NETWORK RECONFIGURATION AND DG SIZING INCORPORATING OPTIMAL SWITCHING SEQUENCE FOR SYSTEM IMPROVEMENT

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KUALA LUMPUR

2018

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2018

UNIVERSITY OF MALAYA

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Registration/Matric No: **KHA140055**

Name of Degree: **Doctor of Philosophy**

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NETWORK RECONFIGURATION AND DG SIZING INCORPORATING OPTIMAL SWITCHING SEQUENCE FOR SYSTEM IMPROVEMENT

ABSTRACT

Minimizing power losses in a distributed system are commonly achieved via optimal network reconfiguration. In the past, network reconfiguration research focused on planning, where the final configuration reporting the lowest power loss being the main goal. However, power losses during the switching operations from the initial state to the final state of configuration was never studied. This research presents the optimal switching sequence path to minimize power losses during the network switching operation. Apart from this contribution, simultaneous optimal network reconfiguration and optimal distributed generation (DG) output generation were also proposed. The proposed methodology involves (1) Optimal network reconfiguration and DG output simultaneously, (2) Optimal network reconfiguration with variable load and the different types of DGs and (3) Optimal sequence of switching operations required to convert the network from the original configuration to the optimal configuration obtained from (1) for both planning and operational mode. The proposed method is applied to reduce power losses and improve the overall voltage profile of the system. The proposed network reconfiguration also considered load profiles, DG output generation, DG types, and DG operating mode to decrease the total daily power loss. The chosen optimization techniques in this work include evolutionary programming (EP), particle swarm optimization (PSO), gravitational Search Algorithm (GSA), and firefly algorithm (FA). To assess the capabilities of the proposed method, simulations using MATLAB were carried out on IEEE 16-bus, IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus radial distribution networks. The obtained results demonstrate the effectiveness of the proposed strategy to determine the sequence path of switching operations, as well as the optimal network configuration and optimal generation output of DG units. The optimal network reconfiguration with optimal DGs output reported high power loss reduction of (23.63%-82.233%) for different test systems. These values exceeded the values reported by other works. The proposed method also produced better voltage profile compared to other published works. The minimum value of the buses voltages was between (0.9502 p.u.-0.98176 p.u.) for different systems. The power losses during optimal switching sequence process were between (365.52kW-9265.5kW) for different systems. These values were much lower compared to any other random case. Furthermore, the optimal sequence keeps the buses voltages within allowable limit during the switching process. Meanwhile, random switching caused voltage violation during the switching process. The daily solution of the network considering load profiles and DG operating mode and type, obtained total daily power losses of 747.76kWh compare to 915.65kWh reported by other works. The proposed method also produced voltage profile within allowable limits. The minimum value of the buses voltages was between (0.985 p.u.-0.989 p.u.) during 24hr. The energy losses during the switching sequence process when considering DG operating mode and type and when the load profile was average, was 465.66 kWh compared to (543.8kWh-586.4kWh) for the different random case. Moreover, the voltage profile during the switching sequence process was within the allowable limit.

Keywords: Switching sequence, distribution network reconfiguration, distributed generation, load profile, voltage profile.

KONFIGURASI SEMULA RANGKAIAN DAN SAIZ DG YANG MENGGABUNGKAN ATURAN PENSUISAN YANG OPTIMUM UNTUK PENAMBAHBAIKAN SISTEM

ABSTRAK

Pengurangan kehilangan kuasa dalam sistem algorithm biasanya dicapai melalui konfigurasi sistem rangkaian yang optimum. Pada masa lalu, penyelidikan terhadap ~~re~~konfigurasi semula rangkaian lebih difokuskan pada bahagian perancangan, di mana matlamat utama adalah untuk mendapatkkan konfigurasi akhir dengan kehilangan kuasa terendah. Walau bagaimanapun, kehilangan kuasa semasa operasi pensuisan bertukar dari keadaan awal ke keadaan konfigurasi akhir belum pernah dikaji. Kajian ini membentangkan laluan aturan pensuisan yang optimum untuk meminimakan kehilangan kuasa semasa operasi pensuisan rangkaian dijalankan. Selain itu, konfigurasi semula rangkaian optimum bersama output DG juga dicadangkan. Metodologi yang dicadangkan melibatkan; (1) Konfigurasi sistem rangkaian yang optimum dan output DG dilakukan secara serentak, (2) Konfigurasi sistem rangkaian yang optimum dengan beban berubah-ubah dan jenis DG~~S~~ yang berlainan, (3) Aturan optimum operasi pensuisan yang diperlukan untuk menukar rangkaian dari konfigurasi asal kepada konfigurasi optimum yang diperolehi dari (1) bagi kedua-dua mod perancangan dan operasi. Kaedah yang dicadangkan, digunakan untuk mengurangkan kehilangan kuasa dan meningkatkan profil voltan. Selain itu, konfigurasi semula rangkaian dengan mengambil kira profil beban, penjanaan output DG, teknologi DG, dan mod operasi DG juga dicadangkan untuk mengurangkan jumlah kehilangan kuasa harian. Teknik pengoptimuman yang dipilih dalam kajian ini adalah evolutionary programming (EP), particle swarm optimization (PSO), Gravitational Search Algorithm (GSA), dan Firefly (FA). Untuk menilai keupayaan kaedah yang dicadangkan, simulasi menggunakan perisian MATLAB dilaksanakan pada rangkaian sistem pembahagian radial bas “IEEE 16-bus”, “IEEE 33-

bus”, “IEEE 69-bus”, dan “IEEE 118-bus”. Keputusan yang diperolehi menunjukkan keberkesanan strategi yang dicadangkan untuk menentukan laluan aturan operasi pensuisan serta konfigurasi sistem rangkaian secara optimum dengan output optimum unit DG. Konfigurasi semula rangkaian dengan output DG yang optimum merekodkan pengurangan yang tinggi terhadap kehilangan kuasa (23.63%-82.233%) bagi sistem uji IEEE yang berbeza-beza, Nilai-nilai bacaan tersebut melebihi dari nilai yang dilaporkan di dalam kajian lain yang diterbitkan. Nilai minima yang didapati bagi voltan bas adalah di antara (0.9502 p.u.-0.98176 p.u.) bagi sistem yang berbeza. Kehilangan kuasa semasa proses aturan pensuisan yang optimum adalah di antara (365.52kW-9265.5kW) untuk sistem yang berbeza. Nilai ini adalah amat rendah dibandingkan dengan kes-kes yang lain. Tambahan pula, aturan optimum sentiasa menetapkan voltan bas berada di dalam had yang dibenarkan semasa proses pensuisan. Sementara itu, pensuisan secara rawak telah menyebabkan pelanggaran voltan semasa proses pensuisan. Penyelesaian harian bagi rangkaian dengan mengambil kira profil beban dan mod operasi serta jenis DG telah merekodkan jumlah kehilangan kuasa harian 747.76kWh berbanding dengan 915.65kWh seperti yang dilaporkan di dalam kajian lain. Kaedah yang dicadangkan juga telah menghasilkan profil voltan di dalam had yang dibenarkan. Nilai minima bagi voltan bas adalah di antara (0.985 p.u.-0.989 p.u.) dalam tempoh 24 jam. Kehilangan tenaga semasa proses aturan pensuisan apabila mempertimbangkan operasi mod DG dan jenisnya serta apabila profil beban adalah sederhana, adalah 465.66 kWh berbanding dengan (543.8kWh-586.4kWh) untuk kes rawak yang berbeza. Tambahan pula, profil voltan semasa proses aturan pensuisan adalah didalam had yang dibenarkan.

Kata kunci: aturan pensuisan, konfigurasi semula rangkaian pengagihan, penjanaan teragih, profil beban, profil voltan.

ACKNOWLEDGEMENTS

Along the way of completing this project, there are people helping me to work out this thesis. First of all, I am grateful to my supervisor, Prof. Dr. Hazlie bin Mokhlis for all his effort in guiding and advising me. His patience in guiding me to finish this project is much appreciated. Prof. Dr Hazlie also organized the project guideline so that I am able to complete this work on time.

My special thanks to my supervisor, Prof. Dr. Saad Mekhilef, and my co-supervisors, Dr. Wardiah Dahalan, for their professional advice and helpful comments related to this work. They have shared their ideas and suggestions in bettering this work.

I would also like to thank my Lab friends, especially Dr. Kanendra, Dr. Shiva, ING, and Jafar. They supported and encouraged me throughout this work.

I wish to express my deepest gratitude to my parents for their support and sacrifice of living without me for a long time. I would like to thank my siblings, husband, and friends for their encouragement and support.

Finally, I would like to thank and offer my regards to others who supported me during completing this work.

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LIST OF SYMBOLS AND ABBREVIATIONS

ABC	:	Artificial Bee Colony
ACO	:	Ant Colony Optimization
AHP	:	Analytic Hierarchy Process
DG	:	Distributed Generation
EA	:	Evolutionary Algorithm
EP	:	Evolutionary Programming
EPSO	:	Evolutionary Particle Swarm Optimization
FA	:	Firefly Algorithm
FWA	:	Firework Algorithm
GA	:	Genetic Algorithm
GSA	:	Gravitational Search Algorithm
HSA	:	Harmony Search Algorithm
ICA	:	Imperialist Competitive Algorithm
ITS	:	Improved Tabu Search
MGA	:	Modified Genetic Algorithm
MPSO	:	Modified Particle Swarm Optimization
MTS	:	Moving Target Search
PQ	:	Constant Power Operating Mode
PSO	:	Particle Swarm Optimization
PV	:	Constant Voltage Operating Mode
RESs	:	Renewable Energy Sources
RGA	:	Refine Genetic Algorithm
SA	:	Simulated Annealing
SABC	:	Simplified Artificial Bee Colony

SI	:	Stability Index
TS	:	Tabu Search

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CHAPTER 1: INTRODUCTION

1.1 Overview

An electrical distribution system is the final stage in an electricity supply system, where electrical power is distributed to customers. In power distribution, power losses occur in the form of heat caused by current flow on the cables (I^2R). As a result of this, high power losses occur for large-scale distribution systems. According to (Sulaima, Mohd Fadhlan, et al., 2014), power losses on the transmission and sub-transmission lines accounted for 30% of total power losses in power system networks, while losses in a distribution network system accounted for 70% of the total losses in power system networks.

A well-known technique in minimizing power losses in distribution systems is network reconfiguration. It is a process of changing the switches' state of the network. This switch is normally open, a state referred to as tie switches, and if its closed, its referred to as sectionalizing switches. Tie switches are used to reconfigure the distribution network, while sectionalizing switches are used to localize damages caused by faults. These switches isolate the faulted subsystem, while the rest of the system is supplied normally. The topological structure of the network is reconfigured by closing the open switches and vice versa. This will reduce power losses and improve the overall voltage profile, provided that the reconfigured topology is optimized. By doing this, the load will be transferred to relatively less heavily loaded feeders from the heavily loaded feeders, which minimize the subsequent power losses.

Another technique that can be used to reduce power losses in a distribution system is interconnecting to a local power supply. By having a local supply, power can be delivered to the loads within a short distance, which reduces the overall power losses. A local power supply from renewable energy sources (RESs), such as mini-hydro, wind, solar, and biomass are commonly found installed in the distribution system, generating electrical power. This type of power supply is called "*Distributed Generations*" (DG). A DG is a small generating unit installed at strategic points in the distribution system, mainly near the load centers. The capacity of DG is usually 10 MW or less (Pilo, Pisano, & Soma, 2011; C.-L. Su, 2010). The integration of DG would lead to improvement in load balance, voltage profile, energy efficiency, and reliability. Therefore, it is crucial to ensure that the DG is at its optimal size and location to maximize its potential benefits. An inappropriate location and size of DG will cause higher power losses in a system, relative to that without a DG. Moreover, the implementation of DG and its related equipment in a distribution system is quite expensive. Therefore, optimal size and appropriate location of DG are essential in maintaining the stability of the system and minimize power losses in the network.

1.2 Problem Statement

Power losses in a distribution system is a severe problem, and it could cause huge revenue loss. For instance, in (Chandramohan, Atturulu, Devi, & Venkatesh, 2010), it was estimated that operational losses due to power losses amounted to USD 5,851.85. Furthermore, in the long run, environmental problems, such as CO_2 pollution, could be an issue, due to increased power requirements generated from conventional power plants to compensate for power losses. Technically, power losses could also reduce the voltage profile, especially in heavily loaded systems. For these reasons, various methods have been proposed by research in this area towards reducing power losses in an electric distribution system. Different optimization methods have been used to find an optimal network reconfiguration. These optimization methods were used due to complexity of the network reconfiguration problem, where there are huge numbers of possible opening switch combinations.

It can be seen from literature that existing methods are limited by certain factors. Firstly, DGs' impact on the reconfiguration process was not considered in depth. Only few works studied DGs in network reconfiguration, such as in (Rao, Ravindra, Satish, & Narasimham, 2013; Wu, Lee, Liu, & Tsai, 2010). These methods incorporate DGs via sequential approach, where network reconfiguration was solved first, and then optimal DGs generation was determined, and vice versa. This approach however does not guarantee optimal results. Therefore, a new approach based on the simultaneous approach is done by (Dahalan, 2013) and also done in this work to ensure that the results are optimal for both network reconfiguration and DG generation. Furthermore, with newly developed optimization techniques, such as gravitational search algorithm (GSA) and firefly algorithm (FA), there is a high possibility to further improve the results if applied for network reconfiguration.

Second, the sequence of switching process from the initial state to the optimal state is not widely considered. The switching sequence will cause huge power losses or load disconnection if it is not optimal. There was only one research on network reconfiguration focusing on minimizing power losses considering switching sequences (Bernardon et al., 2014). In this work, the best sequence of the switches was determined using the Analytic Hierarchy Process (AHP) multi-criteria analysis. Since this method was based on heuristic technique for selecting configurations, it assumes that only remote-controlled switches are considered. This method skips many probabilities of switching sequence paths because it searches for one solution within acceptable time, and high-power losses will still occur during this process. Thus, further research is needed to formulate a method to determine optimal switching sequence that results in minimum power losses.

Third, previous works in network reconfiguration assumed that the DG output generation power is constant. This assumption is only true for controllable DGs, such as mini-hydro or biomass types. However, in the case of photo-voltaic (PV) or wind type DGs cases, its generation is unpredictable due to the intermittent nature of irradiance and wind speed. Therefore, the network reconfiguration result will be inaccurate if the generation is assumed constant. It is therefore crucial to incorporate different types of DG, modes of operation, and load profile to network reconfiguration in order to obtain more practical result.

There are currently no available works on optimal switching sequence considering different DG types, its modes of operation, and dynamic load profiles. Therefore, it is important to analyze the impact of these factors towards determining the optimal switching sequence.

This work proposes simultaneously solving the network reconfiguration and DG output generation and finding an optimal switching sequence. The proposed network reconfiguration and switching sequence is expected to be flexible to cater towards practical conditions based on dynamic load profiles, DG output generation, DG types, and DG modes in finding the optimal daily solution.

1.3 Research Objectives

The main aim of this research is to propose a method that can reduce power losses and improve voltage profile in a distribution network connected to the DGs for planning and operations. The following are the objectives of the work:

1) To propose simultaneous network reconfiguration and DG output generation using evolutionary programming (EP), particle swarm optimization (PSO), gravitational search algorithm (GSA), and firefly algorithm (FA) for power loss reduction and voltage profile improvement.

2) To formulate optimal switching sequence method using evolutionary programming (EP), particle swarm optimization (PSO), gravitational search algorithm (GSA), and firefly algorithm (FA) to minimize power loss and improve voltage profile during reconfiguration process.

3) To analyze optimum daily solution for network reconfiguration and DG output generation by considering the load profiles and DG operating modes and types.

4) To determine optimum switching sequence path for daily operation by considering load profiles and DG operating modes and types.

1.4 Scope of Research

This study proposes simultaneous network reconfiguration and DG output generation for constant load profiles for reducing power losses and improving the overall voltage profile for distribution systems. This work also proposes an optimal switching sequence path to convert the network from the initial form to the optimal form based on minimum power losses and the best voltage profile. Then, both the simultaneous network reconfiguration and DG output generation and switching sequence path methods are applied for its 24 hours data (one day) to obtain optimal solution that accounts for load profiles, DG output generation, DG types, and its operating mode. The constraints of this study are radial structure of the distribution system, voltage bus constraints, and DG capacity.

The proposed method in this work employs meta-heuristic optimization methods, namely evolutionary programming (EP), particle swarm optimization (PSO), gravitational Search Algorithm (GSA), and firefly algorithm (FA). To validate the proposed method, 16-bus, 33-bus, 69-bus, and 118-bus test systems are used. Additional PV and PQ mode of DGs are used on top of the daily load profile. The method is implemented using MATLAB on a PC with 3.07 GHz CPU and 8-GB RAM. Additional PSCAD/EMTDC program is used to model IEEE 33-bus network.

1.5 Methodology of Research

The steps taken to fulfill the objectives of this work are detailed in Figure 1.1.

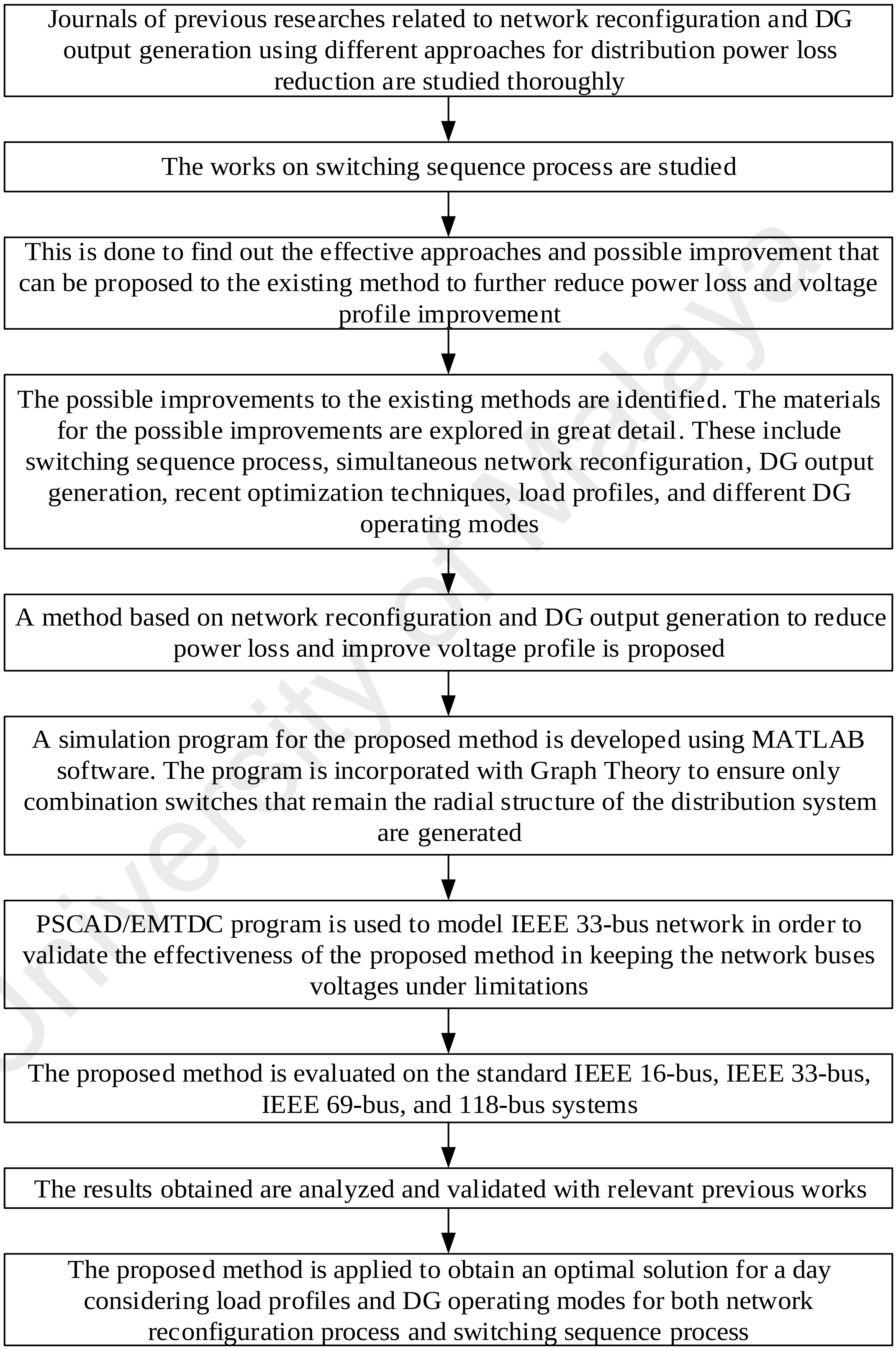

Figure 1.1: Flow chart of research methodology

1.6 Structure of Dissertation

This thesis consists of six chapters and two appendices. The background, problem statements, research objectives, scope and methodology of research are presented in the first chapter.

Previous works on network reconfiguration using heuristic approaches and metaheuristic approaches for power loss reduction are detailed in Chapter 2. The installation of DG for power loss reduction is reviewed as well. Reviews on simultaneous of network reconfiguration and DG output generation are presented, on top of switching sequence. An overview of power losses reduction in dynamic application, considering the important factors such as load profiles and DG operating mode are also discussed.

The problem formulation, implementation of EP, PSO, GSA, and FA in the proposed method are detailed in Chapter 3.

The simulation results are presented, and performance of the proposed method is analyzed in Chapter 4. The analyses are focused on power loss reduction and voltage profiles improvement. The validation and robustness of the proposed method are highlighted at the end of the chapter.

Chapter 5 presents the simulation results on the application of the proposed method for a day, considering load profiles and DG operating mode. The results obtained are analyzed and later discussed.

The conclusions of this research study are presented in Chapter 6, alongside suggestions for future works.

CHAPTER 2: BACKGROUND AND LITERATURE REVIEW

2.1 Introduction

This chapter review the literature on existing methods for power loss reduction in distribution system. The presented methods include optimal network reconfiguration, optimal DG output generation, and sequential optimization of network reconfiguration and DG output generation. The term of ‘DG output generation’ used in this thesis is also referred to as ‘DG sizing’ in other works. Thus, both terms will be used interchangeably here. At the end of this chapter, some areas of improvements on the existing methods will be identified and highlighted.

2.2 Network Reconfiguration

Network reconfiguration is a process of changing the switches’ state of a network. This switch could be normally open, a situation called tie switches, or normally closed, a situation called sectionalizing switches. The topological structure of a network can be changed by closing the open switches, and vice versa. This decrease power losses and improve the overall voltage profile, provided that its optimum reconfiguration is determined beforehand. This will transfer the load to relatively less heavily loaded feeders from heavily loaded feeders, which culminates in reduced power losses. (Nara, Shiose, Kitagawa, & Ishihara, 1992b) proposed a network reconfiguration method to minimize distribution power losses using Genetic Algorithm (GA). They confirmed that the method reconfigured the network with minimal power losses. (Kashem, Ganapathy, & Jasmon, 2000) enhanced voltage stability by reconfiguring a network using a new algorithm. First, a tie and two neighboring switches were generated. The combination switch that generates the maximum voltage stability for the system was determined. The search was then extended to the neighbor of the best branch to check for any combination that results in better voltage stability. The proposed method could enhance voltage stability at no additional cost pertaining to tap-changing transformers, switching equipment, and installed capacitors in the distribution system. A 69-bus test system was used to confirm the proposed method's viability in reducing network power loss. (Das, 2006) used the fuzzy multi objective and heuristic rules approach to reconfigure their network. Their main objectives were to minimize power losses, balance feeder loads, and improve the overall voltage by accounting for specific constraints. These objectives were modeled using fuzzy sets to determine its imprecise nature and its anticipated value for each objective. The Heuristic rules were used to decrease the number of tie switch operation. The simulation results confirmed that the method is able to reduce the search space and minimize computational time, and proved the feasibility of the presented methodology. (Nguyen, Nguyen, Truong, Nguyen, & Phung, 2017) used a runner-root algorithm (RRA) to solve the electric distribution network reconfiguration (NR) problem. His objectives were to minimize real power loss, load balance the feeders, load balance the branches, deviate node voltage, and selecting the number of switching operations using max-min method to affect a final compromised solution. RRA could escape from the local optimal since it creates a re-initialization strategy and jumps at large steps. 33-node and 70-node distribution networks were used to prove the effectiveness of RRA in the case of both single-and multi-objectives. The results were compared with other that of published works, and it was confirmed that a runner-root algorithm is effective for solving single- and multi-objective network reconfiguration problems.

2.3 Distributed Generation Sizing and Placement

Distributed generation (DG) is defined as the electric power generation within distribution networks or on the end-user side of the network (Ackermann, Andersson, & Söder, 2001). DG placement and sizing has been identified as one of the promising solutions for power loss reduction in a distribution system. There are many different technologies for DG based on non-renewable and renewable resources. The combustion engine, combined cycle, combustion turbine, micro turbine and fuel cell forms the former, while photovoltaic, wind turbine, hydro, geothermal and biomass forms the latter (Hung & Mithulananthan, 2013). DG with different resources will report a different location, rating, environmental impact, and operating mode.

Works in minimizing power losses via optimal DG output generation have also been reported. In (Celli, Ghiani, Mocci, & Pilo, 2005), a multi-objective formulation was proposed in order to set the size and location of the DG resources for the system. The methodology allowed the manager to balance between cost of power losses, cost of network upgrading, the cost of energy required by the served customers, and the cost of energy not supplied. A set of non-inferior solutions for the implemented technically were obtained based on a constrained method and genetic algorithm. Meanwhile, (Wang & Nehrir, 2004) presented analytical methods in order to determine the optimal location placement of a DG in a radial distribution networked system. The goal was to minimize the power loss of the network. Since the presented approaches are not repeated algorithms, the presented approaches did not report a convergence problem, and the results were obtained very quickly. To verify the validity of the presented approaches, a series of simulation studies were conducted, and the results show that the proposed methods successfully selected suitable sites to place the DGs. (Hadidian-Moghaddam, Arabi-Nowdeh, Bigdeli, & Azizian, 2017) solved the optimal sizing and siting problem of the DG using a new optimization method. Different objectives were considered using the ant lion optimizer (ALO). The objectives were to reduce DGs losses, DGs' application cost, buses' voltage deviation, and energy cost from the upstream network while improving reliability. The optimization problem was solved as single-objective optimization (SOO) and a multi-objective optimization (MOO). 33 and 69-bus IEEE networks were utilized to find the optimal sizing and siting of the DGs. The result confirmed that ALO is better than PSO and GA in extracting the solution of the optimal sizing and siting problem of the DGs.

2.4 Network Reconfiguration with Presence of DG for Power Loss Reduction

Network reconfiguration and DG installation have been proven to be effective towards reducing power losses in distribution systems. In order to further reduce power losses in a distribution system, both methods were combined. Many works have been conducted for optimal reconfiguration method and optimal DGs output. However, there are not many works on network reconfiguration that took into account the optimal DGs output generation. Most are based on sequential or simultaneous techniques. In the former, the optimal size of DG is determined prior to network reconfiguration. (Wu et al., 2010) is an example of the sequential technique. The Ant Colony Algorithm was used in the proposed reconfiguration method with DG, aiming to minimize power losses and improve the load balance factor of the radial distribution networks. The effectiveness of the proposed method was validated using 33-bus distribution network of 11.4kV system. The results show that network reconfiguration with DG reported lower power losses and better load balancing relative to a system without a DG(s). Meanwhile, (Rao et al., 2013) presented a method to simultaneously solve the DG sizing and reconfiguration problem. His main objective was to reduce total power losses and improve the voltage profile. Sensitive analysis was conducted using the harmony search algorithm to solve the simultaneous process and compare it to Genetic algorithm and refined genetic algorithm. Various scenarios were applied on the 33 and 69 bus system for reconfiguration and DG sizing. The results proved that the simultaneous process is more effective than the sequential process in the context of minimizing power losses and improving voltage profiles. (Liu, Sheng, Liu, & Meng, 2017) carried out a simultaneous distribution network reconfiguration and DG allocation. Prior to network reconfiguration, the uncertainties of load fluctuation were accounted for. The objectives were to minimize the Expected Energy Not Supplied, line loss cost, and switch operation costs. Due to the multi-objective problem, weighting factors were used. The proposed method consists of two periods; the first creates a feasible topology network using binary particle swarm optimization (BPSO), while the second solves the DG allocation using harmony search algorithm (HSA). To deal with the device parameters and uncertainties of load, an interval analysis was applied. They also used the IEEE 33-bus and 69-bus systems and analyzed multiple comparisons and scenarios. The results confirmed that the proposed network reconfiguration algorithm is feasible.

2.5 Methodologies of Network Reconfiguration and DG Sizing Techniques

Many methods have been developed for reconfiguration. However, not many took into account the optimal sizing of the DGs (Dahalan, Mokhlis, Ahmad, Abu Bakar, & Musirin, 2014; Olamaei, Niknam, & Gharehpetian, 2008; Wu et al., 2010). Reported works can be categorized into 'sequential' and 'simultaneous' techniques. In the case of the former, the optimal size of the DGs needs to be determined prior to network configuration, while in the case of the latter, optimal sizing of the DGs and network reconfiguration are simultaneously executed.

Different optimization technique was used to solve network reconfiguration and DG sizing. Figure 2.1 summarize the available techniques.

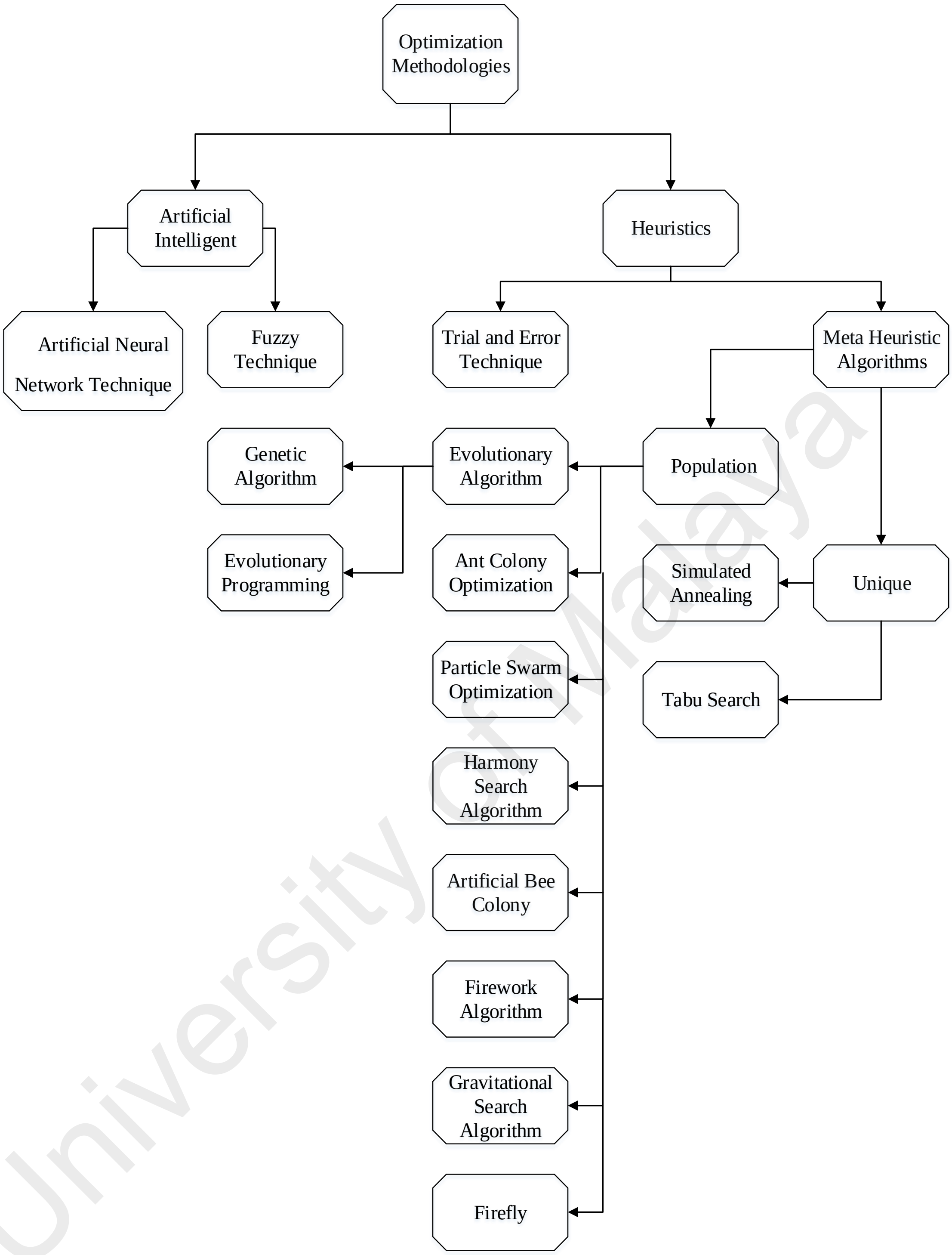

Figure 2.1: Optimization Methodologies of distribution network reconfiguration embedded with DG

2.5.1 Heuristic Technique

A heuristic technique is an optimization process that is used to find an approximation for the optimal solution to a problem, which could be the maximum/minimum values. For it to be effective, we need to formulate the correct function for the problem. The trial-and-error method is an example of a heuristic method (Carreno, Romero, & Padilha-Feltrin, 2008; Gupta, Swarnkar, & Niazi, 2012).

2.5.1.1 Trial and error method

Trial-and-Error represents the most basic method for solving optimization problems, which is characterized by repeated varied attempts, continuing until the agent stops trying, or until it is successful.

Various trial-and-error methods were employed to reconfigure the electrical distribution network. In (Kashem, Jasmon, & Ganapathy, 2000), the interchange switch strategy was used to reconfigure the feeder. It looks for suitable options to reduce losses via a minimal tree-search. A simple formula for power loss was developed to determine the switching option that will result in minimum power loss. The results showed that the proposed method realized the optimal or near optimal configuration of the network in an efficient manner, with minimal computational effort. In (McDermott, Drezga, & Broadwater, 1999), the open-all switch strategy was used to reduce power losses for a radial distribution network. Load flow was used to set a lower bound on the losses. When implementing the proposed strategy, the switches were closed one-by-one, until a radial network was formed. The results showed that the proposed method is more computationally involved compared to other methods, but its control action was more accurate. (Gomes et al., 2005) used the close-all switch strategy. The methodology began with a meshed distribution network, which close all the switches. In order to eliminate loops, the switches were then successively opened. The opening criteria was based on the increased minimum total power loss. The power losses were calculated using a power-flow program. The proposed method managed to avoid the combinatorial explosion of the number of configurations that needs to be tested.

2.5.1.2 Meta-heuristic method

The meta-heuristic method is an iterative generation process that helps the search process efficiently locate near-optimal solutions using learning strategies and intelligently combining different concepts that will help exploit and scour the search space. This strategy can be utilized to look for the exact/near exact optimal solutions. This method can be divided into two distinct categories: Single (unique) solution and Population solution (Gendreau & Potvin, 2010).

(a) ***Single (Unique) solution meta-heuristic method***

This type of method provides one solution at a time. This section presents the most popular algorithms pertaining to this method.

i Simulated annealing

Simulated annealing (SA) is a random search method that solves large combinatorial optimization problems. It can escape the local minima by incorporating a probability function when accepting/rejecting new solutions. It is an iterative algorithm with an initial random solution to the problem, then changing a single element of the solution incrementally in order to find a better one. The algorithm consists of initialization, cooling schedule, perturbation, and acceptance probability to perform the search (Alrefaei & Diabat, 2009).

In (Zhanga, Zhanga, Xina, Zhangb, & Fana, 2012), the author analyzed the reconfiguration of a distribution network with a small capacity of oilfield associated gas DG. The network reconfiguration algorithm in this work is based on simulated annealing. The formulation to minimize losses for the reconfiguration problem is:

$$\min(P_{loss}) = \sum_{i=1}^{Nb} r_i \frac{P_i^2 + Q_i^2}{V_i^2}, \tag{2.1}$$

subject to: $g(x) = 0,$ (2.2)

$S_i \leq S_{i,max}$ (2.3)

$V_{i,min} \leq V_i \leq V_{i,max}$ (2.4)

where P_{loss} is the power loss of system, r_i is resistance of branch i, Nb is total the number of branches, P_i is the active power of branch i, Q_i is the reactive power of branch i, V_i is the voltage of the head node of branch i, $g(x)$ represents topology constraints, $S_{i,max}$ is the maximal capacity of branch i, $V_{i,min}$ and $V_{i,max}$ are the voltage boundaries of branch i. The output production of the oilfield-associated gas DG is relatively stable compared to that of solar/wind DG since gas can easily be stored for use at any time. SA, combined with the Immune Algorithm, was used to avoid the unfeasibility of the solutions in the evolutionary process and accelerate the global optimization searching speed. This combination resulted in improved population characteristics. The algorithm was applied to the IEEE 33 bus. Four DGs were installed on buses 4, 8, 25, and 30. The results confirmed the great benefits of this reconfiguration, where the power loss after the DG is reconfigured is 201.9 kW, while prior to reconfiguration, it was 597.9 kW.

ii Tabu search

Tabu Search (TS) is a meta-heuristic algorithm that can be used to quickly look for an effective solution for the combinatorial problem. Its working principle is based on a memory structure. The information data (such as the current value of the objective function) and previous decisions are stored and tracked to avoid local optimal solutions. Prohibiting recent steps during the search process improves the efficiency of the exploration process. The stored data is used to guide the search for the next solutions in a specific range, which is restricted by the previous steps. Typically, the search process stops after a maximum number of iterations without any improvement to the best solution (Glover, Laguna, & Marti, 2007).

(Lantharthong & Rugthaicharoenchep, 2013) reported the benefits of network reconfiguration to accommodate capacitor placements and DG units in a distribution system to improve both bus voltage and load balancing. The TS algorithm was used to determine the state of the switches for minimizing the load-balancing index without violating any constraints on the system, while the load-balancing index was used to determine the maximum load capacity of the system. The optimization process was used to balance the load and eliminate any overloads. The load-balancing index (LBI) was minimized using the equation:

$$MinLBI = \sum_{k \in B} L_k \left(\frac{|I_{k,t}|}{I_k^{max}} \right)^2 \qquad (2.5)$$

where B is the set of network branches that form the loops, L_k is the length of branch k, $I_{k,t}$ is the current capability of branch k for the feeder reconfiguration pattern t, and I_k^{max} is the maximum current capability of a given branch k. This algorithm was applied on the 69-bus radial network with DGs and capacitors positioned to obtain the optimal network reconfiguration when the balancing index is at its minimum. The results confirmed the algorithm's ability to decrease computational time and obtain the optimal solution(s) while satisfying all the constraints.

In another work based on TS (Rugthaicharoencheep & Sirisumrannukul, 2009), the researchers investigated the reduction of power loss in the distribution system due to the integration of the DG. They used four case studies to show that configuring the network with DGs improved the bus voltage and reduced power losses. The results showed that power loss decrease when both the reconfiguration technique and DG sizing take place simultaneously. Furthermore, the results identified the optimal state of the switches that would result in the lowest power loss while still satisfying the system's constraints. The results proved the effectiveness of the TS algorithm in determining an optimum solution with fewer iterations. Meanwhile, in (Olamaei et al., 2008), a distribution network was reconfigured in order to minimize the number of operation switches, improve the deviation of the bus voltage, and minimize the active power cost generated by the DGs. These effects can be modelled using the following equation (Olamaei et al., 2008):

$$f(\overline{X}) = \sum_{i=1}^{N_{sub}} P_{sub,i} \cdot Price^{i} + \sum_{i=1}^{N_g} C_{Pgi}\left(P_{gi}\right) + w_1 \cdot \sum_{i=1}^{N_{sw}} \left|S_i - S_{o,i}\right| + w_2 \cdot \sum_{i=1}^{N_{bus}} |V_i - V_{rat}| \,, \tag{2.6}$$

where N_{sub} is the number of substations, N_g is the number of DGs, N_{sw} is the number of switches, N_{bus} are the number of buses, $\bar{X}$ is the state variable vector, $P_{sub,i}$ is the i_{th} substation active power, $Price^{i}$ is the electrical energy cost at the i_{th} substation, P_{gi} is the active power of the i_{th} DG, $C_{Pgi}\left(P_{gi}\right)$ is the price of active power generated by the i_{th} DG, S_i is the new state of switch i $S_{o,i}$ is the original state of switch i, V_i is the real voltage on bus i, V_{rat} is the rated voltage on bus i, w_1 and w_2 represent the weighting factors. The basic concept of this method is to determine the configuration of the distribution system, which is then followed by the creation of an initial population and velocity based on the load values and DGs. The objective function was then evaluated using the load flow method. The global and local positions were selected based on the values of the objective function, which was accordingly updated. The process was repeated until the maximum number of iterations was reached. The results proved that the integrated DG improved the system's performance.

(b) ***Population solution meta-heuristic method***

This method provides a concurrently multi-solution. This section will detail the most popular algorithms belonging to the population solutions, such as evolutionary algorithms (EA), ant colony optimization (ACO), particle swarm optimization (PSO), harmony search algorithm (HSA), and artificial bee colony (ABC).

i Evolutionary algorithm

Evolutionary algorithm (EA) is a meta-heuristic method that generates solutions to optimize problems based on natural selection, such as recombination, mutation, selection, and reproduction. In the beginning, poor solutions are selected from the initial population. Then, it randomly provides a candidate solution via a mutation step, which then combines the initial population with the mutation results to form a novel solution via the recombination step. In the end, it reproduces the results, which means that it replicates the most successful solutions found within a population. EA includes genetic algorithm (GA) and evolutionary programming (EP) (Carreno, Moreira, & Romero, 2007; Carreno et al., 2008).

- **Genetic algorithm**

Genetic algorithm (GA) is an optimization methodology based on a model of evolution and adaptation in nature. It can find a globally optimal solution for large-scale combinatorial optimization problems. GA is widely used in optimization, business, and machine learning (Vadivoo & Slochanal, 2009). Since it is easy to model and understand, it is usually utilized for multi-objective optimization. It is also easy to exploit alternate solutions and is flexible for hybrid applications. However, GA can only find the optimal solution if the population has a sufficiently large quantity of data (Ganesan & Venkatesh, 2006).

An improved GA, called Non dominated Sorting - Genetic Algorithm (NSGA) for network reconfiguration was presented in (Chandramohan et al., 2010). The objective function of the method was to minimize the operating cost of the system. They also suggested some criteria that can maximize the system's reliability and improve its power quality. The total amount of active and reactive power was minimized based on the operating cost using the equation:

$$Operating\ Cost = K1 \times PL \times K2 \times QSS \tag{2.7}$$

where $K1$ is the real power price coefficient in $\$/kW$, PL is the real power losses for system transmission, $K2$ is the reactive power price coefficient in $\$/kVAR$, and QSS is the reactive power drawn from the connected transmission system by the distribution system. In (Ganesan & Venkatesh, 2006; Mendoza et al., 2006), the GA method was used to improve the reconfiguration of a power distribution system. GA was also used to avoid the non-feasible solution via its branches form. The branch form is acceptable only if the solution provides a radial network. This method has been used to reduce the amount of power loss from a distribution system. Figure 2.2 illustrates the reconfiguration process. The result confirmed the simplicity and effectiveness of the algorithm. Meanwhile, (Prasad, Ranjan, Sahoo, & Chaturvedi, 2005) presented a radial distribution system with optimal reconfiguration based on the fuzzy mutated method. It deals with non-continuous multi-objective optimization and overcomes the combinatorial nature of the reconfiguration problem. This algorithm maintains the radial property of the network and avoids islanding for any load point via a special coding scheme and an effective convergence characteristic related to a controlled mutation using fuzzy logic. It was shown that the test results on a 69 bus for radial distribution network are satisfactory.

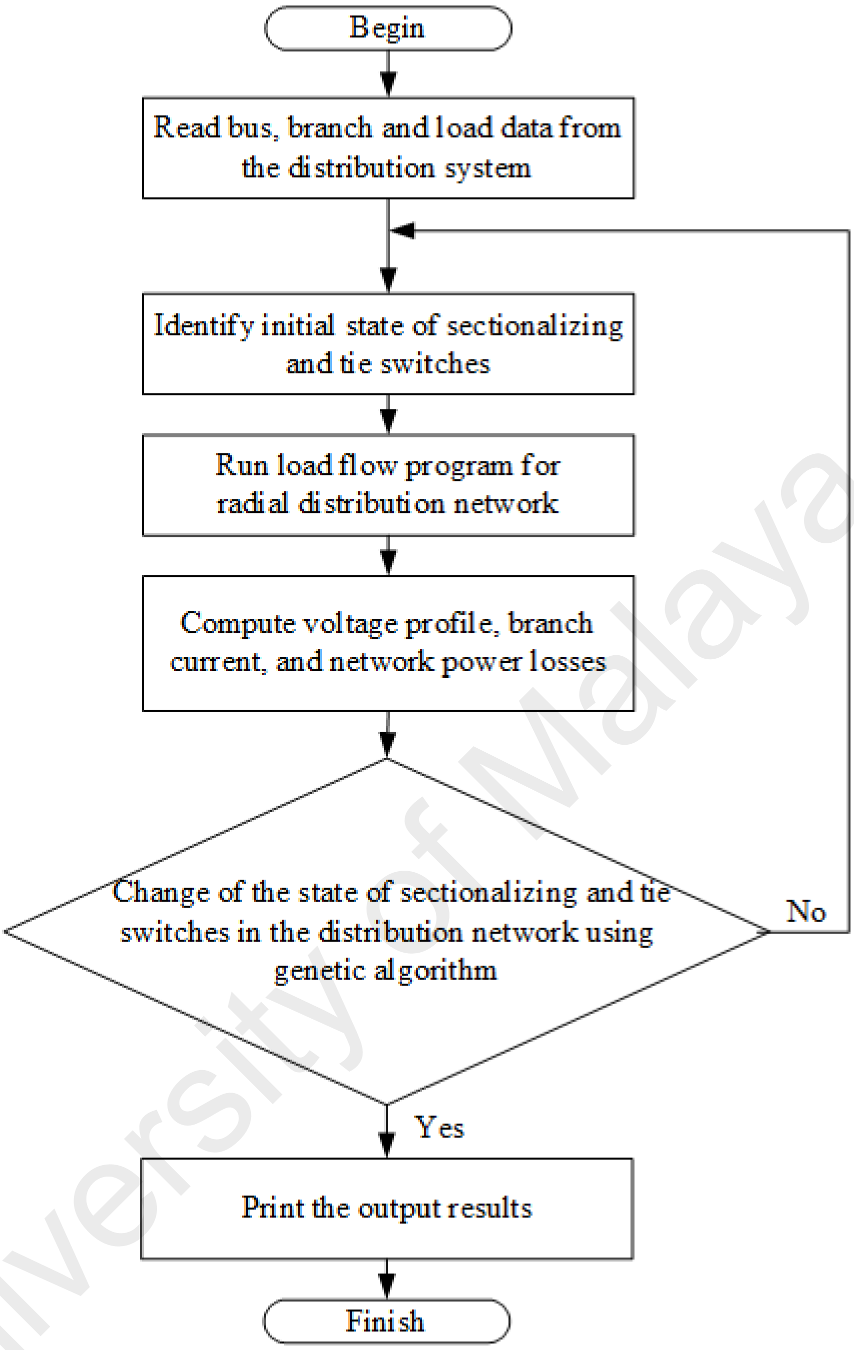

Figure 2.2: Flow chart for network reconfiguration process

A new methodology of codification for the conventional GA was presented in (Aspari & Sreenivasulu, 2013) to reconfigure a radial distribution system of 33 buses in the presence of DGs. This method aimed to minimize power losses and improve the feeder voltage profile, taking into account network reconfiguration constraints, which consist of the radial configuration format, load point voltage limits, feeder capability limits, and no load-point interruption. The main innovation in this method is that the initial population is generated using new types of crossover and mutation operators, which provide the best possible results with acceptable levels of computational effort. This meta-heuristic algorithm reduces the search space and renders the application of the algorithm possible for large distribution systems, since it could deal with problems with complex multi-constraints with minimum computational effort. (Martins & Borges, 2011) proposed a model for active distribution systems. DGs were integrated with a conventional source to expand the system as a requirement for active modern networks. The model's objectives were to plan a safe system that minimizes the cost of the system reliability, network investment, and power losses. Two methodologies based on GA were proposed to solve the uncertain power generation problems caused by the DG. The first analyzed the network reconfiguration and DG location individually, while the second analyzed both network reconfiguration and DG location simultaneously. The total cost for the methods were calculated based on the following equations:

For the first methodology:

$$obf = C_{losses} + ECOST + C_{inv} + C_{trans} \tag{2.8}$$

where C_{losses} is the annualized energy losses costs, $ECOST$ is the expected value of non-distributed energy cost, C_{inv} is the annualized cost of system investments, and C_{trans} is the annualized costs of energy imported from the transmission system.

For the second methodology:

$$obf = \sum_{k=1}^{n_c} p_k\left(C_{losses\ j,k} + ECOST_{j,k} + C_{inv\ j,k} + C_{trans\ j,k}\right) \tag{2.9}$$

where n_c is the number of scenarios considered, p_k is the probability of occurrence of scenario k, $C_{losses\ j,k}$ is the annualized energy losses costs of individual j on scenario k, $ECOST_{j,k}$ is the expected value of non-distributed energy cost of individual j on scenario k, $C_{inv\ j,k}$ is the annualized costs of system investments of individual j on scenario k, and $C_{trans\ j,k}$ is the annualized costs of energy imported from transmission of individual j on scenario k. The results showed that the second method is superior to the first in the context of realizing the model's objectives. The effectiveness and simplicity of the GA algorithm was also confirmed.

(Cho, Shin, Park, & Kim, 2012) proposed a novel objective function to improve the reconfiguration system's reliability under islanding conditions. The objective function was based on reliability cost. Both DGs' reliability cost and customer interruption cost were accounted for. The model was implemented using MATLAB, with GA as its optimization tool. It was found that the DG reliability cost is more influential under a lightly loaded feeder, while the customer interruption cost is more influential under a heavily loaded feeder.

- **Evolutionary programming**

Evolutionary programming (EP) is a stochastic optimization method. Lawrence J. Fogel introduced it in 1960 (Fogel, 1966). It focuses on the linkage between parents and their children instead of seeking to simulate natural genetic operators. The EP algorithm is simple and direct. The basic concept of EP is as follows: First, randomly generate an initial population (parents). Then, the fitness of each parent is calculated using the objective function. After that, a new population (offspring) is generated using the mutation process. Then, both parents and offspring are combined to generate a new population. The new population is sorted based on their fitness value in an ascending order. The first half of the new population is stored as the next generation, while the second half is removed. The process is repeated until the fitness converges, which means that the entire population possess similar levels of fitness (Hsiao, 2004).

(Chakravorty, 2012) proposed a new type of EP algorithm to minimize the loss during reconfiguration for a radial distribution. Based on the heuristic information, a fuzzy controlled EP method was proposed to improve the performance of evolutionary programming. This algorithm adjusts the mutation rate during the evolutionary process that could reduce the combinatorial explosive switching problem to minimize the switching operation to a few numbers. (Hsiao, 2004) proposed a method to solve the network reconfiguration problem for multiple objective functions (minimizing power losses, maintaining voltage quality, enhancing service reliability, and reducing switching time). In this work, the execution of the EP resulted in a non-inferiority optimal solution and is also capable of solving problems with nonlinear and non-differentiable objective functions.

ii Ant colony optimization

The ant colony optimization (ACO) is defined as a novel nature-inspired Meta-heuristic for solving hard combinatorial optimization (CO) problems. It is used to solve hard CO problems in a suitable amount of computation time. ACO is one of the evolutionary methods based on the implementation of finding the shortest path for ants when searching for food. Ants determined the shortest path from the nest to the food source by depositing a hormone called pheromone (Dorigo, Birattari, & Stutzle, 2006; Dorigo & Blum, 2005; Nayak, 2014).

(Wu et al., 2010) proposed a reconfiguration methodology based on an Ant Colony Search Algorithm (ACS) objective to achieve the minimum power losses and increment load balance factor for radial distribution networks with DGs. The load balance was determined using the formula:

$$LB_i = \sum_{i=1}^{nb} \left(\frac{S_i}{S_i^{max}}\right)^2 = \sum_{i=1}^{nb} \frac{P_i^2 + Q_i^2}{S_i^{\max 2}} \tag{2.10}$$

where P_i^2 and Q_i^2 are the active and reactive power for bus i, respectively, nb is the number of the branch, S_i is the complex power at the sending end of branch i, and S_i^{max} is used as a measure of how much branch i is loaded. The results show that lower system losses and better load balancing can be attained when the DG is compared to a system without DG.

However, the work only emphasized the impact of DG on power losses, while the location and capacity of DG are fixed earlier and not detailed. The computational results showed that ACS becomes an extremely powerful method and is superior to the GA. It can be seen that when the distributed generation are installed in a system, a 44.626% of average loss reduction is reported by the ACS compared to 43.803% reported by the GA. (Voropai & Bat-Undraal, 2012) extended the work of (Wu et al., 2010), where the problem of multi criteria reconfiguration of distribution network with DG was presented in the context of power supply reliability under post-emergency conditions and minimum active power loss under normal conditions. An ACO algorithm was used to solve the multi criteria problem for the Mongolian power system, where it analyzed the efficiency of the system in a normal case based on the minimized active power losses. The cell formation method was used to solve the islanding problem. The reported robust solution proved the capability of the ACO in solving hard combinational problems. (Kasaei, 2012) worked along the guidelines reported in (Wu et al., 2010), where he employed the ACO algorithm applications on 10 and 33 bus networks to improve its reliability and efficiency. The algorithm reported better results for the reconfiguration process, regardless of the presence of DGs. Meanwhile, (Tolabi, Ali, & Rizwan, 2015) proposed an approach that combines the fuzzy approach and the ACO algorithm to solve the simultaneous reconfiguration problem. The method also optimizes the location and size of the PV and distribution static compensator in the distribution system. It includes the voltage profile, loss reduction, and load balancing for the feeders. The method was tested on a 33-bus real system. The results showed that simultaneous reconfiguration is indeed possible for optimizing the location and size of the PV and the distributed static compensator, to improve the voltage profile reduce power losses, and balance load feeder. The results show that the fuzzy - ACO combined approach was more accurate and robust compared to the conventional ACO.

iii Particle swarm optimization

Particle swarm optimization (PSO) is another meta-heuristic method used by many researchers for optimization purposes. It was originally proposed by Dr. Eberhart and Dr. Kennedy in 1995 (Eberhart & Kennedy, 1995). PSO was inspired by the food searching behavior of birds or fish. The main concept of the PSO method involves the generation of random particles having random positions and velocities. The fitness value for each particle will then be evaluated, upon which the particles update their respective positions and velocities based on their own searching experience and those relative to others. The same process is repeated until the optimal or near optimal solution is found (Balakrishna & Babu, 2014). Researchers who utilized PSO in their works include the following.

In (Dahal & Salehfar, 2016), PSO was used to determine the optimal placement and sizing of different types of DG units (PV cells, Fuel Cells (FC), synchronous generators, or induction generators) on a multi-phased unbalanced distribution network. The IEEE 123 node network was used as its test system, while in a real experiment, a combination made up of all types of DGs were utilized. The results were compared with the Repeated Load Flow method (RLF), and it was shown that the proposed approach is more effective and quick (in terms of computational time) in allocating DGs. Moreover, optimized DG will improve the voltage profile and reduce power losses.

(Arya, Kumar, & Dubey, 2011) introduced a modified PSO as an optimization technique for the reconfiguration of distribution systems. PSO reports an optimal solution that is computationally less demanding compared to other algorithms. The proposed algorithm works by altering the normally open switches, while also taking into account the stabilization of the supplied loads and minimization of switches on the lines. This strategy minimizes loss via the application of the algorithm and maximizes the number of supplied loads, which means that the best solution can be found more quickly. This is very important for large-scale systems with a higher number of possible configurations. Meanwhile, (Nodushan, Ghadimi, & Salami, 2013) improved the voltage sag index and DG placement via reconfiguration. The performance evaluation index is the number of times the voltage of sensitive loads decreases to the critical voltage. The Binary Particle Swarm Optimization (BPSO) algorithm was used to minimize this index. The simulation results showed that simultaneously using reconfiguration and DG placement can improve the voltage sag index by 75%.

In a different publication, (Balakrishna & Babu, 2014) presented a method based on the PSO algorithm and a load balancing index. The method was used in the optimal reconfiguration process that is embedded with a shunt capacitor bank and a DG unit. Its main objective was to eliminate overloading conditions and balance the feeder loads. A 69-node network embedded with the DG and capacitor units were used to prove the method's effectiveness. The results reported a better voltage profile and load balance. Comparing PSO and tabu search showed that PSO reported better results at a quicker rate.

iv Harmony search algorithm

Harmony search algorithm (HSA) is a music-based Meta-heuristic population search algorithm. It was inspired by the observation that music is the manifestation of the perfect state of harmony. This harmony leads to the search for optimal value of optimization process. HSA could be used to solve various problems, such as power system design and multi-objective optimization. The principle of HSA consists of three operations; memory consideration, pitch adjustment, and random selection. Memory operation is used to find a value from the harmony memory; pitch adjustment is used to choose a value that is modified from harmony memory value; and random selection is used to select a random value from the entire value range. These three operations, combined, form a novel stochastic derivative for searching the optimal solution as opposed to the traditional operation based on basic derivatives (Lee & Geem, 2004; Mahdavi, Fesanghary, & Damangir, 2007).

In (Abdelaziz, Osama, Elkhodary, & El-Saadany, 2012), optimizing the configuration network was compared with and without DG for 32 and 69 bus distribution systems. The optimization process was developed based on HSA and ACO algorithms. The results showed that both algorithms reported optimal solutions for the feeder reconfiguration while the active power losses were minimized. However, HSA required less computation time compared to ACO, but it required more iterations. In (Rao et al., 2013), HSA was used by the sensitivity analysis to identify the optimal location and carrying capacity of the DG simultaneously with the reconfigured feeders. The performances of the proposed method were analyzed via different scenarios implemented on 33 and 69 bus radial networks for three different load levels. The results were encouraging; installing the DG reduced active power loss. The loss percentage increased when the number of the DG increased from 1 to 4. Also, the voltage profile improved when both reconfiguration and DG sizing were simultaneously analyzed. HSA was compared to GA, and the computation results showed that the performance of the HSA was better than GA. Similar work was done in (Safavi, Vahidi, & Abedi, 2014), where the main objectives were to improve the voltage profile and minimize power loss using the following equation:

$$VO_i = \frac{(V_i - V_{min})(V_{max} - V_i)}{(V_{nom} - V_{min})(V_{max} - V_{nom})} \quad (2.11)$$

where VO_i is the voltage profile for node i, V_i is the voltage in bus i, V_{min} is the minimum voltage at each bus (nearly 0.95 pu), V_{max} is the maximum allowable voltage at each bus (nearly 1.05 pu), and V_{nom} is the nominal voltage in each bus. In addition, PSO and HSA algorithms were compared by testing the method on 33 and 69 bus radial systems at three different load levels. The computational results confirmed that HSA is faster than PSO.

v Artificial bee colony

The Artificial bee colony (ABC) is an optimization algorithm based on swarm intelligence, which simulates the foraging behavior of honeybees looking for a high quality food sources (Karaboga & Basturk, 2008). The specific minimal model of forage selection that leads to the emergence of collective intelligence is composed of three necessary components: employed forager bees, unemployed forager bees, and a food source (Karaboga & Akay, 2009). Two principle mode behaviors have also defined recruitment to a nectar source and the abandonment of poor sources. Comprehensive studies were done in many fields utilizing the ABC algorithm to solve numerous practical optimization problems (Jamian et al., 2014; Karaboga & Akay, 2009).

(Rao, Narasimham, & Ramalingaraju, 2008) presented a new population for solving the radial distribution reconfiguration problem based on the ABC algorithm. The objectives of this method were to improve the voltage profile, minimize the real power losses, and balance the feeder where all the loads must be energized. The results obtained were compared with the GA method, and it was confirmed that ABC performed better than GA in the context of the quality of the solution and computation time.

(Jamian et al., 2014) used the ABC algorithm to minimize power loss by simultaneously executing the reconfiguration analysis and DG sizing. The test was conducted on systems embedded with 3 DG units working in the PV mode. The results showed that the simultaneous process decreased power losses and computational time, while avoiding being trapped in local optima.

vi Firework algorithm

The firework algorithm (FWA) is a swarm intelligence based on the stochastic search technique. FWA can be used for optimization and to search for promising areas for use as a solution space. The algorithm is inspired by the phenomenon of exploding fireworks and sparks generated within a space around the fireworks in the sky. FWA is regarded as a novel algorithm, due to its take on the explosive nature of fireworks and the incorporation of this feature when searching for a solution. The algorithm also manages to evenly allocate resources between firework swarms when searching for solutions (Nguyen & Truong, 2015).

(Imran & Kowsalya, 2014) proposed a novel integration technique to minimize power loss and enhance voltage stability when reconfiguring the network and installing the DG in a distribution system. The placement of the DG and network reconfiguration took place simultaneously when using the FWA. The power flow method generates the proper parent node-child node path to guarantee the radiality of the network. The best location for the installation of the DG was identified using the Voltage Stability Index (VSI). Different scenarios were proposed during DG placement and reconfiguration of network to assess the performance of the proposed technique. The results proved that reconfiguring the network and installing the DG simultaneously represents the most effective scenario for minimizing loss and improving voltage profile. The simulated results were compared with the results from HSA and GA, and it was confirmed that the performance of the FWA exceeded that of the HSA and GA in every scenario.

2.5.2 Artificial Intelligent Technique

Artificial intelligent (AI) is a technique that is defined as the science of making intelligent machines, such as intelligent computer programs. Artificial intelligence techniques that have been used to reconfigure networks include fuzzy and firework techniques (Qiu, Lv, & Chen, 2011).

2.5.2.1 Fuzzy technique

The fuzzy technique was introduced as a tool for dealing with soft and uncertain modelling. It is widely used in power systems. The fuzzy variable is modelled using a membership function that determines the degree of membership to a set that varies from zero to one (Qiu et al., 2011).

(Niknam, Fard, & Seifi, 2012; Sedighizadeh, Esmaili, & Esmaeili, 2014) discussed the usage of the multi-objective function to reconfigure network and size DGs. The objectives include the minimization of power loss, total cost, and emissions, and the maximization of the voltage stability index (VSI). The VSI for a radial feeder is presented in the equation below:

$$VSI_r = (V_s)^4 - 4(P_{sr}X_{sr} - Q_{sr}R_{sr})^2 - 4(V_s)^2(P_{sr}R_{sr} - Q_{sr}X_{sr}), r = 1, \cdots, N_{bus} \quad (2.12)$$

where V_s is the voltage amplitude at bus s in (pu), R_{sr} and X_{sr} are the resistance and reactance of branch $s - r$, respectively in pu, P_{sr} and Q_{sr} are the active and reactive power at the sending end of branch $s - r$ in p.u, respectively. The total cost is formulated as follows:

$$Minf = Cost = C_{sub} + \sum_{i=1}^{N_{DG}} C_i \quad (2.13)$$

where $C_{sub}(\$/h)$ is the cost of purchased electrical energy from the main source, $C_i(\$/h)$ is the cost of the power generation by the DG unit i, and N_{DG} is the number of DG. Moreover, the total emission produced by the grid and the DGs is formulated as follows:

$$Minf1 = Emissions = P_{sub} \cdot LF \cdot ER_{grid} \times 8760 + \sum_{i=1}^{N_{DG}} (P_i \cdot CF_i \cdot ER_i \times 8760)$$

(2.14)

where ER_i and ER_{grid} are the emission produce by the DG_i and grid in kg/kWh, respectively, LF is the load factor, CF_i is the DG_i capacity factor, P_{sub} is the imported power in kW, and P_i is the generated power in kW. Since these objectives have different scales and a large data size, a fuzzy technique was used to control data size and unify the scales. In other words, the fuzzy method was used as a decision maker to obtain the best solution form for the multi objective case.

2.5.2.2 Artificial neural network

ANN technique is a computational model inspired by the human brain. It consists of many connected nodes, each one performing a simple mathematical operation. Based on node operation and a set of parameters that are specific to that node, the output of each node is determined. Combining these nodes together and setting their parameters carefully helps the algorithm learn and solve complex functions (Kim, Ko, & Jung, 1993; Salazar, Gallego, & Romero, 2006).

(Kim et al., 1993) reconfigured the feeder strategies using ANN. The proposed method was used to reduce power losses according to the variation of load patterns. To minimize the size of the training set, ANN was designed for two groups. The first estimates the best load level based on the load data of each zone, while the second determine the suitable topology of the system based on the input load level. The proposed method proved the ability of the high-speed control strategy decision and the robustness from the error, which could provide the best solution from imprecise data. The proposed methods could also provide the best solution for constant and the sudden load variations. (Salazar et al., 2006) proposed an algorithm based on ANN theory to determine the best training set for a single neural network with generalization ability clustering techniques. The proposed method was used to solve two electrical systems. The method proved the feasibility of using the NN to solve the reconfiguration problem and its viability for large-scale systems in a real-time environment.

2.6 Overall Summary of Previous Works on Network Reconfiguration

The benefits and limitations of all the techniques are summarized in Table 2.1 Each algorithm has its own features in solving the distribution optimization problem with DGs.

Table 2.1: A brief description of the main benefits and weakness of the most popular algorithms

Algorithm	Main benefits	Weakness	Functions	Reference
Trial and Error	Efficient, accurate, less computational effort, could avoid some of the local minima problems and could find the optimum or near-optimum solution	Slow and sometimes it could be trapped in a local minimum	Used for reconfiguration of radial electrical distribution network	(Gomes et al., 2005; McDermott et al., 1999)
Simulated annealing (SA)	Rapid, surely find the local optimal solution, has the ability of escaping local minima, some inferior solutions can be chosen to join into evolution and diversity of population is remained preferably	It frequently needs a schedule and formulate to optimize the system elements to find the best solution, take a large computation time and have lower performance to find the global optimum	It is applied to a multi-objective inventory problem, used to solve discrete stochastic optimization problems when the range of the objective function is bounded and well suited for solving combinatorial optimization	(Alrefaei & Diabat, 2009; Eldurssi & O'Connell, 2015; Zhanga et al., 2012)
Tabu search (TS)	It presents low computational effort, is able to find good quality configurations, efficient search for optimal or suboptimal value and it could avoid being trapped into cycling of the solutions	Hard to code, convergence property is not guaranteed and lower precision factor	Used to solve a wide range of hard optimization problems such as optimal network reconfiguration and energy distribution	(Eldurssi & O'Connell, 2015; Lantharthong & Rugthaicharoenchep, 2013; Olamaei et al., 2008; Rugthaicharoencheep & Sirisumrannukul, 2009)

Table 2.1: Continued

Algorithm	Main benefits	Weakness	Functions	Reference
Evolutionary algorithm (EA)	Efficient, gave excellent results and computational efficiency	Possible to trapped in to local optima and fewer literature examples	Used to solve distribution network reconfiguration problem	(Carreno et al., 2007; Carreno et al., 2008)
Genetic algorithm (GA)	Simple to implement, easy, with less computational efforts, efficient to search the large solution space without trapped in local minima, able to produce a near optimal solution, give a good solution of a certain problem in a reasonable computation time and robust method for seeking for global solution	Slow and could not find the optimal solution easily	Used to solve the combinatorial optimization problems and distribution reconfiguration problem	(Aspari & Sreenivasulu, 2013; Cho et al., 2012; Ganesan & Venkatesh, 2006; Mendoza et al., 2006; Rao et al., 2013; Safavi et al., 2014)
Evolutionary programming (EP)	Simple and direct	Large convergence time and fewer literature examples	Used in large distribution system under widely varying load conditions	(Chakravorty, 2012; Hsiao, 2004)
Ant colony optimization (ACO)	Efficient algorithm, easy to understand and code	Need high iteration to find the optimum solution and the computation time is very long	Used to solve combinatorial and continuous optimization problems	(Dorigo et al., 2006; Dorigo & Blum, 2005; Eldurssi & O'Connell, 2015; Kasaei, 2012; Nayak, 2014; Tolabi et al., 2015)

Table 2.1: Continued

Algorithm	Main benefits	Weakness	Functions	Reference
Particle swarm optimization (PSO)	Simple, precise, easy to implement, powerful algorithm to aid and speed up the decision-making, able to escape the local optimal solution and can often find good solutions for complicated problems	Does not designed for discrete functions optimization and hard to find the global optimum solution	Used to solve non-linear, combinatorial and continuous functions optimization problem	(Arya et al., 2011; Balakrishna & Babu, 2014; Olamaei et al., 2008; S.-Y. Su, Lu, Chang, & Gutierrez-Alcaraz, 2011)
Harmony search algorithm (HSA)	Comparatively simple, fast, efficient, powerful and required shorter simulation time	Gets into trouble in performing local search for numerical applications	Used to solve continuous, wide variety of optimization problem, optimization process of the network reconfiguration and DG installation and identifying the high-performance regions of the solution space at a reasonable time	(Abdelaziz et al., 2012; Lee & Geem, 2004; Mahdavi et al., 2007; Rao et al., 2013; Safavi et al., 2014)
Artificial Bee Colony (ABC)	Gave effective and efficient solution and easy to code	Need large number of iteration	Used to solve a radial feeder reconfiguration with DG optimization problem and for large scale optimization problems, multi-dimensional and multi-modal optimization problems	(Karaboga & Akay, 2009; Murthy, Satyanarayana, & Rao, 2012; Rao et al., 2008)

Table 2.1: Continued

Algorithm	Main benefits	Weakness	Functions	Reference
Firework algorithm (FWA)	Fast	Hard to find the optimal solution	Used to solve engineering problems like clustering	(Imran, Kowsalya, & Kothari, 2014; Nguyen & Truong, 2015)
Fuzzy technique	Easy to understand, feasible and effective and used to extract the best compromised solution from the set of the Pareto optimal solutions effectively	For large system fuzzy need large memory and large computation time, difficulties in determining the membership function coefficients and fewer literature example	Successful to solve complex problems and suitable for uncertainties objectives or constraints and for multi-criterion decision making	(Eldurssi & O'Connell, 2015; Niknam et al., 2012; Sedighizadeh et al., 2014)
Artificial Neural Network Technique (ANN)	Processing times are very low	Need great computational burden	This approach suitable for online applications and complex function	(Kim et al., 1993; Salazar et al., 2006)

2.7 Switching Sequence Process

There are very few research on network reconfiguration that focuses on minimizing power losses by considering switching sequences. (Bernardon et al., 2014) proposed a method real time configuration of distribution network, incorporating solar photovoltaic panels, small hydropower, and wind turbines DG's. This method uses a heuristic algorithm to set the weights of the criteria. According to this method, only remote-controlled switches are used in the network analysis. The best sequences of the switches were determined by Analytic Hierarchy Process (AHP) multi criteria analysis. The presented method was tested in a real network of a power utility. Different scenarios for distribution reconfiguration within DG were proposed to evaluate the efficiency of the method. The results confirmed the importance of integrated DG to the network for reducing losses and increasing the reliability during automatic configuration of the system. Moreover, the automatic reconfiguration in real-time led to a more efficient use of DG resources and improved network performance. In (Koutsoukis, 2017), an online reconfiguration process for active distribution systems was proposed. The controller of the DG power output was combined with the controller of the switching remote-control to reduce alleviate lines congestion, the curtailment of the DGs, and the mitigate voltage rise issues. To obtained fast and optimal solutions of the optimization model, mixed integer linear disjunctive formulations and ac power flow equations were used. Different distribution systems were used to verify the effectiveness of the proposed method. The results show the effectiveness of the proposed method to reduced switching actions.

2.8 Consideration of Load Profiles, DG Output Generation, DG Type Operating Mode for Power Loss Reduction

Actual load in distribution power system is dynamically changeable with respect to time. The load varies seasonally, daily, and hourly by time and type of the day (weekend or weekday). The distribution system will not operate at minimum power loss with the proposed method without considering load profiles, the network configuration, and DG output generation, and the tap has to be adjusted dynamically based on the load profiles.

DGs have been installed in distribution systems around the world in order to sufficiently supply the demand growth and improve the performance of entire power systems. When a mixed type DGs is connected to the distribution grid, load profiles and DG output generation needs to be taken into consideration, because making decision made without doing so could negatively affect power losses. The DG output generation might be overestimated, leading to increased power loss when the DGs are connected close to each other or the load demand is low, or underestimated, where it would not be able to reduce power losses when the DGs are connected too far from the substation or the load demand is high.

Researchers who considered load variations and DGs mode proved that the total power losses decreased. (Yang, Peng, & Xiong, 2008) considered the load profile in order to minimize power losses without taking into account the DGs, while (Atwa, El-Saadany, Salama, & Seethapathy, 2010) integrated mix renewable resource of biomass, photovoltaic, and wind power to the system in order to minimize the annual power losses, taking into account all demand load conditions. It should be pointed out that DGs can be operated in two modes; PV and PQ, based on the generator or the interface between grid and DGs (Moghaddas-Tafreshi & Mashhour, 2009). These mode were studied in (Niknam et al., 2012) in the case of photovoltaic, wind, and fuel cell DGs in order to solve network reconfiguration issue. Meanwhile, (Ing, Jamian, Mokhlis, & Illias, 2016) analyzed the effect of different DG operating modes when simultaneous network reconfiguration were conducted with DG generation and tap changer setting to obtain the optimal configuration using imperialist competitive algorithm (ICA). Based on daily load profile and irradiance, the safety margin of total DGs penetration were determined. IEEE

33 bus were used to analyze the different DG modes of operations. The results confirmed that the total daily power losses are affected by the DGs' operation modes.

2.9 Summary

Reviewing previously reported works on network reconfiguration area, we surmised that:

Most researchers used the same basic objective (minimize power losses) to solve the reconfiguration problem in a distribution system. The power loss incurred in a network can be reduced via the optimal reconfiguration and optimal DG output generation. However, some works focused only the determination of the DG output generation, while others only on reconfigure networks. Other researches deal with both network reconfiguration and DG output generation. However, problem solving was carried out sequentially. Few reviews proposed a simultaneous network reconfiguration and DG output generation in the network system to observe its effect on power loss in a distribution system. This work proposed a new method to solve the simultaneous network reconfiguration and DG output problems.

The sequence of the switching process from an initial state to an optimal state was not widely studied. There was only one research on network reconfiguration that focuses on minimizing power losses by considering switching sequences. The proposed method, however, did not result in an optimal solution, which means that it needs more work. This work proposed a new method to solve the switching sequence problems.

Most previous works on network reconfiguration assumed that the DG generation power is constant. Few works included the different DG types, mode of operations, and load profile in the network reconfiguration in order to produce more practical results. Furthermore, there are no previous works on optimal switching sequence that took into account the different DG types, mode of operations, and load profiles. This work proposed a new method to solve these problems with considering different DG types, mode of operations, and load profile.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the implementation of simultaneous network reconfiguration and DG output generation for power loss reduction using meta-heuristic approaches. Evolutionary programming (EP), Particle swarm optimization (PSO), Gravitational Search Algorithm (GSA), and Firefly algorithm (FA) are some of the meta-heuristic approaches used in this study. The switching sequence process is also presented here. The PQ and PV mode modelling of DG is presented at the end of this chapter.

3.2 Problem Formulation

The main objective of this work is to minimize power losses and simultaneously improve voltage profile. The fitness function used for the optimization is:

$$Minimize\ F = (P_{loss}^{R} + IVD) \tag{3.1}$$

Since the total fitness function has a different objective unit, the net power loss P_{loss}^{R} is taken as the ratio of the system's total active power loss after reconfiguration P_{loss}^{rec} and before reconfiguration P_{loss}^{0}:

$$P_{loss}^{R} = \frac{P_{loss}^{rec}}{P_{loss}^{0}} \tag{3.2}$$

The power losses equation for a distribution system is given by:

$$P_{loss} = \sum_{N=1}^{M} (R_N \times |I_N|^2) \tag{3.3}$$

where,

P_{loss} = is the total active losses power in the network distribution.

M = is the branch number.

R_N = is the resistance in the branch N.

I_N = is the current in the branch N.

Voltage Profile Index is defined as follows:

$$IVD = max_{i=2}^{n} \frac{(|V_1|-|V_i|)}{|V_1|} \tag{3.4}$$

where,

V_1 = is the nominal voltage.

V_i = is the voltage at bus i.

$i = 2, 3, \cdots, nbus$.

The main constraints that the optimization is expected to fulfill during network reconfiguration with DGs are:

i) Distributed Generator capacity:

$$P_i^{min} \leq P_{DG,i} \ll P_i^{max} \tag{3.5}$$

where,

P_i^{max} and P_i^{min} = the upper and the lower bounds of the DG output. All DG units should function within an acceptable limit.

ii) Power injection:

$$\sum_{i=1}^{k} P_{DG,i} < (P_{Load} + P_{loss}) \tag{3.6}$$

where,

k = Number of the DG.

P_{Load} = the total load of active power of the network.

P_{loss} = the total active power losses of the network. This constraint guarantees that no power from the DGs flow to the grid, which could create a protection issue.

iii) Power balance:

$$\sum_{i=1}^{k} P_{DG,i} + P_{Substation} = P_{Load} + P_{loss} \quad (3.7)$$

This depends on the principle of equilibrium, where the supply of power must be equal to its demand. The summation of power losses and power load should be equal to the total power generated from the DG units and substations.

iv) Voltage magnitude:

$$V_{min} \leq V_{bus} \leq V_{max} \quad (3.8)$$

Each bus should have an acceptable voltage value within the limits of 0.95 and 1.05 (±5 % of rated value).

v) Radial Configuration:

At all time, the distribution network should be in radial form. In order to guarantee this, a graph theory function in MATLAB is used:

$$TF = graphissap\_ntree(G) \quad (3.9)$$

$$TF = \begin{Bmatrix} 1 & radial \\ 0 & not\_radial \end{Bmatrix} \quad (3.10)$$

where, G = is the distribution network.

vi) No load isolation:

All nodes must be energized to ensure that they receive power sources.

3.3 Proposed Simultaneous Network Reconfiguration and DG Output Generation for Static Load

The main objective discussed in this section is the minimization of power losses and improvement of voltage profile in the case of a static load model. For this application, the population size is set to 100, while the iteration size is set to 300.

3.3.1 Evolutionary Programming (EP)

The steps of the proposed EP for network reconfiguration and DG output generation are as follows:

Step 1: Input data are determined, encompassing the bus load and voltage, network configuration, DG location, and the value of the resistance and reactance of the lines.

Step 2: Randomly generate an initial population (parents). The proposed population consists of tie switches and DG output. The variable used in this work for tie switches is represented by S and the DG output is represented by P_{DG}. The initial population should fulfill the constraints listed in (i) - (iv).

For the simultaneous case, both switches' number and DG output should be determined simultaneously, as follows:

$$x = \begin{bmatrix} S_{11}, S_{12}, \cdots, S_{1n}, P_{DG11}, P_{DG12}, \cdots, P_{DG1K} \\ S_{21}, S_{22}, \cdots, S_{2n}, P_{DG21}, P_{DG22}, \cdots, P_{DG2K} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ S_{m1}, S_{m2}, \cdots, S_{mn}, P_{DGm1}, P_{DGm2}, \cdots, P_{DGmK} \end{bmatrix} \tag{3.11}$$

where, m = indicates the population size.

n = is the number of the switches.

K = number of DG.

Step 3: The fitness of each parent (1 to m) is calculated using the objective function. The fitness function is based on active power losses and voltage profile index, as per given in equation (3.1). The power losses on each line is determined using the load flow method.

Step 4: From the initial population, a new population (offspring) are generated using the mutation process. In this step, the offspring are randomly selected using Gaussian mutation operator, as follows:

$$x_{e+m,j} = x_{e,j} + T(\mu, \gamma^2) \tag{3.12}$$

where,

$x_{e+m,j}$ = is the offspring with m number.

$x_{e,j}$ = is the parents.

$T(\mu, \gamma^2)$ = is the Gaussian random variable with mean μ and variance γ^2.

$$\gamma^2 = \beta\left(x_{j\,max} - x_{j\,min}\right)\left(\frac{f_e}{f_{max}}\right) \tag{3.13}$$

where,

β = is a mutation scale range between 0 and 1.

$x_{j\,min}$ and $x_{j\,max}$ = the minimum and maximum random number for each variable, respectively.

f_e = the e_{th} random number fitness.

f_{max} = the maximum fitness.

Step 5: Both parents and offspring are combined to generate a new population. The new population is sorted in an ascending order of its fitness value, as follows:

$$[F_R, Index = sort(x)], \;\; F_{R,best} = F_R(1) \tag{3.14}$$

Where,

F_R = the fitness for reconfiguration process.

The first half of the new population is stored as the next generation, while the second half is removed.

Step 6: The process is repeated until its fitness converges, where all of the population produces similar fitness value.

Step 7: After finishing the iteration number B, the program stops. The best solution, which represents the switch number that form a new network configuration, the output of the DGs, the power losses for this process and the voltage at each bus, and the fitness is then printed out.

Figure 3.1 shows the flowchart of the proposed EP.

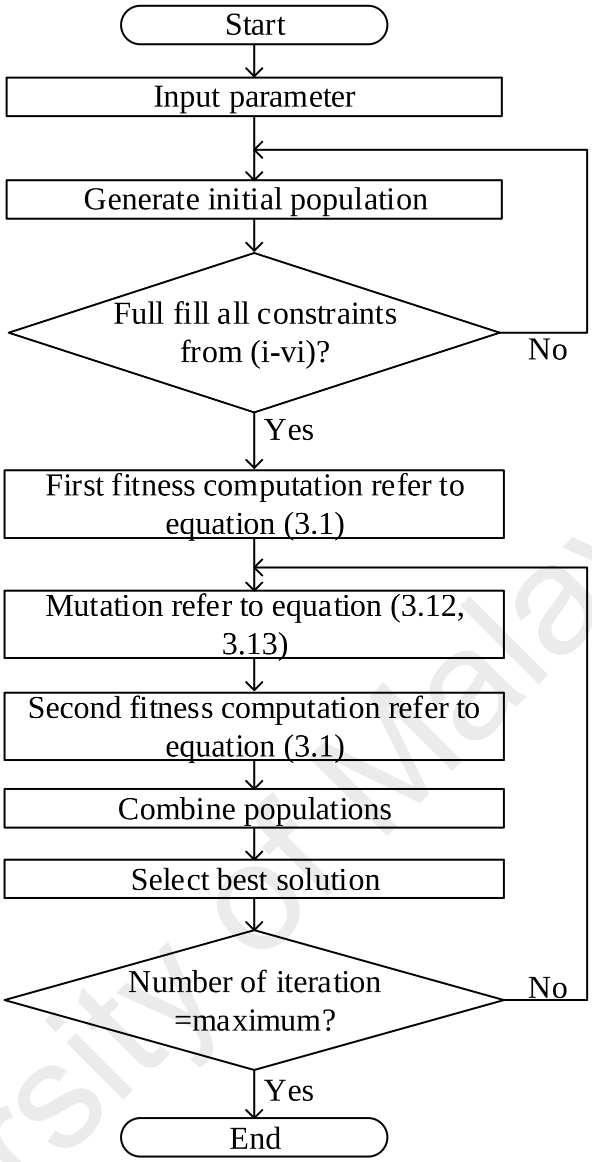

Figure 3.1: Flow chart of EP

3.3.2 Particle Swarm Optimization (PSO)

The steps of the proposed PSO for network reconfiguration and DG output generation are as follows:

Step 1: The input data are determined, encompassing the bus load and voltage, network configuration, DG location, and line impedance, alongside the PSO parameters, such as weighting factors and number of particles (D).

Step 2: Generate an array of random particles with random positions and velocities. Each particle represents tie switch S and DG output P_{DG} that fulfil the set limitations and constraints $(L\&E)$. For the simultaneous case, x_{partic} representing switch numbers and DG output should be determined simultaneously using equation (3.11).

Step 3: Evaluate the fitness value in equation (3.1) for each particle using distributed load flow based on Newton – Raphson method.

Step 4: Each particle updates its position (tie switch S and DG output) and velocity based on its own searching experience called P_{best} and on the experience from the other particle called G_{best}. The update of the particles' position and velocity is done using (Poli, Kennedy, & Blackwell, 2007):

$$x_a^{b+1} = x_a^b + x_a^{b+1} \tag{3.15}$$

$$v_a^{b+1} = Wv_a^b + c_1 r_1 \times \left(P_{best,a} - x_a^b\right) + c_2 r_2 \left(G_{best,a} - x_a^b\right) \tag{3.16}$$

$$W = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{3.17}$$

where,

x_a^b and x_a^{b+1} = the current position of the particle i at iteration b and $b+1$, respectively.

v_a^b and v_a^{b+1} = the current velocity of the particle a at iteration b and $b+1$, respectively.

c_1 and c_2 = the weighting factors.

r_1 and r_2 = a random number between 0 and 1.

w_{max} and w_{min} = the maximum and the minimum weight of the initial, respectively.

$iter$ and $iter_{max}$ = the current iteration number and the maximum iteration number, respectively.

Step 5: The process is repeated until the optimal or near optimal solution is found based on the minimum power losses and the best voltage profile index.

Step 6: Print out the best solution that represents the switch number forming the new network configuration, the output of the DGs, the power losses for this process, and the voltage at each bus, and its fitness.

Figure 3.2 shows the flowchart of the PSO process.

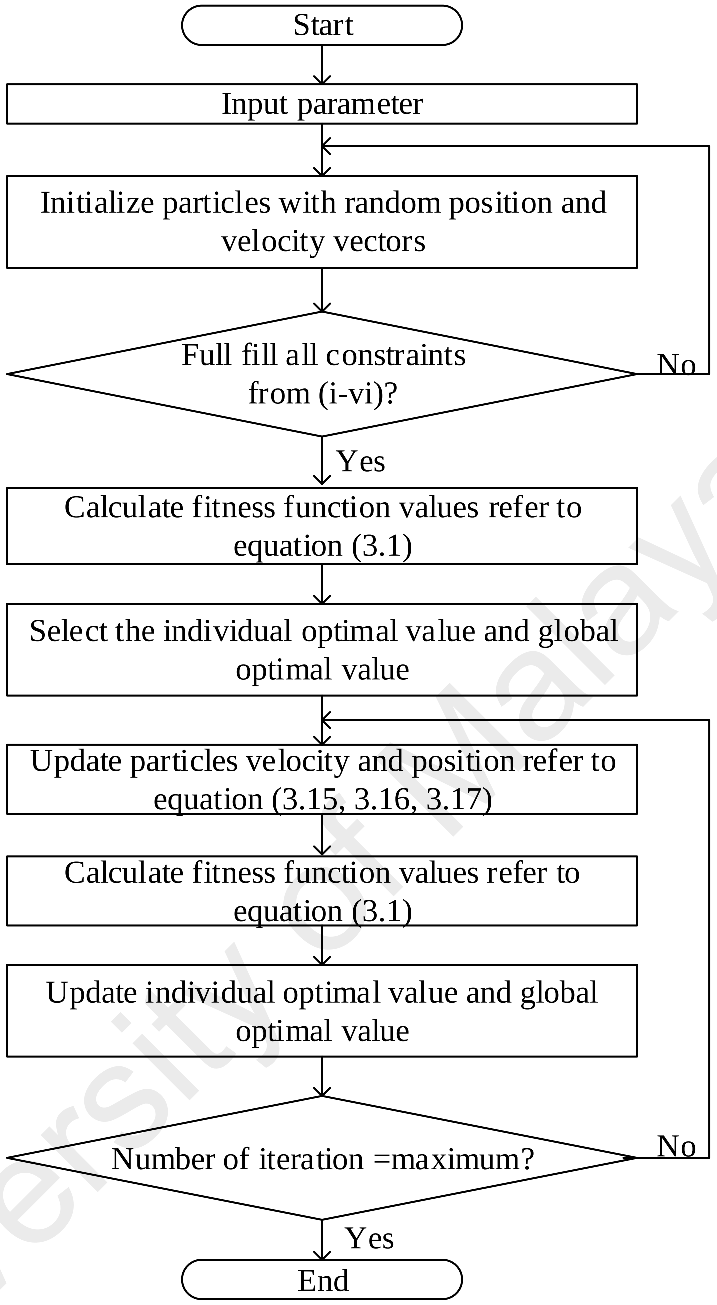

Figure 3.2: Flowchart of PSO

3.3.3 Gravitational Search Algorithm (GSA)

Rashedi et. al originally conceived GSA in 2009 (Rashedi, Nezamabadi-Pour, & Saryazdi, 2009). It is a random search algorithm intended to solve optimization problems and is based on the mass interactions between agents and the law of gravity. In GSA, agents are treated as objects, and their features determined by their masses and by the gravitational force on all objects toward the heavier masses objective based on the objects' global movement. The steps of the proposed GSA for network reconfiguration and DG output generation are as follows:

Step 1: The input data are determined, encompassing such as the bus load and voltage, DG location, and the value of the resistance and reactance of the lines. The parameter that needs to be set in the GSA is the number of mass (N_{mass}).

Step 2: The initial population is determined by selecting random switches to be opened in the distribution network and DGs size to form the masses. Assume that the number of switches to be opened is N_{opened}, then the length of the first part of the mass for network reconfiguration is N_{opened}. Similarly, the length of second part of the mass N_{DG} is the number of the DG to be installed in the distribution system. The set of switches to be opened and DG sizes in the simultaneous case is:

$$Mass_i = \left[S_1^1, S_2^2, \cdots, S_{N_{opened}}^d, D_1^{d+1}, D_2^{d+2}, \cdots, D_{N_{DG}}^{N_d}\right] \quad (3.18)$$

Where $i = 1, 2, \cdots, N_{mass}$, N_d is the number of variables or dimension or component which need to be optimized, and $Mass_i$ represents the position of $i-th$ mass in the $d-th$ dimension or $d-th$ component in $i-th$ mass. S_1^1, S_2^2 and $S_{N_{opened}}^d$ are the switches to be opened in $d-th$ dimension, and D_1^{d+1}, D_2^{d+2} and $D_{N_{DG}}^{N_d}$ are the sizes or output generation of the DG units in MW of $d-th$ dimension installed at selected candidate buses, respectively.

Step 3: Begin the first iteration by using the power flow program to compute the voltage at each bus and the power flow via all network lines. From the results, the power losses and minimum value of the voltage for the entire buses can be determined. We can then apply the fitness equation to calculate the main objectives function, as per equation (3.1).

Step 4: Calculate the gravitational constant G, inertia masses, and Best Mass, and Worst Mass. In order to control the searching accuracy, G is initialized at the beginning and reduced via iteration. Hence, the gravitational constant G is a function of the initial value of the gravitational constant, G_0, and iteration, $iter,$ as follows:

$$G(iter) = G_0 l^{-\alpha \frac{iter}{\max\_iter}} \tag{3.19}$$

Where α is a user specified constant, $iter$ is the current iteration, and $\max\_iter$ is the total number of iteration.

The active gravitational mass, M_a, passive gravitational mass, M_p, and inertial mass of mass i, M_{ii} are computed using the fitness evaluation. According to Newton's law and law of motion, a heavier mass has higher attractions and move more slowly. Hence, in GSA, a heavier mass is represented as a good solution, while the pattern of movement is represented by the explorations. The inertia mass, M_i is updated as follows by assuming that all of the masses are equal to:

$$M_{ai} = M_{pi} = M_{ii} = M_i \tag{3.20}$$

$$m_i(iter) = \frac{fitness_i(iter) - worst(iter)}{best(iter) - worst(iter)} \tag{3.21}$$

$$M_i(iter) = \frac{m_i(iter)}{\sum_{j=1}^{N_{mass}} m_j(iter)} \tag{3.22}$$

Where $fitness_i(iter)$ represents the power loss of the mass i at iteration $iter$, $best(iter)$ while $worst(iter)$ represent the strongest and weakest mass with respect to the lowest and highest power loss in current iteration. The mass of j of the current iteration is represented as $m_j(iter)$. For the minimization problem, store the best and the worst solution, where $best(iter)$ and $worst(iter)$ are defined as:

$$best(iter) = min_{j\in\{1,2,\cdots,N_{mass}\}} fitness_j(iter) \tag{3.23}$$

$$worst(iter) = max_{j\in\{1,2,\cdots,N_{mass}\}} fitness_j(iter) \tag{3.24}$$

Step 5: Calculate the total force using Newton's gravitation theory. The gravitational force, F_{ij} of mass i due to mass j at the current iteration $iter$ can be computed as follows:

$$F_{ij}(iter) = G(iter) \times \left(\frac{M_i(iter)\times M_j(iter)}{R_{ij}(iter)+\varepsilon}\right) \times \left(Mass_j(iter) - Mass_i(iter)\right) \tag{3.25}$$

where M_i is the inertial mass of the mass i, M_j is the inertial mass of mass j, ε is a small constant and $R_{ij}(iter)$ is the Euclidian distance between i and j masses, specified as follows:

$$R_{ij}(iter) = \left\|Mass_i(iter), Mass_j(iter)\right\|^2 \tag{3.26}$$

Step 6: Calculate the acceleration and velocity. The acceleration of the mass i at current iteration, $iter$, in $d-th$ dimension, $a_i^d(iter)$ is defined as follows:

$$a_i^d(iter) = \frac{F_i^d(iter)}{M_{ii}(iter)} \tag{3.27}$$

where $F_i^d(iter)$ is the total force that acts on the mass i of $d-th$ dimension, and is calculated as follows:

$$F_i^d(iter) = \sum_{j\in Kbest, j\neq i}^{N_{mass}} rand_j F_{ij}^d(iter) \tag{3.28}$$

The random number between interval [0, 1], $rand_j$ is introduced in GSA. In order to balance between exploration and exploitation in this algorithm, the former must fade out, while the latter must fade in with the lapse of iterations. In other words, the masses apply force to each other in the beginning, with only one mass applying force to others at the end of the algorithm. Based on the concept, $Kbest$, a function of iteration, which is the set of first K masses with the lowest power loss and biggest mass, is introduced to this algorithm. K_0, which is the initial value of $Kbest$, is set at the beginning and decreased with more iterations. Thus, $Kbest$ decreased linearly with iterations. The next velocity of a mass is given by:

$$V_i^d(iter + 1) = rand_i \times v_i^d(iter) + a_i^d(iter) \tag{3.29}$$

Step 6: Update the masses position's as follows:

$$Mass_i^d(iter + 1) = Mass_i^d(iter) + v_i^d(iter + 1) \tag{3.30}$$

Step 7: Repeat the steps from step 3 until completing the maximum number of iteration.

Step 8: Stop the process after a maximum number of iteration is completed and print out the best solution that represents the switch number that forms the new network configuration, the output of the DGs, the power losses for this process, the voltage at each bus, and its corresponding fitness.

Figure 3.3 shows the flowchart of the GSA process.

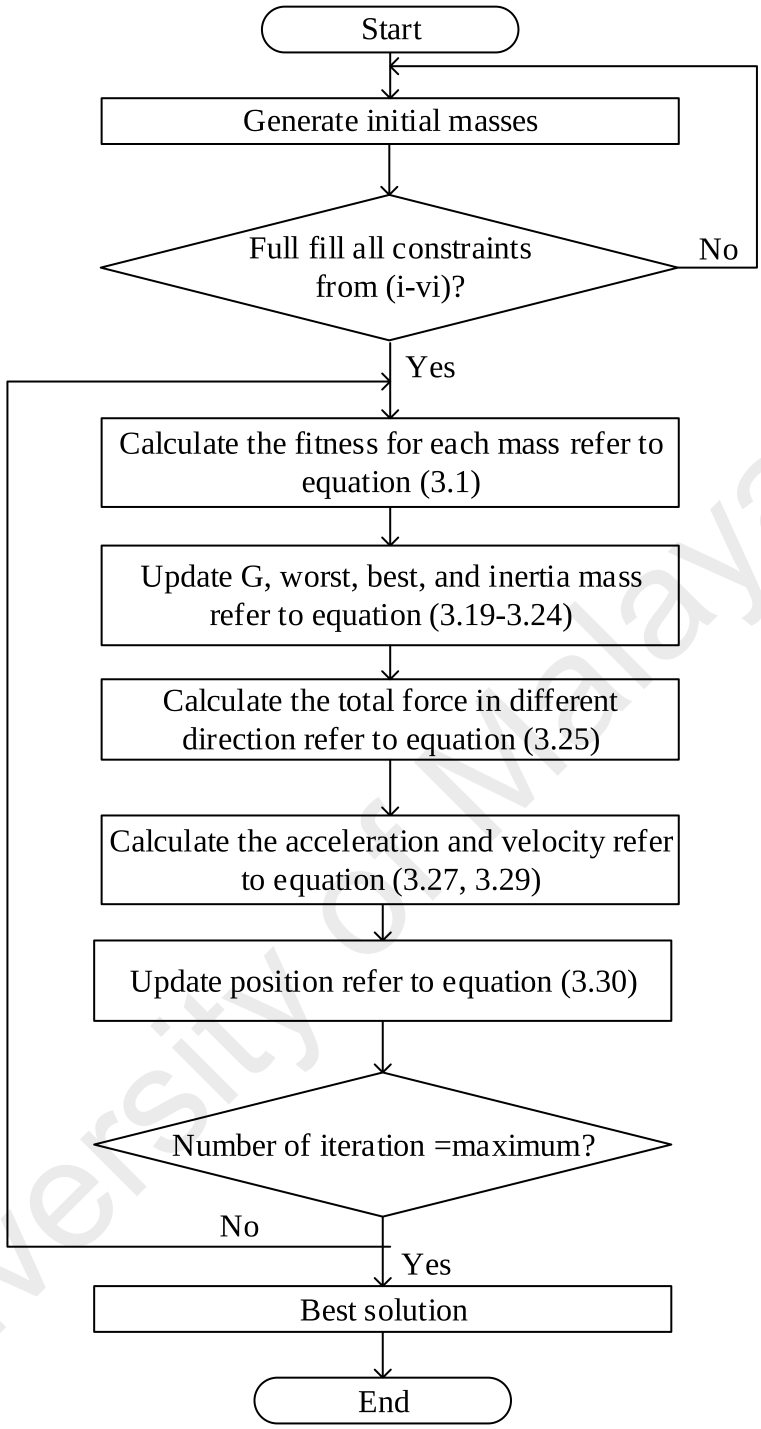

Figure 3.3: Flowchart of GSA

3.3.4 Firefly Algorithm (FA)

Firefly is a recent nature inspired meta-heuristic optimization method developed in 2008 (Yang, 2009). The main feature of FA is based on the flashing characteristics of the firefly (Gandomi, Yang, & Alavi, 2011), with the following sets of assumptions:

a) All fireflies are unisex, where everyone is attracted to one other.

b) The attractiveness of the fireflies is strongly proportional to their brightness. The firefly that are brighter attract the less bright ones, i.e. the less bright ones move towards the brighter ones. Both brightness and attractiveness decrease as the distance between the fireflies increase. If no firefly that are brighter is present, then the fireflies proceed to move randomly.

The firefly's brightness intensity is determined by the landscape of fitness function to be optimized, i.e. the objective function could be maximized/minimized. According to the minimization problem, the level of the brightness is inversely proportional to the fitness function value.

The steps of the proposed FA for network reconfiguration and DG output generation are as follows:

Step 1: The input data are determined, encompassing as the bus load and voltage, DG location, and the value of the resistance and reactance of the lines.

Step 2: The basic firefly parameters are set as $\beta_0 = 1$, $\gamma = 1$, and $\alpha = 0.8$.

Step 3: Generate an array of random fireflies. Each firefly represents the tie switch S and DG output P_{DG} that fulfil all the limitations and constraints $(L\&E)$. In the simultaneous case, $X_{firefly}$ represent both switches number and DG output that needs to be determined simultaneously, as per equation (3.11).

Step 4: Begin the first iteration using the power flow program to compute the voltage at each bus and power flowing through all network lines. From the results, the power losses and minimum value of the voltage for the entire buses can be determined. Then, apply the fitness equation to calculate the main objectives function, as per equation (3.1).

Step 5: Rank the population according to the light intensity (main fitness) and save the best value.

Step 6: Update the fireflies and rank the moves by taking into account the limitation and constraints.

The firefly attractiveness β can be determined using the following formula:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{3.31}$$

where,

β_0 = the attractiveness at $r = 0$.

γ = the coefficient of the light absorption.

r = the distance between any two fireflies.

The Cartesian distance can be express as follows:

$$r_{yz} = \|x_y - x_z\| = \sqrt{\sum_{u=1}^{l} \left(x_{y,u} - x_{z,u}\right)^2} \tag{3.32}$$

where,

$x_{y,u}$ and $x_{z,u}$ = represents a u_{th} component of the Cartesian coordinate x_y and x_z of fireflies y and z, respectively.

The movement of the fireflies, where the firefly y is attracted to firefly z, is determined by:

$$x_y = x_y + \beta_0 e^{-\gamma r_{yz}^2}\left(x_z - x_y\right) + \alpha(rand - 0.5) \tag{3.33}$$

where the second term is caused by the attraction.

while the third term represent the randomized parameter and the random range being be between 0 - 1 and near 1, like 0.8 that quickens the program.

Step 7: Repeat the steps from point 4 until completing the max iteration number (B).

Step 8: Stop the process and print out the best solution that represents the switch number forming the new network configuration, the output of the DGs, the power losses for this process and the voltage at each bus, and its corresponding fitness.

Figure 3.4 shows the flowchart of the FA process.

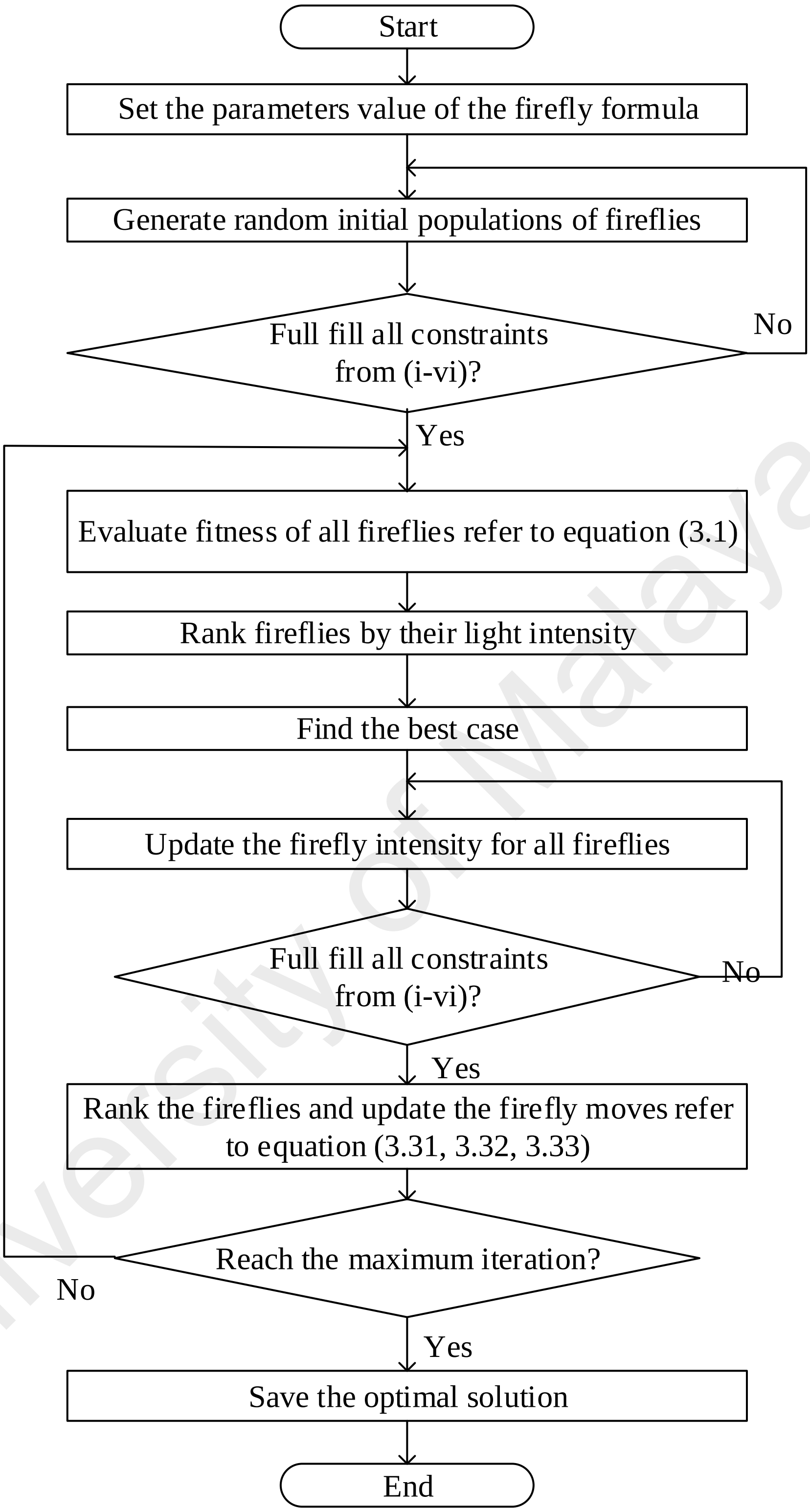

Figure 3.4: Flowchart of FA

Simultaneous Network Reconfiguration and DG output generation method using EP, PSO, GSA, and FA algorithms is summarized in Figure 3.5.

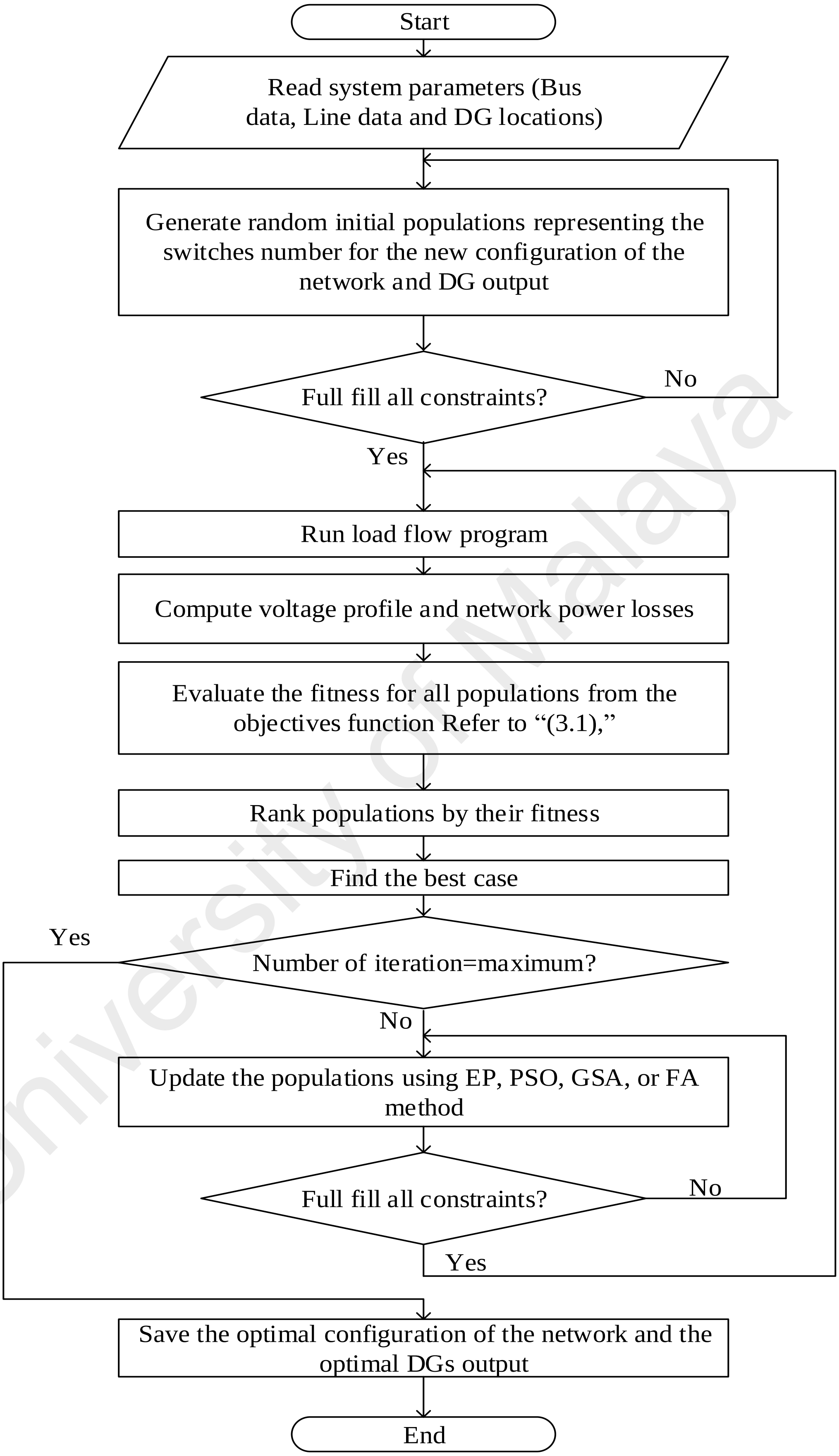

Figure 3.5: General flowchart for Simultaneous Network Reconfiguration and DG output generation method using EP, PSO, GSA, and FA algorithms

3.4 Proposed Switching Sequence Process for Static Load

Once the optimal network reconfiguration and DG output generation are identified, the optimal sequence of opening/closing switches can be identified to change the network from its original form to its final optimal form. The original normally open switch should be changed to normally close, while the same number of normally closed switch should be change to normally open. In this case, there are many probabilities for changing the state of these switches. Generally, if the number of tie switches in the original network is T, then the number of open switch that should be changed is t. The number of the sequence (changing) probability can be calculated by:

$$Pr_{size} = t! \times t! \times 2 \tag{3.34}$$

This equation shows that there is a high number of possibilities. It is therefore crucial to apply the optimization technique to find the optimal switching sequence of the network.

The main steps of this process are:

Step 1: Identify the initial and final configuration of the network.

Step 2: Set the size of the DGs (obtained from configuration process).

Step 3: Remove the replica switch. This means that if one of the switch is still in the same state after reconfiguration, it should be removed. i.e. if any of the switch has the same state of normally open before and after reconfiguration, there is no need to use it in the changing process.

Step 4: Generate random initial populations, x representing the switching changing paths as mentioned in equation (3.35), taking into the account the constraint of voltage limitation.

$$x = \begin{bmatrix} SC_{11}, SO_{12}, SC_{13}, SO_{14}, \cdots, SC_{1q-1}, SO_{1q} \\ SC_{21}, SO_{22}, SC_{23}, SO_{24}, \cdots, SC_{2q-1}, SO_{2q} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ SC_{m1}, SO_{m2}, SC_{m3}, SO_{m4}, \cdots, SC_{mq-1}, SO_{mq} \end{bmatrix} \tag{3.35}$$

Where the variable SC represents the switches that should be closed during the switching changing process, while the variable SO represents the switches that should be open during the switching sequence process.

q = is the number of the steps (number of switching changing steps in each path).

m = indicates the population size.

In this stage, the equality switches should also be accounted for. This means that the same switch should not be changed from closed to open, then open to closed. The same switch should not be closed or open more than once in the same path. Each path consists of several steps (switches opening and closing operation).

Step 5: Compute the power losses and voltage profile for each step during the changing path for each population. This means that each population should have several steps, as follows:

$$N_{steps} = 2 \times t \tag{3.36}$$

Where t is the number of tie switch mentioned previously.

In other words, the normally open switches will be closed, and a t number of the normally closed switches will be open during $2 \times t$ steps in order to change the network's topology. Another constraint that is accounted for here is the closed step that comes before the open step to avoid being disconnected by any bus.

Step 6: Apply the fitness postulated in equation (3.1) for each step of each path (population), then calculate the total fitness for all steps of each path, as follows:

$$F_S = \sum_{s=1}^{N_{steps}} \left(\frac{P_{loss,s}}{P_{loss}^{0}} + IVD_s \right) \tag{3.37}$$

where,

F_S = the fitness for sequence process.

s = step number.

$P_{loss,s}$ = active power losses for step number s.

P_{loss}^{0} = power losses for initial network.

IVD_s = voltage profile index during sequence process.

Step 7: select one of the algorithms (EP, PSO, GSA, and FA) to update the populations in the account of the same constraints in point 4. For EP, use equations (3.12, 3.13), while for PSO, use equations (3.15, 3.16, 3.17), for GSA, use equations (3.29, 3.30), and for FA, use equations (3.31, 3.32, 3.33).

Step 8: Repeat the process from step 5.

Step 9: Save the best solution after the iteration are completed. The solutions are the optimal switching sequence that produces the minimum power losses.

The steps are summarized in a flow chart, shown in Figure 3.6.

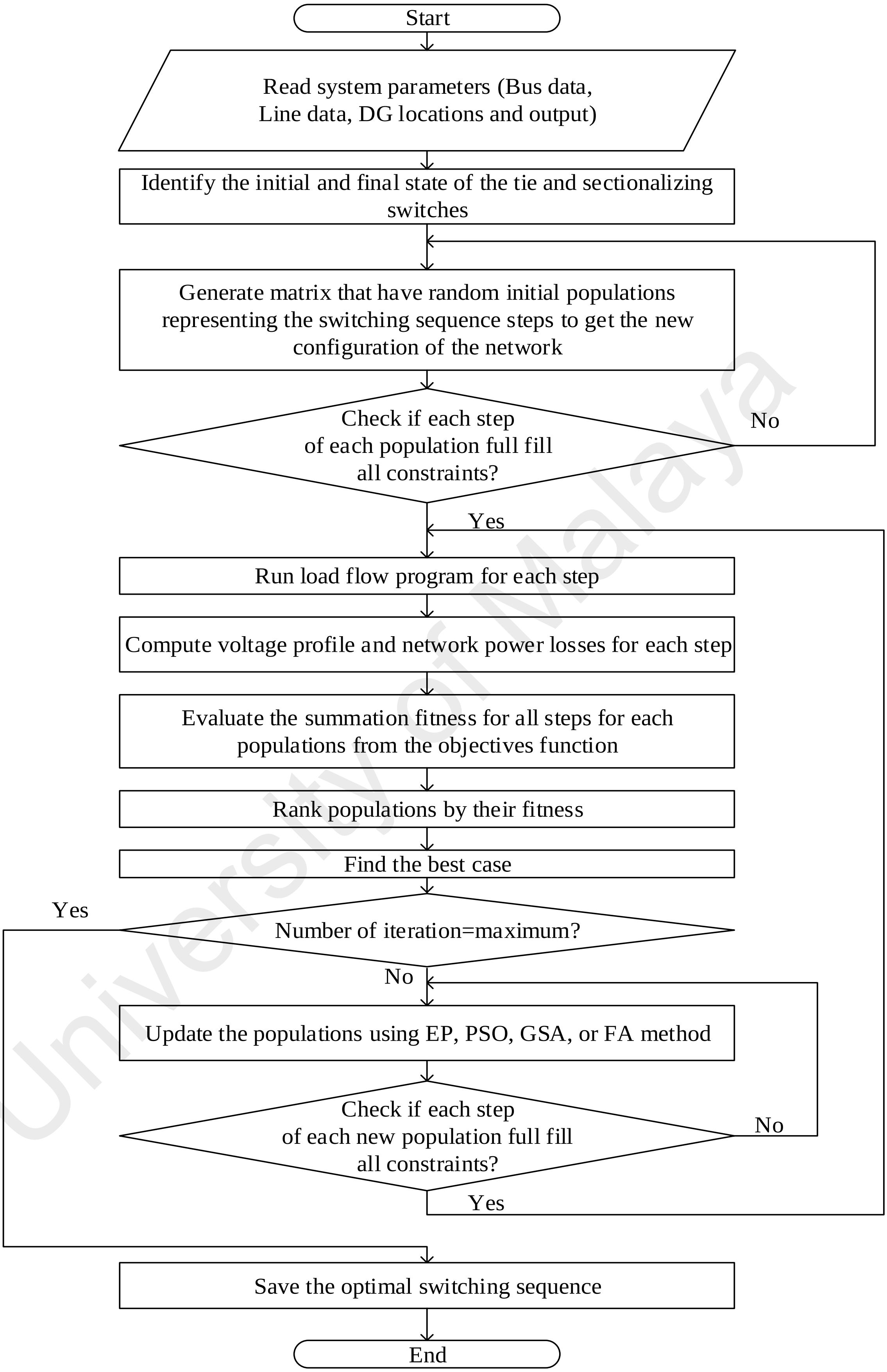

Figure 3.6: Flow chart for Switching Sequence Process using EP, PSO, GSA, and FA algorithms

3.5 Proposed Simultaneous Network Reconfiguration and DG Output Generation for Dynamic Load

It is essential that the reconfiguration is done hourly, which means finding an optimal configuration that is suitable at any hour instead of a configuration for a fixed network. It should be pointed out that the proposed method that looks for the optimal configuration for the network at any hour (i.e one configuration suitable at any hour) instead of making hourly reconfiguration effects the functional capabilities of the circuit breaker.

The main objective of this section is to analyze the minimization/maximization of the total daily power loss and improve the voltage stability index (SI). The SI index proposed in (Aman, Jasmon, Bakar, & Mokhlis, 2013) was used to find the weakest voltage bus in the system that can lead to voltage instability when the load increases. The fitness function F can be presented in the following form:

$$Minimize\ F = \sum_{hr}^{T}(w_1 \times P_{loss}^{R} + w_2 \times si) \tag{3.38}$$

where,

hr = the current time considered.

T = the total hour considered in the time frame.

w_1 and w_2 = the weighting factors $w_1 = w_2 = 0.5$.

Since the total fitness has different objective units, the net power loss P_{loss}^{R} is taken as the ratio between the system total active power loss after P_{loss}^{rec} and before P_{loss}^{0} reconfiguration, as follows:

$$P_{loss}^{R} = \frac{P_{loss}^{rec}}{P_{loss}^{0}} \tag{3.39}$$

The power losses equation for a distribution system is given by:

$$P_{loss}^{rec} = \sum_{N=1}^{M} (R_N \times |I_N|^2) \tag{3.40}$$

where,

P_{loss}^{rec} = the total active losses power in the network distribution.

M = the branch number.

R_N is the resistance in the branch N.

I_N is the current in the branch N.

The formulation of SI Index is as follows (Chakravorty & Das, 2001):

$$SI = |V_s|^4 - 4 \times \{P_r X_{ij} - Q_r r_{ij}\}^2 - 4 \times \{P_r r_{ij} - Q_r X_{ij}\}^2 \times |V_s|^2 \geq 0 \tag{3.41}$$

where

SI = is the voltage stability index.

V_s = is the sending bus voltage in pu.

P_r and Q_r = are the active and reactive load at the receiving end in pu, respectively.

r_{ij} and X_{ij} = are the resistance and reactance of the line $i - j$ in pu.

In an under stable operation, the value of SI should be greater than zero for all buses. When the value of SI becomes closer to one, all buses become more stable. In the proposed algorithm, the SI value is calculated for each bus in the network and sorted from the lowest to the highest value. The bus having the lowest value of SI will be considered in fitness function. Since the fitness equation (3.39) have two terms; one to minimize power losses and one to maximize the SI, the equation should be similar, so in order to minimize the SI, the difference between the rated value of SI (1) and the weakest bus is used, as follows:

$$si = \frac{1 - min(SI)}{max(SI)} \tag{3.42}$$

where

$min(SI)$ and $max(SI)$= are buses with the lowest/highest values of SI, respectively. The second term of equation (3.38) becomes lower by one unit. In this case, equation (3.38) is consistent, and could be minimizing to decrease power losses and improve the voltage profile. The steps for this stage are as follows:

Step 1: Input data are determined, such as the bus load and voltage, DG location, lines resistance and reactance values, DG mode, PV generation output, and load profile.

Step 2: Generate random initial populations, x representing the switches' number and the DGs output, taking into consideration all of the limitations and constraints. The variable used in this work for tie switches are represented by S , while the DG output is represented by P_{DG}. In the simultaneous case, both the number of switches and DG output should be determined simultaneously, as follows:

$$x = \begin{bmatrix} S_{11}, S_{12}, \cdots, S_{1n}, P_{DG11}, P_{DG12}, \cdots, P_{DG1K} \\ S_{21}, S_{22}, \cdots, S_{2n}, P_{DG21}, P_{DG22}, \cdots, P_{DG2K} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ S_{m1}, S_{m2}, \cdots, S_{mn}, P_{DGm1}, P_{DGm2}, \cdots, P_{DGmK} \end{bmatrix} \tag{3.43}$$

where,

m = indicates the population size.

n = the number of the switches.

K = the number of DG.

Step 3: Begin the first iteration based on the power flow program to compute the power flow via all network lines. From the results, the power losses and minimum value of the voltage for the entire bus can be determined.

Step 4: Evaluate the main fitness function in equation (3.38).

Step 5: Choose one of the algorithms (EP, PSO, GSA, and FA) to update the populations, taking into account the same constraints in point 4.

Step 6: Repeat the steps from step 3 until the max iteration number is completed (B).

Step 7: Stop the process and print the best solution that represents the switch number that form the optimal network configuration, the output of the DGs, the daily power losses, and the voltage at each bus for the optimal configuration, and the total fitness plots during all iterations.

The flow chart of implementation of the Simultaneous Network Reconfiguration and DG output generation method, considering the load profile and different modes of DGs for total daily power loss reduction and voltage profile improvement are summarized in Figure 3.7.

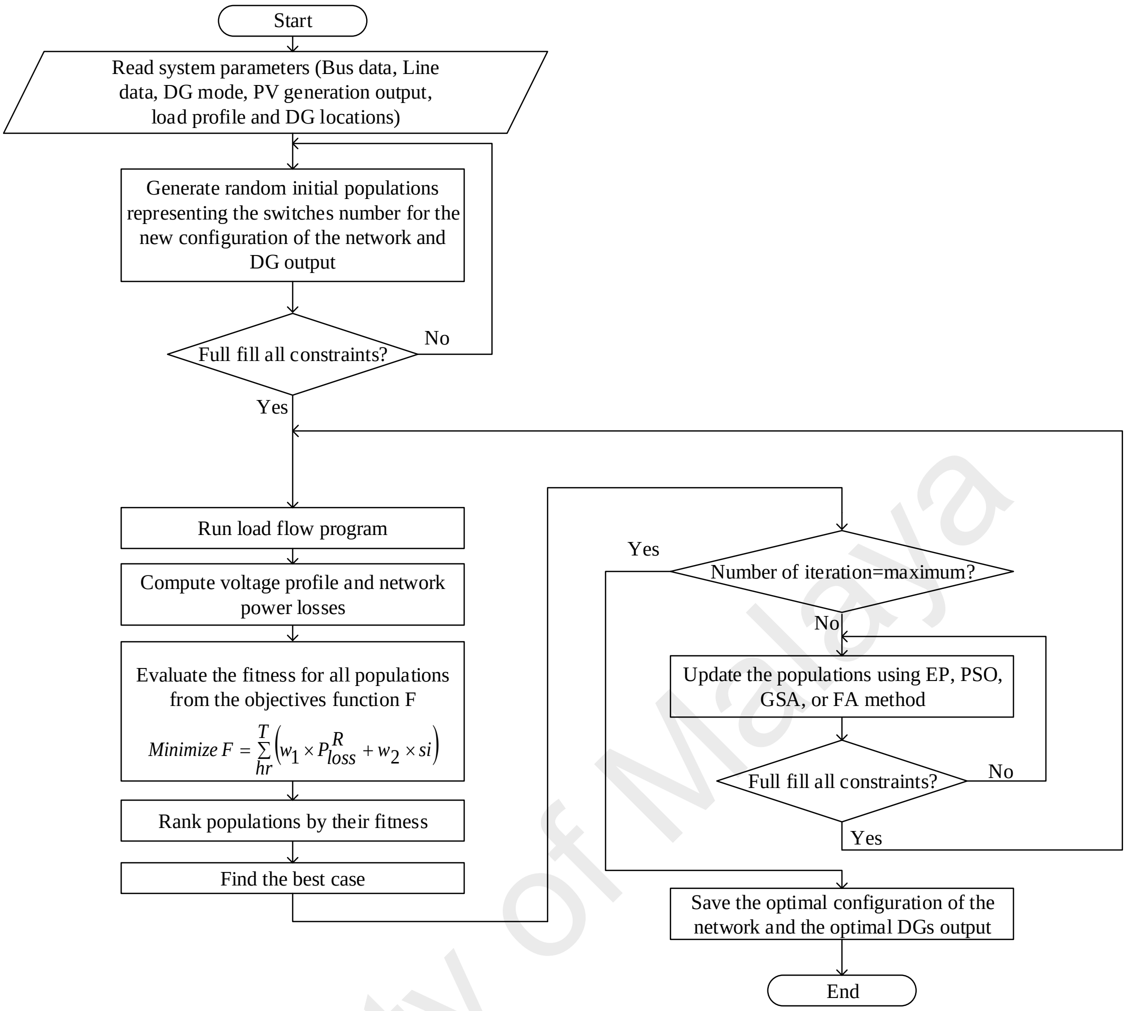

Figure 3.7: Flow chart of the Simultaneous Network Reconfiguration and DG output generation method considering load profile and different mode of DGs for total daily power loss reduction and voltage profile improvement

3.6 Proposed Switching Sequence Process for Dynamic Load

The main objective of the proposed method presented in this section is to minimize the total daily power loss and improve the voltage stability index. Once the configuration process is completed, the DGs output and final configuration of the network are determined. This data will be used in this stage to determine the best path for changing the network from the original form to the optimal form at any hour. The steps for this stage are as follows:

Step 1: Identify the initial and final configuration of the network.

Step 2: Remove the replica switch. This means that if one of the switch is still in the same state after reconfiguration, it should be removed. i.e. if any switch has the same state of being normally open before and after reconfiguration, there is no need to use it in the sequencing process.

Step 3: Generate random initial populations x, where in this case x represents the switching sequence paths mentioned in (3.44), taking into the account the constraint of voltage limitation.

$$x = \begin{bmatrix} SC_{11}, SO_{12}, SC_{13}, SO_{14}, \cdots, SC_{1q-1}, SO_{1q} \\ SC_{21}, SO_{22}, SC_{23}, SO_{24}, \cdots, SC_{2q-1}, SO_{2q} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ SC_{m1}, SO_{m2}, SC_{m3}, SO_{m4}, \cdots, SC_{mq-1}, SO_{mq} \end{bmatrix} \tag{3.44}$$

The variable 'SC' represents the switches, where it should be closed during the switching sequence process, while the variable 'SO' represent the switches that should be open during the switching sequence process. This helps set the size of the DGs (obtained from configuration process)

q is the number of the steps (number of switching sequence steps in each path), while m indicates the population size.

The first row of matrix x represent the first switching sequence path, SC_{11} is the first switch that should be closed (in the first row and first column of the first population), and SO_{12} is the second switch that should be open (in the first row and second column of the first population), and after that, SC_{13} is the third switch that should be closed (in the first row and third column of the first population), then SO_{14} is the fourth switch that should be open (in the first row and fourth column of the first population), and so on, until SC_{1q-1}, SO_{1q}, where SC_{1q-1} represent the switch number $q-1$ that should be closed (in the first row and column number $q-1$ of the first population), and SO_{1q} is the final switch that should be open (in the first row and final column of the first population).

The second row of matrix x represent the second switching sequence path, where SC_{21} is the first switch that should be closed (in the second row and first column of the second population), and SO_{22} is the second switch that should be open (in the second row and second column of the second population), after that, SC_{23} is the third switch that should be closed (in the second row and third column of the second population), then SO_{24} is the fourth switch that should be open (in the second row and fourth column of the second population), and so on until SC_{2q-1}, SO_{2q}, where SC_{2q-1} represent the switch number $q-1$ that should be closed (in the second row and column number $q-1$ of the second population), then SO_{2q} is the final switch that should be open (in the second row and final column of the second population), continuing until population number m.

At this stage, the equality switches constraint should be considered. This means that the same switch should not be changed from closed-to-open, then open-to-closed. Furthermore, the same switch should not be closed or open more than once in the same path. Each path consists of several steps (switches opening and closing operation).

For example, in the case of the 33-bus network, the initial configuration of the network (33, 34, 35, 36, and 37) are normally open. Suppose the final configuration of the network (8, 9, 12, 26, and 33) are normally closed, then the matrix x for example, will be as follows:

$$x = \begin{bmatrix} 36, 8, 37, 26, \cdots, 34, 9 \\ 37, 9, 35, 8, \cdots, 36, 26 \\ \vdots\ \vdots\ \vdots\ \vdots\ \vdots\ \vdots\ \vdots\ \vdots\ \vdots \\ 36, 9, 37, 26, \cdots, 34, 8 \end{bmatrix} \tag{3.45}$$

That means that the first row represents the first switching sequence path. Switch 36 should be closed first, then switch 8 should be opened after that, and switch 37 should be closed, then switch 26 should be open, and so on until the final switch number 9 is opened.

Step 4: Compute the power losses and voltage profile for each step (in each closed or open of the switch operation) during the sequence path for each population. This means that each population should have the number of steps, as follows:

$$N_{steps} = 2 \times t \tag{3.46}$$

Where t is the number of tie switch mentioned previously.

In other words, the normally open switches will be closed, and another t number of the normally closed switch will be open during $2 \times t$ steps in order to change the network's topography. Another constraint that is accounted for here is the closed step that should come before the open step to avoid being disconnected from any bus.

Step 5: The fitness of each population (sequence path) in Eq. (3.45) is calculated for all hours (considering the time frame of the system loading), as follows:

$$F_z = \sum_{hr=1}^{T} \sum_{r=1}^{N_{steps}} \left(w_1 \times P_{loss_r}^{R} + w_2 \times si_r \right) \tag{3.47}$$

where r is the step number; z is the population $(1 \cdots m)$; T is the total hour considered in the time frame; and hr is the current time. In this study, the time frame is considered for 24 hours. This mean that the proposed method will find one optimal switching sequence when applied in any hour of the day (24 hours) to produce minimum power losses and the best voltage index.

Step 6: Choose one of the algorithms (EP, PSO, GSA, and FA) to update the populations, taking into account the same constraints mentioned in point 2 and 3.

Step 7: Repeat the process beginning from step 4.

Step 8: Save the best solution after the maximum iteration is completed. The best solution is the optimal switching sequence path during the time work of the system that produces the minimum power losses.

The flow chart of implementation of the Switching Sequence Process considering load profile and different mode of DGs for total daily power loss reduction and voltage profile improvement is summarized in Figure 3.8.

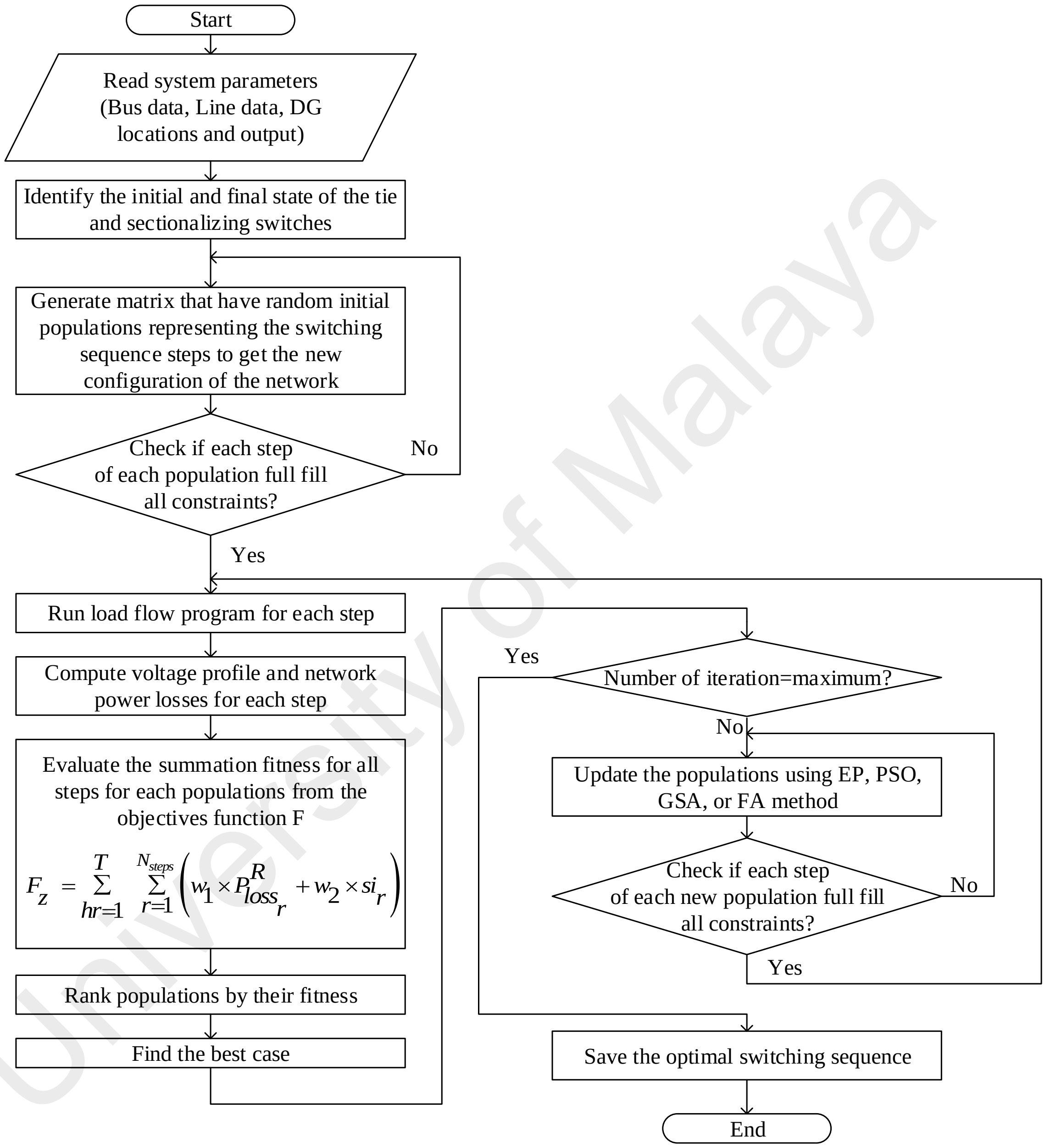

Figure 3.8: Flow chart of the Switching Sequence Process considering load profile and different mode of DGs for total daily power loss reduction and voltage profile improvement

3.7 Summary

This chapter presented the methodologies of simultaneous network reconfiguration and DG output generation and switching sequence process for power loss reduction and voltage profile improvement. The proposed method also considered the PQ and PV mode modelling of the DG and load profile for increased power losses reduction. Meta-heuristic approaches were used, such as EP, PSO, GSA, and FA. The comparison and performance of the proposed methods will be detailed in the next chapter.

CHAPTER 4: PERFORMANCE OF THE PROPOSED METHOD

4.1 Introduction

This chapter discusses the performance of the proposed methods in solving network reconfiguration and DG output generation problem simultaneously. The switching sequence process is also presented. The effectiveness of the proposed methods is demonstrated on a standard IEEE 16-bus, IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus test systems. The line data and bus data of the system are listed in Tables A.1, A.2, A.3, and A.4. The results are compared to the existing meta-heuristic methods. The main consideration in the comparison of the proposed methods with the existing method is the power loss reduction. The impact of the proposed methods to the overall voltage profiles is also presented in this chapter.

4.2 Test System 1: IEEE 16-Bus

An IEEE 16-bus distribution network system was used to test the proposed method. The network consists of three feeders with 15-bus radial distribution system (Zhu, 2002a). In order to solve the 3-feeder system, the system was transferred to a single feeder. It consists of 17 switches, 14 sectionalizing switches, and 3 tie switches. Switches number 15, 16, and 17 are normally open for the original network, while other switches are normally closed, as shown in Figure 4.1. The total real load demand was 28.7 MW, while the system voltage was 12.66 kV. The base value of the apparent power was 100 MVA. The power losses of the network at the initial configuration were 511.43 kW, with 0.9693 p.u. as its lowest bus voltage. The complete bus and line data was given in (Zhu, 2002a) and also in Appendix A Table A-1. The DG in this test system is assumed to be a mini-hydro generation with a capacity of 2 MW. In this work, the optimal locations for the DGs are at bus 8, based on (Hung, Mithulananthan, & Bansal, 2010). The optimal solution is obtained for tie-switch, DG output (real power), and switching sequences. Both the DG output and the tie-switches were determined simultaneously.

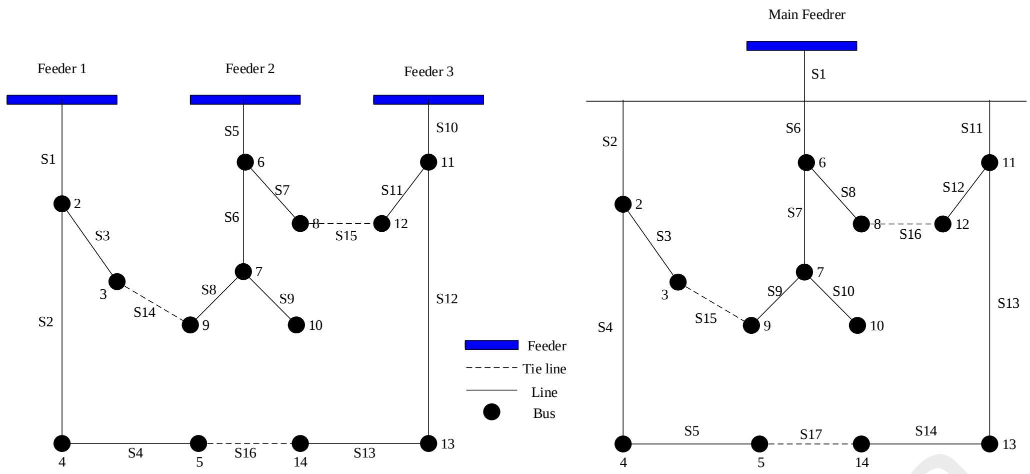

Figure 4.1: IEEE 16-bus distribution network

4.2.1 Simultaneously Network Reconfiguration and DG Output using EP, PSO, GSA, and FA Algorithms for IEEE 16 Bus System

This section focuses on power loss reduction and voltage profile improvement by simultaneous network reconfiguration and DG output.

4.2.1.1 Impact of simultaneous network reconfiguration and DG output generation on power losses

Table 4.1 summarizes the test results obtained using EP, PSO, GSA, and FA and compared to the initial case. The lowest fitness function, F_R, according to equation (3.1), is 0.81646, obtained using FA. This means that FA produces the best solution compared to EP, PSO, and GSA. FA also produces the lowest power losses after network reconfiguration (with DG), at 390.58 kW, while it was 511.43 kW before reconfiguration, which means that the power losses was reduced by 120.85 kW i.e. ~23.63% reduction compared to its initial state. The minimum voltage for all the busses after reconfiguration was improved to 0.9757 p.u., while before reconfiguration, its 0.9693 pu. The normally open switches after reconfiguration were 5, 8, and 9, while before reconfiguration, they were 15, 16, and 17. The DG1 output was 2 MW. However, the computational time taken for using FA was 291.03 s, with 300 iterations for a population of 100, exceeding the other algorithms.

Table 4.1: Network reconfiguration and DG output results for IEEE 16-bus network

Case	**Open switch**	**DG output in MW (Bus number)**	**Bus voltage (pu) (at bus)**		**Reconfiguration fitness function** $F_R = (P_{loss}^R + IVD)$	**Power losses (kW)**	**Losses reduction (%)**	**CPU Time (s)**
			min	**max**				
Initial	15, 16, 17	No DG	0.9693(11)	1(1)	1.059	511.43	---------	0.267
EP	8, 9, 14	DG= 1.6 (8)	0.9748(11)	1(1)	0.87569	420.47	17.785	278.06
PSO	8, 9, 14	DG= 1.999 (8)	0.9757(11)	1(1)	0.843012	404.159	20.975	239.12
GSA	5, 8, 9	DG= 1.892 (8)	0.9754(11)	1(1)	0.82517	394.92	22.781	281.54
FA	5, 8, 9	DG= 2 (8)	0.9757(11)	1(1)	0.81646	390.58	23.630	291.03

4.2.1.2 Impact of simultaneous network reconfiguration and DG output generation on voltage profile

The voltage profile for both the initial and optimal cases using EP, PSO, GSA, and FA are shown in Figure 4.2. It can be seen from the figure that all the buses voltage magnitude for the algorithms are improved to values larger than its initial state. FA reported the best voltage profile.

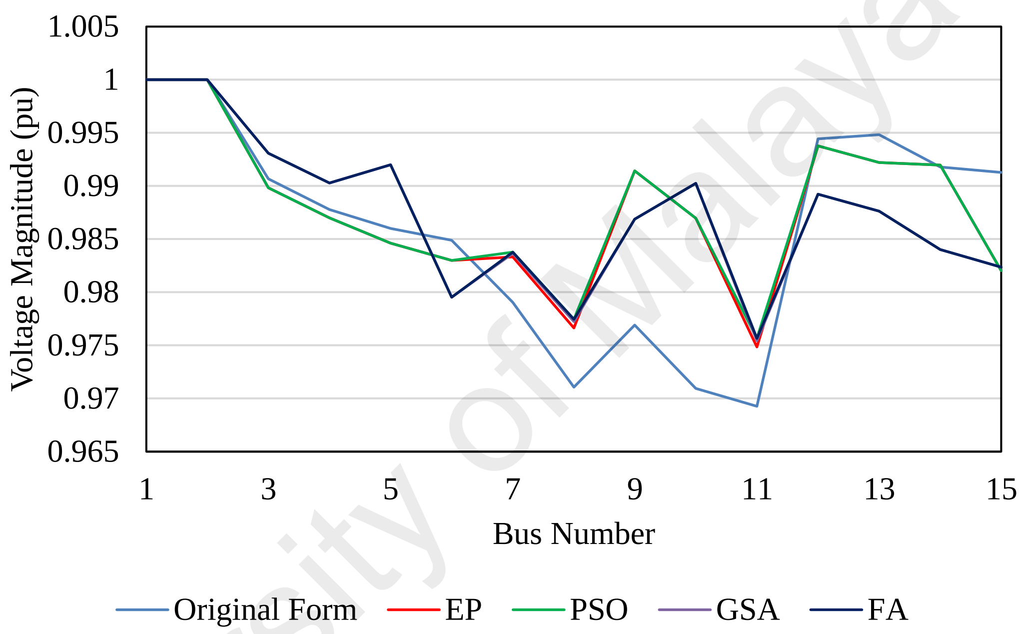

Figure 4.2: Voltage profile for IEEE 16-bus radial distribution network using different algorithms

4.2.1.3 Analysis of overall performance for simultaneous network reconfiguration and DG output generation

To prove the validity of the simultaneous network reconfiguration within the optimal DG output, the robustness test was conducted for the proposed method using different algorithms, and the value comparison is shown in Figure 4.3 in the case of 20 runs. It is evident from the robustness test that GSA or FA reported results that are almost equal in each run and the minimum value of standard deviation compared to the other algorithms shown in Table 4.2. This means that GSA and FA are highly robust compared to EP and

PSO. For each algorithm, there is a global optimal value, which is presented as the minimum value during the 20 times simulation run of the program, which are 0.87569, 0.843012, 0.82517, and 0.81646 for the EP, PSO, GSA, and FA, respectively.

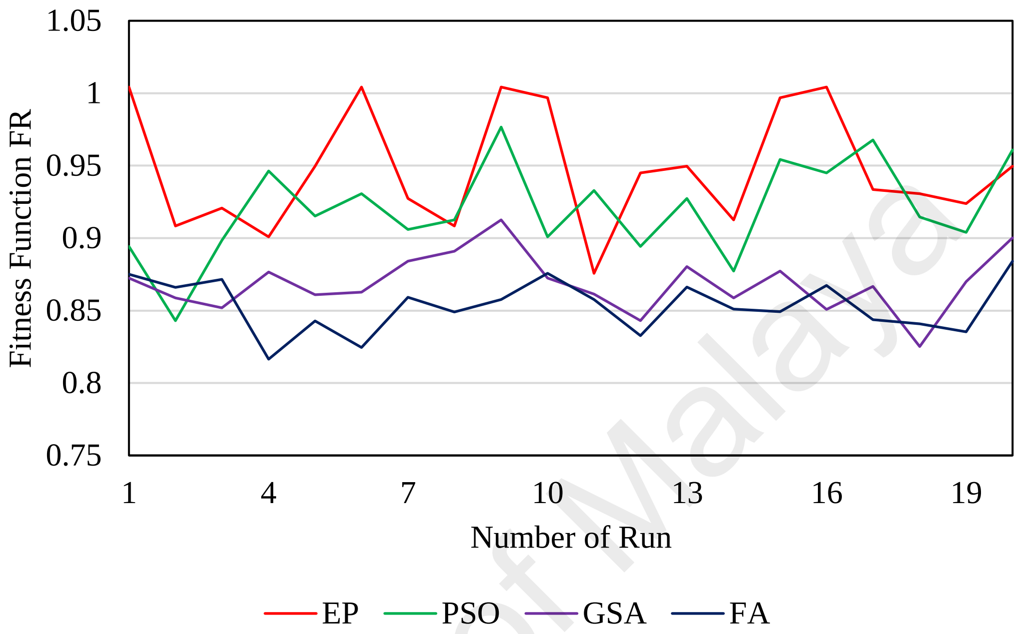

Figure 4.3: Comparison of robustness test of the simultaneous reconfiguration and optimal DG output algorithms for IEEE 16-bus network

Table 4.2: Statistical analysis results for robustness test for network reconfiguration and DG output generation process for IEEE 16-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	0.87569	1.004272	0.947342	0.040754
PSO	0.843012	0.97666	0.920134	0.032834
GSA	0.82517	0.912602	0.868849	0.019821
FA	0.81646	0.88409	0.85331	0.018051

Based on the global cases for each algorithm, the convergence performance for these global values were also compared, and the results shown in Figure 4.4. FA reported the minimum value of the reconfiguration fitness function, F_R, compared to the other algorithms.

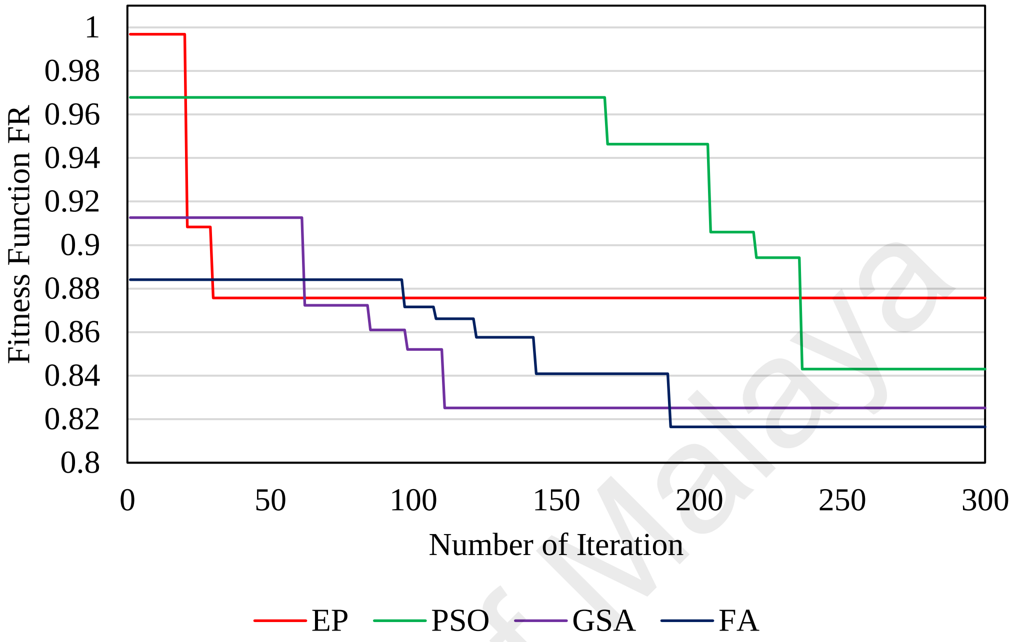

Figure 4.4: Comparison of convergence performance of the simultaneous reconfiguration and optimal DG output algorithms for IEEE 16-bus network

The performance of the proposed method was also compared to published results with similar DG location and shown in Table 4.3. Generally, it is clear that the proposed methods performed better than the published results based on GA, PSO, EP, ABC, MGA, EPSO, MPSO, SABC (Dahalan, 2013). Only EP produce reported a slightly higher power loss compared to EPSO.

Table 4.3: Comparison of simulation result for IEEE 16-bus network

Method	Open switches	Total DG output (MW)	Lowest bus voltage (pu)	Power losses (kW)	Losses reduction (%)
GA (Dahalan, 2013)	7, 8, 13	1.7101	0.9690	430	15.92
PSO (Dahalan, 2013)	4, 8, 16	1.7260	0.9693	430.9	15.74
EP (Dahalan, 2013)	7, 8, 13	1.7650	0.9712	429.9	15.94
ABC (Dahalan, 2013)	4, 8, 16	1.7123	0.9716	430.9	15.74
MGA (Dahalan, 2013)	7, 8, 16	1.7533	0.9714	421.5	17.58
EPSO (Dahalan, 2013)	7, 14, 16	1.7995	0.9716	420.1	17.85
MPSO (Dahalan, 2013)	8, 15, 16	1.7522	0.9703	421.4	17.60
SABC (Dahalan, 2013)	7, 13, 14	1.7288	0.9716	421.9	17.50
Proposed (EP)	8, 9, 14	1.6	0.9748	420.47	17.785
Proposed (PSO)	8, 9, 14	1.999	0.9757	404.159	20.975
Proposed (GSA)	5, 8, 9	1.892	0.9754	394.92	22.781
Proposed (FA)	5, 8, 9	2	0.9757	390.58	23.630

4.2.2 Switching Sequence Process for IEEE 16 Bus System

This section focuses on the optimal switching sequence path to change the network configuration from the original form to the optimal form, based on the configuration process.

Since the IEEE 16-bus network had 3 tie-switches and referring to equation (3.36), there are $3! \times 3! \times 2 = 72$ probabilities, representing the switching sequence paths that could be used to transfer the network from the original form to the expected optimal form.

4.2.2.1 Impact of switching sequence process and DG output generation on power losses and voltage profile

The optimal solution of the network reconfiguration and DG output obtained from Table 4.1 is used to find the best switching sequence from the initial state (15, 16, and 17) to the final state. The final state using EP/PSO is (8, 9, and 14), and using GSA/FA, its (5, 8, and 9). Based on equation (3.39) and by using FA, the best value of sequence fitness function, F_S, is obtained as shown in Table 4.4, equaling 4.77. The power losses during the steps is 2280.3kW. This means that the FA achieved a better optimal solution for switching sequence compared to the other algorithms. The obtained best sequence switching using FA is:

Sequence 1: Sw16 (Close) → Sequence 2: Sw8 (Open),

Sequence 3: Sw15 (Close) → Sequence 4: Sw9 (Open),

Sequence 5: Sw17 (Close) → Sequence 6: Sw5 (Open).

Furthermore, the minimum buses voltages in each switching step for all the algorithm is also presented. The best switching sequence obtained by any algorithm, does not cause the voltage profile to exceed its allowable limit (0.95 – 1.05) p.u. The computational time taken for using FA algorithm is 365.0543 s, with 300 iterations for a population of 100, which exceeds that of the other algorithms.

Table 4.4: Switching sequence results for IEEE 16-bus network

Method	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Sequence fitness function $F_S = \sum_{s=1}^{N_{steps}} \left(\frac{P_{loss,s}}{P_{loss}^{0}} + IVD_s \right)$	Power Losses (kW)	CPU Time (s)
EP	1	16 close	0.9764(11)–1(1)	4.9882	2389.7	250.18
	2	8 open	0.9748(11)–1(1)			
	3	15 close	0.9792(11)–1(1)			
	4	9 open	0.9748(11)–1(1)			
	5	17 close	0.9748(11)–1(1)			
	6	14 open	0.9748(11)–1(1)			
PSO	1	16 close	0.9771(11)–1(1)	4.7965	2293.827	240.816
	2	8 open	0.9756(11)–1(1)			
	3	15 close	0.9797(11)–1(1)			
	4	9 open	0.9757(11)–1(1)			
	5	17 close	0.9757(11)–1(1)			
	6	14 open	0.9757(11)–1(1)			
GSA	1	16 close	0.9769(11)–1(1)	4.821	2305.8	278.73
	2	8 open	0.9753(11)–1(1)			
	3	15 close	0.9796(11)–1(1)			
	4	9 open	0.9754(11)–1(1)			
	5	17 close	0.9754(11)–1(1)			
	6	5 open	0.9754(11)–1(1)			
FA	1	16 close	0.9771(11)–1(1)	4.77	2280.3	365.054
	2	8 open	0.9756(11)–1(1)			
	3	15 close	0.9797(11)–1(1)			
	4	9 open	0.9757(11)–1(1)			
	5	17 close	0.9757(11)–1(1)			
	6	5 open	0.9757(11)–1(1)			

4.2.2.2 Analysis of overall performance for switching sequence process

To prove the validity of the best switching sequence, the robustness test was conducted for the proposed method using EP, PSO, GSA, and FA, and the result was then compared, and the comparison presented in Figure 4.5 for 20 runs. From the robustness, the GSA or FA reported results that are almost equal to each run, and the minimum value of standard deviation compared to the other algorithms is shown in Table 4.5. This means that the GSA and FA algorithm are highly robust and reported a great level of consistency in its output. The minimum value for each algorithm during the 20 runs of the simulation program are taken as the global optimal result. The conversion performance for these global cases for all algorithms are compared and shown in Figure 4.6, and the FA reported the minimum value of the main fitness function, F_S, compared to the other algorithms.

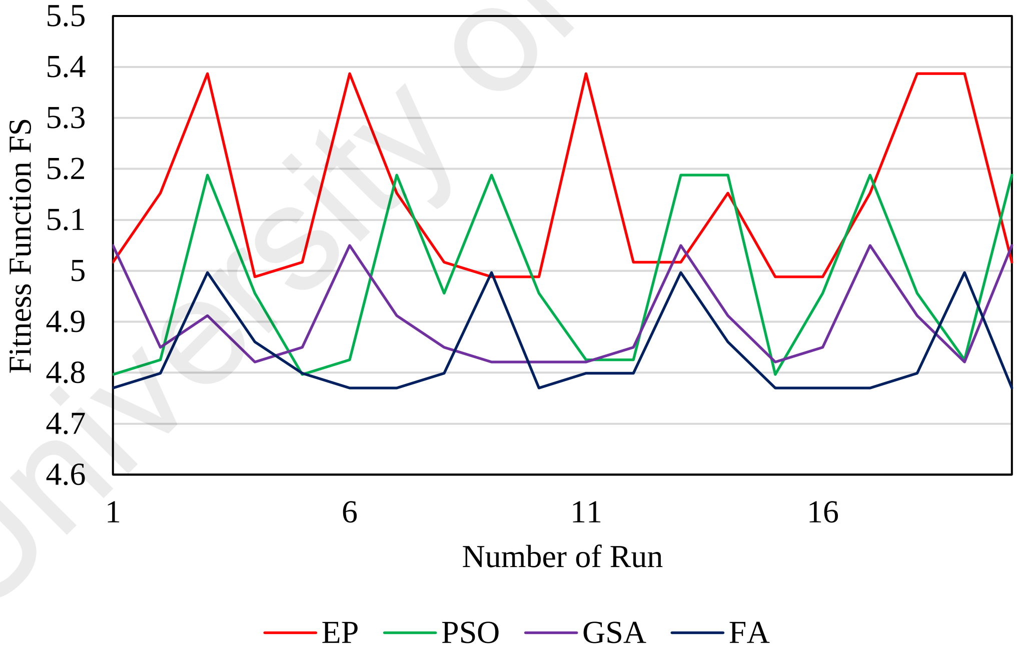

Figure 4.5: Comparison of robustness test of the switching sequence process algorithms for IEEE 16-bus network

Table 4.5: Statistical analysis results for robustness test for switching sequence process for IEEE 16-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	4.9882	5.387	5.12932	0.163782
PSO	4.7965	5.1879	4.980649	0.166363
GSA	4.821	5.0497	4.90364	0.092445
FA	4.77	4.9966	4.83307	0.088037

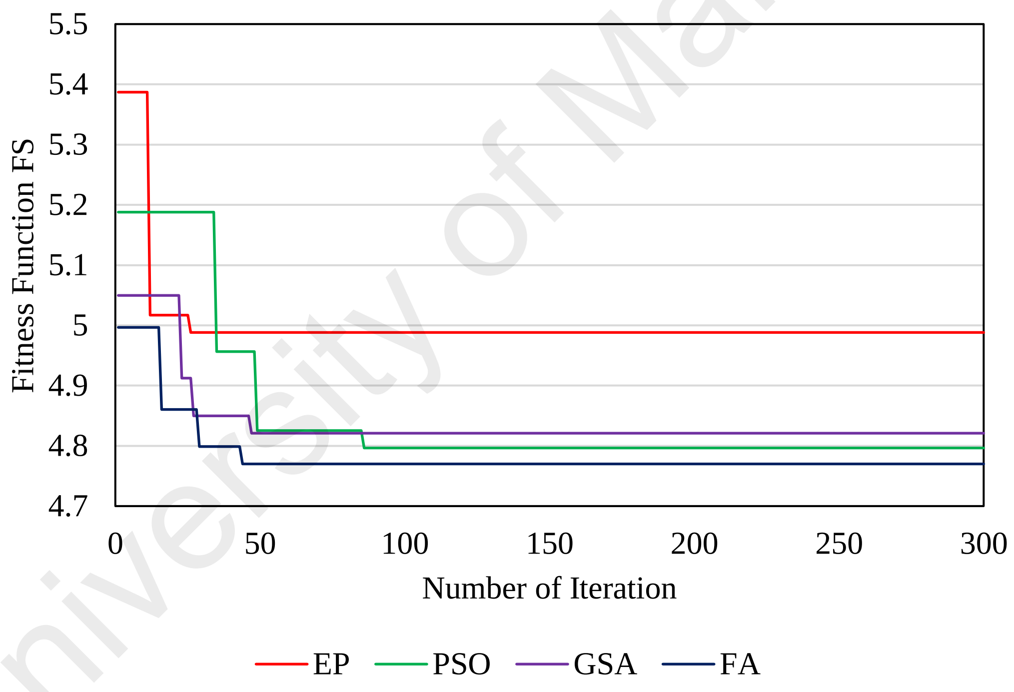

Figure 4.6: Comparison of convergence performance of the switching sequence process algorithms for IEEE 16-bus network

To further validate the results, different random sequence cases are presented in Table 4.6 using different algorithms. It can be seen from the table that the random cases produced more power losses than the optimal sequence.

Table 4.6: Random switching sequence results for IEEE 16-bus network

Method	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Power Losses (kW)
Random case using EP method	1	17 close	0.9726 (11)–1(1)	2589.7
	2	14 open	0.9726 (11)–1(1)	
	3	15 close	0.9775(11)–1(1)	
	4	9 open	0.9727(11)–1(1)	
	5	16 close	0.9768(11)–1(1)	
	6	8 open	0.9749(11)–1(1)	
Random case using PSO method	1	15 close	0.9784(11)–1(1)	2306.964
	2	9 open	0.9735(11)–1(1)	
	3	16 close	0.9771(11)–1(1)	
	4	8 open	0.9756(11)–1(1)	
	5	17 close	0.9756(11)–1(1)	
	6	14 open	0.9756(11)–1(1)	
Random case using GSA method	1	16 close	0.9769(11)–1(1)	2352.3
	2	8 open	0.9754(11)–1(1)	
	3	17 close	0.9754(11)–1(1)	
	4	5 open	0.9754(11)–1(1)	
	5	15 close	0.9795(11)–1(1)	
	6	9 open	0.9754(11)–1(1)	
Random case using FA method	1	17 close	0.9734(11)–1(1)	2392.3
	2	5 open	0.9734(11)–1(1)	
	3	15 close	0.9793(11)–1(1)	
	4	9 open	0.9735(11)–1(1)	
	5	16 close	0.9764(11)–1(1)	
	6	8 open	0.9757(11)–1(1)	

4.3 Test System 2: IEEE 33-Bus

An IEEE 33-bus distribution network system was used to test the proposed method. The network consists of 37 switches, 32 sectionalizing switches, and 5 tie switches. Switch number 33, 34, 35, 36, and 37 were normally open for the original network, while the other switches were normally closed, as shown in Figure 4.7. The total real load demand was 3715 kW, while the system's voltage was 12.66 kV. The base value of the apparent power was 100 MVA. The power losses of the network at the initial configuration were 202.677 kW, with 0.913 p.u. as the lowest bus voltage. The complete bus and line data was given in (Baran & Wu, 1989), and are tabulated in Appendix A Table A-2. The DG in this test system is assumed to be a mini-hydro generation. The capacity for each DG is 2 MW. In this work, the optimal locations for the DGs are located at buses 31, 32, and 33. This location was based on (Rao et al., 2013). An optimal solution was obtained for tie-switch, DG output (real power) and switching sequences. Both DG output and tie-switches were determined simultaneously.

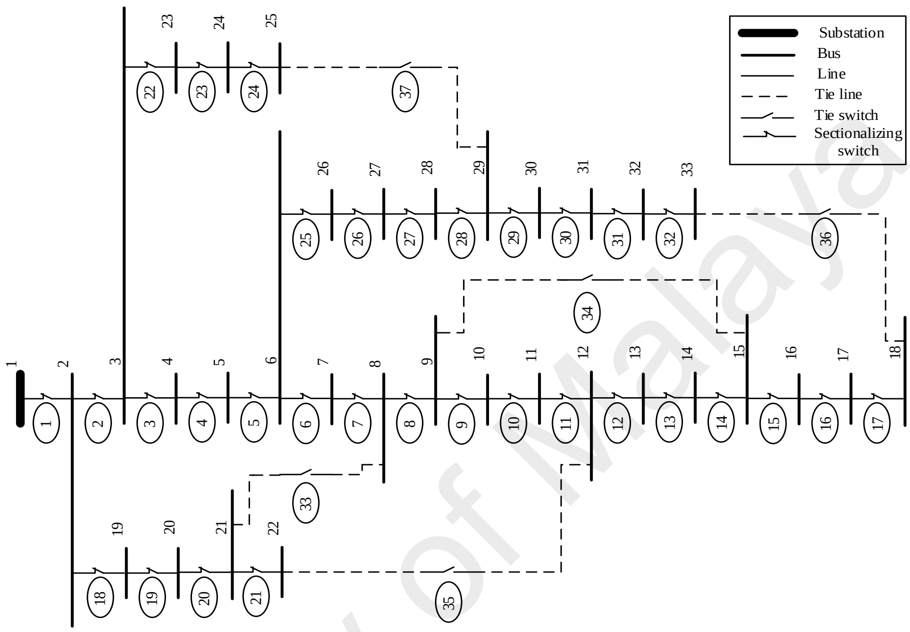

Figure 4.7: IEEE 33-bus distribution network before reconfiguration process

4.3.1 Simultaneously Network Reconfiguration and DG Output for IEEE 33 Bus System

This section focuses on power loss reduction and voltage profile improvement via simultaneous network reconfiguration and DG output.

4.3.1.1 Impact of simultaneous network reconfiguration and DG output generation on power losses

Table 4.7 summarizes the test results obtained using EP, PSO, GSA, and FA and compared to the initial case. The optimal main fitness, F_R, according to equation (3.1), is 0.4105, obtained using FA. This means that FA provide a better value compared to EP, PSO, and GSA. As can be seen in Table 4.7, by using FA, the power losses after network reconfiguration within DG is 72.361 kW, while before reconfiguration, its 202. 6kW, which means that the power losses decreased by 130.239 kWh i.e. ~64.28% reduction compare to its initial state. The minimum voltage for all busses after reconfiguration was improved to 0.9750 pu, while before reconfiguration, its 0.9131 pu. The normally open switches after reconfiguration were 7, 10, 13, 28 and 32, while before reconfiguration, its 33, 34, 35, 36 and 37. The DG1 output was 0.6756 MW, DG2 was 0.516 MW and DG3 was 0.6334 MW. The computation time taken for using FA was 666.997 s, with 300 iterations for a population of a 100, exceeding the other algorithms.

Table 4.7: Network reconfiguration and DG output results for IEEE 33-bus network

Case	Open switch	DG output in MW (Bus number)	Bus voltage (pu) (at bus) min – max	Reconfiguration fitness function $F_R = (P_{loss}^R + IVD)$	Power losses (kW)	Losses reduction (%)	CPU Time (s)
Initial	33, 34, 35, 36, 37	No DG	0.9131(18)–1(1)	1.1135	202.6	---------	0.597
EP	7, 8, 9, 28, 32	DG1= 0.7024(31) DG2= 0.6390(32) DG3= 0.6224(33)	0.9710(9)–1(1)	0.4223	73.971	63.49	563.091
PSO	7, 10, 13, 28, 32	DG1= 0.6120(31) DG2= 0.5200(32) DG3= 0.6340(33)	0.9738(29)–1(1)	0.4116	72.336	64.30	542.406
GSA	7, 9, 13, 28, 32	DG1= 0.6450(31) DG2= 0.5200(32) DG3= 0.5800(33)	0.9742(14)–1(1)	0.4117	72.425	64.25	587.375
FA	7, 10, 13, 28, 32	DG1= 0.6756(31) DG2= 0.5160(32) DG3=0.6334(33)	0.9750(29)–1(1)	0.4105	72.361	64.28	666.997

4.3.1.2 Impact of simultaneous network reconfiguration and DG output generation on voltage profile

The voltage profiles for both initial and optimal cases using EP, PSO, GSA, and FA are shown in Figure 4.8. The buses voltage magnitude in the case of all the algorithms increased relative to its respective initial states. FA reported the best voltage profile.

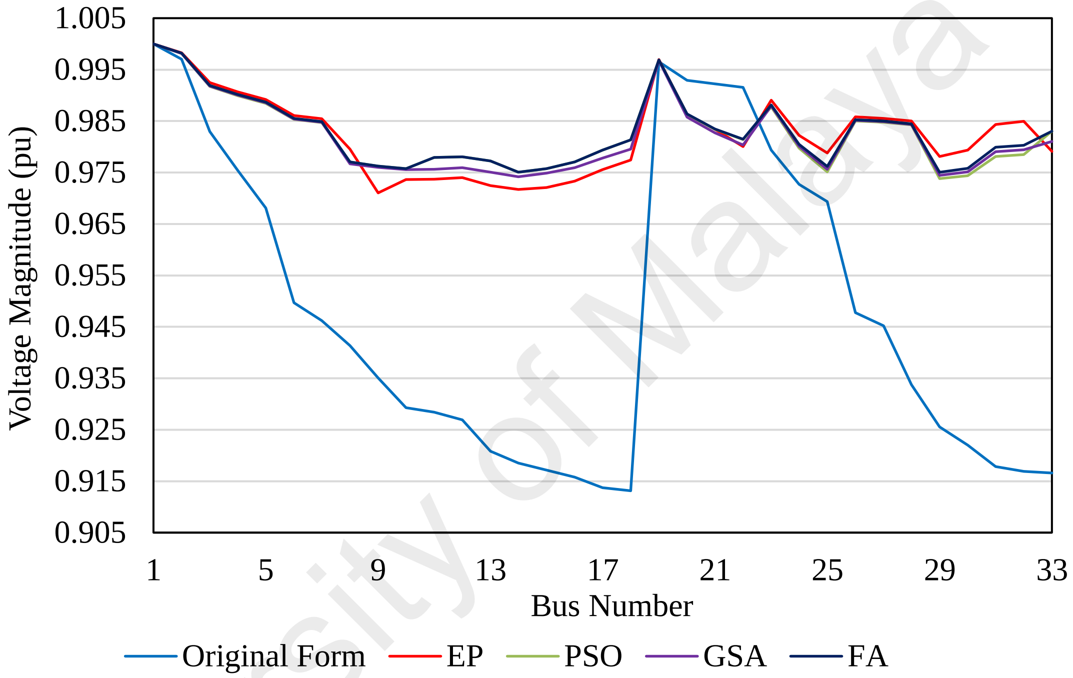

Figure 4.8: Voltage profile for IEEE 33-bus radial distribution network using different algorithms

4.3.1.3 Analysis of overall performance for simultaneous network reconfiguration and DG output generation

To prove the validity of simultaneous network reconfiguration within an optimal DG output, the robustness test was conducted for the proposed method using different algorithms, and the result compared and shown in Figure 4.9 for 20 runs. It is evident that the GSA/FA reported results that are almost equal in each run and the minimum value of standard deviation compared to the other algorithms, as shown in Table 4.8. This mean that GSA and FA are highly robust compared to EP and PSO. For each algorithm, there is a global optimal value representing a minimum value during the 20 time of simulation run of the program, which are 0.4223, 0.4116, 0.4117, and 0.4105 for EP, PSO, GSA, and FA, respectively.

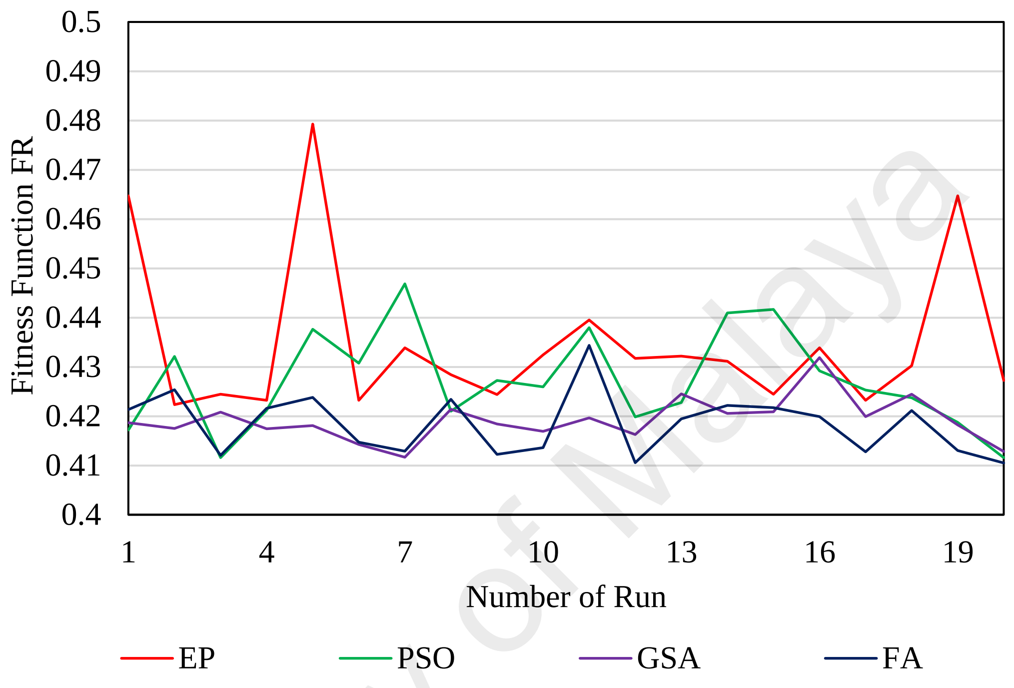

Figure 4.9: Comparison of robustness test of the simultaneous reconfiguration and optimal DG output algorithms for IEEE 33-bus network

Based on the global cases for each algorithm, the convergence performance of these global values was also compared and shown in Figure 4.10. It is evident that the FA obtained the minimum value of F_R relative to the other algorithms.

Table 4.8: Statistical analysis results for robustness test for network reconfiguration and DG output generation process for IEEE 33-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	0.4223	0.479287	0.434739	0.015947
PSO	0.4116	0.446859	0.427166	0.009934
GSA	0.4117	0.431887	0.419218	0.004437
FA	0.4105	0.434373	0.418335	0.006252

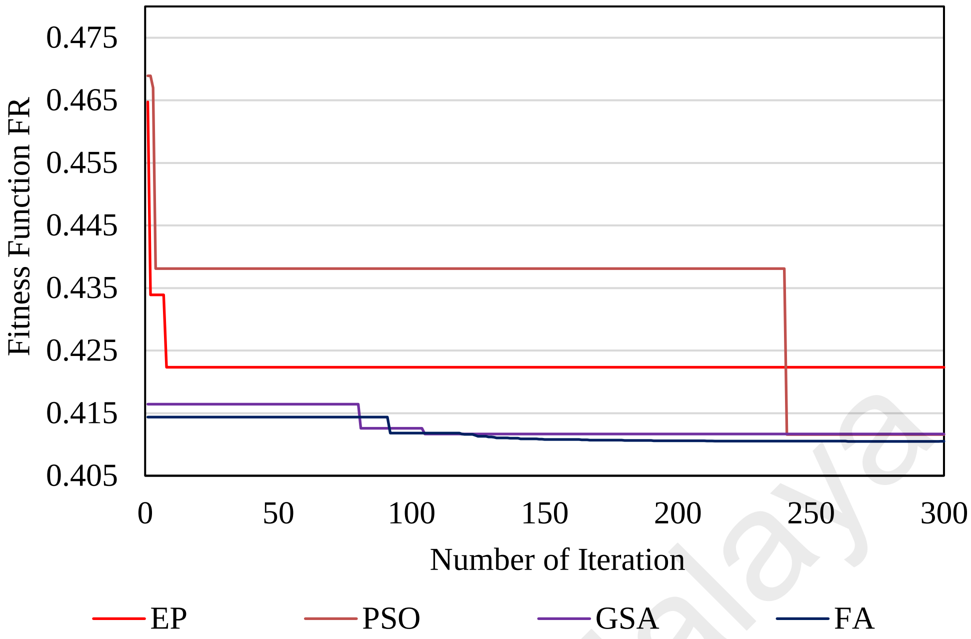

Figure 4.10: Comparison of convergence performance of the simultaneous reconfiguration and optimal DG output algorithms for IEEE 33-bus network

The performance of the proposed method was also compared to that of published result with similarly reported DG location, with the results of the comparison tabulated in Table 4.9. The proposed method, based on PSO, GSA, or FA, exceeded that of the GA, RGA, HSA, EP, PSO, EPSO, ABC, MGA, MPSO, and SABC, while the EP obtained value of power losses exceeding that of HSA.

Table 4.9: Comparison of simulation result for IEEE 33-bus network

Method	Open switches	Total DG output (MW)	Lowest bus voltage (pu)	Power losses (kW)	Losses reduction (%)
GA (Rao et al., 2013)	7, 10, 28, 32, 34	1.9633	0.9766	75.130	62.92
RGA (Rao et al., 2013)	7, 9, 12, 27, 32	1.7740	0.9691	74.320	63.33
HSA (Rao et al., 2013)	7, 10, 14, 28, 32	1.6684	0.9700	73.050	63.95
GA (Dahalan et al., 2014)	7, 10, 14, 28, 32	5.598	0.9899	100.90	50.20
EP (Dahalan et al., 2014)	7, 10, 12, 16, 28	5.429	0.9978	94.100	53.5
PSO (Dahalan, Mokhlis, Bakar, & Jamian, 2013)	7, 12, 29, 33, 37	4.1868	0.9820	89.30	55.92
GA (Dahalan & Mokhlis, 2012)	7, 9, 14, 28, 32	3.8737	0.9772	112.4	44.5
PSO (Dahalan & Mokhlis, 2012)	7, 10, 14, 28, 32	3.3338	0.9772	92.3	51.4
EPSO (Sulaima, Shamsudin, Jaafar, Dahalan, & Mokhlis, 2014)	6, 10, 13, 16, 28	5.429	-------	89.3	55.9
ABC (Dahalan, 2013)	11, 20, 31, 34, 37	2.706	-------	103.9	48.64
MGA (Dahalan, 2013)	7, 10, 12, 16, 28	2.7532	0.985983	96.88	52.11
EPSO (Dahalan, 2013)	6, 10, 13, 16, 28	2.7969	0.986126	89.4	55.81
MPSO (Dahalan, 2013)	7, 9, 14, 28, 32	2.7747	0.977692	92.46	54.30
SABC (Dahalan, 2013)	11, 20, 31, 34, 37	2.6374	0.97698	97.5	51.80
Proposed (EP)	7, 8, 9, 28, 32	1.9638	0.9710	73.971	63.49
Proposed (PSO)	7, 10, 13, 28, 32	1.7660	0.9738	72.336	64.30
Proposed (GSA)	7, 9, 13, 28, 32	1.7450	0.9742	72.425	64.25
Proposed (FA)	7, 10, 13, 28, 32	1.8250	0.9750	72.361	64.28

4.3.2 Switching Sequence Process for IEEE 33 Bus System

This section focuses on the optimal switching sequence path to alter the network configuration from its original form to its optimal form, based on stage number one.

Since IEEE 33-bus network had 5 tie-switches, and as per equation (3.36), there are $5! \times 5! \times 2 = 2880$ probabilities, representing the switching sequence paths that could be used to transfer the network from its original form to its expected optimal form.

4.3.2.1 Impact of switching sequence process and DG output generation on power losses and voltage profile

The optimal solution of network reconfiguration and DG output obtained from Table 4.5 is used to find the best switching sequence from an initial state (33, 34, 35, 36, and 37) to a final state. The final state, using EP, its (7, 8, 9, 28, and 32), using PSO or FA, its (7, 10, 13, 28, and 32), and using GSA, its (7, 9, 13, 28, and 32). Based in equation (3.39) and using GSA, the best value of sequence fitness F_S is obtained as shown in Table 4.10, equal to 4.4381. The power losses during all the steps is 642.22 kW, which means that the GSA reported a better optimal solution for the switching sequence compared to the other algorithms. The obtained best sequence switching using GSA is:

Sequence 1: Sw36 (Close) → Sequence 2: Sw32 (Open),

Sequence 3: Sw35 (Close) → Sequence 4: Sw9 (Open),

Sequence 5: Sw37 (Close) → Sequence 6: Sw28 (Open),

Sequence 7: Sw33 (Close) → Sequence 8: Sw7 (Open),

Sequence 9: Sw34 (Close) → Sequence 10: Sw13 (Open).

Furthermore, the minimum buses voltages in each switching step for all the algorithm is also presented. It is clear that the best switching sequence does not cause the voltage profile to exceed its the allowable limit. The computational time taken for using the GSA algorithm is 520.773 s, at an iteration of 300 for a population of 100, which is lower than that reported by the other algorithms.

Table 4.10: Switching sequence results for IEEE 33-bus network

Method	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Sequence fitness function $F_S = \sum_{s=1}^{N_{steps}} \left(\frac{P_{loss,s}}{P_{loss}^0} + IVD_s \right)$	Power Losses (kW)	CPU Time (s)
EP	1	36 close	0.9704(11)–1(1)	4.5387	803.56	751.108
	2	32 open	0.9670(14)–1(1)			
	3	37 close	0.9671(14)–1(1)			
	4	28 open	0.9669(14)–1(1)			
	5	33 close	0.9748(14)–1(1)			
	6	7 open	0.9674(14)–1(1)			
	7	35 close	0.9756(14)–1(1)			
	8	9 open	0.9742(14)–1(1)			
	9	34 close	0.9759(14)–1(1)			
	10	8 open	0.9710(9)–1(1)			
PSO	1	36 close	0.9659(14)–1(1)	4.4664	787.451	550.836
	2	32 open	0.9648(14)–1(1)			
	3	33 close	0.9733(14)–1(1)			
	4	7 open	0.9679(14)–1(1)			
	5	37 close	0.9679(14)–1(1)			
	6	28 open	0.9679(14)–1(1)			
	7	35 close	0.9738(29)–1(1)			
	8	10 open	0.9738(29)–1(1)			
	9	34 close	0.9738(29)–1(1)			
	10	13 open	0.9738(29)–1(1)			

Table 4.10: Continued

Method	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Sequence fitness function $F_S = \sum_{s=1}^{N_{steps}} \left(\frac{P_{loss,s}}{P_{loss}^{0}} + IVD_s \right)$	Power Losses (kW)	CPU Time (s)
GSA	1	36 close	0.9653(14)–1(1)	4.4381	785.76	520.773
	2	32 open	0.9626(14)–1(1)			
	3	35 close	0.9756(29)–1(1)			
	4	9 open	0.9753(29)–1(1)			
	5	37 close	0.9764(29)–1(1)			
	6	28 open	0.9734(29)–1(1)			
	7	33 close	0.9740(29)–1(1)			
	8	7 open	0.9722(14)–1(1)			
	9	34 close	0.9745(29)–1(1)			
	10	13 open	0.9742(14)–1(1)			
FA	1	36 close	0.9672(14)–1(1)	4.4602	791.84	565.084
	2	32 open	0.9659(14)–1(1)			
	3	35 close	0.9766(29)–1(1)			
	4	10 open	0.9742(10)–1(1)			
	5	37 close	0.9745(10)–1(1)			
	6	28 open	0.9738(29)–1(1)			
	7	33 close	0.9746(29)–1(1)			
	8	7 open	0.9750(29)–1(1)			
	9	34 close	0.9750(29)–1(1)			
	10	13 open	0.9750(29)–1(1)			

4.3.2.2 Analysis of overall performance for switching sequence process

To prove the validity of the best switching sequence, the robustness test was conducted for the proposed method using EP, PSO, GSA, and FA, and the results compared and presented in Figure 4.11 for 20 runs. It is evident that GSA or FA report results that are almost equal in each run and minimum value of standard deviation compared to the other algorithms, as shown in Table 4.11. This means that GSA and FA algorithm are highly robust and realizes a great level of consistency in the output result. The minimum value for each algorithm during 20 runs of the simulation program are taken as the global optimal result. Furthermore, the conversion performance for these global cases for all the algorithms are compared and shown in Figure 4.12. It is also clear that the GSA report the minimum value of F_S compared to the other algorithms.

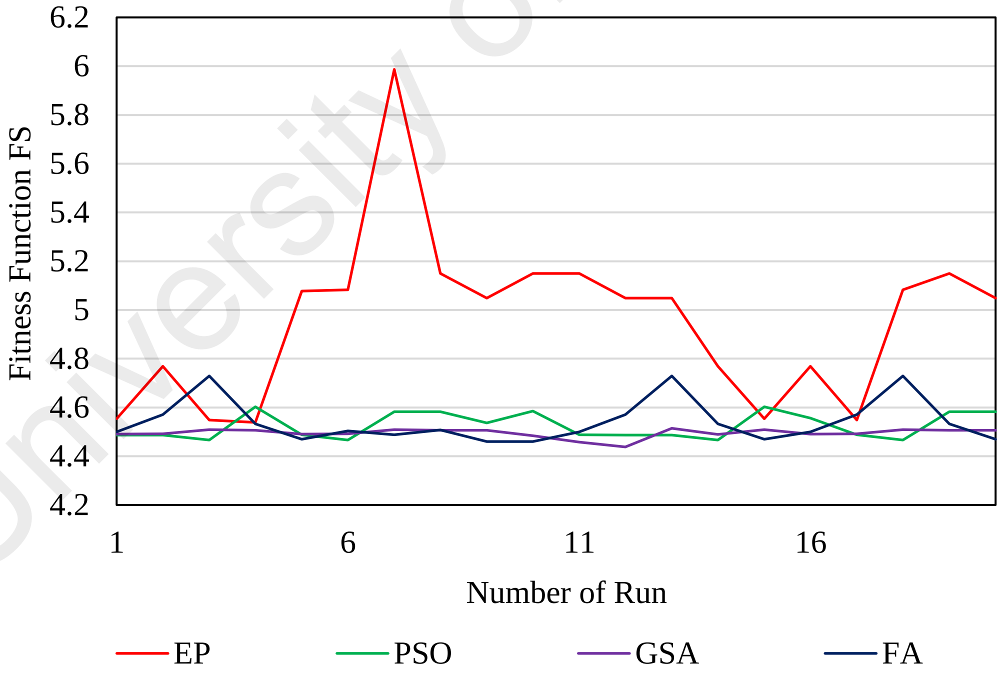

Figure 4.11: Comparison of robustness test of the switching sequence process algorithms for IEEE 33-bus network

Table 4.11: Statistical analysis results for robustness test for switching sequence process for IEEE 33-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	4.5387	5.9869	4.953479	0.342431
PSO	4.466404	4.602795	4.524574	0.093251
GSA	4.438055	4.514505	4.495027	0.018783
FA	4.460182	4.729318	4.541553	0.08817

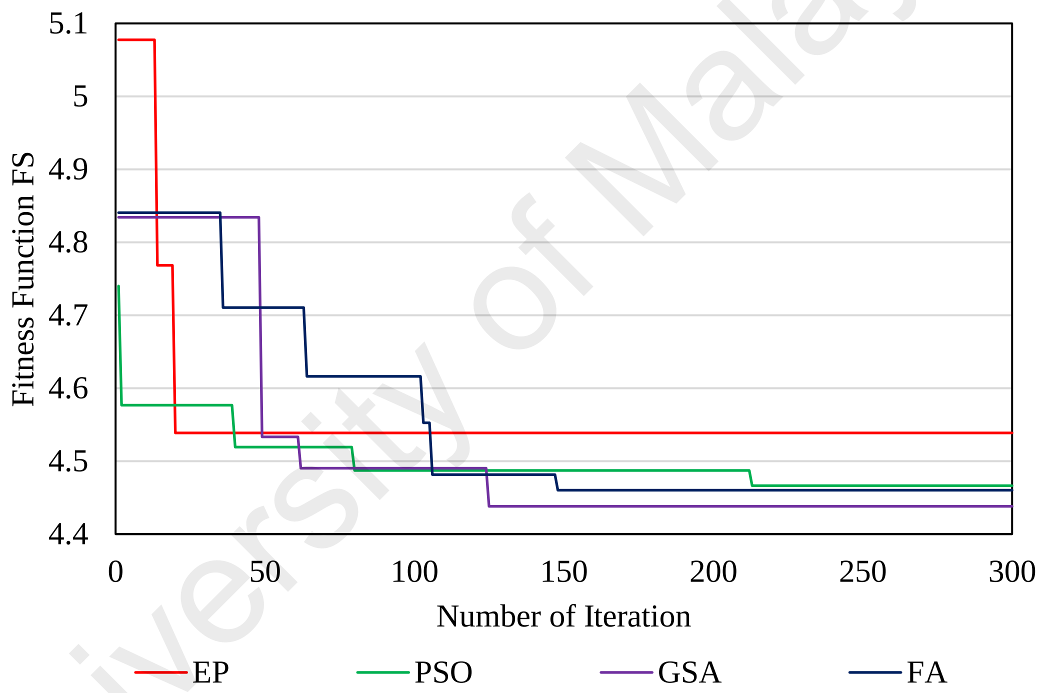

Figure 4.12: Comparison of convergence performance of the switching sequence process algorithms for IEEE 33-bus network

To further validate the results, different random sequence cases are presented in Table 4.12 using different algorithms. Any random case produced larger power losses or bus voltage value exceeding the limitations, or both.

Table 4.12: Random switching sequence results for IEEE 33-bus network

Method	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Power Losses (kW)
Random case using EP method	1	37 close	0.9402(18)–1(1)	853.55
	2	28 open	0.9364(18)–1(1)	
	3	36 close	0.9708(14)–1(1)	
	4	32 open	0.9669(14)–1(1)	
	5	33 close	0.9748(14)–1(1)	
	6	7 open	0.9674(14)–1(1)	
	7	35 close	0.9756(14)–1(1)	
	8	9 open	0.9742(14)–1(1)	
	9	34 close	0.9759(14)–1(1)	
	10	8 open	0.9710(9)–1(1)	
Random case using PSO method	1	36 close	0.9659(14)–1(1)	1074.9
	2	28 open	0.9370(29)–1(1)	
	3	33 close	0.9478(29)–1(1)	
	4	7 open	0.9289(29)–1(1)	
	5	37 close	0.9692(14)–1(1)	
	6	32 open	0.9679(14)–1(1)	
	7	35 close	0.9738(29)–1(1)	
	8	10 open	0.9738(29)–1(1)	
	9	34 close	0.9738(29)–1(1)	
	10	13 open	0.9738(29)–1(1)	
Random case using GSA method	1	34 close	0.9653(14)–1(1)	793.46
	2	13 open	0.9627(14)–1(1)	
	3	35 close	0.9756(29)–1(1)	
	4	9 open	0.9614 (8)–1(1)	
	5	37 close	0.9614(8)–1(1)	
	6	28 open	0.9614(8)–1(1)	
	7	33 close	0.9740(14)–1(1)	
	8	7 open	0.9723(14)–1(1)	
	9	36 close	0.9745(29)–1(1)	
	10	32 open	0.9742(14)–1(1)	
Random case using FA method	1	36 close	0.9672(14)–1(1)	889.32
	2	28 open	0.9414(29)–1(1)	
	3	37 close	0.9685(14)–1(1)	
	4	32open	0.9668(14)–1(1)	
	5	35 close	0.9742(29)–1(1)	
	6	10 open	0.9738(29)–1(1)	
	7	33 close	0.9746(29)–1(1)	
	8	7 open	0.9751(29)–1(1)	
	9	34 close	0.9751(29)–1(1)	
	10	13 open	0.9751(29)–1(1)	

4.4 Test System 3: IEEE 69-Bus

An IEEE 69-bus consists of 73 switches, 68 sectionalizing switches, and 5 tie switches. Switches number 69, 70, 71, 72, and 73 were normally open for the original network, while the other switches were normally closed, as shown in Figure 4.13. The total real load demand was 3801.89 kW. The system's voltage was 12.66 kV. The base value of the apparent power was 100 MVA. The power losses of the network at the initial configuration were 224.56 kW, with 0.90929 p.u. as its lowest bus voltage. The complete bus and line data follows that of (Savier & Das, 2007), and are given in Appendix A Table A-3. The DG in this test system was assumed to be a mini-hydro generation. The capacity for each DG was 2 MW. In this work, the optimal locations for the DGs are located at buses 60, 61, and 62. These locations were based on (Rao et al., 2013). Optimal solutions were obtained for tie-switch, DG output (real power), and switching sequences. Both the DG output and tie- switches were simultaneously determined.

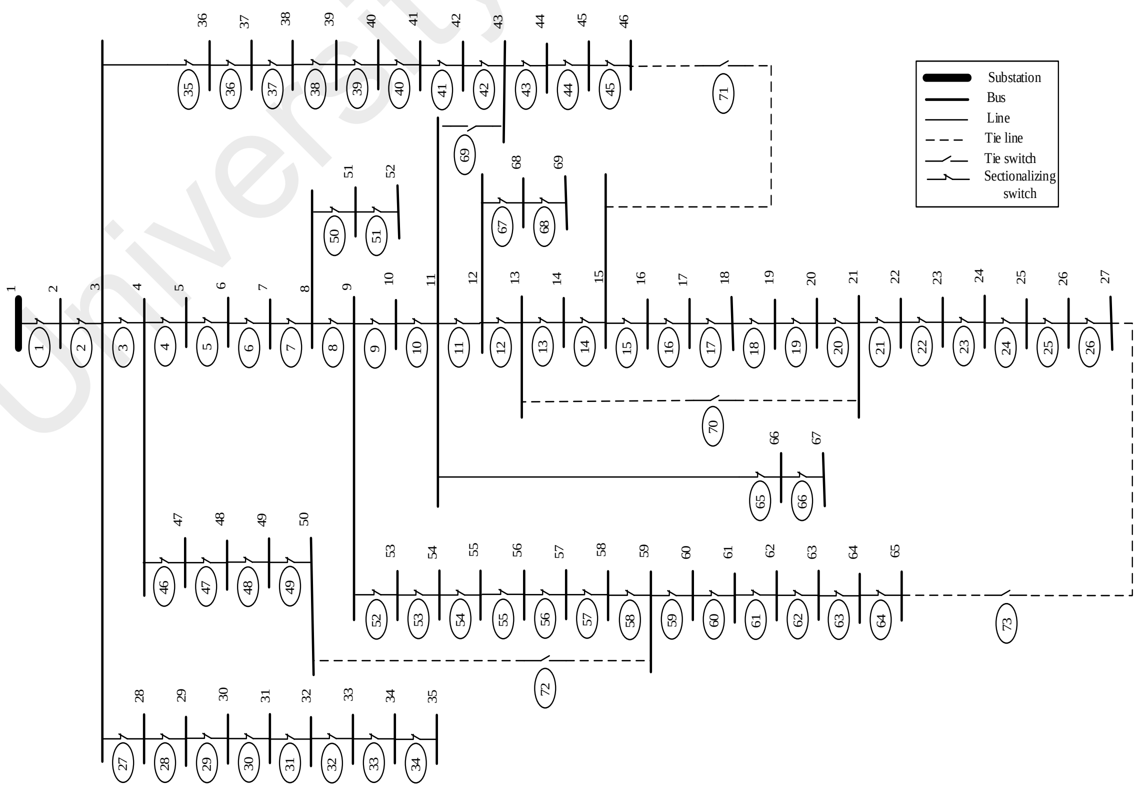

Figure 4.13: IEEE 69-bus distribution network before reconfiguration process

4.4.1 Simultaneously Network Reconfiguration and DG Output for IEEE 69 Bus System

This section focuses on power loss reduction and voltage profile improvement via simultaneous network reconfiguration and DG output.

4.4.1.1 Impact of simultaneous network reconfiguration and DG output generation on power losses

Table 4.13 summarize the test results obtained using EP, PSO, GSA, and FA, and compared the values with that of the initial case. The F_R, according to equation (3.1), is 0.22451, obtained using FA. This means that FA reports a better value than the EP, PSO, and GSA. As seen in Table 4.13, by using FA, the power losses after network reconfiguration within DG is 39.897 kW, while before reconfiguration, its 224.56 kW, which means that power losses were reduced by 184.663 kWh i.e. ~82.233 % reduction compared to its initial state. The minimum voltage for all the busses after reconfiguration was improved to 0.98176 p.u., while before reconfiguration, its 0.90929 p.u. The normally open switches after reconfiguration were 12, 13, 57, 61, and 69, while before reconfiguration, they were 69, 70, 71, 72, and 73. The DG1 output was 0.5412 MW, DG2 was 0.99499 MW, and DG3 was 0.47008 MW. The computation time taken for using FA was 1087.551 s at an iteration of 300 for a population of 100, which is larger than the other algorithms.

Table 4.13: Network reconfiguration and DG output results for IEEE 69-bus network

Case	Open Switch	DG Output in MW (Bus Number)	Bus voltage (pu) (at bus)		Reconfiguration fitness function $F_R = (P_{loss}^R + IVD)$	Power Losses (kW)	Power Reduction (%)	CPU Time (s)
			min	max				
Initial	69, 70, 71, 72, 73	No DG	0.90929(65)	1(1)	1.1172	224.56	---------	0.10985
EP	10, 13, 20, 56, 61	DG1= 0.538 (60) DG2= 0.665 (61) DG3= 0.513 (62)	0.974611(61)	1(1)	0.2534	44.83	79.940	796.361
PSO	10, 13, 17, 56, 61	DG1= 0.564 (60) DG2= 0.737 (61) DG3= 0.572 (62)	0.981684(61)	1(1)	0.25007	44.524	80.173	1013.597
GSA	12, 13, 58, 61, 69	DG1= 0.53531 (60) DG2= 0.99296 (61) DG3= 0.48986 (62)	0.98161(61)	1(1)	0.22486	39.943	82.213	663.797
FA	12, 13, 57, 61, 69	DG1= 0.5412 (60) DG2= 0.99499 (61) DG3= 0.47008 (62)	0.98176(61)	1(1)	0.22451	39.897	82.233	1087.551

4.4.1.2 Impact of simultaneous network reconfiguration and DG output generation on voltage profile

The voltage profile for both initial and optimal cases using EP, PSO, GSA, and FA are shown in Figure 4.14. All buses voltage magnitude for all the algorithms improved to a value larger than its respective initial state. FA reported the best voltage profile.

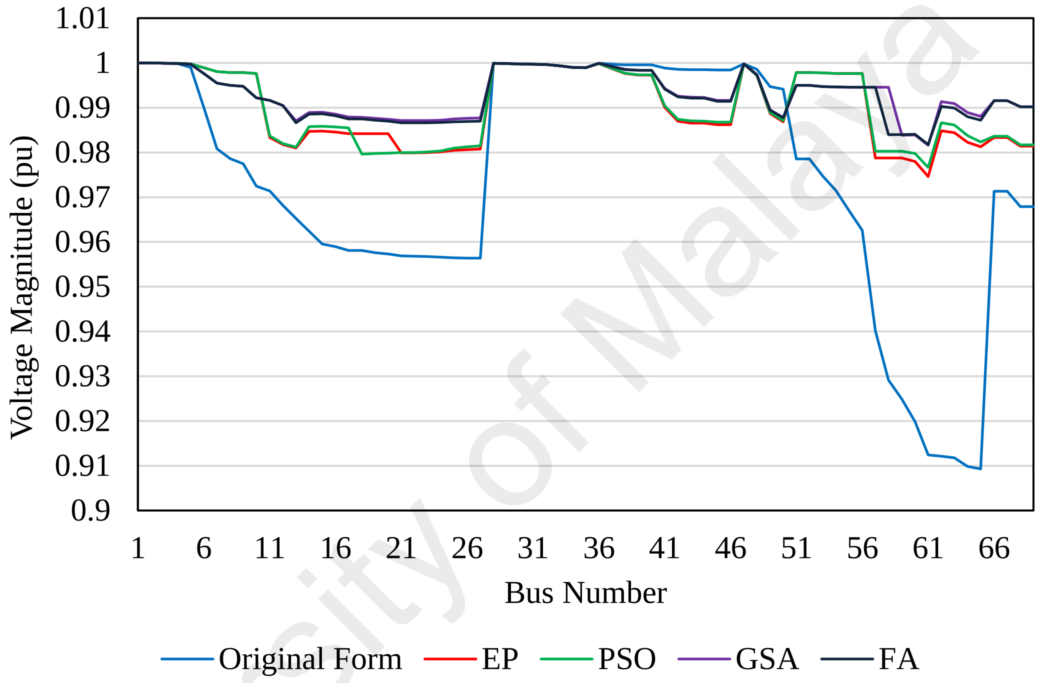

Figure 4.14: Voltage profile of IEEE 69-bus radial distribution network

4.4.1.3 Analysis of overall performance for simultaneous network reconfiguration and DG output generation

To prove the validity of the simultaneous network reconfiguration within optimal DG outputs, the robustness test was conducted for the proposed method using different algorithms, and the results compared and shown in Figure 4.15 for 20 runs. It is evident that the GSA/FA reported results that were almost equal in each run and minimum value of standard deviation compared to the other algorithms, as shown in Table 4.14. This mean that GSA and FA are highly robust compared to EP and PSO. For each algorithm, there is a global optimal value, which represents the minimum value during the simulation of the program, which are 0.2534, 0.25007, 0.22486, and 0.22451 for EP, PSO, GSA, and FA, respectively.

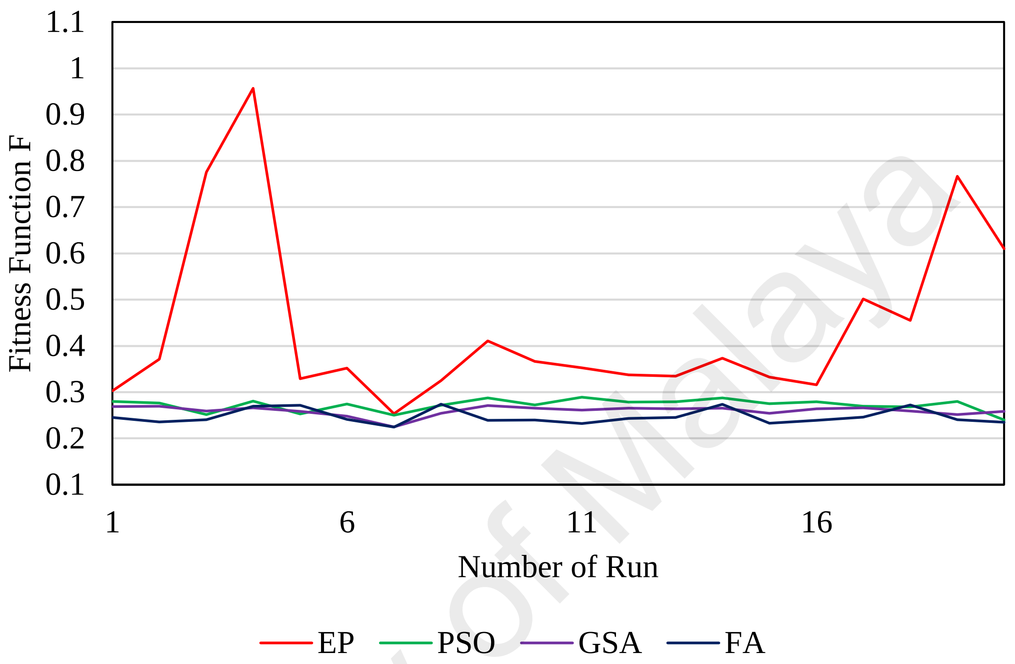

Figure 4.15: Comparison of robustness test of the simultaneous reconfiguration and optimal DG output algorithms for IEEE 69-bus network

Table 4.14: Statistical analysis results for robustness test for network reconfiguration and DG output generation process for IEEE 69-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	0.2534	0.956621	0.441218	0.188789
PSO	0.25007	0.28906	0.272199	0.016505
GSA	0.22486	0.27106	0.259794	0.010245
FA	0.22451	0.273974	0.247164	0.015767

Based on the global cases for each algorithm, the convergence performance for these values were also compared, and the results shown in Figure 4.16. It can be seen that the FA reported the minimum value of F_R compared to that of the other algorithms.

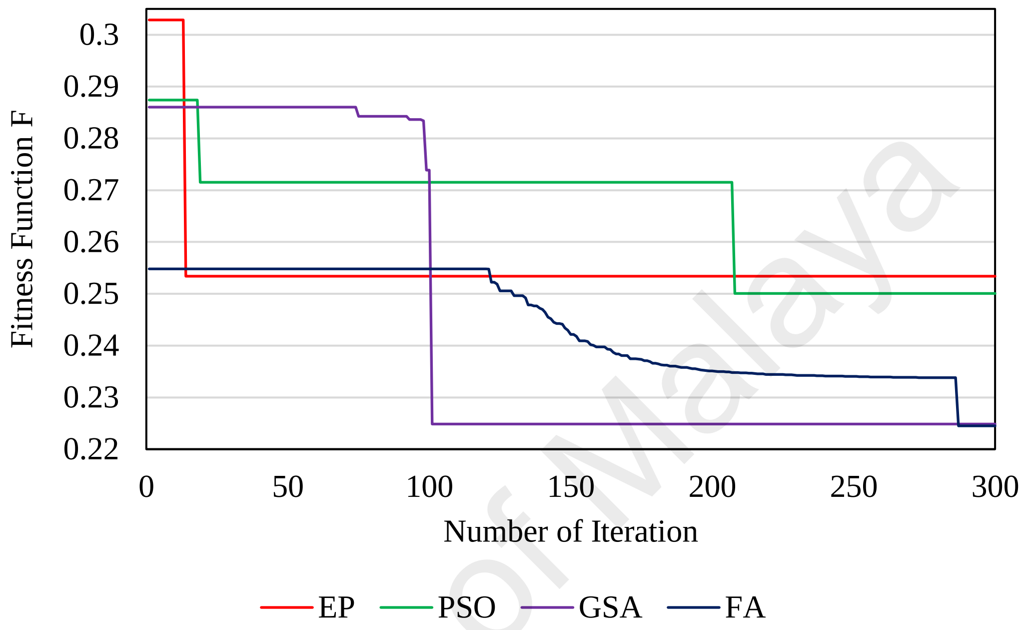

Figure 4.16: Comparison of convergence performance of the simultaneous reconfiguration and optimal DG output algorithms for IEEE 69-bus network

The performance of the proposed method was also compared to that of published result with similar DG location, and the result of this comparison shown in Table 4.15. It is clear that the proposed method, based on GSA or FA, are better than GA, RGA, HSA, PSO, EP, ABC, MGA, EPSO, MPSO, SABC, ICA, and GSA, while EP and PSO reported power losses larger than that of HSA, ICA, and GSA.

Table 4.15: Comparison of simulation result for IEEE 69-bus network

Method	Open Switches	Total DG Output (MW)	Lowest bus voltage (pu)	Power Losses (kW)	Losses reduction (%)
GA (Rao et al., 2013)	10, 15, 45, 55, 62	2.0292	0.9727	46.50	73.38
RGA (Rao et al., 2013)	10, 16, 14, 55, 62	2.0654	0.9742	44.23	80.32
HSA (Rao et al., 2013)	69, 17, 13, 58, 61	1.8718	0.9736	40.30	82.08
GA (Dahalan, 2013)	11, 25, 69, 70, 73	2.6197	-------	74.1	67.01
PSO (Dahalan, 2013)	9,17, 43, 55, 64	2.6383	-------	64.07	71.47
EP (Dahalan, 2013)	12, 49,55,64, 69	2.672	-------	62.7	72.08
ABC (Dahalan, 2013)	17, 55, 61, 69, 70	2.6726	-------	75.9	66.21
MGA (Dahalan, 2013)	10, 25, 69, 70, 73	2.6721	0.99649	70.4	68.66
EPSO (Dahalan, 2013)	9,17, 49, 55, 64	2.6992	0.99649	60.09	72.93
MPSO (Dahalan, 2013)	12,17, 44, 55, 64	2.6811	0.99649	64.01	71.5
SABC (Dahalan, 2013)	13, 56, 64, 69, 70	2.6573	0.99649	70.1	68.79
ICA (Koong, 2015)	61,70,69,57,13	1.4707	0.9757	42.84	81.07
GSA (Koong, 2015)	61,69,19,57,12	1.6362	0.975	42.09	81.40
Proposed (EP)	10, 13, 20, 56, 61	1.716	0.974611	44.83	79.940
Proposed (PSO)	10, 13, 17, 56, 61	1.873	0.981684	44.524	80.173
Proposed (GSA)	12, 13, 58, 61, 69	2.018	0.98161	39.943	82.213
Proposed (FA)	12, 13, 57, 61, 69	2.006	0.98176	39.897	82.233

4.4.2 Switching Sequence Process for IEEE 69 Bus System

This section focuses on the optimal switching sequence path to change the network configuration from its original form to its optimal form based on the configuration process.

Since IEEE 69-bus network had 5 tie-switches and referred to the equation (3.36), there are $5! \times 5! \times 2 = 28800$ probabilities, representing the switching sequence paths that could be used to transfer the network from its original form to its expected optimal form.

4.4.2.1 Impact of switching sequence process and DG output generation on power losses and voltage profile

The optimal solution of network reconfiguration and DG output obtained from Table 4.9 can be used to find the best switching sequence from an initial state (69, 70, 71, 72, and 73) to a final state. The final state using EP is (10, 13, 20, 56, and 61), using PSO, its (10, 13, 17, 56, and 61), using GSA, its (12, 13, 58, 61, 69), and using FA, its (12, 13, 57, 61, and 69). Based on equation (3.39) and using FA, the best value of F_S is obtained as per Table 4.16, equal to 2.029319. The power losses during all the steps is 365.52 kW, which means that FA realized better optimal solution for switching sequence compared to the other algorithms. The obtained best sequence switching using FA is:

Sequence 1: Sw72 (Close) → Sequence 2: Sw57 (Open),

Sequence 3: Sw71 (Close) → Sequence 4: Sw13 (Open),

Sequence 5: Sw73 (Close) → Sequence 6: Sw61 (Open),

Sequence 7: Sw70 (Close) → Sequence 8: Sw12 (Open),

Sw69 (NC).

Moreover, the minimum buses voltages in each switching step for all the algorithm are also presented. It is clear that the best switching sequence does not cause the voltage profile to exceed its allowable limit. The computational time taken to using the firefly algorithm is 1210.051 s, at an iteration of 300 for a population of 100, exceeding that of the other algorithms.

Table 4.16: Switching sequence results for IEEE 69-bus network

Proposed method	Step NO.	Switching Sequence path	Bus voltage (pu) (at bus) min max	Sequence fitness function $F_S = \sum_{s=1}^{N_{steps}} \left(\frac{P_{loss,s}}{P_{loss}^{0}} + IVD_s \right)$	Power Losses (kW)	CPU Time (s)
EP	1	73 close	0.970277(24)–1.0(1)	2.965901	543.13	1091.925
	2	61 open	0.971865(61)–1.0(1)			
	3	72 close	0.974936(21)–1.0(1)			
	4	56 open	0.974587(61)–1.0(1)			
	5	69 close	0.974600(61)–1.0(1)			
	6	10 open	0.971928(21)–1.0(1)			
	7	70 close	0.97461(61)–1.0(1)			
	8	13 open	0.974327(14)–1.0(1)			
	9	71 close	0.974611(61)-1.0(1)			
	10	20 open	0.974611(61)-1.0(1)			
PSO	1	72 close	0.969827(27)–1.0(1)	2.572721	459.241	1051.316
	2	56 open	0.971157(27)–1.0(1)			
	3	71 close	0.975675(65)–1.0(1)			
	4	13 open	0.975674(65)–1.0(1)			
	5	73 close	0.980996(64)–1.0(1)			
	6	61 open	0.976638(61)–1.0(1)			
	7	69 close	0.976639(61)–1.0(1)			
	8	10 open	0.976648(61)–1.0(1)			
	9	70 close	0.976648(61)-1.0(1)			
	10	17 open	0.976647(61)-1.0(1)			

Table 4.16: Continued

Proposed method	Step NO.	Switching Sequence path	Bus voltage (pu) (at bus) min max	Sequence fitness function $F_S = \sum_{s=1}^{N_{steps}} \left(\frac{P_{loss,s}}{P_{loss}^{0}} + IVD_s \right)$	Power Losses (kW)	CPU Time (s)
GSA	1	72 close	0.970133(27)–1.0(1)	2.030647	365.884	980.159
	2	58 open	0.971161(27)–1.0(1)			
	3	71 close	0.978817(65)–1.0(1)			
	4	13 open	0.978816(65)–1.0(1)			
	5	73 close	0.982923(65)–1.0(1)			
	6	61 open	0.981608(61)–1.0(1)			
	7	70 close	0.981606(61)–1.0(1)			
	8	12 open	0.981608(61)–1.0(1)			
		69 NC				
FA	1	72 close	0.970108(27)–1.0(1)	2.029319	365.52	1210.051
	2	57 open	0.971160(27)–1.0(1)			
	3	71 close	0.978533(65)–1.0(1)			
	4	13 open	0.978533(65)–1.0(1)			
	5	73 close	0.982766(65)–1.0(1)			
	6	61 open	0.981757(61)–1.0(1)			
	7	70 close	0.981755(61)–1.0(1)			
	8	12 open	0.981757(61)–1.0(1)			
		69 NC				

4.4.2.2 Analysis of overall performance for switching sequence process

In order to prove the validity of the best switching sequence, the robustness test was conducted for the proposed method using EP, PSO, GSA, and FA, and the results compared and presented in Figure 4.17 for 20 runs. It is evident that the GSA or FA reported results that are almost equal to each run and minimum value of standard deviation compared to the other algorithms, as shown in Table 4.17. This means that the GSA and FA algorithms are highly robust and realizes a great level of consistency in its output results. The minimum value for each algorithm during the 20 runs of the simulation program is taken as the global optimal result. Furthermore, the conversion performance for these global cases in the case of all the algorithms were compared and shown in Figure 4.18. It is evident that the FA reported the minimum value of F_S compared to the other algorithms.

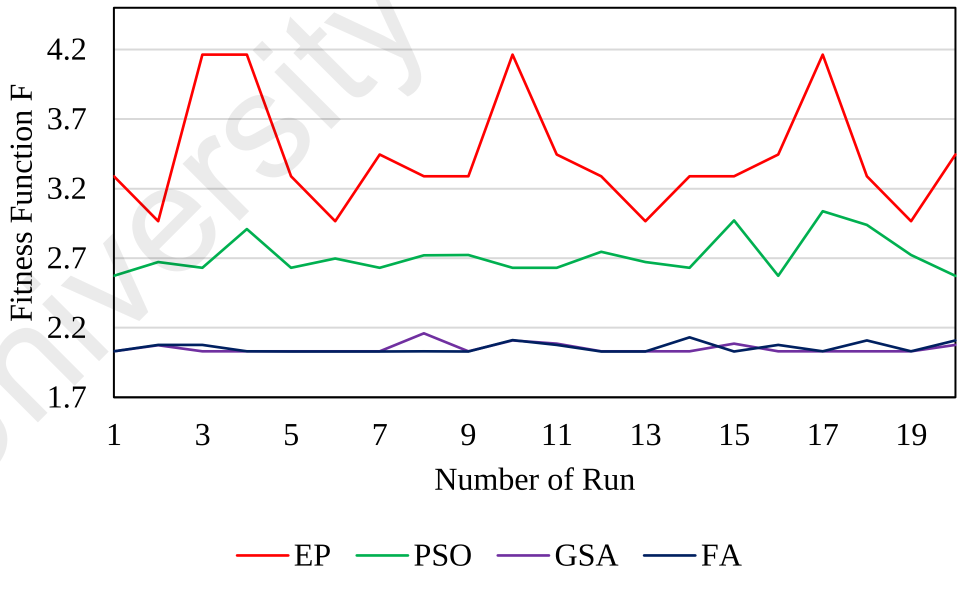

Figure 4.17: Comparison of robustness test of the switching sequence process algorithms for IEEE 69-bus network

Table 4.17: Statistical analysis results for robustness test for switching sequence process for IEEE 69-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	2.965901	4.163204	3.429894	0.408741
PSO	2.572721	3.03781	2.716046	0.13865
GSA	2.030647	2.160154	2.051356	0.036119
FA	2.029319	2.131172	2.056027	0.035737

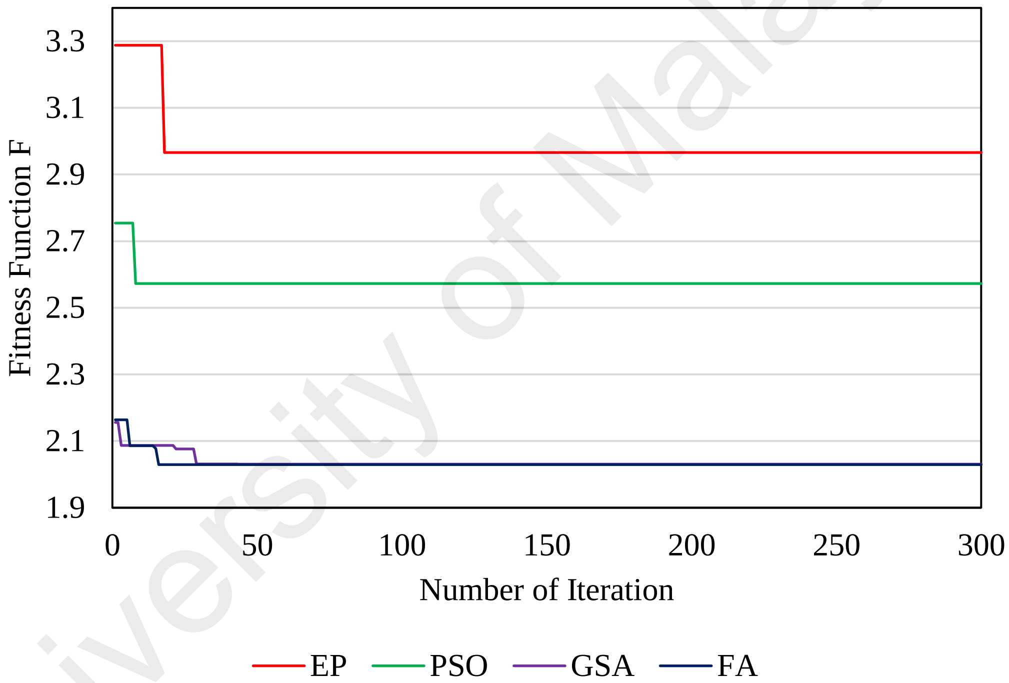

Figure 4.18: Comparison of convergence performance of the switching sequence process algorithms for IEEE 69-bus network

To further validate the results, different random sequence cases are presented in Table 4.18 using different algorithms. Any random case produced larger power losses or bus voltage value that exceeds the limitations, or both.

Table 4.18: Comparison of simulation result between the proposed method and random cases for IEEE 69-bus network

Case	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Power Losses (kW)
Random case using EP method	1	73 close	0.97028(24)– 1(1)	**651.8**
	2	56 open	**0.93594(61)**– 1(1)	
	3	72 close	0.97268(61)– 1(1)	
	4	61 open	0.97459(61)– 1(1)	
	5	69 close	0.9746(61)– 1(1)	
	6	10 open	0.97193(21)– 1(1)	
	7	70 close	0.97461(61)– 1(1)	
	8	13 open	0.97433(14)– 1(1)	
	9	71 close	0.97461(61)– 1(1)	
	10	20 open	0.97461(61)– 1(1)	
Random case using PSO method	1	72 close	0.96983(27)- 1(1)	**485.02**
	2	56 open	0.97116(27)- 1(1)	
	3	73 close	0.97445(23)- 1(1)	
	4	13 open	**0.94893(14)-** 1(1)	
	5	71 close	0.98100(64)- 1(1)	
	6	61 open	0.97664(61)- 1(1)	
	7	69 close	0.97664(61)- 1(1)	
	8	10 open	0.97665(61)- 1(1)	
	9	70 close	0.97665(61)- 1(1)	
	10	17 open	0.97665(61)- 1(1)	
Random case using GSA method	1	71 close	0.98519 (27)- 1(1)	**4442**
	2	58 open	**0.90218 (65)-** 1(1)	
	3	72 close	0.97882 (65)- 1(1)	
	4	13 open	0.97882 (65)- 1(1)	
	5	73 close	0.98292 (65)- 1(1)	
	6	61 open	0.98161 (61)- 1(1)	
	7	70 close	0.98161 (61)- 1(1)	
	8	12 open	0.98161 (61)- 1(1)	
Random case using FA method	1	72 close	0.97011 (27)- 1(1)	**382.22**
	2	57 open	0.97116 (27)- 1(1)	
	3	71 close	0.97853 (65)- 1(1)	
	4	13 open	0.97853 (65)- 1(1)	
	5	70 close	0.97853 (65)- 1(1)	
	6	12 open	0.97853 (65)- 1(1)	
	7	73 close	0.98264 (65)- 1(1)	
	8	61 open	0.98176 (61)- 1(1)	

4.5 Test System 4: IEEE 118-Bus

An IEEE 118-bus consists of 132 switches, 117 sectionalizing switches, and 15 tie switches. Switches number 118, 119, 120, 121, 122, 132, 124, 124, 126, 127, 128, 129, 130, 131, and 132 were normally open in the case of the original network, while the other switches were normally closed as shown in Figure 4.19. The total real load demand was 22709 kW, while the system’s voltage was 11 kV. The base value of the apparent power was 100 MVA. The power loss of the network at the initial configuration were 1297.8 kW, with 0.8688 p.u. as its lowest bus voltage. The complete bus and line data was given in (Zhang, Fu, & Zhang, 2007a), and are given in Appendix A Table A-4. The DG in this test system was assumed to be a mini-hydro generation. The capacity for each DG was 3 MW. In this work, the optimal locations for the DGs were located at buses 24, 42, 47, 74, 78, 94, and 108, as per (Sultana & Roy, 2014). The optimal solution was obtained for tie-switch, DG output (real power), and switching sequences. Both DG output and the tie-switches were determined simultaneously. The selected optimization technique was the FA.

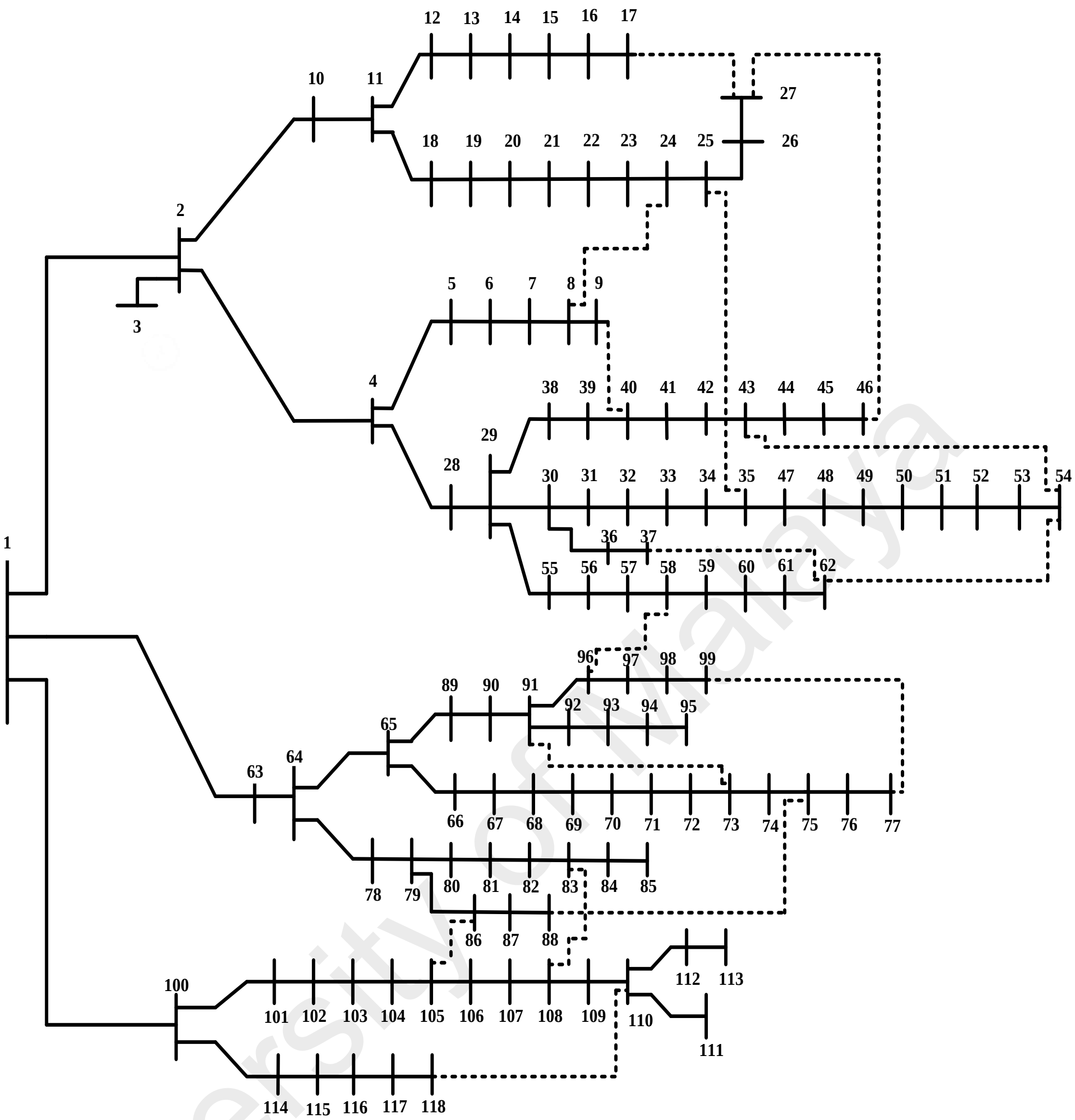

Figure 4.19: IEEE 118-bus distribution network before reconfiguration process

4.5.1 Simultaneously Network Reconfiguration and DG Output for IEEE 118 Bus System

This section focuses on power loss reduction and voltage profile improvement via simultaneously network reconfiguration and DG output for an IEEE 118-bus system.

4.5.1.1 Impact of simultaneous network reconfiguration and DG output generation on power losses

Table 4.19 tabulates the comparison between the initial case and final state after reconfiguration, considering the optimal DG output using FA. Power losses after network reconfiguration within DG was 571.38 kW, while before reconfiguration, it was 1297.8 kW, which means that the power loss was reduced by 726.42 kW i.e. ~55.97 % reduction compared to its initial state. The minimum voltage for all the busses after reconfiguration improved to 0.9502 p.u., while before reconfiguration, it was 0.8688 p.u. The normally open switches after reconfiguration are 41, 25, 21, 121, 122, 58, 38, 125, 70, 127, 128, 81, 130, 131, and 33, while before reconfiguration, they were 118, 119, 120, 121, 122, 132, 124, 124, 126, 127, 128, 129, 130, 131, and 132. The DG1 output was 1.5075 MW, DG2 output was 1.2489 MW, DG3 output was 1.8218 MW, DG4 output was 1.8248 MW, DG5 output was 1.2820 MW, DG6 output was 1.2642 MW, and DG7 output was 2.991 MW.

Table 4.19: Network reconfiguration and DG output results for IEEE 118-bus network

Case	Open Switch	DG Output in MW (Bus Number)	Bus voltage (pu) (at bus)		Reconfiguration fitness function	Power Losses (kW)	Power Reduction (%)
			min	max	$F_R = (P_{loss}^{R} + IVD)$		
Initial	118, 119, 120, 121, 122, 132, 124, 124, 126, 127, 128, 129, 130, 131, 132	No DG	0.8688(77)	1(1)	1.1565	1297.8	---------
Proposed method (FA)	41, 25, 21, 121, 122, 58, 38, 125, 70, 127, 128, 81, 130, 131, 33	DG1= 1.5075 (24) DG2= 1.2489 (42) DG3= 1.8218 (47) DG4= 1.8248 (74) DG5= 1.2820 (78) DG6= 1.2642 (94) DG7= 2.991 (108)	0.9502(54)	1(1)	0.51773	571.38	55.97

4.5.1.2 Impact of simultaneous network reconfiguration and DG output generation on voltage profile

The voltage profile for both initial and optimal case using FA were compared, and the results of this comparison shown in Figure 4.20. All the buses' voltage magnitude were improved to a value larger than its respective initial states.

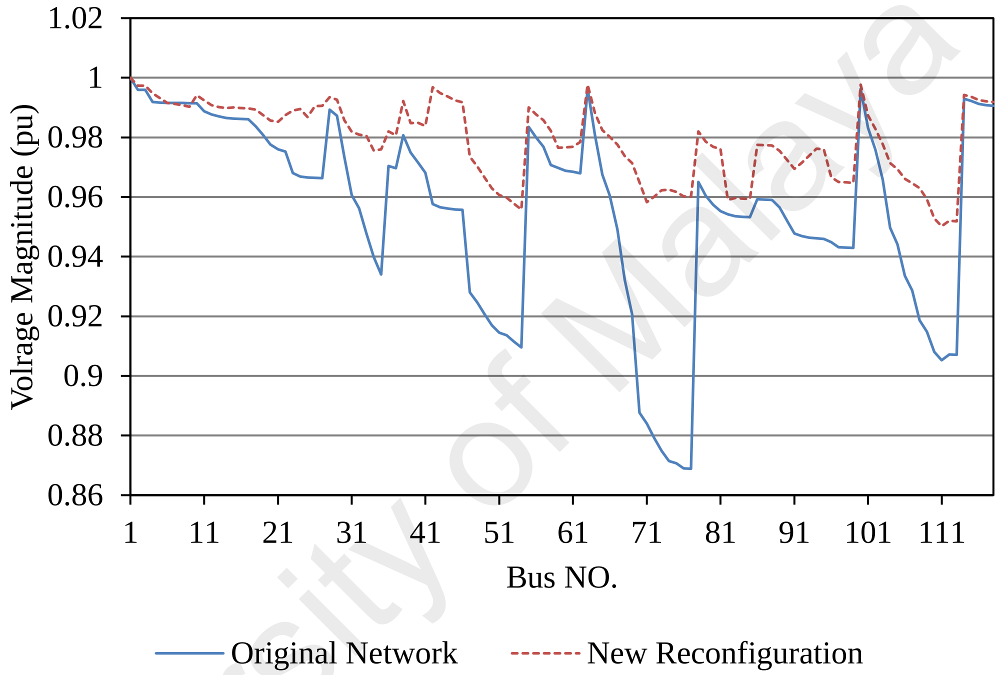

Figure 4.20: Voltage profile of IEEE 118-bus radial distribution network

4.5.1.3 Validation of performance of FA algorithm for simultaneous network reconfiguration and DG output generation

The performance of the proposed method was compared to that of published works, and the comparison shown in Table 4.20. The proposed method, based on FA, is superior to GA, RGA, ITS and MTS.

Table 4.20: Comparison of simulation result for IEEE 118-bus network in case of reconfiguration

Method	Open Switch	Lowest bus voltage (pu)	Power Losses (kW)	Losses reduction (%)
GA (Nara, Shiose, Kitagawa, & Ishihara, 1992a)	43, 120, 24, 51, 49, 62, 40, 126, 74, 73, 77, 83, 31, 110, 35	0.9321	885.56	31.76
MTS (Abdelaziz, Mohamed, Mekhamer, & Badr, 2010)	42, 26, 23, 51, 122, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	0.9323	867.4	33.16
ITS (Zhang, Fu, & Zhang, 2007b)	43, 27, 24, 52, 120, 59, 40, 96, 75, 72, 98, 130, 131, 110, 35	0.9323	865.86	33.28
RGA (Zhu, 2002b)	43, 27, 23, 52, 49, 62, 40, 126, 74, 73, 77, 83, 131, 110, 33	0.9321	883.13	31.95
Proposed Method (FA)	42, 23, 25, 121, 50, 58, 33, 95, 74, 71, 97, 130, 129, 109, 39	0.93231	859.38	33.78

4.5.2 Switching Sequence Process for IEEE 118 Bus System

This section focuses on the optimal switching sequence path to change the network configuration from its original form to its optimal form, based on the configuration process for an IEEE 118-bus test system.

4.5.2.1 Impact of switching sequence process and DG output generation on power losses and voltage profile

The optimal solution of network reconfiguration and DG output obtained from Table 4.19 can be used to determine the best switching changing path to transfer the network from its initial state (118, 119, 120, 121, 122, 132, 124, 124, 126, 127, 128, 129, 130, 131, 132) to its final state (41, 25, 21, 121, 122, 58, 38, 125, 70, 127, 128, 81, 130, 131, 33). The obtained best switching changing path is:

Sequence 1: Sw120 (Close) → Sequence 2: Sw21 (Open),

Sequence 3: Sw119 (Close) → Sequence 4: Sw25 (Open),

Sequence 5: Sw118 (Close) → Sequence 6: Sw41 (Open),

Sequence 7: Sw132 (Close) → Sequence 8: Sw33 (Open),

Sequence 9: Sw129 (Close) → Sequence 10: Sw81 (Open),

Sequence 11: Sw126 (Close) → Sequence 12: Sw70 (Open),

Sequence 13: Sw124 (Close) → Sequence 14: Sw38 (Open),

Sequence 15: Sw123 (Close) → Sequence 16: Sw58 (Open),

(Sw121, Sw122, Sw125, Sw127, Sw128, Sw130, Sw131 are NC).

The optimal fitness for switching sequence path is 8.5017, while the summation of power losses during all steps of the optimal path is 9265.5 kW.

Figure 4.21 shows the voltage profile during the optimal path sequence of switching. It is clear that the best switching sequence path resulted in minimum bus voltage larger than the initial case.

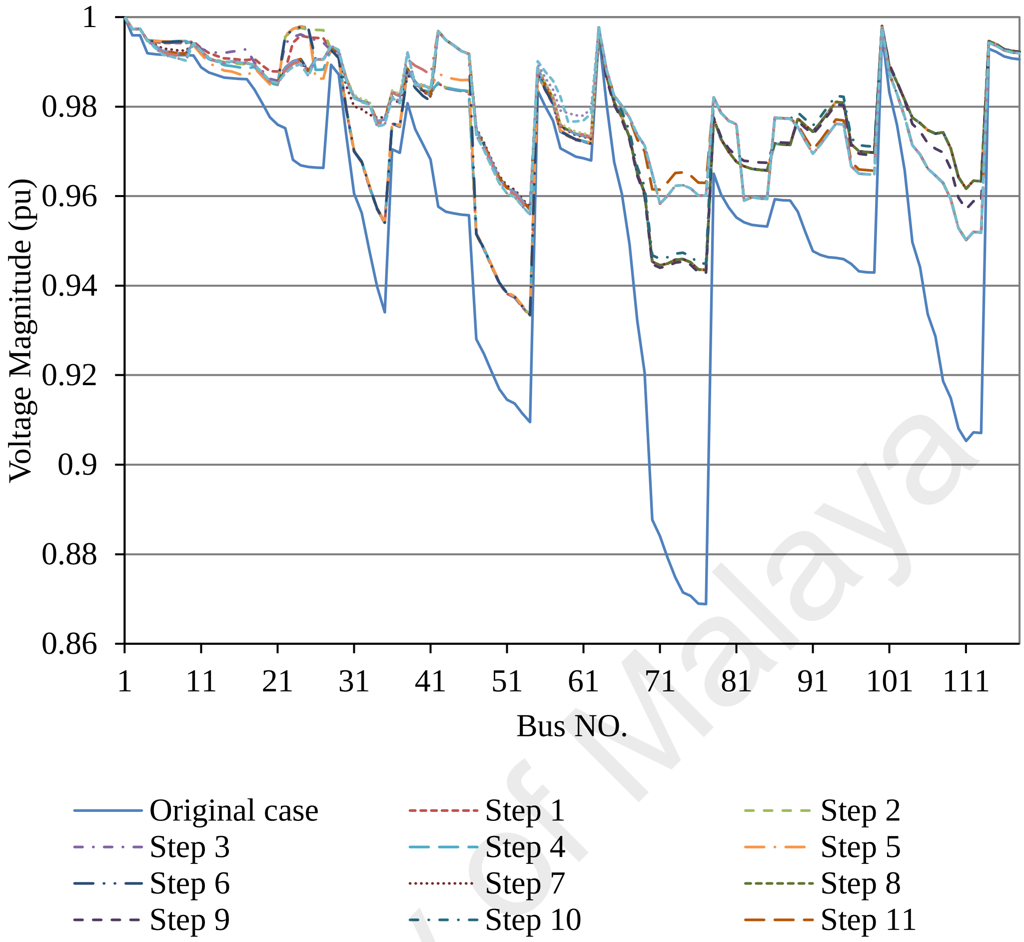

Figure 4.21: Voltage profile of 118-bus radial distribution network for all switching changing steps

4.5.2.2 Validation of performance of FA algorithm for switching sequence process

To validate the results, different random sequence cases are presented in Table 4.21 using FA. Any random case produced larger power losses or bus voltage value exceeding its limitations, or both.

Table 4.21: Comparison of simulation result between the proposed method and random cases for IEEE 118-bus network

Case	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Power Losses (kW)
Optimal switching sequence path using FA	1	120 close	0.93329(54)- 1(1)	9265.5
	2	21 open	0.93347(54)- 1(1)	
	3	119 close	0.93332(54)- 1(1)	
	4	25 open	0.93349(54)- 1(1)	
	5	118 close	0.93362(54)- 1(1)	
	6	41 open	0.93344(54)- 1(1)	
	7	132 close	0.94352(77)- 1(1)	
	8	33 open	0.94352(77)- 1(1)	
	9	129 close	0.94292(77)- 1(1)	
	10	81 open	0.94492(77)- 1(1)	
	11	126 close	0.95021(111)- 1(1)	
	12	70 open	0.95021(111)- 1(1)	
	13	124 close	0.95021(111)- 1(1)	
	14	38 open	0.95021(111)- 1(1)	
	15	123 close	0.95021(111)- 1(1)	
	16	58 open	0.95021(111)- 1(1)	
Random case NO.1 using FA method	1	132 close	0.94352(77)- 1(1)	9305.4
	2	33 open	0.91741(54)- 1(1)	
	3	119 close	0.93909(54)- 1(1)	
	4	25 open	0.91935(54)- 1(1)	
	5	120 close	0.94352(77)- 1(1)	
	6	21 open	0.94352(77)- 1(1)	
	7	118 close	0.94352(77)- 1(1)	
	8	41 open	0.94352(77)- 1(1)	
	9	126 close	0.94352(77)- 1(1)	
	10	70 open	0.94352(77)- 1(1)	
	11	124 close	0.95584(54)- 1(1)	
	12	38 open	0.95584(54)- 1(1)	
	13	123 close	0.95584(54)- 1(1)	
	14	58 open	0.95584(54)- 1(1)	
	15	129 close	0.95584(54)- 1(1)	
	16	81 open	0.95021(111)- 1(1)	
Random case NO.2 using FA method	1	132 close	0.94352(77)- 1(1)	9359
	2	33 open	0.91741(54)- 1(1)	
	3	119 close	0.93909(54)- 1(1)	
	4	25 open	0.91935(54)- 1(1)	
	5	120 close	0.94352(77)- 1(1)	
	6	21 open	0.94352(77)- 1(1)	
	7	118 close	0.94352(77)- 1(1)	
	8	41 open	0.94352(77)- 1(1)	
	9	126 close	0.95704(54)- 1(1)	
	10	70 open	0.95965(54)- 1(1)	
	11	124 close	0.95565(54)- 1(1)	
	12	38 open	0.95584(54)- 1(1)	
	13	123 close	0.95584(54)- 1(1)	

Table 4.21: Continued

Case	Step NO.	Switching Sequence	Bus voltage (pu) (at bus) min max	Power Losses (kW)
	14	58 open	0. 95021 (54)- 1(1)	
	15	129 close	0. 95021 (54)- 1(1)	
	16	81 open	0.95021(111)- 1(1)	
Random case NO.3 using FA method	1	119 close	0.93311(54)- 1(1)	9282.8
	2	21 open	0.93311(54)- 1(1.0024)	
	3	120 close	0.93332(54)- 1(1)	
	4	25 open	0.93349(54)- 1(1)	
	5	118 close	0.93362(54)- 1(1)	
	6	41 open	0.93344(54)- 1(1)	
	7	132 close	0.94352(77)- 1(1)	
	8	33 open	0.94352(77)- 1(1)	
	9	129 close	0.94292(77)- 1(1)	
	10	81 open	0.94492(77)- 1(1)	
	11	126 close	0.95021(111)- 1(1)	
	12	70 open	0.95021(111)- 1(1)	
	13	124 close	0.95021(111)- 1(1)	
	14	38 open	0.95021(111)- 1(1)	
	15	123 close	0.95021(111)- 1(1)	
	16	58 open	0.95021(111)- 1(1)	
Random case NO.4 using FA method	1	132 close	0.94352(77)- 1(1)	9301.1
	2	33 open	0.91741(54)- 1(1)	
	3	119 close	0.93909(54)- 1(1)	
	4	25 open	0.91935(54)- 1(1)	
	5	120 close	0.94352(77)- 1(1)	
	6	21 open	0.94352(77)- 1(1)	
	7	118 close	0.94352(77)- 1(1)	
	8	41 open	0.94352(77)- 1(1)	
	9	126 close	0.95704(54)- 1(1)	
	10	70 open	0.95965(54)- 1(1)	
	11	123 close	0.95695(54)- 1(1)	
	12	58 open	0.95695(54)- 1(1)	
	13	124 close	0.9565(54)- 1(1)	
	14	38 open	0. 95584 (54)- 1(1)	
	15	129 close	0. 95584 (54)- 1(1)	
	16	81 open	0.95021(111)- 1(1)	

4.6 Validation of Switching Sequence Process Based on Real Time Analysis

The voltage stability of the system during switching process was validated using the PSCAD/EMTDC software. The IEEE 33-bus system was selected as the test system for the switching process.

4.6.1 Switching Sequence Process Considering DGs

It can be seen from Table 4.10 that the GSA algorithm reported the optimal solution for the switching sequence process. The obtained best sequence switching using GSA is:

Sequence 1: Sw36 (Close) → Sequence 2: Sw32 (Open),

Sequence 3: Sw35 (Close) → Sequence 4: Sw9 (Open),

Sequence 5: Sw37 (Close) → Sequence 6: Sw28 (Open),

Sequence 7: Sw33 (Close) → Sequence 8: Sw7 (Open),

Sequence 9: Sw34 (Close) → Sequence 10: Sw13 (Open).

Figurer 4.22 shows the IEEE 33-Bus network that is used to apply the switching sequence path. The same switching sequence, number of DGs, and location with optimal output, as described for the GSA algorithm, were modeled. Each DG was connected to the network via a step-up transformer (3.3 kV/12.66 kV), rated 30 MVA each. Each of the three Mini Hydro DG units has a 2 MVA rated capacity, operating at a 3.3 KV voltage level. As pointed out previously, the system voltage is 12.66kV (1 pu), which means that the lower and the upper voltage should be between 12.027kV (0.95 pu) and 13.293kV (1.05 pu). The delay time, which includes the calculation and the sequential steps, and operation time of the circuit breaker, was assumed to be 100 ms, as per practical considerations (Committee, 2003).

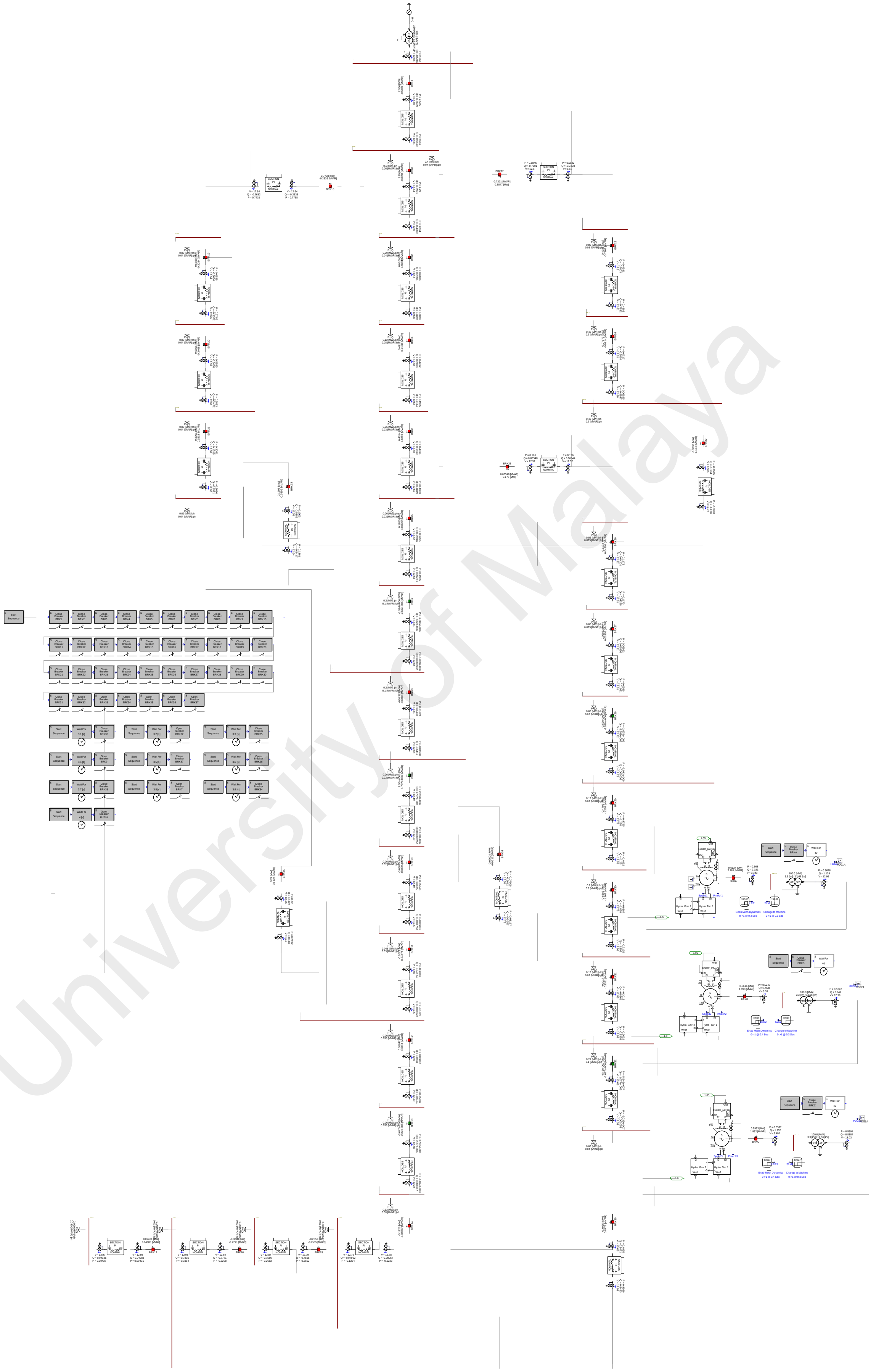

Figure 4.22: IEEE 33 bus system modelled in PSCAD/EMTDC software

Figure 4.23 shows the real-time voltage profile for the switching sequence process within DGs. The time is divided into three intervals:

a) Before the switching sequence process and with DGs, from (2.9s to <3.1s).
b) During the switching process within DGs, from (3.1s to 4.1s). Each step takes 100 ms, thus the switching process is completed after 1 s (i.e at 4.1s).
c) After the switching sequence completed within DGs (>4.1s).

It can be observed that by implementing the switching sequence process, the whole voltages at load buses comes within an allowable limit.

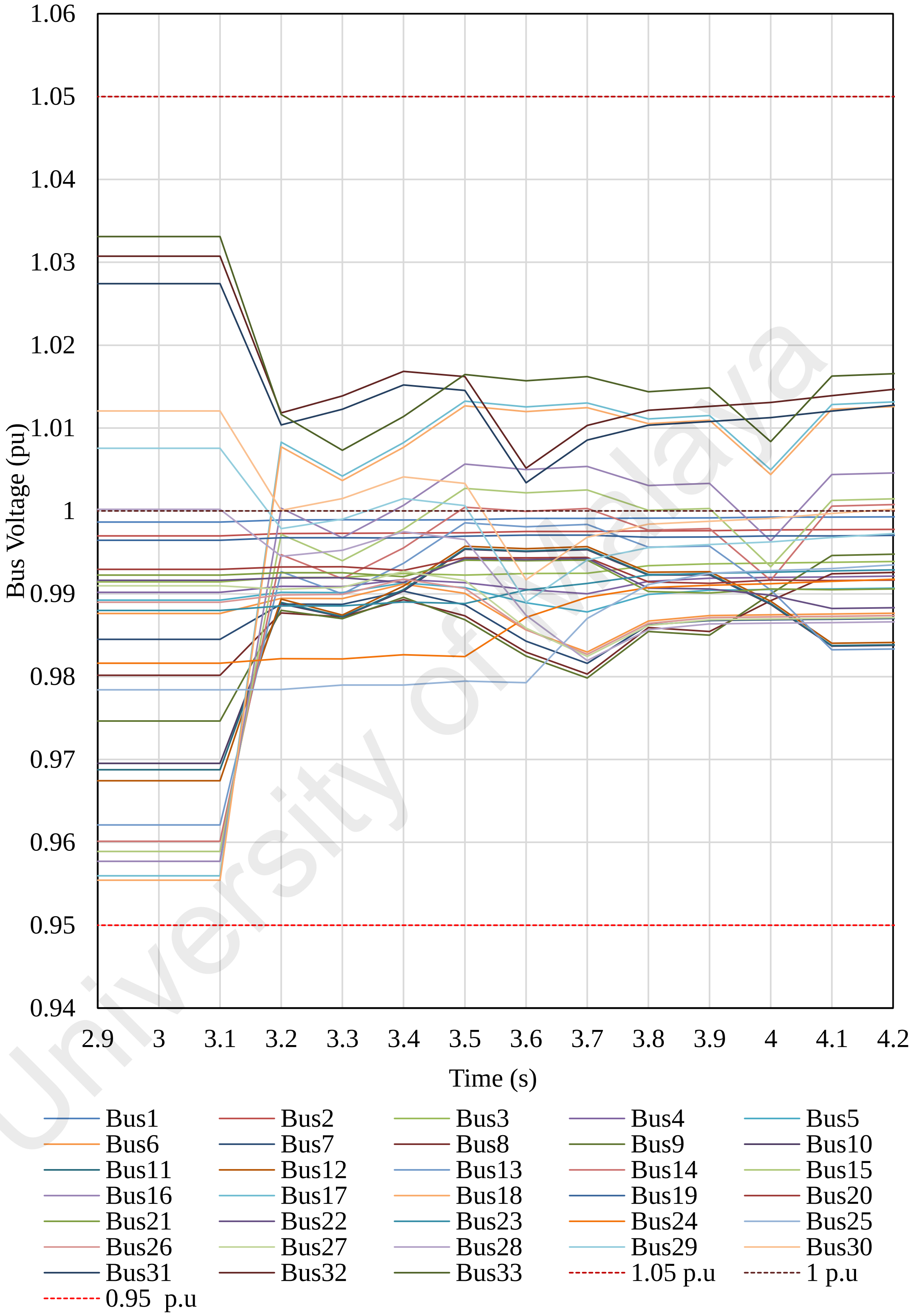

Figure 4.23: Real time voltage profile of 33 bus radial distribution network within DGs

4.6.2 Switching Sequence Process without DGs

Figure 4.24 shows the real-time voltage profile for the switching sequence process without DGs. The time is divided into three intervals:

a) Before the switching sequence process and without DGs, from (2.9s to <3.1s).

b) During the switching process without DGs, from (3.1s to 4.1s). Each step takes 100 ms, thus the switching process is completed after 1 s (i.e at 4.1s).

c) After the switching sequence finished without DGs (>4.1s).

It can be observed that the voltage for some buses is less than 0.95 p.u. before, during, and after the switching sequence process.

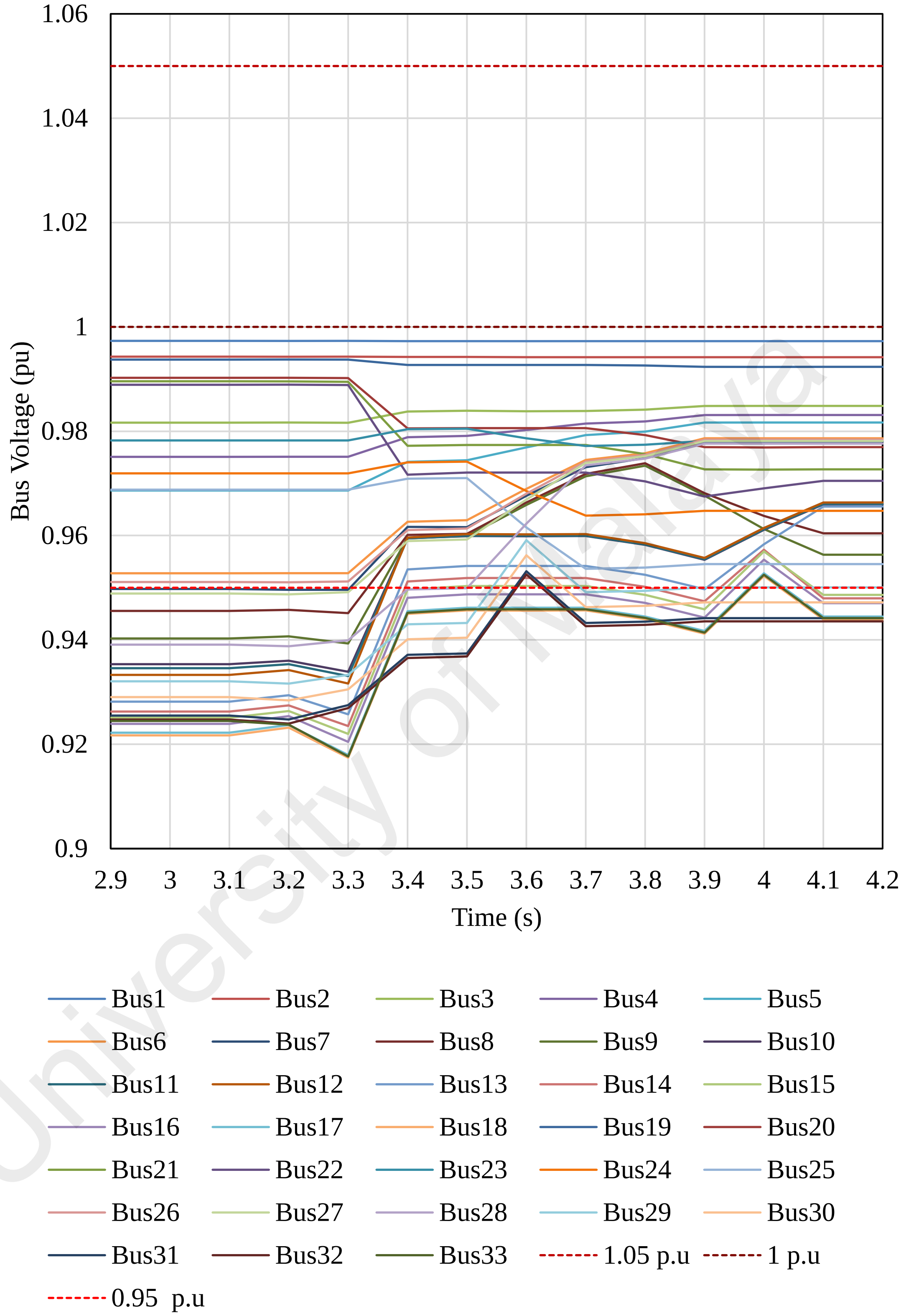

Figure 4.24: Real time voltage profile of 33 bus radial distribution network without DGs

4.6.3 Switching Sequence Process within DGs for Random Case

Figure 4.25 shows the real-time voltage profile for random switching sequence process with DGs. The time is divided into three intervals:

a) Before the switching sequence process with DGs, from (2.8s to <3.1s).
b) During the switching process without DGs, from (3.1s to 4.1s). Each step takes 100 ms, thus the switching process is completed after 1 s (i.e at 4.1s).
c) After the switching sequence is completed, with DGs (>4.1s).

It can be observed that for the random switching sequence, the voltage for some buses are less than 0.95 pu, or larger than 1.05 pu during the switching sequence process. This means that it is essential to determine the switching sequence carefully to avoid overvoltage in the system.

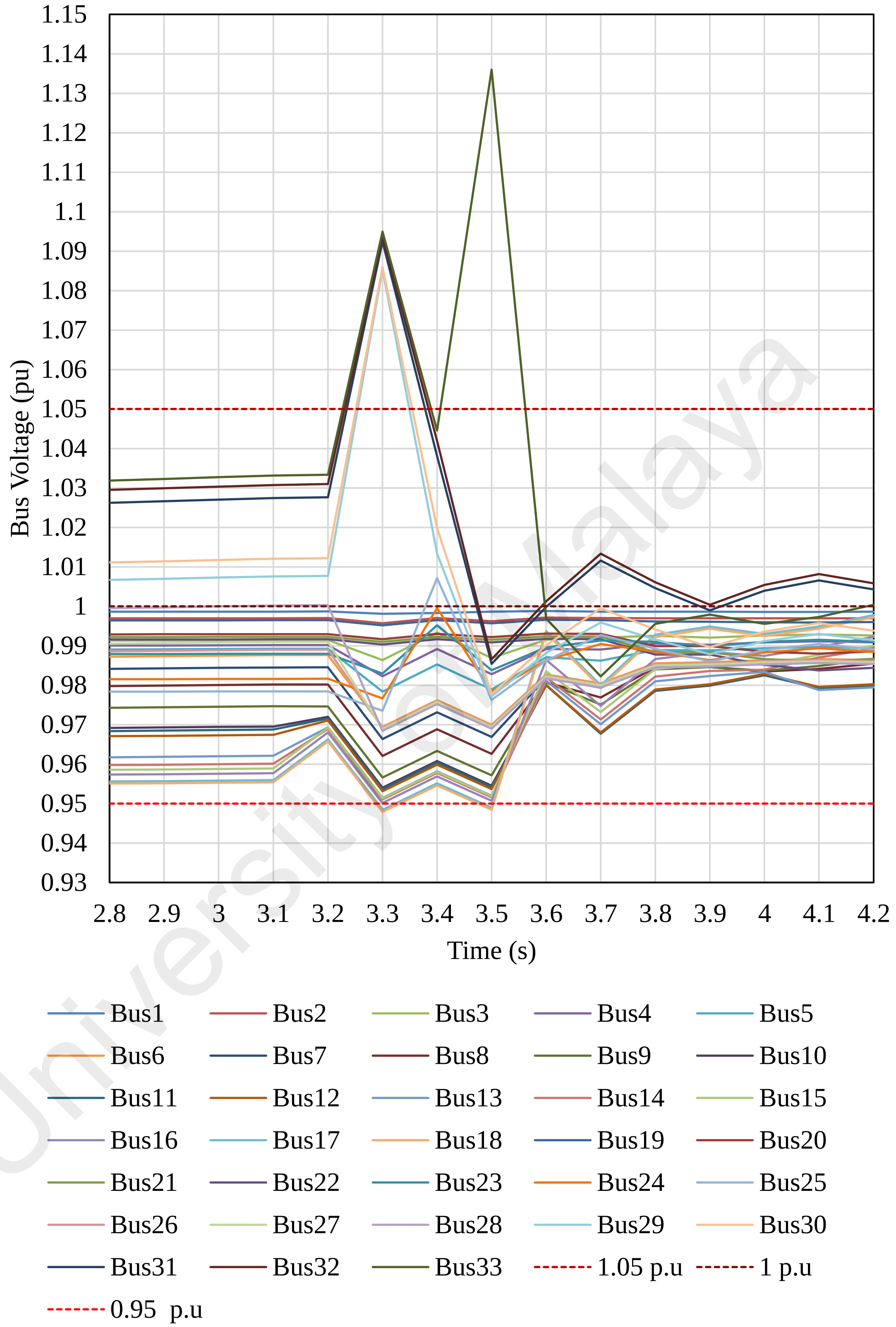

Figure 4.25: Real time voltage profile of 33 bus radial distribution network with DGs for random switching sequence case

4.7 Summary

The performance of the proposed methods has been tested using IEEE 16-bus, IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus systems. The presented approach is of high quality and robustness towards realizing an optimal network configuration and DG output. The results proved that the optimal reconfiguration within the optimal DG output minimized power losses and improve the overall systems' voltage profile. The presented approach is also of high quality when it comes to realizing an optimal switching changing path. Furthermore, it can also be surmised that the proposed method (FA) always report the highest power loss reduction and best voltage profile compared to that of EP, PSO, and GSA. The real-time analysis test using PSCAD/EMTDC software proved that the optimal switching sequence does not cause over voltage or under voltage when implemented in real-time conditions.

CHAPTER 5: APPLICATION OF THE PROPOSED METHOD FOR DAILY OPERATION PLANNING

5.1 Introduction

The performance of the proposed method in solving network reconfiguration and DG output generation simultaneously and switching sequence process is presented in this chapter. Different types of DGs and load profile are applied based on the one-day data to minimize total daily power loss of a distribution system during switching sequence and for the final state. The effectiveness of the proposed methods is demonstrated on a standard IEEE 33 bus test system. The results obtained are compared to existing meta-heuristic methods. The main consideration in the comparison of the proposed methods with the existing method is power loss reduction. The impact of the proposed methods to the overall voltage profiles is also presented in this chapter.

5.2 Application of Daily Distribution Planning Via Proposed Method

The proposed method for EP, PSO, GSA, and FA were detailed in Section 3.3. The following conditions were taken into consideration in the tests:

a) Load profiles
b) DG output generation
c) DG operating mode
d) DG types

Here, the PV generation output based on the solar irradiance was taken from Kuantan in 2008 from the Malaysia Meteorological Department. The peak load per unit of 24 hours is shown in Figure 5.1, as per (Ing, Mokhlis, Illias, Aman, & Jamian, 2015). The value of PV generation output of a day is shown in Figure 5.2, as per (JALAN, 2014).

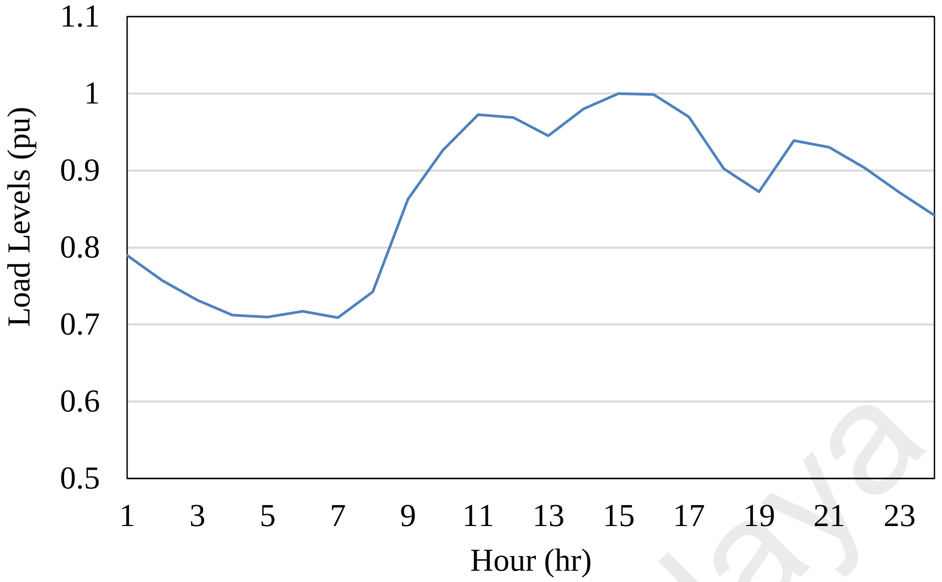

Figure 5.1: Hourly load profile for individual loads

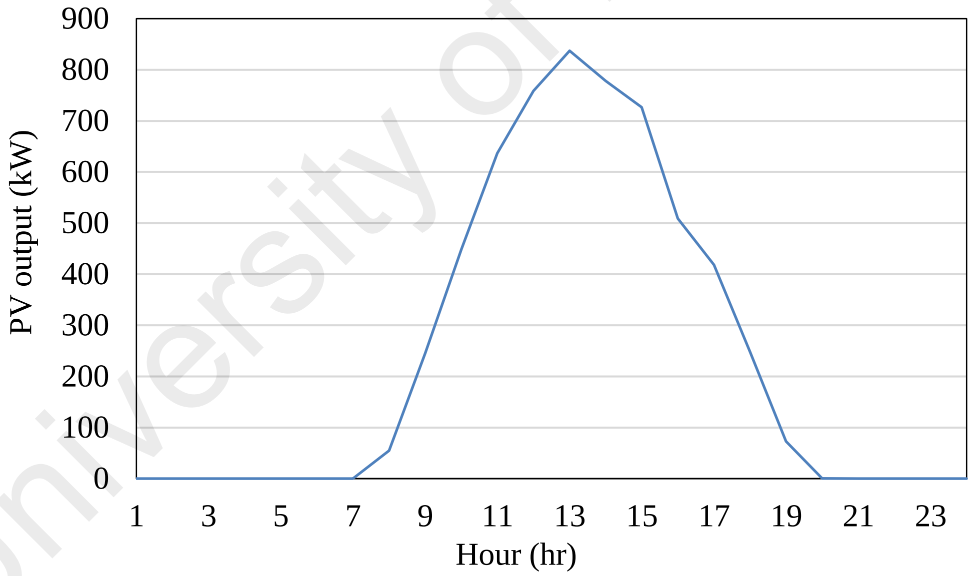

Figure 5.2: Hourly PV power production

The objective function of the proposed method is to minimize the total daily power loss and improve voltage profiles.

5.3 Simulation Results and Analysis

The IEEE 33-BUS system was used. The DGs in this test system was assumed to be mini-hydro, biomass, and PV generation. The maximum capacity for each DG was 2 MW. In this work, the optimal locations for the DGs were located at buses 31, 32, and 33. This location is based on (Rao et al., 2013). The biomass and mini-hydro DGs operated in the PQ mode (which means that the DG generates constant real and reactive powers). Active power was obtained by optimization, while it assumes that no reactive power was injected into the grid, while the photovoltaic unit operates on a PV mode (that means, the DG generates specific active power and bus voltage). This DG model was based on (Ing et al., 2016). The bus voltage was fixed at 1 p.u.

5.3.1 Simultaneously Network Reconfiguration and DG Output

This section focuses on power loss reduction and voltage profile improvement via simultaneously network reconfiguration and DG outputs.

5.3.1.1 Impact of simultaneous network reconfiguration and DG output generation on power losses

The proposed method looks for the best configuration that can realize the lowest daily power losses and best voltage profile at any hour of the day. Table 5.1 summarizes the test results for EP, PSO, GSA, and FA. Since a day is made up of 24 hours, instead of finding different configurations at each hour, the proposed method looks for one solution that best represents any hour of the day. Based on that, the main fitness function F, as per equation 3.38, is evaluated for a 24 hours slot, which is equal to 2.4491 after reconfiguration, while before reconfiguration, its 12.039. The daily power losses after network reconfiguration with DG during 24 hours was 747.76 kWh, obtained by using FA, while before reconfiguration, its 3622.7 kWh, which means that power losses were reduced by 2874.94 kWh i.e. ~79.36% reduction compared to its initial state. The normally open switches after reconfiguration were 8, 9, 12, 26, and 33, as shown in Figure 5.3, while before reconfiguration, they were 33, 34, 35, 36, and 37. The DG1 output was 0.832 MW; DG2 output was shown in Figure 5.2, and that of DG3 was 0.47 MW. DG type, DG mode, and DG location are also presented in the table. The computation time taken for using FA is 3815.1 s, at an iteration of 300 based on a population of 100, which is larger than that of the other algorithms, except EP. It can also be seen that the power losses at any hour after the reconfiguration process are lower than the power losses before the reconfiguration process, as shown in Figure 5.4.

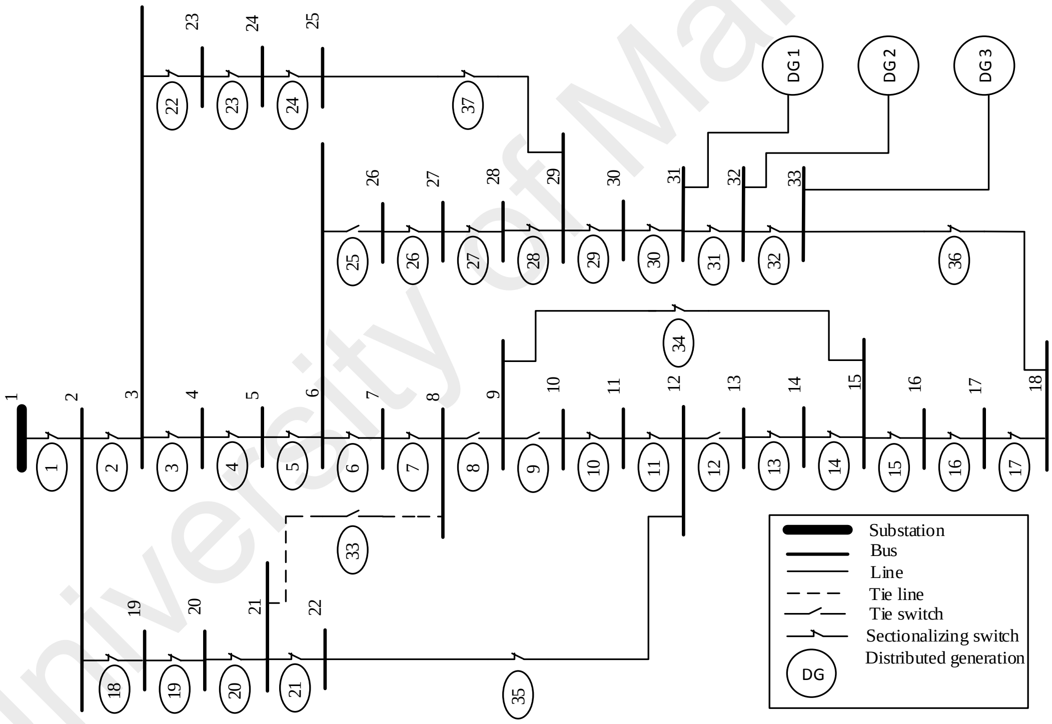

Figure 5.3: IEEE 33-bus distribution network after reconfiguration process

Table 5.1: Network reconfiguration and DG output results per day for IEEE 33-bus network

Case	Open switches	DG output in MW	DG Type	DG Mode	DG Location	Reconfiguration fitness function $F = \sum_{hr}^{T}(w_1 \times P_{loss}^{R} + w_2 \times si)$	Total Daily Power Loss (kWh) for 24 hr	Power Reduction (%)	CPU Time (s)
Initial	33, 34, 35, 36, 37	No DG	------------	-------	---------	12.039	3622.7	---------	2.115
EP	9, 12, 25, 32, 33	DG1= 0.882 DG2= Based on sun radiations DG3= 0.518	Biomass Photovoltaic Mini hydro	PV PQ PV	31 32 33	2.5113	769.93	78.747	7656.2
PSO	8, 10, 12, 25, 33	DG1= 0.866 DG2= Based on sun radiations DG3= 0.568	Biomass Photovoltaic Mini hydro	PV PQ PV	31 32 33	2.4709	750.65	79.279	3706.4
GSA	8, 11, 13, 25, 33	DG1= 0.864 DG2= Based on sun radiations DG3= 0.503	Biomass Photovoltaic Mini hydro	PV PQ PV	31 32 33	2.5004	748.88	79.328	2482.9
FA	8, 9, 12, 26, 33	DG1= 0.832 DG2= Based on sun radiations DG3=0.47	Biomass Photovoltaic Mini hydro	PV PQ PV	31 32 33	2.4491	747.76	79.359	3815.1

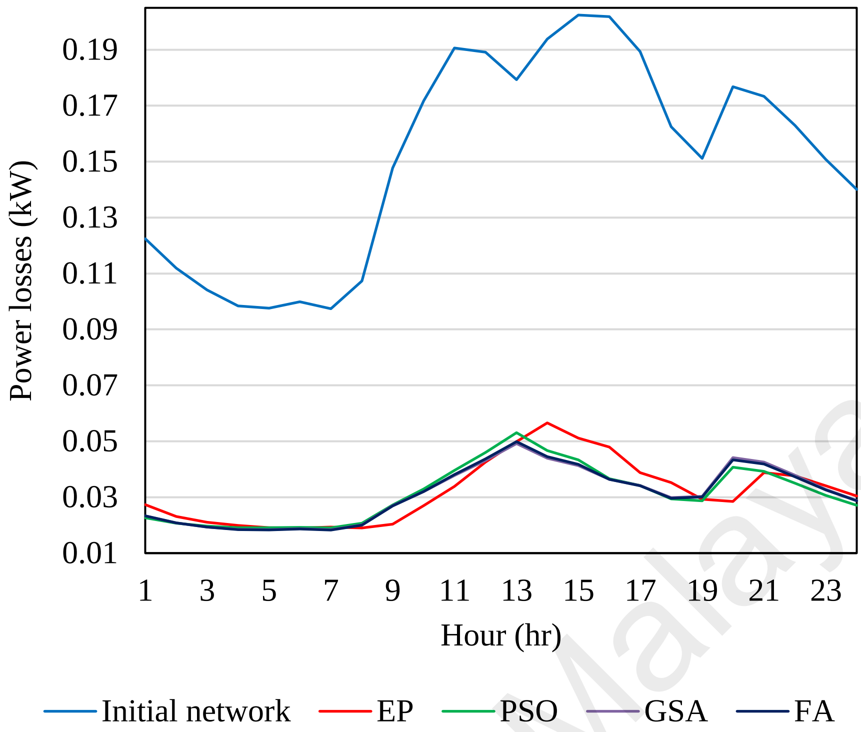

Figure 5.4: Power losses per hour before and after reconfiguration process for IEEE 33-bus network

5.3.1.2 Impact of simultaneous network reconfiguration and DG output generation on voltage profile

Figure 5.5 shows the minimum values of voltage profile (pu) for radial distribution network at any hour of the day. All minimum values of the buses voltage magnitude at any time is larger than its initial state.

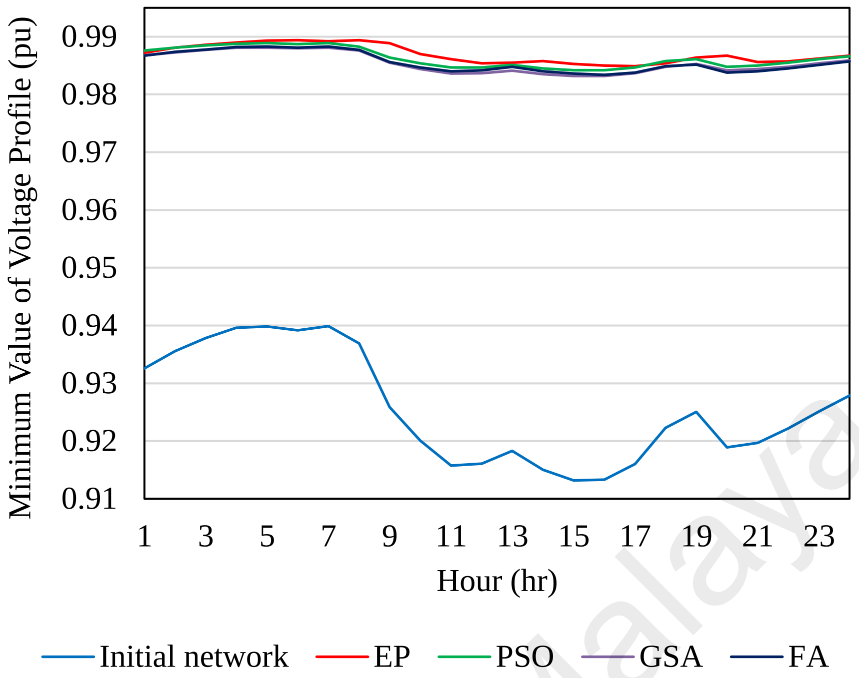

Figure 5.5: Daily minimum value pf voltage profile (pu) for radial distribution network for IEEE 33-bus network

5.3.1.3 Analysis of overall performance for simultaneous network reconfiguration and DG output generation

To prove the validity of the proposed method with DG output, considering load profile and different type of DGs, the robustness test was carried out for the proposed method using the different algorithms, and the result compared and shown in Figure 5.6 for 20 runs. It is evident that the GSA or FA reported almost equal results in each run and the minimum value of standard deviation compared to the other algorithms, as shown in Table 5.2. This means that the GSA and FA are highly robust compared to EP and PSO. In the case of each algorithm, there is a global optimal value representing the minimum value during simulation of the program, which are 2.5113, 2.4709, 2.5004, and 2.4491 for EP, PSO, GSA, and FA, respectively.

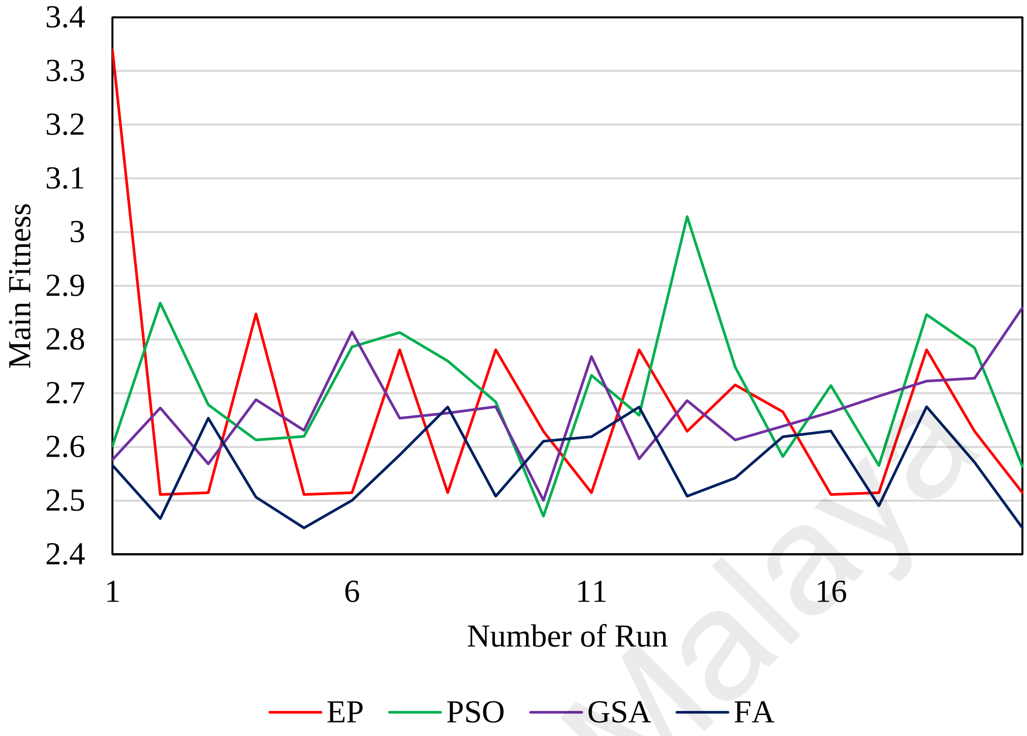

Figure 5.6: Comparison of robustness test of the simultaneous reconfiguration and optimal DG output algorithms per day for IEEE 33-bus network

Table 5.2: Statistical analysis results for robustness test for network reconfiguration and DG output generation process for IEEE 33-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	2.5113	3.339539	2.660076	0.199267
PSO	2.4709	3.028863	2.706054	0.129956
GSA	2.5004	2.85916	2.669745	0.084667
FA	2.4491	2.674791	2.564823	0.077152

Based on the global cases for each algorithm, the convergence performance for these values were also compared, and the results shown in Figure 5.7. It can be seen that the FA reported the minimum value for the reconfiguration fitness relative to that of the other algorithms.

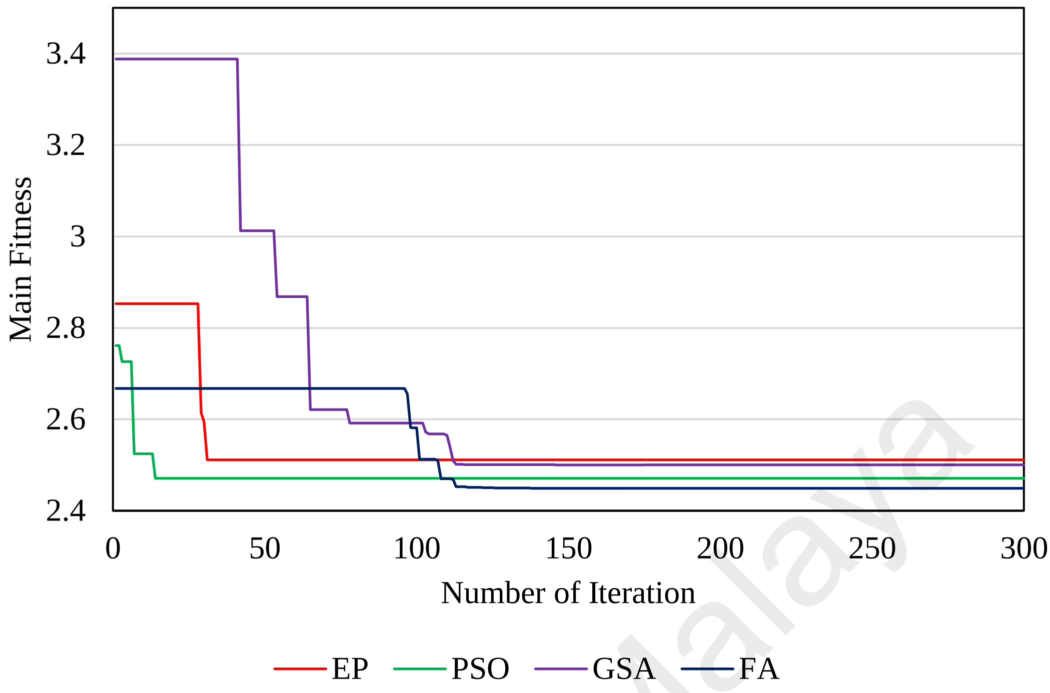

Figure 5.7: Comparison of convergence performance of the simultaneous reconfiguration and optimal DG output algorithms per day for IEEE 33-bus network

The performance of the proposed method was compared to that of published results with similar DG unit's locations, as per Table 5.3. It is evident that the proposed method, based on EP, PSO, GSA, and FA, are better than GSA and ICA.

Table 5.3: Comparison of simulation result of 33-bus system considering variable loads

Method	Open Switches	Total daily Power Losses (kWh)	Total daily Power Losses Reduction (%)
GSA (Ing et al., 2016)	32, 7, 33, 13, 26	915.91	74.717
ICA (Ing et al., 2016)	33, 21, 13, 25, 32	915.65	74.725
Proposed (EP)	9, 12, 25, 32, 33	769.93	78.747
Proposed (PSO)	8, 10, 12, 25, 33	750.65	79.279
Proposed (GSA)	8, 11, 13, 25, 33	748.88	79.328
Proposed (FA)	8, 9, 12, 26, 33	747.76	79.360

5.3.2 Optimal Switching Sequence Path Process

This section focuses on power loss reduction and voltage profile improvement via simultaneously network reconfiguration and DG outputs.

5.3.2.1 Impact of switching sequence path process on power losses

The optimal solution of network reconfiguration and DG output obtained from the first section were used to find the best switching sequence path to transfer the network from its initial state (33, 34, 35, 36, 37) to its final state (8, 9, 12, 26, 33) at any time. From Table 5.4, the obtained best switching sequence path using FA is:

Sequence 1: Sw36 (close) → Sequence 2: Sw9 (open),

Sequence 3: Sw357 (close) → Sequence 4: Sw26 (open),

Sequence 5: Sw35 (close) → Sequence 6: Sw12 (open),

Sequence 7: Sw34 (close) → Sequence 8: Sw8 (open),

Sw33 (NC).

This means that the optimal switching sequence path minimizes the total power losses during all steps at any time. Practically, the state of the switches is changed manually, which require ~15 minutes. This will result in energy losses, as outlined in the same table. According to the proposed method, the optimal fitness for switching sequence path is 21.444. The summation of the power losses during all steps of the optimal path when the voltage level is maximum, minimum, and middle are also outlined in the table. When the load level is minimum (7 hours), the summation of power losses during the steps is 157.9 kW, and the energy is 330.5 kWh, while when the load level is in the middle (9 hours), the summation of the power losses during all steps is 232.83 kW, and the energy is 465.66

kWh. When the load level is maximum (15 hours), the summation of the power losses during all steps is 355.74 kW, and the energy is 711.48 kWh.

Table 5.4: Switching sequence results for IEEE 33-bus network

Proposed Method	Step NO.	Switching Sequence	Sequence fitness function	Load levels	hr	Power losses (kW)	Energy losses (kWh)
EP	1 2 3 4 5 6 7 8	36 close 9 open 35 close 12 open 37 close 25 open 34 close 32 open 33 NC	22.538	Minimum value	7	186.69	373.38
				Average value	9	260.55	521.1
				Maximum value	15	447.13	894.26
PSO	1 2 3 4 5 6 7 8	36 close 10 open 37 close 25 open 35 close 12 open 34 close 8 open 33 NC	21.823	Minimum value	7	175.76	351.52
				Average value	9	246.67	493.34
				Maximum value	15	404.76	809.52

Table 5.4: Continued

Proposed Method	Step NO.	Switching Sequence	Sequence fitness function	Load levels	hr	Power losses (kW)	Energy losses (kWh)
GSA	1 2 3 4 5 6 7 8	36 close 11 open 37 close 25 open 34 close 8 open 35 close 13 open 33 NC	22.223	Minimum value	7	165.25	330.5
				Average value	9	240.43	480.86
				Maximum value	15	373.47	746.94
FA	1 2 3 4 5 6 7 8	36 close 9 open 37 close 26 open 35 close 12 open 34 close 8 open 33 NC	21.444	Minimum value	7	157.9	315.8
				Average value	9	232.83	465.66
				Maximum value	15	355.74	711.48

5.3.2.2 Impact of switching sequence path process on voltage profile

Table 5.5 shows the minimum/maximum values of the voltage profile during the steps of the optimal path sequence of switching at different hours. At each hour, there are 8 lines that represent the minimum values of the buses voltages during the switching sequence process. It is clear that the best switching sequence path does not cause the voltage profile to exceed its allowable limit (less than 0.95 pu and larger than 1.05 pu).

Table 5.5: Minimum and Maximum Values of Voltage Profile for each Step per hr (pu) for 33 bus radial network

Proposed Method	Step NO.	Minimum value of load profile		Average value of load profile		Maximum value of load profile	
		Min value of voltage profile (hr=7)	Max value of voltage profile (hr=7)	Min value of voltage profile (hr=9)	Max value of voltage profile (hr=9)	Min value of voltage profile (hr=15)	Max value of voltage profile (hr=15)
EP	1	0.9852	1	0.9818	1	0.9791	1.0004
	2	0.9852	1	0.9819	1	0.9790	1.0004
	3	0.9852	1	0.9818	1	0.9791	1.0004
	4	0.9853	1	0.9819	1	0.9792	1.0005
	5	0.9875	1	0.9847	1	0.9825	1.0005
	6	0.9877	1	0.9849	1	0.9828	1.0005
	7	0.9894	1	0.9870	1	0.9850	1.0004
	8	0.9894	1	0.9870	1	0.9850	1.0008
PSO	1	0.9852	1	0.9818	1	0.9791	1.0004
	2	0.9852	1	0.9818	1	0.9791	1.0004
	3	0.9861	1	0.9829	1	0.9804	1.0004
	4	0.9860	1	0.9829	1	0.9804	1.0004
	5	0.9860	1	0.9829	1	0.9803	1.0004
	6	0.9861	1	0.9829	1	0.9804	1.0005
	7	0.9889	1	0.9863	1	0.9845	1.0004
	8	0.9889	1	0.9864	1	0.9842	1.0004

Table 5.5: Continued

Proposed Method	Step NO.	Minimum value of load profile		Average value of load profile		Maximum value of load profile	
		Min value of voltage profile (hr=7)	Max value of voltage profile (hr=7)	Min value of voltage profile (hr=9)	Max value of voltage profile (hr=9)	Min value of voltage profile (hr=15)	Max value of voltage profile (hr=15)
GSA	1	0.9851	1	0.9818	1	0.9791	1.0004
	2	0.9850	1	0.9816	1	0.9789	1.0004
	3	0.9846	1	0.9812	1	0.9784	1.0004
	4	0.9844	1	0.9809	1	0.9781	1.0004
	5	0.9870	1	0.9840	1	0.9819	1.0004
	6	0.9853	1	0.9820	1	0.9791	1.0004
	7	0.9881	1	0.9855	1	0.9832	1.0004
	8	0.9881	1	0.9855	1	0.9832	1.0004
FA	1	0.9851	1	0.9817	1	0.9790	1.0004
	2	0.9851	1	0.9818	1	0.9790	1.0004
	3	0.9852	1	0.9819	1	0.9790	1.0004
	4	0.9852	1	0.9819	1	0.9790	1.0004
	5	0.9869	1	0.9840	1	0.9816	1.0004
	6	0.9870	1	0.9840	1	0.9817	1.0004
	7	0.9891	1	0.9866	1	0.9849	1.0004
	8	0.9883	1	0.9856	1	0.9836	1.0004

5.3.2.3 Analysis of overall performance for switching sequence path process

To prove the validity of the best switching sequence, the robustness test was conducted on the proposed method using EP, PSO, GSA, and FA, and the results compared and presented in Figure 5.8 for 20 runs. It is evident that GSA or FA reported results that are almost equal in each run with the smallest standard deviation compared to the other algorithms, as per Table 5.6. This means that the GSA and FA algorithm are highly robust and realizes a great level of consistency in its outputs. The minimum value for each algorithm during the simulation is taken as its global optimal result. Furthermore, the conversion performance for these global cases for the algorithms were compared, and the result of this comparison shown in Figure 5.9. It is evident that the FA reported the minimum value of the main fitness function relative to that of other algorithms.

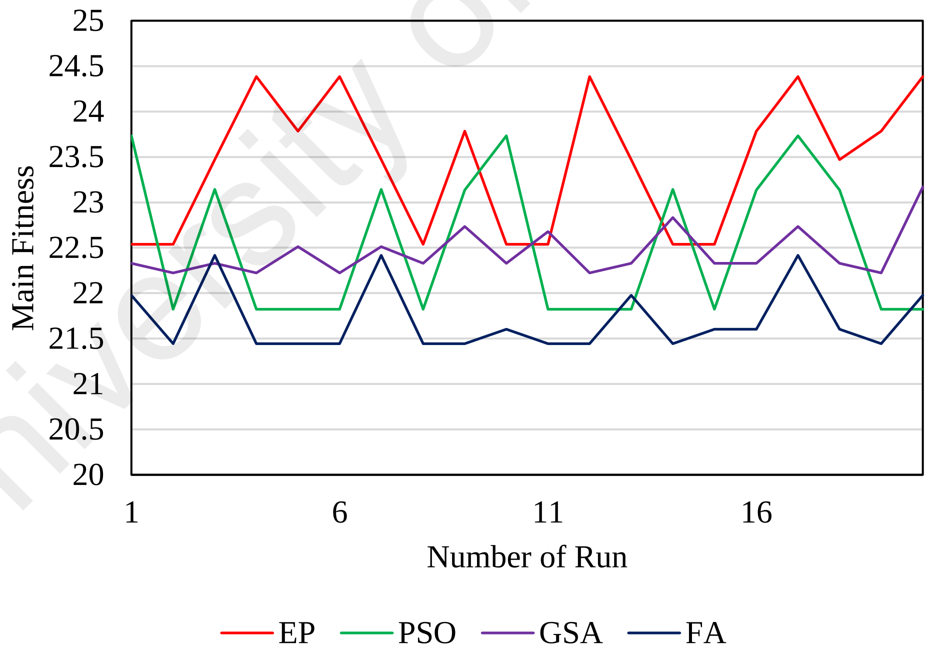

Figure 5.8: Comparison of robustness test of the switching sequence process algorithms per day for IEEE 33-bus network

Table 5.6: Statistical analysis results for robustness test for switching sequence process for IEEE 33-bus network

Proposed Method	Minimum value	Maximum value	Average value	Standard deviation
EP	22.53821	24.385	23.43562	0.748052
PSO	21.82302	23.73329	22.50465	0.796756
GSA	22.22331	23.16949	22.44587	0.257403
FA	21.44395	22.41662	21.70173	0.360225

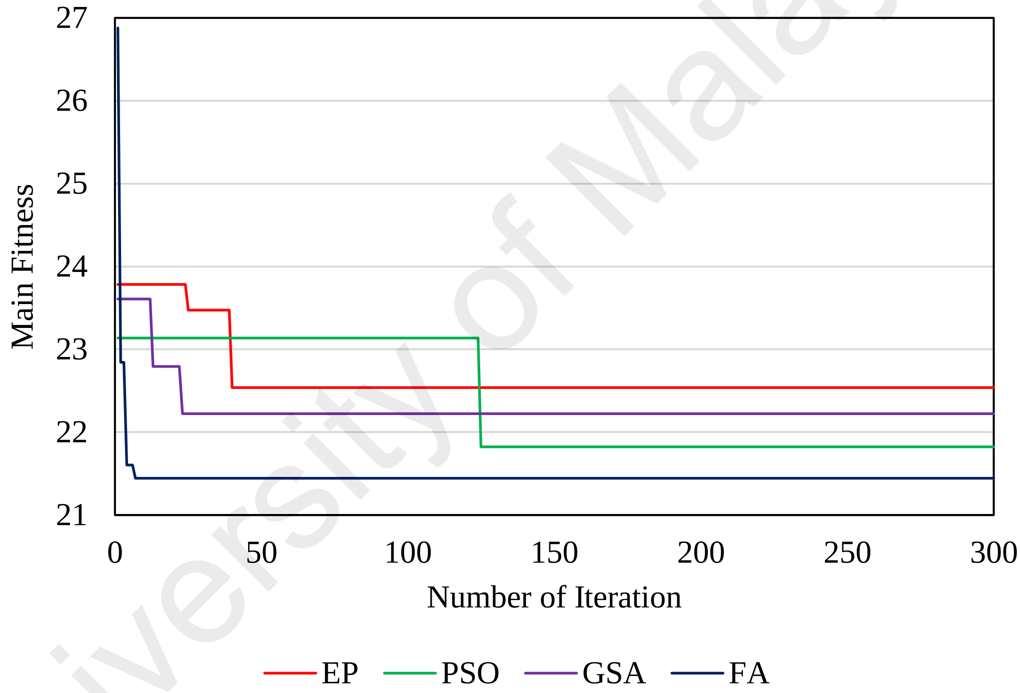

Figure 5.9: Comparison of convergence performance of the switching sequence process algorithms per day for IEEE 33-bus network

The results were further validated using random sequence cases, as presented in Tables 5.7 and 5.8. These cases were randomly selected, and from the Tables, any random case could report larger power losses compared to the proposed method or bus voltage value exceeding its limitations, or both.

Table 5.7: Comparison of simulation result between the proposed method and random cases for IEEE 33-bus network

<table>
<tr><th>Case</th><th>Step NO.</th><th>Switching Sequence</th><th>Load levels</th><th>hr</th><th>Power losses (kW)</th><th>Energy losses (kWh)</th></tr>
<tr><td rowspan="3">Random case using EP</td><td rowspan="3">1st step
2nd step
3rd step
4th step
5th step
6th step
7th step
8th step</td><td rowspan="3">36 close
12 open
35 close
9 open
37 close
25 open
34 close
32 open
33 NC</td><td>Minimum value</td><td>7</td><td>196.2</td><td>392.4</td></tr>
<tr><td>Average value</td><td>9</td><td>271.9</td><td>543.8</td></tr>
<tr><td>Maximum value</td><td>15</td><td>475.4</td><td>950.8</td></tr>
<tr><td rowspan="3">Random case using PSO</td><td rowspan="3">1st step
2nd step
3rd step
4th step
5th step
6th step
7th step
8th step</td><td rowspan="3">37 close
25open
36 close
10 open
35 close
12 open
34 close
8 open
33 NC</td><td>Minimum value</td><td>7</td><td>218.7</td><td>437.4</td></tr>
<tr><td>Average value</td><td>9</td><td>309.4</td><td>618.8</td></tr>
<tr><td>Maximum value</td><td>15</td><td>495.6</td><td>991.2</td></tr>
<tr><td rowspan="3">Random case using GSA</td><td rowspan="3">1st step
2nd step
3rd step
4th step
5th step
6th step
7th step
8th step</td><td rowspan="3">37 close
25 open
36 close
11 open
34close
8 open
35 close
13 open
33 NC</td><td>Minimum value</td><td>7</td><td>204.6</td><td>409.2</td></tr>
<tr><td>Average value</td><td>9</td><td>298.5</td><td>597</td></tr>
<tr><td>Maximum value</td><td>15</td><td>457.7</td><td>915.4</td></tr>
<tr><td rowspan="3">Random case using FA</td><td rowspan="3">1st step
2nd step
3rd step
4th step
5th step
6th step
7th step
8th step</td><td rowspan="3">37 close
26 open
36 close
9 open
35 close
12 open
34 close
8 open
33 NC</td><td>Minimum value</td><td>7</td><td>199.5</td><td>399</td></tr>
<tr><td>Average value</td><td>9</td><td>293.2</td><td>586.4</td></tr>
<tr><td>Maximum value</td><td>15</td><td>452.8</td><td>905.6</td></tr>
</table>

Table 5.8: Minimum and Maximum Values of Voltage Profile for each Step per hr (pu) for 33 bus radial network for random cases

Proposed Method	Step NO.	Switching Sequence	Minimum value of load profile		Average value of load profile		Maximum value of load profile	
			Min value of voltage profile (hr=7)	Max value of voltage profile (hr=7)	Min value of voltage profile (hr=9)	Max value of voltage profile (hr=9)	Min value of voltage profile (hr=15)	Max value of voltage profile (hr=15)
Random case using EP	1	36 close	0.9852	1	0.9818	1	0.9791	1.0004
	2	12 open	0.9835	1	0.9797	1	0.9767	1.0005
	3	35 close	0.9852	1	0.9819	1	0.9791	1.0005
	4	9 open	0.9853	1	0.9819	1	0.9792	1.0005
	5	37 close	0.9875	1	0.9847	1	0.9825	1.0005
	6	25 open	0.9877	1	0.9849	1	0.9828	1.0005
	7	34 close	0.9894	1	0.9870	1	0.9850	1.0004
	8	32 open	0.9894	1	0.9870	1	0.9850	1.0008
Random case using PSO	1	37 close	0.9603	1	0.9512	1.0001	**0.9433**	1.0006
	2	25 open	0.9579	1	**0.9482**	1.0001	**0.9398**	1.0006
	3	36 close	0.9867	1	0.9837	1	0.9814	1.0004
	4	10 open	0.9860	1	0.9829	1	0.9804	1.0004
	5	35 close	0.9860	1	0.9829	1	0.9803	1.0004
	6	12 open	0.9861	1	0.9829	1	0.9804	1.0005
	7	34 close	0.9889	1	0.9863	1	0.9845	1.0004
	8	8 open	0.9889	1	0.9864	1	0.9842	1.0004

Table 5.8: Continued

Proposed Method	Step NO.	Switching Sequence	Minimum value of load profile		Average value of load profile		Maximum value of load profile	
			Min value of voltage profile (hr=7)	Max value of voltage profile (hr=7)	Min value of voltage profile (hr=9)	Max value of voltage profile (hr=9)	Min value of voltage profile (hr=15)	Max value of voltage profile (hr=15)
Random case using GSA	1	37 close	0.9602	1	0.9511	1.0001	**0.9433**	1.0006
	2	25 open	0.9578	1	**0.9482**	1.0001	**0.9398**	1.0006
	3	36 close	0.9866	1	0.9836	1	0.9813	1.0004
	4	11 open	0.9844	1	0.9809	1	0.9781	1.0004
	5	34 close	0.9870	1	0.9840	1	0.9819	1.0004
	6	8 open	0.9853	1	0.9820	1	0.9791	1.0004
	7	35 close	0.9881	1	0.9855	1	0.9832	1.0004
	8	13 open	0.9881	1	0.9855	1	0.9832	1.0004
Random case using FA	1	37 close	0.9601	1	0.9510	1.0001	**0.9432**	1.0006
	2	26 open	0.9571	1	**0.9473**	1.0001	**0.9388**	1.0006
	3	36 close	0.9861	1	0.9830	1	0.9807	1.0004
	4	9 open	0.9852	1	0.9819	1	0.9790	1.0004
	5	35 close	0.9869	1	0.9840	1	0.9816	1.0004
	6	12 open	0.9870	1	0.9840	1	0.9817	1.0004
	7	34 close	0.9891	1	0.9866	1	0.9849	1.0004
	8	8 open	0.9883	1	0.9856	1	0.9836	1.0004

5.4 Summary

A dynamic analysis with different DGs types and modes of operation has been performed. The proposed methods were applied to obtain an optimal configuration, DG output generation, and optimal switching sequence path setting for a day. Photovoltaic, biomass, and mini hydro DG were the types of DG considered for this study. The simulation results confirmed that it is important to consider the load profiles, DG output generation, DG type, and DG operating mode to decrease total daily power loss and improve the voltage profile in distribution operation planning. The simulation results also confirmed that the FA reported better results relative to that of EP, PSO, GSA and ICA in the context of finding the optimal switching sequence.

CHAPTER 6: CONCLUSIONS AND FUTURE WORKS

6.1 Conclusions

This work intended to solve the network reconfiguration and DG output generation simultaneously using different meta-heuristic techniques. An optimal switching sequence technique during network reconfiguration was also proposed. The proposed network reconfiguration and switching sequence caters practical conditions based on dynamic load profiles, DG output generation, various types of DGs, and DG operating modes in finding optimal daily solution. The EP, PSO, GSA, and FA are meta-heuristic methods that have been used by the proposed methods. This work was verified using an IEEE 16, 33, 69 and 118 test systems. These results were also compared to other published results. The objectives of this work have been successfully achieved.

In the first objective, the proposed method successfully obtained optimal network reconfiguration with optimal DGs generation output. The results reported high power loss reduction of 23.63%, 64.3%, 82.233%, and 55.97% for IEEE 16-bus, 33-bus, 69-bus, and 118-bus test systems, respectively. These values exceeded that reported by other works. The proposed method also produced better voltage profile compared to other published works. The minimum value of the buses voltages was 0.9757 p.u., 0.9750 p.u., 0.98176 p.u., and 0.9502 p.u. for IEEE-16 buses 33, 69, and 118, respectively.

For the second objective, the proposed method found the optimal switching sequence of the reconfiguration with its lowest power losses. The power losses during switching sequence process were 2280.3 kW, 785.76 kW, 365.52 kW, and 9265.5 kW for IEEE 16-bus, IEEE 33-bus IEEE, 69-bus, and IEEE 118-bus networks, respectively. These values were much lower compared to any other random switching sequence path. Furthermore, the optimal sequence keeps the buses voltages within allowable limit during the switching process. Meanwhile, random switching caused voltage violation during the switching changing process, which proved the importance of determining the optimal sequence of reconfiguration. This aspect has never been considered in any network reconfiguration methods. Furthermore, the proposed optimal switching method has also been tested using PSCAD/EMTDC in real-time conditions. It was found that the all of the voltages were within the allowable limit during the switching process.

For the third objective, optimum daily solution for network reconfiguration and DG output generation by considering load profiles and DG operating mode was analyzed. The proposed method was tested using a combination of photovoltaic operated in PQ mode, biomass operated in PV mode, and mini hydro operated in PV mode. The results confirmed that the DG operating mode impact the reconfiguration process for both total daily power loss reduction and voltage stability index. The total daily power losses reduction for IEEE 33-bus network was 79.36 %, compared to 74.717% reported by other works.

In the fourth objective, the proposed method of switching sequence path was applied, considering the combination of different DG types, DG operating modes (PQ and PV mode), load profiles, and DG output generation. The results confirmed that it is important to account for the DG operating mode in the switching sequence process for both the total daily power loss reduction and voltage stability index improvement. The energy losses during the switching sequence process when the load profile was average was 465.66 kWh for the IEEE 33-bus networks, which was lower compared to any of the random case of switching sequence path. Moreover, the voltage profile during switching sequence process was within the allowable limit compared to any random case of switching sequence.

6.2 Future Works

The analysis on network reconfiguration and DG based on the proposed method in this work can be further improved. Possible future works include:

1) In this work, the switches and sizes of the DG were searched together during simulation in order to obtain the optimal reconfiguration and optimal size of DG. It is recommended that the switch, DG output generation, and location of DG are combined in the same algorithm, which reduces the processing time due to the fact that it does not need to utilize other methods to determine the optimal location of DG.

2) It is suggested that the number of objective functions, such as minimizing the cost of energy generated by DGs and minimizing the total emissions produced by DGs and the grid be increased to obtain a more comprehensive result.

3) Besides 16-bus, 33-bus, 69-bus, and 118-bus systems, further work can explore much larger networks, such as 129-bus and 185-bus for network reconfiguration. Furthermore, practical load demands, such as residential or industrial load, could also be accounted for, which allows for efficiency and competency of the proposed methods to be observed and compared in greater details.

4) Other optimization techniques, such as Cuckoo Search (CS), Hybrid Intelligent System like Genetic-Fuzzy, or Genetic-Optimal Power Flow could also be explored in any future works involving network reconfiguration.

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