Optimal Allocation of EVs in Electricity Distribution Network to Maintain Uniform Load

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Abstract

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An electricity distribution network comprises of parking lots, electric vehicles, distribution grid, transformers, charging infrastructure, and customer locations. This thesis presents an optimization model for the optimal allocation of parking lots within a distribution system to efficiently supply electric vehicle (EV) loads. The model aims to determine the best capacity and size of parking lots to meet peak hour demands while considering constraints on the permanent operation of the distribution system. Using the Particle Swarm Optimization (PSO) algorithm, the study maximizes total benefits, taking into account data and market prices. Results show that installing parking lots could be economically profitable for distribution companies (DISCOs) and could improve voltage profiles.

The study also explores the impact of battery capacity and charging power rate variations on outcomes, emphasizing the importance of accurately determining these parameters. Additionally, the study highlights the advantages of the proposed approach, including improvements in voltage profiles, reductions in power flow, and enhancements in equipment lifespan. These benefits underscore the potential of the approach to optimize parking lot allocations for EV charging and improve overall distribution network performance and efficiency. Further implementation in suitable locations with appropriate sizes could yield significant technical and financial benefits.

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List of abbreviations

PM	Particulate Matter
EV	Electric Vehicles
HEV	Hybrid EV
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid EV
BEV	Battery Electric Vehicles
GHG	Greenhouse Gas
SDS	Sustainable Development Scenario
DG	Distributed Generation
IEA	International Energy Agency
G2V	Grid-to- Vehicles
V2G	Vehicles-to- Grid
DEVC	Dynamic Electric Vehicle Charging
SEVC	Static Electric Vehicle Charging
DC	Direct Current
AC	Alternating Current
ICPT	Inductively Coupled Power Transfer
LCC	Inductor-Capacitor-Capacitor
LCL	Inductor-Capacitor-Inductor
FCLM	Flow-Capturing Location Model
FRLM	Flow-Refuelling Location Model
IGDT	Information Gap Decision Theory
FISA	Fuzzy Inference System Algorithm
EVSE	Electric Vehicle Supply Equipment
CPL	Commercial Parking Lots

HESS	Hybrid Energy Storage System
PL	Parking Lot
SPL	Smart Parking-Lot
MILP	Mixed-integer Linear Programming
PSO	Particle Swarm Optimization
P_v	The power rate at which the EV is charged
ES	Energy Storage capacity of Electric Vehicle
SoC	State of Charge
DRP	Demand Response Programs
KCL	Kirchhoff's Current Law
KVL	Kirchhoff's Voltage Law
IPMS	Intelligent Parking Management System
MPC	Model Predictive Control
LMI	Linear Matrix Inequality
PID	Proportional–Integral–Derivative
RNN	Recurrent Neural Network
BTDAR	Bipolar Traffic Density Aware Routing
AHP	Analytic Hierarchy Process method
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimizer
WCA	Water Cycle Algorithm
WOA	Whale Optimization Algorithm
COR	Competition Over Resource
GA	Genetic Algorithm

Chapter 1: Introduction

1.1 Environmental impact

Over the last ten years, the escalation of air pollution has emerged as a paramount concern for environmental health, resulting in approximately 7 million deaths annually (Chung et al., 2020). Long-term exposure to contaminated air accounts for 40% of premature deaths globally each year. As populations burgeon and societal development accelerates, governments are compelled to implement effective strategies to address this issue. Human activities, including construction, manufacturing, and transportation, intended to enhance efficiency and modernization, have inadvertently escalated pollution levels worldwide. These activities generate substantial waste and emit greenhouse gases, precipitating ozone layer depletion, global warming, and increased health risks from pollution exposure. However, the magnitude and distribution of dust emissions are contingent upon meteorological and topographical factors during activities (Sarpong et al., 2021). Transportation systems encompass various modes of transit (e.g., buses, vehicles) and associated facilities (e.g., stations), posing significant air pollution exposure risks. For instance, particulate matter (PM2.5) concentrations in transportation settings can exceed ambient levels by 10-40%, as observed in cities like Delhi, India (Andersen et al., 2018).

Consequently, transitioning towards sustainable mobility is imperative in combating global climate change. Electric vehicles (EVs) represent a promising and environmentally friendly solution within the transportation sector. EVs encompass hybrid EVs (HEVs), plug-in hybrid EVs (PHEVs), and battery electric vehicles (BEVs). Widespread adoption of electric vehicles hinges on technological advancements and governmental support. However, the effectiveness of EVs in reducing greenhouse gas emissions (GHGs) is contentious, particularly if the electricity used to charge EVs is derived from traditional fossil fuels (Ghosh, 2020).

On the other hand, escalating concerns regarding fossil fuel depletion and air pollution have prompted increased scrutiny of combustion engine reliance. Electric vehicles offer a viable alternative by eliminating the need for gasoline or liquefied gas, relying solely on stored electricity for propulsion. Moreover, the escalating cost of gasoline has bolstered the appeal of electric vehicles (Cao et al., 2018). Consequently, the automotive industry is undergoing a transformative phase, necessitating substantial advancements to align with Sustainable Development Scenario (SDS) requirements. Global transportation-related greenhouse gas emissions increased by 0.6% in 2018 compared to the preceding decade, reaching 1.6%. Notably, the transport sector is a significant contributor to CO_2 emissions from fuel combustion, accounting for 24% of total CO_2 emissions. Vehicles such as private cars, buses, trucks, and heavy-duty vehicles contribute to around three-quarters of CO_2 emissions from transportation (Mamun et al., 2022).

The concept of electric vehicles originated with the Porsche Group, while the introduction of plug-in hybrid vehicles (PHEVs) can be traced back to General Motors in the late 1960s, marking the inception of PHEVs. An electric vehicle is defined as a vehicle utilizing an electric motor to provide all or part of the mechanical power required for propulsion. The significant fuel consumption by motor vehicles worldwide, coupled with dwindling fossil fuel reserves and environmental pollution, has spurred increased attention towards alternative energy sources. Studies indicate that if current energy consumption trends persist, carbon dioxide emissions could double their 2005 levels by 2050, which is deemed unacceptable from an environmental standpoint and existing roadmap perspectives. Global initiatives aim to halve these emissions by 2050 compared to 2005 levels. One of the most promising methods to achieve this goal, alongside strategies such as distributed energy production and combined heat and power generation, involves the adoption of electric grid-powered or battery-driven motor vehicles. This issue has garnered significant attention worldwide, particularly in developed nations like the United States and Japan, with notable progress also observed in countries like China and India (Kamat and Oren, 2002).

Consequently, the advancement and proliferation of electric vehicles have gained momentum for several reasons. These include the escalating price of fossil fuels, efforts to mitigate environmental impact, reduction of noise pollution associated with fossil fuel vehicles, and the comparative cost-effectiveness of electric vehicle fuel consumption versus traditional vehicles (Guo et al., 2018). Reports from Germany indicate that the growth of electric vehicles is not anticipated to significantly increase electricity demand until 2030. Instead, it is projected to add approximately 1% to total energy capacity, necessitating an additional five gigawatts (GW) of generation capacity. By 2050, this figure could rise to about 4%, requiring an additional 20 GW of capacity (Engle et al., 2018).

Moreover, many countries, such as Canada, are intensifying efforts to promote electric vehicle adoption in line with sustainable development goals. Addressing the concerns of electric vehicle owners, particularly regarding charging during peak times, is paramount. Establishing optimal charging locations that alleviate distribution network strain during peak periods would represent a significant step towards increasing the adoption of clean transportation systems. Therefore, focusing on this issue holds considerable importance in achieving sustainable development objectives and reducing global energy consumption, underscoring the motivation for conducting research in this area (Moradijoz et al., 2013).

Researchers are increasingly focusing on addressing challenges associated with the expanding utilization of electric vehicles (EVs) in advanced societies. One primary concern is the charging infrastructure, with batteries playing a crucial role. Battery depletion fears among EV owners highlight the pivotal role of batteries, leading to close collaboration between battery and vehicle manufacturers globally. Battery manufacturing aims to reduce the cost of producing electric power, with a target of $450 per kilowatt-hour by 2020 (Chen et al., 2021). The impact of EVs on distribution networks is a key challenge, with optimization focusing on charge management and the strategic placement of charging stations to enhance the travel experience for EV owners.

All current electric vehicles rely on electric batteries for their energy needs. However, due to the large volume, weight, and cost of batteries, as well as their limited energy storage density, vehicles often require frequent recharging. This limitation has prompted researchers to explore alternative methods for powering electric vehicles. One such approach is the grid-to-vehicle (G2V) method, where energy is supplied from the grid to the vehicles (in contrast, vehicle-to-grid, or V2G, refers to supplying energy from vehicles back to the grid) (Mao et al., 2018). Implementing this approach requires detailed planning for charging and discharging electric vehicles within the network to maximize its benefits for all stakeholders. Ideally, charging electric vehicles in a way that not only increases the beneficiaries' profits but also reduces the overall energy demand from the grid would be the most favorable outcome.

1.2 Problem statement

Figure 1.1 represents the electricity distribution network, where load distribution is vital for maintaining the proper balance between power generation and consumption, avoiding equipment overload, and ensuring efficient delivery of electricity with minimal losses. The distribution of load within a power system may be affected by several factors, including the time of day, season, and meteorological conditions. Advanced technologies, including smart grids, are increasingly being used to optimise load distribution and enhance the overall efficiency and reliability of power systems.

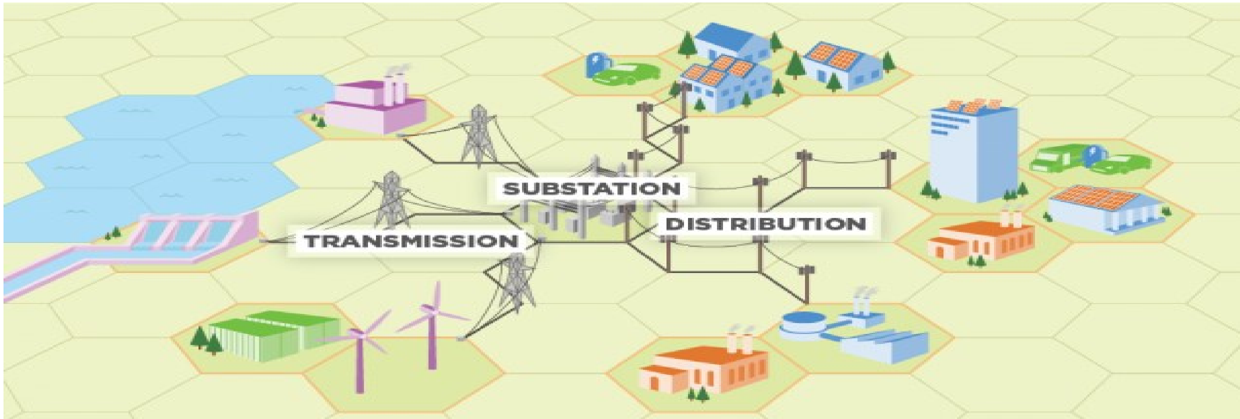

Figure 1.1: An illustration of the electricity distribution network (Effatnejad et al., 2021)

Electric vehicles (EVs) can serve as controllable loads, storing energy during off-peak periods and acting as generation units during peak periods or high electricity prices. They function as Distributed Generation (DG) resources within distribution systems, requiring controlled charging and discharging of batteries (Kempton et al., 2001). Distribution system planners use technologies like DGs and capacitors to provide cost-effective and dependable electricity. Optimal allocation of EV parking lots as a new type of DG is crucial, as it can mitigate network losses, improve voltage profiles, and yield economic benefits. Parking lots also act as charging station of EVs for driving purposes. Incentive mechanisms can encourage EV drivers to contribute to grid stability by using their vehicles as storage devices or by charging them during off-peak periods.

The primary concern in establishing an electric vehicle parking lot is determining the optimal location for construction and operation. Locating a parking lot entails considerations from multiple perspectives. As these stations connect transportation and electrical networks, their placement significantly influences not only vehicle driving patterns but also network performance. Hence, the selection of a parking lot location should encompass both networks. From the perspective of the electricity provider, the ideal site for a parking lot minimizes distribution network losses and necessitates minimal infrastructure development, such as additional lines, dedicated feeders, or transformers. Additionally, the station should facilitate easy network connectivity. Conversely, from the station owner's viewpoint, the priority is selecting a location with the lowest costs, including land prices, network connection expenses, and charging and maintenance unit costs. Thus, the station should ideally be situated where electric vehicle density is highest. Charging stations typically vary in size and capacity based on electric vehicle density. While economic benefits are important, solving this issue solely based on financial considerations is impractical. The primary objective is to determine the optimal location and size of parking lots using various optimization methods, aiming to maximize the revenue and minimize total costs while ensuring power system security. To achieve this, diverse methods have been employed, and in this study, the allocation optimization problem is addressed using the Particle Swarm Optimization (PSO) algorithm in Python software.

1.3 Objectives

The objectives of this thesis are listed below:

- To develop a PSO algorithm to determine the optimal location and size of parking lots to meet the demand of EV owners at peak time
- To improve the distribution system voltage profile
- Increased economic benefit for the distribution system

Design of each objective is discussed in Chapter 3 and the implementation and results are discussed in chapter4. Python software is used as the modeling tool to verify and optimize the objectives.

1.4 Thesis outline

The major research contributions of this study are as follows:

In Chapter 2, a literature review of electric vehicles, the environmental and economic effects of electric vehicles, and the charging of EVs have been discussed.

In Chapter 3, the mathematical model is presented extensively.

In Chapter 4, the model simulation with Python software is demonstrated.

In Chapter 5, simulation model results are discussed in detail. Conclusions and recommendations for future works are presented.

Chapter 2: Literature review

2.1 Electric vehicles (EV)

The increasing focus on clean energy in recent years has led to a widespread embrace of electric vehicles as a key solution for reducing reliance on fossil fuels in transportation. This shift has been enthusiastically supported by both individuals and governments worldwide, leading to a dramatic rise in the number of electric vehicles on the roads. According to reports from the International Energy Agency in 2016, the global number of electric vehicles exceeded 1,000,000 in 2015 (Zhang et al., 2017). Electric vehicles offer several key advantages, including minimal emissions and a significant role in curbing the release of polluting gases. As fossil fuel resources are finite, the adoption of electric vehicles is crucial for reducing fossil fuel consumption. Additionally, electric vehicles boast higher efficiency compared to diesel and gasoline vehicles. In traditional vehicles, 75% of energy is lost as heat and friction, with only 25% converted into driving force. In contrast, electric vehicles lose only about 20% of their energy. Moreover, electric vehicles have fewer components than conventional vehicles, resulting in lower maintenance and repair costs. Some countries also incentivize the purchase of electric vehicles by offering tax reductions and other facilities. These factors collectively contribute to the growing popularity and adoption of electric vehicles globally.

Electric vehicles offer the advantage of being able to charge from electricity generated by various sources, including wind, solar, nuclear, water, and biofuels. This diversity of sources helps reduce dependence on oil and gasoline, leading to less imported fuel and lower costs associated with it. The adoption of electric vehicles in various transportation sectors, including general and goods transportation, is increasing, prompting numerous studies on their design and performance optimization.

Despite these advantages, electric vehicles face limitations such as their lower battery energy compared to fossil fuel vehicles, long recharging times, and limited refueling stations. Unique refueling equipment and a scarcity of charging stations further restrict their adoption. Additionally, energy consumption in electric vehicles is dependent on the vehicle's load, which poses practical limitations. However, due to their positive impact on reducing air pollution, there is a growing effort to design and establish more charging stations. It is important to note that the reduced fuel consumption of electric vehicles leads to lower service costs and, consequently, higher customer satisfaction (Jin et al., 2013).

2.1.1 Background of electric vehicle

Before the onset of global warming concerns, the idea of manufacturing electric vehicles on a large scale was not widely considered. However, electric vehicles offer several advantages that have garnered attention. They are environmentally friendly, with simpler drive systems compared to traditional fossil fuel vehicles. Additionally, electric vehicles are highly efficient, with an efficiency of around 90%, in contrast to fossil fuel vehicles, which have an efficiency of about 30% to 35%. This higher efficiency translates to lower energy consumption, making electric vehicles a focal point for vehicle manufacturers.

Electric vehicles operate using electric motors, with the vehicle's battery responsible for supplying the necessary electric energy. They represent a significant achievement in the automobile and transportation industry, offering a cost-effective mode of transportation.

Electric vehicles also have disadvantages that make their use problematic, some of the main disadvantages of these vehicles can be stated as follows:

- Inability to charge batteries in all conditions
- Dependence on fossil fuel consuming engine (Wong et al., 2021).

International agencies have given a lot of support to electric vehicles in order to manage energy consumption, so that the number of sales and use of these vehicles has become a curve compared to other vehicles. In the following curves figure 2.1 (International Energy Agency ,2021), you can understand the importance and necessity of using electric vehicles in the future and the sales of these vehicles can be seen together.

International agencies have thrown their support behind electric vehicles to manage energy consumption effectively. Consequently, the sales and utilization of electric vehicles have surged, as illustrated by the accompanying curves figure 2.1. These curves underscore the increasing importance and necessity of electric vehicle adoption in the future, signaling a promising trajectory for their sales and utilization compared to conventional vehicles.

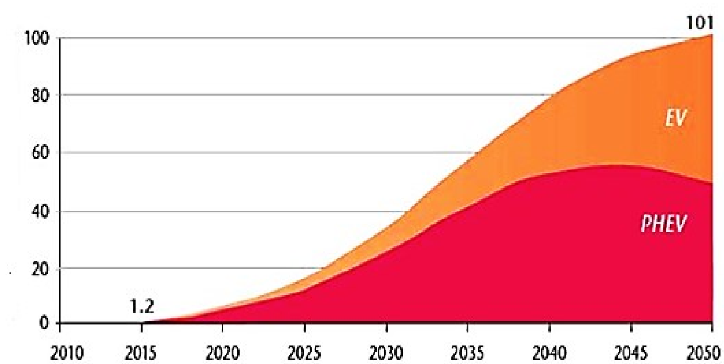

Figure 2.1: Forecasting the sales of electric vehicles until 2050

(International Energy Agency ,2021)

In this regard, various countries have included the use of electric vehicles in their work plan and, relying on this technology, they are trying to take steps to optimize energy management.

Indeed, many countries have incorporated the adoption of electric vehicles into their agenda, recognizing the potential of this technology to optimize energy management. By embracing electric vehicles, these nations aim to mitigate the environmental impact of transportation while simultaneously reducing reliance on fossil fuels. Implementing policies and initiatives to incentivize electric vehicle adoption, governments worldwide are paving the way for a more sustainable and energy-efficient future.

2.1.2 Effects of electric vehicles charging

The widespread adoption of electric vehicles introduces challenges to the electric grid, as it requires additional power from the distribution network. This increase in demand can have various negative effects on the distribution network, which depend on factors such as the penetration level of electric vehicles, charging patterns, locations, driving behaviors, charging modes, start times, battery state of charge (SOC) during charging, and tariffs. The effects of electric vehicles on the distribution network can be categorized into positive and negative effects. Positive effects include the benefits of vehicle-to-grid (V2G) technology, while negative effects include voltage instability, increased peak demand, power quality issues, increased losses, and equipment overload, particularly transformers. These effects are briefly explained below.

Electric vehicles pose a challenge to the stability of the distribution network's voltage due to their non-linear load characteristics. They draw a significant amount of electrical power from the network in a short period to charge their batteries, and this power consumption cannot be accurately predicted. As a result, electric vehicles exhibit different load characteristics compared to traditional loads like industrial and residential loads. To address this issue, it's important to consider the impact of electric vehicles on network voltage stability in a comprehensive and relevant manner. This may involve implementing strategies to manage and mitigate voltage fluctuations caused by electric vehicle charging.

The widespread adoption of electric vehicles can lead to an increase in peak demand on the electric grid, especially when charging is uncoordinated. Studies have shown that uncoordinated charging of electric vehicles can significantly increase peak demand. For example, Wang and Paranjape (2014) found that inconsistent charging of electric vehicles with a 30% penetration level could increase peak demand by 53%. Therefore, the concept of smart charging, which involves coordinated and controlled charging of electric vehicles, is essential to manage peak demand effectively. Moreover, the mass penetration of electric vehicles in distribution networks can also impact power quality. Large accumulations of electric vehicles can lead to high charging demands, causing issues such as unbalance and voltage deviation, particularly in multi-phase systems with non-uniform loads (Hadley, 2006). Shahnia et al. (2011) analyzed the sensitivity of voltage imbalance in a weak pressure distribution network based on the locations and levels of electric vehicle charging and discharging. Their study showed that electric vehicles have a minor effect at the beginning of the feeder but a significant effect at its end, highlighting the importance of considering electric vehicle impacts on power quality.

Shahnia et al. (2011) demonstrated that at a penetration level of 34% of electric vehicles, the voltage imbalance index exceeds the allowed value in weak voltage networks, which is typically 2%. This indicates that the presence of electric vehicles can significantly impact voltage balance in such networks. Furthermore, single-phase electric vehicle charging can also lead to phase imbalances due to the uneven distribution of loads in the three-phase system.Regarding voltage drop, studies suggest that controlled charging of electric vehicles can be accommodated up to a penetration level of 10% without negatively affecting the distribution network's voltage. However, uncontrolled charging may be sustainable up to a penetration level of 60% before adverse effects on voltage become significant (Shahnia et al., 2011). These findings underscore the importance of managing electric vehicle charging to mitigate impacts on voltage stability in distribution networks.

The mass penetration of electric vehicles in distribution networks can lead to an increase in network losses. Studies have shown that factors such as the penetration level of electric vehicles, charging mode, charging level (charging start time), and the use of uncoordinated charging methods can have adverse effects on the voltage profile and losses of the distribution network. However, employing a coordinated and pre-planned charging strategy, as well as using uniformly distributed charging methods near production sources, can help minimize network losses. Additionally, the increase in electric vehicles in the distribution network can increase the load on transformers. To mitigate these effects, it is essential to select transformers with appropriate capacity, engage in optimal network planning, and implement load management strategies (Elnozahy and Salama, 2013).

2.1.2.1 Environmental effects of electric vehicles

Even when considering the scenario where electric energy for electric vehicles is solely produced using fossil fuels in thermal power plants, it can still be more environmentally and economically viable than internal combustion vehicles like gasoline vehicles. This is because the production of mechanical energy in internal combustion engines is significantly less efficient than the production of electric energy in power plants. Additionally, managing pollutant emissions is much simpler when fossil fuels are consumed centrally in power plants and the resulting electrical energy is delivered to electric vehicles, compared to when fossil fuels are consumed individually by vehicles with internal combustion engines (Zhang et al., 2018).

2.1.2.2 Economic effects of electric vehicles

From the perspective of EV owners, the lower fuel and operational costs of EVs compared to vehicles with internal combustion engines are significant advantages. This cost reduction is primarily attributed to the higher efficiency of electric engines in contrast to internal combustion engines. While internal combustion vehicles typically operate at an efficiency of 15-18%, electric vehicles boast efficiencies ranging from 60-70% (Berman et al., 1992). Furthermore, Vehicle-to-Grid (V2G) technology presents an additional opportunity for EV owners to generate revenue by leveraging the energy stored in their batteries to exchange with the grid. However, from the standpoint of the power supply network, the presence of EVs can lead to increased losses and costs within the entire system. Nevertheless, employing appropriate charging methods can effectively mitigate these negative effects. Controlled charging methods, for instance, have been shown to reduce system costs and peak demand by over 50% compared to uncontrolled charging (Kuby and Lim, 2005). This underscores the importance of implementing smart charging strategies to optimize the integration of EVs into the power grid while minimizing adverse impacts.

2.1.3 Electric vehicles charging (Power Sonic. (n.d.))

EV charging is the process of replenishing the energy stored in an EV's battery by connecting it to an electric power source. This process is fundamental for the operation of EVs, which solely rely on electricity as their energy source. Here are the key aspects of EV charging:

2.1.3.1 Charging levels (Power Sonic. (n.d.))

- **Level 1 charging**

This is the slowest and most basic form of charging. It utilizes a standard 120-volt household outlet and is typically employed for overnight charging at home. Level 1 charging provides a charging rate of approximately 2 to 5 miles of range per hour of charging.

- **Level 2 charging**

Level 2 chargers operate at 240 volts and are commonly found in residential garages, workplace charging stations, and public charging stations. They offer a significantly faster charging rate compared to level 1 chargers, typically providing 10 to 30 miles of range per hour of charging.

- **Level 3 charging (DC fast charging)**

Also referred to as fast charging or rapid charging, level 3 chargers utilize high-voltage Direct Current (DC) to charge an EV much more rapidly than level 1 or 2 chargers. These chargers are frequently located along highways and major routes, enabling EVs to gain up to 100 miles of range in as little as 20-30 minutes. The summary comparison of charging levels can be seen in Table 2-1.

Table 2-1 Summary comparison of charging levels

	Level 1	Level 2	Level 3 (Fast charge)
Voltage	120 V	208 or 240 V	100 to 450 V
Current Type	AC	AC	AC
Useful type	1.4 KW	7.2KW	50KW
Maximum output	1.9KW	19.2KW	150KW
Charging time	12h	3h	20 min
Connector	J1772	J1772	J1772Combo, ChAdeMO and supercharger

2.1.3.2 Charging connectors

Different regions and manufacturers may use different types of connectors for EV charging.

- **Level 1 and 2 connectors**

The SAE J1772 EV plug is indeed the most common connector for EVs in Canada and the US. It serves as a standardized interface for level 1 and level 2 charging across various EV models, enabling compatibility and interoperability among charging stations and vehicles. While Tesla vehicles typically come with their proprietary charging connector for use with Tesla Supercharger stations, they also include an adapter that allows them to charge using the SAE J1772 plug, thereby ensuring compatibility with the widespread charging infrastructure.

However, it's important to note that the SAE J1772 connector is primarily used for level 1 and level 2 charging, which are slower charging methods suited for overnight charging at home or at workplace charging stations. For rapid DC fast charging, which offers much faster charging speeds, other connector types such as CCS or CHAdeMO are commonly used.

- **Level 3 connectors**

The CHAdeMO and SAE Combo (also known as CCS for "Combo Charging System") connectors are indeed the most commonly used connectors for fast charging among electric vehicle manufacturers. It's important to note that these two connectors are not interchangeable, meaning a car with a CHAdeMO port cannot charge using an SAE Combo plug, and vice versa. This distinction is akin to a gasoline vehicle that cannot fill up at a diesel pump.

Another key connector is the one used by Tesla vehicles, which is exclusive to Tesla's proprietary charging network. This Tesla connector is used for both level 2 and level 3 charging at Tesla Supercharger stations and is only compatible with Tesla cars. The SAE J1772 standard specifies six charging levels, but only three are currently used for electric vehicles in North America. Level 1 operates at 120VAC, level 2 operates at 208 or 240VAC, and fast charging operates at 200 to 450 VDC. While direct current fast-charge stations are often referred to as level 3, this terminology is incorrect and not recommended. The only standards that currently specify fast charging are CHAdeMO and SAE J1772 Combo. Concurrently, Tesla has developed its own DC fast-charge system, known as the "Supercharger," which is exclusively for Tesla vehicles. (Apata et al., 2023).

In the problem of electric vehicle routing, it is necessary to pay attention to the importance of battery charging stations. First, the warehouse should be equipped to charge vehicle batteries. So that the batteries of the vehicles in the warehouse are fully charged at night and start their journey with a fully charged battery. This action reduces charging costs. Secondly, in addition to the warehouse, public charging stations should also be installed at the desired geographical level. Among the most important limitations that distinguish the electric vehicle routing model from other vehicle routing models is the limitation of calculating the battery charge level at each node.

In electric vehicle routing, careful consideration must be given to the availability and placement of battery charging stations. Firstly, warehouses need to be outfitted with charging infrastructure to ensure that vehicle batteries are fully charged overnight, enabling them to embark on their journeys with optimal battery levels. This proactive approach helps minimize charging costs. Secondly, beyond warehouses, public charging stations should be strategically installed at key geographical locations to support EV operations.

One of the primary challenges distinguishing electric vehicle routing models from traditional vehicle routing models is the need to factor in battery charge levels at each node. Unlike conventional vehicles that rely on fuel availability, EVs' range is determined by battery charge, requiring precise calculation and management of charging needs throughout the route. This necessitates sophisticated algorithms and optimization techniques to efficiently plan routes while accounting for charging constraints and optimizing charging station utilization.

2.1.4 Fast charging stations and their location

As the number of electric vehicles grows, access to charging infrastructure becomes a crucial issue. The large batteries in these vehicles, with lengths of about 1.7 meters and capacities ranging from 5 to 30 kilowatt-hours, represent a significant load for the electric network (Rastegarfar et al., 2013). Charging these vehicles using conventional methods can be time-consuming. For example, residential chargers may take around 14 hours to charge an electric vehicle with normal batteries (Jia et al., 2014). Additionally, due to the limited capacity of home meters, rapid charging of an electric vehicle with a normal battery capacity is not feasible, as the current consumption exceeds the capacity of the home meter.

Fast-charging station deployment is crucial to addressing the issues associated with charging electric cars. Public fast-charging stations can significantly reduce the charging time compared to conventional methods, making them more practical for electric vehicle owners. However, connecting these vehicles to the grid during peak times can lead to increased current flow in distribution transformers, potentially reducing their lifespan and affecting other network components (Rastegarfar et al., 2013). The establishment of fast-charging stations in cities is crucial for the growth of electric vehicles, as it not only provides energy to vehicles but also offers convenience and peace of mind to electric vehicle owners. These stations can charge vehicles to 80-100% of their capacity in approximately 10 to 15 minutes, which is a relatively short time frame (Veneri et al., 2013).

It is essential to choose the best location for electric vehicle fast charging stations while building them. Several perspectives can be considered when locating these stations, as they connect transportation and electrical networks, impacting both vehicle driving behavior and network performance. From the perspective of the electricity company, the ideal location for a fast charging station is where there are minimal losses in the distribution network and minimal development needed, such as adding a new line, dedicated feeder, or transformer. This location should also facilitate easy connection to the network. Conversely, from the station owner's perspective, the best location is where costs are minimized, including land prices, connection costs, and maintenance costs. Therefore, the station should be situated where there is a high density of EVs. Fast charging stations can have varying numbers of charging units depending on the density of EVs in the area. It is essential to use optimization methods to determine the optimal location and size of charging stations, ensuring both cost minimization and power system security. Various optimization methods are employed for this purpose.

2.1.5 Types of location models of charging stations

2.1.5.1 Location based on burgers

In the charging station location model based on nodal demand, the flow of current through the nodes is taken into account. It assumes that electric vehicle charging, known as Plug-in Electric Vehicles (PEVs), takes place at specific geographical nodes within the target planning area, and charging stations are strategically positioned to meet this demand. However, this approach solely considers the straight-line geographical distance between the charging nodes, overlooking constraints related to the density of the transportation network (Zhang et al., 2018).

2.1.5.2 Location based on traffic flow

In this planning model, which relies on traffic simulation, the aim is to estimate the charging requirements for PEVs (Plug-in Electric Vehicles). Typically, these simulations utilize data obtained from real-world trips, which can be costly to acquire in certain regions. Recognizing the dynamic nature of electric vehicle mobility, some researchers have proposed planning methodologies based on traffic flow analysis. In this approach, the flows of vehicles from their origins to destinations are analyzed to gauge the demand for charging, encompassing both the Flow Coverage Location Model (FCLM) and the Fuel-Flow Location Model (FRLM). The FCLM addresses a fundamental challenge of maximizing route coverage by determining the optimal placement of charging stations along flow paths to serve a given number of routes (Berman, et al., 1992). On the other hand, the FRLM, an adaptation of the FCLM, emphasizes route-based demand maximization to ensure that vehicles can be refueled along their journeys (Kuby and Lim, 2005). Unlike the FCLM, where a single charging station along the flow path suffices to cover the flow, the FRLM considers factors such as route distance and vehicle driving range, often necessitating the placement of multiple charging stations to prevent vehicles from running out of fuel mid-journey.

2.1.6 Wireless charging of electric vehicles

An improved version of electric vehicle charging stations is represented by wireless systems. Currently, electric vehicles can only travel a certain distance before needing to be recharged, which requires connecting the vehicle to an electricity source. This limitation results in the installation of electric vehicle charging stations at various locations, similar to gas pumps. However, this can lead to time loss both during charging and while waiting in line, as well as energy loss. By doing away with the requirement for physical connections between the vehicle and the charging station, wireless charging technologies solve these problems. This technology allows for more flexibility in terms of charging location and time, as vehicles can be charged while parked or even while in motion. This can significantly improve the convenience and efficiency of charging electric vehicles, reducing the limitations associated with traditional charging methods.

The development of wireless charging stations for electric vehicles has been a subject of study, with researchers exploring various ideas to improve the technology. One approach involved using transmitter and receiver wires, where the receiver wires were embedded in the vehicle and one or more large transmitter wires were installed on the side or under the roads. However, this approach required high investment costs. Researchers then proposed modifying the wires of the transmitter and receiver to use wires of the same size. The transmitter coil in the station could expand and control the field under its radius based on the reactance reflected from the receiver coil. This modification greatly reduced power losses and minimized the destructive effects of magnetic fields. In this modified system, when an electric vehicle approaches a wireless charging station, the transmitter system detects it and increases its output power by up to 400%. As the vehicle moves away, the transmitter waves gradually decrease. This approach not only reduces the risk to people's health but also minimizes electrical power wastage (Ko and Vaidya, 1998; Kooh and Vaidya, 2018).

A typical EV wireless charging system is shown in Figure 2.2 which includes several steps to charge an EV wirelessly (Li et al., 2018). First, the AC electric power is converted into a DC power supply by modifying the power factor by an AC to DC converter.

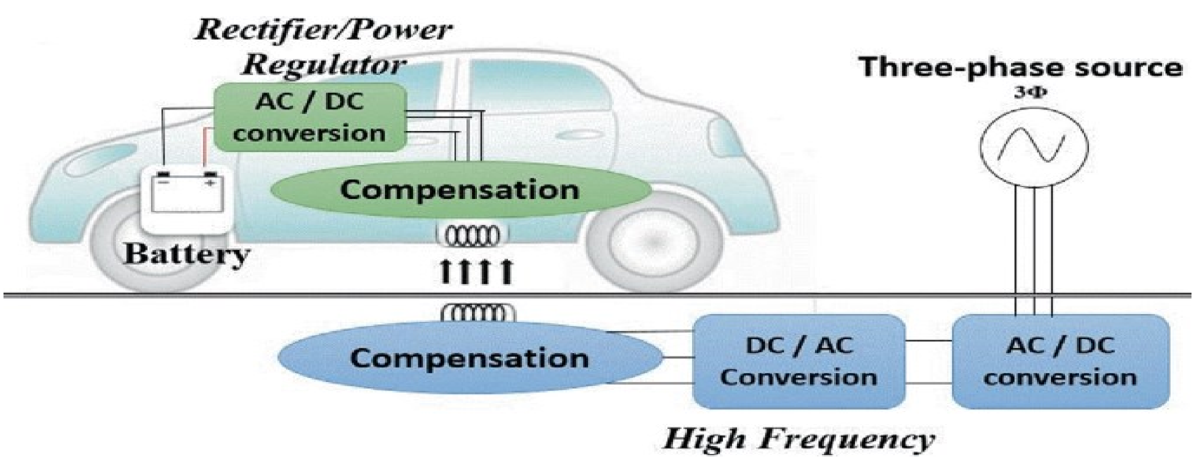

Figure 2.2: A conventional EV wireless charging system (Jain et al., 2024)

After the AC electric power is converted into a DC power supply, the DC power is converted into a high-frequency signal to drive the transmission signal through a compensating network. To enhance safety and protection by preventing insulation failure of the primary winding, a high-frequency isolation transformer may be placed between the DC-AC inverter and the primary winding. The high-frequency current in the transmitter coil generates an alternating magnetic field, inducing an AC voltage in the receiver coil. By resonating the secondary compensator network, the transmitted power and efficiency are significantly improved. Finally, the AC power is rectified to charge the battery (Zhang et al., 2017).

Wireless power transmission systems typically consist of several components, including a rectifier, power factor corrector, inverter, network compensator on the transmitter side, magnetic coupler (transmitter and receiver coil), network compensator on the receiver side, and rectifier for DC chargers. Additionally, an additional DC-DC converter may be included on the transmitter side to complete the wireless charging system. In the field of wireless power transmission for electric vehicles, various topologies have been proposed, defining the connection method as series-series, series-parallel, parallel-parallel, or their combinations (Wang et al., 2004; Villa et al., 2013). These topologies determine how the transmitter and receiver coils are connected in the system. The compensation operation in wireless power transmission systems is typically achieved using a coil and either one capacitor or a combination of capacitors with different LCL or LCC (inductor-capacitor-inductor or inductor-capacitor-capacitor) topologies. In an LCL converter, one or two LC network compensators are used on the sides. The advantage of the LCL topology is that at the resonance frequency, the current on the primary side can be independent of the load condition, acting as an independent current source. On the other hand, the LCC design requires an additional coil, which is usually an additional capacitor in series with the coil to reduce the size and cost of the additional coil, known as the LCC model. Using LCC, a zero switch current can achieve the highest efficiency by adjusting the network compensator parameters. Therefore, when LCC is employed on the secondary side, the reactive power of the secondary side can be compensated to some extent, reducing distortion current (Zhang et al., 2017). Figures 2.3 and 2.4 illustrate the general LCL and LCC topologies, respectively.

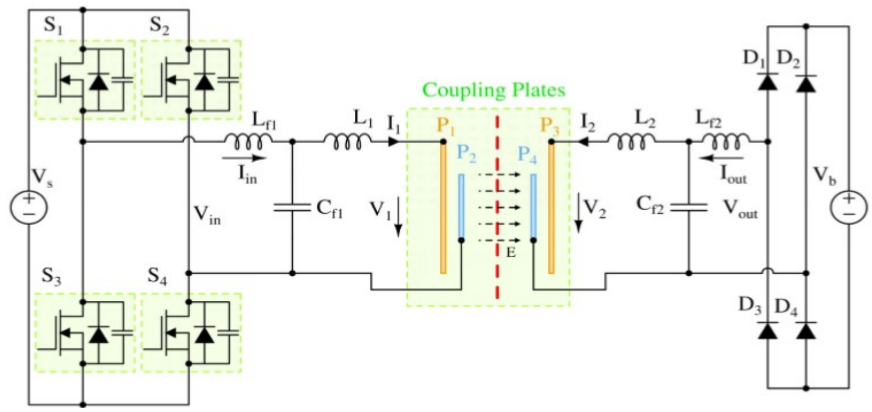

Figure 2.3: LCL compensated topology integrated circuit (Lu et al., 2016)

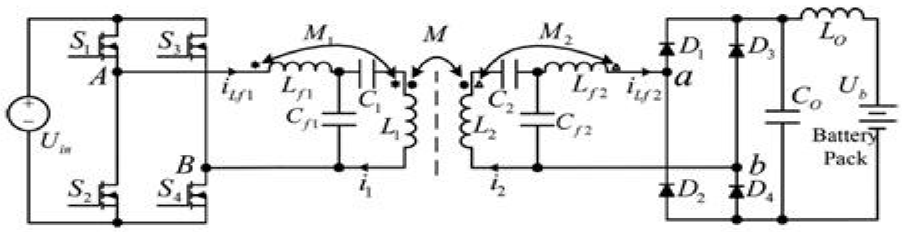

Figure 2.4: LCC compensated topology integrated circuit (Li et al., 2015)

2.1.6.1 Static electric vehicle charging (SEVC)

One of the key challenges facing electric vehicles is their limited maximum range, which is largely determined by battery and charger technology. To address this, various solutions have been proposed, including fast charging, wireless charging, and even charging vehicles while they are in motion. A recent advancement in this field is a new wireless charging system with significantly enhanced capabilities. Currently, most electric vehicles are charged using physical connection wires, requiring a dedicated charging setup at home or other locations. While some areas offer wireless charging services for electric vehicles, these systems typically provide a charging power of around 3.3 kW. While this is sufficient for overnight charging, a more widespread solution is needed to address the range limitation of electric vehicles.

The ideal solution to this challenge would be the ability to wirelessly and rapidly charge electric vehicles on public roads. Encouragingly, recent research indicates that this technology is progressing rapidly and may become a reality in the near future. The figure 2.5 illustrates a local wireless charging station (Manshadi et al., 2017).

Figure 2.5: Static wireless charging station (Manshadi et al., 2017)

2.1.6.2 Dynamic electric vehicle charging (DEVC)

Considering the current trajectory, it's evident that the future of transportation belongs to EVs. While EVs offer numerous benefits, they also face significant challenges, including:

- Limited travel distance
- Few charging stations
- Relatively long time to recharge the batteries

One promising solution to address these issues is Dynamic Electric Vehicle Charging (DEVC), a technology that has the potential to enable virtually unlimited travel distance for EVs. DEVC leverages wireless charging technology to continuously supply power to moving vehicles. Qualcomm, a renowned company primarily recognized for its mobile chipsets, has been at the forefront of researching this technology. Collaborating with the French company Vedcom, Qualcomm designed a 100-meter test track in Versailles to evaluate its DEVC system. The figure 2.6 illustrates a vehicle being charged wirelessly while in motion on the test track (Li et al., 2018).

Figure 2.6: A vehicle moving on a wireless charging station (Li et al., 2018)

2.2 Summary of previous works

Finding the location and capacity of these stations has been the main subject of several studies that have examined the administration and planning of EV charging at charging stations. Tostado et al. (2023) introduced a two-stage stochastic IGDT (Information Gap Decision Theory) model for optimal scheduling of energy communities with smart parking lots. This framework incorporates a stochastic representation of parking lot cost status to address uncertainties. Additionally, it examines uncertainties in the upstream energy market using Information Gap Decision Theory (IGDT), allowing operators to adopt a risk-averse strategy. The optimization problem is formulated as a mixed integer linear programming model, efficiently solvable by average solvers. A case study validates the proposal, highlighting the benefits of optimally utilizing EVs in communities to enhance system efficiency and economy.

Ge et al. (2023) utilized a genetic algorithm to determine the optimal location of charging stations in a traffic network, aiming to minimize urban transportation costs while considering constraints related to traffic density and station capacity. However, this study did not incorporate costs such as land, fixed costs, and operation costs in the optimization process, limiting its general applicability. Pazouki et al. (2023) addressed the simultaneous planning of optimal charging station locations and distributed generation sources, considering financial, technical, reliability, and environmental factors. They employed a genetic algorithm to solve the optimization problem, applying it to a radial distribution network of 33 tiers. Simulation results demonstrated that optimal charging station planning in distribution networks increased total costs by 30%, unsupplied energy by 7%, losses by 50%, and voltage deviation by 85%. Conversely, simultaneous planning of charging stations and distributed generation sources improved total costs by 28%, losses by 36%, supplied energy by 20%, voltage deviation by 63%, and pollution by 28%. Increasing EV availability in distribution networks during optimal charging station planning with distributed generation sources not only reduced total costs but also provided significant benefits to distribution network companies.

Hussain et al. (2022) delved into optimizing waiting times for EVs using a fuzzy inference system. In order to reduce EV waiting times at public EVSE facilities, they formulated waiting time optimisation as a fuzzy integer linear programming problem and presented a brand-new Fuzzy Inference System Algorithm (FISA). In order to arrive at the best answers, their method comprised creating membership functions, expert rules, and formulations for the underlying fuzzy inference system (Hussain et al., 2022). FISA automated correlations among uncertain and independent input parameters, optimizing waiting times for EVs with urgent service needs at each sampling period. Using a Java-based parking lot simulator, they assessed FISA's efficacy and showed that it was more efficient than the most recent scheduling methods. Yan et al. (2022) utilized an improved genetic algorithm to solve a multi-objective optimal planning model considering investment costs and power losses of feeders. They developed the model based on the IEEE 33-bus distribution system, addressing various limitations. Their research highlighted the improved efficiency of the genetic algorithm in overcoming challenges faced by blind search algorithms and enhancing the performance of basic genetic algorithms. Sausen et al. (2022) explored the economic aspects and prioritization of charging and discharging schedules for battery-based EVs in residential buildings. They proposed a mixed-integer finite nonlinear formulation to schedule charging and discharging of EVs, considering battery degradation, charging prioritization, cost reduction, and power demand limits on distribution transformers. Their results indicated a 5.3% reduction in battery degradation when EVs were discharged before charging within a specific charge mode range. Additionally, scheduling charging during lower tariff prices led to a 16.35% cost reduction and prevented overloading of distribution transformers. Baharifard et al. (2022) examined intelligent charging planning for commercial EV parking lots and its impact on distribution network imbalance indicators. The study proposed a two-stage framework. The first stage involved technical parameters such as battery condition, charge/discharge characteristics, and transport parameters including daily distance traveled, entry and exit times at the charging parking lot (CPL), and the number of EVs. This stage calculated the sales and profitability of the EV charging/discharging program for EV users and CPL owners at optimal CPL timing. In the second stage, the effect of CPLs on the distribution network was investigated by calculating imbalance indices in an IEEE standard unbalanced distribution network. The results indicated a 23% increase in average profit for EV users over the total cost of charging the vehicle. Additionally, without changing the distribution network structure and connecting the CPL to active commercial loads, the network imbalance during EV charging could be improved by approximately 30%. Yang et al. (2022) introduced a real-time energy management strategy for parking lots considering the maximum penetration of EVs. The study proposed an intelligent grouping method considering the coupling relationship between EV trip information, battery status, and other characteristics. A charge/discharge priority model based on the participation index of the charging process was developed. Finally, a real-time energy management strategy was formulated to maximize the penetration level of EVs in the current situation. The proposed strategy increased the maximum penetration level of EVs from 20% to 60% in simulations. This strategy is suitable for the gradual growth of the base load, effectively delaying the need for distribution network infrastructure upgrades and reducing overall substation operation costs. It also serves as a reference for operating and improving parking lot charging stations. Li et al. (2022) introduced a method to minimize the cost of demolition in zero net energy architectures with smart parking through EV charging management. The study considered the variety of charging types for EVs and how the service life of hybrid energy storage systems (HESS) affects the power distribution of net zero energy architectures. They proposed a demolition cost minimization method with intelligent parking (IPL) for optimal economic power allocation. The compatibility and economic benefits of the method were verified in random charging scenarios, and the effect of charging types on optimal timing was analyzed.

Konstantinidis et al. (2021) introduced a simple multi-parameter method for efficient charging planning of EVs in their paper. The method focuses on charging EVs at parking lots (PLs), including vehicle-to-grid (V2G) operation and considering the lifetime of EV batteries, distribution network, and local transformer loading. The main objectives are to minimize the charging cost of the total PLs hosting the EVs and to meet all the technical and operational constraints of EVs and PLs. The proposed method utilizes particle swarm optimization (PSO) to derive the EVs' charging schedule. It is compared with conventional charging strategies, where EVs are charged with the maximum power of the charging power converter or the average power required to achieve the state of charge goal, and a conventional charging scheduling method using collected behavior data. The study used real-world data series of electricity prices and parking activity for plug-in EVs. The results from operational scenarios demonstrate the effectiveness of the proposed method, which does not require complex computing, measurement, or communication systems for application.

Nejati et al. (2021) discussed the optimal charging and discharging of EVs in a smart parking lot in their article. The paper presents a residential parking scheme involving 200 EVs, where the scheduling of EV charging and discharging is based on the initial and final state of charge (SOC) values requested by the owners. The proposed plan includes entering the expected time of entry and exit to the parking lot a day before. An optimization problem is formulated to maximize the Smart Parking-Lot (SPL), considering the stochastic behavior of EV owners and the imposed penalty. The goal is achieved by defining stochastic behavior and penalty flexibility. The optimization problem is solved using the particle swarm optimization (PSO) algorithm. The effectiveness of the method is verified through four scenarios, including random behaviors of EV owners in the first scenario and flexibility in fining EV owners in the other three scenarios. Simulation results from all scenarios are compared to demonstrate the features of the proposed scheduling method. Ahmadi et al. (2021) used hybrid meta-heuristic algorithms to solve the optimal location for EV parking lots as well as optimal planning for charging and discharging. In order to provide a workable solution, the research focuses on the issues of optimum EV parking allocation and optimal EV performance scheduling in the smart distribution network. A variety of technical and financial aspects are taken into account. Technical factors include achieving all network requirements and reducing network losses and voltage drop in feeds. The entire cost of buying electricity from the upstream network and the overall cost of charging and discharging in EV parking lots are examples of economic variables. Demand-side management also takes price-based demand response programmes (DRP) into account. To get the best answer, hybrid meta-heuristic algorithms (HMA) are employed. The proposed problem is simulated on the IEEE standard 69 bus network, and the results demonstrate improved voltage profiles, reduced network losses, and overall efficiency of the proposed approach. Alinejad et al. (2021) focused on optimal management for charging and discharging of EVs. The paper first defines the random behavior of EV owners and other real situations, presenting a model for EV charging and discharging plans aimed at maximizing parking profit and minimizing costs for EV owners. The paper also determines fines for owners of defective EVs and the initial entry fee for all vehicles, while considering flexibility in determining fines, to present a complete structure for the energy management of EVs in parking lots. These fines ensure that the cost of unfulfilled charging rights for EVs is covered by fines for owners of faulty EVs, as well as profits for vehicle parks. The proposed method's effectiveness is verified through simulation in three different scenarios, demonstrating the good performance of this enhanced strategy for EV charging management. Rezaei and Golkar (2021) introduced a method to smooth the economic load curve by scheduling the charging and discharging of electric vehicles in the smart grid, using machine learning-based load predictions. The proposed method not only smoothens the load curve but also reduces the cost of purchasing electric energy. Implemented using GAMS software in a commercial building's parking lot dedicated to electric vehicles, the method schedules charging and discharging based on predicted loads for the next day. Simulation results demonstrate the method's efficiency, showing a 17% decrease in peak load, a 16% increase in minimum load, and a 20% decrease in energy purchase costs.

Zhao et al. (2020) introduced a data-driven optimal allocation strategy for shared parking spaces, considering uncertainties in user entry and exit, both from public users and space owners. Employing an agent-based approach, the study delineates a management framework encompassing temporal and spatial dimensions. This framework categorizes parking space access into four temporal phases and two spatial types. Subsequently, an Intelligent Parking Management System (IPMS) is developed based on this framework, aiming to simulate shared parking operations amidst the uncertainties of public and owner user movements. Through detailed sensitivity analyses leveraging real-world data and simulations, the efficacy of the proposed framework and IPMS is evaluated, focusing on parking lots in Beijing, China. Results indicate that the IPMS not only ensures adequate parking space availability for owner users but also significantly enhances space utilization and turnover rates compared to non-collaborative management approaches.

Mehrabi et al. (2018) explored the planning of charging and discharging for EVs in a shared parking setting. Their study introduces an effective scheduling mechanism tailored for multi-house shared parking lots. The mechanism prioritizes optimal distance allocation considering real-time electric load and vehicle demand patterns. Leveraging vehicle data, they devise a hybrid optimization model via centralized scheduling, aimed at maximizing consumer profit. This model is subsequently tackled using an efficient algorithm. The optimization outcomes are then transmitted to the system controller, dictating time interval patterns and energy exchanges between the power grid and the vehicles. The proposed algorithm boasts low complexity while ensuring energy satisfaction for all consumers.

Rajabi-Ghahnavieh and Sadeghi-Barazani (2017) proposed regional methods for determining the optimal location and capacity of fast-charging stations. Their approach considers the development cost of the station and the expected costs of charging electric vehicles as the objective function. The geographical characteristics of electric stations, such as urban routes and areas, are taken into account. The population of electric vehicles is estimated hourly in different areas based on traffic information. Driver behavior is also considered to determine the expected charging demand and consumer costs. Additionally, the expected cost due to network losses is calculated using load spreading and considering network loads in hourly scenarios. Khatiri-Dost and Amirahmadi (2017) proposed a model focused on peak correction and minimizing power losses through coordinated charging and discharging of Plug-in Electric Vehicles (PEVs) within smart grids. Their novel approach enables PEV owners to schedule charging and discharging times based on priority selection. Three distinct time slots are provided for domestic PEV owners to select their preferred timing, accommodating their individual needs. The method accommodates the random plug-in of PEVs and allows for prompt charging and discharging while meeting grid operational criteria. They demonstrated the feasibility and efficacy of their approach using a standard test system consisting of 1537 smart distribution buses, showcasing its potential in managing PEV charging and discharging within smart parking facilities.

Nezamoddini and Wang (2016) delved into risk management and collaborative planning of EVs within smart grids, particularly focusing on the demand response problem (DRP). Their study explores the potential of integrating EVs into demand response mechanisms, presenting a stochastic model from the perspective of independent system operators. This model addresses risk factors stemming from uncertainties in renewable energy sources, load and parking patterns, as well as transmission line reliability. The effectiveness of this model was assessed across various settings, including different area types, EV penetration levels, and risk levels. Enang (2016) proposed the use of a real-time robust controller for managing the charging of parallel electric vehicles, aiming to maximize fuel savings throughout the vehicle lifecycle and real-world driving scenarios. Results demonstrated that these controllers achieved significant fuel savings ranging from 0.03% to 3.71% without requiring access to route preview information. Moreover, incorporating route preview information into real-time controllers led to additional fuel savings of 2.44% during driving. Additionally, employing a real-time vehicle speed control strategy yielded substantial fuel savings compared to Hybrid Electric Vehicle (HEV) technology. Lachhab (2016) explored the design and optimization of robust controllers with low order/fixed structure, focusing on two classes: correct and fractional order controllers. The research offers three methods to adjust these controllers' parameters for real-world control scenarios. The study utilized normal $H\infty$ for control problems and implemented the controllers using MATLAB's fractional order controller toolbox. Additionally, a robust Proportional–Integral–Derivative (PID) controller based on Model Predictive Control (MPC) optimization was employed. By employing this technique, the control issue is converted into a Linear Matrix Inequality (LMI), which can be solved for controller parameter optimisation using typical LMI solvers. The third approach uses recurrent neural networks (RNNs) to optimise linear controllers. This method formulates the control issue as an optimised closed-loop RNN. The investigations demonstrate these controllers' high applicability and effectiveness in controlling the charging of electric vehicles.

You and Hsieh (2015) employed a hybrid genetic algorithm to optimize the placement and size of public charging stations, aiming to minimize both investment and transportation costs. Notably, factors such as charging and operational expenses were disregarded in the optimization process. Conversely, Sharma et al. (2015) introduced an intelligent scheduling strategy for EV charging and discharging, focusing on controlled environments such as parking lots. Their approach involves formulating the problem as a multi-objective scheduling task, considering factors such as maximizing collector profit, minimizing EV charging costs, and achieving target state-of-charge levels. To solve this complex problem, a heuristic dynamic optimization method was utilized, and extensive simulations across different scenarios were conducted to assess scalability and robustness. Hu et al. (2015) introduced the Bipolar Traffic Density Aware Routing (BTDAR) method, aimed at enabling reliable and efficient dynamic wireless charging in vehicular networks, whether they have dense or sparse traffic. In dense networks, the method employs a routing protocol based on link stability, which considers the connectivity of vehicles in the route selection policy to maximize communication stability between vehicles. For distributed networks, a medium-delay routing protocol is introduced to select an optimal route by analyzing the alternating connections of vehicles, thereby minimizing delay. Honarmand et al. (2015) introduced a planning model for EVs in a smart parking lot using stochastic optimization. The model proposes a random charging and discharging scheduling method for a large number of EVs parked in a smart parking lot, where these lots can act as aggregators enabling EVs to interact with companies. The self-scheduling model, designed for smart parking equipped with a photovoltaic system and distributed generators, considers practical limitations, uncertainty in solar radiation, rotating storage requirements, and EV owner satisfaction. Results indicate that the proposed parking energy management system meets both financial and technical objectives, allowing EV owners to benefit by discharging their vehicles and maintaining a favorable state of charge for driving.

In the Table 2-2, a summary of the research conducted in the field of electric vehicle charging management is presented.

Table 2-2 Summary of literature reviews

Method	Aim	Year	Auturs
MILP	Optimum scheduling of energy communities with smart parking lots	2023	Tostado et al.
Genetic Algorithm (GA)	Optimal location of electric charging station and distributed generation sources	2023	Pazouki et al.
Genetic Algorithm (GA)	The optimal location of the charging station	2023	Ge et al.
FIS system	Optimization of waiting time for electric vehicles	2022	Hussain et al.
Genetic Algorithm (GA)	multi-objective optimal chatging planning and station model	2022	Yan et al.
MILP	Charging and discharging timing of battery-based electric vehicles	2022	Sausen et al.
Two stage heuristic method	Smart charging planning for commercial parking lots of electric vehicles	2022	Baharifard et al.
Heuristic method	Real-time energy management for parking considering the maximum penetration of electric vehicles	2022	Yang et al.
Allocation of optimal economic power	Minimizing demolition cost in net zero energy architectures with smart parking through electric vehicle charging management	2022	Li et al.
Particle Swarm Optimization (PSO)	Planning efficient charging of electric vehicles	2021	Konstantinidis et al.
Particle Swarm Optimization (PSO)	Optimal planning of charging and discharging of electric vehicles in a smart parking lot	2021	Nejati et al.
Hybrid meta-heuristic algorithm	Optimal allocation of electric vehicle parking lots and optimal charging and discharging planning	2021	Ahmadi et al.
Heuristic algorithm	Optimal management for charging and discharging electric vehicles	2021	Alinejad et al.
Machine Learning	Smoothing the economic load curve by scheduling the charging and discharging of electric vehicles in the smart grid	2021	Rezaei and Golkar
Agent-based approach	Optimal allocation of shared parking space based on data	2020	Zhao et al.
Hybrid meta-heuristic algorithm	Electric vehicle charge/discharge planning	2018	Mehrabi et al.
Heuristic algorithm	Correcting the peak and minimizing power losses by coordinating the	2017	Khatiri-doost and Amirahmadi

	charging and discharging of plug-in electric vehicles in smart networks		
Meta-heuristic algorithm	optimal location and capacity of a fast charging station	2017	Rajabi-Ghahnavieh and Sadeghi-Barazani
Heuristic algorithm	Investigating risk management and providing collaborative planning of electric vehicles in smart networks considering the issue of demand response	2016	Nezamoddini and Wang
Real-time robust control	Parallel electric vehicle charging management	2016	Enang
Recurrent neural network (RNN)	Electric vehicle charging control	2016	Lachhab
Multi objective scheduling method	Intelligent planning for charging and discharging electric vehicles	2015	Sharma et al.
Hybrid genetic algorithm	Optimal number and size of public charging stations	2015	You and Hsieh
Bipolar Traffic Congestion Aware Routing	Improved dynamic wireless charging approach	2015	Hue et al.
Stochastic optimization	Scheduling electric vehicles in a smart parking lot	2015	Honarmand et al.

In this chapter, research concepts were examined. Therefore, after the introduction of electric vehicles, charging stations, the importance of charging stations, and charging methods of EVs, the literature review was provided in the field of planning and determining the optimal location of EVs. By reviewing the papers, it was found that despite the efforts made in the field of planning and determining the location of EVs charging, there is still a gap in comprehensive research in the field of locating EV charging stations by considering economic and technical concepts in the conditions of load uncertainty. Therefore, the model considered in this research is presented for allocating parking lots in a distribution network with voltage drop checks according to the mentioned conditions.

Chapter 3: Solution approach

3.1 Introduction

In recent times, various challenges such as environmental concerns, dwindling fuel resources, volatile fuel prices, and the necessity to reduce reliance on fossil fuels have led to the recognition of EVs as a valuable asset in both transportation and power systems (Moradijoz et al., 2013). The concept of a smart grid, as highlighted by Gellings (2009), revolves around environmental conservation and incorporates elements like renewable energy sources (such as wind and solar power), demand response systems, and distributed generation technologies like EVs. This approach aims to optimize asset utilization, ensure reliable system operation, and offer greater choice to consumers.

The research by Markel and Bennion (2009) demonstrates that vehicles are parked for approximately 93-96% of the day, making them available for alternative uses such as serving as storage devices for the grid. This availability, combined with the increasing need for cost-effective energy storage solutions in the power system, suggests that EVs could be utilized as limited energy resources in the power system (Peterson and Whitacr, 2010). In addition to serving as storage devices, EVs can also be used as controllable loads. This means they can be operated as batteries to store energy during off-peak periods and as generation units during peak periods or high electricity price intervals. Despite their limited power output, EVs can still be a valuable resource in the distribution system as a distributed generation (DG) resource.

To utilize EVs as distributed generation (DG) resources in the distribution system, the charging and discharging of batteries need to be carefully controlled. Distribution system planners aim to provide economical and reliable electricity to their customers and often deploy technologies such as DGs and capacitors to achieve this goal. DG technologies offer many economic and technical benefits, as highlighted in the work by Moradi and Abedini (2012) and Aman et al. (2012). However, these benefits can only be maximized when the optimal sizes and locations of DG units are determined. Therefore, optimal allocation of DG is a crucial issue that must be addressed in distribution planning. Sound decision-making in this regard can provide benefits to the distribution network, suppliers, and customers alike.

Optimal allocation of parking lots, as a new type of distributed generation (DG), should be prioritized alongside other types of DGs. High penetrations of distribution-connected storage devices or plug-in vehicles can have adverse impacts on the grid due to their charging loads, which are often randomly located or unmanaged additions. However, optimal allocation of parking lots can help mitigate these issues by reducing network losses, improving voltage profiles, and consequently bringing economic benefits for the distribution system company (DISCO).

One of the key distinctions between parking lots and other traditional distributed generators (DGs) is the stochastic nature of their output. In the modeling of parking lots, they function as storage devices, storing electrical power in the batteries of vehicles during times of low electricity prices and delivering power to the distribution system during times of high electricity prices. Additionally, parking lots serve as charging stations for EVs for driving purposes. Due to the stochastic nature of EV owners' behavior, the output of parking lots is also stochastic. One approach to reduce the uncertainty associated with EV owners' behavior is to implement incentive mechanisms. Sufficient incentive mechanisms should be considered to encourage EV drivers to participate in providing power to the network.

The most critical aspect in the construction of an electric vehicle charging station is determining the optimal location for its installation and operation. Locating a parking lot involves various considerations, particularly because it serves as a bridge between transportation and electrical networks. The location and size of the station significantly influence not only the driving patterns of vehicles but also the performance of these interconnected networks. Therefore, the selection of a parking lot location should take into account the requirements of both networks. From the perspective of the electricity company, the ideal location for a parking lot is one that minimizes losses in the distribution network and requires minimal development in terms of adding new lines, dedicated feeders, or transformers. Simultaneously, the station should be easily connectable to the network.

From the perspective of the station owner, the optimal location should be chosen to minimize costs. This includes factors such as the price of land, the cost of connecting to the network, and the cost of charging and maintenance units. Therefore, the station should be situated in an area with the highest density of EVs. Charging stations typically have varying numbers of charging units (capacity) based on EV density. While economic benefits are important, it is not advisable to consider them in isolation when addressing this issue. The primary objective is to determine the optimal location and size of parking lots using various optimization methods to minimize total costs while ensuring power system security. To achieve these goals, various methods have been employed to solve the problem of locating parking lots, one of which will be presented in this research.

In this study, the allocation optimization problem is solved using Particle Swarm Optimization algorithm (PSO) method with Python software. The power loss as well as the investment cost are other objectives that have to be given enough attention. For this reason, a trade-off shall be made between these objectives.

In order to allocate parking lots, some assumptions are taken-into account as follows: (Sioshansi, 2012; Clement et al., 2010; Soares et al., 2012)

1- This study assumes that the distribution company (DISCO) is responsible for supplying customer demand, installing parking lots, and controlling the charging and discharging of EV batteries. DISCO aims to fulfill these responsibilities while minimizing costs and improving the quality and reliability of customer service.

2- It is important to note that in calculating profits, the study assumes that DISCO does not receive compensation from EV owners for battery charging required for driving purposes. Additionally, any vehicle degradation costs due to vehicle-to-grid (V2G) operations are covered by DISCO and paid to EV owners. These assumptions are made to incentivize EV owners to park their vehicles in the parking lot during days with high-priced peak electricity.

3- All vehicles are assumed to be charged and discharged at their maximum charging rate. It is important to note that this assumption is common in several EV studies.

4- In the modeling of parking lots, it is assumed that the initial state of charge (SOC) of EVs has three levels. However, the proposed model can be adapted for use with other SOC levels as well. The initial SOC of vehicles can be adjusted using a suitable distribution function, and parking lots can be optimally placed considering this function.

5- Another assumption made in the modeling of parking lots is that all batteries have the same size. As a result, the output power of the parking lot is assumed to be constant during the discharging state. This assumption is also commonly used in many EV studies.

6- Under traditional approximations used by utilities, there might be 200 peak hours in a year during which an incremental kW h of electricity would be worth 0.5 USD$/kW h (Kempton and Tomic, 2005). Therefore, the maximum hours that vehicles deliver power to the network is assumed to be 200 hours in a year.

In this chapter, the solution approach of electric vehicle discharging has been presented. Figure 3.1 presents the various steps of the proposed solution approach.

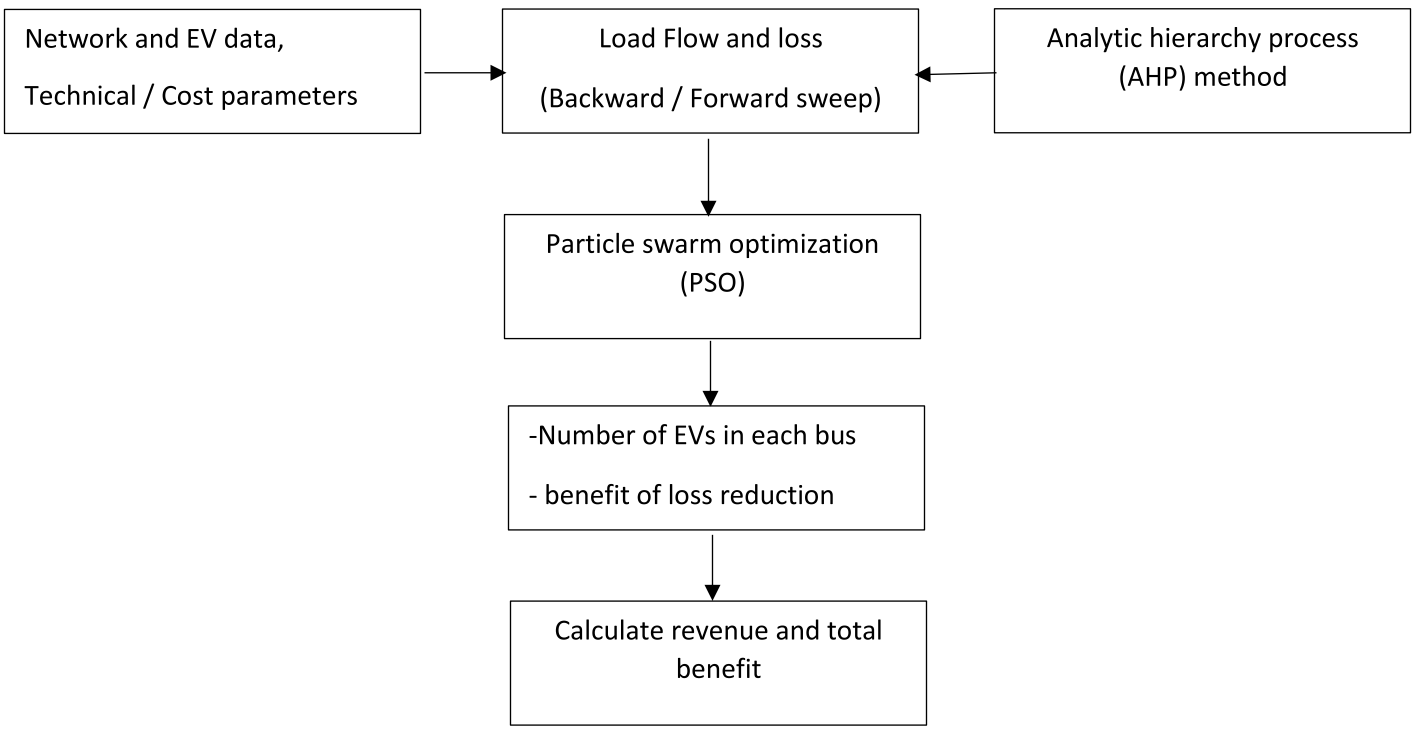

Figure 3.1: Different phases in the suggested solution approach

The proposed model includes the number of parking lots, number of cars, car battery capacity, car charging cost, investment cost, energy price, electricity price, network characteristics, including the number of branches, losses, and income. It consists of multi-objective and multi-constrained that are homogenized based on weighted values. It means that the AHP (Analytic Hierarchy Process) method is employed to calculate the optimal weighting coefficient for each index in the proposed model. Following this, the backward-forward sweep power flow method used to calculate power losses in the distribution network within the context of the optimal parking lot placement problem is explained. This method accurately computes losses, aiding in the identification of optimal parking lot locations to minimize these losses and enhance network efficiency. The Particle Swarm Optimization (PSO) algorithm, employed to determine the number of electric vehicles in each bus and reduce the loss to optimize the proposed model, is then described.

Next step, the revenue is calculated, which is net income minus the required cost, and at the end, the total benefit is computed. Figure 3.1 presents the various steps of the proposed solution approach.

3.2 Mathematical modeling (Moradijoz et al., 2013; Shojaabadi et al., 2016)

To model the problem, we first state the sets, parameters, and variables of the problem. Then we provide objective function and constraints.

3.2.1 Sets

i	Set of parking lots
j	No. of load levels
n	No. of EVs in each parking lot
b	No. of branches in the grid

3.2.2 Parameters

w	Equal weight factor
k	No. of iteration
SOC_i	Initial charging status of the EV (i)
ES_i	Battery capacity of the EV (i)

P_v	The power rate at which the EV is charged
$r(i)$	The net income from the parking lot (i)
Pr_p	The market price at peak times
$CF_{cap}(i)$	The capital cost of the parking lot (i)
C_{ac}	The annual capital cost
$PC(i)$	The capacity of the parking lot (i)
$CF_{pu.driving}(i)$	The cost of purchased energy to charge EVs for driving
P_{roff}	The power of the electricity market in off-peak times
$t(i)$	the required time for full charging of an EV(i)
$P_{parkch}(i, d)$	The required power to charge vehicles from SOC 0 to SOC1
μ_{conv}	Inverter efficiency
C_d	Equipment degradation cost
$CF_{pu.G2V}(i)$	The cost of purchased energy to charge vehicles for V2G power
Pr_{pe}	The purchased energy cost
$price(j)$	The electricity price in load level (j)
$loss(j)$	The network loss in load level (j) without V2G
$loss_{V2G}(j)$	The network loss in load level (j) with V2G

R_b	Resistance of branch (b)
$I_b(j)$	The current of the branch (b) at a time interval (j)
$\lvert V\rvert_{min}$	The minimum allowable voltage in the buses
$\lvert V\rvert_{max}$	The maximum allowable voltage in the buses
$S_{(i\,j)max}$	The MVA capacity of the line between bus i to bus j.

3.2.3 Objectives function

The main objective function of this study consists of 5 cost functions that are homogenized based on weighted values as Eq. (3-1):

$$\text{Max } F = \sum_{i=1}^{N_{V2G}} \big(w_i \times r(i)\big) - (w_2 \times CF_{cap}(i) + w_3 \times CF_{Pu,driving}(i) + w_4 \times CF_{pu,V2G}(i)) + \sum_{j=1}^{J} \big(w_5 \times DC_{loss}(j)\big) \tag{3-1}$$

where N_{V2G} is the number of parking lots, J is the number of load levels, and w1, ..., w5 are weighting coefficients.

In the following, the components of the objective function are examined.

3.2.3.1 Charging time of an EV

The charging time of an electric car depends on several factors, including the battery capacity, the charging power, and the initial state of charge of the battery.

The charging time for full charging of an EV as a function of initial SOC can be calculated as Eq.

$$t(i) = \left(\frac{(1-SOC_i)\times ES_i}{P_v}\right) \tag{3-2}$$

where SOC_i is the initial SOC of vehicle i, ES_i is the battery capacity of Ev_i, and P_v is the power rate with which EV is charged.

By considering three levels of State of Charge (SOC) for batteries, as depicted in table 3-1, the parking lot's input-output power will exhibit three stages, similar to the illustration in figure 3.2.

Table 3-1 Initial SOC of available vehicles at the parking lot (Moradijoz et al., 2013)

Initial SOC	SOC_1 (0.3)	SOC_2 (0.45)	SOC_3 (0.7)
Number of Vehicles	n_1	n_2	n_3

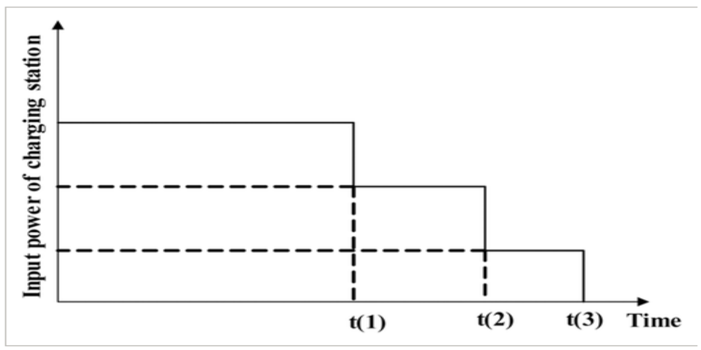

Figure 3.2: Input-output power modeling of the parking lots

(Moradijoz et al., 2013).

It's worth noting that the charging process doesn't always happen at a constant rate. Typically, charging follows a curve where the speed is faster when the battery's State of Charge (SOC) is low, and it slows down as the battery approaches full capacity. This adjustment in charging speed is managed by the battery management system to ensure the battery's health and safety are optimized. Moreover, certain electric vehicles are compatible with different charging speeds, including slower AC charging and faster DC fast charging. The charging duration can vary significantly based on the type of charging station and the capabilities of the EV. With advancements in EV technology, enhancements in charging infrastructure, and progress in battery chemistry, it is probable that charging times for electric vehicles will further improve.

3.2.3.2 Output power of the EVs

The output power of the EVs parking lot is equal to:

$$P_{parkch} = P_v \times n \quad (3\text{-}3)$$

Where "n" represents the number of available vehicles in the parking lot, it denotes the total electrical power that the parking lot can supply to the connected vehicles. This capacity is determined by the parking lot’s charging capacity and the number of charging connectors it possesses. The charging capacity indicates the maximum power that the charging station can deliver at any given moment. This capacity may vary depending on factors such as the type of charging station (AC or DC fast charging), the capabilities of the charging infrastructure, and constraints within the local electrical grid.

For example, if you have a DC fast charging station with a charging capacity of 150 kW and it has two charging connectors, the total output power of the station would be:

Output Power = 150 kW × 2 = 300 kW

This means that the station can deliver a maximum of 300 kilowatts of power to the connected electric vehicles simultaneously.

It is important to consider that although the charging station has a specific output power capacity, individual vehicles may not always draw the maximum available power. The charging rate of each EV is influenced by factors such as the capabilities of the vehicle's onboard charger, the battery's state of charge, and the power supply of the charging station. As a result, the actual charging rate of each vehicle may be lower than the station's maximum output power.

3.2.3.3 Revenues of EVs:

The profit made by parking lots from selling charging services to electric vehicles is calculated as:

$$r(i) = Pr_p \times P_{parkch}(i) \times t_{disp}(i) \tag{3-4}$$

where r(i) is the total revenue gained from i_{th} parking lot, $t_{disp}(i)$ is the total time that the V2G power is dispatched, P_r is market price of electricity at peak time.

3.2.3.4 Required cost

The cost of vehicle-to-grid (V2G) power consists of three components: purchased energy, wear, and capital costs. The purchased energy and wear costs for V2G are additional expenses required specifically for V2G, not for driving. Similarly, the capital cost represents the expense of additional equipment necessary for V2G, distinct from the primary function of vehicles, which is transportation. In addition to the cost of V2G power, this section also models the cost of purchased energy for driving purposes (Kempton W, 2007).

1 - The capital cost of the parking lot

$$CF_{cap}(i) = C_{ac} \times \ PC(i) \tag{3-5}$$

C_{ac} is the annualized capital cost for each vehicle, PC(i) is the capacity of the parking lot (i).

2- Cost of purchased energy to charge EVs for driving

$$CF_{pu.driving}(i) = \sum_{d=1}^{t_n} \frac{P_{roff}}{\mu_{conv}} \times P_{parkch}(i, d) \times t(d) \tag{3-6}$$

Where P_{roff} is the market price of electricity at off-peak times, μ_{conv} is the efficiency of the inverter, $P_{parkch}(i, d)$ is the required power to charge vehicles from SOC 0 to SOC1 during duration of t(d) (it is calculated by Eq. (3-3)), and t(d) it is calculated by Eq. (3-2)).

3- Cost of purchased EVs charging energy to charge vehicles for V2G power

$$CF_{pu.V2G}(i) = Pr_{pe} \times P_{park}(i) \times t_{disp} \tag{3-7}$$

The value of Pr_{pe} represents the purchased energy cost and is calculated using the following equation:

$$Pr_{pe} = \frac{P_{roff}}{\mu_{conv}} + C_d \tag{3-8}$$

where C_d is the cost of equipment degradation due to the extra use for V2G, and μ_{conv} is the efficiency of the inverter.

3.2.3.5 Loss mitigation benefit

The power loss in the distribution system varies due to the output power of parking lots. Therefore, the cost of system loss can be evaluated using the following expression:

$$DC_{loss}(j) = price(j) * (loss(j) - loss_{V2G}(j)) \tag{3-9}$$

Where,

$$loss(j) = \sum_{b=1}^{B} R_b * I_b^2(j) * t(k) \tag{3-10}$$

Where price(j) represents the cost of electricity in load level j, loss(j) is the network loss in load level j without V2G, lossV2G(j) is the network loss in load level j with V2G, R_b is the resistance of branch b, and $I_b(j)$ is the current of branch b at time interval j.

This equation is probably employed to estimate the energy losses in a charging system, aiding in the quantification of efficiency and energy wastage related to different components. It is commonly utilized in engineering and electrical systems analysis to assess the effectiveness of power distribution and consumption.

3.3 Constraints

The objective function is maximized subject to three inequality constraints, which are described as follows:

1. Distribution line capacity limit

   The power flow through the lines must be below the maximum permitted power of the lines due to the line's thermal capacity.

   $S_{(i\,j)} \leq S_{(i\,j)\max}$ (3-11)

   where $S_{i,j}$ is the MVA in the line connecting bus i to bus j, and $S_{(i\,j)\max}$ is the MVA capacity of the line between bus i to bus j.

2. **Voltage drop limit**

   The voltage of each bus should be in the range of minimum and maximum voltages.

   $|V|_{\min} \leq |V_{n_b}| \leq |V|_{\max}$ (3-12)

   where $|V|_{\min}$, $|V|_{\max}$ are minimum and maximum allowable voltages at buses, respectively.

3. **Number of vehicles limit in each parking lot**

   The capacity of each parking lot in a specific area is constrained by the number of EVs in that area. This constraint can be expressed as follows:

   $CP \leq CP_{\max}$ (3-13)

   where $CP_{\max}$ is the maximum capacity of parking lot, which can be installed.

3.4 Calculation of weighting factors: (Jeonghwan et al, 2010)

In this study, AHP is used to calculate the optimal weighting coefficient for each index in Eq. (3-1).

The Analytic Hierarchy Process (AHP) has been utilized to aid decision-making in a variety of applications, including selecting bridge designs and determining product pricing strategies.

3.4.1 Principle of Analytic Hierarchy Process method

This technique, a part of multi-criteria decision-making methods, adheres to four fundamental principles:

- Principle of reversibility:

  If criterion C1 is preferred over criterion C2, then C2 has a reciprocal priority of n/1 over C1. This principle is consistently applied in forming pairwise comparisons, as evident in the pairwise comparison matrices.

- Principle of homogeneity:

  Options and criteria must always be comparable, meaning two options cannot be included in the decision-making model if one is infinitely more important than the other.

- Principle of dependence:

  In hierarchical models, each level depends on its higher level.

- Principle of expectations:

  Any change in the hierarchical model requires repeating all hierarchical steps; for example, adding a criterion necessitates repeating the entire process.

3.4.2 Steps of the Analytic Hierarchy Process method

3.4.2.1 Creating a hierarchical diagram:

In this step, the research factors must be extracted from various sources or obtained from experts. Once the factors and options are identified, the problem is divided into criteria levels and sub-criteria, if applicable. The inclusion of criteria is essential in the Analytic Hierarchy Process (AHP) model; the hierarchical model cannot be constructed without them. For instance, in the figure 3.3, 4 criteria (Criteria) and three options (Alternative) constitute the hierarchical model. The key distinction between hierarchical analysis and the Analytic Network Process (ANP) method lies in the hierarchical and network model itself.

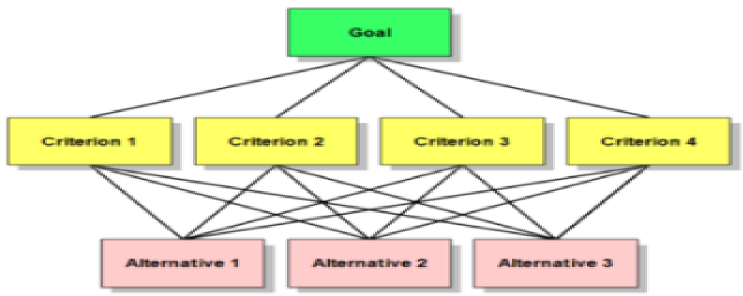

Figure 3.3: A simple model of the Analytic Hierarchy Process **(**Jeonghwan et al, 2010)

3.4.2.2 Forming the matrix of paired comparisons:

In this step, the elements of each level are compared pairwise with other related elements at a higher level, and matrices of paired comparisons are created. To assess the importance and preference in these pairwise comparisons, a scale of 1 to 9 is commonly used, as it can be seen in the table 3-2:

Table 3-2 Preference values for pairwise comparisons

Numerical values	Preferences
9	Completely more vital or completely more
7	desired Very strong preference or importance
5	Strong preference or importance
3	A little more important
1	Equal preference or importance
2,4,6,8	Preferences between the above intervals

$$A = \begin{bmatrix} 1 & {w_1}/{w_2} & \cdots & {w_1}/{w_m} \\ {w_2}/{w_1} & 1 & \dots & {w_2}/{w_m} \\ \vdots & \vdots & \ddots & \vdots \\ {w_n}/{w_1} & {w_n}/{w_2} & \cdots & 1 \end{bmatrix} \tag{3-14}$$

Where m is the number of objectives.

The next step is to compute the eigenvalues and eigenvectors of the reciprocal matrix A.

Let γ_{max} is the maximum eigenvalue of matrix A and s be the corresponding eigenvector such that

$$As = \gamma_{max}\, s \tag{3-15}$$

Mathematically, w can be obtained by normalizing the principle eigenvector of s. (normalize the principle eigenvector s to ensure that the sum of its elements equal1)

$$w = \frac{s}{\sum_{i=1}^{m} s_i} \tag{3-16}$$

3.4.3 Calculating the inconsistency rate:

The inconsistency rate serves as an indicator of the stability of comparisons. In software dedicated to the AHP method, this rate is automatically computed. A rate below 0.1 suggests matrix consistency, while a rate exceeding 0.1 indicates a need to reassess pairwise comparisons. When dealing with a large number of factors in a decision-making problem, inconsistency rates tend to be high, often necessitating extensive adjustments to the pairwise comparison matrix. In such cases, it is advisable to consider using an improved AHP method.

The consistency index of matrix A is calculated as below:

$$I_{CR} = \frac{(\gamma_{max} - m)}{(m-1) * I_{RI}} \tag{3-17}$$

where γ_{max} is maximum eigenvalue of matrix A. If $I_{CR} < 0.1$ the consistency of each weighting coefficient is acceptable. I_{RI} denotes the random index.

3.5 Load flow: (Deosaria et al., 2022)

To solve the optimal parking lot placement problem for a typical radial distribution network, a straightforward power flow method called the backward-forward sweep power flow is employed to calculate power losses.

Load-flow studies are essential for ensuring stable, reliable, and economical transmission of electrical power from generators to consumers through the grid system. With the increasing integration of distributed alternative energy sources, often located in remote areas, load flow studies have become more complex and have sparked renewed interest in the field. Different network buses and branches carry active and reactive power from the producing station to the load in a three-phase AC power system. We refer to the movement of both reactive and active power as "flow" or "load flow." A methodical mathematical technique for determining distinct bus voltages, their phase angles, and the flow of reactive and active power across various branches, generators, and loads in a steady-state setting is provided by power flow studies (Deosaria et al., 2022).

Distributed loads and generation, high R/X ratios, multi-phase and unbalanced operation, radial or poorly meshed networks, and other special issues are faced by distribution systems. These factors make traditional transmission grid load flow methods like the Jacobian-based methods (Newton-Raphson, Gauss-Seidel, and fast decoupled methods) unsuitable for distribution systems. To address these problems, a number of distribution system load flow analysis techniques have been developed. Because of their accuracy in solving problems and computing efficiency, the ladder network theory and the backward/forward sweep methods are the most often utilised among them.

The typical backward/forward sweep method is used to evaluate load flow in radial distribution.

First, a computation is made to arrange the data on the radial distribution from the big dataset into a main line and its derivatives. Once the new nodes are placed into a workable model, their voltages are all adjusted to the nominal voltage. Next comes an iterative procedure where Kirchhoff's Current Law (KCL) is used to compute the branch current in the main line in a backward sweep after currents in derivative lines have been determined. Next, node voltages are calculated using Kirchhoff's Voltage Law (KVL) in a forward sweep. Until the voltage magnitudes at each node in the current iteration and the previous iterations are lower than the tolerance limit, this backward and forward sweep approach is repeated (Deosaria et al., 2022).

3.5.1 Backward sweep:

The procedure for updating branch currents and load flows in the Backward/Forward Sweep technique for load flow analysis is as follows. This update moves towards the branches that are related to the source node from the branches that are the farthest away from it. During the backward propagation phase, the updated load flows in each branch are computed while taking the node voltages from the previous iteration into account. The voltage levels determined in the forward propagation phase are maintained throughout this procedure. Next, using the backward propagation method, the modified power loads in each branch are propagated backward along the feeder. This indicates that the backward propagation proceeds in the direction of the source node, beginning at the node that is farthest away from it (Deosaria et al., 2022).

3.5.2 Forward sweep:

The forward sweep in the Backward/Forward Sweep technique entails updating nodal voltages from first-layer branches to last-layer branches. Computing the voltages at each node, starting with the feeder source node, is the aim of forward propagation. At the feeder substation, the voltage is adjusted to reflect its true value. The effective power in each branch is maintained constant during the forward propagation phase at the value determined during the backward propagation step (Deosaria et al., 2022). The main steps of the suggested method, together with the relevant equations, are listed below.

Step 1: Initialization of voltages (Assume initial voltage at all nodes)

$V^{0}_{node} = V_{line} < 0$ for node = 2, 3,…..,N

(3-18)

N: number of nodes

Step 2: Iteration count initialization, K = 1

convergence_ threshold = tolerance (ε) = 10^{-5}

Step 3: Load current computation.

$I^{k}_{node} = \frac{S^{k-1}_{node}}{V^{k-1}_{node}}$ for node = 2, 3, …., N (3-19)

(s = p + j Q (In the simulation the parking lot is modeled as a bus Q=0))

Step 4: Backward sweep: update current starting from the end nodes

$I_{branch} = I^{k}_{node} + \Sigma\ I_{branch,\ downstream}$

Step 5: Forward sweep (start from the substation and move towards the end nodes)

$V^{k}_{node} = V^{k}_{previous\ node} - Z_{branch} * I^{k}_{branch}$ for all node= 2, 3…., N (3-20)

($Z_{branch} = R_{branch} + jX_{branch} = \sqrt{R^2 + X^2}$)

Step 6: Error

$E^{k}_{node} = |V^{k}_{node} - V^{k-1}_{node}| / V_{line} <= tolerance$ for node = 2, 3…., N (3-

21)

Step 7: Maximum error

$e_{max} = \max (E^{k}_{2}, E^{k}_{3}, E^{k}_{4},……, E^{k}_{node})$ (3-22)

Step 8: The load flow is converging if emax is less than or equal to tolerance (ε). If not, proceed to step 3 and repeat the process after updating the iteration count to K=K+1. The operation of the load flow computation utilising the backward and forward sweep approach is shown in figure 3.4.

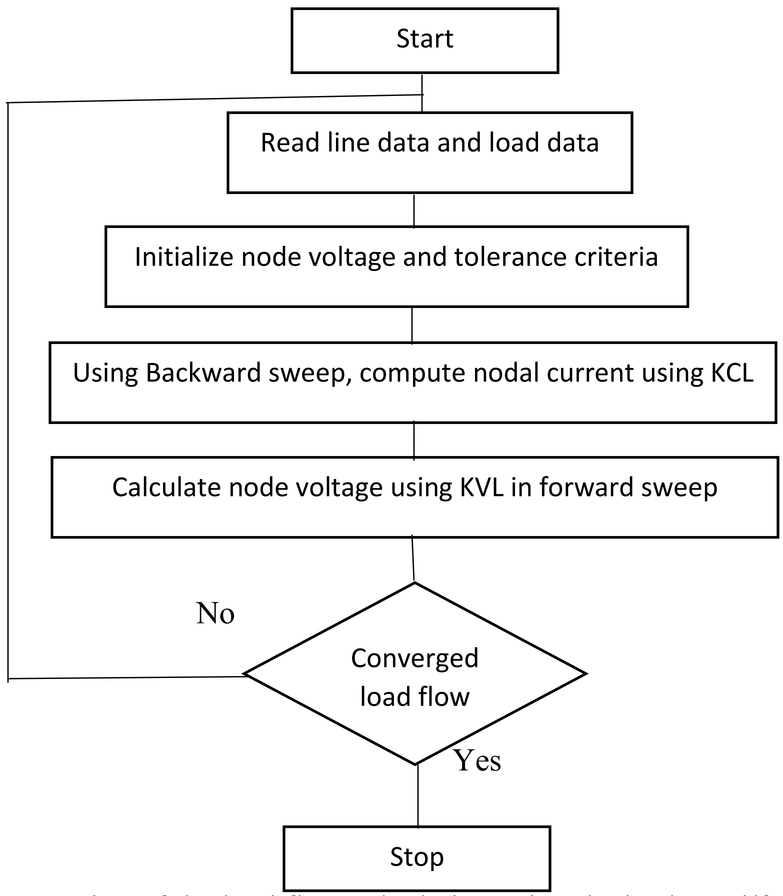

Figure 3.4: Operation of the load flow calculation using the backward/forward sweep method (Deosaria et al., 2022)

3.6 Solving method:

The primary aim of the proposed model is to identify suitable locations and optimal sizes for parking lots by maximizing the objective function. The following section outlines the Particle Swarm Optimization (PSO) algorithm, which is used to solve objective optimization problem are described.

3.6.1 Particle Swarm Optimization (PSO): (Zhao et al., 2023)

The objective function stated in Eq. (3-1), is maximized with PSO. PSO (Particle Swarm Optimization Algorithm) is a nature-inspired optimization technique used to tackle a variety of optimization challenges. It draws inspiration from the collective behavior of groups in nature, like the flocking of birds or the schooling of fish. Originally developed by James Kennedy and Russell Eberhart in 1995, PSO has grown in popularity and is widely used in computational intelligence and optimization. PSO works by simulating the movement of a swarm of particles through a multi-dimensional search space, aiming to find the best solution for a given problem. It is particularly effective for solving optimization problems with numerous variables and complex, non-linear objective functions.

Each member of the group in PSO is characterized by a velocity vector and a position vector in the search space. With each iteration, the particles' new positions are determined based on their velocity and current position in the search space.

In the problem's dimensional space, solutions are represented by matrices with corresponding dimensions. Therefore, the position and velocity of PSO can be denoted by matrices of size X_i = [$x_{i,1}, x_{i,2}, \cdots, x_{i,D}$] and [$V_i = v_{i,1}, vi_{,2}, \cdots, v_{i,D}$], respectively, where $x_{i,j}$ represents the value of position x_i in dimension j, and $V_{i,j}$ represents the value of velocity V_i in dimension j. The operations of the algorithm are also conducted as matrix operations, and the velocity and position update models of the standard PSO are represented as follows:

$$
\begin{cases}
V_{i,j}^{t+1} = w * (\, Vmax_{i,j}^{t}) + c_1 * r_1 * (gBest_j^t - x_{i,j}^t) + c_2 * r_2 * (\, pBest_{i,j}^t - x_{i,j}^t) & (3\text{-}23) \\
x_{i,j}^{t+1} = x_{i,j}^{t} + V_{i,j}^{t+1} & (3\text{-}24) \\
w = wMax - 1 * ((wMax - wMin) \,/\, iters) & (3\text{-}25)
\end{cases}
$$

where j = 1, 2, · · ·, D and c_1 and c_2 are constants representing the acceleration coefficients that control the particle's movement. Parameters r_1 and r_2 are random numbers following a Gaussian distribution and taking values between 0 and 1, and t represents the current iteration number. $gBest_j^t$ represents the value of the j_{th} dimension of the globally optimal particle in the previous t iterations, and $pBest_{i,j}^t$ represents the value of the j_{th} dimension of the optimal position of particle i in the previous t iterations.

The inertia weight parameter, or "w," is a term used in optimisation methods like PSO. The inertia weight ('w') in PSO maintains a balance between the local and global search space exploration. Throughout the optimisation process, Eq 3-25 modifies 'w' to progressively lower its value over iterations, a popular strategy to balance exploration and exploitation. (wMax is the maximum inertia weight, wMin is the minimum inertia weight, and t is the number of iterations)

The process of performing this algorithm is as follows:

- Initialization:

  Initialize a population of particles with random positions and velocities in D dimensions in the search space.

- Estimation:

  Estimate the fitness of each particle in this population.

- Update:

  Calculate the speed of each particle and move to the next position.

- Termination:

  Stop the algorithm if it reaches a certain stop criterion; otherwise, go back to the estimation stage.

The PSO algorithm relies on the interplay between particles' individual experiences (pBest) and the collective best experience of the swarm (gBest) to navigate the search space effectively and converge towards promising regions. PSO is valued for its simplicity, ease of implementation, and its effectiveness in handling non-convex and multi-modal optimization challenges. However, it can sometimes face issues with premature convergence, where particles settle on a suboptimal solution without thoroughly exploring the full search space.

The parameters of PSO that are used in this thesis are as follows:

Vmax= 4

wMax= 0.9

wMin= 0.2

c1= c2= 2

dim=2

PopSize=5

In this thesis the Python software was used for calculating all above sections which is presented in the next capture.

Chapter 4: Results analysis

4.1 Case study:

Figure 4.1 shows the case study's test arrangement (Khalesi et al., 2011). Dispersed generations with power factors of 0.9 lag and ranging from 1 to 5 MW have been regarded as negative loads in order to assess the suggested method. Eight load points are powered by a high-voltage distribution substation with a rating of 132–33 kV that is part of the distribution test network. The network's isolator switches, which have a maximum capacity of 25 MVA, isolate each branch. Every load point in the network has a power factor of 0.9 latency, making them all suitable sites for parking lot installations. The test network's technical specifications are shown in Table 4-1, which loads data in three stages (Khalesi et al., 2011).

Table 4-1: Technical characteristics of branches and load date

Section From To	**R (Ω)**	**X (Ω)**	**L (Km)**	**Load Low Level 1 (MW)**	**Load Medium Level 2 (MW)**	**Load High Level 3 (MW)**
1-3	1.4	1.5	1.5	5	6	8
3-7	2.78	1.5	1.5	7.5	8.8	9.2
1-2	2	4	4	8.3	11.2	9
2-6	2.8	5.5	5.5	4	5	7
1-5	1.7	1.7	1.7	7.5	8.8	9.2
5-9	2.1	4	4	7.3	10.2	8
1-4	2.26	4.5	4.5	6	7	9
4-8	2.4	5	5	7.5	8.7	9.2

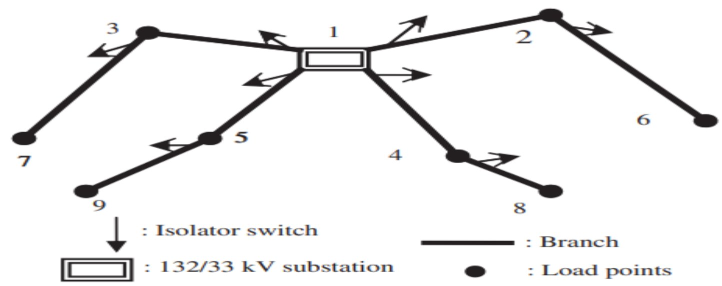

Figure 4.1: Studied test network.

Table 4-2 provides a summary of the system's further technical and financial specifications (Moradijozetal, 2013).

Table 4-2 Technical/Cost parameters

P_v(Kw)	15,50
ES(Kwh)	50,100
t_{disp} (hours/year)	200
Pr_p (Peak Price) USD$/kW h	0.5
C_{ac} USD$/year for each vehicle	304
Car Availability	100%
SOC levels	0.3, 0.45, 0.7
Number of Vehicle per SOC	0.25, 0.25, 0.50
Number of Parking Lots	3
Pr_{off} USD$/kW h	0.05
μ_{conv}	0.85
Cd	0.225
Number of load levels	3
V_{line}	33 kv
V_{min}	0.9 pu
V_{max}	1.1 pu
Price (per load level) USD$/kW h	Light load 0.035 Medium load 0.049 Peak load 0.07

tk (Time duration) h/year	Light load 2190 Medium load 4745 Peak load 1825

The following presumptions are made to maximise parking lot planning: (Kenton and Tomic, 2005; Morijoz et al., 2013)

- The highest billing rate is applied to each vehicle.
- Three degrees of load conditions—light, medium, and peak load—are taken into consideration in this thesis.
- The parking lot is represented in the simulation as a bus (Q = 0).
- It is considered that there are always vehicles available.
- Three degrees of the initial state of charge (SOC) for electric vehicles (EVs) are assumed in parking lot modeling.
- An additional supposition used in the modeling of the parking lot is that every battery has an identical dimension. As a consequence, the output power of the parking lot is continuously in a flat discharging condition.
- According to estimates by traditional utilities, there may be 200 or so peak hours annually during which an extra kWh of power is worth 0.5 USD$/kWh. As a result, it is believed that automobiles provide the network with electricity for no more than 200 hours annually.

4.2 Results:

The AHP approach is used in every scenario to determine the ideal weighting factors. After determining the power loss through a backward-forward sweep, the maximum objective function using the PSO algorithm is used to determine the optimal size (number of EVs in each parking lot) to solve the optimal parking lot placement problem for a radial distribution network.

Additionally, to see the voltage enhancement in the presence of V2G, the voltage profile is examined for each scenario both with and without V2G power.

4.2.1 Scenario 1:

P_v:15 kw and ES :50 Kwh

Based on chapter 3, at first the vector weighting coefficient will be calculated. In all scenarios, all arrays of matrix A equal 1. So, the vector of weighting coefficients is the same in all scenarios.

$$A=\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Thus, the vector of weighting coefficients is calculated using Eq. (3-15) and Eq. (3-16) with the result as below. (The Python code is attached in appendices)

$$s = \begin{bmatrix} 5 \\ 5 \\ 5 \\ 5 \\ 5 \end{bmatrix} \qquad w=\frac{\begin{bmatrix} 5 \\ 5 \\ 5 \\ 5 \\ 5 \end{bmatrix}}{5+5+5+5+5} = \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \end{bmatrix}$$

w = [0.2, 0.2, 0.2, 0.2, 0.2]

In the next step, the location of the parking lot will be determined using load flow, and with the PSO algorithm, the number of EVs in each parking lot will be discovered.

For calculating load flow in this case study, there are 4 lines (1-3-7, 1-5-9, 1-4-8, and 1-2-6). Although the complete steps of all lines are coded in Python and attached to the appendices, one line (1-3-7) is selected as an example to show all the steps mentioned in chapter 3.

Step 1: Initialization of voltages in 8 nodes

$V_2^0 = V_3^0 = V_4^0 = V_5^0 = V_6^0 = V_7^0 = V_8^0 = V_9^0 = V_{line} = 33$ Kv

Step 2: Iteration count initialization, k = 1, ε = 10^{-5}

Step 3: Load Current computation.

$$I_7^1 = \frac{S_7^0}{v_7^1} = \frac{9.2\ (MW)}{33\ (KV)} = 278.78$$

$$I_3^1 = \frac{S_3^0}{v_3^0} = \frac{8\ (MW)}{33\ (KV)} = 242.42$$

Step 4: Update current starting from the end nodes (Backward Sweep) –

$$I_{3-7}^1 = I_7^1 + \Sigma\ I_{\text{branch, downstream}} = 278.78 + 0 = 278.78$$

$$I_{1-3}^1 = I_3^1 + \Sigma\ I_{\text{branch, downstream}} = I_3^1 + I_{3-7}^1 = 242.42 + 278.78 = 524.21$$

Step 5: Forward Sweep

$$V_3^1 = V_{line}^1 - Z_{1\text{-}3} * I_{1-3}^1 = 33000 - 2.051 * 524.21 = 31930.56$$

$$V_7^1 = V_3^1 - Z_{3\text{-}7} * I_{3-7}^1 = 31930.56 - 6.16 * 278.78 = 30212.48$$

Step 6: Error

$E_3^1 = |V_3^1 - V_3^0\ |/\ V_{line} <= \text{tolerance}$ $E_3^1 = |31930.56 - 33000\ |/\ 33000 = 0.0324 > 10^{-5}$

$E_7^1 = |V_7^1 - 7_7^0\ |/\ V_{line} <= \text{tolerance}$ $E_7^1 = |30212.48 - 33000\ |/\ 33000 = 0.0844 > 10^{-5}$

Step 7: Maximum Error

$e_{max} = \max\ (E_3^1, E_7^1) = 0.0844 > 10^{-5}$

Step 8: e_{max} is more than tolerance (ε), then update the iteration count to k=k+1 and go to step 3 and repeat the steps.

- K=2

Step 3: Load Current computation. (line 1-3-7)

$$I_7^2 = \frac{S_7^1}{v_7^1} = \frac{9.2\ (MW)}{30212.48} = 304.51$$

$$I_3^2 = \frac{S_3^2}{v_3^2} = \frac{8\ (MW)}{31930.56} = 250.54$$

Step 4: Update current starting from the end nodes (Backward Sweep)

$I_{3-7}^2 = I_7^2 + \Sigma \; I_{\text{branch, downstream}} = 304.051 + 0 = 304.051$

$I_{1-3}^2 = I_3^2 + \Sigma \; I_{\text{branch, downstream}} = I_3^2 + I_{3-7}^2 = 250.54 + 304.51 = 555.05$

Step 5: Forward Sweep

$V_3^2 = V_{line}^2 - Z_{1\text{-}3} * I_{1-3}^2 = 33000 - 2.051 * 555.05 = 31861.12$

$V_7^2 = V_3^2 - Z_{3\text{-}7} * I_{3-7}^2 = 31861.12 - 6.16 * 304.052 = 29984.53$

Step 6: Error

$E_3^2 = |V_3^2 - V_3^1| / V_{line} <= \text{tolerance}$ $\quad E_3^2 = |31861.12 - 31930.56| / 33000 = 0.0021 > 10^{-5}$

$E_7^2 = |V_7^2 - 7_7^1| / V_{line} <= \text{tolerance}$ $\quad E_7^2 = |29984.53 - 30212.48| / 33000 = 0.0069 > 10^{-5}$

Step 7: Maximum Error

$e_{max} = \max(E_3^2, E_7^2) = 0.0069 > 10^{-5}$

Step 8: e_{max} is greater than tolerance (ε), so update the iteration count to k=k+1 and go to step 3. These steps are repeated, and in K=6, the e_{max} becomes less than tolerance (ε), so the load flow is Converged at iteration 6.

$e_{max} = \max(E_3^6, E_7^6) = 4.28 * 10^{-7} < 10^{-5}$

Then the location of parking lots, the number of EVS, and the benefit of loss reduction (Eq. (3-9) and (3-10)) are obtained using the PSO algorithm. At the end, the benefit of providing peak power (net income – required cost) and total benefit is calculated using Eq. (3-1).

This scenario's outcomes are presented in Table 4-3. It is considered that there are vehicles available in full. Put otherwise, all EV owners respect the agreement. The overall yearly benefit is 188089.803 USD$, as the table show.

Table 4-3 Simulation results of scenario 1

Bus number Optimum number of EVs	6 8 249 302
Benefit of loss reduction $	62266.4
Benefit of providing peak power $	125823.403
Total benefit $	188089.803

Figure 4.2 displays the voltage profile of load locations during peak hours, when parking lots provide electricity to the distribution system. As previously stated, a total of six iterations are needed, with a tolerance of 10-5 p.u.

There is a voltage decrease on buses 6 and 8, as seen in figure 4.2 and table 4-4 (without V2G). Therefore, since the voltage on buses 6 and 8 is less than 0.9 p.u., the optimisation constraint is not in the required range in this scenario. Nonetheless, when V2G power is present, the voltage profile of the buses improves.

It is important to remember that the voltage in every bus is the same as the voltage in every node determined by the load flow technique. (after convergence)

Table 4-4 Voltage magnitude of 9-bus system **(15 Kw)**

Bus Number	Bus Voltages without V2G (p.u.)	Bus Voltages with V2G (p.u.)
1	1	1
2	0.9343	0.9496
3	0.9676	0.9676
4	0.9158	0.9368
5	0.9620	0.9620
6	0.8946	0.9311

7	0.9155	0.9155
8	0.8689	0.9130
9	0.9288	0.9288

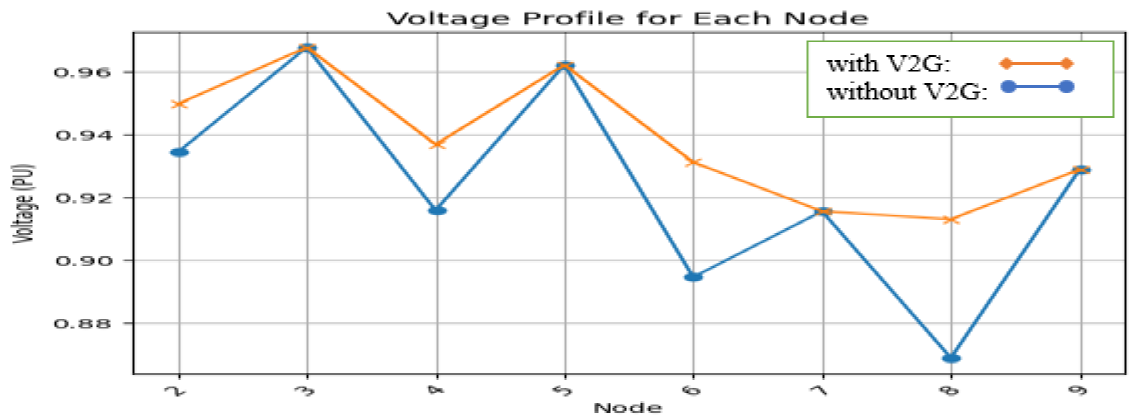

Figure 4.2: Voltage profile in peak load (scenario 1)

4.2.2 Scenario 2:

P_v:50 kw and ES :100 Kwh

The vector of weighting coefficients is calculated like scenario 1.

w = [0.2, 0.2, 0.2, 0.2, 0.2]

Table 4-5 displays the outcome of this case. Vehicle availability is taken for granted to be 100%. Or to put it another way, every EV owner honours the agreement. The statistics show that the overall yearly benefit is 185731.7176 USD$.

Table 4-5 Simulation results of scenario 2

Bus number	6	8
Optimum number of EVs	58	74
Benefit of loss reduction $	66483.2	
Benefit of providing peak power $	119248.5176	
Total benefit $	185731.7176	

Figure 4.3 displays the voltage profile of load points, or parking lots that provide electricity to the distribution system, during peak hours. The needed total number of iterations is six, and the tolerance is 10-5 p.u. Bus numbers 6 and 8 experience a voltage loss when there is no V2G in the network, as shown in figures 4.3 and Table 4-6, since their voltage is less than 0.9 p.u. But when V2G is present, this problem is resolved.

Table 4-6 Voltage magnitude of 9-bus system **(50 Kw)**

Bus Number	Bus Voltages without V2G (p.u.)	Bus Voltages with V2G (p.u.)
1	1	1
2	0.9343	0.9462
3	0.9676	0.9676
4	0.9158	0.9329
5	0.9620	0.9620
6	0.8946	0.9229
7	0.9155	0.9155
8	0.8689	0.9049
9	0.9288	0.9288

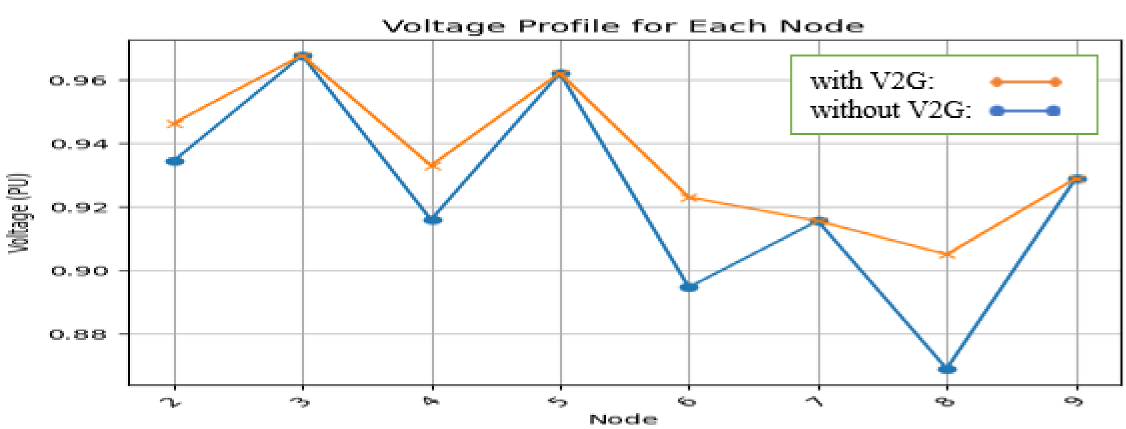

Figure 4.3: Voltage profile in peak load (scenario 2)

4.2.3 Scenario 3:

P_V:100 kw and ES :100 Kwh

w = [0.2, 0.2, 0.2, 0.2, 0.2]

Table 4-7 displays what happened in this particular case. As the statistics show, the benefit's total yearly value is $176902.4823. The availability of vehicles is taken for granted to be 100%. Stated differently, every owner of an EV abides by the agreement.

Table 4-7 Simulation results of scenario 3

Bus number	6	8
Optimum number of EVs	26	32
Benefit of loss reduction $	68552.4	
Benefit of providing peak power $	108350.0823	
Total benefit $	176902.4823	

Figure 4.4 displays the voltage profile of load sites during peak hours when parking lots provide electricity to the distribution system. The total number of iterations needed is six, and the tolerance is 10-5 p.u. Table 4-8 and Figure 4.4 show that there is a voltage reduction at bus numbers 6 and 8, where the voltage is less than 0.9 p.u. (without V2G). In the presence of V2G power, the voltage profile of the buses improves, but the optimization constraints are still within a reasonable range.

Table 4-8 Voltage magnitude of 9-bus system **(100 Kw)**

Bus Number	Bus Voltages without V2G (p.u.)	Bus Voltages with V2G (p.u.)
1	1	1
2	0.9343	0.9449
3	0.9676	0.9676

4	0.9158	0.9306
5	0.9620	0.9620
6	0.8946	0.9200
7	0.9155	0.9155
8	0.8689	0.9001
9	0.9288	0.9288

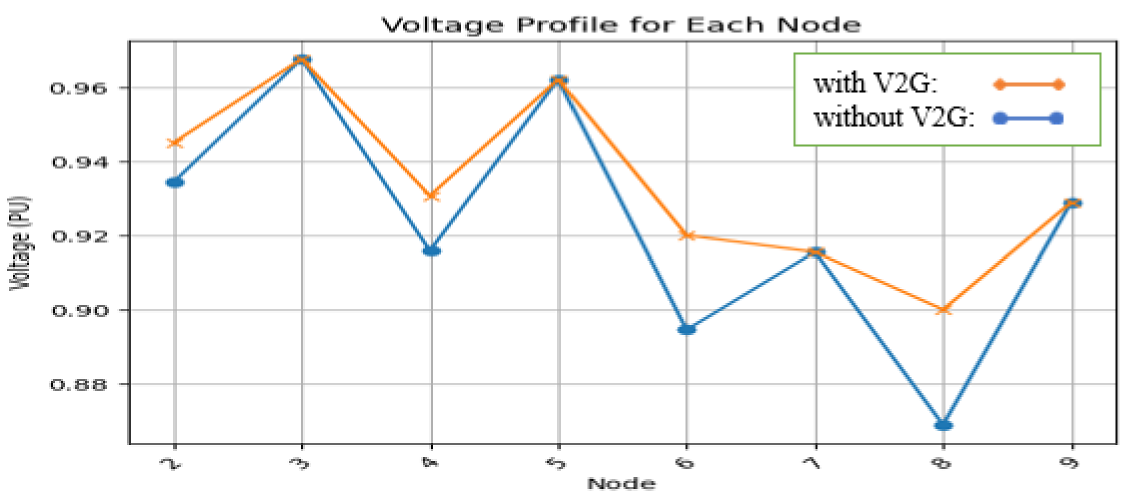

Figure 4.4: Voltage profile in peak load (scenario 3)

4.3 Comparison of results:

In this thesis, an optimisation model is effectively used to calculate the optimal parking lot size and capacity to meet demand during peak hours. This method is compared with another study's total capacity parking lots on the network and loss reduction percentage in this part.

Table 4-9 Results comparison

Methodology	Network condition		Bus number	Optimum number of EVs in each bus	Voltage Drop points (with V2G)	Total capacity of network (W)	Benefit of loss reduction ($)
Proposed approach (PSO)	Peak load (200h)	P_v: 15kw ES: 50 kwh	6 8	249 302	-	8265 KW	62266.4
		P_v: 50 kw ES:100 kwh	6 8	58 74	-	6600 KW	66483.2
		P_v: 100 kw ES:100 kwh	6 8	26 32	-	5800 KW	68552.4
Competition over resource optimization algorithm (Fathy and Almoataz 2020)	Peak load (200h)	P_v: 15kw ES: 50 kwh	2 3 6	100 300 200	8	14625KW	33010
Grey wolf optimizer (Fathy and Almoataz 2020)	Peak load (200h)	P_v: 15kw ES: 50 kwh	2 3 6	107 350 230	8	14625KW	34110.3800
Water cycle algorithm (Fathy and Almoataz 2020)	Peak load (200h)	P_v: 15kw ES: 50 kwh	2 3 6	115 370 250	8	14625KW	38664.450
Whale optimization algorithm (Fathy and Almoataz 2020)	Peak load (200h)	P_v: 15kw ES: 50 kwh	2 3 6	112 360 240	8	14625KW	38436.1490

Genetic Algorithm (Moradijoz et al., 2013)	Peak load (200h)	P_v: 15kw ES: 50 kwh	2 3 6	375 375 225	8	14625KW	38705
Dynamic Programming (Khalesi et al.,2011)	Light load (2190h) Medium load (4745h) Peak load (1825h)	- - -	6, 7, 8 6, 7, 8 6, 8	- - -	- - -	5MW 5MW 5MW	1685881 2792897 679784

Table 4-9 compares the total numbers of EVs, voltage drop points (with V2G), the total capacity of the EV to the network, and the total benefit of loss reduction.

The authors in Moradijoz et al. (2013) estimated and located 975 EVs in the network with a total capacity of 14,625 kW. In contrast, Fathy and Almoataz (2020) explored four methods (COR, GWO, WCA, and WOA approaches), resulting in the location of 600, 687, 735, and 712 EVs in the network, respectively, with the same total capacity of 14,625 kW. On the other hand, Khalesi et al. (2011) did not consider EVs in the distribution network; instead, they estimated and located about 5 MW of DGs in the network, distributed across three load types (light, medium, peak). Consequently, their approach demonstrates the potential for significantly reducing losses and increasing benefits compared to others.

This study achieves a higher benefit in loss reduction with a smaller number of EVs compared to Moradijoz et al. (2013) and Fathy and Almoataz (2020).

In addition, the results in Moradijoz et al. (2013) and Fathy and Almoataz (2020) are based on specific parameters, such as P_v = 15 kW and ES = 50 kWh, without considering other network conditions. Furthermore, the optimization constraint for bus number 8 in Moradijoz et al. (2013) and Fathy and Almoataz (2020) is not within the appropriate range (voltage drop occurs at bus number 8 during peak hours). This thesis, by considering various situations, demonstrates that utilizing fast charging stations and vehicles with higher battery capacities can significantly reduce the total number of EVs while improving voltage drop during peak times.

It is worth mentioning that in this thesis, the benefit of loss reduction is examined, and the benefit of reliability improvement is not checked. While the authors in Moradijoz et al. (2013) and Fathy and Almoataz (2020) also checked the benefit of reliability improvement.

Chapter 5: Conclusion and future works

This Chapter discusses the conclusions derived from implementing the optimization problem for allocating parking lots in a distribution network with checking voltage drop using PSO algorithm. The chapter also proposes future work in the area of optimization for allocation problems using the PSO method.

5.1 Conclusion

The thesis aimed to address the optimal allocation of parking lots within a distribution system to efficiently supply loads. It proposed an optimization model that determines the best capacity and size of parking lots to meet peak hour demands (200h in a year based on Kempton et al. (2005)) and the problem has been optimized considering existed constrains on permanent operation of the distribution system. This model focused on maximizing total benefits, considering data and market prices. Results from the study showed that installing parking lots could be economically profitable for the distribution company (DISCO) and could improve the voltage profile. To optimize the allocation of parking lots, the study utilized the Particle Swarm Optimization (PSO) algorithm, which is a heuristic optimization technique inspired by the social behavior of bird flocking or fish schooling. This algorithm iteratively improves a candidate solution by moving towards the best solution found so far, considering both the candidate solution's own best position and the best position found by other particles in the swarm.

The simulation results indicate that changes in the battery capacity of EVs in parking lots and the power rate at which the EVs are charged (P_v) result in variations in the outcomes. To achieve more accurate results, it is essential to precisely determine the size of the batteries and the power rate at which the EVs are charged. This would involve careful consideration of factors such as the expected usage patterns of the EVs, the charging infrastructure available, and the overall objectives of the optimization process. Fine-tuning these parameters can lead to more precise and effective outcomes in the optimization of parking lot allocations for EV charging.

In addition to the benefits already mentioned, this approach offers several other advantages that should not be overlooked. These advantages include:

1- Improvement in Voltage profile:

By strategically locating parking lot charging stations at peak time, the voltage profile at load points can be improved, ensuring that they remain within acceptable limits.

2- Reduction in power Flow:

The approach helps to reduce power flow in feeders by compensating for losses and supplying part of the required power to load points in the network. This can alleviate stress on feeders, particularly those near high-voltage distribution substations.

3- Enhanced Equipment Lifespan:

By reducing stress on feeders and improving voltage profiles, the approach can contribute to prolonging the lifespan of equipment in the distribution network. This can lead to cost savings and improved reliability of the network.

Overall, these additional advantages highlight the potential of the approach to not only optimize parking lot allocations for electric vehicle charging but also to improve the overall performance and efficiency of the distribution network.

Therefore, this method can provide technical and financial benefits, as indicated by the simulation results, if implemented in suitable locations with appropriate sizes.

5.2 Future works

While the results achieved are well defined and practical and reflects a general trend towards the determination the appropriate size and site of parking lots in different scenarios, several avenues for future research and development can be pursued based on the findings and limitations of this thesis.

These directions include:

1- A simple system with 9 bus was considered in this thesis. The proposed method can be used for a complex system like 33 bus or 69 bus.

2- The weighting coefficient can lead to variations in the results. In this study, the weighting coefficient was equal and all arrays in matrix A were 1. The same approach can be used to examine the effects of various weighting coefficients.

3- It was assumed that all EV owners respected the contract, and the availability of vehicles was 100 percent. If the availability of vehicles is 80 percent or less, it can have an have an effect on the result.

4- Reliability improvement has not been investigated in this thesis, so it can also be investigated in future works.

5- In the modeling of parking lots, it is assumed that the initial state of charge (SOC) of EVs has three levels. The proposed model can be used for other SOC levels.

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Appendices

Python code

Analytic hierarchy process

```
# Importing necessary packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```
# Reading the file
ahp_df = pd.read_csv('/content/all 1.csv')
ahp_df.set_index('Unnamed: 0', inplace=True)
ahp_df
```

```
# We will introduce a function to find the priority index.
# Then we provide the attributes data to this function.
def ahp_attributes(ahp_df):
    # Creating an array of sum of values in each column
    sum_array = np.array(ahp_df.sum(numeric_only=True))
    # Creating a normalized pairwise comparison matrix.
    # By dividing each column cell value with the sum of the respective
column.
    cell_by_sum = ahp_df.div(sum_array,axis=1)
    # Creating Priority index by taking avg of each row
    priority_df = pd.DataFrame(cell_by_sum.mean(axis=1),
                               index=ahp_df.index,columns=['priority
index'])
    priority_df = priority_df.transpose()
    return priority_df
```

```
# Calling the ahp_attributes function,
# To return a table with the priority index for each attribute.
priority_index_attr = ahp_attributes(ahp_df)
priority_index_attr
```

```python
def consistency_ratio(priority_index,ahp_df):
    random_matrix = {1:0,2:0,3:0.58,4:0.9,5:1.12,6:1.24,7:1.32,
                     8:1.14,9:1.45,10:1.49,11:1.51,12:1.48,13:1.56,
                     14:1.57,15:1.59,16:1.605,17:1.61,18:1.615,19:1.62,20:
1.625}
    # Check for consistency
    consistency_df = ahp_df.multiply(np.array(priority_index.loc['priority
index']),axis=1)
    consistency_df['sum_of_col'] = consistency_df.sum(axis=1)
    # To find lambda max
    lambda_max_df =
consistency_df['sum_of_col'].div(np.array(priority_index.transpose()
                                                              ['priority
index']),axis=0)
    lambda_max = lambda_max_df.mean()
    # To find the consistency index
    consistency_index = round((lambda_max-
len(ahp_df.index))/(len(ahp_df.index)-1),3)
    print(f'The Consistency Index is: {consistency_index}')
    # To find the consistency ratio
    consistency_ratio =
round(consistency_index/random_matrix[len(ahp_df.index)],3)
    print(f'The Consistency Ratio is: {consistency_ratio}')
    if consistency_ratio<0.1:
        print('The model is consistent')
    else:
        print('The model is not consistent')
```

```python
consistency_ratio(priority_index_attr,ahp_df)
```

```python
import numpy as np
import matplotlib.pyplot as plt
import math
```

Network data

```python
grid9 = {
    "1-3":{"R": 1.4, "X": 1.5, "L":1.500, "Load1":5, "Load2":6, "Load3":8, "FR":0.05, "t_rep":15, "t_res":1, "Isolations": ["1-3"], "S_max":25},
    "3-7":{"R": 2.78, "X": 5.5, "L":5.500, "Load1":7.5, "Load2":8.5, "Load3":9.2, "FR":0.046 * 5.5, "t_rep":8, "t_res":1, "Isolations": ["3-7"], "S_max":25},
    "1-2":{"R": 2, "X": 4, "L":4.000, "Load1":8.3, "Load2":11.2, "Load3":9, "FR":0.05, "t_rep":15, "t_res":1, "Isolations": ["1-2"], "S_max":25},
    "2-6":{"R": 2.8, "X": 5.5, "L": 5.500, "Load1": 4, "Load2":5, "Load3":7, "FR":0.046 * 5.5, "t_rep":8, "t_res":1, "Isolations": ["2-6"], "S_max":25},
    "1-5":{"R": 1.7, "X": 1.7, "L": 1.700, "Load1": 7.5, "Load2":8.8, "Load3":9.2, "FR":0.05, "t_rep":15, "t_res":1, "Isolations": ["1-5"], "S_max":25},
    "5-9":{"R": 2.1, "X": 4, "L": 4.000, "Load1": 7.3, "Load2":10.2, "Load3":8, "FR":0.046 * 4, "t_rep":8, "t_res":1, "Isolations": [ "5-9"], "S_max":25},
    "1-4":{"R": 2.26, "X": 4.5, "L": 4.500, "Load1": 6, "Load2":7, "Load3":9, "FR":0.05, "t_rep":15, "t_res":1, "Isolations": ["1-4"], "S_max":25},
    "4-8":{"R": 2.4, "X": 5, "L": 5.000, "Load1": 7.5,"Load2":8.7, "Load3":9.2, "FR":0.046 * 5, "t_rep":8, "t_res":1, "Isolations": ["4-8"], "S_max":25},
}

ENS = {
    "2":[0.053, 0.073, 0.105],
    "3":[0.053, 0.073, 0.105],
    "6":[0.053, 0.073, 0.105],
    "4":[2, 3.8, 3.6],
    "7":[2, 3.8, 3.6],
    "8":[2, 3.8, 3.6],
    "9":[2, 3.8, 3.6],
    "5":[6, 8.4, 11.050],
}
```

```
Pv = 15 # kW h
Pv_loss = 13.5 #kwh
Pbattery = 50
ES = 50 # Kw
t_disp = 200 # hours/year
Pr_p = 0.5 #USD$/kW h
Cac = 304 # (USD$/year for each vehicle)
availability = 1.0
SOC = [0.3, 0.45, 0.7]
n_vehic_soc = [0.25, 0.25, 0.50]
Nstations = 2
Pr_off = 0.05 #USD$/KW h
mu_conv = 0.85
Cd = 0.2 #  (USD$/kW h)
num_load_levels = 3 # light medium high
V_line = 33 #kv
Price = [0.035, 0.049, 0.07]  # per load level price
tk_ = [2190, 4745, 1825]
Parking_nodes = [6, 8]
```

Load flow

```
def objFunc(n, w=[0.2, 0.2, 0.2, 0.2, 0.2], grid=grid9, availability=1.0):
    """
    n: Number of vehicles in each parking_node
    w: weighting factors
    grid: input grid
    """


    Nv2g = len(n)
# load flow:

    # Initialize Z values
    Z2 = Z3 = Z4 = Z5 = Z6 = Z7 = Z8 = Z9 = 0

    # Initialize lists for voltage profiles and modified nodes
    voltage_profiles = []
    Active_power = []
    modified_nodes = []
    I_values = []
    Z_values = []
    P_value = []
    Rb_value=[]
    current_values = {}
    impedance_values = {}
    power_values = {}
    V_values = {}
    real_Rb_values = {}

    for j in range(num_load_levels):
        if j == 2:
           for b in grid.keys():
               node = int(b.split("-")[-1])
               Rb, Xb, L = grid[b]["R"], grid[b]["X"], grid[b]["L"]
               Z = math.sqrt(((Rb)**2+ +( Xb)**2 ))
               P = grid[b][f"Load{j+1}"] * 1000  # KW
               I_j = P / V_line
               #print(I_j)
               if node in [2, 3, 4, 5, 6, 7, 8, 9]:
                  globals()[f"Z{node}"] = Z
                  globals()[f"I{node}"] = I_j
                  globals()[f"P{node}"] = P
                  globals()[f"Rb{node}"] = Rb
                  modified_nodes.append(node)
```

```
                  I_values.append(I_j)
                  Z_values.append(Z)
                  P_value.append(P)
                  Rb_value.append(Rb)

    # Sort I and Z based on the number of nodes
    sorted_data = sorted(zip(modified_nodes, I_values, Z_values, P_value,
Rb_value), key=lambda x: x[0])
    sorted_nodes, sorted_I_values, sorted_Z_values, sorted_P_values,
sorted_Rb_value = zip(*sorted_data)

    # Print the sorted data
    for node, I_value, Z_value, P_value, Rb_value in zip(sorted_nodes,
sorted_I_values, sorted_Z_values, sorted_P_values, sorted_Rb_value):

        # Store values in dictionaries
        current_values[node] = I_value
        impedance_values[node] = Z_value
        power_values[node] = P_value
        real_Rb_values[node] = Rb_value

# Load flow analysis for selected nodes
    convergence_threshold=0.00001
    convergence= False
    K = 1
    if node in [3, 7, 2, 6, 5, 9, 4, 8]:
       globals()[f"V{3}_K0"] = V_line * 1000
       globals()[f"V{7}_K0"] = V_line * 1000
       globals()[f"V{2}_K0"] = V_line * 1000
       globals()[f"V{6}_K0"] = V_line * 1000
       globals()[f"V{5}_K0"] = V_line * 1000
       globals()[f"V{9}_K0"] = V_line * 1000
       globals()[f"V{4}_K0"] = V_line * 1000
       globals()[f"V{8}_K0"] = V_line * 1000

       while True:
            I_3_7 = I_7 = power_values[7] * 1000 / globals()[f"V{7}_K{K -
1}"]
            I_3 = power_values[3] * 1000 / globals()[f"V{3}_K{K - 1}"]
            I_1_3 = I_3 + I_3_7

            V_3_K = V_line * 1000 - impedance_values[3] * I_1_3
           # print(V_3_K)
            V_3_PU_K = V_3_K / globals()[f"V{node}_K0"]
```

```
            E_3_K = np.abs((np.abs(V_3_K) - np.abs(globals()[f"V{3}_K{K - 1}"])) / np.abs(V_line*1000))

            V_7_K = V_3_K -  impedance_values[7] * I_7
            #print(V_7_K)
            V_7_PU_K = V_7_K / globals()[f"V{node}_K0"]
            E_7_K=  np.abs((np.abs(V_7_K) - np.abs(globals()[f"V{7}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{3}_K{K}"] = V_3_K
            globals()[f"V{7}_K{K}"] = V_7_K
            emax_3_7 = max(E_3_K , E_7_K)
           # print(emax_3_7)

            I_2_6 = I_6 = power_values[6] * 1000 / globals()[f"V{6}_K{K - 1}"]
            I_2 = power_values[2] * 1000 / globals()[f"V{2}_K{K - 1}"]
            I_1_2 = I_2 + I_2_6

            V_2_K = V_line * 1000 - impedance_values[2] * I_1_2
            V_2_PU_K = V_2_K / globals()[f"V{node}_K0"]
            E_2_K = np.abs((np.abs(V_2_K) - np.abs(globals()[f"V{2}_K{K - 1}"])) / np.abs(V_line*1000))

            V_6_K = V_2_K -  impedance_values[6] * I_6
            V_6_PU_K = V_6_K / globals()[f"V{node}_K0"]
            E_6_K=  np.abs((np.abs(V_6_K) - np.abs(globals()[f"V{6}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{2}_K{K}"] = V_2_K
            globals()[f"V{6}_K{K}"] = V_6_K
            emax_2_6 = max(E_2_K, E_6_K)
           # print(emax_2_6)

            I_5_9 = I_9 = power_values[9] * 1000 / globals()[f"V{9}_K{K - 1}"]
            I_5 = power_values[5] * 1000 / globals()[f"V{5}_K{K - 1}"]
            I_1_5 = I_5 + I_5_9

            V_5_K = V_line * 1000 - impedance_values[5] * I_1_5
            V_5_PU_K = V_5_K / globals()[f"V{node}_K0"]
            E_5_K = np.abs((np.abs(V_5_K) - np.abs(globals()[f"V{5}_K{K - 1}"])) / np.abs(V_line*1000))

            V_9_K = V_5_K -  impedance_values[9] * I_9
```

```
            V_9_PU_K = V_9_K / globals()[f"V{node}_K0"]
            E_9_K=  np.abs((np.abs(V_9_K) - np.abs(globals()[f"V{9}_K{K -
1}"])) / np.abs(V_line*1000))

            globals()[f"V{5}_K{K}"] = V_5_K
            globals()[f"V{9}_K{K}"] = V_9_K
            emax_5_9 = max(E_5_K, E_9_K)
           # print(emax_5_9)

            I_4_8 = I_8 = power_values[8] * 1000 / globals()[f"V{8}_K{K -
1}"]
            I_4 = power_values[4] * 1000 / globals()[f"V{4}_K{K - 1}"]
            I_1_4 = I_4 + I_4_8

            V_4_K = V_line * 1000 - impedance_values[4] * I_1_4
            V_4_PU_K = V_4_K / globals()[f"V{node}_K0"]
            E_4_K = np.abs((np.abs(V_4_K) - np.abs(globals()[f"V{4}_K{K -
1}"])) / np.abs(V_line*1000))

            V_8_K = V_4_K -  impedance_values[8] * I_8
            V_8_PU_K = V_8_K / globals()[f"V{node}_K0"]
            E_8_K=  np.abs((np.abs(V_8_K) - np.abs(globals()[f"V{8}_K{K -
1}"])) / np.abs(V_line*1000))

            globals()[f"V{4}_K{K}"] = V_4_K
            globals()[f"V{8}_K{K}"] = V_8_K
            emax_4_8 = max(E_4_K, E_8_K)
            #print(emax_4_8)
            emax = max(E_2_K, E_3_K, E_4_K, E_5_K, E_6_K, E_7_K, E_8_K,
E_9_K)

        # Check convergence
            if emax <= convergence_thereshold :
                 convergence = True
                 print("Converged at iteration:", K)
                 break
            else:
                 K += 1
            #print(V_2_PU_K, V_3_PU_K, V_4_PU_K, V_5_PU_K, V_6_PU_K,
V_7_PU_K, V_8_PU_K, V_9_PU_K)
            voltage_profiles.extend([V_2_PU_K, V_3_PU_K, V_4_PU_K,
V_5_PU_K, V_6_PU_K, V_7_PU_K, V_8_PU_K, V_9_PU_K])
            voltage_profiles_first_iteration = voltage_profiles[:8]
            #print(voltage_profiles_first_iteration)
```

```
            S=[]
            S3= V_3_K *  I_1_3/1000000 #MVA
            S7= V_7_K *  I_3_7/1000000
            S2= V_2_K *  I_1_2/1000000
            S6= V_6_K *  I_2_6/1000000
            S5= V_5_K *  I_1_5/1000000
            S9= V_9_K *  I_5_9/1000000
            S4= V_4_K *  I_1_4/1000000
            S8= V_8_K *  I_4_8/1000000
            Active_power.extend([S2, S3, S4, S5, S6, S7, S8, S9])
            Active_power_first_iteration = Active_power[:8]
            #print(Active_power)

    # Constraint 1: Distribution line capacity limit
    S_max = 25 #MVA
    for j in range(num_load_levels):
        if j == 2:
           for node in [3, 7, 2, 6, 5, 9, 4, 8]:
              if Active_power[node] <= S_max:
                   #print(Active_power[3])
                   print(True)
              else:
                   print(False)

    # Constraints2: Voltage drop limit

    V_min = 0.9 #Pu
    V_max = 1.1 #Pu
    if j == 2:
       for node in [2, 3, 4, 5, 6, 7, 8, 9]:
        # Check if the node index is within the range of
voltage_profiles_first_iteration
          if 0 <= node-2  < len(voltage_profiles_first_iteration):
             voltage_node = voltage_profiles_first_iteration[node-2 ]
             if V_min <= voltage_node <= V_max:
                print(True)
             else:
                print(f"Node index {node} is out of range.")
                print(False)


    # Constraint 3: Number of vehicles limit in each parking lot
    PC_max = 1000
    PC= n
    for j in range(num_load_levels):
```

```
        if j == 2:
           for node in [3, 7, 2, 6, 5, 9, 4, 8]:
              if np.sum(PC <= PC_max):
                   print(True)
              else:
                   print(False)



    # Calculate losses :
    loss = np.array([0] *num_load_levels)
    loss_v2g = np.array([0]*num_load_levels)
    DC_loss = np.array([0]*num_load_levels)

    for node in [3, 7, 2, 6, 5, 9, 4, 8]:
        Loss_3 = real_Rb_values[3] * (I_1_3)**2 *tk_[j]/1000
        Loss_7 = real_Rb_values[7] * (I_3_7)**2 *tk_[j]/1000
        Loss_2 = real_Rb_values[2] * (I_1_2)**2 *tk_[j]/1000
        Loss_6 = real_Rb_values[6] * (I_2_6)**2 *tk_[j]/1000
        Loss_5 = real_Rb_values[5] * (I_1_5)**2 *tk_[j]/1000
        Loss_9 = real_Rb_values[9] * (I_5_9)**2 *tk_[j]/1000
        Loss_4 = real_Rb_values[4] * (I_1_4)**2 *tk_[j]/1000
        Loss_8 = real_Rb_values[8] * (I_4_8)**2 *tk_[j]/1000

    loss += int(np.sum([Loss_2, Loss_3, Loss_4, Loss_5, Loss_6, Loss_7,
Loss_8, Loss_9]))

    for node in Parking_nodes:
        loss_v2g += (int(Pv_loss*(n[Parking_nodes.index(node)] *
availability))) * t_disp

    DC_loss[j] = (loss[j] - loss_v2g[j]) * Price[j]
    F = np.sum(w[4]*DC_loss)
    return np.sum(F),(np.sum(w[4]*DC_loss))
```

Particle swarm optimization

```
from itertools import combinations
import numpy as np
import random
import time

class solution:
    def __init__(self):
        self.best = 0
        self.bestIndividual = []
        self.convergence = []
        self.optimizer = ""
        self.objfname = ""
        self.startTime = 0
        self.endTime = 0
        self.executionTime = 0
        self.lb = 0
        self.ub = 0
        self.dim = 0
        self.popnum = 0
        self.maxiers = 0

def PSO(objf, weighting_factors, grid, lb, ub, dim, PopSize, iters):

    # PSO parameters

    Vmax = 4
    wMax = 0.9
    wMin = 0.2
    c1 = 2
    c2 = 2

    s = solution()
    if not isinstance(lb, list):
        lb = [lb] * dim
    if not isinstance(ub, list):
        ub = [ub] * dim

    ######################## Initializations

    vel = np.zeros((PopSize, dim))

    pBestScore = np.zeros(PopSize)
    pBestScore.fill(-float("inf"))
```

```
    pBest = np.zeros((PopSize, dim))
    gBest = np.zeros(dim)

    gBestScore = -float("inf")

    pos = np.zeros((PopSize, dim))
    for i in range(dim):
        np.random.seed(0)  # Set seed to 0 for reproducibility
        pos[:, i] = np.random.uniform(0, 1, PopSize) * (ub[i] - lb[i]) +
lb[i]

    convergence_curve = np.zeros(iters)

    ############################################
    print('PSO is optimizing  "' + objf.__name__ + '"')

    timerStart = time.time()
    s.startTime = time.strftime("%Y-%m-%d-%H-%M-%S")

    for l in range(0, iters):
        for i in range(0, PopSize):
            # pos[i,:]=checkBounds(pos[i,:],lb,ub)
            for j in range(dim):
                pos[i, j] = np.clip(pos[i, j], lb[j], ub[j])
            # Calculate objective function for each particle
            # n, w, grid, availability=1.0
            fitness, DC_loss = objf(pos[i, :], w=weighting_factors,
grid=grid, availability=availability)
            if pBestScore[i] < fitness:
                pBestScore[i] = fitness
                pBest[i, :] = pos[i, :].copy()

            if gBestScore < fitness:
                gBestScore = fitness
                s.best = gBestScore
                s.bestIndividual = pos[i, :].copy()
                gBest = pos[i, :].copy()

        # Update the W of PSO
        w = wMax - l * ((wMax - wMin) / iters)

        for i in range(0, PopSize):
            for j in range(0, dim):
                r1 = np.random.random()
```

```
                r2 = np.random.random()
                vel[i, j] = (
                    w * vel[i, j]
                    + c1 * r1 * (pBest[i, j] - pos[i, j])
                    + c2 * r2 * (gBest[j] - pos[i, j])
                )

                if vel[i, j] > Vmax:
                    vel[i, j] = Vmax

                if vel[i, j] < -Vmax:
                    vel[i, j] = -Vmax

                pos[i, j] = pos[i, j] + vel[i, j]

        convergence_curve[l] = gBestScore

        if l % 1 == 0:
            fitness, DC_loss = objf(gBest, w=weighting_factors, grid=grid,
availability=availability)
            print(["iteration: " + str(l)+ ", best PC: "+
                   str(gBest)+ ", Fitness: "+ str(gBestScore)], "data->",
DC_loss)
    timerEnd = time.time()
    s.endTime = time.strftime("%Y-%m-%d-%H-%M-%S")
    s.executionTime = timerEnd - timerStart
    s.convergence = convergence_curve
    s.optimizer = "PSO"
    s.objfname = objf.__name__
    return s

s = PSO(
    objFunc,
    weighting_factors=[0.2, 0.2, 0.2, 0.2, 0.2],

    grid=grid9,
    lb=0,
    ub=1000,
    dim=2,
    PopSize=5,
    iters=275)
s.bestIndividual = np.round(s.bestIndividual).astype(int)
print("Best Position:", s.bestIndividual)
print("Best Value:", s.best)
```

Calculate revenue

```
def objFunc(n, w, grid, availability=1.0):
    """
    n: Number of vehicles in each parking_node
    w: weighting factors
    grid: input grid
    """


    Nv2g = len(n)

    # calculate r -> revenue
    P_park = 0
    for i in range (Nstations):
        P_park += Pv * int(n[i])   * availability
        r = Pr_p * P_park * t_disp

    # calculate CF_cap
    CF_cap = Cac * n

    # calculating CF_pu_driving
    P_parkch = 0
    CF_pu_driving=0
    for i in range(Nstations):
        for d in range(3):
            P_parkch = int(n_vehic_soc[d]*n[i]) * Pv * SOC[d]
            td = (1 - SOC[d])* ES / Pv
            CF_pu_driving += Pr_off / mu_conv * P_parkch * td

    # calulating CF_pu_v2g
    P_park = 0
    for i in range (Nstations):
        P_park += Pv * int(n[i])   * availability
        Pr_pe = Pr_off / mu_conv + Cd
        CF_pu_v2g = P_park * Pr_pe * t_disp
        #print(CF_pu_v2g)

    print("r:",np.sum(r), ",CFcap:",np.sum(CF_cap), ",CF_pu_driving:",
np.sum(CF_pu_driving),  ",CF_pu_v2g:",np.sum(CF_pu_v2g))
    # print(np.sum(r)-np.sum(CF_cap)-CF_pu_driving-np.sum(CF_pu_v2g))
    F1 =(w[0]*r - (w[1]*CF_cap + w[2]*CF_pu_driving + w[3]*CF_pu_v2g))

    F = F1
    return np.sum(F), np.sum(F1)
```

```
objFunc(np.array([249, 302]), w=[0.2, 0.2, 0.2, 0.2, 0.2], grid=grid9,
availability=availability)
```

Check voltage drop with EV

```
n_parking_node6 = 249
n_parking_node8 = 302
P_node6_v2g = n_parking_node6 * Pv
P_node8_v2g = n_parking_node8 * Pv
def objFunc(n, w=[0.2, 0.2, 0.2, 0.2, 0.2], grid=grid9, availability=1.0):
    """
    n: Number of vehicles in each parking_node
    w: weighting factors
    grid: input grid
    """


    Nv2g = len(n)
    # load flow:

    # Initialize Z values
    Z2 = Z3 = Z4 = Z5 = Z6 = Z7 = Z8 = Z9 = 0

    # Initialize lists for voltage profiles and modified nodes
    voltage_profiles = []
    voltage_profiles_v2g = []
    Active_power = []
    modified_nodes = []
    I_values = []
    Z_values = []
    P_value = []
    Rb_value=[]
    current_values = {}
    impedance_values = {}
    power_values = {}
    V_values = {}
    real_Rb_values = {}

    for j in range(num_load_levels):
        if j == 2:
           for b in grid.keys():
               node = int(b.split("-")[-1])
               Rb, Xb, L = grid[b]["R"], grid[b]["X"], grid[b]["L"]
               Z = math.sqrt(((Rb)**2+ +( Xb)**2 ))
               P = grid[b][f"Load{j+1}"] * 1000  # KW
               I_j = P / V_line
               #print(I_j)
               if node in [2, 3, 4, 5, 6, 7, 8, 9]:
```

```
                globals()[f"Z{node}"] = Z
                globals()[f"I{node}"] = I_j
                globals()[f"P{node}"] = P
                globals()[f"Rb{node}"] = Rb
                modified_nodes.append(node)
                I_values.append(I_j)
                Z_values.append(Z)
                P_value.append(P)
                Rb_value.append(Rb)

    # Sort I and Z based on the number of nodes
    sorted_data = sorted(zip(modified_nodes, I_values, Z_values, P_value,
Rb_value), key=lambda x: x[0])
    sorted_nodes, sorted_I_values, sorted_Z_values, sorted_P_values,
sorted_Rb_value = zip(*sorted_data)

    # Print the sorted data
    for node, I_value, Z_value, P_value, Rb_value in zip(sorted_nodes,
sorted_I_values, sorted_Z_values, sorted_P_values, sorted_Rb_value):

        # Store values in dictionaries
        current_values[node] = I_value
        impedance_values[node] = Z_value
        power_values[node] = P_value
        real_Rb_values[node] = Rb_value

    # Load flow analysis for selected nodes
    convergence_threshold=0.00001
    convergence= False
    K = 1
    if node in [3, 7, 2, 6, 5, 9, 4, 8]:
       globals()[f"V{3}_K0"] = V_line * 1000
       globals()[f"V{7}_K0"] = V_line * 1000
       globals()[f"V{2}_K0"] = V_line * 1000
       globals()[f"V{6}_K0"] = V_line * 1000
       globals()[f"V{5}_K0"] = V_line * 1000
       globals()[f"V{9}_K0"] = V_line * 1000
       globals()[f"V{4}_K0"] = V_line * 1000
       globals()[f"V{8}_K0"] = V_line * 1000

       while True:
            I_3_7 = I_7 = power_values[7] * 1000 / globals()[f"V{7}_K{K -
1}"]
            I_3 = power_values[3] * 1000 / globals()[f"V{3}_K{K - 1}"]
            I_1_3 = I_3 + I_3_7
```

```
            V_3_K = V_line * 1000 - impedance_values[3] * I_1_3
            V_3_PU_K = V_3_K / globals()[f"V{node}_K0"]
            E_3_K = np.abs((np.abs(V_3_K) - np.abs(globals()[f"V{3}_K{K - 1}"])) / np.abs(V_line*1000))

            V_7_K = V_3_K -  impedance_values[7] * I_7
            V_7_PU_K = V_7_K / globals()[f"V{node}_K0"]
            E_7_K=  np.abs((np.abs(V_7_K) - np.abs(globals()[f"V{7}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{3}_K{K}"] = V_3_K
            globals()[f"V{7}_K{K}"] = V_7_K
            emax_3_7 = max(E_3_K , E_7_K)

            I_2_6 = I_6 = power_values[6] * 1000 / globals()[f"V{6}_K{K - 1}"]
            I_2 = power_values[2] * 1000 / globals()[f"V{2}_K{K - 1}"]
            I_1_2 = I_2 + I_2_6

            V_2_K = V_line * 1000 - impedance_values[2] * I_1_2
            V_2_PU_K = V_2_K / globals()[f"V{node}_K0"]
            E_2_K = np.abs((np.abs(V_2_K) - np.abs(globals()[f"V{2}_K{K - 1}"])) / np.abs(V_line*1000))

            V_6_K = V_2_K -  impedance_values[6] * I_6
            V_6_PU_K = V_6_K / globals()[f"V{node}_K0"]
            E_6_K=  np.abs((np.abs(V_6_K) - np.abs(globals()[f"V{6}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{2}_K{K}"] = V_2_K
            globals()[f"V{6}_K{K}"] = V_6_K
            emax_2_6 = max(E_2_K, E_6_K)

            I_5_9 = I_9 = power_values[9] * 1000 / globals()[f"V{9}_K{K - 1}"]
            I_5 = power_values[5] * 1000 / globals()[f"V{5}_K{K - 1}"]
            I_1_5 = I_5 + I_5_9

            V_5_K = V_line * 1000 - impedance_values[5] * I_1_5
            V_5_PU_K = V_5_K / globals()[f"V{node}_K0"]
            E_5_K = np.abs((np.abs(V_5_K) - np.abs(globals()[f"V{5}_K{K - 1}"])) / np.abs(V_line*1000))

            V_9_K = V_5_K -  impedance_values[9] * I_9
```

```
            V_9_PU_K = V_9_K / globals()[f"V{node}_K0"]
            E_9_K=  np.abs((np.abs(V_9_K) - np.abs(globals()[f"V{9}_K{K -
1}"])) / np.abs(V_line*1000))

            globals()[f"V{5}_K{K}"] = V_5_K
            globals()[f"V{9}_K{K}"] = V_9_K
            emax_5_9 = max(E_5_K, E_9_K)

            I_4_8 = I_8 = power_values[8] * 1000 / globals()[f"V{8}_K{K -
1}"]
            I_4 = power_values[4] * 1000 / globals()[f"V{4}_K{K - 1}"]
            I_1_4 = I_4 + I_4_8

            V_4_K = V_line * 1000 - impedance_values[4] * I_1_4
            V_4_PU_K = V_4_K / globals()[f"V{node}_K0"]
            E_4_K = np.abs((np.abs(V_4_K) - np.abs(globals()[f"V{4}_K{K -
1}"])) / np.abs(V_line*1000))

            V_8_K = V_4_K -  impedance_values[8] * I_8
            V_8_PU_K = V_8_K / globals()[f"V{node}_K0"]
            E_8_K=  np.abs((np.abs(V_8_K) - np.abs(globals()[f"V{8}_K{K -
1}"])) / np.abs(V_line*1000))

            globals()[f"V{4}_K{K}"] = V_4_K
            globals()[f"V{8}_K{K}"] = V_8_K
            emax_4_8 = max(E_4_K, E_8_K)

            emax = max(E_2_K, E_3_K, E_4_K, E_5_K, E_6_K, E_7_K, E_8_K,
E_9_K)

            # Check convergence
            if emax <= convergence_thereshold :
                 convergence = True
                 print("Converged at iteration:", K)
                 break
            else:
                 K += 1

            voltage_profiles.extend([V_2_PU_K, V_3_PU_K, V_4_PU_K,
V_5_PU_K, V_6_PU_K, V_7_PU_K, V_8_PU_K, V_9_PU_K])
            voltage_profiles_first_iteration = voltage_profiles[:8]
            #print(voltage_profiles_first_iteration)

# Load flow analysis for selected nodes with V2g:
    convergence_thereshold=0.00001
```

```
    convergence= False
    K = 1
    if node in [3, 7, 2, 6, 5, 9, 4, 8]:
       globals()[f"V{3}_K0"] = V_line * 1000
       globals()[f"V{7}_K0"] = V_line * 1000
       globals()[f"V{2}_K0"] = V_line * 1000
       globals()[f"V{6}_K0"] = V_line * 1000
       globals()[f"V{5}_K0"] = V_line * 1000
       globals()[f"V{9}_K0"] = V_line * 1000
       globals()[f"V{4}_K0"] = V_line * 1000
       globals()[f"V{8}_K0"] = V_line * 1000

       while True:
            I_3_7 = I_7 = power_values[7] * 1000 / globals()[f"V{7}_K{K -
1}"]
            I_3 = power_values[3] * 1000 / globals()[f"V{3}_K{K - 1}"]
            I_1_3 = I_3 + I_3_7

            V_3_K_v2g = V_line * 1000 - impedance_values[3] * I_1_3
            V_3_PU_K_v2g = V_3_K_v2g / globals()[f"V{node}_K0"]
            E_3_K_v2g = np.abs((np.abs(V_3_K_v2g) -
np.abs(globals()[f"V{3}_K{K - 1}"])) / np.abs(V_line*1000))

            V_7_K_v2g = V_3_K_v2g -  impedance_values[7] * I_7
            V_7_PU_K_v2g = V_7_K_v2g / globals()[f"V{node}_K0"]
            E_7_K_v2g =  np.abs((np.abs(V_7_K_v2g) -
np.abs(globals()[f"V{7}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{3}_K{K}"] = V_3_K_v2g
            globals()[f"V{7}_K{K}"] = V_7_K_v2g
            emax_3_7_v2g = max(E_3_K_v2g , E_7_K_v2g)


            I_2_6_v2g = I_6_v2g = (power_values[6] - P_node6_v2g) * 1000 /
globals()[f"V{6}_K{K - 1}"]
            I_2_v2g = power_values[2] * 1000 / globals()[f"V{2}_K{K - 1}"]
            I_1_2_v2g = I_2_v2g + I_2_6_v2g

            V_2_K_v2g = V_line * 1000 - impedance_values[2] * I_1_2_v2g
            V_2_PU_K_v2g = V_2_K_v2g / globals()[f"V{node}_K0"]
            E_2_K_v2g = np.abs((np.abs(V_2_K_v2g) -
np.abs(globals()[f"V{2}_K{K - 1}"])) / np.abs(V_line*1000))

            V_6_K_v2g = V_2_K_v2g -  impedance_values[6] * I_6_v2g
            V_6_PU_K_v2g = V_6_K_v2g / globals()[f"V{node}_K0"]
```

```
            E_6_K_v2g =  np.abs((np.abs(V_6_K_v2g) -
np.abs(globals()[f"V{6}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{2}_K{K}"] = V_2_K_v2g
            globals()[f"V{6}_K{K}"] = V_6_K_v2g
            emax_2_6 = max(E_2_K_v2g, E_6_K_v2g)


            I_5_9_v2g = I_9_v2g = power_values[9] * 1000 /
globals()[f"V{9}_K{K - 1}"]
            I_5_v2g = power_values[5] * 1000 / globals()[f"V{5}_K{K - 1}"]
            I_1_5_v2g = I_5_v2g + I_5_9_v2g

            V_5_K_v2g = V_line * 1000 - impedance_values[5] * I_1_5_v2g
            V_5_PU_K_v2g = V_5_K_v2g / globals()[f"V{node}_K0"]
            E_5_K_v2g = np.abs((np.abs(V_5_K_v2g) -
np.abs(globals()[f"V{5}_K{K - 1}"])) / np.abs(V_line*1000))

            V_9_K_v2g = V_5_K_v2g -  impedance_values[9] * I_9_v2g
            V_9_PU_K_v2g = V_9_K_v2g / globals()[f"V{node}_K0"]
            E_9_K_v2g =  np.abs((np.abs(V_9_K_v2g) -
np.abs(globals()[f"V{9}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{5}_K{K}"] = V_5_K_v2g
            globals()[f"V{9}_K{K}"] = V_9_K_v2g
            emax_5_9 = max(E_5_K_v2g, E_9_K_v2g)

            I_4_8_v2g = I_8_v2g = (power_values[8]-P_node8_v2g) *1000 /
globals()[f"V{4}_K{K - 1}"]
            I_4_v2g = power_values[4] * 1000 / globals()[f"V{4}_K{K - 1}"]
            I_1_4_v2g = I_4_v2g + I_4_8_v2g

            V_4_K_v2g = V_line * 1000 - impedance_values[4] * I_1_4_v2g
            V_4_PU_K_v2g = V_4_K_v2g / globals()[f"V{node}_K0"]
            E_4_K_v2g = np.abs((np.abs(V_4_K_v2g) -
np.abs(globals()[f"V{4}_K{K - 1}"])) / np.abs(V_line*1000))

            V_8_K_v2g = V_4_K_v2g -  impedance_values[8] * I_8_v2g
            V_8_PU_K_v2g = V_8_K_v2g / globals()[f"V{node}_K0"]
            E_8_K_v2g =  np.abs((np.abs(V_8_K_v2g) -
np.abs(globals()[f"V{8}_K{K - 1}"])) / np.abs(V_line*1000))

            globals()[f"V{4}_K{K}"] = V_4_K_v2g
            globals()[f"V{8}_K{K}"] = V_8_K_v2g
            emax_4_8 = max(E_4_K_v2g, E_8_K_v2g)
```

```
            emax = max(E_2_K_v2g, E_3_K_v2g, E_4_K_v2g, E_5_K_v2g,
E_6_K_v2g, E_7_K_v2g, E_8_K_v2g, E_9_K_v2g)

            # Check convergence
            if emax <= convergence_thereshold :
                 convergence = True
                 print("Converged at iteration:", K)
                 break
            else:
                 K += 1

            voltage_profiles_v2g.extend([V_2_PU_K_v2g, V_3_PU_K_v2g,
V_4_PU_K_v2g, V_5_PU_K_v2g, V_6_PU_K_v2g, V_7_PU_K_v2g, V_8_PU_K_v2g,
V_9_PU_K_v2g])
            voltage_profiles_v2g_first_iteration =
voltage_profiles_v2g[:8]
            print(voltage_profiles_v2g_first_iteration)



    # Assuming nodes are keys in the grid dictionary
    x_axis_nodes = sorted(list(modified_nodes))

    # Zip the node numbers and voltage profiles
    zipped_data = list(zip(x_axis_nodes,
voltage_profiles_first_iteration))
    zipped_data_v2g = list(zip(x_axis_nodes,
voltage_profiles_v2g_first_iteration))

    # Sort the zipped data by node number
    sorted_data = sorted(zipped_data, key=lambda x: x[0])
    sorted_data_v2g = sorted(zipped_data_v2g, key=lambda x: x[0])

    # Extract sorted node numbers and voltage profiles
    sorted_nodes, sorted_voltage_profiles_first_iteration =
zip(*sorted_data)
    sorted_nodes, sorted_voltage_profiles_v2g = zip(*sorted_data_v2g)

    # Plotting the voltage profiles for each node
    plt.plot(sorted_nodes, sorted_voltage_profiles_first_iteration,
marker='o', label='Node Voltages')
    plt.plot(sorted_nodes, voltage_profiles_v2g_first_iteration,
marker='x', label='V2G Voltages')  # Assuming sorted_voltage_profiles_v2g
contains V2G data
```

```
    plt.xlabel('Node')
    plt.ylabel('Voltage (PU)')
    plt.title('Voltage Profile for Each Node')
    plt.xticks(rotation=45)
    plt.grid(True)
    plt.show()
```