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Original Article

Condition Monitoring of CNC Drill Bit for the Manufacturing Sector Using Wavelet Analysis and Artificial Neural Network Based on Feedforward Multilayer Perceptron (MLP)

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Abstract - *Real-time condition monitoring and precision health assessment systems are necessary for effective maintenance programs in the industrial sector. Rapid advancements in information technology and other engineering technologies have invited more proactive attention from research and development in industrial sectors, 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. The CNC drill machine uses a high-carbon steel drill bit and mild steel material as work pieces in this experiment. The cutting condition parameters are kept constant, and the wear level varies from 0.2 to 0.6 mm. Using an accelerometer, the Data Acquisition system (DAQ) with Lab VIEW software captures the vibration signals for drill bits with different wear conditions. The captured vibration data are analyzed using Continuous Wavelet Transform (CWT) with Morlet and Daubechies wavelet as prime functions. The CWT coefficient is generally used to generate the input 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% accuracy in the wear prediction, and these results show the effectiveness of the combed WT and ANN for the automatic classification of tool wear conditions with a high success rate.*

Keywords - *Artificial Neural Network, Condition monitoring, Lab VIEW software, Wavelets transform analysis.*

1. Introduction

In manufacturing, increasing productivity and product quality is essential for customers. In this, condition monitoring plays a vital role in ensuring product quality. So, preventive maintenance and condition monitoring are required to achieve greater machinery availability, improve manufacturing process quality, enhance machine reliability, maximize profit and productivity, and reduce maintenance costs. Usually, an industrial investor is more concerned about profit and saving on production costs due to heavy competition in the market. To increase productivity, condition monitoring can provide early warnings based on fault detection in the early production stage.

In drilling operations, if the drill tool's condition is not appropriately monitored, the drill tool will stick inside the workpiece, and there is a possibility of breaks if the operation is not stopped. Usually, the condition of the tools is analyzed based on mathematical models, physics-based models, and data-driven models, which use the data using sensors and data acquisition systems. Since the mathematical model analysis is more complex and physics-based models require in-depth knowledge of 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 due to production tolerances and the asymmetric profile of the drilling tool.

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

Drill fault detection techniques have been developed based on wavelet analysis and ANN, such as automatic drill bit fault detection and classification. Experimental work has captured the vibration signals for analysis at different measuring intervals. The bench-type CNC drill uses a high-carbon steel tip drill bit and mild steel material as a workpiece. The drilling condition has been set to 12mm/min feed rate, and the speed is 800 rpm. The drill bit has a drill dia 8 mm, an Overall length of 92 mm, and an angle point of 135. Vibration data was collected and analyzed using accelerometers during the drill bit's life cycle. In this experiment, the direction of the sensor is vertical, and the wear levels (0.0mm, 0.2mm, 0.4mm, and 0.6mm) are changed.

Researchers investigate several drill bit conditions using monitoring methods, including direct and indirect ones. Direct methods like visual inspection, machine vision, and infra-red methodology are used to monitor the drill bit, which will give less accuracy than indirect methods. Indirect methods include use signals like force, vibrations, acoustic emission, etc., in which the signal features have a relationship with wear condition/parameters Indirect methods include the use of signals like force, vibrations, acoustic emission, etc., in which the signal features have a relationship with wear condition/parameters [1].

Acoustic Emission (AE) and vibration-based drill bit monitoring are the most popular indirect methods for accurately assessing micro-level measurement conditions. Acoustic emission is a phenomenon that occurs when, for different reasons, a small surface displacement of a material surface is produced. This happens due to stress waves generated when there is a rapid release of energy in a material or on its surface, which has a frequency range from 10 to 70 kHz with a nonlinear frequency response. In some advanced testing, we can use a 200 kHz sensor for tool wear and an 800 kHz sensor for tool breakage detection, which will come under the broadband acoustic sensor. AE has been widely used for monitoring wear in the laboratory and at the industrial level for monitoring failures like scuffing, fretting, rolling contact fatigue, etc.,.

Furthermore, indirect methods are widely used in drill bit condition monitoring and fault detection. They are used in cutting forces, acoustic emission, temperature, vibration, motor current, and torque [2]. 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 workpiece for the precision of the cutting operation [3]. Garousi M. H. et al. (2024) 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 a drill bit condition monitoring approach in drilling operations based on the vibration signal collected using a sensor and data acquisition system. Advantages of this approach include availability, low cost, extensive information data, nondestructive, reliable, and facilitating continuous online monitoring. This method allows the substituting of another sensor (e.g., an acoustic sensor) or a cost-effective accelerometer [4].

1.1. Research Gap and Novelty of the Proposed Research Work

A research gap exists in identifying the right methodology for predicting drill bit tool wear. The existing research using MLs is more complex and requires more processing time for fault classification. So, there is a high demand for less complex, more accurate, and high-speed algorithms or methodologies to identify the wear level of tools for bench-type CNC machines, particularly drilling machines.

The novelty of this work is the proposal of WPT and ANN in drill condition monitoring. Many researchers have applied this technique to predict the turning machine's faults. However, condition monitoring in the drill bit is still under research since the drill bit has complex features. So, this attempt will open a path to research to identify the drill bit faults, which will be helpful in many fields. The stone drilling process is critical for the oil and gas industries, so there is a massive demand for high-level condition monitoring systems for the drill bits in the oil and gas sector. We believe the proposed methodology will play a significant role in stone drilling operations. The innovation in the research is to apply an accelerometer/ acoustic emission sensor and artificial neural network (deep learning-based analysis), compare the results, and keep the error below 3%, which was not obtained in the previous research.

2. Literature Review

AI algorithms such as ANN, fuzzy-based techniques, Genetic Algorithms, Support Vector Machines, etc, are instrumental in fault diagnosis. So, AI is the future of condition monitoring for preventive maintenance [5]. The Internet of Things and AI have many advantages in predicting the machine's health, which improves the productivity and profit of industry [6, 7]. In the research paper by Miho Klaic et al., a decision tree algorithm has been applied to predict tool wear. The research paper concluded that the methodology assured a 90% success rate and was more reliable. The researcher has not compared the decision tree with deep learning algorithms, a significant research gap in this paper [8].

Rui Zhao et al. surveyed the topic of deep learning and its application for machine health monitoring. In their research article, the authors concluded: "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 precisely to monitor tool wear, and the research concluded that deep learning is a promising technique for assessing any tool wear [9]. P. Krishnakumar et al. used acoustic emission signals for tool condition monitoring during high-speed milling of Ti-6Al-4V. Discrete Wavelet Transform (DWT) extracted vibration and acoustic emission signals coefficients. Machine learning algorithms like decision trees, Naïve Bayes, SVM, and ANN are used to predict the tool condition. The authors concluded that SVM-based vibration analysis predicts tool conditions effectively and assures that prediction accuracy is more than 99% [10].

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 using the noise-assisted LMD method and the BP neural network. Monitoring drill bit wear with multi-signal fusion accuracy is 95.8% [11].

Lang Dai developed a new Deep Learning Model for Online Tool Condition Monitoring Using Output Power Signals. The output power from the sensor mounted on the cutting tool holder during its operation is used for further analysis. The data were analyzed using wider first-layer kernels (WCONV) and Long Short-Term Memory (LSTM) available in the deep learning algorithms. This paper concerns the output power signals and their analysis of deep learning algorithms [12].

Wang et al. have done a survey on tool Wear Monitoring Methods Based on Convolutional Neural Networks. The author concluded that applying convolution neural networks to monitor tool wear and condition is more reliable. They added that the convolution neural network can improve accuracy, which is an excellent significance of the CNN [13].

Chacon et al. used multi-threshold count-based feature extraction at a multi-resolution level based on wavelet packet transform to extract a redundant and non-optimal feature map from the AE signal. Recursive feature elimination reduces and optimizes the number of features, and 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 [14].

Kolar, P. et al. dealt with indirect drill condition monitoring based on machine tool control system data. Workpiece vibration has been monitored in this work, and the correlation of various signal features is evaluated. As a result of this paper, researchers concluded that the root mean square of the vibration and spindle torque signals strongly correlate with flank wear near the bottom of the hole. This paper analyzes spindle current torque, and Z slide drive current torque for flank wear [15].

Reeber T et al. demonstrated two anomaly detection approaches for drill condition monitoring. The XG Boost approach provides timely detection near the end of tool life. Machine learning models have been used to predict tool wear before any risk in the drilling process. The authors also use the unsupervised autoencoder to detect anomalies in reconstruction errors [16].

Anomaly detection using an autoencoder or other neural networks is used to supervise equipment failure and predict the intervals for maintenance. These are unsupervised algorithms that are easy to apply in condition monitoring. Pores and blow holes in the workpiece and potential dimensional inaccuracies (or) monitoring anomalies related to progressive tool wear for tool condition monitoring in CNC machines have been dealt with by Netzer, M., Palenga, Y., and Fleischer [17].

Anomaly detection algorithms for tool wear detection using sensors can be done using a convolutional neural network (or) autoencoder, which is supported by the papers of Sun et al., Li, G et al., Ahmad et al., and Vonhahn, T and Mechefske, C.K [18-21].

Karri, V. and Kiatcharoenpol, T. (2003) used an artificial neural network in drilling machine condition monitoring. This paper applies a feedforward network to predict tool life regarding the number of holes' failures. By benchmarking Root Mean Square (RMS), the results were obtained from thirty-two cutting condition inputs to predict failure in drilling [22].

3. Wavelet Analysis and Kurtosis

A wavelet is a wave-like short oscillating function that begins at zero amplitude and will increase or decrease and then return to zero one or more times. Wavelets are applied to transform the signal under examination into another representation that presents the signal information in a more amenable form for further analysis using AI techniques like machine learning/deep learning. This transformation, 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 transformation in condition monitoring.

Time-frequency analysis of machining signal, feature extraction, signals de-noising, singularity analysis of the tool state density estimation for tool wear classification according to its multi-resolution, sparsity, and localization properties [23, 24].

The wavelet method overcomes the limitations of the Fourier Transform, such as the inability to check continuity, fixed resolution, poor time-frequency localization, and limited time-frequency resolution trade-off, using a multi-resolution technique (time & frequency) [25]. It can 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 [21]. 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: it must have finite energy based on the Fourier transform, the wavelet must have zero mean, and for complex wavelets, the Fourier transform must be both accurate and vanish for negative frequencies. To make the wavelet of the chosen mother wavelet (original wavelet) more flexible, two basic manipulations are applied, which are stretching or squeezing it (dilation) and moving it (translation). The dilation parameter ‘a’ governs the dilation of the wavelet. 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 H.S Kumar and Gururaj Upadhyaya is [26]:

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

The factor 1 over the square root of ‘a’ ensures 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 practical tools for stationary and non-stationary signals. Based on the Equation (3)-(9), the CWT is given as:

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

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 a more compact form as an inner product:

$$T_{a,b} = \langle x, \Psi_{a,b}\rangle \tag{3}$$

The windowing techniques with variable-size regions in wavelet analysis can overcome the limitations of the Short-Term Fourier Transform (STFT). Wavelet analysis allows shorter intervals where more precise high-frequency information is desirable and long regions for low-frequency information. Sometimes, the wavelet is an irregular and asymmetric waveform of effectively limited duration (average value zero), so the varieties of wavelets (Wavelet Families) exist, and an analyst can choose from the wavelet families that suit his application best. This project focuses on Daubechies wavelets (db10) and Morlet wavelets (more) as basic functions based on the role of feature extraction because they have similar characteristics to the extracted signals. Morlet has the following advantages:

1. It is good for harmonic and transient analysis.
2. High-frequency resolution.
3. Continuous wavelet analysis Daubechies have advantages of:
   - Excellent tool for time-frequency localization for sudden change.
   - Multi-scale analysis.
4. Discrete wavelet analysis.

The Morlet wavelet is known by the following Equation (4). Figure 1 shows the Morlet wavelet.

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

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).

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

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

In the wavelet transform, the kurtosis prediction of the vibration signal will help to find the fault as soon as possible. Usually, the wavelet transform is an essential tool for nonlinear and non-stationary signal analysis, which contains Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT). The next step in WPT is to decompose the detailed signal information in the high-frequency region. Thus, WPT is used to decompose the kurtosis of the vibration signal into several sub-signals with different frequency ranges [26]. Kurtosis measures peakedness; hence, it is a fine indicator of signal impulsiveness in fault detection for rotating components, especially drill bits. Kurtosis is expressed as:

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

Where, μ = mean of time series x,
σ = standard deviation of time series x
E{.} is the expectation operation
The -3 is to make kurtosis of the normal distribution of the normal distribution equal to zero.

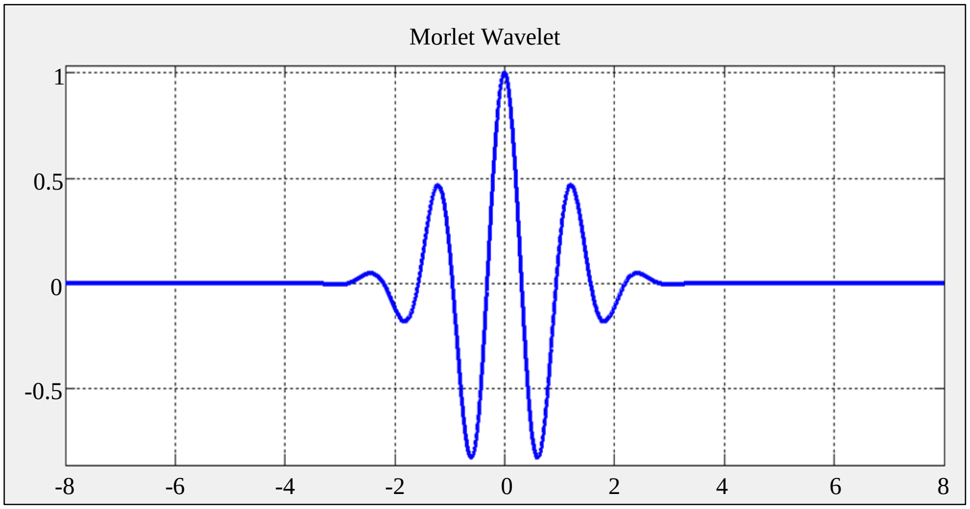


Fig. 1 Morlet wavelet

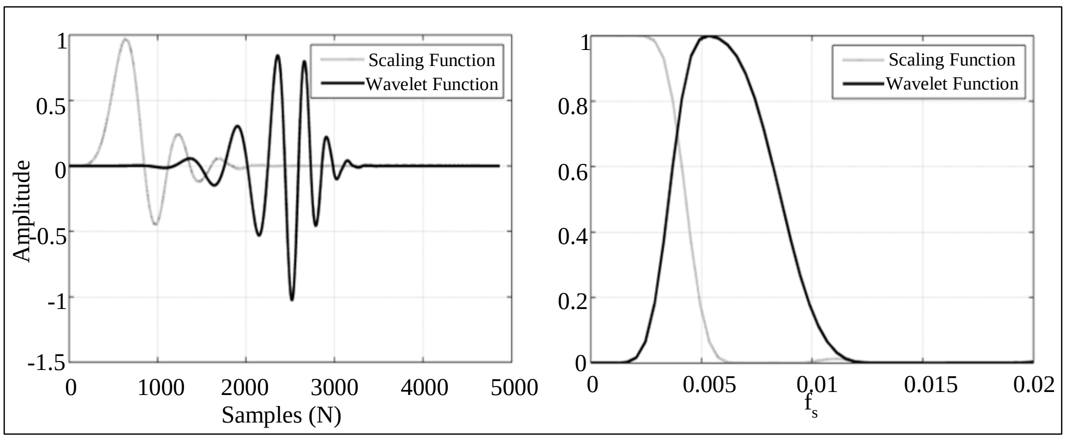


Fig. 2 Daubechies wavelet db 10

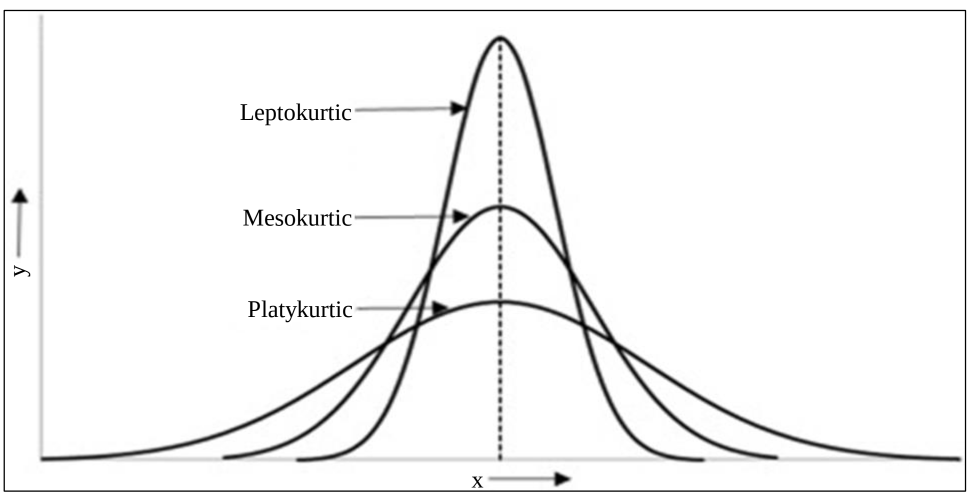


Fig. 3 Kurtosis distribution [27, 28]

Kurtosis has three measures, which are called mesokurtic, leptokurtic, and platykurtic. When the kurtosis distribution statistic is similar to normal distribution or bell curve, it is called mesokurtic distribution. If the kurtosis value is more significant than mesokurtic, it is called leptokurtic distribution. If the kurtosis value is smaller than mesokurtic, it is called platykurtic distribution. Figure 3 shows the various kurtosis distributions.

4. Modelling of Condition-Based Maintenance Using Artificial Intelligence

Traditional monitoring involves a measurement system containing sensors or wireless sensors. The sensor data undergoes signal conditions to process it. Then, the processed signal is converted from analog to digital, and feature extraction is performed.

Finally, the signal is extracted for further analysis in AI techniques to predict machine faults [29, 5]. A block diagram of machine condition monitoring integrating with AI is given in Figure 4. Tool wear Condition Monitoring (TCM) is essential in machining automation. In recent years, Machine Learning (ML) and Deep Learning (DL) based TCM methods have been widely researched [31].

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 [32]. The authors have given a machine condition monitoring model integrated with machine learning algorithms in Figure 5.

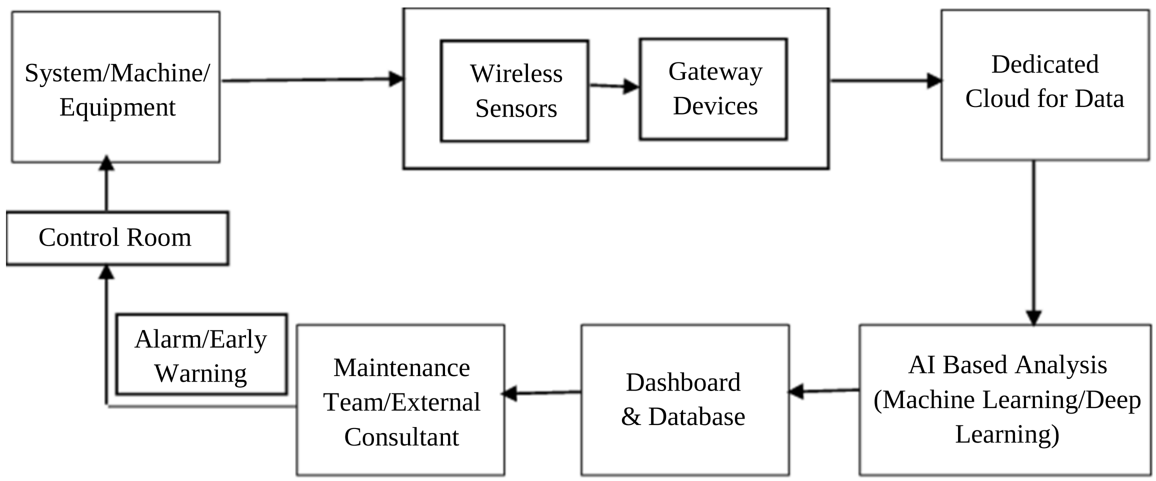


Fig. 4 Machine condition monitoring model integrating with AI techniques [30]

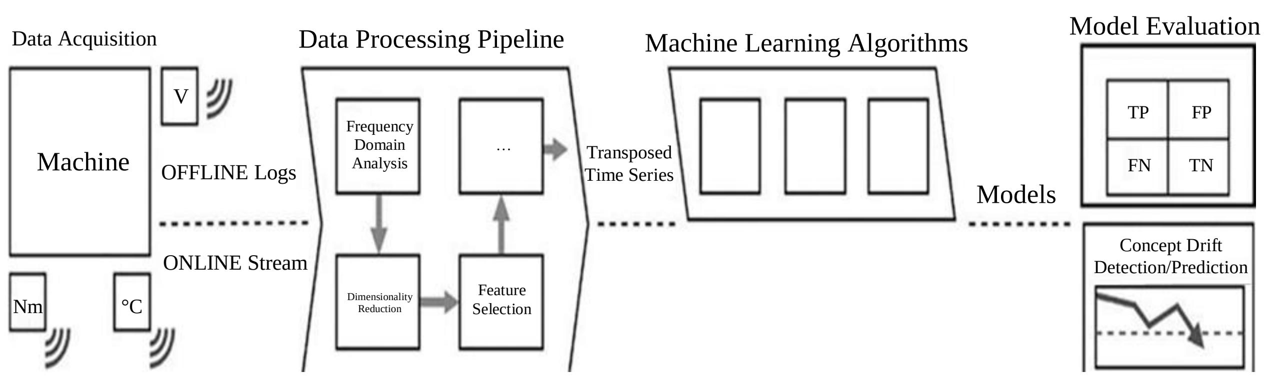


Fig. 5 Machine condition monitoring model integrating with machine learning algorithms [32]

The idea of Artificial Neural Network (ANN) is to create a computing system that simulates the biological neural systems of the human brain. The artificial neural network is beneficial in modeling nonlinear mapping and recognizing distinctive features from chaotic input data, even if it is incomplete.

The behavior of ANN modifies in response to its environment. The inputs will self-adjust while a set is given to the network to produce consistent responses through learning. The learning process can change the weights systematically to achieve the desired results for a given set of inputs. The types of learning are supervised and unsupervised; the supervised learning method is selected based on the environment's knowledge. The popular algorithm related to supervised learning is known as backpropagation. The construction of ANN involves the determination of the network properties 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 function. Also, the ANN determines the weight initialization scheme, the activation calculating formula, and the learning rule in a dynamic system.

Many researchers have presented the application of neural network models in Tool Condition Monitoring (TCM) and the classification of tool wear. Artificial Neural Networks (ANNs) are helpful for online tool wear prediction based on backpropagation networks [33]. The multilayer Feedforward Neural Network with Backpropagation (FFBP) training algorithm is successful in TCM as a tool for fault detection and classification [34].

This work uses the ANN for fault detection and wear condition classification based on multilayer feedforward with backpropagation. An artificial neural network contains many connected neurons, which work as receivers for the impulses from input or other neurons. These neurons transform the input by giving the output or other neurons the outcome. Also, ANN consists of different layers of connected neurons, which receive the input from the previous layer and transfer the production 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 sent to the sum in the summing junction, and the activation function activates it. 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. Learning and storing knowledge will be possible using this model of the ANN.

Typically, in neural network architectures, two types of layers are organized in the shape of a layered neural network. There are the Signal-Layer Feedforward Perceptron (SLP) neural network and the feedforward multilayer perceptron (MLP) ANN. The arrangement of neurons in each layer depends entirely on the user. Hence, they can represent an extensive range of output and input patterns.

Figure 7 shows the limitations in the range of functions or processes they can describe in Signal-Layer Feedforward Perceptron (SLP) neural networks. However, the feedforward Multilayer Perceptron (MLP) neural network is selected in this study because it has a wide range of processes and a more robust representation capacity, which can be achieved by using more than one layer, as shown in Figure 7.

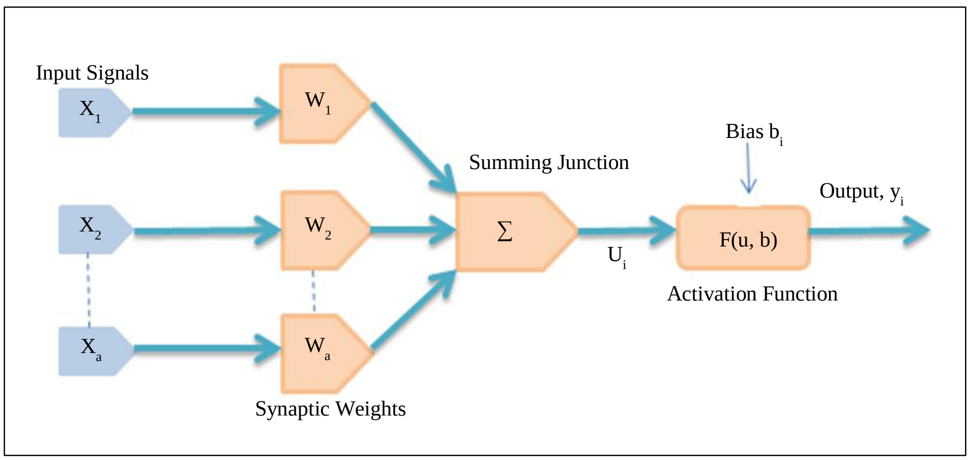


Fig. 6 The model of a neuron

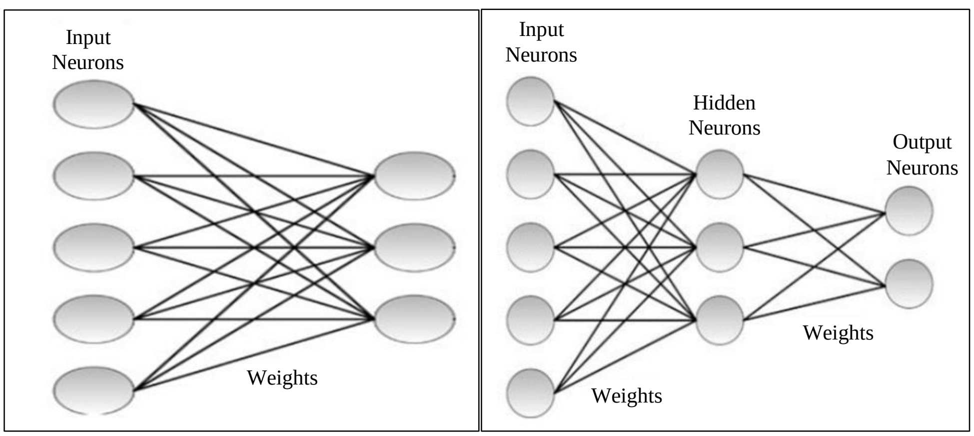


Fig. 7 Typical diagram of a single-layer perceptron and multi-layered feedforward ANN [35]

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 a healthy drill bit. A grinding machine was operated at 450 rpm to create wear with 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 workpiece used in this experiment is mild steel, and the hole was made using healthy tools and wearied tools to collect the vibration data in Figure 7.

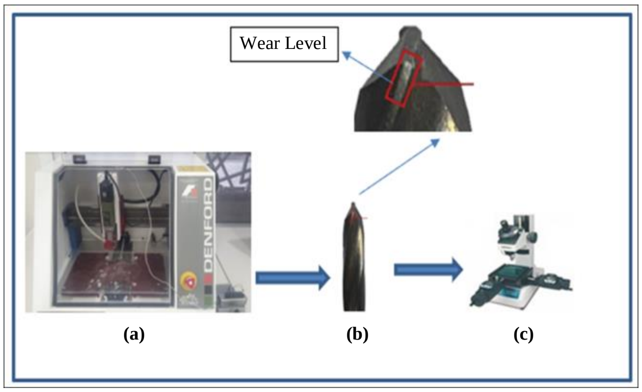


Fig. 8 The process of creating wear levels is: (a) the use of a drill bit in a bench CNC, (b) the wear created at the tip of the drill bit, and (c) The microscope.

In the experimental work, the speed of the drilling condition was set to a 12mm/min feed rate and an rpm of 800. The drill bit has a drill diameter of 8 mm and an Overall length of 92 mm; the angle point is 135. Vibration data was collected and analyzed using accelerometers during the drill bit's life cycle. In this experiment, the direction of the sensor is vertical, and the wear levels (0.0mm, 0.2mm, 0.4mm, and 0.6mm) are changed. Vibration signals are captured by a data acquisition card from national instruments (DAQ Card) using Lab VIEW software.

The DAQ card input is 5V DC with 24-bit Delta-Sigma ADC for precise and high-resolution data acquisition. 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 Lab VIEW software, and this experimental work has been done with a 16000-sampling rate. The signal conditioning device used for the signal processing is type NI – 9234. The sampling rate of NI-9234 is 51.2 kS/s per channel.

The accelerometer's sensitivity is 100 mV/g, which can be adopted for the NI-9234. In this experiment, the workpiece and the drill bit are fixed at the drilling machine, and the distance between the workpiece and the drill bit is adjusted by 50 mm. The drill bit with different wear is employed with the workpiece, 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 Figure 9.

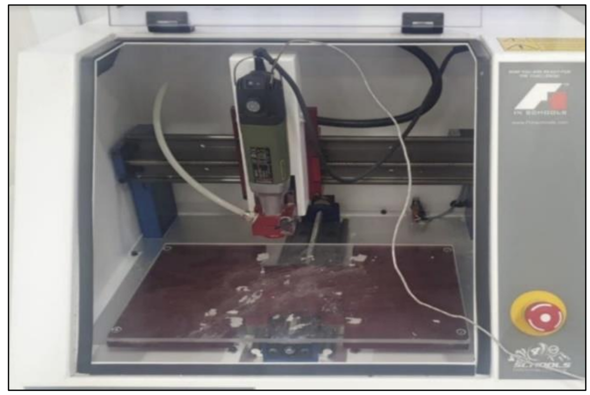
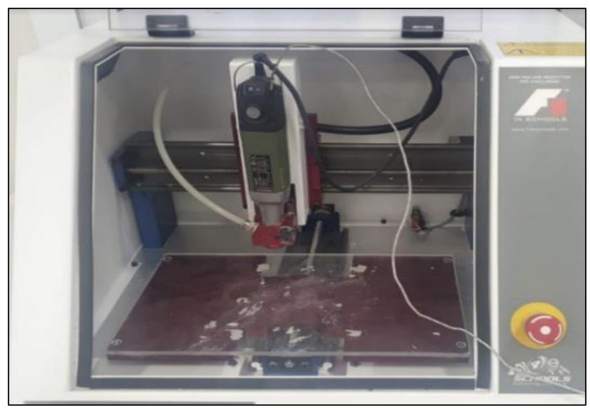


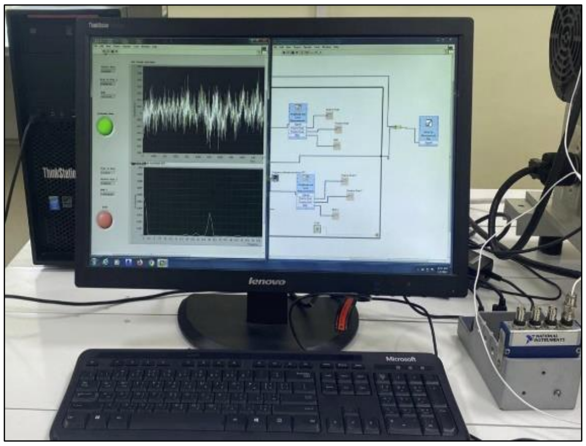
Fig. 9 The adjusting workpiece and drill bit are at the drilling machine

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 analog 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 concerning time and frequency in the Lab VIEW front panel has been collected for further analysis. In each drill bit, 20 experiments were conducted, and the signals were stored in the database.



(a)

(b)



(c)

Fig. 10 Experiment setup (a) Sensor mounting, (b) Signal conditioning and data acquisition, and (c) Lab VIEW's front panel and block diagram.

Finally, Lab VIEW shows the features of the vibration signals in the time and frequency domains, as shown in Figure 10(c). Based on wavelet analysis, MATLAB is used to analyze vibration signals further, and ANN is used 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 bits with different wear conditions. The CWT is also used as a feature extraction method to generate the input feature for ANN. Morlet wavelet (morl) and Daubechies Wavelets (db 10) have been used as a mother wavelet function while obtaining the CWT coefficients.

6.1. Continuous Wavelet Transform (CWT) Analysis

Figure 11 demonstrates comparative graphs of the kurtosis factor of 20 wavelet coefficients for a healthy tool and (0.2, 0.4, 0.6) mm wear. These graphs present the effectiveness of the kurtosis factor in the wavelet scale and then compare it to histograms of the healthy tool and each different wear. This technique shows the ability to distinguish between healthy and faulty conditions.

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

This equation is applied to change the wavelet scale to frequency (Hz): 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 and in Hz. The selected signals were in 280 rpm, so the frequency was equal to (280/60) 4.6 Hz. Figure 13 shows the kurtosis distributions of wavelet transform at a frequency (Hz) for healthy tool and (0.2, 0.4, 0.6) mm wear, respectively.

The wavelet kurtosis decreases when tool wear increases, as shown in Figure 13. This corresponds to the frequency in hertz (proportional to the frequency in hertz ($\propto \frac{1}{scale}$). That refers to the damping of the drill bit increasing due to increased wear. When the wear increases, the contact area of the cutting tool with the workpiece also increases. If friction decreases, the damping and the machine frequency decrease.

The peak at 4.06 Hz for healthy tools shifted to 1.35 Hz for 0.2 mm wear, again decreasing 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 the damped frequency, ω_n is the undamped angular frequency, and ζ is the damping ratio, which increases with increasing tool wear.

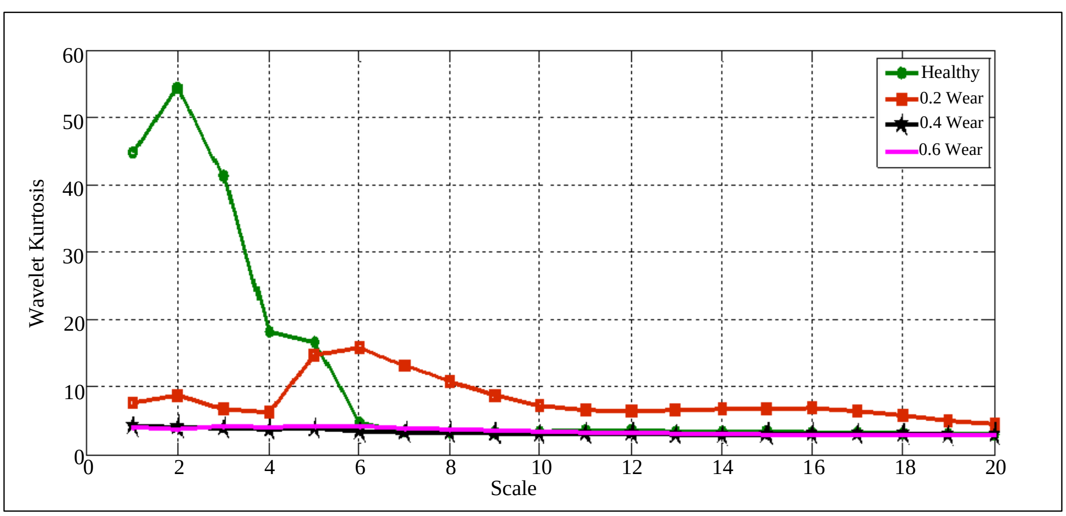


Fig. 11 The Kurtosis distribution for wavelet transform scales [healthy tool and (0.2, 0.4, 0.6) mm wear]

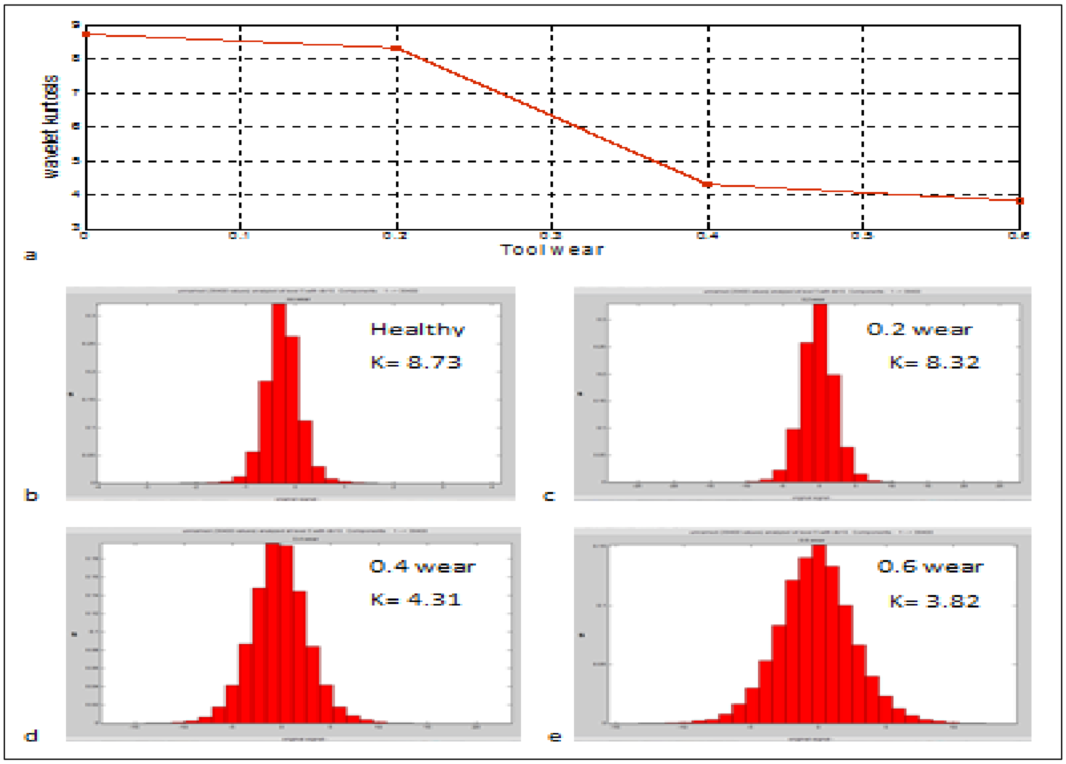


Fig. 12 (a) The average values of wavelet kurtosis by the wear condition and (b-e) the histograms of healthy tool and (0.2, 0.4, 0.6) mm wear.

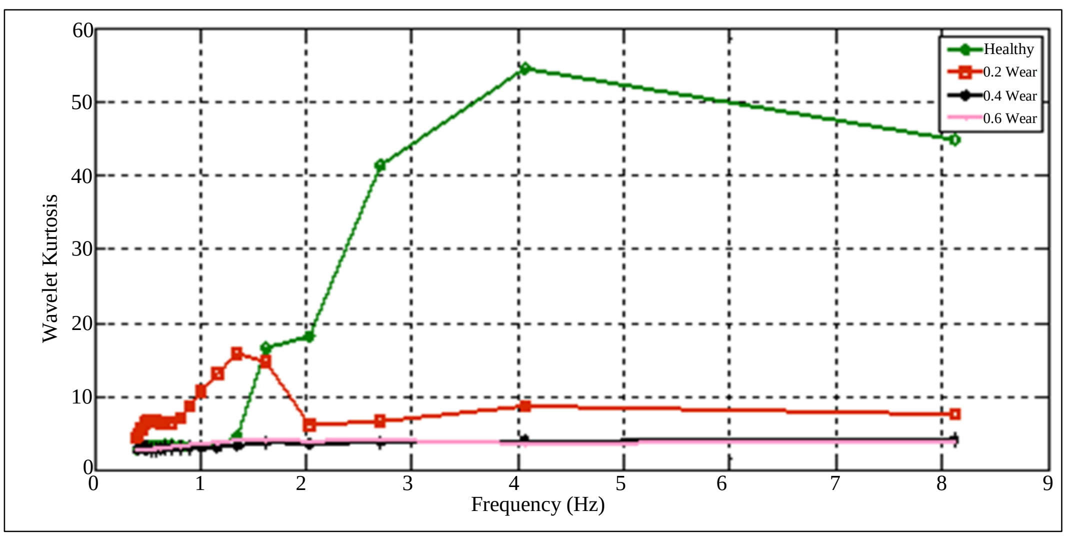


Fig. 13 The Kurtosis distribution for the wavelet transforms at a frequency (Hz) [healthy tool and (0.2, 0.4, 0.6) mm wear]

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

Automatic fault detection and classification of drill bit conditions using the features of wavelet and Artificial Neural Network (ANN) model is proposed in this work. Using the Artificial Neural Network (ANN) to classify the tool wear conditions, the model of ANN is created based on feedforward Multilayer Perceptron (MLP) and Back Propagation. The mathematics related to ANN based on feedforward MLP is as follows;

Mathematics for a neuron in layer l:

$z^{(l)} = W^{(l)}x^{(l-1)} + b^{(l)}$

$z^{(l)}$ = Pre-activation value

$W^{(l)}$ = Weights matrix

$b^{(l)}$ = Bias vector

$x^{(l-1)}$ = Outputs from the previous layer

Apply the activation function

$x^{(l)} = \sigma\left(z^{(l)}\right)$, σ = activation function.

The WPT result features of a peak, RMS, crest factor, kurtosis, shape factor, and impulse factor related to a healthy condition and wear condition are fed 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 wear condition. To build the ANN model, six features are extracted from 10 coefficients for each condition; then, the values are divided into 30 (5x6) values for training and 30 values (5x6) for testing. Also, the healthy condition is normalized as (0 1) and the wear condition as (1 0) for training targets.

The ANN model is created using an input layer with six nodes (extracted features), two hidden layers consist five nodes for each, and an 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. This model has two stages: training and testing. It is trained with a 10E-10 training goal (MSE), a 0.52044 training rate, six attributes (features), and the maximum No. Of iteration (epochs) of 1000 are selected. Figure 15 shows the training process result, in which it reached the desired goal-stopping criteria after 27 epochs. The regression curve for both training targets and the ANN output is shown in Figure 16, and a good correlation between both can be concluded. The results for ANN classification for tool wear condition show a success rate based on the six features. 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 [36]. In training testing signals in ANN, the inputs are given based on collecting signals from accelerometers.

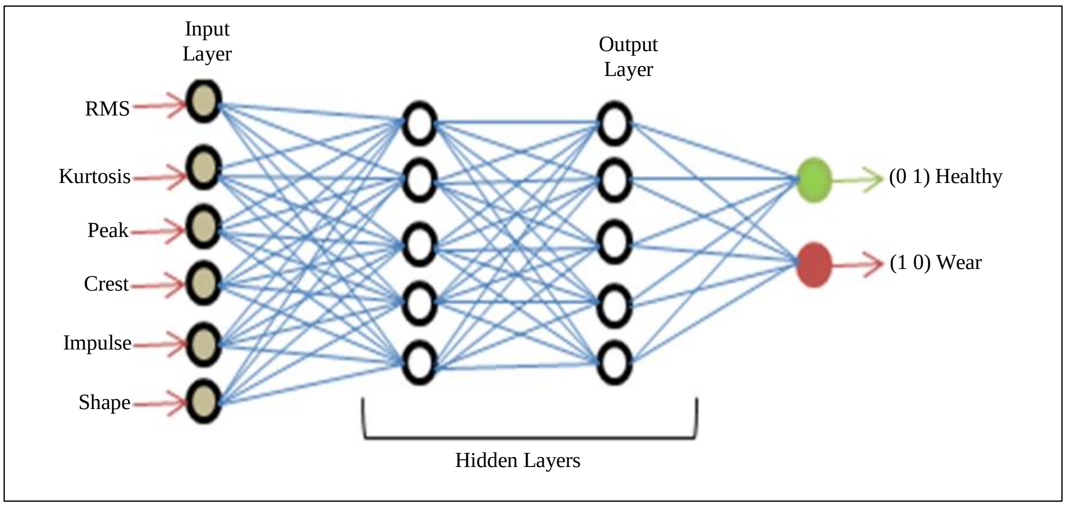


Fig. 14 The model of ANN

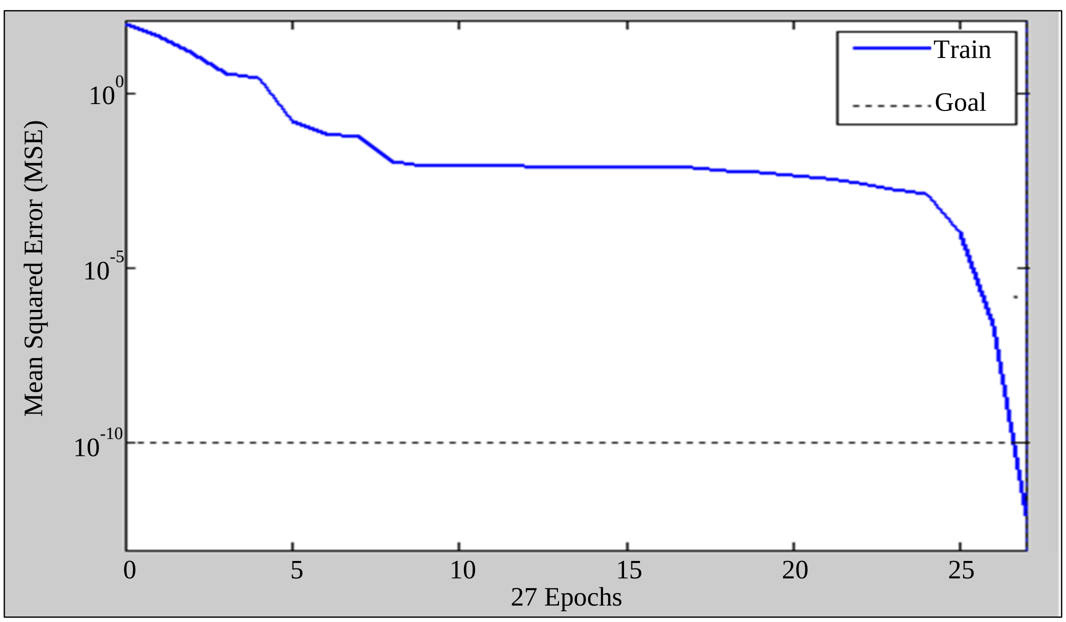


Fig. 15 Training process of ANN

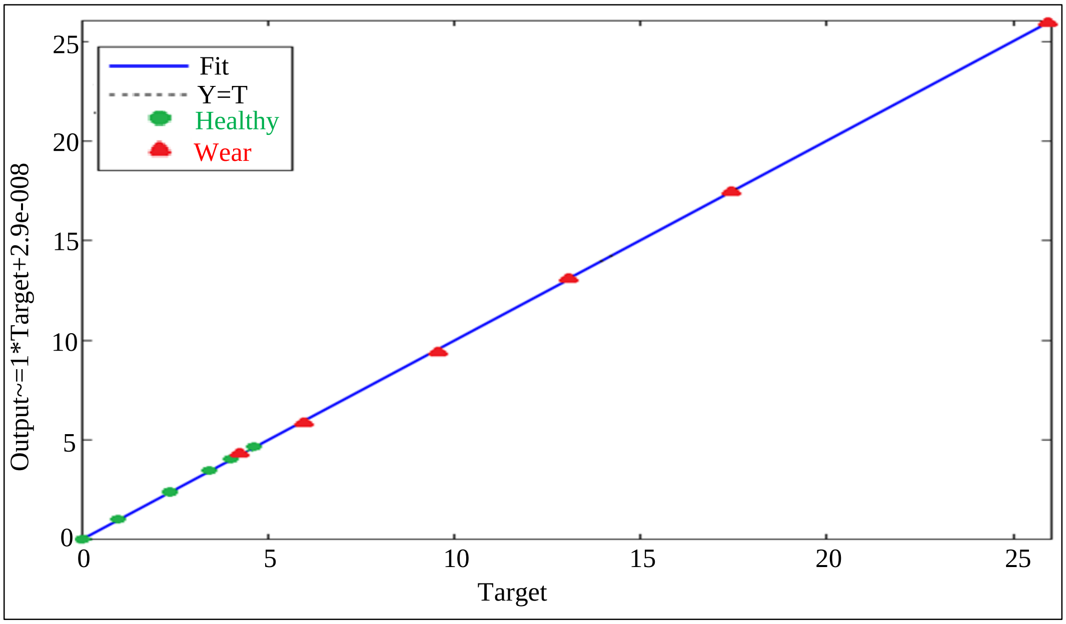


Fig. 16 The regression curve for training targets and the ANN output

The following factors were investigated in the classification of ANN with WPT outcome.

- 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 acceleration data statistics, the following factors were studied:

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

RMS, peak, and kurtosis of the wear signals are used as input for the ANN, which allows better discrimination of the type of faults. In the classification outcome based on the 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% and 98%. So, further analysis is required in the future for less accuracy and less frequency.

Regarding the vertical accelerometer, classification by statistics is a very accurate combination of RMS, peaks, and kurtosis, and the number of neurons achieved 100% accuracy. However, detection errors may reduce machine efficiency and lead to unnecessary maintenance. Measuring a vibration signal using an accelerometer in vertical placement is not precise, and no statistical data achieves an accuracy of 100%. So, finding statistical data and combining it will be important in achieving 100% results. Error values while using WPT output may result from various reasons, such as unrecognized faults, mistakes in placing the sensors, power fluctuation during data acquisition, and less frequency input to ANN. However, networks with more neurons will perform well when trained with the largest number of signals.

Ebner IDY et al. (2005) applied WPT and ANN for milling operations and concluded that WPT and ANN resulted in a considerable improvement in fault classification but did not mention the exact accuracy in the paper [37]. Elyas Salimi and Behrouz Niromandfam (2015) applied WPT and ANN for condition monitoring of hydraulic pumps and achieved a 95% result. The proposed methodology achieves 98% because of the careful selection of features using WPT [38]. The confusion matrix for ANN is given in Figure 17.

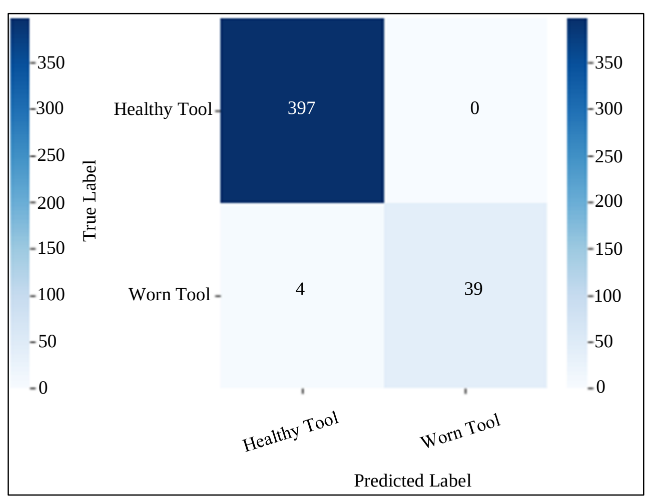


Fig. 17 Confusion matrix in the application of ANN

Accuracy: The ratio of correct predictions (both true positives and true negatives) to the total number of cases examined. While intuitive, accuracy alone can be misleading, especially with tool wear datasets.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives

Precision: The ratio of correctly predicted positive observations to the total predicted positive observations. Precision is particularly important in condition monitoring when the cost of false positives (e.g., unnecessary maintenance) is high.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall (Sensitivity): The ratio of correctly predicted positive observations to all actual positive observations. Recall is crucial in condition monitoring when missing a positive case (e.g., an impending failure) could have severe consequences.

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1-Score: The harmonic mean of Precision and Recall, providing a single score that balances both metrics. The F1-Score is particularly useful when dealing with uneven class distributions, common in condition monitoring, where failure events are typically rare.

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy, precision, recall and F1 score are given in Table 1.

Table 1. Performance matrix of ANN based on FF MLP

Accuracy	98.0456
Precision	98.2345
Recall	98.2344
F1 Score	97.8934

8. Conclusion

Condition monitoring via vibration signal analysis is essential in maintenance management to reduce unscheduled downtime and avoid catastrophic accidents in the industrial sector. Accurate fault detection is critical to avoid downtime and loss in cost and productivity [39, 40]. WPT-based signal analysis is one of the proven methods in the manufacturing industry [41] 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 technique has been developed, which is the 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 distinguish between healthy and worn 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 to be the inputs in ANN. The ANN model based on the supervised learning capability of Multilayer Perceptron (MLP) and Back Propagation has shown effectiveness as automatic drill bit fault detection and classification, proving that the training process has reached the desired goal-stopping criteria after 27 epochs. The ANN performance is shown as a 98% success rate.

So, neural networks are practical tools, and their results depend heavily on the 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. A better result will be obtained when the width of the spectrum increases [42].

However, the accuracy of the results may vary if a large amount of data and nano-level wear are used in the tool. If so, deep learning techniques may give better results, which is the future direction of the work in this area. Six features were taken for the input to the ANN in the present study, which can be increased to have an accuracy of more than 98%. So, there is room for improvement in prediction accuracy of 100% in future research works. The proposed real-time condition monitoring can be applied to monitor the wear of tools in any type of CNC machine used in the manufacturing sector. Normally, the manufacturing sector needs a precise maintenance management technique using modern technologies in which the proposed methodology may play a vital role.

This methodology can be extended to monitor the drill tools that are used in the oil and gas sector for downhole drilling, the mining industry in rock drilling, construction engineering in pile drilling and geotechnical drilling, monitoring surgical drilling in medical industries and also in the drilling operations for composite materials in aerospace industries. This research is highly significant to the academic and scientific community. It will open a path for implementing Industrial 4.0 technologies in manufacturing and process industries to obtain high-accuracy products, maintain reliability in machines and machining processes, reduce downtime and scrap, reduce risk during operations, etc. So, this project has proven the successful correlation between the Wavelet Transform (WT) and the drill bit wear condition using ANN based on the obtained results.

Author Contributions

Conceptualization, R.A., and K.V.; Literature collection, R.A., and K.V.; Formal analysis, R.A., and K.V.; Funding acquisition, R.A., K.V., and KPR; Investigation, R.A, and K.V; Methodology, R.A., KPR, and K.V.; Validation, R.A., and K.V.; Writing-original draft, R.A.; Review and editing, R.A., KPR and K.V. All authors have read and agreed to the published version of the manuscript

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Institutional Review Board Statement

This study was conducted according to the National University of Science and Technology, Oman guidelines.

Data Availability Statement

The original contributions presented in the study are included in the article or supplementary material; further inquiries can be directed to the corresponding authors.

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