MINIMIZING POWER LOSSES BY USING IMPROVED GENETIC ALGORITHM (IGA) FOR DISTRIBUTION NETWORK RECONFIGURATION (DNR)

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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

2014

I declare that this report entitle “Minimizing Power Losses by Using Improved Genetic Algorithm (IGA) for Distribution Network Reconfiguration (DNR)” 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 candidate of any other degree.

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ABSTRACT

Power losses issues persevered over few decades in the high demand utilization of energy electricity in developing countries. Thus, the radial structure of distribution network configuration is extensively used in high populated areas to ensure continuity of power supply in the event of fault. This paper proposes heuristic Genetic Algorithm known as IGA (Improved Genetic Algorithm) in consideration of genetic operator probabilities likewise the progression of switch adjustment in Distribution Network Reconfiguration (DNR) while satisfying the parameters constraints. The IGA algorithm was embodied throughout the process in IEEE 33-bus distribution system in selection of five tie switches. As a consequence, the power losses were ranked in accordance to the minimum values and voltage profile improvement obtainable by the proposed algorithm. The results show that the IGA performs better than GA by giving the minimized value of power losses.

Keywords *: Distribution Network Reconfiguration (DNR), Genetic Algorithm (GA), Improved Genetic Algorithm (IGA)*

ABSTRAK

Isu-isu kehilangan kuasa sepanjang beberapa dekad dalam permintaan penggunaan tenaga elektrik yang tinggi di negara-negara membangun. Oleh itu, struktur jejarian konfigurasi rangkaian pengagihan digunakan dengan meluas di kawasan yang berpenduduk tinggi untuk memastikan kesinambungan bekalan kuasa sekiranya ia gagal berfungsi. Kajian ini mencadangkan heuristik Algoritma Genetik sebagai balasan bagi kebarangkalian operator genetik begitu juga perkembangan suis pelarasan dalam Rangkaian Pengagihan Penyusunan (DNR) manakala memuaskan parameter kekangan. Algoritma ini diguna pakai sepanjang proses dalam IEEE 33 bas sistem pengagihan dalam pemilihan lima suis. Akibatnya, kerugian kuasa berjaya diminimumkan dan peningkatan profil voltan diperolehi oleh algoritma yang dicadangkan. Keputusan menunjukkan bahawa algoritma ini lebih baik daripada algoritma genetik yang biasa dengan mengurangkan kerugian kuasa.

Kata Kunci: Penyusunan Rangkaian Pengagihan (DNR), Algoritma Genetik (GA), Penambahbaikan Algoritma Genetik (IGA)

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CHAPTER 1

INTRODUCTION

1.0 Research Background

Power interruptions are the biggest obstacles to be tackled in the power distribution fields. They come in two types which are scheduled and unscheduled power interruption. Firstly, a scheduled power interruption that is normally conducted by the power utility company for maintenance purposes. Secondly, an occurrence of power failure namely as an unscheduled interruption that happens because of abrupt circumstances for example natural disaster like lightning strikes. Besides natural disaster, there are thousands other causes of power interruptions like low voltage of distribution level, load variations, overload, damage of equipment, damage caused by third party, loose of connection and even work quality [1].

Indeed, numerous researches have been done with the aim of reducing power losses in distribution system while maintaining its quality and reliability of the system itself. Many techniques have been approached such as Distributed Automation System (DAS) and Distribution Network Reconfiguration (DNR) [1-2]. This research attempts to use DNR which is a usable operation in reducing distribution feeder as well as improving the system security.

DNR technique consists of traditional network reconfiguration and heuristic reconstruction method. In order to solve DNR, there are few categories of approaches that can be applied which are switch exchange method, mathematical optimization theory, artificial intelligence algorithm and optimal flow pattern [3].Initially, the traditional network reconfiguration is implemented to reduce power losses, balance the load and stabilize voltage in normal operating conditions where it does not include the impact of network reconfiguration to the system reliability.

There are many researches to reconfigure the distribution network are introduced such as the developing of algorithms like Particle Swarm optimization (PSO), Simulated Annealing (SA), Tabu Search (TS) and Genetic Algorithm (GA). Particle swarm optimization (PSO) algorithm proposed in [2-4] used population-based approach. Modification was done by linearly decrease the inertia weight during simulation. It is capable of finding optimal or near-optimal solution to the test system and it operating time is acceptable for practical applications.

In this paper [3], the authors attempt to use IGA to find the optimal small size subset of features from the original large feature set. It proposed a new modified GA based on enhanced diversity, parents selection and improved genetic operators. The DGA is done through a modified roulette wheel selection procedures to be able to introduce more diverse feature of GA members and to avoid the mating of exact members.

1.1 Problem Statement

Distribution system is the part that connects the load and supply. According to [4], all loads are connected to the transmission lines at substation by distribution system through voltage transformation and switching functions. Hence, distribution system has to be able to cater the loads efficiently. However, fault occurrence at distribution system is inevitable due to loads variation, ageing of transformer, low voltage level at distribution system and the line losses itself. When the fault occur, the distribution system seems to produce losses at a very large number and by definition as said in [1], power losses in distribution system is the difference between the energy generated and the energy sold to the customers . This means that the customer have the rights to obtain as much power as possible from the supply. Hence, reconfiguration is introduced in order to minimize these losses in distribution system and then improved its quality and reliability.

1.2 Objectives

This research is mainly aims on the following:

1. To analyze the performance of IEEE-33 bus distribution system by using Improved Genetic Algorithm (IGA) in MATLAB2013 software.

1.3 Scope

The test system is only on IEEE-33 buses, radial configuration distribution system of 132/11 kV and is being simulated in MATLAB2013 software. In this paper, only one method is used which is Improved Genetic Algorithm (IGA) without considerations of Distributed Generation, DG.

1.4 Chapter Outline

Chapter 1 covers the introduction of thesis. Chapter 2 describes the literature review which guides and evolves through this paper. Chapter 3 presents the IEEE-33 bus distribution system and also describes the methodology of IGA applied in this paper. Chapter 4 shows the results of a simulation to demonstrate the performance of the proposed algorithms and Section 5 contains conclusion of the project.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The overall power system includes generation, transmission, distribution and loads. Distribution system is located at the end of the power systems which connect users and power system and then supply and distribute power to users. Thus, distribution system power capability and quality has to be fully maintained at its best operation. Referring to [1-4], the reconfiguration technique is done to maintain the radiality of the network and to cater all the loads by altering the on/off status of open/closed switch.

Several methods used to realize minimizing power losses such as traditional PSO, EPSO, GA and IGA. This research focuses on IGA, which is the improved version of GA. Genetic Algorithm, GA is a metaheuristic technique where it does not operate on a single point but operate the whole parameter code. Besides that, GA start searching not from a single point but from a group of points and the search is based on probabilistic change rules than uncertain rules. However, this conventional GA has slow convergence rate, local optimum and it ignores cooperation between populations. Thus, by using IGA which is simple, robust search algorithm and it gives good solution rapidly for difficult high-dimensional problem as mentioned in [1,2] actually helps to overcome the flaw of GA.

2.2 Distribution System in Malaysia

In Malaysia, power system has three main parts which have been mentioned earlier which are generation, transmission and distribution. Fig. 2.1 below shows a simple block diagram of a power system in Malaysia.

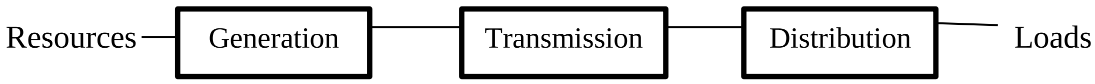


Fig. 2.1: Simple Block Diagram of Power System in Malaysia

The distribution networks have many types of configuration such as petal, mesh, loop and radial configuration. As mentioned in [2], radial configuration is most used distribution networks configuration in Malaysia with lowest initial cost and the only practical solution for rural network with long supply lines and low load densities due to economic reasons. Fig. 2.2 illustrates simple diagram of radial configuration. This type of configuration has such characteristics of supplying on one end only while the feeders are separated in radiated from a single substation to feed the distributors at one end only. However, this configuration has poor service reliability and security. It has no provision for feedback supply to affected customers downstream of the cable fault.

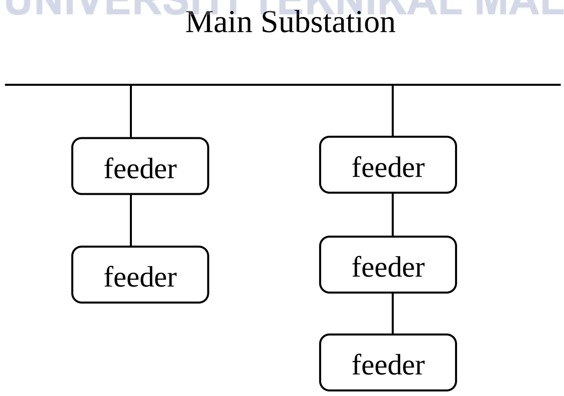


Fig. 2.2: Radial Configuration

Loop configuration, mesh configuration and petal configuration are being shown in Fig. 2.3, 2.4 and 2.5, respectively.

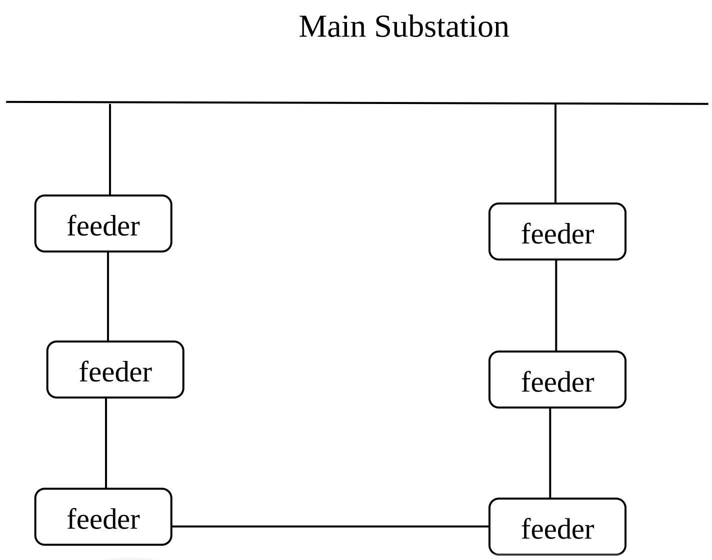


Fig. 2.3 : Loop Configuration

Fig. 2.3 illustrates loop configuration from the same source where several substations are connected from two cables and it ends on one main station. This configuration operated like two different radial configurations and somehow maintaining the uniform size of cable which will make this configuration to cater the network easily [2].

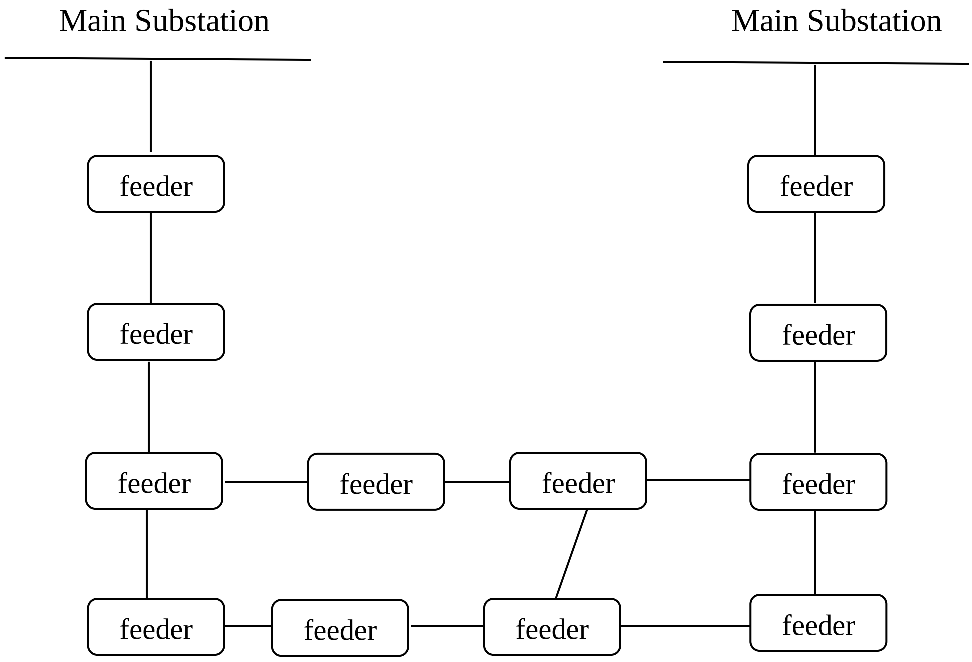


Fig. 2.4 : Mesh Configuration

A mesh configuration illustrated in Fig. 2.4 is the combination of several ring systems. In order to obtain increasing supply security, this configuration has to be an interconnecting circuit. This type of configuration has high network losses but somehow produces higher utilization of circuit capacity [2].

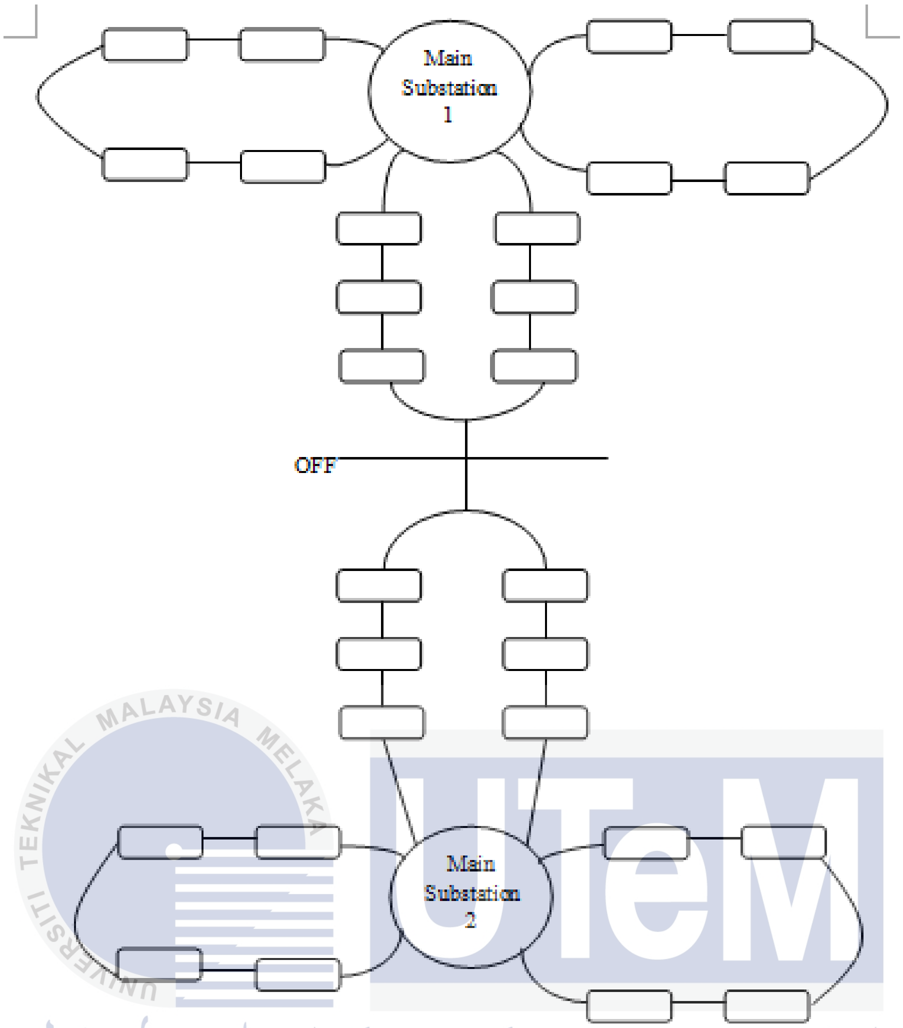


Fig. 2.5 : Petal Configuration

Fig. 2.5 is a petal configuration where it is the interconnection of two loop circuits from different main substations and this configuration can improve level of supply security and reliability [2].

2.3 Theory and Basic Principles

2.3.1 Distribution Network Reconfiguration (DNR)

Traditional network reconfiguration is implemented to reduce power losses, balance the load and stabilize voltage in normal operating conditions where it do not include the impact of network reconfiguration to the system reliability. John Holland are first to introduce the use of distribution system reconfiguration in minimizing power losses. In determining the minimum loss configurations, he use branch and bound type optimization techniques. While in 1989, there are other research done on balancing load and generating loss reduction that introduced an integer programming problem which was said to be the one of the efficient load flow equations.

The heuristic reconstruction method proposed requires closing the switches and separating the network into a small ring network. Then the network is opened each time till the networks is back to the radial structure and this process should reduce losses. Although initial state is not dependable in this method final reconstruction structure, the solution process still gives optimal or near optimal network structure. This method uses Direct Current (DC) calculation while ignoring voltage phase angle and network constraints. Actual distribution network consists of a large number of switches which increase the dimension and then may results in serious “combinatorial explosion” problem [3,4].

According to [4,5] there is also a single ring network optimization problem with only one pair of opened and closed switches which proposed by Ji-Yuan Fan. This method uses a nonlinear integer programming with a quadratic objective function and 0-1 state variables as its mathematical model. This method use shortest path method to easily formed tree network and finding the power supply path for each loads. Therefore, it is easily used for reconstruction optimization of complex network since it algorithm does not need any special requirements to network optimizing [6].

According to [7-9], Distribution Network Reconfiguration (DNR) has various numbers of normally open/closed switches and is usable and important operation in reducing losses of distribution feeder and improving security of the system. As the operating conditions change, optimal operation of distribution system can be realized by reconfiguring the system to minimize losses. However, it is not easy to obtain fast and exact optimal solution in real system because this reconfiguration takes various operational constraints in large scales into account.

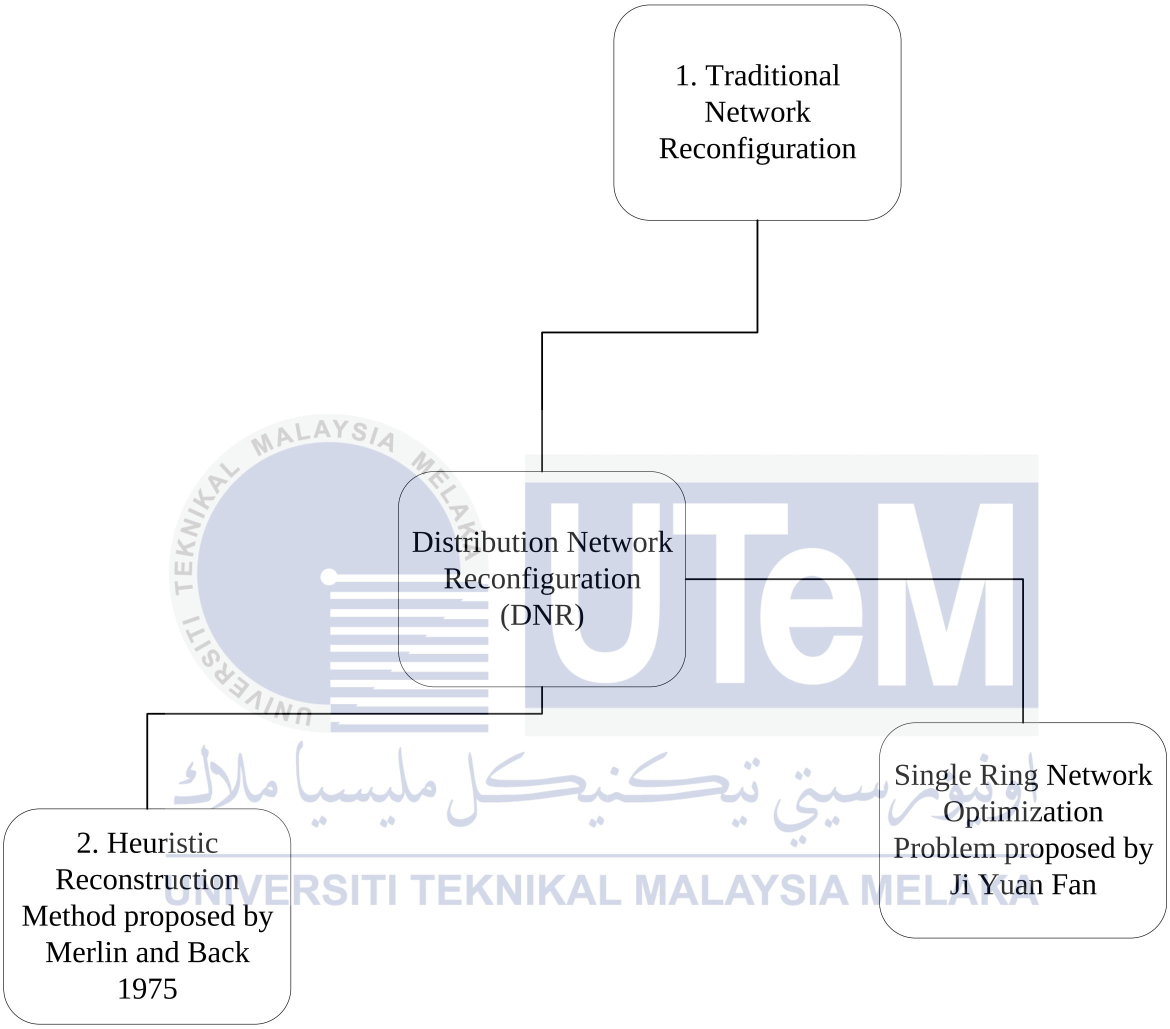


Fig. 2.6 : Evolution of Distribution Network Reconfiguration

2.3.2 Genetic Algorithm (GA)

Before enhancing to Improved Genetic Algorithm (IGA), the concept of GA has to be understood first. According to [8], Genetic Algorithm (GA) is a search technique used in computing to look for possible solution in search problems and optimization. This technique is inspired from evolutionary biology which is consists of inheritance, mutation, selection and crossover (recombination).

Fig. 2.7 below describes simple Genetic Algorithm [9]. Most likely solutions of traditional GA are represented in bit string (0-1) but other encoding can also be considered. GA first defines the chromosomes according to fitness function before going through selection according to *roulette wheel method*. The final stage of GA would be crossover and mutation before obtaining the best solution.

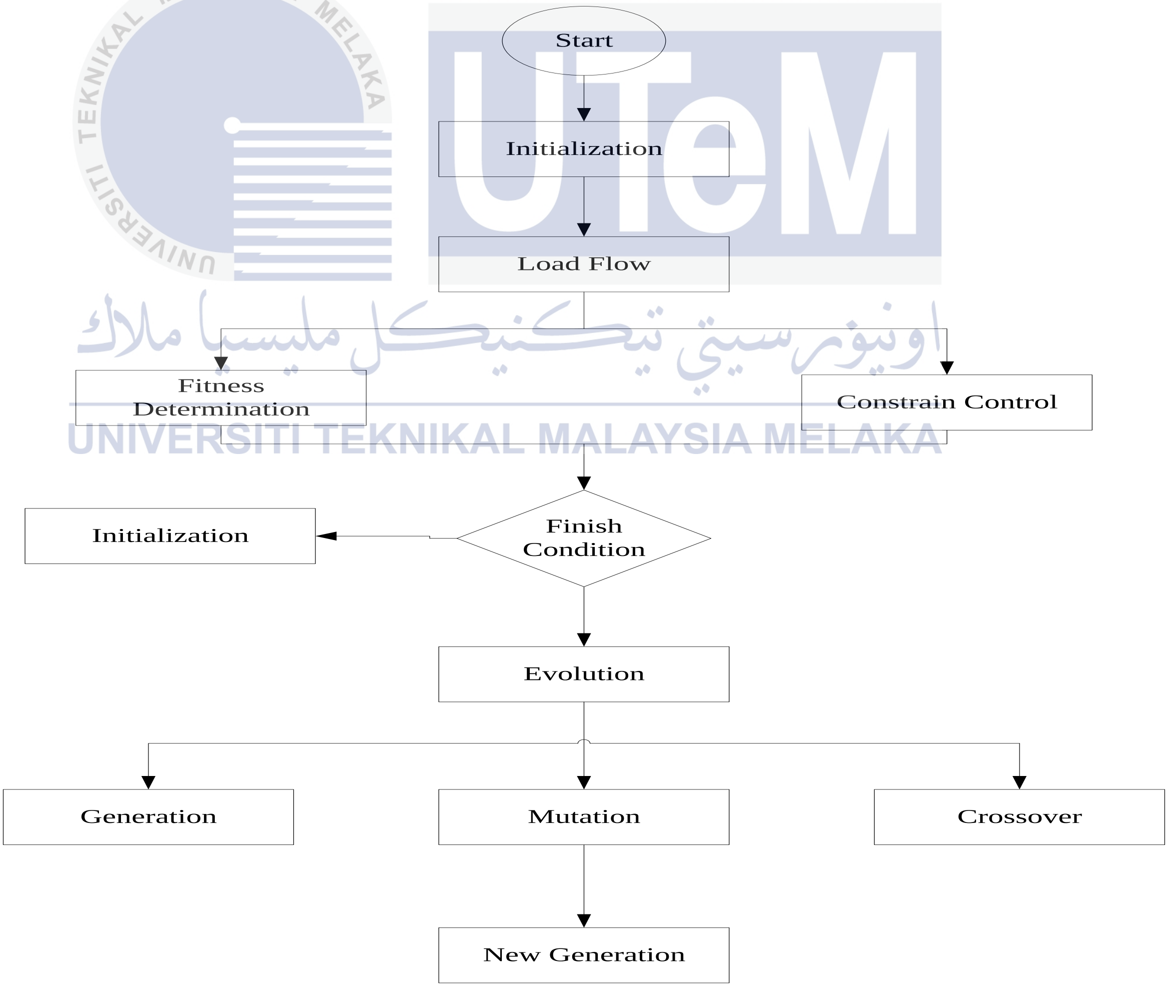


Fig. 2.7 : Flowchart of a Simple Genetic Algorithm [9]

Based on [5], Genetic Algorithm (GA) is inspired from evolutionary theory where its search method is based on natural genetic selection mechanism. GA results in optimization of parameters formed by encoded string groups where actually it introduced biological evolution theory of 'survival of the fittest'. By simulating the best survival of gene string and using the method of random information exchange, GA search for its optimization program. However, it became a flaw when GA performance was affected as a result of constant crossover and mutation rates.

Characteristics of GA are simply said as GA operates the code of the parameter itself, GA start searching from a group of points rather than one point and finally GA search is based on the rules of probabilistic change rather than not uncertain rule. Nevertheless, GA provides the following advantages. Firstly, it produces high possibility of obtaining optimal values in early generations and it has high convergence. Besides that, GA is able to handle sick and discrete optimization problem and also GA has inherent characteristics of parallel computing.

David E. Goldberg in his book [10] defines GA as a search algorithm based on mechanics of natural selection and genetics. GA forms its search algorithm from combined survival of the fittest among string structures with structured and randomized information exchange. In additional, GA efficiently venture historical information to consider new search points with expected improved performance. GA requires natural parameter set of optimization problems to be coded as finite-length strings over some finite alphabet.

A simple GA is actually very simple where it just copy strings and then swap partial strings where it has been composed to three operators which are reproduction, crossover and mutation. This GA is different from the conventional optimization techniques where it involves direct manipulation of a coding and its search from a population, not from a single point. Besides that, GA search through sampling not by a blind search and it uses stochastic operators instead of deterministic rules.

While in [11], Tom V. Matthew defines GA as the search algorithm that is based on the concepts of both natural selection and genetics. The first objective of developing GA is to simulate some processes in natural evolution where it operates on chromosomes (organic device) to encode the structure of living being. Fig. 2.8 below describes the working principle of a simple GA.

```
/* Algorithm GA */
formulate initial population
randomly initialize population
repeat
evaluate objective function
        find fitness function
        apply genetic operators
                reproduction
                crossover
                mutation
until   stopping criteria
```

Fig. 2.8: Working Principle of Simple GA [11]

In GA, the problem is simply described by the coding of variables where the common variable used is a binary string or a vector. However, GA is in its best operations when solution vectors are in binary string. Table 2.1 shows description of GA processes mentioned earlier.

Table 2.1 : Description of GA Processes

GA process	Description
Fitness Function	Derivation of the objective functions and applied to the successive genetic operations. Biological terms define fitness as a measure of the chromosomes reproductive efficiency. From fitness function, chromosomes with high fitness value are selected for the next stage.
Reproduction	The operator that copy better strings in new population. Good strings in the population are being selected before forming mating pool. It is necessary to maintain reproduction in current population so that next population is better produced. Most common used operator in reproduction is *Roulette-Wheel Selection.* These methods choose population with higher fitness for the mating pool.

Crossover	Used to recombine two strings into one better string. This new strings are produced by exchanging information among the mating pool strings. The two strings used to recombine are called 'parent string' while the result of these two is called 'children string'.
Mutation	Due to the repeated use of reproduction and crossover, a homogenous population is produced. Thus, mutation is used as diversity of this problem so that it would not happen. This may produce children string that is different from the parent string.

GA is different than other conventional optimization algorithm as it does not use the parameter but it use the coding of the parameter. Besides that, GA works on a population of a point instead of a unique point and only optimizes the values of the function and not their derived function or other auxiliary knowledge. After all, GA is not a determinist function but use the probabilistic transition function.

2.3.3 Improved Genetic Algorithm (IGA)

After the concept of GA is understood, only then the study of IGA is possible where it is the enhancing of GA. Based on [10-11], IGA gives the following significance where first, it reduces computational time and gives better analysis and solution. IGA also avoid premature convergence and it reduces size of the string. This IGA involves four stages which are fitness function, selection, crossover and mutation. In fitness function, the particular chromosomes are ranked against the other chromosomes. It quantifies optimality of a solution, in this case, chromosomes in a genetic algorithm.

While selection according to Darwin's evolution theory, the survived one is the best one and they could produce new offsprings. The better chromosomes have high chances to be selected as the parents. Meanwhile, crossover selects genes from parents to create new offspring. This is done by randomly choosing a crossover point. The left sides of the point copy from first parent while the right side copy from second parent. Mutation is done after crossover to prevent falling of all solutions in population into a local optimum of solved problems. Mutation process randomly changes the new offspring. For example, in bit string, mutation switch bits 1 to 0 or 0 to 1.

According to [12], it says that typical Radial Distribution System (RDS) uses GA in very large length of binary coding technique for chromosomes since it has large number of branches. So, the results are infeasible solutions which lead to large computational efforts. In order for not getting the invalid solutions, every stages of genetic evolution have to be taken proper measures to ensure the radiality of the network. Genetic Algorithm is possible in defining this problem to such encouragement the need for changes to satisfy the radial structure constraint. By using IGA, it is likely ensure that use of chromosome in a small length can help keeping the radial network during the optimization process.

2.4 Review of Previous Related Works

Network reconfiguration of distribution system is not something new and it has been done over the years ago. Many techniques of reconfiguration has been applied such Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Improved Genetic Algorithm (IGA).

Firstly, the research done in [9-11] is on the effect of distribution network reconfiguration in the power grid. This research works on a large scale distribution network involving mixed integer and nonlinear optimization problem. There are two techniques applied which is mathematical optimization theory and artificial intelligence theorem. The first technique, mathematical optimization theory is conclude such that it can guarantee global optimal solution by theoretically but cannot be applied to the actual distribution network while the second technique which is artificial intelligence algorithm can find out optimal configuration faster but it consumes time. However, GA which falls in the second technique is said to be suitable applied in solving distribution network reconfiguration if the convergence is improved.

Secondly, a particle swarm optimization (PSO) algorithm proposed in [13] is used to solve network reconfiguration to reduce power loss. This algorithm is still a new evolution method which used population-based approach. This research did some modification on PSO by linearly decrease the inertia weight during simulation. As the conclusion, PSO is said to be simplest compared to the other conventional mathematical method. It is capable of finding optimal or near-optimal solution to the test system and it operating time is acceptable for practical applications.

Thirdly, the research in [9] used Genetic Algorithm (GA) in minimizing power losses with consideration of distributed generation, DG. Allocation of DG in 37 buses distribution system is possible to find by using GA. However, GA used in this research includes mixed load model where it is said to produce best solution in fastest computing time. The results shows that there are improvements in voltage profile and loss of active/reactive power. As a conclusion, the research is said to be more realistic if cost, reliability of system and total harmonic distortion is being taken into consideration.

Lastly, reconfiguration in optimization for loss and reliability in distribution systems using improved genetic algorithm (IGA) has being done in [14]. This research used IGA with adaptive crossover and mutation probabilities where the parameters of crossover and mutation probabilities being change at its minimum and maximum to see the effect of 69 buses distribution system. As the conclusion, IGA is said to be able to improve reliability and efficiency, minimize losses and at the same time improved voltage stability and load balancing of the test system.

2.5 Summary of the Chapter

At the aims of minimizing power losses in distribution systems, few techniques are available such as load balancing, reconfiguration, capacitor installation, and introduction of higher voltage levels. Previous studies depicted above are for Distribution Network Reconfiguration (DNR), Genetic Algorithm (GA) and Improved Genetic Algorithm (IGA). However, the proposed algorithm being applied in the research is Improved Genetic Algorithm (IGA) and not considering Genetic Algorithm (GA) because IGA improve reliability and efficiency, takes lower computational effort better than GA. Hence, this paper still applies the concept of GA for IGA but the process of selection has been improved.

CHAPTER 3

METHODOLOGY

3.1 Introduction

3.1.1 Simulation Modeling

In order to successfully implement the IGA algorithm, the IEEE 33 busses of distribution system is tested in MATLAB 2013. The test system consists of 38 switches whereby 5 of them are tie switches and the remaining 33 are sectionalizing switches. Fig. 3.1 below shows the initial state of the 33-bus distribution system before it undergoes any changes from the proposed algorithm of this paper.

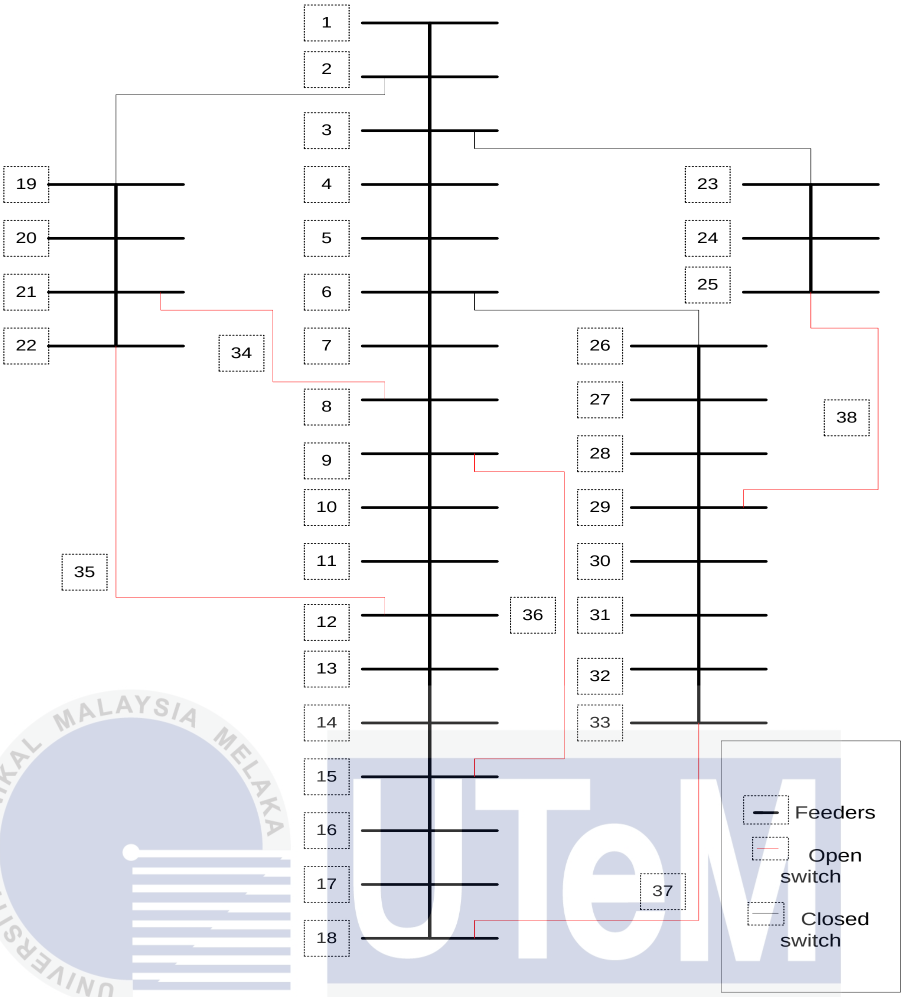
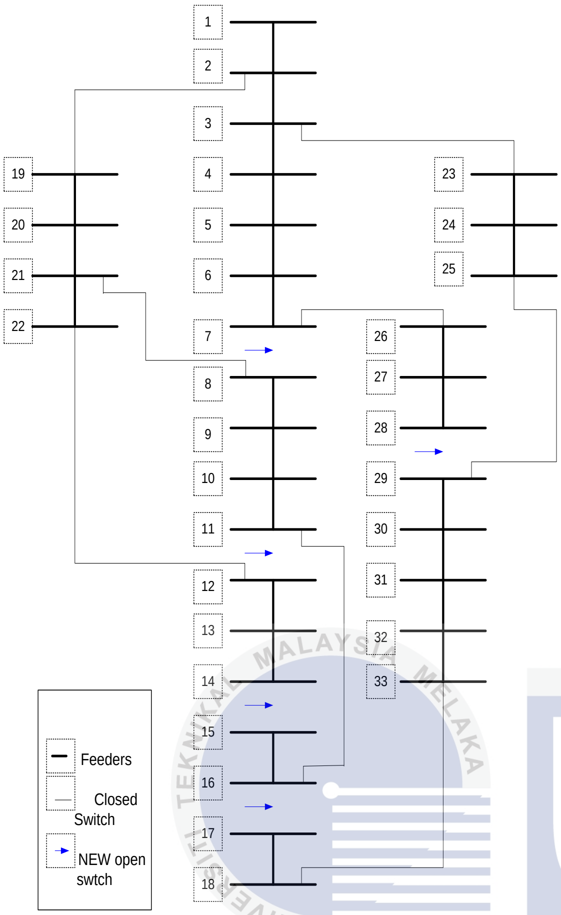


Fig. 3.1: IEEE 33-bus distribution system



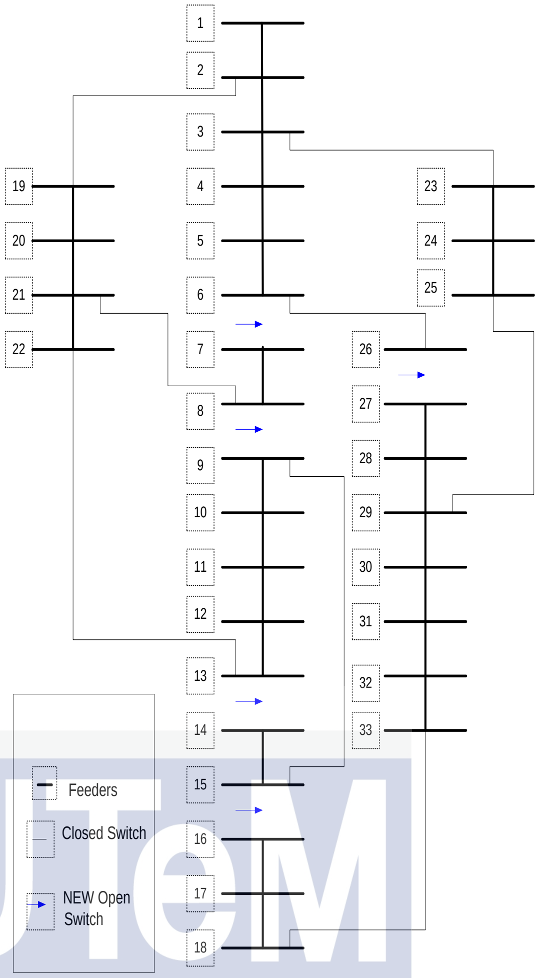


Fig. 3.2(a): Best Cases for Regulated pm (After Reconfiguration)

Fig. 3.2(b): Best Cases for Regulated pc (After Reconfiguration)

3.2 Implementation of IGA using MATLAB

3.2.1 Overview on Conventional GA

The conventional technique of GA (Genetic Algorithm) does not operate on a single point but required the overall process involving the whole parameter code. The operation is based on probabilistic change rules than uncertain rules. Fig. 3.3 below depicts the working principle of a simple GA.

```
/*A Simple GA*/
Initialize population randomly
Calculate fitness function
Apply genetic operators
        Selection
        Crossover
        Mutation
Repeat until maximum  iterations reached
Stop
```

Fig. 3.3: Working Principle of a Simple GA

In GA, the problem is simply described by the coding of variables where the common variable used is a binary string or a vector. However, this conventional GA has slow convergence rate, local optimum and it ignores cooperation between populations. Besides that, A conventional GA seems to find global optimum when operating on a large scale systems and it cannot maintain constant optimization response time [7-11]. Thus, implementing IGA in fact solve the constraint encountered by conventional genetic algorithm, unravel the global optimum faced in large scale systems and reduce the computational time. It has three essential genetic operators which are selection, crossover and mutation.

3.2.2 Flowchart of IGA

The IGA algorithm is simply drawn into a flowchart as shown in Fig. 3.4 below and followed by the elaborations on each processes involved.

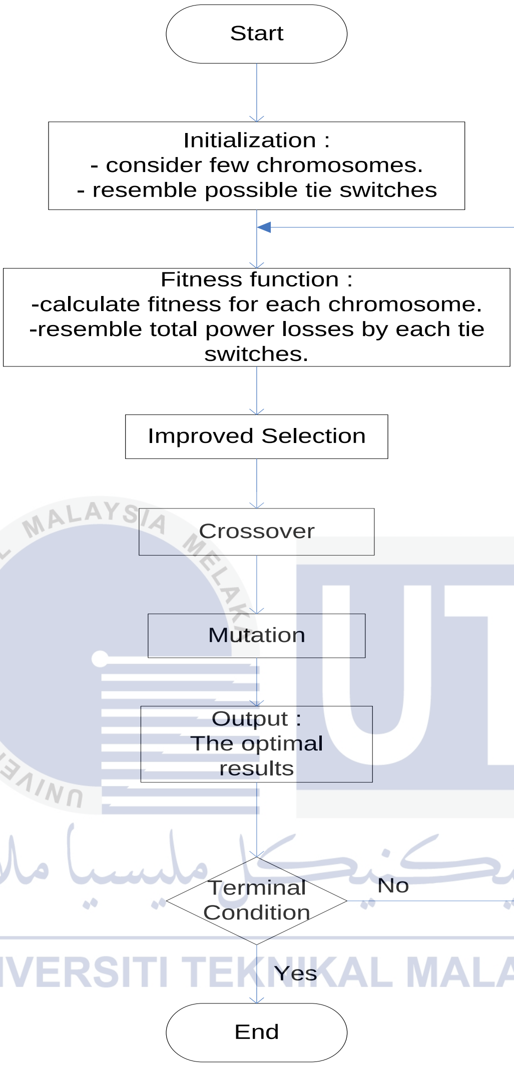


Fig. 3.4: Flowchart of IGA

3.2.3 Problem Formulation

In order to undertake better understanding of the proposed algorithm, all the procedures involved in IGA as referred to Fig. 3.5 above are included in this section. The explanation is briefly in accordance of their genetic definition followed by the working principle of the improved genetic algorithm.

Step 1 : Initialization

The very first step in IGA is initialization where an initial population is being generated. A binary string or sometimes called chromosome is generated randomly to each members of the population. The number of chromosomes resembles number of switches available in the test system. This paper takes IEEE-33 bus distribution system with 5 open switches and 28 closed switches. Initially, crossover probabilities are set to be 0.5 and mutation probabilities are 0.4 where these values are the reference point for this paper.

Step 2 : Fitness Fumction

The fitness resembles total power losses obtained by each switches being selected in the initialization. In this research, the method used to calculate power losses is Newton-Raphson Method due to its ability to converge where the iterations number is independent to the number of buses, N.

During this process for the research, five (5) switches are being randomly picked for calculation of their power losses.

At any given bus of i and j, Newton-Raphson Method equation are given as:

$$Pi = \sum_{j \neq i}^{n} |Yi||Vj||Yij| \cos(\theta ij - \delta i + \delta j) \tag{3.1}$$

$$Qi = -\sum_{j \neq i}^{n} |Yi||Vj||Yij| \sin(\theta ij - \delta i + \delta j) \tag{3.2}$$

Where:

Vi, Vj : voltage magnitude of bus i and j respectively

δi, δj : voltage angle of bus I and j respectively

Step 3 : An Improve Selection Operator

Selection is related to fitness and the most common used method in selection is *roulette-wheel method*. This method attempts to choose from given string which depends on their fitness values. A higher fitness value strings contribute high chances in producing children in the next generations. Thus, the new offspring produce is to be same-like as its parents. The process continues whereby the parent is reflected by the 38 available switches in test system and the child is being resembles by the possible five (5) combination of tie switches that has high probability in producing minimal total power losses are selected.

The following Fig. 3.5 illustrates the working principles of an improved selection operator where it denotes that output 1 is the scattered list of tie switches with their total power losses and after undergoing improved selection operator, they are listed accordingly in ascending order of their total power losses to become new output 1.

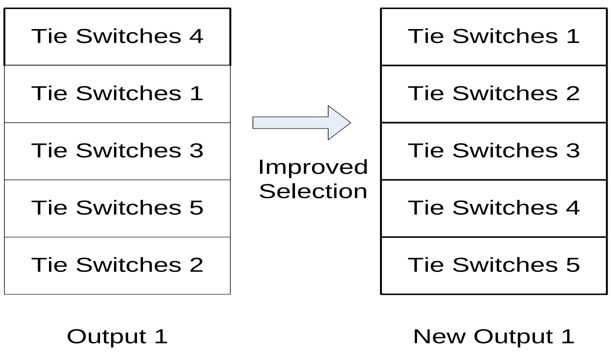


Fig. 3.5: Working Principle of Improved Selection Operator

Step 4 : Crossover

This is the critical feature of IGA because it hugely accelerates search in the earlier evolution of a population and also guides an effective combination of sub solutions between non-similar chromosomes. The two offspring are generated from two parents where each offspring holds few genetic features of each parents. At this step, crossover randomly mates the mating pool of the selected strings obtained from roulette-wheel method. This is simply drawn in Fig. 3.6 that crossover takes the output of selection (child 1) to recombine in order to produce new output that is better than the first one (child 2).

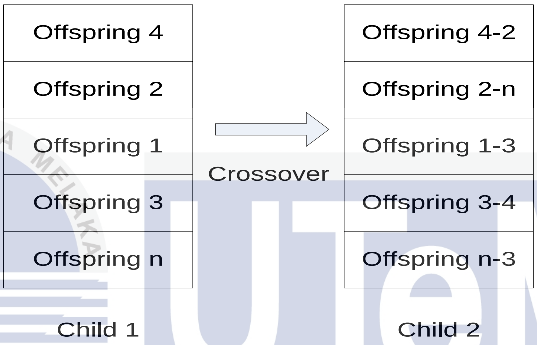


Fig. 3.6: Crossover Operator

Step 5 : Mutation

The last stage is mutation which is simpler than crossover. A mutation process is about random change of a new bit generated or sometimes referred as flipping the bit. However, to obtain good results in mutation GA, it may need about thousand bits of transfer and that is why mutation is treated as the secondary role in GA. Somehow in a binary string, mutation is about complement the chosen bits. Mutations also clearly copy the best combination in the next reproduction to produce new child and this process of mutation is being displayed in Fig. 3.7 below.

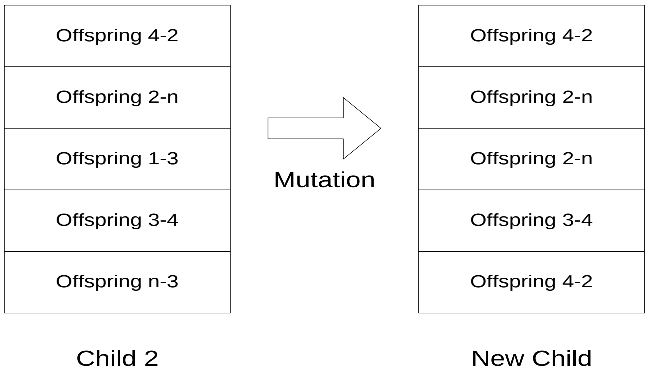


Fig. 3.7: Mutation Operator

3.2.4 Algorithm Steps

The affirmation requirement must be compulsorily done which are the five (5) numbers of possible tie switches and the probabilities of crossover and mutation occurrences.

Step 1: define N as number of population, k as number of iterations and x as the possible selected tie switches. The proposed algorithm start searches for first possible tie switches, x1 for their total power losses using Newton-Raphson Method and the process continues until maximum number of iterations reached. The possible tie switches are listed in matrix form, declared as output1.

Step 2: improved selection operator takes place where output1 is read and adjusted according to their total power losses. The possible tie switches are listed accordingly from the best case of power loss reduction to the worst case of power loss reduction. As an additional to that, the percentage of total power losses for each tie switches is calculated as: power loss (%) = (total power loss/number of population)*100.

Step 3: perform crossover and mutation under consideration of pc and pm value.

Step 4: consider re-fitness calculation for the new (population) combination of tie switches.

Step 5: the process ends when the optimal output is obtained.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This paper is conducted in MATLAB 2013 in order to analyse the effectiveness of the proposed algorithm, IGA. The proposed algorithm with improved selection operator is tested to the initial 33-bus distribution system with 28 closed switches and 5 open switches. The analysis involved the determination of power losses and voltage profile before and after DNR while maintaining the radiality of the original network. The test system equipped with 132/11 kV is being randomly search for any possible combination of 5 tie switches that may produce low power losses compared to the initial total power losses. Besides that, the effectiveness of the proposed algorithm towards test system is also being tested on the voltage profile improvement. Thus, this chapter will analyse both parameters power losses and voltage profile of the test system but somehow the proposed algorithm should be able to maintain the radiality of the original network. There are 8 cases of IGA regulated parameters of genetic operators consisting of the crossover and mutation are considered in determining the results. The result are tabulated in a form of table and figure to ascertain better a view of analysis and evaluation in comparing before and after DNR configuration.

4.2 Parameter Alleviation

The IGA algorithm used is predominantly improved in selection part of a conventional GA. In considering the proposed algorithm of this paper, few parameters have to be controlled to optimize the results efficiently. The control parameters are probability of crossover occurrence, ‘pc’ and probability of mutation occurrence, ‘pm’ are adjusted according to the following conditions and considering minimum and maximum bounds, B_{min} and B_{max} as shown in (1) and (2) below.

Both ‘pc’ and ‘pm’ are important in determining the performance of IGA algorithm. Probability of crossover occurrence, ‘pc’ determines how often the crossover operator is applied for switching in DNR and it should never be too small so that it can cater big scale of test system. Meanwhile, probability of mutation occurrence, ‘pm’ is not supposing too big since it helps to maintain population diversity effectively.

$$p_c = \begin{cases} pc_{min}, \text{ if } G_{div} < B_{min} \\ pc_{max}, \text{ if } G_{div} > B_{max} \end{cases} \quad (4.1)$$

$$p_m = \begin{cases} pm_{min}, \text{ if } G_{div} < B_{min} \\ pm_{max}, \text{ if } G_{div} > B_{max} \end{cases} \quad (4.2)$$

Where:

G_{div} = genetic diversity

4.3 Simulation Results

While configuring the proposed algorithm into MATLAB, few parameters have been controlled in order to maintain the reliability of the results obtained. For maintaining the effectiveness of the results generated from IGA algorithm, few constraints are necessary considered before proceeding to the next process of algorithm.

Number of possible tie switches : 5

Number of iterations : 10

Size of population : 30

Table 4.1 indicates the eight (8) numbers of cases to be imposed in both GA and IGA algorithm. As being mentioned earlier, (pc) represents as probabilities of crossover occurrence, while (pm) is the probabilities of mutation occurrence. There are 8 cases considered during this research however they are separated into two parts for better analysis and understanding. Firstly, case 1 to case 4 involved constant pc values and regulated pm value. Meanwhile, case 5 to case 8 involved regulated pc value and constant pm values.

The parameter setting for Case 1, 2, 3 and 4 is constrained by constant value of crossover probability (pc) and regulated mutation probability (pm). The adjustment for pm is started with 0.2 followed by an increment of 0.2 till it reached the maximum value constraints of 0.8. For case 5, 6, 7 and 8, the performance of the test system is set to constant value of pm with varied value of pc from 0.2, 0.4, and 0.6 rights up to 0.8.

Table 4.1: Cases Consideration

No. of Cases	pc	pm
1	0.5	0.2
2	0.5	0.4
3	0.5	0.6
4	0.5	0.8
5	0.2	0.4
6	0.4	0.4
7	0.6	0.4
8	0.8	0.4

Equation (9) signifies the power losses reduction in percentage to evidently satisfy the performance of power losses before and after reconfiguration. Based upon the parameters above, power losses performance is being analysed individually in kW and for better view the percentage of total power losses compared to the initial is also being shown. The following formula is used to obtain the percentage of total power losses after reconfiguration.

$$\text{Total Power Losses (\%)} = \frac{\text{new power losses}}{\sum \text{power losses}} x100\% \tag{4.3}$$

4.3.1 Minimization of Power Losses

The parameter setting for Case 1, 2, 3 and 4 is constrained by constant value of crossover probability (pc) and regulated mutation probability (pm). The adjustment for pm is started with 0.2 followed by an increment of 0.2 till it reached the maximum value constraint of 0.8.

The proposed algorithm shows great contribution towards the initial 33-bus test system where it has been reduced to approximately 12% to 24% of that initial total power loss of 202.6 kW.

Seeing from Table 4.2, case 2 produce the lowest total power losses of 139.7 kW with tie switches of 8, 26, 13, 15 and 6. It is followed by power losses of 141.4 kW by case 3 with reduction of 17.81% from before reconfiguration and the selected tie switches to be open are 28, 4, 9, 14 and 16. Case 2 and case 3 show great percentages of power losses however case 1 and case 4 both possess 11.84% and 13.3%, respectively which is very low when compared to the other two cases.

Table 4.2: Tie Switches with Total Power Losses for Case 1, 2, 3 and 4

	Before reconfiguration	After reconfiguration			
		case 1	case 2	case 3	case 4
Tie switches	34, 35, 36,37, 38	32, 6, 25, 33, 13	8, 26, 13, 15, 6	28, 4, 9, 14, 16	26, 33, 21, 17, 10
Total Power losses (kW) - *best case*	202.6	159.7	139.7	141.4	155.2
Total Power losses (kW) - *worst case*	-	753.7	815.6	844.1	843.3
Percentage of Total Power Losses Reduction (%)	0	11.84	18.39	17.81	13.3

As for case 5, 6, 7 and 8, the performance of the test system is set to constant value of pm with varied value of pc from 0.2, 0.4, and 0.6 rights up to 0.8.

The generated results obtained from MATLAB for case 5 to case 8 is depicted in Table 4.3 below. Case 6 in Table 4.3 with 125.1 kW of total power losses with switches 14, 28, 11, 7 and 16 is the highest percentage of total power losses reduction of 23.65% compared to the other cases studied. Besides that, case 7 also possess low power losses, 135.6 kW which is 19.83% with 7, 15, 21, 12 and 28 as the selected switches to be open. Similarly here that case 5 and case 8 produce lowest percentages of total power losses.

Table 4.3: Tie Switches with Total Power Losses for Case 5, 6, 7 and 8

	Before reconfiguration	After reconfiguration			
		case 5	case 6	case 7	case 8
Tie switches	34, 35, 36,37, 38	28, 5, 8, 14, 10	14, 28, 11, 7, 16	7, 15, 21, 12, 28	16, 33, 26, 11, 7
Total Power losses (kW) - *best case*	202.6	149.5	125.1	135.6	145.6
Total Power losses (kW) - *worst case*	-	909.3	766.4	966.4	917.8
Percentage of Total Power Losses Reduction (%)	0	15.09	23.65	19.83	16.4

After analyzing both Table 4.2 and 4.3 above, case 2 and case 6 shows the highest percentage of power losses reduction and these results is then being compared with conventional GA as in Table 4.4 below. It can be seen that, conventional GA only minimize 17.8% of power losses compared with IGA which reduce power losses up to 18.4% for case 2. Meanwhile for case 6, IGA minimize 23.7% of power losses when conventional GA only reduces 21.9%.

Table 4.4: Comparison of GA and IGA in Power Losses

After Reconfiguration					
Case	Method	Tie Switches	Total Power Losses (kW) *best case*	Total Power Losses (kW) worst *case*	Percentage of Total Power Losses Reduction (%)
case 2	GA	32,26,5,11,8	141.5	829.9	17.8
	IGA	8,26,13,15,6	139.7	815.6	18.4
case 6	GA	27,30,33,14,9	129.9	926.9	21.9
	IGA	14,28,11,7,16	125.1	766.4	23.7

4.3.2 Improvement of Voltage Profile

In order to analyse the effectiveness of the proposed algorithm, another analysis that can be considered is the performance of the bus voltage profile. Performance of voltage profile is done towards each number of buses to observe the improvement of voltage profile when implementing the proposed algorithm of this paper in comparison with GA. This is to ensure that the proposed algorithm improved the actual voltage profile of the initial 33-bus test system.

The following Table 4.5 and 4.6 below listed the value of voltages obtained at each bus for case 1 to case 4 and case 5 to case 8, respectively. In the meantime, Fig. 4.1 and 4.2 below shows graphically the voltage profile for case 2 and 6 that produce the best improvement when GA and IGA takes place.

As been shown in Table 4.5, case 1 yield great improvement during bus number 3 to bus number 5 followed by the next number of buses with only a slight increase before it rise to maximum voltage profile at bus number 19. After that, it drops to 0.996 p.u and steadily maintain its improvement aside of the conventional GA. Referring to the same Table 4.44, case 3 and 4 have more or less the same voltage profile improvement where the first ten buses acquire only a bit improvement and then the value jump to maximum at bus number 19 before it considerably maintains the slight improvement at the next buses.

For case 5 as represented in Table 4.6 where the voltage profile is impressively being improved from the implementation of IGA comparable with GA for virtually all number of busses except those bus number 19 and 23 that reach maximum value. As for case 7 and 8 that suffers big drops of voltage profile at the first 15 number of buses compared to conventional GA and only able to escalate its value to almost 0.998 p.u at bus number 19. Then, the following number of buses is actually having a crooked improvement of voltage profile.

TABLE 4.5

Voltages at each bus for Case 1, 2, 3 and 4

No. of buses	After reconfiguration							
	case 1		case 2		case 3		case 4	
	SIGA	GA	SIGA	GA	SIGA	GA	SIGA	GA
1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3	0.9938	0.9904	0.9999	0.9939	0.9958	0.9999	0.9999	0.9896
4	0.9938	0.9904	0.9972	0.9939	0.9958	0.9999	0.9999	0.9896
5	0.9952	0.9904	0.9972	0.9952	0.9957	0.9998	0.9999	0.9896
6	0.9952	0.9967	0.9972	0.9952	0.9960	0.9990	0.9994	0.9897
7	0.9959	0.9968	0.9968	0.9961	0.9967	0.9978	0.9986	0.9896
8	0.9959	0.9968	0.9968	0.9958	0.9965	0.9981	0.9988	0.9957
9	0.9959	0.9945	0.9966	0.9957	0.9957	0.9934	0.9986	0.9951
10	0.9958	0.9949	0.9966	0.9957	0.9959	0.9951	0.9986	0.9951
11	0.9958	0.9949	0.9966	0.9970	0.9959	0.9951	0.9994	0.9969
12	0.9970	0.9947	0.9966	0.9970	0.9959	0.9951	0.9994	0.9969
13	0.9970	0.9947	0.9964	0.9954	0.9951	0.9944	0.9994	0.9969
14	0.9958	0.9946	0.9964	0.9954	0.9951	0.9937	0.9982	0.9939
15	0.9958	0.9937	0.9964	0.9955	0.9951	0.9934	0.9983	0.9940
16	0.9961	0.9943	0.9964	0.9955	0.9952	0.9940	0.9987	0.9946
17	0.9958	0.9926	0.9979	0.9954	0.9947	0.9926	0.9978	0.9926
18	0.9958	0.9923	0.9980	0.9941	0.9946	0.9924	0.9978	0.9922
19	0.9998	0.9997	1.0000	0.9998	0.9998	1.0000	0.9999	0.9997
20	0.9980	0.9979	0.9999	0.9979	0.9980	0.9999	0.9997	0.9979
21	0.9972	0.9971	0.9998	0.9972	0.9972	0.9970	0.9996	0.9971
22	0.9971	0.9958	0.9965	0.9971	0.9966	0.9959	0.9995	0.9970
23	0.9938	0.9905	0.9997	0.9939	0.9958	0.9999	0.9999	0.9896
24	0.9939	0.9905	0.9990	0.9939	0.9957	0.9911	0.9998	0.9901
25	0.9941	0.9908	0.9985	0.9941	0.9957	0.9913	0.9973	0.9902
26	0.9952	0.9967	0.9972	0.9952	0.9956	0.9990	0.9994	0.9897
27	0.9952	0.9967	0.9973	0.9952	0.9956	0.9990	0.9994	0.9898
28	0.9946	0.9909	0.9978	0.9952	0.9957	0.9914	0.9994	0.9901
29	0.9943	0.9909	0.9983	0.9943	0.9957	0.9914	0.9973	0.9903
30	0.9960	0.9910	0.9984	0.9944	0.9959	0.9914	0.9974	0.9904
31	0.9958	0.9914	0.9981	0.9942	0.9944	0.9917	0.9974	0.9910
32	0.9958	0.9917	0.9980	0.9941	0.9944	0.9919	0.9975	0.9913
33	0.9959	0.9922	0.9980	0.9941	0.9945	0.9923	0.9977	0.9920

TABLE 4.6

Voltages at each bus for Case 5, 6, 7 and 8

No of buses	After reconfiguration							
	case 5		case 6		case 7		case 8	
	GA	IGA	GA	IGA	GA	IGA	GA	IGA
1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3	1.0000	0.9999	0.9999	1.0000	0.9999	0.9999	0.9999	1.0000
4	0.9885	0.9999	0.9927	1.0000	0.9999	0.9999	0.9999	0.9966
5	0.9885	0.9999	0.9927	1.0001	0.9971	0.9998	0.9999	0.9966
6	0.9986	0.9992	0.9928	0.9997	0.9972	0.9992	0.9937	0.9967
7	0.9884	0.9981	0.9929	0.9995	0.9967	0.9985	0.9937	0.9971
8	0.9884	0.9984	0.9929	0.9995	0.9967	0.9985	0.9937	0.9969
9	0.9940	0.9961	0.9932	0.9962	0.9956	0.9982	0.9940	0.9966
10	0.9945	0.9963	0.9932	0.9962	0.9956	0.9982	0.9933	0.9966
11	0.9944	0.9962	0.9922	0.9974	0.9956	0.9982	0.9933	0.9966
12	0.9943	0.9961	0.9922	0.9974	0.9956	0.9975	0.9933	0.9975
13	0.9943	0.9961	0.9922	0.9969	0.9956	0.9976	0.9947	0.9975
14	0.9942	0.9960	0.9921	0.9965	0.9955	0.9977	0.9947	0.9974
15	0.9929	0.9958	0.9941	0.9963	0.9955	0.9977	0.9945	0.9962
16	0.9935	0.9962	0.9938	0.9964	0.9955	0.9978	0.9958	0.9963
17	0.9914	0.9953	0.9953	0.9959	0.9979	0.9974	0.9962	0.9957
18	0.9911	0.9952	0.9957	0.9958	0.9979	0.9973	1.0000	0.9956
19	0.9998	1.0000	0.9924	0.9999	1.0000	1.0000	0.9935	0.9998
20	0.9980	0.9975	0.9925	0.9990	0.9999	0.9984	0.9935	0.9984
21	0.9972	0.9976	0.9925	0.9987	0.9963	0.9984	0.9934	0.9978
22	0.9957	0.9967	0.9924	0.9981	0.9960	0.9975	0.9997	0.9976
23	1.0000	0.9999	0.9996	0.9991	0.9997	0.9999	0.9990	0.9999
24	0.9889	0.9997	0.9989	0.9991	0.9990	0.9998	0.9984	0.9998
25	0.9890	0.9946	0.9982	0.9992	0.9985	0.9997	0.9937	0.9967
26	0.9886	0.9992	0.9928	0.9997	0.9972	0.9992	0.9937	0.9967
27	0.9886	0.9992	0.9979	0.9998	0.9972	0.9992	0.9982	0.9968
28	0.9889	0.9946	0.9979	0.9995	0.9978	0.9998	0.9982	0.9968
29	0.9892	0.9947	0.9980	0.9994	0.9983	0.9998	0.9982	0.9968
30	0.9893	0.9947	0.9980	0.9995	0.9984	0.9999	0.9982	0.9969
31	0.9899	0.9948	0.9970	0.9956	0.9981	0.9999	0.9973	0.9954
32	0.9902	0.9949	0.9966	0.9956	0.9980	0.9972	0.9969	0.9954
33	0.9908	0.9951	0.9960	0.9957	0.9980	0.9973	0.9964	0.9956

For case 2 and 6, the voltage profile are being shown in graph instead of having the value only in the table in order to show that this two cases have abundant increase of voltage profile comparable with the conventional GA. As displayed in Fig. 4.1 below for case 2, conventional GA shows 0.9939 p.u at bus number 4 and 5 but IGA algorithm successfully increase this value at 0.9972 p.u. For the next bus number, IGA algorithm demonstrates steady improvement of voltage profile and securely maintains this pattern until bus number 33 but somehow still gain maximum at bus number 19.

Meanwhile, Fig. 4.2 presented the voltage profile for case 6 that exhibits the ability of IGA algorithm to surge the voltage profile of that conventional GA. This has been proved when looking at bus number 3 until bus number 18 where IGA algorithm shows huge improvement of voltage profile comparable with GA. Then, the voltage rise to maximum at bus number 19 followed by a sturdy voltage at the next number of buses before both algorithm suffers decline of voltage profile at bus number 32 and 33.

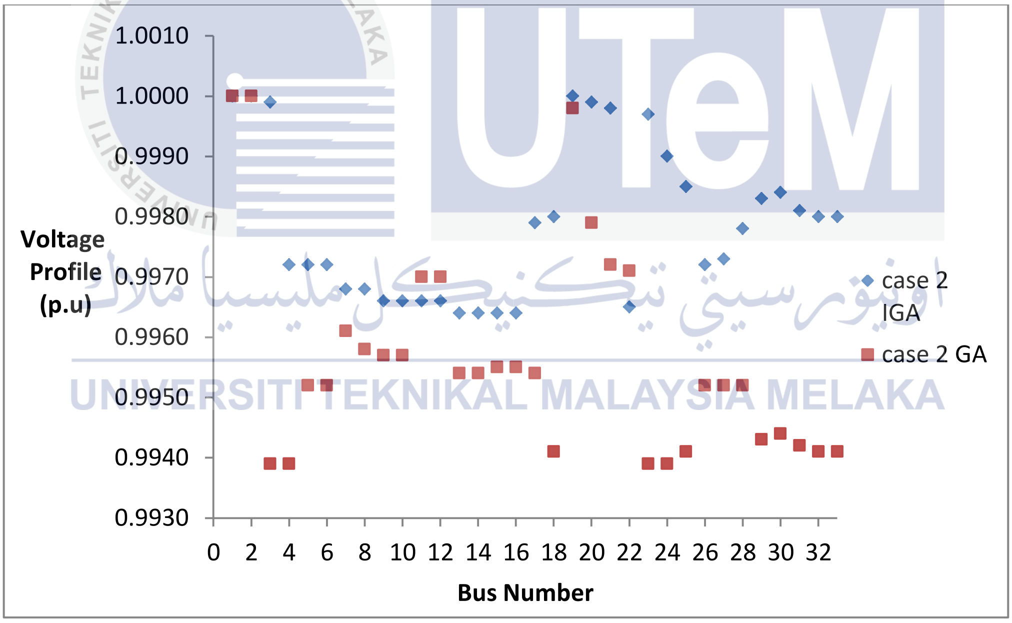


Fig. 4.1: Voltage Profile for case 2

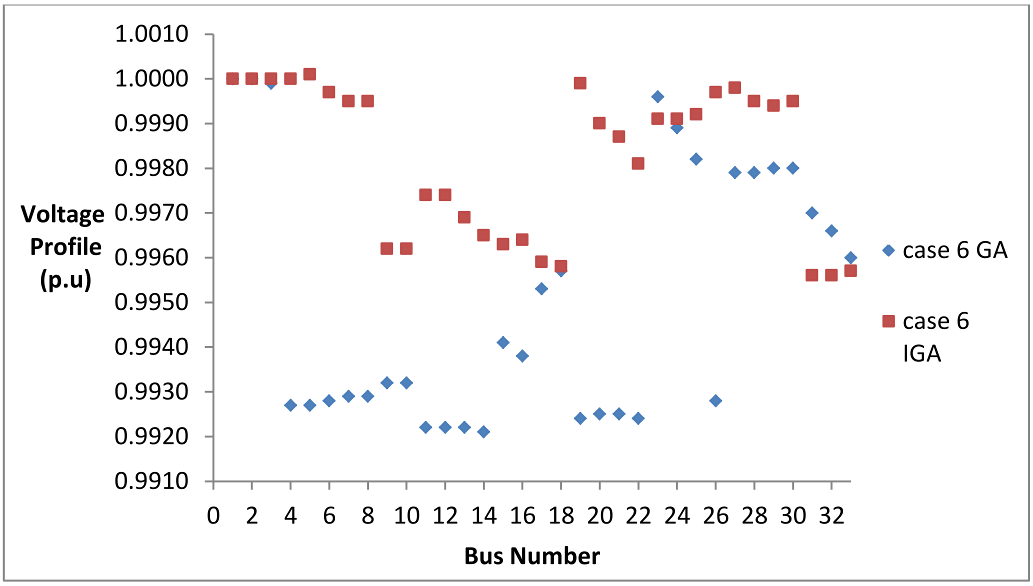


Fig. 4.2: Voltage Profile for Case 6

After analyzing all eight cases that involve both regulated value of (pc) and (pm), it shows that both GA and IGA are able to produce voltage profile within allowable range which is 0.95 p.u until 1.0 p.u. However, IGA algorithm illustrates a firm improvement of voltage profile while GA have insteady improvement for each number of buses. Thus, IGA algorithm has the proficiency of improving the voltage profile of that conventional GA.

CHAPTER 5

CONCLUSION

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In order to minimize power losses in distribution, a Distribution Network Reconfiguration (DNR) should be applied. Distribution Network Reconfiguration is about altering the open/closed switch of the distribution system. There are other approaches available for reconfiguration are Particle Swarm Optimization (PSO), Evolutionary Particle Swarm Optimization (EPSO) and Genetic Algorithm (GA). This paper only focuses on the improved methods of GA which is IGA.

The optimization of power losses and voltage profile improvement in IEEE-33 bus distribution system using IGA algorithm for DNR has been successfully carried out in MATLAB 2013. The validity of the proposed algorithm is performed by adjusting the parameters that influences the power losses and voltage profiles. The parameters regulated are genetic operator probabilities inclusive of crossover and mutation whereby the results show that both GA and IGA results in reduction of power losses and improvement of voltage profile but somehow IGA algorithm demonstrates higher reduction of power losses and better improvement of voltage profile compared than the GA algorithm.

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