AKENTEN APPIAH-MENKA UNIVERSITY OF SKILLS TRAINING AND ENTREPRENEURIAL DEVELOPMENT

OPTIMAL ALLOCATION OF DISTRIBUTED GENERATION AND FAST ELECTRIC VEHICLE CHARGING STATIONS ON THE ASHANTI REGION NETWORK.

BY

ISAAC PREMPEH
(8201200004)

A thesis submitted to the School of Graduate Studies, Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development in partial fulfillment of the requirements for the award of a Master of Philosophy degree in Electrical Power System Engineering.

MAY, 2023

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original work and that no part of it has been presented for another degree at this university or elsewhere.

Candidate's Name: ISAAC PREMPEH

Signature: ………………………… Date: …………………………..

Supervisor's Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of the thesis laid down by the Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development.

Principal Supervisor's Name: ALBERT K. AWOPONE (PhD)

Signature: …………………………. Date: …………………….....

Co-Supervisor's Name: …………………………………………………….

Signature: ………………………….. Date: ………………………..

ABSTRACT

The focus of the study was the optimal placement and sizing of distributed generation(DG) units and fast electric charging stations on the Ashanti region network. DG units would have to be injected while electricity demand from EV charging infrastructure increases. Two metaheuristics were adopted to solve the allocation problem. The IEEE 69 bus and 33KVA Ashanti region distribution networks were used in the study. ETAP and MATLAB environments were used to simulate the design. The particle swarm optimization (PSO) and artificial bee colony(ABC) algorithms were adopted for the solution. The proposed PSO outperformed ABC, TLBO, GA, HHO, WOA, and SA. The proposed PSO and ABC reduced power losses by 68% while maintaining the system voltage profile within 4% of the IEC standard. The two methods can be employed for simultaneous placement even at high penetration levels to reduce network active power loss and improve voltage profile. The Ashanti region analysis predicted a DG-powered fast EVCS on bus 14 to reduce system power loss. The model used can be adopted for examining network loss and voltage profile enhancement when DG units and fast EVCS are to be allocated on other complicated power system networks. An AI-based sizing and placement of distributed generation and fast electric vehicle charging stations will enable power systems to meet consumer needs (e.g., electric vehicle charging) and enhance the deployment of DG units on any network.

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DEDICATION

To my wife,

Thank you for your love, patience, and understanding during this challenging and rewarding journey. Your support has been a constant source of strength, and I am grateful for the many sacrifices you have made to help me achieve my goals. I dedicate this thesis to you as a testament to our shared commitment to each other's success.

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LIST OF ABBREVIATION

ABC	Artificial Bee Colony
BFOA	Bacterial Foraging Optimization Algorithm
BSS	Battery Switching Station
DG	Distributed Generation
ECG	Electricity Company of Ghana
EHO	Elephant Herding Optimization
EHO	Elephant Herding Optimization
EMPA	Enhanced Marine Predators Algorithm
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
EVSE	Electric Vehicle Supply Equipment
GE	General Electric
GHG	Green House Gas
GW	Gigawatt
HHO	Harries Hawk Optimization
IEC	International Electrotechnical Commission
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers

IPP	Independent Power Producers
IWO	Invasive Weed Optimization Algorithm
MRFOA	Manta Ray Foraging Optimization Algorithm
PSO	Particle Swarm Optimization
RET	Renewal Energy Technologies
SSA	Sub-Saharan Africa
TLBO	Teaching Learning-Based Optimization
WCA	Water Cycle Algorithms
WHO	World Health Organisation
WOA	Whale Optimization Algorithm

CHAPTER ONE

INTRODUCTION

1.1 Background

Thomas Alva Edison and Nikola Tesla were two important contributors to the Second Industrial Revolution, which was kicked off by the mechanical creation of electric power. This creation opened the door for a variety of inventions that made use of electricity(Sonal, 2017). In 1882, a steam engine at Pearl Street Station powered a dynamo, which produced a direct current (DC) current. This current was used to power the public lighting on Pearl Street in New York City. This marked the beginning of the generation of electricity at central power plants(ETHW, 2020; Saadat, 1999). As a direct result of these changes in how electricity is made, many cities around the world quickly adopted the new technology and switched out their gas-powered street lamps for electric ones. In the modern world, electricity can be made from many different energy sources, such as coal, nuclear power, natural gas, hydroelectricity, oil, wind, solar, tidal, and geothermal energy (Saadat, 1999; Theraja & Theraja, 2005).

To reap the financial and operational benefits of centralized power generation, several utilities started integrating their distribution networks with their generation stations starting in the middle of the twentieth century(Brown, 1971; ETHW, 2020; Shifera, 2021). Long-distance power transmission came about at the same time that power plant synchronization from various sources started. After that, regional system operators made sure this system was safe to make sure it worked reliably and consistently. In the beginning, the distribution of electricity was handled by separate companies that had no connection to one another(Brown, 1971; Williams, 1964). Both the productivity and the efficiency of the generation went up as technology got better. These large-scale power plant advancements were essential to the process of centralized generation, just as they would later prove to be essential to the entire power system that we make use of today.

The process of producing electricity for local use rather than sending it through the electric grid from a large centralized facility is referred to as a distributed generation. Sometimes people will refer to it as decentralized generation(Institute Environmental and energy study, 2022). Although distributed generation is not a novel idea, it is experiencing a surge in interest as a result of the numerous advantages it offers over traditional forms of power generation(Awopone, 2021; de Castro & Dantas, 2017; P. Prakash & Khatod, 2016a; Shaheen, Elsayed, et al., 2021a; Truong et al., 2020).

Distributed generation (DG) has been used to improve grid reliability and reduce system losses (Elattar et al., 2021a; Hoffman & Johnson, 2020; Pesaran H.A et al., 2017; Shaheen, El-Sehiemy, et al., 2021). Higher levels of distributed generation(DG) system poses power quality issues on the grid since Distributed Generation(DG) units can cause bidirectional power flow, unstable and undependable at a certain time of the day (i.e. solar and wind)(Adetunji et al., 2020a; Azad et al., 2021; Impram et al., 2020a; Injeti & Prema Kumar, 2013; Razavi et al., 2019a; P. D. P. Reddy et al., 2017; Settoul et al., 2021) Though solar and wind form part of DG units their supplies are non-dispatchable, making them unstable and unreliable at certain times of the day (Impram et al., 2020a; Lee et al., 2020a; Razavi et al., 2019a).

Modern mobility has also spurred electric car development(Falfari & Bianchi, 2023). The IEA predicted that the transportation sector could reduce CO_2 emissions by 28% by the year 2030 when electric vehicles are adopted(Adnan et al., 2018a; Falfari & Bianchi, 2023). This advancement in mobility has increased electricity demand(Falfari & Bianchi, 2023).

Electric vehicles(EVs) use chargers for operation to meet customer comfort(Ravi et al., 2021). Charging stations make the usage of electric cars reliable and convenient. In recent times Tesla and Shell have built many fast Charger (FC) stations to decrease range anxiety and promote long-distance EV use (Falfari & Bianchi, 2023; Wang et al., 2021). The power supplied to these stations requires high-voltage lines. It is anticipated that many governments will build high-power fast-charging networks soon due to the growing numbers of EVs(International Energy Agency, 2021). As electric vehicle ownership and technology develop, some experts recommend examining how fast charging stations affect power supply reliability(Fredriksson et al., 2019a; Uko, 2020; Zhang, 2017; Zhang et al., 2018). Some researchers have postulated that the potential integration of fast charging stations on power system reliability must be comprehensively studied as more electric vehicle owners and technology keeps increasing year by year(Fredriksson et al., 2019a; Ravi et al., 2021; Sa'adati et al., 2021a; Wang et al., 2021; Zhang et al., 2018).

Electric cars depend on the power supply at charging stations for them to work. Fast EVCS, which are also grid-friendly, make charging a large number of electric vehicles using power from the grid or renewable sources simple. Most fast charging stations require a significant amount of power to function, and it is not possible to locate them in every available spot on the power grid(Ahmad, Iqbal, Ashraf, Marzband, & Khan, 2022; Csiszár et al., 2020; Luo et al., 2017; A. K. Mohanty et al., 2022). It's important to figure out where to put these fast chargers because if there are too many of them, they could hurt essential power infrastructure. A haphazard installation of fast EVCS may result in bidirectional power flow, harmonic distortion, high power loss, and an unreliable voltage profile (Ahmad, Iqbal, Ashraf, Marzband, & Khan, 2022; Luo et al., 2017; A. K. Mohanty et al., 2022). Again, the optimal placement of fast EVCS can improve the grid's dependability and stability(A. K. Mohanty et al., 2022).

Studies have been conducted to find the optimum location of charging stations based on the transport and distribution network constraints of EVs, multiple shortest paths, and deviation paths (Danese, Garau, Sumper, & Torsæter, 2021; Fredriksson et al., 2019; Naireeta, Rajendra Singh, & Brooks, 2021). Again, researchers like Sa'adati have employed DG integration for technical loss reduction such as voltage profile improvement when demand on the grid increases(Sa'adati et al., 2021a). A recent study suggests that to inject DG units into the network, a rigorous study using appropriate technologies is recommended to avoid future network failures(Iweh et al., 2021a).

In Mohamed and Kowsalya(2014) and Prakash and Lakshminarayana(2018), the Whale Optimization Algorithm(WOA) and Bacterial Foraging Optimization Algorithm(BFOA) have been used for DG unit allocation in an attempt to reduce system loss. Other authors have presented an allocation of solar-powered EVCS for power loss reduction (Ahmad et al., 2021). ABC has been used to solve the allocation of the battery Switching Station(BSS) and DG units (Al-Ammar et al., 2021; Jamian et al., 2014). Authors Reddy et al.(2017) used PSO for the allocation of DG. The Teaching Learning Based Optimization(TLBO) and Harries Hawk Optimization(HHO) algorithms were adopted to minimize power losses on the IEEE 33 bus system(Zeb et al., 2020). However, according to Devabalaji(2015), a swarm-based approach is suggested to perform better.

Babu and Swarnasri(2020) implemented simultaneous placement of DG and EVCS. The TLBO and HHO algorithm was used to find the best places for EVCSs. For DG unit allocation research findings suggest future works should use Artificial Bee Colony instead of other algorithms for superior placement of DG units(Al-Ammar et al., 2021; Babu & Swarnasri, 2020; Jamian et al., 2014).

With Ghana set to use EVs and the gradual introduction of more DG units on the grid, the future outlook of electrical power efficiency and reliability looks gloomy, and an investigation into DG and EVCS allocation is necessary. Again with the increasing demand for EVCS on a smart grid, there is the need to use meta-heuristic optimization in the allocation of fast-charging EVCS to study the voltage profile and power losses of power systems.

1.2 Statement of the problem

Ghana can meet its energy needs using distributed generation units like solar energy since radiation averages 5.35 kWh/m2 nationwide year-round(Awopone, 2021; Awopone & Zobaa, 2017). However, Economic and technological challenges will arise when the country aggressively installs dispersed generating systems (especially PV systems) on the electrical grid(Falfari & Bianchi, 2023). As penetration increases, network topology influences active line losses, and system performance is affected (Impram et al., 2020).

Several methods can be adopted to reduce system losses. These are network reconfiguration, capacitor placement, and DG unit integration(A.M. Shaheen, A.M. Elsayed, Ragab A. El-Sehiemy, 2022; Masoum et al., 2004; Simon Njuguna, 2021). Researchers have adopted network reconfiguration to improve system loss. Other researchers have introduced capacitor banks for the improvement of loss(Dixit et al., 2017; El-Ela et al., 2018a, 2018b; Masoum et al., 2004; Simon Njuguna, 2021). Allocation of DG units has been used to improve system loss(Ahmad, Iqbal, Ashraf, Marzband, & Khan, 2022; Bhumkittipich & Phuangpornpitak, 2013; Chen et al., 1977; Devabalaji et al., 2015; Elseify et al., 2022; Nawaz et al., 2018).

The Enhanced Marine Predators Algorithm(EMPA) has been used for simultaneously distributed generations (DGs) allocation in recent research to improve system performance (A.M. Shaheen, A.M. Elsayed, Ragab A. El-Sehiemy, 2022; Elattar et al., 2021a; Shaheen, El-

Sehiemy, et al., 2021). Other works employ water cycle algorithms to establish distributed generation and capacitor banks on IEEE 33-bus, and 69-bus test systems, and the East Delta network in the Egyptian system (El-Ela et al., 2018). A network of integrated rapid electric vehicle charging stations and distributed generation systems has not been fully investigated in Ghana. Evidence in recent literature proposes that EVs and DG systems would lower power system losses while improving efficiency and reliability. Electric car charging stations and distributed generating systems must be optimally planned and sized to preserve network integrity within the technological limits without substantial transmission system reconstruction.

In Ghana, the energy commission has started issuing permits for the deployment and application of distributed generation units since the year 2019(Energy Commission, 2019b). The energy commission has also developed a concept paper on electric vehicle usage and EV infrastructure application on the Ghana grid(energy commission, 2019a). The concept paper contains a strategy that is geared towards one hundred electric vehicles and ten public charging stations in Ghana by 2020 (energy commission, 2019a; Energy Commission, 2020, 2023). The growth of EV users around the world keeps increasing. This increase around the world also demonstrates that the number of EV users in the country will increase in the future. Will the new DG units and charging stations impact Ghana's distribution system? How will the DG units and charging station units be sized? Which part of the grid best fits these DG units and fast EVCS for their location?

1.3 Objectives

The research aimed to optimally place and size distributed generation(DG) systems and Electric vehicle fast charging stations on the IEEE 69 bus distribution network and the ECG

33KVA distribution network in the Ashanti region of Ghana using artificial intelligence techniques. The research focused on these specific objectives to obtain the general objective:

- To formulate a multi-objective function problem based on power losses and voltage profile deviation for the simultaneous allocation of DG units and fast EVCS.
- To perform a load flow analysis on the IEEE 69 bus radial network and the ECG 33KVA distribution network in the Ashanti region of Ghana.
- To allocate and size distributed generation and Fast Electric vehicle charging stations by using meta-heuristic techniques.
- To analyze the meta-heuristic techniques in terms of the optimal allocation of DG and fast EVCS.

1.4 Significance of the study

This study predicts the most efficient location and size to deploy distributed generation units and electric vehicle fast charging stations on a real part of Ghana's grid infrastructure. This study provides critical information for consideration if fast electric vehicle charging stations are to be introduced on the Ashanti region network. The study provides theoretical and experimental guides in the development of an integrated fast electric vehicle charging station and distributed generation systems for future distribution networks. It also proposes some basic requirements for the implementation of a smart grid from now on and beyond in the context of fast electric vehicle charging stations.

The study provides a modeling design for the simultaneous placement of distributed generation units and fast electric vehicle charging stations on any power system network that can be used by researchers. As the world makes efforts to improve transmission losses by applying DG units and EVCS, this study provides a meta-heuristic technique approach as a solution. The thesis used Particle Swarm Optimization(PSO) and Artificial Bee Colony algorithms as a technique to predict the optimal sizing and allocation of DG units and the location of EVCS. The model can be used for studies on simultaneous placement on other complex power system networks to study the network loss and voltage profile enhancement. The model can also be used to investigate the active and reactive power loss on a system involving DG units and Fast EVCS. The thesis model can be adopted for studies in fast EVCS allocation based on penetration levels in an attempt to meet maximum and minimum technical network parameters.

The study applied the model on a real part of the Ghana grid(i.e. Ashanti region ECG 33KVA distribution network). The load flow studies using the Electrical Transient Analysis Program(ETAP) were employed in the study. As such the primary data and load flow studies from the Ashanti region 33KVA distribution network can be used by the academic community for other studies like predictive load demand, the economics of power distribution infrastructure and power system protection schemes, etc. The data from this study can be used for studies in power system optimization, control, and utilization.

Power system utility companies in the country can use the information in this thesis to get an optimal size and location of both DG units and fast EVCS in the Ashanti region shortly. In recent times the government of Ghana has approved the use of DG units and EVs so any utility company intending to build a DG unit or charging infrastructure in the Ashanti region would have access to the best size and location to site them(Energy Commission, 2023). The study provides information on the placement of DG units in the Ashanti region which will be vital to the independent power producers and privately invested who would be interested in investing in charging infrastructure for EVs in the region and beyond. The results of the study proposed the placement of fast EVCS-powered DG units on the Ashanti region network for improved voltage profile. This can be implemented by system operators for the reliability of power supply and support EV users as penetration of EV levels increases.

Government can save money in terms of minimized system loss and spending on the purchase of power system components. The thesis presents an alternative to the technical losses on the Ghana grid. Many a time system components are replaced with new improved components to upgrade the system in an attempt to reduce power loss. The proposed alternative of reducing power losses where new network components are not introduced can directly affect the cost of generating power and the system maintenance cost. As such system components that would have been purchased by the government for upgrading the network at a cost are reduced. In the long run, government spending on system components such as transmission lines is avoided. This also helps the government to reallocate funds to another area of the power system or economy in general.

This study provides an alternative to providing data support to the Ghana government's electric vehicle policy and proposes a pathway for the implementation of fast electric vehicle charging stations in the Ashanti region. The adaptation of EVs is on the rise and will keep increasing as more incentives are introduced in the EV market. With the saturation of EVs in the country there would be a need to build charger infrastructure on the Ashanti region grid. This study proposes substations that can accommodate these fast charging stations on the Ashanti region distribution network without major improvement on the network. The results of the implementation of fast EVCS can be considered by the energy commission of Ghana in their charging infrastructure allocation under the drive-electric policy. Since the energy commission is the sole agency responsible for issuing distributed generation licensing, the study can also serve as literature and technical documents for the development of DG unit allocation in the Ashanti region of Ghana.

For EV users in Ghana, the thesis paints a better picture of the adaptation of electric vehicles. With fast chargers located in the Ashanti region long-distance traveler who suffers from range anxiety when using their EVs would have reduced stress when traveling in the region. EV users would be assured of charging up at various points within the region at shorter intervals. The study would also provide private investors the opportunity to invest in DG units and EV infrastructure as a way of improving their livelihood. The quality of life of the persons in the region would be improved since the greater adaptation of EVs in the region can limit air pollution from cars in the Ashanti region when fast EVCS is adopted in the region as proposed in this study.

1.5 Limitations

This thesis focused on the allocation of DG and fast EVCS on the IEEE 69 bus test system and the 33KVA ECG Ashanti region distribution network. The two metaheuristic technique is then used to simultaneously allocate DG units and fast EVCS on both networks. The metaheuristic techniques employed in the study were Particle Swarm Optimization(PSO) and Artificial Bee Colony(ABC) algorithms. The study used the AI technique to optimally size the DG units. The study applied two metaheuristic techniques (i.e., ABC and PSO) to the problem of minimized power losses and voltage profile improvement. The convergence characteristics of only ABC and PSO applications are considered in the analysis of the algorithm in the context of the minimum objective functions.

1.6 Delimitations

The ECG 33KVA distribution network is operated as a ring in normal operations to provide power reliability throughout the year. The researcher has adopted the network as a radial system with their most frequently used configuration for the analysis in this thesis. The adaptive

Newton-Rapson load flow technique and backward/forward sweep load flow analysis were adopted for this study. The researcher adopted only fast EVCS with a capacity of 975KW with one hundred charging ports from only five EV manufacturers. The adopted fast EVCS were modeled without vehicle-to-grid technology capabilities.

1.7 General Layout of The Thesis

A chapter-by-chapter summary of the thesis is presented below:

Chapter one focuses on the rationale behind the allocation of DG and EVCS is discussed. This includes the problem of simultaneous allocation of DG units and fast EVCS on the IEEE 69 bus system and the 33KVA distribution system in the Ashanti region. The solution to the allocation problem was attained through four specific objectives. The significance of the thesis to academia, utility companies, policy advisors, the government of Ghana, and the users of EVs is also explained. The technical scope of the thesis in terms of optimization methods is stated. A presentation of the thesis structure is summarized.

Chapter two introduces the development of DG units and EVCS in the available literature. The development of e-mobility in sub-Saharan Africa is elaborated. Theoretical information on DG units and EVCS infrastructure is discussed. The Load flow methods used in simultaneous allocation are also discussed. The chapter again discusses allocation methods for DG placement and sizing along with EVCS integration. The Integration issues of DG units and EVCS are examined from the available literature. The metaheuristic techniques for allocation and placement are identified through a comprehensive review. An empirical review of the optimization methods is summarized.

Chapter three shows the structure of the thesis in terms of the research objectives. The data collection methods and the data used are stated. The proposed mathematical models of the problem are presented alongside simulation techniques adopted to find the optimization solution. The data validation of the simulation is presented in this chapter. The chapter also shows the various case structures adopted for the analysis.

In Chapter Four the results of scenarios for DG and EVCS allocation are discussed for the IEEE 69 bus and Ashanti region 33KVA distribution network. The discussion of the adopted technique is the analysis by comparing with available literature. Artificial bee colony and particle swarm optimization algorithms are compared with each other in terms of objective functions for the Ashanti region network. The results are discussed to show the improvement in the network when the PSO and ABC are adopted for DG unit and EVCS allocation.

The thesis outcome from the simulation has been used to propose some suggestions for further studies on the two networks presented in Chapter Five. Again, Recommendations are made for the simultaneous allocation of DG and EVCS on the IEEE 69 bus and Ashanti Region network to academia, utility companies, Governments, and users of EVs. Future research areas in simultaneous placement are discussed and proposed.

CHAPTER TWO

LITERATURE REVIEW

2.1 Electrical Power Generation in the 21st Century

Most of the activities in the 21st-century world are driven by electricity. The advantages that electricity provides have shifted attention to ways to extract other forms of energy to produce electricity. In other to limit environmental emissions the energy sector focuses on sustainable electrical energy generation units often referred to as distributed generation (DG) or Renewal Energy Technologies (RET) units. These new forms of electricity generation have been used to increase the reliability of grid supply while minimizing system losses. modern electricity utilities producers are being pressured to move toward sustainable generation units due to global emission issues(International Energy Agency, 2020; WHO et al., 2017). This has necessitated rigorous moves in the electrical energy sector to consider smart grid integration at various points in the power distribution system. Another issue for the renewed interest in renewable is the increase in load demand(Hassan, Othman, et al., 2020). General Electric reports that the world is shifting away from an electricity system based primarily on large, centralized generation and transmission and distribution (T&D) technologies and toward one that includes distributed, digitally enhanced, and low-carbon technologies. Traditional and emerging, physical and digital, large and small, are all coming together to form a new power network for the twenty-first century(GE Power, 2018).

Around the world, there is an increasing use of electricity generated from renewable sources(Awopone, 2021; International Energy Agency, 2020; Morgan et al., 2022). This new paradigm shift to renewable energy technology can be attributed to the non-exhaustive, available, and non-polluting nature of RET. In 2021 the renewable energy report published stated that the total global renewable power capacity in 2018 reached 1246 GW, with China producing 404 GW, the United States of America sharing 180 GW, and Germany producing 113 GW. These countries were leading the way when compared with the rest of the world combined as a unit (International Energy Agency, 2020).

2.2 Sub-Saharan Africa Energy Potentials

Over one billion people around the world lack access to electricity, and nearly three billion rely on biomass, such as wood, for cooking(GE Power, 2018). Sub-Saharan Africa and developing Asia account for more than 95 percent of those without electricity. In Africa, the renewable energy landscape is made up of solar photovoltaic, wind, hydro, geothermal, and biomass sources. The use of a combination of these resources is mainly on the availability in the location of the beneficiary country. In 2019 alone the renewable energy mix in sub-Saharan Africa was estimated to be around 50GW(Hoffman & Johnson, 2020). Hydro-generation plants had the maximum share of the total power produced at 35.7 GW. The non-hydro sources such as wind, Geothermal, biomass, and solar form less than 13.8 GW (Hoffman & Johnson, 2020; WHO et al., 2017).

The solar resource in Africa is among the best in the world, but very little of it is used to generate electricity. According to the general electric report for energy generation in Sub-Saharan Africa (SSA), solar generation in this region accounts for only one percent(1%) of global solar generation(Frost & Sullivan, 2018; Hoffman & Johnson, 2020). Hoffman and Johnson (2020) report that the majority of areas in SSA experience over 2000 kWh of solar radiation annually. In addition to the solar resource available in the sub-region, hydropower is also estimated to have a potential of 300 GW capacity. However, only eight percent(8%) of these renewable sources are currently utilized for electricity generation. With this interesting potential, there have been plans by countries in the sub-region to tap into the RET sector as electricity demand continues to rise yearly(GE Power, 2018).

To tap into the potential of RET and also to meet power demand for the subregion the countries have established the West African Power Pool(WHO et al., 2017). These strategies formed as a result of the interdependence of the regional countries and their common interest in promoting stable reliable power at affordable prices. To this end, The planning and prospects for Renewable Energy followed the formal adoption of two major regional policy developments: the 2011/12 West African Power Pool (WAPP) Master Plan and the ECOWAS Renewable Energy Policy (EREP), which aims to increase the region's overall electricity generation mix's share of renewable energy to twenty-three percent(23%) in 2020 and thirty-one percent(31%) in 2030 (ECREEE, 2013).

2.3 Ghana’s Energy Mix Since 2011

In the context of electricity demand, a comprehensive literature review reveals a remarkable and sustained transformation in the landscape of electricity generation capacity over the past decade. From 2011 to 2021, the total grid-installed electricity generation capacity exhibited a striking annual average growth of 9.7%, surging from 2,170 MW to an impressive 5,481 MW(Aboagye et al., 2021; Asuamah et al., 2021; Energy Commission, 2022). Concurrently, the dependable capacity, a vital indicator of reliability in meeting electricity demand, rose significantly, ascending at an annual growth rate of approximately 9.8%, reaching 4,975 MW by 2021. Of notable significance is the astounding fourfold increase in thermal generation capacity, which soared from 990 MW in 2011 to an impressive 3,753 MW in 2021, demonstrating an outstanding annual average growth rate of 14.3%(Energy Commission, 2022; Iweh et al., 2021a). This burgeoning capacity expansion underscores a concerted effort towards bolstering the energy infrastructure.

According to data from the Energy Commission an overview of the energy generation landscape, power plants according to their installed and reliable capacity as Hydro Power

Plants, Thermal Power Plants, and Other Renewables. Figure 2.1 shows the installed generation capacities in Ghana as of 2021 (MW).

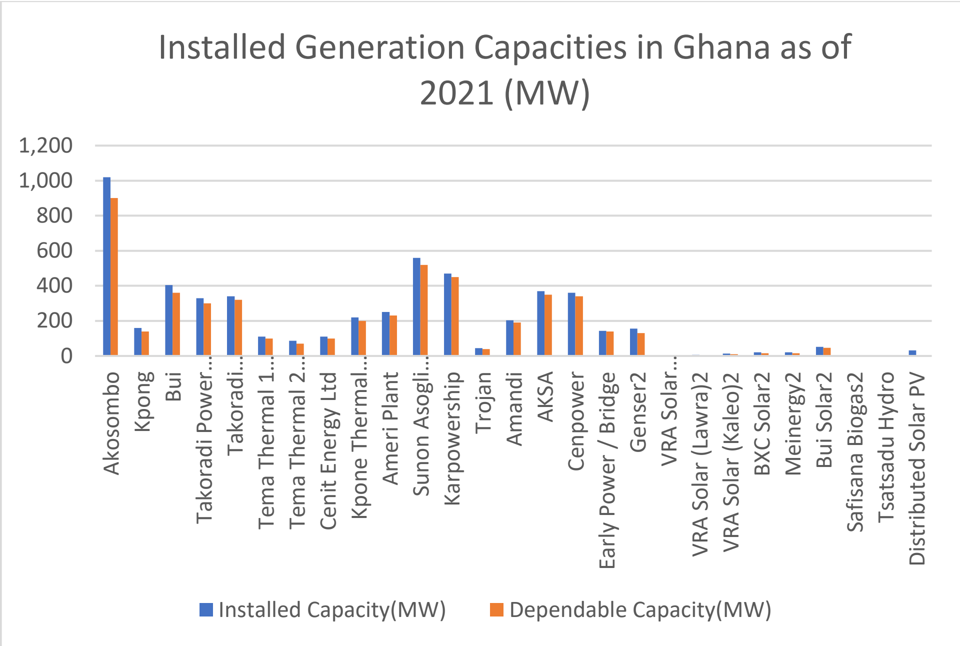

Figure 2 - 1 Installed Generation Capacities in Ghana as of 2021 (MW)

Notably, hydro power plants, with a combined installed capacity of 1,584 MW and led by Akosombo with 1,020 MW, make a substantial contribution to the grid. Parallel to this, the installed capacity for Thermal Power Plants has increased significantly, with a combined total of 3,753 MW by 2021(Awopone, 2017, 2021; Energy Commission, 2022; Iweh et al., 2021a). This development demonstrates the area's dedication to enhancing its energy infrastructure, with major contributions coming from numerous important facilities, including Sunon Asogli Power (Ghana) Ltd. and Karpower ship.

Moreover, this transformative trend suggests a commitment to diversifying and bolstering the energy portfolio, potentially reducing reliance on less sustainable energy sources in the pursuit of a more sustainable and robust power generation system.

Since 2016, Ghana added to its energy mix a 20 MW solar photovoltaic plant owned by BXC Ghana. Within that same year, a 100 kW biogas electricity generation facility was connected to the grid (Energy Commission-Ghana, 2021). On April 12, 2021, the government of Ghana commissioned a 50MW solar system at the Bui hydropower station (Appiah-Adjei Salomey, 2017; Ingram Elizabeth, 2022; Power Africa, 2022). This is Ghana’s largest solar farm and forms part of the first phase of a 250MW project expected to be completed by the end of 2022. To limit environmental emissions the energy sector focuses on sustainable electrical energy generation systems. With many countries trying to limit GHG emissions and control the depletion of fossil fuels, many countries are directing electricity generation toward renewable energy generation Ghana is not an exception(Awopone, 2021).

2.4 Ghana’s Energy Potentials

Ghana ranked first in Sub-Saharan Africa in terms of electrical connectivity relative to population(The World Bank, 2019). This is primarily due to its natural resources and government policies aimed at improving the lives of its citizens. Three main generators are responsible for the country's electrical power production. Recently, IPP adaptation in the energy sector has necessitated the country's rapid growth of power(Nolan et al., 2020).

The electricity generation sector of Ghana, as is the case in most developing countries, is facing serious challenges(Kumi, 2017). According to Kumi(2017), Ghana's chronic energy supply issues over the previous ten years have cost the country $2.1 million daily on average in lost production. Even though installed generation capacity increased during that time, from 1,730 MW in 2006 to 3,795 MW in 2016. The expansion of thermal power generation is the result of numerous limitations, such as the uncertainty of rainfall for hydropower generation paired with the quick increase in demand. According to the energy commission, 2020 report the country's installed power stood at 5,288MW. This total production included the RET component. The

Ghana energy mix as of 2020 consisted of hydropower(32.9%), thermal generation(66.4%), and grid-tie solar photovoltaic(0.7%)(Energy Commission-Ghana, 2021).

Since the introduction of Independent Power Producers(IPP) in the power generation sector, there has been an increase in power supply. The majority of the IPPs are thermal plants. These plants require high financial resources in their operations due to the fuel needed for the production of electricity. Utility firms have been unable to generate enough money due to the rising cost of fuel(www.theghanareport.com, 2022). Another challenge in Ghana's electricity distribution is the high amount of losses in the distribution system, which are mostly caused by outdated distribution equipment and consumer non-payment of revenue. The non-payment of revenues from users of electricity is affecting the finances of the generation companies. In 2022 alone, the Electricity Company of Ghana(ECG) disconnected the Yilo Krobo township for the nonpayment of electricity usage for over five years in an attempt to increase revenue mobilization(Joyonline, 2022).

To mitigate some of these challenges Worldwide economic viability of grid-connected renewable energy systems has proven to be cost-effective in terms of long-term planning(Awopone & Zobaa, 2017). Distributed generation(DG) has been used to increase the reliability of grid supply while minimizing system losses (A.M. Shaheen, A.M. Elsayed, Ragab A. El-Sehiemy, 2022; Elseify et al., 2022; Hoffman & Johnson, 2020; Iweh et al., 2021a; Jamian et al., 2014; Shaheen, El-Sehiemy, et al., 2021). However, The high penetration of renewable energy is limited by high capital costs, system stability requirements, and voltage control needs(Al Abri et al., 2013; Chowdhury et al., 2020; Mondal & Islam, 2009; Razavi et al., 2019a).

To researchers(Adaramola et al., 2014; Awopone, 2021; Gonçalves et al., 2020; Kumi, 2017) Ghana is a great place to use solar photovoltaic technology. Also, a great number of pertinent publications supporting a high potential for a sustainable transition to renewable energy are available as evidence from existing academic research on the use of renewable energy in Ghana. (Asuamah et al., 2021; Awopone, 2021; Awopone & Zobaa, 2017). sadly as much as the potential for RET is high for the country its implementation is not prevalent in the country (Aboagye et al., 2021; Awopone & Zobaa, 2017; International Renewable Energy Agency, 2019).

With the installation of dispersed generation units, several possible advantages to delivered electricity can be realized. It is important to optimally allocate and size distributed generation units in the proper places to fully enjoy these benefits. Otherwise, their installation might have a detrimental impact on the performance of the system and the quality of the power delivered to the customer. For the best integration of dispersed generation, numerous potent optimization technologies have been created over time. As a result, optimization strategies are constantly changing and have recently been the subject of numerous new studies.

2.5 Transportation and Energy sector

Africa is the world's largest importer of secondhand light-duty vehicles (LDVs)(IEA, 2022a). With an average of one million vehicles imported annually, the continent represented 25% of all LDV commerce between 2015 and 2020. The majority of used cars imported into Africa come from the European Union and Japan, while imports from the United States and Korea have increased significantly in recent years. The two largest importers are Nigeria and Libya. Over 50% of all used car imports in 2020 came from them there rest of the distribution is from Benin, Ghana, and Kenya combined(IEA, 2022a).

In the 21st century, advances in the transportation sector have necessitated the development of electric vehicles (EVs). These vehicles have now formed a base for reducing emissions and providing reserves for fossil fuel. In the year 2020, the International Energy Agency recorded ten million electric vehicles around the world. Again the improvement in battery technology around the world has necessitated developments and breakthroughs in the use of electricity across different industries. The best illustration of this is provided by the rising interest in and use of electric automobiles. Currently (2022), transportation makes up 20% of the world's primary energy demand, yet just one percent (1%) of it is electrified(IEA, 2022b). This is a significant opportunity for rising electricity consumption. In 2016, about 750,000 electric cars (EVs) were sold worldwide; by 2026, sales are expected to exceed 10 million annually. More than half of all new car sales will be electrified by 2040. By 2040, it is anticipated that the worldwide electric car fleet will increase demand by 1,800 terawatt hours (TWh)(GE Power, 2018).

2.6 Electric Vehicle

In its 2021 report, the International Energy Agency concludes that electric vehicle registrations increased by forty-one percent (41%) despite the downturn of the COVID pandemic (International Energy Agency, 2021). Many nations are shifting their electricity generation toward the production of renewable energy as a means of reducing GHG emissions and controlling the depletion of fossil fuels. Additionally, adopting electric vehicles in the transportation industry can cut CO_2 emissions by 28% by the year 2030(Adnan et al., 2018b). These new developments in transportation place a burden on the already increasing demand for electricity generation.

Electric vehicles need charging stations for their reliable operation and to meet customer comfort. In recent times there have been fast charging stations. Many countries around the world are developing strategies to roll out high-power fast-charging networks (Fredriksson et al., 2019b; International Energy Agency, 2021). Some researchers have postulated that the potential integration of fast charging station on power system reliability must be comprehensively studied as electric vehicle owners and technology keeps increasing year by year (Fredriksson et al., 2019a; Sa'adati et al., 2021a; Uko, 2020; Zhang, 2017). To alleviate the users' range anxiety and encourage them to use EVs for long-distance trips, many fast Charger(FC) facilities have been installed in the past years, by EV manufacturers (e.g., Tesla) or energy companies (e.g., Shell) (Wang et al., 2021).

2.7 Electric Vehicle Uses in African

The last ten years have not seen the same level of progress for electric automobiles everywhere. Nearly two-thirds of the global market for electric vehicles is accounted for by China, Europe, and the US, whose combined sales in 2021 accounted for ninety-five percent(95%) of the market. Sales of electric vehicles increased to previously unheard-of heights in emerging regions in 2021, more than doubling in Asia to 33000 units, 32 000 in Eastern Europe, Central Asia, and West Asia, and 18,000 in Latin America and the Caribbean(IEA, 2022b). Although electric car sales in Africa remained modest in 2022, they climbed by 90%, with BEVs accounting for 85% of the growth.

Only about 500 electric vehicles were on the road in South Africa in 2019(Collett et al., 2021). Three-fourths of the electric car options in South Africa come from luxury manufacturers. The developing and emerging economies can all be observed to share similar trends (IEA, 2022b). Slower market acceptance in emerging markets and developing nations is also attributed to a lack of widely available charging infrastructure and a lackluster regulatory push.

A few governments in sub-Saharan Africa have begun to declare EV adoption incentives and vehicle electrification targets, such as Rwanda's recently announced tax breaks for EV sales. Additionally, a developing start-up ecosystem for EVs is emerging in the area, with an emphasis on electric two-wheelers in particular. According to estimates from McKinsey, the ecosystem contained more than 20 start-ups as of the end of 2021, which together raised more than $25 million in funding that year(Conzade et al., 2022).

South Africa is the market leader when it comes to EVs. In 2013 the country established an e-mobility program. The program was a multi-stakeholder platform that aimed to facilitate EV deployment through capacity building and experimental initiatives. In 2021, A green paper on the advancement of new energy vehicles was produced by the South African Department of Trade, Industry, and Competition. The report suggested legislative measures including lowering the taxes and getting rid of import taxes on EV parts. Around 300 public electric vehicle charging stations are available throughout South Africa as of 2022(Akabor Nafisa, 2022; IEA, 2022b).

According to the Green Transport Strategy, the government wants to collaborate with businesses to increase the number of EV charging stations fueled by renewable energy(DoT, 2018). A Memorandum of Understanding was signed in 2015 by BMW and Nissan to work together to plan and construct a nationwide network of charging stations for usage by their respective automobiles. The Jaguar Powerway, a network of twenty-two charging stations along important motorways plus thirty charging stations in major hubs, was launched in 2018, expanding this network. More recently, Audi and GridCars collaborated to establish fast and ultra-quick public charging stations across the nation.

Rwanda has determined that to comply with its climate goals as stated in its Nationally Determined Contribution, the total investment required for EV charging infrastructure needs to be ramped up to approximately USD 900 million(UNEP, 2022). A strategy for adopting various incentives to encourage adoption is outlined in a strategic paper on electric mobility adaptation that the Ministry of Infrastructure produced in April 2021(Ministry of Environment, 2020). One proposal calls for a fifteen percent (15%) preferential corporate income tax rate for businesses engaged in e-mobility activities(Ministry of Infrastructure, 2021).

In Kenya, it has been determined that electrifying road transportation is essential to achieving the target of lowering emissions by 3.46 million tons of carbon dioxide equivalent across the transport sector by 2030(IEA, 2022b). A reduction in excise duty from 20% to 10% for BEVs (carrying more than ten people) and a goal of 5% of imported vehicles being electric by 2025 were proposed to support this ambition. In January 2022, ROAM, formerly Opibus, launched its first African-designed and built electric bus in Kenya(Powering Renewable Energy Opportunities, 2021). Since its 2017 start, this company has expanded from domestic electric motorbike and off-road vehicle production.

Kiira Motors, an automaker in Uganda that is controlled by the state will begin producing electric cars (EVs) in 2021, to expand production in the years that would follow(electrive.com, 2020). The new plant will make electric buses for public and commercial transit providers. Technical data is lacking. Since series runs were modest, the 5,000 units are new.

Even though used automobile imports have been prohibited throughout Egypt since 2013 there is a 100% exemption for electric vehicles that are less than three years old from customs duties. In 2018, a presidential order on import tariffs strengthened this prohibition (Leif Petersen, 2019). Electric bus pilot programs are now in progress in significant cities. Using Foton

Motors, a Chinese carmaker, the Ministry of Military Production entered a collaboration to create 500 electric buses annually with at least forty-five percent(45%) domestic components. The alliance aims to construct 2,000 electric buses over the following four years(Sustainable Bus, 2020).

Although the rate and scope of change may vary, electrification will be a significant factor in the transformation of transportation in sub-Saharan Africa and offers significant prospects in all vehicle sectors. To succeed, the transition must, however, be supported by the whole mobility ecosystem, including stakeholders from the public and commercial sectors as well as governments. The region could end up becoming a place where obsolete ICE vehicles are dumped, which would set back the continent's efforts to reduce carbon emissions as the vehicle fleet expands in the years to come(Conzade et al., 2022).

Africa should investigate electric automobiles now. SSA nations will invest heavily in energy capacity during the coming decade. A burgeoning middle class, urbanization, and demographic changes will increase auto ownership during the next decade. Capitalizing on the global EV trend could help SSA regions become energy-secure and cost-effective without relying on imported petroleum and carbon-intensive energy infrastructure.

2.8 Electric Vehicles in Ghana

The installed capacity of Ghana's electrical generation was approximately 5000 megawatts (MW), while the load demand was approximately 2,612 MW. In a relatively short amount of time, Ghana transformed from having a deficit to having additional power generation as a consequence of Independent Power Producers' (IPPs') desire to address the gap(Remeredzai Joseph Kuhudza, 2020). Many of these generator contracts include "Take or Pay" terms, forcing Ghana to pay for the electricity that it doesn't currently require. Ghana spends more than $500 million per year on inactive power-producing capacity. Against this backdrop of increasing Renewable Energy Technologies(RET), the country's energy policy advisor and regulator have proposed the use of electric vehicles in a concept paper. The concept paper and policy seek to have at least one hundred (100) electric vehicles and at least 10 public charging outlets in Ghana by 2020(energy commission, 2019a; Energy Commission, 2023).

SolarTaxi is still the only indigenous manufacturer of EVs in Ghana. The company builds a variety of vehicles, including the 32 kWh Dongfeng JunFeng ER30 SKIO EV, the 35.2 kWh JAC iEV7L, and the Cherry Tiggo 3xe 480 EV SUV. In Ghana, you can rent such EVs for as little as $160 per month(Energy Commission, 2023; Kaledzi, 2021). Accraine Ghana, another startup, also provides secondhand EVs imported from Europe as well as EVSE, EV accessories, and EVs(Remeredzai Joseph Kuhudza, 2020).

The number of EVs in Ghana is estimated at around 1000 as of 2021. This necessitated the building of five charging stations across the capital(Energy Commission, 2020).

The switch to electromobility is now being accelerated by POBAD International. In East Legon's A&C Mall and Accra's Stanbic Heights Mall, POBAD has placed EV charging stations. 200 chargers will be installed by POBAD as part of the project's initial phase throughout southern Ghana(Remeredzai Joseph Kuhudza, 2020). Electric vehicle charging stations will be installed all around Ghana thanks to a partnership between POBAD and the country's electricity provider, the Electricity Company of Ghana (ECG).

2.9 EV Charging Technology

EVs need charging facilities like conventional cars. Charging stations supply electricity from the grid to EV batteries. Physical equipment connects the EV to the distribution grid(Longo, 2017). Power and process are used to classify the charging stations. The charger physically connects the electric vehicle to the distribution grid. Electric Vehicle Charging stations(EVCS) are expanding rapidly(International Energy Agency, 2021). Governmental charging outlets are few despite public and private funding(IEA, 2022b). According to the latest EV Charging Infrastructure Report by Edison Electric Institute(EEI), the global EV fast chargers will rise by approximately 140000 by the year 2030(Satterfield & Schefter, 2022).

2.9.1 Conductive Charging

Power is transferred through physical contact. A conductor provides power to the battery. It is simple and efficient. The Nissan Leaf and Tesla both provide two conductive charging methods. An onboard charger typically used for low-power charging connects the EV to the AC grid using only a control device. Chargers with high amperage are positioned outside the car. This arrangement offers the battery with direct high power without the need for converters.

2.9.2 Inductive Charging

Inductive charging refers to the wireless charging method. Electrical power is transferred to batteries via electromagnetic fields(García et al., 2015; Panchal et al., 2018). This cable-free technology is more reliable in bad weather than its predecessor. This simplifies consistent charging. Parking at a wireless charger-equipped area starts the charging process. Due to its convenience, Audi, Mercedes-Benz, and Porsche will equip some of their vehicles with wireless charging(Yamauchi Mia, 2019).

2.9.3 Battery Swapping

Battery switching stations replace exhausted batteries with full ones. This strategy boosts battery life, rapid recharging, and grid effect. To avoid peak demands, multiple batteries can be recharged at any time. Management costs and other constraints limited this setup's adoption

(Jamian et al., 2014; Y. Zhao et al., 2017). China presently possesses most battery-swapping stations (Shareef et al., 2016).

2.10 Charging levels

Network characteristics and standards determine power configuration in each country. Thus, electric car charging classifications vary. Electric Power Research Institute(EPRI) and the Society of Automotive Engineers(SAE) classify charging levels as AC Level 1, AC Level 2, DC Level 1, and DC Level 2 (Shareef et al., 2016). Retail establishments and parking lots can provide level 2 and rapid charging. This charging company may benefit from charging. Residents install Level 1 or Level 2 overnight charging. Luca Longo(Longo, 2017) presents this classification in modes:

Table 2 - 1 Classification of EV Chargers based on Power Input Characteristics

CLASSIFICATION	CHARACTERISTICS
Mode 1	AC slow charging at 250/480V at 50/60 Hz with a maximum of 16A. For long-term charging at home or business, this mode is typical.
Mode 2	The maximum current of 32 A. The vehicle and connector have control pins, while the supply side has an integrated control box.
Mode 3	This is a three-phase supply at 63A. AC charging with electric vehicle supply equipment (EVSE). Normally in Public stations.
Mode 4	DC level 1 and 2 rapid charging with an external charger. Equipment converts AC to DC. Charging rate in 30 minutes.

2.11 DC Fast Charging Advancements

The Fast EV chargers can theoretically deliver 150 kW DC. DBT and Swiss business EVTEC are installing such systems (Longo et al., 2017). As of today, Tesla Model S (or Model X) may use Tesla Superchargers to charge up to 145 kW(Voelcker John, 2016). Future electric vehicles are likely to handle larger charging powers. Daimler intends to design a station that can charge EVs in under five minutes(Cooper Daniel, 2017).

2.12 Vehicle-to-Grid Technology

A New charging mode dynamic called vehicle-to-grid (V2G) technology is also gaining ground in research. This is mainly due to its financial, environmental, and grid-assistance benefits(Ravi & Aziz, 2022). The vehicle-to-grid (V2G) concept is based on the idea that EVs' batteries and communication capabilities can be used for other purposes during their 95% idle period(Ravi & Aziz, 2022). Most Plugin Electric Vehicles (PEVs) are connected in V2G mode and inject energy if activated(Galiveeti et al., 2018a; G. H. Reddy et al., 2017).

2.13 Distributed Generation(DG)

There is no uniformity in Distributed Generation(DG) definition and size. In different countries, it is known by different names such as dispersed generation, embedded generation, and decentralized generation, among others. Various researchers defined it in their own way; some of them are listed below;

- DG is an electric power source that is directly connected to the distribution network or on the customer site of the meter(Ackermann et al., 2001; Iweh et al., 2021b; Tabors et al., 2016).
- DG as by the International Council on Large Electricity Systems (CIGRE) refers to all generation units with a maximum capacity of a few kW to 100 MW, that are usually

connected to the distribution network and that are neither centrally designed nor dispatched(Iweh et al., 2021b; Pepermans et al., 2005).

- DG refers to Electricity generation units that are connected directly to the local distribution network, as opposed to connecting to the transmission network(Singh et al., 2015).
- The term "distributed generation" refers to the process of producing electricity for local use rather than sending it through the electric grid from a sizable, centralized facility. It is sometimes referred to as "on-site production" or "decentralized generation" (such as a coal-fired power plan(Institute Environmental and energy study, 2022).

Although the concept of DG is not new, it is becoming increasingly popular because of its numerous benefits over fundamental power-generating units(Awopone, 2021; de Castro & Dantas, 2017; Iweh et al., 2021b; P. Prakash & Khatod, 2016b; Shaheen, Elsayed, et al., 2021b; Truong et al., 2020). A microgrid may use distributed generation to power a single building, like a house or company (such as a major industrial facility, a military base, or a large college campus). Distributed generation can enable the delivery of clean, dependable power to more consumers and minimize electricity losses along transmission and distribution networks when connected to the electric utility's lower voltage distribution system(Iweh et al., 2021b). Distributed generation applies to solar PV, mini-hydro, wind, and hydrogen fuel cell Technology.

2.14 Impact of DG on Distribution Network

Distributed generation is becoming more popular than centralized electricity grids(Abdmouleh et al., 2017). The ideal level of dispersed generation in future power systems is unknown. Some studies on the incorporation of distributed generation into centralized electricity systems have been done. Most of the works focus on certain elements of the energy network, such as the distribution network and capacitor banks(Mehigan et al., 2018). Abdmouleh(2017) investigated some typical heuristic optimization techniques with Pro-Con which concludes the need for more investigation into the optimization techniques (Abdmouleh et al., 2017). Due to their unreliable power supply, specialized DG technologies based on Renewable Energy Sources (RESs), such as wind and solar, must also be taken into account. In this regard, experts have identified new issues faced by various types of DG injection on centralized electrical grids(Iweh et al., 2021b; Razavi et al., 2019b; Tabors et al., 2016).

2.15 Environmental Impacts of Distributed Generation

According to published research, fuel combustion was responsible for eighty percent of global pollution(P. Prakash & Khatod, 2016a). Rapid depletion of conventional resources in light of pollution is a major concern in recent times. From this perspective, DGs are attracting the attention of researchers, academicians, and environmentalists. DGs provide a feasible option since most of the DG technologies are powered by renewable resources(D. B. Prakash & Lakshminarayana, 2018a; P. Prakash & Khatod, 2016b; Shafik et al., 2021). Distributed photovoltaic generation has environmental benefits. Greenhouse gas emitting plants can replace conventional generation emissions are decreasing (de Castro & Dantas, 2017).

2.16 Economic Impacts of Distributed Generation

To augment fossil fuel-based power generation in oil and gas-producing countries, innovative, clean, and renewable energy sources are needed. Solar photovoltaic, solar thermal, wind, geothermal, and hydro power can mitigate regional electricity costs by neglecting high-voltage transmission line components(Rugthaicharoencheep & Auchariyamet, 2012). According to Al-Sumaiti et al.(2020), wind provides a better economic advantage over solar PV and diesel generation in Maharashtra(India). Distributed generation can help develop rural areas through electrification by reducing poverty(Al-Sumaiti et al., 2020; Gonçalves et al., 2020; Rugthaicharoencheep & Auchariyamet, 2012). For improved economic impact distributed generation made up of micro-hydro generators and solar provides an energy cost of 0.458US$/kWh which was better than LPG generator and battery storage in Cameroon(Gonçalves et al., 2020). In order research Solar/wind hybrid DG provides an economic advantage over conventional generation systems for utility companies by using renewable energy credits(Kazimierczuk et al., 2022).

2.17 Technical Impacts of Distributed Generation.

According to Awopone(2017), Ghana's energy demand for an optimum economic and sustainable environment can be achieved by aggressively pursuing renewable energy technologies between 2010 to 2040. However, these high level of distributed generation system poses power quality issues on the grid since DGs can cause bidirectional power flow(Impram et al., 2020a). Again DG poses stability and dependability issues because of the uncertainty of DG resources (i.e. solar and wind)(Razavi et al., 2019a). The increasing penetration of dispersed generation (DG) also influences the power quality (PQ) levels in the distribution networks(Angelopoulos, 2004). However, DG integration gives the advantage of reduced operational and maintenance costs and increased protection for critical loads(P. Prakash & Khatod, 2016b). under high DG penetration, the performance of the network is affected since reliability would be compromised(Shaheen, Elsayed, et al., 2021a). System stability in terms of transients and frequency can also affect the system under high penetration levels (A.M. Shaheen, A.M. Elsayed, Ragab A. El-Sehiemy, 2022).

In a case study of Malaysia's distributed network under higher penetration of DG it was observed and concluded that power quality should be considered to prevent total system collapse in the situation of faults or change in climate condition(Lee et al., 2020b). In a system with high PV penetration during transient events, larger voltage drops were found after a fault. Also, the disconnection of a large part of the rooftop PV systems resulted in increased voltage fluctuations and damping times(Impram et al., 2020).

Higher levels of distributed generation(DG) system poses power quality issues on the grid since Distributed Generation(DG) units can cause bidirectional power flow, unstable and undependable at a certain time of the day (i.e. solar and wind) (Impram et al., 2020b; Razavi et al., 2019a). Notable is the fact that inappropriate allocation of PV-DGs can impede penetration by increasing active power loss and lowering the voltage profile (Bawazir & Cetin, 2020; Ntombela et al., 2022). Incorporating DG into a distribution system is always a challenge. The technical sizing and placement of DG must be optimized. If ideal sizing and placement of DG are not properly handled, the distribution system may encounter technical issues, as documented by earlier writers.

In recent research, the authors' major conclusion was that the indiscriminate placement of DG units into the grid not only caused grid instability, as previously discussed but could also trigger the violation of certain technical parameters in the network. As a recommendation to avoid future network failures, intensive analysis using suitable tools should be conducted, before any attempt to inject DG units into the network(Rama Prabha & Jayabarathi, 2016a)(Iweh et al., 2021a).

2.18 Impact of Electric Vehicles on the Grid

The integration of EVs has potential benefits. The benefits that EVs provide are accomplished through supplemental services which in turn leads to economic, environmental, and technical advantages. A study conducted by Mojdehi(2015) demonstrates that EVs can utilize additional services and create cash for their owners. This study again proposes a method for systematically detecting operating conditions that could result in inadvertent DG islanding. The procedure's applicability and generalizability are demonstrated through simulated results based on actual case studies(Mojdehi, 2015). Apart from technical issues associated with high penetration levels of EVs, the model presents great environmental and economic benefits such as a reduction in emissions and EV user bonuses from vehicle to grid integration(IEA, 2022b; Mojdehi, 2015; Sharaf et al., 2022).

In an attempt to improve the reliability of the power system, Zhang(2018) applied the PSO algorithm for the charging of large amounts of EV load. It has been observed that EV load causes increased peak load demand that exceeds the generation system on average days(Zhang, 2017; Zhang et al., 2018). Again high levels of EVs can affect system transformers due to harmonic distortions(Gómez & Morcos, 2003; Razeghi et al., 2014). EVs can also affect the voltage profile by causing the voltage to unbalance in the system. A study conducted on the Malaysia distribution network suggests that uncontrolled charging penetration levels would have to be between twenty to thirty percent to keep the system voltage profile against unbalanced voltage on the system(Tie et al., 2015).

High penetration levels of EVCS can contribute to increased power losses and reduced voltage stability margins(Babu & Swarnasri, 2020a). Studies have been conducted to find the optimum location of charging stations based on the transport and distribution network constraints of EVs, multiple shortest paths, and deviation paths. DG is employed for technical loss reduction such as voltage profile improvement when EVs demand on the grid increases (Sa'adati et al., 2021b; Wang et al., 2021).

2.19 Electric Vehicle Charging Station(EVCS) Planning

Planning EV charging infrastructure requires modeling of charging demand, validation of charging impact, and optimal station placement. The optimal placement of charging stations consider destination charging, including private, public, and workplace parking lot charging, as well as fast charging, making it a viable consumer technology. Fast EVCS has disadvantages on the grid. A complete examination of the pros and weaknesses of existing very fast charging(XFC) stations is provided by Naireeta, Singh, and Brooks. They suggest that a cheaper alternative for fast EVs would be based on silicon carbide storage as a means of storing power for EVCS(Deb et al., 2021a).

Again, transportation electrification can play a crucial role in redesigning smart cities. As the number of electric cars (EVs) on the road increases, it is vitally desired to implement a well-planned and efficient charging infrastructure. Due to their high power consumption fast EVCS installation at every available location is not techno-economically justifiable(Deb et al., 2021b; Gómez & Morcos, 2003; Longo et al., 2017; Sharaf et al., 2022). Zeb(2020) presents an optimum combination of all three types of EV chargers for managing EV demand while minimizing installation cost, losses, and distribution transformer loading. Results show that optimal fast EVCS placement at twenty percent(20%) penetration in commercial feeders leads to optimized reduced costs from $3.55 million to $1.99 million, daily losses from 787kWh to 286kWh, and distribution transformer congestion from 58% to 22%(Zeb et al., 2020a). this show that planning EVCS placement must consider the use of techniques for improved system efficiency.

Another researcher has applied the Route Node Coverage (RNC) optimization planning technique for EVCS allocation. The best location for the EVCS is located by the transportation network which would provide an optimum cluster based on EV demand locations. RNC is an iterative approximation strategy based on probabilistic random walk route selection(short path). To solve the optimization problem a pruned integer stability problem is formulated then a software package is applied to find the optimum position(Fredriksson et al., 2019a). The optimization technique was applied on a real network(i.e. Sioux Falls) and a large-scale case study in southern Sweden to maximize coverage with the EV charging stations. The study suggests that meta-heuristic techniques combined with other variables can be considered in EVCS allocation on real networks.

Another researcher proposed a stochastic method of allocation based on predicting EV demand(Ahmad et al., 2021b). A feed-forward neural network has been applied to solar power EVCS to improve the system voltage profile. The research suggests the use of meta-heuristic techniques for the optimal allocation of EVCS in an attempt to limit energy costs and power system losses(Ahmad et al., 2021b).

2.20 Power Flow Solution Methods in Power System

When analyzing an interconnected power system, the Load Flow Analysis is a crucial first step. The results of a Load Flow Analysis are crucial not only during the expansion or design phases of a power system but also during the operating phases for control and economic scheduling. Under the assumption of constant generation and load, the primary goal of any Load Flow Analysis is to precisely calculate the steady-state voltages and voltage angles of all buses in the network, as well as the reactive and real power flows into each overhead transmission line and power transformer (at Sub-stations). When investigating the system's transient behavior, the load flow solution also supplies the system's beginning circumstances. Multiple power flow solutions under different conditions will be necessary for practice. Iterative methods such as the Gauss-Seidel method, the Newton-Raphson method, and the Fast-decoupled approach require an understanding of the many types of Buses and the data associated with them to be applied to the load flow analysis.

2.20.1 Gauss-Seidel Method

Gauss-Seidel method is a refined version of the Jacobi method, often known as the successive displacement method. The distinction between theGauss–Seidel and Jacobi methods is that the Jacobi method employs the values from the previous step while the Gauss–Seidel method always applies the most recent updated values during iterative procedures(Shima et al., 1999a). The Gauss–Seidel method is often referred to as the sequential displacement method since the second unknown is derived from the first unknown in the current iteration, and the third unknown is derived from the first and second unknowns. To resolve a system of nonlinear load flow equations, the gauss-seidel approach employs an iterative process. During one iteration, the voltages on all the buses are calculated. The procedure is iterated until the bus voltage reaches the target range within the specified tolerance. The bus voltage converges with great sensitivity to the values used at the outset. With the use of real-world data, it's simpler to determine an initial voltage profile that's extremely close to the optimal one. Voltages for all buses smaller than "B" are averaged to derive the (k+1)th iteration value of the bus-"B" voltage, whereas voltages for all buses larger than or equal to "B" are averaged to derive the kth iteration value of the voltage on those buses(Nirupama, 2020; Wadhwa, 2012).

2.20.2 Newton-Raphson Method

Using Taylor's series expansion, the Newton-Raphson technique approximates a set of nonlinear simultaneous equations to a set of linear simultaneous equations(Wadhwa, 2012). The terms are restricted to their closest approximation. Newton Raphson is a more advanced method that uses quadratic convergence than the Gauss-Seidel method(Shima et al., 1999b;

Wadhwa, 2012). The Newton-Raphson approach is better suited for more complex problems. The method requires fewer iterations and less computer time to achieve convergence. This method is more accurate because it is less vulnerable to complicating factors such as slack bus selection and regulating transformers. It takes a huge amount of computer RAM due to the complexity of its code(Dharshini, 2023). This is a drawback of the Newton-Raphson approach.

2.20.3 Backward/Forward Sweep Method

Jacobian-based methods, including Newton-Raphson, Gauss-Seidel, and fast-decoupled methods, struggled with practical networks because of the high R/X ratios(Ouali & Cherkaoui, 2020). This makes the Backward/Forward sweep method preferred over them. Utilizing the radial nature of distribution networks via backward-forward sweeps is one approach to this issue (BFS). Convergence is obtained by splitting the original system of equations into two smaller ones and solving each of those smaller systems, in turn, using the final answers of the other(Ouali & Cherkaoui, 2020). Backward sweep (BS) is the process of determining currents given voltages, and forward sweep (FS) is the reverse (FS). While BFS can only be employed in radial networks, it can be used to mimic dispersed generation such as solar panels in radial networks (Adetunji et al., 2020a, 2020b; Aman et al., 2016a; Bawazir & Cetin, 2020; Kawambwa et al., 2021; Koushik, 2016; Lee et al., 2020b; Nawaz et al., 2018b, 2018a, 2018c; Ntombela et al., 2022; Petridis et al., 2021; D. B. Prakash & Lakshminarayana, 2018b; P. Prakash, 2021).

These characteristics make it so that the Gauss-Seidel and Newton-Raphson methods, which are standard in transmission systems, fall short in terms of performance and resilience when used in distribution systems. In distribution systems, in particular, it is common for assumptions necessary for the simplifications employed in the typical fast-decoupled and

Newton-Raphson techniques to be incorrect. For this reason, it is desirable to have a backward/forward load flow algorithm for distribution systems.

2.21 Optimization Techniques Used in Power System Utility Allocation

Research has been conducted in the area of optimal placement on the distribution system using meta-heuristic techniques. These techniques used have been reviewed based on the link between the techniques used and the objective functions of powerless, voltage profile improvement, the IEEE bus test systems, network reconfiguration technique, and environmental consideration.

2.21.1 Particle Swarm Optimization Algorithm (PSO)

The particle swarm optimization algorithm has been applied for DG placement on a large scale using soft-open points(SOP). In that study, the research proposes the optimal location of DGs through network reconfiguration. The SOP is adopted instead of tie line switches. The results show an enhancement of the voltage profile. The power system losses are reduced which increases the energy efficiency of the system. The optimal configuration, number, and location of DG units, as well as the optimal number, size, and distribution of SOPs, are determined with the use of a modified particle swarm optimizer(Shafik et al., 2019).

To address the issue of power loss in radial distribution systems, Bhumkittipich and Phuangpornpitak(2013) introduced a new method based on particle swarm optimization (PSO) for the placement of DG. By using a single DG installation, the optimum DG placement and size that will result in the greatest loss reduction was obtained. The strategy is tried out on a modified version of the Provincial Electricity Authority's (PEA) radial distribution system, which consists of 26 buses. There is a total power consumption of 5.97 MVAR (8.49 MW) and a power loss of 11.68 kW (26.08 kVAR). The simulation results demonstrate that PSO is capable of achieving the lowest possible power loss(Bhumkittipich & Phuangpornpitak, 2013b).

Other researchers have focused on DG allocation after a natural disaster by applying particle swarm optimization (PSO). According to G. H. Reddy et al.(2017b), the demand for robust distribution networks has arisen in response to the rising incidence of natural disasters. When a natural disaster strikes, the electrical grid suffers significant damage and may be unable to meet demand. Distributed generation (DG) integration into a distribution grid helps restore some load after a natural disaster while also boosting the grid's dependability under normal conditions. To guarantee the DGs are accessible to pick up the loads after natural disasters PSOs have been used to optimally place DG units on the grid for improved reliability(G. H. Reddy et al., 2017).

A modified version of PSO has also been used in DG allocation. Shuaibu(2020) optimize DG placement and size to reduce power loss and improve voltage stability. Binary particle swarm optimization and shuffled frog leap (BPSO-SLFA) algorithms simulate and verify optimal power flow (OPF) on a 33-bus and 69-bus radial distribution system. The results suggest that these algorithms can improve DG allocation and reduce power losses. Power losses were reduced by 31.8244 kW after the increased allocation of DG units. The proposed method(BPSO-SLFA) was more reliable than the grey wolf optimization (GWO) and hybrid Big Bang Big Crunch in terms of sizing and locating DGs in distribution network systems(Shuaibu et al., 2020).

Adetunji et al.(2020b) proposed two swarm-based meta-heuristic algorithms, particle swarm optimization (PSO) and whale optimization algorithm (WOA) to optimize DG unit position and size. Algorithms were applied on two IEEE bus test systems (14- and 30-bus). Comparison results showed that both algorithms produce good solutions and outperform each other in several areas. Compared to the PSOs' 6.47 MW and 11.73 MW, the IEEE 14-bus and 30-bus test system's WOA real power loss drop is 6.14 MW and 10.77 MW. PSO's DG unit size in both bus networks is 133.45 MW, compared to WOAs' 152.21 MW and 82.44 MW. The PSO and WOA have pros and cons in transmission network optimal DG unit sizing(Adetunji et al., 2020a).

2.21.2 Genetic Algorithm (GA)

Aside from PSO, the genetic algorithm has also been used in DG placement and sizing. Cabr(2014) presents a modeled power system by using GA for various DG unit allocation scenarios. The impact of distributed generation on the system has been investigated. Various optimization methods based on the principle of natural selection have been created to handle problems like the location, amount of generation, and control of the power factor of the connected generators. An improved power loss of up to 58.7% was achieved when compared with the base case when DG and capacitors had not been allocated(Cabr, 2014).

2.21.3 Bat Algorithm (BA)

The Bat algorithm has been used to place capacitor banks on the grid. Electricity demand and the installation of capacitor banks have both risen in recent years, along with the number of consumers using the distribution system. The system's benefits are reduced if the capacitor bank is placed in an unfavorable location. The goal function is to reduce the system's overall power loss subject to all limitations. The ideal position of the capacitor can be predicted using the Loss Sensitivity Factor (LSF). To find the optimum allocation for the capacitor banks, the bat algorithm was used. The efficiency and efficacy of the suggested solution have been demonstrated through testing on the IEEE 34-bus distribution system(Devabalaji et al., 2015b).

2.21.4 Artificial Immune System (AIS) algorithm

From a meta-heuristic standpoint, Artificial immune system algorithms have been proposed to determine where best to put numerous DG sources in a distribution network. Using a weighted sum method, a global multi-objective technical index (MOTI) is evaluated to determine the optimal allocation of DG. The solution was achieved by employing a clonal-selection-based artificial immune system (AIS). The proposed method was implemented on a radial distribution system using IEEE-33 buses. Optimal siting of DG sources using AIS and MOTI yields significant gains in distribution system efficiency, as measured by lower real and reactive power losses, a more balanced voltage profile, and greater stability(Meera & Hemamalini, 2017).

2.21.5 Whale Optimization Algorithm (WOA)

Since DG units contribute to Power loss reductions, voltage profile improvement and increased dependability WOA has been used to optimally place them. The optimal size of a DG is calculated using the whale optimization algorithm (WOA) by Reddy et al.(2017). WOA simulates the special hunting techniques used by humpback whales. IEEE 15, 33, 69, and 85-bus test systems are used to gauge the WOA's performance. Various DGs and other evolutionary algorithms were compared to WOA. Results from WOA and index vector approaches are superior to those from the voltage sensitivity index method. According to the findings, type III DG running at 0.9 pf yields the greatest performance(P. D. P. Reddy et al., 2017).

The Whale Optimization Algorithm (WOA) has been used to allocate DG units, with constraints like power conservation, distribution line constraints, DG capacity limits, and DG penetration limits. In this study, the WOA is put to the test by IEEE 12, 33, and 69 bus distribution networks. Numerical simulations and comparative research indicate the efficacy and use of the Whale Optimization Algorithm (WOA). Comparing the findings of the WOA methodology to those of other optimization methods demonstrates its validity(Settoul et al., 2021).

2.21.6 Manta Ray Foraging Optimization Algorithm (MRFOA)

Another heuristic technique has been used for the optimal placement of DG and capacitor banks. The manta ray foraging optimization algorithm has been used for optimal regulation and operation of distribution systems to minimize energy waste, as well as the introduction of quantitative and qualitative power services to satisfy consumers(Elattar et al., 2021a). For this study during peak loading conditions, the energy management system allocates Distributed Generators (DGs) and Capacitor Banks (CBs) concurrently. To model the dynamic operation of automated distribution systems, a realistic fluctuation in daily load was introduced. MRFOA is an efficient and straightforward structural optimizer that mimics three distinct manta ray foraging organizations. MRFOA capability was used to allocate DG units and capacitor banks on IEEE 33-bus, 69-bus, and practical 84-bus distribution networks (TPC). To demonstrate the efficacy of MRFOA, a comparison has been made with contemporary procedures. The achieved findings suggest that the proposed MRFOA is highly successful and robust in comparison to existing optimization strategies(Elattar et al., 2021a).

2.21.7 Elephant Herding Optimization (EHO) Algorithm

Due to its simpler implementation and fewer control parameters, Elephant Herding Optimization (EHO) has been popular among scientists in the past decade (Elattar et al., 2021b; Elhosseini et al., 2019; Khodeir et al., 2022; Turgut, 2021; W. Zhao et al., 2020). This researcher uses a novel elephant herding optimization approach to calculate the optimal dispersed generation size. The EHO was applied to IEEE 15, 33, and 69-bus test systems. The proposed technique with type III DG unit running at 0.9 pf outperforms existing literature methods(Prasad et al., 2019).

2.21.8 Invasive Weed Optimization (IWO) Algorithm

An enhanced equilibrium optimization algorithm (IEOA) in conjunction with a recycling method for building power distribution networks with optimal allocation of numerous distributed generators was presented by Shaheen, Elsayed, and El-Sehiemy(2022). The results demonstrated that the simultaneous integration of the network reconfiguration system and DG is superior when considering the 33-bus and 69-bus distribution test systems at three distinct load levels(A.M. Shaheen, A.M. Elsayed, Ragab A. El-Sehiemy, 2022).

2.21.9 Water Cycle Algorithm (WCA)

The water cycle algorithm (WCA) has been used to locate and size DGs and CBS. The researcher proposed a multi-objective optimization problem based on the benefits of technology, the economy, and the environment. Power losses, voltage variation, electrical energy cost, generation source emissions, and voltage stability index are analyzed in El-Ela et al.(2018) for DG allocation. In the study, three distribution systems—IEEE 33-bus, 69-bus test systems, and the Egyptian East Delta network—are simulated. Simulations show that the WCA optimization strategy outperforms others. The WCA improves system performance and has economic and environmental benefits, according to the data(El-Ela et al., 2018a).

Another comparative study using the Grasshopper Optimization Algorithm (GOA), Salp Swarm Algorithm (SSA), and Moth Flame Optimization Algorithm (MFO) was used to minimize the active power losses, improve the Fast Voltage Stability Index (FVSI), and reduce the total costs, taking into account the penetration level specified margin and the framework of the DG units' operating power factor constraints. The proposed algorithms have been implemented in MATLAB and used in several benchmark IEEE test systems (33-bus, 57-bus, and 300-bus). The obtained results indicate that the proposed optimization platform, particularly when employing MFO, is more effective and successful in determining and locating the optimal locations and capacities of various DG types for obtaining the optimal value of the objective function in minimum time and minimum iterations(Hassan et al., 2022).

2.21.10 Artificial Bee Colony (ABC) Algorithm

Jamian et al.(2014) used ABC for the optimal allocation of Battery swapping stations. the impact of this type of EVCS can be significant on the grid if not properly sighter. They lead to reduced system voltage when operated at peak loads(Longo et al., 2017). In this study, ABC was used to determine the best BSS and DG output size to further optimize the system. Analytical and optimization methods yielded comparable results in determining the ideal position of BSS, which is superior to the random placement of BSS. Moreover, compared to other analyses, the optimal size of BSS and DG output (simultaneously) analysis yields the lowest power loss(Jamian et al., 2014).

Power companies are working to improve transmission line efficiency due to an exponential increase in load demand and a lack of capital resources for system upgrades. This researcher proposes a discrete artificial bee colony technique for simultaneous DG deployment and tie-switch allocation to maximize the system's ability to handle the increasing load. The study used the IEEE 16-Bus, 33-Bus, and 69-Bus radial distribution test systems. The simultaneous DG placement and tie-switch allocation yield superior results. The proposed method also maximized system efficiency, reduced power system losses, enhanced kVA margin, and improved voltage quality(Aman et al., 2016a).

Dixit et al. (2017) proposed the simultaneous adoption of Distributed Generation (DG) and shunt capacitors in a distribution system to reduce active power loss. The Index Vector Method (IVM) and Power Loss Index (PLI) are applied to find the optimal position/location of DGs and shunt capacitors. Nevertheless, their sizes/capacities are selected by a population-based Gbest-guided Artificial Bee Colony (GABC) optimization process. At two distinct load situations, the costs associated with grid power acquisition, DG installation, capacitor installation, and DG operation and maintenance (O&M) are evaluated. In addition, technical and economic studies of various combinations of DGs and shunt capacitors are studied. The suggested methodology is effectively shown on 33-bus and 85-bus radial networks, and the numerical results support the methodology's applicability, significance, and efficacy for identifying the locations and sizes of DGs and shunt capacitors(Dixit et al., 2017).

For ABC application in DG allocation, Al-Ammar(2012) presented the minimized investment cost and power losses. Recent load demand growth has prompted the optimization of distribution networks. The results show that to reduce the overall expense of energy production, power loss, and voltage drop the optimal configuration of DGs within distribution networks is useful. The multi-objective problem is resolved by the artificial bee colony (ABC) algorithm. The proposed ABC algorithm is tested using industry-standard methods. Researchers proposed that most other algorithms can't compare to the ABC algorithm's efficiency(Al-Ammar et al., 2021).

2.21.11 Optimal Placement of Electric Vehicle Charging Stations

This section explores the optimization techniques applied in the placement of EVCS based on power system parameters and transport network configurations.

Some studies suggest that rapid charging stations should be positioned in densely traveled areas where many EVs will utilize them concurrently for the lowest cost(Ahmad, Iqbal, Ashraf, Marzband, & khan, 2022). The researcher presented an ant colony optimization for optimizing fast charging stations in residential areas on a 69-bus system. The results show that under traffic and power system security constraints, ant colony optimization (ACO) reduced the loss cost of rapid charging stations and strains on transmission lines. ACO approach established the optimal placement for a fast-charging station for home electricity distribution with the lowest total cost or loss while satisfying several technological and geographical constraints(Phonrattanasak & Leeprechanon, 2014).

Zeb et al.(2020) optimized the placement of three types of EV chargers to properly manage EV load while minimizing installation cost, losses, and distribution transformer loading. The study employed PSO for the optimal placement of EV chargers. The NUST Pakistan distribution system was used as a validation network for the optimization problem. The Results show that an optimized combination of chargers placed at strategic locations can reduce costs from $3.55 million to $1.99 million, daily losses from 787kWh to 286kWh, and distribution transformer congestion from 58% to 22%(Zeb et al., 2020b).

2.21.12 Integration of Distributed Generation (DG) and EV Charging Stations

After reviewing DG sizing and deployment methods, Rama Prabha and Jayabarathi (2016) recommend including electric vehicle load in future planning(Rama Prabha & Jayabarathi, 2016b). As such other researchers have adopted other meta-heuristic techniques to simultaneously place both DG and EVCS. This session discusses a number of the heuristic techniques employed for the placement of DG and EVCS.

EVCS and DG were installed on a radial distribution network with a multi-objective optimization strategy in Ponnam and Swarnasri,(2020). To decrease the system's active power loss, voltage profile, and voltage stability index, the Harries Hawk Optimization (HHO) and Teaching-Learning Based Optimization (TLBO) algorithms were utilized. To simultaneously allocate DG and EVCS with an emphasis on minimizing power loss and voltage profile variation, it is necessary to employ various intelligent optimization methods(Ponnam & Swarnasri, 2020a). In this study, the appropriate location and sizing of DG and EVCS on distribution networks are investigated. The work is validated on the IEEE 33 bus system by considering a meta-heuristic approach based on the minimization of power loss and the enhancement of the voltage profile. The results further affirm that HHO outperforms TLBO by providing allocation buses with the minimum power loss and improved voltage profile.

Given electricity system penetration, demand response(DR) is considered a smart grid advance. Sharaf et al.(2022) provided an innovative day-ahead sizing approach for energy storage systems of EV parking lots and DGs in smart distribution networks that comply with DR and lower costs to accommodate these advances. The study applied self-adjusted modified particle swarm optimization(SAPSO) algorithms for EV charger placement. Two probabilistic self-adjusted modified particle swarm optimization (SAPSO) algorithms are developed and compared to minimize EV parking lot operational costs while taking into the account distribution system, distributed generation (DG), and energy storage system constraints to accurately solve this optimization model. The IEEE24 reliability test system results are compared to the genetic algorithm and standard PSO to evaluate the created approaches. The results show that the SAPSO algorithm minimizes total operational expenses. The result again shows that the near-optimal day-ahead scheduling of DG units and EV energy storage systems can reduce total operating expenses subject to generation limits in compliance with DR(Sharaf et al., 2022).

Sa’adati(2021) used classical optimization techniques for EV and RET placement. The work simultaneously determined optimal FCS placement and capacity and RES deviation pathways and uncertainties using mixed-integer linear programming (MILP). A 25-node transportation network and 14-bus and 33-bus distribution test systems were applied in the study. The results revealed that fluctuating RES and deviation pathways will affect charging station location, capacity, investment costs, and car charging coverage rates(Sa’adati et al., 2021a).

Galiveeti et al.(2018) assessed the effect of PEV connection on system dependability. In that study, several PEVs are utilized in vehicle-to-grid (V2G) mode to sustain system peak loads. Distributed generation (DG) units are integrated with charging stations to lessen the system impact of plug-in electric vehicle (PEV) charging. Results show that charging stations when combined with solar photovoltaic (PV) panels can minimize peak load strain effects from a large number of PEVs(Galiveeti et al., 2018b). The study also explored the combined impacts of PEV charging and DGs. Impact assessments are conducted for two operational systems

2.22 Comparison and Drawbacks of Optimization Techniques Used in Power System Allocation

The beauty of linear programming (LP) is in its adaptability(Sa’adati et al., 2021a). It does not handle stochastic variables well. The positive aspect of linear programming the solution is the exact solution without approximations. Using linear programming to solve problems is a great way to make better choices. This strategy has a lot going for it, including a wide range of applications, but it does have a few flaws as well. All real problems would have to be converted into a linear form which is quite complicated in multi-objective problems. Most practical parameters of models are rarely known or difficult to convert into an exact linear form which can be after the optimization problem.

As discussed earlier Genetic Algorithm has been used (Masoum et al., 2004; Zhou et al., 2022). In many ways, the GA approach is distinct from other optimization strategies. To reduce the likelihood of becoming stuck at a local optimum, the algorithm considers a set of locations as potential solutions. Using a Genetic Algorithm is simpler to implement due to the few or less-to-nothing parameters needed. Its strength lies in single-objective problem solutions. However, It is time-consuming to find a solution to the issue when dealing with complex multi-objective problems.

Teaching learning-based optimization is not dependent on any algorithm parameters to the function. For the DG units and EV application of power system optimization (Babu et al., 2020; B. Mohanty & Tripathy, 2016). A major drawback to the TLBO is the long computational time as compared to other swarm-based techniques. When considering TLBO for optimal placement or any high-dimensional multimodal problem becomes difficult to solve because of the method's insufficient population diversity and its propensity to slip into local optima.

Optimization using a gray wolf Take on tasks with several objectives and constraints(Shuaibu et al., 2020). The rate of convergence is slow, the local searching ability is poor, and the precision of the solution is low. Advantages of GWO over more conventional optimization algorithms like PSO and GA include its reduced complexity, straightforward concepts, and straightforward implementation. However, GWO has drawbacks, such as a slow convergence time, poor solution precision, and a propensity to quickly settle on a local optimum. As a result, the grey wolf optimization method can converge to an undesirable solution and produce less accurate results. The optimal answer may lie outside the region covered by the pool of available choices.

Ant Colony Optimization has the strengths of avoiding an untimely convergence, quickly identifying an optimal solution, and early discovering the optimal solution(Aboagye et al., 2021; Mirjalili, 2015; Pereira et al., 2006; Remon et al., 2017). The ant colony algorithm is designed to be constantly iterated and updated in real-time. The global minimum is reached by ACO with fewer iterations and at a smaller value than by PSO in the simulations. ACO has a stagnation phase, a slow rate of exploration and exploitation, and a slow rate of convergence.

The strong oscillating behavior of the Schaffer function is what allows the IWO algorithm to converge through its minimization(Rama Prabha & Jayabarathi, 2016b). The optimization of IWO is affected by the longer time when dealing with multi-objective optimization.

EHO avoids being trapped in a local minimum by using fewer tuning knobs than its GWO(Elhosseini et al., 2019; Prasad et al., 2019). Aside from this advantage it suffers from a drawback when it comes to stochastic initialization. Due to this drawback, the elephant herding algorithm would have to be paired with other techniques to achieve optimal performance.

The Manta ray foraging algorithm is used in DG allocation studies(Khodeir et al., 2022; Turgut, 2021; W. Zhao et al., 2020). MRF algorithm is affected by premature convergence of the local optima. Aside from that it can step into stagnation when dealing with multiple objective functions which eventually slows down the convergence rate.

The Whale Optimization Algorithm (WOA) (D. B. Prakash & Lakshminarayana, 2018b; P. D. P. Reddy et al., 2017; Settoul et al., 2021)suffers from problems like local optimal solutions, slow convergence, and less accurate solutions. The algorithm also faces stability issues with the optimal solution.

HHO(Ponnam & Swarnasri, 2020a) has the advantage of minimal parameters, simple structure, fast convergence, and strong local search. Harris hawk optimization is prone to local optimums. However, the algorithm can face longer convergence times when dealing with complex problems.

The PSO has been used to solve DG allocation problems(Bhumkittipich & Phuangpornpitak, 2013b; Kennedy et al., n.d.; Mandal et al., 2008; Okwu & Tartibu, 2021; P. Prakash, 2021; Sharaf et al., 2022; Shifera, 2021). PSO has the advantages of straightforward computational procedures and the capacity to locate a nearly perfect solution. PSO rapidly increases the likelihood of premature convergence and subsequent local optimization trapping. At the outset, the algorithm is given a population of particles that are free to roam the search space at their random speeds and locations. Each step is influenced by the current best-known position close to its origin and directed toward the best-known positions in the search space. PSO is remarkably effective at addressing a wide variety of engineering problems in a short simulation period, in part because it can deal with both discrete and continuous variables.

The Artificial Bee Colony (ABC) is easy to implement and can be navigated effectively(Al-Ammar et al., 2021; Aman et al., 2016b; Jamian et al., 2014; Karaboga, 2010; Karaboga Dervis, 2005). ABC can be exploited in solution space in a complicated optimization problem. When used incorrectly, however, it can be a major hindrance when attempting to resolve difficult issues. ABC is widely applicable in many areas of optimization, though less popular in engineering applications when compared with PSO it can explore local solutions that a closer to the global optima. ABC runs into errors when used to optimize secondary data since new fitness tests must be run to update the algorithm parameters. The convergence time can increase if applied to complex optimization problems

2.23 Implementation of Particle Swarms Optimization Algorithm

The program replicates a flock of migrating birds(Poli et al., 2007). PSO uses solution representation like the genetic algorithm(Mandal et al., 2008; Okwu & Tartibu, 2021; P. Prakash, 2021). Randomly initialize particle location and velocity. PSO never develops new birds from parent birds. Instead, the flock socializes and travels. Each bird in the flock looks in a given direction and then recognizes the optimal place while communicating. Thus, based on its location, each bird travels toward the best bird as quickly as feasible. Birds communicate and shine in this process. Thus, birds learn from their own and others' experiences.

This is implemented by the initialization of a population through randomization. Then each potential solution is tested for fitness. A particle's position fitness is set as p_{best} if it's better than the previous value. After evaluating all particles' fitness, the algorithm continues to the second iteration, where g_{best} is the best value attained by any particle in the neighborhood of p_{best}. The basic flow chart of PSO implementation is shown in figure 2.1 below.

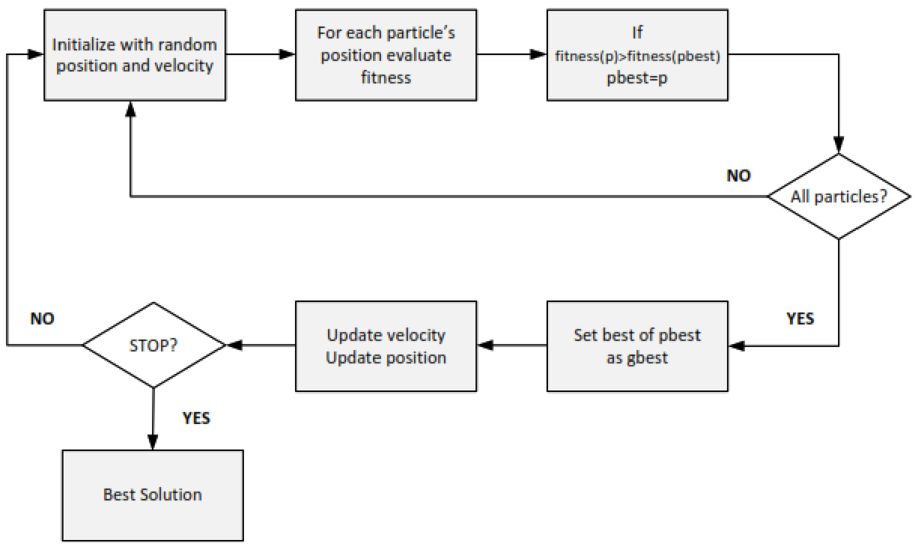

Figure 2 - 2 The Flow Chart Of PSO (Shifera, 2021)

2.24 Implementation of Artificial Bee Colony Algorithm

Karaboga proposed Artificial Bee Colony (ABC) algorithm in 2005(Al-Ammar et al., 2021; Jamian et al., 2014; Karaboga Dervis, 2005). Honeybees' smart foraging inspired this optimization technique. The idea of ABC is based on the self-organization and collective intelligence, foragers technique. Agents in a population(Bee hive) must recruit more bees to locate the best rich food sources whiles forsaking inferior ones. The food source represents an optimal solution for a given problem.

ABC use employed and unemployed bee. Two sets of unemployed bees exist in the population namely the onlooker bee and scout bees. The employer bee search for a food source with the objective of proximity, easy access, and nectar quality. Once the employed bee returns to the hive it goes into the dancing area and performs the waggle dance to the onlooker bees and scout bees. The onlooker bees are attracted to the food source based on the dance and start to exploit the new area for quality nectar.

To implement ABC, firstly the artificial bees randomly discover a population of initial solution vectors and iteratively enhance them by traveling toward better solutions via a neighbor search process and leaving inferior solutions. The search cycle has three steps: moving the worker and observer bees onto food sources and estimating their nectar amounts, determining the scout bees, and guiding them to possible food sources. Probability selects observers for food sources. The scout bee Food-hunting explorers are unguided. The flow chart representation of ABC is shown in figure 2.2.

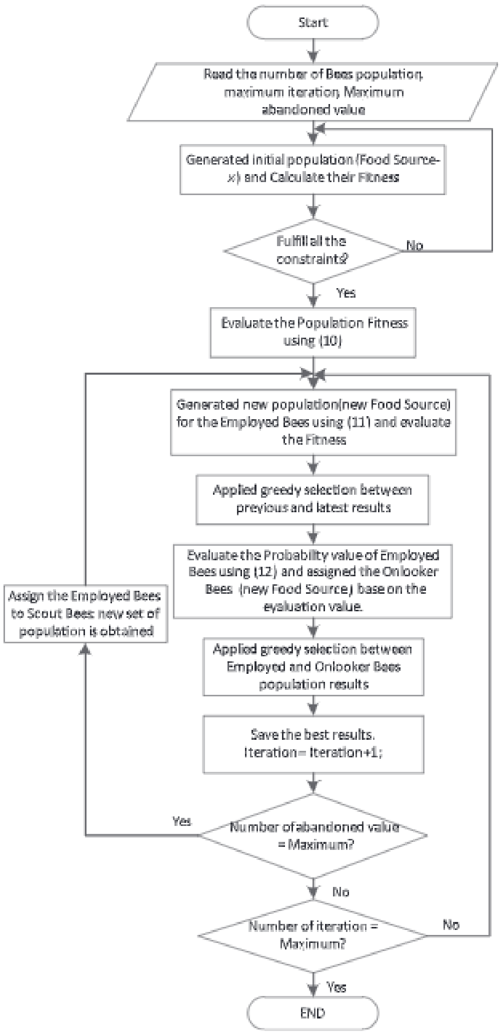

Figure 2 - 3 flow chart of ABC(Jamian et al., 2014)

2.25 Summary of Empirical Review

Most of the technological activities in the 21st century are being driven by electricity. To limit environmental emissions, the energy sector focuses on sustainable electrical energy generation units often referred to as distributed generation(DG) units. Distributed generation units have been used to increase the reliability of grid supply whiles minimizing system losses(Elattar et al., 2021a; Hoffman & Johnson, 2020; Iweh et al., 2021a; Lee et al., 2020b; Shafik et al., 2021). Adnan et al(2018) predict that the transportation sector can reduce CO2 emissions by 28% by 2030 when electric vehicles are adopted. In the year 2020, the International Energy Agency recorded ten million electric vehicles around the world (IEA, 2022b). Electric vehicles(EVs) use chargers for operation In order to meet customer comfort(Uko, 2020). Many countries around the world are developing strategies to roll out high-power fast charging networks(IEA, 2022b). Some researchers have postulated that the potential integration of fast charging stations on power system reliability must be comprehensively studied as more electric vehicle owners and technology keeps increasing year by year(Fredriksson et al., 2019a; Ravi & Aziz, 2022; Sa'adati et al., 2021a; Uko, 2020; Wang et al., 2021; Zhang et al., 2018). EV manufacturers (e.g. Tesla) have adopted fast chargers for electric cars to mitigate the range anxiety of EV owners. This has encouraged the use of EVs for long-distance travel(Wang et al., 2021). Fast Charging stations cannot be installed at every site due to high power consumption(Rama Prabha & Jayabarathi, 2016b).

Higher levels of distributed generation(DG) system poses power quality issues on the grid since Distributed Generation(DG) units can cause bidirectional power flow, unstable and undependable at a certain time of the day (i.e. solar and wind)(Adetunji et al., 2020a; Azad et al., 2021; Impram et al., 2020a; Injeti & Prema Kumar, 2013; Razavi et al., 2019a; P. D. P. Reddy et al., 2017; Settoul et al., 2021). In Mohamed and Kowsalya(2014) and Prakash and Lakshminarayana(2018), the objectives of power losses, voltage stability improvement, and operational cost have been used for DG placement using the Whale Optimization Algorithm(WOA) and Bacterial Foraging Optimization Algorithm respectively. With the increasing demand for EVCS on a smart grid, there is a need to use meta-heuristic optimization in the allocation of fast-charging EVCS to study the voltage profile and power losses.

A hybrid technique, Binary Particle Swarm Optimization and Shuffled Frog Leap Algorithm(BPSO-SLFA) have been adopted in power flow studies to place DG on two radial distribution systems(Shuaibu et al., 2020). An allocation of solar-powered EVCS for power loss reduction(Ahmad et al., 2021b). Jamian et al.(2014) presented ABC to solve the allocation of the battery Switching Station(BSS). The study investigated the technical parameters that affect DG placement on the IEEE 33 bus system. It was proposed that In order to limit energy losses, limit investment, and operational costs Battery Switching Station(BSS) should be introduced alongside DG injection(Jamian et al., 2014).

ABC algorithm has been adopted for DG allocation on the distribution network(Jamian et al., 2014). Al-Ammar et al (2021) suggest that ABC outperformed the standard algorithm. Authors have used PSO for the allocation of DG(Bhumkittipich & Phuangpornpitak, 2013b; P. Prakash, 2021; G. H. Reddy et al., 2017; Shifera, 2021). The Teaching Learning Based Optimization(TLBO) and Harries Hawk Optimization(HHO) algorithms were adopted to minimize power losses on IEEE 33 bus system(Babu & Swarnasri, 2020a). However, according to Devabalaji et al.(2015), a swarm-based approach is suggested to perform better.

Simultaneous placement of DG and EVCS has been done using TLBO and HHO algorithms (Babu et al., 2020). Recent authors suggest that future works should use Artificial Bee Colonies instead of other algorithms for superior placement of DG(Al-Ammar et al., 2021; Babu et al., 2020; Jamian et al., 2014).

CHAPTER THREE

MATERIALS AND METHODS

This chapter describes the modeling process and data used in this study. For the objectives of the study to be reached real data was collected from ECG to build a model in the Electrical Transient Analysis Program(ETAP). The data from ETAP was applied to a MATLAB model for the placement of DG and EVCS with PSO and ABC.

3.1 Data Collection

The researcher obtained the line diagram of the Ashanti Region 33KVA distribution diagram from the Ashanti region of ECG. The Bus voltages and substation loading were collected from substation technicians on site. The data collected from the substation were from October 2021 to September 2022. The peak load of the system within the year under study was used for the modeling in ETAP. The average of the daily peak load and the average of the daily peak bus voltages recorded on the buses are listed in Appendix A.

3.2 System Modelling

The study problem was modeled from the network layout of both the IEEE 69 bus system and the ECG 33kV Ashanti region distribution network. The solution to the allocation problem was developed using objective functions of power loss and voltage profile improvement. The system base data was generated using the Electrical Transient Analysis Program(ETAP). The generated data was fed to the MATLAB program formulated for the load flow and optimal allocation. The load flow technique was modeled using the backward-forward sweep algorithm. The optimization code was formulated and used for the simulation.

3.3 System's layout

The thesis used two networks for the study. The IEEE 69 bus test system was used for the allocation of DG and fast EVCS. The Ashanti region 33KVA distribution network was also adopted as the real part of the Ghana grid.

The IEEE 69 bus system is made up of 69 buses. This test system is structured so that each branch has its own unique set of buses, in addition to 69 nodes, 5 looping lines, and 7 lateral feeders(Abhinav Lal Retrieved December 14, 2022; El-Ela et al., 2018a). At a system voltage of 12.66 kV, this hypothetical system has a total connected load that is equal to 3802.19 kW and a total connected load that is equal to 2694.60 KVAr. The term "load bus" refers to any of the other buses, while "slack bus" refers to bus number 1, which is the primary bus serving the Substation. tie-switches that run from 69 to 73 are left open. Figure 3.2 shows the reference design for the IEEE 69 bus.

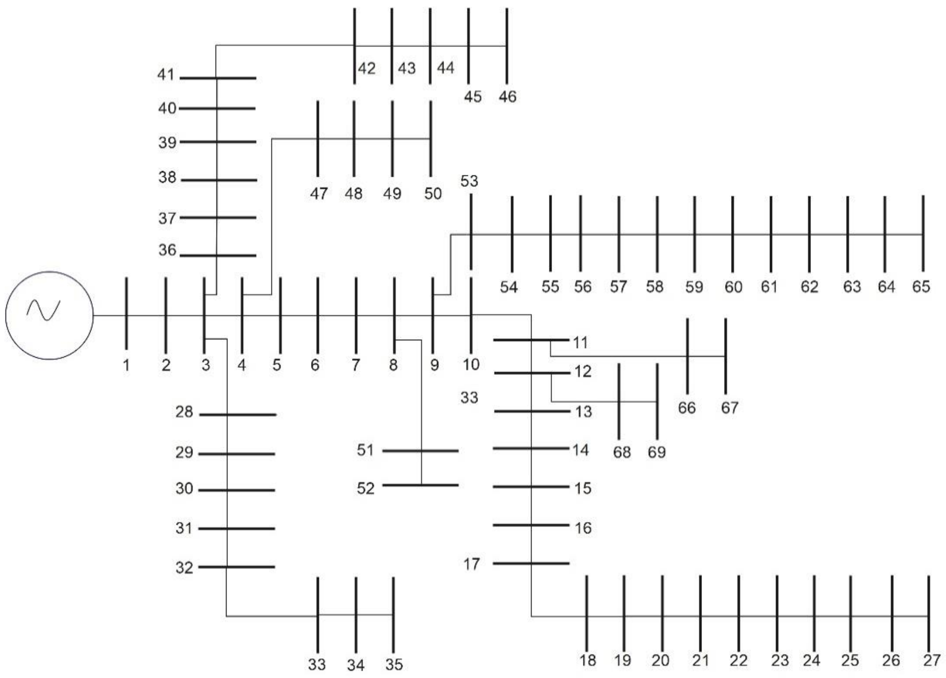

Figure 3 - 1 The Line Diagram of The IEEE 69 Bus Test System

Ashanti Region ECG 33KVA distribution network is a real part of the Ghana grid with 23 substations represented as 50 buses. Each substation has two buses designated A and B(i.e. Suame A, Suame B). The power from the grid is supplied from two bulk supply points Anwomaso and Ridge stations. Each bulk supply point has four buses with lines distributed to other substations. Figure 3.3 also represents the line diagram of the ECG 33KVA Ashanti region network.

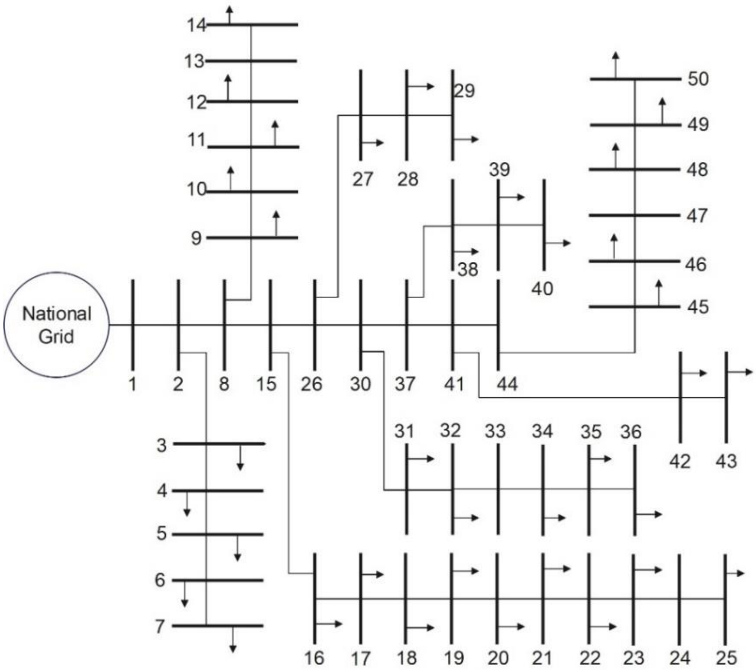

Figure 3 - 2 The Line Diagram Of ECG 33KVA Distribution Network in the Ashanti Region

3.4 Objective Function Formulation

The system model data was cried out as follows in the objective function of the optimization problem, the voltage constraints, and the load flow technique for the placement of DG and EVCS.

The optimization problem was developed as a multi-objective problem of power loss and voltage profile improvement as objective functions for the placement and sizing of DG and fast EVCS.

In a distribution system, power losses on the buses lead to significant voltage variations. The researcher adopted(Adetunji et al., 2020a; Babu et al., 2020; Babu & Swarnasri, 2020a; Ravi et al., 2021) to improve the voltage profile (2) by mitigating power losses (1). Hence, expressed as:

$$f_1 = P_{loss} = \sum_{i=1}^{n} {I_i}^2 R_i \qquad 3.1$$

where I*i* stands for current, *n* represents the number of buses and R*i* represents the resistance at the *i*th bus. Voltage profile Deviation (VDI) is shown in (2) where a voltage reference of 1p.u. is considered.

The voltage deviation index is a measure of the difference between the nominal voltage and the actual system voltage. A Smaller voltage deviation index shows that voltage conditions are better for reliable operation(Le et al., 2007). The voltage deviation index is expressed as(Aman et al., 2016a, 2016b; Kumar et al., 2019; Le et al., 2007; D. B. Prakash & Lakshminarayana, 2018a; Shuaibu et al., 2020) :

$$f_2 = \text{VDI} = \sum_{i=1}^{n} |1 - V_i|^2 \qquad 3.2$$

V*i* represents the potential at *i*th bus. *i* represents the bus under study, *n* identifies the number of buses on the radial system.

The overall objective function is to mitigate system power losses by meeting the operating constraints for voltage profile improvement:

$$OOF = \text{Min } (w_1 f_1 + w_2 f_2) \quad 3.3$$

The solution to the problem is achieved using (3.3) by considering voltages (Vi) at the modes and Current flow(Ii) operational constraints and EVCS as defined by Babu and Swarnasr (2020).

3.5 Problem constraints

The constraints for the optimization problem as applied are shown in (3.4) -(3.9)

3.5.1 Equality Constraints

The grid can be modeled as the total power input when DGs are not introduced on the grid. This is the base case formulation.

$$P_{grid} = P_L + \sum P_d \quad 3.4$$

Here the Grid active power(P_{grid}) is the same as Power Input(P_{in}). P_d is the power demand supplied to the loads. When DGs are introduced on the Network, the total power generated(P_{in}) will be expressed as a function of the injected generation unit or units. This is shown in (3.5)

$$P_{in} = P_L + \sum P_d - \sum_{n=1}^{N} PG_i \quad 3.5$$

PG_i is the active power injector at the bus *i*th DG.

The requirement for the power balance is:

$$\sum_{i}^{n} PG_i - P_L = P_d \quad 3.6$$

$$\sum_{i}^{n} QG_i - Q_L = Q_d \qquad 3.7$$

Where PGi is real power and Qgi is reactive power injected by DG at a specified bus(ith), reactive and active power losses of the bus under study are represented by Q_L and P_L respectively, and power demand for both real and reactive are P_d and Q_d, the total number of buses is n.

The maximum DG penetration as defined in this study is set within 40% of each network demand injection(Nguyen et al., 2020). The total number of DG placements was modeled as

$$\text{Number of locations} = \frac{maximum\ DG\ penetration}{maximum\ DG\ size} \qquad 3.8$$

The EVCS is modeled mathematically based on the average power demand(E_{hj}) of the station(Longo et al., 2017). In (3.9), $E_{h,\,max}$ is described as the maximum of E_{hj} in a given period. If Δt = 1s then $Eg(t)$ becomes power. Also, since energy is expressed in kWh, Δt implemented in the model is 3600/Δt. $E_{h,\,max}$ is the considered peak period from 6 a.m. to 10 p.m.

$$E_{hj} = \sum_{t \in h_j} E_g(\mathrm{t}) \qquad 3.9$$

$$E_{hj} \leq E_{h,max} \forall_j \in month\ m \qquad 3.10$$

$Eg(t)$ is the grid energy consumed by the EVCS. E_{hj} is the hourly average power demand.

3.5.2 Inequality constraints

The inequality constraints for the problem are expressed from (3.8) to (3.14)

Generation Operating Limits Operation limits for the power system must meet the minimum power generation and maximum power generation for DG allocation on a medium voltage network.

$$PG_{imin} \leq PG_i \leq PG_{imax} \quad 3.11$$

$$QG_{imin} \leq QG_i \leq QG_{imax} \quad 3.12$$

PG_{min} is the minimum active power injected on the network while PG_{max} is the maximum real power injected on the network at the optimum bus(PG_i). QG_{min} is the minimum reactive power injected into the network while QG_{max} is the maximum reactive power injected.

3.5.2.1 Voltage Constraints

All the buses on the network must have these standard limits

$$V_{min} \leq V_i \leq V_{max} \qquad i = 1,2,\ldots.n \quad 3.10$$

V_i represents the voltage at the *i*th bus and *i* varies from 1p.u. to the number of system buses.

Line capacity from bus *i* to bus *j* is represented in (3.9). The power flow(S_{ij}) through the transmission line is expressed as:

$$S_{ij} \leq S_{ij,max} \quad 3.11$$

$$S_{ij,max} = 100MVA \quad 3.12$$

The Load rating constraint for the load at each bus is limited to the maximum allowable limit of each line linking the bus and the lumped load connected to it.

$$I_{ij} \leq I_{ij,max} \qquad 3.13$$

EVCS installed capacity is the minimum power demand for 100 EVs from five manufacturers. This EVCS characteristic was adopted by Babu and Swarnasri (Babu & Swarnasri, 2020a). The total demand for the station is limited to 975 KW.

$$EVCS_{total} \leq EVCS_d \qquad 3.14$$

The summary of the constraint parameter for the optimization problem is in Table 3.1 below

Table 3 - 1 Summary of Optimisation Problem Parameters

Parameter	Allocated Limit
Maximum DG size	2000kW
Maximum Voltage at a bus	1.05 p.u.
Minimum Voltage at a bus	0.95p.u.
Total Active power demand(IEEE-69 bus)(Simon Njuguna, 2021)	3.792MW
Maximum DG penetration in kW(IEEE-69 bus)(Simon Njuguna, 2021)	1895.945kW
No. of location(IEEE-69 bus)	From 2 to 69
No. of location(33KVA ECG Ashanti Network)	From 2 to 50
Maximum power demand from fast EVCS	975kW

3.6 Load Flow Modelling

The power flow used was the backward/ forward power flow. This technique was selected because of the non-linear nature of the load flow problem. Again backward/ forward sweep power flow method provides a more convergence ability than Newton-Raphson, Gauss-Seidel, and fast decouple methods in terms of the radial network(Shifera, 2021).

The backward/forward sweep power flow method makes use of the steps in an iterative form. These steps are the equivalent current injections(ECI), Backward sweep represented as bus injection to branch current matrix(BIBC), and forward sweep also formulated as the branch current to bus voltage matrix(BCBV). For the fig. below the power of the load at any selected bus can be expressed as

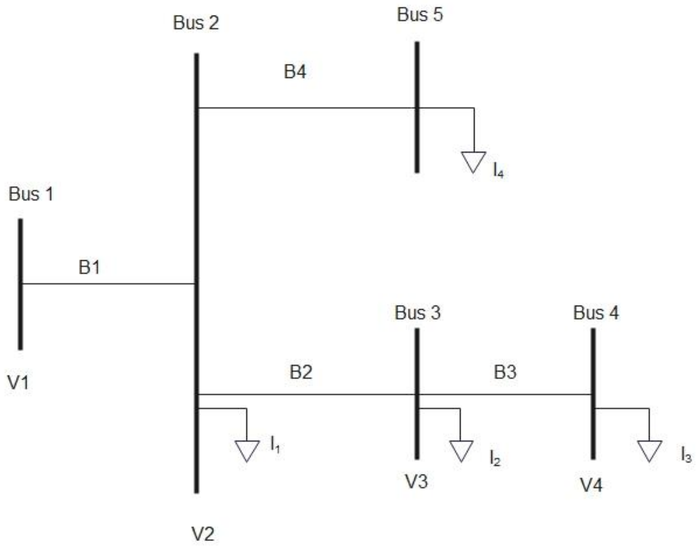

Figure 3 - 3 Represents 5 Bus Load Flow Analysis Using The Backward/Forward Sweep Method

$$S_i = P_i + Q_i \qquad 3.15$$

Where i= 1,2,3,4…N(number of buses) P_i is the real power, Q_i is the reactive power

3.6.1 Equivalent Current Injection

By applying the basic power formula to the equation(3.15) concerning the current injection(CI) and bus voltage. The current injected can be expressed as

$$I_i = I_i^r(V_i) + jI_i^i(V_i^k) = \left(\frac{P_i + jQ_i}{V_i^k}\right)^* \qquad 3.16$$

V_i^k and I_i^k represent the bus voltage and CI of the ith at the kth iteration

The Equivalent current injection at any kth iteration can be expressed as

$$I_i^k = I_i^r(V_i^k) + jI_i^i(V_i^k) = \left(\frac{P_i + jQ_i}{V_i^k}\right)^* \qquad 3.17$$

V_i^k and I_i^k represent the bus voltage and ECI of the *i*th at the kth iteration

3.6.2 Backward Sweep

The backward sweep is formulated by moving from the last bus towards the start of the network and applying the Kirchhoff voltage law(KVL) and Kirchhoff current law(KCL). In this, the voltage is assumed for the forward sweep. Only the power flow in each branch is modified. Running from the back toward the start

$B4 = I_4$ 3.18.1

$B3 = I_3$ 3.18.2

$B2 = I_2 + I_3$ 3.18.3

$B1 = I_1 + I_2 + I_3 + I_4$ 3.18.4

From equation 4 The branch currents and bus current injection can be expressed as

$$\begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{bmatrix} \qquad 3.19$$

Equation (3.19) can be simplified as

$$[B] = [BIBC][I] \qquad 3.20$$

3.6.3 Forward Sweep

The forward sweep applies KVL from bus 1 towards the last bus to the righthand side of the network. This is also known as branch current to bus voltage(BCBV).

$$V_2 = V_1 - (Z_{12}B_1) \quad 3.21.1$$

$$V_3 = V_2 - (Z_{23}B_2) = V_1 - (Z_{12}B_1) - (Z_{23}B_2) \quad 3.21.2$$

$$V_4 = V_3 - (Z_{34}B_3) = V_1 - (Z_{12}B_1) - (Z_{23}B_2) - (Z_{34}B_3) \quad 3.21.3$$

$$V_5 = V_2 - (Z_{25}B_4) = V_1 - (Z_{12}B_1) - (Z_{25}B_4) \quad 3.21.4$$

The matrix notation for equation 3,4,5 can be expressed as

$$\begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \end{bmatrix} = \begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix} - \begin{bmatrix} Z_{12} & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & 0 \\ Z_{12} & 0 & 0 & Z_{25} \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \end{bmatrix} \quad 3.22$$

The matrix in equation 3.22 can be represented in the simplified form as

$$[\Delta V] = [BCBV][B] \quad 3.23$$

Substitute equation 3.20 in equation 3.23

$$[\Delta V] = [BCBV][BIBC][I] \quad 3.24$$

$$[BCBV] = [BIBC]^T[Z_D] \quad 3.25$$

3.6.4 Algorithm for backward/forward Sweep Load Flow

The load flow was applied for the IEEE 69 bus and ECG 33KVA distribution network. The MATLAB script used to solve the load flow problem was done through these steps;

1. Read the line data and bus data from the network
2. Calculate the current injection matrix using equation (3.16 – 3.17)
3. Calculate the backward sweep from the equations(3.20)
4. Generate forward sweep matric from the equation(3.21 – 3.23)
5. Calculate the Distribution load flow using backward and forward sweep matrix(3.20,3.21,3.23,3.24 and 3.25)

6. Initiate iteration k=0
7. Iteration of k=k+1 for initial voltage constrain
8. Update voltages.
9. Return to DLF matrix if the difference in current voltage and previous voltage is less than permissible voltage.
10. Calculate power loss using the branch currently at final node voltages
11. Store branch currents, power loss, and node voltages.
12. Stop power flow.

The load flow biography view is shown in Figure 3.5 below

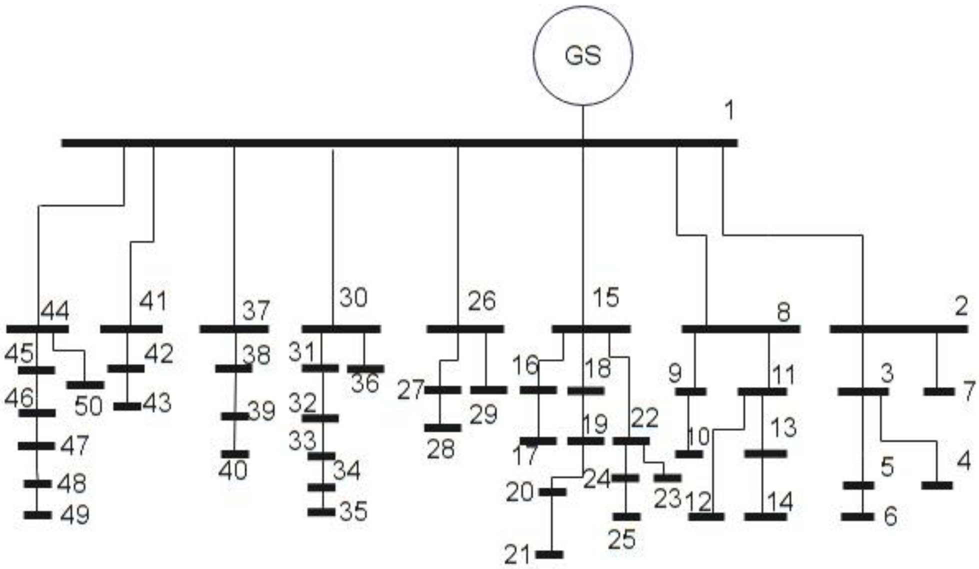

Figure 3 - 4 Biograph Representation Of The Load Flow

3.7 Software modeling

The modeling tools used for the thesis were MATLAB and ETAP. The ETAP was used to model the base case of the Ashanti network. MATLAB was used for the load flow and optimal allocation of DG units and fast EVCS.

3.7.1 ETAP Modeling

The ETAP was selected to build the existing Ashanti region network since the model of the network was not available in software form. The ETAP provides a digital twin of models and has been used in the thesis for base case simulation of the Ashanti network. The ETAP was used to model the network using the library of the secondary data line diagram given by the Electricity Company of Ghana(ECG). The line and bus data generated from the model was then used to feed the algorithm built in the MATLAB environment. The power flow method selected the power flow was an adaptive backward/forward sweep with a precision of 0.01.

The grid is modeled in ETAP as a swing bus supplying power to the bulk supply point at Awomaso and Ridge. The grid is selected from the ETAP library with a short circuit current of and voltage of 33KVA. The line data generated from ETAP is shown in Appendix B. The system load adapted was the peak loading values for the data collected from ECG. This is shown in Appendix C. The EVCS is modeled as a load based on the stochastic nature of EV charging (Ponnam & Swarnasri, 2020b). The system capacity is 975 kW. The system is designed to charge 100 vehicles from five manufacturers of EVs. Details of the EVs are shown in Table 3 – 2.

Table 3 - 2 Characteristics of EV for fast EVCS modeled

Electric Vehicle Model	Power Rating (kW)	No. of CP	Total Rating
BMW i3	44	10	440
CHANG AN YIDONG	3.75	20	75
Chevrolet VOLT	2.2	25	55
SAE J1772 standard	7	30	210
Tesla Model X	13	15	195
The total power rating of EVCS(kW)			975

3.7.2 MATLAB Modelling

The MATLAB 2021 software was used for the optimal placement of DG and EVCS. This included the load flow analysis and the optimization techniques. The modeling of the optimization techniques is presented in this section.

3.8 Modeling of Artificial Bee Colony Algorithm for Simultaneous Placement

Karobaga(2005) introduced the ABC algorithm(Al-Ammar et al., 2021). The food source is denoted by the allocation of DG and the location of EVCS. The onlooker bees find a better solution by studying the food source information with its surrounding source and updating the solution in its memory by using (3.26).

$$F_{ij} = F_{minj} + rand(F_{maxj} - F_{minj}) \quad 3.26$$

where F_{minj} and F_{maxj} represent the solution of the *j*th variable at maximum and minimum. The random number(*rand*) is selected within -2 and 2 (Al-Ammar et al., 2021). (3.26) is used to randomly select food sources by the onlooker bee. To determine whether or not a certain food source is likely the best solution, (3.27) is used.

$$fitness(x_i) = \begin{cases} \dfrac{1}{(1 + f(x_i)}, & iff(x_i) \geq 0 \\ 1 + |f(x_i)| & otherwise \end{cases} \quad 3.27$$

$$P_{prob,i} = \frac{fit_i}{\sum_k^N fit_k} \quad 3.27$$

Where fit_i is the fitness value at the selected solution(i). The fitness at every iteration is fit_k . The variable length is k. The scout bee employs (3.26) when the updated solution is worse than the previous best solution. (11) is used to define the overall solution.

$$F_{new,ij} = F_{ij} + y_{ij}(F_{ij} - F_{kj}) \quad (3.28)$$

where Y_{ij} represents *rand* [-2 2]. F_{kj} represents the location of the solution close to F_{ij} ,

For ABC implementation an initial random solution is produced using (3.29). The new solution is searched by employee and onlooker bees using (3.28)

$$F_i = \{F_{i1}, F_{i2}, \dots F_{iD}\} \qquad (3.29)$$

Figure 3.6 shows the flow chart of ABC algorithm as implemented.

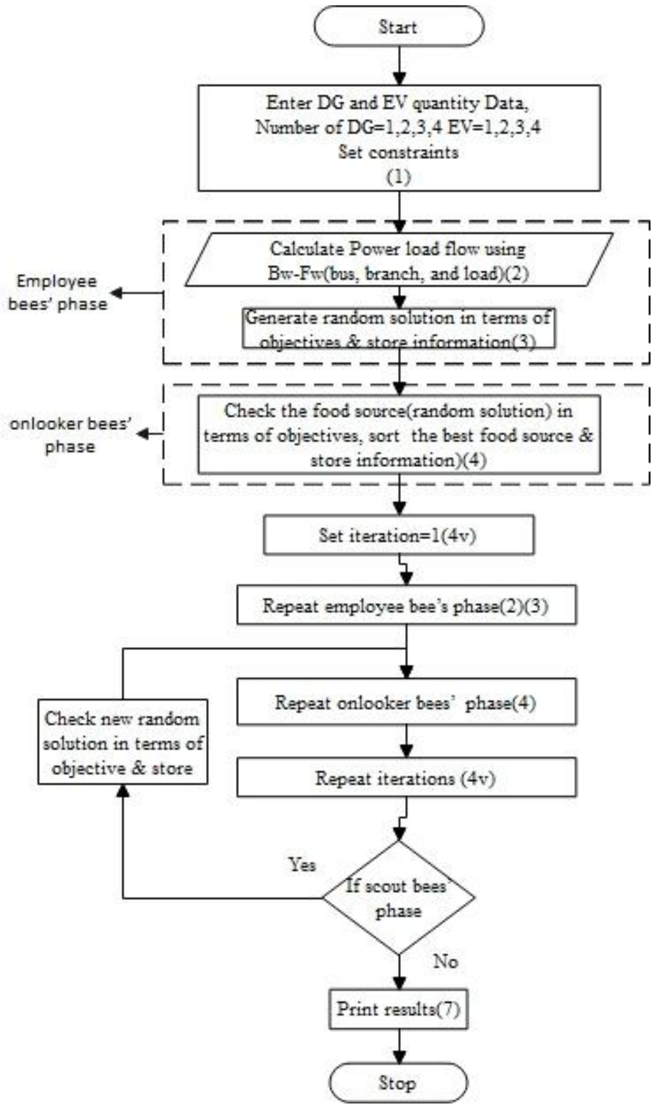

Figure 3 - 5 Flowchart of the Proposed Algorithm

The Algorithm for ABC is :

STEP 1: Input the load, line data, and quantity of DGs/ EV.

STEP 2: Define the algorithm parameters using Table 3 – 3.

STEP 3: A. Calculate power losses using load flow analysis from STEP 1. B. Calculate and store the objectives. C. Evaluate stored values and select the best solutions. D. initialize iteration at 1.

STEP 4: A. Initiate random solutions. Calculate power losses using load flow analysis. B. Solve and store the fitness. C. Solve the objectives and select the best results. D. Find scout bees.

STEP 5: Repeat STEP 4 until iteration =100

STEP 6: Evaluate the probability of the fitness using (3.27) update the solution with (3.28) and store it after updating.

STEP 7: Print the final solution (i.e. optimal locations and size of DG, location of EVCS)

Table 3 - 3 Summary of ABC parameter used for solution

ABC Parameter	Number Chosen
Population size	Num. DG × 40(i.e.40...,160 for cases 1-4)
Max. no. of iterations	100
No. of onlooker bees	Num. DG × 40(i.e.40...,160 for cases 1-4)
Accel. coefficient(a)	2.0
Abandonment Limit	Round(0.6×2(Num. DG +Num. EVCS) ×pop.)

3.9 Modeling of Particle Swarm Optimization Algorithm for simultaneous placement

The PSO algorithm technique was designed by Kennedy and Eberhart in 1995 (Okwu & Tartibu, 2021). In this work, the position and velocity of a particle are defined as x_i^k and v_i^k respectively. The preceding solution is solved using the previous best solution (pbest_{id}). (3.30) and (3.31) are used to improve the individual best to attain the global best in the iterative form (Hassan, Sun, et al., 2020; Mandal et al., 2008). The location of the individual particle is:

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}\,, \qquad 3.30$$

$$i = 1,2,3 \ldots .N_p,\ d = 1,2,3 \ldots .N_g$$

The member of the particle is N_g . N_p represents the swarm population. Equation (3.31) is the velocity of a particle as:

$$v_{id}^{k+1} = w \times v_{id}^{k} + C_1 \times \mathrm{rand}() \times \left(pbest_{id} - x_{id}^{k}\right) + C_2 \times \mathrm{rand}() \times \left(gbest_{d} - x_{id}^{k}\right) \qquad 3.31$$

For each new solution during iteration, the inertia is updated and evaluated using () as:

$$\mathrm{w} = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \qquad 3.32$$

The Algorithm for PSO flow chart is show in Figure 3 – 7 .

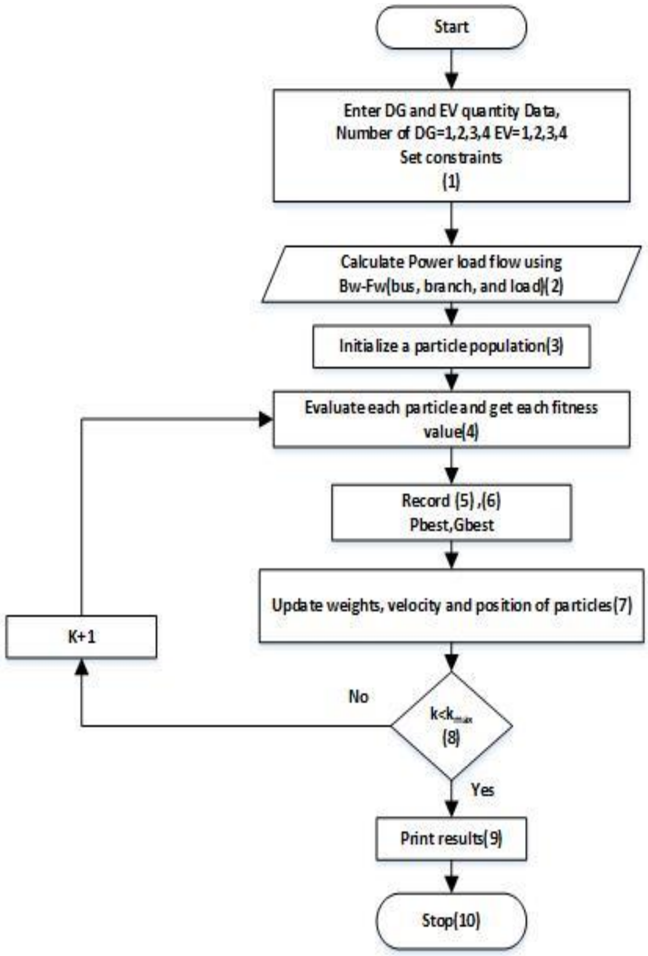

Figure 3 - 6 Flow Chart Of PSO as Implemented

The algorithm runs through the following steps;

STEP 1: Set PSO parameter according to Table 3 – 4 , Enter line and bus data.

STEP 2: Evaluate system power losses using load flow

STEP 3: Generate the particle position and velocity into dimension(D) space randomly.

STEP 4: If voltage constraints are met calculate system power losses with STEP 2.

STEP 5: Compare the current solution with individual function (Pbest). Store current particle position

STEP 6: Select the particle with the minimum individual best from among all stored best. This is the global best (G_{best}).

STEP 7: Update the particle position and velocity.

STEP 8: Allow the particle to go through STEP 5, 6 and 7 for maximum iteration then move to Step 9. In case of high objective value go back to Step 4 and count iteration index by one step.

STEP 9: the optimal solution in print out select the solution with minimum voltage deviation index.

STEP 10 Stop

Table 3 - 4 Summary of PSO Parameters used in Optimization

ABC Parameter	Number Chosen
Population size	Num. DG × 40(i.e.40...,160 for cases 5-8)
Max. no. of iterations	100
Accel. Coeff.(C_1)	1.5
Accel. coeff.(C_2)	2.0
Inertial weight(w)	1

3.10 Validation of System Model

The study adopted the empirical, comparison, and simulation validation methods. In terms of empirical validation the adopted methodologies used in this research have been used for optimal allocation In order studies (Aman et al., 2016a, 2016b; Azad et al., 2021; Hassan, Sun, et al., 2020; Jamian et al., 2014; G. H. Reddy et al., 2017).

The optimization techniques adapted for the research have been previously used for allocation In order areas in power system voltage profile improvement such as network reconfiguration, storage allocation, and DG units and capacitor banks placement. The PSO and ABC have been used for the optimal placement of DG units using the backward/forward load flow technique.

This research applied the PSO and ABC algorithms for the simultaneous placement of DG units and fast EVCS.

The data for the IEEE 69 bus network were also compared with available research data in the MATLAB online database. The line and bus data for the IEEE 69 bus network are shown in Appendix B and C.

In terms of validation by the simulation method, the ETAP was used to simulate the base case for the Ashanti region network. The results from the ETAP simulation are compared to the real data received at the various buses in the real system. The error margins are within the acceptable limits for the IEC standard. The error margins for bus voltages ranged from 0.1 to 2.8. The field data, simulated data, and error margins are provided in Appendix D. A Pearson correlation value of 0.878 was found when comparing field data to ETAP simulation data. Therefore, the ETAP has a 95% degree of confidence, according to the simulated data. The nature of the voltage profile followed the same pattern for both simulated and measured data for the worst-performing buses and the best-performing buses. The results of the study are again compared to the IEC 60038(2009) standard after the optimal placement and the bus voltages are within the limit of 5%. This is better since the required margins are 10% (IEC, 2009, 2018).

3.11 Study Cases Definitions

The study cases were selected based on the available literature to compare the results of the proposed ABC and PSO with existing works. A maximum of three DG units and three EVCS have been used by most authors(Babu Ponnam & Swarnasri, 2020; B. Mohanty & Tripathy, 2016; D. B. Prakash & Lakshminarayana, 2018b; Prasad et al., 2019; P. D. P. Reddy et al., 2017; Sharaf et al., 2022). Additional DG units and fast EVCS were added to the existing work to also validate the behavior of DG unit injection thus the study used up to four DG units and four fast EVCS.

The study cases represent the various scenarios that were simulated for the analysis of the solution. Table 3.10 shows the cases and the parameters considered for the various situations. **Case 0** involves the load flow simulations on the IEEE 69 bus with no Dg units and fast EVCS injected.

Case 1 involves the injection of single DG units and single fast EVCS on the IEEE 69 bus network using the ABC algorithm.

Case 2 involves the injection of two DG units and two fast EVCS on the IEEE 69 bus network using the ABC algorithm.

Case 3 involves the injection of three DG units and three fast EVCS on the IEEE 69 bus network using the ABC algorithm.

Case 4 involves the injection of four DG units and four fast EVCS on the IEEE 69 bus network using the ABC algorithm.

Case 5 involves the injection of one DG unit and one fast EVCS on the IEEE 69 bus network using the PSO algorithm.

Case 6 involves the injection of two DG units and two fast EVCS on the IEEE 69 bus network using the PSO algorithm.

Case 7 involves the injection of three DG units and three fast EVCS on the IEEE 69 bus network using the PSO algorithm. Case 8 involves the injection of four DG units and four fast EVCS on the IEEE 69 bus network using the PSO algorithm.

Case 9 involves the load flow analysis on the Ashanti region network without DG or fast EVCS injection.

Case 10 involves the injection of single DG units and single fast EVCS on the Ashanti region network using PSO and ABC algorithms.

Case 11 involves the injection of two DG units and two fast EVCS on the Ashanti region network using the PSO and ABC algorithm.

Case 12 involves the injection of three DG units and three fast EVCS on the Ashanti region network using the PSO and ABC algorithm.

Case 13 involves the injection of four DG units and four fast EVCS on the Ashanti region network using PSO and ABC algorithms.

Table 3 - 5 Represent The Study Cases and the Parameter Considered For Simulations

Case number	Number of DG injected	Number of EVCS	Algorithm used	Network
0	-	-	-	IEEE 69 bus
1	1	1	ABC	IEEE 69 bus
2	2	2	ABC	IEEE 69 bus
3	3	3	ABC	IEEE 69 bus
4	4	4	ABC	IEEE 69 bus
5	1	1	PSO	IEEE 69 bus
6	2	2	PSO	IEEE 69 bus
7	3	3	PSO	IEEE 69 bus
8	4	4	PSO	IEEE 69 bus
9	-	-	-	Ashanti Network
10	1	1	ABC/PSO	Ashanti Network
11	2	2	ABC/PSO	Ashanti Network
12	3	3	ABC/PSO	Ashanti Network
13	4	4	ABC/PSO	Ashanti Network

3.12 Conclusion

The chapter shows the data collected for the model. This includes the online and field data used to solve the optimization problem. The development of the solution to the optimization problem using the objective functions of minimized power loss and voltage profile improvement. The chapter also demonstrates the validation for the thesis models built. The optimization techniques for simultaneous sizing and allocation of DG units and fast EVCS are also formulated. The various scenarios for analyses are also summarized.

CHAPTER FOUR

RESULTS AND DISCUSSION

This chapter focuses on the simulation results from the different scenarios that this study looked at. The ABC and PSO algorithms are used to find out where the best places are on the IEEE-69 bus system for distributed generation units and fast electric vehicle charging stations. A comparative analysis of the results with related works is done in this chapter. Again, the two algorithms are further tested on a real network in Ghana (i.e., the ECG 33 KVA distribution network in the Ashanti Region) to improve power loss reduction and voltage profile enhancement.

4.1 Case 0: IEEE-69 bus System load flow data

Case 0 represents the load flow study of the IEEE 69 bus system. The data for the base case of the 69 bus system was adapted from the MATLAB online data resource. The network was configured in radial mode. The backward/forward sweep algorithm was used to run a load flow analysis on the IEEE-69 test system with all standard tie switches open.

The active power system losses are shown in Figure 4 – 1 .

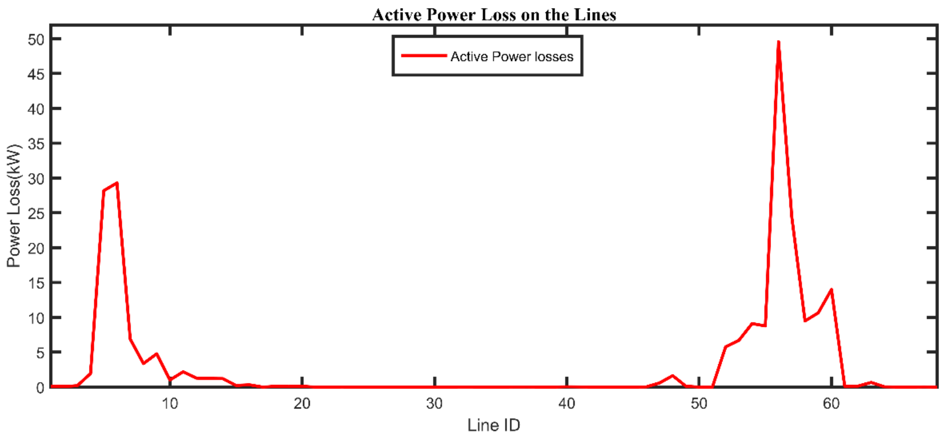

Figure 4 - 1 Active Power Loss on IEEE-69 Bus System

After the load flow studies the active power loss on the network was 225kW and the reactive power loss was 102kVAR. This result is consistent with the online data library for network losses on the IEEE 69 bus system.

Apart from the active power loss, the voltage profile of the network was also studied. Figure 4.2 below shows the voltage profile of the configuration.

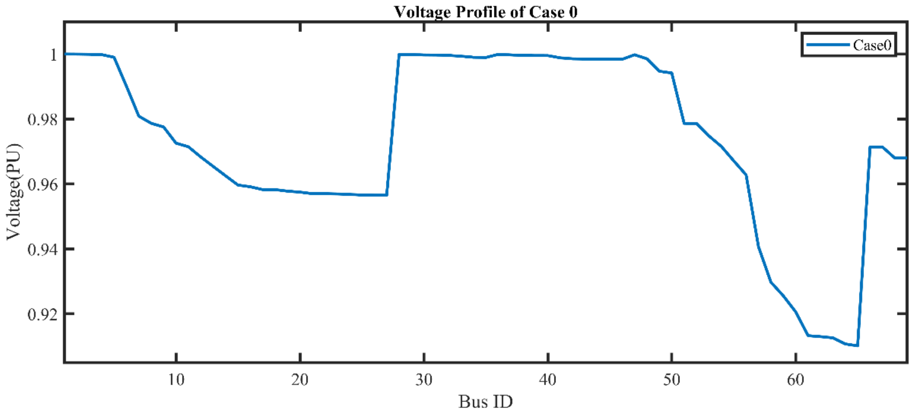

Figure 4 - 2 Shows The Voltage Profile of the IEEE-69 Bus System.

The voltage profile of the IEEE 69 bus system is within the 10% threshold of the IEC 60038 standard. The voltage profile deviation index was 11.64. From the voltage profile shown in Figure 4.2, the critical bus was bus 65 with a voltage of 0.91018 p.u. The total power demand for the system was 3802 kW and 2694 kVAR.

4.2 Case 1: Single Distributed Generation Unit and Single Electric Vehicle Charging Station on IEEE-69 bus System Using ABC

The ABC algorithm was used to optimally place a single DG and single EVCS on the IEEE-69 bus system. After simulations, the system's active power demand was 3802 kW and the reactive power demand was 2694 kVAR. The bar graph in Figure 4.4 below shows the active and reactive power loss on the network.

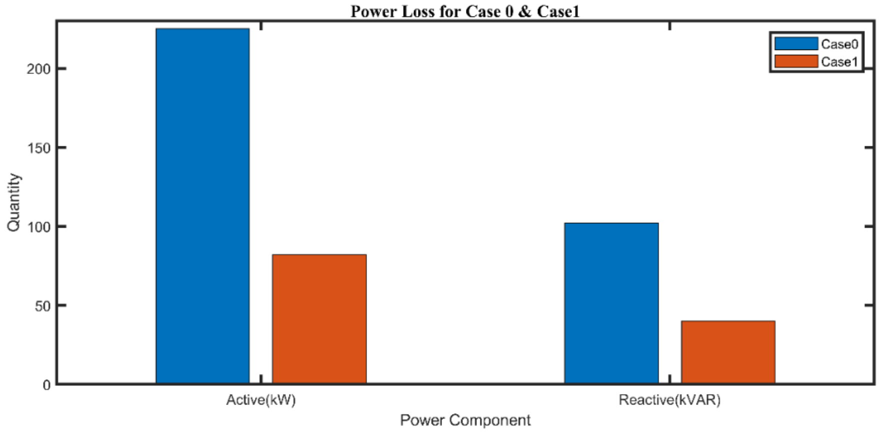

Figure 4 - 3 Active And Reactive Power Loss After DG Unit And Fast EVCS Integration.

From Figure 4.3 above, the power loss before the introduction of DG and EVSC was 225 KW and 102 KVar. The results show that after the introduction of a single DG unit and a fast EVCS, there were significant drops in the losses. The active power loss of the system drops to 82 kW, and the reactive power loss drops to 40 kVar from 225 kW and 102 kVar, respectively. The active power loss percent reduction was 63.56%.

The system voltage profile was also studied after the introduction of the DG units and fast EVCS. Figure 4.4 below shows the comparison of the voltage profiles of the base case and case 1.

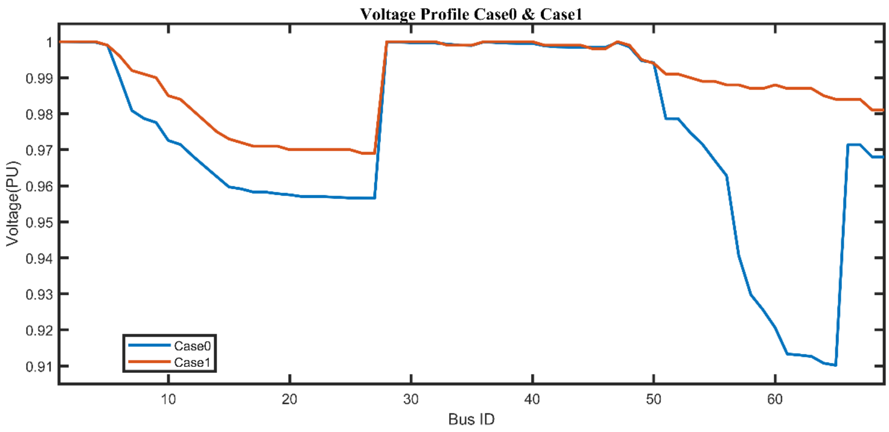

Figure 4 - 4 Voltage Profile of Base Case And Case 1

The base case had a voltage profile deviation of 11.64. From the above graph, it can be deduced that there was a significant improvement in the bus voltages. The voltage deviation after the simultaneous placement of DG units and fast EVCS was 1.7115. Figure 4.4 shows worse-performing buses after the optimal place under Case 1: buses 26 and 27 at 0.969 p.u. The best-performing buses were buses 1, 2, 3, 4, 28, 29, 30, 31, 32, 36, 37, 38, 40, and 47 at bus voltages of 1 p.u.

This result from Case 1 shows that when optimal placement using ABC is used to introduce a single DG unit and single fast EVCS, it can cause a reduction in active power losses. The active power loss on the network can be reduced to 63.56% under the ABC technique. The results from Case 1 again show that to attain less than 5% margins of bus voltage under simultaneous allocation, the DG unit would have to be placed on Bus 61 at a rated capacity of 1913 kW. The fast EVCS would also have to be placed on bus 2 of the network. These technical parameters of active power loss and voltage profile improvement are statistically significant after the installation of DG units and fast EVCS integration. Case 2 demonstrates that the ABC allocation can be used for simultaneous placement in an attempt to reduce the network power loss and again cause an improvement in the voltage profile.

4.3 Case 2: Two Distributed Generation Units and Two Fast Electric Vehicle Charging Stations on IEEE-69 Bus System Using the ABC

For the optimal placement of two DG units and two fast EVCS, the simulated results show that the active power demand of the system remained the same as in case 1. The total active power generation was 3873 kW, and the reactive power demand stood at 2729 kVAR.

The base case is compared with Case 2 in terms of active and reactive power. The power loss on the network is shown in Figure 4.5.

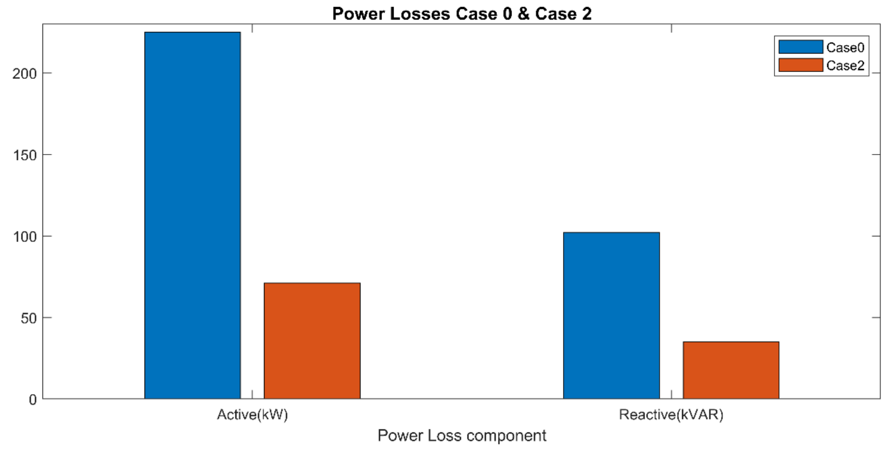

Figure 4 - 5 Power Loss On IEEE-69 System After Integration of DG Units And Fast EVCS

At the optimum placement and size the power loss on the system dropped significantly from 225KW and 102KVar to 71KW and 35KVar respectively. The active power loss on the network represents a 68.44% reduction when compared with the base case. The reactive power loss on the network also improved by 65.68% reduction from the base case.

The Case 2 voltage profile is compared with the base case. The results are shown in Figure 4.6.

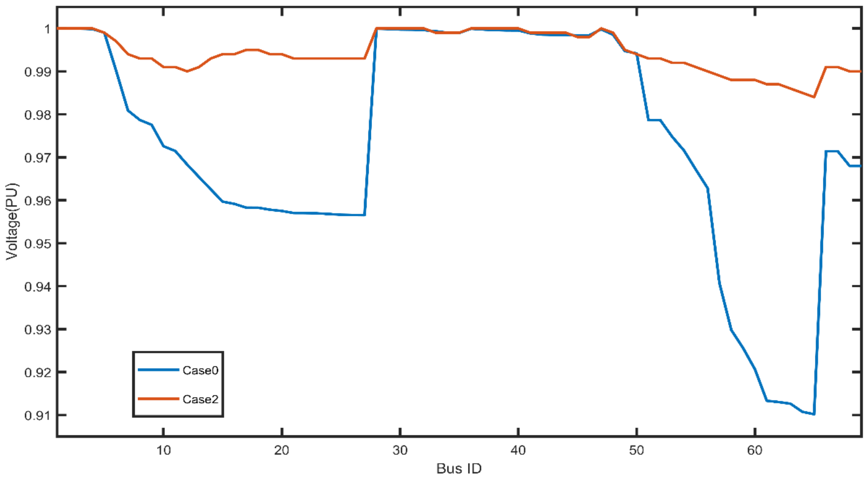

Figure 4 - 6 Voltage Profile of Case 0 and Case 2

The results of Case 2 after the DG unit and EVCS integration show that there can be improvements in the voltage profile of the network. For the optimum voltage deviation of 0.35173, the ABC algorithm was able to place the two DG units on the system. The worst-performing buses after the optimal place under case 2 were buses 65 at 0.984 p.u. The best-performing buses were buses 1, 2, 3, 4, 28, 29, 30, 31, 32, 36, 37, 38, 40, and 47 at bus voltage of 1 p.u.

The results of case 2 show that under optimal placement, the DG units would have to be placed on buses 17 and 61, while the EVCS would be placed on buses 2 and 3. For the minimum voltage deviation of 0.35173 to be achieved, the two DG units must have a combined capacity of 584 KW and 1799 KW, corresponding to buses 17 and 61, respectively. The optimal results demonstrate that two DG units and two EVCS simultaneously located on the network can contribute to an improvement in the active power loss of 68% reduction. In effect, the system voltage profile can be improved up to 5% margins rather than the 10% requirement according to the IEC 60038 standards.

4.4 Case 3: Three Distributed Generation Units and Three Electric Vehicle Charging Stations on IEEE-69 Bus System Using the ABC

The ABC was implemented with the same parameters as cases 1 and 2. In this case, three DG units and three EVCS were introduced on the IEEE-69 bus system.

There were improvements in the power loss, as shown in Figure 4.7 below.

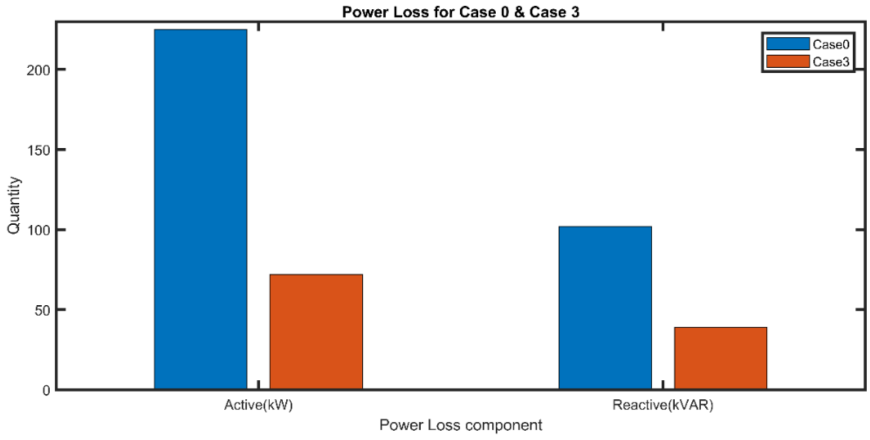

Figure 4 - 7 Power Loss on The System After Integration

The power losses of the system were 72 kW and 39 kVAR. This is an improvement when compared with the base case. The active power decreased by 68% from the base case, while the reactive power decreased by 61.78%. This reduction in power loss on the network is statistically significant, demonstrating that optimal placement can lead to a reduction in power loss on the network.

In terms of voltage profile improvement, the results of case 3 are compared with case 0. Figure 4.8 below also represents the voltage profile for cases 0 and 3.

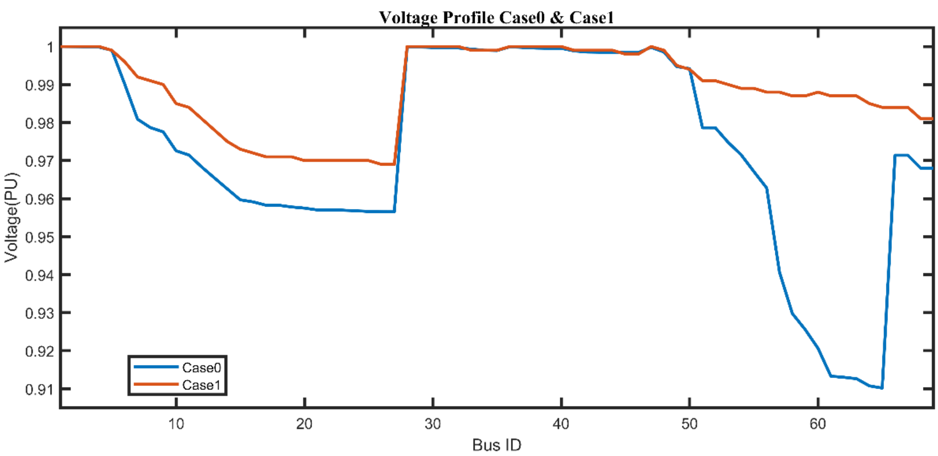

Figure 4 - 8 Voltage Profile of System After DG Units and Fast EVCS

At optimal allocation, the voltage profile deviation was achieved at 0.3596. The results from Case 3 show that there can be improvements in the voltage profile after the introduction of three DG units and three fast EVCS. The minimum bus voltage of the network after the placement was 0.987. The maximum bus voltage after the optimal allocation was 1 p.u. This shows that the worst-smelling bus was bus 27, and the best-performing buses were 1, 2, 3,4,5,28,36, and 47.

For case 3, the DG units would be placed on buses 69, 18, and 61, with a generation capacity of 1358 KW, 275 KW, and 1908 KW, respectively. The EVCS was placed on buses 40, 69, and 29. The results of Case 3 indicate that there can be a significant active power reduction of 68%. Again, the reactive power reduction was significantly reduced to 82.68%. The voltage profile also improved by 5%. This margin is technically significant when compared with the IEC 60038 standard margin of 10%. The ABC algorithm is therefore able to predict the simultaneous allocation of DG units and fast EVCS at improved technical parameters (i.e., power loss and voltage profile enhancement).

4.5 Case 4: Four Distributed Generation Units and Four Electric Vehicle Charging Stations on IEEE-69 Bus System Using the ABC

In this Case 4, the system parameters such as active power demand, active power generation, and the ABC algorithm parameter were maintained as in previous cases. The model was simulated to predict the optimum placement and sizing for four DG units and four fast EVCS.

In terms of the power loss, Figure 4.9 below compares the total active and reactive power losses with the base case (case 0).

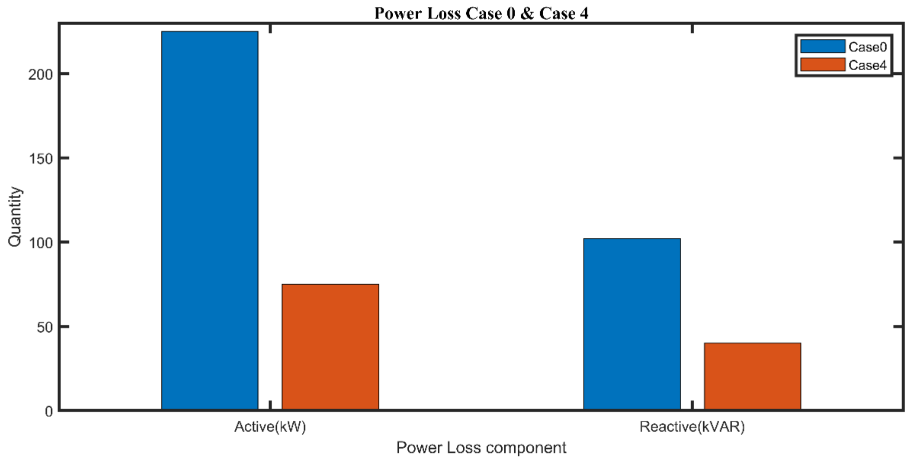

Figure 4 - 9 Power Loss on The System After DG Units and Fast EVCS Integration

The total power loss on the system dropped from 225 kW and 102 KVA to 75 kW and 40 KVAR. The percentage reduction in the active power was significant, as represented by 66.67%. The reactive power loss was also reduced by 82.22%. Despite the introduction of high-capacity chargers on the system, the power loss was significantly improved with the DG unit integration.

The voltage profile of case 4 was also compared with the base case. The results of the simulation in terms of voltage profile are shown in Figure 4.10.

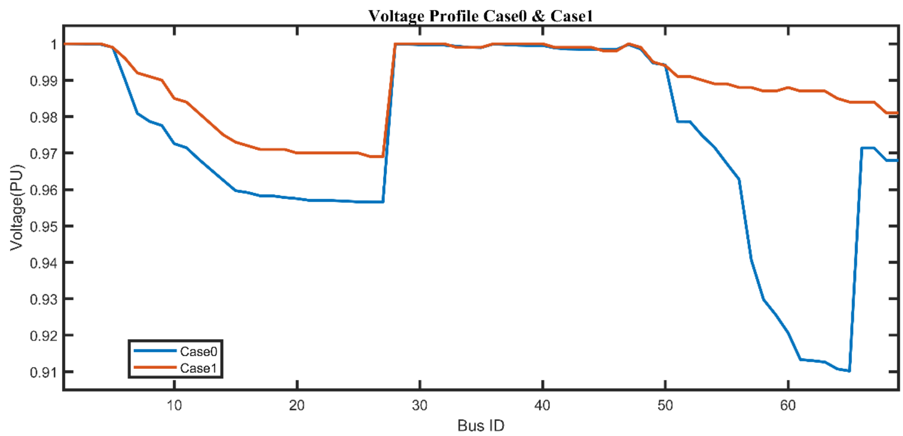

Figure 4 - 10 Voltage Profile Comparison of Case 0 And Case 4

The results after DG unit and EVCS integration show that there can be improvements after the introduction of four DG units and four fast EVCS. At the optimum voltage deviation of 0.22798, the algorithm was able to place the four DG units on the network using the ABC algorithm. The minimum voltage after the placement was 0.986 at bus number 65. The best-performing buses in terms of bus voltage after the placement were 1, 2, 3, 4, 23, 24, 25, 26, 28, 36, and 47. All these buses had a voltage of 1 p.u. after simultaneous placement. Figure 4.10 also demonstrates that the worst-smelling bus was bus 65.

For optimum placement using ABC and up to four DG units and EVCS, the DG units were placed on buses 2, 61, 6, and 23 at a generation capacity of 696 KW, 1850 KW, 167 KW, and 630 KW, respectively. The EVCS were also placed on buses 36, 39, 29, and 5. The system's generation capacity increased slightly for case placement. This increase was by 1 KW from the previous cases. The case 4 results affirm that ABC can be used to optimally place up to four DG units and four EVCS on the IEEE 69 network with a significant improvement in active power reduction of 66.67% and a voltage profile within 5% of the IEC standards.

4.6 Optimal pathway for DG and EVCS on 69 bus system when using ABC algorithm

The results of cases 0, 1, 2, 3, and 4 are compared in terms of power loss, voltage profile, and convergence characteristics. Figure 4.11 shows the power loss on the system for cases 0–4 under ABC optimization.

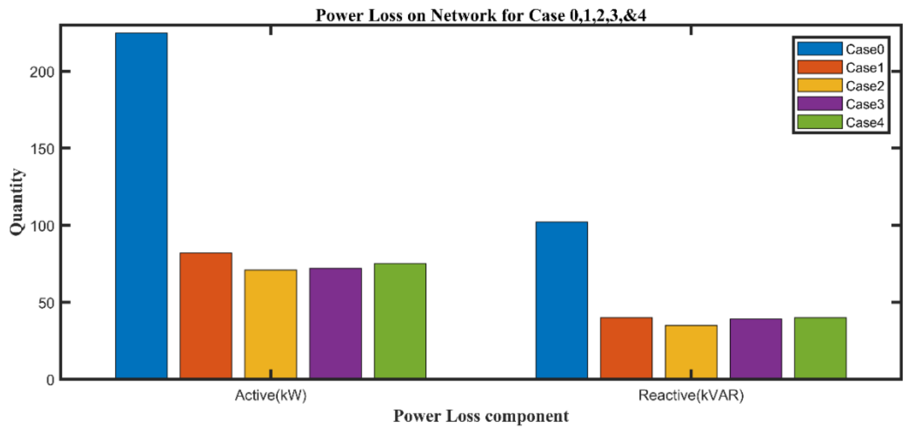

Figure 4 - 11 The Power Loss For All Cases Under ABC Implementation

There are significant improvements on the line in terms of power loss as more DG units and fast EVCS are introduced at an optimal location. The four cases under ABC implementation demonstrate that there is a significant reduction in active power loss when penetration levels of DG units and fast EVCS increase. The percentage reduction in active power loss ranged from 63.56% to 68.44%, which represents substantial energy and cost savings. Case 2 presented the least active power loss on the system after the integration of DG units and fast EVCS, while Case 1 had the highest active power loss. Case 3 followed Case 2 as the next-best reduction in power loss, while Case 4 ranked as the third-best. The difference in active power reduction between case 3 and case 2 was not very significant. The percentage reduction difference between case 3 and case 2 was 0.44%.

When the ABC algorithm was used to place the distributed generation and electric vehicle charging station on a IEEE 69 bus system, there was a significant improvement in the voltage profile for cases 1, 2, 3, and 4 under the ABC algorithm. This is shown in figure 4.11 below, which has the voltage profiles of cases 1, 2, 3, and 4.

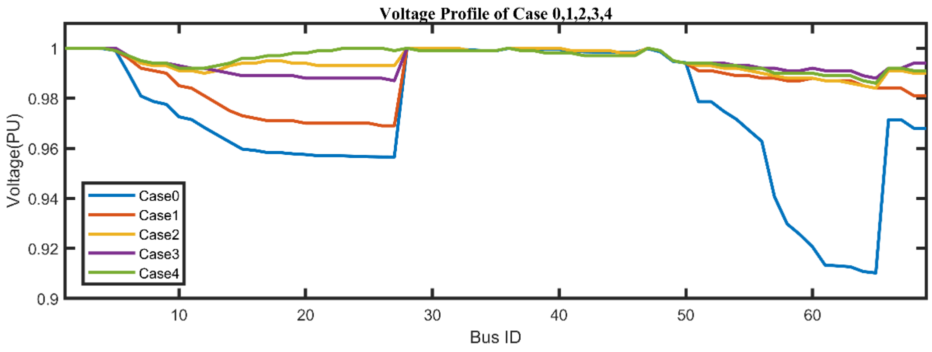

Figure 4 - 12 Voltage Profile of System for Various Cases under ABC Implementation

When all the cases under ABC optimization are compared to each other, Case 4 has the best voltage deviation index of 0.22788. This was followed by case 2 with a voltage deviation of 0.35173. Case 3 had a deviation index of 0.3596, while Case 1 had a deviation index of 1.7115.The results under the ABC shows that the ABC is able to optimally place and size DG units and fast EVCS with an improved voltage profile even when penetration levels increase.

Therefore, the most optimal case for placement and sizing under the ABC technique is case 4. The second-best fit in terms of voltage profile, voltage deviation, and power loss would be case 2. Buses 61 and 69 became noticeable in terms of DG unit placement since they almost appeared in all the cases under the ABC algorithm. On the fast EVCS placement buses, 2 and 69 also appeared in almost all the cases under the ABC algorithm.

According to the results of the ABC approach, the level of reduction may depend on the level of penetration and the best way to use DG units and fast EVCS to reduce active power losses. Various networks may necessitate distinct penetration tactics to minimize active power losses.

Ultimately, the ABC implementation demonstrates that the optimal simultaneous allocation of distributed generation (DG) units and fast EVCS is beneficial for lowering active power losses in a power network. The percentage reductions in active and reactive power loss vary among the four scenarios but are significant in every instance. These findings have consequences for the efficiency and dependability of power networks, and power engineers, legislators, and electrical engineering researchers may find the results of interest.

4.7 Case 5: Single Distributed Generation Unit and Single Fast Electric Vehicle Charging Station on IEEE-69 Bus System Using the PSO.

For case 5, a single DG unit and single fast EVCS were optimally placed on the IEEE 69 bus system using the PSO algorithm. The minimum voltage profile deviation and active power losses were selected as an optimum solution from the simulated results. Before the introduction of DG units and fast EVCS on the network, the power losses on the IEEE-69 bus system remained at 210kW and 143kVAR. The system had a total power demand of 3802 kW and 2694 kVAR.

The power loss on the system is compared with the base case. The power loss graph of the base case and Case 5 is shown in Figure 4.12.

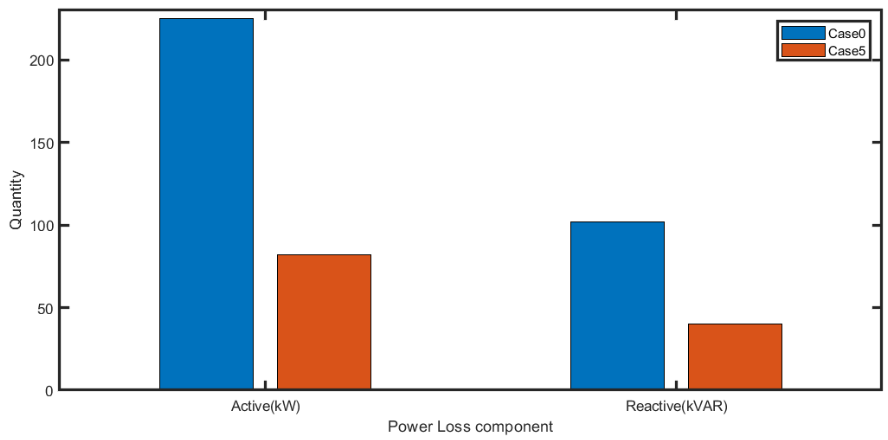

Figure 4 - 13 Power Loss For Case 0 And Case 5

When Case 5 is compared to the base case, power loss is minimized. The system's power loss decreased from 210 kW and 143 kVA after integration to 82 kW and 40 kVAR. There was a considerable drop in active power loss on the system (63.56 percent to be exact). In addition, there was a 59.25% drop in reactive power loss. Integration of the DG unit dramatically reduced power loss despite the addition of high-capacity chargers to the system.

In terms of voltage profile improvement, figure 4.13 indicates the results of the base case scenario as opposed to Case 5.

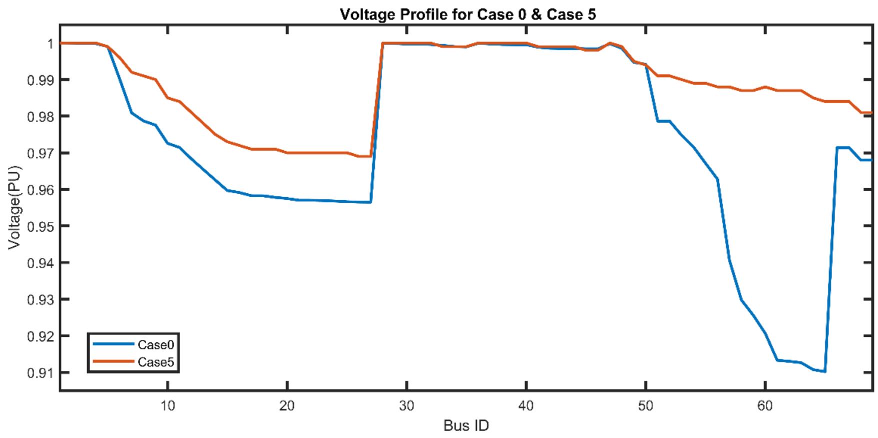

Figure 4 - 14 Voltage Profile of Case 0 and Case 5

When the model was simulated, a voltage deviation result of 1.7115 was selected as the best result for this case. This deviation index showed an improved voltage profile for the test network after the integration of the DG unit and fast EVCS, as shown in figure 4.13. The base case had a voltage profile deviation of 11.64. From the above graph, it can be deduced that there was a significant improvement in the bus voltages. From Figure 4.13, the worst-performing buses after the optimal place under case 5 were buses 26 and 27 at 0.969 p.u. The best-performing buses were buses 1, 2, 3, 4, 28, 29, 30, 31, 32, 36, 37, 38, 39, 40, and 47 at bus voltages of 1 p.u.

The PSO allocated the fast EVCS to bus 2 and the DG unit to bus 61. It was determined that a DG unit of 1913 kW was the optimum size. Case 5's findings demonstrate that active power losses can be reduced when a single DG unit and fast EVCS are introduced via optimal placement using the PSO algorithm. By using the PSO method, the network's active power loss can be decreased by as much as 63.56%. The significance of lowering active power loss is emphasized in Case 5. Consequently, adopting the PSO technique for a single DG unit and single fast EVCS penetration on the IEEE 69 bus system allows for simultaneous allocation, minimizes loss, and improves the network voltage profile.

4.8 Case 6: Two Distributed Generation Units and Two Fast Electric Vehicle Charging Stations on IEEE-69 Bus using PSO.

For Case 6, the PSO algorithm was used to figure out where two DG units and two fast EVCS should go on the IEEE-69 bus system and what size they should be. The system was lost before the placement, and the sizes remained at 210 KW and 143 KVA. After the simulations, the active power demand of the system was 3802 kW. The total reactive power demand on the system was 2694 kVAR. The total power generation on the system was 3873 kW and 2730 kVAR. The results of Case 6 are compared with Case 0 in terms of power loss and voltage profile improvement.

The integration of DG units and fast EVCS caused an improvement in power loss. The active and reactive power losses are shown in Figure 4.14.

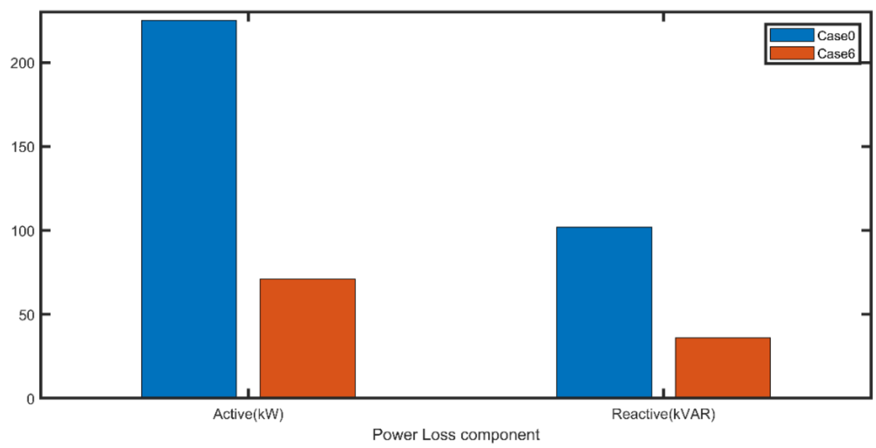

Figure 4 - 15 Power Loss For Case 0 and Case 6

The active power loss dropped significantly from 210 KW to 71 KW after the placement. This represented a drop of 68.44% from the base case. The reactive power losses on the system were also 36 kVAR, which also represented a percent reduction of 64.71%.

The voltage profile of case 6 is compared with case 0. Figure 4.15 below shows the comparison of the base case and after DG units and fast EVCS integration.

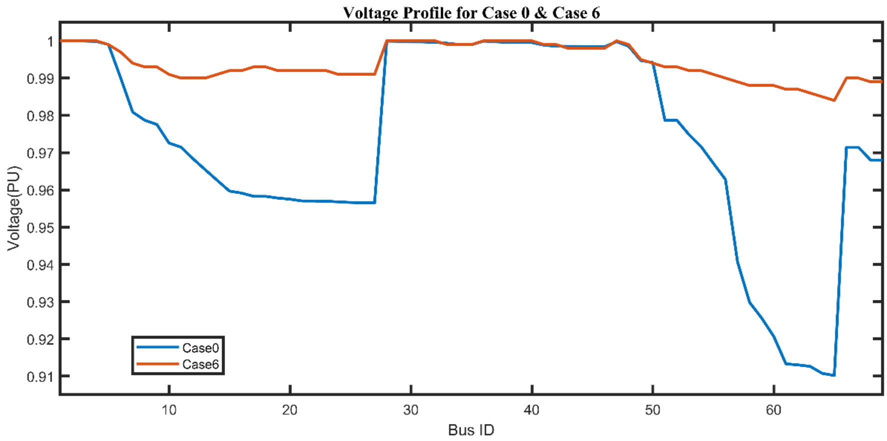

Figure 4 - 16 The Voltage Profiles of Cases 0 and 6

The voltage profile was improved from the base case after the integration of DG units and fast EVCS, as can be shown in Figure 4.15. The optimal result for PSO implementation, in this case, was obtained at a minimum voltage profile deviation of 0.3955. Since the base case (case 0) had a voltage profile deviation of 11.64, the improvement was statistically significant. From Figure 4.15, the worst-performing bus after the optimal place under case 6 was bus 65 at 0.984 p.u. The best-performing buses were buses 1, 2, 3, 4, 28, 29, 30, 31, 32, 36, 37, 38, 39, 40, and 47 at bus voltages of 1 p.u.

Buses 28 and 36 were chosen for the fast EVCS since they were deemed the best locations for them to connect. The DG units were installed on buses 61 and 17, with respective capacities of 1810 KW and 540 KW. The PSO implementation for Case 6 indicates that efficient simultaneous allocation of distributed generation (DG) units and fast EVCS contributes to a

68.44% decrease in active power losses in a power network. The voltage profile enhancement was within the 5% limit, which is an improvement given that the IEC 60038 standard suggests 10%. In this particular scenario, the percentage drops in active and reactive power loss along with the enhancement of the voltage profile make a considerable contribution to operation parameters when the simultaneous placement of two DG units and two fast EVCS using the PSO algorithm is adopted. This evidence of an improved voltage profile and minimized power loss has implications for the efficiency and dependability of power networks and may be of interest to power engineers, legislators, and electrical engineering researchers.

4.9 Case 7: Three Distributed Generation Units and Three Electric Vehicle Charging Stations on IEEE-69 Bus using PSO.

For case 7, the PSO algorithm was used in the concurrent placement and sizing of DG units and fast EVCS for a maximum of three DG units and three fast EVCS. The total power generated was 3871 kW and 2729 kVAR. The system had an overall power demand of 3802 KW and 2694 The comparison of the results of Case 7 and the base case (Case 0) is discussed in terms of power loss and voltage profile improvement.

The power loss for case 7 was compared with the base case. The results of Case 7 demonstrate a significant improvement in the power loss on the IEEE 69 bus network. Figure 4.16 below shows the results of cases 7 and 0 in terms of system power loss.

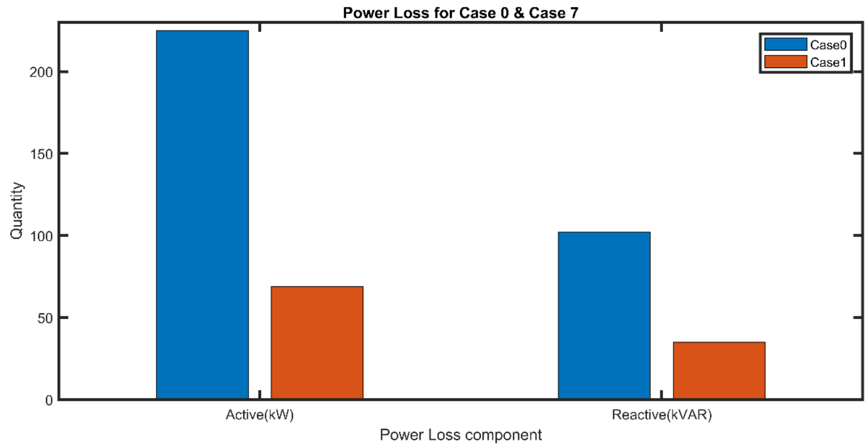

Figure 4 - 17 Power loss for case 0 and case 7

The active power loss after the placement and sizing of DG units and fast EVCS was 69 kW. This power loss, when compared with the base case, represents a reduction of 69.33%. The reactive power loss of 35 kVAR also represented a reduction of 65.69%. These reductions in power loss on the system after DG units and fast EVSC integration are statistically significant.

The model was simulated, and the optimum results were selected using the voltage profile deviation index. Figure 4.17 below shows the voltage profile of cases 0 and 7.

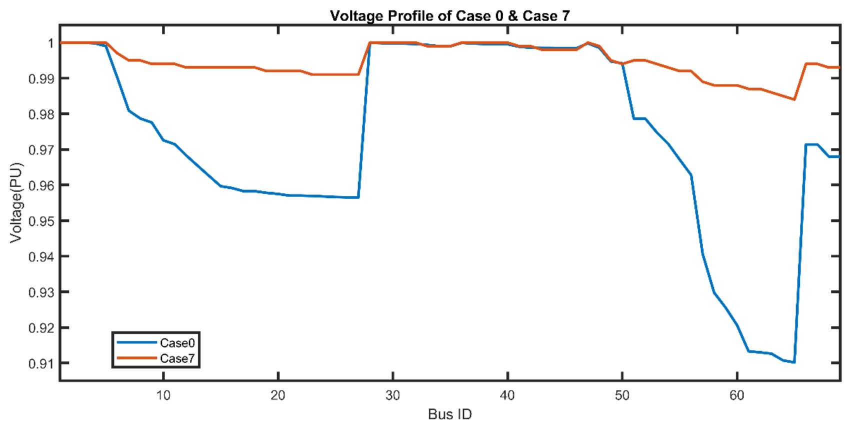

Figure 4 - 18 Voltage Profile of Case 0 and Case 7

The voltage profile was improved after the placement of DG units and fast EVCS. For the optimum allocation, the voltage profile deviation index was 0.32823. The minimum voltage after the placement was 0.984. This occurred on bus 65, making it the worst-performing bus. The buses with the maximum voltage after the placement were 1, 2, 3, 4, 5, 28, 29, 30, 31, 32, 36, 37, 38, 39, 40, and 47. These represent the best-performing buses.

For Case 7, the DG units were placed on buses 11, 18, and 61 at capacities of 482 KW, 400 KW, and 1751 KW, respectively. The fast EVCS were placed on 47, 28, and 36. The results of Case 7 confirm that the PSO technique can be used to optimally place DG units and fast EVCS. Again, the placement of three DG units and three fast EVCS at an optimal location can contribute to an active power loss reduction of 69.33% and an enhancement of the voltage profile within 5% margins of the IEC 60038 standard. The technique's application in three DG units and three fast EVCS integrations is technically significant and can be adopted by system administrators to improve active power loss and voltage profile enhancement on the network.

4.10 Case 8: Four Distributed Generation Units and Four Fast Electric Vehicle Charging Stations on IEEE-69 Bus using PSO.

In this case, the power system model of an IEEE 69 bus system was adopted for optimum placement and size, with a maximum of four DG units and four EVCS. The PSO algorithm parameter was the same as in all previous cases of optimal placement. The total power generation on the system was 3871 KW and 2729 KVAR. The case 8 and base case are compared in terms of power loss and voltage profile enhancements.

In terms of the power loss, Figure 4.18 shows the comparison of case 8 and case 0.

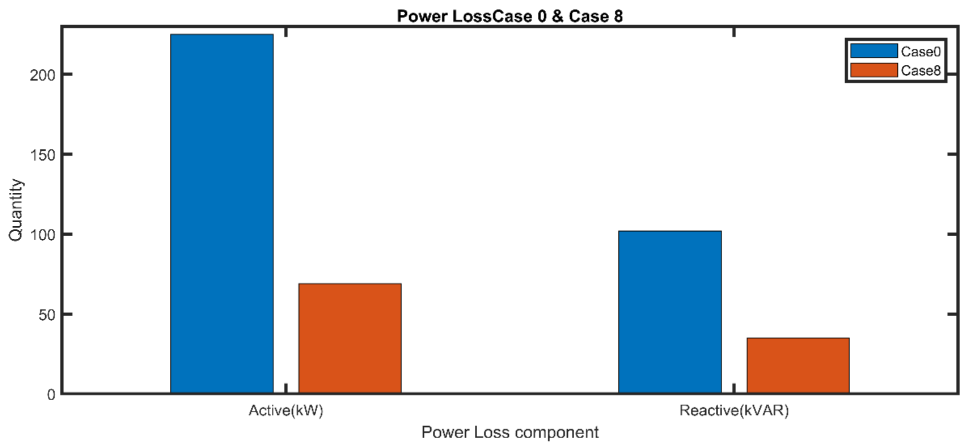

Figure 4 - 19 Power Loss on Case 0 and Case 8

The power loss on the system reduced from 210 kW and 143 kVAR to 69 kW and 35 kVAR, respectively. The percentage reduction of active power was 69.33%, and that of reactive power was 65.69%.

In terms of the enhancement of the voltage profile, Figure 4.19 shows the voltage profile of cases 0 and 7.

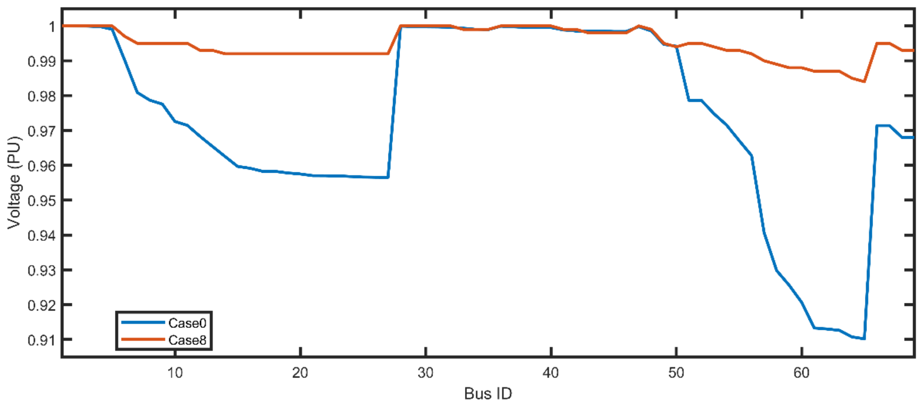

Figure 4 - 20 Voltage Profile of Case 0 and Case 8

The voltage profile deviation index with the minimum overall objective function was selected for optimal placement. The optimal placement occurred at a voltage deviation index of 0.31251. This is an improvement in the voltage profile from the base case 0, as shown in Figure

4.19. The worst-performing bus was bus 65 at 0.984 p.u. A significant number of buses performed well under the optimal placement. The bus voltage remained unchanged even after penetration levels of DG units and fast EVCS. These best-performing buses were the 1, 2, 3, 4, 5, 28, 29, 30, 31, 32, 36, 37, 38, 39, 40, and 47.

The results of Case 8 demonstrate that for optimal placement of four DG units and four fast EVCS, the DG units must be placed on buses 61, 21, 11, and 37 at capacities of 1756 kW, 1319 kW, 572 kW, and 884 kW, respectively. The fast EVCS must also be on buses 37, 28, 47, and 21. The results of Case 8 affirm the PSO technique for optimal allocation of DG units and fast EVCS even under high penetration levels. Again, the optimal placement of four DG units and four fast EVCS contributes to an active power loss reduction of 69.33% and an enhancement of the voltage profile within 4% margins of the IEC 60038 standard. The application of the PSO technique for simultaneous DG units and fast EVCS integration produces significant power loss reduction and improves the voltage profile of the network. This is critical information that can be utilized by power network operators and administrators to reduce power loss and enhance the voltage profile.

4.11 Optimal pathway for DG and EVCS on 69 bus system when using PSO

The optimal path for the PSO algorithm under simultaneous allocation is discussed in this section. The cases under consideration are Case 5, Case 6, Case 7, and Case 8. A comparative analysis of the cases in terms of the minimum voltage profile deviation index and minimum power loss is considered.

The power loss for all cases (Case 5, Case 6, Case 7, and Case 8) under the PSO technique is shown in Figure 4.20.

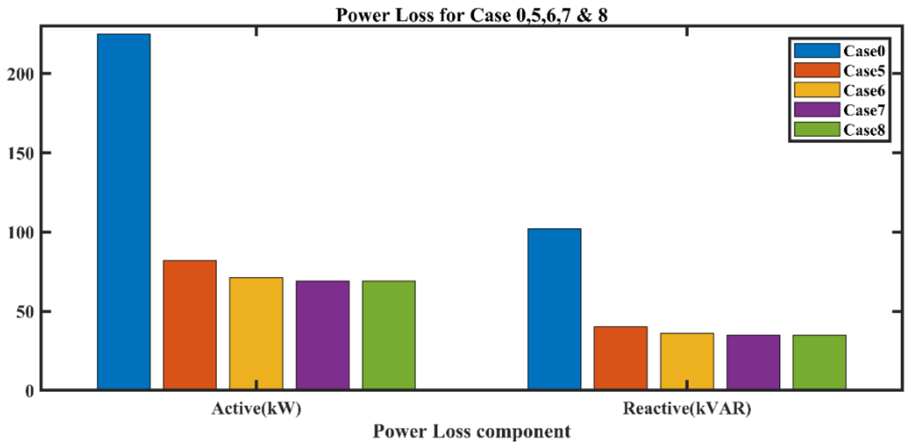

Figure 4 - 21 Power Loss for All Cases Under PSO Allocation

For optimal power loss and voltage profile improvement under the PSO algorithm, Case 8 was selected for the IEEE 69 bus system. Case 8 involved the allocation and sizing of four DG units and four EVCS. Case 8 had the highest power reduction margin of 69.33%. This was followed by case 7 of 69.33%. Case 6 had 68.44%. Case 5 was the worst case under the PSO algorithm, with a reduction of 63.56%. All the active power losses were below 60% when compared with the base case. Therefore, optimal PSO algorithm allocation suggests an improved active power loss reduction when used for simultaneous placement of DG units and fast EVCS, even under high penetration levels.

In terms of the voltage profile enhancement, the comparison of all cases under PSO algorithms is shown in Figure 4.21.

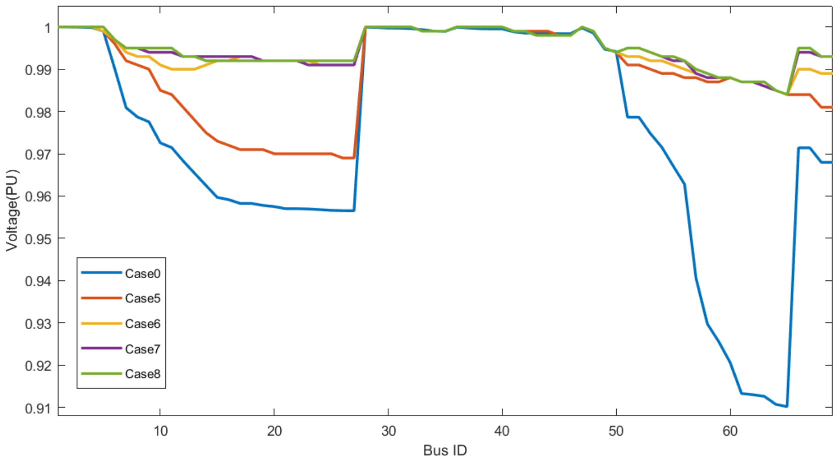

Figure 4 - 22 Voltage Profile of All Cases Under PSO Allocation

The case with the lowest minimum voltage profile deviation index was case 8, with a deviation of 0.31251. The next best voltage profile enhancement index was case 7 (at 0.32823), followed by case 6 with an index of 0.3955. Case 5 presents the worst voltage profile deviation index among the PSO cases (cases 5, 6, 7, and 8). The comparison of all the cases of DG unit and Fast EVCS integration led to an improvement of the system voltage profile within 4% margins.

According to the outcomes of the PSO method, the degree of reduction is dependent upon the level of penetration and the appropriate allocation of DG units and fast EVCS for decreasing active power losses. In order to minimize active power losses, different networks may require varied penetration level strategies under simultaneous placement.

The PSO algorithm's implementation ultimately illustrates that the optimal simultaneous allocation of distributed generation (DG) units and fast EVCS is advantageous for reducing active power losses in a power network between 63 and 69.3 percent. Active and reactive power loss percentage reductions vary among the four scenarios but are significant in each case. Again, the voltage profile improvement was within 4% margins and better when compared with the IEC standard of 10%. These findings have implications for the efficiency and dependability of power networks and may be of interest to power engineers, legislators, and electrical engineering experts.

4.12 Analysis of Simultaneous Allocation of DG and Fast EVCS on IEEE 69-Bus System Using Meta-Heuristic Techniques

The results of the proposed ABC and PSO for simultaneous sizing and placement are compared with existing studies in terms of voltage profile and active power losses. Other meta-heuristic techniques are compared in terms of the technical parameters of the IEEE 69 bus network. The study adopted the placement of three DG units and three fast EVCS for this analysis and comparison with available sources. Again, the comparison considered studies with DG unit integration only for the IEEE-69 bus system. Other studies with simultaneous placement of DG units and fast EVCS implementation on the same type of test network were also considered in the comparison.

The results from cases 3 and 7, when compared with other algorithms in the literature, show that the proposed ABC and PSO outperformed the Genetic Algorithm (GA)(Moradi & Abedini, 2012), Particle Swarm Optimization(PSO) (Moradi & Abedini, 2012) , hybrid GA/PSO(Moradi & Abedini, 2012), Simulated Annealing(SA)(Injeti & Prema Kumar, 2013), Bacterial Foraging Optimization Algorithm(BFOA)(Mohamed & Kowsalya, 2014) , Invasive Weed Algorithm(IWO)(Rama Prabha & Jayabarathi, 2016a) and Whale Optimalisation algorithm(WOA)(D. B. Prakash & Lakshminarayana, 2018a) for simultaneous placement of DG units and fast EVCS.

The bar chart in Figure 4.22 shows the active power loss when compared with various studies and the base case when considering DG units' integration only.

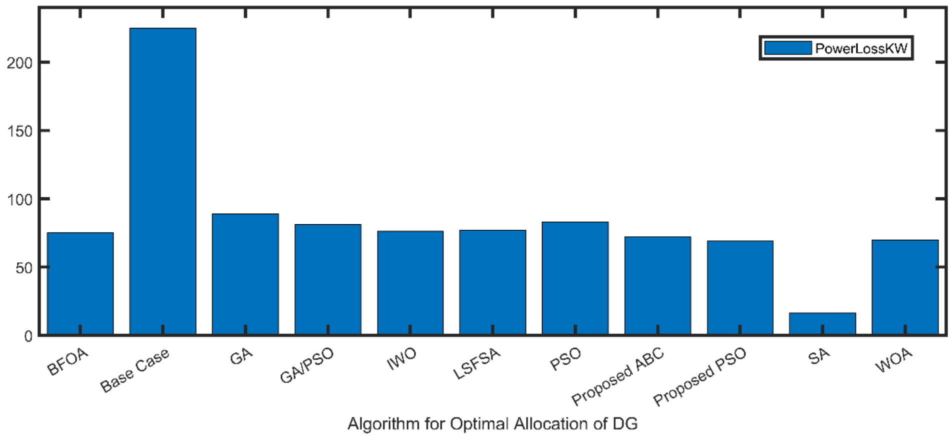

Figure 4 - 23 Active Power Loss for Different Algorithms

In terms of active power loss, SA had the minimum active power loss of 16.26 kW (representing 92.7% reduction) as against proposed PSO's 83.2 kW (69.33%), WOA's 69.72 kW (69%), proposed ABC's 72 kW (68%), BFOA's 75.23 kW (66.56%), IWO's 76.12 kW (66.16%), LSFSA's 77.1 kW (65.73%), GA/PSO's 81.1 kW (63.02%), PSO's 83.2 kW (63.02%), and GA's 89.0 kW (60.44%) Although SA had the maximum percentage reduction, it did not have fast chargers on its network. Fast EVCS contribute to increased active power losses of up to about 292.97% when three EVCS are introduced (Babu & Swarnasri, 2020a). As such, the proposed methods of ABC and PSO perform better in terms of active power losses than SA due to the loading condition resulting from Fast EVCS. The proposed PSO had the lowest active power loss when considering the simultaneous placement of both DG units and fast EVCS. Despite the introduction of a high-capacity active load on the network, the algorithm placement ensured an improved system voltage profile, with the worst-case bus voltage occurring within the IEC voltage constraints of 5%.

The improvement in the voltage profile was also compared with the results of the simultaneous placement and existing studies. In this regard, the worst-performing bus under each optimization technique is considered for comparison with the proposed ABC and PSO. Figure

4.23 below shows the summary of the minimum bus voltage at the worst-performing buses when compared with other algorithms where only DG units were integrated into the IEEE 69 bus system.

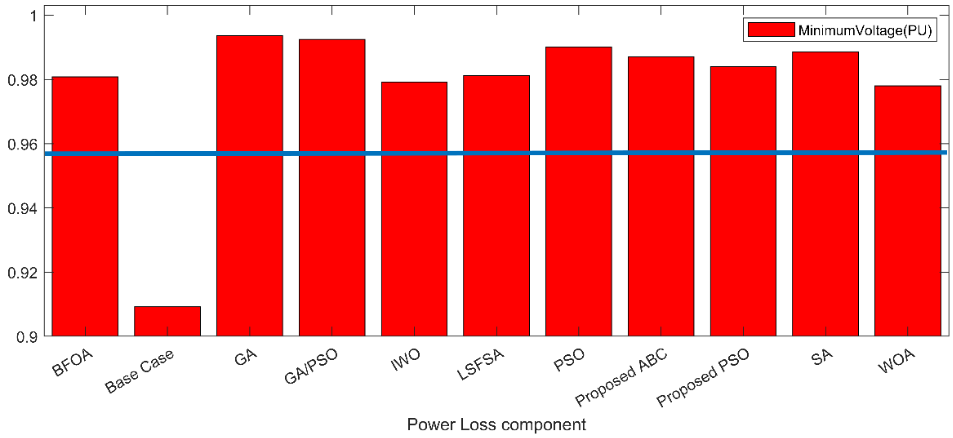

Figure 4 - 24 Worst Performing Bus for DG Allocation Using Different Algorithms

From the comparison of the algorithm results in terms of the worst-performing bus of the IEEE 69 bus network, the proposed ABC had the best voltage at its worst-performing bus as against the proposed PSO at 0.987 and 0.984, respectively.

In terms of the simultaneous allocation of DG units and fast EVCS, Babu and Swarnasri (2020b) and Babu and Swarnasri (2020c) have used HHO and TLBO for allocation. Figure 4.24 shows the active power losses on the system for DG units and fast EVCS allocation when compared with other meta-heuristics methods.

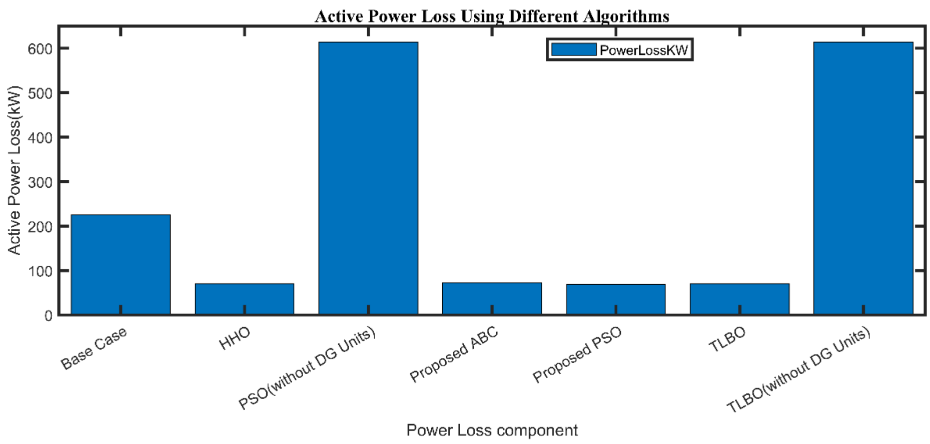

Figure 4 - 25 Active Power Loss Using Different Algorithms

For the minimum active power loss on the system, the proposed PSO outperformed the proposed ABC and HHO(D. B. Prakash & Lakshminarayana, 2018a) and TLBO(D. B. Prakash & Lakshminarayana, 2018a). The proposed PSO had an active power reduction of 69.33% as opposed to the proposed ABC (68%), HHO (68.94%), and TLBO (68.94%). Again, both proposed methods showed great gains in terms of the worst-performing bus on the network. The minimum bus voltage for the proposed PSO was 0.984 and the proposed ABC was 0.987. In terms of the worst-performing bus proposed, ABC had the best over PSO. However, all the worse-performing buses for the two proposed methods were within acceptable limits. Figure 4.24 shows the comparison of worse-performing buses categorized under the optimization method applied.

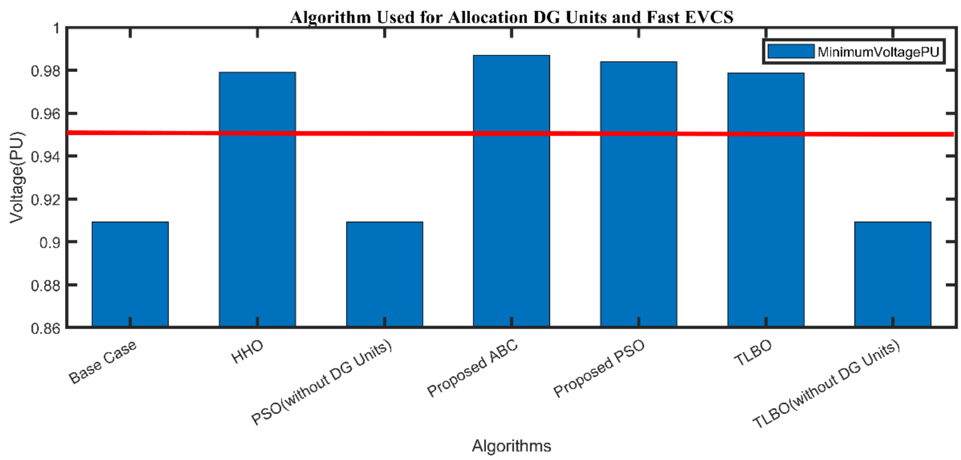

Figure 4 - 26 Worst Performing Bus Using Different Algorithms

The voltage deviation index of the proposed PSO was 0.32823, and that of the proposed ABC was 0.3596. In terms of the voltage deviation index, PSO performed better than ABC. However, both methods were within the IEC 60038 standard's constraints. This affirms the use of both ABC and PSO for the simultaneous allocation of DG units and fast EVCS as a method of improving the voltage profile of the network.

Under optimal simultaneous allocation, the proposed ABC and PSO were compared in terms of how well they met the overall objective function. Figure 4.25 shows how the proposed ABC and proposed PSO converge when they are both placed at the same time.

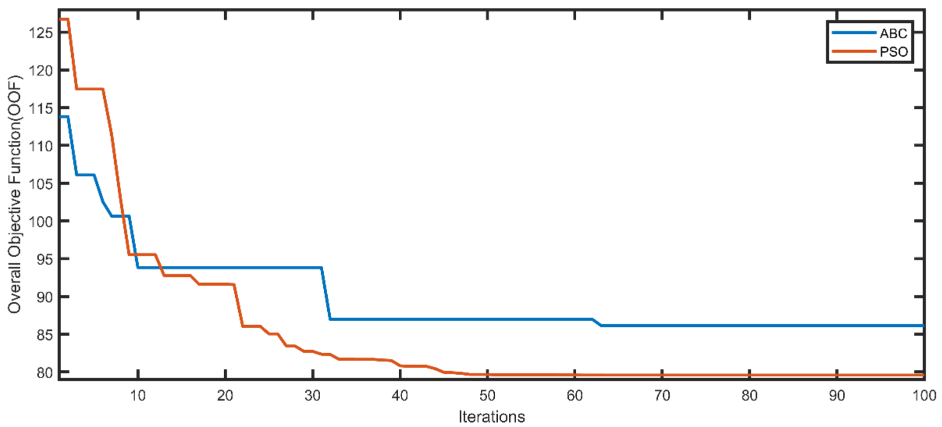

Figure 4 - 27 Convergence Characteristics of ABC And PSO For Selected Case Analysis

The proposed PSO for the optimum case under study (i.e., three DG units and three EVCS) had a minimum overall objective function of 79.5798, and the proposed ABC for the case under study was 86.1419. These results demonstrate that the proposed PSO outperformed the ABC in terms of convergence on the overall objective functions of minimum power loss and voltage deviation index. This demonstrates that the proposed PSO can find the minimum active power loss while providing an enhanced voltage profile under the simultaneous placement of DG units and fast EVCS.

TABLE 4 - 1 Optimal Placement of Three DG Units and Three Fast Evcs

Algorithm	DG location	DG Size(kW)	EVCS location
HHO(Babu Ponnam & Swarnasri, 2020)	11,17,61	490.3, 396.56, 1724.6	2, 28. 47
TLBO(Babu Ponnam & Swarnasri, 2020)	11,17,61	529.49, 380.46, 1719.77	2, 28. 47
Proposed ABC	18, 61, 69	275, 1908, 1358	29, 40, 69
Proposed PSO	11,18,61	482,400, 1751	28,36, 47

For simultaneous placement of DG units and fast EVCS, the proposed PSO predicts the optimal placement of DG units at buses 11, 18, and 61 with ratings of 482 kW, 400 kW, and 1751 kW, respectively. The fast EVCS must be located on buses 28, 36, and 47. Again, the results suggest that buses 18 and 61 are favorable for optimal placement. Table 4.1 above shows a summary of the placement.

In conclusion, the proposed PSO presents the optimal placement for the highest active power reduction, followed by the proposed ABC. The two proposed algorithms can be used for simultaneous placement even under high penetration levels to reduce active power loss on the network while improving the voltage profile. Other meta-heuristics techniques can be used to simultaneously place DG units and fast DG units, but their worst-performing buses after allocation are not preferred when compared to the proposed PSO and ABC. Even with the worst-performing bus after simultaneous allocation, the proposed PSO and ABC outperform other techniques with little DG unit injection under fast EVCS integration. This analysis confirms and reaffirms the use of the proposed ABC and PSO for simultaneous allocation studies, which involve DG units and fast EVCS integration under high penetration levels.

4.13 Case 9: Base Case for ECG 33KVA Ashanti Region Distribution Network without DG units and Fast EVCS injections

The Ashanti region ECG 33KVA distribution network was simulated using the backward/forward sweep load flow method in an ETAP environment. Case 9 was used as the base case for the optimization problem (i.e., allocation and sizing of DG units and fast EVCS).

The active power loss after the simulation is shown in Figure 4.26.

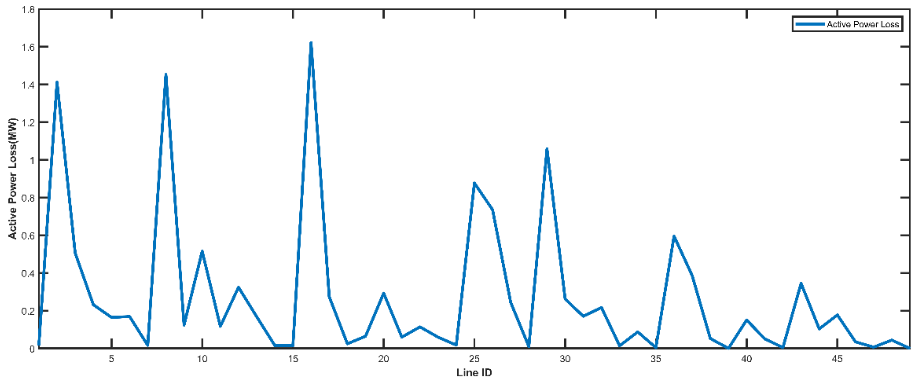

Figure 4 - 28 Active Power Loss for Case 9(Base Case For Ashanti Network)

The network had a system active power loss of 14.53 MW and a reactive power loss of 67.005 MVAR. The line losses were at their maximum on line 16 (from KTI A to KTI B). The line with the minimum loss was line 49 (from Awomaso Station B to Boadi B). This was so because the load centers were close to the substation. There is a sharp drop after line 16, which demonstrates the reduction of system loads as the transmission lines spread to the outskirts of the region from all the bulk supply points.

From the simulation results, it was also possible to see how the voltage changed over time in the ECG Ashanti region network. The voltage profile of the base case for the Ashanti region is shown in Figure 4.27.

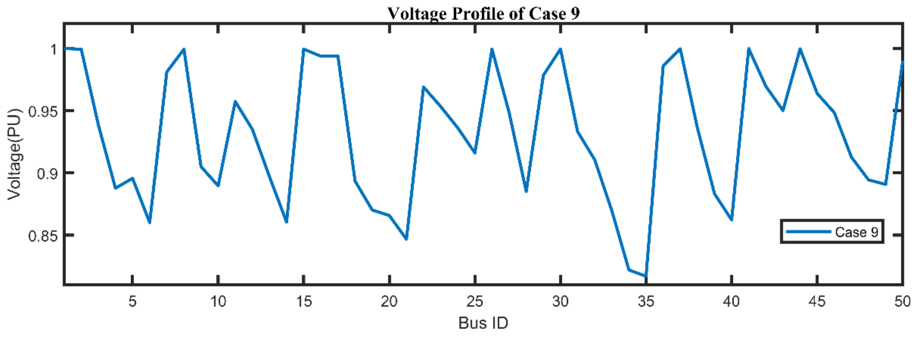

Figure 4 - 29 Voltage Profile Of Case 9(Base Case For Ashanti Region Network)

The voltage profile deviation index was 37.43. The best-performing bus was bus 1. Other buses were very close to it. These buses were 2 (0.9995 p.u.), 8 (0.9995 p.u.), 15 (0.9995 p.u.), 26 (0.9995 p.u.), 30 (0.9996 p.u.), 37 (0.9998 p.u.), 41 (0.9999 p.u.), and 44 (0.9997 p.u.). These buses had the best bus voltages because they were directly connected to the grid. They served as the bulk supply point for the Ashanti region's network. The worst-performing bus on the network was bus 35 (Mampong A substation), with a minimum voltage of 0.817 p.u. The network voltage profile was operating within the IEC 60038 standard.

The voltage profile of the simulated base-case results is compared with the field data collected from the real substations. Appendix D shows the bus voltages of simulated and field bus voltages. The results of the study were compared to the IEC 60038-2009 standard, and the bus voltage was within the 10% limit for the system bus voltage. Despite this, the voltage deviation index of all the buses on the network was 37.43. This deviation index demonstrates that the network suffers from a lot of losses since the required margins range from 10% (IEC, 2009, 2018).

4.14 Case 10: One DG Unit and One Fast EVCS on ECG 33KVA Ashanti Region Distribution Network using ABC and PSO

For Case 10, the proposed ABC and PSO have been employed for the allocation and sizing of a single DG unit and single fast EVCS on the ECG Ashanti region network. The optimal results for a single DG unit and fast EVCS injection are discussed in this section.

In terms of power loss, there were significant improvements after optimal allocation. Figure 4.28 shows the power loss on the network as against the base case(case 9).

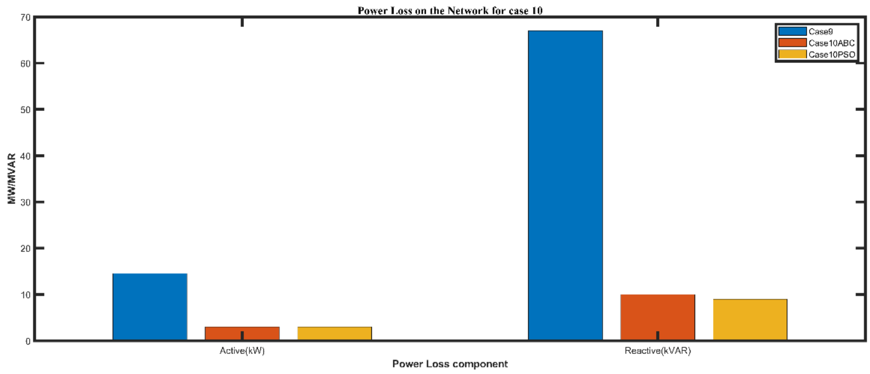

Figure 4 - 30 Power Loss for Case 10 And Case 9

The power loss for the proposed ABC was 3 MW and 10 MVAR. The power loss for the proposed PSO implementation was 3 MW and 9 MVAR. The active power reduction in comparison to case 9 for both ABC and PSO was 79.35%. The reactive power reduction by the PSO method was also 86.57% and that of the ABC method was 85.07%. This power loss reduction in both methods is significant when compared to case 9. In terms of the reactive power loss component, the PSO method was better than the ABC method by a difference of 1 kVAR. This result shows a closeness in the reactive power component under simultaneous placement for both ABC and PSO algorithms.

The voltage profile of the network for Case 10 is shown in Figure 4.29. The comparison of case 10 with the base case (case 9) demonstrates significant improvement from the base case.

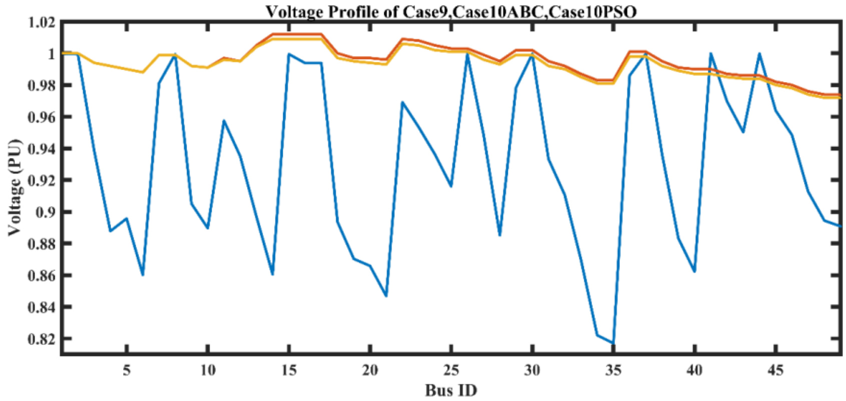

Figure 4 - 31 Voltage Profiles for Case 9 and Case 10

The voltage profile deviation index of the ABC method was 0.61275, and that of the PSO method was 0.71542. The worst-performing buses under the PSO method were buses 48 and 49 at 0.974 p.u. For ABC, bus 48 and bus 49 were the worst buses at 0.972 p.u. The voltage of each bus for both methods was within a limit of 4%, which also demonstrated significant improvement in the system operating voltage. Both methods (ABC and PSO) had a bus voltage that was within the allowable voltage constraints of 10% according to the IEC standards. So in terms of the voltage deviation index, the best-performing algorithm was ABC. Despite the performance of the ABC method, the results of the PSO cannot be ignored since the marginal difference is only 0.10267. PSO also demonstrated an improved voltage profile under simultaneous placement.

The convergence characteristics of the two optimization techniques were also studied in terms of overall minimum objective functions. Figure 4.30 shows the convergence characteristics of the proposed ABC and PSO when using a single DG unit and single fast EVCS.

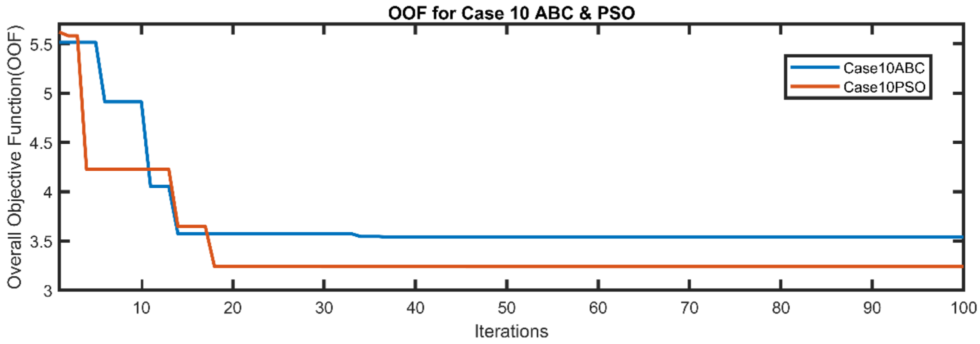

Figure 4 - 32 Convergence Characteristic Of Case 10

The iteration graph for the two methods shows that PSO outperformed ABC in terms of convergence of the minimum overall objective function. The minimum overall objective function of PSO was 3.2393 as opposed to ABC's 3.5389. The PSO convergence characteristics started at 5.678, while the ABC started at 5.5283. In each case, the global solution was obtained for the allocation problem, resulting in the optimal placement of DG units and fast EVCS.

For optimal placement of a single DG unit and fast EVCS, the DG must be on bus 14 at a capacity of 550 kW, while the fast EVCS must be on bus 41. The best meta-heuristic method among the proposed two algorithms is PSO due to its reactive power loss and convergence characteristics. Both PSO and ABC can be used for the simultaneous placement of DG units and fast EVCS. They can enhance the voltage profile and reduce active power loss on the network. The results of Case 10 demonstrate the use of swarm-based optimization techniques as an alternative method to reduce active power loss on a real network when DG units and fast EVCS are to be employed.

4.15 Case 11: Two DG Units and Two Fast EVCS on ECG 33KVA Ashanti Region Distribution Network using ABC and PSO

For case 11, two DG units and two fast EVCS were optimally placed using the ABC and PSO methods. the power loss, voltage profile improvement, and convergence characteristics compared with the base case.

In terms of the power loss by the ABC and PSO methods, the results after simulation are shown in Figure 4.31.

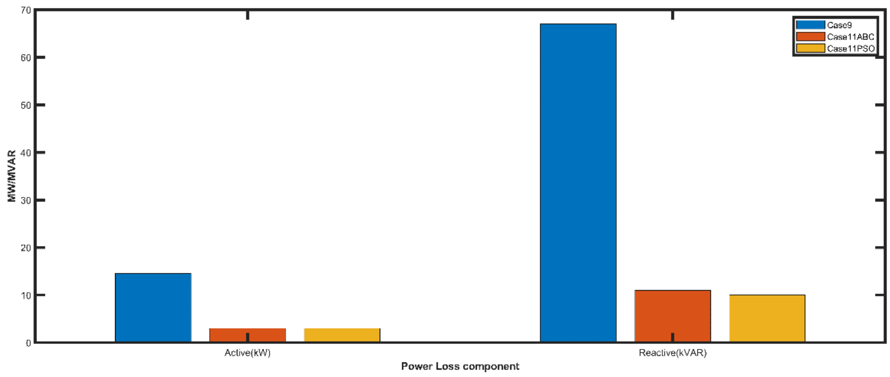

Figure 4 - 33 Power Loss For Case 11

The results of the ABC method show that the power loss dropped from 14.53 MW and 67.005 MVAR to 3 MW and 11 MVAR. This reduction represents 79.35% for the active power and 83.58% for the reactive power when compared to the base case. For the PSO method, the power loss after the integration of DG units and fast EVCS was 3 MW and 10 MVAR. In terms of percentage reduction concerning the base case, the active power represented 79.35% and the reactive power represented 85.07%. This case 11 result shows that PSO allocation outperformed ABC only in terms of a 1 MVAR reactive power loss. However, in relating both algorithm results to the base case, the percentage reduction in power loss is significant.

The voltage profiles for the two techniques are compared with the base case for analysis in this section. Figure 4.32 shows the voltage profile of simultaneous placement under the ABC and PSO for the Ashanti region network.

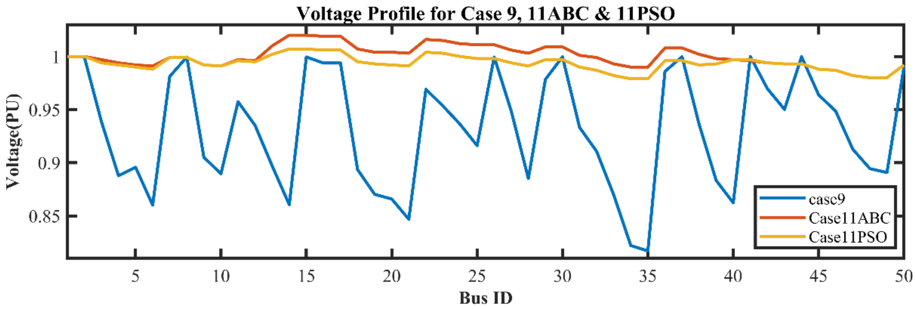

Figure 4 - 34 Voltage Profile For Case 11 and Base Case

In terms of the voltage profile deviation index, PSO outperformed ABC for optimal allocation and sizing. The PSO technique had a voltage deviation index of 0.4432 and a worst-performing bus voltage of 0.979 p.u. In this regard, buses 34 and 35 were the worst-performing buses. The ABC method had a voltage deviation of 0.52878, with a minimum voltage at the worst-performing bus being 0.98 p.u. These worst-performing buses under ABC were buses 48 and 49. Both techniques had a voltage profile that was within the required IEC 60038 standards. The voltage profile was enhanced significantly after simultaneous placement.

The convergence characteristics show that PSO performed better than ABC for Case 11 in terms of minimizing the overall objective function (OOF). This convergency characteristic is shown in Figure 4.33.

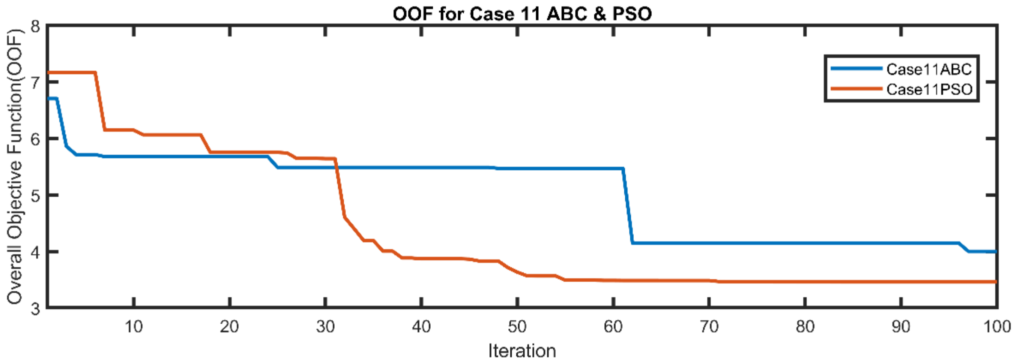

Figure 4.33: Convergence Characteristics of Case 11

The minimum OOF for PSO was 3.4609, and that for ABC was 4.0029. It can be seen from the iteration graph that PSO performed better than ABC in terms of convergence characteristics.

For optimal allocation of two DG units and two fast EVCS, the PSO algorithm results were selected as the best instead of the ABC algorithm. For optimal allocation using the PSO algorithm, the DG units must be placed in buses 40 and 14 at capacities of 300 kW and 460 kW, respectively. The fast EVCS must be placed on buses 30 and 8. The PSO results, which have been demonstrated to be superior in terms of reactive power loss and convergence, are closely matched by the ABC technique. The ABC technique is equally good for the simultaneous allocation of DG units and fast EVCS since it produces a significant improvement in active power loss and voltage profile enhancement. The results from Case 11 show that both algorithms (ABC and PSO) can be used to reduce active power loss (by 79.35%%) while enhancing the system voltage profile (within 4%) under simultaneous allocation of DG units and fast EVCS.

4.16 Case 12: Three DG Units and Three Fast EVCS on ECG 33KVA Ashanti Region Distribution Network using ABC and PSO

Case 12 was about putting three DG units and three fast EVCS in the best place on the Ashanti region network. Case 12 is compared with the base case for analysis. The ABC and PSO algorithm parameters remained the same as in previous cases for this one.

The results after the simulation of Case 12 show that there was a significant improvement in power loss for both ABC and PSO allocation. Figure 4.34 shows the power loss on the network after and before the integration of DG units and fast EVCS as demonstrated in cases 9 and 12.

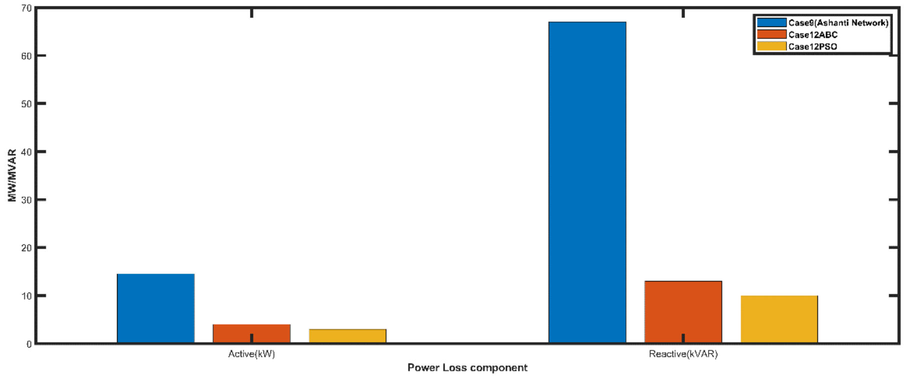

Figure 4 - 35 Power Loss For Case 12 And Case 9

The power losses for the ABC technique were 4 MW and 13 MVAR. This represents a percentage reduction of 72.47% (active power) and 80.60% (reactive power). The PSO method had an active power loss of 3 MW and a reactive power loss of 10 MVAR. The percentage reduction for the PSO in terms of active power reduction was 79.35%. Again, when compared with the base case, the reactive power component after DG units and fast EVCS integration represented 85.07%. In comparing the two algorithms for optimal placement, the PSO is selected as the optimum case in terms of the power loss.

In terms of voltage profile deviation index, PSO outperformed ABC. The voltage profile improved for both algorithms, as shown in Figure 4.35.

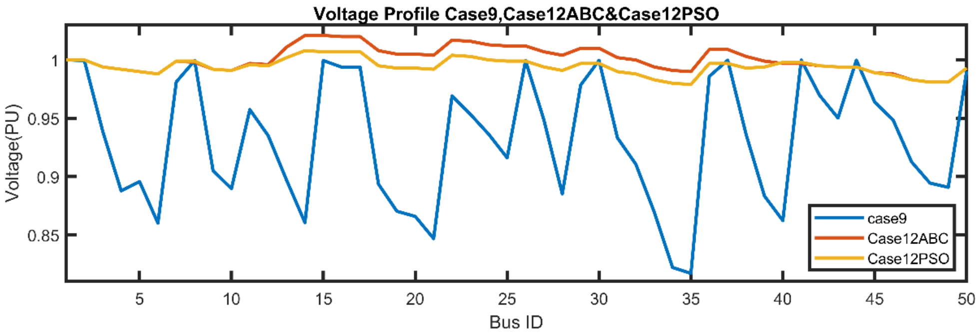

Figure 4 - 36 Voltage Profile of Case 12

The voltage profile deviation index for the PSO method was 0.41166. The ABC also had a voltage deviation index of 0.5659; the deviation index of PSO is better than the ABC. In terms of the bus voltage performance, PSO had the worst bus voltage of 0.979 p.u. at bus 35. Consequently, the ABC method had the worst-performing buses at buses 48 and 49 with a magnitude of 0.981 p.u. The ABC method has a better voltage at its worst-performing bus than the PSO method. However, cumulatively, the PSO produces a better voltage profile than the ABC, as shown in the voltage deviation index score. Both algorithms produce an enhanced voltage profile within the IEC standard after simultaneous placement.

In terms of convergence characteristics, the PSO method converged with the lowest minimum OFF at 3.1758, while the ABC method had the lowest minimum OFF at 4.4823. Figure 4.36 shows the convergence characteristics for both techniques.

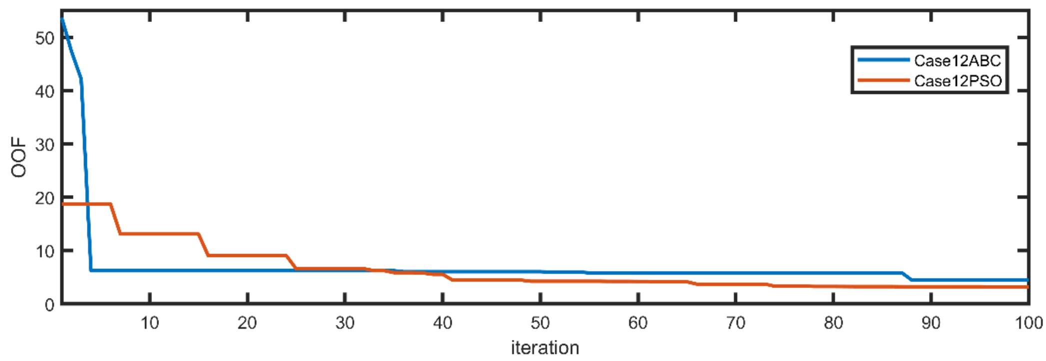

Figure 4 - 37 Convergence Characteristics Of Case 12

The graph demonstrates that the PSO technique presents the minimum OFF, which is better than the ABC approach. The difference in minimum OFF is very marginal. Both algorithms can allocate DG units and fast EVCS without running into local optimal. The global solution to the optimization problem was achieved. This demonstrates that both algorithms can be used for the concurrent allocation of three DG units and three fast EVCS.

For optimal allocation of three DG units and three fast EVCS, DG units must be placed on buses 14, 15, and 40 at capacities of 10.22 MW, 7.78 MW, and 300 kW. The fast EVCS must be allocated to buses 8, 15, and 14. Under this condition, an overall active power reduction of 79.35% will be achieved. The voltage profile can be improved to a deviation index of 93.64%. Under such optimal placement, the bus voltage margins are within 4% of the IEC 60038 standard. This result from Case 12 shows that the simultaneous allocation of three DG units and three fast EVCS leads to significant implications for technical parameters of power loss and voltage profile on the network. The PSO presents a better placement option than the ABC in terms of power loss and voltage profile enhancement. However, the ABC can equally be used for simultaneous placement with a marginal difference in the reactive power loss reduction. This Case 12 result is significant and can be used as an alternative to power loss strategies for system operators and managers.

4.17 Case 13: Four DG Units and Four Fast EVCS on ECG 33KVA Ashanti Region Distribution Network using ABC and PSO

In case 13, a maximum of four DG units and four fast EVCS have been adopted for optimal placement and sizing on the Ashanti region network. PSO was demonstrated to be the best algorithm for placement when compared with ABC. The results of both techniques are all within the IEC standard for network constraints.

The power loss of Case 13 is compared with the base case in Figure 4.37.

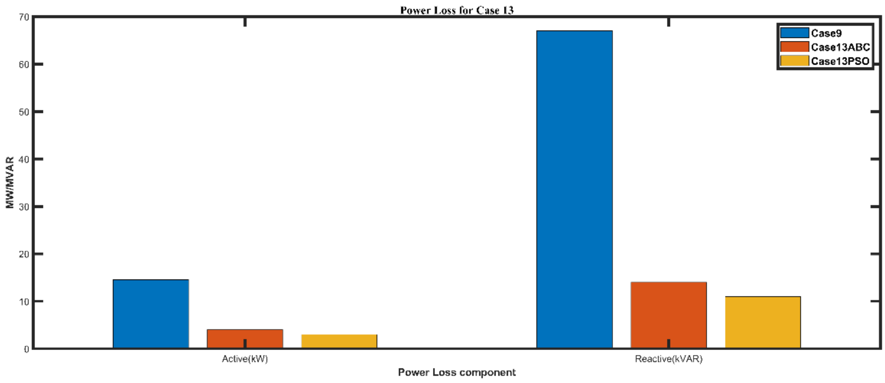

Figure 4 - 38 Power Loss For Case 13 and Base Case

In terms of power loss on the network, using the ABC method resulted in a 4MW and 14MVAR drop in power. The corresponding percentage decrease was 72.47% for active power and 79.11% for reactive power. The PSO approach resulted in a 3MW active power loss and an 11 MVAR reactive power loss. When compared with the base case, the PSO achieved a 79.35% percent reduction in active power use with a corresponding reactive power reduction of 83.58%. The PSO was chosen as the best instance when comparing the two algorithms for optimal placement of power loss.

The voltage profile improvement is also noticed to have improved after the introduction of DG units and fast EVCS. The voltage profile of case 13 and case 9 are shown in Figure 4.38.

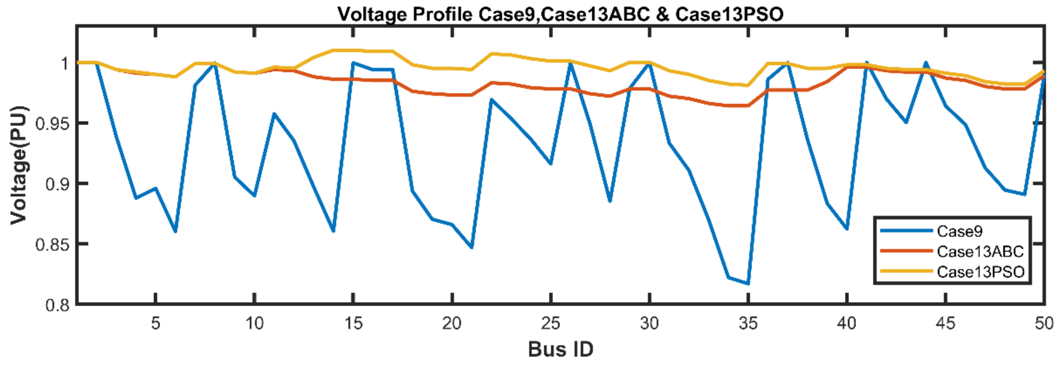

Figure 4 - 39 Voltage Profile For Case 13 and Base Case(Case 9)

For the voltage profile deviation, the PSO technique had the minimum deviation when compared with the ABC technique. For PSO, the deviation index for the voltage profile was 0.35898. PSO's deviation index is better than that of the ABC, which had a voltage deviation index of 1.8233. The worst bus voltage performance was found at bus 35 for PSO, with a value of 0.981 p.u. Thus, buses 34 and 35 had a magnitude of 0.964 p.u., the lowest for the ABC method. The worst-performing bus of the PSO technique has a higher voltage than the ABC method. Nonetheless, the voltage deviation index score demonstrates that the PSO generates a superior voltage profile overall than the ABC. After concurrent allocation of DG units and fast EVCS, both algorithms generate an improved voltage profile within the IEC standard.

The convergence characteristics of the OFF for case 13 are shown in Figure 4.39.

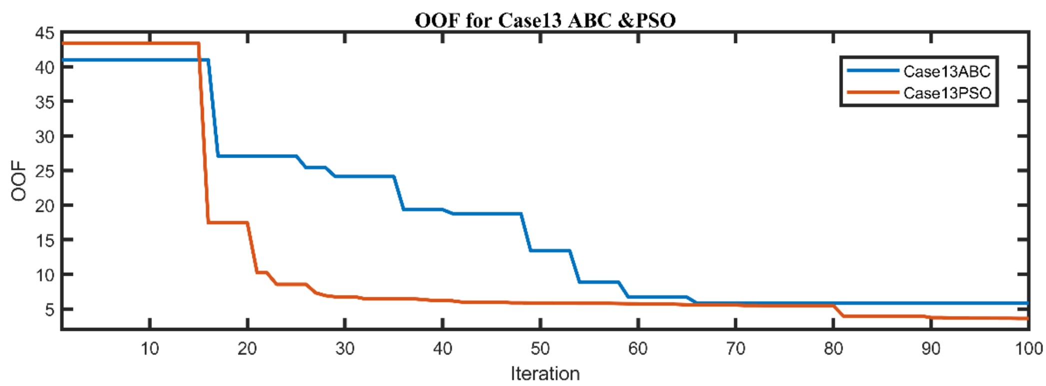

Figure 4 - 40 Convergence Characteristics of Case 13

The PSO was able to converge at a minimum OOF of 3.613. The ABC technique also converged at a minimum OOF of 5.8278. A comparison between the two algorithms' performances in the context of the overall minimized objective function of power loss and voltage profile enhancements shows that PSO outperformed ABC. Both algorithms were able to generate the global solution for the optimization problem within the constraints of the network as proposed. This demonstrates the use of both algorithms for simultaneous placement under various penetration levels.

It can be concluded that for optimal allocation of up to four DG units and four fast EVCS, the DG units must be on buses 40, 14, 15, and 45 with capacities of 250 kW, 10.26 MW, 12.54 MW, and 9.98 MW, respectively. The fast EVCS would have to be placed on buses 8, 45, 14, and 37. The results of Case 13 demonstrate both the strength of PSO and ABC for reducing active power loss while improving the voltage profile within the IEC standard. A significant reduction in active power loss of 79.35% and reactive power loss of 83.58% can be achieved if PSO is adopted for the simultaneous allocation of DG units and fast EVCS. Again, the ABC can be equally used for simultaneous allocation with better system performance in terms of active power loss and bus voltage. However, PSO should be preferred to ABC when it comes to reactive power loss, active power loss, voltage profile enhancement, and convergence characteristics of technical parameters.

4.18 Optimal allocation of DG units and fast EVCS on the Ashanti region network

When all cases under the Ashanti region network were analyzed for optimal allocation, some cases performed better in terms of overall power loss, voltage profile deviation index, and convergence characteristics of overall objective functions.

The power loss on the network was very marginal for all cases under DG units and fast EVCS integration. Figure 4.40 shows the active and reactive power loss for all cases under the Ashanti network.

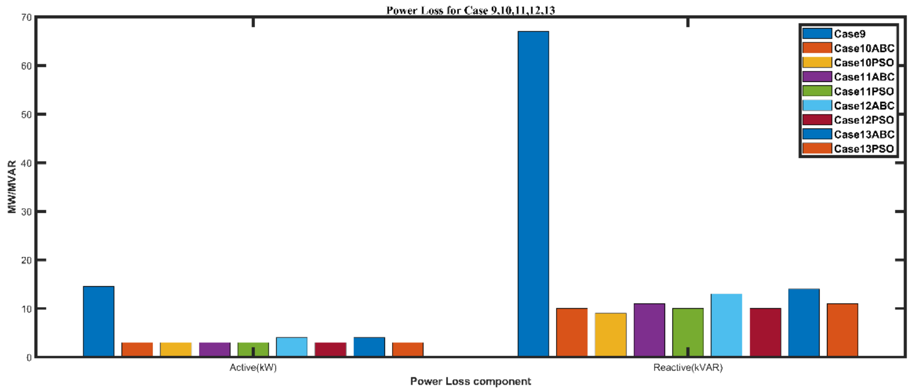

Figure 4 - 41 Power Loss for All Cases Under The Ashanti Region Distribution Network

Among all the cases studied, Case 10 with the PSO method had the lowest power loss of 3MW for the active component and 9MVAR for the reactive component when compared with Case 11(3MW and 10MVAR), case 12(3MW and 10MVAR)and case 13(3MW and 11MVAR). The results from the various scenarios under the Ashanti region network show that the reduction in power loss was constant in terms of active power loss but varied by more than 1 MVAR in the reactive power loss component for all cases. For increasing penetration levels the active power loss was consistent while the reactive power loss changed by margins between 1MVAR to 3MVAR for another case apart from optimal Case 10. This demonstrates that the active power loss on the system can be reduced even with increasing penetration levels, a significant improvement from the base case. The PSO remains the best technique for optimal simultaneous placement of DG units and fast EVCS with the highest active power loss reduction of 79.35%. The reactive power reduction under the optimal PSO technique (Case 10) corresponded to 86.57% of the base case. Despite the performance of the PSO technique on optimal simultaneous allocation, the ABC technique was also able to cause a significant reduction in power loss on the Ashanti region network. The ABC technique also provides an optimal solution at a reduced reactive power loss between 79.11% and 85.07%. Consequently, for optimal power loss on the Ashanti region network, a single DG unit and a single fast EVCS would have to be allocated on the network using the PSO algorithm technique.

The combined voltage profile of all cases (Case 9, Case 10, Case 11, Case 12, and Case 13) under the Ashanti region network is shown in Figure 4.41.

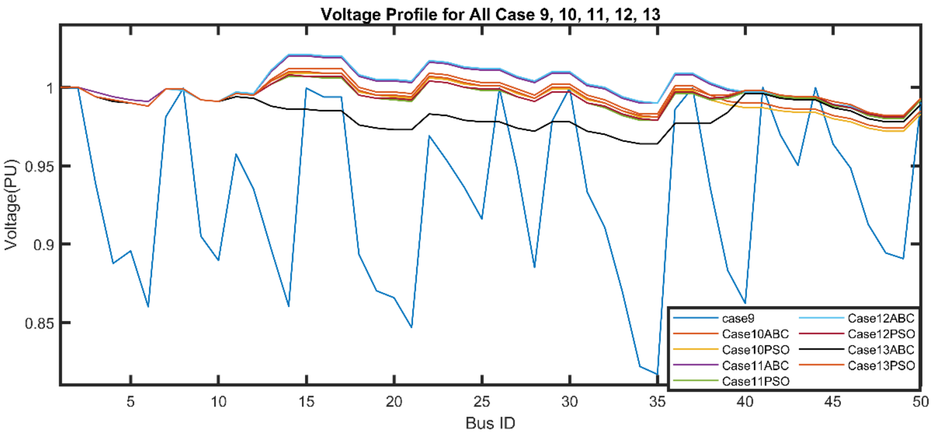

Figure 4 - 42 Voltage Profile for All Cases Under ECG Network

In terms of voltage deviation index, Case 13 of the PSO method had a minimum value of 0.35898. Case 12 (0.41166), Case 11 (0.4432), and Case 10 (0.71542) followed in that order from second to fourth position in the ranking for the minimum voltage deviation index. Case 13, therefore, produced the best voltage profile enhancement after DG units and fast EVCS integration. As can be seen in the order of the deviation index, optimal placement and sizing of additional DG units and fast EVCS led to significant voltage profile improvement. This characteristic of bus voltage levels demonstrates that the PSO algorithm can be used to optimally place DG units and fast EVCS in an attempt to improve the system voltage profile during high penetration levels of DG units and fast EVCS.

The convergence characteristics of all cases under the Ashanti region network are shown in Figure 4.42.

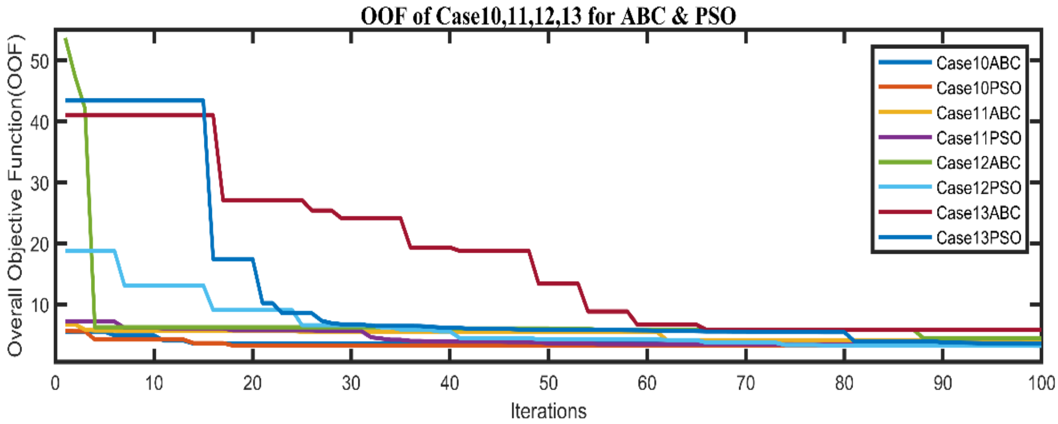

Figure 4 - 43 Convergence Characteristics of All Cases on Ashanti Region Network

In terms of convergence characteristics, case 12 was the best with the most minimum objective functions of 3.1758, followed by case 10 (3.2393), then case 11 (3.4609), and finally case 13 (3.613). All these cases were from the PSO technique. The ABC technique with the minimum OFF close to the PSO method was Case 10 at 3.5389. All other ABC techniques had a minimum OFF that was above 4.00. This comparison demonstrates the superiority of the PSO technique over ABC techniques in terms of overall minimum objective functions. Despite the strength of PSO over ABC in finding the global solution with the most minimum OFF, the ABC technique is a viable option in the simultaneous allocation of DG units and fast EVCS since it was also able to produce an optimal solution for various penetration levels.

The simulations of the cases suggest that the PSO and ABC can be used to simultaneously allocate DG units and fast EVCS to limit power loss and improve the voltage profile, leading to system stability. The results suggest the specific locations for the injection of DG units must be carefully considered to limit power loss and enhance the voltage profile. The EVCS will have to be strategically placed for optimal technical benefits. The comparison of the PSO technique and the ABC technique shows that for the minimum power loss and enhanced voltage profile, a single DG unit of 10.25 MW capacity must be allocated on bus 14, while a fast EVCS is placed on bus 14. This analysis of the cases also demonstrates the application of DG unit-powered fast EVCS on bus 14 of the Ashanti region network for reduced power loss and voltage profile enhancement. Other options, such as DG units and fast EVCS integration, are available when the PSO technique is used for simultaneous placement. For the PSO and ABC algorithms, an improved voltage profile within the IEC 60038 standard can be achieved under various penetration levels. The voltage profile will always be within the standard operating levels when the simultaneous allocation of DG units and fast EVCS is employed using the proposed PSO and ABC techniques.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

This chapter presents the summary of the research findings, the conclusion, and the recommendation for further research in the area of optimal DG units and fast EVCS integration.

5.1 Summary of Findings

A distributed generation system can be used to limit the power loss of traditional power generation systems. Again, the use of electric vehicles is gaining popularity due to new technologies in battery strength and EV charging infrastructure. Fast ECVS are in demand and consume a high amount of electrical energy. If the EV penetration level increases, there is going to be a significant demand for electrical power. This study investigated how these two systems can be optimized to improve system performance in terms of power loss and voltage profile improvement under various scenarios.

The purpose of the study was to determine the optimal allocation and sizing of DG units and fast EVCS on the 33 kV Ashanti region network. The study used the ABC and PSO meta-heuristic techniques to simultaneously place DG units along with fast EVCS. The optimization was simulated in a MATLAB environment using both standard test network data and real network data. The IEEE 69 bus system was used to test the optimization problem. The techniques of ABC and PSO were then applied to the existing 33 kV distribution network in the Ashanti region of Ghana.

The study used mathematical analysis to come up with a multi-objective function for putting both DG units and fast EVCS in the same network at the same time. The objective functions of minimum power loss and voltage profile improvement were formulated. The voltage deviation index approach was adopted and used together with the active power loss in the analysis of the multi-objective function problem for DG units and fast EVCS allocation.

The study performed a load flow analysis on the IEEE 69 bus system and the 33 kV Ashanti region distribution network. The backward/forward sweep load flow method was adopted in the study. Both the ETAP and MATLAB software were used in the load flow studies. The ETAP was used for the simulation of the Ashanti region network, while MATLAB was used for the optimization load flow study.

Under different levels of DG units and fast EVCS penetration, the allocation problem was solved by finding the best way to place and size them on the network. The study has used both ABC and PSO separately for allocation from single DG units and single fast EVCS scenarios to four DG units and four fast EVCS scenarios. The optimal location of both DG units and fast EVCS is proposed in the study. Again, the algorithms have been used to predict the optimal sizes for the DG units for all penetration levels studied.

The study has done a comparative analysis of the simulation placement and sizing of DG units and fast EVCS in terms of power loss and voltage profile improvement. The convergence characteristics of the proposed ABC and PSO are also compared with each other. The results of the study are compared with related works that involved the placement and sizing of DG units only. The results of the study have also been compared with related studies that involved the simultaneous placement of DG units and fast EVCS using non-swarm-based meta-heuristic methods.

5.2 Conclusion

The study has developed a multi-objective optimization solution for simultaneous placement using the objective functions of power loss and voltage profile improvement. The results of the study have shown that the Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) algorithms can be used to optimally allocate DG units and fast EVCS. Both algorithms can predict the most efficient location and size to deploy distributed generation units and fast electric vehicle charging stations. The model developed can be adopted for both IEEE test networks and real networks that are configured in radial mode (e.g., the IEEE 69 bus test network and the 33 kV distribution network in the Ashanti region of Ghana).

The study proposed the use of metaheuristic techniques for optimal placement and sizing of DG units and fast EVCS, which have the ability to reduce power loss by a significant 60% from the base case. The study also shows that the voltage profile of the network can be improved from more than 10% deviation to less than 5% deviation even under high penetration levels of EVs when optimal DG unit allocation and sizing are adopted using the model. The study shows that both ABC and PSO can be used for simultaneous allocation of DG units and fast EVCS on a real network. However, the PSO convergence characteristics under multi-objective functions perform better than ABC in terms of minimum overall objective functions. The study again shows that PSO converges faster than ABC. Despite the convergence characteristics, the results of optimal placement are all within operational bus voltage limits according to the IEC 60038 standard. The study also presents simultaneous DG units and fast EVCS integration as viable alternatives to network reconfiguration, the adaptation of FACTs devices, and an improved power system component approach to improve power system loss even under high penetration levels of EVs.

This study gives important information to consider when fast charging stations for electric vehicles are to be added to the Ashanti region network. The results also show that there can be a significant improvement in the voltage profile if DG units are introduced alongside fast EVCS. The results also give a technical approach to future optimal allocation planning in relation to the integration of both DG units and fast charging stations in the Ashanti region of Ghana. The thesis also gives a technical justification for the deployment of DG unit-powered fast EVCS on the Ashanti region network at some specific buses.

5.3 Recommendation

The research used the model on a part of the grid in Ghana (i.e., the Ashanti region ECG 33KVA distribution network) due to the scope of the work. The research involved load flow studies utilizing the Electrical Transient Analysis Program (ETAP). Further studies in the economic analysis of the installation of DG units and fast EVCS deployment can be done to improve the demand side analysis, which was not covered in this thesis. Economic modeling of EV usage under DG unit integration conditions, location of the EVCS, and time of charge within the day can all be investigated.

The data from the study on the Ashanti region network is vital for private investors involved in EV infrastructure development. These investors can use the results of this study to further investigate the impact of fast EVCS with V2G mode on the network during grid injection when vehicles are in idle mode. The implications of V2G mode at PCC can be considered for further investigation in terms of its performance on the distribution system in terms of stability and reliability.

The thesis model can be adopted for studies in fast EVCS allocation based on penetration levels in an attempt to meet maximum and minimum technical network parameters. Fast EVCS can produce harmonics and bi-directional flow at high penetration levels. Future studies can also consider ways of mitigating the impact of harmonics from DG units and fast EVCS as the use of EVs increases every year.

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APPENDICES

Appendix A: Average of daily Peaks loads and corresponding peak voltages at each Bus

Bus ID Name	Bus ID Number	Average Voltage	MW Loading
AGOGO A	4	29.5	16.843
AGOGO B	28	29.4	20.148
AGONA A	33	29.6	6.721
AGONA B	47	30	5.759
AIRPORT A	9	32.2	24.9
AIRPORT B	18	32.1	25.784
AKYAWKROM A	38	32.8	21.469
AKYAWKROM B	42	32.4	11.206
AKYEASE A	31	32.1	33.224
AKYEASE B	45	32.7	19.584
ASEKYEM A	12	31.7	10.042
ASEKYEM B	23	31.3	7.363
AWOMASO STATION A	30	33	47.979
AWOMASO STATION A1	37	33	31.954
AWOMASO STATION B	44	33	34.995
AWOMASO STATION B1	41	33	11.357
BAREKESE A	5	30.6	7.584
BAREKESE B	20	31.2	9.42
BEKWAI A	14	29.2	7.42
BEKWAI B	25	31	4.737
BOADI A	36	32.6	13.608
BOADI B	50	32.8	9.745
EDWINASE A	7	32.6	17.252
EDWINASE B	29	32.5	20.868
EFFIDUASE A	39	31.9	11.54
EFFIDUASE B	43	31.9	4.457
FAWOADE A	32	31.3	19.472
FAWOADE B	46	32.2	12.652
GridCo	1	33	374.414
KAASE A	11	32.4	25.101
KAASE B	22	32.8	19.418
KTI A	17	32.8	2.84
KTI B	16	32.8	6.748
KUMAWU	40	29.8	3.92
MAMPONG A	35	27.9	3.678
MAMPONG B	49	29.3	2.811
NEOPLAN A	3	32	42.778
NEOPLAN B	27	32.2	41.921

NSUTA A	34	28	6.492
NSUTA B	48	29.4	2.821
OFFINSO A	6	28.6	7.419
OFFINSO B	21	29.7	4.668
RIDGE STATION A	2	33	61.611
RIDGE STATION A1	8	33	61.487
RIDGE STATION B	26	33	63.91
RIDGE STATION B1	15	33	61.035
SUAME A	10	31	12.251
SUAME B	19	32	17.832
SWITCHING STATION A	13	30.4	7.588
SWITCHING STATION B	24	31.7	4.796

Appendix B: line data for 33kV Distribution Network

From Bus	To bus	Line Resistance(R)	Line Reactance(X)
GridCo	RIDGE STATION A	0.04	0.12
RIDGE STATION A	NEOPLAN A	6.21	20.58
NEOPLAN A	AGOGO A	13.03	43.30
NEOPLAN A	BAREKESE A	29.12	61.10
BAREKESE A	OFFINSO A	20.60	68.45
RIDGE STATION A	EDWINASE A	4.97	16.47
GridCo	RIDGE STATION A1	0.04	0.12
RIDGE STATION A1	AIRPORT A	18.62	61.85
AIRPORT A	SUAME A	6.21	20.62
RIDGE STATION A1	KAASE A	6.21	20.62
KAASE A	ASEKYEM A	8.69	28.86
KAASE A	SWITCHING STATION A	40.98	86.19
SWITCHING STATION A	BEKWAI A	21.10	70.10
GridCo	RIDGE STATION B1	0.04	0.12
RIDGE STATION B1	KTI B	2.91	20.03
KTI B	KTI A	0.01	0.02
RIDGE STATION B1	AIRPORT B	18.62	61.85
AIRPORT B	SUAME B	6.21	20.62
SUAME B	BAREKESE B	2.00	9.80
BAREKESE B	OFFINSO B	20.60	68.45
RIDGE STATION B1	KAASE B	6.21	20.62
KAASE B	ASEKYEM B	8.69	28.86
KAASE B	SWITCHING STATION B	40.98	86.19
SWITCHING STATION B	BEKWAI B	21.10	70.10
GridCo	RIDGE STATION B	0.04	0.12
RIDGE STATION B	NEOPLAN B	4.01	19.57
NEOPLAN B	AGOGO B	13.03	43.30
RIDGE STATION B	EDWINASE B	4.97	16.47
GridCo	AWOMASO STATION A	0.04	0.12
AWOMASO STATION A	AKYEASE A	8.01	39.21
AKYEASE A	FAWOADE A	5.60	27.45
FAWOADE A	AGONA A	26.69	88.67
AGONA A	NSUTA A	33.51	111.33
NSUTA A	MAMPONG A	6.70	22.27
AWOMASO STATION A	BOADI A	4.32	21.17
GridCo	AWOMASO STATION A1	0.04	0.12
AWOMASO STATION A1	AKYAWKROM A	10.49	51.36
AKYAWKROM A	EFFIDUASE A	21.60	71.75
EFFIDUASE A	KUMAWU	23.59	78.36
GridCo	AWOMASO STATION B1	0.04	0.12
AWOMASO STATION B1	AKYAWKROM B	10.49	51.36
AKYAWKROM B	EFFIDUASE B	21.60	71.75
GridCo	AWOMASO STATION B	0.04	0.12
AWOMASO STATION B	AKYEASE B	8.01	39.21
AKYEASE B	FAWOADE B	5.60	27.45

From Bus	To bus	Line Resistance(R)	Line Reactance(X)
FAWOADE B	AGONA B	44.07	92.67
AGONA B	NSUTA B	33.51	111.33
NSUTA B	MAMPONG B	6.70	22.27
AWOMASO STATION B	BOADI B	4.32	21.17

Appendix C loading conditions for the various buses for ETAP model

ID	Rating/Limit (MVA)	MW	Amp
Agogo A Load	18	16.769	1035
Agogo B Load	21.57	20.042	1247
Agona B Load	3	2.898	167
Airport A Load	13	12.489	729.9
Airport B Load	8	7.66	452.2
Akyawkrom A Load	10	9.522	550.5
Akyawkrom B Load	7	6.689	376.2
Akyease A Load	14	13.444	773.1
Akyease B Load	7	6.818	377.1
Asakyem B Load	8	7.35	435.8
Askyem A Load	11	10.016	609
Awomaso A1 Load	10	9.87	527.3
Awomaso B Load	5.39	5.271	283.8
Barekese B Load	5	4.687	289.9
Bekwai A Load	8	7.384	469.7
Bekwai B Load	5	4.724	279.4
Boadi A Load	14	13.57	747.5
Boadi B Load	10	9.726	531
Edwinase A Load	18	17.188	968.6
Edwinase B Load	21.57	20.775	1164
Effiduase A Load	8	7.554	456.7
Effiduase B Load	4.69	4.452	254.9
Fawoade A Load	13	12.538	725.7
Fawoade B Load	7	6.705	381.3
Kaase A Load	8	6.998	440.2
Kaase B Load	8	7.073	432
KTI B Load	4	3.905	211.2
KTI B Load2	3	2.839	158.4
Kumawu Load	4.22	3.894	247.9
Mampong A Load	4.062	3.729	244.4
Mampong B Load	3	2.816	169.8
Neoplan A Load	18.26	17.544	1007
Neoplan B Load	22	20.937	1212
Nsuta A Load	3	2.766	181
Offinso A Load	8	7.383	469.8
Offinso B Load	5	4.655	294.5
Ridge A1 Load	9.73	9.499	513.7
Ridge B1 Load	7.31	7.143	385.4
Suame A Load	13	12.215	742
Suame B Load	9	8.363	520.3

Appendix D: Comparison of real bus voltage data to simulated bus voltage data

Bus ID	Field Bus Voltage	ETAP Bus Voltage	Error
AGOGO A	29.5	29.296	0.204
AGOGO B	29.4	29.21	0.19
AGONA A	29.6	28.701	0.899
AGONA B	30	30.118	0.118
AIRPORT A	32.2	29.868	2.332
AIRPORT B	32.1	29.486	2.614
AKYAWKROM A	32.8	30.894	1.906
AKYAWKROM B	32.4	31.998	0.402
AKYEASE A	32.1	30.797	1.303
AKYEASE B	32.7	31.806	0.894
ASEKYEM A	31.7	30.857	0.843
ASEKYEM B	31.3	31.462	0.162
AWOMASO STATION A	33	32.988	0.012
AWOMASO STATION A1	33	32.992	0.008
AWOMASO STATION B	33	32.992	0.008
AWOMASO STATION B1	33	32.997	0.003
BAREKESE A	30.6	29.559	1.041
BAREKESE B	31.2	28.573	2.627
BEKWAI A	29.2	28.396	0.804
BEKWAI B	31	30.231	0.769
BOADI A	32.6	32.536	0.064
BOADI B	32.8	32.683	0.117
EDWINASE A	32.6	32.379	0.221
EDWINASE B	32.5	32.289	0.211
EFFIDUASE A	31.9	29.149	2.751
EFFIDUASE B	31.9	31.357	0.543
FAWOADE A	31.3	30.051	1.249
FAWOADE B	32.2	31.3	0.9
GridCo	33	33	0
KAASE A	32.4	31.595	0.805
KAASE B	32.8	31.98	0.82
KTI A	32.8	32.796	0.004
KTI B	32.8	32.796	0.004
KUMAWU	29.8	28.454	1.346
MAMPONG A	27.9	26.961	0.939
MAMPONG B	29.3	29.396	0.096
NEOPLAN A	32	30.976	1.024
NEOPLAN B	32.2	31.302	0.898
NSUTA A	28	27.128	0.872
NSUTA B	29.4	29.516	0.116
OFFINSO A	28.6	28.384	0.216
OFFINSO B	29.7	27.945	1.755
RIDGE STATION A	33	32.983	0.017
RIDGE STATION A1	33	32.982	0.018

Bus ID	Field Bus Voltage	ETAP Bus Voltage	Error
RIDGE STATION B	33	32.982	0.018
RIDGE STATION B1	33	32.983	0.017
SUAME A	31	29.358	1.642
SUAME B	32	28.719	3.281
SWITCHING STATION A	30.4	29.599	0.801
SWITCHING STATION B	31.7	30.896	0.804

t-Test: Paired Two Sample for Means

	Simulated Data	*Field Data*
Mean	31.508	30.75392
Variance	2.235036735	3.170496
Observations	50	50
Pearson Correlation	0.877845298	
Hypothesized Mean Difference	0	
Df	49	
t Stat	6.232674142	
P(T<=t) one-tail	5.1192E-08	
t Critical one-tail	1.676550893	
P(T<=t) two-tail	1.02384E-07	
t Critical two-tail	2.009575237	

Regression Statistics	
Multiple R	0.877845298
R Square	0.770612367
Adjusted R Square	0.765833458
Standard Error	0.861640378
Observations	50

ANOVA

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	119.7179569	119.71796	161.25278	5.8448E-17
Residual	48	35.63635878	0.7424241		
Total	49	155.3543157			