

**OPTIMAL RADIAL DISTRIBUTION NETWORK
RECONFIGURATION USING MODIFIED SHARK SMELL
OPTIMIZATION**

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**MASTER OF SCIENCE ELECTRICAL ENGINEERING
(Power Systems Option)**

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**A thesis submitted to Pan African University Institute for Basic
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requirement for the award of the Master of Science degree in Electrical
Engineering
(Power Systems Option)**

2018

DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

This thesis is dedicated in thankful appreciation to my beloved parents and to my future children, Jamillah and Jamal.

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TABLE OF CONTENTS

DECLARATION	ii
DEDICATION	iii
ACKNOWLEDGMENT	iv
LIST OF FIGURES	viii
ABBREVIATIONS AND ACRONYM	x
ABSTRACT	xiii
CHAPTER 1 : INTRODUCTION	1
1.1 Background of the Study	1
1.2 Problem Statement	4
1.3 Objectives of the Study.....	5
1.3.1 Main Objective	5
1.3.2 Specific Objectives.....	5
1.4 Justification	5
1.5 Scope of Study.....	6
1.6 Thesis Outline	7
1.7 Summary of Chapter One.....	8
CHAPTER 2 : LITERATURE REVIEW	9
2.0 Introduction	9
2.1 Distribution Network Systems.....	9
2.2 Power System Losses.....	14
2.3 Review on Distributed Generation (DG)	16

2.4	Methods of Network Reconfiguration with Optimization Techniques	19
2.5	Overview of the Shark Smell Optimization (SSO) Algorithm.....	26
2.6	Summary of the Literature Review	31
CHAPTER 3 : METHODOLOGY		32
3.0	Introduction	32
3.1	Formulation of the IEEE 33-Bus Test Radial Distribution Network System	32
3.1.1	Power Flow Equations.....	33
3.1.2	Formulation of the Objective Function and Constraints	35
3.2	Shark Smell Optimization (SSO) Algorithm	38
3.2.1	Fundamental SSO Algorithm	38
3.2.2	Proposed MSSO Algorithm	42
3.2.3	Pseudo Code for MSSO Algorithm	44
3.3	Optimal Network Reconfiguration using the MSSO Algorithm.....	45
3.4	Summary of Methodology	49
CHAPTER 4 : RESULTS AND ANALYSIS.....		50
4.0	Introduction	50
4.1	Simulation Results for IEEE 33-bus System	50
4.1.1	Results for Voltage Profile Improvement	53
4.1.2	Results for Power Losses in the Branches	56
4.2	Comparative Study of Proposed MSSO Algorithm and Other Algorithms	59
4.2.1	Comparative Results for different Algorithms before considering DGs	60
4.2.2	Cost Saving Analysis	61

4.2.3	Comparative Results for different Algorithms considering DGs.....	62
4.3	Summary.....	64
CHAPTER 5 : CONCLUSION AND RECOMMENDATIONS		65
5.0	Overview	65
5.1	General Conclusion.....	65
5.2	Contributions.....	67
5.3	Recommendations	68
REFERENCES		69
LIST OF PUBLICATIONS AND CONFERENCE PAPERS		76
APPENDICES		77
APPENDIX A: IEEE 33-BUS RADIAL DISTRIBUTION SYSTEM AND DG		
SYSTEM DATA		77
A-1	Single Line Diagrams of the Test System.....	77
A-2	Data for 33-bus Test System and the DG units	78
APPENDIX B: MATLAB CODE FOR NETWORK RECONFIGURATION		
USING MODIFIED SHARK SMELL OPTIMIZATION ALGORITHM		80
B-1	Main Source Code for the Algorithm and Load Flow method.....	80
B-2	Function Code for Population of Odour particles (Initial random tie switches)	85

LIST OF FIGURES

Figure 2.1: Single line diagram of a power system.....	10
Figure 2.2: Distributors and Service Mains	11
Figure 2.3: Structure of the Electricity Sector	12
Figure 2.4: Radial Distribution Network	13
Figure 2.5: Ring Main Distribution Network.....	14
Figure 2.6: DG connected to a two-bus system	17
Figure 2.7: Single line diagram for feeder connections system	19
Figure 2.8: Single line Radial Distribution	21
Figure 3.1: A sample distribution system of a single line diagram.....	34
Figure 3.2: Shark's movement towards the prey	38
Figure 3.3: Shark's rotational movement.....	41
Figure 3.4: Flowchart for reconfiguration process.....	47
Figure 4.1: Optimal reconfiguration using MSSO algorithm for 33-bus system.....	52
Figure 4.2: Optimal reconfiguration using MSSO algorithm for 33-bus with DGs	52
Figure 4.3: Voltage profile in the absence of DGs.....	53
Figure 4.4: Voltage profile considering DGs.....	54
Figure 4.5: Real power losses in 33-bus system	56
Figure 4.6: Real power losses in IEEE 33-bus system considering DGs	57
Figure 4.7: Total Cost Lost Analysis of the MSSO Algorithm with Other Algorithms ..	61
Figure 4.8: Convergence characteristics of MSSO and BPSO algorithm.....	63

LIST OF TABLES

Table 3-1: Parameters	46
Table 3-2: Characteristics of the MSSO algorithm.....	48
Table 4-1: Load flow results for different cases of the IEEE 33-bus test system.....	51
Table 4-2: The voltage magnitude profile (p.u) for the IEEE 33-bus RDS	55
Table 4-3: Numerical results for power losses in the IEEE 33-bus RDS	58
Table 4-4: Apparent power losses in the second branch (From bus 2 to 3).....	59
Table 4-5: Comparison of different algorithms for 33-bus test system without DGs.....	60
Table 4-6: Comparison of different algorithms for 33-bus system considering DGs.....	62

ABBREVIATIONS AND ACRONYM

ABC	-	Artificial Bee Colony
ACO	-	Ant Colony Optimization
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
ALO	-	Ant Lion Optimization
ASO	-	Artificial Shark Optimization
BFO	-	Bacterial Foraging Optimization
BPSO	-	Binary Particle Swarm Optimization
CGA	-	Continuous Genetic Algorithm
CI	-	Computer Intelligence
CSA	-	Cuckoo Search Algorithm
DG	-	Distributed Generation
DNS	-	Distributed Network System
DSM	-	Demand Side Management
EA	-	Evolutionary Algorithm
EP	-	Evolutionary Programming
EPSO	-	Evolutionary PSO

ESCOM	-	Electricity Supply Corporation of Malawi Limited
FA	-	Firefly Algorithm
FACTS	-	Flexible Alternating Current Transmission System
FL	-	Fuzzy Logic
GSA	-	Gravitational Search Algorithm
HC-ACO	-	Hyper-Cube framework Ant Colony Optimization
HGAPSO	-	Hybrid Genetic Algorithm Particle Swarm Optimization
HSA	-	Harmony Search Algorithm
HV	-	High Voltage
IEEE	-	Institute of Electrical and Electronics Engineers
IPSA	-	Interactive Power System Analysis
KCL	-	Kirchhoff's Current Law
kW	-	Kilowatt
LV	-	Low Voltage
MATLAB	-	Matrix Laboratory
MSSO	-	Modified Shark Smell Optimization
MPGSA	-	Modified Plant Growth Simulation Algorithm
MW	-	Megawatt

<i>OF</i>	-	Objective Function
PSO	-	Particle Swarm Optimization
PV	-	Photovoltaic
RBFN	-	Radial Basis Function Network
RES	-	Renewable Energy Sources
SSO	-	Shark Smell Optimization
TS	-	Tabu Search

ABSTRACT

With the increasing penetration of renewable energies in the power systems, a mix of energy resources from small scale to large scale improves the system reliability. However, radial distribution network encounters many technical challenges associated with enormous power losses as compared to the rest of the network, which normally leads to poor performance and degradation of the system components. Distributed generation (DG) units are normally integrated into the distribution network system to help improve and support the power voltage profile as well as the performance of system components through power loss mitigation. Network reconfiguration is one of the effective methods for power loss reduction when simultaneously applied with the DG units. The reconfiguration in network topology alters the current flowing through the lines and also minimizes power losses while maintaining the operating constraints. In this study, a metaheuristic nature inspired Modified Shark Smell Optimization (MSSO) algorithm was proposed to identify the optimal network reconfiguration in IEEE 33-bus radial distribution system (RDS). The proposed MSSO algorithm and the load flow analysis (Fast Decoupled Load Flow method) was developed and simulated using MATLAB. The objective was to minimize real power losses while improving the voltage profile. There were four different cases considered and the MSSO algorithm performance was assessed on two scenarios (with and without the presence of distributed generation) in the IEEE 33-bus RDS. The results were compared with other metaheuristic algorithms from the literature for validation. The DG integration to the network reduced power losses by 59.82% from the initial network losses. When optimal switching sequence using the

MSSO algorithm was applied to the network in the presence of DG units, further power loss reduction from 83.76 kW to 64.92 kW was noted. There was a significant improvement in voltage profile from 0.91075 p.u to 0.97002 p.u. Clearly, optimal network reconfiguration in the presence of DG units lead to reduced power losses and an improved voltage profile.

CHAPTER 1 : INTRODUCTION

1.1 Background of the Study

Electricity has become a basic need in our day-to-day activities and every human being is entitled to have access to quality power, which is still a challenge being faced in most developing countries. This is due to the current state of the lacking power network systems which needs to be boosted, and maintained well. The aging transmission and distribution systems are characterized by transformers and lines which are heavily loaded [1]. The power quality supplied from such a system is unreliable and compounded with high power losses all the time. A large sector of the population lacks access to modern electricity since the utility operates on a financial constraint while lacking an enabling environment to attract private investors in the power sector.

One good example of a developing country facing electricity problems is Malawi. The current electricity demand is around 400 MW against the total generation capacity of 351 MW [2] with a deficit in electricity supply of around 49 MW. This has put an enormous stress on the existing system resulting in increased frequency of outages, leading to constrained industrial production and socio-economic services. Although different methods have been put in place to solve issues of supply-demand imbalances, the government has strategically come up with objectives to improve the energy industry and make the network system reliable [1]. Through energy conservation and efficient equipment including the development of technical personnel should help accelerate the

development of the country. Recently, Electricity Supply Corporation of Malawi Limited (ESCOM) acquired a Supervisory control and data acquisition (SCADA) system to remotely control and monitor the power system network. The SCADA system application gathers data and converts it into useful information to help operators to efficiently make informed system adjustments and achieve optimal production output.

Optimization of technical losses in the distribution system is one of the solutions that has been considered in effective planning and modeling of the power system. Power loss reduction will improve the power quality of the system, thus increasing the lifespan of electrical components such as distribution lines and transformers in the system. A reliable distribution system will transmit electric power to the consumer in an elastic manner which maintains protection of equipment and feeders during contingencies [3]. The never-ending power demand growth has stimulated researchers and engineers to bring up novel technologies that are eco-friendly, such as renewable energy sources (RES) (photovoltaic (PV) systems, wind turbines, geothermal, biomass and hydropower). These RES have been increasing in the market and boosting the energy supply in most countries around the world, depending on the availability of the energy source [4]. RES normally generate power in small-scale plants, whose distribution is closer to the source of energy thus creating decentralized power system networks.

Distributed Generation (DG) is electric power generated by either renewables or non-renewables (coal, oil, natural gases) connected to the distribution networks or directly to

loads which generate power from less than a Kilowatt (kW) to tens of Megawatts (MW) [4]. Increase in the production of renewable energies has led to increased penetration of DGs to the power system networks, which has both positive and negative impacts to the network. Some of the advantages of DG integration to the network are power loss reduction, enhancement of power quality, reduction in the cost of power generation and lessening the environmental emissions. DG technologies help in reducing the power utility charges as well as to provide ancillary services at the transmission and distribution level due to their optimization nature to the network system. Some of the adverse circumstances that come along with DG penetration to the power network are; improper installation (location and sizing) may lead to the system being unreliable, back feeding of power, relay malfunctioning with the DGs in the distribution networks and when there is a system blackout the DG units also get interrupted [5].

When the topological arrangement of the distribution feeders is manipulated by varying the tie and sectionalizing switches while maintaining the constraints levels it is called Distribution Network Reconfiguration (DNR) [6]-[9]. The reconfiguration of the network system ensures that all network operations are carried out in lucid and most favorable conditions while maintaining adequate levels of reliability and secure power supply.

1.2 Problem Statement

The distribution network topology normally has radial feeders, which are rigid and vulnerable to outages with over-loading experienced in many parts of the system. Recent studies [10] indicate that over 13% of the total generation is lost in the form of line losses at the distribution level. Most low voltage distribution networks, which supply to load centers are heavily loaded and operate outside their voltage limit requirements [2], which leads to poor quality and unreliable power supply

The additional energy resulting from integration of DGs to the utility grid is encouraged in increasing the power generation [12], while understanding their possible impacts to the network. Despite the reduction in power loss by integration of the DGs into the distribution system, there is still further loss reduction implemented to the network by applying different optimization techniques including network configuration, FACTS devices, shunt capacitor placement and sizing. The incorporation of components such as FACTS devices and capacitors into the distribution system to reduce power losses comes with a high cost of implementation. It is necessary to reduce unnecessary expenses if there are better and cheaper alternatives to the costly options. Therefore, network reconfiguration which does not require any other additional components apart from switch manipulation of the already existing network system has been considered. The research addressed the problem by using the MSSO algorithm for optimal network reconfiguration to reduce total power system losses.

1.3 Objectives of the Study

1.3.1 Main Objective

The main objective of this study was to optimally reconfigure the radial distribution network using a Modified Shark Smell Optimization (MSSO) algorithm.

1.3.2 Specific Objectives

The specific objectives of this research are outlined as follows;

1. To model the radial distribution network with and without the DG units.
2. To determine the optimal switching sequence of the network with minimum power losses by using the Modified Shark Smell Optimization (MSSO) algorithm.
3. To evaluate the performance of the Modified Shark Smell Optimization (MSSO) algorithm in reconfiguration of the radial distribution system in comparison with other existing metaheuristic algorithms.

1.4 Justification

It is essential to look at the technical and economic importance of reduction in distribution network losses when planning to lower energy consumption, cost and balancing load-generation power. FACTS device controllers are very expensive to install to the system compared to capacitors. While capacitors may be relatively inexpensive to install and maintain, they tend to have a problem of poor voltage regulation and only a certain level

of compensation is attainable for stable operating conditions. Before considering any controller device to the network, reconfiguration must be prioritized since it does not have any additional costs in its implementation to the system. Reduced power losses will increase the lifespan of equipment due to enhanced power quality and reliability of the network. Network reconfiguration helps the power system to operate in stable conditions with minimal losses and lessens stress on the transmission and distribution system. If the radial distribution system is not optimum, it will be strenuous to the network causing even more power losses and a high voltage drop. Therefore, it has to be reconfigured in an optimal manner that will not compromise the power system network and give the most efficient and effective results. This study proposed to look at the reduction in power losses since the highest power losses due to unbalanced loads and conductor losses occur in the distribution network system.

1.5 Scope of Study

The research assessed the power losses on an IEEE 33-test bus radial distribution network system to achieve the main objective of the study and **compare with other existing metaheuristic algorithms**. The network reconfiguration problem was solved by using MSSO algorithm, to determine the optimum switching sequence which gave the lowest power losses and improved the voltage profile in the radial distribution network with and without the presence of DG units. **The power and voltage were computed using Fast-**

decoupled load flow method using a Matpower tool in MATLAB. The four different cases considered are as follows;

- Case 1: The initial network before reconfiguration and without DG units,
- Case 2: The reconfigured network without DG units,
- Case 3: The initial network before network reconfiguration with DG units,
- Case 4: Reconfigured network with DG units.

1.6 Thesis Outline

This thesis has been divided into five chapters as follows: Chapter one introduces the general background of the power systems and the challenges that motivated the study. The objectives, scope and procedure of the work to be carried are also highlighted. Chapter two reviews the literature on background theory on distribution systems, losses and network reconfiguration methods that have been applied. Distributed generation (DG) planning methods with network reconfiguration are also explained. The proposed methodology is explained in chapter three. The application of the MSSO algorithm to network reconfiguration problem in the presence of DG units applied to a standard IEEE 33-bus test system is clearly described. Chapter four discusses the simulation results obtained and investigates the findings on the mitigation of power losses and voltage profile improvement. Chapter five concludes the study findings and presents recommendations of the thesis.

1.7 Summary of Chapter One

This chapter dealt with the introduction of the work carried out in the thesis. It covers the general background information of the study on power systems and the optimization methods applied for a reliable and secure network. The problem statement looks at the power loss challenges faced in the distribution network systems with an aim of improving the voltage profile and mitigating total power losses. The main objective and the specific objectives of the study are well articulated. A brief explanation of the justification of the proposed study and the scope of the research on the IEEE 33-test bus RDS in four scenarios is completely covered.

CHAPTER 2 : LITERATURE REVIEW

2.0 Introduction

The literature review in this study looks at the relevant work done by other researchers on radial distribution networks that lead to the fulfillment of the development of this research. There are various studies that have been carried out on power loss challenges in distribution networks and the power system engineers are developing different methods of mitigating overall losses to improve the power system stability and make it more efficient by minimizing the cost.

2.1 Distribution Network Systems

A power system network transfers electricity from the generation plant to the end consumer loads. The power flows through different stages from generation, transmission, distribution and load as shown in fig. 2.1. The distribution system transmits power from the transmission system to the consumers' loads at low voltage levels. Distribution transformers are used to step down the voltage from 33 kV to 415 V for the three-phase consumers or 240 V for the single phase consumers [13].

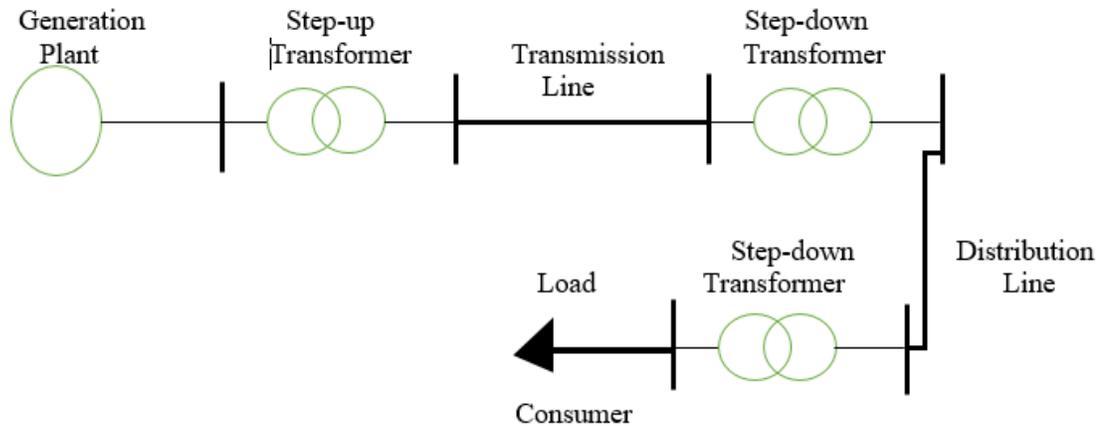


Figure 2.1: Single line diagram of a power system

The distribution network consists of the following;

Distribution substation: The main function of the distribution substation is to step down voltage levels to acceptable limits, switching and protection (by use of switchgear such as fuses, relays and circuit breakers), regulating the voltage, metering and recording operational information.

Primary distribution: Feeders come out of the substation to the secondary distribution systems. They are normally radial with a unidirectional power flow from the substation to loads.

Distribution transformers: These are mainly three phase and pole mounted. The transformers step down the primary voltage for distribution over the secondary mains to the consumers' service.

Distributors and service mains: Distributors are connected at the secondary of the transformers and feed power to different consumers by means of service main as shown

in fig. 2.2. Feeders feed power from various points without distributors tapping from different points, thus the current at the sending end is equal to the current at the receiving end of the line. The distributors feed different consumers from different points; hence the current varies along the entire length.

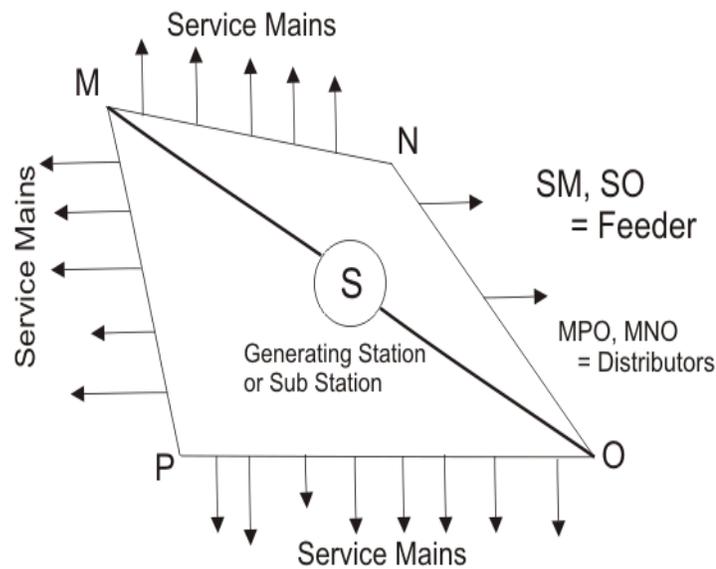


Figure 2.2: Distributors and Service Mains [14]

The types of consumer loads associated with in power systems are divided into industrial, commercial and residential as shown in fig. 2.3. Induction motor loads constitute a major portion of industrial loads while commercial and residential loads consist largely of lighting, compressors, cooling and heating [15]. Power usage varies throughout the day and it must be always available to consumers on demand at any time. The load demand at each location in the distribution system varies according to the power usage at a given time and it is never constant. During peak demand time, the generating station has to increase power supply to match the power demand.

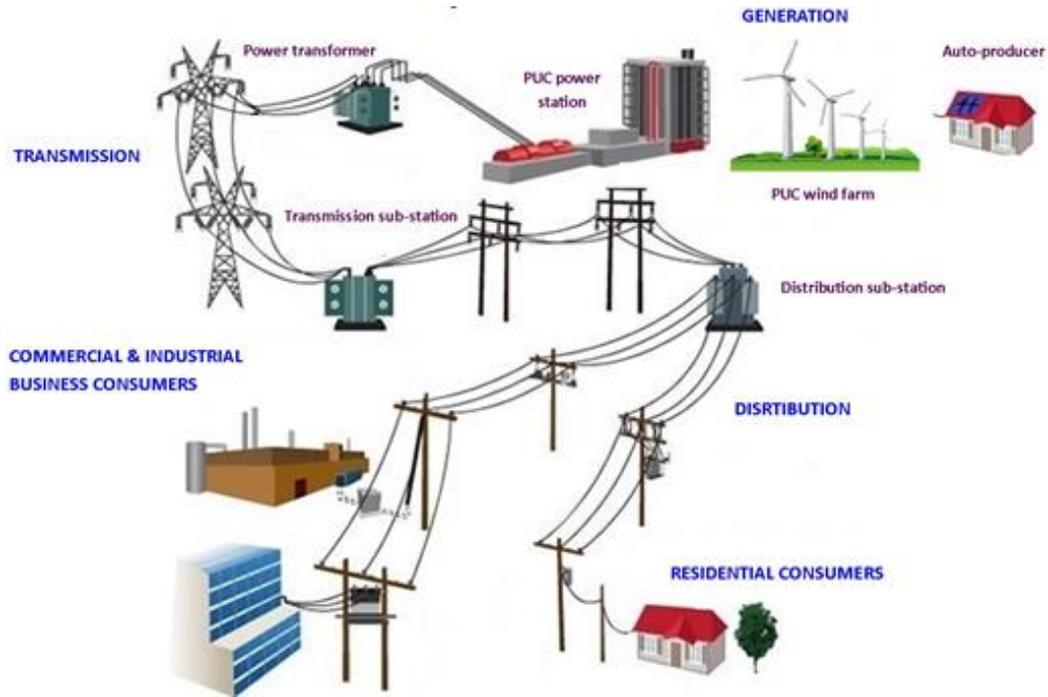


Figure 2.3: Structure of the Electricity Sector [16]

The two common types of distribution networks are radial and ring main distribution systems. In the radial distribution systems (RDS) the feeders radiate from a single substation while in ring main distribution systems the feeders are in a ring form which terminates back to the substation. The primary feeders take power from the distribution substation to the load areas by sub-feeders and lateral branch circuits as shown in fig. 2.4. The amount of switching equipment required is small and the protective relaying is simple. This type of system is widely used in sparsely populated areas. The major drawback in radial systems is an interruption of power supply and hence it is not reliable in case of line faults, transformer failure or feeder failure [17]. Consumers at the end of the line are subjected to serious voltage fluctuations when the load in between changes. For efficient

operation of RDS, automatic circuit breakers are recommended for the reclosing of the service line.

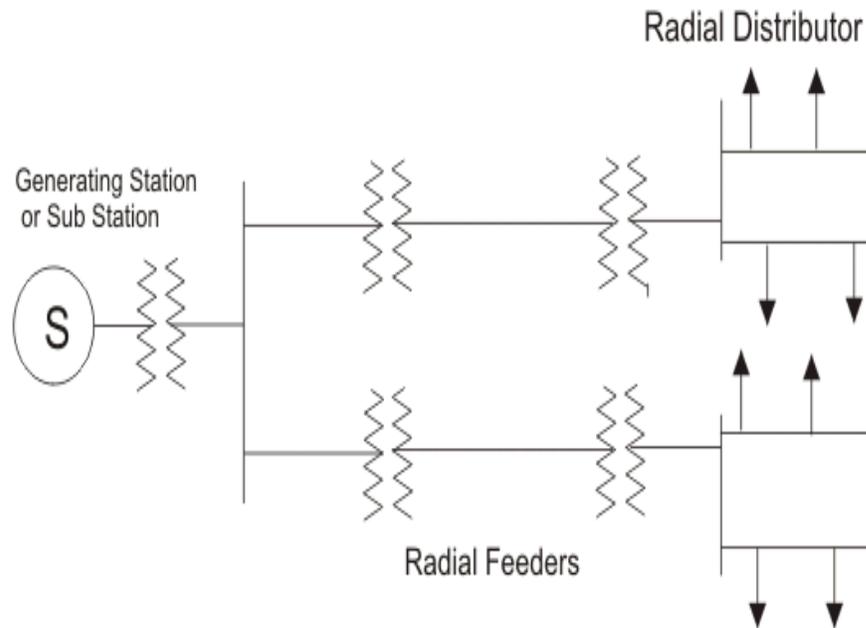


Figure 2.4: Radial Distribution Network

The ring system runs and serves one or more load centers and returns to the same substation. Each consumer is supplied power via two feeders. This type of system is more reliable and experiences lesser voltage fluctuations. It can easily be maintained by isolating one section zone of the ring and still be able to supply power to the loads without any interruptions as shown in fig 2.5. The ring system is generally expensive as compared to the radial system as it has more switches and conductors required in the construction for the power distribution at such low voltages, thus a radial system is a more preferred choice [18]. However, the RDS is less reliable due to its structure that has each bus connected to the source via a single path. Therefore, to use the benefits of a radial structure

and overcome its drawbacks, RDS are built in a way that allows the network to be reconfigured. A finite number of possible radial configurations will give an optimum network in order to optimize a suitable objective function subject to constraints.

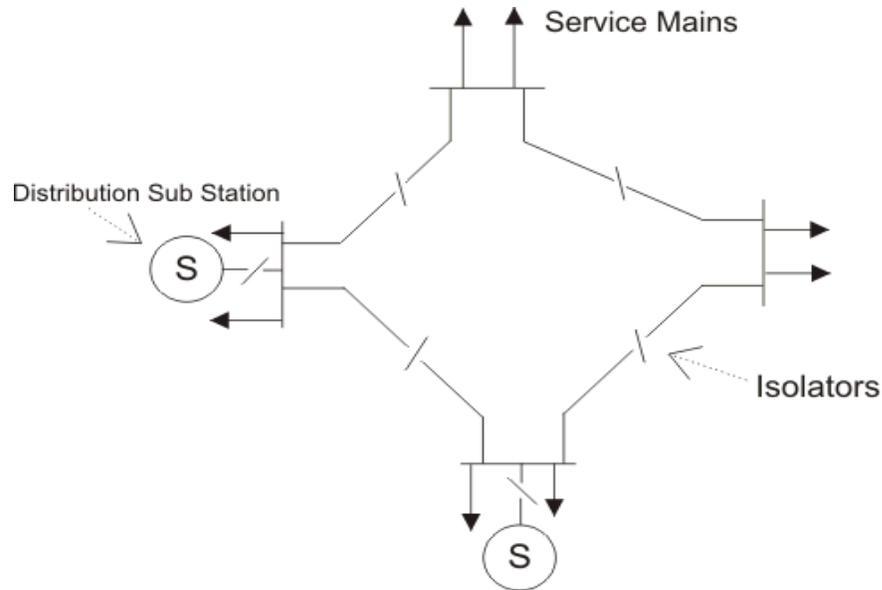


Figure 2.5: Ring Main Distribution Network

2.2 Power System Losses

Electricity supply losses in power system consist of technical losses and non-technical losses. The non-technical losses are caused by actions external to the power systems such as inaccurate meter reading, non-payment of electricity bills, inaccurate estimation of non-metered supplies, inefficiency in business and technology management systems. The technical losses occur in numerous small components in the distribution systems from the step-up transformers through all different stages until the consumer end [19]. Most losses

are experienced during peak demand when all the resources are operating at maximum to match up with the power needed by the end user. As the load increases, the copper losses become more significant. The active power lost in the distribution system is mostly due to copper losses since these losses are a function of the square of current flowing through the line as shown in (2.1).

$$P_{loss} = I^2 R \quad (2.1)$$

It is also noted that anything that changes resistance will affect the amount of power lost in the lines. The amount of real power and reactive power loading at the end of the line determines the magnitude of current in the line. The current flow will increase with more demand for power transmitted through the lines. Another determining factor for current flow is the operating voltage of the line. The apparent power in a radial system is given by (2.2) from which high voltage will result in low current for the same apparent power.

$$S = VI \quad (2.2)$$

Unbalanced loading of the phases can also result in higher line losses. If one of the phases was heavily loaded than the others, the losses would be larger as compared to a balanced load case. The resistance of the line cannot be neglected since it plays a vital role in the line losses. Generally, a long line has higher resistance and larger losses compared to a short line with the same flow of current. Similarly, a small conductor will experience high losses as a result of high resistance than a large conductor.

2.3 Review on Distributed Generation (DG)

The electric utility restructuring has become a major concern on the overall system reliability as the industry expands in size and becomes increasingly complex. Glover *et al.*, [20] mention how digital computers have become major players in assisting engineers in managing the current and future plans of the power system network with the aid of intelligent programs that include transient, power flow, stability and contingency analysis programs. The penetration of distributed generation (DGs) into the utility markets has expanded the market growth with a mix of both renewables and non-renewables. This has encouraged deregulation of the power utilities and resulted in an increase in power market competition in many countries in the West such as USA and Germany. Integration of DG technologies relieves the heavy cost burden on the transmission network system.

The expansion of electrical energy use has placed greater demands on the distribution system. The electrical equipment requires closer monitoring of voltage variations in addition to tolerating any service interruptions and contingencies. For the renewable energy sources, the availability of wind and solar depends on the intermittent levels of the weather which affects the power generated [20]. The effects of DG penetration into the distribution network have been studied and researched on to improve and enhance a smooth integration without any technical difficulties.

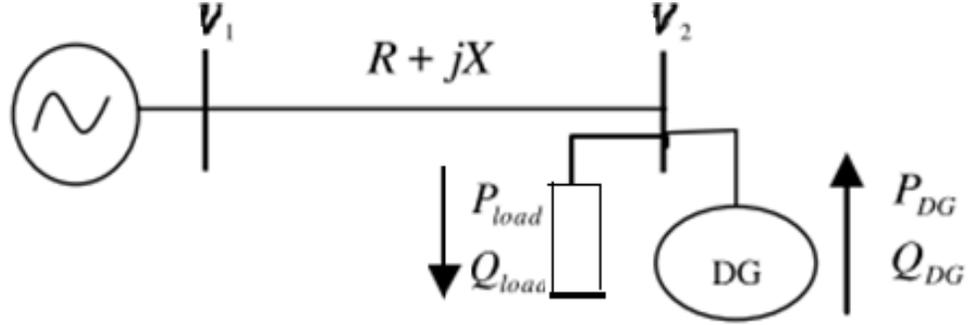


Figure 2.6: DG connected to a two-bus system [21]

From [22], the distribution substation transformers experienced very high core losses due to low loads and very high resistive losses when heavily loaded. The power loss for distribution lines that are connected to a DG is described in equation (2.3) [21];

$$P_{line-loss} = R \times \left(\frac{(P_{load} - P_{DG})^2 + (Q_{load} - (\pm Q_{DG}))^2}{(V_2)^2} \right) \quad (2.3)$$

where $P_{line-loss}$: line losses and R : line resistance

If switched capacitors are properly managed the reactive power output and the power losses in the network can be controlled and reduced, respectively. When the DG in fig. 2.6 is replaced by a feeder switched capacitor the power losses are represented by (2.4).

$$P_{line-loss} = R \times \left(\frac{(P_{load})^2 + (Q_{load} - (\pm Q_C))^2}{(V_2)^2} \right) \quad (2.4)$$

Research conducted on radial distribution networks using network reconfiguration, capacitor placement, DG sizing and placement applied different techniques and algorithms to optimize the system. The different methods had a similar objective to further

reduce power losses while ensuring stability and keeping voltage profiles within acceptable limits [4]. In RDS, optimal placement and sizing of DGs reduces line losses, since most DGs operate at unity power factor. The active power is the most effective in determining the loss reduction as compared to reactive power [23].

Most DG units are based on renewable energies such as mini-hydro, wind, solar, and biofuels [2], which are normally small in size and installed at strategic points in the distribution system. A local supply of power delivered to the loads by the DGs in the distribution systems shortens the distance of power supply from the main generation. This will reduce the overall power losses and improve the voltage profile in the system. It is important to ensure that the DG output is at its optimum because any inappropriate output may cause increased power losses in the system, which may exceed that of the initial configuration [7].

Nanghoguina [4] proposed a technique for identifying an optimal location and sizing of the DG units using a backward-forward sweep method by computing power loss saving based on the branch injected current value. The DG sizing was evaluated using the current injected from the DG and its corresponding voltage magnitude. The performance of the power loss technique used was tested on the IEEE 33-bus radial distribution system and compared to other methods.

2.4 Methods of Network Reconfiguration with Optimization Techniques

The two types of switches used in network reconfiguration are called sectionalizing switches (normally closed) and tie switches (normally open). The switches are used for protection and configuration management. The network topology of the distribution system is changed by altering the switch status (open/closed). Fig. 2.7 shows an example of a distribution network which makes a comprehensible explanation of the operation of switches. The dashed lines 3, 8 and 12 show branches of the network which are normally open tie-switches and the other continuous lines represent branches which are normally closed sectionalizing switches.

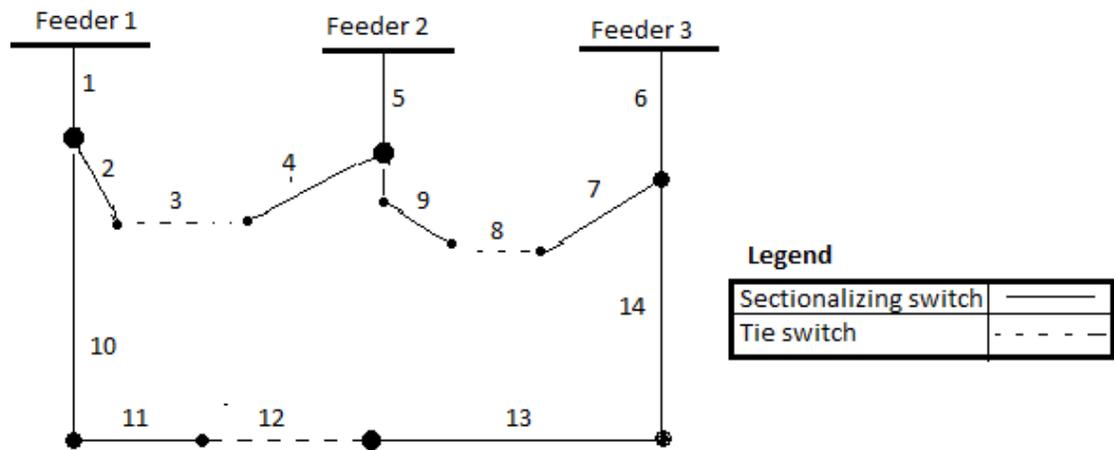


Figure 2.7: Single line diagram for feeder connections system

During feeder reconfiguration, a tie-switch may be closed to transfer loads to different feeders and a sectionalizing switch will be open to maintain the radial structure of the system. Different methods have been developed for the reconfiguration of the distribution network with some of the studies including single- and multi-objective functions with

FACTS devices, capacitor and DG (sizing and placement) playing a role in solving power system problems [6] [7] [23].

Artificial intelligence (AI) methods are the most commonly used optimization techniques due to their execution speed, accuracy and guarantee for global optima. According to Abedinia *et al.*, [25] metaheuristic optimization techniques solve real-world problems which are too complex to work out using conventional methods. Some of the advantages include high flexibility, simplicity and efficiency modeling. Computer Intelligence (CI) is a branch of AI that came up in the early 90s based on nature-inspired computational paradigms and collection of numerical information [26]. Fuzzy logic (FL), Artificial Neural Network (ANN) and bio-inspired algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Tabu Search (TS), Ant Lion Optimization (ALO) and Ant Colony Optimization (ACO) are some of the AI methods that focus on computer-based intelligence. A summary of some of the optimization techniques used in distribution system problems is further explained below.

For a feeder reconfiguration proposed by Charles *et al.*, in [19], the main objective was to reduce economic losses in a network having undesirable conditions. Each optimum configuration of the network identified by the algorithm had to operate within the constraint's limits. In the study proposed by Mohammadi *et al.*, [23], the operating constraints considered were voltage limits and the current capacity of the feeder at each

and every bus. After the reconfiguration of the network, the line losses of each section from bus i to bus $i+1$ were calculated using (2.5).

$$P'_{loss}(i, i+1) = R_i \left(\frac{P'_i{}^2 + Q'_i{}^2}{|V'_i|^2} \right) \quad (2.5)$$

where i is the bus number.

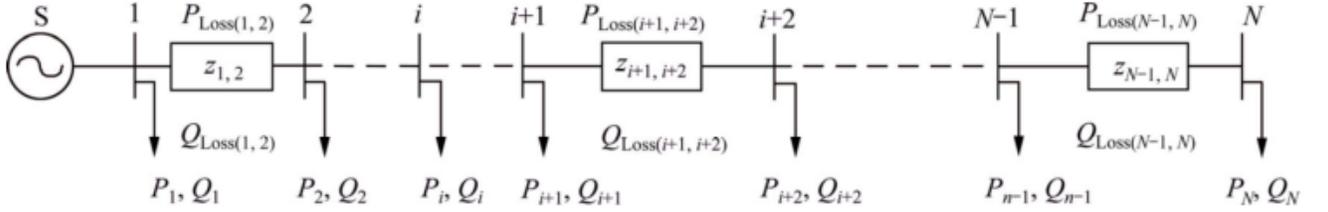


Figure 2.8: Single line Radial Distribution [23]

The losses in each line section shown in fig. 2.8 were summed up to obtain the overall power losses of the system represented by (2.6).

$$P'_{T, loss} = \sum_{i=1}^N P'_{Loss}(i, i+1) \quad (2.6)$$

where i is the bus number and N is the total number of buses.

Bradán *et al.*, [7] proposed a technique which determines the optimal sequence path of switching operations using the firefly algorithm (FA) for daily basis power loss reduction while improving the voltage profile. The installed DGs were optimally placed to the network that had varying loads. The optimal switching sequence path obtained a large number of possible sequences that were generated during optimal network reconfiguration. The first step aimed at finding the DGs real power output and network

reconfiguration with a variable load. The second step determined the optimal switching sequence path to change the network configuration from the original form to the optimal form, from the obtained results in step 1. The proposed method was tested on an IEEE 33-bus distribution network system and compared with other methods that considered variable loads. The algorithm required a large number of population and iteration which took a long computational time.

Reference [6] proposed a Cuckoo Search Algorithm (CSA) to optimize the RDS problem in regard to power losses and voltage profile. The net power loss reduction was calculated by the difference before and after the reconfiguration of the system. The CSA was implemented for RDS by considering a process of each radial structure of the network as a host nest and each egg was taken as a solution randomly generated during initialization. The algorithm was performed on three different IEEE test systems (33-node, 69-node and 119-node), and compared with other different methods in the literature. The author noticed that the method was more applicable on large-scale RDS due to its more noticeable effect on the 119 node test systems. However, the results show that CSA was time-consuming in switching to an optimum feeder configuration.

Charles *et al.*, [19], suggested an ACO algorithm to reconfigure the electric energy distribution system to lower the transmission losses of the Tamil Nadu Electricity Board (TNEB). The algorithm used a probability-based search method to find the most optimal transmission losses with constrained voltage limits and transmission capabilities of a

network. The behavior of ants inspired the development of the proposed approach to solving optimization problems. The path taken by an ant when searching for food is guided by the pheromone (chemical substance) intensity and it will be similar for all ants. The algorithm involved a probability-based search making the decision for the ants simple. The application of the ACO algorithm was tested on a 14-bus transmission system and it showed better performance with a reduction in computational effort in searching for the optimal solution. However, the proposed algorithm had to be tested on a bigger system to validate its performance when applied to a distribution system other than the one used in the literature.

Guliyev [27] proposed a fuzzy logic control system that contained a structure of reactive power sources and voltage ratios. The transformers were optimally corrected through a controlled system of rules which minimized the losses in the network. The choice of condensers' capacity within a distributed generation network and the transformer voltage ratio at the point of connection was providing an optimum mode to assist in power loss reduction. The effect of DGs and the capacitors along with network reconfiguration had a great impact on improving the stability and reliability of the network.

Bacterial Foraging Optimization (BFO) algorithm with a multi-objective function was proposed due to its fast convergence and less computational time when applied in a fuzzy framework [23]. The distribution feeders were reconfigured using the control schemes that showed significant improvement with DGs connected to the system. Each objective

was transferred into the fuzzy domain using its membership function and then the overall fuzzy satisfaction function that considered a fitness function was maximized to gain the optimal solution. The proposed method was tested on an IEEE 69-test bus system and it had improved voltage profile indices and power loss reduction compared to other metaheuristic algorithms. A BFO algorithm with a fuzzy approach performed better as compared to the BFO method alone. However, there is still room for improvement on the convergence rate to reaching an optimum solution.

In [28], Feng and Jianming proposed an optimal solution of a radial basis function network (RBFN) structure that calculated distribution network line losses optimized by a hierarchical GA. The first step determined the parameters of the neural network function and then it was adopted to map the complex nonlinear relation between operating parameters and the energy losses in the system. A hierarchical GA assisted the RBFN structure to overcome the deficiency of training the network and the method proved practical and efficient with accurate calculations of line losses as compared to other methods in the literature. However, a large population had to be generated to obtain accurate optimum results for the network.

According to Wazir and Arbab [29], there are two types of switches (tie and sectionalizing switches) which require great management and protection of the radial network. They proposed a Hybrid Genetic Algorithm Particle Swarm Optimization (HGAPSO), which was a combination of two algorithms to effectively minimize power losses and improve

the voltage profile. The merged algorithm had an added advantage that combined merits for both algorithms breaking through the limitations of PSO. The algorithm had the ability to control convergence and settle quickly to an optimal solution. The network reconfiguration rectified voltage violations to remain within acceptable limits. Optimal reconfiguration in the presence of DGs obtained the minimum power losses as compared to the other cases mentioned in [29]. The initial switches played a vital role in determining the final optimal configuration of the network. There was still room to further reduce the obtained system power losses after reconfiguration.

Rao and Reddy [30], proposed a GA optimization approach to get optimal switching scheme for the reconfiguration of the feeder distribution network. Since the lines connected between the substations to the loads experience major copper losses, GA solved the configuration by identifying the least losses and an improved voltage profile in the obtained solutions. The results showed that the efficiency levels and voltage regulations operated well above 0.9 p.u and had reduced power line losses in the distribution network. However, the algorithm was taking too much computational effort to achieve a global optimum solution.

A Hyper-Cube Framework Ant Colony Optimization (HC-ACO) algorithm was proposed in [31], in the presence of DGs to minimize the real power loss and bus voltage deviation in the RDS. It is an Evolutionary Algorithm (EA) with a strong global search ability and a constructive greedy heuristic rule that avoids premature convergence in a search area.

The algorithm used a positive feedback and heuristic information to discover good solutions and required less practice to reach the optimum switching sequence in an IEEE 33-bus RDS. Further power loss reduction was achieved by reconfiguring the system in the presence of DGs. Despite a few iterations used in HC-ACO to reach the optimum solution, the number of iterations should be reduced even further.

The novel Hybrid Modified Shuffled Frog Leaping Algorithm-Particle Swarm Optimization (HMSFLA-PSO) proposed in [32], solved three different objective functions in the distribution network. The considered objectives were not in line with each other, therefore the obtained set of optimum solutions and fuzzy decision were used to sort out the Pareto-optimal solutions based on importance. The proposed algorithm had a stable performance for solving feeder reconfiguration problem in both small- and large-scale distribution networks. However, the proposed method did not reach the optimum solution with the least power losses when considered with the DGs.

2.5 Overview of the Shark Smell Optimization (SSO) Algorithm

Shark Smell Optimization (SSO) is a metaheuristic GA developed by Abedinia *et al.*, based on the shark's ability to catch prey by its strong sense of smell. A shark has one of the most effective senses and can detect a single drop of blood up to a kilometer away. This algorithm is inspired by the hunting behavior of a shark and its ability to smell an

injured animal from miles away. The mathematical modeling movement of the shark is based on the following assumptions [26];

- When a prey/target is wounded and results in bleeding into the sea (search area). The target source is assumed to be fixed since its velocity is negligible in comparison with the shark's movement.
- There will be a regular injection of blood into the sea with odor particles getting stronger as the shark gets near the injured prey. The effect of water flow on distorting odor particles is neglected.
- Only one injured blood source in the search area of the shark will result in one odor source.

The search process begins when the shark smells odor particles having a weak concentration from the injured animal. As the blood is released in the water, the shark will move towards the prey with a velocity ' V ', guided by the smell of the stronger odor particles, hence leading to a solution with high-quality particles. The rotational movement allows the shark to narrow down the stronger odor particles as it moves forward and this process is called local search of the SSO algorithm. The shark will be guided to the prey by the intensity of blood concentration in the sea. As the concentration becomes stronger, the movement of the shark becomes true and guarantees the attack on the injured animal. This section also discusses the application of the SSO algorithm in engineering problems carried out in the literature.

The authors in [33], proposed the SSO algorithm to optimally locate and size the shunt capacitors required in the distribution system to achieve the minimum cost function due to energy loss and reactive power consumption. The reactive power losses were reduced by installing shunt capacitors in the distribution system. Capacitor placement is greatly influenced by the size, location and type of shunt capacitor to be installed for the optimum use of the capacitors. The SSO algorithm performed better compared to the other algorithms from the literature and it gave optimum results with a simpler formulation that satisfied the constraints.

In [34], Ahmadigorji *et al.*, proposed a multi-year expansion planning of distribution networks in the presence of DGs using a combination of Binary Modified Imperialist Competitive (BMIC) algorithm and an Improved-SSO algorithm. The proposed model optimally determined the time in a year to make reinforcements/investments, specified the expansion schedule and scheming of the size and location of DGs in the distribution system. The effectiveness of the suggested solution method was evaluated and compared on two RDS with other two-stage solution methods from the literature.

Ehteram *et al.*, [35] examined the SSO algorithm for reservoir optimization operations. The reservoir has a stochastic system, thus the SSO algorithm was an appropriate choice to apply to the system feature due to its stochastic nature. In the simulation of the reservoir systems, the results obtained with the application of the SSO algorithm minimized the target function and maximized the profits of the system. The SSO algorithm attained the

optimum objective function with a few iterations. The integration of the SSO algorithm with a highly non-linear algorithm such as fuzzy systems and neural network was recommended to get accurate reservoir behavior to any release decision.

The purpose of the proposed research is to investigate the performance of the proposed MSSO algorithm in solving the network reconfiguration problem for power loss reduction while improving the voltage profile in a real-time system. The methods described in the review on optimization techniques in network reconfiguration had merits and gaps in achieving maximum performance in terms of computational burden and not reaching the global optimum sequence that achieves the minimum losses in the system. Some algorithms may prove to be more superior than others when benchmarking, but underperform when applied to solve real-world problems [36][37]. The approach, programming platform, software and technique used to apply optimization techniques greatly influences the performance depending on the problem being solved. In most systems nowadays, the goal is to achieve an optimization technique that can be applied in real-time [29][38][39].

Heuristic algorithms have a greedy approach with a high efficiency when searching for solutions but sometimes may have trouble converging to a global solution. Despite having a lot of control parameters and large computational requirements, AI algorithms can process a direct search to global optimal [6]. Due to the shark's characteristic of strong concentration when moving towards the prey [33], a Modified Shark Smell Optimization

(MSSO) algorithm was proposed to achieve the objective function of minimizing power loss in a RDS. The modifications made to the SSO algorithm were; elimination of the gradient descent method from the forward movement operator and introducing a sigmoid transformation to the newly obtained position of the shark's forward movement.

The proposed MSSO algorithm was inspired by the PSO algorithm at updating the fitness function in a given population. It has high performance in accuracy, search ability and better computational efficiency within the computational time. It surpasses the enhanced versions of other algorithms and the hybridized algorithms such as HGAPSO, Improved-ABC, GA, PSO, BFA and other 28 other metaheuristic optimization approaches based on the conducted standard benchmark function tests performed on evaluating the stochastic search methods [40].

In conclusion, network reconfiguration plays a major role in manipulating the distribution system to obtain an optimum, efficient and cost-effective network with reduced losses within the constraint limits while maintaining stable conditions. It is not only limited to reducing power losses but also benefits the system in security, improving the voltage profile, network load balancing and efficient use of DG systems.

2.6 Summary of the Literature Review

The literature review covered a general introduction of power systems, distribution networks and different types of distribution systems. The power system losses experienced in the system were described with the mitigation methods applied to the network, with more focus on RDS. The review on distributed generation (DG) looked at the merits of introducing DGs to the distribution system. Different optimization techniques used in network reconfiguration from the literature were described with their merits and gaps. The concept of the original SSO algorithm and its merits were discussed with its application and performance that had been carried out in the literature. The chapter proposed the MSSO algorithm as a better application method for network reconfiguration problems in RDS.

CHAPTER 3 : METHODOLOGY

3.0 Introduction

This chapter sought to meet the objectives of the proposed Modified Shark Smell Optimization (MSSO) algorithm and its application to radial distribution network reconfiguration. The load flow analysis was performed on the IEEE 33-test bus radial distribution system (RDS) modeled under different scenarios. The original SSO algorithm was briefly discussed in this chapter, followed by a detailed explanation of the proposed MSSO algorithm.

3.1 Formulation of the IEEE 33-Bus Test Radial Distribution Network System

The study used an IEEE 33-bus test RDS which comprises of 33 buses, 32 lines and 5 tie switches modeled and simulated in MATLAB. The first bus in the system is taken as the substation which supplies power to all the other buses that are connected to fixed loads as depicted in fig. A1 in the appendix A. Being a radial network, configurations are carried out by manipulating the tie switches and sectionalizing switches in the feeder system. Distribution networks are usually built as interconnected networks, while in operation they are arranged into a radial tree-like structure. This means that distribution systems are divided into subsystems of radial feeders, which contain a number of normally closed switches and normally open switches. Initially, the open line switches before reconfiguration are 33, 34, 35, 36 and 37. The medium load of the system is 3,715 kW

and 2300 kVAr with a base voltage of 12.66 kV. The data bus system is given in Table A-1 at the appendix A. The DG units added to the system were mostly targeting the weak buses while aiming to improve the voltage and assist in power loss reduction. The DGs' sizes and specific locations are shown in Table A-2 at the appendix A, as referenced in [32]. The four different cases considered are as follows;

- Case 1: The initial network before reconfiguration and without DG units,
- Case 2: The reconfigured network without DG units,
- Case 3: The initial network before network reconfiguration considering DG units,
- Case 4: Reconfigured network considering DG units.

3.1.1 Power Flow Equations

In a power system, real power (P) and reactive power (Q) flows from the generating source to the loads through the branches and buses. Load flow studies provide a systematic mathematical approach to determine bus voltages, phase angles, power flows, loads and operating conditions of a power system. Power flow analysis was carried out before and after the network reconfiguration to calculate the nodal voltages, current, power flows and power losses in the system using the Fast-Decoupled method. The load flow operation had to be performed for each iteration of the new configuration identified by the proposed MSSO algorithm to determine the new operating point.

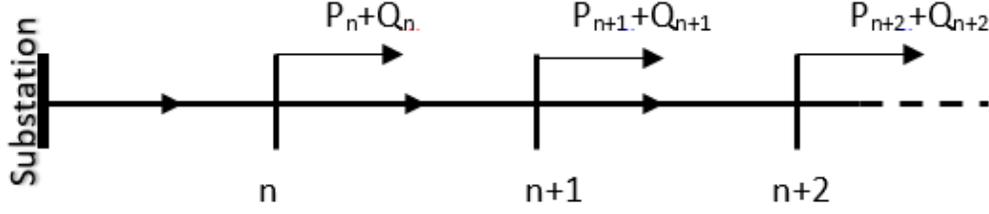


Figure 3.1: A sample distribution system of a single line diagram [33]

Distributed power flow was calculated by the equations derived from the single line shown in Figure 3.1. The injected current at bus n is presented by (3.1) in [33];

$$I_n = \left(\frac{P_n + jQ_n}{V_n} \right) \quad (3.1)$$

Using Kirchhoff's Current Law (KCL), the branch current between the buses n and $n+1$ was calculated as;

$$I_{n,n+1} = I_{n+1} + I_{n+2} \quad (3.2)$$

The loads were assumed to be constant and with no load point interruption. The voltage at bus $n+1$ was given by (3.3) from the fundamental Kirchhoff's Voltage Law (KVL).

$$V_{n+1} = V_n - I_{n,n+2} (r_{n,n+2} + jx_{n,n+2}) \quad (3.3)$$

By applying KCL in (3.2) at the buses, the complex load flow equations can be expressed as follows [41];

$$P_n = \sum_{n=1}^{NL} |Z_{n,n+1} V_n V_{n+1}| \cos(\theta_{n,n+1} + \delta_n - \delta_{n+1}) \quad (3.4)$$

$$Q_n = -\sum_{n=1}^{NL} |Z_{n,n+1} V_n V_{n+1}| \sin(\theta_{n,n+1} + \delta_n - \delta_{n+1}) \quad (3.5)$$

Power loss of any line between buses n and $n+1$ can be determined by (3.6) in [33];

$$P_{loss(n,n+1)} = r_{n,n+1} \left(\frac{P_{n,n+1}^2 + Q_{n,n+1}^2}{|V_{n+1}|^2} \right) \quad (3.6)$$

$$P_{Tloss} = \sum_{n=1}^{NL} P_{loss(n,n+1)} \quad (\text{For all distribution feeders}) \quad (3.7)$$

Power loss after network reconfiguration can be calculated as;

$$P'_{loss(n,n+1)} = r_{n,n+1} \left(\frac{P'_{n,n+1}{}^2 + Q'_{n,n+1}{}^2}{|V'_{n+1}|^2} \right) \quad (3.8)$$

$$P'_{Tloss} = \sum_{n=1}^{NL} P'_{loss(n,n+1)} \quad (\text{For all distribution feeders}) \quad (3.9)$$

The difference of power loss before and after reconfiguration will give the net power loss reduction given by (3.10);

$$\Delta P_{Tloss} = \sum_{n=1}^{NL} P_{Tloss(n,n+1)} - \sum_{n=1}^{NL} P'_{Tloss(n,n+1)} \quad (3.10)$$

3.1.2 Formulation of the Objective Function and Constraints

The objective of the reconfiguration in the radial distribution network was to mitigate the real power losses in the system subject to the constraints. The optimization method has to identify the tie switches and sectionalizing switches that should be altered to obtain a

network that has minimum resistive line losses. The objective function can be expressed by a power variable or current variable and the former was used [42];

➤ **Mathematical model of distribution network reconfiguration**

Minimize $F =$ total power losses, $P_{(Tloss)}$

$$\min f = \sum_{n=1}^{NL} k_n R_n \left(\frac{P_n^2 + Q_n^2}{V_n^2} \right) \quad n \in NL \quad (3.11)$$

Subject to the following constraints;

The voltage limits must be retained within the allowed limits at the buses [43].

$$V_{m,\min} \leq V_m \leq V_{m,\max} \quad (3.12)$$

Feeder's capability must have power limits in the n th branch [44];

$$k_n/P_n/ \leq P_{nmax} \quad n \in NL \quad (3.13)$$

$$k_n/Q_n/ \leq Q_{nmax} \quad n \in NL \quad (3.14)$$

$$k_n/I_n/ \leq I_{nmax} \quad n \in NL \quad (3.15)$$

The radial topology of the network must be maintained;

$$Tie_{sw} = (NL - N_{bus}) + 1 \quad (3.16)$$

$$Sec_{sw} = N_{bus} - 1 \quad (3.17)$$

where

R_n : Resistance in the n th branch.

Q_n : Reactive power in the n th branch.

P_n : Real power in the n th branch.

V_m : Voltage magnitude at node m .

k_n : Status topology of the branches (if branch n is closed $k_n = 1$ and if it is open it is 0).

NL : Set of branches in the network.

N_{bus} : The total number of buses.

When an optimization problem is constrained, it will mathematically determine the optimal allocation of scarce resources subject to a set of constraints. In order to maintain a radial topology, each loop in the network must have only one switch open at all times. The topological radial structure constraints for each candidate is represented by (3.16) and (3.17). There must always be 5 tie switches and 32 sectionalizing switches in the network. There will be no isolated nodes and the final configuration must be radial with all loads connected.

3.2 Shark Smell Optimization (SSO) Algorithm

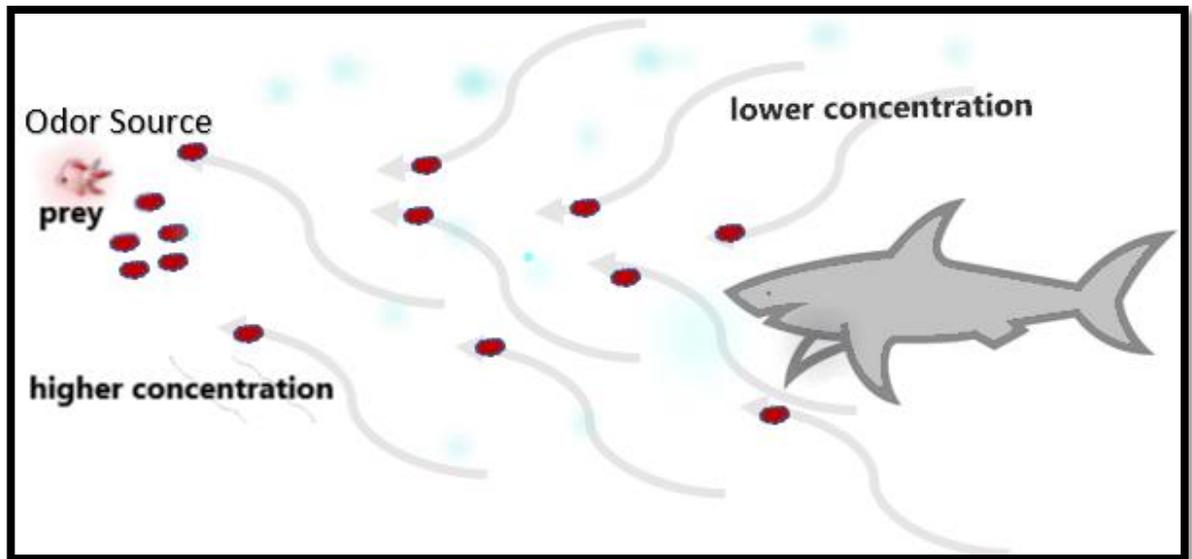


Figure 3.2: Shark's movement towards the prey

3.2.1 Fundamental SSO Algorithm

SSO is modeled based on the shark's behavior to attack its prey once it picks up the blood odor in a search space (sea). This inspires the optimization mechanism to be simulated with the aim of picking up the best solution in a given search space. The following steps briefly explain the algorithm (for a minimization problem) [40]:

I. Initialization of SSO Algorithm

When modeling, a population of initial solutions is randomly generated for an optimization problem in a feasible search area (sea). A source (prey) represents the

optimal solution whilst the quality of the solution is represented by the odor strength at a position. According to [40], the initial solution is given as;

$$x^1 = [x_1^1, x_2^1, x_3^1, \dots, x_{np}^1] \quad (3.18)$$

whereby

$$x_i^1 = [x_{i,1}^1, x_{i,2}^1, x_{i,3}^1, \dots, x_{i,nd}^1] \quad (3.19)$$

$i = 1, 2, 3, \dots, np$, (np is the the population size).

x_i^1 is the i th initial solution (position of the population vector).

$x_{i,j}^1$ represents j th dimension of the shark's i th position or number of decision variable of i th of the shark (x_i^1).

nd is the number of decision variables in an optimization problem.

II. Forward Movement towards the prey

As the blood is released in the water, the shark will move towards the target with a velocity ' V ', guided by the smell of the stronger odor particles, hence leading to a high-quality solution. In correspondence with the position vector, the initial vector is as follows;

$$V^1 = [V_1^1, V_2^1, V_3^1, \dots, V_{np}^1] \quad (3.20)$$

whereby each velocity vector has a dimensional component element;

$$V_i^1 = [V_{i,1}^1, V_{i,2}^1, V_{i,3}^1, \dots, V_{i,nd}^1] \quad (3.21)$$

The increase in shark's velocity is determined by the increase in the odor intensity. In each stage of $V_{i,j}^1$, the velocity limiter is given as follows;

$$|V_{i,j}^k| = \min \left[\left| \eta_k \cdot R1 \cdot \nabla_{i,j}^k + \alpha_k \cdot R2 \cdot V_{i,j}^{k-1} \right|, \left| \beta_k \cdot V_{i,j}^{k-1} \right| \right] \quad (3.22)$$

$$i = 1, 2, \dots, np, \quad j = 1, 2, \dots, nd, \quad k = 1, 2, \dots, k_{\max}$$

where β_k is a velocity limiter ratio for stage k .

η_k is an element in $[0, 1]$.

α_k is the inertia coefficient.

$\nabla_{i,j}^k$ is the gradient of the objective function $\left(\frac{\partial(OF)}{\partial x_j} \Big|_{x_{i,j}^k} \right)$.

The gradient at a position $x_{i,j}^k$, is expressed by $\nabla_{i,j}^k$ (objective function gradient) defined

from the term $\frac{\partial(OF)}{\partial x_j} \Big|_{x_{i,j}^k}$. The rate of momentum α_k becomes constant for stage k (number

of stages for shark's forward movement) and the velocity dependent from its former state.

$R1$ and $R2$ are random values, which give a more random search when determining the

velocity reached by the gradient function and to broaden the search in the algorithm. The

considered sign for the value of $V_{i,j}^k$ depends on the direction of the selected term of the

minimum operator. The velocity vector will determine the new position during the

forward movement of the shark given by;

$$Y_i^{k+1} = x_i^k + V_i^k \cdot \Delta t_k \quad (3.23)$$

$$i = 1, 2, \dots, np, \quad k = 1, 2, \dots, k_{\max} \quad (\Delta t_k - \text{time interval is assumed to be 1})$$

III. Shark's Rotational Movement

The rotational movement allows the shark to narrow down the stronger odor particles in its forward movement. This process is called local search of the SSO algorithm modeled by (3.24);

$$Z_i^{k+1,m} = Y_i^{k+1} + R3.Y_i^{k+1} \quad (3.24)$$

$$i = 1, 2, \dots, np, k = 1, 2, \dots, k_{\max}, m = 1, 2, \dots, M$$

To model the rotational movement of the shark, the number of points M in the local search are connected to form closed contour lines as shown in fig. 3.3, whereby the position of point m of each stage in the local search is $Z_i^{k+1,m}$. As the operator implements a local search around Y_i^{k+1} a random number $R3$ is also generated.

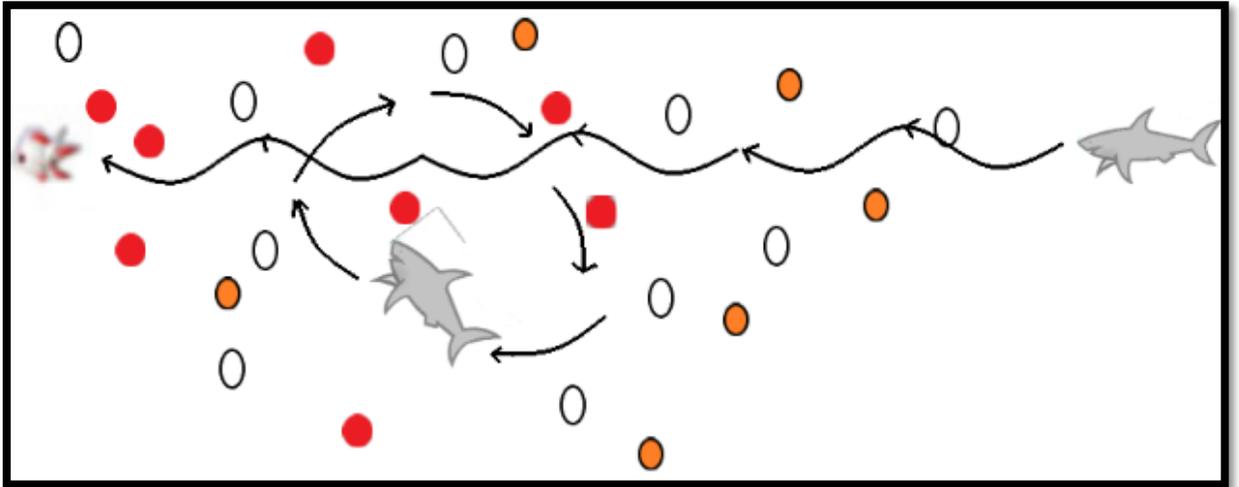


Figure 3.3: Shark's rotational movement

IV. Updating the Particle Position

The shark's search path will continue with the rotational movement as it moves closer to the point with a stronger odor sense as shown in (3.25);

$$X_i^{k+1} = \arg \min \{OF(Y_i^{k+1}), OF(Z_i^{k+1}), \dots, OF(Z_i^{k+1,M})\} \quad (3.25)$$

$$i = 1, 2, \dots, np$$

X_i^{k+1} presents the next position of the shark or the candidate solution with the least objective function (OF) value. The OF should be minimized from the obtained forward movement and rotational movement. The cycle will continue until k reaches the minimum value (best individual) in the given population in a search space chosen for an optimization problem.

3.2.2 Proposed MSSO Algorithm

In the proposed MSSO algorithm, there were two modifications made from the original SSO algorithm which permits the exploration and exploitation capabilities to improve the global search performance in achieving the OF of the network reconfiguration problem. In the main loop of the algorithm, the gradient of the OF was removed from (3.22) in the velocity movement operator for the shark. Instead of finding the minimum of the gradient function from the velocity equation operator, the OF was introduced in the fitness loop which compares the current best position of the shark with the previous best [8]. If the current fitness function is better than the previous it will be updated until the iteration

stops. The global minima from all the particles in a search space will be selected as the global best. Since the shark's movement is non-linear in nature, this permits a sigmoid transformation [45] shown in (3.26) to be introduced in the forward movement operator when a new position is obtained soon after (3.23), for a smooth search capability.

$$\text{sigfun}^{k+1} = \frac{ta}{1 + e^{-y_i^{k+1}}} \quad (3.26)$$

where ta represents the branches in each loop.

The position value of the particles in each stage will settle at the nearest whole number among the given values in the loops created in the network. This will assist in getting a reasonable position towards the prey with the linearized part of the sigmoid moving the shark's non-linearity in a forward manner, thus returning a switch sequence which is identified with an objective function for each value of k .

3.2.3 Pseudo Code for MSSO Algorithm

Begin

Initialization

Set parameters np , k_{max} , η_k , α_k , and β_k ($k = 1, 2, \dots, k_{max}$)

Generate an initial population with all individuals

Generate each decision randomly within the allowable range

Initialize the stage counter $k = 1$

For $k = 1 : k_{max}$

For each odor particle

Calculate fitness value

If new fitness value is better than the previous Local best value

Set the new value as the new Local best

End

Choose odor particle with the best fitness value from all the particles as the Global best

Forward Movement

Calculate each component of the velocity vector, $v_{i,j}$ ($i = 1, \dots, np$, $j = 1, \dots, nd$)

Obtain the new position of shark based on forward movement, Y_i^{k+1} ($i = 1, \dots, np$)

Introduce a sigmoid transformation to the obtained new position, $sigfun^{k+1}$

Rotational movement

Obtain the position of shark based on rotational movement, $Z_i^{k+1,m}$ ($m = 1, \dots, M$)

Select the next position of the shark based on the two movements, X_i^{k+1}

End for k

Set $k = k+1$

Select the best position of shark in the last stage which has the best fitness function

End

3.3 Optimal Network Reconfiguration using the MSSO Algorithm

The application of the proposed MSSO algorithm to the network reconfiguration problem is discussed here. Fig. 3.4 shows the flow chart for the reconfiguration process with the application of the algorithm to the network. The flow process of the proposed MSSO algorithm is as follows:

Step 1: The bus system data and MSSO algorithm parameters such as np , nv , M , η , α , β are generated.

Step 2: Initialization of the population vector for a given population size and $k = 1$. The initial open/closed switches of the network before configuration will present the solution vector, X^1 and the initial fitness (power loss).

Step 3: Each solution obtained per iteration (load flow) returns a fitness function (power losses) which is compared with the previous load flow and ensures that it is in the allowable limits of the system operation.

Step 4: The new position of the shark is determined from the forward movement by moving vector solution X^1 to a new position Y_i^{k+1} using (3.23).

Step 5: A sigmoid function is introduced to the new position of the shark Y_i^{k+1} to linearize the shark's movement and obtains a new position from the tap switches given in the loops.

Step 6: Perform rotational movements to determine the new position of the shark in a local search $Z_i^{k+1,m}$.

Step 7: The new position of the shark is determined by the forward and rotational movements. The best switching sequence with the least power losses in the network between the two movements will be identified and selected.

Step 8: If k is not equal to k_{max} , go to *step 3*.

Step 9: The global minimum of the fitness function is chosen at the last best position

$$X^{Kmax}.$$

The defined parameters shown in the Table 3.1 for the proposed MSSO algorithm shown in the flow process can be fine-tuned depending on the size of the network or changes made to the system. Changing the parameters during the evolution process is an effective method in the application based on an adaptive mechanism. The population of the problem evolves through the forward and rotational movement operators with a randomization to the parameter settings for each stage counter k .

Table 3-1: Parameters

Parameter	Value
α	0.5
β	2
η	0.9
M	50
Decision variables (nv)	5
Population size (np)	50
Number of iterations (k)	20

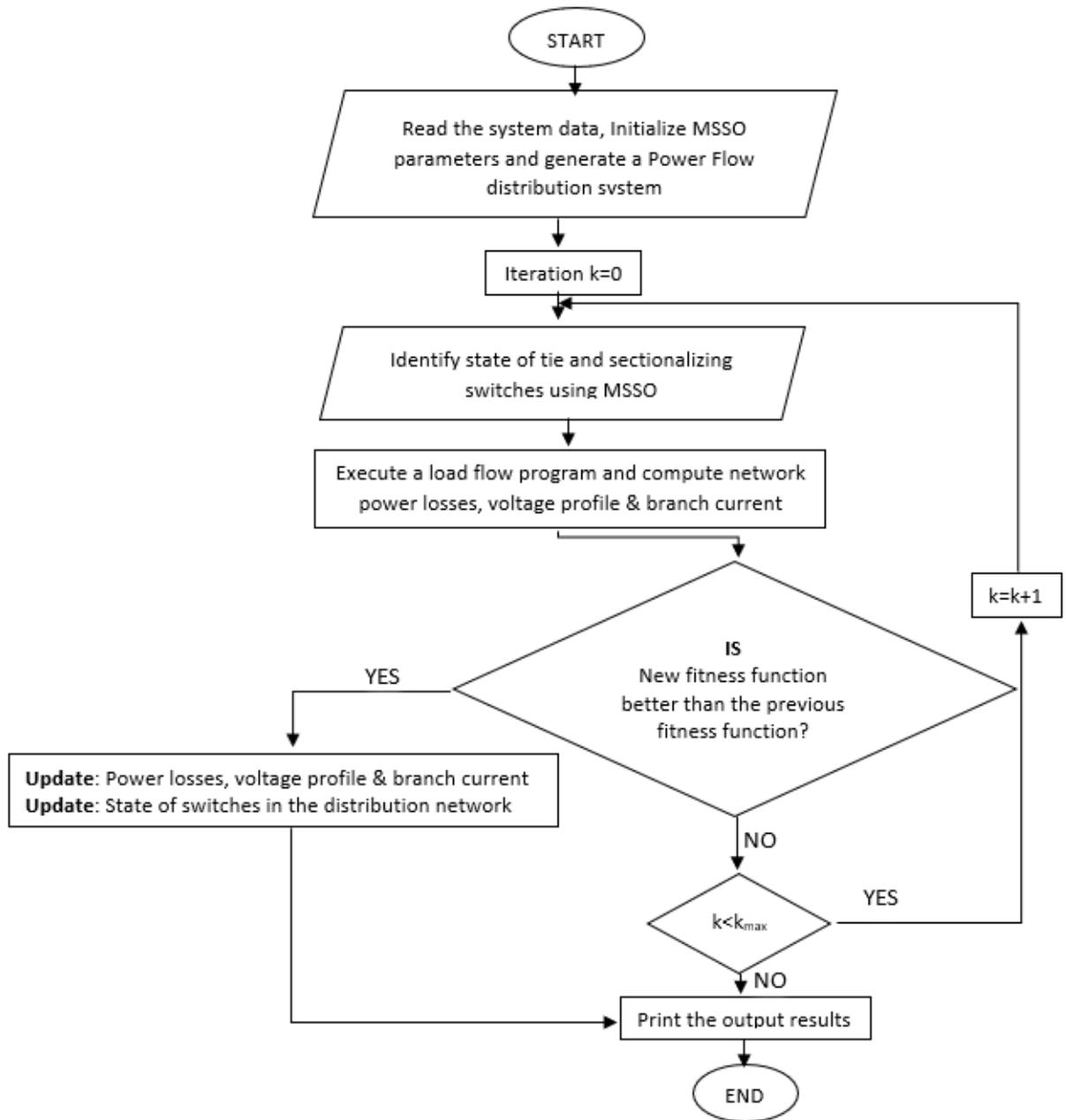


Figure 3.4: Flowchart for reconfiguration process

Table 3-2: Characteristics of the MSSO algorithm

General Algorithm	Real System	MSSO Algorithm
Decision variable	Number of tie switches in the system	Odor particles which show the possible position of shark
Initial solution	Initial tie switches	Initial position of shark
New solution	Tie switches	New position of shark
Best solution	Tie switches	Shark's position with best <i>OF</i>
Fitness function	Power losses	Odor particle intensity
Process of generating new solution	-	Forward & rotational movement operators
Selection	-	Shark's position selected based on two positions of the movement operators
Constraints	Voltage, power & current limits, Switch status (radiality)	-

Table 3-2 explains the relationship of the algorithm and the real power system. A general algorithm shows how the general characteristics relate to the proposed MSSO algorithm with the real power system. The initial population given in (3.27) was randomly created and generated, where the first column represents the number of odor particles in a population, the following five columns represent the switching sequence for a new configuration and its corresponding total power losses of the system in kW.

$$\text{Odor particles} = \begin{bmatrix} 1 : 8 & 13 & 19 & 16 & 28 : & 223.82 \\ 2 : 4 & 32 & 34 & 35 & 37 : & 391.18 \\ 3 : 2 & 22 & 8 & 12 & 15 : & 1275.80 \\ & & & \dots & & \\ & & & \dots & & \\ & & & \dots & & \\ 49 : & 8 & 13 & 19 & 16 & 28 : & 223.82 \\ 50 : & 6 & 32 & 34 & 35 & 37 : & 166.05 \end{bmatrix} \quad (3.27)$$

The configurations in the initial odor particles represent the total system losses in each configuration. It can be noted that the total power losses in the third row exceeded the initial system losses before network reconfiguration (case 1). Since the proposed MSSO algorithm is stochastic in nature, it will perform a random search, thus the initial value setting of variables does not affect the search for an optimal solution.

3.4 Summary of Methodology

In the methodology, a detailed description of specific objectives is carried out in a structured manner with the introduction of different scenarios in the formulation of the IEEE 33-test bus RDS. The power flow equations, formulation of the objective function and the constraints are discussed with an overview of the original SSO algorithm. A detailed discussion of the proposed MSSO algorithm and the changes made to the original SSO algorithm are looked at with its application to network reconfiguration problem, elaborated in a pseudo code, the flow process and the flowchart of the reconfiguration process.

CHAPTER 4 : RESULTS AND ANALYSIS

4.0 Introduction

The mitigation of power losses for different simulation scenarios was conducted on an IEEE 33-bus radial distribution system (RDS) and recorded in this chapter. The first case analyzed the initial total power losses and voltage profile of the base load flow of the system at 100% of the total power load demand. The DG units connected to the IEEE 33-bus test system before reconfiguration and after reconfiguration at specific buses [32] are shown in fig. A2 and Table A-2 in appendix A for case 2 and case 4, respectively. The proposed MSSO algorithm and the load flow analysis were developed and simulated in MATLAB software R2017a on a PC with 2.5GHz, core i7-6500, 8 GB RAM. The proposed MSSO algorithm used in network reconfiguration problem was applied in two cases and compared with the existing methods in the literature to validate the performance. The maximum reduction of the overall power losses and voltage profile improvement in the RDS was analyzed in four cases.

4.1 Simulation Results for IEEE 33-bus System

The load flow analysis was performed using the Fast-Decoupled method to obtain the parameters used in determining the performance of the network system. The data of the test system for a medium active and reactive power loading demand shown in Table A-1 in appendix A. Table 4-1 shows the summary of the load flow results for the four cases

which were used for analysis. The initial load flow simulation (case 1) was used as a reference to show how the other cases had improved from the original configuration of the system, as shown in fig. A1 in appendix A. It had a total power loss of 208.459 kW. It is clear that after network reconfiguration (case 2), the total power losses of the system reduced to 138.927 kW, amounting to 33.35% reduction of the initial network losses in case 1. There was a significant power loss reduction of 59.82% in case 3 when DG units were introduced to the system as compared to the original network (case 1). When the system was reconfigured in the presence of DG units (case 4), there was further power loss reduction of 68.86% which brought the power losses down to 64.9211 kW.

Table 4-1: Load flow results for different cases of the IEEE 33-bus test system

Parameters	Case 1 Original Network	Case 2 MSSO algorithm (Reconfiguration)	Case 3 Considering DGs only	Case 4 DG units + MSSO (Reconfiguration)
Tie-Switch	33 34 35 36 37	7 9 14 32 37	33 34 35 36 37	7 9 14 32 37
Real Power Loss (kW)	208.459	138.9276	83.7629	64.9211
Loss reduction (%)	-	33.35	59.82	68.86
V_{\min} (p.u)	0.91075	0.94234	0.96575	0.97002
Node	18	32	33	32

Fig. 4.1 illustrates the optimal network of the IEEE 33-bus system which had branches 7, 9, 14, 32 and 37 offline after the reconfiguration using the proposed MSSO algorithm for case 2. Case 1 and case 3 had a similar network configuration shown in appendix A in fig. A1 and fig. A2, respectively. The results obtained in case 4 for the system considering DGs had the same tie switches as case 2. This proves that for both cases to obtain the least

system power losses they had to attain a similar optimum switching sequence configuration of the network, as shown in fig. 4.1 and fig. 4.2.

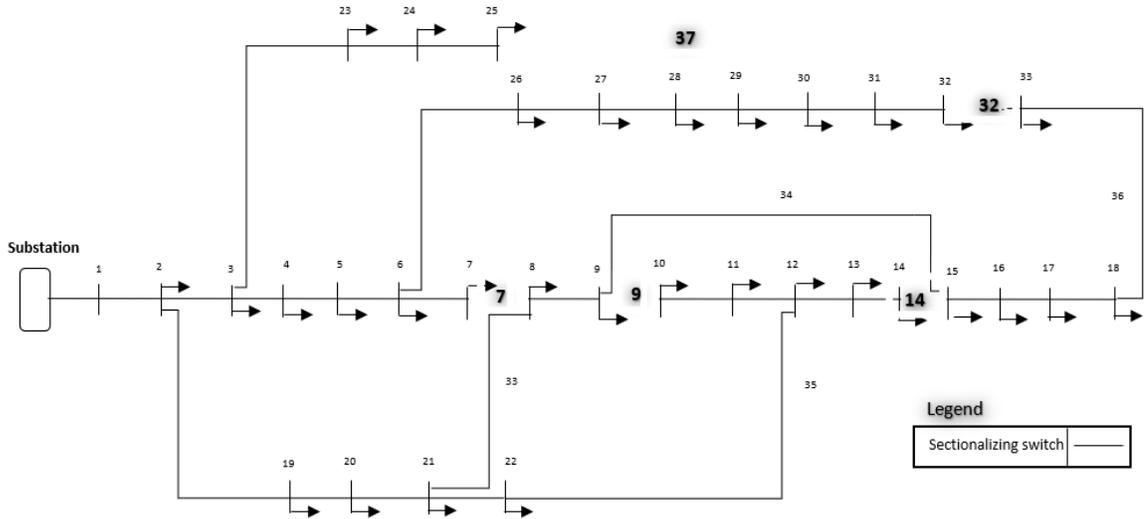


Figure 4.1: Optimal reconfiguration using MSSO algorithm for 33-bus system

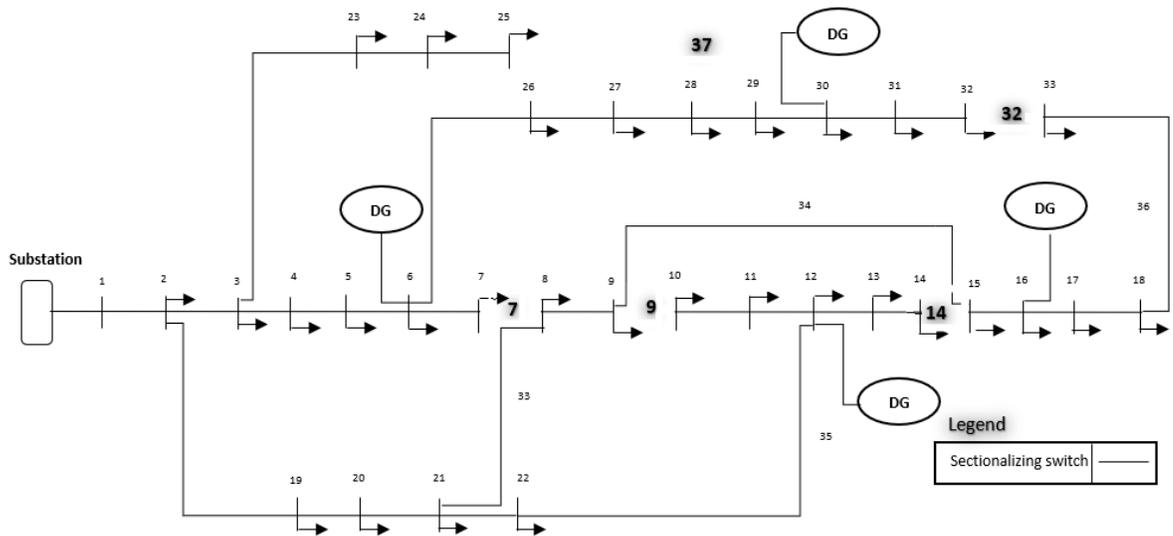


Figure 4.2: Optimal reconfiguration using MSSO algorithm for 33-bus system considering DGs

4.1.1 Results for Voltage Profile Improvement

Fig. 4.3 shows the comparison of the voltage profile before and after network reconfiguration for case 1 and case 2, respectively. The network before reconfiguration in the absence of DGs is represented by case 1. The minimum voltage in case 1 was 0.91075 p.u at node 18. With the MSSO algorithm for optimum switching, the configuration in case 1 was converted into case 2. The result of voltage improvement became 0.94234 p.u at node 32 as shown in case 2 of fig. 4.3. The slight drop in voltage at buses 20, 21 and 22 in case 2 was caused by the changes made to the network topology after network reconfiguration.

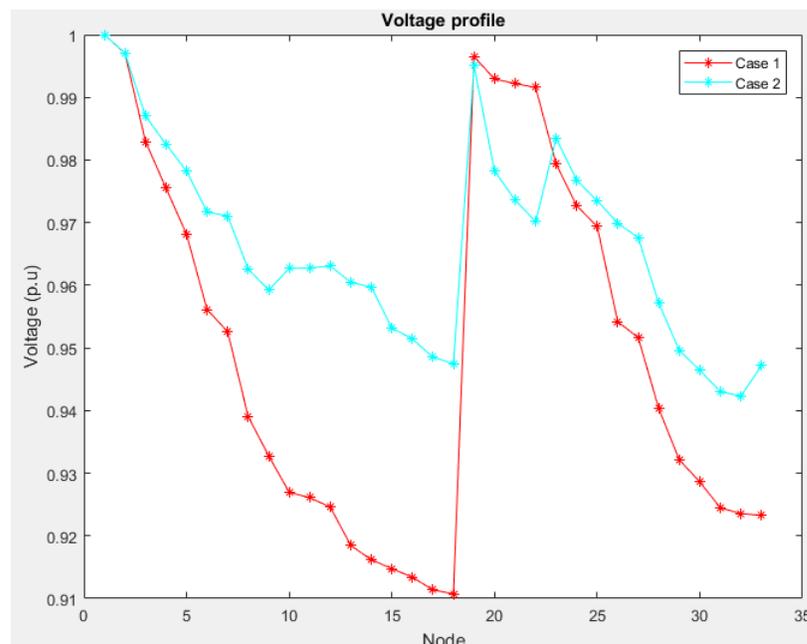


Figure 4.3: Voltage profile in the absence of DGs

Fig. 4.4 depicts the voltage profiles considering DGs before and after network reconfiguration for case 3 and case 4, respectively. The minimum bus voltage rose to 0.96575 p.u at node 33 after considering DGs, depicted in fig. A-2 and Table A-2 in

appendix A. There was a slight voltage improvement from case 3 to case 4 when the network was reconfigured considering DGs. The slight drop in voltage at buses 20, 21 and 22 in case 4 was caused by the changes made to the network topology after network reconfiguration and it can be noted that the buses affected are similar to the ones affected in case 2. The placement of DGs to the radial distribution network had a positive impact with a significant improvement in voltage profile as shown in Table 4-1. The effectiveness of DGs and network reconfiguration can be observed in Table 4-2 in the voltage profile results obtained from the load flow of the four cases analyzed in this study. The reconfiguration had a fair improvement of the voltage profile without any capital cost in case 2. An even further improvement was obtained in case 3 when DGs were considered and in case 4 after reconfiguration with MSSO algorithm while considering DGs, respectively.

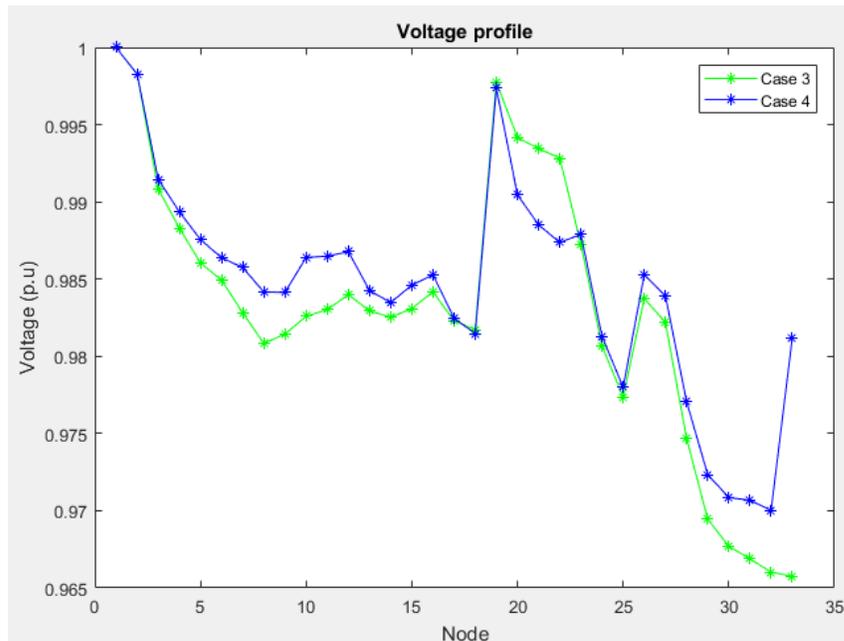


Figure 4.4: Voltage profile considering DGs

Table 4-2: The voltage magnitude profile (p.u) for the IEEE 33-bus RDS

Node	Case 1 Original Network	Case 2 MSSO Reconfiguration	Case 3 Considering DGs Only	Case 4 DGs + MSSO
1	1	1	1	1
2	0.9970	0.9971	0.9983	0.9983
3	0.9829	0.9870	0.9908	0.9915
4	0.9755	0.9825	0.9883	0.9894
5	0.9681	0.9782	0.9860	0.9876
6	0.9561	0.9717	0.9849	0.9864
7	0.9526	0.9711	0.9828	0.9857
8	0.9390	0.9626	0.9808	0.9842
9	0.9328	0.9592	0.9814	0.9841
10	0.9270	0.9627	0.9826	0.9864
11	0.9261	0.9628	0.9830	0.9865
12	0.9246	0.9631	0.9840	0.9868
13	0.9185	0.9605	0.9829	0.9843
14	0.9162	0.9597	0.9825	0.9835
15	0.9148	0.9532	0.9831	0.9846
16	0.9134	0.9514	0.9842	0.9853
17	0.9114	0.9485	0.9823	0.9825
18	0.9108	0.9475	0.9817	0.9815
19	0.9965	0.9951	0.9977	0.9974
20	0.9929	0.9782	0.9942	0.9904
21	0.9922	0.9736	0.9935	0.9885
22	0.9916	0.9701	0.9928	0.9874
23	0.9794	0.9834	0.9873	0.9879
24	0.9727	0.9768	0.9807	0.9813
25	0.9694	0.9735	0.9774	0.9780
26	0.9542	0.9699	0.9837	0.9853
27	0.9516	0.9676	0.9822	0.9839
28	0.9403	0.9571	0.9747	0.9771
29	0.9321	0.9496	0.9694	0.9723
30	0.9286	0.9464	0.9677	0.9709
31	0.9245	0.9430	0.9669	0.9707
32	0.9236	0.9423	0.9660	0.9700
33	0.9233	0.9472	0.9657	0.9812
V_{min}	0.9108	0.9423	0.9657	0.9700
Bus	18	32	33	32

4.1.2 Results for Power Losses in the Branches

The comparison for the real power losses in the branches is shown in fig. 4.5 for the initial network before and after reconfiguration (case 1 and case 2), respectively, and in fig. 4.6 for the network considering DGs before and after reconfiguration (case 3 and case 4), respectively. The power losses in almost every branch in case 2 reduced, except at 18, 19, 20, 21, 33, 34 and 35, where there was a small increase in losses due to load shifting of the feeders altered by the switching as depicted in fig. 4.5.

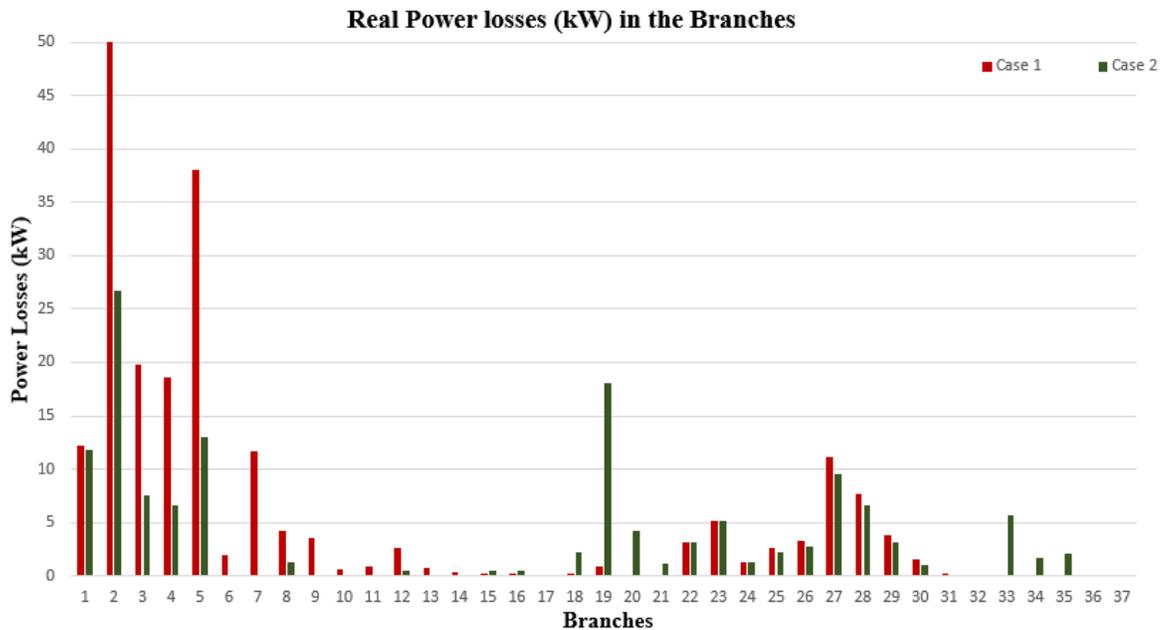


Figure 4.5: Real power losses in 33-bus system

There was a significant drop in power loss when the DGs were considered in case 3 and case 4 as shown in fig. 4.6. Since the optimal switching sequence of the network obtained in case 4 is similar to case 2, they had similar branches that experienced a small increase in power losses due to load shifting of the feeders. The losses in case 4 were lesser as

compared to case 2 due to the presence of DGs which further improved the efficiency of power flow in the network.

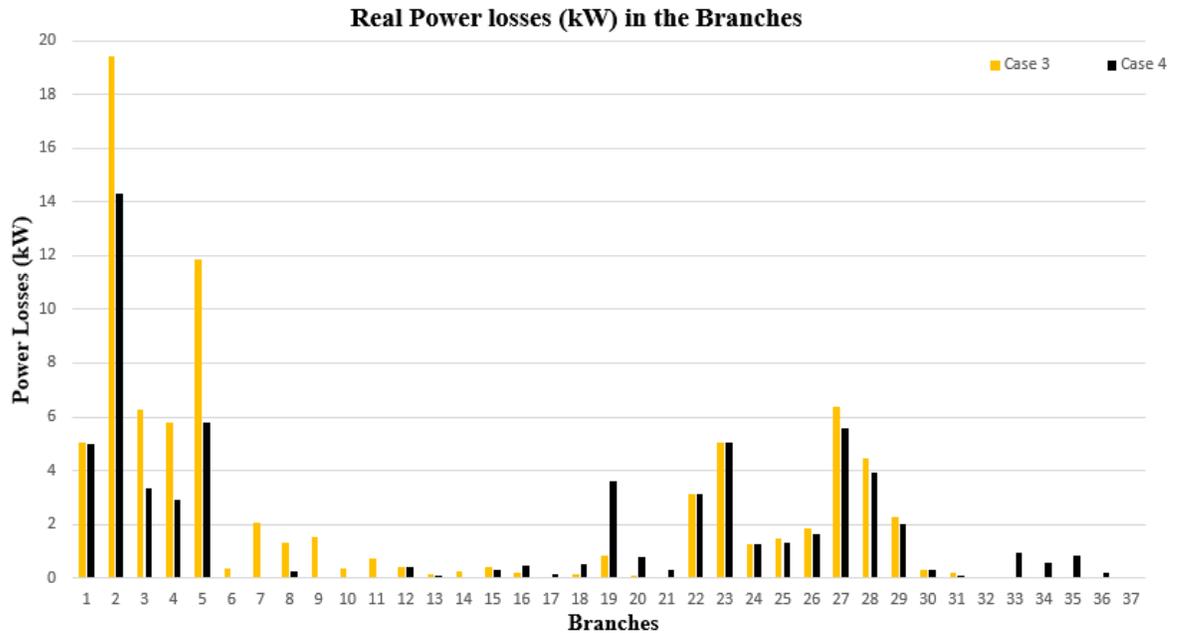


Figure 4.6: Real power losses in IEEE 33-bus system considering DGs

There are two feeder connections in bus 2 and 3 as illustrated in fig. 4.1 which experience a magnificent flow of power to supply to the rest of the network. Since the second branch carries all the bulk power flowing from the substation to supply to the rest of the network, it experiences the highest power losses of the system. The power losses in the feeder lines in case 1 decreased as you moved further from the substation, as a result, there was less strain on power lines and a smooth flow of power. In case 2, the real power losses in the second branch decreased to 26.677 kW due to network reconfiguration. The optimal tie switches had affected the power flow through the branches of the network, reducing the power lost in most of the branches.

Table 4-3: Numerical results for power losses in the IEEE 33-bus RDS

Branches	From bus	To bus	Case 1		Case 2 (MSSO)		Case 3		Case 4	
			Original network		Reconfiguration		Considering DGs		DGs + MSSO	
			P(kW)	Q(kVar)	P(kW)	Q(kVar)	P(kW)	Q(kVar)	P(kW)	Q(kVar)
1	1	2	12.203	6.31	11.836	6.12	5.035	2.60	4.980	2.58
2	2	3	51.602	26.28	26.677	13.59	19.417	9.89	14.311	7.29
3	3	4	19.784	9.95	7.488	3.76	6.268	3.15	3.350	1.68
4	4	5	18.584	9.46	6.594	3.36	5.785	2.95	2.901	1.48
5	5	6	38.004	3.25	13.067	1.12	11.877	1.02	5.795	0.50
6	6	7	1.918	6.34	0.062	0.20	0.330	1.09	0.060	0.20
7	7	8	11.698	8.44	0	0	2.057	1.48	0	0
8	8	9	4.202	3.02	1.241	0.89	1.336	0.96	0.230	0.17
9	9	10	3.566	2.54	0	0	1.550	1.10	0	0
10	10	11	0.557	0.18	0.005	0	0.341	0.11	0.005	0
11	11	12	0.886	0.29	0.034	0.01	0.714	0.24	0.032	0.01
12	12	13	2.680	2.11	0.454	0.36	0.425	0.33	0.432	0.34
13	13	14	0.733	0.96	0.076	0.10	0.143	0.19	0.073	0.10
14	14	15	0.359	0.32	0	0	0.231	0.21	0	0
15	15	16	0.283	0.21	0.452	0.33	0.433	0.32	0.321	0.23
16	16	17	0.253	0.34	0.485	0.65	0.218	0.29	0.452	0.60
17	17	18	0.053	0.04	0.147	0.12	0.046	0.04	0.137	0.11
18	2	19	0.161	0.15	2.260	2.16	0.161	0.15	0.489	0.47
19	19	20	0.832	0.75	18.064	16.28	0.830	0.75	3.592	3.24
20	20	21	0.101	0.12	4.230	4.94	0.101	0.12	0.784	0.92
21	21	22	0.044	0.06	1.177	1.56	0.044	0.06	0.282	0.37
22	3	23	3.182	2.17	3.155	2.16	3.130	2.14	3.126	2.14
23	23	24	5.144	4.06	5.101	4.03	5.061	4.00	5.054	3.99
24	24	25	1.288	1.01	1.277	1.00	1.267	0.99	1.265	0.99
25	6	26	2.564	1.31	2.211	1.13	1.461	0.74	1.289	0.66
26	26	27	3.282	1.67	2.816	1.43	1.869	0.95	1.646	0.84
27	27	28	11.141	9.82	9.510	8.39	6.364	5.61	5.600	4.94
28	28	29	7.722	6.73	6.560	5.71	4.467	3.89	3.936	3.43
29	29	30	3.840	1.96	3.216	1.64	2.271	1.16	2.007	1.02
30	30	31	1.571	1.55	1.085	1.07	0.328	0.32	0.312	0.31
31	31	32	0.210	0.24	0.118	0.14	0.192	0.22	0.111	0.13
32	32	33	0.013	0.02	0	0	0.012	0.02	0	0
33	21	8	0	0	5.621	5.62	0	0	0.926	0.93
34	9	15	0	0	1.742	1.74	0	0	0.587	0.59
35	12	22	0	0	2.148	2.15	0	0	0.819	0.82
36	18	33	0	0	0.018	0.02	0	0	0.170	0.02
37	25	29	0	0	0	0	0	0	0	0
Total Power Losses			208.46	111.66	138.927	91.78	83.764	47.09	65.074	41.1

The loads connected to the buses also had an influence on the power losses in each branch. It can be observed that the reduction in power loss was best when the network reconfiguration was considered with DGs from the results given in case 4 in Table 4.3. There was a further decrease in power losses in the second branch and in all the other branches as compared to case 2 and case 3.

Table 4-4: Apparent power losses in the second branch (From bus 2 to 3)

CASES	P (kW)	Q (kVar)	S(kVA)	Loss reduction %	Comments
Case 1	51.602	26.280	57.909	-	No Investment
Case 2	26.677	13.590	29.939	48.30	Reconfiguration
Case 3	19.417	9.890	21.791	62.37	With DG units
Case 4	14.311	7.290	16.061	72.27	DG units + Reconfiguration

Table 4-4 shows the apparent power losses experienced in the second branch of the IEEE 33-bus RDS in the four cases analyzed. There is a significant apparent power loss reduction in case 4 from the original network (case 1) of 72.27%. It can be noted that the integration of DG units with network reconfiguration plays a major role in improving the losses, and there was a substantial amount of loss reduction as depicted in Table 4-4.

4.2 Comparative Study of Proposed MSSO Algorithm and Other Algorithms

The performance and merits of the proposed MSSO algorithm in network reconfiguration were demonstrated on an IEEE 33-bus test system and the obtained results were validated by comparing with other methods from the literature. The comparison was based on power loss reduction, voltage profile, computational burden and cost saving analysis. The ability

of the proposed MSSO algorithm in solving the network reconfiguration optimization problem used the mechanism depicted in Table 3-1 and the parameters mentioned at the end of chapter 3.

4.2.1 Comparative Results for different Algorithms before considering DGs

The results in Table 4-5 show the comparison of the proposed MSSO algorithm with different algorithms from the literature before considering DG units. The computational time for the proposed MSSO algorithm was 5.7s which was a short time-consuming process for the algorithm to converge to an optimum fitness function. Despite the same minimum voltages for the proposed MSSO algorithm and Hybrid Genetic Algorithm-Particle Swarm Optimization (HGAPSO) algorithm, they had a difference of 0.727 kW in power losses, making the proposed MSSO algorithm a better choice.

Table 4-5: Comparison of different algorithms for 33-bus test system without DG units

PARAMETERS	Proposed MSSO	HSA [6]	SPSO [46]	HGAPSO [29]	BPSO [46]
Tie switches	7 9 14 32 37	7 10 14 28 36	7 9 14 32 37	7 10 14 32 37	7 14 9 28 37
Best real P_{loss} (kW)	138.928	146.390	138.928	139.655	141.632
Loss reduction %	33.35	29.78	33.35	33.01	32.05
V_{min} (p.u)	0.9423	0.9336	0.9423	0.9423	0.9364
Comp. Time (s)	5.7	7.2	21.35	-	24.34

The proposed MSSO algorithm and Selective-PSO (SPSO) algorithm converged to a better fitness function (real power loss) with respect to other algorithms shown in Table 4-5. However, the proposed MSSO algorithm converged to an optimum fitness 15.6s

faster than the SPSO algorithm. The total minimum losses of the IEEE 33-bus system that can be obtained within permissible limits and without violating the constraints of the system were 138.928 kW. The proposed MSSO algorithm obtained better values as compared to other algorithms, thus demonstrating the effectiveness in solving network reconfiguration problems.

4.2.2 Cost Saving Analysis

The operational cost of switching a single switch during reconfiguration is taken to be \$0.041 from [47], and the cost of power per kWh is 0.094\$/kWh using the Malawian energy prices. The total cost of power lost per day before network reconfiguration was \$470.40 depicted in fig. 4.7 in the original network.

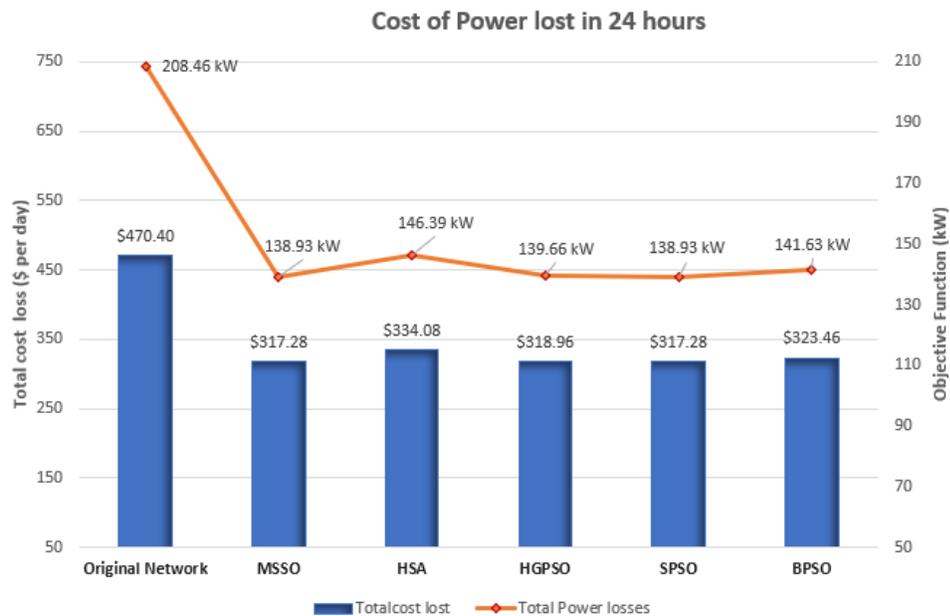


Figure 4.7: Total Cost Lost Analysis of the MSSO Algorithm with Other Algorithms

A cost reduction can be noticed in all the five algorithms applied in the IEEE 33-bus system for power loss reduction. It can be evidently seen from fig. 4.7 that the proposed MSSO algorithm and SPSO algorithm serves better in reducing the power losses and cost saving as compared to the other methods despite the number of switches altered in the network since they both had a similar minimum power loss value after reconfiguration. The total cost of power lost when the proposed MSSO algorithm was applied was the lowest at \$317.28 per day.

4.2.3 Comparative Results for different Algorithms considering DGs

The comparison of the proposed MSSO algorithm with Hybrid Modified Shuffled Frog Leap Algorithm-Particle Swarm Optimization (HMSFLA-PSO) and Binary Particle Swarm Optimization (BPSO) for the IEEE 33-bus test system considering DG units connected at specific buses shown in fig. A2 and Table A-2 in appendix A is tabulated in Table 4-6.

Table 4-6: Comparison of different algorithms for 33-bus system considering DG units

PARAMETERS	Proposed MSSO	HMSFLA-PSO [32]	BPSO
Optimal Tie switches	7 9 14 32 37	9 14 28 32 33	7 8 14 32 37
Best P_{loss} (kW)	64.9211	69.3962	67.1822
Average P_{loss} (kW)	66.5728	70.3263	68.0818
Worst P_{loss} (kW)	68.92481	70.9633	80.2109
Loss reduction %	68.86	66.71	67
V_{min} (p.u)	0.97002	0.95934	0.97002
Comp. Time (s)	5.1	-	29.29
DG placement (bus)	6,12,16,31	6,12,16,31	6,12,16,31
DG size (kW)	1998	1998	1998

It can be noted that four switches were changed in all the three algorithms whereby switches 33, 34, 35, 36 were switched on for BPSO and MSSO algorithm leaving out line 37 out of service. For the HMSFLA-PSO algorithm, switch 37 was online while switch 33 was out of service. The proposed MSSO algorithm performed better than the BPSO algorithm and the HMSFLA-PSO algorithm. Due to the stochastic nature of the proposed MSSO algorithm, 50 runs were performed in order to find the optimum fitness with the best iterations and convergence rate. The average CPU time taken to reach the optimum solution was 5.1s making it the fastest convergence rate as compared to the other algorithms tabulated in Table 4-6.

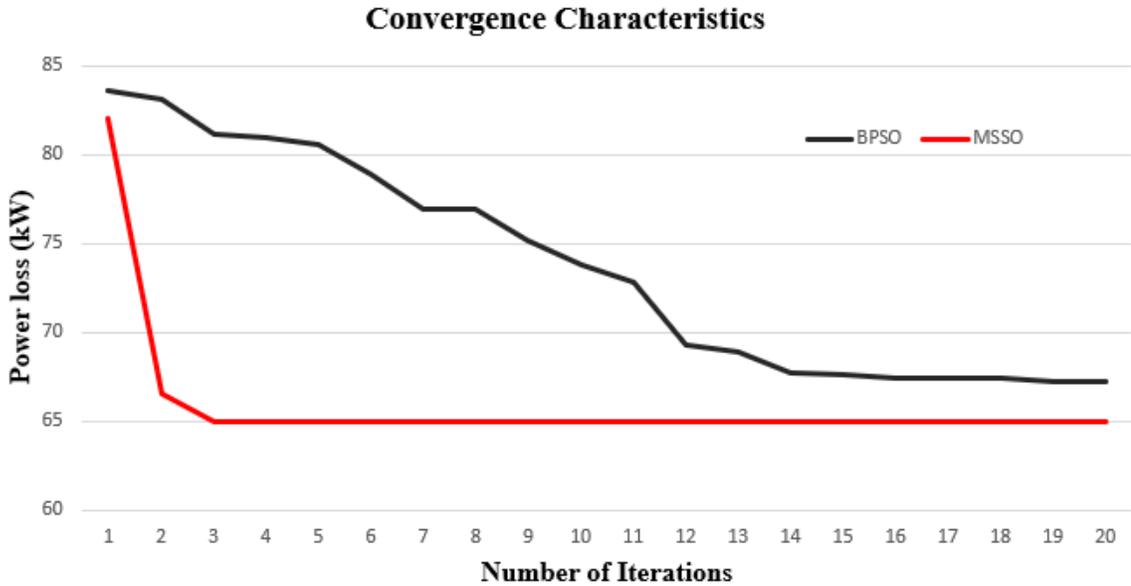


Figure 4.8: Convergence characteristics of MSSO and BPSO algorithm

The convergence rate of the proposed MSSO algorithm and BPSO algorithm are shown in fig 4.8. The algorithm searches for a switching sequence which gives an optimum

fitness function in a network for each load flow carried out in each iteration. The current least power losses in the system's switching sequence population will be maintained in each iteration until the shark smells a better solution with strong odor particles than the previous fitness function. Simulations were carried out for 20 iterations and the optimum solution was obtained after 3 iterations for the proposed MSSO algorithm. It had a faster convergence rate as compared to the BPSO algorithm. It also required shorter simulation time and a smaller number of iterations to reach an optimum solution.

4.3 Summary

The investigations were carried out on the IEEE 33-bus test RDS to optimize the overall distribution losses and improve the voltage profile by using a proposed MSSO algorithm to identify an optimum reconfiguration network with and without DG units, respectively. In the power flow analysis, the effectiveness of the proposed MSSO algorithm was tested and compared in different scenarios carried out in this study. For evaluation purpose, the proposed MSSO algorithm was compared with other algorithms from the literature. The results of the power losses in each and every branch in the network were recorded and tabulated. A graphical presentation of the voltage profiles, power losses, convergence characteristics and evaluation of power loss cost of the IEEE 33-bus test system were shown. A discussion was carried out in this chapter concluding with notable merits of the proposed MSSO algorithm over other algorithms from the literature on network reconfiguration problem.

CHAPTER 5 : CONCLUSION AND RECOMMENDATIONS

5.0 Overview

A general conclusion of the study is drawn with a summary of the results obtained for the proposed Modified Shark Smell Optimization (MSSO) algorithm, in comparison with the other algorithms which were used in network reconfiguration for power loss reduction and voltage profile improvement. Finally, the contributions of the work and future recommendations for further research are presented.

5.1 General Conclusion

The metaheuristic Modified Shark Smell Optimization (MSSO) algorithm was proposed to identify an optimum switching sequence in an IEEE 33-bus test radial distribution system (RDS) that achieved maximum power loss reduction and an improved voltage profile while maintaining the operating constraints of the network. Four different scenarios of the network were used to evaluate the effectiveness of the proposed MSSO algorithm. A comparative study was also carried out to compare the performance of the proposed MSSO algorithm with other algorithms from literature.

The purpose of network reconfiguration is to reduce the power losses in the distribution system during the power flow from the distribution substation to all the connected loads, ensure load balancing is achieved while improving the voltage profile. The loss

minimization through this technique offers the power utilities an opportunity to reduce energy costs using the existing equipment. In the research carried out, it can be noted that after reconfiguration of the system, the feeders were relieved from overloading by distributing the power flow to less loaded lines. The improvement in voltage at the buses indicated a relief of overloading on the feeders of the system.

The obtained results show that DG integration to the network reduced the power losses by 59.82% from the original network losses before introducing DG units. When optimal switch sequencing using the proposed MSSO algorithm was applied to the same network with DG units connected, a further loss reduction from 83.76 kW to 64.92 kW was observed. There was generally a significant improvement in voltage profile from 0.91075 p.u to 0.97002 p.u, with a substantial reduction in power losses of the entire distribution system. Since the DGs assist in supplying additional power to the distribution system, the decrease in power supplied from the substation helped to relieve the overloading experienced in the distribution power lines. This promoted efficient flow of power in the system when it operates in an unstrained manner.

The proposed MSSO algorithm had a higher convergence rate which took less than 6s to converge to the optimum fitness function making it suitable for real-time implementation. The algorithmic robustness and simplicity in coding made it easier to apply to the distribution system problem making it attractive as compared to other algorithms. The greedy search approach and heuristic information thoroughly guided and lead the search

to a speedy discovery of good solutions. The study also looked at the cost analysis of using the proposed MSSO algorithm with other algorithms. In the cost-saving analysis, it can be noted how the reconfigured network using the proposed MSSO algorithm saved \$153.12 per day from the initial network before reconfiguration. In conclusion, the proposed MSSO algorithm was superior over the other algorithms in literature.

5.2 Contributions

The main contribution of this research was to present a metaheuristic algorithm which identified optimum candidate switches that create a radial state topology with the least real power losses and improved voltage profile within a short period of time.

A new evolutionary Modified Shark Smell Optimization (MSSO) algorithm used in this study was inspired by the SSO algorithm and the PSO algorithm. Implementing the proposed MSSO algorithm in network reconfiguration resulted in a more robust and efficient application procedure. The proposed algorithm proved superior by comparing the obtained results to previously applied AI-based algorithms from literature.

The reconfiguration of the network can be used by power engineers and system operators to work with an optimum network topology at all times for a reliable and stable system. This will also facilitate a smooth transition of the network during expansion when incorporating distributed generation and increased growth demand.

The positive effects of the DGs in power loss objective function were emphasized in the results obtained in this study. A drastic decrease in power loss showed how the DGs played a powerful role in reducing the losses in distribution systems while improving the voltage profile.

5.3 Recommendations

There is still more research to be conducted with network operations in radial distribution systems. The areas recommended for future research include considering dynamic loads and DG operation modes, considering premature transformer failure cost, effects of unbalanced distribution systems, considering a combination of optimal capacitor placement and optimal feeder reconfiguration for further loss reduction and application of the proposed MSSO algorithm in a real-time system while considering transient effects of switching operations.

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APPENDICES

APPENDIX A: IEEE 33-TEST BUS RADIAL DISTRIBUTION SYSTEM AND DG SYSTEM DATA

A-1 Single Line Diagrams of the Test System

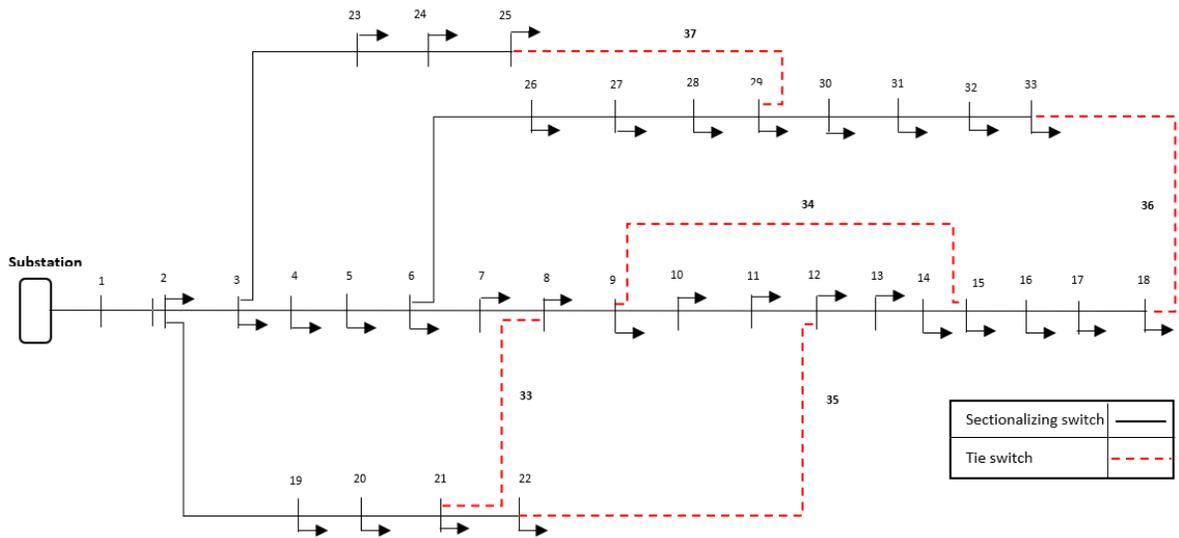


Figure A1: IEEE 33-bus test system

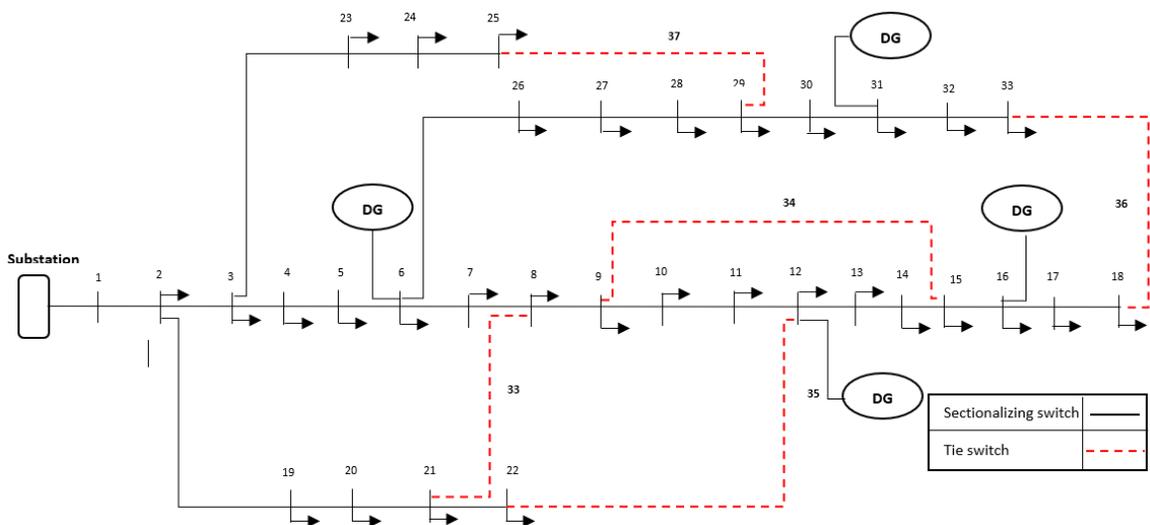


Figure A2: IEEE 33 bus system considering DG units

A-2 Data for 33-bus Test System and the DG units

Table A-1: System data for 33-bus test Radial Distribution System

Serial Number	Sending Node	Receiving Node	P (kW)	Q (KVAr)	R (ohms)	X (ohms)
1	1	2	100	60	0.0922	0.047
2	2	3	90	40	0.4930	0.2511
3	3	4	120	80	0.3660	0.1864
4	4	5	60	30	0.3811	0.1941
5	5	6	60	20	0.8190	0.707
6	6	7	200	100	0.1872	0.6188
7	7	8	200	100	0.7114	0.2351
8	8	9	60	20	1.0300	0.74
9	9	10	60	20	1.0440	0.74
10	10	11	45	30	0.1966	0.065
11	11	12	60	35	0.3744	0.1238
12	12	13	60	35	1.4680	1.155
13	13	14	120	80	0.5416	0.7219
14	14	15	60	10	0.5910	0.526
15	15	16	60	20	0.7463	0.545
16	16	17	60	20	1.2890	1.721
17	17	18	90	40	0.7320	0.574
18	2	19	90	40	0.1640	0.1565
19	19	20	90	40	1.5042	1.3554
20	20	21	90	40	0.4095	0.4784
21	21	22	90	40	0.7089	0.9373
22	3	23	90	50	0.4512	0.3083
23	23	24	420	200	0.8980	0.7091
24	24	25	420	200	0.8960	0.7011
25	6	26	60	25	0.2030	0.1034
26	26	27	60	25	0.2842	0.1447
27	27	28	60	20	1.0590	0.9337
28	28	29	120	70	0.8042	0.7006
29	29	30	200	600	0.5075	0.2585
30	30	31	150	70	0.9744	0.963
31	31	32	210	100	0.3105	0.3619
32	32	33	60	40	0.3410	0.5302
33	21	8	-	-	2.0000	2.0000
34	9	15	-	-	2.0000	2.0000
35	12	22	-	-	2.0000	2.0000
36	18	33	-	-	0.5000	0.5000
37	25	29	-	-	0.5000	0.5000

Table A-2: DG data [32]

Location (Bus#)	Size (kW)
6	499.5
12	499.5
16	499.5
31	499.5
Total	1998

APPENDIX B: MATLAB CODE FOR NETWORK RECONFIGURATION USING MODIFIED SHARK SMELL OPTIMIZATION ALGORITHM

B-1 Main Source Code for the Algorithm and Load Flow method

```

%% MODIFIED SHARK SMELL OPTIMIZATION ALGORITHM
% Done by Shaibu Ali Juma (June 2018)
% Department of Electrical Engineering, (Power Option)
% Pan Africa University, PAUSTI

%% (DEFINE DETAILS OF THE NETWORK RECONFIGURATION PROBLEM)
clear all
clear
clc
% INITIAL NETWORK CONFIGURATION FOR IEEE 33-BUS TEST SYSTEM
mpopt=mpoption('pf.alg','FDXB'); % Fast-Decoupled method using Matpower
data1 = loadcase(DG33); %Load IEEE 33-bus system data with/without DG
units
o = [33 34 35 36 37]; % Open/Tie switches
for c = 1 : length(o)
    data1.branch(o(c), 11) = 0;
end
loadflow = runpf(data1,mpopt); % Run LoadFlow using Fast Decoupled
method
InitialPloss = sum(loadflow.branch(:,14) +
loadflow.branch(:,16))*1e3;%System losses
InitialVoltage = loadflow.bus(:,8); % Voltages at the buses
Voltagegemin = min(InitialVoltage); % Minimum voltage
tap = [8 9 10 11 21 33 35 0 0 % Branches in the network
(Switches)
    2 3 4 5 6 7 18 19 20
    12 13 14 34 0 0 0 0 0
    15 16 17 29 30 31 36 32 0
    22 23 24 25 26 27 28 37 0];
ta = tap';

% INCIDENCE MATRIX
data = loadcase(DG33); % Load IEEE 33 system data with or without DG
units
doc = data.branch;
br = 37; % Branches
bs = 33; % Buses/nodes
matrix = zeros(br, bs); % Create a zero matrix

```

```

        bs1 = doc(:,1);
        bs2 = doc(:,2);
    for d = 1 : br
        matrix(d, bs1(d)) = 1;
        matrix(d, bs2(d)) = 1;
    %% DEFINE MSSO PARAMETERS
    dim = 5;                % Dimension of searching space (switching
sequences)
    n = 50;                % Population size of the particles
    a = 0.5.*rand();      % Inertia/momentum rate bwtm [0-1]
    b = 2.*rand();        % Velocity limiter ratio
    n1 = 0.9.*rand();     % Value in the interval / element bwtm
[0-1]
    t1 = 5.*rand();       % Time+ interval for the stage n given as
1
    M = 20;                % No. of points in the local search of each
stage n
    R1 = -1 + ( 1 + 1 ).*rand( n , dim );%Random no. bwtm [0-1] for
gradient term
    R2 = -1 + ( 1 + 1 ).*rand( n , dim );%Random no. bwtm [0-1] for
momentum term
    maxiter = 30;         % Maximum iteration

%INITIALIZE THE ODOR PARTICLES
x = load('swarm.m');     % Load the randomly created particles
(position)
z = zeros(n, dim);      % Creating a zero matrix of the z
position
y1 = zeros(n, dim);     % Creating a zero matrix of the y1
position
vnew = rand(n, dim);    % Creating an initial velocity
x1 = load('swarm.m');   % Creating a zero matrix of the x1
position
sigmoid = zeros(n, dim); % Creating a zero matrix sigmoid function
fitness = zeros(n,dim); % Creating a zero matrix fitness function
Lbest = load('swarm.m'); % Load the randomly created local best
matrix
Gbest = [33 34 35 36 37]; % Introducing a global best
Xbest = load('swarm.m'); % Load the randomly created best position
flbest = zeros(n, dim); % Creating a zero matrix of local fitness
function
    for k = 1 : n
        flbest(k) = 1000; % Calculating fitness function for local
best(Ploss)
    end

```

```

tic

% MAIN LOOP
for iter = 1 : maxiter

    % CALCULATING FITNESS FUNCTION FOR EACH ODOUR PARTICLE
    for k = 1 : n
        y = Xbest';
        data = loadcase(DG33) ; % Load IEEE 33 system data with or without DG
units
        mat = matrix;
        for m = 1 : dim
            data.branch(y(m,k),11) = 0;
            mat(Xbest(k,m), :) = 0;
        % CHECKING RADIALITY CONSTRAINT OF THE SYSTEM
        for cn = 1 : length(matrix(1,:))
            for r = 1 : length(matrix(1,:))
                if sum(mat(:,r)) == 1
                    row = find(mat(:,r));
                    mat(row,:) = 0;
                end
            end
        end
        if sum(sum(mat)) == 0
            result = runpf(data,mpopt);
            fitness(k) = sum(result.branch(:,14) +
result.branch(:,16))*1e3;
        end

        % UPDATING LOCAL BEST FOR THE SHARK (ODOUR CONCENTRATION)
        if fitness(k) < flbest(k)
            Lbest(k,:) = Xbest(k,:);
            flbest(k) = fitness(k);
        end

        % CALCULATING FITNESS FUNCTION FOR GLOBAL BEST FOR THE SHARK
        u = Gbest';
        data = loadcase(DG33); % Load IEEE 33 system data with/without DG
units
        for jj = 1 : length(u)
            data.branch(u(jj),11) = 0;
        end
        result = runpf(data,mpopt);
        fgbest = sum(result.branch(:,14) + result.branch(:,16))*1e3;
        gbestvolt = result.bus(:,8);
    end
end

```

```

        minvolt = min(gbestvolt);

% UPDATING SHARK'S GLOBAL BEST (STRONGER BLOOD/ODOR CONCENTRATION)
    if flbest(k) < fgbest
        Gbest = Lbest(k,:);
    end
end

%SHARK MOVEMENT
for i = 1 : n
    for j = 1 : dim
        % FORWARD MOVEMENT OF THE SHARK
        vnew(i,j) = min(abs(n1.*R1(i,j) + a.*R2(i,j).*vnew(i,j))...
            ,abs(b.*vnew(i,j))); %Velocity of
Shark

% UPDATING PARTICLES' COORDINATE
y1(i,j) = x(i,j) + vnew(i,j).*t1;%New Position due to forward movement
sigmoid(i,j)= length(nonzeros(ta(:,j)))/(1 + exp(-y1(i,j)));%sig
function
x1(i,j) = ta(ceil(sigmoid(i,j)),j);
%ROTATIONAL MOVEMENT OF THE SHARK
for ii = 1 : M
    R3 = - 1 + ( 1 + 1 ).*rand( n, dim );% Random no. in the range [-1 +1]
    z(i, j) = abs(x1(i,j) + ceil(R3(i,j).*x1(i,j)));% Local search
end
    Xbest(i, j) = min(x1(i,j) , z(i,j)); %Best position
end
end

gbestvolt;
q = sort(Gbest);
ploss = (InitialPloss - fgbest)*100 / InitialPloss;
figure(1)
plot(InitialVoltage, '--r')
hold on
plot(gbestvolt, '-g*')
ylabel('Voltage (p.u)')
xlabel('Node')
title('Voltage profile')
legend('Before Reconfig', 'After Reconfig')
hold off
pause(.1)
% PLOT THE POWER LOSSES
figure(2)
plot(iter, fgbest, 'r.')

```

```

hold on
xlabel('Iterations')
ylabel('Power losses')
title('LoadFlow')
grid on;
pause(.1)
end
disp('      ')
disp('      ')
disp('      ')
disp('      ')
disp('=====')
disp('=====')
disp('*****SIMULATION RESULTS OF 33 BUS DISTRIBUTION NETWORK')
disp('*****')
disp('=====')
disp('=====')
disp('          BEFORE RECONFIGURATION          AFTER RECONFIGURATION')
disp('')
disp('-----')
disp('-----')
disp(['Tie switches:          ', num2str(o), ' ',
      ', num2str(q)] ')
disp('-----')
disp('-----')
disp(['Power loss: ', num2str(InitialPloss), ' kW', ' ',
      num2str(fgbest), 'kW'])
disp('-----')
disp('-----')
disp(['Power loss reduction:  ', ' _____', ' ',
      num2str(ploss), ' %'])
disp('-----')
disp('-----')
disp(['Minimum voltage:', num2str(Voltagemin), ' ',
      ' ', num2str(minvolt), 'pu'])
disp('-----')
disp('-----')
toc
disp('      ')
disp('      ')

```

