# ENHANCED GENETIC ALGORITHM-BASED BACK PROPAGATION NEURAL NETWORK TO DIAGNOSE CONDITIONS OF MULTIPLE-BEARING SYSTEM

LILI AYU WULANDHARI

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For my beloved parents:

My late father Hardi Muardi and Mother Ismituty

My brother Muhammad Fikri Utomo

whose love and support

For all of my friends,

Who always accompany me in my happiness and sadness

Without all of you, it is difficult for me to endure all of these adversities

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# ABSTRACT

Condition diagnosis of critical system such as multiple-bearing system is one of the most important maintenance activities in industry because it is essential that faults are detected early before the performance of the whole system is affected. Currently, the most significant issues in condition diagnosis are how to improve accuracy and stability of accuracy, as well as lessen the complexity of the diagnosis which would reduce processing time. Researchers have developed diagnosis techniques based on metaheuristic, specifically, Back Propagation Neural Network (BPNN) for single bearing system and small numbers of condition classes. However, they are not directly applicable or effective for multiple-bearing system because the diagnosis accuracy achieved is unsatisfactory. Therefore, this research proposed hybrid techniques to improve the performance of BPNN in terms of accuracy and stability of accuracy by using Adaptive Genetic Algorithm and Back Propagation Neural Network (AGA-BPNN), and multiple BPNN with AGA-BPNN (mBPNN-AGA-BPNN). These techniques are tested and validated on vibration signal data of multiple-bearing system. Experimental results showed the proposed techniques outperformed the BPPN in condition diagnosis. However, the large number of features from multiple-bearing system has affected the complexity of AGA-BPNN and mBPNN-AGA-BPNN, and significantly increased the amount of required processing time. Thus to investigate further, whether the number of features required can be reduced without compromising the diagnosis accuracy and stability, Grey Relational Analysis (GRA) was applied to determine the most dominant features in reducing the complexity of the diagnosis techniques. The experimental results showed that the hybrid of GRA and mBPNN-AGA-BPNN achieved accuracies of 99% for training, 100% for validation and 100% for testing. Besides that, the performance of the proposed hybrid accuracy increased by 11.9%, 13.5% and 11.9% in training, validation and testing respectively when compared to the standard BPNN. This hybrid has lessened the complexity which reduced nearly 55.96% of processing time. Furthermore, the hybrid has improved the stability of the accuracy whereby the differences in accuracy between the maximum and minimum values were 0.2%, 0% and 0% for training, validation and testing respectively. Hence, it can be concluded that the proposed diagnosis techniques have improved the accuracy and stability of accuracy within the minimum complexity and significantly reduced processing time.

# ABSTRAK

Diagnosis keadaan sistem kritikal seperti sistem galas berbilang adalah salah satu aktiviti penyelenggaraan yang sangat penting dalam industri kerana adalah penting bahawa kerosakan dikesan lebih awal sebelum pencapaian keseluruhan sistem terjejas. Pada masa ini, isu yang paling signifikan dalam diagnosis keadaan ialah bagaimana untuk memperbaiki ketepatan dan kestabilan ketepatan, serta mengurangkan kerumitan diagnosis untuk mengurangkan masa pemprosesan. Penyelidik-penyelidik telah membangunkan teknik diagnosis berdasarkan metaheuristik, terutamanya, Rangkaian Neural Rambatan Balik (BPNN) untuk sistem galas tunggal dan sebilangan kecil kelas-kelas keadaan.Walau bagaimanapun, teknik-teknik ini tidak boleh digunakan secara terus atau berkesan untuk sistem galas berbilang kerana ketepatan diagnosis yang dicapai tidak memuaskan. Oleh itu, penyelidikan ini mencadangkan teknik hibrid untuk memperbaiki pencapaian BPNN dari segi ketepatan dan kestabilan ketepatan iaitu Algoritma Genetik Adaptif dan Rangkaian Neural Rambatan Balik (AGA-BPNN), dan pelbagai BPNN dengan AGA-BPNN (mBPNN-AGA-BPNN). Teknik-teknik ini diuji dan disahkan keatas data isyarat getaran sistem galas berbilang. Keputusan eksperimen menunjukkan teknik yang dicadangkan mengatasi BPNN dalam diagnosis keadaan. Walau bagaimanapun, bilangan ciri-ciri yang banyak daripada sistem galas berbilang telah menjejaskan kerumitan AGA-BPNN dan mBPNN-AGA-BPNN, dan meningkatkan jumlah masa pemprosesan yang diperlukan secara signifikan. Oleh itu untuk menyiasat lebih lanjut, sama ada bilangan ciri-ciri yang diperlukan boleh dikurangkan tanpa menjejaskan ketepatan dan kestabilan diagnosis, Analisis Hubungan Kelabu (GRA) telah digunakan untuk menentukan ciri-ciri paling dominan dalam mengurangkan kerumitan teknik diagnosis. Keputusan eksperimen menunjukkan bahawa hibrid antara GRA dan mBPNN–AGA-BPNN mencapai ketepatan 99% untuk latihan, 100% untuk pengesahan dan 100% untuk pengujian. Selain daripada itu, pencapaian ketepatan hibrid yang dicadangkan meningkat sebanyak 11.9%, 13.5% dan 11.9% masing-masing dalam latihan, pengesahan dan pengujian apabila dibandingkan dengan teknik piawaian BPNN. Hibrid ini telah mengurangkan kerumitan dimana masa pemprosesan dikurangkan sehingga 55.96%. Selain itu, hybrid telah memperbaiki kestabilan ketepatan sehingga perbezaan ketepatan antara nilai maksimum dan minimum adalah 0.2%, 0% dan 0% masing-masing untuk latihan, pengesahan dan pengujian. Maka, boleh disimpulkan bahawa teknik diagnosis yang dicadangkan telah memperbaiki ketepatan dan kestabilan ketepatan dalam kerumitan minimum dan pengurangan masa pemprosesan yang signifikan.

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## LIST OF ABBREVIATION

| | | |
|---|---|---|
| AGA | - | Adaptive Genetic Algorithms |
| ANN | - | Artificial Neural Networks |
| BA | - | Baseline |
| BPNN | - | Back Propagation Neural Networks |
| CK | - | Cohen's Kappa |
| DC | - | Distinguish Coefficient |
| DE | - | Drive End |
| FDI | - | Fault Detection and Isolation |
| FE | - | Fan End |
| FL | - | Fuzzy Logic |
| GA | - | Genetic Algorithms |
| GRA | - | Grey Relational Analysis |
| GRC | - | Grey Relational Coefficient |
| GRG | - | Grey Relational Grade |
| mBPNN | - | multiple Back Propagation Neural Networks |
| MSE | - | Mean Square Error |
| RAM | - | Reliability, Availability and Maintainability |

# CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

Condition diagnosis is a process of identifying unexpected changes or malfunctions of a component in a system. In general, condition diagnosis involves the following tasks: (1) fault detection, which is to indicate a fault has occurred or not in the system, (2) fault isolation, which is to determine the location of the fault, and (3) fault identification, which is to estimate the size and nature of the fault. Fault detection and fault isolation are considered the most important stages of the condition diagnosis system. Thus, condition diagnosis is often referred to as fault detection and isolation (FDI) (Bocaniala and Palade, 2006). Condition diagnosis must be conducted early before it affects the performance of the whole system. Earliness and effectiveness is the key in condition-diagnosing a system.

Many researchers have proposed various techniques for condition or fault diagnosis, for instance, expert system approaches which was applied to diagnose complex chemical processes (Qian *et al.*, 2003); exact wavelet analysis for machine diagnosis (Tse *et al.*, 2004); multi-class Support Vector Machine for rotating machinery (Yang *et al.*, 2005); model-based approach (Isermann, 2005), wavelet transform and Neural Networks (Srinivas *et al.*, 2010); and Principal

Component Analysis (Min *et al.*, 2011).

Condition diagnosis system is applied in various industries as it is one of the most important requirements to avoid total breakdown of the system. Especially in critical system such as bearing system which are used in many applications. A bearing is a device that allows restrained relative motion between two moving parts. Bearings are used to reduce friction on rotating shaft by providing smooth metal balls or rollers and a smooth inner and outer metal surfaces for the balls to roll against. They are widely used in many applications and different applications have different kind of bearing used. For example the tapered roller bearings are used for automobile wheels (as shown in Figure 1.1), the cylindrical roller bearing for aircraft GA turbine engine, and needle roller bearing for car follower assembly (Harris and Kotzalas, 2007).

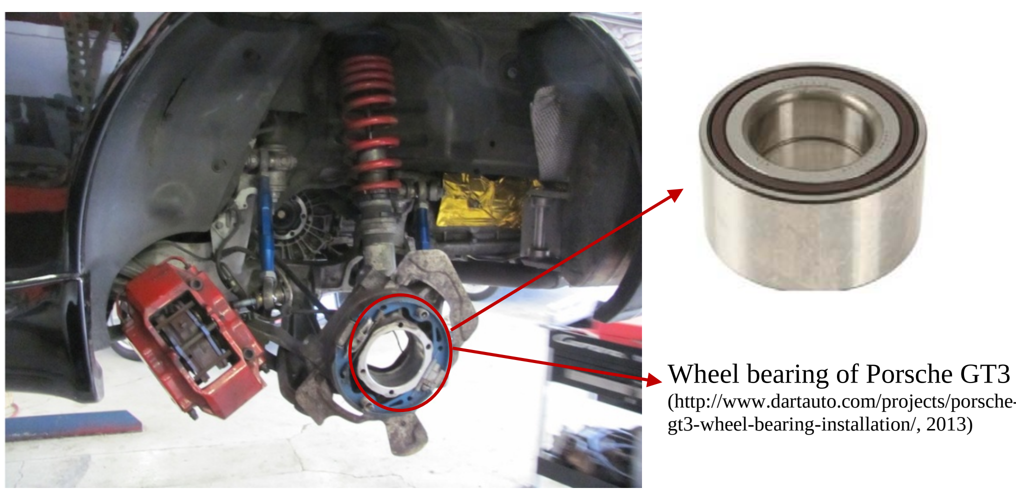



**Figure 1.1** Example of tapered roller bearing in automobile wheels

Appropriate bearing designs can minimize the friction and its failure may cause expensive loss of production (Harnoy, 2003). However, the bearing is one of machine parts which has a high percentage of defect as compared to the other components (Rodriguez and Arkkio, 2008). Therefore, an early and effective condition diagnosis of a bearing is an essential task.

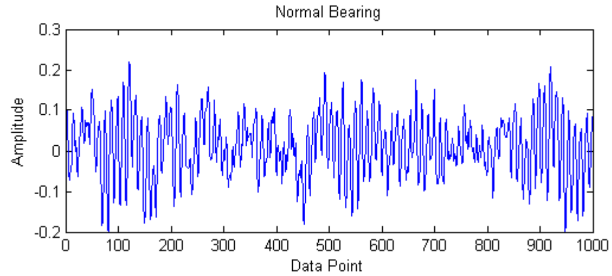
Many researchers have proposed techniques in bearing condition diagnosis. Su and Lin (Su and Lin, 1992), for instance, proposed a technique that used the frequency characteristic of bearing vibration signals. Another researcher applied discrete wavelet transform (DWT) to vibration signals to predict the occurrence of spilling in ball bearings (Mori *et al.*, 1996). Statistical analysis of sound vibration signals was also used by Heng and Nor (Heng and Nor, 1998) for monitoring the rolling element bearing condition. Other fault diagnosis techniques were developed based on empirical mode decomposition (EMD) and Hilbert Spectrum (Yu *et al.*, 2005), and Laplace wavelet enveloped power spectrum (Al-Raheem *et al.*, 2007). Individual metaheuristic techniques such as the genetic algorithms (GA), Fuzzy logic and Artificial Neural Networks (ANNs) have also been used for condition diagnosis (Jayaswal *et al.*, 2010; Rafiee *et al.*, 2007; Wen and Han, 1995). However, individual metaheuristic techniques for condition diagnosis suffer from their own drawbacks such as Back Propagation Neural Networks (BPNN) which are difficult to diagnose a new fault (Hu *et al.*, 2001). Moreover, if condition diagnosis involves many characteristic parameters, BPNN will need much longer network training time, or even be unable to train, thus decreasing the diagnosis accuracy (Enping *et al.*, 2008). Meanwhile, GA encounter difficulties in finding fitness function that effectively work in fault diagnosis (Yangping *et al.*, 2000) and fuzzy logic has drawback of the lack in learning ability (Tiwari *et al.*, 2013). These individual metaheuristic drawbacks can be overcome by forming a hybrid approach that combines the advantages of each technique (Jayaswal *et al.*, 2010). Among the drawbacks, this research addressed the issues related to the accuracy of condition diagnosis especially when it involves multiple bearings, the stability of accuracy and the complexity of the condition diagnosis techniques.

## 1.2 Problem Background

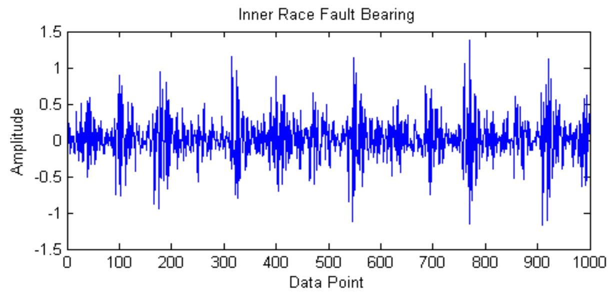
In industry, unexpected faults of a critical system such as bearing system must be minimized. This unexpected condition can lead to total failure of the whole system. An effective diagnosis can detect faults much earlier and unacceptable consequences from total system failure can be avoided. The earliness and effectiveness of condition diagnosis is supported by condition monitoring which provide information regarding the condition of the system. For bearing systems, the vibration signals captured using an accelerometer can be used to represent the conditions of the bearing. The accelerometer records condition of the bearing system continuously. Vibration signals data are commonly used for bearing condition diagnosis since the information regarding the bearing condition is contained in the vibration signals (Min *et al.*, 2011). Vibration signals display different amplitude if a problem in the system exists. As shown in Figure 1.2, the vibration signals of a normal bearing are distinct from faulty bearing. The faulty bearing vibration signals data have much higher amplitude than the normal bearing vibration signals.

However, in a multiple-bearing system, for instances when one of the bearings has problems and the others are normal, the vibration signals that transpired from this condition may not give a representation that visually distinct from the condition when all the bearings are normal (see Figure 1.3). Therefore, it is important to have a technique that is able to accurately diagnose the system condition based on the continuously monitored vibration signals.

Back Propagation Neural Networks (BPNN) is one of the techniques that is used for condition diagnosis (Bakhary *et al.*, 2007; Hoskins *et al.*, 1991; Khanmohammadi *et al.*, 2000; Mitoma *et al.*, 2008; Ogaji and Singh, 2006; Payganeh *et al.*, 2012; Sreejith *et al.*, 2008). BPNN is used to model the behaviours of the system which are then classified. BPNN is an suitable tool for modelling the behaviours of a system since they have the following three important characteristics: generalization ability, noise tolerance and fast response once trained (Puscasu *et al.*, 2000). Even if the training data are affected by noise, BPNN will still be able to generalize the system behaviour with the level of accuracy being proportional to the level of noise (Bocaniala and Palade, 2006).




(a)




(b)

**Figure 1.2** Vibration Signals of Normal Bearing (a) and Faulty Bearing (b)

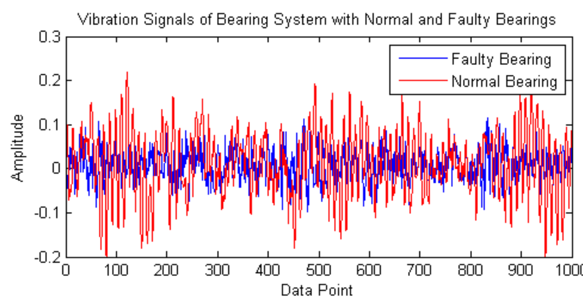



**Figure 1.3** Vibration Signals from Both Bearings Are Normal and One of Bearing is Normal whilst the other is Faulty in a Multiple Bearing System

However, for multiple-bearing cases, individual BPNN cannot give satisfactory results because those cases involve large numbers of features of vibration signals data and condition classes which will affect the topology complexity and connectivity weights of BPNN. The number of features of vibration signals data has influences on BPNN input neurons while condition classes have influences to BPNN output neurons, which consequently influences the number of connectivity weights in BPNN training performance (Hashem, 1997). The connectivity weights has important role in providing a good performance of BPNN, in this case the diagnosis accuracy of a condition. Accuracy is the degree to which the result of a measurement or calculation conforms to the correct value or a standard.

The random initial connectivity weights can induce unsatisfactory of condition diagnosis accuracy from standard BPNN (Chang *et al.*, 2012). The randomness of initial connectivity weights can be minimized by setting up pre-processing techniques to produce better weights for BPNN learning process. Since 1990 researchers have been developing techniques such as two-layers neural networks approaches (Nguyen and Widrow, 1990b), least squares method (Erdogmus *et al.*, 2003; Yam and Chow, 1995), Cauchy's inequality and linear algebraic (Yam and Chow, 2000), geometrical approach (Redondo and Espinosa, 2001; Sookil and Sunwon, 2006), statistical approach (Olden and Jackson, 2002), Particle Swarm Optimization (PSO) (Al-Shareef and Abbod, 2010; Nikelshpur and Tappert, 2013) and Genetic Algorithms (GA) (Chang *et al.*, 2012; Shanti *et al.*, 2009). All of these approaches were used to determine the initial weights of the BPNN in simpler topology and classes compared to the topology and classes of multiple-bearing system. Among these approaches, the GA are superior when they are applied to "gradient descent" based techniques such as BPNN (Srinivas and Patnaik, 1994) and the single bearing system, due to GA are proven capable to deal with vibration signals data (Lee *et al.*, 2007; Zhang and Randall, 2009). However, it cannot be denied that GA are trapped into prematurely convergence issue which affects local optima (Srinivas and Patnaik, 1994; Vellev, 2008).

Two important aspects in learning models are how well the model generalizes the unseen data and how the model deals with the problem complexity. Networks with larger complexity might be expected to have lower result of training and higher of generalization error (Lawrence *et al.*, 1997). This ability of generalization becomes the current issues of BPNN perfomance (Panchal *et al.*, 2011; Piotrowski and Napiorkowski, 2013; Yinyin *et al.*, 2008). It means that BPNN cannot generalize the connectivity weights of training process to similar patterns of unobserved data and this is known as ovefitting (Mahdaviani *et al.*, 2008). The effect of this generalization error is that the diagnosis accuracy of the training, validation and testing process of BPNN will be unstable, known as instability of accuracy.

Instability of accuracy can be identified by running a certain BPNN ten times with the same features, says BPNN 30-30-30-30-16, we can obtain different accuracy significantly since we use initial weights randomly. This is indicated by the range of minimum and maximum points of accuracy which is significantly different as shown in Figure 1.4.

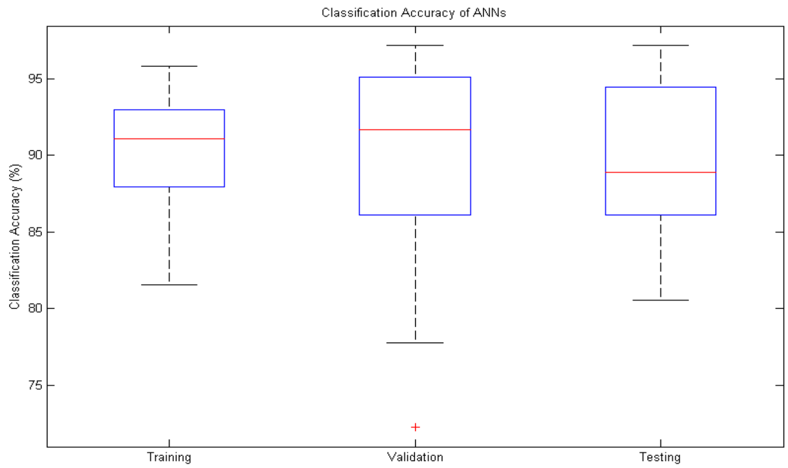



**Figure 1.4** Diagnosis accuracy of BPNN learning process experiments

From Figure 1.4, we can see that the minimum accuracy of training is around 82% and the maximum is around 96% and so the distinction around 14%. The validation and test accuracy as well have high distinction between minimum and maximum values, which is around 25% and 16% repectively. This implies that the BPNN 30-30-30-30-16 performance is unstable as the final weights of ten running BPNN 30-30-30-30-16 are different and do not converge to an optimum weights.The final weights of ten BPNN 30-30-30-30-16 are different because the initial weights were selected randomly. This condition proves that BPNN has conflict between overfitting and generalization which leads to a low learning training speed and the tendency of converging to a local optimum point of the network (Rafiee *et al.*, 2007; Tetteh *et al.*, 1996).

In condition diagnosis purpose, features extraction plays an important role. Features are any parameters extracted from the measurements in order to enhance the condition detection (Li *et al.*, 2003). For multiple-bearing case, large numbers of features of vibration signals data which are recorded from multiple accelerometers are used to diagnose the condition of the bearings. In other words, it involves large features extraction in order to obtain precise condition diagnosis and as such, the BPNN complexity increases. Evidently, the complexity of BPNN influences the processing time (Lawrence *et al.*, 1997). In order to reduce the BPNN complexity, the dominant features for condition diagnosis must be determined and chosen correctly since choosing the features randomly to be used as inputs will consequently influence the diagnosis accuracy and become time consuming (Fischer *et al.*, 1979). The dominant features are the features that contain the most useful information regarding to the multiple-bearing condition. By finding these features an accurate diagnosis of multiple-bearing condition can be obtained in less complexity and processing time.

According to the previous explanation, this research addresses the issues of accuracy, stability of accuracy and complexity in BPPNs for condition diagnosis of multiple-bearing system in which the number of features of vibration signals, or the input neurons, and the number of condition classes are large.

## 1.3 Problem Statement

In the diagnosis field, back propagation neural networks (BPNN) are used as one of techniques to identify the condition of a system. However in multiple bearings case, BPNN encounter some drawbacks due to the complexity of the multiple-bearing condition diagnosis. Therefore, efforts must be taken so that precise condition diagnosis can be achieved. Hybrid approach is one of the attempts which can be conducted to overcome some drawbacks of BPNN and to achieve good accuracy in multiple-bearing condition diagnosis. Thus, the main question of the research is: *"How to develop hybrid mechanism to improve the BPNN performance in terms of accuracy and stability of accuracy, for condition diagnosis for multiple-bearing systems?"*

The sub questions of the main research question are as follows:

1. How to develop optimization based techniques for determining the best initial weights of BPNN to improve the accuracy of condition diagnosis for multiple bearings systems?

2. How to develop multiple classifier strategies for BPNN to improve the stability in accuracy of condition diagnosis for multiple bearings system?

3. How to identify and select the dominant features from vibration signals of bearing conditions data to minimize the BPNN complexity while maintaining the required accuracy and stability of condition diagnosis?

## 1.4 Research Objectives

The objectives of this research are:

1. To propose GA based algorithms with adaptive operator probabilities to obtain the optimal initial weights of BPNN to improve the accuracy of condition diagnosis in multiple-bearing systems.
2. To propose hybrid algorithm for stabilizing the accuracy of GA based-BPNN condition diagnosis algorithm using multiple BPNN.
3. To identify and select dominant features of vibration signals in multiple-bearing system using Grey Relational Analysis (GRA) to minimize the BPNN complexity while maintaining the required accuracy and stability.
4. To validate, test and evaluate the performance the proposed hybrid algorithms using Confusion Matrix and Cohen’s Kappa.

## 1.5 Research Scope

In order to achieve the objectives stated above, the scope of this research is focuses on three parts. First scope encompasses the vibration signals data processing which consists of features extraction and standardization. In this research, the vibration signals data are obtained and validated by the Case Western Reserve University Bearing Data Center (Loparo). This data is captured from three accelerometers that are attached on two bearings, namely Fan End Bearing (FE) and Drive End Bearing (DE), and attached on the Baseline (BA) of the system. The vibration signals data are recorded in seven condition classes which are further improved into sixteen classes of condition diagnosis.

Second, this research elaborates on the development of hybrid approach in BPNN to improve the accuracy and stability of accuracy in condition diagnosis of multiple-bearing system. The hybrid approach use optimization based algorithm namely Genetic Algorithm with adaptive operator probabilities to obtain the optimal initial weights, the BPNN with *"gradient descent momentum"* as the training function for the diagnosis technique and Grey Relational Analysis as the dominant features selection techniques.

And thirdly, this research presents the algorithm evaluation to see the performance of the algorithms in condition diagnosis of the multiple-bearing system. This evaluation is conducted in diagnosis accuracy and stability accuracy which is measured using confusion matrix and Cohen's Kappa approach. From the evaluation, the improvement of the BPNN enhancement algorithm can be clearly compared with the standard BPNN performance without the enhancement algorithm development.

## 1.6 Research Significance

A precise condition diagnosis is an urgent requirement especially in the industrial application. Imprecise diagnosis causes any faults in the system cannot be identified correctly and can affect to the total breakdown of the system. The total breakdown lead to increased of production cost. Therefore, an effort to improve the condition diagnosis accuracy is needed.

One of the issues of existing condition diagnosis techniques is that it cannot generalize the accuracy for the unobserved data. When the accuracy of observed data is not stable for a new data set, this is known as overfitting. If the condition diagnosis technique is overfitting, it is not valid to diagnose the condition of the system because it can give wrong diagnosis for the condition and it is dangerous if used in the industry field. Therefore, a technique to provide a stable accuracy for unobserved data is required.

Precise condition diagnosis of multiple bearing system is achieved by analysing as much as possible information extracted from the vibration signals data. In this research, ten features are extracted from three acceleremoters which record the vibration signals of the multiple-bearing systems. It means this algorithm involves thirty input neurons for the BPNN process. That is quite a large number of neuron which will influence the complexity. The increase in complexity can cause an increase in the processing time, so the diagnose cannot be provided instantly as the industry need. Therefore, dominant features identification and selection are needed to minimize the complexity of condition diagnosis technique while maintaining the required accuracy and stability.

## 1.7 Thesis Organization

This thesis is divided into seven chapters that discuss on issues related to condition diagnosis in multiple bearings system. Each chapter will describe specifically the development of enhancement approaches for BPNN to improve the accuracy and stability of accuracy in condition diagnosis of multiple bearings system. This thesis has outline as follows:

**Chapter 1:** presents the introduction of condition diagnosis and multiple bearings system. This chapter describes current issue in condition diagnosis of multiple bearing system, problem statements, objectives, scope and significances of the research.

**Chapter 2:** explains the literature review of condition diagnosis algorithm. First it explains the establish concept of and techniques for condition diagnosis, followed by description of existing metaheuristic techniques of condition diagnosis especially in bearing system, and also the Back Propagation Neural Networks (ANNs) and Genetic Algorithm in condition diagnosis and multiple ANNs as one of methods to improve ANNs performance. Dominant feature selection techniques and algorithm performance evaluation is presented in the next section. Finally this chapter is ended with the summary of literature review in establish condition diagnosis algorithms.

**Chapter 3:** discusses the methodology of the research that covers research operational framework, problem analysis, algorithm development, data collection and analysis and algorithm performance analysis.

**Chapter 4:** describes the development of genetic algorithms (GA) based approaches for back propagation neural networks (BPNN). It is started by the hybridization of GA-BPNN and Adaptive GA (AGA)-BPNN in order to obtain good condition diagnosis, followed by performance evaluation of GA-BPNN and AGA-BPNN. This chapter is concluded by the summary of the algorithm development and performance evaluation.

**Chapter 5:** presents multiple back propagation neural networks (mBPNN) and adaptive genetic algorithms (AGA) developments. This chapter consists of development of mBPNN-AGA-BPNN developments, performance evaluation and algorithm implementation in bearing system diagnosis.

**Chapter 6:** describes the dominant features identification using grey relational analysis (GRA). It presents the GRA methodology and the performance evaluation of selected dominant features in AGA-BPNN and mBPNN-AGA-BPNN algorithms.

**Chapter 7:** provides the summary of the research, the research contribution for body of knowledge and practical in condition diagnosis of multiple-bearing system, the limitation and future work of this research.

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