Kumamoto University

Kumamoto, Japan

Diagnosis, Classification and Prognosis of Rotating Machine using Artificial Intelligence

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Computer Science and Electrical Engineering

by

Abd Kadir Bin Mahamad

October 2010

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Acknowledgments

I would like to thank Prof. Takashi Hiyama, my supervisor for his support, guidance and encouragement. Many thank to Case Western Reserve University and IMS, University of Cincinnati of NASA Ames Prognostics Data Repository, for providing free download of the bearing fault data sets. I also like to thank Kumamoto University, University Tun Hussein Onn Malaysia and Malaysian Government for their financial support.

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1. “Fault Classification of Induction Motor Bearing Using ANFIS”, *International Student Conference on Advanced Science and Technology, ICAST*, Izmir , Turkey, pp. 323–324 (2010).

Abstract of the Dissertation

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Doctor of Philosophy in Computer Science and Electrical Engineering

Kumamoto University, Kumamoto, Japan, October 2010

Professor Takashi Hiyama, Supervisor

The demand for cost efficient, reliable and safe rotating machinery requires accurate fault diagnosis, classification and prognosis systems. Therefore these issues have become of paramount important so that the potential failures of rotating machinery can be managed properly. Various methods have been applied to tackle these issues, but the accuracy of those methods is just satisfactory only. This research, therefore propose appropriate methods for fault diagnosis, classification and prognosis systems. For fault diagnosis and classification, the vibration data was obtained from Western Reserved University. The vibration signal was processed through pre-processing stage, features extraction, features selection before the developed diagnosis and classification model were built. For fault prognosis systems, the acoustic emission and vibration signals were used as input signals. Furthermore, ANN was used as prognosis systems of rotating machinery failure. The simulation results for fault diagnosis, classification and prognosis systems show that proposed methods perform very well and accurate. The proposed model can be used as tools for diagnosing rotating machinery failures.

CHAPTER 1

Introduction

1.1 Research Problem

Nowadays, the modern rotating machinery industries is rapidly increasing in complexity, which demand the system to operate in higher reliability, safety, lower cost of production and maintenance. Therefore accurate fault diagnosis of machine failure is required. Machine fault diagnosis has evolved from the early time whereas the maintenance is only applied after the fault has occurred in the machine. Then it evolved to become as preventive maintenance in the last few decades before the industries used condition based maintenance which is practised till date. Preventive maintenance is defined as the performance of maintenance before the system face any degradation. Meanwhile condition based maintenance is refered as maintenance action taken based on the information acquired from the target measurement. The effectiveness of this maintenance is measured based on accurate diagnostic strategies which is met. The diagnosis strategies and techniques are still being explored by many researcher, some of them as in [1]–[8]. Several researchers are not just concern to diagnose the machine failure but also to prognose the remaining useful life of machine [9]–[19]. These techniques create new dimension to machine fault diagnosis in order to improve the reliability of the rotating machine.

In order to detect rotating machinery failure, vibration monitoring is widely used, as was published in [20]–[22]. The magnitude of vibration level is increase proportionately following the degradation increment on machine failure. This vibration signal can be analysed using signal processing. The features from vibration signal can be extracted through time, frequency and time frequency domain. Many features can be extracted through those processes such as maximum, minimum, root mean square (RMS), kurtosis, skewness, variance and crest factor [23]. However not all features is significant to represent the degradation information of machine failure. Therefore, it is essential to select only significant features and ignore the rest. This process is called as features selection.

In fact in complexity of modern rotating machinery, it requires more parameters to be taken into account to make diagnosis system more reliable and efficient. The parameters such as current, temperature, voltage or acoustic should be considered as significant parameters. This issue is still being studied by many researchers as essential topic to be addressed.

This thesis propose the method for fault diagnosis, classification and prognosis of rotating machinery which use appropriate features sets, that can improve the accuracy and reliability of machine failure. In this research, we will just consider the vibration and acoustic signals to detect the machine failure due to limited data resources.

1.2 Research Topic

The research topic of this thesis is "Diagnosis, Classification and Prognosis of Rotating Machine using Artificial Intelligence".

The main part of this thesis is to improve the accuracy of diagnosis system based on features or information that are fed into the artificial intelligence (AI) model, therefore the selection of the features is very important. This research explore the possibility of improving this matter by using AI models such as artificial neural network (ANN), fuzzy logic, genetic algorithm (GA) and hybrid systems.

1.3 Objective

The objectives of this research are stated as follows;

1. Development of effective features for AI model.
2. Development of diagnosis, classification and prognosis methods based AI techniques for rotating machine failure.

In order to provide effective features, it is required to establish many features during feature extraction. But the most important thing is providing the useful features during features selection. In this research for features extraction, features from time and frequency domain will consider. Meanwhile for feature selection, the distance evaluation technique will be used due to it simplicity.

On the other hand, in the development of diagnosis, classification and prognosis of rotating machinery failure, the AI techniques will be used. For these purpose three different sets of data will be used for diagnosis, classification and prognosis of machine failure.

1.4 New Contribution

The new contributions are stated as follows;

1. Introduce an effective features selection using distance evaluation technique

assist with ANN for diagnosis and classification of rotating machinery failure.

2. Introduce the hybrid techniques, which optimize the ANN with GA for training process.

3. Introduce ANN to prognose the rotating machinery using acoustic emission measurement data.

4. Introduce ANN method to predict remaining useful life (RUL) of rotating machinery reliability using actual and fitted measurement data.

1.5 Significance

The significance of this research can be described as follow;

1. The effective features selection can improve the optimization of input data. The distance evaluation techniques assisted with ANN can be used to select the very significant features to diagnose and classify the rotating machine failure.

2. The proposed method to optimize the ANN with GA can improve the rotating machine failure diagnosis.

3. The method to prognose the rotating machine failure can contribute to low maintenance cost and improve the machine operation time.

4. The method to predict RUL of rotating machine reliability can optimize the machine reliability and safety and hence adding value to the maintenance practices.

1.6 Literature Review

In this section the general literature review on diagnosis of machine failure is presented. Machine fault diagnosis can be defined as a process to determine whether a machine/system has a fault or not. On the other hand, the objective of prognosis system is to predict the RUL of a failure machine. Basically the machinery fault diagnosis process can be simplified as in Fig. 1.1.

Machinery fault diagnosis include many different measurements; mechanical measurements [21], [24], electrical measurements [25] and tribology [26]. Mechanical measurements typically include vibration, acoustic emission and temperature. While electrical measurements include current, and voltage. Tribology is more concerned with machinery lubrication and oil debris.

Due to development of advance technology of measurement equipment and

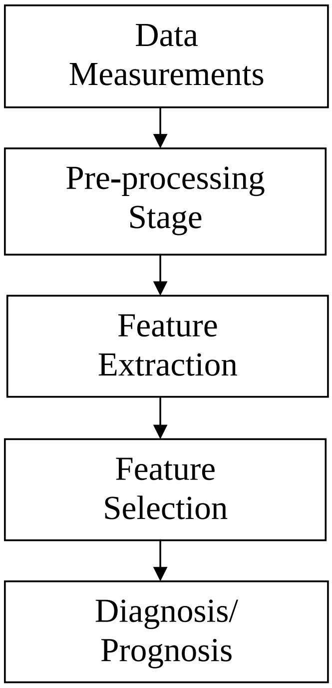


Figure 1.1: Fault diagnosis process

modern computer, the information/data from condition monitoring of machinery becomes vital. Thus this trend makes data fusion essential. Data fusion is defined as a technique to incorporate data from multiple sources to increase the accuracy of diagnosis and prognosis system.

1.6.1 Pre-prosessing stage

Usually the raw data need to be pre-processed before it can be applied for fault diagnosis. This process can reduce the dimension of raw data, which the signal is turning into information. Data sources from rotating machine usually are non-linear, heterogeneous and distributed. Handling proper data preprocessing can improve the performance of fault diagnosis, since the data may have difference in measurements scales, accuracies and uncertainties. For multiple data fusion, the data need to be transformed into time space reference. For this work the special data management procedure is needed to make it accomplished. This transformation process usually takes into account the process such as time propagation, data association and data alignment.

1.6.2 Features Extraction

In order to achieve good performance of machine fault diagnosis, largely depend on appropriate features extraction and features selection techniques. The selection of vital features from targeted machine is the main contribution to increase the effectiveness of fault diagnosis process.

Features extraction techniques can be categorized into three categories; time domain, frequency domain and time-frequency domain. Time domain features extraction techniques include statistical analysis, which in turn includes mean, standard deviation, RMS, skewness, kurtosis, maximum, minimum, and crest factor are selected as statistical features extraction [23].

Standard deviation is to measure the dispersion of data sets from its mean. The more spread of data produce higher deviation. Mean and standard deviation can be described as in (1.1) and (1.2).

$$xm = \frac{1}{K}\sum_{k=1}^{K} x(k) \tag{1.1}$$

$$xstd = \sqrt{\frac{\sum_{k=1}^{K}(x(k) - xm)^2}{K-1}} \tag{1.2}$$

where $x(k)$ is a signal series for $k = 1, 2, \cdots, K$ and K is the number of data points.

RMS can be used as parameters or features to measure overall power content of the signal. This feature is important for time domain features extractions especially in order to detect imbalance problem in rotating machine. RMS is not suitable to use as a feature to detect specific component failure, as it is not sensitive towards incipient machine fault. RMS can be defined as;

$$xrms = \sqrt{\frac{\sum_{k=1}^{K}(x(k))^2}{K}} \tag{1.3}$$

Skewness use the normalized third central moment, which is defined as;

$$xskew = \frac{\sum_{k=1}^{k}(x(k) - xm)^3}{(K-1)xstd^3} \tag{1.4}$$

This feature measure the symmetry, that is the distribution of the data at the left and right sides from the centre point.

Kurtosis, as in (1.5) measure the relative peakedness of the distribution as compared to a normal distribution. Kurtosis can be used to identify the major peaks in data and it uses the normalized fourth of central moment.

$$xkurto = \frac{\sum_{k=1}^{k}(x(k) - xm)^4}{(K-1)xstd^4} \tag{1.5}$$

There are others time domain features analysis which include maximum and minimum values. The maximum value can be defines as;

$$xmax = max(x(k)) \tag{1.6}$$

and the minimum value as;

$$xmin = min(x(k)) \tag{1.7}$$

Crest factor computes the ratio of the peak level of data over the RMS level. Therefore the results from the crest factor show the peak of data corresponding to an increase in crest factor value. This feature is suitable to use for detection of impulsive vibration change in rotating machine fault. Crest factor can be defined as;

$$CF = \frac{xmax}{xrms} \tag{1.8}$$

Typically, time domain features analysis contains the information describing the condition of machine especially during short duration of detection. But these features are not directly noticed, particularly if the machine is still in early stage of faulty.

Therefore, in this above situation, the frequency domain analysis is required. The short time signal processing is a useful technique which can be used to localize the defects. Frequency domain features are proven to have a capability to reveal the fault sign from machine failure as demonstrated in [27] and [23] . Usually Discrete Fourier Transform (DFT) is employed to convert the signal from time domain to frequency domain. Then to compute the DFT signal, the Fast Fourier Transform (FFT) is utilized. Enveloping method such as High Frequency Resonance Techniques (HFRT) is subsequently used to eliminate the unnessecary frequency from the faulty machine [23].

1.6.3 Features Selection

The task of fault diagnosis of modern machine has become difficult due to the growing complexity of machine design. But with the development of advance sensor technology and signal processing techniques, many features can be extracted from targeted machine for fault diagnosis purposes.

Normally, fault diagnosis has uncertainties characteristic. The uncertainties information can be reduced by using multiple source of information. It means that the fault diagnosis capability can be improved by feeding inputs with multiple features. The problem may exist with the increase of features that can increase the difficulty of data analysis. It is unnecessary to employ all the features for fault diagnosis purposes. Some features can contribute significant information of faulty sign while some only contribute less information. Thus, it is necessary to have appropriate feature selection to increase the accuracy of fault diagnosis process.

Various methods can be used for feature selection. Basically the feature selection is done by the following two basic aspects.

1. By evaluating all the candidates features and search for the best among the candidates. In this aspect the consistency of the features is evaluated and

the features which gave the good evaluation are selected as salient features.

2. By evaluating the features based on other evaluation measurement such as distance, information, dependency and classification error rate obtained during measurement.

Various methods can be used for feature selection such as modified distance discriminant technique [28], distance evaluation technique [29]–[31], neural network [32], J48 decision tree algorithm [33] and discrete wavelet [34]. The selection of features selection is essential to increase the accuracy of fault diagnosis system.

1.6.4 Fault Diagnosis Methods

Many fault diagnosis have been applied for fault diagnosis such as AI technique, signal processing, model based, and hybrid methods. Detail explaination is stated below;

1.6.4.1 Artificial Intelligent

Neural network (NN) is widely used for fault diagnosis [1], [26], [35]–[44], due to it ability to do classification and prediction. As one type of AI technique, NN has the ability to learn the new knowledge; same manner like the human gain their new knowledge through learning. This process can be realized by adjusting weights value of the neurons. It can be manipulated as multi input and multi output system, in which the NN can solve, complicated multiple object problems like multiple fault in rotating machine.

NN also has capability to process the information in parallel. This process shows that NN can fuse the information from different input sources simultaneously in similar way human solve their complicated information. Then the new knowledge of the trained neural network is stored in distributed way of the weights. Typically NN has good fault tolerance performance and function approximations. The Feedforward Neural network (FFNN) for instance can be used as NN model that can approximate any nonlinear function with high accuracy.

The basic processing in NN is a neuron. The neurons produces an output corresponds to a weighted sum of numbers at inputs which is a nonlinear function. The function of output can be defined as

$$Y = f\left(\sum_{i=1}^{m} w_i x_i\right) \tag{1.9}$$

where x_i is the input, which $i = 1, 2, 3, \cdots, m$ and Y is an output. f is the nonlinear function and w_i is the weight, $i = 1, 2, 3, \cdots, m$.

There are many nonlinear function used in NN. One of them is sigmoid function, which can be defined as;

$$f(t) = \frac{1}{1 + e^{-ct}} \tag{1.10}$$

where c is constant parameter.

Basically, there are many types of NN available and can be used for fault diagnosis. The FFNN, recurrent neural network (RNN) and radial basis function (RBF) network [40] are among most frequently used for specific purposes. For every NN they have their own configuration and structures. Once the structure is confirmed, the network can be trained to find its optimized parameters. The parameters include number of layers, the number of neurons and its weights.

NN mimic the working mechanism of human brain in which the new knowledge is acquired through learning process. For human brain the knowledge or information is stored in the memory but in NN the information is stored in the interconnection strengths, which are known as the weights. Thus, it is very important to choose the sufficient training data set in order to obtain the optimal performance of neural network. That means the training data set should cover all the information to represent the behaviour of fault diagnosis.

1.6.4.2 Signal Processing

Signal processing is the other method, which is successfully applied as in [2], [5], [6], [20], [21], [45]–[59]. This technique fully depend on digital signal processing, which requires to determine the failure boundary. That means, when the signal from targeted machine pass outside the bounds, it can determine as faulty condition. Vibration signal is the paramount and efficient signal in order to use as indicator for this matter.

Wavelet analysis is one of the signal processing method that is widely used in past research [2], [45]–[48], [52], [53], [56]. Wavelet analysis has special advantages over common signal processing method such as FFT. The wavelet transform has excellent performance to detect transient signal and flexibility in time and frequency resolution [45]. The Continuous Wavelet Transform (CWT) can be performed based on many types of wavelet basis, which means it may produce different results even using the same signal [52]. Therefore, selection of wavelet transform is vital in order to find the optimum wavelet parameter.

There is many application of wavelet transform in order to detect machine fault condition. For instance Ref. [56] propose an analysis of vibration signal from bearings using wavelet packets transform (WPT) to localize the defect at bearing. The technique is then compared to other methods, using filter and continuous wavelet transform, which very good performance with flexibility and computations advantages have been demonstrated. Xingsheng Lou *et al* [60], demonstrated the wavelet transform to process the vibration signal and to generate features vectors. Then, an adaptive neural fuzzy inference system (ANFIS) was used as diagnostic classifier. Ref. [59] present a novel technique of gear fault diagnosis using autocorrelation of continuous wavelet coefficients (ACWC). In conventional continuous wavelet coefficients (CWC), it encompasses too much data in each scale which can however cause information loss while resampling. This proposed technique was introduced to eliminate the drawback of CWC. Other wavelet application was reported using complex Morlet continuous wavelet transform as in [48].

Other signal processing methods have also been applied for fault diagnosis. In [51], the empirical mode decomposition (EMD) was used to process nonlinear and non-stationary signal from fault machine. They claimed, EMD showed satisfactory performance in minimizing energy leakage. Then, [49] proposed ensemble empirical mode decomposition (EEMD), which is an improved method of EMD. This technique can be applied by adding finite white noises to targeted signal, which can eliminate the mode mixing problem, as encountered in EMD technique.

The statistical analysis and spectral method was used for diagnosis of bearing fault as in [5]. The traditional features such as peak-to-peak value, RMS, crest factor and kurtosis were used to examine behavior of bearing defect. But these features do not give information related to location of fault. Therefore, spectral analysis was conducted during testing process. But this paper just emphasizes the application steps to investigate bearing defect development not as solution for diagnostic system.

1.6.4.3 Fuzzy Logic

The fuzzy logic is one of the common intelligent techniques that have been used for fault diagnosis. In [3] a fuzzy logic system was used to interpret vibration signal from motor bearing. The processed signal from the frequency spectrum of vibration signal, which input to fuzzy logic decision system make the fault diagnosis systems, gave excellent results. This technique can be improved accordingly by optimizing it with combination of other intelligent method or optimization algorithm. For example in [28] they proposed modified Fuzzy ARTMAP, which is described by the weighted Manhattan distance to achieved good performance of bearing fault diagnosis. Then in [29], they continue their work with proposes improved Fuzzy ARTMAP, in which this technique is incorporated with Yu's norm algorithm.

The application of intelligent technique like Neuro-Fuzzy system, which combines ANN and fuzzy logic system is easy to develop and perform. The main advantage of Neuro-Fuzzy is that it can learn the characteristic/behavior of a targeted system during training process without requiring developed complicated mathematical models. Enrico Zio *et al* [4] tackled the fault diagnosis problem using Neuro-fuzzy approach. They claimed by using Neuro-Fuzzy the correctness of classification is higher and easily to interpret. Yaguo Lei *et al* [27] proposes a new intelligent fault diagnosis based on statistical analysis as features extraction, an improved distance evaluation technique as features selection and neuro-fuzzy inference system (ANFIS) as fault diagnosis technique. The diagnosis scheme can also been studied according to different pattern classification method during normal and different types of fault under different load condition. The decision making stage is using neuro-fuzzy inference system, which is suitable for complex condition due to it adaptability and non-linear approximation [60].

In order to improve classification performance of ANFIS system, Yaguo Lei *et al* [31] proposes multiple ANFIS model which combines with genetic algorithm (GA). The results show, better classification performance compared to the individual classifiers of ANFIS model.

1.6.4.4 Model Based Methods

In some journal, the researchers propose techniques for fault diagnosis as a system model. For instance in [6], they analyzed the dynamic system of rotor bearing system by utilizing the response surface method analysis which consider effect of bearing design and operating parameters. Meanwhile in [57] presented a combined gear and bearing dynamic model for a gearbox test rig in the presence of faults. In this model it takes into account the slippage in the bearings, the Hertzian contact and the nonlinearity of the bearing stiffness in time variant.

N. Sawalhi *et al* [58], then shown the result of their model to examine a fault in the inner and outer race of rolling element bearings in the presence of gear interaction. They compared the simulated and actual signal from test rig for inner and outer fault, which the diagnosis technique react in same way for both signals.

1.6.4.5 Hybrid Methods

Hybrid system can be defined as a system which combination of various methods since every single technique has its own limitation. As in [7] they present an intelligent method incorporated between ANN and new GA learning algorithm. The new GA are based on hybrid construction of particle swarm optimization (PSO) and gradient descent (GD) techniques. This hybrid techniques are inspired in such a way since PSO can give a good direction to find the optimum of global region. Meanwhile GD algorithm is good to fine tune in determining the optimal solution for final result. B. Samantha *et al* [61] presented to compare 3 types of artificial neural network, which are multilayer perceptron (MLP), radial basis function (RBF) and probabilistic neural network (PNN). All these networks are optimized using genetic algorithm to find the optimum of hidden node and the input features. The same approach was applied by Abhinav Saxena *et al* [62] but they just considered MLP as a suitable NN for their work.

Besides above techniques, there are several other techniques which were successfully applied to diagnose machine failure. In [8], Gaussian Mixture Models (GMM) and hidden Markov Models (HMM) were used to classify faults of rotating machinery. These techniques were selected since both methods are applied successfully to analyze signals which have large variability. However, from the result they concluded that HMM outperforms GMM in classification of bearing faults. In [63], nonlinear characteristic of vibration signal is rearranging into reconstructed phase space (RPS) in which the phase trajectory of different kinds of signal will demonstrate different structure. To describe the phase trajectory of different signal, Gaussian mixture model (GMM) is utilized. GMM is used to fit the distribution of phase trajectory for every fault signal. The maximum likelihood (ML) Bayesian classifier then is utilized to realize the classification of vibration signal. The advantage of this method is that all parameters are obtained to analyze in time series directly.

Meanwhile in [30] and [45], the support vector machines (SVMs) ensemble with AdaBoost algorithm is applied to identify the different fault cases in rotating machine. The testing results show that proposed SVMs ensemble is reliable to identify the severity of incipient faults, which gave better classification performance compared to the single SVMs. The same approach was proposed by [64], but they propose SVM as a classifier to compute optimum wavelet signal decomposition level. The results achieved from the proposed method show it practical to be used for multi-fault diagnosis.

1.7 Structure of Thesis

This thesis is constructed into 6 chapters. Chapter 1 presents the research problem, research topic, objectives, new contribution, significance of the research and general literatures review, which covers the approaches that employed for diagnosis, classification and prognosis of rotating machinery failure.

Chapter 2 presents the development of optimizing ANN with GA for fault diagnosis of rotating machinery failure, while Chapter 3 describes the development of AI techniques for diagnosis and classification of machine failure. Furthermore Chapter 4 explain the development of prognosis system in which the acoustic emission measurements data was used to prognose machine failure.

Chapter 5 presents a method to improve the prediction accurancy of RUL from rotating machinery. To achieve this objective, the ANN model uses time and fitted measurements Weibull hazard rates of RMS and kurtosis from its present and previous points as input and normalized life percentage as output.For this scheme the monitoring data from University of Cincinnati of NASA Ames Prognostics Data Repository was used.

Lastly, Chapter 6 presents the conclusion drawn from this research and the future work is presented.

CHAPTER 2

Optimizing Feedforward Neural Network (FFNN) and Elman Network (EN) with Genetic Algorithm for Fault Diagnosis

2.1 Introduction

Fault diagnosis system can be defined as systems that has a capability to detect and diagnose faults occurred [65]. A 'fault' itself is defined as something that abnormally happens in a system. Therefore, early detection or diagnosis of failure from the system in industries is essential in order to prevent production volume into becoming low and which may affect the production profit, safety issues and other negative implications. This issue is significant to the induction motor bearing (IMB) failure which is one of the most regular components used in industries, thus the diagnosis system towards this component contributes to overall high output production.

A bearing is potential to fail once it reaches a certain limit or when over loaded. In fact, there are various types of bearing damages. A bearing can fail due to fatigue, cracks, deformation, wear and corrosion. Due to advancement in measurement technology today, IMB condition can be determined by using vibration technique [66]–[70] and stator current analysis [71]–[75]. The vibration signal will analyse with signal processing methods where the salient parameters will be extracted from the raw signal. This process is done through features extraction and/or features selection.

Normally, fault diagnosis can tell the 'cause and effect' relationship of system variables through the salient parameter from features selection. In this process, the input of model comes from the parameter or state that may contribute to the change at output. Therefore the selection of parameter for input is important in order to make the model to perform very well. Thus, many researchers proposes to overcome IMB failure by comparing the behaviour of IMB during normal and failure condition. One of the popular techniques in this matter is by using ANN as in [65], [37], [76]– [79].

In 2004, Yang *et al* [38] proposed ART-Kohonen neural network as a new ANN model. They focused on to overcoming the stability-plasticity problem. This problem happens to the system which is unable to learn from a new data because it was trained 'offline'. To overcome this problem, the adaptive resonance theory (ART) networks were developed. This network is an ANN self organizes mapping and successfully proved in real time training and classification. The Kohonen neural network (KNN) also self organizes mapping of two-layer neural network that implements a non-linear projection from high-dimensional input data into low-dimensional array of neurons. The incorporation of these two networks can learn the additional training data without forgetting the pattern of previous training data, thus becomes the solution of stability-plasticity problem.

On the other hand, Chen *et al* [1] introduced intelligent method for diagnosing rotating machinery by using improved backpropagation (BP) neural network incorporated with wavelet neural network (WNN) to diagnose fault in complex turbine generator unit. Due to BP neural network's slow convergent rate and the possibility to be traped in local minimum, they overcame this problem by using orthogonal wavelet function as a solution, since wavelet has been realized in time and frequency domain. WNN can give a good performance in approximation function even against rapidly changing signal, thus it is suitable for fault diagnosis of rotating machinery.

In order to provide practical application of machine fault diagnosis it requires to develop a software or tool for the user or operator to easy determine the condition of particular machine. For instance, Bayir [80] proposed the graphical user interface (GUI) software for fault diagnose of serial wound starter motors using Learning Vector Quantization (LVQ) neural network. The voltages and currents are acquired from the starter motor via data acquisition card before they transfer to the GUI program. They claimed that this program can be used for real time fault diagnosis in service shop of starter motor manufactures. The main drawback of this GUI, it required the expert operator such as supervisor or engineer with knowledge about motor starter operation to run this GUI.

Andhare and Manik [81] presented results of experiments to diagnose of defect in tapered roller bearing using vibration monitoring. A Matlab based GUI was made use of the time domain parameters to diagnose defect at bearings. They concluded that parameters like time waveform, form factor, parameter K and ceptrum are good indicators for tapered roller bearings but parameters such as kurtosis, form factor and skewness are good indicators for roller bearings. However this GUI is just operating in time domain. For bearing failure diagnosis it is important to take into account the frequency domain parameters as the important parameters to determine types of bearings failure.

In this chapter, the development of practical IMB failure model consider two different types; FFNN and EN , are studied. The significance of this study is due to many paper proposed where FFNN is implemented by Chen and from [65],

[37], [76]–[79] to diagnose machine failure, and one paper as in [82] proposed EN for this purpose. To improve the performance of both networks its is utilized using GA to find the optimum weights and biases before it can be used during training process. The performance of the optimum network is measured based on the minimum validation error produced from the network during IMB failure diagnosis.

The structures for FFNN allow the information to flow in one direction from input layer to output layer. On the other hand, EN allows the information to flow in both directions, which are from input layer to output layer and vice versa [83] . The main problem of FFNN is that it requires the large numbers of input neurons [83] and not suitable to use for time series data. Therefore, EN is the option, since they have not suffered from the problems above. However this network is not extended like FFNN due to it's complexity in structures and learning algorithm [84]. For FFNNs, the backpropagation algorithm is utilized as an effective learning algorithm in solving many problems. This algorithm is not working well with EN due to it's complexity in state space.

The selection of FFNN is due to its wide application in many fields area. Meanwhile, for EN is due to its ability to store information for future references and to learn temporal patterns. The successfulness in determining faulty conditions from IMB, helps industries to do further investigations on the root causes of this particular manner. Moreover, this method can ensure the production operation is monitored and will be alerted before IMB completely fails.

In this chapter also, we introduced a simple GUI as a tool for IMB failure. From the results obtained, the network which give good performance is selected as the optimum network. After modelling process, the optimum network parameters (weights and biases) are saved and used in IMB failure GUI. By using GUI, the user only needs to load a desired signal into it to observe the shape of a raw signal, power spectrum and envelope spectrum. The status of a bearing condition will be shown in the left bottom of the GUI.

2.2 Methodology

2.2.1 Vibration Signal

The methodology used to diagnose IMB failure is shown as in Fig. 2.1. The vibration data used in this work is obtained from the Case Western Reserve University website [85]. The apparatus involved in these experiments are 2 hp, 3 phase induction motor (M), accelerometer (Acc), dynamometer (L), and torque transducer (S1). An accelerometer is mounted onto the motor housing at the drive end of the induction motor. The bearing's type used is deep groove ball bearing with an inside diameter of 0.9843 inches, outside diameter of 2.0472 inches, ball diameter of 0.3126 inches, pitch diameter of 1.537 inches and speed of about 1800 rpm. The vibration signal is collected at 12 kHz samples per second from the experimental rig.

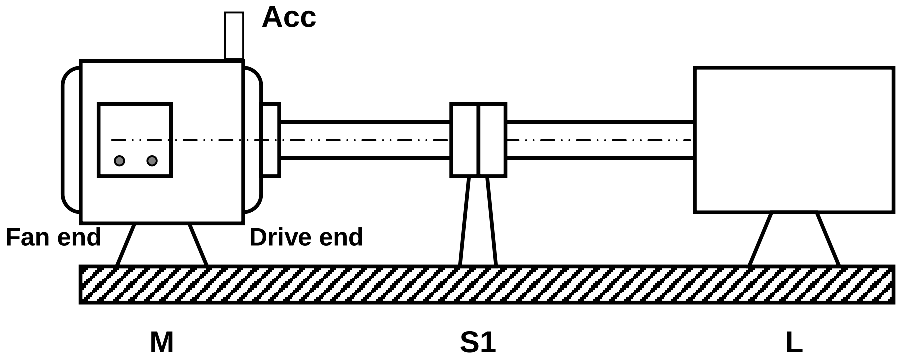


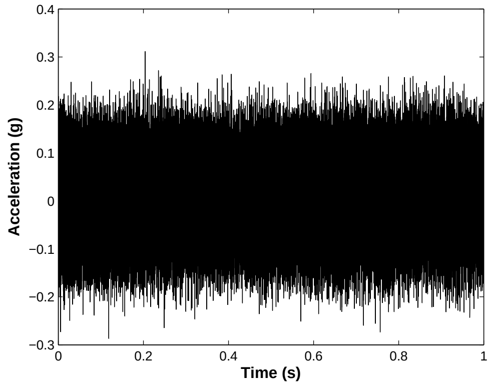
Figure 2.1: A diagram of experimental rig

The bearings are tested under four different loads (0, 1, 2, and 3 hp). Each defect bearing is tested with defect sizes of 0.007, 0.014, and 0.021 inches in which, every single point fault is introduced to the test bearing using electro-discharge machining (EDM). There are four different types of operating conditions obtained from experimental rig, which are from normal condition, inner race fault condition, outer race fault condition and ball fault condition. As a result, a total of 48 datasets can be obtained from this experiment.

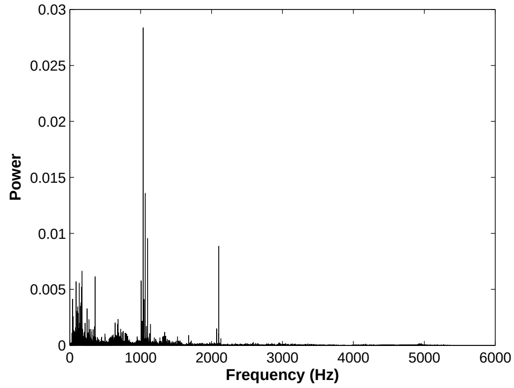
2.2.2 Pre-processing Stage

During pre-processing stage, the vibration signals from a bearing are being converted from time domain to frequency domain through the FFT. This signal is then converted to power spectrum in order to measure the power of a signal at a particular frequency.

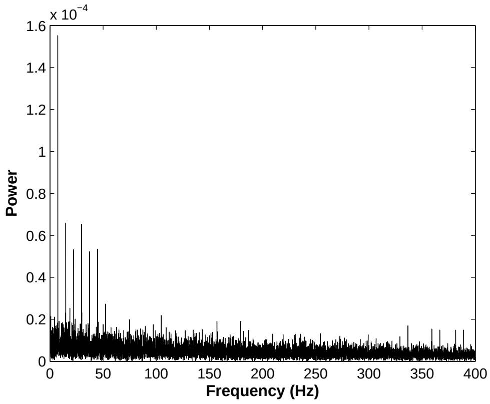
If vibration signal as shown in Fig. 2.2 (a) is defined as $x(k)$, that is discrete in time and frequency, it can be analyzed based on Discrete Fourier Transform (DFT). Eqn. (2.1) shows the finite signal energy of the vibration signal. By calculating the signal energy, the FFT can be applied. A computation of the DFT requires approximately N^2 complex multiplication, however, the FFT equation in (2.2) can reduce the computational complexity to about $N(log_2 N)$ operations [86]. Fig 2.2 (b) shows the power spectrum signal, which can be defined as the square of the absolute value of the $X(n)$ components, as shown in (2.3). According to Parseval's theorem, the energy in time domain is equal to energy in frequency domain. The power spectrum measure the power of signal at a particular frequency in a more usable form.



(a)



(b)



(c)

Figure 2.2: (a) Raw data, (b) power spectrum, and (b) envelope spectrum of vibration data during pre-processing stage

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