OPTIMAL DISTRIBUTION SYSTEM RECONFIGURATION INCORPORATING DISTRIBUTED GENERATION BASED ON SIMPLIFIED NETWORK APPROACH

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OPTIMAL DISTRIBUTION SYSTEM RECONFIGURATION INCORPORATING DISTRIBUTED GENERATION BASED ON SIMPLIFIED NETWORK APPROACH

ABSTRACT

Network Reconfiguration (NR) and Distributed Generation (DG) are well-accepted strategies to minimize power loss and voltage deviation in the Electrical Distribution Network (EDN). Since the NR problem contains a huge combinational search space, most researchers applied meta-heuristic methods to attain optimal NR solution. However, meta-heuristic methods do not always guarantee optimal solution and furthermore they consume huge processing time. This occurs mainly due to (1) random solution's initialization and (2) the verification of solution in each iteration to fulfill the operation constraints during the optimization process. Besides, solving the NR problem simultaneously with DG placement and sizing increases the computational burden due to increase of the search space. With the aim of reducing the computational time and improving the consistency in obtaining the optimal solution as well as minimizing power loss and voltage deviation of the EDN, this work proposes a new method based on a two-stage optimization. This method introduces a technique to simplify the network into a simplified network graph. Then, the simplified network is utilized for guided initializations and generations of the population as well as for the proper population's codification. The proposed method is employed to solve the NR problem and DG integration separately and simultaneously. In addition, this work considered non-dispatchable renewable energy resources and load variations for daily operation. The selected meta-heuristic techniques in this research involve the Firefly Algorithm (FA) and Biogeography-Based Optimization (BBO). To verify the efficiency of the proposed method, simulations were carried out on 33-bus, 69-bus, and 118-bus IEEE test systems. Furthermore, comparisons were performed between the proposed method along with the conventional evolutionary programming, particle swarm optimization, FA and BBO as well as the previous works. The obtained results of the NR problem as well as DG placement and sizing demonstrate the superiority of the proposed method in obtaining a fast and high-quality solution that minimize the power loss and voltage deviation in different case studies.

Keywords: Network reconfiguration, Distributed generation, Renewable energy resources, Meta-heuristic techniques, Load variations.

REKONFIGURASI SISTEM PENGAGIHAN YANG OPTIMUM MENGGABUNGKAN JANAKUASA TERAGIH BERDASARKAN PENDEKATAN RANGKAIAN DIPERMUDAHKAN

ABSTRAK

Penyusunan Semula Rangkaian (NR) dan Janakuasa Teragih (DG) adalah strategi yang dapat diterima dengan baik untuk meminimumkan kehilangan kuasa dan penyimpangan voltan dalam Rangkaian Pengagihan Elektrik (EDN). Oleh kerana masalah NR mengandungi ruang carian gabungan yang besar, kebanyakan penyelidik menggunakan teknik meta-heuristik untuk mencapai penyelesaian NR yang optimum. Walau bagaimanapun, teknik meta-heuristik tidak selalu menjamin penyelesaian yang optimum dan lebih jauh lagi memerlukan masa pemprosesan yang besar. Ini berlaku terutamanya disebabkan oleh (1) permulaan penyelesaian secara rawak dan (2) pengesahan penyelesaian dalam setiap lelaran untuk memenuhi batasan operasi sepanjang proses pencarian. Tambahan pula, penyelesaian masalah NR secara serentak dengan penempatan DG akan meningkatkan beban pengiraan disebabkan peningkatan ruang carian. Dengan tujuan untuk mengurangkan masa pengiraan dan meningkatkan konsistensi dalam mendapatkan penyelesaian yang optimum serta meminimumkan kehilangan kuasa dan penyimpangan voltan dari EDN, kajian ini mencadangkan kaedah baru berdasarkan pengoptimuman dua peringkat. Kaedah ini memperkenalkan teknik untuk mempermudah rangkaian menjadi grafik rangkaian yang dipermudahkan. Kemudian, rangkaian yang dipermudahkan digunakan untuk penghasilan pemula dan populasi terpandu serta pengekodan populasi yang tepat. Kaedah yang dicadangkan digunakan untuk menyelesaikan masalah NR dan integrasi DG secara berasingan dan serentak. Di samping itu, kajian ini juga mengambil kira sumber tenaga boleh diperbaharui yang tidak dapat dihantar dan variasi beban untuk operasi harian. Teknik meta-heuristik yang dipilih dalam penyelidikan ini melibatkan Firefly Algorithm dan

Biogeography-Based Optimization. Untuk mengesahkan kecekapan kaedah yang dicadangkan, simulasi dilakukan pada sistem ujian IEEE 33-bus, 69-bus, dan 118-bus. Selanjutnya, perbandingan dilakukan antara kaedah yang dicadangkan bersama dengan pengaturcaraan evolusi konvensional, pengoptimuman kumpulan zarah, FA dan BBO serta karya sebelumnya. Hasil yang diperoleh dari masalah NR serta penempatan dan ukuran DG menunjukkan kelebihan kaedah yang dicadangkan dalam mendapatkan penyelesaian yang cepat dan berkualiti tinggi yang meminimumkan kehilangan kuasa dan penyimpangan voltan dalam kajian kes yang berbeza.

Kata kunci: Penyusunan semula rangkaian, Janakuasa Teragih, Sumber tenaga boleh diperbaharui, teknik Meta-heuristik, Variasi beban.

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LIST OF SYMBOLS AND ABBREVIATIONS

ACSA	:	Adaptive Cuckoo Search Algorithm
ANN	:	Artificial Neural Network
AWIDPSO	:	Adaptive Weighted Improved Discrete Particle Swarm Optimization
BBO	:	Biogeography-Based Optimization
BPSO	:	Binary Particle Swarm Optimization
BPSOGSA	:	Binary Particle Swarm Optimization Gravity Search Algorithm
DG	:	Distributed Generation
EDN	:	Electrical Distribution Network
EP	:	Evolutionary Programming
EPSO	:	Enhanced Particle Swarm Optimization
FA	:	Firefly Algorithm
FL	:	Fundamental Loops
FN	:	Fundamental Node
FNV	:	Fundamental Nodes Vector
FWA	:	Firework Algorithm
GA	:	Genetic Algorithm
HDM	:	Hierarchical Decentralized Method
HSI	:	Habitat Suitability Index
HSA	:	Harmony Search Algorithm
IHSA	:	Improved Harmony Search Algorithm
IIA	:	Iterative Improved Analytical
ISM	:	Initial Solution Matrix
IVD	:	Index of Voltage Deviation

MOTA	:	Multi-Objective Taguchi Approach
MPSO	:	Modified Particle Swarm Optimization
MTS	:	Modified Tabu Search
NDV	:	Node Degree Vector
NR	:	Network Reconfiguration
PSO	:	Particle Swarm Optimization
PV	:	Photovoltaic
QOTLBO	:	Quasi-Oppositional Teaching Learning Based Optimization
RER	:	Renewable Energy Resource
RGA	:	Refined Genetic Algorithm
SIV	:	Suitability Index Variables
SNG	:	Simple Network Graph
SOS	:	Symbiotic Organism Search
STD	:	Standard Deviation
TLBO	:	Teaching-Learning-Based Optimization
UIM	:	Undirected Incidence Matrix
UVDA	:	Uniform Voltage Distribution Algorithm
WT	:	Wind Turbine

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

1.1 Introduction

With the deregulation of the electricity sector, power utilities are required to ensure that customers receive reliable power supply. At the same time, power utilities also need to operate at optimum cost. One of the problems that would increase the operation cost is power loss. It was estimated that power loss in transmission and distribution systems is the largest individual consumer for any power system operator (Kalambe & Agnihotri, 2014). Also, up to 6% of the electricity is wasted as power loss in the electrical network, mostly occur at the distribution level (Jackson et al., 2015). Thus, it is very crucial to find an effective method to minimize such losses.

One of the well-known approaches to achieve this goal in Electrical Distribution Networks (EDNs) is through Network Reconfiguration (NR). NR is the process of changing some of the EDN's switches from open to close and vice versa. The EDN operators mostly utilize the NR technique to optimize the EDN performance in minimizing power loss (R. S. Rao, K. Ravindra, K. Satish, & S. Narasimham, 2013), improving voltage profile (Badran, Mokhlis, Saad, & Jallad, 2017), achieving load balancing (Eldurssi & O'Connell, 2015) and executing system restoration (Dimitrijevic & Rajakovic, 2015). Obtaining the optimal NR in short computational time is attracting more attention recently due to the advancement in the controlling technology of the EDN by the system operators that allows faster switches' changes for better adaption with the load changes. However, finding the NR solution is still challenging task due to the large combinational search space and the onerous duty of maintaining the radial structure during the EDN's operation.

Another method to reduce the power loss in the distribution networks is to connect the network to one or more Distributed Generation (DG). DG is defined as a small generation unit fixed at a chosen location in the network. The DGs are categorized to (1) Renewable Energy Resource (RER) like biomass, Wind Turbine (WT), and Photovoltaic (PV) and (2) regular DGs such as fuel cells, microturbine, and gas turbine. With proper integration of DGs in the EDN, a significant reduction of power loss can be achieved that directly translates to reduce network operating costs (Grisales-Noreña, Gonzalez Montoya, & Ramos-Paja, 2018).

Besides minimizing power loss, DG based on RER will also reduce environmental pollution causes by central power plants that much dependent on coal as its main source of power generation's fuel. It is predicted that RER could reduce 60% of the carbon emission from the central power plants by the year 2050 (Javanmardi, Nasri, & Sadeghkhani, 2012). Therefore, RERs generation capacity has witnessed a continuous trend of annual growth across the world. Furthermore, by using the RER, less power from central power plants is required to be generated and in long run reducing operation cost of electricity generation.

1.2 Problem Statement

In order to maximize revenue, the electrical power distribution utilities' operators employ many tools to enhance the system performance, i.e. reduce the power loss and the voltage deviation. Many strategies were used for this purpose, however, only a few of them proved their high capabilities and flexibilities like NR and DG integration (Badran, Mekhilef, Mokhlis, & Dahalan, 2017a).

The methods to solve the NR problem can be categorized into heuristic and meta-heuristic methods. Although heuristic methods might require a shorter time to obtain a solution, they commonly trap at local optima and suffer from a lack of accuracy. This occurs due to the incapability of heuristic method to search in multiple directions of the search space. Due to this shortcomings, meta-heuristic methods have been explored extensively to solve NR (B. Sultana, Mustafa, Sultana, & Bhatti, 2016). In general, all meta-heuristic methods rely on creating a random initial population and keep updating this population until it converges to the same solution or the maximum set iteration number. For the NR problem, the number of solutions in the search space is exponentially related to the number of switches in the system. However, the majority of these solutions do not maintain the radiality structure of the system. Hence, these solutions are not feasible and need to be modified which will consequently slow down the search process. Therefore, conventional meta-heuristic methods require large computational time. Moreover, meta-heuristic methods that start the search process without a proper initial population have less possibility of finding the optimal solution and the search process takes a longer time (Elaziz & Mirjalili, 2019; Friedrich & Wagner, 2015). Therefore, most of the previous methods failed in obtaining the optimal NR solution with good consistency.

Researches in minimizing the power loss and voltage deviation were also conducted by finding the solution of DG integration. Most of the prior works depended on the analytical methods or meta-heuristic methods to detect the proper placement and sizing of the DG (Abdmouleh, Gastli, Ben-Brahim, Haouari, & Al-Emadi, 2017). However, due to the large search space, finding the optimal solution is not guaranteed by conventional methods. Furthermore, it has been proven that the improper integration of the DG results in negative impacts on the distribution networks (Anaya & Pollitt, 2015).

Although the results of using NR or DG integration, separately, are encouraging, the works that considered solving NR with the existence of the DG showed better results (Imran, Kowsalya, & Kothari, 2014; T. T. Nguyen, Truong, & Phung, 2016; Rawat & Vadhera, 2019). Nevertheless, most of the existing researches considered solving these problems sequentially. Only a few works considered finding the optimal NR simultaneously with DG integration due to the complexity of solving this problem. Furthermore, solving the NR problem simultaneously with the DG integration leads to further expanding the search space especially for the large-scale distribution networks. Hence, it is vital to propose a new method for efficient exploration of the search space, and consequently finding a higher-quality solution.

Finally, the integration of non-dispatchable renewable energy causes instability in the generated energy as compared to the conventional central generation source. Consequently, this may lead to serious potential risks unless it is managed appropriately. In addition, the hourly loads' variations must be considered to maintain service quality. Hence, the impact of finding the hourly NR in presence of non-dispatchable renewable energy generation and loads variation must be considered. Moreover, considering real data of renewable energy output levels and loads variations has been rarely considered in the prior studies.

1.3 Research objectives

The primary aim of this research is to develop a fast and effective two-stage method to analyze and solve the network reconfiguration problem with DG placement and sizing and load variations. The objectives that need to be achieved are as following:

1. To design fast and optimal network reconfiguration based on the simplified network approach to minimize power loss and voltage deviation.
2. To design optimal DG placement and sizing method for the distribution networks using the simplified network approach.
3. To formulate the network reconfiguration and DG placement and sizing simultaneously using the proposed method.
4. To incorporate variable renewable DG output and load variation in the proposed method.

1.4 Scope of research

This research proposes a new, fast, and optimal two-stage method with guided initialization for finding the simultaneous solution of the NR and DG in the distribution networks. The main aim of this study is to obtain the optimal configuration and DG location and sizing that minimize the power loss and voltage deviation while maintaining the system constraint.

The validity of the proposed method is verified through multiple case studies on well-known, different sizes IEEE 33-bus, 69-bus, and 118-bus distribution test networks. The proposed two-stage method is implemented using the Firefly Algorithm (FA) and Biogeography-Based Optimization (BBO). To the best of the author's knowledge, BBO has not been used to solve the network reconfiguration and DG integration previously. The proposed method results are compared to the conventional Evolutionary Programming (EP), Particle Swarm Optimization (PSO), FA and BBO as well as the previous related works. All the tests were carried out by MATLAB using a PC with an Intel Core 2 Duo, 3.06 GHz processor.

1.5 Thesis Outline

This report includes five chapters. In the first chapter, a brief introduction is presented followed by illustrating the problem statement and the research objectives. Finally, the scope of research and the report outline are stated.

Chapter 2 starts with a general introduction. Then, reviews on network reconfiguration based on heuristic and meta-heuristic methods, graph theory-based methods and two-stage methods. Next, the classical optimization techniques and the meta-heuristic methods for DG placement and sizing are presented. Reviews on network reconfiguration with the presence of DG are also explored. Finally, a brief summary is presented to conclude the limitations of the previous works.

In chapter 3, the problem formulation, the simplified network approach, and the implementation of the meta-heuristic methods to solve the network reconfiguration and DG placement and sizing are detailed.

Chapter 4 presents the proposed method's application for solving the network reconfiguration and DG integration separately. The simulation results are analyzed and discussed. The analysis is focused on the impact of the proposed method on the system performance with regards to the power loss and voltage profile. Furthermore, comparisons between the proposed method and the conventional meta-heuristic methods and previous works are carried out in this chapter.

In Chapter 5, the solution and analysis of the proposed method in solving the network reconfiguration and DG integration sequentially and then simultaneously are detailed. Thereafter, the incorporation of variable DG output and load variation in the proposed method is addressed.

The conclusions of this research study and the recommendations for the future works are presented in chapter 6.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The electric energy industry is continuously developing around the world to meet the growth in the load. The power systems evolved from a single low power generator, providing energy for a limited number of customers, to a highly complex interconnected multi-generators network that needs intelligent methods to guarantee its proper operation.

The electrical power systems consist of three levels, the generation, the transmission, and the distribution. However, It was estimated that power loss in transmission and distribution systems is the largest individual consumers for any power systems (Kalambe & Agnihotri, 2014). In addition, the last decade witnessed a rapid increment in the complexity of the Electrical Distribution Networks (EDN) due to the rise in the number of the connected Distributed Generation (DG) in the EDN. The inappropriate installation of the DG, power loss in the EDN increases (Abdmouleh et al., 2017). On the other hand, by proper integration of the DG, power loss is remarkably reduced (KOLA, 2018). Similarly, Network Reconfiguration (NR) was reported as a highly efficient method to minimize the total active power loss (Usman, Coppo, Bignucolo, & Turri, 2018).

This chapter reviews the previous works that studied the NR in the EDN. The reviewed methods involve heuristic and meta-heuristic methods as well as graph theory-based methods and two-stage methods. Then, the DGs types are explained as well as the methods to integrate the DGs in the EDN. Besides, methods for solving simultaneously the NR while integrating the DGs have been described. Thereafter, the previous works that considered the integration of Renewable Energy Resources (RERs) in the EDN are discussed. At the end of this chapter, some justified conclusions have been identified as a ground for the new method.

2.2 Network Reconfiguration

During the last few years, the importance of EDN in daily life becomes significant. Nowadays most of the electricity companies are facing serious challenges to provide the electrical power supply through EDNs to the customers with the lowest price and highest reliability. The EDN consists of many buses connected through lines. Each bus has an active and reactive load, and each line has an impedance and switch. The status of the switch determines whether the power flow is allowed to pass through this line or not. In the modern EDNs, all the switches can be controlled by a central control unit; thus, the best configuration can be determined based on the system data. The previous process called the NR. NR is considered one of the most effective approaches and it is frequently used due to its high efficiency in reducing power loss and enhancing the bus voltage.

Figure 2.1 presents an explanatory of the NR process of the 14-bus EDN. In Figure 2.1 (a), the EDN is showed in its base case, where switches (s15, s16, s17) are open while the other switches are closed. In figure 2.1 (b), an NR process is preformed and consequently, a new open switches configuration is applied which consists of switches (s4, s8, s13).

NR studies consider single or multi-objectives such as reduce power loss (R. Rao, K. Ravindra, K. Satish, & S. Narasimham, 2013), enhance voltage profile (Badran, Mokhlis, Mekhilef, Dahalan, & Jallad, 2017), optimize load balancing (Eldurssi & O'Connell, 2015), improve the system reliability (Amanulla, Chakrabarti, & Singh, 2012) and achieve system restoration if a fault occurs (Dimitrijevic & Rajakovic, 2015). However, power loss minimization and voltage profile improvement were mainly considered in the NR (Das, Das, & Patra, 2017). The methods to solve the NR problem can be categorized mainly into artificial neural network-based methods, heuristic methods and meta-heuristic algorithms (B. Sultana et al., 2016).

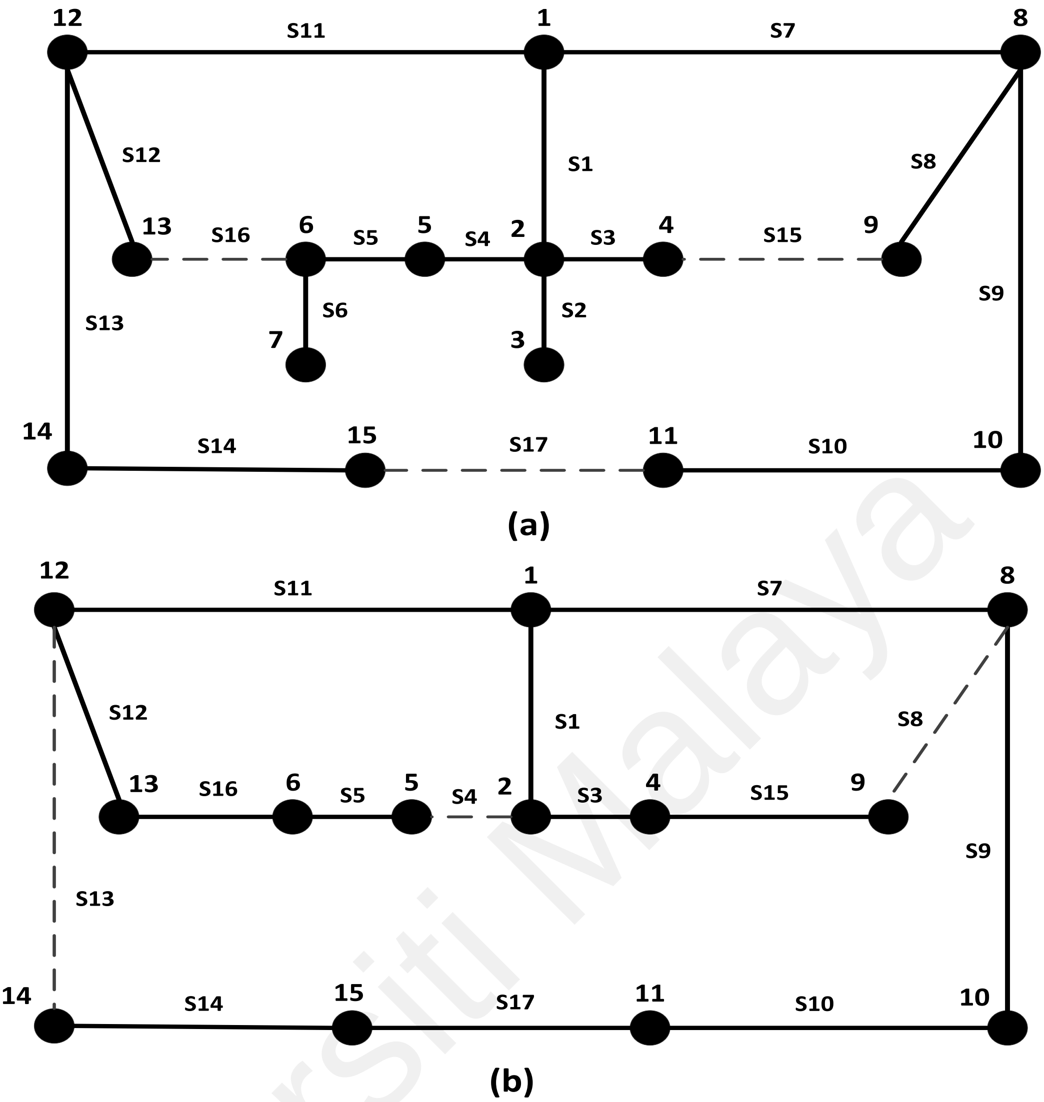

Figure 2.1 An example of network reconfiguration

2.2.1 Artificial neural network methods

Artificial Neural Networks (ANN) is a computing mechanism inspired from the human brain and applied to solve several engineering problems. It basically depends on learning through training samples and then it can find a solution for a given input. ANN have been reported in few studies to solve the NR in the EDN. However, using ANN required long training time that increases rapidly for large EDN. Hence, ANN-based methods are valid only for small and medium distribution systems.

Early works on ANN was reported by (Kim, Ko, & Jung, 1993). Two groups of ANN were utilized to forecast the load and solve the NR. The first ANN group forecasted the load level at each zone of the EDN, while the second ANN group found the NR based on the forecasted load levels. Real power loss minimization was the objective function of the study. The authors of (Kashem, Jasmon, Mohamed, Moghavvemi, & Systems, 1998) developed an ANN model based on the multi-layers' perceptron while the back-propagation approach was used for ANN training. The training sets were created by modifying the constant P-Q load models. The method was applied on a small IEEE test system to find the NR.

The research of (Kashem, Ganapathy, Jasmon, & systems, 2001) employed the conjugate gradient descent back-propagation technique in the ANN mode. The aim of the proposed method is to find the NR that maximize the voltage stability in the EDN. In other work, to utilize the ANN for medium-sized EDN, the ANN training sets number was reduced in (Salazar, Gallego, & Romero, 2006) through clustering technique. The load clustering reduces the ANN input data and enhanced the results of the NR.

2.2.2 Heuristic methods

Heuristic methods rely normally on approximation to speed up the search process for solution. Hence, finding an optimal solution is not guaranteed. Early research on NR widely used heuristic methods to obtain solution.

The sequential switch opening method was used in (Shirmohammadi & Hong, 1989) to reduce the power loss by solving the NR problem during the planning and operation of the EDN. Branch and bound method was presented by (Baran & Wu, 1989) with the aim of power loss reduction and load balancing. In their work, mesh network is created by closing all the normally open switches. Then, switches are opened one by one, while maintaining the radiality, until the optimal open switches combination that minimize the objective function is found.

Goswami and Basu (1992) presented an approximate power flow approach based heuristic method to obtain the NR that reduces the power loss in the EDN. Unlike (Baran & Wu, 1989), one loop is created in one time. Next, Kirchhoff's voltage and current laws equations were solved to find the optimum flow pattern for each individual loop in the EDN. By repeating the process, the open switches configuration was obtained. The algorithm suggested by (McDermott, Drezga, & Broadwater, 1999) starts with opening all the switches in the EDN. Next, the switch that causes least increase in the power loss while serving new load is closed. The proposed algorithm consumes longer computational time since load flow is run whenever a new switch is closed.

(Gomes et al., 2006) proposed a method that starts with closing all switches in the EDN, and consequently many loops are generated. Thereafter, a loop is chosen to be broken based on heuristic technique and optimum power flow calculations. The process is repeated until all loops are broken. The results indicate maintaining a radial solution of the NR. Recently, the authors of (Kovački, Vidović, & Sarić, 2018) solved the problem of the dynamic reconfiguration depending on Lagrange relaxation approach with the objective of minimizing the power loss in the EDN. However, the implementation of the method is complicated.

2.2.3 Meta-heuristic methods

To overcome the shortcomings of heuristic methods, meta-heuristic methods have been explored extensively to solve NR. In general, all meta-heuristic techniques start with generating an initial random population, then a verification is required to ensure that the population fulfils the optimization problem constraints. If any of the population violates one of the constraints, this population is replaced by another feasible population. Next, the population is evaluated and ranked based on the problem's objective function. Thereafter, the population is modified and evaluated again until it converges. For complicated optimization problems, generating feasible population consumes long computational time. Several meta-heuristic techniques were employed to obtain the NR solution in the EDN.

2.2.3.1 Genetic algorithm

Genetic algorithm is an optimization technique inspired by the natural evolution. It normally involves mutation, crossover and selection. Genetic algorithm has been used to obtain the solution of the NR problem in the EDN. Power loss minimization was achieved by finding the NR in (Zhu, 2002). The refined genetic algorithm was used in the study while radiation load flow was utilized for power flow calculations. Genetic algorithm was also used in (de Macêdo Braz & de Souza, 2010) where it was integrated with proposed sequential population codification. The study aimed to reduce the power loss and number of switching operation. The authors in (Wang & Gao, 2013) developed a non-revisiting genetic algorithm to find NR that minimizes the power loss. An archive was employed to store the solutions that have been already visited for faster search process.

2.2.3.2 Evolutionary programming

Evolutionary Programming (EP) is a stochastic optimization technique that values the connections between the parent and children population, rather than the genetic operators (Yao, Liu, & Lin, 1999). EP proved its capability to solve many optimization problems efficiently and its implementation is simple comparing to other meta-heuristic methods. (Yao et al., 1999). The authors in (Song, Wang, Johns, Wang, & Distribution, 1997) integrated EP with fuzzy controller to solve the NR problem for power loss minimization. With the aim of maximizing the EDN loadability, a fuzzy-based evolutionary programming algorithm was developed in (Venkatesh, Ranjan, & Gooi, 2004) to obtain the NR solution. In (Aman, Jasmon, Naidu, Bakar, & Mokhlis, 2013), the discrete EP was utilized to determine the optimal NR which reduces the power loss in the EDN.

2.2.3.3 Particle swarm optimization

Particle swarm optimization (PSO) is a stochastic optimization method that was modeled to act the social behavior of the birds in searching for food (Eberhart & Kennedy, 1995). PSO is considered one of the best search algorithms that do not have any selection method. Each particle from the swarm explores the search space to discover the best food source. PSO was inspired from the natural behavior of the birds' swarm while they are looking for food. The special characteristic of birds' swarm is that it does not have a leader in their group. They communicate with each other to decide where they should move. Each bird inspects the search space to find the food. Then, the whole swarm members change their direction to the one individual bird that has the closest position to the food (Shi, 2001). PSO has been implemented to solve many discrete optimization problems (Jordehi & Jasni, 2015).

PSO was employed to solve the NR in many works such as (Amanulla et al., 2012; Huang & Dinavahi, 2018a). Binary PSO (BPSO) was used in (Amanulla et al., 2012) to minimize the power loss and enhance the reliability of the EDN by finding the NR. The reliability at the load points were evaluated by employing probabilistic reliability models of the EDN. The authors of (Huang & Dinavahi, 2018b) suggested the decimal encoding of the population, whereas, the decoding was performed based on probability-based loop destruction approach. In addition, the direct load flow calculation approach was utilized to evaluate the population. The proposed encoding and the direct load flow approach were implemented using PSO and contributed in reducing the computational time for finding the NR solution that minimize the power loss.

NR was utilized to perform network restoration in (Y. Liu & Gu, 2007). The proposed method depends on topological features of scale-free networks as well as the discrete PSO to find the NR. The effect of the NR solution is evaluated based on the restored nodes importance degree. (Fathy, El-Arini, & El-Baksawy, 2018) used the binary particle swarm optimization gravity search method to explore the EDN's configuration that minimize the power loss of the network. The results were validated by the reliability indices and compared with the original network's configuration.

2.2.3.4 Cuckoo search algorithm

Cuckoo search algorithm is an evolutionary algorithm proposed by (Yang & Deb, 2009) to solve optimization problems. It was inspired by the commit brood parasitic conduct of some cuckoo kinds combined with the Lévy flight conduct of some birds. Solving the NR problem in the EDN is one of the applications of this algorithm. The authors of (Herazo, Quintero, Candelo, Soto, & Guerrero, 2015) implemented the discrete cuckoo search algorithm to obtain the optimal NR of the EDN. The results show that the performance of the discrete cuckoo search is superior to the binary ant colony algorithm.

Cuckoo search algorithm was utilized in (T. T. Nguyen & Truong, 2015) to find the configuration that minimizes the power loss and improve the voltage profile. The radiality constraint of the EDN was maintained by testing all the population and only accepts the population that guarantee the radial operation of the EDN. In (T. T. Nguyen & Nguyen, 2019), the cuckoo search algorithm was modified to increase its capability to solve the NR problem in the EDN. In the suggested improved cuckoo search, a local search mechanism was included to utilize the best solution's neighbors of each iteration. Hence, increase the opportunity of obtaining a global better solution.

2.2.3.5 Firefly algorithm

Firefly Algorithm (FA) is a nature inspired meta-heuristic technique that was recently introduced in (Yang, 2010) and it has great capabilities addressing the discrete and combinational optimization problems (Sayadi, Hafezalkotob, & Naini, 2013; Yang & He, 2013). Also, FA proved its efficiency to solve different optimization problems (Kar, 2016). FA is classified as a swarm-based optimization. Hence, it owns most of swarm-based optimizations features. However, FA has two important superiority over the other optimizations. First, its ability to divide the population into subgroups and then each sub group will deal with a local optimum. Thereafter, the best global solution will be chosen. Second, this subdivision will allow the population to search in different parts of the search space simultaneously. Thus, the computational time will be reduced comparing to other optimizations (Yang, 2010).

The quantum-inspired binary FA was utilized in (Shareef et al., 2014) to solve the NR problem. The objectives of the study are to improve the power quality and reliability of the EDN. A new load flow approach for unbalanced distribution systems was suggested by (Kaur & Ghosh, 2016). NR was solved by utilizing the firefly algorithm in a fuzzy domain for handling the multi-objective function that aims to reduce power loss and voltage deviation as well as load equalizing in the feeders. Recently, a combination of the Selective Firefly Algorithm (SFA) along with a heuristic technique, that depends on a power flow analysis creation, was proposed in (Gerez, Silva, Belati, Sguarezi Filho, & Costa, 2019) to solve the NR problem for power loss minimization.

2.2.3.6 Other meta-heuristic methods

The previous meta-heuristic methods were frequently considered to obtain the optimal solution for the NR. However, other methods have been implemented to find the solution of the NR. Ant colony search algorithm was used in (Su, Chang, & Chiou, 2005) for obtaining an optimal solution of the NR. Total real power loss minimization is the main aim of the study while maintaining the voltage and current constraints. (Abdelaziz, Mohamed, Mekhamer, & Badr, 2010) used the modified Tabu search algorithm to find the NR that minimize the active power losses in the EDN. In addition, the radial structure of the system was maintained by the Kirchhoff method.

A hybrid optimization method was proposed in (Asrari, Lotfifard, & Payam, 2015) to integrate the fuzzy pareto concept with the customized shuffled frog leaping technique for finding the solution of the NR problem. This hybrid method aimed to reduce the computational time by considering only the feasible solutions in the search space. The objective functions of the study include power loss minimization and power quality improvement. The authors of (Masteri & Venkatesh, 2016) presented a method based on classic nonlinear optimization to enhance the probability of finding a high-quality solution for the NR problem. The method relies on a complementarity technique to covert the discontinuous solution to continuous. Hence, use the nonlinear optimization method. The solution found by the proposed method reduced the power loss while maintaining the voltage profile in the allowable ranges.

The runner-root algorithm was employed in (T. T. Nguyen, Nguyen, Truong, Nguyen, & Phung, 2017) to find the solution of the NR problem. The study aims to reduce power loss, load balancing among feeders and lines as well as to reduce switching number and improve the voltage profile. The runner-root algorithm used its features, which are random leap, reinitialization to escape the local optima solution and the capability of searching with small steps around the current best solution, to find the NR solution. A hybrid fuzzy-flower pollination algorithm was utilized in (Mariaraja, Manigandan, & Thiruvenkadam, 2018) to obtain the NR solution in the EDN. The method was tested under normal and abnormal operating scenarios.

2.2.4 Graph theory-based methods

Since NR problem is considered as a remarkably complicated combinational problem, most of the conventional meta-heuristic methods have suffered from slow convergence and suboptimal solutions, especially for the large systems. In addition, lots of generated solutions do not fulfill the system constraints, mainly the radiality constraint. To overcome these demerits, some studies suggested the combination of the graph theory principles with NR problem. Those methods can be classified into two main sets: (a) methods based on spanning tree rules (Ahmadi & Martí, 2015; Dimitrijevic & Rajakovic, 2015; Duan, Ling, Wu, & Zhong, 2015; Muthukumar & Jayalalitha, 2017) and (b) methods based on employing the FLs (Andervazh, Olamaei, & Haghifam, 2013; Gupta, Swarnkar, Niazi, & Bansal, 2010; Mendoza et al., 2006; Souza, Romero, & Franco, 2015).

2.2.4.1 The spanning tree-based methods

A spanning tree is a graph that includes all connected nodes and has no loops. The edges have weights which determine the cost of moving from the source node to the end nodes. Many studies have modeled the EDN as a spanning tree and applied graph theory to find the minimum cost spanning tree. All radial EDN are spanning trees, where the sum of the edges' weights is the objective function value.

In (Dimitrijevic & Rajakovic, 2015), a heuristic graph-based method was presented to obtain the optimum configuration for the service restoration problem in EDN. The method was built based on the rules of the modified Pirm's algorithm to find the minimum spanning tree. The main aim of the NR is to minimize the number of de-energized nodes in the EDN while alleviating the operation cost. The authors of (Duan et al., 2015) implemented an enhanced genetic algorithm to minimize the power losses and improve the reliability through the optimal NR. The genetic algorithm operators, mutation and crossover, were modified to obtain only the feasible radial solutions. In the crossover, one or many switches are exchanged between two spanning trees in the EDN based on Kruskal theory. The results proved the efficiency of the method, but the computation time stills high.

A hybrid algorithm that consists of heuristic technique as well as harmony search algorithm and particle artificial bee colony algorithm was introduced in (Muthukumar & Jayalalitha, 2017). The proposed method employed a discrete graph representation of the EDN to identify the NR solution that minimize the power loss. The improved fast nondominated sorting genetic algorithm was used successfully by (Ji, Shi, & O'Connell, 2018) to obtain the NR that improve the voltage profile and reduce the power loss. Moreover, the authors utilized the essential spanning trees approach to reduce the computational time.

2.2.4.2 The fundamental loops-based methods

The EDNs consists of normally closed switches and normally open ones. By closing all the switches in the EDN, many loops will be generated. The Fundamental Loops (FLs) are chosen from these loops and then one switch from each FL is selected to form the population's combination. This population codification technique reduces the size of the search space because it will eliminate many unwanted populations' combinations.

The research of (Mendoza et al., 2006) integrated genetic algorithm with FLs concept to generate feasible populations and develop new genetic operators (i.e. cross over and mutation). The FLs were used to reduce the search space by eliminating most of the non-radial restricted population. FLs were identified as the set of vectors that assemble a closed loop in a circuit that does not involve any other closed loop. Then, one switch is selected from each FL to be off to form the population. The method succeeded in reducing the time and mitigating the power loss, but it did not ensure the system radiality because the interior nodes might be isolated for some cases. In (Souza et al., 2015), the same FL approach of (Mendoza et al., 2006) was employed to solve the NR but with artificial immune network COPT-AINET and OPT-AINET algorithms instead of genetic algorithm. The study targeted to reduce the real power loss in the EDN.

The authors of (Gupta et al., 2010) developed the method of (Mendoza et al., 2006) to overcome the non-radiality cases. This was accomplished by introducing new radiality rules that prevent isolation of the internal nodes. Furthermore, a multi-objectives function combining genetic algorithm and fuzzy logic methods was formulated. Minimization of total power loss, voltage deviation, number of switching and branch currents in the EDN were the objectives of the study. In (Andervazh et al., 2013), the rules of (Gupta et al., 2010) were integrated with discrete PSO while considering a pareto multi-objectives function. Furthermore, an external archive was used to store non-dominated solutions so that the searching process is accelerated.

The prior review shows the importance of employing the graph theory to accelerate obtaining the solution for the NR problem in the EDN systems. The main demerit of those methods is that most of them start the search process from a random initial solution which leads to slow converge. In addition, most of the previous works studied the test systems under static load case only, whereas it is vital to observe the system behavior under different loads variation's scenarios.

2.2.5 Two-stage methods

Two-stage methods were also reported in many previous research to solve the NR problem in the EDN (Ahmadi & Martí, 2015; Ding & Loparo, 2014; Kashem, Ganapathy, & Jasmon, 1999; Raju & Bijwe, 2008; Tyagi, Verma, & Bijwe, 2018). However, obtaining the optimal solution is not guaranteed in these methods.

A two-stage method to solve the NR problem was suggested by (Kashem et al., 1999). In the first stage, the loop that maximize the load balance in the EDN is found. Then, the second stage choose a switch from that loop to be open so that an improvement in load balancing is achieved. With the aim of real power loss minimization, the authors of (Raju & Bijwe, 2008) introduced a two-stage method for NR in the EDN. Power loss sensitivity of the switches' impedances was used in the first stage. Whereas, the seconds stage utilized the branch exchange approach to improve the first stage solution.

A hierarchical decentralized method was proposed in (Ding & Loparo, 2014) to reduce the power losses in the EDN by finding the NR solution. The EDN is broken down into smaller subsystems, where an agent is allocated to each subsystem. Then, a two-stage method is defined to regulate the reconfiguration of these subsystems. The first stage aims to find the reconfiguration of each subsystem, whereas the second stage coordinates the results of each subsystem to reach a satisfactory configuration. In (Tyagi et al., 2018), the first stage intends to find the configuration that minimizes the reactive power loss by a heuristic method. Then, the second stage uses the improved harmony search algorithm to enhance the system loadability.

In (Ahmadi & Martí, 2015), a two stages method was proposed to get topological reconfiguration of the EDN. First, a heurist technique was utilized to obtain an initial solution for the NR problem. Then, in the second stage, the Mixed-Integer Programming approach was used to find the final NR. In addition, the NR was formulated as a minimum spanning tree problem to accelerate finding the NR solution. The suboptimal solutions were obtained in a short time using this method. Hence, it could be applied only when the optimal solution is not a must.

2.3 Optimal DG placement and sizing

DG is defined as a decentralized energy resource that is connected directly to the EDN to support the network and provide clean energy to consumers (Alanne & Saari, 2006; Ehsan & Yang, 2018; Georgilakis & Hatziargyriou, 2013). The DGs are categorized into renewable DG and non-renewable DGs. Micro turbine, combustion engine and fuel cell are examples of the non-renewable DGs. While, Photovoltaic (PV), Wind Turbine (WT) and biomass are instances of renewable DGs, which also known as RER (Prakash & Khatod, 2016; Zubo et al., 2017).

During the last decade, DG integration in the EDN has been frequently utilized to fulfil one or more from the following objectives:

- Reduce the active power loss (Grisales-Noreña et al., 2018) and the reactive power loss (Hung, Mithulananthan, & Lee, 2014).
- Enhance the voltage profile (Tolabi, Ali, & Rizwan, 2014).
- Improve the EDN reliability (Awad, El-Fouly, & Salama, 2014).
- Reduce the operation cost (Evangelopoulos & Georgilakis, 2013).
- Improve the power quality (Liang, 2016).
- Minimize the pollutant gas emission (Hamida, Salah, Msahli, & Mimouni, 2018).

However, it has been reported that the inappropriate DGs integration in the EDN causes decreases in the system performance such as increasing the power loss in the EDN (Abdmouleh et al., 2017). Therefore, classical optimization techniques and meta-heuristic techniques have been proposed for proper integration of the DGs.

2.3.1 Classical optimization methods

The classical optimization techniques include mainly the analytical techniques, mixed-integer linear programming, optimal power flow techniques and ANN. The analytical techniques rely on repressing the EDN as a mathematical model and then compute the optimal DG placement and sizing by numerical solutions. Although the analytical techniques provide a high-quality solution for the DG integration problem, the analytical techniques need long computational time for the large EDN. On the other hand, mixed-integer linear optimization is a mathematical optimization that aims to maximize or minimize the objective, beside some of the problem variables must be integer.

Index-based techniques are frequently used to solve the DG integration problem. A comparison between the loss sensitivity index and index vectors as well as the voltage sensitivity index techniques were presented in (Murthy & Kumar, 2013). Furthermore, the study proposed many modified hybrid techniques for the DG placement and sizing in the EDN. In (Hung et al., 2014), the penetration level of the PVs was obtained by proposing several kinds of time-varying voltage dependent load models. The PV size was determined by an analytical approach. The proposed method aimed to reduce the active and reactive power loss as well as the voltage deviation in the EDN through the PV placements.

The iterative analytical method (Forooghi Nematollahi, Dadkhah, Asgari Gashteroodkhani, & Vahidi, 2016) and the repeated load flow method (Singh, Sood, & Barnwal, 2016) were employed to find the optimal placement and sizing of RER in the EDN. RERs with different power factors were tested with the aim of reducing the power loss in the EDN. The problem of DG placement and sizing as well as choosing the DG type was modeled as a Mixed integer linear programming in (Rueda-Medina, Franco, Rider, Padilha-Feltrin, & Romero, 2013). The aim of the study was to minimize the investment and operation cost of the DG integration in the EDN.

The authors of (Ochoa & Harrison, 2010) utilized the optimal power flow technique for the RER integration in the EDN. Various scenarios of the demand level and RER penetration were considered in the study with the objective of energy loss minimization. ANN has been utilized in solving the DG installation in the EDN. A multi-layer perceptron ANN with sigmoid activation function was proposed in (Zambri, Mohamed,

& Wanik, 2015) to determine the DG active and reactive power outputs for power loss minimization.

2.3.2 Meta-heuristic methods

Meta-heuristic techniques are widely used for the DG placement and sizing due to their efficiency, simple implementation and flexibility. Thus, these techniques were implemented for multi-objectives cases beside the case of solving the DG problem along with other problem such as NR or demand side management.

Genetic algorithm is commonly utilized to obtain the solutions of the DG sitting and sizing problem. The authors of (Soroudi, Ehsan, & Zareipour, 2011) applied the genetic algorithm to enhance the EDN reliability and reduce the expansion costs by proper DG integration. Similarly, the adaptive genetic algorithm was adapted in (Y. MA, YANG, GUO, & WU, 2012) to enhance the system reliability and minimize the cost through the RER installation. PV, wind turbine and biogas were considered in the study.

The optimal integration of DG was identified by utilizing the FA in (Sulaiman, Mustafa, Azmi, Aliman, & Rahim, 2012). Minimizing the active and reactive power loss as well as reduce the line loading were the objectives of the study. In (M. Othman, El-Khattam, Hegazy, & Abdelaziz, 2016), the supervised FA was adapted to solve the DG integration problem in the balanced and unbalanced EDN. However, finding the optimal solution by these two methods is not guaranteed for large scale EDN.

Power loss minimization was accomplished in (Kansal, Kumar, & Tyagi, 2013) by the optimal placement and sizing of DGs using PSO. Moreover, the optimal power factor for the DG was obtained. The method is applicable to different types of DGs including RER units such as wind farms and photovoltaic. PSO was also utilized in (Meera & Hemamalini, 2019) for multiple RER planning in a meshed EDN. The RERs placement and sizing as well as the power factor were found to enhance the reliability indices, minimize the power loss and improve the voltage profile. With the aim of minimizing the power loss and voltage deviation, (Moravej & Akhlaghi, 2013) utilized the cuckoo search algorithm to obtain the DG location and size in the EDN.

Biogeography-based Optimization (BBO) is a meta-heuristic technique that was inspired by the biogeography behavior of the species in nature. It was proposed by Simon in 2008 (Simon, 2008), and it has been successfully implemented to solve many optimization problems in the power system (H. Ma, Simon, Siarry, Yang, & Fei, 2017), such as economic dispatch (Bhattacharya & Chattopadhyay, 2009) and power management (Bansal, Kumar, & Gupta, 2013). BBO depends on migration and mutation to search for the problem solution. It has certain features in common with genetic algorithms and PSO like sharing information between solutions. However, BBO includes fewer computational steps per iteration which result in faster convergence compared to the other meta-heuristic techniques. Furthermore, in BBO, solutions with low fitness are updated by copying some elements from the good fitness solutions, and consequently, this increases the opportunity of maintaining a high-quality solution (Bhattacharya & Chattopadhyay, 2009). BBO was implemented in (Ghaffarzadeh & Sadeghi, 2016) to identify the optimal placement and sizing of the DGs and capacitors in the EDN. Minimization of total active and reactive power loss, reduction of the power from the feeders and enhancement of voltage profile were the objective of the study. In addition, the total harmonic distortion was investigated. The results show the superiority of the BBO over PSO and GA in obtaining better solutions.

Krill hard algorithm was used in (S. Sultana & Roy, 2016) for optimal interconnection of the DGs. Additionally, biomass, wind turbines and solar cell were optimally placed in the network. The results showed power loss and energy cost reduction comparing other meta-heuristic algorithms. A combination between the PSO and the artificial immune system was presented in (Bhadoria, Pal, & Shrivastava, 2019) to identify the optimal placement and sizing of the DGs. The objectives of the study involve power loss minimization and voltage profile enhancement. The method was tested on radial and meshed EDN.

2.4 Solving the network reconfiguration in presence of DG

Although the application of NR or DG alone already has a good impact on the EDN's performance, studies that adopted both approaches have accomplished a vital improvement in the system performance. The objectives of these studies are similar to the objectives of solving the NR or DG integration separately (Badran, Mekhilef, et al., 2017a). In this section, the research about NR with DG integration is reviewed. The non-renewable DG and the RER are considered in the review.

2.4.1 Network reconfiguration with dispatchable DG integration

Due to the rapid growth in the DG integration in the EDN, it is necessary to consider the DG existence when solving the NR problem. Hence, many studies were suggested to solve the NR problem and dispatchable DG integration in the EDN.

(R. Rao et al., 2013) used the harmony search algorithm to obtain the solution of the NR and DG sizing problem. Whereas, the best DG location was determined based on a sensitivity analysis. The objectives of the work are to decrease the power loss and enhance the voltage profile of the EDN buses. Moreover, the method was tested under the light, normal, and high loads level. The results showed that using the harmony search algorithm is more efficient than using the genetic algorithm or the refined genetic algorithm. The firework algorithm was used in (Imran et al., 2014) to find the optimal NR and DG capacity with the objectives of reducing the power loss and enhancing the voltage stability. The locations of the DG were identified according to the voltage stability index.

The method maintained the radiality of the system by generating the appropriate parent node-child node path of the system. Besides, the method was tested under different uniform load levels.

(Capitanescu, Ochoa, Margossian, & Hatziargyriou, 2015) studied the distribution network in the planning mode and operation mode. The work aimed to maximize the DG output by changing the EDN topology. The problem was formulated using mixed-integer non-linear optimal power flow. The presented results demonstrated that in both modes, using NR is an impressive means to accommodate bigger values of DG in the distribution network. The authors of (Rajaram, Kumar, & Rajasekar, 2015) used a modified plant growth simulation algorithm for minimizing the power loss by finding the optimal NR simultaneously with proper DG sizing. The loss sensitivity index was used to obtain the optimal location of the DG in the EDN. The objective of the study is to reduce the total real power loss.

(T. T. Nguyen et al., 2016) applied the cuckoo search algorithm in solving the problem of NR and DG placement and sizing to reduce power loss and improve the voltage stability. The graph theory was used to check the feasibility of the solution of the NR. Seven different cases were investigated to verify the efficiency of the method. With the aim of total power loss minimization, the authors of (Bayat, Bagheri, & Noroozian, 2016) proposed a Uniform Voltage Distribution based constructive NR Algorithm (UVDA) for solving the NR problem simultaneously with the DGs placement and sizing.

(Hong, Hu, Guo, Ma, & Tian, 2016) introduced a directed graph-based approach for NR and service restoration in the presence of DG intending to minimize power loss. The NR was modeled as a mixed-integer quadratic programming problem, while the service restoration was considered as a mixed-integer linear problem. The authors of (Gampa & Das, 2017) presented a two-stage method to solve the NR problem in presence of the DGs based on the heuristic branch exchange method and by employing the fuzzy genetic algorithm to minimize the power loss while maintaining the EDN operation constraints. The first stage finds the NR solution without considering the DGs, whereas the second stage determines the final open switch combination while finding DGs locations through sensitivity analysis based on power loss minimization and voltage profile improvement.

(Badran, Mekhilef, Mokhlis, & Dahalan, 2017b) introduced a methodology to optimize the distribution system in the operation mode. The method reduces the power loss and enhances the weakest bus voltage by finding simultaneously the optimal NR, DG placement, and sizing as well as the optimal switching sequence from the initial configuration to the final one. Firefly algorithm was used to examine the capabilities of the method with the aim of daily power loss minimization and the EDN's voltage profile enhancement. (Arif, Wang, Wang, & Chen, 2017) presented a method to solve the outage management problem that contains the repair and restoration of the distribution network with the existing of DGs. The method proved its efficiency in reducing the needed time to solve the aforementioned problem.

The uncertainties in loads of the distribution network with the presence of DG were considered in the method proposed by (K.-y. Liu, Sheng, Liu, & Meng, 2017). The method aims to find the NR using the binary particle swarm optimization and then to explore the DG location and size using sensitivity analysis and the harmony search algorithm, respectively. Reducing the cost of the real power loss, minimizing the expected energy not supplied, and lessening the cost of the switch operation are the objectives of the study. Binary PSO has been applied in (Saleh, Elshahed, & Elsayed, 2018) to find the best set of switches to be closed. Then, the conventional PSO has been used for choosing the optimal location and size of the DGs. The results show the positive effect of solving the NR and DG integration sequentially on reducing power loss.

In (Kumar, Singh, Mishra, Jha, & Samantaray, 2018), the NR problem was solved simultaneously with DG installation by applying the bit shift operator-based particle swarm optimization. The objectives include minimizing power loss and improving the voltage profile. Many loads' types were considered to investigate the validity of the proposed method. In (Kaveh, Hooshmand, & Madani, 2018), the system reconfiguration, DG installment, and network rephrasing were optimized simultaneously to reduce power loss and phase unbalancing and enhance the voltage profile. The optimization was accomplished using bacterial foraging with a spiral dynamic.

The authors of (Rawat & Vadhera, 2019) examined the efficiency of integrated PSO, teaching-learning-based optimization as well as Jaya optimization in solving the problem of NR and DG placement and sizing. The results show that Jaya optimization outperformed other optimization algorithms in reducing power loss and enhancing the voltage profile. (Akrami, Doostizadeh, & Aminifar, 2019) presented a two-stage data-driven approach that depends on the μPMUs' measurements to find the hourly configurations for the EDN. The configurations, that minimize the operation cost, were found using a stochastic robust optimization considering the uncertainties in the DGs outputs and the loads.

2.4.2 Network reconfiguration with RER integration

The integration of the RER in the EDN causes difficulties in EDN management due to the intermittent nature of the RER. Therefore, many studies discussed solving the NR along with the RER installation. (Esmaeili, Sedighizadeh, & Esmaili, 2016) proposed a modified multi-objective big bang-big crunch algorithm to solve simultaneously the NR and RER sizing problem based on acquiring the Pareto optimal solution. Wind turbines, PV, and fuel cells are the RER considered in the study. Also, the proposed method aimed to reduce the power loss, improve the voltage stability index as well as cut down the total cost and the emission produced in the EDN. Moreover, the uncertainty of loads was modeled by the triangular fuzzy number concept.

(Zarei & Zangeneh, 2017) suggested a method to find the optimal NR in the presence of the wind turbine in the network. The objectives of the study involved, decreasing the power loss and energy not supplied as well as increasing the voltage stability index and the wind turbine penetration level. Besides, the uncertainties of the loads and the wind turbine's output were considered. However, PV integration was not considered in the study. (Lei, Hou, Qiu, & Yan, 2018) proposed a method for solving the problem of the dynamic NR in presence of DGs in the distribution network. The method depends on identifying the critical switches that are most appropriate for DG integration. The study also considered the loads' uncertainties and RERs' outputs variations.

2.5 Summary

This chapter presents a detailed review of the previous methods of NR and DG integration in the distribution network that was suggested in the previous works. Optimal NR and DG integration are valuable mechanisms to reduce power loss and improve the voltage profile in the distribution networks.

Owing to the complexity of the NR problem, finding an optimal solution is a daunting task that requires high computational time. To address the challenges included in the NR, various methods were proposed to find an optimal solution in a minimum computational time. In this chapter, ANN, heuristic, and meta-heuristic methods, which were previously suggested, are explained and discussed. It was noted that the reviewed works suffer from slow convergence and fail to obtain the optimal solution. However, graph theory-based methods achieved improvement in finding a better solution in a short time since graph theory can be utilized to eliminate many of non-feasible solutions from the search space. In addition, it is worth mentioning that proper meta-heuristic methods' initialization has been rarely considered for solving the NR problem. This chapter also provides a comprehensive review of the classical and meta-heuristic methods that were employed for the DG integration in the distribution network. It should be pointed out that when the DG placement and sizing are not performed properly, it will cause great concerns for the EDN operator such as additional power loss. Thus, further investigation on finding the optimal solution of the DG integration in the EDN is required. The studies that considered solving the NR problem simultaneously or sequentially with the DG were also reviewed in this chapter. Solving the problem of NR and DG at the same time leads to further expansion in the search space. Therefore, although different meta-heuristic methods were considered, most of them were not able to find optimal solutions, especially for medium and large EDN. Hence, supplementary research should be investigated to enhance the solution quality. Finally, it is worth mentioning that previous studies rarely discussed the integration of non-dispatchable RER and their impact on the system configuration when the load is changing hourly.

To address the above issues, the next chapter introduces the simplified network approach and the proposed population codification as well as the proposed two-stage method implementation using meta-heuristic methods.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This research aims to solve the NR simultaneously with DG placement and sizing based on the simplified network approach and two-stage meta-heuristic optimization. Firefly Algorithm (FA) and Biogeography-Based Optimization (BBO) are the meta-heuristic methods employed in this research. The intermittent nature of the RER is also considered.

This chapter explains the problem formulation of the NR and DG integration in the EDN and the operation constraints. In addition, the proposed Simplified Network Graph (SNG) approach and the proposed population codification are described. Then, a detailed explanation of the meta-heuristic methods used in this work is provided. Thereafter, the conventional NR method is described followed by the implementation of the proposed two-stage method using the FA and BBO. Finally, the application of the proposed method considering the load changes and the variations in the RER outputs is illustrated.

3.2 Problem formulation

This section presents the problem formulation for the optimization of NR and DG placement and sizing in the distribution system. The optimization searches for the combination of open switches as well as DGs locations and sizes that minimizes the power loss of the EDN and improve the overall voltage profile while fulfilling the operating constraints.

3.2.1 Objective function

The objectives of this study are to minimize the total real power losses and the voltage deviation of the EDN buses while fulfilling the system constraints. Therefore, the objective function *F* can be expressed as follows (T. T. Nguyen et al., 2016):

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

Where;

P_{loss}^{R}= net power loss.

IVD = index of voltage deviation.

Since the objective function F is twofold with different units, the net power loss P_{loss}^{R} is taken as the ratio between the system total active power loss after reconfiguration P_{loss}^{rec} and the total active power loss before reconfiguration P_{loss}^{0}.

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

The total power loss in the EDN is given by the following equation:

$$P_{loss} = \sum_{t=1}^{nbr} |I_t|^2 l_t R_t \tag{3.3}$$

Where;

nbr= total number of the branches excluding the open switches.

I_t = current at line *t*.

R_t = The resistance of the line *t*.

t = line number.

l_t = the topology status of line *t* (1=close, 0=open).

The Index of Voltage Deviation (IVD) penalizes the highest voltage deviation from the nominal voltage. The smaller value of the index, the better for the EDN performance. IVD is given by the equation:

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

Where;

n = the total number of buses in the EDN.

V_i = the voltage magnitude at bus i.

V_1 = the nominal voltage of the reference bus. In this research, the nominal voltage is 1 p.u. (Rahim et al., 2019).

3.2.2 Operation constraints

All the optimization solutions should never violate any of the following operation constraints:

3.2.2.1 Power balance

In all EDNs, the supply of power must equal the sum of the load demands and power loss.

$$P_{substation} + \sum_{i=1}^{k} P_{DG,i} = P_{load} + P_{loss} \tag{3.5}$$

Where;

$P_{DG,i}$ = the generated power of the DG i

k= the total number of DGs in the EDN.

$P_{substation}$ = the output power from the substation.

P_{load} = the EDN's load.

P_{loss} = the power loss of the system.

3.2.2.2 Voltage constraint

The voltage magnitude V at each bus should stay within specific limits during the operation of the EDN.

$$V_{\min} \leq V_i \leq V_{\max} \tag{3.6}$$

Where;

V_i = the voltage magnitude at bus *i*.

$V_{\min}$ = the lower bound of the voltage magnitude.

$V_{\max}$ = the upper bound of the voltage magnitude.

In this research, $V_{\min}$ is 0.9 p.u. whereas, $V_{\max}$ is 1.1 p.u. (Rahim et al., 2019).

3.2.2.3 Distributed generator capacity

The generated power from each DG should have an acceptable output based on the DG's characteristics. Hence, the output of each DG must fulfill the following equation:

$$P_i^{min} \leq P_{DG,i} \leq P_i^{max} \tag{3.7}$$

Where;

P_i^{min} = the lower bound of the DG output.

P_i^{max} = the upper bounds of the DG output.

3.2.2.4 Power injection

This operation constraint guarantees that no power from the DGs can flow to the substation.

$$\sum_{i=1}^{k} P_{DG,i} < (P_{load} + P_{loss}) \quad (3.8)$$

3.2.2.5 The radiality constraint

The EDN must stay radial after finding the new configuration. In this research, the radiality of the EDN is maintained for all solutions as explained in section 3.4.

3.3 Simplified network graph structure

This section explains in detail the architecture of the SNG. Then, an illustrative example is presented. For a given EDN, the following steps describe the implementation of the SNG:

Step 1: The EDN is represented as an undirected graph; where the buses are the nodes and the switches are the edges.

Step 2: The Undirected Incidence Matrix (UIM) of the EDN graph is determined. The dimensions of the *UIM* are (The number of nodes × the number of edges). All UIM elements are zeros except when two nodes (n_1 and n_2) are connected through an edge e1. Thus, $UIM(n_1, e_1)$=1 and $UIM(n_2,e_1)$=1.

Step 3: From the *UIM*, calculate the Node Degree Vector (NDV) by summing the elements of each UIM's row and store the result in the *NDV*. The dimensions of the *NDV* are (The number of nodes × 1).

Step 4: If any of the NDV's elements equal 1, the corresponding node is removed. e.g. if the $NDV(n_1,1)$=1 and n_2 is the successive node of n_1 through the edge e_1, then the *UIM* is updated by: $UIM\ (n_1, e_1)$=0 and $UIM\ (n_2, e_1)$=0.

Step 5: Steps 3-4 are repeated until none of the NDV's elements equal 1.

Step 6: The nodes with a degree greater than 2 are added to the Fundamental Nodes Vector (FNV).

Step 7: For each Fundamental Node (FN), find the series of successive edges and nodes that connect directly this FN with other FNs (i.e. without passing through any other FNs). The resulted group of edges between two FN forms a path. Since all FN's degrees are greater than two, each FN is at least connected directly to the other three FNs through different paths.

Step 8: Loads of an FN *n* are calculated by:

$$\bar{P}_n + j\bar{Q}_n = (P_n + jQ_n) + \sum_{i=i_1}^{i_m}(P_i + jQ_i) + 0.5 \times \sum_{k=k_1}^{k_u}(P_k + jQ_k) \tag{3.9}$$

Where;

$\bar{P}_n + j\bar{Q}_n$ = The new loads of the FN *n*.

$(P_n + j \times Q_n)$ = The original load of the FN *n*.

$i_{m,n}$ = The set of nodes that are connected to the feeder through only one FN *n*.

$\sum_{i=i_1}^{i_{m,n}}(P_i + j \times Q_i)$ = The sum loads of all nodes $i_{m,n}$.

$k_{u,n}$= The set of non-fundamental nodes that belongs to the paths connected to the FN *n*.

$\sum_{k=k_1}^{k_{u,n}}(P_k + j \times Q_k)$= The sum of loads of all non-fundamental nodes $k_{u,n}$.

Step 9: The impedance of a path *c* that connects two FN n_1 and n_2 is given by:

$$R_c + jX_c = \sum_{i=i_1}^{i_t}(R_i + jX_i) \tag{3.10}$$

Where;

$(R_i + j \times X_i)$= The impedance of switch i that belongs to the path c.

i_t = the total number of switches located between two FN n_1 and n_2.

Step 10: Create the SNG based on the FNs and paths.

Figure 3.1 shows the flowchart of the steps to find the SNG.

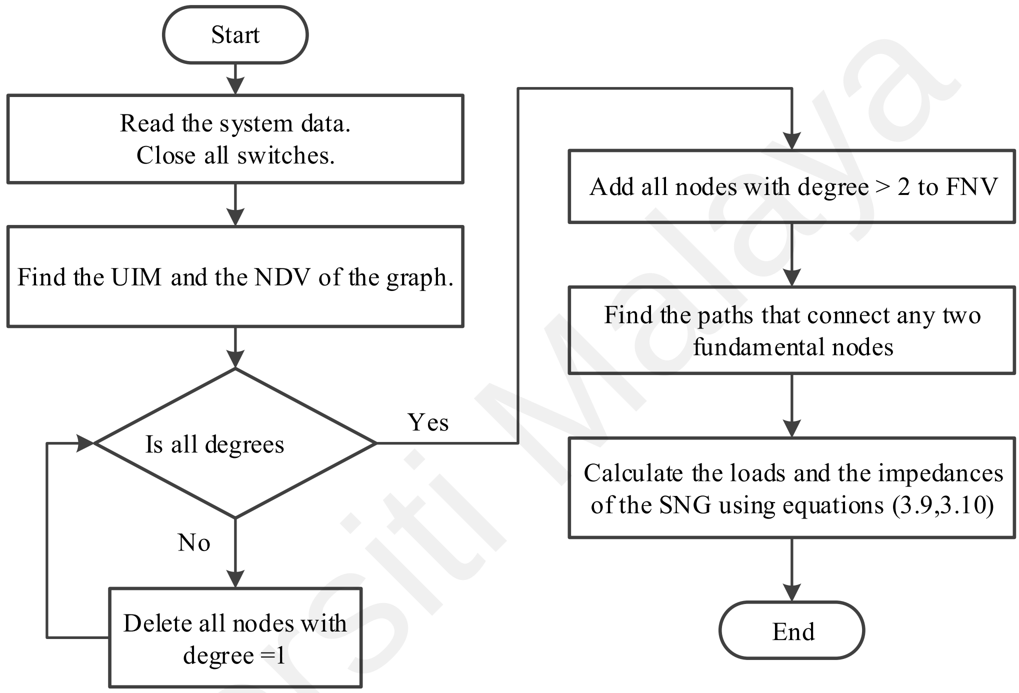

Figure 3.1: Flowchart of the approach of finding the SNG

To illustrate the SNG concept, a 15-bus network shown in Figure 3.2 (a) is taken as an example. The *UIM* and *NDV* matrix for this EDN is given in Figure 3.3. From the *UIM* and *NDV*, it can be observed that nodes 3 and 7 are solely connected to nodes 2 and 6, respectively. Hence, nodes 3 and 7 are removed and consequently switches *S2* and *S6*. Accordingly, the UIM is updated by *UIM*(2,2)=0, *UIM*(3,2)=0, *UIM*(6,6)=0 and *UIM*(7,6)=0. Thereafter, all the remaining nodes' degrees are equal to or greater than two. Therefore, the procedure of creating SNG advances to Step 6. The resulted graph is shown in Figure 3.2 (b). From the updated *NDV* in Figure 3.3, it can be observed that only nodes 1, 2, 8, 12 degrees are greater than two. Hence, they considered as the FNs. The switches that connect those FNs together are gathered to form the paths. For example, the path *P1* contains the switch *S1*. Whereas, the path *P3* contains switches *S3*, *S8*, and *S15*. Then, the FN's loads and the paths' impedances are calculated using equations (3.8 and 3.9). The resulted graph is the SNG of the 15-bus EDN and it is shown in Figure 3.2 (c). The paths of the SNG along with its corresponding EDN's switches are tabulated in Table 3.1.

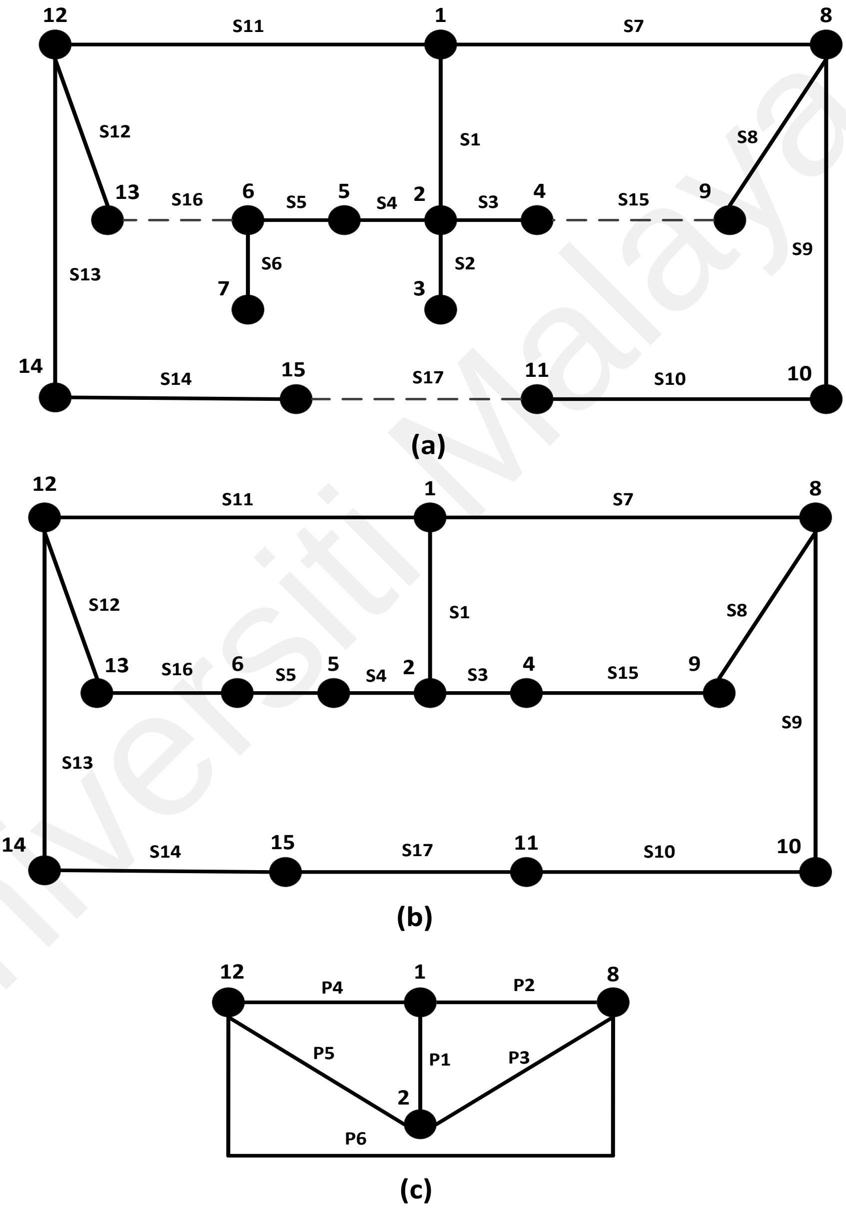

Figure 3.2: Finding the SNG of the 15-bus system

(a) The original 15-bus system.

(b) The 15-bus system after deleting nodes 3 and 7.

(c) The SNG of 15-bus system.

$$
UIM=\begin{array}{c|c}
N/E & \begin{matrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 \end{matrix} \\
\begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \\ 10 \\ 11 \\ 12 \\ 13 \\ 14 \\ 15 \end{matrix} &
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1
\end{bmatrix}
\end{array}
\quad
NDV=\begin{bmatrix} 3 \\ \cancel{4}\;3 \\ \cancel{1}\;0 \\ 2 \\ 2 \\ \cancel{3}\;2 \\ \cancel{1}\;0 \\ 3 \\ 2 \\ 2 \\ 2 \\ 3 \\ 2 \\ 2 \\ 2 \end{bmatrix}
$$

Figure 3.3 The UIM and NDV matrixes of the 15-bus EDN

Table 3.1 The paths and the switches of the 15-bus system

Paths	Switches
P1	S1
P2	S7
P3	S3, S8, S15
P4	S11
P5	S4, S5, S12, S16
P6	S9, S10, S13, S14, S17

3.4 The proposed population codification and maintaining the radiality

In this section, the approach for finding the FLs of a distribution system is explained. Thereafter, the proposed codification for the NR, which accelerates the search process and maintains the system radiality, is illustrated.

As stated in section 3.3, EDNs consist of switches, whereas SNGs are made up of paths. In this work, the procedures of finding the FLs, codifying the population, and maintaining the radiality are similar in both the EDN and SNG. Therefore, to generalize the explanation for both; EDN and SNG, the term branch is used to represent the switch and the path in the description of these procedures.

3.4.1 Determination of the fundamental loops

The distribution system, in its initial status, has a radial structure, i.e. it has no loops and no isolated buses. Starting from the initial topology, when a normally open branch is closed, one unique FL will be created. By repeating this process to all normally open branches, all FLs can be founded. Hence, the total number of the FL is always equal to the number of normally open branches. It is worth mentioning that the number of FLs in the EDN and its corresponding SNG is always identical.

For instance, the FLs' matrixes for the SNG and EDN of the 15-bus system, which was described in section 3.3, is given by:

$$FL_{SNG} = \begin{bmatrix} P3 & P1 & P2 \\ P5 & P1 & P4 \\ P6 & P2 & P4 \end{bmatrix} \tag{3.11}$$

$$FL_{EDN} = \begin{bmatrix} S15 & S1 & S3 & S7 & S8 & \\ S16 & S1 & S4 & S5 & S11 & S12 \\ S17 & S7 & S9 & S10 & S11 & S14 \end{bmatrix} \tag{3.12}$$

3.4.2 Establishing the common paths and the prohibited paths groups

After finding the FLs of the SNG and EDN, it is necessary to define the common branches and the prohibited branches groups. The common branches and the prohibited branches groups play a vital role in maintaining the system radiality.

If the branch is involved in more than one FL, it is called a common branch. Otherwise, it is called an uncommon branch. The prohibited branches groups are defined as the groups of branches that are not allowed to switch off at the same time to maintain the connection among all the nodes in the system.

For example, in Figure 3.2, the common paths of the given SNG are: [P1, P2, P4]. Whereas, the common switches of the EDN are: [S1, S7, S11]. In addition, there is only one prohibited paths group, and one prohibited switches group which are: [P1, P2, P4] and [S1, S7, S11], respectively. It is worth mentioning that the number of common branches and prohibited branches groups increases when the network has a larger number of buses and branches, and a more complex structure.

3.4.3 Radiality of the candidate solution

In this section, the rules to maintain the population radiality is illustrated as follows:

Rule 1: The dimension of the solution vector (population) equals the number of FLs.

Rule 2: Only one branch from each FL should be selected to be open during one population.

Rule 3: If one common branch is selected to be in the solution vector, this common branch will be deleted from the rest of the FLs.

Rule 4: In the EDN level, when one switch from a path is selected in the solution vector, the remainder switches of that path will be deleted from the following FLs' rows.

Rule 5: All the branches of any prohibited group must not be off in one solution vector. For example, for a prohibited group consists of branches b1, b2, and b3, if b1 and b2 are selected to be open, then b3 is deleted from the following FLs. Hence, it can't be selected to be open.

Rule 6: When a branch is deleted from an FL matrix, one from the other branches in the same FL's line will replace this branch to maintain the FL size. Hence, the FL matrix is changing continuously based on the solution vector elements. However, the FL matrix returned to its original form after each iteration.

For instance, in FL_{EDN} shown in equation (3.12), if the first element of the solution vector is S1, then S1 is deleted from the second row of the FL_{EDN} and replaced by one of the following elements (S16, S4, S5, S11, S12).

In (Gupta et al., 2010), the proposed method imposes checking each element of the population whether it violates one of the rules. As a result, this will interrupt the search process and slow down the population's convergence to the final solution. Whereas, according to Rule 6 of this work, the FL matrix is changing based on the prior generated population's elements. Consequently, all the created and updated population are feasible, and the search process persists smoothly. Furthermore, the utilization of SNG assists in accelerating the population's creating and updating as explained in Rule 4. Finally, it is worthy to mention that the decimal codifications are used in this work to code the DGs' locations and sizes during the search process.

3.5 Meta-heuristic methods overview

In this section, a brief overview of the Firefly Algorithm (FA) and Biogeography-Based Optimization (BBO) is presented.

3.5.1 Firefly algorithm

FA was inspired by the flashing behavior of the fireflies in nature. This behavior is essentially used by the fireflies to communicate among each other. When the firefly produces light with an *(I)* intensity, it attracts other fireflies, that have less intensity, in different attractiveness *(β)* based on the distance *(r)* between the two fireflies. The longer the distance between two fireflies, the less the attractiveness. In this algorithm, each population is represented by a firefly location, whereas the objective function is defined as the intensity of each firefly.

The attractiveness between two fireflies *β(r)* is given by:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{3.13}$$

Where;

β_0 = the attractiveness at zero distance.

γ = the light absorption coefficient.

r = the Cartesian distance between two fireflies.

The Cartesian distance between any two fireflies h_l and h_j is r_{lj} and it is given by:

$$r_{lj} = \|h_l - h_j\| = \sqrt{\sum_{k=1}^{d} (h_{l,k} - h_{j,k})^2} \tag{3.14}$$

Where;

d = the problem dimension.

r_{lj} = the Cartesian distance between two fireflies h_l and h_j.

$h_{l,k}$ and $h_{j,k}$ = the kth element of the firefly h_l and h_j, respectively.

For all fireflies, if h_j is brighter (has higher light intensity) than h_l, then h_l is attracted to h_j and h_l is updated by the following equation:

$$h_l = h_l + \beta_0 e^{-\gamma r_{lj}^2} r_{lj} + \alpha(rand - 0.5) \tag{3.15}$$

Where;

α = the randomized parameter. rand is a uniformly distributed random number between 0 and 1.

3.5.2 Biogeography-Based Optimization

BBO populations are represented by habitats where the variables of the habitat are called the Suitability Index Variables (SIV). Each habitat has a Habitat Suitability Index (HSI) which represents the habitat's fitness. The higher the HSI, the better the solution. Also, a habitat with high HSI has more species count (which refers to as S). When the habitat has a large number of species, its immigration rate λ is low since the habitat is almost saturated. For the same reason, when the habitat contains large species' numbers, its emigration rate μ is high since the habitat has many opportunities to other adjacent habitats. On the other hand, the habitat with low HSI, i.e. a small number of species, has a high immigration rate and low emigration rate. Figure 3.4 illustrates the relationship between the immigration rate and emigration rate with the number of species of a single habitat. where S_{max} is the maximum number of species that can be existed in habitat and S_0 is the number of species when the immigration and emigration rates are equal.

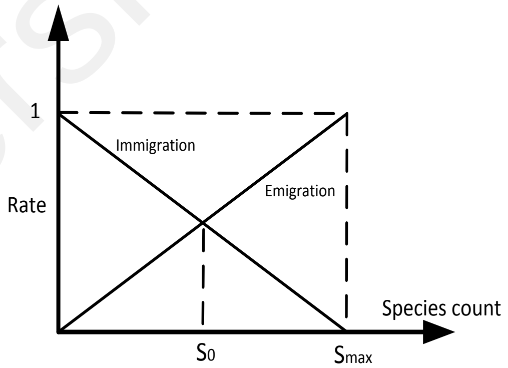

Figure 3.4 The immigration and emigration model for a single habitat.

In this study, for any habitat:

$$\lambda + \mu = 1 \tag{3.16}$$

BBO depends on two mechanisms namely; the migration and mutation. These mechanisms are utilized to update BBO's population and create new solutions. However, BBO also has elitism feature to retain the best solutions from changes. The keep rate parameter determines the rate of elitism habitat during the search process.

(a) ***Migration***

During the habitat's lifecycle, one or more from its SIV tend to migrate to another habitat. The migration decision depends on the comparison between a random value and the immigration rate of the given habitat. High HSI habitats have more species and therefore they have high emigration rate μ and accordingly low immigration rate λ. Therefore, low HSI habitats tend to copy SIVs from the high HSI habitats. If the kth SIV of a habitat H_i is determined to immigrate, then this SIV will be replaced by its corresponding SIV from another random habitat H_j that normally has high HSI. Hence, the migration mechanism assists the population to share information with each other. The habitat is updated by the following equation:

$$H_{i,k} = H_{j,k} \tag{3.17}$$

Where;

$H_{i,k}$ and $H_{j,k}$ = the kth SIV of the habitat i and j, respectively.

The pseudo-code of the migration process is described as follows:

START PROCEDURE Migration mechanism for *n* habitats

FOR *i*=1 to *n* **DO**

IF randomly generated number < λ_i

SELECT: H_i with the immigration rate λ_i

FOR j=1 to n **DO**

IF randomly generated number < μ_j

SELECT: H_j with emigration rate μ_j

Replace a random SIV of H_i with its corresponding SIV from H_j as given in (3.17)

ENDIF

ENDFOR

ENDIF

ENDFOR

(b) ***Mutation***

The mutation is another mechanism in BBO that assists in further exploration of the search space by altering some of the habitat's variables. In BBO, the solution probability (P_S) is inversely proportional to the mutation rate. Hence, habitats with low or high HSI have a high mutation rate because their probability to exist is small compared to the medium HSI habitats. The solution probability (P_S) and the mutation rate for habitat with S species is given by:

$$\dot{P}_S = \begin{cases} -P_S + \mu_{S+1}P_{S+1} \ ; \ S = 0 \\ -P_S + \mu_{S+1}P_{S+1} + \lambda_{S-1}P_{S-1} \ ; \ 1 \leq S \leq S_{max} - 1 \\ -P_S + \lambda_{S-1}P_{S-1}; \ S = S_{max} \end{cases} \tag{3.18}$$

$$m(S) = m_{max}\left(\frac{1 - P_S}{P_{max}}\right) \tag{3.19}$$

Where;

m_{max} = the maximum mutation rate defined by the user.

P_{max} = the argmax of the solution probability.

The following pseudo-code illustrates the mutation mechanism:

START PROCEDURE Mutation mechanism for *n* habitats and $m\ SIV$

FOR *i*=1 to *n* **DO**

SELECT: H_i with the immigration rate λ_i and emigration rate μ_i

Calculate the probability $\dot{P}_S$ using λ_i and μ_i based on equation (3.18)

FOR *j*=1 to *m* **DO**

SELECT: SIV_j of H_i with $\dot{P}_i$

IF SIV_j of H_i is selected

Replace SIV_j of H_i with a randomly generated SIV

ENDIF

ENDFOR

ENDFOR

3.6 The conventional methods for NR and DG integration

In this section, the conventional FA and BBO for solving the NR and DG integration are explained to demonstrate the differences between the proposed method and conventional methods.

3.6.1 Conventional biogeography-based optimization for network reconfiguration and DG integration

The conventional BBO method typically employed the following processes in solving the NR and DG placement and sizing problem in the distribution systems:

Step 1: Read the EDN data, DGs' number (N_{DG}) and allowable sizes, BBO parameters, the maximum number of iterations, the number of habitats N_h and the problem dimension (the number of SIV N_{SIV}) which is given by:

$$N_{SIV} = (N_{FL} + 2 * N_{DG}) \tag{3.20}$$

Step 2: Generate random initial SIVs and assign them to each habitat. The habitats of the conventional BBO are represented by eq (3.21). Each habitat consists of three parts, firstly is the open switches that represent the solution of the NR problem. Then, secondly and thirdly are the locations and sizes of the DGs, respectively.

$$x = \begin{bmatrix} S_{1,1} & \cdots & S_{1,N_{FL}} & DGL_{1,1} & \cdots & DGL_{1,N_{DG}} & DGC_{1,1} & \cdots & DGC_{1,N_{DG}} \\ S_{2,1} & \cdots & S_{2,N_{FL}} & DGL_{2,1} & \cdots & DGL_{2,N_{DG}} & DGC_{2,1} & \cdots & DGC_{2,N_{DG}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{N_h,1} & \cdots & S_{N_h,N_{FL}} & DGL_{N_h,1} & \cdots & DGL_{N_h,N_{DG}} & DGC_{N_h,1} & \cdots & DGC_{N_h,N_{DG}} \end{bmatrix} \quad (3.21)$$

Where;

S = the open switch number.

DGL = the DG location.

DGC = the DG capacity.

Step 3: Thereafter, the iteration is started by applying a radiality check to the open switches' combination in each habitat. If the combination is not radial, then the corresponding habitat should be replaced with other radial combination. Thereafter, the load flow analysis is performed to obtain the power flow in all network lines. Based on the power flow results, the fitness (HSI) of each habitat can be determined based on equation (3.1).

Step 4: The habitat with the highest HSI is identified as the elite habitat.

Step 5: Next, based on the HSI of each habitat, the immigration and emigration rates are calculated as well as the mutation rate.

Step 6: Use immigration and emigration to decide which habitats ought to be modified.

Step 7: For each habitat, based on the mutation rate, some of the medium HSI habitats SIVs will be replaced by random values within the allowable range of the SIV.

Step 8: Iterations are continued by repeating Steps 3-8 until the maximum number of iterations is reached.

Step 9: Output the best habitat along with its HSI. This habitat represents the open switches combination, DGs locations, and DGs sizes that minimize the objective function given by equation (3.1).

3.6.2 Conventional firefly algorithm for network reconfiguration and DG integration

The conventional FA method typically employed the following processes in solving the NR problem:

Step 1: Input the EDN data as well as the FA parameters.

Step 2: The population in the conventional FA is the combination of the open switches in the EDN, whereas the fitness is given by equation (3.1). It starts with generating a random population and then test this combination to check if it fulfills all the system constraints. The population, that do not meet one or more constraints, will be replaced by a new feasible population. This process is repeated until all the populations satisfied the specified constraints.

Step 3: Next, the iteration is started by solving the load flow analysis to obtain the power flow in all network lines. Based on the power flow results, the fitness function of each firefly can be determined.

Step 4: For each firefly, its attractiveness to the other fireflies in terms of its brightness is checked and their locations are subsequently updated based on equations (3.13 to 3.15). Note that the updated population will be rounded to the closest integer number. Next, the system constraints of the updated population are checked. Again, the population that does not meet the system constraints will be replaced with another random feasible population.

Step 5: Ranking of the fireflies will be done next to name the best firefly.

Step 6: Iteration is continued by repeating steps (3) to (6) until the maximum iterations number is reached or until the population converged to the same solution.

Step 7: The best firefly along with its fitness will be determined and the best configuration of open switches that minimizes the objective function given by equation (3.1) is found.

3.7 The proposed two-stage method for optimal network reconfiguration and DG integration

The conventional meta-heuristic techniques suffer from slow convergence and there is no guarantee to obtain the optimal solution. This is due to the random solution's initialization and the continuous radiality check during the search process. To overcome these demerits, the proposed two stages method has been proposed. In the first stage, the EDN is simplified into a smaller size network called the SNG. Then, a meta-heuristic technique is used to find the solution for the SNG. In the second stage, the optimal solution for the EDN is determined using a meta-heuristic that is initialized from the first stage's output. Same or different meta-heuristic technique can be used in the second stage to find the optimal NR for the EDN.

The flowchart of the proposed method to find the optimal NR is shown in Figure 3.5.

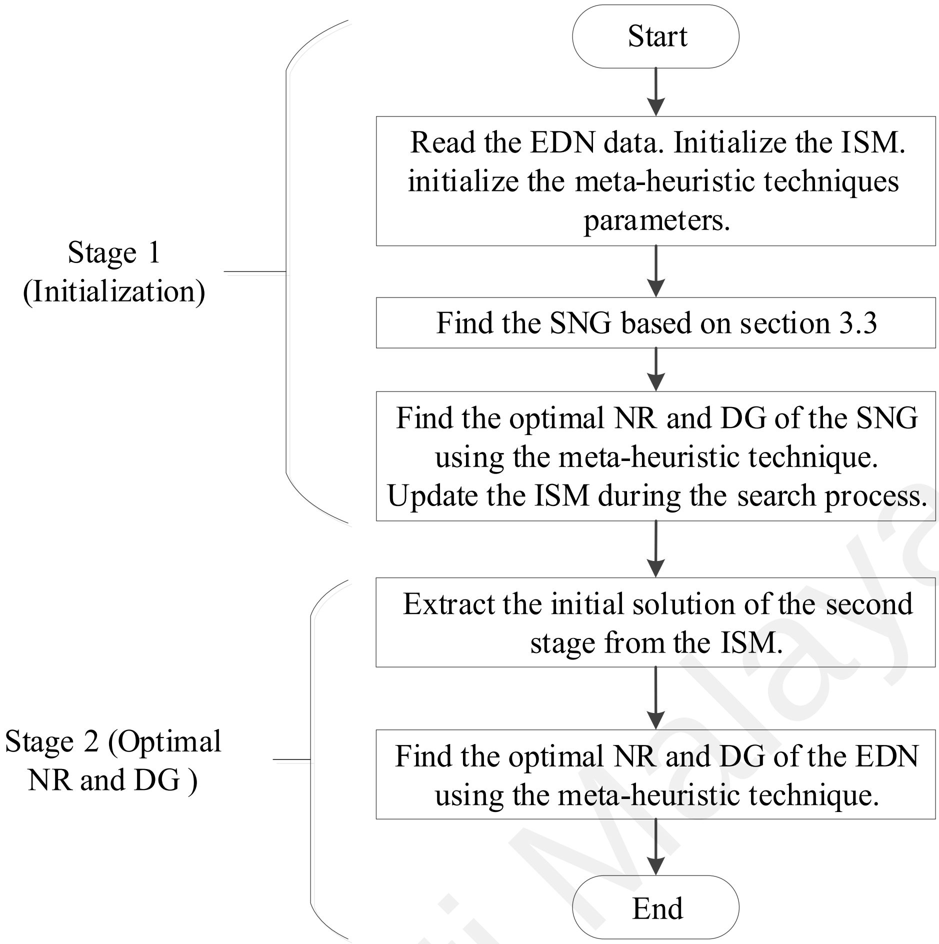

Figure 3.5: Flowchart of the proposed method

3.7.1 The proposed two-stage biogeography-based optimization for optimal network reconfiguration and DG integration

The proposed two-stages BBO is implemented by the following steps. A complete optimization is used individually in each stage of the proposed method. The first stage consists of Steps 1-9, whereas Steps 10-16 represent the second stage.

Step 1: Read the EDN data, DGs' number (N_{DG}) and maximum DG's size, BBO parameters, the maximum number of iterations, the number of habitats N_h, and the problem dimension N_{SIV} given by equation (3.20). Then, initialize a matrix named Initial Solution Matrix (ISM) whose dimensions are ($N_h \times N_{SIV}$). Each line of the ISM contains a single habitat. The rows of the ISM are sorted based on their fitness.

Step 2: Start the first stage by determining the SNG of the EDN through the approach explained in section 3.3 and calculate its loads and impedances based on equations (3.9 and 3.10).

Step 3: Create random initial SIVs for each habitat as stated in section 3.4. Consequently, all the habitats are feasible. In this stage, the SIVs consists of the open paths' indexes and the DGs' locations and sizes. Each habitat occupies one row of the H matrix as presented in equation (3.23).

$$\mathrm{H} = \begin{bmatrix} p_{1,1} & \dots & p_{1,N_{FL}} & DGL_{1,1} & \dots & DGL_{1,N_{DG}} & DGC_{1,1} & \dots & DGC_{1,N_{DG}} \\ p_{2,1} & \dots & p_{2,N_{FL}} & DGL_{2,1} & \dots & DGL_{2,N_{DG}} & DGC_{2,1} & \dots & DGC_{2,N_{DG}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{N_h,1} & \dots & p_{N_h,N_{FL}} & DGL_{N_h,1} & \dots & DGL_{N_h,N_{DG}} & DGC_{N_h,1} & \dots & DGC_{N_h,N_{DG}} \end{bmatrix} \tag{3.22}$$

Where;

p is the open path number.

Step 4: Start the iteration by executing load flow analysis to obtain the power flow in the SNG. Then, evaluate the fitness (HSI) for each population (habitat) using equation (3.1).

Step 5: Rank the habitats based on their HSI and select the elite habitat. Then, update the ISM by replacing the habitats that have the lowest HSI with those that have higher HSI.

Step 6: Calculate the immigration, emigration, and mutation rates as well as the number of species. The calculation is performed for each habitat based on its HSI.

Step 7: Modify the habitats based on the migration and mutation mechanisms. The habitats are modified based on the rules stated in section 3.4.

Step 8: Iterations are carried on by repeating Step 4-8 until iterations reach the maximum number of iterations.

Step 9: End the first stage and move to the second stage. The output of the first stage is the ISM which contains the ranked open paths along with DGs locations and sizes.

Step 10: Strat the second stage by generating initial habitats from the ISM. Each path from the ISM includes one or more switches. However, only one switch is chosen randomly from the path. On the other hand, the DGs locations and sizes from the ISM are transferred without any changes to the population of the second stage. The population of the second stage consists of the combination of open switches' and the DGs locations and sizes. Equation (3.23) shows the habitats matrix in the second stage.

$$x = \begin{bmatrix} S_{1,1} & \dots & S_{1,N_{FL}} & DGL_{1,1} & \dots & DGL_{1,N_{DG}} & DGC_{1,1} & \dots & DGC_{1,N_{DG}} \\ S_{2,1} & \dots & S_{2,N_{FL}} & DGL_{2,1} & \dots & DGL_{2,N_{DG}} & DGC_{2,1} & \dots & DGC_{2,N_{DG}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{N_h,1} & \dots & S_{N_h,N_{FL}} & DGL_{N_h,1} & \dots & DGL_{N_h,N_{DG}} & DGC_{N_h,1} & \dots & DGC_{N_h,N_{DG}} \end{bmatrix} \quad (3.23)$$

Step 11: Start the iteration by executing load flow analysis to obtain the power flow in the EDN. Evaluate the fitness for each habitat using (3.1).

Step 12: Rank the habitats based on their HSI and select the elite habitat.

Step 13: Calculate the immigration, emigration, and mutation rates.

Step 14: Modify the habitats based on the migration and mutation mechanisms. The habitats are modified based on the rules stated in section 3.4.

Step 15: Iterations are carried on by repeating Step 11-15 until iterations reach the maximum number of iterations.

Step 16: Stop the process and output the elite habitat along with its HSI. The result represents the best-found open switches configuration and DGs locations and sizes that minimize the objective function given in equation (3.1).

3.7.2 The proposed two-stage firefly algorithm for optimal network reconfiguration and DG integration

The following steps describe in detail the implementation of the proposed two-stage FA method to solve the NR problem. In this method, FA is used in the first stage to find the initial population whereas, in the second stage, it will be employed again to find the optimal NR. The flowchart of the proposed two-stage method is shown in Figure 3.5 where it consists of Step 1-9 in the first stage and Step 9-15 in the second stage.

Step 1: Read the EDN data and the FA parameters. Then, initialize an Initial Solution Matrix (ISM) ($N_{FF} \times N_{FL}$) where; N_{FF} is the number of the fireflies population whereas N_{FL} is the number of the FLs of the system (dimension of the problem). Each row of the ISM will contain the configuration of the open paths that minimize the given fitness function in the SNG.

Step 2: Start the first stage by finding the SNG of the EDN using the approach proposed in section 3.3 and calculate its loads and impedances based on equations (3.9 and 3.10). Subsequently, find the FLs of the SNG as in section 3.4.

Step 3: Create an initial population as stated in section 3.4. All the generated population are radial. In this stage, the population's elements are the open paths indexes from the FL_{SNG} matrix. Each row of the fireflies' matrix represents individual firefly as follows:

$$\mathrm{H} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,N_{FL}} & DGL_{1,1} & \cdots & DGL_{1,N_{DG}} & DGC_{1,1} & \cdots & DGC_{1,N_{DG}} \\ p_{2,1} & \cdots & p_{2,N_{FL}} & DGL_{2,1} & \cdots & DGL_{2,N_{DG}} & DGC_{2,1} & \cdots & DGC_{2,N_{DG}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{N_h,1} & \cdots & p_{N_h,N_{FL}} & DGL_{N_h,1} & \cdots & DGL_{N_h,N_{DG}} & DGC_{N_h,1} & \cdots & DGC_{N_h,N_{DG}} \end{bmatrix} \quad (3.24)$$

Step 4: Start the iteration by solving a load flow for the population to obtain power flow in all network lines. Based on the power flow results, the power loss and the IVD for the SNG can be determined, and hence the fitness function is calculated using equation (3.1).

Step 5: Update the ISM by replacing the population that has the worst fitness with those that have better fitness.

Step 6: For each firefly, check its attractiveness to all other fireflies by comparing their brightness and update the fireflies based on equations (3.13, 3.14, 3.15) and the rules proposed in section 3.4. All fireflies should be rounded to the closest integer value.

Step 7: Rank the population based on their fitness function.

Step 8: Repeat steps 4 to 8 until the maximum number of iterations is reached, or the population converges to the same solution.

Step 9: End the first stage and move to the second stage. The output of this stage is the ISM. The ISM contains the ranked open paths combinations that represent the solutions of the first stage.

Step 10: Generate the initial population based on the ISM determined from the first stage. Each path from the ISM contains one or more switches. However, only one switch is chosen randomly from each path in the ISM. The population in this stage is the index of the switch in the FL_{EDN} matrix. The initial population's matrix x_s is represented by the fireflies and is given by:

$$x = \begin{bmatrix} S_{1,1} & \dots & S_{1,N_{FL}} & DGL_{1,1} & \dots & DGL_{1,N_{DG}} & DGC_{1,1} & \dots & DGC_{1,N_{DG}} \\ S_{2,1} & \dots & S_{2,N_{FL}} & DGL_{2,1} & \dots & DGL_{2,N_{DG}} & DGC_{2,1} & \dots & DGC_{2,N_{DG}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ S_{N_h,1} & \dots & S_{N_h,N_{FL}} & DGL_{N_h,1} & \dots & DGL_{N_h,N_{DG}} & DGC_{N_h,1} & \dots & DGC_{N_h,N_{DG}} \end{bmatrix} \quad (3.25)$$

Step 11: Start the iteration by solving the load flow for all populations to obtain power flow in all network lines. Based on the power flow results, the power loss and the IVD for the EDN can be determined, and accordingly the fitness function using equation (3.1).

Step 12: For each firefly, check its attractiveness to all other fireflies (compare their brightness) and update the fireflies based on equations (3.13, 3.14, 3.15) and the rules proposed in section 3.4.

Step 13: Rank the population based on their fitness function.

Step 14: Repeat the steps from 11 to 14 until the maximum number of iterations is reached, or the population converges to the same solution.

Step 15: Stop the process and print out the best firefly along with its fitness. The results show the best-found open switches' configuration that minimizes the objective function given by equation (3.1).

3.8 The proposed two-stage method for daily operation

The previous sections considered finding the solution of the NR and DG when the EDN's load is static and the DG's output is controllable. However, in recent years, more RERs are integrated into the EDN, in addition to the continuous changes in the load characteristic. Hence, it is vital to study the case of daily operation where the load is varying hourly and considering the stochastic RER output.

3.8.1 Objective function

The objective function of this case is similar to eq. (3.1). It also contains minimizing the total real power losses and the voltage deviation of the EDN buses while maintaining the system constraints. However, the hour of the day must be referred to in the objective function formula. Hence, in this section, the objective function *F* can be presented as follows:

$$\min(F(h)) = \min\left(P_{loss}^{R}(\mathrm{h}) + \mathrm{IVD}(\mathrm{h})\right) \tag{3.26}$$

$$P_{loss}^{R}(\mathrm{h}) = \frac{P_{loss}^{rec}(\mathrm{h})}{P_{loss}^{0}(h)} \tag{3.27}$$

$$P_{loss}(h) = \sum_{t=1}^{nbr} |I_t(h)|^2 l_t(h) R_t \tag{3.28}$$

$$IVD\ (\mathrm{h}) = max_{i=2}^{n}(\frac{|V_1|-|V_i(h)|}{|V_1|}) \quad (3.29)$$

Where;

$F(h)$ = the objective function at hour h.

P_{loss}^{R}(h) = net power loss at hour h.

$IVD(h)$ = index of voltage deviation at hour h.

h = the hour of the day.

P_{loss}^{rec}(h) = the power loss of the system after reconfiguration.

$P_{loss}^{0}(h)$ = the power loss of the system after reconfiguration.

$I_t(h)$ = the current at line *t* at hour *h*.

R_t = the resistor of line *t*.

$l_t(h)$ = the status of line *t* at hour *h* (1=close, 0=open).

nbr = the total number of branches in the system.

n = the total number of buses in the system.

$V_i(h)$ = the voltage magnitude at bus *i* during hour *h*.

V_1 = the nominal voltage of the reference bus.

It should be pointed out that the power loss before reconfiguration should be calculated for each hour since the load and the RER output are varying.

3.8.2 Operation constraints

All the optimization solutions should never violate any of the following operating constraints at any hour:

3.8.2.1 Power balance:

In all hours, the supply of power must equal the sum of the load demands and the power loss at the hour.

$$P_{substation}(\mathrm{h}) + \sum_{i=1}^{k} P_{DG,i}(\mathrm{h}) = P_{load}(\mathrm{h}) + P_{loss}(h) \quad (3.30)$$

Where;

$P_{substation}(\mathrm{h})$ = the output power of the substation at hour h.

$P_{DG,i}(h)$ = the generated power of the DG *i* at hour *h*.

k= the total number of DGs in the EDN.

$P_{load}(\mathrm{h})$ = the EDN's load at hour h.

$P_{loss}(h)$ = the power loss at hour h.

3.8.2.2 Voltage constraint

The voltage magnitude *V* at each bus should stay within specific limits during the operation of the EDN.

$$V_{\min} \leq V_i(\mathrm{h}) \leq V_{\max} \quad (3.31)$$

Where;

$V_{\mathrm{i}}(\mathrm{h})$ = the voltage magnitude of the bus *i* at hour *h*.

$V_{\min}$ = the lower bound of the voltage magnitude.

$V_{\max}$ = the upper bound of the voltage magnitude.

3.8.2.3 Distributed generator capacity

the generated power from each DG should have an acceptable output based on the DG's characteristics. Hence, the output of each DG must fulfill the following equation:

$$P_i^{min} \leq P_{DG,i}(\mathrm{h}) \leq P_i^{max} \tag{3.32}$$

Where;

P_i^{min} = the lower bound of the DG output.

P_i^{max} = the upper bounds of the DG output.

3.8.2.4 Power injection

This constraint guarantees that no power from the DGs can flow to the substation at any hour of the day.

$$\sum_{i=1}^{k} P_{DG,i}\,(h) < (P_{load}(\mathrm{h}) + P_{loss}(h)) \tag{3.33}$$

3.8.2.5 The radiality constraint

The EDN must stay radial after finding the new configuration. In this research, the radiality of the EDN is maintained for all solutions as explained in section 3.4.

CHAPTER 4: VALIDATION OF THE PROPOSED METHOD

4.1 Introduction

This chapter discusses the performance of the proposed method in solving the NR problem in the EDN. Besides, the efficiency of the proposed method to solve the DG placement and sizing is evaluated. The proposed method is tested on 33-bus, 69-bus, and 118-bus IEEE standard test systems. The obtained results are compared to the conventional EP (Dahalan, Mokhlis, Ahmad, Bakar, & Musirin, 2014), PSO (Dahalan, Mokhlis, Bakar, & Jamian, 2013), FA and BBO as well as to the recently published works. The proposed method in its second stage starts the search for the optimal configuration from the initial population found in the first stage whereas conventional methods start the search process from random populations. Furthermore, conventional methods need to check the population's radiality repeatedly after each population update which increases the computation burden.

4.2 Meta-heuristic parameters' setting and assumptions

Based on empirical tests that gave the best performance, the FA parameters are set to β_0=1, γ=0.5, α=0.2. Similarly, the BBO parameters are set to m_{max} =0.01 and keep rate = 0.1. Whereas, the parameters given in (Dahalan et al., 2014) was used for EP and the parameters of PSO were chosen according to EP (Dahalan et al., 2013). In addition, the conventional methods and the proposed method have the same number of population and maximum number of iterations to ensure the fair comparisons. All the tests were carried out by MATLAB using a PC with an Intel Core 2 Duo 3.06 GHz processor.

Since existing works use different computer specifications, it is not possible to make a fair comparison for computational time. Therefore, comparison with the literature can only be done for voltage profile and the best, average, worst, and Standard Deviation (STD) of the power loss. Besides, all the configurations found in previous works were simulated for a fair comparison. Nevertheless, comparison in computational time between the proposed two-stage FA and BBO as well as the conventional EP, PSO, FA, and BBO is presented to show the superiority of the proposed method.

4.3 Test results for the network reconfiguration

To demonstrate the effectiveness of the proposed method in solving the NR problem in the EDN, it is applied to 33-bus, 69-bus, and 118-bus IEEE test systems.

4.3.1 Test system 1: IEEE 33-bus

The 33-bus IEEE test system (Baran & Wu, 1989) consists of 33 buses and 37 switches; switches 1 to 32 are the normally closed switches and 33 to 37 are the normally open switches. The system has a nominal voltage of 12.66 kV with the minimum and maximum allowable voltage magnitudes range between 0.9 p.u. and 1.1 p.u. The total active and reactive load of the system is 3715 kW and 2300 kvar, respectively. In the base case, the power loss of the system is 210.98 kW with the minimum bus voltage of 0.9038 p.u. Since there are 5 normally open switches in the system, then the FLs number is equal to 5. The details of the 33-bus system can be found in the Appendix A.1.

Figure 4.1 shows the IEEE 33-bus distribution network in the base case. Whereas, its SNG is presented in Figure 4.2. The SNG can be found as illustrated in section 3.3 and it consists of 12 paths and 8 fundamental nodes (i.e. 3, 6, 8, 9, 12, 15, 21, 29) which is smaller than the original EDN. As a result, the search space for the first stage was reduced to only 429 feasible solutions instead of 4×10^5 solutions in the original EDN. Hence, finding the optimal answer in the first stage is very attainable.

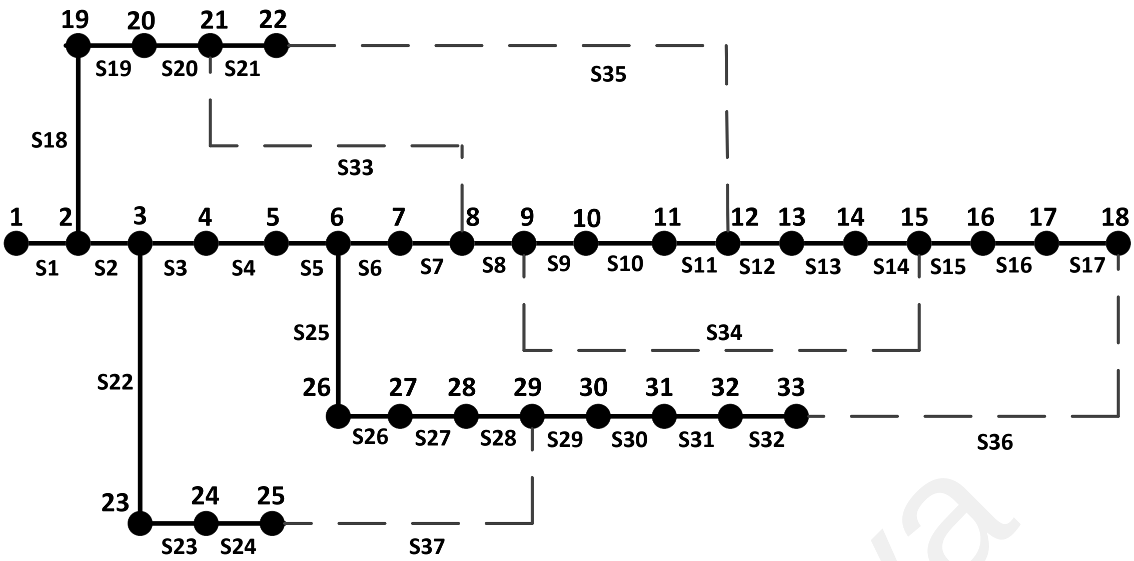

Figure 4.1 IEEE 33-bus distribution network in the base case

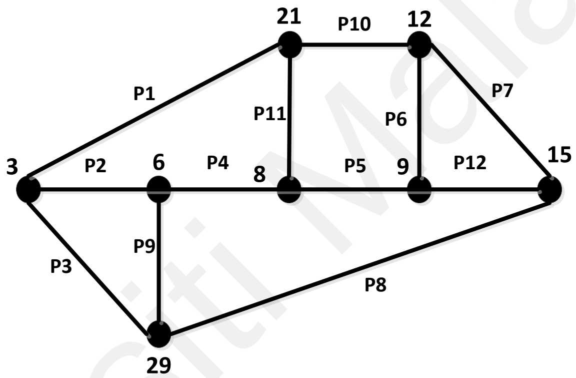

Figure 4.2 The SNG of the IEEE 33-bus

Table 4.1 shows the results found by the conventional EP, PSO, FA, and BBO as well as the proposed two-stage FA and BBO method. In this work, the simulation was run for 500 times, and the best, worst, and average power loss were collected for each run, in addition to the minimum voltage. Then, for each method, the STD of the power loss was calculated to determine the consistency in obtaining the solution.

The optimal open switches configuration that minimizes the specified objective function under the system constraints. is (s7, s9, s14, s28, s32). The resulted power loss in the EDN after reconfiguration is 139.98 kW with the minimum voltage increment to 0.9413 p.u. This value is comparable to the solution found by the other methods and this verified the accuracy of the proposed method. It is worth highlighting that although all methods produced comparable optimal solutions, the STD of the power loss, as well as the total computational time for the proposed method, were significantly reduced compared to the other existing methods.

Table 4.1 NR results for 33-bus

Method	Open switches of the best solution	Power Loss (kW)				Minimum Voltage (p.u.)
		Best	Worst	Avg.	STD	
Base case	33, 34, 35, 36, 37	210.98	-	-	-	0.9038
EP	7, 9, 14, 28, 32	139.98	192.73	148.85	9.84	0.9413
PSO	7, 9, 14, 28, 32	139.98	182.36	149.2	9.78	0.9413
FA	7, 9, 14, 28, 32	139.98	155.04	143.81	4.19	0.9413
BBO	7, 9, 14, 28, 32	139.98	151.93	143.64	3.72	0.9413
Proposed two-stage FA	**7, 9, 14, 28, 32**	**139.98**	**140.71**	**139.99**	**0.101**	**0.9413**
Proposed two-stage BBO	**7, 9, 14, 28, 32**	**139.98**	**140.71**	**139.99**	**0.072**	**0.9413**

The two-stage FA and two-stage BBO have the most consistent performance with STD of only 0.101 kW and 0.072 kW, respectively. In addition, the average power loss of the proposed FA and BBO is 139.99 kW which is very close to the optimal solution. In comparison, the conventional EP, PSO, FA, and BBO have STD values of 9.84 kW, 9.78 kW, 4.19 kW, and 3.72 kW, respectively. Additionally, the average power loss for conventional EP, PSO FA, and BBO amounted to 148.85 kW, 149.2 kW, 143.81 kW, and 143.64 kW, respectively. Hence, the stability of the proposed two-stage method in finding the optimal configuration surpassed the other conventional methods due to the proposed guided initializations resulted from the first stage and the proper population's codification that preserve the search process without any interference.

Figure 4.3 shows the voltage profile before and after reconfiguration. Since all the methods obtained the same solution, the voltage profile is identical. It is noted that in most buses, the voltage enhanced after applying the configuration found by the proposed method, comparing to the voltage profile in the base case.

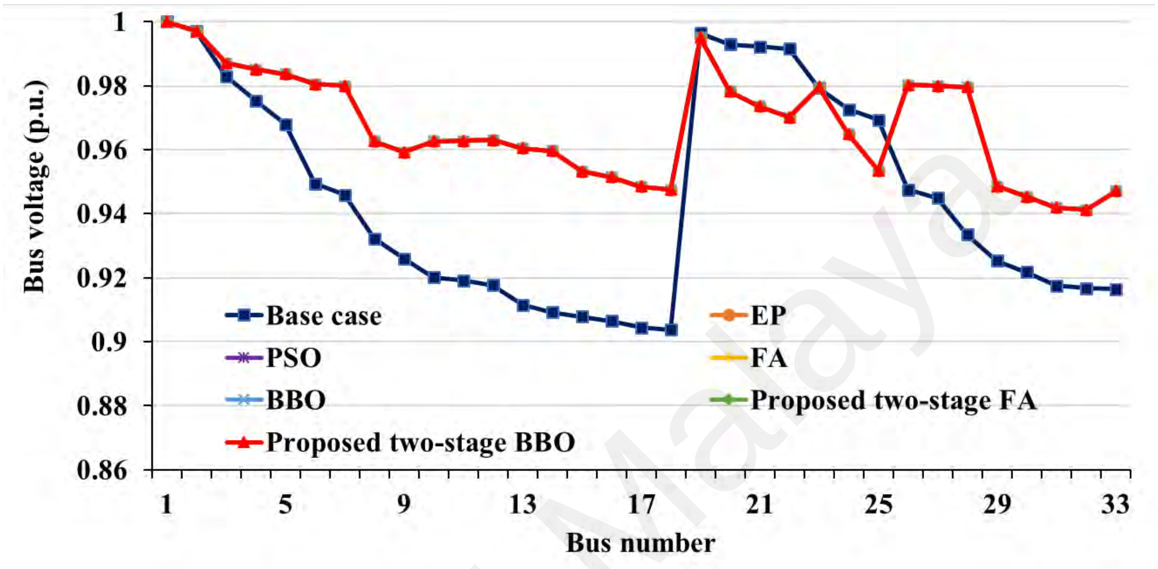

Figure 4.3 Comparison in voltage of the 33-bus for the NR

It is worth mentioning that the open paths' configuration of (P7, P9, P6, P4, P8) was obtained in the first stage of the proposed method for all runs. This configuration contains the optimal switches' configuration, i.e. (s14, s28, s9, s7, s32). Therefore, the optimization search procedure starts from the initial populations that are adjoined to the optimal answer, which subsequently boosts the opportunity of the converge to the optimal solution in a significantly small number of iterations. Directly, a small number of iterations reduces the overall computation time.

As tabulated in Table 4.2, the average number of iterations to converged in the proposed two-stage FA and BBO is 3.2 and 2.9, respectively, whereas they are 13.4, 18.1 31.7, and 9.7 for conventional EP, PSO, FA, and BBO, respectively. Besides, the average time to converged is 1.7s and 1.5s for the proposed FA and BBO method, respectively, which is significantly faster than the average time needed for the conventional EP, PSO, FA and BBO, which are 96s, 35s, 58s and 19s, respectively.

Table 4.2 Comparison of iterations number and computational time for 33-bus

Method	Average iterations number	Average total time (s)
EP	13.4	96
PSO	18.1	35
FA	31.7	58
BBO	9.7	19
Proposed two-stage FA	**3.2**	**1.7**
Proposed two-stage BBO	**2.9**	**1.5**

A comparison of the convergence graphs between the proposed two-stage method and the conventional methods is presented in Figure 4.4. The comparison shows that the proposed two-stage FA and BBO start the convergence from initial solution close to the optimal solution due to the initialization in the first stage. Therefore, smaller number of iterations is required to find the optimal solution as compared to the conventional methods that start the search process without proper initialization.

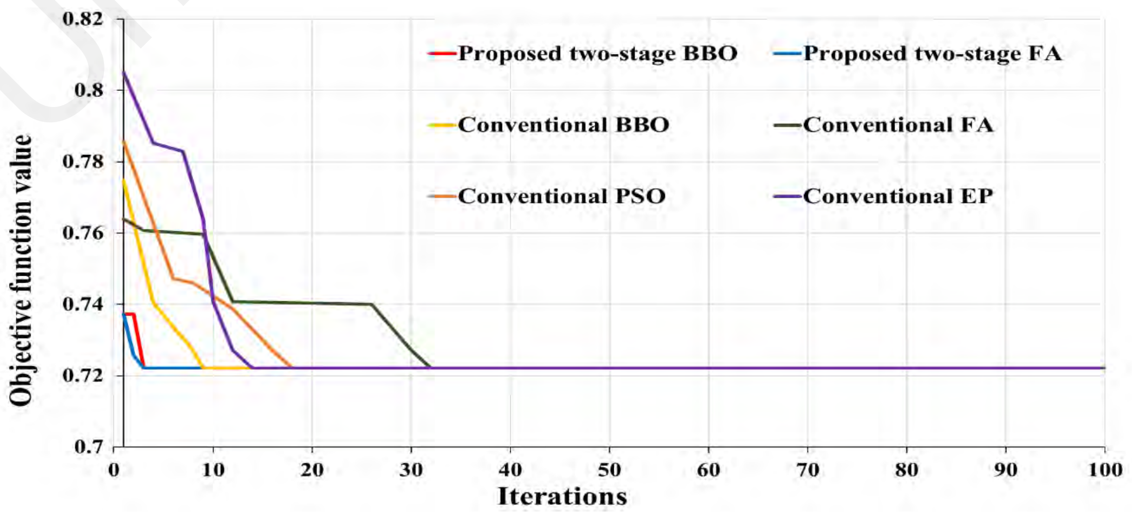

Figure 4.4 Comparison of the convergence graphs for 33-bus

Further analysis regarding the computational time was carried out and the summary is presented in Figure 4.5 for the case of conventional FA. It can be observed that 77% of the total time is consumed to perform the radiality check where it must be checked for each population during initialization as well as during each iteration whenever the population is updated. This is due to the fact that the radiality cannot be guaranteed if the switches combination were chosen randomly. Furthermore, the time needed for the radiality check increases proportionally to the size of the system. Therefore, for large EDN, the radiality check consumes a considerable time in the NR problem. Figure 4.5 summarizes the remaining time allocation for load flow calculations (20%) and optimization process (3%) using conventional FA.

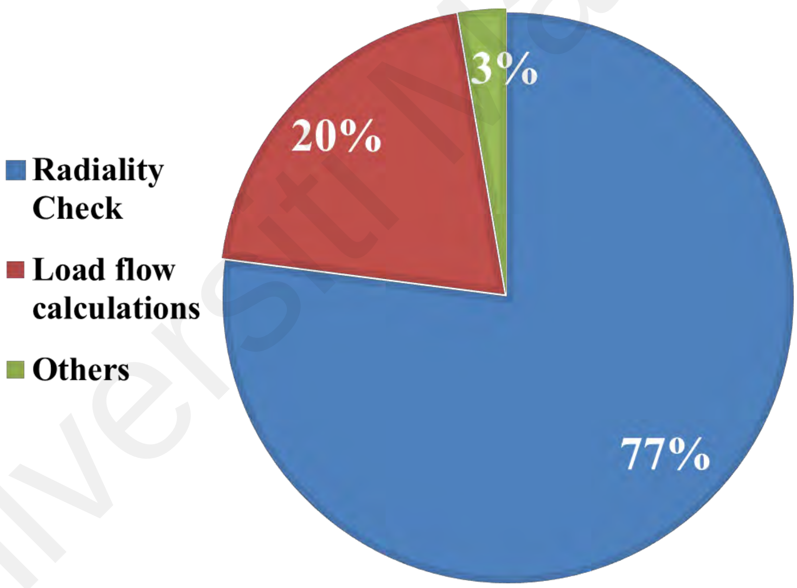

Figure 4.5 Time consumption in the conventional FA method

On the other hand, Figure 4.6 shows the time consumption for the proposed two-stage FA method. The load flow calculations in the first stage consumed 23% of the total time while 71% of the total time is consumed by the load flow calculations in the second stage. The remaining 6% is passed on to the other processes such as population update and optimization procedure. It can be concluded that the proposed two-stage FA method managed to reduce significant iteration numbers and overall computational time due to the proper initialization process and the proposed population codification.

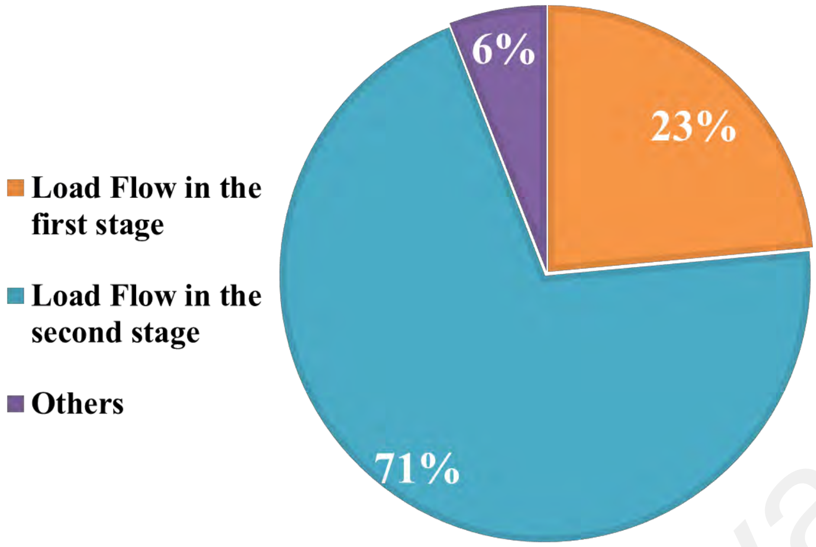

Figure 4.6 Time consumption in the two-stage FA method

The proposed method is also compared against the previous works such as Adaptive Weighted Improved Discrete PSO (AWIDPSO) (Subramaniyan, Subramaniyan, Veeraswamy, & Jawalkar, 2019), Harmony Search Algorithm (HSA) (Rao, Narasimham, Raju, & Rao, 2011), Firework Algorithm (FWA) (Imran & Kowsalya, 2014), two-stage heuristic-Improved Harmony Search Algorithm (IHSA) method (Tyagi et al., 2018) and the Enhanced PSO (EPSO) (A. M. Othman, El-Fergany, & Abdelaziz, 2015) as tabulated in Table 4.3. It has been observed that the proposed two-stage FA and BBO produced comparable solutions as FWA and heuristic-IHSA but with better STD of system power loss comparing to FWA. Also, the average power loss of the proposed method is smaller compared to the methods in the literature.

Table 4.3 Comparison of simulation results of 33-bus

Method	Open switches of the best solution	Power Loss (kW)				Minimum Voltage (p.u.)
		Best	Worst	Avg.	STD	
HSA (Rao et al., 2011)	7, 10, 14, 36, 37	142.68	195.1	152.33	11.28	0.9038
EPSO (A. M. Othman et al., 2015)	7, 9, 14, 24, 32	141.92	-	-	-	0.9336
AWIDPSO (Subramaniyan et al., 2019)	7, 14, 11, 28, 32	141.63	-	-	-	0.9218
FWA (Imran & Kowsalya, 2014)	14, 28, 9, 7, 32	139.98	155.75	145.63	5.49	0.9413
Heuristic-IHSA (Tyagi et al., 2018)	7, 9, 14, 28, 32	139.98	-	-	-	0.9413
Proposed two-stage FA	**7, 9, 14, 28, 32**	**139.98**	**140.71**	**139.99**	**0.101**	**0.9413**
Proposed two-stage BBO	**7, 9, 14, 28, 32**	**139.98**	**140.71**	**139.99**	**0.072**	**0.9413**

4.3.2 Test system 2: IEEE 69-bus

The 69-bus system is a medium-sized test system with 73 switches (Savier & Das, 2007). The normally closed switches are from 1-68 while switches 69-73 are the normally open switches. The 69-bus has a nominal voltage of 12.66 kV and base apparent power of 100 MVA. The total active load is 3802 kW, whereas the total reactive load of the system is 2694 kvar. The power loss in the initial configuration is 224.97 kW and the minimum voltage is 0.9092 p.u. The details of the 69-bus system can be found in the Appendix A.2.

Since this system has 5 normally open switches, it has 5 FLs as well. It worth highlighting that the SNG of this 69-bus system has an identical structure with the 33-bus SNG. However, the fundamental nodes' loads and the paths' impedances are different.

The 69-bus SNG consists of 12 paths and 8 fundamental nodes. Like the 33-bus's SNG, the 69-bus's SNG has 429 feasible solutions as well. Whereas, the 69-bus EDN has a higher number of possible solutions of 1.5×10^7 solutions. The 69-bus EDN and SNG are shown in Figure 4.7 and 4.8, respectively.

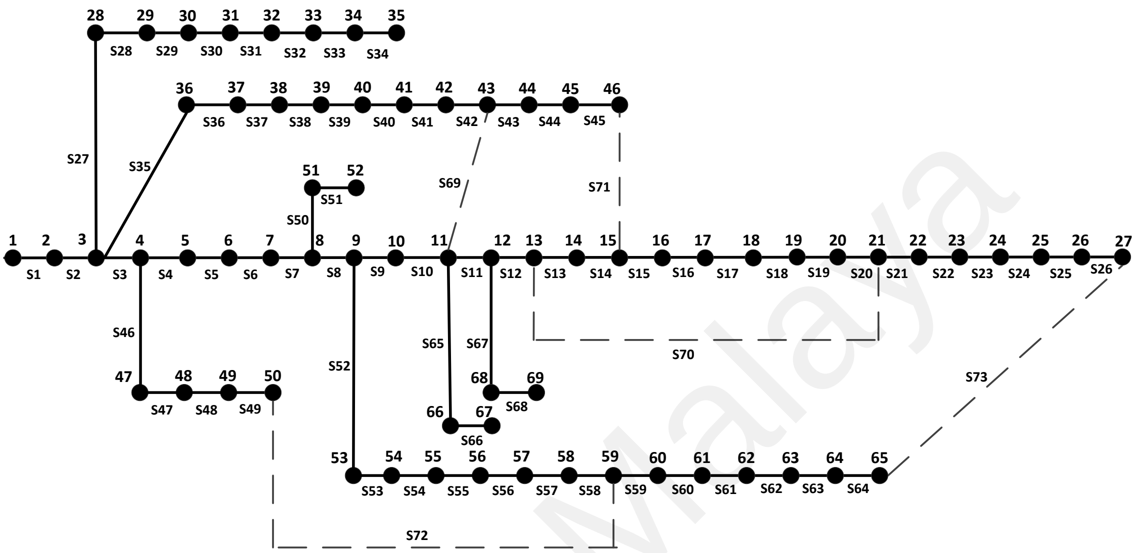

Figure 4.7 IEEE 69-bus distribution network in the base case

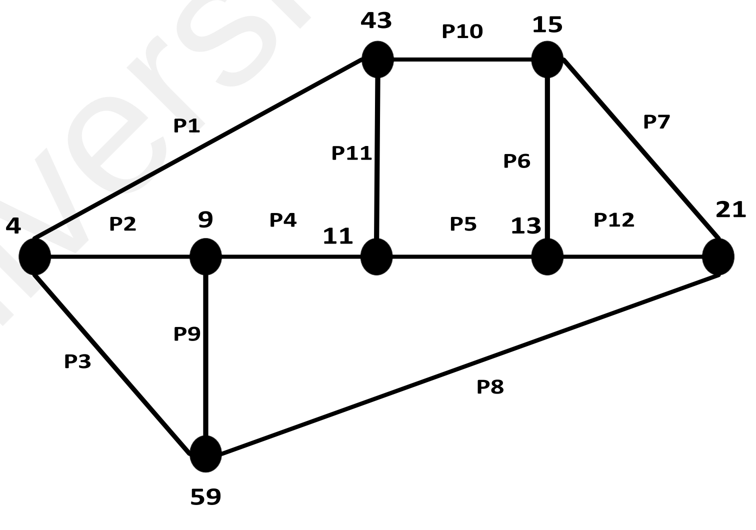

Figure 4.8 The SNG of the IEEE 69-bus

The results of the proposed method are presented in Table 4.4. The open switches' configuration of (s14, s55, s61, s69, s70) minimizes the objective function given in equation (3.1) by reducing the system power loss to 98.61 kW and improving the minimum bus voltage to 0.9495 p.u.

Table 4.4 also shows that the power loss obtained by the conventional EP, PSO, FA, and BBO is 99.06 kW, 98.93 kW, 98.81 kW, and 98.81 kW, respectively. Besides, the consistency of finding the optimal solution by the proposed method is better than the consistency of the conventional methods. This is because the STD of the proposed two-stage FA and BBO are 0.17 kW and 0.14 kW, respectively, which is smaller than the STD of the conventional methods. Furthermore, the average power loss obtained by the proposed FA and BBO are 98.70 kW and 98.63 kW, whereas the conventional EP, PSO, FA, and BBO obtained an average power loss of 112.04 kW, 107.87 kW, 104.62 kW, and 103.07 kW, respectively.

Table 4.4 NR results for 69-bus

Method	Open switches of the best solution	Power Loss (kW)				Minimum Voltage (p.u.)
		Best	Worst	Avg.	STD	
Base case	69, 70, 71, 72, 73	224.97	-	-	-	0.9092
EP	12, 14, 55, 61, 69	99.06	136.84	112.04	11.51	0.9495
PSO	12, 13, 56, 61, 69	98.93	116.92	107.87	7.16	0.9495
FA	12, 55, 61, 69, 70	98.81	116.92	104.62	6.48	0.9495
BBO	12, 55, 61, 69, 70	98.81	115.87	103.07	5.37	0.9495
Proposed two-stage FA	**14, 55, 61, 69, 70**	**98.61**	**99.61**	**98.70**	**0.17**	**0.9495**
Proposed two-stage BBO	**14, 55, 61, 69, 70**	**98.61**	**99.61**	**98.63**	**0.14**	**0.9495**

Figure 4.9 presents a comparison in voltage profile of the 69-bus before reconfiguration and after obtaining the optimal solution. It is observed that in most buses, the voltage improved after applying the configuration found by the proposed method, comparing to the voltage profile in the base case. The voltage profile of the proposed method is slightly better than the voltage profile of the rest methods, although all of them have the same minimum bus voltage at bus 61.

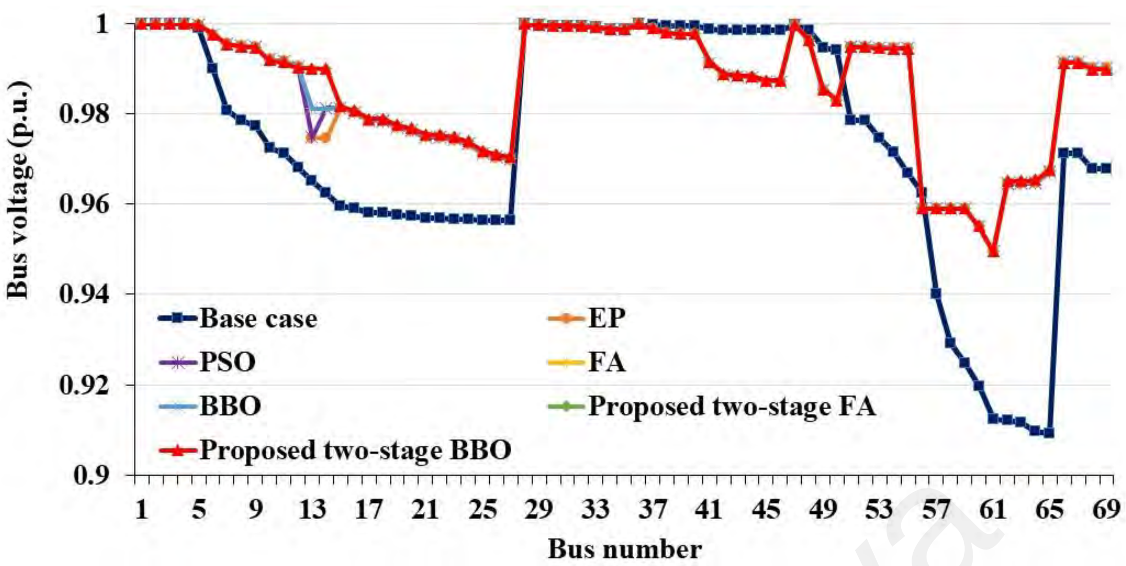

Figure 4.9 Comparison in voltage of the 69-bus for the NR

Table 4.5 presents a comparison between the proposed and conventional methods in the average number of iterations and the average total time required for converging to the final solution. The proposed two-stage FA and BBO needed 5.2 and 4.5 iterations as well as 2.7s and 2.3s, respectively, to converge. On the other hand, the conventional methods needed larger iterations number and consequently longer computational time for converging to the final solution. Moreover, a comparison of the convergence graphs between the proposed method and the conventional methods is presented in Figure 4.10.

Table 4.5 Comparison of iterations number and computational time for 69-bus

Method	Average iterations number	Average total time (s)
EP	16.7	109.1
PSO	20.3	48.6
FA	35.7	87.3
BBO	11.1	26.5
Proposed two-stage FA	**5.2**	**2.7**
Proposed two-stage BBO	**4.5**	**2.3**

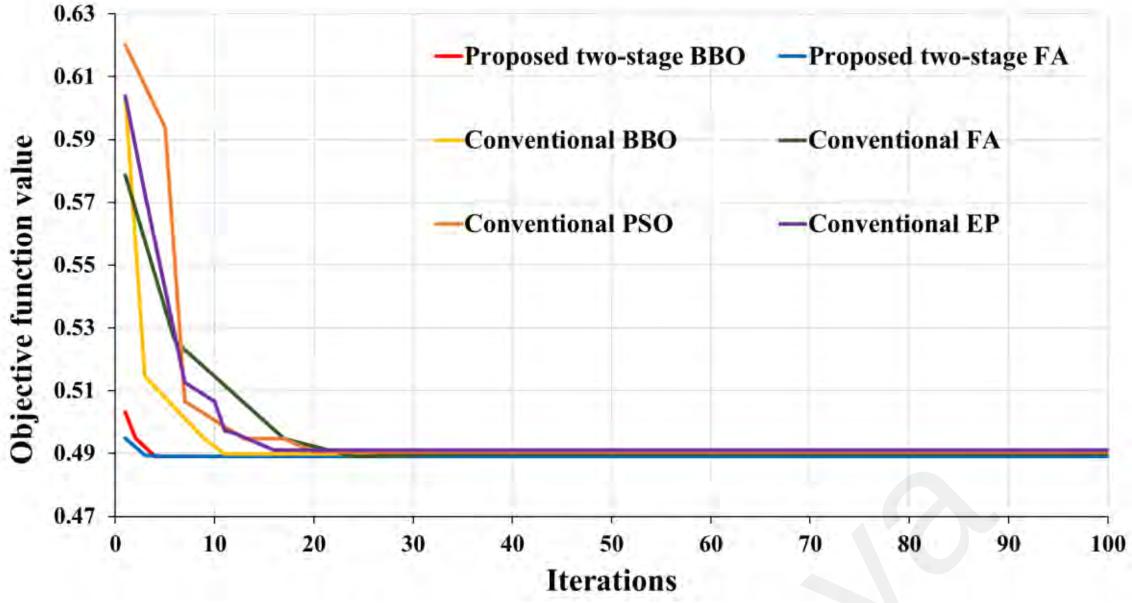

Figure 4.10 Comparison of the convergence graphs for 69-bus

The proposed two-stage FA and BBO are also compared to the works reported in the literature as tabulated in Table 4.6. The results demonstrate that the power loss obtained by the proposed method is smaller than the power loss of the Genetic Algorithm (GA), Refined GA (RGA), HSA (R. Rao et al., 2013) and the Modified PSO (MPSO) (Wu, Dong, & Liu, 2018). In addition, the proposed method achieved a smaller average power loss compared to the Binary Particle Swarm Optimization Gravity Search Algorithm (BPSOGSA) (Fathy et al., 2018), though both methods have the same best solution. Furthermore, the STD of the power loss found by the proposed two-stage FA and BBO is 0.17 kW and 0.14 kW which is smaller comparing to 3.14 kW reported in MPSO (Wu et al., 2018).

Table 4.6 Comparison of simulation results of 69-bus

Method	Open switches of the best solution	Power Loss (kW)				Minimum Voltage (p.u.)
		Best	Worst	Avg.	STD	
GA (R. Rao et al., 2013)	14, 53, 61, 69, 70	103.29	-	-	-	0.9411
RGA (R. Rao et al., 2013)	13, 17, 55, 61, 69	100.28	-	-	-	0.9428
HSA (R. Rao et al., 2013)	13, 18, 56, 61, 69	99.35	-	-	-	0.9428
MPSO (Wu et al., 2018)	14, 47, 51, 65, 70	100.97	110.55	104.95	3.14	-
BPSOGSA (Fathy et al., 2018)	14, 55, 61, 69, 70	98.61	-	171.50	-	0.9495
Proposed two-stage FA	**14, 55, 61, ,69, 70**	**98.61**	**99.61**	**98.70**	**0.17**	**0.9495**
Proposed two-stage BBO	**14, 55, 61, ,69, 70**	**98.61**	**99.61**	**98.63**	**0.14**	**0.9495**

4.3.3 Test system 3: IEEE 118-bus

The 118-bus EDN is one of the largest-sized test systems typically used for distribution system (Zhang, Fu, & Zhang, 2007). For this system, switches 1 to 118 are the normally closed switches, whereas switches 119 to 133 are the normally open switches. This EDN has a nominal voltage of 11 kV with the minimum and maximum voltage magnitudes range between 0.9 p.u. and 1.1 p.u., respectively. The total active and reactive load of this EDN is 22710 kW and 17041 kvar, respectively. The details of the 118-bus system can be found in the Appendix A.3. The power loss of the network before configuration (base case) is 1296.5 kW with the minimum bus voltage of 0.8688 p.u. The 118-bus EDN has 15 FL as it has 15 normally open switches.

The SNG of this EDN consists of 41 paths and 27 fundamental nodes which are (1, 2, 4, 8, 11, 24, 25, 27, 30, 31, 36, 42, 45, 56, 61, 65, 67, 68, 76, 78, 82, 89, 95, 100, 105, 110, 113). Figure 4.11 and 4.12 show the 118-bus EDN and its SNG, respectively. In the EDN diagram, the normally open switches are named based on the destination's bus in the base case (e.g. the switch between bus 2 and bus 10 is the switch number 10). Whereas, the number for the normally open switches is shown in 4.11. For the 118-bus system, there are 7×10^{18} potential configurations candidates which translates to very huge search space. However, a massive amount of these configurations does not satisfy the radiality constraint, and hence cannot be considered as a valid solution. On the other hand, the number of configurations in the SNG of the 118-bus is around 15×10^{3}. Thus, obtaining an initialization that leads to the optimal configuration is more prospective by the proposed method as compared to the conventional methods that generate the initial population randomly.

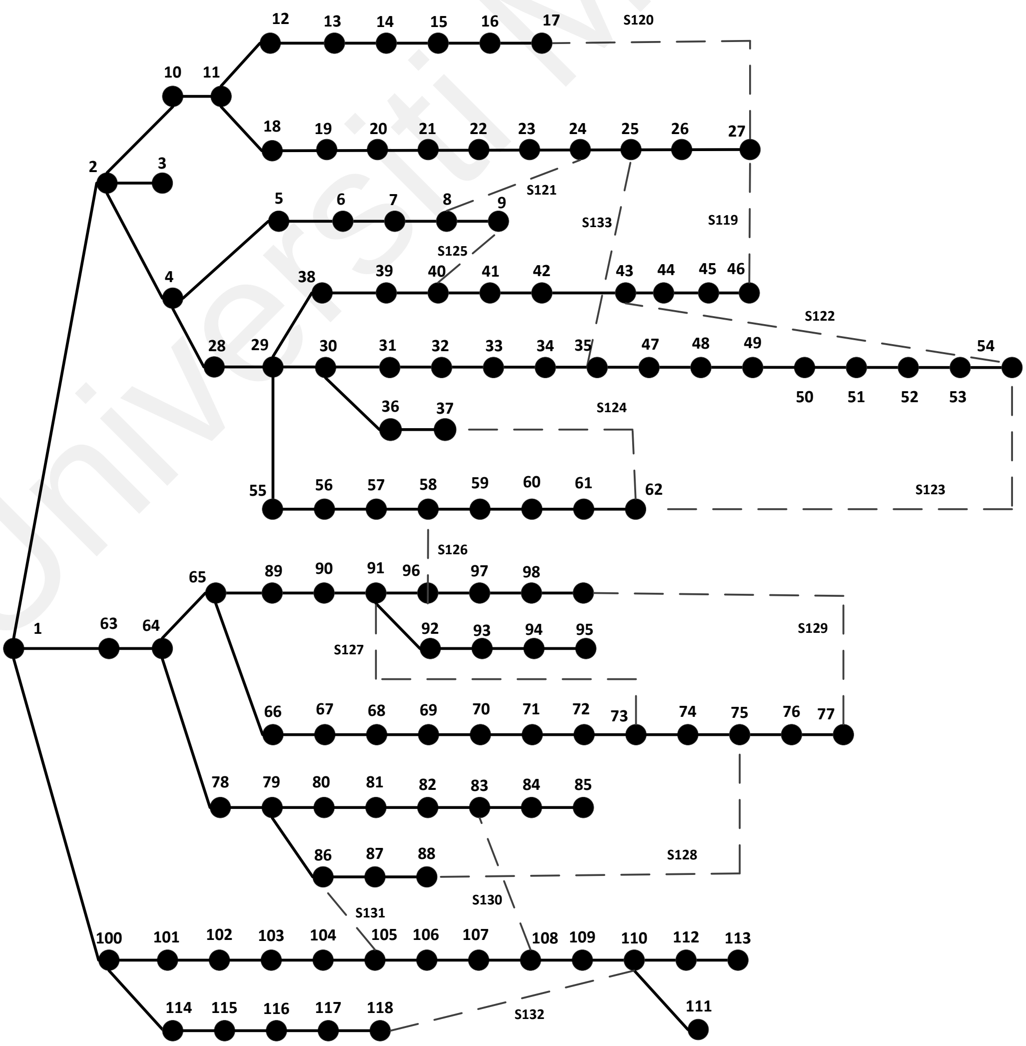

Figure 4.11 IEEE 118-bus distribution network in the base case

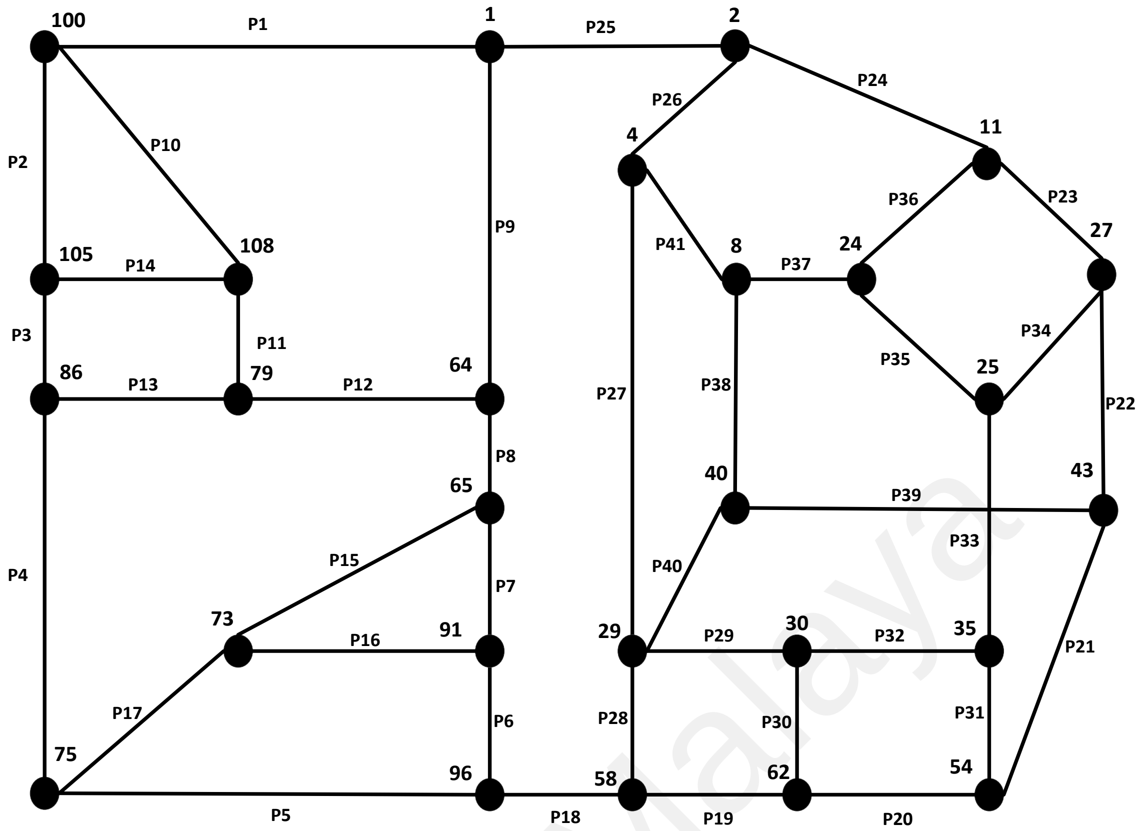

Figure 4.12 The SNG of the IEEE 118-bus

The optimal open switches configuration obtained by the proposed two-stage method is presented in Table 4.7. The open switch configuration is (s24, s26, s35, s40, s43, s51, s59, s72, s75, s96, s98, s110, s122, s130, s131). This configuration reduced the power loss to 853.58 kW and increases the minimum bus voltage of the system to 0.9323 p.u. Furthermore, the results demonstrate a precise consistency in the proposed method performance since the STD of the two-stage FA and BBO is only 6.05 kW and 4.48 kW, respectively. In addition, the average power loss of the proposed two-stage FA and BBO is 857.54 kW and 856.08 kW, respectively, which is close to the optimal answer. On the other hand, the conventional EP, PSO, FA, and BBO methods obtained different solutions that reduce the total power loss to 907.34 kW, 896.88 kW, 872.09 kW, and 871.59 kW, respectively. It should be pointed out that all these solutions are distanced away from the actual optimal solution. Besides, the STD for the conventional EP, PSO, FA, and BBO is 158.43 kW, 159.44 kW 141.16 kW, and 137.74 kW, respectively. Hence, this indicates the poor performance of conventional methods.

Table 4.7 NR results for 118-bus

Method	Open switches of the best solution	Power Loss (kW)				Minimum Voltage (p.u.)
		Best	Worst	Avg.	STD	
Base case	119 to 133	1296.5	-	-	-	0.8688
EP	24, 26, 34, 39, 42, 51, 61, 73, 74, 82, 96, 99, 110, 122,131	907.34	1344.49	1151.16	158.43	0.9319
PSO	22, 25, 34, 38, 42, 49, 60, 73, 75, 96, 98, 110, 122, 130, 131	896.88	1326.67	1140.04	159.44	0.9321
FA	22, 27, 40, 44, 50, 58, 73, 75, 77, 83, 110, 123, 126, 131, 133	872.09	1246.9	1045.19	141.16	0.9287
BBO	24, 26, 35, 39, 42, 51, 60, 71, 74, 77, 96, 110, 122, 130, 131	871.59	1241.49	1036.68	137.74	0.9322
Proposed two-stage FA	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**853.58**	**871.59**	**857.54**	**6.05**	**0.9323**
Proposed two-stage BBO	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**853.58**	**870.49**	**856.08**	**4.48**	**0.9323**

Moreover, a comparison between the voltage profile in the base case and after obtaining the configurations is provided in Figure 4.13. The voltage profile of the proposed method NR achieved great improvement as compared to the base case voltage profile and the voltage profile of the other methods.

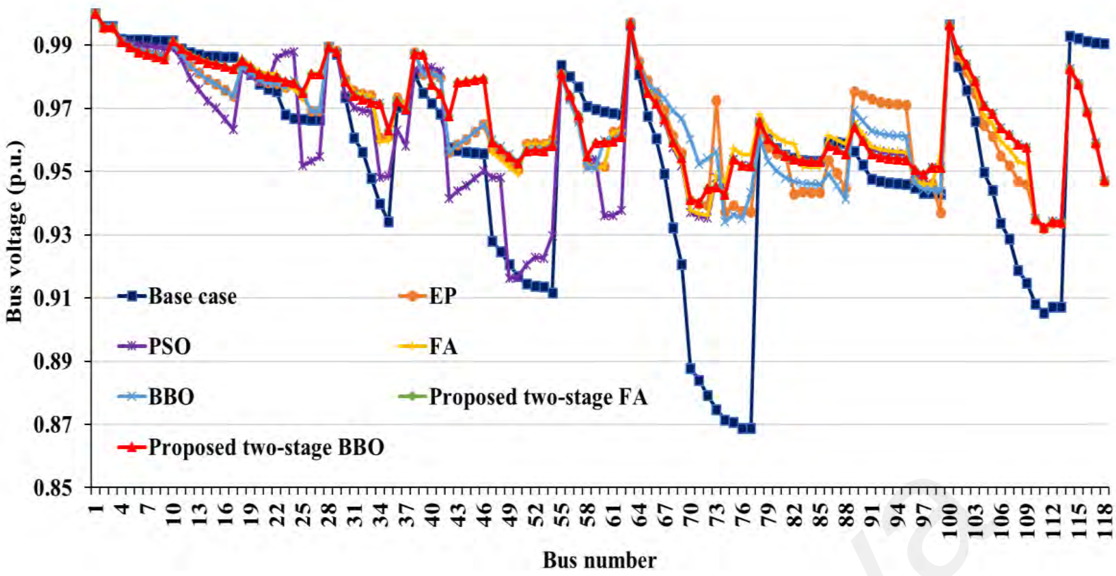

Figure 4.13 Comparison in voltage of the 118-bus for the NR

Table 4.8 presents a comparison between the proposed method against conventional methods with regards to the average computational time and the number of iterations. The proposed two-stage FA and BBO methods managed to find the optimal solution with an average of 15.1 and 14.3 iterations, respectively, and within an average computational time of 7.4s and 6.9s, respectively. On the other hand, the conventional EP, PSO, FA, and BBO consumed an average computational time of 284s, 171s, 208s, and, 132s respectively, to find the NR solution. Also, the number of iterations for conventional EP, PSO, FA, and BBO are 115, 753, 876, and 93, respectively. Moreover, a comparison of the convergence graphs between the proposed method and the conventional methods is presented in Figure 4.14. The superiority of the proposed method over the conventional methods in terms of the quality of the solution as well as computational time is mainly due to the proposed guided initializations as well as the proposed codifications and radiality rules.

Table 4.8 Comparison of iterations number and computational time for 118-bus

Method	Average iterations number	Average total time (s)
EP	115	284
PSO	753	171
FA	876	208
BBO	93	132
Proposed two-stage FA	**15.1**	**7.4**
Proposed two-stage BBO	**14.3**	**6.9**

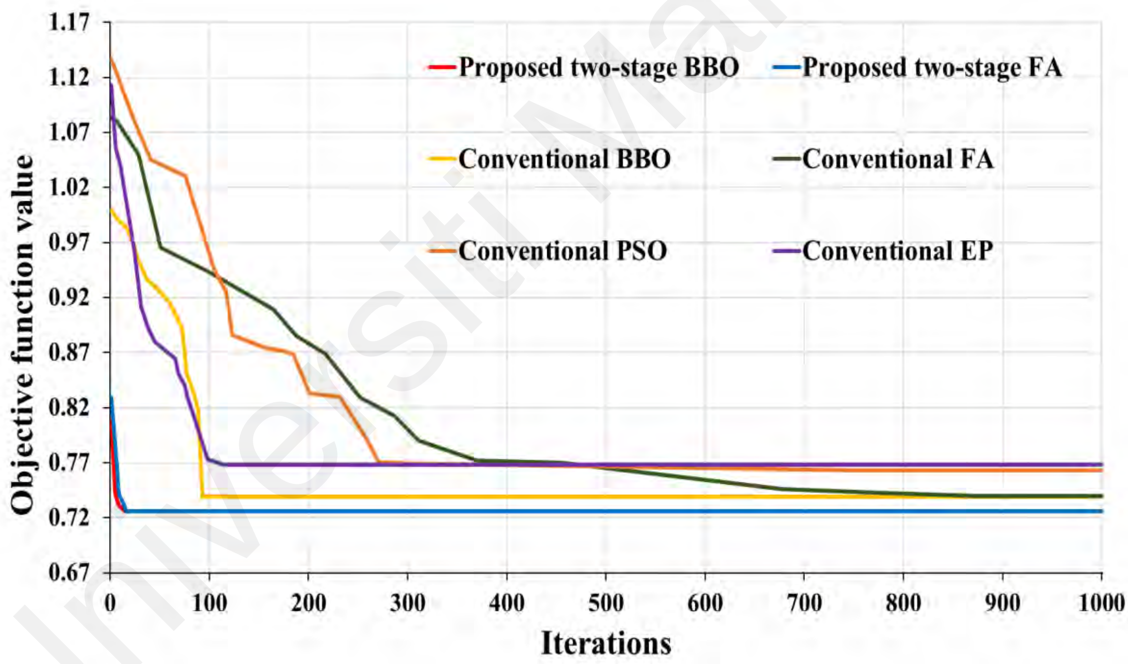

Figure 4.14 Comparison of the convergence graphs for 118-bus

The proposed method is also compared to existing works in the literature as tabulated in Table 4.9. The proposed two-stage method found the same optimal solution as FWA (Imran & Kowsalya, 2014) and the HSA (Rao et al., 2011). However, the STD of the proposed method is smaller than the one found by the FWA and the HSA. In addition, the reduction in average power loss using the proposed method is higher than FWA and HSA methods. It should also be highlighted that the proposed two-stage method produced a better solution compared to the best solution produced by the Modified Tabu Search (MTS) (Abdelaziz et al., 2010), EPSO (A. M. Othman et al., 2015) and Hierarchical Decentralized Method (HDM) (Ding & Loparo, 2014).

Table 4.9 NR results for 118-bus

Method	Open switches of the best solution	Power Loss (kW)				Minimum Voltage (p.u.)
		Best	Worst	Avg.	STD	
Base case	119 to 133	1296.5	-	-	-	0.8688
HDM (Ding & Loparo, 2014)	23, 26, 34, 38, 40, 45, 58, 71, 74, 95, 97, 109, 123, 130, 131	873.62	-	-	-	0.932
EPSO (A. M. Othman et al., 2015)	23, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130 ,131	868.15	-	-	-	0.9323
MTS (Abdelaziz et al., 2010)	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	869.71	884	870	-	0.9321
HSA (Rao et al., 2011)	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	853.58	1282.7	935.01	69.3	0.9323
FWA (Imran & Kowsalya, 2014)	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	853.58	942.34	887.54	29.58	0.9323
Proposed two-stage FA	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**853.58**	**871.59**	**857.54**	**6.05**	**0.9323**
Proposed two-stage BBO	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**853.58**	**870.49**	**856.08**	**4.48**	**0.9323**

4.4 Test results of the distributed generation integration

The proper integration of the DG in the EDN has a great impact on mitigating the power loss and improving the voltage profile. This section discusses the performance of the proposed method in finding the solution of the DG placement and sizing. It is worth mentioning that it is assumed that the maximum capacity of each DG is 2000 kW for the 33-bus and 69-bus and 4000 kW for the 118-bus (R. Rao et al., 2013). The proposed method is tested on 33-bus, 69-bus, and 118-bus IEEE test systems, and the results are compared to the conventional methods as well as the works found in the literature. In this section, all the integrated DGs are dispatchable DGs. Nevertheless, section 5.5 will investigate the integration of the intermittent RER in the EDN.

4.4.1 Effect of the number of DGs on the distribution system performance

To investigate the effect of the number of DGs installed in the EDN on the power loss and voltage deviation, the number of optimal integrated DGs increased gradually for all test systems, and the results are presented in Tables 4.10, 4.11 and 4.12. All the results have been obtained by the proposed two-stage method.

As tabulated in Table 4.10 for the 33-bus EDN, the power loss decreases when the number of DG increases. However, the loss reduction rate is not steady. It is noted that when the number of DGs is more than three, the difference in power loss reduction is marginal. Hence, adding more DGs to the EDN will increase the DG installment and operation cost without promising revenue. Hence, connecting three DGs to the 33-bus EDN is sufficient.

Table 4.10 Analysis of the number of DGs for 33-bus

Number of DG	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-	-	-	210.98	-	0.9038
1	7	2000	2000	115.19	45.4	0.9364
2	13	851	2009	87.16	58.69	0.9685
	30	1157				
3	13	801	2945	72.78	65.50	0.9686
	24	1091				
	30	1053				
4	6	926	3227	67.631	67.94	0.9703
	14	647				
	24	967				
	30	686				
5	6	744	3224	66.34	68.55	0.9713
	9	686				
	15	469				
	24	357				
	30	967				

Table 4.11 shows the impact of DGs' number on power loss and voltage deviation. The results show that the minimum bus voltage in the system remains similar when the number of DGs increases. Additionally, the power loss reduction rate is small especially when the number of DGs is more than two. Therefore, it is adequate to integrate two DGs in the 69-bus to fulfill satisfying improvement in power loss and voltage deviation reduction. However, in this research, three DGs are connected to the 69-bus to provide a fair comparison with the previous works.

Table 4.11 Analysis of the number of DGs for 69-bus

Number of DG	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-	-	-	224.97	-	0.9092
1	58	1872	1872	83.21	63.01	0.9683
2	17	531	2312	71.68	68.14	0.9789
	61	1781				
3	11	625	2659	69.49	69.11	0.979
	22	321				
	61	1713				
4	11	526	3343	67.92	69.81	0.979
	18	380				
	48	718				
	58	1719				
5	9	404	3494	67.53	69.98	0.979
	12	370				
	21	312				
	48	717				
	58	1689				

The number of DGs in the 118-bus EDN is investigated in Table 4.12. The DGs number is varied between 1 and 9, and the power loss and voltage deviation are determined for each case. The results show that the improvement rate of power loss reduction and voltage deviation is decreasing when more than seven DGs is considered. Thus, this research considers installing seven DGs in the 118-bus EDN.

Table 4.12 Analysis of the number of DGs for 118-bus

Number of DG	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-	-	-	1296.5	-	0.8688
1	71	2978	2978	1015.2	21.69	0.9097
2	71	2978	6098	803.73	38.01	0.9117
	109	3120				
3	50	2881	8979	803.73	48.63	0.9545
	71	2978				
	109	3120				
4	50	2875	10422	803.73	52.57	0.9561
	72	2603				
	96	1822				
	109	3121				
5	50	2881	12292	573.4	55.77	0.9562
	72	2533				
	80	2095				
	96	1663				
	109	3120				
6	41	1845	13879	537.68	58.53	0.9567
	50	2763				
	72	2475				
	80	2068				
	96	1628				
	109	3098				
7	30	3708	16605	514.88	60.29	0.9567
	42	1154				
	50	2331				
	72	2533				
	80	2095				
	96	1663				
	109	3120				
8	20	1690	18023	495.03	61.82	0.9567
	30	3450				
	42	1140				
	50	2331				
	72	2533				
	80	2095				
	96	1663				
	109	3120				
9	20	1673	18402	484.81	62.61	0.9567
	30	3101				
	42	1125				
	50	2330				
	58	777				
	72	2533				
	80	2088				
	96	1661				
	109	3114				

4.4.2 Test system 1: IEEE 33-bus

As shown in section 4.3.1, the 33-bus EDN consists of 33 bus while its corresponding SNG has 8 buses only, which represents the FNs of the EDN. In the first stage of the proposed method, the DGs locations and sizes are found for the SNG. Then, in the second stage, starting from the solution of the first stage, the DG location and size for the EDN is determined. The first stage solutions are not mentioned since they are initial solutions.

Table 4.13 presents the results of the proposed method and the conventional methods. The best solution was obtained by the proposed two-stage BBO. Three DGs are added at buses 13, 24, and 30 with capacities of 801 kW, 1091 kW, and 1053 kW, respectively. As a result, the power loss is reduced to 72.78 kW and the minimum voltage is enhanced to 0. 9686 p.u. The proposed two-stage FA also found a sub-optimal solution that mitigates the EDN's power loss to 72.85 kW and raises the minimum voltage to 0.9675 p.u. On the other hand, the solutions found by the conventional EP, PSO, FA, and BBO reduce the power loss to 83.74 kW, 81.2 kW, 78.32 kW, and 76.12 kW, respectively.

To analyses the impact of the DG integration's solutions on the voltage profile, Figure 4.15 shows a comparison in the voltage profile of the 33-bus system for the solutions found by the proposed two-stage FA and BBO as well as the conventional EP, PSO, FA, and BBO. The comparisons show the voltage profile improvement after integrating the DGs in the network. However, the voltage profile of the proposed method solution fulfills a greater enhancement in the voltage magnitude compared to the solutions of the conventional methods and the voltage magnitude in the base case when there is no DG connected to the EDN.

Table 4.13 The results of the DG integration for 33-bus

Method	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-	-	-	210.98	-	0.9038
EP	8	864	3203	83.74	60.31	0.9475
	23	1449				
	30	890				
PSO	9	1015	2632	81.20	61.51	0.9572
	25	580				
	28	1037				
FA	10	942	2788	78.32	62.88	0.9609
	24	762				
	28	1084				
BBO	10	1101	2711	76.12	63.92	0.9646
	24	866				
	31	744				
The proposed two-stage FA	**14**	**761**	**2861**	**72.85**	**65.47**	**0.9675**
	24	**1062**				
	30	**1038**				
The proposed two-stage BBO	**13**	**801**	**2945**	**72.78**	**65.50**	**0.9686**
	24	**1091**				
	30	**1053**				

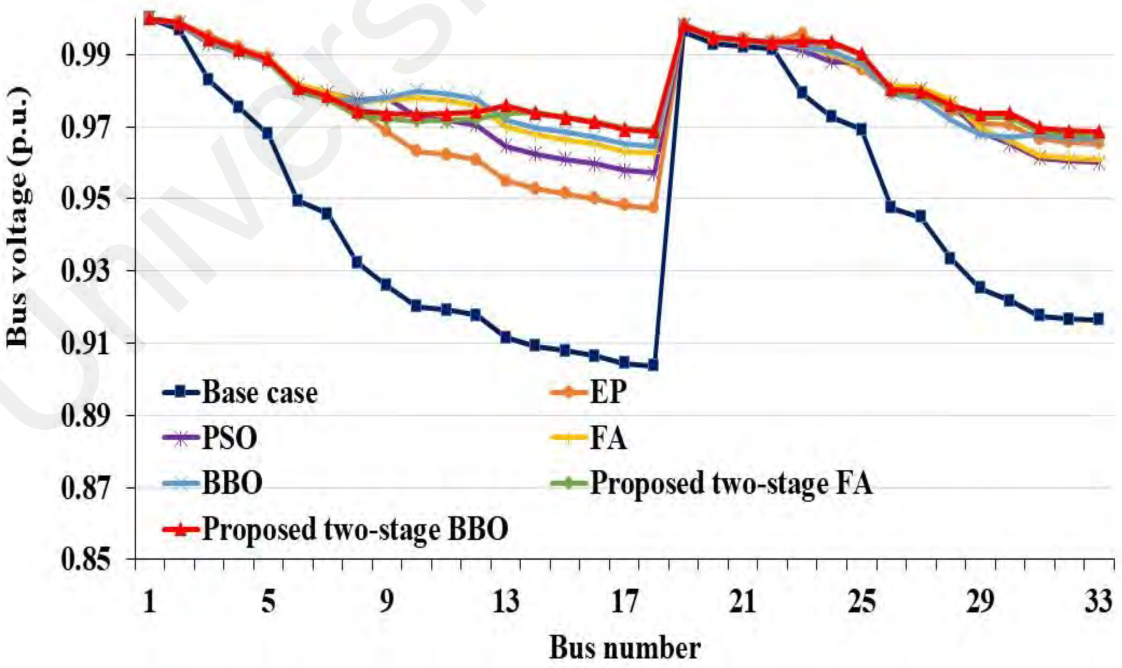

Figure 4.15 Comparison in voltage of the 33-bus for the DG

The proposed method results are also compared against the previous works found in the literature as tabulated in Table 4.14. The solutions found by the proposed two-stage FA and BBO surpasses the solutions of the HSA (R. Rao et al., 2013), FWA (Imran et al., 2014), UVDA (Bayat et al., 2016), Symbiotic Organism Search (SOS) (T. P. Nguyen & Vo, 2018), Multi-Objective Taguchi Approach (MOTA) (Meena, Swarnkar, Gupta, & Niazi, 2017), Iterative Improved Analytical (IIA) method (Forooghi Nematollahi et al., 2016) and Quasi-Oppositional Teaching Learning Based Optimization (QOTLBO) (S. Sultana, Roy, & Systems, 2014). The proposed two-stage FA and BBO minimize the power loss to 72.85 kW and 72.85 kW, respectively. Whereas, the power loss of the HSA, FWA, UVDA, SOS, MOTA, IIA, and QOTLBO is 96.7 kW, 88.68 kW, 74.21 kW, 104.19 kW, 97.47 kW, 138.25 kW and 74.1 kW, respectively. Therefore, it can be concluded that significant enhancement in power loss reduction and voltage profile is achieved by using the proposed method to find the optimal DG placement and sizing in the EDN.

Table 4.14 Comparison of DG integration with the for 33-bus

Method	DG location)	DG size (kw)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-		-	210.98	-	0.9038
HSA (R. Rao et al., 2013)	17	572	1725	96.76	52.26	0.967
	18	107				
	33	1046				
FWA (Imran et al., 2014)	14	589	1792	88.68	56.24	0.968
	18	189				
	32	1014				
UVDA (Bayat et al., 2016)	11	875	2731	74.21	63.39	0.962
	24	931				
	29	925				
SOS (T. P. Nguyen & Vo, 2018)	6	2206	3122	104.19	50.61	0.9501
	28	200				
	29	716				
MOTA (Meena et al., 2017)	30	1340	3280	97.47	53.79	0.9820
	7	980				
	14	960				
IIA (Forooghi Nematollahi et al., 2016)	13	385	1986	138.25	34.47	0.9317
	24	554				
	30	1047				
QOTLBO (S. Sultana et al., 2014)	12	880	3010	74.10	64.87	0.9645
	24	1059				
	29	1071				
The proposed two-stage FA	**14**	**761**	**2861**	**72.85**	**65.47**	**0.9675**
	24	**1062**				
	30	**1038**				
The proposed two-stage BBO	**13**	**801**	**2945**	**72.78**	**65.50**	**0.9686**
	14	**761**				
	24	**1062**				

4.4.3 Test system 2: IEEE 69-bus

The 69-bus IEEE test system composes of 69 buses whereas its SNG has 8 buses only. Hence, the search space for this case in the first stage is noticeably reduced. As presented in Table 4.15, the proposed two-stage FA and BBO obtained solutions that alleviate the power loss to 69.69 kW and 69.49 kW, respectively. The best solution found by the proposed two-stage BBO includes placing the DGs at buses 11, 22, and 61 while their capacities are 625 kW, 321 kW, 1731 kW, respectively. The solutions found by the conventional EP, PSO, FA, and BBO reduce the power loss to 81.92 kW, 80.06 kW, 74.36 kW, and 73.74 kW, respectively.

Table 4.15 The results of the DG integration for 69-bus

Method	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-		-	224.97	-	0.9092
EP	6	820	3720	81.92	63.59	0.9701
	40	1067				
	61	1833				
PSO	24	348	2811	80.06	64.41	0.9689
	37	998				
	63	1465				
FA	61	1232	2430	74.36	66.95	0.9766
	64	424				
	66	774				
BBO	53	392	2752	73.74	67.22	0.98
	61	1768				
	68	592				
The proposed two-stage FA	**18**	**399**	**2586**	**69.69**	**69.01**	**0.9789**
	58	**1727**				
	63	**460**				
The proposed two-stage BBO	**11**	**625**	**2659**	**69.49**	**69.11**	**0.979**
	22	**321**				
	61	**1713**				

The voltage profile for the 69-bus considering the solutions found by the proposed method and the conventional methods is shown in Figure 4.16. The voltage profile of the proposed method's solution outperforms the voltage profile of other methods.

Table 4.16 shows a comparison between the proposed method and the HSA (R. Rao et al., 2013), FWA (Imran et al., 2014), UVDA (Bayat et al., 2016), SOS (T. P. Nguyen & Vo, 2018), and QOTLBO (S. Sultana et al., 2014) methods. The proposed two-stage FA and BBO achieved lower power loss and with better voltage profile as compared to the work found in the literature. It is noted that the proposed method reduced the power loss by 19.91% as compared to the solution found by the HSA while the total DGs' capacity used in the proposed method is smaller than the one used in HSA.

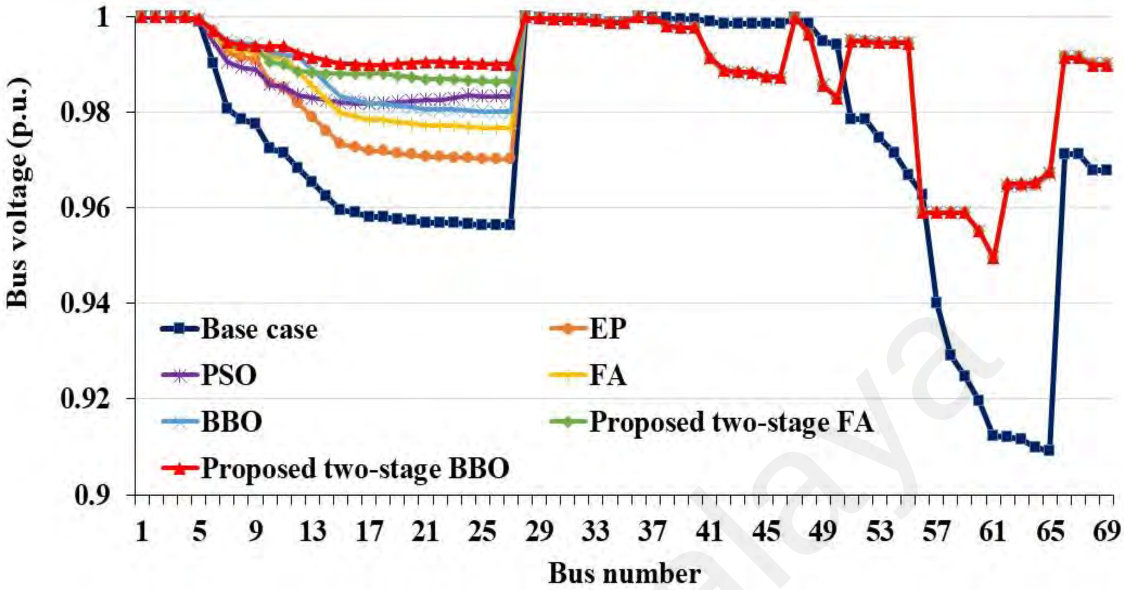

Figure 4.16 Comparison in voltage of the 69-bus for the DG

Table 4.16 Comparison of DG integration with the for 69-bus

Method	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-		-	224.97	-	0.9092
HSA (R. Rao et al., 2013)	63	1302	2689	86.77	61.43	0.9677
	64	369				
	65	1018				
FWA (Imran et al., 2014)	27	225	1831	77.85	65.39	0.974
	61	1198				
	65	408				
UVDA (Bayat et al., 2016)	11	604	2431	72.62	67.72	0.9688
	17	417				
	61	1410				
SOS (T. P. Nguyen & Vo, 2018)	57	258	1982.7	82.07	63.51	0.969
	58	200				
	61	1524				
QOTLBO (S. Sultana et al., 2014)	18	533	2298	71.65	68.15	0.9792
	61	1198				
	63	567				
The proposed two-stage FA	**18**	**399**	**2586**	**69.69**	**69.01**	**0.9789**
	58	**1727**				
	63	**460**				
The proposed two-stage BBO	**11**	**625**	**2659**	**69.49**	**69.11**	**0.979**
	22	**321**				
	61	**1713**				

4.4.4 Test system 3: IEEE 118-bus

The 118-bus IEEE test system consists of 118 buses whereas its SNG contains only 27 buses. Therefore, the search space in the first stage is notably decreased. Tables 4.17 and 4.18 show the DGs' locations and sizes found by the conventional EP, PSO, FA, and BBO as well as the proposed two-stage FA and BBO.

It is noted that when five DGs are connected to the EDN, the best solution is found by the proposed two-stage BBO which reduces the power loss to 573.39 kW while increasing the minimum bus voltage to 0.9561 p.u. The proposed two-stage FA obtained a solution that mitigates the power loss to 576.58 kW and enhances the minimum bus voltage to 0.9533 p.u. Moreover, Table 4.17 show that the solutions found by the conventional EP, PSO, FA and BBO reduce the power loss and voltage deviation by smaller values when compared against the solutions found by the proposed two-stage method. For instance, the solution found by the conventional EP reduced the power loss to 625.4 kW although the total DGs' capacity is larger than the capacity found by the proposed method.

In the same manner, as tabulated in Table 4.18, when seven DGs are connected to the 118-bus EDN, the proposed two-stage BBO achieved a solution that fulfills minimum power loss and voltage deviation followed by the solution found by the proposed two-stage FA. The solution found by the proposed two-stage BBO reduced the power loss to 514.87 kW with a minimum voltage of 0.9566. Hence, the power loss is reduced by 60.29% as compared to the base case. From Tables 4.17 and 4.18, it can be concluded that the proposed two-stage method has the superiority of obtaining better solutions as compared to the conventional methods.

Table 4.17 The results of the DG integration for 118-bus when 5 DGs are connected

Method	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-		-	1296.5	-	0.8688
EP	6	4000	12734	625.48	51.75	0.9468
	52	1717				
	71	2679				
	91	2144				
	111	2192				
PSO	50	2418	10928	612.27	52.77	0.9423
	58	1335				
	70	2384				
	91	1950				
	110	2839				
FA	40	2919	13425	609.29	53.01	0.9516
	48	2907				
	74	2340				
	87	2339				
	110	2918				
BBO	50	2288	11115	603.77	53.43	0.9475
	72	2322				
	81	2295				
	93	1709				
	111	2500				
The proposed two-stage FA	**50**	**2681**	**11935**	**576.58**	**55.52**	**0.9533**
	74	**2311**				
	80	**2085**				
	91	**1990**				
	110	**2868**				
The proposed two-stage BBO	**50**	**2881**	**12292**	**573.39**	**55.77**	**0.9561**
	72	**2533**				
	80	**2095**				
	96	**1663**				
	109	**3120**				

Table 4.18 The results of the DG integration for 118-bus when 7 DGs are connected

Method	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-		1296.5	-	-	0.8688
EP	20	2336	14565	572.25	55.86	0.9391
	32	1586				
	35	1865				
	73	2426				
	81	3363				
	104	1236				
	110	1748				
PSO	73	2501	14885	554.04	57.26	0.9635
	81	2126				
	42	1315				
	109	2936				
	35	1781				
	98	1533				
	50	2692				
FA	32	2296	14091	542.79	58.13	0.9495
	43	1506				
	51	1379				
	71	2595				
	86	1871				
	96	1326				
	110	3119				
BBO	32	2344	14202	530.46	59.08	0.9621
	42	1170				
	52	2126				
	73	2490				
	80	1899				
	91	1301				
	110	2873				
The proposed two-stage FA	**20**	14202	**15771**	**515.02**	**60.28**	**0.9563**
	41	**1833**				
	50	**2732**				
	72	**2533**				
	80	**2094**				
	96	**1663**				
	109	**3119**				
The proposed two-stage BBO	**30**	**3708**	**16604**	**514.87**	**60.29**	**0.9566**
	42	**1154**				
	50	**2331**				
	72	**2533**				
	80	**2094**				
	96	**1663**				
	109	**3119**				

A comparison between the proposed two-stage method and the works found in the literature is tabulated in Tables 4.19 and 4.20 for the case of 5 and 7 connected DGs, respectively. Table 4.19 shows that the solutions found by SOS (T. P. Nguyen & Vo, 2018), TLBO (S. Sultana et al., 2014) and QOTLBO (S. Sultana et al., 2014) reduced the power loss to 798.8 kW, 594.66 kW, and 581.17 kW, respectively. Whereas, the proposed two-stage FA and BBO reduced the power loss to 576.58 kW and 573.39 kW, respectively. Similarly, for the case of 7 connected DGs, Table 4.20 illustrates the superiority of the proposed method as compared against QOTLBO, TLBO, and SOS since the proposed method accomplished better results for power loss mitigation and voltage profile enhancement. Therefore, from the presented observations and comparisons, the preeminence of the proposed method over the conventional methods and works found in the literature is asserted.

Table 4.19 Comparison of DG integration with the for 118-bus when 5 DGs are connected

Method	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-		-	1296.5	-	0.8688
QOTLBO (S. Sultana et al., 2014)	49	3013	12124	581.17	55.17	0.9541
	72	2543				
	82	1665				
	91	1766				
	109	3137				
TLBO (S. Sultana et al., 2014)	49	2775	11084	594.66	54.13	0.9510
	72	2421				
	82	1692				
	91	1867				
	109	2329				
SOS (T. P. Nguyen & Vo, 2018)	68	966	7311	798.80	38.38	0.9117
	70	2597				
	104	793				
	106	509				
	108	2446				
The proposed two-stage FA	**50**	**2681**	**11935**	**576.58**	**55.52**	**0.9533**
	74	**2311**				
	80	**2085**				
	91	**1990**				
	110	**2868**				
The proposed two-stage BBO	**50**	**2881**	**12292**	**573.39**	**55.77**	**0.9561**
	72	**2533**				
	80	**2095**				
	96	**1663**				
	109	**3120**				

Table 4.20 Comparison of DG integration with the for 118-bus when 7 DGs are connected

Method	DG location	DG size (kW)	Total DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	-		1296.5	-	-	0.8688
QOTLBO (S. Sultana et al., 2014)	24	1246	13773	575.95	55.57	0.9538
	42	732				
	47	3539				
	74	2679				
	78	1248				
	94	1086				
	108	3243				
TLBO (S. Sultana et al., 2014)	8	1755	14225	590.49	54.45	0.9454
	10	591				
	36	1536				
	49	2686				
	71	2501				
	79	2494				
	110	2662				
SOS (T. P. Nguyen & Vo, 2018)	67	875	7437	794.18	38.74	0.9117
	68	200				
	69	200				
	70	2501				
	104	678				
	106	722				
	108	2261				
MOTA (Meena et al., 2017)	42	1920	18360	616.98	52.41	0.9679
	48	4380				
	70	2280				
	72	1380				
	78	2880				
	96	1920				
	110	3600				
The proposed two-stage FA	**20**	**1794**	**15771**	**515.02**	**60.27**	**0.9563**
	41	**1833**				
	50	**2732**				
	72	**2533**				
	80	**2094**				
	96	**1663**				
	109	**3119**				
The proposed two-stage BBO	**30**	**3708**	**16604**	**514.87**	**60.29**	**0.9566**
	42	**1154**				
	50	**2331**				
	72	**2533**				
	80	**2094**				
	96	**1663**				
	109	**3119**				

4.5 Summary

This chapter presents the results of the proposed two-stage method to find the optimal NR solution in fast computational time, and with high consistency in finding the solution that minimizes the power loss and voltage deviation. The effectiveness of the proposed method was investigated on 33-bus, 69-bus, and 118-bus EDNs, and the results were compared to the conventional EP, PSO, FA, and BBO as well as the other recent works. Based on the results of the 33-bus, 69-bus, and 118-bus, it can be summarized that the proposed two-stage method outperformed the conventional methods in terms of the voltage profile, computational time as well as the best, the average and the overall STD of the system power loss. Besides, the proposed method found the same or better solution than the reported works since it has a smaller STD and better average power loss. The superiority of the proposed method over the conventional methods is mainly due to the proper population's initializations and the codifications through the proposed SNG approach.

This chapter has also provided an analysis of the number of DGs that should be connected to the 33-bus, 69-bus and 118-bus EDNs. Thereafter, comparisons between the proposed two-stage FA and BBO methods and the conventional EP, PSO, FA and BBO were performed. The results show that the proposed method managed to enhance the solution quality of the DG placement and sizing. Thus, better power loss reduction and voltage profile are achieved by the proposed method. The proposed method results are also compared against the recent works found in the literature, and the comparisons verified the superiority of the proposed method over the HSA, FWA, UVDA, QOTLBO, TLBO, IIA, MOTA and SOS.

CHAPTER 5: PERFORMANCE OF THE PROPOSED METHOD FOR NETWORK RECONFIGURATION AND DG INTEGRATION

5.1 Introduction

The performance of the proposed method in obtaining the solution for the NR and DG integration sequentially and simultaneously is presented in this chapter. The proposed method is tested on 33-bus, 69-bus, and 118-bus IEEE standard test systems, and the solutions of NR and DG are compared against the conventional methods and the recent works. The comparison metrics include power loss minimization and voltage profile improvement. Besides, this chapter presents the results of the incorporation variable DG output and load variation in the proposed method.

5.2 Network reconfiguration with DG integration sequentially

In this scenario, the NR is found first, and then the DG placement and sizing are obtained using the proposed two-stage method. The results of the NR that found in section 4.3 is considered for each method. Thereafter, the search for the optimal DG placement and sizing is conducted.

5.2.1 Test system 1: IEEE 33-bus

The optimal NR solution for the proposed method is (s7, s9, s14, s28, s32). Starting from this configuration, the proposed two-stage method obtained the solution of DGs located at buses 12, 16 and 25, and with the capacities of 536 kW, 503 kW, and 1616 kW, respectively. Consequently, as presented in Table 5.1, the power loss is 56.28 kW and the minimum bus voltage is 0.9723 p.u. On the other hand, the power loss of the solutions found by the conventional EP, PSO, FA, and BBO are 56.45 kW, 56.38 kW, 56.28 kW, and 56.28 kW, respectively. Therefore, the proposed method produced the same or better solution than the conventional method. The solutions found by EP and PSO are suboptimal solutions as compared to the solution found by the proposed method.

Moreover, as shown in Figure 5.1, the proposed method produces a voltage profile with a remarkable improvement compared to the base case.

Table 5.1 The results of the sequential network reconfiguration and DG integration for 33-bus

Method	Open switches	DG location	DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	33,34,35,36,37	-	-	210.98	-	0.9038
EP	7, 9, 14, 28, 32	12	499	56.45	73.24	0.9738
		16	522			
		25	1701			
PSO	7, 9, 14, 28, 32	12	553	56.38	73.27	0.9709
		16	491			
		25	1544			
FA	7, 9, 14, 28, 32	12	536	56.28	73.32	0.9723
		16	503			
		25	1616			
BBO	7, 9, 14, 28, 32	12	536	56.28	73.32	0.9723
		16	503			
		25	1616			
The proposed two-stage FA	7, 9, 14, 28, 32	**12**	**536**	**56.28**	**73.32**	**0.9723**
		16	**503**			
		25	**1616**			
The proposed two-stage BBO	7, 9, 14, 28, 32	**12**	**536**	**56.28**	**73.32**	**0.9723**
		16	**503**			
		25	**1616**			

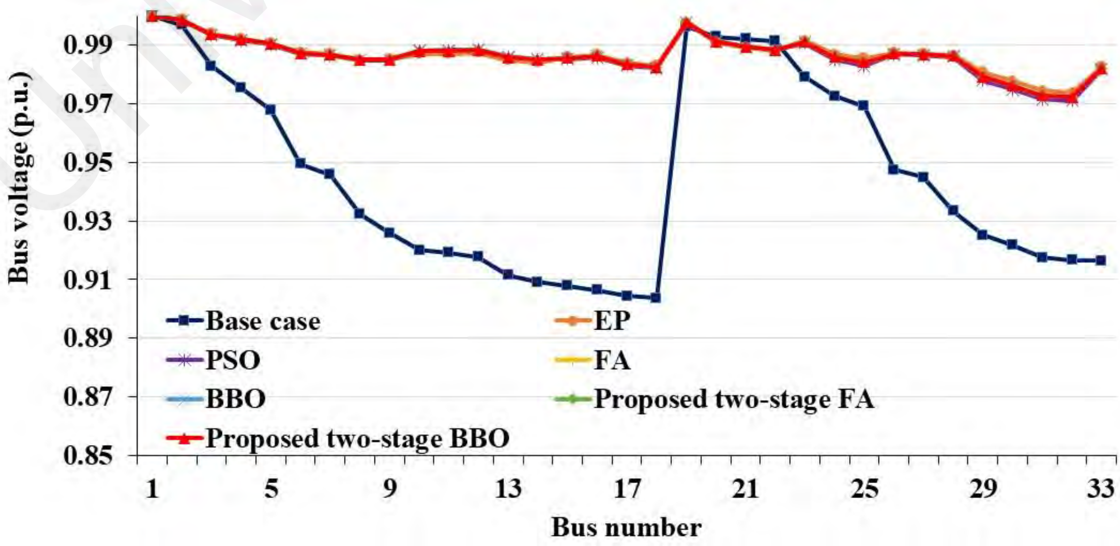

Figure 5.1 Comparison in voltage of the 33-bus for the NR and DG sequentially

The proposed method is additionally compared to the HSA (R. Rao et al., 2013), FWA (Imran et al., 2014), Teaching-Learning-Based Optimization (TLBO) (Rawat & Vadhera, 2019), UVDA (Bayat et al., 2016) and Adaptive Cuckoo Search Algorithm (ACSA) (T. T. Nguyen et al., 2016). The comparison verifies the efficiency of the proposed method since it managed to obtain better solutions than the previous works.

Table 5.2 Comparison results of the sequential network reconfiguration and DG integration for 33-bus

Method	Open switches	DG location	DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	33,34,35,36,37	-	-	210.98	-	0.9038
UVDA (Bayat et al., 2016)	7, 9, 14, 32, 37	12	526	66.60	68.43	0.9757
		15	592			
		30	1125			
FWA (Imran et al., 2014)	7, 9, 14, 28, 32	18	159	83.93	60.22	0.9612
		32	599			
		33	314			
HSA (R. Rao et al., 2013)	7, 9, 14, 32, 37	30	661	97.13	53.96	0.9478
		31	161			
		32	269			
TLBO (Rawat & Vadhera, 2019)	7, 9, 14, 28, 32	17	383	60.00	71.56	0.9803
		21	984			
		29	1747			
ACSA (T. T. Nguyen et al., 2016)	7, 9, 14, 28, 32	12	540	58.79	72.13	0.9803
		16	504			
		29	1754			
The proposed two-stage FA	7, 9, 14, 28, 32	**12**	**536**	**56.28**	**73.32**	**0.9723**
		16	**503**			
		25	**1616**			
The proposed two-stage BBO	7, 9, 14, 28, 32	**12**	**536**	**56.28**	**73.32**	**0.9723**
		16	**503**			
		25	**1616**			

5.2.2 Test system 2: IEEE 69-bus

The proposed method is utilized to find the NR and DG placement and sizing sequentially. The solution obtained by the proposed two-stage BBO reduces the power loss to 35.18 kW and improves the minimum bus voltage to 0.9813 p.u. The open switches configuration is (s14, s55, s61, s69, s70) whereas, the DGs locations 11, 61, 64 with the sizes of 530 kW, 1432 kW, 458 kW, respectively. This solution is better than the solutions found by the conventional EP, PSO, FA, and BBO as shown in Table 5.3. A detailed voltage profile comparison is presented in Figure 5.2.

Table 5.3 The results of the sequential network reconfiguration and DG integration for 69-bus

Method	Open switches	DG location	DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	69, 70, 71, 72, 73	-	-	224.97	-	0.9092
EP	12, 14, 55, 61, 69	7	710	37.84	83.18	0.9783
		27	696			
		61	1290			
PSO	12, 13, 56, 61, 69	10	791	37.53	83.32	0.9807
		26	457			
		61	1570			
FA	12, 55, 61, 69, 70	27	604	36.37	83.83	0.9808
		61	1411			
		68	334			
BBO	12, 55, 61, 69, 70	27	583	35.95	84.02	0.9817
		61	1449			
		66	440			
The proposed two-stage FA	**14, 55, 61, 69, 70**	**11**	**528**	**35.19**	**84.36**	**0.9815**
		61	**1443**			
		64	**501**			
The proposed two-stage BBO	**14, 55, 61, 69, 70**	**11**	**530**	**35.18**	**84.36**	**0.9813**
		61	**1432**			
		64	**485**			

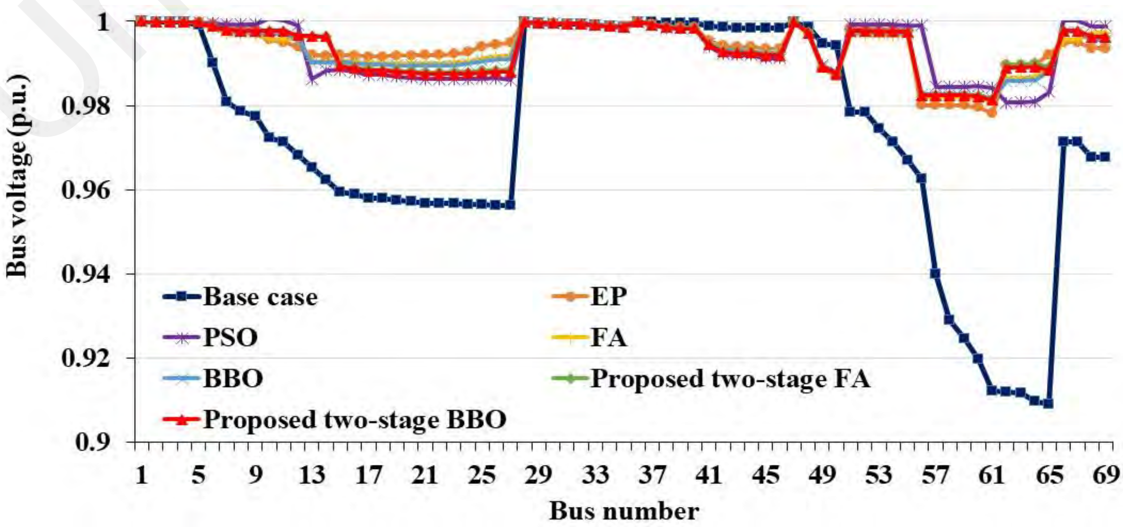

Figure 5.2 Comparison in voltage of the 69-bus for the NR and DG sequentially

A comparison between the proposed method and the previous research was carried out and the results are presented in Table 5.4. The proposed method solution is better than the solutions found by UVDA, FWA, HSA, TLBO, and ACSA. The comparison proves the capability of the proposed method to obtain a high-quality solution that minimizes power loss and voltage deviation.

Table 5.4 Comparison results of the sequential network reconfiguration and DG integration for 69-bus

Method	Open switches	DG location	DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	69, 70, 71, 72, 73	-	-	224.97	-	0.9092
UVDA (Bayat et al., 2016)	14, 58, 61, 69, 70	11	620	37.87	83.16	0.9801
		61	1378			
		64	722			
FWA (Imran et al., 2014)	14, 56, 61, 69, 70	61	1001	43.92	80.48	0.9720
		62	214			
		64	142			
HSA (R. Rao et al., 2013)	13, 18, 56, 61, 69	58	426	59.58	73,52	0.9622
		60	352			
		61	1066			
TLBO (Rawat & Vadhera, 2019)	14, 58, 61, 69, 70	27	288	39.26	82.55	0.9756
		61	1491			
		69	275			
ACSA (T. T. Nguyen et al., 2016)	14, 57, 61, 69, 70	12	369	37.25	83.44	0.9869
		61	1725			
		64	467			
The proposed two-stage FA	**14, 55, 61, 69, 70**	**11**	**528**	**35.19**	**84.36**	**0.9815**
		58	**1443**			
		61	**501**			
The proposed two-stage BBO	**14, 55, 61, 69, 70**	**11**	**530**	**35.18**	**84.36**	**0.9813**
		58	**1432**			
		61	**485**			

5.2.3 Test system 1: IEEE 118-bus

The results of the NR and DG integration sequentially are tabulated in Table 5.5. The solution obtained by the proposed two-stage BBO mitigates the power loss to 514.96 kW while improving the minimum bus voltage to 0.9498 p.u. Whereas, the conventional EP, PSO, FA, and BBO reduce the power loss to 571.51 kW, 576.77 kW, 569.15 kW, and 565.72 kW. In addition, a comparison in the voltage profile is conducted in Figure 5.3. The comparison highlights the improvement of the voltage profile as compared to the base case and the conventional methods.

Table 5.5 The results of the sequential network reconfiguration and DG integration for 118-bus

Method	Open switches	DG location	DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	119 to 133	-	-	1296.5	-	0.8688
EP	24, 26, 34, 39, 42, 51, 61, 73, 74, 82, 96, 99, 110, 122,131	69	1721	571.51	55.92	0.9517
		78	2759			
		82	1580			
		97	1511			
		118	2102			
PSO	22, 25, 34, 38, 42, 49, 60, 73, 75, 96, 98, 110, 122, 130, 131	51	2762	576.77	55.51	0.9428
		58	1489			
		70	1691			
		81	2126			
		110	1942			
FA	22, 27, 40, 44, 50, 58, 73, 75, 77, 83, 110, 123, 126, 131, 133	54	2640	569.15	56.10	0.9509
		71	1431			
		91	2877			
		107	2013			
		111	1721			
BBO	24, 26, 35, 39, 42, 51, 60, 71, 74, 77, 96, 110, 122, 130, 131	30	3338	565.72	56.36	0.9476
		50	1180			
		74	1853			
		104	2336			
		118	1726			
The proposed two-stage FA	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**74**	**1710**	**515.48**	**60.24**	**0.9502**
		79	**2842**			
		96	**1812**			
		107	**1688**			
		111	**1718**			
The proposed two-stage BBO	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**74**	**1616**	**514.96**	**60.28**	**0.9498**
		79	**2801**			
		96	**1767**			
		107	**1893**			
		111	**1701**			

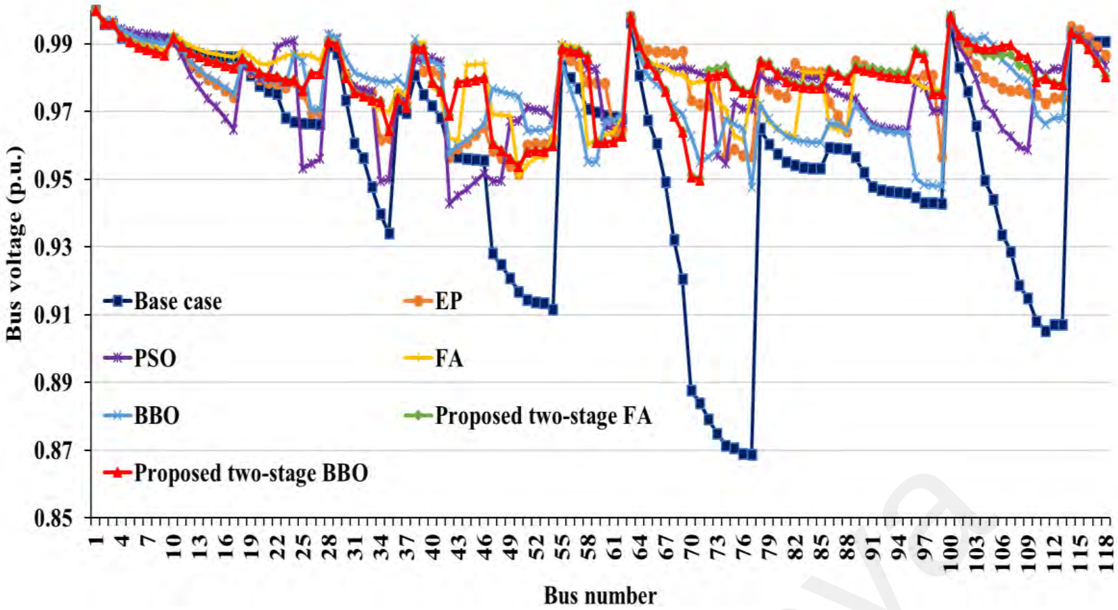

Figure 5.3 Comparison in voltage of the 118-bus for the NR and DG sequentially

The proposed method results are also compared to ACSA (T. T. Nguyen et al., 2016). The solution of the proposed method outperformed the ACSA solution in terms of power loss and voltage deviation minimization as shown in Table 5.6.

Table 5.6 Comparison results of the sequential network reconfiguration and DG integration for 118-bus

Method	Open switches	DG location	DG size (kW)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	119 to 133	-	-	1296.5	-	0.8688
ACSA (T. T. Nguyen et al., 2016)	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	65	5000	631.19	51.32	0.9538
		96	1756			
		111	1714			
The proposed two-stage FA	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**74**	**1710**	**515.48**	**60.24**	**0.9502**
		79	**2842**			
		96	**1812**			
		107	**1688**			
		111	**1718**			
The proposed two-stage BBO	**24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131**	**74**	**1616**	**514.96**	**60.28**	**0.9498**
		79	**2801**			
		96	**1767**			
		107	**1893**			
		111	**1701**			

5.3 Network reconfiguration with DG integration simultaneously

In this scenario, the NR and DG solution is found simultaneously. Hence, the complexity of this scenario is more than the previous scenarios where the search for the NR solution and DG solution is separated.

5.3.1 Test system 1: IEEE 33-bus

The 33-bus IEEE test system is utilized to examine the efficiency of the proposed method in solving the NR and DG integration simultaneously. The number of DGs connected to the system is 3. In the first stage, the combination of the open paths is found as well as the location and the size of each DG. Then, the second stage starts the search process by converting the paths' combination to switches combination whereas the DGs' locations and sizes are transferred without change.

Table 5.7 shows the simulation results of the proposed two-stages methods besides the comparison with the literature. The proposed two-stage BBO found the open switches configuration of (s10, s28, s31, s33, s34) with DGs placed at buses 7, 17, and 25 and sized as 812, 784 and 1182 kW, respectively. This solution reduces the power loss to 52.42 kW and enhances the minimum bus voltage to 0.9727 p.u. Whereas the solution found by the two-stage FA is to open the switches (s10. s27, s30, s33, s34) and to install the DGs at buses 7, 18 and 25, and with outputs of 847, 896 and 1164 kW, respectively. Thus, the resulted power loss is 52.99 kW, and the minimum bus voltage is 0.9674 p.u. On the other hand, the solutions found by the conventional EP, PSO, FA, and BBO are far from the optimal solution found by the proposed method. It is worth mentioning that the power loss reduction of the proposed two-stage FA and BBO compared to the base case are 74.88% and 75.15%, respectively. Whereas, the conventional EP, PSO, FA, and BBO loss reduction are 61.63%, 65.68%, 66.04%, and 69.22%, respectively.

Table 5.7 The results of the simultaneous network reconfiguration and DG integration for 33-bus

Method	Open switches	DG size in kW (Location)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	33, 34, 35, 36, 37	-	210.98	-	0.9038
EP	7, 8, 27, 34 ,35	949 (16), 978 (24), 823 (25)	80.95	61.63	0.9547
PSO	14, 15, 20, 28, 33	958 (8), 892 (23), 1299 (30)	72.01	65.68	0.9649
FA	6, 10, 30, 33, 37	763 (9), 726 (18), 1014 (24)	71.64	66.04	0.9548
BBO	7, 8, 28, 31, 34	971 (7), 1247 (29), 589 (33)	64.93	69.22	0.9563
Proposed two-stage FA	**10, 27, 30, 33, 34**	**847 (7), 896 (18), 1164 (25)**	**52.99**	**74.88**	**0.9674**
Proposed two-stage BBO	**10, 28, 31, 33, 34**	**812 (7), 784 (17), 1182 (25)**	**52.42**	**75.15**	**0.9727**

Furthermore, Figure 5.4 compares the voltage profile of the system for the base case, conventional methods, and the proposed method for the case of NR and DG simultaneously. It is noted that the solution found by the proposed method has a significant impact on voltage profile enhancement compared to the other cases.

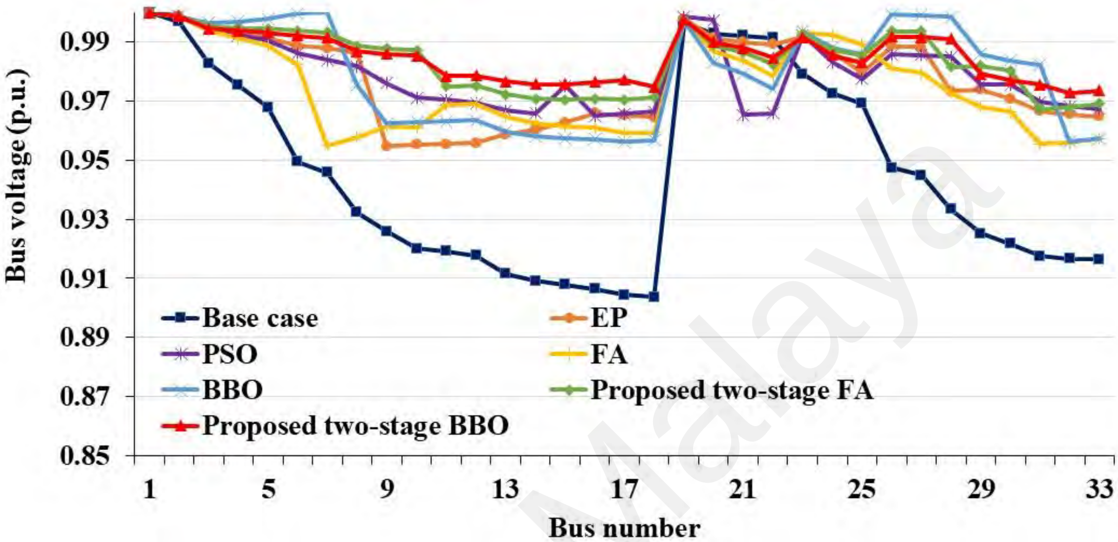

Figure 5.4 Comparison in voltage of the 33-bus for the simultaneous NR and DG

Besides, Table 5.8 presents a comparison between the proposed method solutions and the solutions found by the FA (Badran, Mokhlis, Mekhilef, et al., 2017), HSA (R. Rao et al., 2013), FWA (Imran et al., 2014), TLBO (Rawat & Vadhera, 2019), UVDA (Bayat et al., 2016) and ACSA (T. T. Nguyen et al., 2016) reduced the real power loss to 73.04 kW, 73.05 kW, 67.11 kW, 58.04 kW, 57.28 kW and 53.21 kW, respectively. From the comparison between the results of the proposed method and the works in the literature, it can be concluded that the solutions found by the two-stages BBO and FA surpassed the ones given in the literature.

Table 5.8 comparison results in case of simultaneous NR and DG for 33-bus

Method	Open switches	DG size in kW (Location)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	33, 34, 35, 36, 37	-	210.98	-	0.9038
FA (Badran, Mokhlis, Mekhilef, et al., 2017)	8, 9, 28, 32, 33	841 (31), 340 (32), 591 (33)	73.04	65.38	0.9735
HSA (R. Rao et al., 2013)	7, 14, 10, 32, 28	525 (32), 558 (31), 584 (33)	73.05	73.05	0.9700
FWA (Imran et al., 2014)	7, 14, 11, 32, 28	536 (32), 615 (29), 531 (18)	67.11	68.19	0.9713
TLBO (Rawat & Vadhera, 2019)	6, 10, 14, 32, 37	1329 (8), 1172 (24), 726 (31)	58.04	72.49	0.9751
UVDA(Bayat et al., 2016)	7, 10, 13, 27, 32	1554 (29), 649 (15), 486 (21)	57.28	72.85	0.9760
ACSA (T. T. Nguyen et al., 2016)	11, 28, 31, 33, 34	964 (7), 896 (18), 1438 (25)	53.21	74.77	0.9806
Proposed two-stage FA	**10, 27, 30, 33, 34**	**847 (7), 896 (18), 1164 (25)**	**52.99**	**74.88**	**0.9674**
Proposed two-stage BBO	**10, 28, 31, 33, 34**	**812 (7), 784 (17), 1182 (25)**	**52.42**	**75.15**	**0.9727**

5.3.2 Test system 2: IEEE 69-bus

The proposed two-stage method is also applied to 69-bus to find the solution of the NR simultaneously with the DGs integration. As shown in Table 5.9, the proposed two-stage BBO managed to reduce the power loss to 35.18 kW and improved the minimum bus voltage to 0.9813 p.u. by opening switches (s14, s56, s61, s69, s70) and placing three DGs at buses 11, 61 and 64 with sizes of 530, 1432 and 485 kW, respectively. Meanwhile, the results found by the conventional EP, PSO, FA, and BBO reduced the power loss to 58.71 kW, 52.72 kW, 40.04 kW, and 39.51 kW, respectively. Moreover, the voltage profile comparison is presented in Figure 5.5.

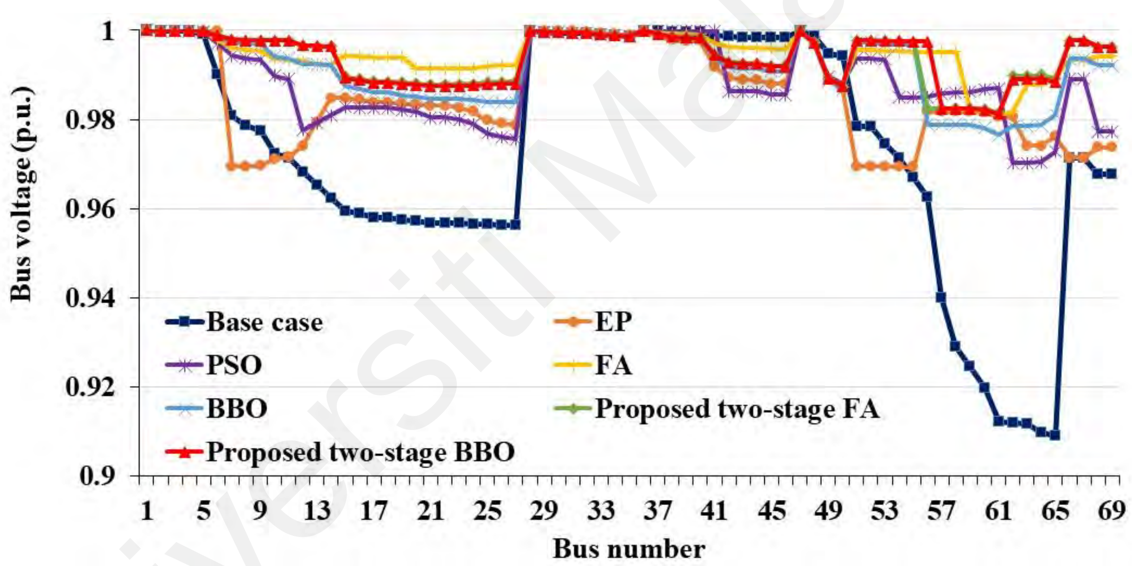

Figure 5.5 Comparison in voltage of the 69-bus for the simultaneous NR and DG

As presented in Table 5.10, the proposed method solutions surpassed the solutions found by FA (Badran, Mokhlis, Mekhilef, et al., 2017), HSA (R. Rao et al., 2013), FWA (Imran et al., 2014), TLBO (Rawat & Vadhera, 2019), UVDA (Bayat et al., 2016), and ACSA (T. T. Nguyen et al., 2016) with regards to power loss reduction. Accordingly, it can be concluded that the proposed method produced a better solution than the previous solutions for the case of solving the NR and DG integration simultaneously.

Table 5.9 The results of the simultaneous network reconfiguration and DG integration for 69-bus

Method	Open switches	DG size in kW (Location)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	69, 70, 71, 72, 73	-	224.97	-	0.9092
EP	6, 13,55, 62, 69	1286 (21), 67 (29), 1451 (61)	58.71	73.90	0.9693
PSO	11, 41, 53, 61, 70	394 (17), 363 (20), 1764 (61)	52.72	76.56	0.9702
FA	14, 19, 58, 62, 69	476 (27), 1469 (62), 302 (69)	40.04	82.20	0.9810
BBO	14, 55, 61, 69, 70	368 (27), 420 (51), 1212 (61)	39.51	82.43	0.9766
Proposed two-stage FA	**14, 55, 61, 69, 70**	**528 (11), 1443 (61), 501 (64)**	**35.19**	**84.36**	**0.9815**
Proposed two-stage BBO	**14, 56, 61, 69, 70**	**530 (11), 1432 (61), 485 (64)**	**35.18**	**84.36**	**0.9813**

Table 5.10 comparison results in case of simultaneous NR and DG for 69-bus

Method	Open switches	DG size in kW (Location)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	69, 70, 71, 72, 73	-	224.97	-	0.9092
TLBO (Rawat & Vadhera, 2019)	9, 7, 13, 57, 63	1201 (63),1759 (50),1417 (12)	48.37	78.49	0.9740
FA (Badran, Mokhlis, Mekhilef, et al., 2017)	12, 19, 57, 61, 69	251 (60), 1232 (61), 452 (62)	40.3	82.08	0.9816
HSA (R. Rao et al., 2013)	69, 17, 13, 58, 61	1066 (61), 352 (60), 425 (58)	40.4	82.04	0.9736
FWA (Imran et al., 2014)	69, 70, 13, 55, 63	1127 (61), 275 (62), 415 (65)	39.25	82.55	0.9796
UVDA(Bayat et al., 2016)	14, 58, 63, 69, 70	1472 (61), 538 (11), 673 (17)	37.11	83.51	0.9816
ACSA (T. T. Nguyen et al., 2016)	14, 58, 61, 69, 70	154 (11), 1724 (61), 553 (65)	37.02	83.54	0.9868
Proposed two-stage FA	**14, 55, 63, 69, 70**	**528 (11), 1443 (58), 501 (61)**	**35.19**	**84.36**	**0.9815**
Proposed two-stage BBO	**14, 56, 61, 69, 70**	**530 (11), 1432 (58), 485 (61)**	**35.18**	**84.36**	**0.9813**

5.3.3 Test system 3: IEEE 118-bus

The optimal solution of simultaneous NR and DG integration for the 118-bus is presented in Table 5.11. The solution found by the proposed two-stage BBO consists of opening the switches (s22, s27, s40, s43, s50, s62, s71, s75, s77, s96, s108, s110, s122, s131, s133) along with five DGs placed at buses 54, 73, 80, 96 and 111 with the capacities of 2598 kW, 2182 kW, 3134 kW, 1984 kW, and 1692 kW, respectively. The aforementioned solution reduces the power loss to 489.21 kW and improves the minimum bus voltage to 0.9568 p.u. Similarly, the solution found by the proposed FA minimizes the real power loss to 493.86 kW and enhances the bus voltage to 0.9577 p.u. From Table 5.11, it can be concluded that the proposed method solution is preferable over the solutions obtained by the conventional EP, PSO, FA, and BBO. Furthermore, a comparison in the voltage profile between all methods is illustrated in Figure 5.6.

A comparison between the proposed method and previous works for the 118-bus is presented in Table 5.11. The total DG size for the proposed method is 11590 kW which smaller than the total size of 119703 kW in the FA (Badran, Mokhlis, Mekhilef, et al., 2017) and slightly larger than the total DGs size of 9918 kW in the ACSA (T. T. Nguyen et al., 2016). Nevertheless, the power loss of the proposed method is significantly smaller than the solution found by FA and ACSA.

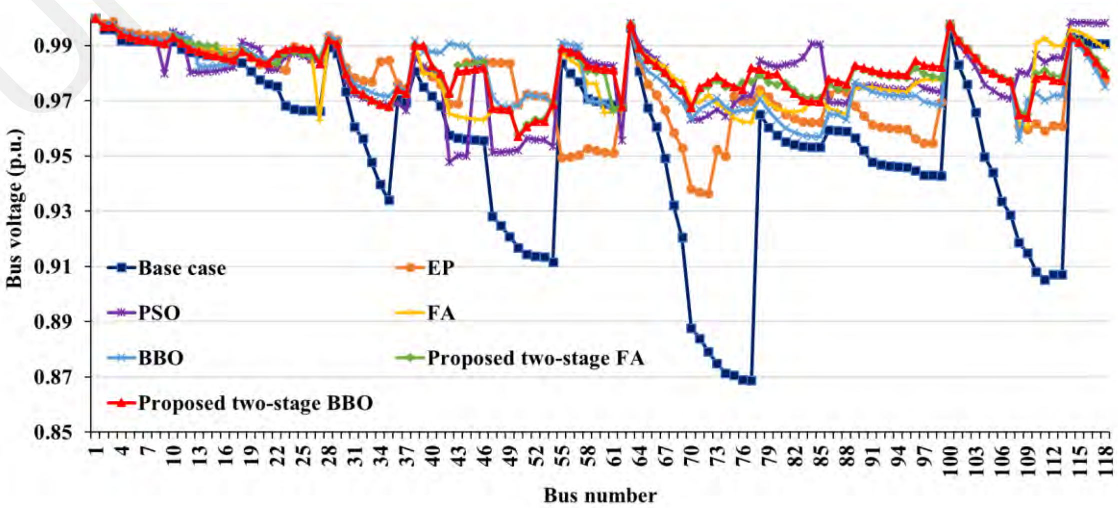

Figure 5.6 Comparison in voltage of the 118-bus for the simultaneous NR and DG

Table 5.11 The results of the simultaneous network reconfiguration and DG integration for 118-bus

Method	Open switches	DG size in kW (Location)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	119 to 133	-	1296.5	-	0.8688
EP	24, 26, 34, 43, 44, 50, 55, 62, 73, 75, 99, 108, 109, 125, 131	2742 (3), 2552 (51), 1995 (87), 2692 (91), 2406 (118)	634.48	51.06	0.9365
PSO	9, 12, 21, 42, 45, 47, 62, 75, 76, 86, 89, 108, 110, 127, 133	2796(51), 3036(58), 2425(84), 2782(118), 1932(73)	618.46	52.29	0.9477
FA	23, 27, 39, 50, 60, 75, 89, 108, 110, 120, 122, 127, 129, 131, 133	2940 (54), 2294 (72), 1675 (84), 1881 (97), 2231 (111)	559.42	56.85	0.9573
BBO	13, 23, 39, 45, 48, 58, 61, 71, 76, 108, 109, 122, 127, 131, 133	1235 (42), 2894 (51), 2871 (73), 2103 (96), 2227 (110)	542.58	58.15	0.9558
Proposed two-stage FA	**16, 23, 40, 43, 50, 61, 71, 76, 87, 96, 108, 110, 122, 131, 133**	**2840 (57), 2283 (73), 2318 (81), 1984 (96), 1762 (111)**	**493.86**	**61.91**	**0.9577**
Proposed two-stage BBO	**22, 27, 40, 43, 50, 62, 71, 75, 77, 96, 108, 110, 122, 131, 133**	**2598 (54), 2182 (73), 3134 (80), 1984 (96),1692 (111)**	**489.21**	**62.27**	**0.9568**

Table 5.12 comparison results in case of simultaneous NR and DG for 118-bus

Method	Open switches	DG size in kW (Location)	Power Loss (kW)	Loss reduction (%)	Minimum Voltage (p.u.)
Base case	119 to 133	-	1296.5	-	0.8688
FA (Badran, Mokhlis, Mekhilef, et al., 2017)	21, 25, 33, 38, 41, 58, 70, 81, 121, 122, 125, 127, 128, 130, 131	1507 (24), 1248 (42), 1821 (47), 1824 (74), 1282 (78), 1264 (94), 2991 (108)	571.38	55.92	0.9502
ACSA (T. T. Nguyen et al., 2016)	22, 25, 33, 39, 42, 58, 70, 81, 121, 122, 125, 127, 128, 130, 131	2533 (50), 3704 (73), 3681 (109)	586.24	54.78	0.9653
Proposed two-stage FA	**16, 23, 40, 43, 50, 61, 71, 76, 87, 96, 108, 110, 122, 131, 133**	**2840 (57), 2283 (73), 2318 (81), 1984 (96), 1762 (111)**	**493.86**	**61.91**	**0.9577**
Proposed two-stage BBO	**22, 27, 40, 43, 50, 62, 71, 75, 77, 96, 108, 110, 122, 131, 133**	**2598 (54), 2182 (73), 3134 (80), 1984 (96),1692 (111)**	**489.21**	**62.27**	**0.9568**

5.4 Overall comparisons for all cases

In the previous chapter, two case studies that include the solutions of the NR and DG separately were considered. In this chapter, the solutions for the NR and DG sequentially and simultaneously are presented. For further performance analysis, this section provides a comparison between these cases for all test systems.

Table 5.13 presents a comparison in power loss and minimum bus voltage for all test systems considering all the case studies. All the solutions are the optimal solutions found by the proposed two-stage BBO. The comparison shows that finding the most efficient technique to minimize the power loss and voltage deviation is to find the solution of the NR and DG simultaneously followed by the solution of NR and DG sequentially. On the other hand, the solution of the DG separately is more efficient than the solution of the NR only. Moreover, a comparison in voltage profile for each case is conducted and the results of the 33-bus, 69-bus, and 118-bus are depicted in Figures 5.7 to 5.9, respectively. Therefore, it is recommended to solve the NR and DG simultaneously to minimize the power loss and voltage deviation.

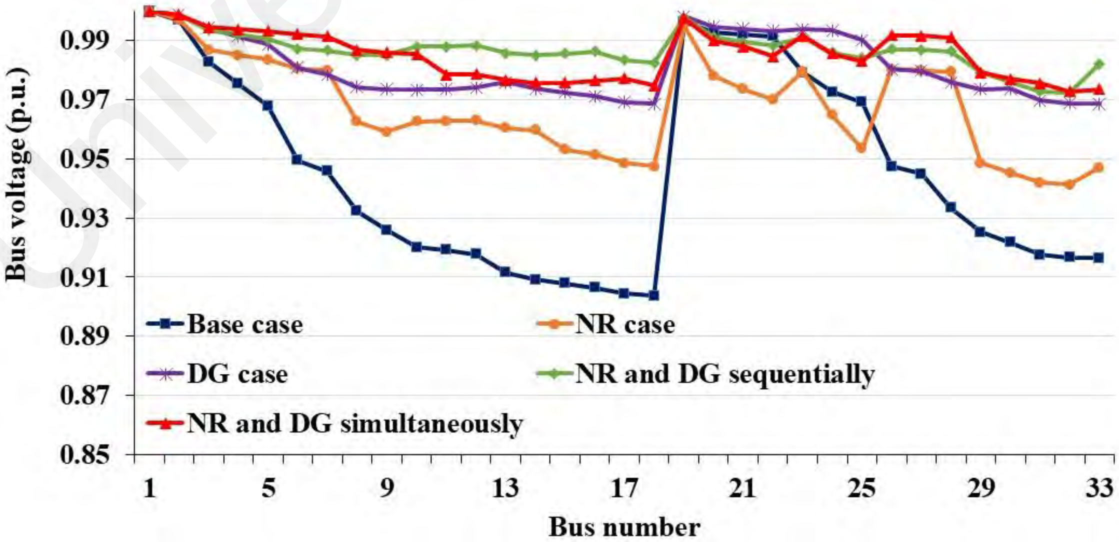

Figure 5.7 Voltage profile comparisons of the 33-bus for different case studies

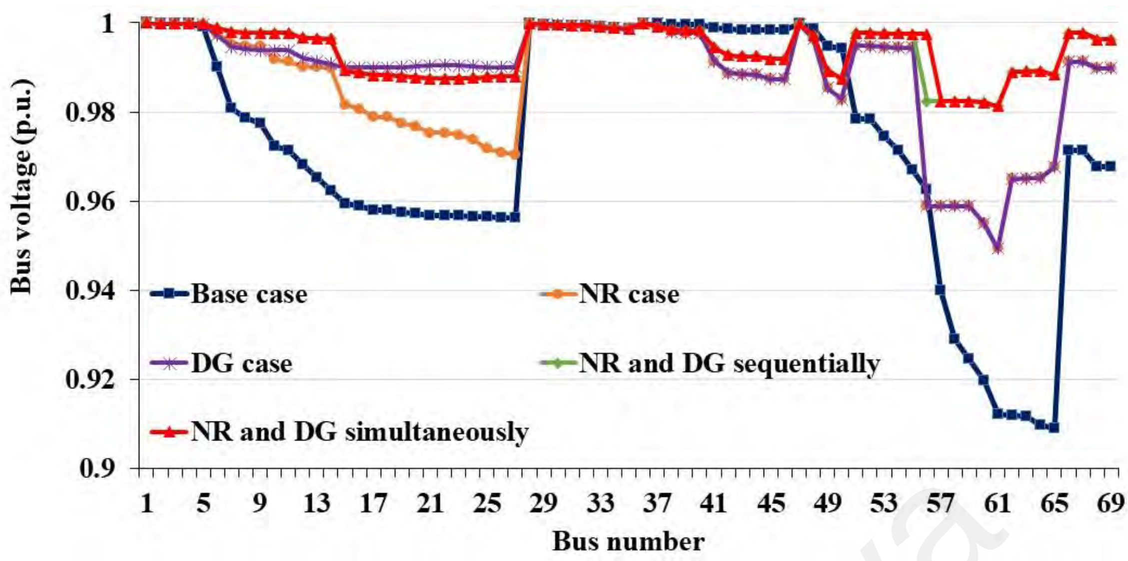

Figure 5.8 Voltage profile comparisons of the 69-bus for different case studies

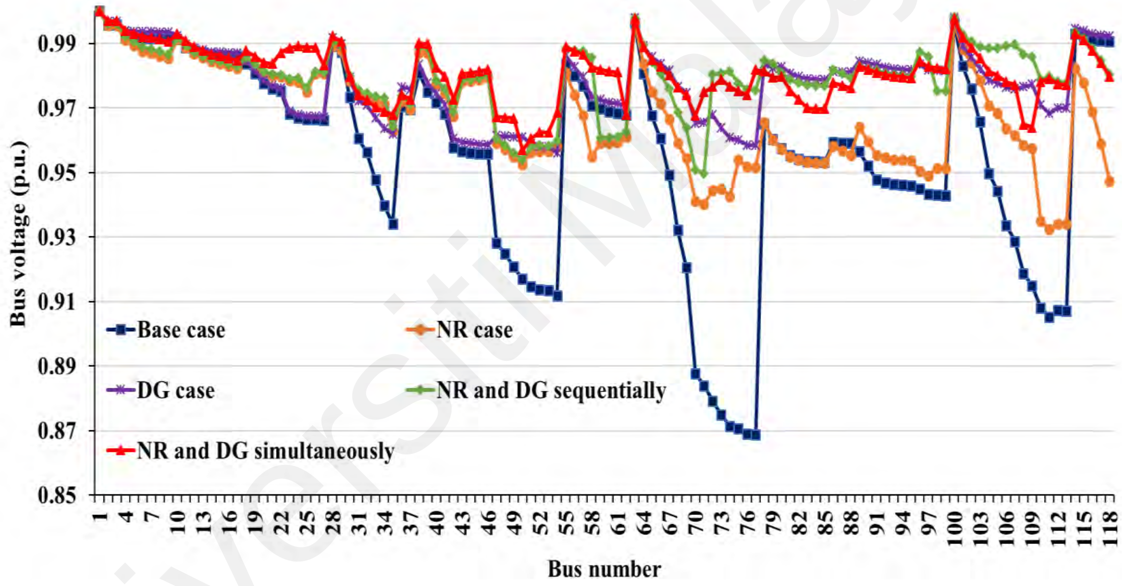

Figure 5.9 Voltage profile comparisons of the 118-bus for different case studies

Table 5.13 Performance analysis of the proposed method for different case studies

Case study	Power loss (kW)	Power loss reduction (%)	Minimum bus voltage (p.u.)
33-bus			
Base case	210.98	-	0.9038
Only NR case	139.98	33.65	0.9413
Only DG case	72.78	65.50	0.9686
NR and DG sequentially	56.28	73.32	0.9723
NR and DG simultaneously	52.42	75.15	0.9727
69-bus			
Base case	224.97	-	0.9092
Only NR case	98.61	56.16	0.9495
Only DG case	69.49	69.11	0.9790
NR and DG sequentially	35.18	84.36	0.9813
NR and DG simultaneously	35.18	84.36	0.9813
118-bus			
Base case	1296.5	-	0.8688
Only NR case	853.58	34.17	0.9323
Only DG case	573.39	55.77	0.9561
NR and DG sequentially	514.96	60.28	0.9498
NR and DG simultaneously	489.21	62.27	0.9568

5.5 Network reconfiguration with variable DG output and load variation

In this scenario, the variable DG output and load variation will be addressed and incorporated in the proposed two-stage method. The significant impact of the hourly NR on the power loss and voltage deviation reduction is investigated. The 33-bus test system is considered, and four RER DGs are placed in this EDN as tabulated in Table 5.14. The Wind Turbines (WTs) are located at buses 10 and 33, whereas the Photovoltaics (PVs) are placed on buses 7 and 14. The locations of the WT and PV are found by the proposed two-stage method considering the average load and DG output.

Table 5.14 Type, location and the maximum capacity of the renewable energy

Type	Location	Maximum Capacity (kW)
WT 1	10	500
WT 2	33	500
PV 1	7	400
PV 2	14	600

5.5.1 Performance analysis for a single day

Table 5.15 shows the hourly variations of the WT, PV, and loads for a single day in California, U.S (U.S energy information administration, 2020, March 1). The PV generation ranges between 0 to 80%, whereas the WT outputs change from 54% in hour 23 into the almost maximum value of 99% at hour 5. The load varies between 64% at hour 13 to 89% at hour 19.

To verify the importance of intraday NR, the following fixed configurations were considered for comparison against the hourly configuration.

- Conf. 1: It is the base case configuration. The open switches of this configuration are s33, s34, s35, s36, s37.
- Conf. 2: It is the optimal open switches configuration found when the load is at peak level, i.e. 100%, while no RER is connected to the system. The open switches are s7, s9, s14, s28, s32.
- Conf. 3: It is the optimal open switches configuration obtained when the load at peak level and the RERs are at their maximum generation level. The open switches of this configuration are s10, s30, s33, s34, s37.

The optimal hourly configurations found by the proposed method are presented in Table 5.16. It is noted that when there are no large changes in the RER generation and load profile, the configuration does not change like hours 9 to 14 and 20 to 23.

Table 5.15 Variations of solar, wind and load for a single day

Hour	PV (%)	WT (%)	Load (%)
1	0	81	74
2	0	81	71
3	0	87	70
4	0	94	69
5	0	99	69
6	0	91	71
7	9	90	73
8	57	78	73
9	80	82	71
10	80	77	69
11	77	78	67
12	74	75	65
13	74	73	64
14	72	72	65
15	68	68	66
16	56	61	70
17	10	62	75
18	7	73	83
19	0	76	89
20	0	70	88
21	0	68	86
22	0	58	84
23	0	54	80
24	0	69	75

Table 5.16 The hourly configurations of the system

Hours	Open switches	Hours	Open switches
1, 2, 7	6, 11, 14, 30, 37	15	10, 30, 33, 34, 37
3, 4, 5, 6	7, 8, 14, 28, 36	16, 18, 19	7, 11, 30, 34, 37
8	11, 30, 33, 34, 37	17, 20, 21, 22, 23	7, 10, 14, 30, 37
9, 10, 11, 12, 13, 14	7, 11, 34, 36, 37	24	7, 11, 14, 30, 37

Table 5.17 shows the power loss obtained for each hour using the proposed method and the power loss resulted from using the fixed configurations for all hours. It is noted that the hourly configuration fulfills lower power loss as compared to the fixed configurations. The total power loss reductions of the hourly configurations with respect to the fixed configurations Conf. 1, 2, and 3 are 24.51%, 25.82%, and 6.54%, respectively. Conf. 3 achieved high power loss reduction when the RERs output level is at their maximum level. On the other hand, the power loss reduction of the hourly configuration is 10% smaller than the power loss of the Conf. 3 when the RERs output is far from the maximum limits like hours 20 to 23.

The minimum bus voltage for each hour resulted from the hourly configurations and the fixed configurations is shown in Figure 5.10. The comparison shows that by using the hourly configurations, the voltage profile further improved as compared to the voltage profile obtained by the fixed configurations.

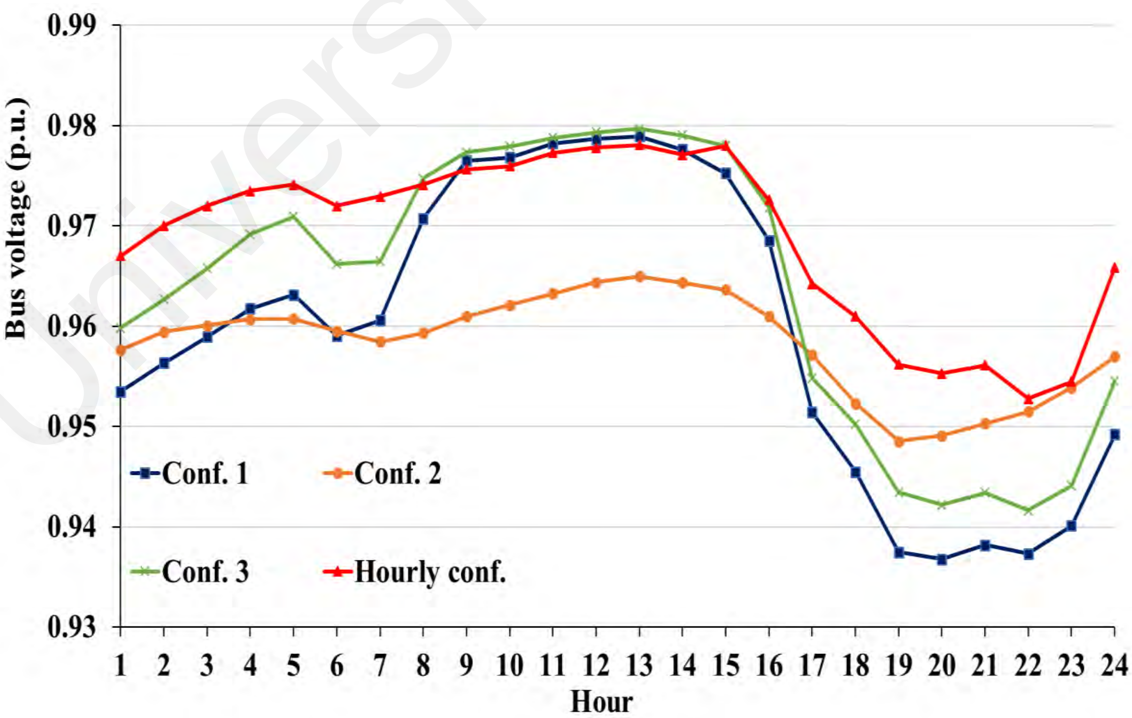

Figure 5.10 Voltage profile comparisons between the hourly configuration and the fixed configurations

Table 5.17 Power loss comparisons between the hourly configuration and the fixed configurations

Hour	Power loss of the hourly configurations [kw]	Power loss of the fixed configurations [kw]		
		Conf. 1	Conf. 2	Conf. 3
1	45.53	60.50	58.55	48.99
2	41.36	54.43	54.00	44.34
3	39.51	50.73	53.21	41.88
4	37.02	47.21	52.91	39.67
5	36.32	46.16	53.87	39.26
6	40.18	51.49	55.17	42.73
7	41.48	52.38	57.38	43.63
8	37.51	45.15	56.53	37.57
9	34.94	42.92	58.47	35.31
10	32.99	40.61	54.81	33.18
11	31.07	38.31	52.39	31.49
12	29.19	35.91	48.93	29.52
13	28.30	34.87	47.38	28.58
14	29.20	35.65	47.79	29.25
15	29.95	36.56	47.33	29.95
16	34.60	43.12	49.81	35.23
17	48.02	65.71	58.65	52.51
18	59.12	81.18	72.81	64.76
19	71.22	99.86	85.55	78.87
20	71.24	100.57	83.93	79.17
21	68.06	96.07	80.05	75.66
22	67.84	96.56	77.19	75.73
23	61.81	87.92	69.93	68.99
24	48.95	67.53	59.83	53.79

5.5.2 Performance analysis for different renewable energy output level

The RERs' capacity level has an influence on the hourly configuration. To analyze this effect, different level of WT and PV capacities is considered, and the results are collected. The RER output level is changing between 0% to 150% of their initial values in 50% step. Since the fixed configuration (Conf. 3) is found by considering the maximum load and RER generation, Conf. 3 is changing based on the RER output level. Hence, Conf. 3 is determined for each RER value, and the results are presented in Table 5.18.

Table 5.18 The open switches of Conf. 3 for deferent RERs' output level

RERs' output level %	Open switches
0	7, 9, 14, 28, 32
50	7, 10, 13, 31, 37
100	10, 30, 33, 34, 37
150	11, 28, 33, 34, 36

The daily power loss obtained by the hourly configurations is presented in Table 5.19. When the RER output level is 0%, the hourly configuration is constant, and it is the same as Conf. 2 since only the load is changing. Hence, the reduction in power loss is only with respect to the base case configuration. However, it is noted that when the output level increases, the importance of the hourly configurations becomes more significant as compared to the fixed configurations Conf. 2 and Conf. 3. Whereas, the relation between the output level and the total power loss reduction with respect to the Conf. 1 (base case) is not linear since it is mainly infected with the similarity between the hourly configuration and the Conf. 1. Furthermore, the comparison between the results of Conf 1. Conf. 2 and Conf. 3 shows that Conf. 3 achieved lower power loss since it considers the RER and load at their maximum level.

It also can be observed from Table 5.19 that increasing the RER output more than 100% does not provide a notable decrease in the daily power loss since the slope of the power loss decreases. Therefore, the chosen capacities of the installed RERs are suitable for this EDN.

Table 5.19 Daily power loss comparisons between the hourly configuration and the fixed configurations for different RERs' output levels

RERs' output level (%)	Total power loss of the hourly configurations [kw]	Total hourly power loss reduction with respect to the fixed configurations (%)		
		Conf. 1	Conf. 2	Conf. 3
0	1795.93	32.57	0	0
50	1291.83	29.25	10.43	2.47
100	1065.42	24.51	25.83	6.54
150	1015.73	26.28	41.91	9.84

It can be concluded that in the case of hourly load variations and non-dispatchable RER integration, obtaining the optimal NR hourly improves the system performance. Hence, it is vital to adapt an NR method that is able to find the optimal solution in a short computational time.

5.6 Summary

This chapter presented the application of the proposed two-stage method to solve the NR and DG placement and sizing. Both the sequential and simultaneous approaches were considered. The proposed method was evaluated on three test systems of different sizes. For all test systems, the proposed method solution for the sequential NR and DG integration outperformed the solutions of the conventional methods and the works found in the literature. Thereafter, solving the NR problem simultaneously with DGs placement and sizing is considered by the proposed method. The solution found by the proposed two-stage BBO for the 33-bus, 69-bus and 118-bus managed to outclass the solutions of the conventional methods in terms of minimizing the power loss and voltage deviation. Furthermore, the proposed method outperformed the works found in the literature in reducing power loss and improving the voltage profile. Moreover, it was observed that solving NR and DG integration simultaneously is more efficient than the sequential solution.

For the case of RERs' output level variation along with load changes, the impact of the hourly configurations on reducing the power loss and enhancing the voltage profile was highlighted. Base case configuration, minimum RER output level configuration, and maximum RER output level, and maximum load configuration are the three fixed configurations that were used for comparisons against the hourly configuration found by the proposed method. The results show that the hourly configuration solutions achieve smaller power loss and voltage deviation as compared to the fixed configurations. In addition, it was demonstrated that the necessity of the hourly configuration growths if the RER output level rises.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion

This research proposes a new two-stage optimization method to simultaneously obtain the optimal network reconfiguration and DG integration in fast computational time and with high consistency. The proposed simplified network approach and the proposed codification have been utilized to find the initial solutions and maintain the radiality constraint during the search process. The proposed method has been implemented using FA and BBO with the aim of minimizing power loss and voltage deviation. This work is verified using 33, 69, and 118-bus IEEE distribution networks and the results are compared against the conventional EP, PSO, FA, and BBO as well as the recent works found in the literature such as the HSA, EPSO, AWIDPSO, heuristic-IHSA, GA, RGA. BPSOGSA, HDM, FWA, MPSO, and MTS.

For the first objective, the capability of the proposed method to find the optimal NR is examined. Results show the superiority of the proposed method in obtaining the same or a better solution than the previously proposed methods with much better consistency and in fast computational time. For the 33-bus, 69-bus, and 118-bus, the power loss was reduced by 33.65%, 56.11%, and 34.11%, respectively. Besides, the proposed two-stage method achieved smaller STD of power loss as compared to the conventional EP, PSO, FA, and BBO, as well as the HSA, FWA, MPSO, and MTS, found in the literature. Moreover, the proposed method required shorter computational time than the conventional method where the proposed two-stage BBO is faster by more than 90% as compared to the conventional BBO for the three test systems.

In the second objective, DGs are integrated into the distribution networks. The proposed method is utilized to find the optimal DG placement and sizing that minimize the power loss and voltage deviation. As compared to the base case, the power loss was reduced by 65.6%, 69.11%, and 55.77% for the 33-bus, 69-bus, and 118-bus, respectively. In addition, a notable improvement in the voltage profile has been achieved by the proposed method. The comparisons between the proposed method, the conventional methods, and the previous works show the proposed method capability to attain the best solutions for the 33-bus, 69-bus, and 118-bus.

For the third objective, the proposed method is employed to solve simultaneously the NR and DG placement and sizing. The solution found by the proposed method for the 33-bus, 69-bus, and 118-bus reduced the power loss by 75.15%, 84.36%, and 62.27%, respectively, as compared to the base case. Furthermore, the proposed method outperformed the works found in the literature in reducing power loss. For instance, the solutions found using the proposed two-stage BBO obtained a power loss smaller by 1.48%, 4.97%, and 16.55% for the 33-bus, 69-bus, and 118-bus, respectively as compared to the ACSA. Moreover, a tremendous system voltage profile improvement was achieved by considering the simultaneous NR and DG solutions. Additionally, it was observed that the simultaneous NR and DG solution is more efficient compared to the sequential solution as well as solving the NR and DG separately. Therefore, the proposed method succeeded in obtaining a high-quality solution to the problem of NR and DG placement and sizing.

In the fourth objective, the incorporation of variable DG output and load variations has been successfully achieved by the proposed method. The value of the hourly NR is examined considering the load changes as well as WT and PV output level variations. The hourly NR is obtained using the proposed two-stage method to minimize power loss and voltage deviation. To analyses the impact of the hourly configuration, its solution is compared against three fixed configurations. The comparison shows that the hourly NR achieves smaller daily power loss by 7% to 26% comparing to the fixed configurations.

Furthermore, it was noted that the significance of the hourly configuration increases when the RERs' output level increases.

6.2 Future work

The analysis of NR and DG integration based on the proposed method can be further improved. The following extension works suggestions that can be conducted in the future are as follows:

1) The proposed two-stage method was successfully implemented using the FA and BBO. Hybrid FA and BBO or other meta-heuristic methods are also possible to be utilized with the aim to achieve better consistency in obtaining the solution as well as shorter computational time.
2) The objective function of this work is minimizing power loss and voltage deviation. Nevertheless, reducing the operation and investment cost, mitigating the number of the switching operation, achieving load balance among the feeders can be also considered for future works.
3) From the perspective of operation, protection system is also interesting to be considered as the constraints in the system.
4) The proposed method can be also employed for system restoration application since its ability to find the optimal NR solution in short computational time has been verified.

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