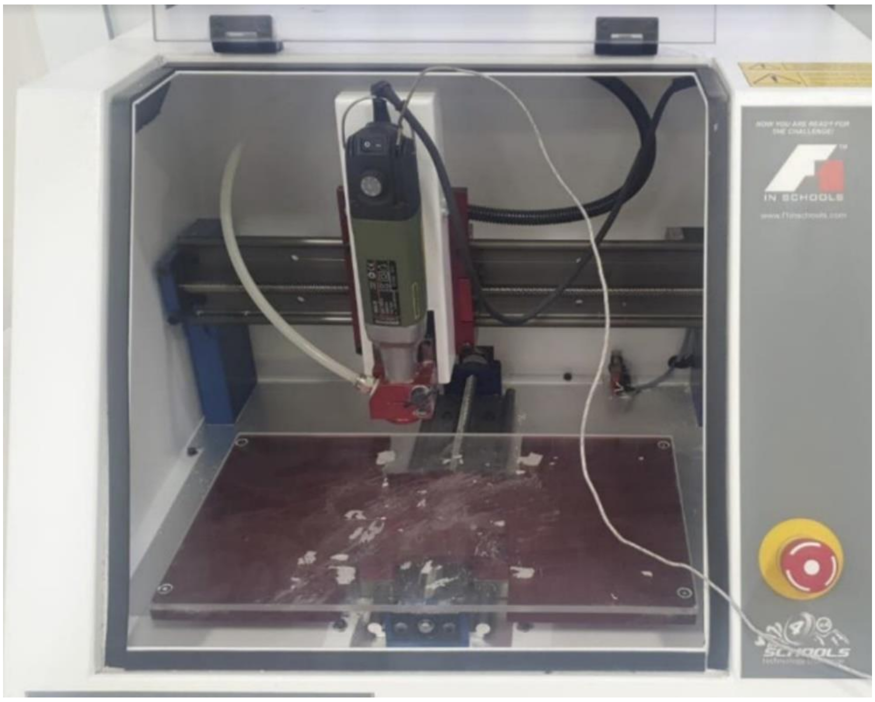

Figure 9. The adjusting work piece and drill bit at the drilling machine.

In this experiment the vibration signals of the drill bit with different wear conditions (healthy, 0.2mm, 0.4mm and 0.6mm) are captured by the accelerometer sensor to shift and convert these signals from analogue to digital form using a PC with data acquisition card from National Instruments (DAQ Card) and Lab VIEW software. Figure 10 shows the experiment setup. The signal has been collected with respect to time and frequency in the LabVIEW front panel for further analysis. In each of the drill bit, 20 experiments have been conducted and collected the signals and stored in the database.

(a) (b) (c)

Figure 10. Experiment setup (a) Sensor Mounting (b) Signal Conditioning and Data acquisition (c) LabVIEW's front panel and block diagram.

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Finally, LabVIEW shows the features of the vibration signals in the time domain and frequency domain as shown in Figure 10(c). For further analysis of vibration signals, MATLAB is used based on Wavelet analysis and ANN for automatic drill bit fault detection and classification.

6. Experimental Results and Discussions

This section presents the results of applying the Continuous Wavelet Transform (CWT) for drill bit with different wear condition. The CWT is used also as features extraction method for generate the inputs feature to ANN. Morlet wavelet (morl) and Daubechies Wavelets (db 10) has been used as a mother wavelet function while obtains the CWT coefficients.

Continuous Wavelet Transform (CWT) Analysis

In Figure 11 the results are demonstrated comparative graphs of kurtosis factor of 20 wavelet coefficients for healthy tool and (0.2, 0.4, 0.6) mm wear, respectively. These graphs present the effectiveness of kurtosis factor in wavelet scale, and then compare it to histograms of healthy tool and each different wears. This technique shows the ability to recognize between the healthy condition and faulty condition.

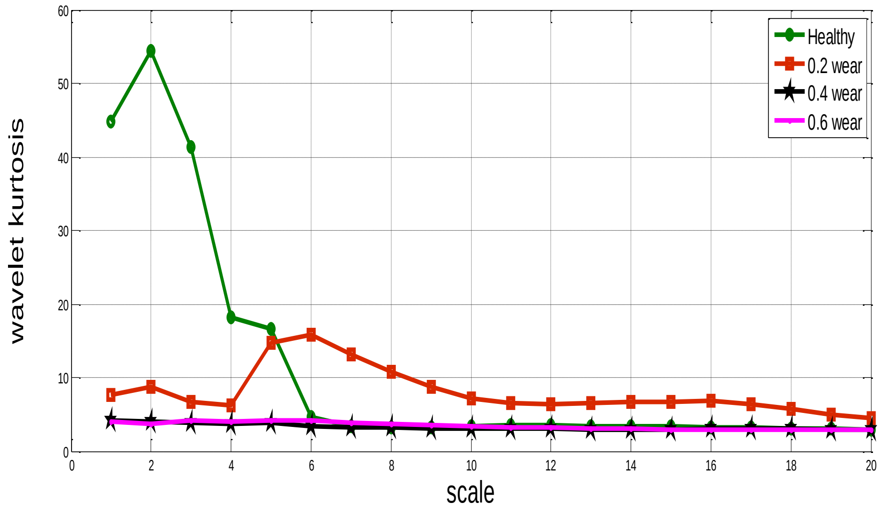

Figure 11. The Kurtosis distribution for wavelet transform scales [healthy tool and (0.2, 0.4, 0.6) mm wear].

The Kurtosis distribution of wavelet transform scales Figure 11 presents that the kurtosis of healthy tool is higher than the fault condition. As the sharp tool produces a signal with less randomness and as the wear progress the randomness of the signal is increased that produce a flat signal distribution as a result the kurtosis value will decrease. This clear in the histograms for healthy tool and (0.2, 0.4, 0.6) mm wears shown in Figure 12 (a-e).

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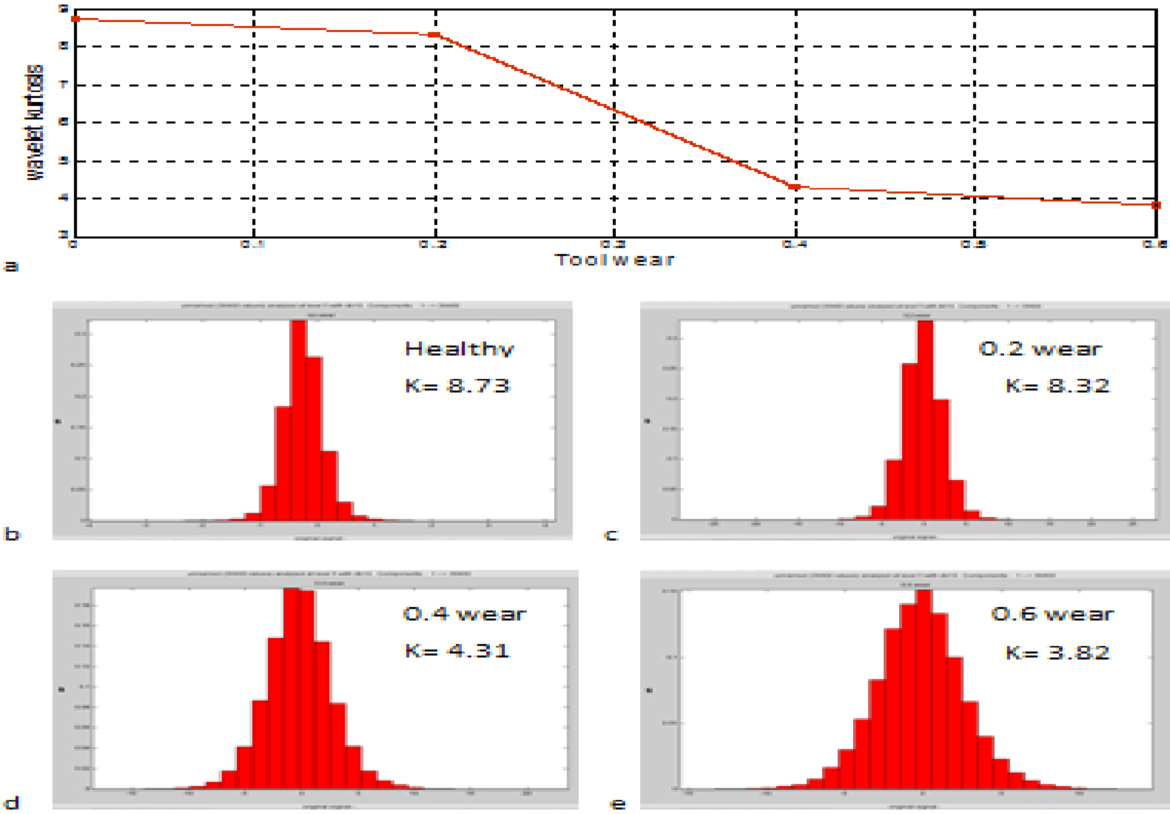

Figure 12. (a) The average values wavelet kurtosis by the wear condition and (b-e) the histograms of healthy tool and (0.2, 0.4, 0.6) mm wear.

To change the wavelet scale to frequency (Hz), this equation is applied: Fa = Fc / a . Δ Where, a is a scale, Δ is the sampling period (0.1), Fc is the center frequency of a wavelet in Hz and Fa is the pseudo-frequency corresponding to the scale a in Hz. In the selected signals were in 280 rpm, so the frequency equal to (280/60) 4.6 Hz. Figure 13 shows the kurtosis distributions of wavelet transform at frequency (Hz) for healthy tool and (0.2, 0.4, 0.6) mm wear, respectively.

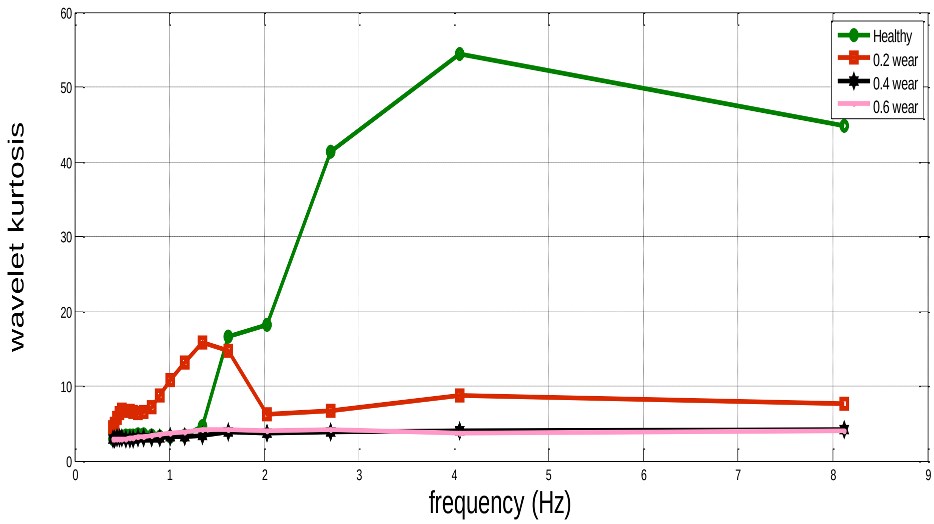

Figure 13. The Kurtosis distribution for wavelet transform at frequency (Hz) [healthy tool and (0.2, 0.4, 0.6) mm wear].

The wavelet kurtosis decrease when tool wear increase as shown in above Figure 13 this is corresponding to frequency in hertz ($\propto \frac{1}{scale}$). That is referring to the damping of the drill bit increase

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as result of increasing in the wear. When the wear increases the contact area of the cutting tool with the work piece also increase. That makes the friction increase, so the damping increase and the machine frequency decrease for lately the peak at 4.06 Hz for healthy tool and shifted to 1.35 Hz for 0.2 mm wear, again decreased for 0.4 and 0.6 mm wear. All that is presented in this equation: $\downarrow \omega_d = \omega_n \sqrt{1 - \uparrow \zeta^2}$ where, ω_d is damped frequency, ω_n is the undamped angular frequency and ζ is damping ratio which increase by increase tool wear.

7. Automatic Fault Detection and Classification of Drill Bit Using ANN

Automatic fault detection and classification of drill bit condition using the features of wavelet and Artificial Neural Network (ANN) model is proposed in this project. By using The Artificial Neural Network (ANN) to classify the tool wear conditions the model of ANN is created based on feed-forward Multi-Layer Perceptron (MLP) and Back Propagation. The result features (peak, RMS, crest factor, kurtosis, shape factor and impulse factor) healthy condition and wear condition are feed to ANN to classify the wear condition. The signal consists of 38400 data for each condition (wear & healthy) and then 10 coefficients are taken for each of these wear conditions. To build the ANN model six features are extracted from 10 coefficients for each condition, then the values divided into 30 (5x6) values for training and 30 values (5x6) for testing. Also, the healthy condition is normalized as (0 1) and wear condition as (1 0) for training targets. The ANN model is created using input layer with six nodes (extracted features), two hidden layers consist five nodes for each and output layer as shown in Figure 14. Back Propagation is applied to minimize the Mean Square Error (MSE) between the ANN outputs and the desired target values.

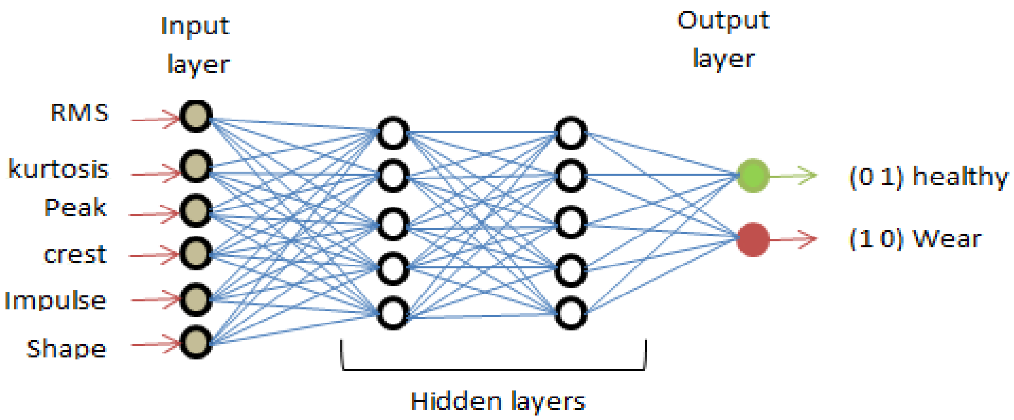

Figure 14. The model of ANN.

In this model two stages are applied which are training stage and testing stage. It is trained with 10E-10 training goal (MSE), 0.52044 training rate, with six attribute (features) and the maximum No. of iteration (epochs) of 1000 are selected. Figure 15 shows the result of training process, in which it reached the desired goal stopping criteria after 27 epochs.

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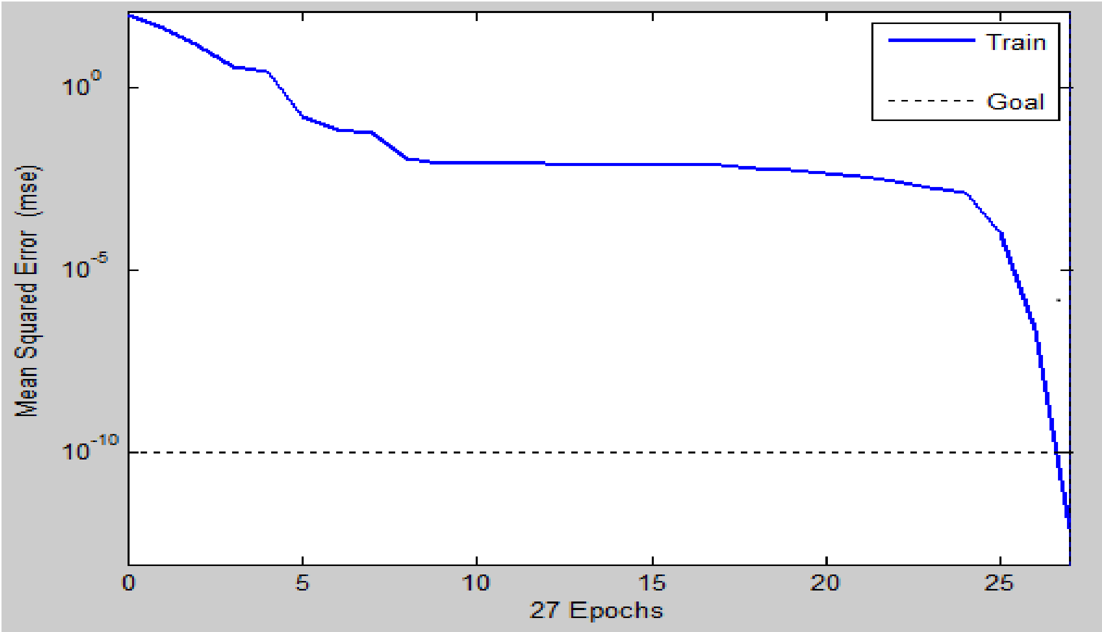

Figure 15. Training process of ANN.

The regression curve for both training targets and the ANN output is shown in Figure 16, a good correlation between the both can be concluded. The results for ANN classification for tool wear condition shown success rate based on the given six features.

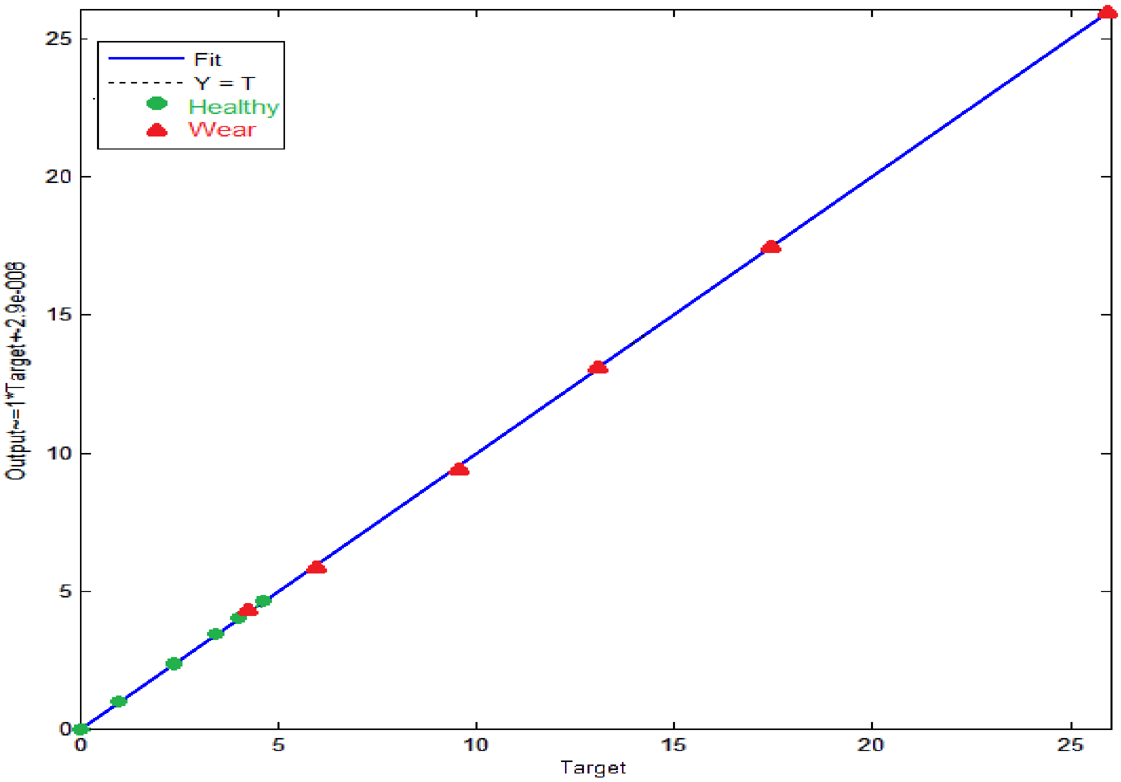

Figure 16. The regression curve for both training targets and the ANN output.

The accuracy of the training process of the neural network is based on (1-L) where L is calculated by keeping the default setting of the loss function in the software [38]. In the training of testing signal in ANN, the inputs are given based on the collection of signals from accelerometers.

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In the classification with ANN with WPT outcome, the following factors was investigated.

- the maximum frequency of the WPT
- the number of neurons in the hidden layer
- the percentage of data used for training the nets

To analyze the effect of the number of neurons in the hidden layer, 5 to 30 neurons with intervals of 5 neurons are given in the ANN.

In the clarification with ANN based on statistics of acceleration data, the following factors was studied.

- The number of neurons in the hidden layer
- The number of statistics
- The percentage of data in training the nets

RMS, Peak, kurtosis of the wear signals are used as input for the ANN which allows better discrimination of the type of faults.

In the outcome of classification based on WPT acceleration signal, the networks built with WPT of 500 Hz or more and 10 or more neurons provide an accuracy of 98% and for less frequency it lies between 95 to 98%. So, it is required to analyze further in future for the less accuracy for lesser frequency.

As far as vertical accelerometer is concerned, classification by statistics are very accurate combination of RMS, peaks and kurtosis and the number of neurons achieved 100% accuracy.

However, detection error may lead to a reduction in efficiency of the machine and it would lead to unnecessary maintenance. The measurement of vibration signal using accelerometer in vertical placement is not so precise, no statistical data achieves an accuracy of 100%. So, finding statistical data and its combination will play an important in achieving 100% results.

Error value while using WPT output may come due to various reasons such as unrecognized faults, mistake in placing the sensors, power fluctuation during data acquisition and less frequency input to ANN. However, the networks with more neurons will perform well perform when trained with largest number of signals.

8. Conclusions

Condition monitoring via vibration signal analysis plays an important role in maintenance management to reduce unscheduled down time and avoid catastrophic accident in industrial sector. To do this an accurate fault detection is important to avoid downtime and loss in terms of cost and productivity [39,40]. WPT based signal analysis is one of the proved method in manufacturing industry [41] which is extended to drill bit condition monitoring in this work. Based on the obtained results the overall conclusion can be summarized as follows:

For more accurate fault detection of the drill bit, An ANN based techniques has been developed, which are wavelet kurtosis factor and the histograms throughout using Morlet wavelet and Daubechies Wavelets as a mother wavelet function (similarity with the extracted fault pulses shape). This technique shows the ability to recognize between the healthy and wear conditions. The wavelet analysis is selected for drill bit vibration signal features extraction. The advantage of wavelet analysis is proven as a multi resolution, scaling and shifting of the wavelet through the vibrational signal. For high performance of the extracted wavelet features; the features are normalized between 0 and 1 in order to be the inputs in ANN. The ANN model based on supervised learning capability of Multi-Layer Perceptron (MLP) and Back Propagation has shown effectiveness to be as automatic drill bit fault detection and classification, as proven that the training process has been reached the desired goal stopping criteria after 27 epochs. And the ANN performance is shown as 98% success rate.

So, neural networks are effective tools and the results they provide depend heavily on dataset used to create them and the choices for their parameters. The data must be collected reliably and accurately to eliminate noise and errors and to extract the perfect features. The network must then be created and trained. The better result will be obtained when width of the spectrum increased [42].

This research is having high significance to academic and scientific community and it will open a path for the implementation of Industrial 4.0 technologies in manufacturing and process industries

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to obtain high accuracy products, maintain reliability in machines and machining processes, reduce the down time and scrap, reduce the risk during the operations etc. So, this project has been proved the successful correlation between the wavelet transform (WT) and the drill bit wear condition using ANN based on the obtained results.

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