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A review on applications of wavelet transform and artificial intelligence systems in fault diagnosis of rotating machinery

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Abstract

Rotating machines play a vital role in many process industries. Vibration analysis is a common form of monitoring their condition. This paper reviews the application of wavelet transforms and artificial intelligence, an advanced form of vibration analysis, for condition monitoring of rotating machines. The review considers different feature extraction methods and shows how wavelet transforms have been applied as a preprocessor for feature extraction with different families of mother wavelet function; and how different artificial intelligence methods have been used for fault classification. It concludes with remarks on the advantages and disadvantages of the applied methods and consideration of future developments to address the current gaps.

Keywords: Rotating Machinery, Wavelet Transform, Artificial Intelligence, Genetic Algorithm, Accuracy Rate.

1. Introduction

Condition monitoring based maintenance strategies for rotating machines are widely used in industry; balancing the cost of frequent maintenance against the effects of failures, which can incur expensive replacement costs, or catastrophic accidents leading to production downtime and potential failure to supply. Breakdown of complex machines can affect profitability due to loss of availability, cost of spares, cost of breakdown labor, and cost of secondary damage and risk of injury to people and the environment. Companies seek to achieve optimum production at the lowest cost so maintenance should be a reliability function rather than a repair function **[1]**. Several techniques for condition monitoring are presented and discussed in the next sections. Vibration monitoring is an appropriate technique for fault detection in all rotating machines **[2-5]** and can be used to detect rolling element bearing faults **[6]**, rotor unbalance **[7, 8]**, and gear faults **[9].** Accelerometers extract vibration signals which can then be analyzed using software to present useful information about the condition of the machine. There are different methods that can be used to interpret the vibration signal starting from the conventional ones like time domain analysis **[10]** and frequency domain analysis where methods like FFT are applied **[6, 11].** Recently, a powerful multi-resolution technique called wavelet transform (WT) has been applied in rotating machinery fault detection and has proved its ability to analyze non-stationary signals **[11-14]**. There are significant advantages of applying a wavelet transform for signal analysis; it is more suitable for non-stationary signals comparing with FFT method **[15]**, and it is able to present a high frequency resolution at low frequencies and a high time resolution at high frequencies and it is able to minimize noise of some raw signals **[16]**. The wavelet transform method has been applied in diverse industries, including biomedical; civil; and manufacturing engineering **[16]**. Recently artificial intelligence systems have been applied in the fault diagnosis of rotating machinery by researchers as automatic fault diagnosis and classification systems **[17-32]**. Automatic fault detection methods can reduce errors due to human misinterpretation **[33]** and various techniques have been deliberate and investigated. This review of the state of the highlights various fault diagnosis techniques for rotating machines, focusing on some of the seminal and more recent developments.

This paper provides an overview of the applications of artificial intelligence systems combined with wavelet transform in fault diagnosis of rotating machineries and then to identify the significant advantages and disadvantages of the different applied systems and to predict future possibilities and approaches. It is divided into seven parts, including the introduction. Section 2 presents a brief review on condition monitoring and fault diagnosis. Section 3 reviews non-automatic fault detection methods for rotating machinery. Section 4 reviews time-domain methods and wavelet functions. Section 5 reviews artificial intelligence systems which have been applied in the context of condition monitoring, after which section 6 reviews the application of these techniques, including the different feature extraction methods. Finally, a conclusion with remarks and recommendation is given in section 7.

2. Condition monitoring and fault diagnosis

Condition monitoring, in terms of maintenance, forms part of a predictive strategy, as it follows this saying: "monitor it, and if it is not deteriorating, leave it alone" **[1].** Data are taken from a machine continuously or periodically in order to assess its condition and make decisions for proper maintenance **[12]**. Condition monitoring has the potential to provide many benefits: in most cases providing early prediction of wear, damage and other faults; frequency of plant shutdowns should be minimized; consumption of energy, spare parts and cost can all be reduced compared to scheduled maintenance strategies; and overall efficiency and quality of products may be improved, resulting in enhanced customer satisfaction **[1]**. Condition monitoring consists of several techniques and each technique has its proper applications and usage; the main techniques in condition monitoring are *vibration analysis* **[34 ,4]** which is used to monitor dynamic systems, rotating machines, and machinery components that have vibration patterns which are used as indicators for their condition; *oil and debris monitoring* **[35, 36]** which is used to assess the condition of the oil and the components that are in contact with oil; *current monitoring* **[34]** which is used to detect faults of electrical equipment such as induction motors; *conductivity and insulation monitoring* **[37]** are used to diagnosis the conditions of conductivity and insulation of electrical equipment; *thermal monitoring* **[38]** is used to diagnose machine faults by monitoring temperature ; and *corrosion monitoring* **[39],** used to detect corrosion which can be used as an indicator of other failures in the machine. Vibration analysis is widely used for condition monitoring of centrifugal pumps **[2,15]**, and the conventional technique of Fast Fourier Transform (FFT) is one of the most popular vibration methods for fault detection, having been widely and successfully applied for analysis of stationary signals **[40, 5, 11-14].** FFT has also been used successfully to extract statistical parameters from frequency domain data **[33]**. However, complex machines usually consists of many different parts and their vibration signals contain many non-stationary signals, for which the FFT is not well suited **[11-15].**

3. Time-Frequency Domain

This section reviews some of the literature relating to time-frequency domain methods, *viz.* the Short Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT); and presents various families of these wavelet transforms.

The presence of non-stationary signals in the vibration data of complex machines provides a need for a method to analyse these signals **[13, 41].** A time-frequency method was proposed by Gabor in 1946 **[42]** which is the Short Time Fourier Transform (STFT) and introduced the elementary concept of wavelet; where STFT is an adjusted Fourier Transform (FT) as a proper time window is applied to window the signal prior to the process of Fourier transforming, and maps a signal into a two-dimensional function of both time and frequency domains **[12],** defined as:

$$F(f,b) = \int_{-\infty}^{\infty} x(t)W(t-b)e^{-i2\pi ft}\, dt \tag{1}$$

Where $x(t)$ is the original signal that has to be multiplied by the window W which is used with time-frequency shift$(t-b)$.

However, STFT has a constant window which makes it incapable of localization in both the time and frequency domains **[12, 41]**. An alternative for STFT, the wavelet transform (WT), was then theoretically discussed by

Goupillaud and his colleagues Grossmann and Morlet in 1984 **[43]**, building on the earlier work of Gabor **[42]**, they set the first mathematical equation for a wavelet, known as continuous wavelet transform (CWT):

$$Wx(a+b;\varphi) = a^{\frac{-1}{2}} \int x(t)\varphi^{*}\left(\frac{t-b}{a}\right)dt \quad (2)$$

Where Wx is the wavelet transform that is linked with the two parameters; a which is the scale parameter, and b is the time parameter, φ is wavelet function, is the complex conjugate, and $x(t)$ is the original signal.

The term wavelet refers to small waves or wave-like-functions that are subject to variation in a short period in the time domain **[13]**. WT is similar to STFT, except WT has a flexible time-frequency resolution that depends on the frequency of the signal **[13]**.

CWT is similar in concept to the Fourier Transform, but uses families of wavelets as its basis functions instead of sine and cosine functions **[17];** a family of wavelets consists of two parameters (scale and translation); hence the signal will be represented as a two dimensional time-scale plane, instead of only one dimensional plane, thus addressing an important limitation of the Fourier Transform **[17]**.

A wavelet transform is a mathematical operation that converts a time domain signal into another form, comprising a series of wavelet coefficients, representing time and scale. To apply a wavelet transform, a wavelet function is required, which represents a small wave with oscillating wavelike characteristics and focuses on its short time energy (e.g. magnitude and zero crossing rate). Wavelet transforms can be classified into three groups: continuous wavelet transform (CWT), discrete wavelet transform (DWT), and wavelet packet transform (WPT) **[17]**. DWT was first introduced and developed by Mallat in 1989 **[44]** where DWT is the discretization of CWT **[13]** which is defined as:

$$DWT(j,k) = 1/(\sqrt{2^{j}}) \int_{-\infty}^{\infty} s(t)\varphi^{*}((t-2^{jk})/2^{j})dt \quad (3)$$

Where j and k are integers that represent scale and translation processes respectively, and 2^{j} and 2^{jk} are scale and time parameters.

DWT also differs from CWT in terms of selection of values for scale (a) and time (b) parameters; there are no constraints in selection with CWT, but with DWT, restrictions apply for the selection of (a, b) parameters **[45]**. In addition, reconstruction of the original signal using DWT is not guaranteed, but it would be possible to use CWT **[46]**. Previously DWT has been applied by many other researchers for applications of rotating machinery accountability diagnosis and mostly combined with AI systems **[47-50]**, further discussions and review on such studies are investigated on section 5. WPT was introduced by Coifman, Meyer, and Wickerhauser in 1992 **[51]** and is a multi-stage filtering method that decomposes a signal into packets or levels of approximation which are denoted with A, and details coefficients which are denoted with D, as illustrated in Figure 1 **[52, 13, 4].** The WPT is defined as:

$$W_{(j,k)}(t) = 2^{\frac{j}{2}} w(2^{j}x-k) j\epsilon Z \quad (4)$$

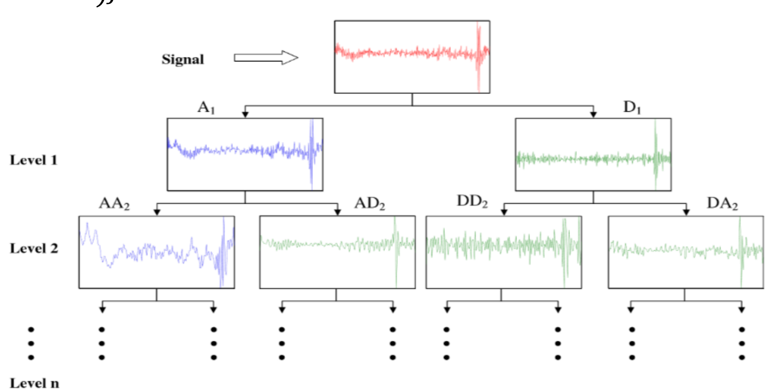
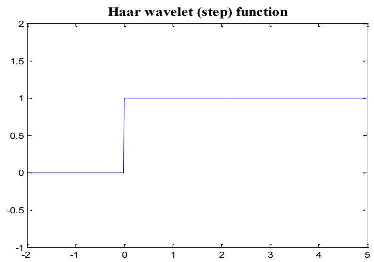


Figure1. Level of approximation (A) and details coefficients (D) in wavelet packet transform **[51]**.

WPT has been applied by many researchers for rotating machinery fault detection **[26, 27, 52-55]**.

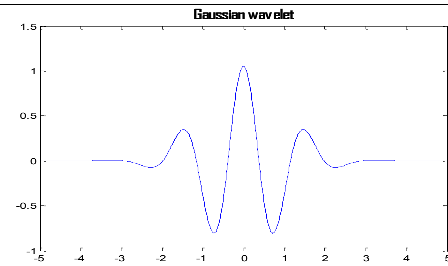
The first published paper on the application of WT for machinery fault detection was published by Leducq in 1990 **[56]**, analysing the hydraulic noise of a centrifugal pump. Since then, WT has been widely applied for machine fault detection and feature extraction of bearing faults **[15,17]**, unbalance and misalignment **[57]** and centrifugal pump faults **[16, 58-60]**. Yan *et al.* **[16]** summarized the applications of wavelet transform in rotating machinery fault diagnosis, following an earlier review by Peng **[14]**; and stated that applications of wavelets in rotating machinery fault diagnosis still faced some challenges. It has been noted that there is a relationship between the extracted signal and the wavelet function at different scales; and that this relation is based on the fact that signal features are better extracted when the wavelet function is similar to the signal. Hence, building new wavelet functions that have more similarity in terms of signal shape with machine fault signals would be the key solution to enhance the efficiency of wavelet transform applications. The importance of the shape of a wavelet basis function when using WT as a pre-processor for feature extraction is a significant reason for research into the development of new wavelet functions that have greater similiarity with the extracted vibration data **[16]**.

There are many different wavelet families that can be used as mother functions to produce a wavelet function that transforms the original signal, using a process of translation, scaling and multiplication. These families include Daubechies, Coiflet, Bi-orthogonal, Reverse biorthogonal, Symlets, Meyer, Morlet, and Gaussian wavelets. The Haar wavelet function is the oldest and simplest wavelet; it has the shape of step function and was introduced by Hungarian mathematician Alfred Haar in 1910 **[61].** Gaussian wavelet function is represented both domains of time and frequency and is infinitely derivable function where Mexican-Hat wavelet function is the second derivative of Gaussian function **[62]** as Gabor introduced Mexican-Hat wavelet function **[42]**. Previously, Goupillaud and his colleagues Grossmann and Morlet in1984 **[43]** introduced the Morlet wavelet function, which is also known as the 'Gabor Wavelet' honoring the first introducer of the original concept of wavelet in 1946. The mathematician Yves Meyer introduced the second orthogonal wavelet called Meyer wavelet in 1985 **[63, 64]**. In 1988, Daubechies proposed a family of wavelets **[65]** which include many different functions and are indicated by (dbN), where N is the order such as db1, db2, db3, db4…etc.; and Coiflet wavelets (denoted by coifN) which are more symmetrical **[63].** The first order db1 has the same characteristics as the original Haar wavelet function. In 1992 Cohen, Daubechies and Feauveau proposed Biorthogonal wavelets **[66]**. Daubechies introduced Symlet wavelet families as modifications to the db family in order to be more symmetrical [**63]**. Daubechies wavelets have been widely used for fault diagnosis of rotating machines; particularly the types db4 **[20, 26, 28]**, db10 **[31]** and db5 **[24]**. Figure 2 shows the most common wavelet functions that have been applied as mother functions for WT in the area of rotating machinery fault diagnosis.



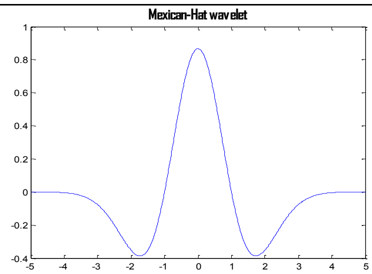
$$\varphi(t) = \begin{cases} 1 & 0 \le t < 1/2 \\ -1 & 1/2 \le t < 1 \\ 0 & elsewhere \end{cases}$$

Haar wavelet function [61]



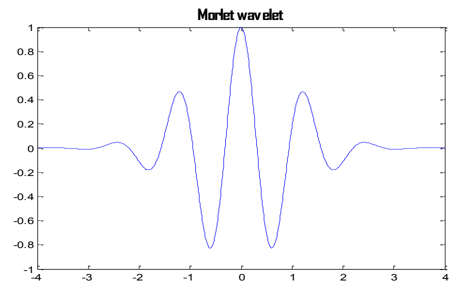
$$f(x) = ae^{-\frac{(x-b)^2}{2c^2}}$$

Gaussian wavelet function [62]



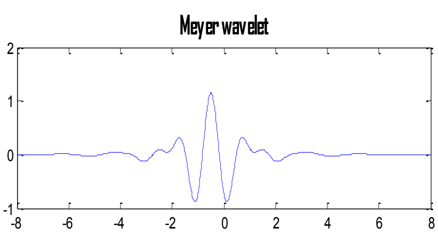
$$\varphi(t) = (1 - t^2)\, e^{-t^2/2}$$

Mexican-Hat wavelet function [42]



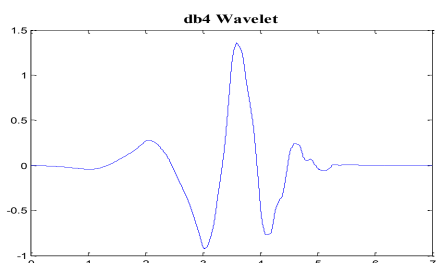
$$\varphi(t) = \frac{1}{\pi^{1/4}}\, e^{i2\pi f t}\, e^{-t2/2}$$

Morlet wavelet function [43]



$$\varphi(w) = \begin{cases} \frac{1}{\sqrt{2\pi}} \sin\left(\frac{\pi}{2}\gamma(\frac{3|w|}{2\pi} - 1)\right) e^{\frac{jw}{2}} if \frac{2\pi}{3} \le \frac{4\pi}{3} \\ \frac{1}{\sqrt{2\pi}} \cos\left(\frac{\pi}{2}\gamma(\frac{3|w|}{4\pi} - 1)\right) e^{\frac{jw}{2}} if \frac{4\pi}{3} |w| \le \frac{8\pi}{3} \\ 0 \quad elsewhere \end{cases}$$

Meyer wavelet function [64]



$$\varphi(x) = \sqrt{2}\, \sum_{k=0}^{2N-1} (-1)^k\, h2N - 1 - k\, \varphi(2x - k)$$

Daubechies [65]

Figure 2 Wavelet functions

4. Rotating machinery non-automatic fault detection methods

Fault detection methods may be automatic or non-automatic. This section reviews non-automatic methods, while automatic techniques are reviewed in the subsequent section.

Non-automatic fault detection has been performed using all three of the common vibration analysis methods: time-domain, frequency-domain and time-frequency (i.e. Wavelet Transform).

Atoui et. al, 2013 [7] proposed DWT and FFT to diagnose rotor imbalance. Vibration signals were extracted from the experimental setup using a piezoelectric accelerometer at three speeds (600, 1200, and 1800 RPM). DWT was used based on Daubechie's wavelet mother function (db3) to decompose the signals of different frequencies and those of useful frequencies were analysed directly by using FFT. The results showed that DWT was better for fault diagnosis than FFT as shown in Figure 3, where (a) refers to FFT analysis with the respective time-domain signal, and (b) refers to DWT analysis with the respective time-domain signal.

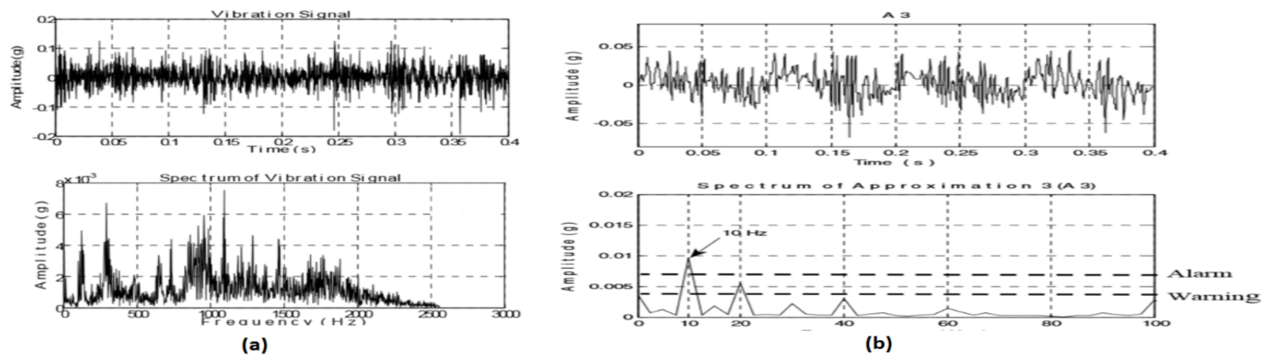


Figure 3 Vibration signal of rotor unbalance and its spectrum for 600 rpm (10Hz) (a) FFT analysis (b) DWT analysis [7].

Isayed et al., 2007 [8] used WPT and FFT to detect four machinery faults, namely, misalignment, unbalance, oil whipping, and shaft crack. The results showed that WPT was more effective than FFT. WPT was used to decompose the signals in order to exploit the mean values of the energy in the signal.

Praneethchandran et al., 2013 [9] implemented a comparative study where two wavelet functions were used to identify gear fault detection. The Lablace and Morlet wavelet functions were linked to the kurtosis factor where wavelet parameters have been optimized to maximize the kurtosis parameter. The Lablace and Morlet wavelet kurtosis were calculated from the wavelet transform. It has been noted that the Lablace wavelet kurtosis was better at detecting gear faults, with performance improving a as the magnitude of the fault increased.

5. Artificial Intelligence systems

Automatic fault detection methods make use of Artificial Intelligence (AI) which seeks to replicate mental capabilities with the support of computational systems [67]. Artificial neural network (ANN) was first introduced by McCulloch and Pitts in 1943 [68], and Fuzzy logic was first introduced by Zadeh in 1965 [69]. Artificial intelligence systems have been applied for centrifugal pump fault diagnosis using different methods for the feature extraction, starting from a simple method of statistical analysis [70-73], later FFT [33, 74, 75], and also a wavelet transform has been applied using time-frequency method [15, 58-60, 76]. ILott [77] proposed ANN with Back Propagation (BP) algorithm to diagnose pump faults. Then, Zouari [78] applied ANN and a fuzzy neural network to diagnose centrifugal pump faults; statistical methods of time and spectral analysis were used for the feature extraction.
There are many types of AI that have been applied as automatic fault diagnosis systems for different rotating machines and components such as Back Propagation-Artificial Neural Network (BP-ANN) or Multilayer Perceptron (MLP) [17-20,23,27-30,32, 79], Radial Basis Function (RBF) [17,19, 27], Probabilistic Neural Network (PNN) [17,19], and Support Vector Machine (SVM) [23,28-31, 79]. In this section, a brief theoretical review and discussion on each type will be presented; for further details, readers are referred to [80, 81]. In the following sections the performance of each type is reviewed and discussed, including a comparative summary of the performance.

5.1 Multilayer Perceptron with Back Propagation Artificial Neural Network

MLP consists of three layers, namely, input, hidden, and output layer of neurons. There may be several hidden layers between the input and output layers. The number of neurons in each section affects the generalization ability of the system, while the number of neurons and hidden layers affects the efficiency of the system. With larger number, there is a possibility of over-fitting the training data and weak generalization of new data. Therefore, some methods might be used to select the proper number of hidden layers and neurons such as Genetic Algorithm [19]. The output layer can be more than one layer according to the required fault classifications. Each hidden layer has a number of neurons; the role of each is to calculate the weighted sum of its inputs and apply the sum as the input of an activation function that is usually a sigmoid function. Back Propagation algorithm has been widely used in training of MLP. It was firstly introduced in 1986 [82]. Figure 4 depicts the basic structure of a MLP network [80].

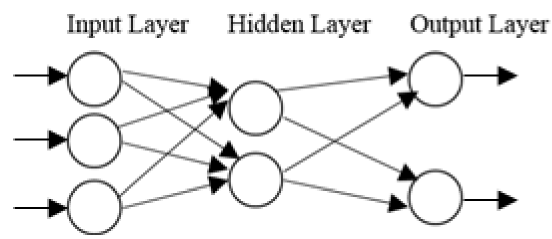


Figure 4 The basic structure of MLP network [80]

Comparative studies have demonstrated the efficiency of MLP over other ANN types [17, 19] while considering important factors that affect efficiency, such as the number of hidden layers and neurons [19]. However, a drawback of MLP is that it is slow in training and needs longer time than other methods [17, 19, 26, 27]; but such weakness can be minimized by reducing the number of input features [18, 20].

5.2 Radial Basis Function

RBF was first defined in 1988 by Broomhead and Lowe [83] as another option after MLP. Initially, its concept had been rooted to the technique of potential functions which was introduced by Bashkirov, Braverman, and Muchnik in 1964 [84]. The hidden layers in a neural network afford a set of functions which create a basis for the input features while they are moving to the hidden area; these functions are known as radial basis function (RBF) [81].

The RBF has some similarity with MLP except that the number of hidden layers is limited to one layer only as shown in Figure 5. The role of hidden layer is to cluster the inputs and a Gaussian kernel function is used for the activation of the hidden layer neurons [80]. The hidden layers are nonlinear in both types of network, but the outputs differ; MLP has a nonlinear output layer whereas the RBF output layer is linear [81].

The advantage of RBF over other AI classifiers like MLP and PNN is the shorter training time [19, 27]. However, the performance of the RBF has been mostly observed to be poorer [19, 17].

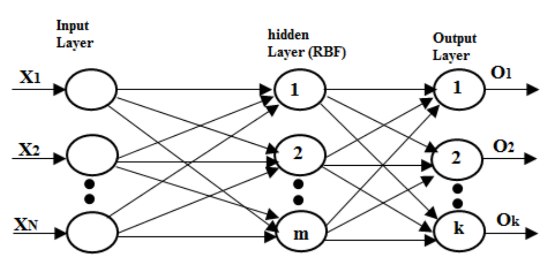


Figure 5 The basic structure of RBF network [85]

5.3 Support Vector Machine

Support Vector Machine (SVM) was initially introduced in 1993 by Corinna Cortes and Vladimir Vapnik **[86]** where used as a new approach for the pattern recognition which employs the non-linear projections of input features to a greater dimensional pattern area [86].

SVM is a curve square optimisation problem which makes it able to provide a globally optimal solution. In addition, it could handle many practical problems with acceptable solutions for small sample sets, high dimensional and non-linear value [30]. There are three main kernel functions that can be used with SVM, namely, linear, polynomial, and RBF functions. In [31]**,** Zhong et al. Selected RBF due to its nonlinear mapping efficiency and ability to map features onto a high dimensional space.

SVM has been widely recommended by many researchers for rotating machinery fault diagnosis as it has proved its high efficiency and out-performance over other AI classifiers e.g. MLP (ANN-BP) [79, 23, 28-30, 32] and RBF [28].

5.4 Probabilistic Neural Network

Probabilistic neural network (PNN) was first introduced in 1990 by Specht [87] and its concept is based on the approximation of the optimum limits between categories. It consists of two hidden layers, the first layer contains a devoted neuron for each training feature and the second layer contains a devoted neuron for each class as shown in Figure 6. PNN shares with RBF the usage of Gaussian Kernel function which is used for the activation of the hidden layer neurons. Training features are applied by PNN to approximate the class probability distribution while training process [88].

PNN has an advantage of saving the training features to escape from the iterative procedure which makes it reasonably fast in training process [19]. However, the large number of stored training features requires a large network [88].

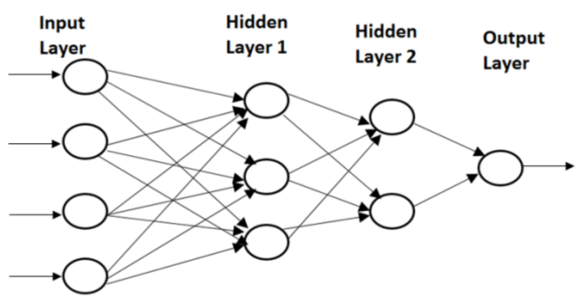


Figure 6 The basic structure of PNN network [85]

6 Application of artificial intelligence systems in rotating machinery faults diagnosis

Applications of machine artificial intelligence in vibration-based continuous monitoring and analysis are attracting researchers. For the purpose of continuous monitoring and fault detection, artificial neural networks-machine learning has been applied.

Artificial intelligence systems have been applied for many different rotating machines and parts such as bearing fault detection **[17-19, 27, 29, 30]**, blower fault detection **[20],** and gear fault detection **[23, 31, 32, 79].**
Al-Raheem & Abdul-karem, 2010 [17] studied the performance of bearing fault diagnosis using three types of artificial neural network which are Multilayer Perceptron (MLP) with BP algorithm, Radial Basis Function (RBF) network, and Probabilistic Neural Network (PNN). Feature extraction was implemented using Laplace wavelet analysis based on the scale-kurtosis value technique for the healthy condition and faulty bearing condition. The most

dominant scales were selected from wavelet scales, the features were extracted are: root mean square RMS, standard deviation (SD), kurtosis in the time domain, the wavelet-scale power spectrum (WPS) peak frequency to the shaft rotational frequency, and (WPS) maximum amplitude. Genetic Algorithm was utilized to optimize the number of hidden nodes. The results illustrated that MLP with BP performed the best classification success rate of 100%, PNN showed a classification success rate of 97.5%, and RBF trailed with a classification rate of 72.1%. Results clearly indicated the advantage of combining wavelet with ANN and particularly with MLP-BP.

Al-Raheem et al., 2008 [18] proposed a new technique for the rolling bearing faults diagnosis using Laplace-Wavelet combined with ANN. Laplace-Wavelet was applied as a pre-processor for time-domain vibration signals of the different bearing conditions and hence generally was applied for the feature extraction of both domains; time and frequency. Laplace was selected as wavelet based function and optimized using genetic algorithm (GA) by maximizing kurtosis of the WT to improve similarity with the extracted vibration signals. The dominant Laplace-Wavelet scales were selected to reduce the number of input vectors and speed up the training process. GA was also applied to optimise ANN classification by minimizing the mean square error (MSE). This work showed the effectiveness of combining Laplace-Wavelet with ANN and illustrated a very high classification success rate of 100%.

Samanta et al., 2006 [19] applied three different AI classifiers, namely, MLP, RBF, and PNN to diagnose bearing faults. GA was used for all classifiers in this study, where for MLP, GA was used to select the number of neurons in the hidden layer and the number of features; for RBF and PNN, GA used to select the width and the number of features. The results showed that GA based feature selection for all classifiers, and based neuron selection for MLP was effective after results both with and without GA were compared. It has been observed that without GA, classification rates were 83.33% (RBF), 85.06% (MLP), and 95.83% (PNN). However, using GA, the classification rates have been improved to 87.50%, 96.53%, and 99.31%, respectively. The selection of six features provided the maximum rate of 100% for both PNN and MLP; RBF achieved its best rate of 99.31% with 8 features selected. This study showed that training the PNN was faster than for the other two classifiers.

Zhenyou Zhang, 2013 [20] integrated WPT and principal component analysis (PCA) together with Back-Propagation (BP) ANN for the fault diagnosis of a rotating machinery which was represented by a blower. WPT was used to extract standard deviations and wavelet packet coefficients (SDWPC). Only one fault was detected which is unbalance. Firstly, features were processed and extracted using SDWPC as direct inputs for ANN and then forwarded to PCA to generate new features to be inputs for ANN. Daubechies (db4) was selected as a wavelet function. This study compared the results with SDWPC alone, and with both SDWPC and PCA as an integrated system. It was observed that results of SDWPC and PCA together were much better than SDWPC alone, as the number of features was reduced; hence, training speed of the ANN was faster. Generally, it was remarked that PCA provided higher speed and accuracy for fault diagnosis.

Zhao et al., 2011[21] proposed WT based on wavelet packet-characteristic entropy combined with ANN and BP as learning algorithm to diagnose the faults of rolling element bearing. Wavelet packet-characteristic entropy was used as a pre-processor to extract the vibration features. Different number of neurons was used and it was clearly observed that the highest test accuracy and training accuracy was achieved with 11 and 33 hidden neurons respectively.

Kankar et al., 2011 [22] proposed three AI methods to diagnose faults of rolling element bearing, namely, support vector machines (SVM), ANN (MLP-BP), and self-organizing maps (SOM). The features were extracted using WT using different wavelet functions as: Meyer, coiflet5, symlet2, Gaussian, complex Morlet and Shannon wavelets. It has been observed that the best results were obtained using Meyer wavelet with SVM at a classification accuracy rate of 98.6667%.

Jedli´nski and Jonak, 2015 [23] presented an automatic gearbox fault diagnosis approach where two AI systems were applied, namely, SVM and MLP. The input features were extracted using CWT and many wavelet functions were tested: Morlet, Birthogonal 3.1, Coiflet3, Daubechies4, Dmeyer, Gaussian, Haar, Mexican-hat, Meyer, reverseBior3.1 and Symlet wavelets. Haar wavelet was found as the best function, having a more similarity with the shape of the signal. Different activation functions were used with MLP: (logistic, exponential and hyperbolic tangent), with different numbers of hidden neurons. The results are shown in Table 2 where it is clearly seen that average performance of SVM slightly outperforms MLP with consideration to the effectiveness of the number of hidden neurons and activation functions. This study proved the importance of signal pre-processing as it was clearly observed that the accuracy of performance was greatly increased with CWT as a pre-processor compared without a pre-processor as shown in Table 2.

Roy et al., 2014 [24] proposed a Radial Basis Function (RBF) neural network combined with different filtering methods, namely, five different 8th order Butterworth filters with varying cutoff frequencies and five different 8th order type-I Chebyshev. Different wavelet functions were used, namely, Daubechies wavelet (db5), Haar wavelet, Discrete Meyer wavelet, Coiflets (coif4), and Symlets (sym4). The results showed that the best performance of RBF-NN was performed using 8th order Type-I Chebyshev filter of a cutoff frequency of 40 Hz combined with (sym4) wavelet function.

Srinivas et al., 2010 [25] proposed ANN based on multilayer feed forward back propagation marquardt algorithm (MLP-BP) and DWT based on Daubechies wavelet function to diagnose faults on rotor unbalance and shaft bent. The results showed the following classification success rates: unbalance at 99.78%, shaft bent at 99.81%, and combined faults of unbalance with shaft bent at 99.45%. This study illustrated different diagnosis procedures such as: selection of Daubechies wavelet function, data normalization, and selection back propagation marquardt as a learning algorithm. It might be noted that such applied procedures have contributed in obtaining the good classification success rates. However, this study has not provided any comparison with other classifiers, training algorithms and wavelet functions.

Liu, 2011 [26] proposed WPT and ANN (MLP) for helicopter gearbox fault detection. Eight different detection locations were identified for the vibration monitoring. WPT used to de-noisie and decompose the vibration signals, then the standard deviations were extracted from the decomposed four levels and used as inputs. For the ANN, three different square errors were proposed; 0.1, 0.01, and 0.001. For longer training time compared to other errors, it has been noted that the classification accuracy results rate was much better for 0.001 at an average rate of 99.25%.

Wuming et al., 2010 [53] combined WPT with RBF-NN to diagnose four different faults in a traction machine for lifts, the four faults are shown in Table 1. Daubechies wavelet represented by (db4) was selected as a mother function for WPT. This study proposed Particle Swarm Optimization (PSO) as a training algorithm for the RBF-NN. PSO has some similarities with GA. However, PSO is said to be much simpler than GA. The results showed high classification accuracy especially for the case when the worm reducer and traction motor were in different axes, at a rate of 100% as shown in Table 1. Finally, this study proved that PSO was a good optimization and training algorithm for RBF-NN.

Table 1 Traction machine faults **[52]**.

Fault description	No of correct diagnosis (40 sets)	Classification success rates
Worm shaft of tractor gear wear, gear backlash increased	38	95%
The shafts of worm reducer and the traction motor are in different axes	40	100%
Tractor and the load-bearing beam fixed base is not strong	39	97.5%
Traction sheave and the elevator car is not in the same straight line	37	92.5%

Wang et al., 2010 [27] presented a study to diagnose two different faults for a ball bearing, namely, inner race fault, and outer race fault. A healthy ball bearing was involved to allow comparison with the faulty conditions. WPT was used to decompose the vibration signals into three levels, and hence input features were extracted (two types of AI system were used, namely, RBF-NN and MLP-BP). The results showed that RBF-NN was more effective than BP-

ANN in terms of classification accuracy rate and training time as shown in Table 2. This study found that RBF-NN was easier to implement and more stable than MLP-BP.

Yanjun et al., 2009 [28] proposed WPT and SVM methods to diagnose a rub impact fault using a test rig of dual-disk cantilever rotor-bearing system. WPT was applied as a pre-processor where the input features were then extracted, and SVM used as a classifier to classify three different modes of rub fault, namely, single point of over-hung impact rub, single point of middle disk impact rub, and uncertain impact-rub. Daubechies wavelet represented by (db4) was selected as a mother function for WPT. Three different kernel functions were used for SVM and it was observed that the performance and classification accuracy was influenced accordingly, where RBF proved to be the best. The average results of SVM were compared with other AI classifiers, namely, MLP-BP and RBF-NN, and SVM proved its out-performance as shown in Table 2.

Sui and Zhang, 2009 [29] presented a study to diagnose the fault of rolling element bearing using SVM and BP-MLP. The feature extraction was based on time-domain using traditional statistical analysis (mean, peak, mean square, variance, standard deviation, root mean square, shape factor, dkewness, kurtosis, impulse factor, clearance factor and crest factor), frequency-domain analysis (Fmean , Fc, Frms and Fstd) , and finally WPT with Daubechies wavelet function to decompose the time-domain signal into 16 packets at level 4. This study compared the obtained results with and without feature selection method using class separability criterion. Firstly the results illustrated the efficiency of using feature selection method. Secondly it was observed that SVM outperformed ANN in the fault classification accuracy as shown in Table 2.

Yajuan Liu and Tao Liu, 2010 [30] presented AI methods, namely, SVM and ANN-BP to diagnose the faults of rolling element bearing of a spindle fan test rig. WPT used to process and extract the features. RBF inner product function was selected as a kernel function as it can nonlinearly classify the feature onto higher dimension space. Table 2 shows the efficiency of SVM over MLP-BP in terms of classification rate accuracy and training time.

Zhong et al., 2010 [31] proposed SVM as an automatic gear box fault diagnosis method. Input features of absolute mean, maximum peak value, RMS, square root value, variance, kurtosis, crest factor and shape factor were extracted using WPT with Daubechies wavelet represented by (db10) and time-domain statistical calculation. The features were selected based on the method of compensation distance evaluation technique (CDET) to reduce the number of features and hence enhance classification accuracy. There are three main kernel functions that can be used with SVM, namely, linear, polynomial, and RBF functions. In this study, RBF has been selected due to its nonlinearly mapping efficiency. Results were obtained for both with normalization and without normalization of values and it were observed that classification accuracy was higher with the normalization for SVM at an overall rate of 100%.

Yang et al., 2011 [32] proposed MLP-BP different conditions for: healthy, unbalance, looseness, misalignment, and gear faults. Features were extracted using both WPT and time-domain statistical analysis. The results were compared with other feature selection methods based on GA and without GA. The average results, shown in Table 2, illustrate the high efficiency of using feature selection based on GA.

Table 2 survey on artificial intelligence applications on rotating machinery fault diagnosis

Ref	Machinery and fault	Pre-processing & features extraction	Selected features	classifier	Accuracy rates
Al-Raheem et al., 2010 [17]	Bearing	Lablace-Wavelet based on the Scale Kurtosis value technique	RMS, SD, Kurtosis, (WPS) Peak frequency, (WPS) maximum amplitude	MLP RBF PNN	100% 97.5% 72.1%
Al-Raheem et al., 2008 [18]	Bearing	Lablace-Wavelet based on the Scale Kurtosis value technique	RMS, SD, Kurtosis, (WPS) Peak frequency, (WPS) maximum amplitude	MLP	100%
Samanta et al., 2006 [19]	Bearing	Original signals used with some pre-processing methods of differentiation and integration, low- and high-pass filtering	Mean, RMS, Variance, Skewness, Kurtosis, normalised higher order (up to ninth) central moments	MLP RBF PNN MLP+GA RBF+GA PNN+GA	85.06% 83.33% 95.83% 99.31% 87.60% 96.53%
Samanta, 2004 [79]	Gear	Original signals used with some pre-processing methods of differentiation and integration, low- and high-pass filtering	Mean, RMS, Variance, Skewness, Kurtosis, normalised higher order (up to ninth) central moments	MLP SVM MLP+GA SVM+GA SVM with 6 features	96.3% 98.6% 100% 98.8% 100%
Zhenyou Zhang, 2013 [20]	Blower Unbalance	WPT with Daubechies (db4) as a mother function	Standard deviations	MLP-BP with PCA and without	NA
Jedli´nski and Jonak, 2015 [23]	Gear	CWT Coiflet3, Daubechies4, Dmeyer, Gaussian, Haar, Mexican-hat, Meyer, reverseBior3.1 and Symlet wavelets		Without pre-processing MLP SVM With pre-processing MLP SVM	 59.50% 60.10% 97% 99.22%
Wang et al., 2010 [27]	bearing	WPT	NA	MLP RBF	91.7% 95%
Yanjun et al., 2009 [28]	rub impact fault	WPT Daubechies (db4)	NA	MLP SVM RBF	82% 99.3% 98.6%
Sui and Zhang, 2009 [29]	bearing	WPT Daubechies (db10)	12 features from original signal (time domain) and 4 features from frequency domain.	Without feature selection MLP SVM With features selection MLP SVM	 85.83% 91.67% 97.50% 98.33%
Yajuan	bearing	WPT	NA	MLP	96.24%

Liu and Tao Liu, 2010 [30]				SVM	93.18%
Zhong et al., 2010 [31]	Gear	WPT Daubechies (db10)	8 statistical features were selected	SVM	100%
Hol and Zhong, 2011 [32]	Unbalance, misalignment, gear, and looseness	WPT	9 statistical features were selected	MLP+GA MLP	97.98% 83.02% (Average accuracy rates)

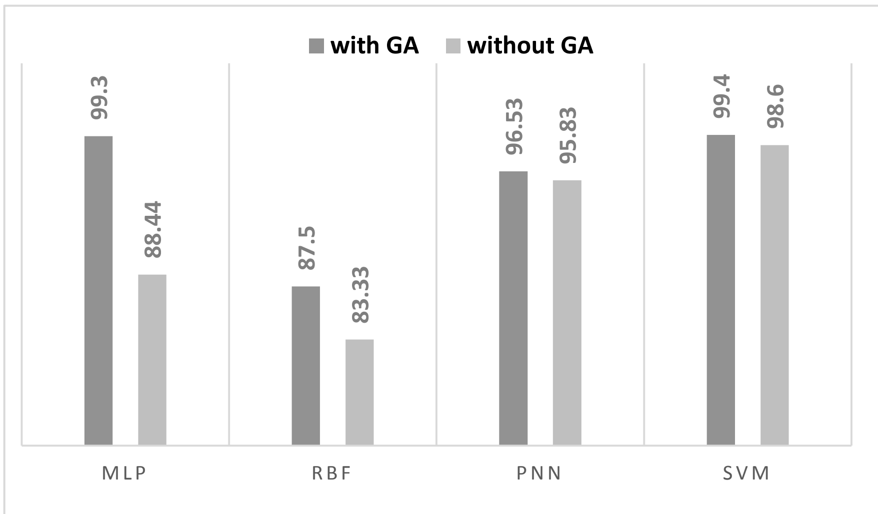


Figure 6 Average Accuracy rates of different AI classifiers with GA and without GA based on the all studies

From the above reviewed literature which is depicted in Figure 6, the following findings are summarized as follows: Average accuracy rates show that the SVM out-performed the other classifiers, MLP, RBF and PNN. It has been noted that SVM performance can be improved by using a good feature selection method such as class separability criterion method and GA-based feature selection. Kernel selection has an influence on the SVM performance, and RBF-kernel has been found to be the best.

On the other hand, MLP was found to be a successful classifier with high accuracy rates if GA is used for the optimization processes in terms of number of feature and hidden neuron selection as shown in Figure 6.

Generally, SVM and MLP can produce comparable results once the proper processes and methods are provided as the average overall accuracy rates based on the comparative studies of SVM and MLP only.

WT was remarked to be a good pre-processor for feature extraction, and particularly, WPT was noted to be the most applied one for the different rotating machineries and components. Daubechies (db4 and db10) found to be more preferable and used as mother functions and that indicated to their higher shape similarity with the original signals.

Testing different wavelet functions would widen options for selecting a wavelet function with a similar shape to the original signal according to the obtained results. However, a better option would be the derivation of a new wavelet function that is designed specifically to be similar in shape to the signal to be analysed.

7 Conclusion

In this paper, fault diagnosis methods of different rotating machines have been reviewed and it has been observed that there is a need to move from conventional techniques to automatic approaches. Throughout the review of the literature, some remarks have been identified. Firstly, the vibration signals extracted from some rotating machinery components, like bearing and gear, may contain non-stationary signals which change with time; hence, conventional vibration analysis methods in the time and frequency domains are not suitable. Thus, the time-frequency domain method of wavelet transform has been applied by many researchers for analysis of non-stationary signals. In addition, WT has been applied successfully with ANN as an automatic diagnosis system and WPT has been applied for the most recent studies and has shown a significant improvement for the different rotating machinery fault diagnosis in terms of signal preprocessing where signal can be broken down into different coefficients and levels. Daubechies wavelet function (db4) has been noted to be highly accepted for the rotating machinery signals as a mother function that works with WT and especially with WPT to decompose the original signals. The appropriate understanding of the shape of the acquired vibration signal would be important in order to select the most similar wavelet mother function from the available wavelet function families and for same cases, it would be even better to derive a new wavelet function.

From the reviewed literature, the high efficiency of SVM for fault classifications and diagnosis of rotating machinery compared to other AI classifiers like ANN-BP, RBF, PNN, in terms of classification accuracy and training time, has been noted. For instance, in a study, SVM outperformed both MLP-BP and RBF-NN classifiers with three different types of fault; in another study, SVM illustrated better performance than MLP-BP after considering that the best results were obtained using feature selection methods where the number of feature was properly selected and minimized; and with another study, SVM again outperformed BP-MLP in terms of classification accuracy rate and time as it was faster for both stages: testing and training. However, an important consideration which influences the performance of SVM is selection of the kernel function; and it has noted that RBF inner product function is a good selection. The more conventional ANN-BP or MLP still have potential to provide good classification accuracy as long as an appropriate feature selection method is applied like GA. It has been noted that the RBF classifier has a faster training time compared to MLP-BP. PNN has an advantage of saving the training features to escape from the iterative procedure, which makes it faster in the training process. However, the large stored training features require a large network and this is a reason for limited usage of PNN as a classifier for fault detection.

Selection of appropriate training algorithms is important to speed up the process of training to obtain the best classification accuracy. Finally, some general important procedures are recommended: data normalization, feature selection method for reducing the number of input features and selection of the most useful and relevant criteria, as well as selecting the most appropriate AI classifier.

References

1. BEEBE, R. S. (2004) Predictive maintenance of pumps using condition monitoring *Elsevier advanced technology.*
2. MCKEE, K. K., FORBES, G., MAZHAR, I., ENTWISTLE, R. & HOWARD, I. (2011) A Review of Major Centrifugal Pump Failure Modes with Application to the Water Supply And Sewerage Industries. *ICOMS Asset Management Conference*. Gold Coast QLD Australia, Asset Management Council.
3. RAO, B. K. N. (Ed.) (1996) *Handbook of condition monitoring*, Elsevier advanced technology.
4. BENDJAMA, H., GHERFI, K., IDIOU, D. & BOUCHERIT, M. S. (2014) Condition monitoring of rotating machinery by vibration signal processing methods. *International Conference on Industrial Engineering and Manufacturing.* Batna University Algeria.
5. AHERWAR, A. & KHALID, M. S. (2012) VIBRATION ANALYSIS TECHNIQUES FOR GEARBOX DIAGNOSTIC: A REVIEW. *International Journal of Advanced Engineering Technology,* 3.

6. AL-TUBI, M. A. S., AL-RAHEEM, K. F. & ABDUL-KAREM, W. (2012) Rolling element bearing element faults detection, power spectrum and envelope analysis. *International conference on applications and design in mechanical engineering.* Penang, Malaysia.
7. ATOUI, I., MERADI, H., BOULKROUNE, R., SAIDI, R. & GRID, A. (2013) FAULT DETECTION AND DIAGNOSIS IN ROTATING MACHINERY BY VIBRATION MONITORING USING FFT AND WAVELET TECHNIQUES. *8th International Workshop on Systems, Signal Processing and their Applications (WoSSPA).* Algiers, IEEE.
8. ISAYED, B., CHEDED, L. & AL-BADOUR, F. (2007) VIBRATION MONITORING AND FAULTS DETECTION USING WAVELET TECHNIQUES *9th International Symposium on Signal Processing and Its Applications.* Sharjah, IEEE.
9. PRANEETHCHANDRAN, M.LOKESHA, M.C.MAJUMDER & K.P.RAMACHANDRAN (2013) Laplace and Morlet Wavelet Analysis for Gear Fault Diagnosis: A Comparative Study. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* 3.
10. AL-TUBI, M. A. S. & AL-RAHEEM, K. F. (2010) Rolling element bearing faults detection, a time domain analysis. *Caledonian Journal of Engineering,* 6.
11. MEHALA, N. & DAHIYA, R. (2008) A Comparative Study of FFT, STFT and Wavelet Techniques for Induction Machine Fault Diagnostic Analysis. *International conference of computational intelligence, man-machine systems cybernetics (CIMMACS '08).* India.
12. PRAKASH, A., AGARWAL, V. K., KUMAR, A. & NAND, B. (2014) A review on machine condition monitoring and fault diagnostics using wavelet transform. *International Journal of Engineering* Technology, Management and Applied Sciences, 2, 84-93.
13. PENG, Z. K. & CHU, F. L. (2004) Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography. *Mechanical Systems and Signal Processing,* 18**,** 199–221.
14. AL-TOBI, M. & AL-RAHEEM, K. F. (2015) Rolling element bearing faults detection, wavelet de-noising analysis. *Universal journal of mechanical engineering,* 5**,** 47-51.
15. MURALIDHARAN, V., SUGUMARAN, V. & INDIRA, V. (2014) Fault Diagnosis of mono block Centrifugal Pump Using SVM. *Engineering Science and Technology, an International Journal, 17, 152-157.*
16. YAN, R., GAO, R. X. & CHEN, X. (2014) Wavelets for fault diagnosis of rotary machines: A review with applications. *Signal Processing, 96, 1-15.*
17. AL-RAHEEM, K. F. & ABDUL-KAREM, W. (2010) Rolling bearing fault diagnostics using artificial neural networks based on laplace wavelet analysis. *International journal of Engineering, Science and Technology,* 2**,** 278-290.
18. AL-RAHEEM, K. F., ROY, A., RAMACHANDRAN, K. P., HARRISON, D. K. & GRAINGER, S. (2008) Application of the Laplace- Wavelet Combined With ANN for Rolling Bearing Fault Diagnosis. *Journal of Vibration and Acoustics,* 130.
19. SAMANTA, B., AL-BALUSHI, K. R. & S.A.AL-ARAIMI (2006) Artificial Neural Networks and Genetic Algorithm for Bearing Fault Detection. *Soft Computing,* 10**,** 264-271.
20. ZHANG, Z., WANG, Y. & WANG, K. (2013) Intelligent fault diagnosis and prognosis approach for rotating machinery integrating wavelet transform, principal component analysis, and artificial neural networks. *The international journal of advanced manufacturing technology,* 68**,** 763-773.
21. ZHAO, W., ZHANG, L. & MENG, X. (2011) Rolling Bearing Fault Diagnosis Using Neural Networks Based on Wavelet Packet-Characteristic Entropy. *Computer science for enviromental engineering and ecoinformatics.* Springer-Verlag Berlin Heidelberg.
22. KANKAR, P. K., SHARMA, S. C. & HARSHA, S. P. (2011) Fault diagnosis of ball bearings using continuous wavelet transform. *Applied Soft Computing,* 11**,** 2300–2312.
23. JEDLINSKI, Ł. & JONAK, J. (2015) Early fault detection in gearboxes based on support vector machines and multilayer perceptron with a continuous wavelet transform. *Applied Soft Computing,* 30**,** 636–641.
24. ROY, S. D., SHOME, S. K. & LAHA, S. K. (2014) Impact of Wavelets and Filter on Vibration-based Mechanical Rub Detection using Neural Networks. *2014 Annual IEEE India Conference (INDICON).* Puna, India, IEEE.

25. SRINIVAS, H. K., SRINIVASAN, K. S. & UMESH, K. N. (2010) Application of Artificial Neural Network and Wavelet Transform for Vibration Analysis of Combined Faults of Unbalances and Shaft Bow. *Advances In theoretical and applied mechanics,* 3**,** 159 - 176.
26. LIU, L.-S., YANG, Y.-H., LI, Z.-Y. & YU, W. (2011) Condition Monitoring for Helicopter Main Gearbox Based on Wavelet Packet Transform and Wavelet Neural Network. *International conference on quality, reliability, maintenance, and safety engineering.* Xi'an, IEEE.
27. D.Y.WANG, W.Z.ZHANG & J.G.ZHANG (2010) Fault Bearing Identification Based on Wavelet Packet Transform Technique and Artificial Neural Network. *International conference on system science, engineering design and manufacturing informatization.* Yichang, IEEE.
28. YANJUN, L., FANLONG, M. & YIBO, L. (2009) Research on Rub impact Fault Diagnosis Method of Rotating Machinery Based on Wavelet Packet and Support Vector Machine *International Conference on Measuring Technology and Mechatronics Automation.* Changchun, IEEE.
29. SUI, W.-T. & ZHANG, D. (2009) Rolling Element Bearings Fault Classification Based on SVM and Feature Evaluation. *Proceedings of the Eighth International Conference on Machine Learning and Cybernetics.* Baoding, IEEE.
30. LIU, Y. & LIU, T. (2010) Rotating Machinery Fault Diagnosis Based on Support Vector Machine *International Conference on Intelligent Computing and Cognitive Informatics.* Kuala Lumpur, IEEE.
31. ZHONG, J., YANG, Z. & WONG, S. F. (2010) Machine Condition Monitoring and Fault Diagnosis based on Support Vector Machine. *International conference of Industrial Engineering Management* Macao, IEEE.
32. YANG, Z., HOI, W. I. & ZHONG, J. (2011) Gearbox Fault Diagnosis based on Artificial Neural Network and Genetic Algorithms. *International Conference on System Science and Engineering.* Macau, China.
33. FAROKHZAD, S. (2013) Vibration Based Fault Detection Of Centrifugal Pump By Fast Fourier Transform And Adaptive Neuro-Fuzzy Inference System. *Journal of mechanical engineering and technology, 1, 82-87.*
34. BISWAS, R. K., MAJUMDAR, M. C. & BASU, S. K. (2013) Vibration and Oil Analysis by Ferrography for Condition Monitoring. *Journal of institution of engineers (India),* 94**,** 267-274.
35. ZHU, J., YOON, J. M., HE, D., QU, Y. & BECHHOEFER, E. (2013) Lubrication Oil Condition Monitoring and Remaining Useful Life Prediction with Particle Filtering *International Journal of Prognostics and Health Management*.
36. LEVI, O. & ELIAZ, N. (2009) Failure Analysis and Condition Monitoring of an Open-Loop Oil System Using Ferrography. *Tribology Letters,* 36**,** 17-29.
37. HAMMERSCHMIDT, U., HAMEURY, J., STRNAD, R., TURZÓ-ANDRAS, E. & WU, J. (2015) Critical Review of Industrial Techniques for Thermal-Conductivity Measurements of Thermal Insulation Materials. *International journal of thermophysics,* 36**,** 1530-1544.
38. DEGERATU, S., ROTARU, P., RIZESCU, S., DANOIU, S., BIZDOACA, N. G., I.ALBOTEANU, L. & MANOLEA, H. O. (2015) Condition monitoring of transformer oil using thermal analysis and other techniques. *Journal of thermal analysis and calorimetry,* 119**,** 1679-1692.
39. DERBYSHEV, A. S., LADYGIN, F. A., EFIMOV, A. N., BERESNEVA, I. A., ZHOLUD, A. S., EFREMKINA, A. I., MEL’NIKOV, V. V. & ZVONKOV, I. N. (2014) Use of corrosion monitoring for evaluating operating equipment and pipeline condition and service life. *Journal of Chemical and Petroleum Engineering,* 50.
40. M.C.PAN & P.SAS (1996) Transient analysis on machinery condition monitoring. *3rd international conference on signal processing.* Bejing, IEEE.
41. AL-BADOURL, F. & L.CHEDECT, A. M. S. (2010) Non-Stationary Vibration Signal Analysis Of Rotating Machinery Via Time-Frequency And Wavelet Techniques *10th International Conference on Information Science, Signal Processing and their Applications (ISSPA 2010)* Kuala Lumpur, IEEE.
42. GABOR, D. (1946) Theory of communication. Part 1: The analysis of information. *Journal of the institution of electrical engineers-part III: radio and communication engineering* 93**,** 429-441.
43. GOUPILLAUD, P., A.GROSSMANN & J.MORLET (1984) Cycle-octave and related transforms in seismic signal analysis. *Seismic signal analysis and discrimination III,* 23.

44. ALSBERG, B. K., WOODWARD, A. M. & KELL, D. B. (1997) An introduction to wavelet transforms for chemometricians: A time-frequency approach. *Chemometrics and Intelligent Laboratory Systems,* 37**,** 215-239.
45. CHEN, B. H., WANG, X. Z., YANG, S. H. & MCGREAVY, C. (1999) Application of wavelets and neural networks to diagnostic system development, 1, feature extraction. *Computers and Chemical Engineering,* 23**,** 899 – 906.
46. GHAREHBOLAGH, G. M., FAROKHZAD, S., ABAD, M. R. A. A. & RANJBARKOHAN, M. (2013) Fault Diagnosis of Crown Wheel and Pinion in Differential Using Acoustic Signals with Discrete Wavelet Transform and Neural Network. *Technical Journal of Engineering and Applied Sciences,* 3**,** 1358-1364.
47. SANZ, J., PERERA, R. & HUERTA, C. (2012) Gear dynamics monitoring using discrete wavelet transformation and multi-layer perceptron neural networks. *Applied Soft Computing,* 12**,** 2867–2878.
48. SARAVANAN, N. & RAMACHANDRAN, K. I. (2010) Incipient gear box fault diagnosis using discrete wavelet transform (DWT) for feature extraction and classification using artificial neural network (ANN). *Expert Systems with Applications,* 37**,** 4168–4181.
49. WANG, H. & CHEN, P. (2007) Intelligent Method for Condition Diagnosis of Pump System Using Discrete Wavelet Transform, Rough Sets and Neural Network. *Second international Conference on Bio-inspired computing: theories and applications, 2007.* Zhengzhou, IEEE.
50. COIFMAN, R. R., MEYER, Y. & WICKERHAUSER, V. (1992) Size properties of wavelet packets IN RUSKAI, M. B. (Ed.) *Wavelets and their applications.* Boston, Jones and Bartlett.
51. RAfiEE, J., TSE, P. W., HARIfi, A. & SADEGHI, M. H. (2009) A novel technique for selecting mother wavelet function using an intelligent fault diagnosis system. *Expert Systems with Applications,* 36**,** 4862–4875.
52. WUMING, H., PEILIANG, W. & QIANGGUO, Y. (2010) Fault Diagnosis of Traction Machine for Lifts Based on Wavelet packet algorithm and RBF Neural Network. *International conference on information sciences.* Chengdu, IEEE.
53. CHEN, C.-H., SHYU, R.-J. & MA, C.-K. (2007) Rotating Machinery Diagnosis Using Wavelet Packets-Fractal Technology and Neural Networks. *Journal of Mechanical Science and Technology,* 21**,** 1058-1065.
54. PATRA, K., PAL, S. K. & BHATTACHARYYA, K. (2006) Drill wear monitoring through current signature analysis using wavelet packet transform and artificial neural network. *International conference on industrial technology.* Mumbai, IEEE.
55. LEDUCQ, D. (1990) Hydraulic noise diagnostics using wavelet analysis. *International Conference on Noise Control Engineering.* Gothenburg- Sweden.
56. AL-RAHEEM, K. F. & ABDUL-KAREM, W. (2010) Rolling bearing fault diagnostics using artificial neural networks based on laplace wavelet analysis. *International journal of Engineering, Science and Technology,* 2**,** 278-290.
57. AL-TUBI, M. A. S. & AL-RAHEEM, K. F. (2015) Rotor misalignment and imbalance detection using wavelet and neural network techniques. *Scottish Journal of arts, social sciences and scientific studies,* 24**,** 33-44.
58. MURALIDHARAN, V. & SUGUMARAN, V. (2013) Selection of Discrete Wavelets for Fault Diagnosis of Monoblock Centrifugal Pump Using the J48 Algorithm. *Applied Artificial Intelligence, 27.*
59. CHEN, H. W. P. (2009) intelligent diagnosis method for a centrifugal pump using features of vibration signals. *Neural Comput & Applic,* 18**,** 397–405.
60. WANG, H. Q. & CHEN, P. (2007c) Fault Diagnosis of Centrifugal Pump Using Symptom Parameters in Frequency Domain. *Agricultural Engineering International: the CIGR Ejournal,* IX.
61. HAAR, A. (1911) Zur theorie der orthogonalen funktionensysteme. *Mathematische Annalen,* 71**,** 38-53.
62. POULARIKAS, A. D. (Ed.) (2010) *Transforms and Applications Handbook*, Taylor & Francis Group.
63. DAUBECHIES, I. (1992) *Ten Lectures on Wavelets*, Society for Industrial and Applied Mathematics.
64. MEYER, Y. (1990) *Ondelettes et Opérateurs*, Hermann.
65. DAUBECHIES, I. (1988) Orthonormal bases of compactly supported wavelets. *Communications on pure and applied mathematics,* XII**,** 909-996.
66. COHEN, A., DAUBECHIES, I. & FEAUVEAU, J. C. (1992) Biorthogonal bases of compactly supported wavelets. *Communications on pure and applied mathematics,* XLV**,** 485-560.

67. CHARNIAK, E. & MCDERMOTT, D. (2000) *Introduction to artificial intelligence*, addison wesley Longman Inc.
68. MCCULLOCH, W. S. & PITTS, W. (1943) A logical calculus of the ideas immanent in nervous activity. *BULLETIN OF MATHEMATICAL BIOPHYSICS,* 5**,** 115-133.
69. ZADEH, L. A. (1965) Fuzzy Sets. *Information and Control,* 8**,** 338-353.
70. SAKTHIVEL, N. R., BINOY.B.NAIR & V.SUGUMARAN (2012a) Soft computing approach to fault diagnosis of centrifugal pump. *Applied Soft Computing,* 12**,** 1574–1581.
71. SAKTHIVEL, N. R., V.SUGUMARAN & B.NAIR, B. (2012b) Automatic rule learning using roughset for fuzzy classifier in fault categorization of mono-block centrifugal pump. *Applied Soft Computing,* 12**,** 196–203.
72. SABERI, M., AZADEH, A., NOURMOHAMMADZADEH, A. & PAZHOHESHFAR, P. (2011) Comparing performance and robustness of SVM and ANN for fault diagnosis in a centrifugal pump. *19th International Congress on Modelling and Simulation.* Perth, Australia.
73. NASIRI, M. R., MAHJOOB, M. J. & VAHID-ALIZADEH, H. (2011) Vibartion signature analysis for detecting cavitation in centrifugal pump using neural networks. *IEEE international conference on mechatronics (ICM).* Istanbul, Turkey, IEEE.
74. FAROKHZAD, S., AHMADI, H. & JAFARY, A. (2013a) Fault Classification Of Centrifugal Water Pump Based On Decision Tree And Regression Model. *Journal of Science and today's world, 2, 170-176.*
75. S.FAROKHZAD, H.AHMADI & A.JAEFARI (2012) Artificial Neural Network Based Classification of Faults in Centrifugal Water Pump. *Journal VIBROENGINEERING* 14.
76. V.MURALIDHARAN, V.SUGUMARAN, P.SHANMUGAM & K.SIVANATHAN (2010) Artificial Neural Network Based Classification For Monoblock Centrifugal Pump Using Wavelet Analysis. *International journal of mechanical engineering, 1, 28-37.*
77. IIOTT, P. W. & GRIFFITHS, A. J. (1997) Fault diagnosis of pumping machinery using artificial neural networks. *Journal of Process Mechanical Engineering,* 211**,** 185-194.
78. ZOUARI, R., SIEG-ZIEBA, S. & SIDAHMED, M. (2004) FAULT DETECTION SYSTEM FOR CENTRIFUGAL PUMPS USING NEURAL NETWORKS AND NEURO-FUZZY TECHNIQUES. *SURVEILLANCE 5 CETIM Senlis.*
79. SAMANTA, B. (2004) Gear fault detection using artificial neural networks and support vector machines with genetic algorithms. *Mechanical Systems and Signal Processing* 18**,** 625–644.
80. ROOIJ, A. J. F. V., JAIN, L. C. & JOHNSON, R. P. (1996) *Neural Network Training Using Genetic Algorithm,* Singapore, World Scientific Publishing Co. Pte. Ltd.
81. HAYKIN, S. (1999) *Neural networks, a comprehensive foundation,* singapore, Pearson Education.
82. RUMELHART, D. E., HINTON, G. E. & WILLIAM, R. J. (1986) Learning representations by back-propagating errors. *Nature,* 323.
83. BROOMHEAD, D. & LOWE, D. (1988) Multivariable functional interpolation and adaptive networks. *Complex Systems,* 2**,** 321-355.
84. BASHKIROV, O. A., BRAVERMAN, E. M. & MUCHNIK, I. B. (1964) Potential function algorithms for pattern recognition learning machines. *Automation and Remote Control,* 25**,** 629-631.
85. KATAGIRI, S. (2001) Applications of artificial neural networks (ANNs) to speech processing. IN HU, Y. H. & HWANG, J.-N. (Eds.) *Handbook of neural network signal processing.* USA, CRC press.
86. CORTES, C. & VAPNIK, V. (1995) Support-vector networks. *Machine Learning,* 20**,** 273-297.
87. SPECHT, D. F. (1990) Probabilistic neural networks *Neural Networks,* 3**,** 109 118.
88. KARTALOPOULOS, S. V. (1996) *understanding neural networks and fuzzy logic- basic concepts and applications,* New Delhi, IEEE.