NEURAL NETWORK APPLIED FOR THE FAULT DIAGNOSIS OF AN AC MOTOR

By

MUHAMMAD ARIFF BIN YAHYA

Submitted to the Electrical & Electronics Engineering Programme
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical & Electronics Engineering)

Universiti Teknologi PETRONAS
Bandar Seri Iskandar
31750 Tronoh
Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

NEURAL NETWORK APPLIED FOR THE FAULT DIAGNOSIS OF AN AC MOTOR

by

Muhammad Ariff Bin Yahya

A project dissertation submitted to the
Electrical & Electronics Engineering Programme
Universiti Teknologi PETRONAS
In partial fulfillment of the requirement for the
Bachelor of Engineering (Hons)
(Electrical & Electronics Engineering)

Approved,

AP Dr K.S Rama Rao
Project Main Supervisor

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK

June 2007

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

Muhammad Ariff Bin Yahya

ABSTRACT

There are many failures of AC motors in the industry for different reasons and huge losses are affected. This failure takes some time to happen and the cause slowly affects the motors. In this project report, the neural network comes with a solution to the problem. The neural networks able to diagnosis the incipient AC motors faults. The network collects all the possible causes to any failure and analyzes it with existing trained data to determine the status of the motor. For example if the motor having degradation on the winding insulation resistance, the network will collect the status of the insulation resistance and compare it with the allowable value of the insulation resistance, thus the output states the future failure with the current value of the insulation resistance on the motor's winding. This project report covers on three fault outputs which are bearing fault, winding fault and overheating fault. All these outputs depend on certain inputs where the inputs are the cause towards the failure. The artificial neural network has various types of usage. For the prediction purposes, **feedfoward-back propagation** network topology will be used. This topology will be is with appropriate training function. The training function for example, Resilient-Backpropagation will be trained and provides values for weights and biases of the network topology. The biases and weights are used to analyze any input fed to this network and come out with its prediction. Furthermore the project report also deals with MATLAB simulation and toolbox. The MATLAB software is able to tolerate the neural networks where all the command and application are in MATLAB based.

ACKNOWLEDGEMENT

In the name of Allah S.W.T. Most Gracious, Most Merciful,

Alhamdulillah, His willing has made it possible for me to complete my Final Year Project (FYP), and the resilient and good health given to me to end up with this dissertation. I would like to take this opportunity to express my sincere appreciation to many people for their support in this study period.

First of all, I would like to express my sincere gratitude to my beloved supervisor Associate Professor Dr. K.S Rama Rao, for his guidance, inspiration and support through the course of this project. In addition for his invaluable advice, understanding, patience and encouragement from the beginning of my involvement in this FYP under title Neural Networks Applied for Fault Diagnosis of an AC Motor.

I am indebted to many individuals who helping me during my FYP where presence of them are the essence to make this successful. Specially, my utmost gratitude to Electrical and Electronics Engineering Lecture, Ms Hazrin Hani who helped a lot in my Neural Network problems. Beside that not forget to Associate Professor Dr. Mukerjee who evaluated my FYP 1 presentation and give a lot of comments and suggestions which really helped in this project.

My heartless gratification also goes to al my colleagues especially Azrul Hisham Othman, Mohd Afiz Zaim and Khairun Nisa' who always being my discussion partner and also making this study period such a memorable event. Finally thank you for others that involved direct or indirectly in my FYP. Without them this project will not be as successful as it is.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

N	Normal condition of the motor
BF	Bearing fault
WF	Winding fault
OH	Overheating fault
PD	Partial discharge
ACL	Actual current flow at load
Vb	Vibration
T	Temperature
WI	Winding insulation resistance
AC	Attenuated Current; i.e Attenuated Current (AC) Motor.
T#	Set of target used for training process; i.e T3 = set of target number 3.
V	Volt; S.I unit for voltage
A	Ampere; S.I unit for current
µmpp	micrometer per pulse; unit used for the vibration measurement
MΩ	Mega ohms (1000000 ohms); unit used for resistance measurement

CHAPTER 1
INTRODUCTION

1.1 Background of study

The study of AC (induction or synchronous) motor fault detection and identification has been of increasing interest during the last 20 years and a great amount of research has been done on the topic related to AC motor fault diagnosis[1]. The fault diagnosis seems to be important since it's able to predict the status of the AC motor in the future. With the prediction capability, the motor can be prevented from complete damage and total loss. On top of that, the prediction can stop the motor to disturb any online process. In the industry, AC motors are widely used and most of them usually online 24hours per day. Once the motor brakes down, all the online process can be affected. In terms of dollars and cents, without the prediction, the industry will encounter double the total losses. One loss is from the motor damage, and the other one is from the online process disturbed. The ability for prediction gives advantages here to repair and replace the respective motor without disturbing the online process. Besides the respective motor is also still in "minor injury", thus not include in major cost.

1.2 Problem identification

For AC motors, there are various causes for fault during normal and abnormal operation. With the available information from the industries only selected faults are considered for this project. These are major and common faults found with AC motors as follows:

- Winding fault
- Bearing fault
- Overheating fault

Along with all these faults, the causes also need to be identified in order to train the network topology. Without the training, the neural network isn't being able to analyze all the causes for the stated faults. The following causes are taken into consideration for the investigation of the faults:

- Partial Discharge (PD) [2]
- Temperature of the stator winding
- Winding insulation resistance
- Vibration[2]
- Current flow at load

For the faults selection, since the faults are common faults, there are possibilities for the neural network to be used with other type of motors (induction motors) [1]. The faults can be prevented if detected early, thus minimizing major damage and cost for repair.

1.2.1 Partial Discharge (PD)

PD are small electrical sparks which occur in stator windings rated 3.3 kV or higher. PD is non-existent or negligible in well-made stator windings that are in good condition. However, if the stator winding insulation system was poorly made, or the winding has weakened due to overheating, coil movement or contagion, then PD will occur [10].

1.2.2 Temperature of the stator winding

Operating the motor in a temperature higher than the design temperature lowers the life of the motor insulation. One common thumb rule for insulation life is that for every 10 °C increase in temperature above the design temperature, the life of the insulation is reduced by half. Exceeding design temperature of the windings stresses the insulation and reduces motor life by causing expansion and contraction of the insulation, which may results in embrittled insulation followed by cracking. The temperature always related to the load of the motor. With the full load condition, the temperature will increase due to current flowing through the stator winding also increase. Thus the overheating fault caused by the temperature must be avoided to prolong the life of the motor [11].

1.2.3 Winding insulation resistance

The resistance of the winding insulation has to be above the standard winding insulation resistance based on the type and capacity of the motor. Once the insulation system is completely bridged the system is then considered shorted and having the winding fault. The winding fault includes open turns, incorrect number of turns and shorted conductors [12].

1.2.4 Vibration

Machinery vibration monitoring has long been recognized as an effective practice for detecting mechanical problems that ultimately cause machinery failure and downtime. The measurement of the vibration is useful for the fault diagnosis especially for bearing and gear fault detection [13].

1.2.5 Current flow at load

The amount of the current flow at the load shall be always monitored to analyze the condition of the motor. It is also affect the temperature and the winding insulation of the motor. If the amount of the current flow is large, it will contribute to overheating fault to the motor.

1.3 Objective and scope

The objective of the project is to study the fault diagnosis of AC motors using **Artificial Neural Networks (ANN)**. It is further proposed to create a system that would be able to analyze all the given input of the AC motors and then come out with the status regarding the incipient motors faults. The information provided should be able to inform the status and the condition of the motors. With the system, any failure of the motors can be eliminated with proper preventive information.

The main focus of the study on the ANN is only on the related types only. There are various types of neural networks with different usage. Since the main objective is related to predict the fault of the AC motors, only one or two types of neural network's topology relevant with this objective. The type of the network topology is **Feed-Forward Back Propagation (FFBP)**, for this project. It will be explained further in the literature and methodology of this project.

For the faults on the motors, only certain available faults will be diagnosed. Only the stated faults (refer to the problem identification) are considered in this project.

CHAPTER 2
LITERATURE REVIEW / THEORY

2.1 What is ANN?

"ANN is relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy efficient packages. This brain modeling also promises a less technical way to develop machine solutions. This new approach to computing also provides a more graceful degradation during system overheating than its more traditional counterparts."[3]

In the computing industry, these biologically method of computing would be the major improvement. In the living aspects, a simple animal brains capable to do things that computers is impossible to do. Computer may able to write those things well like complex mathematical functions and saving large numbers of memory. Unfortunately computer having trouble to recognize a simple patterns from the past then create the solution for the future.

For the time being, the biological research found out an initial understanding of the natural thinking mechanism. The research looks on the brain concept which store information in patterns. From the real lives, certain patterns are hardly to recognize and require us to have an ability to recognize the patterns from many aspects. For example, every people have their own patterns of face. The ability to recognize the face is analysed with study of its pattern from various angles. This concept of recognizing the patterns and analyzing it brought a new arena in the computing technology.

2.2 Artificial neurons and how they work

Figure 1 shows the fundamental processing element of a neural network. In the normal operation a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then outputs the final result. Figure 1 shows the relationship of these four parts.

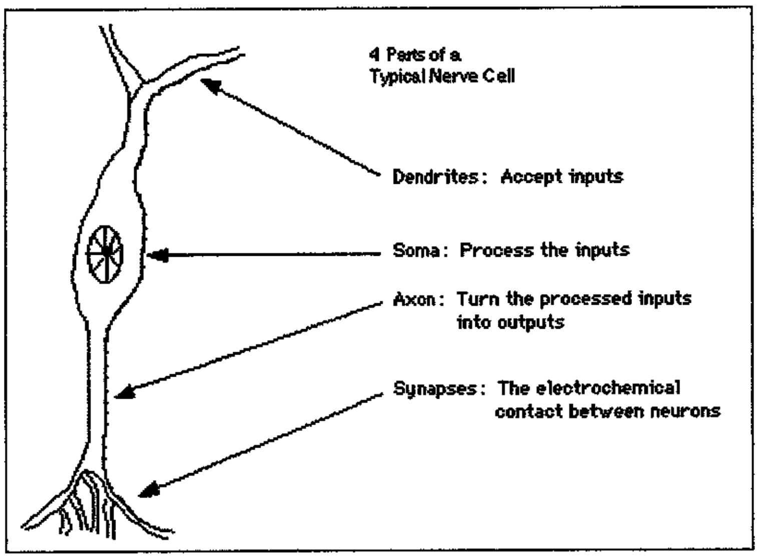


Figure 1: A simple neuron.

"Within humans there are many variations on this basic type of neuron, further complicating man's attempts at electrically replicating the process of thinking. Yet, all natural neurons have the same four basic components. These components are known by their biological names - dendrites, soma, axon, and synapses. Dendrites are hair-like extensions of the soma which act like input channels. These input channels receive their input through the synapses of other neurons. The soma then processes these incoming signals over time. The soma then turns that processed value into an output which is sent out to other neurons through the axon and the synapses."[3]

2.3 The Multiple Layer Perceptron (MLP) and FFBP

From the reading and research, the MLP and the Back Propagation turns to be the same type. This type of neural network used same architecture which contains:

- An input layer neuron
- One or more hidden layers neurons
- An output layer neuron

Figures 2 and 3 show below to see the similarity of the MLP and FFBP.

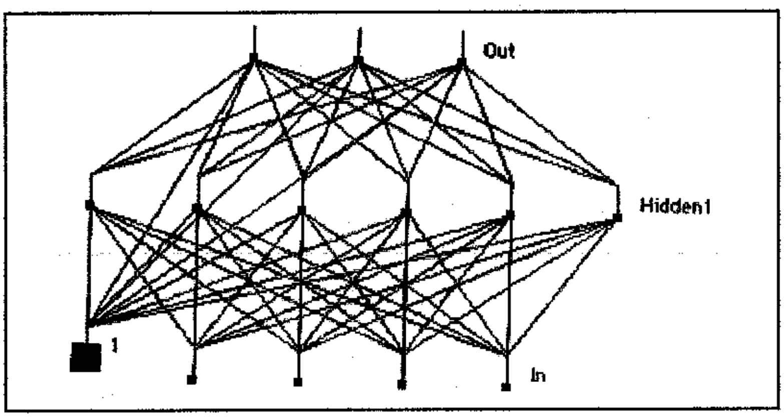


Figure 2: An Example FFBP Network

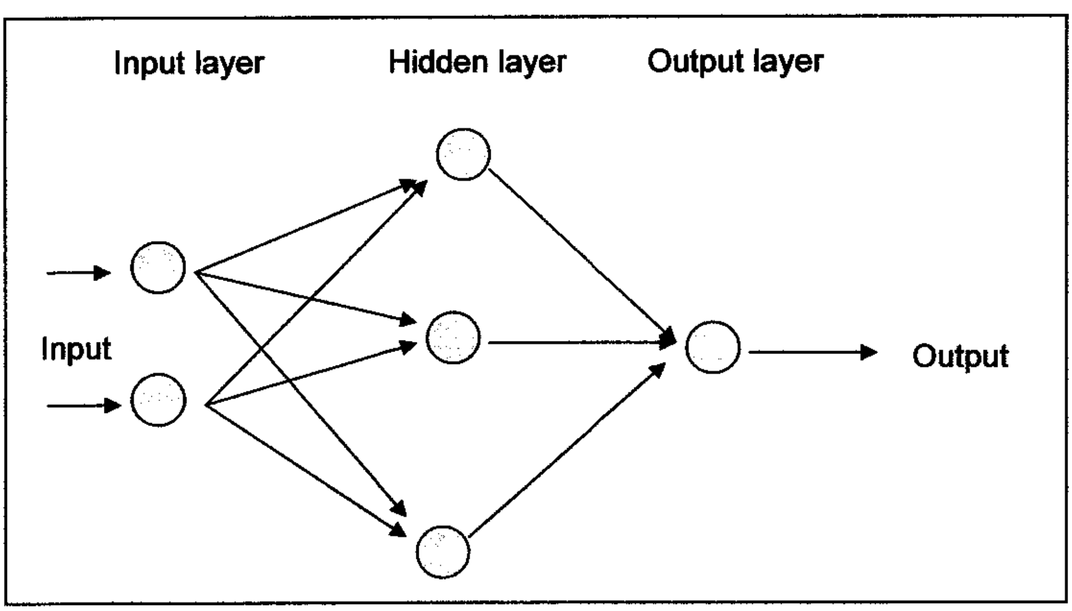


Figure 3: The typical MLP architecture

As observed in figure 2 and 3, the architecture is similar. In the literature, the authors are also relating the MLP with the FFBP type. As figure illustrated, the neurons calculates the weighted sum of its input and use the sum as the input of an activation function, which is commonly a sigmoid function. The sigmoid function is shown in figure 4:

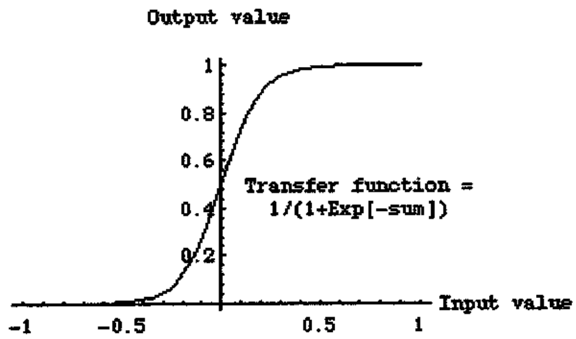


Figure 4: Sigmoid transfer function

The supervised back propagation learning algorithm uses gradient descent search in the weight space to minimize the error between the target output and the actual output. A large number of gradient based search methods are reported in the literature.

The back propagation is widely used rather than the MLP due its popularity. The FFBP has feed forward in the hidden layers. The in and out layers in the MLP and the back propagation indicate the flow of information during recall. Recall is the process of putting input data into a trained network and receiving the answer. Back-propagation is not used during recall, but only when the network is learning a training set.

2.4 FFBP in the MATLAB

In MATLAB, the FFBP function can be generated using the "newff" function. This is to create a network inside the MATLAB command windows. The function newff creates a feedforward network. It requires four inputs and returns the network object.

"net=newff([-1 2; 0 5],[3,1],{'tansig','purelin'},'traingd');"[4]

In the example above; the first input is an R-by-2 matrix of minimum and maximum values for each of the R elements of the input vector. The second input is an array containing the sizes of each layer. The third input is a cell array containing the names of the transfer functions to be used in each layer. The final input contains the name of the training function to be used. As detailed the command above creates a two-layer network. There is one input vector with two elements. The values for the first element of the input vector range between -1 and 2, and the values of the second element of the input vector range between 0 and 5. There are three neurons in the first layer and one neuron in the second (output) layer. The transfer function in the first layer is tan-sigmoid, and the output layer transfer function is linear. The training function is traingd [4]. Beside that the network also can be interfaced by using the Graphical User Interface (GUI) provided inside the MATLAB. The GUI can be run using NNTool function. The interface makes the training process much easier.

CHAPTER 3

MEHODOLOGY / PROJECT WORK

3.1 Procedure and identification

In literature various types of neural networks are reviewed. For this project, only relevant types are selected. The most common types used for fault diagnosis is FFBP rather than MLP. The structures for both of the topologies are almost the same. Figure 5 shows the steps needed to be complete this project.

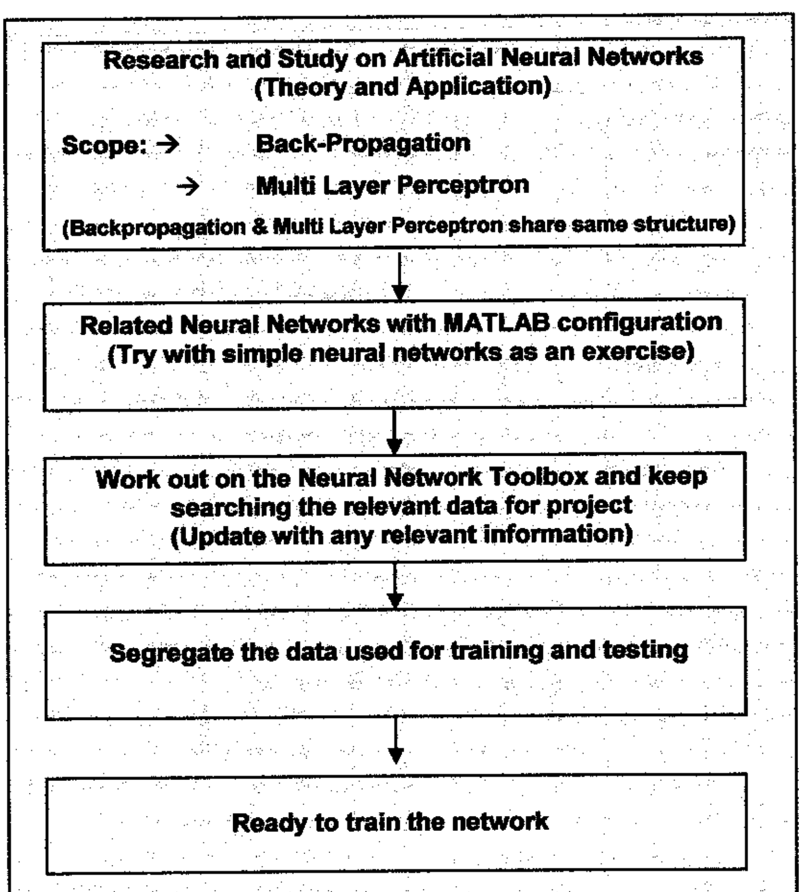


Figure 5: The basic step

Once the corresponding data segregated into their types, then the training process can proceed. The data need to be grouped into 3 types as follows:

- Training Data
- Validation Data
- Testing Data

The training data and validation data are used to train the network. Once the desired result is obtained, then the experienced network can be simulated with the Testing data. For the training process, the breakdown process is as shown in figure 6:

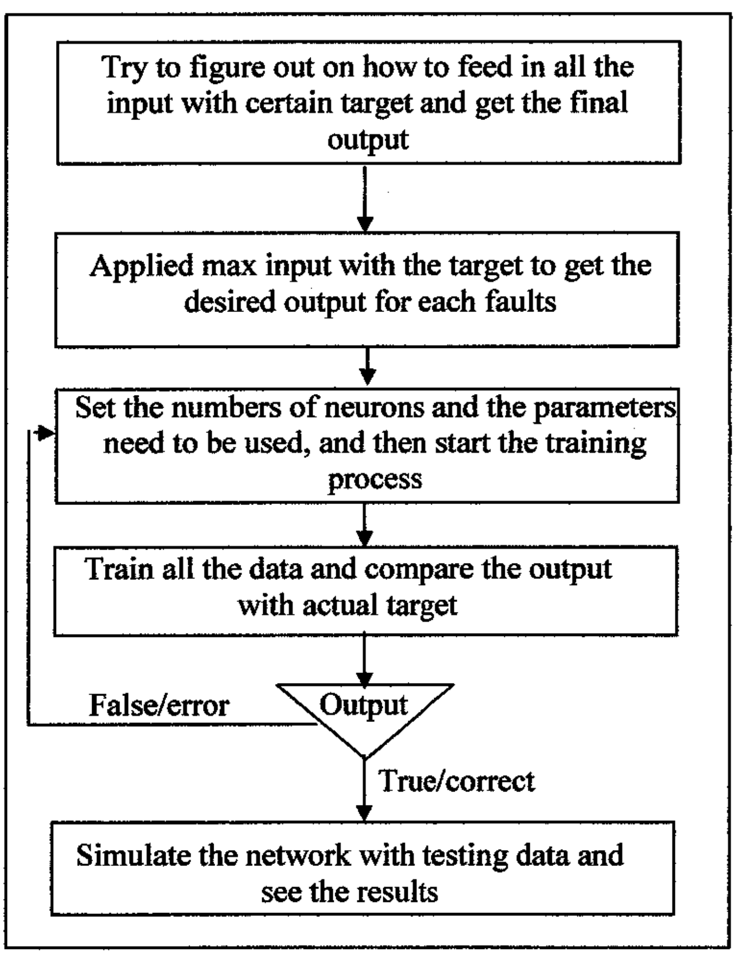


Figure 6: The basic step for the ANN

3.2 Tools

This project ends up with simulation on the diagnosis done by the neural networks. MATLAB software is used to configure the neural networks command and coding. The MATLAB software, there is Graphical User Interface (GUI) for the neural network. It is important to understand how to use the toolbox for this project.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Network structure

The structure adopted for the fault diagnosis using neural network is shown in figure 7. As explained in the introduction and the literature review, this structure is developed according to the back propagation concept.

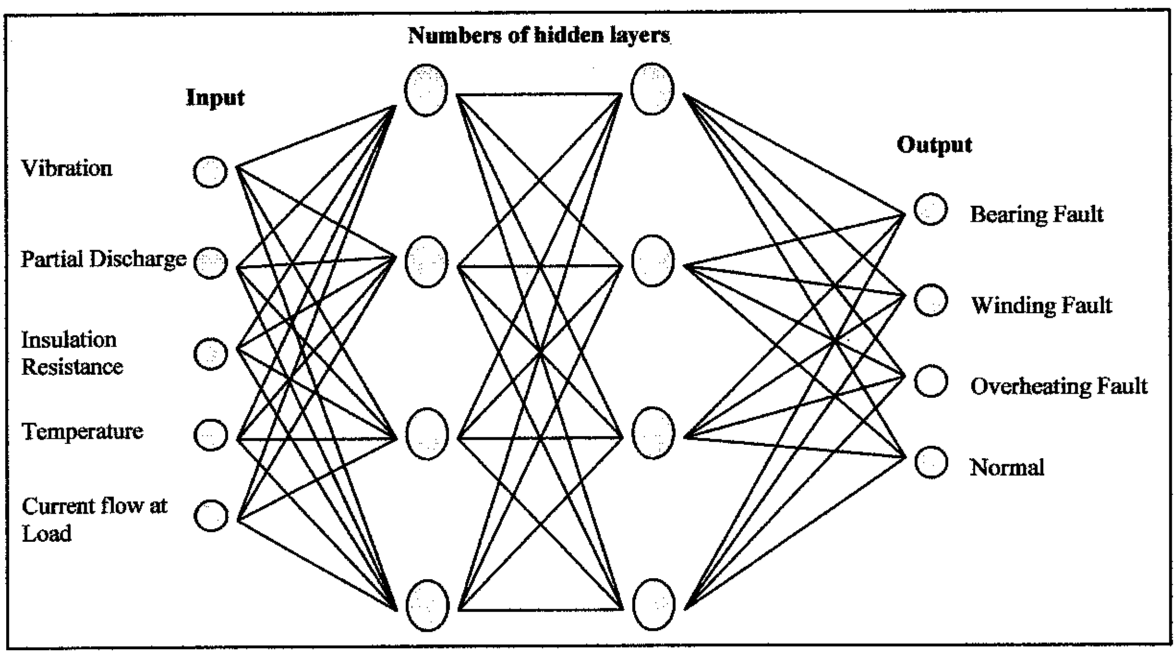


Figure 7: The main structure for the AC motor fault diagnosis using ANN

The figure 7 shows how the input and the out of the network interconnecting each other. The relation of the input and output are as follow:

Vibration	→	Bearing fault
PD	→	Winding fault
Insulation resistance	→	Winding fault
Temperature	→	Overheating fault
Current at load	→	Overheating fault

Each of the input will only give the desired output if the value exceeds the limit as the weight and biases already trained. For the networks structure the number of layers is depending to the training process. The number of layers set will affect the time for the training convergence. As the layers increase, the time for the training output to converge to the target is decreased. On top of that, an extra output is added for a normal condition of the motor. One neuron need to be provided to show that the current condition of the motor is normal. Not all input given to the motor contributes to the fault. For the training process of the structure, the progress is explained in the training topic.

4.2 The rated data [5]

The following data refers to the rated values of the motor.

PD [8]	:	0.47 V
Temperature	:	110 °C
Vibration	:	80 μmpp
Current flow at load	:	625 A
Winding insulation resistance [6, 12]	:	100 MΩ

The rated data is taken from the data sheet of the motor itself. The PD is based on the "Partial Discharge Criticality Reference Graph" from the report for the PD monitoring status of the 11kV, 12MW Synchronous Motors, BCM-101A&B. The PD, temperature and vibration rated values need to be lowered a little bit from its actual data. This is to ensure that the motor did not fail before the diagnosis is performed returned with the results. Thus the new rated data is the lowest critical data for that motor. The selection of the temperature value is based on the current temperature of the motor. Temperature and temperature rise of motor are two different things. For the temperature rise, the measurement is taken by subtracting the ambient temperature. Based on the National Electrical Manufacturers Association (NEMA) the insulation used for the respective motor is class B, since the standard limitation of the temperature rise is 80°C [9]. The rated value selected for the rated current flow at the stator winding is same as in the datasheet. It is because the actual current can be sustained for the winding can be up to 125%. Thus if the fault current reaches the rated current, the motor still can sustain that condition. While for the winding insulation resistance, the value follows the standards stated by *IEEE Std 43-2000, "IEEE Recommended Practice for Testing Insulation Resistance of Rotating Machinery"*, which said that the minimum winding insulation resistance for most dc armature and ac windings built after about 1970 (form-wound coils) is 100 megaohms.

4.3 Normalized value

The structure generated will on suit if combined with data gather from the industries. The formula used for to normalize the data in order to feed the structure is as follow:

$$NormalizeValue = \frac{ActualValue - MaxValue}{MaxValue}$$

***for max value*

$$NormalizeValue = \frac{MinValue - ActualValue}{MinValue}$$

***for min value*

Figure 8: The formula used to normalize data from the actual value [7]

The purpose of normalizing the data as shown in figure 8 is to simplify the various numbers of data into one standard type of data. The simplification is good for the network itself in the training process. It also results with a good performance curve. Two different normalized values are defined because the trend for each data is different. For example, the winding insulation resistance can not be below than the rated values. But the PD can not be exceeded the rated value.

The Table 1 and Table 2 shown the actual data gathered from industries and the normalized value was calculated:

Table 1: The tabulated actual value

Actual				
PD (V)	ACL (A)	Vb (μmpp)	T (°C)	WI (MΩ)
0.490	626	82.25	111.00	90.2
0.120	601	35.00	115.00	144.0
0.300	210	33.00	78.00	90.0
0.498	232	25.00	75.00	100.2
0.200	335	25.00	60.00	150.0
0.350	250	83.21	95.00	125.0
0.400	324	81.92	113.50	142.4
0.210	631	54.00	109.40	95.0
0.110	223	62.00	111.30	91.0
0.250	628	48.00	112.20	120.2
0.501	400	75.20	99.25	90.6
0.522	512	81.25	104.50	100.5
0.550	630	65.10	101.00	102.4
0.130	627	85.12	108.20	137.0
0.320	130	82.22	78.25	93.1
0.487	588	71.02	115.20	103.8
0.260	628	69.20	107.60	124.4
0.190	568	45.20	114.30	142.2
0.390	265	85.33	68.90	126.8
0.350	255	45.00	89.00	129.0
0.485	631	85.50	108.70	64.5
0.105	601	46.50	111.70	160.4
0.352	153	62.00	64.20	77.2
0.501	265	31.02	70.25	100.4
0.125	235	31.00	75.50	164.6
0.330	234	84.32	85.00	104.6
0.453	601	82.12	114.20	164.2
0.450	630	45.50	106.70	95.2
0.440	599	48.60	114.90	95.1
0.422	630	46.20	119.90	100.8
0.491	354	65.60	88.25	84.7
0.514	416	82.15	104.30	100.6
0.489	628	57.89	107.20	102.2
0.214	629	83.14	108.30	144.8
0.465	255	83.25	65.25	85.1
0.479	265	70.21	119.90	100.2
0.240	631	60.23	107.40	156.8
0.280	600	55.12	116.40	143.2
0.440	311	62.40	88.00	111.4
0.351	287	83.95	58.65	140.2

Table 2: The tabulated calculated normalize value

Normalize Value				
PD	ACL	Vb	T	WI
0.0426	0.0016	0.0281	0.0091	0.0980
-0.7447	-0.0384	-0.5625	0.0455	-0.4400
-0.3617	-0.6640	-0.5875	-0.2909	0.1000
0.0596	-0.6288	-0.6875	-0.3182	-0.0020
-0.5745	-0.4640	-0.6875	-0.4545	-0.5000
-0.2553	-0.6000	0.0401	-0.1364	-0.2500
-0.1489	-0.4816	0.0240	0.0318	-0.4240
-0.5532	0.0096	-0.3250	-0.0055	0.0500
-0.7660	-0.6432	-0.2250	0.0114	0.0900
-0.4681	0.0050	-0.4000	0.0199	-0.2020
0.0660	-0.3600	-0.0600	-0.0977	0.0936
0.1106	-0.1808	0.0156	-0.0498	-0.0050
0.1702	0.0080	-0.1863	-0.0816	-0.0240
-0.7234	0.0041	0.0640	-0.0163	-0.3700
-0.3191	-0.7920	0.0278	-0.2886	0.0690
0.0362	-0.0592	-0.1123	0.0474	-0.0380
-0.4468	0.0048	-0.1350	-0.0222	-0.2440
-0.5957	-0.0912	-0.4350	0.0393	-0.4220
-0.1702	-0.5760	0.0666	-0.3736	-0.2680
-0.2553	-0.5920	-0.4375	-0.1909	-0.2900
0.0319	0.0096	0.0688	-0.0118	0.3550
-0.7766	-0.0384	-0.4188	0.0150	-0.6040
-0.2511	-0.7552	-0.2250	-0.4164	0.2282
0.0660	-0.5760	-0.6123	-0.3614	-0.0040
-0.7340	-0.6240	-0.6125	-0.3136	-0.6460
-0.2979	-0.6256	0.0540	-0.2273	-0.0460
-0.0362	-0.0384	0.0265	0.0382	-0.6420
-0.0426	0.0078	-0.4313	-0.0300	0.0482
-0.1021	0.0084	-0.4225	0.0895	-0.0080
-0.0638	-0.0416	-0.3925	0.0445	0.0490
0.0447	-0.4336	-0.1800	-0.1977	0.1530
0.0936	-0.3344	0.0269	-0.0516	-0.0060
0.0404	0.0046	-0.2764	-0.0255	-0.0220
-0.5447	0.0059	0.0393	-0.0153	-0.4480
-0.0106	-0.5920	0.0406	-0.4068	0.1494
0.0191	-0.5760	-0.1224	0.0895	-0.0020
-0.4894	0.0096	-0.2471	-0.0236	-0.5680
-0.4043	-0.0397	-0.3110	0.0577	-0.4320
-0.0638	-0.5024	-0.2200	-0.2000	-0.1140
-0.2532	-0.5408	0.0494	-0.4668	-0.4020

4.4 Target or actual data

The data in Table 3 and 4 are same data but the indication is different. For figure 3, it does indicate the fault condition using number. The variation is only between 0 and 1. Here the value of 0 indicates the corresponding fault did not occur; while value of 1 indicates the corresponding fault occurs. For the Table 4, it is a conclusion from the Table 3. It's tell only the occur fault by refer to the Table 3. Table 4 is fully used in training process in order to compare the output from the network with the actual data. Despite the output data is not exactly same as the actual data; the value will be round up to the nearest value. Beside that, the Table 3 is also used as target in the training process. For example:

From Table 3, for T1 (target 1);

- Normal = 0
- Bearing Fault = 1
- Winding Fault = 1
- Overheating Fault = 1

This condition indicates that for T1 all the faults are occurred.

The Table 3 and Table 4 are the sample taken from the total number of data used in the project. The complete data as per attached in the appendixes section.

In value:

Table 3: The actual data (in value) to be used as target during training process

Target or Actual				
	N	BF	WF	OH
T1	0	1	1	1
T2	0	0	0	1
T3	0	0	1	0
T4	0	0	1	0
T5	1	0	0	0
T6	0	1	0	0
T7	0	1	0	1
T8	0	0	1	1
T9	0	0	1	1
T10	0	0	0	1
T11	0	0	1	0
T12	0	1	1	0
T13	0	0	1	1
T14	0	1	0	1
T15	0	1	1	0

In word:

Table 4: The related fault

Actual Fault
Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault
Winding Fault
Winding Fault
Normal
Bearing Fault
Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault
Winding Fault and Overheating Fault
Overheating Fault
Winding Fault
Bearing and Winding Fault
Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault
Winding Fault and Bearing Fault

4.5 MATLAB

4.5.1 Performance curve

A performance curve is very important to measure the status of the training process towards the target. The measurement taken is mean square error (MSE). The error is the difference between the output of the network and the actual target supplied to the network. In this project, the goal set is zero. It means that the MSE calculated shall be equal to or almost zero. If the resulted MSE returned is a large value, the performance curve is very bad. Then the parameters need to be set accordingly to the input, the transfer function used and its target. After experimenting with the simulation of training process, the performance curve returned a value of 2.356×10^{-7} which is almost zero as shown in the figure 9.

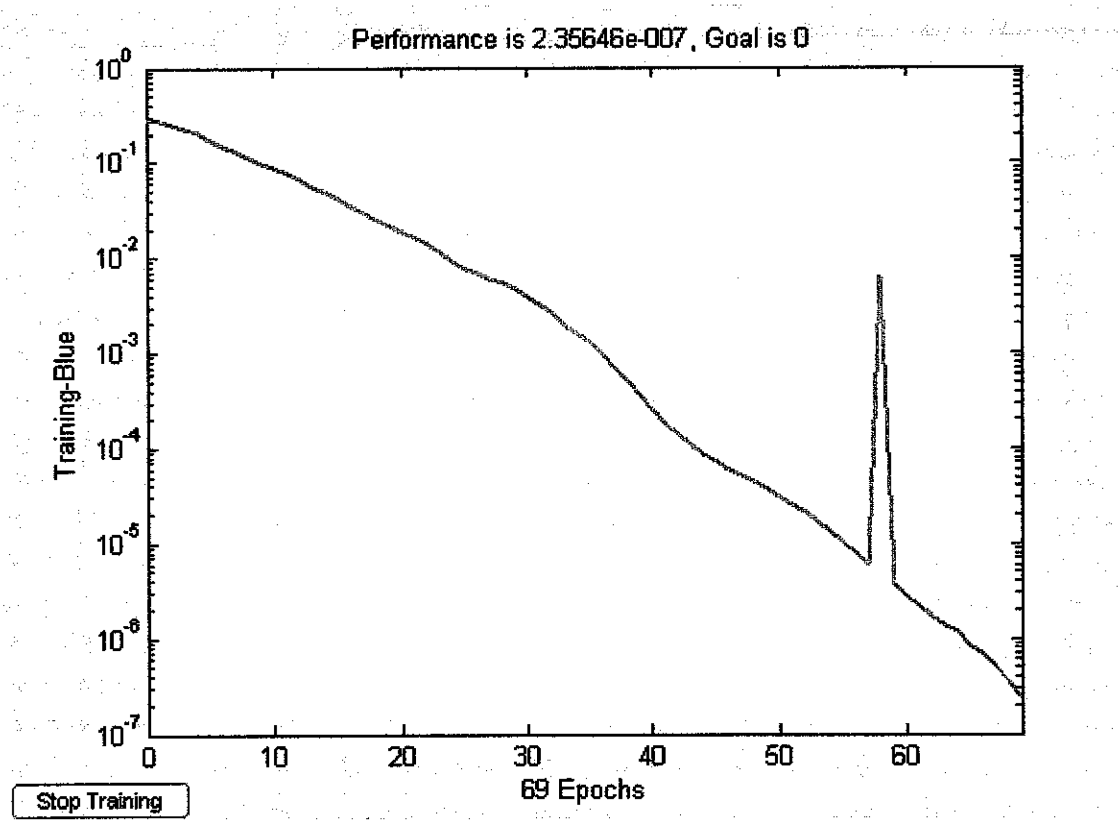
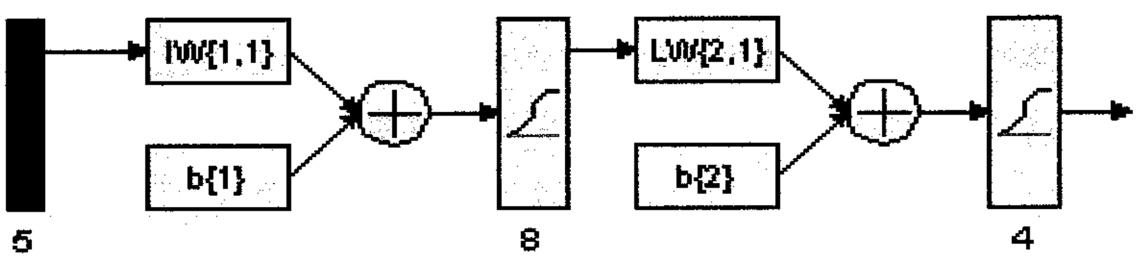


Figure 9: The performance curve

Thus this value is acceptable. The result from the performance curve is a network array which contains weight and biases which are gained from the training process. These values are the most important during the simulation process in order to predict any condition without given any target value.

4.5.2 Network diagram

For the chosen topology, the figure 10 shows the topology for FFBP function.



IW {1, 1} – Weight to layer 1 from Input 1
LW {2, 1} – Weight to layer 2

b {1} – Bias to layer 1
b {2} – Bias to layer 2

Figure 10: The FFBP network diagram

The first layer indicates the input which contains 5 inputs. Then it's connected to the 8 layers of hidden layers. Each of these layers contains variable number of neurons. As the training process is conducted, it is observed that the best number of neurons with the parameters and input are 8 neurons at each layer. For the hidden layer the transfer function used is logsig. As mentioned earlier, the logsig function is used since the output for this network varies between zero and one only. Once the input layers and the hidden layers are connected, the weights and biases are calculated accordingly to reach the target value. For the neurons at the output layers, it follows the number of targets that is required. The connection between the hidden layers and the output layers then follows the same concept as the input layer to the hidden layers. The transfer function used is still the same since the target is same. The change is only the value of weights and biases.

4.5.3 Training parameters

With refer to figure 11 there are 10 parameters values which set for the training process.

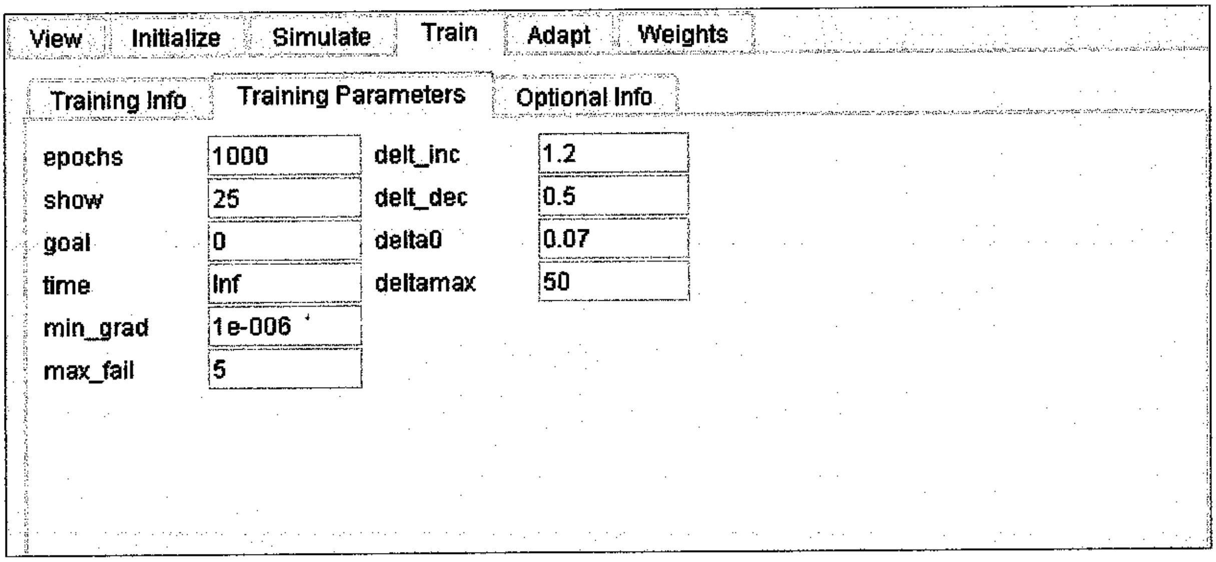


Figure 11: The training parameters associated with the training process

A brief description of the parameters is listed as follows:

Epochs – it is the presentation of the set of training vectors to a network and the calculation of new weights and biases. Thus the number of epochs is to limit the number of iterations for the training process. Once the numbers of epochs are reached, the iterations will stop although the target is not reached yet.

Show – it is the function which is used to show the current iteration of the training process. The iteration at the value set will be shown in the command windows with the update weights and biases.

Goal – It is the target value for the error between the target and output of the network. It is usually set to be zero in order to get precise result. The network will train the data until it reaches the goal set.

Time – For certain data, a lot of time is required to train it. Thus the implementation of the time constraint is important. In this project, the time constraint is rarely observed. The training process did not require a lot of time.

Min_grad – It is the minimum acceptable gradient of the performance curve. If the minimum gradient is reached, it will automatically stop the iteration/training process. If the min_grad occurs, it is hard for the training process to reach the goal.

Max_fail – It is for the maximum numbers of data that can not reach the target. It means that the data is not valid. This is the reason the number of not valid data in every training process did not exceed 5 data values.

Delt_inc - The update value for each weight and bias is increased by a factor delt_inc whenever the derivative of the performance function with respect to that weight has the same sign for two successive iterations.

Delt_dec - The update value is decreased by a factor delt_dec whenever the derivative with respect that weight changes sign from the previous iteration. If the derivative is zero, then the update value remains the same. Whenever the weights are oscillating the weight change will be reduced. If the weight continues to change in the same direction for several iterations, then the magnitude of the weight change will be increased.

Delta0 – It is the minimum step size for the weights change. The minimum value set is 0.07.

Deltamax – It is the maximum step size for the weight change. The maximum value set is 50.

There are many variations of the FFBP algorithm. But for the training process only one algorithm need to be decided. For this project the Resilient Back Propagation (Trainrp) algorithm is selected. The purpose of the selection is to eliminate the harmful effects of the magnitude of the partial derivatives. Thus only the sign of the derivative is used to determine the direction of the weight update. Then the size of the weight update is controlled by the associated training parameters as mentioned earlier [4].

4.7 Training process

The existence of the neural network toolbox helps a lot in the training process. It is because the training process is a "heuristic" process in order to find the best number of neurons and number of layers of the corresponding data and the target value. From the Table 5 up to Table 10, the variation and effect of the number of layers and neurons can be observed.

Table 5: Comparison between the actual and diagnosed results for - Layers: 4; Neurons: 7; Transfer function: logsig

Actual Fault	**Diagnosed Fault**
Validation and Training	
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	Bearing Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	**Bearing Fault and Overheating Fault**
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Bearing and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Bearing Fault	Winding Fault and Bearing Fault
Winding Fault and Overheating Fault	**Bearing Fault, Winding Fault and Overheating Fault**
Overheating Fault	Overheating Fault
Overheating Fault	Overheating Fault
Bearing Fault	**Bearing Fault and Winding Fault**
Normal	Normal
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	**Bearing Fault and Overheating Fault**
Winding Fault	**Bearing Fault and Winding Fault**
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	Bearing Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault

Table 6: Comparison between the actual and diagnosed results for - Layers: 3; Neurons: 8; Transfer function: logsig

Actual Fault	**Diagnosed Fault**
Validation and Training	
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	**Winding Fault and Overheating Fault**
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	Bearing Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Bearing and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault	**Bearing Fault, Winding Fault and Overheating Fault**
Winding Fault and Bearing Fault	**Winding Fault**
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Overheating Fault	Overheating Fault
Bearing Fault	**Bearing Fault and Winding Fault**
Normal	Normal
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	**Bearing Fault and Winding Fault**
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault

Table 7: Comparison between the actual and diagnosed results for - Layers: 6; Neurons: 7; Transfer function: logsig

Actual Fault	Diagnosed Fault
Validation and Training	
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	**Bearing Fault and Overheating Fault**
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Bearing and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Bearing Fault	Winding Fault and Bearing Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Overheating Fault	Overheating Fault
Bearing Fault	**Bearing Fault and Overheating Fault**
Normal	Normal
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	**Normal and Winding Fault**
Normal	Normal
Bearing Fault	**Winding Fault and Overheating Fault**
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault

Table 8: Comparison between the actual and diagnosed results for - Layers: 8; Neurons: 7; Transfer function: logsig

Actual Fault	**Diagnosed Fault**
Validation and Training	
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	**Bearing Fault and Overheating Fault**
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Bearing and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Bearing Fault	Winding Fault and Bearing Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Overheating Fault	Overheating Fault
Bearing Fault	Bearing Fault
Normal	Normal
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	**Normal and Winding Fault**
Bearing Fault	**Bearing Fault and Winding Fault**
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault

Table 9: Comparison between the actual and diagnosed results for - Layers: 9; Neurons: 7; Transfer function: logsig

Actual Fault	Diagnosed Fault
Validation and Training	
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	Bearing Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	**Bearing Fault and Overheating Fault**
Winding Fault	Winding Fault
Bearing and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Bearing Fault	Winding Fault and Bearing Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Overheating Fault	Overheating Fault
Bearing Fault	Bearing Fault
Normal	Normal
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	**Normal and Overheating Fault**
Winding Fault	**Winding Fault and Overheating Fault**
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	Bearing Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault

Table 10: Comparison between the actual and diagnosed results for - Layers: 8; Neurons: 8; Transfer function: logsig

Actual Fault	Diagnosed Fault
Validation and Training	
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	Bearing Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Bearing and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Bearing Fault	Winding Fault and Bearing Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Overheating Fault	Overheating Fault
Bearing Fault	Bearing Fault
Normal	Normal
Bearing Fault, Winding Fault and Overheating Fault	Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Winding Fault	Winding Fault
Winding Fault	Winding Fault
Normal	Normal
Bearing Fault	Bearing Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault

The training data must be valid in order to produce the best weights and biases. A valid data produces the best results for prediction. In addition, by varying the training parameter also can produces the best results. For the training process, all the input will be supplied together with its actual target. This is to train and experience the network toward the fault condition. The network then will calculate the output on the network base to the actual target value. Below are the results for the training process:

- Table 5 results = 5 data not valid
- Table 6 results = 5 data not valid
- Table 7 results = 4 data not valid
- Table 8 results = 3 not valid data
- Table 9 results = 3 data not valid
- Table 10 results = all data valid

From the result only the parameters, weight and biases from the Table 10 are used for simulation of the testing data.

4.8 Testing Data

From the total available data, only 30% of data was selected for testing, while the rest used for training the network. As explained before the training data were provided with actual target during the training process, but for the testing data, it is only used during simulation process without actual target. The actual target is only used to compare with the simulation output. For the simulation, the training data and testing data will be simulated to the trained network to see the output. For the training data, the output will be similar to the training process diagnosed results. This is because the weights and biases used are same. For the testing data, the diagnosed results only known after compare it to the actual fault table. As refer to the Table 11, these are the diagnosed results of the neural network to the condition of the motor.

Table 11: Comparison between the actual and diagnosed results for the testing data.

Actual Fault	Diagnosed Fault
Testing	
Overheating Fault	**Winding Fault and Overheating Fault**
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Winding Fault	**Winding Fault and Overheating Fault**
Bearing Fault and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault	Bearing Fault and Overheating Fault
Bearing Fault and Winding Fault	Bearing Fault and Winding Fault
Winding Fault and Overheating Fault	Winding Fault and Overheating Fault
Overheating Fault	Overheating Fault
Overheating Fault	Overheating Fault
Normal	Normal
Bearing Fault	Bearing Fault

These diagnosed results are used the parameter from the training process in Table 10. From the Table 11, it shows only 2 data diagnosed wrongly.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In the industry, the incipient AC motors faults are very important in order to avoid any failure of motors. The detection of the potential of faulty would reduce the cost of the maintenance for AC motors instead of waiting for the motor to be failed and sent to repair. From process point of view, the failure of motor would bring huge amount of losses to any plant process. With diagnosis and fault detection, in case if the AC motors show the potential to fault, plant process may have schedule shutdown which can avoid any losses. Thus from the condition point of view, the ability of the neural network to diagnosis the status of the AC motor is needed. From the progress of this project, the ability of the neural network to do the diagnosis is proven. With the proper selection of the topology and valid data from the industry, the neural network did its job successfully. All though some error is present in the prediction; it can be reduced with the increase of the total set of input data to the network. This step will experience the network more and help it to come out with better prediction results. For the future works, the fault diagnosis is not limited to the AC motors only but it also can be done for any type of motors, valves, relays and any other instruments used in the industries.

5.2 Recommendations

5.2.1 Better prediction results

For a better prediction results, instead just adjusting the number of layers and neurons, the training data also important. From the project, the numbers of data used for training process are quite limited. Thus the resulted diagnosis can not get 100% correct. For the neural network, the prediction capability can approach to 100% correct. With proper fault data and exact selection of the numbers of layers and neuron, the accuracy of the prediction can be increase.

5.2.2 Implement the neural network into online AC motor

In order to improve the efficiency of the neural network application, the prediction process shall be implemented into online AC motor. Thus the created system is able to diagnosis the current status of the motor. For now, the calculation and prediction process has done with the data collected from the AC motor itself.

5.2.3 Implement the other network topology for prediction

From the research, the prediction capability not limited to FFBP topology only. It also shared together with the Radial Basis Function (RBF). Radial basis networks may require more neurons than standard FFBP networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available [4].

REFERENCES

[1] Heikki Koivo and Jarmo Lehtonen, *Fault Diagnosis of Induction Motor with Dynamical Neural Networks, Control Engineering Laboratory Helsinki University of Technology, Espoo, Finland.*

[2] Ajit Bapat, M.Tech., MBA, P.Eng., *Ground Fault Detection and Protection For Motors*

[3] *http://www.dacs.dtic.mil/techs/neural/references.html*

[4] *Neural Network Toolbox User's Guide, Howard Demuth and Mark Beale.*

[5] Control Data Brushless Synchronous Motor (11kV, 12MW Synchronize Motors), GE Motor.

[6] IEEE Std 43-2000, *"IEEE Recommended Practice for Testing Insulation Resistance of Rotating Machinery".*

[7] "PRINCIPLE OF NEURAL NETWORK" by *H. Wang; PICA* 2001

[8] "PARTIAL DISCHARGE (PD) MONITORING ON STATOR WINDINGS OF 11kV, 12MW SYNCHRONIZE MOTORS BCM-101A&B", *MONTHLY REPORT (JAN 2005 - APR 2006) Prepared by: Azhar Mohamad Appandi I&E Engineer*

[9] Stephen J. Chapman, *Electric Machinery and Power System Fundamentals, 1st edition, McGraw-Hill series in electrical and computer engineering.*

[10] Review of Electrical Tests to Assess Motor Windings, Vicki Warren and Greg Stone, Iris Power Engineering, 1 Westside Drive, Unit 2, Toronto, Ontario M9C 1B2

[11] Fault Zone Analysis "STATOR", *Phil Coley at the 2004 Motor Reliability Technical Conference. PdMA Corporation.*

[12] THEORY OF STATIC WINDING CIRCUIT ANALYSIS, *Howard W. Penrose, Ph.D. BJM Corp, ALL-TEST Division, Old Saybrook, CT 06475*

[13] Datasheet of Model 682A05, *Bearing Fault Detector, IMI Sensors Division of PCB® Piezotronics, Inc, *(US Patent Number 6,889,553).*

APPENDIX A

The indication of the actual data in the training process

	Target or Actual			
	N	BF	WF	OH
T1	0	1	1	1
T2	0	0	0	1
T3	0	0	1	0
T4	0	0	1	0
T5	1	0	0	0
T6	0	1	0	0
T7	0	1	0	1
T8	0	0	1	1
T9	0	0	1	1
T10	0	0	0	1
T11	0	0	1	0
T12	0	1	1	0
T13	0	0	1	1
T14	0	1	0	1
T15	0	1	1	0
T16	0	0	1	1
T17	0	0	0	1
T18	0	0	0	1
T19	0	1	0	0
T20	1	0	0	0
T21	0	1	1	1
T22	0	0	0	1
T23	0	0	1	0
T24	0	0	1	0
T25	1	0	0	0
T26	0	1	0	0
T27	0	1	0	1
T28	0	0	1	1
T29	0	0	1	1
T30	0	0	0	1
T31	0	0	1	0
T32	0	1	1	0
T33	0	0	1	1
T34	0	1	0	1
T35	0	1	1	0
T36	0	0	1	1
T37	0	0	0	1
T38	0	0	0	1
T39	0	1	0	0
T40	1	0	0	0

APPENDIX B

The related actual fault

Actual Fault
Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault
Winding Fault
Winding Fault
Normal
Bearing Fault
Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault
Winding Fault and Overheating Fault
Overheating Fault
Winding Fault
Bearing and Winding Fault
Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault
Winding Fault and Bearing Fault
Winding Fault and Overheating Fault
Overheating Fault
Overheating Fault
Bearing Fault
Normal
Bearing Fault, Winding Fault and Overheating Fault
Overheating Fault
Winding Fault
Winding Fault
Normal
Bearing Fault
Bearing Fault and Overheating Fault
Winding Fault and Overheating Fault
Overheating Fault
Winding Fault and Overheating Fault
Winding Fault
Bearing Fault and Winding Fault
Winding Fault and Overheating Fault
Bearing Fault and Overheating Fault
Bearing Fault and Winding Fault
Winding Fault and Overheating Fault
Overheating Fault
Overheating Fault
Normal
Bearing Fault