OPTIMAL CENTRALIZED AND DECENTRALIZED MANAGEMENT STRATEGIES FOR ELECTRIC VEHICLES CONSIDERING CUSTOMER DEMAND, ROAD AND ELECTRIC GRID INFRASTRUCTURE

by

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ABSTRACT

ALI IHSAN AYGUN. Optimal centralized and decentralized management strategies for electric vehicles considering customer demand, road and electric grid infrastructure. (Under the direction of DR. SUKUMAR KAMALASADAN)

In this dissertation, several methodologies for optimal management of electric vehicle (EV) fleets connected to the power grid are discussed. First, a hybrid methodology is suggested for determining the quickest way for a vehicle to reach the charging station, taking into account both the distance and the current traffic conditions developed based on graph theory. The strategy is accurate, more efficient, and scalable. Second, a technique that considers the shortest distance to the charging station considering the impact and optimal use of the electric grid is developed. The method takes advantage of distance and simultaneously considers the influence on the grid, such as variations in voltage or power. The procedure is tested and quantitative and qualitative analysis is conducted. Also, with the help of a convex optimization methodology, a speed optimization framework is developed that mitigates range anxiety. Next, an optimization methodology is developed that addresses real-time electric car charging congestion as well as centralized and decentralized charging scheduling of electric vehicles. The charging of plug-in electric vehicles (PEVs) has to be handled through the use of "smart" charging processes to lessen the demand that PEVs have on the electrical grid. These studies examine the impact that the actual implementation of four distinct smart charging architectures has on the electric grid, including a centralized and decentralized design. The capabilities of each method are summarized. Further, a methodology for demand-side management and distributed load management is developed, considering customer comfort with the help of an electric vehicle fleet. A new mathematical model of household loads such as air conditioners, water heaters, clothes dryers, and dishwashers considering the weather conditions is developed. It was identified that during high temperatures, the system's operational architecture may derive a significant advantage from these massive demand-responsive loads. Further, a robust energy optimization framework is

proposed that suggests healthy results to keep the grid stable and sustained after optimizing household loads avoiding customer comfort violation. The proposed methodologies are scalable, field implementable, and can collectively managing electric vehicle fleets, and energy usage considering road and grid conditions.

DEDICATION

When I start finding out people in my memory who have supported me to be at the point where I am today, I always get to these people due to their endless love and continuing support.

This thesis is proudly dedicated:

To my father and mother who have sacrificed their life and future to unconditionally support me. It's impossible to thank them adequately for everything they have done for me.

To my lovely wife, Yasemin, without her unconditional love and always support, I wouldn't be where I am today.

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LIST OF SYMBOLS

Δc The amount of energy required to raise the temperature of the air in a room by 1 °F

Δt Time slot length of i

$A_{ceiling}$ Ceiling surface area

A_{tank} Tank surface area

A_{wall} Wall surface area

A_{window} Window surface area

A_{ws} South window surface area

fr_i Flow rate of hot water in time slot i

G_i House heat gain rate during time slot i

H_p One person's heat gain

H_{solar} Radiation power of solar

n_p Total number of persons

P_{AC} AC unit power consumption

P_{WH} CD unit power consumption

P_{WH} WH unit power consumption

$R_{ceiling}$ Ceiling heat resistance

R_{tank} The tank's heat resistance

R_{wall} The ceiling's heat resistance

R_{window} The window's heat resistance

$SHGC$ Windows' solar heat gain coefficient

T_{inlet} Temperature of the inlet water

T_i Temperature in the room during time slot i

T_{out_i} Temperature outdoors during interval i

T_{outlet_i} The tank's outlet water temperature

V_{house} The house's volume

V_{tank} The tank's volume

AC Air Conditioner

ADMM Alternating direction method of multipliers

CD Clothes Dryer

DW Dish Washer

PEV Plug in Electric Vehicle

WH Water Heater

CHAPTER 1: INTRODUCTION

Electric vehicles existed in the early 18th century, even before conventional cars were invented. Vehicles were used and developed until the late of 19th century. The electric car, which was popular at the turn of the 20th century, is currently declining in sales. This situation has arisen for several different factors. In the 1920s, when the nation's road network was finally getting some upgrades, longer-range vehicles were needed. The widespread availability of inexpensive gasoline following the worldwide discovery of massive petroleum reserves reduced the cost of long-distance travel in gas-powered vehicles.

When we come today since 1970, CO_2 emissions have increased by about 90% by 2019, according to EPA [13]. The United States-dominated North American continent accounts for 18% of global emissions, making it the second-highest contributing area. Europe comes in a close second with 17% [14]. The consumption of gasoline accounts for 27% of the pollutants contributing to global warming in the United States. [15]. Some viable alternatives to fossil fuels have been proposed, and extensive research is underway to see if these can be used in place of fossil fuels in various human activities and industrial processes. Greenhouse gas pollution leading to global warming is one of the economic, ecological, and political goals driving this replacement. The transportation industry is one area of human existence negatively impacted by this problem. [16–18]. Nowadays, much research has been contacted on the impact on electric vehicles. To address rising environmental concerns and energy shortages, renewable generating and electric mobility are rising as two of the most viable approaches. [19, 20].

On the other side, the widespread adoption of electric vehicles (EVs) is accompanied by many challenges, such as energy, transportation, and industry. The creation of charging platforms and infrastructure for electric vehicles is required for EV charging to occur, regardless of whether it is done at home or at a public charging station. In addition, the large percentage of EVs in the distribution network is the root cause of the significant capital expenditure required for smart grid technology. Because charging an electric vehicle's battery takes a significant time, the process of charging an electric vehicle requires a comparatively significant quantity of power. On the other hand, the simultaneous or uncoordinated charging of clusters of electric vehicles (EVs) significantly raises the amount of electricity consumed. This results in an unexpected peak on the system and leads to the overloading of the distribution network, which in turn leads to a decrease in voltage quality, an increase in power loss, and the dispatch of energy sources that are not cost-effective. There are two potential solutions available to handle the rising charging demand for electric vehicles (EVs) without compromising the network's operational efficiency, and each of these systems has its own operating domain. In the first place, it is expanding and adequately regulating the system's generation capacity in order to satisfy the peak demand that is brought on by the simultaneous charging of electric cars. This strategy entails significant financial outlay and calls for the installation of up-to-date grid infrastructure. Second, the Demand Side Manage Action (DSCA), which is the alternative approach to control the charging demand of electric vehicles, is hidden in the demand response program. This is a major flaw in the design of the demand response program. It is a term that refers to the actions that are performed by utilities and consumers alike in conjunction with dynamic pricing in order to impact the amount of power that is consumed to achieve optimal billing. The research on electric vehicles' charge scheduling has been the subject of various studies. The word "optimization" refers to a method that may be used to find the most effective answer to any given computing challenge. Most optimization problems involve minimizing or optimizing the value of a function known as the objective function within a practical set defined by limits placed on the variable. This strategy might be utilized to develop a charging schedule for electric vehicles (EVs) that minimizes the expenses associated with charging, maximizes the utilization of renewable energy sources for charging EVs, lowers the volatility in load, and so on. In general, one of the most often used strategies for deploying energy management systems (EMS) is utilizing various optimization techniques. The vast majority of strategies for mathematical optimization guarantee optimal answers for the given difficulty level. To perform an optimization strategy in EMS, which incorporates intelligent charging of electric vehicles, only a few elements need to be anticipated in advance. Just a few aspects can be known in advance and integrated into the conceptualization of the issue, such as day-ahead electricity pricing. The creation of PV and the use of electricity are inherently risky enterprises. The timing of both the arrival and departure of vehicles is not apparent. However, there are a few other ways that might be taken in order to predict such unknown factors. Some smart charging systems that were described in published works made use of models for making forecasts and variable predictions as part of the process of synthesizing an optimization issue. Both probabilistic and deterministic approaches were utilized for the forecast.

1.1 Dissertation Objectives, Main Motivations and Contributions

If the risks associated with EVs are mitigated, the benefits to society will outweigh them. However, a few problems are preventing EVs from gaining mainstream popularity. The critical issues of restricted driving range, low battery performance, and lengthy charging times remain unresolved. [21–23]. It seems that while making charging reservation selections, consumers will think about both journey time and charging cost [24]. Therefore, a system that prioritizes short paths is warranted. In order to eliminate these obstacles, route optimization plays a crucial role until the reach of desirable usage comfort. The driver of an EV may worry about running out of full battery before reaching charging station. It is called range anxiety. Increasing the all-electric range through advanced battery technology or establishing suitable EV infrastructures would help reduce range anxiety. As can be seen, an extensive, long-period data set that contains real-world car journeys and parking activities is plainly necessary to generate better and more trustworthy and realistic results in transportation studies such as fuel economy/battery life, vehicle emissions, and travel behavior and demand.

On the other hand, an increasing number of EVs used will have an extra burden on the grid system. The grid's highest demand point only lasts a few hours. In order to provide the peak demand, expensive power plants are required. When faced with increased power demand, increasing generation capacity was the traditional response; however, this approach severely affects the grid's ability to function. Therefore, providers face this difficulty and respond by charging customers more. Thus, before the usage of electric vehicle reaches peak point, the infrastructure of the system should be considered and completed to solve all these concerns, especially charging demand optimization.

We believe that intelligent buildings outfitted with energy storage systems will significantly impact the power grid's overall energy usage if effective and affordable energy management solutions are developed for them. Energy policymakers might use this information to create better incentives for smart building inclusion into the next-generation smart grid. Throughout our study plan, we have examined a range of issue statements concerning the efficient and cost-effective energy management in smart buildings with the help of electric vehicles. These issue statements are addressed by the techniques provided in this study, both under typical conditions and in the face of uncertainties associated with energy production and consumption. The constructed environment is vulnerable to power outages due to a wide range of weather conditions, which in turn poses risks to customers' daily lives, well-being, and financial stability. We can predict the possible impact of weather condition change on customers' electrical supply lifeline and show how viable activities might mitigate the negative impact. By coordinating electric vehicles in the designated distribution network, the effects of power interruptions and fluctuations due to unexpected conditions may be mitigated. Multiple utility applications, including Demand Side Management (DSM) and Outage Management.

The concept of the "smart home" or "home automation" is also becoming increasingly popular among household products. That is to say, and there are more options for regulating specific loads. The idea of "soft load" was first mentioned. When one load need may be moved from one time period to another, we say it is "soft" (e.g., washing machine and dryer). Although the load demand of PEVs also comes into this category and may be thought of as a type of soft load, PEV loads may be unavailable if the PEVs' owners are out of the house. At the same time, there are always accessible, adaptable loads at home to be charged. Therefore, in this thesis, only soft loads that may be rescheduled are considered.

1.1.1 Main Contribution of the Dissertation

- For EV fleets, a hybrid routing algorithm that minimizes energy consumption is developed and evaluated. The program acts as a consolidator, calculating the most efficient path between two points that use charging stations along the way.

- Hybrid algorithm can deal with negative edges or cycles in a graph.

- Create an algorithm for centralized and decentralized smart charging that is utilized on a fleet of plug-in electric vehicles for optimizing the charging schedule.

- Develop and simulate smart charging scenarios such as cost minimization, valley filling, and vehicle-to-grid application within a microgrid.

- Develop an algorithm to provide auxiliary services in case of interruption in utility and with the help of smart devices household energy management approach is developed.

1.2 Dissertation outline

The dissertation outline is as follows:

Chapter 2 of this thesis contains a literature review, where existing routing optimization methods, centralized and decentralized technologies, and architectures are explored.

Chapter 3 explains the background of graph theory to solve the shortest path problem and to understand the basic terms of a graph. Identify shortest path problems and explain the general concept of Dijkstra and Floyd-Warshall algorithm with an example. To evaluate each algorithm and present the hybrid algorithm with case results. Also, we developed a convex optimization to obtain the best speed range to reach the destination considering the remaining battery capacity.

The primary focus of Chapter 4 is on using a centralized charging algorithm, with the goals of addressing charging schedules for electric vehicles as well as real-time congestion caused by electric vehicle chargers. An explanation is given on the model of the system that is utilized for the simulation. After that, we discuss case studies and the outcomes of simulations and provide information regarding control techniques.

In Chapter 5 explain the background of decentralized charging optimization to solve problems and understand the basic terms of convex optimization and ADMM (Alternating Direction Method of Multipliers). Optimization methods utilize different approaches to keep the power grid balanced and stable.

In Chapter 6, we propose a load dispatch algorithm based on convex optimization with the help of EV fleets. This approach uses a methodology to calculate a residential area's demand and allow electric vehicles to meet total demand as a supplier. Then, with the help of real-time pricing (RTP), demand spikes are shifted or mitigated by considering customers' comfort. This section contains the system model for simulation purposes, provides information on the control algorithm and concludes the case studies and the simulation results.

In Chapter 7 conclusion and future works are presented.

CHAPTER 2: ELECTRIC VEHICLE-GRID INTEGRATION AND OPTIMIZATION TECHNIQUES :LITERATURE REVIEW

Market interest in electric vehicles has been on the rise again due to the optimism that these vehicles can alleviate these problems. If electric vehicles are widely used, it will be possible to reduce or eliminate emissions of greenhouse gases and so improve air quality. The causes mentioned above for a surge in EV interest were essential in this development. In their Low PHEV scenario, EPRI projects that plug-in hybrid electric vehicles (PHEVs) will make up no more than 20% of the new vehicle market in 2050, while in their Medium PHEV scenario, they will make up 62%, and in their High PHEV scenario, they will make up 80%. [1]. In Fig. 2.1 [1], the prediction of BEV and PHEV's sales share and market share from 2010 to 2050 are compared.

According to JP Morgan's research [2], electric vehicles are the wave of the future, and several car companies are making plans to switch to electric vehicles exclusively by 2025. There will be significant shifts in materials, gasoline prices, and automakers in the coming decade. As part of their efforts to tackle climate change, European Council members 'three' voted unanimously to mandate the widespread use of electric vehicles by the year 2050. As a result, BEV sales in Germany, the UK, France, Spain, and Italy increased. Fig 2.2 demonstrate the vehicle share of European countries in the first half of 2020. By the end of 2020, the share of electric cars in these five nations will have grown from 63 percent to 77 percent across the European Union.

However, plug-in hybrids are not gaining much traction in North America or Europe. Thus hybrids and BEVs are expected to dominate over the next decade. Plug-in electric vehicles (BEVs and PHEVs) will increase in popularity in Europe, where their percentage of new vehicle sales is expected to climb from about 2% in 2017 to over 9% in 2025, nearly

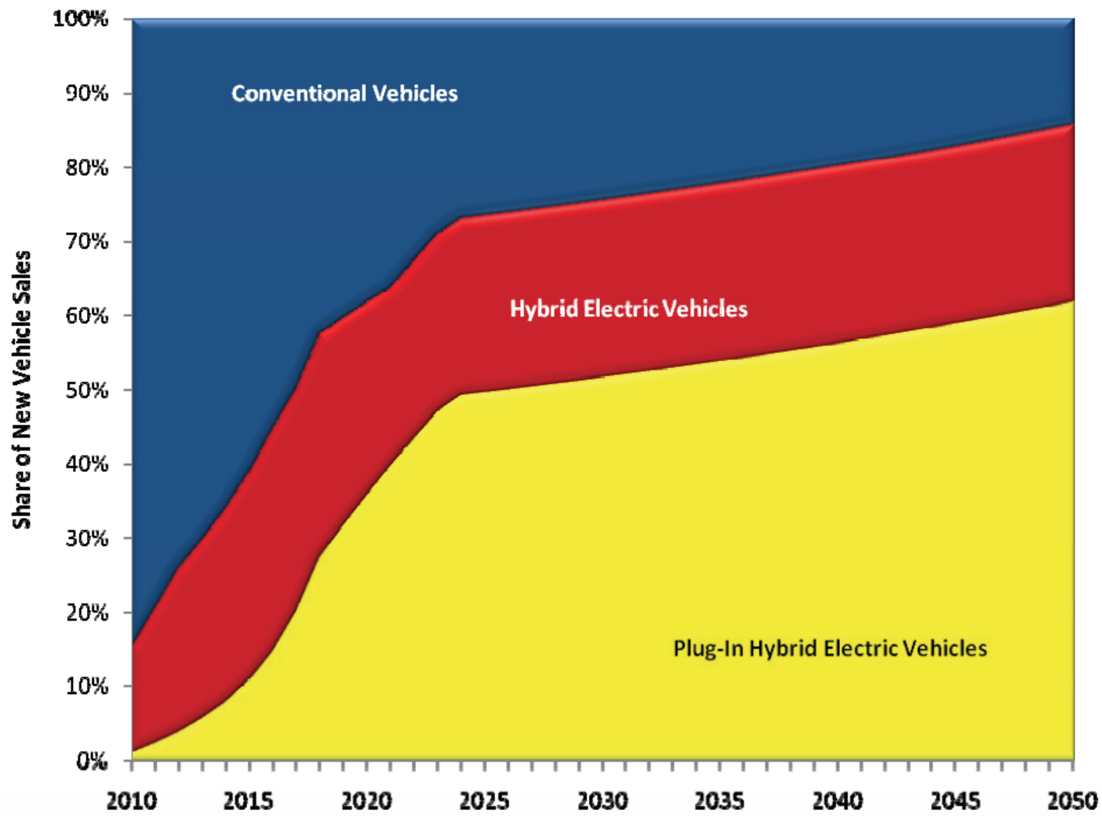


Fig. 2.1: Share of new vehicle sales [1].

exceeding 1.5 million cars by the middle of the next decade. There will be a rapid shift away from ICE-only cars, and by 2025, it is projected that only plug-in electric vehicles and HEVs will be offered. J.P. Morgan predicts that sales of plug-in electric cars in Japan and Korea will reach 384,000 vehicles, representing a 6% market share. In comparison, sales of HEVs would hit 1.8 million vehicles, or 27% of total sales, over that period. Meanwhile, in the United States, stricter fuel efficiency rules will undoubtedly encourage manufacturers to extend their EV choices, but maybe not with the same degree of urgency as in Europe, where carbon dioxide emissions limits and fines are looming. However, it is predicted that by 2025, EV sales (including BEVs, PHEVs, and hybrids) will account for more than 38% of the market [25]. Projected global electric vehicle penetration is demonstrated in Fig. 2.3.

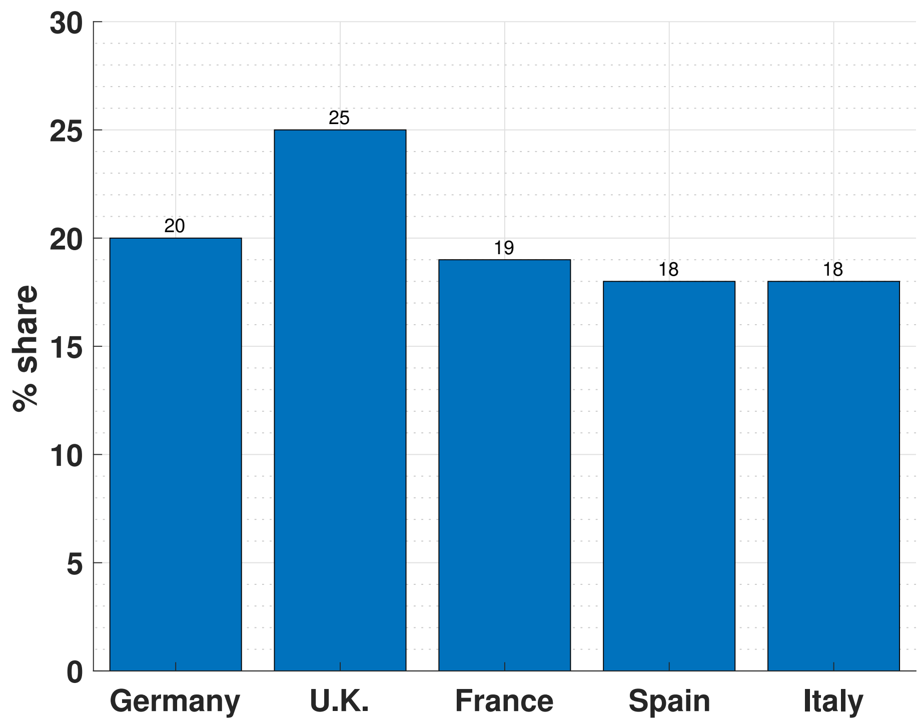


Fig. 2.2: Share of new vehicle sales in Europe [2]

2.1 Renewable energy penetration

This yearly growth in global energy consumption may be attributed to rising global industrialization and rising home electricity usage. To meet the demands of a growing global populace, industrialization has been speeding up everywhere, particularly in emerging nations. Increasing household energy consumption yearly is the second contributor to total energy demand growth. Especially in industrialized countries, the quantity and variety of energy-hungry home equipment such as refrigerators, entertainment, cooking, and cleaning machines is steadily rising. There has been a rise in both the prevalence of these devices and the duration of their usage. In light of the lifestyle shift brought on by the recent COVID-19 epidemic, this is more true than ever. However, the globe now faces a significant dilemma as a result of the ever-increasing need for energy. The amount of carbon dioxide (CO_2) released into the atmosphere each year by factories and power plants is also rising (Fig. 2.4).

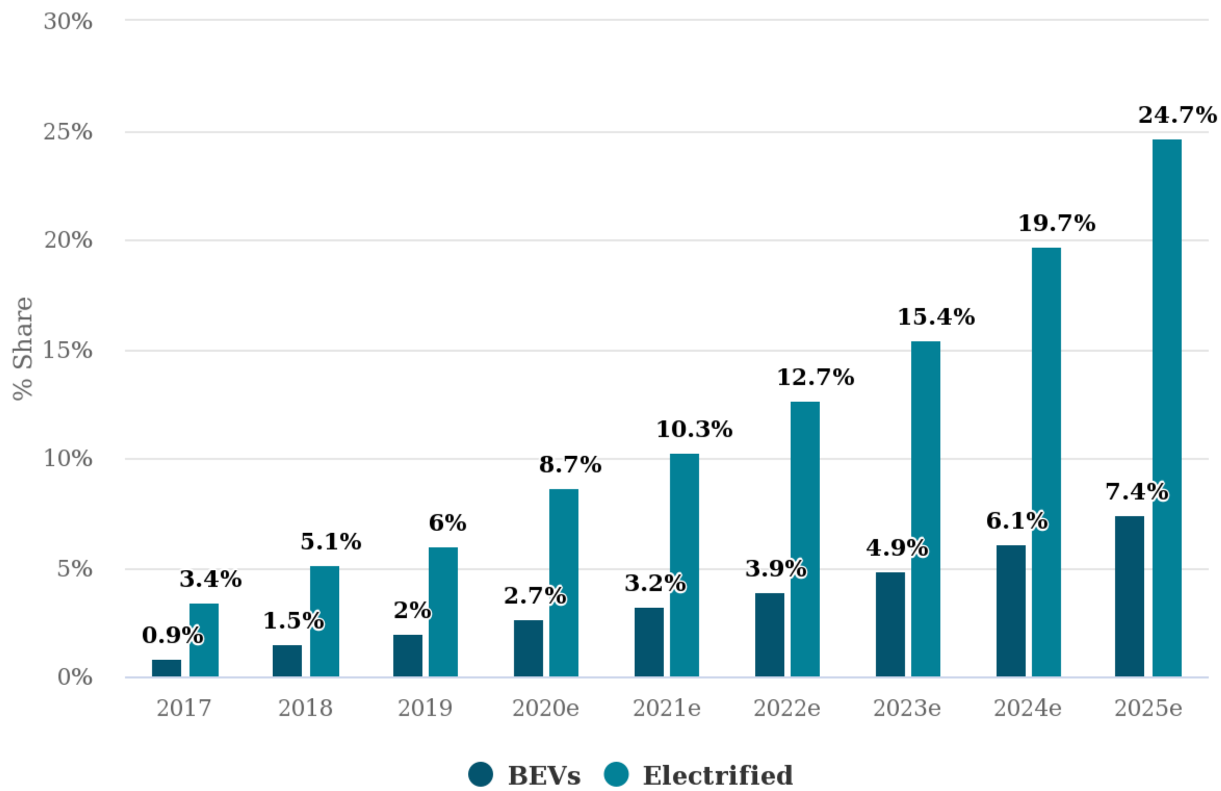


Fig. 2.3: Projected share of electric vehicle. [2]

It destroys the ozone layer, which shields Earth from dangerous UV rays. Depleting the ozone layer, along with a rise in the concentration of carbon dioxide (CO_2) and other greenhouse gases like methane and nitrous oxide, leads to an increase in the average temperature of the Earth's atmosphere, a process known as global warming. Extreme weather occurrences, iceberg melting, and rising sea levels are just some ways this phenomenon alters our weather. Polar and marine ecosystems are vulnerable to these shifts. There have been various efforts to reduce CO2 and other greenhouse gas emissions to lessen the impact of these gases on the environment. Nowadays, many types of research have been contacted about the impacted of electric vehicles. First one is integration with renewable energy. The use of renewable energy sources and electric transportation are two of the most promising approaches to address rising environmental concerns and a lack of available energy sources. [19, 20]. Fig. 2.5 showing effect of EV penetration on CO_2 emission.

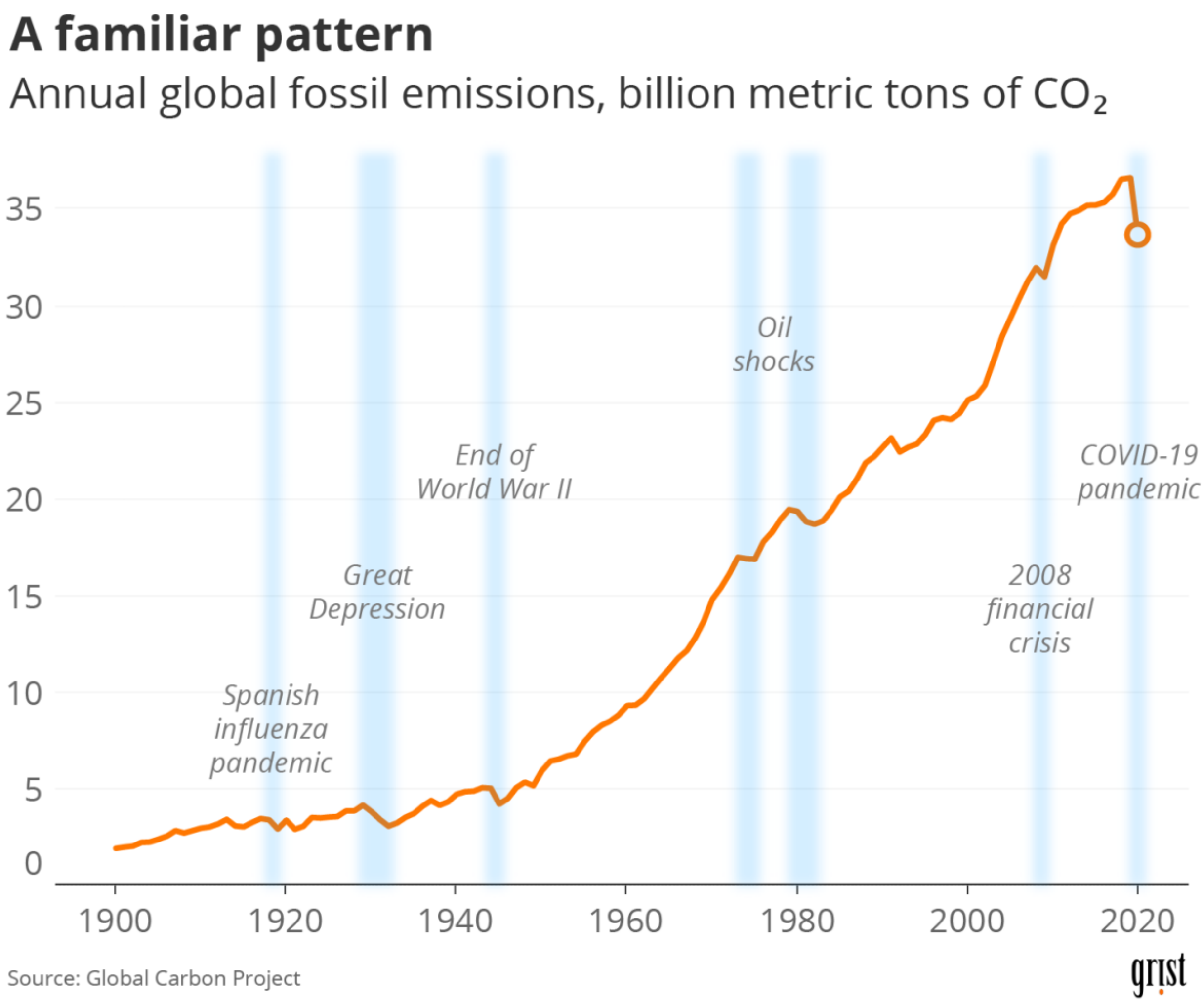


Fig. 2.4: The global amount of carbon dioxide (CO2) released yearly [3].

According to International Energy Agency, a switch to low-carbon sources is approaching, the agency said in its annual report for 2016, which was issued on November 13 [26]. If nations stick to their current and declared plans, the percentage of renewable energy might nearly double, from 26% now to 44% in 2040, and it would overtake coal as early as 2026. The combined share of solar PV and wind power in an overall generation might increase from 7% to 24% (Fig. 2.6). The PV and wind generation have attracted attention. [27] reveals that evaluated many scenarios with specified percentages of renewable power output in 2050, ranging from 30% to 90%, with an emphasis on 80% [with roughly 50% from variable wind and solar photovoltaic (PV) generation].

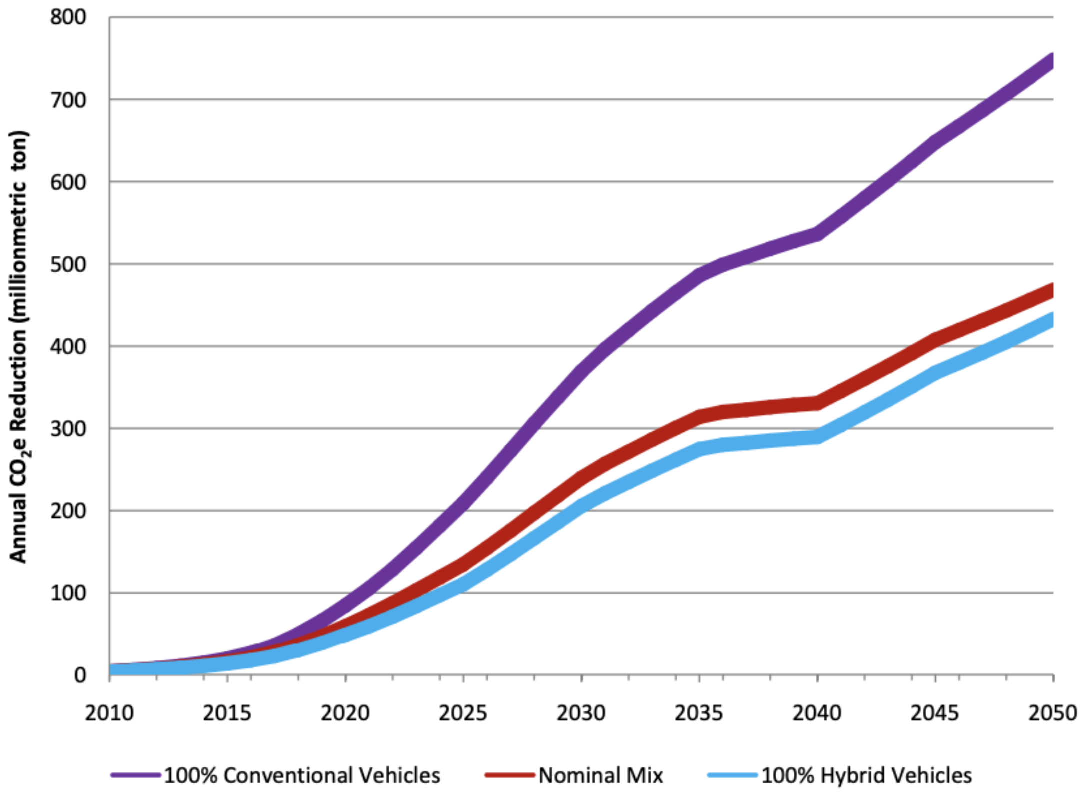


Fig. 2.5: CO_2 emission based on types of cars. [1].

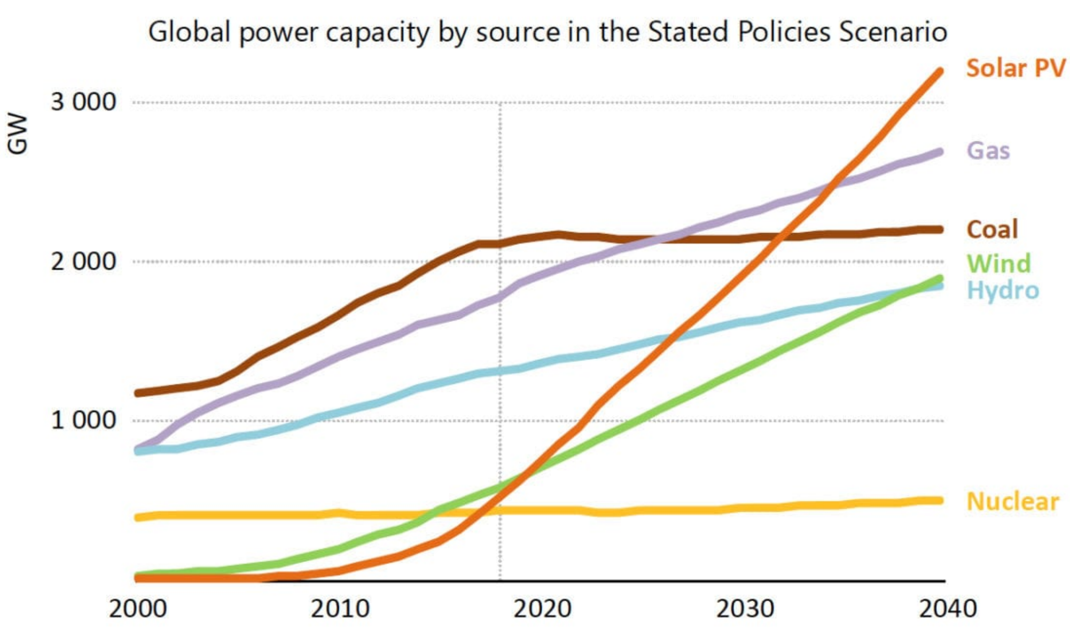


Fig. 2.6: Global power capacity by source. [4].

Government incentives like investment tax credits and lower tax rates have been implemented in various countries in the wake of the 2015 Paris climate accord to increase the use of clean and renewable energy sources, including photovoltaics (PV), wind, geothermal, and hydropower. Especially PV panels, which can generate electricity from sunshine, may be mounted on the top of apartments or significant commercial buildings built green. PV generation, however, has a variable output that shifts from peak sunny hours to gloomy days. Battery Energy Storage Systems (BESS) [28] are necessary because the load demand needs a constant energy supply regardless of the weather. Given this, a future power system with increased penetrations of both technologies, such as renewable energy and EVs, may benefit from beneficial synergies. [29–31]. In light of recent advancements, EVs are seen as significant resources for smart grid because of their ability to operate as flexible mobile energy storage. Two-way communication and energy transfer between electric vehicles (EVs) and the grid are made possible by vehicle-to-grid (V2G) technology. [32, 33].

2.2 Energy Markets

Quick charging stations, public and private parking lots, and residential garage charging stations will all play a part in the future distribution power system that facilitates energy exchange with electric vehicles [34]. Customers can take part in the functioning of the electrical grid. Since this is the case, a new market structure is required to facilitate transactions between buyers and sellers. There is competition between running a fleet and making a profit in the energy trade. Vehicles would be great for transporting things and storing energy if only both functions were possible at the same time. However, those two aims may become incompatible when a fleet's schedule and operational demands are set against utilizing cars for energy transactions.

In addition, various parties, including energy providers, electric vehicle original equipment manufacturers, charging equipment manufacturers, government agencies, and fleet managers, will need to work together for V2G to be implemented. Both the hardware and the utilities must be able to accommodate the technology. The new market model should provide several advantages, based on reliable operation and communication and handle increasing number of electric vehicles. As a result, many energy pricing models are already in use. Utilities in the United States, and particularly in California, have adopted TOU prices to encourage commercial customers to reduce their energy consumption during peak hours. However, some countries utilize even more adaptable pricing models. Spot pricing is a method for dealing with the intermittent nature of renewable energy sources by adjusting prices hourly. The cost of energy as a whole may be drastically altered by using dynamic pricing. Power supplied by V2G would help stabilize prices during times of high demand. This would stabilize prices and lessen daily price swings. From the consumer's perspective, the goal of marketing is to minimize costs. At the same time, the benefits to utilities include lower reliance on the power grid, fewer transmission losses, greater system efficiency, and a more stable supply and energy demand. [35–38] examined the impact of smart charging algorithms on the grid at the state level.

2.3 Grid Integration

Since the advent of EV technology, further research has been published on voltage loss and deviation. Research suggests either large or small effects, depending on the context. We might anticipate divergent findings due to contextual factors like system configuration and operational mode. Power system decision-makers will need to factor in the anticipated demand for charging stations as the number of EVs on the road continues to rise. [39]. Fig. 2.7 [5] demonstrates of possible issues of grid integration. Some of them are as follows. Electric vehicle battery sizes ranging from 16 kWh up to 100 kWh, which leads to overloaded and voltage fluctuations. In [33, 40, 41], suboptimal dispatch, voltage swings, and decreased system efficiency are only some of the issues that can arise from unregulated and random charging in a distributed power system. Also, there are studies about the power quality of the grid system after integrating electric vehicles.

Power delivered to the electric grid can be used as a proxy for the impact of V2G technology on the power system. Numerous issues, including overvoltage in the electric grid,

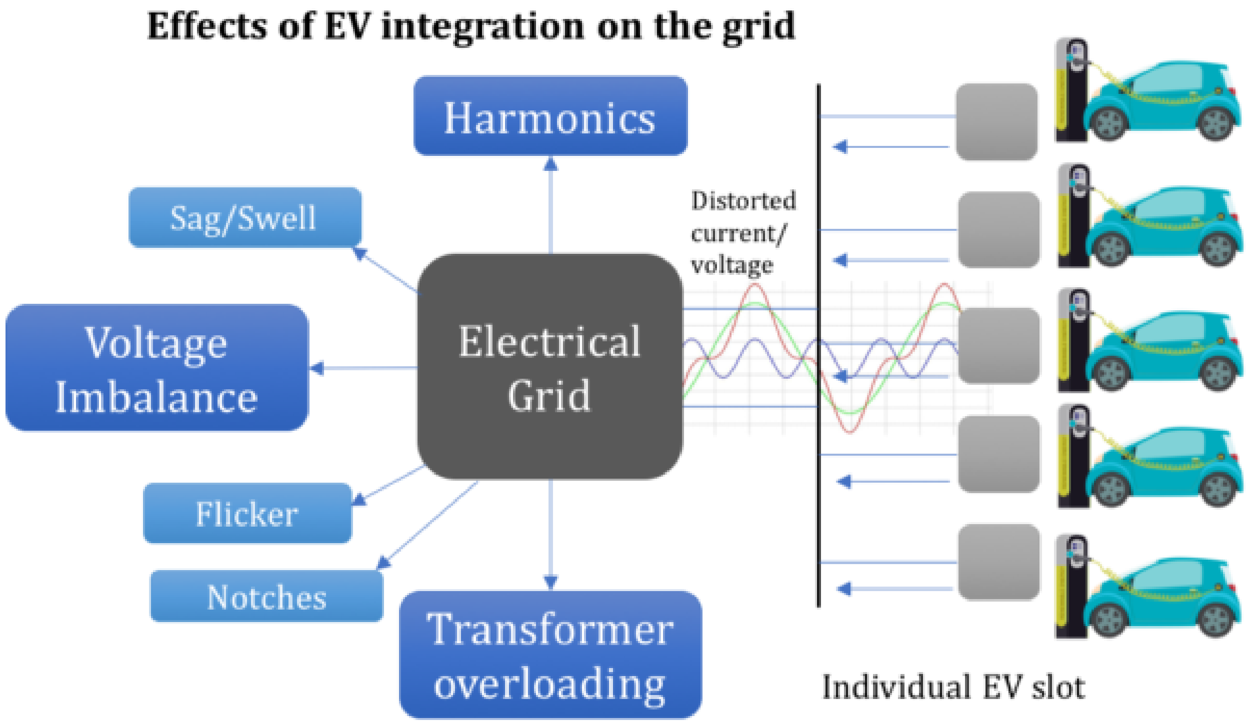


Fig. 2.7: Effects of EV integration on the power grid [5].

deterioration of power quality, accelerated damage of lines, failure of distribution transformers, more significant fault currents, etc., are brought on by the EVs' unpredictable charging habits. A switch from AC to DC power is used to charge the EVs. High-frequency converters are used to effect the conversion, however, they introduce unwanted harmonics into the electrical system. Overloading distribution transformers due to harmonics is a problem that will reduce the transformers' lifespan.

2.3.1 Stability

In this specific situation, voltage stability refers to the power grid's capacity to maintain a constant voltage at the buses once a disturbance has been removed. Sudden load increases are a significant cause of voltage fluctuations. The charging of electric vehicles will generate an abrupt increase in load, leading to voltage instability. According to the author of article [42], EV charging loads are detrimental to the reliability of distribution networks. The voltage fluctuations in the distribution system produced by EV charging loads were illustrated by the author in reference [43]. Additionally, they demonstrated a comparative analysis of the results obtained from various pricing structures (like uncoordinated and tariff based). The effects of EV load on nodal voltage fluctuations were studied by the author of reference [44]. Using the IEEE 30 test system, they found that EV usage directly affects the amount of voltage variation at each given node. The author of reference [45] demonstrated that a drop in distribution voltage occurs when a significant number of EV chargers are connected to the system. Overloading is another issue arising from the increasing number of connected EVs.

2.3.2 Harmonics

It is already well-established that chargers play an essential role in EV networks. Power electronics are an integral part of EV charging stations' construction. When an electric vehicle charging system is in use, the switching in its power electronics might create harmonics, which can have a detrimental effect on the power quality of the electric grid. [46, 47] shows that when electric vehicles connect to the grid system, chargers create harmonics. Every manufacturer produces a different type of charger. Especially first generation of chargers causes 3rd and fifth harmonics. Also, transformers efficiency, bench life, and temperature calculations according to a different loads case is another research topic [48–51]. From the previous literature on EV charging's effects on the electric grid, we may deduce that charging EVs in a single direction (from the grid to the batteries) can lead to severe problems for the electric grid and power system as a whole. V2G systems, which allow for bidirectional power flow, can help alleviate these issues and improve the electric grid's power quality with careful planning and implementation. Since the EV market is expected to grow, implementing vehicle-to-grid technology is essential for ensuring the continued reliability of the power grid in the years to come.

2.3.3 Frequency

The frequency of a power grid might diverge from its allowable value if there is an imbalance between generation and load demand. Since charging a large number of electric vehicles would significantly raise the grid's peak demand, more power will need to be generated to keep the grid's frequency within safe limits as the number of electric vehicles is expected to rise. Further, the load demand is expected to be subject to increasing unpredictability due to unknowns in the number of EV connections and the duration of connection and disconnection. If the utility cannot meet the total demand and collapses for a while, it also effects voltage frequency.

2.3.4 Voltage Sag

In this sense, a center of commerce electric vehicle charging station represents a significant power demand. The voltage drops when many EVs are plugged into the grid during times of high demand. It is possible for the terminals of electric vehicle charging stations to experience negative feedback from voltage sag induced by plug-in electric vehicles or transmission grid problems. These voltage dips might shorten the battery's lifespan in EVs and cause the charging station to function abnormally. In addition to the magnitude and nature of voltage dips, the charger's operational status also plays a role in the impact of voltage dips.

2.3.5 Under/Over Voltage

A rise in the number of EVs connected to the grid has resulted in a rise in power consumption from end users. As a result, it is the leading reason for low voltage during high demand for charging. Because of this, the distribution network needs to be modified to account for the number of EVs and their charging station locations. Serious undervoltage issues were avoided using preemptive random prediction. In contrast, wind and solar technologies are becoming increasingly competitive as new energy production methods get more refined. Problems with the grid's stability and voltage regulation might be triggered by electrical energy outside anyone's control. Suppressing variations in wind and solar energy, improving access to new energy generation, and compensating EV charging and new energy generation against one other are all possible through optimum regulation of EV charging and discharging.

2.3.6 Power Quality

Companies manage power quality requirements while manufacturing EVs to minimize disastrous repercussions on the grid. As noted in the literature, power electronics devices are causes of harmonics and other power quality concerns in the grid. Therefore, since EV chargers employ power electronics devices that feature switching semiconductor-based parts, harmonics are created while converting power is carried out. Harmful sequence components in the load currents are also created in EV charging stations, compromising the converter's performance. These hazardous sequence components cause a second-order harmonic ripple in the DC link voltage, which results in distortions in the grid's currents.

2.3.6.1 Imbalance

One of the most severe power quality issues is the imbalance generated by charging electric vehicles. While many public charging stations use three-phase electricity, many residences are only fitted for single-phase charging. Both the voltage and current amplitude and phase are off in this scenario. A negative sequence current/voltage is produced due to this event. A single-phase load imbalance in a power three-phase system can occur if the phase parameters are not synchronized across all three phases. Charging electric vehicles causes nonlinear electrical loads, which consume much power quickly and might cause distribution system imbalances.

2.4 Battery Technology

Fig. 2.8 [6] shows type of rechargeable batteries. Most of EV brands use Lithium-ion (Li-ion) batteries because of their high energy density [52, 53], but compared with internal combustion engine, Li-ion batteries still have shorter range. EVs can be divided into three groups; hybrid electric vehicle (HEV), plug-in electric vehicle (PEVs) [54] and battery electric vehicle (BEV) [54] according to the various available technologies.

- Hybrid Electric Vehicle (HEV)

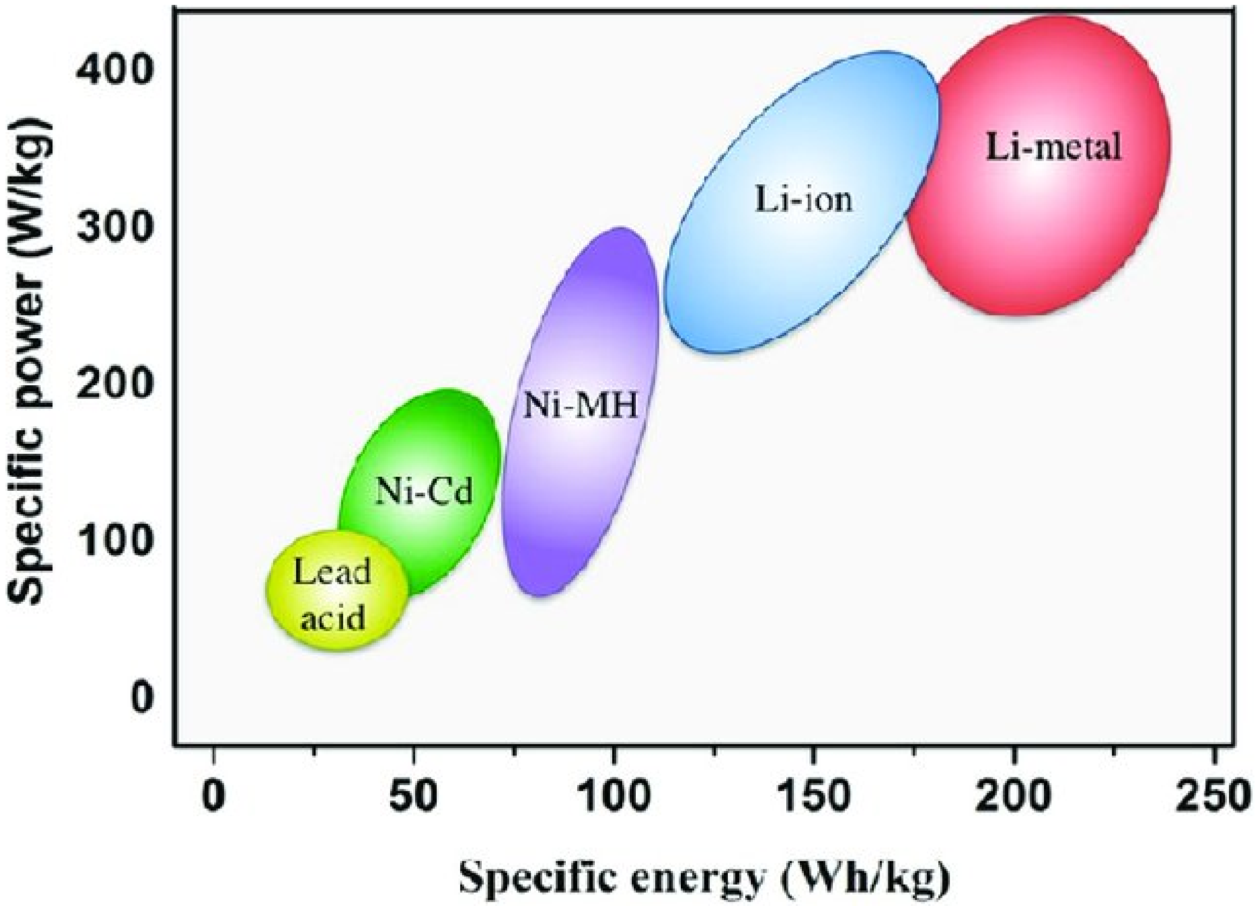


Fig. 2.8: Ragone chart [6].

The internal combustion engine (ICE) is the primary power source in hybrid electric cars. Electricity is stored in a battery and used to power the electric motor found in HEVs. By applying regenerative braking, the battery may be recharged. The battery pack in question cannot be connected to the power grid. The fuel efficiency and pollution levels of vehicles of this sort are improved.

- Plug-in Hybrid Electric Vehicle (PHEV)

The internal combustion engine (ICE) and electric motor of a plug-in hybrid electric vehicle operate in tandem to propel the vehicle. Connecting this car to a public power system will allow for the charging of its battery. They have a battery pack far bigger than hybrid electric cars, enabling them to go greater distances.

- Battery Electric Vehicle (BEV)

This type of cars have only electric battery. They charge by plugging into the power system. They are not depend on fossil fuel and they have zero emission technology.

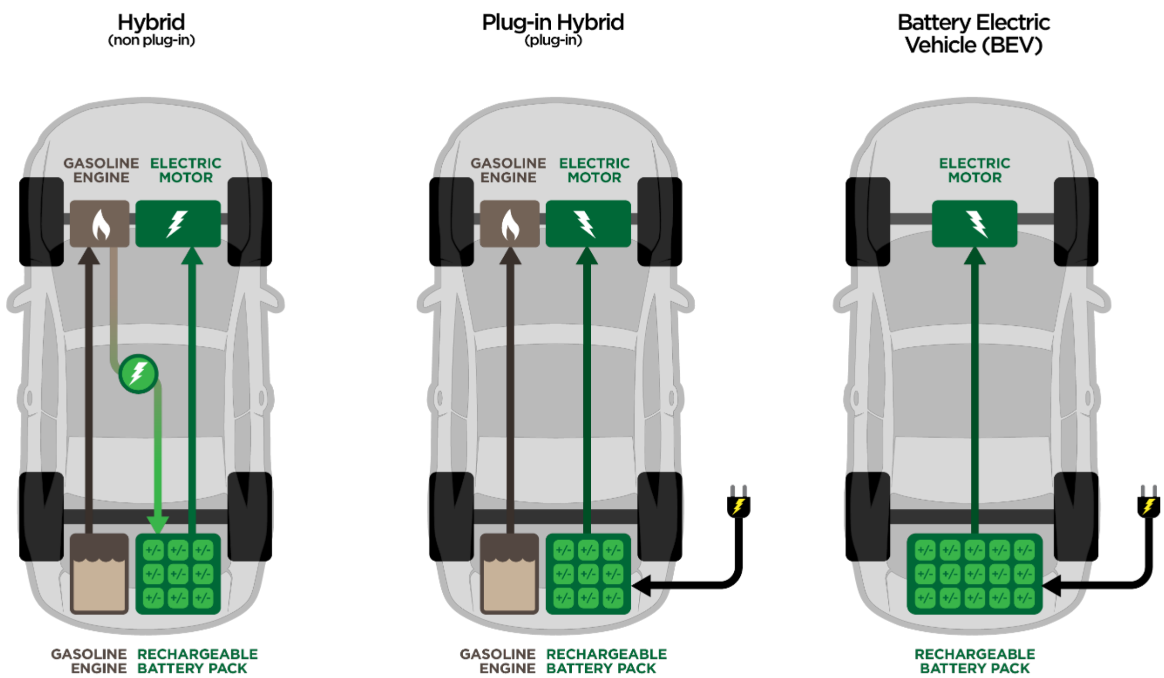


Fig. 2.9: Types of electric vehicles.

2.5 Charger Types

Gas stations are commonplace, but plug-in electric vehicles (PEVs) charging facilities are not. The requirement for PEV charging infrastructure, also known as electric vehicle supply equipment, is a key drawback of PEVs. Customers need to have easy access to outputs so that they may charge their PEVs. Three distinct charging tiers are available now: Standard Charging (slow charging), Fast Charging (fast charging-AC), and Level 3 Fast Charging, which is Direct current. There is a distinct charging rate for each tier of charging.

- AC Level Charging

Common types of PEV charging are AC level 1 and level 2 charging. All-night recharging with AC level 1 and 2 chargers is the norm for most BEV and PHEV owners. Standard 120-volt household outlets may be used with the AC level 1 charger with most PEVs. Most plug-in electric vehicle (PEV) owners can get by with just 4 or 5 miles per hour of charging, provided by AC level 1 charging. While convenient, AC level 1 charging is best suited for PHEVs and smaller battery-powered BEVs due to its slow charging pace. AC level 2 charging is commonly utilized by owners with higher battery capacities. However, it does necessitate the installation of extra equipment in the user's home. AC level 2 chargers, on the other hand, need to be connected to 240-volt outlets, which are commonly located on the walls of garages. Electric dryers and massive air conditioners also utilize these plugs. Compared to AC level 1 charging, the range and efficiency of AC level 2 charging is 10–20 miles per hour.

- DC Fast Charging

Among the three charging standards now on the market, DC level 3 charging is the most efficient. 50–70 miles of the range may be added in 20 minutes with DC level 3 charging. While AC slow and fast chargers do this in the vehicle, level 3 chargers do it in the electric vehicle supply equipment. There are now three main DC fast chargers available: the J1772 combo charger, the Charge de Move charger, and the Tesla supercharger [10]. However, installing level 3 chargers in homes would be prohibitively costly. Consequently, the vehicle manufacturers and the government are the primary parties with incentives to deploy level 3 charges.

2.6 EV Charging Station

This graph (Fig. 2.10), which dates back to 2011, illustrates the growth of electric vehicle (EV) charging infrastructure in the United States, both public and private. Over the past several years, there has been a steady increase in the number of EVSE ports and the number of charging stations for electric vehicles. Since 2014, researchers at the National Renewable Energy Laboratory have kept separate records for each of the two values. Between 2015 and

2020, it is anticipated that the number of charging stations will increase by more than four. In 2021, there was a more than 55 percent growth in the number of charging stations [7].

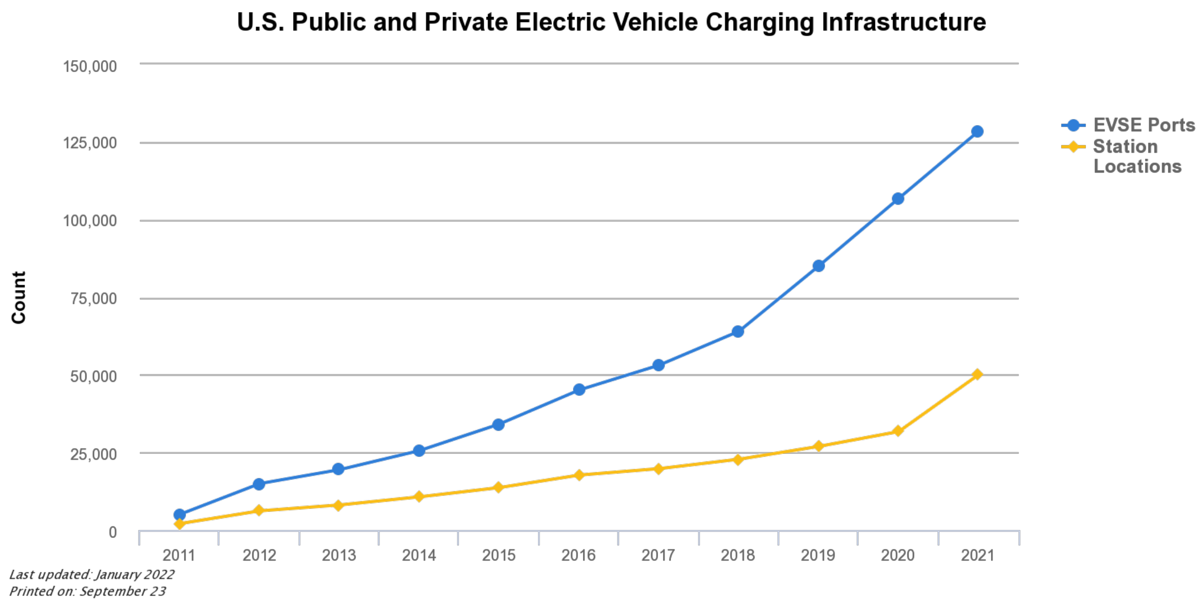


Fig. 2.10: Charging station number in the US [7].

Since 2015, when there were less than 32,000 outlets nationwide, the number of publicly available charging stations has quadrupled, according to statistics from the IEA. The organization predicts a massive increase in that number by the end of the decade, reaching anywhere from 800,000 to 1.7 million, depending on the policies in place. (President Joe Biden has proposed a national network of 500,000 charging stations as part of the country's infrastructure, and 62% of respondents to a poll conducted by the Pew Research Center expressed support for this idea.)

2.7 Electric Vehicle Range

When electric cars became commercially available to the public, vacationing by car was out of the question to vacation by car. Numerous significant barriers, such as the high price of electric vehicles, the shortage of charging stations around the country, and the sluggish charging times of batteries, have long impeded long-distance travel. Now that these hurdles have been cleared, driving long distances in an electric vehicle is a viable option and is almost

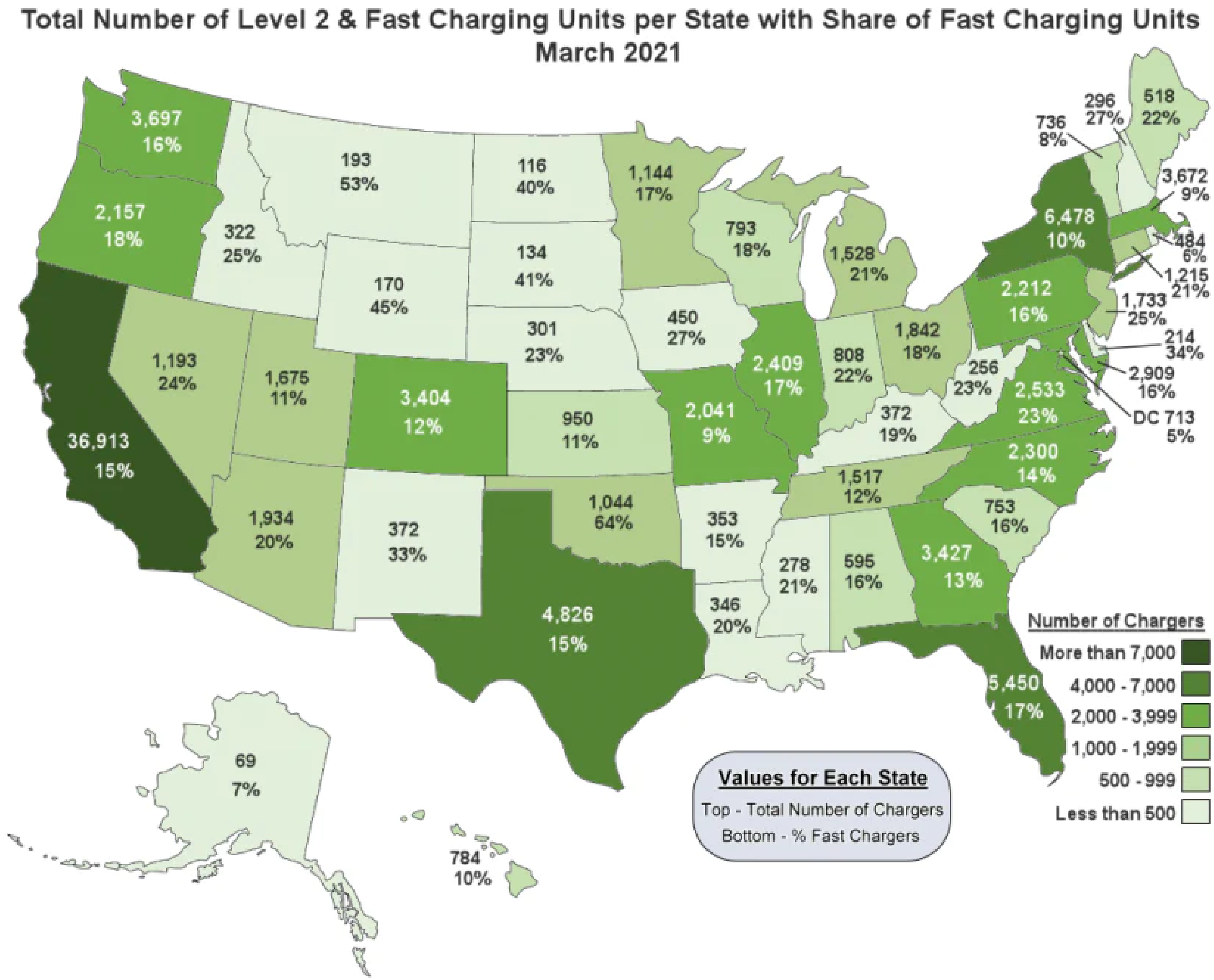


Fig. 2.11: Charging station share based on state in US [8].

as easy as operating a gas-powered car. Figure 2.12 illustrate the miles of different electric vehicles.

It is somewhat similar to the issue of "what MPG will I get?" for a gas-powered vehicle, which defies a simple response. The same factors have an effect, but sometimes more pronounced. It is conditional on variables like velocity, acceleration, wind speed and direction, temperature, altitude, terrain, load, tire condition, and others. Figure 2.13 shows how range is affected by speed. It can go up to 244 miles at top speed, while most users will see ranges closer to the middle of the colored area in the table below. The range may be quite extensive; Top Gear achieved 18 mpg when driving a 48 mpg-rated-Prius around a track, while

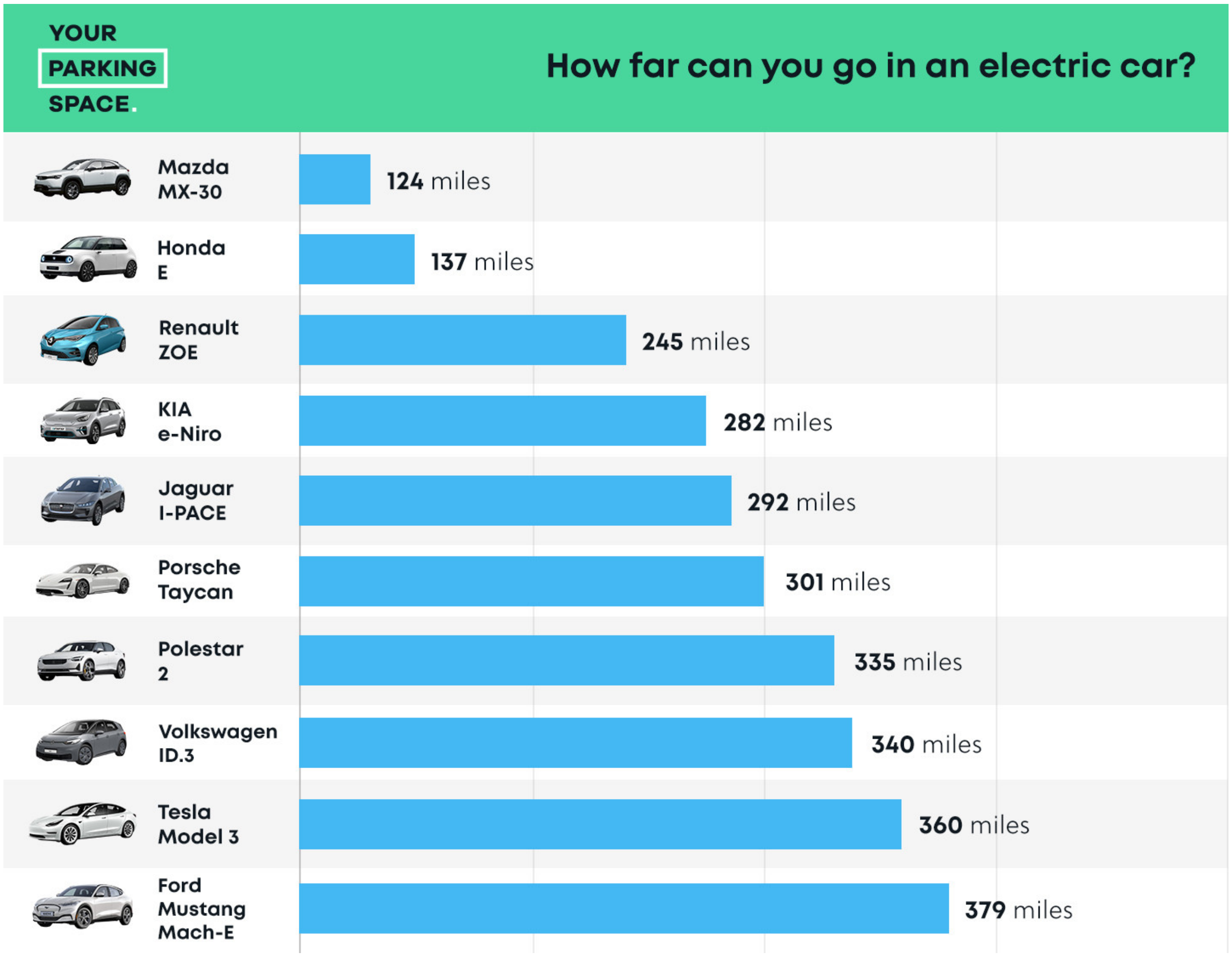


Fig. 2.12: Electric vehicle range of different types based on miles [9].

hypermilers have achieved 90 mpg.

2.8 Vehicle to grid services

With the advent of hybrid AC-DC power systems in the future, V2G will be more important than ever for PEV adoption. With V2G, PEVs may serve as both controlled loads and energy sources, calling them "distributed energy storage." Peak shaving, valley filling, power supply, and auxiliary services like voltage control, frequency regulation, etc., are just a few of the many possible applications for the energy stored in PEVs. As PEVs are often only driven less than five percent of the time, compensation for the remaining ninety-five percent of the day when they are plugged in for recharging provides a significant advantage and incentive for PEV owners to sign up for V2G services. PEVs may serve as a useful kind

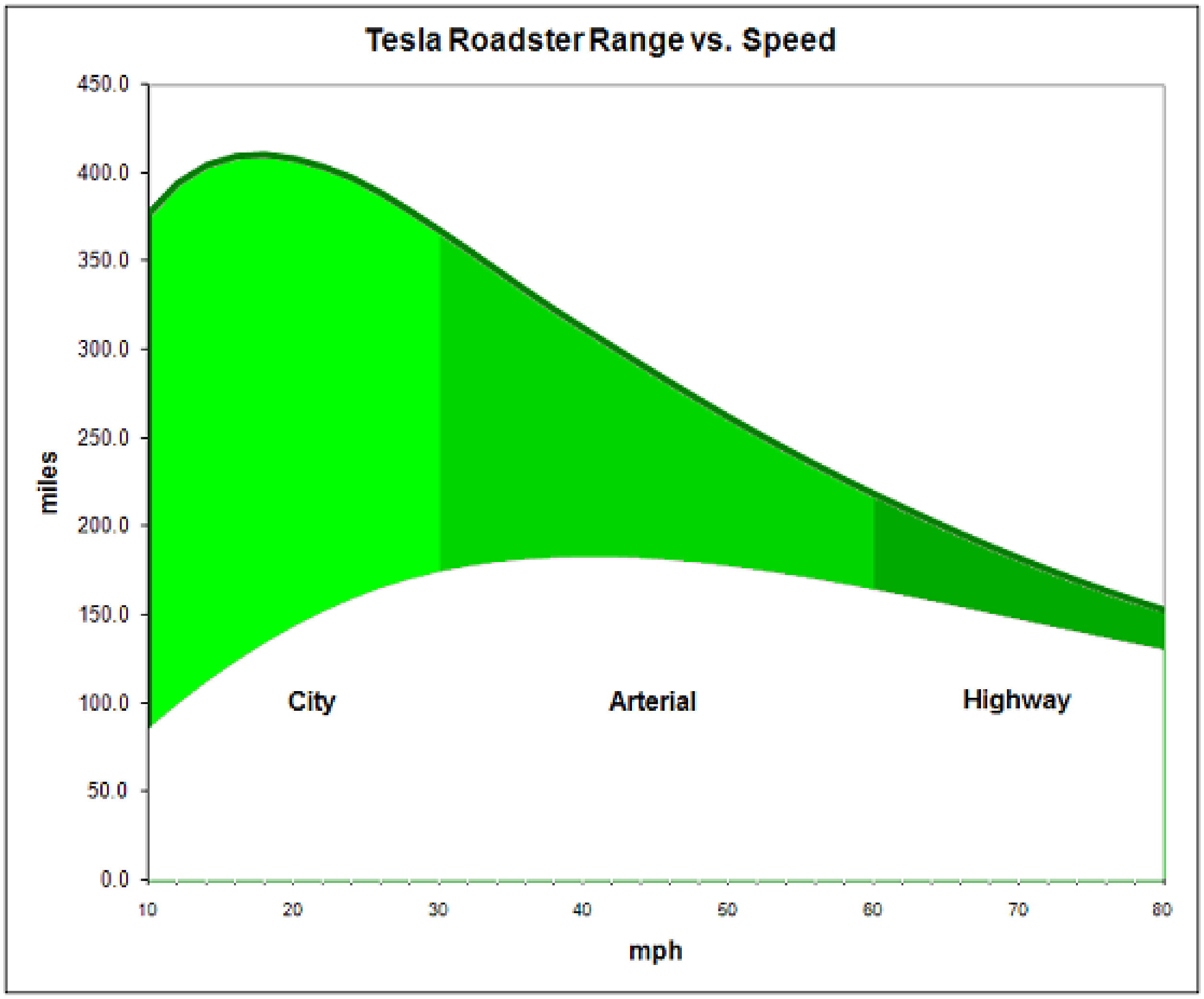


Fig. 2.13: Speed range comparision of Tesla vehicle [10].

of distributed energy storage in hybrid AC-DC power systems, which has several advantages. Public electric vehicles (PEVs) are a good example; they are often positioned close to both local loads and distributed sources of energy supply, making them easy to include into management systems for both. In this way, the hybrid AC-DC power system may independently manage energy without consulting other systems or far-flung loads and resources. Instead of relying on massive generating units in the utility, which will be significantly impacted by the PEVs charging, the PEVs and distributed generators are located close to the local load. They may be coordinated to achieve local objectives. PEV V2G services are also well-suited to the fact that some power and energy needs are best met on a regional rather than national scale. For instance, PEVs and their chargers can provide reactive power compensation at the neighborhood level, which is best given locally through voltage management through voltage amplitude regulation support. However, utility grid transmission and distribution losses can be as high as 7-10%, making independent power supply impractical for many uses. Transmission line congestion can be alleviated and energy consumption lowered by employing plug-in electric vehicles at off-peak hours. Thanks to all these considerations, utility networks may increase asset usage and postpone investments in new generating and transmission equipment.

2.9 Cost of Charge

There has been a gradual but steady increase in Americans purchasing electric vehicles in recent years. Although gas-powered vehicles still account for the vast majority of sales, electric vehicles are rapidly growing in popularity and already account for around 2% of the market. Technology adoption rates vary significantly from one state to the next, with California's rate of 8 percent being significantly higher than the national average.

The expense of an electric car, especially gas-powered vehicles, is a significant concern for many individuals considering making the switch. To determine the actual cost of becoming green in each state, we factored in various variables, including gasoline, electricity, mileage, insurance, EV incentives, taxes, registration fees, maintenance, emissions testing, and more.

The following figures (Fig. 2.14) demonstrate how the average cost to increase an electric or gas-powered vehicle's range by 100 miles across various markets has varied over time.

Electric vehicles, like the Tesla Model 3 in particular, have a yearly maintenance cost of \$190. The typical yearly cost of maintaining a gas-powered vehicle is \$964.60; this includes the cost of parts and labor for the most common vehicle in the United States, the Toyota Rav 4. For this calculation, yearly mileage of over 13,000 miles was used. A year's worth of servicing an electric car costs around \$321 less than that of a gas-powered vehicle.

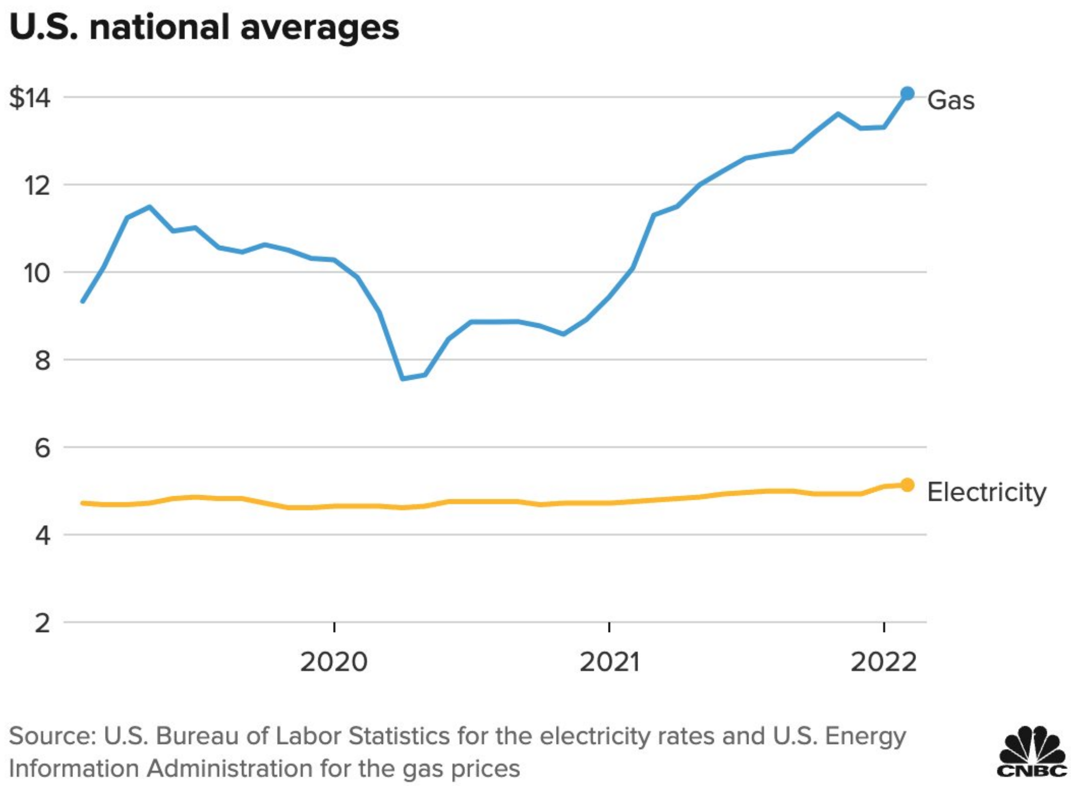


Fig. 2.14: Average cost to increase an electric or gas-powered vehicle's range by 100 miles [11].

2.10 Graph Theory

The fields of computer science and mathematics are the primary academic institutions that study graph theory, a graphical representation of a set of objects connected by connections. The issue of the Koinsber Bridge appeared for the first time in history in 1735, which is considered to be the beginning of the notion of graph theory [55]. The notion of the Eulerian graph was developed with the assistance of the difficulty posed by the Koinsber Bridge. After that, Euler did some research on the idea behind the Koinsber Bridge issue, and as a result, he came up with a novel structure that came to be known as the Eulerian Graph. After that, in 1840, A.F. Mobius introduced the notion of two graphs, namely the complete graph and the bipartite graph [56]. Kuratowski demonstrated that both of these graphs are planar in the domain of recreational issues by applying them to a few recreational problems and using them in conjunction with each other [57]. In 1845, Gustav

Kirchhoff proposed the notion of a tree structure that did not contain cycles [58]. The authors also explained how the G.T. ideas might be applied to calculate electrical circuits' current. Thomas Gutherie presented the four color problems in 1852; these problems are still utilized extensively in modern computer applications [59]. After then, in 1856, Thomas came up with the idea for the Hamiltonian graph. P. Kirkman and Hamiltonian, and this particular kind of graph has seen a lot of use in the research that has been done on it [60]. H. proposed the conundrum problem the following year, 1913. Dudeney, utilizing the earlier ideas presented in the G.T. [61]. [62] in the year 1878, James Joseph Sylvester was the first person to use the phrase "Graphs." He established a comparison between two different aspects of algebra, namely co-variants and quantic invariants, and explained how the two are similar. In 1941, while researching colorations, Ramsey came up with the idea that would later become known as the external graph theory. Up to that point, most scientists have incorporated G.T. notions into their bodies of work. In recent years, graphs have become increasingly prevalent in various fields, including modeling social networks (S.N.s), examining large amounts of data, natural language processing (NLP), complicated network analysis, and pattern recognition applications.

Graphs that reflect information networks, data organizers, computing systems, estimating movement, and other concepts are utilized in computer science. For instance, the connection structure of a website may be shown using a directed graph in which the vertices represent web pages, and the direct edges represent links leading from one page to another. It is possible to solve issues about social networks, transportation, genetics, device architecture, neurodegenerative condition development maps, and challenges in various other research fields by employing a standardized approach. Because of this, the development of graph algorithms is an essential topic of discussion in computer science. The shift to the new visual style has also been made public and can be seen in the updated graphic schemes. Graph mapping methods, which are used for the rule-based manipulation of graphs in memory, are complementary to graphic repositories because they both allow for the transaction-safe, continuous storing and querying of graph-structured data.

Graphic design is playing an increasingly important role in the field of computer science. Any future technology that has to be developed and any future system that needs to be tested may easily use graphs. The value is derived from the notion that information flow control and flow may be represented in directed graphs for every system. This is the foundation upon which the value is built. The theory of graphs is utilized in the production of microchips and circuits, as well as in the design of operating systems, information server systems, file storage systems, and software flow control networks. In computer science, the philosophy of graphs has given rise to developing its own set of mathematical graph algorithms. In the field of computer science, such algorithms are implemented in a wide variety of different kinds of projects. Graph theory is utilized to create circuit connections in the field of electrical engineering. Topologies are the names given to certain types of circuit connections. Series, bridge, star, and parallel topologies are all examples of different topologies.

2.11 Graph Theory Modeling

Using vertices and edges, the field of graph theory provides a mechanism for quantitatively constructing research aims. The formula for a graph G is $G = (V, E)$, where V and E are two variables

- A collection of vertices is denoted by the letter 'V'.
- A collection of edges, denoted by the letter 'E'.
- Every edge is split into two nodes.

Assuming G is a graph, the sets of vertices and edges in $V(G)$ and $E(G)$, respectively, make up the graph. If $i \in j$, then vertex i is incident with edge j. 'Adjacent' refers to a pair of vertices that are both incident with the same edge. The pair of vertices i and j in the graph G is represented as i, j, and the edge connecting them is denoted as $a_i j$.

$$\mathrm{a}_{ij} = \begin{cases} 1;\ (\text{when } i \text{ and } j \text{ connected}) \\ 0\ (\text{otherwise}) \end{cases} \tag{2.1}$$

The adjacent matrices to the graphs that are seen in Figure 2.15 are as follows:

- V = {1,2,3,4,5}
- E = {{1,2}, {2,3}, {3,1}, {3,4}, {4,2}, {4,5},{5,2}}
- G = (V, E)

$$\mathbf{Adjacentmatrix} = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \end{bmatrix}$$

Every vertex is associated with list that is collection of its neighbour vertex or links. This list is called adjacency list that stores all connections. Adjacency list of Fig. 2.16 is given Table 2.1.

Table 2.1: Adjacency list of edges

1	2	3		
2	3	4	5	
3	1	2	4	
4	2	3	5	
5	2	4		

2.11.1 Weighted Graph

In the case where G is a weighted graph, each edge has a certain numeric value. As a result, we may define the weighted matrix for G as Wij.

$$
\mathrm{W}_{ij} = \begin{cases} \text{"Weight of Edge," (when i and j are linked to one another.)} \\ \text{0 (i=j)} \\ \text{Infinite (There is no boundary between i and j.)} \end{cases} \tag{2.2}
$$

Most transportation networks may be represented as weighted graphs, where nodes represent charging stations or power bus stops and edges between them might represent streets or traffic flow.

2.11.2 Directed Graph

There are essentially two types of graphs. Directed graphs are those in which each edge points in a certain direction (Fig. 2.15). These are one-way connections, or edges. If the tips of the edges $i \in E$ in the undirected graph $G = (E; V)$ are sorted in a certain order, then the resulting graph is a directed graph. A pair of vertices from each edge is converted into an arc (tail and head). It is written that $a_{xy} = (i, j)$, where i is the exit and j is the entrance.

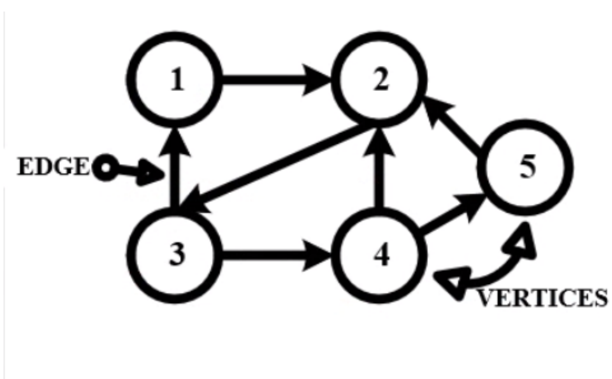


Fig. 2.15: Directed Graph.

2.11.3 Undirected graph

Edges in undirected graphs (Fig. 2.16) don't point in any particular direction. These arrowlike connections stand for mutual ties. Specifying the set of vertices $V = (V1, V2, ..., Vn)$ where $n \geq 1$ and the family of edges $E = (e1, e2, ..., em)$ is enough to construct a graph $G = (V; E)$ in the (undirected) setting. Assume that the pairings along the edges of V are random and unsorted. Each endpoint of the edge $e_{xy} = x, y$ is denoted by the corresponding vertex x or y.

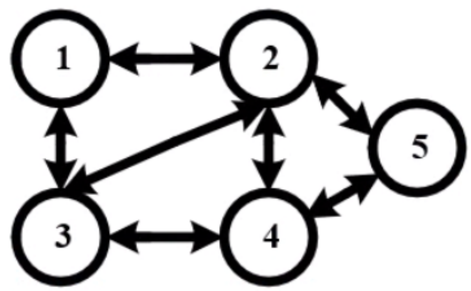


Fig. 2.16: Undirected graph.

2.11.4 Definition of Path

A path in a graph is an instruction for finding the set of edges one must follow to get from one vertex to another. In Fig.2.15's directed graph $G = (V, E)$, for instance, there are several paths from vertex 3 to vertex 2. Fig. 3.3 emphasizes a particular route.

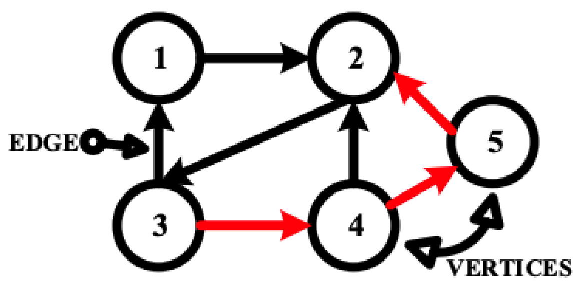


Fig. 2.17: Example of path between 2 nodes.

2.11.5 Formulation of Shortest Path

An undirected graph is used to describe the routing issue. $G = (V, E)$ is the equation of a graph, where V=$(v0, v1, ..., vn)$ represents the collection of vertices. And the collection of edges is denoted by $E = ((vi, vj) : vi, vj \in V, i < j)$. Vertices $(v1, v2, ..., vn)$ represent charging stations in the graph model, together with a number of automobiles. The aim is to reduce the multi-factored overall route cost for all cars.

2.12 Shortest Path Problem

The literature refers to the issue of finding optimal routes for vehicles as the recommender problem. Given the distribution of available cars, trip requests, and default system settings, the problem is often presented as an optimization model to determine the best options for spatial motions. Traditional route planning involves calculating the optimal way from point A to point B while adhering to limitations. Driving distance (fastest route), travel time (shortest route), energy usage, or a mix of these can all be considered constraints. The vehicle routing problem was initially examined by Dantizing and Ramser [63]. As a general rule, people used to try to find the shortest possible route, whether it meant saving money or reducing the amount of time spent in the car. According to Neaimeh et al. [64], a significant number of persons who have driven electric vehicles have reported feeling what is known as "range anxiety." It turns out that many drivers would adjust their driving behavior, most notably the route that they choose to take to get to their destination. The shortest path method developed by Dijkstra is used in this process since it helps discover the most efficient way, increasing the vehicle's range. The objective is not just to locate the route that uses the least amount of energy but also to assist with range anxiety and to make drivers feel more at ease with e-mobility. In Nunzio and Thibault's [65] work, an online range estimating tool is developed. This tool is based on calculating the path that uses the least amount of energy. The vehicle's energy consumption, including the effects of traffic, is modeled, and the range of the vehicle may be determined using a method called the shortest path algorithm (Bellman-Ford). A modified version of Dijkstra's algorithm is applied in the study by Storandt and Funke [66], which incorporates battery switch stations into the network. In order to include the regenerated energy of the electric car, this adjustment is accomplished by employing Johnson's shifting approach. In actuality, battery swap stations are not developed; nonetheless, charging stations are becoming more evident. The strategy taken by Storandt et al. (2013) is comparable to that taken by Storandt and Funke [66], with the exception that is charging stations are used rather than battery swap stations. Additionally, it has been suggested that work be done on optimizing many criteria simultaneously. These criteria would include the travel duration and the maximum number of recharging events.

Following the surge in interest in EVs, researchers have been looking into ways to cut down on journey times, and energy usage [67]. Optimal paths for electric vehicles are an emerging field of study. Vehicle dynamics may be ignored in the more common routing difficulties. However, a vehicle dynamical model is introduced in routing optimization because of gas emissions and decreasing energy sources. In [68, 69], the shortest path algorithm takes distance-dependent cost functions in the first place. When this is the case, we look for the shortest possible route from the starting point to the final destination. The constraint in these studies, there are no multiple trips for vehicles. It states that each car returns to the charging point in a given day and gets charged until the battery is full. [70] start with minimizing total driving distance. All cars are considered the same, meaning they have the same battery capacity. In this model, also they have addressed multiple trips in a day.

Condrad and Figliozzi propose a strategy referred to as [71] to account for the fact that cars have fixed ranges. Specific nodes can act as charging stations, and the amount of time it takes to charge fully is predetermined. They also deal with time window constraints. They present a solution for recharging the version of routing problems. The article [72] discusses the objective role of traffic. Time on the road, gas money and environmental costs are objective functions. Also, Bektas and Laporte are considered in [73], fuel and environment cost variable is associated with the type of vehicles and speeds.

Under the availability of charging stations, Yang and Sun reference [74] came up with a plan for EVs. Stations and vehicle routes are always in the same place: battery capacity and driving range as taken limitations. However, time windows and stations are not considered, so EV capacity may exceed if an unlimited number of EVs reach the charging station simultaneously. [70, 75] in those studies, the charging schedule of electric cars and the locations of charging stations are coupled to answer the routing problem. The main concern of those studies is mostly neglecting traffic conditions. Lower driving distance could be less energy saver than other route options if there is high traffic congestion. Traffic conditions directly affect the state of charge. [24, 76] are also take traffic into consideration. The speed of EVs and traffic conditions are dynamic instead of a constant number.

Optimizing traveling time or distance may provide an energy-efficient route selection, but these selections are not enough. Based on energy consumption, route selection method is studied in [77–79]. As the EVs' energy consumption is a limitation of the shortest way, the goal is to achieve the lowest possible consumption. This strategy might be counterproductive because regenerative braking increases the route's energy cost. Energy may be recycled in an electric car. It is possible to recharge the battery by recharging it with kinetic or potential energy. Even while this research might help reduce the price of traveling in EVs, only a small number of them have focused on the possibility of making multiple EVs.

2.12.1 Shortest Path Algorithms

There are a variety of ways that people driving EVs can get where they are going. We work on the assumption that EV drivers always choose the quickest route. The concept of the shortest path has several applications. Many disciplines have benefited from path approaches, including operations research, robotics, transportation, and others.

Shortest path problems can be divided into several categories:

- The pathways that are the shortest distance between two nodes in a network.
- The graph's shortest pathways originate from a single source node.
- The graph's shortest routes terminate at a single node.
- The shortest pathways possible between each of the graph's nodes.

The primary goal of a routing algorithm is to determine the path from a source s to a destination t with minimal cost, which might be distance, time, or energy. The parameters needed to solve issues with each approach are distinct. The optimal solution may be determined by plugging in a set of factors, such as a weighted matrix whereby distance, cost, and travel time all play a role. Following is a standard set of solutions for path problems:

- Dijkstra Algorithm
- Bellman-Ford Algorithm
- Floyd-Warshall Algorithm
- Johnson's Algorithm

Different route algorithms exist, such as those for solving single-source shortest path problems (SSSP) and all-pairs shortest path issues (APSP). The Dijkstra and Bellman-Ford Algorithms can resolve the problem of a single destination. However, Floyd-Warshall and Johnson's approach readily implement the all-pair route issue. Combining or altering the algorithms mentioned above has led to the creation of several research. For the SSSP issue of positive length, [80] optimized the Dijkstra method. Using unweighted graphs, the dynamic method presented by [81] was developed to solve the APSP problem. APSP may be solved with an algorithm developed by [82] for directed graphs over the real number line.

In this study, we have provided Floyd-Warshall [83] (shortest traveling time) and Dijkstra methods [84] (shortest distance) which are widely used and easy to implement. We choose two different methods to eliminate the drawbacks of each method.

2.12.2 All Pair Shortest Path

The all pairs shortest path issue involves finding the shortest route between any two points in a network.

2.12.3 Johnson Algorithm

An example of a weighted directed graph can be solved using the Johnson method. Donald B. Johnson produced a paper in 1977 proposing that graphs and weights might have a negative value. Applying the Dijkstra single-source shortest-path method to each vertex is the quickest option. However, this technique fails when dealing with negative-weight edges. The Johnson method relies on both the Bellman-Ford and the Dijkstra algorithms; the concept behind it is to re-weight all edges and make them all positive (using Bellman-Ford) and then use the Dijkstra algorithm on each vertex. Pseudocode is given in Fig. 2.18.

Algorithm 1 Johnson Algorithm

```
G'.V = G.V + n
G'.E = G.E + ((s,u) for u in G.V)
weight(n,u) = 0 in G.V
Dist = BellmanFord(G'.V,G'.E)
for edge(u,v) in G'.E do
weight(u,v) += h[u] - h[v]
end
L = [] /*for storing result*/
for vertex v in G.V do
L += Dijkstra(G, G.V)
end
return L
```

Fig. 2.18: Pseudocode of johnson algorithm.

2.12.4 Floyd-Warshall Algorithm

Specifically, the shortest path between any two vertices in a given network may be calculated with the help of the Floyd-Warshall method. Negative edge weights are supported by the Floyd-Warshall algorithm. The Floyd-Warshall algorithm is an instance of dynamic programming. A graph with weights is the algorithm's input. Pseudocode is given in Fig. 2.19.

The Distance Matrix (D) and the Sequence Matrix (S) are generated by the algorithm from these parameters (S). The distance matrix stores the value of the distance between any two vertices, whereas the sequence matrix stores the total number of vertices traversed along the path. In Fig. 2.20 a small example is created and iteration steps are explained.

Iteration steps:

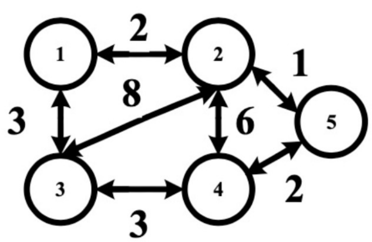
D^1= We look other edges' distance if $d_{i1} + d_{1j}$ is less than current distance.

This iteration $d_{23} < d_{21} + d_{13}$, so we update d_{23} and d_{32}.

Algorithm 2 Floyd-Warshall Algorithm

function Floyd Warshall (Graph, Source, Target)
Initialization of cost matrix D
for i:=1 to n do
for j :=1 to n do
for k :=1 to n do
If D$[j,k]$ > D$[j,i]$ + D$[i,k]$
D$[j,k]$ = D$[j,i]$ + D$[i,k]$
end

Fig. 2.19: Pseudocode of floyd-warshall algorithm.



$$D^{(0)} = \begin{vmatrix} 0 & 2 & 3 & \infty & \infty \\ 2 & 0 & 8 & 6 & 1 \\ 3 & 8 & 0 & 3 & \infty \\ \infty & 6 & 3 & 0 & 2 \\ \infty & 1 & \infty & 2 & 0 \end{vmatrix} \dashrightarrow D^{(1)} = \begin{vmatrix} 0 & 2 & 3 & \infty & \infty \\ 2 & 0 & 8 & 6 & 1 \\ 3 & 8 & 0 & 3 & \infty \\ \infty & 6 & 3 & 0 & 2 \\ \infty & 1 & \infty & 2 & 0 \end{vmatrix}$$

$$D^{(2)} = \begin{vmatrix} 0 & 2 & 3 & \infty & \infty \\ 2 & 0 & 5 & 6 & 1 \\ 3 & 5 & 0 & 3 & \infty \\ \infty & 6 & 3 & 0 & 2 \\ \infty & 1 & \infty & 2 & 0 \end{vmatrix} \dashrightarrow D^{(3)} = \begin{vmatrix} 0 & 2 & 3 & 8 & 3 \\ 2 & 0 & 5 & 6 & 1 \\ 3 & 5 & 0 & 3 & 6 \\ 8 & 6 & 3 & 0 & 2 \\ 3 & 1 & 6 & 2 & 0 \end{vmatrix}$$

$$D^{(4)} = \begin{vmatrix} 0 & 2 & 3 & 6 & 3 \\ 2 & 0 & 5 & 6 & 1 \\ 3 & 5 & 0 & 3 & 6 \\ 6 & 6 & 3 & 0 & 2 \\ 3 & 1 & 6 & 2 & 0 \end{vmatrix} \dashrightarrow D^{(5)} = \begin{vmatrix} 0 & 2 & 3 & 6 & 3 \\ 2 & 0 & 5 & 6 & 1 \\ 3 & 5 & 0 & 3 & 5 \\ 6 & 6 & 3 & 0 & 2 \\ 3 & 1 & 5 & 2 & 0 \end{vmatrix}$$

Fig. 2.20: Example of floyd-warshall application.

D^2=We look other edges' distance if $d_{i2} + d_{2j}$ is less than current distance.

This iteration,

$d_{14} < d_{12} + d_{24}$,

$d_{15} < d_{12} + d_{25}$,

$d_{35} < d_{32} + d_{25}$, so we update $d_{14}, d_{41}, d_{15}, d_{51}$ and d_{35}, d_{53}.

D^3=We look other edges' distance if $d_{i3} + d_{3j}$ is less than current distance.

This iteration,

$d_{14} < d_{13} + d_{34}$, so we update d_{14} and d_{41}.

D^4=We look other edges' distance if $d_{i4} + d_{4j}$ is less than current distance.

This iteration,

$d_{35} < d_{34} + d_{45}$, so we update d_{35} and d_{53}.

D^5=We look other edges' distance if $d_{i5} + d_{5j}$ is less than current distance.

$d_{24} > d_{15} + d_{54}$,

so we update d_{24}, d_{42}.

All iterations are done. Thus, we stop the process. After completing whole iteration final weighted matrix is obtained.

$$\begin{bmatrix} 0 & 2 & 3 & inf & inf \\ 2 & 0 & 8 & 6 & 1 \\ 3 & 8 & 0 & 3 & inf \\ inf & 6 & 3 & 0 & 2 \\ inf & 1 & inf & 2 & 0 \end{bmatrix} -> \begin{bmatrix} 0 & 2 & 3 & 5 & 3 \\ 2 & 0 & 5 & 3 & 1 \\ 3 & 5 & 0 & 3 & 5 \\ 5 & 3 & 3 & 0 & 2 \\ 3 & 1 & 5 & 2 & 0 \end{bmatrix}$$

2.12.5 Dynamic Programming

If you need to make a series of decisions that affect one another, the mathematical method of dynamic programming can help. It gives a methodical approach to finding the best possible choice in a given situation. Unlike linear programming, there is no universally accepted mathematical definition of "the" dynamic programming issue. However, dynamic programming is more of a method than a specific solution. Therefore the equations utilized in practice will vary depending on the task. Because of this, knowing when and how dynamic programming processes may solve an issue requires a certain amount of imagination and understanding of the overall structure of dynamic programming problems. The easiest method to learn these abilities is to gain practical experience in several dynamic programming domains and then examine the commonalities between these settings. Consequently, illustrative material of various kinds is supplied.

2.12.6 Single Source Shortest Path

Single source problem developed in order to find shortest path from a given source to all other nodes in a graph.

2.12.7 Bellman Ford Algorithm

The Bellman-Ford algorithm is a dynamic method that calculates shortest routes from a single source vertex to all of the other vertices; it is slower than Dijkstra in the same issue, but it can handle negative weights (some of the edge weights are negative numbers). In their respective books from 1956 and 1958, the algorithm was first described by Richard Bellman and Lester Ford. Pseudocode is given in Fig. 2.21.

Algorithm 3 Bellman Ford Algorithm

```
function bellmanFord(G, S)
for each vertex V in G
distance[V] ≤ infinite
previous[V] ≤ NULL
distance[S] ≤ 0
for each vertex V in G
for each edge (U,V) in G
tempDistance ≤ distance[U] + edgeweight(U, V)
if tempDistance ≤ distance[V]
distance[V] ≤ tempDistance
previous[V] ≤ U
for each edge (U,V) in G
If distance[U] + edgeweight(U, V) ≤ distance[V]
Error: Negative Cycle Exists
return distance[], previous[]
```

Fig. 2.21: Pseudocode of bellman ford algorithm.

2.12.8 Dijkstra Algorithm

It is generally agreed upon that the Dijkstra algorithm is the most effective method for locating the shortest path from a specific source node to all other network nodes. The user is responsible for determining whether they want the graph to be directed or undirected in their application. The Dijkstra method is an example of a greedy algorithm that finds the shortest path from one edge to another in a graph by selecting the vertices that are geographically closest to one another and then repeatedly searching for edges that are geographically farther apart from one another. When calculating the distances, we will stick with the same approach. The inputs required by the procedure are a weighted graph and a starting vertex V. The method will not be of any use if the values of the edges are negative. Pseudocode is given in Fig. 2.22. Fig. 2.23 illustrates a small example is created, and iteration steps are explained.

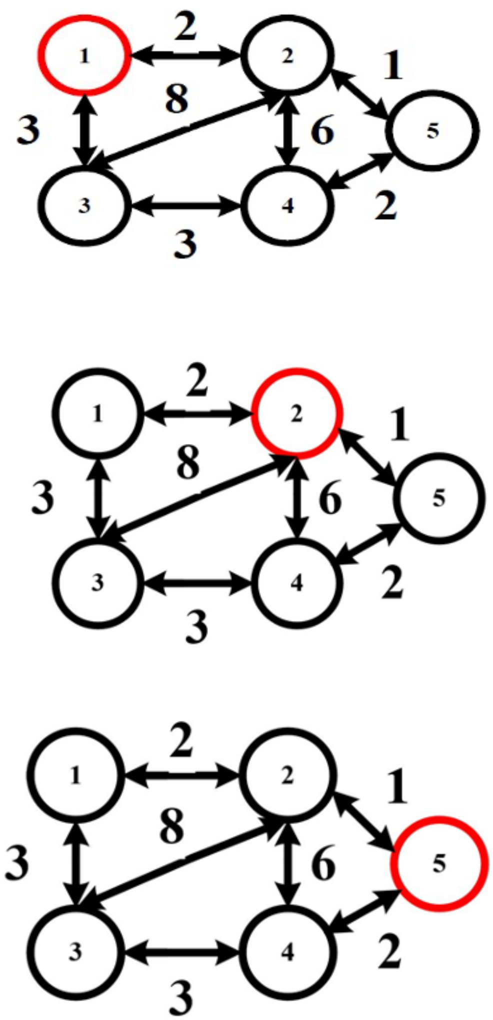
Steps of Dijkstra Algorithm :

Algorithm 4 Dijkstra Algorithm

```
1: function Dijkstra (Graph, Source, Target)
   for each vertex v in Graph: //initialization
   dist[v]:= infinity, //initialization
   dist[origin]:=0; //Distance from origin to origin is '0'
   Q:= the set of all nodes in Graph
2: while Q has positive element do : //main loop
   k := index of the smallest positive value in Q
   if dist[k]= infinity ; break // there is no route from origin to destination
   if k=Target; break // reach the destination
   remove k from Q
3: for each j neighbors of k //where j has not been removed from Q
   if Q[j] > Q[k] + Q[k, j] then
   Q[j] := Q[k] + Q[k, j]
   end if
   end for
   end while
   return Dist[ ]
```

Fig. 2.22: Pseudocode of dijkstra algorithm.

Iteration steps:



V	1	2	3	4	5
1	0_1	2_1	3_1	∞	∞

V	1	2	3	4	5
1	0_1	2_1	3_1	∞	∞
2		2_1	3_1	8_2	3_2

V	1	2	3	4	5
1	0_1	2_1	3_1	∞	∞
2		2_1	3_1	8_2	3_2
5			3_1	5_5	3_2

Fig. 2.23: Example of dijkstra application.

D^1= We start with source nodes (Node 1). Destination is Node 5. If there is a connection, we write distance value otherwise, we assign infinity. After finishing first iteration, we choose the smallest distance around neighbor. Subscript numbers show which node you have visited to reach that node.

D^2=Now, vertex 2 is the current node.This iteration,

$d[2] + weight(2,4) < d[4]$

$d[2] + weight(2,5) < d[5]$

is satisfied, update $d[4]$ to $d[5]$.

D^3=Now, vertex 5 is the current node.This iteration,

$d[5] + weight(5,4) < d[4]$

is satisfied, update $d[4]$. We reach Node 5 and all nodes are visited to reach Node 5. Path is 1-2-5 and the shortest path distance is 3. Algorithm stops calculate when it reaches final destination.

2.12.9 Greedy Algorithm

A greedy algorithm is one way to solve a problem by picking the best possible course of action given the available data. This method does not consider the possibility that the present best result may not lead to the greatest possible outcome in the long run. The algorithm never backs down from a choice, even if it was made in error initially.

Any optimization issue needing the maximum or lowest optimum solution may be tackled with this straightforward and instinctive approach. This algorithm's greatest strength lies in its simplicity in terms of explanation and implementation.

A greedy approach often has a manageable runtime complexity. On the other hand, a greedy solution may be implemented only if the issue statement has the two characteristics listed below:

The property of "greedy choice" states that a global (overall) optimum solution may be attained by selecting the best possible alternative at each stage. A problem has an optimum substructure if and only if the optimal solutions to each subproblems are contained in the optimal solution to the whole.

2.13 Centralized Optimization

Charging for all cars in a given area is managed by a single entity under the centralized control architecture. The aggregator pulls in the PEV data and adjusts everyone is charging times to save the most money on power. In a location with an aggregator, the centralized design makes it possible to even out the profile of the accumulated electric load. This design simplifies PEV charging because all vehicle data is accessible to a central authority. Although this is a commonplace control architecture, it is not without its share of problems. Even though the overall load is consistent, each vehicle's charge profile might have spikes that drive up the bill significantly. Due to the inherent risk of relying on a single system to handle such a massive volume of data, a failsafe mechanism must be included. Complexity rises with the number of cars on the road, necessitating robust computational resources to handle the flood of data and carry out the optimization required to supply personalized PEV charging plans. Centralized systems allow any individual or group, such as customers, to have one-on-one conversations with a single administrator. As long as it keeps track of events, this server should be able to monitor, collect, and evaluate data in real time and send suitable control signals to all relevant parts. Centralized control systems have been made possible by the rapid growth of communication networks and extremely powerful computers over the past two decades. It is common knowledge that several centralized control systems have attempted to optimize the functioning of microgrids. In order to maximize the value of a microgrid and optimize its operation during interconnected operations, i.e., to optimize the output of local generators and energy exchanges with the distribution network, a centralized controller was initially proposed in [85]. When it comes to keeping tabs on and fine-tuning the performance of power plants and other infrastructure involved in the production and distribution of electricity, nothing beats an energy management system (EMS). [86] provides a mathematical description of the microgrid energy management problem and a centralized control architecture.

A centralized control algorithm [87] oversees most of the devices in a power system. The generators are managed by a control system that ensures optimum power flow, economic dispatch, reactive power optimization, and so on. Controlling thousands of cars at once is a complex task due to the increasing number of variables involved. There have been and are several active research aimed at figuring out how to make electric cars scalable. The aggregator monitors data exchanged between electric vehicles and the electrical grid and used that information to make decisions for each EV. Centralized charging that prioritizes reducing the overall cost of power was created by Anglani et al. [88]. Most centralized charging methods prioritize reducing power costs. However, if there is an interruption, it may be intrusive to EV drivers.

In order to optimally deploy scattered resources for the subsequent period, the central coordination center gathered important information from dispersed controllable devices and forecasted data [89]. In-depth analyses of centralized energy-management architecture may be found in several academic journals. According to [90], a two-tiered strategy for energy management is ideal, with the schedule level achieving the economic-operation scheme through projections and the dispatch level dispatching controlled DGs using real-time data. Reference [91] proposes a centralized scheduling algorithm to optimize the charging scheme in a microgrid where electric vehicles are the norm, considering charging costs and customer convenience. Intending to reduce the expenses of running a microgrid that serves a residential area and has a concentrating solar power unit, a centralized energy management optimization model was developed in Reference [92]. In Reference [93], developing a two-stage stochastic demand-side management model for a commercial building microgrid was prompted by the unpredictability of solar-generation outputs, loads, microgrid availabilities, and microgrid energy needs. Esmaili et al. [93] create several centralized charging solutions to optimize several factors, such as system cost, CO2 emission, power loss, power frequency, EV owner satisfaction, and so on. The use of heuristic algorithms and optimization techniques has led to the successful resolution of such issues. To minimize energy cost and adhere to substation supply limits, a hierarchical control strategy is given in [94] for regulating the loads of charging stations for electric vehicles in a distribution network. Schedules are set under anticipated demand. To optimize the charging of an electric vehicle (EV) fleet represented as a single, so-called aggregated battery, dynamic programming (DP)-based optimization approach is provided in the mentioned study [95]. However, the previously mentioned articles do not consider the dynamic nature of EV arrival/departure timings and charging patterns; Qi et al. [96] use receding horizon control-based strategies to address the uncertainties in the dynamic charging systems. In [97], online algorithms are created for coordinating the charging of EVs in order to save the system money and reduce the harmful effects of EVs on the distribution network. Remember that the authors of these publications are mainly thinking about the kinetics of electric vehicle charging. Considering both the aggregator's revenue and the customers' expectations and expenses, Jin et al. [98] investigate EV charging scheduling issues from the consumers' perspective. The goal of the research presented in paper [99] is to concurrently optimize the EV charging cost and the risk of load mismatch between the predicted and the actual EV loads. In contrast to earlier works, [98] and [99] take into account both static and dynamic pricing scenarios. The scale of the optimization challenge for a centralized charging approach grows in proportion to the number of electric vehicles. Another potential obstacle is collecting reliable data from an extensive fleet of EVs. Thus, the challenge of developing a workable, centralized EV charging method persists.

Because of the increasing prevalence of decentralized power plants, storage facilities, renewable energy sources, and prosumers/consumers, centralized algorithms are considered useless due to the overwhelming complexity of the agents that will need to be managed in future power grids [100, 101].

2.14 Power Flow

Monitoring, controlling, and making decisions referring to power systems all benefit greatly from the power flow problem. This has prompted the quest for a viable solution to the rise of power systems' impact on the power flow problem. Since the power flow is responsible for determining the complicated nodal voltages from which line flows, currents, and losses may be computed, it naturally places a large computational burden on the power system. About 50 years ago, standard methods for regulating power flows were initially implemented.

The ACOPF issue is non-linear and nonconvex, yet it has been addressed in a number of ways [102]. Linear programming (LP) [103], Newton's technique [104], the interior point method [105], and the decoupling method are only few of the methods that have been presented to solve the standard OPF calculation. Historically, several methods for breaking down the OPF issue have relied on a parallelization of computing [106].

The OPF issue needs to be transformed into a convex one before it can be used in practice. For this reason, the Direct Current Optimal Power Flow (DC OPF) issue is typically used in the industry [107] due to the greater accuracy it provides. A plethora of optimization techniques and relaxations have been presented for this problem [108]. Similarly, in [109], an Augmented Lagrangian Alternating Direct Inexact Newton (ALADIN) approach is used to solve AC OPF in a decentralized way.

2.15 Decentralized Optimization

Each agent or collection of agents in a decentralized control system makes its own decisions without needing a central authority figure. Decisions are made using nearby information, such as voltage and frequency readings, and there are few such connections. It stands to reason, then, that decentralized control mechanisms do not require a high level of connectedness. Without channels of communication and information exchange, it is impossible to guarantee that the system as a whole will be optimized, stable, or reliable. However, With distributed approaches, agents may not only use local measures but also share and receive data as needed. Therefore, similar to centralized control methods, this control system may achieve global optimization, dependability, and stability [110].

Centralized control algorithms are not sustainable for fleets with thousands of cars. Multiple ongoing investigations have been aimed at figuring out how to increase the electric car fleet's scalability. There is research that proposes subdividing the issue into manageable chunks. The problem with this strategy is that it does not guarantee optimal outcomes, even though it provides a scaling solution [111]. Moreover, if parameters shift, these research could become useless. Another strategy for dealing with the issue of scalability is distributed optimization. Given the inherent graph structure of electricity transmission and distribution networks, distributed optimization approaches lend themselves readily to this domain. Distributed optimization techniques have been the subject of substantial research since at least the 1960s. Dual decomposition, which employs a gradient approach to solve the dual issue, is a paradigmatic case in point. Every unit has optimized its primary (local) variables at each cycle's end according to the market's secondary (dual) variables. After that, the dual variables are revised to reflect any changes in supply and demand, with equilibrium price parity being the end aim. The literature on power systems has several examples of distributed algorithms, such as two-phase techniques similar to a single iteration of dual decomposition. In the first stage, a system establishes dynamic pricing over a specific period (often hourly during the next 24 hours). After this first phase, the costs remain the same, allowing devices to collaboratively optimize their power flows with little to no extra coordination. Recently, a distributed approach based on a typical dual decomposition on subsystems that are the maximum cliques of the power network has been presented to solve the dual OPF. In order to theoretically and practically converge to an optimal solution, dual decomposition methods require a large number of technical constraints, such as the stringent convexity and the finiteness of all local cost functions. Using an enhanced Lagrangian [112] can relax the technical requirements, leading to the multipliers technique. Thanks to this minor modification, the local (convex) cost functions need neither be strictly convex nor necessarily finite for the multipliers technique to converge under light technical circumstances. The lack of subsystem independence is a drawback of this approach. Instead, we may utilize the alternate direction method of multipliers (ADMM) [113] to accomplish both separability and robustness for distributed optimization. Before, researchers used augmented Lagrangian techniques (among them ADMM) to analyze power systems using static, single-period objective functions on a limited number of dispersed subsystems, each representing a different region's worth of power generation and consumption.

Each PEV in a decentralized control architecture generates its own charging schedule based on the demand in its immediate area. By eliminating the requirement for an aggregator in favor of decentralized power management, the charging costs of each car may be kept to a minimum. Instead of trying to find the best possible charging schedule for the entire world, this instance focuses on optimizing things locally. Since the user is the single custodian of their charging schedule, the decentralized control architecture makes privacy issues moot. The result is better user adoption than with a centralized system. The amount of data processing required is reduced when each car makes its charging schedule. The lack of consideration for global loads in the charging algorithm is the primary shortcoming of the decentralized control design. While it's possible to optimize PEV charging on a per-vehicle basis, doing so may cause the aggregate electric load profile to be less smooth than desired due to unexpected spikes and dips. The avalanche effect describes this phenomenon. The decentralized control architecture is more likely to be implemented in real-world applications and is more practical than the centralized control architecture. This is due to the decentralized control architecture's scalability and higher customer acceptance. This is as a result of the fact that the decentralized control architecture has a greater possibility of being implemented.

2.16 Generation Dispatch and Load Management Applications

Cost and emission reduction through better generator dispatch and load management has been a hot topic for the past few decades. From the looks of this research, most contemporary load management programs are time-shifting oriented [114], with only a few focusing on spatial shifting. In [115], a collection of techniques for optimizing demand resources using day-ahead and real-time changes using inputs from both the supply and demand sides was developed. In [116], many aspects, including distributed generation, bidding, and demand response on pricing, were taken into account to construct a load forecasting-based load management approach. As interest in trading energy has grown, so needs to maximize both bidding curves and the actual LMP. Under a pricing structure for electricity, an estimate of household demand response was employed to mitigate peak costs. Load management in a spatial frame might be explored when more controlled loads, like EVs, become accessible and popular. Load management on the time frame when emission concerns are also taken into account is the focus of another combined economic/emission/load profile management dispatch algorithm [117]. Several load control strategies were examined to determine which was most effective in lowering operational expenses and carbon emissions.

The term "load side management" can refer to several different strategies, from the traditional direct load control to the dropping real-time pricing [118]. Particularly for a long time, load management has been used, and optimization techniques have been presented to reduce generating cost, for example [119], maximize supplier's profit, for example [120], or minimize deviation from users' intended consumptions, for example [121]. To begin, DSM is rarely used unless in extreme situations where there is a high demand and little supply, such as during the few warmest days of the year. We anticipate that demand response will be increasingly utilized to not only mitigate peak loads and rebalance loads for financial gains but also to enhance security and decrease reserves by adjusting elastic loads to unpredictable renewable generation. Regarding heating, ventilation, and air conditioning (HVAC), numerous models have been established to calculate the potential savings from enacting the demand side management and demand response techniques. Some sophisticated components with intricate operating limitations were argued in [122] to function more realistically if loads were treated as separate entities. Therefore, the authors ran simulations and conducted performance tests on an actual device to construct a dynamical model for HVAC loads. In [123], the authors presented an algorithm that would assist aggregators of demand response programs in automatically planning the energy used by thermostatically regulated loads and making better judgments on the dispatch of their events.

2.17 Energy Efficiency

After Texas, California was the second-highest consumer of energy in 2016. However, its per-capita consumption is relatively low. The improvement in energy efficiency is to take responsibility for this [124]. Energy efficiency is the practice of minimizing the amount of energy needed to run an appliance or system while maintaining the same level of performance. For example, changing lights from incandescent or fluorescent to LED lighting will offer the same amount of lighting but lower energy usage. Lighting accounted for about half of all power used in 1995 but now only uses around 17.5 percent of what it did in 2012; computers and office equipment accounted for 7 percent in 2004 but 14 percent in 2012; and cooling systems accounted for 17.5 percent in 1993 but only 15 percent in 2012. In 2012, HVAC, lighting, and other end users accounted for 75% of total energy usage [3], as reported by the Energy Analysis and Environmental Impacts Division at Lawrence Berkeley National Laboratory [125].

CHAPTER 3: A GRAPH THEORY BASED ELECTRIC VEHICLES ROUTING METHODOLOGY FOR A REGION

3.1 Chapter Introduction

Several situations in graphs need us to be aware of the shortest path between any two given nodes. This philosophy also underpins the generalized water and electrical delivery networks. As an illustration, a train track system is our most useful one. If a traveler has to get from one station to another, he must determine the most direct route between the two. The station is the vertices, or node, and the rails, or edges. Routing principles in computer networks benefit significantly from this. It is possible for there to be several ways to get from one node to another. In contrast, the shortest route is the one along which the total weight of all edges traversed is the smallest.

In this chapter, we develop and evaluate a hybrid routing algorithm for EV fleets that minimizes energy consumption. The main contributions of the proposed architecture are,

- The shortest path issue is addressed from a graph-theoretical perspective which helps address the direction of the vehicles and at the time multi dimensional in nature.
- A hybrid algorithm that considers not only the physical distance between cars but also their speeds, directions, battery levels, and the number of other vehicles on the road.
- The approach is scalable to fit a variety of situations.

3.2 Research Objectives

Heavy traffic is a common issue in most major cities throughout the world. Nearly every country with a steady or expanding economy also experiences yearly growth in the number of cars and trucks it registers. Together with the broader trend of urbanization, this is worsening air quality and straining road networks, particularly in densely populated places. As a result of congestion and the lengthening of travel times are problems many cities in industrialized countries face. In its capacity as an integrator, the algorithm finds the most efficient path between two points that permits stops at many charging stations. This combined method can handle routing in both forward and backward directions, shown by negative edges and cycles. In this process, actual data is used to test the algorithms. Range, speed, charging station proximity, and traffic conditions are also taken into account by this method. Graph theoretic modeling of routing issues forms the basis of the method. Next, we will go through the theory's basis.

3.2.1 Designed Road Network

Developing a route algorithm, the model is accepted $|O|$=origin of EVs, $|D|$=final destination of EVs, and $|C|$= charging stations. EVs may unable to visit several charging stations because of limited battery capacity. With given graph $G = (V, E)$, the distance between two nodes should minimize (Distance=$|O|$+ $|C|$ + $|D|$). Path calculation is divided into 3 categories.

- From the Source to the Charging Station
- Charging Station to Charging Station
- Charging Station to Final Destination

3.3 Stochastic Modeling of EV Loads and Graph Matrix

If G is a weighted graph, every edge has associated numerical weight. Then, the weighted matrix for G is W_{ij} is defined

$$\mathrm{W}_{ij} = \begin{cases} \text{Weight of Edge; (when i and j connected)} \\ 0 \text{ (i=j)} \\ \text{Infinite (There is no edge between i and j)} \end{cases} \tag{3.1}$$

Transportation networks are mostly modeled by weighted graphs, where vertices represent a model of charging locations or power bus stations. In contrast, pairs of edges can model the streets or traffic flow.

An argument for electric cars' unpredictability is presented here. The modeling process places a premium on driving time, parking time, and charging time. The adoption of EVs causes an increase in the load on the power grid's buses. The first element is considered when deciding where EV charging stations are placed.

Location of EVs with recharge needs in the Nev traffic network is as follows:

$$P_{\text{ev}} = n_{\text{ev}}, n_{\text{ev}} \in N \tag{3.2}$$

where n_{ev} is the node number of EV places found in the traffic graph. The following criteria are used to determine the location of the charging stations:

$$P_{\text{cs}} = n_{\text{cs}}, n_{\text{cs}} \in N \tag{3.3}$$

where n_{l} is the node number of the charging station as found in the traffic network.

- Travelling Time

The amount of time spent traveling as a whole is quite important, and it need to be cut down as much as feasible.

$$min \in (T) \tag{3.4}$$

$$T = t_{\text{o-ch}} + t_{\text{ch-des}} \tag{3.5}$$

T stands for the whole duration,$t_{\text{o-ch}}$ stands for the time spent traveling from the starting point to the charging station, and $t_{\text{ch-des}}$ stands for the time spent traveling from the charging station to the final destination.

- Cost Minimization

The formula for the cost function is as follows:

$$Cost = aD_{\mathrm{t}} + bT_{\mathrm{t}} \tag{3.6}$$

where D is the total distance traveled by car. Vector a values are measured in units of 0.04 \$/mile. Time spent traveling, denoted by $\mathrm{T_t}$ is the full duration of the trip. The velocity of a vector b is approximately 0.035 \$/min.

- Charging Space

In order to cut down on the overall amount of time spent waiting, the total number of cars shouldn't go over the maximum capacity of the charging station.

$$0 \leq N_{\mathrm{car}} \leq N_{\mathrm{max\text{-}capacity}} \tag{3.7}$$

- Speed of EVs

Driving speed is depend on traffic condition. Different lengths of road would have traffic and it affects the speed of EVs.

3.3.1 Comparison of Two Methods

The practical utility of any technique depends on a number of factors. Both methods are compared in Table 3.1. Growing the number of nodes in Floyd Warshall's requires more time and space. In Table 3.1, we can see the typical simulation runtime after 100 iterations. Also, [126] results are pretty similar based on running time and memory usage.

The Dijkstra approach, on the other hand, is a blind search. It looks for the least-worst choice and then chooses that one. However, if there is a disadvantage, the outcome will be subpar. If reducing power use is a priority, then certain edges in the graph may incur a negative cost due to the optimization process. In Fig. 3.1, the Dijkstra algorithm would

Table 3.1: Result of dijkstra method

Simulation Time (Average)	Dijkstra (s)	Floyd Warshall (s)
10*10 matrix	3.144e-04	0.0086
50*50 matrix	0.0021	0.0017
100*100 matrix	0.0020	0.0041
250*250 matrix	0.0165	0.0479
500*500 matrix	0.0210	0.4834

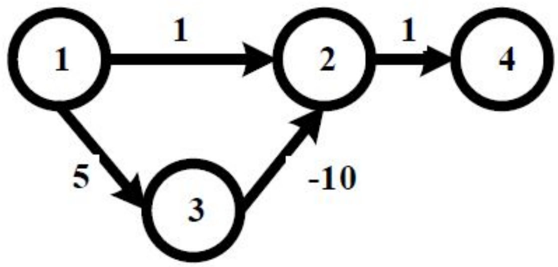


Fig. 3.1: Directed graph with negative edge.

initially evaluate the relationship between nodes 2 and 3, where 1 is the edge weight and 5 is the edge weight, respectively. The algorithm selects the second node to be the active node. The route will go as follows: 1-2-4, and it will cost a total of 2. Floyd-Warshall, on the other hand, examines each and every edge, leading to a route of 1-3-2-4 and a total cost of -4 for the algorithm. Moreover, secondly, algorithms get caught in an infinite loop if there is an undirected path between two nodes. In Fig. 3.2, for instance, if vehicles reach nodes 2 or 3, neither algorithm detects the negative circle and cannot complete the computation. Hybrid algorithms also handle negative edges and cycles. Table 3.3 provides a quick comparison of the two approaches.

Table 3.2: Comparison of two methods

	Dijkstra (s)	Floyd Warshall (s)
Space Complexity	O(A)	O(B^2)
Time Complexity	O(B^2)	O(B^3)
Working with Negative Edges	X	V
Working with Negative Cycles	X	X
	A=Number of edges B=the number of nodes	

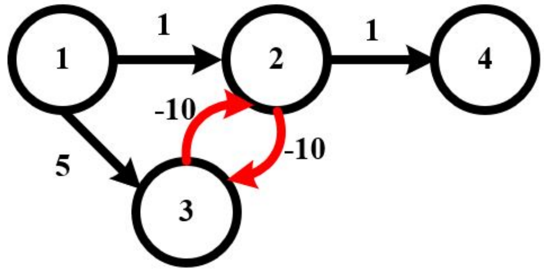


Fig. 3.2: Graph with negative cycle.

3.4 Hybrid Algorithm For Route Selection

Incorporating electric cars as a load requires careful consideration of driving range and State of Charge (SoC). Batteries drain faster and travel farther throughout the driving duration. Drivers may need to make more than one station stop daily if their vehicles' batteries run low.

Several research projects have been conducted to find ways to reduce routing issues. It is important to remember that every research takes a unique method. Time and distance are examples of circumstances that take precedence over others. The length of time it takes to drive from one place to another depends on several factors, including the distance, the speed of an EV, and the frequency and severity of traffic congestion. In contrast, factors such as the weather, the characteristics of the drivers, and so on are less significant. Due to battery characteristics, it is essential to have a strategy for frequent charging when on extended trips. Developing a management technique that takes into account the optimal management of the EV fleet will be a primary research path and priority.

In this study, we devised a hybrid routing strategy (Fig. 3.3) to circumvent these roadblocks by locating charging stations halfway between a vehicle's origin and destination. Each automobile or a whole fleet can benefit from a hybrid strategy. Researchers have often sided with drivers when evaluating automobile routing algorithms. Any of these programs never compromises users' sense of security. The method may be expanded to handle more complicated routing scenarios.

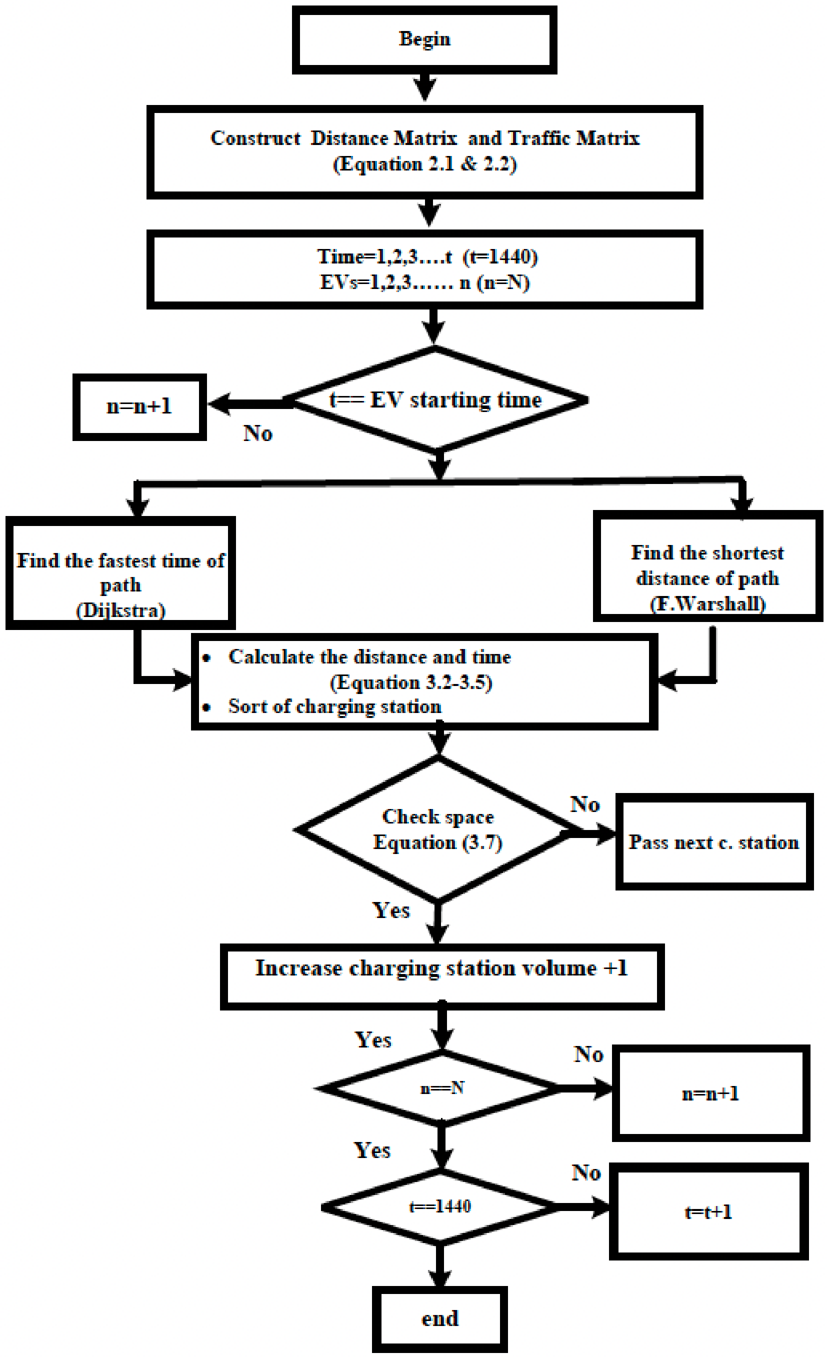


Fig. 3.3: How to hybrid algorithm works.

3.5 Case Studies of Routing Algorithm

We will get the basics out of the way first. Given a collection of n vertices and a set of m directed edges, G = (V, E) is an edge-weighted, directed or undirected graph. A city is represented as a graph, with each vertex representing a place or traffic volume in that area. We use Google Maps to determine distances in the first input matrix. Table 3.3 provides the density levels used to generate the second input matrix in Fig. 3.4 The red lines at 7 and 8 indicate slow traffic, while the green lines show how quickly drivers may get through the affected areas. The average speed of vehicles is acknowledged to be 30 miles per hour if there is no traffic, and it varies according to the traffic density as stated in table 3.3. If a charging station is available, EVs will stop at that location each time. Ten artificial recharge stations are placed at various locations across the simulation. As part of the hybrid algorithm, electric vehicles are restricted to traveling on brightly colored yellow roads. For the sake of this discussion, let us suppose that the origin and destination of EVs are both known. The hybrid method uses the cost function (Eqn. 3.6) to compare the available stations and select the most optimal one.

Table 3.3: Speed range based on traffic density

Density Level	**-4**	**-3**	**-2**	**-1**	**1**	**2**	**3**	**4**
Speed	**50**	**45**	**40**	**35**	**30**	**25**	**20**	**15**

3.5.1 Routing Algorithm with One Stop - Case 1

Scenario 1 is depicted in Fig 3.13. Two electric cars, number 1 and 2, are deployed in various areas and are headed in distinct directions. Using a combination of the Dijkstra, Floyd-Warshall, and hybrid algorithms, we can see that there is only one charging station for each vehicle and three directional dashes. The optimal charging station selection is shown in Tables 3.4, 3.5, and 3.6, which are the product of algorithms. Both the EV-1 and EV-2 hybrid algorithms take the Floyd-Warshall and Dijkstra paths, respectively. The findings indicate that the overall distance and travel time may rise even if a traffic-free alternate route is available. When compared to the other two approaches, the result from the hybrid algorithm is more logical.

After a simple case study is put into action, we scale up the number of EVs to 200. There are several jump-off and drop-off places for the vehicles, and a Matlab program generates

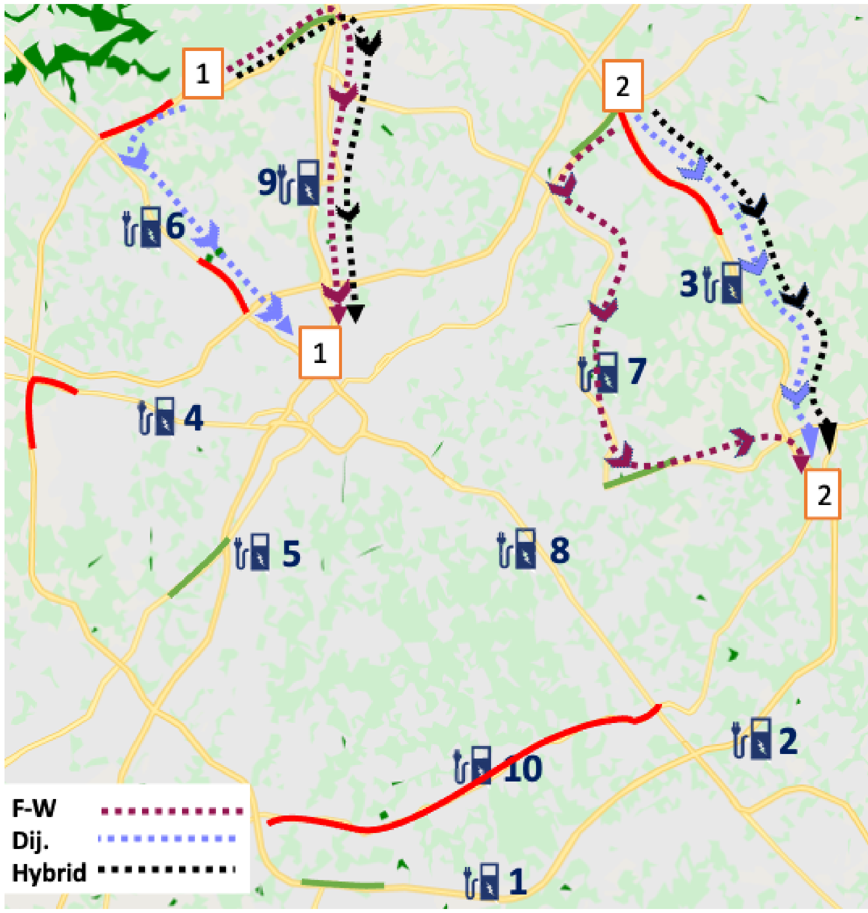


Fig. 3.4: Location of charging stations and vehicles with single stop.

Table 3.4: Result of dijkstra method

	C. Station	Distance (mile)	Time (min)	Cost
Car 1	6	9.9	19.8	1.089
Car 2	3	12.6	25.2	1.386
Total		22.5	45	2.475

Table 3.5: Result of floyd-warshall method

	C. Station	Distance (mile)	Time (min)	Cost
Car 1	9	11.4	19.36	1.1336
Car 2	7	18.7	35.64	1.9954
Total		30.1	55	3.129

the positions of each. You may find the outcomes in Table 3.7.

The hybrid algorithm saves up to % 7 in terms of total travel time, as well as reaching the destination at almost the closest distance.

Table 3.6: Result of hybrid algorithm

	C. Station	Distance (mile)	Time (min)	Cost
Car 1	9	11.4	19.36	1.1336
Car 2	3	12.6	25.2	1.386
Total		24	44.56	2.5196

Table 3.7: Comparison of algorithms

	Distance (mile)	Time (min)	Cost
Dijkstra	3221.3	6442.6	354.343
Floyd-Warshall	4460.6	8733.9	484.11
Hybrid Algorithm	3239.5	6396.1	353.443

3.5.2 Routing Algorithm with Multiple Stop-Case 2

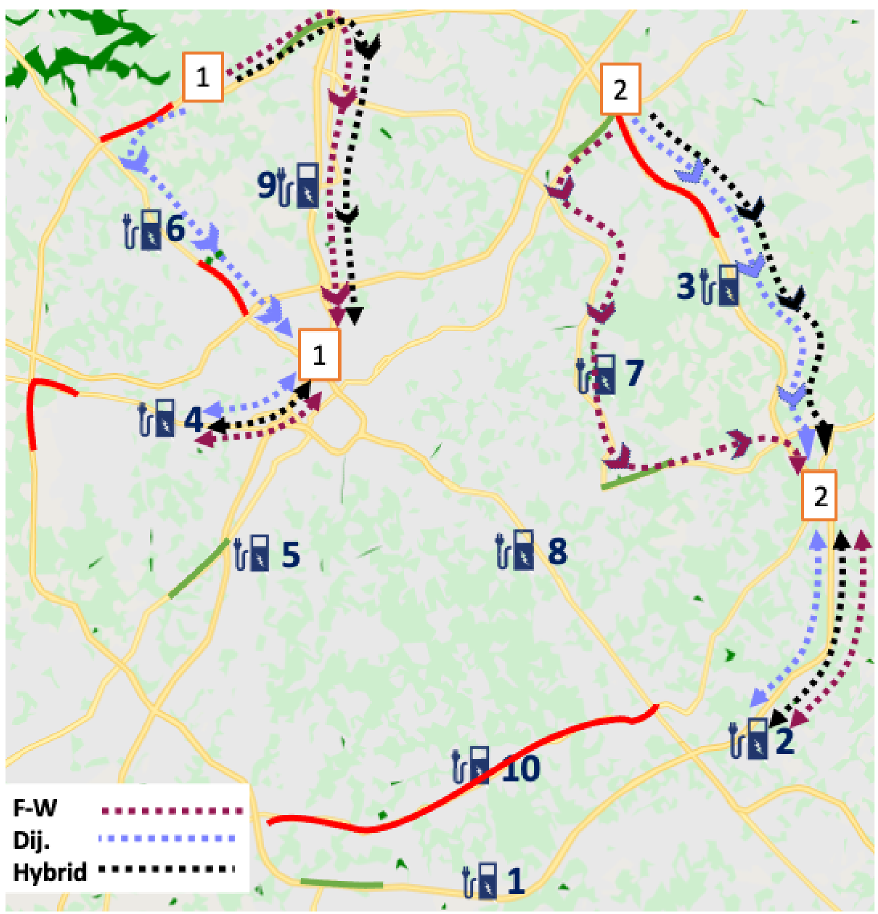


Fig. 3.5: Location of charging stations and vehicles with multiple stop.

We have accounted for the possibility that EVs will need to visit several charging stations here. The system consistently ranks each charging station, from best to worst. The vehicle's position is updated whenever it reaches the first charging station. If a parking space is unavailable, the algorithm will use a charging station as a new starting point and direct the EV to the optimal charging site, as determined beforehand. All possibilities are calculated before cars start driving, so the algorithm does not spend time again in order to find the next best option. In Fig. 3.5, charging stations and cars are represented by the number 1 to 10. The need for recalculation and waiting time can be eliminated if all charging outlets are organized. Tables 3.8, 3.9, and 3.10 show the optimal charging station selection outcomes achieved by various algorithms. All the programs here take the same path.

Table 3.8: Result of dijkstra method

	C. Station	**Distance (mile)**	**Time (min)**	**Cost**
Car 1	**6-4**	**25**	**50**	**2.75**
Car 2	**3-2**	**32.7**	**76.8**	**3.996**
Total		**57**	**126.8**	**6.746**

Table 3.9: Result of floyd-warshall method

	C. Station	**Distance (mile)**	**Time (min)**	**Cost**
Car 1	**9-4**	**31.3**	**59.16**	**3.322**
Car 2	**7-2**	**44.5**	**87.24**	**4.833**
Total		**75.8**	**146.4**	**8.155**

Table 3.10: Result of hybrid algorithm

	C. Station	**Distance (mile)**	**Time (min)**	**Cost**
Car 1	**9-4**	**31.3**	**59.16**	**3.322**
Car 2	**3-2**	**32.7**	**76.8**	**3.996**
Total		**64**	**135.96**	**7.318**

Implementing a small-scale case study, we then increase the fleet size to 200 EVs. Matlab's technique randomly creates starting and ending locations for the vehicles, with a wide range of options for each. The outcomes are summarized in the table below.

Table 3.11: Comparison of algorithms

	Distance (mile)	**Time (min)**	**Cost**
Dijkstra	**6457**	**12914**	**710.27**
Floyd-Warshall	**8962**	**17738**	**979.31**
Hybrid Algorithm	**6499**	**12317**	**676.385**

As previous case the hybrid algorithm saves up to % 5 in terms of total travel time, as well as reaching the destination at almost the closest distance. It is clearly seen that both cases hybrid algorithm is giving the optimum options.

3.5.3 Speed Optimization of Vehicles

Drivers who are unsure about their vehicle's state of charge (SoC) and the amount of energy needed to get to their destination might experience "range anxiety," which is a barrier to the widespread adoption of electric cars (EVs). The majority of the approaches that are used to estimate these variables make use of simplified models that are based on several assumptions. These assumptions can lead to substantial inaccuracy, mainly if dynamic and environmental circumstances are ignored. Most methods of range assessment use the incorrect assumption that the combined efficiency of the inverter drive and electric motor remains constant during the journey. In contrast, in reality, this assumption is false. In this case, we present a convex optimization technique for optimization vehicle speed consideration environment effects. During a trip, vehicles are affected by rolling resistance and aerodynamic drag force (Fig. 3.6). To accelerate, vehicles need to exceed these forces.

- Rolling Resistance Force

The force known as rolling resistance is created by the friction between the tires and the road. The rolling resistance force is 0 when the wheel is at a complete halt. Rolling resistance is a force that opposes the forward motion of a vehicle. With motion, the vehicle experiences this force, which can be determined by multiplying the rolling resistance coefficient Cr by the normal force between the vehicle and the road. The normal force exerted by a vehicle on

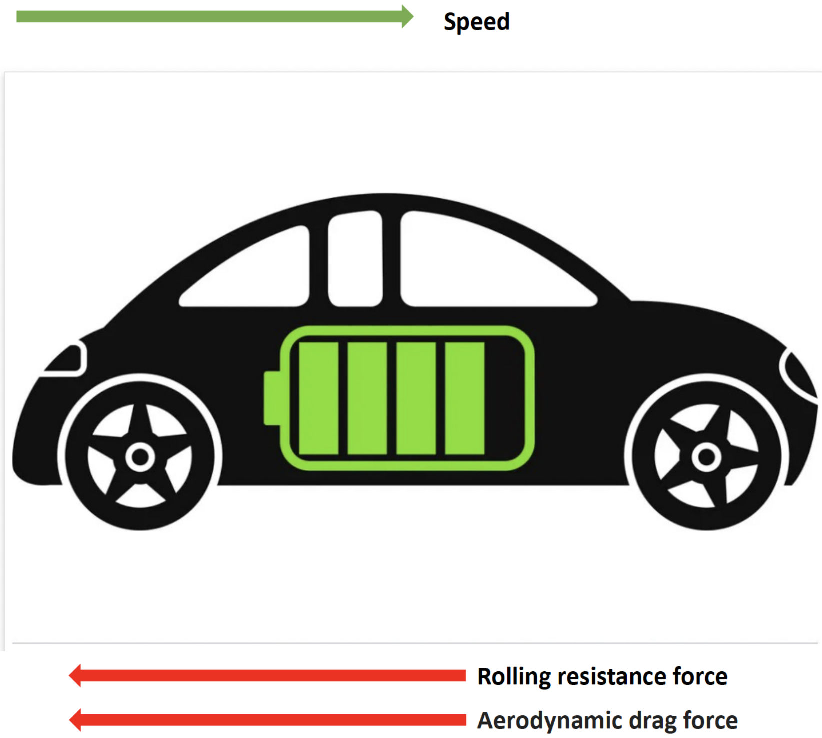


Fig. 3.6: A schematic representing the forces that are operating on an EV .

a horizontal plane is proportional to the product of the vehicle's mass, m, and the universal gravitational constant, g.

$$F_{\text{roll}} = c_r mg \cos(\theta) \tag{3.8}$$

When a road has an angle of inclination, the normal force is calculated as the weight m.g multiplied by the cosine of the road angle. It is essential to know that the rolling resistance force does not rely on the vehicle's speed and always acts in the opposite direction of the driving motion. It is essential to have a low value for the coefficient Cr to minimize frictional losses.

- Aerodynamic drag force

Because the air is being forced to flow around the moving vehicle, the aerodynamic drag force acts in opposition to the motion of the vehicle as the speed of the vehicle increases. It is possible to determine it by taking the product of the aerodynamic drag coefficient Cd, the front area of the vehicle Af, the air density, and the square of the vehicle speed v, and then dividing that result by 2.

$$F_{\text{aero}} = \frac{1}{2} c_d A_f \rho v^2 \tag{3.9}$$

It is also essential to remember that the aerodynamic drag is unaffected by the mass of the vehicle but has a solid relationship to the speed at which the vehicle is traveling. When traveling at speeds more than 70 to 80 kilometers per hour, an automobile's force of aerodynamic drag is greater than the force exerted by rolling resistance.

Second, the drag coefficient for a contemporary vehicle ranges between 0.25 and 0.35 on average. Coefficients for SUVs, characterized by their generally boxy designs, fall in the range of 0.35 to 0.45.

Now that the equation for traction force has been expanded, we can see the variables that determine the forces acting on the vehicle: vehicle mass and road angle affect rolling resistance and gradient force; vehicle speed determines aerodynamic drag force; and the remainder of traction force determines acceleration. Power output from the powertrain may be calculated by multiplying the traction force by the vehicle's velocity. The following formula reveals the whole amount of power a car needs:

$$P_{\text{net}} = (F_{\text{aero}} + F_{\text{roll}}) * V * n \tag{3.10}$$

and relation of vehicle battery capacity is obtain by:

$$Ecap = \int_0^T P_{net} * dt \tag{3.11}$$

where V is the speed of vehicle and n is the efficiency in the transmission. The parameter used in order to develop case study is shared in table 3.12.

We develop objective function in Eq. 3.12 and we assume that there are different speed

Table 3.12: Specifications of speed optimization

	Value
Mass of body 'm'	**1500**
Acceleration of gravity 'g'	**9.81**
Rolling resistance coefficient 'Cr'	**0.03**
Drag Coeffient 'Cd'	**0.35**
Frontal area of the body 'Af'	**1.88**
Density of fluid 'ρ'	**1.2**

limit during the trip. Based on the trip, we apply convex optimization and find the best speed value during the travel. Algorithm take total traveling time and car battery capacity. Then, with applying power requirement equation algorithm find optimum vehicle speed during the travel.

$$\begin{aligned} \min \quad & E_{\text{car}} \Delta t \\ & 0 \ \leq V_{\text{car,t}} \leq V_{\text{lim}} \\ & 0 \ \leq P_{\text{car,t}} \leq P_{\text{i,max}} \\ & E_{\text{i,req.}} \leq E_{\text{car}} \end{aligned} \tag{3.12}$$

Based on the amount of capacity and total traveling time, algorithm is calculating optimum car speed considering also speed limit of the roads. Fig. 3.7 show if vehicle has 5 kwh battery capacity and final destination is 1 hour away. The first half of road has 55 mph speed limit and second half has 85 mph speed limit. Fig. 3.8 demonstrate power consumption of travel.

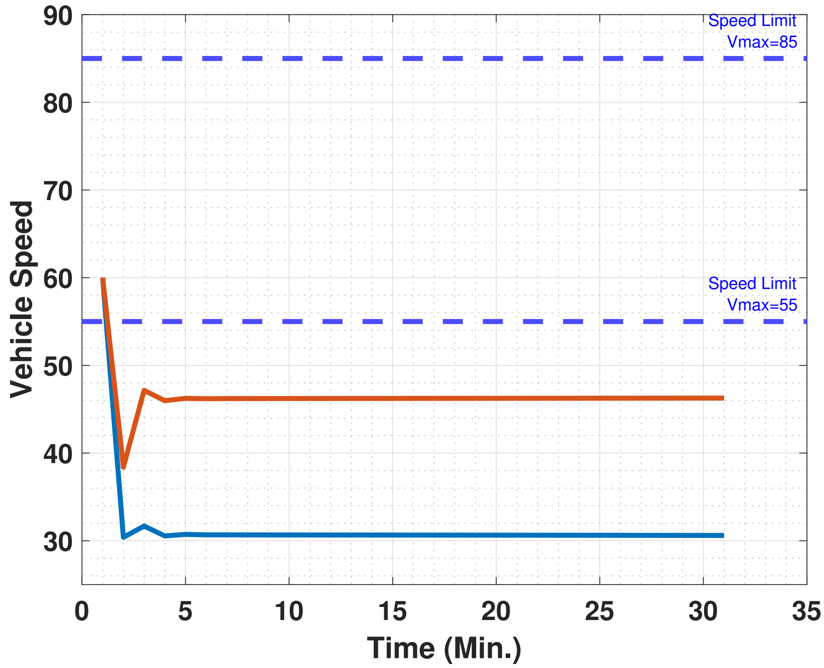


Fig. 3.7: Vehicle speed.

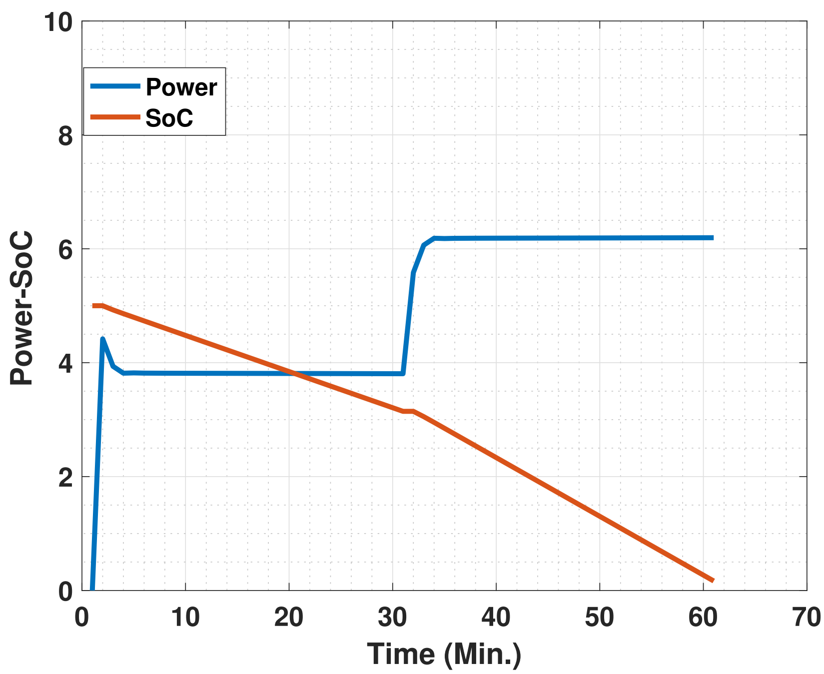


Fig. 3.8: Power demand of vehicle.

If vehicle has 10 kwh battery capacity and final destination is 1 hour away then we obtain Fig. 3.9. This time vehicle speed is fluctuating within speed limits. Fig. 3.10 demonstrate power consumption of travel.

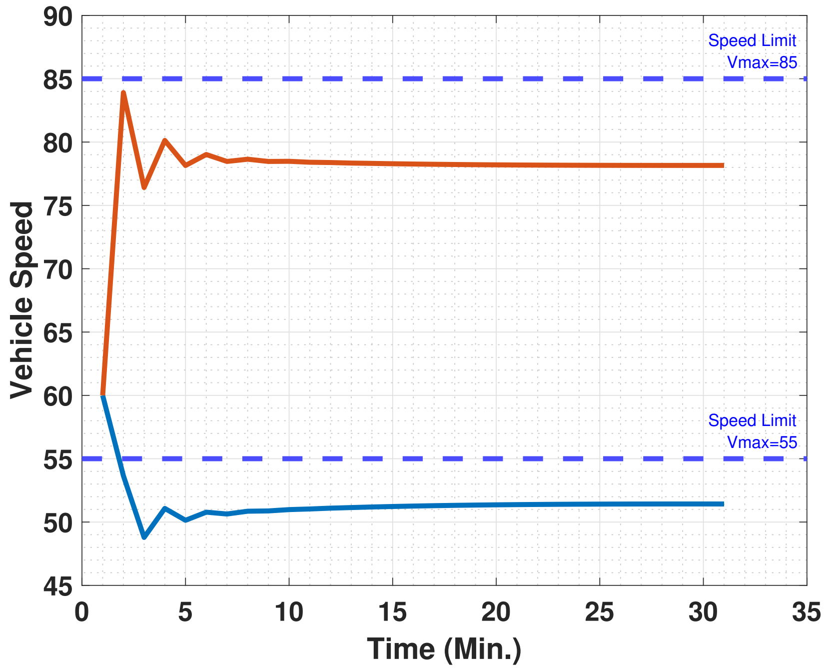


Fig. 3.9: Vehicle speed.

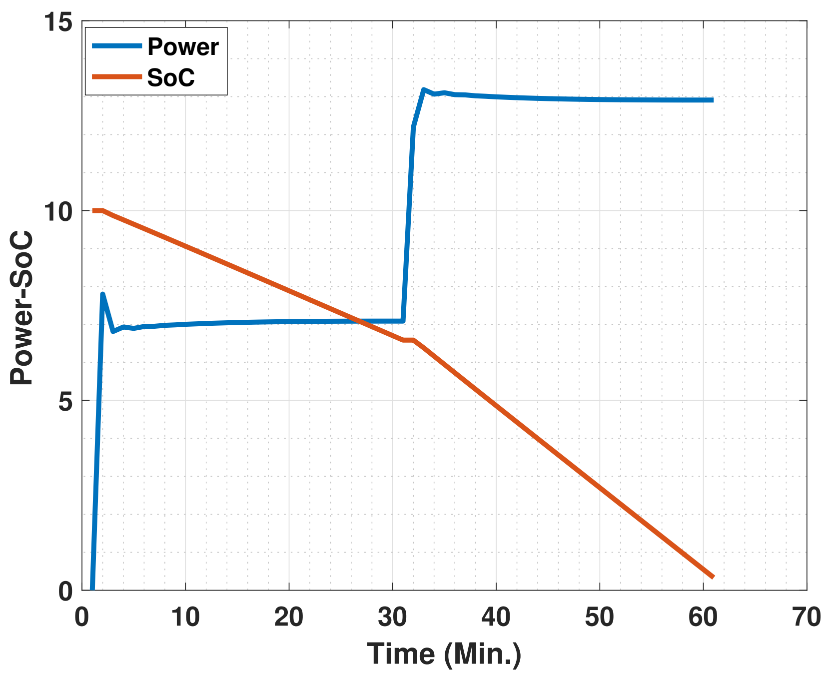


Fig. 3.10: Power demand of vehicle.

3.6 Chapter Summary

In this study, we introduce a hybrid routing algorithm that considers traffic while seeking the most convenient charging locations for a specific car. There is evidence that congestion influences the efficiency of route planning. We can save much time every day with even a modest fleet of electric vehicles. Also, we take one more step to optimize vehicle speed in order to reach the destination with a remaining battery to decrease range anxiety. Because of its scalability, the technique may be used for more intricate and extensive routing problems.

CHAPTER 4: MANAGEMENT OF ELECTRIC VEHICLES CHARGING CONSIDERING CHARGING STATION AVAILABILITY

4.1 Chapter Introduction

In this section, we investigate the potential for a centralized charging algorithm to alleviate congestion in charging electric cars both in real-time and through advanced scheduling. In the study, individual electric vehicles are not considered; rather, a central aggregator collects data on the charging of all vehicles from buses. This data is then used to lower bus demand by managing EV fleet distribution. Instead of focusing primarily on lowering the costs associated with each vehicle, the centralized charging algorithm is designed to cut total fleet operating expenditures. The system can offer an accurate forecast as long as it is aware of the travel pattern and duration of stay for the whole day. We design an algorithm that calculates the optimal number of electric vehicles connected to the power grid by finding the maximum number of people each bus is permitted to transport. This allows us to determine the optimal number of electric cars connected to the grid. The main contributions of this chapter are

- Transformation of the global optimization problem into a distributed optimization problem.
- A smart management algorithm is proposed with different approaches.
- The devised approach takes into account both the grid side and the demand side.
- The approach that has been suggested can determine the best strategy to maintain the grid's equilibrium.

4.2 Background of Optimal Power Flow

The solution to the optimal power flow (OPF) problem is foundational to many power system operations and strategies. It is designed to optimize some statistics while following particular guidelines for how power should flow and how the system should be run. For the most part, the OPF problem is a non-convex one with a high degree of difficulty. By recasting the OPF problem as a convex optimization problem, the power network topology has recently been studied to optimize system operations. The ACOPF is at the center of the power markets that are managed by the Independent System Operator (ISO), and it is solved in some form every year for system planning, daily for day-ahead markets, on an hourly basis, and even every five minutes. It was initially developed in 1962, and there have not been many significant changes to the formulas since then. Because of advancements in both computing power and solution algorithms, we are now able to model a greater number of the limitations and do away with the superfluous restrictions and approximations that were previously essential to locate a solution in a fair amount of time. One example is the modeling of nonlinear voltage magnitude restrictions as linear thermal proxy constraints.

4.2.1 Formulation of Power Flow

When circumstances are in a steady state, the power flow is what is utilized to determine the magnitude and phase angle of the voltage at each bus in a power system. This is done using the system. In addition, the active (P) and reactive (Q) power flows of the whole network of power lines and buses are simultaneously estimated. Pk, which stands for net injected active power, Qk, which stands for net injected reactive power, Vk, which stands for bus voltage, and k, which stands for bus phase, are the four variables that are utilized in the computation of power flow at each bus (bus phase angle). Calculations of power flow allow for the derivation of the remaining two variables from the first two. Slack bus, represented by the symbol Vk, is equal to 1 pu, whereas slack bus, designated by the symbol k, is equal to 0. Given this, we need to locate Pk and Qk as soon as possible. Pk and Vk are used as a starting point to determine Qk and k in order to address the problem of power flow in PV buses. Since the Pk and Qk of the PQ buses are already known, the power flow computation also includes the calculation of the Vk and k values for each and every PQ bus. Equation (4.1) is what is used when one is generating the nodal equations for a power system network. YBus is the admittance matrix of the power grid, and I and V are N 1 vectors of current and voltage at the bus terminals. The net complex power that is injected into bus k is displayed by the equation (4.2), where Ik is the conjugate of the vector that represents the injected current at the kth bus.

$$\begin{gathered}\mathcal{I} = Y_{Bus}\mathcal{V} \\ P_k + jQ_k = V_k I_k^* \\ P_k = P_{G_k} - P_{L_k}, Q_k = Q_{G_k} - Q_{L_k}\end{gathered} \tag{4.1}$$

Equation (4.2) is another version of the nodal equations based on YBus components.

$$I_k = \sum_{n=1}^{N} Y_{kn} V_n \tag{4.2}$$

Equations and (3.6) are derived by substituting (3.2) in (3.4) and taking Vk = |Vk| k and Ykn = |Ykn| kn.

$$\begin{gathered}P_k + jQ_k = V_k \left[\sum_{n=1}^{N} Y_{kn} V_n\right]^*, \quad k = 1, 2, 3, \ldots \\ P_k + jQ_k = |V_k| \sum_{n=1}^{N} |Y_{kn}| \, |V_n| \, e^{j(\delta_k - \delta_n - \theta_{kn})}\end{gathered} \tag{4.3}$$

Active and reactive power balancing may be obtained in equation (4.3) as the real and imaginary portions, where Gkn and Bkn are the real and imaginary parts of YBus matrix components, i.e., Ykn = Gkn + jBkn.

$$
\begin{aligned}
P_k &= |V_k| \sum_{n=1}^{N} |V_n| \left[G_{kn} \cos(\delta_k - \delta_n) + B_{kn} \sin(\delta_k - \delta_n)\right] \\
Q_k &= |V_k| \sum_{n=1}^{N} |V_n| \left[G_{kn} \sin(\delta_k - \delta_n) - B_{kn} \cos(\delta_k - \delta_n)\right]
\end{aligned}
\tag{4.4}
$$

Furthermore, the power flows transferred by a line between buses k and n are computed by (4.4), where gkn and bkn are the conductance and susceptance of the power line, measured in Siemens, respectively.

$$
\begin{aligned}
P_{kn} &= |V_k|^2 g_{kn} - |V_k| |V_n| g_{kn} \cos(\delta_k - \delta_n) - |V_k| |V_n| b_{kn} \sin(\delta_k - \delta_n) \\
Q_{kn} &= -|V_k|^2 (b_{kn} + b_k) - |V_k| |V_n| g_{kn} \sin(\delta_k - \delta_n) + |V_k| |V_n| b_{kn} \cos(\delta_k - \delta_n)
\end{aligned}
\tag{4.5}
$$

4.2.2 Proposed Formulation of Power Flow for Central Control Managing EVs Charging

Due to the EVs' inter-temporal restrictions, solving multi-period power flow across a constrained horizon is essential when considering power flow with the distribution system and electric cars. Due to the nonlinearity of the power balancing equations, worldwide optimum solutions for AC power flow cannot be guaranteed. In order to include EVs in a distribution network while taking into account the limits imposed by charging EVs, we employ the matpower power flow algorithm. Imagine a power grid like the one in Fig.4.1. This system's power-balance equation is given by:

$$
\begin{aligned}
Pg_j(t) - Pd_j(t) = Pagg_j(t) + \sum_{k:j\longrightarrow k} P_{jk}(t) - \sum_{i:i\longrightarrow j} \\
(P_{ij}(t) - r_{ij} l_{ij}(t)))
\end{aligned}
\tag{4.6}
$$

$$
Qg_j(t) - Qd_j(t) = \sum_{k:j\longrightarrow k} Q_{jk}(t) - \sum_{i:i\longrightarrow j} (Q_{ij}(t) - x_{ij} l_{ij}(t))
\tag{4.7}
$$

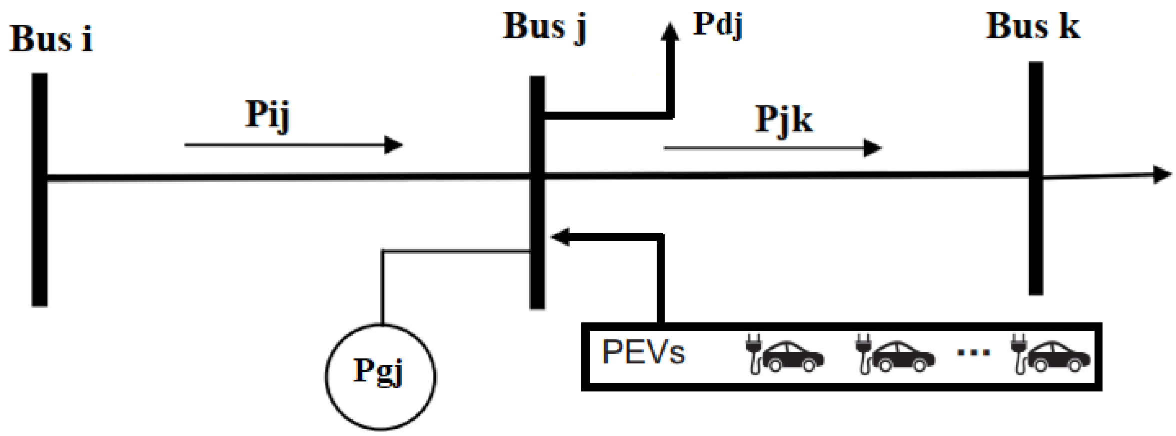


Fig. 4.1: Including PEVs in a branch flow model.

The charging capacity of the aggregator linked to bus j at time t is denoted here by $Pagg_j(t)$. Both $u_j(t)$ and $l_ij(t)$ represent the square of the magnitude of the current flowing from bus i to bus j during a certain time interval. It is possible to calculate the maximum allowable voltage and current flow by

$$u_i^{min} \leq u_i(t) \leq u_i^{max} \tag{4.8}$$

$$l_{ij}^{min} \leq l_{ij}(t) \leq l_{ij}^{max} \tag{4.9}$$

The aggregator acts as a bridge between the distribution system operator (DSO) and the electric vehicles (EVs) to facilitate smart charging of the EVs. The aggregator is provided with information about the EVs' current states, including their level of charge, the time of arrival and departure, and the number of available batteries. All electric vehicles' charging capacities add up to the aggregator's power, j.

$$Pagg_j(t) = \sum_{n=1}^{M_j} Pv_{j,n}(t) \tag{4.10}$$

where Mj is the number of electric vehicles that are under the aggregator's control and linked to the bus, and where PVj, n is the charging power for those vehicles.

4.3 Objective Functions

For electric car and grid system integration to go well, an objective model is established.

- Power Dispatch

Every day's worth of power supply must be met by charging the same amount (i.e., 24 hours).

- Minimum Energy Loss

In order to ensure stability, the grid has a maximum capacity. The peak demand for electricity on the grid rises in tandem with charging activities, which means that widespread adoption of electric vehicles will place a strain on the infrastructure. As a result, it's important to control energy consumption within a range. The sum of all energy lost may be expressed by the formula

$$E_{loss} = E_{sub} - E_{load} - E_{EV} \tag{4.11}$$

where E_sub denotes the total amount of energy pulled from the substation, E_load denotes basic loads other than PEVs, and E_EV denotes the total amount of energy drawn from the PEVs.

$$f_{obj} = \textstyle\sum_{t \in T} P_0(t)\Delta t \tag{4.12}$$

The goal of optimization is to find the time period Δt for which the total amount of energy extracted from the substation is minimized.

- Minimum Voltage Deviation

$$\min f_{volt} = \frac{1}{N_T} \sum_{t=1}^{N_T} \left[\frac{1}{N_{bus}} \sum_{i=1}^{N_N} \Delta V_i(t) \right] \tag{4.13}$$

Bus n's voltage deviation at time t is denoted by $\Delta V_{\mathrm{i}}(t)$; N_{bus} is the total number of buses. We consider keeping the voltage within $\pm 10\%$ of the nominal value.

- Minimum Power Loss

$$\min f_{loss} = \frac{1}{N_T} \sum_{t=1}^{N_t} [R_{loss}(t)] \tag{4.14}$$

In this case, the ratio of power loss at time t is represented as Rt.

- Charging Space

In order to minimize overall waiting time, the number of cars should not exceed the capacity of charging space.

$$0 \leq N_{\text{car}} \leq N_{\text{max-capacity}} \tag{4.15}$$

- Power Output

The power output of the charger must be within a certain range.

$$P_{\text{out,min}} < P_{\text{g2v}}(t) < P_{\text{out,max}} \tag{4.16}$$

- Charging Time

The time spent charging should not exceed the scheduled departure time.

$$t \in (T_a \sim T_d) \tag{4.17}$$

Ta/Td means you'll be arriving/leaving at that specific time.

4.4 Power Flow in Matpower

Within this part, we will discuss how matpower deals with the flow of electricity. The various sub-functions of the algorithm are going to be dissected one at a time. In spite of the many iterative solutions that are readily available in matpower, the NR approach is the one that is being evaluated in this thesis. The major areas of interest in matpower's technique will be the function of the admittance matrix, the function that creates the vector of complex bus power injections, and the Newton-Raphson solver. In order to begin the iterative process of comparing the mismatch power injections of the network, the AC Power Flow function (also known as "runpf.m") included inside matpower is responsible for carrying out the actions described above. When matpower is being used, just one generator is chosen to be used for the reference bus; this generator serves not only as the actual power slack reference but also as the angle reference. We have specified "V" and "P" for the remaining generator buses, which indicates that those buses will be used as PV buses. Because the loads are also accounted for in the case data, any bus that does not contain a generator is designated as a PQ bus, and its P and Q information is shown in its entirety. After that, the voltage angles,, and the voltage magnitudes, |V|, are utilized to, respectively, define the real and reactive components of the power balancing equations. In addition to that, the continuous injections into the generator are considered to be read.

4.5 Case Studies and Results

Here, we present case studies based on the IEEE 123-bus test system; the details of this system are described in [127]. We propose and develop a unique and scalable approach for optimizing EV aggregators, as seen in Fig. 4.2. In Fig. 4.3, we present and build a unique approach that is both scalable and suggested for the optimization of electric vehicle aggregators. The analysis finds that, except for charging stations, the fixed loads used at each node in the 123 bus system do not vary over time. A 10 kilowatt maximum for the charger's output has been established. Total sample duration is 1440 minutes, with a time interval of 1 minute defined by Δt.

4.5.1 Case 1-Charging stations are connected single bus

In this case, all charging stations are connected to the same bus, which is bus 21. The electric vehicle (EV) data aggregator is now cataloging the locations of bus 21's charging facilities. The 123 bus system and aggregator connection are shown in Figure 4.3. The algorithm figures out the bus's maximum load. Daily bus load (MW) is depicted in Fig. 4.4,

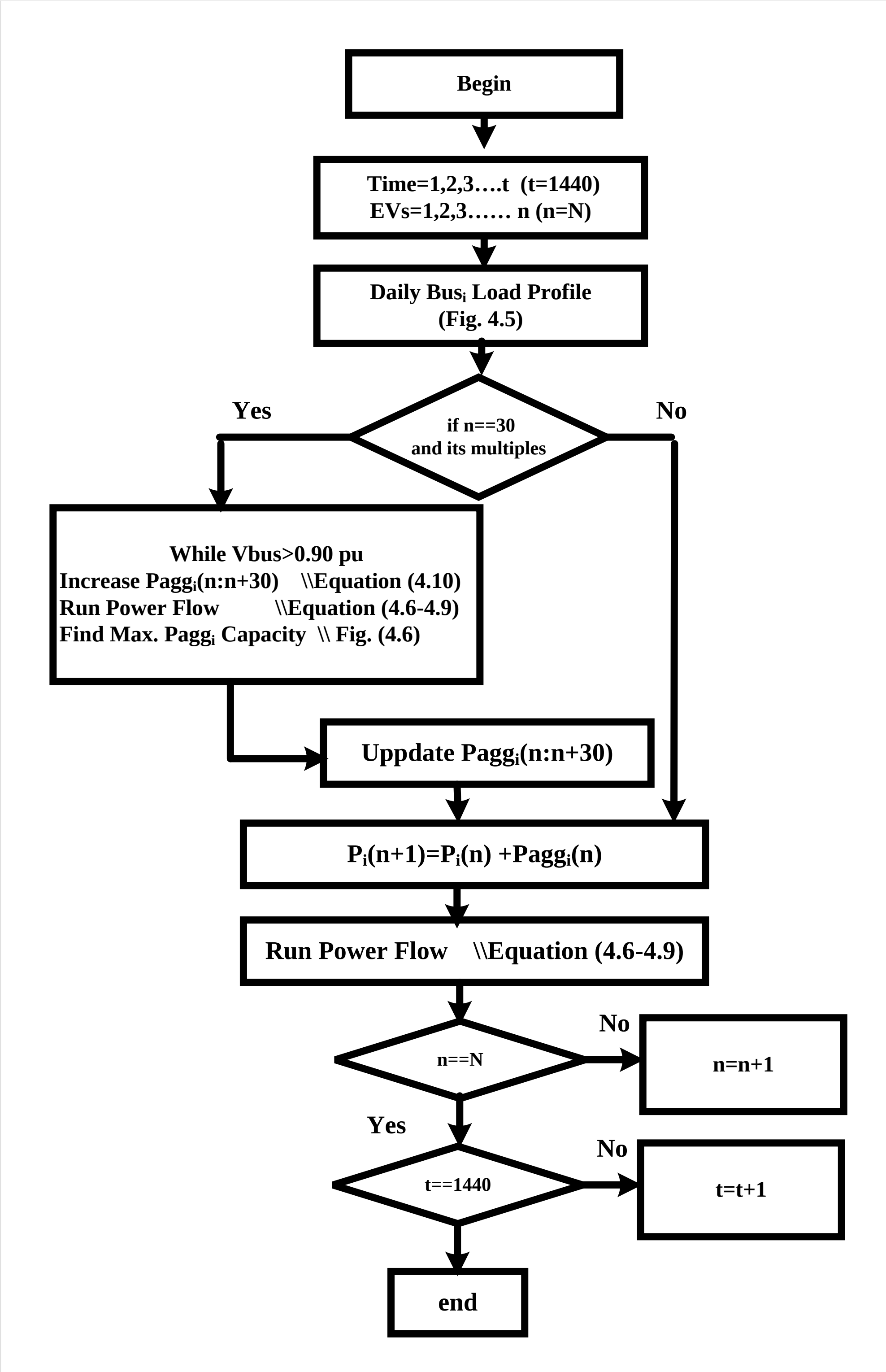


Fig. 4.2: Flow chart of EV capacity calculation.

and the maximum load profile is depicted in Fig. 4.5, both of which result from iterative calculations. The algorithm increases bus power daily until bus voltages drop below the threshold. The bus voltage is being monitored at each repetition to ensure it does not drop below the 0.9 pu threshold (Fig 4.9). We decide the maximum number of cars that can be charged simultaneously depending on the number of bus places currently available (Fig. 4.10). The maximum number of electric vehicles that may be charged at once, as well as the bus voltage and power demand, are all factors that the algorithm takes into account. For example, Fig. 4.4 depicts 123 bus voltage with only daily load power, while Fig. 4.5 depicts 123 bus voltage with maximum bus power.

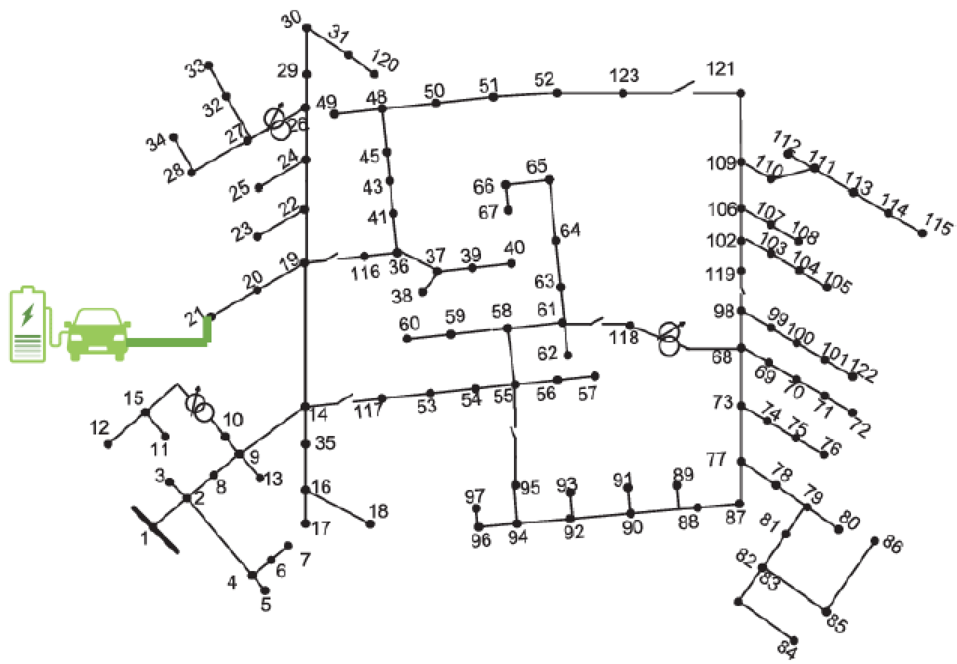


Fig. 4.3: 123 bus IEEE test system with a single aggregator.

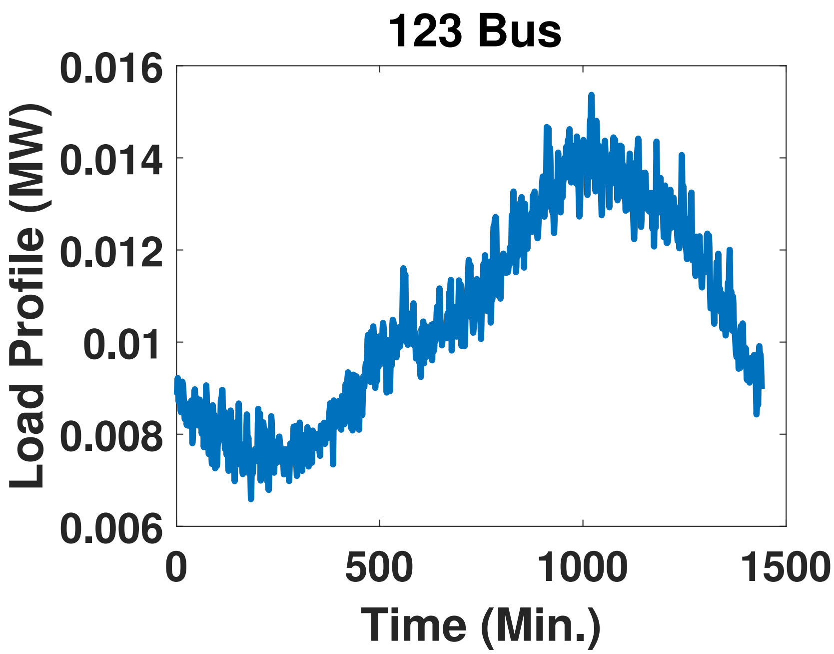


Fig. 4.4: Single bus load profile.

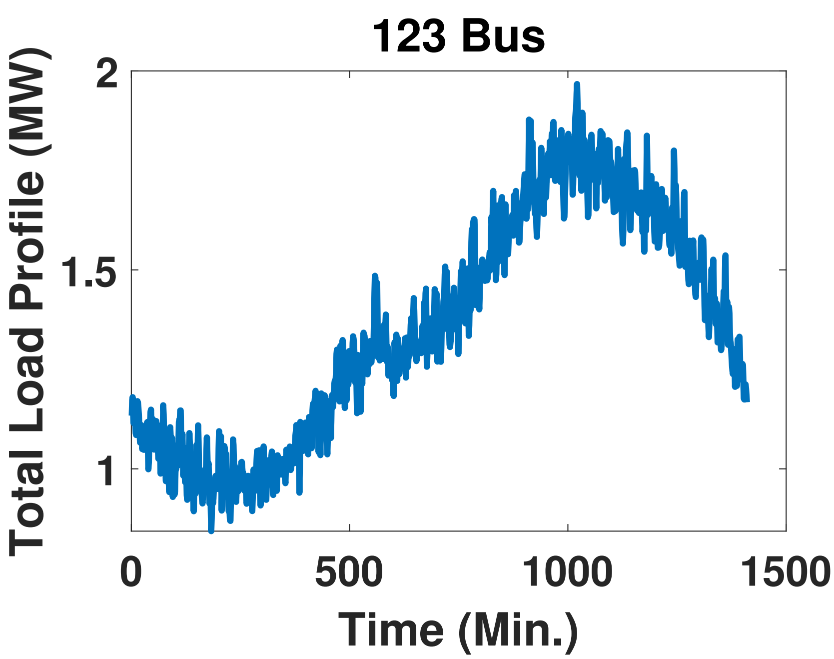


Fig. 4.5: Total load profile.

The daily load profile of all but bus 21 (seen in Fig. 4.4) of the 123 buses is shown. Figure 4.5 demonstrate total load profile of 123 bus system.

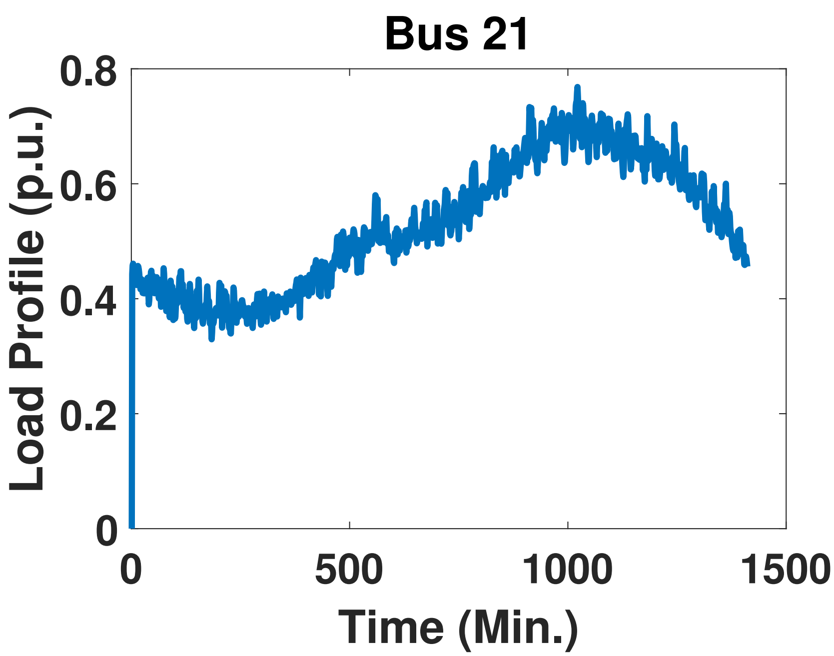


Fig. 4.6: Bus 21 load profile.

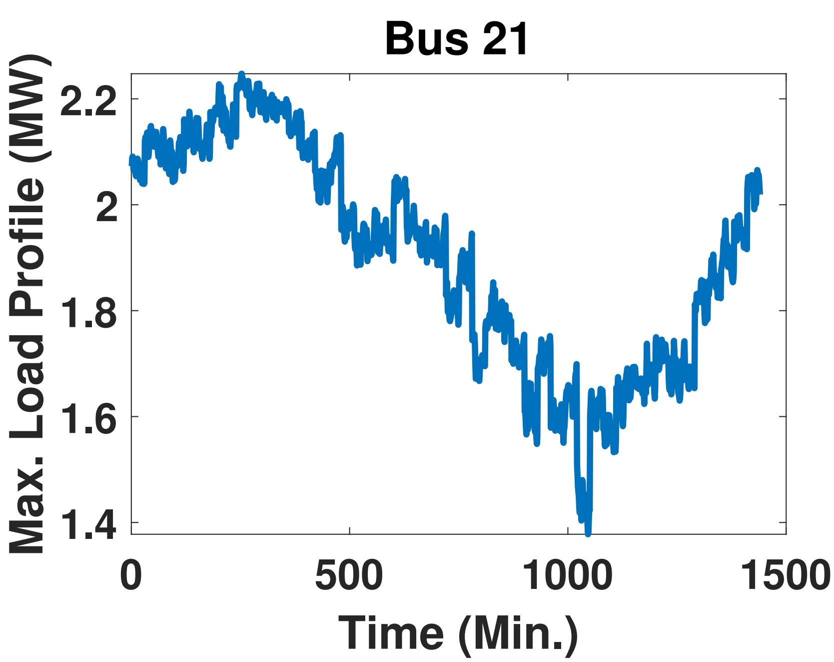


Fig. 4.7: Bus 21 maximum load profile.

Figure 4.6 depicts the daily load profile of bus 21, and Figure 4.7 depicts the maximum load profile, both of which are calculated using an iterative technique.

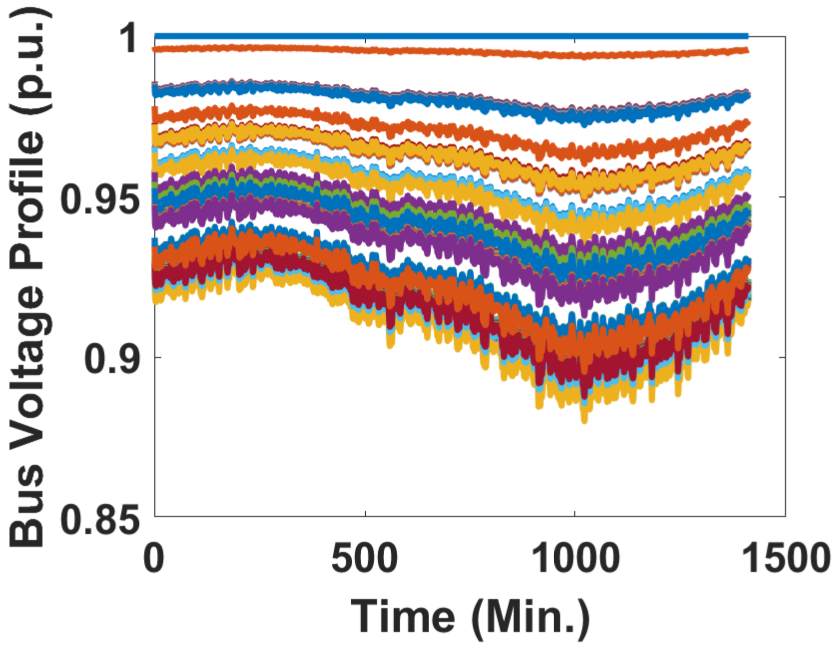


Fig. 4.8: 123 bus voltage profile with nominal load.

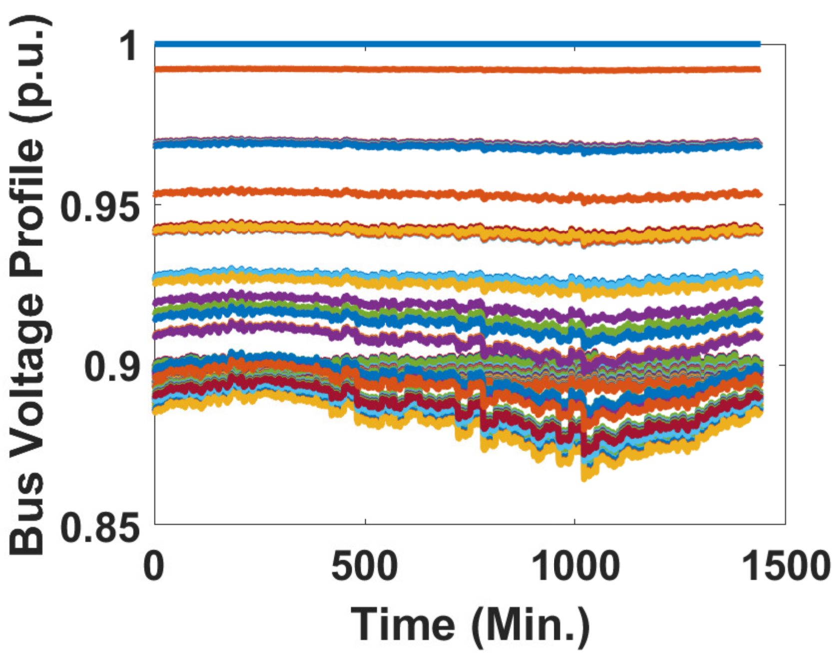


Fig. 4.9: 123 bus voltage profile with maximum load.

Fig. 4.8 shows voltage profile of bus 123 bus system before iteration and 4.9 showing voltage profile with maximum demand of bus 21. In Fig. 4.10 we can see maximum capacity of electric vehicle number of bus 21.

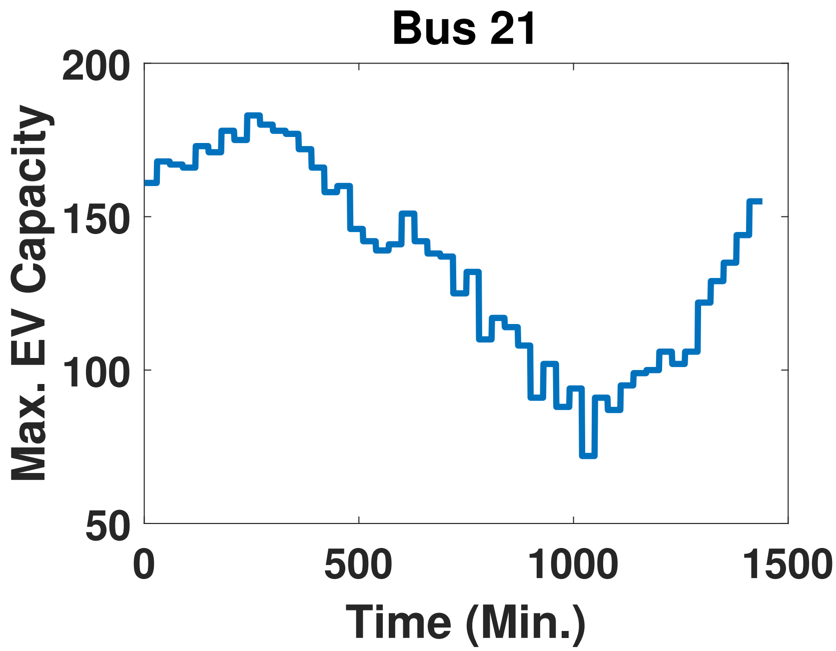


Fig. 4.10: EV capacity of bus 21

4.5.2 Case 2- Charging stations are connected three separate buses

Bus 11, Bus 21, and Bus 31 each have their aggregators. The program determines how many vehicles can fit into each bus. Iteratively estimated bus load profiles (in megawatts) for each day. Unless the bus voltages are below the minimum threshold, the iterative algorithm will raise the daily power of the bus. The bus voltage is monitored at each repetition to ensure it does not drop below 0.9 pu. We determine the maximum number of automobiles that each bus may charge simultaneously based on their individual capacities. The algorithm takes into consideration a variety of criteria, including the maximum number of electric cars that can be charged at the same time, the bus voltage, and the amount of electricity that is required. In Fig. 4.11 IEEE 123 Bus system and connected buses are represented.

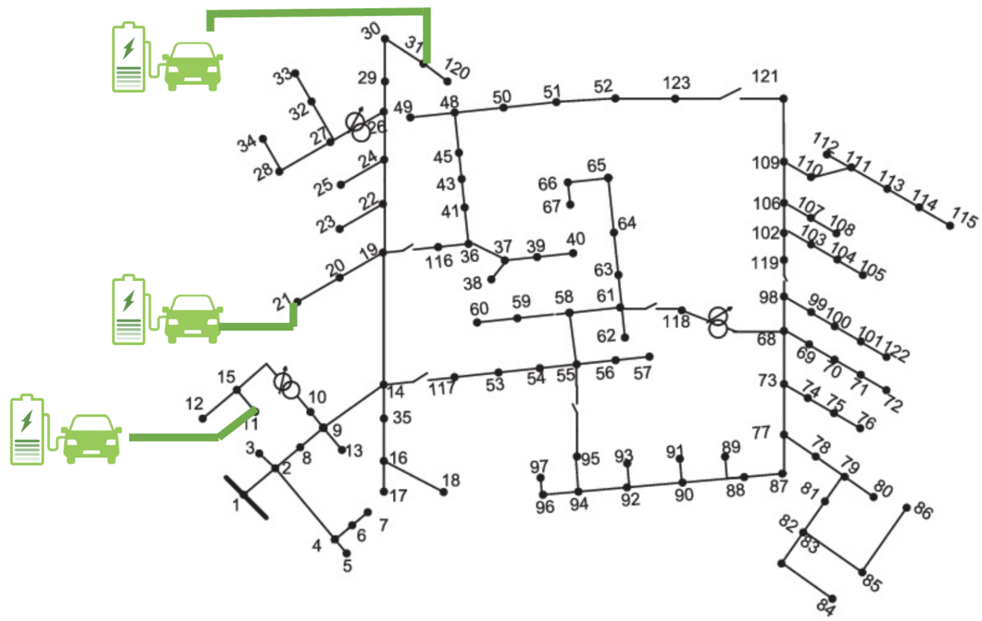


Fig. 4.11: Three aggregators for the 123 IEEE test system.

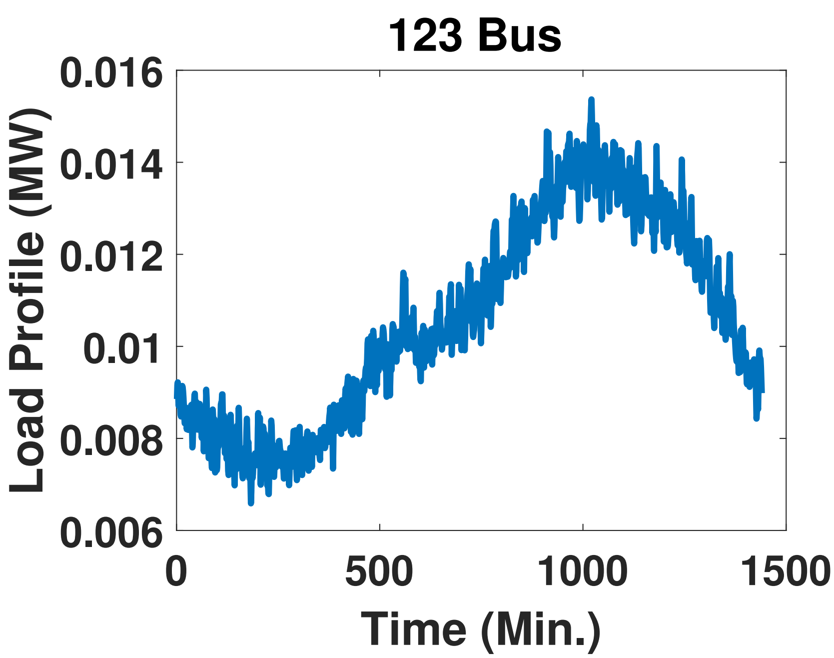


Fig. 4.12: Single bus load profile.

Daily load profiles for all of the buses in the 123 system, with the exception of routes 11, 21, and 31, are depicted in Fig. 4.12, while the whole system's load profiles are shown in Fig. 4.13.

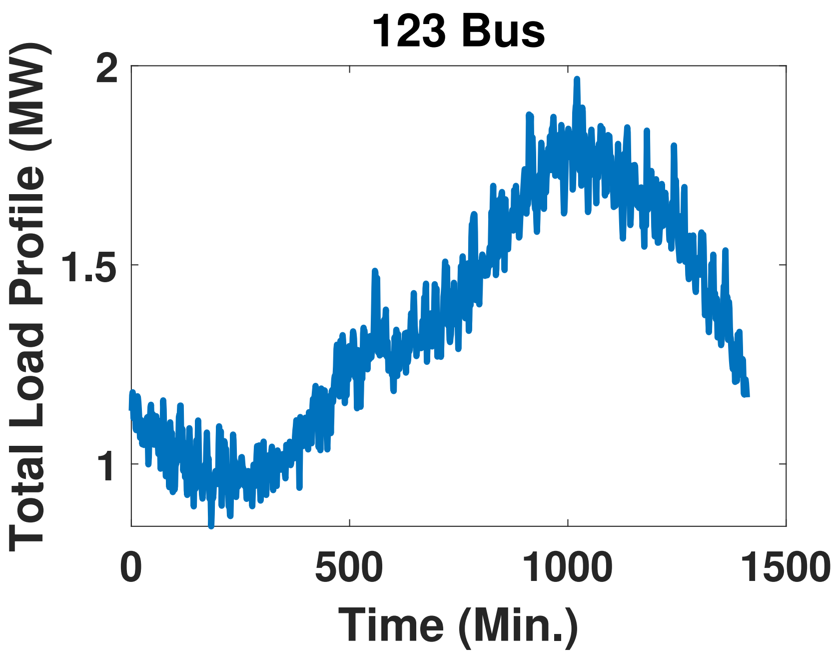


Fig. 4.13: Total load profile.

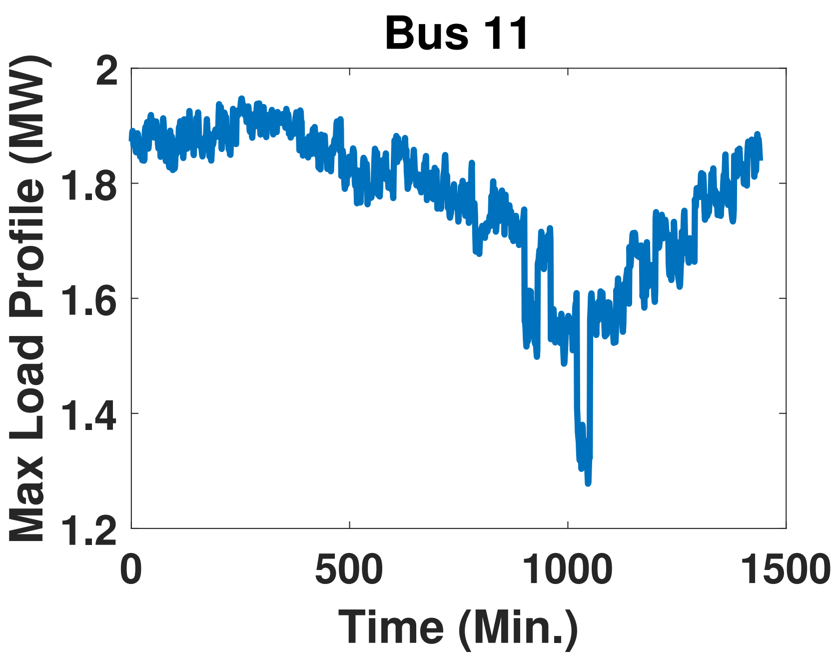


Fig. 4.14: Bus 11 maximum load profile.

In Fig. 4.14, we can see the bus 11 maximum load profile. The daily maximum number of EVs carried by Bus 11 is depicted in Fig. 4.15.

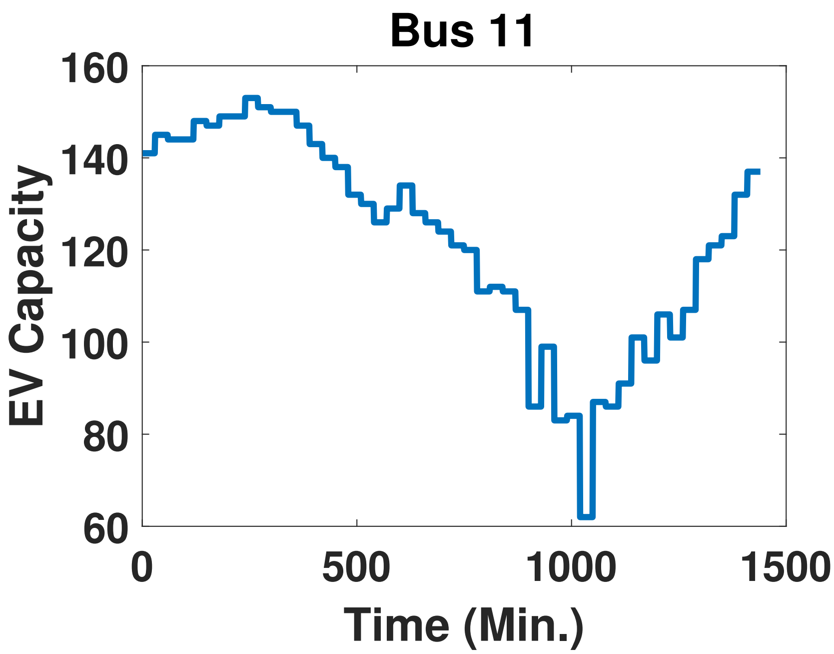


Fig. 4.15: Bus 11 EV capacity.

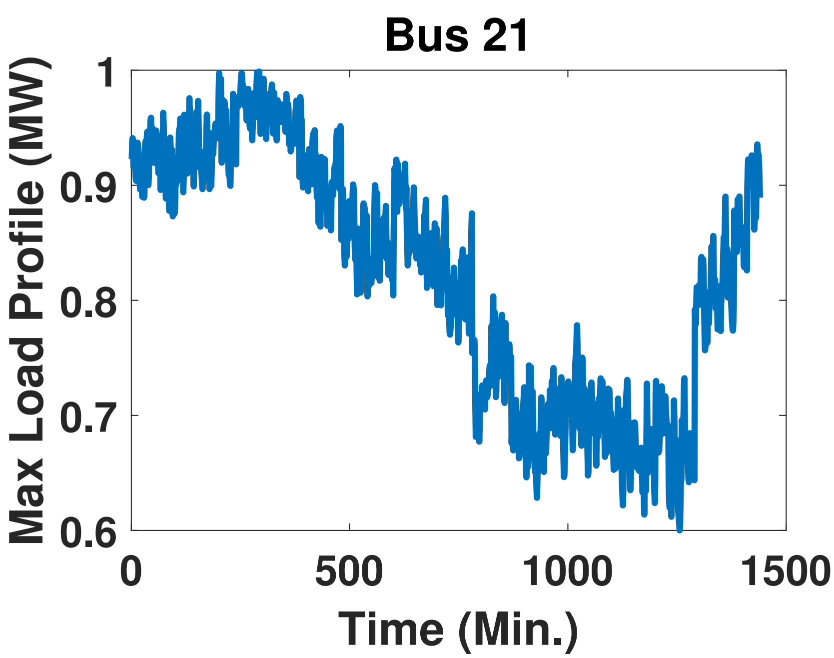


Fig. 4.16: Bus 21 Maximum load profile.

Fig. 4.16 depicts the bus 21's maximum load profile. Bus 21's daily maximum EV capacity is depicted in Fig. 4.17.

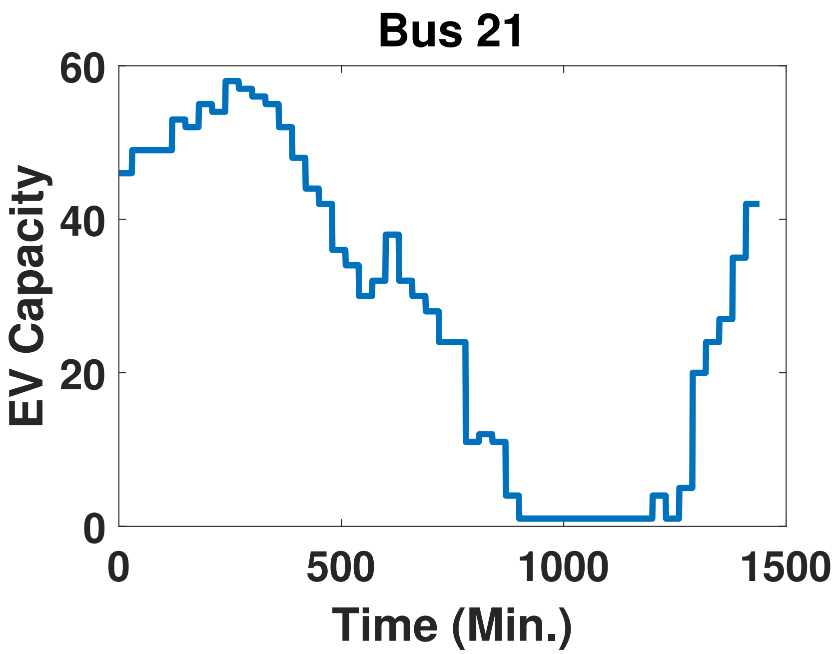


Fig. 4.17: Bus 21 EV capacity.

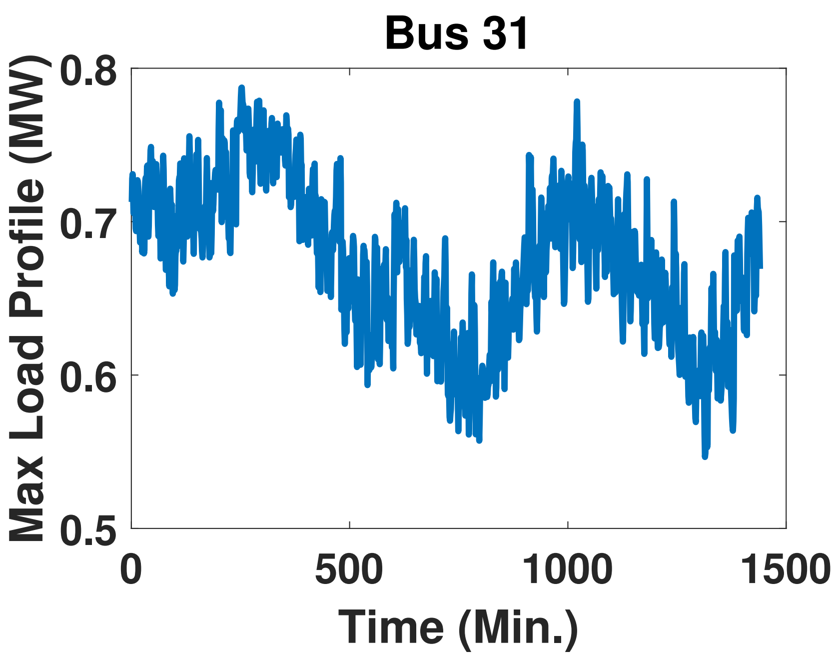


Fig. 4.18: Bus 31 maximum load profile.

You can see the bus 31's maximum load profile in Fig. 4.18. Daily EV capacity of bus 11 is depicted in Fig. 4.19.

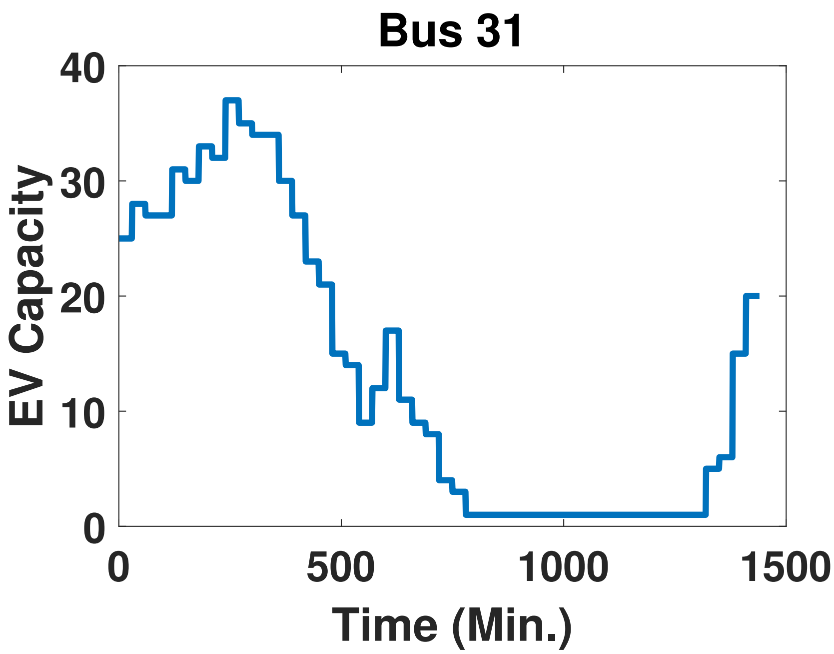


Fig. 4.19: Bus 31 EV capacity.

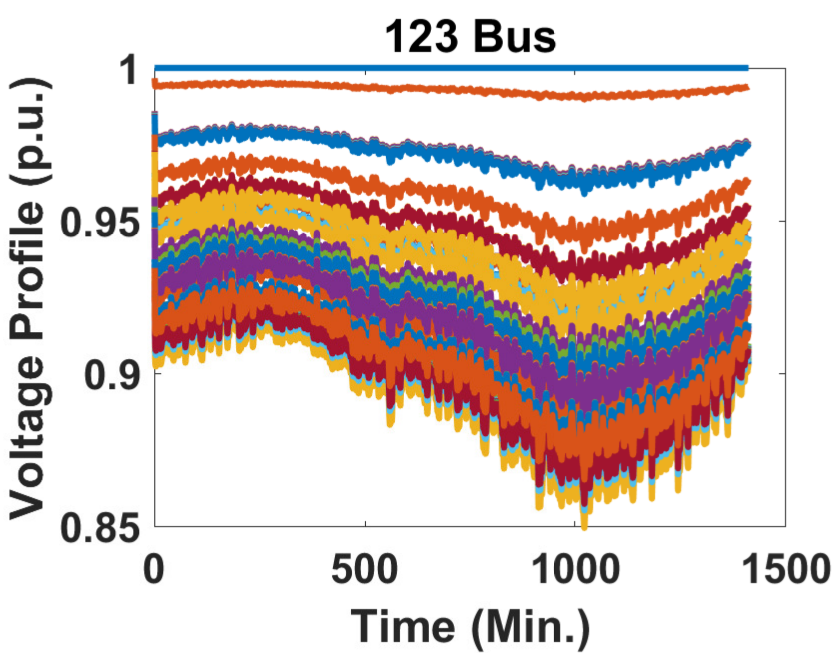


Fig. 4.20: 123 bus voltage profile with nominal load.

Fig. 4.20 depicts the voltage profile of the bus 123 system before iteration, and Fig. 4.21 depicts the voltage profile during peak demand on buses 11, 21, and 31.

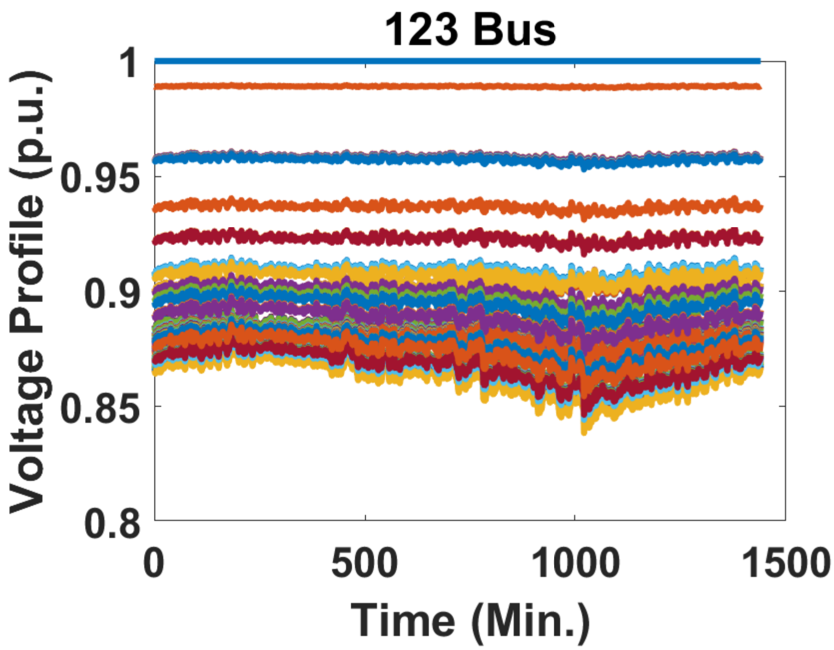


Fig. 4.21: 123 bus voltage profile with maximum load.

4.5.3 Case 3 - Vehicle Distribution Control

Assuming each bus has a one-to-three connection, and using the charging points depicted in Fig. 4.22 as an example. The distribution method only takes into account the streets that are bright yellow. Graph theory is used in the production of a matrix.

We established nearly similar charging power requirements for each bus after determining their maximum vehicle capacity. Across the day, cars are scattered throughout the city, and without a command algorithm, 150 EVs will stop by each bus. The origin, final destination, and estimated time of departure for the vehicle are all assumed to be known. Before an EV takes off, a list of charging stations is sorted by their distance from the vehicle. While electric vehicles (EVs) are on their way to the nearest charging station, a distribution algorithm will determine whether or not the bus has room for any more passengers. If the bus is at capacity, the EV will have to move on to the next closest station and wait there until a spot opens

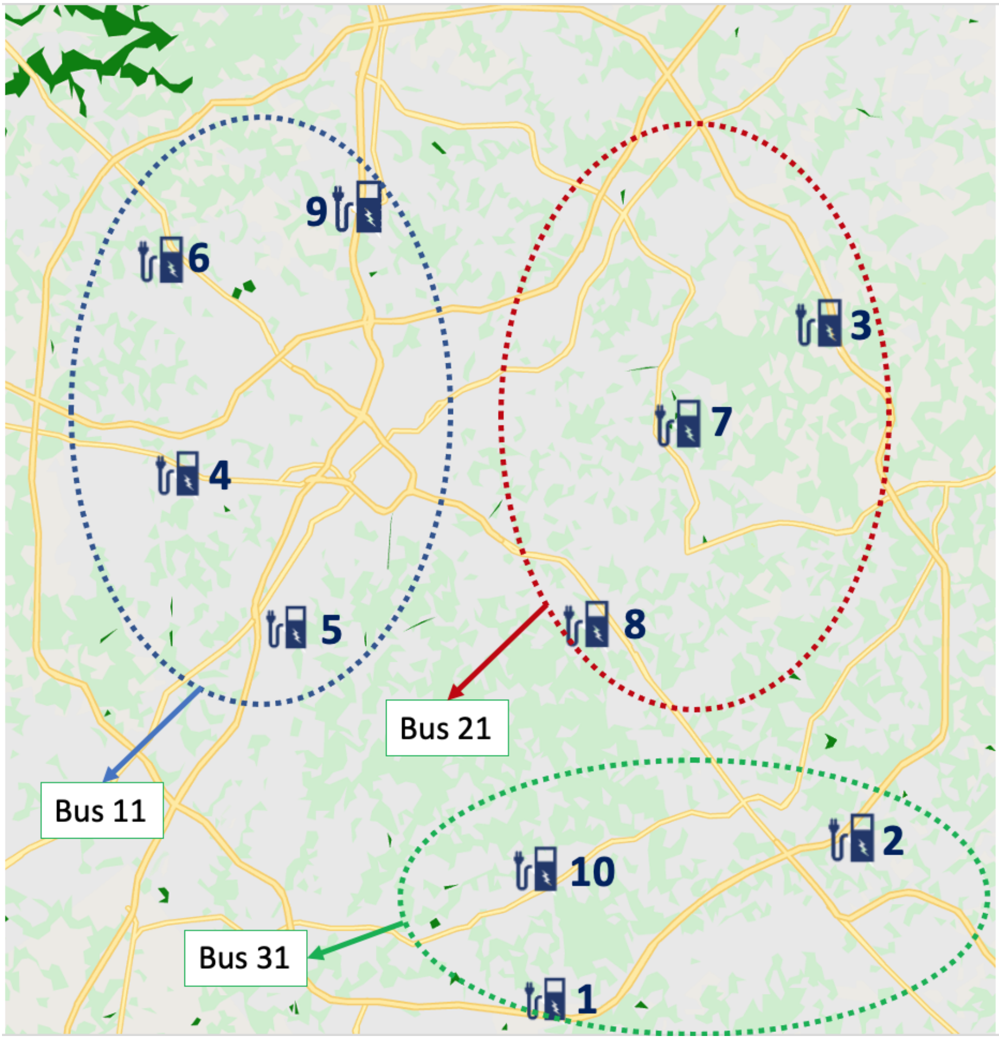


Fig. 4.22: Location of charging stations.

up. It's evident that the maximum bus capacity is not exceeded when a control method is used.

Following the execution of the rerouting algorithm, the final number of EVs with the control algorithm is displayed in Fig. 4.24.

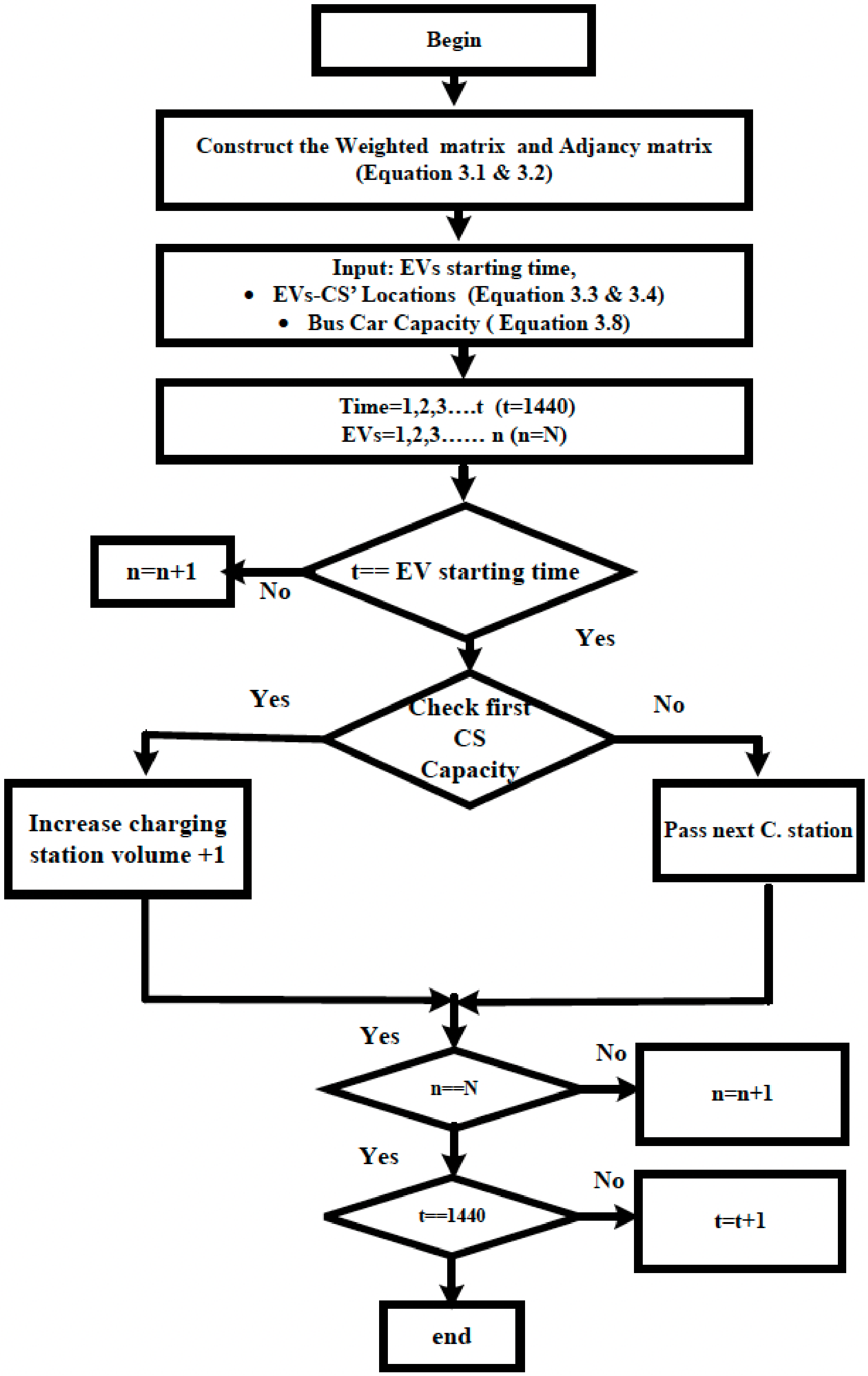


Fig. 4.23: Diagram of the car distribution application.

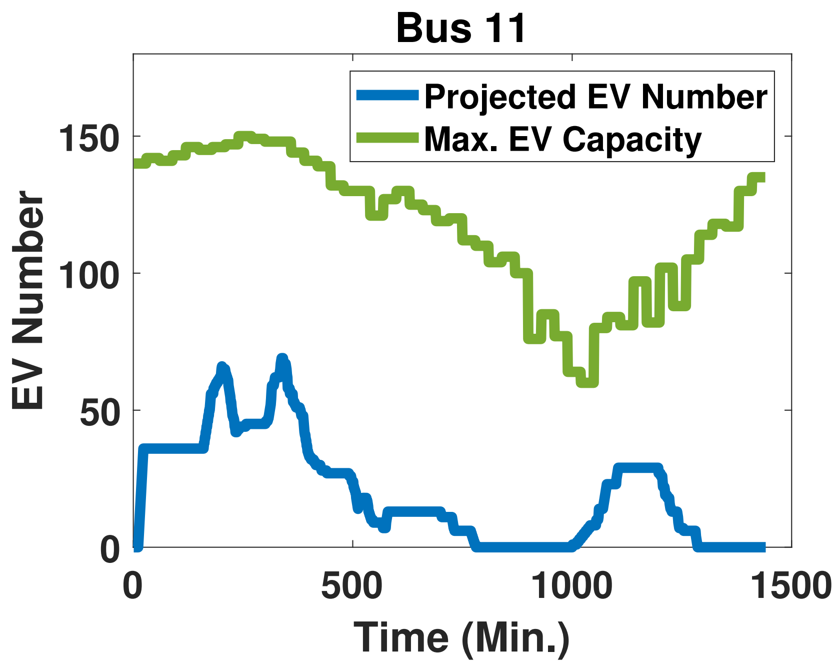


Fig. 4.24: Bus 11 car distribution before algorithm.

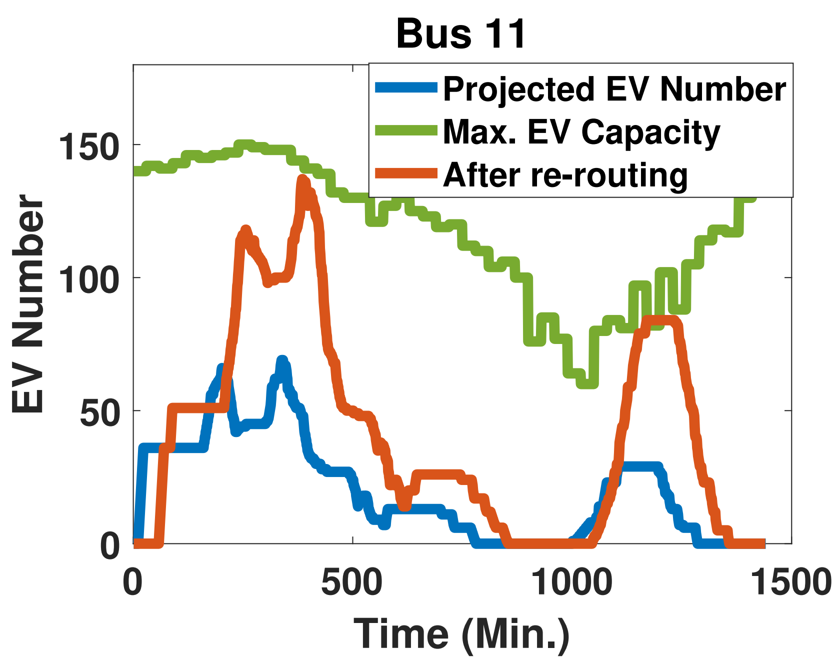


Fig. 4.25: Bus 11 car distribution after algorithm.

Fig. 4.24 and Fig. 4.25 displays the predicted number of EVs for a day and also the maximum EVs capacity of bus 11. The number 11 bus is the most powerful and can accommodate the most EVs. If there's no room on buses 21 and 31, an algorithm will guide the electric vehicles.

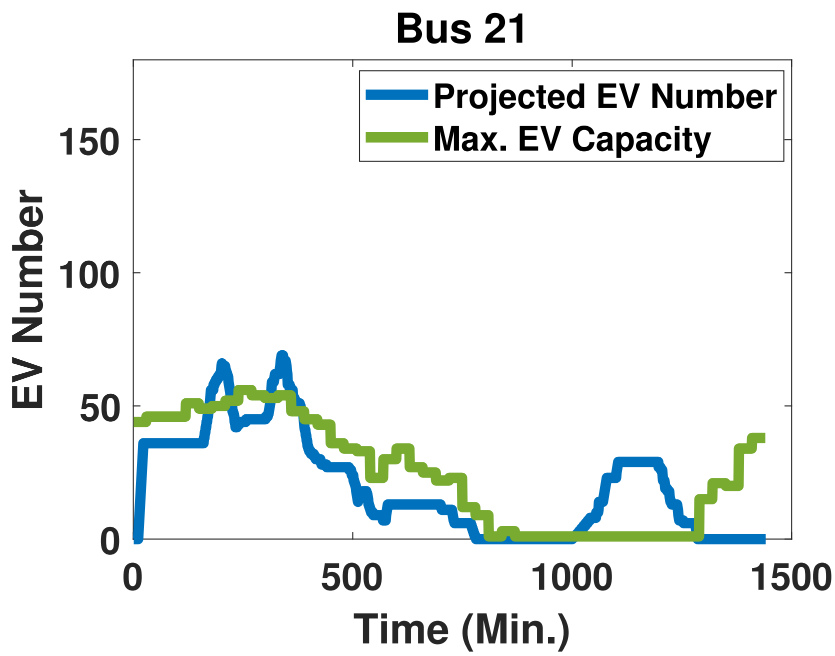


Fig. 4.26: Bus 21 car distribution before algorithm.

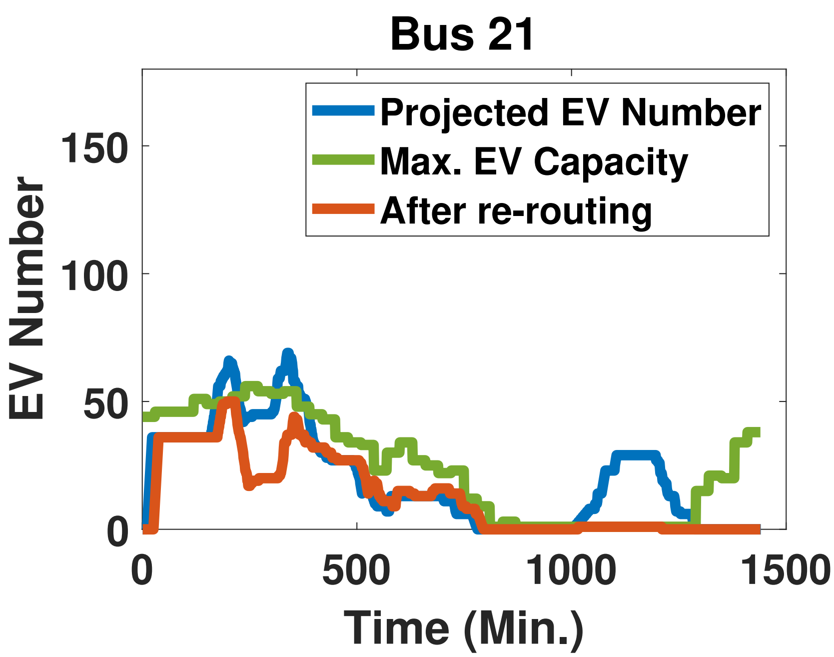


Fig. 4.27: Bus 21 car distribution after algorithm.

After performing the rerouting algorithm, the final number of EVs with the control method is displayed in Fig. 4.26. Fig. 4.27 displays the predicted number of EVs during a day and also the maximum EVs capacity of bus 21.

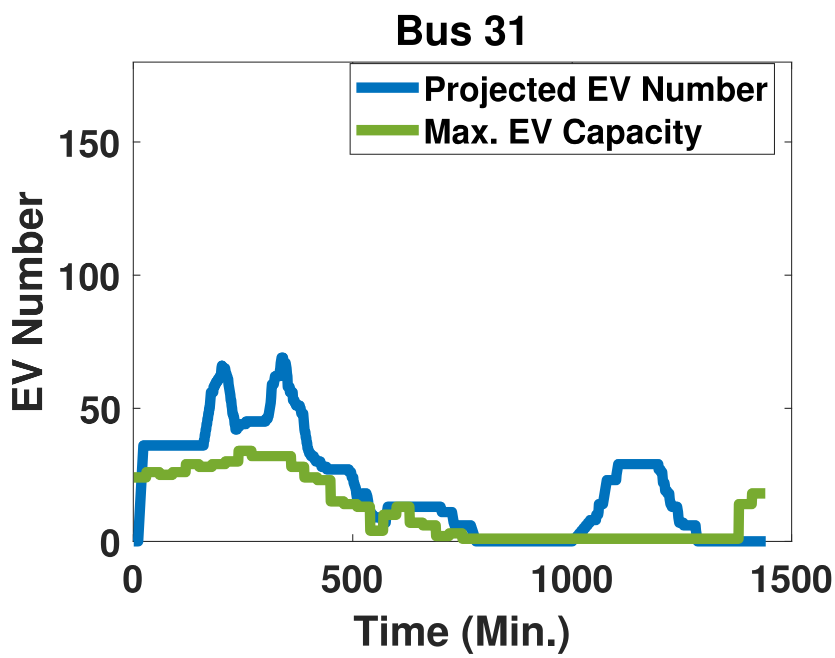


Fig. 4.28: Bus 31 car distribution before algorithm.

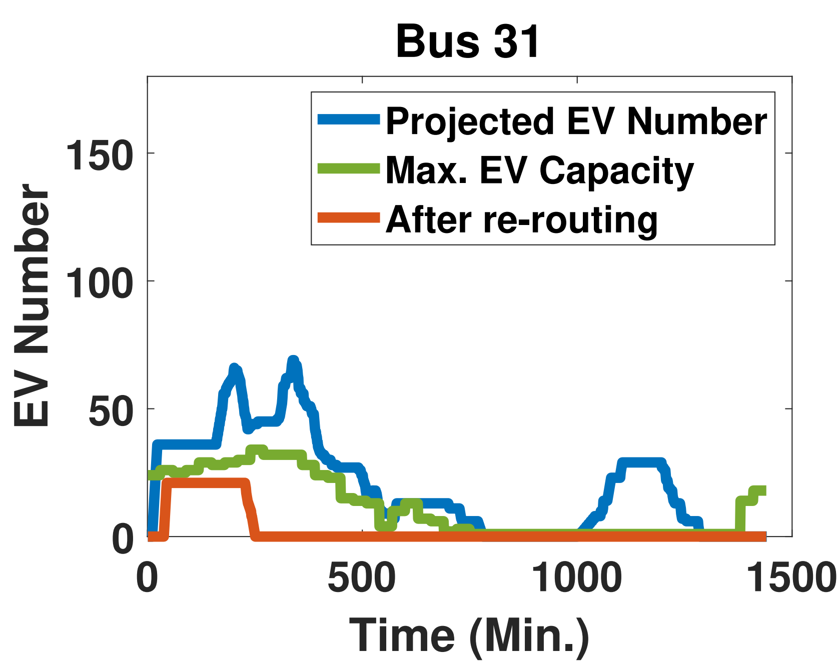


Fig. 4.29: Bus 31 car distribution after algorithm.

Following the execution of the rerouting algorithm, the final number of EVs with the control algorithm is displayed in Fig. 4.28. Fig. 4.29 displays the predicted number of EVs for a day and also the maximum EVs capacity of bus 31.

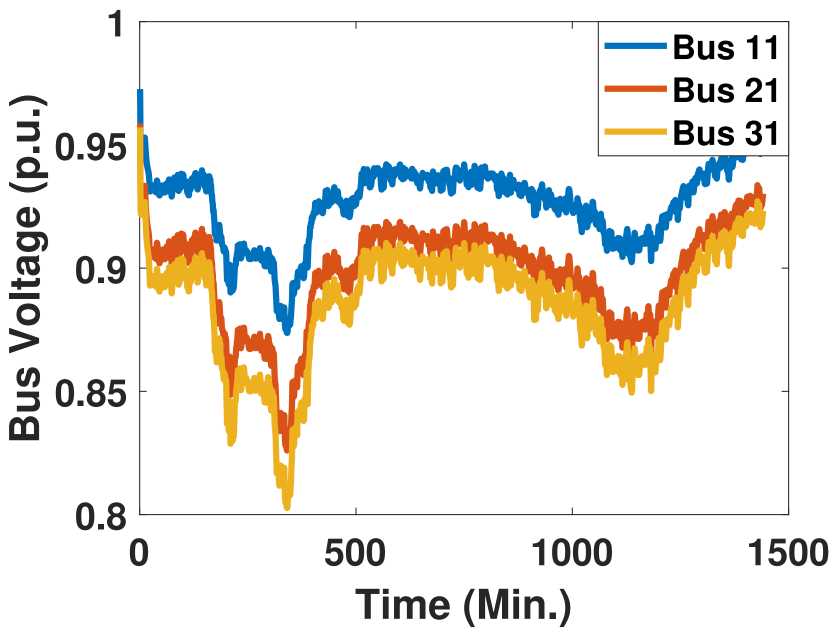


Fig. 4.30: Bus voltages before algorithm.

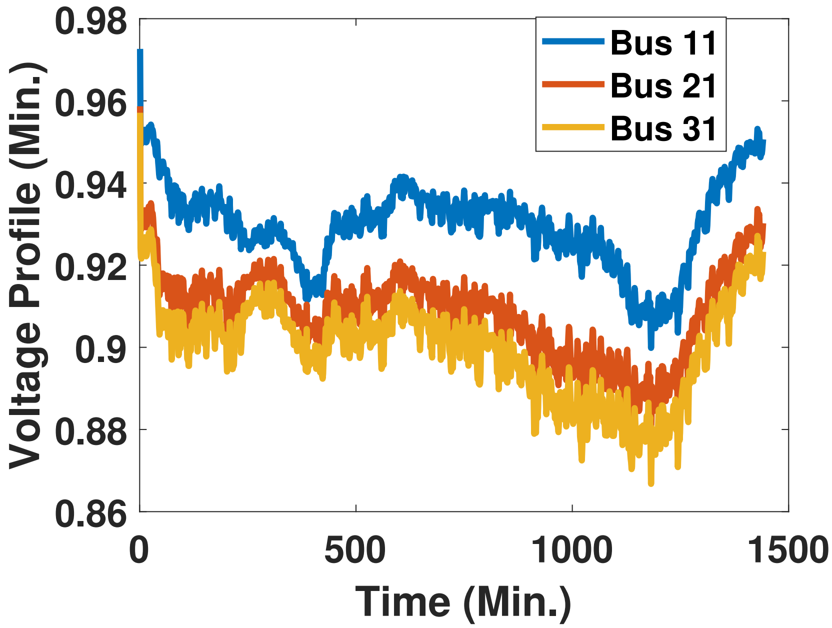


Fig. 4.31: Bus voltages after algorithm.

Fig. 4.30 shows voltage profile of 3 buses before routing algorithm and it can be seen that bus voltages is dropping around 0.8 p.u. After utilizing routing algorithm this voltage drop is avoiding in Fig. 4.31.

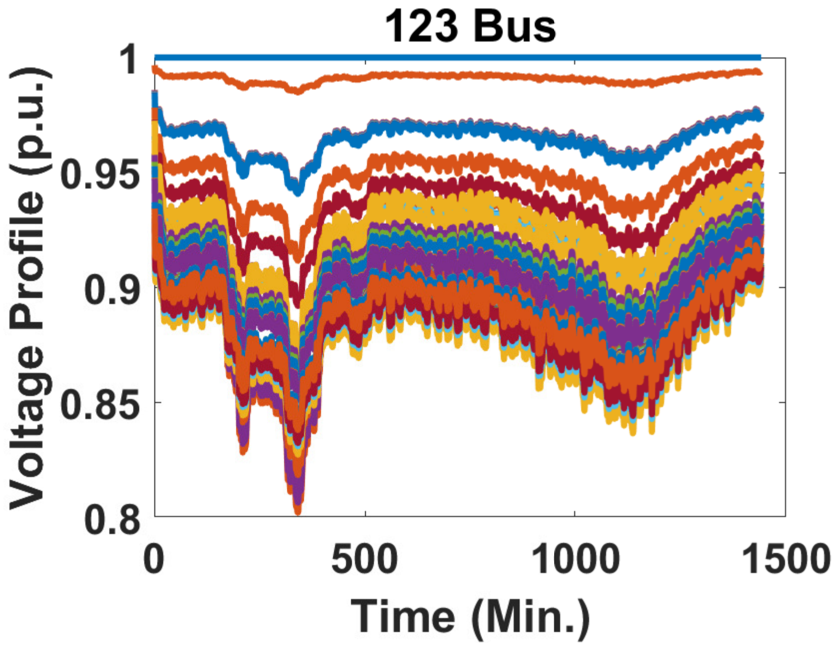


Fig. 4.32: 123 bus voltages before algorithm.

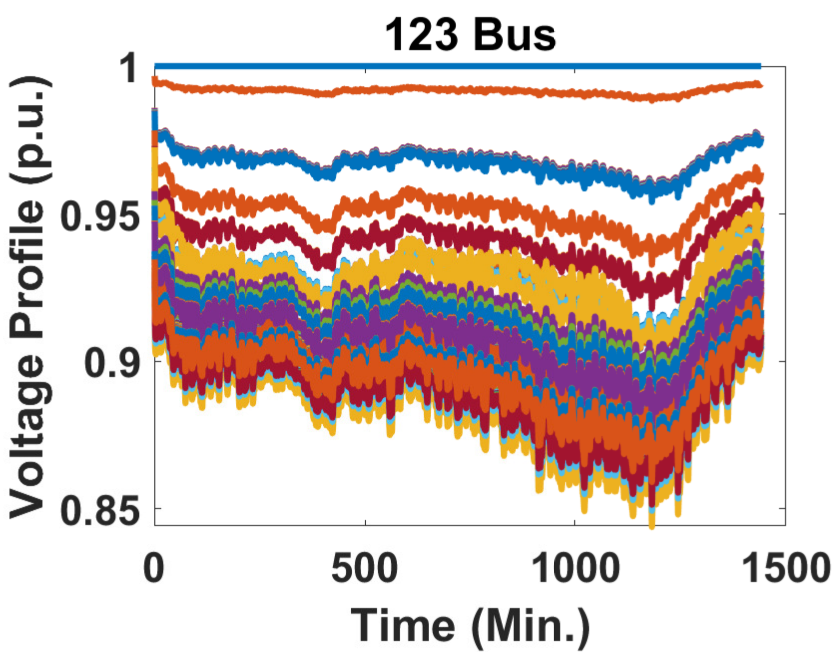


Fig. 4.33: 123 bus voltages after algorithm.

Fig. 4.32 shows voltage profile of bus 123 bus system before routing algorithm and it can be seen that bus voltages is dropping around 0.8 p.u. After utilizing routing algorithm this voltage drop is avoiding in Fig. 4.33.

4.6 Chapter Summary

This study details the development of a novel control algorithm for a centralized electric vehicle charging system that uses a charging station-laden electrical grid based on the IEEE 123 standard. The case studies show that the proposed control architecture considers both the load electric vehicles put on the power system and the versatility of EVs. The control method paves the way for a more stable power grid. Though just three buses were used in this research, the system might be expanded to include additional electric vehicles.

CHAPTER 5: DECENTRALIZED CHARGING APPROACH TO MANAGE ELECTRIC VEHICLE FLEETS FOR BALANCED GRID

5.1 Chapter Introduction

Within the scope of this investigation, we propose a strategy for the distributed optimization of coordinating the charging behaviors of electric vehicles based on the alternative direction method of multipliers (ADMM). This methodology calculates the maximum carrying capacity of buses, making it possible for several electric vehicles to share a single power source. The main contributions are

- The architecture models the global optimization problem into a distributed optimization problem.
- The management algorithm considers V2G framework.
- The devised technique takes the grid side and demand side into account.

5.2 Convex optimization

The goal of each of our problem formulations is to produce a convex optimization problem, which can be thought of as the process of reducing the value of a convex function while adhering to convex limitations. We find that working with convex problems is easiest since there is only one optimal solution to a convex optimization problem—the local minimum is the same as the global minimum. Numerous strategies for distributed optimization need the possession of this characteristic.In order to investigate the relevance of this, we must first define a convex set and a convex function. We have no idea where to begin if we don't do this. In order for a set to be considered convex, it must allow for the drawing of a line segment between any two locations within the set without ever leaving the set itself. This line segment can connect any two points in the set. A convex function is one that returns a value that is convex. As a consequence of this, if a portion of the line that connects x1 and x2 is

$$x = \theta x_1 + (1 - \theta)x_2 \tag{5.1}$$

with 0≤ θ ≤ 1, then a convex set C is defined as

$$x_1, x_2 \in \mathbf{C}, \quad 0 \leq \theta \leq 1 \Longrightarrow \theta x_1 + (1 - \theta)x_2 \in \mathbf{C} \tag{5.2}$$

One can consider the polyhedra to be the solution set of a limited number of linear inequalities and equality expressions, namely Ax≤b and Cx = b. Using variables in the following manner allows us to design a convex optimization:

$$\begin{aligned} \text{min} \qquad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq b_i, i = 1, ..., m \end{aligned} \tag{5.3}$$

in which both the objective and the constraints are convex

$$f_i(\alpha x + \beta y) \leq \alpha f_i(x) + \beta f_i(y) \tag{5.4}$$

The variables x are the optimization variables for the issue, which are often referred to as primary variables. Problems that are convex can be handled by employing any number of strategies that are both dependable and effective. Problems with convexity are notoriously hard to identify and express. Converting formulations of optimization problems into convex forms may be accomplished via a number of different methods. Convex optimization, on the other hand, may be used to solve various difficulties, and in the field of control engineering, many challenges are formulated in the form of convex optimization problems. This is also true for a large number of the issues associated with the management of EV charging, which is why we focus on convex optimization problems.

5.3 Distributed optimization

An optimization issue may be solved using distributed optimization by first breaking it down into a set of subproblems that are easier to handle and then solving a master problem that iteratively gets closer and closer to finding the best solution to the initial problem. We are able to reduce the amount of time spent computing in comparison to centralized optimization if the master approach converges quickly enough and the subproblems are simple enough to be solved without much effort. Take into consideration the following difficulty with optimization:

$$\begin{aligned} \min \quad & f(x_1) + g(x_2) \\ \text{subject to} \quad & x_1 \in C_1, x_2 \in C_2 \end{aligned} \tag{5.5}$$

where $f(x_1)$ and $g(x_2)$ are subsystems with x_1 and x_2 are conditionally separable variables.

The problem mentioned above can be divided into two parts, where x_1 and x_2 can be solved separately.

5.3.1 Primal Decomposition

However, if $f(x_1)$ and $g(x_2)$ have a common element, the problem is not separable. In the case of such real-world problems as

$$\min f(x) = f_1(x_1, y) + f_2(x_2, y) \tag{5.6}$$

two sub-problems can be minimized first and then the main problem can be minimized using an iterative procedure. This can be represented as

$$\begin{aligned} \text{subproblem1: minimize}_{x1} \quad & f_1(x_1, y) \\ \text{subproblem2: minimize}_{x2} \quad & f_2(x_2, y) \end{aligned} \tag{5.7}$$

with optimal values $\delta_1(y)$ and $\delta_2(y)$. Then the original problem become

$$\text{master problem: minimize} \quad \delta_1(y) + \delta_2(y) \tag{5.8}$$

with variables of y. This can be represented in the primal decomposition form as, solve sub-problems (parallel) such as a) Find x_1 that minimizes $f_1(x_1, y)$ with a sub-gradient $g_1 \in \delta_1(y)$ b) Find x_2 that minimizes $f_2(x_2, y)$, with a sub-gradient $g_2 \in \delta_1(y)$. Then update connecting variables such that $y = y - a(g_1 + g_2)$ where a is step size. Each step of algorithm makes the solution closer of the main problem.

5.3.2 Dual Decomposition

The purpose of dual decomposition is to iteratively optimize the primary problem's dual variables after first optimizing a group of subproblems. If we consider equation 5.6 and modify variables y_1, y_2 as:

$$\begin{aligned} \text{minimize} \quad & f(x) = F_1(x_1, y) + F_2(x_2, y) \\ \text{subject to}: \quad & y1 = y2 \end{aligned} \tag{5.9}$$

New y_1 and y_2 are local versions of variable y. In order to reformulate of main problem, we consider the Lagrangian of modified problem. (Equation 5.9)

$$\mathrm{L}(x_1, y_1, x_2, y_2) = F_1(x_1, y1) + F_2(x_2, y2) + \lambda^T(y_1 - y_2) \tag{5.10}$$

using the Lagrangian variables represented by the vector λ. Generally speaking, there are two types of problems that may be distinguished. We can minimize (x_1, y_1) and (x_2, y_2) separately.

$$\begin{aligned} \text{subproblem1} \quad & g_1(\lambda) = inf_{x1,y1}(F_1(x_1, y_1) + \lambda^T(y_1) \\ \text{subproblem1} \quad & g_1(\lambda) = inf_{x2,y2}(F_2(x_2, y_2) + \lambda^T(y_2) \end{aligned} \tag{5.11}$$

After modified problem, main problem become as follow:

$$\text{main problem : maximize} \quad g(\lambda) = g_1(\lambda) + g_2(\lambda) \tag{5.12}$$

Dual decomposition is a method for solving a primary problem by focusing on and improving its dual variables.

- Find a simultaneous solution to the dual subproblems.
  Minimizes $f_1(x_1, y1)$+$\lambda^T(y_1)$ by calculating Find x_1, y_1 t
  Minimizes $f_2(x_2, y_2)$-$\lambda^T(y_2)$ by calculating x_2, y_2.

- Refresh dual variables.
  $\lambda = \lambda - a(y_2 + y_2)$ where a is step size.

The most optimal solution to the original problem is further refined with each repetition. If you're interested in a thorough examination of the particulars of dual decomposition, you may learn more by referencing [113].

The idea behind distributed optimization is to break down a complex optimization problem into smaller, more manageable pieces, and then use an iterative approach to gradually get closer and closer to an optimal solution. Decentralized optimization provides various advantages for us over centralized optimization if the subproblems are easy to solve and the time it takes to converge is short.

$$\begin{aligned} \min \quad & f(x) + g(z) \\ \text{subject to} \quad & x1 \in C_1, x2 \in C_2 \end{aligned} \tag{5.13}$$

We can see that the problem above can be divided into two parts, because we can solve for X_1 and X_2 separately. This kind of problems are called parallelizable problems. However, if $f(x)$ and $g(x)$ have common element, this application is not used. Such as:

$$\min f(x) = F_1(x_1, y) + F_2(x_2, y) \tag{5.14}$$

5.3.3 Alternating direction method of multipliers (ADMM)

The primary and dual disadvantages of decomposition are that they require a convex objective function in order to converge to an optimal solution, and non-convex objectives are not supported. Because linear objective functions are used in many optimization situations, this restriction can be rather stringent. The ADMM is a regularization parameter to dual decomposition that was proposed to overcome this difficulty. Specifically, ADMM is a technique for solving convex optimization problems by partitioning them into smaller, more smaller portions. And it's great for handling massive convex issues. Initially put out the concept in the mid-1970s, while variations on the notion date back to the mid-1950s. Through the '80s, researchers examined this method, and by the '90s, nearly all of the theoretical findings described here had been proven. We may attribute ADMM's relative obscurity now to the fact that it was invented before large-scale distributed computing systems and many optimization problems were available. In this section, we present a information of the element of ADMM. ADMM is a numerical algorithm that is developed for solving optimization problems. ADMM combine advantage of decomposability of dual ascent and superior converge properties of the method of multipliers [113]. Definition is given below,

$$\begin{aligned} \min \quad & f(x) + g(z) \\ \text{s.t.} \quad & Ax + Bz = c \end{aligned} \tag{5.15}$$

optimization variables $x \in \mathbb{R}^n$, and $z \in \mathbb{R}^m$, where $x \in \mathbb{R}^{pxn}$, $B \in \mathbb{R}^{pxm}$, and $c \in \mathbb{R}^p$ are taken as parameters. x and z are calculated by using iteration method, each iteration x is first calculated with keep z remain same and then z is solved with using x which updated in the previous step. The equation details are given following equations.

$$x^{k+1} := \underset{z}{\operatorname{argmin}} \left\{ f(x) + \frac{\rho}{2} \sum_i \left| Ax + Bz^k - c + u^k \right\|_2^2 \right\} \tag{5.16}$$

$$z^{k+1} := \arg\min_{x} \left\{ g(z) + \frac{\rho}{2} \left\| x^{k+1} + Bz - c + u^k \right\|_2^2 \right\} \tag{5.17}$$

$$u^{k+1} := u^k + Ax^{k+1} + Bz^{k+1} - c \tag{5.18}$$

where $\rho > 0$ denotes the penalty parameter and u is representing the lagrangian multipliers.

5.3.4 ADMM-based Smart Charging Algorithm

In this paper, EVs charging schedule is controlling by a aggregator, which is collect all car and grid in formations. The role of the aggregator is crucial in bridging the gap between the distribution system and the fleet of electric cars. To optimize schedule of electric vehicles we develop a ADMM algorithm. EVs charging schedule is optimizated by considering power system. This approach is found to be an efficient way to increase the power grid reliability and resiliency. With help of ADMM method, a smart charging method is developed [128] New algorithm can be defined as;

$$P_{agg}^{k+1} := \underset{Pagg}{\operatorname{argmin}} \left\{ f_{obj} + I_N + \frac{\rho}{2} \sum_i \left\| P_{agg} - 1^T P_{Vi}^k + u^k \right\|_2^2 \right\} \tag{5.19}$$

$$P_{Vi}^{k+1} := \arg\min_{P_{Vi}} \left\{ I_{V_i} + \frac{\rho}{2} \left\| P_{agg}^{k+1} + 1^T P_{Vi} + u^k \right\|_2^2 \right\} \tag{5.20}$$

$$u^{k+1} := u^k + \sum_i (P_{agg}^{k+1} - 1^T P_{Vi}^{k+1}) \tag{5.21}$$

where $P_{agg_i} \in R^{1xT}$ represents the charge profile of aggregator i, $|.\|_2^2$ stands for the Euclidean norm, 1 represents the column vector of Mi ones, and $P_{V_i} = [P_{V_{i,1}}, ..., ; P_{Vi,Mi}]^T$ is the matrix of charging power of the plug-in electric vehicles (PEVs) in aggregator I where Mi is the number of plug-in electric vehicles (PEVs), and $P_{V_{i,n}} \in R^{1xT}$; n = 1,....,Mi is the charging profile of PEV n in aggregator i. The indicator functions I_N and I_{V_i}, respectively, are used to indicate the restrictions of the network and the aggregated vehicle charging, respectively:

$$
\begin{aligned}
\mathrm{I}_N &= \begin{cases} 0, & \mathbf{P}_{\text{agg}} \\ \infty, & \text{otherwise} \end{cases} \\
\mathrm{I}_{V_i} &= \begin{cases} 0, & \mathbf{P}_{V_{i,1}} \\ \infty, & \text{otherwise} \end{cases}
\end{aligned}
\tag{5.22}
$$

The aggregator is connecting one bus of IEEE 123 test system and the sum of charging power of EVs is controlled by the aggregator, i.e.,

$$
P_{\text{agg,i}}(t) = \sum_{n=1}^{M} P_{\text{Vi,n}}(t) \tag{5.23}
$$

Assumptions of this application:

- We assume that the time needed to charge an electric vehicle (EV) is twenty-four hours long and that this time is broken up into intervals of five minutes.
- Depending on the type of service that the aggregators intend to offer, there are several goals that they might have for their electric vehicle fleet.
- End of the day, EVs charging requirements should be meet.
- Immediately after arriving, electric vehicles begin their charging processes.
- Electric vehicles strive to get the highest possible charging rate.

5.4 Optimization for Electric Vehicle Aggregators

By participating in demand-side management, end-use customers can reduce both their power expenditures and usage during periods in which wholesale electricity prices are high or when there is a shortage of energy supply. This entails adjusting their regular patterns of use in reaction to adjustments in the cost of energy or changes in the pay incentives offered to customers. End-use consumers have the flexibility to cut back on their power use and prices during these periods. As a direct result of this, end-use customers can reduce the overall amount of electricity they consume, lowering the amount of money they spend on their monthly power bills. [94–96]. Managing demand-side resources is a notion that has been explored since at least the 1890s, as detailed in [97]. When electric utilities went through a phase of restructuring and deregulation in the 1990s, there was a concerted attempt made to incorporate DSM as an essential part of new market developments of this kind. This was followed by the barriers that began to arise in the new wholesale energy markets. This endeavor continued right up until the turn of the decade. [129]. To that goal, the United States government has enacted various measures to reduce potential roadblocks for people taking part in the DSM. Both electricity system operators and end-use users stand to reap significant benefits from participating in these initiatives. Load shifting, peak clipping, and valley filling are three basic load management procedures to smooth out the peak demand.

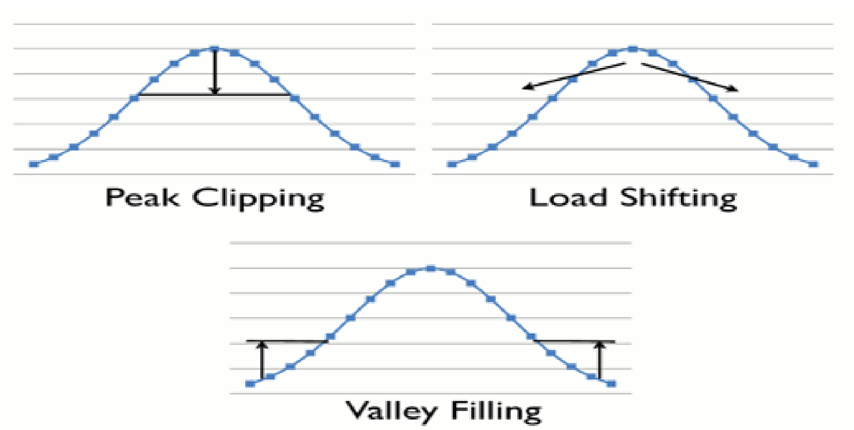


Fig. 5.1: Strategies of load management.

- Peak clipping :Switching off interruptible loads during peak load periods helps the grid operator reduce the peak demand, and is a more conventional kind of load control. Thermostatically regulated loads that the grid operator or aggregator may directly manage are the most typical types of loads included in the interruptible load category. By doing so, utilities may have more direct influence on the thermally regulated loads of their customers. The impact this has on the load profile is seen in Fig. 5.1. This strategy has recently gained popularity among utilities as a means to achieve excellent economic dispatch and keep those costly units off the grid during peak demand. Utilities that do not have adequate generation to satisfy peak demand might also benefit from this procedure. [130].

- Valley filling: Utilities often resort to this method for effective load management. If you look at the daily load profile, you'll see that there are times when the demand is lower than usual. Utilities won't just turn off their equipment during non-peak hours and turn it back on at peak times, therefore there will still be costs incurred during those times. Utilities would rather have more demand at slow times than spend money starting and stopping units, thus they may provide discounts or other incentives to customers who agree to increase their consumption during slow times. Create a variable energy pricing that is high during peak times and low during off-peak times to achieve this. Water heaters, dish washers, washing machines, and dryers are all loads that customers may plan to use during off-peak times. [130].

- Load shifting:This strategy is another practice utilities utilize to accomplish outstanding load control. This method combines the best of peak shaving and valley filling. In this case, customers still have the same level of daily consumption, but they must alter their consuming habits. They will change their consumption to be during the off-peak hours instead of peak hours. Utilities can do this by offering dynamic energy prices or providing demand response programs that reward users for reducing their energy consumption. [130].

These potential advantages offered by these various methods include:

- Decreased need for costly peaking units as a result of reduced peak grid demand. As of 2019, the United States' DSM potential has been projected to reach anywhere from 38 GW to 188 GW. When peaks are reduced, it may be possible to postpone investments in transmission system infrastructure that would be needed to increase system capacity. [131].

- Decreasing wholesale energy costs and lessening of price swings. The high cost of generating power to meet peak demand can be mitigated by increasing demand elasticity even somewhat. [129, 132].

- The reliability of the system has been significantly enhanced. DSM resources are able to be scheduled in the auxiliary services market in the event that they are required for regulation, spinning reserve, or to assist in the integration of renewable energy sources. [133].

- The end user benefits from lower power bills and new income prospects made possible by the regional electricity market operator.

5.5 Case Studies

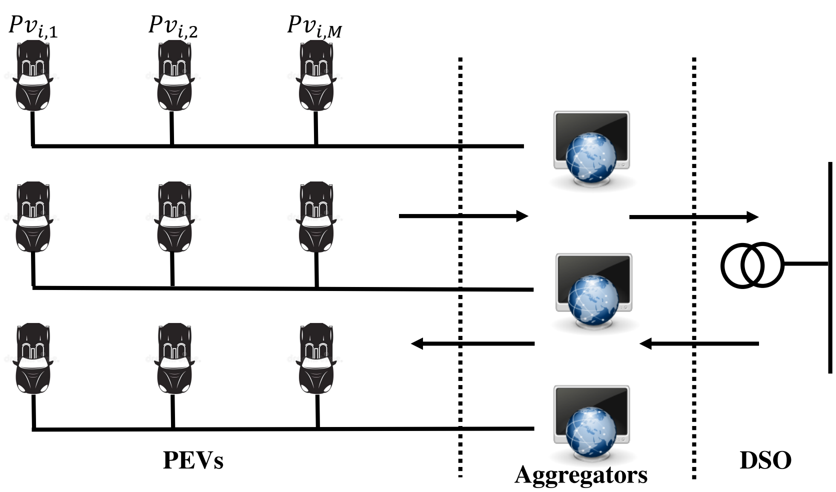


Fig. 5.2: Communication direction of the system.

The aggregator handles communication between the DSO and the EVs, allowing for more efficient charging of the electric cars. The aggregator is given details on the present status of the EVs, such as the charge levels of their batteries, the timings of their arrival and departure, and their overall capacity. The aggregater's charging capacity, j, is the sum of the charging capacities of all electric cars.

$$Pagg_j(t) = \sum_{n=1}^{M_j} Pv_{j,n}(t) \tag{5.24}$$

where M_j is the total number of aggregator-managed EVs on the bus and $P_{Vj,n}$ is the charging capacity of the vehicles. The following period's state of charge (SOC) for PEV k is determined at each charging interval by:

$$SOC_n(t) = SOC_n(t-1) + \frac{\eta Pv_{j,n} \Delta t}{C_{b,n}} \tag{5.25}$$

where η represents the charging efficiency, $C_{b,n}$ represents the capacity of the battery, Δt represents the time interval, and $SOC_n(t)$ represents the starting state of charge (SOC) of the battery before charging begins. The $SOCs$ and the battery voltage level are controlled in a pre-specified range-

$$SOC_n^{min} \leq SOC_n(t) \leq SOC_n^{max} \tag{5.26}$$

$$V_{battery,n}^{min} \leq V_{battery,n}(t) \leq V_{battery,n}^{max} \tag{5.27}$$

Depending on the current flow constrains charging and discharging of the batteries temperature will be also controlled within the limit as following:

$$T_n^{min} \leq T_n(t) \leq T_n^{max} \tag{5.28}$$

where T is the temperature level.

Considering cars life span, batteries should not be over-charged or over-discharged.

$$E_{\mathrm{min}} < E_{\mathrm{t}} < E_{\mathrm{max}} \tag{5.29}$$

The standard for charge and discharge power rates should be adhered to by the charger's output.

$$P_{\text{charge,min}} < P_{\text{g2v}}(t) < P_{\text{charge,max}} \tag{5.30}$$

The total amount of time for charging should not exceed the departure time.

$$t \in (T_a \sim T_d) \tag{5.31}$$

Ta/Td are arriving/departure times.

5.5.1 Aggregator 1-Charging Cost Minimization

The primary goal of this strategy is to shift peak loads to off-peak times when electricity rates are lower. Scheduling EV charging to optimize the cost of power purchase and punish any degradation from the various on-off positions is presented using a convex optimization model that incorporates real-time price (RTP) prediction. Utilities are the primary providers of electrical power. The suggested optimum charging strategy is implemented by an aggregator acting as a central controller. In Fig. 5.3, we see the many actions that make up the application process. Each lingering EV reflects the optimization's final outcome. The problem's objective function is as follows.

$$\begin{aligned}
\min \quad & p^T P_{\text{agg}} \Delta t \\
\text{subject to} \quad & 0 \ \leq P_{\text{agg}} \leq P_{\text{agg,max}} \\
& 0 \ \leq P_{\text{i,t}} \leq P_{\text{i,max}} \\
& Soc_{i,t} \leq Soc_{\text{max}} \\
& Soc_{\text{i,req.}} \leq Soc_{\text{i,dep}}
\end{aligned} \tag{5.32}$$

where Δ t represent time step of calculation and p is the price of electricity. Equation 5.32 is applied $Fobj$ in equation 5.19-5.21 by taking into considering equation 5.24 to 5.31.

We use 50 and 250 EVs, respectively. In each case, initial soc and final soc demand are assumed to be known, and according to the electricity price, the ADMM algorithm creates a charging schedule for each car. For each case, we considered that there are 50 spaces which means 50 cars can get charged simultaneously. Table 5.1 demonstrate the parameters of the case study.

Table 5.1: Parameters of case studies

Number of EV	**50**	**250**
Battery Capacity	**30 kW**	**30 kW**
Number of Space	**50**	**50**
Initial Soc	**%30**	**%30**
Final Soc	**%100**	**%100**
Charging Rate(min.)	**0 kW**	**0 kW**
Charging Rate(max.)	**7 kW**	**7 kW**
Δt	**5 min.**	**5 min.**

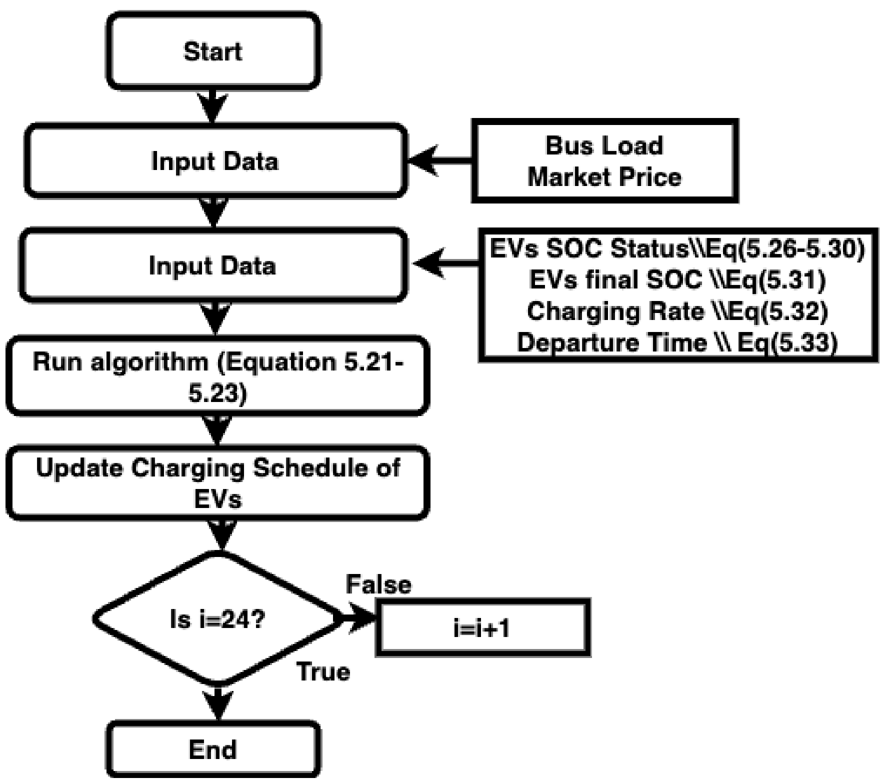


Fig. 5.3: Optimization process for different applications.

ADMM algorithm calculates the minimum charging cost based on the demand of the aggregator and then, according to the charging schedule, it sends an on-off signal to chargers. Electric vehicles are allowed to charge more than once if it is necessary. Figure 5.4 shows giving the result of the ADMM iteration with 50 cars. Also, there is a uncontrolled load that is obtained by taking an example from [134] and Table 5.2 shows how much money users can save with optimization. Fig. 5.5 gives ADMM effect with 250 EVs; in this case, there are only 50 spaces for charging, so some vehicles need to wait until there is space. If this 50 space is occupied by vehicles, the ADMM algorithm finds the next best charging period for others. After running the algorithm, we can see that there are many on-off charging positions are obtained. The battery is one of the most important and expensive components in EVs and multiple on-off situations lead to a decrease in the life of the battery. To avoid this disadvantage, we modify the objective function as:

$$\min \quad p^T(P_{agg} + \alpha * D)\Delta t \tag{5.33}$$

where D represents the degradation cost is that defines as:

$$\mathrm{D} = \textstyle\sum_{t=1}^{1440} abs[P_{\mathrm{i,t}} - P_{\mathrm{i,t\text{-}1}}] \tag{5.34}$$

Fig. 5.6 shows new results with different penalty coefficients of α and algorithm also optimizes output power.

Table 5.2: Charging cost

	Uncontrolled Load	**Controlled Load**	**% Saving**
Cost	**2257.2 $**	**1035.2 $**	**%54**

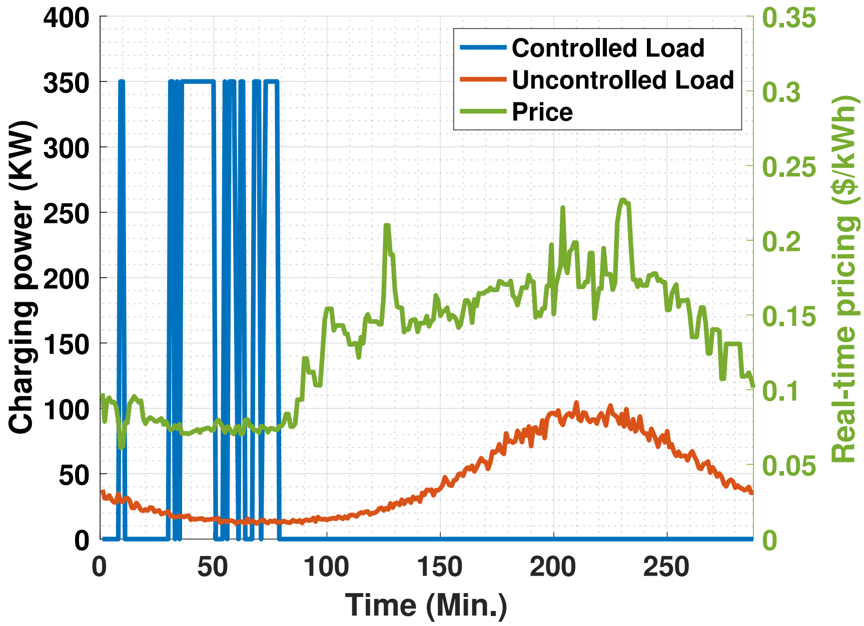


Fig. 5.4: Charging schedule with proposed approach with 50 EVs.

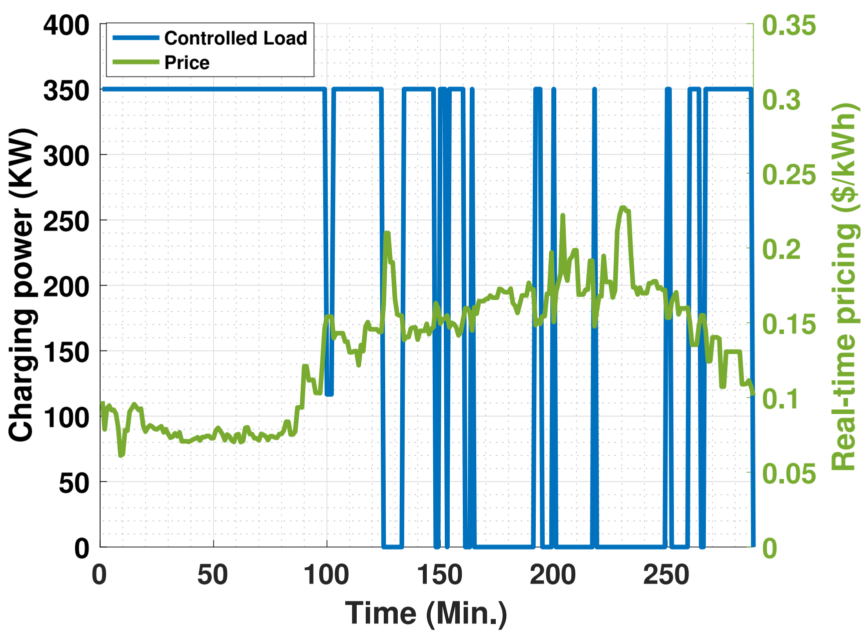


Fig. 5.5: Charging schedule with proposed approach with 250 EVs.

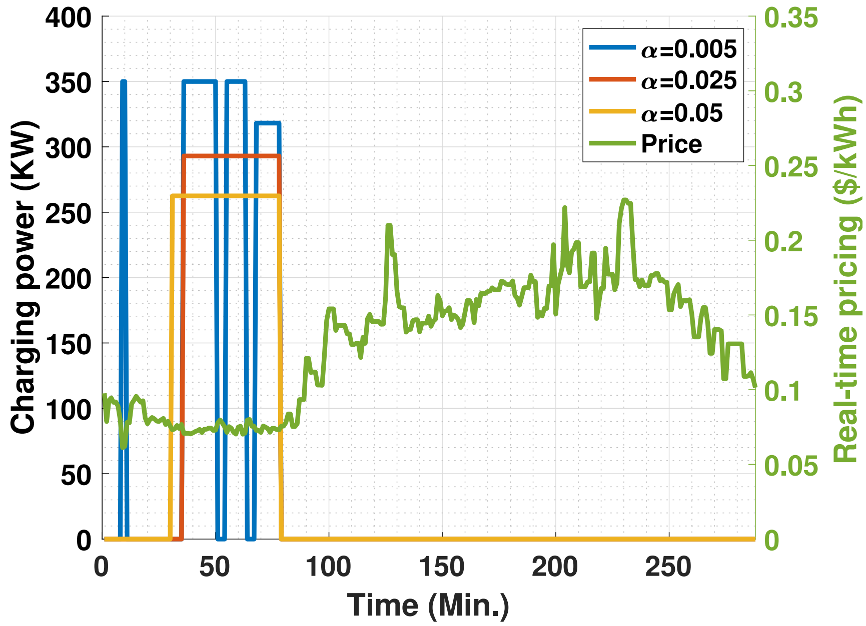


Fig. 5.6: Charging schedule with different α values.

5.5.2 Aggregator 2-Vehicle to Grid (V2G) Application

Because of its rapid response to changes in grid demand, V2G has the potential to be a more cost-effective and efficient alternative to traditional methods of peak-shaving and valley-filling. [135]. [136–138] show EV owners can generate income while charging their cars and provide extra support to eliminate the negative impacts on the grid from charging. The objective function is formulated:

$$\begin{aligned} \min \quad & p^T(B + P_{\text{agg}} + \alpha * D)\Delta t \\ \text{subject to} \quad & P_{\text{agg,min}} \le P_{\text{agg}} \le P_{\text{agg,max}} \\ & P_{\text{i,min}} \le P_{\text{i,t}} \le P_{\text{i,max}} \\ & Soc_{\text{min}} \le Soc_{\text{i,t}} \le Soc_{\text{max}} \\ & Soc_{\text{i,req.}} \le Soc_{\text{i,dep}} \end{aligned} \tag{5.35}$$

where $\Delta\ t$ represents the time step of the calculation, p is the price of electricity, B is the selected bus load, D represents the degradation cost and α is the coefficient of degradation cost. Equation 5.35 is applied $Fobj$ in equations 5.19-5.21 by taking into consideration equations 5.24-5.31. According to the electric price (Fig. 5.4), the ADMM algorithm determines the V2G period during a day. Fig. 5.7, Fig. 5.8 and Fig. 5.9 show the given result of the ADMM iteration with 50 cars and different values of α. Parameters of 50 EVs which are given in Table 5.1 are valid also in this case study.

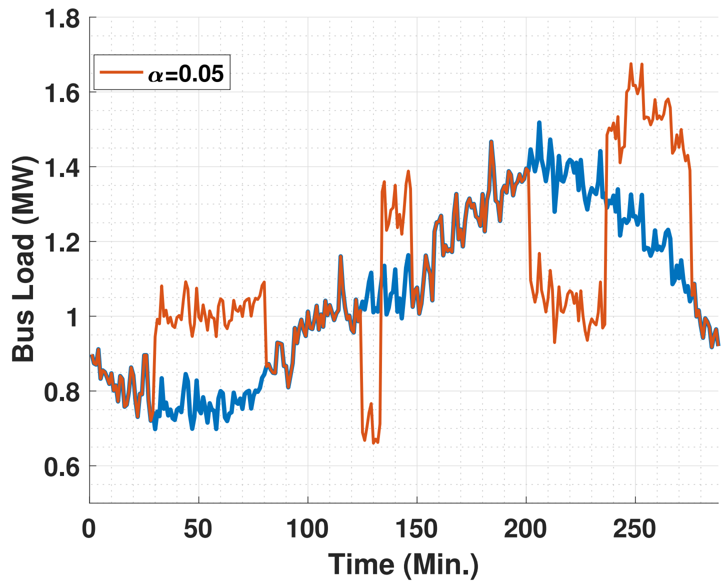


Fig. 5.7: Load profile after V2G implementation.

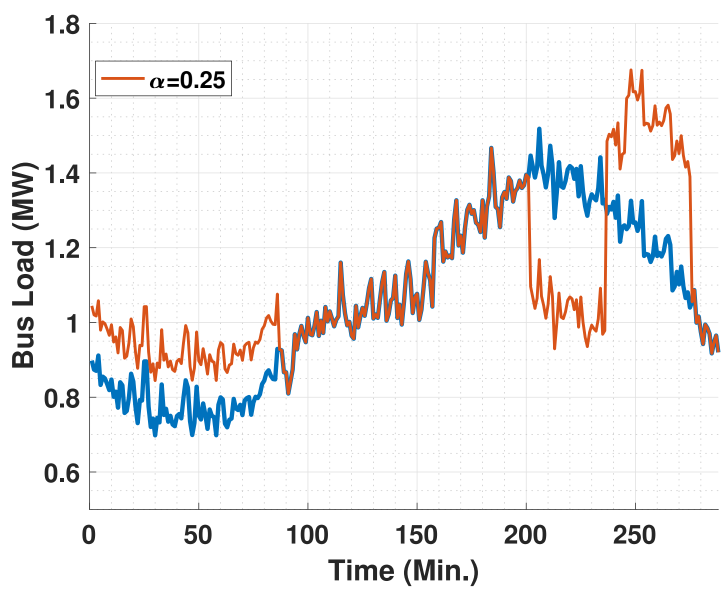


Fig. 5.8: Load profile after V2G implementation.

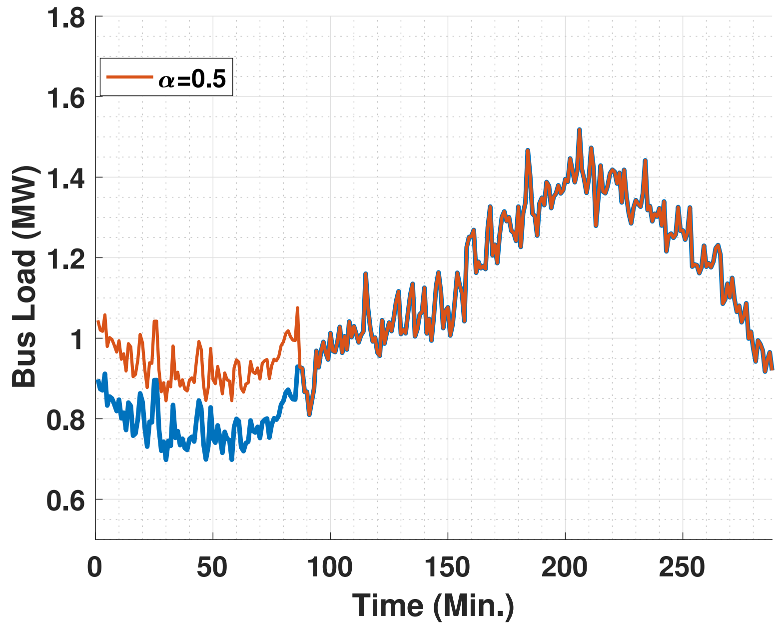


Fig. 5.9: Load profile after V2G implementation.

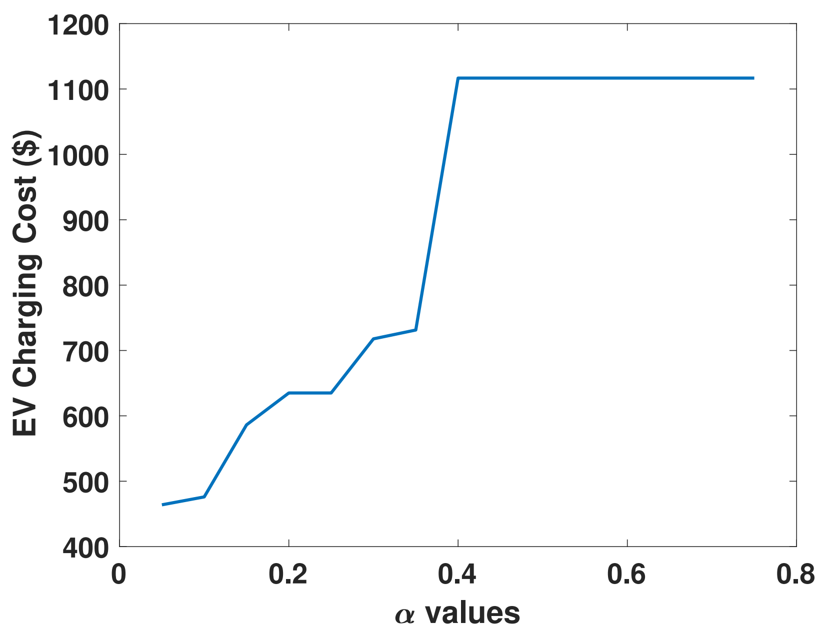


Fig. 5.10: EV charging cost with different α number.

When we increase α to 0.5 algorithm does not provide any gain on EVs side and just completes charging duties (Fig. 5.9). We can arrange the α number based on how much gain we want to provide. Fig. 5.10 gives EV charging cost with different values of α coefficient.

5.5.3 Aggregator 3-Valley Filling Approach

Technology that "fills the valleys" during periods of low electricity demand (known as "valleys" or "off-peak" periods) is gaining popularity. The goal of valley filling is to schedule charging for electric vehicles in such a manner that the resulting demand meets the valley in the otherwise constant demand. This eliminates the potential for any future spikes in energy use. The objective function is formulated:

$$\begin{aligned} \max \quad & (D_{min} + P_{agg})\Delta t \\ \text{subject to} \quad & 0 \ \leq P_{\mathrm{agg}} \leq P_{\mathrm{agg,max}} \\ & 0 \ \leq P_{\mathrm{i,t}} \leq P_{\mathrm{i,max}} \\ & Soc_{\mathrm{i,min}} \ \leq Soc_{\mathrm{i,t}} \leq Soc_{\mathrm{i,max}} \\ & Soc_{\mathrm{i,req.}} \leq Soc_{\mathrm{i,dep}} \end{aligned} \tag{5.36}$$

where $\Delta\ t$ represent time step of calculation. Equation 5.36 is applied $Fobj$ in equation 5.19-5.21 by taking into considering equation 5.24-5.31 and the constant profile of bus demand $B \in \mathbb{R}^n$ is presumed familiar(Fig. 5.11). ADMM algorithm finds a period when demand is lower than other times. Charging schedules are to fill the valley and obtain smooth power demand, preventing the creation of new peak points. We modified uncontrolled load which we used in Fig. 5.4 for 50 cars and 250 cars respectively and add an extra load on bus load.

Figure 5.11 shows the bus load before adding EV demand, and figures 5.12 and 5.13 show the result of 50 and 250 EVs with and without ADMM algorithm. EV parameters which are given in Table I are valid also in this case study except for space limitation. After adding EVs as additional loads, ADMM algorithms use charging demand power to use it for filling the valley. Table 5.3 demonstrates the percentage of improvement.

Table 5.3: Filling of gap percentage

Number of EV	**50**	**250**
Percentage %	**4.8**	**22**

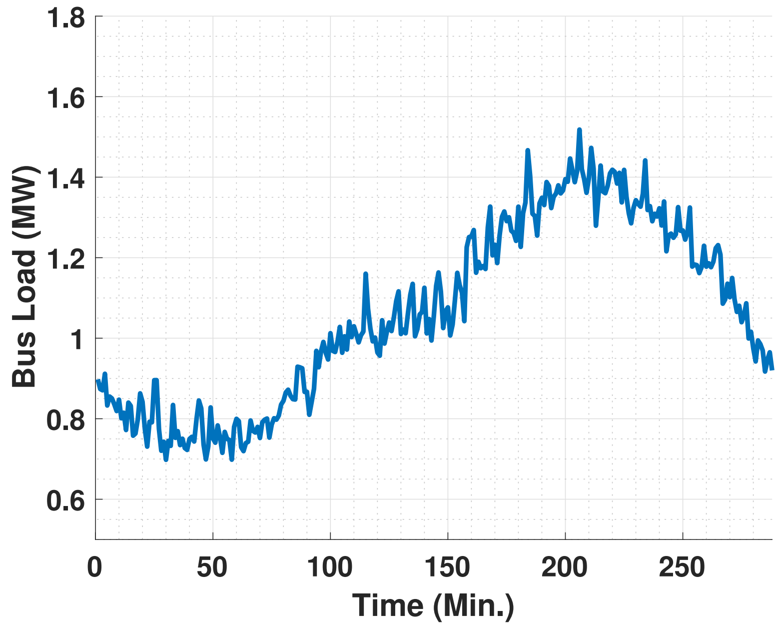


Fig. 5.11: Bus power demand.

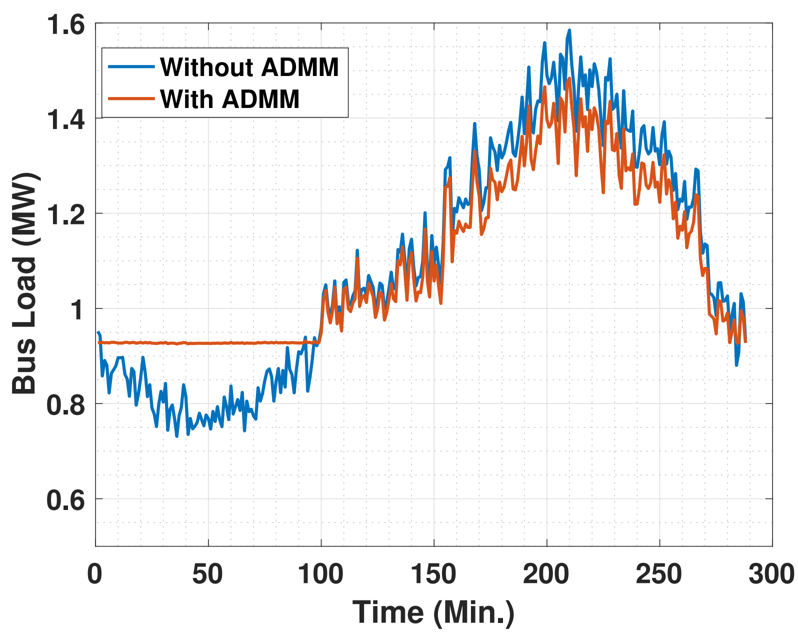


Fig. 5.12: Load profile after valley filling with 50 EVs.

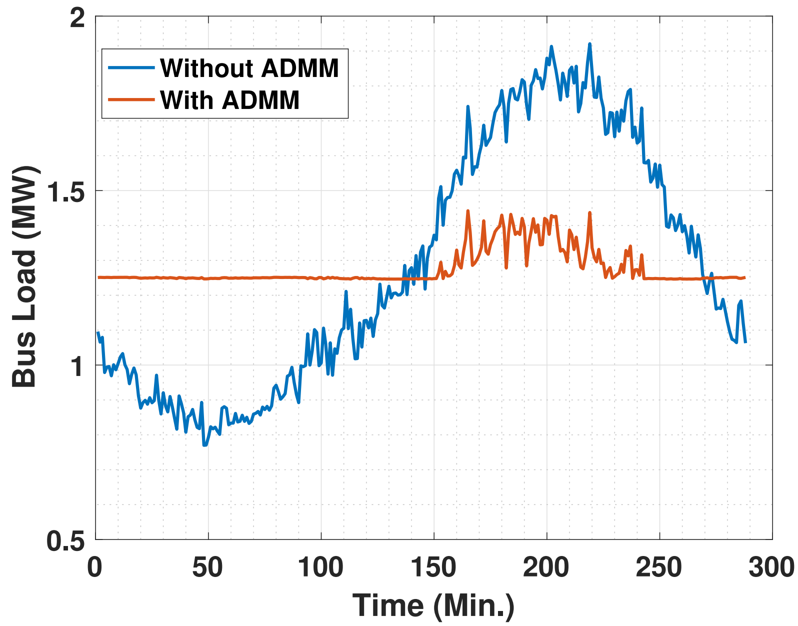


Fig. 5.13: Load profile after valley filling with 250 EVs.

5.5.4 Aggregator 4-Charging Cost Minimization with Limited Supply

So far, we keep utility first and consider utility health and durability. On the other hand, some drivers may need a quick charge than others. In this case, we developed a customer-friendly charging approach and put some privilege coefficient based on driver requests if there is a limited supply point. We consider that 75 vehicles need to charge their batteries in 12 hours. In each period, the total charging energy of all vehicles cannot exceed $C_{\max}$ which is the maximum supply limit by the utility. Thus, energy distribution should be planned based on urgency and charging period.

$$\textstyle\sum_{i=1}^{N} P_{\mathrm{i,t}} \leq C_{\max} \quad t = 1, .., 288, \quad i = 1, .., N \tag{5.37}$$

The vehicle groups have different preferences for how much charge they get over time. The target minimum charge profiles have the form, given:

$$Soc_{t,i}^{\mathrm{tar}} = \left(\frac{t}{T+1}\right)^{\gamma_i} Soc_i^{\mathrm{des}}, \quad t = 1, .., 288, \quad i = 1, .., N \tag{5.38}$$

where, γ sets the urgency for charging vehicles, with smaller values indicating more urgency. The final value of the target minimum charge level for vehicle i is based on γ, the urgency level and the charge value that rises more quickly with smaller γ. Soc_i^{des} gives the final value of the target minimum charge level for vehicle i. The charging demand $s_{t,i}$ in period t for EVs i is given by:

$$s_{t,i} = \left(Soc_{t,i}^{\text{tar}} - Soc_{t,i}\right), \quad t = 1, \ldots, T+1, \quad i = 1, \ldots, N \tag{5.39}$$

Besides the mean of total power demand S is defined:

$$S = \frac{1}{(T+1)N} \sum_{t=1}^{T+1} \sum_{i=1}^{N} s_{t,i}^2 \tag{5.40}$$

Our objective function is minimize the mean of total demand with maximum limit,

$$\begin{aligned} \text{min} \quad & p^T(P_{\text{agg}})\Delta t \\ \text{subject to} \quad & C_{\text{min}} \leq C_{\text{agg}} \leq C_{\text{max}} \\ & P_{\text{i,min}} \leq P_{\text{i,t}} \leq P_{\text{i,max}} \\ & Soc_{\text{min}} \leq Soc_{\text{i,t}} \leq Soc_{\text{max}} \\ & Soc_{\text{i,req.}} \leq Soc_{\text{i,dep}} \end{aligned} \tag{5.41}$$

Case study parameters are given in Table 5.4.

Table 5.4: Parameters of case study

	Group 1	**Group 2**	**Group 3**
Number of EV	**25**	**25**	**25**
Battery Capacity	**30 kW**	**30 kW**	**30 kW**
Initial % Soc	**20**	**0**	**30**
Desired % Soc	**60**	**100**	**75**
γ	**0.5**	**0.3**	**2**
$\mathbf{C_{max}}$		**75 kw**	
Total Charging Time		**1440 min.**	

Fig. 5.14 shows the result of charging schedules. Group II has the lowest *soc* and the lowest

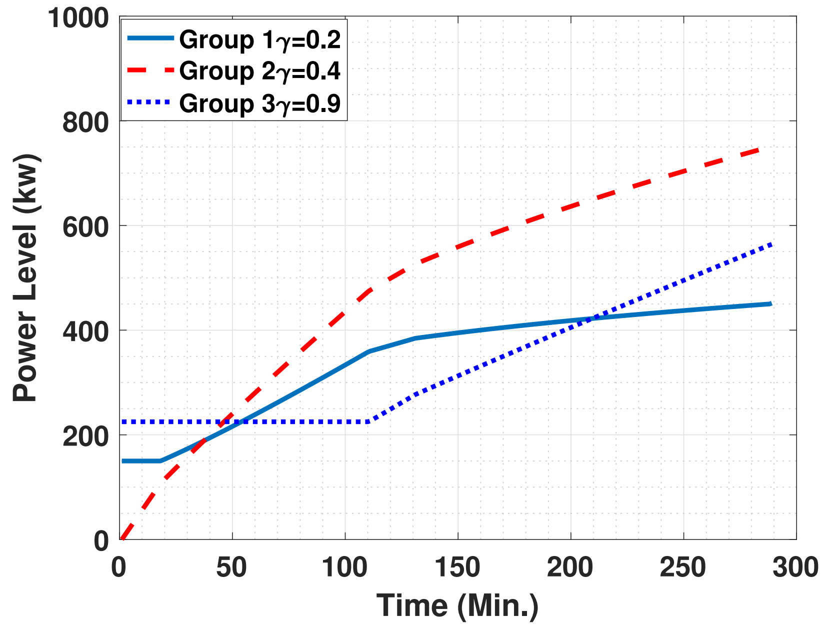


Fig. 5.14: Charging schedule with customer request.

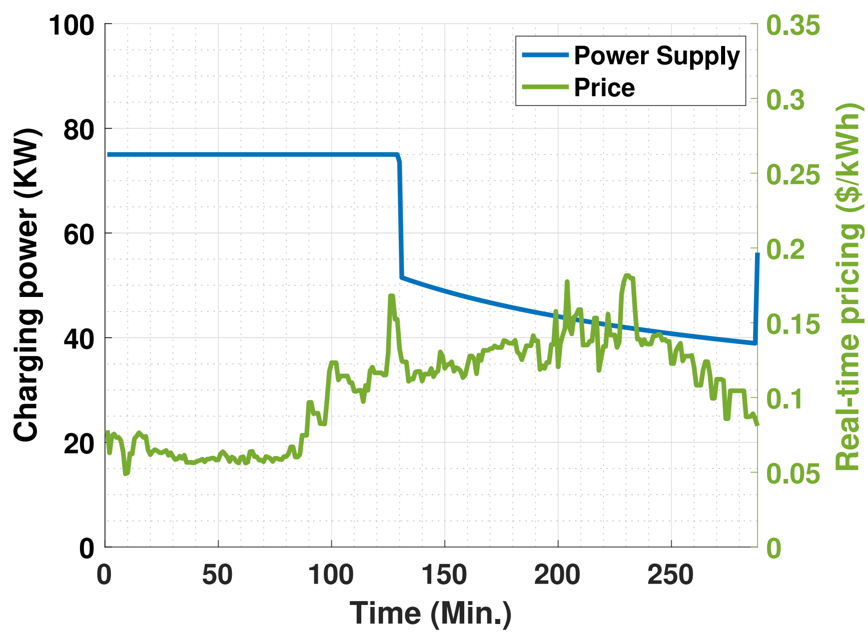


Fig. 5.15: Power supply and electric price relation.

γ values and we can see that group II's charging period starts immediately and the group I and group II follow in respectively. With a limited power supply, the utility can manage to charge demand according to emergency and complete the process within a desirable hour.

This case study results help us to increase the comfort level of customers.

5.6 Chapter Summary

This chapter discussed an ADMM approach to create a novel distributed control method for determining the best time to charge electric vehicles. A generic algorithm is developed based on distributed optimization. The results shows that the suggested control mechanism can successfully fill the valley or minimize the highest peak load. The approach can potentially boost EV adoption and power grid reliability. In addition, the grid and the customers benefit from the deployment of dynamic pricing framework. The method also helps customers to cut down their monthly energy bills. The discussed four use cases showcase the advantage of the framework.

CHAPTER 6: MANAGEMENT OF RESIDENTIAL DEMAND WITH ELECTRIC VEHICLES DURING GRID OUTAGE

6.1 Chapter Introduction

Utilities constantly encourage customers to modify their power use patterns. Utilities plan, carry out, and keep close tabs on all operational activities that might ensure consistent service and encourage customer involvement in programs that help them cut back on energy consumption. Demand-side management is the term for these kinds of initiatives (DSM). Customer engagement and the success of these efforts may be boosted in a number of ways. Customers can save money on their energy bills or increase their profits by delaying their usage of electricity during peak hours. This is made possible through the attractive technique of financial incentives. Utilities also engage customers through educational programs meant to encourage healthier power usage patterns. Utilities do not expect a decrease in overall energy usage, but rather a shifting of loads away from the day's peaks and towards its valleys. One of the ultimate goals of DMS programs is to help utilities avoid or delay the need to invest in or construct new power plants, transmission lines, and distribution networks, and this change can help them do exactly that. The use of battery-operated energy storage devices is a simple illustration of this. It is possible to use such systems to store energy produced during non-peak times and then release it to meet peak times of need. Today, DSM algorithms are even more effective at resolving the supply-demand gap in networks where power is provided intermittently by renewable energy sources. DSM can be done in a variety of ways. One of the two primary strategies for reducing energy use is the introduction of more energy-efficient products and systems. As another method for controlling demand and making the most of all available utility resources, load profile shaping is worth exploring.

The main contributions are

- We provide a convex optimization-based load dispatch strategy that takes use of an EV fleet.
- This approach entails estimating the demand in a certain neighborhood and then using electric vehicles as a provider to meet that need.
- The suggested HEM algorithm's distinguishing feature is its capacity to manage chosen appliances and keep total home power usage within a given limit, all while taking into account customer preferences and providing the user with greater operational freedom. Client preferences are included into real-time pricing (RTP) to either re-route or decrease demand spikes.

6.2 Distributed Energy Resources

DG is shorthand for distributed generation, which describes power sources that are too small to provide a whole utility grid. As opposed to the conventional large-scale infrastructure, which is connected to the transmission system, DG systems are distributed and instead connected to the distribution grid. Solar photovoltaic (PV), modest wind systems, cogeneration/ combined heat and power (CHP), and fuel cells are all examples of DG. Due to declining technological costs and supportive legislation, distributed solar PV installed at the customer's location has emerged as the most prominent and expanding technology in recent years. One of DG's most appealing features is its potential to place power generation in closer proximity to consumers than conventional plants. As a result, there may be less need for expensive, massive upgrades to existing utility infrastructure like high-voltage transmission lines. Direct current (DC) is more efficient than alternating current (AC) because it minimizes line losses that occur when electricity is sent over long distances.

Without DER, transmission and distribution infrastructure investments may have to be postponed or cancelled. There are at least two ways in which they achieve this goal: either by reducing overall grid demand (as with an energy efficiency program that slows the rise of peak demand) or by providing an alternative to new wiring (as with the deployment of solar panels and battery storage that is tailored to a particular grid upgrade). All of these routes have the potential to avert costly infrastructure modifications including those to transformers, cables, capacitors, and even substations.

By meeting both energy and capacity needs, DER helps delay the need for costly investments in new generation. Distributed generation may supply power where it's needed, while DER that can adjust load (such as energy efficiency, storage, demand response, and electric vehicles) can help smooth out the system at peak periods and prevent the need for costly new capacity. Avoiding the need for peaker plants, which produce large amounts of pollution, is one of the benefits of a well-coordinated portfolio of DER. And if the right prices are being sent out, DER may ease transmission congestion and cut down on line losses, which are the equivalent of the money saved on energy delivery.

Some consumers want control over where their electricity comes from and how much they use, and distributed energy resources allow them to do both while still benefiting the larger grid. While the number of consumers who would like to do so is not yet at 100%, it is growing rapidly thanks to the declining prices and expanding availability of DER. As EVs gain popularity and the price of solar panels, batteries, and other energy-saving technologies continues to drop, this trend is expected to quicken.

6.3 Concept of Smart Grid

The current power grid uses a conventional infrastructure to produce, transmit, distribute, and regulate electrical power. The flow of electricity is just one way, from power plants to end users. Most of the energy infrastructure in industrialized nations was built more than 50 years ago and is rapidly becoming antiquated. Six million people in the Atlantic coast were without electricity for two days after Hurricane Sandy's destruction of the environment. These examples highlight the need of developing and implementing more efficient strategies for energy production and management. We need to upgrade the system to make power generation more efficient. The SG is the name for the modern, computerized power grid that supplies electricity to homes and businesses around the world. The need for power is growing steadily. Therefore, the SG is the best option for lowering power consumption, cutting emissions, and shoring up the entire power grid's security. A smart grid (SG) is a two-way energy network that can efficiently coordinate the efforts of all its users to generate and distribute clean, affordable power. The term "next-generation power distribution network" refers to the incorporation of technology and capabilities into the power grid that will allow for more intelligence and more dynamic customer interaction.

By improving infrastructure, Smart Grids (SG) may boost delivery of essential amenities. Power reliability, facility utilization optimization, energy distribution capacity extension, disruption management, automated response to system disturbances, renewable energy source deployment, dispersed power source integration, automated operation and maintenance, decreased greenhouse gas emissions, shaving peak loads, grid security, Plug-in Electric Vehicles (PEVs), new energy storage options, and increased consumer choice are all improved by SG.

V2G systems and microgrids are the two main SG concepts. Electric V2G is being utilized to send discharged energy back to the grid so that it may be used to generate electricity and offer other ancillary services. Changing the rate of modulation is another method for doing this with two-way power flows. Microgrids coordinate energy sources, storage options, and loads to enable decentralized power generation. The microgrid can control the electricity's frequency, voltage, and demand. In island mode, a microgrid is able to independently regulate faults and voltages, yet operating in the same linked operational mode as the main grid.

More widespread usage of distributed renewable energy generation (DG) on a local scale has the potential to lessen the need for fossil fuels like coal and natural gas while also limiting the release of greenhouse gases. In the event that the primary power grid has an outage, a DG-based power distributed power grid might prove to be of great assistance, since it may significantly improve electricity dependability and quality. Because of the decentralized nature of power generation, a stable electricity market would be possible. Thus, a dynamic pricing solution would be of great use in the SG. Weather also presents a barrier to the creation of demand and supply of power, an area where DG may play a significant role. It's not simple to keep track of this SG, but that's why study of the topic is expanding.

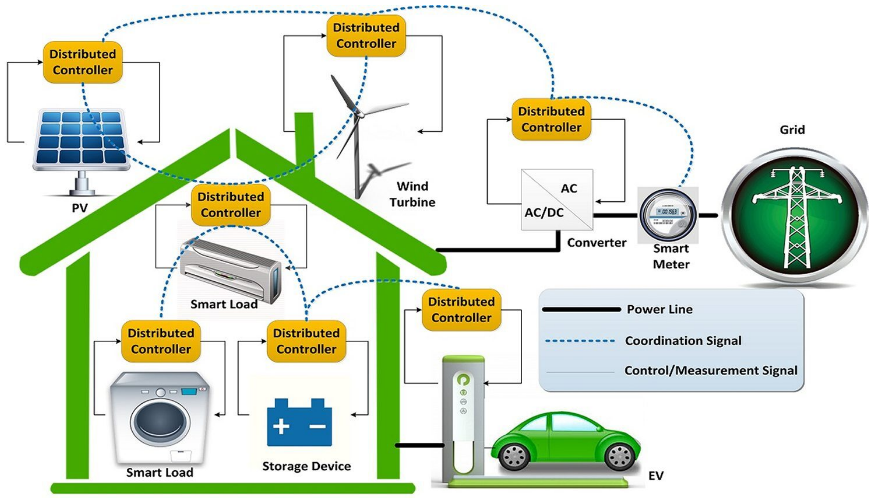


Fig. 6.1: Smart home design. [12]

Individuals will have access to the timely data they require. If there is ever a power outage, the SG will be an invaluable resource for emergency power management. In order to produce renewable energy at scale and efficiency, a sophisticated power system is required. On the other hand, it would be impossible to build that kind of infrastructure without careful planning on the part of the government. The current generation would stand to gain quite a lot from participating in the SG. In such an intelligent grid, elements such as smart meters or sensor-based components would be deployed, which would present a security risk. The storing of energy is yet another issue that is of the utmost importance and is in great demand. Under those circumstances, the management of energy will be significantly impacted by the use of energy storage. By utilizing this advanced and bi-directional communication infrastructure, The supplier would be able to govern competitive markets while also interacting in real time with energy consumers. This would be possible. Since this is a developing field, studies are still being conducted, and SG has not yet taken on its final form. But now there is a plan in place, and the route ahead is unmistakable. The compass directions vary from country to country. But in the end, they're all want the same things. While the electrical industry may be able to provide transformation, the construction industry may be able to provide heating, ventilation, and air conditioning (HVAC), and the consumer industry may be able to provide smart products.

6.4 Problem Statement

Under specific constraints, the energy dispatch algorithm problem is a type of non-linear programming problem with the goal of minimizing power consumption and user satisfaction. Residential loads are classified into two types:

- Fixed loads: These loads are accepted as constant and non-controllable such as TV, refrigerator, lights, microwave and so on.
- Shiftable loads: These loads such as air conditioner, washing machine, clothes dryer pattern may be adjusted to a different source or time slot to function on its own without affecting consumers' lifestyles .

6.4.0.1 Air Conditioner

Air conditioner model is provide the room temperature and power consumption of model during on/off positions. It compares the room temperature to the set point to regulate the temperature. Then cooling or heating coils are activated to keep the room temperature within the user-specified settings. Detailed air conditioner model is analysed in study [139]. The mathematical model of air conditioner that is used for simulink purpose is defined as:

$$T_{i+1} = T_i + \Delta t \cdot \frac{G_i}{\Delta c} + \Delta t \cdot \frac{C_{HV,AC}}{\Delta c} \cdot W_{AC,i} \tag{6.1}$$

Every time period temperature is unique, based on the previous interval's temperature, the room's heat gain or loss, and the AC unit's cooling capacity. It is used to calculate the room temperature by factoring in these variables. The heat gain (Gi) rate of the house is primarily determined by air infiltration, solar irradiance, and heating losses through the walls, windows, and ceiling. The formula for calculating heat gain rate is:

$$G_i = \left(\frac{A_\text{w}}{R_\text{w}} + \frac{A_\text{c}}{R_\text{c}} + \frac{A_\text{window}}{R_\text{window}} + \frac{11.77B \text{ Btu}}{F \times fx^3} \times n_{ac} \times V_\text{house} \right) \\ \times (T_{\text{out },i} - T_i) + SHGC \times A_\text{w,s} \times H_\text{solar} \times \frac{3.412 \frac{Btu}{Wh}}{10.76 \frac{ft^2}{m^2}} + H_p \tag{6.2}$$

Calculate the energy (Δc) needed to raise a home's temperature by 1 .

$$\Delta c = C_\text{air} \times V_\text{house} \tag{6.3}$$

The status of the air conditioning system is either on or off. It only uses electricity when it is turned on. The AC unit's energy consumption is determined as follows:

$$P_{AC,i} = P_{AC} \cdot W_{AC,i} \tag{6.4}$$

$\text{P}_\text{AC,i}$	The power consumption for AC unit at time slot i.	
P_AC	The AC system's rated power.	(6.5)
W_AC	The AC unit's state (I/0) at time slot i.	

6.4.0.2 Water Heater

This thesis presents a model that simulates the interior temperature and energy consumption of a domestic EWH by using a single mass, single element model. The model's construction relies on an assessment of the tank's mean water temperature and energy flow (the amount of electricity used over time). Because of the vast differences in EWH size and consumption patterns between the residential, industrial, and manufacturing sectors, it is essential to distinguish between them. Depending on the size of the home, residential EWHs can hold anywhere from 10 to 80 gallons of water and generate a consumption profile that is similar in shape to the daily load profile observed by utilities. The idle losses and hot water use need to be accounted for, therefore knowing when in the year the model is being tested is essential. The next sections will go into further detail on these and related topics. A model of a water heater is created so that the tank's hot water temperature and the heater's energy consumption at different times of the day can be calculated. The heating coils in the water heater are turned on if the water's temperature falls below the lower limit of the desired temperature range and off if the water's temperature exceeds the upper limit of the desired temperature range. The tank's water temperature is impacted by factors such as outside temperature, tank design, and so on. The temperature is calculated using the following formula [139].

$$\begin{aligned} \mathrm{T}_{\text{outlet },i+1} &= \frac{T_{\text{outlet }}\left(V_{\text{tank }}-f_{\text{ri }}\cdot \Delta t\right)}{V\ \text{tank}}+\frac{T_{\text{inlet }}\cdot f_{ri}\cdot \Delta t}{V_{\text{tank}}}+\frac{1\text{gal}}{8.34\text{lb}} \\ &\times\left[p_{wh,i}\times\frac{3412\text{Btu}}{kWh}-\frac{A_{\text{tank }}\times\left(T_{\text{outlet }},i-T_{a}\right)}{R_{\text{tank}}}\right]\times\frac{\Delta_{t}}{60\frac{\text{min}}{h}}-\frac{1}{V_{\text{tank}}} \end{aligned} \tag{6.6}$$

The water heater's power usage is determined by its condition throughout time. Only when the water heater is turned on is power consumption estimated and expressed as:

$$P_{WH,i}=P_{WH}\cdot W_{WH,i} \tag{6.7}$$

$\mathrm{P}_{\mathrm{WH,i}}$	The power consumption for WH unit at time slot i.	
P_{WH}	The WH system's rated power.	(6.8)
W_{WH}	The WH unit's state (I/0) at time slot i.	

6.4.0.3 Clothes Dryer

The characteristics of the clothes dryer are divided into two categories: those connected to the heating coil and those linked to the motor. The latter requires a manageable amount of electricity and hence operates continually; nevertheless, the heating coil should be maintained. The main power requirement is determined as follows:

$$P_{CD,i}=P_{CD}\cdot W_{CD,i} \tag{6.9}$$

$P_{CD,i}$	The amount of electricity that a CD unit consumes during time slot i.
P_{CD}	The CD system's rated power.
W_{CD}	The CD unit's state (I/0) at time slot i.

(6.10)

6.4.0.4 Dish Washer

The load model of an dish washer is developed using power consuming data. Using equation (7) we calculate the rated power consumption of dish washer for each time interval.

$$P_{DW,i} = P_{DW} \cdot W_{DW,i} \tag{6.11}$$

$P_{DW,i}$	The amount of electricity that was consumed by the DW unit during time slot i.
P_{DW}	The DW system's rated power.
W_{DW}	The DW unit's state (I/0) at time slot i.

(6.12)

6.5 Case Studies and Results

During a blackouts or supply shortage people would like to at least critical loads remain operate without interruption. Lighting, coffee machine, freezer, cooking, and other loads fall under this category. Our critical loads vary between 1 and 2.5 kW in case studies. There are also controllable loads that power demands are between 1.5 to 5 kW which are demonstrate in Table 6.1 and in Fig. 6.3 total on/off position is reflecting during a day. To obtain results, we create a one typical residential home with several loads and assume that loads are randomly open and closed at first, then with help of mathematical models we compare results if loads are uncontrollable and controllable. The objective function is solved by using CVX program implemented in MATLAB. The optimization problems are subject to the following constraints:

- We consider charging time is 24 hours, and it is divided into 1 minutes intervals.
- End of the day, loads requirements should be met.
- It is presumed that all of the optimization problem's parameters are already known.
- The number of shifted devices must be non-negative.
- Shiftable devices are permitted to work for a specific period of time.

Table 6.1: Power consumption of loads

	A.C.	**W.H.**	**C.D.**	**D.W.**
Power Rate (kW)	**4.5**	**4**	**3.5**	**1.5**

6.5.1 Distributed Power Dispatch Algorithm

In a modern distribution system, renewable energy-based distributed generation sources can be integrated, and the usage of percentage has been overgrowing. We developed distributed power dispatch approach with the help of electric vehicles. We assumed that there are 20 houses and 60 electric vehicles that are capable supply power during the outage or supply interruption. We divided vehicles into three groups in table II, each group's vehicles have different power rate. In order to provide constant and long-term power, cost function is design in opposite of power rate. As a result, lower rate of vehicle fleet is chosen less if it is not needed at time period.

In this case total power that is supplied in each time period must equal the demand:

$$\sum_{i=1}^{n} P_i(t) = d_t \tag{6.13}$$

Each car has a minimum and maximum amount of power it can provide.

$$P_i^{min} \leq P_{i,t} \leq P_{\mathrm{i}}{}^{max} \tag{6.14}$$

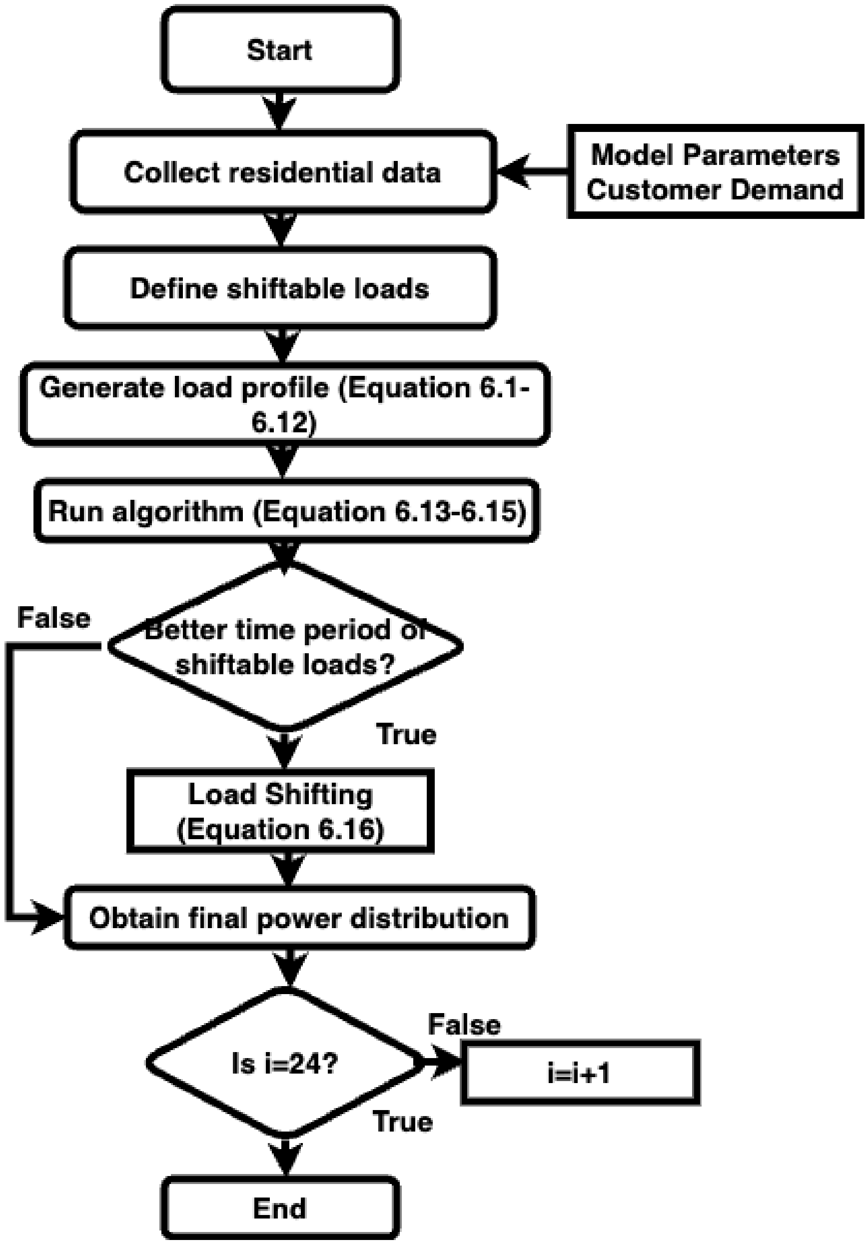


Fig. 6.2: Algorithm steps.

We assume that cost functions are quadratic:

$$\phi_i(u) = \alpha_i u + \beta_i u^2 \tag{6.15}$$

Coefficients of cost function are given Table 6.2.

After utilizing convex optimization algorithm, power supply is calculated in Fig 6.4.

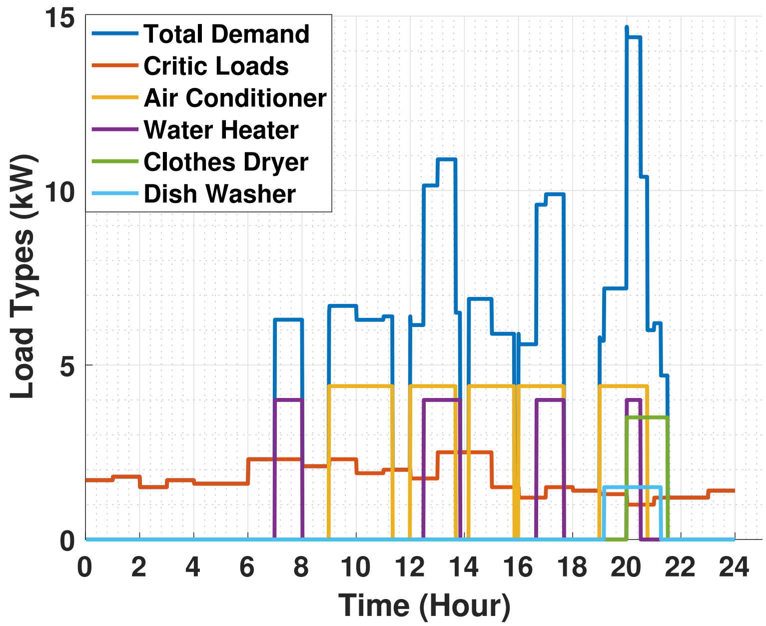


Fig. 6.3: Loads Data.

Table 6.2: Parameters of cost function

	Car Number	α	β	Pmax	Pmin
Group 1	20	1	0.1	10	0
Group 2	20	1.25	0.2	7	0
Group 3	20	1.5	0.3	3	0

6.5.2 Flexible Load Shifting

People can be flexible about deadline of some chores. Mostly they would do these duties after works and it creates extra burden on utilities. However, through load shifting, loads might move to off-peak times, while overall consumption remains unchanged. We assume that, clothes dryer and dish washer are flexible and can move some other time period based on real time pricing chart. With help of algorithm, according to the electricity price, the algorithm creates a charging schedule for each car loads with considering time limits of customers. Table 6.3 is giving details of customer demand. The objective function of the

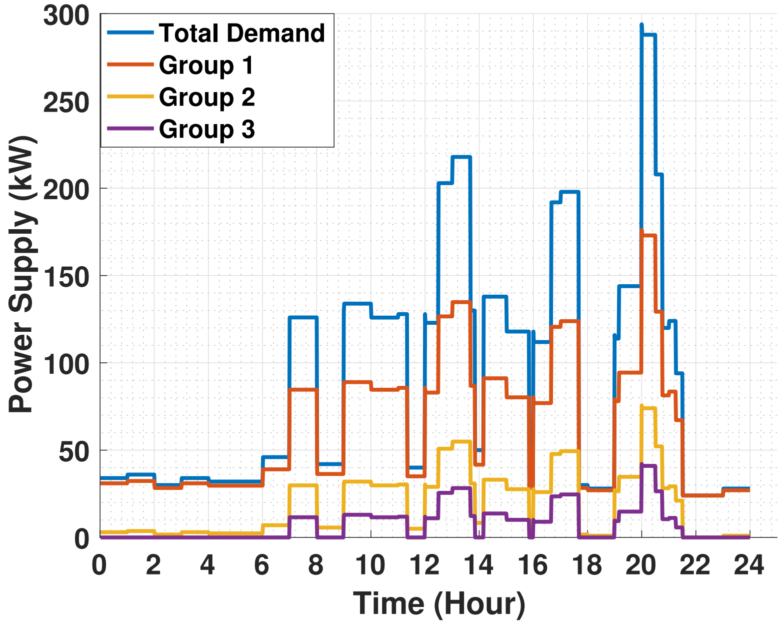


Fig. 6.4: Power distribution result.

problem is:

$$\begin{aligned} \min \quad & p^T P_{\text{demand}} \Delta t \\ \text{subject to} \quad & 0 \leq P_{\text{demand}} \leq P_{\text{demand,max}} \\ & 0 \leq P_{\text{load,t}} \leq P_{\text{load,max}} \end{aligned} \tag{6.16}$$

where Δ t represent time step of calculation and p is the price of electricity which is green line in Fig. 6.5. After implementing convex optimization we obtain new load demand in Fig.

Table 6.3: Desired shift period of loads

	Power rate	**Desired Period**
Clothes Dryer	**3.5 kW per device**	**00.00 am-12.00 pm**
Dish Washer	**1.5 per device**	**12.00 pm-00.00 am**

6.5. It can be clearly seen that, peak demand is now decreased by help of price minimization. Based on new demand, we calculate power distribution supply again and Fig. 6.6 represents new results.

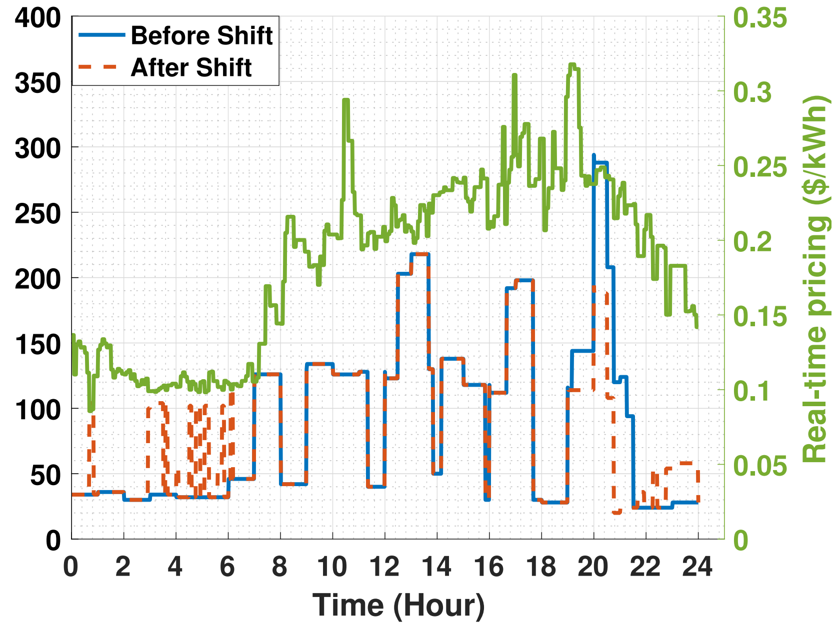


Fig. 6.5: Power distribution after load shifting.

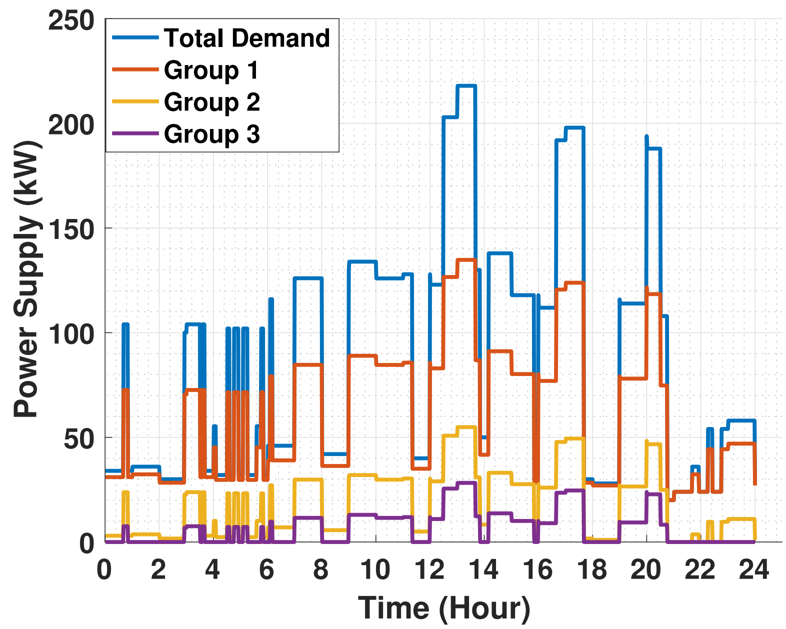


Fig. 6.6: Power supply after load shifting.

6.6 Customer Comfort Consideration

So far, we assume that the air conditioner and the water heater are randomly opened and closed during a day. In most of the residential house, the air conditioner and water heater have the biggest importance from point of customer satisfaction. In order to meet this satisfaction, we modeled each appliance and they have its own comfort level settings.

6.6.1 Room Temperature

In order to calculate room temperature we use equation 6.1-6.4 and coefficient are defined in table 6.4. In Fig. 6.7 demonstrate solar radiation data and Fig. 6.8 outdoor temperature and indoor temperature are calculated based on random on-off position. In this case, room temperature is fluctuating. The room temperature choice for the space cooling unit can be determined 70 for complex optimization.

Table 6.4: Parameters of A.C. model

Parameter	**Value**	**Unit**
House size	**21312**	**ft**
Afloor, Aceiling,Awall,Awindow	**2000,2664,1564,228**	**sq ft**
Rceiling,Rwall,Rwindow	**32,12,2**	ft^2***°F (btu/h)**
Number of people	**3**	**people**
Capacity of the AC unit	**15000**	**BTU**
SGHC	**0.67**	
Cair	**0.0195**	**BTU/ °F.** ft^3
Aws	**32**	**sq ft**
Hp	**392**	**BTU/h**
Density of air	**0.075**	**sq ft**
AC temperature set point	**70**	**°F**
AC power consumption	**4.5**	**kW**
Δt	**1**	**min**

After utilizing convex optimization, in Fig. 6.8 we can see room temperature is almost constant except midday, but the differences is only 5 The reason is air conditioner BTU is not enough to keep room temperature at desired level. Also, with help of optimization A.C does not have to work with maximum capacity, in Fig. 6.9 we have corresponding power demand based on the BTU rate, 1 BTU/h is taken **0,000293071** kW.

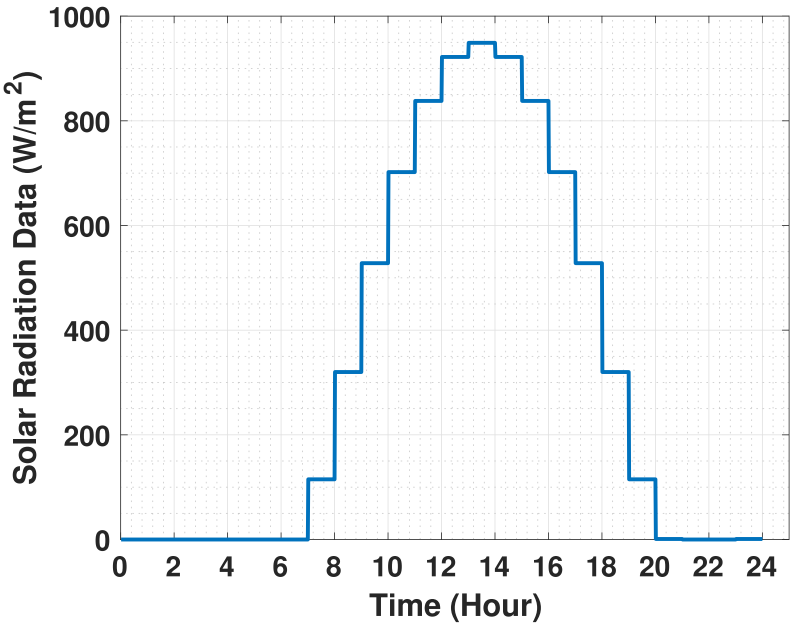


Fig. 6.7: Solar radiation data.

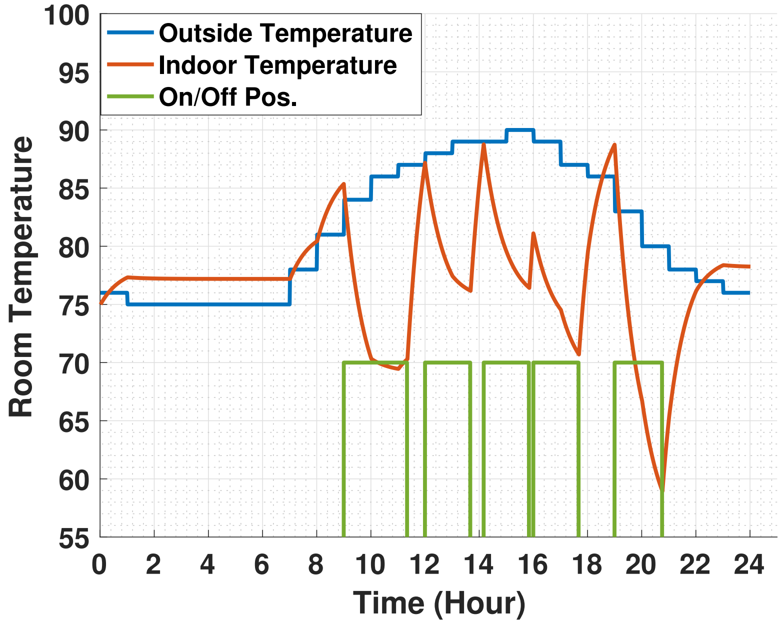


Fig. 6.8: Room temperature with random control.

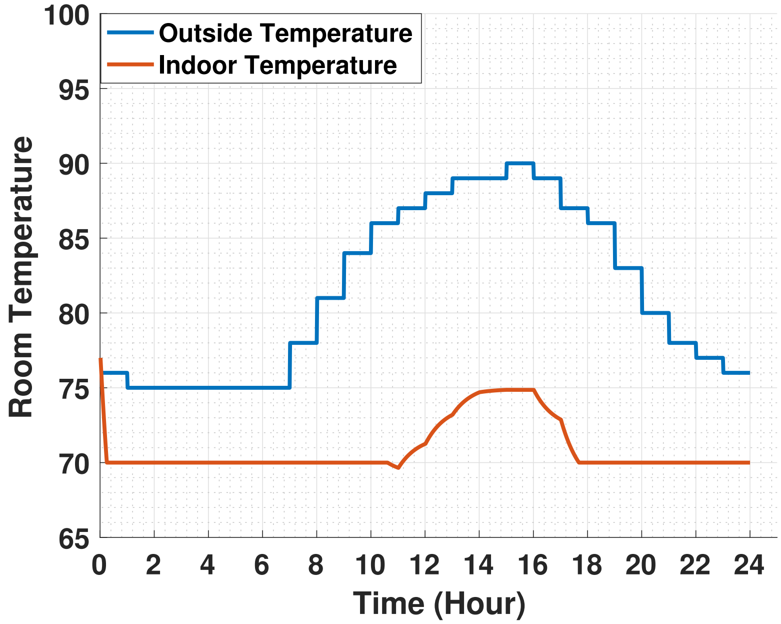


Fig. 6.9: Room temperature with algorithm.

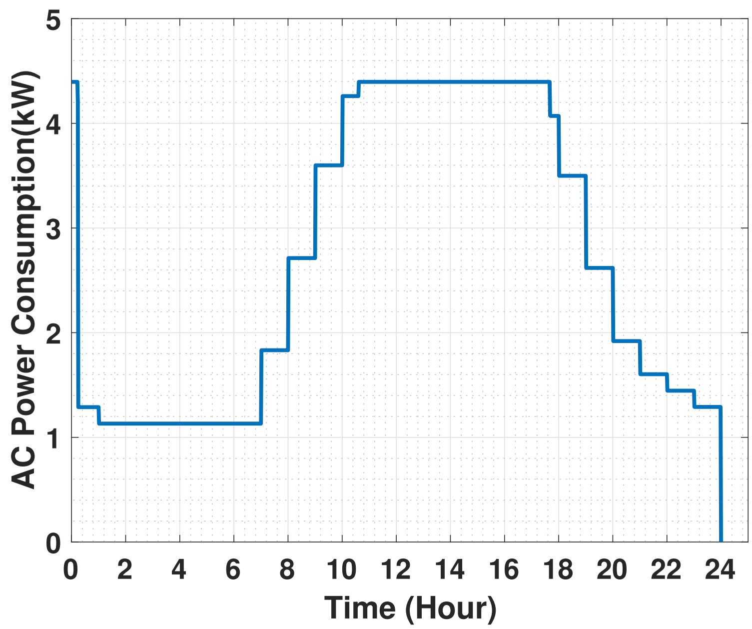


Fig. 6.10: Power consumption of A.C after algorithm.

6.6.2 Water Temperature

In order to calculate water temperature we use equation 4 and coefficient are defined in table 6.7-6.7. Fig. 6.11 showing water temperature with water usage and heater on/off position without any optimization. The hot water temperature choice for the water heater is set 100 . Then we apply convex optimization to keep water temperature at 100 ith same water usage. After running the algorithm, we have constant heat water with small interruption in Fig. 6.12.

Table 6.5: Parameters of W.H model

Parameter	Value	Unit
Water tank size	**80**	**gallons**
Inlet temperature	**68**	
Water tank A value	**14**	ft^2
Water tank R value	**16**	ft^2 * **(btu/h)**
WH power comsumption	**4.5**	**kW**
Water consumption	**Fig. 6.11 Green Line**	**gallons/min**
Δt	**1**	**min**

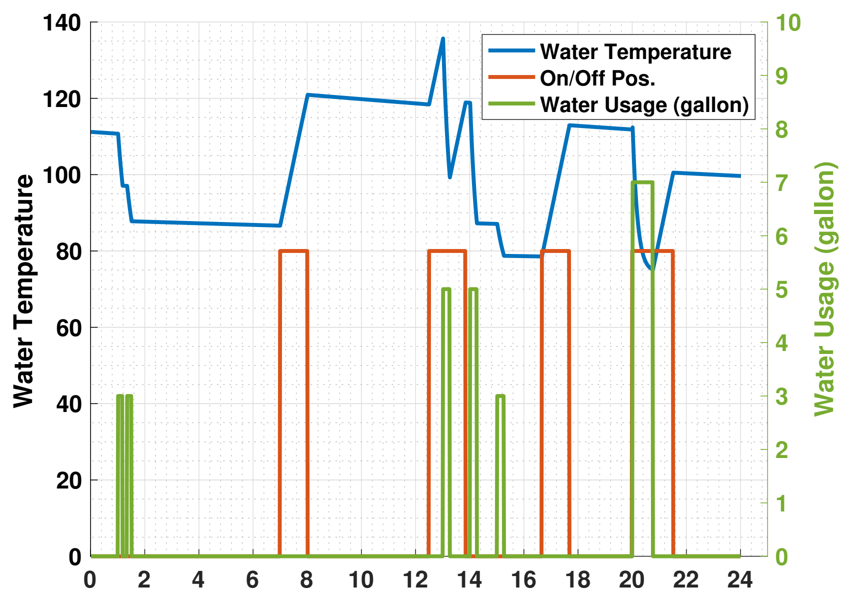


Fig. 6.11: Water temperature with random control.

After mitigating customer comfort violation, we calculate total demand again which is shown in Fig. 6.13.

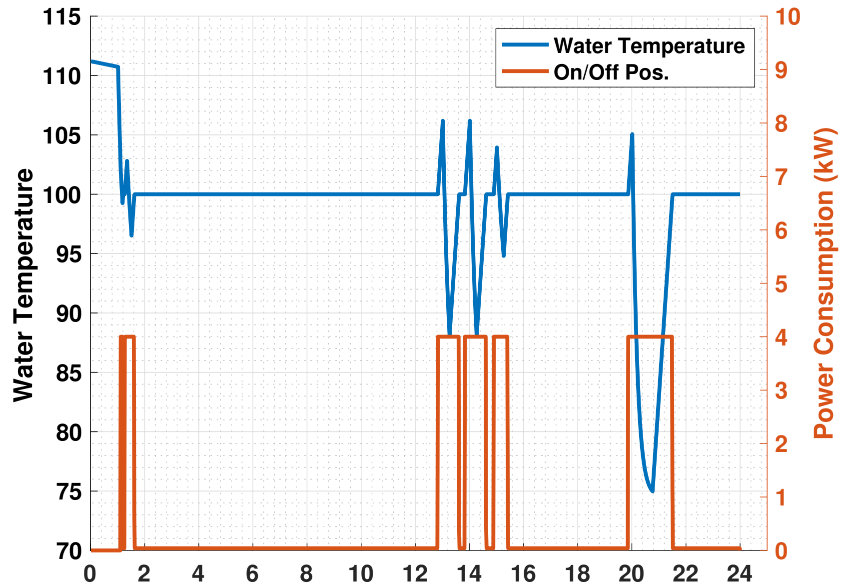


Fig. 6.12: Water temperature after control algorithm.

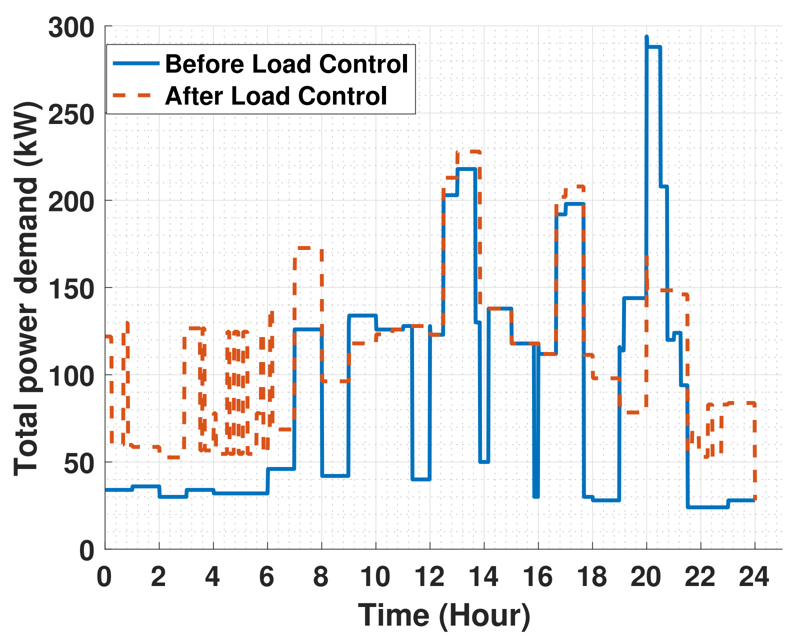


Fig. 6.13: Load demand comparison.

6.7 Chapter Summary

In order to acquire the decentralized power supply, a new convex control method is developed and implemented with the aid of the CVX solver. This results shows that the suggested control mechanism may successfully decrease the maximum peak load without compromising the comfort of the customers. Algorithms have the potential to increase the use of electric vehicles and the reliability of the power grid. In addition, the grid and the customers benefit from the deployment of dynamic prices. All of the findings demonstrate that there is another option available to clients that can reduce their energy bills. While just three use cases were considered for this research, there is potential for them to be scaled up and included into other types of load models.

CHAPTER 7: CONCLUSIONS AND FUTURE WORK

This dissertation proposed electric vehicle management methodologies, including routing and power management with centralized and decentralized controllers based on an aggregator approach to manage electric vehicle charging congestion and maximum grid demand. The dissertation also proposes a framework for using electric vehicles as energy supply during shortage or non-availability of electric grid supply. The main contributions are as follows:

- A hybrid routing technique is developed that identifies the nearest charging stations for a specific car while also considering the decrease in power system vulnerabilities. The technique considers the range and speed of the EV, as well as the proximity to a charging station and the level of criticality of the SoC. The hybrid method can be used for a single vehicle or a whole fleet. The algorithms used in most research for directing cars have always favored drivers. However, in the proposed approach, the power consumption of the electric grid is monitored during vehicle routing calculations, and the charging station-bus connection is also considered. The flexibility of electric vehicles and the strain on the power grid are factors that the suggested control architecture takes into account. It has been observed that the routing algorithm contributes to the electricity system's reliability as well as the safety and satisfaction of the user.

- A methodology that takes into account EV charging schedules and real-time EV charging congestion is developed. For this, a central aggregator collects information on bus charging scenarios to govern the distribution of the whole fleet of electric cars rather than just one at a time which is then used to reduce the total electric demand at that location. The method is developed to determine the maximum number of passengers that an electrical node can hold, enabling several electric cars to share a single power source.

- A novel scalable distributed convex optimization framework is developed for EV aggregators based on decentralized control. This framework was motivated by the success of the Alternating Direction Method of Multipliers (ADMM) in solving the common EV aggregator optimization challenge. The scalability of the framework is tested for valley filling, cost reduction, and vehicle-to-grid (V2G) applications. Since ADMM allows for formulating both global and local objectives, it is suitable for applications considering several EV aggregators, unlike centralized control.

- As a part of the Vehicle to grid (V2G) application, to achieve a distributed power supply, a convex control method has been developed that efficiently minimizes the maximum peak load without compromising the customers' comfort. It has been demonstrated that algorithms may assist in improving the penetration of electric vehicles (EVs) and power grid systems, as well as the use of smart gadgets. In addition, deploying dynamic prices benefits both the grid and the client sides of the business.

7.1 Future Works

A few items have been recognized that have the potential to bring value to this research in the future.

- As opportunities for future research first, multiple aggregators models can be established that allow flexibility in using electric grid and road infrastructure.

- Scalability of the proposed architecture considering the significant number of cars and buses should be studied.

- Another scope of future work is the integration of building and electric vehicle fleets together as a part of building and vehicle-to-grid methodology, where consumer comfort and local constraints are taken into consideration.

LIST OF PUBLICATIONS

J1 A. Joshi, A. I. Aygun, S. Kamalasadan and B. K, "Inverter Angle Induced Optimized Frequency Regulation Approach For AC-DC Micro-Grids Using Consensus-Based Identification," in IEEE Transactions on Industry Applications, 2022.

C1 A. I. Aygun and S. Kamalasadan, "An Optimal Approach to Manage Electric Vehicle Fleets Routing," 2022 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE), 2022.

C2 A. I. Aygun and S. Kamalasadan, "An Optimal Approach to Manage Electric Vehicle Fleets Routing," 2022 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE), 2022.

C3 A. I. Aygun, A. Joshi and S. Kamalasadan, "An Alternating Direction Method of Multipliers (ADMM) Based Optimal Electric Vehicle Fleets Charging In Active Electric Distribution Network," 2022 IEEE Global Conference on Computing, Power and Communication Technologies (GlobConPT), 2022.

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APPENDIX A: Dijkstra Algorithm

```
function [shortestPath, Cost] = dijkstra(Graph, Source, Destination)
%% Input Testing
totalNodes = size(Graph);
totalNodes = max(size(Graph));
%% Dijksrta Algorithm
for i1 = 1:totalNodes
    costDijkstra(i1,:) = [Inf, Inf];
    distancee(i1,:) = [Inf, Inf];
end
costDijkstra(Source,:) = [0 0];
foundNodes = Source;
nodesFound=1;
Status='Found';
for i1 = 2:totalNodes+1
    currentNode = foundNodes(nodesFound);
    if currentNode==Destination
        break;
    end
    for i2 = 1:totalNodes
        if Graph(currentNode,i2)~=0
        if costDijkstra(i2,2)> (costDijkstra(currentNode,2)
        +Graph(currentNode,i2))
            costDijkstra(i2,2)=costDijkstra(currentNode,2)
            +Graph(currentNode,i2);
        costDijkstra(i2,1)=currentNode;
```

```
        path(i2,1)=costDijkstra(i2,1)  ;
        distance(i2,:)=costDijkstra(i2,2)  ;
            end
        end
    end
    shortMatrix=find(costDijkstra(:,2)>=costDijkstra(currentNode,2)

    costDijkstra(:,2)<Inf);
    for i2 = 1:nodesFound
        c = shortMatrix==foundNodes(i2);
        %c find(shortMatrix==shortestPath(i2));
        shortMatrix(c)=[];
    end
    if isempty(shortMatrix)
        Status='Not Found';
        break;
    end
    lengthShortMatrix=length(shortMatrix);
    minCost=costDijkstra(shortMatrix(1),2);
    minCostPosition=shortMatrix(1);
    for i2 = 2:lengthShortMatrix
    if costDijkstra(shortMatrix(i2),2)<minCost
   %&& costDijkstra(shortMatrix(i2),1)==currentNode
            minCost=costDijkstra(shortMatrix(i2),2);
            minCostPosition=shortMatrix(i2);
            if minCostPosition==Destination
                break
```

```
            end
        end
    end
    foundNodes = [foundNodes, minCostPosition];
    nodesFound = nodesFound+1;
end
% clearvars -except Status costDijkstra Source Destination totalNodes;
%% Shortest Path
shortestPath=[];
if strcmp(Status, 'Not Found')
    Cost=Inf;
    return;
end
Cost=costDijkstra(Destination,2);
currentNode=Destination;
for i1 = 1:totalNodes
    shortestPath=[currentNode shortestPath];
    if currentNode==Source
        if Source == Destination
            shortestPath = [currentNode shortestPath];
        end
        return;
    end
    currentNode=costDijkstra(currentNode,1);
end
end
```

APPENDIX B: Floyd-Warshall Algorithm

```
function [D,P] = FloydWarshall(D,carNoX)
prevD = D;
P = zeros(size(D));
for k = 1:length(D)
   D = min(D,D(:,k) + D(k,:));
   P(D<prevD) = k;
   prevD = D;
%
a=carNoX(1);
b=carNoX(2);
%
pathx=[a,b];
pathway=P(a,b);
%
while pathway >0
pathx = [ pathx(1) pathway pathx(2:end) ];
pathway= P(a,pathway);
end
end
end
```

APPENDIX C: IEEE 123 Bus OPF Code

```
function mpc = case12
%Master Network of splitted 123 bus system
%% MATPOWER Case Format : Version 2
mpc.version = '2';
%% system MVA base
mpc.baseMVA = 1;
%% bus data
%bus_i type Pd Qd Gs Bs area Vm Va baseKV zone Vmax Vmin
mpc.bus = [
 1 3 0 0 0 0 1 1 0 4.16 1 1.05 1.05
 2 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
 3 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9
 4 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9
 5 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
 6 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9
 7 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9
 8 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9
 9 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9
 10 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
 11 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9
 12 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9
 13 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9
 14 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9
 15 1 0    0 0 0 1 1 0 4.16 1 1.1 0.9          % 0.65832 0.35667
 16 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
```

17 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

18 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

19 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

20 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9 % 0.264993 0.1633367

21 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

22 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

23 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

24 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

25 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

26 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

27 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

28 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

29 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

30 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

31 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

32 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

33 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

34 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

35 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

36 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

37 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

38 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

39 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

40 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

41 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

42 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

43 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

44 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

45 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

46 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

47 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

48 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

49 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

50 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

51 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

52 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

53 1 0.035 0.025 0 0 1 1 0 4.16 1 1.1 0.9

54 1 0.070 0.050 0 0 1 1 0 4.16 1 1.1 0.9

55 1 0.046667 0.031667 0 0 1 1 0 4.16 1 1.1 0.9

56 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

57 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

58 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

59 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

60 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

61 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

62 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

63 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

64 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

65 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

66 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

67 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

68 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

69 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

70 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

71 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

72 1 0.025 0.011667 0 0 1 1 0 4.16 1 1.1 0.9

73 1 0.046667 0.0333336 0 0 1 1 0 4.16 1 1.1 0.9

74 1 0.025 0.011667 0 0 1 1 0 4.16 1 1.1 0.9

75 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

76 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

77 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

78 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

79 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

80 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

81 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

82 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

83 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

84 1 0.081666 0.060001 0 0 1 1 0 4.16 1 1.1 0.9

85 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

86 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

87 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

88 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

89 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

90 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

91 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

92 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

93 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

94 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

95 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

96 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

97 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

98 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

99 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

100 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

101 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

102 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

103 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

104 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

105 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

106 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

107 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

108 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

109 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

110 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

111 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

112 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

113 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

114 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

115 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

116 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

117 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

118 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

119 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

120 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

121 1 0.013333 0.0066667 0 0 1 1 0 4.16 1 1.1 0.9

122 1 0.0066667 0.0033333 0 0 1 1 0 4.16 1 1.1 0.9

123 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

124 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9

```
 125 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
 126 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
 127 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
 128 1 0 0 0 0 1 1 0 4.16 1 1.1 0.9
];

%% generator data
% bus Pg Qg Qmax Qmin Vg mBase status Pmax Pmin Pc1 Pc2 Qc1min Qc1max Qc2min
mpc.gen = [
 1 0 0 10 -10 1 1 1 15 0 0 0 0 0 0 0 0 0 0 0
];

%% branch data
% fbus tbus r x b rateA rateB rateC ratio angle status angmin angmax
mpc.branch = [
 1 2 1.00E-02   1.00E-02 0 999 999 999 0 0 1 -360 360  % 1.00E-02 1.00E-02
 2 3 0.0232 0.0475 0 999 999 999 0 0 1 -360 360
 3 4 0.0441 0.0447 0 999 999 999 0 0 1 -360 360
 3 5 0.0629 0.0638 0 999 999 999 0 0 1 -360 360
 3 9 0.0174 0.0356 0 999 999 999 0 0 1 -360 360
 5 6 0.0503 0.051 0 999 999 999 0 0 1 -360 360
 5 7 0.0818 0.0829 0 999 999 999 0 0 1 -360 360
 7 8 0.0629 0.0638 0 999 999 999 0 0 1 -360 360
 9 10 0.0116 0.0238 0 999 999 999 0 0 1 -360 360
 10 14 0.0566 0.0574 0 999 999 999 0 0 1 -360 360
 10 11 0.0566 0.0574 0 999 999 999 0 0 1 -360 360
 10 15 0.0174 0.0356 0 999 999 999 0 0 1 -360 360
```

11 38 1.00E−02 1.00E−02 0 999 999 999 0 0 1 −360 360

16 12 0.0629 0.0638 0 999 999 999 0 0 1 −360 360

16 13 0.0629 0.0638 0 999 999 999 0 0 1 −360 360

15 20 0.0378 0.0383 0 999 999 999 0 0 1 −360 360

15 21 0.0478 0.098 0 999 999 999 0 0 1 −360 360

38 16 0.1069 0.10846 0 999 999 999 0 0 1 −360 360

17 18 0.0944 0.0957 0 999 999 999 0 0 1 −360 360

17 19 0.0881 0.0893 0 999 999 999 0 0 1 −360 360

20 17 0.0252 0.0255 0 999 999 999 0 0 1 −360 360

21 22 0.0629 0.0638 0 999 999 999 0 0 1 −360 360

21 24 0.0174 0.0356 0 999 999 999 0 0 1 −360 360

22 23 0.0818 0.0829 0 999 999 999 0 0 1 −360 360

24 25 0.1322 0.134 0 999 999 999 0 0 1 −360 360

24 26 0.0145 0.0297 0 999 999 999 0 0 1 −360 360

26 27 0.1385 0.1404 0 999 999 999 0 0 1 −360 360

26 28 0.0159 0.0327 0 999 999 999 0 0 1 −360 360

28 39 1.00E−02 1.00E−02 0 999 999 999 0 0 1 −360 360

28 31 0.0116 0.0238 0 999 999 999 0 0 1 −360 360

39 29 0.0203 0.0455 0 999 999 999 0 0 1 −360 360

29 30 0.0159 0.0358 0 999 999 999 0 0 1 −360 360

29 34 0.0566 0.0574 0 999 999 999 0 0 1 −360 360

30 36 0.1259 0.1276 0 999 999 999 0 0 1 −360 360

31 32 0.0174 0.0356 0 999 999 999 0 0 1 −360 360

32 33 0.0203 0.0416 0 999 999 999 0 0 1 −360 360

33 37 0.0116 0.0238 0 999 999 999 0 0 1 −360 360

34 35 0.0755 0.0766 0 999 999 999 0 0 1 −360 360

21 40 1.00E−02 1.00E−02 0 999 999 999 0 0 1 −360 360

```
40  41  0.0217   0.0445  0  0  0  0  0  0  1  -360  360;
41  42  0.0377  0.0845  0  999  999  999  0  0  1  -360  360
41  46  0.0145  0.0297  0  999  999  999  0  0  1  -360  360
42  43  0.0755  0.0766  0  999  999  999  0  0  1  -360  360
42  44  0.0629  0.0638  0  999  999  999  0  0  1  -360  360
44  45  0.0818  0.0829  0  999  999  999  0  0  1  -360  360
46  47  0.0818  0.0829  0  999  999  999  0  0  1  -360  360
46  48  0.0145  0.0297  0  999  999  999  0  0  1  -360  360
48  49  0.1259  0.1276  0  999  999  999  0  0  1  -360  360
48  50  0.0116  0.0238  0  999  999  999  0  0  1  -360  360
50  51  0.0503  0.051  0  999  999  999  0  0  1  -360  360
50  53  0.0145  0.0297  0  999  999  999  0  0  1  -360  360
51  52  7.55E-02  7.66E-02  0  999  999  999  0  0  1  -360  360
53  54  0.0087  0.0178  0  999  999  999  0  0  1  -360  360
53  55  0.0145  0.0297  0  999  999  999  0  0  1  -360  360
55  56  0.0145  0.0297  0  999  999  999  0  0  1  -360  360
56  57  0.0145  0.0297  0  999  999  999  0  0  1  -360  360
58  57  0.029  0.0594  0  999  999  999  0  0  1  -360  360
15  59   1.00E-02  1.00E-02  0  999  999  999  0  0  1  -360  360
59  60  0.0232  0.0475  0  999  999  999  0  0  1  -360  360
60  61  0.0116  0.0238  0  999  999  999  0  0  1  -360  360
61  62  0.0072  0.0148  0  999  999  999  0  0  1  -360  360
62  63  0.0159  0.0327  0  999  999  999  0  0  1  -360  360
62  65  0.0203  0.0416  0  999  999  999  0  0  1  -360  360
63  64  0.0159  0.0327  0  999  999  999  0  0  1  -360  360
65  66  0.0629  0.0638  0  999  999  999  0  0  1  -360  360
65  68  0.0435  0.0891  0  999  999  999  0  0  1  -360  360
```

66 67 0.0629 0.0638 0 999 999 999 0 0 1 −360 360

68 69 0.0319 0.0653 0 999 999 999 0 0 1 −360 360

68 70 0.048 0.0229 0 999 999 999 0 0 1 −360 360

68 123 1.00E−02 1.00E−02 0 999 999 999 0 0 1 −360 360

69 127 1.00E−02 1.00E−02 0 999 999 999 0 0 1 −360 360

70 71 3.36E−02 0.016 0 999 999 999 0 0 1 −360 360

71 72 0.0672 0.032 0 999 999 999 0 0 1 −360 360

72 73 0.0816 0.0389 0 999 999 999 0 0 1 −360 360

73 74 0.0624 0.0297 0 999 999 999 0 0 1 −360 360

75 76 0.0503 0.051 0 999 999 999 0 0 1 −360 360

75 80 0.0159 0.0327 0 999 999 999 0 0 1 −360 360

75 105 0.0145 0.0297 0 999 999 999 0 0 1 −360 360

128 75 0.0203 0.0416 0 999 999 999 0 0 1 −360 360

76 77 0.0692 0.0702 0 999 999 999 0 0 1 −360 360

77 78 0.0818 0.0829 0 999 999 999 0 0 1 −360 360

78 79 0.0692 0.0702 0 999 999 999 0 0 1 −360 360

80 81 0.0692 0.0702 0 999 999 999 0 0 1 −360 360

80 84 0.0116 0.0238 0 999 999 999 0 0 1 −360 360

81 82 0.0881 0.0893 0 999 999 999 0 0 1 −360 360

82 83 0.1007 0.1021 0 999 999 999 0 0 1 −360 360

84 85 2.32E−02 4.75E−02 0 999 999 999 0 0 1 −360 360

84 94 0.0406 0.0831 0 999 999 999 0 0 1 −360 360

85 86 0.0058 0.0119 0 999 999 999 0 0 1 −360 360

86 87 0.013 0.0267 0 999 999 999 0 0 1 −360 360

86 88 0.0275 0.0564 0 999 999 999 0 0 1 −360 360

88 89 0.0101 0.0208 0 999 999 999 0 0 1 −360 360

89 90 0.0145 0.0297 0 999 999 999 0 0 1 −360 360

89 92 0.1699 0.1723 0 999 999 999 0 0 1 –360 360

90 91 0.0145 0.0297 0 999 999 999 0 0 1 –360 360

92 93 0.1196 0.1212 0 999 999 999 0 0 1 –360 360

94 95 0.0261 0.0534 0 999 999 999 0 0 1 –360 360

95 96 0.0441 0.0447 0 999 999 999 0 0 1 –360 360

95 97 0.0159 0.0327 0 999 999 999 0 0 1 –360 360

97 98 0.0566 0.0574 0 999 999 999 0 0 1 –360 360

97 99 0.013 0.0267 0 999 999 999 0 0 1 –360 360

99 100 0.0755 0.0766 0 999 999 999 0 0 1 –360 360

99 101 0.013 0.0267 0 999 999 999 0 0 1 –360 360

101 102 0.0692 0.0702 0 999 999 999 0 0 1 –360 360

101 103 0.0174 0.0356 0 999 999 999 0 0 1 –360 360

103 104 0.0503 0.051 0 999 999 999 0 0 1 –360 360

105 106 0.0159 0.0327 0 999 999 999 0 0 1 –360 360

105 124 1.00E–02 1.00E–02 0 999 999 999 0 0 1 –360 360

106 107 3.19E–02 6.53E–02 0 999 999 999 0 0 1 –360 360

107 108 0.0174 0.0356 0 999 999 999 0 0 1 –360 360

108 126 0.0464 0.095 0 999 999 999 0 0 1 –360 360

109 110 0.0566 0.0574 0 999 999 999 0 0 1 –360 360

109 113 0.0159 0.0327 0 999 999 999 0 0 1 –360 360

110 111 0.0818 0.0829 0 999 999 999 0 0 1 –360 360

111 112 0.1762 0.1786 0 999 999 999 0 0 1 –360 360

113 114 0.0566 0.0574 0 999 999 999 0 0 1 –360 360

113 116 0.0188 0.0386 0 999 999 999 0 0 1 –360 360

114 115 0.1448 0.1467 0 999 999 999 0 0 1 –360 360

116 117 0.1133 0.1148 0 999 999 999 0 0 1 –360 360

116 125 0.05797 0.11876 0 999 999 999 0 0 1 –360 360

```
 117 118 0.0755 0.0766 0 999 999 999 0 0 1 -360 360
 118 119 0.1448 0.1467 0 999 999 999 0 0 1 -360 360
 118 120 0.0315 0.0319 0 999 999 999 0 0 1 -360 360
 120 121 0.1322 0.134 0 999 999 999 0 0 1 -360 360
 121 122 0.0818 0.0829 0 999 999 999 0 0 1 -360 360
 123 128 1.00E-02 1.00E-02 0 999 999 999 0 0 1 -360 360
 124 109 1.45E-02 2.97E-02 0 999 999 999 0 0 1 -360 360
];
%%----- OPF Data -----%%
%% generator cost data
% 1 startup shutdown n x1 y1 ... xn yn
% 2 startup shutdown n c(n-1) ... c0
mpc.gencost = [2 0 0 3 0.01 40 0;];
%% convert branch impedances from Ohms to p.u.
[PQ, PV, REF, NONE, BUS_I, BUS_TYPE,...
PD, QD, GS, BS, BUS_AREA, VM,...
VA, BASE_KV, ZONE, VMAX, VMIN, ...
LAM_P, LAM_Q, MU_VMAX, MU_VMIN] = idx_bus;
[F_BUS, T_BUS, BR_R, BR_X, BR_B, RATE_A, RATE_B, RATE_C, ...
TAP, SHIFT, BR_STATUS, PF, QF, PT, QT, MU_SF, MU_ST, ...
ANGMIN, ANGMAX, MU_ANGMIN, MU_ANGMAX] = idx_brch;
Vbase = (mpc.bus(1, BASE_KV)/sqrt(3)) * 1e3;       %% in Volts
Sbase = mpc.baseMVA * 1e6;  %% in VA
mpc.branch(:, [BR_R BR_X]) = ...
mpc.branch(:, [BR_R BR_X]) / (Vbase^2 / Sbase);
%results=runpf(case12)
%plot(results.bus(:, 8))
```