OPTIMAL DISTRIBUTION SYSTEM RECONFIGURATION INCORPORATING DG AND VARIABLE LOAD PROFILE USING ARTIFICIAL NEURAL NETWORK

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FACULTY OF ENGINEERING
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OPTIMAL NETWORK RECONFIGURATION INCORPORATING DISTRIBUTED GENERATION AND VARIABLE LOAD PROFILE USING ARTIFICIAL NEURAL NETWORK

ABSTRACT

Optimal network reconfiguration is a common method used in distribution systems to ensure minimum power losses are always attained. This is very important task for achieving cost effective operation. Due to varying load demands, conventional network reconfiguration techniques have to be repeated whenever system loading changes to find a new configuration that has minimum power losses. This task is time consuming and ineffective approach for a real time application. Therefore, this research proposes an Artificial Neural Network (ANN) technique for optimal distribution network reconfiguration to overcome long processing time, mainly in load variation case. The proposed method involves; (1) Implement optimal network reconfiguration with variable load profile and DG generation using meta-heuristic techniques for ANN modelling (2) Designing an ANN model for optimal network reconfiguration (3) Train the proposed ANN model on the generated data using different split ratios for optimal network reconfiguration. The applied meta-heuristic techniques in this work are Evolutionary programming (EP) and Particle swarm optimization (PSO). To evaluate the performance of the proposed ANN method, simulation conducted on MATLAB were conducted on IEEE 16-bus, IEEE 33-bus and IEEE 69-bus system. The proposed network reconfiguration based on ANN significantly reduces the computational time to find the optimal solution while avoiding additional calculations. The results show that the proposed ANN technique is more than 90% faster than the conventional methods for varying load profile.

Keywords: Distribution network reconfiguration, distributed generations, artificial neural networks, variable load, voltage profile.

KONFIGURASI OPTIMUM SISTEM PENGAGIHAN MENGAMBILKIRA PENJANA TERAGIH DAN BEBAN PROFIL BERASASKAN RANGKAIAN KECERDIKAN BUATAN

ABSTRAK

Konfigurasi ulang rangkaian yang optimum adalah kaedah umum yang digunakan dalam sistem pengedaran untuk memastikan kehilangan kuasa minimum selalu dicapai. Ini adalah tugas yang sangat penting untuk mencapai operasi yang menjimatkan. Oleh kerana tuntutan beban yang berbeza-beza, teknik konfigurasi ulang jaringan konvensional harus diulang setiap kali pemuatan sistem berubah untuk mencari konfigurasi baru yang memiliki kehilangan daya minimum. Tugas ini memakan masa dan pendekatan yang tidak berkesan untuk aplikasi masa nyata. Oleh itu, penyelidikan ini mencadangkan teknik Artificial Neural Network (ANN) untuk konfigurasi semula rangkaian pengedaran yang optimum untuk mengatasi masa pemprosesan yang panjang, terutamanya dalam kes variasi beban. Kaedah yang dicadangkan melibatkan; (1) Laksanakan konfigurasi ulang rangkaian yang optimum dengan profil beban berubah dan generasi DG menggunakan teknik meta-heuristik untuk pemodelan ANN (2) Merancang model ANN untuk konfigurasi ulang rangkaian yang optimum (3) Latih model ANN yang dicadangkan pada data yang dihasilkan dengan menggunakan nisbah perpecahan yang berbeza untuk konfigurasi semula rangkaian yang optimum. Teknik meta-heuristik yang diterapkan dalam karya ini adalah pengaturcaraan Evolusi (EP) dan pengoptimuman kumpulan zarah (PSO). Untuk menilai prestasi kaedah ANN yang dicadangkan, simulasi yang dilakukan pada MATLAB dilakukan pada sistem IEEE 16-bus, IEEE 33-bus dan IEEE 69-bus. Pengaturan semula rangkaian yang dicadangkan berdasarkan ANN secara signifikan mengurangkan masa pengiraan untuk mencari penyelesaian yang optimum sambil mengelakkan pengiraan tambahan. Hasil kajian menunjukkan bahawa teknik ANN yang

dicadangkan lebih daripada 90% lebih cepat daripada kaedah konvensional untuk pelbagai profil beban.

Kata kunci: Konfigurasi rangkaian pengedaran, generasi yang diedarkan, rangkaian saraf tiruan, beban ubah, profil voltan.

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LIST OF SYMBOLS AND ABBREVIATIONS

AE	:	Absolute Error
ANN	:	Artificial Neural Network
BPSO	:	Binary Particle Swarm Optimization
CSA	:	Cuckoo Search Algorithm
DABC	:	Discrete Artificial Bee Colony
DEP	:	Discrete Evolutionary Programming
DG	:	Distributed Generation
DNR	:	Distribution Network Reconfiguration
EP	:	Evolutionary Programming
FNSGA	:	Fast Non-dominated Sorting Genetic Algorithm
FWA	:	Firework Algorithm
GA	:	Genetic Algorithm
HSA	:	Harmony Search Algorithm
MSE	:	Mean Square Error
NN	:	Neural Network
PSO	:	Particle Swarm Optimization
RGA	:	Refined Genetic Algorithm
RRA	:	Runner Root Algorithm
SA	:	Simulated Annealing
VSI	:	Voltage Stability Index

CHAPTER 1: INTRODUCTION

1.1 Overview

In electrical power delivery system, a distribution system is the final stage where electrical power is distributed to various types of consumers (residential, commercial, and industrial). One of the most important goals for electric utilities is to deliver a continuously high-quality power supply within cost effective operation. Unfortunately, in a distribution system, due to the impedances of the cables, there is always power loss through the heating effect (I^2R). Thus, large scale distribution systems suffer from high power losses. It was reported that distribution network system accounted for 70% of the total losses in power delivery system, while the remaining 30% is related to transmission and sub-transmission lines (Sulaima et al., 2014). In (Chandramohan, Atturulu, Devi, & Venkatesh, 2010) the estimated operational losses due to power loss in United State was amounted to 5,851,85 USD annually.

A well-accepted technique for minimizing the power losses in distribution systems is through distribution network reconfiguration (DNR). DNR is a process of altering the network topology by changing the status of sectionalizing switches (normally closed) and tie switches (normally open), while maintaining the radial structure of the network without isolating any load. The network structure is reconfigured by closing and opening the switches. This technique will reduce the power losses and improve the overall voltage profile, provided that the optimal reconfiguration could be determined.

Another technique to reduce the power losses in distribution system is by supplying the loads from a close distance, which is done by integrating a local power supply into the distribution network. An example of local power supply is renewable energy sources, such as solar, wind, biomass and mini-hydro. It is reported that renewable energy sources will have the fastest growth in the electricity sector, providing almost 30% of power demand in 2023, up from 24% in 2017 (International Energy Agency, 2018, October). This type of power supply is referred to as Distributed Generations (DG). These small supply units are installed in distribution network at critical points, mainly near load centers. Distribution generation development and application have got more and more attention, due to their impact on distribution network. The integration of DG units with optimal size and location will maximize its potential to reduce the overall power losses. Moreover, integrating DG will lead to improvement in voltage profile, reliability, and energy efficiency.

1.2 Problem statement

The need for electrical power is continually increases with the rapid economic growth around the world. As a result, significant portion of the electrical power is lost in the distribution process. Power losses will also reduce the voltage profile and the lifetime of equipment, especially in the heavily loaded areas. Hence, it is crucial to apply effective power loss reduction techniques such as network reconfiguration. Various methods have been proposed in the past aiming towards power loss reduction in electrical distribution system.

From literature, it can be observed that existing methods on network reconfiguration are limited by certain factors. Firstly, previous research considered static load or uniform load, where all the loads in the system are assumed change at the same percentage. However, in practical scenario the loads in distribution system are not uniform and made up of different load types. Moreover, each type of load changes independently during the day, which makes the loading of distribution system dynamic. Due to these limitations, different load types (residential, commercial, and industrial) with variable loading conditions need to be considered.

Secondly, since the loads in distribution system in practical always vary, the optimal configuration has to be recalculated through iterative optimization process, which is time consuming. To reduce the computational time, ANN (Artificial Neural Networks) was applied for network reconfiguration problem to find the optimal solution as reported in (Kashem, Jasmon, Mohamed, & Moghavvemi, 1998; Kim, Ko, & Jung, 1993) (Fathabadi, 2016; Salazar, Gallego, & Romero, 2006). However, these methods require a large number of trained neural networks to find solutions for large systems. This happen since the number of proposed ANNs is dependent on the number of switches in the system. In addition, pre-calculation step such as clustering before ANN training process is required. Therefore, a new model of ANN for network reconfiguration based on less number of neurons and shorter training time is required.

Thirdly, previous ANN for network reconfiguration did not incorporate DG units in the reconfiguration process. DG units are nowadays essential in distribution systems to minimize power losses, improve voltage profile, provides reliable and uninterrupted power supply. Furthermore, with the application of DG based on renewable energy, sustainable power generation with minimum environmental impact can be achieved. Hence, it is crucial to consider different types of DGs in network reconfiguration in order to imitate more practical conditions.

1.3 Research Objectives

The main aim of this research is to develop optimal Distribution Network Reconfiguration (DNR) using Artificial Neural Network (ANN). The objectives are as following:

1) To implement optimal network reconfiguration with variable load profile and DG generation using EP and PSO.

2) To design an ANN model for network reconfiguration using data generated from EP and PSO Network reconfiguration.

3) To analyze the proposed ANN model with the generated data using different split ratios for optimal network reconfiguration

1.4 Scope of Research

This work proposes optimal network reconfiguration for constant and variable load profiles to reduce the active power loss and improve the overall voltage profile for distribution systems. This work also proposes an ANN approach to find the optimal configurations in distribution systems for dynamic load profile. It also considers incorporating different DG types in the system. The constraints of this study are radial structure of distribution system, bus voltage constraints and DG capacity.

The proposed method in this research implements meta-heuristic optimization methods and artificial intelligence technique, which is Artificial Neural Network (ANN). The meta-heuristic optimizations are Evolutionary programming (EP) and Particle Swarm Optimization (PSO). The proposed method is implemented on 16-bus, 33-bus, and 69-bus test systems. MATLAB software is used in this study on a PC with 3.06 GHz CPU and 3-GB RAM.

1.5 Thesis Outline

The report consists of five chapters. An overview, problem statement, research objectives, scope of research and methodology are presented in first chapter.

Chapter 2 reviews on previous work on network reconfiguration based on heuristic, meta-heuristic, and artificial intelligence approaches for power loss reduction. Approaches incorporating DGs in network reconfiguration problem and service restoration are also presented.

Chapter 3 contains problem formulation, constraints, implementation of meta-heuristic techniques and proposed ANN method.

Chapter 4 consists of simulation results and performance of the proposed method. Discussion is focused on active power loss reduction and voltage profile improvement.

Finally, conclusion of this research is presented in chapter 5, with suggested future works.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter reviews on existing methods for power loss reduction in distribution system. The presented methods include optimal network reconfiguration, optimal network reconfiguration with DG and Artificial Neural Network (ANN) applications in network reconfiguration. The term 'DG' used in this literature is referred to as 'Distributed generations'. Both terms will be used interchangeably in this chapter. At the end of this chapter, research gap on optimal network reconfiguration will be highlighted.

2.2 Conventional Network reconfiguration

Network reconfiguration is a process of changing the switches' state of a network. This switch could be normally open, a situation called tie switches, or normally closed, a situation called sectionalizing switches. The topological structure of a network can be changed by closing the open switches, and vice versa. The optimal network reconfiguration process will decrease power loss and improve the system voltage profile. The network reconfiguration process will transfer the load to comparatively less heavily loaded feeders from heavily loaded feeders, which culminate in reduced power losses. The concept of distribution network reconfiguration (DNR) was firstly proposed by (Merlin, 1975), the proposed method used a branch-and-bond approach to solve DNR problem.

(Nara, Shiose, Kitagawa, & Ishihara, 1992) proposed a network reconfiguration method to minimize distribution power losses using Genetic Algorithm (GA). They confirmed that the method reconfigured the network with minimal power losses. (Kashem, Ganapathy, & Jasmon, 2000) enhanced voltage stability by reconfiguring a network using a new algorithm. First, a tie and two neighboring switches were generated. The combination switch that generates the maximum voltage stability for the system was determined. The search was then extended to the neighbor of the best branch to check for any combination that results in better voltage stability. The proposed method could enhance voltage stability at no additional cost pertaining to tap-changing transformers, switching equipment, and installed capacitors in the distribution system. A 9-bus test system was used to confirm the proposed method's viability in reducing network power loss.

(Das, 2005) used the fuzzy multi objective and heuristic rules approach to reconfigure their network. Their main objectives were to minimize power losses, balance feeder loads, and improve the overall voltage by accounting for specific constraints. These objectives were modeled using fuzzy sets to determine its imprecise nature and its anticipated value for each objective. The Heuristic rules were used to decrease the number of tie switch operation. The simulation results confirmed that the method is able to reduce the search space and minimize computational time, and proved the feasibility of the presented methodology. (Nguyen, Nguyen, Truong, Nguyen, & Phung, 2017) used a runner-root algorithm (RRA) to solve the electric distribution network reconfiguration (DNR) problem. The objectives were to minimize total losses, load balancing, deviate node voltage, and determining switching operations numbers using max-min method to affect a final compromised solution. RRA could escape from the local optimal, since it creates a re-initialization strategy and jumps at large steps. 33-node and 70-node distribution networks were used to prove the effectiveness of RRA in the case of both single-and multi-objectives. The results were compared with other that of published works, and it was confirmed that a runner-root algorithm is effective for solving single-and multi-objective network reconfiguration problems.

2.3 Network Reconfiguration with Presence of Distributed Generation

Network reconfiguration and DG installation have been proven to be effective towards reducing power losses in distribution systems. In order to further reduce power losses in a distribution system, both methods were combined. Distributed generation (DG) is the electric power generation within distribution networks or on the end-user side of the network (Kakran & Chanana, 2018). There are many different technologies for DG either based on non-renewable and renewable resources. The combustion engine, combined cycle, combustion turbine, micro turbine and fuel cell forms are non-renewable, while photovoltaic, wind turbine, hydro, geothermal and biomass are renewable resources (Abdmouleh, Gastli, Ben-Brahim, Haouari, & Al-Emadi, 2017).

Many works have been conducted for optimal reconfiguration method and optimal DGs output. In (Li, Wang, Zhang, & Guo, 2019), Ant Colony Algorithm proposed for network reconfiguration with time-varying DG. The main objective of this work was to minimize power loss and improve voltage profile in distribution networks. The proposed method was evaluated on IEEE 33-bus test system of 11.4kV. the results show proved that lower power loss is obtained and better voltage profile from NR with DG, rather than without DG. Meanwhile, (Rao, Ravindra, Satish, & Narasimham, 2012) presented a method for simultaneous DG sizing and NR problem. This work focused on total power loss reduction and voltage profile improvement. Harmony Search Algorithm (HSA) was utilized to conduct sensitivity analysis to solve the problem. The simulation results were compared with Genetic Algorithm (GA) and Refined Genetic Algorithm (RGA). Different scenarios were studied on IEEE 33-bus and IEEE 69-bus test systems for NR and DG sizing.

(Liu, Sheng, Liu, & Meng, 2017) carried out a simultaneous distribution network reconfiguration and DG allocation. Prior to network reconfiguration, the uncertainties of load fluctuation were accounted for. The objectives of the proposed method are minimizing Expected Energy (Not Supplied), switching operations cost, and line loss cost. Since the problem is multi-objective, weighting factors were applied. This work consists of two periods: first, using Binary Particle Swarm Optimization (BPSO) for creating feasible topologies in distribution network. Second, utilizing HSA for allocating DGs in the network. To deal with the device parameters and uncertainties of load, an interval analysis was applied. They also used the IEEE 33-bus and 69-bus systems and analyzed multiple comparisons and scenarios. The results confirmed that the proposed network reconfiguration algorithm is feasible.

2.4 Methodologies of network reconfiguration and DG sizing techniques

Different optimization technique was used to solve network reconfiguration with DG. Figure 2.1 summarize these techniques.

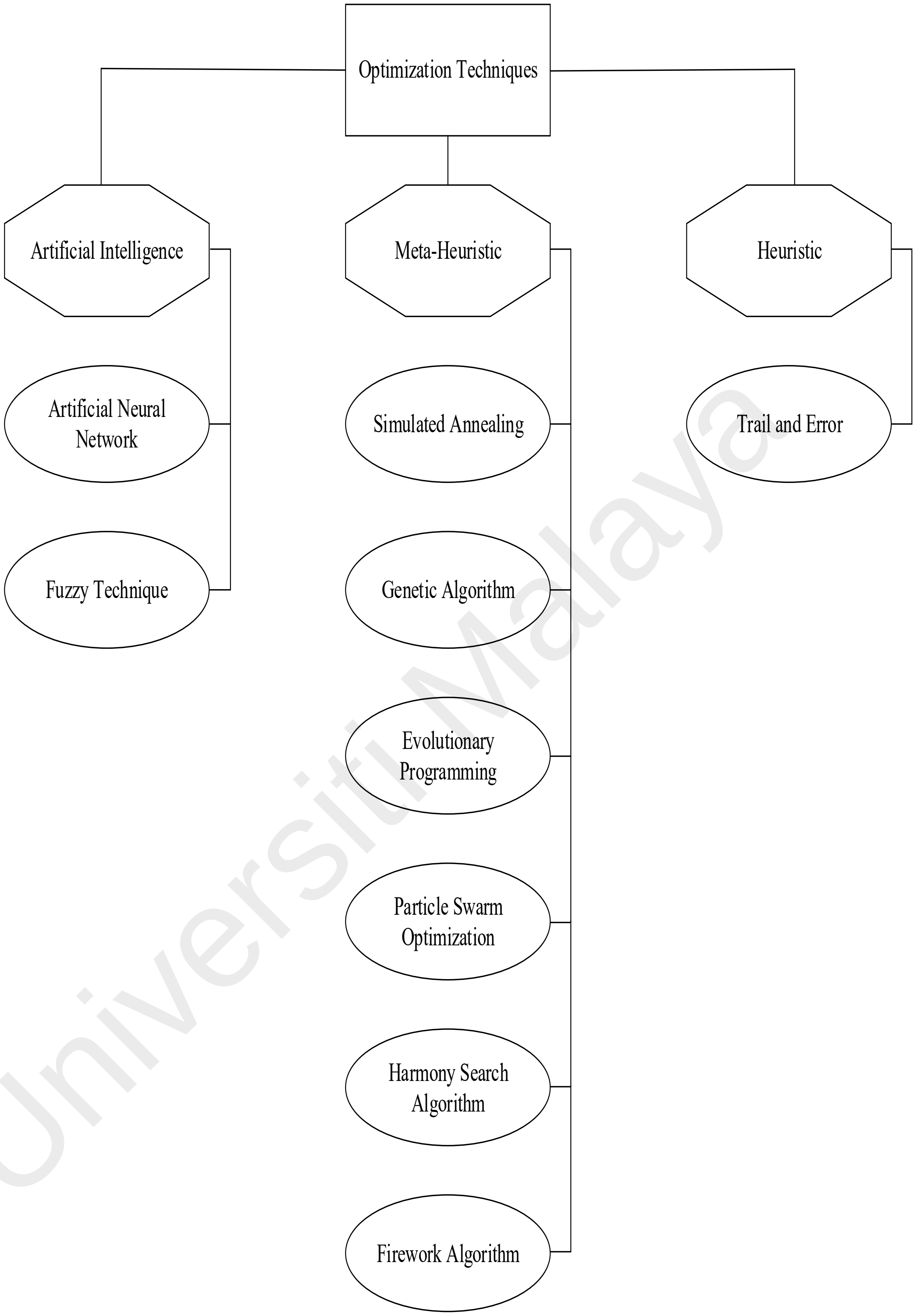


Figure 2.1: Optimization Methodologies of distribution network reconfiguration embedded with DG

2.4.1 Heuristic technique

A heuristic technique is an optimization process that is used to find an approximate for the optimal solution to a problem, the optimal solution could be the maximum/minimum values. For it to be effective, the correct function for the problem need to be formulated. In (Kashem, Jasmon, & Ganapathy, 2000), the reconfiguration of the feeder is done using interchange switch strategy. Where minimal-tree search technique is used to find options for losses reduction. This technique determines the suitable switching option that will result in minimal power loss. From the results, it can be observed that proposed method attained near optimal solution of the distribution network with minimal computational burden. In (McDermott, Drezga, & Broadwater, 1999), unique strategy is proposed where all network switches are opened, then load flow was applied to set minimum limit for losses. The network is reformed by closing switches one-by-one until minimum losses is achieved. The results show that proposed method is more accurate, however, it is more computationally involved. (Gomes et al., 2005) proposed an opposite strategy where all network switches are closed, which forms a meshed distribution network. The switches opening criteria to eliminate the loops was based on the increase minimum power loss. The losses were calculated by load flow program. This method was able to manage the large number of configurations to be test without combinatorial explosion.

2.4.2 Meta-heuristic technique

The meta-heuristic method is does not require predefined rules and is considered an iterative generation process (called particles) that search for optimal solutions using learning strategies and intelligently combining different concepts. This strategy has the capability to look for the exact/near exact optimal solutions. However, it takes longer computational time compared to other approaches. There are various techniques under this category, which will be discussed in the following sections.

2.4.2.1 Simulated Annealing

Simulated Annealing (SA) is a probabilistic search method that find approximation for large combinatorial optimization problems. It incorporates a probability function which makes it escape the local minima when accepting/rejecting new solutions. At each iteration of the simulated annealing algorithm, a new point is randomly generated, then incrementally changing a single element in the solution to find a better one. The algorithm consists of initialization, cooling schedule, perturbation, and acceptance probability to perform the search (Koziel, Rojas, & Moskwa, 2018).

In (Zhanga, Zhanga, Xina, Zhangb, & Fana, 2012), simulated annealing optimization is used for network reconfiguration process. The work analyzed the reconfiguration with a small capacity of gas type DG (oilfield). The objective of the proposed work was to minimize the power loss using the following equation:

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

where P_{loss} is the power loss, Nb is total the number of branches, r_i is resistance of branch i , P_i is the active power of branch i, Q_i is the reactive power of branch i, V_i is the voltage of the head node of branch i.

The output generation of the associated gas DG can be stored for use later, which makes it relatively stable compared to that of solar/wind DG. The combination of simulated annealing and Immune Algorithm was able to speed the search for optimal solution process and avoid the unfeasible solution during the evolutionary process. The combination of the two algorithms resulted in enhancement of population characteristics. The algorithm was tested on IEEE 33 bus, with four DGs were installed on buses 4, 8, 25, and 30. The results show that proposed method presented better solution quality in the reconfiguration process.

2.4.2.2 Genetic algorithm

Genetic Algorithm (GA) is a popular optimization technique based on a model of biological evolution and adaptation in nature. GA successive generation of population during the search process leads the process towards finding optimal solution. GA. One of the features of GA is easy to model, it is usually implemented in optimization problems and machine learning (Mirjalili, 2019). In GA, the initial population is generated randomly, then it is evolved toward better solution through mutation or crossover processes. The algorithm terminated either when population converges, or maximum number of generations has been reached. However, GA can only obtain the optimal answer if the population has a adequately large quantity of data (Ganesan & Venkatesh, 2006).

An improved GA is proposed in (Chandramohan et al., 2010), the technique called Non dominated Sorting - Genetic Algorithm (NSGA) that was implemented for network reconfiguration. The main objective of this work was to minimize the operating cost of distribution system. Maximizing the system's reliability and power quality improvement are also suggest in this work. The operating cost equation suggested to minimize the active and reactive power loss is as following:

$$Operating\ Cost = K1 \times PL \times K2 \times QSS \tag{2.2}$$

where $K1$ is the real power coefficient in S/kW, PL is the real power losses for system transmission, $K2$ is the reactive power coefficient in $S/kVAR$, and QSS is the drawn reactive power from the transmission system connected to distribution system. In (Souifi, Kahouli, & Abdallah, 2019), a multi-objective distribution network reconfiguration is implemented using GA. Two objectives were considered, minimizing the investment cost and reducing the active power loss. The method is test on IEEE 10-bus system for both objectives individually. The results show the efficiency of proposed method and capability of obtaining the solutions in short time.

A new methodology of codification for the conventional GA was presented in (Aspari & Sreenivasulu, 2013) to reconfigure a radial distribution system of 33 buses in the presence of DGs. The main objective was to minimize the power loss and improve the system's voltage profile, while maintain system constraints. Such as, radiality, voltage limits, feeder capacity, and continuous supply of load. The main contribution of this method is using new types of crossover and mutation operators. Which results in optimal solution with reasonable computational time. This technique makes the application of large distribution system possible, while reducing the search space, since the management ability of the algorithm to deal with multi-constraints with minimal computational burden. Furthermore, GA with variable number of population is proposed in (M. Abdelaziz, 2017) to reduce the number of computational burden.

In (Peñaloza, Yumbla, López, & Padilha-Feltrin, 2019), GA was used with MINLP for distribution network reconfiguration and distributed generation. The main objective is minimizing the power loss. The results show that proposed method has better convergence with good quality solution compared to others. Furthermore, in (Jakus, Čađenović, Vasilj, & Sarajčev, 2020), optimal distribution network reconfiguration is done using hybrid heuristic-genetic algorithm. A combination of heuristic approach and AG is proposed in this work. The proposed method allows its application to a real size distribution networks with high degree of complexity. Two objective function are considered: minimizing total power loss and minimizing of loading index. The proposed method is applied to various standard distribution network test cases. The simulation results show the accuracy and computational effectiveness of the proposed method.

2.4.2.3 Evolutionary programming

Evolutionary Programming (EP) is a stochastic optimization method introduced by Lawrence J. Fogel in 1960 (Fogel, 1998). This technique focuses on the connection between old population and new population. Therefore, mutation process is applied directly on the population. The process of this optimization starts with random initial population (parents). Then, new population (offspring) is generated by applying the objective function on each parent using the mutation process. Then, the combination of parents and offspring is sorted based on their fitness value and the next generation is selected from the best population with better fitness value (Hsiao, 2004).

In (Chakravorty, 2012) a new approach of EP technique is presented to minimize the power loss during reconfiguration process in the system. An improvement on the performance of EP was proposed using a heuristic formulation (fuzzy controlled EP technique). This technique regulates the mutation rate during the optimization process, as a result, the reconfiguration switching problem complexity is reduced to minimize the switching operations. In (Aman, Jasmon, Naidu, Bakar, & Mokhlis, 2013) a discrete evolutionary programming is used to solve NR problem. The gaussian mutation is replaced with simple discrete process, where the offspring is generated by replacing one side of tie switch with one sectionalizing switch. As a result, 'n' number of solutions will be generated for each particle in the population. Thus, the solution is obtained in short span of time.

(Shanmugapriyan, Karuppiah, Muthubalaji, & Tamilselvi, 2018) proposed a method to reduce the power loss by integrating DG's in distribution system. This work considered different types of DG's such as, active power DG's, reactive power DG's and both active and reactive power DG's. The proposed method is consisting of two-stages, first, heuristic method was used to select the optimal location for DG's. The second stage used

Differential Evolutionary algorithm to determine the optimal DG sizing. The result show that proposed method attained better solution compared to PSO.

2.4.2.4 Particle swarm optimization

Particle Swarm Optimization (PSO) is meta-heuristic method used by many researchers for optimization purposes. It was originally proposed by Dr. Eberhart and Dr. Kennedy in 1995 (Eberhart & Kennedy, 1995). PSO was inspired by the food searching behavior of birds or fish. In the initial stage of PSO, particles are generated having random positions and velocities. In the following stage, the fitness value of each particle is evaluated based on the objective function. Then, these particles update their position and velocity based on their searching experience and other relative particles. The process repeated until the particles converge of maximum number of interactions is reached (Bansal, 2019). Researchers who utilized PSO in their works include the following.

In (Dahal & Salehfar, 2016), proposed an optimal placements and sizing of DG (PV, Fuel cells) units utilizing PSO on multi-phased unbalanced distribution network. The test system used was IEEE 123 node system, as well as a combination of all types of DGs we used for real experiment. From the comparison with the Repeated Load Flow method (RLF) results, it is observed that proposed approach is more efficient and quicker. Moreover, optimal allocation of DGs will reduce the total losses and improve the voltage profile. In (Firdaus, Penangsang, & Soeprijanto, 2018), BPSO algorithm was utilized along with load voltage stability index. The main objective was to minimize the power loss and improve the voltage stability index. The method is implemented on IEEE 33-bus system evaluate the effectiveness of proposed method. The results show that better load balance and voltage profile is obtained compared to PSO and Tabu Search.

Sequential integration of NR and DG with variable load profile is proposed by (Saleh, Elshahed, & Elsayed, 2018). Binary particle Swarm Optimization is used to obtain optimal solution. Where size and location of DG is determined by PSO. The results show that the integration of NR and DGs represent significant reduction in power loss and voltage deviation compared to separately integrating NR or DGs to distribution network. In (Pegado, Ñaupari, Molina, & Castillo, 2019), Improved selective binary particle swarm optimization (IS-BPSO) is used to solve reconfiguration of distribution networks problem. The main objective was to reduce the power loss in distribution system. The method is implemented on 33-bus and 94-nodes systems. The results show that proposed method is efficient and guarantees the achievement of global optimization.

2.4.2.5 Harmony search algorithm

Harmony Search Algorithm (HSA) is a music-based Meta-heuristic population search algorithm. It was inspired by the observation that music is the manifestation of the perfect state of harmony. In recent years, HSA has received significant attention. The merits of HAS have led to its application to power system design and multi-objective optimization problems. The operating concept of HAS consists of three elements: memory consideration, pitch adjustment and random selection. The harmony memory value is extracted during memory operation. Then, a modified value is chosen from harmony memory values using pitch adjustment. Finally, a random selection from the whole value range is during random selection stage. These operations forms stochastic derivative for searching process which is different from traditional basic derivative operations (Lee & Geem, 2004; Mahdavi, Fesanghary, & Damangir, 2007).

In (A. Y. Abdelaziz, Osama, Elkhodary, & El-Saadany, 2012), Network reconfiguration process was compared to with and without DG for two test systems 32 bus and 69 bus. HSA along with ACO optimization algorithms were utilized in the proposed work. The results show that both algorithms obtained optimal solutions for distribution network reconfiguration with minimal power loss. However, the computation time for HSA was less than ACO. In (Rao et al., 2012), HSA was utilized with sensitivity analysis to find optimal DG location and sizing simultaneously with network reconfiguration process. The proposed method was applied on IEEE 33-bus and IEEE 69-bus test systems with different scenarios for different load levels (light, normal, heavy). The results show that the number of DGs is inversely proportional with power loss reduction value. The performance of HSA was compared to GA, and the analysis shows that HSA was better than GA. Similar work was done in (Krishna, Kumar, Venkatesh, & Gokulakrishnan, 2018), one test system was used 33 bus system and HSA optimization algorithm were used. It can be observed form the results that HSA was better than other methods.

(Roosta, Eskandari, & Khooban, 2019) proposed an integrated approach for power loss minimization for unbalanced distribution network in the presence of DGs. HAS was used to reduce the total power loss, enhance the voltage profile, and increase voltage stability index. The results show that rearrangement of redistribution network gives better performance with optimal installation of DG units.

2.4.2.6 Firework algorithm

The Firework Algorithm (FWA) is a meta-heuristic technique based on the stochastic search technique. FWA can solve optimization problems search for possible areas for use as a solution space. The algorithm is inspired by the phenomenon of exploding fireworks and sparks generated within a parameter the fireworks. Due to the ability of FWA to mimic the explosive nature of fireworks with the incorporation of its features during the search process, FWA is considered as novel algorithm. This algorithm is able to allocate possible resources evenly between firework sparks when searching for solutions (Nguyen & Truong, 2015).

In (Imran, Kowsalya, & Kothari, 2014), a novel integration technique for network reconfiguration and DG placements in distribution system is proposed in this work. The objective is to minimize the power loss and enhance the voltage profile. The NR and DG placement is done simultaneously using FWA. The radiality is maintained during the process through power flow method that generates proper parent node-child node. The allocation of DG install location is done using Voltage Stability Index (VSI). The proposed work considered different scenarios during network reconfiguration process and DG placement to evaluate the performance of the proposed method. The result show simultaneous NR and DG placement gives the most effective scenario for power loss minimization and voltage profile improvement. The results were compared with other techniques such as I-ISA and GA, and it can be observed from the results the FWA performance is better than other methods.

(Badran, Mokhlis, Mekhilef, & Dahalan, 2018) proposed simultaneous integration of NR and DG sizing. The main objective if the work is to minimize the power loss while improving the voltage profile of the bus and maximizing DG capacity. FA was utilized for simultaneous integration and the results showed that proposed method obtains better quality solution compared to other methods. In (Naguib, Omran, & Talaat, 2017) the power loss is reduced by integrating NR and DG in distribution network. FA was used for simultaneous optimization of NR and DG. In this work, fixed and variable type of DG are considered. Based on hourly probability, DG size and location are determined. It can be observed form results that proposed method improved the quality of solution.

2.4.3 Artificial intelligent technique

Artificial Intelligent (Al) refers to the simulation of human intelligence in machines. The goals for artificial intelligence include learning, reasoning, and perception. Artificial intelligence techniques can be utilized in network reconfiguration problem in distribution systems such as: fuzzy techniques and Artificial Neural Network techniques (Qiu, Lv, & Chen, 2011).

2.4.3.1 Fuzzy technique

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

(Niknam, Fard, & Seifi, 2012; Sedighizadeh, Esmaili, & Esmaeili, 2014) proposed a multi-objective function for NR and DG sizing using fuzzy logic technique. maximization of VSI and power loss reduction, total cost reduction, and emissions reduction are the objectives discussed in this work. Each objective has different scale and data size; thus, fuzzy technique is utilized to unify the scales and control the data size. Where, fuzzy works as a decision maker to attain the optimal answer for the multi-objective NR and DG sizing problem.

2.4.3.2 Artificial neural network

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

(Kim et al., 1993) reconfigured the feeder strategies using ANN. The proposed method was used to reduce power losses according to the variation of load patterns. To minimize the size of the training set, ANN was designed for two groups. The first estimates the best load level based on the load data of each zone, while the second determine the suitable topology of the system based on the input load level. The proposed method proved the ability of the high-speed control strategy decision and the robustness from the error, which could provide the best solution from imprecise data. The proposed methods also provide the best solution for constant and the sudden load variations.

A similar approach was proposed by (Kashem et al., 1998) to minimize the power loss according to load variations. ANN was designed for a training set, this set is generated by varying P-Q load, then an optimal topology of the system based on the input load pattern using NR. The proposed method presented high accuracy for predicting the optimal system topology to minimize the power loss. However, a large number of training networks would be required for large distribution systems, which is time consuming. (Salazar et al., 2006) proposed an algorithm based on ANN theory to determine the best training set for a single neural network with generalization ability clustering techniques. The results show that proposed method was capable to determine the optimal configuration in short span of time. The method proved the feasibility of using the NN to solve the reconfiguration problem and its viability for large-scale systems in a real-time environment. In (Fathabadi, 2016) an ANN based approach proposed to solve DNR problem, where a clustering technique was applied on the load data using Dynamic Fuzzy C-Means (DFCM), to reduce the number of inputs of the ANN size. The simulation results show that proposed technique obtain optimal configuration in short time and less number of neurons.

2.5 Overall summary of previous works on network reconfiguration

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

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

Algorithm	Main Benefits	Weakness	Functions	Reference
Trial and Error	Accuracy, probability to evade e local minima and able to attain near optimal solution	Long computational time, with probity of being trapped in local minima	Network reconfiguration of distribution systems	(Gomes et al., 2005; McDermott et al., 1999)
Simulated Annealing (SA)	Robust , surely attain optimal local solution, able to avoid local minima.	frequent requirement of operating schedule to optimize the system parameters, long computation time	Utilized in multi-objective problems, used to solve discrete stochastic optimization problems.	((Koziel et al., 2018); Eldurssi & O'Connell, 2015; Zhanga et al., 2012)
Genetic Algorithm (GA)	Simple, easy, fast searching in large solution space without falling in local minima, ability to attain a near optimal and global solution.	Long computational time.	Solve combinatorial optimization problems and network reconfiguration problem in distribution systems.	(Eldurssi & O'Connell, 2014), (M. Abdelaziz, 2017), ((Peñaloza et al., 2019)

Table 2.1: Continued

Algorithm	Main Benefits	Weakness	Functions	Reference
Particle Swarm Optimization (PSO)	Simple, accurate, easy to formulate, useful for speeding up the decision-making, ability to avoid local optimal solution. Attain good solutions for complex problems.	Unable to solve discrete optimization problems.	Solve non-linear, combinatorial, and continuous functions optimization problems	(Firdaus et al., 2018), (Saleh et al., 2018),(Napis, Khatib, Hassan, & Sulaima, 2018), (Napis et al., 2018)
Evolutionary Algorithm (EA)	Effective, present satisfactory results and computational efficiency	Probability of being trapped into local optima and fewer literature examples	Solve network reconfiguration problem in distribution systems	(Aman et al., 2013; Shanmugapriyan et al., 2018)
Harmony Search Algorithm (HSA))	Relatively simple, fast Computational time.	Gets into trouble in performing local search for numerical applications	Utilized to solve wide variety of optimization problem and combinatorial optimization problems.	(Rao et al., 2012), (Roosta et al., 2019), (Krishna et al., 2018)

Table 2.1: Continued

Algorithm	Main Benefits	Weakness	Functions	Reference
Firework Algorithm (FWA)	Fast, effective	Long computational Time	Used to solve engineering problems like clustering	(Imran. Kowsalya. & Kothari, 2014; Nguyen & Truong. 2015), (Badran et al., 2018)
Fuzzy Technique	simple, utilized in multi-objective problems. Able to find best compromised solution from the set of the Pareto optimal solutions effectively	Unsuitable for problems, since it requires large memory and take large computation time.	Successful to solve complex problems and Suitable for uncertainties objectives or constraints and for multi-criterion decision making	(Eldurssi & O'Connell. 2015; Niknam et al. 2012; Sedighizadeh et al., 2014)
Artificial Neural Network Technique (ANN)	Processing time is very fast	Need training burden	This approach suitable for online applications and complex function	(Kim et al., 1993), (Kashem et al., 1998), (Fathabadi, 2016)

2.6 Summary

From the reviewed, it can be observed that majority of researchers used similar objective function (minimize power losses) to solve the network reconfiguration problem for distribution system. The power loss incurred in distribution system can be minimized via the optimal network reconfiguration and Distributed Generation installation. Different methods have been applied to solve network reconfiguration and only ANN based method considered the dynamic load profile. Nevertheless, the network reconfiguration ANN methods require per-calculation techniques or large number of neural networks. While actual load in distribution power system is dynamically changeable with respect to time. The load varies seasonally, daily, and hourly by time and type of the day (weekend or weekday). The distribution system will not operate at minimum power loss with the proposed method without considering load profiles and the network configuration. DGs have been installed in distribution systems around the world in order to sufficiently fulfil the electricity demand and improve power system's performance. However, few works focused on utilizing artificial neural network into distribution network reconfiguration problem.

Most previous works on network reconfiguration assumed that the DG generation power is constant. Few works included the different DG types and load profile in the network reconfiguration in order to produce more practical result. Furthermore, there are no works on optimal network reconfiguration using ANN that took into account the different DG integration and different DG types.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the proposed optimal network reconfiguration for active power loss reduction in distribution system. Evolutionary programming (EP) and Particle swarm optimization (PSO) are meta-heuristic approaches used in this study. Both approaches are used to generate training data for proposed Artificial Neural Network (ANN) model for network reconfiguration.

3.2 Problem Formulation

The main objective for reconfiguration of distribution systems is to find a topology which results in minimum active power loss by transferring the heavily load feeders to less heavily loaded feeders. The integration of distributed generation (DG) units in the system results in further reduction in power loss. In this work the main objective is to reduce the power loss by achieving the optimal configuration. Therefore, the main objective of this study is

$$\mathrm{F} = \min(P_{loss}^{R}) \tag{3.1}$$

Where P_{loss}^{R} represents the net power loss which is taken as the ratio of system's total active power loss after the reconfiguration process and before the reconfiguration. This is represented by the following equation:

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

Where P_{loss}^{rec} is the power loss after reconfiguration and P_{loss}^{0} is the power loss before reconfiguration.

The power loss equation is given by:

$$P_{T,loss} = min\left\{\sum_{i=1}^{m} R_i\left(\frac{P_i^2 + Q_i^2}{V_i^2}\right)\right\} \tag{3.3}$$

Where,

$P_{T,loss}$ = is the total active power loss in the network.

m = is the number of closed branches.

P_i = is the active power.

Q_i = is the reactive power.

V_i = is the voltage at the receiving terminal of branch i

R_i = is the resistance of branch i.

The objective function is subject to the following constraints. These constraints should be satisfied during the process of determining optimal network reconfiguration:

i. DG capacity

$$0 \leq P_{DGi} \leq P_{DGi}^{max} \tag{3.4}$$

Where,

Where P_{DGi} is the DG output at branch i; P_{DGi}^{max} is the upper bound of DG output.

ii. Power Balance

$$\sum_{i=1}^{N} P_{DG,i} + P_{Sub} = \sum_{k=1}^{br} P_{load} + P_{T,loss} \quad (3.5)$$

Where,

N = is the total number of DGs.

P_{Sub} = is the power supplied by the substation.

P_{load} = is the active power of the load.

This equation implies that the power of the load and the total power loss is equal to the total power generated by DG units and substation.

iii. DG power injection

$$\sum_{i=1}^{N} P_{DG,i} < \sum_{k=1}^{br} P_{load} + P_{T,loss} \quad (3.6)$$

This equation implies that the total power injected by the DGs is less than the sum of total load power and total power loss.

iv. Bus voltage

$$V_{min} \leq V_i \leq V_{max} \quad (3.7)$$

Where $V_{i,min}$ and $V_{i,max}$ represent the upper and lower bound of permitted voltage. The allowed limit within 10% (0.9 p.u to 1.1 p.u).

v. Radial Structure of the network

The radial structure of distribution network must be maintained during reconfiguration process and all loads must be served. MATLAB $graphisspantree$ function is used.

$$TF = graphisspantree(C) \tag{3.8}$$

$$TF = \begin{cases} 1 & radial \\ 0 & not\_radial \end{cases} \tag{3.9}$$

Where,

$graphisspantree$ = returns True (1) if C is a spanning tree and False (0) otherwise, A spanning tree must touch all the nodes and must be acyclic.

C = the distribution system.

3.3 Network Reconfiguration with variable load profile and DG for Power Loss Minimization

The main objective in this section is the minimization of active power loss in the case of variable load model in the presence of DGs. To model the proposed Artificial Neural Network (ANN) for network reconfiguration, a set of data of optimal configuration for different loading conditions are required. This task can be achieved by using any optimization techniques. In this work, Evolutionary Programming (EP) and Particle Swarm Optimization (PSO) are chosen due to their simplicity, reasonable convergence time and proven to work well for network reconfiguration application

3.3.1 Overview of Artificial Neural Network (ANN)

Neural networks (NN) are set of algorithms. They are inspired by the biological neural network system in human brain. They consist of input layer, number of hidden layers and output layer. NN is based on a collection of densely connected nodes called neurons, usually in a feed forward way (Yao, 1999). The input layer propagates the received information to output layers through the hidden layers, where each node (neuron) has an associated weight w_{ij}. A group of data consists of input and output can be represent by equation (3.10).

$$Training\ Set = \{(I_1, O_1), (I_2, O_2), \dots, (I_p, O_p)\} \tag{3.10}$$

Where (I_p, O_p) represents the input and the desired output for a single training pattern.

The training process is a matter of adjusting the weights w_{ij} between neurons until a good mapping function f is achieved. The relation between input layer and hidden layer is shown in equation (3.11).

$$Net_{H_n} = \sum_{j}^{h} \sum_{i}^{p} x_i w_{ij} \tag{3.11}$$

Where,

Net_{H_n} = is the total output of the hidden layer H_n.

h = is the number of neurons in the hidden layer H_n.

p = is the number of input patterns to input layer x.

w_{ij} = is the weight associated with each connection between inputs and hidden layers.

Then, equation (3.12) is the output of hidden layer H_n represented by the activation function as follows:

$$Out_{H_n} = f(Net_H) \tag{3.12}$$

Where f is the activation function of the hidden layer.

Generally, the Sigmoid (logsig) activation function is selected for the non-linear mapping because it has smooth gradient and its output values is bonded between 0 and 1 making clear distinctions on prediction. Equation (3.13) shows the relation between input and output of hidden layer H_n.

$$Out_{H_n} = \frac{1}{1 + e^{-(Net_H + b_H)}} \tag{3.13}$$

Where b_H is the bias of the hidden layer.

The input to the next layer is the output of hidden layer H_n. If there is more than one hidden layer, the process is repeated as in Equations (3.11-3.13). The training process continue until the mean square error (MSE) is minimized, which is the squared sum of the difference between the desired output and NN output for all patterns (Kim et al., 1993).

$$E(w) = \frac{1}{n}\sum_{i=1}^{p}(O_t - O_{NN})^2 \tag{3.14}$$

Where,

O_t = is the desired output.

O_{NN} = is NN output for single training pattern.

n = is the total number of outputs.

During the learning process, the training algorithm updates the weights according to direction function $r(t)$ (Salazar et al., 2006). In this paper Levenberg-Marquardt which is a second-order optimization algorithm is applied. It is considered as the fastest backpropagation algorithm for medium size NN. The algorithm can be represented by the following equations.

$$\Delta w_t = \epsilon \, r(t) \tag{3.15}$$

$$r(t) = [J^T J + \mu I]^{-1} J^T e \tag{3.16}$$

$$w_{t+1} = w_t + \Delta w_t \tag{3.17}$$

Where,

J = is the Jacobian matrix containing the first derivatives of NN errors with respect to weights and biases.

e = is a vector containing network errors.

ϵ = is the learning rate (0.1).

3.3.2 Evolutionary Programming (EP)

The EP steps for network reconfiguration for variable load profile distribution system with DGs are as follows:

Step 1: Set the input data for EP such as bus data, line data, population size, DG output, maximum iteration, and minimum error.

Step 2: Generate random initial populations, which are the tie switches in distribution system to be opened represented by S. This population should fulfill the constraints (i)-(v).

$$S_{jn} = \begin{bmatrix} S_{11}, & S_{12}, & \cdots & S_{1n} \\ S_{21}, & S_{22}, & \cdots & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{m1}, & S_{m2}, & \cdots & S_{mn} \end{bmatrix} \quad (3.18)$$

Where,

j = $1,2,3, \dots, m$ which represents the population index.

m = represents population size.

n = represents the number of switches in the network.

Step 3: Start the calculation of fitness function by using the objective function (3.3). Newton–Raphson is used to calculate the objective function for each population and get the active power loss values through the entire network.

Step 4: The initial population in step 2 undergoes mutation process to produce offspring, in which the first switch S_{j1} in each population from j = 1 to m, is mutated using Gaussian mutation operator as in equation (3.11) to produce offspring. Then the process is repeated for switch S_{j2} and so on until switch S_{jn}.

$$S_{m+j,n} = S_{m,n} + N(0, \beta(S_{n\,max} - S_{n\,min})\left(\frac{f_j}{f_{max}}\right)) \quad (3.19)$$

Where,

$S_{m+j,n}$ = is mutated population (offspring).

$S_{m,n}$ = is the old population (Parents).

N = is random Gaussian number.

β = is the search step.

$S_{n\,max}$ = is the maximum random number for tie switch.

$S_{n\,min}$ = is the minimum random number for tie switch.

f_j = is the fitness value for random switch population j.

f_{max} = is the maximum fitness value in switch group.

Step 5: The parents and offspring are combined in new population and sorted in an ascending order based on the fitness value (power loss). Then, the first half of the new population is selected to become the new population for the next generations.

Step 6: Finally, the process is repeated from step 4 – 6 until the difference between the maximum fitness value and minimum fitness value is less than minimum error (ME) using equation (3.20) or maximum iteration reached.

$$f_{max} - f_{min} \leq \text{ME} \tag{3.20}$$

Step 7: After finishing, the program stops. The best solution which represents the new configuration of the network, the power losses for this configuration and the voltage at each bus is presented out.

The complete flow chart of the proposed Network Reconfiguration based EP is shown in Figure 3.1.

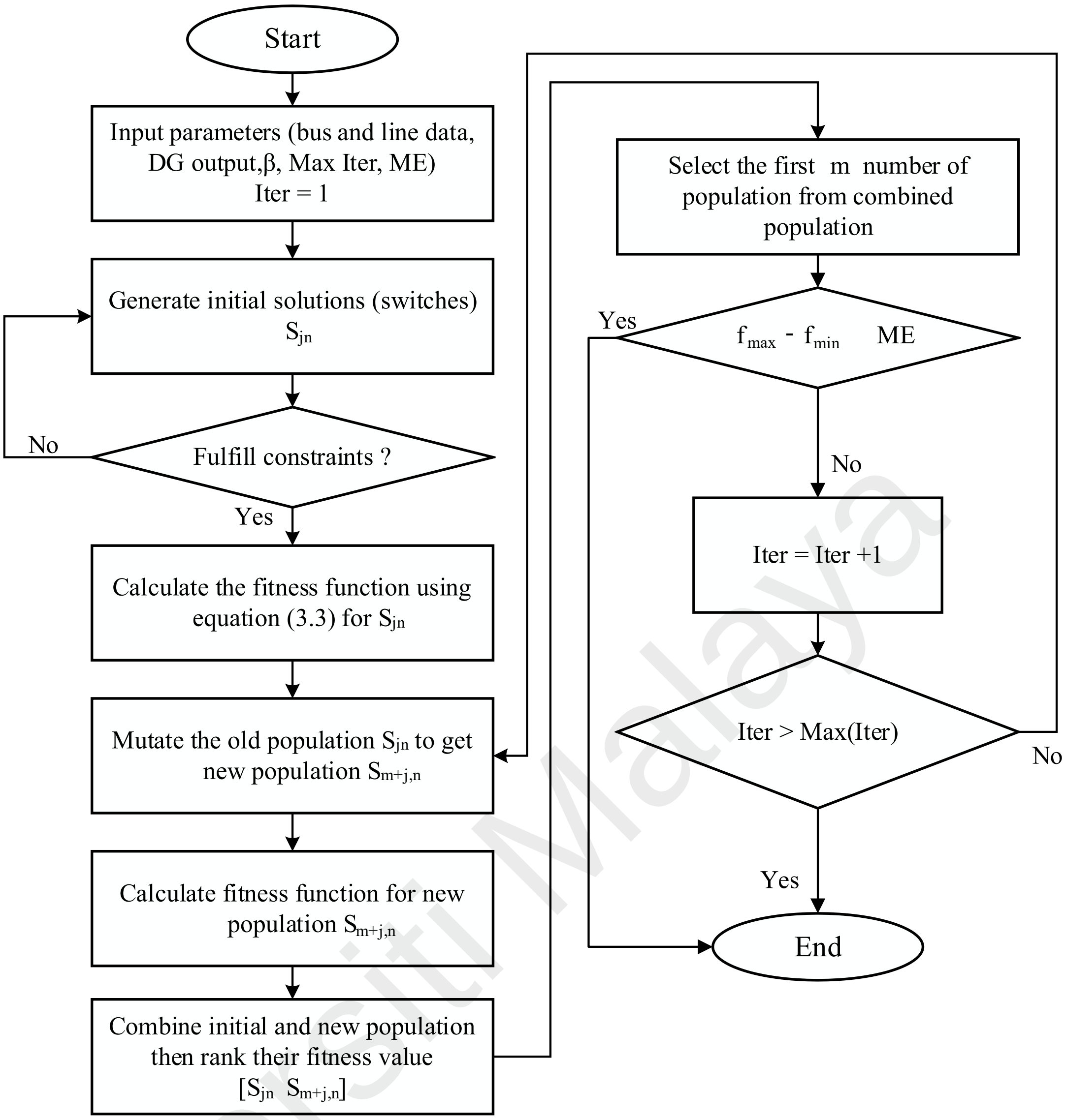


Figure 3.1: Network Reconfiguration based EP flow Chart

3.3.3 Particle Swarm Optimization (PSO)

The PSO steps for network reconfiguration for variable load profile distribution system with DGs are as follows:

Step1: Set the input data for PSO such as bus data, line data, population size, DG output, maximum iteration and PSO parameters, such as weight of inertia, cognitive and social coefficient.

Step 2: Generate random particles with random positions S_i and velocities v_i. Each group of particles represent a combination of tie switches that fulfill the system constraints.

Step 3: Evaluate each particle by the objective function in equation (3.3) to determine its fitness value.

Step 4: Update each particles' position and velocity based on its own experience in the search space P_{best} and the experience of other particles G_{best}. The updating process of positions and velocities is done using (Kennedy, 2006):

$$S_i^{t+1} = S_i^t + v_i^{t+1} \tag{3.21}$$

$$v_i^{t+1} = w(t)v_i^t + c_1 r_1 \times (P_{best} - S_i^t) + c_2 r_2 \times (G_{best} - S_i^t) \tag{3.22}$$

$$w(t) = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{3.23}$$

Where,

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

v_i^t and v_i^{t+1} = current velocity of the particle i at iteration t and $t+1$, respectively.

c_1 and c_2 = cognitive and social coefficient.

r_1 and r_2 = random values generated every velocity update (0 ~ 1)

w_{max} and w_{min} = maximum and minimum inertia coefficient.

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

Step 5: Finally, the process is repeated until the optimal or sub-optimal answer is found.

Step 6: After finishing, the program stops. The best solution which represents the new configuration of the network, the power losses for this configuration and the voltage at each bus is presented out.

The complete flow chart of the proposed Network Reconfiguration based PSO is shown in Figure 3.2.

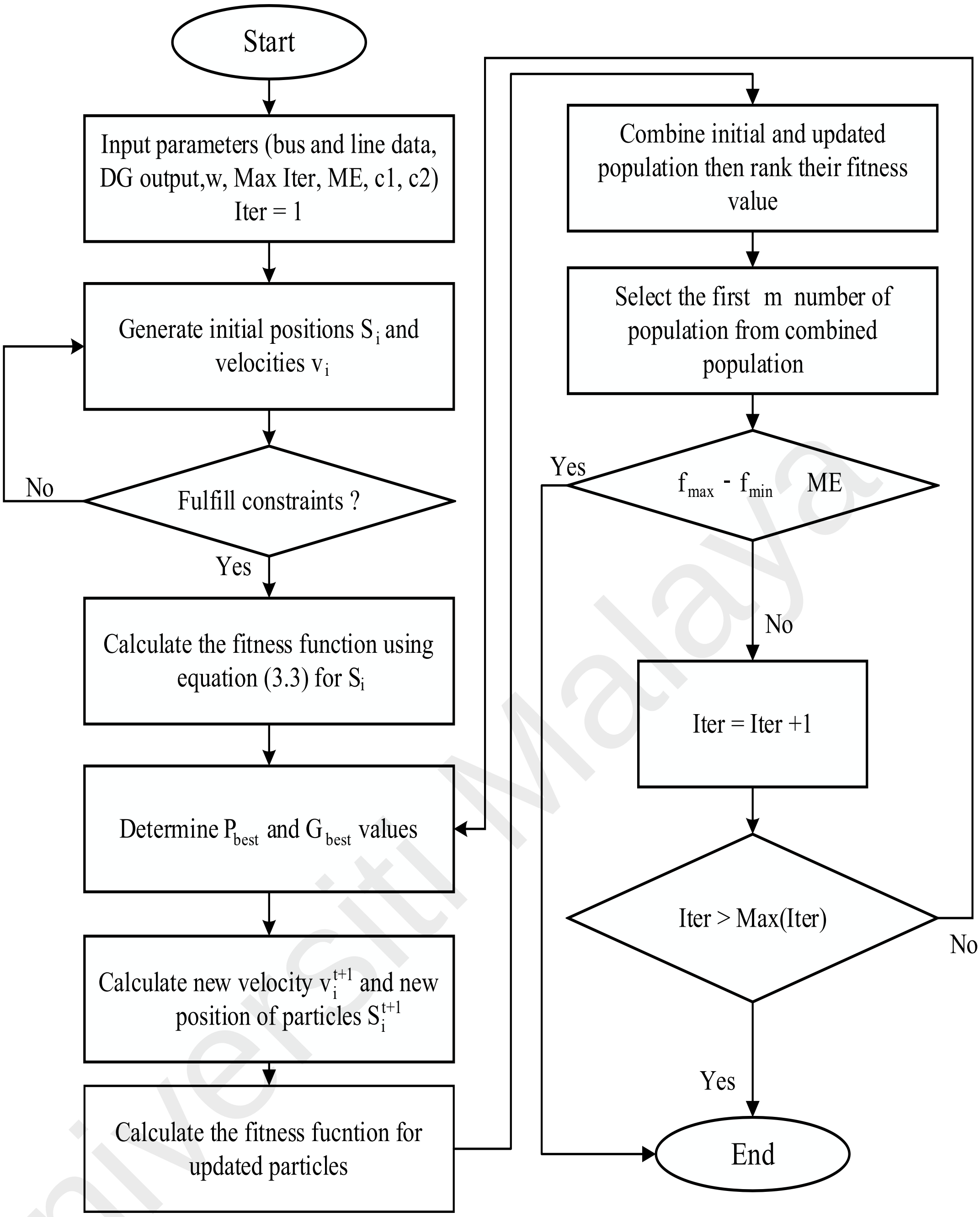
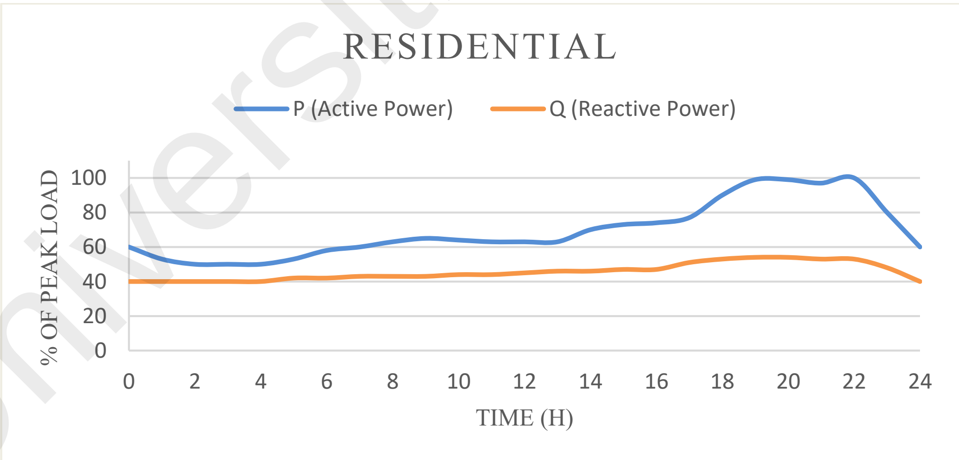


Figure 3.2: Network Reconfiguration based PSO flow Chart

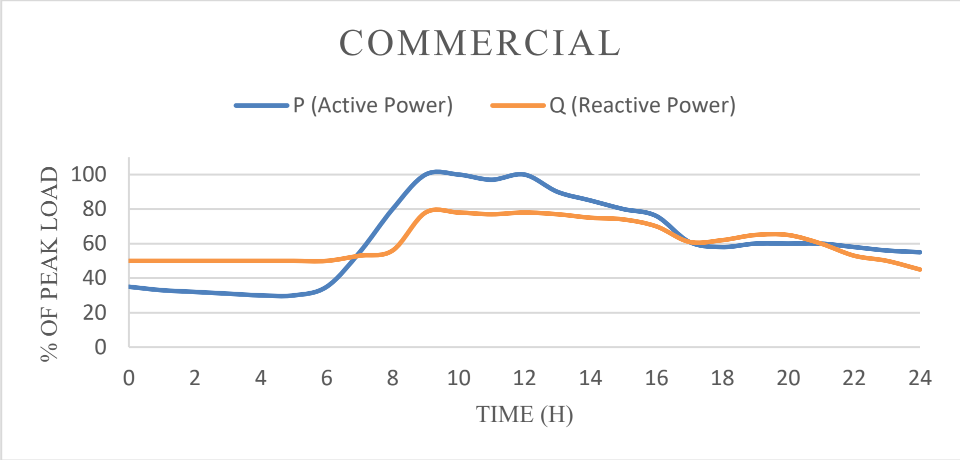
3.4 Proposed Optimal Network Reconfiguration based Artificial Neural Network

3.4.1 Load Groups

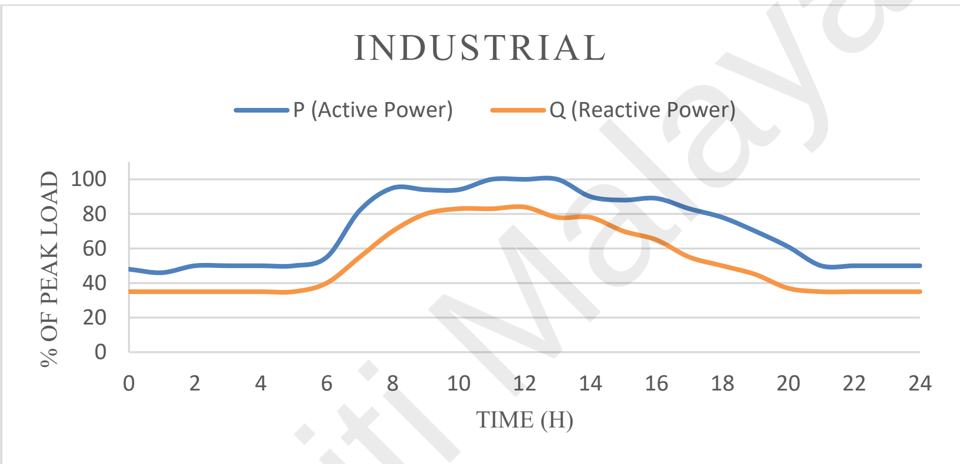
The technique proposed in (Kashem et al., 1998) on the loading modelling is implemented in this work. First, the system is divided into three load groups m (residential, commercial, and industrial). Where each load group has similar characteristics in which the changes of loads in each load group presents similar behavior. Second, the load groups can operate on estimated levels p according to their peak demand load curves as shown in Figure 3.3 (Kashem et al., 1998). The number of estimated load group levels is determined based on the range of the actual loads as shown in Table 3.1. The actual and estimated load levels are represented as percentage of peak demand. As a result, the total number of load patterns will be p^m. These patterns represent the training set that will be used as inputs to ANN.



(a)



(b)



(c)

Figure 3.3: Daily load curves in peak load percentage

(a) Residential, **(b)** Commercial, **(c)** Industrial

Table 3.1: Estimated operating load levels

Load level	**Actual load levels (% of peak demand)**	**Estimated load levels (% of peak demand)**
1	$45 \leq 54$	50
2	$55 \leq 64$	60
3	$65 \leq 74$	70
4	$75 \leq 84$	80
5	$85 \leq 94$	90
6	$95 \leq 100$	100

3.4.2 ANN Design

The proposed ANN technique for distribution system reconfiguration is shown in Figure 3.4. The input consists of load patterns (operating percentages of the three load groups) and the output is the switch number. The number of ANNs will be equal to the number of tie switches in the system, where each ANN will give one switch to be opened. The output of all ANNs will give optimal configuration for a specified load pattern. The relation between the input and output of DNR problem is non-linear. Therefore, a normalization layer is added before the input layer of ANN. The purpose of this normalization layer is to normalize the switch numbers to increase the learning performance of ANN models. The normalization process is done for each group of switches associated with a particular ANN model. Thus, this process is repeated according to the number of tie switches in the system. This step changes the values of optimal switches data to be set in the range between 0 and 1.

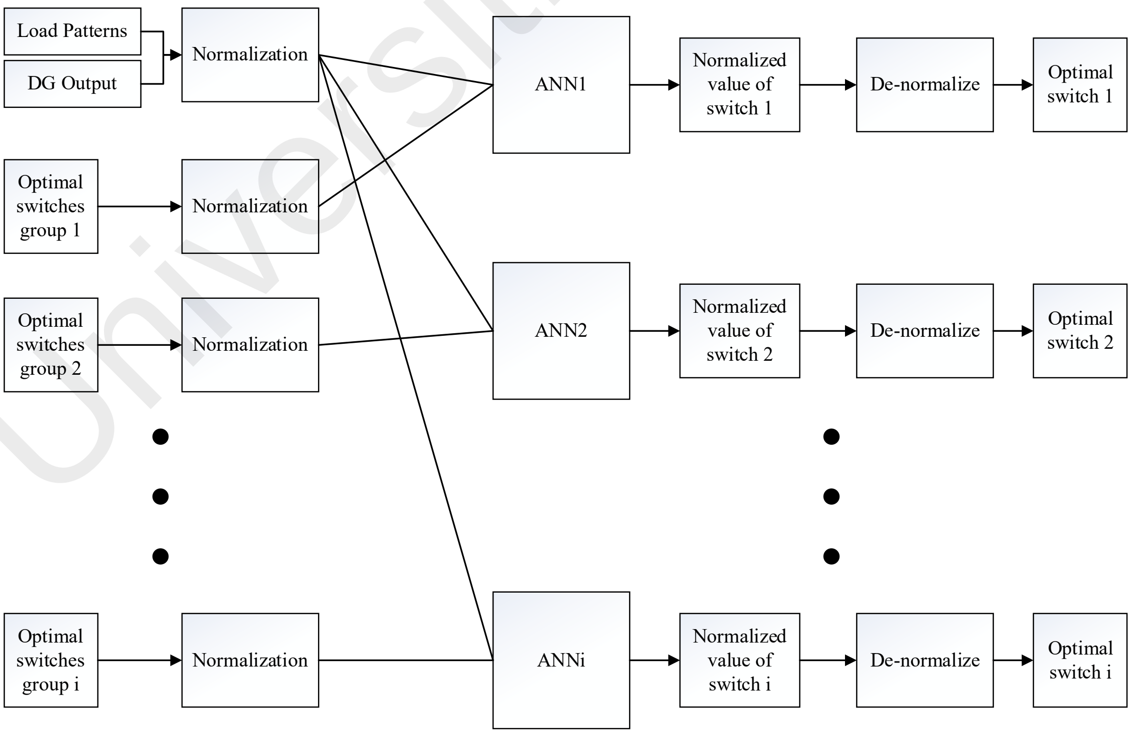


Figure 3.4: Proposed ANN design for distribution system reconfiguration

3.4.2.1 ANN Training Steps

Each individual ANN model is trained only for one switch, while the input for all ANNs models does not change. The process of training is iterative, since choosing the appropriate number of neurons in the hidden layer is done by trial and error. The training will start with one neuron and then the number is increased until a good convergence is achieved. The weights are initialized as random values. During the training process, the weights are adjusted iteratively to minimize the mean-squared-error. The steps for training ANN are as follows:

Step 1: generate the training data for ANN by using EP optimization in such a way the data is represented as follows.

$$Data = \begin{pmatrix} & & G_1 & G_2 & \cdots & G_p \\ LP_1 & DG_1 & OS_{11} & OS_{12} & \cdots & OS_{1p} \\ LP_2 & DG_2 & OS_{21} & OS_{22} & \cdots & OS_{2p} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ LP_m & DG_m & OS_{m1} & OS_{m2} & \cdots & OS_{mp} \end{pmatrix} \tag{3.10}$$

Where,

OS_{mp} = is the optimal tie switch in a switch group G_p for a load pattern LP_m.

m = is the number of load patterns.

p = is the number of switch groups.

DG_m = is the DG output for m load pattern

LP_m = is the operating percentage for residential, commercial, and industrial loads.

Step 2: The training for the ANN is conducted twice with different percentages for the generated data. First training is implemented using 70% of the data, second training is implemented using 60% of data. The data for training the ANN is randomly selected from generated data, which consists of load patterns as inputs and optimal switches as desired output for ANN model.

Step 3: Normalize all switches in the first optimal switch group G_1, starting from OS_{11} to OS_{m1} using equation (3.25), then repeat for the rest of the optimal switch groups, for $p = 2,3, \dots, p$ (giving a matrix of $m \times p$ elements of normalized optimal switches).

$$OS_{(norm)} = \frac{OS_{m1} - \min(OS_{m1})}{\max(OS_{m1}) - \min(OS_{m1})} \tag{3.11}$$

Step 4: Train the first ANN on the first group of optimal switches G_1, starting with one neuron and random initial weights.

Step 5: The training process continue for specific number of iterations, while the weights are updated each iteration.

Step 6: Store the final value of weights after convergence.

Step7: Test the network accuracy on the remaining data (30% of training data) using the weight values in step 6. RMS and absolute error (AE) are used to determine the level of learning the ANN of the data. If the RMS value is below 0.1, then the network has reached satisfactory level of training (Kashem et al., 1998).

Step 8: If the desired accuracy is achieved, continue to step 9. Otherwise, the number of neurons is increased by 1, then repeat steps 5-7.

Step 9: Train the other ANN models using the same procedure from step 4-7 based on the number of optimal group switches G_p.

3.4.2.2 Testing Accuracy of Trained ANN

The accuracy of the developed ANN model is tested using, the remaining 30% of generated data from the first training and 40% of the generated data from the second training. This remaining data is new to the developed ANN, which means that network has not been trained on these load patterns. The ANN is evaluated based on the number of correct predictions for unseen data and the number of correct responses for seen data.

This is done by using the combined ANN model to find the output of all load patterns and compare with the actual values.

3.5 Summary

This chapter presented the methodologies of network reconfiguration using meta-heuristic such as EP and PSO, and artificial intelligence such as ANN techniques for power loss reduction in distribution system with variable load profile and DGs. The comparison and performance of the proposed methods will be discussed in the next chapter.

CHAPTER 4: PERFORMANCE OF THE PROPOSED METHOD

4.1 Introduction

This chapter discusses simulation results and performance of the proposed method in solving network reconfiguration problem. The effectiveness of the proposed method is demonstrated on standard IEEE 16, IEEE 33, and IEEE 69 bus test system. The results are compared with existing meta-heuristic and ANN techniques from literature. The main consideration in comparison of the proposed method and other method is power loss reduction and voltage profile improvement.

4.2 Test system 1: IEEE 16-bus

An IEEE 16-bus distribution system was used to evaluate the proposed method. The network consists of 17 switches as 14 switches are sectionalizing switches and 3 tie switches. The default configuration of the network is 16, 17 and 18 as opened switches, while other switches are closed, as shown in Figure 4.1. The system voltage is 12.66 kV, while the total real and reactive power loads are 28.7 MW and 16.3 MVAR, respectively. The power loss of the default operating condition is 511.43 kW and the lowest bus voltage is 0.9693 p.u.

4.2.1 Network Reconfiguration Using Meta-heuristics techniques for IEEE 16 Bus System

This section presents the implementation of meta-heuristic techniques in distribution network reconfiguration problem. It focusses on power loss reduction and voltage profile improvement.

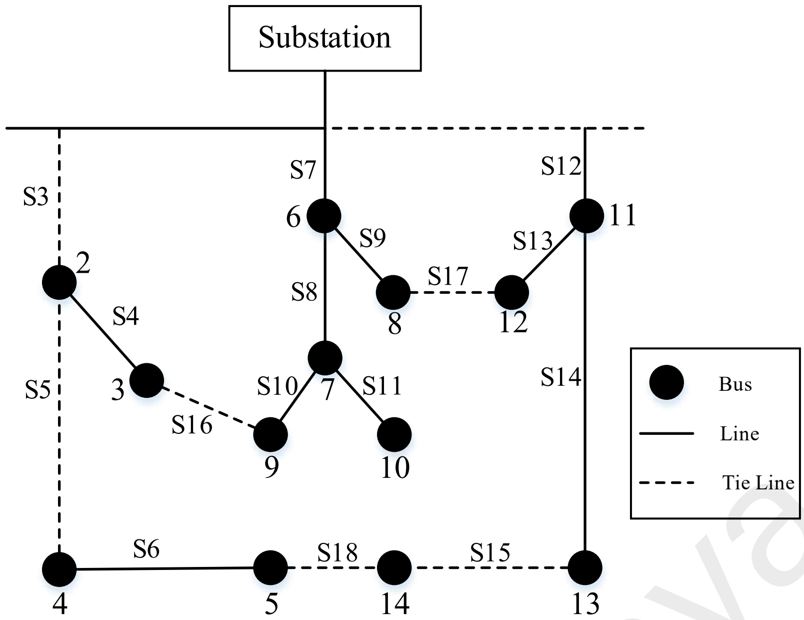


Figure 4.1: IEEE 16-bus distribution network

4.2.1.1 Impact on Power Loss

The results obtained using EP and PSO are summarized in Table 4.1 and compared with the default case (before reconfiguration). Newton-Raphson load flow (NRLF) algorithm is used to calculate the power loss in this work. The optimal objective function, F, according to equation (3.1) is 0.9141, which is obtained by both EP and PSO. The power loss before configuration is 511.704 kW obtained by (NRLF) and after configuration the power loss decreased to 466.339 kW which is 8.87% reduction. The optimal switches to be opened are 9, 10 and 18. The processing time taken by EP is 6.378 s, while PSO had faster processing time of 5.127 s.

4.2.1.2 Impact on Voltage Profile

Figure 4.2 shows the voltage profile for default and optimal configurations using EP and PSO for different percentage loading profile of Residential (R), Commercial (C) and Industry (I). It can be noticed that the buses voltage magnitude has improved significantly compared to the default case in all algorithms. For example, before reconfiguration the lowest voltage magnitude was at bus 12 with 0.9693 p.u. However, after reconfiguration the voltage increased to 0.972 p.u. EP and PSO reported the same voltage profile.

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

Case	**Open switches**	**Bus voltage** (**Min** – **Max**)	**Objective function** $\min F = P_{loss}^{R}$	**Power loss (kW)**	**Loss reduction (%)**	**Processing time (s)**
Initial	16, 17, 18	0.969(12) – 1(1)	1	511.704	-	0.489
EP	9, 10, 18	0.972(12) – 1(1)	0.9141	466.339	8.87	6.378
PSO	9, 10, 18	0.972(12) – 1(1)	0.9141	1466.339	8.87	5.127

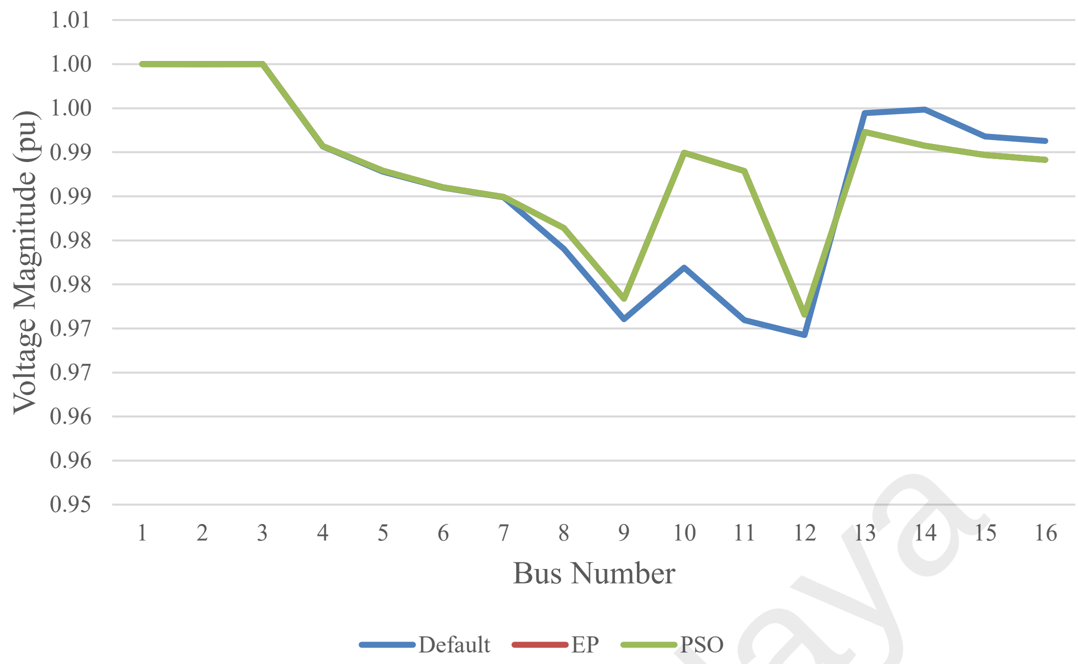


Figure 4.2: Voltage profile for IEEE 16-bus network using different algorithms

4.2.2 Network reconfiguration Using Meta-heuristics for IEEE 16 Bus System with variable load profile and DG

The 16-bus distribution system with variable load profile and DGs is shown in Figure 4.3. The system is divided into three load groups (residential, commercial, industrial), each load group has 6 operating levels from 50% to 100% of peak demand, which results in 216 different load patterns. One DG is installed in the system where the location of the installed DG units is at bus 8. The DG is made up of Photo-voltaic (PV) system. The DG output profile for active power is shown in Figure 4.4 (Ing, Jamian, Mokhlis, & Illias, 2016). Optimal network reconfiguration based on EP and PSO were implemented on the test system. Table 4.2 shows the optimal network reconfiguration for 20 different load patterns. As shown in the table the power loss after reconfiguration is lower than default case. For example, at load percentage of 100% R, 50% C and 70% I, the default configuration gives 134.08 kW. While the optimal configuration for this load pattern is 9, 10,and 18 with power loss of 166.2 kW which is equal to 8.28% power reduction. The maximum power loss reduction occurred at load percentage 50% R, 90% C and 80% I. the power loss reduction percentage is 11.94%.

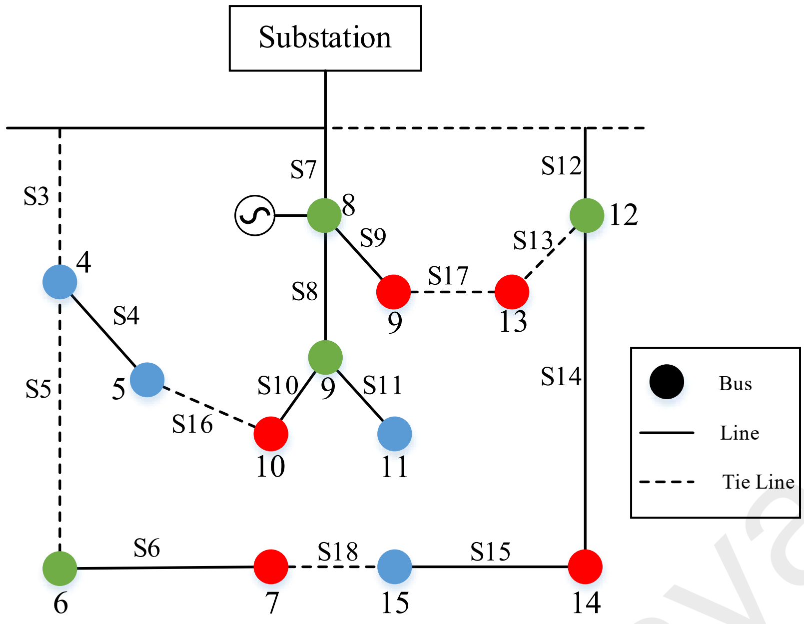


Figure 4.3: IEEE 16-bus distribution network with different load groups and DGs

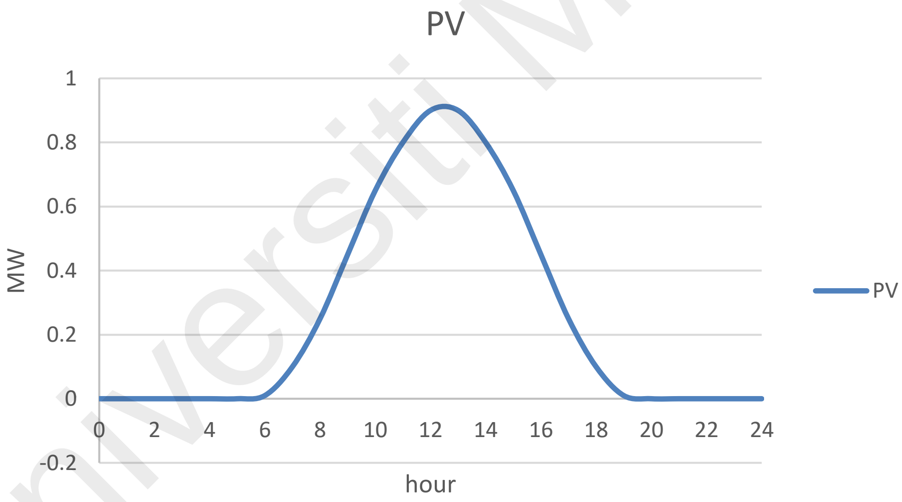


Figure 4.4: DG output profile for a day

Table 4.2: Optimal Configuration for different load profile using EP & PSO for IEEE 16-bus network

Operating Percentage %			Default	Optimal	Before configuration (kW)	After configuration (kW)		Loss Reduction %
R	C	I				EP	PSO	
50	80	70	16, 17, 18	9, 10, 18	282.77	260.17		7.99
50	90	80		9, 10, 18	355.63	313.15		11.94
50	90	90		9, 10, 18	365.89	335.88		8.20
50	100	70		9, 10, 18	416.85	386.83		7.20
60	80	90		9, 10, 18	310.47	283.55		8.67
70	70	50		9, 10, 18	229.39	211.10		7.97
70	90	70		9, 10, 18	365.89	336.56		8.02
80	60	50		9, 10, 18	189.93	174.08		8.35
80	90	70		9, 10, 18	377.11	346.33		8.16
90	70	50		9, 10, 18	250.53	230.26		8.09
90	70	100		9, 10, 18	293.36	266.99		8.99
90	100	60		9, 10, 18	452.88	418.57		7.57
100	50	70		9, 10, 18	181.21	166.20		8.28
100	60	80		9, 10, 18	233.87	213.49		8.71
100	70	70		9, 10, 18	277.39	253.29		8.69
100	70	80		9, 10, 18	285.96	260.63		8.86
100	80	50		9, 10, 18	320.27	294.63		8.00
100	80	60		9, 10, 18	327.86	300.84		8.24
100	90	80		9, 10, 18	411.81	376.30		8.62
100	100	90		9, 10, 18	496.60	453.67		8.64

4.2.3 Network Reconfiguration Using proposed ANN technique for IEEE 16 Bus System with variable load profile

The proposed ANN technique is implemented on the proposed 16-bus distribution system shown in Figure 4.5, where the load is divided into three load groups (residential, commercial, industrial). Each load group has 6 operating levels from 50% to 100% of peak demand, which results in 216 load patterns. From the solution of network reconfigurationfor of 16-bus system, most of the configurations are the same, and can be grouped into two distinct configurations as tabulated in Table 4.3. It can be observed from this table that one switch is changing. Therefore, one ANNs are used for the training which are ANN3. The final structure of the training network is determined based on the most accurate results of ANNs outputs. While the structure of both ANN's is similar regarding input and output neurons, the number of neurons in the hidden layer is different.

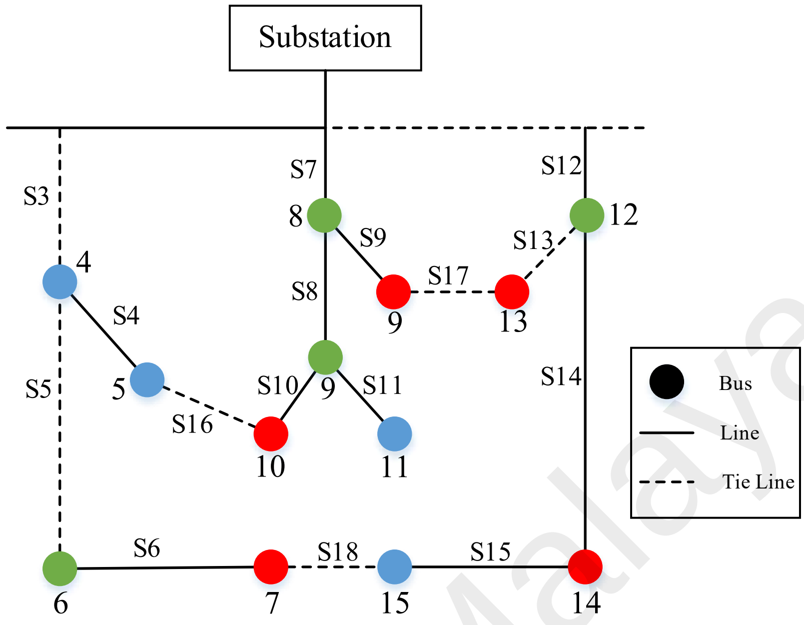


Figure 4.5: IEEE 16-bus distribution network with different load groups

Table 4.3: Optimal unique configuration of all load patterns for IEEE 16-bus network

Optimal configuration number	Tie switches to be opened	Number of occurrences
1	S9, S10, S18	211
2	S9, S10, S6	5

4.2.3.1 Performance of Network Reconfiguration based on ANN

The performance of first ANN (70-30%) model is shown in Table 4.4, The number of neurons in hidden layer is 2 for ANN3. Additionally, the table shows the accuracy (absolute error) and MSE of the ANN model. ANN3 accuracy is 100% which corresponds to 216 optimal solutions. Similarly, the performance of the second ANN (60-40%) model is shown in Table 4.5. The model ANN3 achieved 100% accuracy.

4.2.3.2 Impact of proposed ANN technique on power loss

Figure 4.6 shows the power loss before and after configuration for all 216 load patterns using the proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding power loss. The average power loss reduction for all cases is 8.36%. as shown in the figure the power loss after reconfiguration using ANN is lower than before reconfiguration (default). For example, the power loss in 100% loading is 511.704 kW, with switches 16, 17, and 18 open. However, proposed ANN technique response is that switches 9, 10 ,and 18 are open, with power loss of 466.339 kW.

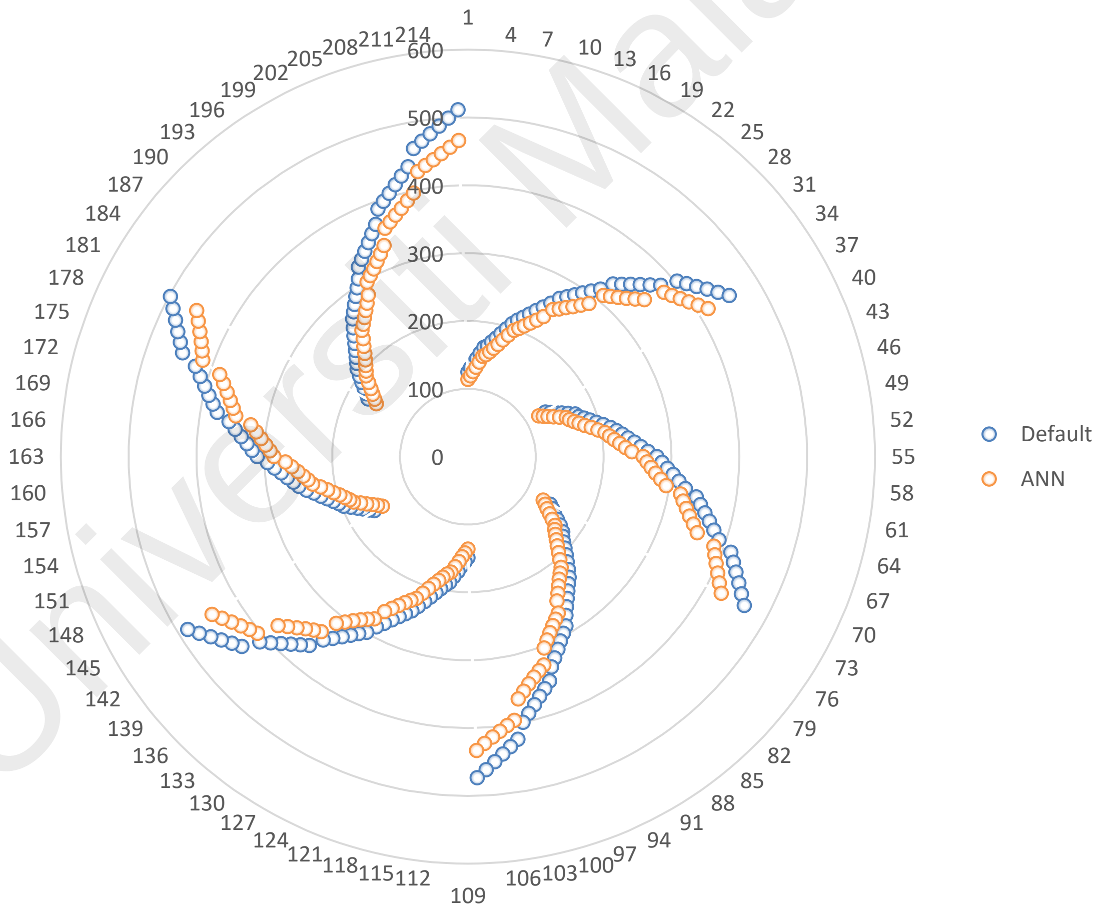


Figure 4.6: Power loss comparison for IEEE 16-bus network before and after reconfiguration using proposed ANN technique

Table 4.4: ANN (70-30%) model performance for IEEE 16-bus network

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN3	3-2-1	100%	4.1e-11	151	151	-	65	65	-	3

Table 4.5: ANN (60-40%) model performance for IEEE 16-bus network

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN3	3-2-1	100%	4.1e-11	151	151	-	65	65	-	3.6

4.2.3.3 Impact of proposed ANN technique on voltage profile

Figure 4.7 shows the voltage profile for default and optimal configurations for all load patterns the using proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding minimum bus voltage. It can be noticed that the minimum buses voltage magnitude has improved after reconfiguration compared to the before reconfiguration (default), while the overall voltage profile increased in all load patterns by an average of 0.17%.

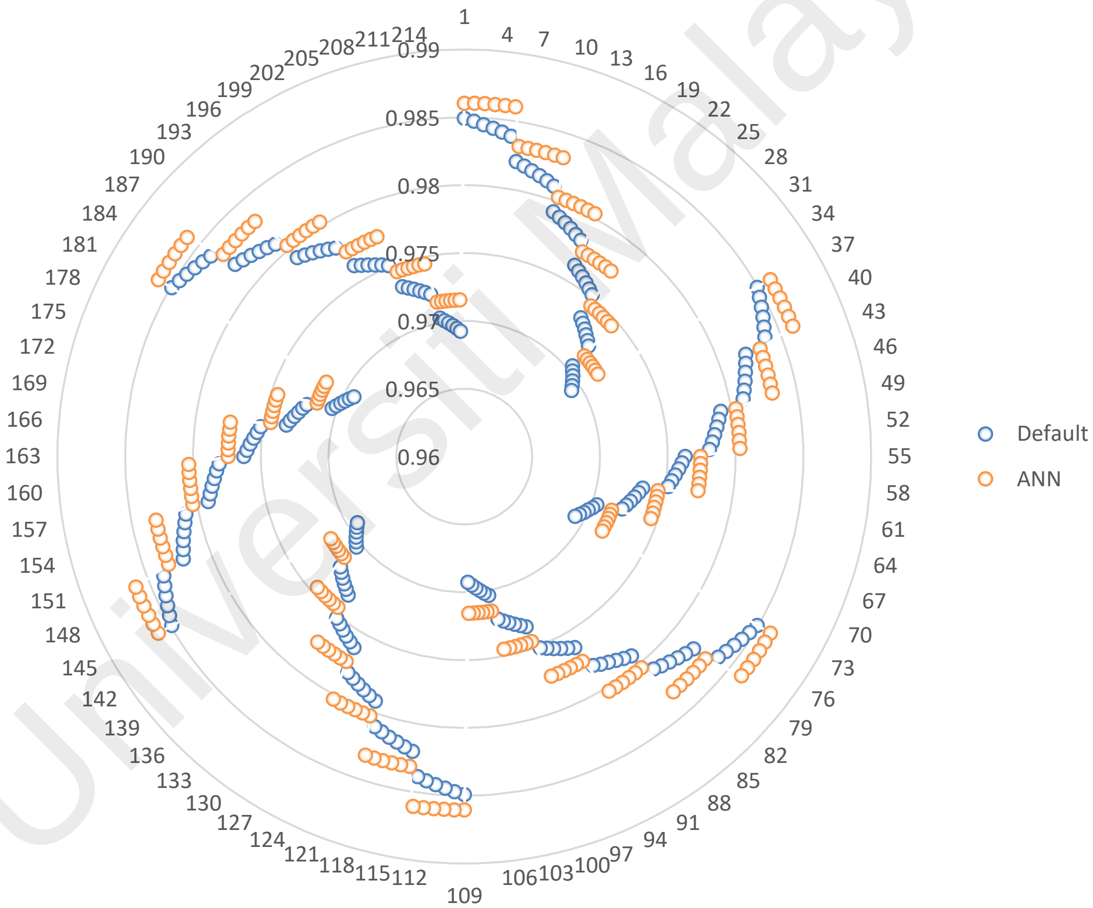


Figure 4.7: Voltage profile for IEEE 16-bus network before and after reconfiguration using proposed ANN technique

4.2.4 Network Reconfiguration Using proposed ANN technique for IEEE 16 Bus System with variable load profile and DG

The 16-bus system with variable load profile and DG shown in Figure 4.3 is used to test the proposed optimal network reconfiguration based on ANN. The total number of different load patterns is 216. From the solution of optimal network reconfiguration for this load pattern, there were 2 distinct configurations as tabulated in Table 4.6. The number for each configuration found is also presented in the same table. Based on this results, one ANN is used for the training, which is ANN3. The final structure of the training network is determined based on the most accurate results of ANN models outputs. While the structure of each individual ANN's does not change regarding input and output neurons, since the number of load groups are three (R, C and I) and the output of each ANN model is an optimal switch. The number of neurons in the hidden layer is determined during the training of ANN models.

Table 4.6: Optimal unique configuration of all load patterns for IEEE 16-bus network with DG

Optimal configuration number	Tie switches to be opened	Number of occurrences
1	S9, S10, S18	211
2	S9, S10, S6	5

4.2.4.1 Performance of Network Reconfiguration based ANN

The performance of the proposed ANN model based on the absolute error which is represented by the accuracy. ANN3 accuracy is 100%, which corresponds to 216 optimal solutions out of 216 load patterns. The overall accuracy of the final solution is 100%. Similarly, the second ANN (60-40%) model (ANN3) achieved 100% accuracy.

4.2.4.2 Impact of proposed ANN technique on power loss

Figure 4.8 shows the power loss before and after configuration for all 216 load patterns using the proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding power loss. As shown in the figure, the power loss after reconfiguration is less than before reconfiguration (default). Additionally, the average power loss reduction for all cases is 8.32%.

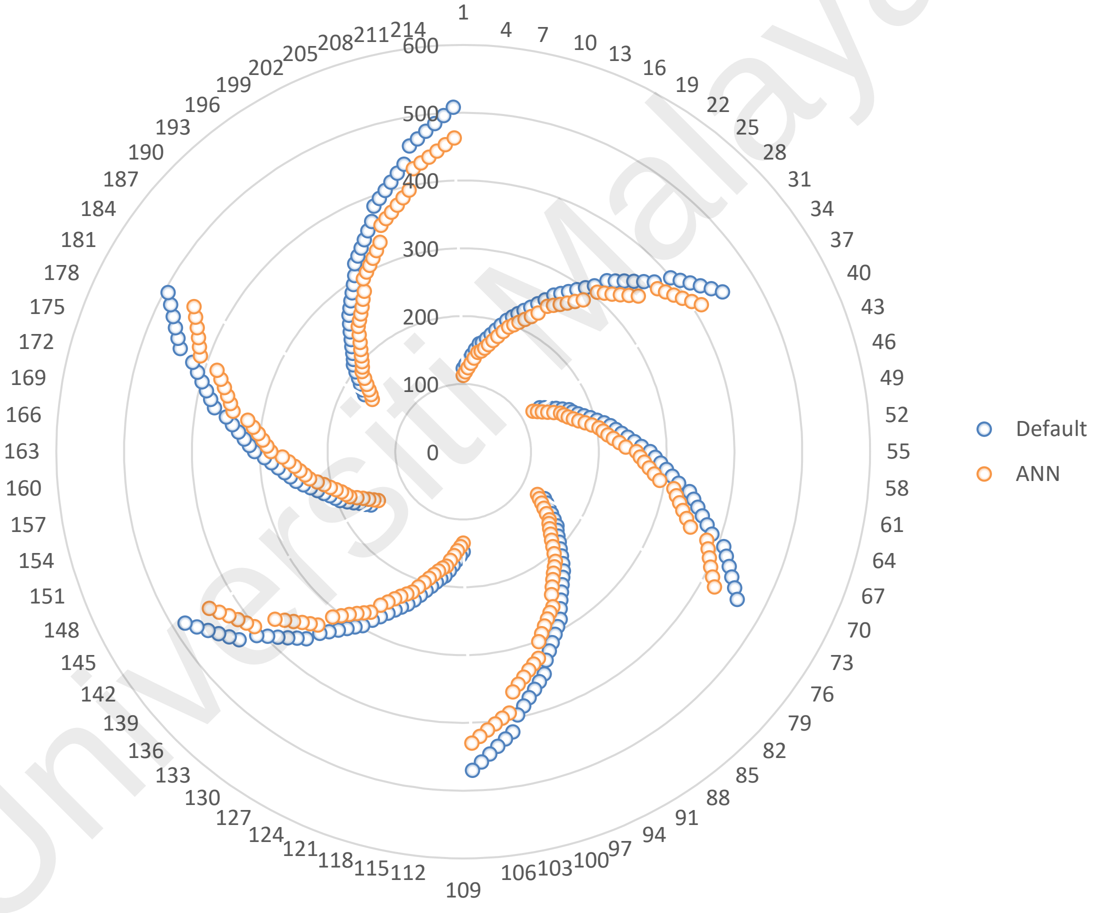


Figure 4.8: Power loss comparison for IEEE 16-bus network before and after reconfiguration using proposed ANN technique

4.2.4.3 Impact of proposed ANN technique on voltage profile

Figure 4.9 shows the voltage profile for default and optimal configurations for all load patterns using the proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding minimum bus voltage. It can be noticed that the minimum buses voltage magnitude has improved compared to the default case, while the overall voltage profile increased in all load patterns by an average of 0.15%.

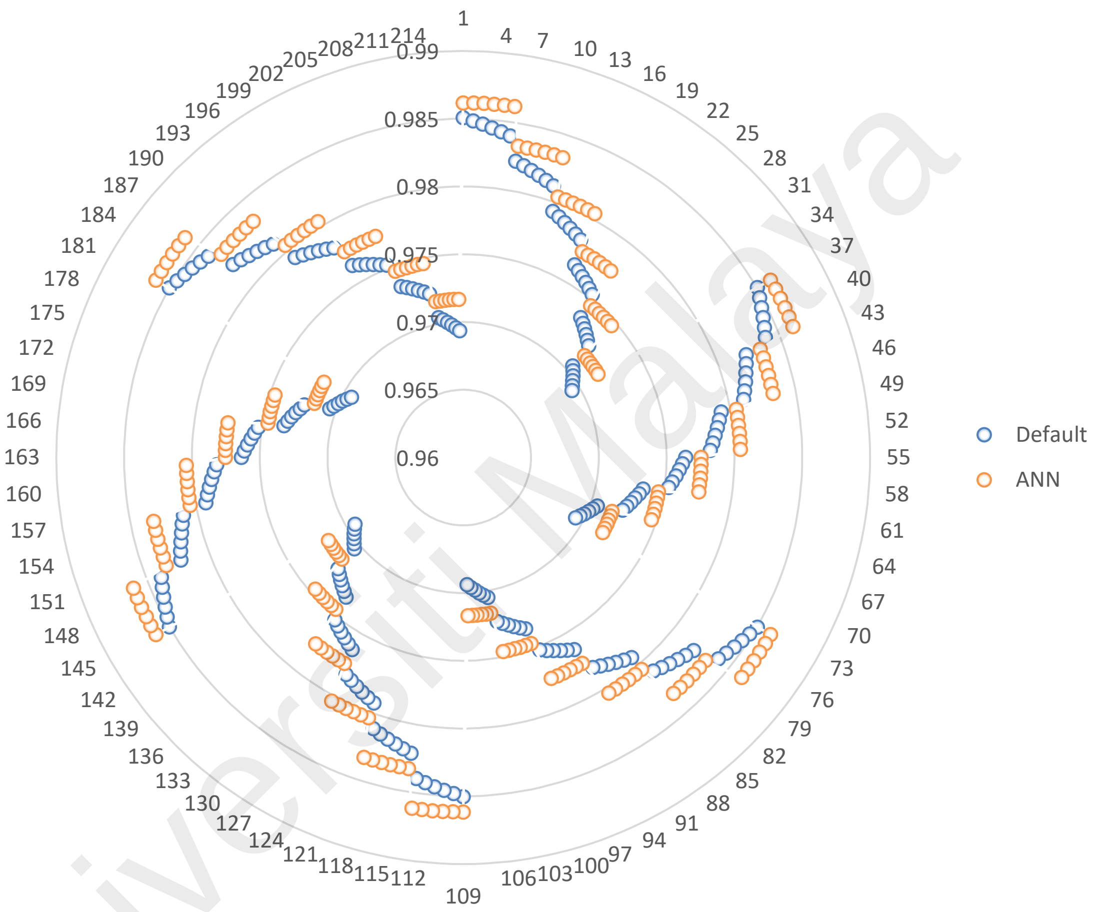


Figure 4.9: Voltage profile for IEEE 16-bus network before and after reconfiguration using proposed ANN technique

4.2.5 Comparative analysis on the performance of proposed ANN technique in Network Reconfiguration for IEEE 16-bus system

To evaluate the performance of the proposed ANN technique, a consistency test was conducted using EP, PSO and proposed ANN technique. The objective of the test is to measure the robustness of the technique to find the optimal answer. First, the proposed ANN technique and other techniques were executed for 20 times to find the optimal configuration for all load patterns (216 case). The result is shown in Figure 4.10, the figure shows the best and worst number of optimal configurations found in the 20 runs by the different techniques for all the cases. Additionally, the figure shows the average number of optimal configurations found for all runs. The proposed ANN technique managed to obtain the optimal configurations for all load patterns in the best run. Meanwhile, the best run for EP over 20 runs achieved 202 optimal configurations out of 216, while PSO achieved 209 optimal configurations. The average number of optimal configurations obtained for all 216 cases for 20 runs is 214 by proposed ANN technique which is 99%, 195 by EP which is 93.5% and 203 by PSO which is 96.8%. Figure 4.11 shows power loss comparison between proposed ANN technique, EP and PSO for the best run. The average power loss reduction for all techniques of 8.36%, 8.15% and 8.22% respectively.

Second, the comparison value for processing time is shown in Table 4.7. All algorithms provide exactly the same optimal configuration and power loss value for default case. However, the computation time to find the optimal configuration to minimize the power loss is 6.378s for EP and 5.127s for PSO. On the other hand, the execution time (excluding training time) for the proposed ANN technique is 0.050s, which is very fast compared to both meta-heuristic methods.

Table 4.7: Statistical analysis for processing time for network reconfiguration for IEEE 16-bus network

	Tie switches opened	**Power Loss (kW)**	**Loss Reduction %**	**Vmin (p.u)**	**Processing Time (s)**
EP	9, 10, 18	466.339	8.87	0.972	6.378
PSO	9, 10, 18	466.339	8.87	0.972	5.127
Proposed ANN	9, 10, 18	466.339	8.87	0.972	**0.050**

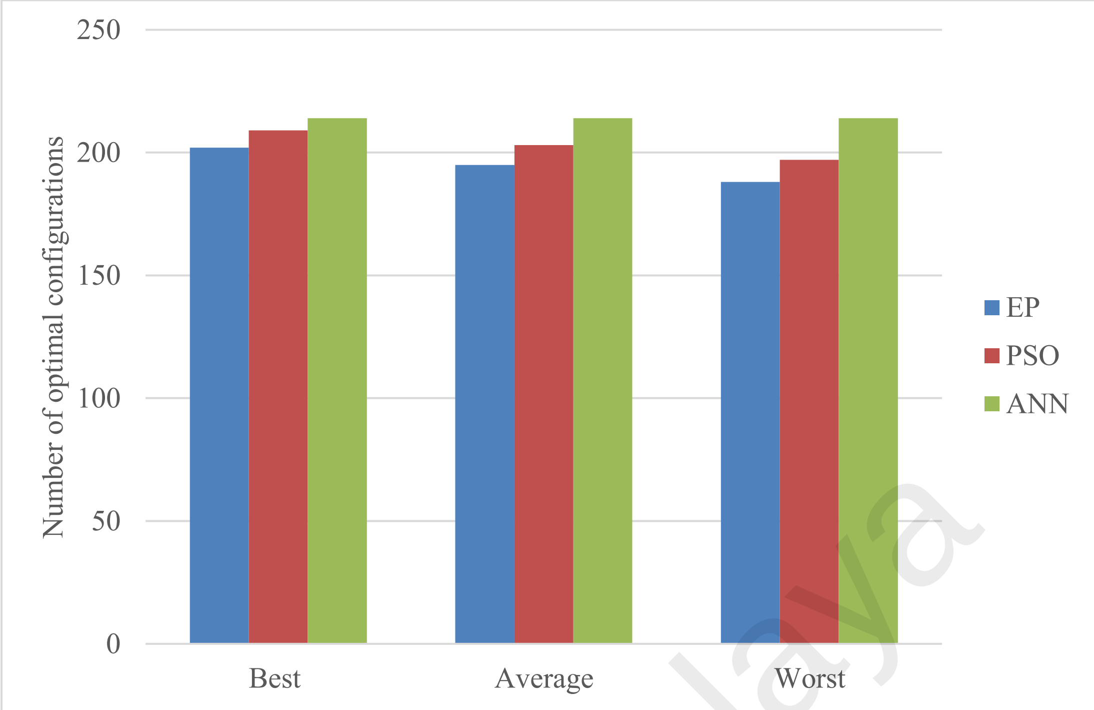


Figure 4.10: consistency performance comparison between EP, PSO and proposed ANN for all load patterns in IEEE 16-bus network

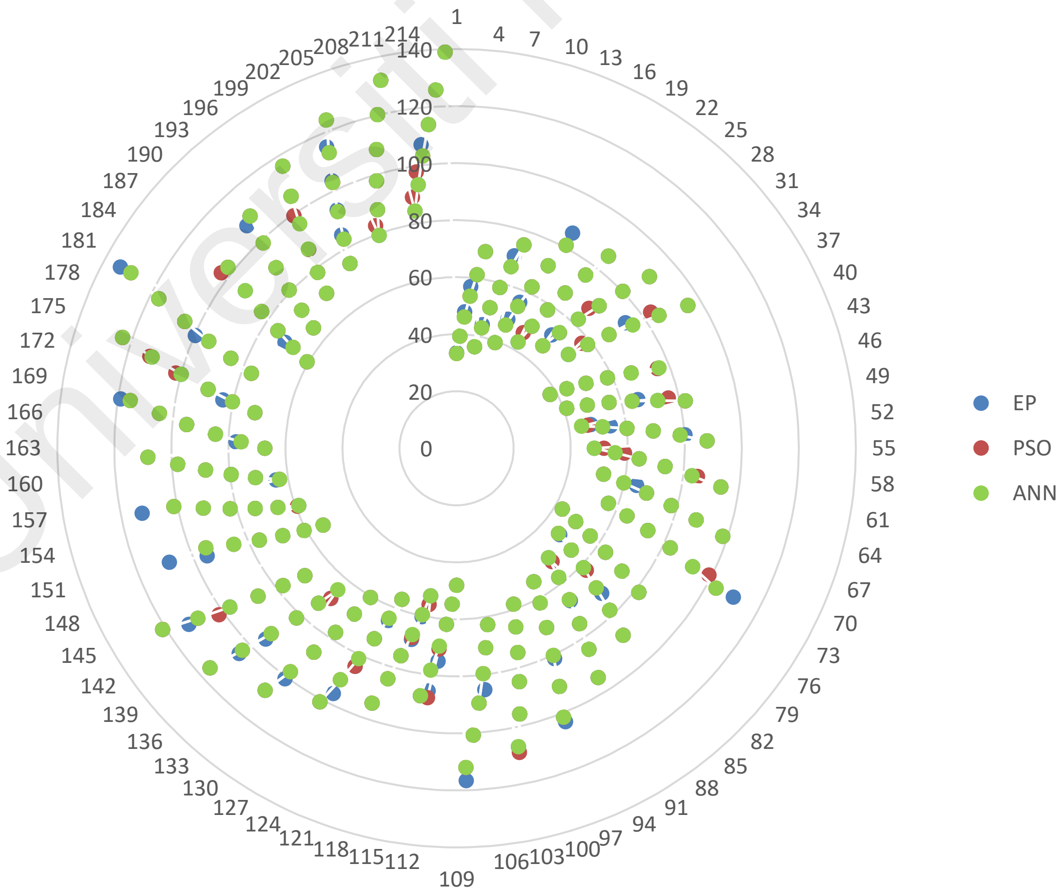


Figure 4.11: Power loss comparison between EP, PSO and proposed ANN for all load patterns in IEEE 16-bus network

Furthermore, to verify the proposed ANN technique, a comparison with other published works is also conducted, as shown in Table 4.8. The optimal configurations obtained from references that used Fast Non-dominated Sorting Genetic Algorithm (FNSGA) (Eldurssi & O'Connell, 2014), Mixed Integer Hybrid Differential Evolution (MIHDE) (Su & Lee, 2003) and Switching Indices (SI) (Shivakumar, Kumar, & Marulasiddappa, 2014) were re-evaluated at 100% loading to determine the power loss using the same load flow program. The results are presented in Table 4.8. The optimal configuration is 9,10, and 18 which results in 8.87% power loss reduction.

Table 4.8: Comparison of simulation results for IEEE 16-bus network

Method	Tie switches opened	Power Loss (kW)	Loss Reduction %	Vmin (p.u)
Initial configuration	16, 17, 18	511.43	-	0.9693
FNSGA (Eldurssi & O'Connell, 2014)	9, 10, 18	466.34	8.87	0.972
MIHDE (Su & Lee, 2003)	9, 10, 18	466.34	8.87	0.972
SI (Shivakumar et al., 2014)	9, 10, 18	466.34	8.87	0.972
EP	9, 10, 18	466.34	8.87	0.972
PSO	9, 10, 18	466.34	8.87	0.972
Proposed ANN	9, 10, 18	466.34	8.87	0.972

4.3 Test system 2: IEEE 33-bus

An IEEE 33-bus distribution system was used to evaluate the proposed method. The network consists of 37 switches as 32 switches are sectionalizing switches and 5 tie switches. The default configuration of the network is 33, 34, 35, 36 and 37 as opened switches, while other switches are closed, as shown in Figure 4.12. The system voltage is 12.66 kV, while the total real and reactive power loads are 3.7 MW and 2.3 MVAR, respectively. The power loss of the default operating condition is 208.459 kW and the lowest bus voltage is 0.9108 p.u.

4.3.1 Network Reconfiguration Using Meta-heuristics techniques for IEEE 33 Bus System

This section presents the implementation of meta-heuristic techniques in distribution network reconfiguration problem. It focusses on power loss reduction and voltage profile improvement.

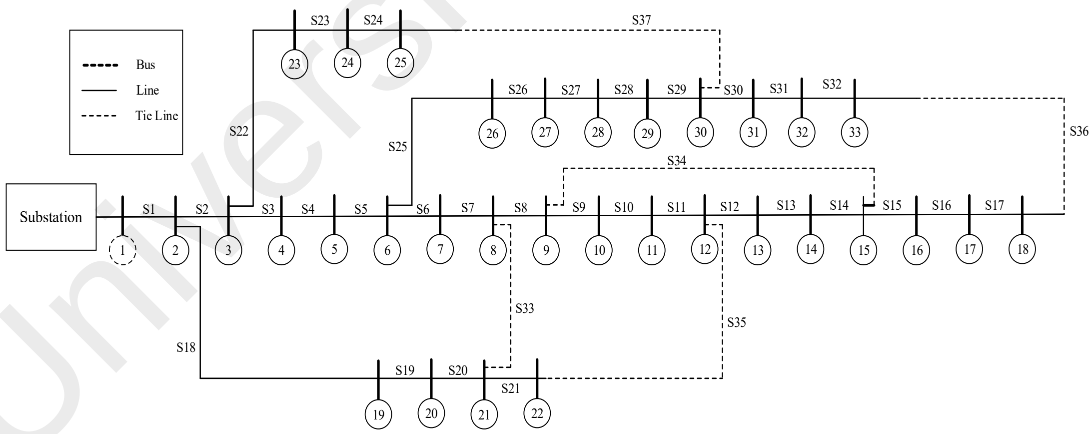


Figure 4.12: IEEE 33-bus distribution network

4.3.1.1 Impact on Power Loss

The results obtained using EP and PSO are summarized in Table 4.9 and compared with the default case (before reconfiguration). Newton-Raphson load flow (NRLF) algorithm is used to calculate the power loss in this work. The optimal objective function, F, according to equation (3.1) is 0.6664, which is obtained by both EP and PSO. The power loss before configuration is 208.459 kW obtained by (NRLF) and after configuration the power loss decreased to 138.927 kW which is 33.35% reduction. The optimal switches to be opened are 7, 9, 14, 32, 37. The processing time taken by EP is 14.106 s, while PSO had faster processing time of 12.062 s.

4.3.1.2 Impact on Voltage Profile

Figure 4.13 shows the voltage profile for default and optimal configurations using EP and PSO for different percentage loading profile of Residential (R), Commercial (C) and Industry (I). It can be noticed that the buses voltage magnitude has improved significantly compared to the default case in all algorithms. For example, before reconfiguration the lowest voltage magnitude was at bus 18 with 0.910 p.u. However, after reconfiguration the voltage increased to 0.947 p.u. EP and PSO reported the same voltage profile.

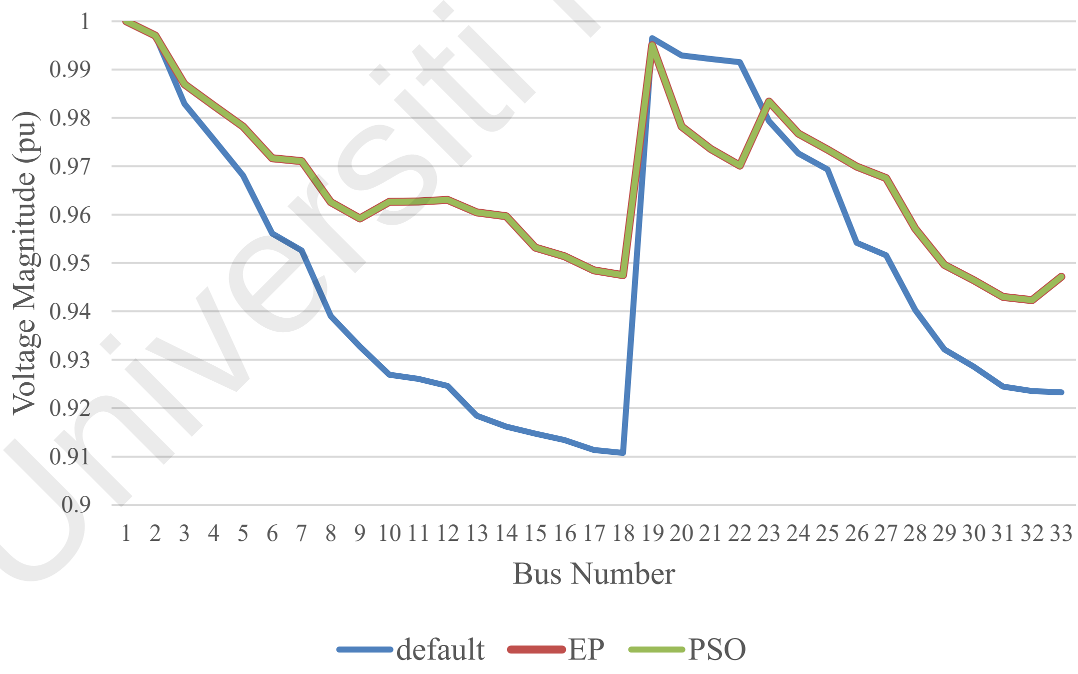


Figure 4.13: Voltage profile for IEEE 33-bus network using different algorithms

Table 4.9: Network reconfiguration results for IEEE 33-bus network

Case	Open switches	Bus voltage Min – Max	Objective function $\min F = P_{loss}^{R}$	Power loss (kW)	Loss reduction (%)	Processing time (s)
Initial	33,34,35,36,37	0.9107(18) – 1(1)	1	208.4592	-	0.513
EP	7,9,14,32,37	0.9423(32) – 1(1)	0.6664	138.9275	33.35	14.106
PSO	7,9,14,32,37	0.9423(32) – 1(1)	0.6664	138.9275	33.35	12.062

4.3.2 Network reconfiguration Using Meta-heuristics for IEEE 33 Bus System with variable load profile and DG

The 33-bus distribution system with variable load profile and DGs is shown in Figure 4.14. The system is divided into three load groups (residential, commercial, industrial), each load group has 6 operating levels from 50% to 100% of peak demand, which results in 216 different load patterns. Three DGs were installed in the system where the location of the installed DGs units are at buses 18, 29 and 32 based on (Imran et al., 2014). These DGs are made up of Photo-voltaic (PV) system. The DGs output profile for active power is shown in Figure 4.15 (Ing et al., 2016). Optimal network reconfiguration based on EP and PSO were implemented on the test system. Table 4.10 shows the optimal network reconfiguration for 20 different load patterns. As shown in the table the power loss after reconfiguration is lower than default case. For example, at load percentage of 100% R, 50% C and 70% I, the default configuration gives 134.08 kW. While the optimal configuration for this load pattern is 7, 9, 14, 36 and 37 with power loss of 75.05 kW which is equal to 44.03% power reduction. . The maximum power loss reduction occurred at load percentage 100% R, 50% C and 70% I. the power loss reduction percentage is 44.03%.

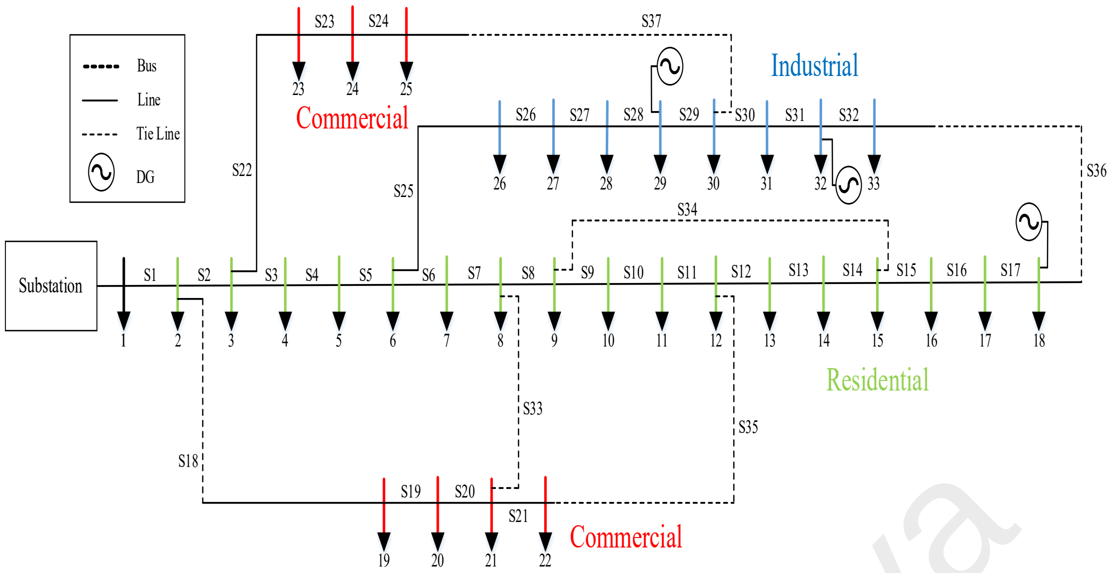


Figure 4.14: IEEE 33-bus distribution network with different load groups and DGs

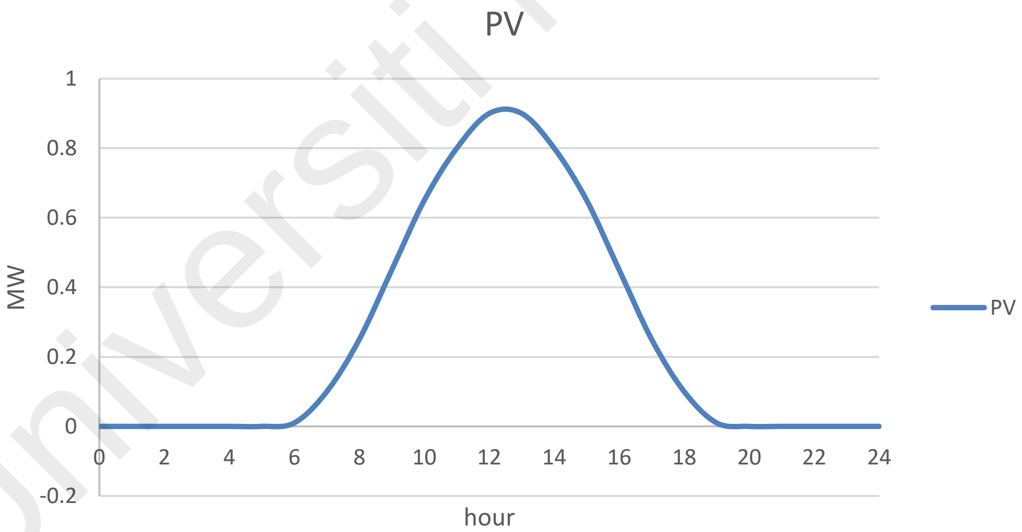


Figure 4.15: DG output profile for a day

Table 4.10: Optimal Configuration for different load profile using EP & PSO for IEEE 33-bus network

Operating Percentage %			Default	Optimal	Before configuration (kW)	After configuration (kW)		Loss Reduction %
R	C	I				EP	PSO	
50	80	70	33, 34, 35, 36, 37	7, 9, 14, 31, 37	78.60	57.98		26.23
50	90	80		7, 9, 14, 31, 37	94.97	70.69		25.56
50	90	90		7, 9, 14, 31, 37	108.54	80.11		26.19
50	100	70		7, 9, 14, 31, 37	87.17	66.64		23.55
60	80	90		7, 9, 14, 31, 37	116.42	83.04		28.68
70	70	50		7, 9, 14, 32, 37	75.19	50.14		33.32
70	90	70		7, 9, 14, 32, 37	106.32	74.84		29.61
80	60	50		7, 9, 14, 36, 37	83.70	52.64		37.11
80	90	70		7, 9, 14, 32, 37	120.09	81.88		31.82
90	70	50		7, 9, 14, 36, 37	100.92	63.05		37.53
90	70	100		7, 9, 14, 32, 37	174.00	108.34		37.74
90	100	60		7, 9, 14, 32, 37	126.73	85.26		32.72
100	50	70		7, 9, 14, 36, 37	134.08	75.05		44.03
100	60	80		7, 9, 14, 32, 37	153.16	89.61		41.49
100	70	70		7, 9, 14, 36, 37	142.31	86.97		38.89
100	70	80		7, 9, 14, 32, 37	157.57	96.01		39.07
100	80	50		7, 9, 14, 36, 37	120.18	74.73		37.82
100	80	60		7, 9, 14, 36, 37	132.88	83.33		37.29
100	90	80		7, 9, 14, 32, 37	167.38	108.49		35.19
100	100	90		7, 9, 14, 32, 37	189.89	125.83		33.74

4.3.3 Network Reconfiguration Using proposed ANN technique for IEEE 33 Bus System with variable load profile

The proposed ANN technique is implemented on the proposed 33-bus distribution system shown in Figure 4.16, where the load is divided into three load groups (residential, commercial, industrial). Each load group has 6 operating levels from 50% to 100% of peak demand, which results in 216 load patterns. From the solution of network reconfigurationfor of 33-bus system, most of the configurations are the same, and can be grouped into six distinct configurations as tabulated in Table 4.11. It can be observed from this table the first three tie switches don't change in all 6 configurations. Therefore, two ANNs are used for the training which are ANN4 and ANN5. The final structure of the training network is determined based on the most accurate results of ANNs outputs. While the structure of both ANN's is similar regarding input and output neurons, the number of neurons in the hidden layer is different.

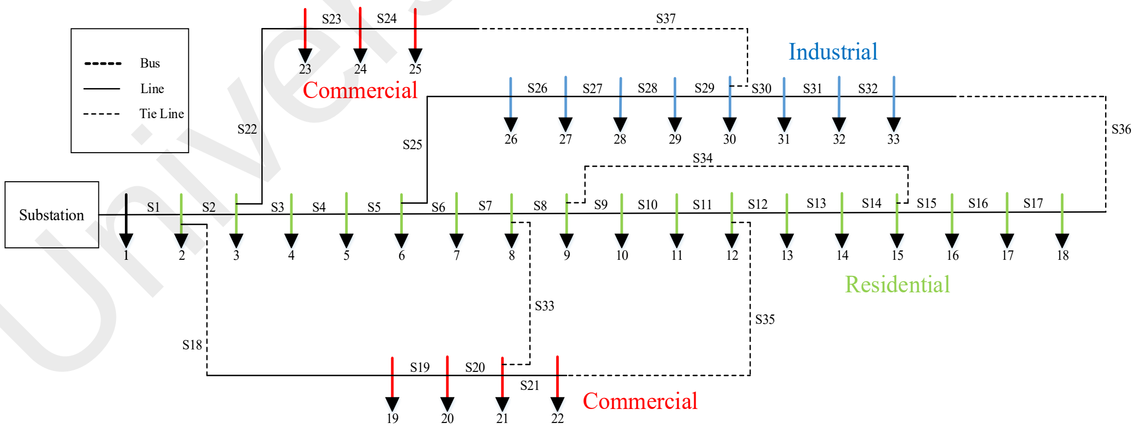


Figure 4.16: IEEE 33-bus distribution network with different load groups

Table 4.11: Optimal unique configuration of all load patterns for IEEE 33-bus network

Optimal configuration number	Tie switches to be opened	Number of occurrences
1	S7, S9, S14, S32, S37	75
2	S7, S9, S14, S32, S28	68
3	S7, S9, S14, S31, S28	9
4	S7, S9, S14, S31, S37	31
5	S7, S9, S14, S36, S28	18
6	S7, S9, S14, S36, S37	15

4.3.3.1 Performance of Network Reconfiguration based on ANN

The performance of each both ANN training models is shown in Table 4.12 and 4.13, the tables show the structure, accuracy, Mean Square Error (MSE), training and testing results for each ANN model. while the structure of both ANN's is similar regarding input and output neurons, which corresponds to the number of load groups and the tie switch, respectively. The number of neurons in hidden layer is 3 for ANN4 and 2 for ANN5 in both trainings, which is reasonable, because the variation in switch for group switch 4 is three, while for group switch 5 is two. Additionally, the tables show the accuracy (absolute error) and MSE of each ANN model as well as the overall accuracy of the model in DNR process. ANN4 accuracy is 99.07% for ANN (70-30%) which corresponds to 214 optimal solutions for switch group 4 out of 216 load patterns, while 98.61% for ANN (60-40%). ANN5 give 100% optimal solution for switch group 5 for the two trainings models. The training time required by ANN (70-30%) is 4.1 minutes and 4.5 for ANN (60-40%). The average accuracy of combined training for both ANN models is 98.84%.

Table 4.12: ANN (70-30%) model performance for IEEE 33-bus network

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN4	3-3-1	99.07%	2.2e-04	151	151	-	65	63	2	2.6
ANN5	3-2-1	100%	1.7e-08	151	151	-	65	65	-	1.5
Combined ANN	-	99.07%	-	151	151	-	65	63	2	4.1

Table 4.13: ANN (60-40%) model performance for IEEE 33-bus network

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN4	3-3-1	98.61%	4.8e-06	151	151	-	65	62	3	3
ANN5	3-2-1	100%	1.1e-09	151	151	-	65	65	-	1.5
Combined ANN	-	98.61%	-	151	151	-	65	63	3	4.5

4.3.3.2 Impact of proposed ANN technique on power loss

Figure 4.17 shows the power loss before and after configuration for all 216 load patterns using the proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding power loss. The average power loss reduction for all cases is 33.44%. as shown in the figure the power loss after reconfiguration using ANN is lower than before reconfiguration (default). For example, the power loss in 100% loading is 208.459 kW, with switches 33,34,35,36 and 37 open. However, proposed ANN technique response is that switches 7,9,14,32 and 37 are opened, with power loss of 138.928 kW.

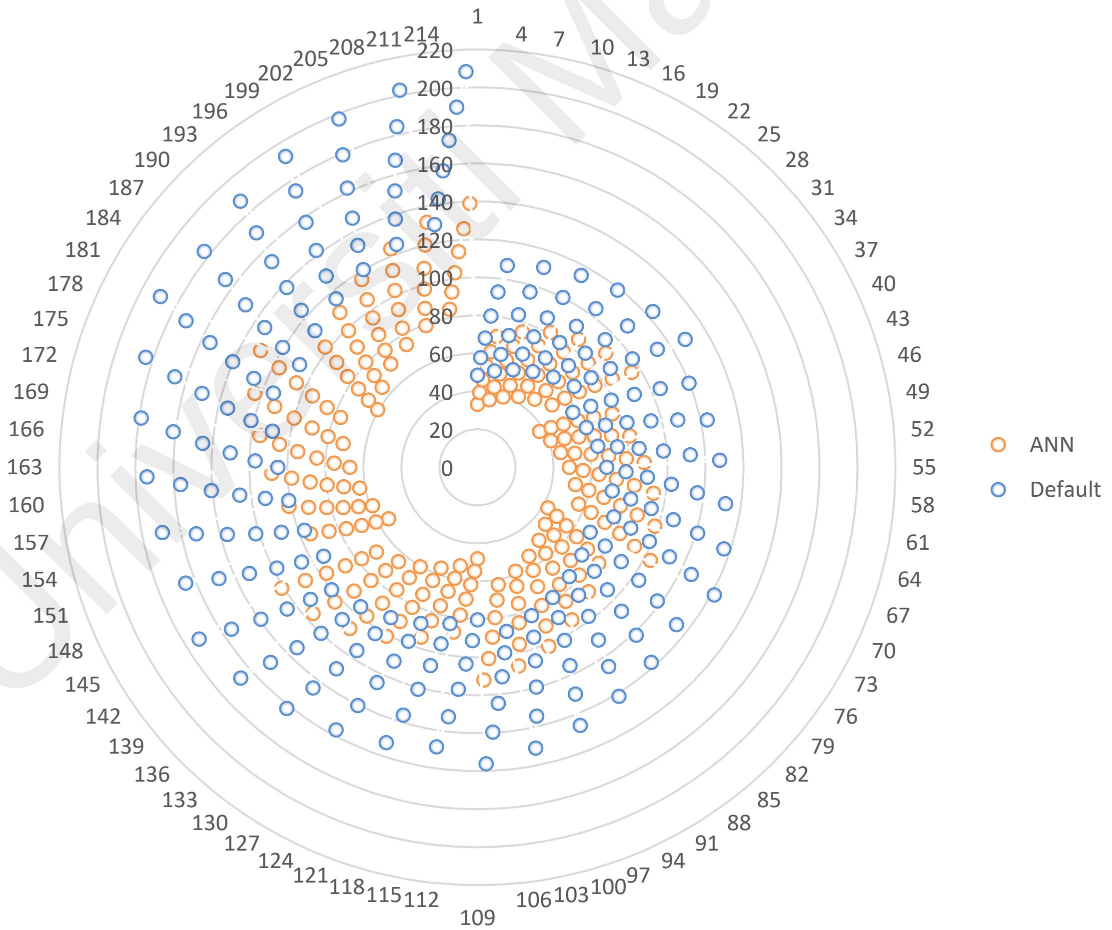


Figure 4.17: Power loss comparison for IEEE 33-bus network before and after reconfiguration using proposed ANN technique

4.3.3.3 Impact of proposed ANN technique on voltage profile

Figure 4.18 shows the voltage profile for default and optimal configurations for all load patterns the using proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding minimum bus voltage. It can be noticed that the minimum buses voltage magnitude has improved compared to the default case, while the overall voltage profile increased in all load patterns by an average of 2.37%.

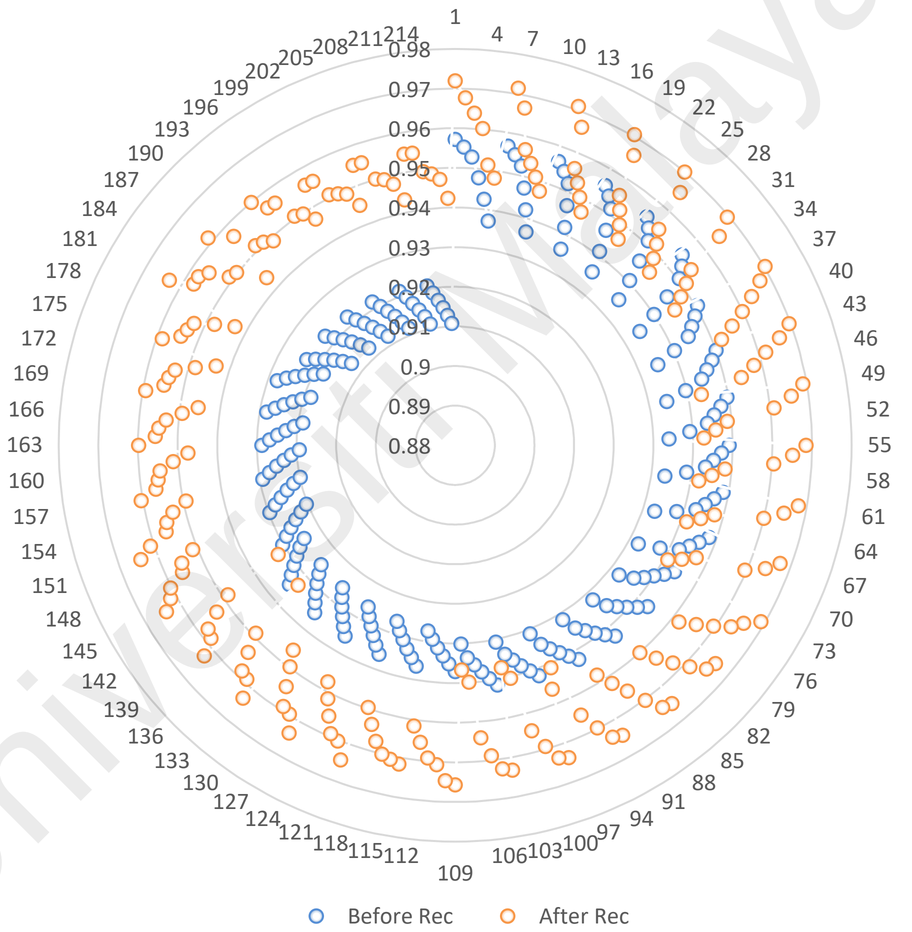


Figure 4.18: Voltage profile for IEEE 33-bus network before and after reconfiguration using proposed ANN technique

4.3.4 Network Reconfiguration Using proposed ANN technique for IEEE 33 Bus System with variable load profile and DG

The 33-bus system with variable load profile and DG shown in Figure 4.14 is used to test the proposed optimal network reconfiguration based on ANN. The total number of different load patterns is 216. From the solution of optimal network reconfiguration for this load pattern, there were 35 distinct configurations as tabulated in Table 4.14. The number for each configuration found is also presented in the same table. Based on this results, five ANNs are used for the training, which are ANN1 to ANN5. The final structure of the training network is determined based on the most accurate results of ANN models outputs. While the structure of each individual ANN's does not change regarding input and output neurons, since the number of load groups are three (R, C and I) and the output of each ANN model is an optimal switch. The number of neurons in the hidden layer is determined during the training of ANN models.

Table 4.14: Optimal unique configuration of all load patterns for IEEE 33-bus network with DG

Optimal configuration number	Tie switches to be opened					Number of occurrences
1	5	8	7	10	12	7
2	7	8	13	10	25	28
3	7	8	14	10	25	1
4	7	8	14	10	27	59
5	7	9	13	26	36	2
6	7	9	13	27	36	11
7	7	9	13	28	36	5
8	7	10	14	26	36	15
9	7	10	14	27	36	9
10	7	10	13	28	36	2
11	7	10	13	27	32	19
12	7	10	13	28	32	6
13	7	10	13	27	36	10
14	7	10	28	32	35	4
15	7	10	12	27	32	13
16	7	10	12	28	32	3
17	6	9	28	32	35	7
18	7	9	27	32	35	11
19	7	11	27	32	35	8
20	6	11	21	28	32	4
21	6	9	27	32	35	8
22	7	9	28	32	35	4
23	6	9	21	27	32	1
24	6	9	21	28	32	1
25	7	11	26	32	35	1
26	7	10	12	26	32	2
27	7	10	13	26	32	4
28	7	10	13	25	32	1
29	7	10	13	25	36	3
30	7	10	13	26	36	7
31	7	10	14	25	36	2
32	7	8	14	10	28	8
33	7	8	14	10	26	1
34	7	8	13	10	27	4
35	7	8	13	10	26	1

4.3.4.1 Performance of Network Reconfiguration based ANN

Tables 4.15 presents the performance of the proposed ANN (70-30%) model. ANN1 and 2 accuracy is 100%, while ANN3, 4 and 5 accuracy are 99.07% which corresponds to 214 optimal solutions out of 216 load patterns. The overall accuracy of the final solution (combination of all ANN models) is 97.22%. Table 4.16 presents the performance of the proposed ANN (70-30%) model. ANN1 and 2 accuracy is 100%, while ANN3 and 5 accuracy are 98.61% which corresponds to 213 optimal solutions out of 216 load patterns. The overall accuracy of the combination of all ANN models is 96.29%. The average accuracy for ANN (70-30%) model and ANN (60-40%) model is 96.76%.

4.3.4.2 Impact of proposed ANN technique on power loss

Figure 4.19 shows the power loss before and after configuration for all 216 load patterns using the proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding power loss. The average power loss reduction for all cases is 40.27%.

Table 4.15: ANN (70-30%) model performance for IEEE 33-bus network with DG

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN1	3-3-1	100%	1.4e-15	151	151	-	65	65	-	1.5
ANN2	3-5-1	100%	3.6e-04	151	151	-	65	65	-	1.8
ANN3	3-5-1	99.07%	5.3e-05	151	151	-	65	63	2	2.5
ANN4	3-4-1	99.07%	7.5e-05	151	151	-	65	63	2	3
ANN5	3-5-1	99.07%	2.4e-04	151	150	1	65	64	1	1.4
Combined ANN	-	97.22%	-	151	150	1	65	60	5	10.2

Table 4.16: ANN (60-40%) model performance for IEEE 33-bus network with DG

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN1	3-3-1	100%	6.4e-10	151	151	-	65	65	-	1.3
ANN2	3-5-1	100%	1.7e-02	151	151	-	65	65	-	2
ANN3	3-5-1	99.07%	3.2e-02	151	151	-	65	63	2	2.7
ANN4	3-4-1	98.61%	8.3e-03	151	151	-	65	62	3	3.1
ANN5	3-5-1	98.61%	1.6e-04	151	150	1	65	63	2	2.6
Combined ANN	-	96.29%	-	151	150	1	65	58	7	11.7

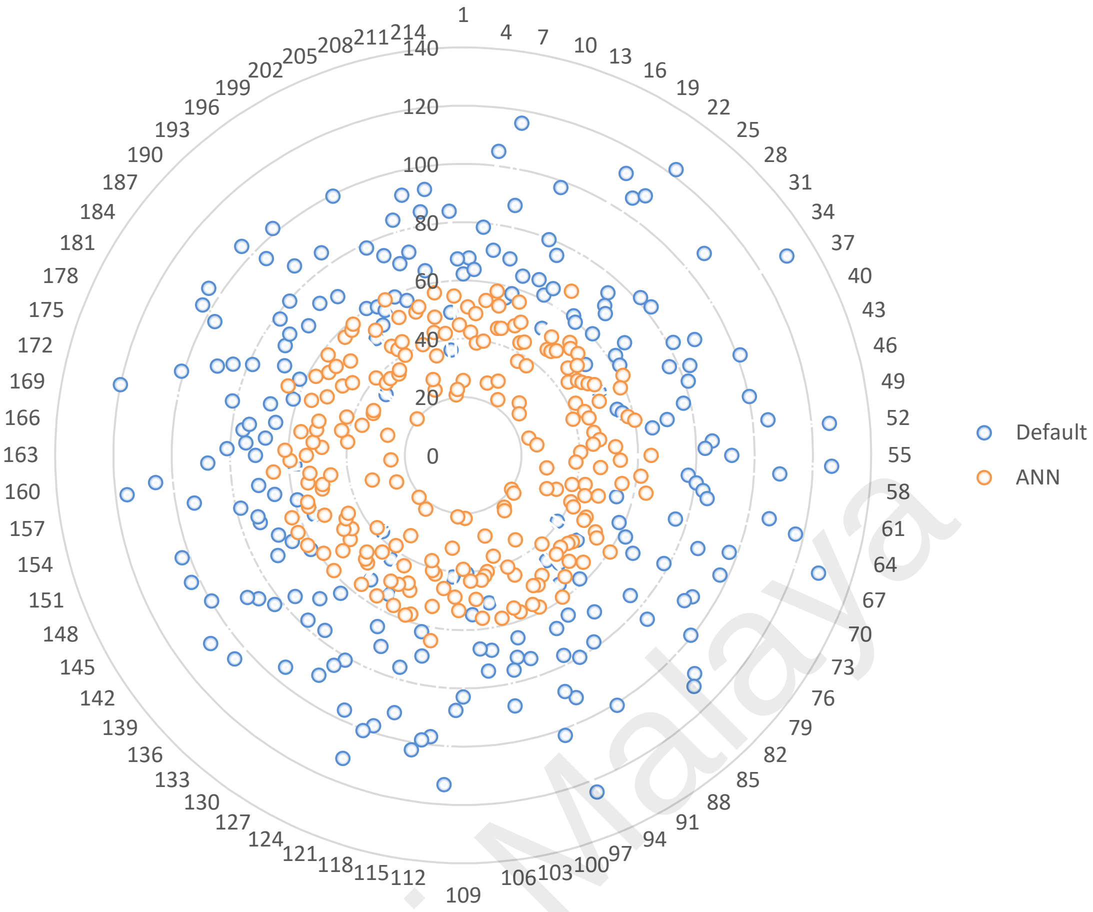


Figure 4.19: Power loss comparison for IEEE 33-bus network before and after reconfiguration using proposed ANN technique

4.3.4.3 Impact of proposed ANN technique on voltage profile

Figure 4.20 shows the voltage profile for default and optimal configurations for all load patterns using the proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding minimum bus voltage. It can be noticed that the minimum buses voltage magnitude has improved compared to the default case, while the overall voltage profile increased in all load patterns by an average of 1.69%.

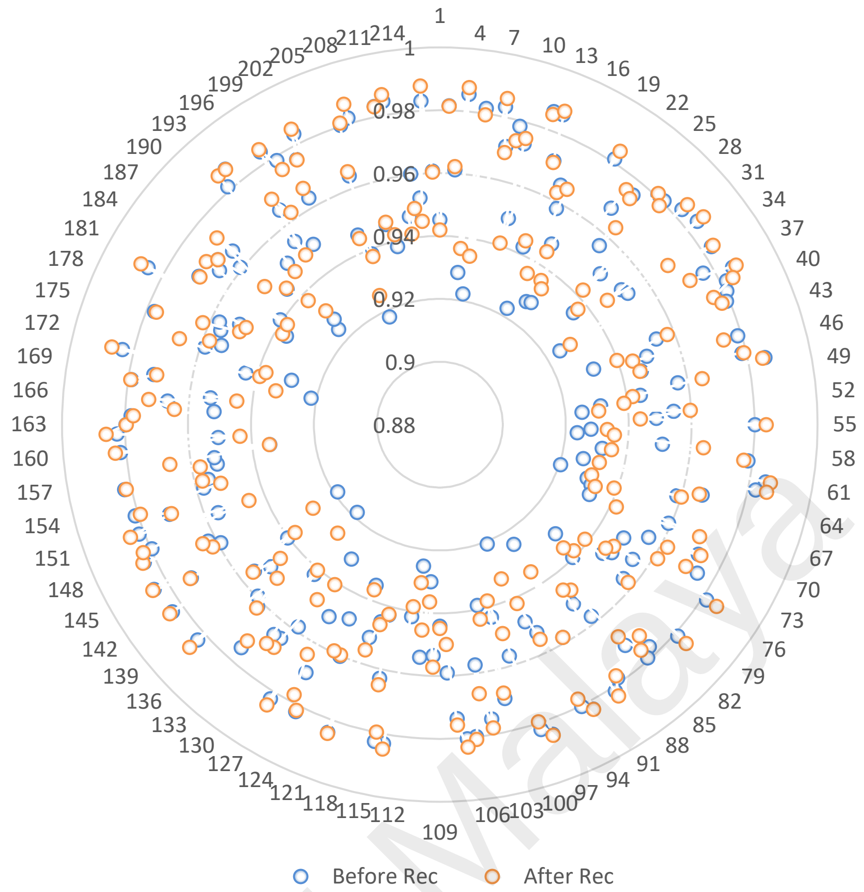


Figure 4.20: Voltage profile for IEEE 33-bus network with DG before and after reconfiguration using proposed ANN technique

4.3.5 Comparative analysis on the performance of proposed ANN technique in Network Reconfiguration for IEEE 33-bus system

To evaluate the performance of the proposed ANN technique, a consistency test was conducted using EP, PSO and proposed ANN technique. The objective of the test is to measure the robustness of the technique to find the optimal answer. First, the proposed ANN technique and other techniques were executed for 20 times to find the optimal configuration for all load patterns (216 case). The result is shown in Figure 4.21, the figure shows the best and worst number of optimal configurations found in the 20 runs by the different techniques for all the cases. Additionally, the figure shows the average number of optimal configurations found for all runs. The proposed ANN technique managed to obtain the optimal configurations for 214 load patterns out of 216 in the best run. The sub-optimal configurations found by the proposed ANN technique for the two load patterns are presented in Table 4.17. Although the solution of ANN different from the optimization solution, only one switch is different from the optimization solution and the power loss differences between two techniques are also small by 0.7%. Meanwhile, the best run for EP over 20 runs achieved 180 optimal configurations out of 216, while PSO achieved 190 optimal configurations. The average number of optimal configurations obtained for all 216 cases for 20 runs is 212 by proposed ANN technique which is 98%, 165 by EP which is 76% and 178 by PSO which is 82%. Figure 4.22 shows power loss comparison between proposed ANN technique, EP and PSO for the best run. The average power loss reduction for all techniques of 33.44%, 32.65% and 33% respectively.

Second, the comparison value for processing time is shown in Table 4.18. All algorithms provide exactly the same optimal configuration and power loss value for default case. However, the computation time to find the optimal configuration to minimize the power loss is 30.47s for EP and 18.65s for PSO. On the other hand, the time for the proposed ANN technique is 0.052s execution time (not including training), which is very fast compared to both meta-heuristic methods.

Table 4.17: Comparison between optimal configuration and ANN alternative configuration response for IEEE 33-bus network

Load Pattern	Optimal switches	Power Loss	ANN Response	Power Loss
42	7, 9, 14, 32, 28	75.737	7, 9, 14, 31, 28	76.289
195	7, 9, 14, 36, 28	86.971	7, 9, 14, 32, 28	87.083

Table 4.18: Statistical analysis for processing time for network reconfiguration for IEEE 33-bus network

	Tie switches opened	Power Loss (kW)	Loss Reduction %	Vmin (p.u)	Processing Time (s)
EP	7, 9, 14, 32, 37	138.928	33.35	0.9423	30.47
PSO	7, 9, 14, 32, 37	138.928	33.35	0.9423	18.65
Proposed ANN	7, 9, 14, 32, 37	138.928	33.35	0.9423	**0.052**

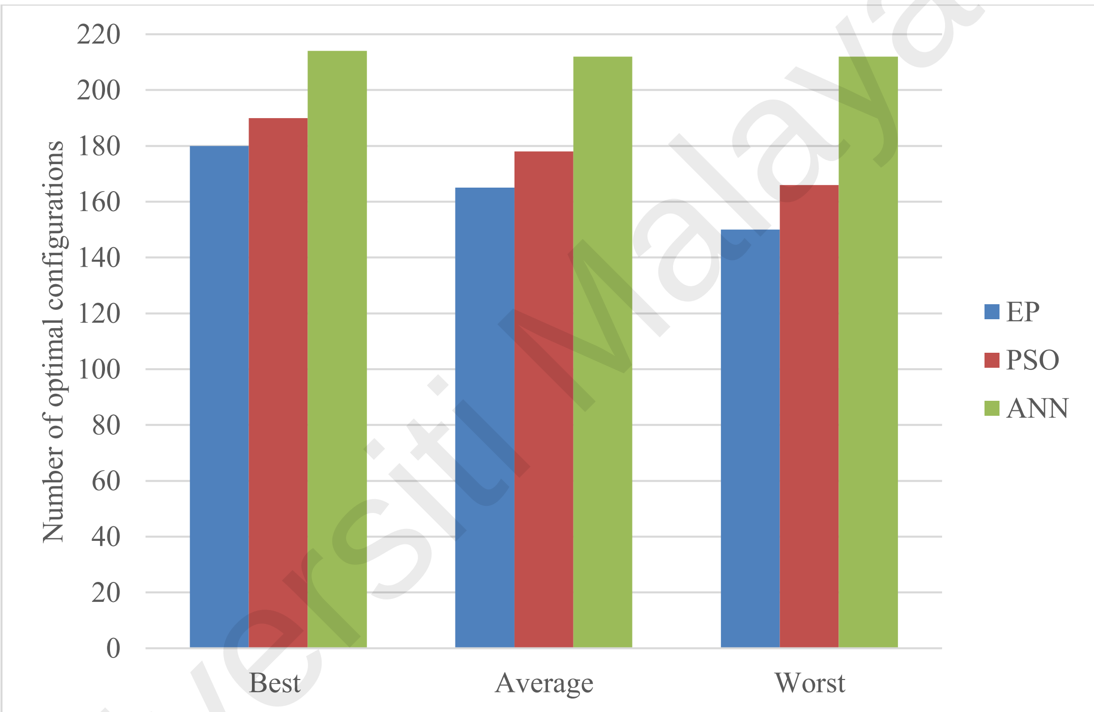


Figure 4.21: consistency performance comparison between EP, PSO and proposed ANN for all load patterns in IEEE 33-bus network

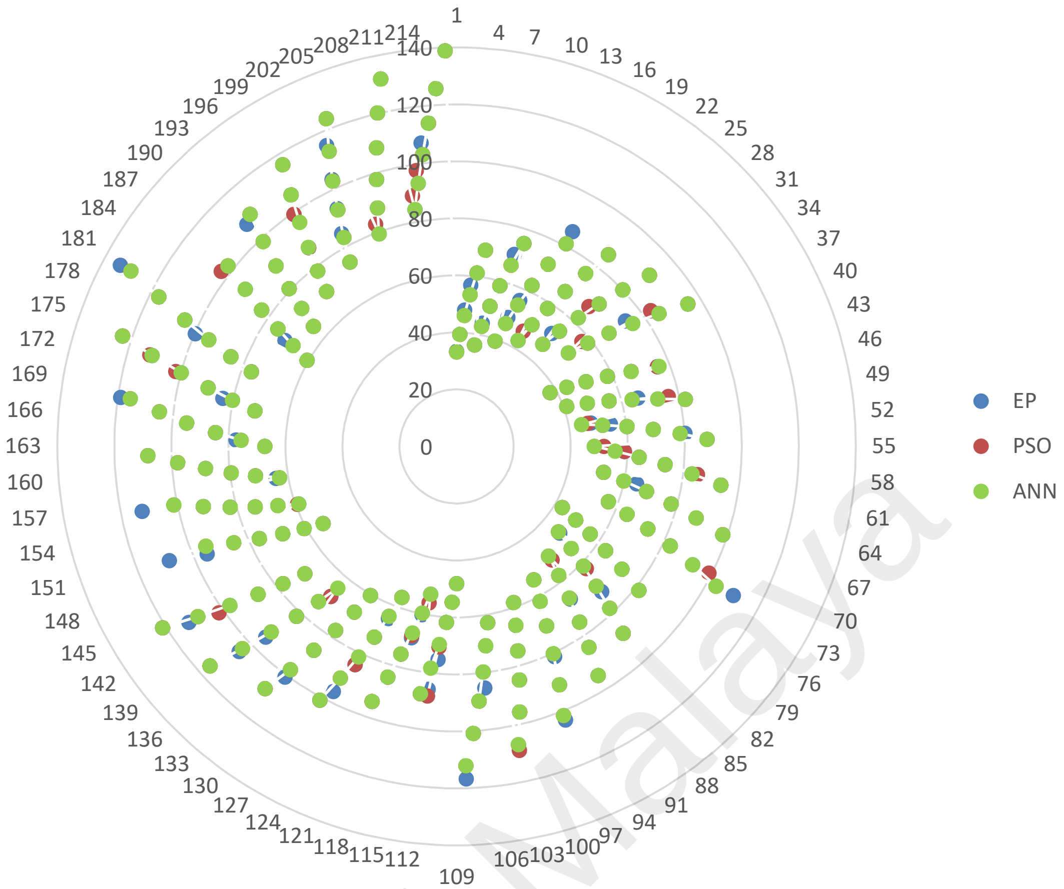


Figure 4.22: Power loss comparison between EP, PSO and proposed ANN for all load patterns in IEEE 33-bus network

Furthermore, to verify the proposed ANN technique, a comparison with other published works is also conducted, as shown in Table 4.19. The optimal configurations obtained from references that used Harmony Search Algorithm (HAS) (Rao et al., 2012), Discrete Evolutionary (DEP) (Muhammad et al., 2018), Cuckoo Search Algorithm(CSA) (Nguyen & Truong, 2015) and Fireworks Algorithm (FWA) (Imran et al., 2014) were re-evaluated at 100% loading to determine the power loss using the same load flow program. The results are presented in Table 4.16. The proposed ANN technique obtained the optimal solutions as in other references except Ref (Imran et al., 2014), which higher than others. The optimal configuration is 7, 9, 14, 32, 37, which results in 33.35% power loss reduction.

Table 4.19: Comparison of simulation results for IEEE 33-bus network

Method	Tie switches opened	Power Loss (kW)	Loss Reduction %	Vmin (p.u)
Initial configuration	33, 34, 35, 36, 37	208.459	-	0.9108
HSA (Rao et al., 2012)	7, 9, 14, 32, 37	138.928	33.35	0.9423
DEP (Muhammad et al., 2018)	7, 9, 14, 32, 37	138.928	33.35	0.9423
CSA (Nguyen & Truong, 2015)	7, 9, 14, 32, 37	138.928	33.35	0.9423
RRA (Nguyen et al., 2017)	7, 9, 14, 32, 37	138.928	33.35	0. 9423
FWA (Imran et al., 2014)	7, 9, 14, 28, 32	139.98	32.85	0.9413
RGA (Zhu, 2002)	7,9,14,32,33	139.532	33.07	0.9378
EP	7, 9, 14, 32, 37	138.928	33.35	0.9423
PSO	7, 9, 14, 32, 37	138.928	33.35	0.9423
Proposed ANN	7, 9, 14, 32, 37	138.928	33.35	0.9423

4.4 Test system 3: IEEE 69-bus

An IEEE 69-bus distribution system consists of 73 switches where, 68 switches are sectionalizing switches and 5 tie switches. The default configuration of the network is 17, 22, 25, 58 and 37 as opened switches, while other switches are closed, as shown in Figure 4.23. The system voltage is 12.66 kV, while the total real and reactive power loads are 3.8 MW and 2.7 MVAR, respectively. The power loss of the default operating condition is 224.975 kW and the lowest bus voltage is 0.9092 p.u.

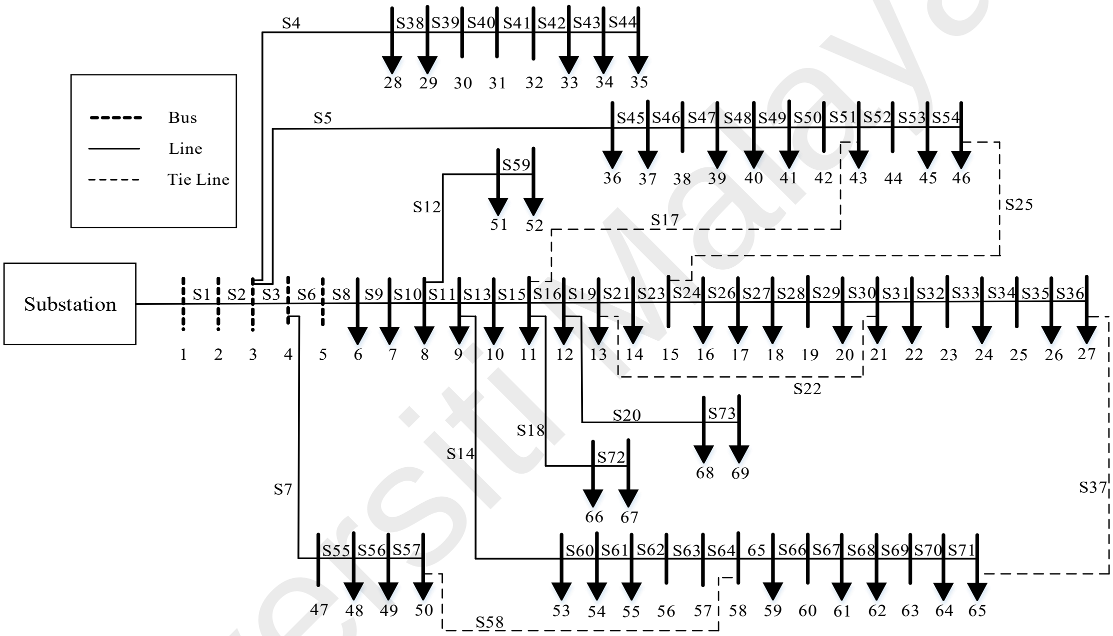


Figure 4.23: IEEE 69-bus distribution network

4.4.1 Network Reconfiguration Using Meta-heuristics techniques for IEEE 69 Bus System

This section presents the implementation of meta-heuristic techniques in distribution network reconfiguration problem. It focuses on power loss reduction and voltage profile improvement.

4.4.1.1 Impact on Power Loss

The results obtained using EP and PSO are summarized in Table 4.20 and compared with the default case (before reconfiguration). Newton-Raphson load flow (NRLF) algorithm is used to calculate the power loss in this work. The optimal objective function, F, according to equation (3.1) is 0.436, which is obtained by both EP and PSO. The power loss before configuration is 224.975 kW obtained by (NRLF) and after configuration the power loss decreased to 98.161 kW which is 55.37% reduction. The optimal switches to be opened are 17, 22, 23, 63, 68. The processing time taken by EP is 49.012 s, while PSO had faster processing time of 11.901 s.

4.4.1.2 Impact on Voltage Profile

Figure 4.24 shows the voltage profile for default and optimal configurations using EP and PSO for different percentage loading profile of Residential (R), Commercial (C) and Industry (I). It can be noticed that the buses voltage magnitude has improved compared to the default case in all algorithms. For example, before reconfiguration the lowest voltage magnitude was at bus 65 with 0.9092 p.u. However, after reconfiguration the voltage increased to 0.953 p.u. EP and PSO reported the same voltage profile.

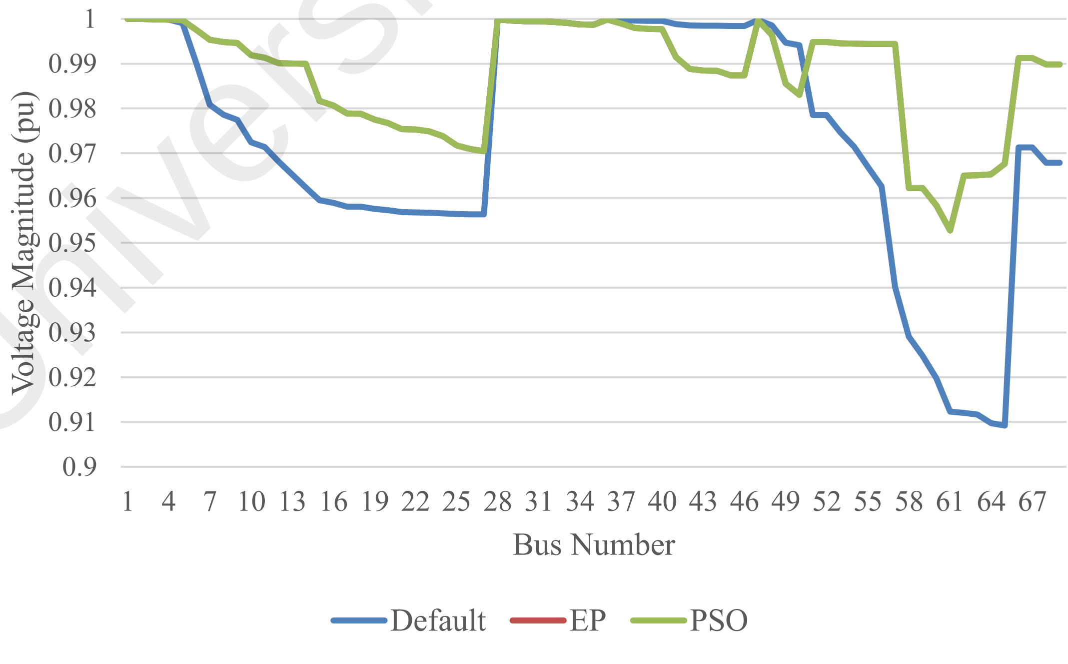


Figure 4.24: Voltage profile for IEEE 69-bus network using different algorithms

Table 4.20: Network reconfiguration results for IEEE 69-bus network

Case	Open switches	Bus voltage Min – Max	Objective function $\min F = P_{loss}^{R}$	Power loss (kW)	Loss reduction (%)	Processing time (s)
Initial	17, 22, 25, 58, 37	0.90929 (65) – 1(1)	1	224.975	-	1.0629
EP	17, 22, 23, 63, 68	0.9528(61) – 1(1)	0.436	98.161	56.37	49.012
PSO	17, 22, 23, 63, 68	0.9528(61) – 1(1)	0.436	98.161	56.37	11.901

4.4.2 Network reconfiguration Using Meta-heuristics for IEEE 69 Bus System with variable load profile and DG

The 69-bus distribution system with variable load profile and DG is shown in Figure 4.25. The system is divided into three load groups (residential, commercial, industrial), each load group has 6 operating levels from 50% to 100% of peak demand, which results in 216 different load patterns. Three DGs were installed in the system where the location of the installed DGs units are at buses 61, 62 and 65. These DGs are made up of Photo-voltaic (PV) system. The DGs output profile is shown in Figure 4.15. Optimal network reconfiguration based on EP and PSO were implemented on the test system. Table 4.21 shows the optimal network reconfiguration for 20 different load patterns. As shown in the table the power loss after reconfiguration is lower than default case. For example, at load percentage of 100% R, 50% C and 70% I, the default configuration gives 123.25 kW. While the optimal configuration for this load pattern is 17, 22, 23, 65 and 68 with power loss of 56.21 kW which is equal to 44.03% power reduction.

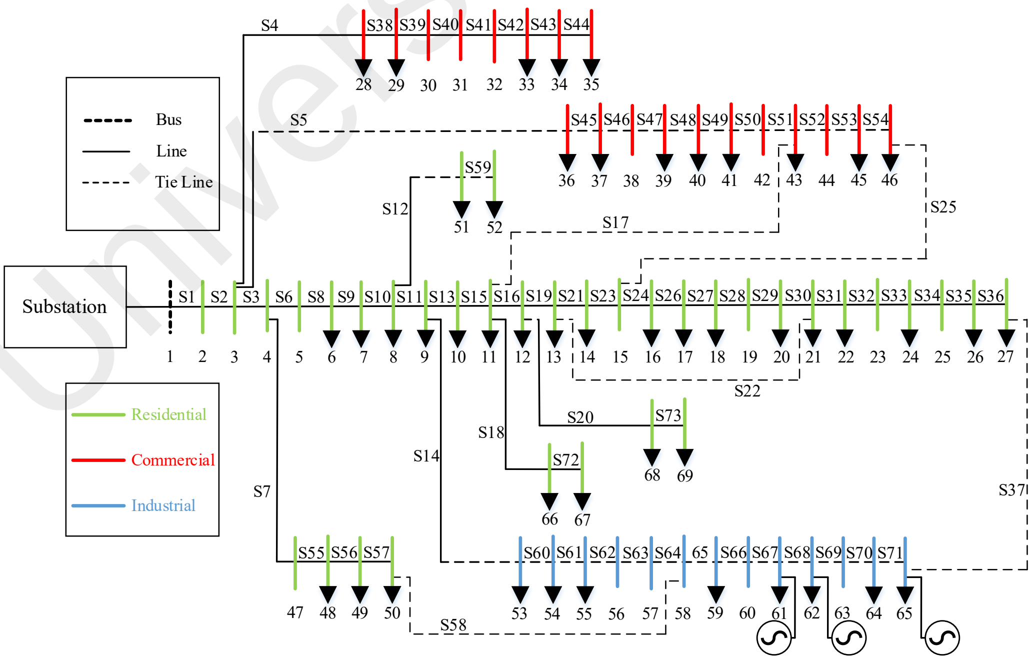


Figure 4.25: IEEE 69-bus distribution network with different load groups and DGs

Table 4.21: Optimal Configuration for different load profile using EP & PSO for IEEE 69-bus network

<table>
<tr><th colspan="3">Operating Percentage %</th><th rowspan="2">Default</th><th rowspan="2">Optimal</th><th rowspan="2">Before configuration</th><th colspan="2">After configuration</th><th rowspan="2">Loss Reduction %</th></tr>
<tr><th>R</th><th>C</th><th>I</th><th>EP</th><th>PSO</th></tr>
<tr><td>50</td><td>80</td><td>70</td><td rowspan="20">17, 22, 25, 58, 37</td><td>17, 22, 23, 62, 68</td><td>94.51</td><td colspan="2">41.80</td><td>26.23</td></tr>
<tr><td>50</td><td>90</td><td>80</td><td>17, 22, 23, 62, 68</td><td>121.95</td><td colspan="2">53.09</td><td>25.56</td></tr>
<tr><td>50</td><td>90</td><td>90</td><td>17, 22, 23, 63, 68</td><td>153.66</td><td colspan="2">65.78</td><td>26.19</td></tr>
<tr><td>50</td><td>100</td><td>70</td><td>17, 22, 23, 62, 68</td><td>94.58</td><td colspan="2">42.06</td><td>23.55</td></tr>
<tr><td>60</td><td>80</td><td>90</td><td>17, 22, 23, 64, 68</td><td>159.20</td><td colspan="2">68.54</td><td>28.68</td></tr>
<tr><td>70</td><td>70</td><td>50</td><td>17, 22, 23, 65, 68</td><td>60.23</td><td colspan="2">28.28</td><td>33.32</td></tr>
<tr><td>70</td><td>90</td><td>70</td><td>17, 22, 23, 65, 68</td><td>104.58</td><td colspan="2">47.22</td><td>29.61</td></tr>
<tr><td>80</td><td>60</td><td>50</td><td>17, 22, 23, 65, 68</td><td>65.22</td><td colspan="2">30.75</td><td>37.11</td></tr>
<tr><td>80</td><td>90</td><td>70</td><td>17, 22, 23, 62, 68</td><td>110.34</td><td colspan="2">50.21</td><td>31.82</td></tr>
<tr><td>90</td><td>70</td><td>50</td><td>17, 22, 23, 65, 68</td><td>70.75</td><td colspan="2">33.71</td><td>37.53</td></tr>
<tr><td>90</td><td>70</td><td>100</td><td>17, 22, 23, 63, 68</td><td>216.85</td><td colspan="2">93.51</td><td>37.74</td></tr>
<tr><td>90</td><td>100</td><td>60</td><td>17, 22, 23, 63, 68</td><td>91.78</td><td colspan="2">43.15</td><td>32.72</td></tr>
<tr><td>100</td><td>50</td><td>70</td><td>17, 22, 23, 65, 68</td><td>123.25</td><td colspan="2">56.21</td><td>44.03</td></tr>
<tr><td>100</td><td>60</td><td>80</td><td>17, 22, 23, 63, 68</td><td>152.65</td><td colspan="2">68.49</td><td>41.49</td></tr>
<tr><td>100</td><td>70</td><td>70</td><td>17, 22, 23, 62, 68</td><td>123.29</td><td colspan="2">56.54</td><td>38.89</td></tr>
<tr><td>100</td><td>70</td><td>80</td><td>17, 22, 23, 62, 68</td><td>152.67</td><td colspan="2">68.66</td><td>39.07</td></tr>
<tr><td>100</td><td>80</td><td>50</td><td>17, 22, 23, 64, 68</td><td>76.78</td><td colspan="2">36.92</td><td>37.82</td></tr>
<tr><td>100</td><td>80</td><td>60</td><td>17, 22, 23, 62, 68</td><td>98.90</td><td colspan="2">46.09</td><td>37.29</td></tr>
<tr><td>100</td><td>90</td><td>80</td><td>17, 22, 23, 63, 68</td><td>152.74</td><td colspan="2">69.03</td><td>35.19</td></tr>
<tr><td>100</td><td>100</td><td>90</td><td>17, 22, 23, 62, 68</td><td>186.54</td><td colspan="2">82.90</td><td>33.74</td></tr>
</table>

4.4.3 Network Reconfiguration Using proposed ANN technique for IEEE 69 Bus System with variable load profile

The proposed ANN technique is implemented on the proposed 69-bus distribution system shown in Figure 4.26, where the load is divided into three load groups (residential, commercial, industrial). Each load group has 6 operating levels from 50% to 100% of peak demand, which results in 216 load patterns. From the solution of network reconfigurationfor of 69-bus system, most of the configurations are the same, and can be grouped into four distinct configurations as tabulated in Table 4.22. It can be observed from this table that Switch group 4 is the only changing group with switch numbers 62, 63, 64 and 65, thus only 1 ANN is need for training in this case. The structure of the training network is determined based on the most accurate results of ANN models.While the structure of the ANN model is similar to pervious system in the input and output layers, the number of neurons in the hidden layer is different.

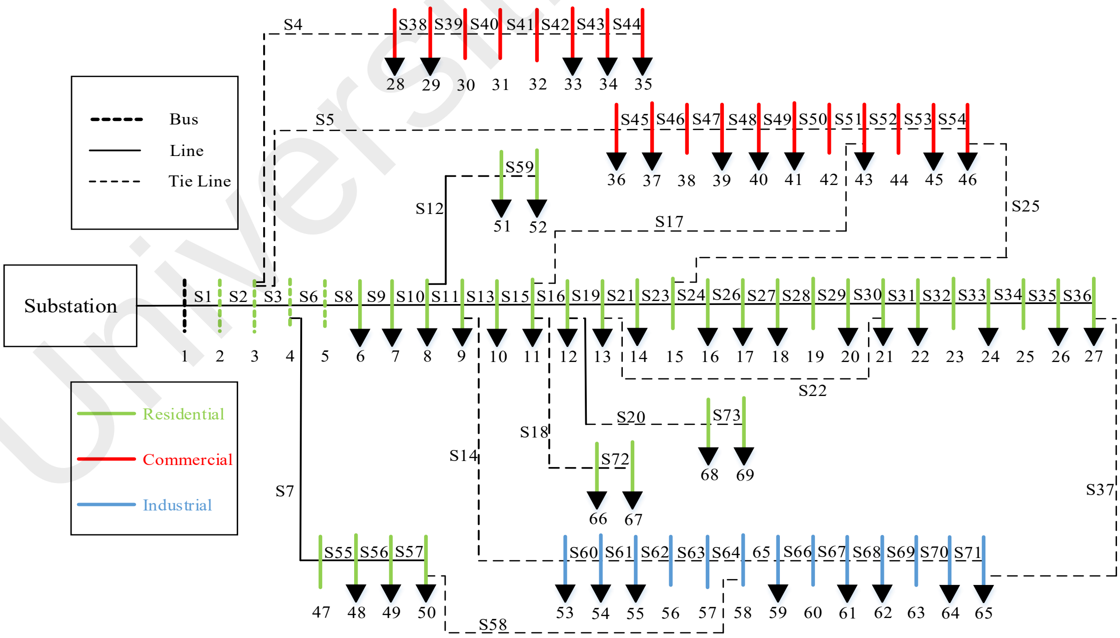


Figure 4.26: IEEE 69-bus distribution network with different load groups

Table 4.22: Optimal unique configuration of all load patterns for IEEE 69-bus network

Optimal configuration number	Tie switches to be opened	Number of occurrences for this optimal configuration
1	S17, S22, S23, S62, S68	53
2	S17, S22, S23, S63, S68	48
3	S17, S22, S23, S64, S68	53
4	S17, S22, S23, S65, S68	62

4.4.3.1 Performance of Network Reconfiguration based on ANN

The performance of both ANN training models is shown in Tables 4.23 and 4.24, the tables show the structure, accuracy, MSE, training and testing results for each ANN. while, the structure of ANN's is similar regarding input and output neurons, which corresponds to the number of load groups and the tie switch, respectively. The number of neurons in hidden layer is 4 for both models ANN4. Additionally, the tables show the accuracy (absolute error) of each ANN model. The models (ANN4) achieved 100% accuracy which corresponds to 216 optimal solutions for switch group 4 out of 216 load patterns. The overall accuracy of combined ANN models is 100%.

Table 4.23: ANN (70-30%) model performance for IEEE 69-bus network

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN4	3-4-1	100%	7.3e-09	151	151	-	65	65	0	2.5

Table 4.24: ANN (60-40%) model performance for IEEE 69-bus network

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN4	3-4-1	100%	6.4e-05	151	151	-	65	65	0	3.7

4.4.3.2 Impact of proposed ANN technique on power loss

Figure 4.27 shows the power loss before and after configuration for all 216 load patterns using the proposed ANN technique. A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding power loss. The average power loss reduction for all cases is 55.20%. as shown in the figure the power loss after reconfiguration using ANN is lower than before reconfiguration (default). For example, the power loss in 100% loading is 224.975 kW, with switches 17, 22, 25, 58 and 37open. However, proposed ANN technique response is that switches 17, 22, 23, 63 and 68 are opened, with power loss of 98.161 kW.

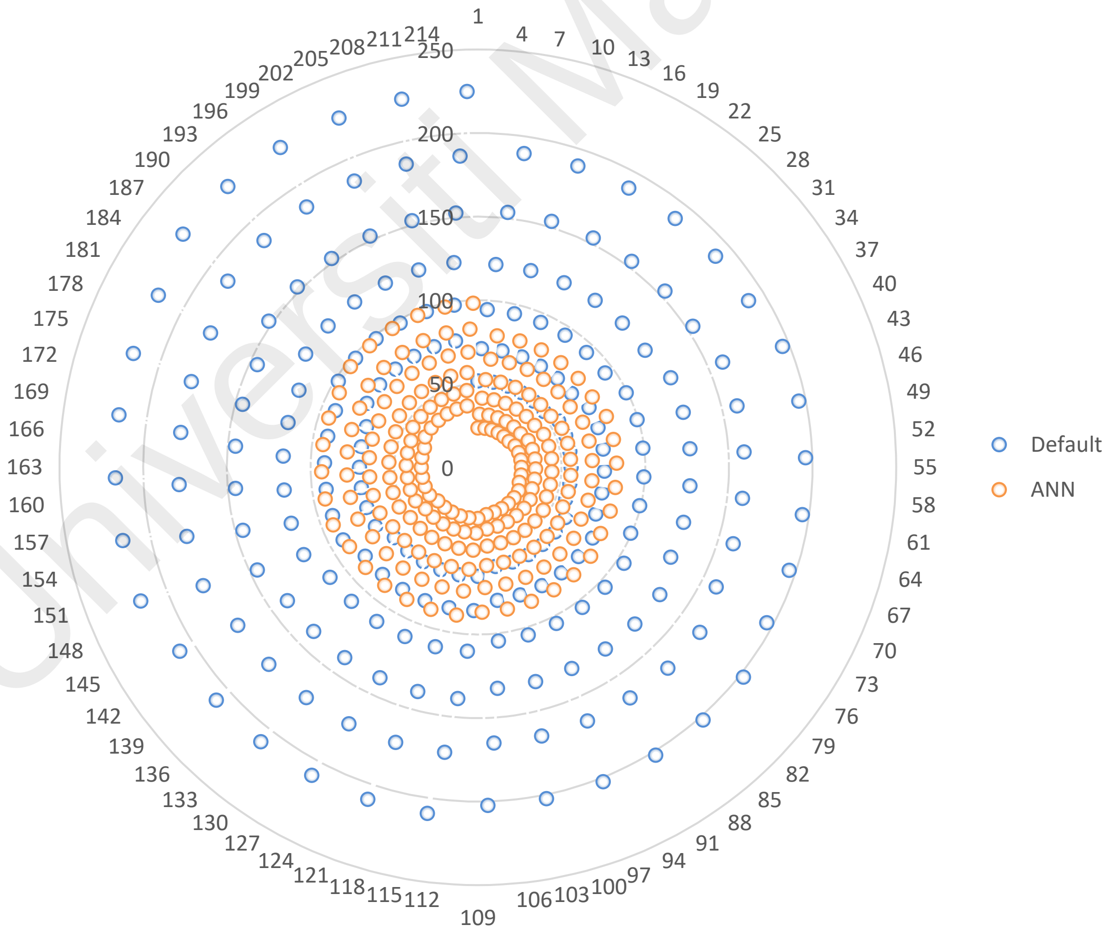


Figure 4.27: Power loss comparison for IEEE 69-bus network before and after reconfiguration using proposed ANN technique

4.4.3.3 Impact of proposed ANN technique on voltage profile

Figure 4.28 shows the voltage profile for default and optimal configurations for all load patterns the using proposed ANN technique. . A spider web graph is used due to the large number of load patterns. the outer circle numbers represent the load patterns, while the vertical axe represents the corresponding minimum bus voltage. It can be noticed that the minimum buses voltage magnitude has improved compared to the default case, while the overall voltage profile increased in all load patterns by an average of 3.4%.

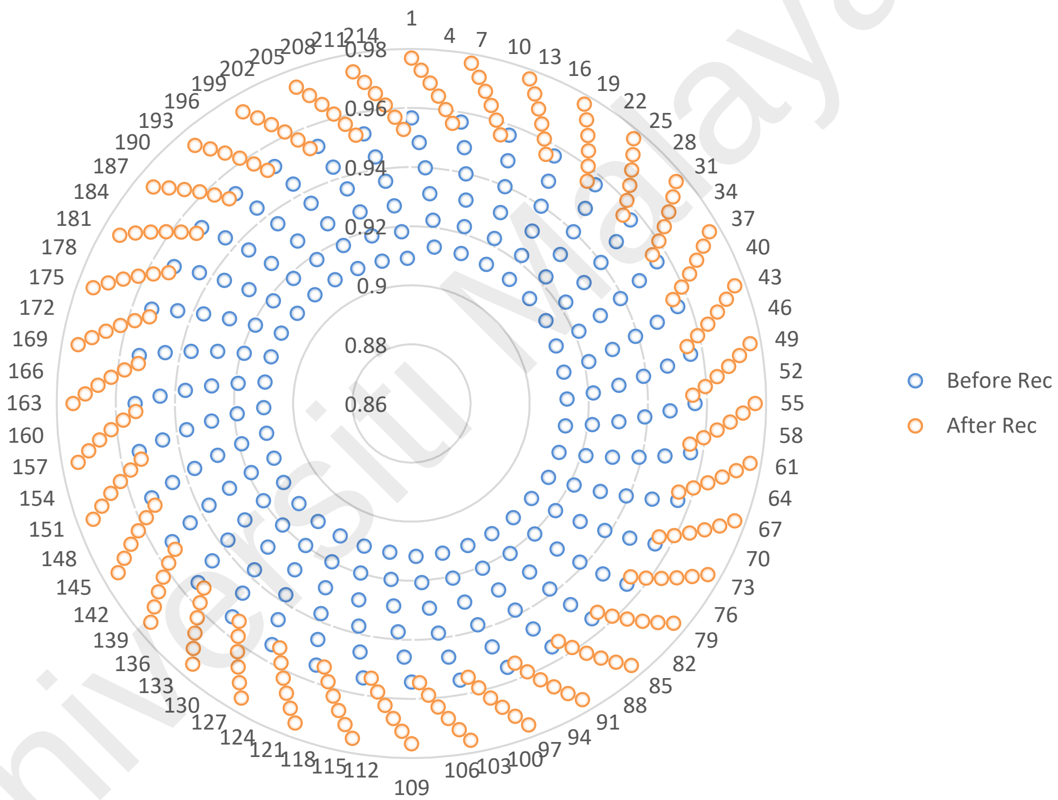


Figure 4.28: Voltage profile for IEEE 69-bus network before and after reconfiguration using proposed ANN technique

4.4.4 Network Reconfiguration Using proposed ANN technique for IEEE 33 Bus System with variable load profile and DG

The 69-bus system with variable load profile and DG shown in Figure 4.25 is used to test the proposed ANN optimal network reconfiguration based. The total number of different load patterns is 216. From the solution of optimal network reconfiguration for this load patterns, there were 29 distinct configurations as tabulated in Table 4.25. The number for each configuration found is also presented in the same table. Based on this results, five ANNs are used for the training which are ANN1 to ANN5. The final structure of the training network is determined based on the most accurate results of ANN models outputs.

Table 4.25: Optimal unique configuration of all load patterns for IEEE 69-bus network with DG

Optimal configuration number	Tie switches to be opened					Number of occurrences
1	17	22	23	63	68	11
2	17	22	23	64	68	18
3	17	22	23	65	68	19
4	17	22	23	62	68	15
5	17	22	23	64	70	18
6	17	22	23	65	70	27
7	17	22	23	63	70	21
8	17	22	23	62	70	17
9	17	19	23	65	70	20
10	17	19	23	62	70	13
11	17	19	23	64	70	17
12	17	19	23	63	70	22
13	15	19	23	65	70	4
14	17	19	21	65	70	3
15	17	19	21	64	70	3
16	16	17	21	63	70	10
17	16	17	21	62	70	12
18	16	17	21	64	70	14
19	16	17	21	65	70	10
20	15	19	23	63	70	3
21	15	16	21	65	70	2
22	15	16	21	62	70	1
23	15	16	21	63	70	2
24	15	16	21	64	70	3
25	15	16	23	65	70	1
26	15	16	23	62	70	1
27	15	19	23	64	70	4
28	17	19	21	62	70	3
29	15	19	23	62	70	1

4.4.4.1 Performance of Network Reconfiguration based ANN

Table 4.26 presents the performance of the ANN (70-30%). ANN1, 4 and 5 have accuracy of 100%, while ANN3 is 99.53% and ANN2 accuracy is 99.07% which corresponds to 214 optimal solutions out of 216 load patterns. The overall accuracy of this model (combination of all ANN models) is 98.15%. Table 4.27 show the performance of ANN (60-40%). similarly, ANN 1 and 5 achieved 100% accuracy as other model. However, ANN 3 and 4 have 99.07% accuracy which corresponds to 214 optimal solutions out of 216 load patterns. The overall accuracy of this model (combination of all ANN models) is 97.69%. The average accuracy of the two ANN (70-30%) and ANN (60-40%) models is 97.29%.

4.4.4.2 Impact of proposed ANN technique on power loss

Figure 4.29 shows the power loss before and after configuration for all 216 load patterns using the proposed ANN technique. As shown in the figure the power loss after reconfiguration is less than before reconfiguration. Additionally, the average power loss reduction for all cases is 37.4%.

4.4.4.3 Impact of proposed ANN technique on voltage profile

Figure 4.30 shows the voltage profile for default and optimal configurations for all load patterns using the proposed ANN technique. The figure shows the minimum bus voltage at each load pattern. It can be noticed that the minimum buses voltage magnitude has improved compared to the default case, while the overall voltage profile increased in all load patterns by an average of 1.35%.

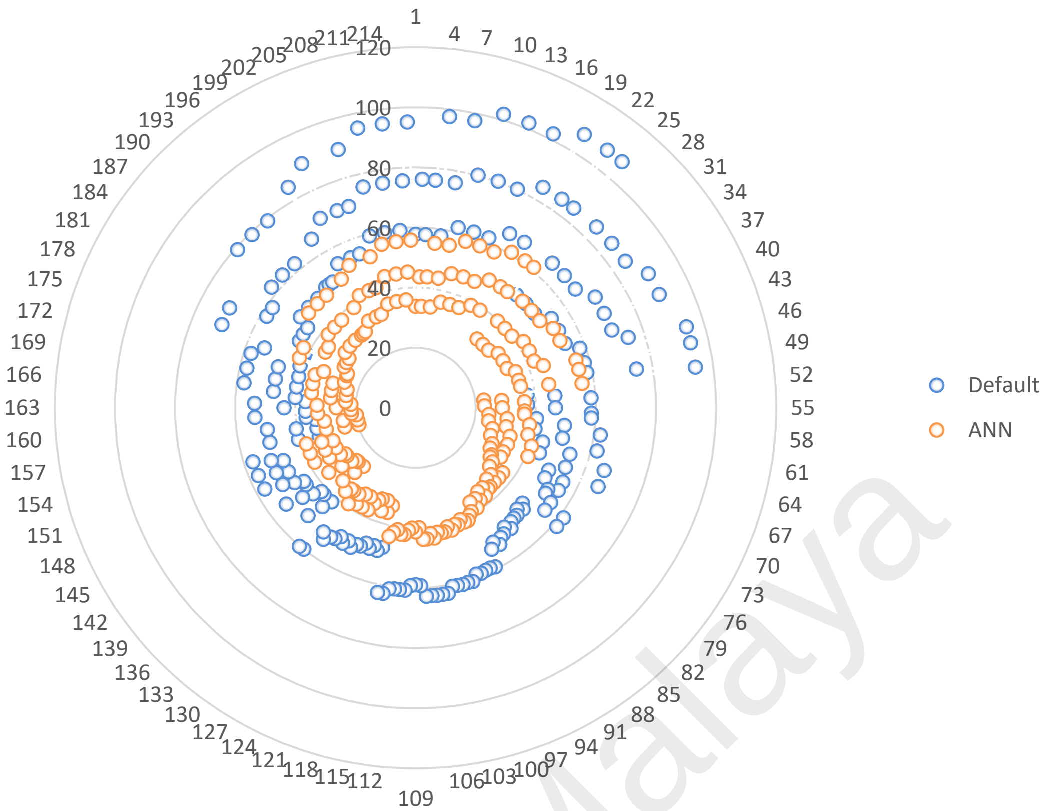


Figure 4.29: Power loss comparison for IEEE 33-bus network before and after reconfiguration using proposed ANN technique

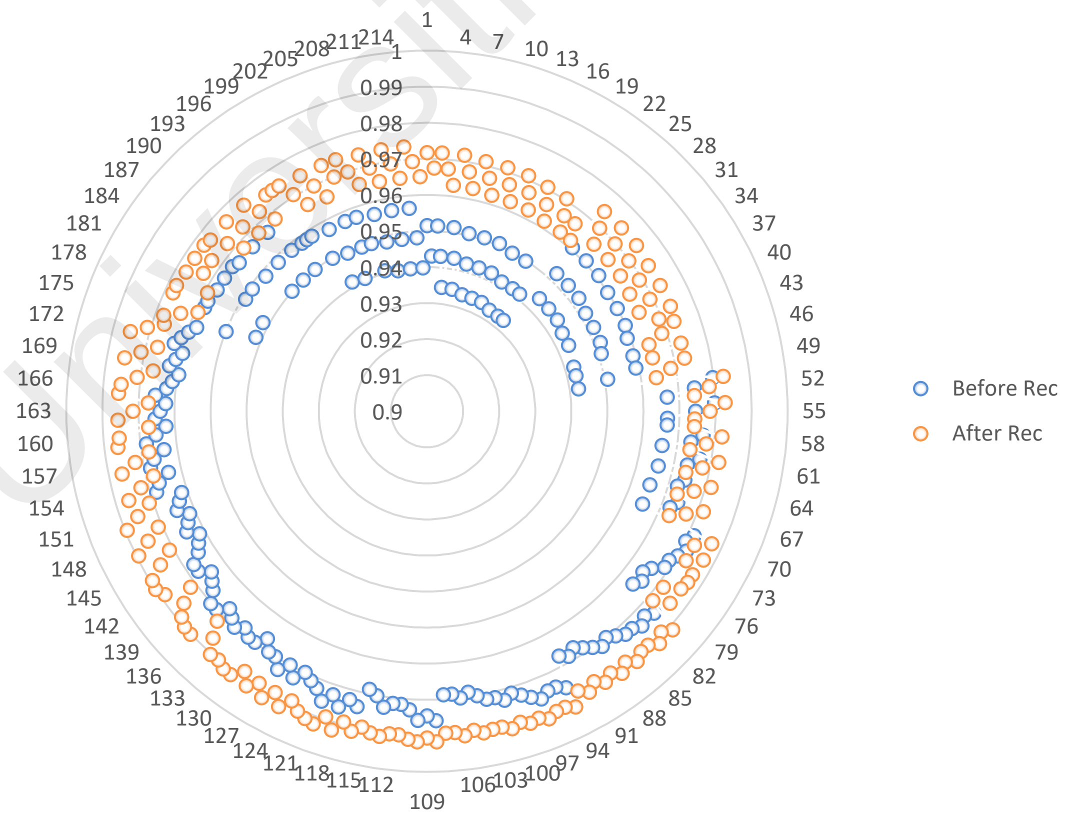


Figure 4.30: Voltage profile for IEEE 33-bus network with DG before and after reconfiguration using proposed ANN technique

Table 4.26: ANN (70-30%) model performance for IEEE 33-bus network with DG

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN1	3-3-1	100%	2.8e-06	151	151	-	65	65	-	1.3
ANN2	3-4-1	99.07%	4.3e-04	151	150	1	65	64	1	1.8
ANN3	3-4-1	99.53%	7.6e-11	151	151	-	65	64	1	2.4
ANN4	3-4-1	100%	1.6e-03	151	151	-	65	65	-	3
ANN5	3-5-1	100%	1.9e-16	151	151	-	65	65	-	0.9
Combined ANN	-	98.15%	-	151	150	1	65	63	2	9.4

Table 4.27: ANN (60-40%) model performance for IEEE 33-bus network with DG

ANN Number	Structure	Accuracy	MSE	Training Results			Testing Results			Time (min)
				cases	Correct	Alternative	cases	Correct	Alternative	
ANN1	3-3-1	100%	5.3e-03	151	151	-	65	65	-	1.1
ANN2	3-4-1	99.53%	7.9e-02	151	151	-	65	64	1	2.1
ANN3	3-4-1	99.07%	1.6e-08	151	151	-	65	63	2	2.8
ANN4	3-4-1	99.07%	2.7e-02	151	151	-	65	63	2	2.9
ANN5	3-5-1	100%	3.7e-09	151	151	-	65	65	-	1
Combined ANN	-	97.69%	-	151	150	-	65	63	5	9.9

4.4.5 Comparative analysis on performance of proposed ANN technique in Network Reconfiguration for IEEE 69-bus system

To evaluate the performance of the proposed ANN technique, a consistency test was conducted using EP, PSO and proposed ANN technique. The objective of the test is to measure the robustness of the technique to find the optimal answer. First, the proposed ANN technique and other techniques were executed for 20 times to find the optimal configuration for all load patterns (216 case). The result is shown in Figure 4.31, the figure shows the best and worst number of optimal configurations found in the 20 runs by the different techniques for all the cases. Additionally, the figure shows the average number of optimal configurations found for all runs. The proposed ANN technique managed to obtain the optimal configurations for all load patterns in the best run. Meanwhile, the best run for EP over 20 runs achieved 176 optimal configurations out of 216, while PSO achieved 186 optimal configurations. The average number of optimal configurations obtained for all 216 cases for 20 runs is 212 by proposed ANN technique which is 98%, 164 by EP which is 76% and 179 by PSO which is 83%. Figure 4.32 shows power loss comparison between proposed ANN technique, EP and PSO for the best run. The average power loss reduction for all techniques of 55.20%, 31.85% and 32.6% respectively.

Second, the comparison value for processing time is shown in Table 4.28. All algorithms provide exactly the same optimal configuration and power loss value for default case. However, the computation time to find the optimal configuration to minimize the power loss is 26.47s for EP and 21.34s for PSO. On the other hand, the time for the proposed ANN technique is 0.054s, which more computationally effective compared to both meta-heuristic methods.

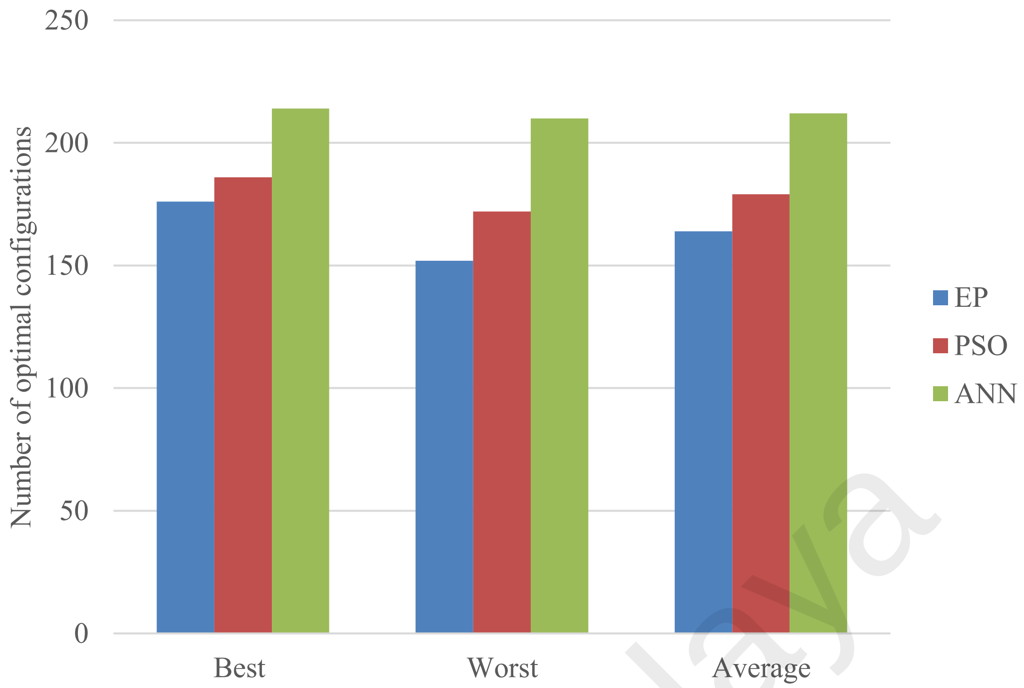


Figure 4.31: consistency performance comparison between EP, PSO and proposed ANN for all load patterns in IEEE 69-bus network

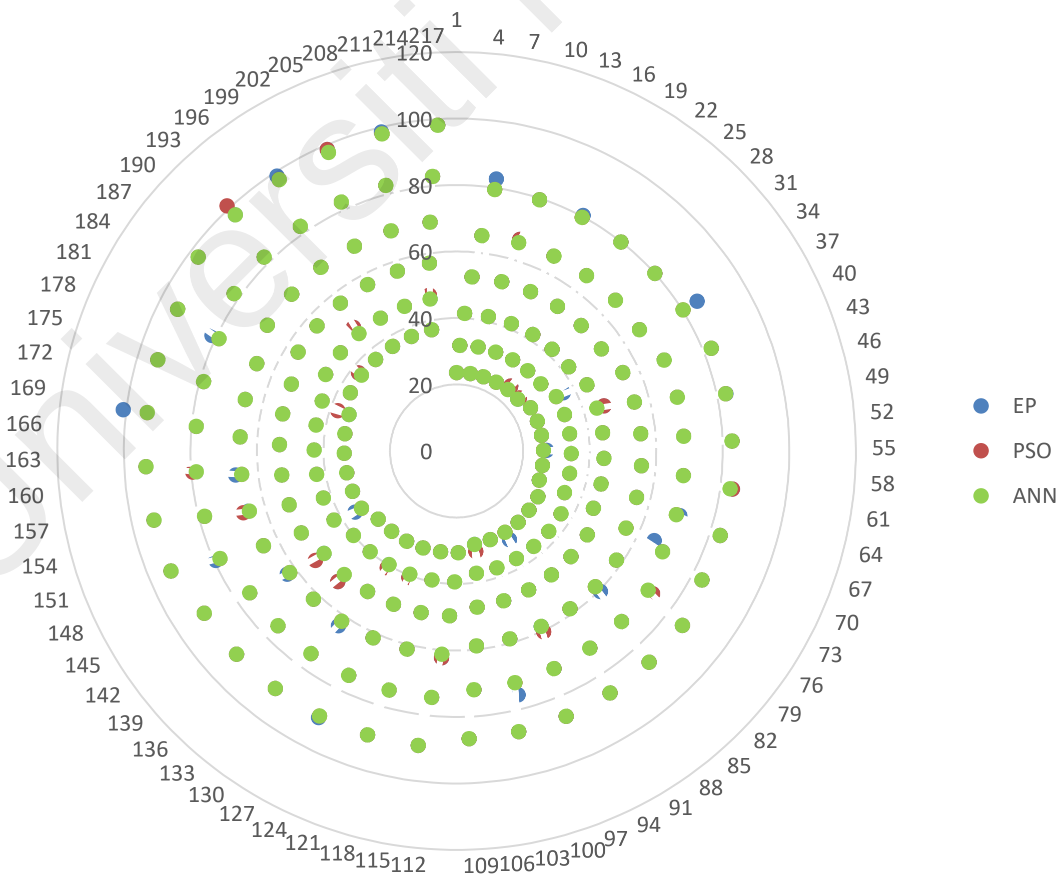


Figure 4.32: Power loss comparison between EP, PSO and proposed ANN for all load patterns in IEEE 69-bus network

Table 4.28: Statistical analysis for processing time for network reconfiguration for IEEE 69-bus network

	Tie switches opened	Power Loss (kW)	Loss Reduction %	Vmin (p.u)	Processing Time (s)
EP	17, 22, 23, 62, 68	98.16117	56.37	0.9528	26.475
PSO	17, 22, 23, 62, 68	98.16117	56.37	0.9528	21.338
Proposed ANN	17, 22, 23, 62, 68	98.16117	56.37	0.9528	**0.054**

Furthermore, to verify the proposed ANN technique, a comparison with other published works is conducted in Table 4.29. The optimal configurations obtained from Fast Non-dominated Sorting Genetic Algorithm (FNSGA), Cuckoo Search Algorithm (CSA), Discrete Artificial Bee Colony (DABC), and Fireworks Algorithm (FWA) at base case of 100% loading is presented. The power loss for all techniques is almost similar with value around 98.161 kW. The proposed method presents similar results as other optimization techniques.

Table 4.29: Comparison of simulation results for IEEE 69-bus network

Method	Tie switches opened	Power Loss (kW)	Loss Reduction %	Vmin (p.u)
Initial configuration	17, 22, 25, 58, 37	224.975	-	0.90929
FNSGA (Eldurssi & O'Connell, 2014)	15, 19, 23, 63, 69	99.35	55.85	0.9428
CSA (Nguyen & Truong, 2015)	16, 19, 23, 63, 70	98.59	55.73	0.9495
FWA (Imran et al., 2014)	16, 19, 23, 63, 70	98.59	55.73	0.9495
DABC (Aman, Jasmon, Bakar, & Mokhlis, 2014)	15, 16, 23, 63, 70	100.28	55.42	0.9428
EP	15, 22, 23, 63, 68	98.161	56.37	0.9528
PSO	17, 22, 23, 63, 68	98.161	56.37	0.9528
Proposed ANN	17, 22, 23, 63, 68	98.161	56.37	0.9528

CHAPTER 5: CONCLUSION

5.1 Conclusion

In this work, an ANN technique has been successfully proposed for optimal network reconfiguration considering variable load and DG profiles. The proposed network reconfiguration based on ANN was verified using an IEEE 16, IEEE 33 and 69 bus test systems. The results were compared to other published results from literature.

The proposed ANN technique performs equally well as other techniques, with regards to the power loss reduction and voltage profile improvement. The results reported high power loss reduction of 8.87%, 27.4% and 56.37% for 16, 33 and 69 test systems, respectively. While the minimum value of buses voltage was 0.972 p.u, 0.9423 p.u and 0.9528 p.u for 16, 33 and 69 test systems, respectively. On the other hand, the proposed ANN technique outperforms other techniques in consistency of giving optimal solutions. The results reported that the consistency of proposed method is 100% for 16 bus system, while other methods reported 93.5% and 96.8% for EP and PSO, respectively. Additionally, the consistency for 33 bus system was 99.06% for the proposed ANN technique, while other methods reported a maximum consistency of 87.9% in PSO. Moreover, the execution time for proposed ANN method is very efficient, with 0.050s, 0.052 and 0.054 for 16, 33 and 69 test systems to find the optimal solution for default case compared to other methods.

The reported results verified that proposed method ANN technique achieved high accuracy to obtain optimal configurations. The accuracy for ANN model for 16, 33 and 69 test systems are 100%, 99.07% and 100% respectively. The number of neurons used for each ANN model is small as compared to previous works. However, it is sufficient to achieve a good learning and accurate predicting ANN model. The number of neurons used for 33 test system is 3 and 4 neurons for ANN4 and ANN5, respectively. In 69 test system, one ANN model was used in the training with 4 neurons.

5.2 Future Work

The proposed network reconfiguration based on Artificial Neural Network can be further improved. Possible future works include:

1) Further studies need to be carried regarding the protection equipment in the distribution systems. Since the electrical flow of the network is modified during network reconfiguration.
2) Further analysis can be explored on larger distribution system, such as 118-bus, 137-bus and 205-bus for NR based ANN. Furthermore, work can be done on incorporating battery storage devices and electric vehicles.
3) Further studies need to be carried on minimizing the total investment on the distribution systems, such as minimizing the energy cost, minimizing new branches construction cost and protection devices cost.

REFERENCES

Abdelaziz, A. Y., Osama, R. A., Elkhodary, S. M., & El-Saadany, E. (2012). *Reconfiguration of distribution systems with distributed generators using ant colony optimization and harmony search algorithms.* Paper presented at the 2012 IEEE Power and Energy Society General Meeting.

Abdelaziz, M. (2017). Distribution network reconfiguration using a genetic algorithm with varying population size. *Electric Power Systems Research, 142*, 9-11.

Abdmouleh, Z., Gastli, A., Ben-Brahim, L., Haouari, M., & Al-Emadi, N. A. (2017). Review of optimization techniques applied for the integration of distributed generation from renewable energy sources. *Renewable energy, 113*, 266-280.

Aman, M., Jasmon, G., Bakar, A., & Mokhlis, H. (2014). Optimum network reconfiguration based on maximization of system loadability using continuation power flow theorem. *International journal of electrical power & energy systems, 54*, 123-133.

Aman, M., Jasmon, G., Naidu, K., Bakar, A., & Mokhlis, H. (2013). *Discrete evolutionary programming to solve network reconfiguration problem.* Paper presented at the IEEE 2013 Tencon-Spring.

Aspari, S. K., & Sreenivasulu, J. (2013). Reduction of energy loss based on network reconfiguration and distributed generation in radial distribution system. *Int J Innovat Res Electr Electron Instrum Control Eng (IJIREEICE), 1*, 2321.

Badran, O., Mokhlis, H., Mekhilef, S., & Dahalan, W. (2018). Multi-Objective network reconfiguration with optimal DG output using meta-heuristic search algorithms. *Arabian Journal for Science and Engineering, 43*(6), 2673-2686.

Bansal, J. C. (2019). Particle swarm optimization. In *Evolutionary and swarm intelligence algorithms* (pp. 11-23): Springer.

Chakravorty, J. (2012). Network reconfiguration of distribution system using fuzzy controlled evolutionary programming. *International journal of engineering science and advanced technology*.

Chandramohan, S., Atturulu, N., Devi, R. K., & Venkatesh, B. (2010). Operating cost minimization of a radial distribution system in a deregulated electricity market through reconfiguration using NSGA method. *International journal of electrical power & energy systems, 32*(2), 126-132.

Dahal, S., & Salehfar, H. (2016). Impact of distributed generators in the power loss and voltage profile of three phase unbalanced distribution network. *International journal of electrical power & energy systems, 77*, 256-262.

Das, D. (2005). A fuzzy multiobjective approach for network reconfiguration of distribution systems. *IEEE Transactions on Power Delivery, 21*(1), 202-209.

Eberhart, R., & Kennedy, J. (1995). *A new optimizer using particle swarm theory.* Paper presented at the MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science.

Eldurssi, A. M., & O'Connell, R. M. (2014). A fast nondominated sorting guided genetic algorithm for multi-objective power distribution system reconfiguration problem. *IEEE Transactions on Power Systems, 30*(2), 593-601.

Fathabadi, H. (2016). Power distribution network reconfiguration for power loss minimization using novel dynamic fuzzy c-means (dFCM) clustering based ANN approach. *International journal of electrical power & energy systems, 78*, 96-107.

Firdaus, A. A., Penangsang, O., & Soeprijanto, A. (2018). Distribution network reconfiguration using binary particle swarm optimization to minimize losses and decrease voltage stability index. *Bulletin of Electrical Engineering and Informatics, 7*(4), 514-521.

Fogel, D. B. (1998). *Artificial intelligence through simulated evolution*: Wiley-IEEE Press.

Ganesan, L., & Venkatesh, P. (2006). Regular paper distribution system reconfiguration for loss reduction using genetic algorithm. *J. Electrical Systems, 2*(4), 198-207.

Gomes, F. V., Carneiro, S., Pereira, J. L. R., Vinagre, M. P., Garcia, P. A. N., & Araujo, L. R. (2005). A new heuristic reconfiguration algorithm for large distribution systems. *IEEE Transactions on Power Systems, 20*(3), 1373-1378.

Hsiao, Y.-T. (2004). Multiobjective evolution programming method for feeder reconfiguration. *IEEE Transactions on Power Systems, 19*(1), 594-599.

Imran, A. M., Kowsalya, M., & Kothari, D. (2014). A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks. *International journal of electrical power & energy systems, 63*, 461-472.

Ing, K. G., Jamian, J. J., Mokhlis, H., & Illias, H. A. (2016). Optimum distribution network operation considering distributed generation mode of operations and safety margin. *IET Renewable Power Generation, 10*(8), 1049-1058.

International Energy Agency. (2018, October). Renewables 2018 - Analysis and forecasts to 2023. Retrieved from https://www.iea.org/reports/renewables-2018

Jakus, D., Čađenović, R., Vasilj, J., & Sarajčev, P. (2020). Optimal Reconfiguration of Distribution Networks Using Hybrid Heuristic-Genetic Algorithm. *Energies, 13*(7), 1544.

Kakran, S., & Chanana, S. (2018). Smart operations of smart grids integrated with distributed generation: A review. *Renewable and Sustainable Energy Reviews, 81*, 524-535.

Kashem, M., Ganapathy, V., & Jasmon, G. (2000). Network reconfiguration for enhancement of voltage stability in distribution networks. *IEE Proceedings-Generation, Transmission and Distribution, 147*(3), 171-175.

Kashem, M., Jasmon, G., & Ganapathy, V. (2000). A new approach of distribution system reconfiguration for loss minimization. *International journal of electrical power & energy systems, 22*(4), 269-276.

Kashem, M., Jasmon, G., Mohamed, A., & Moghavvemi, M. (1998). Artificial neural network approach to network reconfiguration for loss minimization in distribution networks. *International journal of electrical power & energy systems, 20*(4), 247-258.

Kennedy, J. (2006). Swarm intelligence. In *Handbook of nature-inspired and innovative computing* (pp. 187-219): Springer.

Kim, H., Ko, Y., & Jung, K.-H. (1993). Artificial neural-network based feeder reconfiguration for loss reduction in distribution systems. *IEEE Transactions on Power Delivery, 8*(3), 1356-1366.

Koziel, S., Rojas, A. L., & Moskwa, S. (2018). *Power loss reduction through distribution network reconfiguration using feasibility-preserving simulated annealing.* Paper presented at the 2018 19th International Scientific Conference on Electric Power Engineering (EPE).

Krishna, K. S., Kumar, K. S., Venkatesh, S., & Gokulakrishnan, G. (2018). Distribution System Feeder Reconfiguration using Improved Hybrid Harmony Search Algorithm. *International Journal of Pure and Applied Mathematics, 118*(18), 3983-3993.

Lee, K. S., & Geem, Z. W. (2004). A new structural optimization method based on the harmony search algorithm. *Computers & structures, 82*(9-10), 781-798.

Li, H., Wang, A., Zhang, Y., & Guo, B. (2019). *Dynamic Reconfiguration of Distribution Network Considering Time-varying Characteristics of DG.* Paper presented at the 2019 6th International Conference on Systems and Informatics (ICSAI).

Liu, K.-y., Sheng, W., Liu, Y., & Meng, X. (2017). A network reconfiguration method considering data uncertainties in smart distribution networks. *Energies, 10*(5), 618.

Mahdavi, M., Fesanghary, M., & Damangir, E. (2007). An improved harmony search algorithm for solving optimization problems. *Applied mathematics and computation, 188*(2), 1567-1579.

McDermott, T. E., Drezga, I., & Broadwater, R. P. (1999). A heuristic nonlinear constructive method for distribution system reconfiguration. *IEEE Transactions on Power Systems, 14*(2), 478-483.

Merlin, A. (1975). Search for a minimal-loss operating spanning tree configuration for an urban power distribution system. *Proc. of 5th PSCC, 1975, 1*, 1-18.

Mirjalili, S. (2019). Genetic algorithm. In *Evolutionary algorithms and neural networks* (pp. 43-55): Springer.

Muhammad, M. A., Mokhlis, H., Naidu, K., Franco, J. F., Illias, H. A., & Wang, L. (2018). Integrated database approach in multi-objective network reconfiguration for distribution system using discrete optimisation techniques. *IET Generation, Transmission & Distribution, 12*(4), 976-986.

Naguib, M. G., Omran, W. A., & Talaat, H. E. (2017). *Optimal reconfiguration and DG allocation in active distribution networks using a probabilistic approach.* Paper presented at the 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe).

Napis, N. F., Khatib, T., Hassan, E. E., & Sulaima, M. F. (2018). An improved method for reconfiguring and optimizing electrical active distribution network using evolutionary particle swarm optimization. *Applied Sciences, 8*(5), 804.

Nara, K., Shiose, A., Kitagawa, M., & Ishihara, T. (1992). Implementation of genetic algorithm for distribution systems loss minimum re-configuration. *IEEE Transactions on Power Systems, 7*(3), 1044-1051.

Nguyen, T. T., Nguyen, T. T., Truong, A. V., Nguyen, Q. T., & Phung, T. A. (2017). Multi-objective electric distribution network reconfiguration solution using runner-root algorithm. *Applied Soft Computing, 52*, 93-108.

Nguyen, T. T., & Truong, A. V. (2015). Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm. *International journal of electrical power & energy systems, 68*, 233-242.

Niknam, T., Fard, A. K., & Seifi, A. (2012). Distribution feeder reconfiguration considering fuel cell/wind/photovoltaic power plants. *Renewable energy, 37*(1), 213-225.

Pegado, R., Ñaupari, Z., Molina, Y., & Castillo, C. (2019). Radial distribution network reconfiguration for power losses reduction based on improved selective BPSO. *Electric Power Systems Research, 169*, 206-213.

Peñaloza, J., Yumbla, J., López, J., & Padilha-Feltrin, A. (2019). *Optimal Distribution Network Reconfiguration with Distributed Generation using a Genetic Algorithm.* Paper presented at the 2019 IEEE PES Innovative Smart Grid Technologies Conference-Latin America (ISGT Latin America).

Qiu, R., Lv, X., & Chen, S. (2011). A survey on artificial intelligence algorithm for distribution network reconfiguration. In *Robotic Welding, Intelligence and Automation* (pp. 497-504): Springer.

Rao, R. S., Ravindra, K., Satish, K., & Narasimham, S. (2012). Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. *IEEE transactions on power systems, 28*(1), 317-325.

Roosta, A., Eskandari, H.-R., & Khooban, M.-H. (2019). Optimization of radial unbalanced distribution networks in the presence of distribution generation units by network reconfiguration using harmony search algorithm. *Neural Computing and Applications, 31*(11), 7095-7109.

Salazar, H., Gallego, R., & Romero, R. (2006). Artificial neural networks and clustering techniques applied in the reconfiguration of distribution systems. *IEEE Transactions on Power Delivery, 21*(3), 1735-1742.

Saleh, O. A., Elshahed, M., & Elsayed, M. (2018). Enhancement of radial distribution network with distributed generation and system reconfiguration. *Journal of Electrical Systems, 14*(3).

Sedighizadeh, M., Esmaili, M., & Esmaeili, M. (2014). Application of the hybrid Big Bang-Big Crunch algorithm to optimal reconfiguration and distributed generation power allocation in distribution systems. *Energy, 76*, 920-930.

Shanmugapriyan, J., Karuppiah, N., Muthubalaji, S., & Tamilselvi, S. (2018). Optimum placement of multi type DG units for loss reduction in a radial distribution system considering the distributed generation. *Bulletin of the Polish Academy of Sciences. Technical Sciences, 66*(3).

Shivakumar, L., Kumar, G. K., & Marulasiddappa, H. (2014). Implementation of Network Reconfiguration Technique for loss Minimization on a Standard 16 Bus Distribution System. *International journal of Soft Computing and Engineering (JJSCE), 3*(6), 154-157.

Souifi, H., Kahouli, O., & Abdallah, H. H. (2019). Multi-objective distribution network reconfiguration optimization problem. *Electrical Engineering, 101*(1), 45-55.

Su, C.-T., & Lee, C.-S. (2003). Network reconfiguration of distribution systems using improved mixed-integer hybrid differential evolution. *IEEE Transactions on Power Delivery, 18*(3), 1022-1027.

Sulaima, M. F., Mohd Fadhlan, M., Jali, M. H., Daud, W., Bukhari, W. M., & Baharom, M. F. (2014). A comparative study of optimization methods for 33kV distribution network feeder reconfiguration. *International Journal of Applied Engineering Research, 9*(9), 1169-1182.

Yao, X. (1999). Evolving artificial neural networks. *Proceedings of the IEEE, 87*(9), 1423-1447.

Zhanga, F., Zhanga, Y., Xina, X., Zhangb, L., & Fana, L. (2012). Study on oilfield distribution network reconfiguration with distributed generation. *Int J Smart Grid Clean Energy (SGCE), 1*, 135-141.

Zhu, J. Z. (2002). Optimal reconfiguration of electrical distribution network using the refined genetic algorithm. *Electric Power Systems Research, 62*(1), 37-42.

LIST OF PUBLICATIONS AND PAPERS PRESENTED

YOUSSEF, H. H., MOKHLIS, H. B., TALIP, M. S. A., ALSAMMAN, M., MUHAMMAD, M. A., & MANSOR, N. N. (2020). Distribution network reconfiguration based on artificial network reconfiguration for variable load profile. Turkish Journal of Electrical Engineering & Computer Sciences, 28(5), 3013-3035.