Optimization of Simultaneous Energy Storage Sizing & Network Reconfiguration in an Active 11kV Radial Distribution Network

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Thesis Summary

There is an increasing pressure for the UK to move towards a low carbon emission. The Electric power system has a major contribution by shifting to the decarbonization of power sector for a low emission target. It is important to know that the electric generation is not the only sector in the power system that affect the CO_2 emissions, there is also an indirect emission as results of losses. This Thesis presents a novel approach to coordinate the simultaneous operation of network reconfiguration with the sizing and the allocation of energy storage systems in distribution networks for losses reduction aim. The major challenge of this work is to solve this hard-stochastic optimization problem with an algorithm that has the capability to find the optimum solution in a reasonable computational time to help utilities to use it for online applications.

This thesis proposes a developed optimization technique for network reconfiguration to enhance the search space and improve the computational time and the convergence issue of the particle swarm optimization. The thesis also presents a novel comparison between a previously adopted engineering approach used by Western Power Distribution Company and the new proposed modified algorithm in term of losses reduction, and computational time. The similarities, the differences, the advantages and the shortcomings for both approaches were highlighted. Moreover, two different utilizations for Monte Carlo Approach were investigated in this thesis. The first is aimed to decrease the search space of the proposed modified algorithm by proposing Multi Stages Modified Particle Swarm approach for distribution network reconfiguration problem solution. The second application for Monte Carlo Method is for sizing the battery storage units for more losses' reduction.

Results show that merging the network reconfiguration and the sizing and the allocation of battery storage systems in distribution networks allow more losses reduction more than using each strategy in isolation. Furthermore, it was concluded that the new developed algorithm technique could be applied using the real distribution network giving the optimum losses reduction in a reasonable computational time, which in turn could be used for online implementation.

Keywords: Carbon Dioxide Emission Reduction, Distribution Losses Reduction, Distribution Network Reconfiguration, Energy Storage Systems, Particle Swarm Optimization, Monte Carlo Simulation, Minimum Node Voltage Method, Distribution Network

Dedication

I would like to dedicate this thesis to my late mother, dad and my sisters for all the love, encouragement and the support to complete this work.

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List of Abbreviations

ACO	Ant Colony Optimization
ANN	Artificial Neural Network
BESS	Battery Energy Storage Systems
CCC	Committee on Climate Change
CSA	Cucoo Search Algorithm
CVR	Conservation Voltage Regulation
CO_2	Carbon Dioxide
CO_{2e}	Carbon Dioxide emission
DER	Distributed Energy Resource
DG	Distributed generation
DN	Distribution Network
DNO	Distribution Network Operator
DNR	Distributed Network Reconfiguration
DSM	Demand Side Management
EPSO	Evolutionary Particle Swarm Optimization
ES	Energy Storage
ESS	Energy Storage Systems
FALCON	Flexible Approaches for Low Carbon Optimized Network
FWA	Fire Work Algorithm
GA	Genetic Algorithm
GHG	Greenhouse Gas

GSO	Group Search Optimization
HBMO	Honey Bee Mating Optimization
HSA	Harmony Search Algorithm
IA	Immune Algorithm
MC-PSO	Multi Swarm Cooperative particle swarm optimization
MCS	Monte Carlo Simulation
MNV	Minimum Node Voltage Method
NOP	Normally open points
NSPSO	Non-Dominated Sorting Particle Swarm Optimization
NTL	Non-Technical Losses
OFGEM	Office Gas and Electricity Market
OPF	Optimal Power Flow
PV	Photo voltaic
REPSO	Rank Evolutionary Particle Swarm Optimization
SA	Simulating Annealing
SEDG	Sustainable Electricity and Distributed Generation
SPSO	Selective Particle Swarm Optimization
TL	Technical Losses
UK	United Kingdom
UKGDS	United Kingdom Generic Distribution System
UPSO	Unified PSO
WPD	Western Power Distribution

Nomenclature

c_1, c_2	Acceleration variable
G_{best}	Best position achieved by the entire particles in the swarm
i	Particle in a swarm
I_j	the current through branch j
j	Branch index
k	The index for the current iteration
k_{max}	The maximum number of iterations
min	Script referring to minimum values
max	Script refereeing to maximum value
N_{br}	Total number of branches
N_{bus}	Total number of bus
$N_{main\ loops}$	Total number of main loops
Off- peak	Script referring to off peak demand
P_{best}	Best position for particle (i) based on its own experience
$peak$	Script referring to peak demand
R_j	the resistance of branch j
$rand_1, rand_2$	Script referring to a random number from 0 to 1
S	Swarm Size
V_i^k	Velocity for the particle (i) for the iteration (k)
ω	Inertia weight

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1 CHAPTER 1 INTRODUCTION

1.1 Overview

There is an increasing pressure for the UK to move towards a low carbon emission. Electric, business, transportation, residential, industrial and other sectors are culprits. Electricity generation is not the only sector in the power system that affect the CO_2 emissions, there is also an indirect emission as results of losses. The work presented in this thesis concentrates on network reconfiguration and, the integration of distributed energy resources in distribution networks for losses reduction.

Distribution Network Reconfiguration (DNR) is recommended not only as a losses' reduction scheme but also in emergency situations for example, in case of any failures. It is a necessity to understand that the hard-decision-making process due to the hard-mathematical stochastic DNR problem representation, is one of the main challenges for this approach. There is no one correct method of solving this problem, and several methods have been suggested. Utilities are looking for a technique that merges the benefits of finding an optimum solution at sufficient speed to allow for real-time network configuration. The majority of researchers have validated their algorithm choices through simulation on different size test networks. Although these test networks could help researchers to compare their theoretical studies with the previous work done in that point, it is not apparent if the advantages claimed can make the transition to a real-world situation. Real networks give a clear picture of how the solution method could be applied in real life with real value of variable loads and what are the problems that could be faced to meet the utilities expectations.

The work in this thesis expands on the work presented by previous authors by looking at modifications to the particle swarm optimization technique to speed its solution time. A novel Multi Stage Modified Particle Swarm Optimization was developed in this thesis for improving the search space, the computational time and the convergence of the technique which represent the major issues of this algorithm using a test distribution network and an 11 kV OHL network in Milton Keynes, UK.

A key challenge of adding distributed energy resources such as wind or solar units is their uncertain nature as they are dependent on weather condition. For this reason, it is convenient to consider energy storage as an additional component in the Network. This introduces another challenge which is selecting the correct size and location and managing their operation because a wrong selection could represent a burden and may increase the losses instead of reducing it.

The published literature in peer-reviewed journals indicates that there is a gap for the simultaneous network reconfiguration, sizing and allocation of battery energy storages in distribution network for losses reduction. For this reason, the thesis will focus on finding a novel approach to coordinate between the selection of the right size and location for the battery energy storage while having the flexibility of changing the normally operating points for optimum losses reduction.

Furthermore, this thesis conducts a novel comparison between the performance of the proposed algorithm for network reconfiguration and a previously engineering based algorithm using two distribution networks in terms of losses reduction and the computational time using the test and the real OHL distribution network.

1.2 Thesis aim and objective

The main aim of this thesis is reducing the losses in distribution networks to reduce the CO_2 emission through multi stages levels. The first level is through network reconfiguration for static and variable load. The second level is by merging the energy storages in conjunction with the network reconfiguration considering charging and discharging operational modes. To achieve this aim, the following objectives were included:

1. Carry out a detailed survey about the DNR definition, advantages and challenges and the different algorithms used for solution.
2. Classify the DNR solution techniques into 4 categories: heuristic, meta heuristic, mathematical and hybrid and compare between them in term of global solution, computational time and network validation
3. Propose a new modification to the particle swarm technique to improve the issues related to convergence and computational time.
4. Validate the proposed modified particle swarm technique using a test distribution network and compares between the proposed modification and the previous modifications by previous researchers using the same network.
5. Suggest a new Multi Stage Modified Particle Swarm Optimization technique that merges the modified PSO to Monte Carlo for better computational time and validate it using the previous test network.
6. Conduct a simultaneous network reconfiguration in conjunction with battery energy storage sizing and allocation for losses reduction. In this scope, a Monte Carlo technique is suggested to size the energy storage while the modified PSO was used for DNR.
7. Validate the proposed modified particle swarm using a section of the 11kV OHL network in the Milton Keynes area, located in the United Kingdom, to allow a validation of the methodology within a more representative situation
8. Implement a previously used engineering method using both the test and the real distribution network.

9. Compares between the performance of the proposed modified particle swarm and a previously used engineering method in terms of similarities, differences, advantages and shortcomings.

1.3 Thesis Statement

In this thesis, Optimum network reconfiguration and sizing and allocation of storage batteries are merged to reduce the distribution losses. A New Hybrid technique is suggested considering both the accuracy and the computational time.

1.4 Thesis Organization

This thesis consists of eight chapters organized in the following manner:

The first chapter gives a brief introduction about the main topic of this thesis, aim and objectives. Also presents a layout for the rest of the thesis.

Chapter 2 reviews two strategies for losses reduction in distribution network. The first is through distribution network reconfiguration (DNR). In this section, DNR problem is explained showing the reasons of considering it a hard optimization problem. A literature review has been presented including all the intelligent and hybrid techniques used by previous researchers for solving this problem. Another strategy has been presented for losses reduction is the integration of storage batteries in distribution networks. A survey has been conducted looking closely about the different techniques used for determining the storage size and site for optimum losses reduction. The studies joining both approaches together are also reviewed.

Chapter 3 presents how losses could be reduced for a DNR optimization problem through a modified version of particle swarm optimization algorithm (MPSO). The IEEE 33 network is selected to validate the technique. In this chapter, the theory of the particle swarm algorithm is explained. The modifications added to the basic technique are stated. A comparison is held between the modified particle swarm and other versions of based swarm techniques to show the effectiveness of the modifications in terms of losses reduction, voltage improvement and computational time to suggest a technique that could be valid to real network implementation.

Chapter 4 presents a new developed methodology, Multi Stage Modified Particle Swarm algorithm (MSMPSO) that benefit from the MPSO results applied in the previous chapter, tests its flexibility to respond to variable load for an active DNR problem while reducing the computational time. This proposed methodology includes three stages and hence come the suggested name. MSMPSO is validated through the IEEE 33 network. Monte Carlo Simulation (MCS) is selected to simulate load uncertainty in distribution network. This chapter compares between the MPSO and MSMPSO performance with respect to losses reduction, voltage improvement and computational time.

Chapter 5 merges the energy storage sizing and allocations in parallel with the network reconfiguration for losses reduction. Monte Carlo simulation technique was suggested for sizing the batteries while the modified particle swarm was used for network reconfiguration considering both the charging and discharging modes and not any of them in isolation using the test network.

Chapter 6 validates the MPSO for finding the best normally opened point for optimum losses via a large 11 kV OHL distribution network located in Milton Keynes, UK. This study considered a winter and a summer day representing the maximum and the minimum load respectively.

Chapter 7 validate a previously used engineering heuristic technique, the Minimum Node Voltage method using the IEEE 33 bus network and the large 11 kV OHL distribution network located in Milton Keynes, UK. A comparison was carried out for both the proposed MPSO and the Min Node Voltage Method showing the similarities, the differences, the advantages and the shortcomings.

Chapter 8 concludes the thesis and explains several points that can be investigated as future work.

2 CHAPTER 2 BACKGROUND

2.1 Problem Description

UK plays a vital role in securing the Paris Agreement, 2015, where 195 countries adopted the first universal global climate deal by setting a plan to avoid dangerous climate change. The main aim of this agreement was limiting the temperature rise to below 2^{o} C above pre industrial levels [1]. As a part of the agreement, $100 bn should be mobilized yearly in climate finance to developing countries by 2020. UK pledged to provide £5.8 bn between 2016-2020, where the Business, Energy and Industrial Strategy (BEIS) manages £2bn. Deforestation, Energy Decarbonization, Green Finance and Climate Legislation and governance are the four sectors of the BEIS technical assistance program to reach the Paris Agreement aim. The UK developed a set of Key Performance Indicators (KPI) published in Climate Finance Results report for 2018 [2] to track the results where the Greenhouse gas emission reduction was one of them.

There is increasing pressure for the UK to move towards a low carbon emission. A Committee on Climate Change (CCC) was launched 10 years ago to advise the UK Government and Devolved Administrations on emissions targets and report to Parliament on progress made in reducing greenhouse gas (GHG) emissions and tackling climate change [3]. It was recommended that the UK reduce the GHG emission 80% below the 1990 by 2050 ideally without sacrificing the benefits of economic growth and rising prosperity. In 2018, The department for Business, Energy and Industrial Strategy published on the progress executed for GHG emission reduction of UK up to 2017 [4]. This progress is illustrated in Figure 2-1. In this figure, it was shown that Carbon Dioxide (CO_2) is the main culprit in GHG emissions. For Example, the GHG emission in 1990 is 794.2 MtCO_2e; 75% of this value is due to the CO_2 emission. The Power sector has the dominant share of CO_2 emission compared to other sectors as clearly shown in Figure 2-2. This figure shows the UK annual CO_2 emission from different sectors during 1990 -2017. It is observed that the CO_2 emission from the power sector in 1990 is 242 of 594 MtCO_2e compared with 105 of 456 MtCO_2e in 2017. This high decay of the energy supply was mainly due to the decarbonisation of the power sector to achieve the emission reduction target. The decarbonisation of the power sector has been achieved by switching from coal and gas power stations to renewable generation in particular, many low scale distributed energy resources (DERs) such as wind power and solar panels.

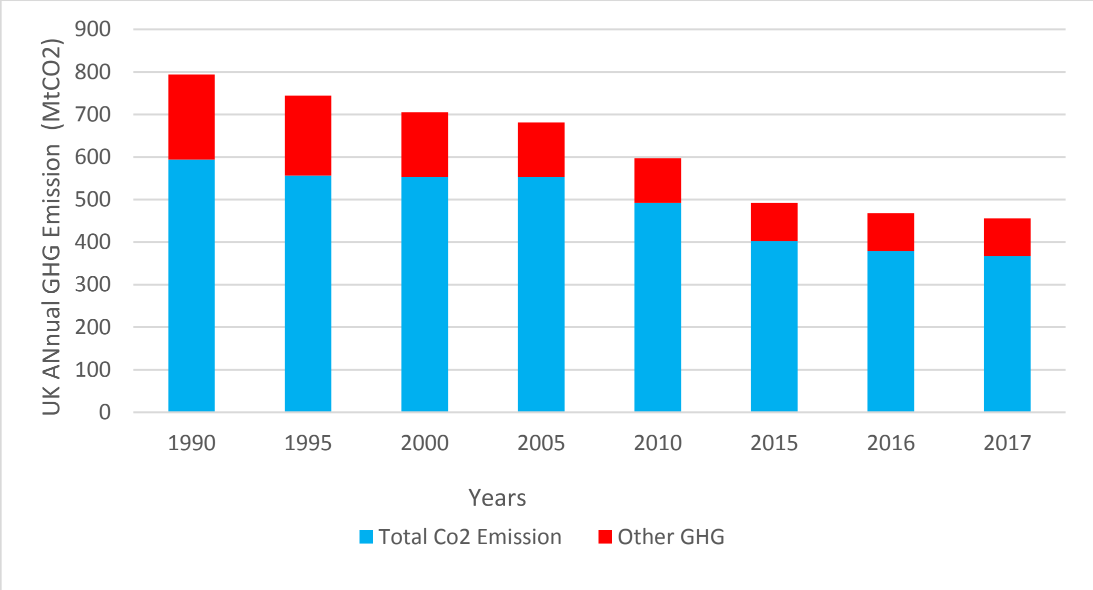


Figure 2-1 UK Annual GHG Emission during 1990-2017

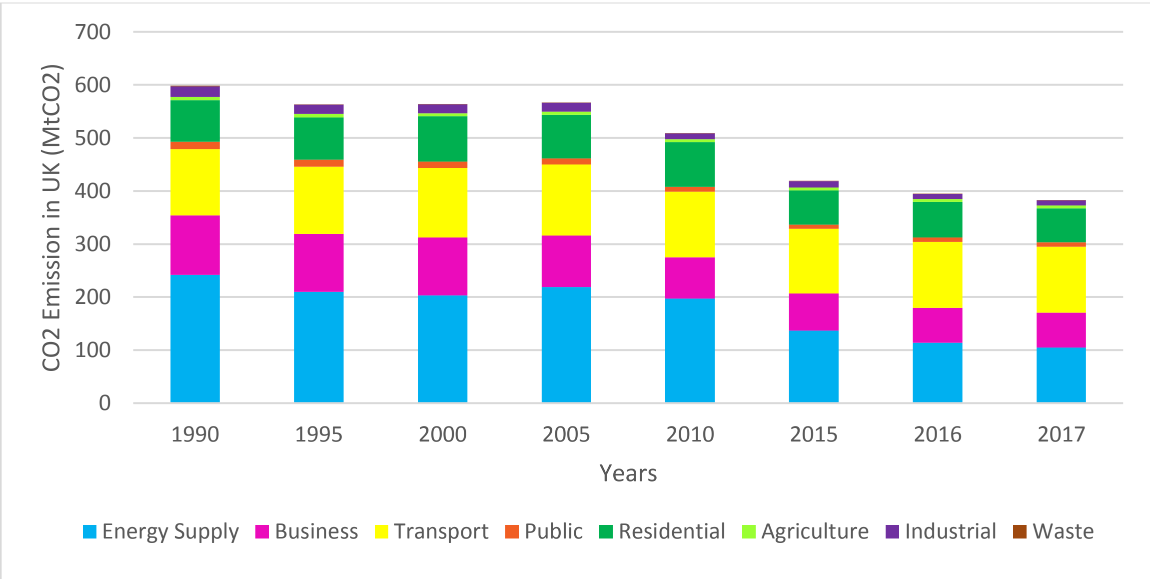


Figure 2-2 Total UK Emission of CO2

Electricity generation is not the only sector in the power system that affect the CO_2 emissions, there is also an indirect emission as results of losses. The total losses of the UK are 8% of the total generation as reported by the department for Business, Energy and Industrial Strategy in 2018 [5]. In this report the emission factor that convert from 1 kWh to 1 kg CO_2e was calculated for both the generation, and the combined transmission and distribution losses for 2016 to be 0.28266 and 0.0249 respectively. It should be noted that this factor changes annually as well as with the fuel mix consumed in UK power station changes. For this reason, the emission factors reported for 2016 are less than the emission factors calculated for 1990 (0.70395 for the generation and 0.0506 for the transmission and distribution losses). Since the total CO_2 emission from the generation sector for UK is 84,007 k tones of CO_2, then the equivalent losses emission is 6,720 k tones. Reducing the losses on the Network will reduce the overall emissions and help the UK to achieve the 2050 target.

In 2009, A report was prepared for the Office Gas and Electricity Market (OFGEM) to understand the main factors of Electric Losses in Distribution Networks. In this report, the electric losses were defined as the difference between the measured input energy to the distribution system and that leaving it [6]. There are two types of distribution losses: technical losses (TL) and non-technical losses (NTL). TL are caused by the physical properties of the power system components. the main reasons of the technical losses are listed in [6] and are summarized in the following points:

1. The waste of energy due to the heat resultant from the current path through the underground cables or overhead transmission lines.
2. Poor power factor.
3. 2-3% of the total technical losses are consumed by the meters.
4. Third of the technical losses are wasted in the transformers and known as “Fixed losses” because it does not depend on the load.
5. The way the distribution network is configured.

In contrast, (NTL) are also known as commercial losses. They are due to:

1. Meters inaccuracy; defined by the difference between the amount of energy delivered through the meters and the amount registered by the meters.
2. Electricity theft; defined by the Energy delivered to customers and not measured by the energy meters. This could be done by disconnecting the meters, reversing them, bypassing them to remove measurements or by cyber-attack to information systems.

2.2 Losses Reduction Schemes in Distribution Networks (DNs)

Technical losses (TL) are the main concern of this thesis. TL could be addressed directly as well as indirectly. The main methodologies participating directly in losses reduction goal were reviewed in [6] and [7] .Demand Side Management (DSM) is an example of indirect methods used for losses reduction. DSM is defined in [8] by the planning, implementation and monitoring of utility activities that are designed to influence customer use of electricity. As a result, it changes the time pattern and magnitude of utility’s load. The main goal of DSM is encouraging the clients to reduce their power consumption during the peak demand or shift their energy use to off peak hours to flatten the load curve. Consumers are gaining benefit through DSM by reducing their meters reading. On the other hands, utilities get indirect benefit by avoiding paying high power purchase during peak hours, and load reduction during peak hours. This will decrease the losses through transformers and line losses, thus will reduce the fuel used and correspondingly, the amount of the greenhouse gas emission. Examples of common direct losses reduction schemes are illustrated in Figure 2-3. The first scheme is regulating the network voltage by controlling reactive power flow in a system through shunt capacitor placement. The capacitor is a source of reactive power that could reduce the inductive reactance of the line loading, thus reducing the reactive losses. Identifying the required numbers of capacitors, their site and size are the major challenge for this scheme. Recently, this scheme has been merged with Conservation Voltage Regulation (CVR) scheme leading to a significant demand reduction in distribution networks and accordingly more losses reduction. CVR is lowering the distribution voltage in a controlled manner while keeping the lowest customer utilization voltage suitable with the level determined by the standard organizations [9]. A study was published in [10] tested the impact of selecting the right value for a capacitor at different voltage values. It was concluded that the losses increased significantly by increasing the voltage by 10% of the rated values as well as reducing the voltage below the rated values (90-99% of the rated values). In contrast, regulating the voltage at the rated values with optimum placement of capacitor reduced the IEEE 33 Network losses. The second approach listed in Figure 2-3 for losses reduction, is the Distribution Network Reconfiguration (DNR). It is another approach to save the electric energy in low voltage networks. DNR is defined by "the process of changing the structure of the distribution network by changing the status of sectionalizing switches (normally closed switches) and tie switches (normally open switches) to maintain the radial topology of the distribution network in order to maintain the operation and the protection as simple as possible [11]. This scheme is considered highly complex decision making for dispatchers and require an extensive numerical computation. The convergence, the accuracy, and the computational time for these techniques are the major challenges for DNR. Apart from this, frequent changes in the configuration may cause the miscoordination of protective devices. The third scheme for losses minimization in DN is the integration of DER which may include energy storage. The advantages gained by different renewable DG technologies can be classified into technical, economic and environmental benefits [12]. Technical benefits include nullifying the need for grid reinforcement, increased power loss reduction, improved reliability, voltage stability, power quality improvement and supply security. Despite these several benefits offered by renewable DGs, several challenges still exist in the integration of DGs in current power distribution networks. The unsuitable placement and sizing of DERs as well as the mismanagement of charging and discharging time in case of having Distributed Energy Storage can result in high power losses, voltage instability, and power quality and protection degradation in the power distribution networks. Very few Researchers that have thought about DNR previously, have also included other elements such as DER and capacitors and such work is very recent [13, 14]. The survey of this thesis is divided in two sections. The first covers the DNR scheme while the second focuses on sizing and allocating the ESS in DN and the way they could affect the losses reduction. This thesis is designed to consider both DNR and then DNR in conjunction with DER as it felt that these can no longer be considered in isolation and a consolidated optimization offers the best way forward for losses reduction. A summary of work undertaken looking at both DNR and DER is also described.

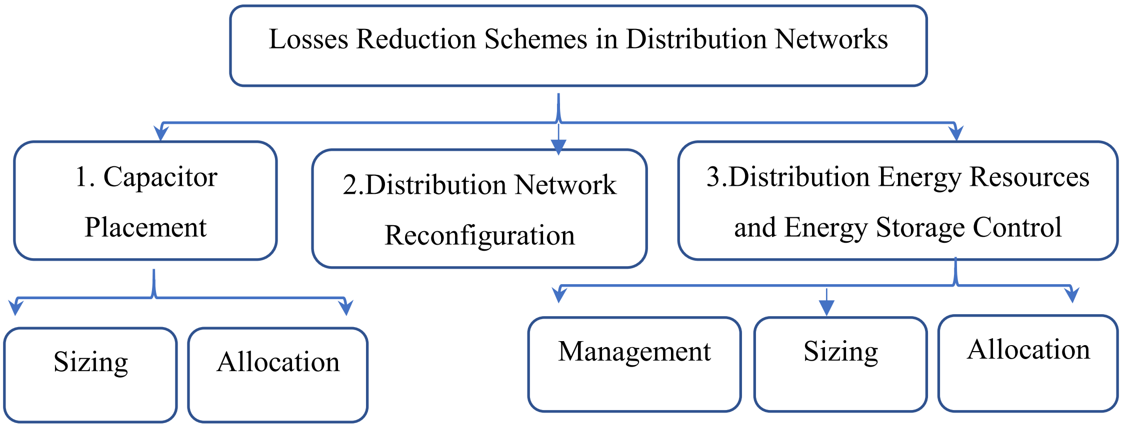


Figure 2-3 Losses Reduction Schemes in Distribution Networks

2.3 Distribution Network Reconfiguration

2.3.1 DNR Definition, Advantages, and Challenges

Distribution networks consist of many interconnected circuits linked by switches designed for management and protection schemes. There are two types of switches: the first is sectionalizing switches which are normally closed; the second is tie line switches which are normally opened providing separation between feeders. Usually, tie switches are closed to transfer loads from one feeder to another while sectionalizing switches are opened to restore the radial structure or to isolate areas during faults. Distribution Feeder / network reconfiguration (DRF/ DNR) is the process of changing the network structure by changing the status of these linking switches, thus redirecting the power flow for a better network performance keeping the radial structure. The DNR importance is highlighted in emergencies; During a fault, the fault location should be identified immediately, the smallest part of the system should be isolated to minimize the number of affected consumers, then a solution should be developed to correct the fault that occurred and finally the switches are changed again to maintain their normal status [15, 16]. DNR features do not only include contingency conditions but also, their merits could improve the distribution network to obtain an efficient and secure power system. This could be achieved by reducing the losses, protecting the line from overloading via load balancing. Transferring the loads from highly loaded feeders or transformers to lightly loaded ones, help to smooth out the load demand, thus postponing the investment of building new generation stations. DNR could also reduce the generation cost by facilitating the integration of renewable resources especially in peak. Figure 2-4 summarizes the features and challenges of DNR.

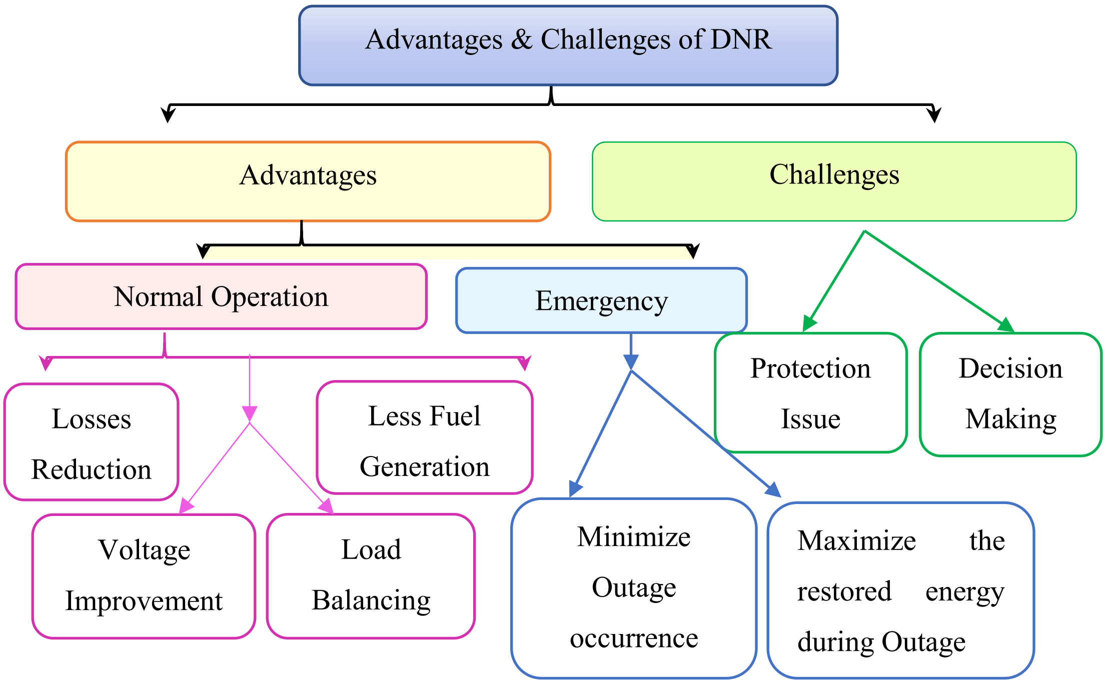


Figure 2-4 Advantages and Challenges of DNR

In contrast, the major challenge for DNR is the possible impact on the coordination of the protective devices. As the configuration changes, the direction of the power flow and the faults level in the branches change. This in turn may cause malfunction of the protective devices (usually set on fixed values of short current magnitude) used in the distribution networks. Recently , this issue was considered in [17] by implementing hourly reconfiguration in a smart distribution systems considering the operational conditions of the protective devices.

Another challenge for DNR concluded from the previous researches, is the complexity of decision-making process [7], as it requires an extensive numerical calculation. DNR is considered complicated, nonlinear, discrete, constrained combinatorial, stochastic optimization problem. Its complex combinatorial nature is due to the large probability obtained by changing the switches to find the optimum configuration to realize the objective function within the constraints. Its stochastic nature is due to the continuous change of demand hourly. Its discrete nature is due to the state of switches with change between on and off. Many solution techniques have been proposed and modified. At present DNR is done by the dispatcher in an emergency only based on a heuristic methodology derived from understanding the Network alternatives for any given situation. The advantages of being able to solve the optimization computationally in real time will allow a more accurate means of undertaking the network reconfiguration under normal operation as well as emergency running.

2.3.2 General Objective functions and Constraints

Since DNR is considered a complex optimization problem, seeking an optimum solution requires satisfying the objectives functions and the constraints. Losses and switching reduction, load balancing, voltage drop improvement, service restoration and DG integration are the most relevant objectives functions used for DNR problem. Figure 2-5 summarize the general constraints of the DNR. Keeping the values of node voltage, line current and protective devices current within the operating limits while maintaining the radial topology of the network after switching, are considered the main operational constraints. Integration of DGs, which is one of the advantages gained of DNR, will add other constraints that need to be considered such as the allowed energy to be penetrated in the system and others. Installing DG in a distribution network has an impact on power flow, voltage and reliability indices. This impact will be positive if they are correctly coordinated with the rest of the network. DG back up generation could feed the loads in case of any fault. Therefore, the duration of the outage could be decreased. Moreover, DG could enable the injection of power into the network when utility generation could not supply the load demand especially in peak time. As a result, the probability, the duration and the number of failures could be reduced. To accomplish the previous aim, the allocation and the sizing of DGs could be considered in DNR analysis.

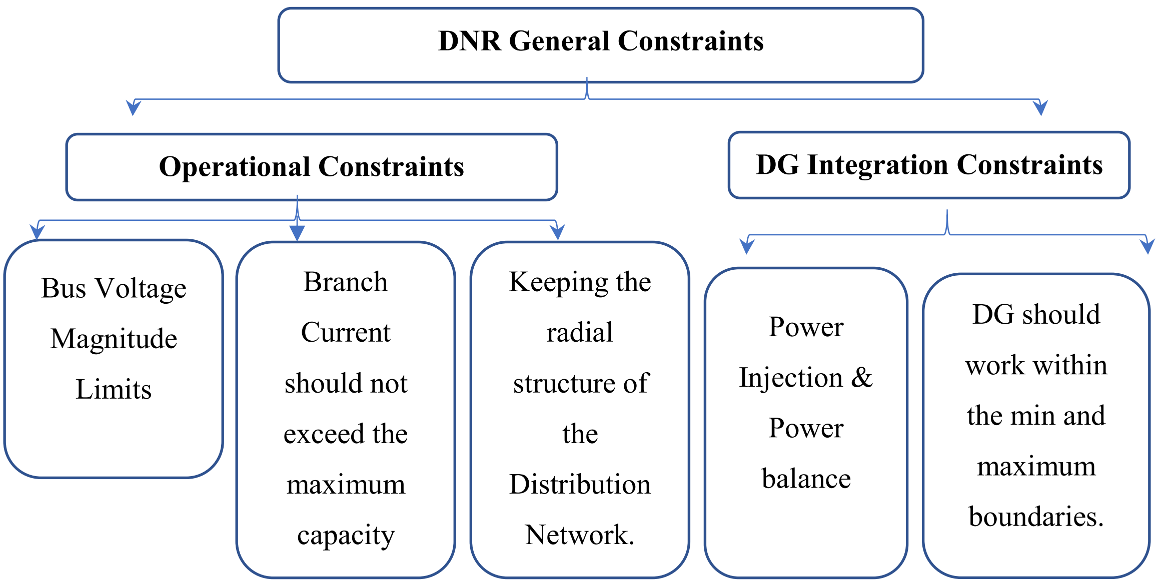


Figure 2-5 DNR general Constraints

2.3.3 DNR Optimization Algorithms Classification

DNR Solution techniques are surveyed in [11, 18-20] . In this thesis, they are generalized into 4 categories: heuristic, meta heuristic, mathematical and hybrid solution techniques. Figure 2-6 shows the classification of the techniques used for solving the DNR problem.

2.3.3.1 Heuristic techniques

These techniques are knowledge-based approaches. They select the optimal switches configuration based on knowledge and operational experience. This experience is developed based on power system simulation under different operating conditions. Although the heuristic algorithms are very fast to solve the reconfiguration problems, which is one of the main requirements of real time distribution automation, these algorithms achieve an approximate solution (near optimum solution) rather than a global optimum solution. Table 2-1 includes examples of the heuristic techniques used for DNR, their theory and the studies used them for losses reduction. Loop Cutting algorithm [21], Branch Exchange technique [22], Trial and Error [23], Optimum Load Flow methodology [24], Loop Eliminating method [25] and Minimum Node Voltage method [26] are examples of heuristic techniques used in DNR solution. Because most of these techniques struggle to find a global minimum, they will mostly not be considered further in this thesis except for the Minimum Node Voltage method which is discussed in Chapter 7.

2.3.3.2 Meta Heuristic Techniques

Meta Heuristic techniques mean upper level methodologies that deal with the network reconfiguration as an optimization problem and solve them iteratively using learning strategies and intelligently combining different concepts that will help to improve the search space. They achieve global optimum solution, but the computational time is too high due to their probabilistic nature and their random selection which made the convergence speed slow. Meta Heuristic techniques used for DNR solution are described in Table 2-2. This table also includes some example of the studies working with these techniques for losses reduction.

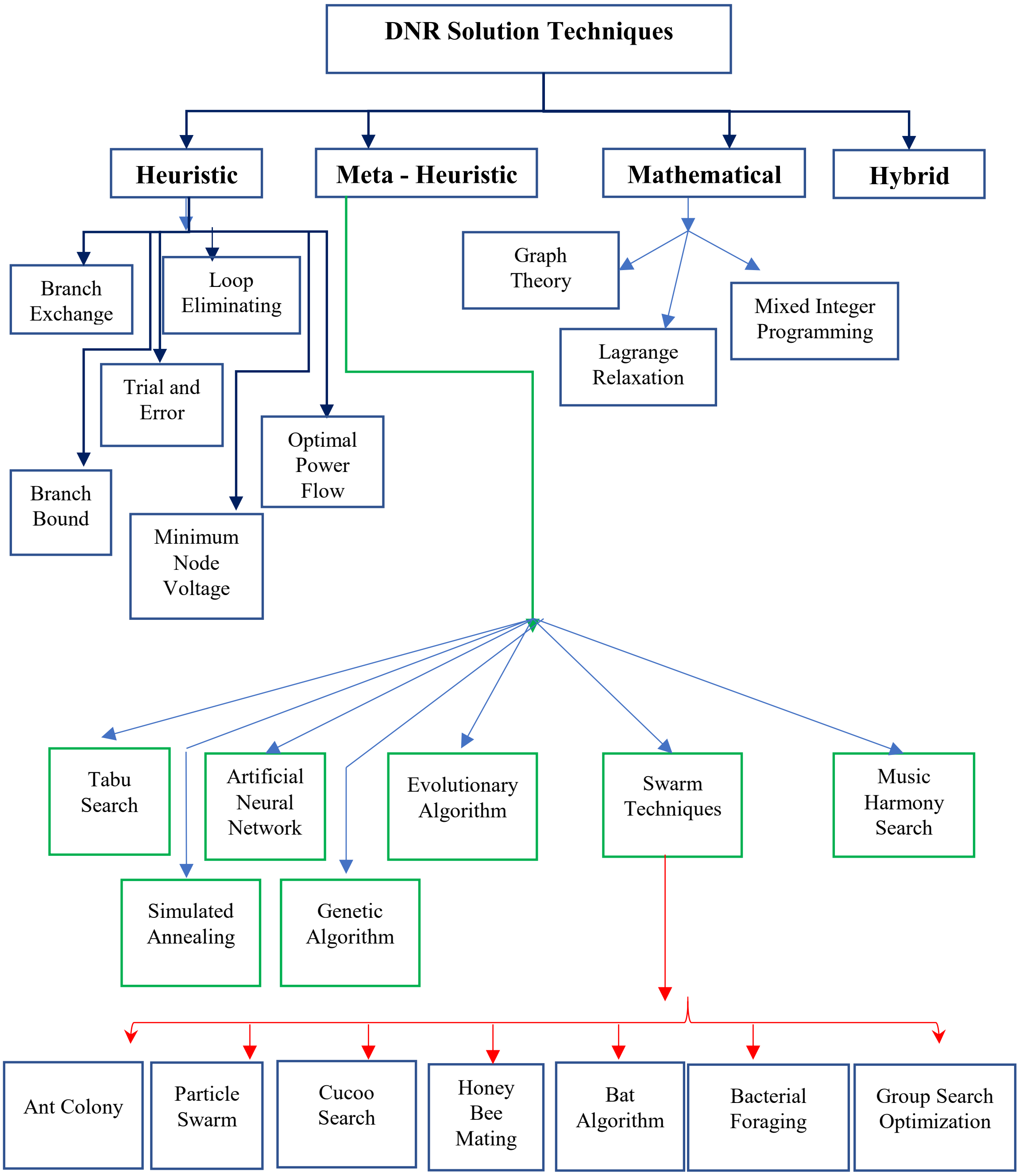


Figure 2-6 DNR Solution Technique Classification

Table 2-1 Examples of Heuristic techniques used in DNR solution

Technique	Year	Methodology Description	Studies
Loop Cutting	1989	This method is also known as "Sequential Branch Method". The network is initially meshed, and then a load flow is carried out to determine the branches current. Finally, the radial structure is gained by opening the switch carrying the minimum power in each loop.	[21]
Branch Exchange	1989	This methodology open one switch and closed another and the switching pairs should yield the best losses reduction.	[22]
Trial and Error	2000	The method looks for suitable options to reduce losses through a minimal tree-search. A simple formula for power loss was developed to determine the switching option that will result in minimum power loss.	[23]
Optimal Power Flow (OPF)	2006	all branches are initially closed, and from the OPF results, a heuristic technique based on sensitivity analysis is used to determine the next loop to be broken by opening one switch. Then the list of switches that are candidates to be opened is updated, and the above process is repeated until all loops are broken, making the distribution system radial.	[24]
Loop Eliminating method	2010	The network is initially meshed and the switches with large voltage differences were opened because they could cause more system losses.	[25]
Minimum Node Voltage method	2016	All branches are initially closed. Then running a power flow to determine the nodes having the minimum independent node voltage. The branches having the lowest power flow are considered the new NOP.	[26]

Table 2-2 Meta Heuristic techniques Description used in DNR

Methodology	Description	References
Genetic Algorithm (GA)	GA was proposed by Holland in 1975. It applies the principles of genetic evolution to make change in the population the evolution process includes three stages: crossover, selection and mutation. Genetic Algorithm, Evolutionary Algorithm, Evolutionary Programming, Differential Programing are very closed techniques to same genetic concept.	[27]
Simulating Annealing (SA)	SA was presented in 1983 in [28]. This technique is based on the cooling process of a melting metal to solidify in its minimum energy state.	[29-31]
Artificial Neural Network (ANN)	Neural Network works in two modes: the first is offline using a large data base of all possible operating conditions; the second mode is online responsible of optimum reconfiguration.	[32]
Tabu Search (TS)	It was presented by Glover in two series during 1989 and 1990. This technique models the human memory process.	[33-36]
Ant Colony Optimization (ACO)	ACO was proposed in 1992 by M. Dorigio. It was inspired from the behavior of real ants while searching their food. Transition state, local update and global update are the 3 steps of the algorithm.	[37-42]
Particle Swarm Algorithm (PSO)	In 1995, J. Kennedy and R. Eberhart have mathematically simulated the social behavior of bird flock and fish schools searching their corn presenting a new meta heuristic technique, the PSO [43]. There are many variants on this search approach available that be will be discussed latter in chapter 3.	[44, 45]
Honey Bee Mating	HBM is a method inspired from the behavior of bees	[46]
Harmony Search Algorithm (HSA)	HAS was presented by Geem et al. in 2001. It was inspired by the reproduction of musicians' behavior during playing their musical instruments which represent the population to obtain	[47-50]

	certain pleasing harmony (the global solution required) based on the given objective function.	
Bacterial Foraging Optimization Algorithm	It was developed in 2002. It is based on the behavior of the bacteria in human intestine.	[51]
Bat Algorithm	The main idea was borrowed from the behavior of bats for finding food.	[52]
Immune Algorithm	This technique imitates the behavior of genes and antibodies while defending the human body from viruses and bacteria.	[53]
Shuffled Frog leaping Algorithm	This method was proposed in 2003 including two kind of search: local and global. A population of frogs is divided into several parallel communities called memeplex [54]. The local search is performed for each memeplex resembling the PSO concept. For the global exchange of information, the best selected frogs from each memeplex will be redistributed in the whole population ensuring a good quality evolution of total population. In this global exchange of information frogs are shuffled periodically which is like shuffled complex evolution algorithm.	[55]
Quantum Fire Fly	It was developed by K.N.Krishnanad and D.Ghose in 2005. This methodology is based on the flashing characteristics of fireflies. This method has not been applied to the problem area discussed in this thesis to date but was used for reliability and power quality through network reconfiguration.	[56]
Cucoo Search (CSA)	CSA was developed by Yang and Deb in 2009. It was inspired by some species of a bird family called cuckoo. These birds put their eggs in the nests of other host birds by selecting the recently spawned nests and removing existing eggs that increase hatching probability of their eggs. The host bird takes care of the eggs presuming that the eggs are their own, but when they discover that the eggs are not their own, they will either throw out the eggs or build new nests in new places.	[57, 58]

	Each egg in a nest represents a solution and a cuckoo egg represents a new solution.	
Group Search Optimization (GSO)	GSO is an optimization algorithm based on animal searching behavior and their group-living theory developed in 2009.	[59]
Fire Work Algorithm (FWA)	FWA is a swarm intelligence based stochastic search technique, recently developed by Tan and Zhu in 2010 [60]. In FWA, The FWA is presented and implemented by simulating the explosion process of fireworks. In the FWA, two explosion (search) processes are employed and mechanisms for keeping diversity of sparks are also well designed.	[61]

2.3.3.3 **Mathematical Techniques**

Mathematical modeling technique such as Graph Theory, Mixed Integer Programming [62], Lagrange relaxation [63] and others were also suggested to solve the DNR. Although they can give global optimum solution, they take too long time to create the model. This time increase exponentially with the size of the network [64]. Therefore, these will not be considered further in this thesis.

2.3.3.4 **Hybrid Techniques**

It was concluded from the previous researches that knowledge-based algorithms did not reach the global solutions and most of the time fall into local ones. Furthermore, probabilistic techniques are time consuming due to their high probabilistic nature, which could affect their implementation on real time distribution reconfiguration although reaching optimal solutions. Based on this, the need for introducing a new approach to combine between the accuracy, the time consuming and feasible solutions led the researches to suggest combinatorial or hybrid techniques. These methodologies combine between different algorithms to improve the search space, achieving global solution in a fewer number of iterations which speed up the computational time. So far, several hybrid techniques have been proposed to solve the reconfiguration problems as well as the allocation and sizing of DGs for losses reduction. Table 2-3 highlights some hybrid approaches used for DNR solution.

Table 2-3 Examples of Hybrid techniques for DNR for losses reduction

<table>
<tr><th>Ref</th><th>Hybrid technique</th><th>Reason</th><th>Objective</th><th>Reference</th></tr>
<tr><td>[65]</td><td>SA-ACO</td><td>To improve the computational time and the accuracy of the SA</td><td>(Losses reduction, Voltage Improvement and Minimum Switching Operation)</td><td>Real Network</td></tr>
<tr><td>[66]</td><td>ACO- GA</td><td>To improve the search performance of crossover operators in Genetic Algorithm.</td><td>Losses Reduction</td><td>Theoretical</td></tr>
<tr><td>[67]</td><td>PSO+ HBMO</td><td>To enhance the performance of HMBO and avoid the convergence to local optimal solution</td><td>Losses Reduction</td><td>Test Network</td></tr>
<tr><td>[68]</td><td>Fuzzy -ACO</td><td rowspan="4">To Speed up the computational time.

To improve both the accuracy and the global search of the swarm algorithms</td><td>Losses Reduction and Load Restoration</td><td>Real Network</td></tr>
<tr><td>[69]</td><td>PSO-ACO</td><td>Losses reduction and voltage improvement</td><td>Theoretical</td></tr>
<tr><td>[70]</td><td>REPSO

(Evolutionary Programing and PSO)</td><td>Losses Reduction</td><td>Theoretical</td></tr>
<tr><td>[71]</td><td>GA-PSO</td><td>Losses Reduction and Voltage Improvement</td><td>Theoretical</td></tr>
</table>

2.3.4 **Discussion**

Table 2-4 compares between the previous classified methodologies in term of theory, advantages and drawbacks suggesting that hybrid methodologies could give better results than individual algorithms in terms of computational time and accuracy. For this reason, in this thesis, a hybrid optimization algorithm is suggested to solve the DNR problem considering losses reduction in DNs.

Table 2-4 Comparison between the methodologies used for DNR solution

	Heuristic	Meta Heuristic	Mathematical	Hybrid
Theory	Based on expert knowledge	Based on Nature methodologies.	Based on deterministic rules	Combine between techniques
Advantages	Fast	Global optimum solution with the possibility of falling in local optimum solution in case of multi objective function	Deterministic Global solution	Less computational time compared to meta heuristic and mathematical Global optimum solution
Drawbacks	Local optimal	Time consuming Convergence	Not suitable for large network as the time increase exponentially with the size	

Particle Swarm algorithm was selected as a starting point for this research because it has many useful aspects, stated in [72] and summarized as:

1. the straightforward concept, easy implementation, and very few parameters that need to be adjusted, as explained latter in chapter 3, compared to HSA and SA.
2. In PSO, every particle remembers its own previous best value as well as the neighborhood best; therefore, it has a more effective memory capability than the GA.
3. Unlike SA, the final solution does not depend on the initial iterations.
4. It is considered a fast technique compared to ANN, SA and HSA that take lot of iterations to reach the optimum solution

The possibility of falling in local minimum solution for multi objective function problems, the large probabilities of initial random positions and the convergence of the algorithm are the main issues of this technique. By solving any of them, PSO could be modified for real network validation. For this reason, many trials were implemented to modify the basic PSO for enhancing the performance. These trials are surveyed in Table 2-5.

Table 2-5 Different Modification added to basic PSO technique for DNR Solution

Year	Modified PSO Version	Reference
2006	The improved PSO use the chaos optimization to overcome the influence of particles' random initialization and realize detail searching in solution space.	[73]
2009	Changing the inertia weight to decrease linearly from 0.9 to 0.2 for 1500 iterations. Another modification is the implementation of a position check to make sure that none of the particles have flied out of the search space bounds or violated the constraints. In this study the author has used only 5 particles.	[74]
2010	In this version of swarm, the author suggests varying the value of inertia weight from 0-9 to 0.2 for 1000 iterations compared to (0.9 to 0.4) for the typical PSO. It was concluded that the optimum solution was found after 300 runs.	[75]
2012	In this method, the particle gets information from all the neighbor not only the best one. Also, another equation for velocity was used.	[76]
2014	To improve the total search ability of the PSO algorithm, the proposed method gets use of the mutation and crossover operators to increase the diversity of the population.	[77]
2015	An Improved PSO based on statistics has been presented. Scenarios library is formulated during the optimization process to influence the evolution of particle swarm by calculating the Pearson correlation coefficient between the fitness value and each dimension of the particles.	[78]
	An Adaptive Bi group PSO based on BPSO has been proposed by R. Cheng to strengthen the swarm's global optimum ability and enhancing the slow convergence of the algorithm.	[79]
2016-2017	A modified version of swarm based on the work undertaken in this thesis was suggested by integrating both the concept of tree diagram and voltage and current constraints for filtering the initial positions of the PSO to improve the search space and reduce the computational time of the algorithm.	[80, 81]
	A Unified PSO is presented to include 500 iterations for reducing the shortcoming of swarm technique.	[82]

2.4 Distributed Energy Resources in Distribution Network

Integrating DER in Distribution Networks is another proposed scheme for losses reduction in low voltage networks. The merits and the challenges of this scheme are surveyed in this section. For achieving the maximum benefit, both the size and the allocation should be studied as well as the type of DER should be specified, to meet the required goal of losses reduction. In this scope, the previous research papers studying both the capacity and the allocation of DER are classified in this section based on the target of their studies.

2.4.1 DER Advantages and Challenges

In addition to the potential for CO_2 reduction from renewables, DERs may be favorable for the electricity market because they represent a key solution for utilities and electricity market operators to reduce the investments in transmission and distribution system along with the option of decreasing the losses. Also, they offer the opportunity for community energy and energy cost reduction through peer-peer trading. It could also play a key role to reduce the cost of the supply during peak demand hours. They also could provide a spinning reserve during contingency. More advantages were discussed in section 2.2. Despite these several benefits offered by DERs, several challenges should be considered [83]:

1. An increased share of DG may induce power flows from the low voltage into the medium voltage, thus protection schemes at both voltage levels must be designed accordingly.
2. DERs that needs power electronic converters to be connected to the grid contribute to higher harmonics.
3. Inappropriate DG allocation can cause low or over voltage in the network.

It is the responsibility of the system operator to manage the operation of DERs considering the previous challenges for better power system and secured performance.

2.4.2 Energy Storage Sizing and Allocation in Distribution Network

Integrating DER in a distribution network, is the second approach suggested for losses reduction. DER can come in many forms such as wind power and solar panels. Due to the uncertain nature of renewable energy, it is convenient to consider energy storages. There are five categories of energy storage: mechanical, electro-chemical, thermal, electrical and chemical [84] .However, Battery energy storage (BESS) deployment is increasing, because it can react very quickly and therefore assist with grid stability much better than some of the other forms of storage. The major benefits of BESS are frequency balancing control, load shaving/levelling, helping with renewable generation integration, to help avoid outages and to offer local power quality improvement [85]. BESS sizing and allocating in distribution network is important, because suboptimal location and capacity could represent extra losses and cost. Research papers have addressed the sizing and the placement of batteries in distribution system from three main point of views: facilitating the integration of renewable energy sources, economic benefit through appropriate planning and peak shaving and load leveling.

Current literature has focused on facilitating the integration of renewable energy in distribution network by coordinating the charging and discharging times. In [86], a genetic algorithm based on formulating a multi objective function that considers both losses and voltage deviations is used for optimum sizing of BESS in the presence of PV. A PSO approach based on loss sensitivity index for battery placement considering BESS parameters is presented in [87] . Another study for calculating the minimum size required for battery to meet both uncertainties in load demand and wind is presented in [88]. The methodology is tested on a system consisting of commercial facilities deriving their energy requirements from wind turbine. A Monte-Carlo simulation approach is used for calculating the reliability indices presented by the authors to maintain the reliability. Furthermore, power injection and losses indices for identifying the appropriate size and location of battery source inverters (BSI) used with PV units are introduced in [89]. It was found through theoretical and practical networks validation that; BESS optimal capacity and placement in the presence of Renewable Energy Source (RES) has an important effect on losses reduction and voltage profile enhancement.

Alternative work has looked at the Economic benefit for optimum BESS size and placement. A bi-level optimization technique is presented in [90] for minimizing the cost. BESS is modeled through many parameters such as state of charge (SOC) limits and round-trip efficiency. A modified 33 bus IEEE network with PV units and wind turbines is used for validation. A hybrid Tabu Search (TS) - PSO was proposed in [91] for sizing and allocating the BESS in a 21-node distribution network incorporating a wind turbine. It was concluded that the right selection for BESS capacity and size, is a part of the optimal power system planning while satisfying technical constraints.

Both peak shaving and load leveling are suggested for deferring the annual generation upgrade and reducing the running fuel for spinning reserve. Peak shaving is defined as removing the peak demand consumption, while peak leveling is decreasing the difference between the maximum and the minimum valley in demand curve. In [92], a statistical method based on specific indices, is used for scheduling the operation of batteries in a 63/20 kV distribution network in Iran. The maximum power offered or absorbed by the BESS is adjusted by applying weighted minimum module ideal point method based on PSO for optimal BESS allocation in 21-node distribution network including different RES in [32].It was found that allocating BESS near to weak bus voltage improve the voltage, while placing them at the points having heavy loads, or adjacent to RES nodes, optimizes their power offer, and maximizes their power absorption respectively. Research papers [93-97] reveal that both BESS sizing and allocation for peak shaving or load leveling are correlated to the economic benefit. In [93], the cost saving is calculated considering the batteries' cost, maintenance, investment and operational cost after installing the batteries at law voltage side of the transformer in an 11-bus distribution network in Germany. The PSO algorithm was proposed in [94] to solve the multi objective problem for maximizing the economic benefit from a BESS installation considering losses reduction, load shifting, the investment, maintenance and operational cost in the presence of wind turbines. A planning strategy based on GA and linear programing is suggested in [95] to develop both BESS location and capacity to defer system upgrades and getting the maximum arbitrage benefit through the IEEE-33 bus network through different scenarios. A daily active power adjustment to shave peak load demand for one month is studied in the first stage of an exhaustive search method in [96]. The second stage is studying the maximum cost benefit through one year, by repeating the algorithm for the rest of the months for one year. Another power management strategy for BESS sizing for peak load shaving in a university campus is presented in [97] to maximize the annual profit for the campus in the presence of PV units. The strategy is based on coordinating the BESS charging in law cost price or during the excess of PV output.

2.5 Simultaneous Reconfiguration, Sizing and Allocation of ESS in DN

The distribution network reconfiguration and the optimum integration of DG have been always studied separately. However, the integration of these two strategies could bring more merits to the whole system. Only few studies have aimed to consider both. These studies are regrouped in Table 2-6. Table 2-6 explains the aim of these studies, the solution technique used per each author and the networks used for validation. It was concluded from this table that there is a gap in the literature for the simultaneous network reconfiguration, sizing and allocation of Energy Storage in distribution network for losses reduction. For this reason, the thesis will spotlight a method of finding an approach to coordinate between selection of the right size and location for ESS while having the flexibility of changing the NOP for optimum losses reduction. The vast majority of this work has been undertaken in parallel with developments within this thesis and so was unavailable while the bulk of this work in this thesis was being undertaken. The remaining reference used a heuristic methodology which is considered non-optimal.

Table 2-6 Simultaneous Reconfigurations and Optimum DG integration in Distribution Network Studies

Reference	Objective	Solution technique	Type of DG used	Network Validation
[98]	Keeping the radial network topology while minimizing the	Strength Pareto Evolution algorithm was proposed to solve	Solar panels and wind turbine.	The IEEE 33 network

	active losses, the annual operational cost and the pollutant gas emission	the multi objective function problem. A decision making based on fuzzy set has been used to compromise the best solution.		
[61]	Optimal reconfiguration and DG placement in DN for minimum losses reduction, and voltage deviation index.	Fireworks Algorithm was proposed to simultaneously reconfigure the network and allocate the DG units. Voltage Index Stability is used to identify the DGs locations.	The type of DGs are not specified	The IEEE 33 and the IEEE 69 networks.
[99]	Optimal reconfiguration and DG sizing simultaneously while assuming constant locations to DGs.	Evolutionary Particle Swarm Algorithm (EPSO) has been proposed to hybrid the Evolutionary Programming (EP) to Particle Swarm (PSO)	The type of DGs are not specified	The IEEE 33 network modified with 4 DGs connected at fixed bus locations at 6,18,22 and 29.
[100]	Optimal allocation and sizing for DG units and shunt capacitors for losses reduction and voltage profile improvement.	Hybrid Harmony Search with the artificial Bee Colony Algorithm. Spanning Tree has been used for keeping the radial structure of the networks.	The type of DGs are not specified	The IEEE 69 network and the IEEE 118 node
[101]	Optimal siting and sizing simultaneously with network	A heuristic technique based on uniform voltage distribution	The type of DGs are not specified	The IEEE 33 network is used for validation.

	reconfiguration for losses reduction.	Algorithm has been used.		
[102]	Optimal network reconfiguration and DG placement	Adaptive Cucoo search Algorithm	The type of DGs are not specified	The IEEE 33, the IEEE 69 and the IEEE 119 bus networks were used for validation
[103]	Minimizing the Energy Not supplied as well as the cost for an optimum deployment of DGs, EES with network reconfiguration.	A stochastic mixed integer linear programming model was developed.	Wind, Solar and EES	The IEEE 119 bus networks was used for validation
[104]	Simultaneous DNR and optimum DG power penetration in DN for minimum power losses, operation cost, and pollutant gas emissions as well as maximizing the voltage stability index	Multi-objective Hybrid Big Bang-Big Crunch. Graph Rules are used for radiality check.	Three DGs with the technology of wind Turbine, FC, and PV. Their size and locations were initially assumed by the author.	The IEEE 32 and 25 bus networks.
[105]	Instantaneous distributed resources allocation considering the reconfiguration concept to maximize	A new Teaching Learning Based Optimization technique was proposed for solution.	The type of DGs are not specified	The IEEE 33 network considering different load levels.

	the annual energy loss reduction while maintaining a better node voltage profile.	The proposed integrated approach employs NR after the optimal allocation of DGs.		
[106]	Simultaneous Reconfiguration and DG placement	GA was proposed for DG placement. A heuristic methodology (Tie Loop Lines Matrix) has been used for reconfiguration.	The type of DGs are not specified	Test and real network in Yazd City were used.
[107]	Reduce the network loss with the simultaneous utilize of DNR and DG allocation.	An evolutionary algorithm, Invasive Weed Optimization, is proposed for this problem.	The type of DGs are not specified	IEEE 33 network and real network
[108]	Optimal allocating the DG with DNR for reducing the costs of line upgrades, energy losses, switching operations required, and DG capital, operation and maintenance costs), as well as environmental emission reduction	Non-dominated sorting genetic algorithm was proposed to solve the problem.	photovoltaic (PV) modules, wind turbines (WT), and gas turbines (GT).	The IEEE 38 and the IEEE 119 bus network
[109]	Simultaneously allocate DGs and Shunt capacitors in DN within an	Improved PSO Also, node sensitivity-based guided search algorithm (GSA) is	The type of DGs are not specified	The IEEE 33 and 69 bus networks

	optimum DNR to maximize the annual profit for utilities by reducing the annual charges on energy losses, peak power losses, and substation capacity release against the annual charges incurred to purchase DERs.	also suggested to enhance the overall performance of the optimizing tool.		
[13]	Solving the loss minimization problem with the optimal sizing and allocation of DGs and capacitors with and without Network reconfiguration under 7 cases.	Autonomous Group Particle Swarm Optimization was suggested for solution.	The type of DGs are not specified	The IEEE 69 Network
[14]	Finding a radial topology with optimum of DG and capacitor installation to minimize the power loses while satisfying the operational constraints under 5 cases.	Genetic Algorithm using MATLAB Optimization toolbox Sensitivity Analysis was used to determine the locations for the DGs in the test network.	The type of DGs are not specified	The IEEE 33 Network

2.6 Summary

In this chapter, the background around the electric sector as a main contribution for CO_2 emissions in UK was introduced. Reducing the electric losses in the distribution network in the UK, is considered one of the approaches that could be used to decrease CO_2 emissions. Network Reconfiguration, Integration of DG and the addition of capacitors are some of the main schemes for losses reduction in DN. This chapter surveys two of these approaches: DNR and the DGs integration in DN.

Network Reconfiguration is the ability to change the NOP while keeping the radial structure of distribution network and maintain the voltage and the branches current within the limits. DNR was described as a hard optimization, stochastic, nonlinear problem. The solution techniques were classified into four categories: heuristic, meta heuristic, mathematical and hybrid techniques. A comparison was carried out to explain the advantages and the disadvantages of each of them. Although heuristic techniques were considered fast solution, they are not widely used as they could not reach the global solution. Hybrid techniques are favorable in term of accuracy, and computational time compared to meta heuristic techniques. Particle Swarm Optimization was selected as a base for studying the DN in this thesis due to the straightforward concept, easy implementation and only few parameters to adjust. For this reason, it is widely used for this type of application.

Integrating Distributed Energy Resources (DERs) in DN was widely used to solve the overloading capacity problem or reducing the outage occurrence for a secured power system. In this thesis, the DER integration has been introduced as an approach for losses reduction, since it is typically connected closed to loads, so they work in parallel with the utility grid. To get the maximum benefit of this approach, both the size and the location should be studied. DER has many forms, this thesis considers Energy Storage systems as these may be used to represent DER in times of high load but also required charging at low load. By studying ESS, DERs are automatically a subset of this study

It was concluded from the literature that several researches were conducted to study the DNR, and the sizing and the allocation of DGs separately while only few researches mix both approaches together. It was also found that research papers addressed the sizing and placement of batteries in distribution system for three perspectives: facilitating the integration of renewable energy sources, economic benefit through an appropriate planning and peak shaving and load leveling. Furthermore, there is a gap in the literature for the simultaneous network reconfiguration, sizing and allocation of Battery Energy Storage in distribution network for losses reduction. For this reason, the thesis will spotlight a method of finding an approach to coordinate between selection of the right size and location for BEES while having the flexibility of changing the NOP for optimum losses reduction.

However, other authors have been undertaking similar work in parallel with the work undertaken as part of the research presented in this thesis. The dates of their publications are 2017 and 2018. The difference between their work and the work presented in this thesis is highlighted in Table 2-7.

Table 2-7 A comparison between the studies considering the simultaneous DNR and EES deployment

Ref.	Aim of the study	The network used	Solution Method	Differences
[110]	A planning study based on coordinating the soft open points locations, DG inverters for reactive power adjustment, and the Distributed Energy Storages with the DNR to minimize the cost investment	The IEEE 33 bus network is used	Mixed Integer second order optimization technique using MATLAB	The work presented in this reference assumed both the size and the locations for 6 DGs of 1.8 MW and 1 MW of battery with 81% of efficiency.
[103]	The main goal of the simultaneous consideration of DNR with DG and EES deployment is supporting a large scale of renewable energy integration by minimizing the energy not supplied as well as the cost.	The IEEE 119 bus network	Stochastic Mixed Integer Linear Programming (S-MILP) method was used.	The work presented in this reference is a planning study for 3 years, where the author assumed the size of energy storage used of 1MW with an expected life time of 15 years.
This Thesis	Finding the best NOP simultaneously with the best size and site for 5 batteries for maximum losses reduction.	The IEEE 33 bus network is used	Hybrid algorithm based on PSO was used for DNR while Monte Carlo was used for BESS sizing.	The work presented in this thesis did not assume neither the size nor the locations of the batteries. Each loop is separately optimized, and this justifies the reason of having 5 batteries.

3 CHAPTER 3 MODIFIED PARTICLE SWARM OPTIMIZATION

3.1 Background

In chapter 2, the importance of energy storage and dynamic network reconfiguration was discussed to reduce losses in the Network. Different optimization techniques were introduced, and it was decided that particle swarm approach was appropriate optimization routine for investigation. As the process of optimization on a Network is complicated it is first desirable to test the processes that will be undertaken on a small test Network. The United Kingdom Generic Distribution System (UKGDS) is a collection of power system network model that represents UK distribution networks. They were developed by the Centre for Sustainable Electricity and Distributed Generation (SEDG). Six different models were available at [111]. It was found that these models are high voltage networks. By this way, the resistance losses reduction - which is the main concern of this thesis - will not be effective in this voltage level. For this reason, no previous published research papers were using them for network reconfiguration problem. The IEEE have a collection of different test networks that can be used for research such as IEEE-123 bus, IEEE -34 bus, IEEE -13 bus, IEEE-37 bus presented in 1991 [112] and updated in 2001 [113]. Research conducted by the Power and Energy Research Group in Queensland University in Australia, 2011, summarizes the most used test network in educational research and classify them into 3 categories transmission, distribution and unbalanced test networks [114]. It was recommended that the best distribution networks for research study are the IEEE 16 bus, IEEE 30 bus, IEEE 33 bus, IEEE 94 bus, IEEE 69 bus and IEEE 119 bus. It was found in chapter 2, that most of research papers studying DNR, used the IEEE 33 bus or IEEE 69 bus. The IEEE 33 bus network was chosen in this thesis because it has a reasonable number of loops and is a single feeder. It is convenient for comparing the proposed Modified Particle Swarm Optimization (MPSO) to other previous researches using the same network with different forms of PSO algorithms. The IEEE 16 bus and the IEEE 30 bus don't have sufficient loops to properly investigate DNR. In contrast , the IEEE 94 bus network is not used previously by researchers for DNR application due to the presence of a high number of feeders and tie switches (11 feeders and 13 tie switches)[114]. When the tie switches number increases, the number of loops and the number of the solution probabilities increases which add more complexity and time consumption for researchers to test the performance of their suggested solution techniques. Also, less authors refer to the IEEE 69 in conjunction with DNR compared to the IEEE 33 Network.

3.2 Case Study

The IEEE 33 bus network, 12.6 kV, shown in Figure 3-1, was selected for optimum configuration for losses reduction. The IEEE 33 network consists of 32 normally closed switches (sectionalizing switches) and 5 normally open switches (Tie line switches). The system load is assumed to be constant. The initial tie lines switches of the network are from bus 33 to bus 37 before any reconfiguration. The total number of loops that should be formed by closing the tie switches is 5 loops. The system load is 3715 kW and 2300 kVAr. The network load and line data are given in [22].

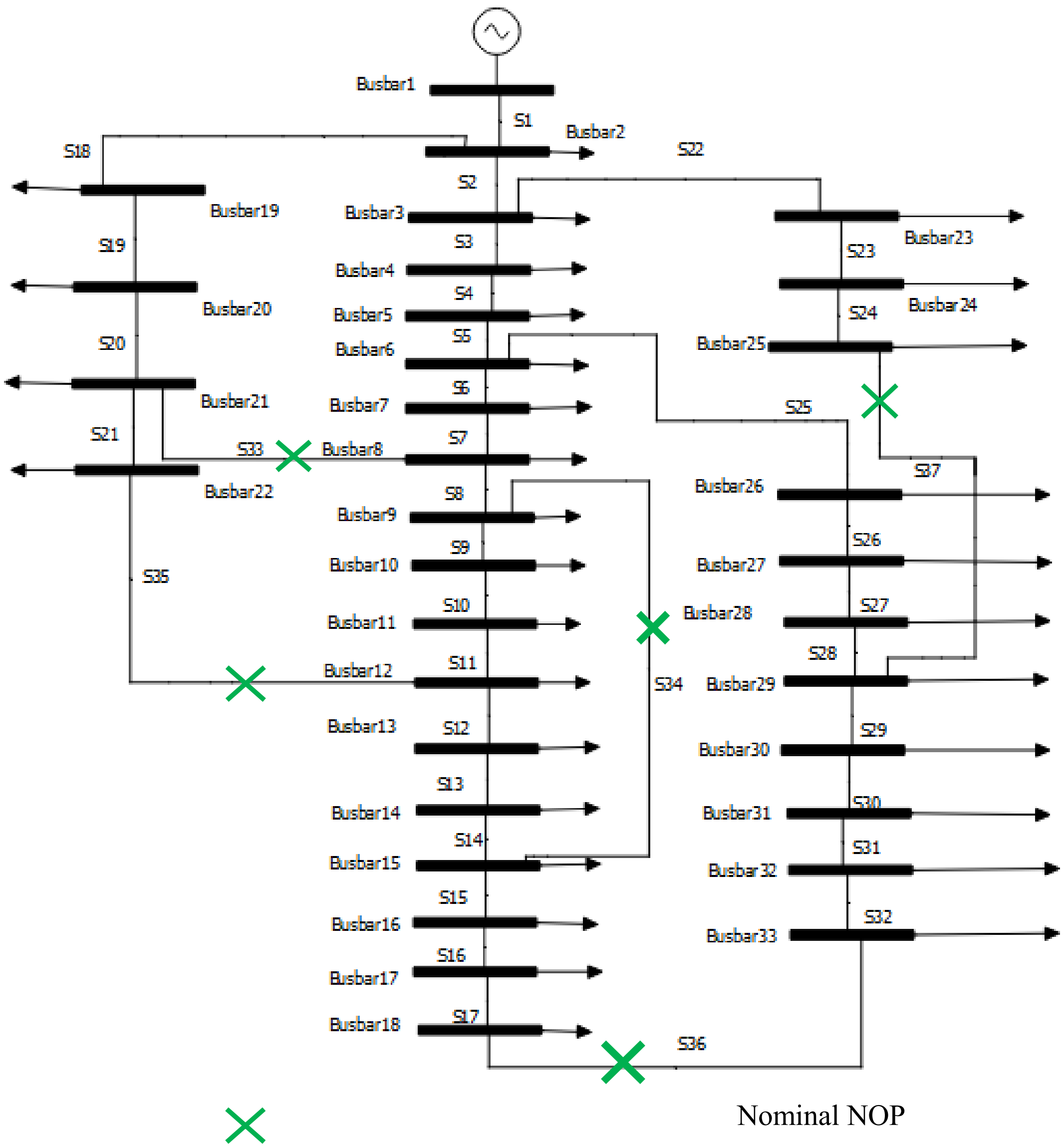


Figure 3-1 IEEE 33 bus Network (IPSA Window)

3.2.1 Problem Formulation

In this research, multiple objective function problem is not considered as the work in this thesis is mainly directed for line losses minimization as it is proportional to the carbon dioxide reduction. Therefore, the main objective function for the DNR optimization problem could be described as:

$$\text{Min Power}_{losses} = \sum_{j=1}^{N_{br}} (I_j^{\,2})\, R_j \tag{1}$$

Where:

I_j the current through branch j

j Branch index

N_{br} the total number of branches

R_j the resistance at branch j

3.2.2 General Constraints

Three constraints are needed for optimum losses reduction:

- Node voltage limit

The bus voltage magnitude should be within the permissible limits to maintain power quality. The minimum value of the voltage is chosen to be 0.9 and the feeder voltage is set up to 1.0 pu.

$$V_{min} \leq V_{bus} \leq V_{max} \tag{2}$$

- Feeder capacity limit

The magnitude of the feeder's branch current (I_j) should not exceed the maximum value of the allowed current passing in the branch (I_{max}) eliminating the insulation failures assuming that thermal limits are achieved.

$$I_j \leq I_{max} \tag{3}$$

- Maintain the radial topology

To maintain a straightforward operation at conditions and avoid issues with adaptive protection of the distribution power grid, a radial configuration is preferred. It is stated that each loop should contain a tie line and a corresponding sectionalizing switch. Thus, to retain a radial network structure, when a tie is closed in a loop, only one switch should be open in the same loop. To retain this topology, the following criteria should be considered:

- The total number of main loops obtained by closing all the ties

$$N_{main\ loops} = \quad (N_{br} - N_{bus}) + 1 \qquad (4)[115]$$

Where:

$N_{main\ loops}$ the total number of main loops in distribution network

N_{bus} The total number of bus in distribution network

- The total number of closed switches (N_{CS})

$$N_{CS} = N_{bus} - 1 \qquad (5)\ [116]$$

- The total number of tie switches should be the same as the number of main loops

The Interactive Power System Analysis (IPSA) tool was used for network simulation and load flow calculations using python programming language.

3.3 DNR using typical Particle Swarm Optimization (PSO)

3.3.1 Particle Swarm Optimization (PSO) background, terminologies and symbols

As explained in chapter 2, The typical PSO is a mathematical representation to the social behavior of a group animals or birds working in a given area searching for food (bee) as shown in figure 3.2 [43]. Particles move through the search space adjusting their velocities and their positions according to their own experience and to their neighbouring particles experience to find the optimal solution based on equations 6 and 7 respectively [117]. The searching space is composed of all the possibilities that could represent a solution for the fitness function. This in turn explains the high processing time used to perform the calculations. This technique has some common terminologies and constants defined in table 3.1 and 3.2 respectively.

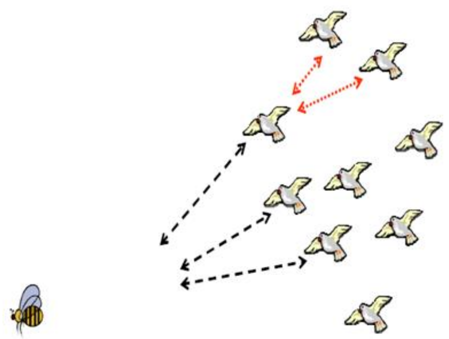


Figure 3-2 PSO biological concept

Table 3-1 PSO symbols and terminologies

Particle	i	Each bird or (possible solution) in the swarm is referred to a particle
Position	X_i	A bird location with respect to the corn
Personal best	P_{best}	the best location found individually by each bird with respect to the food. Each bird compares the current location to P_{best} , if the current location is better, then P_{best} is updated.

Global best	G_{best}	the best location found by all birds in the swarm with respect to the corn. Best bird location is compared to G_{best}, if it is better, then the G_{best} is updated.

Table 3-2 PSO constant definition [117]

Swarm Size	S	Swarm Size and known as Population size is the number of particles in swarm. A swarm is commonly used from 20 to 50 particles.
Inertia Weight	ω	Inertia Weight constant; is a parameter that represents the fluidity of the medium where the particles moves. It is introduced by Shi and Eberhart in 1998. This is a time decreasing function, calculated using (8). Many researches were conducted to specify the range for ω .It was found the max and min ω giving the best solution is from 0.9 to 0.4.
Acceleration constant	c_1 , c_2	Acceleration constants control the movement of the particles toward P_{best} and G_{best}. R. Eberhart proposed to set these constants to 2.0 for almost all applications

$$V_i^{K+1} = \omega * V_i^{k} + c_1 * rand_1 * \left(P_{best_k} - X_{i_k}\right) + c_2 * rand_2 * \left(G_{best_k} - X_{i_k}\right) \quad (6)$$

$$X_i^{k+1} = X_{i_k} + V_i^{k+1} \quad (7)$$

$$w^k = \frac{(w_{max} - w_{min})}{k_{max}} * \mathrm{k} \quad (8)$$

Where:

V_i^{k} Particle velocity at iteration (k)

ω Inertia Weight constant

c_1 , c_2 Acceleration constant

$rand_1, rand_2$ Random number between 0, 1.

P_{best_k} Best position for particle (i) based on its own experience at iteration (k)

G_{best_k} Best position achieved by the entire particles in the swarm at iteration (k)

X_{i_k} Position of particle (i) in iteration (k)

3.3.2 Particle Position, P_{best} and G_{best} Representation in DNR problem

Most of research presented in chapter 2 investigating the DNR using different IEEE network through PSO based algorithms represented the individual particle (i) in their search space by selecting random switches. This could justify their infinite search space due to the enormous number of probabilities that could include non-feasible configurations initially. The position of the particle (X_i) is the index of the switch per loop [118]. It should be stated that the particles positions should be positive numbers and integer as they represent switches indices. During each iteration, P_{best} and G_{best} are updated and recorded based on the objective function. P_{best} is the configuration realizing best fitness function (losses reduction) for the same particle (i); while G_{best} is the configuration achieving best losses reduction for all the particles in the swarm during one iteration.

3.3.3 DNR using typical and variants PSO

In chapter two, many researches used PSO, modified versions of PSO and other swarm algorithm such as ACO to solve the DNR problem on different IEEE test networks, but in this section, we will focus on which of these researches used the IEEE 33 test network for validation for losses reduction, voltage improvement and computational time as it is necessary to reduce the time to be closer to real time. Table 3.3 compares these references in term of losses reduction, best configuration found and the computational time. It was found that the highest losses reduction achieved using typical PSO were conducted in [44] ,and [45] as illustrated in table 3.3 who reported that the losses were reduced to around 126 kW, but unfortunately after applying their suggested configuration of tie switches and running a simple load flow using IPSA, the losses are calculated differently from those described and the values they publish as shown in table 3-3. For this reason, the results calculated by both researches are being treated as suspicious even though they quote to give the minimum computational time and lowest losses. The remainder of research using typical PSO in [119], did not reach the minimum solution and their solutions probably fell into local minima rather than covering the global search space. For this reason, the majority of research work modifies the technique by hybridizing it with others AI techniques such as PSO Evolutionary Algorithm (EPSO) [99], and Rank Evolutionary PSO (REPSO) [70], Genetic Algorithm (GA-PSO) and others. Under this criteria , the lowest losses reported was 120 kW, conducted by M.F.Sulaima using EPSO [99] . The author published another paper using the same network , and compared his technique to typical PSO modified version (REPSO) in [70] suggesting it also, as it reached 120.7kW while EPSO reaches 131 kW as shown in table 3. The highest losses found were achieved using bit shift operator based PSO. Research papers using BPSO gives slightly higher losses compared to SPSO, ACO, AACO with Graph theory, GA-PSO and MCPSO that suggested the same configuration. It is noticed that the computational time is not always calculated or given within the literature, and the lowest computational time reported was achieved using GA-PSO is 5.7 seconds. The configuration from each study was coded into IPSA to cross check the quoted values. In most cases these look accurate.

Table 3-3 Results of research studies applying typical PSO in the IEEE 33 bus network

Ref. Number	Year	Algorithm	Losses (kW)	Suggested Configuration	Computational time (sec)	Min. Voltage	Losses (kW) / IPSA
[120]	2010	ACO	137	7-9-14-28-32	Not calculated	___	140
[39]	2010	ACO	139.68	7-9-14-37-32	Not calculated	0.937	136
[121]	2011	AACO-graph theory	139.55	7-9-14-37-32	Not calculated	0.937	136
[44]	2012	PSO	126.4	7-10-28-14-32	16.2	0.893	170
[45]	2014	PSO	125.8	8-17-33-34-28	25.06	0.998	150
[70]	2014	PSO	146	6-14-33-28-34	28.65	___	177.8
[122]	2014	BPSO	141.6	7-9-14-28-32	24.34	0.936	140
		SPSO	138.92	7-9-14-37-32	21.35	0.942	136
[99]	2014	EPSO	120	16-7-10-25-13	Not calculated		165.2
[70]	2014	EPSO	131.1	14-33-17-26-8	13.62	___	157.7
		REPSO	120.7	32-28-11-33-34	9.97	___	142.3
[123]	2015	ACO-FUZZY	143.69	31-37-7-14-9	Not calculated		140.5
[124]	2015	PCMH	139.7	7-9-14-32-33	10.96	0.97	136
[125]	2015	GA-PSO	139.6	7-9-14-37-32	5.7	0.937	136
[126]	2015	IPSO	126	7,9,14,28,32	Not calculated	0.945	140
[119]	2015	PSO	147.49	9-14-7-17-37	Not calculated	0.927	143.14

[79]	2015	Adaptive Bi group PSO	122.67	7-9-14-28-32	Not calculated	___	140
[127]	2016	MCPSO	138.9	7-9-14-37-32	Not calculated	0.942	136
[128]	2016	Bit Shift operator based PSO	164.37	13,16,27,33,35	Not calculated	0.929	172.5
[82]	2017	UPSO	140	7-9-14-28-32	Not calculated	___	140

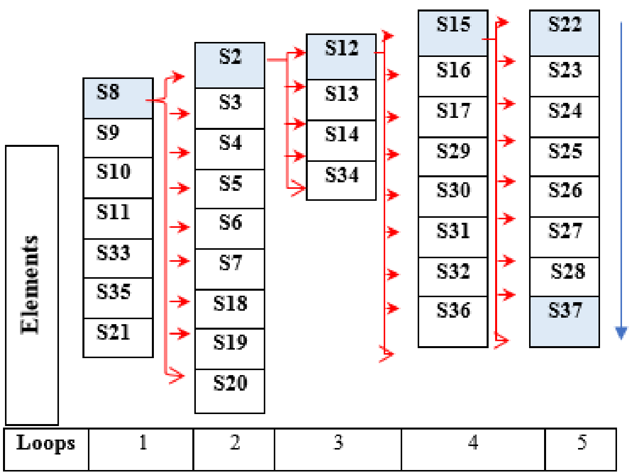
3.4 DNR using Modified Particle Swarm Optimization (MPSO)

3.4.1 Sectionalizing the network and search space formulation using tree diagram

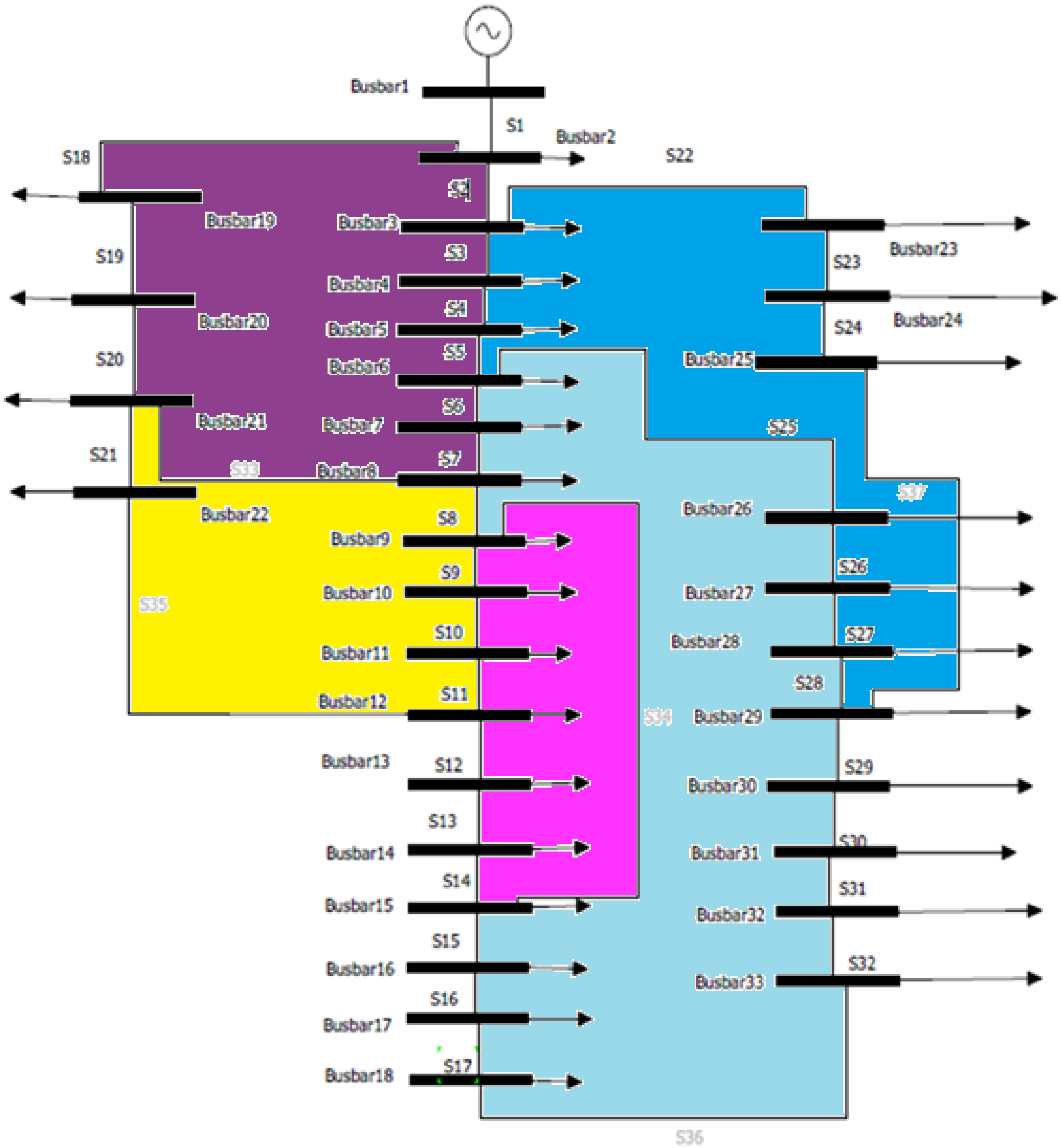
In this thesis, the idea of sectionalizing the network presented by Ankush Tandon in [122], was collaborated with the basic knowledge of probabilities, tree diagram; to generate the probabilities including one switch from each of the five-loop. Tree diagrams present a more straightforward method than previous research, to simulate the radial concept presenting one of the modifications suggested by the thesis to PSO algorithm helping to reduce the search space (16128 configurations). Previous researches used to search any 5 switches to be opened and any 5 to be closed. Thus, their search space could include infinite number of failed probabilities. The IEEE 33 network is divided in five loops, the elements for each loop are presented in Figure 3-3(a). This figure explains how a configuration such as (S8, S2, S12, S15, and S22) could be formulated based on tree diagram. The first element of each of the 4 loops should pass through all the elements existing in the 5th loop. It should be noted that S1 is not included in the search space as it connects the network to the main supply. Also, the switches common between different loops, illustrated in Table 3-4, are only stated once to avoid their duplication. For example, if S33 is considered an option in loop 2, it would result in an invalid network configuration. Figure 3-3(b) shows the 5 loops of the test network and their elements of switches.

Table 3-4 Common switches between loops for the IEEE 33 Network

Switch Number	Common loops	Switch Number	Common loops
S33	Loop1 & loop 2	S7	Loop 2 & loop 5
S9	Loop1 &loop 3	S8	Loop 1& loop 5
S10	Loop1 & loop 3	S34	Loop 3 & loop5
S11	Loop 1 & loop 3	S28	Loop 4 & loop 5
S3	Loop 2 & loop4	S27	Loop 4 & loop 5
S4	Loop 2& loop 4	S26	Loop 4 & loop 5
S5	Loop 2& loop 4	S25	Loop 4 & loop 5
S6	Loop 2& loop 5		



(a)



(b)

Figure 3-3 IEEE 33 bus network's loops and their elements

3.4.2 **Filtered Initial Positions in search space**

Initial positions in typical PSO algorithm are always selected randomly, but in this thesis, the losses, voltage and current constraints using equations (1-3) are applied in the first position selection as explained in Figure 3-4 to reduce the number of iterations used to reach the optimum solution and hence the computational time. For example, the configuration shown in Figure 3-3 (a) -(S8, S2, S12, S15, and S22) -gives total losses of 803 kW, much higher than the initial losses of the network and for this reason it was discarded. In contrast, (S8, S7, S34, S28, S16) is another example that gives total losses of 153 kW and satisfies all the previous constraints. For this reason, it could be included in the initial positions.

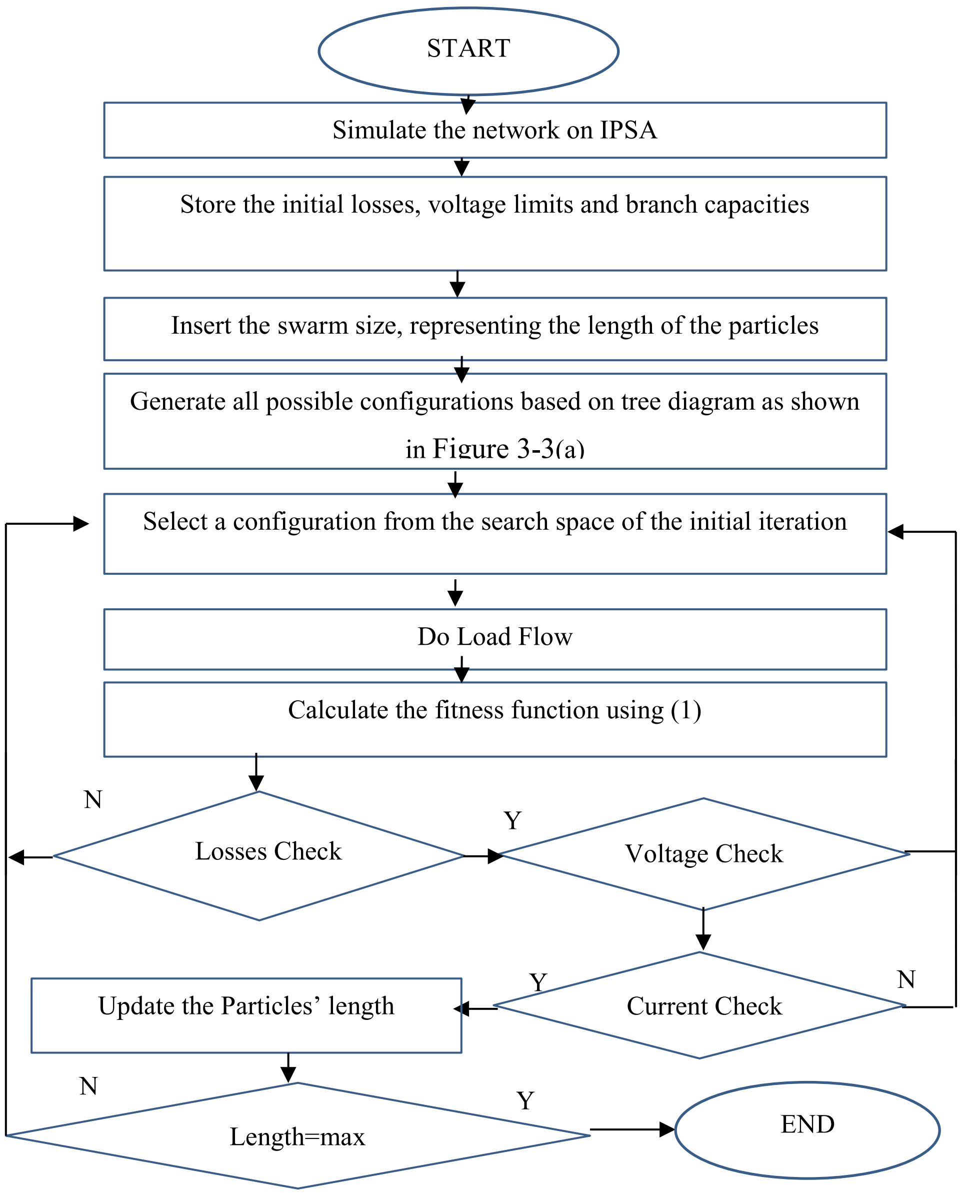


Figure 3-4 Filtered Random Initial Positions

3.4.3 Software Implementation

In chapter 2, it was realized that most published research papers studying DNR used MATLAB to build their models. In this thesis, Interactive Power System Analysis (IPSA) is used to simulate the network and build the optimization algorithm used. IPSA allows easy user interface for load flow calculations and gives the opportunity to control the network through individual designed programs using python language. Figure 3-5 shows the mechanism for using the IPSA software, where the coded python script includes the proposed optimization algorithm (shown in Figure 3-7 and Figure 3-8) is called by IPSA to control the inputs of the network simulated in Figure 3-1.

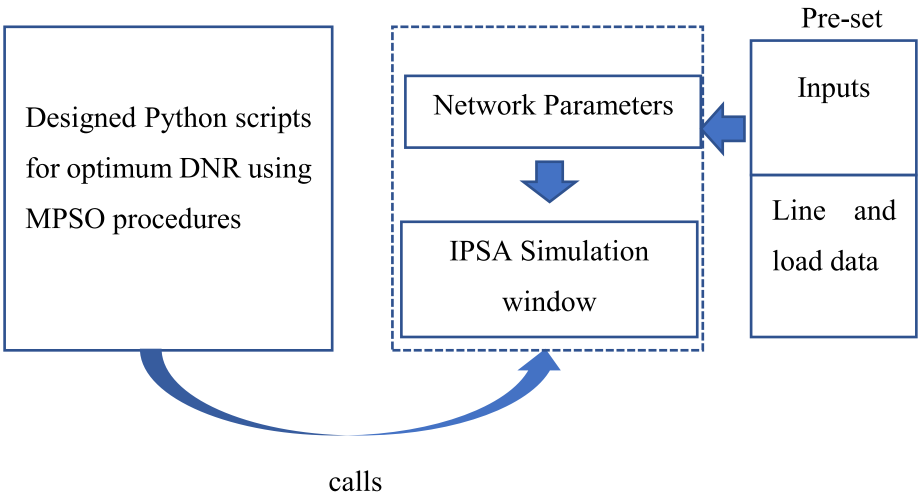


Figure 3-5 IPSA Software Theory of Operation

3.4.4 Position Control and Conversion criteria

After updating the particles positions by adding the velocity using equation (7), some positions (switches indices) could exceed the total number of switches in the existing network, (S37 in this network), or could be negative number, which is illogical as shown in Figure 3-6 (a). In this case, the position control will replace the switch having an index more than the maximum index in the network (S57), by the maximum one in the network (S37) as shown in Figure 3-6 (b). In typical versions of swarm, these infeasible positions were discarded automatically, then losing some probabilities. This position control algorithm was suggested in [74] and was applied in this thesis. Although, this algorithm retains all the particles in the search space, it could duplicate some switches in the same particle position, and violate the total tie switch number conditions, which are calculated to be five, and only in this case the particle should be discarded. Figure 3-6 (c-d) shows an example of discarded probability after applying the position control. By replacing S57 by the S37, the total number of suggested ties switches will be four instead of five as explained above in section 3.4, and for this reason this probability is discarded.

33	34	35	36	57

(a)

33	34	35	37	57

(c)

33	34	35	36	37

(b)

33	34	35	37	37

(d)

Figure 3-6 Example of position control procedures

One of the main keys to obtain accurate results using IPSA is to initialize the software after each load flow calculation for each position, because it was found that, the software gives inaccurate results after successive switching if a non-logical network configuration is used as a starting point. If there is no starting point for each position, each time the program will compute the load flow solution to find the losses at this position, it will calculate a new generated active power and new generated reactive power for the network. These calculated values will be used latter as given data base for the next new position, which could be not compatible with it. For this reason, a known configuration should be selected to be an initial attempt before each trial. In this study, the initial attempt is meshing the network after each trial.

3.4.5 MPSO Procedures

The integration of sectionalizing the network into five loops and using tree diagram to formulate a search space including radial configurations, introducing losses, voltage and current constraints for filtering the initial positions, and applying the position control algorithm to retain the particles within the search space are the main modifications added to the typical PSO for better performance. The procedures for the modified particle swarm are explained below in Figure 3-7.

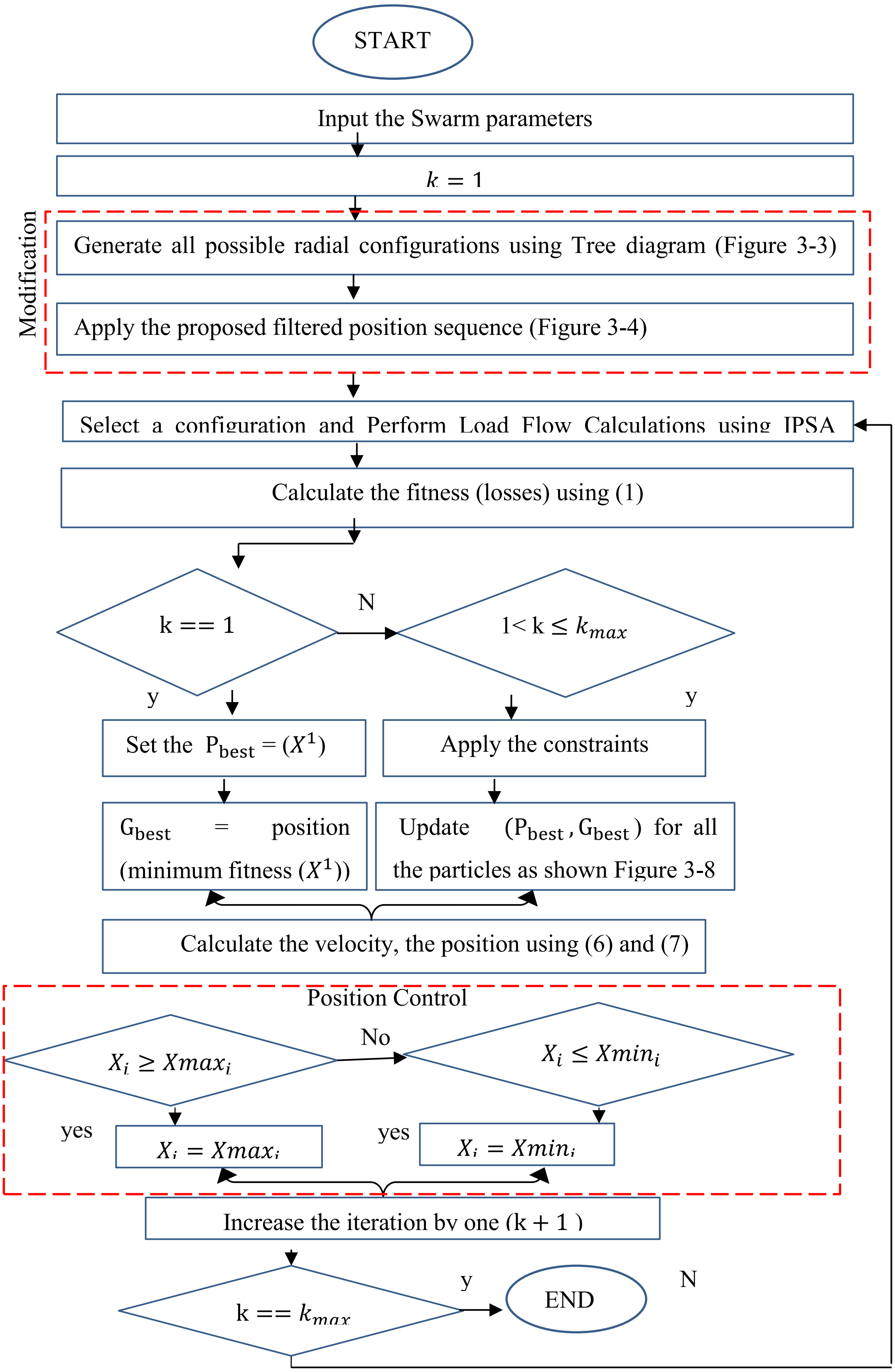


Figure 3-7 MPSO Procedures

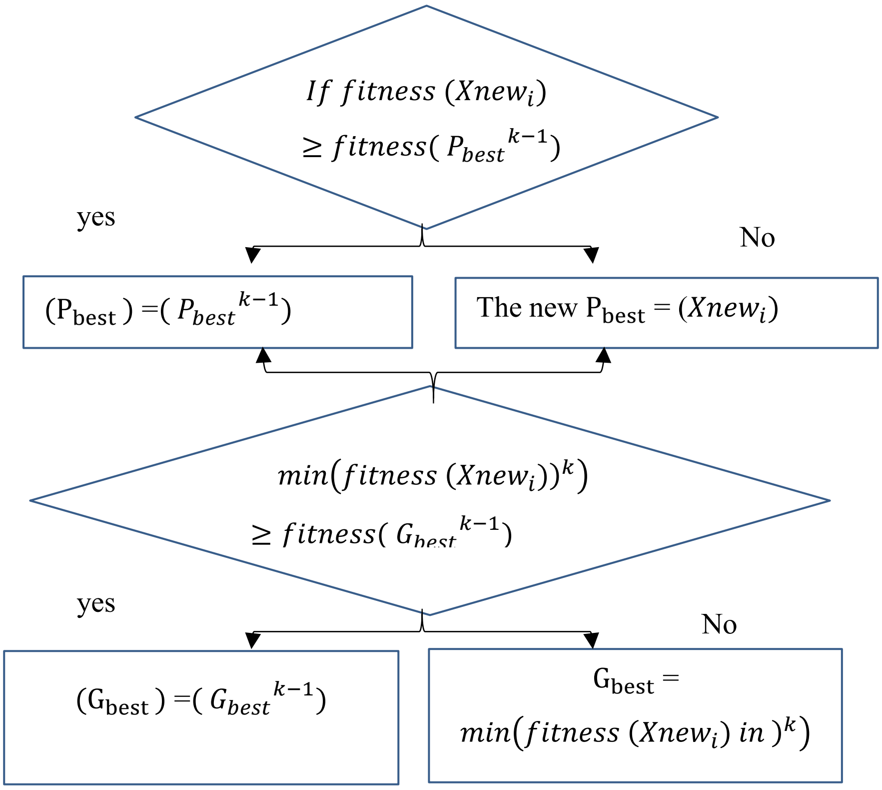


Figure 3-8 Position and velocities update procedures

3.5 Results and Discussion

The IEEE 33 network was simulated using IPSA software for losses, load flow and optimization technique implementation. Developed software has been designed to implement the (MPSO) using PYTHON 2.7.8, on a 2.4GHz, core (TM) i7-5500CPU with 8.0- GB RAM. The initial ties switches were set to 33 to 37 yielding a total loss of 193.6 kW. After applying the suggested algorithm, the losses are reduced to 136.36 kW reducing 29.68% of the initial value. Due to the stochastic nature of swarm algorithms, 50 runs are performed to find the best number of particles and iterations for optimum fitness function. In each trial, the best, the worst and the average value of the computational time were noted in Table 3-5. Also, the mode which represents how often the best losses occurred during one trial, is recorded. To decide the corresponding swarm size and the maximum iterations number for this problem, 25 ,50 and 70 iterations were tried for 50 runs for different swarm size. It was noticed that 25 iterations and a population size of 50 particles were reasonable choice because during the different iterations test, the algorithm gives the same losses value which means that there is unlikely to be a requirement to increase the iterations number. It should be noted that a single run includes 25 iterations. Figure 3-9 shows the convergence characteristic for the proposed algorithm. An improvement in the theoretical voltage profile is observed after applying the suggested algorithm. The minimum bus voltage after reconfiguration raised to 0.94 at bus 32 instead of 0.918 at bus 18 before reconfiguration, as shown in Figure 3-10.

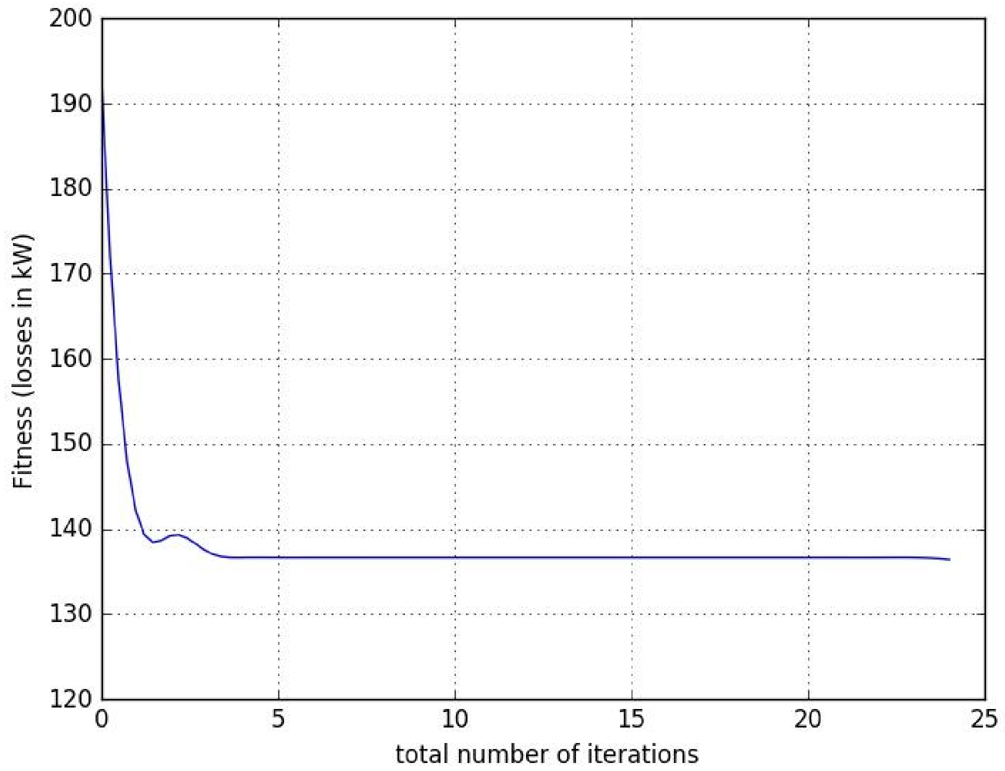


Figure 3-9 MPSO Fitness function convergence

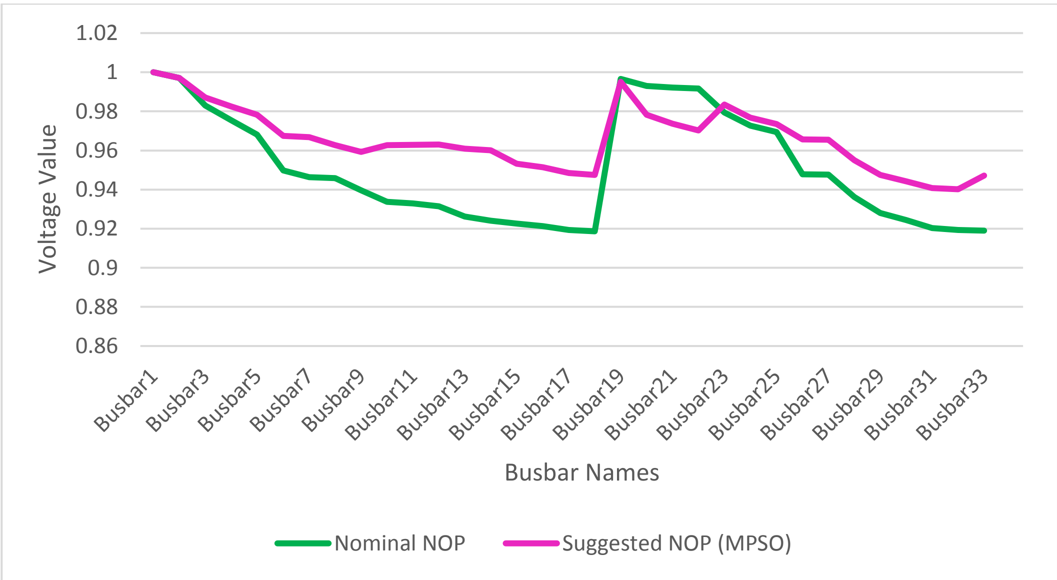


Figure 3-10 Voltage Profile improvement using the suggested NOP of MSPO

Table 3-5 Statistical Results of MPSO

Swarm Size	Iterations	Best losses	Mode	Worst losses	Average time
50	25	136.36 kW	52%	143	17.5 sec

A Comparison between the MPSO results and previous researches is presented in Table 3-3. The proposed modifications added to a typical PSO achieved 29% of losses reduction. This proposed MPSO suggested the same configuration as the SPSO, ACO, AACO with Graph theory, GA-PSO and MCPSO methods. However, it is a more straightforward method to use without adding extra equations to the basic technique. To check the optimum losses obtained, a program was designed to include all the possible configurations. This was used to calculate the losses across the entire search space using a simple load flow without any optimization algorithm. The minimum losses obtained confirm the optimization results found by MPSO.

3.6 Conclusion

In this chapter, the IEEE 33 distribution network was selected for validating DNR open points positions using optimization algorithms. Based on a comparison in chapter 2 between the different AI algorithms, swarm algorithms were the most applicable to this work. Since a typical PSO did not reach the global minimum solution and takes a large computational time due to the infinite probabilities in search space, previous researchers modified and hybridized others technique with the basic PSO for better performance. The collaboration of sectionalizing the network into five loops and using tree diagram to formulate a search space including radial configurations, introducing losses, voltage and current constraints for filtering the initial positions, and the position control algorithm to retain the particles within the search space were added to the typical PSO for better performance. It was found that the proposed MPSO reduced the calculated active power losses to 136 kW, suggesting the same configuration [S7-S9-S14-S37-S32] suggested by SPSO, ACO, AACO with Graph theory, GA-PSO and MCPS in a more straightforward method. Developed modifications allow the algorithm to be performed in a much more reasonable time span of 17.5 seconds which is still high for real time applications. It should be noted that the computational time was calculated for comparison purpose only. The results were compared to previous research. The time span is important as the loads in a network are continuously varying and not static. Therefore, it is important to think about the impact of a variable load, and to understand if analysis under variable load can be used to adopt the technique further to improve the performance of the optimization method. Chapter four will investigate this case.

4 CHAPTER 4 MULTI STAGE MODIFIED PARTICLE SWARM OPTIMIZATION

4.1 Background

In chapter three, a modified version of particle swarm algorithm (MPSO) was presented looking closely at the initial random particles position selection and a tree diagram algorithm was proposed to generate all the possible configurations including only one possible tie switch from each loop for keeping the radial structure of the network. The initial positions are filtered after applying the losses, voltage and current constraints, which in turn accelerates the computational time required for reaching the optimum solution instead of the random position selection of typical PSO techniques. A position control algorithm was applied in this research to maintain the particle positions within the feasible solution regions. It was concluded that the suggested modification improved both the calculated losses and the computational time after being validated using the IEEE 33 distribution network by suggesting [S7-S9-S14-S37-S32] to be the optimum NOP. assuming the basic IEEE static load which is not the case in real power system. This chapter concentrates on applying the MPSO algorithm under variable load to test the efficiency of the technique to support active DNR on one hand and on the other hand, to reduce the time required to undertake the optimization for this network by reducing the search space by discarding the switches that would not be feasible solutions under varying load conditions.

4.2 Uncertainty in Power System causes and solution methodologies

Electric power networks are complex systems that work on satisfying customer demand by controlling the outputs of the available generation units. The main reasons of uncertainty in power system are summarized in Figure 4-1. Unplanned outage, equipment failures, the dynamic fuel prices as well as the availability of renewable energy resources such as wind, and solar cells represent examples of uncertainty causes affecting the generation system. Other forms of uncertainty are due to customers demand as they depend on the environmental variation in climate and economic load growth. The changing in weather does not only affect the customer loads but also, can be proportional to line loading and cable current capacity in transmission systems.

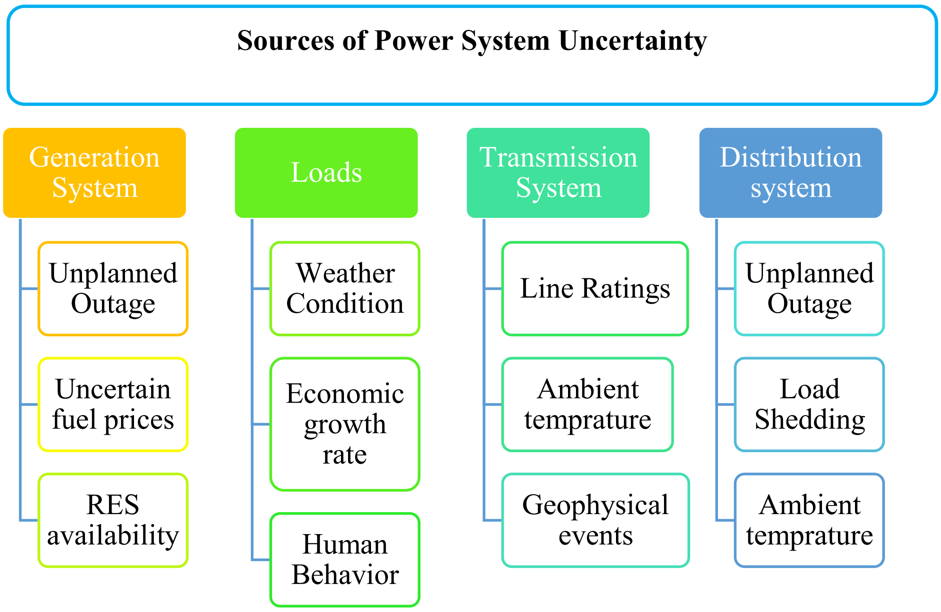


Figure 4-1 Sources of uncertainty in power system

Uncertainty in power system should be represented because neglecting the variation could lead to higher losses through poorer network configuration. There are two basic types of mathematical representation quantitative and qualitative uncertainty [129]. The quantitative uncertainty is quantifiable in numerical terms by mathematical functions with deterministic parameters. Three basic methodologies are mostly used for the modeling of this type of uncertainty in power systems, namely Probabilistic Analysis, Interval Arithmetic and Monte Carlo Simulations [130]. The qualitative uncertainty is initially expressed in vague, non-numeric terms such as “approximately equal to” or “a small percentage”. For the treatment of this type of uncertainty, Fuzzy Arithmetic Analysis is used. In this chapter, Monte Carlo Simulation (MCS) Analysis was selected to simulate the uncertainty of loads in distribution networks. MCS has significant advantages compared to other stated methods as they are analytical methods, and the basic computational part (the second step) for MCS is deterministic, therefore there is no need to simplify the mathematical models for the application to be applicable [130]. But, for obtaining good results, the sampling procedure must be repeated many times, and this makes the method rather time consuming when applied to large systems.

4.3 Monte Carlo Simulation (MCS)Technique

Monte Carlo simulation is a very useful mathematical technique for analyzing uncertain scenarios and providing probabilistic analysis of different situations. It is a type of numerical simulation that relies on repeated random sampling and statistical analysis to compute the results of a stochastic process by taking into consideration the risks of input parameters that could affect this process [131]. MCS was given its name by Stanislaw Ulam and John von Neumann, who invented the method to solve neutron diffusion problems at Los Alamos in the mid-1940s. MCS procedures are explained in [130, 131] and summarized in Figure 4-2. Three steps are the core for MCS; the first is building a deterministic model. In this step, the basic model or the one close to real scenario is used, where the mathematical model is solved to obtain the desired solution. To accomplish this step, it is necessary to need to identify the risk components which are dependent on stochastic variable and for this reason, random numbers are generated to allow variance. After performing this step, the model is run, and the deterministic model is recalculated each time the random number are generated to build a history of data and finally a statistical analysis is performed after thousands of trials.

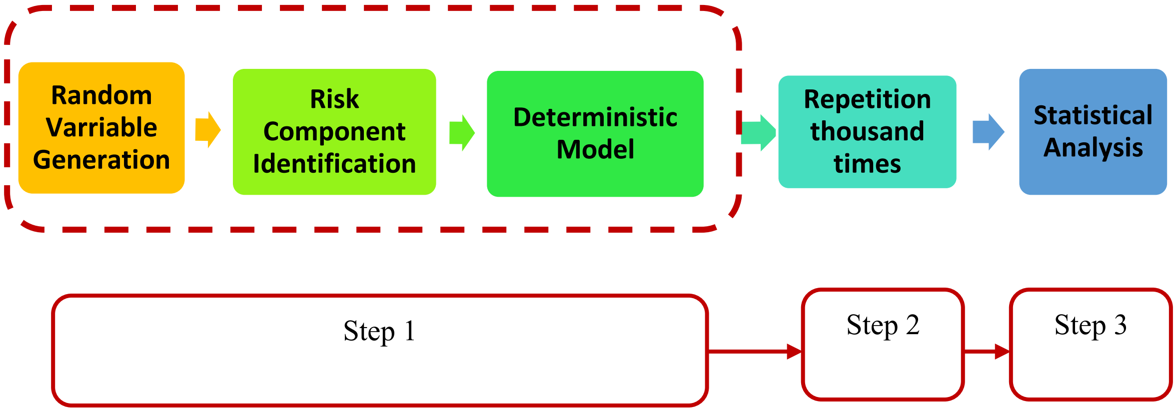


Figure 4-2 Monte Carlo Procedures

MCS has been used in wide range of application in power system to study uncertainty in different topics such as reliability and security evaluation , probabilistic load flow , unit commitment and others [132]. In this thesis, MCS was selected to simulate the uncertainty in load demand location for a fixed value of load and their reflection on the selection of optimum NOP for best losses reduction.

4.4 Load Representation with respect to DNR in previous researches

It is well known that loads in electric power system are varying continuously per day depending on the weather conditions and customer behaviors as stated previously in Figure 4-1. For a secure power system, the feeder capacities and the protection devices ratings should be considered when load change. Researchers work on finding methodologies to simulate the load to study the power system under variable load conditions. As previously explained in chapter two, many research papers directed their work to study DNR. Most of them considered the load static such as [44-47, 49-51, 53, 55, 57-59, 65-68]. Few research papers represented the changing in load in different methodologies as illustrated in table 4-1.

Table 4-1 Variable load representation in previous research papers

Ref	year	Algorithm	Variable load representation
[133]	2012	Simulated Annealing	A load level coefficient is used to reflect the changing in loads to obtain an actual operating power load. This coefficient changes between [1.00,1.02, 1. 04,1.06, 1.07 ,1.08]
[48]	2013	HSA	The light, normal and heavy load were simulated by using a load factor varying between 0.5, 1,1.6 respectively
[116]	2014	NSPSO	Average load profile is assumed to be forecast and divided into 6 periods. In each period, the load is considered constant.
[134]	2014	SPSO	4 load conditions are simulated: base case, light, medium and high (-5%, +5% and 10% of base case load)
[61]	2014	FWA	In both papers, the light, normal and heavy load were simulated by using a load factor varying between 0.5, 1,1.5 respectively
[71]	2014	GA-PSO	
[27]	2015	GA	The bus locations for residential, industrial, commercial and school customers were assumed. The load hours are divided into four cases where in each case consists of approximately similar load patterns in a given period of time.

In this chapter, load demand variation is represented by generating 32 random numbers representing the new generated bus loads to meet the same IEEE total load. This allows the uncertainty of where the load is located and how it could change with time to be represented. Keeping the total load, the same, allows for a clearer validation of the gain in losses reduction. In other words, redistributing the load randomly during peak hour by changing the percentage loading of each bus. This could imitate what happen in real network when a sub feeder goes out of service during peak hour. The procedures for random load generation is shown in Figure 4-3 .

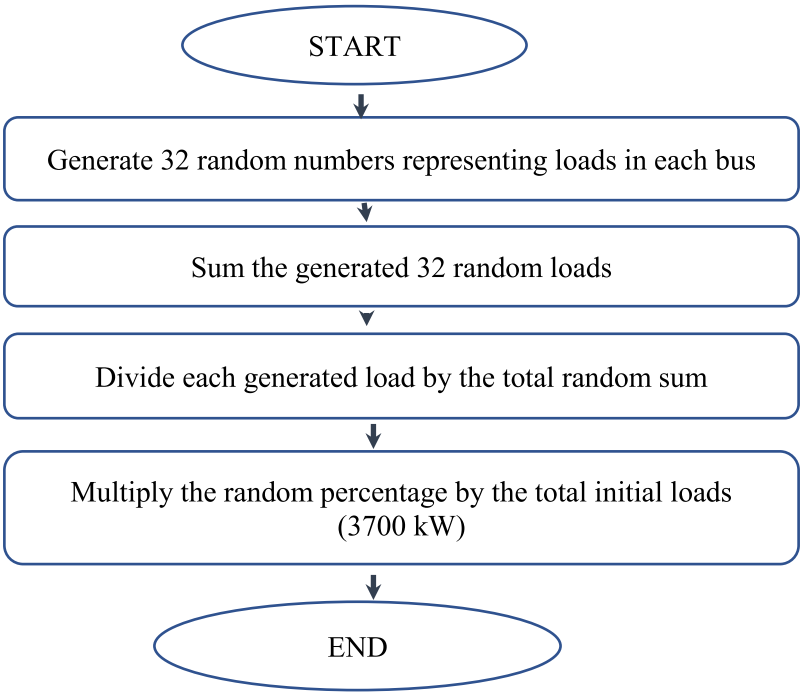


Figure 4-3 Random Load Generation Procedures

4.5 Proposed Multi Stage Modified PSO (MSMPSO)

One of the main disadvantages of using the swarm technique is the infinite search space, this was partially solved in chapter three by suggesting tree diagram and integrating some constraints in the initial positions' selection, that helped to formulate a reasonable search space composed of 16128 configurations, each is composed of one switch from each loop. In this chapter, a new method MSMPSO is suggested, where the MPSO- proposed previously in chapter 3- is considered the first stage of this new suggested technique and will be tested under variable random load during the second stage to imitate the realistic system on one hand and to reduce the search space in the third stage on the other hand. Proposed MSMPSO is another modification added to MPSO by adding another two stages after implementing the MPSO, and therefore called by Multi stages Modified MPSO.

4.5.1 Stage two: MCS-MPSO for random load generation

In this stage, the proposed technique integrates the Monte Carlo Simulation (MCS) concept to MPSO as shown in Figure 4-4 to simulate the load variation during 1000 trials during peak hours. In each trial, the new generated load is given to MPSO, previously explained in chapter three to find the configuration giving the optimum losses during 25 iterations.

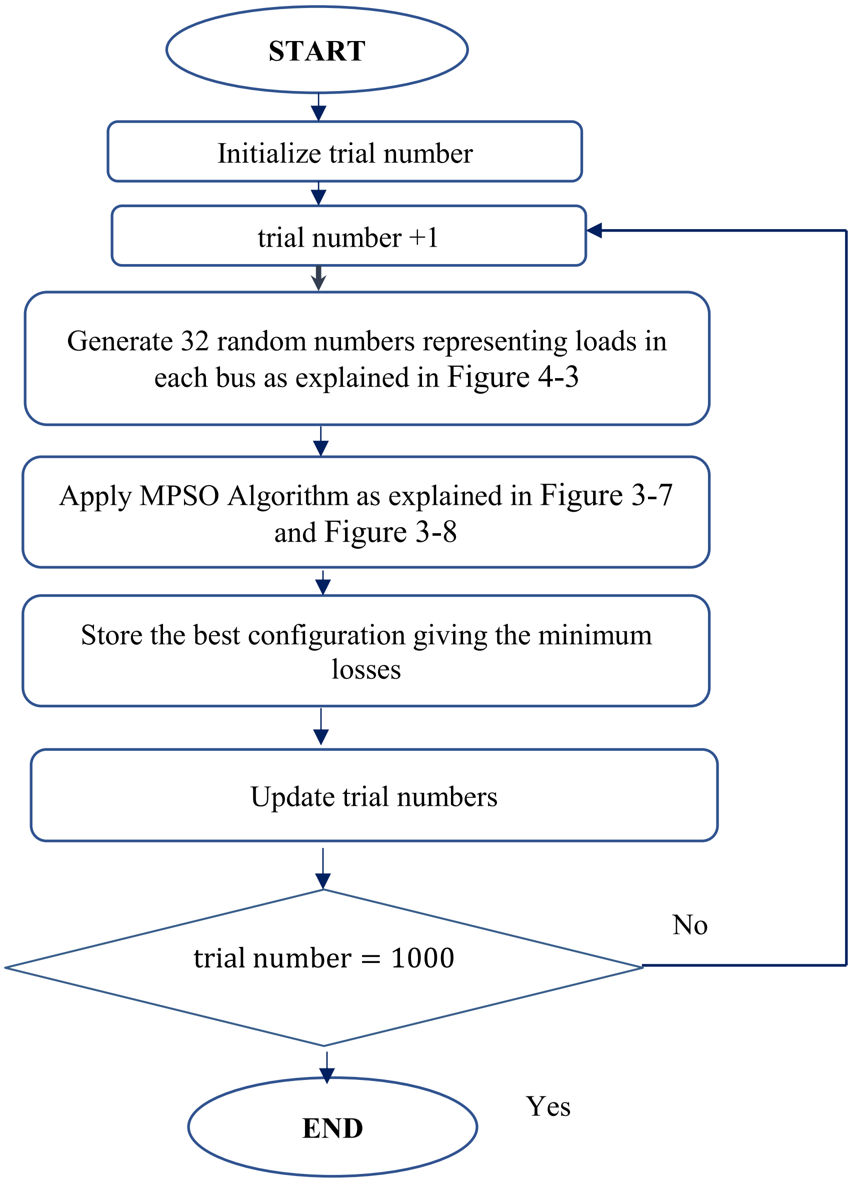


Figure 4-4 MPSO using Variable load via MCS

Figure 4-5 shows the normal distribution of losses during 1000 trials, while Figure 4-6 shows the losses range during the different trials. It was found that 58 trials achieved losses less than 130 kW while only 20 trials having losses more than 160kW. Both having low probabilities to occur. The highest range of losses is between [140-145] kW through 235 trials. The lowest losses found is 122.3 kW at trial number 239, while the maximum losses are 176 kW found at trial number 95. The generated random load at each bus for both trials is shown in Figure 4-7 and Figure 4-8 respectively. Both figures illustrate how Monte Carlo could randomly vary the load through each bus bar by changing the percentage loading while keeping the same IEEE total load. For example, the load at bus 2 in trial No.239 is 97.08 kW while in trial No.95 is 5.024 kW. The least load generated in trial 239 and 95 are 37.632 kW and 5.0326 kW at bus 11 and bus 2 respectively. Maximum load generated in both trials did not exceed 250 kW. Table 4-2 includes the configurations suggested by MPSO to reach the optimum losses. It is clearly shown that the best configuration for trial 239 is achieved after 22 iterations while for trial No. 95 is achieved in 14 iterations. These values were cross checked by being manually entered in the substation loads of the IEEE model simulated in IPSA window without using any optimization algorithm for losses calculation for checking the values calculated by MPSO, and the results are very closed to the output.

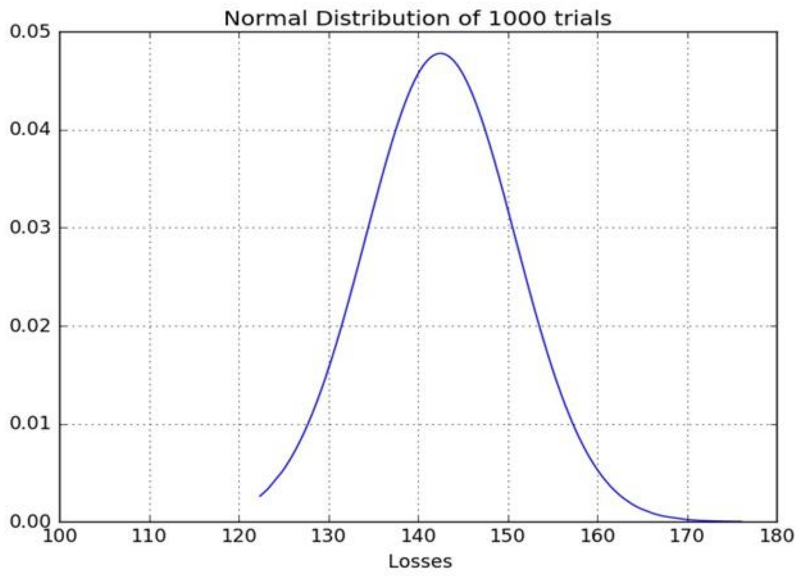


Figure 4-5 Normal distribution of losses during 1000 trials

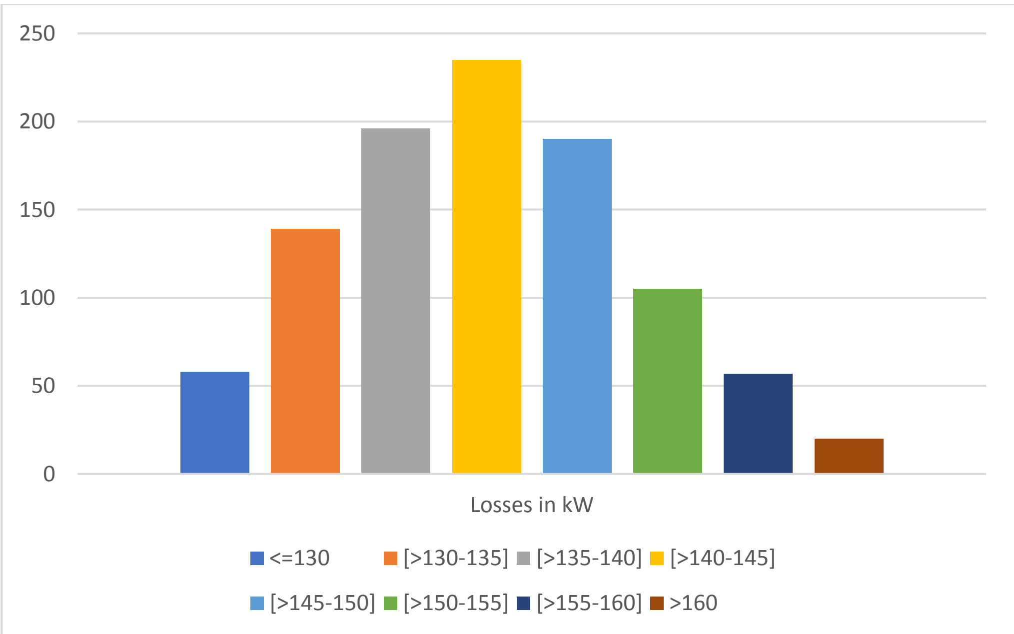


Figure 4-6 losses during 1000 trials

Table 4-2 Trials No.239 and No.95 results in 1000 trials

losses	Trial	Configuration	Losses using MPSO (kW)	iteration	Losses using IPSA load flow (kW)
Min	239	[10, 7, 14, 28, 32]	122.3	22	122.7
Max	95	[9, 7, 14, 28, 16]	176.0	14	176.46

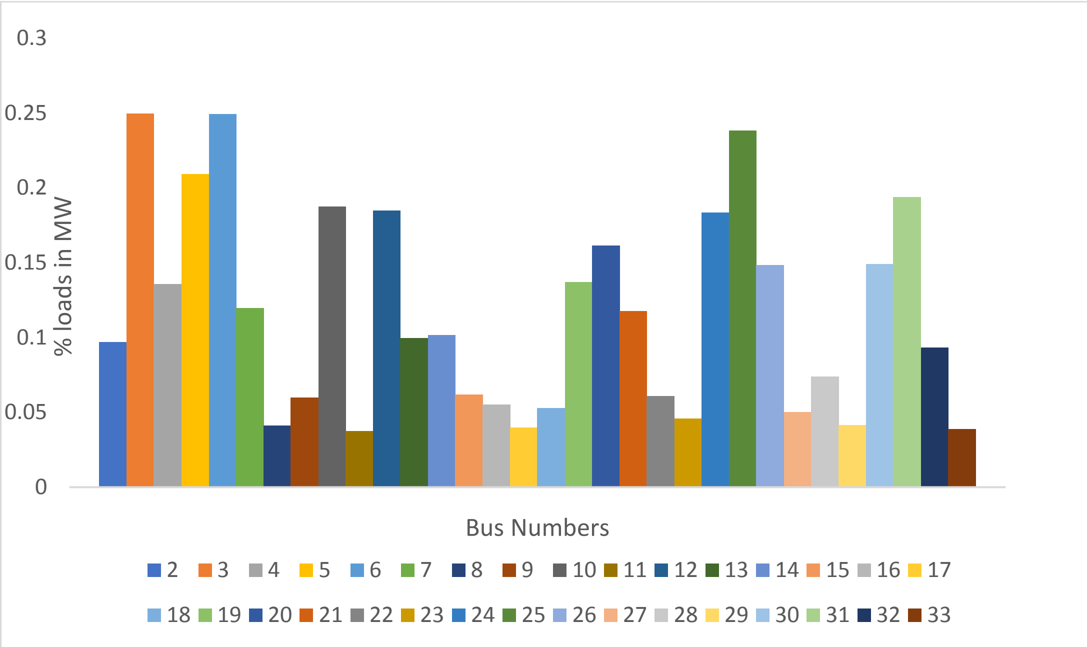


Figure 4-7 loads in MW per bus distribution in trial No.239 achieving less losses

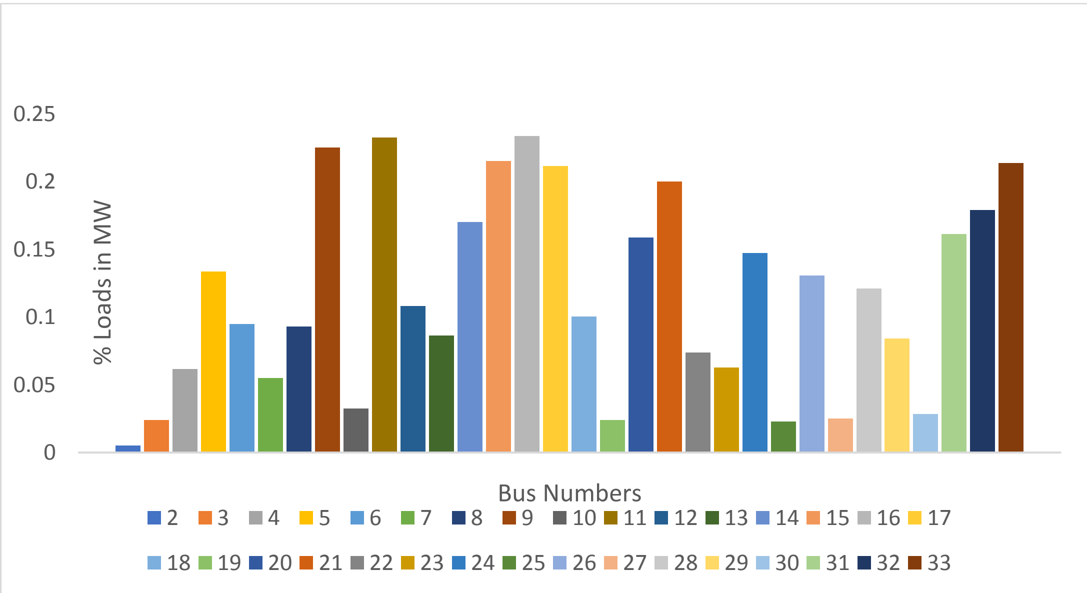


Figure 4-8 loads in MW per bus distribution in trial No.95 achieving highest losses

To benefit from the data saved during the 1000 searches, switches that are mostly commonly identified as optimum NOP by MPSO, represent the most likely configuration for the tie switches in the case of a varying load (The 5 most common become the starting position). Table 4-3 shows the number of repeated switches during the trials. The five most repeated switches are [9, 7, 14, 16 and 28]. These switches were the most repeated per each 200 trials of the 1000 trials as shown in Figure 4-9. This figure indicates how many times each of the suggested tie switches is repeated per each 200 trials and confirms that there is no need to increase the number of trials more than 1000 since there is no results variation. This configuration differs than the result obtained by MPSO [9-7-14-37-32] as detailed in chapter three. In other words, the NOP configuration is not the same during static and variable load. It should be noted that 21 switches are not repeated during the search which means that they could not represent an optimum tie switch. Each color represents an individual loop as represented in Figure 3-3 (b). The elements of each loop were previously stated in Figure 3-3(a).

Table 4-3 Repeated switches in 1000 searches

Switches	S2	S3	S4	S5	S6	S7
No/1000 trials	0	0	0	0	31	969
Switches	S8	S9	S10	S11	S12	S13
No/1000 trials	0	463	405	132	1	86
Switches	S14	S15	S16	S17	S18	S19
No/1000 trials	781	84	380	373	0	0
Switches	S20	S21	S22	S23	S24	S25
No/1000 trials	0	0	0	0	0	0
Switches	S26	S27	S28	S29	S30	S31
No/1000 trials	0	13	979	0	0	1
Switches	S32	S33	S34	S35	S36	S37
No/1000 trials	27	0	132	0	135	8

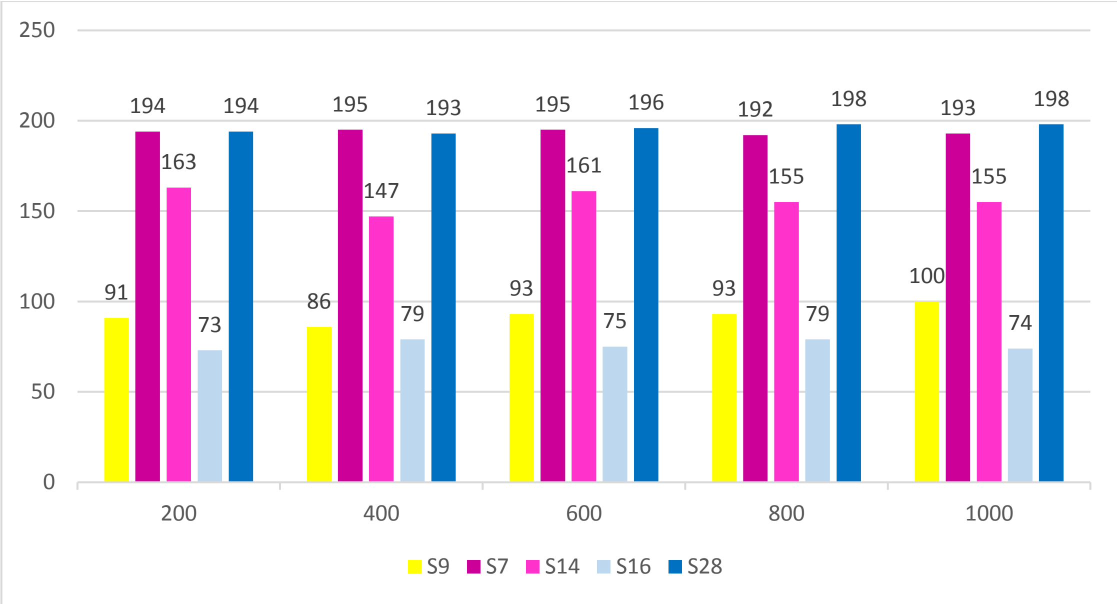


Figure 4-9 The Most repeated tie switches in 1000 trials

4.5.2 Third Stage: Search Space Reduction

The main aim of this stage is to reduce the search space by neglecting the non-repeated switches illustrated in Table 4-3 as they could not represent a solution for 1000 trials of variable random loads. By this way a new search space is generated including 270 configurations compared to 16128 configurations in the suggested MPSO in the first stage. The new elements of each loop are illustrated in Table 4-4.This in turns reduces the computational time and enhances the conversion criteria of the initial stage of MPSO, as will be discussed in next section. A stopping criterion is added to stop the algorithm when the optimum configuration is found without completing all the given iterations numbers set to 25 as stated in chapter three. This criterion starts by comparing the calculated losses in each iteration to the previous one, if the difference is less than 0.5 kW, then a counter will start to count to 10; which means if the calculated losses did not change significantly for 10 continuous iterations, the algorithm will stop. The counter value is selected after trying different number combinations manually; 5,10, 15 and 20. It was found that the least average computational time is achieved by setting the counter to 5. In this case, the average computational time was calculated to be 5.7 seconds- same value achieved by [125] presented in Table 3-3. The highest value of computational time is found by setting the counter to 20. To decide the accurate value for the counter, 50 trials are performed; In each trial the optimum losses, the corresponding configuration and the computational time were stored. It was found that by decreasing the value of the counter to 5, the optimum configuration is repeated 35 out of 50 trials, compared to 46 trials in case of setting the counter to 10. For this reason, the counter was set to 10 to reduce the risk of not getting the best solution, and there is no need to add extra time by setting the counter to 15 or 20. This value of mode-which represents how often the best solution is repeated during the run- is not always stated by the researchers.

Table 4-4 New Search Space Elements per each loop

Loops No.	1	2	3	4	5
New Elements	S9-S10-S11	S6-S7	S13-S14-S34	S15-S16-S17-S32-S36	S27-S28-S37

4.6 Results and Discussion

The main target of this chapter was reached by testing the MPSO through variable load using MCS and enhancing the computational time of the algorithm by reducing the search space to only 270 configurations. By giving this new search space to MPSO, [S7-S9-S14-S37-S32] is suggested as an optimum configuration for the IEEE 33 network confirming the output found from the first stage. MSMSPO reduced the computational time of the basic swarm algorithm to 17.5 seconds in stage one by applying MPSO, and then it was reduced again by neglecting the non-repeated switches to be 9 seconds. The stopping criterion added allow the algorithm to stop after reaching the optimum value without completing the maximum number of iterations given. Figure 4-10 shows that both MSMPSO and MPSO reached the optimum solution but MSMPSO stopped at the 14^{th} while the MPSO proceeded to all the given maximum number of iterations. Both reduce the losses to 136 kW, but the convergence and the computational time of the MSMPSO are much better, as shown in Figure 4-10, which represents a comparison between the fitness losses function obtained by both techniques. In this figure, the proposed MSMPSO is faster than the MPSO and reaches the optimum losses in iterations number less than MPSO, which confirm the effectiveness of the technique with respect to convergence and computational time.

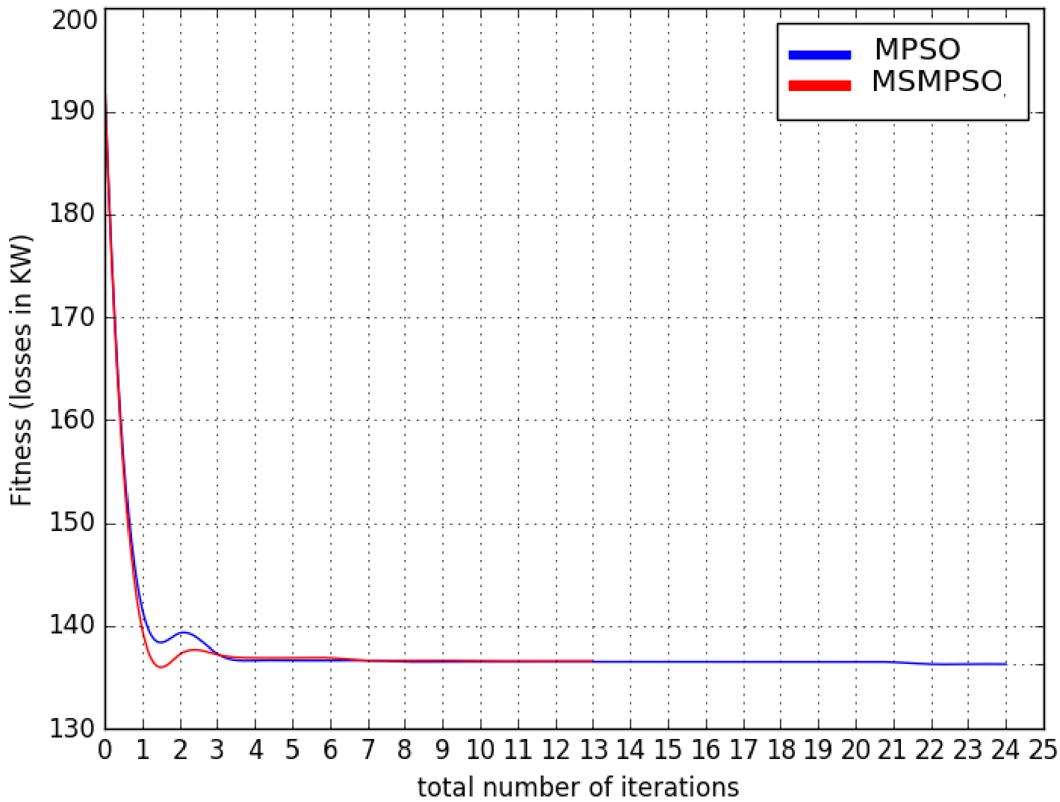


Figure 4-10 Fitness function for both MPSO and MSMPSO algorithms

Due to the stochastic nature of swarm algorithms, 50 runs are performed to find the best number of particles for optimum fitness function. In each trial, the best, and the worst value of the fitness function (the losses) are recorded as well as the computational time, as illustrated in Table 4-5. In additions, the mode, which represents how often the configuration giving the best losses is repeated during the 50 trials. It should be noted that the second and the third stages of the suggested MSMPSO enhanced mainly the accuracy of the algorithm, and this is concluded from the value of mode, that increased from 52% to 92%, as illustrated in Table 4-5. Figure 4-11 shows the NOP locations in IEEE 33 network in static and variable load.

Table 4-5 MSPSO -MPSO Statistical results

Algorithms	Best Losses (kW)	Worst Losses (kW)	%Mode	Time (sec)
MPSO	136	143	52%	17.5
MSMPSO	136	139.6	92%	9

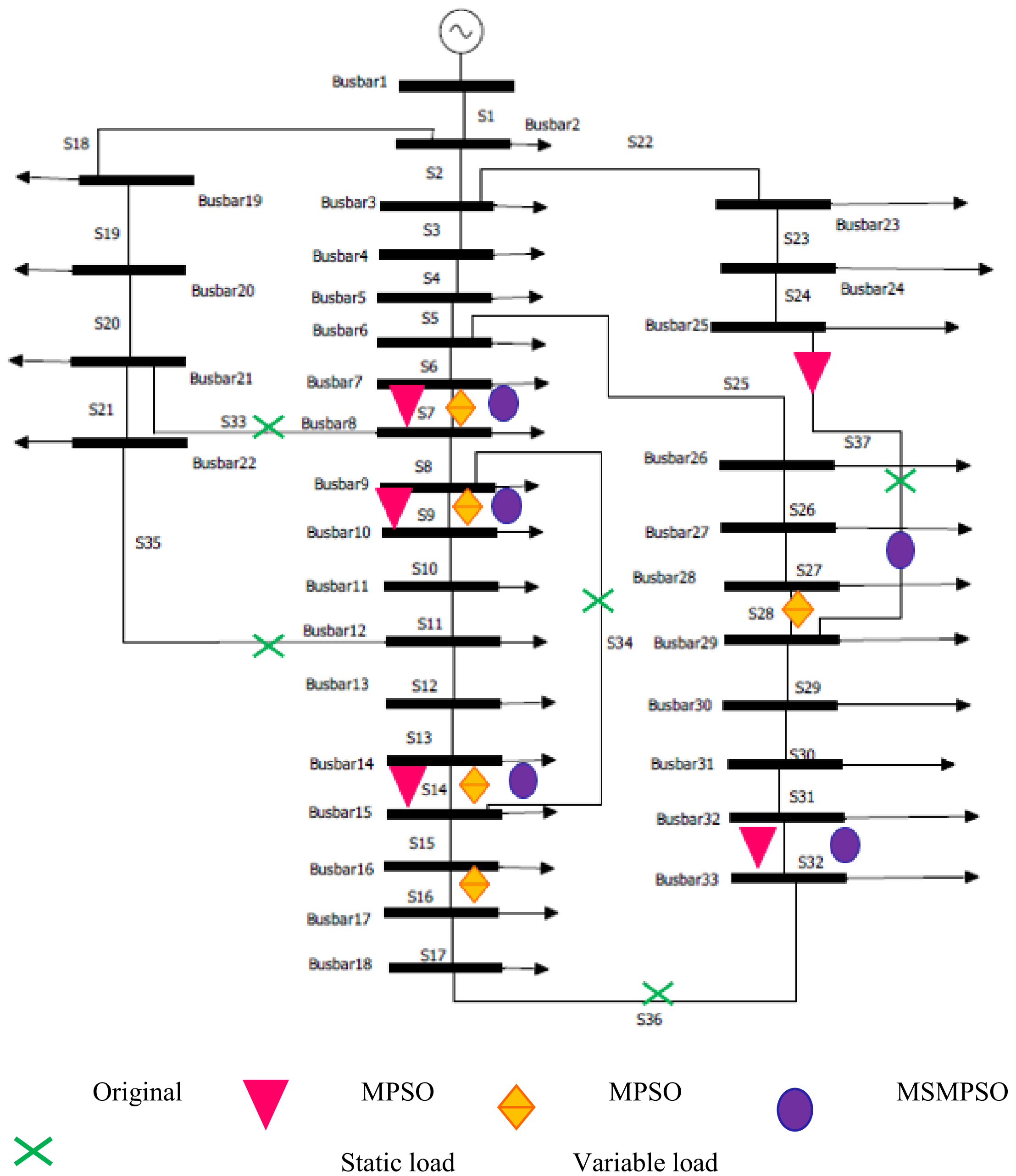


Figure 4-11 Optimum ties location in IEEE 33 network

4.7 Conclusion

In this chapter, the main reasons of uncertainty in power system generation, transmission, distribution and demand were stated. Probabilistic Analysis, Interval Arithmetic, Monte Carlo Simulations (MCS) and Fuzzy Arithmetic Analysis are examples of the mathematical methodologies used to model uncertainty. In this work, Monte Carlo Simulation (MCS) was selected to simulate load uncertainty in a distribution network. A Multistage Modified Particle Swarm methodology (MSMPSO) was proposed for improving the computational time of MPSO and implementing an active DNR through variable load. The proposed process is composed of three stages; the first is implementing MPSO; The second is using Monte Carlo (MCS) for generating variable load during 1000 trials. The third stage is building on the results of the second stage, by performing MPSO again after adjusting the search space. It was found that the five most repeated switches are [9, 7, 14, 16 and 28] represent the most likely configuration for the tie switches in the case of a varying load. This configuration differs than the result obtained by MPSO [9-7-14-37-32] for static load. In other words, the NOP configuration is not the same during static and variable load. Another finding was recorded during the thousand trials, that 21 switches were not repeated and hence they could be neglected from the search space. A new search space consisting of 270 configurations is given to MPSO in stage 3 of MSMPSO. Both MSMPSO and MPSO suggest the same configuration for losses reduction at static load. The performance of MSMPSO is much better in convergence rate and computational time. MSMPSO reduced the overall time to only 9 seconds which could be reasonable for real time applications.

Since Power networks are systems consisting of DERs, many researchers have suggested their integration using DNR for enhancing the active losses reduction. DERs could be renewable energy sources such as wind turbines or solar cells, or other sources of energy storage. To integrate them, the size, the location should be adjusted to do not represent a burden on the system. The next chapter will study the effect of DERs integrating on losses reduction in the IEEE 33 bus network.

Research Novelty: Development of MPSO technique by integrating MCS for load variation and search space reduction and proposing Multi stage Modified Particle Swarm Optimization.

5 CHAPTER 5 ENERGY STORAGE (ES) IN IEEE -33 DISTRIBUTION NETWORK

5.1 Background

Previous chapters discussed how dynamic reconfiguration is applied on a distribution network to reduce the losses. To help with this, particle swarm algorithm is modified through multi stages during static load via MPSO and variable load through MSMPSO for getting an optimum DNR. The IEEE 33 test network calculated losses were reduced from 193 to 136 kW during only 9 seconds. This computational time was achieved after implementing MCS which served to simulate the uncertainty of load distribution on one hand and on the other hand adjusting the search space of the MPSO based on statistical analysis. Based on the survey presented in chapter two, it was demonstrated that there are several strategies to reduce the losses in distribution network. Changing the NOP is one of them as was explained in chapters 3, and 4. A second strategy is the integration of DGs to the distribution network. To help with this, the number, the type as well as the sizing and the location of the DG need to be identified. A mix between both strategies also has suggested showing how DNR could be effective in distribution network in terms of losses reduction after integrating DGs. The authors in [135] assumed the best locations and then they focused on sizing the DGs, then they implemented DNR for better losses reduction comparing between different optimization techniques. Reference [136] focused on finding the optimum location and size for integrating DGs in the distribution network without DNR. Furthermore, [27, 40, 44, 133] focused on DNR after modifying the test networks by assuming both the location and the size of DGs added to the networks. Chapter 2 reveals that few references studied the simultaneous reconfiguration with the sizing and the allocations of DGs units. Most of them did not specify the kind of DGs used in their studies such as [61, 101, 102, 105-107, 109] while other research papers used PV or Wind for their studies such as [98, 108]. Only [103, 110] used EES in conjunction with DGs to maximize the renewable energy share in distribution network through a planning study. Both papers assumed the size of EES. This chapter investigates the integration of standalone storage units for minimum losses. For achieving this goal, the size and the location for the storage units should be calculated. The literature presented in chapter 2 shows that previous researches studied the sizing of BESS from three perspectives; the first is facilitating the integration of renewable energy in distribution network; the second is for planning purpose; the third is for peak shaving and load leveling for deferring the annual generation upgrade and reducing the running fuel for spinning reserve. The work in this research is different because it focusses primary on losses reduction in the presence of active DNR. The main aim is to calculate the best sizing and location for batteries in the IEEE 33 network for losses reduction while at the same time keeping the flexibility around being able to change the open point in the network for maximum losses reduction. The combination between them is not straightforward. ES sizing and allocation are studied in an operational mode that combine between the discharging and the charging mode. This has not been considered before in previous literature.

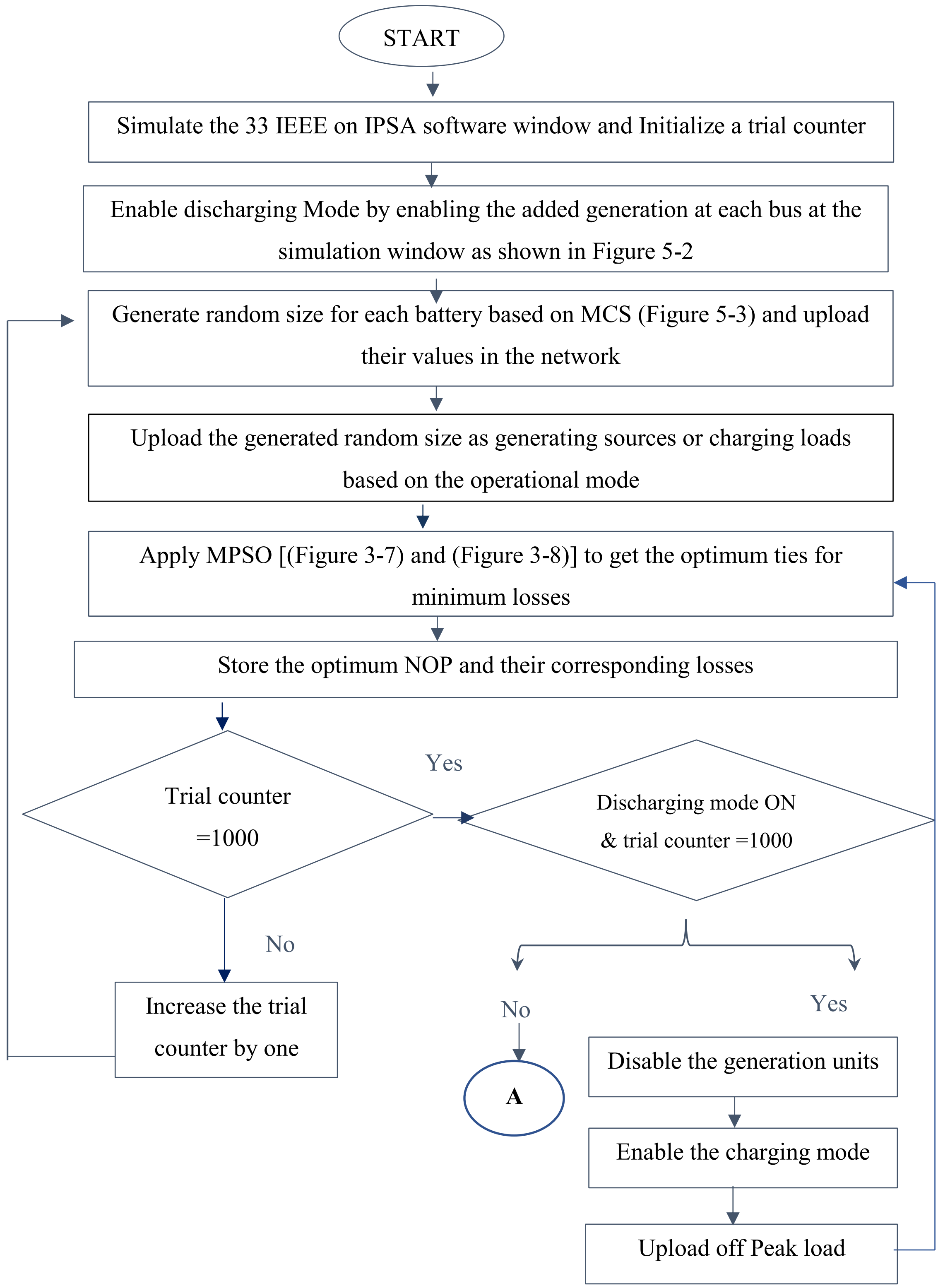
5.2 Study Assumption

This study is based on three assumptions: the first is a fixed total capacity for added storage units; the second is the proportion of off-peak load with respect to the full peak load during charging mode. The third assumption is the battery efficiency. Each of these is described below.

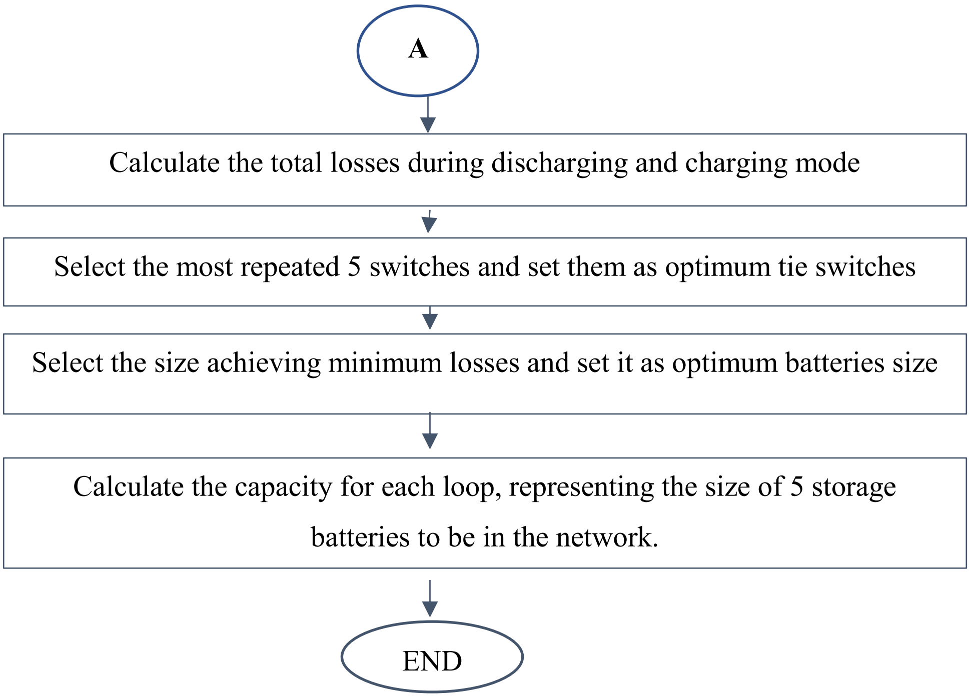
1. The total amount of added stored energy is set to 500 kW. This is not at a fixed location and its distribution needs to be solved as part of the process. This is representative of 75% the total share of renewable energy in UK, including wind and PV only that need to be connected to storage batteries to solve their nature of being weather condition nature. The total share of renewable energy in UK is around 20% of the total generation [137].
2. Since battery charging and discharging time management is important from the perspective of peak load. The battery should be charged during off-peak hours. The off-peak load for 33 IEEE network is assumed to be 73% of the initial given load.
3. Batteries losses are negligible compared to the losses within the network. In this work, the capacity of the batteries used are not considered only their power ratings.
4. Batteries' capacities are considered large enough to continue charging/discharging as long as the system is needing them.

5.3 Sizing & Siting Energy Storage (ES) in distribution network

To identify the optimum size of Battery Energy storage system (BESS) if DNR is considered, Monte Carlo simulation method (MCS) was suggested for sizing while DNR problem was solved by the proposed MPSO. Both MPSO and MCS are explained in chapter three and four respectively. Figure 5-1 shows a proposed BESS sizing procedure. In this research, both the storage batteries 'sizes and locations are suggested to be studied in an operational mode that merges between both the discharging (at full peak load) and charging mode (at off peak load) respectively and not considering any of them in isolation as the best location and size during charging will be different than during discharging. The study begins by connecting 32 storage units to all buses, with a random size generated using MCS during a thousand trials; their summation always fixed at 500 kW (as previously explained in section 5.2). In each trial, the optimum NOPs were found based on MPSO. MSMPSO was not proposed in this application because it gives the same result as MPSO (but better performance in computational time and conversion characteristic. Since the computational time is not the target here, MPSO was preferred). A statistical analysis has been performed latter to filter the most repeated 5 ties to represent the optimum open switches for each mode. The BESS size achieving the minimum total losses during both charging and discharging was selected to be the best size.


START
Simulate the 33 IEEE on IPSA software window and Initialize a trial counter
Enable discharging Mode by enabling the added generation at each bus at the simulation window as shown in Figure 5-2
Generate random size for each battery based on MCS (Figure 5-3) and upload their values in the network
Upload the generated random size as generating sources or charging loads based on the operational mode
Apply MPSO [(Figure 3-7) and (Figure 3-8)] to get the optimum ties for minimum losses
Store the optimum NOP and their corresponding losses
Trial counter =1000
Yes
Discharging mode ON & trial counter =1000
No
Increase the trial counter by one
No
Yes
A
Disable the generation units
Enable the charging mode
Upload off Peak load

(a)



(b)

Figure 5-1 Energy Storage Sizing procedures in both operational modes

Table 5-1 illustrates the differences and similarities through the different operational modes. The main difference between charging and discharging mode was the way the storage units were represented in the IEEE network. During discharging mode, BESS were simulated as generating units, while in charging mode BESS were represented as loads. BESS representation is not the only difference but also the demand load. In discharging mode, the full IEEE load are considered while in charging mode, the off-peak values are used; off peak loads are assumed to be 73% of full peak IEEE loads as explained in section 5.2. The sizing procedures for both charging and discharging were previously explained in Figure 5-1.

Table 5-1 Differences and Similarities between BESS operational modes

	Differences		Similarities
	BESS Representation	Demand load	
Charging Mode	32 random generated loads	Off peak load (73% full load)	BESS sizing procedures shown in Figure 5-1 are similar in all modes.
Discharging Mode	32 random generating units	Full peak load	

5.3.1 **Discharging Mode (Mode 1)**

Discharging mode is initially operated by activating the generating units connected to each bus representing the storages batteries. Figure 5-2 shows the BESS representation in the IEEE 33 distribution network using IPSA during discharging mode. 32 random size are generated to represent the BESS size based on MCS as explained in Figure 5-3 for 1000 trials. In each trial, the 32 generated size, the optimum configuration found by MPSO, and the calculated losses are stored.

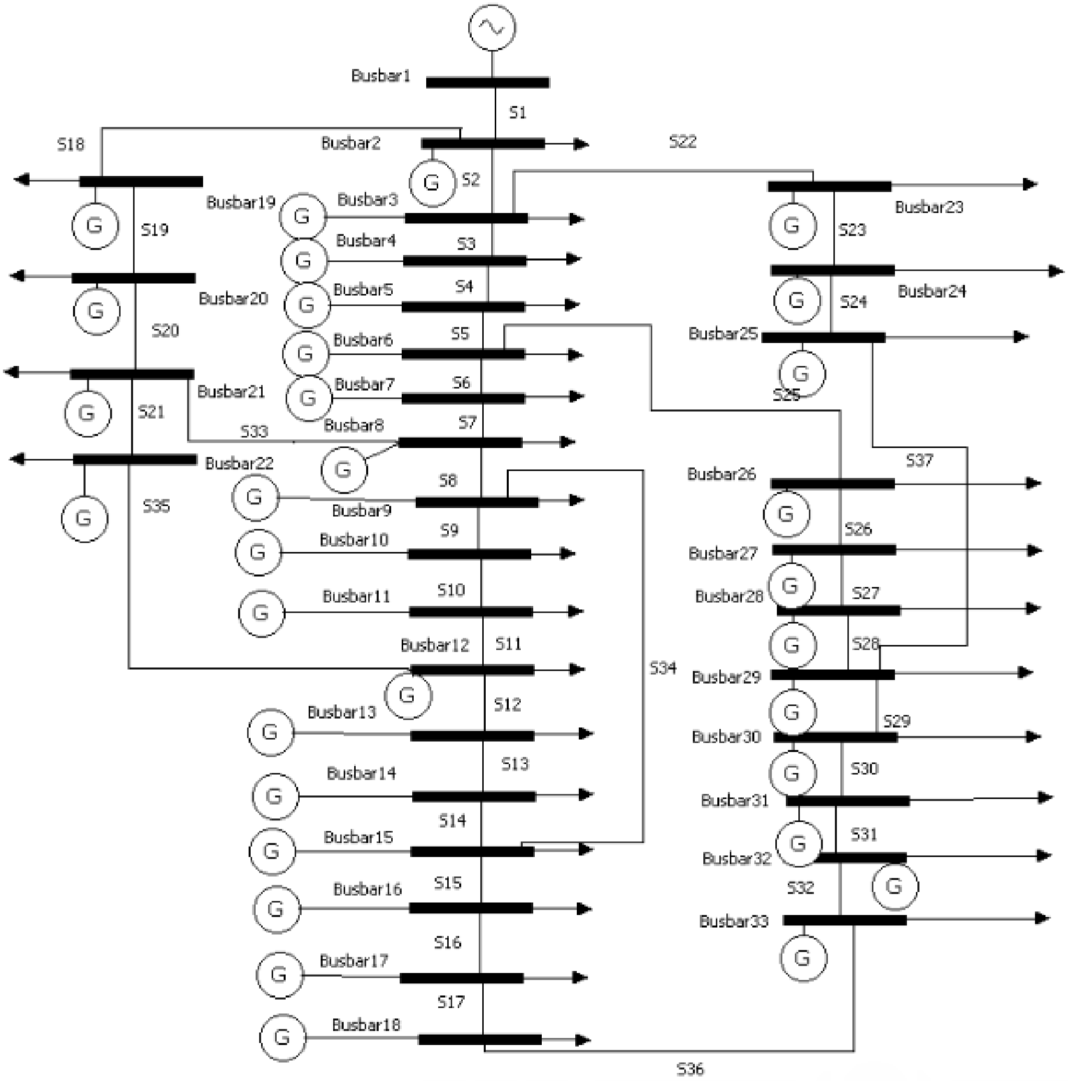


Figure 5-2 BESS representation during discharging mode

Table 5-2 shows the number of repeated open switches during 1000 trials for a fixed load and random generation based on MCS for getting minimum losses in the IEEE 33 test network shown in Figure 5-3. It was concluded that [S7-S9-S14-S37-S32] are the most repeated switches and for this reason they are suggested to be best NOP during discharging mode. Figure 5-4 shows the optimum open points in discharging mode. It is remarked that these open points are same as the ones suggested by MPSO in Chapter 3.

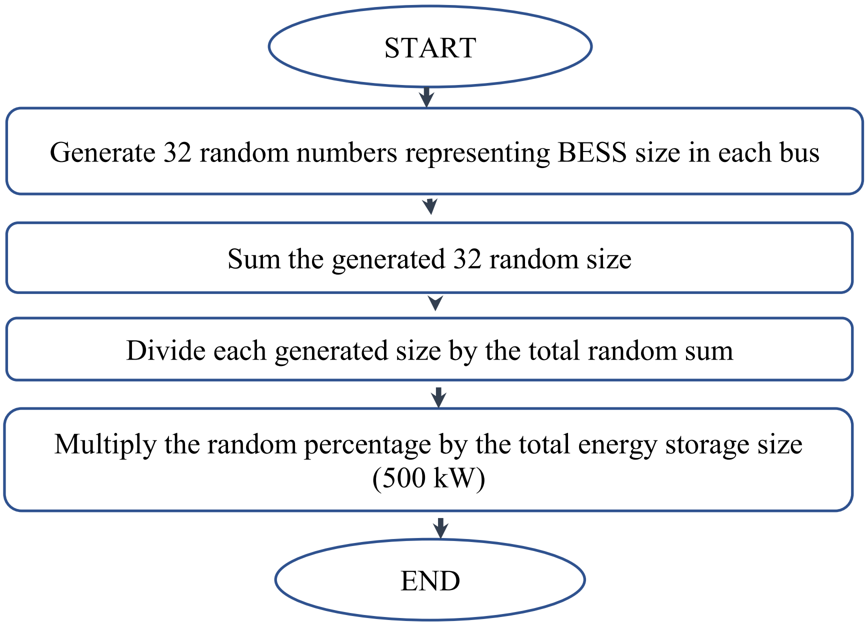


Figure 5-3 Random BESS Sizing Procedures

Table 5-2 Frequency of switches during 1000 trials in discharging mode

Switches	S2	S3	S4	S5	S6	S7
No/1000 trials	0	0	0	0	203	797
Switches	S8	S9	S10	S11	S12	S13
No/1000 trials	10	566	193	231	0	113
Switches	S14	S15	S16	S17	S18	S19
No/1000 trials	711	0	0	25	0	0
Switches	S20	S21	S22	S23	S24	S25
No/1000 trials	0	0	0	0	0	0
Switches	S26	S27	S28	S29	S30	S31
No/1000 trials	0	1	13	0	0	45
Switches	S32	S33	S34	S35	S36	S37
No/1000 trials	852	0	276	0	78	986

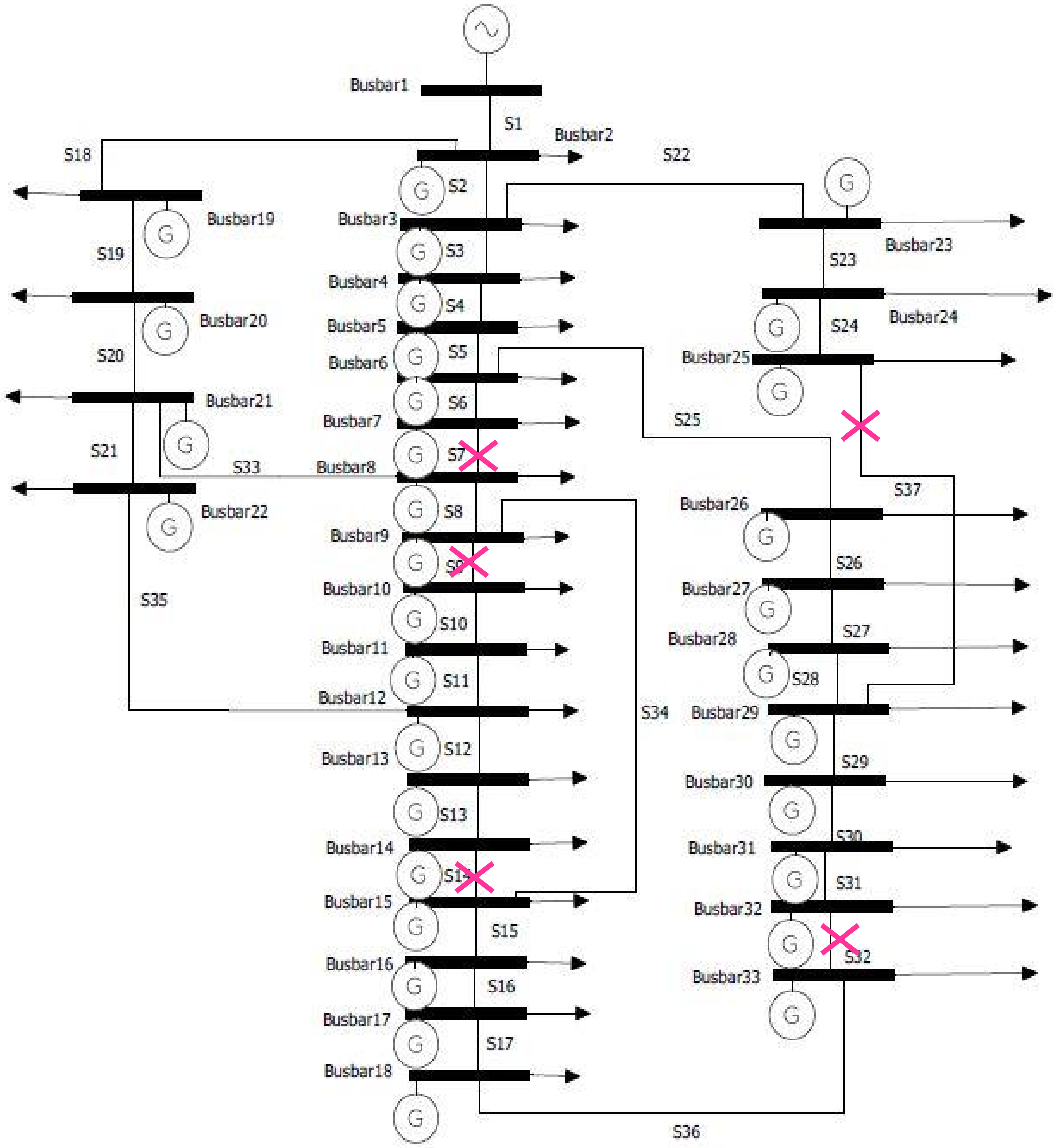


Figure 5-4 Suggested Optimum Tie Switches in Discharging Mode

5.3.2 Charging Mode (Mode 2)

After disabling the discharging mode as previously explained in Figure 5-1, the charging mode was operated by simulating the storage batteries as loads randomly distributed and highlighted over all buses as shown in the IEEE 33 network in Figure 5-5. In this mode, the batteries are assumed to charge at off peak hours, for this reason the off-peak loads are assumed to be 73% of the total full IEEE load as stated in section 5.2. The procedures followed to find the best size for BESS, were shown in Figure 5-1.MCS was selected for expecting the best size of BESS as explained in Figure 5-3, while MPSO was applied to find the best NOP during 1000 trials during the charging mode. The number of NOP switches found each time during the different trials are presented in Table 5-3.This table shows the number of repeated normally open switches during 1000 trials for a fixed load based on MCS for getting minimum losses of the IEEE 33 network shown in Figure 5-5. It was concluded that [S7-S9-S14-S37-S32] are the most repeated switches during charging mode. 503 trials suggest this configuration for NOP which is the same configuration suggested during discharging mode. For this reason, this configuration was suggested as an optimum configuration for the network during both operational modes confirming the results found in chapter 3.

Table 5-3 Frequency of NOP during charging mode

Switches	S2	S3	S4	S5	S6	S7
No/1000 trials	0	0	0	0	58	942
Switches	S8	S9	S10	S11	S12	S13
No/1000 trials	1	692	124	183	1	16
Switches	S14	S15	S16	S17	S18	S19
No/1000 trials	800	0	0	34	0	0
Switches	S20	S21	S22	S23	S24	S25
No/1000 trials	0	0	0	0	0	0
Switches	S26	S27	S28	S29	S30	S31
No/1000 trials	0	2	193	0	0	2
Switches	S32	S33	S34	S35	S36	S37
No/1000 trials	826	0	183	0	138	805

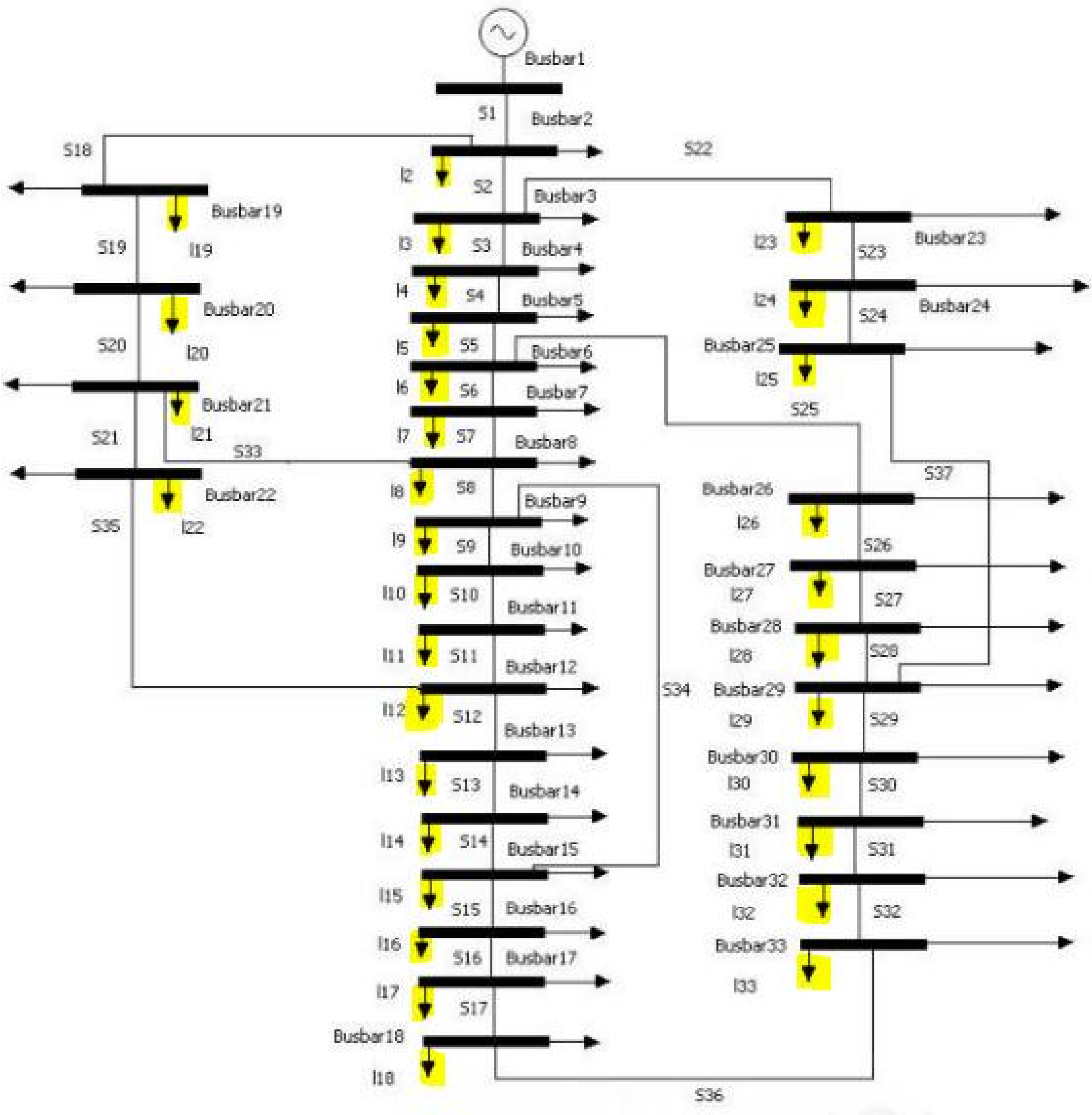


Figure 5-5 BESS representation during charging mode

Figure 5-6 shows the optimum tie switches found by MPSO after the 1000 trials in the distribution network during charging mode.

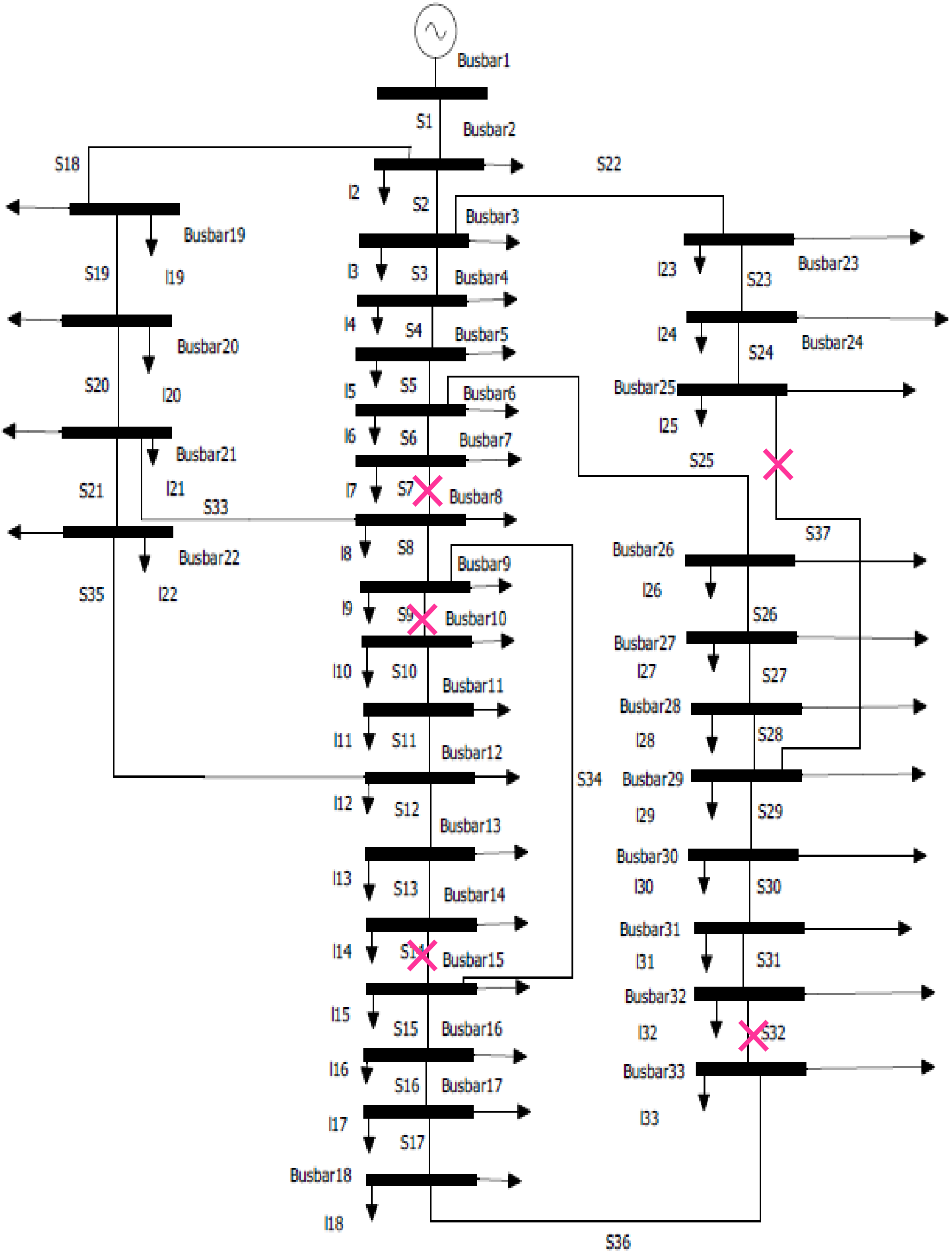


Figure 5-6 Optimum NOP in charging mode

The complexity in adding storage to the network arises because the best location for charging the batteries (close to the grid infeed) is different from the best location for discharging the batteries (far away from the grid infeed). Figure 5-7 shows the calculated total losses' range during 1000 trials during both modes. The lowest and the highest value of total losses are 228 and 240 kW respectively. The most repeated range (373 trials) is between 230-232 kW. The size achieving the lowest total losses during the thousand trials, was presented in Table 5-4, and was selected to be the optimum for both modes.

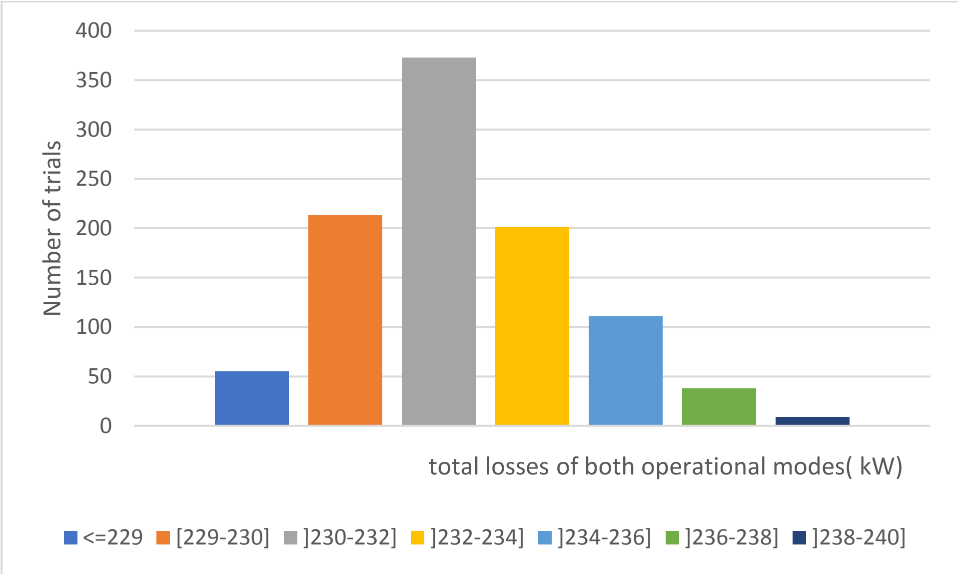


Figure 5-7 Losses range in both operational modes

It was found that trial No. 308 recorded the lowest total calculated losses for both operational modes suggesting the ties switches to be S7, S9, S14, S37 and S32. The size of energy storages at this trial was presented in Table 5-4 and was proposed to be the optimum for losses reduction during both operational modes. To simplify the 32 energy storages' size to only 5, one per each loop, the capacity for each loop was calculated as illustrated in Table 5-5. In this table, these calculated capacities are approximated to the nearest industrial available range to meet the standards [138] . To decrease the number of storage locations to only 5, one pear each loop, the sites having a battery size less than 10 kW (highlighted in green in Table 5-4) are ignored as they have negligible impact. That is, 9 of 32 of the storage sites are neglected. In other words, at these bus locations [2-4-5-11-12-16-18-25-33] batteries should not be connected. Table 5-5 shows the possible sites per each loop and the calculated capacities for each loop. For example, the first loop in this table, is fed from G8, G9, G10, G11, G12, G21, and G22. Then the size for the capacity of all generating units feeding loop1 is 107.13 kW. Since the optimum size found by MCS for G11 and G12 is less than 10 kW, then their locations are neglected from this loop. In other words, it is possible to allocate only one storage battery of 107.13kW at bus 8, 9, 10, 21 or 22.

Table 5-4 Suggested Storage Size in both operational mode

BESS Sites	G2	G3	G4	G5	G6	G7
BESS Sizes	6.23	15.63	1.09	4.21	11.42	14.19
BESS Sites	G8	G9	G10	G11	G12	G13
BESS Sizes	24.80	26.306	12.057	0.63	4.09	28.32
BESS Sites	G14	G15	G16	G17	G18	G19
BESS Sizes	24.7	23.47	0.69	14.59	1.038	25.44
BESS Sites	G20	G21	G22	G23	G24	G25
BESS Sizes	24.69	13.84	25.38	25.61	27.8	2.365
BESS Sites	G26	G27	G28	G29	G30	G31
BESS Sizes	15.40	19.03	14.36	25.03	27.22	23.71
BESS Sites	G32	G33				
BESS Sizes	13.09	3.4				

Table 5-5 Expected Storage Capacities for both operational modes

Loops	1	2	3	4	5
Batteries sites/ each loop	G8-G9-G10-G11-G12-G22-G21	G2-G3-G4-G5-G6-G7-G19-G20	G13-G14-G15	G16-G17-G18-G30-G31-G32-G33	B23-B24-B25-B26-B27-B28-B29
Updated sites/ each loop	G8- G9-G10-G21-G22	G3- G6-G7-G19-G20	G13-G14-G15	G17-G30-G31-G32	G23-G24-G26-G27-G28-G29
Capacity in KW	107.13	102.9	76.55	83.76	129.6
Approximated capacities in kW	110	105	80	85	130

To allocate the 5 storages into the updated sites presented in Table 5-5, the procedures used are shown in Figure 5-8. It should be noted that:

1. The number of remaining locations was calculated to be 23. This was mainly depending on the excluded buses having size less than 10 kW, as previously stated in Table 5-4.
2. The total number of probabilities calculated based on tree diagram to get all the possibilities of having 5 batteries' locations, one per each loop is 1800 possibilities.

It was demonstrated that the best batteries locations are at bus 21,19,15,31 and 24, reducing the losses to 115.7 kW in discharging mode and 113.8 kW in charging mode. It should be noted that these locations and capacities suggested were based on MCS after running 1000 trials studying these suggested sizes during both charging and discharging and not any of them in isolation. The best NOP found based on MPSO are S7, S9, S14, S37 and S32. These optimum locations as well as the best NOP for the IEEE 33 test network are shown in Figure 5-9 .

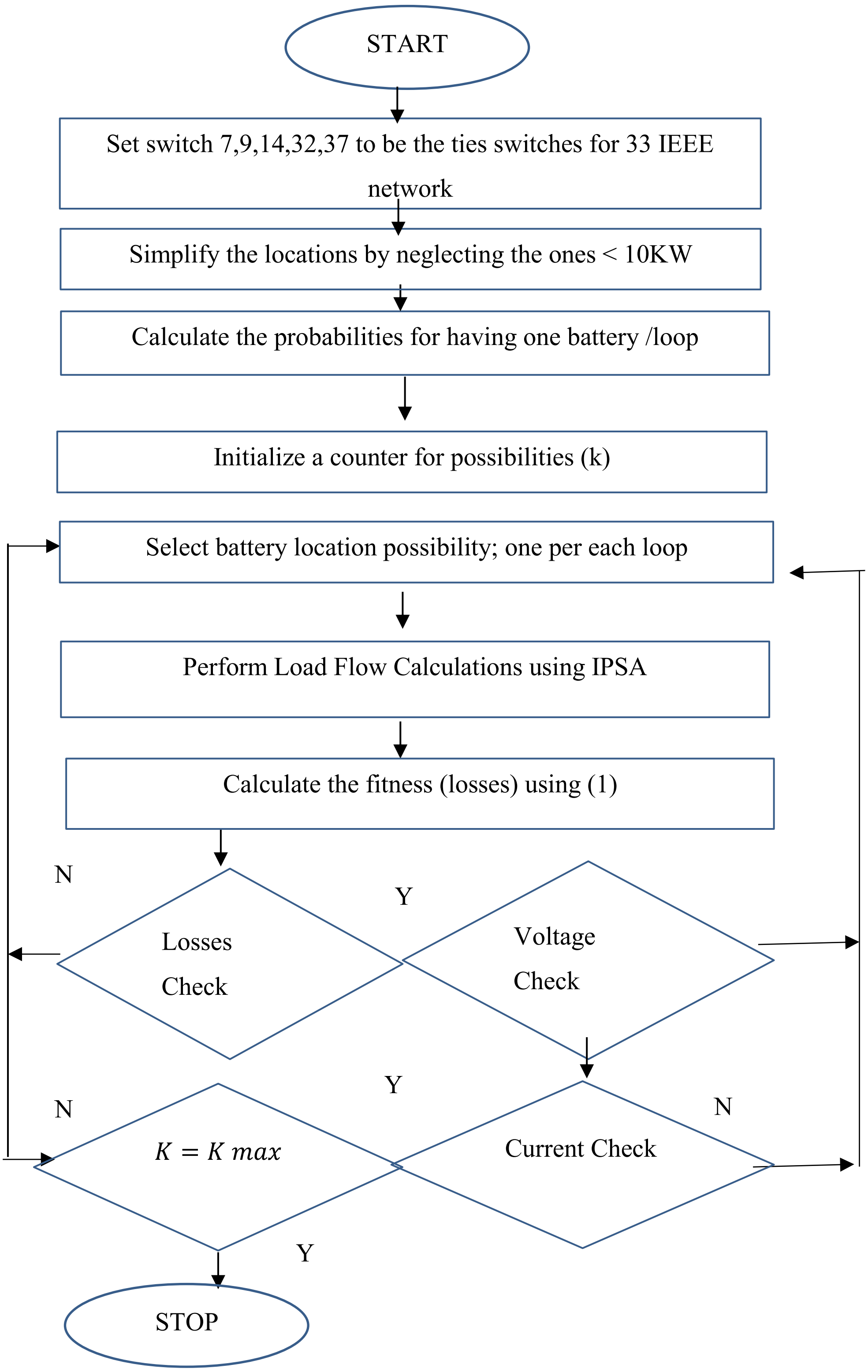


Figure 5-8 Optimum Allocation Procedures

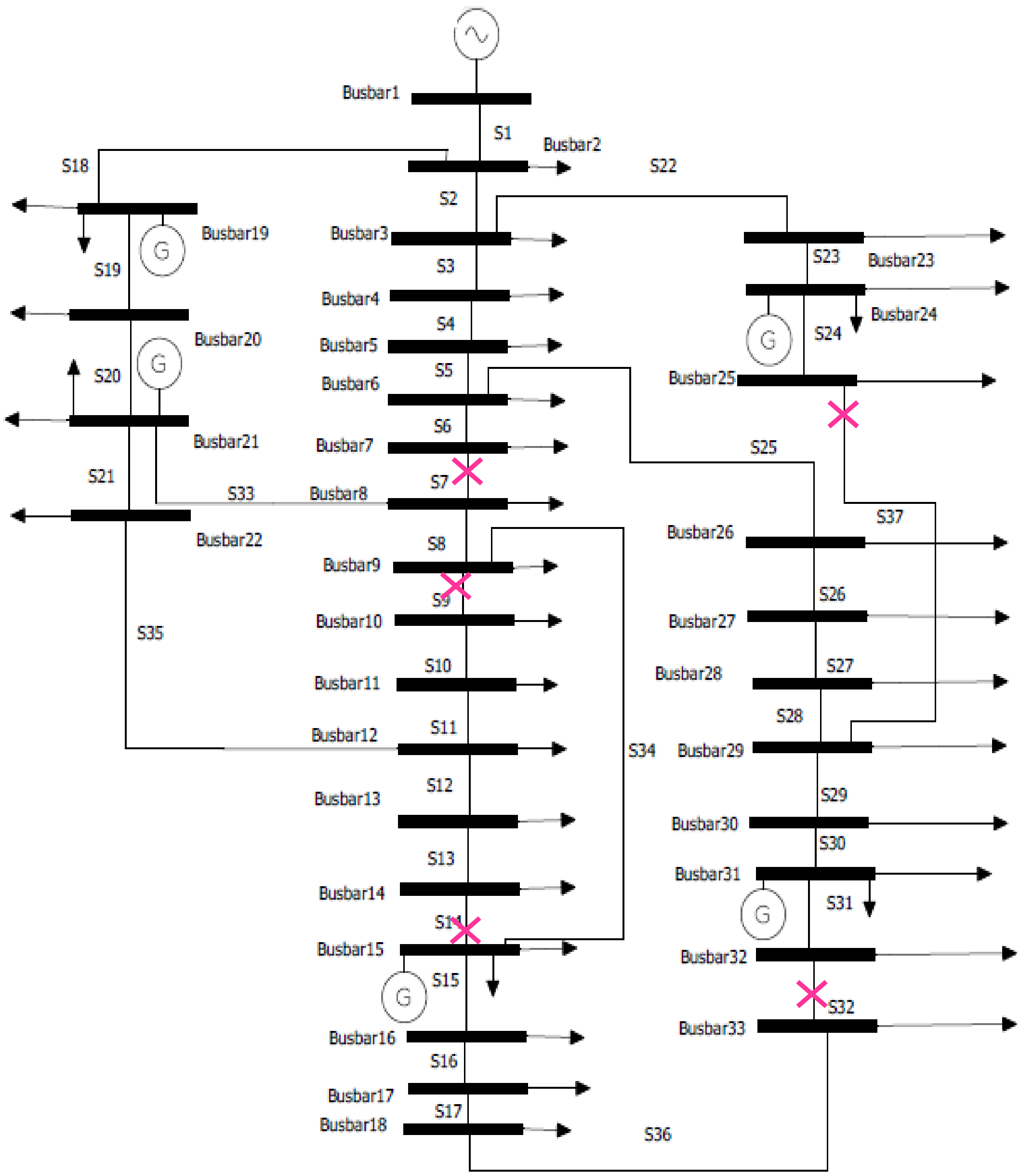


Figure 5-9 Best NOP and Storages locations during both operational modes

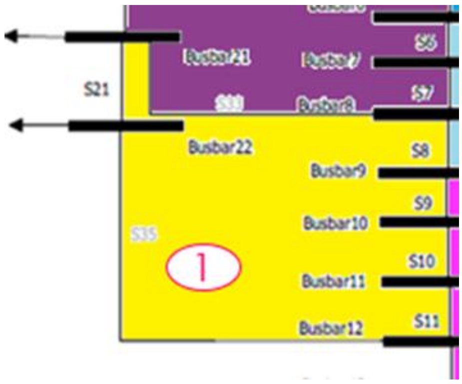
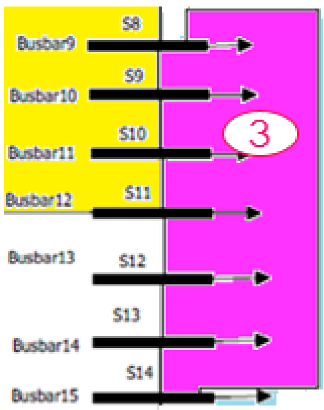
5.4 BESS Sites Justification

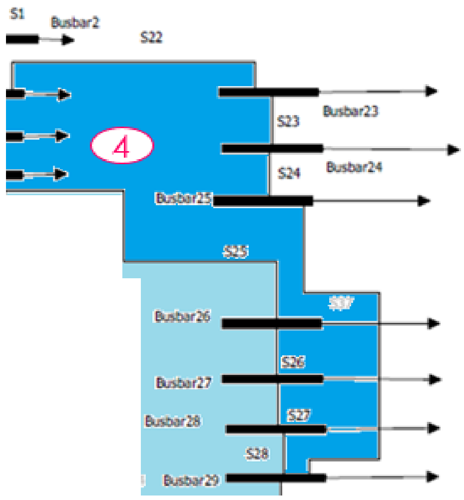
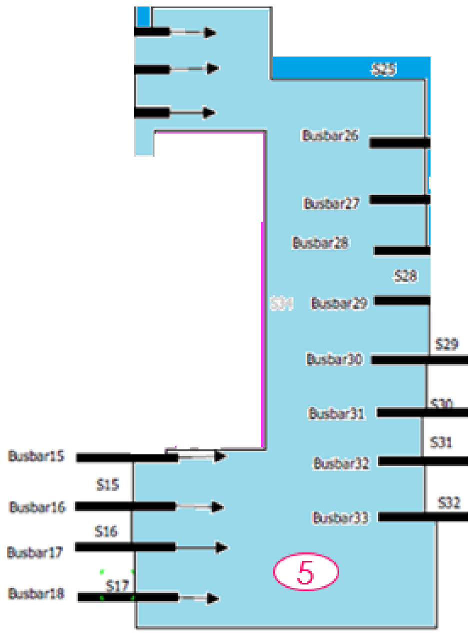
To justify the optimum locations for adding electric storage units found by employing Monte-Carlo technique, other locations are studied based on the electrical concept for locating the storage batteries stating that " the closest to the feeder, the less losses achieved during charging, and the furthest from the feeder is the less losses during discharging " assuming that there are no other forms of generation , only the grid. Since the IEEE 33 bus network is divided into 5 loops based on the initial tie switches given in the basic model, a storage unit was proposed to supply each loop. The closest and the furthest bus with respect to the feeder supplying each loop are illustrated in Table 5-6 and their justification in each of the 5 loops are explained in Table 5-7. It should be noted that the minimum charging losses highlighted in Table 5-8 is achieved when the storage units are located at 21-2-13-30-23, near to the feeder of each loop, as expected. The calculated charging losses in this case is 111.03 kW. This value is slightly less than that calculated by the suggested optimum site for both operational mode (at 21,19,15,31 ,24) found by MCS after 1000 trials reducing the charging losses to 113.67kW. This is because allocating the storages near to the feeders, reduces the impedance to the ES and thus the losses. Based on Table 5-6, 4 possible charging configurations and one discharging configuration could be formulated as stated in Table 5-8 and Table 5-9 respectively. All of them need to be studied in terms of losses to find the best for both charging and discharging mode. At these locations, the capacities calculated in Table 5-5 are configurations tested in IPSA through a load flow during charging (at off peak load) and discharging (at full IEEE load) to calculate the total losses for both operational modes.

Table 5-6 the closest and the furthest bus with respect to the feeder in IEEE 33 Network

Loops	1	2	3	4	5
Bus	8-9-10-11-12-22-21	2-3-4-5-6-7-19-20	13-14-15	16-17-18-30-31-32-33	23-24-25-26-27-28-29
Feeding branch	S20	S1	S35	S15 -S29	S22-S25
The closest bus to the feeding branch	21	2	13	16-30	23-26
The furthest bus from the feeding branch	10	7	15	33	29

Table 5-7 Closed and Furthest bus Justification in each loop of the IEEE 33 bus network

<table>
<tr><td>Loop</td><td></td><td>Closed and Furthest Bus Justification</td></tr>
<tr><td>One</td><td>
</td><td>S20 is the feeding branch of the first loop. Consequently, bus 21 is the closed bus to S20. For this reason, it is the best to locate the storage unit in the charging mode. The furthest bus is bus 10 as S9 is the NOP for this loop. In this case the current will pass through Z1+Z18+Z19+Z20+Z21+Z35 +Z11+Z10. The impedance in this case to bus 10 is 7.58 Ω.</td></tr>
<tr><td>Two</td><td>
</td><td>Since S1 is feeding both bus 2 and bus 19, the closest bus is bus 2 because it is the nearest to the feeding branch S1. To get the farthest bus, the impedance from bus 2 to bus 7 is calculated (Z1+Z2+Z3+Z4 +Z5+Z6=3.2 Ω), and the impedance from bus 19 to 21 is calculated (Z1+Z18+Z19+Z20=2.938 Ω). For this reason, bus 7 is farther than bus 19 from the feeding point as the impedance is directly proportional to cable length.</td></tr>
<tr><td>Three</td><td>
</td><td>In loop 3, since S8, S9, S10 and S11 are already included in loop1. They are excluded from loop 3. The parameters of this loop are S12, S13, S14 and S34. The feeding branch to this loop is considered S35. The closest bus is bus 13 and the furthest bus is bus 15.</td></tr>
</table>

Four		In loop 4, S22 and S25 are two feeding branches to this loop. The closest buses to S22 and S25 are bus 23 and bus 26 respectively. Then the furthest bus to S22 is S25 since S37 is NOP. In this case the current will pass through Z1+Z2+Z22+Z23+Z24. The impedance to bus 25 is 3.48 Ohm. The furthest bus to S25 is bus 29. The impedance in this case is Z1+Z2+Z3+Z4+Z5+Z25+Z26+Z27 +Z28 and equal to 5.1709 Ω. For this reason, bus 29 is the best selected to locate the BESS during the discharging mode.
Five		In loop 5, there are two feeding branches S15 and S29. The nearest bus to S15 is bus 16, while bus 30 is the closest to S29. The furthest bus to S15, is bus 33, because S32 is already a NOP. The current path will be in this case passing by Z1+Z18+Z19+Z20 +Z33+Z8+Z34+515+Z16+Z17+Z36. The impedance is calculated in this case to be 12.5303 Ω. The furthest bus to S29 is bus 32 because bus S32 is a NOP. In this case the current will pass through: Z1+Z2+Z3+Z4+Z5+Z25+Z26+Z27+Z28 +Z29+Z30+Z31. The impedance in this case is =8.0119 Ω. For this reason, bus 33 was selected the furthest in this loop for locating the batteries in discharging mode.

It was found that the best charging losses highlighted in Table 5-8 are achieved when the storage units are located at 21-2-13-30-23, near to the feeder of each loop, as expected. The calculated charging losses in this case is 111.03 kW. This value is slightly less than that calculated by the suggested optimum site for both operational mode (at 21,19,15,31 ,24) found by MCS after 1000 trials reducing the charging losses to 113.67kW. This is because allocating the storages near to the feeders, reduces the impedance path to the BESS and then the losses. However, the discharging losses at this configuration is much higher than the optimum for both operational modes (at 21,19,15,31 and 24). Table 5-9 includes the best discharging locations for adding the 5 storage units in the IEEE 33 network -far than the feeders - reducing the losses to 107.6 kW, as expected. This site decreased the losses in discharging mode compared to the best locations found by MCS for both operational mode at 21,19,15,31 and 24. This indicates that the MCS selects the optimum locations meeting the lowest losses for both charging and discharging modes. Figure 5-10 and Figure 5-11 show the best possible site for adding 5 storages in charging mode (near to the feeder) and discharging mode (further from the feeder) respectively. It should be noted the NOP are set during both modes to S7, S9, S14, S37 and S32.

Table 5-8 Other Possible charging locations

New locations	Charging losses	Discharging losses	Total losses
21-2-13-23-16	111.48	119.65	231.13
21-2-13-26-16	114.078	116.72	230.8
21-2-13-23-30	111.03	118.93	229.96
21-2-13-26-30	113.98	116.16	230.14

Table 5-9 Other Possible discharging location

New locations	Charging losses	Discharging losses	Total losses
10-7-15-33-29	124.47	107.608	232.078

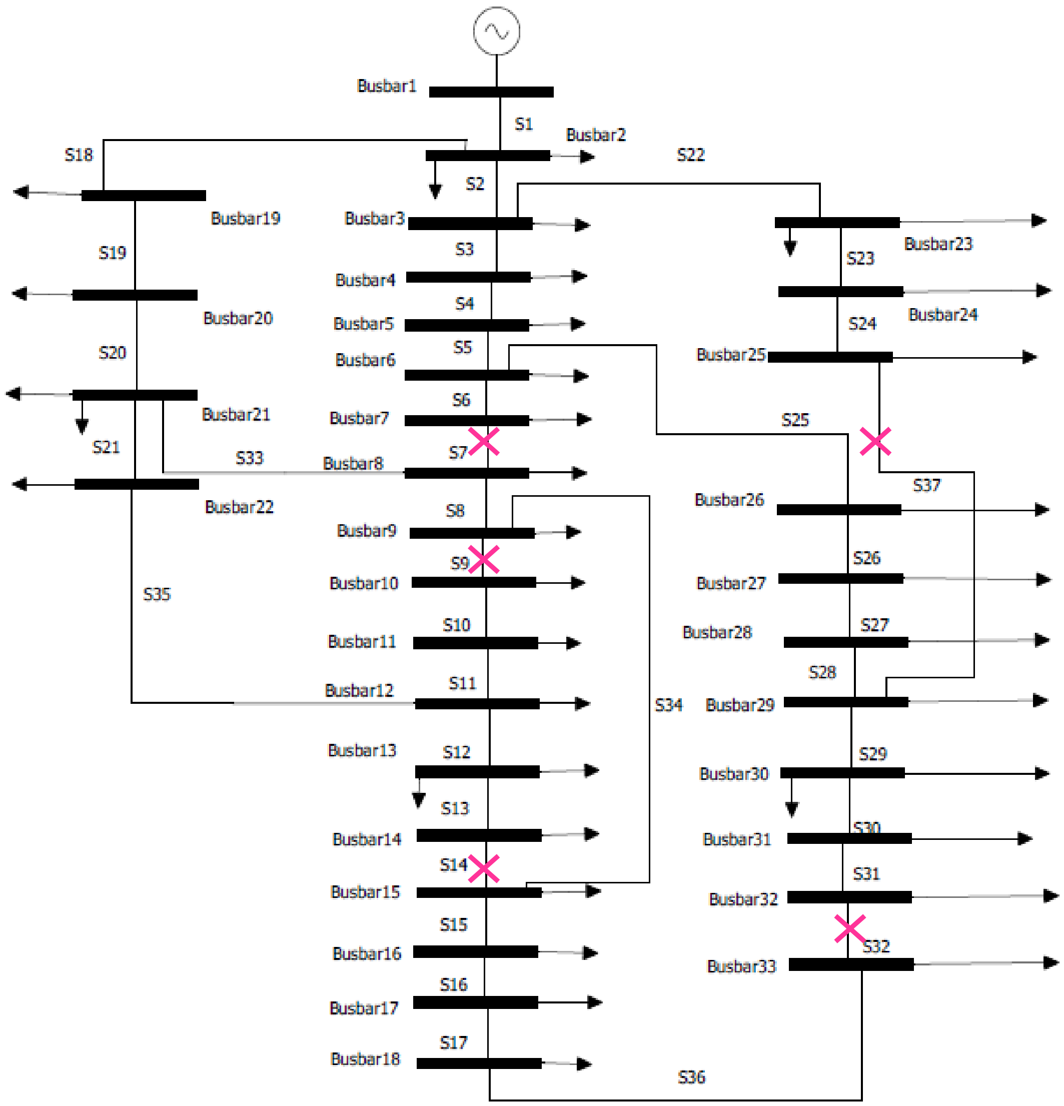


Figure 5-10 Best BESS locations closest to the feeders during charging only

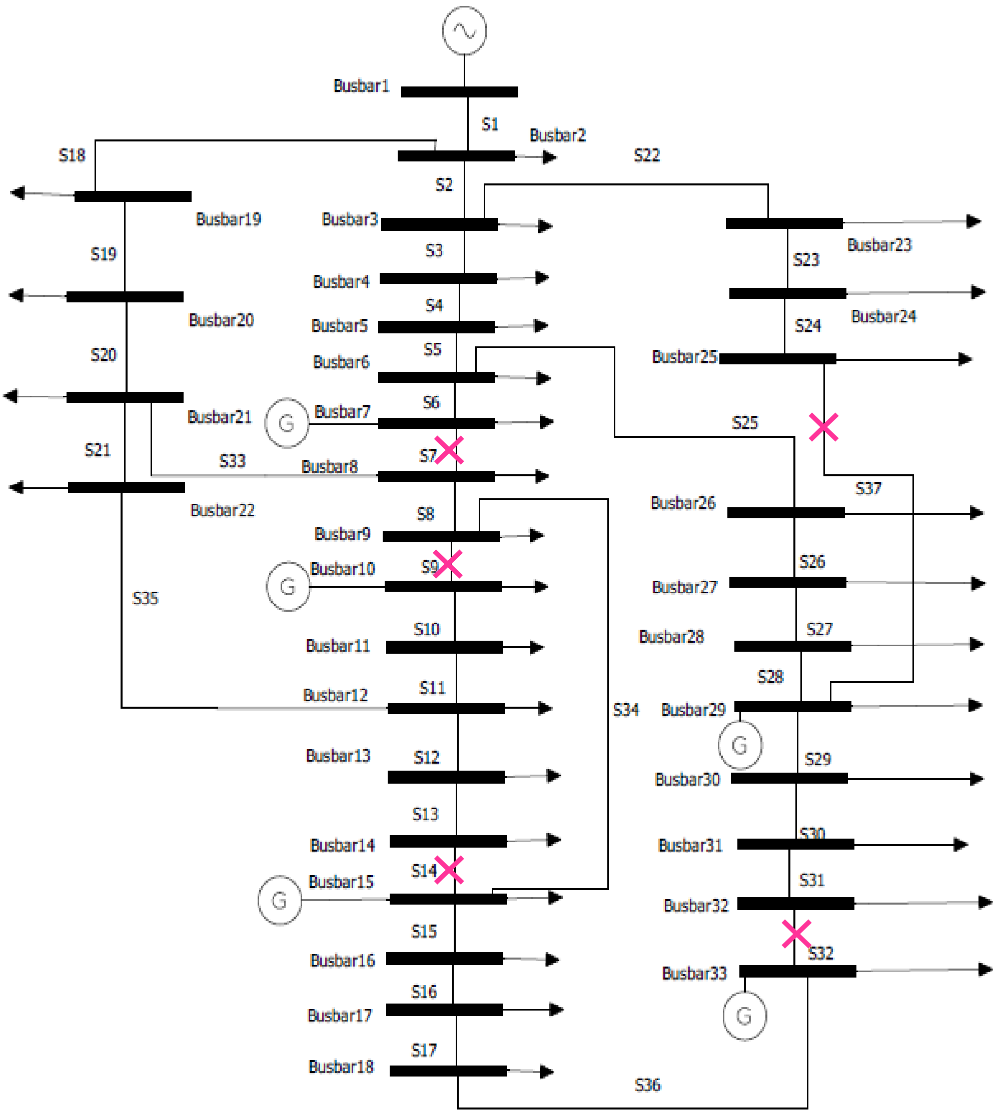


Figure 5-11 Best BESS locations furthest from the feeders during discharging only

5.5 Results and discussion

This chapter suggests the integration of standalone storage units considering network reconfiguration for decreasing the calculated losses than 136 kW. This value was found by MPSO (chapter 3) and MSMPSO (chapter 4) after changing the initial ties switches of the IEEE 33 bus network to S7, S9, S14, S37, S32 at static load. A wrong size or location could represent an extra burden on the power system during charging and discharging modes. For this reason, this chapter's main aim was studying the best size and location of adding storage units in the presence of an active DNR. An operational mode considering both the charging and discharging mode, was suggested to propose only one solution for sizing and allocating the storage batteries in the distribution network. In this mode, the same random size was tested for both operational mode (Figure 5-1) and the total losses were calculated. It was found that the best batteries locations would be at bus 21,19,15,31 and 24 (Figure 5-9), reducing the losses to 115.7 kW in discharging mode and 113.8 kW in charging mode, with suggested capacities of 110, 105, 80, 85 and 130 kW respectively as illustrated in Table 5-10.

Table 5-10 Suggested Site, Size of the BESS and NOP during the proposed operational mode

	Operational Mode
Storage locations	21,19,15,31,24
Storage capacities	110, 105, 80, 85 and 130
Ties Switches	S7, S9, S14, S37, S32
Charging losses (off-peak)	113.8 kW
Discharging losses (full-peak)	115.7 kW
Total losses (kW)	229.5

This operational mode gives clearer picture for decision making process and for this reason, both the calculated capacities and sites are considered the best for this network. Figure 5-12 shows the losses reduction improvement through the different scenarios, starting from the initial IEEE case, passing by the DNR by changing the ties switches position (in chapter 3 and 4) and finally by adding storage devices during discharging and charging mode. It was concluded that adjusting the size and the locations of storage units in the presence of an adequate tie switches selection enhance the distribution losses. Figure 5-13 shows a significant improvement in voltage profile after implementing the tie switch reconfiguration. The minimum voltage is raised to be 0.94 at bus 32 instead of 0.91 at bus 18, from the original IEEE model. A slight improvement is observed after adding storage batteries for losses reduction during charging mode to reach 0.945.

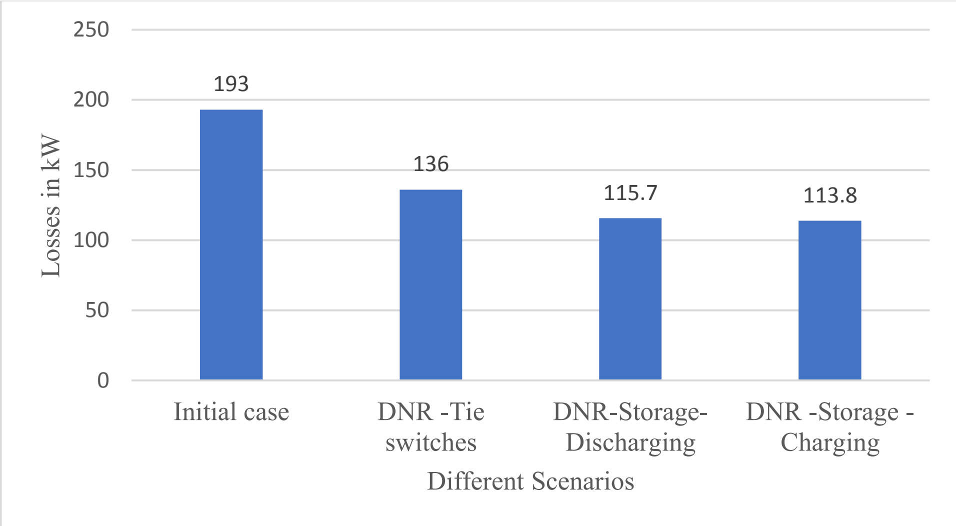


Figure 5-12 Losses Improvement in the IEEE 33 Network

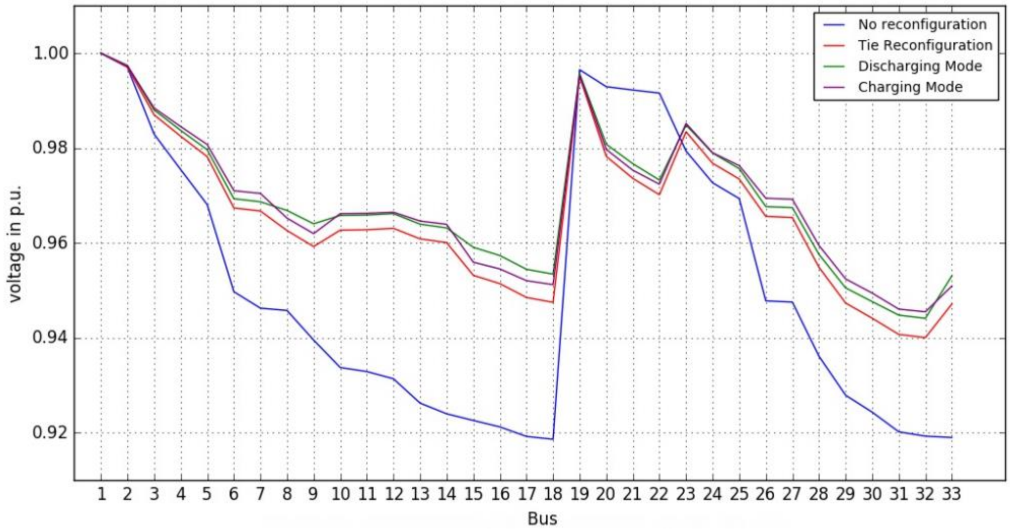


Figure 5-13 Voltage Improvement in the IEEE 33 network

Based on the report presented by the department for Business, Energy and Industrial Strategy in 2018 [5], the emission factor that convert from 1 kWh to 1 kg CO_2e was calculated for the combined transmission and distribution losses for 2016 to be 0.0249. The tie switches reconfiguration decreased the losses by 56 kW per hour equivalent to 1.39 kg CO_2e per hour at peak load, while the optimum site and capacity for BESS achieve around 1.9 kg CO_2e per hour reduction

5.6 Conclusion

The main target of this chapter was sizing and allocation of energy storage units in the IEEE 33 distribution network considering DNR. MCS was suggested for sizing the storage units by generating random size at each bus within a total size of 500 kW during 1000 trials. During each trial, MPSO was used to find the optimum NOP. The size achieving the lowest losses was selected to be the optimum size for energy storages. To reduce the storage units to a lower number, 5 storage units, one supplying each loop of the network, the capacity for each loop was calculated by adding the size of the battery at each bus existing in this loop. To allocate these 5 storages units, one per each loop, the buses having negligible size was excluded from the search and the total number of probabilities was calculated. These procedures of sizing and siting the storage units are undertaken in an operational mode that merges between the discharging mode and the charging mode respectively. This is achieved by testing the same generated random size- using MCS- considering both the charging and the discharging to have a global picture to decide both the best size and location for the storage units for total losses reduction. During the discharging mode, the storage units are simulated as generating units added to each bus bar at the IEEE 33 network at full load. In contrast, the storage devices are represented as load at each bus, at off peak load during the charging mode. The off-peak loads are assumed to be 73% of the full peak IEEE load. It was found that the same NOP was suggested for both charging and discharging by declaring S7, S9, S14, S37 and S32 the optimum ties for best losses reduction. The sites and the sizes calculated through this mode did not give the minimum losses during charging mode nor the discharging mode, but it gives the optimum with respect to the total calculated losses during both modes.

Furthermore, it was concluded that adjusting the size and the locations of storage units in distribution networks considering DNR decreased the losses through the different scenarios implemented: Tie Switches Reconfiguration (using MPSO at static load in chapter 3), Tie switches reconfiguration (using MCS at variable load in chapter 4), and by adding storage devices in charging and discharging modes. The losses have been reduced to 115.7 and 113.7 kW in discharging and charging mode respectively.

These performed scenarios (chapter 3 - chapter 5) did not only enhance the losses but also the minimum voltage bus that raised from 0.91 at bus 18 in the initial case to 0.945 by the integration of storage units considering the DNR at bus 32.

Research Novelty*: *Sizing standalone storage batteries in the IEEE 33 network using Monte Carlo Simulation Method in the presence of network reconfiguration using Modified Particle Swarm Optimization Technique. To have a full picture, the total losses during both charging and discharging mode need to be considered together and each mode should not be considered in isolation.

6 CHAPTER 6 11 kV OHL DISTRIBUTION NETWORK

6.1 Background

Different strategies for losses reduction in distribution networks have been explained through the previous chapters. The concept of network reconfiguration by changing the normally open points was the first strategy presented. The addition of storage units is another existing methodology for achieving the thesis target. Charging and discharging scenarios were studied for identifying the best storage units' locations and capacities for minimum losses in the presence of DNR. All the stated strategies were tested using the IEEE 33 test network- as it was common through lot of research papers for comparing the losses reduction results- to identify a specific mathematical optimization technique that could be adopted to be used in case of a real distribution network. This mathematical method should reach the global optimum solution in a reasonable computational time. Also, it should have the ability to respond to variable load due to the changing demand. The PSO algorithm was modified in chapter 3 and was suggested as a DNR solution within the IEEE 33 bus network. The main aim of this chapter is to validate the MPSO using a real distribution network, a section of the 11kV OHL network in the Milton Keynes area, located in the United Kingdom, to allow a validation of the methodology within a more representative situation. The coded programs were adjusted using python language to the distribution network and simulated through IPSA.

6.2 11kV Network Description

The 11 kV OHL distribution network of Milton Keynes, shown in figure 6-1, is composed of 262 buses and 265 branches, fed from two substations, the first is near WINSLOW, 1.71 MW and the second is at NEWTON ROAD, 6.38 MW. The network is composed of five feeders: Way 3, WAY 6 at WINSLOW, and another three feeders at NEWTON ROAD, Way 5, Way 8 and Way 4. Table 6-1 describes the 11kV network. Figure 6-1 is a representation for the whole OHL network while Figure 6-2 shows the network in the simulation window of IPSA. The total losses were calculated using the nominal NOP- as shown in table 6-2-to be 85 kW based on a simple load flow using IPSA. The Demand load was estimated by Western Power Distribution based on the load type on each feeder and then scaled for the measured feeder load current. A day in winter (23rd of January) was chosen as this represents close to maximum demand where losses will be highest and the impact of DNR more widely beneficial. Another summer day (the 3rd of July) was also studied representing the minimum load and minimum losses reduction for this network.

Table 6-1 11 kV OHL network description

	nodes	branches	loads	substations	feeder	NOP
	262	265	127	2	5	5

Table 6-2 Nominal NOP for the 11 kV OHL distribution network

Tie Switch Given Name	From bus	Bus Name	To bus	Bus Name
S13	262042	Swanbourne Station	202014	Swanbourne Station
S34	261701	Swanbourne Station	200988	Stewkley Sewage
S64	265395	Cresent Bletchley	265392	St.George Road Bletchley
S82	264874	Newton LongVille	242292	Brookfield Road
S105	261705	Stwekley Sewage	275789	Wing Road Stewkely

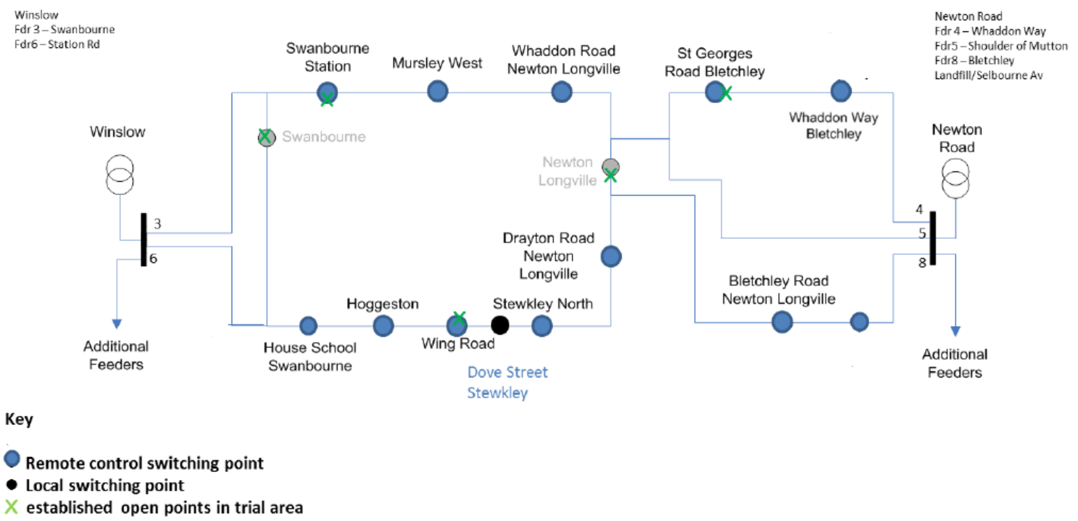


Figure 6-1 11kV OHL distribution network

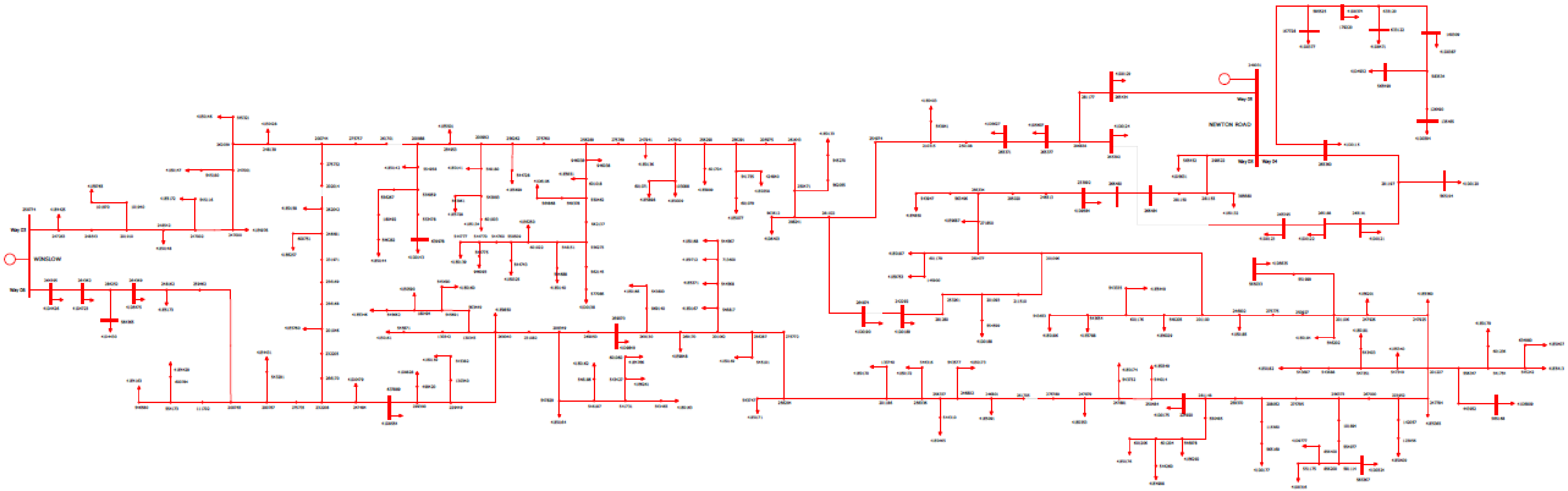


Figure 6-2 11kV OHL distribution network in IPSA Simulation Window

6.3 Problem Formulation and General Constraints

Problem definition and the constraints used in this network are the same discussed in section 3.2.1 , for the IEEE 33 Network. Losses reduction is the main goal of this thesis and it was calculated based on (1) in section 3.2.1. Three constraints were considered:

1. **Bus voltage limits**

   The bus voltage magnitude should be within the permissible limits as stated in (2) in section 3.2.2. The minimum value of the voltage was chosen for this network to be 0.95 and the main primary voltage is set to 1.05 pu.

2. **Feeder Capacities**

   The magnitude of the branch current should not exceed the maximum value of the allowed current passing in the feeder's branch as previously explained in (3) in section 3.2.2. It should be noted that the main 5 feeders' capacities and MVA of the 11 kV OHL represented in Figure 6-1 are included in table 6-3.

Table 6-3 Feeder Current Capacity

Feeder	Winter MVA rating (MVA)	Calculated current Capacity (A)
S1	9	490
S31	4	255
S58	9	500
S59	10	570
S65	10	570

3. **Radial structure**

   To keep a radial structure, only one switch in each loop should be open. It should be noted that the total number of loops is equal to the total number of existing ties switches. Therefore, 5 switches will be suggested to be NOP in this network.

6.4 DNR using MPSO in the 11 kV OHL Network

In chapter 3, MPSO was suggested as a method to solve the DNR stochastic optimization problem for selecting the optimum NOP for minimum losses. Sectionalizing the network into many loops and using tree diagram to formulate a search space including radial configurations, introducing losses, voltage and current constraints for filtering the initial positions, and the position control algorithm to retain the particles within the search space were the modification added to the typical PSO for better performance. It was found that MPSO reaches the global optimum solution in a reasonable computational time when it was validated through the IEEE 33 network. Furthermore, this technique was flexible enough to respond to variable load -generated by Monte Carlo technique-as explained in chapter 4, aiming to be applied for real distribution networks. In this section, MPSO was validated through the 11kV distribution network for best losses reduction. The different modifications added to the basic technique were explained in section 3.4 while the procedures and the flow chart of MSPO was explained in 3.4.5

6.4.1 Sectionalizing the 11kV OHL distribution network

As previously explained in chapter 3, sectionalizing the network is the first step for implementing MPSO to formulate the search space. To help with this, the 11kV distribution network is divided into 5 loops as represented in Figure 6-3 .The parameters of each loop are included in table 6-4 and represented in Figure 6-4. Figure 6-4 (a) represents the elements of loop A. Figure 6-4 (b), Figure 6-4 (c), Figure 6-4 (d) represent the switches in loop B, C, D respectively. Loop E is very large and for this reason it was divided in two sections shown in Figure 6-4 (e) and Figure 6-4 (f) respectively including the switches from S32 to S57 of loop E. The switches common between more than one loops, are stated only once, to avoid the duplication of switches in a single configuration. For example, S11 is shared between the first and the second loop, but it is only stated in loop A to avoid duplication that would result in invalid configurations, as stated in Table 6-4. It should be noted that some branches are excluded as they connect the main feeders to the substations such as S1, S31 for loop A, S58 and S59 in loop B and S65 in loop C. The Excluded branches are represented in Table 6-4.

Table 6-4 11 kV Distribution network loop elements

loops	**Loops Elements**	**No. of switches /loop**	**Excluded Parameters**
A	[S2:S30]	29	S1, S31
B	[S32: S57]	26	S58, S59
C	S60, S61, S62, S63 S64 and S127	6	S65
D	[S66: S83]	18	None
E	[S84:S126]	43	None

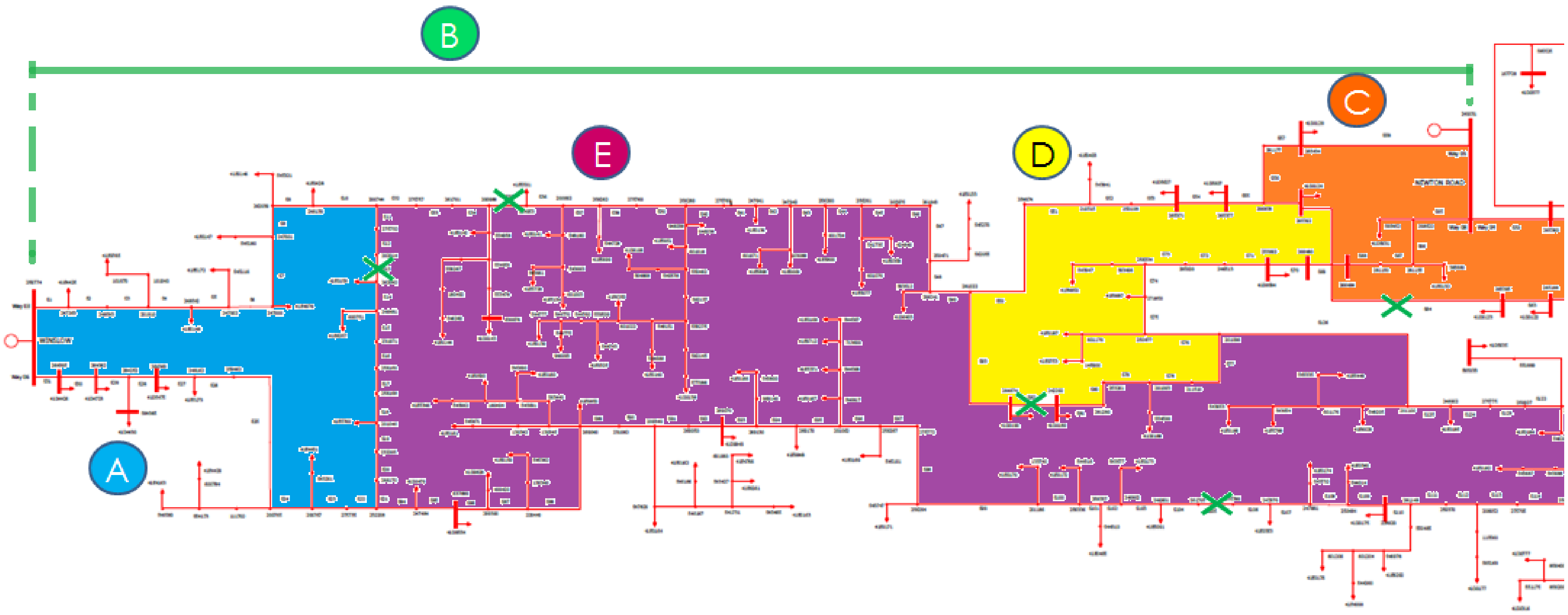
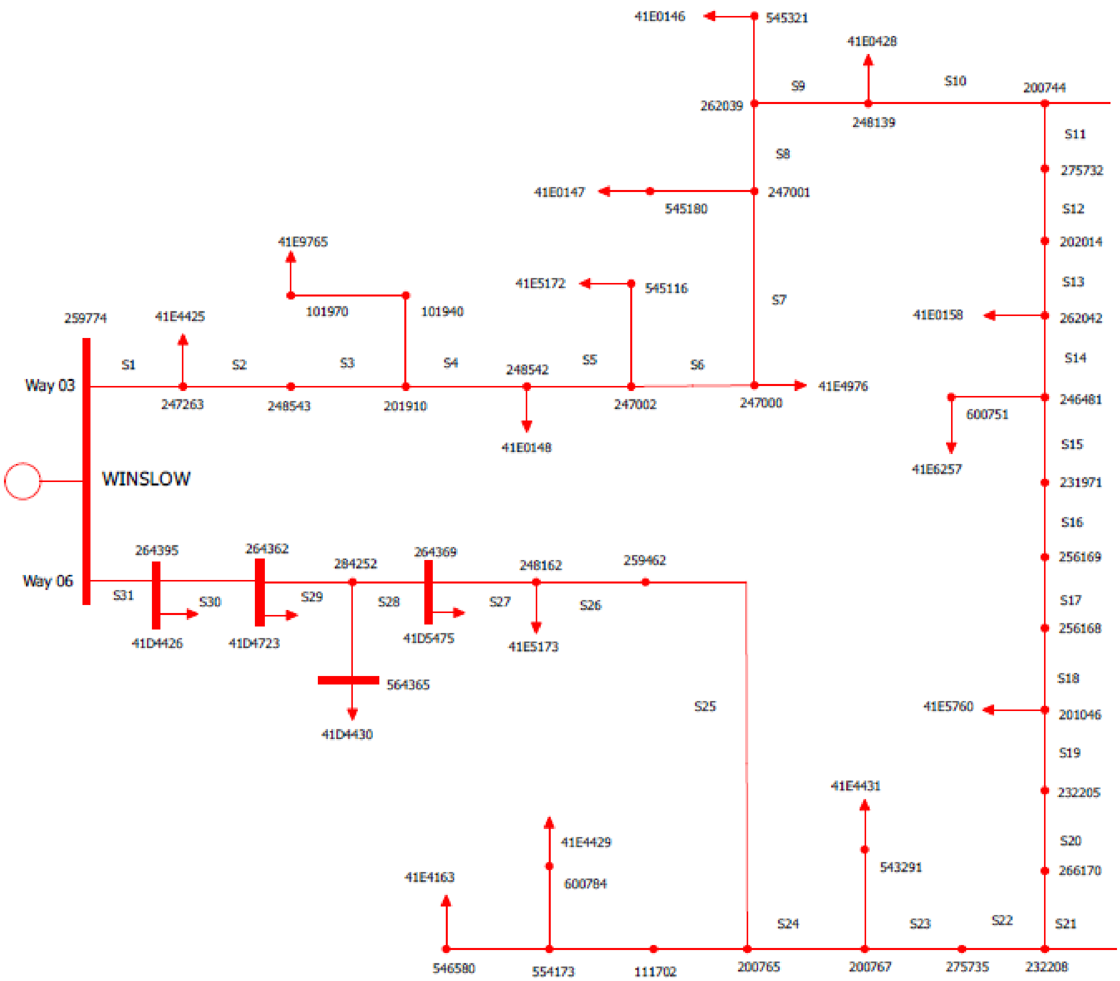
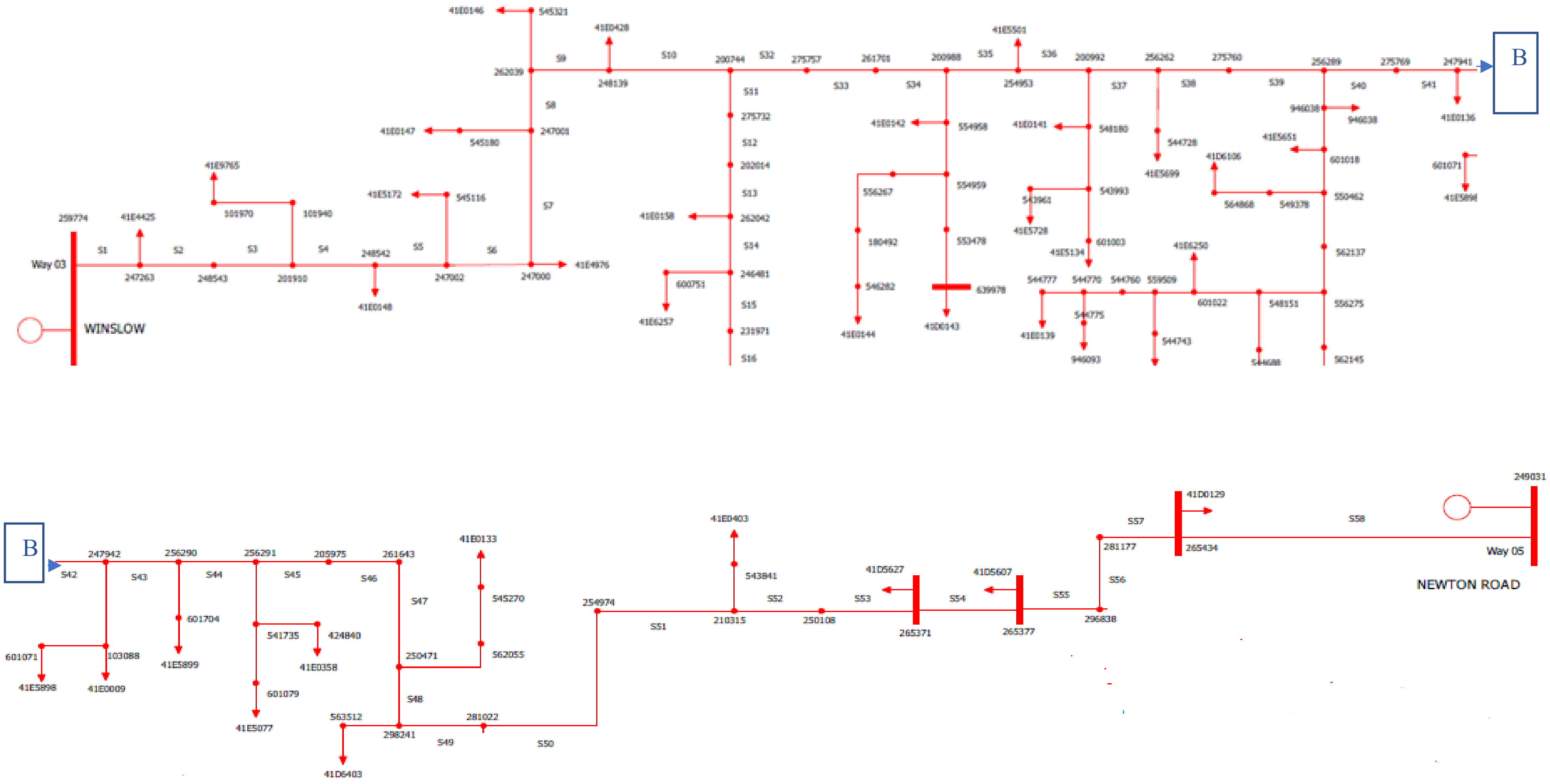


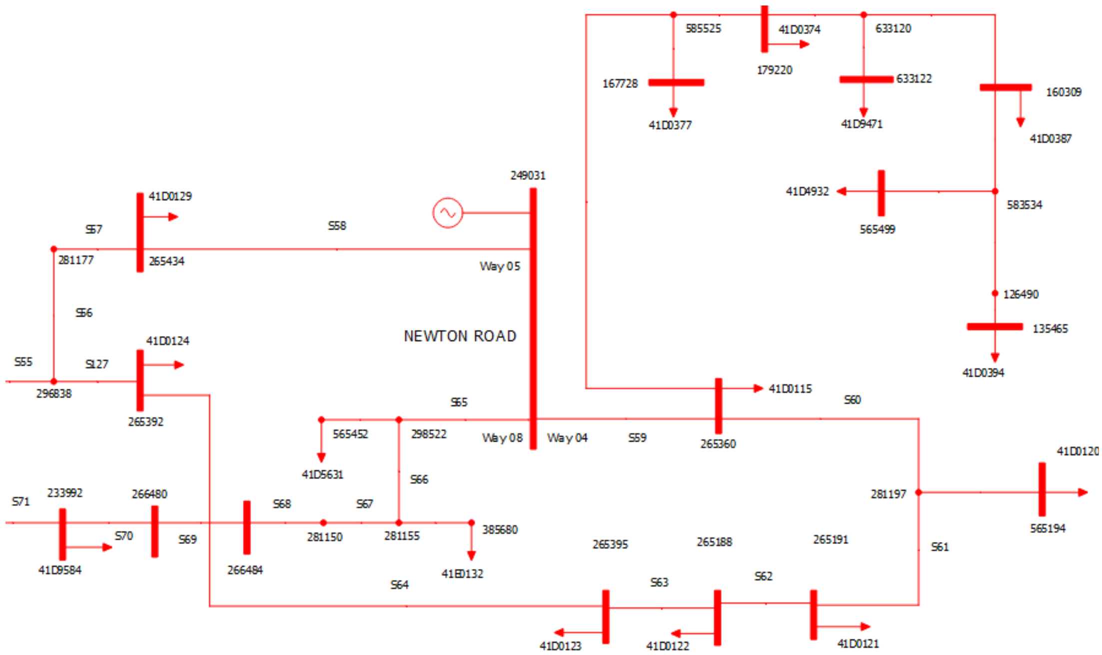
Figure 6-3 Representation of the 11kV distribution network loops


41E0146
545321
41E0428
S9
S10
200744
262039
248139
S11
275732
S8
41E0147
247001
545180
S12
202014
41E9765
S13
41E5172
545116
S7
41E0158
262042
101970
101940
259774
41E4425
S14
S1
S2
S3
S4
248542
S5
S6
Way 03
41E4976
246481
247263
248543
201910
247002
247000
600751
41E0148
S15
41E6257
WINSLOW
231971
S16
264395
264362
264369
284252
248162
259462
256169
Way 06
S31
S30
S29
S28
S27
S26
S17
256168
41D4426
41D4723
41D5475
41E5173
564365
S18
41E5760
201046
S25
41D4430
S19
41E4431
232205
41E4429
S20
543291
266170
41E4163
600784
S24
S23
S22
S21
546580
554173
111702
200765
200767
275735
232208

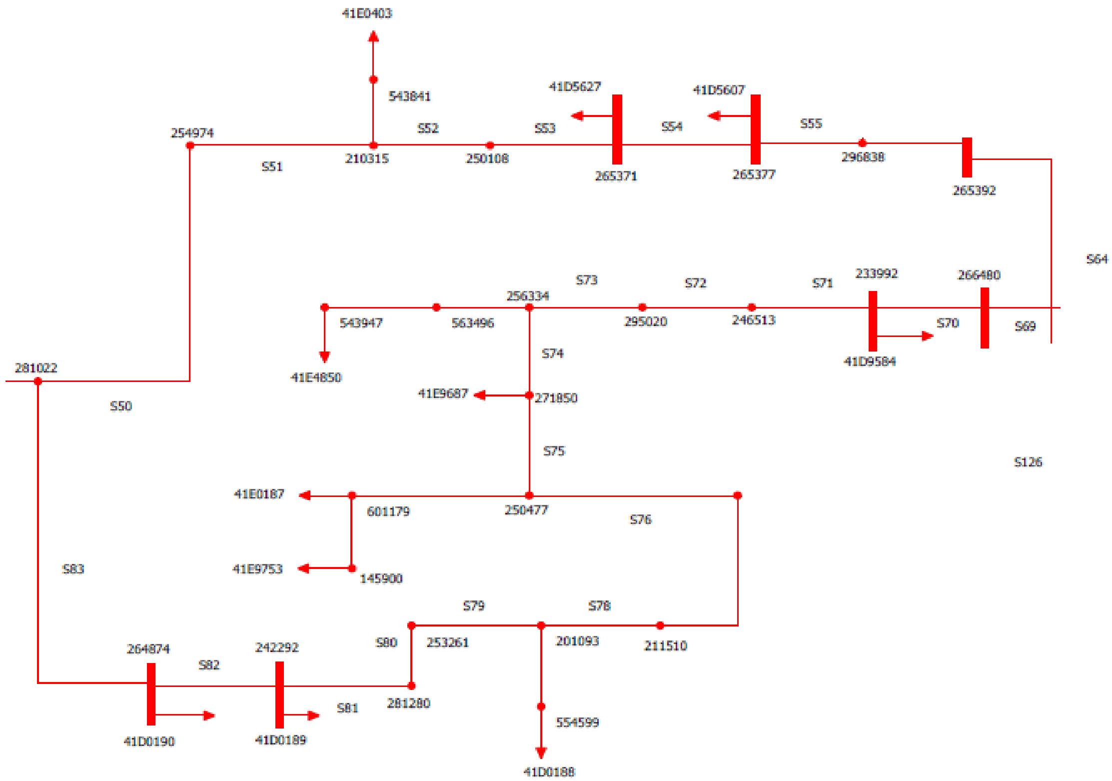
(a) Loop A



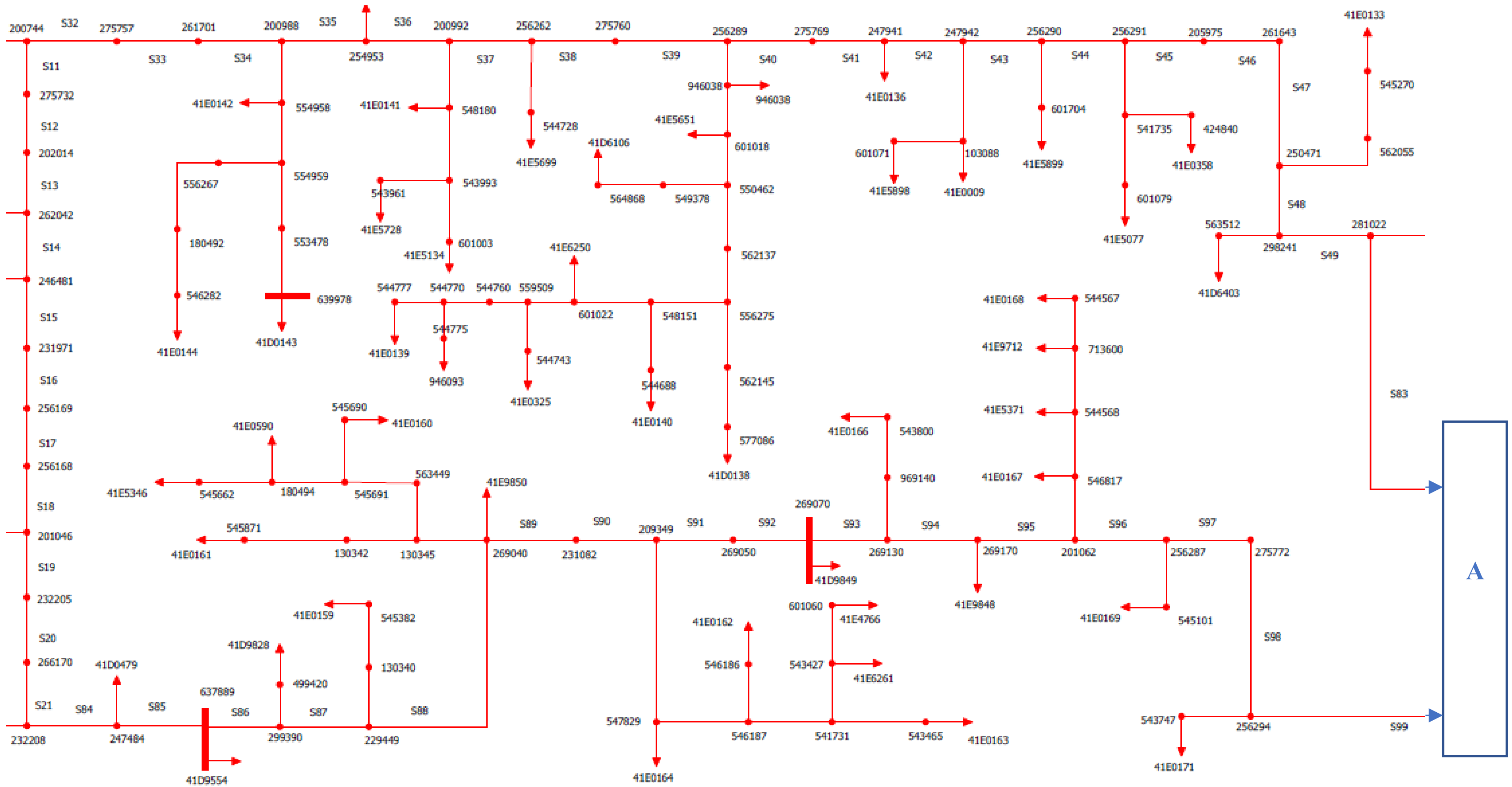
(b) Loop B



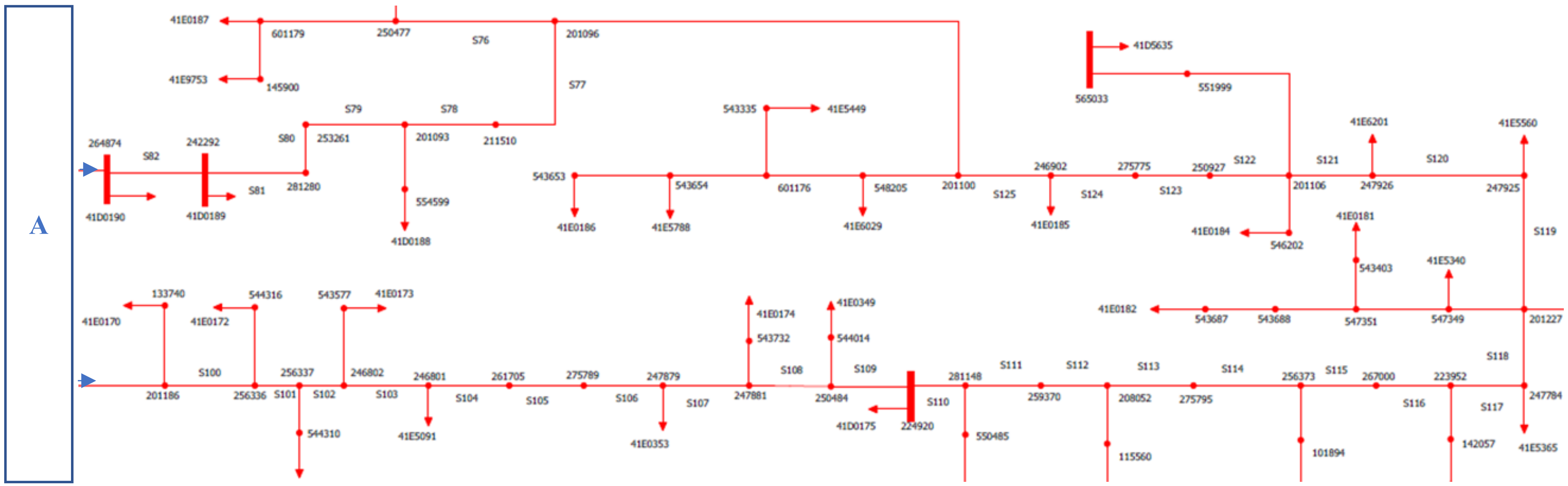
(c) Loop C



(d) Loop D



(e) Section 1 of loop E



(f) section 2 of loop E

Figure 6-4 Switches distribution per loops in the OHL

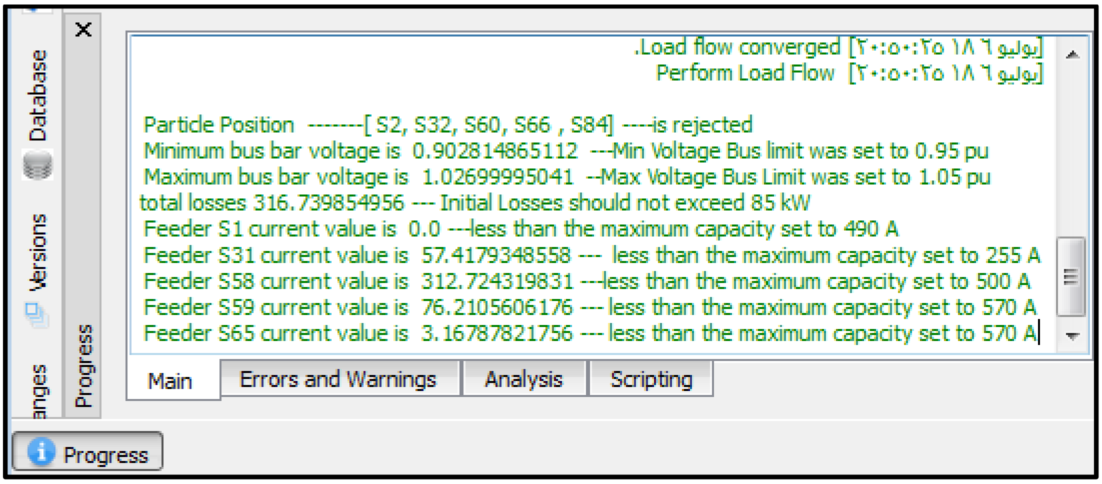
6.4.2 Filtered Initial Position

Unlike the typical PSO that selects their initial positions randomly, MPSO benefits from the previous step of sectionalizing the distribution networks into many loops and worked on using tree diagram algorithm to generate a search space including radial configurations by selecting only one switch from each loop. [S2, S32, S60, S66, S84] – highlighted in Table 6-5 and shown in Figure 6-5 (a) is an example of a configuration generated by tree diagram. Filtering the initial positions does not mean only build a search space consisting of radial configurations but also selecting the configurations satisfying voltage and current constraints with losses less than the initial losses achieved by nominal ties switches calculated to be 85 kW. This filtration process previously explained in chapter 3 and was shown in Figure 3-4 is performed to reduce the number of iterations used to reach the optimum configuration. Although the highlighted configuration in Table 6-5 is radial configuration, it will not be selected in the initial positions as shown in Figure 6-5 (a), because the calculated losses are 316 kW and the lowest bus voltage was calculated to be 0.902 p.u., lower than the minimum bus voltage limits set to this network (0.95 p.u). On the other hand, [S17, S45, S62, S82 and S99] is an example of an accepted initial position represented in Figure 6-5 (b), because the calculated losses are 80 kW, the minimum and the maximum value of the bus voltage are 0.99 and 1.026 respectively. Figure 6-5 shows the snapshots of the results window of the coded optimization program.

Table 6-5 Examples of Generated Configurations in the search Space by Tree Diagram

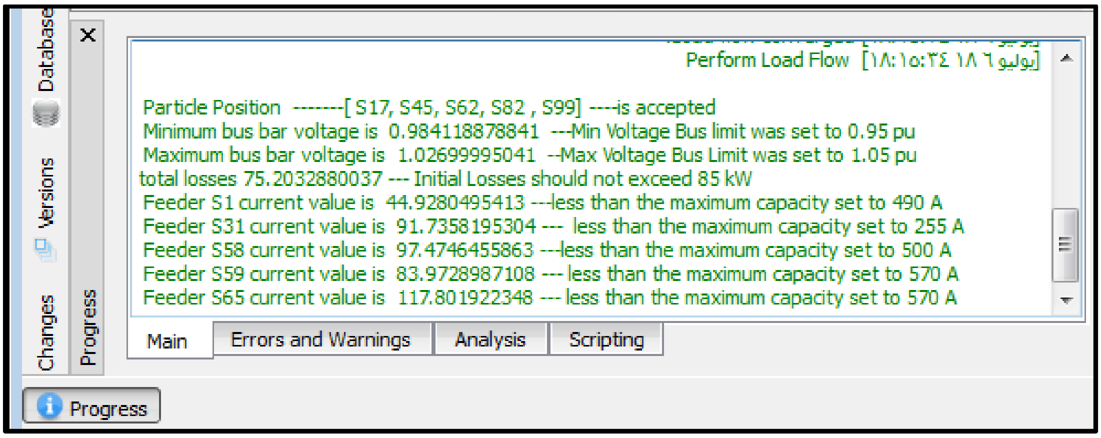
	Loop A	**Loop B**	**Loop C**	**Loop D**	**Loop E**
Loop Parameters	S2	S32	S60	S66	S84
			S61		
		S33	S62	S67	
	S3	S34	S63	S68	S85
	S4	S35	S64	S69	S86
	S5 ⋮ S28	S36 ⋮ S55		S70 ⋮ S81	S87 ⋮ S124
	S29	S56		S82	S125
	S30	S57		S83	S126

S2	S32	S60	S66	S84



(a)

S17	S45	S62	S82	S99



(b)

Figure 6-5 Examples of initial positions selections

6.4.3 Position Control

Another modification added to typical PSO was the position control, that was applied in the IEEE 33 network to prevent the non-feasible positions after updating the particles velocities using equations (6) and particles positions (7) and will be applied in this distribution network too after adjusting the maximum and the minimum boundaries of particle positions to be adopted to this network. These non-feasible positions could occur only when the new calculated positions exceed the largest or the lowest switch index in this network. It should be noted that the particles positions are represented as switches indices in the distribution network. The largest switch index for this network was set to S127, and the lowest index was considered S2, as S1 was already excluded from the search space because it is one of the 5 feeders connecting the network to the generating source. Instead of just discarding these possibilities as previously done in the typical swarm technique, the position control algorithm used in MPSO work on correcting this possibility by checking the index value. For example, if the switch index, was calculated to be S128, then the position control will adjust the switch index to be S127. On the other hand, if the new calculated position was S1, it will be automatically replaced by S2. Although this algorithm maintains the particles within the search space, but it could duplicate some positions, and only in this case, this possibility will be discarded. The Position Control Algorithm is represented in Figure 3-7.

6.4.4 **MPSO Procedures**

The procedures of MPSO were explained in chapter 3 in Figure 3-7 and Figure 3-8 and they are briefly summarized in this section. MPSO is the modification of typical PSO, and then the terminologies explained in Table 3-1 are the same used for MPSO. It should be noted that the particles positions (X_i) are represented as the switches' indices. P_{best} is the configuration realizing best fitness function (losses reduction) for the same particle (i); while G_{best} is the configuration achieving best losses reduction for all the particles in the swarm during one iteration. MPSO solution steps are:

1. Sectionalize the 11kV distribution network to 5 loops as shown in Figure 6-3
2. Generate all the possible configurations using tree diagram to select only one switch from each of the 5 loops as illustrated in Table 6-4 to generate the whole search space. By this way, the search space consists of 3,501,576 configurations. This number was calculated by multiplying the number of switches belonging to each of the 5 loops [29*26*6*18*43].
3. Select 50 configurations to be the initial positions after applying the filtration process explained in section 6.4.2, by applying losses, voltage and current constraints.
4. Initialize two counters, the first to count the iterations and the second for the particles
5. Update the iteration counter
6. Calculate the losses using (1) and checking current and voltage constraints for each particle of the 50 initial positions
7. Consider the initial positions to be the P_{best} if this is the first iteration and then identify the G_{best} ; if this was not the first iteration, follow the procedures explained in Figure 3-8 to identify both P_{best} for each particle and G_{best} for all the particles .

8. Calculate the particle velocities and the positions using (6) and (7) respectively.
9. Check the iteration counter, if it reaches the maximum stop the algorithm else repeat the steps from 5 to 9.

6.4.5 MPSO Results for a Winter day (Maximum Load)

6.4.5.1 Losses and Voltage Improvement

The 11kV distribution network was simulated using IPSA software for losses, load flow calculation and optimization technique. The initial ties switches were S13, S34, S64, S82 and S105. The calculated losses were 85 kW. After applying the suggested algorithm, the losses were reduced to 61.7 kW. To select the maximum number of iterations required to reach the best NOP, 25, 50 and 70 iterations were run for 50 trials for best NOP selection. It was noticed that 25 iterations were reasonable choice because during the 25, 50 and 70 iterations test, the algorithm gives the same losses value which means that there is unlikely to be a requirement to increase the iterations number. Due to the nature of this network, which is an overhead Network with many small farms along long lengths of line small impedances between different switches in a loop, and low values of loads, in the addition to the stochastic nature of swarm technique, the algorithm suggests many configurations giving nearly the same value of optimum losses. This is not unexpected and indicates that multiple switch positions would be suitable. For Example, to select the tie switch in loop A, the NOP suggested by MPSO fluctuates between S11 to S21, and this is logical since a zero value of load has been estimated at bus 262042, and another small load at bus 201046. The same case is repeated for the selection of the tie switch in both loops D and E. In loop D, S79, S80, and S81 are very close to each other, and there is no connected load between them. For these reasons there are not much difference in the calculation of losses by selecting any of them. In loop E, MPSO oscillates between S110, S111 and S112; both S111 and S112 are very close to each other's and there is no load connected to either of them. The connected load at bus 281148- connected between S110 and S111- is only 6 kW. S18, S46, S64, S81 and S110 is an example of the suggested configurations by MPSO for reaching the optimum losses for this network of 61.7 kW. Table 6-6 includes the suggested NOP and their connected bus in the OHL network. Figure 6-6 shows the convergence of the fitness function for the previous suggested configuration to the OHL network during 25 iterations. This optimum loss was achieved in the 17^{th} iteration. The results were crossed check by manually setting the switches suggested by MPSO to be open points and running an IPSA load flow without any optimization program. Figure 6-7 shows both the nominal and the new normally open points for the 11kV distribution network. Furthermore, it was noticed that the suggested NOP configuration improved the voltage profile for the 11kV network. The minimum voltage node using the nominal configuration was 0.986 pu at bus 544014. This value has been raised and the new min voltage node becomes 0.999 pu at bus 224920.Figure 6-8 shows the voltage profile enhancement compared to nominal NOP.

Table 6-6 New Suggested Ties by MPSO during a Winter day

NOP	From bus	Bus Name	To bus	Bus Name
S18	201046	The Lodge Winslow Road S	256168	
S46	205975	Whaddon Road	261643	NEWTON LONGVILLE WHADDON
S64	265395	Caernarvon Cresent Blet	265392	ST GEORGES ROAD BLETCHLE
S81	242292	BrookFiled Road Newton L	281280	Brookfield Road Newton L.
S110	224920	Dove Street Stwekley	281148	----

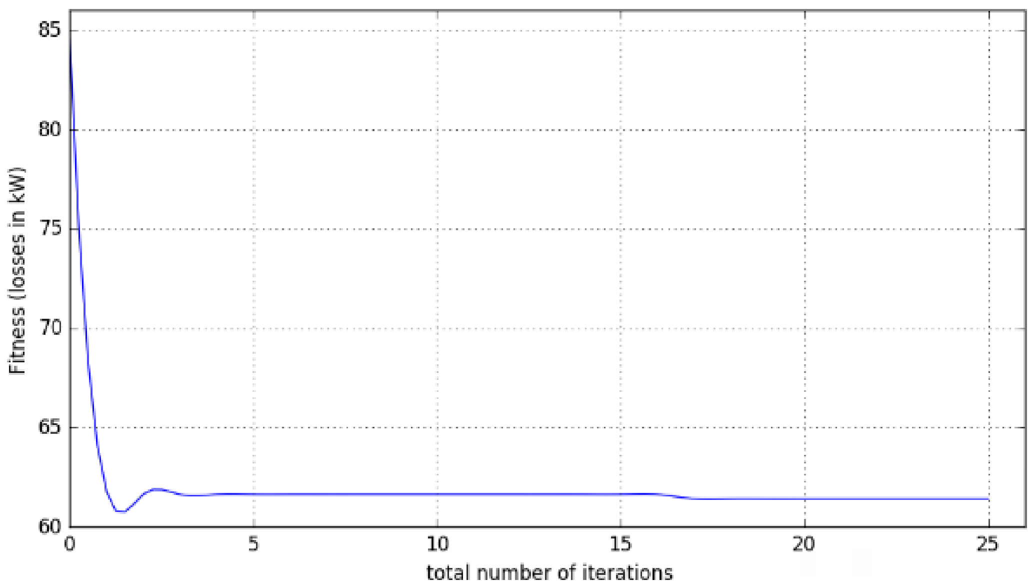
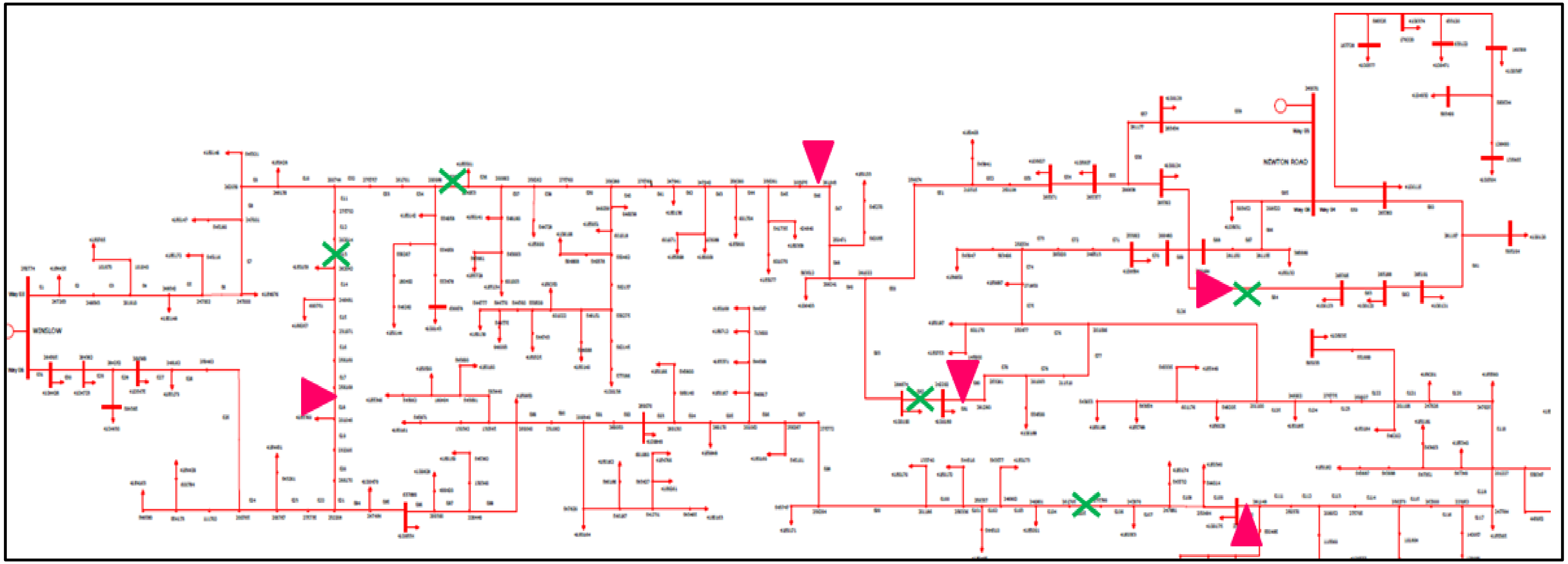


Figure 6-6 MPSO Fitness Function for the 11kV network



Nominal Normally Open Point

Suggested Normally Open Points by MPSO

Figure 6-7 Suggested NOP by MPSO for the 11kV network during a winter day

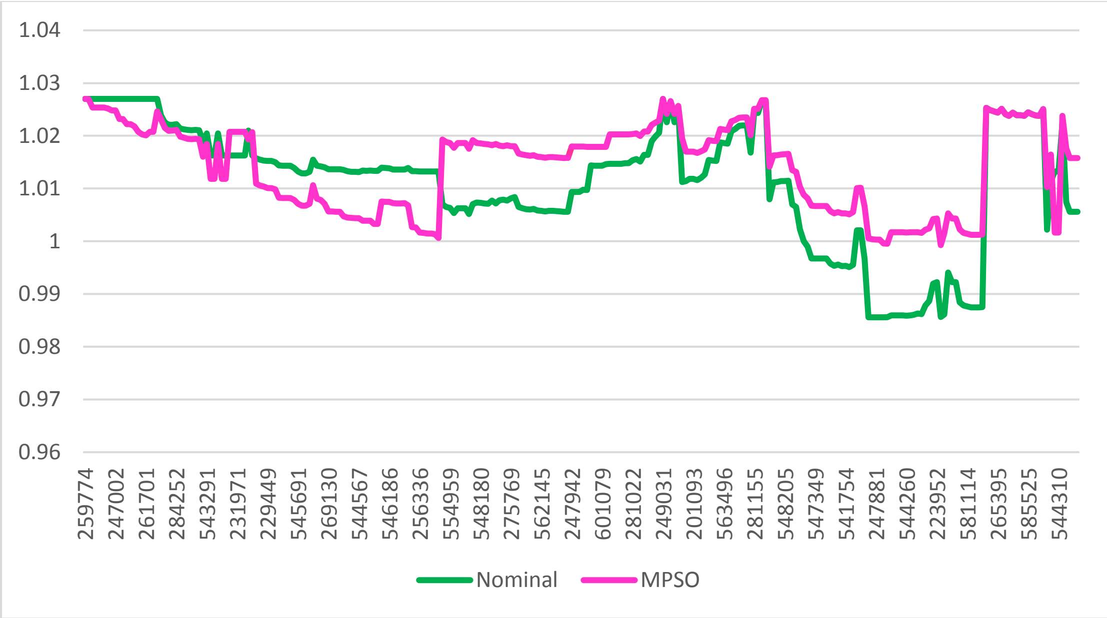


Figure 6-8 Voltage Profile Improvement for Maximum Load

6.4.5.2 **Computational time**

The computational time of MPSO mainly depends on many factors: the generated initial search space which is calculated based on the number of switches per each loop, the particles number that represents the swarm size and the iterations numbers. The generated initial search space for this network was very large and consists of 3,501,576 configurations as explained in 6.4.4. To identify both the particles and the iterations number, 50 trials have been run to test the 50 and 100 particles within 25, 50 and 70 iterations. An inaccurate selection for both numbers increases the risk of falling in local optimum solution. It was found that 50 particles within 25 iterations are enough to reach the optimum solution. The average computational time for this network was calculated to be 67 seconds. This time includes the time spent to select the initial 50 positions satisfying the losses, the voltage and the current constraints for the 11 kV OHL network as mentioned in 6.4.2, added to the time spent to perform the algorithm to reach the optimum solution. It should be noted that the initial positions are important as they accelerate the algorithm to reach the optimum solution in a smaller number of iterations. The 67 seconds is a value that is approaching real time and this method offers a feasible means of selecting DNR compared to other methodologies such as Genetic Algorithm , Adaptive PSO or Adaptive Ant Colony technique that performed their optimum results after being applied for a 135 bus test network within 403 , 723 and 391.3 seconds respectively [37].

6.4.6 MPSO Results for a Summer day (Minimum Load)

6.4.6.1 Losses and Voltage Improvement

The main aim of this section is to apply the MPSO procedures explained in section 6.4.4 for the 11-kV distribution network during a summer day to calculate the losses reduction for a minimum load. By this way, the losses reduction of this network that could be achieved in summer will be studied as well as during the winter. The 3rd of July was selected based on Western Power Distribution Company report after simulating the network via IPSA software. It was found that the calculated losses using the initial tie switches in summer is 3.36 kW. After applying the suggested algorithm to find the best tie switches, the losses were reduced to 2.6 kW. To select the maximum number of iterations required to reach the best NOP during winter, 25, 50 and 70 iterations were run for 50 trials for best NOP selection. It was noticed that 25 iterations were enough as explained previously in section 6.4.4. For this reason, 25 iterations were also selected to be the maximum number of iterations to find the best NOP during summer too. Due to the nature of this network – previously explained in section 6.4.4. – and the stochastic nature of PSO algorithm, many configurations were suggested giving the same losses reduction value. [S17, S46, S64, S79, S112] is an example of a suggested configuration for the Summer. Table 6-7 includes the suggested NOP and their connected bus in the OHL network. Figure 6-9 shows the convergence of the fitness function for the previous suggested configuration to the OHL network during 25 iterations. The optimum loss was achieved in the 17th iteration. The results were crossed check by manually setting the switches suggested by MPSO to be open points and running an IPSA load flow without any optimization program. Figure 6-10 shows the voltage profile enhancement compared to nominal NOP. Figure 6-11 shows both the nominal and the new NOP for the 11kV network during a summer load.

Table 6-7 New Suggested Ties by MPSO during a Summer Day

NOP	From bus	Bus Name	To bus	Bus Name
S17	256168	______	256169	______
S46	205975	Whaddon Road	261643	NEWTON LONGVILLE WHADDON
S64	265395	Caernarvon Cresent Blet	265392	ST GEORGES ROAD BLETCHLE
S79	253261	______	201093	______
S112	259370	______	208052	______

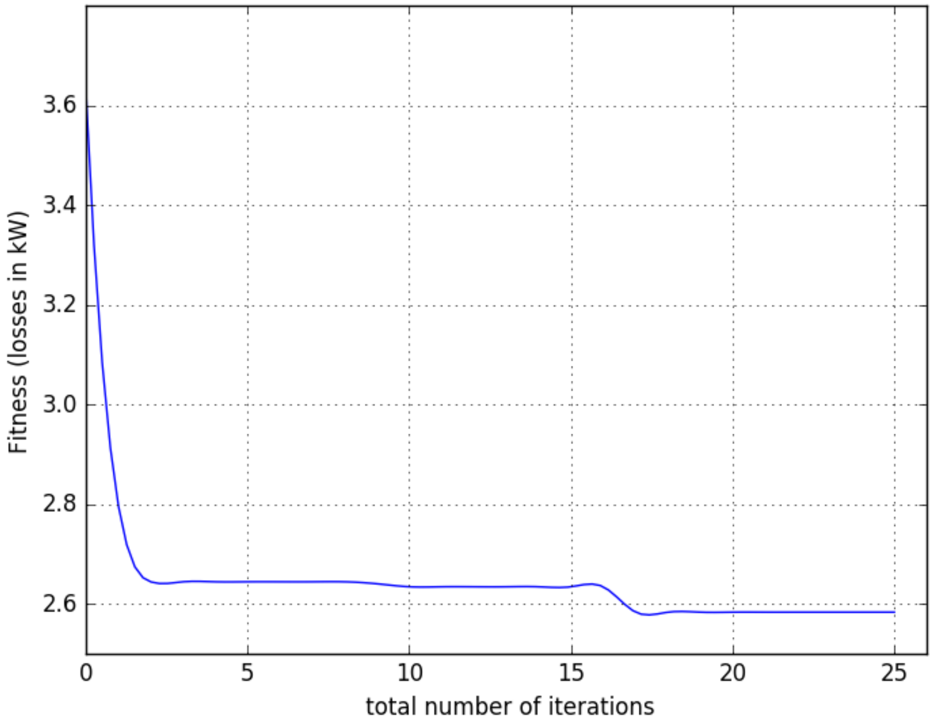


Figure 6-9 MPSO Fitness Function for the 11kV network during a summer day

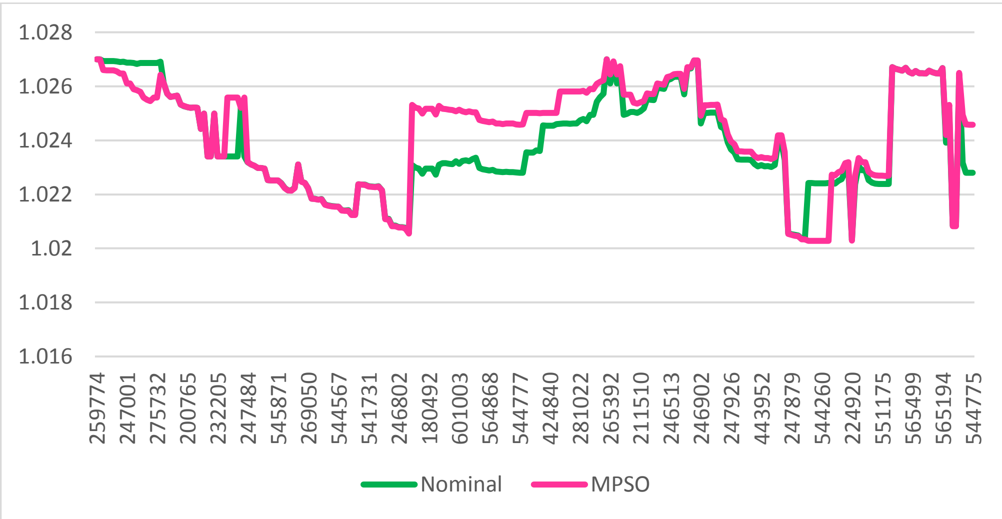
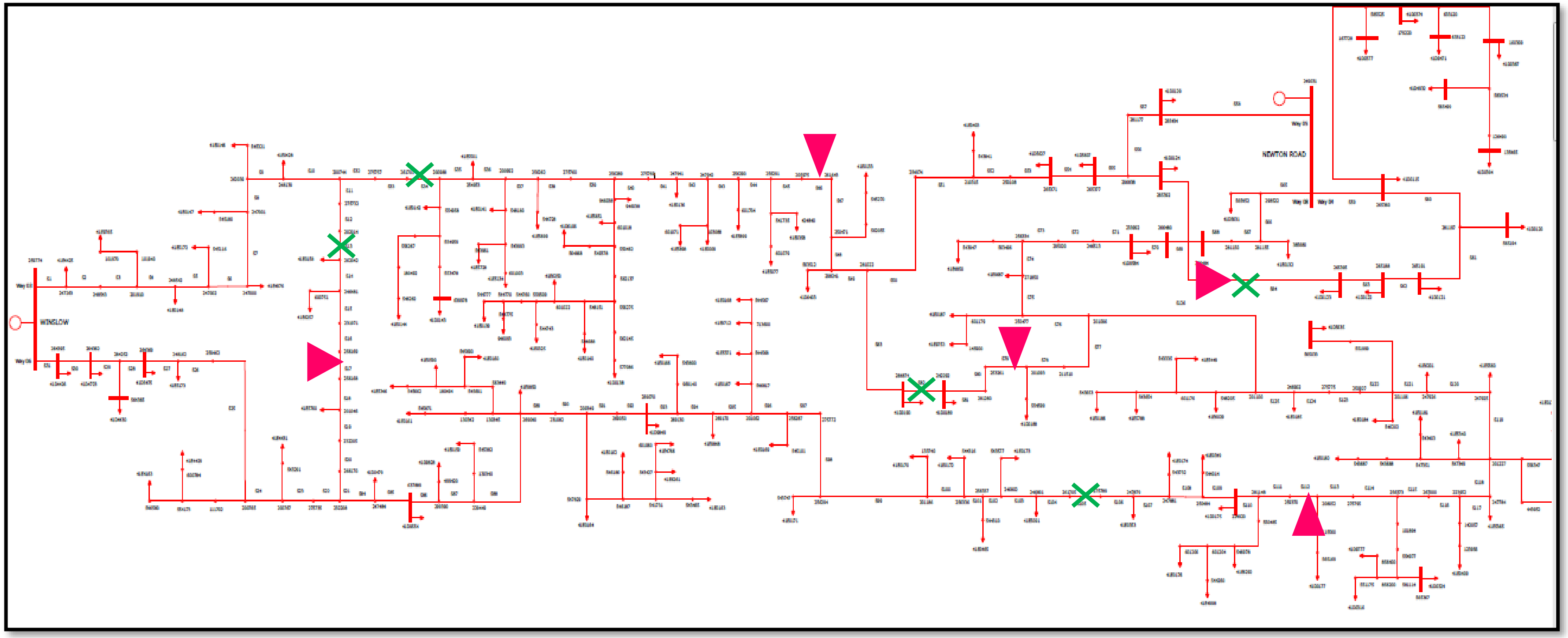


Figure 6-10 Voltage Profile Improvement for Minimum Load

Figure 6-10 shows that the suggested NOP configuration improved the voltage profile for the 11kV network. The suggested open points raised slightly the minimum bus voltage for the OHL network during the summer loads to 1.02028 pu. at node 281148 compared to 1.018 at node 543732 using the nominal configuration.



Nominal NOP

Suggested NOP using MPSO during the summer day.

Figure 6-11 Suggested NOP by MPSO for the 11kV network during a Summer day

6.4.6.2 **Computational time**

To calculate the average computational time for the proposed MPSO to reach the optimum solution, 50 trials have been performed. In each trial, the losses of the Network have been calculated as well as the suggested open points and the time that the proposed algorithm undertake to reach this reduction. It was found that the average time that the algorithm is using to reach the optimum solution is 35.5 seconds. It should be noted that this time is less than the average time that the algorithm undertakes to reach the optimum solution in winter (67seconds).

6.5 Conclusion

The main target of this chapter was to confirm that MPSO was as feasible solution for undertaking optimization on a real Network as well as on the IEEE networks which is much smaller than a real Network. In this case, MPSO was used to investigate DNR for a real distribution network for optimum losses reduction. An 11kV OHL of Milton Keynes distribution network consisting of 265 branches and 262 bus bars was used and simulated in IPSA. MPSO, was suggested in chapter 3 for DNR solution. It is an optimization algorithm based on modifying the particle swarm by sectionalizing the networks into many loops and integrating tree diagram to formulate a radial search space, then introducing losses, voltage and current constraints to filter the initial positions aiming to reduce the number of iterations for reaching the optimum NOP.

It was concluded that MPSO is reaching the optimum solution for the large real distribution network with losses reduction of 27.4% during maximum load in a winter day and with 22% during a summer day. The calculated minimum voltage point is raised from 0.985 to 0.999 pu for the 11 kV OHL network during winter and from 1.018 pu to 1.020 during a summer day. The results were cross checked by manually setting the suggested NOP found by each technique in IPSA and running a load flow without any optimization algorithm for losses calculation while testing the current and voltage boundaries set for this network. It was found that the results were identical for both techniques.

As there were no batteries connected to this Network it is not considered useful to apply the battery sizing and location technique as it would not be possible to easily validate this.

Research Novelty: MPSO was applied to a real distribution Network. during both a winter and a summer day for maximum and minimum load. The results show that the MPSO method gives good results in a sufficiently time scale to be of practical consideration for use on a large Network.

7 CHAPTER 7 MINIMUM NODE VOLTAGE METHOD COMPARISON

7.1 Background

Previously the DNR problem has been defined in chapter 2 and PSO has been modified through chapter 3 and chapter 4 to find the best NOP for maximum losses reduction. This technique was validated through two case study: the IEEE 33 network and an 11kV distribution network in Milton Keynes, UK. It was found that the proposed optimization algorithm reaches the optimum losses for both small and large real networks. It was demonstrated that the computational time of the algorithm is higher for the 11kV distribution network than the small one and this is due to the large search space including several probabilities. In this chapter, an adopted Engineering-based technique, Minimum Node Voltage Method (MNV), was introduced in [139] under project FALCON "Flexible Approaches for Low Carbon Optimized network" managed by the Western Power Distribution (WPD) company. FALCON aimed to look at new flexible ways to manage and enhance the distribution network in the future. The 11kV distribution network of Milton Keynes area was a part of the project. MNV was one of the methodologies suggested to be used for finding the best NOP [26] . This method was previously used to validate the impacts of DNR as a means of reducing losses and adding network flexibility. For this reason, this methodology was validated against the IEEE 33 network as well as the 11 kV OHL network to compare the results found by the proposed MPSO to MNV in respect to losses reduction, voltage improvement and the computational time.

7.2 Min Node Voltage Method (MNV) Concept

Minimum Node Voltage method is an adaptation of the sequential opening method. Both start by meshing the network initially by closing all the existing ties. The sequential method sorts the branches having the lowest power and start by opening one branch at a time, through many load flows runs until reaching the required number of ties. In contrast, MNV carries out a single load flow analysis, and the lowest nodes voltage having more input current than outputs were determined. Examples of the minimum node voltages are included in Figure 7-1. In this figure different cases are included. In this figure, bus 2 is considered a minimum node voltage for different Network configuration types described in Figure 7-1(a) , Figure 7-1(b) and Figure 7-1(c). Figure 7-1(a) illustrates the minimum voltage node at bus 2 where two branches carrying reverse currents flow are feeding a single load. Figure 7-1(b) shows two branches carrying two reverse current supplying a third branch. Figure 7-1 (c) is an example of a node having three input branches feeding a single load. Figure 7-1 (d) is a distribution point so it could not be selected as a minimum node. The branches connected to these minimum node voltages having the lowest power flow are established. Once the right number of NOPs is reached, the new configuration is announced. MNV procedures are shown in Figure 7-2.

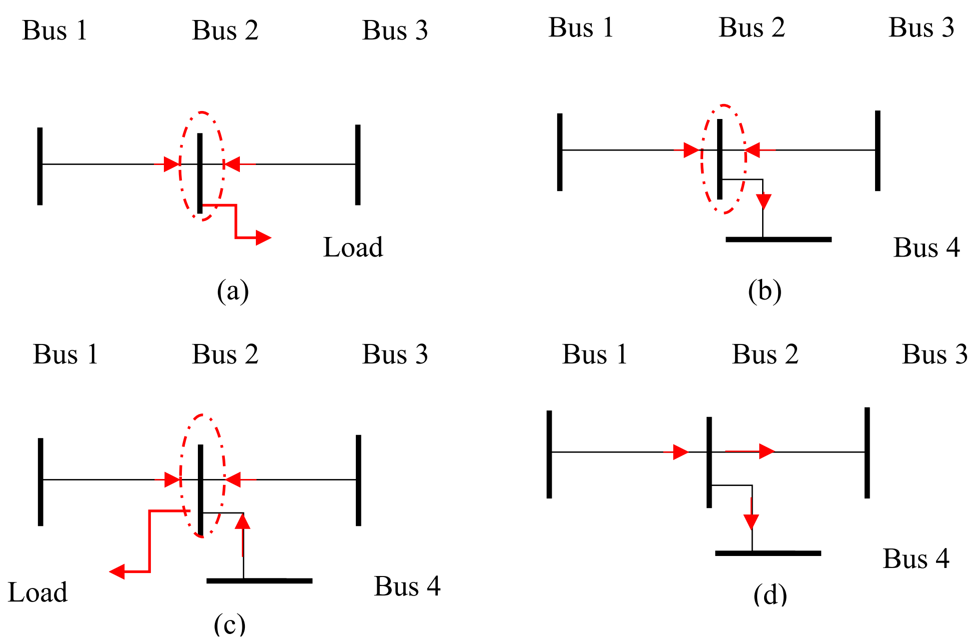


Figure 7-1 Examples of minimum nodes voltage in a distribution network

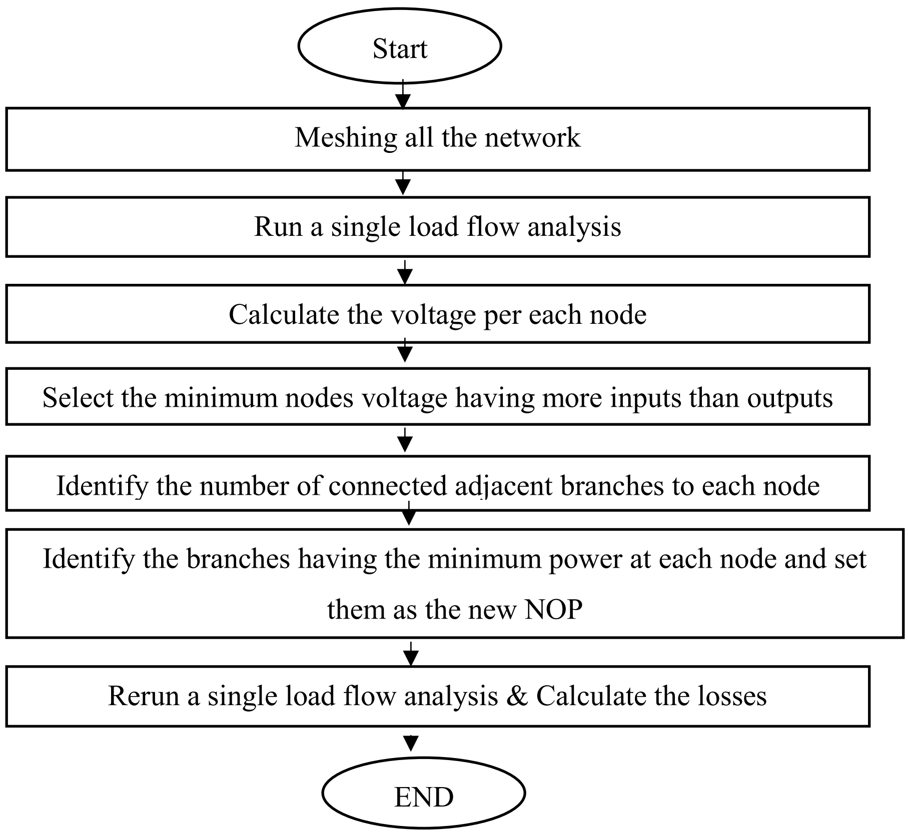


Figure 7-2 Minimum Node Voltage Method Procedures

7.3 Case Study 1: IEEE 33 Network Reconfiguration using MNV

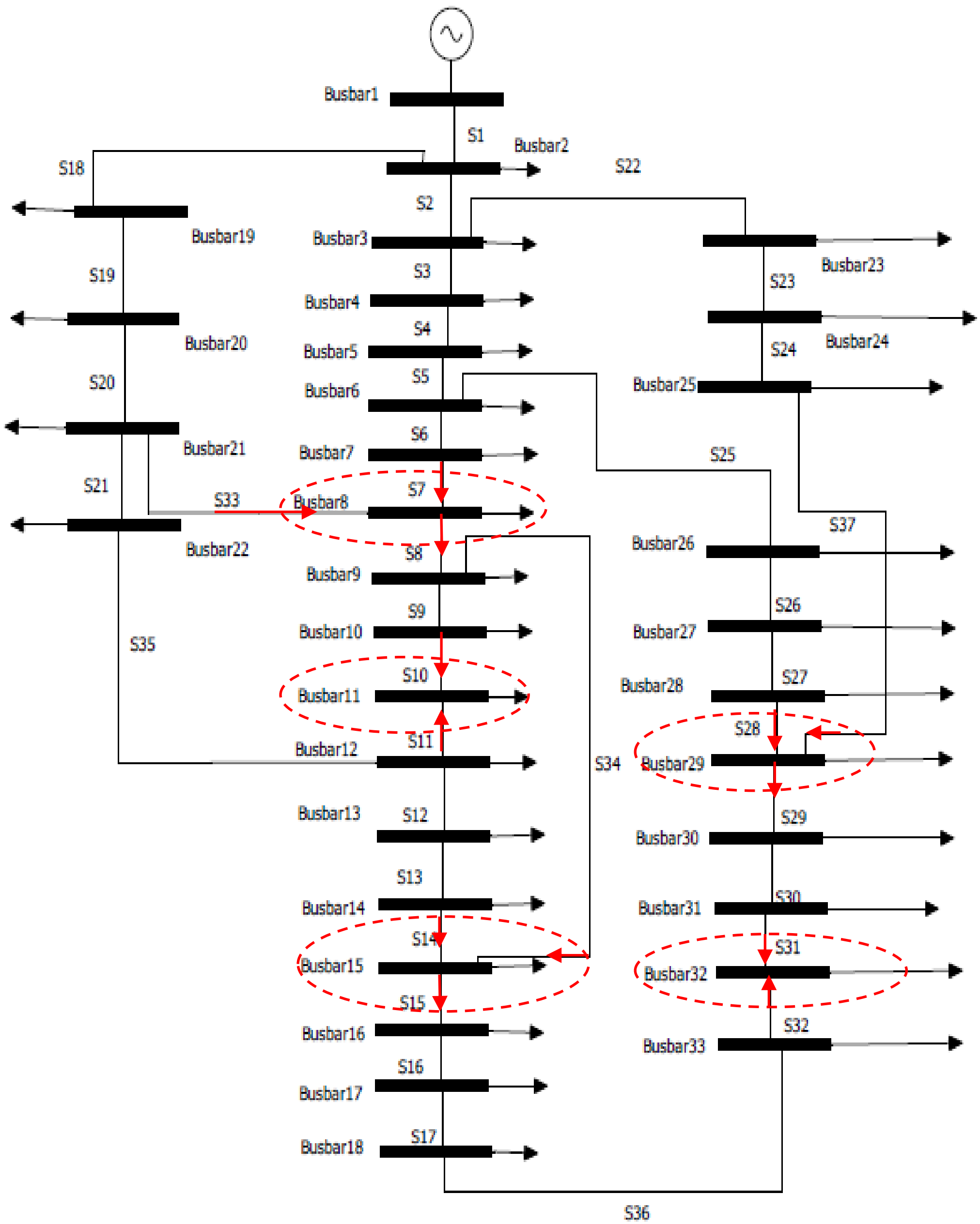
The minimum node voltage method was validated against two case studies, the first is the IEEE 33 network and the second is the 11kV distribution network by running the Network in the original configuration, then changing the Network and running in the configuration suggested by the following method.

7.3.1 MNV Validation

The IEEE 33 network shown in Figure 3-1 was described in section 3.2. It consists of 32 closed switches and 5 NOP. The initial ties switches were S33, S34, S35, S36 and S37. The initial losses for the test network were calculated 193.6 kW. Unlike the proposed MPSO, either sectionalizing the network in loops nor voltage and current limits were considered in the MNV. The new NOP for the IEEE network were found by following the procedures explained in Figure 7-2. A python script has been coded to validate the MNV using IPSA for losses and computational time calculation. The IEEE 33 network was initially meshed. Then a load flow study has been performed using IPSA to identify the minimum voltage nodes within the distribution network. The minimum voltage nodes for the IEEE 33 network are circled in Figure 7-3. These nodes are bus 11 connected to S10 and S11, bus 15 connected to branch S14, S15 and S34, bus 29 connected to branch S37, S28 and S29, bus 32 connected to branch S31 and S32, and bus 8 connected to branch S7, S8 and S33. After identifying the nodes having the minimum voltage, the adjacent branches connected to these nodes having the lowest power were selected to be the new NOP. The power of the adjacent branches connected to the minimum nodes are illustrated in Table 7-1 .The suggested new NOP based on MNV (S7, S10, S14, S32 and S37) are shown in Figure 7-4. The losses are reduced to 137 kW calculated in 0.16 seconds. This value of losses has been checked by switching off the suggested new ties manually and running a load flow. The losses obtained were identical to the calculated by MNV under the same load conditions.

Table 7-1 Suggested branches to be NOP based on MNV for the IEEE network

	Bus 11		Bus 15			Bus 29			Bus 32		Bus 8		
Branch	S10	S11	S14	S15	S34	S37	S28	S29	S31	S32	S7	S8	S33
Power (MW)	0.01	0.027	0.042	0.21	0.23	0.36	0.37	0.62	0.26	0.06	0.26	0.36	0.31
NOP	**S10**		**S14**			**S37**			**S32**		**S7**		



Minimum Node Voltage

Figure 7-3 Minimum Voltage Points for the IEEE 33 network

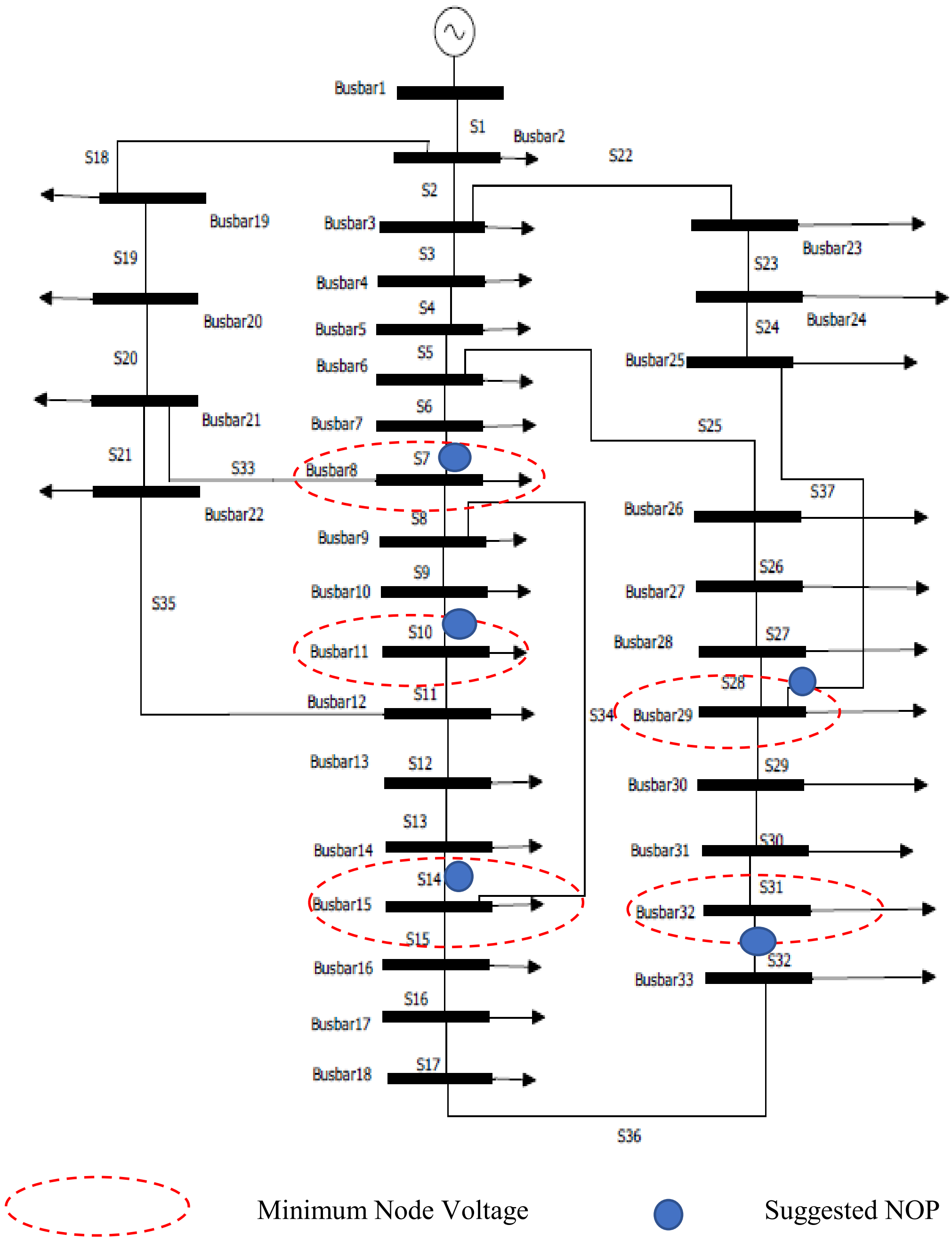


Figure 7-4 Suggested NOP for the IEEE 33 network

7.3.2 Comparative Study

The IEEE 33 network was studied using two different techniques; The first is the Minimum Node Voltage method, which is an example of an engineering-based methodology. The second is the MPSO, example of an optimization algorithm, previously explained in chapter 3. Both techniques have been cross checked by manually opening the suggested NOP and running a load flow for losses calculation using IPSA. The main aim of this section is to compare the results found by both the MNV and the MPSO for the same working network under the same load conditions. It was demonstrated in chapter 3 that MPSO has achieved the optimum losses by proposing S7, S9, S14, S37 and S32 as new NOP for the IEEE 33 network. This tie switches configuration is very closed to the NOP suggested by MNV shown in Figure 7-4 (S7, S10, S14, S37 and S32).

7.3.2.1 Losses and Voltage Improvement

Following the MPSO procedures described in Figure 3-7 and Figure 3-8 , the losses of IEEE 33 network was reduced as previously noted in chapter 3 in section 3.5 to 136.36 kW reducing 29.68% of the initial value. This value is slightly less than the losses reduction achieved by Min Node Voltage method that decreased the losses to 137 kW. The main reason for this that both methodologies suggested 4 similar NOP (S7, S14, S37, S32). The 5th tie is different as the heuristic technique proposed S10 while the optimization technique recommended S9, because S10 has less power compared to S9 as shown previously in Table 7-1.

Losses reduction is not considered the only benefit gained from DNR but also the voltage improvement. Both techniques the MPSO and MNV have improved the voltage profile of the IEEE 33 network similarly as shown in Figure 7-5. In this graph, the minimum bus voltage after reconfiguration using both MNV and MPSO raised to 0.94 at bus 32 instead of 0.918 at bus 18 before reconfiguration in the initial case as demonstrated earlier in chapter 3. Figure 7-6 shows the initial NOP of the IEEE 33 network compared to the NOP obtained by the MNV and the proposed MPSO.

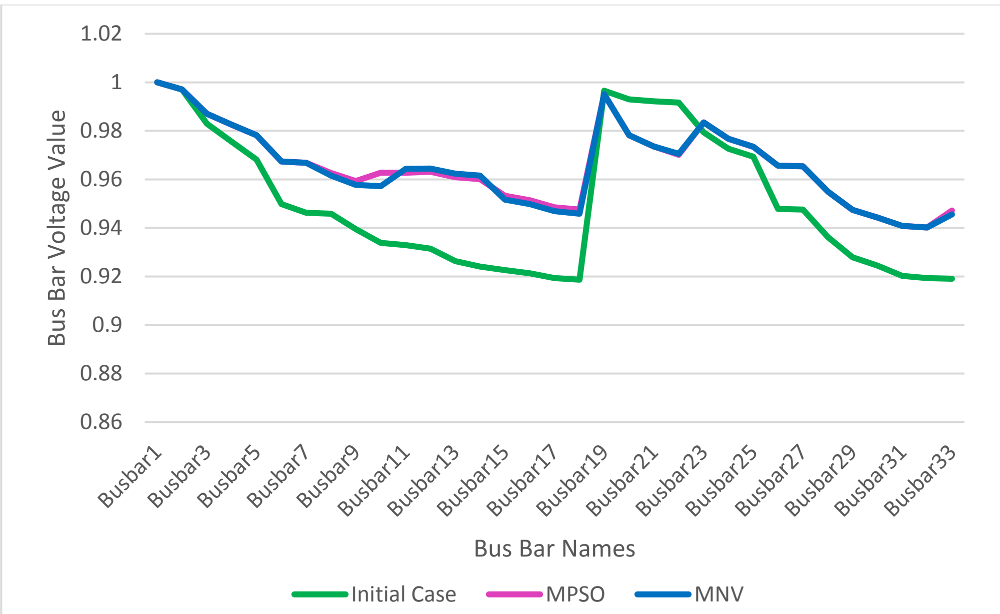


Figure 7-5 Voltage Profile Improvement Comparison

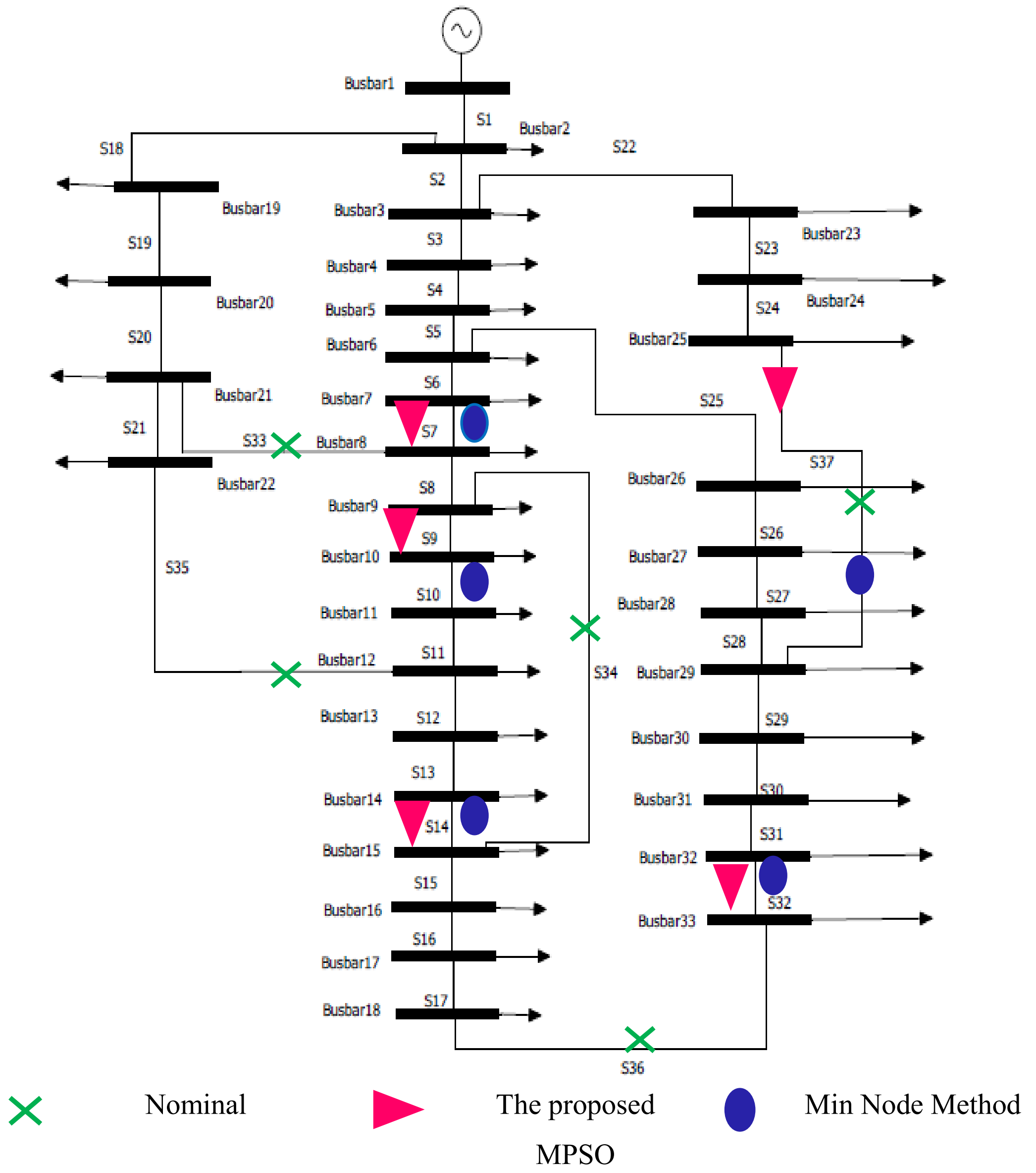


Figure 7-6 Comparison between the suggested NOP for the IEEE 33 network using different solution techniques

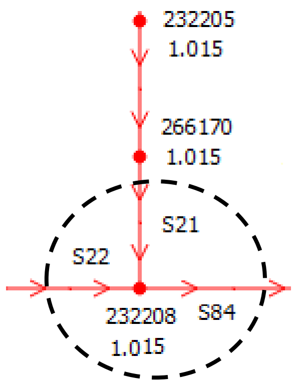
7.3.2.2 Computational time

The losses reduction and the computational time are considered the main factors deciding the performance of any algorithm applied in the DNR. MNV is a knowledge-based technique based on engineering expert and for this reason, the NOP configuration found was based on a single load flow. Unlike the proposed MPSO, which is a probability-based optimization technique that used many load flows runs through many iterations to reach the optimum solution. It was found that the MNV achieved a very closed losses reduction to the proposed MPSO for 0.16 seconds. This time is very short compared to the proposed MPSO which takes around 17.5 seconds.

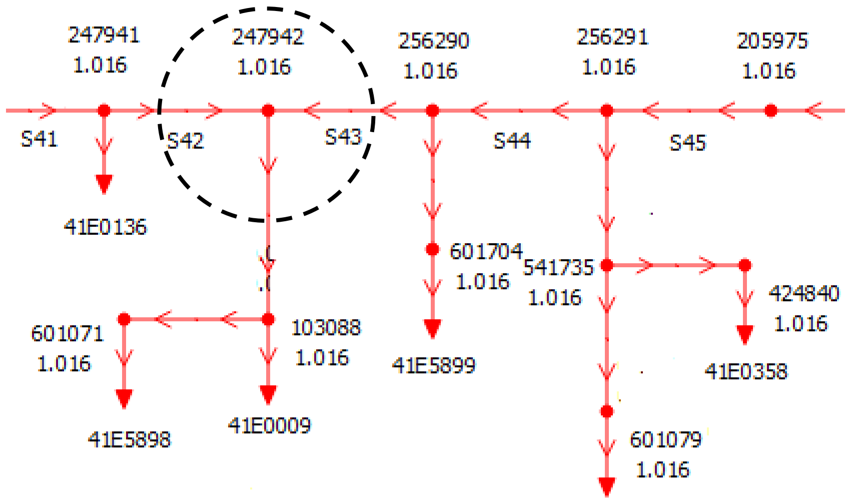
7.4 Case Study 2: The 11 kV Network Reconfiguration using MNV

7.4.1 MNV Validation

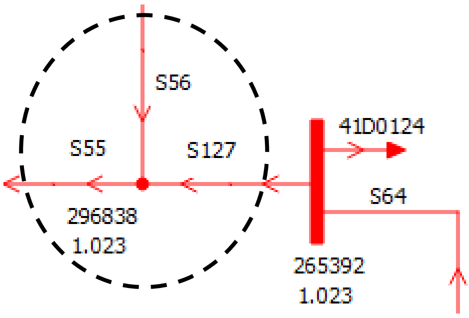
The 11 kV OHL network, described in chapter 6, is composed of 262 buses and 265 branches, fed from two substations. The initial losses for this network was 85 kW. The initial NOP are illustrated in Table 6-2 to be S13, S34, S64, S82 and S105. Following the procedures of the minimum node voltage methodology shown in Figure 7-2, the 11 kV OHL distribution network has been initially meshed. The nodes branches carrying input current more than the branches carrying output currents described previously in Figure 7-1, were identified after running a single load flow using IPSA. Figure 7-7 shows the minimum voltage point in the 11kV network. Figure 7-7 (a) shows that the lowest voltage node is at 232208 connected to S21, S22 and S84. Although bus 232205, bus 266170 and bus 232208 seems to have the same voltage magnitude, the lowest is bus 232208 which has a calculated voltage equal to 1.015163p.u. compared to 1.015162 p.u. at bus 232205 and 1.01578p.u. at bus 266170. Obviously, it is not possible with the level of accuracy of the load flow to assume that this is the correct answer – but it provides an indication of the correct location. S21 was selected to be a NOP because it has the lowest power rating compared to other adjacent branches. The same steps used to identify the first least voltage point and the corresponding NOP are the same procedures followed in the rest of the other minimum nodes voltage as shown in Figure 7-7 (b, c, d, e) respectively. Table 7-2 represents the adjacent branches linked to each of the lowest voltage point showing the power rating of each of them to justify the NOP selection.



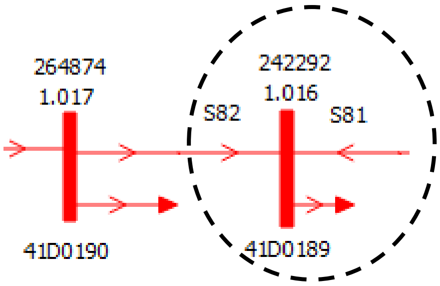
(a) loop A



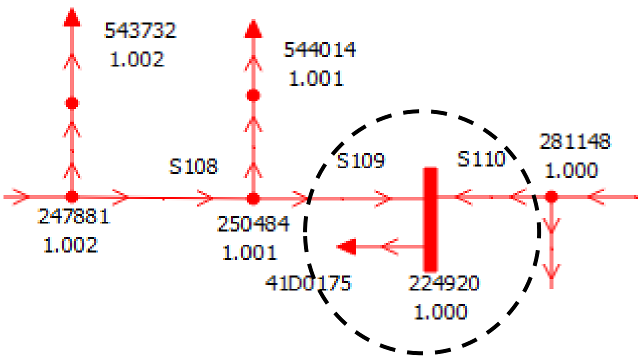
Loop B



(a) Loop C



(b) loop D



(c) Loop E

Figure 7-7 Minimum Voltage Point in the 11kV network

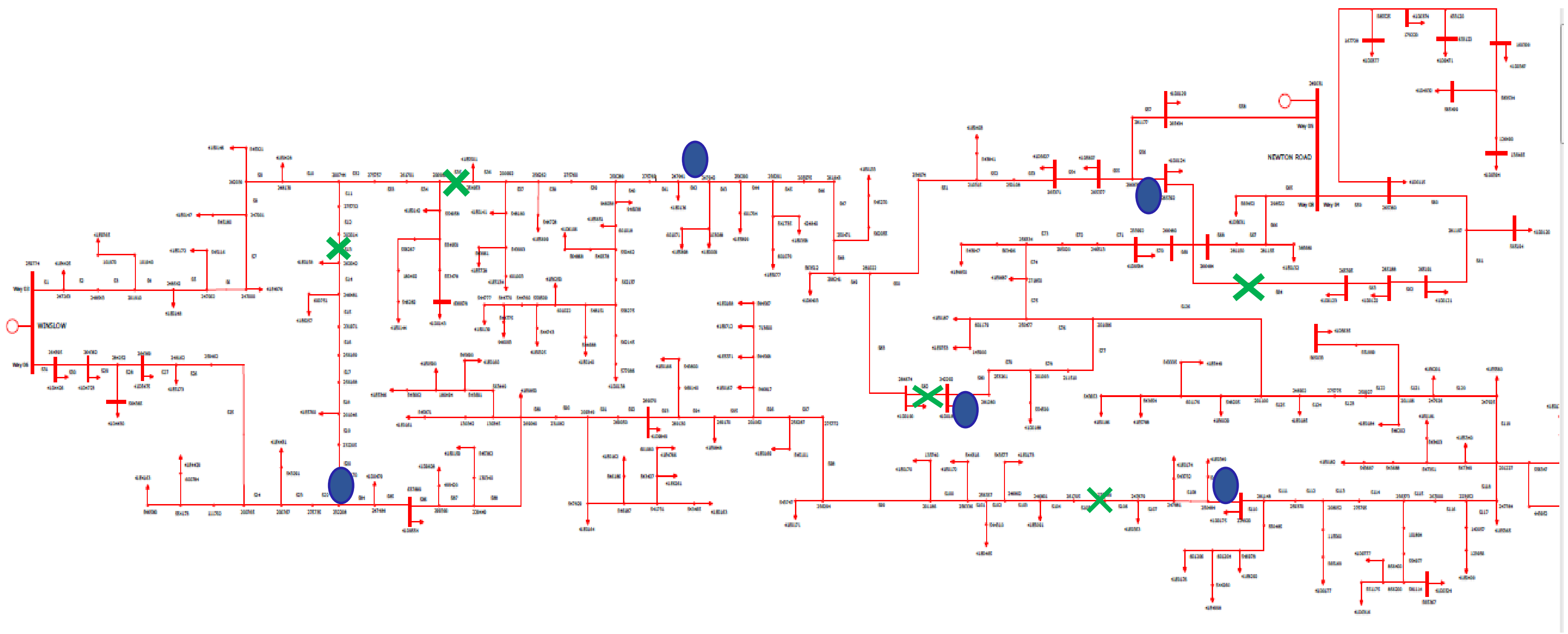
Table 7-3 includes the suggested NOP and their connected bus bars areas in the 11kV distribution network. It was found that S21, S42, S127, S81 and S109 shown in Figure 7-8 are the best NOP, reducing the losses to 69.kW.

Table 7-2 Suggested branches to be NOP based on Minimum Node Voltage Method

Bus	232208		247942		296838			242292		244920	
Connected branches	S21	S22	S42	S43	S55	S56	S127	S81	S82	S109	S110
Power (MW)	0.34	0.49	0.95	0.96	1.97	1.68	0.29	0.04	0.18	0.15	0.2
NOP	S21		S42		S127			S81		S109	

Table 7-3 New Ties by Min Node Voltage Method

NOP	From bus	Bus Name	To bus	Bus Name
S21	232208	Farm A	266170	Farm A
S42	247941	Farm B	247942	----
S127	296838	-----	265392	---
S81	242292	-----	281280	Brookfield Road Newton
S109	224920	Dove Street Stwekley	250484	----



Nominal NOP

NOP found by MNV

Figure 7-8 Suggested NOP by Minimum Node Voltage Method for the 11kV network

7.4.2 Comparative Analysis

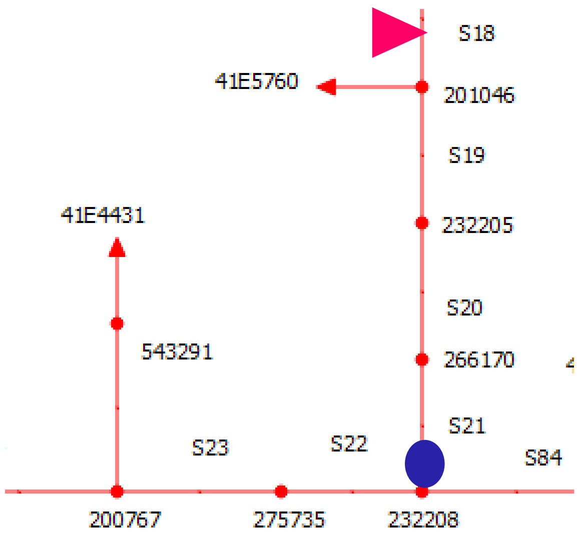
The 11kV distribution network has been studied using the Min Voltage Node method and the proposed MPSO explained in chapter 6 for investigating using DNR for losses reduction. The main aim of this section is to compare the results found by both the MNV and the proposed MPSO for the same working network. As previously explained in chapter 6, MPSO starts by sectionalizing the network into 5 loops (A, B, C, D, and E) as described earlier in Figure 6-3. The elements of each of these loops were included in Figure 6-4. Sectionalizing the network helped to generate the search space for the proposed MPSO based on tree diagram which guarantee the generation of radial NOP selection as it selects a single switch from each loop. Examples of generated NOP configurations based on tree diagram were included in Table 6-5. Losses reduction was the primary goal for this study. The network has been simulated via IPSA and the best NOP found from both techniques (MPSO and MNV) have been cross checked by manually setting them open points and then running a load flow without any optimization algorithm. It was demonstrated in chapter 6 that MPSO has reached the optimum losses via many configurations due to the nature of the network, which is an overhead Network with many small farms along long lengths of line small impedances between different switches in a loop. S18, S46, S64, S81 and S110 is an example of configurations suggested by the proposed MPSO achieving the optimum losses as previously mentioned in chapter 6 in section 6.4.5. In this chapter, these tie switches configuration, will be compared with the NOP suggested by the MNV (S21, S42, S127, S81 and S109) with respect to losses reduction, voltage improvement and computational time.

7.4.2.1 Losses and Voltage Improvement

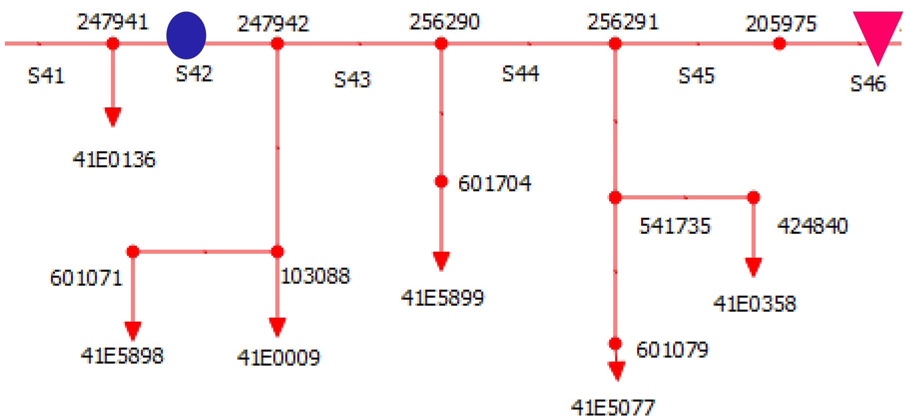
Table 7-4 compares between the NOP in the nominal case and the NOP by each method and their corresponding losses. It is noticed that both techniques suggested S81 to be a NOP, but the rest of suggested NOP are different but very closed to each other. Both techniques gave similar percentage of losses reduction of 29 % for the IEEE 33 network. The proposed MPSO surpassed the MNV for the 11 kV OHL network reaching 61kW compared to 69 kW achieved by MNV. The main reason for obtaining very close NOP locations is the nature of this network having low values for impedance and connected loads between the switches. Figure 7-9 shows the locations of the non-identical NOP found by both techniques in loop A, B and C and E respectively. For Example, S18 is selected to be best NOP for loop A by MPSO while S21 is considered the best open switch for the same loop by the min node voltage method. They are geographically and electrically close to each other as they are separated by a low value of impedance and only 1 kW of load located at bus number 201046 as shown in Figure 7-9 (a). The same case is repeated for loop B , C and D as shown in Figure 7-9 (b,c,d); In loop B, S46 and S42 are separated by very low impedance and although there are different loads located at bus number 247942, 256290 and 256291, but their sum is 39 kW. In loop C, S127 and S64 are both connected to bus number 265392 from different sides and the same case is repeated in loop E.

Table 7-4 Best NOP for the 11kV distribution network

	A	B	C	D	E	Losses kW
Nominal	S13	S34	S64	S82	S105	85
MPSO	S18	S46	S64	S81	S110	61.7
Min Node Voltage	S21	S42	S127	S81	S109	69



Loop A



Loop B

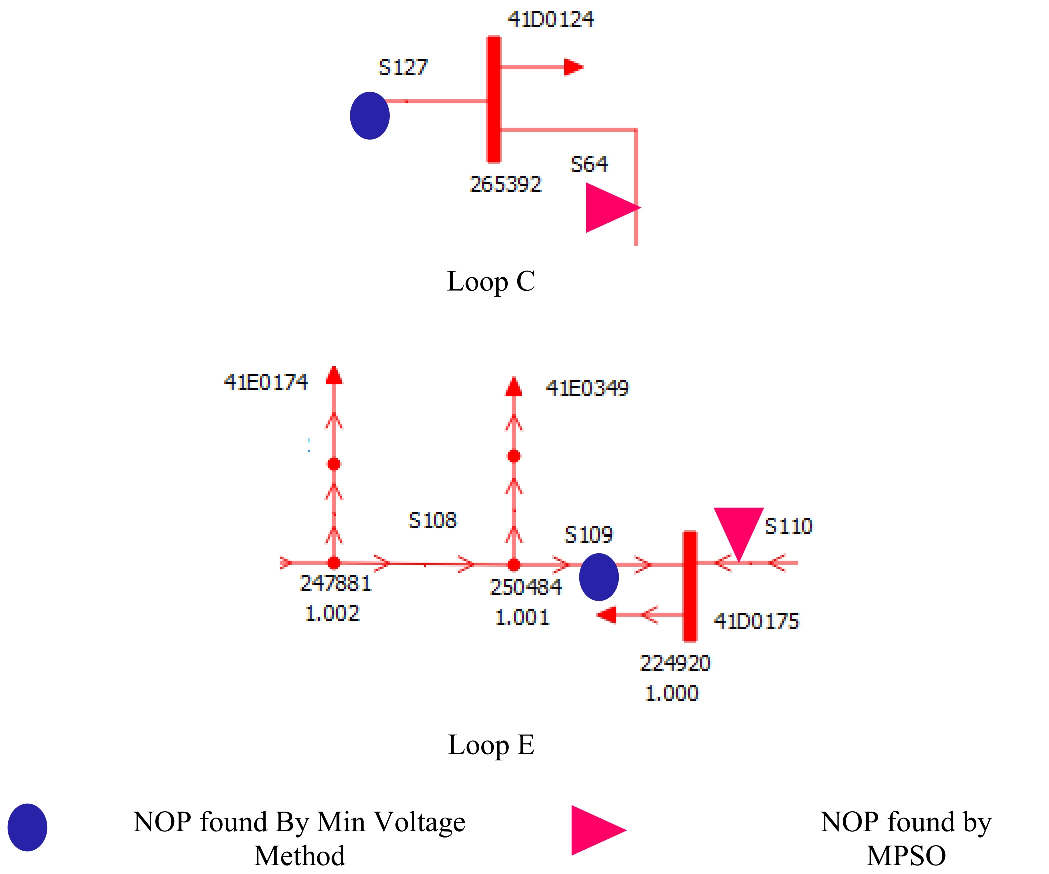
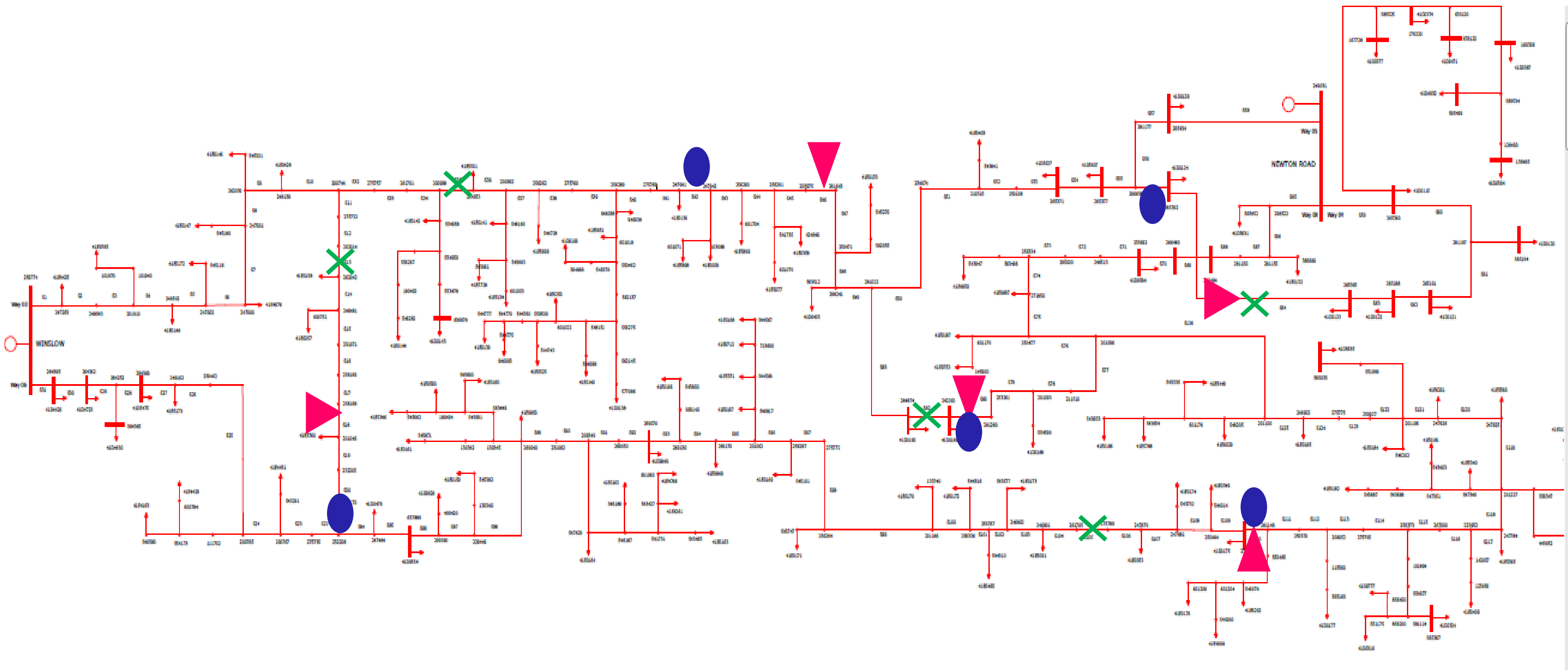


Figure 7-9 Non-Identical NOP locations found by both techniques for the 11 OHL network

Figure 7-10 shows both the nominal and the optimum NOP found by both techniques in the 11 kV OHL distribution network. Figure 7-11 compares between the voltage improvement in the 11kV network through the nominal NOP and the open ties suggested by both techniques. It is noticed that the minimum voltage node using the nominal configuration is 0.986 pu at bus 544014. This value has been raised and the new min voltage node becomes 0.999 pu at bus 224920 by both techniques.

7.4.2.2 **Computational time**

The computational time for the technique is significant only in case of validating DNR online. Since MNV is a based engineering technique, that depends on a single load flow operation. It suggests the NOP in 0.7 seconds. This time is very short compared to MPSO that take 67 seconds for suggesting the right configuration. This large computational time of MPSO was due to the large search space composed of 3,501,576 configurations as explained in 6.4.4.



Nominal NOP MPSO NOP Min Node Voltage Method NOP

Figure 7-10 Optimum NOP by both techniques

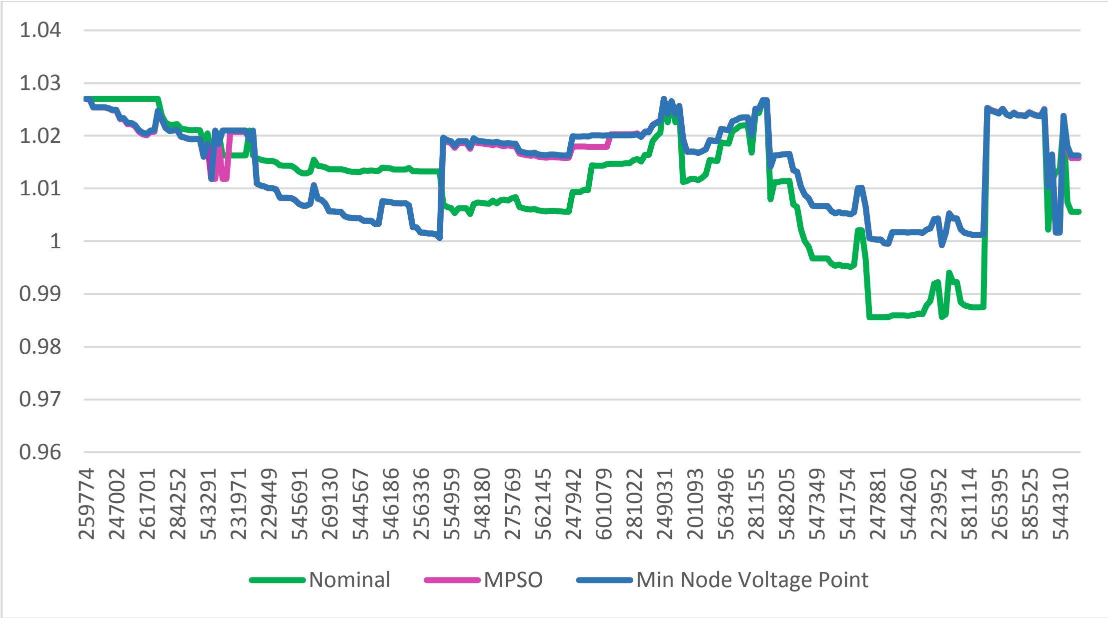


Figure 7-11 Voltage Profile Improvement for the 11 kV OHL network

7.5 Results Discussion

The MNV and the MPSO methods have been compared to each other in section 7.4. In this section, the difference and the similarities of both techniques are highlighted in

Table 7-5.

Table 7-5 Similarities and Differences between MNV and MPSO

	MNV	MPSO
Similarities	1. Both have been implemented against small and large networks 2. Both improved the voltage by the same level. The voltage curve for the IEEE 33 and the 11kV OHL network have been superposed as shown in Figure 7-5 and Figure 7-11.	
Differences 1. Losses Reduction	Losses have been decreased for the IEEE 33 bus by 29.2% from the initial value and for the large 11 kV OHL network by 18.8 %. from the initial value.	Losses have been decreased for the IEEE 33 bus by 29.5% from the initial value and for the large 11 kV OHL network by 27.4%. from the initial value.

	MNV	MPSO
2. Computational Time	Very fast for both small and large networks. The computational time for the IEEE 33 bus network is 0.16 seconds and for the 11 kV OHL network is 0.76 seconds.	The MPSO is considered fast compared to other algorithms as proved in chapter 3. However, compared to MNV, the MPSO is considered time consuming. The MPSO takes around 17.5 seconds to reach the optimum losses for the IEEE 33 networks. This time has been increased for the 11kV network to 67 seconds.

Min Node Voltage method is more straightforward compared to the proposed MPSO, also it does not require high mathematical optimization backgrounds. Further work is required to prove the flexibility of MNV to be used for large networks at this time if they include any extra DGs or storage devices. As this is a very fast heuristic method it also offers benefits for real-time DNR. Although the MNV reaches a losses reduction value for the IEEE 33 network (137 kW) very closed to the optimum results found by MPSO (136 kW) in a very short time (0.16 seconds) compared to the computational time consumed by both MPSO (17.5 seconds) or the MSMPSO (9 seconds calculated in chapter 4), this technique has some disadvantages that are recommended to be modified:

1. This technique does not guarantee to keep the voltage nor the current within the limits because there are no constraints for current or voltage to control them.
2. This technique did not find the minimum losses for large distribution network
3. This technique does need to check that minimum voltage node locations are not adjacent to already found existing minimum voltage location or at the end of a feeder and this is complex to code with the level of accuracy of the load flow.

In contrast, the main disadvantage of the MPSO is the time compared to the MNV. For this reason, the hybridization of the technique with other algorithms is suggested to accelerate the algorithm. This idea has been already presented and implemented in chapter 4 by introducing the Multi Stage Modified MPSO that uses Monte-Carlo for enhancing the search space. This hybridization reduced the time for the MPSO for the IEEE 33 network to 9 seconds. Although this time is still higher than the time used by MNV for the same network (0.16 seconds), but MPSO have the following advantages that are not satisfied by the MNV:

1. It guarantees radial configurations through Tree Diagram as explained in chapter 3.
2. This algorithm achieved the optimum losses for both small and large distribution networks
3. The voltage and the current are kept within the limits due to the given constraints.

7.6 Conclusion

In this chapter, a previously used engineering-based technique, the Minimum Node Voltage Method, has been explained and compared. The procedures for this technique have been described. Two cases studies were used to validate the methodology to suggest the best NOP for maximum losses reduction. The first network was the IEEE 33 bus network while the second was the 11kV distribution network in Milton Keynes, U.K. The main goal of this chapter was to compare the performance of this technique to the proposed MPSO explained previously in chapter 3. It was demonstrated that both techniques give very close losses reduction percentage for small network while the MPSO surpasses the MNV for the larger distribution network. The MNV is very fast technique compared to the MPSO for both working networks. For this reason, it could be applicable for online DNR after covering the shortcomings of this technique with respect to both voltage and current limits and radial topology. By improving these shortcomings, this methodology could be applied in close to real time.

8 CHAPTER 8 CONCLUSION & FUTURE WORK

8.1 General Conclusion & Innovation

The main aim of this thesis is to investigate DNR as a method to reduce the active losses in distribution network thus helping to research a method to reduce carbon dioxide emissions. Losses reduction could defer building of new steam generation units to compensate for the annual demand growth rate. Two strategies for reducing losses were considered; network reconfiguration of the distribution network and integrating storage devices in the network. This research uses a novel approach in the way it considers implementation of both methods in conjunction while at the same time considering the impact of variable load.

Network Reconfiguration is considered a complex stochastic optimization problem and for this reason many researchers work on selecting, improving and hybridizing the algorithms suggested for finding the best NOP for the distribution network. There are 4 main categories of undertaking calculations behind network reconfiguration: the heuristic, the meta heuristic, the mathematical and the hybrid technique. Heuristic technique based on expert knowledge gives approximate solution, but can be fast to implement, however, they are not preferred method for real Networks. Mathematical methods give deterministic solution, but these are hard to apply on large networks because the time to solution increases exponentially with the size of the network. Meta heuristic techniques, known as intelligent techniques, are preferred as they give optimum solution but in high computational time. Hybrid technique work on integrating many solution methods to obtain the optimum solution within a reasonable computational time

In this thesis, a new technique based on particle swarm optimization algorithm- Multi stages Modified particle Swarm optimization technique (MSMPSO)- was developed to find the optimum normally open point in the distribution network.

- The first stage of the technique starts by modifying the basic particle swarm algorithm (MPSO) in chapter 3 by generating a search space of radial configurations using the concept of tree diagram, filtering the initial positions (by the addition of losses, voltage and current constraints) and applying the position control that retain all the particles to be within the search space.

  [Novel contribution to knowledge: Modified Optimization technique to decrease the search space and increase the performance time]

- These modifications were validated using the IEEE 33 test distribution network using a static load. The results of MPSO were compared to previous researchers that used the same network with respect to losses reduction, voltage improvement and computational time. It was found that the MPSO suggests the same configuration proposed by some based PSO techniques in a much reasonable computational time, which is still high for real applications.

[Novel contribution to knowledge: Theoretical validation of Modified Optimization technique and comparison to other solutions]

As the load is not static but continually varying, a Monte Carlo technique was integrated to MPSO to test its flexibility to respond to variable generated load.

[Novel contribution to knowledge: Integration of Monte-Carlo load variations in conjunction with a modified particle swam algorithm]

- The results of the Monte-Carlo analysis showed that despite a random variation in load that only a small subsection of switches was ever utilised. This resulted in a further development of the MPSO called the Multi Stage Modified Particle Swarm Optimization, MSMPSO, which use Monte-Carlo analysis to further reduce the search space and improve the performance time.

[Novel contribution to knowledge: Integration of results of Monte-Carlo analysis to further reduce the search space of the MPSO algorithm]

- It was concluded that both MPSO and MSMPSO suggests the same optimum configuration for the IEEE 33 network and hence same losses reduction, but in a lower computational time reaching only 9 seconds enhancing the convergence of the algorithm and confirming its ability to respond to variable load aiming to be implemented in real network.

The second method suggested for losses reduction is the integration of storage units in the distribution network described in chapter 5. To help with this both the size and the location should be correctly considered because inaccurate capacity or site could represent an extra burden on the power system. The majority of previous research studied the sizing of BESS from three points of views: facilitating the integration of renewable energy, planning purpose and for peak shaving and load leveling. This thesis looked at the problem in conjunction with DNR.

The work presented in this thesis is different because it studies the optimum size and site for integrating BESS in the presence of an active distribution network focusing primary on losses reduction. In other word, the best size and site for BESS is calculated while keeping the flexibility of changing the NOP for maximum losses reduction. For achieving this, it was suggested to use Monte Carlo technique for sizing five different batteries, one per each loop of the IEEE 33 network, while finding the best NOP using MPSO.

This thesis suggests an operational mode that includes both modes simultaneously considering uploading off-peak load during charging mode and peak load during discharging operational mode to have a full picture for decision making process.

[Novel contribution to knowledge: The development of a new method of sizing energy storage in a system in conjunction with DNR]

It was concluded that mixing both strategies together, the optimum selection of NOP while integrating storage units with suitable size and location reduced the losses from 193 kW at the initial case to 116 kW and 114 kW in discharging and charging mode respectively for the IEEE 33 network. The voltage has been raised from 0.91 p u initially to 0.945 p u.

By this way the main target of this thesis to look at ways of reducing losses and carbon dioxide emission reduction have been studied and validated through the IEEE 33 distribution network. To check the ability to validate this for real network, an 11 kV OHL distribution network was used in chapter 6. This network is larger than the test network used before, consisting of 262 buses and 265 branches.

[Novel contribution to knowledge: The use of MPSO in investigating loss reduction on an existing 11kV distribution Network]

The MPSO, which is a modified version of particle swarm algorithm and represents the first stage of the new developed technique, Multi Stage Modified PSO, has been tested through the OHL network.

- It was found that MPSO reach the optimum solution for both small and large network with calculated losses reduction of 29.5 % and 27.4% respectively using maximum load.
- The computational time of MPSO varies from small to large network. In the IEEE 33 network, the average computational time reached 17.5 seconds compared to 67 seconds for the 11kV network for maximum load. The main reason for this is the large search space used for selecting the initial position. This search space is mainly depending on the number of branches connected to the nodes. In the IEEE network, the search space includes 16128 configurations compared to 3,501,576 in the 11kV network.
- The minimum calculated voltage has been raised from 0.98 to 0.99 pu using maximum load.

Since it is expected that MPSO and MSMPSO reach the same optimal value of losses as was proved through chapter 3 and 4 before, only the MPSO was used on the real network. The results generated by this have been compared to those produced using heuristic method based on engineering background called, Min Node Voltage method.

[Novel contribution to knowledge: comparison of minimum voltage method with MPSO method on an 11kV Network]

The Minimum Node Voltage point has been compared in chapter 7, using two distribution networks, the IEEE 33 bus network and the OHL network using the same load for MPSO. A comparison was held between the MPSO, which is based on intelligent algorithm and the minimum node voltage method, which is based on engineering background, showing the similarities and the differences of both techniques after being validated for both distribution networks. It was demonstrated that both the heuristic and intelligent methods give very close losses reduction percentage for small network while the MPSO surpass the MNV for the larger distribution network. under same load conditions. Both achieved nearly the same voltage improvement for the same portion of the network under the same load conditions.

The main contributions of this thesis are summarised in the following points:

1. Integrating the concept of tree diagram method to the sectionalizing of the distribution network to formulate a determined search space for the basic particle swarm algorithm instead of using random switches.
2. Filtering the initial positions selection by adding the constraints to improve the selection of particle positions in the early iterations and hence accelerate the algorithm.
3. Developing a modified optimization technique, Multi Stage Modified MPSO, composed of three stages to benefit from the modifications added to the basic swarm algorithm in the first stage, test the flexibility to respond to variable load by the addition of Monte Carlo algorithm in the second stage and then reduce the computational time through the third stage.
4. Sizing and allocating the batteries storage devices in the distribution network while keeping the flexibility to optimally reconfiguring the network for minimum losses and CO_2 reduction.
5. Comparing the developed MPSO to Minimum Node Voltage method using both test and real distribution networks through the IEEE 33 and the 11kV OHL distribution network.

8.2 **Future Work**

This thesis presents different strategies for losses reduction in a distribution network. However, the following list gives a selection of ideas that could be considered for further work:

Theoretical Analysis

- In this research, the losses reduction was considered the main objective function for network reconfiguration as it is very correlated to carbon dioxide reduction. In this point another area could be considered by studying, the fault level, and the number of switching.
- The network reconfiguration has been merged with the integration of battery storages for maximum losses reduction in distribution networks. There is another scope to study the combination of both to demand side management for optimum benefit.
- In this work, Monte Carlo Simulation- example of a statistical technique -is used to look for the best size for storage batteries that should be integrated in the distribution network. The next step in this area is to study the best sizing using an optimization technique and then compare with the results found by Monte Carlo in term of losses reduction assuming having the same percentage of storage energy share.
- The siting procedures used in this work are valid for small networks because after calculating the capacity of each loop, and after simplifying the search space, all the probabilities have been studied to decide the optimum bus to locate the storage device per loop. Further theoretical study needs to be applied in case of large distribution networks.
- There is scope for future work to look at the cost study of the addition of 5 storage batteries for the IEEE 33 network. In this research point, the type of the suggested storage batteries is required to be identified, and then a compulsory industrial research should to be undertaken to know the price of both the batteries and the power electronics converters that must be included. Then a payback study is required to know the total economic benefit compared to losses reduction.
- This research assumes that the battery charge and discharge at its maximum power rating and efficiency is inherently dealt with by assuming that the time of charge/discharge is adjusted. There is a need to extend the study to consider the following constraints:
    - Maximum power injection
    - Daily charging and discharging cycles
    - Daily Stored Energy
    - Efficiencies of the energy storage system
- More theoretical analysis is required to modify the shortcomings of Minimum Node Voltage technique by including both the power flow and the radiality constraints to guarantee the secured operation while being implemented for distribution networks.

Real Network Validation

- Although it is expected that the Multi Stage Modified Particle Swarm Optimization gives the same losses reduction for the 11 kV OHL network achieved by MPSO, but there is a need to know how much this technique will be effective in computational time reduction.
- In General, this thesis targets the losses reduction in distribution network by investigating the DNR in conjunction with sizing and allocating the storage units as a proposed solution strategy. Initially, DNR has been studied against two distribution networks. However, the combination of sizing and allocating the storage devices in the presence of an active DNR is only validated using the IEEE 33 bus network. Further work is certainly required to validate this combination against the 11 kV OHL network for improving the losses reduction obtained by changing the NOP.
- Running a field trial for sizing and allocating battery storage units simultaneously with DNR in distribution networks would be desirable as a final validation. To undertake such a trial the following would need to be considered:
    - The practical network should be well understood and sectionalised into loops
    - Locations of practical DNR switching should be identified to help reduce search spaces further.
    - The load and any primary feeders should be continuously measured to get good historical data and close to real time data.
    - The methodology described within this thesis should be used to size and locate energy storage at a fixed value along with relative DNR location for different historical loads.
    - The nearest practical battery storage locations to those decided optimally should be selected - taking into consideration the requirement to be distant from people from a noise perspective.
    - The battery storage should be charged at low load and discharged at high load and recorded load at each substation and within each storage unit should used to determine the DNR open switch configuration in close to real time from those practically available and calculate the theoretical saving in losses.
    - This theoretical value should be compared to any reduction in the feeder loads to help establish if the loss reductions are practically occurring as expected. A week on and week off type operation is suggested so that performance without the DNR and energy storage can be compared.

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10 APPENDIX PUBLICATIONS

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Utilization of Battery Energy Storage Systems (BESS) in Smart Grid: A Review

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Abstract

The uncertainty in fuel cost, the ageing of most existing grid, the lack of utilities' supply capacity to respond to the increasing load demand, and the lack of automatically power restoration, accelerate the need to modernize the distribution network by introducing new technologies, putting the smart grid (SG) on spot. The aim of this paper is to carry out a detailed survey of the major requirements of (SG) and discuss the operational challenges arising from the integration of distributed generation (DG) in distribution networks (DN). These requirements dictate the necessity to review the energy and communication infrastructure, the automatic control, metering and monitoring systems, and highlight the features of smart protection system for a robust and efficient distribution grid. In addition, the paper aims to classify the energy storage systems (ESS) and explain their role for utilities, consumers and for environment. This includes the pumped hydro systems (PHS) and compressed air systems (CAS), battery energy storage systems (BESSs), double layer and superconductive capacitors, and electric vehicles (EVs). Since BESSs emerged as one of the most promising technology for several power applications, the paper presents an overview of their main features, management and control systems and operational modes. A survey about the utilization of BESSs in power system is presented.

Key words

Smart Grid (SG), Energy Storage systems (ESS), Battery Energy Storage Systems (BESS), Battery Management Systems (BMS), Battery Storage Applications.

1. Introduction

Existing power grids are generally unidirectional, used to carry power from central generating stations to area with a large number of customers. Most generating stations operate at low efficiency not exceeding 40% and without recovering wasted heat. This hierarchical topology of power network coupled with lagging investments in infrastructures could decrease the system stability in case of any rise in electric demand. The fluctuation in fuels cost, together with the inability of the of utility companies to expand their generation capacity in line with the rising demand for electricity, accelerate the need to modernize the distribution network by introducing new technologies that can help with the demand side management and revenue protection making the network smarter to operate. Smart grid is a network that uses information, cyber secure, communication technologies, and computational intelligence to create an automated and distributed advanced energy delivery network to achieve a safe, reliable, efficient, and sustainable system. It coordinates the need and capabilities of all generators, grid operators, end users, and electricity market stakeholders to operate all part of the system as efficiently as possible, minimizing costs and environmental impacts while maximizing system reliability, and stability [1].The "Two way flow of electric power'', which is one of the major characteristic of this kind networks, means that the electricity could be generated in the distribution grid benefiting from power generation by using solar panels ,wind turbines or other sources of renewable energy. By this way, the electricity can also fed back into the grid by users. The SG could respond to events that occur anywhere in the grid, such as power generation, transmission, distribution, and consumption, and adopt the corresponding strategies [2, 3]. Table I gives a comparison between existing grid and SG .

Table I. Comparison between existing and smart grid

	Traditional Grid	Smart Grid
Communication	One Way	Two Way
Generation	Centralized	Distributed
Sensors	Few	Throughout
Monitoring	Manual	Self
Restoration	Manual	Self
Reliability	less	reliable
Efficiency	less	high
Oil consumption	high	less
CO2 emission	high	less
Consumers Choices	Few	Many
Cost	less	high
Protection	Failures and Blackouts	Adaptive and islanding

The paper is organized as follows: compression between current and the suggested smart grid. A highlight of the main requirements of a smart grid. It also gives an explanation of the role of energy storage systems in power system application for utilities, environment as well as for consumers. It classifies the different categories of energy storage systems and an overview of battery energy storage system. A section explains the features of a battery management system and finally a review of the different applications of battery storage schemes in power system.

2. Smart Grid Requirements

A SG consists of five subsystems: Energy Infrastructure, Smart Metering System, Communication System, Monitoring, Management and Automation system and Smart Protection system [3]. Each subsystem will be briefly discussed in the following sections.

A. Energy Infrastructure

The bidirectional flow of power in Smart grid does not only lie on the conventional generation stations, but also it introduces the concept of generation in distribution system. In spite of this increases the flexibility and reliability of the system, it complicates the power flow. Distributed generations (DGs), virtual power plants (VPP) and micro grid (MG) are considered to be the main elements of SG energy infrastructure. A brief description of each element is given below.

1) Distributed Generation (DGs)

The DG takes advantages of distributed energy resources (DER), such as wind and solar panels, with aim to improve the power quality. Each DER is connected to the power grid via power electronic devices and a switching power interface to control the current drawn to the SG [4]. DG has their own associated devices for communication, power flow monitoring, smart metering systems, protection equipment, energy storage systems, automatic voltage control, and dynamic line rating. Nonetheless, the integration of DGs in the power network is not problem free. Their high integration could cause wide fluctuations resulting from the renewable resources on one hand, and insulation damage to equipment when the voltage increases on the other hand.

2) Virtual Power Plants (VPP)

Due to the associated operational problems of DGs integration, it is necessary to develop active control strategies to facilitate their integration. Otherwise; the distribution network could face a lot of operational problems. For such reason, the Virtual Power Plant (VPP) is presented to facilitate and control the DGs in the distribution network.VPP, represented in figure 1 is an information and communication system with centralized control over an aggregation of distributed generation, controlled loads, and storage devices. Its main role is the management of the electric flow of energy within the main grid [5]

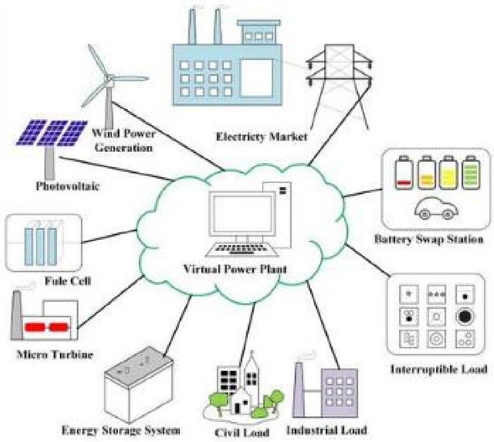

Figure 1 Virtual Power Plant

3) Micro grid (MG)

Another requirement for DGs integration, is the micro grid (MG), as shown in figure 2, which consists of different distributed power sources at low voltage side of the distribution network, which could be operated into two modes [3,6]. The first is in grid mode, where the customers share power generated from their DGs with the main grid. The second mode is islanded mode. In case of emergency or power shortage, the MG shift to islanded mode automatically, where the customers are disconnected from the main grid, but still could be supplied from their DGs. This ability of islanding mode could provide a high level of reliability in case of any disturbances. However, the control of large number of DGs is facing many operational and technical problems such as the bidirectional power flow in grid connected mode, the frequent change of voltage and frequency during the connection and disconnection of DGs, and few others. For this reason, many control schemes [6] and protection approaches [7] should be investigated to maintain a high level of power quality, stability, power flow balancing and reliability.

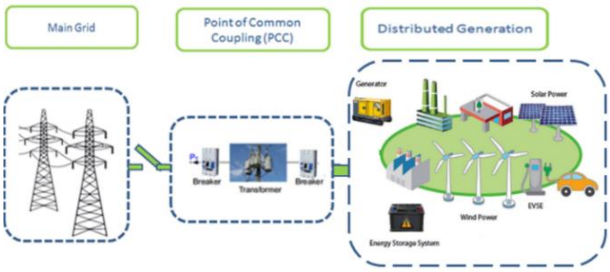

Figure 2 Micro-grid

B. Smart Metering System

In SG, power consumption information needs to be gathered, integrated and analyzed for optimum decision making on both consumer and utility side. Therefore, metering, monitoring and communication systems should be upgraded and modified for a secured, précised information system. Automatic Meter Reading (AMR) is introduced for one-way communication grid, for automatically collecting the consumption and the data from the energy meters and sending them to a central data base for billing, troubleshooting and analyzing [2, 3]. Due to its one-way communication, the utilities could not take any online corrective action based on the measurements received from the meters. Thus, this type of meter does not support the transition to smart grid. Automatic Meter Infrastructure (AMI) is then introduced for two-way communication systems. By this way, utilities can meet their basic target of load management and instantaneous information about load demand for a better power system operation. Smart Meters (SM) are similar to AMI, and sometimes they could be considered the most essential component of the AMI. They record information hourly or sub- hourly and send the gathered data to utilities for power generation and distribution decision making with information feedback to encourage customer to reduce consumption.

C. Communication System

Communication systems in SG should support the bidirectional flow of power and information between the different sections in SG, as it enables system sensing and monitoring, utility and customers' linkage to detect the real time demand, and self-correction capability in case of any failure. The main requirements and the challenges of communication systems in SG, such as the quality of service, reliability, security, and scalability are discussed in [4]. SG communication systems could be wired or wireless. Installing large wired communication system for monitoring the power grid costs time and money. Moreover, whenever any fault occurs in the system, communication becomes difficult, sometimes even impossible. Only wireless sensor network can resolve this kind of problems. Low cost wireless sensor has paved the way for grid automation, real time monitoring and remote control of system elements such as primary and secondary sub stations, power lines, capacitor banks, feeder switches, fault indications and other physical facilities. Wireless Sensor Networks (WSNs) with their affordable low cost and numerous desirable features enable utilities to monitor their remote facilities any time with applications such as Supervisor Control and Data acquisition System (SCADA).

D. Smart Monitoring, distributed automation and management System

Distributed automation (DA) is the use of SCADA for the remote monitoring and control of the distribution network [8]. It also integrates the real time operation information, grid structure, equipment status, customer automation control, data communication and information management, that realize the efficiency and reliability improvement on one hand and the management of distribution grid on the other hand due to the flexible control. Network reconfiguration, fault Identification, service restoration, load management, load shedding and others are the application of distributed automation in SG
[8]. Management in SG is an essential application of DA in SG. It mainly focus is onto three goals: the first goal is energy efficient and demand profile improvement through shifting, scheduling or reducing the demand in order to reshape the demand profile in peak hours [3], the second goal is minimizing the energy losses which is very challenging due to the integration of renewable resources and distributed generation, the third goal is the reduction of CO_2 emission for a secured green environment, through an optimized cost for utilities. However, minimizing generation cost is not directly equivalent to minimum emission as the cost of renewable energy source is not always the lowest. In order to realize the previous management objectives, optimization and intelligent systems, and other tools are reviewed in [3].

E. Smart Protection System

A smart protection system should have many characteristics to improve the reliability, the stability and the security of power system [3]. A smart protection system should have:

1. Predictive ability to prevent failures from happening by expecting the weak points in the network such as the failures due to load fluctuation, the thermal capacities of generators and others.
2. Self-correction capability after a fault by locating the fault and isolating it to avoid cascade failures.
3. Automatic network reconfiguration by finding all the plans to supply the customers to avoid outage considering the radial configuration, minimum losses and the minimum time of restoration through changing the state of the switches by employing optimization and intelligent techniques.
4. Maintain the power system reliability by reducing the impact of DGs on the grid without scarifying the system reliability.
5. MG protection, as they could work in two modes in grid and in islanded mode. New protection schemes are developed in this area [7]

6. The ensure security and privacy to prevent attackers from penetrating the software and getting access of control to destabilize the grid in unpredictable way.

3. Energy Storage System Role

This section discusses the features of integrating the advanced electric energy storage technologies for both utilities and consumers side, taking into account the impact on the consumer the environment, as represented in figure 3. The following points highlight the benefits aimed to be achieved through energy storage systems [9]:

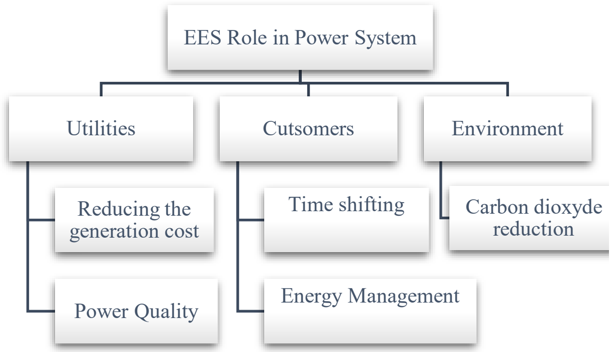

Figure 3 EES role in power system

1. Reducing generation cost is one of the major benefits of the integration of ESS into the utilities, by storing the electric power generated of the less cost plants during night and discharges them during peak hours maintaining a secured continuous supply for all customers.
2. Another target of ESS, is keeping the reliability and the continuity of power supply. Many electric utilities proposed the renewable energy resources as alternative resources. The uncertainty of these resources is considered one of their main challenges, as they depend on weather conditions. Then ESS could store the energy when it is available and used when it is needed. By this way they could minimize the environmental impacts caused by the combustion of fossil fuels during the traditional generation process, reducing the fuel used on one hand, an reducing the environmental and the global warming problems on the other.
3. ESSs could also be used by the utilities to ensure the electric power system stability under the unexpected load demand and generation conditions. They could replace the online spinning reserve that is synchronized to the grid and supplied by part loaded generators operating at reduced efficiency, thus, reducing the thermal losses and the inefficient operation of the part loaded generators.
4. In addition, ESSs are not used only to mitigate the short-term power loss as they are commercially available and cost effective such as uninterruptable power supply (UPS), but also, they could be installed as a substitute for emergency generators during an outage.
5. Furthermore, considering the consumers side, they could also benefit by using the electric storage systems in the off peak as low-price tariff, and discharging the energy when the demand is high. This is known by electrical energy time shifting. This could lead to an efficient utilization of energy as they could reduce the cost of their electric consumption bill on one hand, and it is known by End User Energy Management. On the other hand, ESS system owners could benefit by selling the stored energy to other customers or to the electric utilities in the peak hours, which they could benefit financially from their storage batteries.

4. Energy Storage Systems Selection & Classification

Currently, there are two factors that characterize the selection of an ESS [10]. The first is the energy that could be stored in the device. The second is the rate at which the energy could be transferred in or out the device. The appropriate selection is based mainly on the application requirements response time, energy storage, efficiency required, and life time as illustrated in table II.
According to [9], the ESS is classified into 5 categories: mechanical, electrochemical, chemicals, electrical and thermal as shown in figure 4. The following section discusses the most common three storage systems used for power applications.

Table II ESS selection consideration [11]

	Matching Power demand	Providing back up power	Enabling the RE	Power quality
Discharged power		(1:200) MW	20kW:10MW	<10ms :10
Response time	<10 min	10ms:10 min	<1ms	<20ms
Energy Stored	(1:1000) MWh	(1:1000) MWh	(10kWh:200 MWh)	50kWh: 500kWh
Efficiency	High	Medium	High	Low
Life time	High	High	High	Low

A. Mechanical Energy Storage system

1) Pumped Hydro System (PHS)

PHS, shown in figure 5(a), uses two water reservoir storage areas, one above the other, to store energy. This is done by pumping water from the lower one to the upper one during off-peak periods and then, during peak-load hours, allowing the water to flow from the upper reservoir to the lower one, turning a generator and converting the hydro-potential energy into electricity. Their long-life time and their high efficiency are the main advantages. However, the dependence on topographical conditions and large land use are considered the main drawbacks [9, 10, and 12].

2) Compressed Air Energy System (CAES)

CAES, shown in figure 5(b), uses excess power generated by power stations to compress air during off peak periods. During peak periods this air is then decompressed in a compression chamber before being fed to turbines, increasing energy production during peak periods [9, 12]. Their advantages could be summarized in their large capacity to store the electric energy, their low trip efficiency and their geographic locations are their main disadvantages [9].

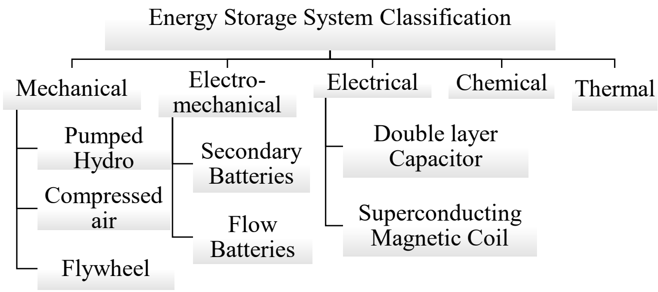

Figure 4 ESS Classification

3) Flywheels

Flywheels, shown in figure 5(c), uses off peak energy to rotate a rotor attached to a wheel within a vacuum. Energy is conserved in kinetic energy until it is needed during high demand period; this energy is used to generate power [12]. They take up relatively little space, have lower maintenance requirements compared to batteries, and have a long-life span [13]. However, flywheels have a high level of self-discharge due to air resistance and bearing losses and they suffer from low current efficiency [9].

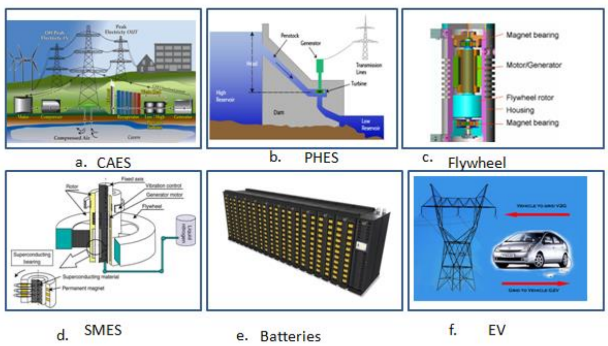

Figure 5 ESS Categories

B. Electrochemical Storage Systems

Electrochemical storage systems, shown in figure 5 (d), are divided in two types: secondary battery, and flow batteries. Secondary batteries store energy in chemical during charging and discharge electrical energy when connected to a load. Flow batteries are rechargeable ones. The electrolyte is stored separately in tanks and pumped through an electrochemical cell that converts chemical energy to electric and vice versa. The amount of energy stored in the battery depends on the volume and the size of the electrolyte in the tanks, while the power depends mainly on the speed of ion transfer across the membrane [14]. Lead Acid (LA), Nickel Cadmium (NiCd), Lithium ion (Li ion), Sodium Sulphur (NaS), and Sodium Nickel Chloride (NaNiCl) are the different kinds of secondary batteries. Vanadium Redox, Hybrid and Zinc Bromine are the main common types of Flow batteries. Based on [9,15,12,13,16]], a comparison between the different types of batteries is given in table III.

C. Electrical Storage Systems

Double layer Capacitor (DLC) and Superconductive Magnetic Energy Storage system (SMES) represent the electrical category for ESS. Super capacitors are electrochemical double layer capacitors that store energy into the electric field. They do not require any heating or cooling, they do not need any maintenance as they do not have any moving parts and their life time is measured in decades, so that they are considered very efficient [13]. They have high power density, but relatively low storage ability when compared to batteries. Superconducting magnetic energy storage (SMES), shown in figure 6 (e), is a type of EES that store energy in the magnetic field created by the flow of dc current in a superconducting coil [11,12,13]. The coil can discharge very quickly when it is necessary. They are very efficient and have very fast response. On the other hand; they are very expensive due to the superconductive material and need cooling, thus they are used for short duration energy storage applications such as power quality [9, 11, and 13].

D. Electric Vehicles

Electric vehicles (EV), shown in figure 5(f), are developing in recent years. They are connected to grid and can retrieve and inject a controlled amount of electric energy. On one hand they could be considered as active load that increases the demand during charging mode. On the other hand, they could be operated as storage units to supply the customers while they are parking during discharging mode. Coordinated charging schedules could minimize the annual peak load, decreases the system losses and increase the power factor of the distribution grid [17].

5. Battery Energy Storage Overview

A typical BESS consists of a battery bank where multiple batteries are connected in series parallel configuration to provide the desired storage capacity. A bidirectional power electronic converter could be attached to the battery bank. Thus, both real and reactive power can be delivered or absorbed independently according to the power system demand requirements. The inverted voltage from the dc battery source is always different than the grid voltage. Therefore, a transformer is used to convert the BESS output to match the transmission and distribution voltage level [18-20]. Therefore, the operation of each of them is coordinated by a battery management system (BMS), while the overall operation of all the system is coordinated by a supervisor control.

Table III BESS Comparison

	Applications	Advantages	Disadvantages
LA	-Emergency power supply -Standalone systems with PV, wind. -Starter batteries for vehicles	Low Cost	-Low Energy density -Their capacity decrease when large power is discharged
NiCd	-Power tools -Mobile phones -laptops	-Low maintenance cost -Resistance to high temperatures -Long life span	Expensive toxic
Li ion	-Cell phones -Electric bicycles -Electric cars -Laptops	-High energy density -Long life span -Low maintenance	Too Expensive
NaS	-Combined power quality -Time shifting - renewable integration	-High power -High energy density -Low cost	As their operating temperature reach [300 - 350 °C], then they require a heat source, thus reducing the battery performance, efficiency and increase their cost
VRFB	large power applications -Power quality control	Large capacity Long life span Low cost Fast response	Low energy density
Zn/Br	Still new technology	High power High energy density	Toxic

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7. Battery Management System

To help the BESS to operate in optimum conditions, BMS is required for the following reasons [15]:

1. operation, such as the current, the voltage, the temperature through the supervisor control. Based on this information, it could in turn estimate many variables, such as battery state of charge (SOC) and battery state of health (SOH) based on physics-based models. SOC represents how much charges is left in a battery over a single cycle, while SOH represents how much the battery capacity remains for the present cycle compared to the original battery capacity.
2. Estimating the time remaining based on the applied load profile.
3. Providing optimal charging pattern.
4. Allowing a safe operation of BESS based on the thermal management and by maintaining the safe operation between the current and the voltage limits.

8. BESS application in power system

Many industry experts believe that the use of energy storage technologies including the batteries, are crucial for many applications as summarized in figure 6.

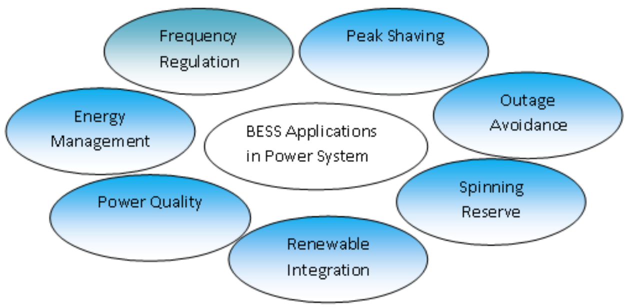

Figure 6 BESS Applications

A. Frequency Control

Due to the inversely proportional relation between the frequency and the load, any significant increase in load cause the frequency to slow down, as the frequency is measured through the rotating speed of the generator shaft. Similarly, the frequency may increase in case of load loss due to any threshold. Thus, keeping the frequency within a tight tolerance requires the amount of power produced at any time match the demand. A certain amount of active power, usually called frequency control reserve, is kept available to perform this control. Three levels of control are generally used to maintain this balance between load and generation: primary, secondary and tertiary control [21]. Primary frequency control is a local automatic control that adjusts the active power generation of the generating units and the consumption of controllable loads to restore quickly the balance between load and generation and counteract frequency variations. All the generators that are located in a synchronous zone are fitted with a speed governor to perform this control automatically. In particular, it is designed to stabilize the frequency following large generation or load outages. While primary control limits and stops frequency excursions, secondary frequency control is suggested to bring the frequency back to its target value through a centralized automatic control scheme. Only the generating units located in the area where the imbalance originated should participate in this control. It is mainly used in all large interconnected systems because manual control does not remove overloads on the tie lines quickly enough. Tertiary frequency control refers to manual changes in the dispatching and commitment of generating units. This control is used to restore the primary and secondary frequency control reserves, to manage congestions in the transmission network, and to bring the frequency and the interchanges back to their target value when the secondary control is unable to perform this last task. BESS are not only used due to their fast response in providing the active power compensation during under frequency events, but also, they are used to save real power in over frequency situations. Comparing with conventional generating units, the capacities and the location of BESS are flexible and also their precise control can be much superior to conventional ones [22]

B. Renewable Energy Integration and Outage Avoidance

The integration of renewable energy resources into the power grid is driven, by environmental and economical regulations aiming for reducing the carbon emission resulting from fuel combustion during conventional electric generation on one hand and reducing the rising price of fuels on other hand Integration of large amounts of renewable resources presents important challenges in terms of load dispatch, reserves and ramping requirements. The uncertainty of renewable energy produced is another problem that affects their large-scale integration in the power grid. Solar and wind energy are considered the two largest sources of renewable energy used. Both are unpredictable, and weather depended; hence their output can vary significantly. Therefore, a sudden loss of renewable generation could potentially lead to a collapse of voltage and frequency which could have its effect on the power grid stability. Also, this variability will cause undesired ramps in the output which create further integration challenges for the grid operators. To tackle these drawbacks, energy storage systems are one of the suggested solutions to integrate renewable energy generation to the existing power networks. By smoothing out the fluctuations and the sudden load changes, the battery energy storage systems could serve as back up sources during transmission line or large generation loss to avoid blackouts which are one of the main concerns of utilities. A research carried out in [23] to study the role of BESS in outage avoidance. A survey on the different control's techniques for BESS for renewable smoothing applications is presented in [24].

C. Energy Management and Peak Shaving

The major role of BESS is to enable the time shifting of energy by storing the energy during off peaks and using it when the demand increases during on peak. By this way, electric energy production will be maintained in constant level. This technique is very efficient for both customers and utilities, as it ensures power quality through the continuous power delivery to the customers on one hand and realizes the energy management during on peak on the other hand. Many references studied the BESS application in energy management such as [25], where a BESS is proposed for integration of 3kW wind energy to facilitate the match between the energy demand and supply of the household for a better energy management.

9. Conclusion

In this paper, smart grid requirements have been reviewed and the most common energy storage systems have been stated. A comparison between the different battery storage systems has been presented, as they are one of the most promising technologies for several power applications. The features, and the management system for BESS have been explained. Frequency regulation, RES integration, outage avoidance, and energy management are reviewed.

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Distribution Network Reconfiguration in Smart Grid System Using Modified Particle Swarm Optimization

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Abstract—**One of a major characteristic of a smart protection system in Smart grid is to automatically reconfigure the network for operational condition improvements or during emergency situations to avoid outage on one hand and to ensure power system reliability the other hand. This paper proposes a modified form of particle swarm optimization to identify the optimal configuration of distribution network effectively. The difference between the Modified Particle Swarm Optimization algorithms (MPSO) and the typical one is the filtered random selective search space for initial position, which is proposed to accelerate the algorithm for reaching the optimum solution. The main objective function is to minimize the power losses as it represents waste of operational cost. The suggested method is tested on a 33 IEEE network using IPSA software. Results are compared to studies using other forms of swarm optimization algorithms such as the typical PSO and Binary PSO. 29.68% of losses reduction has been achieved during a less computational time.**

Keywords—Smart Grid; Distribution System; Distributed Network Reconfiguration; co_2 emmissions; Modified Particle Swarm Optimization

I. INTRODUCTION

The uncertainty in fuel cost, the ageing of most existing grid, the lack of utilities' supply capacity to respond to the increasing load demand, and the lack of automatically power restoration, is accelerating the need to modernize the distribution network by introducing new technologies, putting the smart grid (SG) on spot. SG is a network that uses information, cyber secure, communication technologies, and computational intelligence to create an automated and distributed advanced energy delivery network to achieve a safe, reliable, efficient, and sustainable system. It coordinates the need and capabilities of all generators, grid operators, end users, and electricity market stakeholders to operate all part of the system as efficiently as possible, minimizing costs and environmental impacts while maximizing system reliability, and stability [1].

The integration of Renewable Energy Resources (RES) and Energy storage (EES) in distribution system, which justify the bidirectional flow of power in SG, is not only the major requirements of SG, but also smart metering, monitoring and communication systems are required to gather the power system consumption information, send it via wireless communication network to electric utilities to manage and analyze the data for optimum decision making for both utilities and costumers. These requirements add more complexity on power system and dictate the necessity of having a smart protection system that should be predictive enough to expect the failures, automatically isolate the faults after detection, and select the optimum configuration to avoid outage and supply the consumers based on intelligent algorithms to ensure power system reliability [2].

A Distribution system consists of many interconnected mesh circuits, operated as radial, linked by breakers. There are two types of switches: sectionalizing switches which are normally closed and tie line switches which are normally open. Distributed network reconfiguration (DNR) is the process of changing the structure of the distribution network by changing the status of the sectionalizing and tie switches to maintain the radial topology [3]. There are three stages for DNR [4]:

1. Network Data Collection: This stage includes lines impedances, load demand, and available generation.
2. Network Organization: this stage includes the study of the different probabilities due to the change of switches states based on mathematical optimization algorithms.
3. Load Transfer: This is the implementation of the second stage via remote control switches.

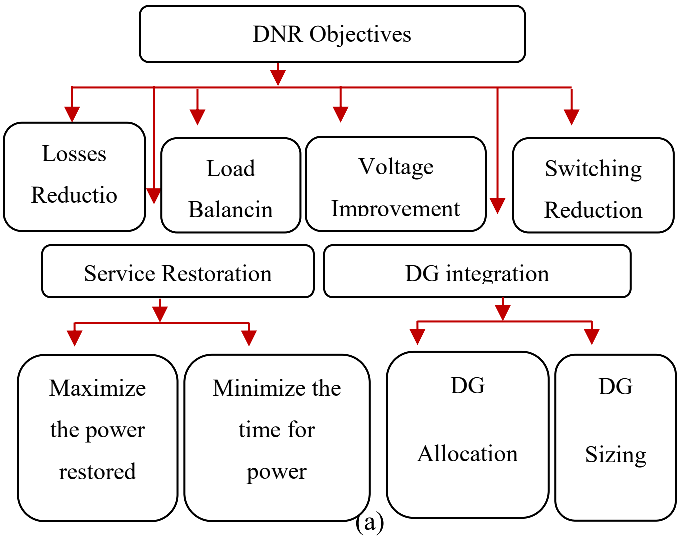
In this paper, DNR definition and stages are explained in section I. The reasons for considering DNR a complex optimization problem is stated, and the mathematical formulation for DNR objectives and constraints are surveyed in section II. The 33 IEEE network is selected to be a case study. Network data and the DNR problem formulation are stated in section III. The proposed Modified Particle Swarm (MPSO) included in section IV, is explained and the difference between the suggested method and the original PSO are highlighted. The Results are included in section V proving the effectiveness of the technique.

II. DNR MATHEMATICAL DESCRIPTION

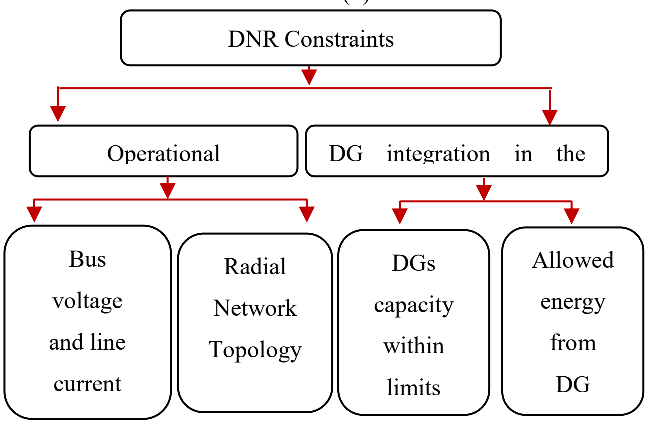
A.DNR Objectives and Constraints

DNR is considered highly complex, nonlinear, discrete, combinatorial, stochastic optimization problem [4, 5]. The non-linearity of this problem is due to the electrical equipment and

the power electronic devices used in the network [4]. Its complex combinatorial nature is due to the large probability obtained by changing the switches in order to find the optimum configuration to realize the objective function within the constraints [6]. Its stochastic nature is due to the continuous change of demand. Its discrete nature is due to the change of the state of switches between on and off. Therefore, this problem could be described mathematically as a hard-Non-Polynomial (NP) optimization problem [4, 6].
The main features of DNR are highlighted during emergency (a fault), as a part of the system should be isolated to minimize the number of affected consumers by feeding them from another feeder. DNR merits do not serve the system only in contingency condition but also, could improve the system reliability and efficiency by reducing the line losses and protecting them from over loading through load balancing. Also, it could facilitate the integration of renewable energy especially in peaks, thus reducing the generation cost. Previous researches can be classified mathematically and regrouped in figure 1 surveying all the objective functions and the constraints for DNR problem. It should be noted that the losses reduction gained a great deal of attention as it brings unnecessary operational cost. Moreover, the power losses occurred in distribution system, are too high compared to that of generation and transmission due the low voltage level and the high current passing through the distribution lines. For this reason, losses reduction is selected to be the main objective for DNR in this research.



(a)



(b)

Figure 1 DNR objectives and constraints

B. DNR Optimization algorithm Classification

In this paper, DNR Optimization techniques are classified into three categories: Heuristic, Meta heuristic and Mathematical algorithms. Due to the inaccuracy of heuristic algorithms and the complexity of the mathematical ones, most of recent researches focuses on Meta heuristic techniques or hybridize them for better performance.
Heuristic techniques are knowledge-based techniques; in other words, they select the optimum configuration based on operational experiences [7]. Although they are fast to solve the DNR problem, they achieve an approximate solution rather than a global optimum one. Meta heuristic techniques are probabilistic algorithms used usually in power system operation and planning to deal with uncertainties by modeling the stochastic factors in power systems such as random outages of components and uncertain variation in loads and weather conditions [8]. They achieve global optimum solution, but the computational time is too high due to their probabilistic nature and their random selection which makes their convergence speed slower [9]. These algorithms are based on artificial intelligence (AI). They follow a set of nature inspired methodologies that simulate biological phenomena and represent them into computational tools to address complex problems hard to be solved by traditional approaches. They are based on population search which means that many entities are simultaneously sent in parallel to solve the same problem [10]. The success of this method is mainly due to the possibility of obtaining results much better than heuristic algorithms. The most common AI techniques addressing the losses reduction used for DNR problems are surveyed in this section and regrouped in figure 2.
Simulating Annealing (SA) was proposed by Kirkpatrick, Gelatt and Vecchi in 1983[11], based on the cooling process of a melting metal slowly cooled to solidify in its minimum energy state. Song Nie et al. used this algorithm to study the impact of distributed generations on network reconfiguration during normal and post fault operation [12]. An IEEE 33 bus network was used to evaluate the proposed technique Although SA algorithm could achieve optimal solutions, it can be very time consuming and its performance depend on initial parameter [13]. Furthermore, the complexity of the cooling parameters could be considered a significant disadvantage, as there is no general base to select the best parameters for a given problem [14]. For these reasons, this algorithm is not suggested for real implementation until to be modified. ANN is another based artificial intelligent technique used for DNR applications. Few researches such as [15, 16] used this technique due to the large offline training time which could be a major problem facing the large-sized real networks. Therefore, this algorithm is not suggested for online operation, although it can achieve optimum configurations. Another new, simple, meta-heuristic technique, Music Based Harmony Search (MBHS), is presented by Geem et al. in 2001 [17]. It was inspired by the reproduction of musicians' behaviour during playing their musical instruments which represent the population to obtain certain pleasing harmony (the global solution required).

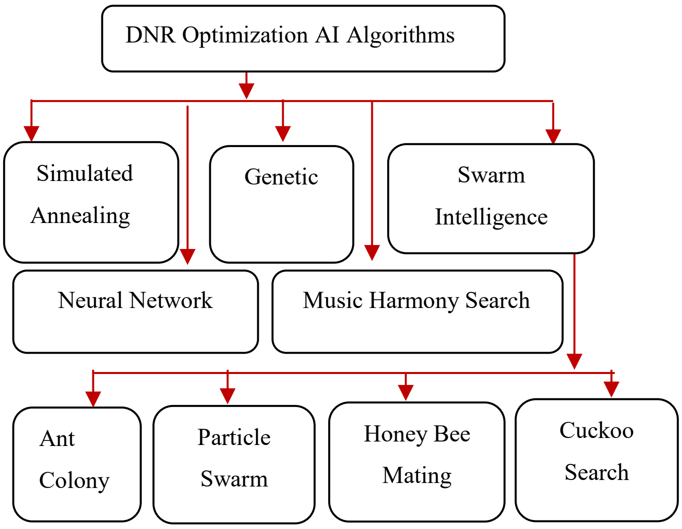


Figure 2 Most Common DNR Algorithms

In [18], the author applied this technique onto two distributions network: 33 and 69 IEEE buses through different loading conditions for losses reduction, proving the effect of DG installation on voltage and losses reduction improvement. In [19], the authors used an improved version of the technique using variable values of harmony search parameters. The suggested technique has been validated on a 33 busses IEEE network and compared to other Meta heuristic techniques such as traditional HAS, GA, RGA and ITS. It was found that, IMBHS takes less number of iterations to reach the optimal solution compared to all mentioned techniques, so that this technique is recommended in emergency service restoration problem. A self-adaptive harmony search Algorithm (SAHSA) was proposed by H.Savari et al. in 2010, by adding another step in the traditional HSA to improve the accuracy and the convergence rate on one hand, and to reduce the defect of initial parameters across the problem [20]. Unlike the previous researches [18, 19] where HSA was used to reduce the active power losses through network reconfiguration, D. Rani has suggested the SAHSA for both active and reactive power losses [21]. The proposed method is tested on 33 and 69 IEEE busses, and compared to MHSA. It was found that both techniques got the same value of active and reactive power losses, but the SAHSA reached these optimal results in less number of iterations. Also, the worst and the average fitness values found by SAHSA are better than MHSA. It was noticed that HAS passed through different stages from the traditional version to the self-adaptive form to modify the accuracy and reducing the number of iterations to achieve the optimum fitness value. Therefore, it is suggested in real time applications such as load balancing and network restoration. However, the addition of another step to improve the search space has an impact on the time taken compared to other algorithms.
Swarm Intelligence optimization techniques are another Meta heuristic algorithm family, based on social behaviour of swarming animals such as birds, ants and fishes. This category includes Ant Colony Optimization technique (ACO) proposed by proposed by M. Dorigio in 1992 in his PhD thesis [22], Particle Swarm Optimization (PSO) suggested by J.Kennedy and R.Eberhart in 1995 [23], Honey Bee Mating Optimization (HBMO), and finally Cuckoo Search Optimization Algorithm (CSA) developed by developed by Yang and Deb in 2009[24]. Many researches were carried out using PSO technique for optimum network reconfiguration considering the presence of DGs addressing the real losses reduction [25, 26, and 27]. AW.Dahalan et al. studied the power losses reduction and voltage improvement using PSO[26], validating his technique on a 33 IEEE network to prove its effectiveness, while in [27], the author tested the approach on a CIGRE distribution network including different DGs forms(such as wind turbines, photovoltaic, storage batteries and fuel cells) in order to improve the service reliability. Although PSO is a powerful simple algorithm, it was initially designed only for continuous functions not for discrete ones. This in turn pushes J.Kennedy and R.Eberhart to modify their algorithm and introduce a binary version of particle swarm technique (BPSO) in 1997[28].Significant researches are now shifting from single to multi objective function. For this reason, multi objective particle swarm was developed in 2004 by CoelloCoello [29]. A research has been carried out by A.Arya et al., for optimum distribution configuration, where a multi- objective particle swarm (MOPSO) has been used for maximum power restoration, load balancing and minimizing the switching operation and bus voltage deviation [30]. The author validated his algorithm on a 10 IEEE bus to prove the effectiveness of the approach. Both authors in [26, 30] agreed that PSO is better than GA in computational time and the number of iterations to achieve the optimum solution. Another research was presented by S.Tuldhar et al. for multi objectives functions dynamic reconfiguration problems proposing a Non Dominant Storing particle Swarm algorithm (NSPSO) [31] .The key difference in this study, that the author considered the uncertainty of both the generation of renewable energy resources and the variation of load demand. And here 33 IEEE systems is used, to test 3 cases studies and to compare between static and dynamic reconfiguration. In order to improve the computational time and the convergence characteristic, a simple modification to BPSO has been proposed in [32] by improving the search space and changing the sigmoid transformation rules used in binary form to limit the velocity between 0 and1, introducing a selective particle Swarm Algorithm (SPSO). A.Tandon and D.Saxena studied the optimum configuration considering the losses reduction to compare between the BPSO and SPSO [33] by testing their approach on a 33 and 69 IEEE bus network. Distribution losses, voltage profiles, number of switching, computational time and the convergence rate were the main comparative points. Results concluded that the SPSO outperformed over BPSO in losses reduction and voltage improvement. Overall, PSO is simple robust technique suggested by many references for DNR optimizations including distributed generations as it could support multi objective functions. Furthermore, the computational time and the convergence rate could be considered significant features of this approach. In this paper, a modified particle swarm optimization

(MPSO) is suggested based on a filtered random selection technique for initial positions. This modification has been proposed to reduce the computational time required to get the global optimum solution.

III.CASE STUDY

In this section, the 33 IEEE networks, 12.6 kV, shown in figure 3, is selected for optimum configuration for losses reduction. This network is specially used for comparing the results as it was studied in many previous researches. Interactive Power System Analysis (IPSA) tool is used for distribution network simulation and load flow calculations using python programming language.

A.Network Description

The 33 IEEE network consists of 37 branches, 32 normally closed switches (sectionalizing switches) and 5 normally open switches (Tie line switches). The system load is assumed to be constant. The initial tie lines switches of the network are from bus 33 to bus 37 before any reconfiguration. The total number of loops that should be formed by closing the tie switches is 5 loops, and then the dimension of the search space. The system load is 3,715 kW and 2300 kVAr. The network line data are illustrated in the appendix [34].

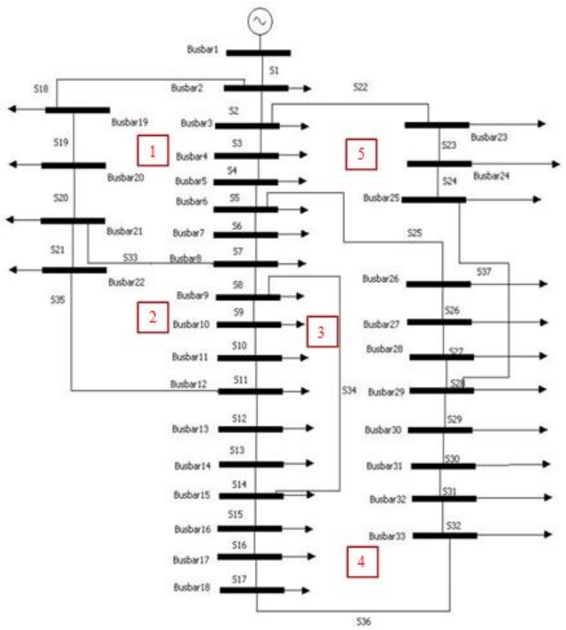


Figure 3 33 IEEE Network (IPSA window)

B. Problem Formulation

In this research, line losses minimization during operation is the objective function used for DNR optimization problem and could be described as:

$$\text{Min Power}_{losses} = \sum_{j=1}^{n} \left(I_j^{\,2}\right) R_j \qquad (1)$$

Where :

j is the branch number

N is the total number of branches

I_j is the current at branch j

R_j is the resistance at branch j

B. *Constraints*

Three constraints are considered for optimum losses reduction:

1. Node voltage limit

The bus voltage magnitude should be within the permissible limits to maintain power quality. The minimum and the maximum values of the voltage are chosen to be 0.9 and 1.0 respectively.

$$V_{min} \leq V_{bus} \leq V_{max} \qquad (2)$$

2. Feeder capacity limit

The magnitude of the feeder's branch current (I_j) should not exceed the maximum value of the allowed current passing in the branch (I_{max}) eliminating the insulation failures assuming that thermal limits are achieved.

$$I_j \leq I_{max} \qquad (3)$$

3. Maintain the radial topology

In order to maintain a simple, inexpensive operation and protection of distribution power grid, radial configuration is preferred. It is stated that each loop should contain a tie line and a corresponding sectionalizing switch. Thus, to retain a radial network structure, when a tie is closed in a loop, only one switch should be open in the same loop [30]. To retain this topology, the following criteria should be considered:

1. The total number of main loops obtained by closing all the ties:

$$N_{main\ loops} = (N_{br} - N_{bus}) + 1 \qquad (4)$$

Where:

N_{br} is the total number of branches

N_{bus} is the total number of buses

2. The total number of sectionalizing switches

$$N_{br} = N_{bus} - 1 \qquad (5)$$

3. The total number of tie switches should be the same as the number of main loops.
4. The elements' selection of each loop

The 33 IEEE network is divided into 5 loops, including 5 tie switches and 32 sectionalizing switches; the members for each loop are illustrated in figure 3, based on [33]. It should be noted that the switch S1 is not included in any loop which means that it could not be disconnected, as it connects between the main supply and the network loops. The switches common between more than one loops, are stated only one time, and this to eliminate the repeated switches inside a configuration. For example, S2 is common between loop (1) and loop (5), but it is an element only in loop (1). In this research, the total search space for initial radial configurations is 16128 configurations calculated based on the tree diagram probability method which generates all the possible configurations that include only one tie switch from each of the main loops. Fig4 shows an example of how tree diagram could be used to generate a configuration such as (S8, S2, S12, S15, and S22). The first element of each of the 4 loops should pass through all the elements existing in the 5th loop. Another configuration could be (S8, S2, S12, S15, and S23) and so on until (S8, S2, S12, S15, and S37).

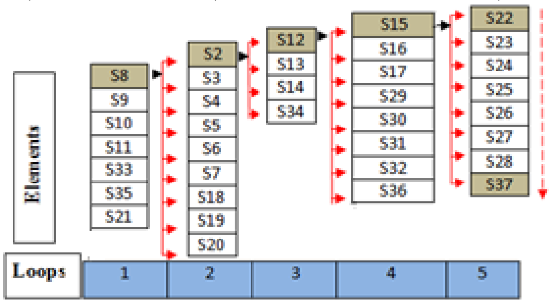


Figure 4 Example of a radial configuration in the search space by tree diagram

IV. DNR USING MPSO ALGORITHM

A. Typical PSO Method

The typical PSO is inspired by the ability of a group of some species of animals to work as a whole in a given area searching for corn. This seeking behavior is validated through equations in a real valued search space. Particles move through the search space adjusting their positions and their velocities according to their own experience and to their neighboring particles experience in order to find the optimal solution based on equations (6) and (7). The searching space is composed of all the possibilities that could represent a solution for the fitness function. This in turn explains the high processing time used to perform the calculations. The analogy between the biological system and the engineering case study is explained in the next section.

$$V_i^{K+1} = w * V_i^k + c_1 * rand_1 * (P_{best_k} - X_{i_k}) + c_2 * rand_2 * (G_{best_k} - X_{i_k}) \quad (6)$$

$$X_i^{k+1} = X_{i_k} + V_i^{k+1} \quad (7)$$

$Where$:

w the inertia weight, it is a decreasing function calculated according to equation (9).

V_i^k is the velocity for the particle (i) for the iteration (k)

c_1, c_2 Acceleration variable usually set to 2.0

$rand_1, rand_2$ a random number from 0 to 1

P_{best} Best position for particle (i) based on its own experience.

G_{best} Best position achieved by the entire particles in the swarm

$$w^k = \frac{(w_{max} - w_{min})}{iter_{max}} * \text{iter} \quad (9)$$

$Where$

w_{max} is 0.9, w_{min} is 0.4, $iter_{max}$ is the total number of iterations and iter is the current iteration.

1. Particle's position and velocity Representation for PSO in a DNR problem

The individual particle (i) in this case is composed of a set of the tie switches $(S_{1,\ldots\ldots} S_n)$ that are to be opened in a radial system, where (n) is the size of the particle, in a swarm of (S) particles. It should be noted that the particle's size is the same size of tie switches in a system. The position of the particle (X_i) is the index of the tie switch per loop. For example; X_i = [S33, S34, S35, S36, S37], means that (S33) is the first switch selected to be opened for loop (1), while the second switch to be opened is (S34) and etc. It should be stated that the particles positions should be positive numbers and integer as they represent switches indices. In this research, the non-integer numbers are rounded up or down to the nearest digit, for example S3.2 is S3. The initial velocities are assumed to be zeros.

2. P_{best} and G_{best} representation in a DNR problem

In PSO, during each iteration, P_{best} and G_{best} are updated and recorded based on the objective function. In other words, P_{best} is the configuration realizing best fitness function (losses reduction) for the same particle; while G_{best} is the configuration achieving best losses reduction for all the particles for one iteration.

B. Implementation of MPSO in Network Reconfiguration

In this research, MPSO is used for optimum losses reduction. The main difference between the original PSO and the MPSO is the filtered random selective search space in the initial position, which improves the searching capability of the particles in less computational time by neglecting the infeasible particles based on the current and the voltage constraint after load flow calculations, and this in turn accelerate the algorithm. MPSO flow chart is represented in fig.5 and fig.6.

1. Filtered Random Initial Position Selection:

Although PSO is based on a random initial selection for positions and velocities, in this paper, a filtered random selection procedure illustrated in fig.7, is suggested to control the initial positions of the particles. It should be noted that implementing such modification accelerated the particles search and in turns reduced the excitation time of the overall program for reaching the global optimum solution.

2. Position Control

After updating the particles using equation (7), some positions could exceed the total number of switches in the existing network, (S37 in this network), or could be negative number, which is illogical. In previous version of swarm, these infeasible positions are discarded, thus losing some probabilities. Thus, to maintain a feasible search space, a position control algorithm has been suggested in [35] and is applied in this paper. Position Control's procedures are illustrated in figure 5.

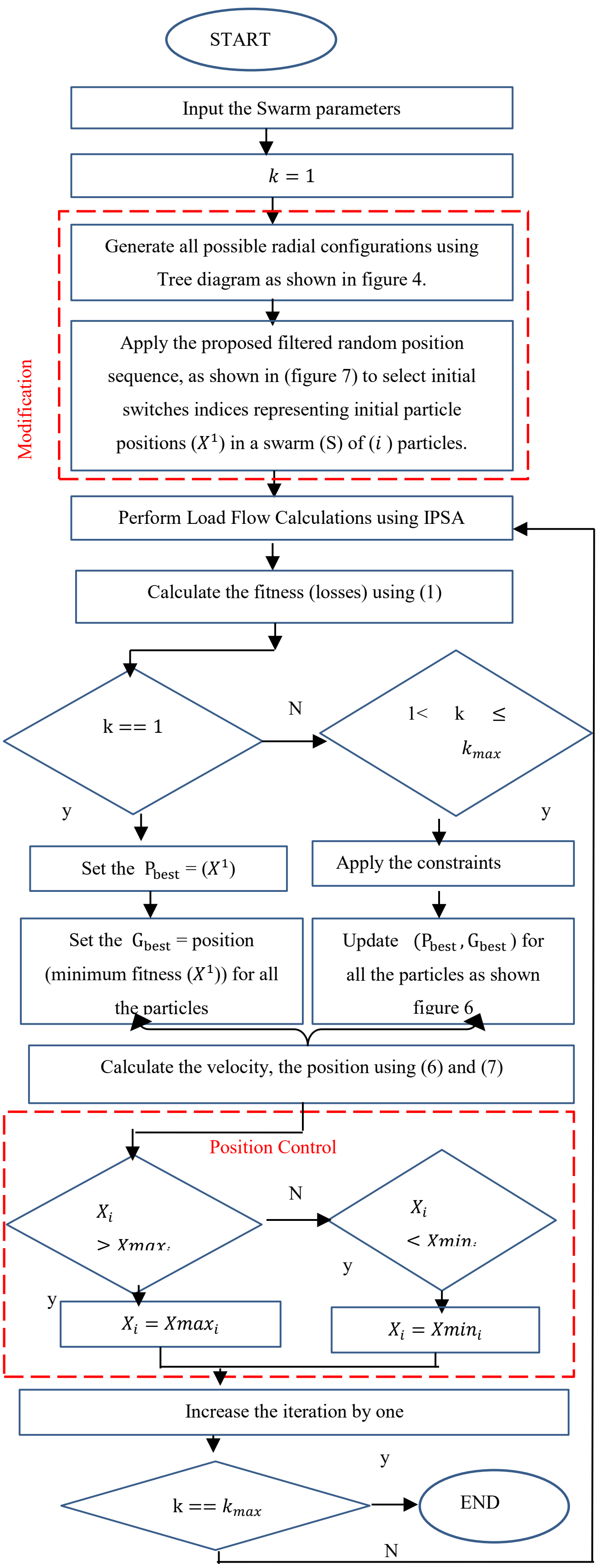


Figure 5 MPSO Flow Chart

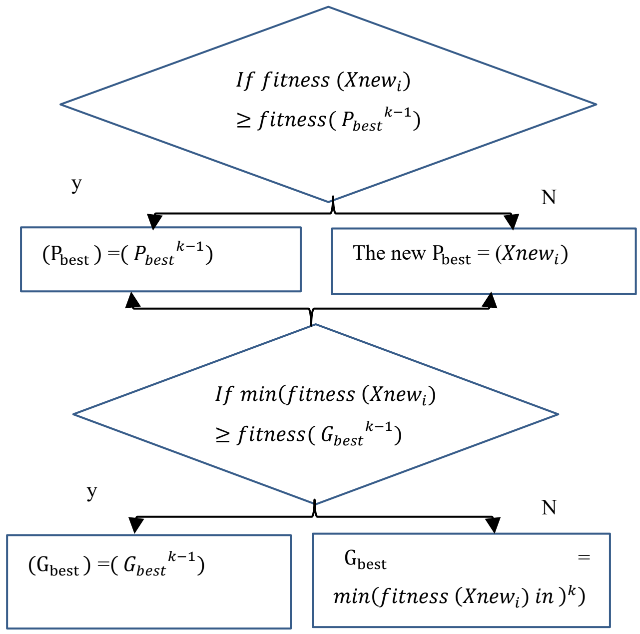


Figure 6 Pbest and Gbest Update

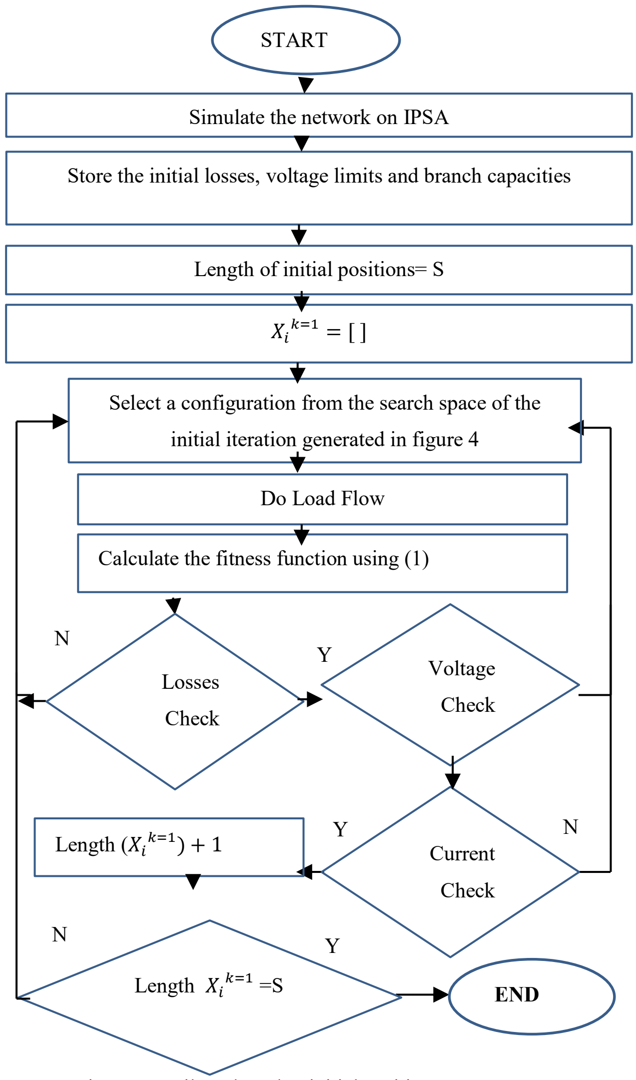


Figure 7 Filtered randominitial position sequence

Although, this algorithm retains all the particles in the search space, it could duplicate some switches in the same particle position, and violate the tie switch number conditions, which are calculated to be 5, and only in this case the particle should be discarded.

3. Conversion Condition

One of the main keys to obtain an accurate algorithm is to initialize the software after each losses' calculation for each position. It was found that, when the algorithm changes the positions without a reference configuration, it gives inaccurate results leading to a long computational time. For this reason, a known configuration should be selected to be an initial attempt before each trial. In this study, the initial attempt is meshing the network after each trial. For example, the initial tie configuration for the 33 IEEE systems is [S33, S34, S35, S36, and S37]. It could be considered as a particle position. Thus initially, the network is totally closed and then after opening the tie configuration, the network is closed again until selecting other tie configurations in the swarm size.

4. IPSA Software for 33 IEEE network Validation

Interactive Power System Analysis (IPSA) is a software tool developed specifically for power system design and operation applications providing a fast and accurate analysis of electrical power systems through an intuitive user interface [36]. Analysis options include load flow, fault level and the software can be driven by Python programing language. Figure 8 shows the mechanism for IPSA software, where the designed python script including the proposed optimization algorithm (shown in figure 5, figure 6) is called by IPSA to control the inputs of the network (as illustrated in Appendix) simulated in figure 3.

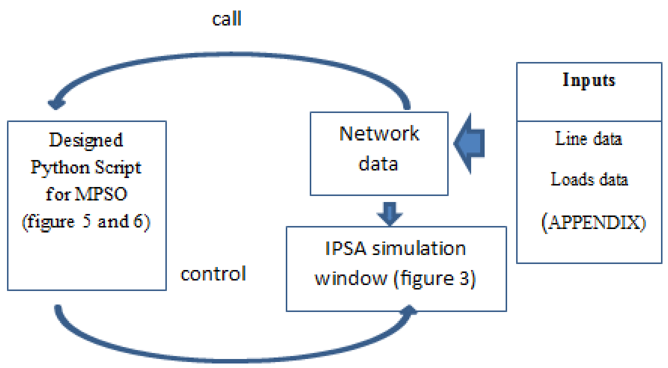


Figure 8 IPSA software diagram

Table 1 MPSO Parameters

PSO Parameters	Swarm Size	Weighting factor	Acceleration constant C1, C2	Initial velocity
	50	[0.9-0.4]	2.0	0.0

V.RESULTS AND DISCUSSION

A. *Losses Reduction*

The 33 IEEE network is simulated using IPSA software for losses, load flow and optimization technique implementation. Developed software has been designed to implement the (MPSO) using PYTHON 2.7.8, on a 2.4GHz, core (TM) i7-5500CPU with 8.0- GB RAM. In this paper, the initial losses are 193.6 kW. The maximum and minimum bounds for voltage magnitude are set to 0.9 to 1.pu. Load flow results are compared to previous research for validation [37]. The initial ties switches were from line 33 to 37. After applying the suggested algorithm, the losses are reduced to 136.36kW reducing 29.68% of the initial value. MPSO parameters used during simulation for reconfiguration are summarized in table 1. Due to the stochastic nature of swarm algorithms, 50 runs are performed in order to find the best number of particles and iterations for optimum fitness function. In each trial, the best, the worst and the average value of the fitness function (the losses) are recorded as well as the computational time, as illustrated in table 2. In additions, the mode, which represents how frequent the best losses occurred during one trial, is recorded. It was found that a population size of 50 particles during 25 iterations is sufficient for finding the optimal losses value. Figure 9 shows the convergence characteristic for the proposed algorithm.

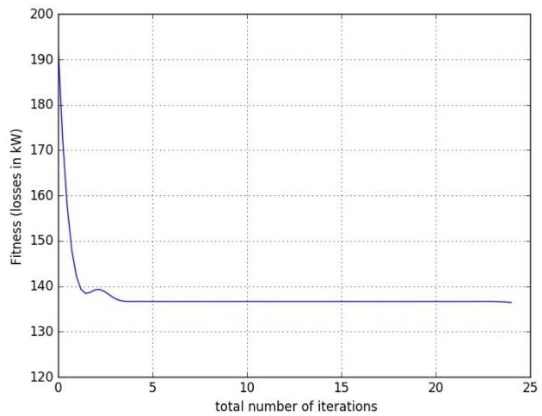


Figure 9 Fitness Function convergence using MPSO

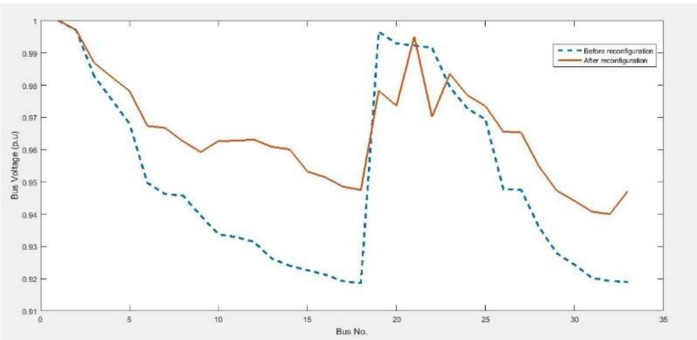


Figure 10 Voltage Profile Improvements

Table 2 Statistical Simulation Using MPSO

Particles	iterations	Best losses	% Mode	Worst losses	Average	time
50	25	136	52%	143	135	17.5

B. Voltage Improvement

A significant improvement in voltage profile is observed after applying the suggested algorithm. The minimum bus voltage after reconfiguration rise to 0.94 at bus 32, from 0.918 at bus 18 initially before reconfiguration, as shown in figure 10.

Table 3 33IEEE network using dif ferent Swarm Algorithms

	Algorithm	Switches	Losses (kW)	Min. Volt
without Reconfiguration	Initial	33,34,35, 36,37	193.3	0.918
After Reconfiguration	PSO [25]	33,28,34,8,17	149.8	0.931
	PSO [26]	7 ,10,28 14,32	140.5	0.941
	BPSO [33]	7,9,14,28,32	139.8	0.941
	SPSO [33]	7,9,14,32,37	136.3	0.942
	MPSO	7,9, 14, 32, 37	136.3	0.940

A Comparison between the MPSO results and previous researches using different form of swarm algorithms, is presented in table 3. The proposed modifications added to the typical swarm technique achieved 136.36 KW. The losses calculation of the suggested tie configurations in [25-26] are recalculated using python/IPSA, and the results are illustrated in table 3. The suggested MPSO, which is based on a filtered random position selection surpass the typical swarm used in both [25], [26] not only in losses reduction, but also in the excitation time. MPSO saved 56.7 KW of losses for 17.5 seconds compared to 43.2 KW of losses reduction by the typical swarm in [25] for 25 seconds. Also, the proposed algorithm MPSO, achieved more losses reduction than Binary Particle Swarm used in [35], and suggest the same tie switches given by Selective Particle Swarm (SPSO) in [33], achieving the same losses reduction. This in turn confirms that the added modifications improved both the power losses reduction and the computational time.

VI. CONCLUSION

In this paper, the MPSO is proposed for network reconfiguration for losses reduction and in turns voltage improvement. The modification added to the typical PSO technique has accelerated the computational time to get an optimum solution.33 IEEE network was used for validation using IPSA software. MPSO reduced the power losses by 29.68% for 17.5 seconds. The results are compared to other versions of swarm at static load, and it has been shown that the algorithm gives better losses reduction than typical PSO and in less computational time and give the same percentage of losses reduction given by SPSO. In this paper, the algorithm is tested for 50 trials to select the swarm size and the maximum iterations number required for optimum solution. The proposed technique will be tested on variable load for real network implementation.

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APPENDIX - 33 IEEE line data

	From	To	R (Ω)	X (Ω)	P (kW)	Q (kVAR)
S1	1	2	0.0922	0.047	100	60
S2	2	3	0.493	0.2512	90	40
S3	3	4	0.3661	0.1864	120	80
S4	4	5	0.3811	0.1941	60	30
S5	5	6	0.8190	0.7070	60	20
S6	6	7	0.1872	0.6188	200	100
S7	7	8	0.7115	0.2351	200	100
S8	8	9	1.0299	0.7400	60	20
S9	9	10	1.044	0.7400	60	20
S10	10	11	0.1967	0.0651	45	30
S11	11	12	0.3744	0.1298	60	35
S12	12	13	1.4680	1.1549	60	35
S13	13	14	0.5416	0.7129	120	80
S14	14	15	0.5909	0.5260	60	10
S15	15	16	0.7462	0.5449	60	20
S16	16	17	1.2889	1.7210	60	20
S17	17	18	0.7320	0.5739	90	40
S18	2	19	0.1640	0.1565	90	40
S19	19	20	1.5042	1.3555	90	40
S20	20	21	0.4095	0.4784	90	40
S21	21	22	0.7089	0.9373	90	40
S22	3	23	0.4512	0.3084	90	50
S23	23	24	0.8980	0.7091	420	200
S24	24	25	0.8980	0.7071	420	200
S25	6	26	0.2031	0.1034	60	25
S26	26	27	0.2842	0.1474	60	25
S27	27	28	1.0589	0.9338	60	20
S28	28	29	0.8043	0.7006	120	70

S29	29	30	0.5074	0.2585	200	600
S30	30	31	0.9745	0.9629	150	70
S31	31	32	0.3105	0.3619	210	100
S32	32	33	0.341	0.5302	60	40
S33	8	21	2.00	2.00	-	-
S34	9	15	2.00	2.00	-	-
S35	12	22	2.00	2.00	-	-
S36	18	33	0.500	0.500	-	-
S37	25	29	0.500	0.500	-	-

Radial Distribution Network Reconfiguration (DNR) for Power Losses Reduction Using a Modified Particle Swarm Optimization (MPSO)

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ABSTRACT

Recently, losses reduction gained a great deal of attention in distribution system due to low voltage level and the high current passing through the lines, pushing the distribution utilities to improve their profit margins on one hand by reducing the unnecessary operational cost, and improving their delivered power quality on the other hand by maintaining the system reliability, and the continuity of supply for varying load demand. Load balancing, voltage regulation, network reconfiguration and others are different techniques used to reduce the losses. This paper addresses the distribution network reconfiguration (DNR) to minimize the network losses. A new modified form of particle swarm optimization is used to identify the optimal configuration of distribution network effectively. The difference between the Modified Particle Swarm Optimization algorithms (MPSO) and the typical one is the filtered random selective search space for initial position, which is proposed to accelerate the algorithm for reaching the optimum solution. The suggested MPSO is tested via 33 and 69 IEEE networks. A benchmark comparison has been conducted to prove the effectiveness of MPSO compared to previous optimization techniques

1.INTRODUCTION

Distribution system consists of many interconnected mesh circuits, operated as radial, and linked by switches. There are two types of switches: sectionalizing switches which are normally closed and tie line switches which are normally open. Distributed network reconfiguration (DNR) is the process of changing the structure of the distribution network by changing the status of the sectionalizing and tie switches to maintain the radial topology [1]. DNR is considered highly complex, nonlinear, discrete, combinatorial, stochastic optimization problem [2, 3]. Heuristic, Meta heuristic, mathematical and hybrid techniques are introduced for solving the complexity of DNR optimization problem. Heuristic techniques are knowledge-based approaches, not suitable for large networks as they give local minimum solution in a very large processing time. Meta heuristic methods are probabilistic algorithms, based on artificial intelligent methods. They achieve global optimum solution in a high computational time due to their probabilistic nature and their random selection which makes their convergence speed slower. Metaheuristic techniques include Simulating Annealing algorithm (SA), Artificial Neural Network (ANN), Music based Harmony Search (MHS), Genetic Algorithm (GA) and swarm intelligent algorithms. Many researchers worked on improving them by integrating them with each other's or with other optimization algorithms to solve their computational time problem In this research paper, the distributed network reconfiguration (DNR) problem is briefly defined. The optimizations' algorithms suggested for solving DNR are stated. Particle Swarm Optimization Algorithm (PSO) is selected for active losses reduction. PSO is also reviewed and the Modified PSO suggested in this paper is deeply explained and verified through the 33 and 69 IEEE test networks. A benchmark comparison is conducted. Finally, the results are discussed in the last section.

2. PARTICLE SWARM ALGORITHM REVIEW

Particle Swarm Algorithm is one of the swarm intelligence optimization techniques based on social behaviour of swarming animals, introduced by J.Kennedy and R.Eberhart in 1995, when they mathematically imitate the social behaviour of bird flock and fish schools searching for corn, introducing this meta heuristic optimization method [4]. Particles "birds" move through the search space adjusting their positions and their velocities with respect to their own experience and to their neighbouring particles experience to find the optimal solution. Typical swarm has been modified many times through many researchers improving the technique. Binary PSO (BPSO) was introduced in 1997, applying a sigmoid function for velocity and position equation to limit their values [0,1]to deal with discrete functions [5]. Multi objective particle swarm was developed in 2004 by CoelloCoello [6]. More versions of swarm were introduced by hybridizing two or more intelligent techniques together to improve the computational time and the convergence of the algorithm such as Rank Evolutionary PSO (REPSO), the integration between the genetic algorithm and PSO (GAPSO), and others. In this research paper, a modification was added to the technique by controlling the initial position generation via tree diagram algorithm, which in turns improves the searching capability of the particles in less computational time by neglecting the infeasible particles based on the given constraints, accelerating the algorithm

3. NETWORKS DISCRIPTION

3.1 33 BUS DISTRIBUTION SYSTEM

The 33 IEEE network, 12.6 kV, shown in figure 1,consists of 37 branches, 32 normally closed switches (sectionalizing switches) and 5 normally open switches (Tie line switches). Interactive Power System Analysis (IPSA) tool is used for distribution network simulation and load flow calculations using python programming language. The initial tie lines switches of the network are from bus 33 to bus 37 before any reconfiguration. The total number of loops that should be formed by closing the tie switches is 5 loops. The system load is 3,715 kW and 2300 kVAr. The network line data are given in [7].

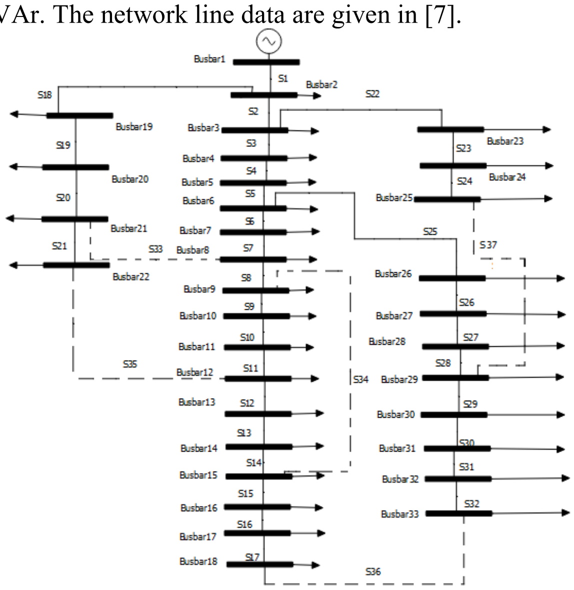

Figure 1 33 IEEE network (IPSA simulation window)

3.2. 69 BUS DISTRIBUTION SYSTEM

the single line diagram of 69 IEEE network, 12.6 kV, 10 MVA,shown in figure 2, consists of 73 branches, 68 normally closed switches .The network line data are given in[8].The total active losses calculated before reconfiguration is 226 KW. The minimum voltage value occurs at bus 65 , 0.909 pu. The initial ties are from 69 to 73 respectively. Five loops are formed by closing the initial 5 ties .

3.3 GENERAL PROBLEM FORMULATION

In this research, line losses minimization during operation is the objective function used for DNR optimization problem and could be described as:

$$\text{Min Power}_{losses} = \sum_{j=1}^{n} (I_j^{\,2})\, R_j \qquad (1)$$

Where :

j	is the branch number
N	is the total number of branches
I_j	is the current at branch j
R_j	is the resistance at branch j

3.4 GENERAL CONSTRAINTS

Three constraints are considered for losses reduction:

(i) Node voltage limit

The bus voltage magnitude should be within the permissible limits to maintain power quality.

$$V_{min} \le V_{bus} \le V_{max} \qquad (2)$$

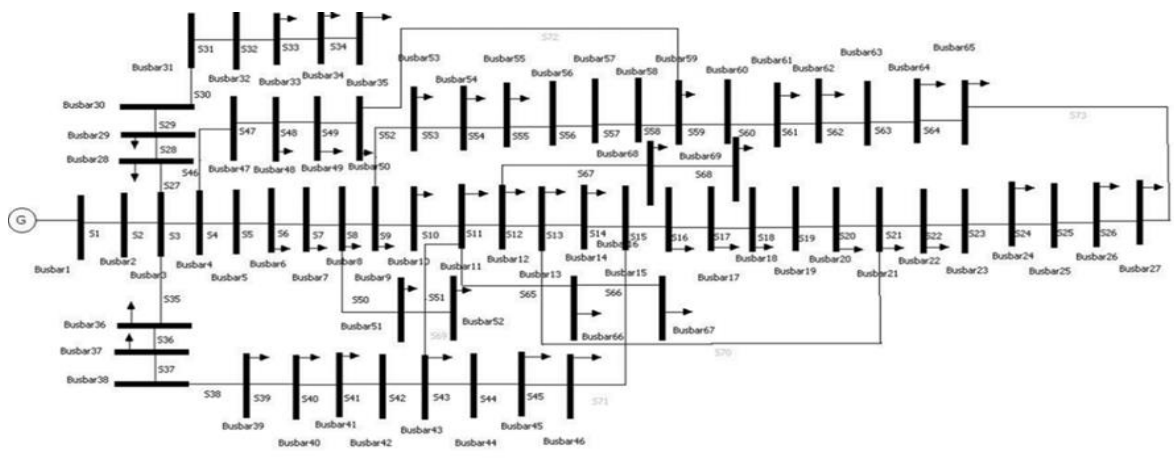

Figure 2 69 IEEE distribution network (IPSA simulation window)

(ii) Feeder capacity limit

The magnitude of the feeder's branch current (I_j) should not exceed the maximum value of the allowed current passing in the branch (I_{max}) eliminating the insulation failures assuming thermal limits are achieved.

$$I_j \leq I_{max} \qquad (3)$$

(iii) Maintain the radial topology

For a simple, inexpensive operation and protection of distribution power grid, radial configuration is preferred. It is stated that each loop should contain a tie line and a corresponding sectionalizing switch. Thus, to retain a radial network structure, when a tie is closed in a loop, only one switch should be open in the same loop. To maintain this topology, the following criteria should be considered:

1. The total number of main loops obtained by closing all the ties:

$$N_{main\ loops} = (N_{br} - N_{bus}) + 1 \qquad (4)$$

Where:

N_{br} is the total number of branches

N_{bus} is the total number of buses

2. The total number of sectionalizing switches

$$N_{cs} = N_{bus} - 1 \qquad (5)$$

3. The total number of tie switches should be the same as the number of main loops.

4. MODIFIED PARTICLE SWARM OPTIMIZATION

In this research, the individual particle (i) is composed of a set of the tie switches (S_1….., S_n) that are to be opened in a radial system, where (n) is the size of the particle, in a swarm of (S) particles. It should be noted that the particle's size is the same size of tie switches in a system. The position of the particle (X_i) is the index of the tie switch per loop. $Pbest_{\,i}$ is the configuration realizing best fitness function (losses reduction) for the same particle; while $Gbest_i$is, the configuration achieving best losses reduction for all the particles for one iteration. The modifications accelerate the convergence rate and the computational time. These modifications are:

- the random selective search space
- the position control algorithm.

4.1. <u>RANDOM SELECTIVE SEARCH SPACE</u>

The main difference between the typical PSO and the suggested modified particle swarm (MPSO), is the filtered random selective search space in the initial position based on tree diagram theory method which generates all the possible configurations including only one tie switch from each of the 5 loops composing the test network. The elements for each loop of the 69 network is illustrated in table 1. In this research, the total search space for initial radial configurations for both 33 and 69 networks are 16128 and 139776 configurations respectively calculated based on the tree diagram probability. The search space for the 33 IEEE network is studied in [9,10]. It should be noted that some switches should not be within the search space such as:

1. S1, S2 link between the main supply and the overall system
2. [S27-S34], [65-66] and [67-68] Could not formulate any loops

Table 1 Search Space for 69 IEEE network

loops	Elements
1	S11, S12, S13, S14, S43, S44, S45, S71
2	S4, S5, S6, S7, S8, S46, S47, S48, S49, S52, S53, S54, S55, S56, S57, S58
3	S3,S9,S10,S35,S36,S37,S38,S39,S40,S41,S42,S69
4	S21, S22, S23, S24, S25, S26, S59, S60, S61, S62, S63, S64, S73
5	S15, S16, S17, S18, S19, S20, S70

4.2. POSITION CONTROL

After updating the particles using equation (7), some positions could exceed the total number of switches in the existing network, (S37 and S69, in the 33 and the 69-bus system respectively) or could be negative number, which is illogical. In previous version of swarm, these infeasible positions are discarded, thus losing some probabilities. To maintain a feasible search space, a position control algorithm has been suggested in [11] and is applied in this paper. Although, this algorithm retains all the particles in the search space, it could duplicate some switches in the same particle position, and violate the tie switch number conditions, which are calculated to be 5, and only in this case the particle should be discarded.

4.3. MPSO Solution Steps:

A Designed software has been implemented following MPSO steps discussed below using python language 2.7.8. to communicate with IPSA 2.4. on a 2.4GHz, core (TM) i7-5500CPU with 8.0- GB RAM for losses reduction. MPSO flow chart is deeply explained and presented in [9].

1. Enter the swarm parameters including the acceleration constants, the weighting factor and the swarm size (S).
2. Generate all possible configuration using tree diagram method based on table 1.
3. Select several configurations equal to (S), having losses less than the initial losses using (1), and satisfying voltage and current constraints using (2) and (3), to represent the random initial positions for the particles P_{best}.
4. Set the configuration having the minimum losses to be G_{best}
5. Calculate the velocity and the position for each particle in the swarm size S using (6) and (7).

$$V_i^{K+1} = w * V_i^{k} + c_1 * rand_1 * (P_{best_k} -$$

$X_{i_k}) + \quad c_2 * rand_2 * (G_{best_k} - X_{i_k}) \quad (6)$

$$X_i^{k+1} = X_{i_k} + V_i^{k+1} \quad (7)$$

Where:

w the inertia weight, it is a decreasing function, calculated using (9).

V_i^k the velocity for the particle (i) for the iteration (k)

c_1 $\&c_2$ Acceleration variable usually set to 2.0

$rand_1$ & $rand_2$ random number from 0 to 1

P_{best} Best position for particle (i) based on its own experience.

G_{best} Best position achieved by the entire particles in the swarm

$$w^k = \frac{(w_{max} - w_{min})}{iter_{max}} * \text{iter} \quad (9)$$

Where

w_{max} is 0.9, w_{min} is 0.4, $iter_{max}$ is the total number of iterations and iter is the current iteration.

6. Increase the iteration by one
7. Calculate the fitness function using (1) for all the particles.
8. Apply the constraints using (2) and (3)
9. Update the P_{best} and the G_{best}
10. Apply the position control to maintain the particles within the feasible search space.
11. Repeat the steps from 6 to 10 until a termination criterion are satisfied.

5. SIMULATIONS, RESULTS & DISCUSSION

The proposed MPSO algorithm is tested through the 33 and the 69 IEEE test systems for optimum losses.

5.1. LOSSES REDUCTION

MPSO reduced the initial losses in the 33-bus system from 193 to 136.36 KW saving 56.7 KW. Similar trend is observed in the 69 IEEE network as, the losses have been decreased from 226 KW to 100.3 KW saving 126 KW. Table 2 illustrates the performance of MPSO for losses reduction and voltage improvement for both the 33 and 69 IEEE networks respectively. Figure 3 shows the conversion characteristic for MPSO for both networks.

5.2. VOLTAGE IMPROVEMENT

MPSO has a significant effect on the bus bar voltage as shown in figure 4. The minimum bus bar voltage rises after the reconfiguration from 0.918 at bus bar 18 to 0.94 in the 33-bus IEEE network, and from 0.905 to 0.942 at bus 61 for the 69 IEEE network.

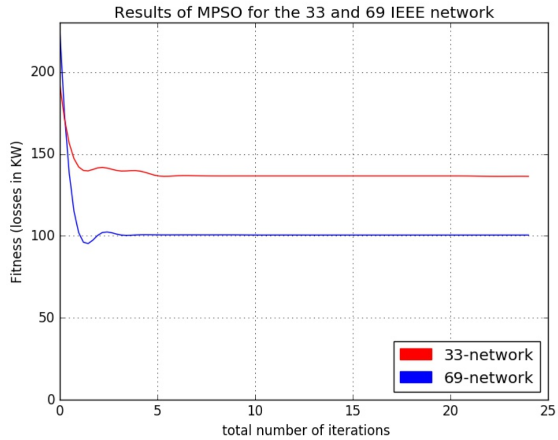

Figure 3 Fitness function for the best particle using MPSO

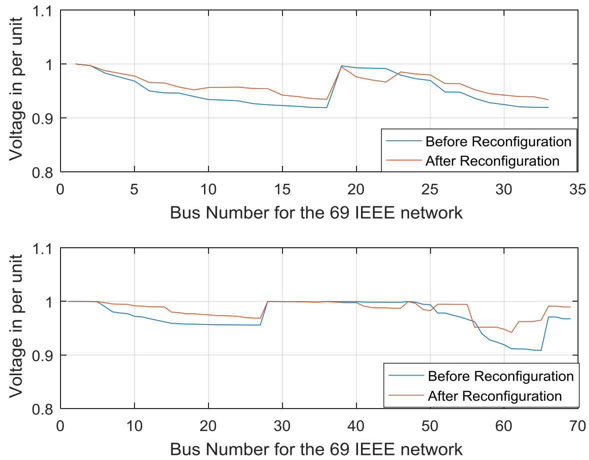

Figure 4 Voltage Profile Improvement

Due to the stochastic nature of swarm algorithm, 50 runs are performed to select the swarm size and the maximum iterations required for reaching the optimum configuration. It was found that 50 particles are suitable for both test network. However, many previous research papers stated that 40-70 iterations are suitable for large network [11], it was found that 25 iterations are suitable for both networks.

5.3. BENCHMARK COMPARISON

Table 3 and 4 compare between the performance of the proposed MPSO and other algorithms including the typical PSO [12], Binary PSO (BPSO) [10], Multi Cooperative PSO(MCPSO) [13], and Selective PSO for the 33 and the 69 test networks respectively. The losses are recalculated using Python/IPSA software. It should be noted that MPSO suggests nearly the same configuration proposed by SPSO for both networks. Both algorithms MC PSO and the proposed MPSO achieve the minimum losses for the IEEE 33 network but the proposed MPSO surpasses the losses reduction calculated by MCPSO for the 69 network

Table 2 MPSO performance for 33 and 69 bus networks

	Reconfiguration	Ties	Losses	Min voltage
33 IEEE network	Before	33-34-35-36-37	193.3	0.918
	After	9-7-14-37-32	136.3	0.940
69 IEEE network	Before	69-70-71-72-73	226	0.909
	After	14-55-69-61-70	100.3	0.942

Table 3 MPSO Results Comparison for the IEEE 33 Network

Algorithms	Optimum Ties	Losses	Min. Voltage
PSO [12]	33,28,34,8,17	149.8	0.931
BPSO [10]	7,9,14,28,32	139.8	0.941
MCPSO [13]	7,9,14,32,37	136.3	0.942
SPSO [10]			
MPSO			

Table 4 MPSO Results Comparison for the IEEE 69 bus Network

Algorithms	Optimum Ties	Losses	Minimum Voltage
BPSO [10]	13,20,55,61,69	107.05	0.942
MCPSO [13]	12, 18,58,61,69	103.62	0.942
SPSO [10]	14,56,61,69,70	100.6	0.942
MPSO	14,55,61,69,70	100.6	0.942

6. CONCLUSION:

In this research paper, the MPSO is proposed for network reconfiguration for losses reduction and in turns voltage improvement. The 33 and 69 IEEE test networks are used for validating the effectiveness of the suggested MPSO technique to deal with small and large networks. The modification added to the typical PSO accelerates the algorithm. IPSA software has been used for load flow calculations. A software program has been developed in python language for MPSO implementation. MPSO did not only reduce the losses reduction for both networks saving 56.7 KW for the 33-test network while saving 126 KW for the 69-distribution system, but also improved the minimum voltage for both networks.

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