"I hereby declare that I have read through this report entitle "*A DNR and DGs Sizing concurrently by using combination of SOM and Evolutionary Programming*" and found that it has comply the partial fulfillment for awarding the degree of *Bachelor of Electrical Engineering (Industrial Power)*"

Signature :..

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Date :..

A DNR AND DGs SIZING CONCURRENTLY BY USING COMBINATION OF SOM AND EVOLUTIONARY PROGRAMMING

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A report submitted in partial fulfillment of the requirements for the degree of Bachelor of Electrical Engineering (Industrial Power)

Faculty of Electrical Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2015

I declare that this report entitle "*A DNR and DGs Sizing Concurrently by using combination of SOM and Evolutionary Programming*" is the result of my own research except as cited in the references. The report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature :...

Name :...

Date :...

To my beloved mother and father

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ABSTRACT

The improvement of the energy performance that means the reduction of energy loss is one of the important parts that must be developed. The installing of the Distributed Generation (DG) in distribution system can improve the voltage profile and the power loss reduction but the DG must be installed at suitable position or bus in the network system. The objectives of this study are to identify the suitable of DGs position, minimizing the power losses and determine the suitable size of DGs that can be installed to the system. In this work, 2 methods are combined; *Self-Organizing Maps (SOM)* for DGs positioning and implementation of *Evolutionary Programming (EP)* as an optimization method for determining of power loss and DGs sizing. The combination of these methods is applied to the IEEE 33-bus and 69-bus standard system. To determine the validity of the results, the combinations of SOM and EP for both systems are compared with the original configuration system, and reconfiguration using EP with random position of DGs in the systems respectively. The SOM and EP programming has been simulated in MATLAB environment. The combination of SOM-EP is suitable to apply in 33kV system which achieves the objectives of the study. However, the combination of SOM-EP is not suitable for 69 kV system because power losses reduction is not globally solve.

ABSTRAK

Penambahbaikan prestasi tenaga yang bermaksud pengurangan kehilangan tenaga ialah salah satu bahagian yang penting yang perlu dibangunkan. Pemasangan *Distributed Generation* (DG) dalam sistem pengagihan boleh meningkatkan Profil Voltan (VPI) dan Pengurangan Kehilangan Kuasa (PLR) tetapi DG perlu dipasang di tempat atau bas yang sesuai didalam sistem rangkaian. Objektif kajian ini ialah untuk mengenalpasti kedudukan yang sesuai bagi DG, meminimumkan kehilangan kuasa, dan menentukan saiz yang sesuai bagi DG yang akan dipasang kedalam sistem. Dalam kajian ini, 2 teknik telah digabungkan; *Self-Organizing Map (SOM)* bagi menentukan kedudukan DG, dan perlaksanaan *Evolutionary Programming (EP)* sebagai kaedah pengoptimum untuk pengenalpastian kehilangan kuasa dan saiz DG. Gabungan kaedah ini digunakan kepada standard IEEE 33 sistem bas dan 69 sistem bas. Untuk menentukan kesahihan keputusan, gabungan antara SOM dan EP bagi kedua-dua sistem dibandingkan dengan konfigurasi sistem asal dan konfigurasi menggunakan EP dengan kedudukan rawak bagi DG di dalam sistem masing-masing. Pengaturcaraan SOM dan EP telah disimulasi dalam persekitaran MATLAB. Gabungan SOM-EP sesuai digunakan dalam sistem 33kV yang telah mencapai objektif kajian. Walau bagaimanapun, gabungan SOM-EP tidak sesuai bagi sistem 69kV kerana tidak menyelesaikan pengurangan kehilangan kuasa.

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CHAPTER 1

INTRODUCTION

1.1. Motivation

Nowadays, the improvement of the electrical power system is one of the big aspects that must be considered. The technology, the power utility, and the green technology are the examples of issue that must be improved. The electrical power consists of many process. Start from the generation, transmission, distribution, until to the consumer. The power system will ensure that the light can continue light up. The power engineer must be ensure that the supplied power must be enough with the demand. Power quality is important thing that the engineer should be faced. The improvement of the energy performance that means the reduction of energy loss is one of the important parts that must be developed. The distribution of electrical power system is the last stage of power system before it will arrive to the consumer. To ensure the consumer can get enough power, the distribution network must have low power loss. To reconfigure the distribution network, the technique of reconfiguration also must be improved and use the proper method to get the best configuration of network.

1.2. Problem Statement

Increasing the area of industry, urban, and resident cause the increasing the demand of electricity. The increasing the demand of electricity became the challenging task to the power engineer which must ensure that the electrical power can be supplied consistently. Starting from the generation until to the distribution, the engineer should be alert to any problem that can cause the reduction of electrical power. The configuration of distribution network is one part that must be alert because lots of the power losses occur at distribution network. The switching status at the network can affect the losses value. The installing of the Distributed Generation (DG) also can improve the voltage profile and power loss reduction but the DG must be installed to the suitable position or bus at the network in order to improve the efficiency of distribution network. The requirement of network reconfiguration technique become the main issue to get the best switching status of network and ensure that the network in radial form. The network reconfiguration also must be considered to the time of switching configuration. The previous research state that the reconfiguration of switching status elements is complex combinatorial because the reconfiguration of network consist a lot of switching element. The technique of reconfiguration or usually knows the reconfiguration algorithm must be achieve the aim of the reconfiguration by including the suitable size of DG.

1.3. Objective

The main objectives of this research are:

i. To identify the suitable position of DG in the distribution network based on the bus characteristics.
ii. To minimize the power losses in the distribution network.
iii. To analyse the suitable size of DGs in the network system.

1.4. Scope

This research are to identify the suitable position of DGs inside the network system by using SOM technique and for minimizing power losses and determine the suitable size of DGs by using the implementation of Evolutionary Programming. The distribution network system is in radial form and the data system use the standard IEEE 33- and 69-bus systems.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

These parts are divided into four sections which are Distribution Network Reconfiguration (DNR), Distributed Generation (DG), Self-Organizing Maps (SOM), and Evolutionary Programming (EP). For the Distribution Network Reconfiguration, the research about the distribution system will be presented in this chapter to explain more about the distribution network system, the purpose of DNR, and the reconfiguration process. For the Distributed Generation (DG), there will be explain about the advantage to the network, the impact to the distribution network, and the characteristic of the bus that has been installed with DG. The SOM also will be used during this project. This part will explain about the SOM, the function of SOM, and the operation of SOM. And the last part is about the Evolutionary Programming. That will explain about the EP, the function of EP, the different of EP with another algorithm, and the benefit of EP to the system.

2.2 Distribution Network Reconfiguration (DNR)

The energy distribution utilities around the world are confronting the required of more efficient networks, because of the awareness from the public, so the management of the network becomes more common in the world.

The distribution is one of the important parts that will link the consumer with the transmission systems. The network reconfiguration is one of the tasks that must be face for the power engineer. The authors in [1] have explain that the distribution network reconfiguration is the changing the structure of distribution feeders by modifies changing the open/close status of the sectionalizing (normally closed) and tie (normally open) switches. This paper also state that the loss reduction in network reconfiguration is highly complex combinatorial, non-differentiable and constrained nonlinear mixed integer optimization problem, due to high number of switch elements in the network. The ROREDN tells about the optimization problems which is the modification of distribution feeders‟ structure by changing the status of open/closed switches [2]. The contributions of ROREDN are increasing the network efficiency and improve the system quality in term of power loss reduction, increasing reliability, energy restoration, voltage stability, and load balancing.

The paper [3] state that the network reconfiguration is the process of altering the topology of distribution feeders‟ structure by changing the open/closed status of its sectionalizing and tie switches with the aim to get the minimal losses topology. The authors in [4] state that the reconfiguration is not only to reduce the power losses, but also to relieve the overloading of the network components. This paper also state that the network reconfiguration is a complicated combinatorial, non-differentiable and optimization problems owing constrain to the enormous number or candidates switching combinations in the system. The objectives of the reconfiguration also stated at this paper which are the minimizations of system‟s power loss, the voltage and current constraints violation, and the switching number. In [5] state that the network reconfiguration is the varying process the topological arrangement of distribution feeders by changing the open/closed status of sectionalizing and tie switching. The reconfiguration is used for system loss reduction, load balancing, and enhances voltage fluctuation in distribution network.

The purpose of DNR is to find the operating structure in radial for minimizing the power loss. The [6] state that the distribution automation is the address for reconfiguration of radial distribution networks by the aim of achieving minimum losses operation. This paper state the reconfiguration solution strategy for minimum losses is divided into two different parts; dealing with the closing phase which is given in charge to neutral network, and controlling the opening phase which is based on deterministic algorithms, which locally checks the existence of a mesh in the current network configuration. In paper [7] state that the reconfiguration of network is to maintain the radial topology and to reduce the power losses at the feeders, to enhance the voltage profile for customers, and to increase the reliability levels. To solve the optimal of reconfiguration problems should consider the proper modeling of distribution networks elements and the electrical loads. The algorithms to handle the configuration changes in the network topology in a timely manner, the load-flow calculations, the composition of the objective functions and constraints. The optimization and the decision-making technique used to define the idea electrical configuration. In reconfiguration, the elements that‟s should be consider is the radial topology, the voltage limits, and the current profile constraint.

The most of distribution network operate radially, even though there are some interconnecting tie lines available to increase the system reliability. The tie lines will make the network to accommodate to the variation of load to achieve reduction of line losses [8]. The [9] state that the importance of smart reconfiguration for the operating conditions of such radial networks. The radial reconfiguration of the network is a viable option for ensuring optimal or nearly optimal operation in the presence of several constraints and the demand of variable power. The authors in [10] state that to minimize the energy losses is the radial reconfiguration of the electrical distribution systems based on the bio-inspired meta-heuristic Artificial Immune System. The process can be applied to determine the radial and connected network topology that minimizes the energy losses ad meets operational constraints. The apart of quality issues such as maintaining the node voltages within permissible limits and the feeder power losses minimization by appropriate selection of the network reconfiguration. The configuration in radial explored having better node voltage profile, the less of feeder power losses, and betters the reliability indices. The feeder power loss and the node voltage deviation are the important quality of power objectives that must be included in the distribution network reconfiguration [11].

For the [12] state that have 2 variations of network reconfiguration problems. First of the problem is the given of the input of distribution network with some initial state, by considering the loss at a single branch. If there are buses downstream of the faulty branch, the new switch state will be finding by lowest number of switch change operations and can bring back the power to those affected buses. The second of reconfiguration problem is like at the first problem, which finds the new switches state and the set of transformer tap-changer adjustments, so the power can bring back to the affected buses. The aim of both problems are same, which is the minimization of buses without power and with limits the voltage outside operational.

2.3 Distributed Generation (DG)

Nowadays, the Distributed Generation (DG) has been utilized to the electrical network. Paper [13] state that the some of the DG"s advantages to the network are power loss reduction, environmental friendly, improvement of voltage, postponement of system upgrading, and the increasing the reliability. Some of the optimize tool have been modified to enhance their performance in solution or to overcome the limitation of the tool. This paper state that one advantage of deploying a DG-units is to minimize the total system of real power loss, while satisfying certain of operating constraints.

The DG should properly plan and operated to provide benefits to the distribution network. Otherwise, it can cause degradation of power quality, reliability, and the power system control. So, the main goals of proposed planning algorithm are to find the best locations for the new DG and the optimal size that will be installed to the network. The minimizing different function is related to the cost of energy losses. That is the statement from [14]. The authors in [15] state that the amount of distributed-generation resources (DGRs) and consider the reactive-power sources (RPSs) in the selected buses are determine by taking account of the outputs, with different load levels, tap positions of voltage regulators (VRs) and the status of sectionalizing switches, in order to achieve the aim to minimize the power cost, energy losses, and the total required reactive power. The condition of the operating system and the characteristic of DG will give the impacts to the system performance. To minimize the cost of power and energy losses and the total required reactive power, the amount of DGRs and RPSs in selected buses should be compute to make up the given total of distribution generation.

The [16] state that the DG can reduce the capital cost for the system by deferring the distribution facilities. The function of DG are to reduces the power flow of the system, improve the voltage profile, minimizing the system losses, relieving the heavy loaded feeders, and can extend the lifetime of the equipment. The [17] propose the switch placement schemes to improve the system reliability for radial distribution systems with Distributed Generation (DG) under the fault conditions. The system"s operating condition, DGs characteristics and location will give the impact to distribution systems either positive or negative impact. This paper present that the positive impact includes the improvement of system reliability, loss reduction, deferment of new generation, and improvement of power quality. To get the benefits, DG must be reliable, dispatchable, of appropriate size, and at suitable location.

The [18] state that the increasing the penetration of DGs in distribution systems, the siting and sizing of DGs in the planning of distribution system becoming increasingly important. The inappropriate siting and sizing of DGs could lead to much negative effect such as the configuration of the relay system, the voltage profiles, and the losses in the network. The objectives of DG optimal location in radial are to minimize the network loss and to improve the voltage in distribution systems. To determine the optimal locations and sizes of DGs, three indices including the losses, voltage profile, and the short-circuit level are used.

The [19] state that the diffusion of DG into the network could be beneficial to improve the operation of network, but the excessive amount of DG in operation can cause the violations of the system constrains. This paper state that the weighted sum of individual objectives is formulated by considering the investment, the operation and reliability costs, the voltage profile improvement and loss reduction, DG cost and power losses, voltage profile and the voltage stability.

The [20] state that the main factors associated with the multiple DG sizing and placement procedure is scrutinized through a multi-objective optimization approach. The factors include the voltage stability, the power losses and the network voltage variations. To solve the multi-objective optimization problems, the Pareto Frontier Differential Evolution (PFDE) algorithm is presented. This paper state that the advantages of installing DGs of an existing system are postponing the upgrade of an existing systems, peak shaving, power loss reduction, low maintenance cost, high reliability, power quality improvement, the possibility to exploit CHP generation, meet the increasing demand without requirement of extravagant investment, and the shorter construction schedules.

The [21] state that the distributed generation is generally operated at a constant, pre-set, power factor and there is a need to preserve the power factor during optimization. The [22] state that the objective functions of the tailored OPF by giving the installed capacity of DG is to minimize the total reactive power (VARh) which provided by the grid to the distribution network. The distributed generation plants typically operate at constant power factor which present the most benefit to the active power production.

A propose of multi-objective methodology for optimal distributed generation allocation and the sizing for distribution systems. The objective function consider to the minimizing of cost for active and reactive losses, and to improve the voltage profile and reliability of the distribution systems. This statement was state in [23]. The [24] state that technical advantage cover wide varieties of benefits, such as line loss reduction, peak shaving, improvement of system voltage profile and hence increased the power quality an relieved transmission and distribution congestion as well as grid reinforcement. To obtain the best objective, the optimal DG size and bus location must be determined. The multi-objective optimization covers optimization of both cost and loss simultaneously.

2.4 Self-Organizing Maps (SOM)

SOM is one type of artificial neural network (ANNs) which the methodology was introduced by Kohonen in 1989. This mathematical model is designed based on the human‟s brains. The [25] state that the purpose of SOM is to transform the incoming input patterns into a one or two dimensional discrete map. All nodes are forced to be self-organized through the feedback path and that‟s why the system is called Self Organizing Maps (SOM).

The [26] state that the principal goal of SOM is to transform the patterns of arbitrary dimensionality into the responses of one- or two-dimensional arrays of neurons and to perform the transform adaptively in a topological ordered fashion.

2.5 Previous Techniques Review (Evolutionary Programming)

An evolutionary programming (EP) is a based technique to present the optimal placement of distributed generation (DG0 units which energized by the renewable resource such as wind and solar in a radial distributed generation. This statement was state by [27]

The evolutionary programming (EP) is an optimization algorithm based on the simulated evolution which is mutation, competition and the selection. Paper [28] state that the highly-nonlinear dynamic problem is an efficient evolutionary programming algorithm to solve the generation expansion planning (GEP) problem. Paper [29] state that the evolution is the process of biological optimization by including the mutation, competition and the selection. This paper states that the evolution is the result of the fundamental stochastic process which interacts in population from the generation to generation.

The improvement of evolutionary programming (EP) method is to solve the problems of reactive power optimization. The [30] state that the method with dynamic mutation and the metropolis selection is used to solve the multi-objective reactive power optimization with presented the deregulation environment. This multi-objective function includes the minimization the losses of the network, the voltage deviation, and the compensation cost.

The [31] state that the improvement of EP and its hybrid version combined with the non-linear interior point (IP) technique is to solve the optimal reactive power dispatch (ORPD) problems. This paper state the objective of ORPD is to achieve the adequate voltage profile with satisfies the operational constrains and minimizes the active losses.

As the branch of EA, to generate the new individuals, the EP uses only the mutation operator. The [32] state that the mutation has greater exploratory power than crossover and the EP is less likely to fall into the local minima. The [33] state that the EP only uses the mutation operator toreproduce offspring populations. It has been proving to get the better global search ability than other EA even though the converging is very slow.

The other function use of Evolutionary Algorithms (EP) is to determine the location of distributed generation (DG). The [34] state that the main aim the proposed algorithm is to determine the best location of generators with their optimal size by minimizes the different functions.

The Evolutionary Programming uses as the primarily on mutation operators to get the solutions of function optimization problems (FOPs). The EP is the important category of Evolutionary Algorithms (EAs). This statement was state at the [35] paper. The [36] present that the self-adaptive evolutionary programming (SAEP) is used to solve the non-linear and discrete optimization problem. This paper also states the SAEP was developed based on the stochastic mechanism and evolutionary process. The EP technique is a stochastic optimization method in the area of evolutionary computation. This statement was state by [37]. This technique uses the mechanics of evolution to produce the optimal solution to a given problems. This technique works by evolving the population of candidate solutions toward the global minimum through the use of a mutation operator and selection scheme.

The [38] state that the EA including the EP is the artificial intelligence which is the methods for optimization based on the natural selection mechanics, such as mutation, recombination, reproduction, selection, and etc. For the statement from [39], the genetic merit and the evolutionary algorithm is the possibility of applying them through a very large number of decision variables and complex description of function objective and limiting conditions. The evolutionary algorithms differ from the genetic algorithms based on the variety of data coding methods and the use of genetic operators fitted for a specified problem. The aim is to find the optimum, or very close to the optimum solution.

The [40] state that the optimal power flow (OPF) is a static, nonlinear optimization problem by calculate a set of optimum variables from the network state, the load data and the parameter of the system.

The evolutionary programming (EP) technique is a method to identify the optimal switching plan for feeder reconfiguration. The [41] state that to solve the optimization problems of distribution feeder reconfiguration, each switch combination must be encoded by a chromosome. The length of chromosome is equal with the number of load zones of power distribution system. The position of each gene in a chromosome represents the zone id and the content of each gene in a chromosome represents the source zone of the gene.

2.6 Summary

In this chapter, the background of the project and the related information from previous work for distribution network reconfiguration analysis, distributed generation, the SOM, and the EP has been discussed. There are many topics of implementation of EP to the DNR in the previous works. Nevertheless, the implementation of combination of SOM and EP algorithm in order to solve the power losses and DGs sizing in the DNR is not yet done by others. Meanwhile the important of this study is the combination and implementation of SOM and EP algorithm as to achieve the objectives as explained in the previous chapter.

CHAPTER 3

METHODOLOGY

3.1. Overview

In this part, the process of power losses, SOM, and EP are explained in detail. It consists of three parts. Part 1 is the mathematical formulation and the process of power losses analysis. The Part 2 will explain the process of SOM and how to analyse the result from the SOM and the Part 3 will explain the implementation method of EP based on the flow chart.

3.2. Part 1: Mathematical Formulation

The objective of the Distribution Network Reconfiguration is to minimize the power losses in the distribution network. The analysis of power losses is based on the Newton-Raphson method.

Step 1: Forming of Y_{bus}.

Step 2: The initial values of bus voltages $|\mathbf{V}_i|^0$ and the phase angles δ_i^0 for i=2, 3,…, n for load buses and phase angles for PV buses assumed as $|\mathbf{V_1}| = 1.0$, and $\delta_1 = 0^o$.

Step 3: The calculation of P_i and Q_i for each bus based on the following equations:

$$P_i = \sum_{k=1}^{n} V_i V_k Y_{ik} \cos(\delta_i - \delta_k - \theta_{ik}) \qquad (3.1)$$

$$Q_i = \sum_{k=1}^{n} V_i V_k Y_{ik} \cos(\delta_i - \delta_k - \theta_{ik}) \qquad (3.2)$$

Step 4: The scheduled errors ΔP_i and ΔQ_i for each load bus calculate based on the following relations; (sp=scheduled value, cal=calculated value)

$$\Delta P_i^{(r)} = P_{i_{sp}} - P_{i_{(cal)}}^{(r)} \quad i = 2, 3, \dots, n \qquad (3.3)$$

$$\Delta Q_i^{(r)} = Q_{i_{sp}} - Q_{i_{(cal)}}^{(r)} \quad i = 2, 3, \dots, n \qquad (3.4)$$

Step 5: The elements of the Jacobian matrix (***J1*, *J2*, *J3*,** and ***J4*)** are calculate based on following equations:

The diagonal and the off-diagonal elements of $\boldsymbol{J_1}$ are:

$$\frac{\partial P_i}{\partial \delta_i} = \sum_{j \neq i} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \qquad (3.5)$$

$$\frac{\partial P_i}{\partial \delta_j} = -|V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \ ; \ j \neq i \qquad (3.6)$$

The diagonal and the off-diagonal elements of $\boldsymbol{J_2}$ are:

$$\frac{\partial P_i}{\partial |V_i|} = 2|V_i||Y_{ii}| \cos\theta_{ii} + \sum_{j \neq i} |V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \qquad (3.7)$$

$$\frac{\partial P_i}{\partial |V_j|} = |V_i||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \ ; \ j \neq i \qquad (3.8)$$

The diagonal and the off-diagonal elements of $\boldsymbol{J_3}$ are:

$$\frac{\partial Q_i}{\partial \delta_i} = \sum_{j \neq i} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \qquad (3.9)$$

$$\frac{\partial Q_i}{\partial \delta_j} = -|V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \ ; \ j \neq i \qquad (3.10)$$

The diagonal and the off-diagonal elements of $\boldsymbol{J_4}$ are:

$$\frac{\partial Q_i}{\partial |V_i|} = -2|V_i||Y_{ii}| \sin\theta_{ii} + \sum_{j \neq i} |V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \qquad (3.11)$$

$$\frac{\partial Q_i}{\partial |V_j|} = -|V_i||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \ ; \ j \neq i \qquad (3.12)$$

Step 6: The linear simultaneous equation is solve directly by ordered triangular factorization and Gaussian elimination.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} \boldsymbol{J_1} & \boldsymbol{J_2} \\ \boldsymbol{J_3} & \boldsymbol{J_4} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta|\boldsymbol{V}| \end{bmatrix} \qquad (3.13)$$

Step 7: The new voltage magnitudes and phase angles are calculate by using these equations

$$\delta_i^{(k+1)} = \delta_i^{(k)} + \Delta\delta_i^{(k)} \tag{3.14}$$

$$\left|V_i^{(k+1)}\right| = \left|V_i^{(k)}\right| + \Delta\left|V_i^{(k)}\right| \tag{3.15}$$

Step 8: The process is continued until the residuals $\Delta P_i^{(k)}$ and $\Delta Q_i^{(k)}$ are less than the specified accuracy

$$\left|\Delta P_i^{(k)}\right| \leq \varepsilon \tag{3.16}$$

$$\left|\Delta Q_i^{(k)}\right| \leq \varepsilon \tag{3.17}$$

The process of power losses calculation is shown by using the flow chart below (Figure 3.1).

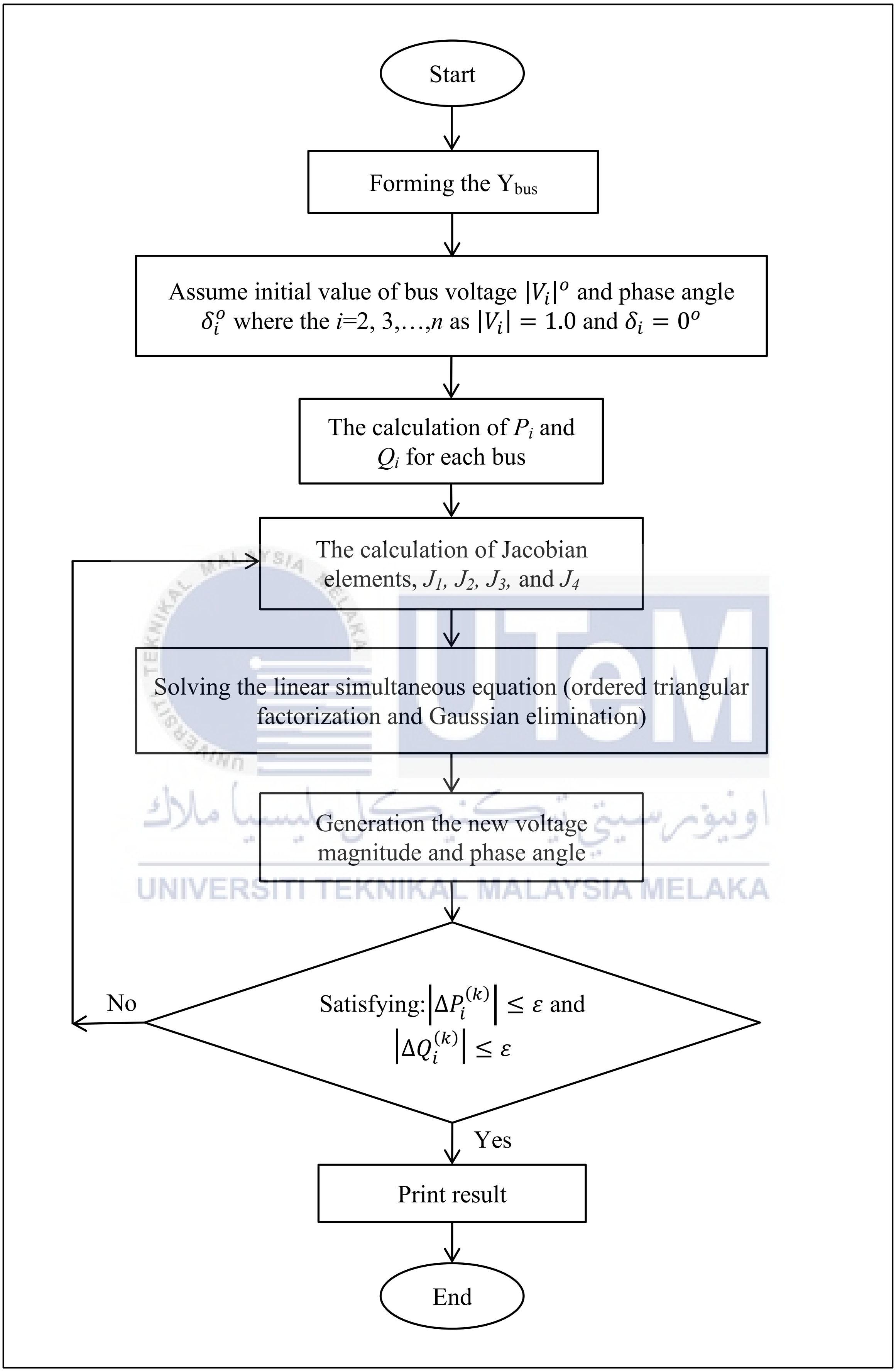


Figure 3.1: The flow chart of power losses calculation

3.3. Part 2: Implementation of Self-Organizing Maps (SOM)

The objective of using Self-Organizing Maps (SOM) is to determine the best position to install the DG inside the network based on the bus characteristics. The SOM method was simplified by the SOM Toolbox which includes the creation, visualization, and analysis of SOM. The SOM Toolbox will use a Matlab as the computing environment. The steps of SOM operation are as following below.

Step 1: The data that will be used at the SOM are exported from the data file. The bus data which will use is the standard of IEEE 33-bus and 69-bus data. The data include the active and reactive power, the line data, and other related data for this analysis.

Step 2: The data structure must be normalize. The normalizing of variables is one of the important parts to perform the data structure. The normalization information is copied to the map structure during the trained of SOM. The normalization method should be set which the method consists of five implemented method.

Step 3: The SOM should be creates, initializes and trains based on the given data by using default parameters. The "som_make" is the basic function to use during the creating and training the SOM. The number of neurons will be set at this part.

Step 4: The given data structure should be label automatically based on already labeled data. The labels from one data or map structure will be transferred to another data or map structures.

Step 5: One of the important parts in SOM is the visualization. The component planes, U-matrices must be show as well as empty planes and fixed-colour planes. One of the groups of visualization functions at SOM Toolbox is high-level tools for making cell-style visualizations.

Step 6: The figure that created by "som_show" must be added the hits, labels, and trajectories. The kind of markers to add will define at the first arguments and the second arguments gives the markers or their places. The further modify the markers such as the colour, size and type is defined from the optional arguments.

Step 7: The number of "hits" for each map units must be calculates such as the data histogram.

Step 8: The further modify marks by the modes of „hits“ which to display the hit histograms.

Step 9: The final step of SOM is display the result by using U-matrices. The components planes, U-matrices should be shown as the result of process. The analysis result of SOM based on the U-matrix which will produce from this part.

The flow chart of SOM programming process is shown as figure below (Figure 3.2).

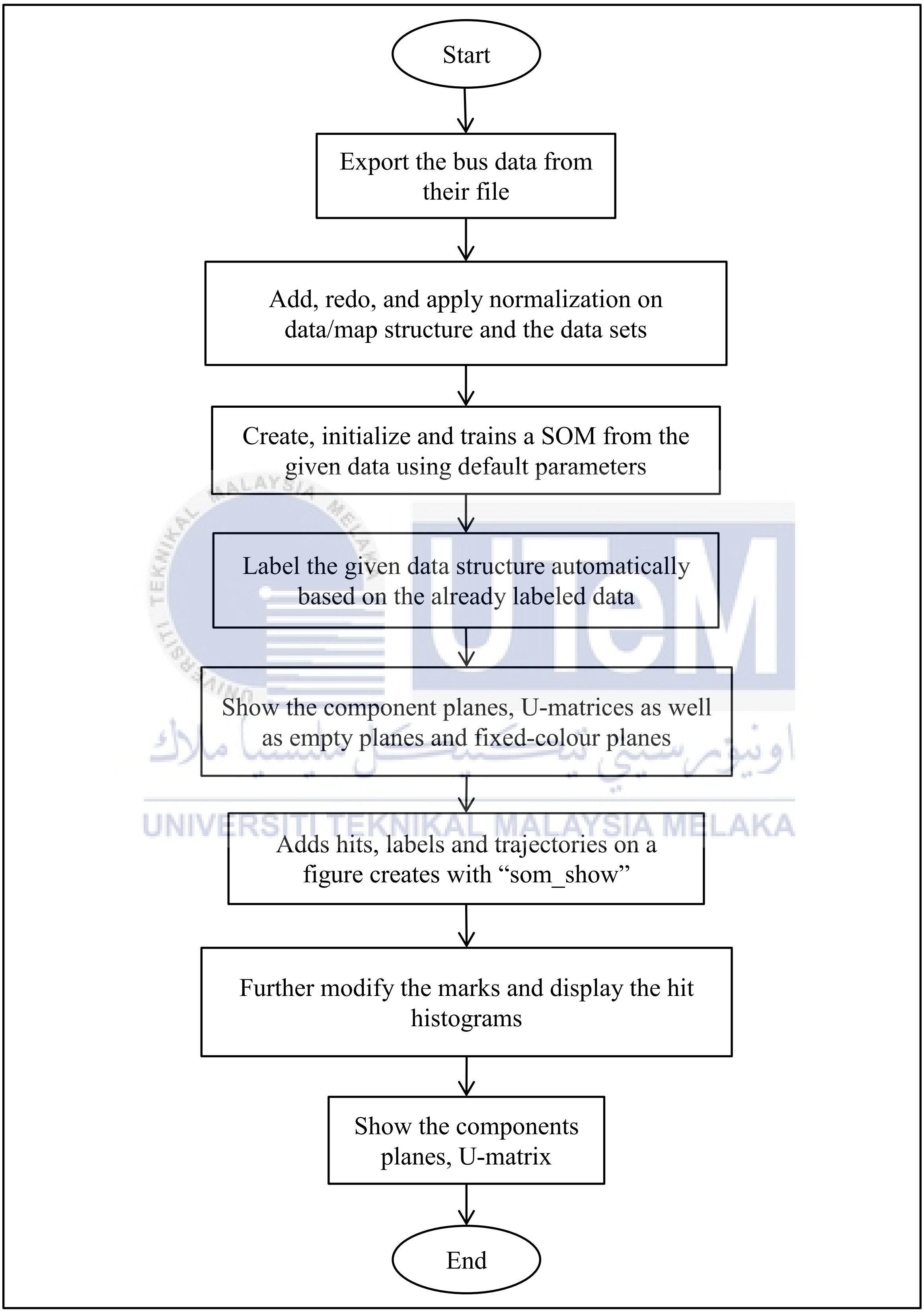


Figure 3.2: The flow chart of Self-Organizing Maps (SOM)

The previous process is the process of SOM programming inside the MATLAB. The analysis process of Self-Organizing Maps (SOM) is defined as below.

Step 1: The data that will be used at the SOM are exported from the data file. The standard of of IEEE 33-bus and 69-bus data will use for SOM process. The data include the active power (MW), reactive power (MVAR), apparent power (MVA), and the power factor.

Step 2: The topology type which use in the process is „hexagonal‟. The „hexagonal‟ topology type will form the hexagonal structure map between the neurons in U-matrix

Step 3: The normalization method is set for the SOM process. The normalization method consist of four methods; *var, range, log,* and *logistics*. Each methods have their characteristics to process the input data.

Step 4: Number of neurons is one of the important part for SOM training. The number of neurons will set start from 120 to 400 by the increament is 20.

Step 5: Run the SOM.

Step 6: After finish the training, the SOM will show the final training time, Topoghraphic error, and Quantization error. This data will be used in SOM analysis which to determine the best number of neurons and the normalization method. The training time, Topographic error, and the Quantization error should be recorded.

Step 7: The SOM will generate the U-matrix and Plane Representation. This is the result of SOM process. The SOM analysis will be analyze based on the U-matrix and Plane Representation.

After finish all the steps above, the process will be repeated by changing the number of neurons (120 to 400 by the increament is 20). After finish the number of neurons, the SOM process will repeated by using a different normalization method (*var, range, log* and *logistics*). The flow char of SOM analyze process is shown as figure below (Figure 3.3)

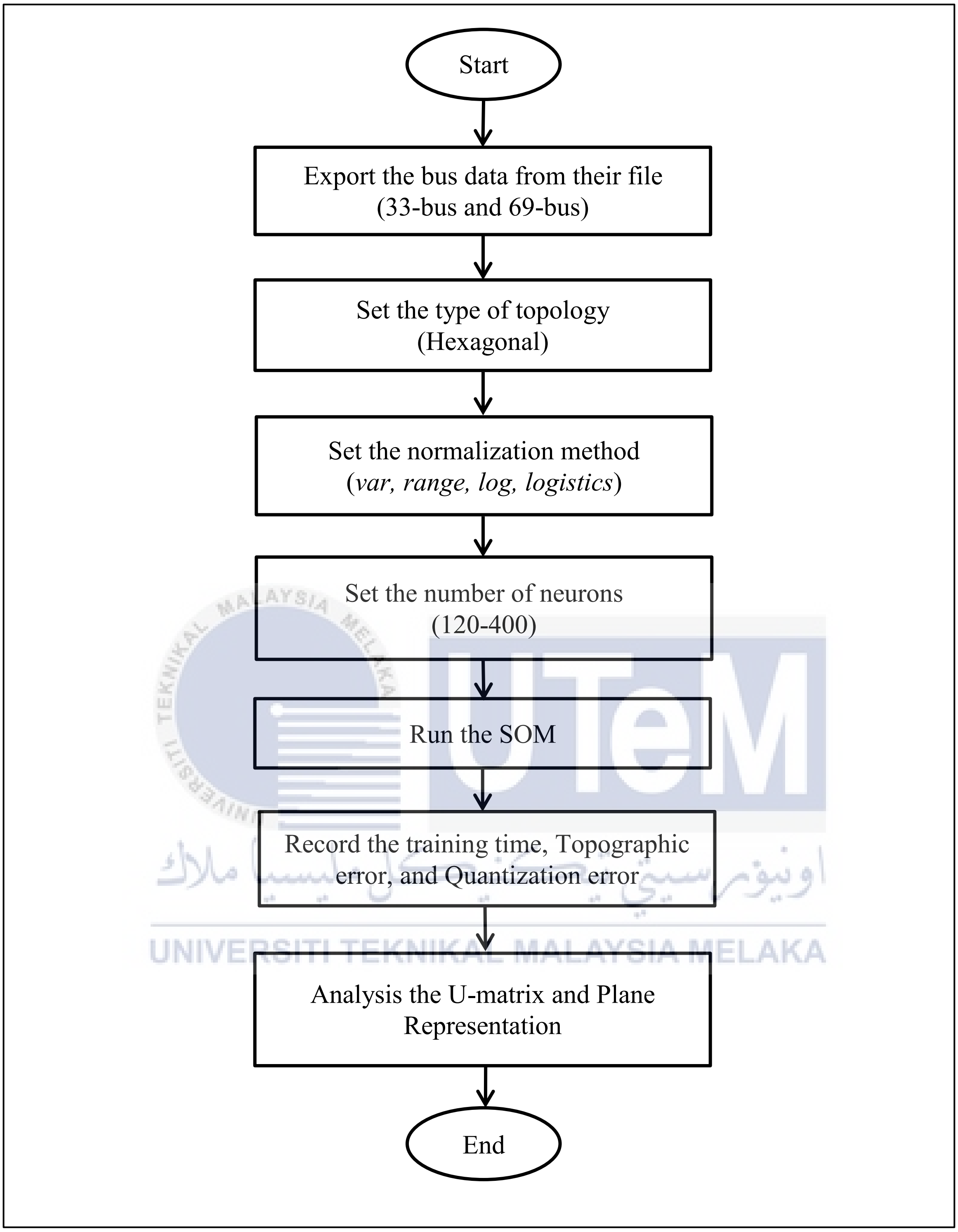


Figure 3.3: The flow chart of Self-Organizing Maps (SOM) analyze process

3.4. Part 3: Implementation of Evolutionary Programming (EP)

The Evolutionary programming is one of the Evolutionary Algorithm (EA) which to determine the optimization inside the distribution power system. The EP consists of five methods during to achieve the objectives to optimize the system and to minimize the power system losses. The EP consists of initialization, statistics, mutation, competition, and convergence [38].

For this project, the process of EP will include the DG with their position inside the network. The position of DG was determined from the SOM analysis (Part 2). The EP will determine the status of open/closed switch of network to get the minimum losses and to determine the suitable size of DG which will inject to network. The steps of EP are as following below.

Step 1: The original bus data and the number of UPFC will export to the programming. The UPFC stand for Unified Power Flow Controller which is the basic power system parameters such as transmission voltage, impedance and phase angle. All the data are very important because the data are the characteristics of the bus and the network. The bus data is the standard of IEEE 33-bus and 69-bus data.

Step 2: From the data that was collected, the initial population will be generated. The initial population is the first configuration of the network and will be as a reference.

Step 3: The network must include the DGs because the objective of DNR is include the DG. The DGs must be including to the network based on their position which was determine from SOM analysis. The aim to determine the size of DGs is to improve the losses inside the network.

Step 4: The one of important part in EP is the power flow calculation. This calculation will determine the losses based on the bus data. The calculation process was present at Part 1.

Step 5: The next process after the power flow calculation is getting the new population of the random numbers. The Gaussian mutation method will be used to generate the new population.

$$X_i = X_{ij} + N(0, \sigma^2) \tag{3.18}$$

$$\sigma^2 = \beta\left(X_{j_{max}} - X_{j_{min}}\left(\frac{f_i}{f_{max}}\right)\right) \tag{3.19}$$

$X_{i+m,j}$: The mutated (new population)

X_{ij}: The parents

N: Gaussian random variable (mean μ and variance σ^2)

β: Mutation scale ($0<\beta<1$)

$X_{j_{max}}$: Maximum random number for every variable

$X_{j_{min}}$: Minimum random number for every variable

f_i: Fitness for the i^{th} random number

f_{max}: Maximum fitness

Step 6: The evaluation of the objective function and the fitness function for each individual. The fitness function will recalculate in order to get the new fitness value based on the population during the mutation process.

Step 7: The convergence test is required to find the stopping criteria of the evaluation. The convergence criteria are specified based on the different between the maximum and minimum fitness (≤ 0.0001).

$$fitness_{max} - fitness_{min} \leq 0.0001 \tag{3.20}$$

If the stopping criteria not achieve, the process will repeat to Step 4.

Step 8: if the stopping criteria is achieve, the result for switching status, the losses, and the size of DGs should printed. After the result is printed, the analysis of radial network connection should be getting manually based on the switching status of the bus.

The flow chart of Evolutionary programming is shown at figure below (Figure 3.4).

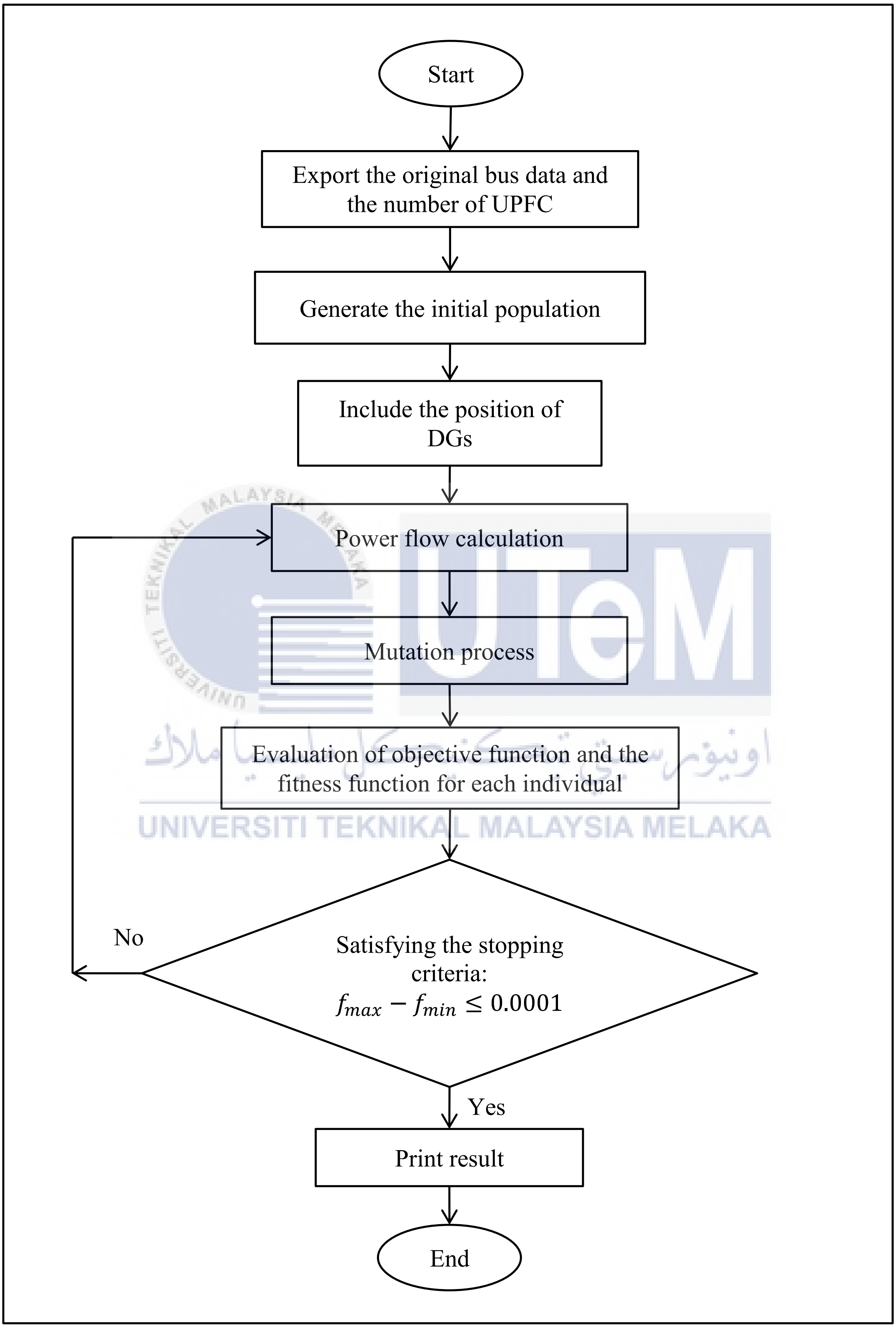


Figure 3.4: The flow chart of Evolutionary Programming

3.5. Summary

The power flow calculation is the main part of evolutionary programming. This calculation will determine the final result and to achieve the objective of power losses. The Self-Organizing Map is the part which to get the suitable position of DGs that will use inside the EP. The EP is the main process to achieve the objective of the project. So, the SOM and EP will combined for DNR and DGs analysis to achieve the project objectives.

CHAPTER 4

RESULT

4.1. Overview

The method of the project has been written by using MATLAB version (R2010a) package in window based computer. Four sets of SOM parameters which are the normalization methods and the number of neurons need to be applied and optimized for SOM classification of the numerical features. The SOM-Toolbox has been use as a SOM library to run the SOM programming. In this section, the result of SOM was collected which will be used to determine the suitable bus from the 33-bus and 69-bus systems which will use to place the DGs based on the characteristics of bus (MW, MVAR, MVA, and power factor, *pf*). For the Evolutionary Programming (EP) result, the result of switching configuration, the power losses for the system, and the size of DGs has been tabulated in this chapter.

4.2. Project Result

The simulation of SOM programming consists of the combination between the various normalization methods (*‘var’, ‘range’, ‘log’,* or *‘logistic’*) and the optimum number of neurons. The „*var*‟ data input will normalize the variance variable to unity and the means to zero. For the „*range*‟ input data will scale the variable values between zero and one. The „*log*‟

is a logarithmic transformation and the „*logistics*" or softmax transformation scales all possible values between zero and one [25].

The simulations of SOM for 33-bus and 69-bus data are represented with different types of normalization method for SOM classification. The optimum numbers of neurons for each types of normalization method are selected from 120 to 400 by increment is 20. The results are recorded and tabulated.

For the optimization by using EP method, the result for each case was collected by 20 times to get the lowest of power losses and the switching configuration must be in radial. In this paper, three cases have been executed by using standard IEEE 33-bus and 69-bus data system.

A. *Case 1:* The reconfiguration by using Evolutionary Programming method without DGs.
B. *Case 2:* The Reconfiguration by using Evolutionary Programming method with random DGs position. The DGs positions are referred with paper [*43*].
C. *Case 3:* The reconfiguration by using Evolutionary Programming with combination of SOM classification result as DGs position.

4.2.1. Results for SOM (33-bus System)

The SOM is use to analyse the 33-bus data which to determine the suitable bus to place the DGs inside the network. The SOM is executed in MATLAB software with the number of neurons start from 120 to 400.

Table 4.1: Result from MATLAB simulation using hexagonal topology and „*var*" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.025	0.000	2.0
140	[16, 9]	0.018	0.061	1.0
160	[18, 9]	0.010	0.000	2.0
180	[18, 10]	0.009	0.000	1.0
200	[20, 10]	0.005	0.061	2.0
220	[20, 11]	0.004	0.030	2.0
240	[22, 11]	0.002	0.242	6.0
260	[22, 12]	0.001	0.000	4.0
280	[23, 12]	0.001	0.000	7.0
300	[23, 13]	0.001	0.182	7.0
320	[25, 13]	0.000	0.000	10.0
340	[24, 14]	0.000	0.000	9.0
360	[26, 14]	0.000	0.030	12.0
380	[27, 14]	0.000	0.000	14.0
400	[27, 15]	0.000	0.030	16.0

Table 4.2: Result from MATLAB simulation using hexagonal topology and „range" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.005	0.121	0.0
140	[16, 9]	0.004	0.061	1.0
160	[18, 9]	0.003	0.000	1.0
180	[18, 10]	0.002	0.000	1.0
200	[20, 10]	0.002	0.030	2.0
220	[20, 11]	0.001	0.030	2.0
240	[22, 11]	0.001	0.000	3.0
260	[22, 12]	0.000	0.212	5.0
280	[23, 12]	0.000	0.030	6.0
300	[23, 13]	0.000	0.061	9.0
320	[25, 13]	0.000	0.091	10.0
340	[26, 13]	0.000	0.121	9.0
360	[26, 14]	0.000	0.061	12.0
380	[27, 14]	0.000	0.242	14.0
400	[29, 14]	0.000	0.030	18.0

Table 4.3: Result from MATLAB simulation using hexagonal topology and „*log*“ normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[24, 5]	0.008	0.061	0.0
140	[23, 6]	0.004	0.000	1.0
160	[27, 6]	0.002	0.030	1.0
180	[26, 7]	0.001	0.000	2.0
200	[29, 7]	0.001	0.061	2.0
220	[31, 7]	0.000	0.000	2.0
240	[30, 8]	0.000	0.000	3.0
260	[33, 8]	0.000	0.061	4.0
280	[35, 8]	0.000	0.000	4.0
300	[33, 9]	0.000	0.000	6.0
320	[36, 9]	0.000	0.303	9.0
340	[38, 9]	0.000	0.000	9.0
360	[40, 9]	0.000	0.000	13.0
380	[38, 10]	0.000	0.121	12.0
400	[40, 10]	0.000	0.030	16.0

Table 4.4: result from MATLAB simulation using hexagonal topology and „*logistic*"
normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[17, 7]	0.005	0.000	1.0
140	[18, 8]	0.003	0.061	1.0
160	[20, 8]	0.003	0.030	3.0
180	[20, 9]	0.002	0.000	2.0
200	[22, 9]	0.001	0.000	3.0
220	[22, 10]	0.001	0.000	3.0
240	[24, 10]	0.001	0.030	3.0
260	[24, 11]	0.000	0.030	6.0
280	[25, 11]	0.000	0.000	4.0
300	[27, 11]	0.000	0.000	7.0
320	[27, 12]	0.000	0.030	9.0
340	[28, 12]	0.000	0.091	7.0
360	[30, 12]	0.000	0.091	11.0
380	[29, 13]	0.000	0.152	15.0
400	[31, 13]	0.000	0.061	18.0

4.2.2. Result for SOM (69-bus System)

The SOM analysis is applied to get the suitable but which will place the DGs inside the network based on the characteristic of the bus. The 69-bus data is use in SOM to analyse the buses based on the parameters or features inside the buses. The SOM is executed in MATLAB software with the number of neurons start from 120 to 400 by the increment is 20.

Table 4.5: Result from MATLAB simulation using hexagonal topology and „*var*" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.019	0.203	0.0
140	[16, 9]	0.022	0.130	1.0
160	[18, 9]	0.014	0.145	0.0
180	[18, 10]	0.012	0.203	1.0
200	[20, 10]	0.008	0.130	1.0
220	[20, 11]	0.009	0.246	1.0
240	[22, 11]	0.005	0.116	1.0
260	[22, 12]	0.006	0.174	2.0
280	[23, 12]	0.004	0.072	2.0
300	[23, 13]	0.003	0.087	4.0
320	[25, 13]	0.002	0.072	4.0
340	[24, 14]	0.002	0.043	4.0
360	[26, 14]	0.001	0.159	6.0
380	[27, 14]	0.001	0.072	6.0
400	[27, 15]	0.001	0.058	9.0

Table 4.6: Result from MATLAB simulation using hexagonal topology and „*range*‟ normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.006	0.217	1.0
140	[18, 8]	0.004	0.217	0.0
160	[18, 9]	0.003	0.116	1.0
180	[20, 9]	0.003	0.232	1.0
200	[20, 10]	0.002	0.203	1.0
220	[22, 10]	0.001	0.246	1.0
240	[22, 11]	0.002	0.174	1.0
260	[24, 11]	0.001	0.145	2.0
280	[23, 12]	0.001	0.145	3.0
300	[25, 12]	0.001	0.058	4.0
320	[25, 13]	0.001	0.029	4.0
340	[26, 13]	0.000	0.072	4.0
360	[28, 13]	0.000	0.014	7.0
380	[27, 14]	0.000	0.029	7.0
400	[29, 14]	0.000	0.043	12.0

Table 4.7: Result from MATLAB simulation using hexagonal topology and „*log*" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[20, 6]	0.013	0.188	0.0
140	[20, 7]	0.006	0.261	0.0
160	[23, 7]	0.006	0.188	1.0
180	[23, 8]	0.004	0.145	1.0
200	[25, 8]	0.004	0.217	1.0
220	[24, 9]	0.005	0.203	1.0
240	[27, 9]	0.002	0.101	1.0
260	[29, 9]	0.002	0.116	2.0
280	[28, 10]	0.002	0.159	3.0
300	[30, 10]	0.001	0.116	5.0
320	[32, 10]	0.001	0.159	5.0
340	[31, 11]	0.001	0.101	5.0
360	[33, 11]	0.001	0.072	5.0
380	[35, 11]	0.000	0.072	6.0
400	[33, 12]	0.000	0.043	9.0

Table 4.8: The result from MALAB simulation using hexagonal topology and „*logistic*“ normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[13, 9]	0.004	0.188	0.0
140	[16, 9]	0.004	0.275	0.0
160	[16, 10]	0.003	0.551	0.0
180	[16, 11]	0.002	0.159	1.0
200	[18, 11]	0.002	0.101	1.0
220	[18, 12]	0.001	0.043	1.0
240	[20, 12]	0.001	0.159	3.0
260	[20, 13]	0.001	0.072	2.0
280	[22, 13]	0.001	0.043	2.0
300	[21, 14]	0.001	0.087	4.0
320	[23, 14]	0.000	0.072	3.0
340	[24, 14]	0.000	0.087	4.0
360	[24, 15]	0.000	0.043	6.0
380	[25, 15]	0.000	0.043	5.0
400	[25, 16]	0.000	0.087	9.0

4.2.3. Case 1: Result of Reconfiguration by using EP method without DGs

Table 4.9: The result of Power Losses by using EP without DGs for IEEE 33-bus system

No.	Computation Time (sec)	Opened Switch	Power Losses (pu)
1	56.513162	32, 9, 14, 37, 7	0.1175
2	87.833100	14, 37, 7, 10, 32	0.1181
3	88.282462	14, 37, 7, 10, 32	0.1181
4	89.185813	14, 37, 7, 10, 32	0.1181
5	88.394490	14, 37, 7, 10, 32	0.1181
6	87.835214	14, 37, 7, 10, 32	0.1181
7	88.169205	14, 37, 7, 10, 32	0.1181
8	88.745063	14, 37, 7, 10, 32	0.1181
9	87.929748	14, 37, 7, 10, 32	0.1181
10	88.561833	14, 37, 7, 10, 32	0.1181
11	88.502105	14, 37, 7, 10, 32	0.1181
12	87.895086	14, 37, 7, 10, 32	0.1181
13	87.627465	14, 37, 7, 10, 32	0.1181
14	88.399397	14, 37, 7, 10, 32	0.1181
15	88.019784	14, 37, 7, 10, 32	0.1181
16	88.625499	14, 37, 7, 10, 32	0.1181
17	87.971429	14, 37, 7, 10, 32	0.1181
18	88.811087	14, 37, 7, 10, 32	0.1181
19	87.826930	14, 37, 7, 10, 32	0.1181
20	100.212068	14, 37, 7, 10, 32	0.1181

Table 4.10: The Result of Power Losses by using EP without DGs for IEEE 69-bus system

No.	Computation Time (sec)	Opened Switch	Power Losses (pu)
1	37.079338	9, 26, 57, 20, 71	0.0551
2	52.192723	12, 55, 64, 69, 17	0.0482
3	47.669224	12, 55, 64, 69, 17	0.0482
4	56.126946	12, 55, 64, 69, 17	0.0482
5	51.656888	12, 55, 64, 69, 17	0.0482
6	58.664436	12, 55, 64, 69, 17	0.0482
7	44.791916	12, 55, 64, 69, 17	0.0482
8	51.036638	12, 55, 64, 69, 17	0.0482
9	52.712383	12, 55, 64, 69, 17	0.0482
10	48.794868	12, 55, 64, 69, 17	0.0482
11	51.506640	12, 55, 64, 69, 17	0.0482
12	49.657786	12, 55, 64, 69, 17	0.0482
13	50.586235	12, 55, 64, 69, 17	0.0482
14	50.639340	12, 55, 64, 69, 17	0.0482
15	55.262618	12, 55, 64, 69, 17	0.0482
16	52.891309	12, 55, 64, 69, 17	0.0482
17	55.265544	12, 55, 64, 69, 17	0.0482
18	49.662606	12, 55, 64, 69, 17	0.0482
19	47.568680	12, 55, 64, 69, 17	0.0482
20	48.463745	12, 55, 64, 69, 17	0.0482

4.2.4. Case 2: Result of Reconfiguration by using EP method with random DGs position

Table 4.11: The Result of Power Losses and size of 4 DGs for IEEE 33-bus system

No.	Computation Time (sec)	Opened Switch	Power Losses (pu)	DG1 size (B6)	DG2 size (B18)	DG3 size (B22)	DG4 size (B29)
1	59.875212	7, 14, 36, 37, 10	0.0928	0.5990	0.7520	2.1270	2.6840
2	92.967023	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
3	93.740980	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
4	93.429909	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
5	94.418949	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
6	93.174029	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
7	92.964775	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
8	92.591244	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
9	91.970489	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
10	93.961643	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
11	93.428558	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
12	93.031407	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
13	94.253650	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
14	93.751939	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
15	92.556247	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
16	91.901585	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
17	93.553832	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
18	93.520673	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
19	94.291861	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610
20	93.819597	7, 14, 37, 11, 32	0.0912	0.6210	0.5140	2.5240	2.8610

Table 4.12: The Result of Power Losses and Size of 4 DGs for IEEE 69-bus system

No.	Computation Time (sec)	Opened Switch	Power Losses (pu)	DG1 size (B21)	DG2 size (B10)	DG3 size (B46)	DG4 size (B62)
1	46.82769	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
2	47.33525	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
3	47.513611	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
4	47.259408	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
5	48.76283	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
6	46.95481	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
7	48.245999	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
8	46.549166	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
9	48.98565	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
10	49.524714	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
11	46.926041	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
12	48.659258	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
13	48.501831	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
14	45.250228	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
15	52.59172	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
16	47.806862	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
17	48.671507	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
18	47.316569	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
19	49.733741	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760
20	48.89942	12, 55, 64, 69, 17	0.0407	1.5760	1.4870	1.4820	1.3760

4.2.5. Case 3: result of Reconfiguration by using EP method with combination of SOM Classification result as DGs position

Table 4.13: The Result of Power Losses and Size of DGs for IEEE 33-bus system

No.	Computation Time (sec)	Opened Switch	Power Losses (pu)	DG1 size (B24)	DG2 size (B25)	DG3 size (B30)	DG4 size (B32)
1	58.762846	14, 31, 11, 37, 7	0.0878	0.5420	0.8950	2.4470	2.3480
2	90.068398	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
3	89.731535	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
4	89.673873	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
5	99.209643	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
6	89.878594	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
7	89.858906	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
8	89.855944	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
9	104.487645	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
10	90.294317	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
11	89.887119	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
12	89.657880	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
13	107.484650	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
14	91.464313	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
15	90.409972	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
16	91.327008	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
17	89.168681	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
18	89.696718	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
19	90.242227	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610
20	90.046531	7, 14, 37, 11, 32	0.0897	0.6210	0.5140	2.5240	2.8610

Table 4.14: The Result of Power Losses and Size of DGs for IEEE 69-bus system

No.	Computation Time (sec)	Opened Switch	Power Losses (pu)	DG1 size (B49)	DG2 size (B50)	DG3 size (B61)	DG4 size (B64)
1	44.341013	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
2	45.811409	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
3	43.806995	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
4	44.69245	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
5	44.212518	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
6	45.544503	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
7	45.160444	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
8	42.596622	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
9	44.156876	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
10	44.263152	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
11	42.805342	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
12	43.922506	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
13	44.570937	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
14	44.863806	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
15	48.415473	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
16	44.925803	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
17	45.26057	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
18	45.908468	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
19	43.945413	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760
20	47.861431	12, 55, 64, 69, 17	0.0421	1.5770	1.4870	1.4810	1.3760

CHAPTER 5

ANALYSIS AND DISCUSSION OF RESULT

5.1. Overview

The result for SOM method and EP programming has been collected in previous chapter. Four sets of SOM parameters which are the normalization methods and the number of neurons was applied and optimized for SOM classification for bus classification. In this section, the analysis result of SOM to determine the suitable bus from the 33-bus and 69-bus systems which will use to place the DGs based on the characteristics of bus (MW, MVAR, MVA, and power factor, *pf*). From the SOM result obtained, the suitable bus will selected and use in the implementation of Evolutionary Programming (EP) as DGs placement to achieve the power loss reduction.

5.2. The Simulation and Test System

The case study used the test system which consists of standard IEEE 33-bus and 69-bus radial distribution systems as shown in Figure 5.1 and 5.2. The 33-bus radial distribution system consists of a substation, 32 normally closed tie switches, and 5 normally open tie switches at bus 33, 34, 35, 36, and 37. The total active and reactive power loads are 3715 kW and 2300 kVAr respectively. The initial active and reactive power loss for this system are 202.771 kW ad 135.236 kVAr [42].

For the 69-bus radial system, it consist of a substation, 68 normally closed tie switches, and 5 normally open tie switches at bus 69, 70, 71, 72, and 73. The total active and reactive power loads are 3802 kW and 2694 kVAr respectively. The initial active and reactive power loss are 225 kW and 102.16 kVAr respectively [42]

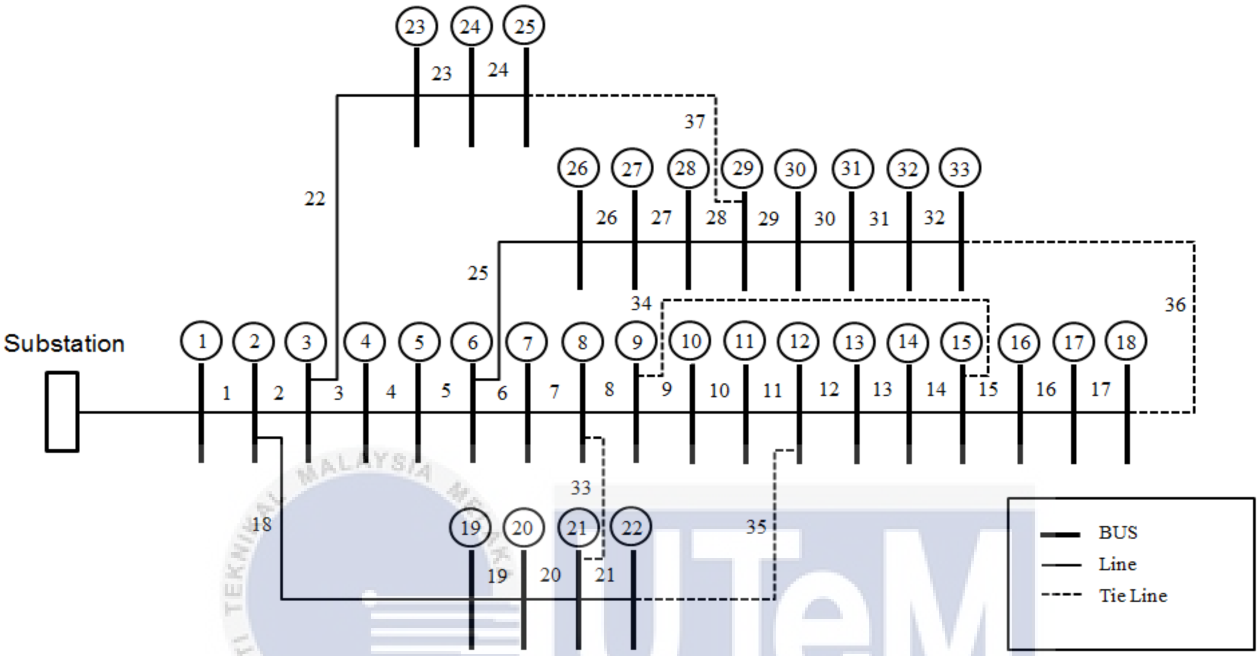


Figure 5.1: Standard IEEE 33-bus radial distribution system

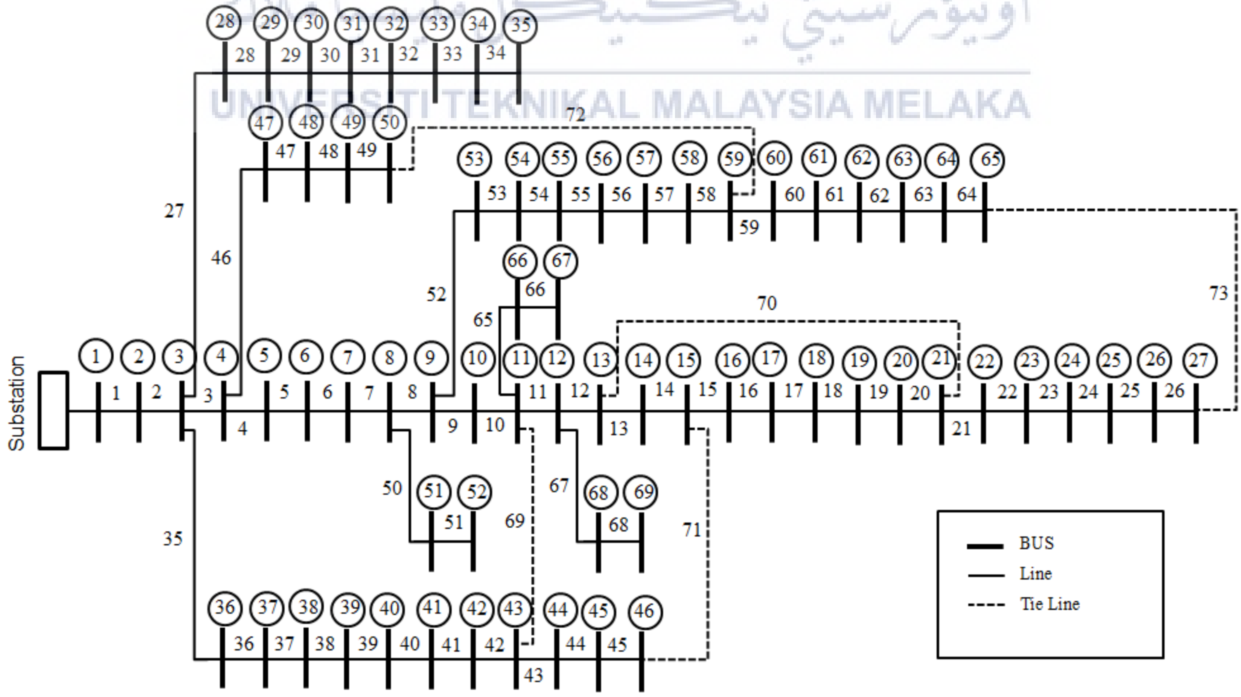


Figure 5.2: Standard IEEE 69-bus radial distribution system

Three cases have been executed in determining their reliability of combination between SOM and EP in the test system to achieve the best configuration and reduction of power losses.

A. In this first case (Case 1)

The reconfiguration strategy is applied in the system is based on EP method without DGs.

B. In this second case (Case 2)

The reconfiguration strategy is applied in the system is based on EP method with random DGs position [43].

C. In this third case (Case 3)

The reconfiguration strategy is applied in the system is based on EP method with the result of SOM classification as DGs position (SOM-EP).

5.3. Analysis and Discussion

The bus classification is done by using SOM programming and the analysis of the reconfiguration is done by using EP method. The bus characteristics (MVA, MW, MVAr, and *pf*) are considered as the main feature SOM programming for bus classification. The analysis of SOM result is based on the generated neurons in U-matrix. For EP method, the tie switches and sectionalizing switches are considered as the control variables and obtain using the EP method. This programming is running randomly and takes approximately 20 times by using MATLAB software and the minimum power losses with radial configuration of distribution network is selected. The results are presented consists of five opened switches, total power losses and four size of DGs. In this chapter, four important parts will be discussed;

i. Part A: SOM classification result and analysis

ii. Part B: Power losses reduction

iii. Part C: DGs sizing

iv. Part D: Voltage profile improvement

5.3.1. Part A: SOM Classification Result and Analysis

- **IEEE 33-bus system**

The SOM is use to analyse the 33-bus data which to determine the suitable bus to place the DGs inside the network. The SOM is executed in MATLAB software with the number of neurons start from 120 to 400. The range of neurons number is use to find the small value of quantization and topographic error with the fast training time. The training time is considered fast when the time is lower or equal to 5 seconds which the good mapping in capability and quality.

Table 5.1: Analysis result for SOM simulation using hexagonal topology and „*var*" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.025	0.000	2.0
140	[16, 9]	0.018	0.061	1.0
160	[18, 9]	0.010	0.000	2.0
180	[18, 10]	0.009	0.000	1.0
200	[20, 10]	0.005	0.061	2.0
220	[20, 11]	0.004	0.030	2.0
240	[22, 11]	0.002	0.242	6.0
260	[22, 12]	0.001	0.000	4.0
280	[23, 12]	0.001	0.000	7.0
300	[23, 13]	0.001	0.182	7.0
320	[25, 13]	0.000	0.000	10.0
340	[24, 14]	0.000	0.000	9.0
360	[26, 14]	0.000	0.030	12.0
380	[27, 14]	0.000	0.000	14.0
400	[27, 15]	0.000	0.030	16.0

Based on the above table, the best number of neurons for „*var*" normalization method is 260 because the training time is faster than other which produces the small values of quantization and topographic errors (0.001 and 0.000). That"s mean, the simulation only take 4.0 second to training and generate the U-matrix with the small errors. So, for 33-bus and „*var*" normalization method type, the best number of neurons is 260.

Table 5.2: Analysis result for SOM simulation using hexagonal topology and „range" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.005	0.121	0.0
140	[16, 9]	0.004	0.061	1.0
160	[18, 9]	0.003	0.000	1.0
180	[18, 10]	0.002	0.000	1.0
200	[20, 10]	0.002	0.030	2.0
220	[20, 11]	0.001	0.030	2.0
240	[22, 11]	0.001	0.000	3.0
260	[22, 12]	0.000	0.212	5.0
280	[23, 12]	0.000	0.030	6.0
300	[23, 13]	0.000	0.061	9.0
320	[25, 13]	0.000	0.091	10.0
340	[26, 13]	0.000	0.121	9.0
360	[26, 14]	0.000	0.061	12.0
380	[27, 14]	0.000	0.242	14.0
400	[29, 14]	0.000	0.030	18.0

Based on the above table, the best number of neurons for „*range*" nomalization method is 240 because the simulations only take 3.0 second to train and generate the U-matrix with the small values of quantization and topographic errors (0.001 and 0.000). The best of neuron"s number are chosen by consider the lowest errors and training time. So, the best number of neurons for „*range*" nomalization method type is 240.

Table 5.3: Analysis result for SOM simulation using hexagonal topology and „*log*" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[24, 5]	0.008	0.061	0.0
140	[23, 6]	0.004	0.000	1.0
160	[27, 6]	0.002	0.030	1.0
180	[26, 7]	0.001	0.000	2.0
200	[29, 7]	0.001	0.061	2.0
220	[31, 7]	0.000	0.000	2.0
240	[30, 8]	0.000	0.000	3.0
260	[33, 8]	0.000	0.061	4.0
280	[35, 8]	0.000	0.000	4.0
300	[33, 9]	0.000	0.000	6.0
320	[36, 9]	0.000	0.303	9.0
340	[38, 9]	0.000	0.000	9.0
360	[40, 9]	0.000	0.000	13.0
380	[38, 10]	0.000	0.121	12.0
400	[40, 10]	0.000	0.030	16.0

Based on the above table, the lowest value of quantization and topographic errors with the faster training time is 220. Both errors are zero (0.000). The errors value is same with the number of neurons is 240 but it can"t be the best because the training time is higher than the time for 220 neuron"s number. The training time for 220 neuron"s number is 2.0 seconds but for the 240 neuron"s number is 3.0 seconds. So, the selected number of neurons is which have the lowest training time.

Table 5.4: Analysis result for SOM simulation using hexagonal topology and „*logistic*“ normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[17, 7]	0.005	0.000	1.0
140	[18, 8]	0.003	0.061	1.0
160	[20, 8]	0.003	0.030	3.0
180	[20, 9]	0.002	0.000	2.0
200	[22, 9]	0.001	0.000	3.0
220	[22, 10]	0.001	0.000	3.0
240	[24, 10]	0.001	0.030	3.0
260	[24, 11]	0.000	0.030	6.0
280	[25, 11]	0.000	0.000	4.0
300	[27, 11]	0.000	0.000	7.0
320	[27, 12]	0.000	0.030	9.0
340	[28, 12]	0.000	0.091	7.0
360	[30, 12]	0.000	0.091	11.0
380	[29, 13]	0.000	0.152	15.0
400	[31, 13]	0.000	0.061	18.0

Based on the above table, the lowest value of quantization and topographic errors for „logistics“ normalization method are 0.000 respectively. The lowest value of errors is occur at the number of neurons is 280. The 280 number of neurons is still considering as a faster training time because the time is lower than 5 seconds. So, for „*logistic*“ normalization method, the best number of neurons is 280.

From the analysis, the best for number of neurons for 33-bus data system is selected from the four type of normalization method by comparing the result from the best neuron‟s number for each normalization method. The comparison is use to decide the best normalization type based on the lowest quantization and topographic errors. The comparison of the method is shown as table below (Table 5.5).

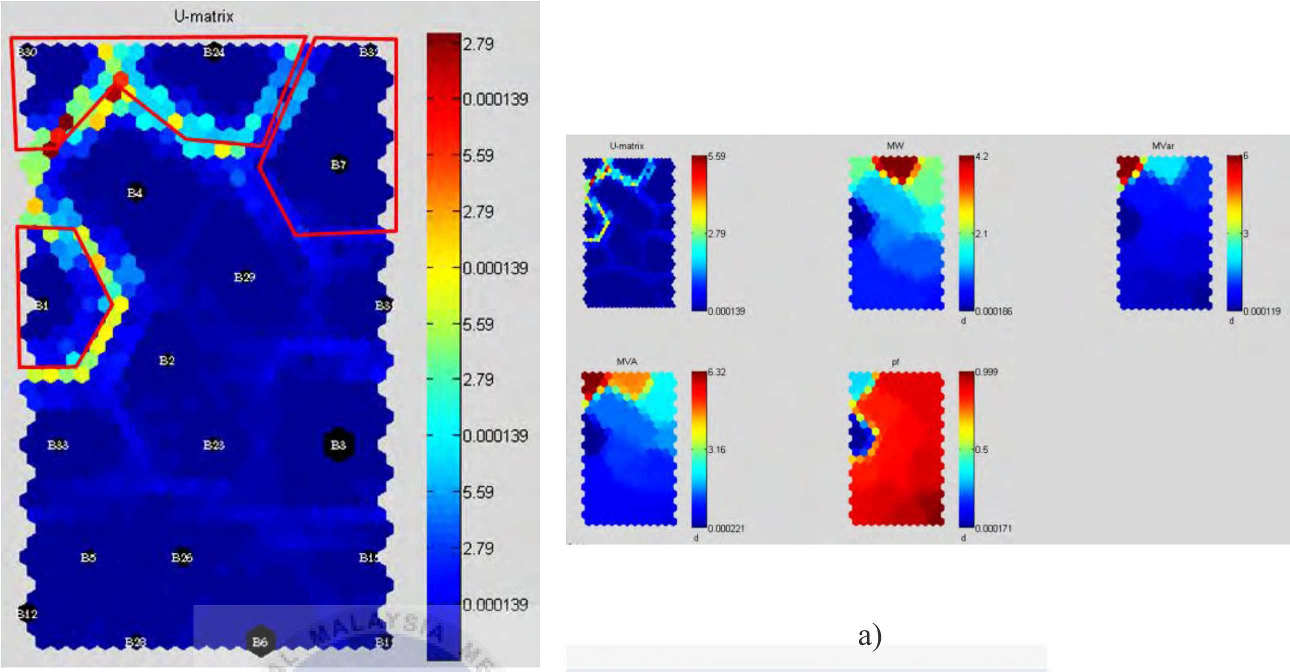
Table 5.5: The comparison between the types of normalization method

Normalization method	No. of neurons	Simulation result			
		Map size	Quantization errors	Topographic error	Training time (sec)
var	260	[22, 12]	0.001	0.000	4.0
range	240	[22, 11]	0.001	0.000	3.0
log	220	[31, 7]	0.000	0.000	3.0
logistic	280	[25, 11]	0.000	0.000	4.0

Based on the above table, the best normalization method is „*log*‟. The quantization and the topographic errors for „*log*‟ are zero and the training time is faster (3.0 sec). The quantization and the topographic errors are the lowest value and the training time is the faster than other normalizes method. So, the best of normalization method for 33-bus data is „*log*‟ by the number of neurons is 220.

The best of number of neurons for each normalization method are represented with the U-matrix as the graphically result. The U-matrix is the final analysis for SOM result to choose the suitable buses for DGs. So, the analysis of U-matrix for each normalization method is shown as below.

i. The hexagonal lattice, „*var*‟ nomalization method with 260 number of neurons



b)

a)

Figure 5.3: a) The U-Matrix for "*var*‟ nomalization method with 260 numbers of neurons b) the Plane Representation Showing Data Contribution of Four Bus Characteristics for SOM Classification

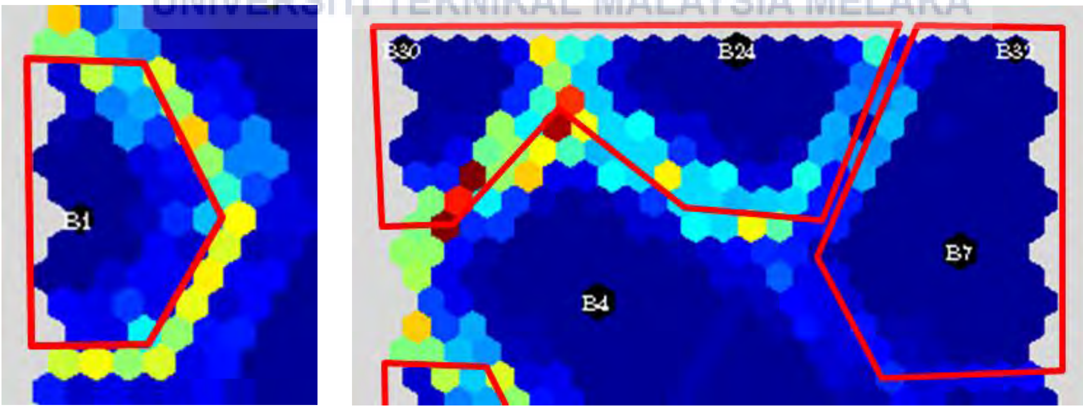
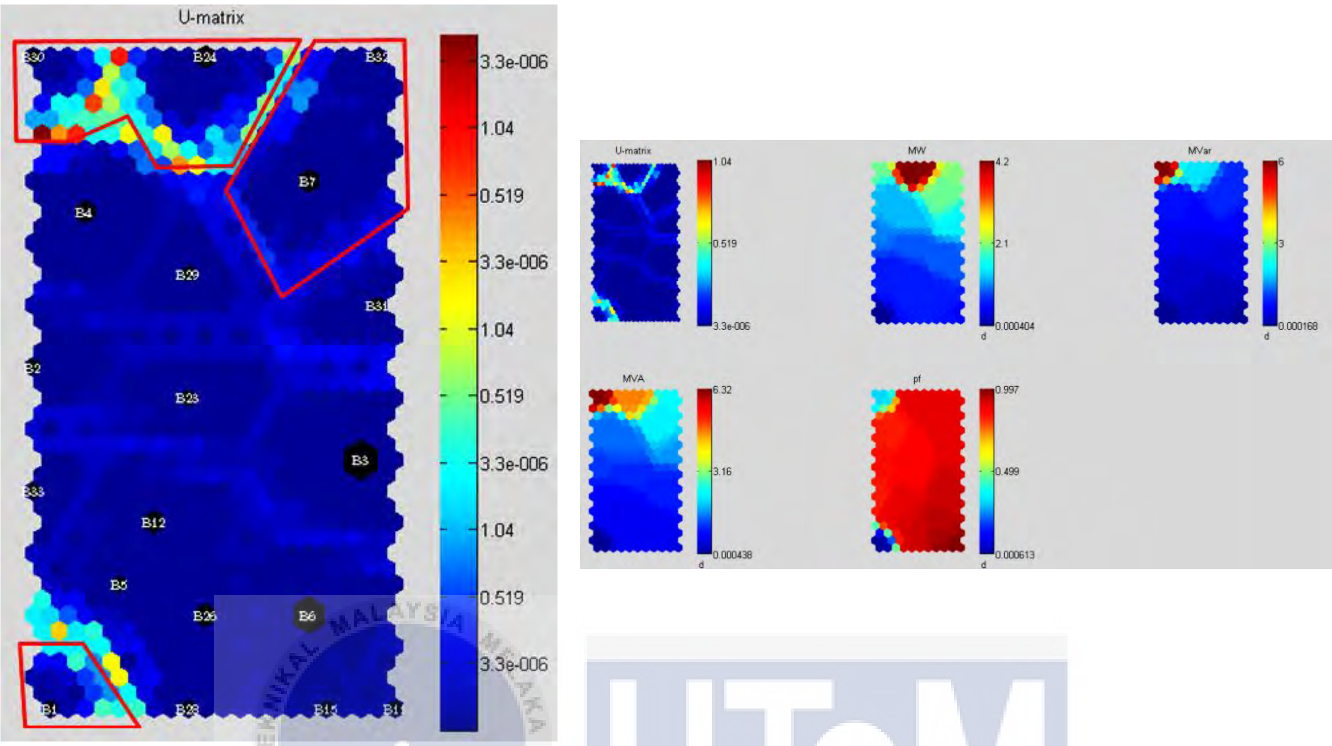


Figure 5.4: The classification of IEEE 33-bus data (B1, B30, B24, B32, and B7)

ii. The hexagonal lattice, „*range*" normalization method with 240 number of neurons



a) b)

Figure 5.5: a) The U-Matrix for „*range*" normalization method with 240 numbers of neurons b) the Plane Representation Showing Data Contribution of Four Characteristics for SOM Classification

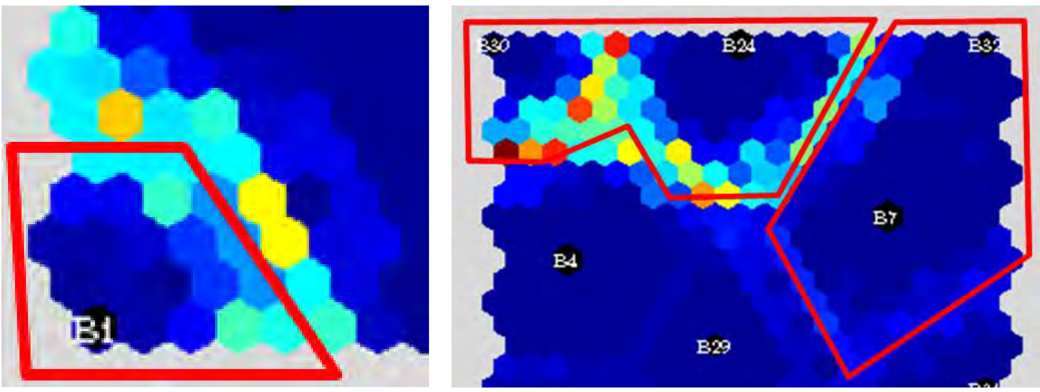
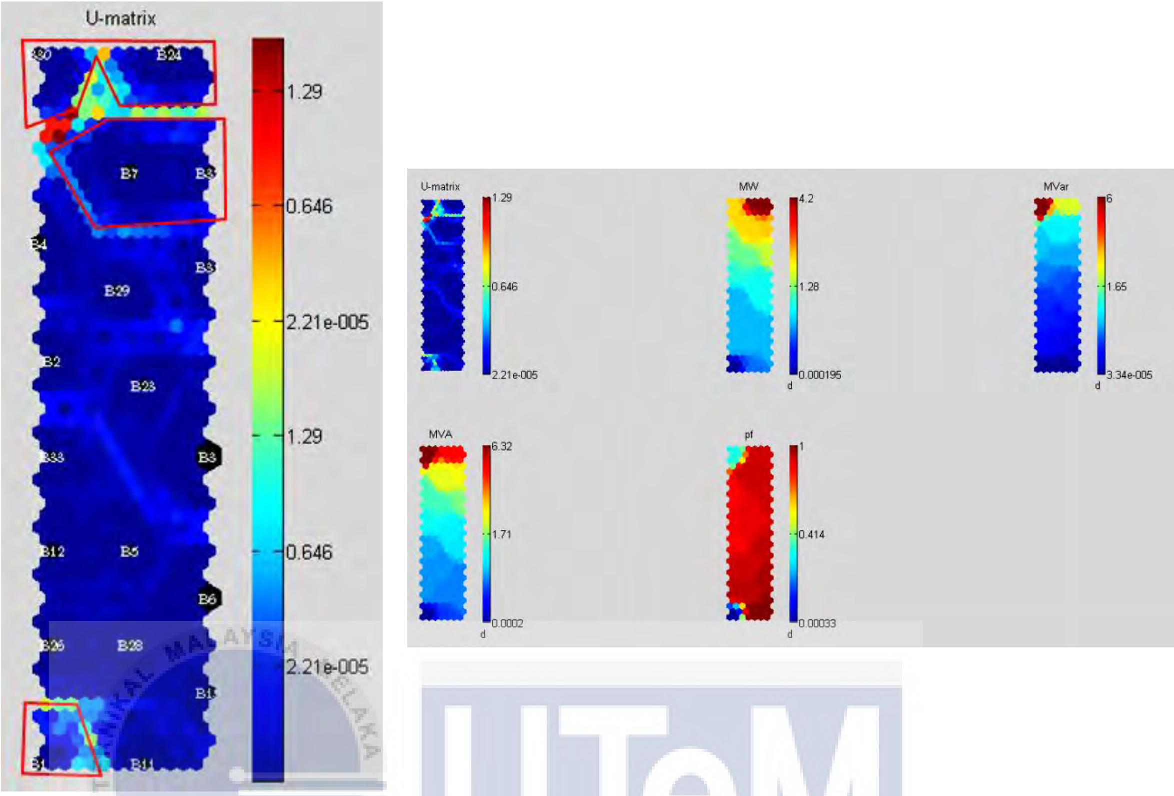


Figure 5.6: The classification of IEEE 33-bus data (B1, B30, B24, B32, and B7)

iii. The hexagonal lattice, „log" nomalization method with 220 number of neurons



a) b)

Figure 5.7: a) The U-Matrix for „log" nomalization method with 220 numbers of neurons b) the Plane Representation Showing Data Contribution of Four Characteristics for SOM Classification

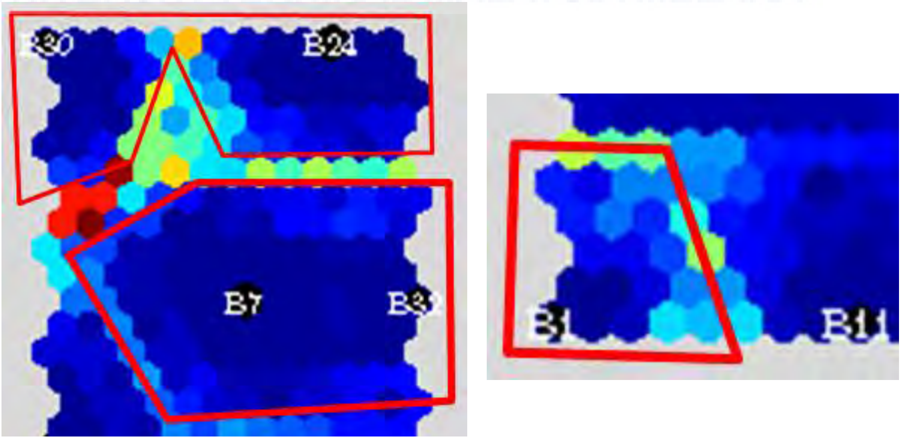
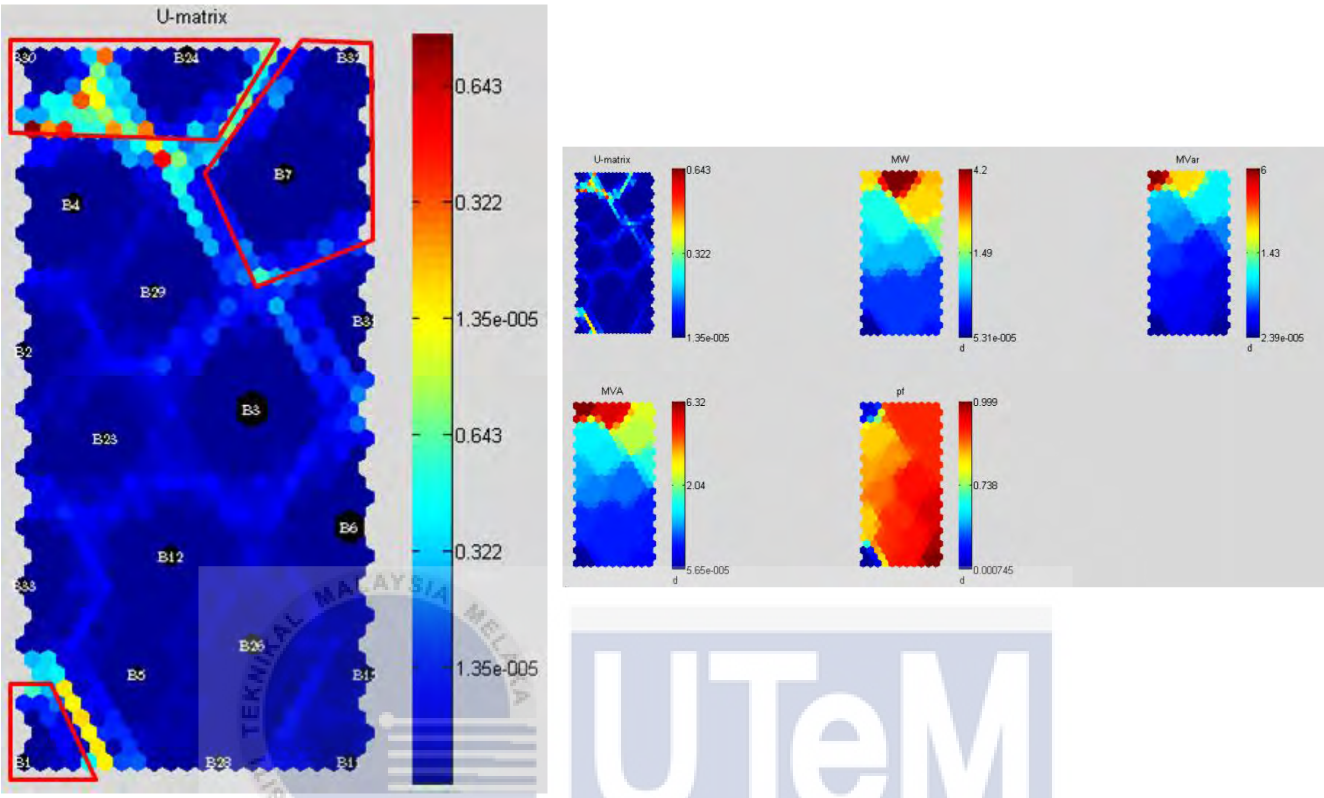


Figure 5.8: The classification of IEEE 33-bus data (B1, B30, B24, B32, and B7)

iv. The hexagonal lattice, „*logistic*" normalization method with 280 number of neurons



a) b)

Figure 5.9: a) The U-Matrix for „*logistic*" nomalization method with 280 numbers of neurons b) the Plane Representation Showing Data Contribution of Four Characteristics for SOM Classification

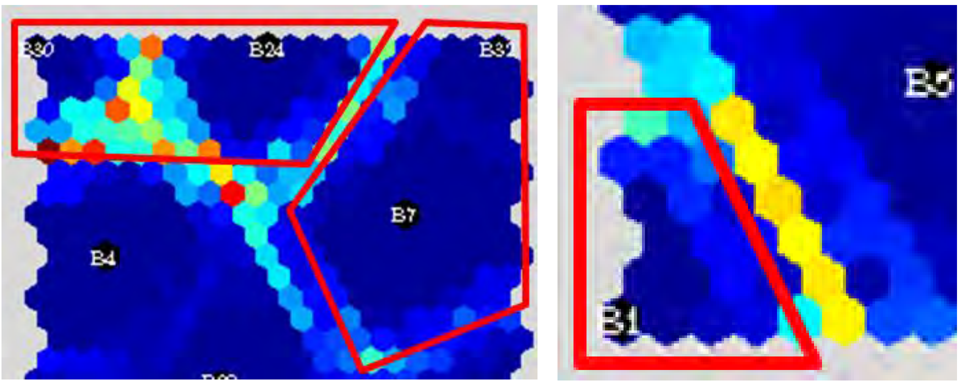


Figure 5.10: The classification of IEEE 33-bus data (B1, B30, B24, B32, and B7)

- **SOM Analysis**

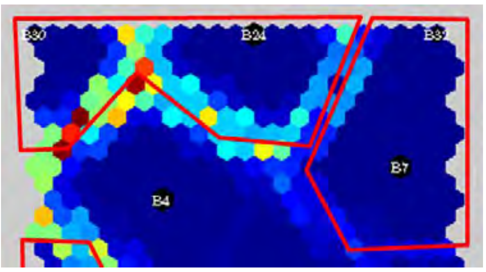
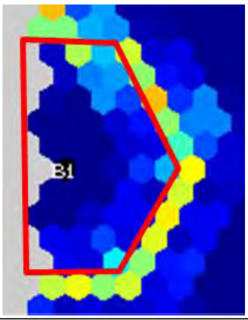
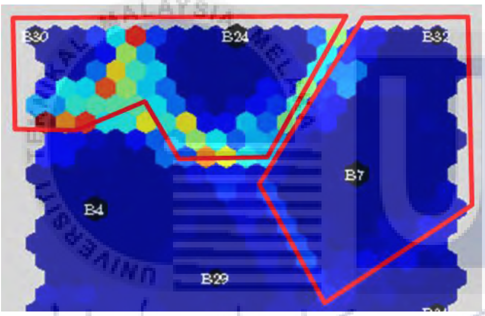
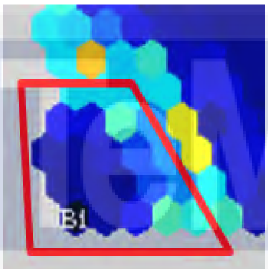
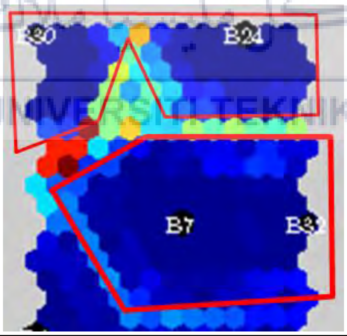
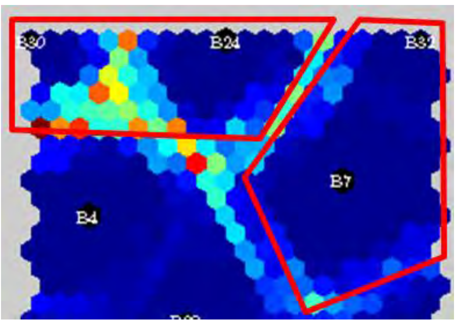
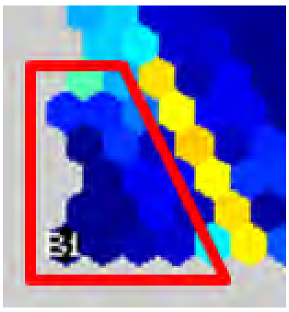
Based on the U-matrix in Figure 5.3, 5.5, 5.7, and 5.9 above, the neurons are labeled by B1 to B33 present the standard IEEE 33-bus data. From all figure above, the B1, B7, B32, B24, and B30 were separate with other buses because the forming of light boundary area which means that the bus have different characteristics between the neurons among the buses. The figures of the Plane Representation demonstrated the component of bus characteristics and from this figures, no uniform distributions are found through the plane. Each plane is important in contribution of IEEE 33-bus classification process.

Based on the all figure above, the B24 is the highest value in MW plane representation (dark red) and followed by B30, B32 and B7 (light green). For MVAr plane representation, the B30 is the highest value followed by B24, B32 and B7. This situation is same with MVA Plane Representation. The B1 is a darkest blue at all plane representation which means that this bus have a lowest value of load (MW, MVAr, MVA and *pf*) and it"s not suitable bus for DG placing.

Based on the bus data, the B24 and B25 have same characteristics of load (MW, MVAr, MVA, and *pf*). So, in the U-matrix figure, the B25 is overlapped with B24. In Evolutionary Programming, the DG will place in 4 buses only. From the SOM result, the suitable buses to place the DG are bus 24 (B24), bus 25 (B25), bus 30 (B30), and bus 32 (B32). The B7 is not selected because from the U-matrix result, the B32 have small different with B7. Based on Figure 5.3b), 5.5b), 5.7b) and 5.9b), the MW plane shows that the B32 is bit higher of MW value compared to B7.

- **SOM Result and Analysis Summary**

Table 5.6: The Summarization of IEEE 33-bus SOM Classification

Normalization Method	U-matrix Classification	Bus Classification from U-matrix	Bus Selected for 4 DGs
var	 	B1, B24, B25, B7, B30, B32	Bus no. 24, Bus no. 25, Bus no. 30, Bus no. 32
range	 	B1, B24, B25, B7, B30, B32	Bus no. 24, Bus no. 25, Bus no. 30, Bus no. 32
log	 	B1, B24, B25, B7, B30, B32	Bus no. 24, Bus no. 25, Bus no. 30, Bus no. 32
logistic	 	B1, B24, B25, B7, B30, B32	Bus no. 24, Bus no. 25, Bus no. 30, Bus no. 32

- **IEEE 69-bus system**

The SOM analysis is applied to get the suitable but which will place the DGs inside the network based on the characteristic of the bus. The 69-bus data is use in SOM to analyse the buses based on the parameters or features inside the buses. The SOM is executed in MATLAB software with the number of neurons start from 120 to 400 by the increment is 20. The result of SOM will show the value of quantization and topographic errors. The training time of the simulation is considered fast when the time is lower or equal to 5 seconds which the good mapping capability and quality.

Table 5.7: Analysis result for SOM simulation using hexagonal topology and „*var*‟ normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.019	0.203	0.0
140	[16, 9]	0.022	0.130	1.0
160	[18, 9]	0.014	0.145	0.0
180	[18, 10]	0.012	0.203	1.0
200	[20, 10]	0.008	0.130	1.0
220	[20, 11]	0.009	0.246	1.0
240	[22, 11]	0.005	0.116	1.0
260	[22, 12]	0.006	0.174	2.0
280	[23, 12]	0.004	0.072	2.0
300	[23, 13]	0.003	0.087	4.0
320	[25, 13]	0.002	0.072	4.0
340	[24, 14]	0.002	0.043	4.0
360	[26, 14]	0.001	0.159	6.0
380	[27, 14]	0.001	0.072	6.0
400	[27, 15]	0.001	0.058	9.0

Based on the Table 5.7, the best number of neurons for „*var*" normalization method is 340 because the training time is faster than other which produces the small values of quantization and topographic errors (0.002 and 0.043). The training time for 340 number of neurons is 4.0 seconds. The 340 number of neurons is chosen even though the training time is 4.0 seconds because the quantization and topographic errors are the lowest than other. That training time still consider as a faster because lower than 5 seconds. So, the best number of neurons for „*var*" is 340.

Table 5.8: Analysis result for SOM simulation using hexagonal topology and „*range*" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[15, 8]	0.006	0.217	1.0
140	[18, 8]	0.004	0.217	0.0
160	[18, 9]	0.003	0.116	1.0
180	[20, 9]	0.003	0.232	1.0
200	[20, 10]	0.002	0.203	1.0
220	[22, 10]	0.001	0.246	1.0
240	[22, 11]	0.002	0.174	1.0
260	[24, 11]	0.001	0.145	2.0
280	[23, 12]	0.001	0.145	3.0
300	[25, 12]	0.001	0.058	4.0
320	[25, 13]	0.001	0.029	4.0
340	[26, 13]	0.000	0.072	4.0
360	[28, 13]	0.000	0.014	7.0
380	[27, 14]	0.000	0.029	7.0
400	[29, 14]	0.000	0.043	12.0

Based on above table, the lowest value of quantization and topographic errors with the faster training time is 320. The other value of quantization errors is lower than the errors for 340 neuron"s number, but the topographic errors and the training time is lower than other. So, the best number of neurons for „*range*" normalization method is 320.

Table 5.9: Analysis result for SOM simulation using hexagonal topology and „*log*‟ normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[20, 6]	0.013	0.188	0.0
140	[20, 7]	0.006	0.261	0.0
160	[23, 7]	0.006	0.188	1.0
180	[23, 8]	0.004	0.145	1.0
200	[25, 8]	0.004	0.217	1.0
220	[24, 9]	0.005	0.203	1.0
240	[27, 9]	0.002	0.101	1.0
260	[29, 9]	0.002	0.116	2.0
280	[28, 10]	0.002	0.159	3.0
300	[30, 10]	0.001	0.116	5.0
320	[32, 10]	0.001	0.159	5.0
340	[31, 11]	0.001	0.101	5.0
360	[33, 11]	0.001	0.072	5.0
380	[35, 11]	0.000	0.072	6.0
400	[33, 12]	0.000	0.043	9.0

Based on the table above, the lowest value of quantization and topographic errors by the faster training time is 360 numbers of neurons. The lowest value of quantization errors is 0.000 but the values of topographic errors and the training time is still higher than other. The choosing of best value for all simulation result must be considered together. So, the best number of neurons for „*log*‟ nomalization method is 360.

Table 5.10: Analysis result for SOM simulation using hexagonal topology and „*logistic*" normalization method

No. of neurons	Simulation result			
	Map size	Quantization errors	Topographic error	Training time (sec)
120	[13, 9]	0.004	0.188	0.0
140	[16, 9]	0.004	0.275	0.0
160	[16, 10]	0.003	0.551	0.0
180	[16, 11]	0.002	0.159	1.0
200	[18, 11]	0.002	0.101	1.0
220	[18, 12]	0.001	0.043	1.0
240	[20, 12]	0.001	0.159	3.0
260	[20, 13]	0.001	0.072	2.0
280	[22, 13]	0.001	0.043	2.0
300	[21, 14]	0.001	0.087	4.0
320	[23, 14]	0.000	0.072	3.0
340	[24, 14]	0.000	0.087	4.0
360	[24, 15]	0.000	0.043	6.0
380	[25, 15]	0.000	0.043	5.0
400	[25, 16]	0.000	0.087	9.0

Based on the above table, the best number of neurons for „*logistic*" normalization method is 380. The training time is 5.0 seconds which still consider as the faster time, and the quantization errors is a lowest value than other which is 0.000 and same with the topographic errors which is the lowest value (0.043). So, based on the errors value, the best number of neurons for „*logistic*" nomalization method is 380.

From the SOM analysis of 69-bus data, the best number of neurons is selected from the four types of normalization method by comparing the result from the best number of neurons from each normalize method. The comparison is use to determine the best normalization method between the four type of method. The comparison between the methods is based on the value of quantization and topographic errors with the faster training time. The comparison of the method is shown at Table 5.11 below.

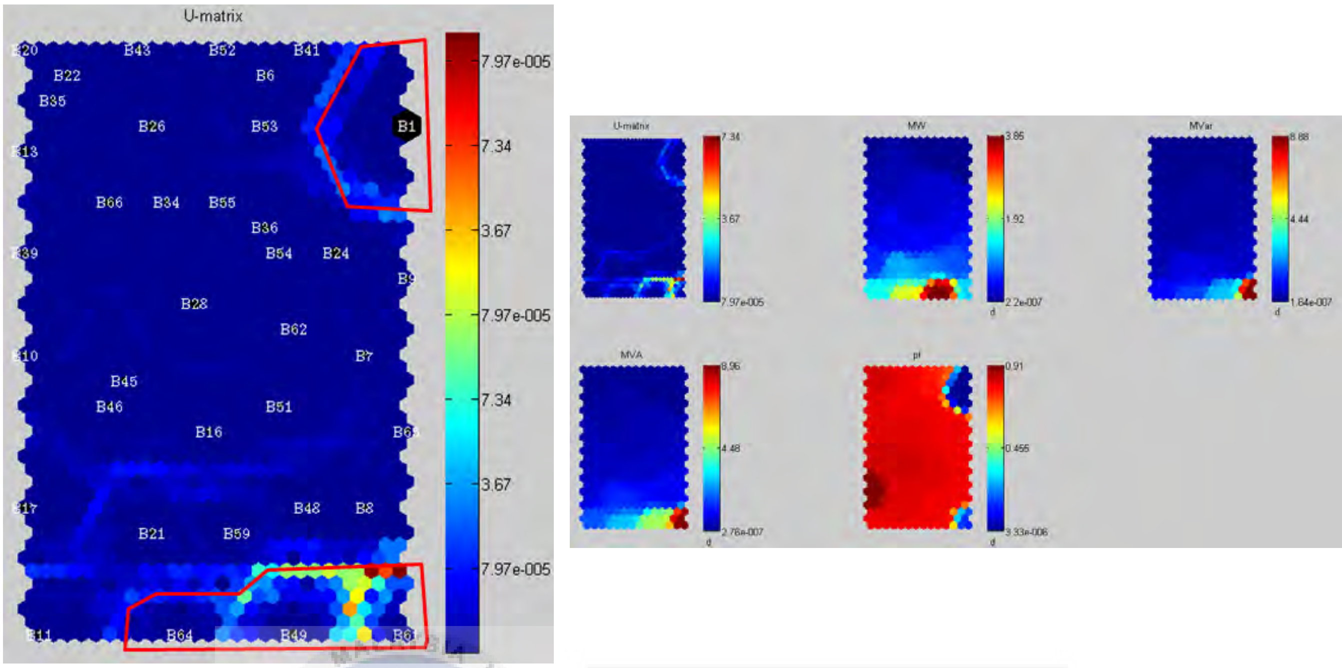
Table 5.11: The comparison between the types of normalization method

Normalization method	No. of neurons	simulation result			
		Map size	Quantization errors	Topographic error	Training time (sec)
var	340	[24,, 14]	0.002	0.043	4.0
range	320	[25, 13]	0.001	0.029	4.0
log	360	[33, 11]	0.001	0.072	5.0
logistic	380	[25, 15]	0.000	0.043	5.0

Based on the above table, the best normalization method is „*range*‟. The quantization errors is not the lowest value (0.001) but the topographic errors is the lowest value (0.029) and the training time is faster that other method (4.0 seconds). So, the best normalization method for 69-bus data is „*range*‟ with the number of neurons is 320.

The U-matrix is the final analysis for SOM result to choose the suitable buses for DGs. So, the analysis of U-matrix for each normalization method is shown as below.

i. The hexagonal lattice, „*var*" normalization method with 340 number of neurons



a) b)

Figure 5.11: a) The U-Matrix for "*var*" nomalization method with 340 numbers of neurons b) the lane Representation Showing Data Contribution of Four Bus characteristics for SOM Classification

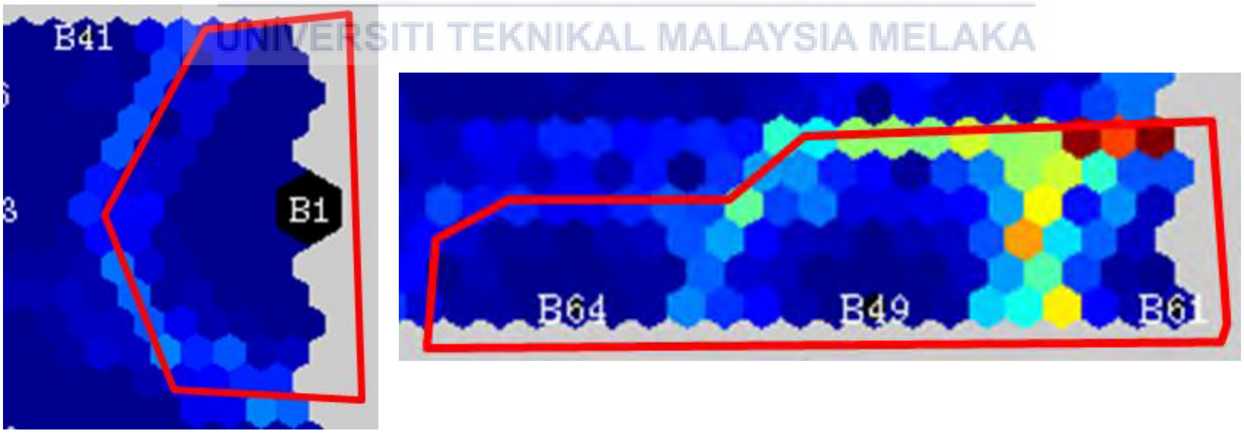
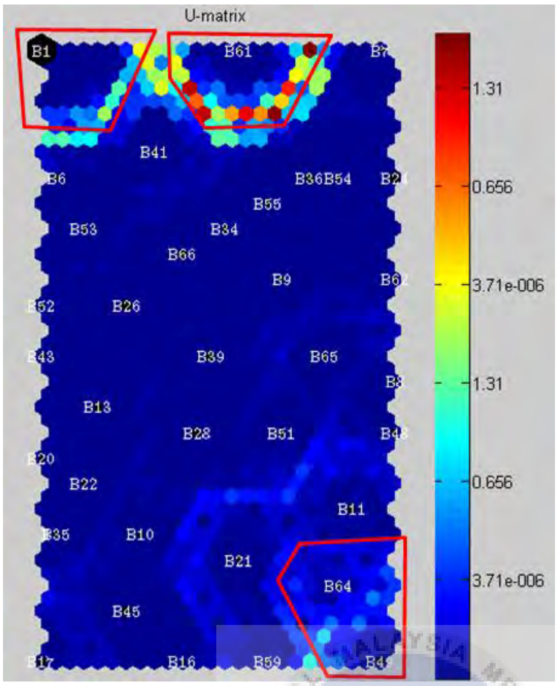
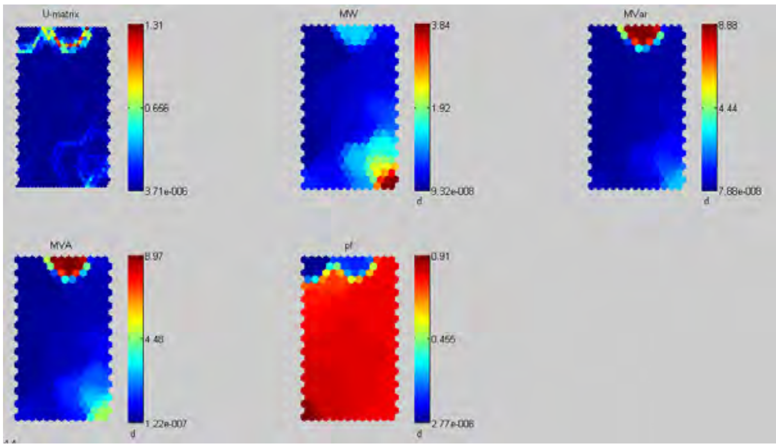


Figure 5.12: The classification of IEEE 69-bus data (B1, B49, B61, and B64)

ii. The hexagonal lattice, „*range*" nomalization method with 320 number of neurons





a) b)

Figure 5.13: a) The U-Matrix for „*range*" nomalization method with 320 numbers of neurons b) the Plane Representation Showing Data Contribution of Four Characteristics for SOM Classification

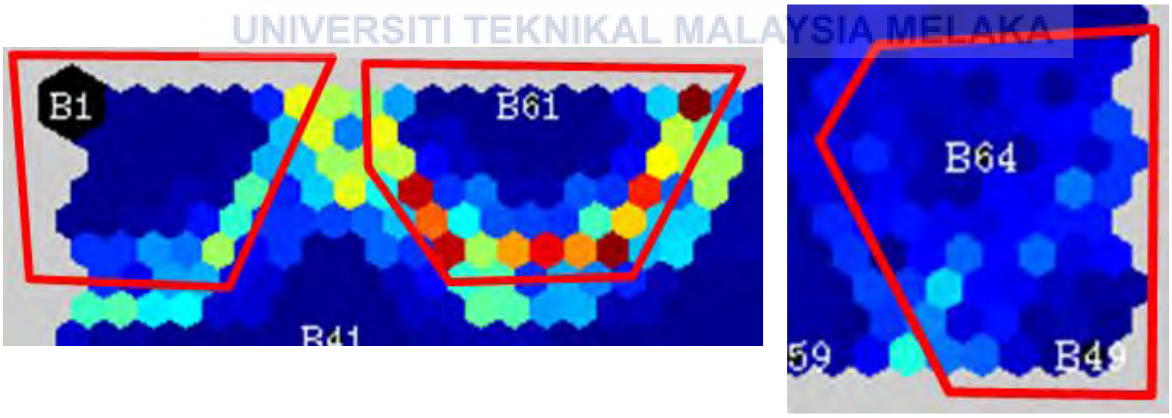
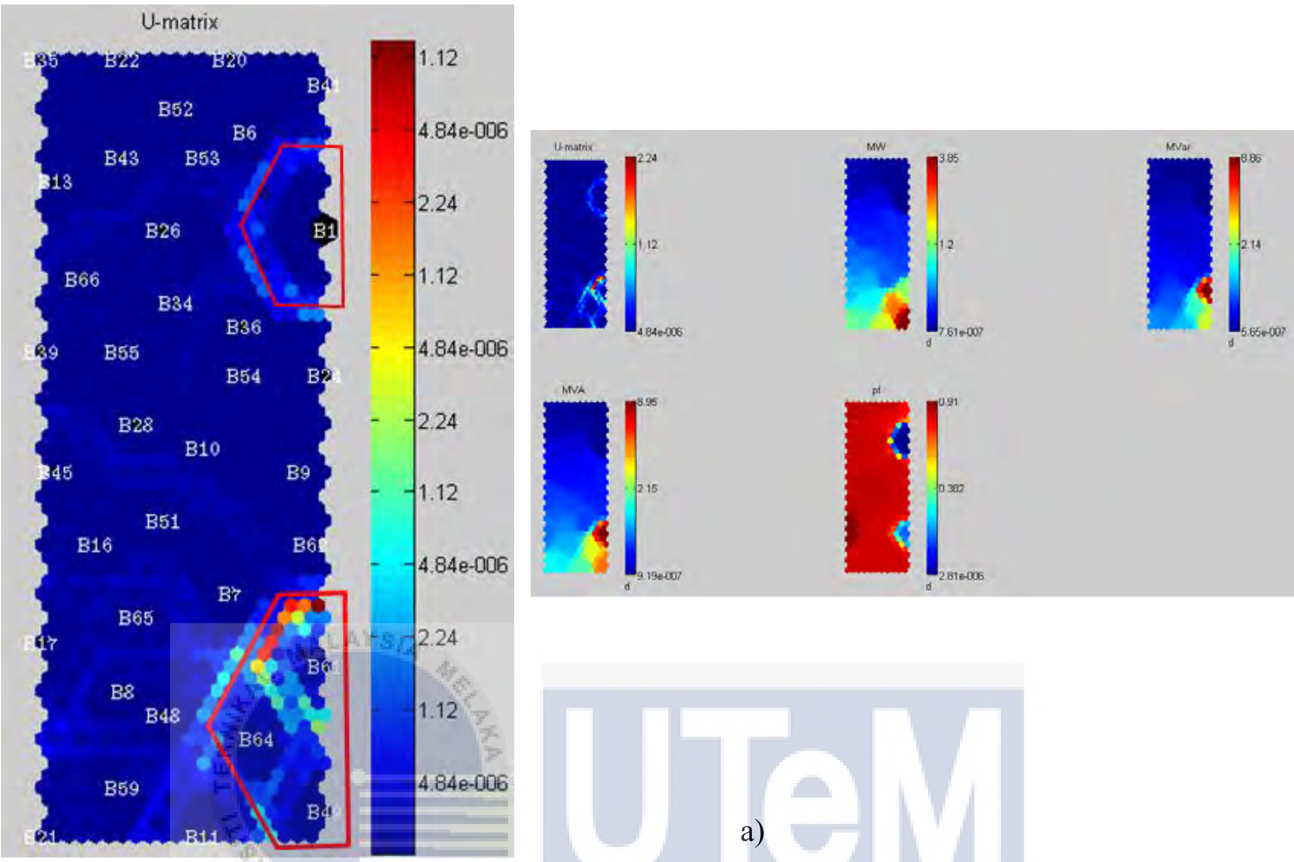


Figure 5.14: The classification of IEEE 69-bus data (B1, B49, B61, and B64)

iii. The hexagonal lattice, „*log*‟ nomalization method with 360 number of neurons



b)

a)

Figure 5.15: a) The U-Matrix for „*log*‟ nomalization method with 360 numbers of neurons b) the Plane Representation Showing Data Contribution of Four Characteristics for SOM Classification

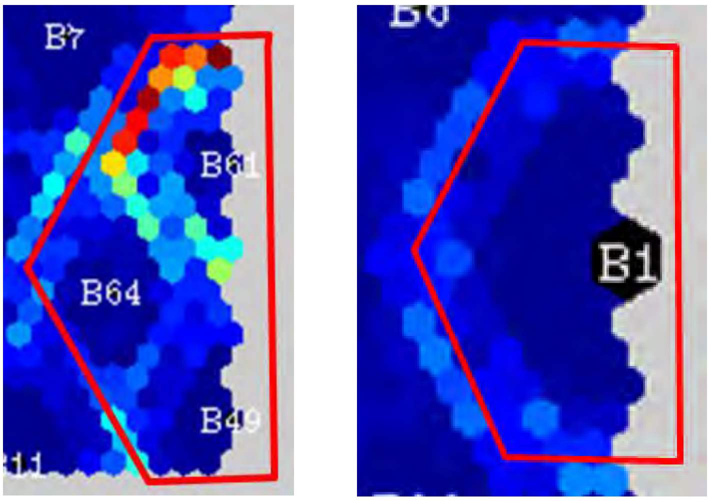
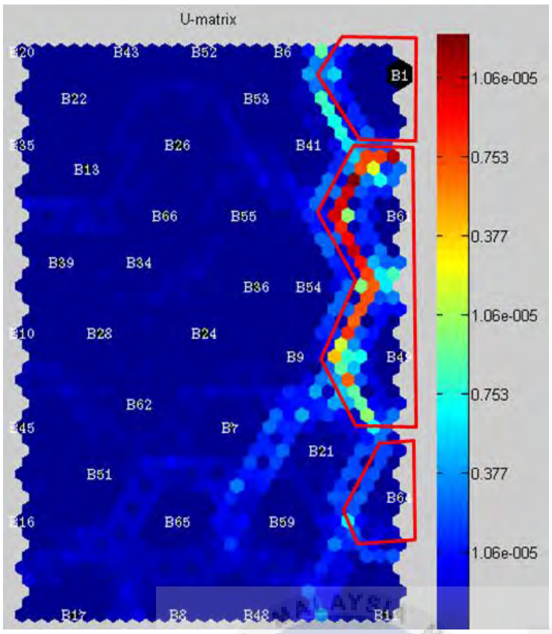
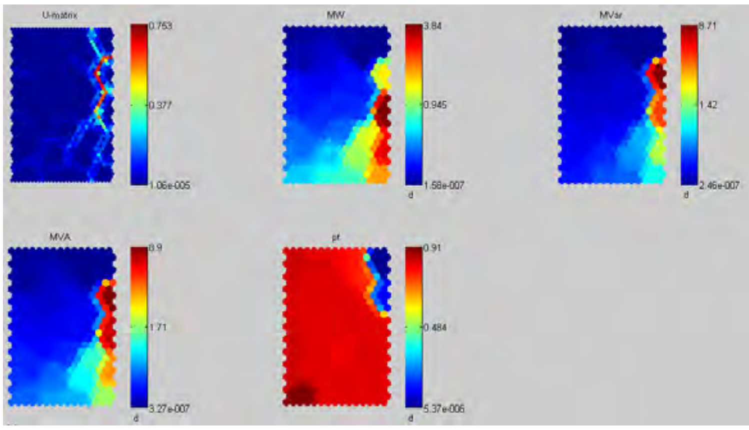


Figure 5.16: The classification of IEEE 69-bus data (B1, B49, B61, and B64)

iv. The hexagonal lattice, „*logistic*" normalization method with 380 number of neurons





a) b)

Figure 5.17: a) The U-Matrix for „*logistic*" normalization method with 380 numbers of neurons b) The Plane Representation Showing Data Contribution of Three Numerical Calculated Data for SOM Classification

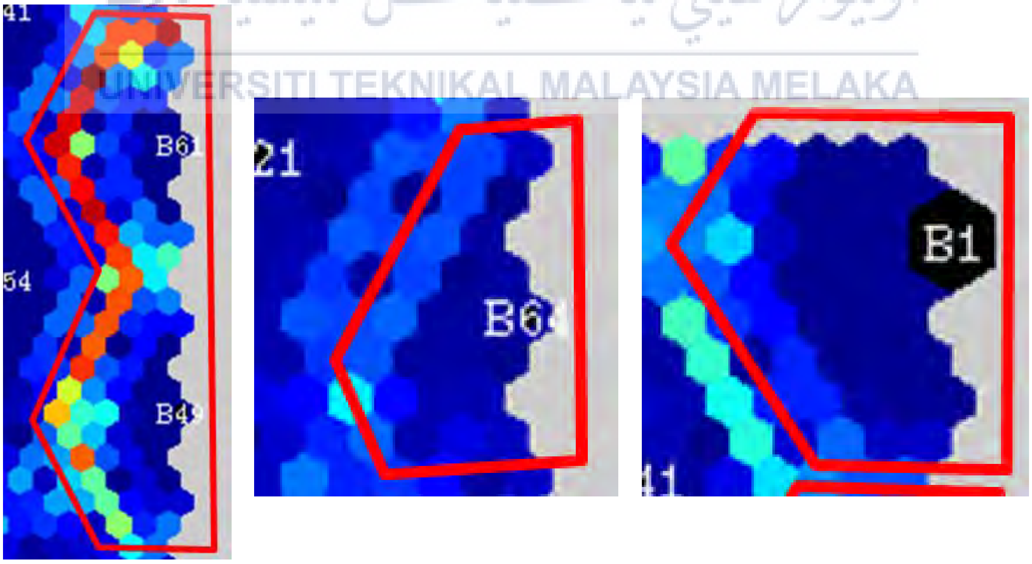


Figure 5.18: The classification of IEEE 69-bus data (B1, B49, B61, and B64)

- **SOM Analysis**

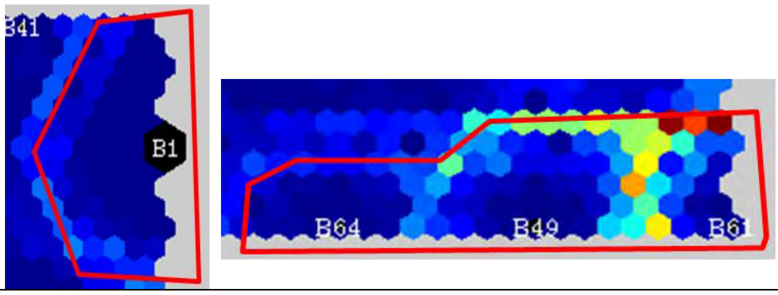
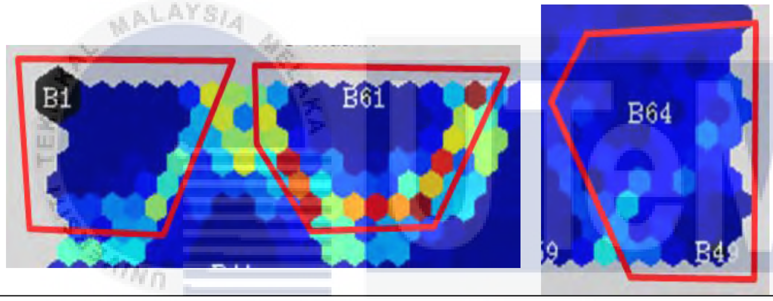
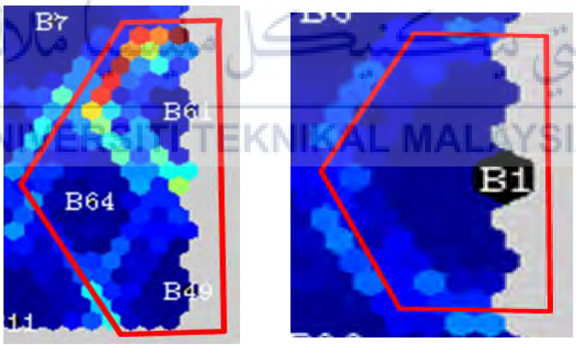
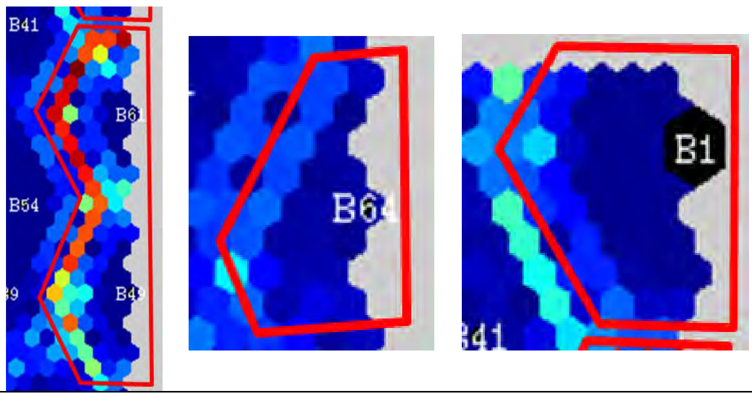
Based on the U-matrix in Figure 5.11, 5.13, 5.15 and 5.17 above, the neurons are labeled by B1 to B69 presented the standard IEEE 69-bus data. Based on all figure of classification result above, the B1, B49, B61, and B64 were separate with other buses because the forming of light boundary area which means that the bus have different characteristics between the neurons among the buses. The figure of the Plane Representation demonstrated the component of bus characteristics and from this figures, no uniform distributions are found through the plane. Each plane is important in contribution of IEEE 69-bus classification process.

Based on the all figure above, the B49 is the highest value in MW plane representation (dark red) and followed by B64 (orange) and B61 (yellow). For MVAr plane representation, the B61 is the highest value followed by B49 and B64. This bus condition is same with the MVA lane Representation. From the Plane Representation, the B1 is the darkest blue at all Plane Representation which means that this bus have a lowest value of load (MW, MVAr, MVA, and *pf*). The B1 has big black neurons which mean that lot of buses have same characteristics with B1. The similar bus characteristics with B1 are B2, B3, B4, B5, B15, B19, B23, B25, B30, B31, B32, B38, B42, B44, B47, B56, B57, B58, B60, and B63. All this bus is not suitable to place the DG because it has lowest value of load (MW, MVAr, MVA, and *pf*).

Based on the bus data, the B49 share the same characteristics of load with B50. In U-matrix, the B25 overlapped under the B24. As same as in 33-bus system, 4 DGs will be installed in the network system. So, 4 buses will be selected as a DG place. Based on all figures above, the suitable bus to place the DGs are bus 49 (B49), bus 50 (B50), bus (B61) and bus (B64).

- **SOM Result and Analysis Summary**

Table 5.12: The Summarization of IEEE 69-bus SOM Classification

Normalization Method	U-matrix Classification	Bus Classification from U-matrix	Bus Selected for 4 DGs
var		B1, B49, B50, B61, B64	Bus no. 49, Bus no. 50, Bus no. 61, Bus no. 64
range		B1, B49, B50, B61, B64	Bus no. 49, Bus no. 50, Bus no. 61, Bus no. 64
log		B1, B49, B50, B61, B64	Bus no. 49, Bus no. 50, Bus no. 61, Bus no. 64
logistic		B1, B49, B50, B61, B64	Bus no. 49, Bus no. 50, Bus no. 61, Bus no. 64

5.3.2. Part B: Power Losses Reduction

Table 5.13 and Table 5.14 shows the result obtained after the reconfiguration of IEEE 33-bus and 69-bus radial distribution network for original configuration, Case 1, Case 2, and Case 3. For IEEE 69-bus, the positions of DGs in Case 2 are 10, 21, 46, and 62 [43]. For the Case 4, the position of DGs placed based on the SOM result above. The parameters that have been considered are open switch (tie-switch), total power losses, power loss reduction and the percentage of loss reduction.

Table 5.13: Performance Analysis of EP method (IEEE 33-bus)

Case	Opened Switches	Total Power Losses (kW)	Power Loss Reduction (kW)	Percentage of Loss Reduction (%)
Original Configuration	33, 34, 35, 36, 37	202.771	-	-
Case 1: Reconfiguration using EP without DGs	14, 37, 7, 10, 32	118.1	84.67	41.76
Case 2: Reconfiguration using EP with Random 4 DGs Position [43]	7, 14, 37, 11, 32	91.2	111.57	55.02
Case 3: Reconfiguration using GA with 4 DGs Position [44]	7, 14, 21, 28, 32	98.2	104.571	51.57
Case 4: Reconfiguration using SOM-EP with 4 DGs Position	7, 14, 37, 11, 32	89.7	113.07	55.76

From Table 5.13, the total power losses for these three cases of reconfiguration is greatest different from the original configuration network. For the Case 1, the total power loss is 118.10 kW which the power loss reduction from the original configuration is 84.67 kW and the percentage of reduction is 41.76 % which is closer to half percent of reduction. For Case 2 and Case 4, the total power losses are 91.20 kW and 89.70 kW respectively. The positions of DGs for IEEE 33-bus radial system in these cases are 6, 18, 22, and 29 [43]. The Case 3 is a reconfiguration of IEEE 33-bus by using General Algorithms (GA) with 4 DGs position [44]. The total power losses for this method is 98.2 kW which the loss reduction is 104.57 kW from the original of 33-bus configuration and the percentage of reduction is 51.57%. Based on three cases, the percentage of loss reduction are more than half percent (55.02 %, 55.76 % and 51.57%) which the power loss reductions are 111.57 kW, 113.07 kW and 104.57 kW. Based on all the cases in table above, the 4 DGs installed in distribution system was improved the reduction of power losses around 10 % compared from the reconfiguration without DGs. From the result above, the combination of *Self-Organizing Map* and *Evolutionary Programming* (SOM-EP) for IEEE 33-bus radial distribution network is better of total power losses (89.70 kW) compared with Case 1, Case 2 and Case 3. The Figure 5.19 below shows the graph of total power losses for better analysis and the Figure 5.20 represent the graph of percentage of loss reduction for IEEE 33-bus system.

In the reconfiguration process for optimal power losses, the sectionalizing switches are contributed for power losses reduction. Firstly, the opened switches at original configuration of IEEE 33-bus radial distribution network are 33, 34, 35, 36, and 37. For the Case 1, the opened switches are 14, 37, 7, 10, and 32 while for Case 2 are similar with Case 4 which are 7, 14, 37, 11, and 32. For Case 3, the opened switches are 7, 14, 21, 28, and 32. All of the switch reconfigurations above, the distribution network are in radial configuration.

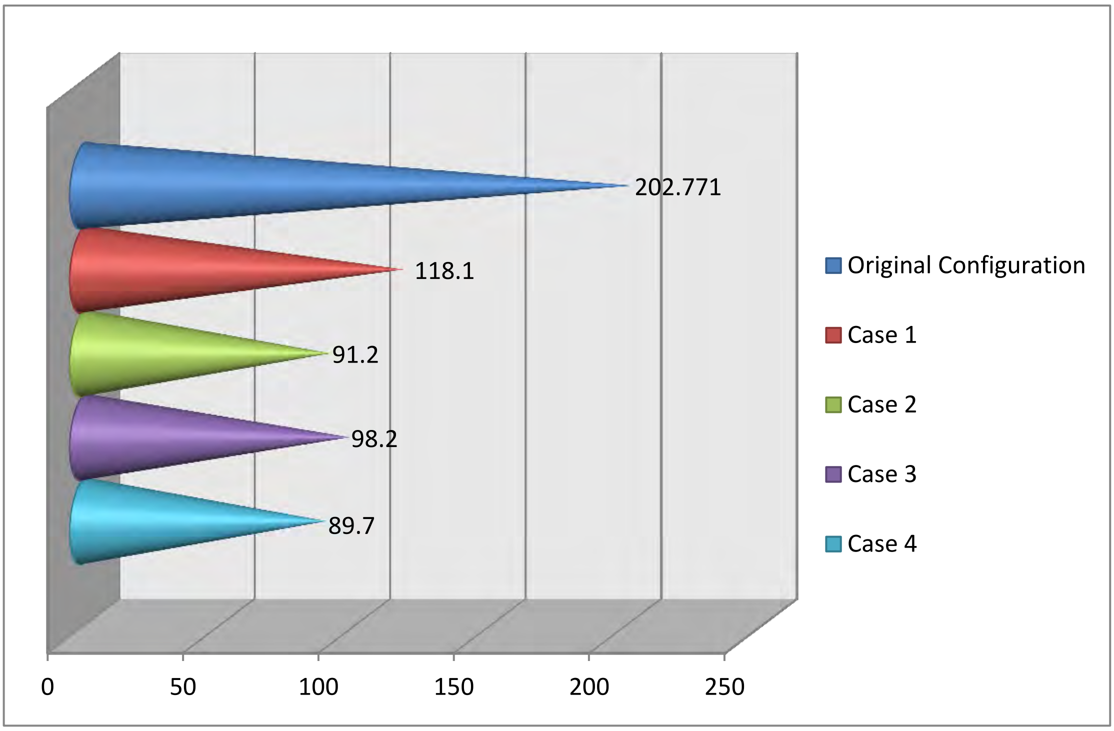


Figure 5.19: Comparison Graph of Total Power Losses for IEEE 33-bus

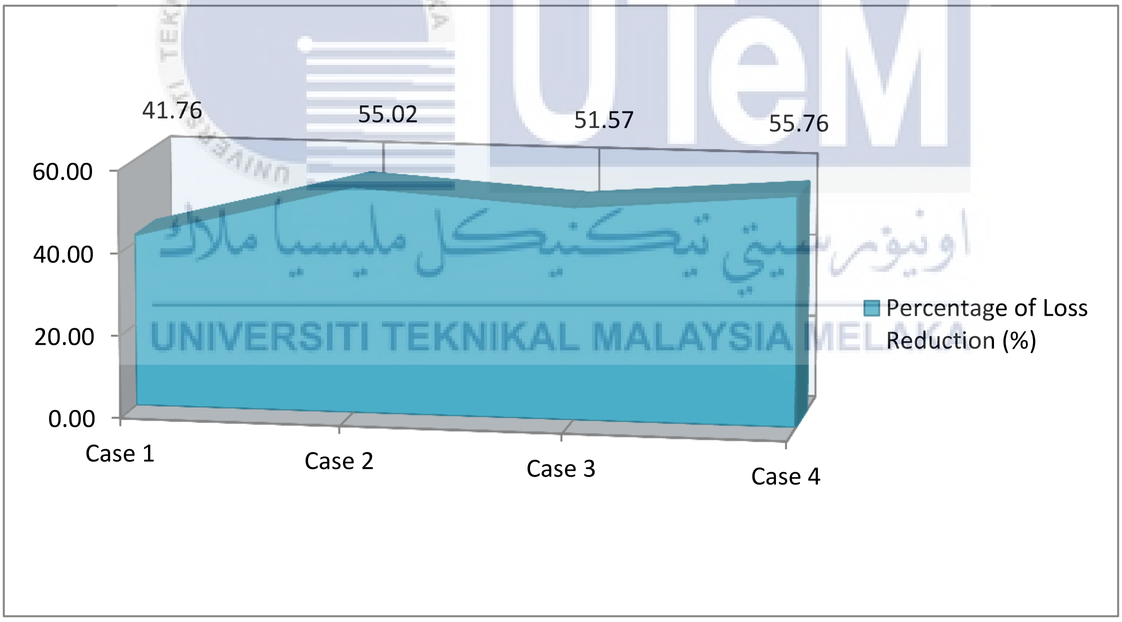


Figure 5.20: Graph for Percentage of Loss Reduction

Table 5.14: Performance Analysis of EP method (IEEE 69-bus)

Case	Opened Switches	Total Power Losses (kW)	Power Loss Reduction (kW)	Percentage of Loss Reduction (%)
Original Configuration	69, 70, 71, 72, 73	225	-	-
Case 1: Reconfiguration using EP without DGs	12, 55, 64, 69, 17	48.2	176.80	78.58
Case 2: Reconfiguration using EP with Random 4 DGs Position [43]	12, 55, 64, 69, 17	40.7	184.30	81.91
Case 3: Reconfiguration using SOM-EP with 4 DGs Position	12, 55, 64, 69, 17	42.1	182.90	81.29

From Table 5.14 above, the total power losses for all three cases of reconfiguration have greatest different from the original configuration network. For Case 1, the total power loss is 48.20 kW which the power loss reduction is 176.80 kW. The reduction of power reduction is more than half percent from original power loses (78.58 %). In Case 2, the position of 4 DGs for IEEE 69-bus are at 10, 21, 46, and 62 [43]. For Case 2, the total power loss is 40.70 kW. The power loss reduction is 184.30 kW from the original configuration which is 225 kW. The percentage of reduction for this case is more than 80% from the original configuration (81.91%). In Case 3, the reduction of power loss is not too different with Case 2. But the reduction is lower than in Case 2 which is 182.90 kW from the original configuration. The total power loss for Case 3 is 42.10 kW and the percentage of reduction is 81.29%. The total power loss for Case 3 is 1.4 kW higher than in Case 2 which 0.62% different in percentage of reduction between Case 2 and Case 3. Based on the overall result above, the combination of *Self-Organizing Map* and *Evolutionary Programming* (SOM-EP) for IEEE 69-bus reconfiguration cannot cater the requirement of lowest power loss reduction. The Figure 5.21 below shows the graph of total power losses for better analysis and the Figure 5.22 represent the graph of percentage of loss reduction for IEEE 69-bus system.

In the reconfiguration process for optimal power losses, the sectionalizing switches are contributed for power losses reduction. Firstly, the opened switches at original configuration of IEEE 69-bus radial distribution network are 69, 70, 71, 72, and 73. For the Case 1, the opened switches are 12, 55, 64, 69, and 17, and these configurations are similar with Case 2 and Case 3. All of this switches reconfiguration above, the distribution network are in radial reconfiguration.

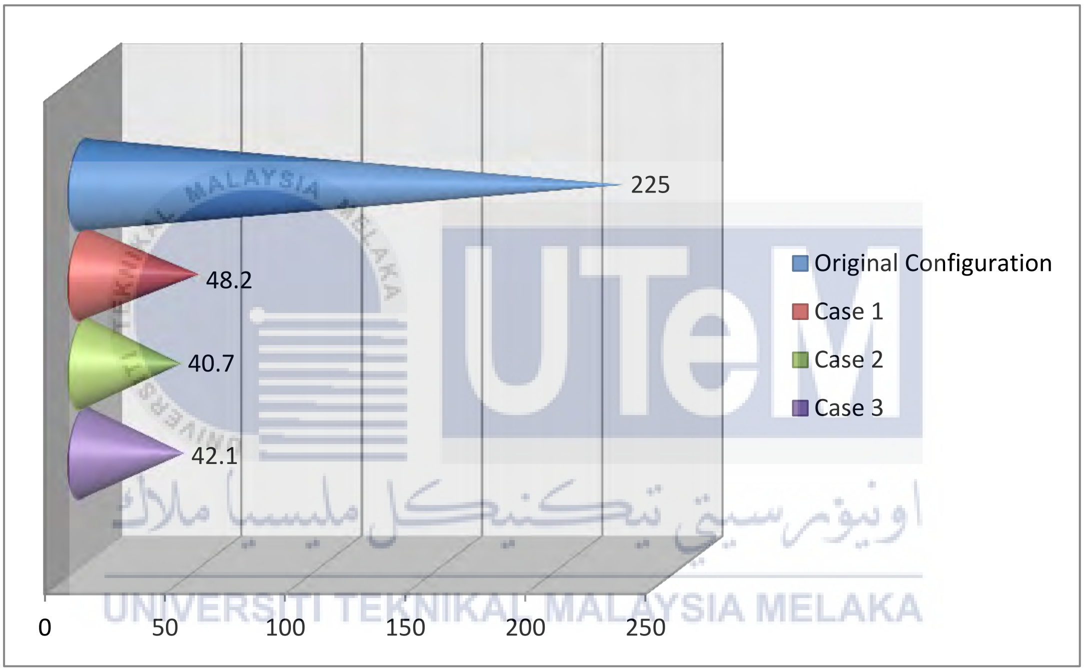


Figure 5.21: Comparison Graph of Total Power Losses for IEEE 69-bus

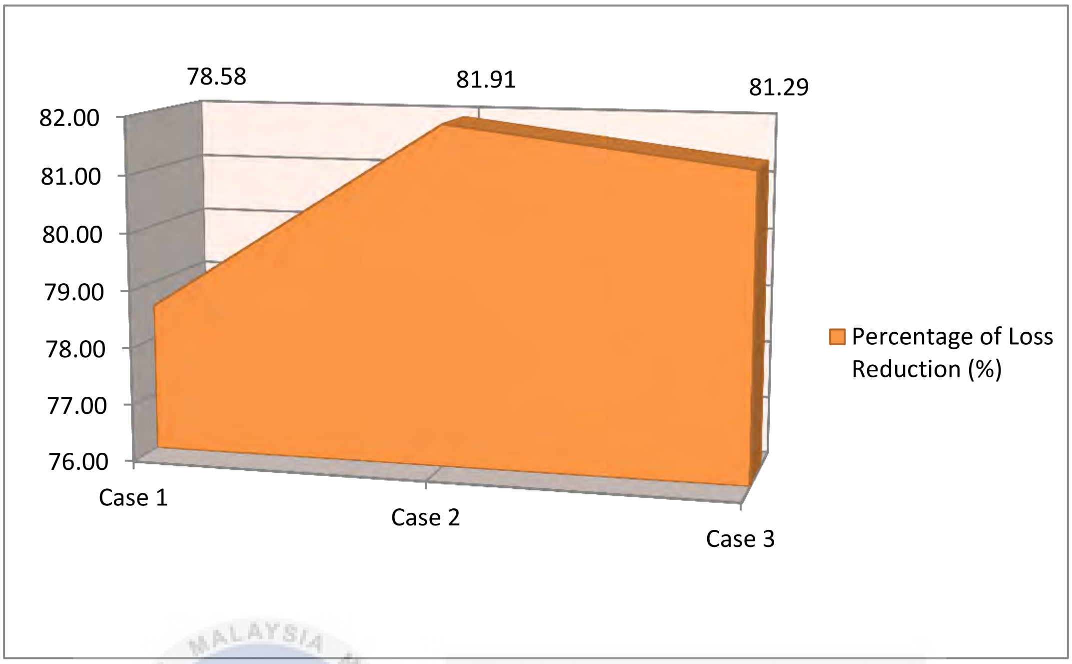


Figure 5.22: Graph for Percentage of Loss Reduction

5.3.3. Part C: DGs Sizing

The Table 5.15 below shows the size of DGs based on Case 2 and Case 3 for IEEE 33-bus system. The size of DGs in the system and its position can affect to the value of total power losses in the system. The maximum active output of DG in this study is set to 5 MW.

Table 5.15: The Size of DGs for IEEE 33-bus system

Case	Location		Size of DG (MW)
Case 2: Reconfiguration using Ep with Random 4 DGs position	DG 1	6	0.6210
	DG 2	18	0.5140
	DG 3	22	2.5240
	DG 4	29	2.8610
Case 3: Reconfiguration using SOM-EP with 4 DGs position	DG 1	24	0.6210
	DG 2	25	0.5140
	DG3	30	2.5240
	DG 4	32	2.8610
Case 4: Reconfiguration using GA with 4 DGs position [44]	DG 1	6	1.2100
	DG 2	12	1.4200
	DG3	25	0.5500
	DG 4	32	2.6700

Based on Table 5.15 above, the size of four DGs in Case 2 and Case 3 are determined by using Evolutionary Programming to achieve the lowest total power loss in distribution system. The position of the DGs was set to the system and the programming will determine the DGs sizes. For Case 2, the DGs size at bus 6, 18, 22, and 29 are 0.621 MW, 0.514 MW, 2.524 MW, and 2.861 MW. The position of DGs for Case 2 is taken from paper [43]. The sizes of DGs in Case 2 are similar with size of DGs for Case 3. The different between Case 2 and Case 3 are the position of DGs in the system which is 24, 25, 30, and 32. The size of DGs for Case 2 and Case 3 are compared with the Case 4. From the Table 5.15 above, the total size of DGs fro Case 2 and Case 3 are higher from the total size of DGs for Case 4. The total sizes of DGs for Case 2 and Case 3 is 6.52 MW and for Case 4, the total size of DGs is 5.85 MW.

The Table 5.16 below shows the result of DGs sizing for IEEE 69-bus system. The size of DGs will affect to the total power loss in the system.

Table 5.16: The Size of DGs for IEEE 69-bus system

Case	Location		Size of DG (MW)
Case 2: Reconfiguration using Ep with Random 4 DGs position	DG 1	21	1.5760
	DG 2	10	1.4870
	DG 3	46	1.4820
	DG 4	62	1.3760
Case 3: Reconfiguration using SOM-EP with 4 DGs position	DG 1	49	1.5770
	DG 2	50	1.4870
	DG 3	61	1.4810
	DG 4	64	1.3760

Based on Table 5.16 above, the size of four DGs in Case 2 and Case 3 are determined by using Evolutionary programming to achieve the lowest total power loss. For Case 2, the DGs size at bus 21, 10, 46, and 62 are 1.576 MW, 1.487 MW, 1.482 MW, and 1.376 MW. These sizes of DGs have reduced the total loss of 40.70 kW as tabulated in Table 5.14. For Case 3, the sizes of DGs do not have much of different with sizes of DGs in Case 2. The sizes of DGs in Case 3 are 1.577 MW, 1.487 MW, 1.4810 MW, and 1.376 MW. The total size of DGs for both cases is 5.921 MW. The positions of DGs for Case 3 are determined from the result of SOM classification as explained at Table 5.12 (Part A).

5.3.4. Part D: Voltage Profile Improvement

The Table 5.17 below shows the result of voltage profile improvement for Case 1, Case 2, and Case 3. The voltage profile improvement shows the effect of voltage profile in the system with and without the DGs.

Table 5.17: The Voltage Profile Improvement for IEEE 33-bus system

Bus. No	Voltage Magnitude		
	Case 1	Case 2	Case 3
1	1.000	1.000	1.000
2	1.000	1.000	1.000
3	0.999	0.999	0.999
4	0.998	0.999	0.999
5	0.998	0.998	0.998
6	0.997	0.997	0.998
7	0.997	0.997	0.997
8	0.996	0.997	0.996
9	0.996	0.996	0.996
10	0.996	0.996	0.996
11	0.997	0.996	0.996
12	0.997	0.997	0.997
13	0.996	0.997	0.997
14	0.996	0.997	0.996
15	0.996	0.996	0.995
16	0.995	0.996	0.995
17	0.995	0.996	0.995
18	0.995	0.996	0.995
19	1.000	1.000	1.000
20	0.998	0.998	0.998
21	0.997	0.998	0.998
22	0.997	0.998	0.997
23	0.998	0.999	0.999
24	0.998	0.998	0.998
25	0.997	0.998	0.998
26	0.997	0.997	0.997
27	0.996	0.997	0.997
28	0.995	0.996	0.997
29	0.995	0.995	0.996
30	0.994	0.995	0.996
31	0.994	0.995	0.996
32	0.994	0.995	0.996
33	0.995	0.996	0.995

From the Table 5.17 above, the result of voltage profile improvement. The improvement of voltage profile for Case 3 can observed at bus 28 to bus 32. The voltage profile in Case 3 for bus 28 was improved from 0.995 pu to 0.997 pu, and for bus 30 to 32, the voltage profile was improved from 0.994 pu to 0.996 pu. For other buses, the voltage profiles at most of buses are similar for the three cases. The Figure 5.23 below shows the graph of voltage profile improvement. The figure below shows the comparison between the cases.

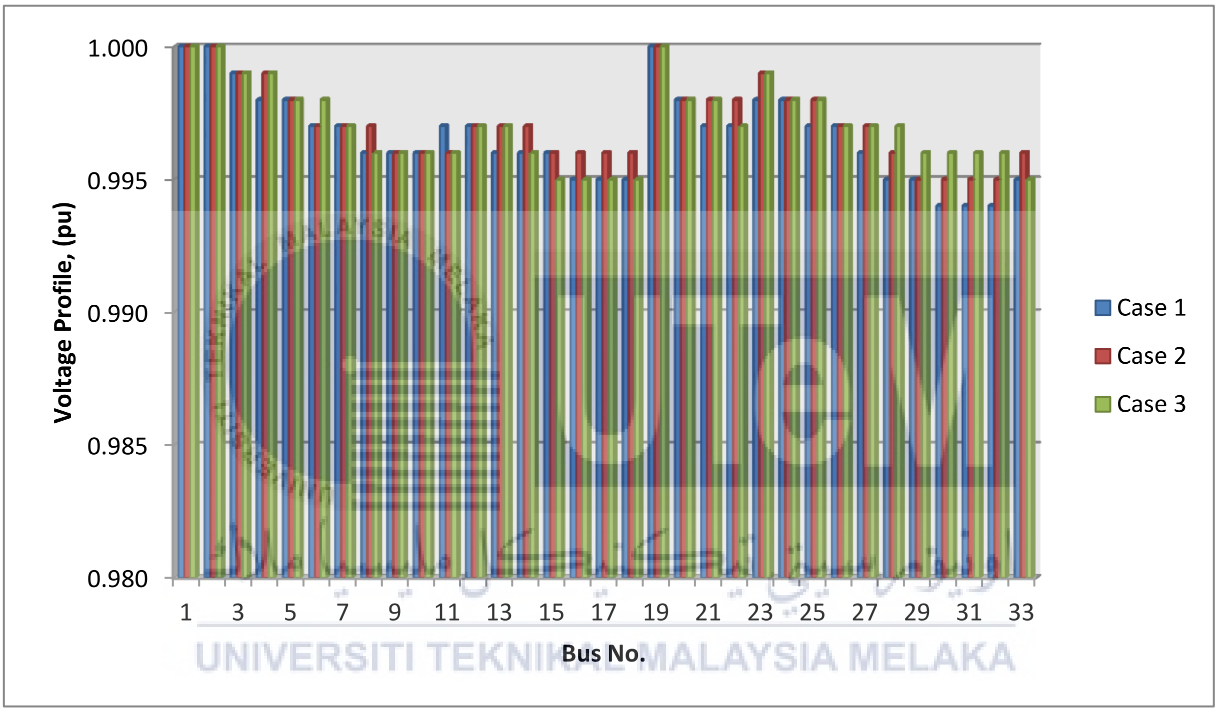


Figure 5.23: The Voltage Profile Improvement for IEEE 33-bus system

The Table 5.18 below shows the result of voltage profile improvement for case 1, Case 2, and Case 3.

Table 5.18: The Voltage Profile Improvement for IEEE 69-bus system

Bus. No	Voltage Magnitude		
	Case 1	Case 2	Case 3
1	1.000	1.000	1.000
2	1.000	1.000	1.000
3	1.000	1.000	1.000
4	1.000	1.000	1.000
5	1.000	1.000	1.000
6	1.000	1.000	1.000
7	1.000	1.000	1.000
8	1.000	1.000	1.000
9	1.000	1.000	1.000
10	0.999	0.999	0.999
11	0.999	0.999	0.999
12	0.999	0.999	0.999
13	0.998	0.999	0.998
14	0.999	0.999	0.999
15	0.999	0.999	0.999
16	0.999	0.999	0.999
17	0.999	0.999	0.999
18	0.998	0.999	0.998
19	0.998	0.999	0.998
20	0.998	0.999	0.998
21	0.998	0.999	0.998
22	0.998	0.999	0.998
23	0.998	0.999	0.998
24	0.998	0.999	0.998
25	0.998	0.999	0.998
26	0.998	0.999	0.998
27	0.998	0.999	0.998
28	1.000	1.000	1.000
29	1.000	1.000	1.000
30	1.000	1.000	1.000
31	1.000	1.000	1.000
32	1.000	1.000	1.000
33	1.000	1.000	1.000
34	1.000	1.000	1.000
35	1.000	1.000	1.000
36	1.000	1.000	1.000
37	1.000	1.000	1.000
38	1.000	1.000	1.000

39	1.000	1.000	1.000
40	1.000	1.000	1.000
41	0.999	1.000	0.999
42	0.999	1.000	0.999
43	0.999	1.000	0.999
44	0.999	1.000	0.999
45	0.999	0.999	0.999
46	0.999	0.999	0.999
47	1.000	1.000	1.000
48	1.000	1.000	1.000
49	0.999	0.999	0.999
50	0.999	0.999	0.999
51	1.000	1.000	1.000
52	1.000	1.000	1.000
53	1.000	1.000	1.000
54	1.000	1.000	1.000
55	1.000	1.000	1.000
56	0.997	0.998	0.998
57	0.997	0.998	0.998
58	0.997	0.998	0.998
59	0.997	0.998	0.998
60	0.997	0.997	0.998
61	0.997	0.997	0.998
62	0.997	0.997	0.998
63	0.997	0.997	0.998
64	0.997	0.997	0.997
65	0.998	0.999	0.998
66	0.999	0.999	0.999
67	0.999	0.999	0.999
68	0.999	0.999	0.999
69	0.999	0.999	0.999

From the Table 5.18 above, the result of voltage profile improvement show that the Case 2 has better value compared with Case 1 and case3. The improvement of voltage profile can observed at bus 13, bus 18 to bus 27, bus 41 to bus 44, and bus 65. At these buses shows that the voltage profile of Case 2 is higher than other cases. The higher value of voltage profile for Case3 are at bus 60 to bus 63. The Figure 5.24 below shows the bar graph of voltage profile improvement for IEEE 69-bus system.

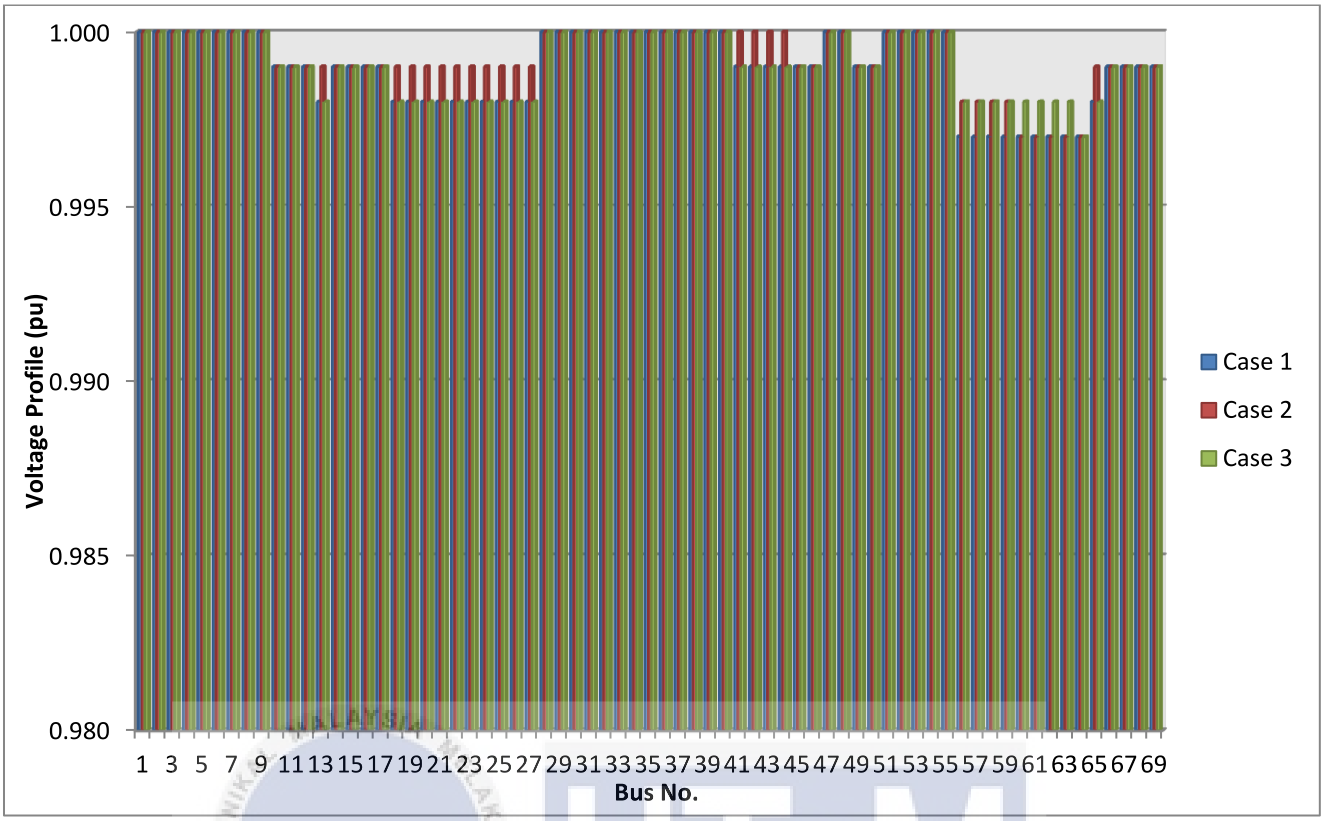


Figure 5.24: The Voltage Profile Improvement for IEEE 69-bus system

5.4. Summary

From the result and analysis, as a whole, the combination of *Self-Organizing Map* and *Evolutionary Programming* (SOM-EP) in a reconfiguration of distribution system and DGs sizing has been successfully applied and implemented in a test data 33kV distribution system. The result obtained shows that the capability of this combination in power loss reduction also the voltage profile improvement. The SOM-EP shows the classification of bus characteristics for the 33-bus data system in determining of DGs location and optimizing total power losses for the systems. For the 69kV distribution system, the SOM-EP is not suitable to apply in this system based on the result of total power reduction which higher compared to the reconfiguration using EP with random DGs location (Case 2).

CHAPTER 6

CONCLUSION AND RECOMMENDATION

6.1. Conclusion

This report discusses a combination of *Self-Organizing Map* (SOM); which one of the artificial neural networks (ANNs), and a type of optimizing algorithm; *Evolutionary Programming* (EP). The analysis considered the bus classification, power losses reduction, *Distributed Generation* (DGs) sizing, and the voltage profile improvement has been done successfully. The results of the reconfiguration have shown that in comparison between three cases, the SOM-EP for 33kV system gives better result in Power Loss Reduction which achieving the objective function of optimizing development. For the 69kV system, the combination of SOM-EP is not suitable to be applied based on the result achieved.

6.2. Recommendation

In order to get more convincing solution in achieve the best power optimization, further development of Evolutionary Programming can be suggested. The *Self-Organizing Map* (SOM) can be combined with other algorithms in order of best optimizing power distribution system in future research. Apart from SOM technique, other artificial neural networks technique can be applied as a bus data classification to achieve the suitable DGs placing.

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APPENDIX A

Project Gantt Chart

Task\ Week	1	2	3	4	5	6	7	8	9	12	13	14	15	16	17	18
Project continued (FYP 2)	/	/	/	/	/	/	/	/	/	/	/					
Brief for FYP 2		/														
Final Report Draft submission to supervisor											/					
Correction of Final Report Draft												/				
Final Report submission to Panel and Supervisor													/			
FYP 2 Seminar														/		
Final Report improvement															/	
Final Report submission to FYP Committee																/