MULTI-OBJECTIVE OPTIMAL PLANNING OF DISTRIBUTED GENERATORS USING IMPROVED GREY WOLF OPTIMIZER AND COMBINED POWER LOSS SENSITIVITY

by

Mohamed Sodani

Submitted in partial fulfillment of the requirements
for the degree of Master of Applied Science

at

Dalhousie University
Halifax, Nova Scotia
April 2021

This thesis is dedicated to my parents.For their love ,support and encouragement throughout my life

Table of Contents

List of Tables

List of Figures

Abstract

Over the past several years, there has been increased research and industry interest in finding ways to successfully integrate Distributed Generators (DGs) into distribution networks. The main reason for the recent surge in interest is the demonstrable benefits that DGs bring to power systems, such as notable reductions in power loss and improved reliability. However, to take full advantage of these benefits, it is crucial to determine optimal allocation (i.e., size and location) of the DGs in distribution networks. This thesis proposes and develops a hybrid approach to determining optimal sizing and location for Distributed Generator (DG) sources within a distribution system. The approach uses the Combined Power Loss Sensitivity (CPLS) factor along with the Improved Grey Wolf Optimizer (I-GWO) algorithm. In the proposed method, CPLS is employed to find candidate locations for incorporating DG in a network, and the I-GWO algorithm is used to determine optimal sizes and locations for the DG from the CPLS-suggested candidate buses. The aim is to simultaneously minimize power loss, enhance voltage stability, and improve the voltage profile through the application of the novel multi-objective strategy. The algorithm proposed in this work is evaluated using IEEE-33 and IEEE-69 bus radial distribution networks, and three types of DG contributions are investigated in order to compare performance and efficiency metrics. The results indicate that the proposed hybrid method, when compared to other popular optimization techniques , effectively achieves optimal results with regard to its multi-objective functions.

List of Abbreviations used

ABC Artificial Bee Colony.

ACO Ant Colony Optimization.

ALO Ant Lion Optimizer.

ASO Atom Sereach Optimization.

BBO Biogeography-Based Optimizer.

BH Black Hole.

BSA Backtracking Search Algorithm.

CHIO Coronavirus Herd Immunity Optimizer.

CPLS Combined Power Loss Sensitivity.

CSA Cuckoo Search Algorithm.

CSS Charged System Search.

DA Dragonfly Algorithm.

DE Dolphin Echolocation.

DGs Distributed Generators.

DLH Dimension Learning-based Hunting.

EA Evolutionary Algorithms.

FOA Fruitfly Otimization Algorithm.

GA Genetic Algorithm.

GOA Grasshopper Optimization Algorithm.

GS Gauss Seidel.

GSA Gravitational Search Algorithm.

GWO Grey Wolf Optimizer.

HGSO Henry Gas Solubility Optimization.

HHO Harris Hawks Optimizer.

I-GWO Improved Grey Wolf Optimizer.

ICA Imperialist Competitive Algorithm.

LCA League Championship Algorithm.

NR Newton Raphson.

NSA Number of Search Agents.

PSO Particle Swarm Optimization.

RDS Radial Distribution System.

SA Simulating Annealing.

SBA Social-Based Algorithm.

SSA Slap Swarm Algorithm.

TLBO Teaching-Learning-Based Optimization.

TS Tabu Search.

TVD Total Voltage Deviation.

VD Voltage Deviation.

VSI Voltage Stability Index.

WOA Whale Optimization Algorithm.

Acknowledgements

There are many who helped me along the way on this work.Without their support, guidance and encouragement this work would not have been accomplished. I would like to take a moment to thank them:

Firstly , I would like to offer special thank to Dr.El-Hawary who passed away while I was under his supervision at the beginning of my academic journey. Secondly, I would like to thank my supervisor Dr.Timothy Little and Co-supervisor Dr.Hamed Aly for their guidance and support. A special thanks to Dr.Hamed for helping me with the publication and the assistant through each stage of this work.I would never forget to extend a special thanks to committee members Dr.Gu and Dr.Phillips.

I also would like to thank my home country Libya. A special thank as well to Sirte University in my hometown. I also wish to thank the Libyan-North American Scholarship Program and Faculty of Graduate Studies for their financial support.

Last but not least,My appreciation also goes out to all my colleagues for their encouragement and support all through my studies.

Lastly,I would like to express my deepest appreciation to my parents,brothers,sisters and friends. For their endless love and support. Without their tremendous understanding and encouragement , it would be impossible for me to complete my study.

Chapter 1

INTRODUCTION

1.1 Background

An electric power system is divided into three main subsystems (generation, transmission and distribution), with transmission lines connecting loads at distribution system with power from generation stations . Although approximately 30% of power losses in the system occur at the transmission level, nearly 70% of the losses occur at the distribution level, making distribution systems a major focus of research. In power systems, the distribution portion connects high-voltage transmission networks to low-voltage consumer service points. Distribution systems are a critical part of electric power systems, as the power supply on the consumer side requires efficient distribution. Therefore, investment in distribution systems comprises a substantial portion of the overall investment in power systems (Reddy et al., 2017).

Distribution systems also provide connections for major loads (e.g., commercial, domestic, industrial) within a network. As a result, service quality can be heavily dependent on power continuity and the maintenance of supply voltage with specific frequencies and limits. Distribution systems typically encounter a number of challenges, including high R/X ratio in transmission lines, rapid spread in loads, power loss, power factor, system reliability, and issues related to voltage profile. The installation of DGs units in the vicinity of load centers may assist in resolving or at least mitigating some or all of these challenges (Abou El-Ela et al., 2016).

Nowadays, many traditional power plants are being replaced with DG units as an alternative option for supplying load demand. The increased use of these units in power systems brings notable advantages that includes decreases in distribution network congestion, the ability to supply sensitive loads during power outages, and a general improvement in system performance through better voltage profiles and decreased power loss. Along with enhanced performance, other motivations for adopting DG in power grids are its reputation for being environmentally friendly as well as a gateway to renewable energy technologies, and its beneficial ability to position energy generation in an open electric power market (Razavi et al., 2019).

Distributed generation, unlike centralized generation, produces electric power in small generation units located near energy consumers. The units may be either a conventional or renewable type. Also known as "dispersed" or "decentralized" generation. Figure 1.1 shows the difference between centralized generation system and DG as decentralized generation system (Ehsan and Yang, 2018). DG can bring significant economic and environmental advantages through optimal placement and sizing within power systems (HA et al., 2017). Therefore, extensive research has been conducted to determine the most appropriate location and size for DG units to achieve optimal system performance.

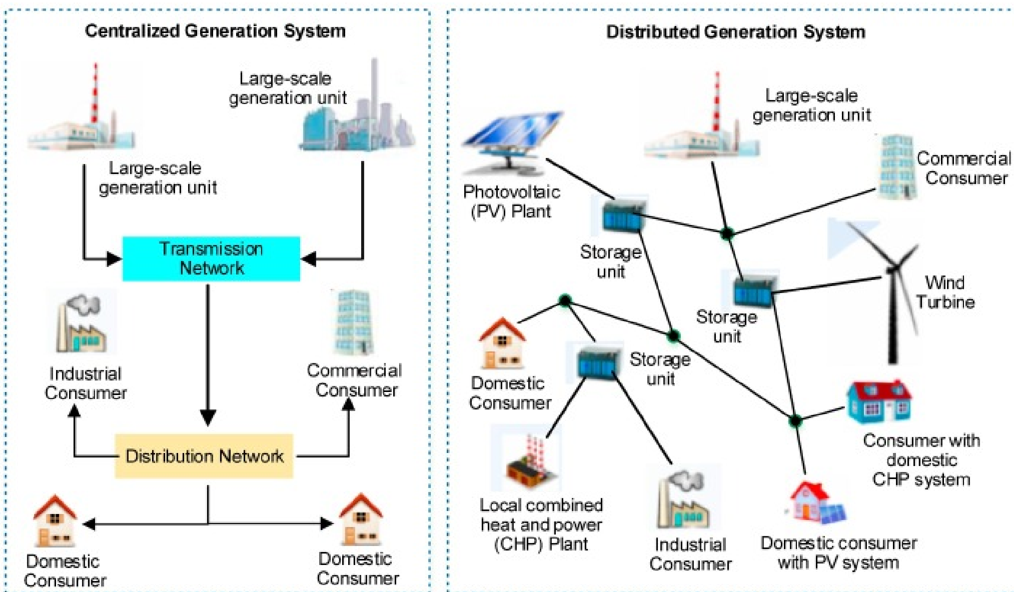


Figure 1.1: Centralized and Distributed Generation System

1.2 Motivation

To obtain maximum benefits from distributed generation, it is crucial for researchers and operators to find a way to determine DG units' optimal location and capacity, as errors in placement or size could cause more system loss than in systems that do not have DG. System loss is already a major problem in utilities, so contributing to the problem by misplacing or inappropriately sizing DG units would cause issues not just on the supply side but also on the demand side (Reddy et al., 2017). Due to the critical importance of DG unit placement and sizing, solving the optimization problem is the primary motivation of this thesis work.

1.3 Thesis Objective

Distributed generator (DG) is included within distribution systems for the following main reasons: to reduce power loss, to lower Voltage Deviation (VD), and to boost the Voltage Stability Index (VSI). In view of these goals, the present work uses a hybrid of the CPLS factor and I-GWO algorithm to determine optimal location and sizing for DG units within radial distribution systems. The primary contributions of this study to the literature are given in the summary below:

- A hybrid optimization technique is introduced to remedy the shortfalls that may occur in metaheuristic optimization techniques, especially with regard to decreasing search space. The present work proposes a hybrid approach that combines CPLS and the I-GWO heuristic optimization technique.

- The purpose in creating a hybrid approach using CPLS and I-GWO is to determine optimized location and sizing for DG units within radial distribution in order to minimize power loss, enhance voltage stability, and improve voltage profile.

- The majority of the studies that focus on DG optimization problems tend to deal only with single objective functions. The present research, however, considers the optimization problem as multi-objective and aims for simultaneous optimization of more than one function.

- The algorithm proposed in this work is evaluated using IEEE- 33 and IEEE-69 bus radial distribution networks. Additionally, three types of DG contributions are investigated in order to compare performance and efficiency metrics.

- To measure the effectiveness of the proposed approach, comparison tests for I-GWO along with some well-known optimization strategies are conducted. The comparisons use standard IEEE-33 and IEEE- 69 bus distribution systems under a range of operating scenarios.

1.4 Thesis Outline

The rest of the work is organised as follows:

Chapter 2 – Literature Review.

The second chapter provides the reader with a comprehensive literature review about few methods that have been proposed regarding DG allocation problem.

Chapter 3 – Heuristic Optimization Techniques.

This chapter reviews some of the heuristic optimization techniques that found in the literature.

Chapter 4 – Overview of Proposed Hybrid Method.

This chapter explain the development and implementation of the proposed hybrid technique which include Improved Grey Wolf Optimizer and Combined Power Loss Sensitivity .

Chapter 5 – The Problem Formulation.

The mathematical formulation that includes the objective function and system constraints used are presented in this chapter.

Chapter 6 – Test Results and Discussion.

The developed approach is tested on a two radial distribution system and the results obtained are discussed.

Chapter 7 – Conclusion and Future Research.

The last chapter presents the concluding remarks and the possible directions in which this work can be extended.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

Finding the optimal installation of distributed generator (DG) in various kinds of distribution systems is an ongoing challenge for system planners, engineers, and researchers in the field. Over the past decade, many different approaches have been proposed and developed in the literature. This chapter looks at the main research which has been conducted in relation to DG and also considers integration problems. In addition, the chapter reviews and analyzes a few recent methods that have been proposed regarding optimal DG sizing and placement.

2.2 Distributed Generator

Until recently, stand-by or back-up power sources for domestic and small-scale commercial consumers was generally provided by small generation under conditions of grid power outages. Diesel generation was one of the most types of DG back then. However, thanks to recent improvements, DG technologies can now be applied to domestic and small-scale commercial customers as well as support a whole network operating parallel to the grid. DG energy technologies may be classified as being either renewable or non-renewable. Renewable energy technology works with energy sources from wind, tides, sun, geothermal, etc., while non-renewable technology includes gas turbines, micro turbines, internal combustion engines, and so on. Despite being quite small in comparison to central generation, DG is still sufficiently large to provide the power needs of a small-scale customer base (Kashem et al., 2006).

Distributed generators, which operate in distribution systems, provide electricity in homes and small commercial businesses. There are several different types of DGs, but one of the main feature of each is the real and reactive power injection. Table 2.1 lists the main DG type based on power injection (Kola, 2018).

Table 2.1: DG type based on power injection and its technology.

No.	DG Type	Power Factor	technology
1.	Injecting only real power P+	1	Solar or micro turbine
2.	Injecting only reactive power Q+	0	Capacitors bank
3.	Real and reactive power injecting	$0 < PF < 1$	Synchronous machines

There are numerous environmental, economic and technical advantages to integrating DG units in existing systems. The main advantages are listed below.

1. Environmental:
   - Decreased greenhouse gas emissions.
   - No waste water.
   - Drastically reduces land use for transmission construction.
2. . Economical:
   - Reduced costs associated with installation, operation, and maintenance
   - Investment deferrals related to facility upgrades
   - Lower reserve requirements and related expenditures.
   - Lower fuel costs as a result of improved efficiency.
3. . Technical:
   - Overall increases in system efficiency.
   - Improved voltage profile.
   - Improved power quality.
   - Improved system reliability.
   - Decreased system losses.

2.3 DG Integration Challenges

As DG integration in electric power systems becomes increasingly viable, the benefits of using DG are also becoming more evident. For instance, DG may be used to lower congestion rates in transmission and distribution networks or to supply sensitive loads during power outages. It may also be used to enhance system performance through boosting voltage profiles and reducing power losses.However,DG brings in different technical challenges such as power equality and voltage stability issues (Gupta and Seethalekshmi, 2019).

Recently, the motivation to integrate DG into existing systems has been prompted not only by technical but also environmental concerns (Heideier et al., 2020). As the harmful environmental effects of traditional thermal power plants becomes more widely known to their customer base, companies are looking for alternative substitutes to generate electrical power to satisfy customer demand. This is happening at the same time as renewable energy technologies are experiencing rapid advances and their costs are decreasing. However, it is not enough simply to adopt a new technology because of its environmental friendliness; in order to achieve optimal DG installation outcomes, placement and sizing must be appropriate to the need. To determine the right placement and sizing for DG, several different approaches such as deterministic, heuristic and analytic procedures have been proposed and developed in the literature. The next sections present a review of the most promising of these methods.

2.4 Sizing and Location

To maximize the advantages of integrating DG into existing systems, the DG units need to be the right size and at the right location. Done correctly, DG can provide benefits such as reduced overall operation and maintenance expenditures, improved voltage profile, reduced system loss, better power quality, and enhanced reliability and stability. Below is a selection of the main technical strategies and classifications employed in DG allocation and sizing.

2.4.1 Analytical Method

Despite being mostly inappropriate for larger and more complex networks, analytical approaches work well in smaller and less complex systems. According to Willis (2000), Willis proposed using the well-known 2/3 rule (developed to determine suitable capacitor placement) for finding the best DG placement bus candidates. In other words, the DG would be installed at a rating which is 2/3 that of the utilized load and 2/3 the length of the radial feeder located down-stream of the source substation . The 2/3 rule, however, is best suited to distributed and all reacted loads that are uniform, have a radial configuration, and contain a fixed conductor size across the distribution network. Such parameters restrict the rule's applicability, making it appropriate mainly only to single DG planning systems.

Another approach employed an analytical DG placement and sizing strategy for loss reduction in power distribution systems. This approach uses a novel expression of the power flow problem that is direct, non-iterative, and does not apply convergence issues (Elsaiah et al., 2014). Elsaiah found the proposed power flow solution to be especially suited to power flow estimations that are fast and repetitive. The researcher also devised a priority list according to loss sensitivity factors in order to determine the best locations for the investigated DG units. As well, sensitivity analysis was conducted to find the best power factor and size. Based on the outcomes, a number of solutions were presented as viable options for decreasing overall system loss.

Keane and O'Malley (2005) investigated maximizing DG sizing for an Irish system. Their experiment involved utilizing a constrained Linear Programming method. The aim of the investigation was to see if Ireland could satisfy the European regulation regarding the percentage of renewable resources to be applied for energy production by 2010; for Ireland, the regulation stipulated 13.2%. In their investigation, the researchers linearized the nonlinear constraints in order to apply them for the Linear Programming strategy. As well, they installed a DG unit for each system bus and ranked each candidate bus to accord with its optimal objective function value.

Hedayati et al. (2008) used a continuous power flow approach for determining which buses were most vulnerable to voltage collapse. The most sensitive bus sets were ranked according to severity, a designation which then was applied to allocate possible bus locations for single or multiple DG source placements. The researchers Hedayati et al. (2008) suggested using an iterative method to optimally place the DG. Next, a range of DG capacities that were fixed a priori were included in the distribution system, after which a traditional power flow approach was used to calculate the voltage profiles, power transfer capacity, and real power losses . Another DG of identical capacity was used in a subsequent iteration and included in the next sensitive bus. This process of iteration continued to the point when the system results had achieved acceptable values. However, this strategy did not attempt to optimize DG sizing .

Duong, in Hung et al. (2010), employed analytical expression to determine the optimal power factor and size various kinds of DGs, with the aim of reducing losses in distribution systems. The researcher tested three distribution systems of different complexity and size applied a number of load flow solutions. The test results indicate that loss reduction is significantly affected by the DGs location, operational power factor and size. Duong Hung et al. (2010) noted that losses can be significantly decreased if the DGs are correctly located, operated and sized.

Griffin et al. (2000) analyzed DG optimal location by considering two kinds of continuous loads (uniform-increasing and uniform-distributed). Their main aim in this work was decreasing line losses. The researchers found that optimal siting for DGs in large part depends on load distribution in the feeder. Further, they noted that there was a significant decrease in loss in cases where the DG was located at or near the end of a load that was uniform-increasing, whereas the optimal placement for uniform distribution was the middle of the load .

Another paper applied analytical studies to find optimal placement for DGs to minimize total losses in different type of distributed load profiles (e.g., uniform, increasing and centrally distributed) in radial systems. Optimal DG placement and size were analyzed by looking at the impacts of static load models. However , as these studies applied the phasor current injection technique with unrealistic load profile assumptions namely, uniform, increasing, and centrally distributed).the solutions are not applicable to real systems Gozel et al. (2005).

Mahmoud et al. (2015) used an analytical approach to investigate the viability of minimizing power losses by finding optimal allocations of DGs in a range of electrical distribution systems. The researchers' strategy was applied find the most suitable DG combinations that would minimize loss. In their work, DG allocations were conducted by employing two IEEE test systems (i.e., 33- and 69-bus systems).

2.4.2 Meta-heuristic Optimizations Method:

Metaheuristic methods, which are applicable to optimization problems, can be readily modified to deal with the various aspects unique to studies on power systems. Over the years, a broad range of optimization algorithms and strategies have been used to tackle energy technology problems related to DGs. Of these, metaheuristic global optimization approaches are becoming increasingly popular for solving real-life problems and global optimization functions, due to their relative simplicity, adaptability, and robustness. A selection of the main optimization methods applied in the literature to address the DG integration problem is presented below.

According to Teng et al. (2002), Teng et al. proposed a value-based approach Genetic Algorithm (GA) to tackle the DG issue. Their strategy was successful in maximizing the DG benefit aspect of the cost/benefit ratio when applying relevant boundary constraints (e.g., voltage drop, feeder transfer capacity, and ratio index). One drawback in their proposal was the assumption that the DG bus locations would be utility-provided. Other metaheuristic methods were developed that aim to position DG units optimally within a network, including another work based on Backtracking Search Algorithm (BSA) El-Fergany (2015). This approach is intended to place DGs throughout Radial Distribution System (RDS). To do so, an objective function and weighting factor are adopted to decrease the network's real losses while improving the voltage profile and subsequent operational performance. To test its viability, BSA is tested on 33- and 94-bus on the system (El-Fergany, 2015).

Nguyen and Truong (2015) developed a reconfiguration strategy that used a Cuckoo Search Algorithm (CSA) for reducing active power losses and optimizing voltage magnitude. CSA represents a novel approach to metaheuristic algorithms for solving optimization problems and is based on the cuckoo bird's obligate brood parasitism, where the cuckoo lays its eggs in other birds' nests. The researchers test the CSA's effectiveness using 33-, 69- and 119-node distribution network systems.

In Prakash and Lakshminarayana (2016), Prakash and Lakshminarayana use a Particle Swarm Optimization (PSO) algorithm to find a DG's optimal size and placement. The authors analyze and compare IEEE 33- and 69-bus radial distribution systems, with the individual systems applied to two cases. The results indicate that the PSO approach used in this study is effective not only for determining the size and location of a DG, but also for minimizing power loss Prakash and Lakshminarayana (2016). Meanwhile, the researchers in Yammani et al. (2012) apply a population-based algorithm known as shuffled frog leaping. Although this approach is useful in solving a variety of complex nonlinear, non-differentiable and multimodal problems, it significantly slows the speed of convergence and also leads to premature convergence.

In Li et al. (2013) adopted game optimization theory for optimizing multi-objective functions in order to precisely determine a DG's best-case size and placement. The proposed strategy was tested on an 8-bus network. Around the same time, Ameli et al. (2014) used a multi-objective PSO algorithm both for DG optimal placement and sizing and for contract pricing the power generated. The strategy was applied to a 33-node RDS. The authors found that their approach not only improved the reliability of the power supply, but also enhanced the voltage stability and profile, and cut power losses (Ameli et al., 2014).

A nature-inspired Whale Optimization Algorithm (WOA) was proposed for finding optimal DG sizing. This approach employs the humpback whale's hunting strategies, which is known to be unique behavior among whales. The aim of the study was to enhance the voltage profile and reduce system power losses using WOA. To that end, the method was applied to IEEE 15-, 33-, 69- and 85-bus radial distribution systems that had a range of different DGs Reddy et al. (2017).

An animal behavior-based algorithm was also applied in Sobieh et al. (2017) with the Grey Wolf Optimizer (GWO). As with the other studies, the authors were looking to optimize the placement, size and number of DGs in order to reduce power loss and enhance the voltage profile in RDS. GWO was tested on IEEE 33- and 69-bus systems under a variety of scenarios featuring DG units (Sobieh et al., 2017).

2.4.3 Hybrid Optimization Methods:

The hybrid approach addresses the inherent disadvantages found in the metaheuristic optimization approach and also notably reduces the required search space. As its name implies, the hybrid strategy combines two or more optimization methods to find the best solution Kola (2018). The next section presents the main research conducted using the hybrid method.

In Gandomkar et al. (2005) , Gandomkar et al. employ a hybrid approach to solve DG integration and sizing problems. The researchers use Genetic algorithm and Tabu search together to decrease the real power loss that are dependent on boundary conditions. In so doing, they limited DG number and gross capacity and enhanced the objective function by applying penalty terms to deal with constraint violations. The researchers in Tan et al. (2013) also employed a hybrid algorithm,this time is population base and using PSO and Gravitational Search Algorithm (GSA). The goal as , in the other works, was to determine the best size and placement in a distribution system for the multiple DGs under study. Voltage profile and real power loss in the system were considered in the tests, along with DG quantity, greenhouse gas emission (Tan et al., 2013).
A hybrid algorithm was employed in Kefayat et al. (2015) , using an Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) algorithm to test for ,among other considerations, energy costs, emission, voltage stability, and total active power losses. The objective in using ACO-ABC algorithm was find the optimal size and location for the DGs. For the test, the authors applied two scenarios with different energy source. (Kefayat et al., 2015) .

Mohan and Albert (2017) tested a hybrid GA-PSO algorithm with the intention of reducing losses in a radial distribution system while sustaining reasonable voltage profiles. The testing focused on the optimal placement and size of DGs with the aim to boost voltage stability and decrease operational costs and loss. The authors tested their algorithm on IEEE 33- and 69-bus systems (Mohan and Albert, 2017) .

In Jegadeesan and Venkatasubbu (2017), Jegadeesan and Venkatasubbu developed a hybrid algorithm that combined GA with ABC. Their aim was to reduce loss by determining optimal sizing and placement for multiple capacitors and DGs in radial distribution systems. To test the hybrid algorithm, it was applied to IEEE 33- and 69-bus radial systems . In a related study, Javidtash et al. (2017) combined non-dominated sorting GA with a fuzzy method in order to decrease real power loss, cost, voltage deviations, and emissions. The hybrid algorithm was tested on a standard 34-bus test micro grid (Javidtash et al., 2017).The researchers in Alzaidi et al. (2019)

combined the metaheuristic WOA and Slap Swarm Algorithm (SSA) algorithms into WOA-SSA. This strategy intended to reduce overall real power loss as well as minimize voltage deviation through the installation of multiple DG units across two radial distribution systems (Alzaidi et al., 2019) .

More recently,in Suresh and Edward (2020), a hybrid approach was used for optimizing DG size and placement in distribution system in order to decreases losses. The method combined the Grasshopper Optimization Algorithm (GOA) and the CSA strategies, representing an upgrading of the GOA optimization behaviour. The author applied the hybrid GOA-CSA algorithm in search of the best placement and size for DG units to minimize power loss while optimizing power flow and enhancing voltage profile. The proposed hybrid algorithm used MATLAB as platform, testing it on 33 and 69 IEEE systems (Suresh and Edward, 2020)

2.5 Summary

This chapter started with an overview of the distributed generations and their challenges in integrating into the system.This was followed by a review of different approaches for DG allocation problem.

Chapter 3

HEURISTIC OPTIMIZATION TECHNIQUES

3.1 Introduction

The branch of mathematics and computational science that deals with the procedures and procedures employed to identify the "best" solution of a certain "optimization" problem is know as optimization. In these problems the goal is to lessen or increase one or more objective functions depending on one or more variables and some constraints. The constraints that indicate the nature of system for an optimization problem which affect the objective function under consideration along with other operational limitations.

Different methods can lead to solve the problems. Often, the objective function and/or the limitations of system are non-linear in nature which change the optimization problem into a non-linear problem. Nevertheless, a wide variety of optimization problems such as linear programming have been solved using specially designed optimization methods.

Power systems involve complex problems and are linked to a large amount of data sets. In a simulation situation, even if one can create an exact algorithm, and uses it to find the best optimal solution to a problem, the solution time and space complexity may not allow the use of such system. However, problems whose dimensions and complexity do not require the use of exact solution method can be solved by using partial or approximate solutions. This is the case for many problems. The objective of Heuristic algorithms is to use approximate solutions and identify the optimum solution among all possible options. A search space is defined as the collections of all possible solutions to a given problem. Heuristic solutions are systems that involve a compromise between quality and speed at which solution can be found in order to find a solution that is acceptable within a time frame that is reasonable. Many difficult have been solved by evolving heuristic techniques. Hybrid techniques also which involve combined heuristic techniques or use conventional techniques such as statistical analysis can solve extremely complicated problems (Pezzini et al., 2011).

Some Heuristic algorithms attain a sequence of locally best available choices and create the solution in a progressive way. While they are efficient at computing, they do not ensure or guarantee the overall optimum solution (global optimum). Actually, at every stage a decision which looks good is made without taking into account the future results. This creates an imperfect solution since it does not contain any previous guarantee to be a globally best solution. Such algorithms are used when one does not need a perfect answer, but an approximate answer fulfills the initial need. If one needs to improve the quality of answer, different suitable heuristic methods can be used to meet such requirements as discussed later (Pezzini et al., 2011).

A family of searching algorithms which could approach and solve complicated optimization problems were first introduced in mid-80s and were called metaheuristics (Mirjalili and Lewis, 2016). The most striking feature of metaheuristic algorithms is that they are simple and require no special knowledge related to the optimization problem under consideration. This is why most of these algorithms are able to provide only approximate solutions.

Since Metaheuristic algorithms move towards an optimum solution by evaluating an objective function and compare the later results with earlier optimized results, therefore they can be viewed as advanced versions of heuristic algorithms. Metaheuristic algorithms are driven from nature and are built to solve problems in a general method (Mirjalili and Lewis, 2016).

Metaheuristic algorithms which are inspired by nature, use biological or physical phenomenons to solve optimization problems. They can be classified into four groups: evolution-based, physics-based, swarm-based and human-based methods. A more detailed overview of these algorithms is presented in next sections (Nadimi-Shahraki et al., 2021).

3.2 Evolution Based Techniques

Natural laws of evolution are the source of inspiration for evolution-based methods. The process of search begins with a randomly created population which is evolved over later generations. The best thing about these algorithms is that they use the best available set of individuals to form next group of individuals. In this method population is optimized over the course of generations. Below is the list of most common evolution-based techniques:

3.2.1 Genetic Algorithms

The Genetic Algorithm (GA)is an advanced form of evolutionary search in general evolutionary computation context. Holland (1975) first developed the GAs followed by Goldberg and Holland (1988) and De Jong (1985). Three basic parameters of genetics and natural selection namely selection, crossover and mutation are core search strategies used by GAs. To choose parent individuals, selection is used which is based on the fitness function. After parent chromosomes are selected, they move to the crossover stage where they produce two descendants. Crossover is advantageous in the sense that new individual can have best qualities of the both parents. The new offspring will have slightly different genes which would be the result of applying the mutation operator. Novelty in genetic material is ensured by the virtue of mutation. Once this population is completed, the new generation would replace the older generation and selection-crossover-mutation process will start over for next generation. In order to ensure the retention of best solution and not losing it by stochastic character of above procedure, De Jong (1985) proposed a special procedure for replacement and called it elitism. This procedure makes a copy of the best individuals from present generation and pass it to the next generation without making any changes.

3.2.2 Genetic programming

If each individual in the population is considered a computer program in a genetic algorithm, it can be termed as genetic programming. The reproduction method comprises of selection of a computer program from available programs based on the fact that how well it fits, i.e. fitter individuals have more chance of being selected, and then allowing it to stay in by making a copy and adding to new population. Then, the crossover program produces offspring program from the parents programs which had been selected by virtue of their fitness. The size and shape of offspring programs is different than that of parent programs. Mutation operation can also be applied to genetic programing. After genetic operation is completed on current population also known as old generation, the offspring population, also known as new generation, swaps the older population, also known as older generation. In the new population, the fitness of each individual is measured, and the process starts repeating itself over the course of many generation. The state of process at every stage of highly decentralized, locally controlled and highly parallel process consists of population based on current set of individuals.Table 3.1 shows more evolution based algorithms.

The observed fitness of individuals dealing with the problematic environment in the current population is the driving force behind this process. This algorithm will generate population of programs which will express increased average fitness over the course of many generations, as will be visible. The result of genetic programming is typically the best so far individual appeared over a course of generations (Koza, 1995).

Table 3.1: Evolution -based optimization algorithms

Algorithm	Year	Inspiration	Reference
Biogeography-Based Optimizer (BBO)	2009	Inspired by mathematics of biogeography	(Simon, 2008)
Evolutionary Algorithms (EA)	2013	Inspired by genetic inheritance	(Dasgupta and Michalewicz, 2013)

3.3 Physical – Based Techniques

Physical rules in the world are mimicked by Physics-based methods. The most common algorithms are:

3.3.1 Simulating Annealing

First algorithms extending local search methods which have a clear strategy to get out of the local optima are commonly known as Simulating Annealing (SA) (Kirkpatrick et al., 1983). Four component are required: A comprehensive explanation of system configuration; a random producer of “moves” or reorganization or components in a configuration; a quantitative objective function consisting of the compromises to be made and an annealing timeframe of temperature and time period for which the system needs to be advanced. The basic idea is to exclude the moves which result in solutions of inferior quality from the local optima. This way, likelihood of having such moves decreases over time during search process. Despite having been proposed in 1983, SA is still being studied and applied to many optimization problems. It is also used as a component of other search algorithms. Further studies to produce more effective SA models are being undertaken because of its excellent role in metaheuristic field.

3.3.2 Gravitational Local Search Algorithm

To find superior solutions, this algorithm tries to find the optimal solution to the problem by starting to search randomly in a solution space and then finding in the "local" area around the starting stage. When present halt conditions are satisfied or when a solution which is found which according to algorithm is the best solution, the process completes. This type of algorithm is a repair-based system where a it starts with a solution that's already present and then tries to "repair" it by varying one or more ingredients of solution in order to bring it near the optimal solution. This type of algorithm employs natural laws of gravity that apply on a moving body through space and mimics those principles of gravity to deal with solution at hand and create a repaired solution that is optimal (Webster and Bernhard, 2003).

Table 3.2 shows more algorithms in this category.

Table 3.2: Physics -based optimization algorithms

Algorithm	Year	Inspiration	Reference
Charged System Search (CSS)	2010	Inspired by principles from physics and mechanics	(Kaveh and Talatahari, 2010)
Black Hole (BH)	2013	Black hole phenomenon	(Hatamlou, 2013)
Atom Sereach Optimization (ASO)	2019	inspired by basic molecular dynamics	(Zhao et al., 2019)
Henry Gas Solubility Optimization (HGSO)	2019	Inspired by Henry's law	(Hashim et al., 2019)

3.4 Swarm Based Techniques:

The third group of methods which are inspired from nature consists of swarm-based techniques. These models imitate the social behavior of group of animals. The most common algorithm are:

3.4.1 Particle Swarm Optimization

Kennedy and Eherhart in mid-1990s developed the method called The Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995) . The behaviour of animals such as birds and insects is simulated in the PSO algorithm using stochastic optimization methods. In order to find the best optimal solution in a search space, these algorithms use the exact same principles as birds and insects do to find the best place in a flock or swam respectively. The beginning point of PSO algorithms is like bunch of particles which comprise random available feasible solutions. In a swarm, every single particle is given a starting velocity and they start moving in problem search space as soon as they are assigned a velocity. From this search space, the algorithm starts picking particles based on the best fitness which in turn tracks back to the best location achieved by these particles across the whole crowd. Depending upon the application of algorithm, the rules that govern the updating of PSO algorithms are based on many striking features which are adjusted and modified.

3.4.2 Whale Optimization Algorithm

Mirjalili and Lewis introduced a new nature-inspired metaheuristic optimization algorithm, known as WOA in 2016 (Mirjalili and Lewis, 2016). The biggest and intelligent mammals in the world are whales. The special hunting method used by whales based on bubble-net attacking technique to search food is the source of derivation for this algorithm. Humpback whales swim around the target and create bubbles around 9-shaped path in order to search for food. Circling the target, bubble-net attacking (exploitation phase) and searching for target (exploration phase) are the main steps taken by whales in this process.

Table 3.3 shows Some recent algorithms in this category

Table 3.3: Swarm-based optimization algorithms

Algorithm	Year	Inspiration	Reference
Fruitfly Otimization Algorithm (FOA)	2012	Fruit fly	(Pan, 2012)
Dolphin Echolocation (DE)	2013	Inspired by dolphin	(Kaveh and Farhoudi, 2013)
Ant Lion Optimizer (ALO)	2015	Hunting mechanism of antlions in nature	(Mirjalili, 2015)
Dragonfly Algorithm (DA)	2016	Behaviours of dragonflies in nature	(Mirjalili, 2016)
Grasshopper Optimizer Algorithm (GOA)	2017	Mimics the behaviour of grasshopper swarms in nature	(Saremi et al., 2017)
Harris Hawks Optimizer (HHO)	2019	Behavior and chasing style of Harris' hawks in nature	(Heidari et al., 2019)

3.5 Human Base Techniques

This group of metaheuristic techniques are inspired from human behaviors. Among these methods, some of the most commonly used methods are:

3.5.1 Tabu Search

This method was presented by (Glover, 1986). In this strategy, a Tabu list which consists of successive approximations, is created which helps in avoiding returning to the same solutions which have already been explored. Because of the fact that the Tabu list has a specific length, the list can be reconsidered after a number of stages. First in-first out method is used whenever a new solution is added to the list i.e. each new solution replaces the oldest solution. New approximation can be produced in multiple ways. The Tabu Search (TS) algorithm employs the procedure given below: at any stage, a fixed number of new approximations are created around the current solution X. However, only those approximations are considered which are not listed on the Tabu list. The best solution is included in the Tabu list and as well as used to replace the current solution among new approximations.

3.5.2 Harmony Search

Geem et al. (2001) introduced a new metaheuristic algorithm in 2001, known as Harmony search algorithm. This algorithm is based on the technique used by musicians in tuning. There are many benefits of the HS algorithm. One of the major points is that by considering all of the current vectors or solution, a new vector solution produced.

This method has gained a significant attention and has been utilized in a number of science and engineering problems. However, like other metaheuristic algorithms, there serious are issues with these types of algorithms. For numerical applications, it easily finds itself in problems of conducting a local search. Some better versions of HS algorithms were presented including improved harmony search (IHS) algorithm , self-adaptive global-best harmony search (SGHS) algorithm , Global-best harmony search (GHS) algorithm , and novel global harmony search (NGHS) algorithm in order to improve their optimization performance.

Other human-based techniques are listed in Table 3.4

Table 3.4: Human-based optimization algorithms

Algorithm	Year	Inspiration	Reference
Imperialist Competitive Algorithm (ICA)	2007	Inspired by imperialistic competition	(Atashpaz-Gargari and Lucas, 2007)
League Championship Algorithm (LCA)	2009	Inspired by the competition of sport teams in a sport league	(Kashan, 2009)
Teaching-Learning-Based Optimization (TLBO)	2011	Inspired by the influence of a teacher on learners	(Rao et al., 2011)
Social-Based Algorithm (SBA)	2013	Inspired by social behaviour	(Ramezani and Lotfi, 2013)
Coronavirus Herd Immunity Optimizer (CHIO)	2020	Inspired by herd immunity concept	(Al-Betar et al., 2020)

Regardless of the nature, the population-based metaheuristic optimization algorithms possess or share common feature. Exploration and exploitation are the common stages in the search process (Mirjalili and Lewis, 2016).

- Exploration stage:operators that explore global search space must be included in the optimizer. In this stage, as much as possible randomization of movements should be introduced as possible.

- Exploitation stage: This step comes after the exploration stage. It can be defined as a process that investigates the promising search area in detail.

In general, the exploration is preferred at the early stages of search process. However, it is required to successively provide way to exploitation of potential solution as the search process moves forward. Therefore, the exploitation is connected to the ability of local search in the potential areas of design space identified in the exploration stage. Due to the stochastic nature of the optimization process, the most difficult task is to find a suitable balance between exploration and exploitation of the search space during the development of any metaheuristic algorithm. In general, one should pay attention to find a balance between exploration and exploitation of any search space, in order to improve the search capability. Since the balance between exploration and exploitation is depending on the characteristics of the problem, it is quite challenging to solve this problem. This requires dynamic change in the balance during evolution process (Hussain et al., 2019).

3.6 Summary

The development of Heuristic approaches has been used to solve complex optimization problems. This chapter provided a basic knowledge of most popular heuristic optimization techniques, and how they are applied in common optimization problems.

Chapter 4

OVERVIEW OF PROPOSED HYBRID METHOD

4.1 Introduction

To enhance system performance, the present work proposes a structure for DG placement and sizing that relies on multi-objective criteria. The proposed structure employs a hybrid approach consisting of combined power loss sensitivity (CPLS) and the improved grey wolf optimizer (IGWO). An overview of the new method is presented in the following sections.

4.2 Using Combined Power Loss Sensitivity to Optimize DG Location and Placement

Various factors of real power loss sensitivity can be calculated to determine potential optimal node placement for DGs. By estimating the sensitivity of nodes, the search space can be decreased (Abdel-mawgoud et al., 2018). However, it is worth bearing in mind that DG placement and installation do not have an effect on real power loss only. This is because DGs are also able to supply reactive power, which means they can also play a major role in reactive power loss. Combined loss sensitivity, therefore, is formulated using data from real power loss as well as reactive power loss (Kumar et al., 2017).

Combined power loss sensitivity (CPLS) analysis uses changes in active and reactive power loss from active and reactive power that has been injected from a distribution network DG and capacitor. We can employ the forward-backward sweep-based load flow algorithm to calculate CPLS for every bus using the following formulation:

$$\partial S_{\text{loss}}\,(m,k) = \partial P_{\text{loss }(m,k)} + j\partial Q_{\text{loss}(m,k)} \tag{4.1}$$

We can also express combined loss sensitivity in relation to reactive power as follows:

$$\frac{\partial S_{\text{loss}}\ (m,k)}{\partial Q_K} = j\frac{\partial Q_{\text{loss}(m,k)}}{\partial Q_k} = \mathrm{X}(m,k)\left(\frac{2Q_k}{|V_k|^2}\right) \tag{4.2}$$

After determining loss sensitivity in relation to real power, combined loss sensitivity in relation to the real power can be formulated as follows:

$$\frac{\partial S_{\text{loss}}\ (m,k)}{\partial P_K} = \frac{\partial P_{\text{loss}}\ (m,k)}{\partial P_k} = \mathrm{R}(m,k)\left(\frac{2P_k}{|V_k|^2}\right) \tag{4.3}$$

Where $P_{\text{loss }(m,k)}$, $\partial Q_{\text{loss}(m,k)}$ are the active and reactive power loss between bus m and k . whereas P_k and Q_k are the active and reactive power at bus k

Using (4.2) and (4.3), based on simple implementation for distribution system consists of two buses bus m and k ,we can determine CPLS for every bus according to the forward-backward sweep-based load flow algorithm, as expressed in (4.4) below:

$$\mathrm{CPLS}(m,k) = \mathrm{R}(m,k)\left(\frac{2P_k}{|V_k|^2}\right) + j\mathrm{X}(m,k)\left(\frac{2Q_k}{|V_k|^2}\right) \tag{4.4}$$

Where ,

$CPLS(m,k)$ CPLS value with respect to real and reactive power injection at bus k., $R(m,k)$ and $X(m,k)$ resistance and reactance of line between m ,k.

V_k is the voltage at bus k.

Those buses that feature high CPLS values may be designated as candidate buses in capacitor and DG installations. CPLS may be used as a means to reduce program simulation time as well as an algorithm's search space (Muthukumar and Jayalalitha, 2016).

4.3 Grey Wolf Optimizer Algorithm

4.3.1 Introduction

As its name implies, the grey wolf optimizer (GWO) is based on the renowned hunting instincts and social leadership of grey wolf packs as shown in Figure 4.1. In the algorithm, three leader wolves (alpha[α], beta[β], and delta [δ]) work to find optimal solutions by guiding the rest of the wolf pack (omega [ω]) into promising "hunting" zones, with the collective aim of finding an optimal global solution (Mirjalili et al., 2014) .

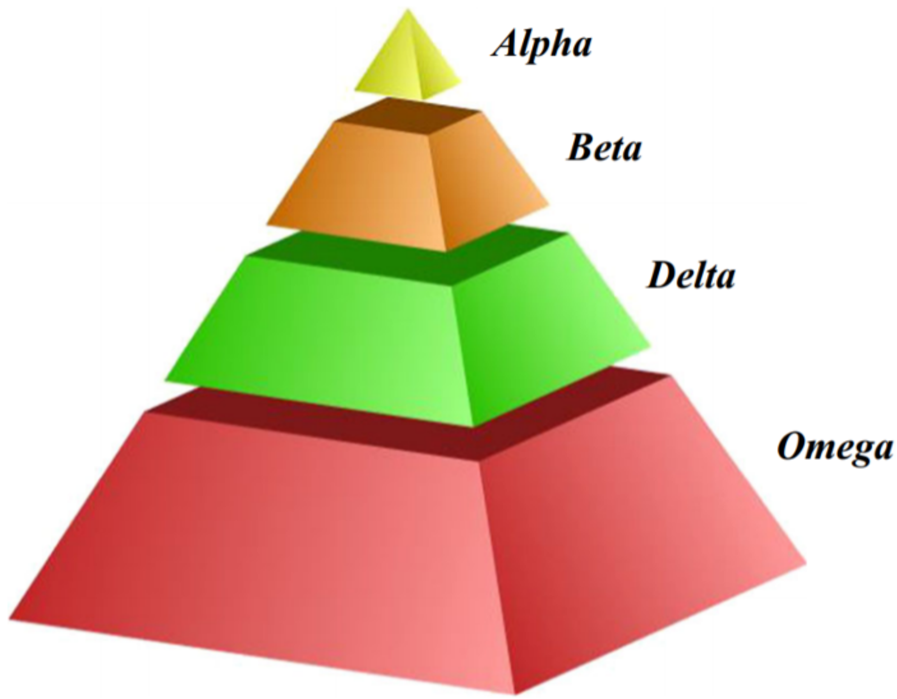


Figure 4.1: Hierarchy Of Grey Wolf

Alphas (α): In a typical wolf pack, the leaders are one male and one female. These two wolves share the task of decision-making in relation not only to hunting, but also to resting places, waking time, etc. The alphas must mate within the pack. Interestingly, alphas are rarely the strongest or largest members in a wolf pack, but they are the most adept at managing the other wolves.

Betas (β): The next level down from alphas in the grey wolf pack hierarchy is the beta level. Beta wolves are generally subordinate to alphas. Their main role is to assist and support the alphas in making decisions and other pack-related activities. In a pack, the betas represent the best replacement candidates for alphas, should the alpha die or become infirm with age. Beta wolves respect and take direction from alphas, but they are able to command lower-level wolves on their own. Other roles played by beta wolves are advisor to alphas and pack disciplinarian.

Deltas (δ): In the grey wolf pack, deltas are subordinate to alphas and betas, but not to omegas. The delta wolves play roles such as hunters, sentinels, scouts, elders, and caretakers. The hunters assist alphas and betas during the hunt. They may also independently provide the pack with food. The sentinels serve as pack protectors. As scouts, deltas warn the pack of any approaching danger. Elder deltas may be former alphas or betas and provide the pack with seasoned experience. Caretaker deltas look after the wolves that are sick, injured, or weakened with age.

Omega (ω): In a grey wolf pack, omegas are the lowest in rank. Their role is essentially that of scapegoat. If they want to remain in the pack, omega wolves must submit to all the other wolves, by, for instance, being the last to eat. Despite their subordinate position, omegas are crucial to the strength of the pack. This is because when omegas are lost (through death or desertion), internal fighting breaks out within the ranks. The omegas thus serve as the primary vent for the pack's disagreements and frustrations. Therefore, the omegas are key to the pack maintaining its dominance structure. Omegas may also occasionally serve as babysitters.

Along with social hierarchy, group hunting comprises another characteristic of grey wolf social behaviour. Muro et al. (2011) breaks down the main components of grey wolf pack hunting as:

- Tracking and chasing the prey while sometimes being visible to the prey and sometimes not.

- Encircling, closing in on, and harassing the prey, with the intent of preventing its escape.

- Attacking the prey.

The next section mathematically models the social hierarchy and hunting methods of grey wolf packs, with the aim of designing and optimizing the grey wolf optimizer (GWO).

4.3.2 Mathematical Model and Algorithm

In mathematically modelling a grey wolf pack's social hierarchy through the design of the GWO, we set the alpha (α) as the best-fit solution. The beta (β) and delta

(δ) wolves are our second- and third-best solutions, respectively, while the remainder of the potential solutions are the omegas (ω). Hence, for the hunting (optimization), the GWO is steered according to the traits of the α, β, and δ wolves, while the ω follow behind (Mirjalili et al., 2014).

One key trait of grey wolf hunting behaviour is encircling the prey, as mentioned earlier. The mathematical modelling of encircling may be expressed using Eqs.(4.5) and (4.6), as below:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{Z_p}(t) - \vec{Z}(t)\right| \tag{4.5}$$

$$\vec{Z}(t+1) = \overrightarrow{Z_p}(t) - \vec{A} \cdot \vec{D} \tag{4.6}$$

where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ denote coefficient vectors, $\vec{Z}$ represents a grey wolf's position vector,and $\vec{Z_p}$ demarcates the prey's position vector. The vectors and may be formulated as:

$$\vec{A} = 2\vec{a} \cdot \overrightarrow{r_1} - \vec{a} \tag{4.7}$$

$$\vec{C} = 2 \cdot \overrightarrow{r_2} \tag{4.8}$$

where:

a components decrease linearly through the iterations from 2 to 0,

r_1, r_2 represent random vectors positioned between 0 and 1

Therefore, by using Eqs.(4.5) and (4.6), we can revise a grey wolf's position within a certain area near its prey for any random location.

Hunting the prey

As mentioned above, grey wolves track and chase their prey until finally encircling it. These movements are typically initiated and led by the alpha wolves, with the betas and deltas participating as support. For our abstract search space, we initially have no clue where the optimum (our prey) is situated. So, to mathematically simulate the wolves' hunting behavior, we assume that our alphas, which are our best candidate solutions, have some knowledge of the prey's location, followed respectively by our betas and deltas. We thus save these three best solutions, while the remaining search agents (the wolves) have their locations updated based on the current best position.

By employing Eqs.(4.9),(4.10) and (4.11), both the positions and scores for the alphas, betas and deltas (i.e., our first three search agents, respectively) may be revised, as follows:

$$\overrightarrow{D_\alpha} = \left|\vec{C}_1 \cdot \overrightarrow{Z_a} - \vec{Z}\right|, \tag{4.9}$$

$$\overrightarrow{D_\beta} = \left|\vec{C}_2 \cdot \overrightarrow{Z_\beta} - \vec{Z}\right| \tag{4.10}$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{Z_\delta} - \vec{Z}\right| \tag{4.11}$$

Then, by utilizing the following mathematical expressions, the prey's position vector in relation to the alphas, betas and deltas may be formulated as:

$$\overrightarrow{Z_1} = \overrightarrow{Z_\alpha} - \vec{A}_1 \cdot \left(\overrightarrow{D_\alpha}\right), \tag{4.12}$$

$$\overrightarrow{Z_2} = \overrightarrow{Z_\beta} - \overrightarrow{A_2} \cdot \left(\overrightarrow{D_\beta}\right) \tag{4.13}$$

$$\overrightarrow{Z_3} = \overrightarrow{Z_\delta} - \overrightarrow{A_3} \cdot \left(\overrightarrow{D_\delta}\right) \tag{4.14}$$

Equation (4.15) expresses how the best position may be formulated by averaging those of the alphas, betas and deltas:

$$\vec{Z}(t+1) = \frac{\overrightarrow{Z_1} + \overrightarrow{Z_2} + \overrightarrow{Z_3}}{3} \tag{4.15}$$

Search agents are able to revise their positions within a two-dimensional search space based on the alpha, beta, and delta wolves, as depicted in Figure 4.2. The figure illustrates how the end position represents a random place inside a circle defined by the alpha, beta, and delta positions within the allotted search space. Hence, the alpha, beta, and delta wolves work together to estimate the prey's position, while the remaining wolves have their positions randomly updated near the prey.

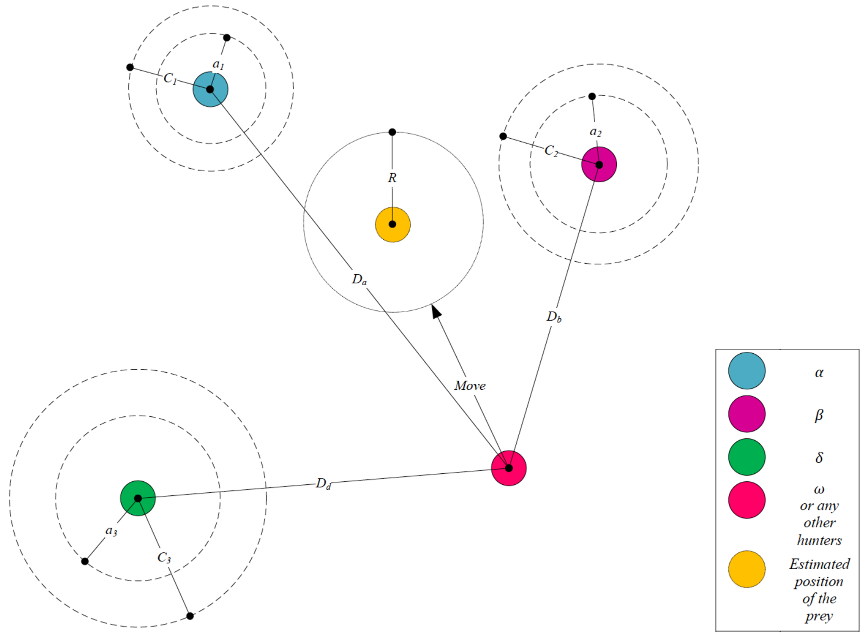


Figure 4.2: Attacking the prey

Attacking the prey

A hunt is considered ended when the prey stops moving. To mathematically model the concept of approaching the prey, we chose to reduce the “a” value. In our model, “a” is a random value occurring within the interval [-a,a], where “a” diminishes from 2 down to 0 during several iterations. As depicted in Figure 4.3(a), random values of “a” occurring in [-1,1] indicate that the subsequent position for a search agent may involve any position between where it presently is located and where its prey is located.

Searching for prey

In general, grey wolf packs usually search for prey in accordance with the alpha, beta, and delta wolves' positioning. A typical strategy is to diverge from the other wolves when searching for prey, and then to converge for the attack. The mathematical modelling of divergence requires us to use random values that are either greater than 1 or less than -1 in order to prompt our search agent's divergence away from the prey's position. The prompt to diverge leads to exploration, which enables a global search by the GWO algorithm. Figure 4.3(b) illustrates how $|A| > 1$ prompts the wolves' divergence away from one prey in search of another prey with a better fit.

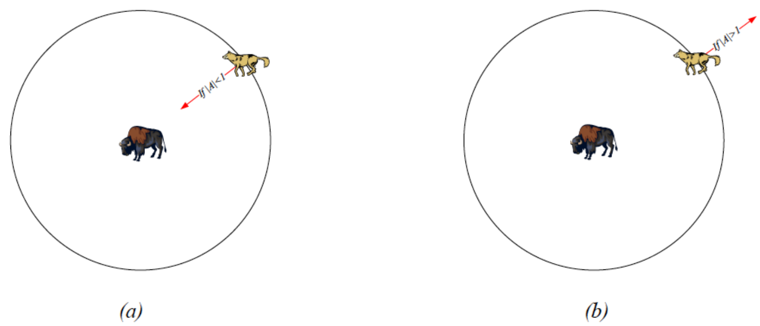


Figure 4.3: Searching for the prey

The operators proposed enable the search agents in the GWO algorithm to revise their position according to those of the alpha, beta, and delta wolves and to direct an attack against the prey. However, the solution search within the GWO algorithm tends to stagnate with these types of operators. While the proposed encircling technique denotes a degree of exploration, the GWO requires additional operators for the concept of exploration to be stressed (Mirjalili et al., 2014).

4.4 Improved Grey Wolf Optimizer (I-GWO)

As touched on previously in this chapter, the grey wolves' hierarchical structure of leadership and hunting strategy inspires the GWO algorithm. However, due to considering only the best alpha, beta and delta wolves for the movement method, the algorithm has a number of limitations, the main ones being an imbalance between exploitation and exploration, premature convergence, and a lack of population diversity (Tu et al., 2019). To mitigate these problems, we propose an improved grey wolf optimizer (I-GWO) that incorporates a new search strategy via selecting and updating.

The three phases of the proposed I-GWO are: initializing, movement, and selecting and updating (Nadimi-Shahraki et al., 2021) .

Initializing phase

This phase features number of wolves being randomly distributed within a given search space.

Movement phase

In this phase, the I-GWO includes another movement strategy, namely the Dimension Learning-based Hunting (DLH) search strategy. The DLH method has each individual wolf being taught (learned) by its neighbors in order to potentially assume the new position of $Z_i(t)$.

In the DLH approach, every dimension of the $Z_i(t)$ wolf's new position may be formulated using Eq. (4.19). Each individual wolf learns from all neighbors as well as from a randomly selected wolf (from Pop). Based on this strategy, another candidate for the wolf $Z_i(t)$ position, called $Z_{i-DLHA}(t+1)$, is generated, in addition to the one generated from Eq.(4.15), namely $Z_{i-GWO}(t+1)$.

To formulate the new wolf $Z_i(t)$ position, radius $R_i(t)$ must be calculated by finding the Euclidean distance separating the candidate position $Z_{i-GWO}(t+1)$ from the present position $Z_i(t)$, as expressed in Eq. (4.16):

$$R_i(t) = \|Z_i(t) - Z_{i-GWO}(t+1)\| \tag{4.16}$$

Next, neighboring wolves of $Z_i(t)$, as indicated by $N_i(t)$, are formulated in Eq. (4.17) with respect to radius $R_i(t)$, with D_i denoting Euclidean distance between $Z_i(t)$ and $Z_j(t)$.

$$N_i(t) = \{Z_j(t) \mid D_i\left(Z_i(t), Z_j(t)\right) R_i(t), Z_j(t) \in Pop\} \tag{4.17}$$

Following the building of the $Z_i(t)$ neighborhood, the multi-neighbor learning stage proceeds, as expressed in Eq. (4.18)

$$Z_{i-DLHA}(t+1) = Z_{L,d}(t) + \text{rand} \times \left(Z_{n,d}(t) - Z_{n,d}(t)\right) \tag{4.18}$$

Selecting and updating phase

The selecting and updating phase has roughly three steps. In the first step, a comparison of the fitness values for the two candidates – $Z_{i-GWO}(t+1)$ and $Z_{i-DLHA}(t+1)$ – is done to determine the better candidate, as expressed in Eq. (4.19):

$$Z_i(t+1) = \begin{cases} Z_{i-GWO}(t+1), & \text{if } f\left(Z_{i-GWO}\right) < f\left(Z_{i-DLH}\right) \\ Z_{j-DLH}(t+1) & \text{otherwise} \end{cases} \tag{4.19}$$

In the second step, the new $Z_i(t+1)$ position needs to be updated. So, if the candidate's fitness value is below $Z_i(t)$, the candidate updates $Z_i(t)$. If it is not below $Z_i(t)$, the value stays the same in the Pop. After doing this process for every individual, as a third step in the selecting and updating stage, the iterations (iter) counter is raised by a count of one. This enables the search to be iterated until the selected iteration number (maxiter) has been reached.

4.5 Proposed Technique

As detailed in the previous section, the I-GWO approach improves the wolves' hunting search strategy through the application of a new approach called dimension learning-based hunting (DLH). However, when tackling more complex optimization problems, the I-GWO strategy tends to converge towards local minima.

In optimization, aspects such as population diversity, exploration and exploitation, and initial population characteristics need to be considered in the design of schemes meant to improve performance and convergence (Tu et al., 2019). Equally important is the trade-off between these factors that occurs during the process of optimization, as it in large part determines the convergence performance. More specifically, if the exploration aspect has too much weight in the formulation, the algorithm unable will not be able to converge to the global optimum. Conversely, if the exploitation has too much weight, there is a slow convergence, along with a tendency to fall into the local optimum.

Population diversity is likewise an important aspect of the algorithm's performance. Low diversity means that search agents will cluster within a small location, causing local convergence, while high diversity leads to a scattering of the search agents across a broad area, resulting in poor convergence (Ibrahim et al., 2018).

This work proposes a novel two-part hybrid approach for enhancing the I-GWO algorithm's performance. The first part of this new technique involves optimal siting through the application of the combined power loss sensitivity factor (CPLS). The second part determines optimal sizing for DGs at feasible locations through the application of the improved grey wolf optimizer (I-GWO) metaheuristic optimization algorithm. The proposed novel strategy is detailed below.

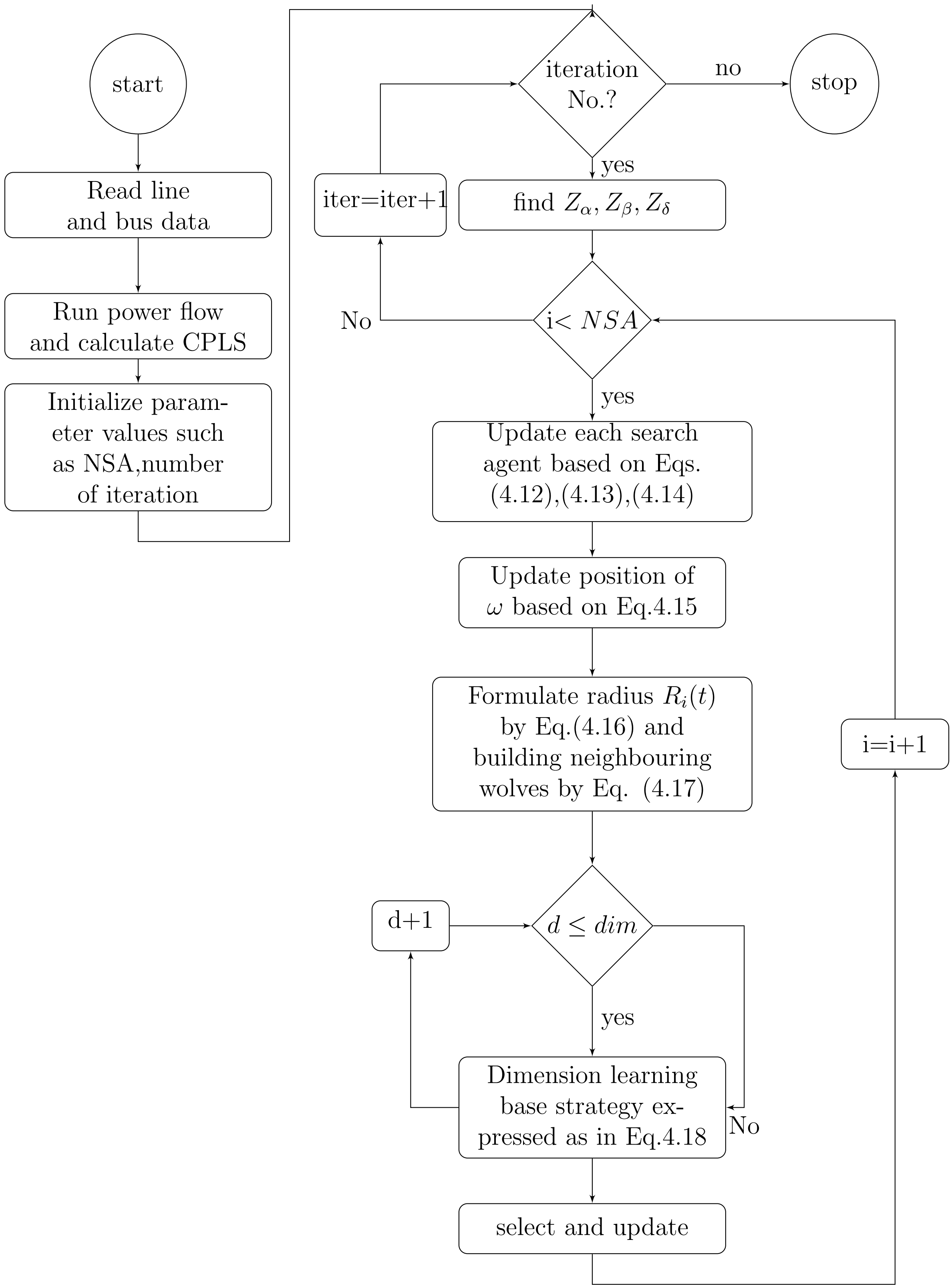


Figure 4.4: Flowchart of the Proposed Technique

Implementation of proposed technique

The implementation of the proposed strategy occurs over a number of steps, with the ultimate aim of obtaining optimal allocation for the DG units' size and site. Figure 4.4 illustrates this process with a flowchart of instructions.

Step 1: Read system data.

Step 2: Perform load flow, determine CPLS, and calculate potential buses for DGs.

Step 3: Initialize maximum iteration (itmax), Number of Search Agents (NSA), and problem constraints.

Step 4: Generate a population of grey wolves using the grey wolf optimizer, initializing the position of the α, β, and δ wolves. Calculate objective function of the population using the load flow approach.

Step 5: Check constraints for every search agent to determine the best solution. If the constraints are satisfied, calculate multi-objective function; if the constraints are violated, discard results.

Step 6: Update α, β and δ wolves' positions, neglecting the omega's position. Next, include the omega's position using Eqs. (4.9),(4.10),(4.11) and (4.12),(4.13),(4.14) to find the optimal solution thus far.

Step 7: Calculate the search agents' new positions according to the positions of the α, β, and δ wolves, as given in Eq. (4.15).

Step 8: Formulate the radius Ri(t) by utilizing the Euclidean distance from Eq. (4.16) and building a neighborhood in Eq. (4.17).

Step 9: Perform the selecting and updating phase through selecting the lowest fitness value between $Z_{i-GWO}(t+1)$ and $Z_{i-DLHA}(t+1)$, using Eq. (4.19).

Step 10: The stop criterion represents the maximum iterations in the proposed study. When this criterion is satisfied, the simulation stops. The DG units' optimal sizing and site location, satisfying all the distribution system's specified constraints, are then obtained.

4.6 Summary

The steps of the proposed hybrid technique were discussed in detail in this chapter. The steps of the novel strategy include using CPLS and I-GWO for finding optimal allocations of DG and capacitors. Also discussed were the development and implementation of the proposed novel algorithm.

Chapter 5

THE PROBLEM FORMULATION

5.1 Introduction

To facilitate distributed generator (DG) planning within distribution networks, the improved grey wolf optimizer (I-GWO) with the combined power loss sensitivity (CPLS) approach are applied in this work. However, deploying DG in the grid requires not only optimal planning of DG placement but also correct sizing of the units. There are two main steps involved in DG planning: the first is determining the best placement bus for radial distribution grids, and the second step is ensuring accurate sizing of the DG. In addition to adhering to constraints regarding equality and inequality, the installed DG must be able to enhance the voltage profile and minimize active power loss as well as optimize the voltage stability of the network. This chapter explores the problem formulation and system constraints for solving issues around DG rating and optimal placement, with the aim of finding both the optimal DG rating and the optimal location bus for the radial distribution system being tested.

5.2 Load Flow Analysis:

Traditional Gauss Seidel (GS) and Newton Raphson (NR) strategies can be less than efficient as analyzing tools for distribution systems. That is because these networks have features such as unbalanced loads, high R/X and radial structure that may require different approaches. More specifically, the special features of distribution systems can make the analysis of their power flow computation relatively challenging in comparison to analyzing transmission systems. There are two categories of approaches that have been used for analyzing balanced and unbalanced radial distribution systems. The first category employs techniques to modify conventional methods (e.g., NR and GS), while the second category uses backward and forward sweep-based processes that apply Kirchhoff's laws. Recently, thanks mainly to their computational efficiency, low memory needs, and strong convergence features, backward and forward sweep-based algorithms are increasing in usage in the analysis of distribution system loads. The present study investigates the application of the backward and forward sweep technique for determining possible solutions to load flow (Eminoglu and Hocaoglu, 2008)

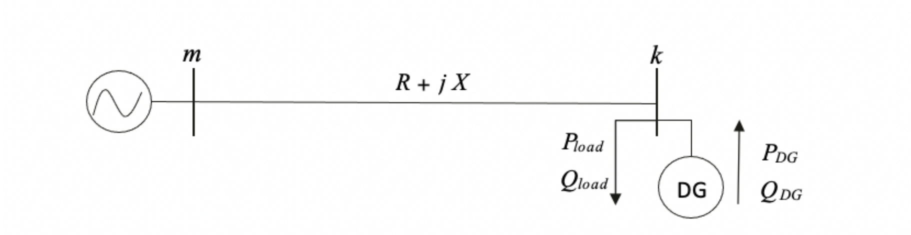


Figure 5.1: Single-line diagram of simple two-bus system with DG

Figure 1 depicts a single-line diagram for RDS. As shown, the load flow equations and transferred power for bus k are obtainable from the figure, as expressed in (5.1),(5.2),and (5.3) below:

$$P_k = P_m - P_{k,\text{ Load}} - X_{m,k}\left(\frac{P_m^2 + jQ_m^2}{|V_m|^2}\right) \tag{5.1}$$

$$Q_k = Q_m - Q_{k,\text{ Load}} - X_{m,k}\left(\frac{\bar{P}_m^2 + jQ_m^{\bar{m}}}{|V_m|^2}\right) \tag{5.2}$$

$$V_k^2 = V_m^2 - 2\left(R_{m,k}P_m + X_{m,k}Q_m\right) + \left(R_{m,k}^2 + X_{m,k}^2\right)\left(\frac{P_m^2 + jQ_m^2}{|V_m|^2}\right) \tag{5.3}$$

Where:

$R_{m,k}, X_{m,k}$ resistance and reactance in the branch between buses k and m,respectively

P_m, Q_m indicate active and reactive powers flowing in bus m, respectively.

P_k, Q_k indicate active and reactive powers flowing in bus k, respectively.

$P_{k,\text{ Load}}$, $Q_{k,\text{ Load}}$ signify real and reactive demands in bus k, respectively; and

V_k, V_m represent voltage magnitudes in bus k and bus m, respectively.

5.3 Problem Formulation

When employing the proposed strategy, the DG integration problem can be framed like a mixed integer nonlinear optimization problem that features highly nonlinear equality and inequality constraints. In using this approach, the optimal location, and size of the DG units can be determined, with the aim of minimizing the multi-objective function. This involves the aspect of real power losses. The branch current's real and reactive losses can be decreased through injections of real and reactive power via capacitors, along with appropriately rated DG units positioned at suitable locations and having suitable voltage profiles. These DG units restricted with specific constraints in the distribution network. The multi-objective function can be expressed as in the equations below.

5.3.1 Minimizing Real Power Loss

$$F_1 = \text{ Min real } \left(\sum\nolimits_{i=1}^{N} S_{i \text{ Total loss}}\right) \tag{5.4}$$

Where:

F_1 denoted to the single objective function for power loss minimization.

N Indicates the bus branch number, and

$S_{i \text{ Total loss}}$ denotes total loss of complex power

Further, because total complex power comprises active and reactive power, the active and reactive losses may be formulated as:

$$P_{k, \text{ loss}} = R_{m,k} \left(\frac{P_k^2 + JQ_k^2}{|V_m|^2}\right) \tag{5.5}$$

$$Q_{k, \text{ loss}} = X_{m,k} \left(\frac{P_k^2 + JQ_k^2}{|V_m|^2}\right) \tag{5.6}$$

where (5.5),(5.6) represent active power loss and reactive power loss for bus k, respectively.

Distributed generation offers a viable and sustainable way to improve energy efficiency while also lowering the cost of energy. Because of this, DG is being increasingly integrated into distribution systems and must therefore be added to the analysis of power flow. Active and reactive power flow that includes DG in bus k may be expressed as presented below(Kansal et al., 2013).

- Real power injections scenario . These function in fuel cells, PV cells, micro-turbines, etc., and are formulated as in (5.7) and (5.8) :

  Thus, when: $PF_{DG} = 1$

$$P_k = P_m - P_{k,\text{ Load}} - P_{k,\text{ loss}} + P_{k,DG} \tag{5.7}$$

$$Q_k = Q_m - Q_{k,\text{ Load}} - Q_{k,\text{ loss}} \tag{5.8}$$

- Reactive power injections scenario . These function as KVAR compensators, capacitors, synchronous compensators, etc., and are formulated as in (5.9) and (5.10):

  Thus, when: $PF_{DG} = 0$

$$P_k = P_m - P_{k,\text{ Load}} - P_{k,\text{ loss}} \tag{5.9}$$

$$Q_k = Q_m - Q_{k,\text{ Load}} - Q_{k,\text{ loss}} + Q_{k,DG} \tag{5.10}$$

- Real and reactive power injections scenario . These function in power factors ranging from 0 to 1, and are formulated as in (5.11) and (5.12):

  Thus ,when : $0 < PF_{DG} < 1$

$$P_k = P_m - P_{k,\text{ Load}} - P_{k,\text{ loss}} + P_{k,DG} \tag{5.11}$$

$$Q_k = Q_m - Q_{k,\text{ Load}} - Q_{k,\text{ loss}} + Q_{k,DG} \tag{5.12}$$

Where,

$P_{k,DG}$ represents real power as generated in the DG for bus k;

$Q_{k,DG}$ represents reactive power as generated in the DG for bus k; and

PF_{DG} represents the power factor for bus k.

5.3.2 Voltage Deviations:

For various reasons, distribution systems may experience voltage variations. For example, line impedances may lead to major voltage drops, or available reactive generation may be unable to satisfy increasing customer demand for reactive power. As well, the use of long radial feeders in rural locations may prevent reactive power transmission. This will cause a drop in voltage at customer-connection load points. For these reasons, load bus voltage positioned at remote ends is typically lower compared to load bus voltage positioned closer to substations (Zimann et al., 2019).

Variations in voltage are referred to as voltage deviations. These may be defined as differences between actual and nominal voltage levels, such that the smaller the bus voltage deviation from nominal voltage, the more functional the system. The Total Voltage Deviation (TVD) refers to the sum total of the squared value of absolute voltage differences between nominal and actual voltage in all buses within a given system (Saha and Mukherjee, 2019). This may be expressed as:

$$TVD = \sum_{n=1}^{NB} (V_n - V_{ref})^2 \tag{5.13}$$

Where,

V_n indicates bus voltage value for bus n;

V_{ref} indicates reference voltage typically equal to 1 p.u., and

NB indicates bus number.

The objective function to improve voltage profile can be expressed as in 5.14:

$$F_2 = TVD = \sum_{n=1}^{NB} (V_n - V_{ref})^2 \tag{5.14}$$

Where,

F_2 The second objective function represented by Total of Voltage Deviation.

5.3.3 Voltage Stability Index:

In the present work, the voltage stability index (VSI) represents a distribution system's security level and measures each bus system's vulnerability to voltage collapse using 5.15. Higher VSI values indicate a more stable bus and a relatively low potential for voltage collapse.(Murty and Kumar, 2015)

$$VSI_{(k)} = |V_m|^4 - 4\left((P_k + P_{k,\text{ Load}})\,X - (Q_k + Q_{k,\text{ Load}})\,R\right)^2 - 4$$
$$\left((P_k + P_{k,\text{ Load}})\,X + (P_k + P_{k,\text{ Load}})\,R\right)|V_m|^2 \quad (5.15)$$

$$F_3 = \frac{1}{\sum_{n=1}^{NB} VSI_{(n)}} \mid \quad (5.16)$$

Where,

$VSI_{(k)}$ indicates to the voltage stability index for at the bus k;

F_3 indicates to the third objective function represented by voltage stability index.

5.3.4 Multi-Objective Function

It was observed that most of the work done in DG optimization problems has been focused on various single objective functions which often leads to a conflict between these objectives (Kaur and Jain, 2017). However, in this work, the optimization problem has more than one objective function and it is optimized, simultaneously. The multi-objective function minimizes the power loss, improves voltage profile and maximizes voltage stability index.The parameter of the proposed method can be illustrated in Table 5.1 and the MOF is given by 5.17.

$$MOF = \mathcal{R}_1 * F_1 + \mathcal{R}_2 * F_2 + \mathcal{R}_3 * F_3 \quad (5.17)$$

Where,

R_1 represent the weighting factor related to power loss minimization

R_2 indicates to the weighting factor related to total voltage deviation.

R_3 weighting factor related to voltage stability

MOF represent multi-objective function.

The value of the weight's factors is designed to give the corresponding priority to each objective function due to the presence of DG and depend on the required analysis. The summation value of the weighting factors is equal to one.

$$\mathcal{R}_1 + \mathcal{R}_2 + \mathcal{R}_3 = 1 \tag{5.18}$$

In this research,the power loss reduction is considered as the main concern of any system .Therefore, the value of the weight for the power loss minimization received a big value at 0.5, while the weight for the TVD minimization and voltage stability maximization is 0.25 each.

5.4 Optimization Problem Constraints

5.4.1 Equality Constraints

Equality constraints comprise nonlinear power flow equations that express the need for conserving real and reactive powers at RDS buses. Constraints involving active and reactive power balanced at distribution system may be written as:

$$P_{\text{supply}} + \sum_{d=1}^{ND} P_{DG}(d) = P_{T,\text{ Load}} + P_{\text{T,loss}} \tag{5.19}$$

$$Q_{\text{supply}} + \sum_{d=1}^{D} Q_{DG}(d) = Q_{T,\text{ Load}} + Q_{\text{T,los}} \tag{5.20}$$

Where,

P_{supply} and Q_{supply} denote active and reactive power originating in the main feeder, respectively;

$P_{T,\text{ Load}}$ and $Q_{T,\text{ Load}}$ represent the system's total active and reactive load, respectively;

P_{DG} and Q_{DG} indicate DG-penetrated active and reactive power;

ND denotes total number of DG; and

$P_{\text{T,loss}}$ and $Q_{\text{T,loss}}$ express total active and reactive system loss, respectively.

5.4.2 Inequality Constraints

Two inequality constraint sets have to be satisfied. the boundary constraints imposed on the system which consists of the voltage limits, and the DG technical constraints which consists of DG size limits and DG power factor. They can be expressed as:

1. Limits to voltage:
   Each bus in the system should be operated within the minimum and the maximum operating voltage values.

$$V_{\min} \leq V_i \leq V_{\min} \tag{5.21}$$

   Where $V_{\min}$ and $V_{\min}$ may be chosen as 0.95 p.u and 1.05 p.u, respectively

2. Technical constraints to DG:

   - Firstly, Limiting the DG size so as not to exceed the power supplied by the substation and restricting the power flow in feeders to ensure that they do not approach their thermal limits are another set of the inequalities imposed on the distribution system.

$$P_{DG,\min} \leq \sum_{d=1}^{ND} P_{DG}(d) \leq P_{DG,\max} \tag{5.22}$$

$$Q_{DG,\min} \leq \sum_{d=1}^{ND} Q_{DG}(d) \leq Q_{DG,\max} \tag{5.23}$$

     Where,
     $P_{DG,\min}$ and $P_{DG,\max}$ represent a DG unit's minimum/maximum allowed output active power; and;
     $Q_{DG,\min}$ and $Q_{DG,\max}$ represent a DG unit's minimum/maximum allowed output reactive power.

   - Secondly, The DG power factor is allowed for values within upper and lower limits determined by the type and nature of the DG to be installed in the distribution network.

$$PF_{DG,\min} \leq PF_{DG} \leq PF_{DG,\max} \tag{5.24}$$

More specifically, the power factor of DG ranges from maximum power factor $PF_{DG,\max}$ to minimum power factor $PF_{DG,\min}$.

Table 5.1: The parameter of the proposed method

The proposed Parameter	IEEE- 33 Bus System	IEEE- 69 Bus System
Max iteration	100	100
Max power factor	1	1
Min power factor	0.7	0.7
Max real Power (DG)	3000 KW	3000KW
Min real Power (DG)	300KW	300KW
Max reactive Power (DG)	1500 KVAR	1500 KVAR
Min reactive Power (DG)	150 KVAR	150 KVAR

5.5 Summary

This chapter discusses the mathematical formulation of the DG optimization problem. In order to find the best location and size of DGs in radial distribution system. Minimizing real power losses and improving voltage profile as well as preventing voltage collapse by using voltage stability index are presented in this chapter. Equality and inequality constraints are presented as well.

Chapter 6

TEST RESULTS AND DISCUSSION

6.1 Introduction

By employing both IEEE-33 and IEEE-69 radial distribution systems, the hybrid combined power loss sensitivity (CPLS) and improved grey wolf optimizer (I-GWO) methods will be tested for their performance capabilities. Also in this chapter, those two methods' efficiency and feasibility in allocating DG optimally for radial distribution systems will be tested in comparison to well-known optimization approaches. The simulations are conducted in MATLAB M-files, using MATLAB R2019b.
In the present study, we chose IEEE 33 and IEEE 69 bus radial distribution systems for our test cases for three main reasons. Firstly, distribution networks are often radially connected, and secondly, a distribution system's radial nature contributes to its simplicity and the cost-effectiveness of its configuration (Bouchekara, 2020). A third consideration for choosing these two different sizes of systems was to use them as suitable benchmarks for implementing our proposed strategy of evaluating the algorithm's robustness under a range of scenarios.

6.2 IEEE 33 Bus system

Figure 6.1 shows a standard 33-bus radial distribution system. This has been chosen for the initial test system to show the proposed method's effectiveness in multi-objective function. There are 33 buses in the system and 32 branches featuring active and reactive loads of 3.715MW and 2.3MVAR, respectively, operating with base values of 10MVA and 12.66kV. Without DG installation, system power loss measures 210.99 kW, and 143.03 KVAR. Additionally, the system's minimum voltage total 0.90378 p.u., the voltage stability summation total 25.54, and the voltage deviation summation total 1.80 p.u. Hamouda and Zehar (2006) present a detailed depiction for the test system that includes data related to line and load. Further, multi-objective function is employed by utilizing CPLS and I-GWO for a population of 50 and maximum of 100 iterations.

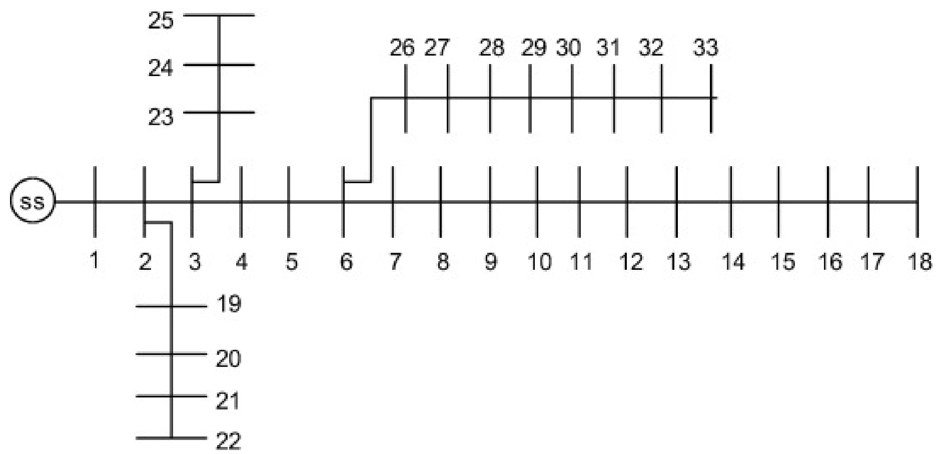


Figure 6.1: Single line diagram of a IEEE 33-bus system.

6.3 DG Identification for Allocation

In the simulation tests, CPLS analysis has been used to decrease search space and provide an accurate solution toward DG localization recognition. Buses that have high CPLS values are considered candidates for capacitor and DG installation. Figure 6.2 depicts candidate buses for the IEEE-33 bus system as 6, 8, 3, 28, 4, 5, 9, 24, 13, 10, 29, 31, 23, 20, 25, 30, and 2. CPLS has been utilized as a way to increase the search efficiency for both the simulation time and the proposed optimization algorithm.

To measure how the different DGs affect the systems under study, three cases are considered to assess voltage stability and DG allocation.

Case 1: System integration of Q-type-based DGs

The Q-type-based DG has been typically employed in distribution networks as a means to enhance system capacity and voltage. This is accomplished by the injection of reactive power into distribution systems (e.g., Synchronous motors, Capacitors, and kVAR compensator). Table 6.1 depicts real and reactive power losses as well as minimum voltage which occurs after different DG types are placed. As can be seen

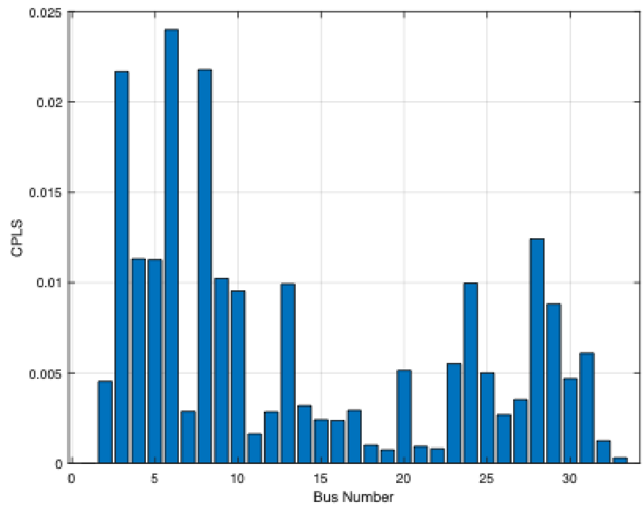


Figure 6.2: Combined power loss sensitivity profile for IEEE 33 bus system

in the table 6.1, in a Q-type case, a 33-bus test system's optimal placement location is bus 8.

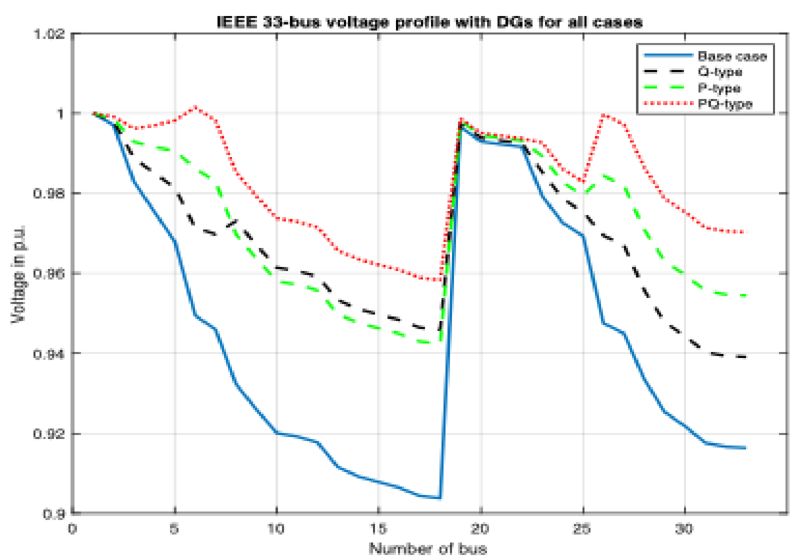


Figure 6.3: Voltage profile of IEEE-33 bus system.

Table 6.1 also shows that through the integration of Q-type-based DG in a distribution system, there is a reduction in total active power loss of 120.38 KW, denoting a power loss decrease of just under 43% and a minimum bus system voltage of 0.9390 p.u.. Figure 6.3 depicts the IEEE-33 bus system voltage profile with/without placement for various DG types. The figure indicates that Q-type DGs demonstrate a more improved voltage profile in comparison to the Base case. Furthermore, as illustrated in Figure 6.4, the system voltage deviation summation drops to 1.07, while the system voltage stability index summation is raised to 27.9. Figure 6.5 presents the convergence characteristics of the proposed hybrid technique for cases 1.

Table 6.1: DG Allocation in 33- bus system at different case studies

		Base Case	Case 1 (Q-type)	Case 2 (P-type)	Case 3 (PQ-type)
DG Location		-	8	6	6
DG Size	kW	-	-	2590.2	2559.7
	kVAR	-	1500	-	1761.9
PL (kW)		210.99	120.383	111.027	67.868
QL (kVAR)		143.03	82.549	81.682	54.834
Min bus voltage No.		18	33	18	18
Vmin (p.u)		0.90378	0.93907	0.94237	0.95837
VSI		25.5	27.9	28.5	29.8
LR %		0.00	42.9	47.3	67.8

Case 2: System integration of P-type-based DGs

The P-type-based DG is currently the most popular in the industry for injecting active power only into certain systems, e.g., photovoltaic (PV) systems. At bus 6, the installed capacity value for single DGs is 2,590.2 kW. Table 6.1 presents the sizes obtained for various DG types. From the table, losses after DG placement significantly decrease (from 210.99 kW to 111.02 kW), giving a 47% reduction in power loss.

Moreover, if only P-type-based DG active power is injected, there is also an improvement in the voltage profile. Figure 6.3 depicts that the system's minimum obtained voltage has improved in comparison to the obtained voltage for DGs in Case 1. Additionally, the system voltage deviation summation drops to 0.92 as shown in Figure 6.4, while the system voltage stability index summation rises to 28.5 . Figure

6.6 illustrates the convergence characteristics of the proposed hybrid technique when applied to the P-type case.

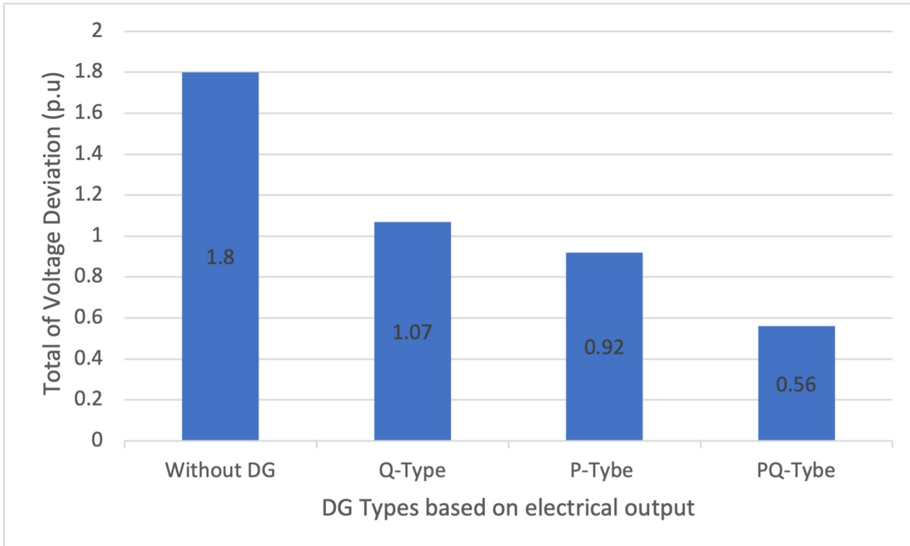


Figure 6.4: Summation of voltage deviation of different proposed cases for DG

Case 3: System integration of PQ-type-based DGs

PQ-type-based DGs provide better outcomes in comparison to either Q-type- or P-type-based DGs, as the PQ-type injects both active and reactive power. Table 1 shows minimum voltages along with real/reactive power losses after placing various DG types. From the table, bus 6 represents the 33-bus system's optimal placement, and there is an increase in the minimum voltage for the case PQ-type. Hence, it can be inferred from Table 1 that in DGs which inject both kinds of power (active and reactive), there is a greater reduction in losses in comparison with the other mentioned DGs. Table 6.1 also presents that the losses in PQ-type DGs are lower than the losses in the other mentioned DGs.

In addition to the above improvements, there is an improvement in the voltage profile in PQ-type DGs, as illustrated in Figure 6.3. The figure shows that the minimum voltage obtained in the presented system is much better than that obtained in the other mentioned types of DGs. Moreover, the system voltage deviation summation decreases to 0.56 (see Figure 6.4), while the system voltage stability index summation rises to 29.8 . In Figure 6.7, the proposed hybrid technique's convergence characteristics in the IEEE 33-bus system PQ-type case units are shown.

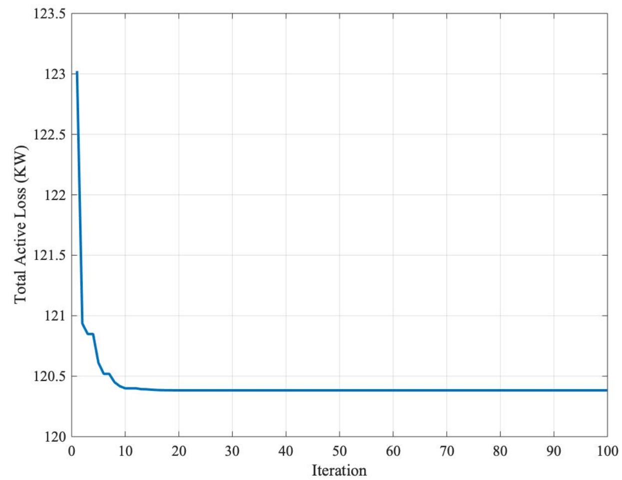


Figure 6.5: Convergence curve of the proposed method 33-bus system for case 1

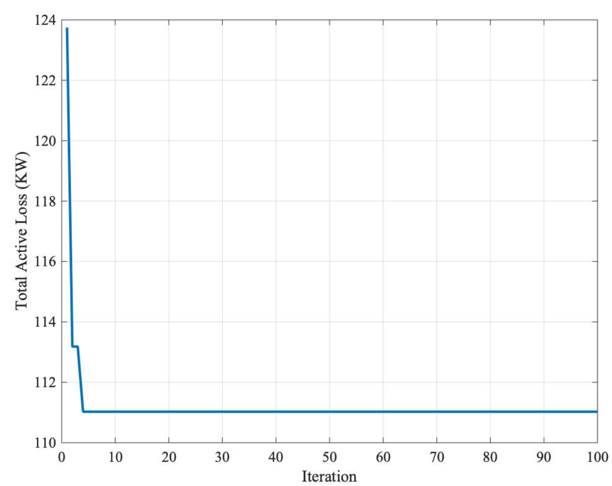


Figure 6.6: Convergence curve of the proposed method 33-bus system for case 2

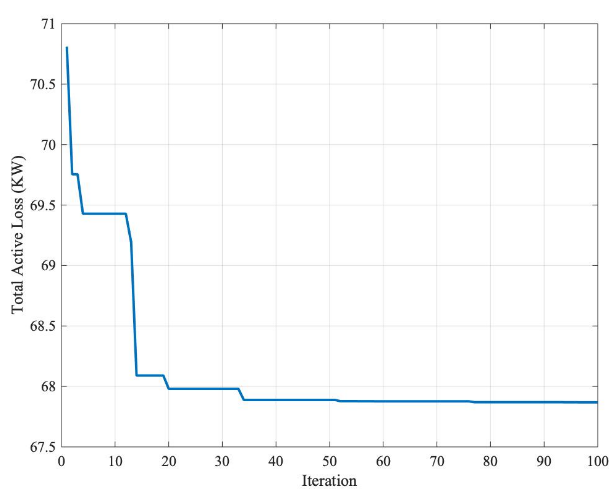


Figure 6.7: Convergence curve of the proposed method 33-bus system for case 3

6.4 Validation

The results will be evaluated for the first system IEEE-33 bus system to prove the efficiency of the proposed approach in DG allocation. The current study uses two validation stages. In the first stage, the proposed technique is compared to that of the original I-GWO, while in the second stage, the proposed technique's optimization is compared with other well-known optimization techniques.

6.4.1 Stage 1: Testing the effect of CPLS of the Proposed Technique in Comparison to Original I-GWO

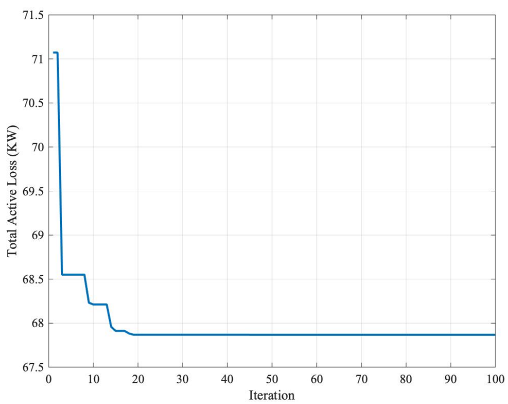
The proposed strategy has been evaluated in comparison to the original I-GWO to determine the effectiveness of the proposed method's sensitivity analysis. The results of the simulation are conducted on an IEEE 33-bus system. In the test, Case 3 is adopted, as it has more variables and is thus considered as the most complex. Table 6.2 shows a comparison of the proposed method and the I-GWO approach for values of power loss reduction across 20 trials. In the I-GWO test system, all network buses are assumed to be potential DG unit placement candidates. The sole exception to this assumption is the first bus, which connects with the generation station's main feeder.

Table 6.2: A comparison between I-GWO and the proposed technique in terms of power loss reduction

Method	Average (KW)	Minimum (KW) (Best)	Maximum (KW) (Worst)
I-GWO	70.33	67.86	74.09
Proposed technique	68.46	67.86	70.90

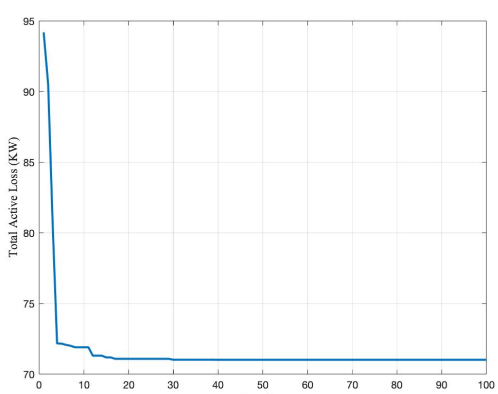
After conducting the 20 trails, the average and best values for the proposed method and the I-GWO approach indicate a better solutions convergence for the proposed strategy than for the I-GWO. At the same time, the differences seen between the proposed and the I-GWO approaches' best and worst values point to the proposed method's superiority. While both the proposed and the I-GWO strategies share the same best solution at 67.86 KW, the convergence curves indicate that the proposed method had a faster convergence as shown in Figures (6.8a),(6.8b) .This convergence

due to the reduction in the search space caused by CPLS.On the other hand, the worst solution obtained by the proposed method and I-GWO technique was at 70.90 KW ,74.09 KW respectively as shown in (6.9a),(6.9b).
After carrying out 20 runs on the IEEE 33 bus system, we found that there is an 80% chance for our proposed method to achieve the optimal solution of 67.86 KW, and a 20% probability for our approach to achieve results ranging between 68 KW and 70.9 KW, inclusive. However, the chance to obtain an optimal solution drops to 65% with the I-GWO technique, while the probability for obtaining a local solution of 68 KW to 74.09 KW is only 35%.



(a) The proposed technique (67.86) (b) I-GWO technique (67.86)

Figure 6.8: Convergence curve for the best solution in IEEE 33-bus system.



(a) The proposed technique (70.90) (b) I-GWO technique (74.09)

Figure 6.9: Convergence curve for the worst solution in IEEE 33-bus system.

6.4.2 Stage 2: Validation of Proposed Technique in Comparison to Well-known Optimization Methods

Tables 6.3, 6.4, and 6.5 summarize the results (e.g., DG size, DG location, minimum voltage, total power loss) for both the proposed technique and some popular methods such as PSO, ALO, and WOA. Based on these summaries, it can be seen that the proposed technique achieved better results in comparison to all other mentioned methods. Moreover, as shown in the tables, when locating optimally-sized DGs in optimal locations, there is a notable decrease in total loss and improvements in voltage profiles.

Table 6.3: Comparison between proposed results of 33-bus system for Case-1 and other optimization techniques

	WOA (Reddy et al., 2017)	ALO (VC et al., 2018)	Proposed method
DG Location	15	30	8
DG size (kVAR)	612.04	1258	1500
Vmin (p.u.)	0.9224	0.9165	0.93907
Power loss (KW)	183.93	151.37	120.383

Table 6.4: Comparison between proposed results of 33-bus system for Case-2 and other optimization techniques

	WOA (Reddy et al., 2017)	ALO (VC et al., 2018)	PSO (Aman et al., 2013)	Proposed method
DG Location	15	30	7	6
DG size (kW)	1061	1542.67	2895.1	2590.2
Vmin (p.u.)	0.9327	0.9272	0.9501	0.94237
Power loss (KW)	133.5	125.16	114.89	111.027

Table 6.5: Comparison between proposed results of 33-bus system for Case-3 and other optimization techniques

	WOA (Reddy et al., 2017)	ALO (VC et al., 2018)	Proposed method
DG Location	15	30	6
DG size (kVA)	1255.89	1940.3	3017.4
Vmin (p.u.)	0.939	0.9386	0.95837
Power loss (KW)	108.4	78.43	67.868

6.5 IEEE 69-Bus Test System

An IEEE 69-bus test radial distribution system is also considered here in order to verify the proposed strategy's effectiveness. As shown in Figure 6.10, the second system comprises 69 buses and 68 lines, has its source at the first bus, and features a total load of 3.80 MW/2.69 MVAR. Furthermore, the second test system functions using a standard base voltage (12.66KV) along with standard base power (10MVA). Prior to integrating the capacitors and DGs in the test system, there is an active power loss of 224.99 KW in the system and the minimum bus voltage is at 0.9091 p.u. for bus 65. As well, the system voltage stability summation is at 61.21, while the voltage deviation summation is at 1.83 p.u. Table B.1 shows the load and line data for this system (Das, 2008).

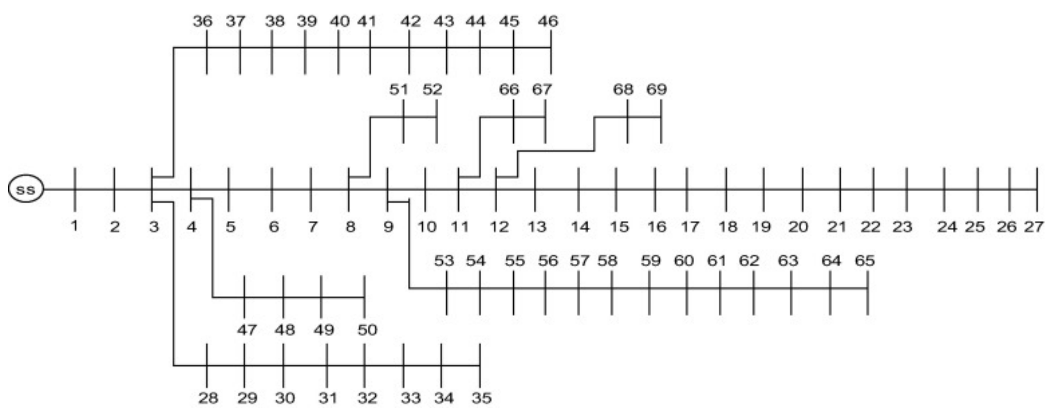


Figure 6.10: Single line diagram of a IEEE 69-bus system.

6.6 DG Allocation Identification

In general, CPLS can be measured according to changes in active and reactive power loss in relation to injected active/reactive power in the capacitors and DGs in a distribution network. Hence, buses that have high CPLS values are potential candidates for capacitor and DG installation. As presented in Figure 6.11, candidate buses for nearly half the system buses are: 57, 58, 7, 6, 61, 60, 10, 59, 55, 56, 12, 13, 14, 54, 15, 53, 8, 64, 49, 11, 9, 17, 65, 16, 5, 48, 21, 19, 41, 63, 68, 34, 20 and 62. Here, CPLS can be utilized for decreasing the total simulation time and the search agent in the proposed optimization approach.

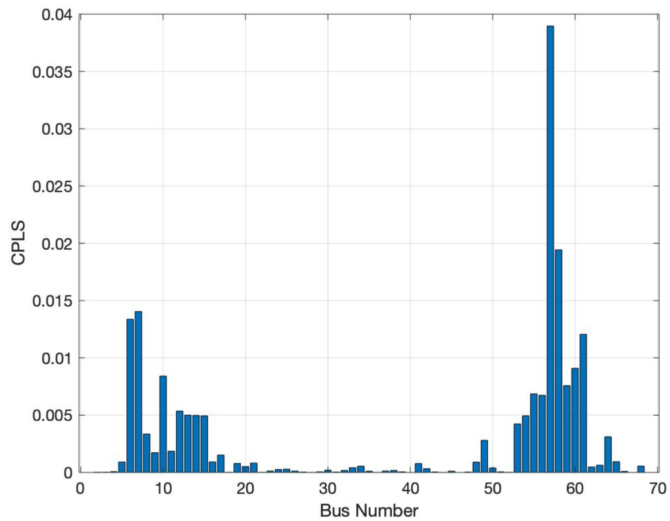


Figure 6.11: Combined power loss sensitivity profile for IEEE-69 bus system

An additional investigation is also considered in the present study that uses DG outputs. The proposed hybrid approach is applied to a number of cases, as presented in the following sections.

Case 1: System Integration of Q-type-Based DG

Table 6.6 presents reactive minimum voltage and power loss following Q-type-based DG placement. Bus 61 is the optimal location in the 69-bus test system. Furthermore, the total active power loss decreases to 152.04 KW for a drop of 32.4%, while bus 65 has the minimum bus system voltage of 0.9307 p.u.. As shown in Figure 6.12, there is a significant enhancement of the voltage profile when the Q-type-based DG is incorporated. Figure 6.13 shows the system voltage deviation summation drops down to 1.50 p.u., while the system voltage stability index summation has increased up to 62.34,. Figure 6.14 presents the proposed hybrid method's convergence characteristics of the Q-type case.

Table 6.6: DG Allocation in 69-bus system at different case studies

		Base Case	Case 1 (Q-type)	Case 2 (P-type)	Case 3 (PQ-type)
DG Location		-	61	61	61
DG Size	kW	-	-	1872.7	1828.5
	kVAR	-	1330	-	1300.6
PL (kW)		224.99	152.041	83.222	23.168
QL (kVAR)		102.197	70.535	40.568	14.410
Min bus voltage No.		65	65	27	27
Vmin (p.u)		0.9091	0.9307	0.96829	0.97247
VSI		61.21	62.34	64.62	65.72
LR %		0.00	32.4	63	89.7

Case 2: System Integration of P-type Based DG

P-type based DG has been recently gaining in popularity. It is the preferred method in the industry when injecting active power for radial distribution systems (e.g., PV). Bus 61 shows the installed capacity value for a single DG as 1,872.7 kW. Table 6.6 presents the loss reduction and sizes for various DG types after placement. As can be seen in the table, after placement of the DGs, losses decrease (from 224.99 kW to 83.222 kW), giving a 63% decrease in power loss. Additionally, the voltage profile is enhanced when active power as P-type based DG is injected. Figure 6.12 depicts the improvements in the system's obtained minimum voltage in comparison with DG-obtained voltage (as in Case 1). Figure 6.13 shows a reduction in the system voltage deviation summation to 0.87, along with a 64.62 increase in system voltage stability index summation. Figure 6.15 presents the proposed hybrid method's convergence characteristics for a P-type case.

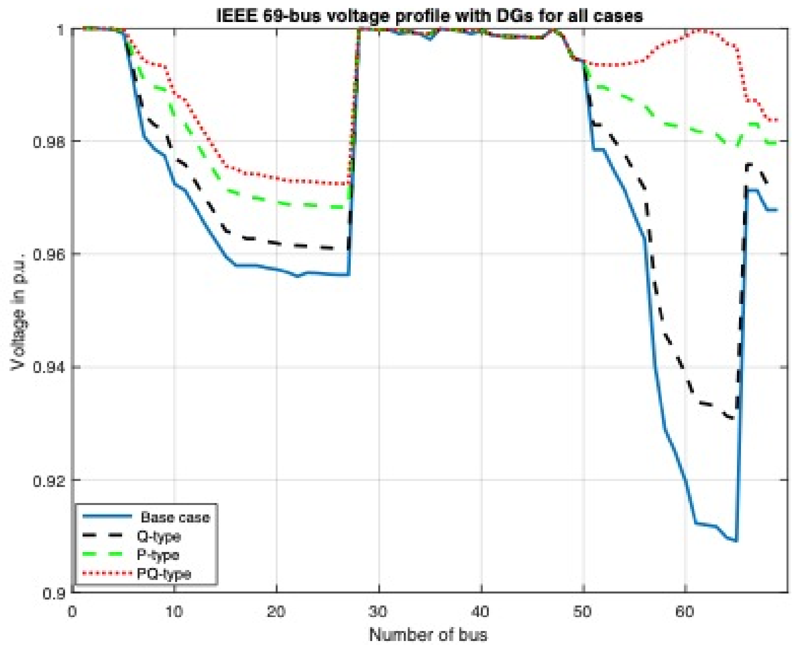


Figure 6.12: Voltage profile of IEEE-69 bus system.

Case 3: System Integration of PQ-type-Based DG

For the second test system, the PQ-type-based DG designates the optimal sizes and locations for DG types utilizing the proposed technique. Table 6.6 presents a listing of the obtained results. As can be seen, the PQ-type-based DG results are better than those for either the Q-type or P-type. This is likely because PQ-type-based DGs inject active and reactive power into the distribution network.

In Table 6.6, the minimum voltages and real reactive power losses are given for various DG types after placement. As shown, bus 61 is the best placement in the 69-bus system, as the minimum voltage has been enhanced to 0.9724 p.u. The results in Table 6.6 also infer that employing a DG with the capability to inject active and reactive power reduces losses in comparison to DGs that do not have that capability. Additionally, the results indicate that the obtained DG size was found to be higher for the PQ-type in comparison with obtained sizes for the other DG types. At the same time, losses were lower in PQ-type-based DGs compared to the others which is 23.16KW.

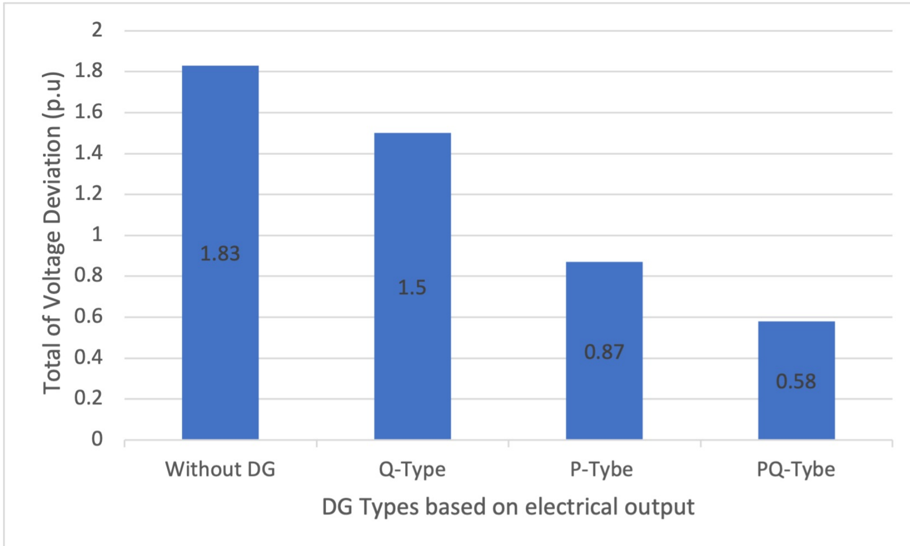


Figure 6.13: Summation of voltage deviation of different cases for DG for IEEE 69 system

Figure 6.12 shows an improvement in voltage profile for PQ-type DGs, indicating that the obtained minimum voltage has been improved in comparison with that of the other types of DGs. Figure 6.13 illustrates an enhancement of the system voltage deviation summation (0.58), along with an enhancement of the system voltage stability index summation (65.72). Meanwhile, Figure 6.16 depicts the proposed method's convergence characteristics of PQ-type case units in an IEEE 69-bus system. As shown in the figure, the proposed method's convergence curves indicate that the approach is a viable optimization strategy that can even determine an optimal solution when the variables are increasing.

6.7 Validation

The proposed strategy will be evaluated for the second system IEEE-69 test system both to compare the various IEEE test systems and to demonstrate the proposed technique's advantages. The current study uses two validation stages. In the first stage, the proposed technique is compared to that of the original I-GWO, while in the second stage, the proposed technique's optimization is compared to those of some popular optimization methods.

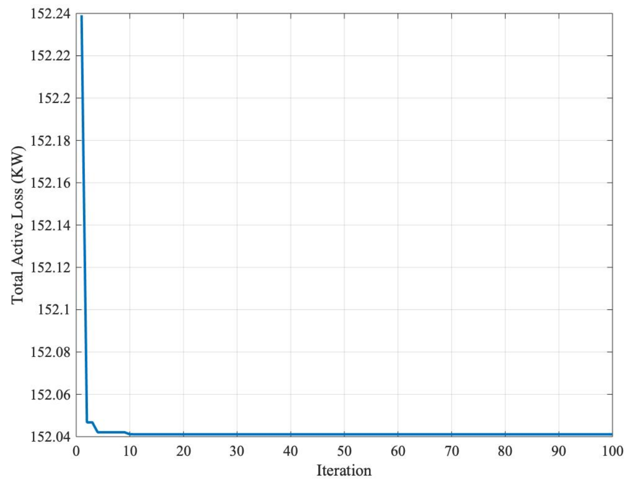


Figure 6.14: Convergence curve of the proposed method 69-bus system at case 1

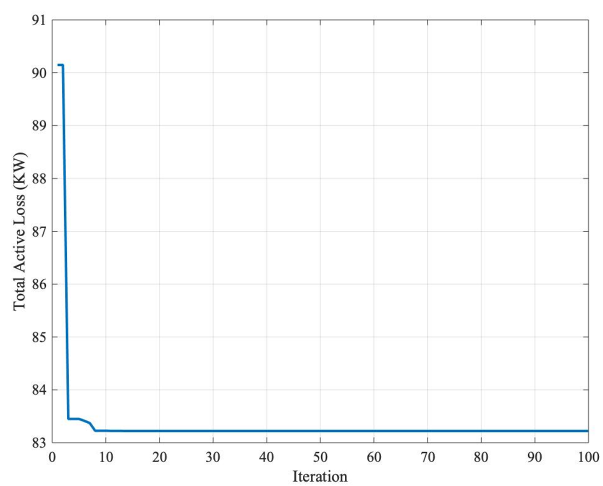


Figure 6.15: Convergence curve of the proposed method 69-bus system at case 2

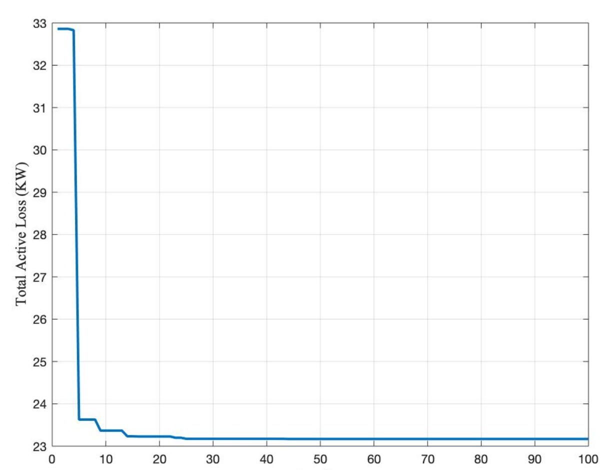


Figure 6.16: Convergence curve of the proposed method 69-bus system at case 3

6.7.1 Testing the effect of CPLS of the Proposed Technique in Comparison to Original I-GWO

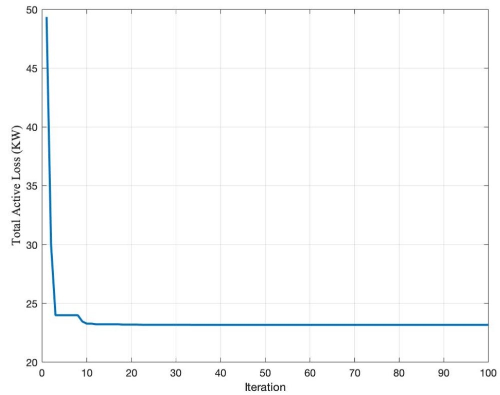
The structure proposed in this work utilizes a hybrid strategy comprising the improved grey wolf optimizer and power loss sensitivity methods. The CPLS is considered here as a way to decrease the search space and find the best solution for locality recognition while avoiding local optima. The primary aim at this point is determining CPLS effectiveness. The approach has already been tested in this study earlier on a different IEEE system.The results of the simulation are conducted on an IEEE 69-bus system. Case 3 is adopted, as it has more variables and is thus the most complex of the three cases. In the I-GWO test system, all network buses are assumed to be potential DG unit placement candidates. The sole exception to this assumption is the first bus, which connects with the generation station's main feeder.Table 6.7 shows a comparison of the proposed method and the I-GWO approach for values of power loss reduction across 20 trials.

Table 6.7: A comparison between I-GWO and the proposed technique in terms of power loss reduction for IEEE-69 bus system

Method	Average (KW)	Minimum (KW) (Best)	Maximum (KW) (Worst)
I-GWO	27.01	23.16	36.6
Proposed technique	23.32	23.16	24

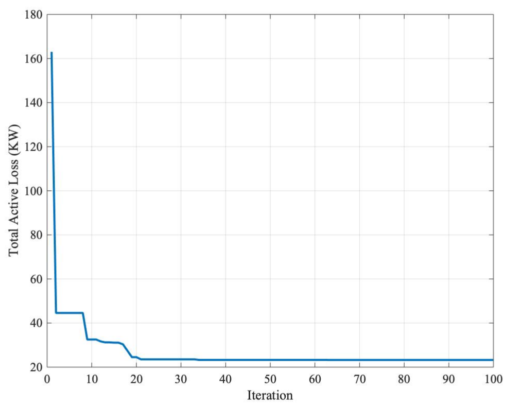
After conducting the 20 trials, it can be seen that the proposed technique has a lower potential for achieving a local solution compared with the I-GWO strategy. At the same time, the clear differences between the proposed and the I-GWO approaches' best and worst values point to the proposed method's superiority. However, combining the introduced CPLS and I-GWO techniques helps to balance the local and global search methods, and deals appropriately with the local optima.

Figures (6.17a),(6.17b) show convergence curves for the best solution for both the proposed technique and I-GWO technique in IEEE-69 bus at 23.16 KW.As shown in Figure (6.18a),the worst solution of the proposed method is 24 KW, while it was 36.6 KW in case of I-GWO technique as shown in Figure (6.18b).



(a) The proposed technique (23.16) (b) I-GWO technique (23.16)

Figure 6.17: Convergence curve for the best solution in IEEE 69-bus system.



(a) The proposed technique (24) (b) I-GWO technique (36.6)

Figure 6.18: Convergence curve for the worst solution in IEEE 69-bus system.

Based on the results on Figures (6.17) and (6.18) , The difference can be seen after CPLS was installed. CPLS was able to reduce the search space of the optimization problem as a result the proposed method was able to avoid the local solution as well as arrive at the optimal solution faster.

Furthermore, after carrying out 20 runs on the IEEE 69 bus system, we found that there is a 75% chance for our proposed method to achieve the optimal solution of 23.16 KW, and a 25% probability for results achieved by our strategy to fall between 23 and 24 KW, inclusive. Meanwhile, the chance for obtaining the optimal solution drops down to 55% when the I-GWO approach is used. At the same time, we found that there is a 45% chance of remaining in a local solution of somewhere between 26 KW and 36.6 KW.

6.7.2 Validating Proposed Method in Comparison to Popular Optimization Strategies

Tables 6.8, 6.9, and 6.10 summarize the results (e.g., DG size, DG location, minimum voltage, total power loss) from both the proposed technique and some popular methods such as PSO, ALO, and WOA. Based on these summaries, Tables 6.8 and 6.9 there are small improvements can be seen . however, the proposed method achieved better results in comparison to all other mentioned method in table 6.10.

Table 6.8: Comparison between proposed results of 69-bus system for Case-1 and other optimization techniques

	WOA (Reddy et al., 2017)	ALO (VC et al., 2018)	Proposed method
DG Location	61	61	61
DG size (kVAR)	1329.99	1329.9	1330
Vmin (p.u.)	0.9307	0.9307	0.93073
Power loss (KW)	152.06	152.064	152.04

Table 6.9: Comparison between proposed results of 69-bus system for Case-2 and other optimization techniques

	WOA (Reddy et al., 2017)	ALO (VC et al., 2018)	PSO (Aman et al., 2013)	Proposed method
DG Location	61	61	61	61
DG size (kW)	1872.82	1872.82	2026.4	1872.7
Vmin (p.u.)	0.9683	0.9683	0.96	0.9682
Power loss (KW)	83.23	83.227	84.04	83.222

Table 6.10: Comparison between proposed results of 69-bus system for Case-3 and other optimization techniques

	WOA (Reddy et al., 2017)	ALO (VC et al., 2018)	Proposed method
DG Location	61	61	61
DG size (kVA)	2217.39	2217	2243.8
Vmin (p.u.)	0.9724	0.9724	0.9724
Power loss (KW)	27.96	27.9	23.16

6.8 Scenarios for multi-objective function based weight factor values:

The objective function used in the present study is known as the multi-objective function (MOF). In MOF, the optimization of three single-objective functions occurs simultaneously, effectively maximizing line voltage stability while significantly reducing power loss and enhancing the voltage profile. Each individual MOF term is multiplied by a weight factor between (0,1), which is defined according to the importance of the term. For clarification purposes, I will now explain how weight factor values impact the results.

To illustrate how weight factors of differing values (e.g., R1, R2, R3) can affect MOF, we conduct a simulation using an IEEE 69 bus system. Note that the two scenarios feature different values of weight factors. For our first test scenario, we use case 2, as it is currently an industry favorite for power injection as active power, such as photovoltaic (PV). In a situation without the installation of DG, the voltage stability index registers as 61.21, the voltage deviation summation is around 1.83 p.u., and system power loss is approximately 224.99 KW.

In the first scenario, the primary system concern centers on power loss reduction. Hence, the weight factor value of power loss reduction is 0.5, indicating its high level of significance However, the weight factor for voltage stability maximization and voltage deviation reductions is only half that of power loss reduction, or 0.25 for each one individually. In applying the weight factor values, we see a decrease in losses from 224.99 KW down to 83.22 KW, which represents a 63% reduction in power loss. Additionally, the voltage stability index jumps from 61.21 up to 64.62, and the voltage deviation total drops to 0.87. from 1.83 p.u.

Unlike the first scenario, the system's main concern for the second scenario is voltage stability. Accordingly, the weight factor value of voltage stability maximization in this scenario is set at 0.5. Power loss reduction and voltage deviation reduction are both set at 0.25, showing their lesser significance to the system. Under this scenario, there is a drop in losses from 224.99 KW down to 98.9 KW. This represents a system reduction loss of 56%, whereas the first scenario charted a reduction of 63%. Furthermore, the objective of primary concern (voltage stability) in scenario two shows only a slight increase to 65.51 in comparison to the objective of primary concern in the first scenario (power loss reduction) which increased to 64.62. However, the slight change still has an impact on the total voltage deviation, which edged up to 0.79 p.u. in comparison to 0.87 p.u.

From these results, we can see that the voltage for the systems in both scenarios is relatively stable, with all of the buses obtaining results within an acceptable range. That having been said, it is still clear that scenario two added increased loss to the system. Thus, these results support the values for the weight factors proposed in the present study.

6.9 Summary

A multi-objective optimization strategy for determining optimal placement and sizing of DGs was presented in this chapter. Three objectives were chosen for the optimization problem: improvement of voltage profile, maximizing of system stability, and minimizing of the system's total real power loss. The adopted technique was used in 33-bus and 69-bus radial distributed systems. The results clearly showed the proposed hybrid technique to be efficient as well as highly applicable in solving multi-objective optimization problems related to DG allocation.

Chapter 7

CONCLUSIONS AND FUTURE RESEARCH

7.1 Conclusions

Power systems can be divided into three main subsystems, namely, generation, transmission, and distribution. Of these three subsystems, distribution systems provide power to the various commercial, industrial and domestic customers via remote generation stations, with the generated power being transferred (through high-voltage transmission lines) to a load center. However, most distribution networks nowadays are defined as "active", which simply means that some of the power provided by these systems is generated by distributed generator (DG) units within the distribution system. As a relatively new addition to distribution systems, DG improves overall system performance by reducing power loss and boosting system reliability and capacity. The use of DG also lengthens the life of infrastructure and is more environmentally friendly than conventional power sources. However, to achieve these benefits, the Distributed Generators (DGs) must be placed at optimal locations and be optimally sized. Therefore, the integration of DGs into distribution networks is essentially an optimization problem formulated by system planner-designated constraints.

This study presented a novel approach aimed at finding the optimal sizing and placement for DGs in a distribution system. The hybrid method developed in this work combined the improved grey wolf optimizer (I-GWO) with power loss sensitivity (CPLS), based on the simulation results the following may be concluded:

The CPLS sensitivity analysis introduced in the work was highly capable of determining suitable candidate nodes. The overall aim was to include DG in the radial distribution systems as a way to decrease search space in the optimization's methodology.

The main reason for developing the hybrid strategy with I-GWO and CPLS was to find optimal sizing and location for the IEEE 33 and IEEE 69 bus systems. The simulation results clearly demonstrated that the proposed algorithm could be applied to determine both global and near-global best settings for control variables in IEEE 33-bus and IEEE 69-bus power systems. Moreover, the simulations revealed the superiority of the proposed approach in comparison to other methods with the same or similar objective.

Overall, the optimal sizing and location problem was solved for DGs involving multi-objective functions. These include the three key aspects of improvements to voltage stability, minimizing of power loss, and enhancement of voltage profile. More specifically, the proposed strategy enhanced the voltage stability index in both of the systems, pointing to an increase in the systems' security levels. Loss reduction also comprises a major objective function, with better results obtained for both systems compared to other techniques when the proposed system was applied. Finally, voltage deviation was reduced in both systems under this study's novel approach, which is an indication of power equality and improvements in the voltage profile.

This study compared different values for multi-objective weight factors, demonstrating that the proposed weight factor values resulted in significant loss reduction along with the maintenance of voltage within the acceptable range across all buses.

To validate the proposed approach, two standard distribution network IEEE 33-bus and IEEE 69- bus systems employed, along with two validation stages. The first stage compares the novel method with the I-GWO, and the second stage compares the method's optimization with some other popular optimization strategies. The results indicate that the developed method give better results than the methods used for comparison with regard to the required objective function. Furthermore, the results showe that including PQ-type-based DGs in a system provides much better results in comparison to the inclusion of either P-type-based or Q-type-based DGs. The study results clearly demonstrate the proposed approach's efficiency in determining optimal sizing and location for DG.

7.2 Future Research

There are several potential directions in which the present research could be extended. Some of these are listed below:

- The developed strategy could be used to determine optimal ratings and locations for multiple DGs.

- The approach developed in this thesis could be applied to improving I-GWO exploration and exploitation phases through hybridizing additional meta-heuristic optimization methods.

- The multi-objective optimization problem presented in this work could be applied to minimize the substation total emission productions or substation total electrical energy cost.

- The proposed strategy could also be utilized in other typical power system optimization problems.

Bibliography

Abdel-mawgoud, H., Kamel, S., Tostado, M., Yu, J., and Jurado, F. (2018). Optimal installation of multiple dg using chaotic moth-flame algorithm and real power loss sensitivity factor in distribution system. In *2018 International Conference on Smart Energy Systems and Technologies (SEST)*, pages 1–5. IEEE.

Abou El-Ela, A. A., El-Sehiemy, R. A., Kinawy, A.-M., and Mouwafi, M. T. (2016). Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement. *IET Generation, Transmission & Distribution*, 10(5):1209–1221.

Al-Betar, M. A., Alyasseri, Z. A. A., Awadallah, M. A., and Doush, I. A. (2020). Coronavirus herd immunity optimizer (chio). *Neural Computing and Applications*, pages 1–32.

Alzaidi, K. M. S., Bayat, O., and Uçan, O. N. (2019). Multiple dgs for reducing total power losses in radial distribution systems using hybrid woa-ssa algorithm. *International Journal of Photoenergy*, 2019.

Aman, M., Jasmon, G., Bakar, A., and Mokhlis, H. (2013). A new approach for optimum dg placement and sizing based on voltage stability maximization and minimization of power losses. *Energy Conversion and Management*, 70:202–210.

Ameli, A., Bahrami, S., Khazaeli, F., and Haghifam, M.-R. (2014). A multiobjective particle swarm optimization for sizing and placement of dgs from dg owner's and distribution company's viewpoints. *IEEE Transactions on power delivery*, 29(4):1831–1840.

Atashpaz-Gargari, E. and Lucas, C. (2007). Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. In *2007 IEEE congress on evolutionary computation*, pages 4661–4667. Ieee.

Bouchekara, H. (2020). Comprehensive review of radial distribution test systems.

Das, D. (2008). Optimal placement of capacitors in radial distribution system using a fuzzy-ga method. *International Journal of Electrical Power Energy Systems*, 30(6-7):361–367.

Dasgupta, D. and Michalewicz, Z. (2013). *Evolutionary algorithms in engineering applications*. Springer Science & Business Media.

De Jong, K. A. (1985). Genetic algorithms: A 10 year perspective. In *Proceedings of an International Conference on Genetic Algorithms and Their Applications*, volume 1, pages 9–177. Lawrence Erlbaum Associates.

Ehsan, A. and Yang, Q. (2018). Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques. *Applied Energy*, 210:44–59.

El-Fergany, A. (2015). Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm. *International Journal of Electrical Power & Energy Systems*, 64:1197–1205.

Elsaiah, S., Benidris, M., and Mitra, J. (2014). Analytical approach for placement and sizing of distributed generation on distribution systems. *IET Generation, Transmission Distribution*, 8(6):1039–1049.

Eminoglu, U. and Hocaoglu, M. H. (2008). Distribution systems forward/backward sweep-based power flow algorithms: a review and comparison study. *Electric Power Components and Systems*, 37(1):91–110.

Gandomkar, M., Vakilian, M., and Ehsan, M. (2005). A genetic–based tabu search algorithm for optimal dg allocation in distribution networks. *Electric power components and systems*, 33(12):1351–1362.

Geem, Z. W., Kim, J. H., and Loganathan, G. V. (2001). A new heuristic optimization algorithm: harmony search. *simulation*, 76(2):60–68.

Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers operations research*, 13(5):533–549.

Goldberg, D. E. and Holland, J. H. (1988). Genetic algorithms and machine learning.

Gozel, T., Hocaoglu, M. H., Eminoglu, U., and Balikci, A. (2005). Optimal placement and sizing of distributed generation on radial feeder with different static load models. In *2005 International Conference on Future Power Systems*, pages 2–pp. IEEE.

Griffin, T., Tomsovic, K., Secrest, D., and Law, A. (2000). Placement of dispersed generation systems for reduced losses. In *Proceedings of the 33rd annual Hawaii international conference on system sciences*, pages 9–pp. IEEE.

Gupta, N. and Seethalekshmi, K. (2019). Review of analyzing techniques in technical challenges related to distributed generation. *International Journal of Applied Engineering*, 14(2).

HA, M. P., Huy, P. D., and Ramachandaramurthy, V. K. (2017). A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms. *Renewable and Sustainable Energy Reviews*, 75:293–312.

Hamouda, A. and Zehar, K. (2006). Efficient load flow method for radial distribution feeders. *Journal of Applied Sciences*, 6(13):2741–2748.

Hashim, F. A., Houssein, E. H., Mabrouk, M. S., Al-Atabany, W., and Mirjalili, S. (2019). Henry gas solubility optimization: A novel physics-based algorithm. *Future Generation Computer Systems*, 101:646–667.

Hatamlou, A. (2013). Black hole: A new heuristic optimization approach for data clustering. *Information sciences*, 222:175–184.

Hedayati, H., Nabaviniaki, S. A., and Akbarimajd, A. (2008). A method for placement of dg units in distribution networks. *IEEE transactions on power delivery*, 23(3):1620–1628.

Heidari, A. A., Mirjalili, S., Faris, H., Aljarah, I., Mafarja, M., and Chen, H. (2019). Harris hawks optimization: Algorithm and applications. *Future generation computer systems*, 97:849–872.

Heideier, R., Bajay, S. V., Jannuzzi, G. M., Gomes, R. D., Guanais, L., Ribeiro, I., and Paccola, A. (2020). Impacts of photovoltaic distributed generation and energy efficiency measures on the electricity market of three representative brazilian distribution utilities. *Energy for Sustainable Development*, 54:60–71.

Holland, J. (1975). Adaptation in natural and artificial systems: an introductory analysis with application to biology. *Control and artificial intelligence*.

Hung, D. Q., Mithulananthan, N., and Bansal, R. (2010). Analytical expressions for dg allocation in primary distribution networks. *IEEE Transactions on energy conversion*, 25(3):814–820.

Hussain, K., Salleh, M. N. M., Cheng, S., and Shi, Y. (2019). On the exploration and exploitation in popular swarm-based metaheuristic algorithms. *Neural Computing and Applications*, 31(11):7665–7683.

Ibrahim, R. A., Abd Elaziz, M., and Lu, S. (2018). Chaotic opposition-based grey-wolf optimization algorithm based on differential evolution and disruption operator for global optimization. *Expert Systems with Applications*, 108:1–27.

Javidtash, N., Jabbari, M., Niknam, T., and Nafar, M. (2017). A novel mixture of non-dominated sorting genetic algorithm and fuzzy method to multi-objective placement of distributed generations in microgrids. *Journal of Intelligent & Fuzzy Systems*, 33(4):2577–2584.

Jegadeesan, M. and Venkatasubbu, S. (2017). Minimization of cost by simultaneous placement of multi-dgs and capacitors in distribution system using hybrid optimization. *International Journal of Advances in Computer and Electronics Engineering*, 2(6):8–14.

Kansal, S., Kumar, V., and Tyagi, B. (2013). Optimal placement of different type of dg sources in distribution networks. *International Journal of Electrical Power & Energy Systems*, 53:752–760.

Kashan, A. H. (2009). League championship algorithm: a new algorithm for numerical function optimization. In *Soft Computing and Pattern Recognition, 2009. SOCPAR'09. International Conference of*, pages 43–48. IEEE.

Kashem, M., Le, A. D., Negnevitsky, M., and Ledwich, G. (2006). Distributed generation for minimization of power losses in distribution systems. In *2006 IEEE Power Engineering Society General Meeting*, pages 8–pp. IEEE.

Kaur, N. and Jain, S. K. (2017). Multi-objective optimization approach for placement of multiple dgs for voltage sensitive loads. *Energies*, 10(11):1733.

Kaveh, A. and Farhoudi, N. (2013). A new optimization method: Dolphin echolocation. *Advances in Engineering Software*, 59:53–70.

Kaveh, A. and Talatahari, S. (2010). A novel heuristic optimization method: charged system search. *Acta Mechanica*, 213(3):267–289.

Keane, A. and O'Malley, M. (2005). Optimal allocation of embedded generation on distribution networks. *IEEE Transactions on Power Systems*, 20(3):1640–1646.

Kefayat, M., Ara, A. L., and Niaki, S. N. (2015). A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources. *Energy Conversion and Management*, 92:149–161.

Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks*, volume 4, pages 1942–1948. IEEE.

Kirkpatrick, S., Gelatt, C. D., and Vecchi, M. P. (1983). Optimization by simulated annealing. *science*, 220(4598):671–680.

Kola, S. S. (2018). A review on optimal allocation and sizing techniques for dg in distribution systems. *International Journal of Renewable Energy Research (IJRER)*, 8(3):1236–1256.

Koza, J. R. (1995). Survey of genetic algorithms and genetic programming. In *Wescon conference record*, pages 589–594. western periodicals company.

Kumar, A., Babu, P. V., and Murty, V. (2017). Distributed generators allocation in radial distribution systems with load growth using loss sensitivity approach. *Journal of The Institution of Engineers (India): Series B*, 98(3):275–287.

Li, R., Ma, H., Wang, F., Wang, Y., Liu, Y., and Li, Z. (2013). Game optimization theory and application in distribution system expansion planning, including distributed generation. *Energies*, 6(2):1101–1124.

Mahmoud, K., Yorino, N., and Ahmed, A. (2015). Power loss minimization in distribution systems using multiple distributed generations. *IEEJ Transactions on Electrical and Electronic Engineering*, 10(5):521–526.

Mirjalili, S. (2015). The ant lion optimizer. *Advances in engineering software*, 83:80–98.

Mirjalili, S. (2016). Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. *Neural Computing and Applications*, 27(4):1053–1073.

Mirjalili, S. and Lewis, A. (2016). The whale optimization algorithm. *Advances in engineering software*, 95:51–67.

Mirjalili, S., Mirjalili, S. M., and Lewis, A. (2014). Grey wolf optimizer. *Advances in engineering software*, 69:46–61.

Mohan, V. J. and Albert, T. A. D. (2017). Optimal sizing and sitting of distributed generation using particle swarm optimization guided genetic algorithm. *Advances in Computational Sciences and Technology*, 10(5):709–720.

Muro, C., Escobedo, R., Spector, L., and Coppinger, R. (2011). Wolf-pack (canis lupus) hunting strategies emerge from simple rules in computational simulations. *Behavioural processes*, 88(3):192–197.

Murty, V. V. and Kumar, A. (2015). Optimal placement of dg in radial distribution systems based on new voltage stability index under load growth. *International Journal of Electrical Power & Energy Systems*, 69:246–256.

Muthukumar, K. and Jayalalitha, S. (2016). Optimal placement and sizing of distributed generators and shunt capacitors for power loss minimization in radial distribution networks using hybrid heuristic search optimization technique. *International Journal of Electrical Power & Energy Systems*, 78:299–319.

Nadimi-Shahraki, M. H., Taghian, S., and Mirjalili, S. (2021). An improved grey wolf optimizer for solving engineering problems. *Expert Systems with Applications*, 166:11–17.

Nguyen, T. T. and Truong, A. V. (2015). Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm. *International Journal of Electrical Power & Energy Systems*, 68:233–242.

Pan, W.-T. (2012). A new fruit fly optimization algorithm: taking the financial distress model as an example. *Knowledge-Based Systems*, 26:69–74.

Pezzini, P., Gomis-Bellmunt, O., and Sudrià-Andreu, A. (2011). Optimization techniques to improve energy efficiency in power systems. *Renewable and Sustainable Energy Reviews*, 15(4):2028–2041.

Prakash, D. and Lakshminarayana, C. (2016). Multiple dg placements in distribution system for power loss reduction using pso algorithm. *Procedia technology*, 25:785–792.

Ramezani, F. and Lotfi, S. (2013). Social-based algorithm (sba). *Applied Soft Computing*, 13(5):2837–2856.

Rao, R. V., Savsani, V. J., and Vakharia, D. (2011). Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. *Computer-Aided Design*, 43(3):303–315.

Razavi, S.-E., Rahimi, E., Javadi, M. S., Nezhad, A. E., Lotfi, M., Shafie-khah, M., and Catalão, J. P. (2019). Impact of distributed generation on protection and voltage regulation of distribution systems: A review. *Renewable and Sustainable Energy Reviews*, 105:157–167.

Reddy, P. D. P., Reddy, V. V., and Manohar, T. G. (2017). Whale optimization algorithm for optimal sizing of renewable resources for loss reduction in distribution systems. *Renewables: wind, water, and solar*, 4(1):1–13.

Saha, S. and Mukherjee, V. (2019). A novel multiobjective chaotic symbiotic organisms search algorithm to solve optimal dg allocation problem in radial distribution system. *International Transactions on Electrical Energy Systems*, 29(5):e2839.

Saremi, S., Mirjalili, S., and Lewis, A. (2017). Grasshopper optimisation algorithm: theory and application. *Advances in Engineering Software*, 105:30–47.

Simon, D. (2008). Biogeography-based optimization. *IEEE transactions on evolutionary computation*, 12(6):702–713.

Sobieh, A., Mandour, M., Saied, E. M., and Salama, M. (2017). Optimal number size and location of distributed generation units in radial distribution systems using grey wolf optimizer. *Int. Electr. Eng. J*, 7(9):2367–2376.

Suresh, M. and Edward, J. B. (2020). A hybrid algorithm based optimal placement of dg units for loss reduction in the distribution system. *Applied Soft Computing*, 91:106191.

Tan, W. S., Hassan, M. Y., Rahman, H. A., Abdullah, M. P., and Hussin, F. (2013). Multi-distributed generation planning using hybrid particle swarm optimisation-gravitational search algorithm including voltage rise issue. *IET Generation, Transmission & Distribution*, 7(9):929–942.

Teng, J.-H., Luor, T.-S., and Liu, Y.-H. (2002). Strategic distributed generator placements for service reliability improvements. In *IEEE Power Engineering Society Summer Meeting,*, volume 2, pages 719–724. IEEE.

Tu, Q., Chen, X., and Liu, X. (2019). Hierarchy strengthened grey wolf optimizer for numerical optimization and feature selection. *IEEE Access*, 7:78012–78028.

VC, V. R. et al. (2018). Ant lion optimization algorithm for optimal sizing of renewable energy resources for loss reduction in distribution systems. *Journal of Electrical Systems and Information Technology*, 5(3):663–680.

Webster, B. and Bernhard, P. J. (2003). A local search optimization algorithm based on natural principles of gravitation.

Willis, H. L. (2000). Analytical methods and rules of thumb for modeling dg-distribution interaction. In *2000 power engineering society summer meeting (Cat. No. 00CH37134)*, volume 3, pages 1643–1644. IEEE.

Yammani, C., Maheswarapu, S., and Matam, S. (2012). Multiobjective optimization for optimal placement and size of dg using shuffled frog leaping algorithm. *Energy Procedia*, 14:990–995.

Zhao, W., Wang, L., and Zhang, Z. (2019). Atom search optimization and its application to solve a hydrogeologic parameter estimation problem. *Knowledge-Based Systems*, 163:283–304.

Zimann, F. J., Batschauer, A. L., Mezaroba, M., Stangler, E. V., and dos Santos Neves, F. d. A. (2019). Investigation of voltage regulation with active and reactive power with distributed loads on a radial distribution feeder. In *2019 IEEE 15th Brazilian Power Electronics Conference and 5th IEEE Southern Power Electronics Conference (COBEP/SPEC)*, pages 1–6. IEEE.

Appendix A

IEEE 33 Bus System Data

Table A.1: A IEEE 33-Bus System Line and Load Data

Branch No.	Sending Bus	Receiving Bus	R(ohm)	X(ohm)	PL(KW)	QL(KVAR)
1	1	2	0.0922	0.047	100	60
2	2	3	0.493	0.2511	90	40
3	3	4	0.366	0.1864	120	80
4	4	5	0.3811	0.1941	60	30
4	5	6	0.819	0.707	60	20
6	6	7	0.1872	0.6188	200	100
7	7	8	1.7114	1.2351	200	100
8	8	9	1.03	0.74	60	20
9	9	10	1.044	0.74	60	20
10	10	11	0.1966	0.065	45	30
11	11	12	0.3744	0.1238	60	35
12	12	13	1.468	1.155	60	35
13	13	14	0.5416	0.7129	120	80
14	14	15	0.591	0.526	60	10
15	15	16	0.7463	0.545	60	20
16	16	17	1.289	1.721	60	20
17	17	18	0.732	0.574	90	40
18	2	19	0.164	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3083	90	50

Continued on next page

Table A.1 – continued from previous page

Branch No.	Sending Bus	Receiving Bus	R(ohm)	X(ohm)	PL(KW)	QL(KVAR)
23	23	24	0.898	0.7091	420	200
24	24	25	0.896	0.7011	420	200
25	6	26	0.203	0.1034	60	25
26	26	27	0.2842	0.1447	60	25
27	27	28	1.059	0.9337	60	20
28	28	29	0.8042	0.7006	120	70
29	29	30	0.5075	0.2585	200	600
30	30	31	0.9744	0.963	150	70
31	31	32	0.3105	0.3619	210	100
32	32	33	0.341	0.5302	60	40

Appendix B

IEEE 69 Bus System Data

Table B.1: A IEEE-69-Bus System Line and Load Data

Branch No.	Sending Bus	Receiving Bus	R(ohm)	X(ohm)	PL(KW)	QL(KVAR)
1	1	2	0.0005	0.0012	0.0	0.0
2	2	3	0.0005	0.0012	0.0	0.0
3	3	4	0.0015	0.0036	0.0	0.0
4	4	5	0.0251	0.0294	0.0	0.0
5	5	6	0.3660	0.1864	2.60	2.20
6	6	7	0.3811	0.1941	40.40	30.00
7	7	8	0.0922	0.0470	75.0	54.0
8	8	9	0.0493	0.0251	30.0	22.0
9	9	10	0.8190	0.2707	28.0	19.0
10	10	11	0.1872	0.0691	145.00	104.00
11	11	12	0.7114	0.2351	145.0	104.0
12	12	13	1.0300	0.3400	8.0	5.50
13	13	14	1.0440	0.3450	8.0	5.50
14	14	15	1.0580	0.3496	0.0	0.0
15	15	16	0.1966	0.0650	45.5	30.0
16	16	17	0.3744	0.1238	60.0	35.0
17	17	18	0.0047	0.0016	60.0	35.0
18	18	19	0.3276	0.1083	0.0	0.0
19	19	20	0.2106	0.0690	1.00	0.60
20	20	21	0.3416	0.1129	114.0	81.0
21	21	22	0.0140	0.0046	5.30	3.50
22	22	23	0.1591	0.0526	0.0	0.0

Continued on next page

Table B.1 – continued from previous page

Branch No.	Sending Bus	Receiving Bus	R(ohm)	X(ohm)	PL(KW)	QL(KVAR)
23	23	24	0.3463	0.1145	28.0	20.0
24	24	25	0.7488	0.2475	0.0	0.0
25	25	26	0.3089	0.1021	14.0	10.0
26	26	27	0.1732	0.0572	14.0	10.0
27	3	28	0.0044	0.0108	26.0	18.60
28	28	29	0.0640	0.1565	26.0	18.60
29	29	30	0.3978	0.1315	0.0	0.0
30	30	31	0.0702	0.0232	0.0	0.0
31	31	32	0.3510	0.1160	0.0	0.0
32	32	33	0.8390	0.2816	14.0	10.0
33	33	34	1.7080	0.5646	19.5	14.0
34	34	35	1.4740	0.4673	6.0	4.0
35	3	36	0.0044	0.0108	26.0	18.55
36	36	37	0.0640	0.1565	26.0	18.55
37	37	38	0.1053	0.1230	0.0	0.0
38	38	39	0.0304	0.0355	24.0	17.0
39	39	40	0.0018	0.0021	24.0	17.0
40	40	41	0.7283	0.8509	1.20	1.0
41	41	42	0.3100	0.3623	0.0	0.0
42	42	43	0.0410	0.0478	6.0	4.30
43	43	44	0.0092	0.0116	0.0	0.0
44	44	45	0.1089	0.1373	39.22	26.30
45	45	46	0.0009	0.0012	39.22	26.30
46	4	47	0.0034	0.0084	0.0	0.0
47	47	48	0.0851	0.2083	79.0	56.40
48	48	49	0.2898	0.7091	384.70	274.50
49	49	50	0.0822	0.2011	384.0	274.50

Continued on next page

Table B.1 – continued from previous page

Branch No.	Sending Bus	Receiving Bus	R(ohm)	X(ohm)	PL(KW)	QL(KVAR)
50	8	51	0.0928	0.0473	40.50	28.30
51	51	52	0.3319	0.1114	3.60	2.70
52	9	53	0.1740	0.0886	4.35	3.50
53	53	54	0.2030	0.1034	26.40	19.00
54	54	55	0.2842	0.1447	24.0	17.20
55	55	56	0.2813	0.1433	0.0	0.0
56	56	57	1.5900	0.5337	0.0	0.0
57	57	58	0.7837	0.2630	0.0	0.0
58	58	59	0.3042	0.1006	100.0	72.00
59	59	60	0.3861	0.1172	0.0	0.0
60	60	61	0.5075	0.2585	1244.0	888.0
61	61	62	0.0974	0.0496	32.0	23.0
62	62	63	0.1450	0.0738	0.0	0.0
63	63	64	0.7105	0.3619	227.0	162.0
64	64	65	1.0410	0.5302	59.0	42.0
65	11	66	0.2012	0.0611	18.0	13.0
66	66	67	0.0047	0.0014	18.0	13.0
67	12	68	0.7394	0.2444	28.0	20.0
68	68	69	0.0047	0.0016	28.0	20.0

Appendix C

List of Publications

The paper titled “ Optimal Planning of Distributed Generation Using Improved Grey Wolf Optimizer and Combined Power Loss sensitivity” ,To be sent to IEEE of Electrical Power and Energy System. In Press