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DEPARTMENT OF ELECTRICAL POWER ENGINEERING

OPTIMAL PLACEMENT OF LARGE-SCALE ELECTRIC VEHICLE AND DISTRIBUTED GENERATION IN POWER SYSTEM TO ENHANCE POWER QUALITY

By

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Thesis submitted in fulfillment of the requirements for the degree of Doctor of Engineering in the Department of Electrical Power Engineering, Faculty of Engineering and the Built Environment

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As the candidate’s supervisor, I agree to the submission of this thesis.

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DECLARATION

I hereby declare that this thesis is my original work, and all sources have been properly cited or referenced. Additionally, this work has not been partially or completely published previously for another degree at another university.

This research was duly supervised by Professor Musasa Kabeya and Professor Katleho Moloi at the Durban University of Technology.

Submitted by:

9 October 2024

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DEDICATION

In loving remembrance of my grandmother, Madlamini Ntombela, and my father, Nkosinathi Ntombela, to whom I dedicate this doctorate thesis. It is my heartfelt wish that they may witness the unwavering commitment I have put into this work from the realms of heaven. Thank you for raising me. I have become exactly what you have always perceived in me, and I have successfully improved the situation at home, just as you have always had faith in me.

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May we all get divine benefits.

ABSTRACT

The widespread adoption of electric vehicles (EVs) and renewable distributed generators (REDGs), including photovoltaic (PV) systems and wind turbine generators, has garnered significant attention in global power systems. These energy sources are recognized as environmentally friendly. However, substantial integration of EVs and REDGs can lead to voltage fluctuations that exceed acceptable limits and result in reverse power flows at interconnection points within the power grid. Such excessive voltage variations can adversely affect consumer electric loads, while reverse power flows can disrupt the overall power transmission system. Consequently, the extensive integration of EVs and REDGs poses challenges for both consumers and power utilities. To address these issues, previous studies have suggested reactive power control strategies, such as employing power electronic converters linked to distributed generations (DGs) to mitigate voltage deviations. This research proposes a method for the optimal integration of EVs through bidirectional charging and REDGs within power systems, aiming to effectively manage voltage, active power, and reactive power flows at interconnection points. Additionally, it involves identifying suitable locations and sizes for electric vehicle charging stations and calculating associated system costs. The control objectives are framed as an optimization problem, which is addressed using a hybrid genetic algorithm combined with an improved particle swarm optimization algorithm (HGAIPSO).

The research was structured into three distinct sections, with the efficacy of the proposed methodology illustrated through numerical simulations conducted in MATLAB. The initial section focused on identifying the optimal location for the charging station and the appropriate number of electric vehicles (EVs) per charging station within the power system, utilizing the GA, PSO, IPSO, and HGAIPSO algorithms. This analysis was performed on an IEEE-30 bus system. The simulation outcomes from this initial case revealed that the strategic placement and coordination of EV charging stations, as facilitated by the HGAIPSO algorithm, led to a reduction in power losses, an enhancement of voltage profiles, and an overall improvement in power quality. Specifically, the results indicated a decrease in real power loss of 40.70%, 36.24%, and 42.94% for types 1, 2, and 3 of EV allocation, respectively, while the voltage profile at the buses improved to approximately 1.01 pu.

The second section involved the allocation of EVs to function as loads in a grid-to-vehicle (G2V) system and as generators in a vehicle-to-grid (V2G) system, in conjunction with renewable energy distributed generators (REDGs). This was tested on a more advanced distribution network, specifically the IEEE-118 bus test system, employing the HGAIPSO algorithm. The simulation results indicated that the proposed HGAIPSO method significantly improves power quality and reduces the overall installation costs when compared to the baseline scenario.

The final section provided a comparative analysis regarding computation time and iterations between the proposed HGAIPSO and various other optimization techniques, including GA, PSO, and IPSO. This analysis was conducted on the IEEE-118 bus system with the allocation of V2G, G2V, and REDGs. The simulation results demonstrated that the proposed HGAIPSO method is faster and more effective in terms of computation time for complex networks, achieving optimal solutions more efficiently.

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LIST OF ABBREVIATIONS

REDG	Renewable Energy Distributed Generators
EV	Electric Vehicle
CS	Charging Station
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
IPSO	Improved Particle Swarm Optimization
HGAIPSO	Hybrid Genetic Algorithm Particle Swarm Optimization
GHGs	Greenhouse Gases
ICE	Internal Combustion Engine
ICEVs	Internal Combustion Engine Vehicles
HEVs	Hybrid Electric Vehicles
PV	Photovoltaic
VD	Voltage Deviation
LE	Lost Energy
V2G	Vehicle-to-Grid
G2V	Grid-to-Vehicle
ERV	Electric Road Vehicles
CD	Charge Depletion
UDDS	Urban Dynamometer Driving Schedule
CHAdeMO	Charge-de-Mover

SOC	State-of-Charge
LIS	Lithium-ion Battery
ZEBRA	Zero Emissions Batteries Research Activity
WECSs	Wind Energy Conversion Systems
IMG	Industrial Micro Grid
CHP	Combined Heat and Power
UNFCCC	United Nations Framework Convention on Climate Change
EVIA	Electric Vehicle Industry Association
DEFF	Department of Environment Forestry and Fisheries
DoT	Department of Transport
COT	Cost Optimization Technique
EVM	Electric Vehicle Management
AMI	Advanced Metering Infrastructure
WSN	Wireless Sensor Network

CHAPTER ONE: INTRODUCTION

Chapter One offers a succinct summary of the research initiative and introduces the study. It highlights the increasing prevalence of electric vehicles (EVs) and the challenges they present to power systems. The importance of optimizing EV charging schedules is emphasized, as it plays a crucial role in managing their impact on grid stability, energy costs, and environmental sustainability. This chapter will outline the context, objectives, and framework of the research project.

1.1 Research Background and Motivation

1.1.1 Present status and future trends of EV technology in South Africa

The number of road vehicles in South Africa experienced a significant increase of 33%, rising from 8.6 million in 2017 to 11.5 million in 2022. Automobiles represent approximately 66% of the total vehicle fleet in the country [1]. Current projections suggest that the total number of motor vehicles may exceed 14 million by the year 2050. Additionally, global production of new vehicles is anticipated to grow to between 1.2 million and 1.5 million units by 2035, reflecting an increase in global output from the current 0.68% to 1%. Annual data reveals that the average number of new motorcars added to the national roadways each year from 2009 to 2019 was 350,000 [2]. The decline in automobile sales observed from 2014 to 2018 was attributed to an economic recession, a trend that is expected to continue influencing the future growth of the vehicle population in the country. Over the past decade, newly manufactured vehicles accounted for about 5% of the total vehicle population, with estimates suggesting that by 2050, there will be more than 0.8 million of these vehicles.

Electric vehicles are increasingly recognized as an effective solution for reducing greenhouse gas emissions in the transportation sector, as well as addressing the heightened pollution caused by exhaust emissions. The history of battery-powered vehicles dates back to 1820, while the first internal combustion engine (ICE) vehicles were developed in 1886 [3]. Despite the early invention of electric vehicles, their market presence was largely eclipsed by the mass production of ICE automobiles in the early 20th century. To combat global greenhouse gas (GHG) emissions from road transportation, the number of electric vehicles is rapidly increasing in various nations. On a global scale, the total number of electric motor vehicles rose by 2 million units in 2018 [4].

In the same year, the total numbers of electric two-wheelers, electric buses, electric light commercial vehicles, and electric trucks reached 260 million, 4.6 million, 2.5 million, and between 1,000 and 2,000, respectively. In 2017, approximately 33% of these vehicles were sold. China holds the largest market share for electric vehicles, accounting for 42% of the global total [5,6]. Meanwhile, Europe and North America each represent a 25% share of the overall market. By 2018, the global number of chargers for light-duty vehicles had reached 5.2 million, with 540,000 of these being publicly accessible. Additionally, there were 157,000 fast chargers specifically designed for buses, contributing to an improved ratio of chargers to vehicles [7,8,9]. In 2017, the worldwide stock of electric buses and two-wheelers amounted to 370 million and 250 million units, respectively [10].

The history of electric vehicles in South Africa dates back to the 1970s. However, the lack of support for industry development led to a decline until a resurgence in 2013. By the end of 2018, South Africa had over 1,000 electric vehicles and 100 charging stations, as illustrated in table 1-1 [11,12,13,14,15]. While developed nations are pursuing various projects to manufacture electric vehicles for all transportation categories, South Africa's current focus is primarily on private passenger and light commercial vehicles. The projected electric vehicle population of 3,500 by 2021 was unlikely to materialize. Furthermore, the forecast of 14,000 electric vehicles by 2030, significantly lower than what could be achieved with proactive initiatives, appears improbable given the current pace of development [16].

Numerous countries in Europe, North America, and China have struggled to meet their electrification targets for vehicle fleets. For South Africa to reach its goal of 145,000 electric vehicles (EVs) by 2030, it will necessitate remarkable and unified efforts, particularly in light of the anticipated global average growth rate of EVs, which exceeds 30%, as reported by the Electric Vehicle Industry Association (EVIA) [17]. The initial objective was to achieve at least 3,000 electric vehicle sales annually starting in 2021. According to the World Reference Scenario, South Africa is projected to have only 2.4 million electric vehicles by 2040, reflecting global EV market trends [18]. In contrast, the Gross Domestic Product Scenario, which relies on national economic data, forecasts a higher total of 320,000 vehicles. The sluggish adoption of EV technology in the nation can be attributed to a lack of political commitment and inadequate incentives [19].

In 2023, the national Department of Environment, Forestry and Fisheries (DEFF) collaborated with a manufacturer to pilot and demonstrate solar-powered electric vehicles as part of their initiative to promote EVs across the country. The charging activities were conducted at the DEFF premises [20]. Furthermore, these vehicles were outfitted with solar panels to facilitate charging while in transit, as well as through regenerative braking. The private sector is initiating a program to establish charging stations along three key road corridors in South Africa, connecting Pretoria to Cape Town, Johannesburg to Durban, and Durban to Cape Town. Currently, the existing network of predominantly low-speed charging infrastructure is mainly focused in the Pretoria to Cape Town region. [21].

Electric vehicle imports from Europe to South Africa incur a customs duty of 25%, which is higher than the 18% tax imposed on internal combustion engine vehicles. Given the abundance of critical raw materials in Southern Africa, the region is well-positioned to become a manufacturing centre for electric vehicles, serving both its own needs and those of the broader African market [22]. The analysis indicates that investing in local electric vehicle production could yield substantial advantages for South Africa, leveraging its robust industrial foundation. It is crucial to tackle the issues that led to the halt of Joule's electric vehicle development in 2017, particularly those associated with high production costs [23].

Table 1-1: Electric vehicle population (millions) in South Africa as of 2017

Type of Electric Vehicle	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
Light duty vehicles	2.00	2.15	2.38	2.44	2.50	2.56	2.61
Motorcycles	0.33	0.36	0.37	0.36	0.35	0.35	0.34
Motorcars	5.60	6.11	6.85	7.01	7.17	7.34	7.50
Heavy duty vehicles	0.33	0.34	0.37	0.37	0.37	0.38	0.38
Minibuses	0.29	0.29	0.30	0.31	0.32	0.33	0.34
Buses	0.05	0.05	0.06	0.06	0.06	0.06	0.07
Other vehicles	0.22	0.22	0.23	0.23	0.24	0.24	0.23
Total	8.80	9.52	10.6	10.79	11.01	11.25	11.48

1.2 Impact of a rapid deployment of large-scale EVs and REDGs in power systems

Variations in load demand have consistently necessitated the adaptability of power transmission networks to fluctuating conditions. Unfortunately, this adaptability has resulted in voltage oscillations that surpass the acceptable variation limits at several buses, alongside increased power losses. As a result, it is essential to determine the optimal placement and scale of electric vehicles (EVs) to improve the voltage profile and reduce electrical power losses. Research forecasts that global consumption will grow at an average rate of 1.6 percent annually until 2030 [24]. This trend is anticipated to persist through that year. Consequently, EVs are expected to assume a more prominent role in the future power systems. The rising adoption of electric vehicles within the electrical transmission network sectors is attributed to their generally beneficial impact on power systems. EV systems are crucial for the advancement of smart grid technology and constitute the foundation of intelligent electrical networks [25,26].

The integration of distributed generation (DG) units into the distribution network as a source of energy supply is driven by technological progress and a global transition towards renewable energy sources [27,28]. The significance of distributed generation resources within the distribution network has been amplified by various factors, including improved reliability, reduction of peak clipping losses, demand response capabilities, and considerations related to economic and environmental impacts. Renewable energy sources, characterized by their cleanliness and abundance, present a viable alternative to fossil fuels [29]. The emergence of the smart grid concept is closely linked to the proliferation of renewable distributed generation sources and the necessity to meet consumption demands at the point of use. Presently, energy grids, encompassing electricity, natural gas, and district heating and cooling, are interconnected with users across industrial, commercial, and residential sectors. Although numerous studies have been conducted on energy infrastructure, there remains a lack of comprehensive research focused on the integration of these systems, despite the significant advantages they provide, such as the effective utilization of their composite and flexible characteristics [30,31].

The importance of enhancing electricity efficiency measures has garnered significant attention due to the limited availability of fossil fuel resources, the escalating impacts of global warming, the unpredictable nature of renewable energy systems, and the political ramifications of energy dependence [32,33]. Expensive thermal power plants are required to operate during times of high demand and throughout peak consumption seasons. This increased demand will inevitably necessitate the construction of new power plants and the improvement of existing infrastructure [34,35,36]. Therefore, to mitigate the need for substantial investments in equipment construction and development, the concept of a smart grid that encourages consumer participation on the demand side may be explored [37]. Demand response refers to the adjustment of energy consumption by consumers in reaction to fluctuations in electricity pricing or incentives designed to curtail power usage during peak demand times. The primary aim of demand response is to decrease power consumption during peak periods when energy market prices are high or when the system's storage capacity is strained due to anticipated contingencies [38].

Electricity distribution networks play a crucial role in delivering power to essential and industrial electrical needs in developed countries. In recent years, a variety of technologies have emerged that have significantly altered the generation, transmission, and distribution of electricity to consumers. Innovations such as distributed generation and electric vehicles present both challenges and opportunities for the power grid, particularly in relation to distribution networks [39,40]. Electric vehicles equipped with Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) technologies have the potential to greatly impact the efficient operation of network energy management systems. A demand response program can be effectively implemented by charging vehicle batteries during off-peak periods when electricity prices are typically lower. The stored energy can subsequently be utilized during peak demand times by returning it to the grid in vehicle mode. Various energy storage technologies can also help mitigate peak consumption [41].

Research has indicated that uncoordinated charging and discharging of electric vehicles can severely compromise distribution networks. The consequences may include increased maximum load, heightened losses, and a decrease in both voltage and load factor within the system. Furthermore, studies have demonstrated that the most effective remedy for these negative impacts is the establishment of a collaborative protocol for the charging and discharging of vehicles [42]. The energy stored in electric vehicle batteries often remains unused during extended parking periods. If these vehicles can connect to the power grid, they can leverage the energy stored in their batteries to offer ancillary services, such as alleviating peak power demand and providing reserve rotational energy [43].

1.3 The importance of the optimal placement of EV charging stations and REDGs in power systems

In the early 1990s, the market saw the emergence of new competitors as numerous countries adopted open energy markets and liberalized electricity generation. Traditional power generators emit carbon dioxide, which contributes to global warming. In contrast, solar and wind energy sources produce significantly lower emissions compared to fossil fuels such as coal, gas, and oil [44,45]. Government incentives are designed to motivate independent power producers (IPPs) to utilize renewable energy sources. Initially, power system designs did not incorporate considerations for electric vehicle (EV)-integrated transmission system configurations. It is essential for EVs to be optimally located and sized to meet both technical and economic requirements of the system. Decision-making algorithms predominantly utilize optimal allocation and sizing methods. By reconfiguring the electrical transmission network and strategically positioning EVs, it is possible to enhance power loss reduction and improve voltage profiles [46,47,48]. The HGAIPSO, an AI-driven technique, is employed in this study to effectively arrange particles for the restructuring of electric transmission networks. This research also delineates the methods for transmitting and injecting EVs into electrical grids to regulate reactive power and avert power outages. Furthermore, algorithms such as PSO, IPSO, and GA are discussed. An analysis of the requirements for electric vehicle charging stations is also performed. It will require time for energy systems to adapt to the technical implications of integrating EVs. Therefore, connecting EVs to electrical transmission networks is crucial for minimizing power losses and voltage fluctuations [49].

The growing adoption of electric vehicles and distributed generation sources within distribution networks necessitates the implementation of a robust control program to manage the charging and discharging of these vehicles as a new load, in conjunction with energy production from distributed generation sources [50,51]. This study aims to establish a comprehensive planning framework that addresses the technological constraints of the network while considering the privacy and convenience of electric vehicle owners, distributed generation resource operators, and other relevant stakeholders. Electric vehicle coordinators and owners of distributed generation resources are motivated to enhance their profits through a specialized optimization algorithm that accommodates their specific requirements and limitations [52]. To achieve their goals, electric vehicle owners supply coordinators with essential information, including anticipated arrival and departure times at the parking facility, as well as the initial and final charge levels of their vehicles. This information is employed to determine the most effective charging and discharging strategy for the vehicles [53]. Conversely, owners of distributed generation assets seek to maximize their earnings by gaining insights into the available distributed generation sources and the current electricity market prices [54,55].

The network operator, after identifying the most efficient plan for vehicle charging and discharging along with the best approach for generating distributed resources, investigates various scenarios by sourcing energy from the market, modifying the production schedule for distributed generation resources, and adjusting the vehicle charging and discharging timetable [56]. Following this, the operator formulates a strategy for the energy utilization of available resources aimed at minimizing operational costs while meeting the load demands of the network. The key results of this planning phase encompass the resource consumption patterns, the procedures for electric vehicle charging and discharging, and the electricity acquired from the network [57,58]. While these outcomes may be optimal for vehicle owners and decentralized generation sources, they do not necessarily ensure adherence to the technological constraints of the network. After conducting load distribution calculations, the network operator evaluates all technical limitations of the network. Should any requirements remain unfulfilled, the operator advances to the next stage of optimization by implementing additional constraints. This iterative process continues until all network limitations are satisfied [59,60].

The transportation sector and power generation industries primarily depend on fossil fuels as their main energy source. The urgent necessity to explore alternative energy sources for these sectors is underscored by the diminishing reserves of fossil fuels. The oil economy, which is heavily relied upon by vehicle users and manufacturers worldwide, faces significant limitations in its future viability [61]. The emissions of greenhouse gases (GHGs) resulting from fossil fuel combustion have a profound effect on global warming. Researchers project a 54% rise in oil demand within the transportation sector by 2035. The Energy Information Administration (EIA) anticipates a considerable increase in oil prices over the next twenty years. In response to these challenges, various initiatives aimed at reducing oil consumption have emerged. Electric vehicles present a promising alternative for the transportation sector and are witnessing rapid growth. Economic analyses suggest that Internal Combustion Engine Vehicles (ICEVs) will gradually be replaced by Electric Vehicles (EVs) in the coming years [62,63,64].

In light of the challenges posed by global warming, energy security, and geopolitical concerns surrounding fossil fuel supplies, the adoption of electric vehicles within the transportation sector appears to be a viable solution. Electric vehicles can serve as a distributed and decentralized energy resource for the electric grid. Notably, most vehicles remain stationary and parked approximately 95% of the time. The vehicle-to-grid (V2G) concept, introduced by Kempton, enables these vehicles to remain connected to the power grid, allowing them to efficiently supply the energy stored in their batteries [65]. Electric vehicle technology can assist the grid during peak demand periods by providing services such as peak power reduction, spinning reserves, and management of voltage and frequency. Recently, there has been an increased integration of significant renewable energy distributed generation (REDG) sources, such as wind and photovoltaic (PV) solar energy, into the grid. These various random events are often unpredictable and challenging to anticipate. The rise in REDG implementation within the electrical sector in recent years has been driven by the need to comply with stringent energy regulations and to address concerns regarding energy security [66,67].

1.4 Problem Statement

An alternative method for monitoring the load curve to decrease peak demand and address low-demand intervals involves the adoption of an intelligent vehicle-to-grid (V2G) system. This system presents numerous benefits for the power grid, such as providing electricity during peak times, serving as a source of energy storage, regulating frequency, enhancing voltage stability, and bolstering the overall reliability of the network [68,69,70]. Electric vehicles can connect to the power grid when not in use, enabling them to transfer the energy stored in their batteries back to the grid. Consequently, electric vehicles can operate as both consumers and generators at different times throughout the day, leading to modifications in the power system's load curve [71,72].

An electric vehicle owner maintains a continuous connection to the power grid to obtain the necessary electricity for vehicle operation and battery recharging. Depending on individual usage patterns and needs, the owner utilizes the vehicle and accesses the stored energy at various times during the day [73,74]. If the owner does not require the energy, they have the option to sell it back to the power grid during peak demand periods when electricity prices are higher. Therefore, the strategic management of electric vehicles as decentralized and flexible energy storage presents innovative opportunities for balancing supply and demand within the electrical supply system. Researchers have suggested methods to optimize the charging and discharging processes of electric vehicles, thereby alleviating the high power demand from their batteries and achieving a more evenly distributed load curve [75,76,77].

1.5 Research aims and objectives

The objective of this research is to develop a planning methodology aimed at identifying the most suitable locations and capacities for electric vehicle charging stations within a power system. These charging stations are required to support regulated charging and to incorporate renewable energy sources, such as wind and solar power. A multi-objective function is proposed to optimize both the placement and sizing of Renewable Energy Distributed Generators (REDGs) alongside electric vehicle charging stations. Achieving these goals necessitates the minimization of power losses, voltage fluctuations, and overall system costs. The HGAIPSO methodology introduced is capable of providing optimal solutions for all potential scenarios within a large-scale smart grid featuring 30 and 118 buses. By concurrently optimizing the locations of electric vehicle charging stations and renewable energy distributed generators, it is possible to enhance the capacity of EV charging stations while reducing the operational costs associated with both conventional and renewable energy systems. The following enumeration outlines the specific aims of this study:

- To present a comprehensive literature review of vehicle-to-grid (V2G) and grid-to-vehicle (G2V) technology;
- To develop an optimization algorithm, i.e. the hybrid genetic algorithm particle swarm optimization (HGAIPSO) for Load Profile and Load Flow Analysis in power systems with a large-scale Electric Vehicles penetration;
- To improve power quality by minimizing power losses and enhancing the voltage profile in power networks integrated with Electric Vehicles and Renewable Energy Distributed Generation; and
- Presenting an efficient method for allocating EV charging stations alongside REDGs in power system, whilst adhering to the standard grid code.

1.6 Research Questions

- What are the qualities of a system that is enabled for vehicle-to-grid (V2G) technology that justify its adoption regardless of cost-effectiveness, the ability to comply with regulations, or any other limitations that may be present?

- What are the most important parts of a Standard Operating Procedure (SOP) that will regulate the day-to-day use of V2G technology assets, as well as their deployment in an emergency?

1.7 Contributions of the study

The list below are the research contributions:

- To determine the best position of the charging station and the number of EVs per charging station on the power system using the GA, PSO, IPSO, and HGAIPSO algorithms respectively on the grid-to-vehicle (G2V) system.
- Allocation of EVs to serve as loads, i.e. G2V system, and generators, i.e. vehicle-to-grid (V2G) system, combined with REDGs using the HGAIPSO algorithms.
- A comparison analysis regarding computing time or iterations of the proposed HGAIPSO and other optimization methods, including GA, PSO, and IPSO.

1.8 Thesis Structure

The thesis is arranged into eight chapters. The introduction is the first chapter where an overview of the increasing penetration of EVs and the challenges they pose to power systems, importance of optimizing EV charging schedules to manage their impact on grid reliability, and environmental sustainability and research objectives and motivation for developing optimal charging control strategies are discussed in this chapter.

Chapter Two This chapter reviews existing studies on electric vehicle (EV) charging scheduling and the integration of renewable energy distributed generation (REDGs) into power systems. It examines various optimization techniques, control strategies, and modeling approaches employed in EV charging management, as well as the status of EVs within the South African power system.

Chapter Three discusses modeling and system analysis where descriptions of the mathematical model for representing EV charging behavior, including charging demand, vehicle types and charging infrastructure, incorporation of power system constraints, such as grid capacity, voltage limits, and renewable energy generation variability and consideration of dynamic factors, including user preferences and grid conditions, are discussed in this chapter.

Chapter Four: This chapter discusses control strategies that integrate demand response mechanisms, smart charging algorithms, and vehicle-to-grid (V2G) capabilities to improve grid flexibility and reliability, as well as the consideration of communication protocols, data exchange platforms, and interoperability standards for electric vehicle charging infrastructure.

Chapter Five is the optimization framework involves the creation of a system for establishing optimal electric vehicle (EV) charging schedules on a large scale. This includes formulating objective functions aimed at minimizing energy costs, grid congestion, and emissions, while maximizing the utilization of renewable energy and overall system efficiency. Additionally, it encompasses the selection of optimization algorithms, such as linear programming, mixed-integer programming, or metaheuristic techniques, to effectively address the scheduling problem.

Chapter Six proffers case studies and simulations; application of the developed optimization framework, and control strategies to representative power system scenarios, simulation studies to evaluate the performance of the proposed approach under different operating conditions, EV penetration levels, and grid configurations and analysis of key performance indicators, such as energy costs, grid congestion, emissions reduction and user satisfaction, are discussed in this chapter.

Chapter Seven is the implementation challenges and considerations discussion of challenges in implementing optimal EV charging control strategies in practical power system environments and consideration of technical, economic, regulatory, and behavioral factors influencing EV adoption and charging behavior.

Chapter Eight draws the conclusion and future directions, summary of key findings, contributions and implications of the research; recommendations for policy-makers, utilities and stakeholders to promote optimal EV charging and integration into power systems and identification of future research directions, including scalability, robustness and integration with other renewable energy and grid management technologies.

1.9 Research Output

1.9.1 List of Published Journal Papers

1. Ntombela, M.; M, Kabeya.; Moloi, K. A Comprehensive Review for Battery Electric Vehicles (BEV) Drive Circuits Technology, Operations, and Challenges. World Electr. Veh. J. 2023, 14, 195. https://doi.org/10.3390/wevj14070195
2. Ntombela, M.; M, Kabeya.; Moloi, K. A Comprehensive Review of the Incorporation of Electric Vehicles and Renewable Energy Distributed Generation Regarding Smart Grids. World Electr. Veh. J. 2023, 14, 176. https://doi.org/10.3390/wevj14070176
3. Ntombela, M.; M, Kabeya. Reduction of Power Losses and Voltage Profile Improvement in a Smart Grid Incorporated with Electric Vehicles. Sustainability 2023, 15, 10132. https://doi.org/10.3390/su151310132
4. Ntombela, M.; M, Kabeya. Load Profile and Load Flow Analysis for a Grid System with Electric Vehicles Using a Hybrid Optimization Algorithm. Sustainability 2023, 15, 9390. https://doi.org/10.3390/su15129390

1.9.2 List of Journal Papers under review

1. Ntombela, M.; M, Kabeya.; Moloi, "Strategic Forecasting Methodology for Integration of Electric Vehicles and Renewable Energy Distributed Generators into the Power System". **Under review** on International Review on Modelling and Simulations (I.RE.MO.S.)
2. Ntombela, M.; M, Kabeya.; Moloi, "Efficient management of electric vehicle charging scheduling for widespread electric vehicle integration in power systems". **Under review** on Journal of Electrical Engineering and Technology
3. Ntombela, M.; M, Kabeya.; Moloi, "Discussion of challenges in implementing optimal EV charging control strategies in practical power system environments and GHG emissions from road transportation in South Africa. **Under review** on International Review of Electrical Engineering (I.R.E.E.)

1.9.3 List of Published Conference Papers

1. M. Ntombela, M. Kabeya and K. Moloi, "Optimal Placement of EV Charging Stations in the Distribution Network to Avoid Power Losses," 2023 International Conference on

Electrical, Computer and Energy Technologies (ICECET), Cape Town, South Africa, 2023, pp. 1-5, doi: 10.1109/ICECET58911.2023.10389332.

2. M. Ntombela, M. Kabeya and K. Moloi, "Review of the Technology and Problems Faced by Electric Vehicles Drive Circuits," 2023 International Conference on Electrical, Computer and Energy Technologies (ICECET), Cape Town, South Africa, 2023, pp. 1-6, doi: 10.1109/ICECET58911.2023.10389460.
3. M. Ntombela, M. Kabeya and K. Moloi, "Analysis of Load Flow with a Hybrid Optimization Algorithm for Connecting Electric Vehicles to the Grid," 2024 Conference on Information Communications Technology and Society (ICTAS), Durban, South Africa, 2024, pp. 227-231, doi: 10.1109/ICTAS59620.2024.10507117.
4. M. Ntombela, M. Kabeya and K. Moloi, " Electric Vehicles to Grid Technology Load Flow Analysis Using Hybrid Optimization Algorithm," 2024 International Conference on Electrical, Computer and Energy Technologies (ICECET), Sydney, Australia, 2024, pp. 1-5
5. M. Ntombela, M. Kabeya and K. Moloi, " Voltage and Load Profile Analysis for a Grid System with Incorporation of Electric Vehicles," 2024 International Conference on Electrical, Computer and Energy Technologies (ICECET), Sydney, Australia, 2024, pp. 1-5
6. M. Ntombela, M. Kabeya and K. Moloi, “Integration of Electric Vehicles and Renewable Energy Distributed Generators into the Smart Grid using Optimization Methods”, 2024 IEEE PES/IAS Power Africa, Johannesburg, South Africa, 2024, pp.1-5.

1.9.4 List of Submitted Conference Papers

1. M. Ntombela, M. Kabeya and K. Moloi,” Renewable Energy Distributed Generation Placement and Sizing to Power Network using Optimization Method” submitted to SAUPEC2025.
2. M. Ntombela, M. Kabeya and K. Moloi,” Optimal Placing of Wind Power Renewable Energy Distributed Generation to Power Network for Power Quality. Submitted to SCOPES-2024.

1.9.5 List of Awards

Editor’s choice article “A Comprehensive Review of the Incorporation of Electric Vehicles and Renewable Energy Distributed Generation into Smart Grids”

Summary

This chapter presented a brief overview of the research endeavor and encompasses the introductory section. Additionally, it included a summary of the increasing prevalence of electric vehicles (EVs) and the challenges they pose to power infrastructures. The importance of optimizing the schedules for charging electric vehicles (EVs) is in efficiently controlling their impact on the stability of the power grid, the costs of energy, and the sustainability of the environment. The objectives of the thesis and its organization were defined. Chapter Two below will offer a review of relevant literature on the topic under study.

CHAPTER TWO: LITERATURE REVIEW

Introduction

Chapter Two discusses the state of some works by other researchers emphasizing the same goals pursued in this study, the applied methodologies and the results presented on EV charging and its integration into electricity grids together with REDGs. An analysis of various optimization methodologies, control tactics and modelling approaches employed in the management of electric vehicle charging is conducted. The chapter also provides an analysis of the various optimization techniques and control tactics employed in the distribution of EV charging stations. The present condition of electric vehicles (EVs) in South Africa is also examined.

2.1 State of Art of Electric vehicles into the Power System

From the viewpoint of the power system, electric vehicles (EVs) represent an additional means of storing electrical energy. What distinguishes them is their ability to move within the electric grid. For example, they can be positioned at different locations within the grid for varying lengths of time [78,79]. While EVs can be integrated into systems with multiple assets, researchers are investigating the idea of an EV manager or aggregator. Another critical issue concerning EVs is their interaction with the power infrastructure. If EVs operate without centralized management, they tend to charge in an unregulated fashion, commonly referred to as dumb charging. This allows electric vehicle owners the flexibility to choose when and where to charge their vehicles. Various charging patterns have been identified, with surveys conducted in Europe and the United States revealing common behaviors regarding EV charging [80,81]. Typically, EVs are charged either at the end of the day for convenience or when the battery is nearly depleted. Electric vehicles can recharge their batteries at diverse locations, including residential areas, commercial zones, or workplaces, depending on the specific timeframe. Conversely, when EVs are overseen by an external entity or an EV aggregator, their charging can occur in a more regulated manner [82].

The adoption of smart charging systems can significantly improve the efficiency of power transmission and aid in lowering electricity consumption on the grid. Furthermore, utilizing solar and wind energy for charging electric vehicles can enhance their overall sustainability [83,84]. Additionally, smart charging provides electric vehicle owners with access to innovative features, including the capability to adjust charging frequency. It is projected that smart charging will reduce the energy costs associated with electric vehicles by 60% through the provision of ancillary services [85]. Moreover, electric vehicle batteries play a crucial role in both the charging process and the storage of energy that can be fed back into the power grid. Electric vehicle charging systems can be categorized into unidirectional and bidirectional types. The concept of utilizing EV batteries to return electricity to the power grid, known as Vehicle-to-Grid (V2G), is depicted in Figure 2-1 [86,87]. This process entails a power exchange between the grid and the battery through multidirectional electric loads. Conversely, when energy flows from the grid to the electric vehicle, it is termed Grid-to-Vehicle (G2V), which requires unidirectional electric chargers. G2V systems are known for their high reliability and ease of use [88,89]. To enable a broader range of services through electric vehicles, the implementation of two-way power exchange technologies, such as V2G and G2V, is essential. V2G electric vehicles are generally connected to the power grid to improve network performance during peak demand periods, while G2V systems allow EVs to draw electricity from the grid to charge their batteries.

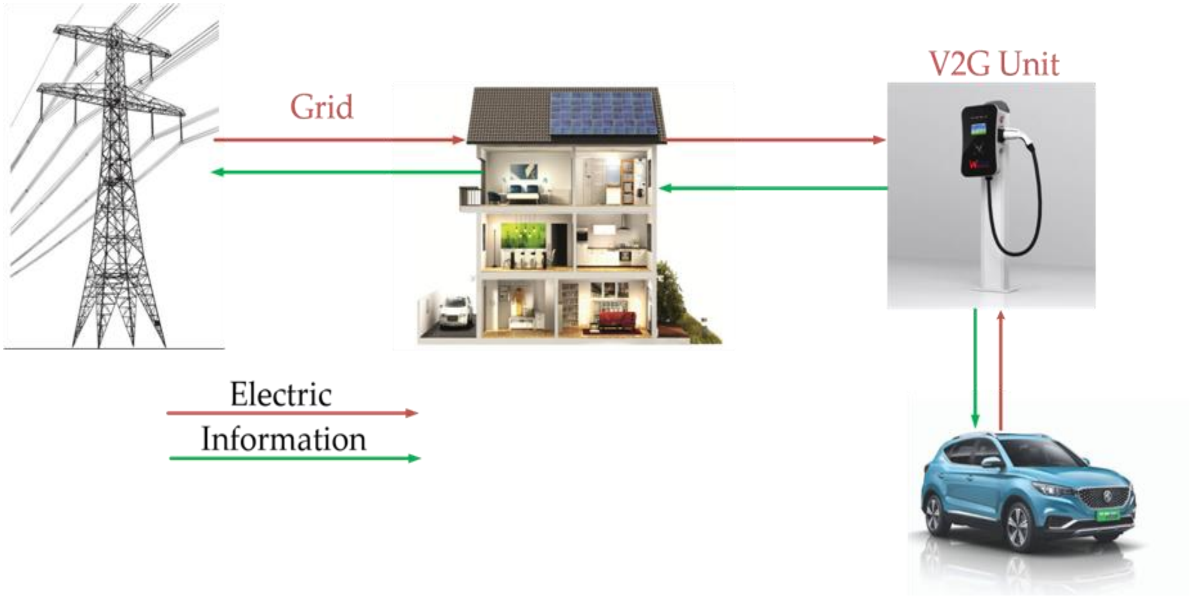

Figure 2-1: Vehicle-to-Grid Architecture structure [90]

Figure 2-2 illustrates a schematic representation of the intelligent charging mechanism associated with vehicle-to-grid (V2G) technology within power networks [90,91]. The authors in [92] conduct a comprehensive review of the literature concerning electric vehicles (EVs) and investigate the potential implications that may directly or indirectly influence public charging infrastructure. The research referenced in [92,93] evaluates both the positive and negative effects of EV charging on power systems. The primary emphasis of the authors, as highlighted in the reviews found in [94], is on optimal charging methodologies. In a distinct study, researchers explored the principles of centralized and decentralized charging strategies, data mining methodologies, and the forecasting of load demands over mid-range, short-term, and long-term intervals [95]. The authors in [96] investigated EV charging systems that incorporate energy storage solutions and diesel generators. Siddhant Kumar et al. analyzed various battery charging configurations, as noted in [97].

The document [98] provides a thorough examination of battery chemistry, classification, material composition, and the effects of charging speed on current batteries. It also offers recommendations for selecting the appropriate battery based on specific applications. In the literature cited as [99], researchers have explored the energy management systems for EVs to mitigate the fluctuations associated with wind power integration. The study referenced in [100] advocates for the use of distributed photovoltaics (PVs) and wind energy to lower the operational expenses of EV charging stations while enhancing the proportion of renewable energy in their design. The authors in [101] analyzed the charging practices employed for electric vehicles in Germany, concentrating on established standards and technological advancements within the EV industry. The integration of electric vehicles with the electrical grid was examined by researchers, as noted in [102]. Additionally, a study in [103] focused on electric vehicles as a service, addressing the current challenges and associated applications.

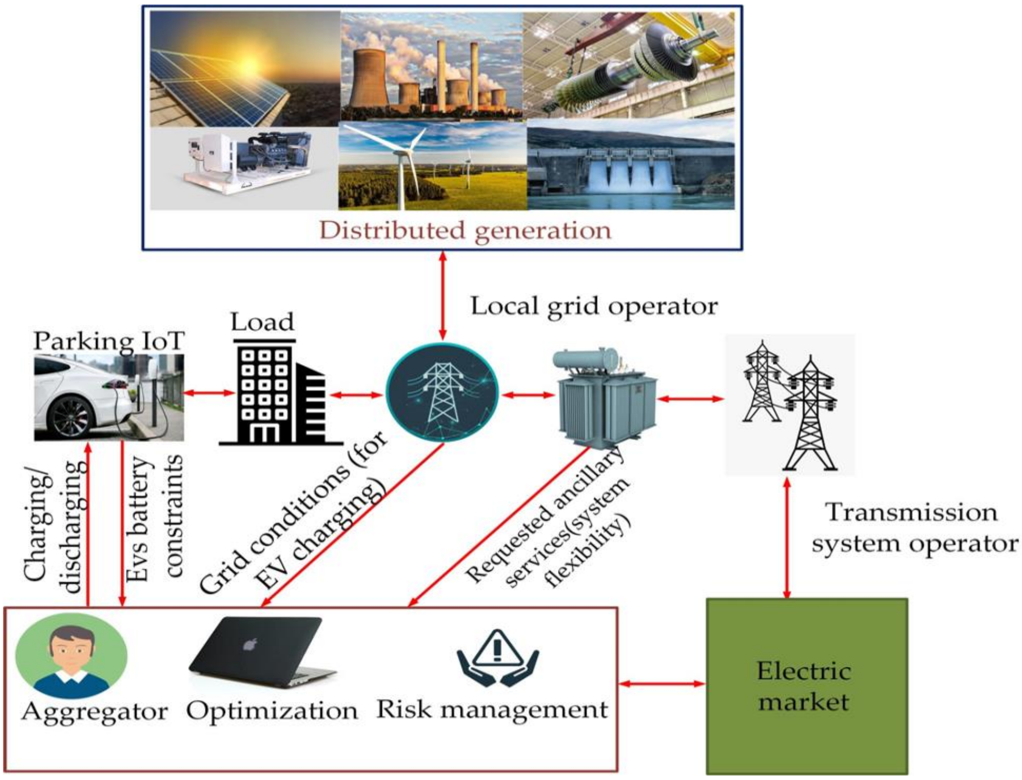

Figure 2-2: Schematic of power system V2G smart charging [104]

Numerous studies have suggested the use of optimization problems to address scenarios that require the simultaneous evaluation of electric vehicles (EVs) and smart grids (SGs). The authors in reference [105,106] apply an Optimal Power Flow (OPF) approach to manage electric vehicle charging, with the objective of minimizing grid losses, greenhouse gas (GHG) emissions, and overall energy costs. The findings reveal that electric vehicles can have varying effects depending on the specific objectives being pursued. The investigation presented in [107] explores the advantages of integrating stationary storage systems with electric vehicles to reduce operational expenses and mitigate the release of harmful emissions in commercial settings. The results indicate that electric vehicles are beneficial for providing electricity during periods of high energy prices. In reference [108], an Optimal Power Flow (OPF) framework is employed to optimize the operational costs associated with electricity generation and EV charging. This OPF framework is used to ascertain the optimal quantity and timing for EV charging. A detailed case study, as referenced in [109], examines the impact of plug-in hybrid electric vehicles (PHEVs) at various charging levels and the implementation of demand-side management (DSM) strategies. The research suggests that shifting EV charging to nighttime hours is advantageous for both EV owners and the electrical grid. The results are presented with standard coefficients [110].

Demand-side management and similar strategies are anticipated to play a crucial role in the future of electrical systems. The studies referenced in papers [111,112] present an optimization approach aimed at enhancing customer utility by reducing the impact of electricity price fluctuations. Research detailed in [113] explores a voluntary home load shedding strategy to ensure the reliable operation of the grid during significant demand surges. The advantages of demand-side management (DSM) for both consumers and utilities are demonstrated in [114], emphasizing the necessity of recognizing flexible loads. This is achieved through the application of two distinct methodologies. In [115], a Demand-Side Management (DSM) approach is employed to decrease the gap between the actual load curve and a predetermined target load curve.

The impact of electric vehicles (EVs) on demand profiles is examined in reference [116]. Additionally, reference [117] discusses efforts to integrate electric vehicles (EVs) into demand response (DR) strategies that actively involve consumers. Reference [118] introduces a robust game-theoretic approach for scheduling electric vehicle charging, aimed at alleviating peak demand and optimizing periods of low demand. Moreover, reference [119] explores the vehicle-to-grid (V2G) technology concept to achieve similar goals. Both studies aim to formulate an optimization problem that aligns a load profile with a predetermined load curve. A coordination method is suggested in reference [120] to effectively manage EV charging, with a particular emphasis on utilizing renewable energy sources. Other researchers focus on a specialized intelligent load management technique for electric vehicles, addressing technical considerations such as loss minimization and maintaining voltage within acceptable limits, as noted in reference [121]. The authors conducted a comprehensive investigation to identify the key parameters influencing the impact of electric vehicles on distribution systems, which include driving behaviors, charging characteristics, charging schedules, and market saturation of electric vehicles. There are two identified areas for improvement: the integration of additional models and the calculation of reliability indices that take into account the load from electric vehicles (EV) and vehicle-to-grid (V2G) technologies [122,123].

Multi-Agent Systems (MAS) have emerged as an effective strategy in power engineering, especially in contexts involving electric vehicles (EVs). The study referenced in [124] integrates a MAS modeling framework with a specific Optimal Power Flow (OPF) methodology to identify the optimal bus locations for Electric Vehicles (EVs) and assess their State of Charge (SOC), with the primary objective of minimizing losses. In [125], MAS theory is applied to clarify market operations and facilitate the integration of electric vehicles into a designated grid, where these vehicles are overseen by an aggregator. Furthermore, a framework for agent-based analysis was established in [126] to evaluate the effects of widespread electric vehicle adoption. This tool is designed to analyze scenarios in which electric vehicles can effectively alleviate demand fluctuations, thereby optimizing the use of renewable energy sources and ensuring voltage stability. The analysis encompasses a comprehensive model of the vehicle, personal mobility patterns, and the power system.

Numerous researchers have explored the simultaneous integration of electric vehicles and renewable energy sources, particularly focusing on their potential to stabilize the variable power output from renewable generators. A comprehensive stochastic process model is introduced in [127] to mitigate congestion in power lines and ensure sufficient voltage levels. This methodology allows electric vehicles to utilize energy derived from renewable sources. In [128], a framework is outlined for the incorporation of plug-in hybrid electric vehicles (PHEVs) into the current electric power grid. The document offers an in-depth analysis of the existing configuration of these systems, including a governmental initiative for electric vehicles (EVs) and a practical case study demonstrating the implementation of controlled charging and vehicle-to-grid (V2G) technology within that framework. The study in [129] examines the integration of renewable distributed energy, solar panels, energy storage systems, and electric vehicles. It highlights the role of storage devices in minimizing power generation losses from photovoltaic systems while aligning with electric vehicles.

Researchers examine the effects of various electric vehicle charging techniques. The study referenced in [130] evaluates the influence of uncontrolled charging versus coordinated charging on voltage levels and grid losses at different penetration rates. A methodology for assessing the impact of plug-in hybrid electric vehicles (PHEVs) on electric power systems is introduced in reference [131], considering various penetration levels and theoretical scenarios for electric vehicle charging. The European Project MERGE provides a comprehensive analysis of both dynamic and steady-state assessments, as noted in [132]. This investigation is conducted within a demonstrative framework that encompasses market and technical activities. Some authors advocate for the implementation of targeted charges in the daily electric vehicle market to encourage charging during periods of low line congestion. The application of various electric vehicle charging strategies is performed on a medium voltage distribution network, as detailed in references [133,134].

An optimization method is employed to determine the maximum capacity of EVs that the grid can accommodate without necessitating additional improvements. The research in [135] analyzes four different methods for electric vehicle charging, taking into account both economic and technical factors. The research presented in [136] analyzes the impacts of several categories of electric vehicles, considering different charging levels and degrees of market penetration. A Demand-Side Management (DSM) strategy is employed to avert undesirable surges in demand and congestion inside the distribution grid. [137] analyzes the integration of electric vehicles into distribution systems. A detailed framework is provided to delineate the technology implications and particular charging methodologies necessary to attain diverse goals. In [138], various optimization issues are introduced to determine electric vehicle charging configurations. The difficulties are examined from the perspective of three separate entities: consumers, system operators, and wind power providers. The results underscore the importance of the chosen aims in shaping the ultimate attributes of electric vehicles.

The Vehicle-to-Grid (V2G) concept has been extensively studied across various research initiatives. An optimization model presented in [139] supports the effective integration of V2G technology within energy management systems. A comprehensive analysis of the effects of electric vehicles (EVs) with V2G capabilities is detailed in [140]. This operational framework utilizes data from the independent Spanish system operator to perform an economic dispatch that incorporates electric vehicles into its calculations. The input parameters encompass multiple scenarios related to renewable energy sources, generators, the prevalence and trends of electric vehicles, as well as demand curves. The findings indicate that an increase in the deployment of electric vehicles, in conjunction with renewable energy sources, is associated with a decrease in prices [141]. Regarding V2G technology, a significant benefit of electric vehicles (EVs) is their capacity to provide ancillary services effectively [142]. The authors of [143,144] suggest leveraging electric vehicles (EVs) as a storage solution within buildings, taking into account Demand-Side Management (DSM) strategies. The research in [145] explores the use of V2G technology for supplying energy and ancillary services, employing an algorithm designed to enhance benefits for EV aggregators. Evidence suggests that this algorithm contributes to reduced billing costs and enhances the flexibility of the system.

Numerous studies highlight the critical role of the aggregator in enabling electric vehicles to engage in the power market. The function of the EV aggregator is thoroughly explained in reference [146], which also provides an in-depth examination of related literature. Various concepts have been introduced regarding the integration of an aggregator within a market framework. An algorithm is employed in references [147,148] to predict the demand and pricing for electric vehicles, as well as to establish optimal scheduling. Documents [149,150] outline two distinct methods for integrating an aggregator agent into day-ahead markets. The advantages and disadvantages of these methods are assessed, supported by a comprehensive numerical analysis that refines the optimization process. The optimization of electric vehicle (EV) charging and discharging is achieved in reference [151], where an aggregator agent enables the active involvement of an EV fleet in the market. Specialized algorithms are implemented to prevent technological issues that may occur during the charging of electric vehicles, as noted in reference [152]. The authors in reference [153] suggest a charging strategy for electric vehicles aimed at preventing grid congestion and minimizing electricity expenses. The impact of two scheduling strategies for electric vehicle charging on the day-ahead market is examined in reference [154,155,156].

In reference [157], the authors investigate the effects of electric vehicles on the variability of mobility patterns associated with them. They conduct this analysis by utilizing a specific battery model alongside Monte Carlo methods to map the movements of electric vehicles, drawing on mobility data from Barcelona. The model accounts for uncertainties related to both the electric vehicles themselves and the demand on the grid. The results, which stem from a modified distribution grid, explore the consequences of two distinct battery charging methods [158]. Researchers in the electric vehicle sector employ Monte Carlo simulations and Markov chains to accurately represent the movement and charging behaviors of electric vehicles within a grid framework, as demonstrated by the authors in publication [159]. The assessment of battery consumption during travel or charging is based on probability distributions derived from the status of the electric vehicles. The impact evaluation focuses on technical aspects such as losses, power flow rates, and voltage levels. An optimization power flow (OPF) approach proposed in [160] aims to minimize system costs. The inherent uncertainties linked to driving behavior are incorporated as probabilistic constraints [161]. It is demonstrated that the likelihood of exceeding grid limits can be reduced at a relatively low additional cost compared to a deterministic approach.

2.2 EV charging and REDGs integration into power systems

The integration of renewable energy distributed generation (REDG) into the electrical grid has made significant strides, fostering optimism for the future. However, challenges arise as the electrical grid must contend with the unpredictability and variability of renewable energy sources, including wind and solar photovoltaics [167]. The power generated from these REDGs can fluctuate considerably, influenced by elements such as wind speed and solar radiation, which may lead to output levels that either surpass or fall short of the demand for electricity. In essence, these REDGs are characterized by inconsistent output, limited capacity credit, and a lack of effective communication. Extensive research has demonstrated that wind energy conversion systems (WECS) and photovoltaic (PV) solar systems can be integrated into the grid in a secure and economically viable manner [168]. One approach to ensure that the grid can accommodate the power output from this renewable energy distributed generators is the implementation of stationary energy storage systems (ESS) or managed dispatch loads. However, the high costs associated with this technology may significantly increase the overall expenses related to the integration of REDG into the power grid.

The integration of electric vehicles (EVs) without Renewable Energy Distributed Generation (REDG) indicates a potential reduction in power grid load by 10% annually; however, this scenario may lead to a daily cost increase of 1.7% and a rise in emissions by 3%. Conversely, when EVs equipped with Vehicle-to-Grid (V2G) technology are utilized alongside REDG, there is a decrease in costs by 0.9% and a reduction in emissions by 4.3% each day. These findings illustrate the optimal interaction between electric vehicles and renewable energy generation within the smart grid framework [169]. Figure 2-3 illustrates the complementary relationship between wind and photovoltaic (PV) solar energy. The subsequent sections will explore the interaction between PV solar sources and EVs within the electrical grid. By employing a charging station located in a public space or office, power fluctuations from REDG can be alleviated in V2G mode through the integration of EVs and wind energy [170]. The diagram assumes that the necessary communication and control systems for V2G and charging scenarios are established, as previously detailed [171].

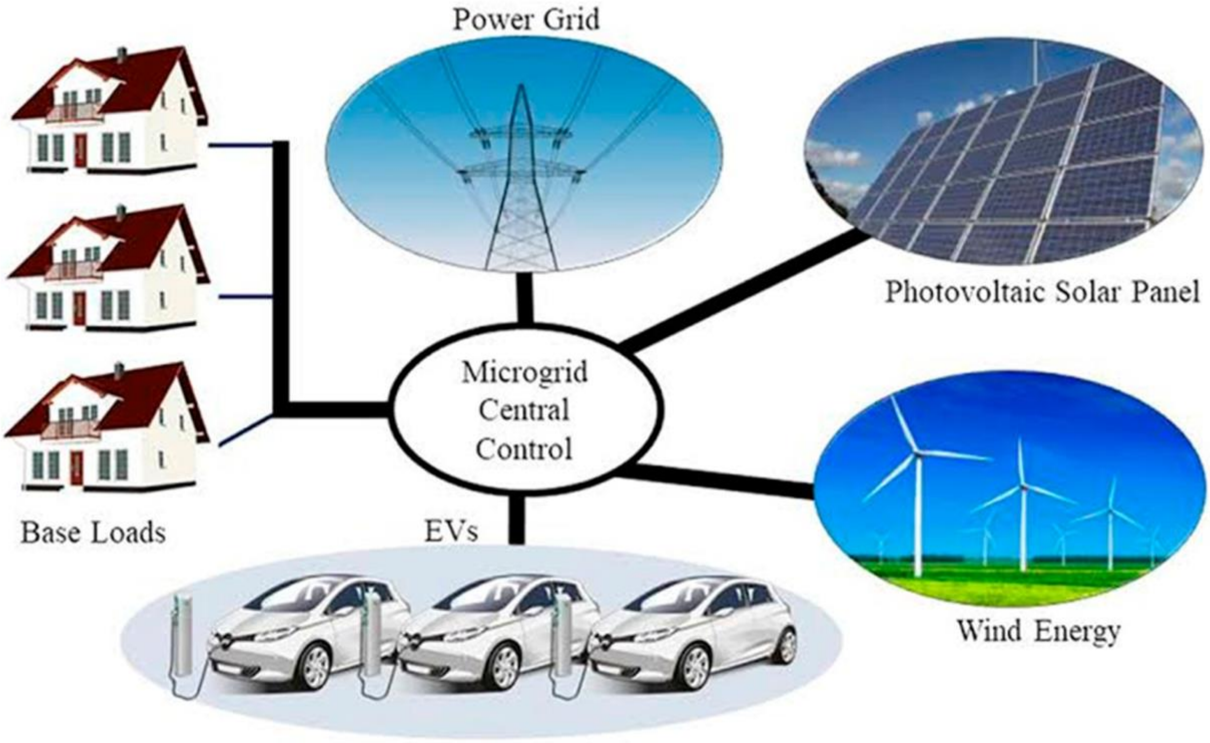

Figure 2-3: Wind and solar photovoltaic panels connecting electric vehicles to the grid [170]

2.2.1 EVs with Wind Energy (REDG)

The implementation of wind energy conversion systems (WECSs) for electricity generation is a viable option. Researchers have explored various scenarios to assess the impact of WECSs and electric vehicles (EVs) on the energy grid to determine their practicality [172]. Lund and Kempton's seminal research evaluates the potential of electric vehicles to provide ancillary services and assist in grid regulation within the United States power market through their engagement with distributed energy resource networks. The maximum amount of wind energy that can be reliably integrated into an isolated electrical system in conjunction with electric vehicles was established in previous studies [173]. The potential effects of electric vehicles on primary frequency control are analyzed through a study of their interactions during smart charging modes. The vehicle-to-grid (V2G) services provided by electric vehicles have enhanced the proportion of renewable energy sourced from wind turbines in off-grid systems. Pillai et al [174,175]. utilized the Hourly Energy PLAN model alongside short-duration dynamic simulation scenarios to investigate the feasibility of creating an off-grid power grid on the Danish island of Bornholm, aimed at integrating a significant volume of wind energy [176,177]. The V2G framework allows for the aggregation of electric vehicle batteries for frequency regulation purposes.

The research conducted by Pillai et al. revealed that considerable variations in wind power penetration led to frequency instability [178,179]. Their study suggests that it is feasible to incorporate 42 MW of wind power into the energy grid through vehicle-to-grid (V2G) services, utilizing aggregated electric vehicle (EV) battery storage with a capacity of 16 MW [180]. Short-term dynamic models were able to integrate only 70% of the installed wind energy capacity, while hourly simulations could accommodate 82% of the available capacity. In both scenarios, V2G played a crucial role in maintaining stable frequencies [181]. The authors posited that operators of government-owned plug-in hybrid electric vehicles (PHEVs) would engage in collaboration. Their findings highlight the existence of various contributing factors. The deployment of smart grid technology is a unique occurrence, and adjustments in charging behaviors are sufficient to lower costs and ease the burden on the electrical infrastructure. The use of 500,000 PHEVs could lead to a 4% increase in wind power capacity by 2030 [182,183]. Although the importance of smart metering and other communication technologies for the effective integration of electric vehicles and wind energy conversion systems into the power grid was acknowledged, these components were not included in the authors' analysis.

Recent research has investigated the role of plug-in hybrid electric vehicles in connecting wind energy facilities to the microgrid. A dispatch system has been developed to meet the continuously changing electricity demands. To improve efficiency, the proposal incorporates a synchronized wind-PEV framework. Without the inclusion of PEVs, there is a significant gap between the microgrid's anticipated daily power output from wind energy systems and the actual consumption, as there are no loads available to utilize the surplus electricity generated [184,185]. The integration of PEVs greatly enhances the effectiveness of matching supply and demand. The power profile created during the charging and discharging phases of PEVs through vehicle-to-grid (V2G) technology remains consistent. Liu et al. conducted an insightful study on the interactions between thermal generation units, plug-in hybrid electric vehicles (PHEVs), and large-scale wind power systems [186,187]. The authors argue that the intelligent scheduling of PHEVs can provide economic advantages for power networks and improve the management of variable production from renewable sources like wind energy. Evaluations that take into account factors such as battery life cycles and the diverse capacities and driving patterns of PHEVs can significantly enhance real-world reliability.

2.2.2 EVs with PV Solar Energy (REDG)

The effectiveness of photovoltaic solar energy in industrial electricity generation has been confirmed. Photovoltaic solar panels are often combined to provide electricity to the grid. The increasing adoption of electric vehicles is associated with a higher use of photovoltaic (PV) solar energy for charging and grid support. Numerous studies indicate that the installation of photovoltaic solar panels on the roofs of parking garages is economically beneficial for electric vehicle charging [188,189]. Furthermore, as demonstrated by the authors, vehicle-to-grid (V2G) transactions can be facilitated within these photovoltaic solar systems, leading to cost savings and enhanced grid performance through careful generation scheduling [190].

Tulpule et al. [191] investigated the photovoltaic solar-powered charging station at workplaces from the perspectives of energy economics and environmental impact, comparing optimal charging strategies with uncontrolled options. This research took into account factors such as parking costs and location to analyze how variations in solar insolation affect the charging behaviors of electric vehicle drivers during work hours [192,193]. The results reveal that implementing solar charging at the workplace can lead to a reduction of 0.6 tons of CO_2 emissions annually, while a home charging system can achieve up to a 55% decrease in emissions for a single vehicle [194]. Adopting a home charging strategy can result in an emission reduction of as much as 85%, whereas an optimal charging approach can lower emissions by 0.36 tons of CO_2. The presence of smart meters and communication infrastructure makes the home charging scenario appear more expensive than a photovoltaic-based charging station at the workplace. A conventional layout for a public solar-powered electric vehicle charging station is depicted in Figure 2-4 [195].

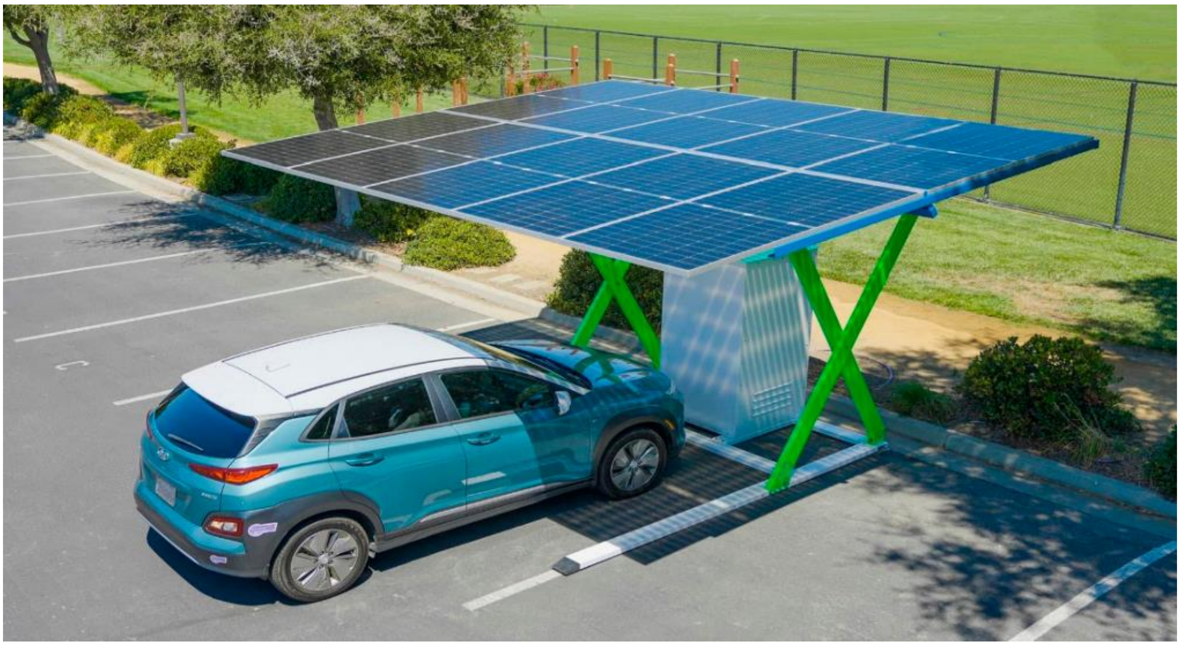

Figure 2-4: PV solar charging station at the parking lot [196]

Commuting employees have the opportunity to take advantage of the charging stations provided by solar photovoltaic systems installed on the rooftop of parking garages during daylight hours. This concept is explored by the authors of [196]. Their study found that solar energy generation reaches its highest levels in the summer, achieving up to 12.6 kWh, with a significant portion of this energy either being returned to the grid (V2G) or consumed within the office premises [197]. Given this information, the prolonged period required to recoup the initial investment may be justifiable. Although the output of up to 3.78 kWh may seem modest, it is deemed adequate for wintertime consumption. There is a lack of comprehensive research regarding winter costs, yet winter applications could greatly improve the project's viability [198]. The interaction between the photovoltaic solar system and the grid is modeled in [199], employing a bidirectional DC charger to supply power to electric vehicles. Additionally, the adjustment of the ramp rate of a photovoltaic inverter's output is demonstrated.

This research investigates three potential methods for implementing electric vehicle (EV) charging: providing grid assistance during the charging process, offering grid support without engaging in charging, and facilitating charging while simultaneously delivering additional services, such as vehicle-to-grid (V2G) capabilities [200]. The results reveal that, although there are considerable fluctuations in power output from the 1.2 kW photovoltaic array due to overcast weather, which can reach up to 22.5% of the DC bus voltage per second, the electric vehicle charger successfully alleviates these variations. A generation scheduling approach for an industrial microgrid (IMG) is analyzed, concentrating on dynamic plug-in electric vehicle (PEV) charging. This approach integrates both combined heat and power (CHP) systems and distributed renewable energy generation (REDG) through photovoltaic solar technology [201]. Dynamic optimal power flow (DOPF) is introduced as a cost-effective strategy. Aligning the IMG's generation schedule with the photovoltaic and PEV systems leads to a significant reduction in overall operational and charging expenses. Despite the notable variability in power output from photovoltaic systems, these fluctuations can be effectively managed through simple communication and control strategies [202].

The solar carport charging station illustrated in Figure 2-5 can be connected to the electrical grid through a bidirectional DC/AC power converter. The two charging stations, labeled 1 and 2, represent specific charging terminals associated with the electrical grid in this diagram [203]. The electric vehicles at these stations can operate as energy storage systems by utilizing their DC/AC converters to provide additional support to the grid. A bidirectional DC charger, which is directly linked to the photovoltaic (PV) controller, can capture excess electricity to charge electric vehicles. The authors of [204] suggest that the DC power system will emerge as a viable and attractive option for the next generation of electric grids. This electric model allows for dual charging methods due to its well-designed charging interface.

During peak demand periods, when photovoltaic power generation is at its lowest, electricity can be discharged from the batteries. A thorough examination of the widespread implementation of photovoltaic solar systems and electric vehicles is presented in [205]. This research explores the effects of integrating large rooftop photovoltaic systems with electric vehicle charging and voltage regulation support. This mutually beneficial relationship provides advantages for both parties; for example, electric vehicles (EVs) support extensive photovoltaic (PV) solar systems by offering voltage assistance, while vehicle-to-grid (V2G) services alleviate pressure on the power grid. The integration of photovoltaic solar systems and electric vehicles in this manner has shown a reduction in voltage fluctuations by approximately 15% [206].

In the study cited as [207], a regional distribution system was developed using the IEEE 123-node feeder. However, the actual power flow scenarios in modern power systems can vary significantly from their idealized conditions, often with relatively short distances involved. This highlights the need for additional research into the effects and limitations of employing large-scale photovoltaic solar power for grid support, particularly during the charging of electric vehicles and the implementation of vehicle-to-grid transactions. A comprehensive feasibility assessment of photovoltaic solar installations in parking lots in the Swiss city of Frauenfeld is presented in [208]. This study suggests that, in the future, solar panels installed in parking areas could generate enough energy to charge 15 to 40 percent of electric vehicles. While the approach taken was straightforward, it failed to account for the importance of transportation and the system's complexity. Collectively, these studies indicate a probable relationship between the adoption of electric vehicles and solar photovoltaic systems [209].

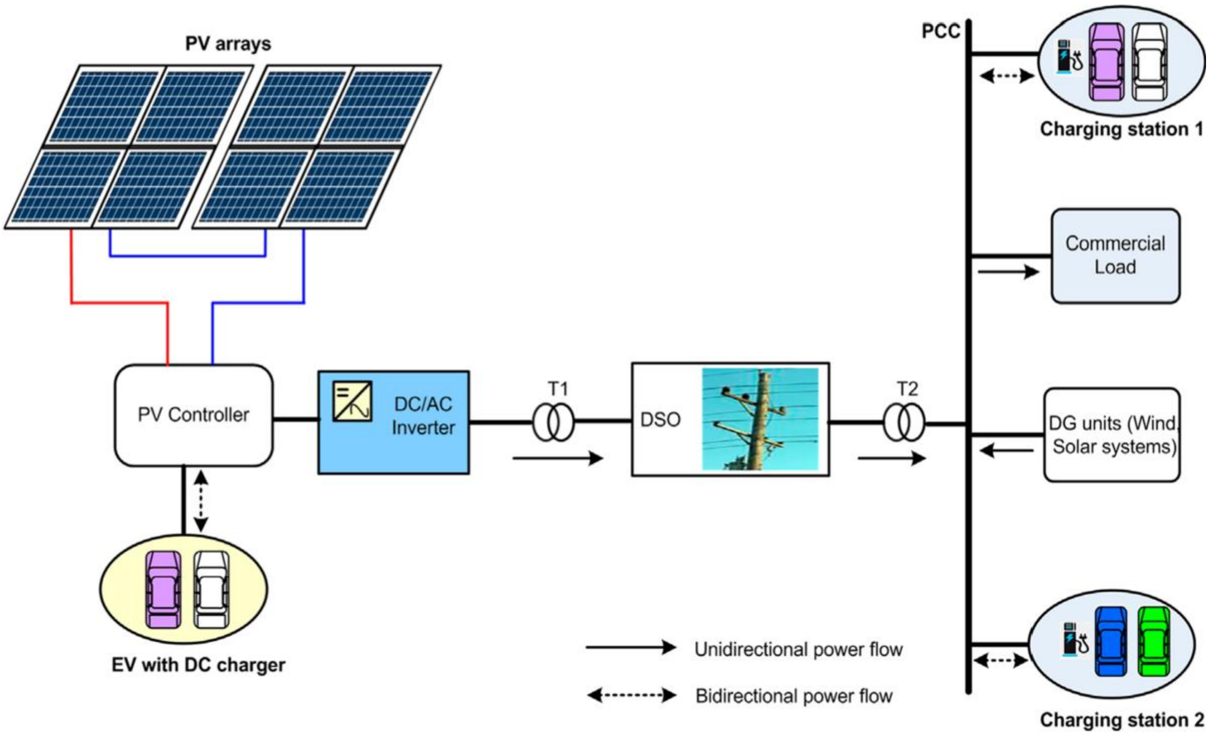

Figure 2-5: PV solar charging station connected to the grid [209]

2.3 Review of the Impact and status of EVs in South Africa

South Africa continues to play a substantial role in greenhouse gas (GHG) emissions stemming from road transportation. The current power infrastructure, when utilized for charging electric vehicles, results in higher carbon emissions compared to those generated by modern internal combustion engine (ICE) vehicles [210]. The findings indicate that the positive effects of electric vehicles on emission reduction in South Africa are expected to begin increasing after 2040, driven by a transition to a low-carbon power system and the rising adoption of electric vehicles. It is estimated that electric motors will decrease the overall greenhouse gas emissions from motor vehicles by 19% by 2050, while ICE vehicles are projected to account for 63% of these emissions [211,212]. The analysis underscores that the adoption of electric vehicles and advancements in automotive technology will play a crucial role in mitigating greenhouse gas emissions from road transport.

By the year 2050, the total reduction in emissions attributed to electric vehicles is anticipated to surpass that of vehicles powered by internal combustion engines. It is projected that the power infrastructure will still rely partially on carbon-based energy sources by 2050, and utilizing non-renewable energy for charging electric vehicle batteries would result in higher emissions [213,214]. The primary obstacles to the widespread adoption of electric vehicles (EVs) in the country include the high costs associated with purchasing EVs and the inadequate charging infrastructure available nationwide. Additionally, the limitations in power supply within South Africa impede the swift rollout of electric vehicles, as their charging requirements would place further strain on the energy infrastructure. This situation underscores the considerable advantages of improving national electricity generation through the use of renewable energy sources [215,216,217]. The government's formulation of policy frameworks, which include specific targets for electric vehicle sales, the development of charging infrastructure, and various incentives, will play a crucial role in fostering the growth of electric vehicle technology within the country.

Transportation facilitates the movement of goods and people within global economic and social activities. It has become the second largest source of global greenhouse gas (GHG) emissions due to its integral role in socio-economic functions [218]. Road transport alone accounts for 90% of emissions from this sector, and its contribution continues to grow. If left unaddressed, GHG emissions from transportation are projected to increase more swiftly than those from any other sector in the future [219]. In 2015, countries around the world, under the guidance of the

United Nations Framework Convention on Climate Change (UNFCCC), established the Paris Agreement to confront the pressing issue of climate change. This Agreement requires nations to define their climate change adaptation and mitigation goals through a reporting mechanism known as nationally determined contributions to the UNFCCC [220]. Without significant and decisive changes, GHG emissions from the transportation sector, especially from road vehicles, will hinder the achievement of the objectives set forth in the Paris Agreement.

Numerous regions across the globe are actively pursuing the development of advanced transportation vehicles that utilize alternative energy sources instead of fossil fuels, with the objective of alleviating their harmful environmental effects [221]. It is important to acknowledge that fossil fuels have been the primary energy source for over a century, offering dependable and cost-effective energy. However, alternative renewable energy sources must demonstrate their capability to instill confidence in both industrial and societal domains, proving their viability as a preferred option [222]. The electrification of road transport presents significant advantages, such as decreasing air pollution in urban areas and reducing greenhouse gas (GHG) emissions. In 2019, electric vehicles (EVs) contributed to a reduction of 53 million metric tons of carbon dioxide equivalent (Mt CO_2e), highlighting the considerable potential of road transport for effective emissions reduction [223]. Electric vehicles are poised to play a significant role in global efforts to lower greenhouse gas (GHG) emissions in the medium to long term.

Electric vehicles, encompassing battery EVs and plug-in hybrid EVs (PHEVs), hold substantial promise for decreasing global greenhouse gas (GHG) emissions from road transportation. In recognition of this potential, several countries are allocating significant resources to electrify their transportation systems and transition away from fossil fuels by initiating projects with specific timelines [224,225,226]. A thorough evaluation of the enhanced benefits resulting from the emissions reductions achieved through the adoption of electric vehicles (EVs) compared to internal combustion engine (ICE) vehicles is crucial at both national and regional levels. The transition to electric vehicles (EVs) markedly decreases the consumption of gasoline and diesel in road transportation, along with the associated greenhouse gas (GHG) emissions [227].

South Africa's integrated resource planning outlines a comprehensive approach for the development of energy resources in the country through the year 2030 [228]. This national planning framework indicates that coal will remain a crucial element of the energy mix moving forward. The energy sector in South Africa is responsible for 80% of the nation's total greenhouse gas (GHG) emissions, with power generation and liquid fuel production contributing 50% of this total. Additionally, transportation represents 28% of the country's overall energy consumption, leading to 11% of the national GHG emissions [229]. Projections suggest that by 2050, renewable energy sources will constitute 76% of South Africa's energy generation, resulting in a reduction of carbon intensity to 139 grams per kilowatt-hour. Furthermore, the research initiative aims to achieve a global reduction in electricity intensity of approximately 50% by the year 2050.

Electric vehicles are increasingly recognized as a vital mode of transportation on a global scale. Although there is a wealth of information regarding transport emissions worldwide, there is a notable lack of data specifically pertaining to sub-Saharan Africa [230,231,232]. The gradual uptake of electric vehicles (EVs) in South Africa, combined with high carbon emissions from the national electrical grid, existing policy frameworks, and socio-economic factors, raises concern about the ability of EVs in South Africa to significantly reduce greenhouse gas (GHG) emissions, as observed in other regions. To meet its goal of reducing national emissions by one-third over the next decade, it is imperative for the automotive sector to actively engage and acknowledge the significance of electric vehicles (EVs), while also promoting advancements in internal combustion engine (ICE) vehicle technology [233].

2.3.1 Carbon intensity of a country's electricity system and the potential for reducing emissions through the use of electric motorcars

The electrical grid plays a crucial role in determining the greenhouse gas emissions linked to electric vehicles. In South Africa, the carbon intensity of the electricity system stands at 950 grams of CO_2 per kilowatt-hour (g CO_2 kWh^-1), which is double that of the European Union's rate of 429 g CO2e kWh^-1 [234,235]. Consequently, the carbon intensity associated with charging electric vehicles (EVs) in South Africa is the highest in the world, reaching 1,002 grams of CO_2 equivalent per kilowatt-hour (g CO_2e/kWh), which is also twice the global average. This emission level surpasses that of new internal combustion engine (ICE) vehicles [236]. In 2015, the average CO_2 emission rates for gasoline and diesel vehicles were recorded at 148 grams per kilometer (g km−1). These figures are below the 1999 recorded rates of 190 g CO_2 km−1 for petrol and 245 g CO_2 km−1 for diesel light commercial vehicles.

In 2018, electric vehicles emitted an average of 95 grams of carbon dioxide equivalent per kilometer (g CO_2e km-1) on a global scale, representing a 60% reduction compared to petrol internal combustion engine (ICE) vehicles and a 40% reduction relative to hybrid vehicles [237,238]. A mere 1% decline in the average fuel economy of new vehicles could lead to the carbon intensity of charging electric vehicles through grid energy becoming lower than the fuel efficiency of new internal combustion engine vehicles in the near future. Ongoing technological advancements are expected to consistently lower emissions from future vehicles incorporated into the national fleet, as illustrated in Figure 2-6 [239]. Current forecasts suggest that new internal combustion engine (ICE) vehicles will achieve a reduction in emissions of approximately 20 million metric tons of CO_2 equivalent (63%) by the year 2050. Furthermore, electric vehicles are projected to contribute an additional decrease of 11 million metric tons of CO_2 equivalent (19%) [240,241]. These emissions projections are consistent with academic expectations that electric vehicles will generate 9 million metric tons of carbon dioxide equivalent by 2050. The findings of this study further reinforce the role of electric vehicles (EVs) in achieving an 8% net reduction in emissions in South Africa by 2040 [242].

The primary factor contributing to the more pronounced reduction in emissions from internal combustion engine (ICE) vehicles, as opposed to electric vehicles, is the disparity in the number of vehicles, with ICE vehicles expected to retain a larger market share than their electric counterparts. If electric vehicles achieve widespread adoption in South Africa, road transport emissions are projected to peak around the year 2030 [243,243,244]. By the end of 2050, the anticipated emission reduction potential of electric vehicles is expected to exceed that of internal combustion engine vehicles, as depicted in Figure 2-7. For the transportation sector to effectively support the goals of the Paris Agreement, it is essential that electric vehicles account for at least one-third of all new vehicle sales by 2030. To ensure that internal combustion engine vehicles in developing nations do not exceed 30% of the new vehicle fleet by 2050, a significant increase in the adoption of electric vehicles is crucial [245].

In the absence of new technologies or electric vehicles, the baseline emissions from vehicles purchased between 2020 and 2050 are estimated to reach approximately 57 million metric tons of CO_2 equivalent [246,247]. Currently, the total potential reduction in emissions from motor vehicles could surpass 32 million metric tons of CO_2 equivalent. By 2050, electric vehicles are anticipated to reduce carbon dioxide (CO_2) emissions by 1.5 billion tons on a global scale. Electric vehicles have the potential to significantly lower greenhouse gas (GHG) emissions linked to fossil fuel use in internal combustion engine vehicles worldwide. It is forecasted that by 2060, electricity will become the leading energy source for motor vehicles, surpassing oil [248].

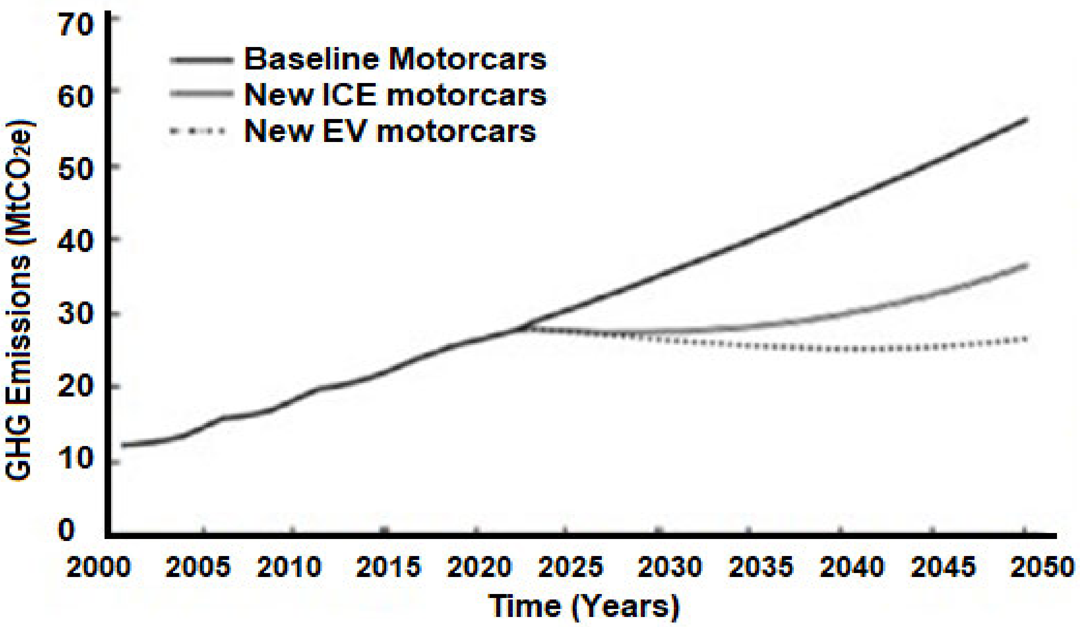

Figure 2-6: An analysis of mitigation measures for new motor vehicles in South Africa using motor vehicle technology [249]

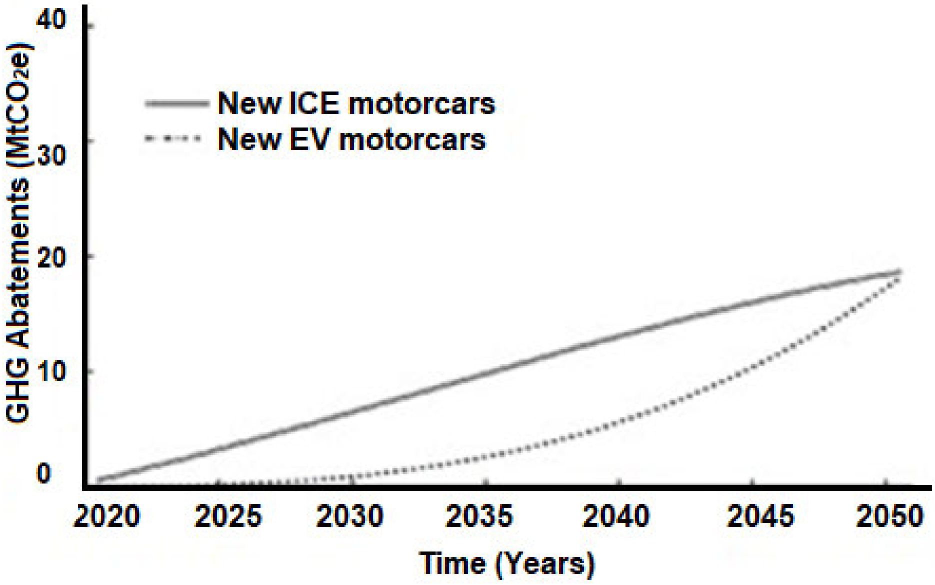

Figure 2-7: Complete and comprehensive reduction of emissions [249]

Electric motor vehicles powered by non-renewable energy sources will progressively augment emissions significantly. By 2050, electric vehicles will represent one-third of the emissions generated by new automobiles [250]. Currently, charging electric vehicles via the existing power system, which depends on coal for over 70% of its energy production, leads to increased carbon emissions. These emissions are 23% greater than the carbon emissions generated from fuel usage. Countries with a carbon-intensive electricity infrastructure, like South Africa, exhibit higher well-to-wheel emissions than batteries charged with renewable energy sources. The present conditions require prioritizing the decarbonization of the electrical grid over the electrification of the vehicle fleet [251].

The adoption of clean energy can further diminish the anticipated 30% energy demand from electric vehicles by 2045, which is presently included in the overall transport fuels consumption [252]. This timeframe coincides with the moment when sales of new electric vehicles will exceed those of conventional automobiles, hence intensifying the decrease in emissions. The assertion corresponds with the projections established by the International Energy Agency (IEA) [253]. By strategically harvesting solar radiation, South Africa can generate adequate renewable energy to counterbalance the carbon emissions generated by electric vehicles. Although the carbon intensity of the electrical grid may constrain the mitigation potential of electric vehicles (EVs), it is projected that electric automobiles will decrease total CO_2 equivalent emissions by 155 million metric tons by 2050. This corresponds to the anticipated 190 million metric tons of carbon dioxide equivalent emissions from all electric vehicles in the country between 2015 and 2050 (DEFF, 2020) [254]. Additional reductions in emissions can be attained by recharging batteries using renewable energy sources. The use of non-renewable energy to power automobiles in the European Union is unlikely to achieve the net-zero emissions target set by the Paris Agreement for 2050 [255].

2.3.2 Obstacles to the widespread use of electric vehicles in South Africa

Many nations are implementing strategies aimed at addressing climate change through the establishment of policies that prioritize the reduction of greenhouse gas (GHG) emissions and promote changes in lifestyle. A viable approach involves transitioning to low-carbon economies that prioritize environmental sustainability [256] . According to Goldman Sachs, while the shift to a low-carbon economy poses significant challenges, it also offers both opportunities and hurdles for global economies. To ensure the success of worldwide decarbonization initiatives, four key actions must be taken. First, it is crucial to develop a robust legal and institutional framework that supports a strategy aimed at reducing carbon emissions. The next step involves translating low-carbon goals into actionable strategies tailored for each economic sector [257]. The third action requires the creation of necessary policies and procedures to effectively implement the plan. Finally, it is important to launch public awareness campaigns that address the socio-economic impacts associated with the transition to a low-carbon economy.

The South African government, specifically the Department of Transport (DoT), has embarked on a significant initiative across various major centers to assess the effectiveness of government vehicles and to encourage the integration of advanced clean technologies, such as electric vehicles [258]. The DoT has developed a strategy aimed at electrifying up to 5% of the vehicle fleet belonging to the government and state-owned enterprises by the year 2030. Implementing this strategy would facilitate the establishment of battery charging facilities, thereby extending access to even the most remote areas of the nation [259]. In Cape Town, an investigation has been launched to determine the necessary actions for the successful execution of this national policy. This investigation encompasses an evaluation of the cost structure associated with battery charging and the optimal placement of charging stations to enhance user accessibility. Additionally, there is a pressing need to upskill the current workforce in South Africa's automotive sector to effectively manage the emerging technologies [260].

To improve the efficiency and cost-effectiveness of electric vehicles, it is crucial to modify driving behaviors. The longevity of the battery is influenced by several factors, including the distance covered, charging habits, and driving styles. Electric vehicles perform exceptionally well in urban environments characterized by frequent starts, stops, and lower speeds [261]. Regenerative braking offers an innovative approach to charging by leveraging driving patterns. Internal combustion engines contribute to approximately 75% of emissions associated with urban transportation [262,263]. This data suggests that peak travel times, such as morning and evening, provide a valuable opportunity for battery recharging throughout the day. This presents a significant potential for the replenishment and storage of renewable energy. However, due to the insufficient charging infrastructure in South Africa, many drivers need to enhance their driving skills and learn how to optimize battery life effectively [264].

South Africa necessitates comprehensive policy incentives that go beyond simply addressing capital and operational expenditures. Since 2014, the implementation of reduced taxes on new electric vehicles (EVs) and the improvement of charging infrastructure, alongside increased taxes on internal combustion engine (ICE) vehicle sales, has resulted in a surge in EV demand in China [265,266]. It is imperative for South Africa to urgently address the significant issue of high import taxes, which account for 42% of the capital cost of electric vehicles (EVs). These taxes are markedly higher than those imposed on internal combustion engine (ICE) vehicles. The global market dynamics contribute to this challenge, as countries advancing EV technology prioritize meeting domestic needs over exporting these innovations [267]. Allocating dedicated parking spaces in urban areas with lower fees for electric vehicles compared to internal combustion engine (ICE) vehicles at public and commercial sites could facilitate easier recharging, lower operational costs, and enhance psychological incentives for the adoption of electric vehicle (EV) technology [268,269].

Countries like China have implemented initiatives to simplify the registration process for electric vehicles (EVs). To promote widespread adoption of EVs, it is crucial to impose tax incentives and offer subsidies until the pricing of EVs becomes comparable to that of internal combustion engine (ICE) vehicles. In South Africa, the long-standing ineffectiveness of a carbon tax on new vehicle sales in curbing CO_2 emissions from road transport highlights the potential of electric vehicles as a vital tool for reducing emissions in both the transport sub-sector and the broader energy sector [270,271]. A carbon tax alone is insufficient for achieving emission reductions unless it is complemented by alternative measures, such as the promotion of electric vehicles. The Integrated Resource Plan 2019 emphasizes the necessity of integrating renewable energy storage into South Africa's energy framework by 2030 [272]. This strategy has enabled Eskom, the national power utility, to initiate a pilot project focused on battery storage. It is important to explore the potential storage solutions that may arise from the expected increase in electric vehicles in the country. Implementing regulations that promote electric vehicle charging during off-peak demand periods can enhance the storage capacity for renewable energy resources. While electric vehicles have not yet made a significant impact on the current energy mix in South Africa, they hold the promise of serving as a means to store renewable energy [273,274,275].

2.4 Examination of different optimization techniques and control strategies used in EV charging stations allocations

2.4.1 GA algorithm

In their study, Auglt, Hooshmand and Ataei [276] utilized Genetic Algorithms (GA) to estimate the size and position of the charging station (CS) units. Cost function-based methods offer the most optimal solution, but they need significant computer resources and exhibit sluggish convergence. The topic has been considered in relation to costs, but the calculations of cost functions may result in uncertainty on the precise dimensions of charging station CS units at appropriate locations. In [277], Rahmat-Allah Hooshmand utilized a Real-Coded Genetic Algorithm (RCGA) to tackle the problem of determining the optimal placement of capacitor banks in unbalanced distributed systems with mesh/radial designs. Fixed and switched capacitors were strategically employed to minimize losses and regulate voltages in transmission lines.

In reference [278], Jalilzadeh, Galvani, Hosseinian, and Razavi introduced a methodology that employs a Real Coded Genetic Algorithm (RCGA) to identify the optimal values for both fixed and switched capacitors within transmission networks. Various commercially available capacitors were utilized to simulate loads across different load levels. The RCGA technique was applied in this research to ascertain the suitable capacitor ratings. Additionally, Boyerahmadi and Poor conducted an investigation using genetic algorithms to examine voltage patterns in transmission networks [279]. The study implemented reactive power injection to improve voltage profiles at remote buses from the slack buses. An evolutionary algorithm was utilized to determine the optimal parameters for reactive power injection, resulting in an improved voltage profile and a decrease in losses.

In reference [280], Carpinelli indicates that charging stations (CSs) can be optimally placed within radial transmission networks by identifying nodes that exhibit the lowest minimum system losses. This challenge was framed as an optimization problem focused on reducing real power loss while satisfying both equality and inequality constraints. The selection of locations was based on the relationship between the sensitivity of active power loss and the real power injected through the charging station. The researchers emphasized the increasing benefits that result from the installation of additional facilities in particular regions, continuing until the point at which it becomes economically unfeasible. This analysis is limited to the consideration of active power loss.

In a study conducted by Hajizadeh in [281], the authors investigated the impact of genetic algorithms on reducing power loss and improving voltage profile in radial networks through the placement of shunt capacitors and dispersed generation plants. The study revealed that strategically placing dispersed generating plants and capacitors in optimal locations results in voltage profiles characterized by reduced losses. The optimal placement for shunt capacitors is in a transmission facility that is situated close to the load. Within the context of GA, the population undergoes adaptive changes across generations by imitating the biological mechanisms that take place in an ecosystem [282]. The concept of Evolutionary Adaptation is shown by genetic algorithms, which are unconstrained optimization techniques. The Genetic Algorithm uses natural selection and evolution to initiate the resolution of an optimization problem with an objective function f(x), where x = x_1, x_2, x_3, ..., x_n, representing optimization parameters in N-dimensions. Genes and chromosomes are the fundamental components of the genetic algorithm (GA). The GA gene is a representation of a binary code, as the optimization parameters in GA standard are represented in binary code string. Genes are amalgamated to form chromosomes. The Genetic Algorithm (GA) is considered one of the most effective methods for parameter search. Moreover, the GA (Genetic Algorithm) differs from traditional optimization and search strategies in several ways [283]:

- Rather than being parameterized in GA, parameters are typically coded;
- This method searches over a population of points rather than a single point by relying just on objective functions in place of additional information like derivatives; and
- By eliminating the use of derivatives, only objective functions are used instead.

2.4.1.1 GA offers several advantages, namely:

- They may be applied to a wide range of optimization issues since they are not subject to local optimum trapping;
- A vast set of solutions are scanned quickly;
- The end solution is not affected by bad proposals since they are simply discarded; and

- Since it chooses its own behavior based on internal principles, the algorithm does not need to be familiar with the rules controlling the problem.

2.4.1.2 GA Parameters choice

For GA to converge rapidly, it is essential to select appropriate parameters. In the absence of any guidelines, there is a mechanism developed to determine these parameters in the method. The following are GA parameters [284]:

2.4.1.2.1 Initial population

Normally, the GA operates on an N-chromosome population. A random number is assigned to the first number in this population. This means that each vector represents one possible search solution. There are typically 2 to 2.5 times as many genes as there are in N populations.

2.4.1.2.2 Scaling

Sometimes, an objective function needs to be scaled into a fitness function by means of a scaling operator (a pre-processor). By preventing premature convergence in the early stages of evolution, and speeding up convergence at the later stages, it works to prevent premature convergence.

2.4.1.2.3 Criteria for termination

Following the calculation of fitness, the termination criterion needs to be determined. Several methods are used to determine this. Amongst them are the following:

- After a certain amount of accuracy is achieved; and

- There has been a pre-defined finite number of generations reached. A winner is declared and the problem solved based on the best match amongst the population.

2.4.1.2.4 Selection

Using this operator, chromosome fitness values are used to select good chromosomes and the resulting mating pool produced. There are a number of ways to accomplish this, but Roulette Wheel Selection is the most common. Roulette wheels are biased according to the fitness of each candidate solution. There are M strings in the population, so the wheel is spun M times.

By performing this operation, the measure that is calculated reflects the fitness of candidates from the previous generation [285].

2.4.1.2.5 Mutation and Crossover

Most cross-overs and mutations on based on user preferences. Amongst them is the cross-over operator. Chromosomes are mated in pairs and the mated pairs crossed over with a probability Pcross to generate candidate offspring. In general, there is a probability between 0.6 and 1.0 of parental chromosome cross-over [286] The candidate offspring have some of their genes inverted with a probability of Pmut. In the GA, this operation is called mutation. As a result, a new population is generated. The mutation operator ensures that there is diversity within the population to prevent premature convergence. Usually, 0.01 or 0.1 is used to calculate the probability of mutation [287].

2.4.1.2.6 Elitism

Whenever the best number in the newly generated population is less than that in the old population, when a population is created, the poorest chromosome is replaced by the best chromosome in the previous population. This ensures that the algorithm's convergence is achieved. Elite parent preservation is referred to as ‘elitism’.

2.4.2 Implementation of GA steps

GA is when the population represents candidate solutions due to n chromosomes. Each chromosome represents a real value vector with m dimensions, where m is the quantity of variables that were optimized. Figure 2-8shows the GA flowchart used to resolve engineering challenges. The stages for implementing a Genetic Algorithm are used to generate the flowchart.

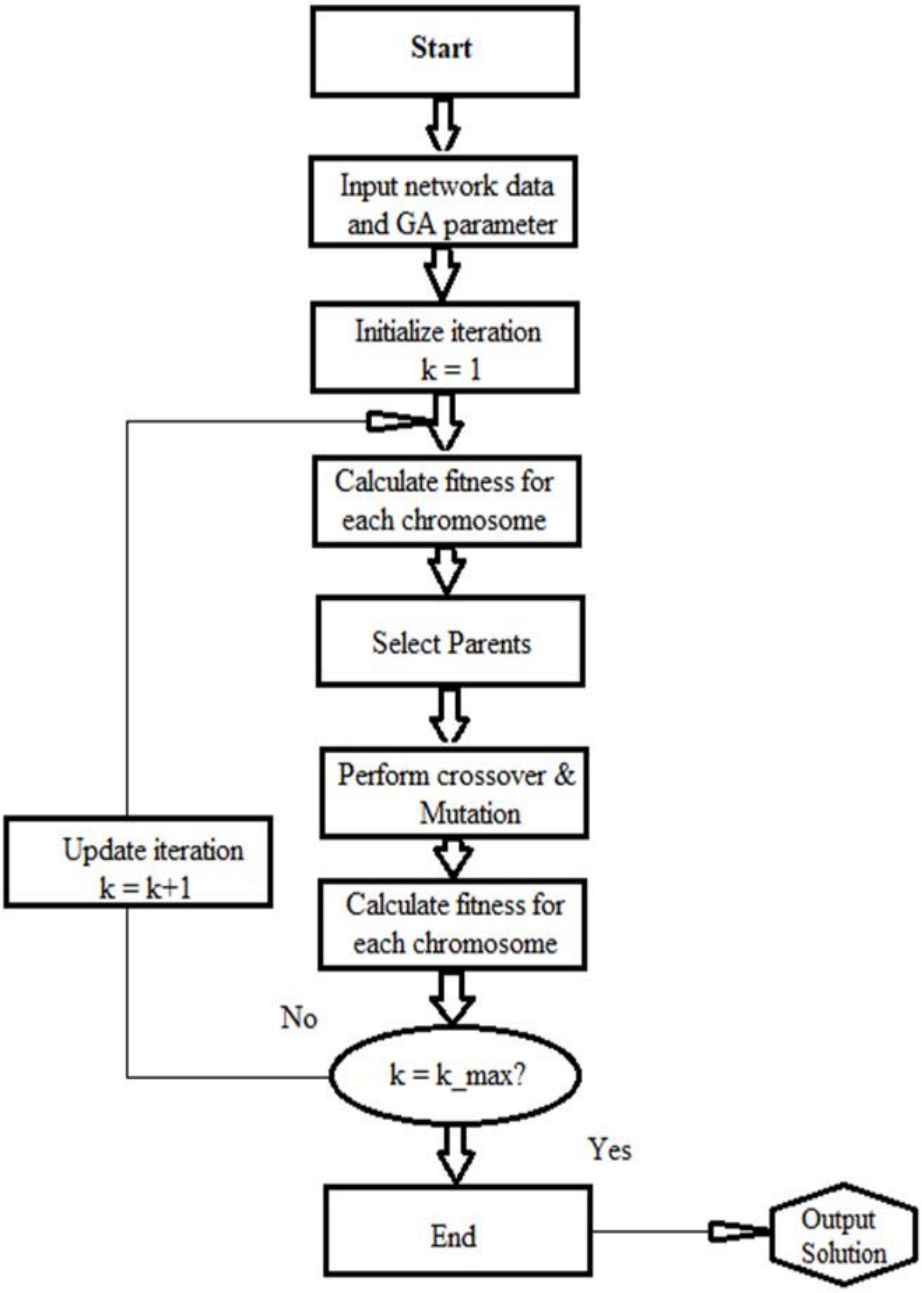

Figure 2-8: Steps for the implementation of a Genetic Algorithm

2.5 PSO algorithm

In [288], Hajizadeh and Hajizadeh propose that transmission planning should be conducted using a PSO-based approach. A multi-objective framework was developed to optimize the sizing and positioning of dispersed generation assets in transmission systems, resulting in reduced power loss costs. The adopted technique utilizes a Particle Swarm Optimization (PSO) and weight approach to establish an optimal balance between the two expenses. Zou and Agalgaonkar in [288] conducted a study where they utilized shunt capacitors and CS units to create voltage support zones in transmission networks. This method narrows down the search area by numerically and analytically determining the specific voltage zones of interest. By strategically deploying CS units and shunt capacitors utilizing Particle Swarm Optimization (PSO) to enhance voltage stability and minimize power losses, it is recommended to decrease the financial expenditure associated with these components [289].

Ziari et al. have suggested an approach in [290] for the optimal allocation and sizing of capacitors. The goal is to minimize transmission line losses and enhance voltage profiles. The findings demonstrated that the suggested approach exhibited superior accuracy and resilience in comparison to genetic algorithms and non-linear programming. In [291], Khanjanzadeh et al. examined how the position and capacity of a CS might improve voltage stability in radial distributed systems using PSO. They compared the accuracy and convergence of the PSO algorithm with the GA approach. The Particle Swarm Optimization (PSO) method was determined to be superior to the Genetic Algorithm (GA) method in terms of both accuracy and convergence speed.

In [292], Varesi introduced a PSO-based method to optimize the allocation of CS units in the power system. The goal was to minimize power losses and enhance voltage profiles. The load flow algorithm and PSO were effectively combined to select the optimal mix of CS unit types, sizes and locations. The researcher solely examined two categories of computer science units. Mohammed and Nasab [293] utilized a multi-objective Particle Swarm Optimization (PSO) technique to optimize the size and placement of the CS. The study utilized a hybrid objective function consisting of two components: The Power Loss Reduction Index and the Reliability Improvement Index. The study only considered the reductions in active power.

In their study, Mancer, Mahdad and Srairi utilized a Novel Binary Particle Swarm Optimization (NBPSO) technique to enhance the total voltage profile of power transmission networks [294]. They achieved this improvement by integrating the optimal positioning of shunt capacitors while considering certain restrictions. The NBPSO method utilized a near global optimization methodology to ascertain the most effective capacitor sizing and placements. Shunt capacitors were included in the process of determining the size and location of capacitors. In a recent study conducted by Mehdi Nafar, discrete particle swarm optimization (DPSO) was employed to enhance the voltage profile of the transmission system and minimize total harmonic distortion (THD) in a distributed generating and capacitor system [295]. Their objective function included a component that avoided the occurrence of harmonic resonance between the capacitor's reactance and the system's reactance. The limits included limitations on voltage, voltage limit, the number and size of capacitors, and generator limitations. The proposed methodology was evaluated by conducting experiments on an altered iteration of the IEEE 33-bus test system.

In reference [296], Hajforoosh and Seyed M employed Particle Swarm Optimization to reduce costs related to active losses, capital investment in CS, operational expenditures, and emissions. They identified limitations within the genetic algorithm (GA) and particle swarm optimization (PSO) techniques, noting that both methods frequently become ensnared in local optima. This indicates that the outcomes produced by these approaches may not reliably yield the most advantageous results. To address this issue, they utilized advanced artificial intelligence methodologies. The procedural steps of the PSO algorithm are illustrated in Figure 2-14. The PSO algorithm creates a population of particles that are randomly scattered throughout the search space. Each particle represents a potential solution to the problem and is assigned a fitness value [297]. The optimization process is guided by this fitness level. As time progresses, particles tend to converge towards the most beneficial location, having previously identified their optimal position and the best solution. The updated velocity of each particle is influenced by three elements: its prior velocity, its current best position, and the best position attained by the entire swarm in the past.

2.5.1.1 Parameter choices of PSO

The limit imposes restrictions on the present velocity. The following parameters indicate the resolution, or fitness, achieved by defining which regions between the present position and the target position will be searched. As a result, particles move in larger steps and might miss good solutions if it is very high. Conversely, if is too low, particles move around long distances before reaching desired solutions. There is a risk that their exploration is insufficient and are thus captured in local minimum solutions [298].

2.5.1.2 Weighting Coefficients

In the stochastic acceleration formula, for high values, the target region is approached shortly, or passed over. In the meantime, low values permit particles to wander farther from the target zone before being drawn back [299]. As the number of iterations increases, it is possible to adopt parameters within the range (1-2), but in many applications there are often constants.

The study controls the rate at which other particles are influenced by their memories and the typical values of their memories.

2.5.1.3 Inertia Weight

By choosing an inertia weight that is appropriate for each exploration, a balance is achieved between global and local explorations. Exploration and exploitation are balanced by the choice of the inertia weight [292]. Typically, the optimization process starts with a large inertia weight and gradually reduces it throughout.

2.5.1.4 Termination criterion

In the following iterations of the initial phase, there are several updates and evaluations until a stopping condition is reached. There are generally two types of stopping condition: a predefined maximum number of iterations or a maximum level of precision [293].

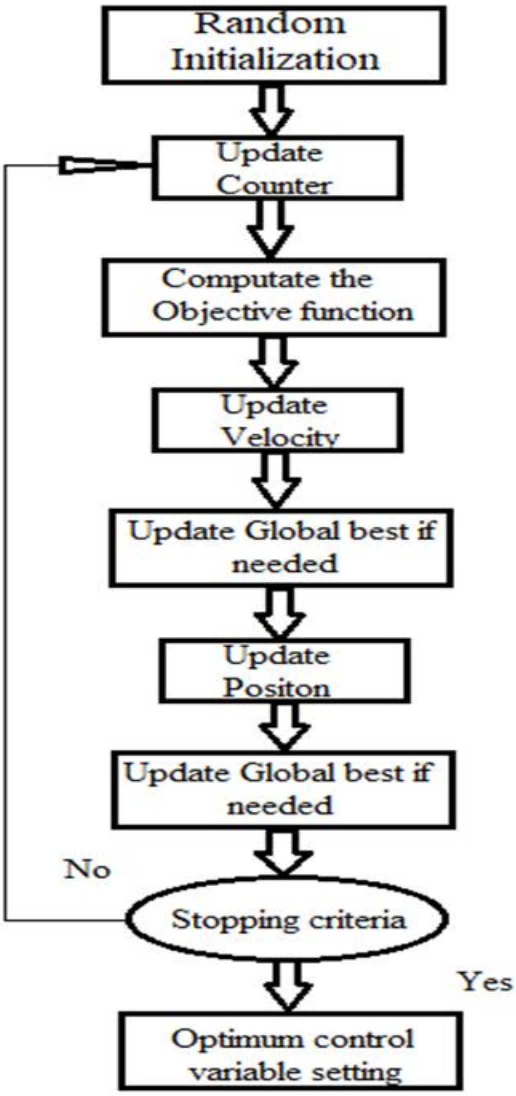

Figure 2-9: Flow chart of a Particle Swarm Optimization algorithm

2.6 IPSO algorithm

In [294], the IPSO referenced by Ziari and Platt employed optimal scheduling of distributed generation (DG) and capacitor banks to minimize dependability and line loss expenses, together with the investment costs related to electrical networks. In their research, they employed crossover and mutation operators to mitigate the risk of entrapment in local minima by minimizing power loss, preserving the voltage profile, and ensuring the stability margin. They exclusively accounted for authentic power losses during the simulation of IPSOs. In [300], Jain, Singh, and Srivastava devised a technique for optimizing the placement and sizing of numerous distributed generators (DGs) via Improved Particle Swarm Optimization (IPSO).

The researchers determined that the strategy outperformed existing traditional and analytical techniques for the placement of a single distributed generator (DG) [301].

In [302], the IPSO-based method proposed by Reddy et al. is an application for loss reduction in unbalanced radial transmission systems. Their study presented an efficient algorithm for determining where, what kind and what size of capacitor bank to install in unbalanced radial systems. In addition, a selected bus identification method was described for determining optimal capacitor placement locations using power loss indices (PLI) analysis. In unbalanced radial systems, the researcher used the IPSO approach to determine the optimal capacitor bank sizing. In [303], a power loss reduction model was implemented by Jamian et al. to size DGs and reduce power losses by selecting the survival particles that will remain in the next iteration.

There are n particles in the population of the IPSO algorithm, each representing a candidate solution. m is the number of optimized parameters for each particle, and each particle is an m dimensional real value vector. These parameters represent dimensions of the problem space. There are several steps in the process of IPSO [304]. Moreover, the IPSO algorithm needs to be adapted to each type of optimization problem that it must solve. Figure 2-10 shows how a specially personalized IPSO algorithm works to solve engineering optimization problems.

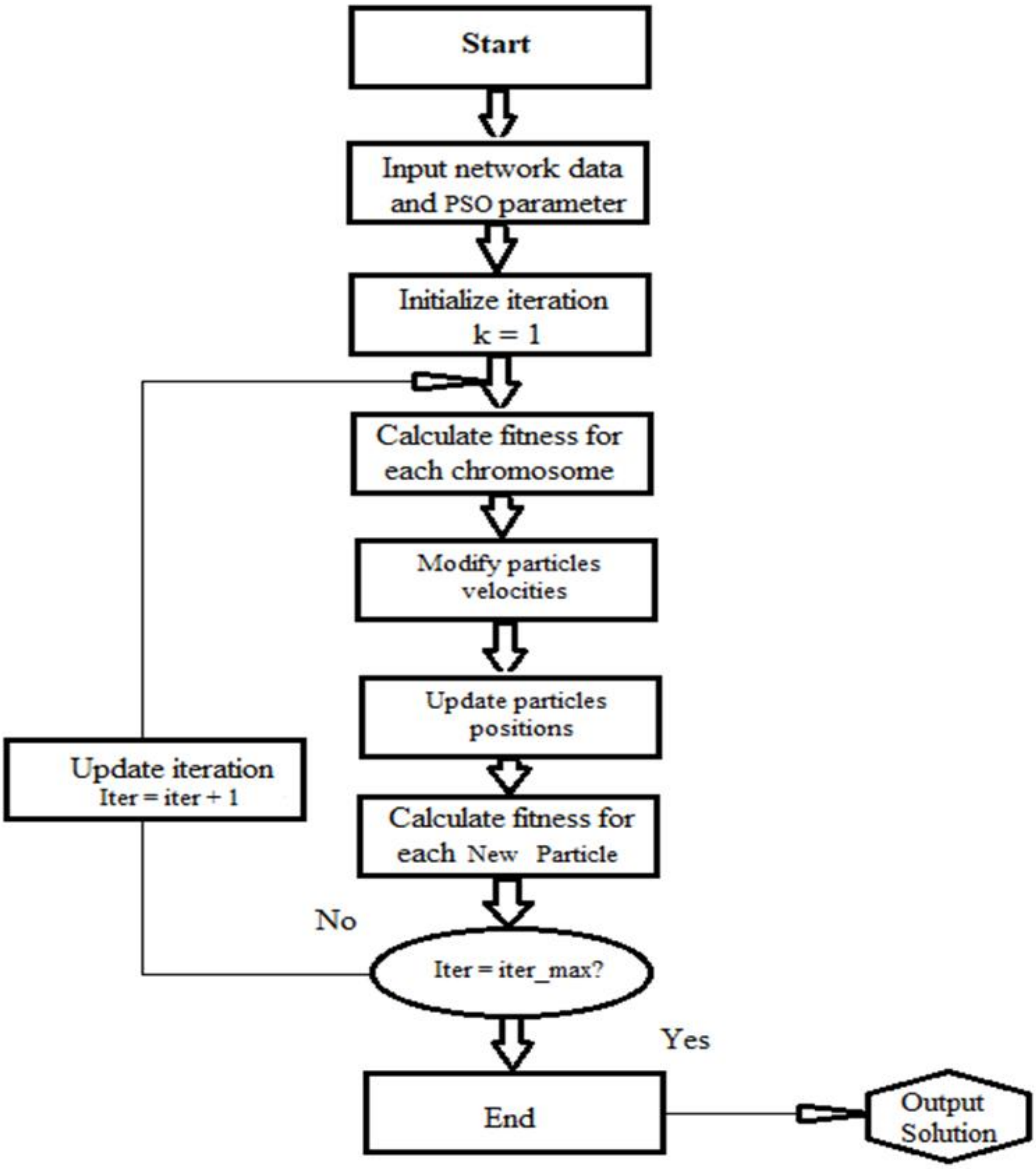

Figure 2-10: Flowchart showing steps for the IPSO algorithm

Summary

This chapter explored the potential role of electric vehicles as energy storage solutions for renewable energy across various regions. It emphasized the reduction of emissions from motor vehicles and highlighted the necessity of thoroughly evaluating the impacts of alternative transportation methods, especially those related to road travel. The lack of strong policies to promote and support electric vehicles hinders the rapid advancement of this technology. Furthermore, the absence of clear goals, defined timelines, attractive incentives, and adequate infrastructure obstructs effective planning by developers and other stakeholders. Consumers with limited financial means often find the initial costs of electric vehicles prohibitive, leading them to opt for more affordable internal combustion engine vehicles. The significant disparities in wealth, where a small segment of the population controls a large portion of economic resources, further restrict the market potential for electric vehicles (EVs). The government has an increased responsibility to address these challenges, with assistance from various stakeholders. These limitations illustrate that to effectively reduce transportation emissions, it is crucial to consider not only the transportation technologies but also the sociocultural factors that influence travel behavior. A careful assessment and implementation of strategies to enhance local services and minimize the need for commuting are vital. The following chapter will outline the modeling and system analysis.

CHAPTER THREE: MODELLING AND SYSTEM ANALYSIS

Introduction

Chapter Three offers an elaborate depiction of the mathematical framework used to simulate EV charging behavior. This includes a thorough explanation of charging demand, vehicle kinds and charging infrastructure. Integration of power system limitations, such as grid capacity, voltage thresholds and fluctuations in renewable energy generation. Analysis of dynamic variables, such as customer preferences, grid circumstances and real-time electricity costs.

3.1 Development of an optimization framework for determining optimal EV charging schedules at large-scale

3.1.1 IEEE-30 Bus Electrical Network

The IEEE-30 bus test is used to simulate the electrical infrastructure in the central United States, representing a subset of the larger American Electric Power System. These buses' potential model voltage ranges from 33 to 132 kilovolts [305]. No attention is paid to line restrictions during the IEEE-30 bus test. The line diagram of the test system is shown in Figure 3-1, and the busload injection of the IEEE-30 bus test system is shown in Table 3-1. The IEEE test system features both of these schematics.

Table 3-1: Injection bus load table for test system

Bus	Load (MW)	Bus	Load (MW)	Bus	Load (MW)
1	0.0	**11**	0.0	**21**	17.5
2	21.7	**12**	11.2	**22**	0.0
3	2.4	**13**	0.0	**23**	3.2
4	67.6	**14**	6.2	**24**	8.7
5	34.2	**15**	8.2	**25**	0.0
6	0.0	**16**	3.5	**26**	3.5
7	22.8	**17**	9.0	**27**	0.0
8	30.0	**18**	3.2	**28**	0.0
9	0.0	**19**	9.5	**29**	2.4
10	5.8	**20**	2.2	**30**	10.6

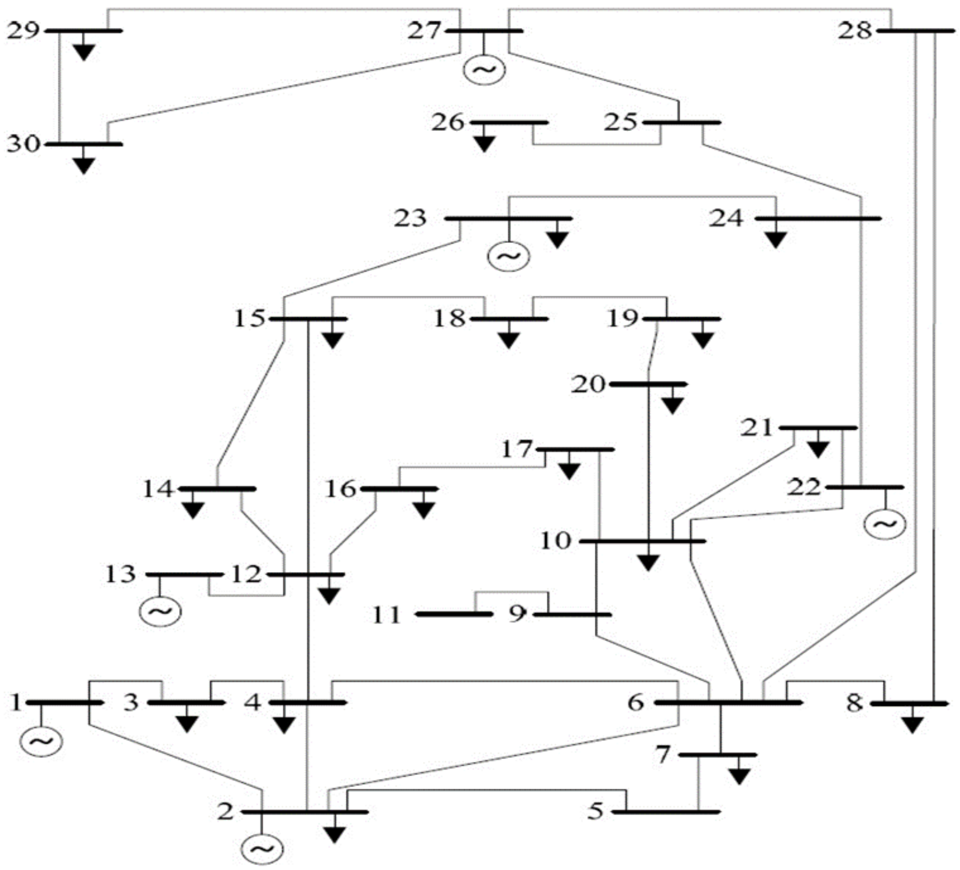

Figure 3-1: IEEE-30 bus test system [306]

3.1.2 Types of EVs and Number of EVs Used

This research aims to optimize the placement and size of three distinct classes of electric vehicles (EVs) under the condition that EVs are functioning in any of the three scenarios outlined below.

- In Scenario A, a Type 1 EV charging station injects active power, with the number of EVs to be employed decided by the suggested algorithm and one EV installed for every selected bus.
- Scenario B: A Type 2 EV charging station that injects both active and reactive power. The quantity of EVs to be employed is decided by the proposed method, and one EV is installed per chosen bus.
- Scenario C: The Type 3 EV charging station injects active power and absorbs reactive power, and the number of EVs to be employed is calculated by the proposed algorithm. One EV is installed for each chosen bus.

3.1.3 Methods for Selecting Weights in Multi-Objective Optimization

In a multi-objective function, the designer might assign different weights to different objectives. The author of this study highlights the importance of reducing actual power loss because doing so can reduce total operating costs and increase power network efficiency. Since the other two factors are also crucial, a study was conducted to determine the best weights combination for the multi-objective function by examining the impact of the weights on fitness. In this analysis, the researcher assumed that weight values were positive and within the following range: W1 was in the range of 0.6-0.80, whereas W2 and W3 were constrained to the range of 0.1-0.30.

This was done to place greater weight on the index for reducing real power loss, while all three indices were still taken into account as part of the multi-objective function. Note that in every case, the equation |W1| + |W2| + |W3| = 1 must hold true. The value of 68.81 MVAR was obtained through an estimation of the reactive power in the base case by utilizing the Newton Raphson methodology. This value was utilized for valid comparisons. The number of EVs in both the optimization work and the comparative work was the same. There is a 0-12 MW actual power limit for 1, 2 and 3 EVs, a 0-3 MVAR reactive power limit, and a 3-0 MVAR reactive power restriction respectively.

3.2 Description of the mathematical model for representing EV charging behaviour, including charging demand and charging infrastructure

When scheduling the charging and discharging of a vehicle, it is important to avoid programming the vehicle to be in both charging and discharging modes at the same time [307].

$$\{X\,(v,t)\ +\ Y\,(v,t)\ \leq\ 1\,\forall t\ \in\ \{1,2,\ldots,T\}\,;\ \forall v\ \in\ \{1,2,\ldots,V\}\,;\ X\,,Y\ \in\ \{0,1\}\} \tag{3-1}$$

The equation that describes the continuity of vehicle charging and discharging during the planning period is presented as follows:

$$E_s(v,t) \;=\; \{\left(\; Es\,(v,t) = \; Es\,(v,t\,-\,1) \,+\, \eta_v^{charge} \,+\, P_{EV}^{charge}\,(v,t) * \,\varDelta t + \frac{1}{D_v^{charge}} \times (P_{EV}^{charge}\,(v,t) * \,\varDelta t \right) \forall t \,\in (1,2,\dots,T)\,;\, \forall v \in (1,2,\dots,V\,)\} \tag{3-2}$$

The maximum capacity for recharging and discharging the battery of each vehicle during a specific time period is limited.

$$P_{EV}^{charge}(v,t) \;\le\; P_{charge,y}^{max} \times \; X\,(v,t)\,\forall t \;\in\; \{1,2,\dots,T\}\,;\,\forall v \in\; \{1,2,\dots,V\,\} \tag{3-3}$$

$$P_{EV}^{discharge}(v,t) \;\le\; P_{discharge,y}^{max} \times \; X\,(v,t)\,\forall t \;\in\; \{1,2,\dots,T\}\,;\,\forall v \in\; \{1,2,\dots,V\,\} \tag{3-4}$$

Ensuring that an electric vehicle's battery is discharged to a specific level and charged to a specific amount helps prevent the battery from failing prematurely and extends its overall lifespan:

$$(Es\,(v,t) \;\le\; \psi_v^{max}\forall t \;\in\; \{1,2,\dots,T\}\,;\,\forall v \;\in\; \{1,2,\dots,V\,\}\;) \tag{3-5}$$

$$(Es\,(s,v,t) \;\le\; \psi_v^{min}\forall t \;\in\; \{1,2,\dots,T\}\,;\,\forall v \;\in\; \{1,2,\dots,V\,\}\;) \tag{3-6}$$

which are computed using the following formulae:

$$\psi_v^{max} = \; \phi_v^{max} \times E_{BatCap,v} \qquad \forall v \;\in\; \{1,2,\dots,V\,\} \tag{3-7}$$

$$\psi_v^{min} = \; \phi_v^{min} \times E_{BatCap,v} \qquad \forall v \;\in\; \{1,2,\dots,V\,\} \tag{3-8}$$

The restrictions on the hourly charging and discharging of the battery are directly related to the amount of energy stored in the battery during the previous period and its overall maximum capacity.

$$\frac{1}{\eta_v^{DCharge}} \times \left(P_{EV}^{DCharge}\,(v,t) \times \,\Delta t\right) \le \; E_s\,(v,t-1) \qquad \forall t \;\in\; \{1,2,\dots,T\}\,;\,\forall v \;\in\; \{1,2,\dots,V\,\} \tag{3-9}$$

$$\eta_v^{DCharge} \times P_{EV}^{DCharge}(v,t) \times \Delta t \leq \left(\psi_v^{max} - E_s(v,t-1)\right) \quad \forall t \in \{1,2,\ldots,T\}\,;\ \forall v \in \{1,2,\ldots,V\} \tag{3-10}$$

The specified energy capacity for each vehicle's battery upon exiting the parking lot is as follows:

$$SOC_{des}^{v} = SOC_{initial}^{v} + r\,and\,number\,(0,[1 - SOC_{initial}^{v}]) \qquad \forall v \in \{1,2,\ldots,V\} \tag{3-11}$$

The frequency with which the status can transition between charge and discharge modes, and vice versa, is contingent upon the age of the automobile batteries. The intended charge/discharge profile for the vehicles is generated through linear programming that utilizes binary variables [308]:

$$P_{Des}^{Charge}(v) = \left[P_{EV}^{Charge}(v,t)\right] \qquad v \,\epsilon\, \{1-V\}, t \,\epsilon\, \{1-T\} \tag{3-12}$$

$$P_{Des}^{Discharge}(v) = \left[P_{EV}^{Disharge}(v,t)\right] \qquad v \,\epsilon\, \{1-V\}, t \,\epsilon\, \{1-T\} \tag{3-13}$$

3.2.1 Formulations pertaining to non-renewable distributed generation sources

Privately owned non-renewable distributed generation sources focus on profit maximization as their primary objective:

$$f_{1,2} = max\,(\sum_{t=1}^{T}[\sum_{j=1}^{J}\{P_{REDG}(j,t) \times Pr_{MRT}(t) - C_{REDG}(j,t)\}] \times \Delta t \tag{3-14}$$

3.2.2 Limitations on non-renewable distributed generation sources

The expense associated with non-renewable resources is represented as a mathematical function that depends on their energy production. Consequently, when utilizing the linear programming optimization technique, it is essential to take into account cost functions that have suitable approximations in the designated format [310]:

$$C_{REDG}(j,t) = a_j + bj^{*}\,P_{REDG}(j,t) \qquad \forall t \in \{1,2,\ldots,T\}\,;\ \forall v \in \{1,2,\ldots,V\} \tag{3-15}$$

The constraints regarding the upper and lower limits of production capacity for non-renewable distributed generators are outlined as follows:

$$P_{REDG}\ (j,t) \leq\ P_{REDGj}^{max}\ \times u(j,t) \qquad \forall t\ \in\ \{1,2,\ldots,T\}\ ;\ \forall v \in\ \{1,2,\ldots,V\ \} \tag{3-16}$$

$$P_{REDG}\ (j,t) \leq\ P_{REDGj}^{min}\ \times u(j,t) \qquad \forall t\ \in\ \{1,2,\ldots,T\}\ ;\ \forall v \in\ \{1,2,\ldots,V\ \} \tag{3-17}$$

The expense associated with the construction of non-renewable distributed generators is determined through the following calculation:

$$SU\ (j,t) =\ S_{Cj}\ \times (u(j,t) - u(j,t-1))\ \ : SU(j,t) \geq 0 \tag{3-18}$$

The rate of electricity production from non-renewable distributed sources may fluctuate at the following rates:

$$\left(P_{REDG}(j,t+1) -\ P_{REDG}\ (j,t)\right) \leq RUP_{REDG}^{j} \tag{3-19}$$

$$\left(P_{REDG}(j,t+1) +\ P_{REDG}\ (j,t)\right) \leq RUP_{REDG}^{j} \tag{3-20}$$

By employing linear programming that incorporates binary variables, it is possible to identify the optimal distribution that creates a resource production pattern:

$$P_{Des}^{DG}\ (j) = [P_{REDG}\ (j,t) \qquad jv\ \epsilon \{1-J\}, t\ \epsilon \{1-T\} \tag{3-21}$$

The total power produced, combined with the power obtained from the energy market, must equal the amount of power utilized:

$$P_{NTW}(t) + \sum_{w=1}^{W} P_w(t) + \sum_{pv\ =1}^{PV} P_{pv}(t) + \sum_{j\ =1}^{J} P_{DG}(j,t) + \sum_{v\ =1}^{V} P_{EV}^{Charge}\ (v,t) + \sum_{v\ =1}^{V} P_{EV}^{Charge}\ (v,t) +\ P_{LOAD}(t) +\ P_{LOSS}(t) \qquad \forall t \in\ \{1,2,\ldots,T\} \tag{3-22}$$

The network faces a number of technical limitations, outlined as follows:

$$P_n(t) =\ \sum_{m=1}^{N} |V_n(t)|\,|V_m(t)|\left|Y_{n,m}\right| COS\ \left(\ \delta_m(t) -\ \delta_n(t) + \delta_{n,m}\right) \forall n,t \tag{3-23}$$

$$Q_n(t) = \sum_{m=1}^{N} |V_n(t)|\,|V_m(t)|\left|Y_{n,m}\right| SIN\left(\delta_m(t) - \delta_n(t) + \delta_{n,m}\right) \forall n,t \tag{3-24}$$

$$|S(n,m,t)| \leq S_{n,m}^{max} \qquad \forall t \in \{1,2,\ldots,T\};\ \forall n,m \in \{1,2,\ldots,N\} \tag{3-25}$$

$$V_n^{min} \leq V(n,t) \leq V_n^{max} \qquad \forall t \in \{1,2,\ldots,T\};\ \forall v \in \{1,2,\ldots,N\} \tag{3-26}$$

$$P_{NTW}(t) \leq P_{NTW}^{max} \qquad \forall t \in \{1,2,\ldots,N\} \tag{3-27}$$

$$P_{TRANS}(n,t) \leq P_{TRANS}^{max} \qquad \forall t \in \{1,2,\ldots,T\};\ \forall v \in \{1,2,\ldots,N\} \tag{3-28}$$

Wind and solar energy are the main sources of electricity for wind turbines and photovoltaic systems. Previous research has employed probabilistic functions to model their power generation, as outlined in the following section:

$$f(I_r^t) = \left\{\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\right\} \times I_r^{t(\alpha-1)} \times (1 - I_r^t)^{\beta-1}\ for\ 0 \leq I_r^t \leq 1, a \geq 0, \beta \geq 0 \tag{3-29}$$

The output power of the photovoltaic system can be determined for varying radiation intensities at specific moments by examining the distribution of projected radiation intensity across different areas and utilizing the function that converts radiation into power, as demonstrated below [311].

$$P_{pv} = \eta^{pv} \times S_r^{pv} \times I_t^r(1 - 0.005 \times (T_a - 25)) \tag{3-30}$$

This study models wind speed behavior via the Rayleigh probability density function.:

$$f\left(V_f^t\right) = \left(\frac{k}{c}\right) \times \left(\frac{V_f^t}{c}\right)^{(k-1)} \times e^{-(\frac{V_f^t}{c})^k} \qquad 0 \leq V_f^t \leq \infty \tag{3-31}$$

The power output of the wind turbine can be determined at any moment by utilizing the power conversion function specified in the following equation:

$$P_w = \{\, 0 \leq V_f^t \leq V_{ci} \,\} = P_{rated} \times \frac{\left(V_f^t - V_{ci}\right)}{(V_r - V_{ci})} P_{rated} \,\}\ V_r \leq V_f^t \leq V_{co}\ 0 \qquad V_{co} \leq V_f^t \tag{3-32}$$

The procurement of energy from the market alters the optimal production timetable for distributed generation resources, thereby affecting the preferred charging and discharging patterns of electric vehicles. The aim is to devise a strategy for the allocation of available resources to satisfy the needs of electric vehicle owners and distributed generation sources, while simultaneously minimizing technological constraints on the network and reducing operational costs [312]. To accomplish these goals, the system operator employs the cost optimization technique (COT) described below for all scenarios. The first section outlines the costs associated with losses and the expenses incurred from energy purchased in the market. The subsequent components of the equation clarify that owners of distributed energy resources and electric vehicles will receive compensation for their participation in the proposed framework [313].

$$\begin{aligned} COT \ = min\Bigg(\sum_{t=1}^{T}\Bigg\{&(P_{NTW}\ (t)^{*}\ Pr_{MRT}(t) +\ P_{LOSS}\ (t)^{*}\ Pr_{LOSS}(t)) \\ &+ \left|\sum_{j=1}^{J}(P_{REDG}(j,t) -\ P_{Des}^{REDG}(j,t)\right| \times\ K_{REDG} \\ &+ \left|\sum_{v=1}^{V}(P_{EV}^{Charge}(v,t) -\ P_{Des}^{Charge}(v,t)\right| \times\ K_{Charge} \\ &+ \left|\sum_{v\ =1}^{V}(P_{EV}^{Charge}(v,t) -\ P_{Des}^{Charge}(v,t)\right| \times K_{Discharge}\Bigg\} \times \Delta t\Bigg) \end{aligned} \quad (3\text{-}33)$$

3.3 Constrains of Models

3.3.1 System Inequality constraints

The voltage at each bus at a given time, denoted as $V_{i.t}$, is constrained by the minimum voltage V_{min} and the maximum voltage V_{max}. The rates of discharging and charging are restricted by the minimum discharging and charging values $P_{dc.min}$ and $P_{ch.min}$, while the maximum discharging and charging rates are defined by $P_{dc.max}$ and $P_{ch.max}$, respectively [314]. Additionally, the number of electric vehicles (EVs) η_{EV} ,t is bounded by the minimum η_{min} and maximum η_{max} values, and the current I_{tj} flowing between bus i and bus j is limited by the maximum current I_{max}.

$$V_{min} \leq V_{i.t} \leq V_{max} \tag{3-34}$$

$$P_{dc.min} \leq P_{dc,t} \leq P_{dc.max} \tag{3-35}$$

$$\eta_{min} \leq \eta_{EV} \leq \eta_{max} \tag{3-36}$$

$$I_{tj} \leq I_{max} \tag{3-37}$$

3.3.2 System Equality Constraints

The power flow must guarantee that the active power $P_{G_{i,t}}$ and reactive power $Q_{G_{i,t}}$ produced are equal to the load demand and the line losses occurring between bus i and bus j at time t.

$$\begin{aligned} P_{G_{i,t}} = {} & P_{d_{i,t}} \pm P_{ev_{i,t}} \\ & + V_{t,t} \sum_{t=1}^{Nbus} V_{j,t} \left[G_{tj} \cos(\delta_{t,t} - \delta_{j,t}) + B_{i,j} \sin(\delta_{t,t} - \delta_{j,t}) \right] \end{aligned} \tag{3-38}$$

$$Q_{G_{i,t}} = Q_{d_{i,t}} + V_{t,t} \sum_{t=1}^{Nbus} V_{j,t} \left[B_{tj} \cos(\delta_{t,t} - \delta_{j,t}) + G_{i,j} \sin(\delta_{t,t} - \delta_{j,t}) \right] \tag{3-39}$$

- $P_{ev_{i,t}}$ represents the overall power either consumed or supplied at bus i by the electric vehicles (EVs).
- B_{tj} denotes the susceptance connecting bus i and bus j. and
- $Q_{d_{i,t}}$ is demand reactive power

3.3.3 Test System Details

The system being investigated is the IEEE 118-bus system, and the display of this network can be found in Figure 3-2. Table 3-2 shows generator data of the IEEE-118 bus system. Table 3-5 depicts the limitations of the system [315].

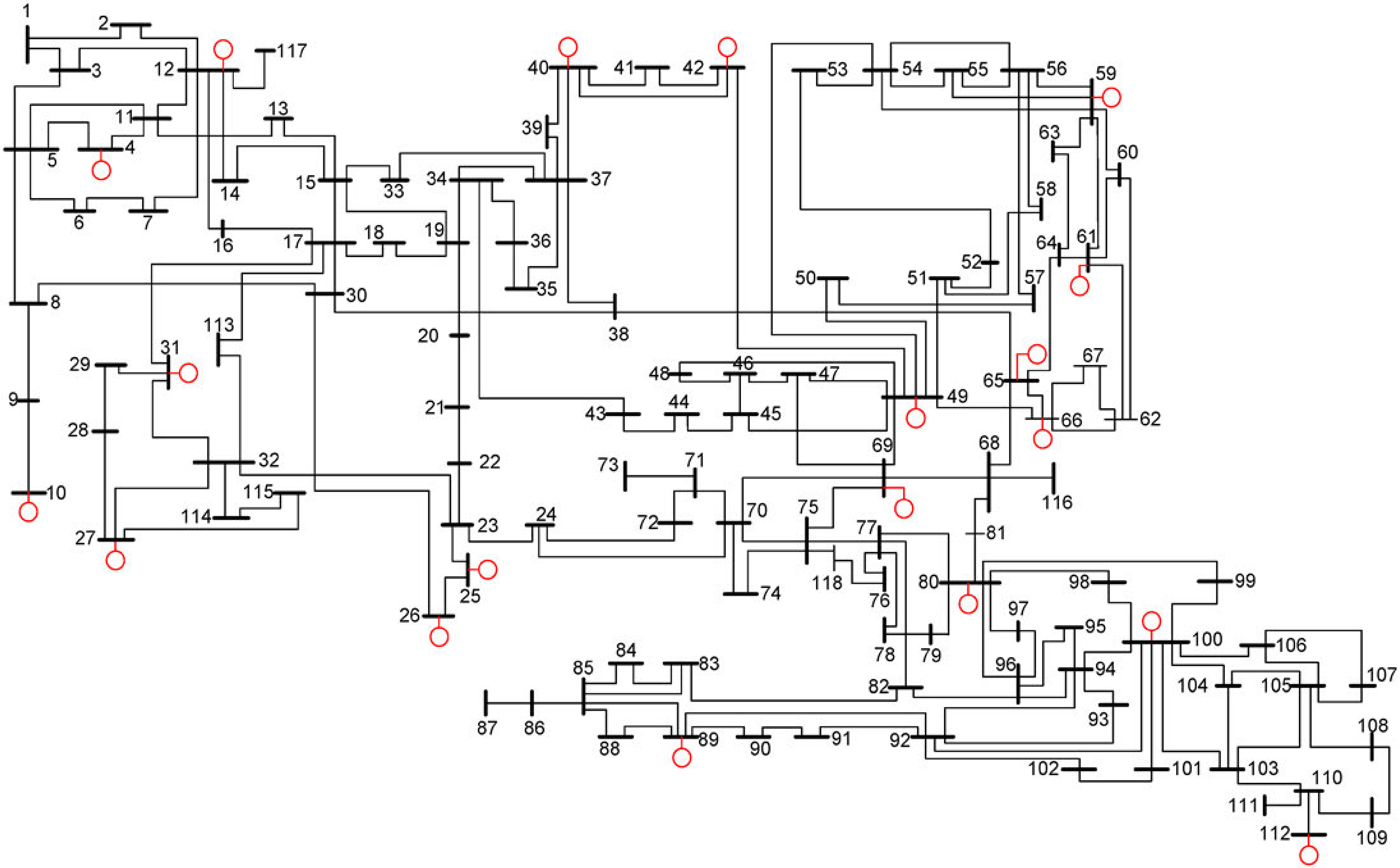

Figure 3-2: IEEE 118-Bus Test System One-Line Diagram [316]

Table 3-2: Generator Data of the IEEE-118 Bus System

Bus No.	P_G (MW)	Q_G (MVar)	P_{max} (MW)	Q_{max} (MVar)	Q_{min} (MVar)
10	450	-5	550	200	-147
12	85	91.27	185	120	-35
25	220	49.72	320	140	-47
26	314	9.89	414	1000	-1000
31	7	31.57	107	300	-300
46	19	-5.25	119	100	-100
49	204	115.63	304	210	-85
54	48	3.9	148	300	-300
59	155	76.83	255	180	-60
61	160	-40.39	260	300	-100
65	391	80.76	491	200	-67
66	392	-1.95	492	200	-67
69	513.48	-82.39	805.2	300	-300
80	477	104.9	577	280	-165
87	4	11.02	104	1000	-100
92	607	0.49	1100	9	-3
100	252	108.87	352	155	-50
103	40	41.69	140	40	-15
111	36	-1.84	136	1000	-100

Table 3-3: The initial power flow and the specifications of the system itself

Configuration of the system	**Value**
Vsys (kV)	13.24
Nbus	118
BASE MVA	100.00
S_{Load} (MVA)	22.7089 + j 17.1475
PTotalloss (kW)	1291.9812
QTotalloss (kVar)	977.9570
V_{min} (p. u) at bus	0.8574 at 77

Table 3-4: Limitations of the system

Constraint	Value
Voltage limits	$0.90 \leq V_i \leq 1.05$ p. u
PV sizing limits for 118-bus system	$0 \leq P_{sr} \leq 22709$ kW
WT sizing limits for 118-bus system	$0 \leq P_r \leq 22709$ kW

3.4 Consideration of dynamic factors, including user preferences, grid base conditions, and real-time electricity prices

3.4.1 Base Scenario

The lack of integration between REDGs and charging stations leads to a system power loss cost of R15,066,000.00. Therefore, the total expenditure amounts to R405,930,000.00. The cumulative voltage violations for the day total 93.6672 V, and the load factor is 0.7154. This research presents an analysis to assess the effectiveness and influence of establishing charging stations and REDGs. Figure 3-3 illustrates the anticipated wind velocities in South Africa, whereas Figure 3-4 depicts the projected solar irradiation. Figure 3-5 depicts the daily load profile over the course of the day.

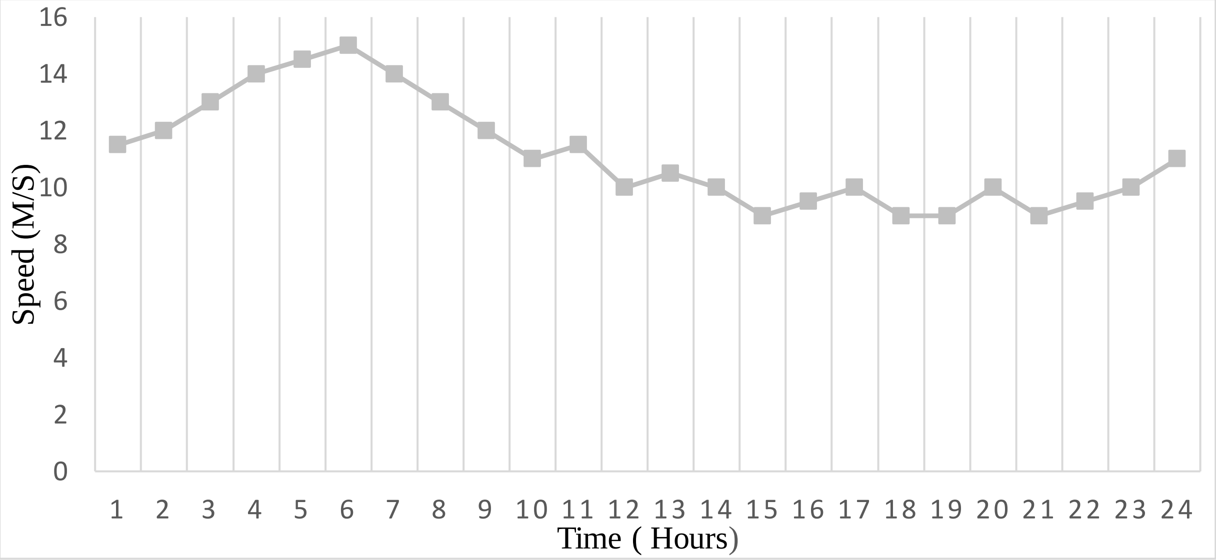

Figure 3-3: Forecasted wind speeds during the day

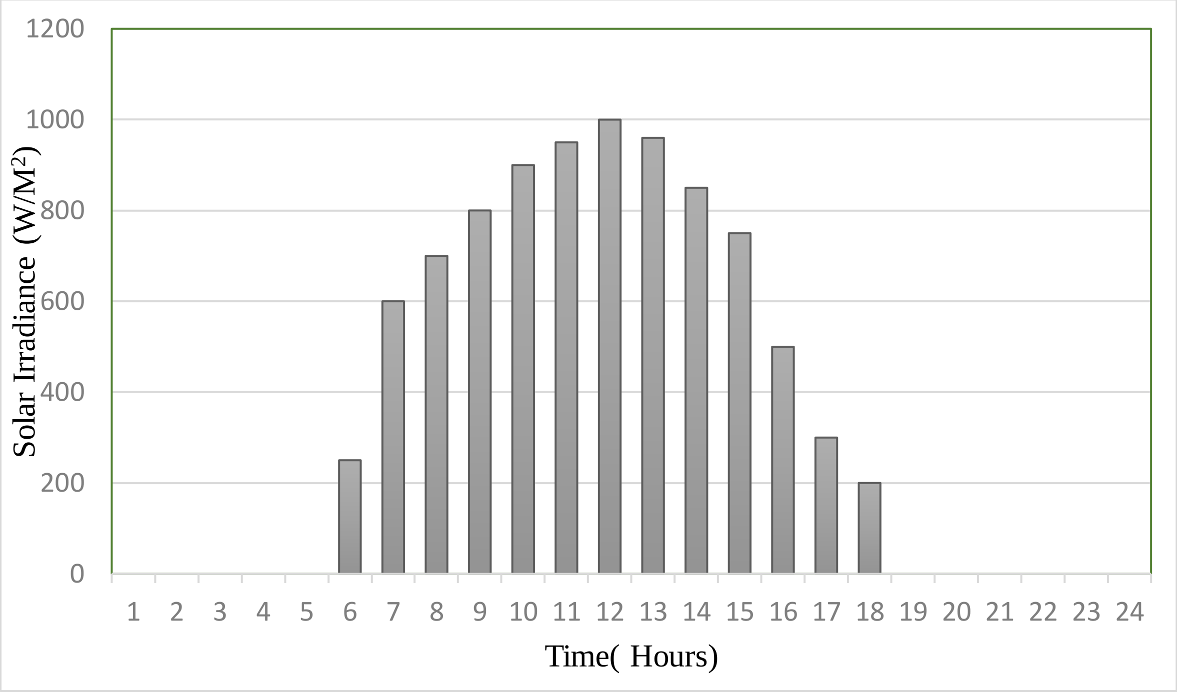

Figure 3-4: Forecasted solar irradiance during the day

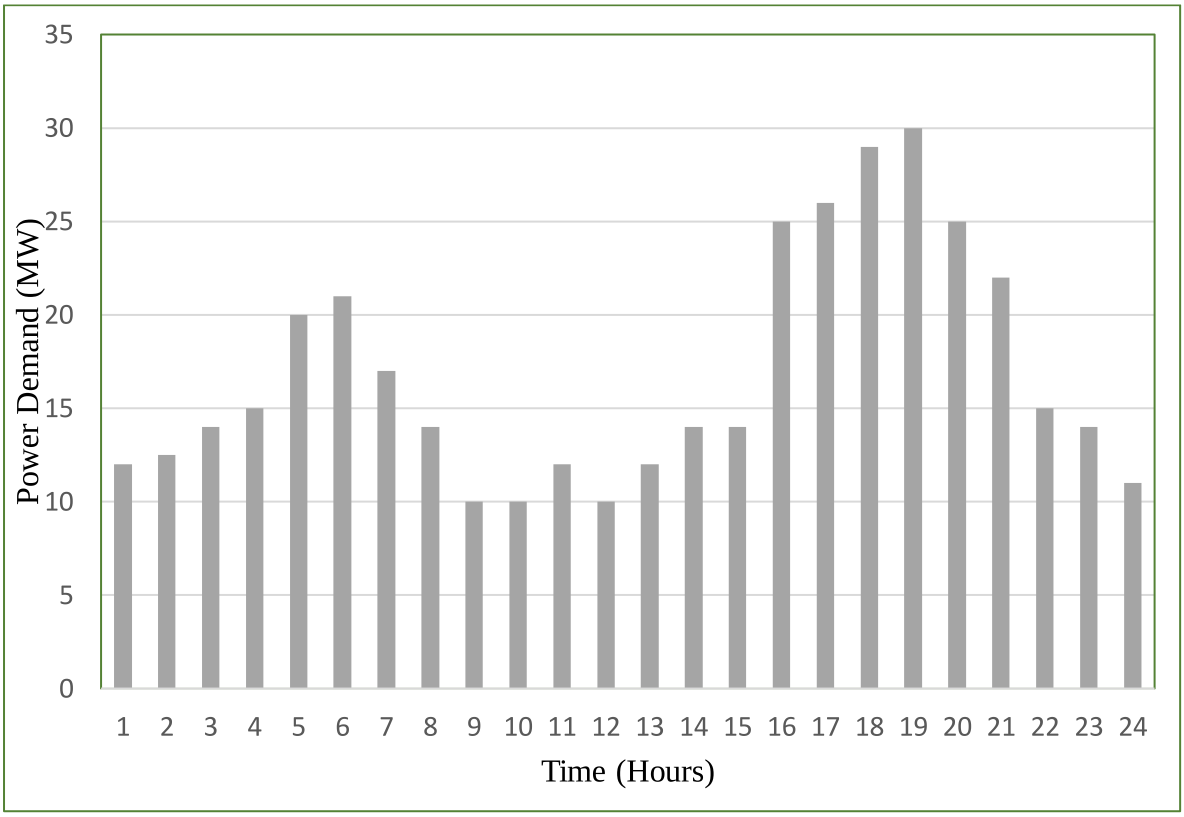

Figure 3-5: Daily load profile

Summary

In relation to modeling the behavior of electric vehicle charging, this chapter offered a comprehensive description of the mathematical framework that is applied. The need for charging, the many types of vehicles, and the infrastructure for charging were all thoroughly discussed in this chapter. The discussion included constraints on the power system, such as grid capacity limitations, voltage thresholds and fluctuations in the amount of energy generated by renewable sources. Real-time electricity pricing, consumer preferences and grid conditions were some of the dynamic aspects taken into consideration in the analysis. Included in this package were both the base case and particular values of interest. The following chapter describes the optimization framework.

CHAPTER FOUR: OPTIMIZATION FRAMEWORK

Introduction

The fourth chapter outlines the development of an optimization methodology aimed at identifying the most efficient charging schedules for electric vehicles on a broad scale. This results in the creation of an optimization framework for establishing ideal electric vehicle charging schedules on a broad scale. The formulation of objective functions aimed at minimizing energy costs, grid congestion, and emissions, while maximizing renewable energy utilization and system efficiency, along with the selection of optimization algorithms—such as linear programming, mixed-integer programming, or metaheuristic techniques—effectively addresses the scheduling problem.

4.1 Formulation of objective functions

The weight values in this study are restricted to positive values, as follows:

- W_1 was between 0.6 and 0.8; and
- W_2 and W_3 were restricted between 0.2 and 0.3

This was done to ensure that the multi-objective function considers all three indices (f_1, f_2 and f_3) while also ensuring that the real power loss reduction index, as previously stated, receives much attention. All of the effects of weight values and fitness are shown in Table 4-1. It is also crucial to remember that each situation requires that the condition $|f_1|+|f_2|+|f_3|=1$ be met.

Table 4-1: The Effects of Weights on Fitness

Weight 1 (f_1)	Weight 2 (f_2)	Weight 3 (f_3)	Best Fitness
0.5	0.1	0.4	0.909
0.5	0.4	0.1	0.910
0.6	0.1	0.3	0.910
0.5	0.3	0.2	0.909
0.6	0.3	0.1	0.909
0.7	0.1	0.2	0.910

The set of weights chosen, which yielded the optimal minimal fitness, is presented in Table 4-1. The multi-objective function is defined by equation 4-1, and the selected weights are detailed as follows.:

W1=0.5, W2=0.3, and W3=0.2. (4-1)

$$MOF = 0.5f_1 + 0.3f_2 + 0.2\,f_3 \tag{4-2}$$

Note that f$_1$ is the total voltage deviation at each bus for 24 h, which is expressed by equation 4-3 below:

$$f_1 = \sum_{t=1}^{24} \sum_{i=1}^{Nbus} \left|1 - V_{i,t}\right| \tag{4-3}$$

In this context, *Nbus* represents the total number of buses, while $V_{i,\,t}$ denotes the voltage magnitude at each bus at a given moment. Additionally, *f*$_2$ signifies the overall Loss of Energy (LE), which is defined by the equations presented in 4-4, 4-5, and 4-6.

$$f_2 = LE = \sum_{t=1}^{24} \sum_{i=1}^{Nbus} P_{REDG_{i,t}} - \sum_{t=1}^{24} P_{loss_t} - \sum_{t=1}^{24} \sum_{i=1}^{Nbus} P_{d_{i,t}} \tag{4-4}$$

$$P_{REDG_{i,t}} = \sum_{w=1}^{N.PWT_i} PW_{w,t,t} + \sum_{w=1}^{N.PWT_i} PP_{PV,t,t} \tag{4-5}$$

$$P_{loss_t} = \sum_{t=1}^{Nbus} \sum_{j>1}^{Nbus} \left[V_{t,t}^2 + V_{j,t}^2 - 2V_{j,t}V_{j,t}COS(\,\delta_{t,t} - \delta_{j,t}\,)\,\right] \tag{4-6}$$

Where

- $PP_{PV,t,t}$ represents the output power produced by the photovoltaic panel at a designated time;
- $P_{d_{i,t}}$ denotes the active power demand;
- $N.PWT_i$ indicates the number of wind turbine stations located at bus I;
- $P_{REDG\,i,t}$ refers to the active power generated by REDG at bus i during time t;
- $N.PV_i$ signifies the number of photovoltaic stations present;
- $PW_{w,t,t}$ indicates the power generated by the wind turbine;
- $G_{i,j}$ represents the conductance between bus i and bus;
- P_{loss_t} denotes the total power loss at a specific time, and
- $\delta_{i,t}$ indicates the voltage angle at a particular bus.

The power output of a wind turbine can be determined as a function of wind speed by utilizing equation 4-7.

$$PW_{w,t,i} = \begin{bmatrix} 0 & for\ V_{i,t} < V_{c,i}\ and\ V_{t,i} > V_{co} \\ P\left(\dfrac{V_{i,t} - V_{c,i}}{V_r - V_{c,i}}\right) & for\ V_{c,i} \leq V_{i,t} \leq V_r \\ P_{r_i} & for\ V_r < V_{i,t} \leq V_{co} \end{bmatrix} \tag{4-7}$$

Where

- $V_{c,i}$ is cut-in speed,
- V_{co} is cut-out speed.
- $V_{i,t}$ is wind speed time t,
- V_r is rated speed, and
- P_{r_i} is rated power from the turbine at bus i,

The output power of photovoltaic unit can be determined using equation 4-8 as a function of sun irradiance.:

$$PPV_{pv,t,t} = \begin{Bmatrix} \dfrac{P_{sr_i} \times G_{s,t}^2}{G_{std} \times X_C} & \& & 0 < G_i \leq X_c \\ \dfrac{P_{sr} \times G_{s,t}}{G_{std}} & \& & G_{s,i} \geq X_c \end{Bmatrix} \tag{4-8}$$

Where

- G_{std} is global irradiance and is forecasted to be 1000W/m2,
- P_{sr_i} is rated power from the photovoltaic panels at bus i,
- X_c is specific irradiance point set to be 120W/m^2, and
- $G_{s,t}$ is solar irradiance at each specific time

f$_3$ forms part of the multi objective function and is the total cost, which is formulated using equations 4-9 and 4-10 as follows:

$$f_3 = \sum_{t=1}^{24} (P_{sub_t} \times 1.2 \times C_m) + \sum_{t=1}^{24} f_{ch\_t} - \sum_{t=1\ dc\_1}^{24} f + \sum_{t=1_{loss,t}}^{24} P \times C_m + OM_{REDG} + AL_{REDG} \tag{4-9}$$

$$P_{sub,t} = \sum_{i=1}^{Nbus} (P_{d_{i,t}} + P_{loss,t} - \sum_{i=1}^{Nbus} \sum_{k=1}^{n_{EV}} P_{dc_{i,k,t}} + \sum_{i=1}^{Nbus} \sum_{k=1}^{n_{EV}} P_{ch_{i,k,t}} - \sum_{i=1}^{Nbus} P_{REDG_{i,t}} \tag{4-10}$$

where

- C_m represents the expense associated with acquiring purchasing power from the market;
- n_{EV} denotes the quantity of vehicles present during each time interval; and
- P_{sub_t} indicates the power produced by the primary substation.

EVs are modeled as active power sources during discharging and controllable loads during charging. The discharging energy price C_{m-DC} exceeds only the expense of market purchasing power, which incentivizes EV owners to connect their vehicles to the grid for discharging, and is computed using equations 4-11 and 4-12[317].

$$f_{ch_1} = \sum_{t=1}^{Nbus} \sum_{k=1}^{N_{EV}} P_{ch_{i,k,t}} \times C_m \tag{4-11}$$

$$f_{disch_1} = \sum_{t=1}^{Nbus} \sum_{k=1}^{N_{EV}} P_{dc_{i,k,t}} \times C_{m-DC} \tag{4-12}$$

Where

- f_{disch_1} denotes the income generated by electric vehicle owners for discharging during peak hours. and
- f_{ch_1} expresses the EV charging cost

The overall investment cost (IC) associated with REDG units can be represented by equation 4-13 as detailed below.:

$$IC_{REDG} = \sum_{i=1}^{Nbus} \left(\sum_{PV=1}^{N.PV_i} C_{SREDG} P_{sr_{pv.i}} + \sum_{W=1}^{N.PT_i} C_{WREDG} Pr_{w.i} \right) \tag{4-13}$$

The annual installment (AI) required by the utilities for the investment in renewable energy station installation can be defined by equations 4-14 and 4-15:

$$AL_{REDG} = CRF \times CL_{REDG} \tag{4-14}$$

$$CRF = \frac{i_{rt}\ (i_{rt} + 1)^N}{(i_{rt} + 1)^N - 1} \tag{4-15}$$

- N is the number of years and is taken as 20
- CRF is the annual loan payment on the borrowed money
- i_{rt}, the rate of interest, was taken as 10%

The annual operational and maintenance cost of the REDG unit is articulated by equation 4-16 as follows:

$$\begin{aligned} OM_{REDG} = {} & 365 \\ & \times \sum_{t=1}^{24} \left(\sum_{t=1}^{Nbus} \sum_{PV=1}^{N.PV_i} PPV_{pv,t,t} \times OM_{pv} \right. \\ & \left. + \sum_{t=1}^{Nbus} \sum_{w=1}^{N.PWT_i} PV_{w,t,t} \times OM_w \right) \end{aligned} \tag{4-16}$$

4.2 Selection of optimization algorithms to solve the scheduling problem efficiently

To facilitate the efficient distribution of Renewable Energy Distributed Generators (REDGs), the proposed solution integrates Genetic Algorithm (GA) with Improved Particle Swarm Optimization (IPSO), as illustrated in Figure 4-1, with procedural steps detailed in equations 4-17 to 4-26. The objective is to position REDGs and Electric Vehicles (EVs) within the power system while adhering to the system's constraints. REDGs are strategically allocated to specific buses within the transmission network. The selection of these buses for REDG placement is influenced by parameters that affect power flow and the sensitivity of power loss. The HGAIPSO algorithm effectively streamlines this selection process by minimizing the total number of iterations [318]. By considering sensitivity factors, HGAIPSO successfully determines optimal locations for REDG installation. A flow chart depicting this process is presented in Figure 4-2.

$$g_k(\vec{X}) \le 0 \qquad k = 1,2,\ldots.,K \tag{4-17}$$

$$h_e(\vec{X}) \le 0 \qquad e = 1,2,\ldots.,E \tag{4-18}$$

$$\underline{L}_j \le x_j \le \overline{U}_j \qquad j = 1,2,\ldots.,D \tag{4-19}$$

$$\vec{o}_1 = \vec{x}_1 + \beta \times (\vec{x}_2 - \vec{x}_3) \tag{4-20}$$

$$\vec{o}_2 = \vec{x}_2 + \beta \times (\vec{x}_3 - \vec{x}_1) \tag{4-21}$$

$$\vec{o}_3 = \vec{x}_3 + \beta \times (\vec{x}_1 - \vec{x}_2) \tag{4-22}$$

$$f(\vec{x}_1) \le f(\vec{x}_2) \le f(\vec{x}_3) \tag{4-23}$$

$$\omega = (\omega_{max} - \omega_{max}).\frac{(k_{max} - k)}{k_{max}} + \omega_{min} \tag{4-24}$$

$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \qquad 4.1 \le \varphi \le 4.2 \tag{4-25}$$

$$\begin{aligned} V_i(t+1) = C\{\omega v_i(t) + ((c_{1f} - c_{1i})\frac{k}{k_{max}} + c_{1i}).r_1(t)[pbest_i(t) - x_i(t)] \\ + ((c_{2f} - c_{2i})\frac{k}{k_{max}} + c_{2i}).r_2(t)[leader_i(t) - x_i(t)]\} \end{aligned} \tag{4-26}$$

c_1i =2.7; c_{1f} =0.3; c_2i =0.4; c_{2f} =2.6;

$c_1 = ((c_{1f} - c_{1i}) \times (k/k_{max})) + c_{1i}$; $c2 = ((c_{2f} - c_{2i}) \times (k/k_{max})) + c_{2i}$;

$v_{max}(j) = (\max(X(,j))) \times penalty\ factor$

if particle velocity(ij) = 0 if rand < 0.5

$V(i, j) = rand \times v_{max}(j)$

else

$V(i, j) = -rand \times v_{max}(j)$

```
        end
            end
X(i,j) = X(i,j)  +V(i,j)
```

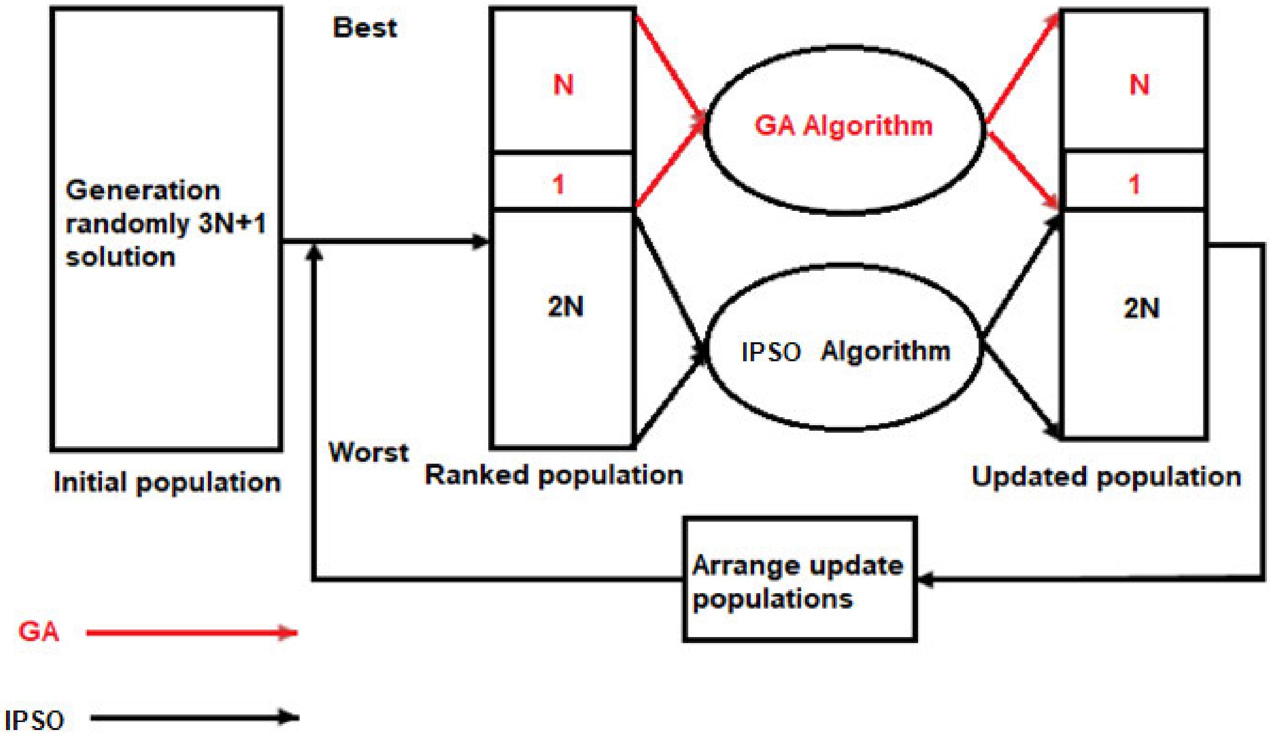

Figure 4-1: GA and IPSO combination (HGAIPSO)

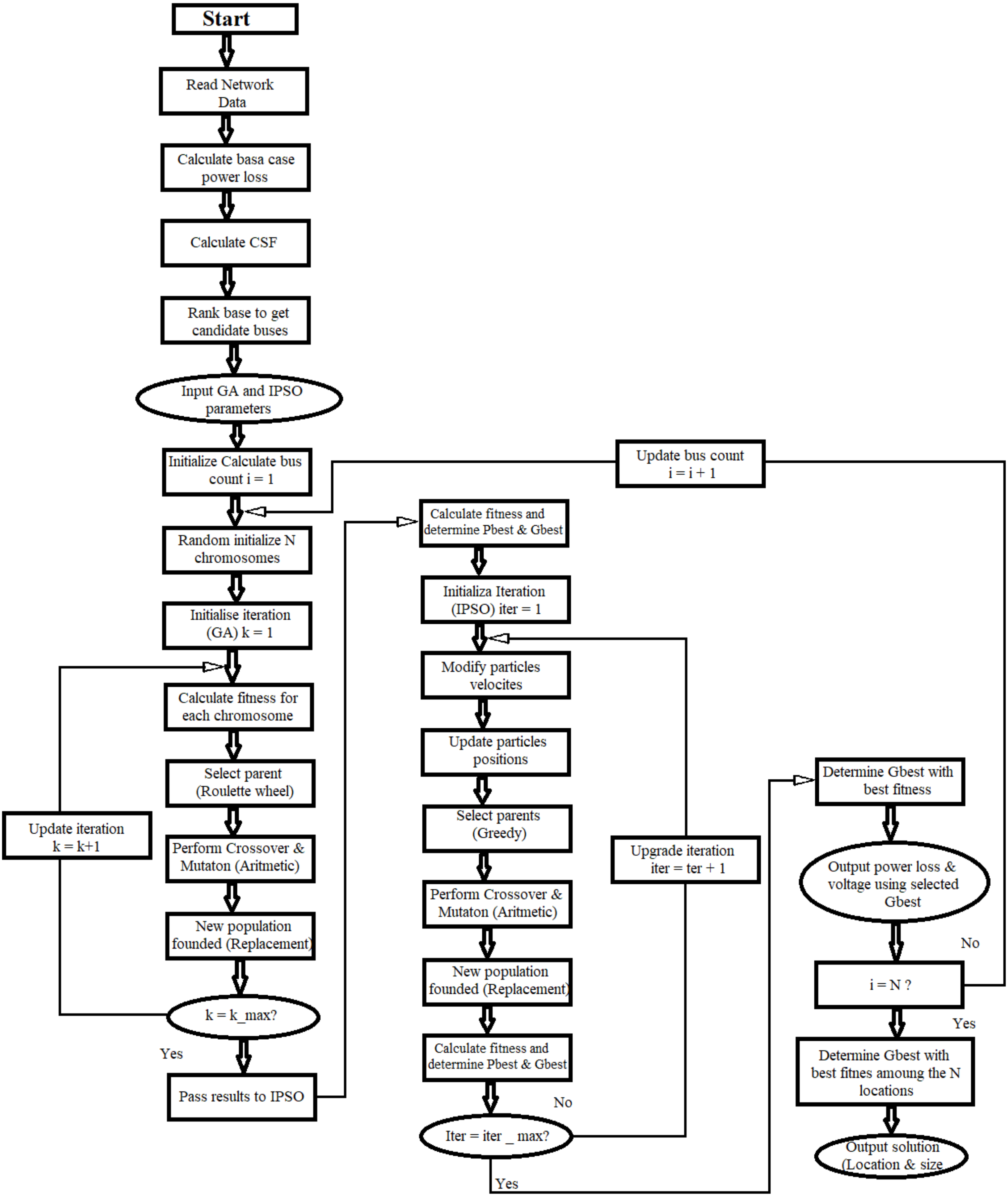

Figure 4-2: Flowchart showing the detailed steps of the proposed algorithm

Summary

While concurrently maximizing the usage of renewable energy and system efficiency, the objective functions are designed to minimize energy expenditures, grid congestion and emissions. This is accomplished by the formulation of such functions. In order to effectively address the scheduling issue, it is recommended to make use of optimization strategies such as linear programming, mixed-integer programming, or metaheuristic methodologies. The following chapter describes the control strategies.

CHAPTER FIVE: CONTROL STRATEGIES

Introduction

In the fifth chapter, the focus is on the construction of control systems that can be used to implement efficient charging strategies, either in real-time or in preparation. The integration of demand response mechanisms, smart charging algorithms and vehicle-to-grid (V2G) capabilities enhance grid flexibility and reliability. Consideration of communication protocols, data exchange platforms and interoperability standards for EV charging infrastructure is paramount.

5.1 Integration of demand response mechanisms, smart charging technologies and vehicle-to-grid (V2G) capabilities to enhance grid flexibility and reliability

5.1.1 Wireless Charging System

In [319], the authors introduce a novel wireless charging system with an embedded battery state diagnosis through the use of an electrochemical impedance spectroscopy (EIS) test. EIS is a powerful technique used to investigate chemical–physical battery changes due to ageing or failure events. The EIS test involves using the PRBS signal simultaneously with the CC charging. In the abovementioned study, simulation EIS tests were performed on a battery impedance model characterized by its equivalent circuit model. Circuit parameters were evaluated by fitting experimental impedance data. The simulation results confirmed that it is possible to charge and identify battery impedance at the same time by using the PRBS embedded in the control system [320].

An accurate estimation of impedance was achieved, which enhanced the peak-to-peak PRBS excitation signal. Additionally, a slight increase in the inductance of the CLC filter contributed to improved accuracy in impedance estimation. This adjustment also led to a reduction in the ripple of the charging current during the constant current (CC) charging phase. The methodology proposed in this research enables the monitoring of battery impedance each time the battery undergoes charging [321]. Consequently, this facilitates the prevention of failure events and extends the lifespan of the battery. Furthermore, charging protocols can be adjusted based on the state of the battery. Numerous initiatives have been undertaken by various industries to advance battery technologies that ensure a greater number of charging and discharging cycles. Lithium-ion batteries are particularly promising and widely utilized due to their high energy density and enhanced power-to-mass ratio, which allow for lighter and more compact designs at competitive prices [322]. Therefore, owing to their superior energy and power densities coupled with reasonable costs, lithium-ion batteries are preferred as energy storage systems across a range of applications. Conversely, lithium batteries exhibit significant sensitivity to temperature and operational conditions, particularly in scenarios of overcharging or deep discharging.

5.1.2 Electric Vehicles and the Smart Grid

Figure 5-1 depicts the management and implementation of the Virtual Power Plant (VPP) within a vehicle-to-grid context. The electric vehicle aggregator functions similarly to a digital power plant in relation to the energy market and the power grid [323]. The figure also demonstrates the interaction between the Central Management System (CMS) and the aggregator control center (local VPP control) concerning the status of the aggregated electric vehicle fleet at the charging station, which includes data such as state of charge (SOC) and available power [324]. In instances where the Distribution System Operator (DSO) or Transmission System Operator (TSO) requires additional power, the VPP command center is capable of utilizing the full battery capacity. The VPP control room oversees the data and power transactions among various participants in the energy market, including consumers, generators, and grid operators. The authors in [325] approach VPP operation as an optimization challenge aimed at minimizing costs. Implementing a fleet of electric vehicles for demand-side management, dynamic load balancing, and energy storage through the vehicle-to-grid (V2G) concept can lead to a cost reduction of 26.5%. The calculations included the costs related to purchasing an electric vehicle, the time required for charging, and the time needed for discharging [326].

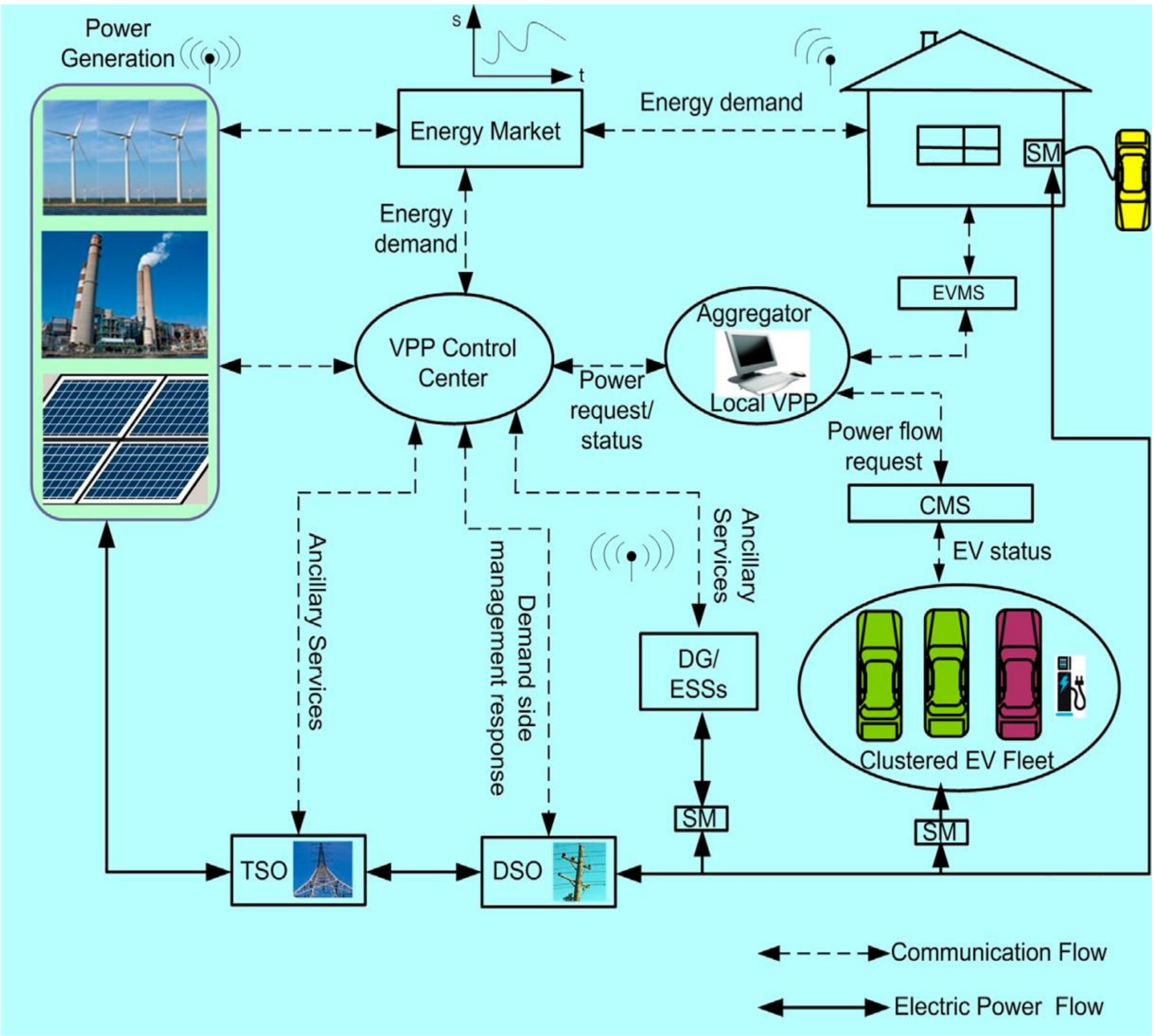

Figure 5-1: Context, implementation and regulation of Vehicle-to-Grid (V2G) technology [327]

The landscape of power generation and distribution is undergoing significant transformation with the increasing integration of distributed energy resources (DERs) into the energy market. The timing and location of DER electricity production and consumption are critical factors that add complexity to the already challenging task of managing the current electrical system. The implementation of a smart grid enhances the overall reliability, efficiency, and safety of the electricity network [328]. The term "smart grid" describes a system that employs advanced networking technologies to connect sophisticated energy meters, robust control systems, and other related devices.

The potential of electric vehicles (EVs) as variable loads and dispatchable distributed energy resources can be fully harnessed through their incorporation into the power grid. The growing number of electric vehicles necessitates a comprehensive assessment and enhancement of the smart grid's framework, a subject of ongoing research by experts in the field. Standardizing communication technologies and protocols for electric power distribution is a crucial step toward achieving a fully functional smart grid [329]. Detailed proposals for charging electric vehicles utilizing the existing power infrastructure are now publicly accessible. Furthermore, electric vehicle management (EVM) systems facilitate two-way communication between a grid operator or aggregator and an electric vehicle. The integration of a smart meter (SM) within the EVM system allows for real-time monitoring and management of energy consumption. Advanced bidirectional data transfer enables intelligent scheduling in a smart grid context, significantly influenced by the dynamics of electric vehicle charging [330,331].

5.1.3 Smart Charging of EV

Unregulated electric vehicle charging could lead to unexpected outcomes, as highlighted in the previous sections. These unintended effects include, but are not limited to, the overburdening of power system infrastructure and heightened electricity demand, which can lead to reduced efficiency in power supply. For this reason, advanced charging methods, often referred to as "smart charging," have received considerable focus in academic discussions. The objectives of clever pricing strategies may differ. Certain studies in the literature concentrate on reducing system-related expenses or charging costs in the electricity market, often leading to valley-filling charges [332]. Moreover, several studies concentrate on directly simulating the supply side, while others seek innovative methods to alleviate potential adverse impacts on the electricity grid. An optimized algorithm is essential for effectively scheduling and leveraging the advantages of the niche electric vehicle market. With the increasing integration of electric vehicles into power networks, there is an escalating necessity to identify ideal solutions amid diverse constraints. The various aims of the implemented EV system, including the reduction of charging costs, greenhouse gas emissions, or power system losses, impose distinct constraints [333,334].

The authors of [335] presented energy resource scheduling for smart grids incorporating distributed energy resources (DER) and vehicle-to-grid (V2G) participation one day in advance. Intelligent optimal scheduling utilizes an adapted variant of the particle swarm optimization technique. Electric vehicles are designed to comply with demand response efforts.

Coordinating intelligent electric vehicles within a smart grid framework has demonstrated a reduction in overall operating expenses. A price-optimized algorithm for vehicle-to-grid (V2G) operations and scheduled electric vehicle (EV) charging is suggested in [336]. RFID tag technology is employed to facilitate this intelligent charging. To enhance revenue, the authors created a web-based mobile application enabling EV owners to specify their preferences for charging parameters, including the intended state of charge (SOC), arrival and departure times, and the availability of vehicle-to-grid (V2G) services. Scheduled pricing was determined to be more cost-effective. Drivers utilizing a flexible charging setup achieved a 10% save, whilst enterprise commuters realized a 7% savings. The driver variable charging technique can decrease peak power consumption by up to 56% [337,338].

The authors of [339] propose a real-time approach to mitigate power losses and enhance the voltage profile of the smart grid. Research is being undertaken on PEV charging behaviors to elucidate the effects of PEVs on the power grid at different penetration levels, considering both uncontrolled and regulated charging. Substantial power losses and elevated costs associated with electricity generation have been seen due to the unregulated charging of PEVs inside the modified IEEE 23 kV distribution system, at both high penetration rates of 63% and low penetration rates of 16% [340]. These movements may reach up to 0.83 p.u., still below the 0.9 p.u. threshold. The voltage profile can be enhanced by as much as 0.9 p.u. by coordinated charging methods, resulting in reduced losses. Ferreira et al. [341] developed a smart charging system that employs data mining techniques to improve charging based on usage history. Web-based applications enable mobile devices, such as smartphones, to interact with the charging station and the electric vehicle system. Data obtained from a GPS-enabled mobile device is utilized to ascertain the battery charge status in an electric car. A significant drawback of this architecture is the sluggish response time of its communication lines. In an ideal scenario, the machine would autonomously manage all aspects of the process, without external assistance (e.g., from the operator) [342].

5.1.4 The Use of Electric Vehicle Smart Grid Technologies

Smart grids utilize energy management systems (EMSs) to monitor energy supply and consumption in real-time, analyze the data, and provide reports. Widespread adoption of smart meters is essential for the complete realization of online EMS services within the smart grid [343]. The integration of electric vehicles into the power grid depends significantly on precise, real-time data concerning the energy consumption of each EV, with a smart meter (SM) serving a crucial function in collecting this information. Consequently, SMs enable day-ahead and intraday energy forecasting methodologies, in addition to energy pricing. The primary functions of smart meters inside the smart grid. Consequently, cutting-edge technology included in smart metering must be employed to address the diverse requirements presented by electric vehicles (EVs) [346]. The phrase “advanced metering infrastructure” (AMI) refers to a network that enables real-time two-way communication with smart meters. Electric vehicles and advanced metering infrastructures are among the eight critical requirements for the successful adoption of smart grids.

The components of the AMI system integrate to create a cohesive and comprehensive entity. Home area networks, smart meters, computers, software, and advanced sensor networks exemplify communication technology. The AMI framework can utilize wireless or broadband over power line (BPL)/power line communication (PLC) to facilitate bidirectional communication among the utility network, smart meters, diverse sensors, computer network infrastructure, and electric vehicle management system (EVMS) [347]. A more effective command and administration system can be established with data from the AMI. The astute scheduling of electric vehicles is feasible with a smart grid that integrates Advanced Metering Infrastructure (AMI). The AMI technology employed by the authors of [348], alongside the EV charging infrastructure examined in their study, facilitated the charging of electric vehicles at any time and for any cost. The use of electric vehicles via an AMI platform can decrease peak energy consumption by 36%. The proportion of energy utilized during peak hours is lowered by 54%. As a result, the electrical grid experiences a reduction in stress during peak demand periods [349].

Figure 5-2 presents a summary of the accessible AMI setups for electric vehicle smart grid communications. It pertains to data collected by SMs regarding energy usage or production. Smart meters can utilize many communication protocols, like BPLC and WiMAX, to transmit collected data over a FAN, LAN, or HAN [350]. The MDMS oversees data management, storage, and analysis subsequent to receiving data from the AMI head-end system after collection and validation. Both the utility and the EV aggregator are able to access the energy data within the MDMS. Energy Management Systems (EMSs), Meter Data Management Systems (MDMSs), utility service providers, and the energy market all get advantages from the bidirectional connection facilitated by a client web portal. Among the numerous AMI features emphasized by the authors of [351], bidirectional power measurement and communication, seamless networking, and enhanced data storage are particularly significant. These properties are crucial for energy applications related to electric vehicles (EVs). This report analyzes several aspects of Advanced Metering Infrastructure (AMI) adoption concerning electric car charging, vehicle-to-grid (V2G) services, and vehicle-to-home (V2H) applications. AMI systems serve as a practical initial step towards facilitating ubiquitous capabilities such as measurement and communication, hence enabling enhanced energy management in the context of V2G connectivity [352].

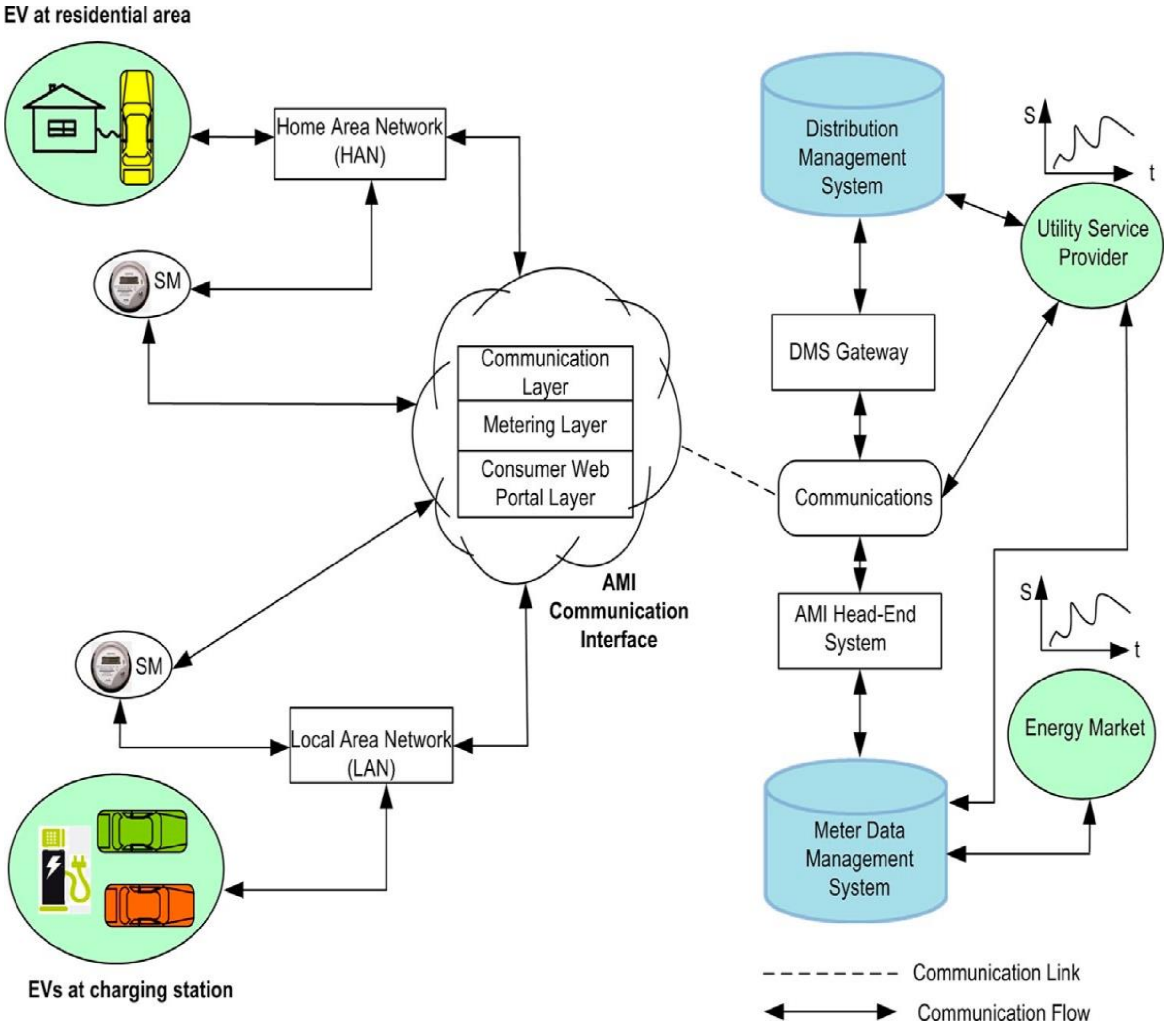

Figure 5-2: A review of the vehicle-to-grid framework's AMI design [353]

5.2 Consideration of communication protocols, data exchange platforms, and interoperability standards for EV charging infrastructure

The bidirectional communication network of the smart grid regulates numerous decentralized energy resources across extensive, remote areas, facilitating various forms of demand response. In this instance, a significant amount of land [354]. Request and acknowledgement forms of communication will likely play a crucial part in the information interchange between electric vehicles (EVs) and the smart grid, involving various system components such as smart meters (SMs). Two alternatives for communication solutions exist, each dependent on the smart grid's approach for integrating electric vehicles. Initially, the researcher examines the wire that transmits data between the advanced sensors and the EVMS and SMs [355]. The second category pertains to connectivity between SM data centers and grid operators or aggregators. PLC and wireless communication technologies exemplify the former, whilst 3G, WiMAX, and 4G LTE represent cutting-edge mobile network solutions.

The dynamic mobility of electric vehicles introduces new challenges for the power industry's monitoring, communication, and control systems. When the electric vehicle is outside the range of its Home Area Network or Local Area Network, theoretically, an improved smart meter should facilitate its connection to an alternative aggregator, energy supplier, or visiting network. A reliable communication system with worldwide coverage is essential for the proper management of these tasks. The authors of [356] assert that smart metering infrastructure gains advantages from advancements in wireless communication technologies. The extensive proliferation of electric vehicles in the real world creates an optimal context for their applications. For optimal operation, electric vehicles (EVs) must have the capability to connect to charging stations at any time and location to replenish their batteries or supply energy back to the grid (V2G). The GO or EV aggregator requires a method to accurately identify each EV in near-real time to ensure the correct amount of electricity is billed [357]. Electric vehicles must learn knowledge of peak demand periods or real-time energy price trends to contribute to the grid. Moreover, wireless sensor networks (WSN) are increasingly recognized in the smart grid as a viable control network. Recent research has proved the potential of WSN in DG and MG operations.

A comparable method can be utilized within the wireless sensor network to enhance electric vehicle adoption. Nonetheless, considerable obstacles persist in the extensive implementation of WNSs for electric vehicle applications, particularly in vehicle-to-grid services. The range is inferior to that of other wireless technologies, resulting in packet delays and a diminishing success rate as hop counts increase. A data system based on a wireless sensor network (WSN) is introduced for vehicle-to-grid applications in [358]. The wireless connection between car-grid operators is conducted with minimal messaging to optimize grid capacity, electric vehicle reliability, and data transmission. Numerous research, including this one, have sought to integrate the WSN architecture for V2G transactions with an advanced EV system. Additionally, other scholars have investigated and evaluated ZigBee technology, specifically for electric vehicle applications [359]. ZigBee is a low-bandwidth protocol that is easy to deploy. ZigBee technology has the potential to transform vehicle-to-grid (V2G) applications, provided that certain challenges are addressed, such as communication latency, inadequate memory, and interference from other devices utilizing the same transmission medium. A summary of various prospective wireless technologies for electric vehicle (EV) applications, including vehicle-to-ground (V2G) services, is presented in Table 5-1 below.

Table 5-1: Technologies for vehicle-to-grid wireless communication

S/N	Frequency of Operation	Type of Technology	Operation Distance
1	2.40 GHz	Bluetooth	1–100 m
2	13.560 MHz	Near Field Communication (NFC)	5–10 cm
3	5.85–5.925 GHz	IEEE 802.11p	500–1000 m
4	2–6 GHz	WiMAX	2–5 km
5	2.40 GHz (Worldwide) 868 MHz (Europe) 915 MHz (North America)	ZigBee	10–100 m

Safeguarding the smart grid against cyberattacks, such as price manipulation and system congestion caused by malware, necessitates a robust and secure communication network between electric vehicles and the utility or power market. Cybersecurity concerns are valid, since hackers can readily compromise an electric vehicle (EV) connected to the grid network [360]. Protected electric vehicle services for visitors utilizing the network are a crucial amenity that host networks ought to offer. Should these concerns remain unresolved, electric vehicles will not attain their full potential in utility and reliability within the energy industry. Figure 5-3 illustrates the interconnections between electric vehicles and the smart grid, along with the communication network architecture and functionalities that facilitate these interactions. The wireless communication method employed is dictated by the transmission range and data load between interacting hotspots [361].

The smartphone depicted in this diagram utilizes its integrated GPS and/or Bluetooth functionalities to serve as a conduit between the electric vehicle management system (EVMS), charging station, and aggregator. The CAN gateway transmits all electric vehicle status information externally. The WiMAX protocol pertains to long-distance communications involving aggregators, energy markets, and utilities (TSO/DSO) [362]. The utilization of the Near Field Communication (NFC) protocol facilitates automatic Bluetooth connection, minimizing the necessity for over eight user engagements, hence enhancing smart grid reliability.

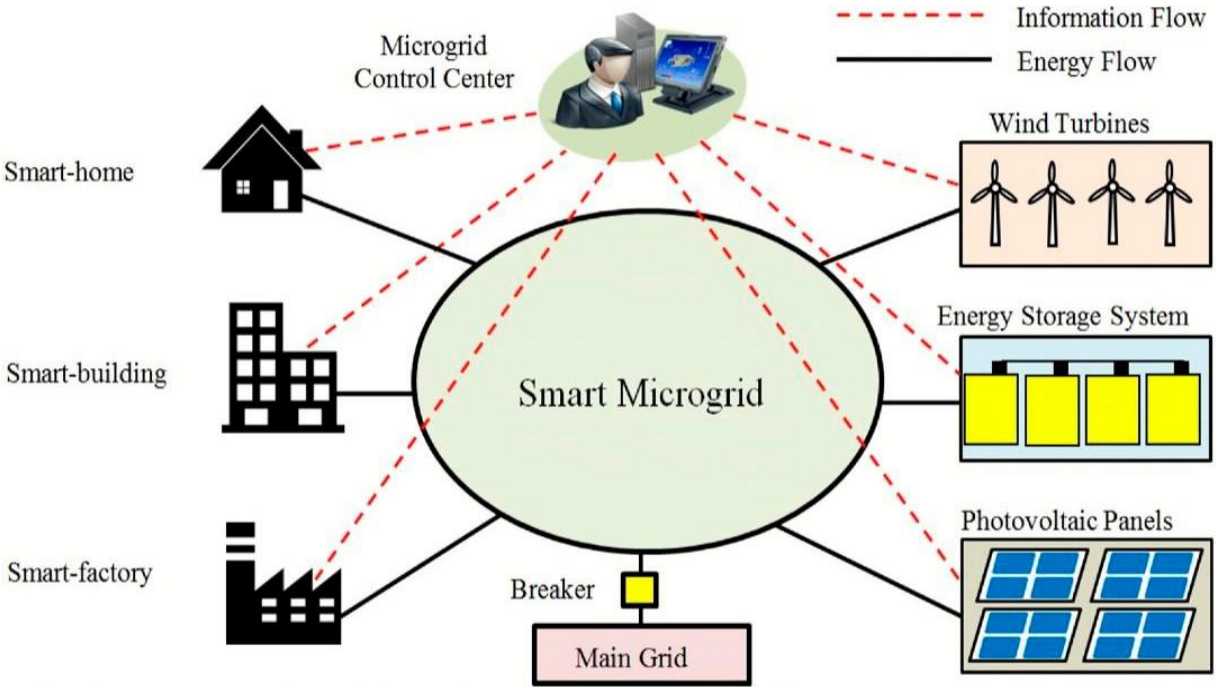

Figure 5-3: Smart grid and electric vehicle communication network architecture [363]

Summary

Increased adaptability and dependability of the power system can be achieved by the use of demand response mechanisms, intelligent charging algorithms, and vehicle-to-grid (V2G) capabilities. Research on the communication protocols, data sharing platforms, and interoperability standards that pertain to the infrastructure for charging electric vehicles.

CHAPTER SIX: CASE STUDIES AND SIMULATION

Introduction

In the sixth chapter, the researcher will apply the optimization framework and control strategies that he has built to several power system configurations that are typical. The suggested method will be subjected to simulation studies in order to evaluate its performance under a variety of operating scenarios, energy penetration levels, and grid configurations. Analysis of important performance measures, including but not limited to emissions reduction, grid congestion, energy prices, and user satisfaction.

6.1 Part 1: Results, Analysis and Discussion

6.1.1 Power Loss on Scenario A

The Newton-Raphson method was used to assess power losses and voltage levels once it was determined that four distinct CS sizes and locations should be used. Calculations of power loss were evaluated and contrasted with those obtained through the use of various approaches. It was demonstrated that the HGAIPSO methodology was able to achieve a decrease in real power loss that was 40.7040% for type 1 CS. This reduction was significantly larger than the reductions achieved by GA (25.1002%), PSO (31.4187%) or IPSO (31.849%) respectively, as shown in Figure 6-1 and Table 6-1. The CS allocated by using the suggested method exhibited good results with EV allocations for loss reduction when compared to the CS that was acquired by using other techniques. This was determined by comparing the CS that was obtained using the proposed method to the CS that was obtained using other methods. The HGAIPSO method performs better than the GA, PSO and IPSO approaches when it comes to selecting the optimal placement and size for a type 1 CS in order to reduce power loss over the electrical transmission system. This is because the HGAIPSO method uses a hybridized version of these three methods.

Table 6-1: A comparison of results obtained using Type 1 CS

Method	Bus Number	CS Size	Power Losses		Power Loss Reduction		%Power Loss Reduction	
		MW	MW	MVar	MW	MVar	%MW	%MVar
Without EV CS			17.8798					
GA	11	11.472	13.3919	-	4.4879	-	25.1002	-
	10	11.904						
	19	11.052						
	24	11.772						
PSO	10	11.694	12.2622	-	5.6176	-	31.4187	-
	15	11.394						
	20	11.378						
	30	10.577						
IPSO	10	11.625	12.1851	-	5.6947	-	31.8499	-
	10	11.956						
	22	11.995						
	30	11.986						
HGAIPSO	19	11.7099	10.6020	-	6.2778	-	40.7040	-
	21	11.9937						
	24	11.9960						
	30	11.7061						

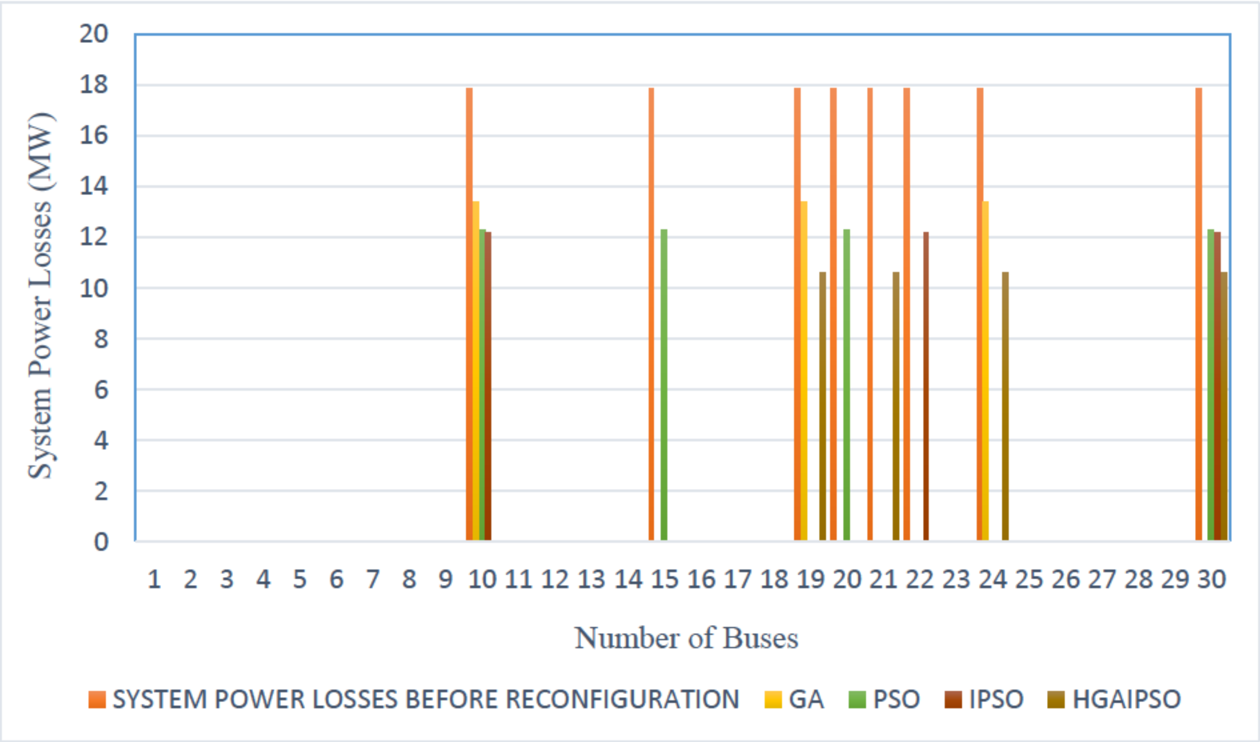

Figure 6-1: Using Type 1 CS comparing the power loss data

6.1.2 Voltage Profile on Scenario A

Table 6-2 and Figure 6-2 illustrates a comparison of voltage levels in two scenarios: one without electric vehicles and another with an optimal number of electric vehicles positioned and sized within the charging station (CS). This analysis was conducted utilizing Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Improved Particle Swarm Optimization (IPSO), and Hybrid Genetic Algorithm with Improved Particle Swarm Optimization (HGAIPSO). It is important to note that while the IEEE-30 bus system allows voltage levels to fluctuate between 0.95 per unit (pu) and 1.1 pu, the presence of a charging station can still influence the system's ability to maintain stable voltage. As depicted in Table 6-2 and Figure 6-2, the integration of electric vehicles does not lead to voltage levels that exceed safe thresholds. All bus voltages remained within the acceptable range of 0.95 pu to 1.1 pu, as confirmed for each bus. Furthermore, the application of the HGAIPSO method successfully elevated the bus voltage from below the minimum requirement to a compliant level of at least 1.01 pu.

Table 6-2: Bus voltage results for profile comparison using Type 1 CS

Bus No:	Without CS	GA	PSO	IPSO	HGAIPSO
1	1.050	1.050	1.050	1.050	1.050
2	1.044	1.044	1.044	1.044	1.044
3	1.027	1.026	1.024	1.024	1.026
4	1.017	1.018	1.018	1.018	1.018
5	1.010	1.010	1.010	1.010	1.010
6	1.010	1.014	1.014	1.014	1.016
7	0.992	1.005	1.004	1.005	1.006
8	1.012	1.012	1.012	1.012	1.012
9	1.030	1.045	1.044	1.045	1.055
10	1.013	1.03	1.027	1.035	1.050
11	1.072	1.082	1.082	1.082	1.082
12	1.045	1.052	1.053	1.051	1.059
13	1.071	1.071	1.071	1.071	1.071
14	1.028	1.036	1.038	1.034	1.046
15	1.020	1.033	1.036	1.033	1.046
16	1.025	1.036	1.035	1.035	1.049
17	1.011	1.026	1.024	1.026	1.044
18	1.005	1.025	1.025	1.017	1.040
19	1.023	1.023	1.021	1.013	1.041
20	1.002	1.024	1.024	1.017	1.042
21	1.001	1.019	1.015	1.019	1.040
22	1.001	1.02	1.016	1.021	1.046
23	1.004	1.021	1.02	1.017	1.040
24	0.991	1.014	1.007	1.008	1.041
25	0.994	1.01	1.012	1.013	1.034
26	0.976	0.992	0.994	0.995	1.017
27	1.005	1.017	1.024	1.025	1.038
28	0.998	1.012	1.013	1.014	1.017
29	0.985	0.997	1.015	1.017	1.030
30	0.973	0.986	1.014	1.017	1.030

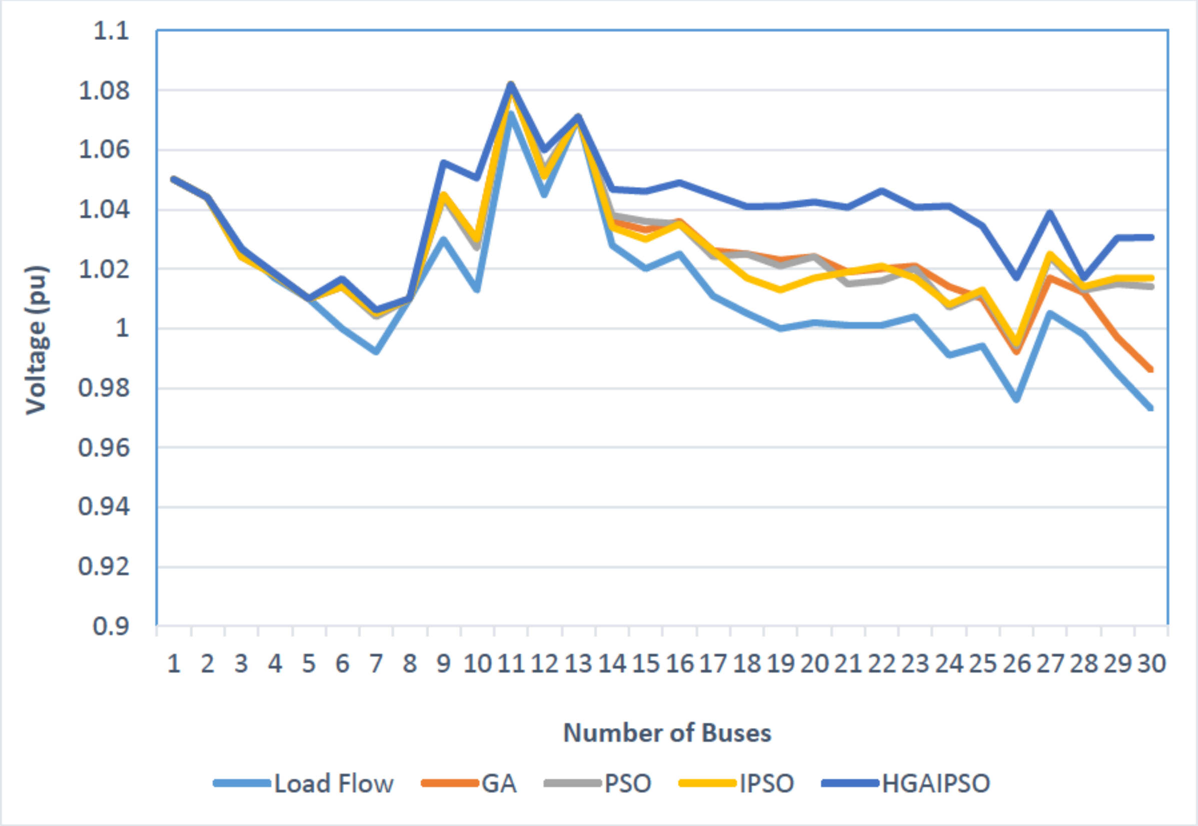

Figure 6-2: Bus voltage results for profile comparison using Type 1 CS

6.1.3 Power Loss on Scenario B

The columns in Table 6-4 on physical fitness and EV size served as a reference for the selection of the four best locations for type 2 CS and their corresponding optimal sizes. In the following list, the four most advantageous locations are shown in ascending order of increasing success, and the optimal CS sizes that correspond to those locations are also included. Electric vehicles on buses 19 and 23 generate a total of 11.7872MW and 2.9609MVar of energy respectively. Electric vehicles on bus 24 generate a total of 12.0001MW and 1.3702MVar of power.

Using the HGAIPSO approach to optimize the placement and size of this type 2 CS can result in a reduction of real power losses by 36.2403%, as shown in Table 6-4 and Figure 6-3. This can be accomplished by minimizing the EV's overall footprint. This result is much superior to the outcomes obtained by employing GA (32.2923% reduction), PSO (31.5890% reduction), or IPSO (33.1638% reduction).

Table 6-3: Comparison of results using Type 2 CS

Method	Bus Number	EV Size	Power Losses		Power Loss Reduction		%Power Loss Reduction	
		MW	MW	MVar	MW	MVar	%MW	%MVar
Without EV CS			17.8798					
GA	10	11.35 + j1.22	12.2260	-	5.6538	-	31.5890	-
	23	11.47 + j1.17						
	24	11.92 + j2.04						
	30	11.816 + j1.468						
PSO	10	11.474 + j2.159	12.1060	-	5.7738	-	32.2923	-
	17	11.981 + j0.919						
	20	11.67 + j2.309						
	30	11.349 + j3						
IPSO	10	11.83 + j0.001	11.9500	-	5.9298	-	33.1648	-
	21	11.433 + j3						
	24	11.739 + j3						
	30	11.995 + j0.001						
HGAIPSO	19	11.7872 + j2.9609	11.4001	-	6.4797	-	36.2403	24.2585
	23	11.7548 + j3.0002						
	24	12 + j1.3702						
	30	11.8308 + j1.5817						

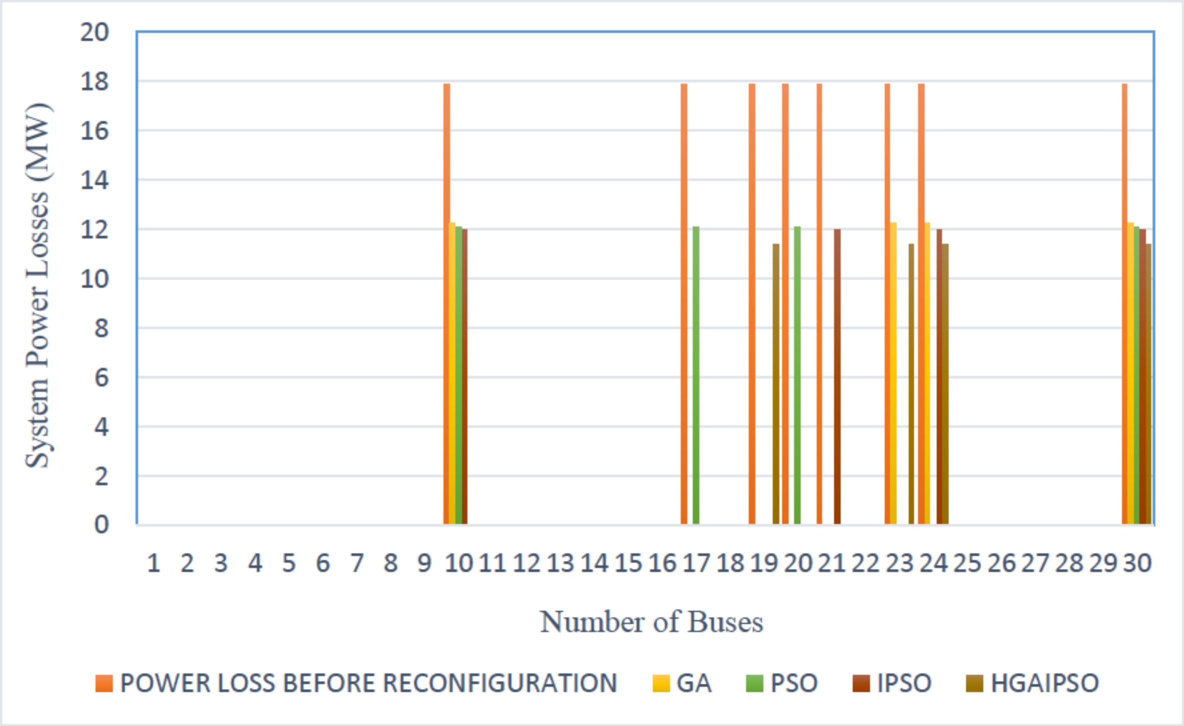

Figure 6-3: Comparison of power losses using Type 2 CS

6.1.4 Voltage Profile on Scenario B

After determining where the type 2 electric vehicles charging station should go and how large they should be, we looked at the voltage profile of the IEEE-30 bus system. The results of the investigation into the voltage levels of the bus are illustrated in Table 6-4 and Figure 6-4. This scenario is contrasted with another in which CSs were placed in a variety of locations and their performance was evaluated using a variety of measures, as well as with a third situation in which there were no EVs present.

Table 6-4: Bus voltage profile comparison using Type 2 CS

Bus No:	Without CS	GA	PSO	IPSO	HGAIPSO
1	1.050	1.050	1.050	1.050	1.050
2	1.044	1.044	1.044	1.044	1.044
3	1.027	1.026	1.024	1.024	1.026
4	1.017	1.018	1.018	1.018	1.018
5	1.010	1.010	1.010	1.010	1.010
6	1.014	1.015	1.013	1.015	1.017
7	1.005	1.005	1.004	1.005	1.067
8	1.010	1.010	1.010	1.010	1.010
9	1.046	1.047	1.041	1.047	1.058
10	1.031	1.034	1.022	1.034	1.056
11	1.082	1.082	1.082	1.082	1.082
12	1.055	1.054	1.049	1.054	1.061
13	1.071	1.071	1.071	1.071	1.071
14	1.04	1.038	1.031	1.038	1.051
15	1.038	1.035	1.027	1.035	1.052
16	1.038	1.038	1.032	1.038	1.053
17	1.035	1.030	1.021	1.030	1.050
18	1.029	1.022	1.022	1.022	1.049
19	1.028	1.018	1.017	1.018	1.051
20	1.033	1.021	1.020	1.021	1.052
21	1.023	1.027	1.012	1.027	1.048
22	1.024	1.028	1.012	1.028	1.053
23	1.022	1.027	1.014	1.027	1.049
24	1.013	1.025	1.003	1.025	1.050
25	1.022	1.024	1.009	1.024	1.043
26	1.004	1.006	0.991	1.006	1.026
27	1.035	1.031	1.022	1.031	1.047
28	1.015	1.015	1.013	1.015	1.018
29	1.032	1.023	1.012	1.023	1.041
30	1.037	1.024	1.011	1.024	1.045

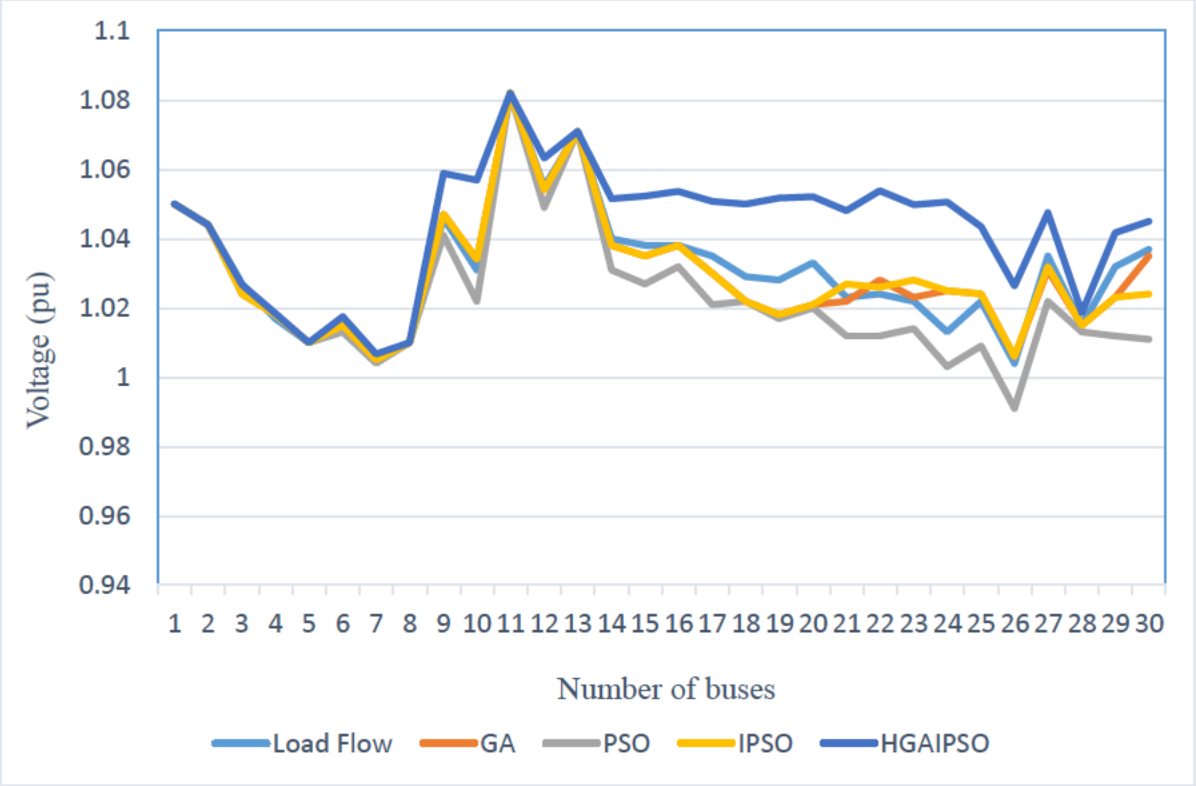

Figure 6-4: Bus voltage profile comparison using Type 2 CS

The voltages in a system devoid of electric vehicles are illustrated in Figure 6-4, contrasted with the voltages in a system where control strategies (CS) have been optimally positioned and scaled utilizing Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Improved Particle Swarm Optimization (IPSO), and Hybrid Genetic Algorithm with Improved Particle Swarm Optimization (HGAIPSO). Although the voltages remain within the acceptable range of 0.95 pu to 1.1 pu, the presence of CS has the potential to destabilize the voltage levels in an IEEE-30 bus system. The permissible range for this parameter is established between 0.95 pu and 1.1 pu. As depicted in Figure 6-4, the implementation of CS did not result in any voltage levels exceeding local regulatory limits. Throughout all simulations, it was observed that each bus voltage consistently remained within the defined range of 0.95 pu to 1.1 pu. The effectiveness of the HGAIPSO strategy in reducing bus voltage confirmed that none of the bus voltages were recorded above the allowable threshold.

6.1.5 Scenario C: Type 3 CS

Four optimal locations for type 3 CS, their corresponding optimal sizes were selected based on the columns in Table 6-3 that indicate fitness and CS sizes. These columns only provide the most fundamental information regarding fitness levels and associated EV CS sizes. According to their relative success, the best locations and the corresponding ideal EV CS sizes are: Bus 19's EV which generates 12.0010 MW and uses 0.4882 MVar of electricity. The electric vehicles on bus 24 produce 11.9470 MW and consume 0.5042 MVar of energy. The electric vehicles on bus 21 produce 11.9179 MW and consume 0.0692 MVar of energy.

Table 6-5: Analyzing the Variability of Type 3 EV Results

Method	Bus Number	EV Size	Power Losses		Power Loss Reduction		%Power Loss Reduction	
		MW	MW	MVar	MW	MVar	%MW	%MVar
Without EV CS			17.8798					
GA	10	$9.0384 - j0.0882$	11.5265	-	6.3533	-	35.6967	-
	18	$11.1120 - j0.7150$						
	22	$11.7480 - j0.5891$						
	30	$10.0081 - j0.4870$						
PSO	10	$11.885 - j0.7970$	11.1056	-	6.7742	-	37.8874	-
	18	$10.8811 - j0.3215$						
	20	$11.5631 - j0.8990$						
	30	$11.5310 - j0.3831$						
IPSO	10	$12.0215 - j0.5260$	11.2099	-	6.6699	-	37.3041	-
	19	$10.8610 - j0.3002$						
	22	$11.9170 - j0.8370$						
	30	$11.9560 - j0.5260$						
HGAIPSO	19	$12.0010 - j0.4882$	10.2021	-	7.6777	-	42.9406	24.212
	21	$11.9470 - j0.5042$						
	24	$11.9179 - j0.0692$						
	30	$11.3651 - j0.5807$						

A comparison of the results of power loss as a function of the various approaches is presented in Table 6-3 and Figure 6-5 respectively. These discoveries are discussed alongside the power reductions that can be attributed to the aforementioned factors. The HGAIPSO method is superior to either the PSO or IPSO approaches in terms of the amount of power loss it is able to reduce by 42.9406 percent. The results achieved with the technique that was proposed were significantly superior to those that were produced using GA (35.6967%), PSO (37.12887%) and IPSO (37.301%) respectively.

Figure 6-5: Bus voltage profile comparison using Type 3 EV

6.1.6 Voltage Profile on Scenario C

Table 6-6 and Figure 6-6 clearly indicates that the application of the HGAIPSO method resulted in a significant rise in the bus voltage. This suggests that the positioning of the electric vehicles as well as their size were maximized as a result of their incorporation. The study was successful in raising the bus voltage from 0.973 pu to 1.01 pu by implementing a variety of optimal adjustments to the size and number of type 3 electric vehicle charging station. The optimal location of Type 3 EV CS and optimization of their sizes made it possible for this to take place. This indicates that the limit was set at a value of 1.095 pu, which would show that this value was chosen limit. As a result of these, the bus voltage profile was subsequently increased which can be interpreted as a positive result.

Table 6-6: Type 3 CS voltage profile comparison on the bus

Bus No:	Without CS	GA	PSO	IPSO	HGAIPSO
1	1.05	1.05	1.05	1.05	1.05
2	1.044	1.044	1.044	1.044	1.044
3	1.027	1.026	1.024	1.024	1.0267
4	1.017	1.018	1.018	1.018	1.0184
5	1.01	1.01	1.01	1.01	1.01
6	1.013	1.013	1.013	1.013	1.0164
7	1.004	1.004	1.004	1.004	1.006
8	1.01	1.01	1.01	1.01	1.01
9	1.043	1.042	1.041	1.041	1.0551
10	1.027	1.024	1.022	1.022	1.0495
11	1.082	1.082	1.082	1.082	1.082
12	1.051	1.05	1.049	1.049	1.0594
13	1.071	1.071	1.071	1.071	1.071
14	1.035	1.033	1.031	1.031	1.046
15	1.032	1.03	1.027	1.027	1.0451
16	1.034	1.032	1.032	1.031	1.0483
17	1.023	1.021	1.021	1.019	1.0439
18	1.024	1.022	1.022	1.015	1.0396
19	1.017	1.017	1.017	1.011	1.0394
20	1.018	1.02	1.02	1.013	1.0411
21	1.016	1.012	1.012	1.011	1.0392
22	1.018	1.012	1.012	1.012	1.0449
23	1.017	1.014	1.014	1.012	1.0392
24	1.006	1.003	1.003	1.004	1.0394
25	1.01	1.009	1.009	1.004	1.0323
26	0.993	0.991	0.991	0.986	1.0148
27	1.022	1.022	1.022	1.015	1.0363
28	1.013	1.013	1.013	1.012	1.0166
29	1.011	1.012	1.014	1.020	1.0265
30	1.011	1.015	1.017	1.025	1.0950

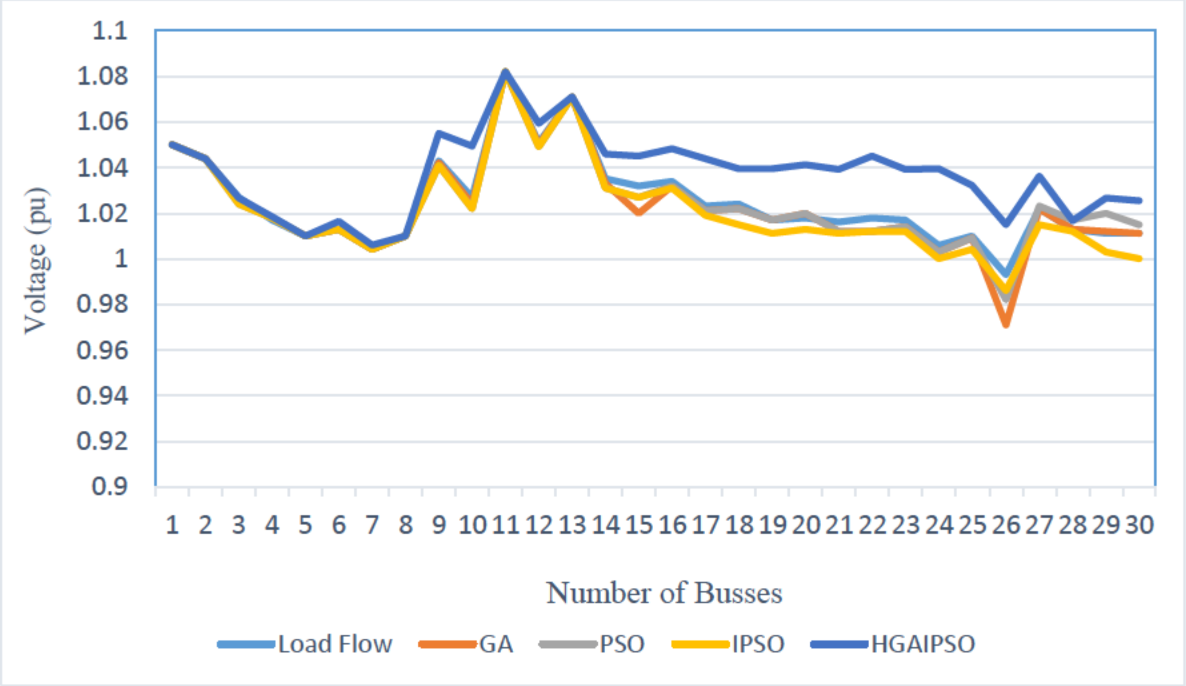

Figure 6-6: Type 3 CS voltage profile comparison on the bus

Summary

After discovering that optimizing the placement and size of electric vehicle charging stations would reduce power losses and improve voltage profiles, the problem of power losses in systems could be solved. This chapter presented HGAIPSO, a hybridized algorithm designed to enhance voltage profiles while decreasing system power losses. By combining the sensitivity factors with the test run on the IEEE-30 bus test system, the number of algorithm iterations was successfully decreased. Fourteen buses were selected as suitable EV locations for the IEEE-30 bus test. The HGAIPSO method was shown to be more effective at reducing it than the GA, PSO and IPSO approaches in three distinct types of CS located via the IEEE-30 bus. The greatest bus voltage, 1.01 pu, was generated in each of the three scenarios, proving that the voltage profile was improved overall. This shows that HGAIPSO is superior to GA, PSO and IPSO when it comes to optimizing the value of this parameter, as it decreased the losses experienced by the IEEE-30 bus test system and had the potential to improve the voltage profile of the system.

6.2 Part 2: Results, Analysis and Discussion

6.2.1 Scenario 1

The placement of charging stations was carried out without the utilization of REDGs. The charging of EVs was limited to off-peak hours and utilized a charging method that was manageable. During the charging time, the ideal number of EVs was allocated to each electric vehicle charging station. Table 6-4 presents the best locations for charging stations, as well as their sizes and the number of EVs already in operation. The data shown in Table 6-5 indicates that when compared to the base scenario, the total cost is dropped by 2.43%, the voltage variations (VV) increased by 1.45%, the energy lost (EL) is decreased by 3.28%, the total energy cost from the grid is reduced by 2%, and the cost of power loss is decreased by 1.16%. All of these changes are presented in comparison to the basic scenario. As a result, the flow of electricity was maximized by strategically allocating the placement and the charging of these EVs.

Table 6-7: Optimal placements and dimensions of REDGs and charging stations locations

Studied Scenarios	**Charging stations location**	**EVs numbers**	**Charging station size (kWh)**	**Solar charging station size (MW)**	**Wind charging station size (MW)**
Scenario 1	113	28	32.9982		
	71	13	49.9854	–	–
	44	14	22.9882		
	18	21	48.1524		
Scenario 2	117	123	530.1258	0.5285	4.0825
	70	174	482.2554	4.0447	4.5615
	43	206	691.0154	4.0184	1.9987
	21	134	462.1224	3.9824	3.1455
Scenario 3	117	309	2.0215	1.0156	2.1554
	76	257	879.1525	4.1465	2.5148
	42	314	2.1854	2.1456	4.2256
	19	206	1.1488	4.5147	1.2454

Table 6-8: Results obtained through simulation

	Base scenario	**Scenario 1**	**Scenario 2**	**Scenario 3**
Load factor	0.7154	0.7562	0.8020	0.8465
Voltage violation (p.u)	1	0.8256	0.3545	0.3514
Energy Lost (p.u)	1	0.8151	0.6252	0.5247
Cost of power per day (R)	405,930,000.00	397,437,852.00	367,581,340.00	285,618,368.00
V_{min} at bus (p.u)	0.8212	0.8210	0.8620	0.9144
Cost of purchased power	390,404,000.00	382,326,000.00	250,908,000.00	191,954,000.00
EVs charging cost (R)	–	264,852.00	557,2140.00	10,849,720.00
Revenue for discharging of EVs (R)	–	–	–	712,118
Cost of power lost (R)	15,066,000.00	14,847,000.00	12,161,800.00	11,770,500.00
Solar power cost (R)	–	–	18,863,600.00	18,445,000.00
Wind power cost (R)	–	–	80,075,800.00	62,568,800.00
REDGs total cost (R)	–	–	98,939,400.00	81,013,800.00

6.2.2 Scenario 2

There was a successful integration of the charging stations outfitted with REDGs into the system. The EVs will only be able to recharge during the off-peak hours by utilizing a charging strategy that is regulated. The charging stations and REDGs are classified according to the most effective allocations and sizes, which are outlined in Table 6-5. There has been an increase in the size of the charging stations in this Scenario in comparison to the first scenario. When compared to Scenario 1, the VV, EL and overall cost were all reduced by 71.05%, 34.39% and 8.22%, respectively. In addition, the amount of money spent on electricity obtained from the grid was reduced by 35.15 %, as shown in Figure 6-7.

On account of the introduction of REDGs, the charge rate is increased in these allocated charging stations in comparison to the scenario one, as shown in Figures 6-8 and 6-9. Figure 6-10 illustrates a reduction of 18.085% in the costs that are associated with power outages. In comparison to Scenario 1, the minimum voltage magnitude of the system suffered an increase of 3.93%. As a result of Figure 6-12 demonstrating that the voltage profile was enhanced in comparison to Scenario 1, the effectiveness of the REDGs in conjunction with the charging stations has been validated.

6.2.3 Scenario 3

The most optimal locations and sizes of charging stations and REDGs were determined. The EVs were exclusively charged during the off-peak period and discharged in an optimal manner during the on-peak period. Table 6-4 provides the precise information regarding the optimal locations and sizes of the charging stations and REDGs. It is worth noting that the sizing of the charging stations has been enhanced in comparison to Scenario 2. Table 6-5 shows that in comparison to Scenario 2, the VV, EL and overall cost were decreased by 11.24%, 22.41% and 21.95% respectively. This confirms the efficiency of REDGs when utilizing a manageable charging and discharging method. It is important to observe that EVs served as a source of electricity during periods of high demand, as depicted in Figure 6-9. Table 6-5 demonstrates that, as compared to Scenario 2, the total size of REDGs decreased by 12.92%, leading to a 19.02% decrease in the yearly investment cost of REDGs.

The money generated from the utilization of EVs amounted to R10,849,720.00. This resulted in a reduction in charging expenses. Moreover, as depicted in Figure 6-7, the overall expenditure on purchasing power witnessed a decrease of 24.29%. Figure 6-10 demonstrates a 4.11% decrease in the cost associated with power loss. Table 6-5 demonstrates that the load factor has been raised to 86.52% and the load profiles are shown in Figure 6-11. Consequently, in comparison to Scenarios 1 and 2, Scenario 3 had the lowest maximum load. This resulted in the lowest cost for reserving maximum power in charging stations, as depicted in Figure 6-7. Table 6-6 and Figure 6-12 displays instances of voltage violation, while Table 6-7 and Figure 6-13 present data on lost energy. These figures demonstrate that the voltage profile has improved and the amount of lost energy has decreased in comparison to Scenario 1 and 2. This confirms the efficacy of the REDGs in conjunction with the charging stations.

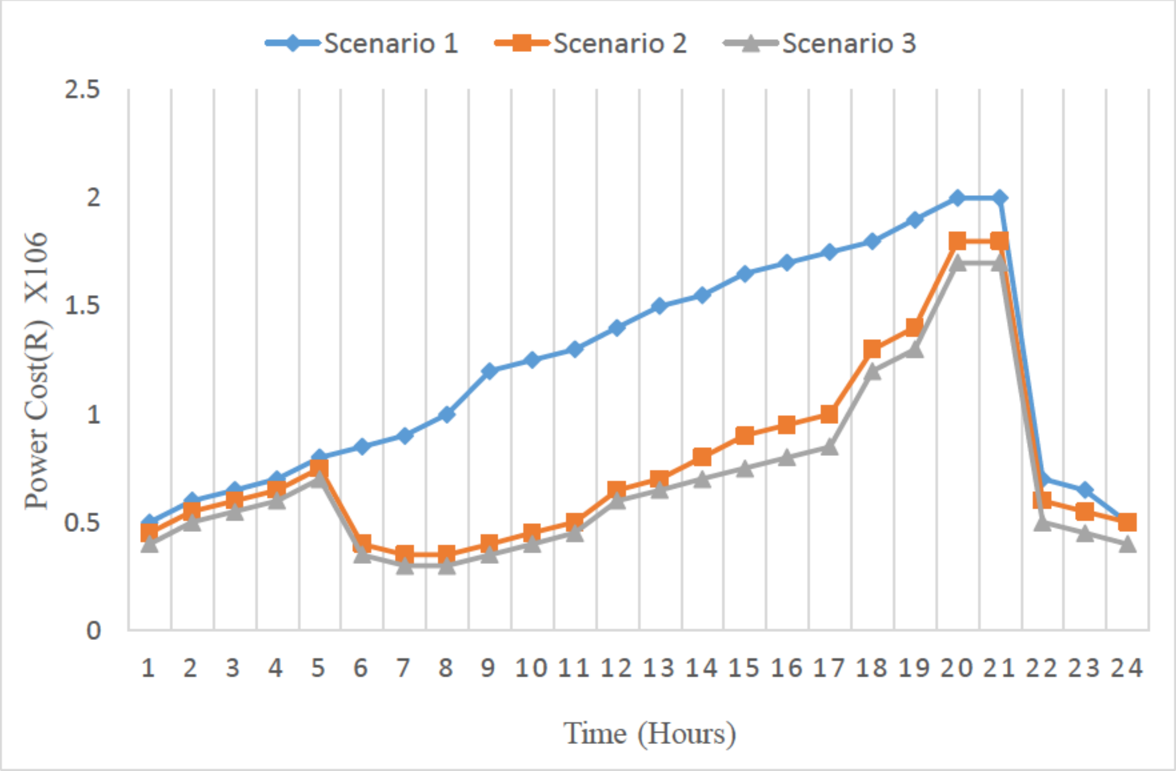

Figure 6-7: The price of the power that was acquired from the grid in its entirety

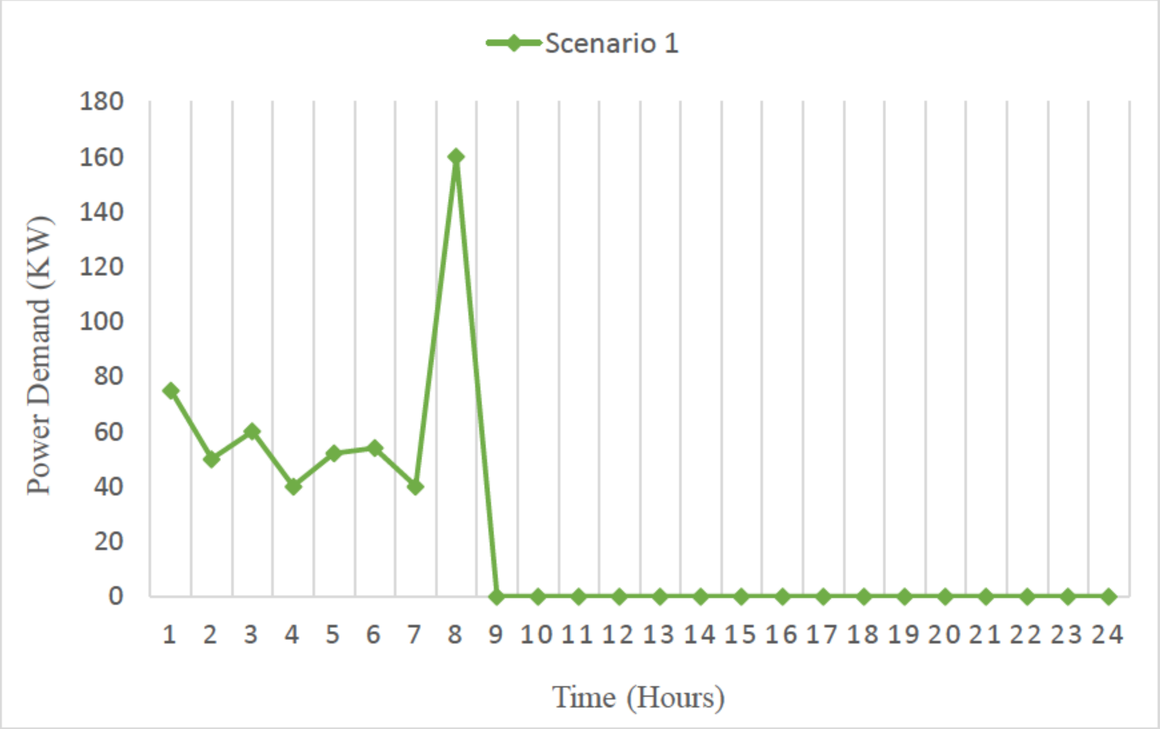

Figure 6-8: The sum of the power that charging stations have consumed and contributed

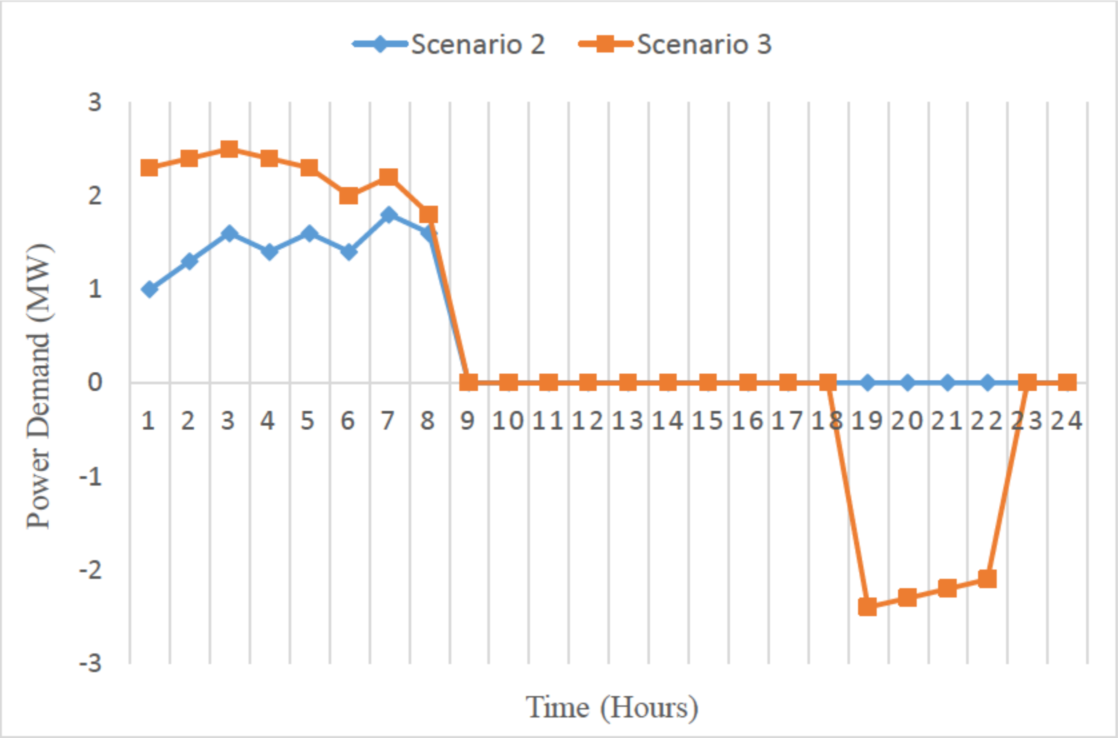

Figure 6-9: The sum of the power that charging stations have consumed and contributed consumed

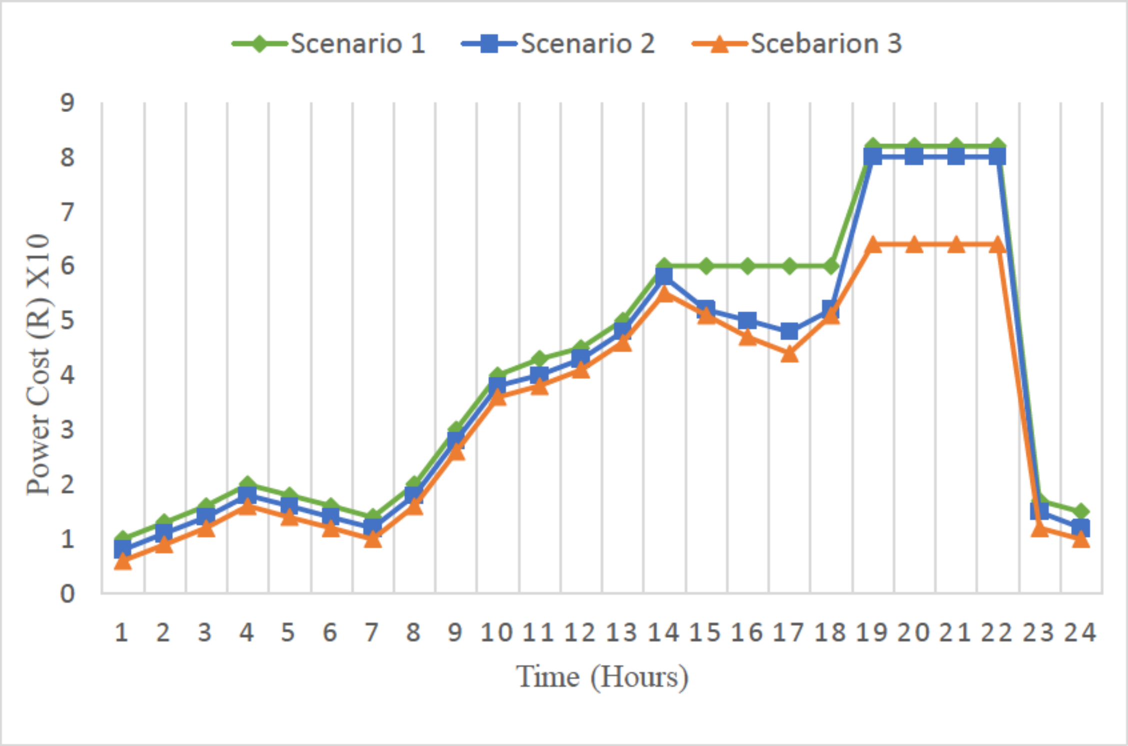

Figure 6-10: Losses cost in power that occur during the daytime

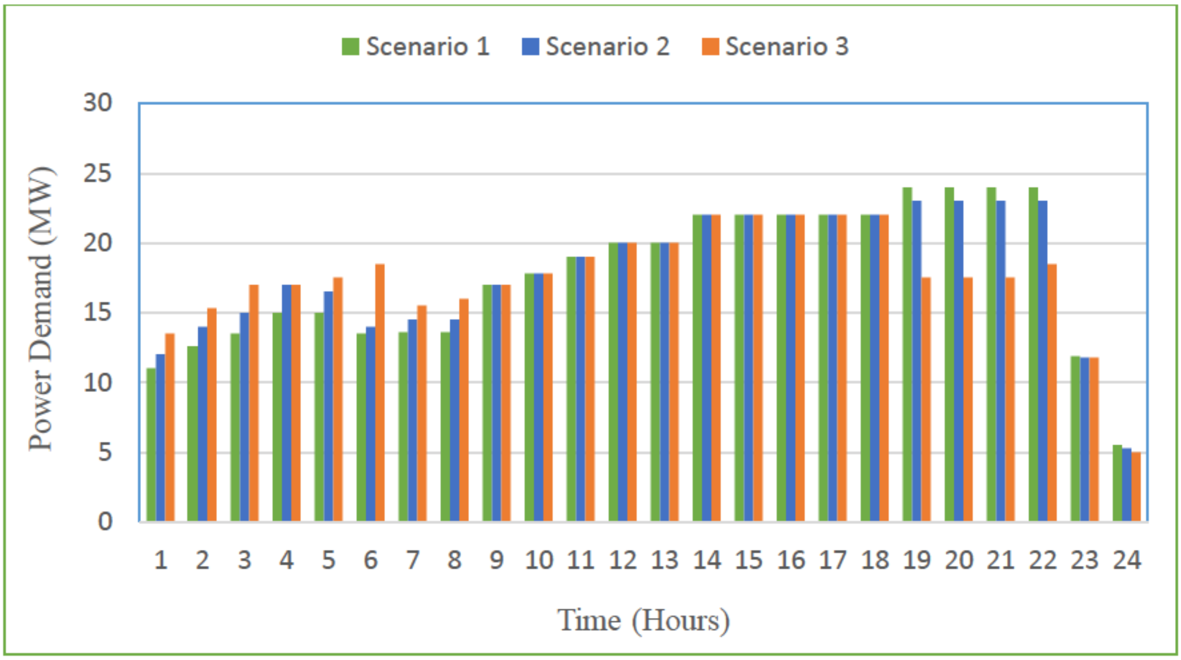

Figure 6-11: Different scenarios involving the loading of profiles

Table 6-9: Different algorithms violated the voltage in each of the three scenarios

	Voltage Violation		
Optimization Algorithm	**Scenario 1**	**Scenario 2**	**Scenario 3**
GA	0.9989	0.3025	0.3692
PSO	1.0015	0.5411	0.6084
IPSO	0.9990	0.4143	0.7703
HGAIPSO	0.9993	0.2904	0.2603

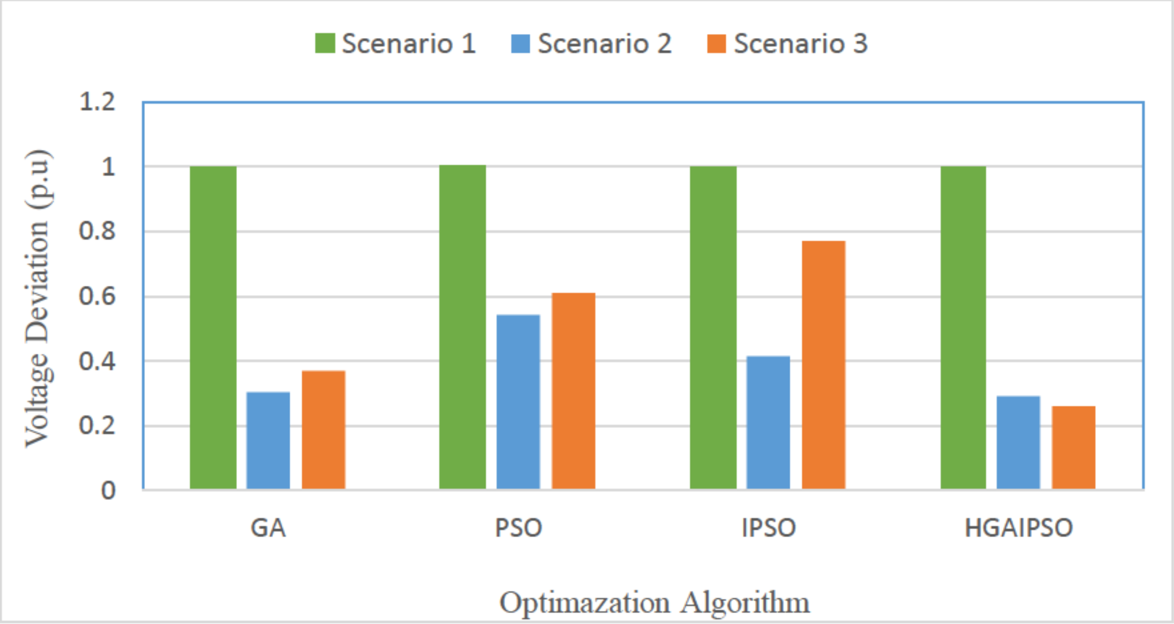

Figure 6-12: Voltage Violation by various algorithms during all 3 Scenarios

Table 6-10: Amount of energy lost by a variety of algorithms across all three scenarios

	Lost Energy		
Optimization Algorithm	**Scenario 1**	**Scenario 2**	**Scenario 3**
GA	0.9879	0.7505	0.5345
PSO	0.9895	0.7758	0.5545
IPSO	0.9990	0.6975	0.5272
HGAIPSO	0.9801	0.6335	0.4951

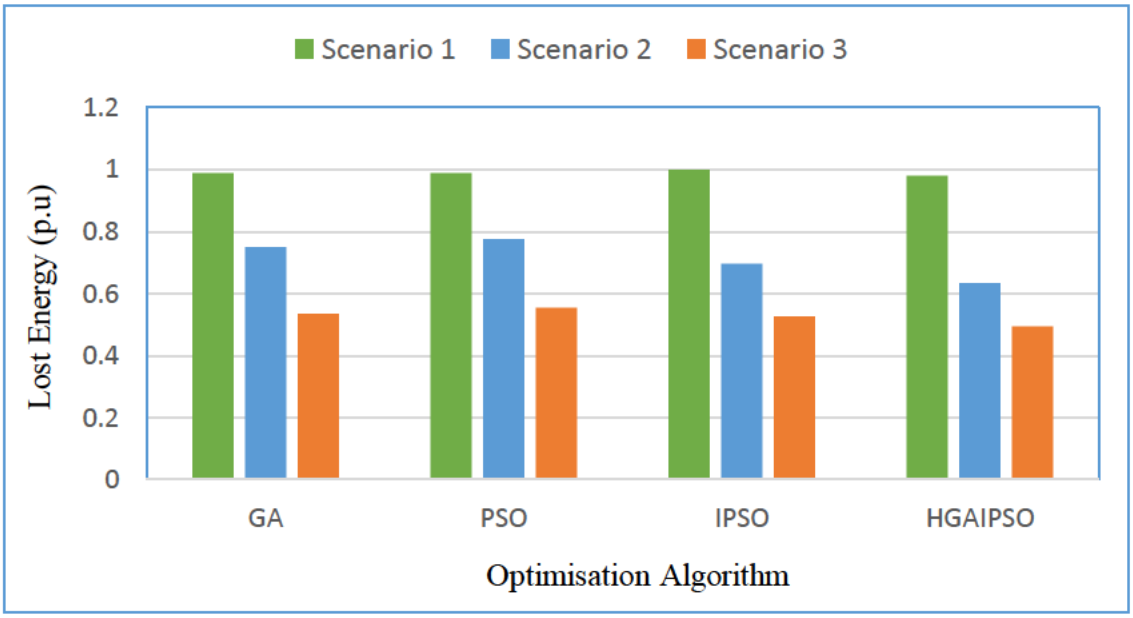

Figure 6-13: Amount of energy lost by a variety of algorithms across all three scenarios

6.3 Part 3: Results, Analysis and Discussion of Simulated studies to evaluate the performance of the proposed approach under different operating conditions

6.3.1 Scenario 1

As can be observed from the data in Tables 6-8 and 6-9, the HGAIPSO technique has proven to be effective in achieving the goal of attaining the least value of the objective functions. In addition, it is important to point out that it has reached the highest overall number of electric vehicles, which is some proof that the technique that was recommended is productive. Figure 6-14 illustrates the convergence curves as well as the best solution that was produced via the use of a number of computational approaches in scenario 1. The performance of the algorithm with sixty iterations is showing that the algorithm is effective.

Table 6-11: Comparison of the results acquired during Scenario 1 through the use of a variety of optimization algorithms at the 118-bus

Optimisation Method	Voltage violation (p.u)	Energy lost (p.u)	Bus with charging station	EVs per charging station
GA	0.9988	0.9879	98	10
			61	28
			46	13
			19	15
PSO	1.0014	0.9895	102	16
			83	25
			58	18
			19	15
IPSO	0.9989	0.9801	98	22
			92	19
			38	15
			19	13
HGAIPSO	0.9992	0.9794	110	28
			71	18
			45	21
			19	19

Table 6-12: A comparison of the outcomes achieved from the multi-objective function through Scenario 1 using different optimization techniques applied to the 118-bus system

Optimization Method	Best Solution	Worst Solution	Average Solution	Standard Violation
GA	0.9753	0.9792	0.9772	0.0018
PSO	0.9838	0.9898	0.9867	0.0029
IPSO	0.9754	0.9762	0.9758	0.0003
HGAIPSO	0.9750	0.9784	0.9769	0.0009

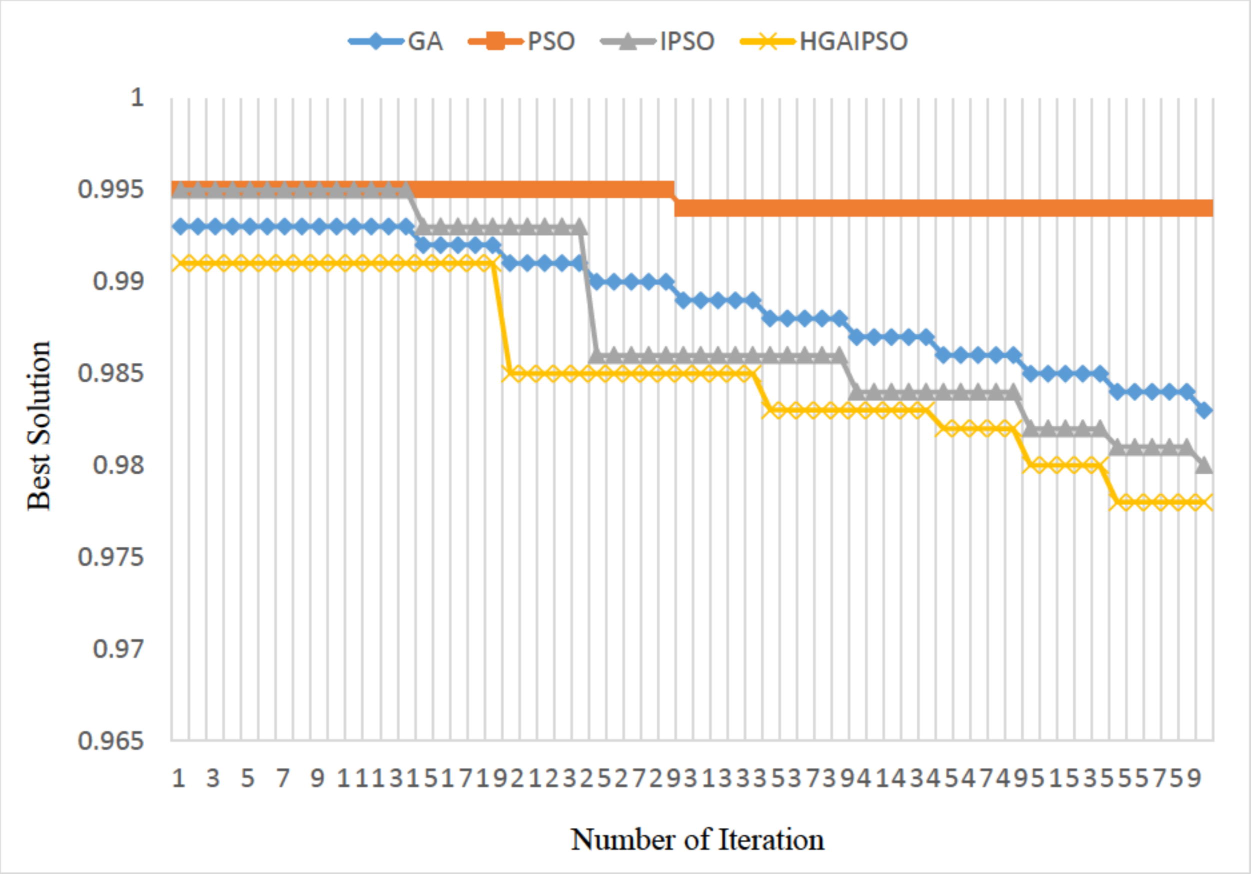

Figure 6-14: During Scenario 1, convergence curves generated by a variety of computation algorithms

6.3.2 Scenario 2

According to Table 6-10, the ultimate cost has been lowered to 90.67 %, despite the fact that the initial expense for REDGs obtained using HGAIPSO is the greatest, this is shown in the Table 6-10. The results of the HGAIPSO algorithm are presented in Table 6-11 and Figure 6-15. Not only has it obtained the highest total number of EVs, but it has also achieved the lowest value of the objective functions.

Table 6-13: Comparison of the results acquired by Scenario 2 through the use of a variety of optimization algorithms at the 118-bus system

Optimization Method	Voltage violation (p.u)	Energy lost (p.u)	Bus with charging station	EVs per charging station	Solar charging station size (MW)	Wind charging station size (MW)
GA	0.4107	0.8414	118	93	2.1147	1.9988
			72	180	2.4865	4.1847
			26	172	3.1788	2.7415
			5	164	1.9789	2.2587
PSO	0.6005	0.6972	113	95	1.6418	4.0142
			72	205	3.1189	3.1578
			47	152	1.3891	1.2125
			4	147	2.9991	0.9567
IPSO	0.5227	0.8763	112	74	2.1871	3.2458
			72	220	4.1735	4.1547
			25	218	0. 6149	1.5142
			3	138	0.5990	2.0115
HGAIPSO	0.3785	0.7218	113	130	0.7958	3.8415
			73	169	4.1845	4.2854
			47	204	4.1985	3.0515
			17	229	2.9587	3.0012

Table 6-14: Comparative analysis of the outcomes of the multi-objective function through Scenario 2 using a variety of optimization techniques applied to the 118-bus system that was used

Optimization Method	Best solution	Worst solution	Average solution	Standard Deviation
GA	0.7544	0.8616	0.8063	0.0537
PSO	0.8271	0.8734	0.8463	0.0241
IPSO	0.7601	0.8244	0.8018	0.0361
HGAIPSO	0.6821	0.7901	0.7104	0.0305

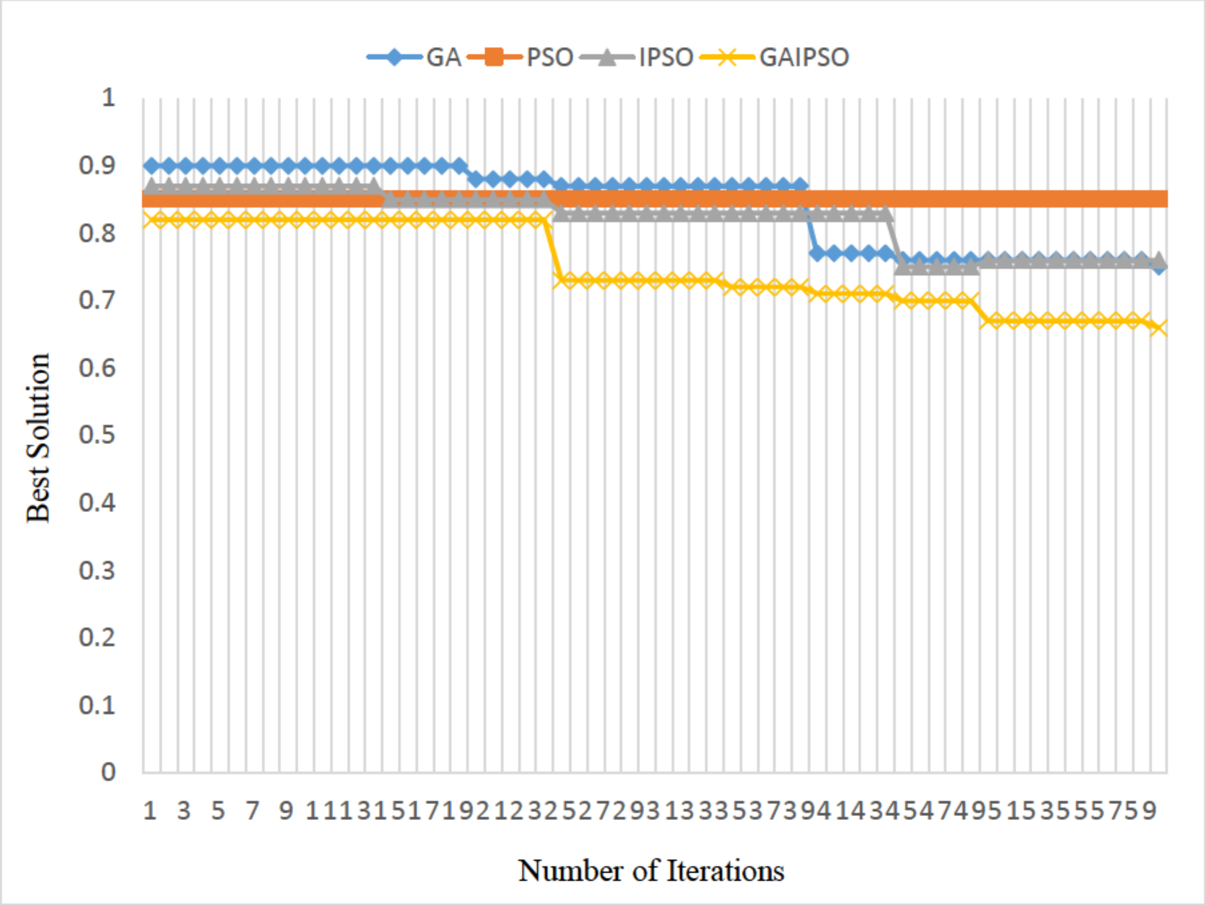

Figure 6-15: During Scenario 2, convergence curves generated by a number of different algorithms

6.3.3 Scenario 3

As can be seen in Table 6-12, the utilization of GA, PSO and IPSO resulted in a decrease in voltage violation as compared to Scenario 2. This was demonstrated by the fact that the voltage violation was of a lower magnitude. The implementation of HGAIPSO, on the other hand, led to a decrease in the number of voltage violations as well as the amount of capital expenditures linked with REDGs. The capacity of V2G to reduce the overall cost of the system is further reinforced by the results presented. As is evident from the data presented in Table 6-13 and Figure 6-16, HGAIPSO was able to successfully achieve the lowest value for the objective functions.

Table 6-15: A comparison of the outcomes produced by Scenario 3 through the use of a variety of optimization algorithms at the 118-bus system

Optimization Method	Voltage violation (p.u)	Energy lost (p.u)	Bus with charging station	EVs per charging station	Solar charging station size (MW)	Wind charging station size (MW)
GA	0.41725	0.6154	112	342	0.8330	2.1985
			70	245	4.0114	1.9454
			46	114	3.1210	4.0121
			21	202	4.1458	2.0541
PSO	0.5871	0.6856	104	333	0.8899	1.5154
			70	200	3.1924	3.0858
			33	275	4.1082	1.5267
			17	207	1.9238	4.1739
IPSO	0.8434	0.6281	110	279	4.2151	3.2198
			68	228	2.4170	2.9054
			51	246	3.3390	2.0258
			9	267	2.3994	2.9875
HGAIPSO	0.3027	0.5064	112	306	3.7352	3.5894
			72	257	2.1831	2.8451
			44	315	2.8747	1.8884
			221	201	2.9856	1.8954

Table 6-16: A comparative analysis of the outcomes derived from the multi-objective function through Scenario 3 using a variety of optimization algorithms applied to the 118-bus system

Algorithm	Best solution	Worst solution	Average solution	Standard violation
GA	0.5962	0.6410	0.6136	0.0240
PSO	0.6454	2.6783	1.3328	1.1653
IPSO	0.6956	0.7333	0.7121	0.0193
GAIPSO	0.5433	0.5898	0.5661	0.0133

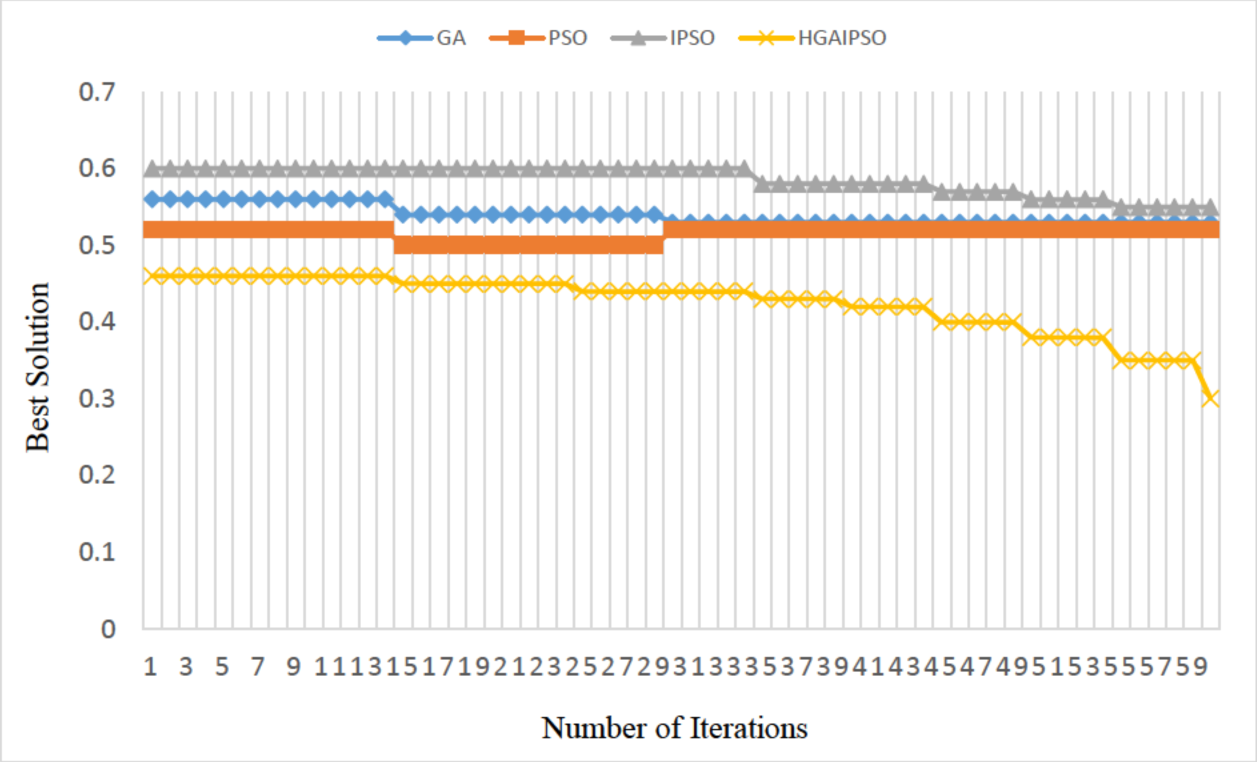

Figure 6-16: During Scenario 2, convergence curves generated by a number of different algorithms

6.4 Analysis of key performance indicators, such as energy costs, grid congestion, emissions reduction and user satisfaction

The influence of socio-economic conditions plays a crucial role in determining vehicle ownership, travel frequency, and occupancy trends. The demand for electric vehicles is shaped by three key socio-economic factors. First, the characteristics of the vehicles themselves, including their pricing and battery capabilities. Second, social determinants such as lifestyle choices, income levels, household composition, and educational attainment [364]. Lastly, external factors involve fuel costs and the presence and accessibility of necessary infrastructure. Typically, consumers engage in a comparative evaluation of similar products before finalizing a purchase in the marketplace. The acceptance and integration of electric vehicles in South Africa hinge on achieving cost parity with internal combustion engine vehicles.

The appeal of electric vehicles is diminished by their higher purchase prices, which are approximately 30% greater than those of traditional vehicles. Projections indicate that the costs associated with electric vehicles (EVs) will likely remain elevated in comparison to internal combustion engine (ICE) vehicles until 2050 [365]. Currently, electric vehicle prices exceeding R0.5 million are beyond the financial reach of most working-class individuals in South Africa. These prices correspond to the 70th percentile of ICE vehicle costs in Cape Town and are typically accessible only to the affluent segment of the population. It is anticipated that price parity between electric vehicles and internal combustion engine vehicles will continue until the late 2020s. Exploring the feasibility of introducing affordable micro-EVs that meet commuter transportation requirements, inspired by approaches taken in China, represents a promising avenue for investigation [366].

The travel behaviors of South Africans are shaped by various socio-economic factors and can be categorized into three main types of trips: educational (50%), work-related (45%), and business-related (5%). These patterns indicate a significant concentration of travel within urban areas. The growth of electric vehicles (EVs) in the marketplace is hindered by the high costs of their batteries, limited vehicle range, and inadequate fast-charging infrastructure. For electric vehicles and plug-in hybrid electric vehicles (PHEVs) to gain widespread societal acceptance, it is crucial that the expenses related to charging and discharging their batteries, along with their usage patterns, align with national power consumption profiles. Presently, battery costs account for approximately 40% to 50% of the overall price of electric vehicle units [367]. The slow uptake of electric vehicles is largely due to their high total costs, which impede the achievement of goals aimed at reducing CO_2 emissions. However, advancements in battery technology and increasing competition from new market entrants are anticipated to significantly lower battery prices in the future.

Electric vehicles present distinct challenges that are not adequately addressed by existing auto finance options, thereby complicating the process of securing suitable loans from financial institutions for their acquisition. As a result, in addition to regulatory initiatives, financial incentives are crucial to close the disparity gap [368]. The South African government is contemplating the introduction of incentives for manufacturers to encourage the production of affordable vehicles, particularly in response to the reduced demand stemming from high costs. South Africa exhibits significant social inequality, with a pronounced disadvantage faced by the underprivileged segments of the population. Approximately 50% of individuals are classified as chronically disadvantaged, while only 4% enjoy prosperity and live in conditions that surpass the average. The middle class is expanding; however, it remains relatively small, accounting for 20% of the population. Furthermore, 25% of the populace frequently experiences fluctuations in their economic status, moving in and out of poverty. Generally, individuals with lower incomes tend to purchase older technology vehicles within the country [369].

6.4.1 Greenhouse gas (GHG) emissions from road transportation in South Africa

In 2015, road transport emitted 56.14 million metric tons of carbon dioxide equivalent (Mt CO_2e), however in 2019, emissions rose to 59.49 Mt CO_2e. The emissions surpass those documented in DEFF (2020), although align closely with the emissions generated from energy consumption profiles published by researchers [370]. In 2015, road transport in South Africa consumed a total of 422 petajoules (PJ) from gasoline and 365 PJ from diesel. The burning of these fuels produced a total annual emission of 56.29 million metric tons of carbon dioxide, comprising 29.24 million metric tons from petrol and 27.05 million metric tons from diesel in that year. The emissions exceeded the projected 54 Mt CO_2 for 2020, notwithstanding the current mitigating initiatives. Road transport emissions in South Africa increased from 33.3 Mt CO_2e in 2000 to 43.4 Mt CO_2e in 2010 [371]. Road transport constitutes nearly the entirety of fuel use, with diesel accounting for 76% of this total in the country. The little discrepancy between the results of this study and the DEA analysis might be ascribed to the application of different approaches for quantifying the emissions.

In 2015, road transport was responsible for emitting 56.14 million metric tons of carbon dioxide equivalent (Mt CO_2e). By 2019, this figure had increased to 59.49 Mt CO_2e. These emissions exceed those reported in the DEFF (2020) but are consistent with the emissions derived from energy consumption profiles as indicated by researchers [372]. In South Africa, road transport consumed a total of 422 petajoules (PJ) from gasoline and 365 PJ from diesel in 2015. The combustion of these fuels resulted in an annual emission of 56.29 million metric tons of carbon dioxide, which included 29.24 million metric tons from petrol and 27.05 million metric tons from diesel. This level of emissions surpassed the anticipated 54 Mt CO_2 for 2020, despite ongoing mitigation efforts. Furthermore, road transport emissions in South Africa rose from 33.3 Mt CO_2e in 2000 to 43.4 Mt CO_2e in 2010 [373]. Road transport accounts for nearly all fuel consumption in the country, with diesel representing 76% of the total. The slight variation between the findings of this study and the DEA analysis may be attributed to the use of different methodologies for calculating emissions.

The average emissions associated with each type of road transport are experiencing a consistent increase. Tax rates are highest for heavy-duty vehicles and lowest for motorcycles. In 2009, the average annual emissions varied across different vehicle types. Buses and trucks emitted 39 tons of CO_2 equivalent per vehicle, minibuses produced 8 tons, light-duty vehicles generated 4 tons, and motor cars released 3 tons of CO_2 equivalent per vehicle. The overall mean carbon dioxide equivalent emissions per vehicle for all road transport in 2009 stood at 5.1 tons [374]. By 2015, this average had increased to 5.4 tons per vehicle. Projections indicate that carbon dioxide emissions from road transport in South Africa could exceed 100 million metric tons by 2050. Therefore, it is crucial to implement a range of energy conservation measures within the transportation sector in South Africa. Neglecting to take these actions may lead to a more than twofold increase in the demand for transport energy and the associated CO_2 emissions by 2050 [375].

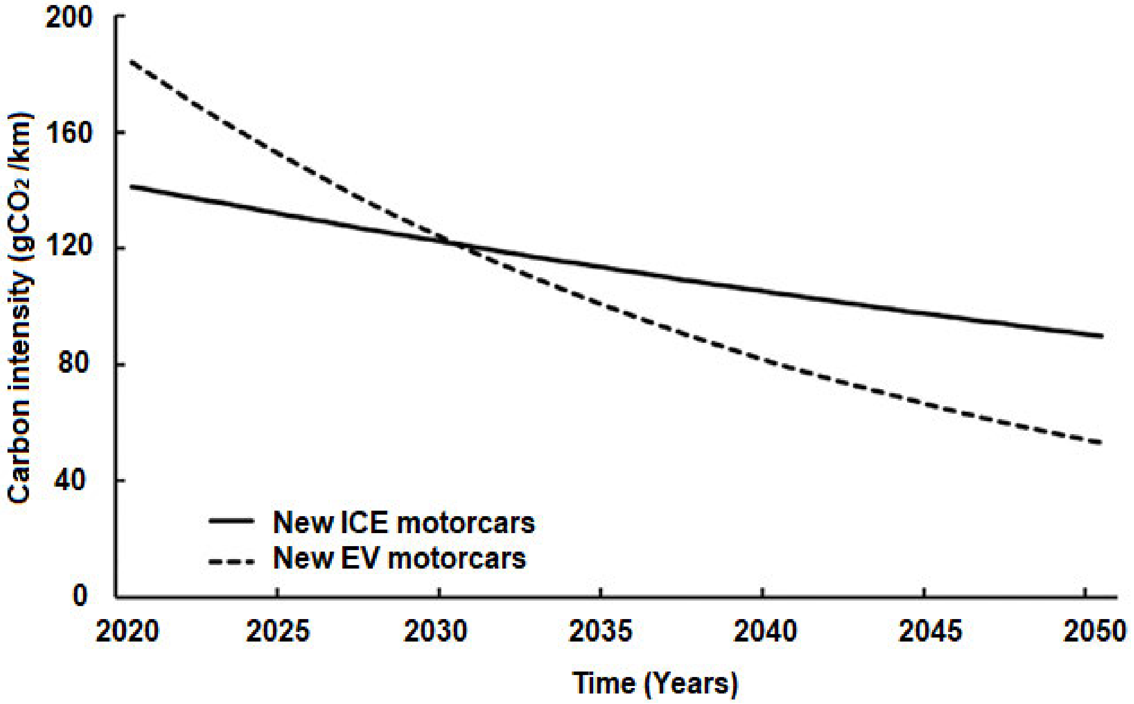

Figure 6-17: Anticipated carbon intensity of newly manufactured automobiles in South Africa [375]

Summary

The researcher applied the created optimization framework and control approaches to many typical power system settings. Simulation studies were done to evaluate the efficacy of the proposed technique across various operational scenarios, energy penetration levels, and grid topologies. An analysis and discussion were conducted on the outcomes of these simulation studies. Furthermore, there was a discussion on the examination of important performance indicators, encompassing factors such as the reduction of emissions, grid congestion, energy pricing, and customer satisfaction. The next chapter is chapter seven which is the implementation challenges and considerations

CHAPTER SEVEN: IMPLEMENTATION CHALLENGES AND CONSIDERATIONS

Introduction

The seventh chapter will address the challenges that arise when designing effective charging control strategies for electric vehicles under real-world power system situations. Consideration is given to the technical, economic, regulatory and behavioural factors that impact the adoption of electric vehicles and charging patterns. Strategies can be developed to address concerns of interoperability, cybersecurity, privacy and equity in respect to electric vehicle charging infrastructure.

7.1 Discussion of challenges in implementing optimal EV charging control strategies in practical power system environments

Connecting a significant number of electric vehicles to the power grid, even in ideal conditions, presents a complex challenge that requires careful monitoring and evaluation of its potential financial, operational, and control benefits. Various models for integrating electric vehicles into the electrical grid have been explored, with further research focusing on the effects of electric vehicles on the distribution system. Recent studies suggest that the majority of electric vehicle charging infrastructure will likely be installed in private residences. Public, commercial, and workplace charging stations are expected to be frequently used for recharging electric vehicles [376]. The effects of electric vehicle charging are projected to have immediate consequences for the electric power distribution infrastructure. These outcomes may range from a simple rise in power transformer temperatures to the urgent need for the development of entirely new power distribution facilities.

A variety of strategies for integrating extensive electric vehicle fleets with the power grid to harness their potential benefits have been extensively explored in existing literature. In this scenario, the electric vehicle operator and the utility provider emerge as the two principal stakeholders. The benefits derived from advanced management, information and communication technology, and operational efficiencies outweigh the associated costs. Recently, there has been a notable increase in scholarly interest regarding the role of the electric vehicle aggregator. This aggregator is responsible for coordinating all operational activities among the Distribution System Operator (DSO), Transmission System Operator (TSO), and various energy service providers. Its primary role is to facilitate communication between electric vehicle owners and the various entities within the energy market [377]. The core idea behind the virtual power plant (VPP) involves the aggregation and management of electric vehicles as a cohesive distributed energy resource, which is crucial for the effective integration of electric vehicles. The VPP aggregator enables electric vehicles to participate in the energy market on behalf of the DSO, TSO, or Grid Operator (GO).

In scenarios where multiple electric vehicles are interconnected, each driver effectively becomes a power broker within the energy sector. Electric vehicle owners will employ two-way communication and control systems to respond to inquiries from the DSO, TSO, and other market participants. A recent innovative approach to electric vehicle integration has been introduced, aimed at assisting owners in minimizing charging costs and reducing strain on the grid. Although the aggregator functions as a third party, it remains partially engaged in the integration process [378]. An example of this phenomenon can be seen in price-sensitive products within the energy sector. Interacting with each electric vehicle owner raises the standards for energy planning, security, and management, leading to questions regarding the viability of the integration model. As the number of variables increases, the task of selecting the most suitable solution becomes increasingly intricate. [379].

The battery sector is crucial for the electric vehicle's capacity to penetrate the energy market. Lithium-ion (Li-ion), lead-acid (Ha), and nickel-metal hydride (NiMH) are examples of several chemistries employed in battery technology. Comprehensive investigation into battery technology is crucial to initiatives aimed at substantially augmenting the global prevalence of electric vehicles [380]. This commonly presents additional challenges in reducing beginning expenses, enhancing vehicle performance (such as range), and achieving substantial profit margins in the energy sector. Frequent charging and discharging substantially diminish battery longevity in V2G applications. In recent years, scholars have focused on this phenomenon due of its significance. Peterson et al. [381] conducted a study examining the charge degradation of lithium-iron-phosphate (LiFePO4) battery cells over time in both vehicle-to-grid (V2G) and conventional driving modes. The battery loss capacity was computed based on the number of driving days, total energy consumption, and battery capacity. Their research indicates that this type of battery may endure multiple cycles of charging and discharging with no capacity degradation. Guenther et al. [382] examined the deteriorating characteristics of Li-ion batteries using an aging model.

The loading pattern encompassed a wide range of variations related to driving conditions, charging methods, and peak shaving through vehicle-to-grid (V2G) transactions. The integration of V2G transactions is estimated to shorten the battery lifespan by approximately three years, as it leads to an increase in both the frequency of discharge cycles and the depth of discharge. However, the application of advanced charging strategies has the potential to enhance battery durability [383]. While certain electric vehicle (EV) application scenarios, particularly those involving V2G transactions, show promising prospects, additional research is necessary to further clarify the factors influencing battery lifespan. In creating a realistic battery model for these evaluations, it is crucial to consider aspects such as calendar aging, self-discharge, and aging cycles. It is expected that, in the near future, compact and cost-effective batteries with significant energy and power capabilities will become available [383].

A summary of various battery technologies currently employed in the automotive sector is provided in Table 7-1. Therefore, advanced real-time communication is vital for the exchange of information, including pricing, energy forecasts, and driving characteristics of electric vehicles among the involved parties [384]. The smart grid platform plays a critical role in ensuring the smooth operation of this system. As the smart grid continues to develop, it may offer a more attractive pathway for electric vehicles to integrate into the energy sector, thanks to its accessible and sophisticated communication infrastructure. The following sections will deliver an in-depth analysis of the previously mentioned interaction scenarios between electric vehicles and smart grids. Recent advancements in battery technology have been facilitated by lithium [385].

The characteristics of lithium-ion batteries, including their energy supply, lightweight design, cost-effectiveness, non-toxic nature, and rapid charging capabilities, position them as the most promising battery technology available. These batteries exhibit a gravimetric energy density that ranges from 118 to 250 Wh/kg. Efforts are currently underway to enhance their specific energy capacity for further improvements [386]. Typically, the anode electrodes in lithium-ion batteries are constructed from silicon nanoparticles (SiNPs), which are known for their high energy density. Lithium batteries are recognized for having the lowest equivalent mass and the highest electrochemical potential. They also demonstrate efficiency and longevity. However, their cost exceeds 700 USD per kWh, and they pose risks of fire and property damage if subjected to overheating. The mass transport limitations within the electrolyte and electrodes can lead to significant polarization in lithium batteries that are designed for enhanced performance. The degree of polarization is influenced by various factors, including the dynamic and kinetic properties of the materials, the battery's design, and the mechanisms involved in charging and discharging. To mitigate solid-phase diffusion polarization, Chen and colleagues have proposed reducing the size of the active material particles. Their findings indicate that when the number of active material particles is halved, the concentration of lithium-ion battery (LIB) is significantly diminished [387]. Conversely, when the active material particles are increased in size, the concentration difference of Li-ions becomes considerably larger. Battery types and sizes utilized by electric vehicle manufacturers are detailed in Table 7-1.

Table 7-1: Battery type and size by EV Companies

Company	**Electric Vehicle Model**	**Types of Battery**	**Battery Size [kWh]**
BYD	E6/BEV	Lithium iron phosphate (LIP)	78
Toyota	Prius (ZVW35)/PHEV	Lithium nickel cobalt aluminum oxide (NCA)	4.5
MiniCoope	MiniCoope SE	Lithium manganese oxide (LMO)	70
Volvo	XC40 P6 Rechargable	Nano lithium iron phosphate (NLIP)	60
Mercedes-Benz	EQA 250 Progressive	Lithium manganese oxide (LMO)	30
BMW	IX3 M Sport	Lithium manganese oxide (LMO-NMC)	5
Audi	e-tron 55 Quattro	Lithium manganese oxide (LMO-NMC)	85
Jaguar	I-Pace EV400 AWD SBlock	NiMH	70
Porsche	Taycan	Lithium manganese oxide (LMO-NMC)	65

7.1.1 EV Charging and Electric Grid Interaction

A primary application of EV charging systems is in electric vehicles. Various levels of charging power and durations are accessible for electric vehicles. These benchmarks signify the charging rate of an electric car, whether it is sluggish or rapid. Home and office charging facilities typically require 8 hours for PHEVs and 20 hours for BEVs, whereas public and commercial charging stations necessitate 15 minutes to an hour [388]. Table 7-2 indicates that AC Level 1 is attainable in a standard residential environment, whereas AC Level 2 is more appropriate for workplaces, cinemas, shopping centers, and other public and commercial venues [388]. It is anticipated that public, private, and commercial charging stations would provide access to DC quick charging (DC Level 1–3). The charging power supplied is frequently dictated by the DC bus voltage, which is generally less than or equal to 400 VDC, as indicated by current research on EV batteries. The duration required to fully charge an electric vehicle's battery pack is influenced not only by the charging level parameters (voltage and current ratings) but also by the battery's storage capacity [389]. The ideal technique for standardizing the fast-charging portfolio is subject to dispute.

Fast-charging is necessary to fully recharge the EV battery in a brief period. To enable both regular AC charging and DC fast charging, automotive manufacturers globally partnered with the Society of Automotive Engineers (SAE) to create a unified charging station. A single unit connector (SAE combo standard) supports AC single-phase, AC three-phase (AC fast-charging), and ultra-fast DC charging. The CHAdeMO fast-charging standard is receiving significant endorsement in the electric vehicle market. This standard was established by the Tokyo Electric Power Company (TEPCO) [390]. This phenomena, akin to the swift refueling of internal combustion engine vehicles, will enhance public confidence in the safety and feasibility of electric vehicles. Up to 36 kW, up to 90 kW via Level 2 DC fast charging, and up to 62.5 kW according to the CHAdeMo standard, as demonstrated in a recent study by Chaundhry and Bohn, who sought to establish that DC fast charging can facilitate vehicle-to-grid (V2G) technology. The literature examines both AC Level 1 and AC Level 2 methodologies.

Table 7-2: SAE J1772 compliant AC/DC charging characteristics

Power capacity [kW]	**Voltage level [V]**	**Current capacity [A]**	**Power level type**	**Remark(s)**
1.4	120VAC	12	AC Level 1	Single phase supply (EV with on-board charger) Charging time PHEV: 7.30 h BEV: 16.30 h
Up to 40	200–500VDC	Less than 80	DC Level 1	3-phase supply (EVSE with off-board charger) 20 kW charger PHEV: 25 min BEV: 1.30 h
19.2	240VAC	Up to 80	AC Level 2	Single/Three -phase supply (EV with on-board charger) 3.3 kW charger PHEV: 3.00 h BEV: 7.30 h 7 kW charger PHEV: 1.30h BEV: 3.30 h
Up to 100	200–500VDC	Less than 200	DC Level 2	Three -phase supply (EVSE with an off-board charger) 45 kW charger PHEV: 10 min BEV: 20 min
420	–	–	AC Level 3	Under development
Up to 240	200–600VDC	Less than 400	DC Level 3	Under development

The existing power grid, while supplying AC voltages to loads, is suboptimal. A rectifier power circuit is essential for charging an electric vehicle's battery pack. Nonetheless, financial and thermal constraints restrict the power capacity of the rectifier circuit [391]. The dimensions and capacity of the rectifier circuit directly correspond to the circuit specifications utilized in electric vehicle applications. Consequently, they exert a considerable influence on DC fast-charging infrastructure. In the forthcoming decade, this will be the most practical method for charging electric vehicles, and charging stations will be regarded similarly to gas stations today. The substantial power consumption of these stations is a challenge, necessitating an independent power supply, the design of the power conversion interface, and extended battery longevity [392]. DC quick charging infrastructures for V2G services must undergo feasibility studies to thoroughly clarify their characteristics and performance.

In the context of smart grids, the SAE standard J1772 was updated in October 2012 to make V2G and charging solutions for electric vehicles more flexible. Included in this category are the communication portfolios for reversible energy flows, DC rapid charging standards, and electric vehicle supply equipment (EVSE), all of which needed for PHEVs [393]. Article 625 of the NEC and the standard IEC 62196 from the International Electro-Technical Commission are excellent resources for anyone thinking about building a charging station for an electric vehicle. In the near future, new low-EMI bidirectional power converters for electric chargers may make V2G compatibility in EVs the norm. The AC Level 1 and 2 charging setups (electric vehicle with on-board charger) are depicted in Figure 7-1 [394]. In both the AC Level 1 and 2 setups shown in Figure 7-1, an on-board charger is supplied with AC power to charge the EV. The charging station and EV battery pack are shown in close proximity to one another in both the DC Level 1 and 2 versions shown in Figure 7-1.

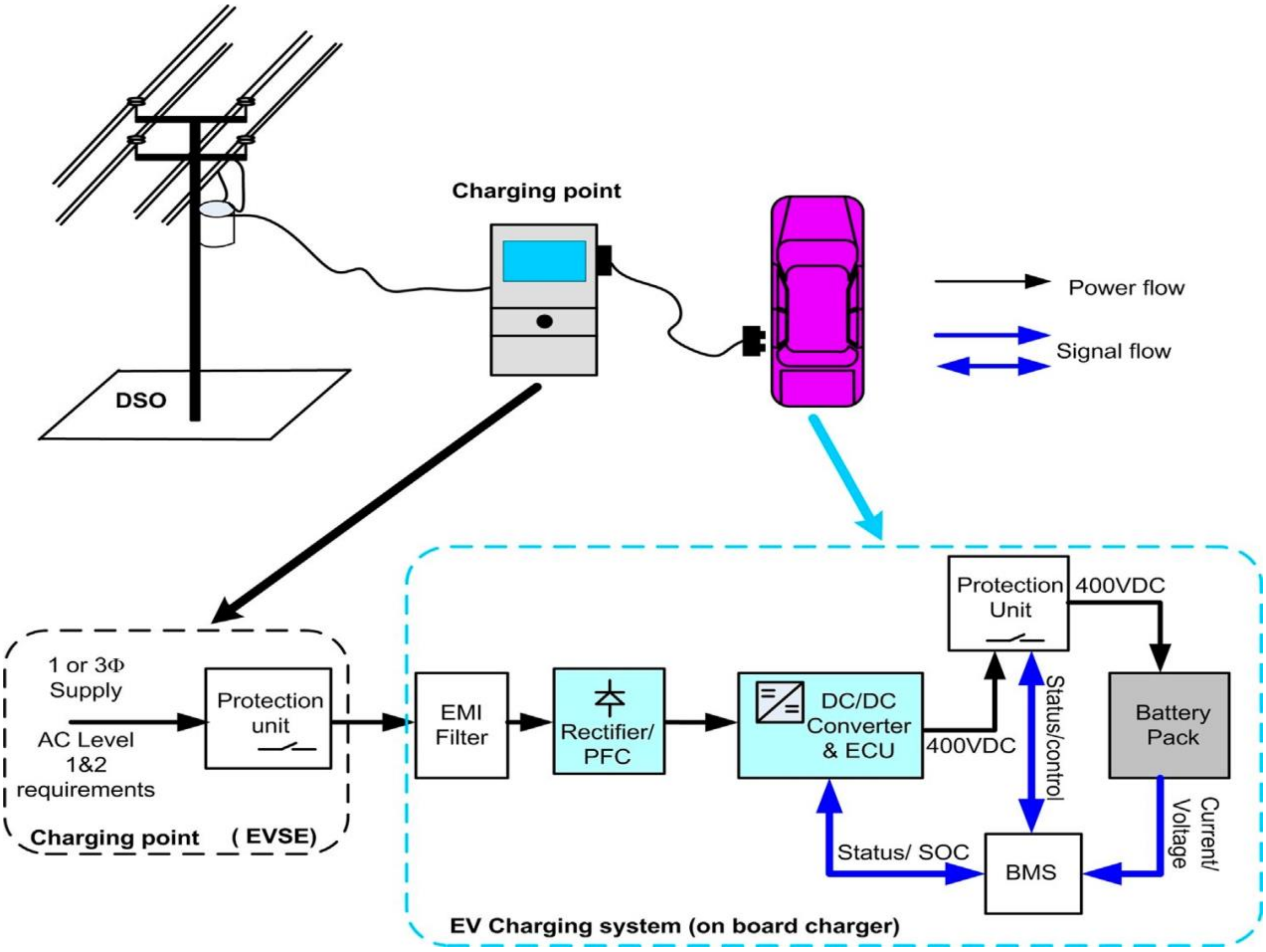

Figure 7-1: Onboard EV charging configuration at AC level 1 and 2 setups

Figure 7-2 illustrates EVSE with an off-board charger. It takes almost as much energy to recharge an electric vehicle with current EV battery technology as it does to power a single European or American household for a day. Adding additional electric vehicles to a charging circuit increases energy usage proportionally. This symbolizes the strain that modern electricity infrastructure is under. This includes the establishment of norms and price systems, in addition to making suggestions for legislation. Authors in [395] found that using a 3.3 kW charger at 220 V/15 A will raise a home's current usage by 17–25%. Different potential charging techniques have recently been discussed in the literature, with special emphasis being placed on how they would be affected by factors such as the owner's driving behavior and the present grid model. Such schemes include but are not limited to the following: uncontrolled (dumb) charging, dual-tariff charging, and smart or intelligent charging. When an electric vehicle is plugged into an unmonitored power source, the charging process begins instantly [396]. The effects of this pricing strategy on electrical grids have been the subject of numerous research studies. Almost all of the research on this available in the literature indicates that this type of charging further overloads the power distribution system and raises the cost of investments.

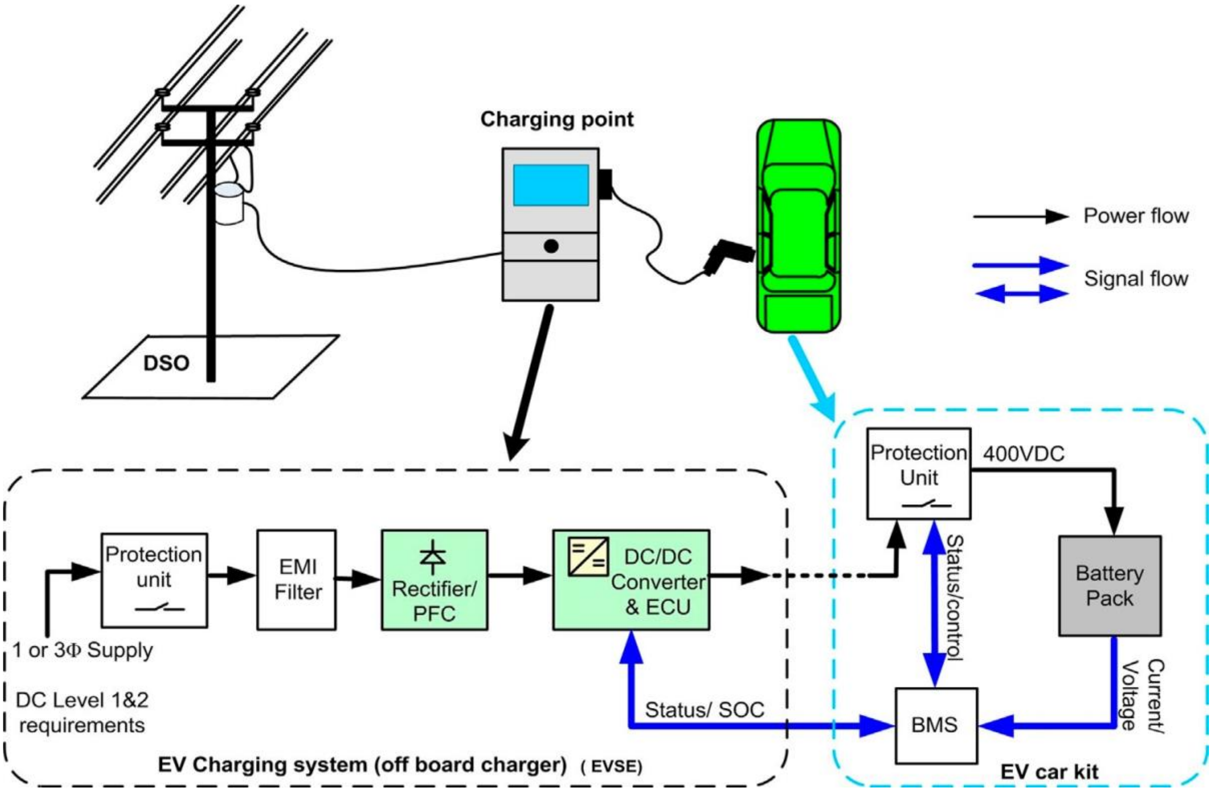

Figure 7-2: Off-board EV charging configuration at DC level 1 and 2 frameworks

The impact of EV loading on the power distribution network is significant, as noted previously. Additional stress on the electrical grid is caused by the charging of electric vehicles. Insufficient control over this additional load might exacerbate the depreciation of power system components and trigger relay tripping in the event of extreme overload. According to the authors of [397], the incremental investment costs in power distribution system facilities can be reduced by as much as 60–70% when EV smart charging schemes are used. Mitigations, such as moving this increased demand to a valley time or optimizing the available power via coordinated charging schemes, are used to keep the distribution system running smoothly and safely while accommodating for the widespread adoption of EVs. Although load shifting can save anywhere from 5 to 35% of the required investment cost, energy losses can approach 40% of the true values [398]. Researchers have extensively studied how charging electric vehicles will affect power grid loading while taking into account large distribution networks.

7.1.2 Electric Vehicles Using the V2G System Architecture

Electric vehicles can function as dynamic loads, pulling electricity from the grid (during charging) or dynamic ESS and supplying power back into the grid depending on their charging and operational demands. The latter is sometimes referred to as the V2G concept. As a resource for V2G services, EVs are impractical due to their low storage capacity and the fact that they are few in number and dispersed in terms of location [399]. In order to implement the V2G concept, vast numbers of EVs are aggregated in diverse ways, each of which is optimized for a distinct group of control strategies and objectives. When electric vehicles are combined into a single, manageable distributed energy source, the electric grid is better able to regulate and control the system. When EVs interact with the smart grid, either unidirectional or bidirectional V2G services can be realized. Assuming the former, V2G and V2G are both feasible when charging an EV [384]. The usefulness and efficiency of this collective EV-grid connection has been the subject of extensive research.

One of the key drawbacks of this system is the high cost and lengthy time commitment required to install anti-islanding and other complete safety protection measures. However, the EV can only draw power from the grid in one direction (to charge the battery). Therefore, it cannot contribute to the system in any way. One study in particular used a 20 kWh battery with the BC to provide 6.6 kW of regulating capacity, whereas a 20 kWh battery with the UC was able to meet energy demands of up to 3 kW [400]. The bidirectional charger increases annual revenue by 12.3% compared to the unidirectional charger while considering battery capacity fading. The monetary benefits of bidirectional power flow architecture may be dampened by protection and metering systems. Using bidirectional power flow to benefit from V2G is proven to be nearly as beneficial as using unidirectional power flow. One-way power flow may be superior to two-way power flow in some cases, such as when the power capacity for V2G transactions needs to be lowered.

On the other hand, the VPP's conceptual architecture offers a scenario for aggregation that makes V2G a reality by facilitating communication and control between the utility entity (control center) and the EV fleet. Depending on the underlying control philosophy and aggregation technique, different VPP frameworks in the V2G environment can be modeled to address grid and EV inclusion challenges [401]. The VPP supports both a centralized and decentralized organizational structure. An overarching management structure in a VPP, decisions and data flow are facilitated at the VPPC, but in a distributed control system, these tasks are performed independently of one another. On the other hand, the spatial VPP model is hierarchical in nature, facilitating communication and decision making at multiple levels [402]. Based on the information it receives from the smart meters and the energy market, the VPPC makes choices and offers certain updated requests to the VPP resources in real-time. The VPP design and the shared EV batteries can help the electric power system decrease mistakes in demand and consumption estimates.

7.2 Consideration of technical, economic, regulatory and behavioural factors influencing EV adoption and charging behaviour

The impact of EVs on the power grid is being studied by numerous institutions, including universities, corporations, government labs and think tanks. This article presents several approaches for incorporating EV technology into the power sector's smart grid architecture. However, the prospect of V2G schemes being ran successfully through interaction between electric vehicles and the smart grid has not been thoroughly explored in practice. Improvements still need to be made to smart grid and V2G technology before electric vehicles can be integrated without a hitch. Some examples of areas for improvement include battery technology and interfaces for supplying energy and information. In addition, significant research and development is needed to improve the efficiency and reduce the price of a wide range of technologies, including EV charging infrastructure [403]. Research and tests are already underway to bring the V2G concept to life. Kempton et al. conducted the first experimental project to assess whether EVs can feed the grid (V2G) to provide real-time frequency regulation. The project showcased a wide range of realistic V2G deployment techniques for grid support. There is only one electric vehicle in the sample. Therefore, generalizing the results to a large fleet of EVs presents challenges.

7.2.1 Intelligent EV Scheduling

The charging of electric vehicle batteries presents a significant new issue to the grid due to the effect of EVs on load demand. In conclusion, if the charging of electric vehicles is managed intelligently, a substantial redistribution of load can occur. This purpose necessitates the coordinated efforts of intricate grid management, market operators, and electric vehicle management systems. The adoption of intelligent charging techniques has been advised to mitigate distribution system overload resulting from electric vehicle charging, as previously discussed [404. The actualization of this concept is nearer than ever due to recent implementations of smart grid test-beds and the ongoing incorporation of smart grid technologies into the current electrical infrastructure. Wireless communication, GPS infrastructure, and smart metering are becoming prominent components of the smart grid system. The proportion of drivers utilizing the internet via mobile devices is swiftly rising. The European Union's 2015 legislation on automatic accident notification (CAN) may serve as a mechanism to improve V2G communication for road safety and rapid emergency responses. Smart charging infrastructure and communication hubs may be conceptualized as supplementary services to an existing wireless network [405].

The smart meter can be designed as firmware instead of hardware, while incorporating roaming services to accommodate the transient characteristics of electric vehicles and enable dynamic pricing and data exchange for efficient EV scheduling. Numerous firms seek to employ programmers to facilitate communication between their electric vehicles and the smart grid [406]. Better Place is a global corporation showcasing the viability of transportation electrification via several initiatives, including battery switching stations (BSS). When an electric vehicle's battery starts to diminish, it can be replaced with a fully charged unit from the battery swapping station, allowing work to continue uninterrupted. The implementation of this method in battery switching facilities directly enhances EV reliability. Reports indicate that replacing batteries requires approximately five minutes [407]. Comparable stations have lately been inaugurated in prosperous locales, including Tokyo, Israel, China, the Netherlands, and

Denmark. Daimler and Enel are spearheading a trial initiative named e-mobility in three Italian cities: Pisa, Rome, and Milan. The Enel Company's smart meters and RFID/GPRS communication technology constitute the intelligent charging system utilized in this project, which also connects the electric car to a central control center [408]. These pilot projects demonstrate the potential and insights gained from intelligent electrification in the transportation sector.

7.2.2 Influence of REDGs and EVs

The ability of electric vehicles to accelerate the broad adoption of renewable energy generation technologies, especially wind and solar photovoltaic energy, is a common subject of research among academics. The integration of electric vehicles into this process will greatly enhance the REDG's integration into the grid. However, further scientific research and cost-benefit analysis are required because of the interdisciplinary character of this concept. Current demonstration projects are investigating the impacts and viability of electric vehicle interaction with the Renewable Energy Distribution Grid [409]. The vehicle features 23 CHAdeMO DC fast-charging connections, 6 of which are bidirectional, facilitating vehicle-to-grid (V2G) charging. Two hundred electric vehicles, notably Nissan Leafs and Mitsubishi iMiEVs, compatible with CHAdeMO DC fast charging, will be deployed as part of the effort. Two hundred twenty-nine electric vehicle charging stations will be established. Electric cars will enable the incorporation of intermittent renewable energy sources by utilizing excess electricity produced by these sources and supplying it back to the grid during peak demand periods (i.e., V2G). Fast-charging vehicle-to-grid services integrating electric vehicles and distributed renewable energy sources are expected to be tested [410].

7.2.3 Effects, Possibilities, and Constraints of V2G

Electric vehicles are frequently consolidated in V2G schemes and regarded as variable distributed energy resources that provide supplementary services to the electric grid. Extensive study has demonstrated the efficacy of the concept, indicating it as the most promising candidate for the future power grid architecture. Examples of energy sources utilized in the implementation of Energy Storage Systems (ESSs) to maintain electric grid stability include dedicated battery storage systems, pumped hydroelectric storage, flywheels, and concentrated solar power (CSP) [411]. The extensive implementation of V2G in the energy sector sharply contrasts with this. Certain options, including as pumped hydroelectric storage, may prove to be more economically viable than vehicle-to-grid (V2G) systems. The CPS surpasses the conventional battery pack utilized in electric vehicles due to its 99% efficiency and prolonged storage lifespan. The utilization of a CPS plant as an energy storage solution for peak demand management and control will become progressively more attractive as technology advances. Abu Dhabi, United Arab Emirates, houses the largest concentrated solar power (CSP) plant globally. The International Energy Agency (IEA) forecasts an increase in the share of clean power systems (CPSs) and alternative energy sources contributing to the power grid. Additional study is required to establish that electric vehicles can be economically viable compared to future energy storage systems in vehicle-to-grid interactions [412].

Vehicle-to-grid (V2G) schemes have demonstrated their efficacy as a feasible answer to the challenges confronting the energy sector. The widespread acceptance of electric vehicles can mostly be ascribed to initiatives aimed at reducing the transportation sector's reliance on fossil fuels. Should V2G transactions be adopted, the EV infrastructure must be enhanced to accommodate increased EV involvement in the energy market. Smart meters, high-speed connectivity, bidirectional power converters, and emerging competitors exemplify technological advancements. Electric vehicle manufacturers have been sluggish in deploying a substantial quantity of electric vehicles capable of delivering vehicle-to-grid services, partly due to the hesitance of electric vehicle customers to engage in such agreements [413]. There is ongoing discussion on whether manufacturers should offer two electric vehicle models: a regular EV and a vehicle equipped for vehicle-to-grid (V2G) technology, the latter of which incurs a higher cost. This technology may be perceived as superfluous by owners, who may be reluctant to engage in the energy market. Sales may significantly decline if this is executed. To provide manufacturers and customers with a credible alternative in the energy market, it is essential to bridge this knowledge gap through comprehensive studies and research.

Recent evaluations of V2G adoption have presumed the presence of a deregulated electrical market wherein electricity generators (e.g., Generation Companies) and market participants (e.g., energy brokers) establish their own rates for fulfilling consumers' electricity demands [415]. The optimization of price adjustments (bidding) has been documented in the literature to reduce the fees, charges, or investment expenses related to V2G or power distribution networks. This research demonstrates that V2G transactions are feasible alternatives for EV scheduling from both technological and financial perspectives. Investigation into diverse energy sectors is getting progressively essential as electric vehicles gain broader acceptance and their complete capabilities are actualized. Foley et al. [416] examined the impact of electric car recharging on the Republic of Ireland's integrated wholesale electricity market. When evaluating the influence of electric vehicles on regulated (monopoly) versus deregulated (competitive) energy markets, it is essential to recognize that these market types will respond differently to trends.

This analysis predicts that by 2035, electric vehicles will have substantially penetrated the automotive market. Similarly, the prospects for V2G technology are promising. The electricity markets in many nations may hinder the adoption of this technology for some. In contrast to the United States, where an increasing number of states are transitioning to a more deregulated energy market, the electrical sector in the Republic of Korea remains heavily controlled. Recent years have lacked sufficient emphasis on the comparative analysis required to determine the impact and feasibility of electric vehicles' interaction with the grid across various energy markets [417]. As the VPP has demonstrated the dynamic nature of distributed energy resources, the introduction of EVs will similarly reveal the advantages of the smart grid. Furthermore, a digital STATCOM and additional functionalities are viable. In the future, further investment in distributable renewable energy sources such as wind and photovoltaic solar is anticipated. Research into the aforementioned areas can significantly enhance the advantages of the smart grid and the effectiveness of the connection between the two systems [418,419]. The integration of additional power systems into the more efficient virtual power grid can be facilitated by the grid's established V2G services.

Summary

This chapter explored the challenges of developing efficient charging control methods for electric vehicles in real-world power system conditions, considering the technical, economic, regulatory and behavioral factors that impact the adoption of electric vehicles and charging behavior. Strategies were developed to address concerns around interoperability, cybersecurity, privacy, and equity in respect of electric vehicle charging infrastructure.

CHAPTER EIGHT: CONCLUSION AND FUTURE DIRECTIONS

Introduction

Chapter Eight provides a concise overview of the significant discoveries, contributions and consequences of the research. It also offers suggestions for policy-makers, utilities and stakeholders to enhance the efficiency of electric vehicle charging and its integration into power systems. Additionally, it identifies potential areas for future research and explores the integration of electric vehicles with other renewable energy sources and grid management technologies.

8.1 Summary of key findings, contributions, and implications of the research

This project aimed to identify a strategy for effectively integrating a substantial number of Renewable Energy Distributed Generators (REDGs) with electric vehicle charging stations. This methodology aims to mitigate waiting lines, power loss, voltage violations, and the overall annual costs associated with electric vehicle charging stations and renewable energy distributed generation systems. The use of an efficient optimizer, HGAIPSO, successfully addressed the challenge of allocating charging stations for electric vehicles and renewable energy distributed generators in smart grids. Three distinct scenarios have been examined: the optimal integration of electric vehicle charging stations without renewable energy distributed generators (REDGs); the optimal integration of EV charging stations with REDGs employing a regulated charging and discharging strategy; and the optimal integration of EV charging stations in the absence of REDGs.

Each of these possible possibilities has been examined meticulously. The simulation findings indicate that the scenario involving the seamless integration of Renewable Energy Distributed Generation (REDGs) and electric vehicle charging stations, alongside a well-regulated charging and discharging strategy, yields the most favorable results. In comparison to the baseline scenario, the VV, EL, and overall cost have all experienced significant reductions in this specific scenario. The devised optimizer outperforms previous established algorithms in efficiently resolving the allocation problem of REDGs and electric vehicle charging stations. Both serve as instances of generators employed in the development of renewable energy.

It is observed that if the number of EVs is increased beyond the optimal number, the voltage profile will shift in a way that reduces bus voltages, whilst still being within acceptable limits. The objectives of the study were accomplished, and the HGAIPSO optimization approach was found to be superior to GA, PSO and IPSO in reducing transmission losses in power grids through the optimal placement and sizing of EVs. In this research, the transmission network modification problem was approached using a GA and PSO hybrid technique, which proved to be both efficient and accurate. In order to preserve the unique characteristics of each individual, this plan uses a combination of methods. In addition, the system employs a mending strategy to meet the radial requirements for each GA chromosome or PSO particle, drastically cutting down on the total amount of solution space. The hybrid method can find the globally optimal solution, and it converges quickly without ever becoming stuck in a local minimum. The hybrid method concurrently finds optimal solutions for a large number of run iterations while using less computing time on average and having a lower standard deviation in losses than earlier methods. The suggested method can find the globally optimal solution, and it converges quickly without ever becoming stuck in a local minimum.

8.2 Recommendations for policy-makers, utilities and stakeholders to promote optimal EV charging and integration into power systems

The government's transportation strategy lacks comprehensive targets and criteria for electric vehicles in South Africa. Establishing such targets and standards is crucial for facilitating the adoption of electric vehicles, as highlighted by the International Energy Agency. These plans are intended to meet the objectives set forth by the established targets. Additionally, the development of charging standards is vital for determining suitable technologies for the production or importation of electric vehicles within the country, especially considering the variety of charging standards in use worldwide. In China, the private sector has successfully propelled the electric vehicle industry by offering innovative solutions that align with governmental policy objectives. The specifications are critical for selecting technologies that will perform effectively under South Africa's climatic conditions. Therefore, assessing electric vehicle technology and its suitability for the South African context is of utmost importance.

The typical daily distance covered by motor vehicles in South Africa is around 40 kilometers; however, it is common for many individuals to embark on longer journeys. Consumers have the option to choose from electric vehicle models that offer a range exceeding 300 kilometers to meet their business needs. Therefore, employing effective marketing strategies that consider vehicle features, pricing, and existing infrastructure is advantageous. The current lack of adequate charging infrastructure is viewed as a significant obstacle to the widespread adoption of electric vehicles in South Africa. The commercial sector has proactively developed rapid-charging stations and associated infrastructure at various public locations, such as shopping centers and business parks. Nevertheless, governments in countries experiencing growth in the electric vehicle market have taken on the responsibility of building charging infrastructure, even while managing other pressing priorities. Enhancing the quantity and accessibility of charging stations can greatly increase the market demand for electric vehicles.

The current transportation system heavily depends on fossil fuels, and transitioning its infrastructure and operations to alternative energy sources is a costly endeavor. Consumers have the option to choose from three different charging methods available in the market: conductive, inductive, and battery swapping. The choice may be influenced by factors such as convenience and cost-effectiveness. The lengthy processes of technology transfer and consumer acceptance hinder the swift reduction of emissions from road transport through electric vehicles. Additionally, since it is often more convenient for many electric vehicle users to charge their batteries at home, it is crucial to assess the availability of private charging options in conjunction with public and commercial charging facilities.

Transportation plays a vital role in the global economy and is increasingly recognized as a significant source of greenhouse gas emissions. This study utilized a proxy measure of motor vehicle emissions to demonstrate the potential for advancements in vehicle technologies to mitigate greenhouse gas emissions from road transportation in South Africa. Road travel in South Africa generates over 50 million tons of carbon dioxide equivalent (Mt CO_2e). Motor vehicles are the primary source of road emissions, accounting for 45.74% of the total emissions, and their contribution is steadily increasing over time. Currently, their emissions are rising at a rate exceeding 3% annually. Heavy-duty vehicles represent the second largest source of pollution. Without intervention, greenhouse gas emissions from road transport are expected to more than double by 2050.

The adoption of electric vehicle technologies in South Africa remains limited, with lower uptake rates compared to other nations. However, the market for these vehicles is expected to expand over time, leading to a greater contribution to greenhouse gas (GHG) reduction. Projections indicate that electric vehicles could decrease automotive emissions by 20% from the baseline levels established in 2020 by the year 2050. Furthermore, it is anticipated that the proportion of annual emissions reductions attributed to electric vehicles will surpass that of internal combustion engine vehicles around 2050. Enhancing the emission reductions from electric vehicles will require a rapid decrease in the carbon intensity of the national power grid, which will subsequently lower the emissions associated with the entire lifecycle of energy production and consumption. Currently, South Africa's power system has a high carbon intensity, making it a net emitter of emissions when compared to the existing use of liquid fuels.

By 2050, it is expected that South Africa's vehicle fleet will include both internal combustion engine vehicles and electric vehicles. Given that the power grid is likely to remain partially dependent on non-renewable energy sources, the charging of electric vehicles may lead to increased emissions. Therefore, decarbonizing the grid is crucial to ensure that transportation aligns with the commitments outlined in the Paris Agreement. With the country's rich renewable energy resources, especially solar power, electric vehicles have the potential to serve as both a source and a storage solution for the national electrical grid. Nevertheless, ongoing technological advancements will continue to minimize the emissions produced by internal combustion engine vehicles. The exploration of electric vehicles' energy storage capabilities and the role of renewable energy in reducing transportation emissions are currently prominent research topics in South Africa.

8.3 Identification of future research recommendations

These findings have also highlighted subjects that provide momentum for further research, most obtained via the development of this work.

- Due to the absence of actual usage scenarios for EVs in ancillary service applications, the problem of battery ageing in the context of delivering ancillary services using EVs has not been adequately addressed. This is because of the shortage of EVs;

- In the context of auxiliary services and local grid support, the evaluation of the benefits and drawbacks associated with EV collaboration has not been taken into consideration. In light of the requirements of a number of European nations, as well as the requirements of a variety of regions and locations, this study has the potential to disclose which concepts are the most directly applicable.
- In the field of communication technologies for electric vehicle coordination, the process of gathering electric vehicles in a centralized manner in order to provide a service that is capable of producing multiple megawatts (MW) requires a significant number of vehicles, generally in the thousands. In addition, it is necessary to have a communication system that is both dependable and quick with all of these vehicles in order to guarantee that there will be a minimal amount of delay.
- In order to provide help to the local grid through active power solutions and reactive power alternatives, the integration of electric vehicle charging stations with other options, such as photovoltaic inverters, electric space heating and electric boilers, has not been looked into.

Summary

Recommendations for policy-makers, utilities and stakeholders to promote optimal electric vehicle charging and integration into power systems, as well as identification of future research directions, and integration with other renewable energy and grid management technologies, were discussed. The chapter also included a summary of the most important findings, contributions and implications of the research.

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