CONDITION MONITORING OF A FAN USING NEURAL NETWORKS

BY

BO ZHANG

A THESIS SUBMITTED IN PARTIAL FULFILMENT

OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE (M.Sc.) IN COMPUTATIONAL SCIENCES

THE SCHOOL OF GRADUATE STUDIES

LAURENTIAN UNIVERSITY

SUDBURY, ONTARIO, CANADA

THESIS DEFENCE COMMITTEE/COMITÉ DE SOUTENANCE DE THÈSE

Laurentian Université/Université Laurentienne

School of Graduate Studies/École des études supérieures

Title of Thesis Titre de la these	CONDITION MONITORING OF A FAN USING NEURAL NETWORKS		
Name of Candidate Nom du candidat	Zhang, Bo		
Degree Diplôme	Master of Science		
Department/Program Département/Programme	Computational Sciences	Date of Defence Date de la soutenance	January 24, 2014

APPROVED/APPROUVÉ

Thesis Examiners/Examinateurs de thèse:

Dr. Kalpdrum Passi
(Co-supervisor/Co-directeur de thèse)

Dr. Markus Timusk
(Co-supervisor/Co-directeur de thèse)

Dr. Amr Abdel-Dayem
(Committee member/Membre du comité)

Dr. Sabah Mohammed
(External Examiner/Examinateur externe)

Approved for the School of Graduate Studies
Approuvé pour l'École des études supérieures
Dr. David Lesbarrères
M. David Lesbarrères
Director, School of Graduate Studies
Directeur, École des études supérieures

ACCESSIBILITY CLAUSE AND PERMISSION TO USE

Abstract

Fan is widely used in various industrial fields and it plays a key role in cooling the machinery. For the machinery to work properly, the fan system should remain in stable and error-free condition. Condition monitoring, as a maintenance tool, is introduced to fan system's fault diagnosis.

Many available methods are used in condition monitoring, such as vibration monitoring and thermal monitoring. The vibration monitoring method was used in the experiment. A fan system based on Machinery Fault Simulator™ (MFS) was used to simulate fan's different conditions in the laboratory. An accelerometer was installed on the top of the bearing housing. It was used to detect the vibration signal of the fan when it was working. A data acquisition program designed in LabVIEW was used to record and preprocess the raw vibration signal. The collected data was used to detect the condition of the fan system.

Neural network was used for the fault diagnosis. The raw vibration signal is a one-dimensional time domain series data, while the neural network requires multidimensional features as input data. Therefore, it is important to preprocess the raw vibration signal data. Two different preprocessing methods, time-domain features and Auto Regressive (AR) model features were used to preprocess separately. The neural network model was trained by these two methods respectively. The results

showed that the AR model gave better features than that by the time domain features method.

The condition monitoring system consisted of the following parts: data acquisition, data storage, data preprocessing and the display of results. Some methods were programmed in Matlab, which were called by Matlab scripts in the LabVIEW software. The hybrid programming method helped to generate an efficient program which provided high accuracy of fault diagnosis.

Acknowledgements

During my study at Laurentian University, I have been lucky to receive valuable suggestions and support from my mentors.

I would like to acknowledge my supervisors Dr. Kalpdrum Passi and Dr. Markus Timusk. Dr. Passi introduced me to the data mining field and helped me in selecting my research direction and topic. I express my sincere gratitude and indebtedness to Dr. Timusk who introduced me to condition monitoring and the equipment used for gathering data for a fan. He helped me correct mistakes in my experiment and pointed me to work in the right direction. He was always able to help me with laboratory experimental set up.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

As science and technology has progressed, modern industry has developed towards large-scale, high-speed, continuous and automated manufacturing processes. Whereas technological improvements of modern equipment bring more economic benefits, it causes the faults in the equipment to be increasingly complex, which can have grave consequences. If the fault is not found and repaired in time, it may lead to serious problems, such as the halt of production led by any breakdown of equipment, potential threat the safety of employees, and may even cause environmental pollution.

Rotating machinery are the key components of equipment that are widely used in power generation sector, petrochemical industry, metallurgical industry, machinery industry, aviation industry and national defense industry. The U.S. Electric Power Research Institute statistics show that 30%~50% of the reasons shut down the power plants were caused by faults in the rotating machinery, such as turbine generators, fans and pumps [35]. Depending on the importance, the equipment can be divided into three categories: critical equipment, necessary equipment and auxiliary equipment. Air blower, primary air fan, power generator, boiler feed pump are listed as critical equipment. As a result, research institutes and enterprises attach great importance to fault diagnosis in fans.

Fan is widely used in various industrial fields. In factory premises, the operation of equipment generates enormous amounts of heat, but their operation requires the maintenance of certain temperature conditions. High temperature causes overheating, which may break the machines. Good heat dissipation ability helps the machines and equipment to be in good working condition for a long time. Air-cooled radiator, which has the fan as a key component, exudes a tremendous amount of heat. It is used to maintain machine's temperature. Wind energy is a renewable, widely distributed and non-pollution source of energy [30], fan blades are the key components of wind turbines.

Nowadays, fans are increasing used in machinery at a large-scale, run at high-speed and can be complex. Fans working at high-speed for a long time in harsh working conditions, with inappropriate maintenance and excessive demands may cause faults. The failures of high-speed fans may cause equipment damage, personal injury and huge economic losses. Therefore, monitoring the fan's condition is critical.

Machinery and equipment wear out with continuous use over a period of time. Many reasons may cause failures, such as deficiencies in material and processing; improper assembly practices and service conditions; inappropriate maintenance and excessive demands. Many machinery failure cases show that the failure rates are different in different periods of continuous time. When the failure rates are plotted on a graph based on time, the results look like 'bath-tub' curve, as showed in Figure 1.1 [4].

The bath-tub curve can be divided into three different periods: wear-in period, normal use period and wear-out period. The curve shows significant different features in the three periods.

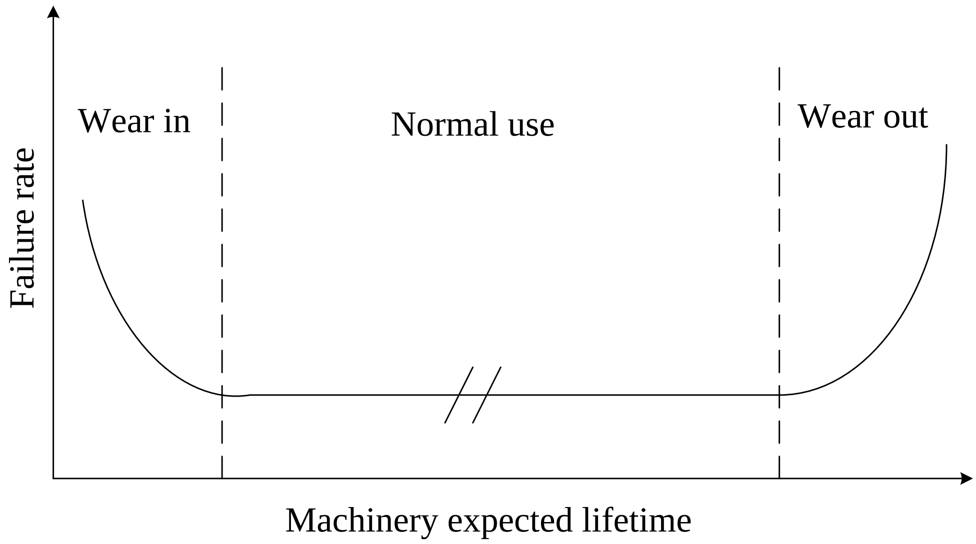


Figure 1.1 Bath-tub Curve

Failures that happen in the early time of expected life are in very high frequency; this early time period is called wear-in period. This unusual high frequency failure may be caused by design errors, manufacturing mistakes, installation mistakes or commissioning errors. Normally all the machinery needs a run-time test after installation. Failure or potential threat of failure is easier to handle when it happened in the early test run. Wear that happens in normal use period typically occurs during the majority of the life of a machine. The machineries have passed high frequency failure rate wear-in time and then work in a stable producing period. This period is a relatively low failure rate time when operating within design specifications in a long time as the machinery has passed the early run-time test. Wear-out failure rate will increase sharply when the lifetime is close to the end of a machine's design life due to fatigue, wear mechanisms, corrosion and obsolescence, and operational history. In any case, failures will happen at any time of the life of a mechanical product, that’s why maintenance is necessary during machine's whole lifetime.

1.2 Fault Diagnosis

The history of fault diagnosis is closely related to equipment maintenance. In the development history of equipment technology, equipment maintenance includes three basic categories, run to failure, scheduled and condition based maintenance [37]. The first generation of equipment maintenance, run-to-failure maintenance, was the main maintenance method in the early times of Industrial Revolution. This kind of maintenance was performed when the machinery failed, for instance, using a new light bulb to replace the broken one. Scheduled maintenance, which is the second generation maintenance, developed with assembly line mass production from 1920 to 1960, performed at scheduled time intervals, for instance, oil changes on the car every 8000 kilometers. The machinery manufacturers usually do various tests to confirm the machinery’s maintenance circle, which makes scheduled maintenance reliable and cost-effective. For complex machinery, it has many components; systems are needed for planning and controlling work. With the advent of the computers, the maintenance timetable is scheduled. The benefit of the second generation maintenance is high plant availability, long equipment life and low costs. From 1960 to now, Condition-based maintenance, which is considered as the third generation of maintenance, is widely used all over the world. It is a high reliable maintenance method, which has higher factory availability. It is a safety maintenance method too, which help the maintenance engineers to avoid dangerous environment. The cost is low as most of the jobs are finished automatically by the computer. Condition maintenance involves obtaining machinery's condition in its whole life and gives engineers effective information in time. Nowadays, the machinery is designed for reliability and maintainability, and the importance of hazard studies such as failure modes and effects analyses is well understood. With the help of smaller, faster computers, expert systems are designed for analysis of data collected from the condition monitoring equipment. It helps engineers to obtain the condition of the machinery in real time, and make plans for maintenance on time. The condition monitoring maintenance needs multiple skills and teamwork; it is also used to optimally schedule maintenance, with the purpose of maximum production and avoidance of catastrophic failures. Figure 1.2 shows the change of failure rate in the machinery's whole lifetime under the condition of maintenance.

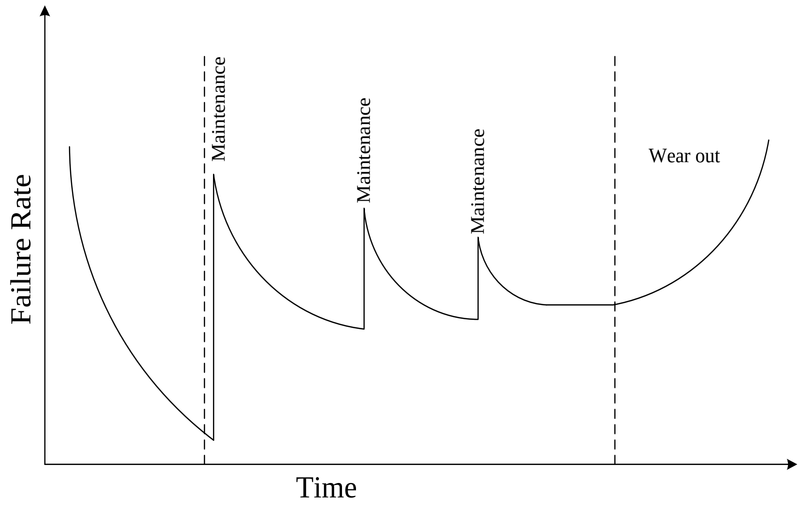


Figure 1.2 Failure Rate with Maintenance

Fault Diagnosis is an emerging discipline that is based on reliability theory, information theory, cybernetics theory and systems theory [21]. It uses modern test instruments and computer technology as technical means to study on a variety of diagnostic objects' features.

Fault diagnosis theory is generally composed of three parts [36]. The first part is physical and chemical study of fault diagnosis, such as physical and chemical reasons of electrical and mechanical components' corrosion, and vibration; the second part is information theory of fault diagnosis, which is focused on fault signal's acquisition, selection, processing and analysis; the last part is diagnostic logic, mathematical principle, which is mainly using logical method, presumption, and artificial intelligence methods to analyze and determine the location and cause of the failure parts.

Machine condition diagnosis technique is a multidisciplinary integrated technology. It includes monitoring the equipment's operational conditions, finding the failure parts, causes and severity of failures, predicting equipment's reliability and remaining lifetime and proposed control measures without disassembly.

Since the seventies, there has been significant development of diagnostic techniques for different types of machinery. For the purpose of saving resources and reducing costs, problems on integrated engineering and life cycle costs were considered. These were great driving forces for the development of equipment diagnostic technology [18]. On the technical side, 1960s was the era of the development of computer and electronic technology. As a result mathematical techniques such as Fast Fourier Transform and algorithm languages were developed. Signal analysis technology was developed as hardware and software. The development of Acoustic Emission technology, infrared temperature measurement technology, oil analysis technology, spectral analysis technology of vibration signals and various kinds of nondestructive testing technologies, promoted the development of Equipment Diagnostic techniques with hardware and software [18].

Fault diagnosis is widely applied in quality control, process control and process monitoring as a maintenance tool. In these procedures, a series of physical parameters, such as vibration, oil quality, sound pressure, temperature and any parameters that provide insight of the condition of the machine are monitored for the purpose of determining machine integrity.

Vibration signal and state quantity are the most common and effective methods in machine condition diagnosis. Vibration signal and its feature information reflect the condition of the whole system when the machinery and the structural system are working. Dynamic test instruments collect, record, and analyze dynamic signals and are used to detect system state and fault diagnosis.

1.3 Artificial Intelligence and Neural Network

In the early times experts diagnosed the condition of the equipment by hearing, feeling and watching the equipment carefully. All the information was compared with the experts' knowledge which they learned by their experience. Based on this information, the experts were able to detect the problem in the equipment. However, the experts were unable to monitor the equipment all the time. It was a waste of time and money. It was difficult to train skilled experts either. All of these problems have led to the development of other convenient, low cost methods to do failure diagnosis. It was found that neural network is an ideal technique for failure diagnosis.

Long before the emergence of electronic computers, humans began to explore the secrets of intelligence, to simulate the human brain. In general, study on artificial intelligence can be related to traditional symbolic artificial intelligence technology and artificial neural network technologies [6]. In fact, these two kinds of technologies simulated the perspectives of psychology and physiology, which are adapted to understand and deal with different aspects of things. Currently, people are doing research from various angles on how to combine these two technologies.

As we all know, humans are intelligent, can remember things, do activities with purpose, acquire knowledge by learning and enriching them in the subsequent study. Humans are also able to use the knowledge to explore, find and create unknown things. So intelligence is the integrated ability of individual purposeful behavior, reasonable thinking and adapting to the environment effectively. It is the ability of people to understand objective things and use knowledge to solve problems. According to the above description, the individual human intelligence has comprehensive capacity.

Artificial intelligence was introduced in 1965 [29]. It studies how to make computers imitate human brains' activities such as reasoning, designing, thinking and learning. It is used for dealing with complex problems. Based on modern neuroscience research, scientists believe that the nature of intelligence is coupling mechanism. Neural network is a highly complex large nonlinear adaptive system, which is made of a large number of simple processing units [7]. The research of modern neuroscience believes that the cerebral cortex is a widely connected giant complex system, which includes about a hundred billion neurons, and these neurons are connected by hundred billion dendrites and axons that constitute a large neural network system [12]. Artificial neural network is designed to simulate the behavior of brain’s neural network. The artificial neurons have processing capacity, and can send and receive analog signals from other neurons in a certain form. Transmission and processing by the neurons is performed simultaneously. As a result, artificial neural network can perform massively parallel processing. Studies have shown that the information stored in the brain's memory is achieved by changing the coupling strength of the synaptic [34]. The coupling strength of the synaptic determines the signal strength between neurons. Information is distributed among the neurons, which have the capability of processing and storing information. Distributed storage of information provides a good foundation for parallel processing and fault tolerance. The artificial neural network can be trained, which changes the strength of the coupling and as a result the system acquires new knowledge.

Each artificial neuron can receive input signals from other neurons, with a weight value, and the sum of all weighted inputs determines the neuron's activation status. The weight value is equivalent to connection strength of synaptic.

Assume n inputs as x_1, x_2, ... x_n, and their corresponding weight values as w_1, w_2 , ... w_n， all of the inputs and corresponding weights constitute the input vector X and weight vector W:

$$X = (x_1, x_2, ...x_n) \tag{1.1}$$

$$W = (w_1, w_2, ...w_3) \tag{1.2}$$

The cumulative effect of the input signal is called the network input of this neuron as shown below *equation 1.3*.

$$net = \sum x_i w_i \tag{1.3}$$

The vector form is written as:

$$net = XW \tag{1.4}$$

After the neuron gets the network input, it has an appropriate output. According to biological neuron's features, each artificial neuron has a threshold. When the total inputs exceed the threshold value, the neuron is in activation status; otherwise, the neuron is in inhibitory status. Usually the artificial neurons have a transformation function that makes the system widely used. This function is used to process the inputs and is called activation function, denoted as f:

$$o = f(net) \tag{1.5}$$

where o is the output of the neuron. This function is also used to amplify the output or to limit the output in an appropriate range. Typical activation functions as shown in Figure 1.3 are (a) linear function, (b) ramp function, (c) threshold function and (d) Squashing function [19].

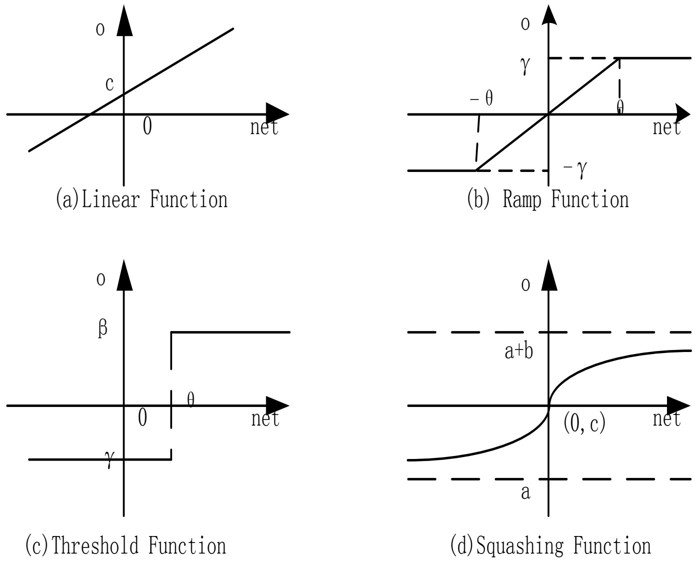


Figure 1.3 Typical Activation Functions

Linear function is the basic activation function. It is used for linear amplification or reduction of the neuron's output. The general form is:

$$f(net) = k \times net + c \tag{1.6}$$

where k is amplification factor, c is displacement, are constants.

Linear function is very simple, but its linearity reduces the network performance significantly. Under certain conditions, it degenerates the multiple layers neural network into a single layer neural network. But these neurons are able to use this function in the final layer of multilayer networks as function approximates.

Ramp function is a piecewise linear function, it limits the results in a given range $[-r, r]$:

$$\mathrm{f(net)} = \begin{cases} r & if\ net \geq \theta \\ k \times net & if\ |net| < \theta \\ -r & if\ net \leq \theta \end{cases} \tag{1.7}$$

r , as a constant, is the maximum output of the neuron.

Threshold function is used to determine if the network input is over threshold θ :

$$f(\text{net}) = \begin{cases} \beta & if\ net > \theta \\ -\gamma & if\ net\ \le \theta \end{cases} \tag{1.8}$$

In practical applications, this function's binary form is used widely:

$$f(\text{net}) = \begin{cases} 1 & if\ net > \theta \\ 0 & if\ net\ \le \theta \end{cases} \text{ or } f(\text{net}) = \begin{cases} 1 & if\ net > \theta \\ -1 & if\ net\ \le \theta \end{cases} \tag{1.9}$$

Squashing function is commonly used in the hidden layers of multilayer networks, its general form is:

$$f(\text{net}) = \text{a} + \frac{b}{1 + \exp(-d \times net)} \tag{1.10}$$

where a, b, d are constants.

The minimum and maximum of this function is a and $\text{a} + \text{b}$ respectively. While $\text{a} = 0$ and $\text{b} = 1$, the function is:

$$f(\text{net}) = \frac{1}{1 + \exp(-d \times net)} \tag{1.11}$$

There are also some other functions that can be used here, like expansion square function and hyperbolic functions [33]:

$$f(\text{net}) = \begin{cases} \dfrac{net^2}{1 + net^2} & if\ net > 0 \\ 0 & else \end{cases} \tag{1.12}$$

where the minimum and maximum values are 0 and 1.

$$f(\text{net}) = \tanh(\text{net}) = \frac{e^{net} - e^{-net}}{e^{net} + e^{-net}} \tag{1.13}$$

where the minimum and maximum values are -1 and 1.

Squashing function is widely used because of its nonlinearity and continuously differentiability, but most importantly this function has a great gain control of the signal.

The domain of the function can be made dependent on the actual situation. When $|net|$ is small, $f(net)$ has a large gain, otherwise it has a small gain. This is helpful to prevent the output from going into saturation.

In 1980s, led by Rumelhart and McCelland, the research team proposed the Back Propagation Learning algorithm of multilayer feed forward network, which is called BP algorithm for short [14]. It is a supervised learning algorithm, and is used for weights and threshold learning.

BP neural network is mainly used for:

(i) Function approximation: the input data and output data is used to train a network in order to approximate a function

(ii) Pattern Recognition: Use a specific output vector connected with its input vector

(iii) Classification: Use the input vector to do classification in a suitable manner

(iv) Data Compression: Reduce the vector's dimension for convenient transmission and storage

In about 80%-90% applications, BP neural networks and its variations were used [15]. BP neural network is the core part of feed forward neural network.

BP neural network is a multilayer feed forward network. Three layered BP neural network is shown in Figure 1.4, where each node is a neural. The network consists of input layer, hidden layer and output layer. The nodes in the front layer and back layer are linked by weights. The nodes between the adjacent layers are connected to each other, while the nodes in the same layers are not connected to each other.

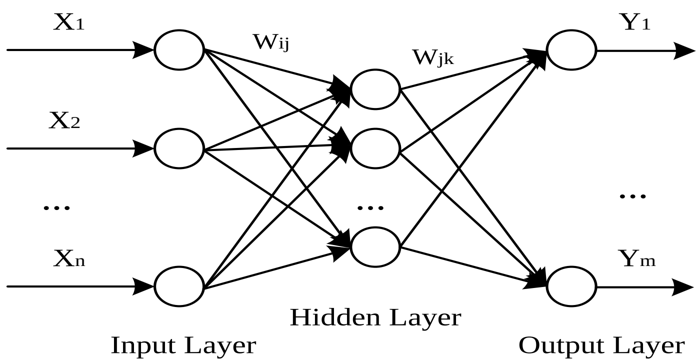


Figure 1.4 BP Network

The main idea of BP neural network learning algorithm consists of two processes: the signals are transferred forward and the errors are back propagated. In order to predict by BP neural network, the first step is to train the network. The trained BP neural network has the ability of associative memory and prediction.

1.4 Literature Review

The present research was a study of the fault types of fan and its fault diagnosis. In this section literatures were reviewed related to fan fault types, condition monitoring and some fault diagnosis methods.

1.4.1 Fan Fault Types

A. EI-Shafei [10] has studied the fan fault types and fault diagnostics in his paper. He discussed the most common faults in fans, which include: bearing faults, installation faults, unbalance and aerodynamic excitation. He introduced a step-by-step procedure of the diagnosis method to reach an accurate and reliable diagnosis in a reasonable time frame. The first step in his experiment was to detect if the vibration level of the fan system is high. If the vibration level was not high, the fan was acceptable, which means it was healthy; otherwise the next step was to check for the bearing fault. If the bearing were normal, then the user would check the installation faults. If the installation was correct, the next step was to check the unbalance and then check if there were aerodynamic defect frequencies. This method was used to check any possible faults step by step. If no fault was found in the process, it meant the fault was not due to fan.

N. Dileep, K. Anusha and C. Satyaprathik [8] introduced how to use vibration analysis to do condition monitoring of forced draft fan. This paper mainly used vibration monitoring which is commonly used method for fans and any other rotating machines. The paper is focused on the causes for forced draft fan's vibration. The unusual higher vibration might cause faults in the fan system such as: unbalance, misalignment, eccentric rotor, bent shaft and mechanical looseness. They used the Fast Fourier Transforms (FFT) to analyze the vibration signal. In their test, the fan was operating at 2200 RPM, belt was driven by an 1800 RPM motor, and the rotating speed of the belts was 500 RPM. As a result, the significant vibration detected would be at the frequency of 2200 RPM or 1 x RPM of the fan. The problems in the fan would generate more vibrations with the frequencies related to the rotating speed. They analyzed the unusual vibration frequencies and the likely causes by FFT analysis.

1.4.2 Fan's Condition Monitoring Techniques

This research is focused on the fan's condition monitoring and fault diagnosis. Usually the process of fan's condition monitoring consists of four parts, which are shown in Figure 1.5 [20]. Condition monitoring is widely used in industry, as it helps the enterprises to reduce cost of maintenance, predict machinery failure, improve machinery reliability and optimize the equipment performance.

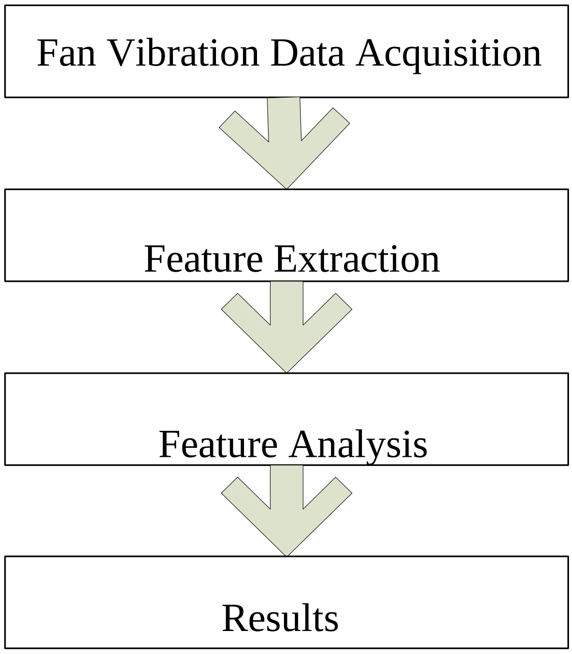


Figure 1.5 Fan's Condition Monitoring Process

This condition monitoring method has been used in industry practice for a long time. Many different methods have been used, but the most prominent method is vibration monitoring. All fans generate noise and vibration; however the background vibration signal is less than the background noise signal in real practice. The vibration signal can supply enough information on the condition of the fans.

Donald S. Doan and Mitty C. Plummer [9] introduced vane axial fans' condition monitoring methods. They compared the results from five different test methods to detect common faults in vane axial fans. They used five different instruments from different manufacturers: PdMA EMax, Baker MPM, Cognitive Vision CV395B, Bentley Nevada Adre and Swantech. The Swantech analyzer was used to dedicate stress wave. The PdMA EMax and Baker MPM were used for measuring motor current signatures. The Cognitive Vision CV395B and the Bentley Nevada ADre were used to do spectrum analysis. These methods were used to measure either the current or the vibration based indications of faults. After comparison, they found electric motor current analysis offers substantial sensitivity in detecting common faults of axial vane fans. Vibration analysis at the bearing caps of the motor is also sensitive. The monitoring on the cowling of the fan was insensitive to the faults induced in the fan and the bearings in this study.

Asad Said Juma, AI Zadjali and G.R. Ramashkumar [38] studied the condition monitoring of centrifugal blower using vibration analysis. This paper discusses fan system's various misalignment conditions. The misalignment conditions include parallel misalignment and angular misalignment. A centrifugal blower was used in their experimental setup. A fan was connected to the motor shaft through an electromagnetic coupling. The LabVIEW software was used to acquire vibration signals with data acquisition unit. The software displayed vibration spectrum in time domain and frequency domain. The frequency domain spectrums were analyzed for failure diagnosis.

1.4.3 Fault Diagnosis Methods

As mentioned before, the most popular condition monitoring method for rotating machinery is vibration signal detection. But how to use vibration signal to analyze the fan's state becomes a new problem. Relevant literature about the methods for vibration signal analysis is discussed below.

(1) Spectrum Analysis

The traditional spectrum analysis technology, based on Fourier Transform, is the widely used method for vibration processing. Modern spectrum analysis software and spectrum analyzer make this technology widely applied in the industry.

Bing Yuan [3] introduced how to use Fourier Transform spectrum analysis methods in blast furnace's bag filter‘s fan system fault diagnosis. In practical work, the collected signal is usually time domain signal, such as the vibration signal. The occurrence of failure will change the signal's spectrum structure. These changes are complicated to analyze in time domain but obvious in frequency domain. Fourier Transform is used to convert the signal from time series to frequency spectrum. Spectrum analysis solves the following problems: obtain the frequency components and distribution of the vibration signal, and calculate the amplitudes at different frequencies. This method will show the frequencies and the amplitudes of the vibration signal caused by different faults. When the blades of a blast furnace's bag filter's fan were changed in Hunan Valin Xiangtan Iron and Steel Company, it was found that the vibration was heavier than before. Vibration sensors were used to collect the vibration signal, and it was found that the abnormal frequency peaked at 12.25 Hz, which was the same frequency as the motor's rotating speed. It was believed that this heavier vibration came from the unbalance of new blades. They used dynamic balance technology on site to adjust the blades, and reduce the vibration for the blades to work in healthy condition.

(2) Machine Learning

Machine learning, a branch of artificial intelligence, can be used for fault diagnosis. The core content of machine learning is to design some algorithm models which are able to learn from data. These data are used to optimize the algorithm models, so that these models have the ability to predict based on new data.

Neural network, as a machine learning method, is an effective tool for processing nonlinear problems. For complex nonlinear systems, multilayer feed-forward neural networks are used frequently in fault diagnosis. Based on back propagation algorithm, neural network is good for its nonlinear mapping ability, generalization capability and fault tolerance capability. The neural network is a very effective tool to use the feature state as an input training set for classification, in order to achieve fault diagnosis.

J. Rafiee, F. Arvani and M.H. Sadeghi [27] introduced how to use artificial neural network condition monitoring methods on a gearbox. In this paper they collected vibration signal as the original data, use wavelet packets to preprocess the data for feature extraction. Wavelet analysis has advanced abilities in decomposing and denoising, it is also good at signal analysis. The wavelet packet decomposition method was used to process the signal, obtain the datasets for training the neural network. Figure 1.6 shows the process that the original signal is divided into 16 sub-wavelets and their standard deviation is used for the analysis.

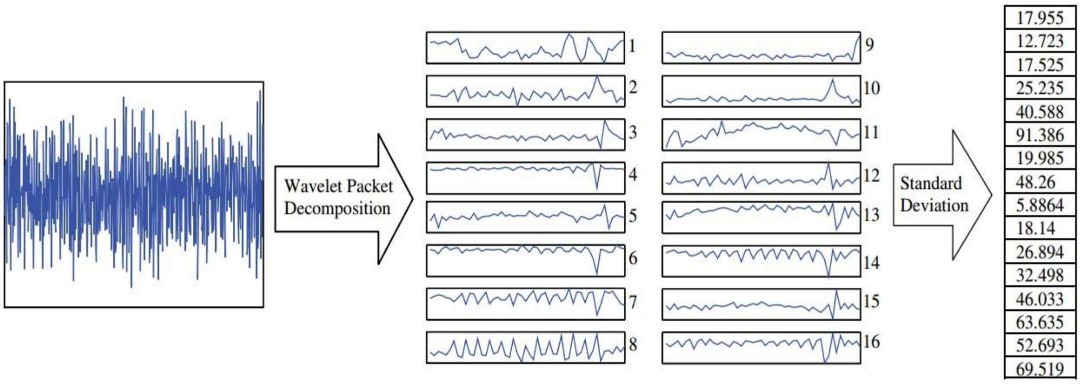


Figure 1.6 Wavelet Packet Coefficients and Their Relevant Standard Deviation [27]

They used the standard deviations of the wavelets as an input for the neural network training set. The output vectors consist of five fault types: no fault, slight wear, moderate wear, broken teeth and faulty bearing. Their test shows neural network is an effective method for gearbox condition monitoring.

1.5 Present Research

As discussed above, condition monitoring technology is widely used in machinery failure diagnosis. The condition monitoring technology includes the following parts: monitoring device selection, features selection, features analysis, and diagnosis method selection. At each step there are many different choices based on the monitoring device, cost, and environment. Some fault diagnosis doesn't need to get the results in time, the researchers may collect the data and process it later, but some needs to be processed in time. The main goal of this thesis was to examine appropriate methods for fan's condition monitoring and fault detection by vibration analysis.

In this research, one accelerometer was used to collect the vibration signal. In many papers FFT or wavelet analysis are used to process the vibration signal. Usually these methods require expertise in this area to do the analysis. It is required to know the state of the health condition and the features of different faults. Based on the state of health condition, the fault alarm has to be set for the faults. When the monitoring results are above the alarm limits, the system will show the faults. This is a very complicated process, and requires preliminary work, which makes the cost uncontrollable and the time to develop such a system can be unpredictable. As a result, in this thesis a machine learning method neural network algorithm was used to do the condition monitoring analysis. Using neural network model does not require a lot of knowledge of the device, and does not require much preliminary work. The neural network model is like a black box that only requires training the model, and making the model optimized for specific work.

One accelerometer was used in this research, so the data is one dimensional. But the neural network model needs a multidimensional input. The problem is converted to data processing. In this research we use auto regressive methods to calculate the eigenvectors, and these eigenvectors can be used as the input of the neural network.

In this research Virtual Instrument software LabVIEW was used to design the system. It is powerful for data acquisition, but the computing capability of LabVIEW is not that powerful. Although it has the Watchdog Agent Prognostics Toolkit, which includes the neural network model for fault diagnosis, it takes a very long time for training. The Matlab software has the powerful computing capability, and it also has an effective tool, Neural Network Pattern Recognition Tool to do the job. The capability of data acquisition of LabVIEW and the computing capability of Matlab were used together as an efficient way to collect and analyze data from a faulty device such as a fan. The LabVIEW has the Matlab scripts to combine them together. The designed system works in LabVIEW environment, collects data from the accelerometer, then the Matlab scripts are called to do the data processing, and data analysis work. Based on the results returned from Matlab, the system displays the fault diagnosis results in a GUI.

1.6 Thesis Outline

This thesis presents the research work in six chapters. Chapter 1 provides an overview of the background of fan fault diagnosis. It introduces the failure, history of maintenance, condition monitoring and fault diagnosis. It also introduces the artificial intelligence and neural network, which is used to do failure diagnosis. It reviews some literatures in fan vibration condition monitoring. It covers the fan's fault types, common condition monitoring methods, vibration signal processing methods and faults diagnosis.

Chapter 2 presents fan's structure, parameters and its failure type such as fan blades unbalance, rotor unbalance, bearing fault.

Chapter 3 describes the experiments of fan vibration data acquisition in different conditions. To diagnose these different health conditions, a laboratory test device is set up, which includes the test bench, data acquisition device and a computer. The speed of the motor is set at 10hz, 20hz and 30hz, respectively. The data acquisition device includes the accelerometers and NI PXIe-4492 cards. The Virtual Instrument was programmed in LabVIEW 2011, which is used for controlling the test measurements and data acquisition. It presents the software component of data acquisition in the experiment. It also introduces the Data Acquisition (DAQ) Assistant, Power Spectrum and Write to Measurement File function which is used in the component.

Chapter 4 introduces the classification technology Artificial Neural Network, which is used in the classification process. The vibration signal is a one-dimensional time sequence, while Artificial Neural Network needs multidimensional inputs. The Auto Regression (AR) model is introduced and used to calculate the parameters of vibration signal, which are used as the vibration signal's features. Matlab is used to create, train, test and save the back propagation Neural Network. In Chapter 4 we also used the traditional method Amplitude Domain Features to do classification, and compared them.

Chapter 5 describes how Matlab software and LabVIEW software work together in data acquisition and vibration analysis. The Matlab scripts can be used for Matlab and LabVIEW hybrid programming. The Matlab scripts function in LabVIEW can call Matlab functions automatically. The trained Neural Network can be used in Matlab scripts to do classification in LabVIEW.

Chapter 6 presents the conclusions. The research shows the applications of using neural network in fan condition monitoring. The software is able to detect the common fan failures such as fan blades unbalance, rotor unbalance and bearing fault. LabVIEW is user friendly software which is easy to do LabVIEW and Matlab hybrid programming. This hybrid programming reflects the powerful data acquisition ability of LabVIEW and the computing ability of Matlab.

CHAPTER 2

FAN'S FAILURE TYPES AND VIBRATION ANALYSIS METHODS

2.1 The Structure of Fan

Fan, as a rotating component, is widely used in different mechanical fields such as aviation, marine, power machinery and ventilation equipment. The rotating machinery fan is basically combined of three parts: the drive device, such as the motor, transmission device, such as the shaft and the blades. Usually in order to control the speed of the blades' rotating speed, the electronic control unit, or gearbox is added.

2.2 Parameters of Fan

Fan's parameters include the following features: wind velocity, air volume, wind pressure, lifetime and noise. These parameters impact the performance of the fan. Based on these parameters, researchers are able to make condition monitoring plans.

Wind velocity is the air flow velocity of fan's air inlet and outlet. The level of wind velocity will affect the amount of wind and the level of noise. The increase of wind velocity will increase the wind volume in same surface area. The friction between airflow, blades, frame and heat sink will cause noise. The noise will increase with the increase of wind velocity.

Wind volume is the volume of air that passes the air outlet in unit time. Wind volume is equal to average wind velocity times the size of fan. For the same fan, the higher wind velocity will cause larger wind volume.

Wind pressure means that fan will generate air pressure difference between air inlet and outlet. The wind pressure will influence the air supplying distance. The higher wind pressure will send the air to farther distance. Wind pressure is determined by blade's shape, surface area, height and rotating speed. Rotating speed impacts the wind speed, wind volume, wind pressure, noise, power and even lifetime, it marks the performance of the fan. However, high rotating speed also means more friction, vibration and noise, the lifetime of bearing and some other consumable equipment will be shortened, and the power consumed will also increase. Fan's lifetime is determined by its components, especially the consumable components, such as the bearing, fan blades and electronic component. On working for a long time, the rotating components will wear out gradually. Affected by the environmental and unknown factors, the failure of the components is unpredictable. That is why researchers need to design condition monitoring equipment to monitor the fan's working conditions.

2.3 Fault Types of Fan

For a long time, the vibration problems of fan affect the operation of machinery. There are many reasons that cause the fan to brake; most of the reasons are the vibration fatigue. Even if the machinery works in stable condition, the fan is influenced by periodic exciting force. The fan's faults are not only the blades failure as people usually think, but also include other components of fan, such as the motor, bearing and bearing house, sometimes even includes the gearbox and electronic control unit.

Typical failures of rotating machinery include unbalance, misalignment, static and dynamic friction. Fan blades unbalance, rotor unbalance and bearing failure are the main failures of fans, which will cause the equipment's abnormal vibration. These abnormal vibrations shorten the life of the equipment, and cause some other unpredictable damages.

2.3.1 Fan Blades Unbalance

A fan commonly uses three or more blades. The reasons that cause blades' unbalance are [5]:

(1) The original weight and shape of each blade is different. The blades are made of different materials, such as metal, wood and plastic. In the production process of these blades, due to the manufacturing process and materials, it is difficult to ensure that the weight and shape of each blade is exactly the same.

(2) It is difficult to ensure that the installation of these three or more blades is completely symmetrical.

(3) After long time running, the abrasion, scaling, and unpredictable problems happen on these blades, which will make the weight and shape of these blades different.

Therefore, the center of the principal axes of inertia for a fan in actual working conditions more or less deviate from the axis of rotation which is showed in Figure 2.1. When the blades are rotating at high-speed, the centrifugal force of the blades is an unbalanced force; this situation is called fan unbalance. Fan unbalance will generate the internal stress in the spindle, which will cause the spindle metal fatigue. It will also generate abnormal vibration and noise, the bearing and other parts will wear out accelerated.

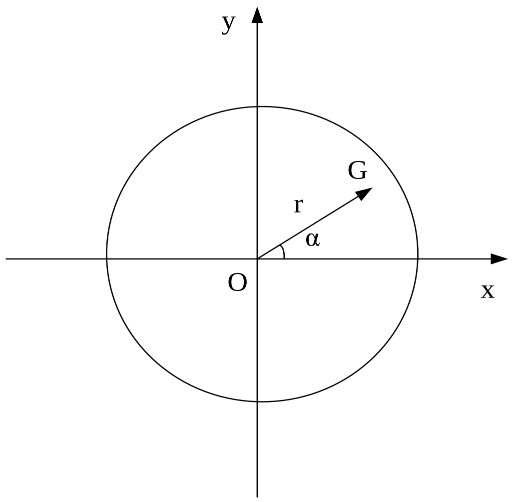


Figure 2.1 The Deviation of the Center of the Principal Axes

Assume the unbalance force is G, which exists in the position of radius r, angle α, as shown in Figure 2.1. Then, the amount of unbalance is the product of G and vector r.

$$U = G \cdot r \tag{2.1}$$

The value is $\mathrm{U} = \mathrm{Gr}$ and the unit is $\mathrm{g} \cdot \mathrm{mm}$. In engineering it is also written as:

$$\mathrm{U} = \mathrm{U}\angle\alpha \tag{2.2}$$

This is the form of polar coordinate.

2.3.2 Rotor Unbalance

The spindle of the fan is rigid rotor. In ISO 1925 [31], the definition of rigid rotor is: rotor (body capable of rotation) whose deflection is caused by a given unbalance distribution is below acceptable limits at any speed up to the maximum service speed.

There are many reasons causing the rotor shaft vibration, such as the original mass unbalance, rotating parts shedding and rotor components corrosion. The mechanism of rotor shaft unbalance is the mass point of each cross-section of rotor does not coincide with the cross-section's geometric center. When the rotor is rotating, the centrifugal force of each cross-section constitutes a space-continuous force system, the deflection curve of the rotor is a space-continuous three-dimensional curves.

As shown in Figure 2.2, the space-continuous force system and the rotor's deflection curve is rotating, the rotation speed is the same with the rotor's speed, which will cause frequency vibration.

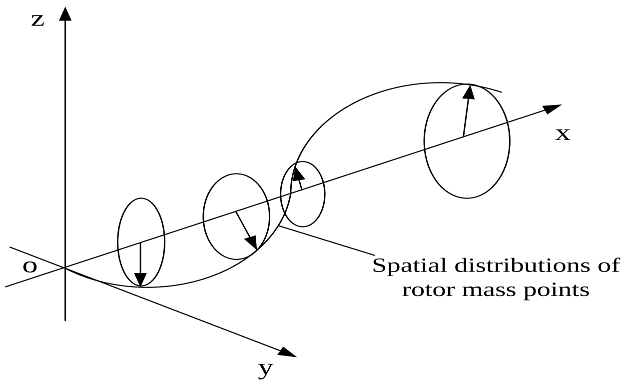


Figure 2.2 Spatial Distributions of Rotor Mass Points

2.3.3 Bearing Fault

The huge pressure from the rotating of spindle is applied on the spindle bearing. While the fan's rotation is on unbalanced condition, the bearing wear out is accelerated.

Rolling bearing is constituted by outer race, inner race, rolling elements and separator; the rolling elements are installed between outer and inner rings. In most situations, the outer race is static with the bearing housing, while the inner race is rotating with the shaft. The rolling elements are necessary and important; it transmits the loads from the moving parts, such as the shaft, to the bearing house. The forms of rolling elements includes: spherical, cylindrical, canonical and drum shape.

Due to rolling bearing's own structural features, processing and assembly errors, the movement of components in the shaft and complex force system, when the shaft is rotating with loads, it creates incentives to bearings and their housing, that led to bearing vibration. This kind of vibration may cause the bearing fatigue, wear out, deform. The failure of bearing will make the fan more unbalanced conversely. Figure 2.3 shows the vibration generating process of bearing system.

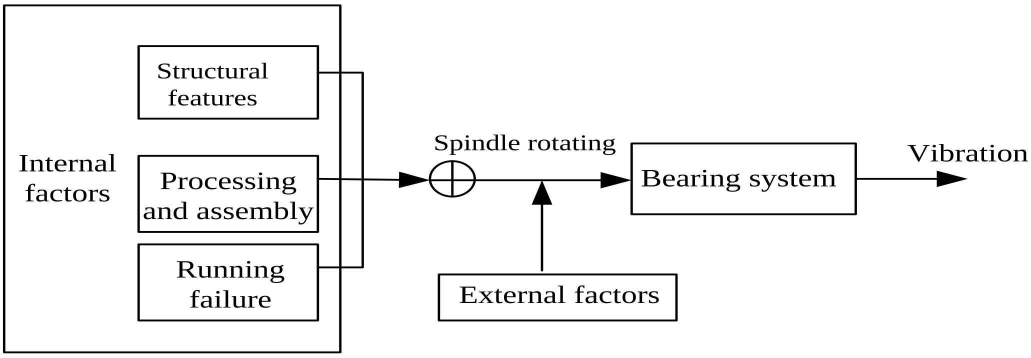


Figure 2.3 The Vibration Generation of Bearing

CHAPTER 3

EXPERIMENTAL METHODOLOGY

3.1 Laboratory Apparatus

In order to test and validate a prototype condition monitoring system, the ideal situation would be to collect data and perform experiments on a fan in a plant exhibiting all of the fault conditions of interest. However, there were some practical limitations that make it impractical to do this. This test required various data sets collected from different fault conditions of a fan. In modern industry, most of machinery is highly reliable with a very long designed life. In order to collect all of the operating data from different fault conditions of a fan, the time required would be too long to be practically feasible. Furthermore, intentionally faulting equipment in a factory would interrupt production and cause equipment damage which would not be acceptable. For these reasons, the experiments required were conducted in the laboratory using a machinery diagnostics simulator with a fan attachment.

The objective of the experimental work is to evaluate potential methods of detecting faults in a fan. The experimental apparatus was similar with the fans used in industry. Typically, a fan system includes the following parts: the motor, the transmission shaft, the fan blades and a control unit. The difference between the fans used in a factory and laboratory apparatus is that they may have a gearbox to control the rotation speed of the shaft in practical work, but the electric control unit was used here to set the rotation speed of the motor’s output in laboratory. The rest parts were similar with the fan used in field except the size.

The apparatus employed for the experiments had three capabilities. The first capability was that it was able to simulate the fan’s normal operation. The second capability was that it was possible to seed faults on the fan and to operate it under these faulty conditions. The last capability was it was able to collect data from an accelerometer installed on the fan’s bearing housing.

The laboratory platform that was used is a commercially available Machinery Fault Simulator™ (MFS) manufactured by Spectra Quest of Richmond, Virginia. This MFS is designed to reproduce multiple types of machine faults such as shaft or coupling misalignment, mechanical looseness, motor faults, rolling element bearing faults, rotor unbalance and pump faults. In the case of the present work, the test bench used in fan’s fault simulation and its schematic was shown in Figure 3.1 and Figure 3.2:

Figure 3.1 Photo of Test Bench

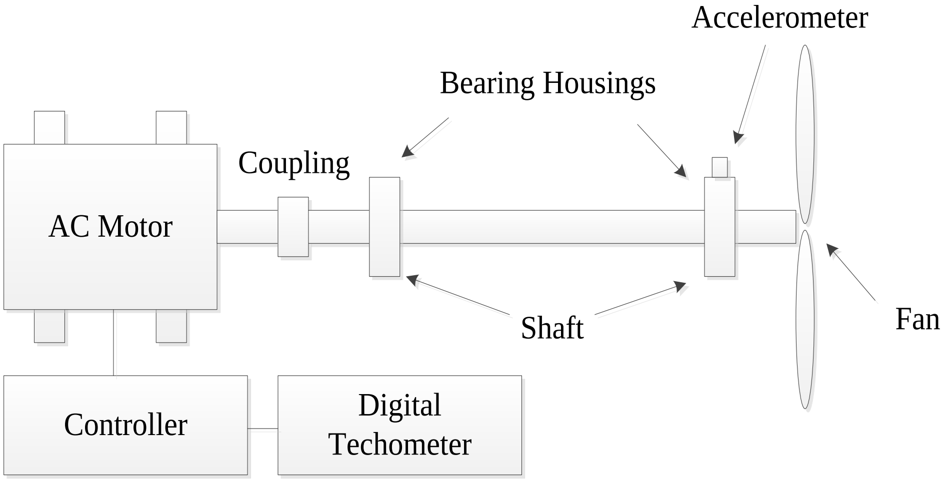


Figure 3.2 Schematic of the Test Apparatus

The equipment used to control the rotating speed of the motor was a Lenze AC Tech Controller. The test bench was fitted with a digital tachometer to measure and display the rotating speed of the motor. There are six buttons on the keypad, which are used to start or stop the drive, change the speed, and change the rotation direction. In the case of this work the motor was operated in three states: low speed, medium speed and high speed corresponding to 10Hz, 20Hz and 30Hz respectively.

As mentioned in Chapter 2, the common fan failure modes include: fan blade unbalance, rotor unbalance and bearing faults.

Figure 3.3 depicted the fan used for these tests. The blade length is 16 inches (also the radius of the fan assembly). The bore is 1/2 inch. It has aluminum blades, a steel spider and hubs, with cadmium plated setscrews.

Figure 3.3 Fan Used In the Test Mounted On the Test Stand

The original fan was in healthy condition; taking the original fan as the healthy (no fault) condition. The unbalance condition is the most common type of fan fault. An unbalance condition can be the result of several factors including contamination of fan blades, such as dust, grease, damage during operation from impact of blades or from manufacturing defect. In order to simulate the blade unbalance condition, a small mass was added to one of the three blades, shown in Figure 3.4 below.

Figure 3.4 Unbalanced Fan Blade Fault

In order to simulate the rotor unbalance, a cocked bearing housing was used. The lower surface of the cocked bearing housing that contacted with the rotor base was designed to achieve about a 0.5 degree tilt. In this test the cocked bearing housing was installed close to the fan, this tilt of the bearing housing would cause an unwanted stress to the rotor, which would cause the rotor unbalance. If left uncorrected, this fault type would result in progressive failure of the fan, the motor and the rolling element bearings. The cocked bearing housing was shown in Figure 3.5.

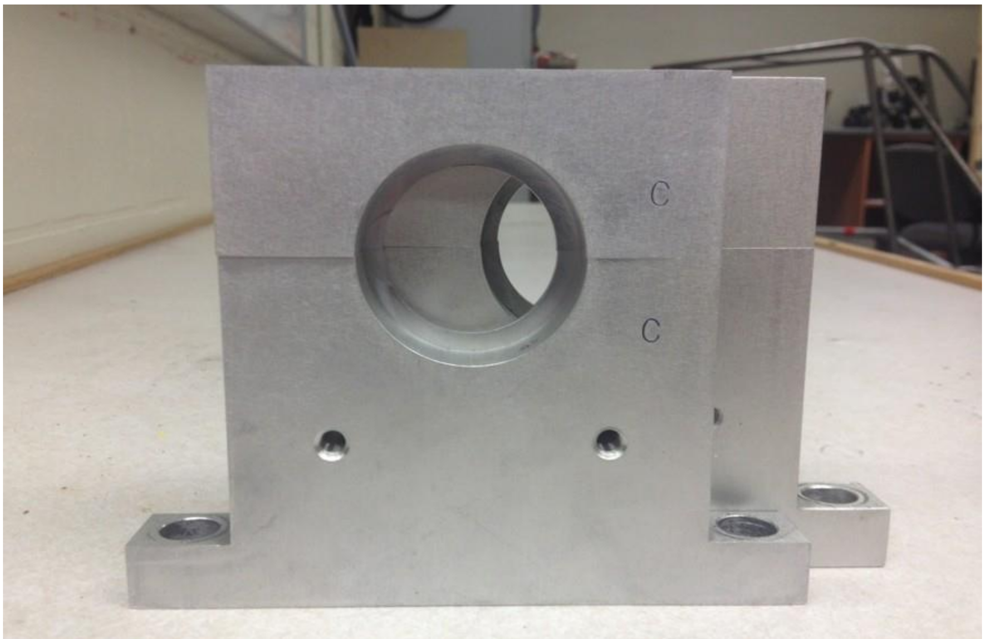


Figure 3.5 Cocked Bearing Housing Used For Rotor Unbalance

The last fault type examined was a rolling element bearing fault. Typically there are many different types of bearing faults that can occur in the operation period of the fan, such as damped, flaking, scratches, scuffling, cracks and wear. As a rotating system, fan is working on a very high speed for a long time. This may cause the bearings overheating. If the bearings are rotating on overheating condition for very long time, the lubricant will lose through the seal, which will cause the bearing damping. The damped bearing will aggravate overheating. This is commonly happened in very harsh environment, where the fans were widely used. Due to the limited condition in the laboratory, in this case the damped bearing is selected as the failure bearing. In this experiment the bearing was installed in the bearing housing, but typically the bearing would be in the motor of the fan. As a result, this damped bearing kit provided a high damped factor than the standard healthy bearings, which are virtually no damping. The resonance amplitude from standard healthy bearing was high, which caused high vibration; on the other side, the damped bearing was able to reduce the resonance amplitude. The vibration would be reduced either, however it is harder to drive, the engine load would increase. The damped bearing kit is used which was shown in Figure 3.6 to simulate the condition.

Figure 3.6 Bearing Fault

In practical work, fans usually have three different speeds: low speed, middle speed and high speed, so in the test, the speeds of the fan were set as 10Hz, 20Hz and 30Hz to simulate the different speed levels.

3.2 Instrumentation and Data Acquisition Apparatus

In this test, it was required to measure parameters that represented the health of the fan such as speed and vibration. These transducer measurements needed to be logged for various operating speeds and conditions. In order to record these parameters, some advanced hardware was used in the experiment.

Platinum Low-cost Industrial ICP ® Accelerometer, which is made by ICP ® Sensor, was used for measuring the vibration signal in the test [25]. It is now widely used for general industrial purpose all over the world. A piezoelectric element is used by the accelerometer to convert the mechanical motion into an electrical signal. The value of the electrical signal reflects the amplitude of the vibration of the object that the accelerometer is attached to. The accelerometer used in these studies is shown in Figure 3.7.

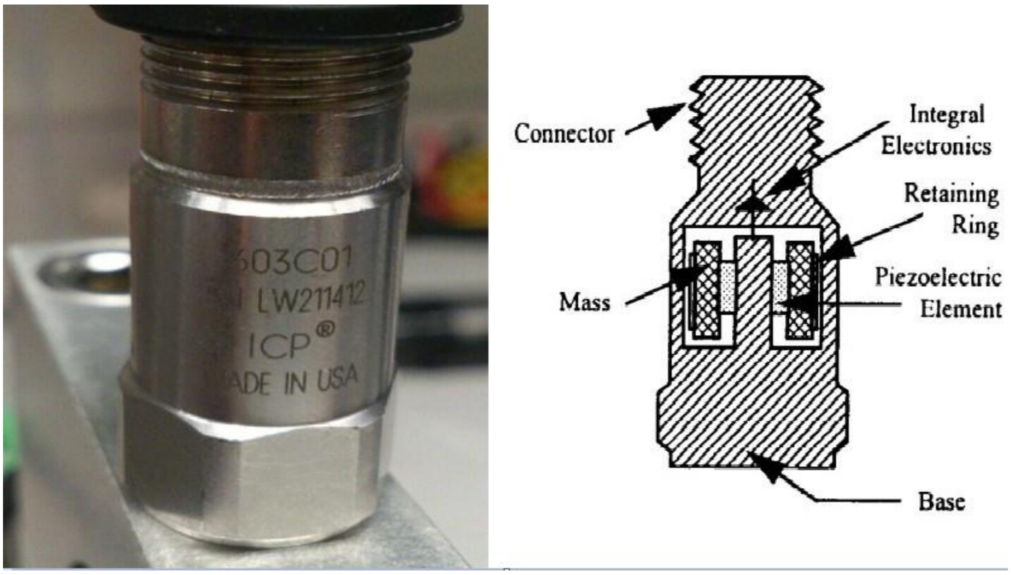


Figure 3.7 Platinum Low-cost Industrial ICP ® Accelerometer [25]

As shown in Figure 3.7, this accelerometer was set on the top of the bearing housing using a screw in stud mount. This accelerometer would detect the vibration motion in the vertical direction. The specifications of this accelerometer are listed below in table 3.1:

Table 3.1 Platinum Low-cost Industrial ICP® Accelerometer Specifications [25]

	Features
Sensitivity	(±10%) 100 mV/g (10.2 mV/(m/s²))
Frequency Range	(±3dB) 30 to 600000 cpm (0.5 to 10000 Hz)
Measurement Range	±50 g (±490 m/s²)
Electrical Connector	2-Pin MIL-C-5015

A data acquisition module manufactured by National Instruments (model number PXIe-4492) was used to collect the accelerometer data. This data acquisition module is specifically designed for sound and vibration applications [23]. Polyurethane Jacketed Cable connected the accelerometer to the data acquisition module. The cable is shown in Figure 3.8:

Figure 3.8 Polyurethane Jacketed Cable [26]

The NI PXIe-4492 module was used to interface with the accelerometers by the cables. This NI PXIe-4492 module was shown in Figure 3.9:

Figure 3.9 The NI PXIe-4492 Module

The features of this NI PXIe-4492 module are listed in Table 3.2 below.

Table 3.2 NI PXIe-4492 Module Features

Channels	8 channels
OS	Window 7
Software	LabVIEW 2010
Sample rate	2000 Hz
AC/DC	Software-selectable coupling

The NI PXIe-4492 module is installed in a Computer system which is based on PXI Express Chassis NI PXIe-1082. This chassis features a high bandwidth backplane in order to meet different high-performance test and measurement needs [22]. In this experiment, the NI PXIe-4492 module is installed in the chassis for fan’s vibration signal collection. Figure 3.10 shows the PXI Express Chassis NI PXIe-1082 Computer system.

Figure 3.10 Data Acquisition Chassis NI PXIe-1082 Used In Experiments

3.3 Software Development Environment

National Instruments LabVIEW (Laboratory Virtual Instrument Engineering Workbench) is a graphical programming language, similar with other traditional programming languages. LabVIEW was used to set the data acquisition parameters and control the data acquisition in general. LabVIEW also defines the basic rules such as data structure, data types and module calls. The functional integrity and program flexibility is as strong as traditional programming languages. It is a powerful virtual instrument development tool, mainly used in instrument control, data acquisition, data analysis and display [28].

The LabVIEW program written for this work performed the following functions:

(i) Acquisition of the vibration signal

(ii) Display of the vibration signal

(iii) Display of the preliminary analysis of the vibration data

(iv) Storing the vibration signal data for further analysis and training of fault detection programs

Based on the functions, the fan's vibration signal acquisition program was designed. This model detects the vibration signal by accelerometers, displays the original vibration signal, FFT spectrum and power spectrum in the front panel. After the data acquisition process, the collected data was saved to the determined file path in the .LVM format. Data was saved in a form that can be used to train an automatic algorithm which the user used to do fault diagnosis.

The .lvm file was the basic format of LABVIEW file system. A portion of an example .lvm file was depicted in Table 3.3 below.

Table 3.3 Format of the Saved Data

Header	LabVIEW Measurement		
Date	2013/01/02		
Time	From 23:33:35.7422 to 23:33:40.7457		
Channels	2		
Samples	10000		5000
Time	Vibration Value	Frequency	Frequency Value
0.000000	0.081953	0.000000	0.002957
0.000500	0.043367	0.200000	0.002146
0.001000	0.011805	0.400000	0.000107
0.001500	-0.013797	0.600000	7.091776E-5
0.002000	-0.013645	0.800000	1.416097E-5
0.002500	0.009676	1.000000	7.638201E-5
…	…	…	…
4.999500	-0.002003	999.800000	1.998395E-5

Each data file in the saved data shown in Table 3.3 has segment headers which record the basic information of test, such as the number of channels and record time. The data were recorded by column, which included the time, vibration amplitude value, frequency and their amplitude values. The data would be used for further processing. Figure 3.11 is the front panel and block diagram of the data acquisition model.

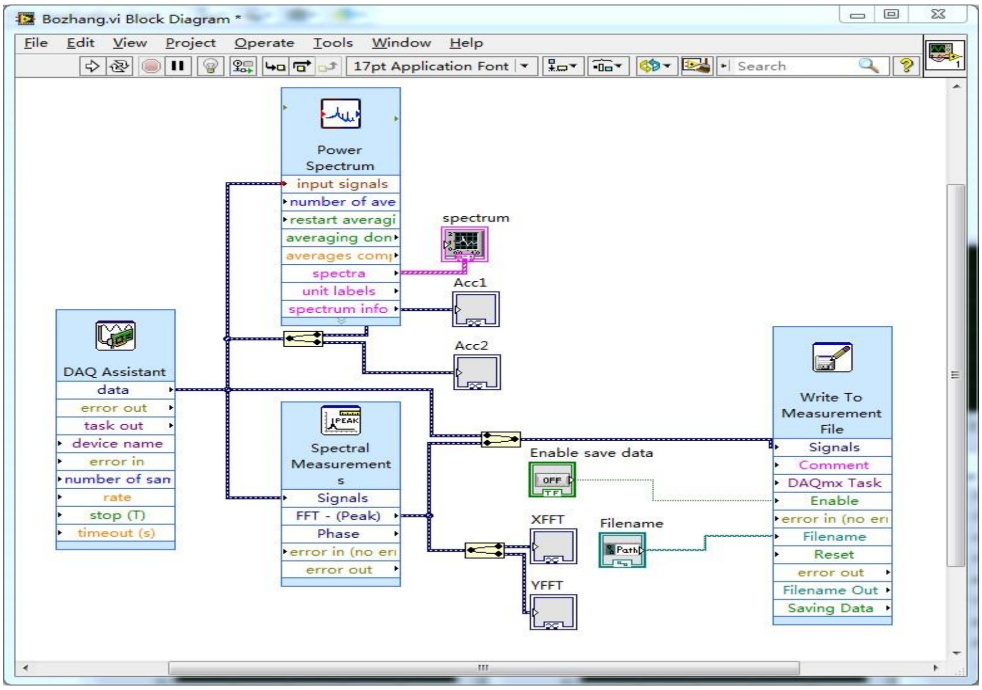


Figure 3.11 Data Acquisition Sub-program

Figure 3.12 shows font panel display with the results.

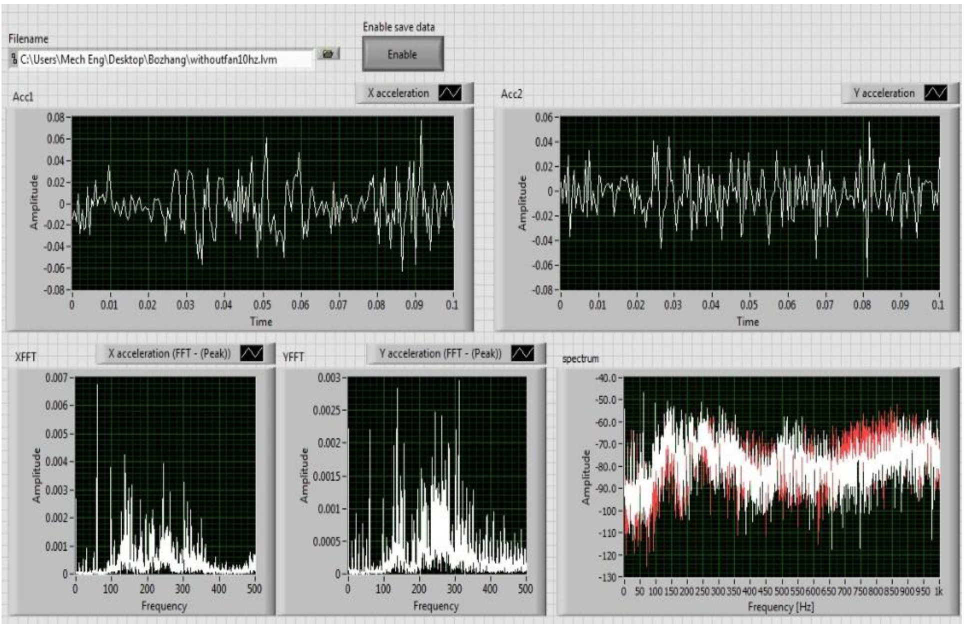


Figure 3.12 Data Acquisition Results Display

3.4 Experimental Procedure

In this experiment, the task was to collect fan's vibration signals in different states of health. As previously mentioned, four different conditions of fan were tested: healthy (no fault), fan blade unbalance, cocked housing and bearing fault. The NI PXIe-4492 module would pick out the samples by the sample rate that was set up in the DAQ Assistant function. The samples was saved, processed and analyzed in LabVIEW. The combinations of fan's conditions and speeds were shown in Table 3.4:

Table 3.4 The Combinations of Fan's Condition and Speeds

Fan's Condition	Rotating Speed(Hz)	Sample Rate
Healthy	10	2000Hz
	20	
	30	
Blade unbalance	10	
	20	
	30	
Cocked housing	10	
	20	
	30	
Bearing fault	10	
	20	
	30	

The experimental steps were listed below:

Step1: Configure the test bench, install the accelerometer on the top of the baring housing and connect it to the computer system by cable

Step2: Select fan's test condition from healthy, blades unbalance, rotor unbalance and bearing fault

Step3: Start the motor at the specified test speed (10Hz/20Hz/30Hz) and wait for motor to reach desired set point

Step4: Run LabVIEW program to collect test samples

Step5: Save data for further processing

Step6: Return to Step2 for different fault condition

3.5 Preliminary Analysis of Vibration Measurements

Based on the data collected in the experiment, Table 3.5, Table 3.6 and Table 3.7 showed the example samples in 0.4 seconds of four different conditions at different rotating speed:

Table 3.5 Vibration Signal of Four Different Fan Conditions at Speed 10Hz

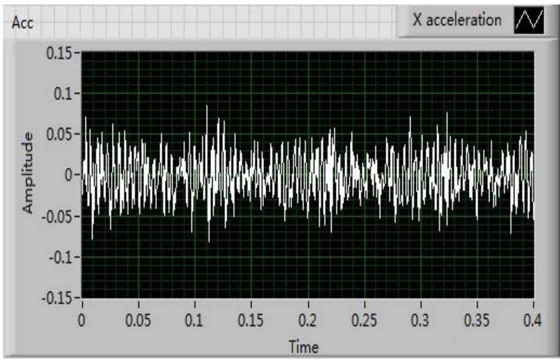
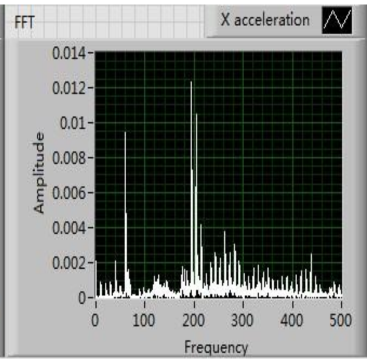
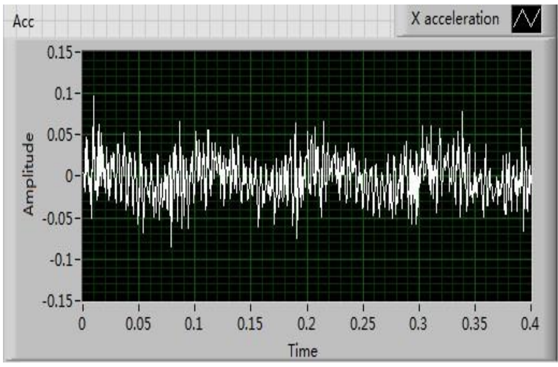
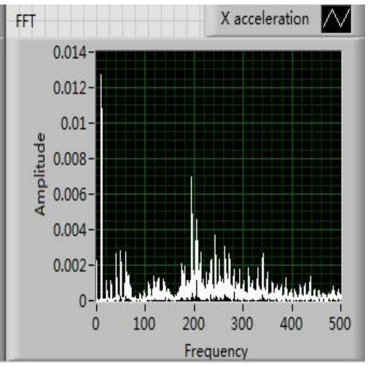
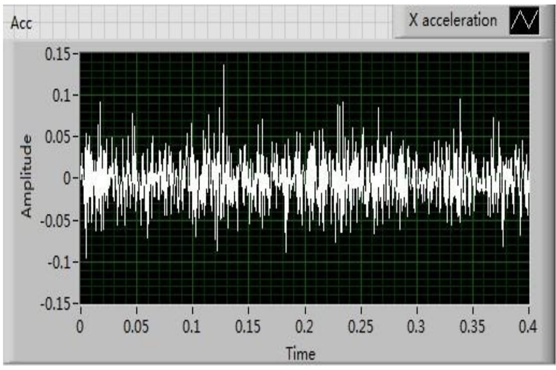
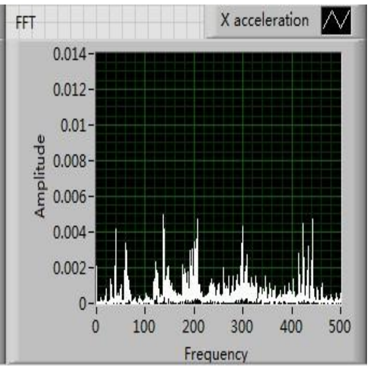
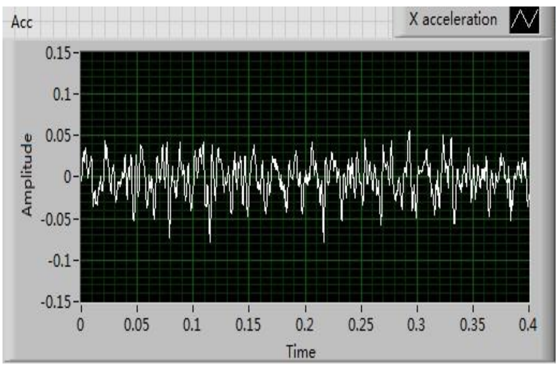
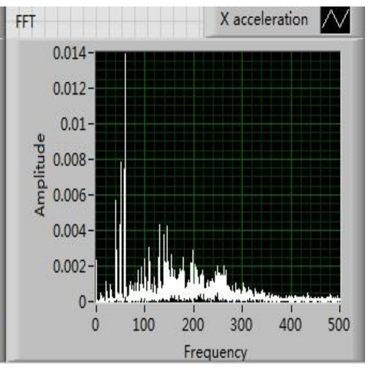
<table>
<tr><th>Fan’s Condition</th><th>Vibration Signal</th><th>FFT</th></tr>
<tr><td>Healthy</td><td>
</td><td>
</td></tr>
<tr><td>Unbalanced fan</td><td>
</td><td>
</td></tr>
<tr><td>Cocked Bearing Housing</td><td>
</td><td>
</td></tr>
<tr><td>Damped Bearing fault</td><td>
</td><td>
</td></tr>
</table>

Table 3.6 Vibration Signal of Four Different Fan Conditions at Speed 20Hz

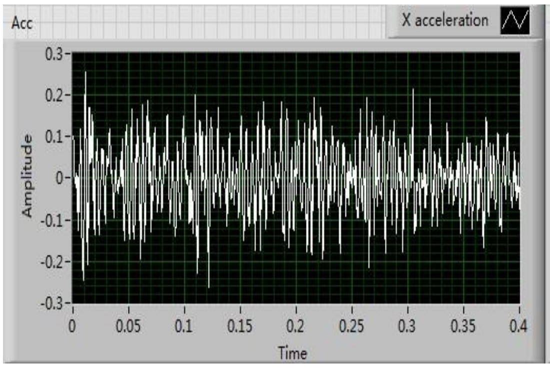
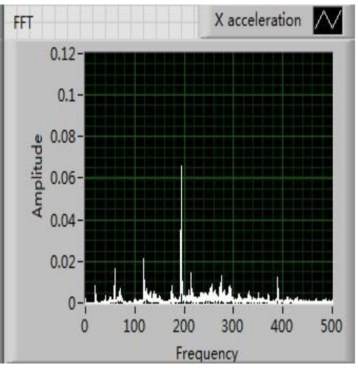
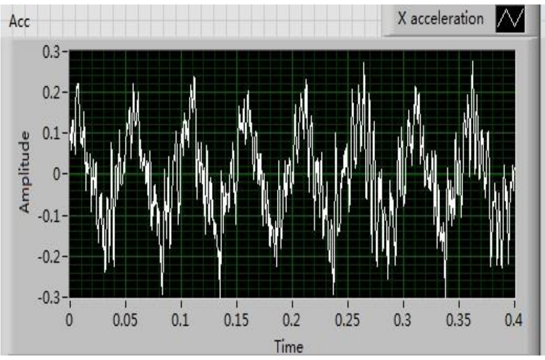
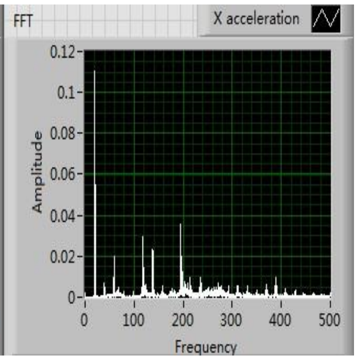
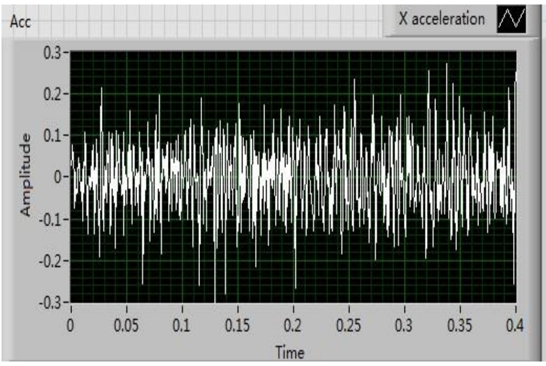
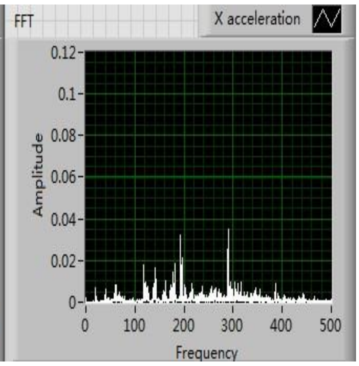
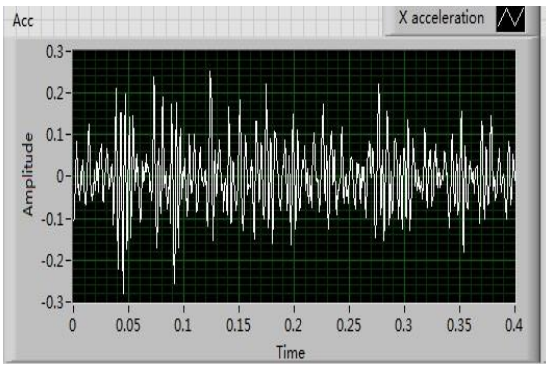
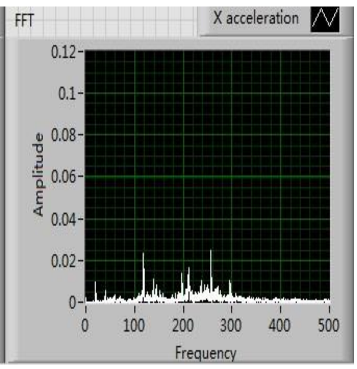
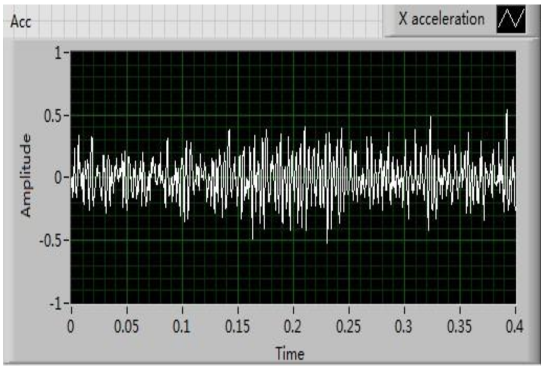
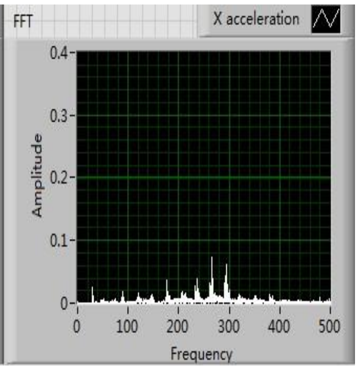
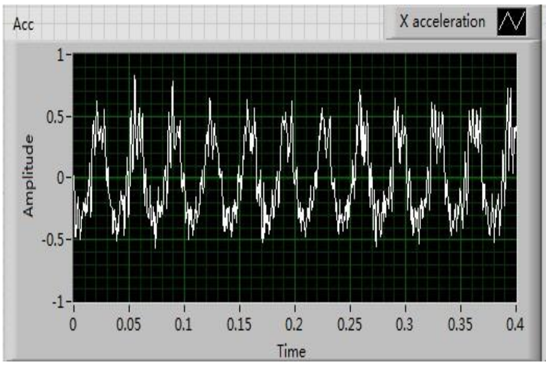
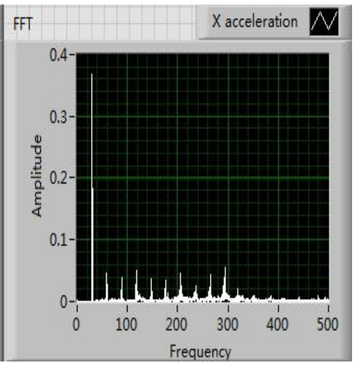
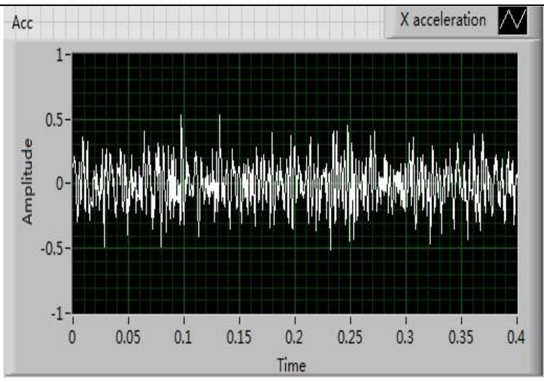
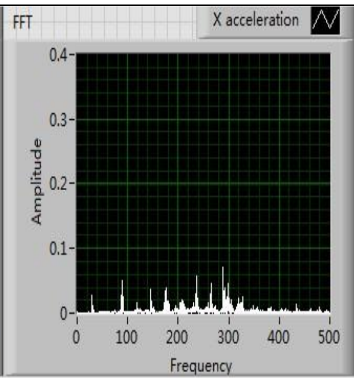
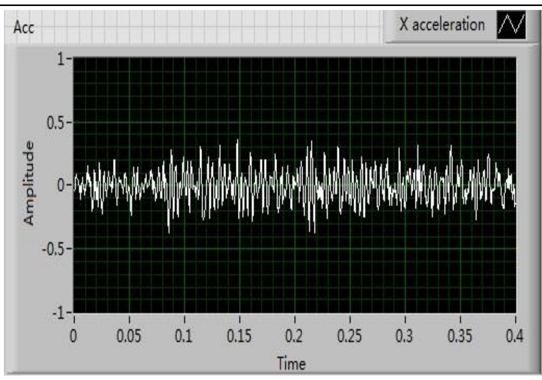
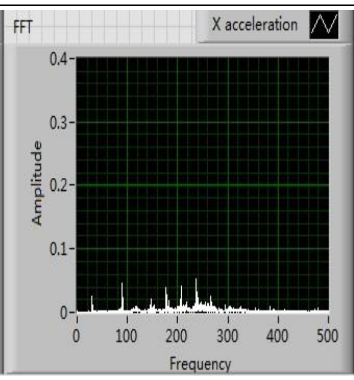
Fan's Condition	Vibration Signal	FFT
Healthy		
Unbalanced fan		
Cocked Bearing Housing		
Damped Bearing fault		

Table 3.7 Vibration Signal of Four Different Fan Conditions at Speed 30Hz

Fan's Condition	Vibration Signal	FFT
Healthy		
Unbalanced fan		
Cocked Bearing Housing		
Damped Bearing fault		

These tables showed the vibration signal of four different conditions such as healthy fan, unbalanced fan, cocked housing and bearing fault at different speed. It is obvious that the vibration of healthy fan is much smoother; the maximum amplitude of vibration is stabilized, which came from the normal machine operation, such as the motor, bearing and fan blades. However, when the blades were unbalanced, it was significant that the sine wave appeared based on the rotating speed. When the rotating speed is 10Hz, which means the first order is 10Hz, the blades turned a circle every 0.1 seconds, the sine wave with the circle time 0.1 seconds is obvious from the raw vibration signal, which is appeared at the first order. The vibration signal of unbalanced fan is not stable. The vibration signal of cocked bearing housing condition is more complicated than the unbalanced fan condition, it was similar with the signal of healthy condition, but a little bit more than that, the reason is the unknown stress from the cocked housing influenced the vibration. When the bearing is damped, the damping will reduce the vibration, so the vibration of the damped bearing condition was less than healthy condition.

When the speed is increasing to 20Hz and 30Hz, the vibration of healthy condition is increased a little bit than the vibration at 10Hz. The sine wave is more significant. Especially at the speed of 30Hz, the circle time of the sine wave was 0.033 seconds, which appeared at the first order with the rotating speed. The vibrations were more severe when the speed increases in the condition of cocked bearing housing and damped bearing. But they were still following the fact that happed at the speed 10Hz.

CHAPTER 4

NEURAL NETWORK USED FOR CONDITION MONITORING

4.1 Neural Network Input Data Preparation

The input of neural network model needs multidimensional data, but the raw vibration signal is a one-dimensional time series data. so the fan's vibration signal should be preprocessed to fit the intelligent system. The raw vibration signal need to be converted to multiple features, which support the intelligent system learn how to distinguish between features representing healthy and faulty machine operation. This chapter describes the training of the intelligent decision support system. Two different data preprocessing methods, time domain features and auto regressive model, were compared in the training process. The trained auto regressive model was used to build the intelligent system.

4.2 Time Domain Features

Using the raw time domain vibration signal for analysis is a popular, simple and effective method [24]. The original vibration signal can directly reflect fan's working condition. However, there are some reasons that the raw vibration signal was not suitable as the input data for training the neural network. There was no significant difference between adjacent samples, which would cause too many similar samples in the data set. This would make the training data set too large to deal with. The training time would be extremely long. On the other side, the neural network needs multidimensional data as the input data, while the raw vibration data is just one dimension. Thus feature extraction is needed for processing the raw vibration data that can reduce the size of the training set while preserving features that correspond to the condition of the fan.

4.2.1 Time Domain Features Selection

Many important statistical features were used to describe the raw vibration data, some of them were: Root Mean Square Value, Peak to Peak Value, Kurtosis, Crest factor, Impulse factor and Energy in time domain [24].

Root mean square value is a kind of statistical measure of vibration magnitude. It has been shown to be a very effective feature and it shows rotating machinery's condition. Usually it is used for some kinds of faults which are caused by the vibration signal changing slowly. The formula of root mean square is:

$$X_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{4.1}$$

Peak to Peak value shows the difference between the maximum value and the minimum value in a time interval. The formula is given as:

$$X_{pp} = X_{max} - X_{min} \tag{4.2}$$

Kurtosis is a feature used to measure the peak of Probability density distribution curve's mean value. The formula is given as:

$$\mathrm{k} = \frac{\sum_{i=1}^{N}(X_i - \bar{X})^4}{(N-1)S^4} \tag{4.3}$$

where S is the standard deviation of X

Crest factor is used to measure a waveform. It shows the ratio of peak value to the average value of the waveform. The formula is given as:

$$\mathrm{c} = \frac{Peak\ Value}{RMS} \tag{4.4}$$

Impulse factor shows the ratio of peak value to the mean value. The formula is given as:

$$\mathrm{i} = \frac{Peak\ Value}{(\sum_{i=1}^{N} X_i)/N} \tag{4.5}$$

Energy in time domain is a feature used to measure the power of the waveform in a certain period. The formula is given as:

$$\mathrm{E} = (\frac{\sum_{i=1}^{N}\sqrt{|X_i|}}{N})^2 \tag{4.6}$$

These six features are selected as the input features of the neural network. In each data set, the sampling rate is 2000k, which means there are 10000 samples in each segment of time series data. Based on the sample rate and the rotating speed of the fan system, 400 samples were selected as a period to calculate their features which were mentioned above. The reason why 400 samples were chose as a segment of time series data was they represented two complete revolutions of the rotating fan (10Hz rotating frequency). Matlab was used to calculate the features, the code is listed below:

```
load healthy10hz.txt;
x=healthy10hz(:,1);
count=0;
for i=1:400:10000
    count=count+1;
    line=x(i:i+399);
    xpeak=max(line);
    xmean=mean(line);
    xpeaktopeak=max(line)-min(line);
    xrms= sqrt(mean(line.^2));
    xkurtosis=kurtosis(line);
    xcrest=xpeak/xrms;
    ximpulse=xpeak/xmean;
    xenergy=(mean(sqrt(abs(line))))^2;
    healthy10hzinput(count,1)=xrms;
    healthy10hzinput(count,2)=xpeaktopeak;
    healthy10hzinput(count,3)=xkurtosis;
    healthy10hzinput(count,4)=xcrest;
    healthy10hzinput(count,5)=ximpulse;
    healthy10hzinput(count,6)=xenergy;
end
```

For each of the data sets, the code was used to calculate the features. The feature set values are the input data for the BP neural network module and a sample of feature values is shown in Table 4.1.

Table 4.1 Samples of Fan's Time Domain Vibration Signal Features

Root Mean Square Value	Peak to Peak	Kurtosis	Crest Factor	Impulse Factor	Energy in Time Domain
0.0305677440585906	0.180720000000000	2.96802086811348	2.55429382849917	-42.5572504001376	0.0204268463229155
0.0293271152544450	0.196416000000000	3.21946367421624	3.08567682892999	-50.2937935844762	0.0201018473802840
0.0253768866434911	0.141075000000000	2.79614539757837	2.51575383918794	-34.1592324686603	0.0177105145084378

4.2.2 Neural Network Training Based on Time Domain Features

After the neural network input data is prepared, the neural network is used to classification. The BP Neural Network module flowchart is shown in Figure 4.1:

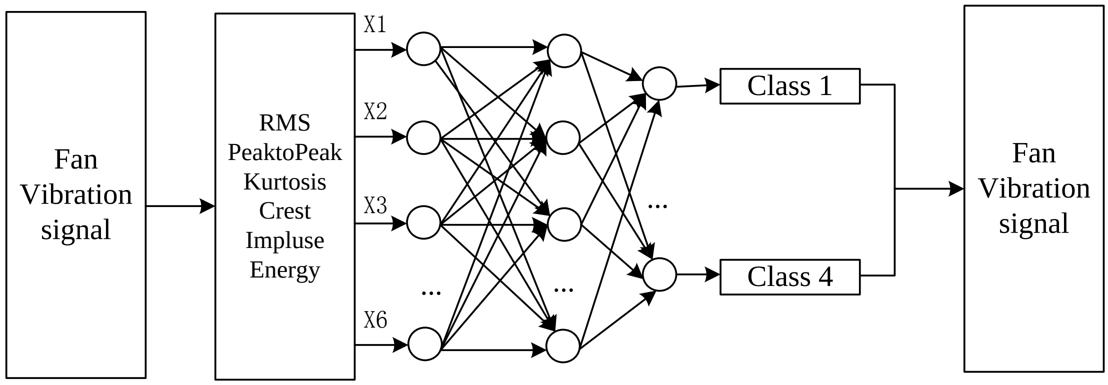


Figure 4.1 Module flowchart

The number of nodes at the input layer is determined by the number of features in the input vector (in this case, it is six). The next step is to define the number of hidden layer nodes. The nodes' number of hidden layer has a great impact on the prediction accuracy of BP neural network. If the nodes number is small, the neural network can't learn well and the time of training will increase, as well as the training accuracy is impacted. If there are too many nodes in hidden layer, the training time will again increase, and the neural network will be over-fitting. The number of hidden layers can be calculated by the functions shown in equations 4.7 and 4.8.

$$l < \sqrt{(m+n)} + a \quad (4.7)$$

$$\ell > \log_2 n \quad (4.8)$$

n is the number of input nodes; m is the number of output nodes; a is a constant number between 1 and 10.

In practical work, the first step is to calculate the range of the number of nodes based on these functions; then to determine the best number in the given range. As mentioned before, there are 6 input nodes based on the fan vibration signal feature vector and 4 output nodes based on the fan's conditions we detected. According to the functions, the number of hidden layer's nodes range from 4 to13.

This number influences the results, but there is no proof to show what the optimal number of nodes is, and how the number influences the results. In this research, using Matlab modeling of the BP Neural Network, different numbers were tried as the number of hidden layer nodes. The results based on the different numbers of hidden layer nodes are list in Table 4.2:

Table 4.2 Classification Accuracy with Different Number of Hidden Layer Nodes

No. of hidden layer nodes	4	5	6	7	8	9	10	11	12	13
Accuracy	38%	43%	39%	47%	45%	59%	60%	64%	68%	67%

The number of hidden layer nodes was selected as 12 as it gave the best accuracy in the above results.

In this test, the fan vibration signal's features from four different conditions are labeled as 1,2,3,4. Based on the labels, the target output values were set as shown in Table 4.2:

Table 4.3 Target Output Values

Fan’s condition	Target output values
Healthy	1000
Blades unbalance	0100
Rotor unbalance	0010
Bearing fault	0001

Matlab provides a wide variety of toolboxes for different purposes. In Matlab 2010, there is a neural network toolbox called Neural Network Pattern Recognition Tool. It has a graphical user interface (GUI), through which users can easily design and simulate a neural network. It is based on the BP neural network algorithm. The work flow for the neural network design and training process has seven primary steps:

(i) Collect the data we need in the test and pre-processing

(ii) Create and Configure the original network

(iii) Initialize the weights and biases

(iv) Use the pre-processed data to train the network

(v) Validate the network

The first step was accomplished by data acquisition using the LabVIEW programs and data preprocessing in Matlab programs described earlier, the rest of the steps are done in the Neural Network Toolbox software.

The next step is choosing the suitable wizard which is shown in Figure 4.2. It is well known that neural networks are widely used in different application area, such as classification, curve fitting, clustering and dynamic time series. In this research test, the Pattern Recognition and Classification wizard was selected to perform the task fan's condition monitoring and fault detection.

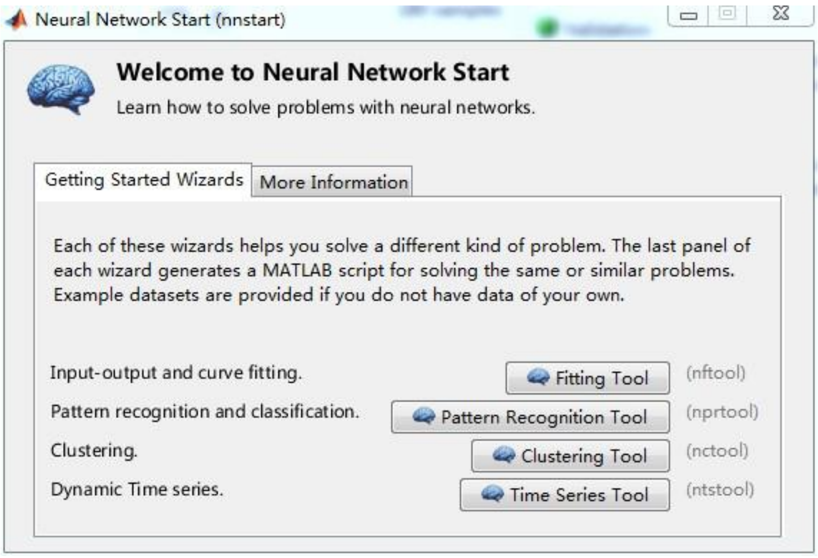


Figure 4.2 Neural Network Function Selection

In this step, the feature vector sample set is divided into three sub sets as shown in Figure 4.3. The 70% sample set which includes 210 samples is used as training set. These samples are inputted to the network for training. The network will adjust the weights according to the classification error based on the training samples. Another 15% sample is used for validation. It is like the test set that is used to check the network in each loop, when the validated samples are used it is still in the training process. The rest 15% sample set are used for testing. After all of the training is finished, it is the final test of network performance, but has no effect on training results.

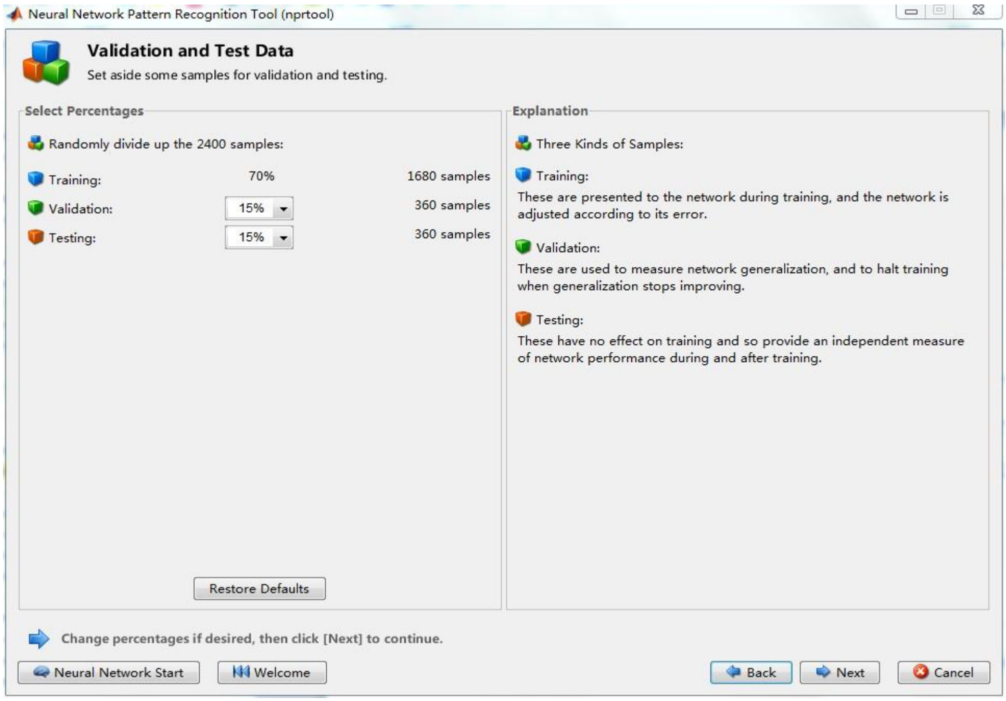


Figure 4.3 Determine the Percentages of Training, Validation and Testing data

In the next step, the number of hidden layer nodes needs to be defined. As mentioned before, 12 hidden layer nodes are used as shown in Figure 4.4.

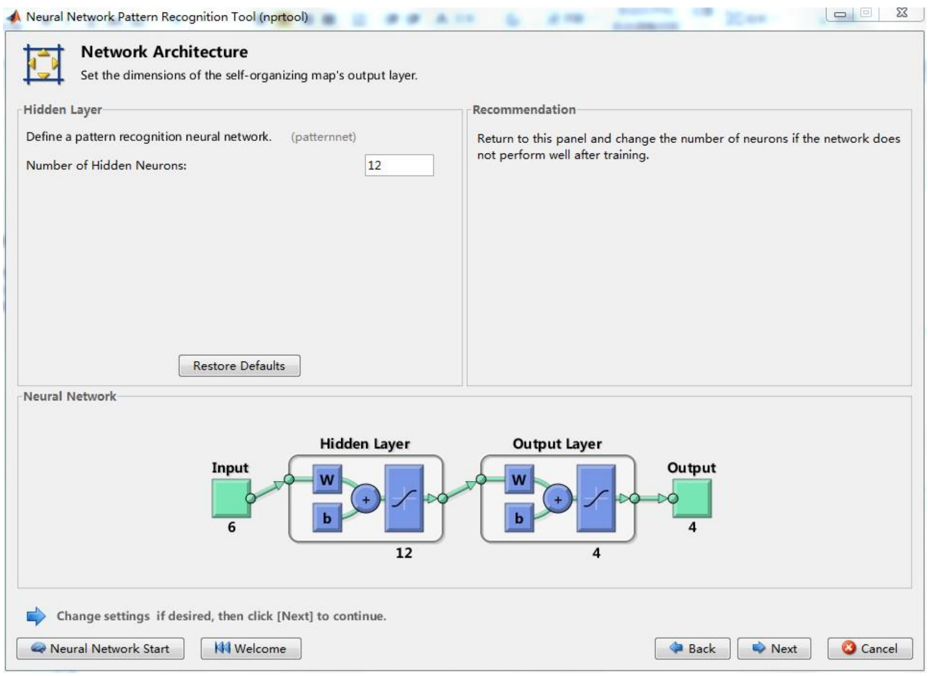


Figure 4.4 Determine the Number of Hidden Neurons

The following step shows the process of training as shown in Figure 4.5. It includes the brief introduction of the training process. It is clear that the data is sorted randomly; it also includes the brief information on training time, performance, gradient and validation checks. The training process was very fast, it took 2 seconds to finish the training process, which was acceptable. Figure 4.6 shows the test result.

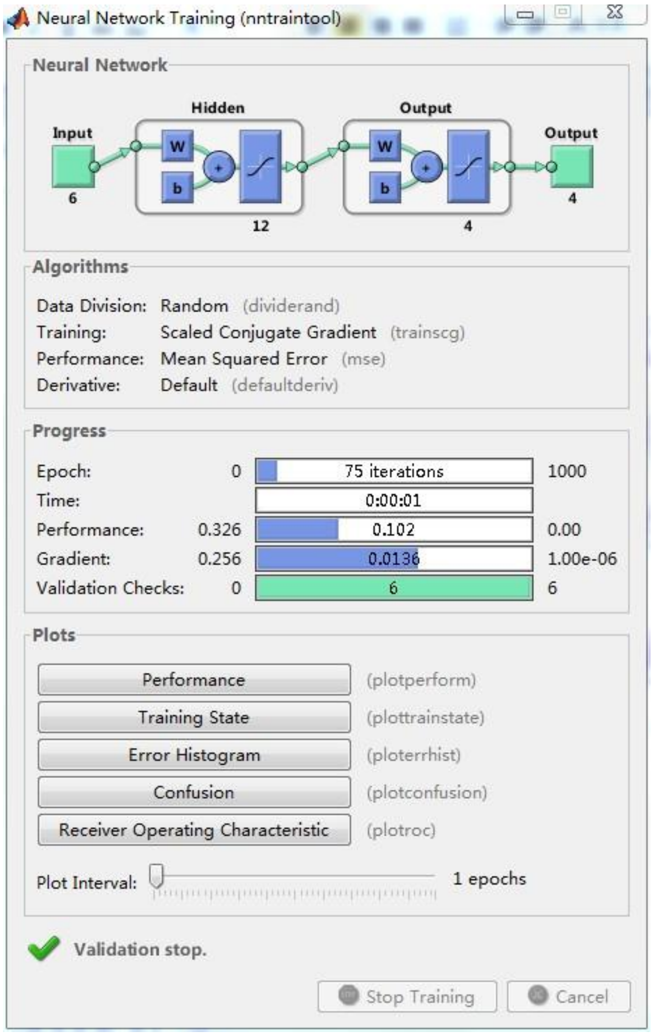


Figure 4.5 Training Process of Neural Network Model

Figure 4.6 Training Results for Four Conditions with Different Speeds

As previously mentioned, the feature vector sample set was divided into three subsets: training set, validation set and testing set. Each of these subsets and the feature vector sample set were used to test the trained neural network model. The first three matrices show the results of the training set, validation set and testing set and the fourth matrix shows the results of the combined data set. The columns in the matrices show the target classes, while the rows show the output classes. For example, in the Training Confusion Matrix, the target class and the output class of the 30 samples was found to be class 1, which means the classification result was correct (the background color is green). They were 14.3% samples of the training set. Meanwhile, the target class of 2 samples was class 1, but the output class was class 2, which means the classification result was wrong (the background color is red). They were 1% samples of the training set. The percentages shown in green color in the last row (the background color is grey), columns 1, 2, 3 and 4 show how many samples in the trained results were classified to the target classes, and the percentages shown in red color show how many samples in the trained results were not classified to the target classes. For example, in the Training Confusion Matrix, 55.6% of the samples which were expected to class 1 were classified as class 1, the rest of the samples which were expected to class 1 were classified as other classes. The last column (the background color is grey) are the results of the output classes. The percentages in green show in each output class how many samples were classified correctly, and the percentages in red show how many samples were classified incorrectly. For example, 52.6% samples of the output class 1 were classified correctly, the rest 47.4% samples in output class 1 were from other expected classes. The last row-column (the background color is blue) are the test results. For example, in the Training Confusion Matrix 70% of the samples in training set were classified correctly and 30% of the samples in the training set were classified incorrectly.

The last matrix shows the test results of all the features. It is clear that 68% of the samples were classified correctly, which means for all of the 300 feature vector samples, 96 samples were classified to the wrong class.

From this test, it was obvious that using only one accelerometer to collect data, information was not available for training the BP neural network module. One accelerometer just gave us the information from the top of the bearing house. If we want to obtain more vibration signal information, we need more accelerometers which should be installed in different positions in order to get data from other dimensions.

The question to ask is if other methods exist that may help us use one accelerometer to give sufficient information to train the neural network? In the following section, we discuss the AR model to obtain input features.

4.3 Auto Regressive Model and Eigenvectors

The information acquired by data acquisition is the vibration signal; it is a one-dimensional time series. In order to use BP neural network for classification, the time series has to be converted to feature vector set.

Auto Regressive (AR) model [16] is a time series analysis method, its model parameters contains all the important features about the machinery's condition, accurate AR model reflects the objective rules of dynamic system. AR model's AR coefficients are very sensitive to state changes in dynamic system. Therefore, the actual AR coefficients were used as the feature vector to analyze dynamic system's state.

4.3.1 Data Preprocessing by AR Model

AR model is a widely used model in practical work, and the function is a set of linear equations. Based on the knowledge of digital signal processing, a P-order AR model is equivalent to a P-order linear predictor. Based on the output of the AR model, the prediction parameters are calculated, which is the linear prediction coefficient. This linear prediction coefficient was used in voice coding at first, so it is named Linear Prediction Coding (LPC) [2]. The AR model's coefficients can be calculated by linear prediction analysis.

Assume collected fan vibration signal is $\mathrm{x(t)}$, its autoregressive model is:

$$\mathrm{x(t)} = \sum_{k=1}^{n} \varphi_k x(t-k) + e(t) \tag{4.9}$$

where t is time φ_k $(\mathrm{k} = 1,2,\dots,\mathrm{n})$ are AR model's parameters. $e(t)$ is model's residuals, it's a white noise with zero mean and variance equal to σ^2.

AR model's parameters and its autocorrelation $\mathrm{R(k)}$ satisfy this function:

$$\begin{bmatrix} R_1 & \cdots & R_p \\ \vdots & \ddots & \vdots \\ R_p & \cdots & R_1 \end{bmatrix} \begin{bmatrix} a_2 \\ \cdots \\ a_{p+1} \end{bmatrix} = \begin{bmatrix} -R_2 \\ \cdots \\ -R_{p+1} \end{bmatrix} \tag{4.10}$$

This is AR model's canonical equation, which is also named Yule-Walker function [13]. The solution of the canonical equation is the LPC coefficient.

Because of the autoregressive parameters $\varphi_k (k = 1,2,\dots,n)$ reflect the features of fan's vibration, the variance of the residuals σ^2 is closely related to output characteristics of fan's vibration, $\varphi_k(k = 1,2, \dots, n)$ and σ^2 can be used as eigenvectors $\mathrm{A} = \varphi_1, \varphi_2, \dots, \varphi_n, \sigma^2$ to identify the fan's state.

There are many algorithms used to calculate AR model's parameters, such as Burg's lattice-based method, Forward-backward approach, Geometric lattice approach, Least-squares approach and Yule-Walker approach. In practice work, Forward-backward approach is often used to calculate AR model's parameters [13].

Once the signal has been analyzed by AR model into discrete parameters, these parameters are able to be used for classification. Every set of parameters is able to show the state of fan in a time interval. This process is able to simplify the data and convert the one-dimensional data to multidimensional data, which can be the input to an neural network model.

When using AR model to process vibration signal, users choose the number of AR model parameters. However the users need to find the right number. That's because if AR model is used to fitting the time series, there is eventually a number that fits best, and this number is the optimal choice for AR model. If a number is smaller than the optimal value, it is like using a low-level curve to fit a high-level curve. It will smooth the curve, but some important signal will be missing in the process. If the number is bigger than the optimal value, background noise will be taken as real signal that will lead to false peak and increase the computation.

Nowadays, two optimal value selection methods are widely used:

Final Prediction Error (FPE) [1]

$$\mathrm{FPE(n)} = \frac{N+n}{N-n}\sigma^2 \tag{4.11}$$

An Information Criterion (AIC) [11]

$$\mathrm{AIC(n)} = \mathrm{Nln}\sigma^2 + 2n \tag{4.12}$$

where N is the number of samples, n is the number of AR model parameters, σ^2 is model's residual variance.

The fan's vibration signal was collected from the accelerometers installed on the bearing housing. One set of samples was used to calculate the number of parameters. The speed of rotation was 1800 r/min. The sampling frequency was 2000 Hz; the sampling time was 5 seconds. Therefore, there were 10,000 samples in the vibration signal.

All of the 10,000 samples, which were collected from no fault condition with speed 10Hz, were used to calculate the FPE and AIC curves in Matlab. The FPE and AIC curves are shown in Figure 4.7 and Figure 4.8:

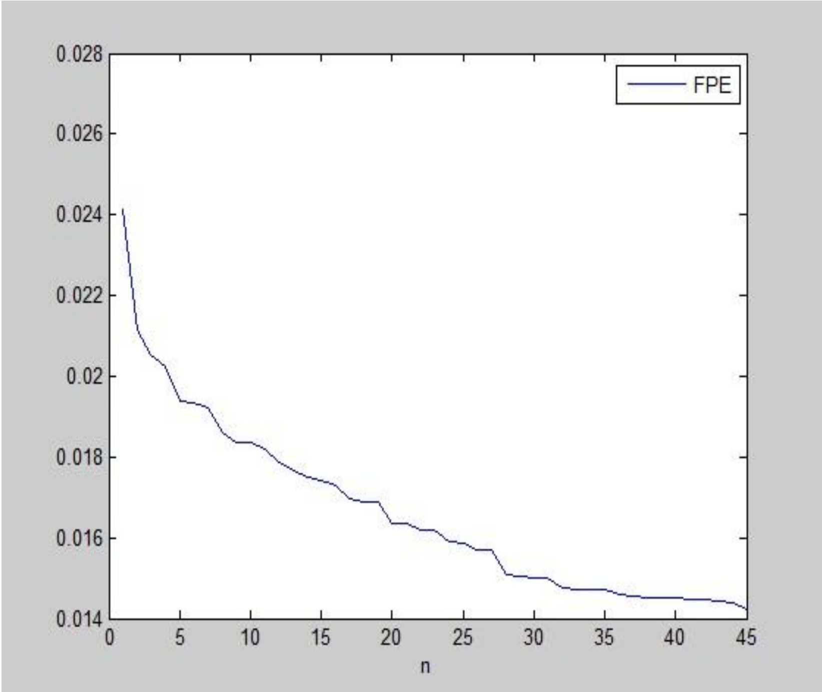


Figure 4.7 FPE Curve (no fault condition with speed 10Hz)

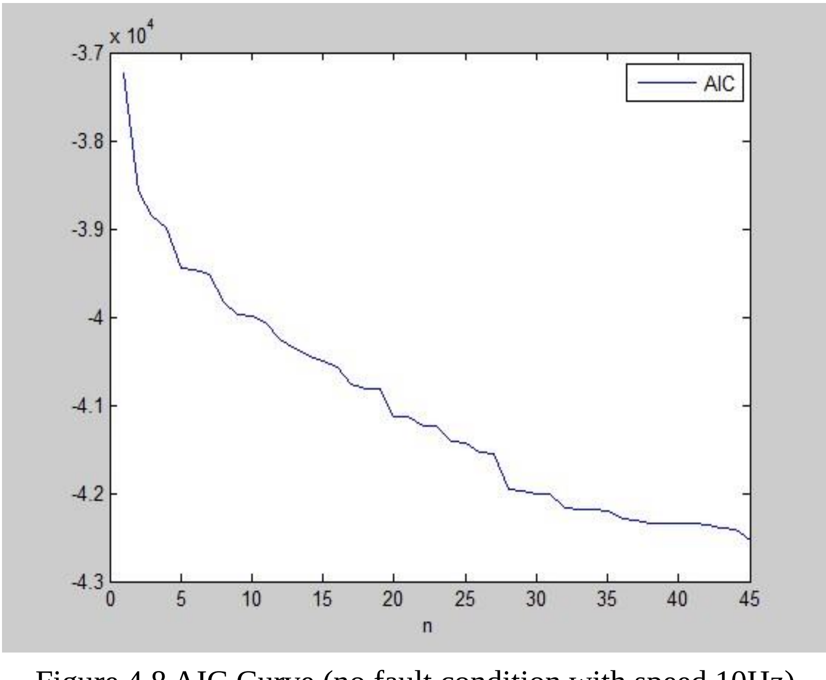


Figure 4.8 AIC Curve (no fault condition with speed 10Hz)

From these two charts, it is clear that with the increase of n, the variance is reduced. FPE and AIC curves both reduced sharply when n is in the small range. In the bigger range of n, the FPE and AIC curves reduce slowly. Considering various factors, n=20 is an acceptable solution.

Minimizing the prediction error in the least squares sense, Linear Prediction Coding (LPC) is used to determine the coefficients of the forward linear predictor. It is used in filter design, eigenvalue extraction and speech coding.

As the number of the parameters is determined, the fan's vibration signal $x(t)$ is used as the AR (20) model's output. The parameters calculated from LPC by every 20 fan vibration signal samples can be used as the fan vibration features.

LPC uses the autocorrelation method of AR modeling to find the filter coefficients. LPC computes the least squares solution to:

$$\mathrm{Xa} = \mathrm{b} \tag{4.13}$$

where:

$$X = \begin{bmatrix} x(1) & 0 & \cdots & 0 \\ x(2) & x(1) & \ddots & \vdots \\ \vdots & x(2) & \ddots & 0 \\ x(m) & \vdots & \ddots & x(1) \\ 0 & x(m) & \ddots & x(2) \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & x(m) \end{bmatrix},\ a = \begin{bmatrix} 1 \\ a(2) \\ \vdots \\ a(p+1) \end{bmatrix},\ b = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{4.14}$$

and m is the length of x.

Solving the least squares problem via the normal equations

$$X^H \mathrm{Xa} = X^H b \tag{4.15}$$

Leads to the Yule-Walker equations:

$$\begin{bmatrix} R_1 & \cdots & R_p \\ \vdots & \ddots & \vdots \\ R_p & \cdots & R_1 \end{bmatrix} \begin{bmatrix} a_2 \\ \cdots \\ a_{p+1} \end{bmatrix} = \begin{bmatrix} -R_2 \\ \cdots \\ -R_{p+1} \end{bmatrix} \tag{4.16}$$

where r = [r(1) r(2) ... r(p+1)] is an autocorrelation estimate for x. The Yule-Walker equations are solved in flops by the Levinson-Durbin algorithm [17].

As mentioned before, LPC algorithm is commonly used in filter design and speech coding, it is also used in eigenvalue extraction. In the process of eigenvalue extraction, the estimated signal is not necessary to calculate. The predictor coefficients and model's residuals are needed as the eigenvalue.

In each original fan vibration signal data file, there are 10,000 acceleration samples, and as the number of parameters is 20, every 400 samples are used to calculate their eigenvalues. The Matlab code is given below:

```
load cocked10hz.txt
x=cocked10hz(:,2);
count=0;
for i=1:400:10000
    line=x(i:i+399);
    count=count+1;
    input11(count,:)=lpc(line,20);
end
```

One of the feature vector samples is shown in Table 4.3:

Table 4.4 AR Model Feature Vector Sample

1	-0.05587988408509 70	-0.248416638884 469	0.2210663080076 17	0.32324899188629 1	-0.05201846208716 90	0.15775083978932 6
0.004547738108713 85	-0.03474437082387 30	-0.200407646454 255	0.1092804090016 44	-0.06676488579550 04	-0.03482710149996 07	0.06735173975364 75
0.096743636362441 9	-0.02381874415842 70	0.1354270232029 07	0.1524863954060 70	0.09377824707236 15	-0.03605680269552 61	0.07671600561115 55

The feature vector sample is the concentrated expression of the selected 400 vibration signal samples. It includes the features of the 400 samples, which can be used in classification algorithm.

The BP neural network training process includes a lot of iterations, which means it needs a long time for training. Using feature vectors instead of the original vibration signal may effectively reduce the computation, which makes the training process more efficient.

4.3.2 Neural Network Training Based on AR Model

Feed-forward Neural Network is composed of input layer, hidden layer and output layer, each layer has a certain number of neurons. The diagnostic model is shown in Figure 4.9:

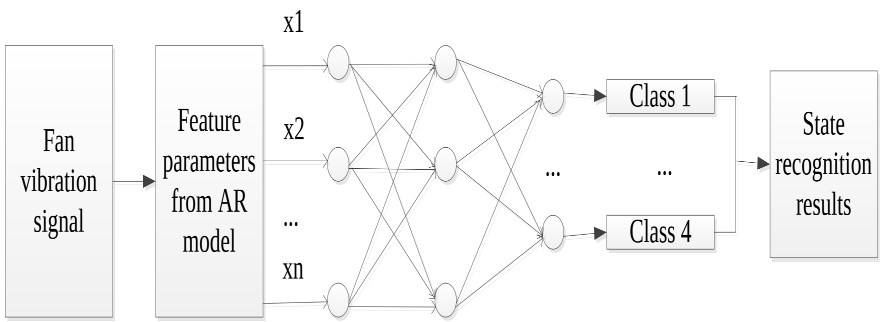


Figure 4.9 Diagnostic Model Flowchart

The fan vibration signal is used to build AR model, and then the feature parameters are selected as eigenvectors. All of the eigenvectors are inputted into the neural network.

There are 20 input nodes based on the fan vibration signal feature vector. According to the functions discussed earlier, the number of hidden layer's nodes range from 5 to19.

This number influences the results, but there is no proof to show what the optimal result is, and how the number influences the results. In this research, using Matlab modeling of the BP Neural Network, we try these different numbers as the number of hidden layer nodes. Figure 4.10 shows the results.

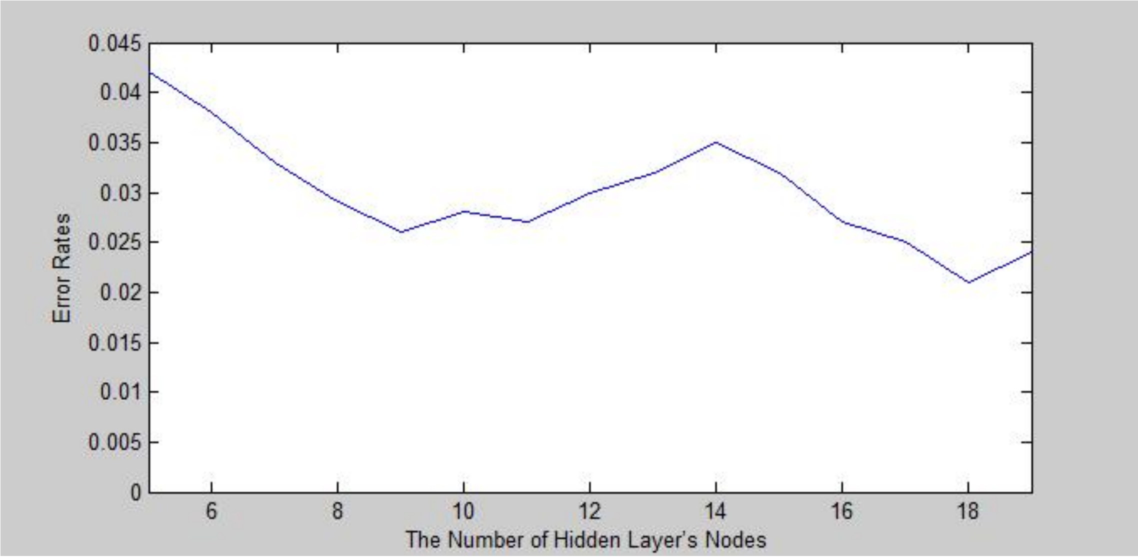


Figure 4.10 Error Rates in Different Number of Hidden Layer Nodes

The figure shows the classification error rates in different number of hidden layer nodes. It is clear that having different number of hidden layer nodes has no significant effect on the classification results. All of the results based on different number of hidden layer nodes are acceptable. Therefore, 18 hidden layer nodes have been selected for the test.

The fan's vibration signal classification algorithmic modeling, which is based on BP neural network, includes: BP neural network modeling, BP neural network training and BP neural network classification.

The algorithm flowchart is given in Figure 4.11:

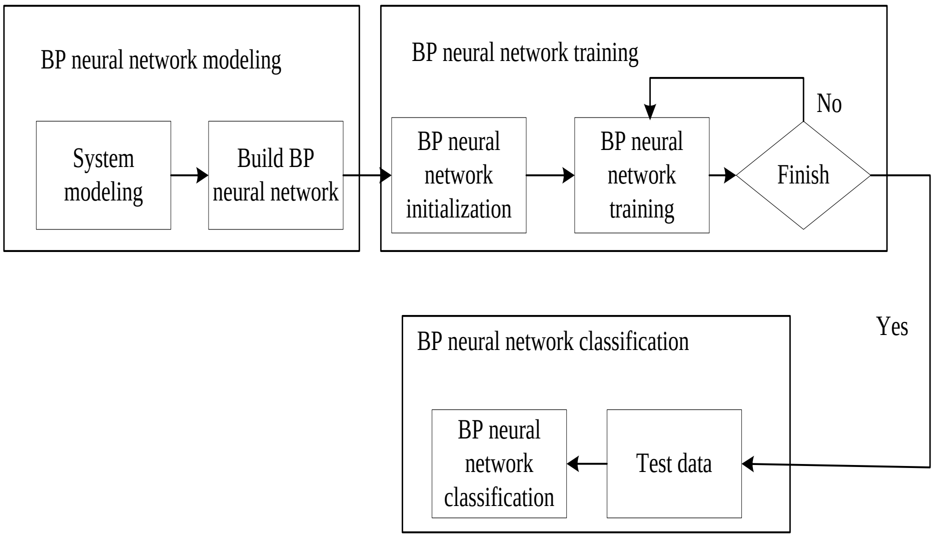


Figure 4.11 BP Network Flowchart

The BP neural network modeling is based on the features of input and output. The AR model of fan vibration signal has 20 features. As a result, the structure of fan vibration signal classification BP neural network is 20-18-4, which means the input layer has 20 nodes, the hidden layer has 18 nodes and the output layer has 4 nodes.

The BP neural network use training set as input data for training the neural network. If the trained BP neural network satisfies user's need, this BP neural network is able to do classification.

Based on the AR model, the fan vibration signal's features from 4 different conditions are labeled by 1,2,3,4. The AR model features are saved in data1.mat, data2.mat, data3.mat and data4.mat. Each of the data have 21 dimensions, the first dimension is the class label. Based on the labels, set the expected output value: if the class label is 1, the expected output vector is [1 0 0 0]; if the class label is 2, the expected output vector is [0 1 0 0]; if the class label is 3, the expected output vector is [0

0 1 0]; if the class label is 4, the expected output vector is [0 0 0 1]. This step is similar to the processing method we used earlier.

After all of these input vectors, output vectors, hidden layer numbers were known, the Neural Network Pattern Recognition Tool was used to train the network. This step was similar with the training process used when the input features are Root Mean Square Value, Peak to Peak Value, Kurtosis, Crest factor, Impulse factor and Energy in time domain.

Figure 4.12 shows the test results. The correct classification rate of the trained neural network model was 100%, which means for the entire 300 feature vector samples all of them were classified to the right class. This shows that preprocessing by the AR model gives accurate results for classification by the neural network. The 100% is achieved in the ideal conditions in the lab. It may not give 100% results in an industrial setting.

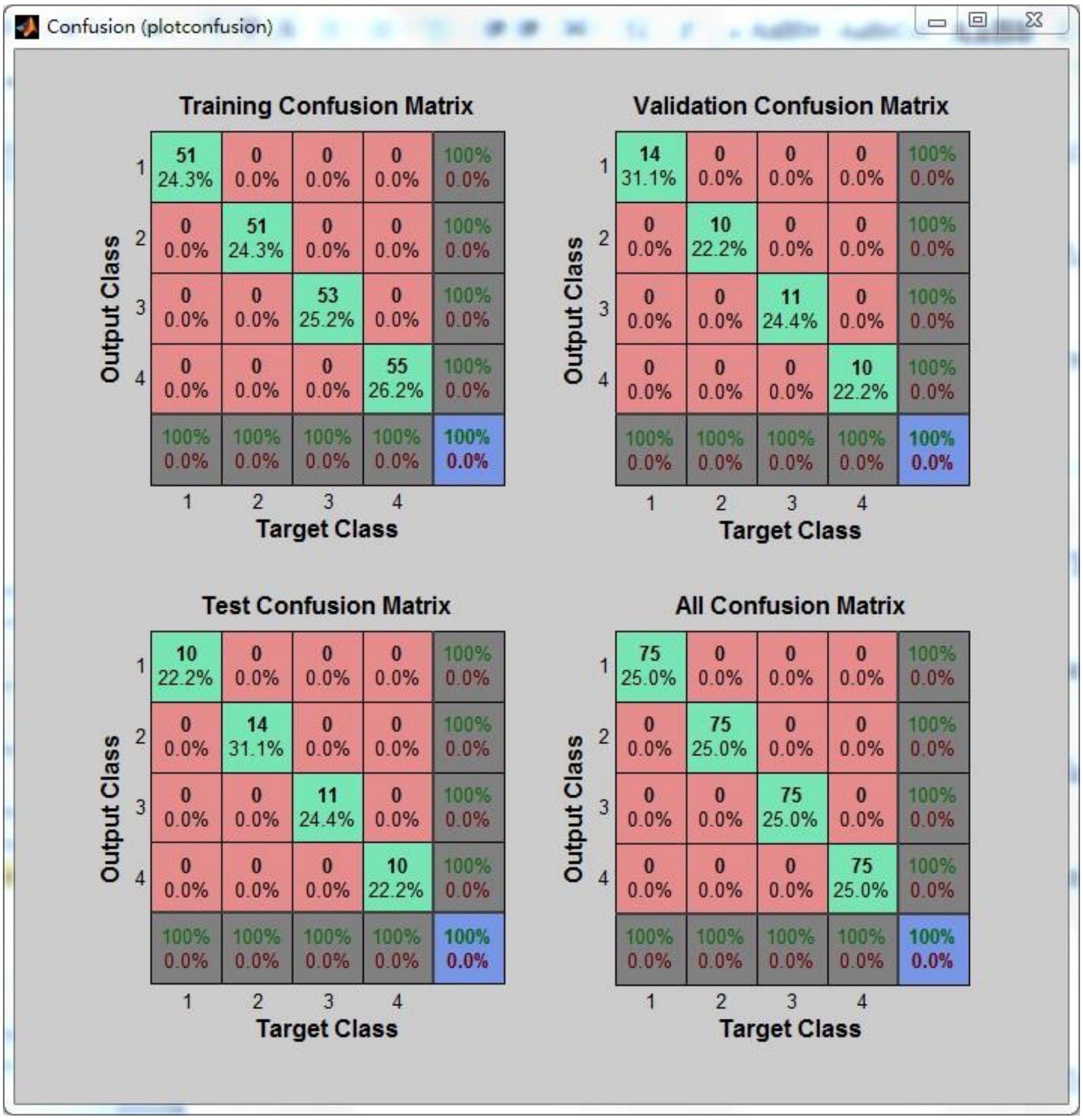
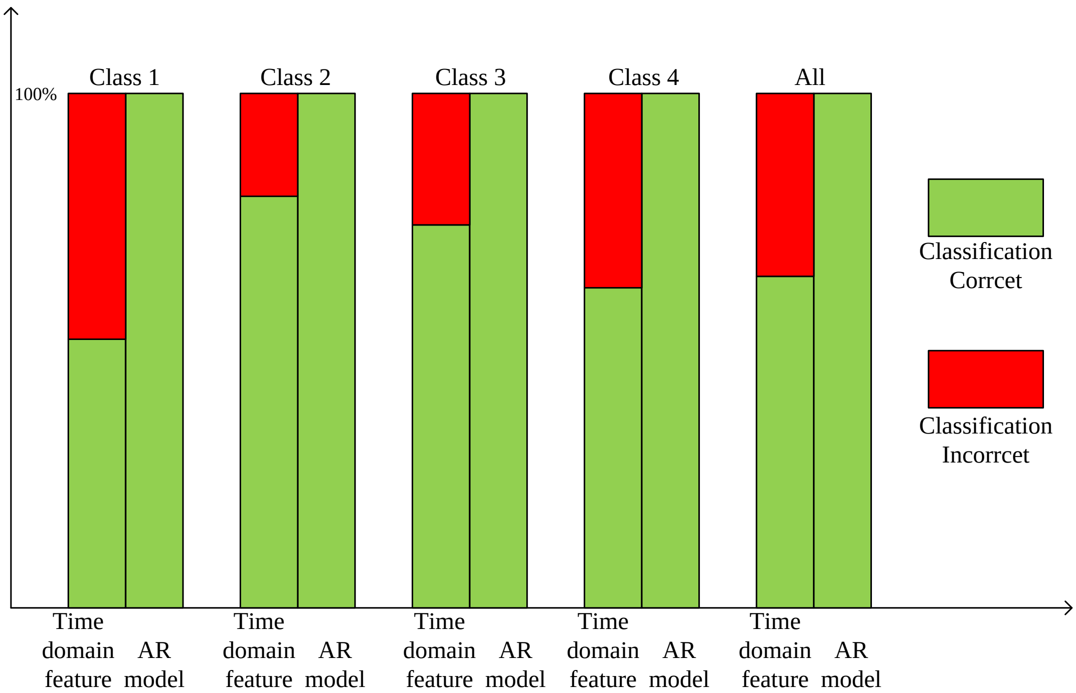


Figure 4.12 Training Results for the Four Conditions

4.4 Comparison of the Results

In this chapter, two different methods were used for processing the original data, and the processed data was used as input to train the neural network. The results show that the features that were calculated by traditional methods such as time domain features do not train the neural network well. Enough information cannot be obtained to do classification by traditional method if the experiments equipment is limited. The comparison of the results is shown in Figure 4.13:



Method	Classification	Class 1	Class 2	Class 3	Class 4	All
Time domain features	Correct	52%	81.3%	74.7%	64.0%	68%
	Incorrect	48%	18.7%	25.3%	36.0%	32%
AR model	Correct	100%	100%	100%	100%	100%
	Incorrect	0%	0%	0%	0%	0%

Figure 4.13 Time Domain Features and AR Model Comparison

Based on the above results, we chose the AR model to process the original fan vibration signal. As the trained BP neural network that used the AR model features as input satisfies the request, the next step is to save the trained BP neural network model as shown in Figure 4.14.

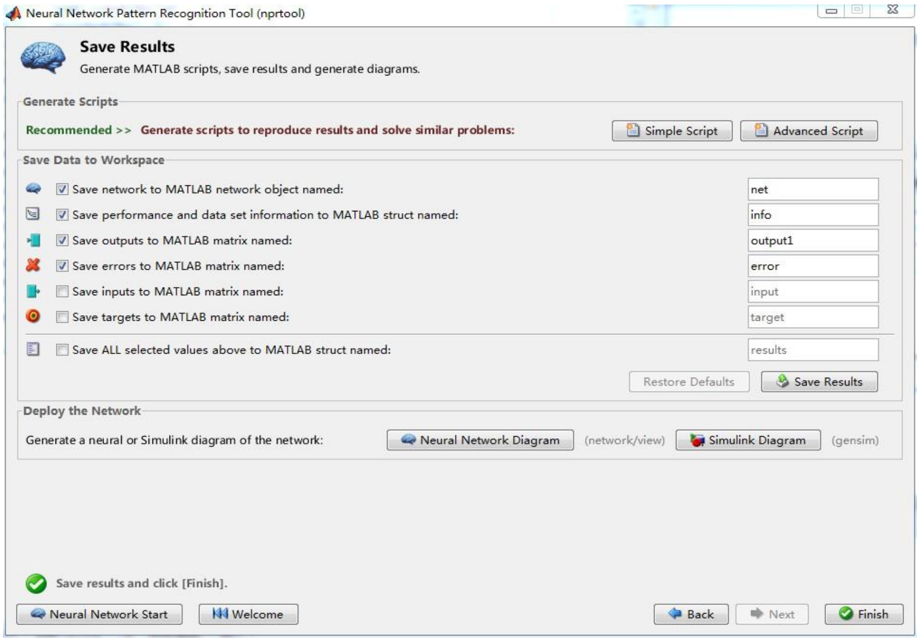


Figure 4.14 The Function Used to Save Results

The neural network toolbox software uses the network object to store all of the information that defines a neural network, which is the net file shown in the figure.

CHAPTER 5

IMPLEMENTATION USING LABVIEW AND MATLAB SOFTWEAR

5.1 Matlab Scripts

The powerful data acquisition ability is the advantage of LabVIEW, but the numerical calculation ability of LabVIEW is not as good as its data acquisition ability. Although Watchdog Agent^{TM} Prognostics Toolkit, which is developed by center for Intelligent Maintenance Systems (IMS), added diagnostic function to LabVIEW, the condition monitoring applications based on Watchdog Agent^{TM} cannot do fault diagnosis fast and properly [32]. The reason is LabVIEW programming language is not optimized for numerical calculation; the program will spend a lot of time to compute if there is massive data to be processed.

Thus LabVIEW developed the Matlab Scripts function to call Matlab programs, which is a powerful computing program. Matlab and LabVIEW programs should be installed on the same computer. If the Matlab scripts are used in LabVIEW program, the LabVIEW program will call the Matlab command window automatically in order to achieve Matlab and LabVIEW hybrid programming.

5.2 LPC Function in LabVIEW

This sub VI Figure 5.1 shows how to call Matlab LPC function from LabVIEW. The raw vibration signal samples were used to do the test. The data, which was loaded to the program, was one-dimensional waveform signal. But Matlab is based on matrix, so the data should be converted to matrix.

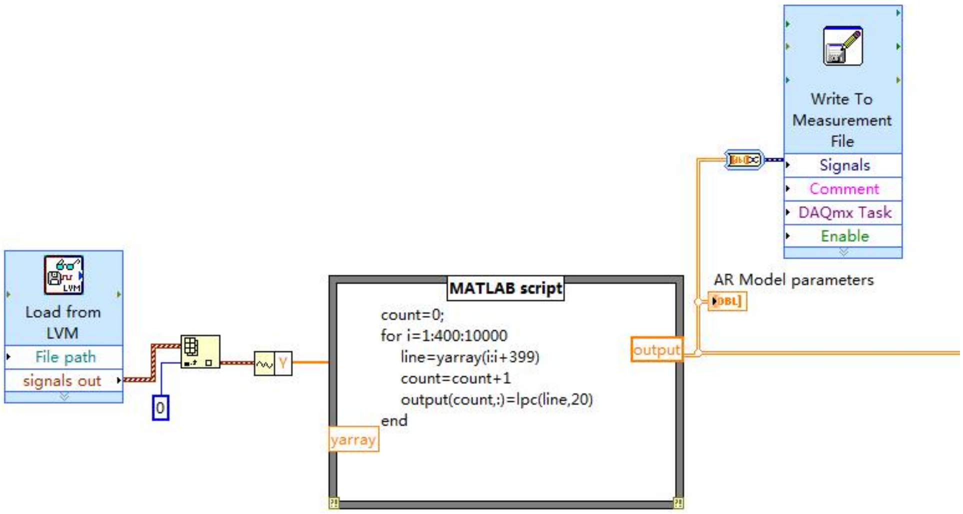


Figure 5.1 Matlab Script of LPC Function

The raw vibration signal was converted to AR model parameters, which was the feature vector that included 20 features. The Figure 5.2 shows 100 samples of the 20 features.

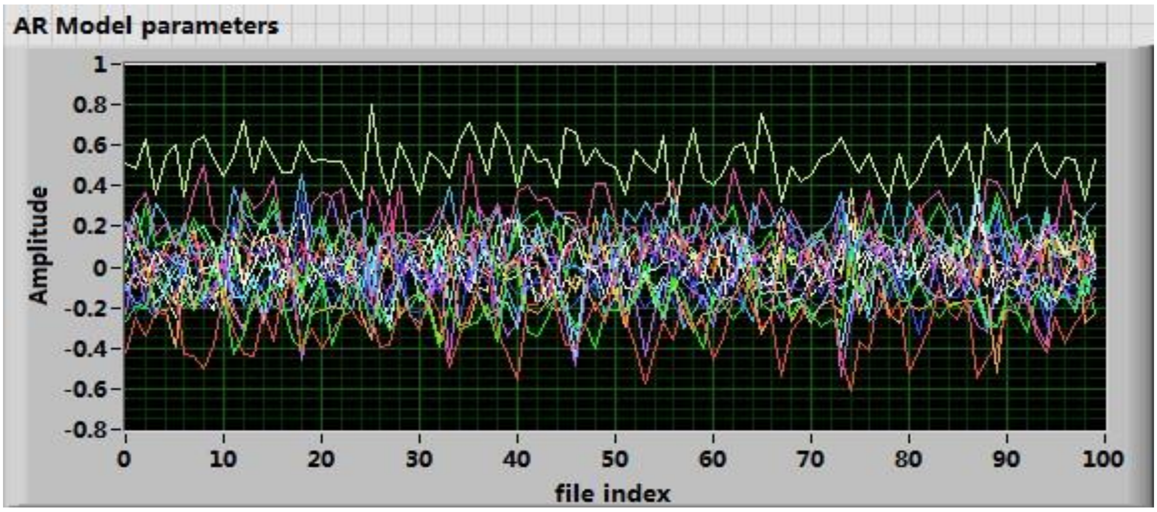


Figure 5.2 AR Model Parameters Display in LabVIEW (100 samples)

5.3 BP Neural Network Model Script

The function of the Matlab script shown in Figure 5.3 is used to call the trained BP neural network model from saved Matlab file. As mentioned before, the neural network toolbox software uses the network object to store all of the information that defines a neural network.

The network object was added to the LabVIEW path, which was called from the Matlab script. AR model feature vector set was used as the input of the Matlab script.

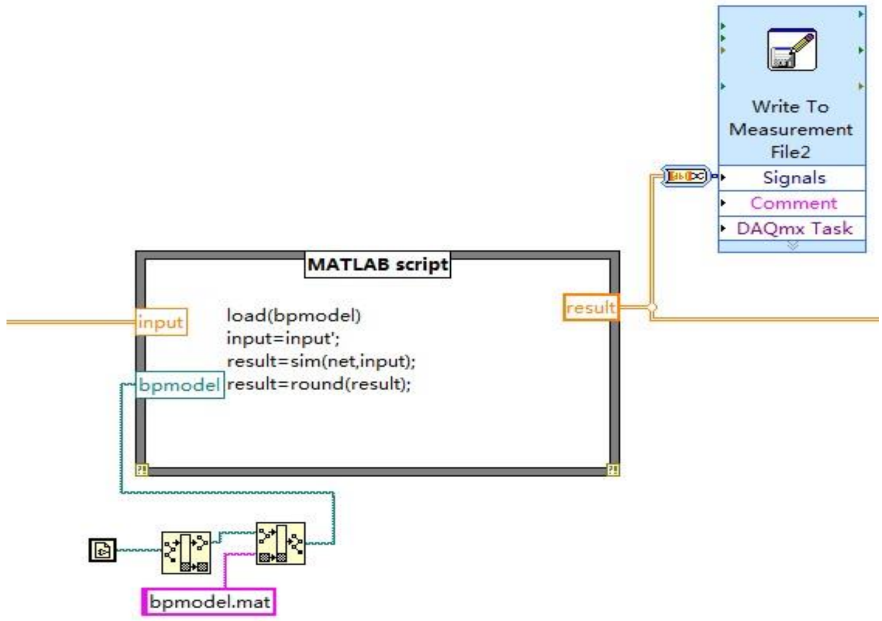


Figure 5.3 BP Neural Network Model Script

The output of the BP neural network model classification function was a one-dimensional array which was close to the class label. The following step normalizes the class label. It is obvious that the result is close to 0 and 1. Call the round function in Matlab which is used to round the number to nearest integer, which is 0 and 1. The result of the classification process is shown in Figure 5.4. The results read as 1000 in the first row show that the class is 1 as 1 appears in column 1. Similarly, results read as 0100 will mean the class is 2 as 1 appears in column 2. The column number that has the 1 gives the class number of the condition of the fan.

1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000

Figure 5.4 Classification Results

In this test, the input feature vectors were transferred from vibration signals of healthy fan. The result shows all of the samples are classified to class 1, which is the correct class.

5.4 Graphical Display of the Results

The output of the BP neural network model is the class label. As mentioned before, class label 1000, 0100, 0010 and 0001 means healthy fan, fan blades unbalance, rotor unbalance and bearing fault respectively.

Since the class labels are listed by columns, number of 1's is calculated in each column in order to get how many samples are classified to their target class. The Matlab script was called to do the counting process as shown in Figure 5.5.

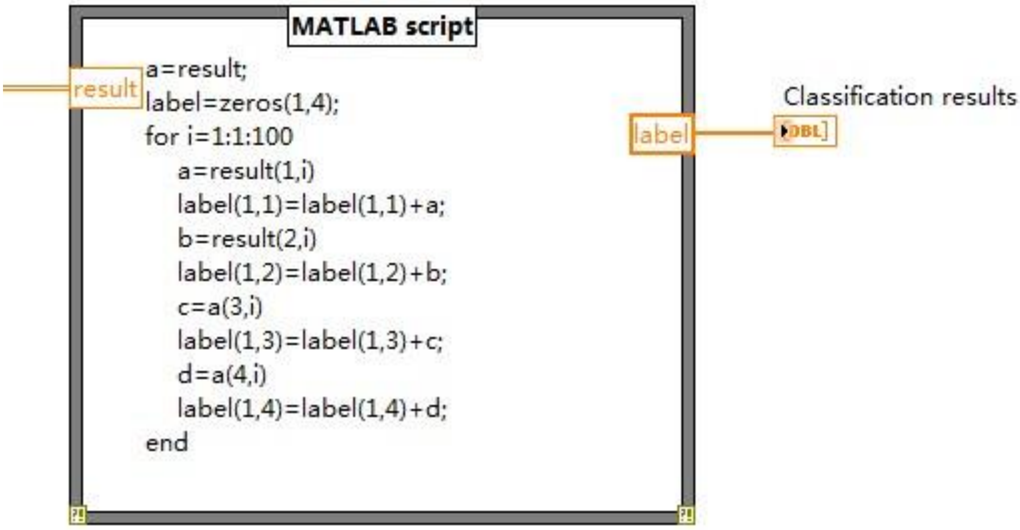


Figure 5.5 Results Output

The count result was shown in this graphical display window which is shown in Figure 5.6. The white bar showed the numbers of samples belonging to class 1. The test data used in this process was healthy fan vibration signal. The classification result was correct.

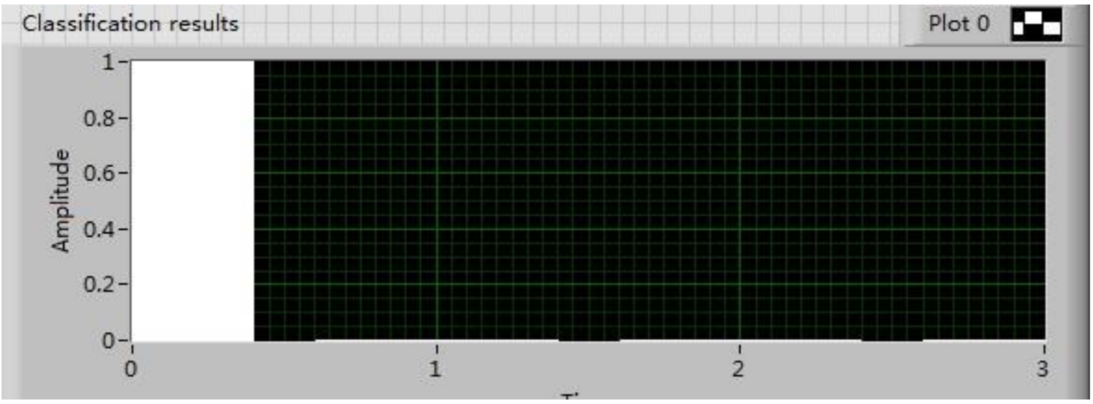


Figure 5.6 Results Display in LabVIEW

5.5 Condition Monitoring System

The condition monitoring system consists of the sub-functions, such as the data acquisition model, data preprocessing by AR model, classification based on the trained neural network model, and display of results. Figure 5.7 shows the front panel of the condition monitoring system. In the front panel, it included the waveform of the raw vibration signal, the FFT signal, and the AR model parameters which is the feature vector and the classification result. It also had the save file function which was used to save the original vibration signal and classification results for further research. Figure 5.7 and Figure 5.8 show the front panel and block diagram, respectively, of the whole condition monitoring system.

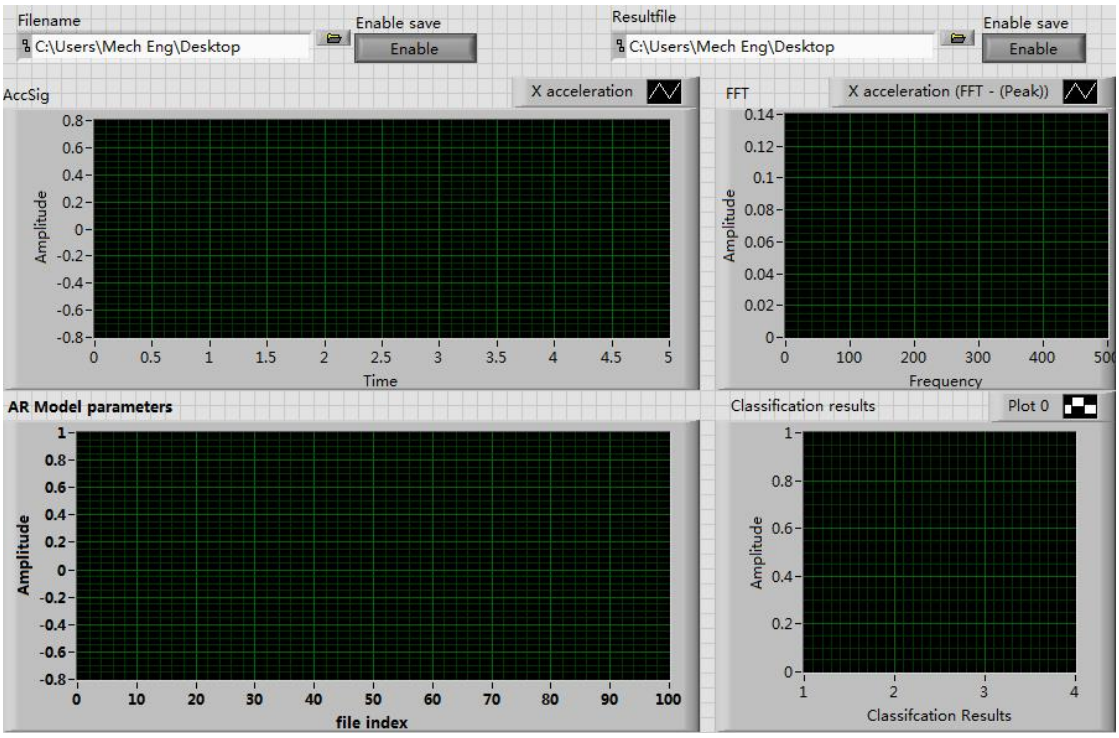


Figure 5.7 condition Monitoring System Front Panel

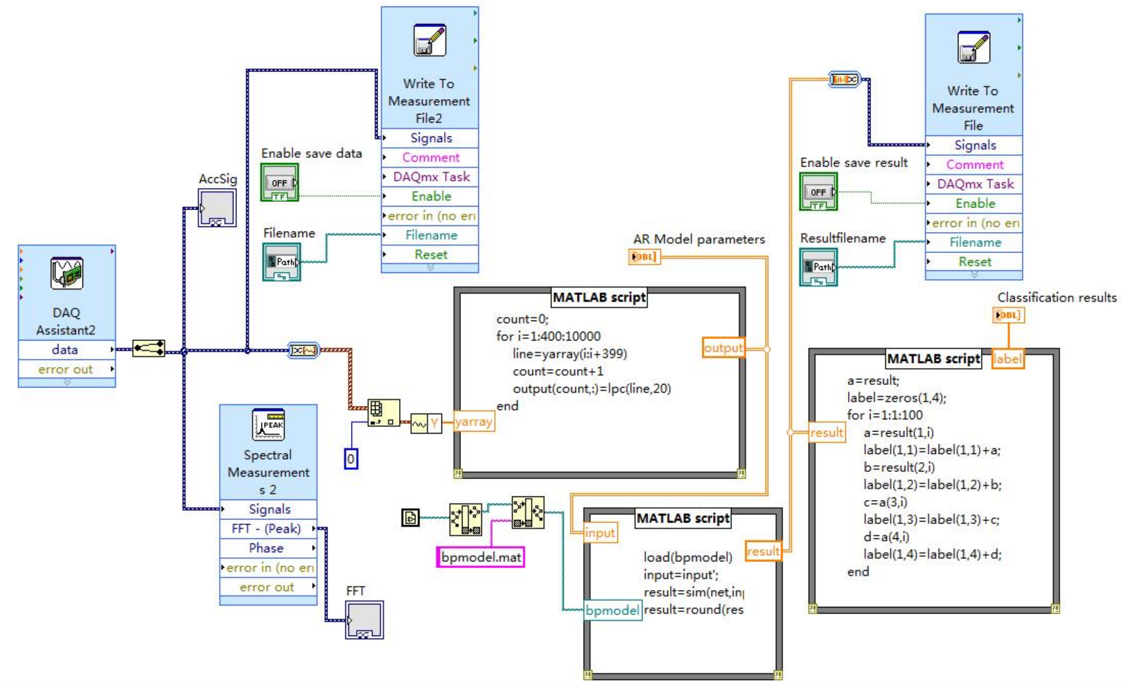


Figure 5.8 Condition Monitoring System Block Diagram

In the block diagram, the DAQ assistant was used to collect fan's vibration signal, the spectral measurements function were used to transfer the raw vibration signal to FFT waveform. The program also included these three Matlab scripts that were mentioned before, the LPC AR model function, the classification function and the result counting function.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

As science and technology progresses, the need of fault diagnosis has also increased. Fan provides powerful heat dissipation ability in the machinery. Fans have been used in a complex environment for a long time. Timely and accurate detection of the health situation of the fans is very important. It impacts the efficiency of the factory and the safety of the workers.

This thesis studied on applying neural networks for failure diagnosis. Back Propagation (BP) neural network is now widely used in different areas; it is a powerful tool for classification. But when we want to use BP neural network to do classification, the input data should be processed by appropriate method. The appropriate method will make the result satisfy users’ needs. The LabVIEW program was used to collect and process data and call Matlab functions for the classification. The results from the experiment show that the AR model is the appropriate preprocessing method for calculating the input data for the neural network. The powerful computing ability of Matlab and the data acquisition ability of LabVIEW can be perfectly combined together.

The system designed in LabVIEW works well for fault diagnosis. After the fan vibration signal is collected, the system shows the class results in a short time. The results show that the system is a good fault diagnosis tool for fan condition monitoring.

Since the equipment used for the experiments was limited, there are still some other problems that have not been discussed in this thesis. In future study, other types of faults such as gearing box faults and motor faults may be considered. All of the faults tested in the project were in extreme cases; however, faults normally get worse gradually. Less extreme faults will be tested in the future. Extra accelerometers can be used to get more vibration details and database can be used in the program for data storage. Other classification techniques such as rough sets can be tested and compared with the neural network for fault detection. It would be useful to detect faults in the industrial setting.

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