

**SOLAR PHOTOVOLTAIC SYSTEM FAULT IDENTIFICATION
USING ARTIFICIAL INTELLIGENCE**

MOHAMAD SYAHMI DAMIA BIN MOHAMAD NOR



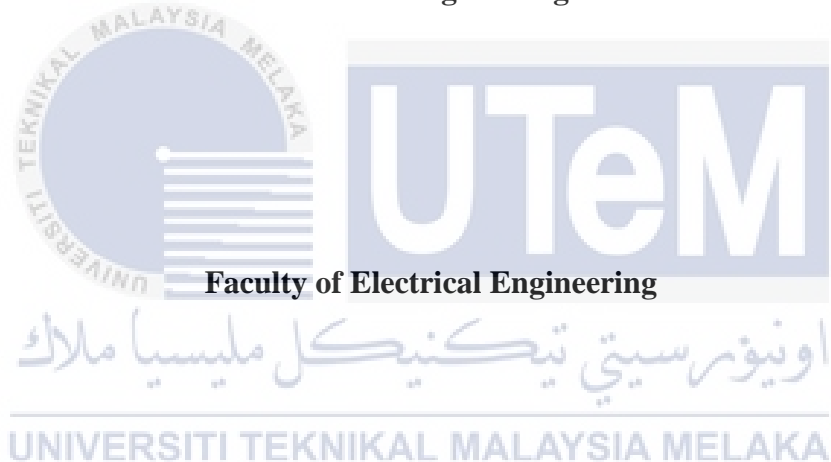
**BACHELOR OF ELECTRICAL ENGINEERING WITH HONOURS
UNIVERSITI TEKNIKAL MALAYSIA MELAKA**

2019

**SOLAR PHOTOVOLTAIC SYSTEM FAULT IDENTIFICATION USING
ARTIFICIAL INTELLIGENCE**

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**A report submitted
in partial fulfillment of the requirements for the degree of
Bachelor of Electrical Engineering with Honours**



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2019

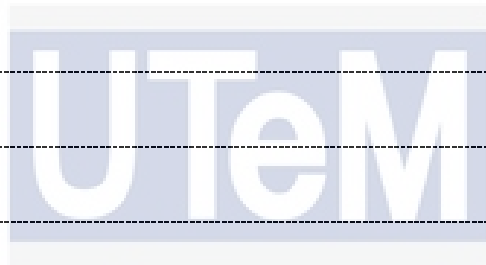
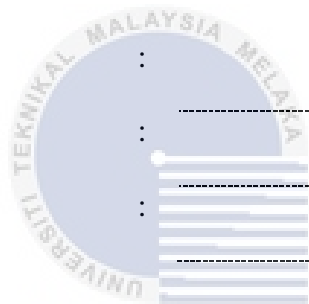
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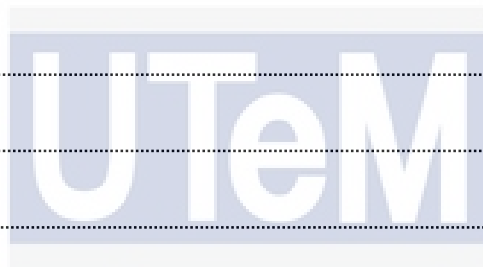
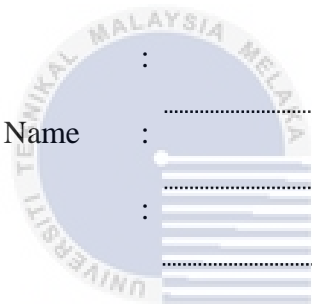
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DEDICATIONS

To my beloved mother and father



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Alhamdulillah, all praises to Allah, the most Gracious and the most Merciful for all the blessings and strengths that He had graced upon me for the entire process of this Final Year Project (FYP) until I am able to complete it well. I would like to take this opportunity to express my appreciation for those great people that have contributed to the success of this project.

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ABSTRACT

Solar photovoltaic system is design to generate electricity and operate reliably over the entire life of the product. Despite this, there are still failures could occur that can affect the performance of the product. Power failures could be one of the causes. The causes of fault could be from lightning, natural disaster, animal etc. The most advanced solutions, such as expert systems are related to knowledge-based systems. However, the subject field is experiencing congestion as it is unable to learn or adapt to new situations. This thesis is dedicated to implement artificial neural networks (ANNs) for fault identification at the solar photovoltaic system. ANNs is a computing system that inspired from biological neural network such as human brain and has ability to extract significant links from data presented. In principle, ANNs can remove the limitation of expert system as it has adaptive structure. Back propagation neural network (BPNN) was used in this project as it has simplest form but effective. Supervised learning is the training method that been used. The results from this thesis demonstrate that BPNN have high accuracy and give good performance in fault identification at solar photovoltaic system.

اوتنور سیتی تکنیکل ملیسیا ملاک

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ABSTRAK

Sistem fotovoltaik solar adalah direka bentuk untuk menjana elektrik dan beroperasi dengan baik sepanjang hayat produk. Walaupun begitu, terdapat kegagalan yang boleh berlaku seterusnya menjejaskan prestasi produk. Kegagalan kuasa boleh menjadi salah satu punca tersebut. Punca-punca kesalahan boleh diakibatkan dari petir, bencana alam, haiwan dan sebagainya. Penyelesaian yang paling maju, seperti sistem pakar adalah berkaitan dengan sistem berasaskan pengetahuan. Bagaimanapun, bidang pelajaran dalam kawasan ini sedang mengalami kesusahan kerana ia tiada keupayaan untuk belajar atau menyesuaikan diri dengan situasi baru. Tesis ini didedikasikan untuk melaksanakan artificial neural networks (ANNs) untuk mengenalpasti kesalahan pada sistem fotovoltaik solar. ANNs adalah sistem pengkomputeran yang diilhamkan daripada rangkaian neural biologi seperti otak manusia dan mempunyai keupayaan untuk mengekstrak hubungan penting dari data yang dikemukakan. Pada dasarnya, ANNs boleh menghapuskan batasan sistem pakar kerana ia mempunyai struktur penyesuaian. Back propagation neural network (BPNN) digunakan dalam projek ini kerana ia mempunyai bentuk yang paling mudah tetapi berkesan. Pembelajaran yang diselia adalah teknik latihan yang digunakan. Hasil dari tesis ini menunjukkan bahwa BPNN mempunyai ketepatan yang tinggi dan memberikan prestasi yang baik dalam mengenal pasti masalah pada sistem fotovoltaik solar.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	-	Artificial neural network
PV	-	Photovoltaic
BPNN	-	Back propagation neural network
DC	-	Direct current
AC	-	Alternating current
w	-	Weight
MLP	-	Multilayer perceptron
i	-	Nodes in input layer
j	-	Nodes in hidden layer
k	-	Nodes in output layer
t	-	Target output
n	-	Step of iteration
η	-	Momentum term
MPPT	-	Max power point tracking error
nntool	-	Neural network tool
FYP	-	Final year project
traingdx	-	Gradient Descent backpropagation algorithm with adaptive learning
learnngdm	-	Gradient descent with momentum weight/bias learning
MSE	-	Mean squared error
epoch	-	Iteration
MCB	-	Miniature circuit breaker
R	-	Regression
L1	-	Line 1
L2	-	Line 2
L3	-	Line 3
E_p	-	The averaged sum squared error
α	-	Learning parameter
I_k	-	The input for output layer
δ	-	The error signal
ϕ	-	Transfer function
t_{pk}	-	The expected output value k th output node
y_{pk}	-	The real output value of k th output node

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CHAPTER 1

INTRODUCTION

1.1 Project Background

Artificial neural networks (ANN) was a main tool that work as machine learning for the purposes of acquiring and storing knowledge. ANNs work as a brain system that have ability to learn system behaviors during a training process. The capable of ANN in making future generalization by fact that the algorithm can be subjected to previously unseen data and provide system performance predictions by provide realistic output for input not encountered during training. Generally, the application of these technologies was more focus on complex signal processing and pattern recognition. however, these technologies established before the technologies of computer dawn, and has survived for a long period.

The history of neural networks has been divided in four stages and that are beginning of neural networks, first golden age, quiet years and renewed enthusiasm which shows the interplay among biological experimentation, modelling and computer simulation, hardware implementation [1]. The first person who attempt to established models of neural network are McCulloch and Pitts in 1943. The ideas were about what can a simple neural network could do in term of principle and computing any arithmetic or logical function. The McCulloch-Pitts neuron models is simple yet has significant computing potential. This model can only generate a binary output with the fixed value of threshold and the weight. The beginning of neural network occurs between 1940s to 1950s. A lot of works were attempts during those years to improve the neural network systems.

The first golden age of neural networks happened between 1950s to 1960s. The idea of using perceptron neural was invented by Frank Rosenblatt, Charles Wightman, and others between 1957s and 1958s. Perceptron neural was updated in term of weight, deciding and reacting based on the threshold. Today, Frank Rosenblatt was known as the founder of Neurocomputing. Slightly later, Bernard Widrow working with his

graduate students in developed a different type of neural network processing element called ADALINE. This neural network was equipped with a powerful new learning law which, unlike the perceptron learning law, is still in wide- spread use [1]. Before the era of quiet years started, back propagation was proposed by others researcher in 1963s. Back propagation does not have feedback connection, but the errors are propagated during training.

In the quiet years during 1970s, A great deal of neural network research went on under the headings of adaptive signal processing, pattern recognition, and biological modelling [1]. Many of the researcher were began to publish their work during those year. In those years, Paul Werbos has developed the basic idea around 1974 about the backpropagation algorithm for his thesis at Harvard University that was rediscovered in 1986 by Rumelhart and has a lot of importance nowadays [2].

The last stage was about renewed enthusiasm that occurs in 1980s. In those year, many of researchers were brave enough to propose and submit the neural network development. In the years of 1983s to 1986s John Hopfield, an established physicist of worldwide reputation, had become interested in neural networks a few years earlier [1]. The papers that has been established by John Hopfield and then have persuade hundreds of highly qualified scientist, mathematician and technologies to join the emerging field of neural network. By time passing, back propagation had made a comeback improvement in term of using multi hidden layer and this have led this network to gained recognition. Multi-layered perceptron or back propagation have advantages in solving nonlinearly separable problems, big computation, local optima and overfitting.

1.2 Motivation

Nowadays, power generation based on solar photovoltaic sources has increase progressively during the last few decades [3]. Solar photovoltaic has played a key role in evolution of the electricity factor [4]. The development of solar photovoltaic has increase due to the efficiency of itself. This statement was proof by with the recent record 44.7% of efficiency by the maximum attainable output power that been absorb from the sun energy [3], [5]. Although the solar photovoltaic has become a great technology for power generation, the harm of this technology will still give effect to humanity.

Solar photovoltaic is an electrical power system that cannot run from problem when fault occur. Fault is abnormal current that flow from the source to the load. A fault in electrical system usually a big problem that can give a threat to the continuity of electrical supply [6]. As the fault occurs in solar photovoltaic, it will give a harmful damage to the solar panel or the load. In power plants, fault can normally occur due to various type of cases such as lightning, equipment damage or natural disaster [6]. Furthermore, a heavy current can cause the cable to melt and this will lead the equipment on fire [4].

In a nutshell, a fault detection is needed in solar photovoltaic panel to avoid the harmful to effect humanity. This will be a further step before the fault problem become even serious. Moreover, this will lead an opportunity to engineer or technician in helping of detecting the fault.

1.3 Problem statement

In electrical system, fault is common things that happen when the equipment is too old or because of some other cases such as lightning and equipment damage. In solar photovoltaic system, fault can occur if there is lack of supervision for the system mechanism. The problem when using solar PV for generation side is its PV system need to be supervised by technician or engineer that proficient with the system. To overcome this problem, performing back propagation model of neural network (BPNN) will lead in helping to supervise the solar photovoltaic system. Several types of fault would happen in solar photovoltaic such as line to line fault, ground fault, open and short-circuited fault and mix match fault [7]. These faults will degrade the performance of solar photovoltaic system and decrease the output power.

Moreover, performing a manual checking may give harm to the technician or engineer because of less accuracy in determined the fault and it is potentially dangerous since the solar photovoltaic system that may run at large voltage and current. Among of those faults, line to line and ground fault are the most common fault in solar photovoltaic system but it is hard to be detected [7]. In order to avoid manual checking, fault detection in solar photovoltaic is needed so that it can verify what type of fault happen and make the things easier for the technician or engineer.

Furthermore, this project is about detecting fault by reading the value of abnormal voltage and abnormal current. Potential problem may occur at direct current

(DC) side of the solar PV when reading was taken. Bridging fault or shading are some example of potential problem. As the fault occur, back propagation neural network (BPNN) will showing the result. BPNN need to be trained many times so the approximate value of fault can be determined. BPNN is a feed forward control (FFC), so the output of voltage or current itself need to be trained again so it can learn in detecting the voltage that not suitable for the solar photovoltaic. The training may take some time and need to be repeated many times, but the process will give an advantage in getting the fault.

1.4 Objective

1. To implement fault detection in solar photovoltaic using back propagation neural network (BPNN).
2. To analyses the systems accuracy and performance in detecting fault at solar photovoltaic.

1.5 Scope of Project

The back propagation neural network (BPNN) technique is used to analyses the fault detection in solar photovoltaic. The software that used in performing simulation for back propagational neural network (BPNN) is MATLAB. Next, the types of fault may occur at solar photovoltaic are DC and AC sides fault based on line 1, 2 and 3. Solar photovoltaic at FKE UTeM Plus SW 255 (mono) has been used in this project to collect the fault data. Moreover, Types of input in BPNN for training and testing is current while the output is power. Lastly, the data for both DC and AC side fault were collect from 10.00 am to 3.00 pm.

CHAPTER 2

LITERATURE REVIEW

2.1 Biological Neural Network

Past few decades, the study on the construction and operation of our brain and nervous system have given a lot of benefit for operation system. The basic building block of the nervous system is the neuron. Neuron consist of cell body, dendrites and an axon as shown in Figure 2.1. Neural network architectures are based on the human brain and nerve cells. The signal flow in neuron goes from the dendrites, through the cell body and out through the axon.

The nucleus is the main part of a neuron that connected to the other part neuron body to form neuron network. The connection of the nucleuses is made by dendrites and axon that was called synaptic connection. The impulses can be pass through other neuron by using synapses which are located on the dendrites. The neuron is activated when the signals received surpass a certain threshold [8]. The output area of the neuron is a long branch that called axon and the dendrites will be the input. When a series impulse received by the dendrites, the neuron will be activated and emit impulse through the axon.

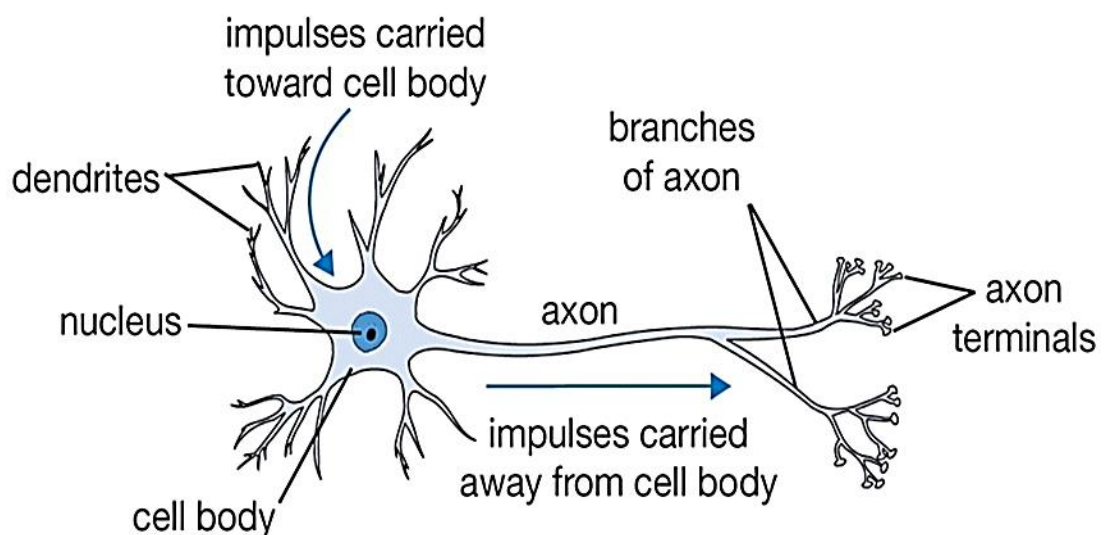


Figure 2.1 Biological Neuron [9]

2.2 Artificial Neural Networks Basic Structure

In ANNs structure, weight refers to the strength or amplitude that connected between two of nodes. Figure 2.2 shows schematic processing units for ANNs. The multiple of input are connected to the unit shown at the center. Each connection has its own strength, given w_1, w_2, \dots, w_n . When the process begins, the units of the network will perform a weighted sum on the inputs and uses a nonlinear threshold function, f , to compute its output. The calculated result then will be emitted to each of the output connections.

The ANNs consists of three main part body which is input, hidden and output layer. Figure 2.3 shows an ANNs with three connected layers. The input layer brings the initial data into the system for further processing by artificial neuron subsequent layer. By getting the input is the first step in artificial neural network workflow. The hidden layer take place between input and output layer and consist of features detector unit that respond to particular features that appear at input layer. The output of the hidden layer will be generated via activation function. Output layer is the last layer in ANNs structure. It read as the output the network. This unit will collect the information and transmit it accordingly.

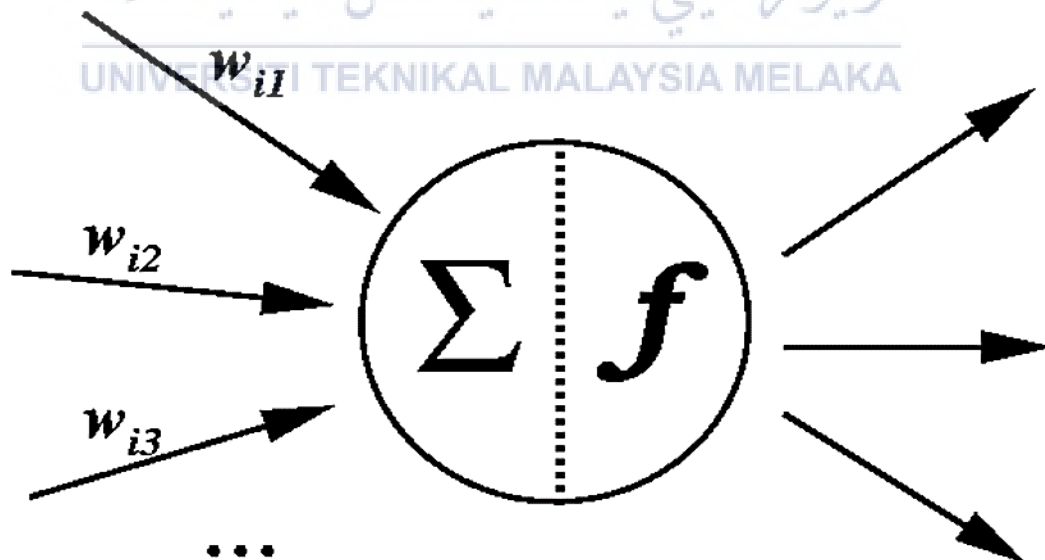


Figure 2.2 Schematic Processing Unit of ANNs [9]

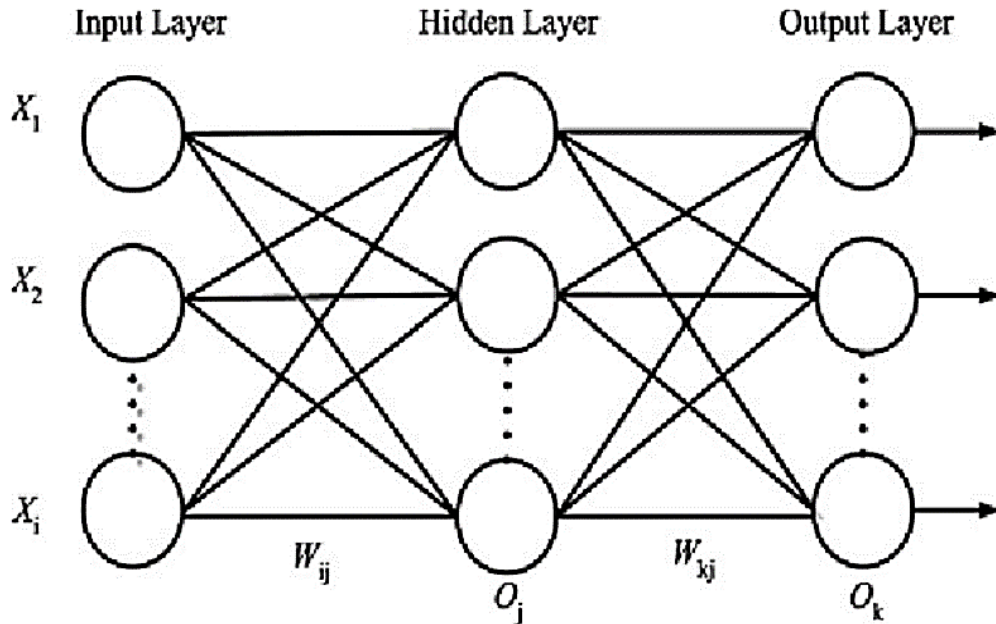


Figure 2.3 ANNs With Three Connected Layers [9]

2.3 Characteristics of ANNs

A neural network is massively parallel distributed processor that made up with simple processing unit that has natural tendency for storing knowledge and making it available for use. ANNs characteristics need to be consider before utilizing them for solving practical problem such as fault identification in solar PV.

2.3.1 Mapping capabilities

ANNs can be considered as black box as it can transform the input vectors x from an n -dimensional space to an output vector y in m -dimensional space $F : x \rightarrow y$. By using a proper and absolute ANNs architecture, the types of mappings can be approximately known. Mapping problems can occur when there are no restrictions such as linear separability is placed on the input-output pattern pairs.

2.3.2 Learning and generalization

Learning in ANNs consist of supervised, reinforcement and unsupervised. Supervised learning uses a training set consist of input pattern and output pattern as

the target value. The output may regard as network teachers to the input. This network leaning need to compute the output for the current network weight and adjust the weight so that it can minimize the difference between the actual output with desired output. Reinforcement learning uses less of supervision and its signal is simple as yes or no at end of the given task to indicate whether the task is done with satisfactorily. Last, unsupervised learning only use input data and there is no training signal. This learning only needs to proof the data set true or not, for example grouping the same pattern.

Generalization regarding the Artificial Neural Network (ANN) is defined as the network's ability to deal with unseen patterns [10]. Generalization can serve as efficient mode of memorization and storage. By having generalization, a lot of details that human brain cannot store can be identified, learned and stored at neural networks such as unlimited number of specific events, facts, relationships and other details that related to human experiences. In fact, generalization is an intelligent behavior.

2.3.3 Parallel Processing

The ANNs are computer mods that try to imitate the brain's learning function [10]. Parallel processing structure has large numbers of processors and many interconnections between them. The artificial neural networks consist of a set of neurons or processing units that are connected by means of weights connection [10]. The power of the neural network lies in the enormous number of interconnections.

2.3.4 Fault Tolerance

Fault tolerance can ensure their reliability when significant portions of a network are lost [11]. Furthermore, fault tolerance can ensure the fidelity and reality of the relationship between input and output of the system. Fault tolerance is to verify that the presence of errors can be overcome by changing the variable parameters in the network such as the synaptic weight of the network [12].

2.4 Back Propagation Neural Network (BPNN)

2.4.1 Overview

Usually, neural network needs to be trained or adjusted so that a particular of input can lead to a targeted output. BPNN need to be trained many times so the approximate value of output can be determined. Neural network was trained like a human brain that consist of input, weight (hidden layer) and output. BPNN undergoes supervised training with a lot number of patterns. The number of neurons in input layer determines the dimensions of the input and the number of neurons in output layers determined the dimensions of the outputs.

Furthermore, the weights are been adjust based on the comparison of the output and the target until the network output match the target value [13]. This hidden layer output is determined by using a threshold function with the activations of the input. Next, the activation of the hidden layer than will become the input for the target output. Figure 2.4 shows the line diagram of working BPNN.

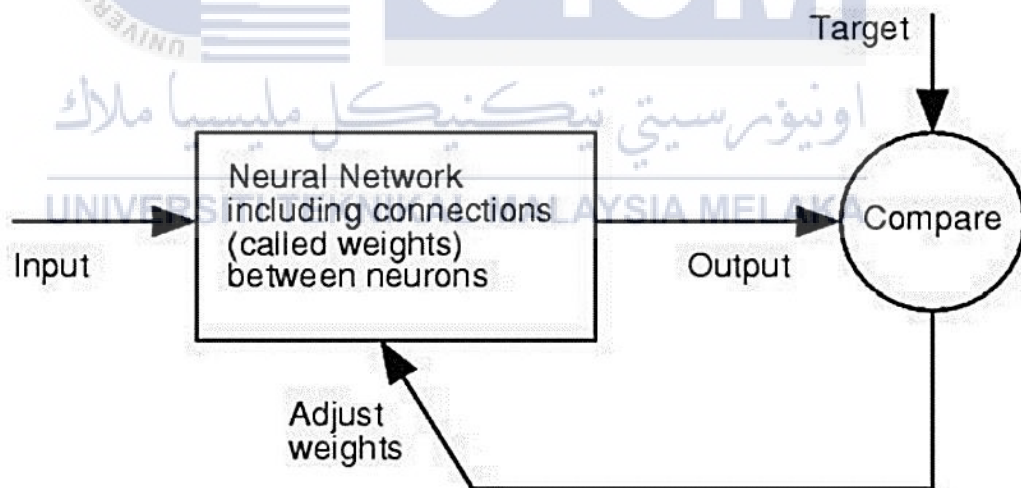


Figure 2.4 Line Diagram of BPNN [13]

BP neural network was the first and simplest type of artificial neural network this day. The information only moves in one flow in this neural network. BPNN does not have feedback connections, but the errors are back propagated during training. This is because BPNN can only flow in forward direction. BPNN also work as normal neural network that consist of input for the data collection, hidden layer for the data

processing by neurons and the output for the results [14]. It is also be known as a model of prediction parameters. BPNN is defined as the multilayer perceptron (MLP) with a multi of input values. The input values that been multiplied by the weight are led to the hidden layer of neuron [14]. There is no loop or cycles in this network and the data processing can extend over multiple unit as this BPNN use the MLP. The output of first layer will not affect other layer for further training. The total input to a hidden layer is calculated as the sum of the values for all connection coming to the neurons. Figure 2.5 shows the structure of BPNN.

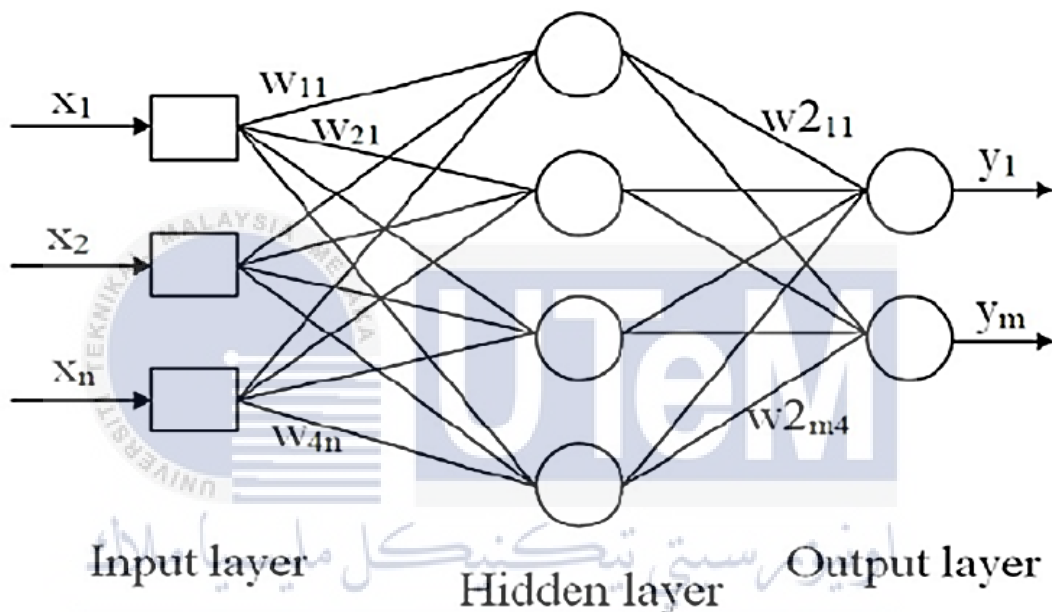


Figure 2.5 Structure of BPNN [15]

In other project that using BPNN, T. Khatib et al. developed an artificial neural network for solar prediction in Malaysia [16]. The feed forward multilayer perceptron model was been provided with four input for calculations. The training process of the algorithm consist of initializing the weight of the neuron and the measured output is compare with the desired value to calculate the error and then the weight are changed based on the error. This will lead the error to propagated backward for update the weight of the previous layer [14] [16].

Next, Adel Mellit and Alessandro Massi Pavan provided a back propagation neural network for solar radiance forecasting Italy [17]. The MLP model with a back-propagation training algorithm was proposed in this project. Therefore, the 24-hour solar irradiance can be predicted by using MLP neural network [14]. This result of

previous study project is the proved that BPNN method is precise and suitable for getting the output of fault in solar PV.

2.4.2 Training by Error Back Propagation

The feed-forward calculation of the output state during the training phase is combined with backward error propagation and weight adjustment calculations that represent the learning or training of the network. The error will be back propagated during training as the back propagation did not have feedback connections. Figure 2.6 shows the structure of error back propagation. The definition of error term is depending on the difference between the output value (target value), t_l with the result of the feedforward calculations, y_l . The term error is defined for a given pattern and summarized for that pattern overall output neurodes. The nodes for input layer can be written as, i , the nodes for hidden layer, j , and the nodes for output layer, k . The averaged sum square error,

$$E_p = 0.5 \sum_{l=1}^R (t_{pk} - y_{pk})^2 \quad (2.1)$$

The goal of the training process is to minimize the average of sum squared error. The averaged sum squared error is the sum error of overall neurodes divided by the total of the number pattern. By this method the amount of revision of the weight values between any two nodes of two neighboring may be taken proportional to the gradient $\left(\frac{\partial E_p}{\partial w}\right)$. The hidden and output layer are shown,

$$\Delta_p w_{jk} = -\alpha \left(\frac{\partial E_p}{\partial w_{jk}}\right) \quad (2.2)$$

Where α is learning parameter. The input for output layer,

$$I_k = \sum_{j=0}^n w_{jk} y_j \quad (2.3)$$

Referring to equation (2.3),

$$\left(\frac{\partial E_p}{\partial w_{jk}}\right) = \left(\frac{\partial E_p}{\partial I_{pk}}\right) \cdot \left(\frac{\partial I_{pk}}{\partial w_{jk}}\right), \quad \left(\frac{\partial I_{pk}}{\partial w_{jk}}\right) = y_{pj} \quad (2.4)$$

Let,

$$\left(\frac{\partial E_p}{\partial w_{pk}}\right) = -\delta_{pk} \quad (2.5)$$

Then,

$$\begin{aligned} \Delta_p w_{jk} &= \alpha \delta_{pk} y_{pj} \\ j &= 0, 1, 2, \dots, n \quad k = 0, 1, 2, \dots, R \end{aligned} \quad (2.6)$$

The output value of kth node of the output layer,

$$y_k = \Phi[I_k] = \Phi \left[\sum_{j=0}^n w_{jk} y_j \right] \quad (2.7)$$

By referring equations (2.5) and (2.7)

$$\begin{aligned} \delta_{pk} &= -\left(\frac{\partial E_p}{\partial w_{jk}}\right) = -\left(\frac{\partial E_p}{\partial y_{pk}}\right) \cdot \left(\frac{\partial y_{pk}}{\partial I_{pk}}\right) \\ &= -\left(\frac{\partial E_p}{\partial y_{pk}}\right) \cdot \Phi'[I_{pk}] \end{aligned} \quad (2.8)$$

Where,

$$\begin{aligned} \Phi'[I_{pk}] &= \frac{\partial}{\partial I_{pk}} [1 + e^{-I_{pk}}]^{-1} \\ &= y_{pk}(1 - y_{pk}) \end{aligned} \quad (2.9)$$

From equation (2.1),

$$\frac{\partial E_p}{\partial y_{pk}} = -2(t_{pk} - y_{pk}) \quad (2.10)$$

$$\begin{aligned}\delta_{pk} &= -\left(\frac{\partial E_p}{\partial y_{pk}}\right) \cdot \Phi'[I_{pk}] \\ &= 2(t_{pk} - y_{pk})y_{pk}(1 - y_{pk})\end{aligned}\quad (2.11)$$

So, the value of revision of the weight values between hidden layer and output layer are,

$$\Delta_p w_{jk} = 2\alpha(t_{pk} - y_{pk})y_{pk}(1 - y_{pk})y_{pj}\quad (2.12)$$

Next, for the weight values between input and hidden layer for the amount of revision are,

$$\Delta_p w_{ji} = -\alpha\left(\frac{\partial E_p}{\partial w_{ji}}\right) = -\alpha\left(\frac{\partial E_p}{\partial I_{pj}}\right) \cdot \left(\frac{\partial I_{pj}}{\partial w_{ji}}\right)\quad (2.13)$$

According to the equation below,

$$y_j = \Phi[I_j] = \Phi\left[\sum_{i=0}^n w_{ji} y_i\right], \quad i = 1, 2, \dots, n\quad (2.14)$$

$$\frac{\partial I_{pj}}{\partial w_{ji}} = y_{pi}\quad (2.15)$$

Let,

$$\delta_{pj} = -\left(\frac{\partial E_p}{\partial w_{pj}}\right) = -\left(\frac{\partial E_p}{\partial y_{pj}}\right) \cdot \left(\frac{\partial y_{pj}}{\partial I_{pj}}\right)\quad (2.16)$$

According to equation (2.14)

$$\frac{\partial y_{pj}}{\partial I_{pj}} = \Phi'[I_{pj}] = y_{pj}(1 - y_{pj})\quad (2.17)$$

Let,

$$\frac{\partial E_p}{\partial y_{pj}} = \sum_{k=1}^R \left(\frac{\partial E_p}{\partial I_{pk}}\right) \cdot \left(\frac{\partial I_{pk}}{\partial y_{pj}}\right)\quad (2.18)$$

$$I_{pk} = \sum_{j=0}^Q w_{jk} y_{pj}, \quad \frac{\partial I_{pk}}{\partial y_{pj}} = w_{jk}\quad (2.19)$$

Referring to equation (2.5) we have,

$$\frac{\partial E_p}{\partial y_{pj}} = - \sum_{k=0}^R \delta_{pk} w_{jk} \quad (2.20)$$

And,

$$\delta_{pj} = \sum_{k=0}^R \delta_{pk} w_{jk} y_{pj} (1 - y_{pj}) \quad (2.21)$$

$$\begin{aligned} \Delta_p w_{ji} &= \alpha \delta_{pj} y_{pi} \\ &= \alpha \sum_{k=0}^R \delta_{pk} w_{jk} y_{pj} (1 - y_{pj}) y_{pi} \end{aligned} \quad (2.22)$$

The actual iteration formula for training may be taken as.

$$\Delta w_{ij}(n+1) = \alpha \delta_{pj} y_{pi} + \eta \cdot \Delta w_{ij}(n) \quad (2.23)$$

Where; n=step of iteration,

η =momentum term

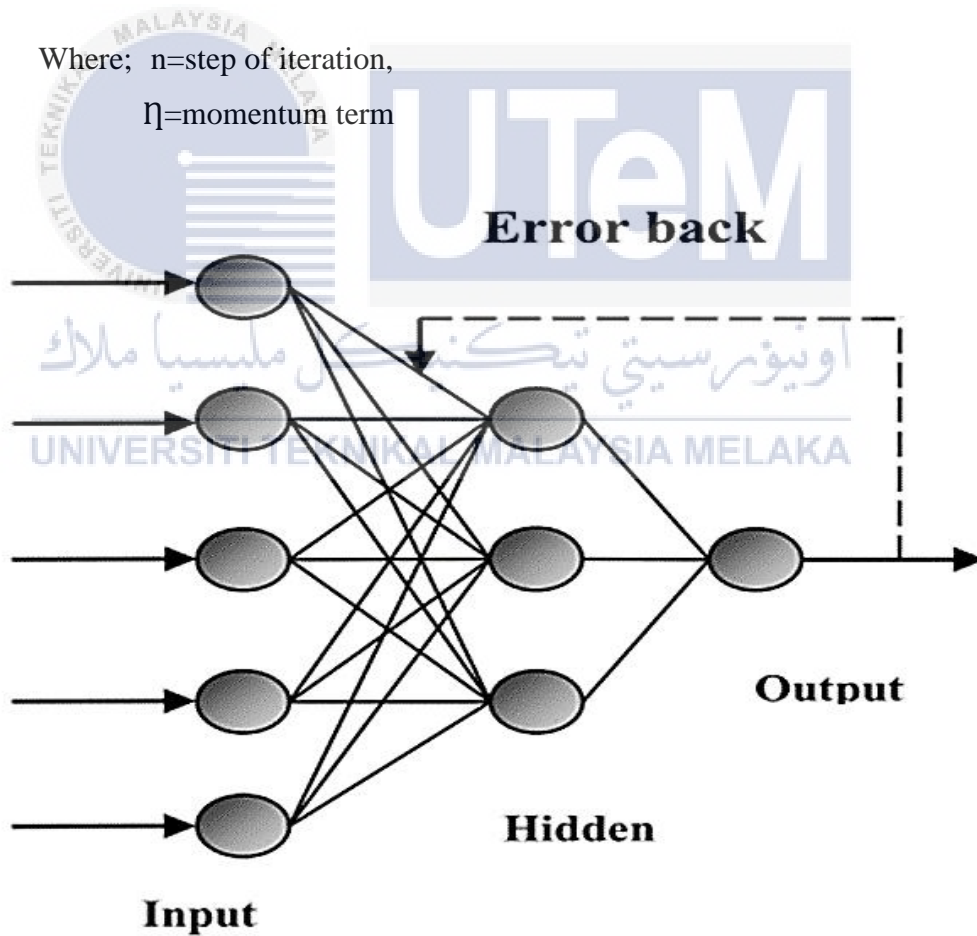


Figure 2.6 Structure of Error Back Propagated [18]

2.4.3 Multilayer Perceptron (MLP)

The most well-known structure for BPNN is MLP. The MLP network has many numbers of inputs and many hidden layers with any number of units. MLP has been applied successfully to solve some difficult and various problems that were built on a preliminary supervised training with error back propagation algorithm using and error correction learning rule [19]. MLP use linear combination function in the input layers and commonly use sigmoid activation in the hidden layer [18]. All the input, hidden and output layer have its own connection. Figure 2.7 shows the MLP model.

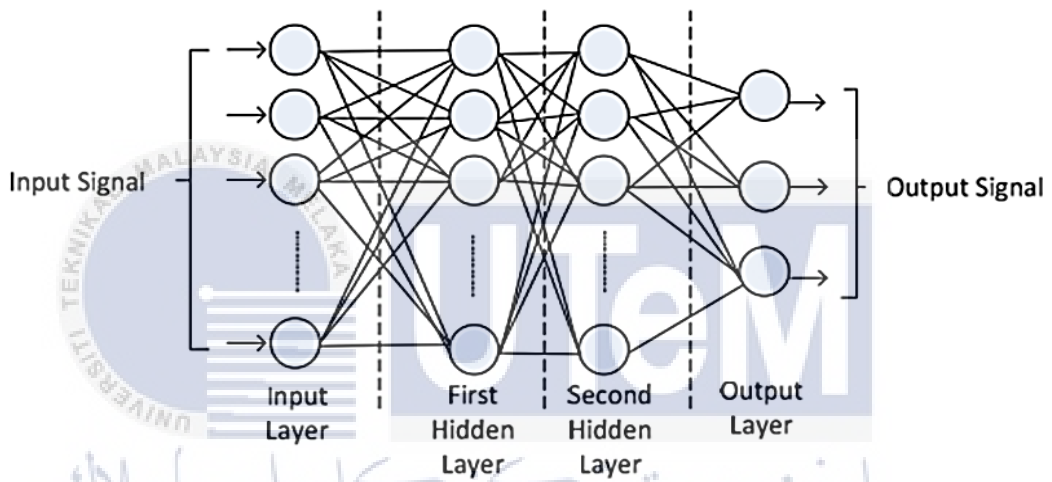


Figure 2.7 Multilayer Perceptron Model [20]

By providing enough data, enough hidden units and enough training time, a MLP with just one hidden layer can learn to approximate virtually any function to any degree of accuracy [18]. Although one hidden layer is sufficiently provided with enough data but there is situation when a network with two or more hidden layers may require fewer hidden units and weights than a network with one hidden layer, so extra hidden layer sometimes can improve generalization [18],[19]. Consider a neural network with input signal I_j to the neuron in hidden layer. Each neuron in the hidden layer sum ups its input signal after weighting them with the strengths of respective to connections W_{ij} from the input layer and computes its output Y_i as a function Φ of the sum. The sum of the weighted input of the hidden layer,

$$I_j = \Phi \sum_{i=1}^n W_{ij} y_i \quad (2.24)$$

where, Φ can be a simple transfer function. The output of the neuron in the hidden layer can be computed as equation (2.14) and the output value of the output layer can be computed as equation (2.7).

2.5 Classification of fault in DC and AC side of solar PV

Faults at solar PV can be divided to two part and that are DC and AC side fault at solar PV. DC and AC side are divided by the inverter in the middle. Inverter can convert from DC to AC. Figure 2.8 shows the classification of fault in solar PV.

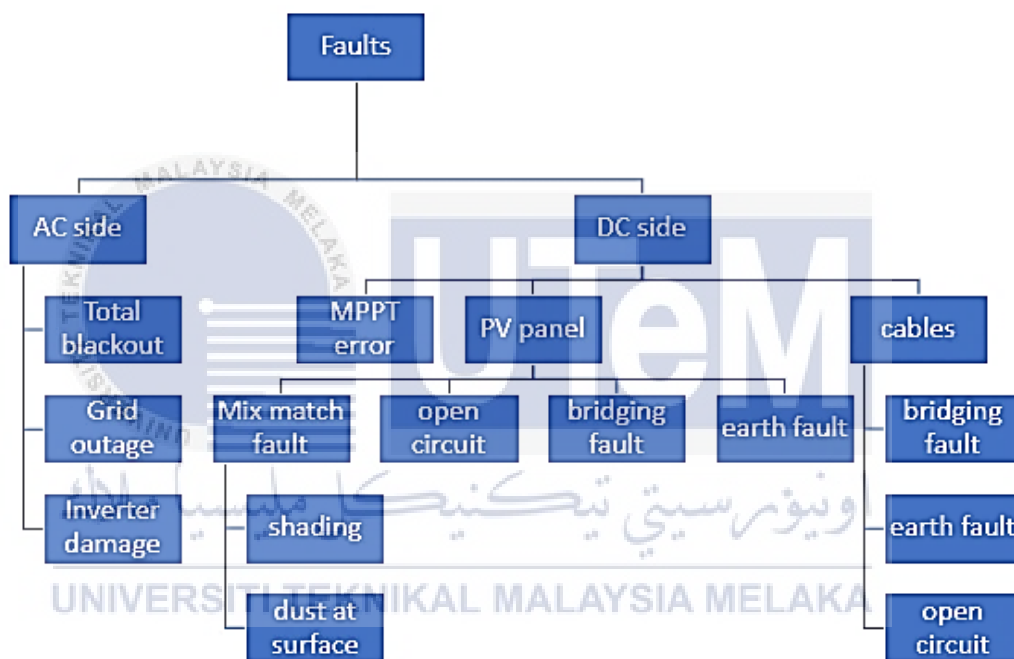


Figure 2.8 Classification of Fault in Solar PV

2.5.1 Faults in AC side

At AC side there is two types of fault that can be identified as exterior faults for system and that are grid outage and total blackout [3]. When there are grid outage and blackout happen, there is no electricity flow which mean no power at AC side. Grid outage happen due to the lightning or animals that had damaged the grid. Total blackout is happening when utility mandated. As there is no power flow at AC side, circuit breaker will be functioning to isolate the AC side from the system. This will

help to prevent the technician from getting harm while do the maintenance. In the meantime, most PV inverters have transformers which can provide good isolation between PV arrays and power grids and perfect electrical protection. When there is no cable or module that broken or breakdown, but the AC power output is still become low. This means that the power loss happens at AC side due to the fault that happen in inverter. Inverter react as anti-islanding protection and it can protect power from DC side to flow at AC side. Overheating can make inverter breakdown. Cross referencing Tables, Figures and Formulas

2.5.2 Fault in DC side

Fault at DC side are classified in three major types and the faults are PV panel fault, cables fault and maximum power point tracking error (MPPT). These faults will lead to non-functioning for the system.

2.5.2.1 Faults in PV panel

There are four main types of fault that could occur at PV panel and that are mix match, open circuit, bridging and earth faults. First, earth fault occurs when the circuits develop unintentional ground path. This will lead a short circuit path to the ground. Two types of grounding such as system grounding and equipment grounding are provided for the PV system [3]. The solar inverters will start operating as controller for internal short circuit when the current flow in negative value. Bridging fault happen when low resistance connection two points of different potential in module [3].

Moreover, this will happen when two or more nodes unintentionally connected. There will be short circuit fault between the two nodes. Failure to insulate cables such as animal cable insulation, mechanical damage, water intake or corrosion causes these problems.

Next, open circuit fault happen when one path that carrying the current that series with the load are broken or disconnected. This will lead to open circuit voltage that are maximum voltage available from solar cell when the value of current is zero. The open circuit fault may happen due to poor connections between cell in solar panel. Furthermore, the unplugging of connection at PV panel may lead to this fault. Figure 2.9 shows the voltage and current curve of solar cell when open circuit fault happens.

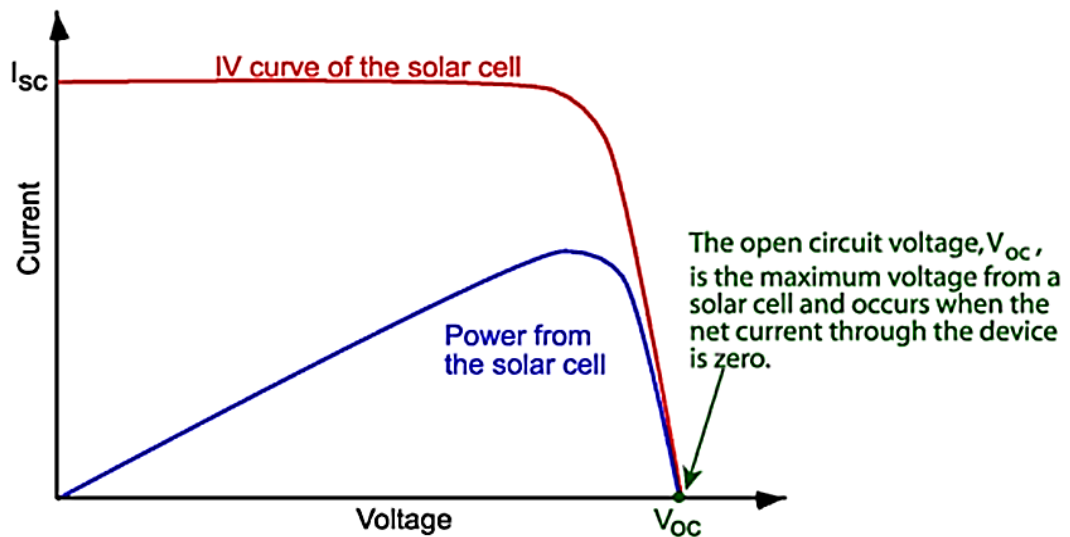


Figure 2.9 Voltage and Current Curve for Open Circuit Fault [20]

Last, the mix match fault in PV panel will occur when there is changes in electrical parameter in group or one of the solar cells. This fault will lead to irreversible damage on PV panel and large amount of power loss [3]. This fault happen because of a part of the PV panel are shaded by building itself, trees, clouds or other light blocking resources.

2.5.2.2 Max power point tracking error (MPPT)

MPPT increases the power fed to the inverter from PV panel by making it operate at the most efficient voltage [3]. The performance of MPPT reduce when failure occurs at charge regulator as the regulator cannot get the finest power from PV panel to charge the battery with the best voltage and maximum current. The output voltage and output power reduce when fault occur.

2.5.2.3 Faults at cable

There are three main types of fault that could occur at cable and that are bridging fault, earth fault and open circuit. Earth fault may generate high fault current when the cable generate path to the ground that will lead to short circuit. When high current flow at the cable, it may lead to fire hazard. This will harm the consumer. The

example of earth fault is when cable of PV junction box is contacting with the ground. Insulation failure cable due to the animal chewing also will lead to the earth fault.

Next, bridging fault may due to the cables at connection box make unintentional path to each other. There will be short circuit current between the cables. The bend area of cable also can cause bridging fault. Last, open circuit happen due to the unplugging of connectors at connection box or wire that breaks. Open circuit will lead to no current flow at the cables and result in high or maximum value of voltage.

2.6 Summary

In reviewing this literature, all the information and knowledge about the Artificial neural network and types of fault occur at solar PV are been studied. The theoretical findings from the books, journals and papers are being compared in order to increase our information and understanding the project. The previous work and theory that can be related in this project are based on basic structure and characteristics of ANNS and Back propagation neural network.

Generally, the ANNs consists of three main part body which is input, hidden and output layer. By using a proper and absolute ANNs architecture, the input can be transforming to output needed as the mapping can approximately be known. Learning in ANNs consist of supervised, reinforcement and unsupervised. Supervised learning is when the input and output pattern work as the target value to get the optimal weight. Reinforcement learning uses less of supervision and its signal is simple as yes or no at end of the given task to indicate whether the task is done with satisfactorily. Unsupervised learning is to proof the data set true or not by using the input data only without training signal. Backpropagation neural network only flow in forward direction because it does not have feedback connections. Multilayer perceptron consists of many numbers of inputs and many hidden layers with any number of units and be well-known in BPNN as it has solved various problem.

Finally, there are two types of fault which is DC and AC sides fault that occur at solar PV. By referring to previous studies, DC sides fault occur between the PV panel to the inverter while AC side fault occur between the inverter to consumer or utility grid.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The process of the project will be discussed in order to achieve the objective of the project. This chapter consist of the process flow chart for the project. The flow process for literature review and simulation for fault identification by using MATLAB software will be explained in this chapter. In this proposed project, neural network tool (nntool) from MATLAB was used in determined the optimal weight when training process begin. All the training process will automatically be been generated by nntool after the settings were done.

3.2 Flow Chart Process

In this section, the overall flow of project is shown in Figure 3.1. The process is starting by studied the related journal within the research area to understand more about this project. In the literature review, a lot of journal paper, article, thesis, reference book and online information had been searched to enhance the knowledge and get the idea for this project. The background research will provide information and identification research area for analysing the project. This will prevent from finding the wrong information. Next, the researched about solar PV system is done to understand more about the system and each of the equipment use for the system such as PV panel, inverter, junction box, etc. The next step in the flow process is the research of type may happen in solar PV and research on Back Propagation Neural Network (BPNN). In the research of fault identification, a lot of technique that been used in order to get the result for fault identification and BPNN was one of the techniques. Then, the research on solar PV fault identification using BPNN is done. In this research, the structure of the neural network that need to use in this project was known. By getting all the information that needed, fault identification for solar PV by using BPNN can be implement using MATLAB R2016a. Figure 3.1 shows two stage of methodology in the flow chart. First stage represents for Final Year Project 1(FYP1)

in semester 7 while the second stage represent for Final Year Project 2(FYP2) in semester 8. In stage 2, the process is starting by gather the result from MATLAB for the fault detection in solar PV. Then, the output value will be analysing in graph to know whether the training are success or not and the accuracy of the system will analyses the actual output and the network output value from the testing. The value of error from actual output and network output must be smaller for a better system accuracy. This thesis presents a new and integrated analytical approach to estimate Proposed methodology.

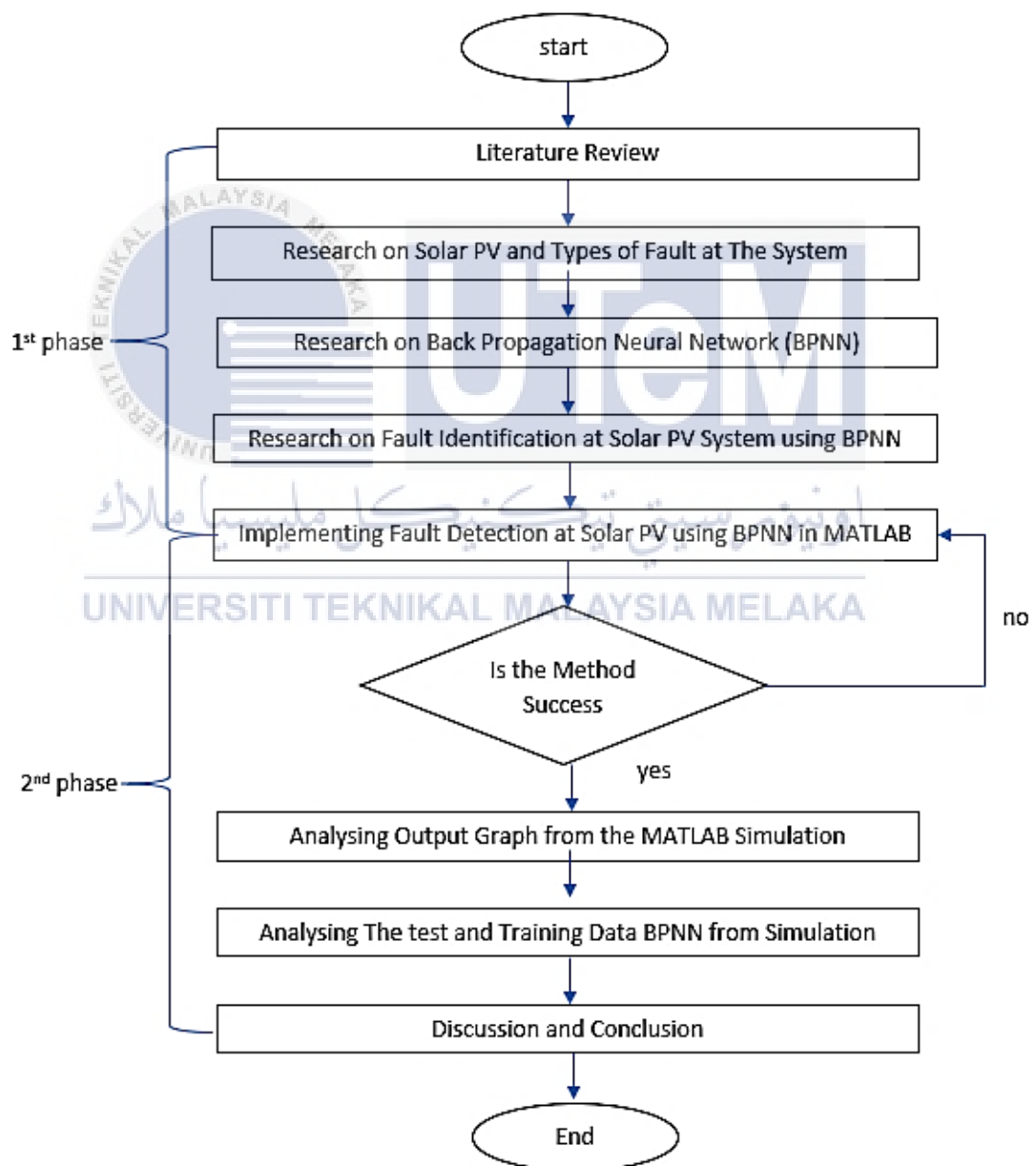


Figure 3.1 Flowchart for The Methodology of The Project

3.3 Flowchart of Fault Detection on Solar PV using MATLAB

Firstly, the network topology has been determined by knowing the value how many nodes of input, hidden and output layer. In this project, only one hidden layer is needed in this project. The input layer consists of three nodes of neurons same as the output layer. The three nodes of input layer are the line 1, 2 and 3 of current at solar PV while the three nodes at output layer are line 1, 2 and 3 of the power in the system. Next, the network properties will be set based on learning algorithm, training function and performing function. Then, the BPNN will be train using neural network tool in MATLAB. If the training success, then the optimal weight threshold is obtained. If not success, the BPNN weight threshold length need to be determined again. The BPNN weight threshold length were automatic been update in neural network tool. In the simulation, there is trained error data inside of the BPNN. The trained error data of BPNN is been set as fitness. The best result of the fitness function will be selected to do the crossover operation between input and hidden layer. When the best results of crossover are obtained, the mutation will take the lead. Equation (2.14) and (2.24) will take place in this process. After the optimal weight threshold is obtain, the actual fault data of DC and AC side of solar PV will be test with the optimal weight. These tests were run to get the neural network output. There were calculations error between the actual output and the neural network output to analyses the neural network accuracy. Then the simulation result is success and been discussed. Figure 3.2 shows the flowchart of fault detection in solar PV.

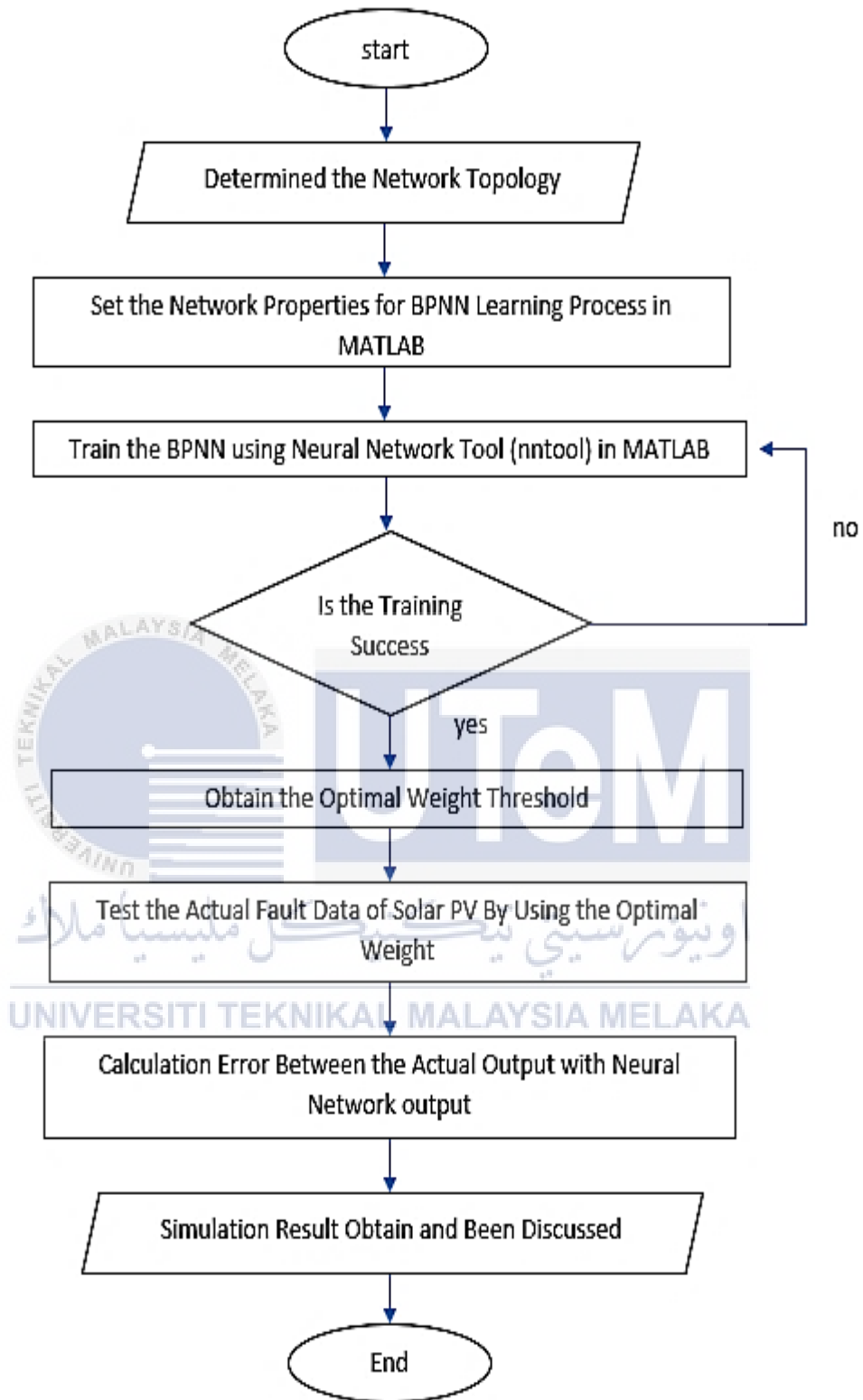


Figure 3.2 Flowchart for Fault Detection in Solar PV

3.4 Fault Data Collected from Solar PV

The fault data were collected from solar PV that using Plus SW 255 (mono) panel type. The maximum power that this panel type can collect is 6.12 kilowatts and the panel with 24 unit were placed at the rooftop of FKE building. The fault data for DC and AC side solar PV was collected during the peak hour from 10.00am to 3.00pm because the irradiance of the sun is high, and more power can flow from the PV panel. If fault happen, the value of the power will become zero and non-power will be flow at the string during fault. The miniature circuit breaker (MCB) at DC and AC side will be shut down in certain period to get the fault value for power and current. Each of the strings for DC and AC side of solar PV were control by the MCB. If MCB at string 1 is shutdown, there will be no current flow at line 1 and this is to show that the fault happens at line 1. As no current flow at line 1, there will no power flow at line 1. The fault data for DC and AC side were collected in different days because this is the easiest way to differentiate the fault types. Table 3.1 shows the type of faults that happen to the solar PV.

Table 3.1 Types of Fault

Types of fault	
DC side faults	AC side fault
Line 1	Line 1
Line 1 and 2	Line 1 and 2
Line 1, 2 and 3	Line 1, 2 and 3

3.5 Training the Neural Network

In order to perform supervised back propagation neural network, the data for the input value from the solar PV is needed. The input data for the training is the value of current from each string 1, 2 and 3. For each string, it has approximately 301 value of data that been collected from 10.00am to 3.00pm. So, there will 3 input at the input layer. The data of the output value is set as target value and been used for training the neural network. Power that flow at string 1, 2 and 3 of solar PV system will be the output data. Same as the input layer, there will be 3 output at the target value. The training of the neural network will be run in two ways. The first way is the normal data without fault will be used to train the neural network until obtain the optimal weight.

By using the optimal weight, the second way will be implemented by testing the fault data of DC and AC side with the optimal weight. As the starting point, all the data needed for the training will be save at the workspace in MATLAB. Figure 3.3 shows the data that been saved in workspace.

Name	Value	Min	Max
input_AC_fault_L1	1x1 cell		
input_AC_fault_L1...	1x1 cell		
input_AC_fault_L1...	1x1 cell		
input_DC_fault_L1	1x1 cell		
input_DC_fault_L1...	1x1 cell		
input_DC_fault_L1...	1x1 cell		
networktraining	1x1 network		
networktraining_e...	1x1 cell		
networktraining_e...	1x1 cell		
networktraining_e...	1x1 cell		
networktraining_e...	1x1 cell		
networktraining_e...	1x1 cell		
networktraining_e...	1x1 cell		
networktraining_o...	1x1 cell		
networktraining_o...	1x1 cell		
networktraining_o...	1x1 cell		
networktraining_o...	1x1 cell		
networktraining_o...	1x1 cell		
networktraining_o...	1x1 cell		
networktraining_o...	1x1 cell		
output_AC_fault_L1	1x1 cell		
output_AC_fault_L...	1x1 cell		
output_AC_fault_L...	1x1 cell		
output_DC_fault_L1	1x1 cell		
output_DC_fault_L...	1x1 cell		
output_DC_fault_L...	1x1 cell		
test_outputs_AC_f...	3x301 double	-0.0408	1.8037
test_outputs_AC_f...	3x301 double	-0.0939	1.8037
test_outputs_AC_f...	3x301 double	-0.0484	1.9229
test_outputs_DC_f...	3x301 double	-0.0163	1.6822
test_outputs_DC_f...	3x301 double	-0.0939	1.7431
test_outputs_DC_f...	3x301 double	-7.0961e-04	1.4465

Figure 3.3 The Workspace Data

In order to perform the training, MATLAB R2016a is used in this project to develop classification of input, output and analyse the error of the training by referring to the output of the network. By wrote a coding 'nntool' at the command window of the MATLAB, the Neural Network/Data Manager will pop out. Next, the input and target data and the training network will be import as shown in the Figure 3.4. Then, network properties are set up as Figure 3.5 by on how many layers that is needed, the training function, performing function and adaption learning function. For training function, Gradient Descent backpropagation algorithm with adaptive learning (traingdx) was choose as because it can adjust weight to measures the output error and calculate the gradient of the error in the descending gradient direction. The training will stop when the maximum number of epoch (repetitions) is reached, the maximum amount of time is exceeded, performance is minimized to the goal and the performance gradient falls below minimum gradient. Gradient descent with momentum weight/bias learning (learngdm) was used to minimize the mean squared error between the network output and actual rate error. As the number of epoch increase, the training error will continue to decrease. The mean squared error was choose as the performing function because the value of the training always non-negative and close to zero. The value of the training will be the best as it is close to the zero.

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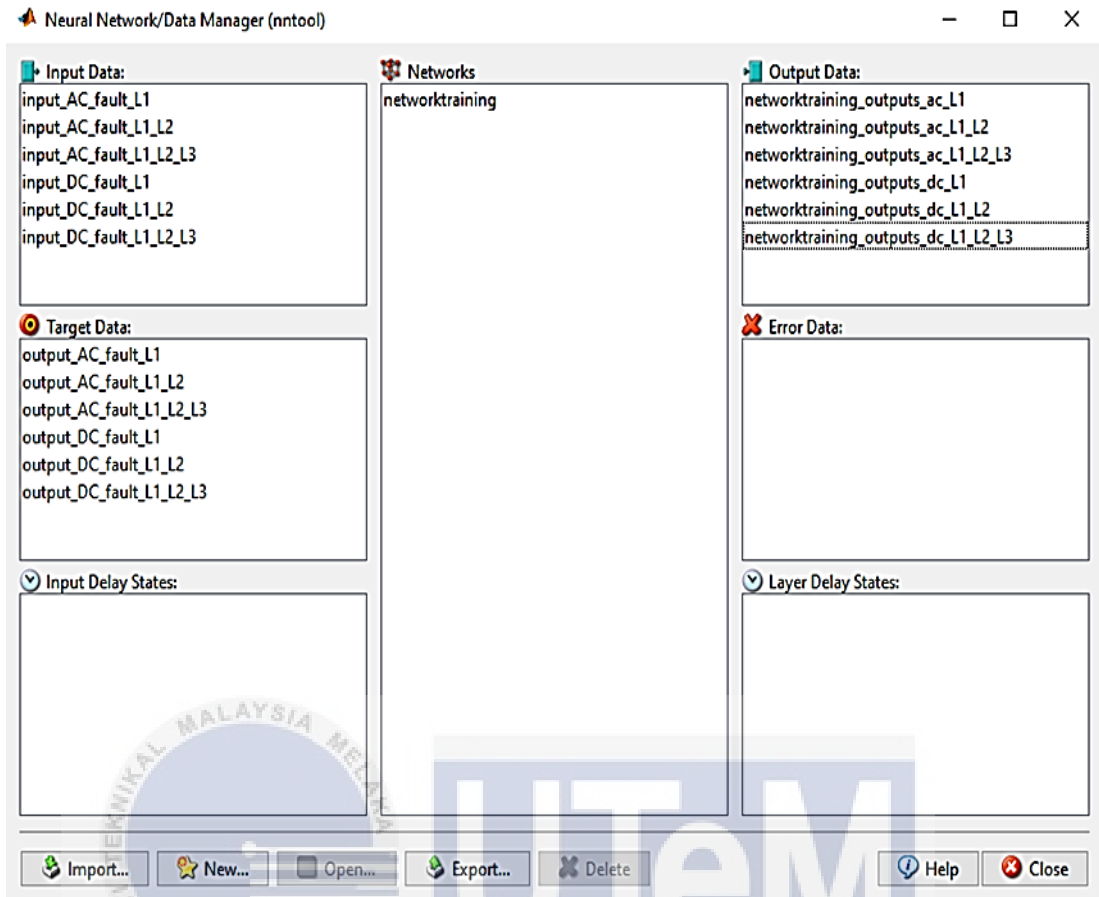


Figure 3.4 Neural Network/Data Manager

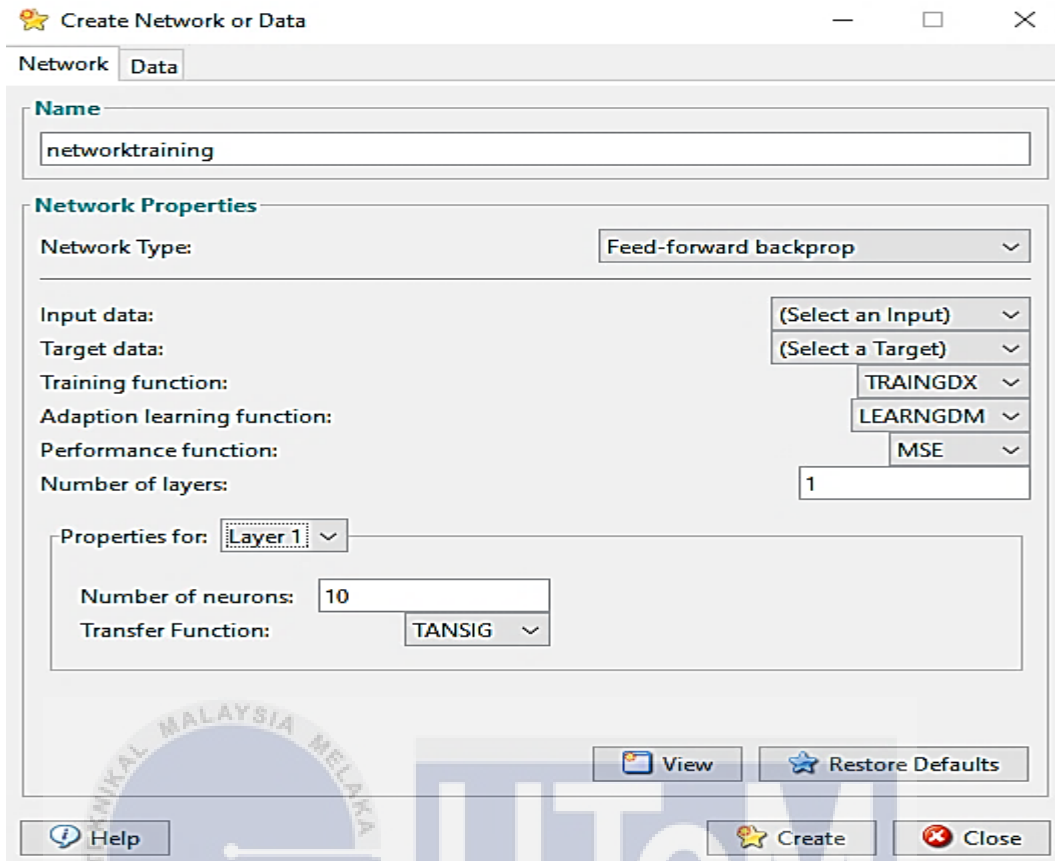


Figure 3.5 Network Properties

After setting the network properties, the structure of the neural network can be view before the training begin to run. This will help in changing the parameter of the neural network if structure of the neural network does not follow what needed. Figure 3.6 shows the structure of neural network after setting the parameter.

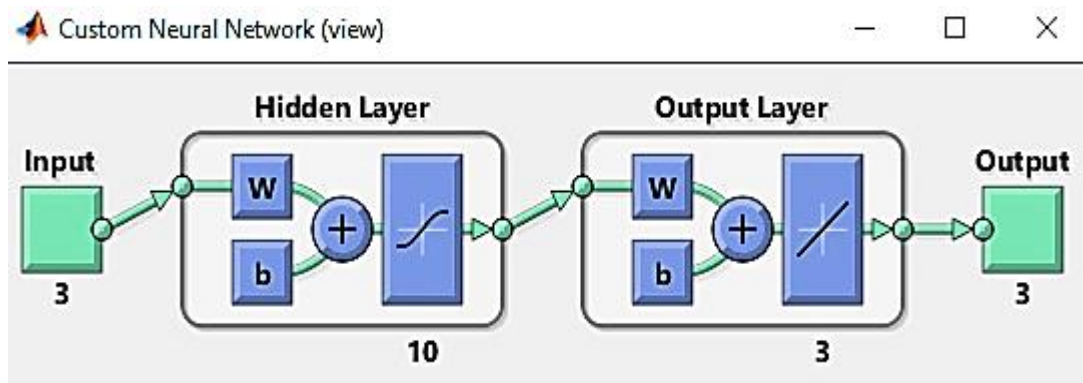


Figure 3.6 The Structure of Neural Network in MATLAB

The training parameter need to be set up before the system run. The training parameter is set on epochs/iterations, goal of the output value, maximum failed for the training, etc. The training is better when there are large number of epochs and long duration training. The input and output selected must be identical. If AC side fault data is been choose for the input, the output also must be selected from the same data or else the result for the training will not achieved. Figure 3.7 shows the training parameter that need to be set up. When the system is running, the network will train until the regression plot achieved its stability. This training process stop when the maximum epoch reached. This training process will be run for the weight adjustment until the convenient weight has been reached. In the training process, the weight will be automatically adjusted by the neural network. Figure 3.8 shows the training process of the neural network. The training process will be keep going until the weight is been initialized. Then the weight will be used to train the DC and AC side of solar PV fault data to know the neural network accuracy and performance in detecting fault at solar PV. The result of the training process will be shown in chapter 4. Lastly, the graph of performance and regression will be obtain from neural network training.

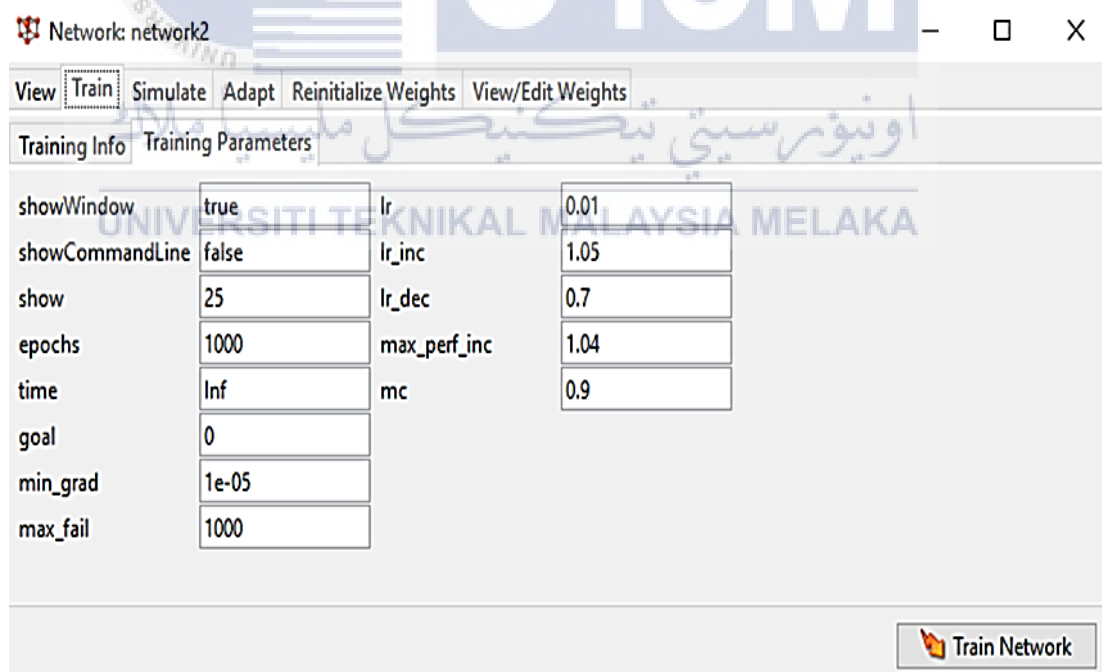


Figure 3.7 Training Parameter

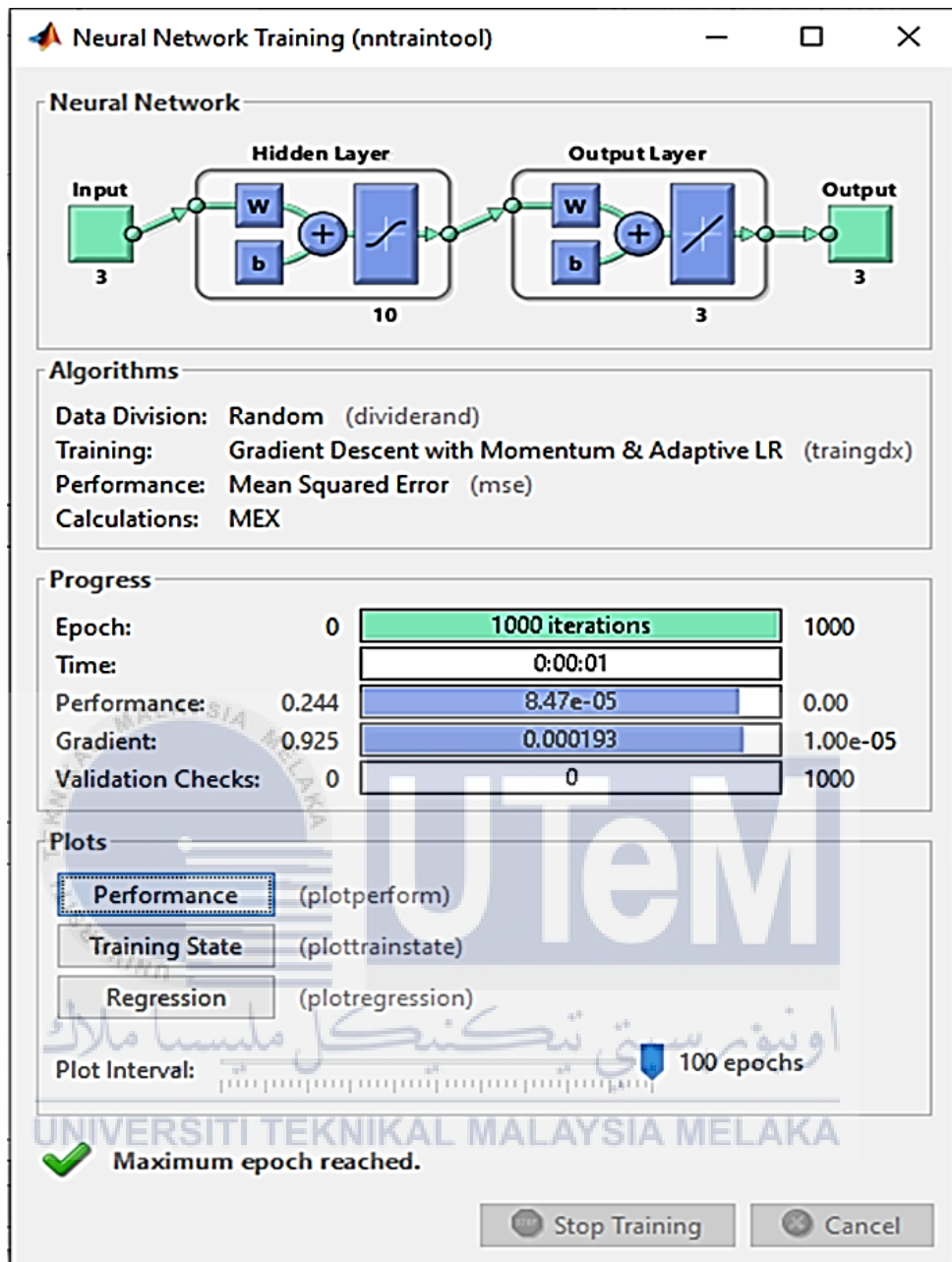


Figure 3.8 Training Process

3.6 Testing The Neural Network

The optimal weight will be used in testing the Neural Network. The fault data for both DC and AC side will be used as the test data in order to confirm the actual predictive output of the network. The output data for the testing Neural Network should be same as the actual output. The error will be calculated then by subtract the actual output with the test output. The lower the error of test output data, the higher

accuracy of the training Neural Network. Figure 3.9 shows a technique in testing the Neural Network.

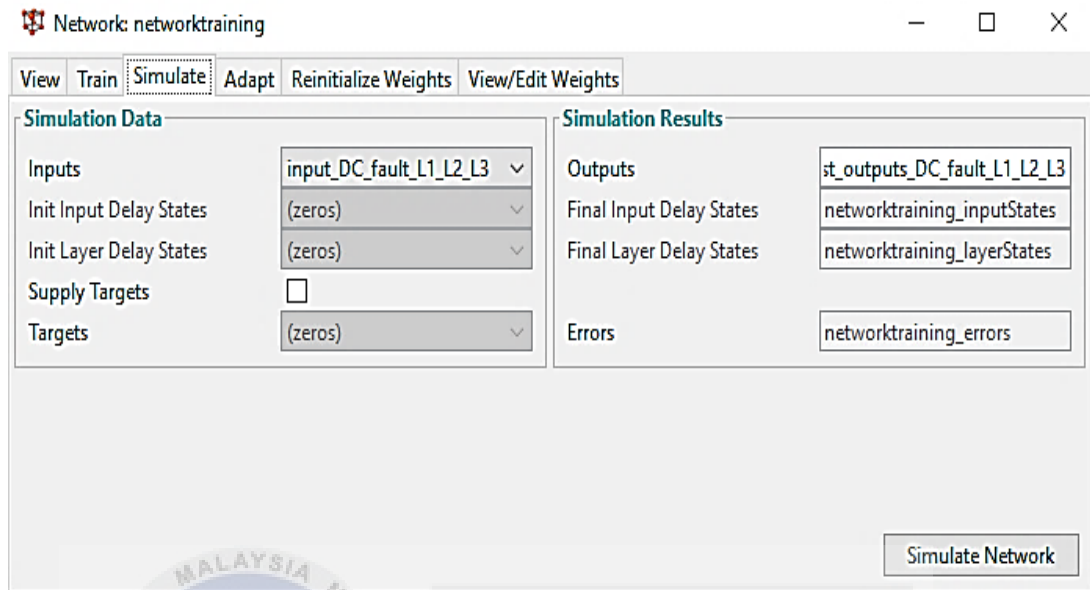


Figure 3.9 Test The Neural Network

3.7 Summary

This part of study briefly explains about the flow of the project from the beginning until the end. The method that been shown in this part are supervised and unsupervised learning of the neural network. In the supervised learning, the current value from fault data of solar PV are been used at the input layer while the power from fault data at solar PV are been used at the output layer to determine the optimal weight. The unsupervised learning is been used to proof the data are set true or not using the optimal weight from the supervised learning. This study conducted to implement the fault detection using BPNN and to analyses the system accuracy.

MATLAB software is used to implement and observe the neural network accuracy for fault detection in solar PV. The accuracy of the neural network system is been determined by comparing the actual output with the test output of the neural network.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 The Collected Data of DC and AC side Fault

The results are been obtained by implement back propagation neural network (BPNN) in MATLAB R2016a to identify fault at solar PV. There are three types of data of solar PV at Fakulti Kejuruteraan Elektrik (FKE) UTeM that have been gathered for references. First, the normal data with no fault have been used to train the neural network for the weight adjustment. The data will be collected from 10.00 am until 3.00 pm as it is the peak hour when the sun offers high energy and the sun is highest in the sky and most intense. The value of the current and power are varying due to the environmental issues such as shaded by tree or the solar panel orientation as the sun's energy do not proper hit the PV panel. When some part of the PV panel been shaded, the system will produce a low value of current and power because there are less irradiances collected by the PV panel. As the higher irradiance collected by the solar PV, the greater power of the solar PV generated. Figure 4.1 shows the current graph for normal data of solar PV while Figure 4.2 shows the power graph for normal data of solar PV. The line power graph imitates as the line current graph because the current is proportional to the power. The value of power at solar PV will decrease as the value of current decrease. To implement BPNN in MATLAB, the value of current in each line of solar PV are set as input while the value of power for each line are set as target value. So, there were three nodes at each input and output layer which is line 1, 2 and 3. The normal data of the DC side is been used in training process for getting the optimal weight.

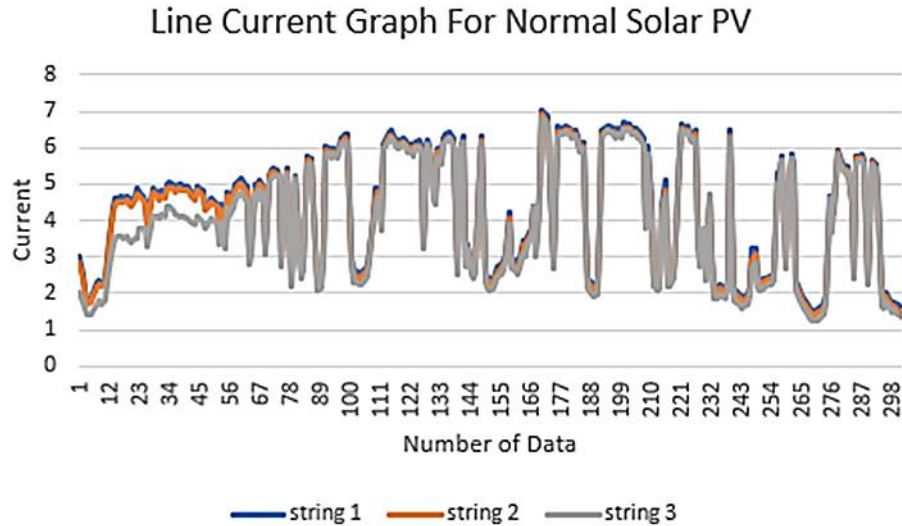


Figure 4.1 The Line Current Graph For Normal Solar PV

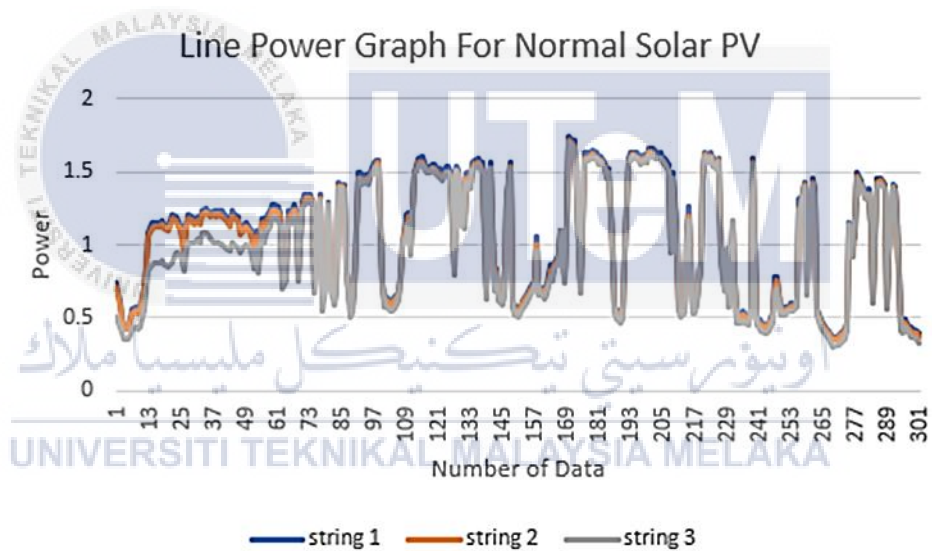


Figure 4.2 The Line Power Graph For Normal Solar PV

The MCB for string 1 at DC side was shut down to make sure there is no current flow at the DC side. This is to show that there were open circuit at line 1 of DC side solar PV. The value of current will become zero as there is no flow of current from the PV panel to the inverter. Figure 4.3 shows the line current graph for fault at line 1 at DC side solar PV. The value of power at line 1 at DC side will become zero as fault happen because there is no flow of current. This is because current is proportional to the value power. Figure 4.4 shows the line current graph for fault at line 1 DC side solar PV.

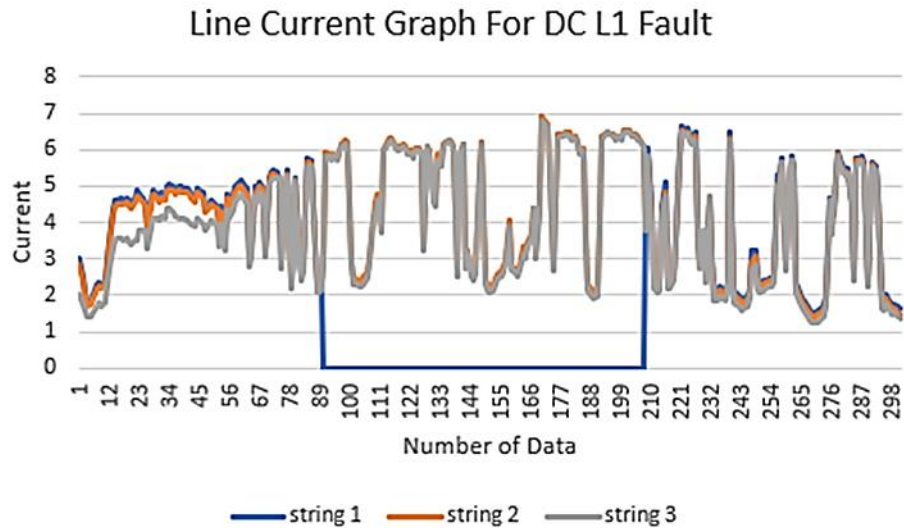


Figure 4.3 The Line Current Graph For DC Line 1 Fault

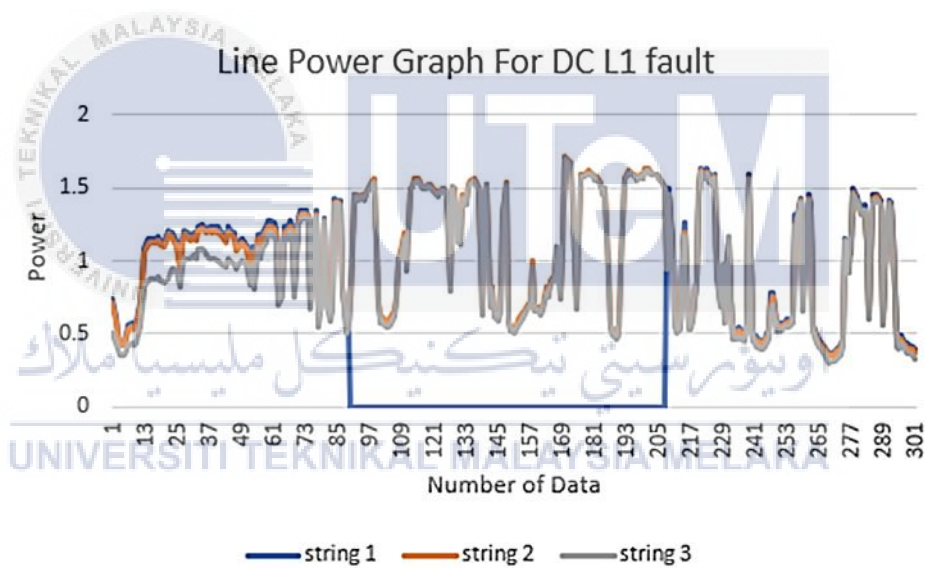


Figure 4.4 The Line Power Graph For DC Line 1 Fault

The MCB for string 1 and 2 at DC side was shut down to make sure there is no current flow at the DC side. The value of current will become zero as there is no flow of current at line 1 and 2 from the PV panel to the inverter. Figure 4.5 shows the line current graph for fault at line 1 and 2 at DC side solar PV. The value of power at line 1 and 2 at DC side will become zero as fault happen because there is no flow of current and the power value of solar PV are proportional to current value. Figure 4.6 shows the line current graph for fault at line 1 and 2 DC side solar PV.

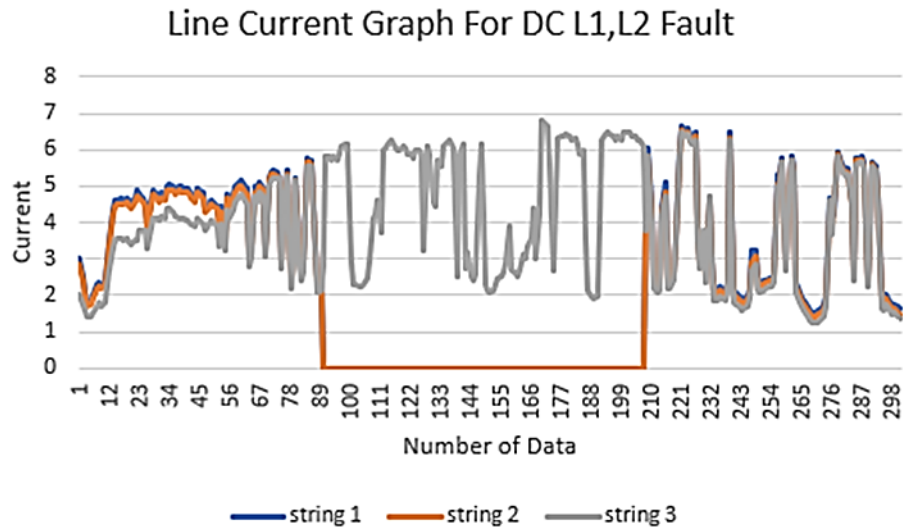


Figure 4.5 The Line Current Graph For DC Line 1 and 2 Fault

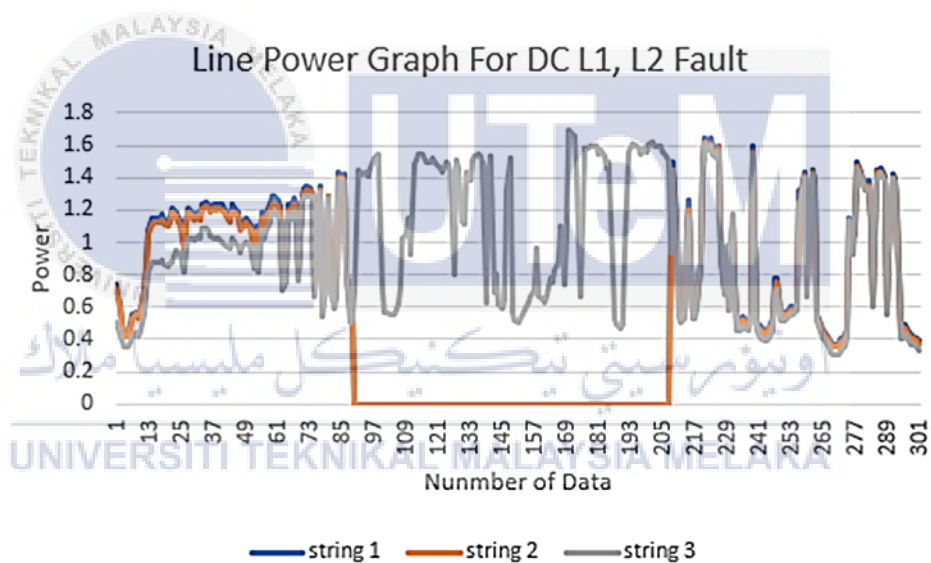


Figure 4.6 The Line Power Graph For DC Line 1 and 2 Fault

The MCB for string 1, 2 and 3 at DC side was shut down to make sure there is no current flow at the DC side. The value of current will become zero as there is no flow of current from the PV panel to the inverter. Figure 4.7 shows the line current graph for fault at line 1, 2 and 3 at DC side solar PV. The value of power at line 1, 2 and 3 at DC side will become zero as fault happen because there is no flow of current and the power value of solar PV are proportional to current value. Figure 4.8 shows the line current graph for fault at line 1, 2 and 3 DC side solar PV.

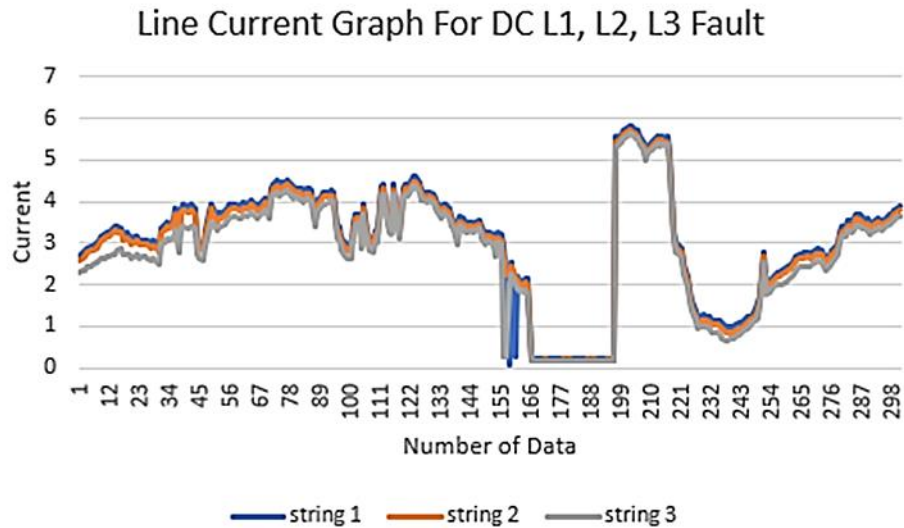


Figure 4.7 The Line Current Graph For DC Line 1, 2 and 3 Fault

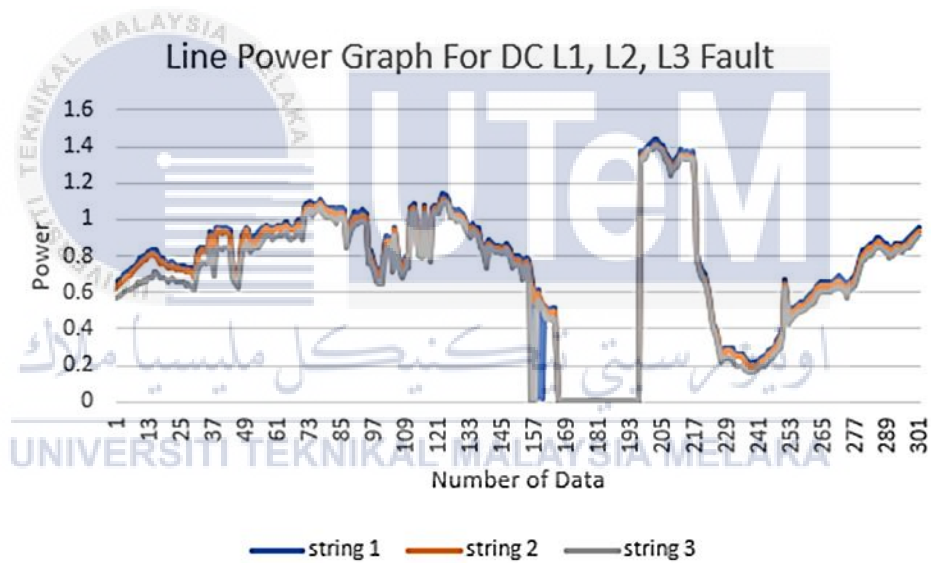


Figure 4.8 The Line Power Graph For DC Line 1, 2 and 3 Fault

The MCB for string 1 at AC side was shut down to make sure there is no current flow at the AC side. The value of current will become zero as there is no flow of current from the inverter to load. This is to show that open circuit occur at line 1 of AC side solar PV. Figure 4.9 shows the line current graph for fault at line 1 at AC side solar PV. The value of power at line 1 at AC side will become zero as fault happen because there is no flow of current and the power value of solar PV are proportional to current value. Figure 4.10 shows the line current graph for fault at line 1 AC side solar PV.

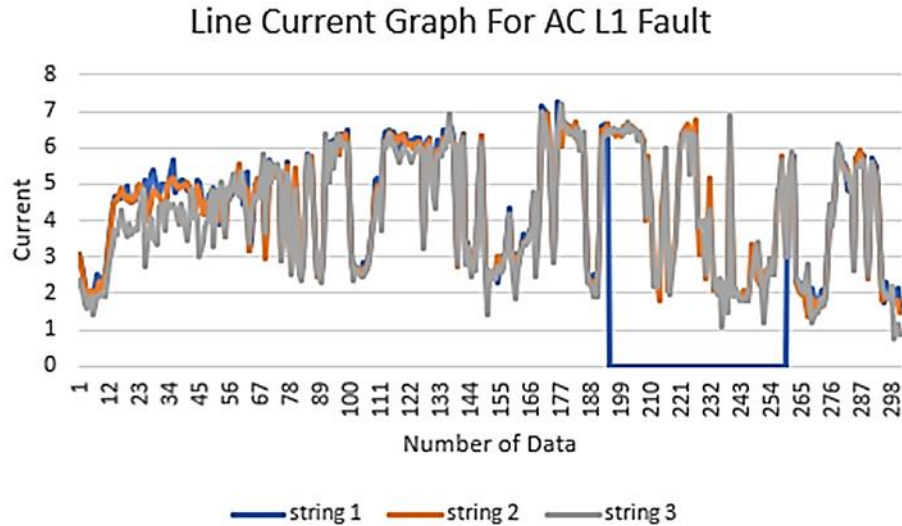


Figure 4.9 The Line Current Graph For AC Line 1 Fault

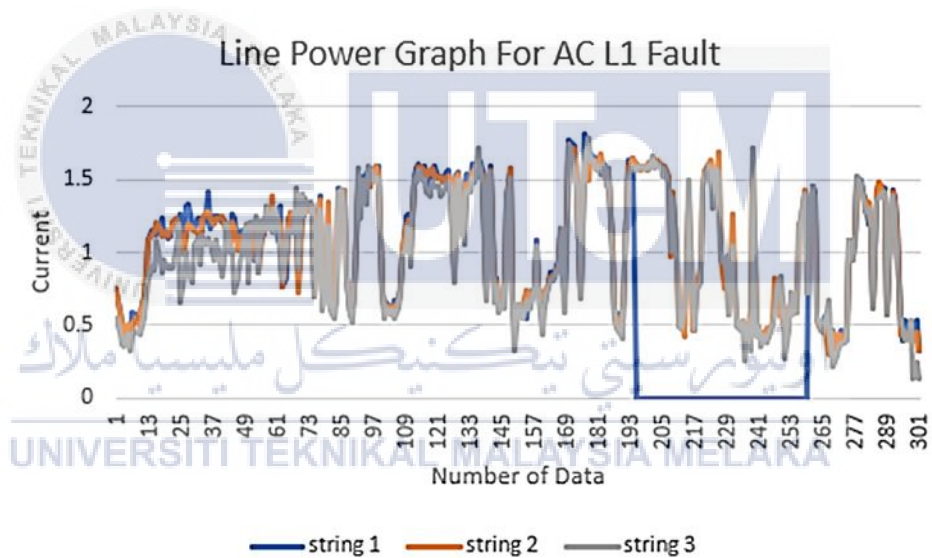


Figure 4.10 The Line Power Graph For AC Line 1 Fault

The MCB for string 1 and 2 at AC side was shut down to make sure there is no current flow at the AC side. The value of current will become zero as there is no flow of current from the inverter to load. Figure 4.11 shows the line current graph for fault at line 1 and 2 at AC side solar PV. The value of power at line 1 and 2 at AC side will become zero as fault happen because there is no flow of current and the power value of solar PV are proportional to current value. Figure 4.12 shows the line current graph for fault at line 1 and 2 AC side solar PV.

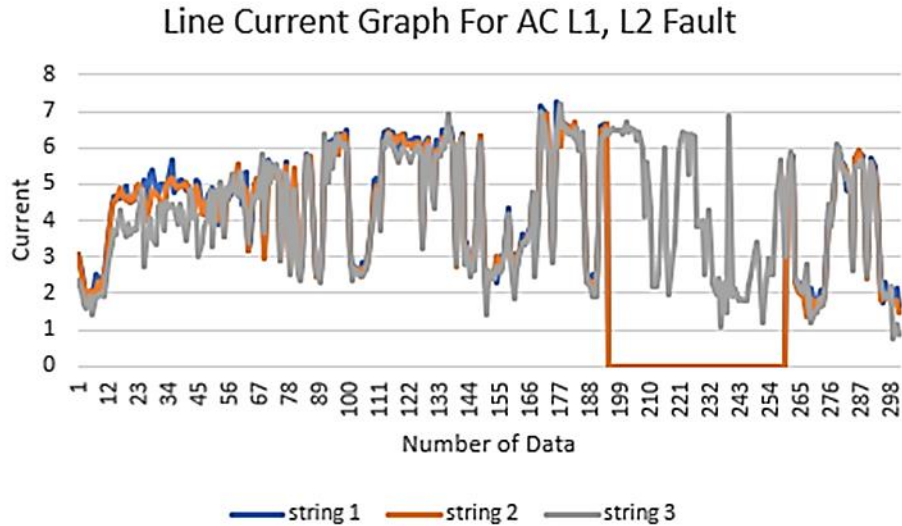


Figure 4.11 The Line Current Graph For AC Line 1 and 2 Fault

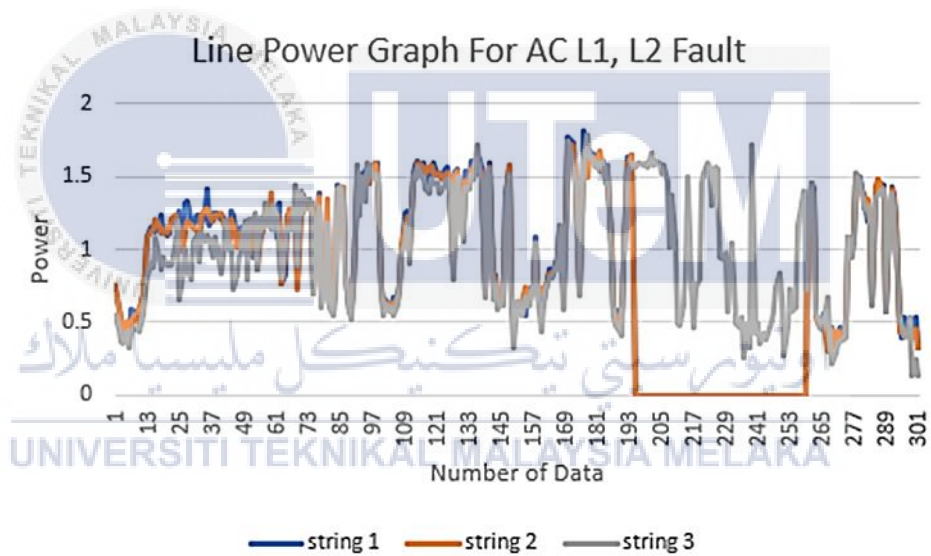


Figure 4.12 The Line Power Graph For AC Line 1 and 2 Fault

The MCB for string 1, 2 and 3 at AC side was shut down to make sure there is no current flow at the AC side. The value of current will become zero as there is no flow of current from the inverter to load. Figure 4.13 shows the line current graph for fault at line 1, 2 and 3 at AC side solar PV. The value of power at line 1, 2 and 3 at AC side will become zero as fault happen because there is no flow of current and the power value of solar PV are proportional to current value. Figure 4.14 shows the line current graph for fault at line 1, 2 and 3 AC side solar PV.

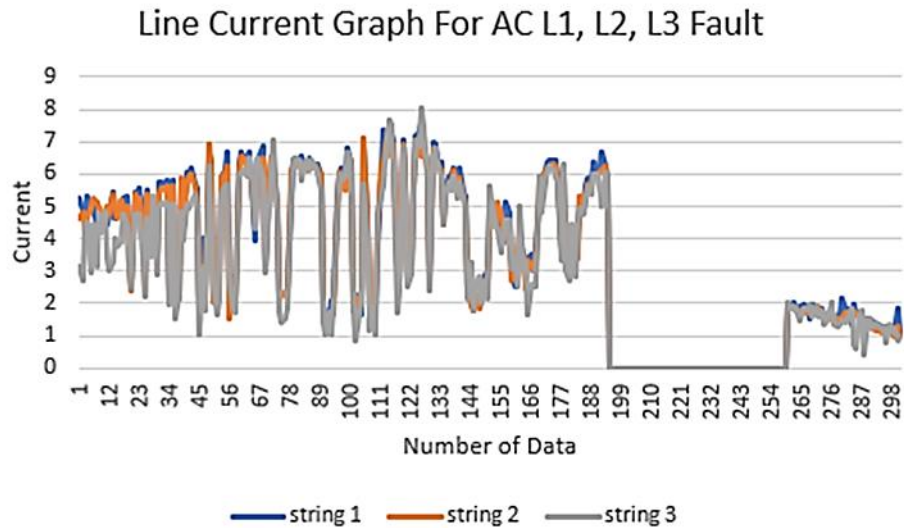


Figure 4.13 The Line Current Graph For AC Line 1, 2 and 3 Fault

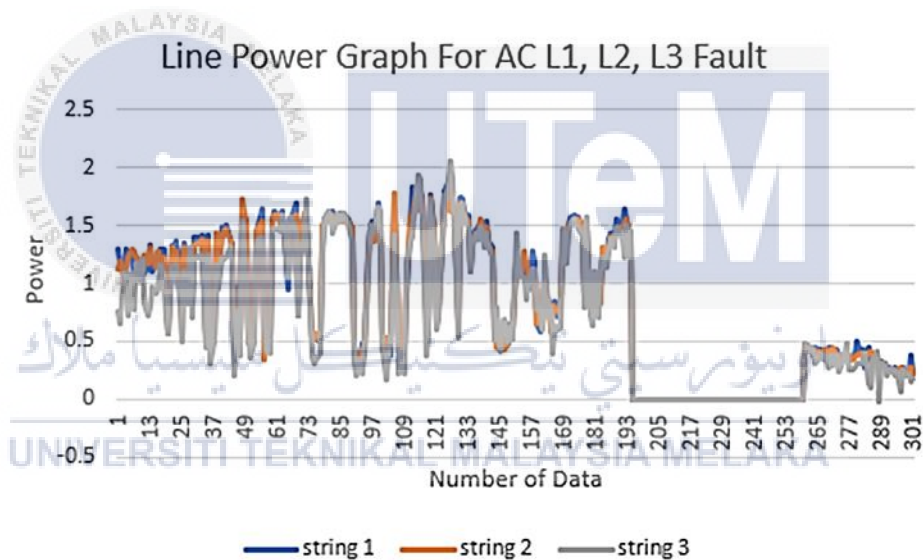


Figure 4.14 The Line Power Graph For AC Line 1, 2 and 3 Fault

4.2 Optimal Weight Update

The input of the data at the input layer consist of three neurons which refer to string 1 to string 3 current. The target data at the output layer also consist of three neurons which refer to string 1 to string 3 power. The hidden layer then is built with 10 neurons. The next steps are shown as section 3.5. In the training process, Variable Learning Rate Backpropagation (VLRB) are used in training this process because it can minimize the error on the validation set. Furthermore, VLRB is good when training

at higher number of weights as the performance does not decrease. VLRB that been choose is 'traingdx'. The adaptive learning rate of 'traingdx' will attempt to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface. The training process was succeed as shown in Figure 3.10. Mean squared error (MSE) is a network performance function. The network performance was measures as the mean of squared error. The normal data for solar PV were used for training neural network to get the ideal weight. Figure 4.15 until Figure 4.18 shows the ideal weight from training process. Bias are the neurons that been attached to the start or end of the input and each of hidden layer. Bias do not have any incoming connections but it still has outgoing connections to contribute for the output of ANN. If bias are absence, the model will train over point passing through origin and the model will not become as flexible it can. The activation of function will trigger as the bias will control the training process.

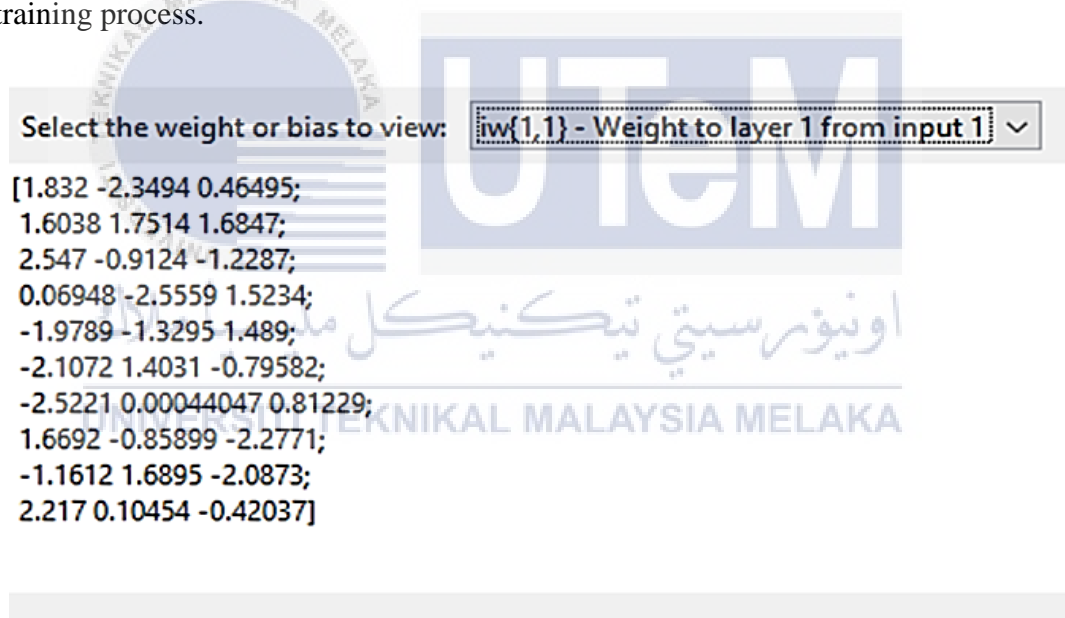


Figure 4.15 Weight to Layer 1 from Input 1

Select the weight or bias to view: ▼

[0.42618 0.019754 -0.40848 -0.15279 -0.23376 -0.20206 -0.42266 -0.41694 0.22715 -0.48992;
1.2682 -0.022409 -0.39421 0.28071 -0.31681 -0.10159 -0.46235 -0.5178 -0.48894 0.58759;
-0.40567 0.096985 0.7886 -0.39767 0.2102 -0.88934 0.33056 -0.59003 -0.60185 -0.61442]

Figure 4.16 Weight to Layer

Select the weight or bias to view: ▼

[-3.0223;
-2.2352;
-1.8175;
-1.3036;
0.53951;
-0.52228;
-1.0673;
1.3658;
-2.3801;
3.6834]


The image contains a watermark for Universiti Teknikal Malaysia Melaka (UTeM). It features the university's logo, which consists of a stylized 'U' and 'M' with horizontal lines, and the text 'UTeM' in a large, bold font. Below this, the name of the university is written in Malay: 'اونيورسيتي تيكنيكل مليسيا ملاك' and in English: 'UNIVERSITI TEKNIKAL MALAYSIA MELAKA'.

Figure 4.17 Bias to Layer 1

Select the weight or bias to view: ▼

[0.68859;
0.22837;
0.40028]

Figure 4.18 Bias to Layer 2

4.3 Neural Network Training Analysis

Next, the training process will be continuing to apply at the fault data for DC and AC side of solar PV by using the ideal network from neural network training before. The validation data set is a sample data that been using again from the training model to get the best performance model. The best performance is taken from the epoch that have the lowest validation error. The validation accuracy was a measure place of how the model fits. In this training, the validation accuracy and training accuracy were both low for DC and AC side fault training performance. This is because the model was generalizing well. If the validation accuracy is low while training accuracy is high, the model is overfit. If the model is overfit, the training data will give negative impact to the performance of the model new data. This will lead to inaccuracy when doing testing process. The error will reduce after a few epochs of training, but the error might increase on the validation data set as the network start overfitting the training data. The training is better when there are large number of epochs and long duration training. Overfitting are being checked and avoided in this training process to eliminate errors that can be caused for future predictions and observations. For example, Figure 4.19 shows the mean squared error value 0.00098075. The MSE value is the best at at the lowest possible value because the lowest training error will give a good training result. The meaning of MSE being very small that closed to zero is that the desired outputs and the neural network outputs for the training set have become very close to each other. If the MSE value to high during training process, the desired outputs and the neural network outputs for the training set will far apart and this will lead to a wrong prediction during the testing process. Figure 4.19 until Figure 4.24 shows the graph for training performance at each of the DC and AC side fault.

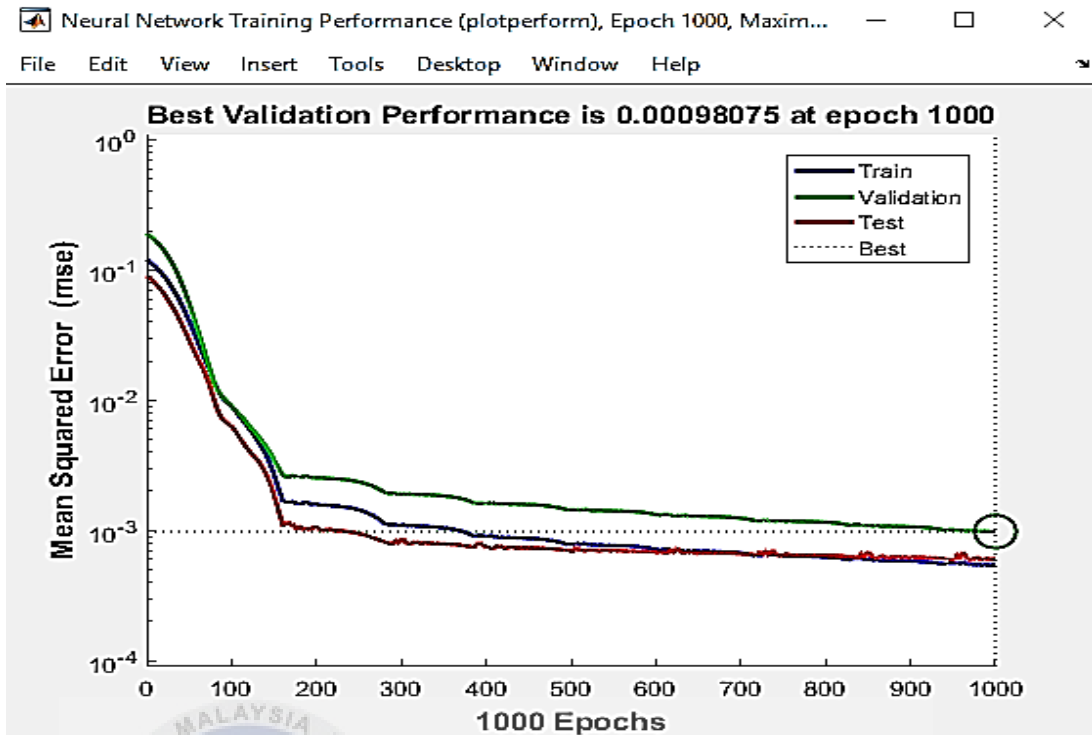


Figure 4.19 AC Line 1 Fault Training Performance Graph

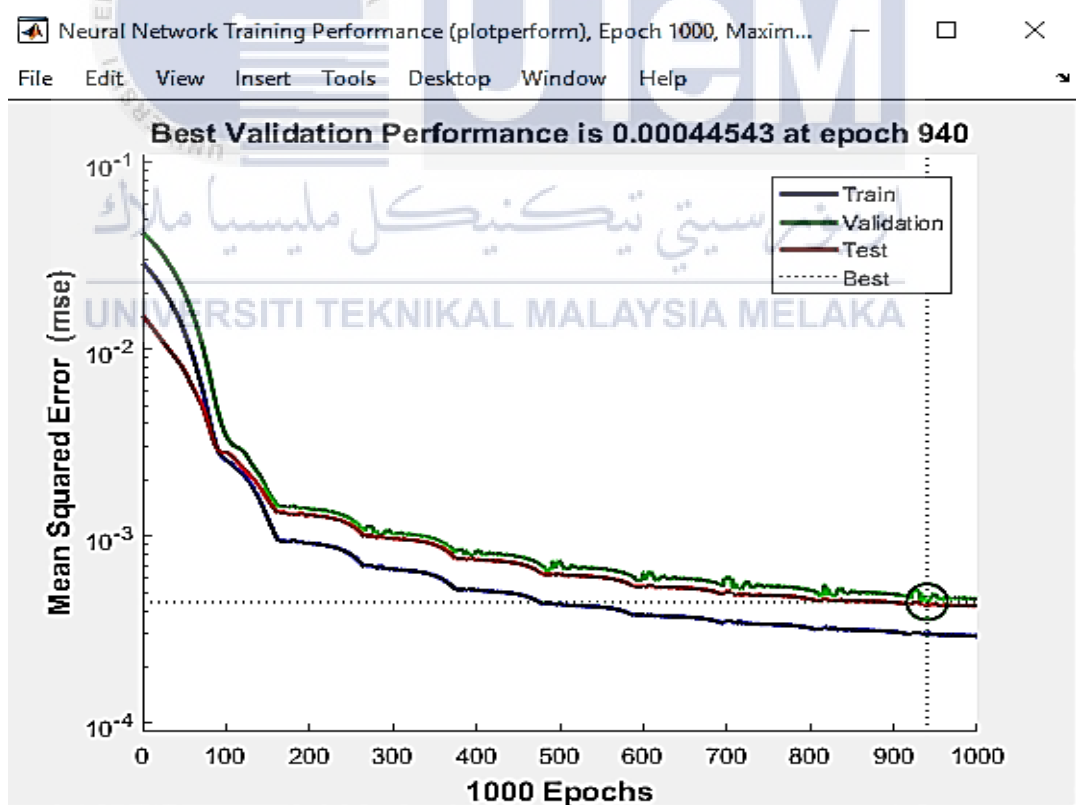


Figure 4.20 AC Line 1 and 2 Fault Training Performance Graph

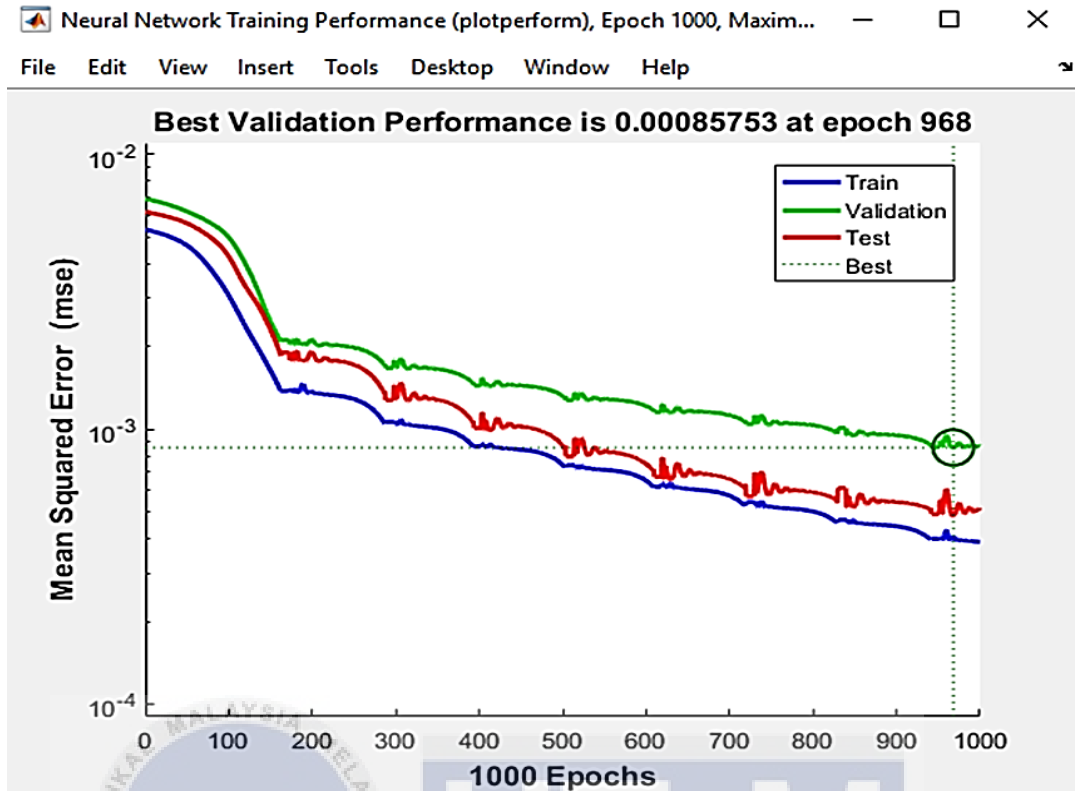


Figure 4.21 AC Line 1, 2 and 3 Fault Training Performance Graph

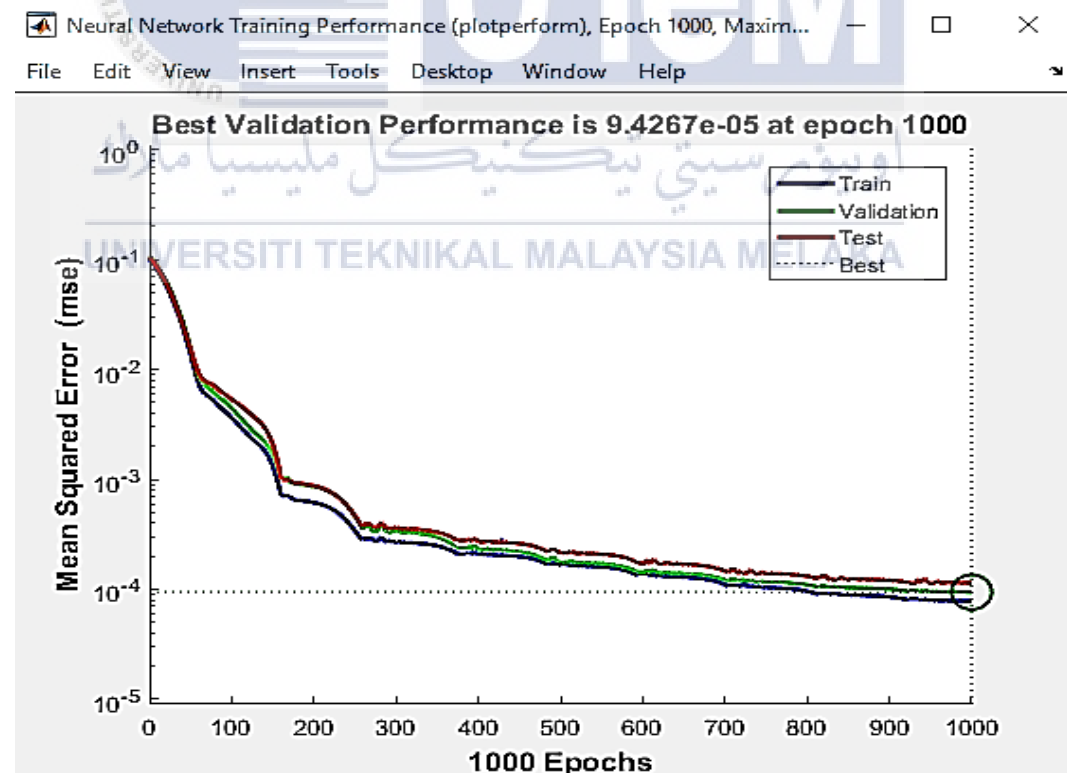


Figure 4.22 DC Line 1 Fault Training Performance Graph

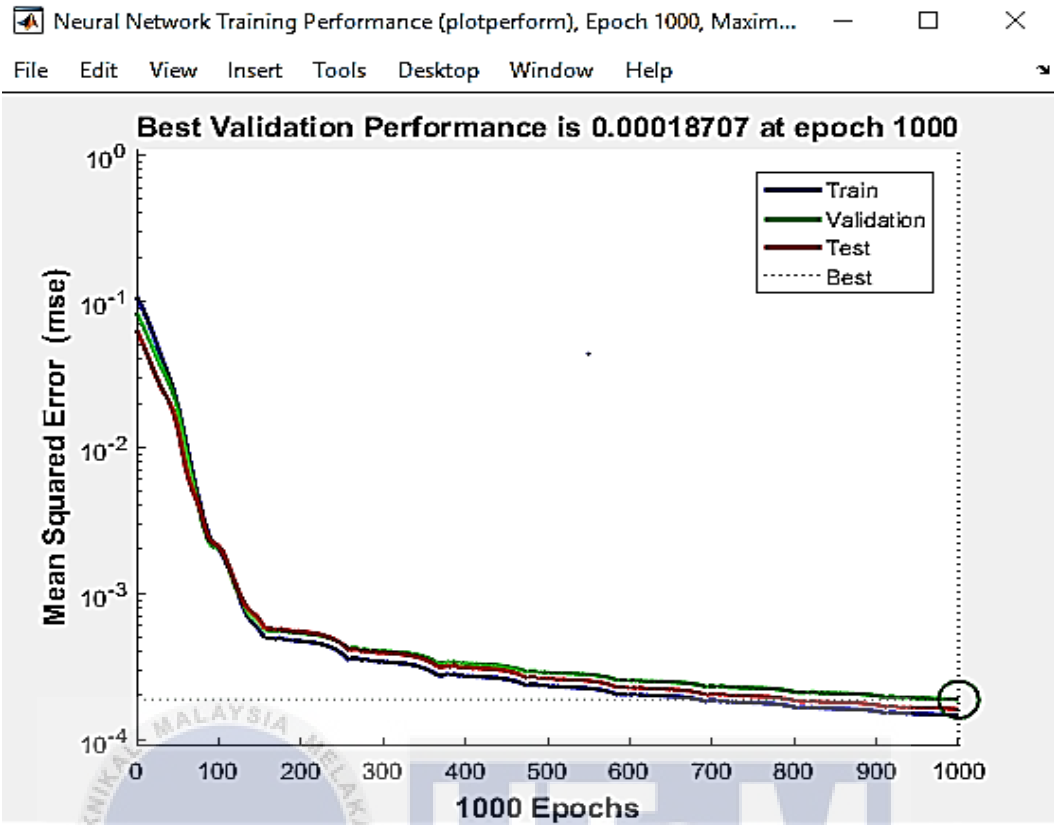


Figure 4.23 DC Line 1 and 2 Fault Training Performance Graph

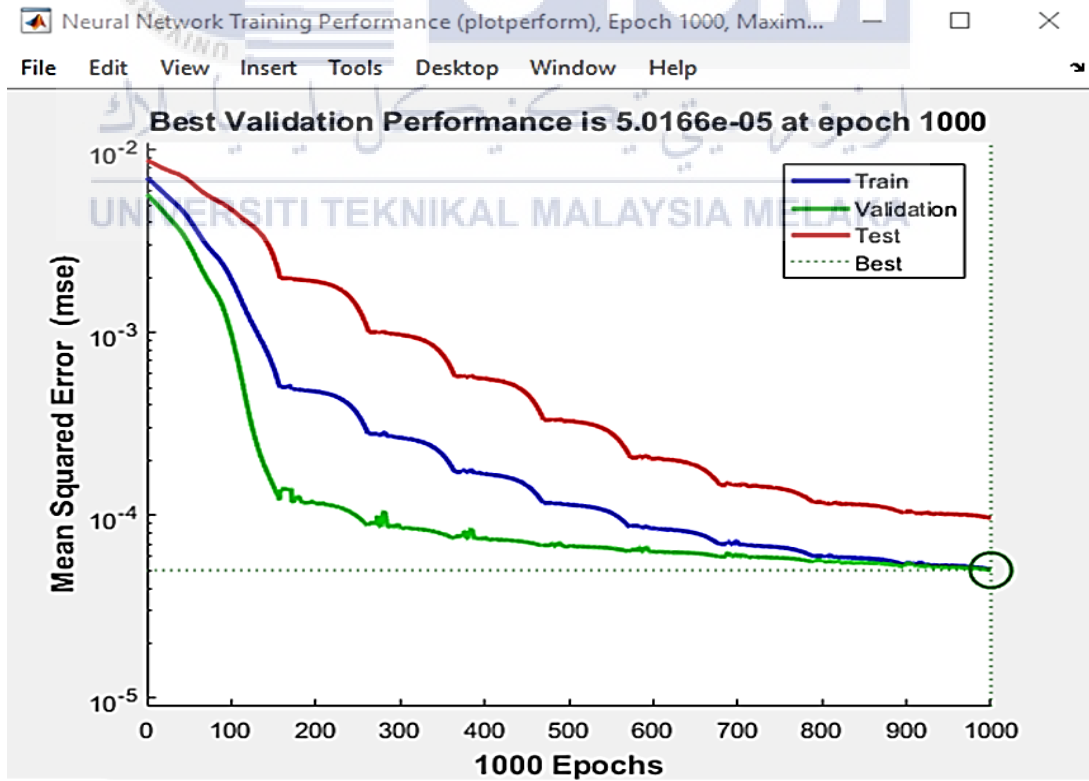


Figure 4.24 DC Line 1, 2 and 3 Fault Training Performance Graph

The regression plot achieved its stability when $Y=T$. All the test, training and validation have achieved their stability as the fit is linearly with the target data. This shows that the output of the neural network is close enough to the actual data and it has a high accuracy of prediction. The prediction will be wrong and not accurate if the fit is not linearly with the target data. The dashed line represents the perfect target while the solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If $R = 1$, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. Figure 4.25 until Figure 4.30 shows the Neural Network training regression graph for each of the faults that occur at solar PV. The results obtained show that the neural network training was successfully done as the regression value for each training was approximately one.

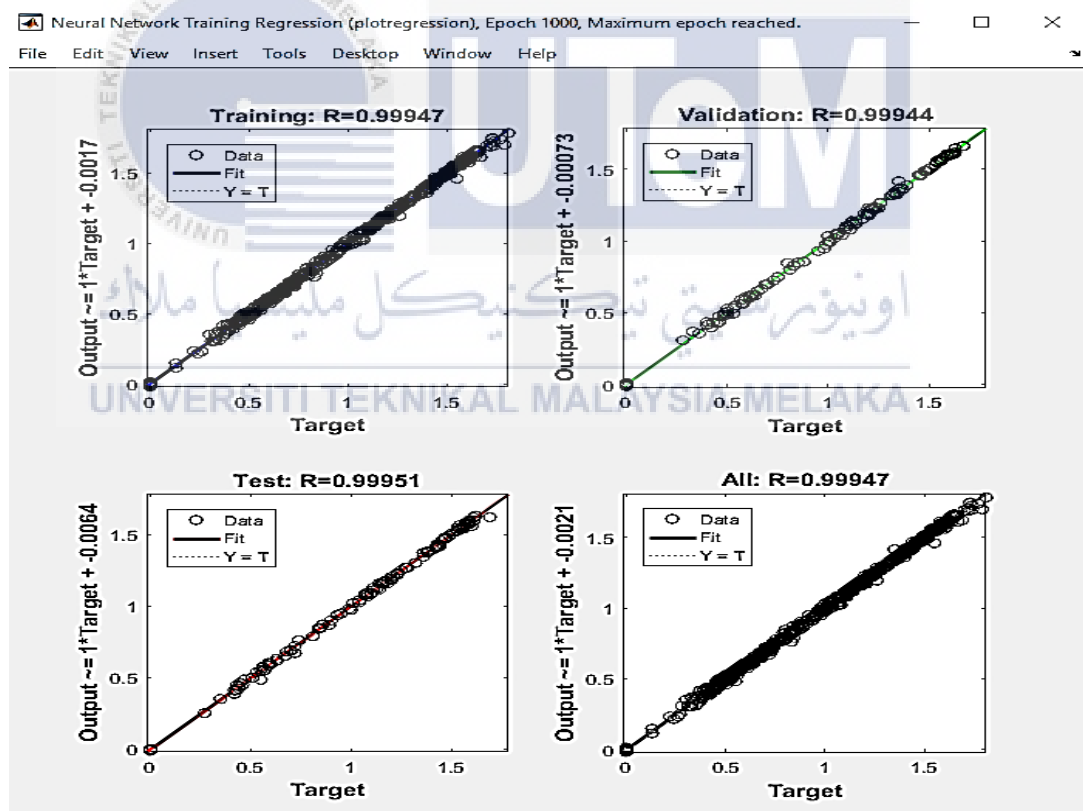


Figure 4.25 Training Regression AC Line 1 Side Fault Graph

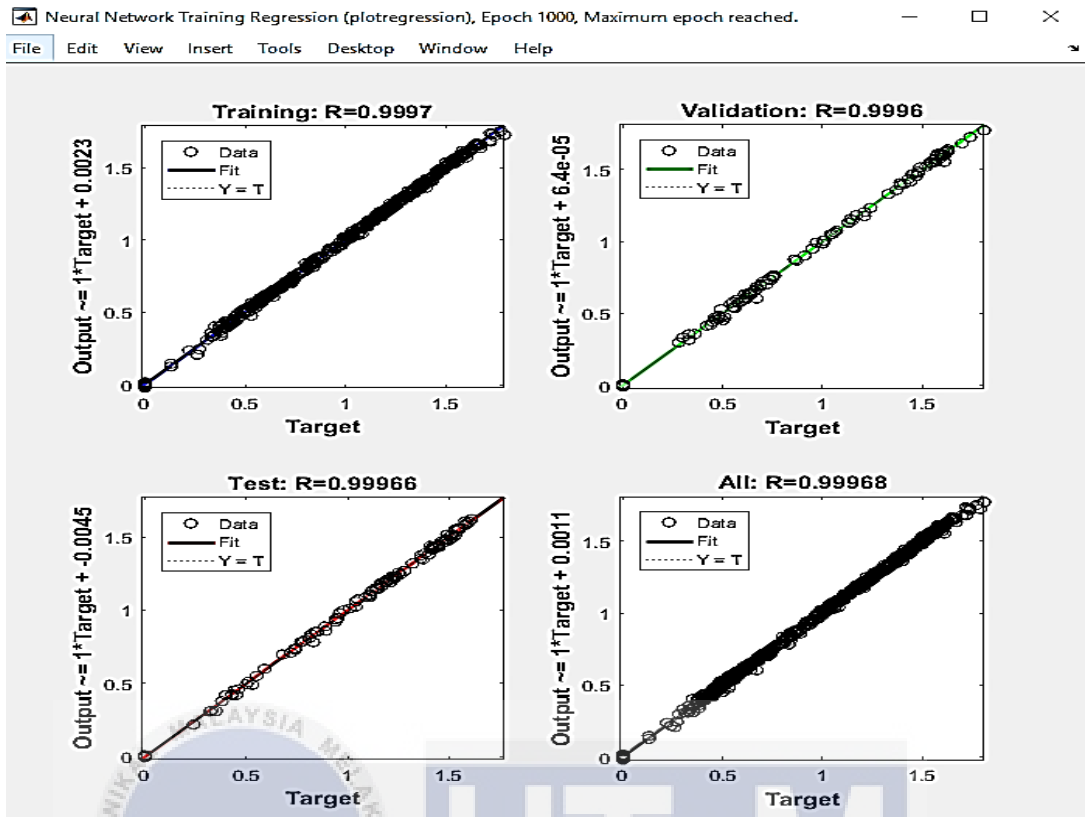


Figure 4.26 Training Regression AC Line 1 and 2 Side Fault Graph

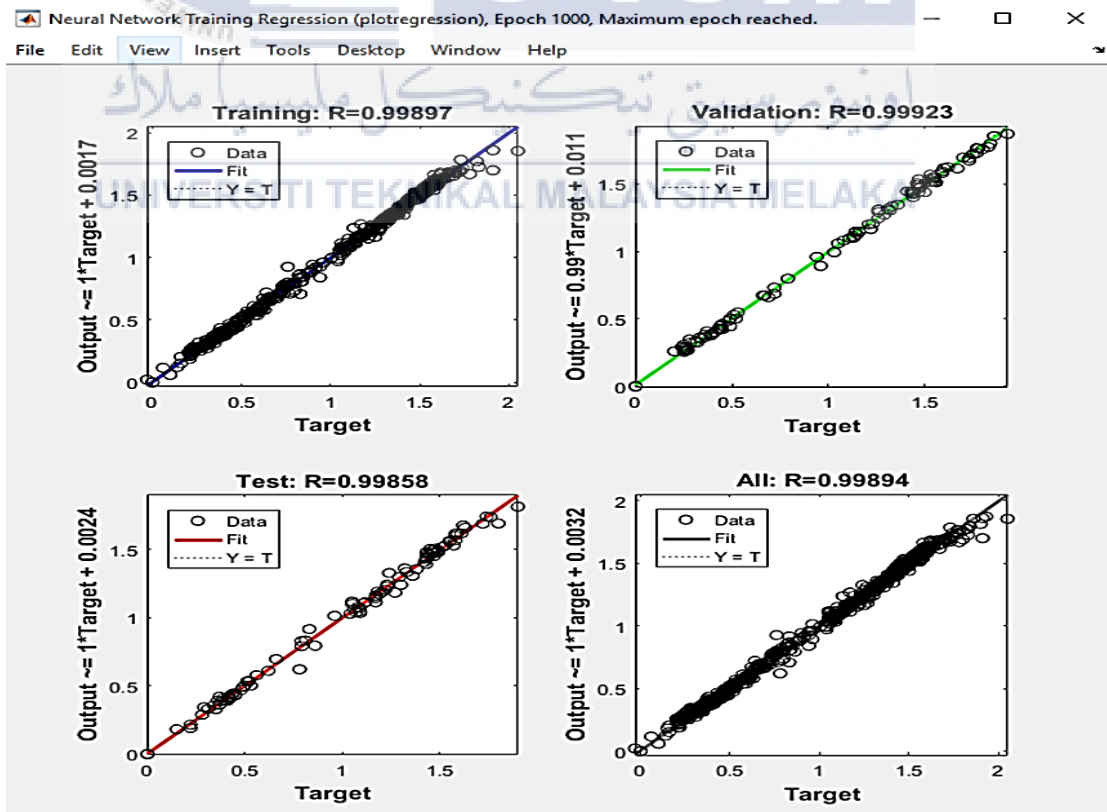
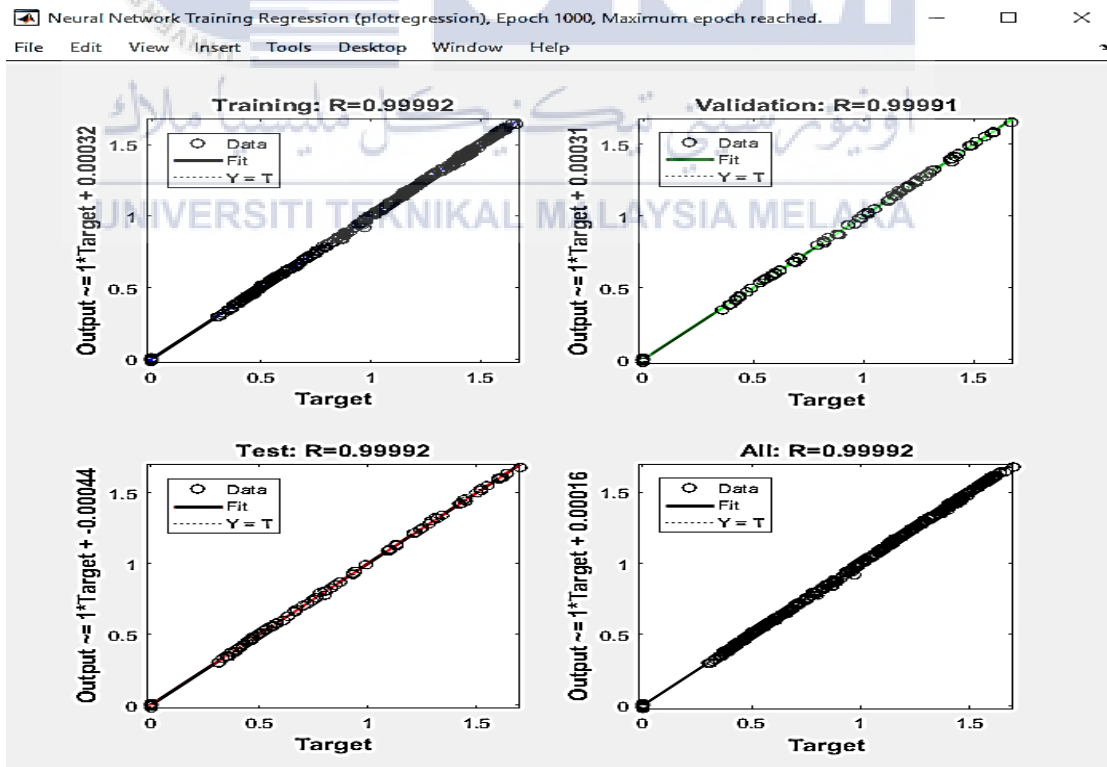
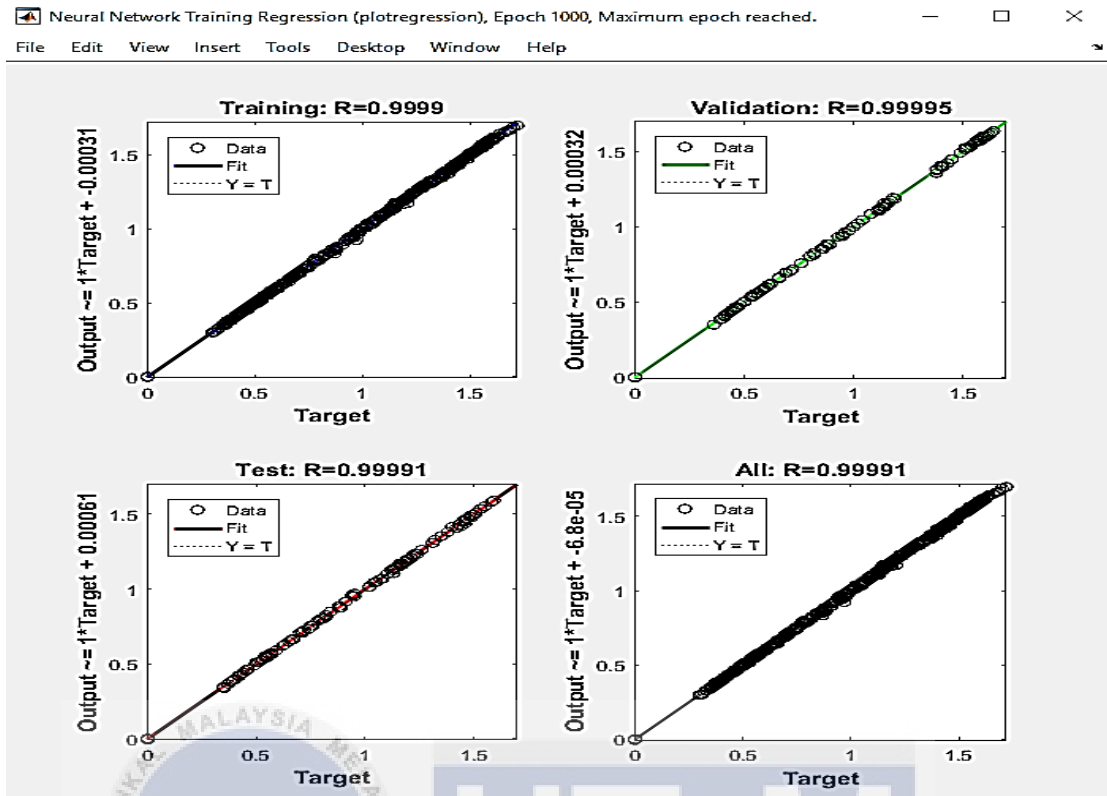


Figure 4.27 Training Regression AC Line 1, 2 and 3 Side Fault Graph



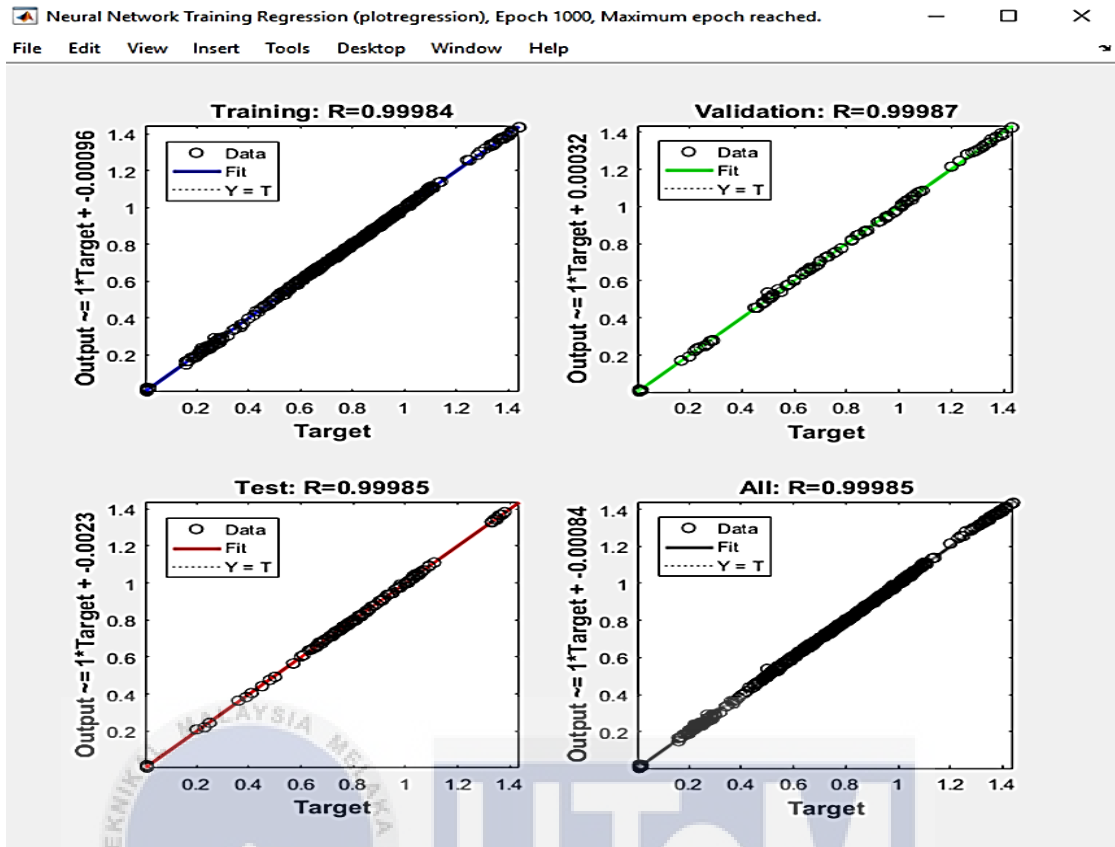


Figure 4.30 Training Regression DC Line 1, 2 and 3 Side Fault Graph

4.4 Neural Network Test Analysis

The testing of Neural Network will be applied at each of faults at DC and AC side of solar PV. The testing data is generated from the training Neural Network. Table 4.1 until Table 4.6 shows the testing result for each fault at DC and AC side of solar PV. The calculated errors between the actual output and testing output were low indicates that the neural network tests were accurate because the values of the testing output were closed to the values of the actual output. If the calculated error is high, the training neural network process need to be run again until the optimal weight been obtained. The lower the errors between the actual output and testing output, the more higher the system accuracy and the training gave a good performances. There were ten samples of actual output and testing output to calculate error as shown in Table 4.1 until Table 4.6. The other values of actual output and test output were shown in APPENDIX A and APPENDIX B.

Table 4.1 Testing Condition For AC Line 1 Fault

No.	Actual output (kw)			Testing output (kw)			Error (kw)		
	L1	L2	L3	L1	L2	L3	L1	L2	L3
1	0	1.61	1.56	0.2251	1.3607	1.5105	-0.2251	0.1993	0.0495
2	0	1.6	1.60	0.2350	1.3837	1.5570	-0.2350	0.2163	0.0430
3	0	1.57	1.59	0.2291	1.3646	1.5424	-0.2291	0.2054	0.0476
4	0	1.59	1.58	0.2313	1.3739	1.5433	-0.2313	0.2161	0.0367
5	0	1.57	1.59	0.2288	1.3630	1.5428	-0.2288	0.2070	0.0472
6	0	1.62	1.56	0.2266	1.3682	1.5085	-0.2266	0.2518	0.0515
7	0	1.61	1.66	0.2484	1.4170	1.6124	-0.2484	0.193	0.0476
8	0	1.61	1.58	0.2294	1.3723	1.5273	-0.2294	0.2377	0.0527
9	0	1.63	1.61	0.2384	1.3965	1.5601	-0.2384	0.2335	0.0499
10	0	1.61	1.60	0.2318	1.3762	1.5427	-0.2318	0.2338	0.0573

Table 4.2 Testing Condition For AC Line 1 and 2 Fault

No.	Actual output (kw)			Testing output (kw)			Error (kw)		
	L1	L2	L3	L1	L2	L3	L1	L2	L3
1	0	0	1.56	-0.0002	-0.0568	1.6370	0.0002	0.0568	-0.0770
2	0	0	1.6	-0.0030	-0.0525	1.6724	0.0030	0.0525	-0.0724
3	0	0	1.59	-0.0019	-0.0542	1.6591	0.0019	0.0542	-0.0691
4	0	0	1.58	-0.0021	-0.0539	1.6613	0.0021	0.0539	-0.0813
5	0	0	1.59	-0.0019	-0.0542	1.6591	0.0019	0.0542	-0.0691
6	0	0	1.56	-0.0002	-0.0568	1.6370	0.0002	0.0568	-0.0770
7	0	0	1.66	-0.0065	-0.0462	1.7166	0.0065	0.0462	-0.0566
8	0	0	1.58	-0.0012	-0.0553	1.6503	0.0012	0.0553	-0.0703
9	0	0	1.61	-0.0033	-0.0519	1.6768	0.0033	0.0519	-0.0668
10	0	0	1.6	-0.0021	-0.0539	1.6613	0.0021	0.0539	-0.0613

Table 4.3 Testing Condition For AC Line 1, 2 and 3 Fault

No.	Actual output (kw)			Testing output (kw)			Error (kw)		
	L1	L2	L3	L1	L2	L3	L1	L2	L3
1	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
2	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
3	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
4	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
5	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
6	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
7	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
8	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
9	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254
10	0	0	0	-0.0478	-0.0484	-0.0254	-0.0478	-0.0484	-0.0254

Table 4.4 Testing Condition For DC Line 1 Fault

No.	Actual output (kw)			Testing output (kw)			Error (kw)		
	L1	L2	L3	L1	L2	L3	L1	L2	L3
1	0	0.73	0.69	0.0151	0.6688	0.6643	-0.0151	0.0657	0.0257
2	0	1.46	1.45	0.1813	1.2297	1.3632	-0.1813	0.2303	0.0868
3	0	1.46	1.44	0.1797	1.2248	1.3575	-0.1797	0.2352	0.0825
4	0	1.44	1.42	0.1725	1.2031	1.3322	-0.1725	0.2369	0.0878
5	0	1.45	1.44	0.1784	1.2200	1.3554	-0.1784	0.2300	0.0846
6	0	1.43	1.41	0.1714	1.1991	1.3299	-0.1714	0.2309	0.0801
7	0	1.47	1.46	0.1830	1.2354	1.3686	-0.1830	0.2346	0.0914
8	0	1.53	1.52	0.2022	1.2919	1.4367	-0.2022	0.2381	0.0833
9	0	1.55	1.53	0.2088	1.3120	1.4589	-0.2088	0.2380	0.0711
10	0	1.56	1.54	0.2079	1.3088	1.4564	-0.2079	0.2512	0.0836

Table 4.5 Testing Condition For DC Line 1 and 2 Fault

No.	Actual output (kw)			Testing output (kw)			Error (kw)		
	L1	L2	L3	L1	L2	L3	L1	L2	L3
1	0	0	0.69	-0.0265	-0.0922	0.7237	0.0265	0.0922	-0.0537
2	0	0	1.45	0.0075	-0.0669	1.5182	-0.0075	0.0669	-0.0682
3	0	0	1.44	0.0078	-0.0672	1.5136	-0.0078	0.0672	-0.0736
4	0	0	1.42	0.0087	-0.0684	1.4928	-0.0087	0.0684	-0.0728
5	0	0	1.44	0.0079	-0.0673	1.5113	-0.0079	0.0673	-0.0713
6	0	0	1.41	0.0088	-0.0685	1.4905	-0.0088	0.0685	-0.0805
7	0	0	1.46	0.0073	-0.0666	1.5227	-0.0073	0.0666	-0.0627
8	0	0	1.52	0.0041	-0.0626	1.5770	-0.0041	0.0626	-0.0570
9	0	0	1.53	0.0029	-0.0602	1.5948	-0.0029	0.0602	-0.0684
10	0	0	1.54	0.0030	-0.0612	1.5926	-0.0030	0.0612	-0.0526

Table 4.6 Testing Condition For DC Line 1, 2 and 3 Fault

No.	Actual output (kw)			Testing output (kw)			Error (kw)		
	L1	L2	L3	L1	L2	L3	L1	L2	L3
1	0	0	0	0.0129	0.0140	0.0104	-0.0129	-0.0140	-0.0104
2	0	0	0	0.0104	0.0110	0.0110	-0.0104	-0.0110	-0.0110
3	0	0	0	0.0134	0.0114	0.0138	-0.0134	-0.0114	-0.0138
4	0	0	0	0.0133	0.0116	0.0108	-0.0133	-0.0116	-0.0108
5	0	0	0	0.0105	0.0109	0.0140	-0.0105	-0.0109	-0.0140
6	0	0	0	0.0129	0.0140	0.0104	-0.0129	-0.0140	-0.0104
7	0	0	0	0.0104	0.0110	0.0110	-0.0104	-0.0110	-0.0110
8	0	0	0	0.0134	0.0114	0.0138	-0.0134	-0.0114	-0.0138
9	0	0	0	0.0104	0.0110	0.0110	-0.0104	-0.0110	-0.0110
10	0	0	0	0.0134	0.0114	0.0138	-0.0134	-0.0114	-0.0138

4.5 Summary

The objective of the study was achieved as the back propagation neural network (BPNN) can accurately detect the fault at solar PV as were shown in the result. As the error of the actual output and testing output were low, the neural network system will lead to good performance and high accuracy. Neural network trainings gave a good performance as the regression value of the training were close to one. The good performance of neural network in training will lead to obtain the optimal weight needed. Lastly, optimal weight was used to get the prediction value of the neural network. As the prediction value close to actual output value, this indicates that the

trainings and testing neural network were done successful. If the calculated error is high, the neural network needs to be train again until the optimal weight been obtained.



CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The Neural Network based on fault identification in solar photovoltaic is introduced in this thesis. Back Propagation Neural Network (BPNN) was used for training solar PV system model. The simulation was run using MATLAB. The normal data and fault data of solar PV were collected for training and testing process. The hidden layer, learning rate and data collected were used in getting the optimal weight. The training process of the Neural Network were succeed as shown in chapter 4.3. The optimal weight then will used for testing process. This process is to confirm the actual predictive output should be same as the actual output of the data that been collected. The calculated errors were low as the accuracy of the training network is high.

The network can identify the fault types independently on the current values and the types of fault of solar PV. From the simulation, the result that been obtain show that the proposed neural network manages to detect and classify the types of fault accurately. A negligible error was found in the result of fault types identification. The errors were too small and be neglected. The error can actually be further reduced by increasing the number of training and generalization, but it may consume a lot of time.

5.2 Future Works

For future research, more complex of solar photovoltaic system that can produced high power for utility used such as solar system that connected with more solar PV panel with similar Neural Network structure can be develop for real time application.

In order to reduce the cost of operation and maintenance and improve diagnosis efficiency, the intelligent diagnosis methods represented by neural network are the focus of current research. For other support detection equipment such as the satellite observations, infrared detection and sensor are not suitable for large scale use due to the high cost.

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APPENDICES

APPENDIX A ACTUAL OUTPUT DATA OF SOLAR PV

output_AC_fault_L1 =

Columns 1 through 17

0.7300	0.6000	0.5200	0.4400	0.3700	0.4000	0.5900	0.5800	0.5600	0.5700	0.7000	0.8400	1.0800	1.1500	1.1400	1.1200	1.1700
0.7500	0.5900	0.5000	0.4400	0.5000	0.4400	0.5000	0.5500	0.5100	0.5900	0.6800	0.8500	1.0800	1.1300	1.1400	1.2100	1.1700
0.5400	0.4500	0.3700	0.3500	0.4400	0.3200	0.4300	0.4500	0.4600	0.4400	0.5500	0.6800	0.8100	0.9100	0.8800	1.0800	0.9500

Columns 18 through 34

1.2300	1.1400	1.1000	1.1100	1.2000	1.2100	1.1600	1.2600	1.1100	1.3200	1.3300	1.2100	1.1500	1.2300	1.2400	1.1500	1.2600
1.1100	1.1400	1.1100	1.1400	1.2100	1.2400	1.2000	1.1300	0.9900	1.1100	1.2000	1.1600	1.1500	1.1300	1.0200	1.2300	1.2700
0.8600	0.9500	0.8900	0.9100	0.8900	1.0100	1.2000	0.6500	0.8300	1.0000	0.8600	0.8000	1.0600	1.1000	0.9200	1.1100	1.0600

Columns 35 through 51

1.4200	1.1700	1.2500	1.2500	1.2500	1.2100	1.2200	1.1900	1.0500	1.2600	1.2400	1.0700	1.0400	1.1500	1.0400	1.2000	1.0600
1.2700	1.2300	1.2000	1.2300	1.2300	1.2500	1.2000	1.1400	1.0400	1.2100	1.1700	1.0200	1.1100	1.1000	1.1200	0.9800	0.9700
1.1000	1.0700	0.9500	1.0800	1.0100	0.8300	0.9400	1.2000	1.0000	1.0300	0.7300	0.8200	0.9400	0.9900	1.2000	0.8000	1.2100

Columns 52 through 68

0.9500	1.0000	1.0600	1.1000	1.1400	1.1800	1.2200	1.3000	1.2800	1.0800	1.3200	0.7700	0.8200	1.2300	1.2300	1.1500	1.2000
1.0900	1.2300	0.8700	1.1100	1.1400	1.2700	1.2300	1.3800	1.1900	1.2400	1.1900	0.7700	0.9700	1.2000	1.2800	1.2600	1.2200
1.1900	1.2500	0.8600	1.2200	1.1500	1.3200	1.1700	1.1400	1.3100	1.1900	0.9600	0.8100	1.0300	1.1500	1.1400	1.1400	1.4400

Columns 69 through 85

0.7900	1.3900	1.3700	1.3200	1.3500	1.3000	0.7200	1.2700	1.3800	0.6700	0.8400	1.2800	0.6800	0.7000	0.7600	1.4400	1.4300
0.7200	1.2400	1.3600	1.2800	1.3300	1.3200	0.7000	1.2500	1.3600	0.6200	0.7800	1.3400	0.7900	0.6700	0.7200	1.4200	1.4300
0.8900	1.4000	1.2500	1.3400	1.3500	1.3200	0.7000	1.1800	1.2900	0.6000	0.7400	1.1800	0.6000	0.5400	0.6600	1.4200	1.4300

Columns 86 through 102

1.3900	0.8500	0.5700	0.6100	0.7800	1.4100	1.5300	1.3800	1.5400	1.5600	1.4500	1.5800	1.5900	1.6000	0.7400	0.6200	0.6500
1.4300	0.8300	0.5900	0.6100	0.7400	1.5100	1.4600	1.4900	1.4800	1.4700	1.4500	1.5600	1.5900	1.5400	0.7100	0.6400	0.6300
1.3300	0.8100	0.5700	0.5200	0.7400	1.5800	1.2400	1.5000	1.3300	1.6000	1.5600	1.4900	1.5100	1.5100	0.7000	0.5500	0.6200

Columns 103 through 119

0.6000	0.6200	0.6700	0.6700	0.7700	0.9900	1.2500	1.2600	1.0300	1.5100	1.5800	1.6100	1.5300	1.6000	1.5400	1.4600	1.5300
0.6200	0.5900	0.6300	0.6400	0.7400	1.0200	1.1700	1.2200	0.9600	1.4800	1.5100	1.5900	1.5800	1.5600	1.5200	1.5600	1.5800
0.5800	0.6000	0.5500	0.6200	0.7200	0.9900	1.0300	1.1800	0.9100	1.5100	1.4800	1.5700	1.4900	1.5000	1.4200	1.3800	1.4800

Columns 120 through 136

1.5900	1.5100	1.5300	1.4900	1.5500	1.5600	1.5000	0.8800	1.5400	1.5500	1.3300	1.1900	1.5400	1.4900	1.6100	1.6100	1.5300
1.5200	1.5100	1.5200	1.4800	1.5100	1.5300	1.4900	0.8300	1.5100	1.5400	1.2200	1.1500	1.4700	1.4500	1.5500	1.5700	1.5800
1.4600	1.4500	1.3800	1.4000	1.4600	1.4800	1.4500	0.7900	1.4100	1.5000	1.1200	1.0500	1.4300	1.4100	1.5100	1.4800	1.7200

Columns 137 through 153

1.6200	1.5600	0.6900	1.4900	1.5900	0.7400	0.8200	0.6700	0.6700	0.6600	1.3600	1.5700	0.6300	0.5500	0.5600	0.5600	0.6300
1.5700	1.5300	0.6800	1.4600	1.5700	0.7300	0.8100	0.6800	0.6400	0.6900	1.3400	1.5800	0.7000	0.5100	0.5700	0.5800	0.6300
1.5500	1.4500	0.6700	1.5000	1.5500	0.6600	0.7700	0.5900	0.6400	0.6100	1.3600	1.5100	0.5900	0.3300	0.6400	0.5800	0.5500

Columns 154 through 170

0.5500	0.7000	0.7200	0.7600	1.0800	0.7400	0.7300	0.6400	0.7200	0.8700	0.8100	0.8600	0.9400	1.1400	0.7200	1.1200	1.7700
0.7400	0.6600	0.6900	0.7500	0.9900	0.7700	0.7000	0.6900	0.7400	0.8400	0.8200	0.8400	0.9200	1.1300	0.8400	1.1100	1.7300
0.6700	0.6100	0.6200	0.7500	1.0400	0.7000	0.4400	0.6100	0.7100	0.8100	0.8100	0.8200	0.9200	1.1700	0.5900	0.9800	1.7400

Columns 171 through 187

1.7400	1.7300	1.3900	0.7500	1.1900	1.8100	1.6700	1.6700	1.6600	1.6500	1.6000	1.5800	1.5900	1.5200	1.4900	1.0400	0.5800
1.7000	1.7200	1.4600	0.7000	1.2400	1.6100	1.4900	1.6200	1.6400	1.6200	1.5900	1.6700	1.5400	1.5000	1.5400	1.0200	0.5700
1.6300	1.5300	1.4500	0.6800	1.0600	1.6100	1.7900	1.6300	1.6300	1.5700	1.6000	1.5400	1.6100	1.4600	1.5800	0.8700	0.5300

Columns 188 through 204

0.5500	0.5900	0.5500	0.9000	1.6300	1.6400	1.6500	0	0	0	0	0	0	0	0	0	0
0.5400	0.4900	0.5300	0.9300	1.5900	1.6100	1.6500	1.6100	1.6000	1.5700	1.5900	1.5700	1.6200	1.6100	1.6100	1.6300	1.6100
0.4800	0.4300	0.4100	0.9500	1.5400	1.5600	1.6000	1.5600	1.6000	1.5900	1.5800	1.5900	1.5600	1.6600	1.5800	1.6100	1.6000

Columns 205 through 221

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.5900	1.5900	1.5300	0.9800	1.4100	1.0000	0.5900	0.5400	0.4200	1.0700	1.3500	0.4700	0.5700	0.7500	0.9000	1.4400	1.5700
1.5200	1.5800	1.4700	1.0100	1.3700	1.0500	0.4900	0.4800	0.6100	0.8500	1.4900	0.7200	0.4600	0.7400	0.8000	1.4500	1.5200

Columns 222 through 238

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.6100	1.6400	1.5500	1.5400	1.6900	0.9800	0.7500	0.8800	0.5800	1.2600	0.7800	0.5000	0.5000	0.5100	0.5000	0.4900	0.6100
1.5900	1.5600	1.3000	1.5700	1.5500	0.9400	0.9300	0.9800	0.5700	1.0400	0.8100	0.4900	0.4600	0.5300	0.2600	0.4900	0.3300

Columns 239 through 255

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.6200	0.4700	0.4700	0.4500	0.4500	0.4800	0.4200	0.5300	0.8200	0.7200	0.5600	0.5300	0.4700	0.6200	0.6500	0.5900	0.5900
1.7200	0.4200	0.4900	0.3500	0.4200	0.3800	0.4200	0.5000	0.5700	0.7400	0.8400	0.6900	0.2700	0.4600	0.7200	0.5700	0.6000

Columns 256 through 272

0	0	0	0	1.1600	1.4500	1.4200	0.5600	0.4800	0.4800	0.5600	0.4700	0.3100	0.4600	0.3600	0.3800	0.4700
1.2000	1.2200	1.4300	0.7300	1.2100	1.4300	1.3800	0.5300	0.4600	0.4700	0.4900	0.3000	0.3400	0.4500	0.3300	0.4300	0.3800
1.1700	1.2400	1.4000	0.7300	1.1600	1.4600	1.3600	0.5600	0.4800	0.4500	0.5000	0.6700	0.3800	0.2200	0.2800	0.3500	0.3700

Columns 273 through 289

0.4200	0.5000	1.0900	1.0700	1.0700	1.5100	1.5000	1.4100	1.3700	1.2000	1.1800	0.6400	1.4200	1.4700	1.4500	1.4400	0.6100
0.4100	0.4900	1.0100	1.0000	1.1000	1.4500	1.4200	1.4000	1.3600	1.3400	1.1600	0.6600	1.4200	1.4800	1.4500	1.3900	0.5800
0.3800	0.4000	1.0900	0.9500	1.0400	1.5200	1.4800	1.4000	1.2800	1.3100	1.1800	0.6200	1.3600	1.3700	1.4000	1.4100	0.5800

Columns 290 through 301

0.8800	1.4300	1.3700	1.2000	0.4800	0.4000	0.5300	0.4300	0.4100	0.3900	0.5300	0.3300
0.9500	1.4100	1.3400	1.1800	0.4400	0.4300	0.4400	0.4300	0.4000	0.3900	0.4500	0.3300
0.9400	1.3900	1.3100	1.0400	0.5100	0.4600	0.3900	0.4200	0.5300	0.1300	0.2400	0.1300

output_AC_fault_L1_L2 =

Columns 1 through 17

0.7300	0.6000	0.5200	0.4400	0.3700	0.4000	0.5900	0.5800	0.5600	0.5700	0.7000	0.8400	1.0800	1.1500	1.1400	1.1200	1.1700
0.7500	0.5900	0.5000	0.4400	0.5000	0.4400	0.5000	0.5500	0.5100	0.5900	0.6800	0.8500	1.0800	1.1300	1.1400	1.2100	1.1700
0.5400	0.4500	0.3700	0.3500	0.4400	0.3200	0.4300	0.4500	0.4600	0.4400	0.5500	0.6800	0.8100	0.9100	0.8800	1.0800	0.9500

Columns 18 through 34

1.2300	1.1400	1.1000	1.1100	1.2000	1.2100	1.1600	1.2600	1.1100	1.3200	1.3300	1.2100	1.1500	1.2300	1.2400	1.1500	1.2600
1.1100	1.1400	1.1100	1.1400	1.2100	1.2400	1.2000	1.1300	0.9900	1.1100	1.2000	1.1600	1.1500	1.1300	1.0200	1.2300	1.2700
0.8600	0.9500	0.8900	0.9100	0.8900	1.0100	1.2000	0.6500	0.8300	1.0000	0.8600	0.8000	1.0600	1.1000	0.9200	1.1100	1.0600

Columns 35 through 51

1.4200	1.1700	1.2500	1.2500	1.2500	1.2100	1.2200	1.1900	1.0500	1.2600	1.2400	1.0700	1.0400	1.1500	1.0400	1.2000	1.0600
1.2700	1.2300	1.2000	1.2300	1.2300	1.2500	1.2000	1.1400	1.0400	1.2100	1.1700	1.0200	1.1100	1.1000	1.1200	0.9800	0.9700
1.1000	1.0700	0.9500	1.0800	1.0100	0.8300	0.9400	1.2000	1.0000	1.0300	0.7300	0.8200	0.9400	0.9900	1.2000	0.8000	1.2100

Columns 52 through 68

0.9500	1.0000	1.0600	1.1000	1.1400	1.1800	1.2200	1.3000	1.2800	1.0800	1.3200	0.7700	0.8200	1.2300	1.2300	1.1500	1.2000
1.0900	1.2300	0.8700	1.1100	1.1400	1.2700	1.2300	1.3800	1.1900	1.2400	1.1900	0.7700	0.9700	1.2000	1.2800	1.2600	1.2200
1.1900	1.2500	0.8600	1.2200	1.1500	1.3200	1.1700	1.1400	1.3100	1.1900	0.9600	0.8100	1.0300	1.1500	1.1400	1.1400	1.4400

Columns 69 through 85

0.7900	1.3900	1.3700	1.3200	1.3500	1.3000	0.7200	1.2700	1.3800	0.6700	0.8400	1.2800	0.6800	0.7000	0.7600	1.4400	1.4300
0.7200	1.2400	1.3600	1.2800	1.3300	1.3200	0.7000	1.2500	1.3600	0.6200	0.7800	1.3400	0.7900	0.6700	0.7200	1.4200	1.4300
0.8900	1.4000	1.2500	1.3400	1.3500	1.3200	0.7000	1.1800	1.2900	0.6000	0.7400	1.1800	0.6000	0.5400	0.6600	1.4200	1.4300

Columns 86 through 102

1.3900	0.8500	0.5700	0.6100	0.7800	1.4100	1.5300	1.3800	1.5400	1.5600	1.4500	1.5800	1.5900	1.6000	0.7400	0.6200	0.6500
1.4300	0.8300	0.5900	0.6100	0.7400	1.5100	1.4600	1.4900	1.4800	1.4700	1.4500	1.5600	1.5900	1.5400	0.7100	0.6400	0.6300
1.3300	0.8100	0.5700	0.5200	0.7400	1.5800	1.2400	1.5000	1.3300	1.6000	1.5600	1.4900	1.5100	1.5100	0.7000	0.5500	0.6200

Columns 103 through 119

0.6000	0.6200	0.6700	0.6700	0.7700	0.9900	1.2500	1.2600	1.0300	1.5100	1.5800	1.6100	1.5300	1.6000	1.5400	1.4600	1.5300
0.6200	0.5900	0.6300	0.6400	0.7400	1.0200	1.1700	1.2200	0.9600	1.4800	1.5100	1.5900	1.5800	1.5600	1.5200	1.5600	1.5800
0.5800	0.6000	0.5500	0.6200	0.7200	0.9900	1.0300	1.1800	0.9100	1.5100	1.4800	1.5700	1.4900	1.5000	1.4200	1.3800	1.4800

Columns 120 through 136

1.5900	1.5100	1.5300	1.4900	1.5500	1.5600	1.5000	0.8800	1.5400	1.5500	1.3300	1.1900	1.5400	1.4900	1.6100	1.6100	1.5300
1.5200	1.5100	1.5200	1.4800	1.5100	1.5300	1.4900	0.8300	1.5100	1.5400	1.2200	1.1500	1.4700	1.4500	1.5500	1.5700	1.5800
1.4600	1.4500	1.3800	1.4000	1.4600	1.4800	1.4500	0.7900	1.4100	1.5000	1.1200	1.0500	1.4300	1.4100	1.5100	1.4800	1.7200

Columns 137 through 153

1.6200	1.5600	0.6900	1.4900	1.5900	0.7400	0.8200	0.6700	0.6700	0.6600	1.3600	1.5700	0.6300	0.5500	0.5600	0.5600	0.6300
1.5700	1.5300	0.6800	1.4600	1.5700	0.7300	0.8100	0.6800	0.6400	0.6900	1.3400	1.5800	0.7000	0.5100	0.5700	0.5800	0.6300
1.5500	1.4500	0.6700	1.5000	1.5500	0.6600	0.7700	0.5900	0.6400	0.6100	1.3600	1.5100	0.5900	0.3300	0.6400	0.5800	0.5500

Columns 154 through 170

0.5500	0.7000	0.7200	0.7600	1.0800	0.7400	0.7300	0.6400	0.7200	0.8700	0.8100	0.8600	0.9400	1.1400	0.7200	1.1200	1.7700
0.7400	0.6600	0.6900	0.7500	0.9900	0.7700	0.7000	0.6900	0.7400	0.8400	0.8200	0.8400	0.9200	1.1300	0.8400	1.1100	1.7300
0.6700	0.6100	0.6200	0.7500	1.0400	0.7000	0.4400	0.6100	0.7100	0.8100	0.8100	0.8200	0.9200	1.1700	0.5900	0.9800	1.7400

Columns 171 through 187

1.7400	1.7300	1.3900	0.7500	1.1900	1.8100	1.6700	1.6700	1.6600	1.6500	1.6000	1.5800	1.5900	1.5200	1.4900	1.0400	0.5800
1.7000	1.7200	1.4600	0.7000	1.2400	1.6100	1.4900	1.6200	1.6400	1.6200	1.5900	1.6700	1.5400	1.5000	1.5400	1.0200	0.5700
1.6300	1.5300	1.4500	0.6800	1.0600	1.6100	1.7900	1.6300	1.6300	1.5700	1.6000	1.5400	1.6100	1.4600	1.5800	0.8700	0.5300

Columns 188 through 204

0.5500	0.5900	0.5500	0.9000	1.6300	1.6400	1.6500	0	0	0	0	0	0	0	0	0	0
0.5400	0.4900	0.5300	0.9300	1.5900	1.6100	1.6500	0	0	0	0	0	0	0	0	0	0
0.4800	0.4300	0.4100	0.9500	1.5400	1.5600	1.6000	1.5600	1.6000	1.5900	1.5800	1.5900	1.5600	1.6600	1.5800	1.6100	1.6000

Columns 205 through 221

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.5200	1.5800	1.4700	1.0100	1.3700	1.0500	0.4900	0.4800	0.6100	0.8500	1.4900	0.7200	0.4600	0.7400	0.8000	1.4500	1.5200

Columns 222 through 238

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.5900	1.5600	1.3000	1.5700	1.5500	0.9400	0.9300	0.9800	0.5700	1.0400	0.8100	0.4900	0.4600	0.5300	0.2600	0.4900	0.3300

Columns 239 through 255

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.7200	0.4200	0.4900	0.3500	0.4200	0.3800	0.4200	0.5000	0.5700	0.7400	0.8400	0.6900	0.2700	0.4600	0.7200	0.5700	0.6000

Columns 256 through 272

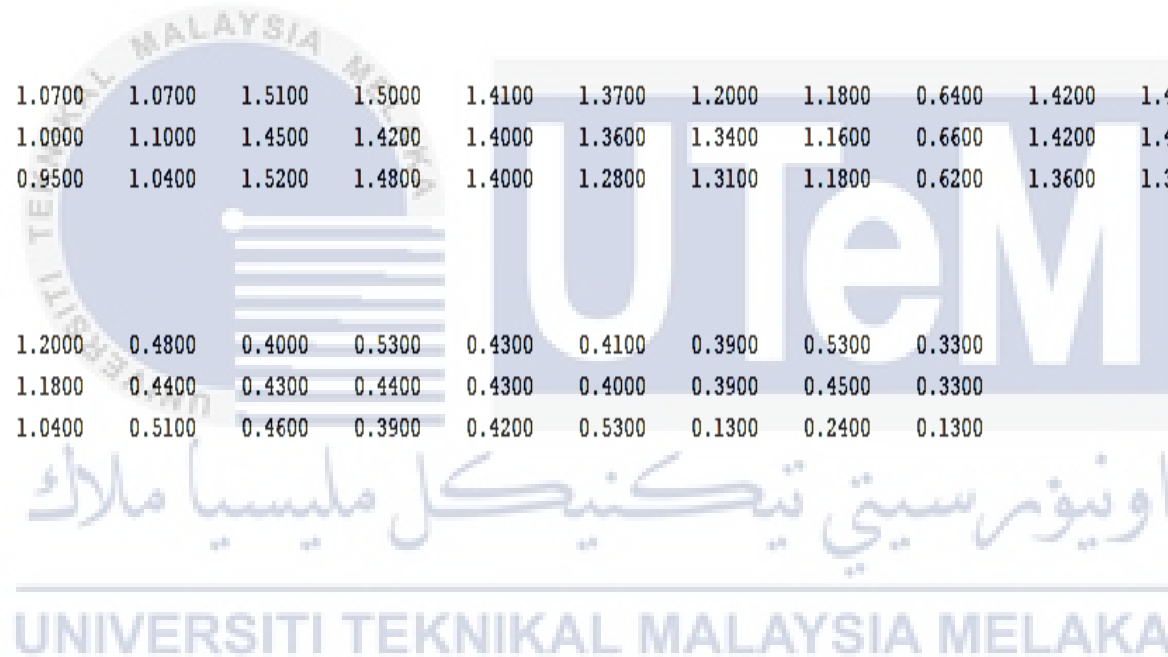
0	0	0	0	1.1600	1.4500	1.4200	0.5600	0.4800	0.4800	0.5600	0.4700	0.3100	0.4600	0.3600	0.3800	0.4700
0	0	0	0	1.2100	1.4300	1.3800	0.5300	0.4600	0.4700	0.4900	0.3000	0.3400	0.4500	0.3300	0.4300	0.3800
1.1700	1.2400	1.4000	0.7300	1.1600	1.4600	1.3600	0.5600	0.4800	0.4500	0.5000	0.6700	0.3800	0.2200	0.2800	0.3500	0.3700

Columns 273 through 289

0.4200	0.5000	1.0900	1.0700	1.0700	1.5100	1.5000	1.4100	1.3700	1.2000	1.1800	0.6400	1.4200	1.4700	1.4500	1.4400	0.6100
0.4100	0.4900	1.0100	1.0000	1.1000	1.4500	1.4200	1.4000	1.3600	1.3400	1.1600	0.6600	1.4200	1.4800	1.4500	1.3900	0.5800
0.3800	0.4000	1.0900	0.9500	1.0400	1.5200	1.4800	1.4000	1.2800	1.3100	1.1800	0.6200	1.3600	1.3700	1.4000	1.4100	0.5800

Columns 290 through 301

0.8800	1.4300	1.3700	1.2000	0.4800	0.4000	0.5300	0.4300	0.4100	0.3900	0.5300	0.3300
0.9500	1.4100	1.3400	1.1800	0.4400	0.4300	0.4400	0.4300	0.4000	0.3900	0.4500	0.3300
0.9400	1.3900	1.3100	1.0400	0.5100	0.4600	0.3900	0.4200	0.5300	0.1300	0.2400	0.1300



output_AC_fault_L1_L2_L3 =

Columns 1 through 17

1.3000	1.1800	1.1100	1.2900	1.2200	1.2200	1.0700	1.0800	1.1400	1.1700	1.0800	1.1400	1.3300	1.1100	1.2000	1.1400	1.2900
1.1300	1.1900	1.0400	1.1400	1.2300	1.3000	1.2700	1.2200	1.2100	1.0900	1.2500	1.1700	1.3200	1.2200	1.1400	1.2700	1.1500
0.7600	0.6600	1.0900	1.0900	0.7200	1.0900	0.7800	1.1800	1.0400	1.2000	0.8300	0.7200	0.7900	0.9600	0.9200	0.9400	1.1600

Columns 18 through 34

1.2900	0.8900	0.6300	1.3300	1.3100	1.3600	1.1800	0.6700	1.3400	1.1500	1.2800	0.8000	1.4000	1.4000	1.3900	1.4200	0.5200
1.2300	0.7600	0.5700	1.3200	1.2400	1.2800	1.0500	0.5400	1.3200	1.0900	1.2600	0.8400	1.3300	1.3500	1.3400	1.3800	0.5000
1.0600	0.7300	0.5600	1.1400	1.1400	1.1500	0.8300	0.5000	1.1100	0.8200	1.3200	0.7000	1.2000	1.2300	1.2400	1.2300	0.4500

Columns 35 through 51

1.4200	0.4400	0.5400	1.4100	1.0500	1.4800	1.4300	1.5100	1.3800	1.3500	0.4000	0.9600	0.5500	1.6200	1.5400	0.5800	0.5400
1.3700	0.4500	0.5000	1.4400	1.0800	1.4300	1.4500	1.4600	1.3800	1.2800	0.4200	0.7600	0.4800	1.7200	1.5200	0.4800	0.5000
1.2400	0.3100	0.4900	1.1600	0.9400	1.2300	1.2000	1.2300	1.3100	1.2200	0.2100	0.7600	0.3800	1.5300	1.0600	0.5900	0.3600

Columns 52 through 68

0.6300	1.4300	1.5000	1.6400	0.4700	0.6500	0.4900	1.5300	1.6300	1.5900	1.5800	1.6200	1.4400	0.9400	1.4700	1.5900	1.6900
0.5300	1.4300	1.4900	1.5300	0.3400	0.5700	0.4900	1.5200	1.5900	1.5900	1.5100	1.5400	1.4300	1.0800	1.5400	1.5300	1.5900
0.4800	1.3100	1.3800	1.4000	0.6100	0.4300	0.3900	1.4600	1.4600	1.4700	1.4500	1.5900	1.4500	1.0500	1.5800	1.5300	1.4300

Columns 69 through 85

0.7200	1.4400	1.5800	1.5300	1.2200	0.5100	0.5100	0.5100	0.5700	1.2600	1.5600	1.6000	1.5300	1.6200	1.5400	1.5800	1.6100
0.7900	1.4100	1.6000	1.5000	1.1800	0.5100	0.5200	0.5600	0.5200	1.5000	1.5200	1.5900	1.5600	1.5900	1.5600	1.5300	1.5300
0.7200	1.2300	1.3800	1.7300	1.1600	0.3600	0.3100	0.3500	0.4000	1.3100	1.5600	1.6200	1.5900	1.4400	1.5300	1.6100	1.5300

Columns 86 through 102

1.5700	1.5700	1.5500	1.4700	0.4600	0.3800	0.3400	0.4800	0.4900	1.2900	1.4700	1.5400	1.3800	1.6900	1.5500	0.5200	0.5000
1.5300	1.5700	1.5200	1.4900	0.4200	0.3200	0.3100	0.4200	0.3800	1.2100	1.5000	1.4400	1.3600	1.5900	1.5200	0.4200	0.5300
1.6100	1.5500	1.5100	1.3600	0.3200	0.2100	0.3400	0.2200	0.4100	1.1300	1.5000	1.4300	1.4700	1.6600	1.6000	0.4500	0.1600

Columns 103 through 119

0.4300	0.3800	1.7200	1.1500	0.5200	0.4400	0.4200	0.9000	1.4600	1.8300	1.6600	1.8400	1.8000	1.7500	0.7400	0.6200	1.7600
0.4500	0.4700	1.7800	1.1300	0.5500	0.4700	0.4300	1.0600	1.5700	1.5800	1.7000	1.8600	1.6200	1.7300	0.7300	0.6200	1.7400
0.3700	0.4900	1.4100	1.0300	0.2200	0.4000	0.2200	1.1700	1.3600	1.4000	1.6100	1.9300	1.9000	1.5600	0.3700	0.5700	1.7200

Columns 120 through 136

1.4800	0.6600	0.7800	1.4000	1.8000	1.8300	1.9100	1.7400	1.6000	0.6700	1.7500	1.7300	1.6000	1.5900	1.1400	1.4200	1.4700
1.4700	0.6600	0.7500	1.3800	1.7700	1.7800	1.6200	1.8200	1.5400	0.6600	1.7000	1.6700	1.5800	1.5400	1.1100	1.3700	1.4300
1.3600	0.6000	0.6800	1.3500	1.7700	1.7300	2.0500	1.9100	1.5000	0.5300	1.6700	1.7000	1.5800	1.4700	1.1100	1.3200	1.4300

Columns 137 through 153

1.4900	1.5400	1.3900	1.5400	1.3600	1.3200	0.6200	0.7100	0.5100	0.4400	0.4500	0.4800	0.6600	0.6100	1.1900	1.1700	1.1100
1.4200	1.5500	1.3800	1.4800	1.3300	1.2700	0.5900	0.4500	0.4200	0.5400	0.4300	0.5200	0.5300	0.6000	1.1400	1.1700	1.0900
1.3800	1.4800	1.3200	1.4300	1.3200	1.2300	0.5200	0.7900	0.4100	0.6300	0.6900	0.4900	0.6200	0.5100	1.4300	1.1700	1.0700

Columns 154 through 170

1.2300	1.0900	0.9500	1.2700	1.1900	0.6600	0.5900	0.8400	0.9600	0.8300	0.6500	0.7900	0.8500	0.7100	0.8800	1.2600	1.4300
1.2800	1.1700	1.0100	1.0500	1.0800	0.6600	0.7600	0.8800	1.0500	0.8000	0.5900	0.8100	0.7600	0.7900	0.7400	1.4400	1.4100
1.0400	0.8600	1.0000	1.1300	1.1200	0.7700	0.8300	0.6100	1.2400	0.7300	0.8000	0.3900	0.6300	0.6000	0.6200	1.4700	1.1800

Columns 171 through 187

1.5100	1.5700	1.5900	1.5800	1.5800	1.4900	0.8900	1.4900	0.8200	0.9100	0.8900	0.8900	0.9500	1.2700	1.2600	1.3800	1.4400
1.5100	1.5100	1.5500	1.5600	1.5500	1.4400	0.8800	1.4900	0.7500	0.7400	1.0600	0.8700	0.8300	1.3100	1.2300	1.3200	1.4000
1.4200	1.5200	1.5500	1.5100	1.4700	1.4200	0.8000	1.5800	0.7200	0.6400	1.1000	0.7000	1.0600	1.2300	1.1400	1.2600	1.3900

Columns 188 through 204

1.4100	1.5600	1.4700	1.5400	1.6400	1.5300	1.4100	0	0	0	0	0	0	0	0	0	0
1.3900	1.4700	1.4700	1.4900	1.5200	1.5500	1.3800	0	0	0	0	0	0	0	0	0	0
1.3200	1.4800	1.4600	1.3800	1.2300	1.5000	1.4500	0	0	0	0	0	0	0	0	0	0

Columns 205 through 221

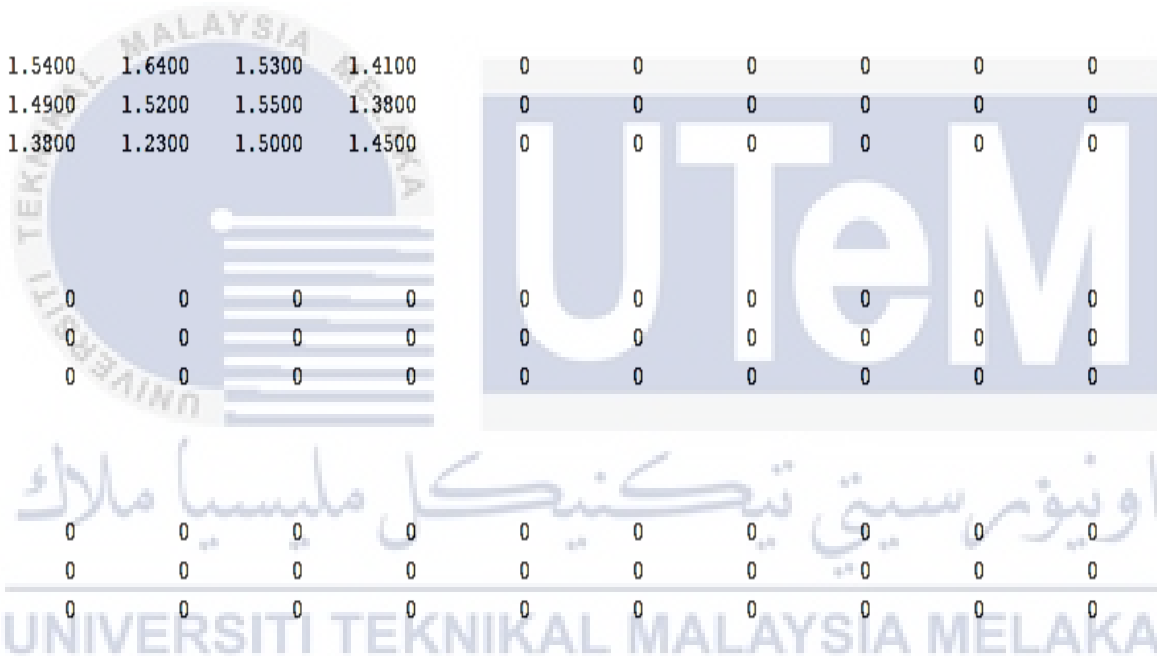
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Columns 222 through 238

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Columns 239 through 255

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0



Columns 256 through 272

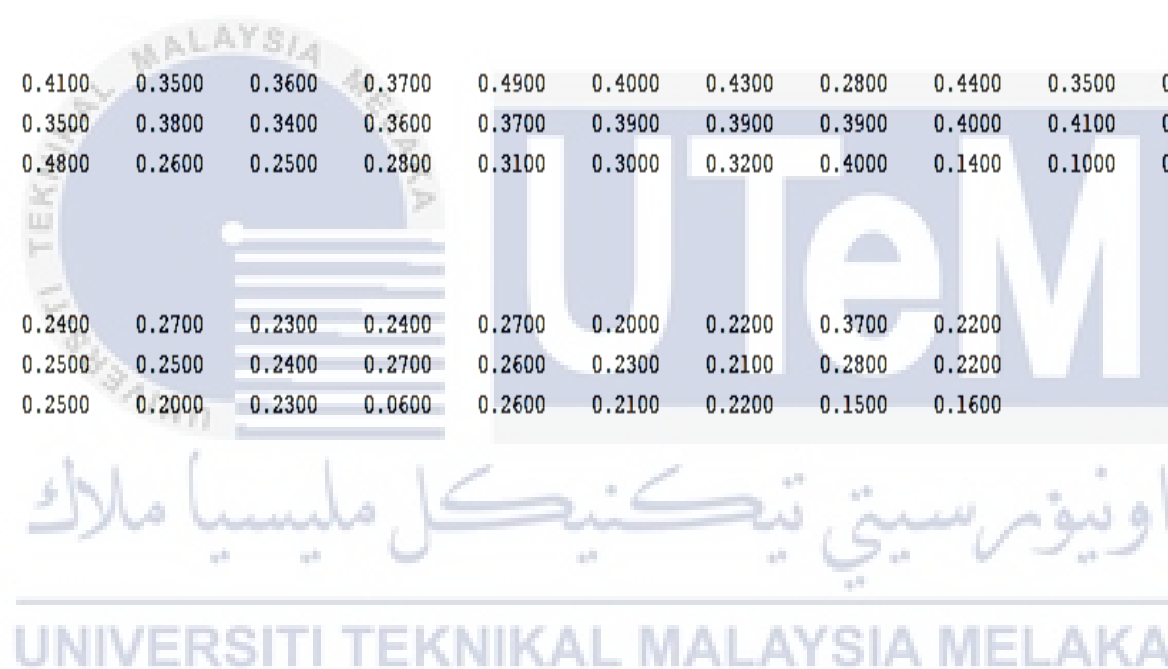
0	0	0	0	0.4500	0.4600	0.4500	0.3800	0.4400	0.4200	0.4300	0.4100	0.3400	0.4400	0.4400	0.3800	0.4200
0	0	0	0	0.4600	0.4600	0.4100	0.4200	0.4000	0.4100	0.4000	0.4000	0.4200	0.4100	0.4000	0.4400	0.3700
0	0	0	0	0.4800	0.4300	0.4500	0.4200	0.3000	0.3400	0.3900	0.3600	0.3800	0.2800	0.3700	0.2900	0.3800

Columns 273 through 289

0.3800	0.3100	0.3800	0.4100	0.3500	0.3600	0.3700	0.4900	0.4000	0.4300	0.2800	0.4400	0.3500	0.3600	0.3500	0.3200	0.3300
0.3600	0.3600	0.3800	0.3500	0.3800	0.3400	0.3600	0.3700	0.3900	0.3900	0.3900	0.4000	0.4100	0.3400	0.4000	0.3100	0.3100
0.2400	0.2700	0.4000	0.4800	0.2600	0.2500	0.2800	0.3100	0.3000	0.3200	0.4000	0.1400	0.1000	0.3300	0.4100	-0.0300	0.3000

Columns 290 through 301

0.3000	0.2800	0.2700	0.2400	0.2700	0.2300	0.2400	0.2700	0.2000	0.2200	0.3700	0.2200
0.3100	0.2500	0.2600	0.2500	0.2500	0.2400	0.2700	0.2600	0.2300	0.2100	0.2800	0.2200
0.3000	0.2000	0.2600	0.2500	0.2000	0.2300	0.0600	0.2600	0.2100	0.2200	0.1500	0.1600



output_DC_fault_L1 =

Columns 1 through 17

0.7400	0.6100	0.5000	0.4400	0.4400	0.4900	0.5600	0.5700	0.5500	0.5700	0.7100	0.8500	1.0800	1.1500	1.1500	1.1500	1.1500
0.7100	0.5900	0.4800	0.4200	0.4200	0.4600	0.5300	0.5500	0.5300	0.5500	0.6800	0.8300	1.0500	1.1100	1.1200	1.1300	1.1200
0.5000	0.4300	0.3900	0.3500	0.3500	0.3800	0.4200	0.4400	0.4200	0.4400	0.5500	0.6700	0.8200	0.8700	0.8800	0.8800	0.8800

Columns 18 through 34

1.1700	1.1400	1.1300	1.1600	1.2100	1.1900	1.1600	1.1400	0.9800	1.1300	1.2100	1.1900	1.1700	1.1900	1.1600	1.2400	1.2500
1.1400	1.1100	1.1000	1.1300	1.1800	1.1600	1.1300	1.1100	0.9500	1.1000	1.1800	1.1600	1.1400	1.1600	1.1400	1.2100	1.2200
0.8900	0.8600	0.8500	0.8700	0.8800	0.9500	0.9400	0.9300	0.8200	0.9500	1.0200	1.0200	1.0100	1.0400	1.0200	1.0900	1.0900

Columns 35 through 51

1.2300	1.2100	1.2400	1.2400	1.2300	1.2300	1.2100	1.1900	1.1600	1.2300	1.2100	1.1900	1.0900	1.1200	1.1500	1.1300	1.1100
1.2100	1.1900	1.2100	1.2000	1.2100	1.2000	1.1800	1.1600	1.1300	1.1900	1.1800	1.1600	1.0700	1.0900	1.1200	1.1000	1.0900
1.0700	1.0400	1.0200	1.0200	1.0200	1.0000	0.9900	0.9800	0.9600	1.0200	1.0000	0.9800	0.9400	0.9700	1.0000	0.9900	0.9700

Columns 52 through 68

0.9900	1.1000	0.9300	1.1800	1.1200	1.1900	1.2400	1.2800	1.2800	1.2600	1.2200	0.7900	0.8800	1.2300	1.2100	1.2700	1.2300
0.9300	1.0600	0.8700	1.1500	1.0900	1.1500	1.2000	1.2400	1.2400	1.2200	1.1900	0.7700	0.8200	1.2000	1.1800	1.2400	1.2100
0.8400	0.9800	0.8100	1.0800	1.0200	1.0800	1.1300	1.1800	1.1900	1.1600	1.1200	0.7000	0.7500	1.1700	1.1400	1.2000	1.1600

Columns 69 through 85

0.8100	1.2900	1.3400	1.3500	1.3400	1.3000	0.7100	1.2300	1.3500	0.6200	0.8000	1.2900	0.8400	0.6700	0.7400	1.4300	1.4000
0.8000	1.2700	1.3100	1.3200	1.3200	1.3000	0.7000	1.2200	1.3200	0.6000	0.7600	1.2800	0.7900	0.6500	0.7100	1.4000	1.4000
0.7600	1.2500	1.2800	1.2900	1.2900	1.2900	0.6700	1.2200	1.3100	0.5400	0.7200	1.2700	0.7000	0.5900	0.6500	1.3800	1.3800

Columns 86 through 102

1.4200	0.8200	0.6000	0.6000	0	0	0	0	0	0	0	0	0	0	0	0	0
1.3900	0.8200	0.5700	0.5800	0.7300	1.4600	1.4600	1.4400	1.4500	1.4300	1.4700	1.5300	1.5500	1.5600	0.7100	0.6100	0.6100
1.3700	0.8200	0.5100	0.5300	0.6900	1.4500	1.4400	1.4200	1.4400	1.4100	1.4600	1.5200	1.5300	1.5400	0.7200	0.5700	0.5700

Columns 103 through 119

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.5900	0.5900	0.6100	0.6500	0.7500	1.0000	1.1300	1.1900	0.9600	1.4900	1.5100	1.5700	1.5700	1.5400	1.5100	1.5100	1.5300
0.5500	0.5500	0.5600	0.6100	0.7200	1.0200	1.0500	1.1500	0.9300	1.4800	1.5100	1.5400	1.5500	1.5200	1.5000	1.4900	1.5200

Columns 120 through 136

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.5200	1.4800	1.4800	1.4500	1.5000	1.4900	1.4700	0.8200	1.5000	1.4900	1.2100	1.1200	1.4500	1.4200	1.5200	1.5500	1.5700
1.5000	1.4700	1.4600	1.4400	1.4900	1.4800	1.4500	0.8000	1.5100	1.4600	1.1300	1.1100	1.4300	1.3900	1.5100	1.5300	1.5500

Columns 137 through 153

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.5400	1.5100	0.6600	1.4500	1.5300	0.7100	0.8200	0.6500	0.6200	0.6700	1.3100	1.5400	0.6000	0.5500	0.5500	0.5600	0.6000
1.5300	1.5000	0.6300	1.4600	1.5300	0.6900	0.8000	0.6200	0.5900	0.6400	1.3200	1.5200	0.5700	0.5200	0.5100	0.5300	0.5600

Columns 154 through 170

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.6400	0.6600	0.6900	0.7300	1.0000	0.6900	0.6800	0.6600	0.6900	0.8200	0.7900	0.8600	0.9100	1.0900	0.7700	1.1200	1.7200
0.6000	0.6300	0.6600	0.7000	0.9600	0.6600	0.6500	0.6300	0.6600	0.7800	0.7500	0.8300	0.8800	1.1000	0.7400	1.0400	1.7000

Columns 171 through 187

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.6900	1.6800	1.3700	0.7000	1.1300	1.6000	1.6000	1.6100	1.6200	1.6000	1.5700	1.5800	1.5400	1.4800	1.5000	0.9500	0.5600
1.6700	1.6600	1.4100	0.6700	1.1400	1.5800	1.5800	1.5900	1.6000	1.5900	1.5500	1.5700	1.5300	1.4600	1.4900	0.8900	0.5300

Columns 188 through 204

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.5300	0.5100	0.5300	0.9500	1.5700	1.5900	1.6200	1.6000	1.5900	1.5600	1.5900	1.5700	1.6300	1.6300	1.6100	1.6000	1.6000
0.4900	0.4700	0.4900	0.9400	1.5600	1.5800	1.6100	1.5900	1.5800	1.5500	1.5800	1.5600	1.6100	1.6200	1.6000	1.5900	1.5900

Columns 205 through 221

0	0	0	1.0200	1.4900	1.1300	0.5900	0.5600	0.5700	1.0800	1.2600	0.5900	0.5800	0.6400	0.8800	1.4800	1.6400
1.5800	1.5500	1.5100	0.9600	1.4500	1.0600	0.5600	0.5400	0.5600	1.0600	1.2000	0.5600	0.5600	0.6200	0.8700	1.4300	1.6200
1.5600	1.5500	1.5100	0.9400	1.4500	1.0100	0.5400	0.5100	0.5300	1.0500	1.1600	0.5300	0.5300	0.5900	0.8500	1.4400	1.6100

Columns 222 through 238

1.6100	1.6400	1.5900	1.5600	1.6000	0.9900	0.7200	0.8700	0.6300	1.1200	0.7400	0.5100	0.5100	0.5400	0.5200	0.5100	0.5700
1.5800	1.6100	1.5500	1.5300	1.5800	0.9600	0.7000	0.8700	0.6100	1.1400	0.7400	0.4900	0.4900	0.5200	0.5000	0.4800	0.5500
1.5700	1.6000	1.5400	1.5200	1.5600	0.8800	0.6800	0.9700	0.5800	1.1700	0.7500	0.4600	0.4600	0.4800	0.4700	0.4500	0.5200

Columns 239 through 255

1.5900	0.5000	0.4900	0.4800	0.4500	0.4500	0.4700	0.5300	0.7800	0.7800	0.5700	0.5600	0.5700	0.5800	0.6000	0.5900	0.6200
1.5600	0.4800	0.4700	0.4500	0.4300	0.4300	0.4500	0.5000	0.7000	0.7500	0.5400	0.5400	0.5500	0.5600	0.5800	0.5700	0.6000
1.5500	0.4500	0.4300	0.4100	0.3900	0.3900	0.4100	0.4600	0.6600	0.7000	0.5200	0.5200	0.5200	0.5400	0.5500	0.5500	0.5800

Columns 256 through 272

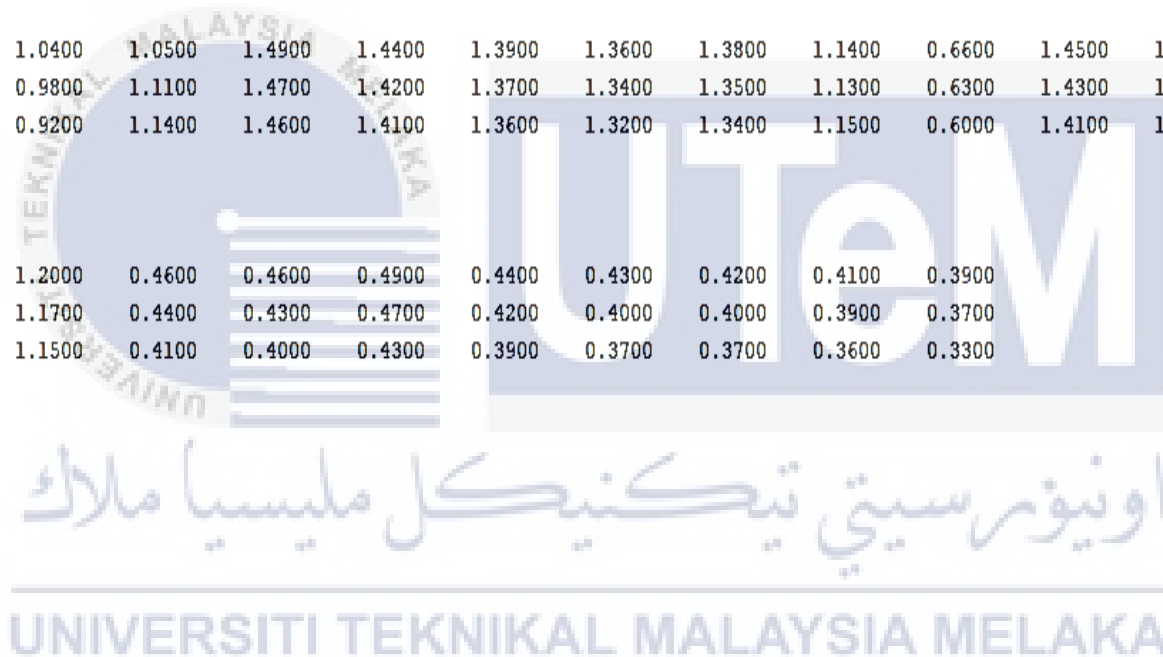
1.3200	1.3100	1.4300	0.7100	1.0900	1.4500	1.3700	0.5600	0.4900	0.4600	0.4400	0.4100	0.3800	0.3700	0.3700	0.3800	0.4000
1.2500	1.2600	1.4100	0.6900	1.1000	1.4300	1.3500	0.5400	0.4700	0.4400	0.4200	0.3900	0.3600	0.3500	0.3500	0.3600	0.3800
1.2400	1.2400	1.4000	0.6600	1.0600	1.4200	1.3300	0.5200	0.4400	0.4100	0.3900	0.3500	0.3200	0.3000	0.3100	0.3100	0.3300

Columns 273 through 289

0.4200	0.4700	1.1500	1.0400	1.0500	1.4900	1.4400	1.3900	1.3600	1.3800	1.1400	0.6600	1.4500	1.4500	1.4600	1.4100	0.6100
0.4000	0.4600	1.0900	0.9800	1.1100	1.4700	1.4200	1.3700	1.3400	1.3500	1.1300	0.6300	1.4300	1.4300	1.4400	1.3800	0.5800
0.3600	0.4100	1.1400	0.9200	1.1400	1.4600	1.4100	1.3600	1.3200	1.3400	1.1500	0.6000	1.4100	1.4200	1.4200	1.3800	0.5600

Columns 290 through 301

0.9100	1.4200	1.4000	1.2000	0.4600	0.4600	0.4900	0.4400	0.4300	0.4200	0.4100	0.3900
0.9300	1.4000	1.3700	1.1700	0.4400	0.4300	0.4700	0.4200	0.4000	0.4000	0.3900	0.3700
0.9600	1.4000	1.3700	1.1500	0.4100	0.4000	0.4300	0.3900	0.3700	0.3700	0.3600	0.3300



output_DC_fault_L1_L2 =

Columns 1 through 17

0.7400	0.6100	0.5000	0.4400	0.4400	0.4900	0.5600	0.5700	0.5500	0.5700	0.7100	0.8500	1.0800	1.1500	1.1500	1.1500	1.1500
0.7100	0.5900	0.4800	0.4200	0.4200	0.4600	0.5300	0.5500	0.5300	0.5500	0.6800	0.8300	1.0500	1.1100	1.1200	1.1300	1.1200
0.5000	0.4300	0.3900	0.3500	0.3500	0.3800	0.4200	0.4400	0.4200	0.4400	0.5500	0.6700	0.8200	0.8700	0.8800	0.8800	0.8800

Columns 18 through 34

1.1700	1.1400	1.1300	1.1600	1.2100	1.1900	1.1600	1.1400	0.9800	1.1300	1.2100	1.1900	1.1700	1.1900	1.1600	1.2400	1.2500
1.1400	1.1100	1.1000	1.1300	1.1800	1.1600	1.1300	1.1100	0.9500	1.1000	1.1800	1.1600	1.1400	1.1600	1.1400	1.2100	1.2200
0.8900	0.8600	0.8500	0.8700	0.8800	0.9500	0.9400	0.9300	0.8200	0.9500	1.0200	1.0200	1.0100	1.0400	1.0200	1.0900	1.0900

Columns 35 through 51

1.2300	1.2100	1.2400	1.2400	1.2300	1.2300	1.2100	1.1900	1.1600	1.2300	1.2100	1.1900	1.0900	1.1200	1.1500	1.1300	1.1100
1.2100	1.1900	1.2100	1.2000	1.2100	1.2000	1.1800	1.1600	1.1300	1.1900	1.1800	1.1600	1.0700	1.0900	1.1200	1.1000	1.0900
1.0700	1.0400	1.0200	1.0200	1.0200	1.0000	0.9900	0.9800	0.9600	1.0200	1.0000	0.9800	0.9400	0.9700	1.0000	0.9900	0.9700

Columns 52 through 68

0.9900	1.1000	0.9300	1.1800	1.1200	1.1900	1.2400	1.2800	1.2800	1.2600	1.2200	0.7900	0.8800	1.2300	1.2100	1.2700	1.2300
0.9300	1.0600	0.8700	1.1500	1.0900	1.1500	1.2000	1.2400	1.2400	1.2200	1.1900	0.7700	0.8200	1.2000	1.1800	1.2400	1.2100
0.8400	0.9800	0.8100	1.0800	1.0200	1.0800	1.1300	1.1800	1.1900	1.1600	1.1200	0.7000	0.7500	1.1700	1.1400	1.2000	1.1600

Columns 69 through 85

0.8100	1.2900	1.3400	1.3500	1.3400	1.3000	0.7100	1.2300	1.3500	0.6200	0.8000	1.2900	0.8400	0.6700	0.7400	1.4300	1.4000
0.8000	1.2700	1.3100	1.3200	1.3200	1.3000	0.7000	1.2200	1.3200	0.6000	0.7600	1.2800	0.7900	0.6500	0.7100	1.4000	1.4000
0.7600	1.2500	1.2800	1.2900	1.2900	1.2900	0.6700	1.2200	1.3100	0.5400	0.7200	1.2700	0.7000	0.5900	0.6500	1.3800	1.3800

Columns 86 through 102

1.4200	0.8200	0.6000	0.6000	0	0	0	0	0	0	0	0	0	0	0	0	0
1.3900	0.8200	0.5700	0.5800	0	0	0	0	0	0	0	0	0	0	0	0	0
1.3700	0.8200	0.5100	0.5300	0.6900	1.4500	1.4400	1.4200	1.4400	1.4100	1.4600	1.5200	1.5300	1.5400	0.7200	0.5700	0.5700

Columns 103 through 119

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.5500	0.5500	0.5600	0.6100	0.7200	1.0200	1.0500	1.1500	0.9300	1.4800	1.5100	1.5400	1.5500	1.5200	1.5000	1.4900	1.5200

Columns 120 through 136

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.5000	1.4700	1.4600	1.4400	1.4900	1.4800	1.4500	0.8000	1.5100	1.4600	1.1300	1.1100	1.4300	1.3900	1.5100	1.5300	1.5500

Columns 137 through 153

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.5300	1.5000	0.6300	1.4600	1.5300	0.6900	0.8000	0.6200	0.5900	0.6400	1.3200	1.5200	0.5700	0.5200	0.5100	0.5300	0.5600

Columns 154 through 170

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.6000	0.6300	0.6600	0.7000	0.9600	0.6600	0.6500	0.6300	0.6600	0.7800	0.7500	0.8300	0.8800	1.1000	0.7400	1.0400	1.7000

Columns 171 through 187

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1.6700	1.6600	1.4100	0.6700	1.1400	1.5800	1.5800	1.5900	1.6000	1.5900	1.5500	1.5700	1.5300	1.4600	1.4900	0.8900	0.5300

Columns 188 through 204

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.4900	0.4700	0.4900	0.9400	1.5600	1.5800	1.6100	1.5900	1.5800	1.5500	1.5800	1.5600	1.6100	1.6200	1.6000	1.5900	1.5900

Columns 205 through 221

0	0	0	1.0200	1.4900	1.1300	0.5900	0.5600	0.5700	1.0800	1.2600	0.5900	0.5800	0.6400	0.8800	1.4800	1.6400
0	0	0	0.9600	1.4500	1.0600	0.5600	0.5400	0.5600	1.0600	1.2000	0.5600	0.5600	0.6200	0.8700	1.4300	1.6200
1.5600	1.5500	1.5100	0.9400	1.4500	1.0100	0.5400	0.5100	0.5300	1.0500	1.1600	0.5300	0.5300	0.5900	0.8500	1.4400	1.6100

Columns 222 through 238

1.6100	1.6400	1.5900	1.5600	1.6000	0.9900	0.7200	0.8700	0.6300	1.1200	0.7400	0.5100	0.5100	0.5400	0.5200	0.5100	0.5700
1.5800	1.6100	1.5500	1.5300	1.5800	0.9600	0.7000	0.8700	0.6100	1.1400	0.7400	0.4900	0.4900	0.5200	0.5000	0.4800	0.5500
1.5700	1.6000	1.5400	1.5200	1.5600	0.8800	0.6800	0.9700	0.5800	1.1700	0.7500	0.4600	0.4600	0.4800	0.4700	0.4500	0.5200

Columns 239 through 255

1.5900	0.5000	0.4900	0.4800	0.4500	0.4500	0.4700	0.5300	0.7800	0.7800	0.5700	0.5600	0.5700	0.5800	0.6000	0.5900	0.6200
1.5600	0.4800	0.4700	0.4500	0.4300	0.4300	0.4500	0.5000	0.7000	0.7500	0.5400	0.5400	0.5500	0.5600	0.5800	0.5700	0.6000
1.5500	0.4500	0.4300	0.4100	0.3900	0.3900	0.4100	0.4600	0.6600	0.7000	0.5200	0.5200	0.5200	0.5400	0.5500	0.5500	0.5800

Columns 256 through 272

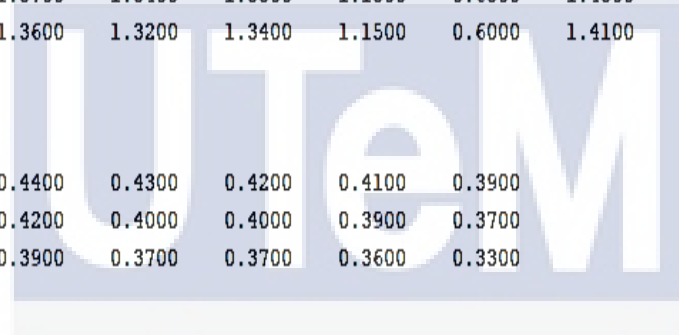
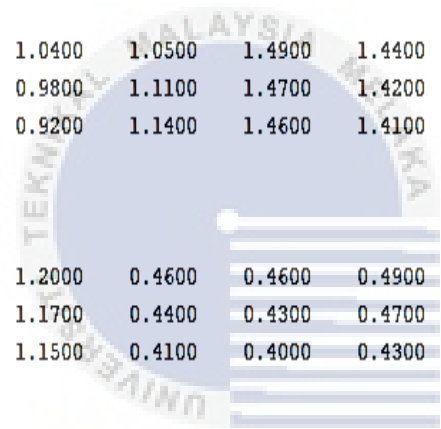
1.3200	1.3100	1.4300	0.7100	1.0900	1.4500	1.3700	0.5600	0.4900	0.4600	0.4400	0.4100	0.3800	0.3700	0.3700	0.3800	0.4000
1.2500	1.2600	1.4100	0.6900	1.1000	1.4300	1.3500	0.5400	0.4700	0.4400	0.4200	0.3900	0.3600	0.3500	0.3500	0.3600	0.3800
1.2400	1.2400	1.4000	0.6600	1.0600	1.4200	1.3300	0.5200	0.4400	0.4100	0.3900	0.3500	0.3200	0.3000	0.3100	0.3100	0.3300

Columns 273 through 289

0.4200	0.4700	1.1500	1.0400	1.0500	1.4900	1.4400	1.3900	1.3600	1.3800	1.1400	0.6600	1.4500	1.4500	1.4600	1.4100	0.6100
0.4000	0.4600	1.0900	0.9800	1.1100	1.4700	1.4200	1.3700	1.3400	1.3500	1.1300	0.6300	1.4300	1.4300	1.4400	1.3800	0.5800
0.3600	0.4100	1.1400	0.9200	1.1400	1.4600	1.4100	1.3600	1.3200	1.3400	1.1500	0.6000	1.4100	1.4200	1.4200	1.3800	0.5600

Columns 290 through 301

0.9100	1.4200	1.4000	1.2000	0.4600	0.4600	0.4900	0.4400	0.4300	0.4200	0.4100	0.3900
0.9300	1.4000	1.3700	1.1700	0.4400	0.4300	0.4700	0.4200	0.4000	0.4000	0.3900	0.3700
0.9600	1.4000	1.3700	1.1500	0.4100	0.4000	0.4300	0.3900	0.3700	0.3700	0.3600	0.3300



اونيورسيتي تيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

output_DC_fault_L1_L2_L3 =

Columns 1 through 17

0.6600	0.6700	0.6800	0.7000	0.7100	0.7200	0.7300	0.7500	0.7700	0.7900	0.8000	0.8000	0.8200	0.8300	0.8300	0.8300	0.7800
0.6300	0.6500	0.6600	0.6700	0.6900	0.6900	0.7100	0.7300	0.7500	0.7600	0.7800	0.7800	0.8000	0.8100	0.8000	0.8000	0.7600
0.5700	0.5800	0.5900	0.6000	0.6100	0.6100	0.6300	0.6400	0.6600	0.6500	0.6700	0.6600	0.6800	0.6800	0.7100	0.7100	0.6800

Columns 18 through 34

0.7900	0.7800	0.7500	0.7700	0.7700	0.7500	0.7400	0.7500	0.7500	0.7300	0.7400	0.7300	0.7000	0.8300	0.8500	0.8500	0.8400
0.7700	0.7600	0.7300	0.7400	0.7500	0.7200	0.7300	0.7200	0.7200	0.7100	0.7200	0.7000	0.6800	0.8000	0.8200	0.8300	0.8200
0.6800	0.6800	0.6600	0.6700	0.6800	0.6600	0.6600	0.6600	0.6600	0.6400	0.6500	0.6300	0.6100	0.7300	0.7500	0.7700	0.7600

Columns 35 through 51

0.8500	0.9300	0.7800	0.9500	0.9600	0.9500	0.9500	0.9600	0.9400	0.7500	0.7200	0.7100	0.8000	0.9100	0.9600	0.9400	0.8900
0.8300	0.9100	0.7600	0.9200	0.9400	0.9200	0.9300	0.9300	0.9100	0.7200	0.7000	0.6900	0.7800	0.8900	0.9400	0.9100	0.8600
0.7700	0.8300	0.6900	0.8300	0.8400	0.8300	0.8400	0.8500	0.8300	0.6800	0.6600	0.6300	0.7200	0.8100	0.8700	0.8600	0.8200

Columns 52 through 68

0.9100	0.9100	0.9300	0.9500	0.9600	0.9700	0.9600	0.9600	0.9600	0.9700	0.9600	0.9700	0.9900	0.9700	0.9600	0.9600	0.9800
0.8800	0.8800	0.9000	0.9200	0.9400	0.9500	0.9300	0.9300	0.9400	0.9500	0.9400	0.9500	0.9700	0.9400	0.9400	0.9400	0.9500
0.8500	0.8400	0.8500	0.8800	0.9000	0.9100	0.9100	0.8900	0.9000	0.9100	0.9100	0.9100	0.9300	0.9000	0.8900	0.9000	0.9200

Columns 69 through 85

1.0000	0.9600	1.0600	1.0900	1.1000	1.0800	1.0900	1.0900	1.1100	1.0900	1.0700	1.0600	1.0600	1.0600	1.0500	1.0600	1.0600
0.9800	0.9300	1.0300	1.0600	1.0800	1.0600	1.0700	1.0800	1.0900	1.0600	1.0500	1.0400	1.0400	1.0300	1.0200	1.0300	1.0300
0.9300	0.8900	1.0000	1.0300	1.0500	1.0200	1.0300	1.0500	1.0600	1.0300	1.0100	1.0100	1.0100	1.0000	0.9800	1.0100	1.0100

Columns 86 through 102

1.0500	0.9000	0.9900	1.0100	1.0400	1.0300	1.0400	1.0500	1.0300	0.8200	0.8300	0.7600	0.7300	0.7100	0.7100	0.8400	0.9100
1.0200	0.8700	0.9600	0.9900	1.0100	1.0100	1.0100	1.0200	1.0100	0.8000	0.8000	0.7300	0.7100	0.6900	0.6900	0.8200	0.8800
0.9800	0.8400	0.9200	0.9600	0.9700	0.9800	0.9900	0.9900	0.9800	0.7600	0.7700	0.7000	0.6600	0.6500	0.6500	0.7900	0.8500

Columns 103 through 119

0.9000	0.7700	0.9600	0.8000	0.7600	0.7400	0.8000	0.7900	1.0700	1.0900	0.9700	0.8500	0.8500	1.0800	0.8800	0.8300	1.0600
0.8800	0.7500	0.9400	0.7700	0.7300	0.7200	0.7800	0.7700	1.0500	1.0700	0.9400	0.8300	0.8200	1.0600	0.8600	0.8000	1.0300
0.8600	0.7100	0.9100	0.7300	0.7000	0.6800	0.7400	0.7400	1.0300	1.0400	0.9100	0.8000	0.7900	1.0300	0.8300	0.7700	1.0100

Columns 120 through 136

1.0800	1.0700	1.1100	1.1400	1.1300	1.1100	1.0500	1.0500	1.0400	1.0500	1.0300	1.0100	0.9800	0.9400	0.9800	0.9600	0.9500
1.0600	1.0500	1.0900	1.1100	1.1000	1.0800	1.0300	1.0200	1.0200	1.0200	1.0100	0.9900	0.9500	0.9200	0.9500	0.9400	0.9200
1.0400	1.0300	1.0600	1.0900	1.0900	1.0600	1.0100	1.0100	0.9900	1.0000	0.9900	0.9600	0.9300	0.9000	0.9300	0.9200	0.9000

Columns 137 through 153

0.8900	0.8700	0.7800	0.8900	0.8800	0.8600	0.8600	0.8600	0.8500	0.8600	0.8700	0.8300	0.7800	0.8000	0.8000	0.7900	0.7100
0.8700	0.8500	0.7600	0.8700	0.8600	0.8300	0.8400	0.8400	0.8200	0.8400	0.8500	0.8100	0.7600	0.7800	0.7800	0.7600	0.6900
0.8500	0.8400	0.7300	0.8500	0.8400	0.8200	0.8200	0.8200	0.8100	0.8200	0.8300	0.7800	0.7400	0.7600	0.7500	0.7400	0.6700

Columns 154 through 170

0.7900	0.7800	0.7100	0.5900	0.0200	0.6100	0.0200	0.5300	0.5100	0.5000	0.5100	0.5100	0.0100	0.0100	0.0100	0.0100	0.0100
0.7700	0.7600	0.6700	0.5500	0.5500	0.5900	0.5400	0.5100	0.4900	0.4800	0.4900	0.4900	0.0100	0.0100	0.0100	0.0100	0.0100
0.7500	0.7400	0.0100	0.0100	0.5000	0.5600	0.5100	0.4800	0.4600	0.4500	0.4600	0.4500	0.0100	0.0100	0.0100	0.0100	0.0100

Columns 171 through 187

0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100
0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100

Columns 188 through 204

0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.3700	1.3700	1.4000	1.4100	1.4300	1.4400	1.4400	1.4100
0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.3400	1.3500	1.3700	1.3900	1.3900	1.4100	1.4100	1.3900
0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	1.3300	1.3300	1.3500	1.3800	1.3900	1.4000	1.4000	1.3800

Columns 205 through 221

1.4100	1.3700	1.3400	1.2800	1.3200	1.3400	1.3500	1.3800	1.3600	1.3700	1.3600	1.3700	1.2600	0.8100	0.7300	0.7100	0.7000
1.3800	1.3500	1.3200	1.2500	1.2900	1.3100	1.3300	1.3500	1.3400	1.3500	1.3300	1.3400	1.2300	0.7900	0.7000	0.6800	0.6800
1.3700	1.3300	1.3000	1.2400	1.2800	1.2900	1.3100	1.3400	1.3300	1.3300	1.3300	1.3300	1.2000	0.7800	0.6900	0.6700	0.6600

Columns 222 through 238

0.6000	0.5200	0.4400	0.3800	0.3200	0.2800	0.2900	0.2900	0.2900	0.2900	0.2600	0.2600	0.2600	0.2600	0.2400	0.2200	0.2100
0.5800	0.5000	0.4200	0.3700	0.3000	0.2600	0.2600	0.2800	0.2800	0.2600	0.2500	0.2500	0.2500	0.2400	0.2200	0.2000	0.2000
0.5600	0.4800	0.4000	0.3400	0.2700	0.2200	0.2400	0.2400	0.2400	0.2300	0.2100	0.2000	0.2000	0.1900	0.1700	0.1600	0.1600

Columns 239 through 255

0.2200	0.2200	0.2300	0.2400	0.2500	0.2600	0.2800	0.2900	0.2900	0.3400	0.3700	0.4100	0.6700	0.4800	0.5000	0.5100	0.5200
0.2000	0.2000	0.2100	0.2200	0.2300	0.2400	0.2600	0.2700	0.2900	0.3000	0.3500	0.3900	0.6500	0.4700	0.4800	0.4900	0.5000
0.1600	0.1700	0.1800	0.1900	0.2000	0.2100	0.2300	0.2400	0.2600	0.2700	0.2900	0.3600	0.6200	0.4300	0.4500	0.4600	0.4800

Columns 256 through 272

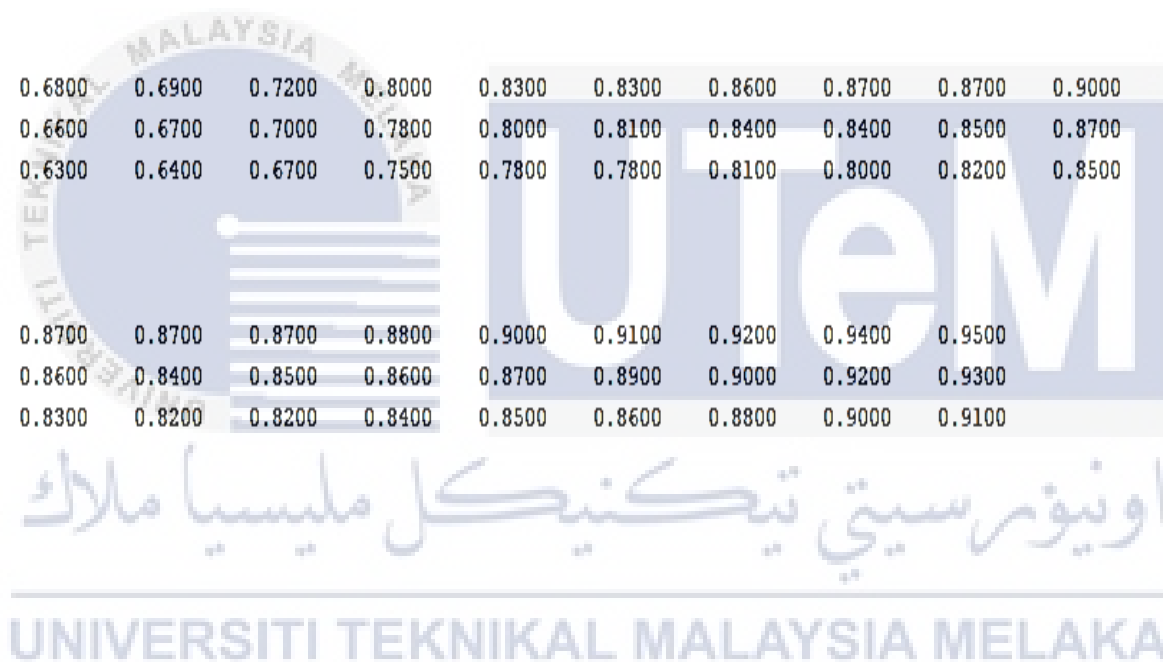
0.5400	0.5500	0.5500	0.5700	0.5800	0.6000	0.6100	0.6400	0.6600	0.6600	0.6600	0.6600	0.6600	0.6600	0.6800	0.6900	0.6800
0.5200	0.5200	0.5300	0.5400	0.5600	0.5800	0.5900	0.6200	0.6400	0.6400	0.6400	0.6400	0.6400	0.6400	0.6600	0.6600	0.6500
0.4900	0.4900	0.5000	0.5100	0.5200	0.5400	0.5500	0.5800	0.6000	0.6000	0.6000	0.6000	0.6000	0.6100	0.6200	0.6300	0.6200

Columns 273 through 289

0.6600	0.6300	0.6600	0.6800	0.6900	0.7200	0.8000	0.8300	0.8300	0.8600	0.8700	0.8700	0.9000	0.9000	0.8900	0.8700	0.8700
0.6300	0.6100	0.6400	0.6600	0.6700	0.7000	0.7800	0.8000	0.8100	0.8400	0.8400	0.8500	0.8700	0.8800	0.8600	0.8500	0.8500
0.6000	0.5700	0.6100	0.6300	0.6400	0.6700	0.7500	0.7800	0.7800	0.8100	0.8000	0.8200	0.8500	0.8500	0.8400	0.8200	0.8200

Columns 290 through 301

0.8400	0.8500	0.8700	0.8700	0.8700	0.8700	0.8800	0.9000	0.9100	0.9200	0.9400	0.9500
0.8200	0.8300	0.8500	0.8600	0.8400	0.8500	0.8600	0.8700	0.8900	0.9000	0.9200	0.9300
0.7900	0.8000	0.8200	0.8300	0.8200	0.8200	0.8400	0.8500	0.8600	0.8800	0.9000	0.9100



APPENDIX B TEST OUTPUT DATA OF NEURAL NETWORK

test_outputs_AC_fault_L1 =

Columns 1 through 17

0.7346	0.6135	0.5202	0.4448	0.3591	0.4281	0.6312	0.5923	0.5678	0.5691	0.7180	0.8428	1.0565	1.1295	1.1137	1.0992	1.1463
0.7493	0.6100	0.5343	0.4526	0.5223	0.4760	0.4978	0.5538	0.5076	0.6157	0.6867	0.8442	1.0591	1.1147	1.1107	1.1817	1.1509
0.5899	0.5094	0.4316	0.4015	0.4875	0.3626	0.4722	0.4820	0.4909	0.4857	0.5904	0.7105	0.8117	0.9122	0.8779	1.0363	0.9542

Columns 18 through 34

1.2220	1.1120	1.0811	1.0984	1.1860	1.1816	1.1452	1.2919	1.1091	1.3056	1.3378	1.1818	1.1540	1.2228	1.2381	1.1251	1.2309
1.1187	1.1277	1.0927	1.1159	1.1908	1.2169	1.1943	1.0989	0.9789	1.0888	1.1786	1.1534	1.1445	1.1279	1.0027	1.2025	1.2540
0.9014	0.9483	0.8871	0.9268	0.8978	1.0082	1.1998	0.6958	0.8630	1.0577	0.9020	0.7989	1.0878	1.1155	0.9834	1.0965	1.0525

Columns 35 through 51

1.4017	1.1410	1.2352	1.2382	1.2372	1.1615	1.1986	1.1863	1.0395	1.2491	1.2457	1.0741	0.9952	1.1513	1.0449	1.2278	1.0721
1.2739	1.2057	1.1970	1.2175	1.2173	1.2194	1.1925	1.1443	1.0450	1.2169	1.1594	1.0151	1.0743	1.0977	1.1362	0.9500	1.0003
1.1246	1.0546	0.9652	1.0968	1.0372	0.7789	0.9485	1.1975	1.0092	1.0382	0.7250	0.8541	0.9307	1.0343	1.1949	0.8912	1.1693

Columns 52 through 68

0.9383	0.9797	1.0728	1.1085	1.1332	1.1729	1.2174	1.2751	1.2760	1.0681	1.3161	0.7722	0.8157	1.2130	1.2075	1.1286	1.2122
1.1006	1.2049	0.8695	1.1327	1.1512	1.2691	1.2297	1.3420	1.2069	1.2170	1.1969	0.7803	0.9778	1.2081	1.2577	1.2311	1.2583
1.1675	1.2473	0.9086	1.2106	1.1564	1.3110	1.1918	1.1325	1.3068	1.1915	1.0058	0.8189	1.0207	1.1639	1.1288	1.1436	1.4273

Columns 69 through 85

0.8234	1.3749	1.3569	1.3035	1.3462	1.2942	0.7304	1.2497	1.3782	0.6991	0.8760	1.2683	0.6502	0.7113	0.7747	1.4484	1.4364
0.7154	1.2481	1.3593	1.2923	1.3372	1.3217	0.7068	1.2505	1.3552	0.6165	0.7789	1.3217	0.7854	0.6766	0.7286	1.4137	1.4171
0.8724	1.3647	1.2420	1.3482	1.3729	1.3257	0.7106	1.2024	1.3131	0.6204	0.7735	1.1763	0.6297	0.5873	0.6815	1.4402	1.4364

Columns 86 through 102

1.4100	0.8505	0.5824	0.6174	0.7978	1.4626	1.5322	1.4150	1.5607	1.5679	1.4728	1.6123	1.6253	1.6299	0.7652	0.6281	0.6643
1.4132	0.8357	0.5972	0.6187	0.7407	1.4903	1.4492	1.4595	1.4660	1.4638	1.4391	1.5474	1.5674	1.5249	0.7182	0.6640	0.6379
1.3404	0.8218	0.6200	0.5735	0.7485	1.6216	1.2475	1.5463	1.3460	1.5833	1.5774	1.5195	1.5299	1.5279	0.7225	0.5846	0.6523

Columns 103 through 119

0.6140	0.6307	0.7009	0.6787	0.7854	0.9787	1.2436	1.2567	1.0400	1.5355	1.6112	1.6448	1.5772	1.6265	1.5637	1.4860	1.5709
0.6351	0.5908	0.6459	0.6540	0.7359	1.0138	1.1757	1.2248	0.9586	1.4687	1.4856	1.5855	1.5548	1.5391	1.4996	1.5204	1.5505
0.6209	0.6148	0.6073	0.6485	0.7298	1.0015	1.0742	1.1982	0.9377	1.5425	1.4959	1.6034	1.5281	1.5197	1.4431	1.3949	1.4942

Columns 120 through 136

1.6048	1.5307	1.5622	1.5055	1.5806	1.5859	1.5258	0.8932	1.5606	1.5775	1.3125	1.1781	1.5504	1.4954	1.6357	1.6332	1.5781
1.4984	1.4904	1.4974	1.4639	1.4865	1.5107	1.4692	0.8262	1.4862	1.5148	1.2318	1.1439	1.4513	1.4295	1.5295	1.5330	1.5699
1.4853	1.4752	1.3939	1.4337	1.4707	1.5062	1.4734	0.8074	1.4349	1.5158	1.1527	1.0823	1.4464	1.4314	1.5227	1.4982	1.7505

Columns 137 through 153

1.6527	1.5761	0.7041	1.5045	1.6148	0.7461	0.8372	0.6615	0.6914	0.6559	1.3479	1.6038	0.6110	0.5678	0.5706	0.5715	0.6338
1.5577	1.5095	0.6705	1.4458	1.5463	0.7327	0.8101	0.6921	0.6320	0.7041	1.3368	1.5516	0.7144	0.5302	0.5674	0.6026	0.6415
1.5580	1.4806	0.6824	1.5289	1.5737	0.6837	0.7952	0.6144	0.6690	0.6470	1.3654	1.5373	0.6142	0.3670	0.6316	0.6028	0.5886

Columns 154 through 170

0.4951	0.7364	0.7229	0.7702	1.0810	0.7434	0.7401	0.6344	0.7258	0.8869	0.8105	0.8803	0.9406	1.1467	0.6715	1.1092	1.7792
0.7473	0.6669	0.7002	0.7609	1.0004	0.7681	0.7066	0.7024	0.7489	0.8349	0.8295	0.8532	0.9289	1.1386	0.8245	1.1007	1.7559
0.6750	0.6342	0.6590	0.7756	1.0368	0.7089	0.4800	0.6490	0.7288	0.8243	0.8290	0.8391	0.9337	1.1828	0.6091	1.0064	1.7287

Columns 171 through 187

1.7548	1.7659	1.4102	0.7555	1.1684	1.8037	1.6523	1.6879	1.6890	1.6750	1.6307	1.6399	1.6215	1.5506	1.5390	1.0336	0.5848
1.6925	1.6856	1.4430	0.7026	1.2128	1.5759	1.4947	1.6079	1.6463	1.6072	1.5795	1.6376	1.5430	1.4814	1.5220	1.0102	0.5850
1.6360	1.5266	1.4827	0.7014	1.0325	1.6044	1.7385	1.6389	1.6475	1.5892	1.6138	1.5727	1.6349	1.4831	1.6246	0.8960	0.5633

Columns 188 through 204

0.5702	0.6287	0.5860	0.8952	1.6679	1.6802	1.6919	0.2251	0.2350	0.2291	0.2313	0.2288	0.2266	0.2484	0.2294	0.2384	0.2318
0.5530	0.4948	0.5400	0.9424	1.5910	1.5998	1.6478	1.3607	1.3837	1.3646	1.3739	1.3630	1.3682	1.4170	1.3723	1.3965	1.3762
0.5426	0.4759	0.4783	0.9592	1.5614	1.5849	1.6223	1.5105	1.5570	1.5424	1.5433	1.5428	1.5085	1.6124	1.5273	1.5601	1.5427

Columns 205 through 221

0.2136	0.2272	0.1973	0.0696	0.1638	0.0790	-0.0069	-0.0066	-0.0112	0.0330	0.1845	-0.0000	-0.0137	0.0253	0.0384	0.1838	0.2147
1.3308	1.3631	1.2814	0.8587	1.1793	0.8782	0.5756	0.5315	0.3867	0.8323	1.2134	0.4380	0.5672	0.7064	0.7818	1.2335	1.3310
1.4643	1.5264	1.4119	0.9532	1.2970	1.0080	0.5248	0.5483	0.6433	0.7322	1.4210	0.7442	0.4719	0.7245	0.7824	1.3795	1.4745

Columns 222 through 238

0.2291	0.2276	0.1428	0.2220	0.2267	0.0565	0.0458	0.0624	0.0046	0.0703	0.0367	-0.0077	-0.0141	-0.0024	-0.0408	-0.0072	-0.0351
1.3708	1.3726	1.1625	1.3443	1.3748	0.8351	0.6971	0.8023	0.5599	0.9457	0.7200	0.4867	0.4980	0.5005	0.5154	0.4830	0.5866
1.5277	1.5073	1.1587	1.5178	1.4929	0.8765	0.9185	0.9497	0.6369	0.8933	0.8060	0.5677	0.4947	0.6137	0.2255	0.5762	0.2963

Columns 239 through 255

0.2594	-0.0172	-0.0110	-0.0214	-0.0199	-0.0198	-0.0219	-0.0047	-0.0069	0.0271	0.0150	0.0068	-0.0377	-0.0158	0.0209	0.0050	0.0055
1.4431	0.4683	0.4700	0.4662	0.4452	0.4961	0.4236	0.5330	0.6974	0.6808	0.5165	0.5003	0.4970	0.6019	0.6320	0.5855	0.5831
1.6587	0.4802	0.5452	0.4391	0.4666	0.4412	0.4581	0.5652	0.5120	0.7540	0.8307	0.7324	0.2638	0.4491	0.7363	0.6226	0.6289

Columns 256 through 272

0.1043	0.1215	0.1672	0.0245	1.1547	1.4591	1.4198	0.5938	0.4992	0.4965	0.5686	0.5079	0.3226	0.5087	0.3753	0.3857	0.5102
0.9914	1.0325	1.1879	0.6831	1.2086	1.4184	1.3732	0.5452	0.4773	0.4762	0.4734	0.3026	0.3419	0.4589	0.3697	0.4437	0.3706
1.0804	1.1641	1.3121	0.7310	1.1756	1.4714	1.3846	0.5937	0.5228	0.5106	0.4942	0.6234	0.3987	0.2977	0.3594	0.3685	0.4451

Columns 273 through 289

0.4356	0.5488	1.0910	1.0717	1.0642	1.5109	1.4948	1.4079	1.3420	1.1793	1.1647	0.6411	1.4119	1.4680	1.4430	1.4245	0.6213
0.4035	0.5112	1.0182	0.9870	1.0870	1.4271	1.4038	1.3798	1.3435	1.3123	1.1675	0.6655	1.3979	1.4499	1.4176	1.3754	0.5756
0.4116	0.4791	1.0933	0.9671	1.0525	1.5126	1.4815	1.4089	1.2758	1.3282	1.1868	0.6368	1.3604	1.3701	1.3929	1.4121	0.5943

Columns 290 through 301

0.8667	1.4126	1.3450	1.1685	0.4896	0.4025	0.5721	0.4320	0.4403	0.4223	0.5155	0.3734					
0.9349	1.3858	1.3259	1.1561	0.4189	0.4414	0.4576	0.4501	0.4011	0.4178	0.4405	0.3567					
0.9398	1.3941	1.3002	1.0544	0.5095	0.4939	0.4653	0.4576	0.5150	0.1764	0.2815	0.2071					

test_outputs_AC_fault_L1_L2 =

Columns 1 through 17

0.7346	0.6135	0.5202	0.4448	0.3591	0.4281	0.6312	0.5923	0.5678	0.5691	0.7180	0.8428	1.0565	1.1295	1.1137	1.0992	1.1463
0.7493	0.6100	0.5343	0.4526	0.5223	0.4760	0.4978	0.5538	0.5076	0.6157	0.6867	0.8442	1.0591	1.1147	1.1107	1.1817	1.1509
0.5899	0.5094	0.4316	0.4015	0.4875	0.3626	0.4722	0.4820	0.4909	0.4857	0.5904	0.7105	0.8117	0.9122	0.8779	1.0363	0.9542

Columns 18 through 34

1.2220	1.1120	1.0811	1.0984	1.1860	1.1816	1.1452	1.2919	1.1091	1.3056	1.3378	1.1818	1.1540	1.2228	1.2381	1.1251	1.2309
1.1187	1.1277	1.0927	1.1159	1.1908	1.2169	1.1943	1.0989	0.9789	1.0888	1.1786	1.1534	1.1445	1.1279	1.0027	1.2025	1.2540
0.9014	0.9483	0.8871	0.9268	0.8978	1.0082	1.1998	0.6958	0.8630	1.0577	0.9020	0.7989	1.0878	1.1155	0.9834	1.0965	1.0525

Columns 35 through 51

1.4017	1.1410	1.2352	1.2382	1.2372	1.1615	1.1986	1.1863	1.0395	1.2491	1.2457	1.0741	0.9952	1.1513	1.0449	1.2278	1.0721
1.2739	1.2057	1.1970	1.2175	1.2173	1.2194	1.1925	1.1443	1.0450	1.2169	1.1594	1.0151	1.0743	1.0977	1.1362	0.9500	1.0003
1.1246	1.0546	0.9652	1.0968	1.0372	0.7789	0.9485	1.1975	1.0092	1.0382	0.7250	0.8541	0.9307	1.0343	1.1949	0.8912	1.1693

Columns 52 through 68

0.9383	0.9797	1.0728	1.1085	1.1332	1.1729	1.2174	1.2751	1.2760	1.0681	1.3161	0.7722	0.8157	1.2130	1.2075	1.1286	1.2122
1.1006	1.2049	0.8695	1.1327	1.1512	1.2691	1.2297	1.3420	1.2069	1.2170	1.1969	0.7803	0.9778	1.2081	1.2577	1.2311	1.2583
1.1675	1.2473	0.9086	1.2106	1.1564	1.3110	1.1918	1.1325	1.3068	1.1915	1.0058	0.8189	1.0207	1.1639	1.1288	1.1436	1.4273

Columns 69 through 85

0.8234	1.3749	1.3569	1.3035	1.3462	1.2942	0.7304	1.2497	1.3782	0.6991	0.8760	1.2683	0.6502	0.7113	0.7747	1.4484	1.4364
0.7154	1.2481	1.3593	1.2923	1.3372	1.3217	0.7068	1.2505	1.3552	0.6165	0.7789	1.3217	0.7854	0.6766	0.7286	1.4137	1.4171
0.8724	1.3647	1.2420	1.3482	1.3729	1.3257	0.7106	1.2024	1.3131	0.6204	0.7735	1.1763	0.6297	0.5873	0.6815	1.4402	1.4364

Columns 86 through 102

1.4100	0.8505	0.5824	0.6174	0.7978	1.4626	1.5322	1.4150	1.5607	1.5679	1.4728	1.6123	1.6253	1.6299	0.7652	0.6281	0.6643
1.4132	0.8357	0.5972	0.6187	0.7407	1.4903	1.4492	1.4595	1.4660	1.4638	1.4391	1.5474	1.5674	1.5249	0.7182	0.6640	0.6379
1.3404	0.8218	0.6200	0.5735	0.7485	1.6216	1.2475	1.5463	1.3460	1.5833	1.5774	1.5195	1.5299	1.5279	0.7225	0.5846	0.6523

Columns 103 through 119

0.6140	0.6307	0.7009	0.6787	0.7854	0.9787	1.2436	1.2567	1.0400	1.5355	1.6112	1.6448	1.5772	1.6265	1.5637	1.4860	1.5709
0.6351	0.5908	0.6459	0.6540	0.7359	1.0138	1.1757	1.2248	0.9586	1.4687	1.4856	1.5855	1.5548	1.5391	1.4996	1.5204	1.5505
0.6209	0.6148	0.6073	0.6485	0.7298	1.0015	1.0742	1.1982	0.9377	1.5425	1.4959	1.6034	1.5281	1.5197	1.4431	1.3949	1.4942

Columns 120 through 136

1.6048	1.5307	1.5622	1.5055	1.5806	1.5859	1.5258	0.8932	1.5606	1.5775	1.3125	1.1781	1.5504	1.4954	1.6357	1.6332	1.5781
1.4984	1.4904	1.4974	1.4639	1.4865	1.5107	1.4692	0.8262	1.4862	1.5148	1.2318	1.1439	1.4513	1.4295	1.5295	1.5330	1.5699
1.4853	1.4752	1.3939	1.4337	1.4707	1.5062	1.4734	0.8074	1.4349	1.5158	1.1527	1.0823	1.4464	1.4314	1.5227	1.4982	1.7505

Columns 137 through 153

1.6527	1.5761	0.7041	1.5045	1.6148	0.7461	0.8372	0.6615	0.6914	0.6559	1.3479	1.6038	0.6110	0.5678	0.5706	0.5715	0.6338
1.5577	1.5095	0.6705	1.4458	1.5463	0.7327	0.8101	0.6921	0.6320	0.7041	1.3368	1.5516	0.7144	0.5302	0.5674	0.6026	0.6415
1.5580	1.4806	0.6824	1.5289	1.5737	0.6837	0.7952	0.6144	0.6690	0.6470	1.3654	1.5373	0.6142	0.3670	0.6316	0.6028	0.5886

Columns 154 through 170

0.4951	0.7364	0.7229	0.7702	1.0810	0.7434	0.7401	0.6344	0.7258	0.8869	0.8105	0.8803	0.9406	1.1467	0.6715	1.1092	1.7792
0.7473	0.6669	0.7002	0.7609	1.0004	0.7681	0.7066	0.7024	0.7489	0.8349	0.8295	0.8532	0.9289	1.1386	0.8245	1.1007	1.7559
0.6750	0.6342	0.6590	0.7756	1.0368	0.7089	0.4800	0.6490	0.7288	0.8243	0.8290	0.8391	0.9337	1.1828	0.6091	1.0064	1.7287

Columns 171 through 187

1.7548	1.7659	1.4102	0.7555	1.1684	1.8037	1.6523	1.6879	1.6890	1.6750	1.6307	1.6399	1.6215	1.5506	1.5390	1.0336	0.5848
1.6925	1.6856	1.4430	0.7026	1.2128	1.5759	1.4947	1.6079	1.6463	1.6072	1.5795	1.6376	1.5430	1.4814	1.5220	1.0102	0.5850
1.6360	1.5266	1.4827	0.7014	1.0325	1.6044	1.7385	1.6389	1.6475	1.5892	1.6138	1.5727	1.6349	1.4831	1.6246	0.8960	0.5633

Columns 188 through 204

0.5702	0.6287	0.5860	0.8952	1.6679	1.6802	1.6919	-0.0002	-0.0030	-0.0019	-0.0021	-0.0019	-0.0002	-0.0065	-0.0012	-0.0033	-0.0021
0.5530	0.4948	0.5400	0.9424	1.5910	1.5998	1.6478	-0.0568	-0.0525	-0.0542	-0.0539	-0.0542	-0.0568	-0.0462	-0.0553	-0.0519	-0.0539
0.5426	0.4759	0.4783	0.9592	1.5614	1.5849	1.6223	1.6370	1.6724	1.6591	1.6613	1.6591	1.6370	1.7166	1.6503	1.6768	1.6613

Columns 205 through 221

0.0024	-0.0011	0.0052	-0.0010	0.0098	0.0032	-0.0299	-0.0299	-0.0285	-0.0141	0.0055	-0.0234	-0.0301	-0.0230	-0.0163	0.0069	0.0019
-0.0604	-0.0555	-0.0640	-0.0869	-0.0699	-0.0843	-0.0835	-0.0840	-0.0896	-0.0928	-0.0644	-0.0937	-0.0798	-0.0937	-0.0934	-0.0661	-0.0598
1.6015	1.6481	1.5590	1.0813	1.4649	1.1422	0.5857	0.5925	0.6697	0.9156	1.5545	0.7825	0.5452	0.7900	0.8861	1.5296	1.6082

Columns 222 through 238

-0.0012	-0.0002	0.0114	-0.0004	0.0005	-0.0072	-0.0075	-0.0031	-0.0285	0.0018	-0.0175	-0.0298	-0.0301	-0.0291	-0.0335	-0.0297	-0.0309
-0.0553	-0.0568	-0.0737	-0.0565	-0.0577	-0.0902	-0.0903	-0.0881	-0.0896	-0.0853	-0.0936	-0.0848	-0.0798	-0.0879	-0.0623	-0.0853	-0.0687
1.6503	1.6370	1.3857	1.6392	1.6282	1.0007	0.9979	1.0535	0.6697	1.1201	0.8701	0.6015	0.5452	0.6422	0.3153	0.6082	0.4190

Columns 239 through 255

-0.0094	-0.0302	-0.0300	-0.0303	-0.0302	-0.0303	-0.0303	-0.0297	-0.0290	-0.0221	-0.0161	-0.0246	-0.0323	-0.0302	-0.0239	-0.0286	-0.0285
-0.0398	-0.0783	-0.0831	-0.0753	-0.0771	-0.0760	-0.0762	-0.0852	-0.0882	-0.0939	-0.0933	-0.0933	-0.0643	-0.0796	-0.0935	-0.0892	-0.0895
1.7542	0.5293	0.5812	0.4969	0.5155	0.5039	0.5062	0.6060	0.6467	0.8052	0.8887	0.7626	0.3523	0.5429	0.7750	0.6628	0.6674

Columns 256 through 272

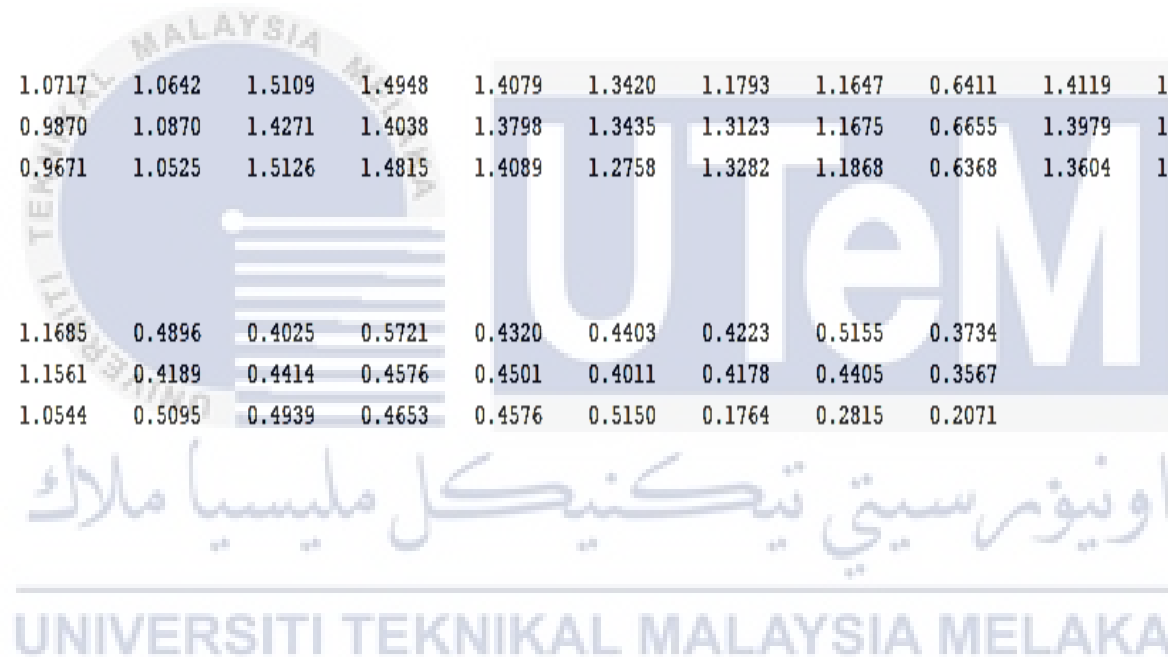
0.0092	0.0112	0.0094	-0.0233	1.1547	1.4591	1.4198	0.5938	0.4992	0.4965	0.5686	0.5079	0.3226	0.5087	0.3753	0.3857	0.5102
-0.0793	-0.0760	-0.0693	-0.0937	1.2086	1.4184	1.3732	0.5452	0.4773	0.4762	0.4734	0.3026	0.3419	0.4589	0.3697	0.4437	0.3706
1.2557	1.3333	1.4766	0.7850	1.1756	1.4714	1.3846	0.5937	0.5228	0.5106	0.4942	0.6234	0.3987	0.2977	0.3594	0.3685	0.4451

Columns 273 through 289

0.4356	0.5488	1.0910	1.0717	1.0642	1.5109	1.4948	1.4079	1.3420	1.1793	1.1647	0.6411	1.4119	1.4680	1.4430	1.4245	0.6213
0.4035	0.5112	1.0182	0.9870	1.0870	1.4271	1.4038	1.3798	1.3435	1.3123	1.1675	0.6655	1.3979	1.4499	1.4176	1.3754	0.5756
0.4116	0.4791	1.0933	0.9671	1.0525	1.5126	1.4815	1.4089	1.2758	1.3282	1.1868	0.6368	1.3604	1.3701	1.3929	1.4121	0.5943

Columns 290 through 301

0.8667	1.4126	1.3450	1.1685	0.4896	0.4025	0.5721	0.4320	0.4403	0.4223	0.5155	0.3734
0.9349	1.3858	1.3259	1.1561	0.4189	0.4414	0.4576	0.4501	0.4011	0.4178	0.4405	0.3567
0.9398	1.3941	1.3002	1.0544	0.5095	0.4939	0.4653	0.4576	0.5150	0.1764	0.2815	0.2071



test_outputs_AC_fault_L1_L2_L3 =

Columns 1 through 17

1.3256	1.1894	1.1229	1.2961	1.2051	1.1954	1.0106	1.0659	1.1083	1.1726	1.0254	1.1260	1.3317	1.0920	1.1978	1.1066	1.2903
1.1180	1.1677	1.0481	1.1433	1.2006	1.2660	1.1780	1.1939	1.1769	1.1128	1.1653	1.1491	1.2921	1.1833	1.1407	1.2188	1.1788
0.8275	0.6110	1.0903	1.1391	0.6718	1.0741	0.6611	1.1638	1.0171	1.1893	0.7537	0.6900	0.7480	0.9411	0.9374	0.8843	1.1836

Columns 18 through 34

1.2968	0.9341	0.6627	1.3302	1.3190	1.3636	1.2064	0.7262	1.3407	1.1543	1.2936	0.7974	1.4133	1.4096	1.4052	1.4383	0.5545
1.2467	0.7649	0.5712	1.3228	1.2521	1.3016	1.0435	0.5359	1.3348	1.0892	1.2832	0.8415	1.3540	1.3776	1.3550	1.3920	0.5123
1.0855	0.7884	0.5987	1.1685	1.1786	1.1780	0.8873	0.5471	1.1331	0.8556	1.3173	0.7176	1.2216	1.2525	1.2687	1.2610	0.4896

Columns 35 through 51

1.4404	0.4631	0.5746	1.4366	1.0430	1.5102	1.4742	1.5519	1.4094	1.3571	0.3939	1.0089	0.5940	1.6949	1.5828	0.6353	0.5624
1.3854	0.4845	0.5028	1.4359	1.0708	1.4335	1.4564	1.4675	1.3900	1.2964	0.4418	0.7378	0.5022	1.6966	1.4570	0.4587	0.5248
1.2625	0.3949	0.5531	1.1641	0.9678	1.2482	1.2023	1.2646	1.3390	1.2437	0.2520	0.7960	0.4505	1.5605	1.0538	0.5756	0.4145

Columns 52 through 68

0.6857	1.4633	1.5445	1.6944	0.5433	0.7001	0.5189	1.5917	1.6967	1.6645	1.6328	1.6711	1.4848	0.9308	1.5470	1.6481	1.7394
0.5565	1.4348	1.4859	1.5016	0.3294	0.5892	0.5105	1.5154	1.5972	1.5937	1.5141	1.5468	1.4316	1.0766	1.5383	1.5267	1.5646
0.5151	1.3376	1.4053	1.4246	0.5836	0.4877	0.4337	1.5008	1.4982	1.5235	1.4772	1.6045	1.4896	1.0564	1.6403	1.5593	1.4646

Columns 69 through 85

0.7217	1.4761	1.6458	1.5839	1.2275	0.5442	0.5408	0.5293	0.5985	1.2662	1.6200	1.6375	1.5773	1.6548	1.5837	1.6027	1.6294
0.7901	1.4321	1.5890	1.5347	1.2070	0.5369	0.5539	0.5891	0.5398	1.4329	1.5372	1.5774	1.5331	1.5572	1.5322	1.5075	1.5120
0.7283	1.2539	1.3915	1.7528	1.1875	0.4384	0.3564	0.3902	0.4633	1.3210	1.6004	1.6263	1.6137	1.4484	1.5518	1.6069	1.5264

Columns 86 through 102

1.5950	1.6011	1.5879	1.4869	0.4473	0.4217	0.3673	0.5016	0.5461	1.2792	1.5031	1.5442	1.3888	1.6991	1.5728	0.5813	0.5361
1.5193	1.5420	1.4995	1.4676	0.4415	0.3225	0.3284	0.4166	0.3774	1.2185	1.4759	1.4241	1.3585	1.5860	1.4940	0.4140	0.5506
1.6098	1.5682	1.5200	1.3662	0.3572	0.2465	0.4097	0.2503	0.4561	1.1424	1.5127	1.4509	1.4636	1.6496	1.6011	0.4636	0.1934

Columns 103 through 119

0.4339	0.3656	1.7613	1.1378	0.5169	0.4650	0.4274	0.8926	1.4944	1.8627	1.7105	1.8235	1.7550	1.7791	0.7298	0.6277	1.7724
0.4759	0.4815	1.6770	1.1208	0.5711	0.5010	0.4732	1.0725	1.5239	1.3989	1.6925	1.9229	1.6679	1.6897	0.7348	0.6281	1.7445
0.4208	0.5158	1.3984	1.0310	0.2906	0.4632	0.2529	1.1718	1.3240	1.4604	1.6168	1.8769	1.8251	1.5486	0.4321	0.5870	1.6964

Columns 120 through 136

1.4842	0.6625	0.7962	1.3855	1.7943	1.8233	1.7921	1.7425	1.6048	0.6836	1.7615	1.7327	1.6126	1.6003	1.1343	1.3885	1.4648
1.4417	0.6651	0.7457	1.3640	1.7802	1.7782	1.6660	1.8196	1.4984	0.6650	1.6839	1.6640	1.5461	1.4982	1.1062	1.3558	1.3918
1.3599	0.6183	0.7100	1.3363	1.7360	1.6971	1.8889	1.8648	1.4853	0.5917	1.6340	1.6807	1.5741	1.4729	1.1066	1.3133	1.4226

Columns 137 through 153

1.4871	1.5591	1.3734	1.5436	1.3404	1.3063	0.6120	0.7892	0.5294	0.4485	0.4510	0.4979	0.7488	0.6271	1.1839	1.1645	1.1070
1.4015	1.4974	1.3610	1.4447	1.3217	1.2653	0.5885	0.4253	0.4119	0.5580	0.4173	0.5169	0.5114	0.6033	1.1638	1.1738	1.0902
1.3685	1.4866	1.3075	1.4259	1.3100	1.2420	0.5284	0.7433	0.4298	0.6116	0.6477	0.5025	0.6421	0.5406	1.3556	1.1723	1.0901

Columns 154 through 170

1.2125	1.0453	0.9491	1.2566	1.1919	0.6896	0.5700	0.8103	0.9727	0.8600	0.6914	0.8166	0.8717	0.6956	0.9149	1.2972	1.4328
1.2486	1.1184	1.0069	1.0610	1.1007	0.6582	0.7636	0.8700	1.0894	0.7929	0.5843	0.8096	0.7497	0.7923	0.7349	1.4162	1.4038
1.0256	0.8378	1.0061	1.1432	1.1373	0.7429	0.8265	0.6212	1.2274	0.7670	0.7612	0.4187	0.6565	0.6226	0.6536	1.4938	1.1831

Columns 171 through 187

1.5427	1.6045	1.6247	1.6203	1.6259	1.5028	0.8949	1.5216	0.8536	0.9513	0.8527	0.8936	0.9909	1.2678	1.2496	1.3846	1.4578
1.4959	1.4957	1.5293	1.5441	1.5300	1.4294	0.8781	1.4773	0.7558	0.7136	1.0490	0.8584	0.8244	1.3037	1.2359	1.3271	1.3990
1.4356	1.5442	1.5588	1.5313	1.4883	1.4310	0.8265	1.5887	0.7520	0.6998	1.0909	0.7139	1.0235	1.2244	1.1742	1.2698	1.4039

Columns 188 through 204

1.4223	1.5919	1.5096	1.5746	1.6888	1.5806	1.4320	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478
1.3932	1.4636	1.4557	1.4815	1.4411	1.5284	1.3827	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484
1.3311	1.4946	1.4970	1.3928	1.2783	1.5223	1.4574	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254

Columns 205 through 221

-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478
-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484
-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254

Columns 222 through 238

-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478
-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484
-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254

Columns 239 through 255

-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478	-0.0478
-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484	-0.0484
-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254	-0.0254

Columns 256 through 272

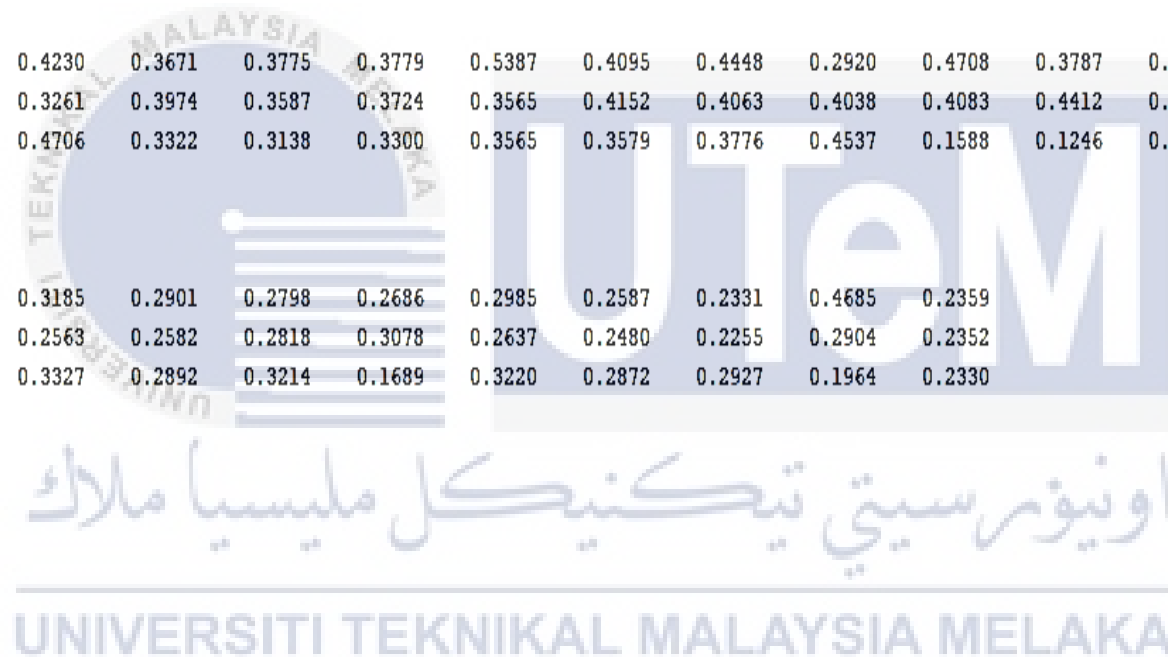
-0.0478	-0.0478	-0.0478	-0.0478	0.4656	0.4696	0.4853	0.4095	0.4642	0.4384	0.4769	0.4146	0.3443	0.4766	0.4604	0.3948	0.4456
-0.0484	-0.0484	-0.0484	-0.0484	0.4783	0.4613	0.4279	0.4412	0.4025	0.4364	0.4091	0.4135	0.4361	0.4157	0.3985	0.4750	0.3674
-0.0254	-0.0254	-0.0254	-0.0254	0.4960	0.4595	0.4665	0.4489	0.3629	0.4158	0.4536	0.4446	0.4806	0.3985	0.4547	0.4080	0.4257

Columns 273 through 289

0.3799	0.3365	0.3871	0.4230	0.3671	0.3775	0.3779	0.5387	0.4095	0.4448	0.2920	0.4708	0.3787	0.3938	0.3317	0.3561	0.3699
0.3782	0.3834	0.3983	0.3261	0.3974	0.3587	0.3724	0.3565	0.4152	0.4063	0.4038	0.4083	0.4412	0.3653	0.3906	0.3363	0.3037
0.3305	0.3472	0.4397	0.4706	0.3322	0.3138	0.3300	0.3565	0.3579	0.3776	0.4537	0.1588	0.1246	0.4086	0.4402	0.0715	0.3691

Columns 290 through 301

0.3287	0.3516	0.2996	0.3185	0.2901	0.2798	0.2686	0.2985	0.2587	0.2331	0.4685	0.2359
0.3258	0.2883	0.2587	0.2563	0.2582	0.2818	0.3078	0.2637	0.2480	0.2255	0.2904	0.2352
0.3805	0.2967	0.3458	0.3327	0.2892	0.3214	0.1689	0.3220	0.2872	0.2927	0.1964	0.2330



test_outputs_DC_fault_L1 =

Columns 1 through 17

0.7234	0.6070	0.4940	0.4250	0.4296	0.4793	0.5511	0.5619	0.5391	0.5600	0.6950	0.8349	1.0489	1.1138	1.1177	1.1318	1.1182
0.6993	0.5871	0.4839	0.4143	0.4222	0.4651	0.5337	0.5542	0.5322	0.5487	0.6791	0.8133	1.0222	1.0867	1.0964	1.1029	1.0942
0.5187	0.4428	0.3967	0.3502	0.3582	0.3903	0.4313	0.4513	0.4312	0.4508	0.5590	0.6691	0.8124	0.8590	0.8724	0.8714	0.8681

Columns 18 through 34

1.1376	1.1131	1.1074	1.1331	1.1819	1.1634	1.1378	1.1132	0.9600	1.1116	1.1810	1.1623	1.1446	1.1715	1.1441	1.2148	1.2249
1.1169	1.0885	1.0743	1.1094	1.1590	1.1428	1.1109	1.0877	0.9325	1.0863	1.1681	1.1487	1.1222	1.1513	1.1271	1.2027	1.2107
0.8720	0.8496	0.8407	0.8630	0.8510	0.9385	0.9440	0.9348	0.8144	0.9508	1.0105	1.0206	1.0114	1.0408	1.0203	1.0828	1.0852

Columns 35 through 51

1.2094	1.1893	1.2080	1.2126	1.2059	1.2042	1.1859	1.1637	1.1372	1.2019	1.1923	1.1700	1.0703	1.1027	1.1276	1.1102	1.0876
1.1965	1.1748	1.1963	1.1888	1.1915	1.1845	1.1701	1.1467	1.1159	1.1824	1.1694	1.1456	1.0513	1.0721	1.1068	1.0909	1.0724
1.0621	1.0321	1.0124	1.0225	1.0083	1.0025	0.9891	0.9784	0.9582	1.0137	0.9997	0.9808	0.9429	0.9788	1.0039	0.9885	0.9725

Columns 52 through 68

0.9860	1.0871	0.9212	1.1672	1.1055	1.1667	1.2207	1.2497	1.2575	1.2358	1.2016	0.7785	0.8711	1.2142	1.1912	1.2506	1.2113
0.9235	1.0475	0.8624	1.1455	1.0867	1.1476	1.1982	1.2361	1.2442	1.2146	1.1778	0.7619	0.8121	1.2023	1.1825	1.2400	1.2042
0.8434	0.9882	0.8087	1.0850	1.0193	1.0845	1.1391	1.1767	1.1914	1.1658	1.1223	0.6959	0.7530	1.1697	1.1374	1.2012	1.1692

Columns 69 through 85

0.8000	1.2689	1.3231	1.3348	1.3241	1.2814	0.7044	1.2226	1.3375	0.6209	0.7998	1.2780	0.8412	0.6633	0.7302	1.4290	1.4001
0.7970	1.2742	1.3132	1.3211	1.3099	1.2926	0.7011	1.2220	1.3193	0.6034	0.7560	1.2831	0.7896	0.6474	0.7053	1.3987	1.3892
0.7511	1.2469	1.2748	1.3000	1.2948	1.2893	0.6646	1.2126	1.3050	0.5469	0.7151	1.2743	0.7093	0.5895	0.6472	1.3842	1.3871

Columns 86 through 102

1.4126	0.8105	0.5893	0.5976	0.0151	0.1813	0.1797	0.1725	0.1784	0.1714	0.1830	0.2022	0.2088	0.2079	0.0200	-0.0022	-0.0029
1.3796	0.8210	0.5801	0.5836	0.6688	1.2297	1.2248	1.2031	1.2200	1.1991	1.2354	1.2919	1.3120	1.3088	0.6627	0.5839	0.5798
1.3728	0.8062	0.5191	0.5341	0.6643	1.3632	1.3575	1.3322	1.3554	1.3299	1.3686	1.4367	1.4589	1.4564	0.7058	0.5615	0.5570

Columns 103 through 119

-0.0044	-0.0051	-0.0029	0.0037	0.0201	0.0683	0.0751	0.0956	0.0532	0.1910	0.1990	0.2123	0.2145	0.2054	0.1954	0.1958	0.2019
0.5695	0.5674	0.5818	0.6136	0.6854	0.8587	0.9124	0.9665	0.8189	1.2571	1.2806	1.3223	1.3287	1.3016	1.2709	1.2734	1.2903
0.5487	0.5434	0.5562	0.5977	0.6945	0.9439	0.9480	1.0425	0.8642	1.4010	1.4293	1.4699	1.4784	1.4480	1.4146	1.4140	1.4371

Columns 120 through 136

0.1980	0.1868	0.1853	0.1762	0.1932	0.1918	0.1834	0.0318	0.1990	0.1837	0.0910	0.0870	0.1738	0.1612	0.2004	0.2066	0.2141
1.2790	1.2459	1.2418	1.2135	1.2653	1.2612	1.2353	0.7332	1.2789	1.2394	0.9638	0.9327	1.2088	1.1705	1.2863	1.3056	1.3263
1.4229	1.3832	1.3773	1.3467	1.4058	1.3999	1.3721	0.7590	1.4331	1.3674	1.0122	1.0140	1.3340	1.2892	1.4313	1.4504	1.4790

Columns 137 through 153

0.2058	0.1966	0.0063	0.1813	0.2048	0.0141	0.0299	0.0052	0.0007	0.0078	0.1381	0.2059	-0.0015	-0.0093	-0.0104	-0.0082	-0.0033
1.3016	1.2758	0.6215	1.2254	1.2983	0.6571	0.7237	0.6119	0.5920	0.6291	1.0928	1.3024	0.5777	0.5373	0.5330	0.5439	0.5757
1.4513	1.4168	0.6154	1.3713	1.4487	0.6616	0.7500	0.6105	0.5825	0.6240	1.2149	1.4511	0.5699	0.5201	0.5124	0.5272	0.5555

Columns 154 through 170

0.0030	0.0060	0.0108	0.0175	0.0586	0.0115	0.0093	0.0059	0.0115	0.0288	0.0249	0.0362	0.0449	0.0837	0.0233	0.0744	0.2618
0.6020	0.6196	0.6423	0.6700	0.8447	0.6460	0.6349	0.6250	0.6460	0.7306	0.7088	0.7561	0.7895	0.9161	0.7035	0.9128	1.4602
0.5966	0.6132	0.6419	0.6819	0.8847	0.6461	0.6334	0.6107	0.6461	0.7387	0.7197	0.7797	0.8234	1.0055	0.7108	0.9432	1.6364

Columns 171 through 187

0.2514	0.2486	0.1616	0.0115	0.0928	0.2223	0.2236	0.2262	0.2297	0.2252	0.2160	0.2204	0.2062	0.1858	0.1939	0.0437	-0.0082
1.4320	1.4249	1.1595	0.6510	0.9470	1.3522	1.3553	1.3616	1.3723	1.3600	1.3326	1.3444	1.3040	1.2426	1.2669	0.7994	0.5439
1.6045	1.5939	1.3103	0.6435	1.0426	1.5027	1.5085	1.5202	1.5306	1.5140	1.4842	1.5013	1.4508	1.3806	1.4088	0.8099	0.5272

Columns 188 through 204

-0.0141	-0.0163	-0.0140	0.0572	0.2183	0.2275	0.2318	0.2275	0.2257	0.2150	0.2235	0.2173	0.2344	0.2355	0.2333	0.2264	0.2262
0.5106	0.4968	0.5130	0.8274	1.3389	1.3646	1.3777	1.3646	1.3592	1.3295	1.3530	1.3358	1.3852	1.3875	1.3815	1.3608	1.3616
0.4886	0.4741	0.4880	0.8869	1.4926	1.5260	1.5391	1.5260	1.5208	1.4816	1.5124	1.4901	1.5469	1.5528	1.5446	1.5237	1.5202

Columns 205 through 221

0.2184	0.2164	0.2016	1.0174	1.5048	1.1108	0.5871	0.5572	0.5719	1.0724	1.2447	0.5871	0.5783	0.6387	0.8777	1.4974	1.6822
1.3397	1.3310	1.2887	0.9524	1.4336	1.0508	0.5608	0.5427	0.5600	1.0582	1.2043	0.5610	0.5589	0.6212	0.8659	1.4224	1.6203
1.4924	1.4912	1.4375	0.9427	1.4546	1.0167	0.5374	0.5126	0.5313	1.0521	1.1705	0.5354	0.5352	0.5904	0.8501	1.4533	1.6261

Columns 222 through 238

1.6543	1.6722	1.6212	1.5961	1.6397	0.9675	0.7244	0.8441	0.6342	1.1083	0.7340	0.5070	0.5133	0.5381	0.5203	0.5050	0.5674
1.5788	1.6020	1.5438	1.5170	1.5601	0.9367	0.6970	0.8371	0.6135	1.1494	0.7331	0.4903	0.4899	0.5176	0.4998	0.4855	0.5528
1.5950	1.6089	1.5618	1.5367	1.5656	0.8687	0.6715	0.9133	0.5832	1.1671	0.7323	0.4644	0.4620	0.4865	0.4739	0.4552	0.5200

Columns 239 through 255

1.6334	0.4962	0.4929	0.4725	0.4432	0.4452	0.4605	0.5285	0.7935	0.7843	0.5712	0.5617	0.5706	0.5796	0.5948	0.5872	0.6191
1.5495	0.4837	0.4706	0.4504	0.4289	0.4343	0.4490	0.5054	0.6973	0.7541	0.5492	0.5504	0.5520	0.5672	0.5819	0.5746	0.5982
1.5603	0.4531	0.4383	0.4208	0.3965	0.4016	0.4188	0.4702	0.6628	0.7027	0.5215	0.5198	0.5240	0.5404	0.5546	0.5475	0.5751

Columns 256 through 272

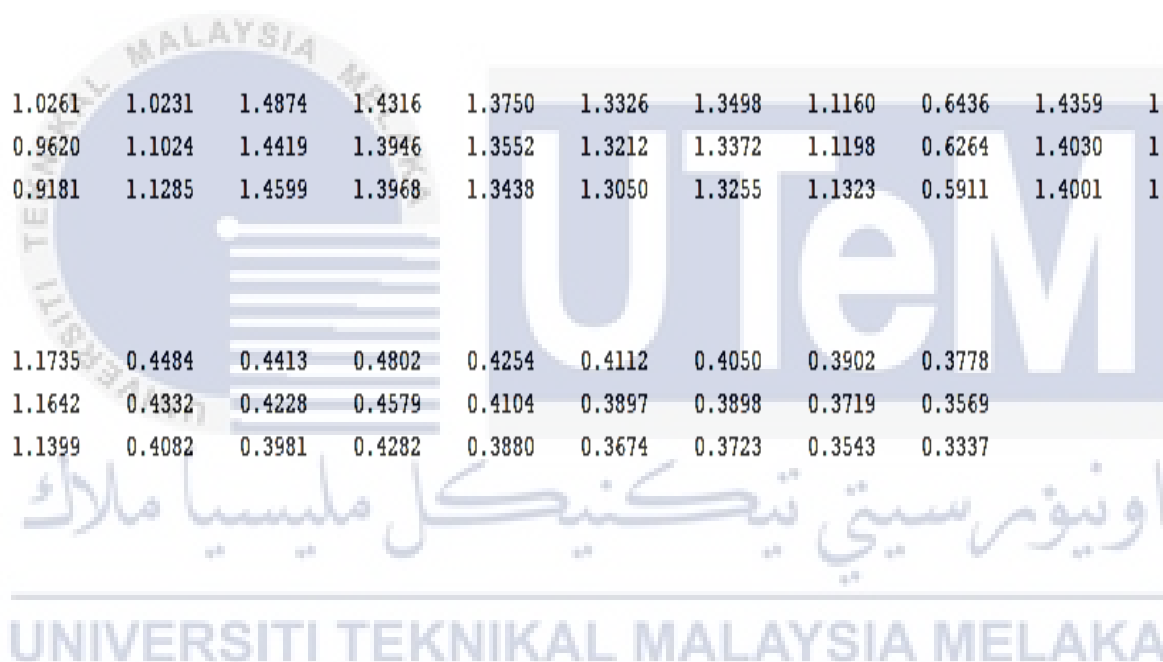
1.3013	1.2941	1.4353	0.7036	1.0794	1.4434	1.3551	0.5573	0.4860	0.4510	0.4362	0.3935	0.3670	0.3591	0.3541	0.3674	0.3855
1.2558	1.2628	1.3988	0.6907	1.0975	1.4073	1.3376	0.5420	0.4735	0.4351	0.4181	0.3866	0.3498	0.3429	0.3371	0.3477	0.3647
1.2373	1.2437	1.4023	0.6552	1.0608	1.4238	1.3305	0.5187	0.4455	0.4151	0.3908	0.3556	0.3234	0.3078	0.3101	0.3131	0.3391

Columns 273 through 289

0.4060	0.4599	1.1493	1.0261	1.0231	1.4874	1.4316	1.3750	1.3326	1.3498	1.1160	0.6436	1.4359	1.4364	1.4414	1.3918	0.5967
0.3852	0.4523	1.0992	0.9620	1.1024	1.4419	1.3946	1.3552	1.3212	1.3372	1.1198	0.6264	1.4030	1.4009	1.4010	1.3622	0.5734
0.3575	0.4170	1.1458	0.9181	1.1285	1.4599	1.3968	1.3438	1.3050	1.3255	1.1323	0.5911	1.4001	1.4129	1.4126	1.3592	0.5493

Columns 290 through 301

0.8877	1.4052	1.3644	1.1735	0.4484	0.4413	0.4802	0.4254	0.4112	0.4050	0.3902	0.3778
0.9171	1.3793	1.3466	1.1642	0.4332	0.4228	0.4579	0.4104	0.3897	0.3898	0.3719	0.3569
0.9324	1.3756	1.3460	1.1399	0.4082	0.3981	0.4282	0.3880	0.3674	0.3723	0.3543	0.3337



test_outputs_DC_fault_L1_L2 =

Columns 1 through 17

0.7234	0.6070	0.4940	0.4250	0.4296	0.4793	0.5511	0.5619	0.5391	0.5600	0.6950	0.8349	1.0489	1.1138	1.1177	1.1318	1.1182
0.6993	0.5871	0.4839	0.4143	0.4222	0.4651	0.5337	0.5542	0.5322	0.5487	0.6791	0.8133	1.0222	1.0867	1.0964	1.1029	1.0942
0.5187	0.4428	0.3967	0.3502	0.3582	0.3903	0.4313	0.4513	0.4312	0.4508	0.5590	0.6691	0.8124	0.8590	0.8724	0.8714	0.8681

Columns 18 through 34

1.1376	1.1131	1.1074	1.1331	1.1819	1.1634	1.1378	1.1132	0.9600	1.1116	1.1810	1.1623	1.1446	1.1715	1.1441	1.2148	1.2249
1.1169	1.0885	1.0743	1.1094	1.1590	1.1428	1.1109	1.0877	0.9325	1.0863	1.1681	1.1487	1.1222	1.1513	1.1271	1.2027	1.2107
0.8720	0.8496	0.8407	0.8630	0.8510	0.9385	0.9440	0.9348	0.8144	0.9508	1.0105	1.0206	1.0114	1.0408	1.0203	1.0828	1.0852

Columns 35 through 51

1.2094	1.1893	1.2080	1.2126	1.2059	1.2042	1.1859	1.1637	1.1372	1.2019	1.1923	1.1700	1.0703	1.1027	1.1276	1.1102	1.0876
1.1965	1.1748	1.1963	1.1888	1.1915	1.1845	1.1701	1.1467	1.1159	1.1824	1.1694	1.1456	1.0513	1.0721	1.1068	1.0909	1.0724
1.0621	1.0321	1.0124	1.0225	1.0083	1.0025	0.9891	0.9784	0.9582	1.0137	0.9997	0.9808	0.9429	0.9788	1.0039	0.9885	0.9725

Columns 52 through 68

0.9860	1.0871	0.9212	1.1672	1.1055	1.1667	1.2207	1.2497	1.2575	1.2358	1.2016	0.7785	0.8711	1.2142	1.1912	1.2506	1.2113
0.9235	1.0475	0.8624	1.1455	1.0867	1.1476	1.1982	1.2361	1.2442	1.2146	1.1778	0.7619	0.8121	1.2023	1.1825	1.2400	1.2042
0.8434	0.9882	0.8087	1.0850	1.0193	1.0845	1.1391	1.1767	1.1914	1.1658	1.1223	0.6959	0.7530	1.1697	1.1374	1.2012	1.1692

Columns 69 through 85

0.8000	1.2689	1.3231	1.3348	1.3241	1.2814	0.7044	1.2226	1.3375	0.6209	0.7998	1.2780	0.8412	0.6633	0.7302	1.4290	1.4001
0.7970	1.2742	1.3132	1.3211	1.3099	1.2926	0.7011	1.2220	1.3193	0.6034	0.7560	1.2831	0.7896	0.6474	0.7053	1.3987	1.3892
0.7511	1.2469	1.2748	1.3000	1.2948	1.2893	0.6646	1.2126	1.3050	0.5469	0.7151	1.2743	0.7093	0.5895	0.6472	1.3842	1.3871

Columns 86 through 102

1.4126	0.8105	0.5893	0.5976	-0.0265	0.0075	0.0078	0.0087	0.0079	0.0088	0.0073	0.0041	0.0029	0.0030	-0.0250	-0.0296	-0.0297
1.3796	0.8210	0.5801	0.5836	-0.0922	-0.0669	-0.0672	-0.0684	-0.0673	-0.0685	-0.0666	-0.0626	-0.0610	-0.0612	-0.0931	-0.0859	-0.0855
1.3728	0.8062	0.5191	0.5341	0.7237	1.5182	1.5136	1.4928	1.5113	1.4905	1.5227	1.5770	1.5948	1.5926	0.7552	0.6150	0.6105

Columns 103 through 119

-0.0298	-0.0298	-0.0297	-0.0289	-0.0250	-0.0016	0.0014	0.0074	-0.0090	0.0059	0.0045	0.0022	0.0018	0.0035	0.0052	0.0052	0.0041
-0.0848	-0.0844	-0.0855	-0.0885	-0.0931	-0.0873	-0.0855	-0.0810	-0.0910	-0.0649	-0.0631	-0.0602	-0.0596	-0.0618	-0.0640	-0.0640	-0.0626
0.6015	0.5970	0.6105	0.6513	0.7552	1.0729	1.1146	1.2157	0.9785	1.5477	1.5702	1.6037	1.6104	1.5859	1.5590	1.5590	1.5770

Columns 120 through 136

0.0048	0.0067	0.0069	0.0082	0.0056	0.0059	0.0072	-0.0202	0.0044	0.0073	0.0063	0.0053	0.0086	0.0100	0.0044	0.0033	0.0018
-0.0635	-0.0658	-0.0661	-0.0677	-0.0645	-0.0649	-0.0664	-0.0939	-0.0630	-0.0666	-0.0820	-0.0828	-0.0683	-0.0703	-0.0630	-0.0616	-0.0596
1.5657	1.5341	1.5296	1.5044	1.5522	1.5477	1.5250	0.8334	1.5725	1.5227	1.1941	1.1751	1.4952	1.4578	1.5725	1.5881	1.6104

Columns 137 through 153

0.0033	0.0051	-0.0285	0.0073	0.0035	-0.0268	-0.0210	-0.0287	-0.0293	-0.0282	0.0113	0.0033	-0.0295	-0.0300	-0.0301	-0.0300	-0.0297
-0.0616	-0.0639	-0.0895	-0.0666	-0.0618	-0.0919	-0.0939	-0.0891	-0.0872	-0.0900	-0.0736	-0.0616	-0.0862	-0.0823	-0.0817	-0.0829	-0.0853
1.5881	1.5612	0.6674	1.5227	1.5859	0.7166	0.8205	0.6605	0.6331	0.6766	1.3881	1.5881	0.6195	0.5722	0.5655	0.5790	0.6082

Columns 154 through 170

-0.0290	-0.0286	-0.0276	-0.0258	-0.0061	-0.0275	-0.0280	-0.0286	-0.0275	-0.0214	-0.0231	-0.0179	-0.0134	0.0043	-0.0237	0.0012	-0.0086
-0.0882	-0.0894	-0.0910	-0.0927	-0.0897	-0.0912	-0.0905	-0.0894	-0.0912	-0.0939	-0.0937	-0.0937	-0.0926	-0.0836	-0.0936	-0.0856	-0.0418
0.6467	0.6651	0.6953	0.7382	1.0145	0.7000	0.6859	0.6651	0.7000	0.8154	0.7875	0.8648	0.9237	1.1587	0.7775	1.1118	1.7431

Columns 171 through 187

-0.0063	-0.0056	0.0096	-0.0275	0.0069	0.0003	-0.0000	-0.0007	-0.0014	-0.0004	0.0014	0.0005	0.0033	0.0068	0.0055	-0.0136	-0.0300
-0.0465	-0.0479	-0.0697	-0.0912	-0.0815	-0.0575	-0.0570	-0.0560	-0.0550	-0.0565	-0.0591	-0.0577	-0.0616	-0.0660	-0.0644	-0.0926	-0.0829
1.7143	1.7055	1.4696	0.7000	1.2049	1.6304	1.6348	1.6437	1.6525	1.6392	1.6149	1.6282	1.5881	1.5318	1.5545	0.9210	0.5790

Columns 188 through 204

-0.0302	-0.0302	-0.0302	-0.0070	0.0009	-0.0011	-0.0019	-0.0011	-0.0007	0.0016	-0.0002	0.0011	-0.0024	-0.0028	-0.0023	-0.0009	-0.0007
-0.0796	-0.0783	-0.0796	-0.0901	-0.0584	-0.0555	-0.0542	-0.0555	-0.0560	-0.0593	-0.0568	-0.0587	-0.0534	-0.0528	-0.0537	-0.0558	-0.0560
0.5429	0.5293	0.5429	1.0034	1.6215	1.6481	1.6591	1.6481	1.6437	1.6126	1.6370	1.6193	1.6658	1.6702	1.6636	1.6459	1.6437

Columns 205 through 221

0.0009	0.0011	0.0041	1.0174	1.5048	1.1108	0.5871	0.5572	0.5719	1.0724	1.2447	0.5871	0.5783	0.6387	0.8777	1.4974	1.6822
-0.0584	-0.0587	-0.0626	0.9524	1.4336	1.0508	0.5608	0.5427	0.5600	1.0582	1.2043	0.5610	0.5589	0.6212	0.8659	1.4224	1.6203
1.6215	1.6193	1.5770	0.9427	1.4546	1.0167	0.5374	0.5126	0.5313	1.0521	1.1705	0.5354	0.5352	0.5904	0.8501	1.4533	1.6261

Columns 222 through 238

1.6543	1.6722	1.6212	1.5961	1.6397	0.9675	0.7244	0.8441	0.6342	1.1083	0.7340	0.5070	0.5133	0.5381	0.5203	0.5050	0.5674
1.5788	1.6020	1.5438	1.5170	1.5601	0.9367	0.6970	0.8371	0.6135	1.1494	0.7331	0.4903	0.4899	0.5176	0.4998	0.4855	0.5528
1.5950	1.6089	1.5618	1.5367	1.5656	0.8687	0.6715	0.9133	0.5832	1.1671	0.7323	0.4644	0.4620	0.4865	0.4739	0.4552	0.5200

Columns 239 through 255

1.6334	0.4962	0.4929	0.4725	0.4432	0.4452	0.4605	0.5285	0.7935	0.7843	0.5712	0.5617	0.5706	0.5796	0.5948	0.5872	0.6191
1.5495	0.4837	0.4706	0.4504	0.4289	0.4343	0.4490	0.5054	0.6973	0.7541	0.5492	0.5504	0.5520	0.5672	0.5819	0.5746	0.5982
1.5603	0.4531	0.4383	0.4208	0.3965	0.4016	0.4188	0.4702	0.6628	0.7027	0.5215	0.5198	0.5240	0.5404	0.5546	0.5475	0.5751

Columns 256 through 272

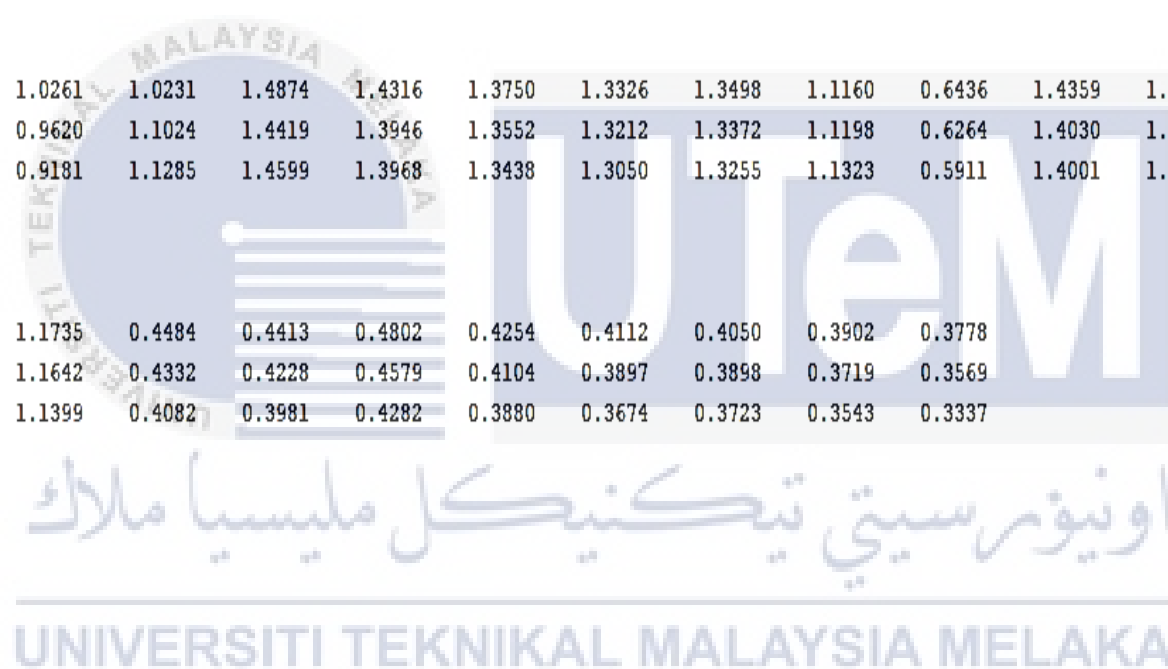
1.3013	1.2941	1.4353	0.7036	1.0794	1.4434	1.3551	0.5573	0.4860	0.4510	0.4362	0.3935	0.3670	0.3591	0.3541	0.3674	0.3855
1.2558	1.2628	1.3988	0.6907	1.0975	1.4073	1.3376	0.5420	0.4735	0.4351	0.4181	0.3866	0.3498	0.3429	0.3371	0.3477	0.3647
1.2373	1.2437	1.4023	0.6552	1.0608	1.4238	1.3305	0.5187	0.4455	0.4151	0.3908	0.3556	0.3234	0.3078	0.3101	0.3131	0.3391

Columns 273 through 289

0.4060	0.4599	1.1493	1.0261	1.0231	1.4874	1.4316	1.3750	1.3326	1.3498	1.1160	0.6436	1.4359	1.4364	1.4414	1.3918	0.5967
0.3852	0.4523	1.0992	0.9620	1.1024	1.4419	1.3946	1.3552	1.3212	1.3372	1.1198	0.6264	1.4030	1.4009	1.4010	1.3622	0.5734
0.3575	0.4170	1.1458	0.9181	1.1285	1.4599	1.3968	1.3438	1.3050	1.3255	1.1323	0.5911	1.4001	1.4129	1.4126	1.3592	0.5493

Columns 290 through 301

0.8877	1.4052	1.3644	1.1735	0.4484	0.4413	0.4802	0.4254	0.4112	0.4050	0.3902	0.3778
0.9171	1.3793	1.3466	1.1642	0.4332	0.4228	0.4579	0.4104	0.3897	0.3898	0.3719	0.3569
0.9324	1.3756	1.3460	1.1399	0.4082	0.3981	0.4282	0.3880	0.3674	0.3723	0.3543	0.3337



test_outputs_DC_fault_L1_L2_L3 =

Columns 1 through 17

0.6511	0.6663	0.6800	0.6969	0.7062	0.7087	0.7317	0.7443	0.7689	0.7799	0.7953	0.7946	0.8148	0.8239	0.8267	0.8219	0.7771
0.6332	0.6476	0.6544	0.6743	0.6868	0.6892	0.7084	0.7204	0.7446	0.7592	0.7710	0.7735	0.7900	0.8020	0.7975	0.7954	0.7518
0.5670	0.5834	0.5885	0.6034	0.6110	0.6133	0.6284	0.6403	0.6558	0.6546	0.6647	0.6646	0.6772	0.6844	0.7072	0.7156	0.6760

Columns 18 through 34

0.7907	0.7741	0.7531	0.7662	0.7732	0.7475	0.7447	0.7469	0.7475	0.7323	0.7424	0.7302	0.6990	0.8192	0.8466	0.8497	0.8402
0.7588	0.7519	0.7248	0.7344	0.7443	0.7226	0.7227	0.7252	0.7226	0.7080	0.7177	0.7031	0.6792	0.7984	0.8128	0.8279	0.8156
0.6817	0.6780	0.6582	0.6682	0.6777	0.6577	0.6618	0.6599	0.6577	0.6411	0.6507	0.6322	0.6122	0.7308	0.7473	0.7652	0.7531

Columns 35 through 51

0.8530	0.9350	0.7766	0.9419	0.9546	0.9515	0.9489	0.9565	0.9422	0.7421	0.7274	0.7113	0.8019	0.9132	0.9650	0.9391	0.8876
0.8280	0.9011	0.7569	0.9110	0.9297	0.9178	0.9181	0.9257	0.9084	0.7226	0.7054	0.6936	0.7814	0.8819	0.9342	0.9106	0.8587
0.7679	0.8241	0.6913	0.8337	0.8407	0.8322	0.8364	0.8465	0.8293	0.6723	0.6533	0.6348	0.7180	0.8151	0.8662	0.8593	0.8149

Columns 52 through 68

0.9159	0.9071	0.9279	0.9423	0.9606	0.9671	0.9597	0.9545	0.9599	0.9761	0.9683	0.9737	0.9926	0.9671	0.9624	0.9692	0.9862
0.8839	0.8812	0.8961	0.9166	0.9322	0.9447	0.9371	0.9318	0.9344	0.9452	0.9400	0.9455	0.9652	0.9418	0.9341	0.9351	0.9556
0.8434	0.8375	0.8515	0.8759	0.8966	0.9085	0.9008	0.8932	0.8963	0.9124	0.9068	0.9167	0.9301	0.9016	0.8920	0.9026	0.9252

Columns 69 through 85

1.0024	0.9640	1.0585	1.0872	1.1078	1.0833	1.0930	1.0999	1.1061	1.0825	1.0723	1.0607	1.0624	1.0555	1.0497	1.0594	1.0624
0.9753	0.9298	1.0343	1.0678	1.0791	1.0582	1.0658	1.0789	1.0911	1.0600	1.0519	1.0452	1.0469	1.0339	1.0222	1.0354	1.0329
0.9404	0.8951	1.0016	1.0365	1.0507	1.0297	1.0353	1.0518	1.0610	1.0269	1.0164	1.0201	1.0153	0.9987	0.9943	1.0114	1.0073

Columns 86 through 102

1.0464	0.9023	0.9898	1.0147	1.0392	1.0401	1.0410	1.0443	1.0367	0.8249	0.8284	0.7618	0.7272	0.7102	0.7095	0.8396	0.9048
1.0215	0.8698	0.9534	0.9910	1.0139	1.0120	1.0130	1.0222	1.0169	0.7992	0.7993	0.7345	0.7078	0.6879	0.6906	0.8196	0.8845
0.9889	0.8419	0.9260	0.9602	0.9813	0.9841	0.9937	0.9957	0.9902	0.7625	0.7674	0.6956	0.6619	0.6469	0.6471	0.7889	0.8509

Columns 103 through 119

0.9033	0.7800	0.9658	0.7997	0.7618	0.7482	0.8035	0.7981	1.0721	1.0878	0.9760	0.8534	0.8542	1.0784	0.8830	0.8305	1.0598
0.8827	0.7492	0.9404	0.7717	0.7345	0.7248	0.7818	0.7694	1.0491	1.0687	0.9360	0.8270	0.8218	1.0587	0.8567	0.8016	1.0330
0.8577	0.7086	0.9110	0.7308	0.6956	0.6813	0.7379	0.7392	1.0313	1.0438	0.9131	0.7973	0.7907	1.0361	0.8212	0.7654	1.0093

Columns 120 through 136

1.0779	1.0719	1.1050	1.1316	1.1274	1.1001	1.0476	1.0394	1.0336	1.0433	1.0279	1.0032	0.9715	0.9388	0.9700	0.9621	0.9480
1.0608	1.0488	1.0846	1.1108	1.1035	1.0791	1.0229	1.0228	1.0081	1.0183	1.0078	0.9790	0.9462	0.9156	0.9416	0.9335	0.9160
1.0358	1.0289	1.0616	1.0893	1.0847	1.0542	1.0011	1.0021	0.9905	1.0008	0.9896	0.9546	0.9234	0.8918	0.9235	0.9109	0.8956

Columns 137 through 153

0.8932	0.8753	0.7773	0.8902	0.8771	0.8520	0.8589	0.8563	0.8457	0.8591	0.8626	0.8311	0.7821	0.7983	0.7950	0.7822	0.7084
0.8603	0.8453	0.7520	0.8603	0.8502	0.8251	0.8323	0.8326	0.8223	0.8324	0.8451	0.8019	0.7570	0.7721	0.7695	0.7570	0.6849
0.8408	0.8271	0.7236	0.8404	0.8296	0.8061	0.8070	0.8112	0.7964	0.8093	0.8210	0.7721	0.7242	0.7503	0.7390	0.7264	0.6570

Columns 154 through 170

0.7901	0.7812	0.7211	0.5830	0.0003	0.6087	0.0341	0.5235	0.5070	0.4936	0.5089	0.5126	0.0129	0.0104	0.0134	0.0133	0.0105
0.7645	0.7493	0.6676	0.5583	0.5389	0.5891	0.5417	0.5139	0.4908	0.4815	0.4961	0.4937	0.0140	0.0110	0.0114	0.0116	0.0109
0.7361	0.7238	-0.0007	0.0176	0.4991	0.5575	0.5070	0.4800	0.4602	0.4485	0.4652	0.4561	0.0104	0.0110	0.0138	0.0108	0.0140

Columns 171 through 187

0.0129	0.0104	0.0134	0.0104	0.0134	0.0104	0.0104	0.0130	0.0104	0.0129	0.0104	0.0133	0.0134	0.0105	0.0134	0.0104	0.0130
0.0140	0.0110	0.0114	0.0110	0.0114	0.0110	0.0110	0.0139	0.0110	0.0140	0.0110	0.0116	0.0114	0.0109	0.0114	0.0110	0.0139
0.0104	0.0110	0.0138	0.0110	0.0138	0.0110	0.0110	0.0134	0.0110	0.0104	0.0110	0.0108	0.0138	0.0140	0.0138	0.0110	0.0134

Columns 188 through 204

0.0104	0.0101	0.0133	0.0104	0.0133	0.0104	0.0130	0.0104	0.0133	1.3678	1.3628	1.3924	1.4220	1.4334	1.4465	1.4455	1.4144
0.0110	0.0133	0.0116	0.0110	0.0116	0.0110	0.0139	0.0110	0.0116	1.3422	1.3420	1.3705	1.3882	1.3947	1.4076	1.4012	1.3879
0.0110	0.0136	0.0108	0.0110	0.0108	0.0110	0.0134	0.0110	0.0108	1.3281	1.3281	1.3520	1.3810	1.3864	1.3974	1.3995	1.3812

Columns 205 through 221

1.4131	1.3687	1.3322	1.2672	1.3107	1.3270	1.3509	1.3796	1.3628	1.3716	1.3596	1.3709	1.2585	0.8134	0.7322	0.7119	0.7000
1.3817	1.3486	1.3189	1.2528	1.2960	1.3164	1.3327	1.3533	1.3440	1.3529	1.3355	1.3445	1.2387	0.7900	0.7045	0.6845	0.6803
1.3755	1.3334	1.3000	1.2427	1.2823	1.2974	1.3078	1.3411	1.3257	1.3335	1.3254	1.3357	1.2045	0.7722	0.6809	0.6634	0.6500

Columns 222 through 238

0.6030	0.5216	0.4382	0.3742	0.3099	0.2817	0.2803	0.2875	0.2843	0.2802	0.2523	0.2485	0.2544	0.2496	0.2344	0.2236	0.2110
0.5868	0.5079	0.4226	0.3598	0.2958	0.2484	0.2564	0.2671	0.2676	0.2567	0.2394	0.2427	0.2428	0.2348	0.2163	0.1919	0.1923
0.5572	0.4813	0.4027	0.3390	0.2745	0.2243	0.2356	0.2440	0.2385	0.2300	0.2015	0.1956	0.1898	0.1811	0.1607	0.1466	0.1404

Columns 239 through 255

0.2177	0.2209	0.2306	0.2358	0.2465	0.2598	0.2780	0.2849	0.2784	0.3348	0.3639	0.4081	0.6704	0.4866	0.5076	0.5171	0.5299
0.1918	0.1916	0.2073	0.2125	0.2227	0.2333	0.2514	0.2647	0.2841	0.2939	0.3492	0.3900	0.6589	0.4707	0.4880	0.5007	0.5128
0.1526	0.1556	0.1758	0.1816	0.1988	0.2045	0.2243	0.2384	0.2582	0.2767	0.2978	0.3675	0.6220	0.4429	0.4576	0.4698	0.4839

Columns 256 through 272

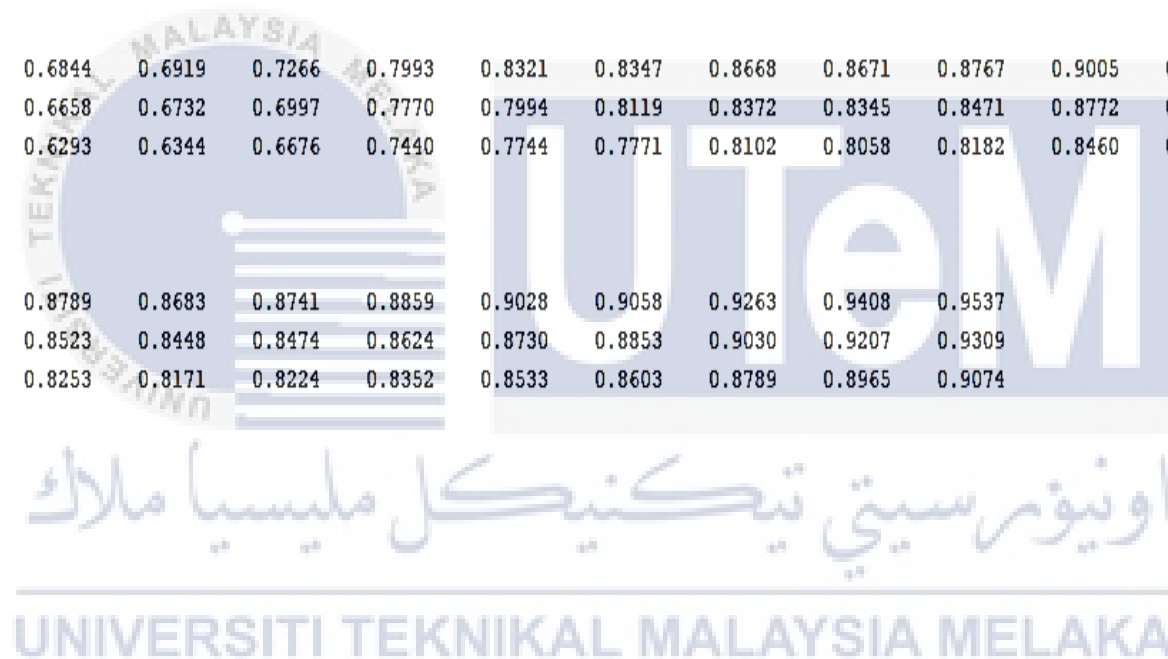
0.5476	0.5527	0.5571	0.5730	0.5907	0.6028	0.6180	0.6420	0.6637	0.6630	0.6702	0.6719	0.6645	0.6696	0.6880	0.6933	0.6791
0.5305	0.5357	0.5438	0.5558	0.5731	0.5879	0.6028	0.6328	0.6466	0.6495	0.6458	0.6513	0.6436	0.6484	0.6629	0.6676	0.6611
0.4965	0.4992	0.5023	0.5141	0.5287	0.5450	0.5572	0.5835	0.6019	0.6022	0.6061	0.6067	0.6037	0.6105	0.6250	0.6339	0.6203

Columns 273 through 289

0.6601	0.6301	0.6582	0.6844	0.6919	0.7266	0.7993	0.8321	0.8347	0.8668	0.8671	0.8767	0.9005	0.9051	0.8925	0.8733	0.8792
0.6359	0.6174	0.6440	0.6658	0.6732	0.6997	0.7770	0.7994	0.8119	0.8372	0.8345	0.8471	0.8772	0.8725	0.8598	0.8498	0.8496
0.5986	0.5755	0.6056	0.6293	0.6344	0.6676	0.7440	0.7744	0.7771	0.8102	0.8058	0.8182	0.8460	0.8468	0.8339	0.8223	0.8208

Columns 290 through 301

0.8432	0.8526	0.8673	0.8789	0.8683	0.8741	0.8859	0.9028	0.9058	0.9263	0.9408	0.9537
0.8170	0.8295	0.8470	0.8523	0.8448	0.8474	0.8624	0.8730	0.8853	0.9030	0.9207	0.9309
0.7871	0.7972	0.8147	0.8253	0.8171	0.8224	0.8352	0.8533	0.8603	0.8789	0.8965	0.9074



APPENDIX D KEY MILESTONE OF PROJECT

Key milestone	
Project Progress	Duration
Collect all of Journal and Literature Review	September 2018
Research background	October 2018
Write progress report draft	October 2018
Collect the initial data	November 2018
Do an analysis for data collected	November 2018
First seminar PSM 2018/2019	November 2018
Submit report	December 2018
Develop simulation using MATLAB	January 2019
Analysis the result	April 2019
Write the report	April 2019
Final seminar	May 2019
Submit report	May 2019
Hard cover and CD	June 2019

