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The Impact of PEV User Charging Behavior in Building Public Charging Infrastructure

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THE IMPACT OF PEV USER CHARGING BEHAVIOR IN BUILDING PUBLIC CHARGING INFRASTRUCTURE

by

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THE IMPACT OF PEV USER CHARGING BEHAVIOR IN
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Plug-in electric vehicles (PEVs) play a significant role in the development of green cities since they generate less pollution than conventional vehicles. To promote PEV adoption and mitigate range anxiety, charging infrastructure should be deployed at strategic locations that are readily accessible to the public. Nebraska is working on the expansion of charging infrastructure around the state; however, stakeholders face several difficulties in trying to minimize irregular charging behaviors. Most electric vehicle users plug in and leave their vehicles for an extended time at public parking lots designated for PEVs. Some users even leave their vehicles for longer than 24 hours. Prolonged idle time is a concern for other PEV users who need to charge their vehicles to complete their planned trip. This thesis proposes several well-known regression methods to predict the idle time to help policymakers minimize the impact of irregular charging behaviors. In addition, PEV user charging behavior has a significant influence on the distribution network and its reliability. In addition, to increase efficiency in management of the electric grid, this thesis also proposes several well-known regression methods to predict the energy consumption of a charging session. The performance of different regression methods for predicting the idle time as well as energy consumption are characterized using established statistical metrics.

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Nomenclature

PEV	Plug-In Electric Vehicle
EV	Electric Vehicle
ICE	Internal Combustion Engine
BEV	Battery Electric Vehicle
PHEV	Plug-In Hybrid Electric Vehicle
EREV	Extended Range Electric Vehicle
HEV	Hybrid Electric Vehicle
LIB	Lithium-Ion Batteries
LI/S	Lithium-Sulfur Batteries
LOL	Loss of Life
SOC	State of Charge
V2G	Vehicle to Grid
CSs	Charging Stations
MURB	Multi-Unit Residence Building
EPS	Electrical Power System
QOS	Quality of Service
RSQ	Coefficient of Determination
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
EVSE	Electric Vehicle Supply Equipment
KPI	Key Performance Indicator
SOC	State of Charge
GDP	Gross Domestic Product
MLR	Machine Learning in R
IDE	Integrated Development Environment
MMH	Maximum Marginal Hyperplane

CHAPTER 1

INTRODUCTION

1.1 General

This chapter outlines the motivation for the research conducted in this thesis. The chapter also outlines the main objectives of the research and the structure of each chapter in the document.

1.2 Motivation

Many apparent difficulties impede the widespread adoption of electric vehicles, including purchase cost, range anxiety due to limitation of driving range, and the need for public charging infrastructure [1], [2]. The development of battery technology leads to more affordable and longer-range electric vehicle models, addressing the first two difficulties in widespread adaption. However, the rapid development of electric vehicles requires a reasonable strategy in building charging infrastructures on the roads to meet the demand for all users, as well as encourage others to use electric vehicles instead of conventional ones. Many challenges appear due to the variation in charging demands as well as battery sizes. Limited information is available about the effect of charging behaviors on public charging stations in any given area. However, an adequate analysis and prediction of the variables that affect charging behavior is necessary for effective planning to allow policymakers to optimize the locations and pricing strategies for the charging stations to have an optimal transition to electrified transportation.

Currently, there are more than 25,000 charging stations across the United States [3]. However, to optimize the locations, occupation, and utilization of the public charging stations, information about the charging sessions in every area should be collected and analyzed to understand how the users interact with the current charging infrastructure and how policymakers might improve the regulations for efficiently using the charging infrastructure. In this research, critical parameters correlated with charging and parking behavior are collected from the existing public charging stations in the state of Nebraska to be processed and analyzed.

1.3. Thesis Objectives

The main objective of this research is to deepen the understanding of charging behavior in public charging stations in Nebraska by collecting and analyzing data from existing charging stations in the state. This analysis will aid policymakers in amending the regulations for using the charging infrastructure more efficiently by placing the charging infrastructure in optimal locations as well as increasing the utilization rate of the charging stations by applying the most suitable price policy. In addition, this thesis proposes several well-known regression methods to predict the idle time in order to help policymakers minimize the impact of irregular charging behaviors. Also, to increase efficiency in management of the electric grid, this thesis also proposes several well-known regression methods to predict the energy consumption of a charging session. The performance of different regression methods for predicting the idle time as well as energy consumption is characterized using established statistical metrics.

1.4. Thesis Organization

This research will start by examining the fundamental knowledge of electric vehicles, the differences between the three main types of electric vehicles, and the types of batteries used in the electric vehicles. Next, charging infrastructure is introduced as a critical factor in expanding the development and adoption of electric vehicles. Then, an investigation of the existing research on the impact of PEV user charging behavior on the electric grid and charging infrastructure policy is presented, including the results found in that research. After a background of previous studies has been reviewed and investigated, the methodology used in this research as well as the parameters needed to be analyzed are introduced. Then, the analysis and results of PEV user charging at public charging stations in Nebraska is performed and presented, showing the different behaviors that are observed for the various parameters examined. Finally, conclusions and future work are presented in the last chapter. A brief outline of the thesis is as follows:

1. Chapter 1 is an introduction.
2. Chapter 2 offers a review of fundamental knowledge in electric vehicles, explaining the differences between the three types of electric vehicles and the batteries used, as well as a general overview of the charging infrastructure. Next is a literature review for the previous studies on the influence of PEV user charging on the electric grid and charging stations.
3. Chapter 3 explains the methodology used to predict PEV user charging in public charging stations in Nebraska.
4. Chapter 4 offers analytics of PEV user charging in public charging stations in Nebraska.
5. Chapter 5 discusses the results of machine-learning models applied to predict the idle time and energy consumption.
6. Chapter 6 discusses the conclusions and future work, and offers a summary of what has been achieved with this research.

CHAPTER 2

LITERATURE REVIEW

2.1 Electric Vehicles

2.1.1 General Background

An electric vehicle (EV) is a vehicle that utilizes an electric engine instead of a combustion engine used in traditional vehicles. It uses a rechargeable battery to store the electricity needed to operate the electric motor. An EV is known as an environmentally friendly vehicle that produces no emissions. Since an EV has less moving components, maintenance is cheaper than the conventional vehicle because there is no need for oil changes or tune-ups, replacements of timing belts, and there's no exhaust [4]. Figure 2.1 shows the major differences between electric vehicles and conventional vehicles.

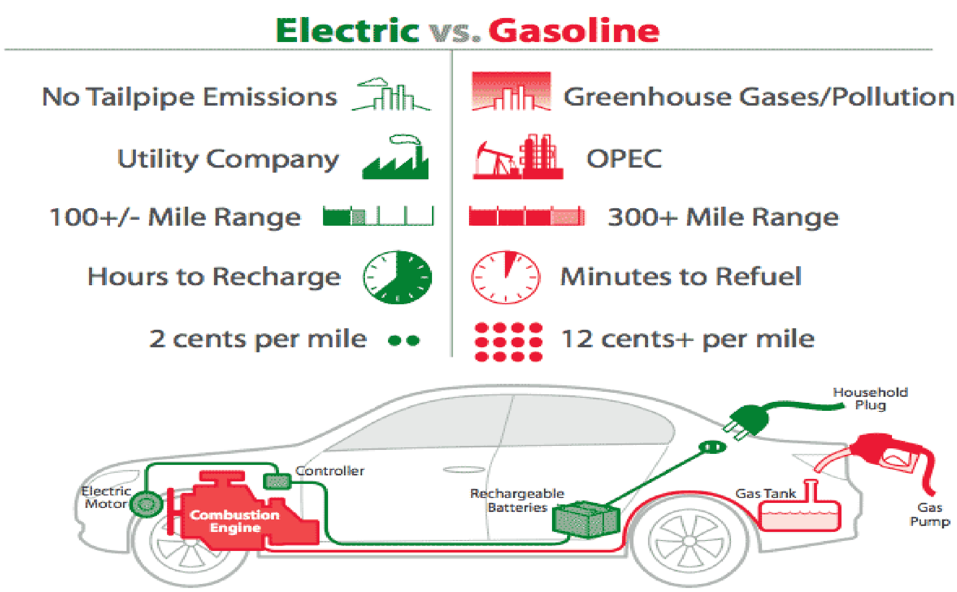


Fig 2.1 Major difference between electric vehicles and conventional vehicles.

(Source: https://www.plugincars.com/electric-cars)

EV has been used since the 1900s in multiple applications [5]. However, new improvements in battery technology and research and development by large vehicle companies have led to the significant increase in electric vehicles nowadays [6].

2.1.2 Electric Vehicle Types

2.1.2.1 Battery Electric Vehicles (BEV)

Battery electric vehicles, BEVs, are more commonly named EVs. They are entirely electric vehicles with the ability to store energy with high-capacity battery sets and have no gasoline engine, fuel tank, or exhaust pipe, which are essential in conventional vehicles. The regenerative braking technique is another method for BEVs to recharge their batteries by using the electricity generated from the braking process [7]. BEVs are further identified as plug-in EVs because of the utilization of the external charging source to charge the battery. The energy stored in the battery is utilized to control the electric motor and all onboard electronics. BEVs generate no harmful emissions caused by conventional vehicles. Figure 2.2 shows the key components of an all-electric vehicle.

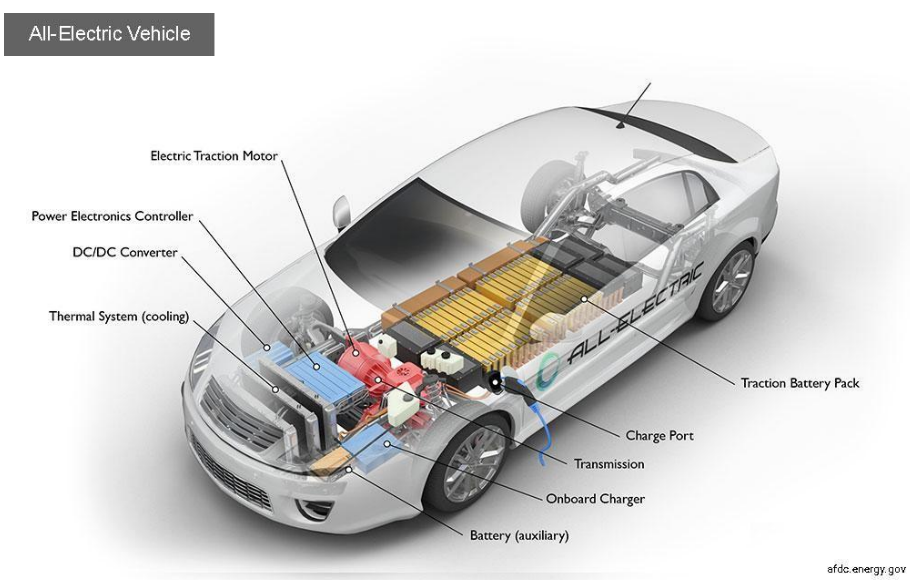


Fig 2.2 Key components of an all-electric vehicle.
(Source: afdc.energy.gov)

Typically, as is shown in Table I, most BEV can travel around 100-200 miles on a fully charged battery, which is less than the typical 350-400-mile range for gasoline cars. However, these ranges could be significantly shortened in different conditions such as driving in hilly terrain, running the air conditioner in hot weather, or using the heater in cold weather [8].

TABLE I

EXAMPLES OF BEVS AVAILABLE IN THE U.S. BY THE END OF 2018

Make/Model	**Type**	**Battery Pack (kWh)**	**Range (miles)**
Tesla Model S 100D	BEV	100	351
Tesla Model S P100D	BEV	100	337
Tesla Model 3	BEV	78.5	310
Tesla Model X 100D	BEV	100	295
Tesla Model X P100D	BEV	100	289
Tesla Model S 75D	BEV	75	275
Chevy Bolt	BEV	60	238
Tesla Model X 75D	BEV	75	237
Nissan LEAF	BEV	30	151
VW e-Golf	BEV	35.8	125
Ford Focus Electric	BEV	33	115
BMW i3	BEV	33	114
Fiat 500e	BEV	24	87

(Source: EVAdoption.com)

2.1.2.2 Plug-In Hybrid Electric Vehicles (PHEV)

Plug-in hybrid electric vehicles, PHEVs, known as extended-range electric vehicles (EREVs) are powered by both gasoline and electricity. PHEVs are powered by an external electrical charging outlet that can store energy in the battery through "plugging in" and a regenerative braking technique that converts the vehicle's kinetic energy to electrical energy stored in the battery

[9]. The combustion engine increases the capacity of the vehicle by recharging the battery at slow speeds. Figure 2.3 shows the key components of a PHEV.

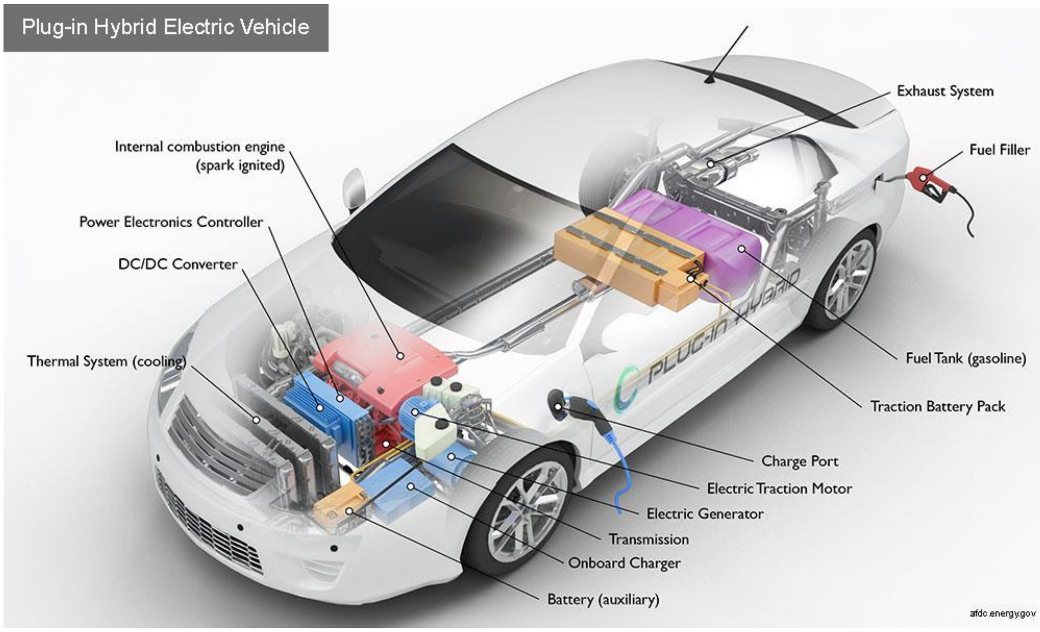


Fig 2.3 Key components of a plug-in hybrid electric vehicle.
(Source: afdc.energy.gov)

Typically, as can be seen in Table II, a PHEV model can go 10-40 miles before using its combustion engine [10].

TABLE II
EXAMPLES OF PHEVS AVAILABLE IN THE U.S. BY THE END OF 2018

Make/Model	Type	Battery Pack (kWh)	Range (miles)
Chevy Volt	PHEV	18.4	53+ Gasoline
BMW i8	PHEV	7	23+ Gasoline
Toyota Prius	PHEV	9	25+ Gasoline
Ford Fusion Energi	PHEV	7	21+ Gasoline
Ford C-Max Energi	PHEV	7.6	20+ Gasoline
Volvo XC90 T8	PHEV	10.4	17+ Gasoline

(Source: EVAdoption.com)

2.1.2.3 Hybrid Electric Vehicles (HEV)

Hybrid electric vehicles (HEVs) are manufactured for receiving either a high-grade performance regarding tailpipe emissions or a fuel saving. The braking system of the vehicle can be used to convert the vehicle's kinetic energy to electrical energy stored in the battery. HEVs start by utilizing the electric motor at slow speeds and then switch to the gas motor as the speed increases. The motors are operated by a controller that regulates performance to achieve the best efficiency for driving conditions [11]. Figure 2.4 shows the key components of a hybrid electric vehicle.

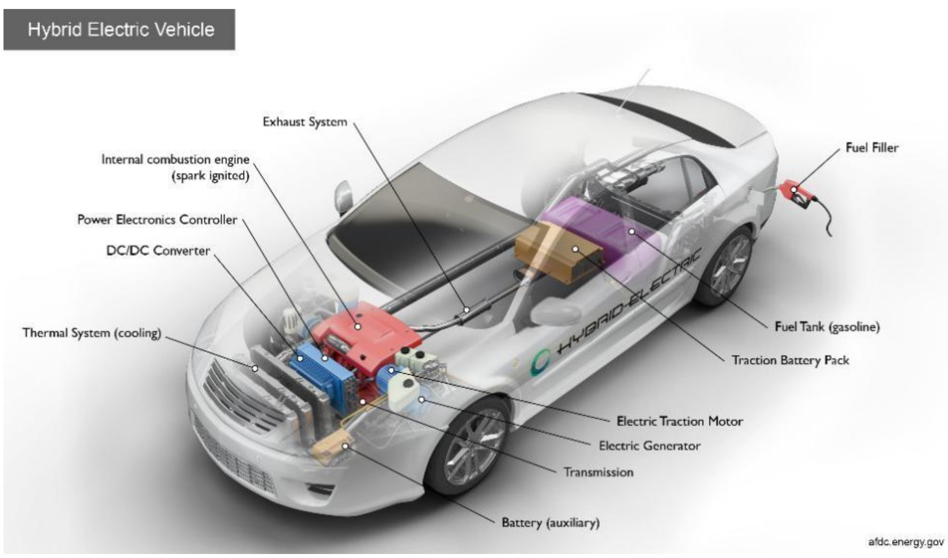


Fig 2.4 Key components of a hybrid electric vehicle.
(Source: afdc.energy.gov)

Examples of hybrid electric vehicles on the road today are the Chevrolet Tahoe Hybrid, Toyota Prius, Camry Hybrid, Ford C-Max, Honda CR-Z, and Kia Optima Hybrid.

2.1.3 Battery Technologies Used in Electric Vehicles

More and more, batteries are used as the energy storage and power source for renewable power systems [12], [13]. Various types of battery technologies are currently available such as lithium-ion, solid-state, aluminum-ion, lithium-sulfur, and metal-air batteries.

2.1.3.1 Lithium-Ion Batteries

Lithium-ion batteries, called LIBs, are the most utilized batteries in the electric vehicle world because of their outstanding performance, and they will most likely prevail in the next decade [14]. Tesla and Nissan are conducting research to better improve this technology. To understand the charging process in LIBs, charged lithium-ion batteries are moved from the anode to the cathode in the electrolyte. LIBs have an extraordinary cyclability—the number of times the battery can be recharged while still preserving its efficiency. A downside of this kind of battery is that it overheats easily, causing a strong fire [15], [16]. Safety devices were developed and improved by many manufacturers to limit the injuries caused by overheated batteries [17]. LIBs nowadays utilize silicon or graphite anodes. Plenty of energy can be stored in a small space by using a lithium anode [18]. Figure 2.5 shows the schematic structure of a lithium-ion battery.

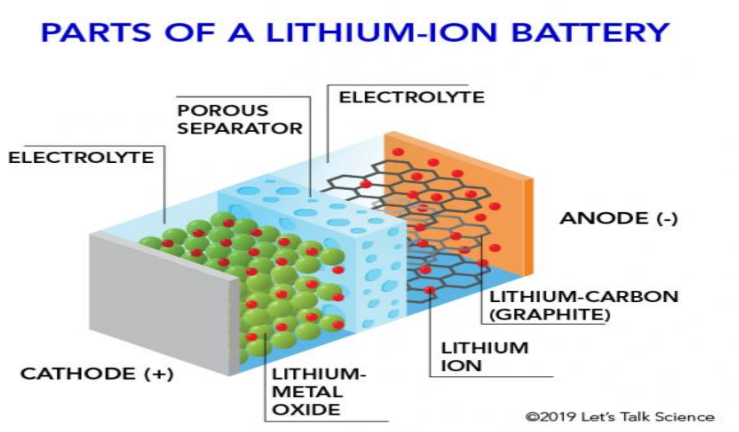


Fig 2.5 Schematic structure of a lithium-ion battery.
(Source: https://letstalkscience.ca)

2.1.3.2 Solid-State Batteries

Solid-state batteries have solid elements. This design has many benefits: An extended lifetime diminishes the demand for heavy and costly cooling devices, reducing the electrolyte losses, and the capability to work in an extensive temperature range [19]. Figure 2.6 shows the schematic structure of a solid-state battery.

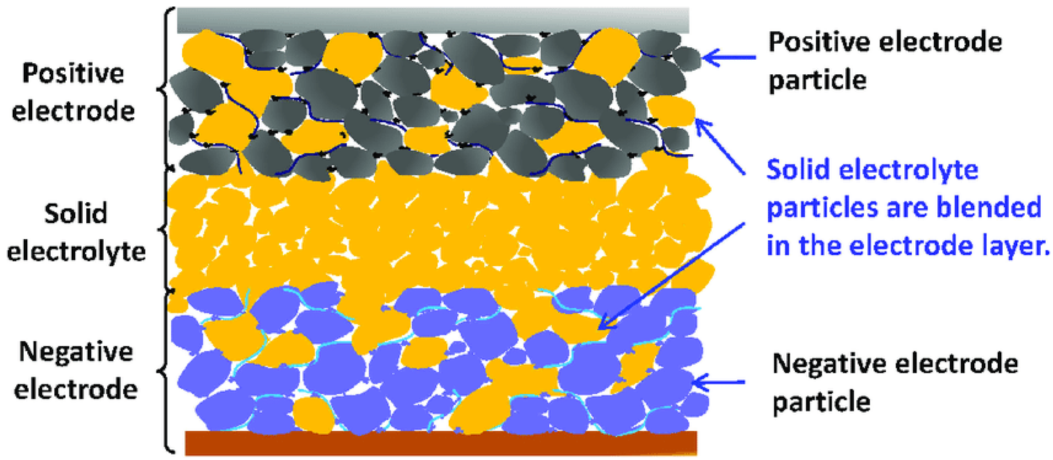


Fig 2.6 Schematic structure of a solid-state battery.
(Source: [20])

2.1.3.3 Aluminum-Ion Batteries

Aluminum-ion batteries have similar characteristics as lithium-ion batteries except that they have an aluminum anode. One of the aluminum-ion battery’s advantages is enhancing safety at a low price. However, its biggest weakness is the cyclability [21]. Recently, many studies have suggested a solution through utilizing an aluminum metal anode and a graphite cathode. This also gives exceptional lowered charging duration and the strength to bend [22]. Figure 2.7 shows a schematic structure of an aluminum-ion battery.

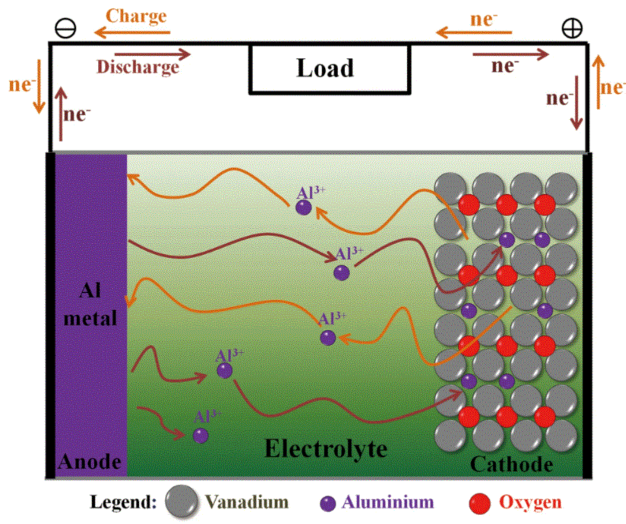


Fig 2.7 Schematic structure of an aluminum-ion battery.
(Source: [23])

2.1.3.4 Lithium-Sulfur Batteries

Lithium-sulfur batteries (Li/S) have a lithium anode and a sulfur-carbon cathode. They have an advantage of offering a special theoretical energy density and a lower cost than LIBs, but they have low cyclability, which is considered a major disadvantage [24]. However, many researchers are working to enhance their performance. Li/S batteries have been used by NASA to power space journeys, and they have been commercialized by Oxis Energy [25]. Figure 2.8 shows a schematic structure of a lithium-sulfur battery.

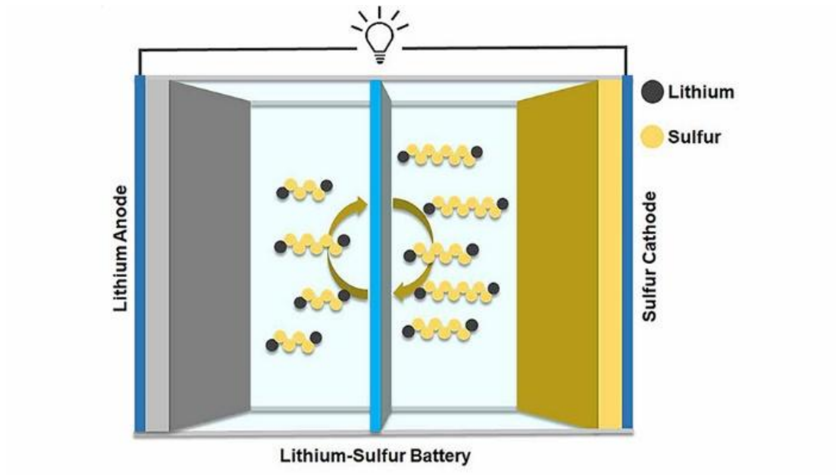


Fig 2.8 Schematic structure of a lithium-sulfur battery.

(Source: https://aip.scitation.org)

2.1.3.5 Metal-Air Batteries

Metal-air batteries have a pure metal anode and an ambient air cathode. Besides the weight of the battery, having an air cathode is considered a major feature. There are many variants for the metal, but lithium, aluminum, zinc, and sodium remain the forerunners. Cyclability and lifetime in metal-air or metal-oxygen prototypes are recognized as the notable disadvantages [26]. Figure 2.9 shows a schematic structure of a metal-air battery.

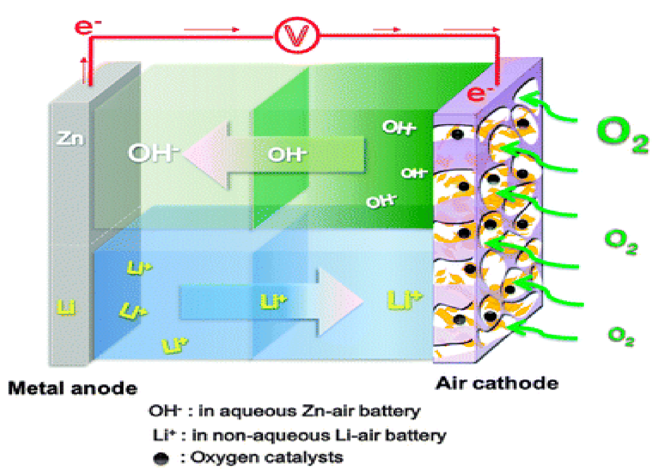


Fig 2.9 Schematic structure of a metal-air battery.

(Source: [27])

2.1.4 Sales and Market Share of Electric Vehicles

The electric vehicle market has been growing rapidly due to the development of rechargeable batteries and the development of charging infrastructure. The year 2018 ended with $2 million sales worldwide, which is 72% over 2017 at an average market share of 2.1% [28]. Figure 2.10 shows the worldwide sales for the last four years. All-electric vehicles accounted for 69% of plug-in electric vehicles sales, while PHEVs accounted for 31%.

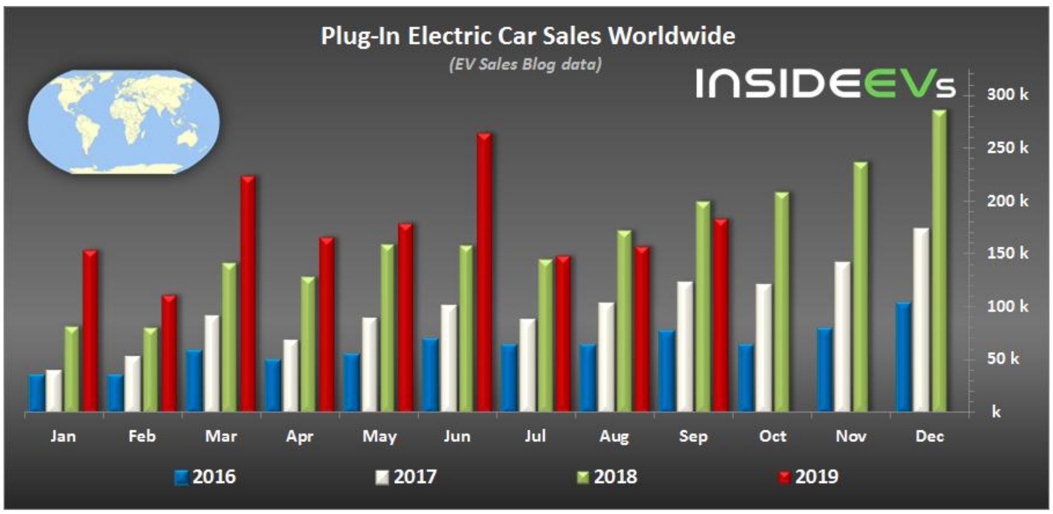


Fig 2.10 Plug-in electric car sales worldwide.
(Source: [28])

In addition to the global market, U.S. sales of electric vehicles reached 361,307 in 2018 as can be seen in Figure 2.11; sales in the U.S. rapidly increased in 2018, around 81% over 2017. Tesla Model 3 was responsible for the largest sales in 2018; around 139,000 vehicles were sold in 2018. As can be seen in Figure 2.12, all-electric vehicles accounted for 67% of plug-in electric vehicle sales, while PHEVs accounted for 33%.

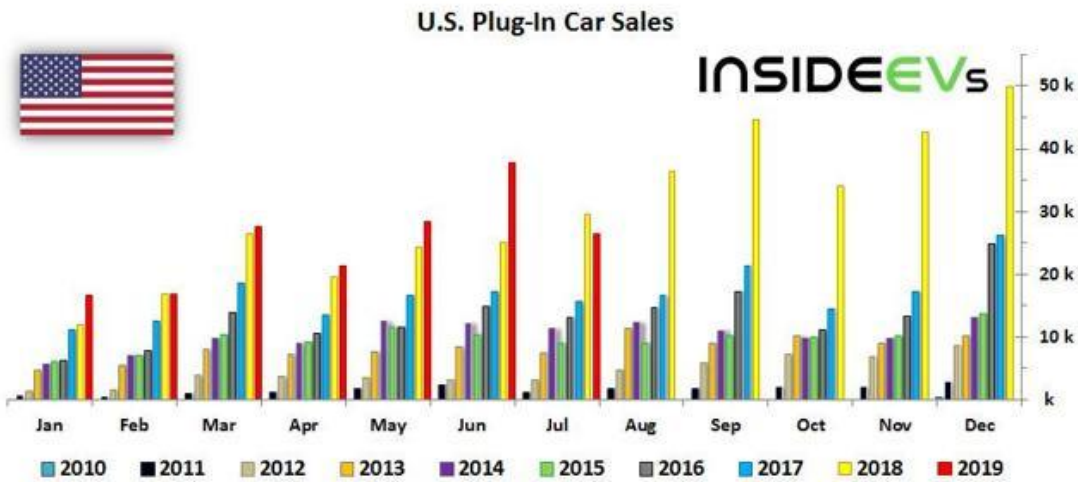


Fig 2.11 U.S. plug-in car sales.

(Source: [28])

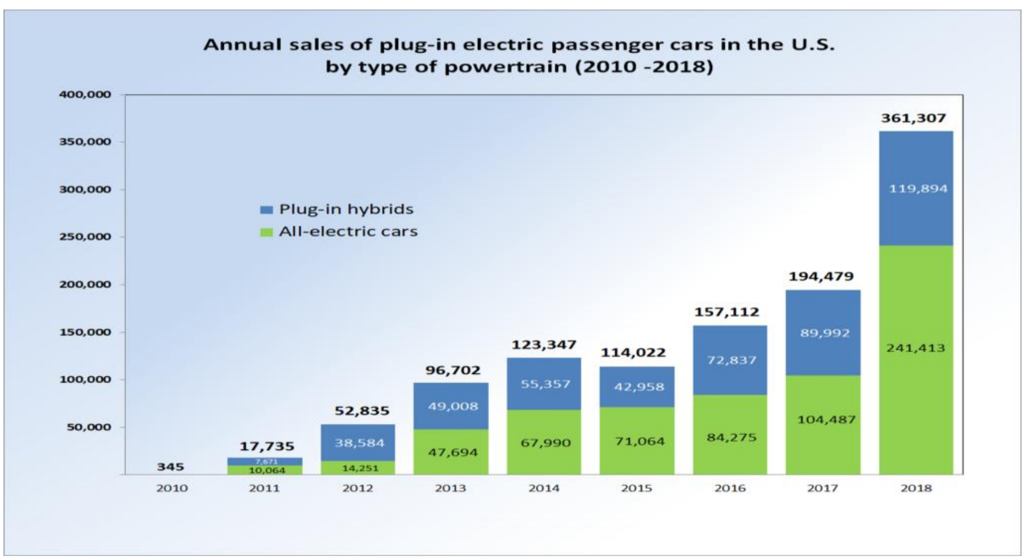


Fig 2.12 Annual sales of plug-in electric vehicles in the U.S.

(Source: [28])

2.2 Charging Infrastructure

2.2.1 General Background

Charging infrastructure is a vital factor in growing the sales of electric vehicles. According to the U.S. Department of Energy, at the end of 2019 there were around 25,000 public charging stations in the United States [3], more than 90% of which were AC-charging. With range anxiety being a primary concern of drivers, more charging stations away from homes have been installed to extend the range of electric vehicles.

The rapid development of electric vehicles requires a reasonable plan in building charging stations to meet the demand for all users and to encourage others to use electric vehicles instead of conventional ones. Most studies have found that drivers do more than 80% of their charging at home, the same way they might charge their cellphones [29]. In addition to home charging, charging installations at workplaces can provide an option to individuals who do not have charging equipment at home. Nevertheless, to have a productive charging system, it will be necessary to extend this charging foundation with options that are easy to utilize, available, and modestly priced. The absence of access to charging infrastructure is considered one of the prominent disadvantages to module electric vehicle reception for some Americans, especially those who live in multifamily residences [30].

2.2.2 Charging Methods

There are several different methods of delivering energy to the vehicle; this is commonly done in the form of high-voltage alternating current (AC) or high-voltage direct current (DC). Those methods are the most essential portions of electric vehicle charging infrastructure. Many different designs for the couplers and ways to connect the car are manufactured to support the varieties of vehicle options. Nowadays, three different power levels have been specified for accommodating the present power grid standards of the national electricity generating utilities: Level 1, Level 2, and Level 3.

Level 1 refers to single-phase alternating current (AC), which is the slowest charging method. This method is common for residential and commercial buildings. According to the Society of Automotive Engineers' standard, this means 120 volts deliver 1.4 kW of power at 12 amps and 1.9 kW of power (on-board) in North America [31], while it might be 10 or 16 amps at 240 volts delivering 3.7 kW of power in Europe [32]. The PEV might include a regular domestic power cord to connect the vehicle to a domestic socket outlet or a Level 1 charging station. This method is particularly suitable for overnight charging.

Level 2 refers to single- or three-phase alternating current (AC) sources of 240V at up to 80 amps; it transfers up to 19.2 kW of power [33]. Manufacturers produced two types of Level 2 charging equipment: "conductive" and "inductive." In North America, the J1772 standard has been determined to cover the connector and charging cable used in Level 2 applications. The connector is also generally called a "coupler" [32].

Level 3 refers to "fast charging." It is usually used for commercial and public applications to charge in a very short time. Level 3 chargers provide extremely high currents of up to 200 amps at 450 VAC delivering up to 62.5 kW of power. Moreover, Level 3 chargers could be a direct current (DC), delivering up to 240 kW of power at currents up to 400 amps and up to 600V DC [33].

TABLE III
THREE DIFFERENT POWER LEVELS OF POWER GRID STANDARDS OF NATIONAL ELECTRICITY GENERATING UTILITIES

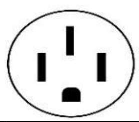
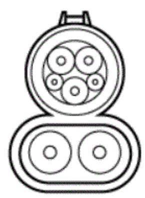
Power Level Types	Locations	Supply Circuit	Power (kW)	Fully Charge Duration BEV/ PHEV
Level 1	Home or Office	120 VAC 1-Phase (20A)	1.4kW at 12A-1.9kW (On-Board)	12-20Hours/7 Hours
Level 2	Private or Public Ports	240 VAC 1-Phase (40-80A)	7.7kW-19.2kW (On-Board)	4-6 Hours/3 Hours
Level 3/DC Fast Charging	Commercial Stations Like a Filling Station	450VAC/600VDC 3-Phase/DC 200A/400A	6.5 kW-240 kW (Off-Board)	0.5 Hours 10-15 Minutes

2.2.3 Charging Coupler

Currently, there are several competing industry commercial standards, including an SAE J1772, Hybrid coupler, like Jumbo, and the Japanese CHAdeMO. For example, SAE J1772 is designed for single-phase electrical systems with 120V or 240V such as those used in the U.S., Canada, and Japan where it is the most common connector, while the Combo J1772 coupler enables charging from either a standard 15-amp AC wall socket or a DC connection of up to 90 kilowatts. These systems are being proposed for public fast-charging stations [34]. The challenge is in Level 3 charging stations connector compatibilities, so it is important for the vehicle's driver to know if it is compatible with the connector available before planning for a trip. For example:

1. **Asian**: Nissan Leaf, Mitsubishi i-Miev, etc. These cars use the CHAdeMO connector standard.
2. **American/European**: Chevrolet Bolt, Chevrolet Spark, BMW i3, Mercedes, Volkswagen, etc. These cars use the SAE Combo CCS standard.
3. **Tesla**: Model S and Model X. Tesla uses its own connector standard.

TABLE IV
MOST COMMON CONNECTORS FOR CHARGING ELECTRIC VEHICLES [35]

Connectors	**Symbol**	**Level**	**Asian Makes**	**US/EU Makes**	**Tesla**
Wall Outlets Nema 515 Nema 520	 	1	With Adapter	With Adapter	With Adapter
PortJ1772		2	Yes	Yes	With Adapter
Nema 1450 (RV Plug)		2	With Adapter	With Adapter	With Adapter
CHAdeMO		3	Yes	No	With Adapter
SAE Combo CCS		3	No	Yes	No
Tesla HPWC		2	No	No	Yes
Tesla Supercharger		3	No	No	Yes

2.2.4 Charging Infrastructure Locations

Home: Today, a majority of recharging is done at home, and overnight [36]. That is usually when electricity is cheapest, and users approach it like plugging in a cellphone at night. For owners of battery-electric cars, it is often optimal to install a charging station in their garage or carport. For plug-in hybrids, many owners simply use the 120-volt charging cords.

Workplace: Charging at work is slowly growing in popularity [37]. It is a good way for corporations to cut their carbon footprint, it is not prohibitively expensive to install, and it is an attractive employee perk, whether or not the company or landlord charges a fee for it.

Public sites: Finally, there are thousands of public charging stations throughout the U.S. and Canada, and the number grows each week. Virtually all public sites offer Level 2 charging, with a few offering DC fast charging as well, increasingly with both CHAdeMO and CCS cables. Some public charging is free, while other sites impose a fee, using a number of different (and mostly) incompatible networks that generally require up-front membership. It is strongly recommended that an electric vehicle user have a smartphone app to locate charging stations.

2.2.5 Charging Station Networks

Many charging networks operate the various charging stations around the world. Not all networks are present everywhere, and some are limited to certain areas. The charging station infrastructure can be spilt into two categories:

1. Smart charging stations, also known as networked charging stations or connected stations
2. Non-networked charging stations, which do not require a membership to activate

As can be seen in Figure 2.13, in 2018 there were around 22,000 public charging stations in the U.S., made up of 19,575 Level 2 EVSE stations and 2,368 DC fast-charging stations; over 60% of them belong to one of four charging networks—ChargePoint, Tesla, Blink, and SemaCharge. Among the 19,975 AC stations, some 37% are connected by ChargePoint and another 13% by Tesla, followed by Blink (8%). On the other hand, EVgo comprises 31% of the 2,368 DC fast-charging stations, followed by Tesla (17%), ChargePoint (15%), and Greenlots (10%) [29].

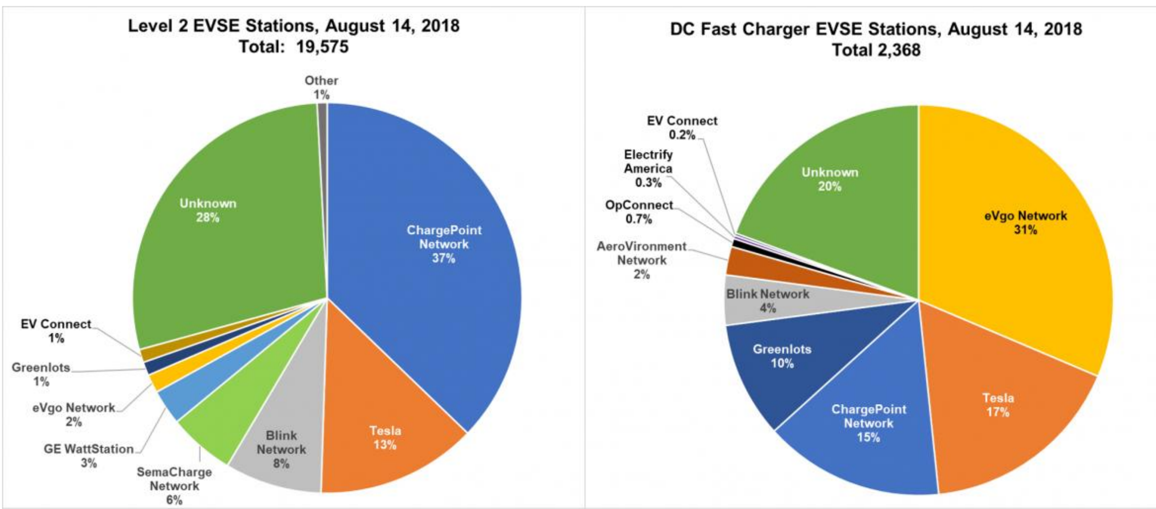


Fig 2.13 Charging station network share in the U.S.

(Source: [29])

2.3 Related Work

2.3.1 General Background

Climate change has been a serious issue around the world for a long time, and innumerable resolutions have been offered to decrease the issues caused by global warming[38], [39]. In the outcome of the Paris Agreement of 2015, each country was required to decrease the emission levels in a dynamic action to oppose climate change [40]. Most countries started to reduce the emissions in their transportation division by encouraging people to use electric vehicles instead of conventional vehicles [41]. The number of electric vehicles on the road has been significantly increasing worldwide and in the U.S. in recent years [42]. This success is due to the combined efforts of politics and industry over the past several years—notably, with plug-in electric vehicles (PEVs), which enable users to plug in their vehicles and drive solely with electricity or in combination with fuel. Because of the rapid penetration of PEV sales per year, more charging infrastructure needs to be installed on the roads to adequately serve consumers. Thus, policymakers avail from understanding the charging behaviors of PEV users in order to optimize the locations and characteristics of public charging stations in local municipalities [43]. Vehicle manufacturers also benefit from information about the usage of electric vehicles to improve performance, efficiency, and range [44].

2.3.2 Impact of PEV User Charging on the Electric Grid

PEV user charging has a significant influence on the distribution network and its reliability [45], [46]. Many researchers have published review articles analyzing the charging event data in existing charging stations in both residential and public locations to study PEV user charging and its impact on the power grid. These papers gathered and examined data from charging point aggregators, GPS installed in some EVs, or surveys asking about the preferences of EV drivers [47]–[56].

Authors of [57] formulated a methodology to predict the influence of EVs' charging on the power network by analyzing the EV sales and the speedy penetration of EVs in the transportation sector, as well as the charging and usage behaviors of owners. The authors assume that it would be required to analyze the impact of charging EVs on the power network for various purposes:

1- The charging demand would not consistently increase in the entire grid area; however, the increase would be anticipated in specific areas, such as residential areas.

2- Battery modules demand special charging features that can likely diminish the flexibility regarding displacing the charging loads to off-peak.

Many parameters were taken into account in this research, such as the size and time of peak demand, the shape of the load curve, the total energy needed, and the load characteristics. Many factors could be the basis for estimating the demand, such as:

(i) the consumers' purchase as well as approbation,

(ii) technological improvements in the types of vehicles and their important parts like the battery module,

(iii) the charging profile of the battery,

(iv) generation time and additional relevant infrastructure,

(v) availability of charging points, and

(vi) the influence on the current power network.

Therefore, individual thoughts of all scenarios that occur from these factors are not often reasonable because of many potential scenarios and the need for reliable and trustworthy data on future cases of these factors. The authors suggest two workable strategies to handle this circumstance: first, manufacturing a new battery with exceptional features that can meet the requirements of shortening the time needed for the charging cycle. The second approach is to displace the charging load into off-peak time by encouraging users to charge the battery in off-peak, which can reduce the load in the peak demand time.

Authors of [58] studied the impact of EVs on the current electric network. They developed an equation where the current power supply meets demand and other problems of imbalance. This research acquired results in evaluating the influence of the invasion of EVs on the overall power grid; however, it did not consider the charging behavior of EV users. On the other hand, authors of [59] determined the charging behavior that guards the power grid against congestion as well as meets the preferences of EV drivers. This study classified the charging management into centralized and decentralized. While the centralized technique concentrates on the centralized unit that controls the charging of the EVs directly, the decentralized technique allows for indirect influence on the charging behavior through various techniques, such as a price signal broadcast.

Authors of [60] studied the electricity demand profile by analyzing the users' charging behaviors. They focused on the time and location of the charging sessions. An algorithm was developed to predict the changes in PHEV charging demand over time. Moreover, authors of [61], [62] utilized information from traveling surveys to generate a load profile for charging electric vehicles, considering that EVs are traveling like conventional vehicles.

Authors of [63] determined the EV charging behavior on weekdays and weekends through analyzing multiple charging stations and interpreting the travel data of six European countries. The authors used the data available in charging stations as well as the travel data to predict the capacity of electricity needed to charge EVs. In the same purpose, authors of [64] employed data from charging points to predict the challenges in the electric network created by charging EVs. The data were analyzed to trail the charging and travel behavior such as starting time, charging location, and duration of the charging events for real EVs users in more than two years.

Authors of [65] analyzed 7,704 EV charging sessions to 65 EVs in northeast England to define the recharging users' behaviors. This study concludes that recharging behaviors happened during off-peak time. Moreover, authors of [66] analyzed 580,000 charging events in Northern California to estimate the benefits of smart charging using the actual trips and users' characteristics.

Authors of [67] showed that charging PHEVs at frequent occasions of the day could cause a serious issue by raising or reducing the distribution transformer performance. Moreover, enabling fast charge could easily cause the overloading of a distribution transformer even with the low number of PHEVs penetrated in the transportation sector.

Authors of [68] created a probabilistic charging model by using data from EVs to simulate the drive behavior of electric vehicles with regard to their required power. The authors' work was focused on trips starting and ending at home. The model is used in grid integration with electric vehicles. The methodology that integrates users' driving behavior, charging behavior, charging price, and charging time was developed in [69] by analyzing the charging and traveling behavior of EV users to get the effectiveness of their behavior on the power grid.

Many graphs were created in [70] to determine transformer loss of life (LoL) based on the scenarios. The benchmark was based on a normal load without EVs. Once EVs were introduced, a 10X increase in the LoL was shown. Over one year, a LoL in urban areas can increase from 0.002 to 0.014, mostly because of a large summer load. Once the EVs are introduced into the load, they begin to overload the system and the transformers begin to lose life more quickly. The main difference shown between scenarios is whether they are fast-charging or slow-charging. When slow charging, the EV normally charges at home during peak afternoon hours, when fast charging, the vehicle charges during off-peak hours of commuting. Because of this relationship, slow charging actually puts more strain on power equipment than fast charging, which is the opposite of what is expected.

With many studies on how the EV load will affect the grid, authors of [71] account for charging as a static load, with the main interest in the peaks. This study looks to see how the vehicles charge and where to look to effectively analyze how and where the charging occurs rather than to just say a certain city will have another peak from charging. The authors' model represents charging profiles. The charging speed is based on how many ports are connected. If a 230V EV is charging and another 230V is connected, the results show a slight increase in charging. But, if the other vehicle begins charging, the speed decreases by 1.5%. If the second vehicle is a 400V EV, charging goes up by 1.5% whether or not it is charging. If both vehicles are 400V EVs, then charging is dropped by about 7%. The battery degradation of 230V and 400V are then shown. They both decrease at about the same rate, but 230V EVs are the only vehicles with more than 200 sessions, so the data were very broad for the 400V EVs. For 300 sessions, the 230V EVs typically drop to about 93% of their original capacity; at 100 sessions, which is where the data are uncertain in 400V EVs, 230V EVs are at about 98% and 400V EVs are at about 97%. This may not seem significant, but if these vehicles are driven for the next 10 years, many sessions will be added, and the degradation seems to be a linear relationship to the amount of sessions.

Authors of [72] conducted research to alleviate the stress that a large EV penetration will have on the grid. Currently, power generation has to have enough power to supply peak use but is not used efficiently during off-peak hours, and the large EV penetration can help make current generation more efficient while not having to build new generation facilities to fulfill the needs. Smart scheduling strategies are limited by charging and discharging rate limits, initial SOC (state of charge), travel habits, final energy demand, and battery capacity. On the power system side, they are limited by generation capacity, network structure, transformer capacity, frequency requirements, and voltage requirements. The authors looked into many different algorithms to solve the problem, but they found that the ones that worked well required a subscription, and the ones that didn't did not work well. One of the problems for them not working well was that they were overloaded with information when a large number of EVs were introduced. The authors believe that in the future, charging stations will be able to implement vehicle-to-grid (V2G), variable charging, and a normal charging rate.

Authors of [73] found that EV penetration will cause major conflict on the low-voltage system. Because of this, they used a rural and urban and also generic network. It was found that about 40% penetration would exceed thermal limits of the low-voltage network. They also mention that their real-world EV charging data would be more useful if there was a larger dataset to estimate the penetration levels.

2.3.3 Impact of PEV User Charging on the Charging Infrastructure Development

Currently, public charging stations are in high demand due to the high penetration of electric vehicles on the road, and this demand is expected to grow [74]. Municipalities have started planning for deploying more charging stations by taking into account the location of charging stations as well as user charging patterns. Research on public charging infrastructure has been conducted following the invasion of electric vehicles. Most research tends to concentrate on the location of charging infrastructure using data from charging points in a given area [75]–[81].

Authors of [82] looks to find the barriers to placing charging stations in residential neighborhoods. This research is based in Canada where they have a target to achieve a 30% share of vehicle sales by EVs. The large increase is mainly due to 85% of electricity being provided via hydropower. This allows them to save a substantial amount of greenhouse gas emissions when switching to electric vehicles. Multi-unit residential buildings (MURBs) are a key factor in residential charging infrastructure. They currently account for almost 30% of households and are planned to be almost 70% of new construction. The authors discuss how current residents are trying to purchase an EV but have to rely on a work charger or significant charging network in place. If they are able to get a charger at the MURBs, they will not have to rely on the network as much and would feel more comfortable buying one.

Authors in [83] look at two situations where an EV user would either be dissatisfied or would keep a potential owner from purchasing a vehicle. They consider this a failure of a charging station and state that this can be caused either by a malfunction where the station needs to be repaired or by another vehicle taking up the station at the same time as another vehicle would like to charge. The problem and potential failure they are looking into is that if this is a growing trend among stations, it could cause a cascade since the EV that was looking to charge has to find another station, which would then affect other EVs looking to charge.

The main purpose of the research in [84] is to give the grid operators' points of critical operation areas given the location of optimal charging station (CS) locations. The authors propose an optimization model for CS placement and then to incorporate a reliability check for the grid based on DC power flow to ensure it stays within the limits. They mention that when the paper was written, there was no research to ensure that the grid remains stable once new CSs are introduced into the grid. The method proposed consists of the models of the electrical power system (EPS), the road network, charging technology, costs, EV trajectories, and requested quality of service (QOS). These data then move to the object function to find the CSs' placement minimal costs based on constraints from charging reliability, QOS, and the EPS reliability check. The results show the optimal locations for CS placement, the EPS power flows, and generation outputs.

Authors of [85] consider parking time to be a significant indicator in determining public parking locations for charging stations, which means that parking demand and duration were studied to predict precise locations for charging points in public parking.

Study in [86] suggests an intelligent charging control algorithm that actively determines the most appropriate charging station for the PEVs' drivers, reduces the charging expenses, and limits the overloading of transformers. In the same purpose, authors of [87] propose an algorithm to better scheduling an online request in the charging stations according to the user's need and preferred charging locations.

Authors of [88] analyze 4,933 charging sessions in Australia to estimate the consumption of energy, charging duration, daily charging frequency, starting time of charging sessions, and time to the next charging sessions. This estimation helps to understand the usage of charging points depending on EV owners' behaviors. Moreover, authors of [89] conducted a study based on 109,000 charging sessions and mainly focused on four districts since they are well-established with charging infrastructure, where the other districts have a significantly smaller infrastructure. The authors then compared the connection time with the charge time and found that there is charging happening only 4%-5% of the time. The rest of the time the vehicle is just connected and not allowing other vehicles to use it.

Authors of [90] conducted research to find the correlations, if any, of the behavior of EV drivers to how they charge their car. About 3 million charging sessions were analyzed, and it was found that the time of day that the session starts (for the most part) determines how long a session will last. In the same purpose, authors in [91] found that the location and the start time of the charging session have the greatest influence on the charging behavior, due to parking behavior aligning with charging behavior.

Authors of [92] used three different vehicle groups—private, commercial, and company—as well as three different charging structures in their project—domestic, work, and public. These parameters were used to construct a model they called ALADIN (Alternative Automobiles and

Diffusion and Infrastructure), and the results from this model were used as inputs in their eLOAD (electricity LOad curve ADjustment).

Authors of [93] conducted research to bring ideas to electric vehicle supply equipment (EVSE), or charging stations, to make them easier for customers. This is done by using pricing to restrain people from leaving a vehicle at an EVSE for an extended period of time. They also want to create a mobile app that estimates charge time left for customers as well as a way for the electric utility company to save money on the supply end. They have gathered data at UCLA over an almost-two-year period to get the best solutions.

Authors of [94] looked to predict when a certain charging station would be available for use. Traditionally, this is done using historical statistical data; however, machine learning nowadays can be used to do this. The utilization levels are at almost 40%, which causes competition and wait times for certain stations. Predicting when each station will be open can reduce a driver's wait time significantly. The authors' validation was consistent but did have a few spikes that could lead to future studies on why these happen consistently throughout the data. The model was correct within 15% of accuracy for six hours and 20% for 12 hours. Once they tested it beyond a day, it became drastically worse in predicting when each station would be available.

Authors of [95] seemed to want to determine how to most effectively make charging stations a business-viable option. They are only being supplied by many government subsidies and then normally being run publicly. The stakeholders could be multiple entities but are described as the municipality, the EV user, the actual companies producing and installing them, and the grid operators. Each of them has their own objectives when it comes to their normal operations, and this research tries to study how those operations will tie in to having charging stations. The objective for municipalities is to have better air quality. This can be calculated by the charging infrastructure but is not 100% accurate as they cannot know how many miles are used by visitors outside of the city. The authors discuss charge-time ratio as a well-researched KPI (key performance indicator). Charge-time ratio is calculated by dividing by the total charge time by the total connection time. By incentivizing users to repark after a full charge, space will free up for other users, which could then lead to a decision of not placing another charging port there since it is no longer utilized at a high rate. Being able to manage parking is another issue that municipalities are having trouble with; they are receiving complaints that people cannot park in a charging stall, even though it will not be used that day.

Authors of [96] looks at analyzing previous rollout strategies for EVs and how EVs have impacted the market and can be improved. They started the government roll-out strategies based on GPS locations of drivers. During this time, they received complaints from non-EV owners that the parking pressure was high, so this is where the demand-driven approach was presented. They divided the development process into three units: processing charging data, identifying the practitioners' rollout process and requirements, and building a web-based assessment platform. The dataset they are using is more than 7 million charging sessions with 8,650 charging stations. They used charge point records along with meter values to determine the transaction in the four major cities of the Netherlands. They started with Excel as it was readily available and known. They reached capacity with storage within Excel and had to move into a programming langue, which made the analysis easier as they could cut out data that were invalid.

Authors of [97] looked at three different scenarios to evaluate charging events and their impacts on electric mobility feasibility. The first scenario was that a vehicle would recharge whenever it was stopped for a period of time (two, four, or six hours); this would have three subsets in it. The second scenario tested the hypothesis of recharging only during night hours. The third scenario was that a vehicle would charge during the day on weekdays whenever needed. Driving data were collected using an on-board logger and combined with external data about street characteristics. The database was used to characterize day-to-day driving behavior and energy consumption on a second-by-second basis. In total, the database was comprised of 6,228 days and 33,000 trips. About 307,800 km were driven over 8,028 hours. The data were used to determine the amount of energy that could be saved by switching to EVs. Relaxed driving behavior only consumes 0.17 kWh/km while some more aggressive driving can consume almost 1 kWh/km. Some of this energy can be gained back through regenerative braking. With this taken into consideration, the average energy saved is between -60% to -70%. This number is also corroborated in other studies that resulted in similar values. Their last observation was that 50% of parking was found to last less than one hour. They recommend that fast charging stations be implemented as this would allow vehicles to charge to 100% SOC and have a full battery range again.

Authors of [98] seem to want to include every aspect of the EV experience that could play a part in their charging behavior. Because of this, they group them into three separate categories: driver-related, infrastructure-related, and vehicle-related. Driver-related is the intention of a driver to charge their EV. The two ways to look at this are based on experienced drivers knowing where and when they need to charge and knowing how people are going to plan their routes so they can have charging capabilities. Another aspect that some consider relevant is the interaction between drivers to let each other know if a charger is open. Infrastructure-related is how a user is going to use a station based on its geographic location. This research area is to show that stations are used for longer periods of time than at shopping centers. The authors also use this to keep a consistent flow of vehicles on a charger; if it is too low there is no point in adding more, but if the density of EVs for a region is high and there is a need for more infrastructure, more should be added. Vehicle-related helps determine how long a car needs to charge, either based on the kWh of the battery or if the battery can handle the amount of current that is going to be used.

In [99] authors focus on two different aspects: distinguishing user types and developing parameters to measure charging behavior. They used 1.6 million charge sessions to analyze the behavior. Occupation of the charger was the concern, and they could not find any correlations over day to day or even month to month; however, when looked at year to year, they noticed a strong correlation between occupancy, and it had a mean with about a 10% deviation from the mean. Although this is true, there are still chargers that have more than 70% occupancy and some with 0% occupancy, which makes this not as reliable as it might seem. They conclude that if charging stations are in places where customers want them, they are occupied more often, but if they are placed around busy regions, more kWh are charged there.

This paper [100] looks to maximize profits for the service providers at each stage of deployment due to the increasing EV-charging requirements, and it takes into account the construction cost and power constraints from the power grid. They first form the hypothesis of how long-term increases in the charging demand will need to be deployed and relate that to the short-term charging done based on power and space constraints. They will then see how this process will maximize profits for the distributers. Next, they run through an algorithm that will combine or remove the charging locations that are not profitable. Once this is finished, they test on real traffic data to demonstrate the efficiency.

The authors of [101] looks to identify how to manage parking pressure for EVs, along with how new users think they will charge based on a stated choice experiment. Questioning how new users will use the infrastructure is a main point in how public chargers roll out. This has been the topic for every country trying to implement EVs since there is currently not a private-business case for the charging structure. Since the government must intervene and place them before users are willing to purchase an EV, they must do so in a manner that makes sense to the upcoming users. So far, studies have found that there are two peaks for charging session starting times, which indicate a business charging in the morning and a home charging in the late afternoon/night. These studies have since been modified to see how range affects the user decisions instead of looking at peak times only. They also found in this paper that users in urban and densely populated areas are looking for workplace and parking charging structure. This shows that when planning the infrastructure of charging stations, it is necessary to have charging for apartment buildings and parking garages in dense areas, which could be slow-charging structures, but they also need to look at fast-charging infrastructure for people who travel a lot since range is a limiting factor for many. They need to look to split up the layout into more categories in order to fulfill the wants instead of placing all stations based on one assumption.

This paper [102] goes through the research process of designing a cost profile for charging stations that could increase the efficiency. They sent surveys to EV users and policymakers for their process. The policy was to charge the EV driver a certain amount for each hour after their charging was complete. This number was changed for each of the three categories of charging levels. They asked many questions to determine when they would most likely move their vehicle, if at all. They also asked about night charging and if they would move their car after it finished charging. This was put in the survey since most EVs are plugged in around 5 p.m. and are finished before 9 a.m. at the latest. Since this study was only done for EV users, the general Dutch public was not analyzed, so the results could be heavily skewed. This study was done since they believed that non-EV users could not fully predict their own charging behavior before actually owning an EV. They also noticed that most respondents were full-EV owners and not plug-in-hybrid owners.

For charging point operators, they found that even a small fee could increase efficiency. They also found that they should try to focus on a different approach where parking pressure is a problem and limit the fee to only very long session times. The fee also must be clearly portrayed for each station for the policy to work.

Authors of [103] looked at three different regression algorithms to find the most accurate one in determining the idle time of vehicles. They did this using machine learning that processed data from the Netherlands. The three different models were: Random Forest, Gradient Boosting, XGBoost. They looked for literature reviews that performed similar models. One of the studies found that about 61.4% of total connection time was idle time. They then discussed that this misrepresents the charging infrastructure, and instead of building new charging stations, they can better manage the ones that are currently there. Next, they looked at a study that used a web-based structure to analyze a large database that could then be accessed by the public to look at what is available. The last study looked at consumer behavior and how that would play a role in the charging profile.

In [104] the authors wanted to figure out the driving patterns of EV users. They use about 1,500 EVs in China and collected the data from September 1, 2015, to September 1, 2016. They found there to be five clusters and four types of multifaceted driving patterns. Their two main determinations would be proper dimensions of a driving pattern, and then they would have to derive a pattern based on the parameters and data. For the parameters, they used driving velocity, acceleration, daily distance, idle time of driving, and the driving range versus the trip range. They categorized the models as Level 1 and Level 2. Level 1 is focused on daily driving behavior, while Level 2 is multifaceted and focuses on a broader scale to see how they drive throughout a week and uses the Level 1 clusters to determine how they are similar. They noticed that if many different driving patterns were in a region, that region also had a great deal of GDP development. They also detailed the shortcoming of the research and what changes they would have made. It would be difficult to get all of the data needed as there are many types of EVs, even some that are not yet on the market. Some citizens may own one but it not be their primary vehicle. Another possibility is that they only had a year of data. If multiyear studies were done, they could see how the patterns change from year to year or just have more data on the scenarios being investigated. Working on finding the driving patterns is very difficult in general study and takes a lot of data to perform correctly. If this study were to be done again, this model would have better results but would have to be extensive in the research.

Reading through different literature articles, the authors [105] found that one barrier to buying an EV stood out: range anxiety. Some experts have said that range anxiety is simply a mindset that is psychological and not technical in nature, which means that adding more infrastructure will not change their view. The research delves into interviewing experts and consumers across 17 cities in five Nordic countries. They want to answer the following questions: Is range anxiety a true barrier to EV adoption? If so, is range anxiety technical or mental, or both? Does range anxiety decrease with experience? They believe the paper will bring comprehensive insight to the range anxiety problem and possibly new policy based on their evidence, while also improving consumer understanding of an innovation. For the jeopardy aspect, they found that 25% of respondents said the limited range of the EV was their main factor of disinterest with cost of ownership being second at 17.5%. Also, 90% of respondents said they are disinterested due to range travel less than 80 km per day, and 10% drive more than 80 km. This shows that even though it is a major issue, 90% of people can make their daily travel demand in about any EV. The perversity shows that the public started out saying they need an EV that goes much farther than 100 km, and now there are EVs that can go more than 300 km, but the public is now demanding 500-600 km of range.

Authors of [106] focused on looking at four main hypotheses about charging stations. The first is that EVs with a larger battery capacity lead to a higher kWh usage per charging station. The more stations per acre leads to a higher kWh usage per station, the more addresses per acre will correspond to a lower number of kWh usage per station, and the more cars per acre leads to a lower kWh usage per charging station.

Authors of [107] analyzed the effect of car-sharing EVs that do not have designated charging stations. These vehicles utilize public charging infrastructure and can cause large usage in public charging ports while they are not in use. They use two main sources for the data that they are looking for—one being the free-floating EV sharing data that were captured in Amsterdam, which included the location, battery level, and if the vehicle was charging. They found a correlation with different neighborhoods that included the age group of 18-45, high population density, low vehicle ownership, and location near railway stations. They found that only 11.2% of rides end at a charging station, which may be reasonable since they are normally used for short trips instead of long distances. The battery level really only plays a role if it is less than 30%. They also found that vehicles at 80% also play a significant role; however, they couldn't find an explanation for this. People under 45 have a very high correlation with the pickup and ending location, but population density did not. They found a correlation between vehicle ownership and the use of the system, which they think may have to do with vehicles being a preferred method of travel while low ownership may indicate that people prefer a different method of transportation (i.e., bicycle, walking, bus). The number of employed individuals is a strong correlation.

In this paper [108], authors concluded that the Level 2 chargers are mainly used for office or overnight charging while the fast-charging network is used for urgency or opportunity charging. In their survey, they found that the main reason to charge is not a range issue, but rather time left or possibility of running ahead of schedule. They suggested that a charging network specifically for taxis can be done at lunch locations or a typical location for taxis to have to wait for their clients (airports, shopping, meeting locations). The last conclusion is that a fast-charging station is a very effective alternative to home and workplace chargers if there is limited parking or simply no parking available. They did suggest that the standard needs to be higher for the charging station (needs to charge almost as fast as filling a tank of gasoline).

Authors of [109] looked at a pricing model that will shift the charging station (CS) load away from the residential peak by increasing prices of overused stations with long wait times and make underutilized CSs cheaper so vehicles will go slightly out of their way to use them. They are going to use an algorithm to find the optimum charging station based on travel time, wait time, and charging cost. Wait times and travel times have already been defined, but for charging time they reworked the models. Instead of each station having their independent pricing strategy, they decided to interconnect the CSs so that all the charging times were based on demand at the station. Their pricing model is used to minimize the total load, so they take the residential load into account along with the EV load.

The research presented in [110] focuses on different methods that can be used to determine driving techniques. They used input data from vehicles such as velocity, acceleration, power demand, battery state of charge, and using GPS to determine driving patterns. The techniques use AI-based models, Markov-based models, exponentially decreasing-based models (EDM) and telemetric-based models. The AI model will find a complex solution with nonlinear, multivariable, and constrained functions that will predict future techniques. The Markov approach uses a memoryless process that will develop a stochastic process to find probability distribution of the next state of a Monte Carlo simulation, mathematical expectation, or probability maximization. The telemetric technique takes real-time information such as travel distance, road grade, and speed limits to forecast their future driving. The Markov model could be the most accurate of the models.

Authors of [111], [112] proposed a hybrid kernel density estimator (HKDE) that uses both Gaussian- and Diffusion-based KDE (GKDE and DKDE) to predict the stay duration and charging demand of electric vehicles (EVs). Their conclusion is since DKDE has higher accuracy in general and GKDE tends to result in better estimation for users who charge the EV irregularly, the HKDE evaluates and categorizes the charging pattern regularity of a user, and determines which KDE to use by a novelty detection method based on the user's historical data.

Authors of [103] proposed a model to represent the resultant common behavior of EV drivers in an area using real EV data collected from a major North American campus network and part of the London urban area. The results of the model show that variances in the behavioral parameters change the statistical characteristics of charging duration; vehicle connection time and EV demand profile, which has a substantial effect on congestion status in CSs.

CHAPTER 3

METHODOLOGY

To support PEV adoption, charging infrastructure should be expanded in public places and workplaces to serve different types of users. This thesis mainly focuses on studying PEV user charging at public charging stations in the state of Nebraska. This thesis will aid policymakers in understanding the charging behaviors of PEV users in order to optimize the characteristics, size, and location of public charging stations.

A universal issue in this field is the impact of the user-charging behavior on the electric grid, especially in residential areas. In this research, however, data were collected from public charging stations to study trends in both charging and parking duration and to facilitate forming effective policies to optimize the public charging infrastructure in Nebraska. In addition, trends in energy consumption are studied to inform the utility companies how the charging behavior at public charging stations could affect the stability of the electric grid. A hurdle in this research is the analysis of a large amount of semi-random data, which leads to difficulties in finding a predictive model to describe the charging and parking behaviors.

3.1 Data Collected

Data are collected and analyzed from available Level 2 charging points located throughout Nebraska from January 2013 to December 2019 as shown in Table V. The charging stations are single phase 40A, 240V. The total dataset has 27,481 charging events. Figure 3.1 shows the Nebraska Community Energy Alliance (NCEA) members participating in this research conducted at University of Nebraska-Lincoln. The analysis is primarily based on the charging sessions, and for each charging session, the following information is considered: the ID and location of the station, start and end time, connection duration, charging duration, kWh consumed, and unique driver ID. Table V includes some yearly usage statistics of the charging stations.

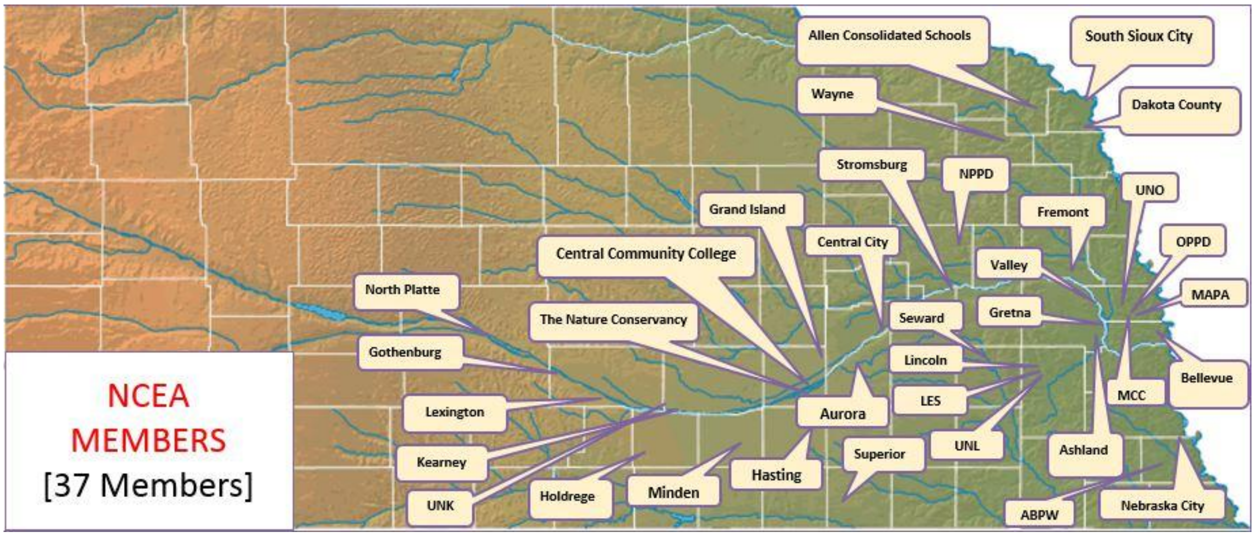


Fig 3.1 NCEA members participating in the research.

TABLE V
SUMMARY OF THE USAGE OF CHARGING STATIONS

Year	**Cumulative Number of Charging Ports**	**Number of Unique Users**	**Number of Sessions**	**Energy (MWh)**	**Connection Duration (Hours)**	**Charging Duration (Hours)**
2013	10	20	552	3.4	1,774	1,038
2014	18	45	947	4.9	3,727	1,593
2015	32	97	1,822	14.2	18,371	3,936
2016	70	211	2,825	23.9	30,735	6,315
2017	78	431	4,692	34.8	45,159	9,707
2018	90	787	7,389	61.2	684,18	14,982
2019	97	1,118	9,254	106.096	777,09	23,321
Total	97	1252	27,481	248.5	245,893	60,892

3.2 Data Variables

Before using smart charging networks in the United States, the electric vehicle user requires a membership, which allows the operator to identify the unique data for every user. In this work, the ChargePoint Operator website [113] is used to collect the variables needed to analyze the charging behavior, which are:

- **EVSE ID -** the unique ID for the stations used in every session,
- **EVSE location** - the location of the EVSE used in every session,
- **start date** - the date when the electric vehicle plug-in to EVSE, including mm/dd/yyyy and time of day hh:mm:ss,
- **end date -** the date when the electric vehicle plug-out for EVSE, including mm/dd/yyyy and time of day hh:mm:ss,
- **energy consumption** - the energy consumed during the charging session,
- **unique driver ID** - the unique user ID for the users,
- **charging duration** - the time required to charge EVs fully or partially,
- **connection duration** - the duration between the beginning and the end of the session, and
- **idle time** - the difference between the connection and charging durations.

3.3 Data Processing

Before analysis, some of the data were removed; sessions from the charging point data that lasted less than five minutes without charging were excluded. These instances occurred mainly due to technical difficulties where PEV users were unable to properly connect their vehicles to the port. Such instances account for 8.7% of the total sessions. In addition, sessions that lasted for more than 200 hours were also excluded from the study. These account for 0.41% of the total sessions. These instances often occur when state-owned EVs are plugged into the station during holidays, or when not in use. In total, 25,291 charging sessions were analyzed to investigate the charging behavior.

3.4 Machine-Learning Algorithms

For the purpose of predicting the charging behavior for the PEV user in terms of how long the user will stay at the parking lot after a full charge, as well as the energy consumption when the user plugs in, several supervised machine-learning algorithms could be used. XGBoost, rpart, Random Forest, and SVM are the algorithms chosen in this research to predict the idle time and the energy. The following subsection explains more about the algorithms used in this research:

1- Gradient Boosting Machine (XGBoost)

Boosting frameworks are often chosen due to their effortlessness and extraordinary outcomes on average size datasets. XGBoost, in particular, has seen widespread use in data science due to its high accuracy, flexibility, speed, and efficiency [114]. It is used to solve regression, classification, and ranking problems [9]. XGBoost's concept is to improve the performance of computational power for boosted tree algorithms. This algorithm is considered to be one of the fastest to incorporate tree ensemble approaches, using information from all data points in a leaf to decrease the search space of potential feature splits [103].

2- Decision Tree (rpart)

The rpart package found in the R tool can be applied for the classification of decision trees and can be utilized to generate regression trees. Recursive partitioning is a key mechanism in data mining, facilitating investigation of the formation of the dataset. The resulting models can be interpreted as binary trees.

3- Random Forest (RF)

Random forests, also known as random decision forests, are a famous ensemble training method. It is commonly applied for both classification and regression and functions by building an aggregation of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees' leverage [115].

Ensemble methods use multiple learning models to gain better predictive results. In the case of a random forest, the model creates an entire forest of random uncorrelated decision trees to arrive at the best possible answer. Random forest aims to overcome the correlation issue by picking only a subsample of the feature space at each split. Fundamentally, it aims to de-correlate the trees and cut the trees by setting stopping criteria for node splits. Random forest algorithm offers an excellent accuracy among current algorithms, and runs efficiently on large datasets. It can manipulate thousands of input variables without variable deletion. It creates an inner straight estimate of the generalization error as the forest building progresses.

4- Support Vector Machine (SVM)

Commonly, support vector machines are recognized as a classification method; however, they can be used in both classification and regression problems. It can simply manipulate various, continuous, and categorical variables. SVMs build a hyperplane in multidimensional space to separate different classes, creating an optimal hyperplane through an iterative process, which is applied to reduce the error. The ultimate output of SVM is a maximum marginal hyperplane (MMH) that best separates the dataset into classes. SVMs offer very high accuracy compared to other classifiers such as logistic regression and decision trees. It is known for its kernel trick to handle nonlinear input spaces and is used in a variety of applications such as face detection, intrusion detection, classification of emails, and handwriting recognition.

3.5 Machine-Learning Algorithms' Accuracy Evaluations

For the purpose of evaluating model performance, model evaluation metrics are used to evaluate and compare the four machine-learning algorithms. The following subsection explains more about the evaluation metrics used in this research:

1. Coefficient of determination (R^2)

R^2 is an important performance metric for any regression analysis. Used in statistical models for many applications, it provides a quantification of how well the model predicts the relationship between the input data and the generated output. A model that always generates a perfect prediction would have an R^2 of one, while a model whose predictions do not respond at all to input parameters would have an R^2 of zero.

Formally, R^2 is defined by equation (1), where the numerator is the sum of squares of the residuals (or errors), divided by the sum of squares for the test set. This can also be understood as a ratio of variances, indicating what portion of the variance in the result is accurately predicted by the model.

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \qquad (1)$$

2. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is another common statistical metric, quantifying the average amount of error between a prediction and a test set. RMSE has the same units as the variable being predicted. It is defined by equation (2) and is simply the standard deviation of the residuals or errors. RMSE provides information on how far, on average, a model's predictions are from their expected values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2} \qquad (2)$$

3. Mean Absolute Error (MAE)

Like the RMSE, mean absolute error (MAE) is also commonly used to quantify the average amount of error between a prediction and a test set. Instead of calculating the standard deviation of residuals, the MAE is simply the average of the absolute value of the residuals, as seen in equation (3). While RMSE and MAE are similar, RMSE gives a higher weight to larger errors before averaging. When the MAE is significantly lower than the RMSE, it can indicate a larger spread in the values of the residuals.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \qquad (3)$$

CHAPTER 4

ANALYTICS

After organizing the data by time of day and day of week, analysis is conducted on the charging sessions of the PEV users in public charging stations. Moreover, the data about connection duration are used to analyze the charging and parking behavior in the public charging stations by using a mathematical model. The variables collected from the sessions will be presented in this chapter.

4.1 PEV Connection Start and End Date

The connection time variable refers to when the users start their charge sessions. Both the time of day and day of the week will be considered in this analysis. As the daily usage of electric vehicle owners is somewhat random, there is also randomness in their charging behavior. Connection starting time is a critical variable in this analysis as it helps to determine the most common times for users to plug in and start the charging session. These data could be used to analyze PEV user behavior in order to avoid overcrowding of the charging stations.

Figure 4.1 shows the distribution of start times for users to start their connection sessions. It is apparent that most users use the public charging stations between 6 a.m. and 6 p.m. As can be seen in Figure 4.1, the most preferred time for users to start their sessions is at 1 p.m., with 13% of the total sessions starting between 1:00 p.m. and 1:59 p.m. However, Figure 4.2 shows the distribution of times that users end their connection sessions. It is apparent that end times are much more evenly distributed; times between 6 a.m. and 6 p.m. are roughly the same.

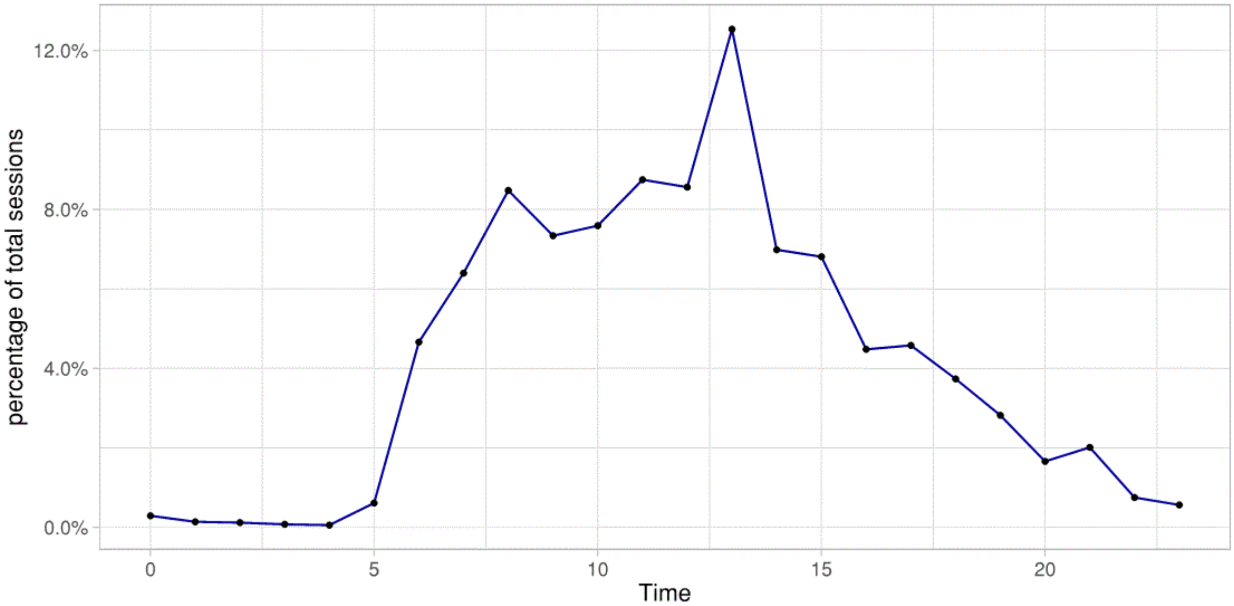


Fig. 4.1 The percentage of total sessions with a given start time.

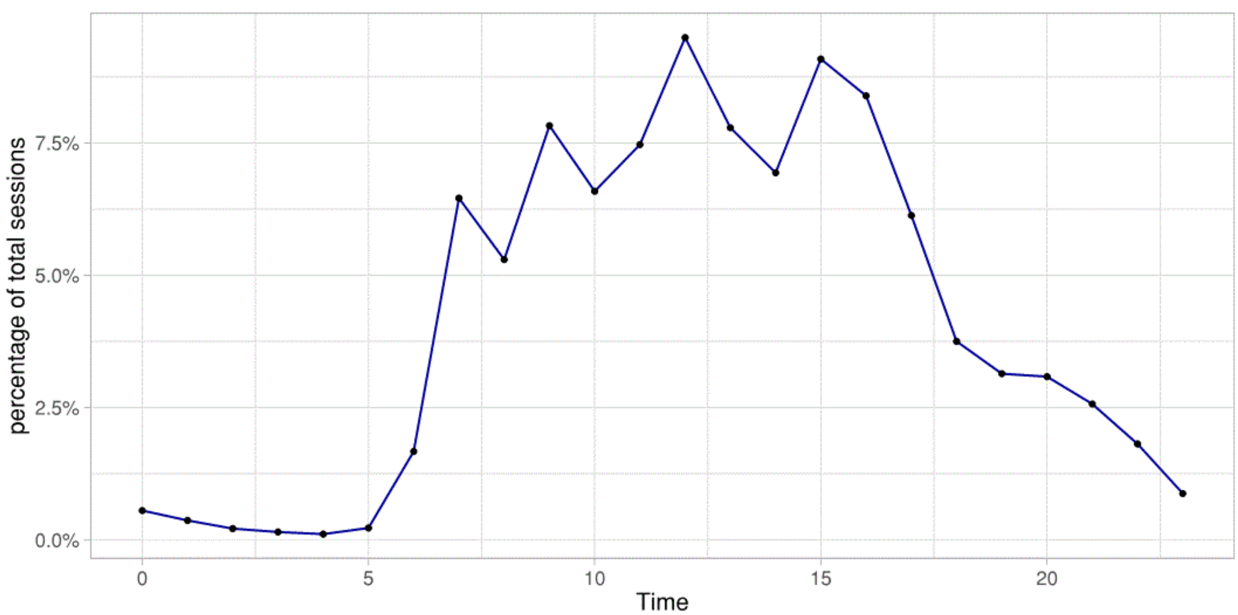


Fig. 4.2 The percentage of total sessions with a given end time.

Figure 4.3 shows the distribution of times that users start their connection sessions on different days of the week. It is apparent that weekdays are evenly distributed and different from the distributions in weekend days. Figure 4.4 shows the distribution of times that users start their connection sessions on both weekdays and weekends.

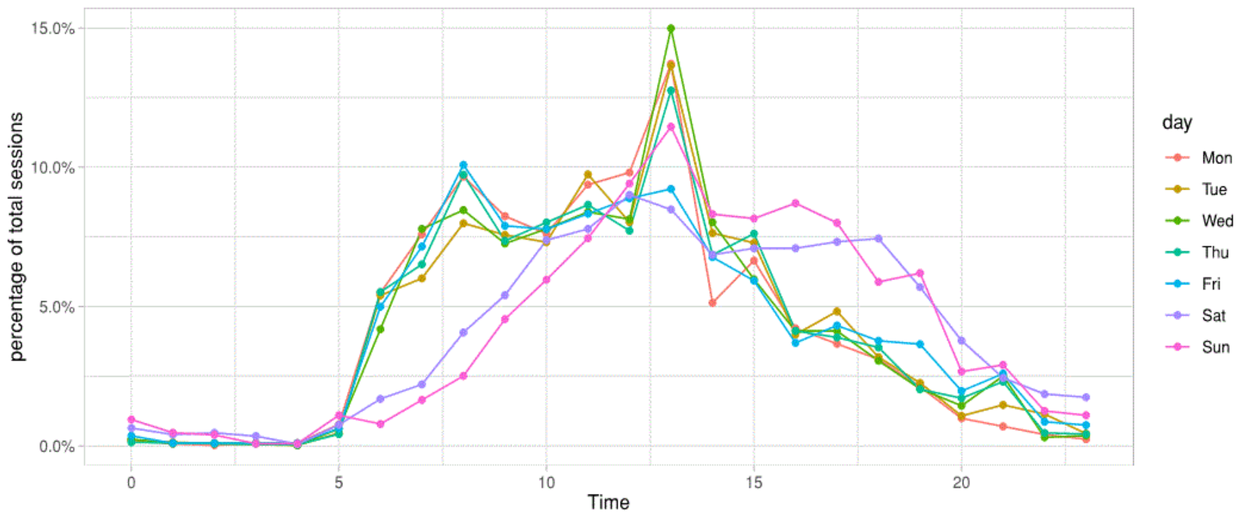


Fig. 4.3 The percentage of total sessions per day with a given start time.

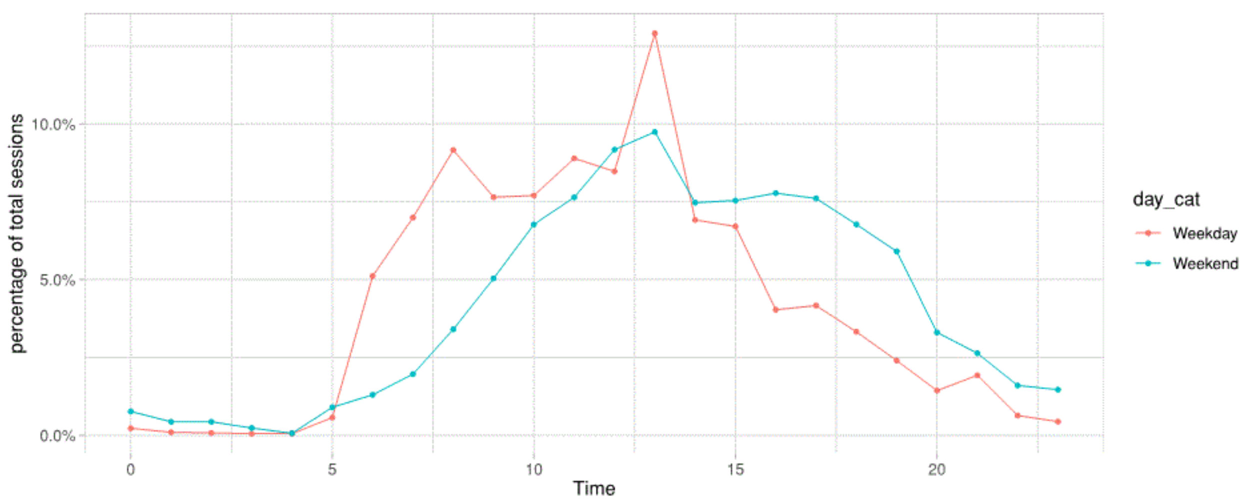


Fig. 4.4 Percentage of total sessions by type of day with a given start time.

4.2 Charging Station Locations

To analyze user behavior in different types of public charging stations, the station locations are divided into four groups: education (universities and schools), workplace (charging stations owned by companies), shopping center (malls and other retail centers), and public parking (downtown and other public parking lots). Figure 4.5 shows the start times of charging sessions, taking into account the type of charging location. These results show that in the education category, there is a peak in demand when students or staff come to school at 9 a.m. and a second peak in demand after lunchtime at 2 p.m. The public parking lot category has its peak demand at 1 p.m., when many users go downtown during lunchtime. The workplace category shows two peaks in demand: the first is in the early morning at 6:00 and a second peak after lunchtime at 1:00. In the shopping center category, an unexpected peak occurs at 10 a.m. It is hypothesized that this peak occurs when the shopping center opens.

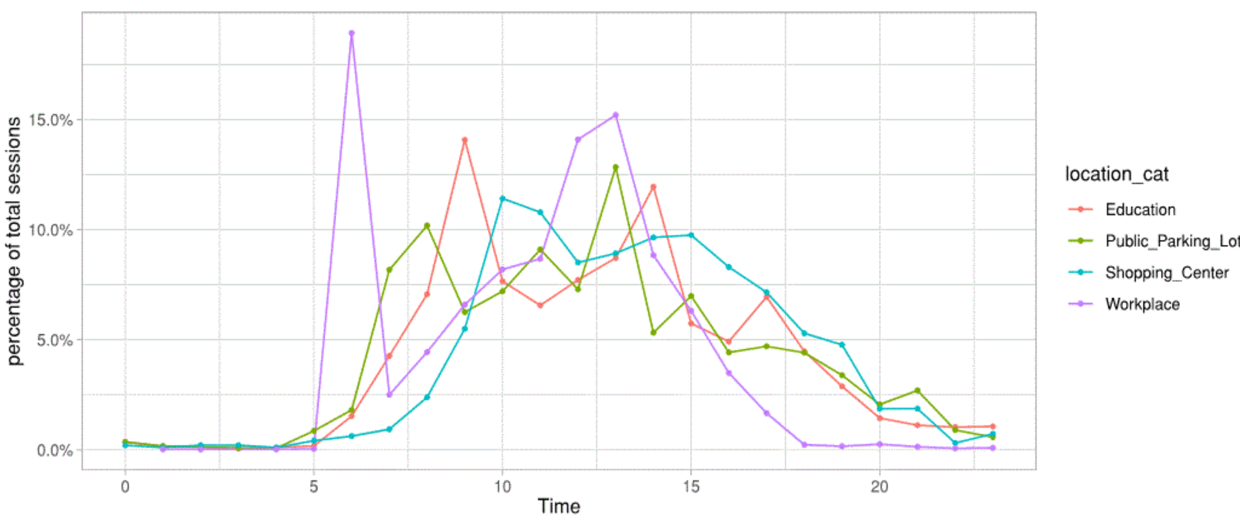


Fig. 4.5 Percentage of sessions with a given start time, for four types of charging station locations.

4.3 Energy

Energy usage is measured in kilowatt-hours (kWh) and can be done using a time interval or an amount of sessions. Both time of day and day of the week are analyzed along with the monthly and daily energy usage. The monthly and daily usage will help predict future energy usage as more charging stations and more PEVs are on the road.

Figure 4.6 shows the amount of energy used for every month. The figure shows that there has been a steady uptick in the amount of energy used on a monthly basis. It is also apparent for every year that there is more energy used during the summer months than the winter months.

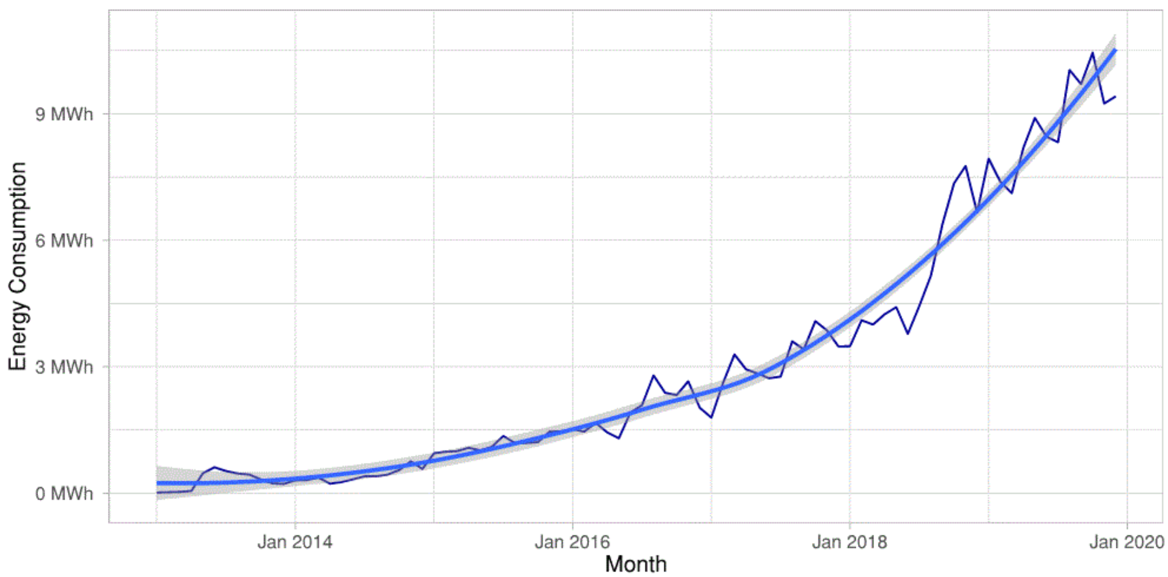


Fig. 4.6 kWh charged for all stations over a given month.

Figure 4.7 shows the energy usage for every day in the study; there has been an overall trend of this increasing, but it also shows that the day-to-day usage varies drastically as the user behavior is somewhat random in nature. Daily energy consumption can be used instead to predict the energy usage on days with large events such as sporting events, parades, or festivals. Figure 4.8 is similar to Figure 4.7 but is a scatterplot.

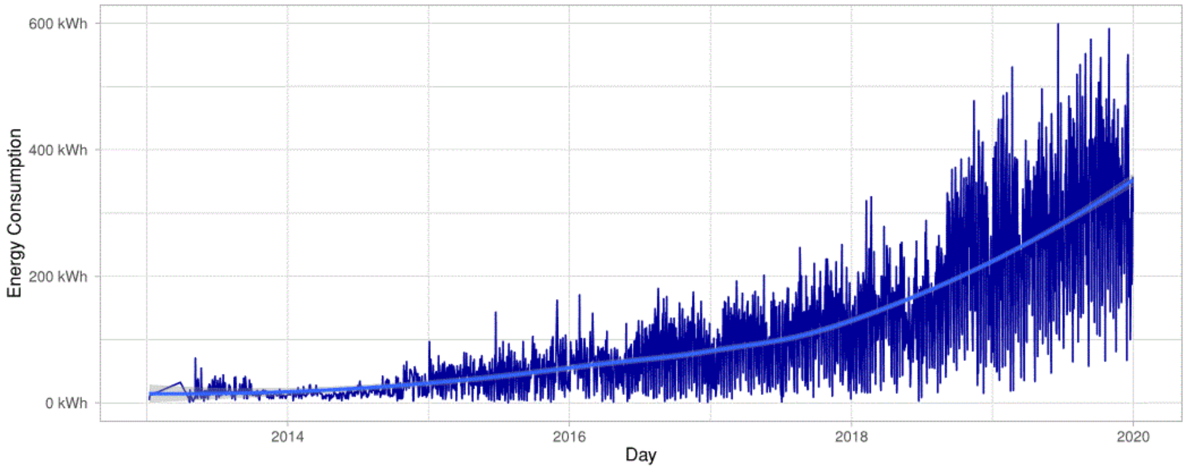


Fig. 4.7 kWh charged for all stations over a given day.

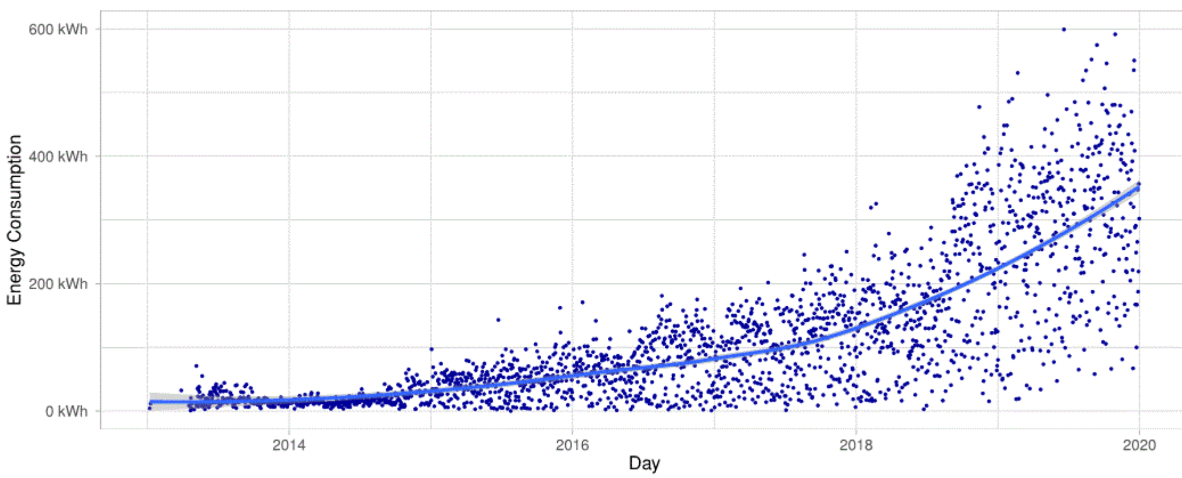


Fig. 4.8 kWh charged for all stations over a given day.

Another factor to consider is the amount of energy used per session. As PEVs start to have larger batteries and can charge at greater speeds, the kWh/session will rise. Figure 4.9 shows how this has risen over the seven years of the study. Although there are still many sessions that do not have a large energy usage, the overall trend shows that more PEVs are beginning to use more energy. This can also point toward users becoming more comfortable with their vehicle as they are waiting until they have less mileage left before charging. Moreover, the rapid penetration of Tesla 3, which has a larger battery, could be the reason behind the usage of more energy per session.

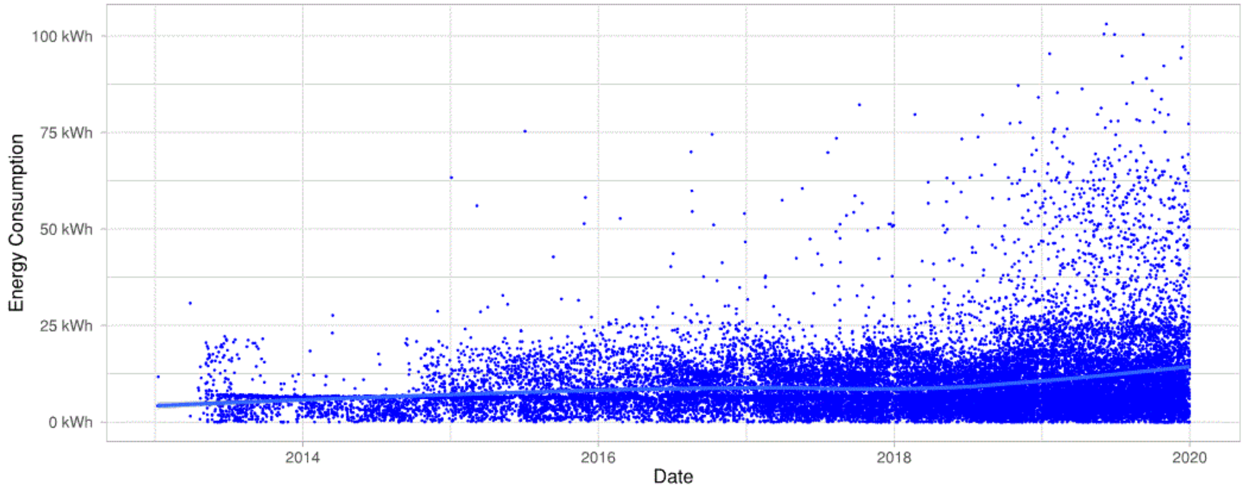


Fig. 4.9 kWh charged for every session.

By analyzing weekly and hourly energy usage, grid operators can better plan how the grid will be impacted by electric vehicle charging. By using these data with the location of the charging stations, grid operators can calculate contingency plans to see how the current grid will handle the new load and if they need to plan for an improved infrastructure moving forward. Figure 4.10 shows the average amount of energy used each day of the week. This information can be used to estimate the overall usage as the penetration level of electric vehicles increase.

Figures 4.10 and 4.11 can be used together to help determine when the peak production will be for each day, and how much energy will be used for that given day. This can then be compared with the current load profile to see if charging stations will cause a significant impact on grid operations. Figure 4.10 shows that there is a significant drop in energy used on public charging stations on Saturday and Sunday compared with the weekdays, which could show that most electric vehicles are used for commuting to and from work. This could then be rationalized by Figure 4.11, where the energy used rises between 6 a.m. and 9 a.m. The slight decrease at 10 a.m. could be explained by electric vehicles not needing to be charged very much from their commute. The peak usage at 1 p.m. can be explained from vehicles that charge after lunchtime.

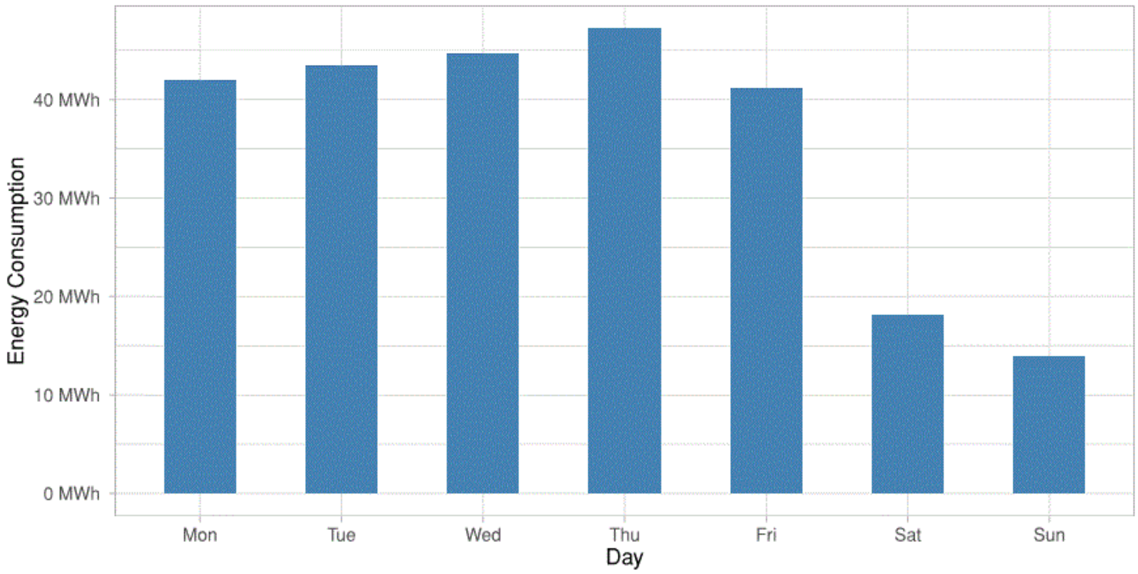


Fig. 4.10 Sum of kWh charged for given day of the week since 2013.

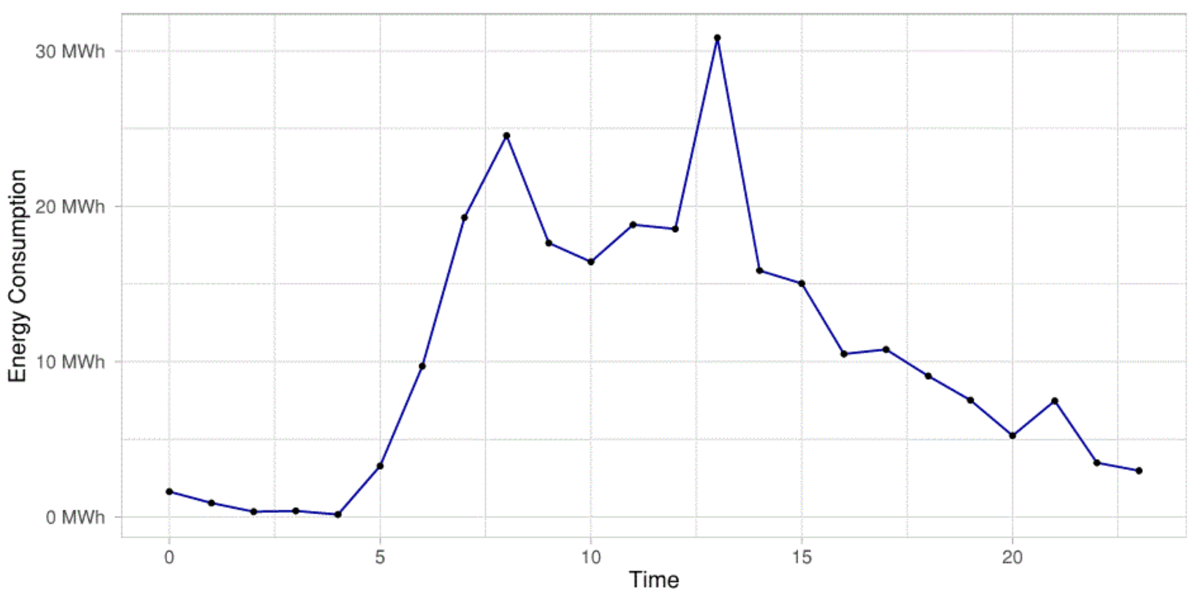


Fig. 4.11 Sum of kWh charged for given hour of the day since 2013.

Comparing the number or percentage of sessions with energy consumption can give insights on how each category behaves when charging. Figure 4.12 shows that from 2013 to 2015 a large majority of charging sessions only took between 0 and 12 kWh of charge. Comparing this with 2017 to 2019, more charging sessions took place between 12 and 20 kWh of charge. This change could be because of multiple reasons, but the main two are that individuals are becoming more comfortable in their electric vehicle—as more charging stations are placed, individuals are allowing their vehicle to get to a lower level before charging again—and that newer vehicles have a larger battery.

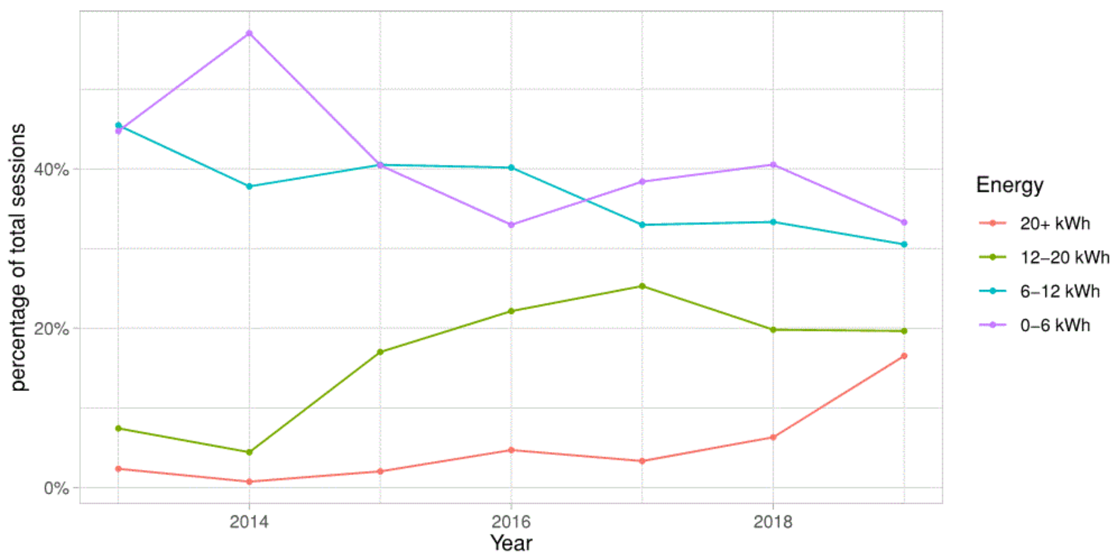


Fig. 4.12 Percentage of sessions versus kWh over a given year.

4.4 Connection and Charging Duration

The data collected provide a connection duration for each session, defined as the time between the plug in and plug out points, as can be shown in Figure 4.13. In addition, a charging duration for each session, defined as the time the vehicles are charged, as can be shown in Figure 4.14. These data allow for comparing the time the vehicles are charged (charging duration) with the total time the vehicles are parked and connected.

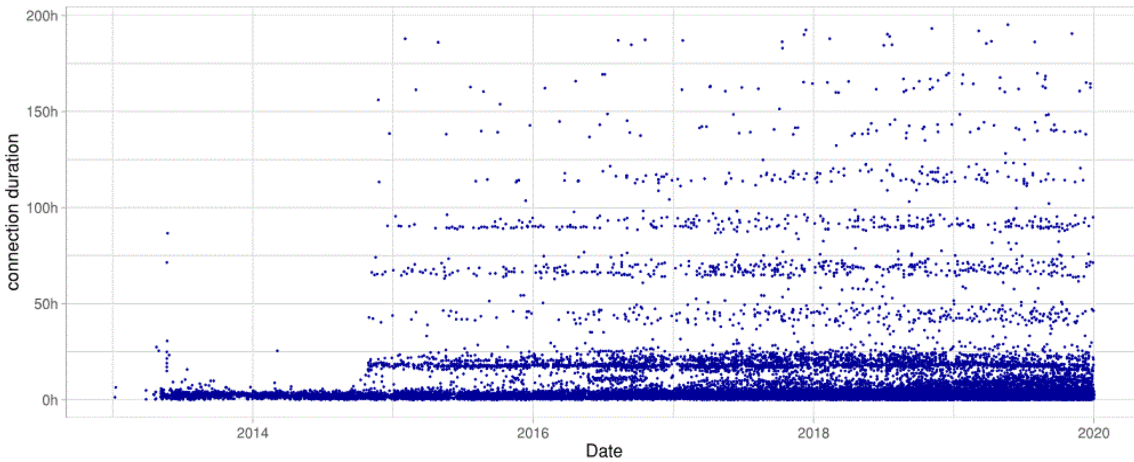


Fig. 4.13 Connection duration for every session since 2013.

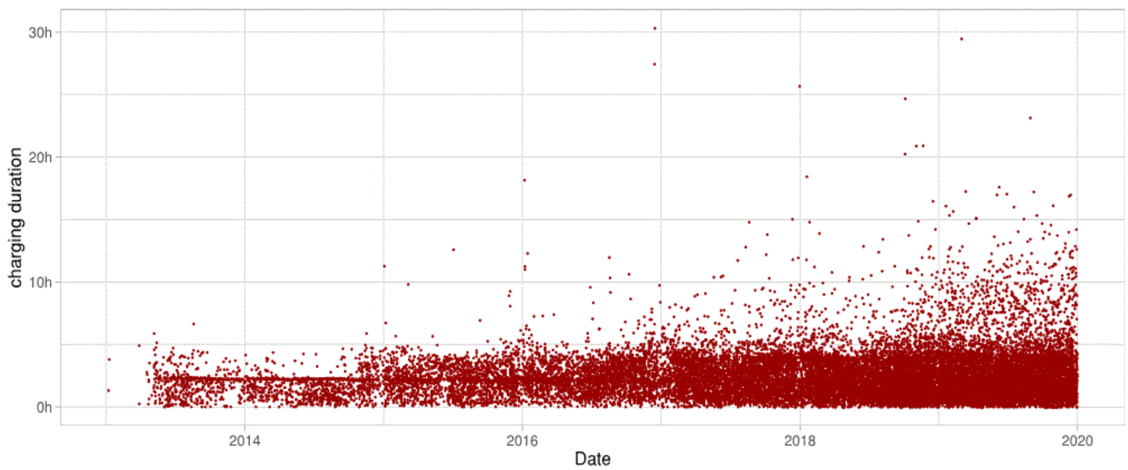


Fig. 4.14 Charging duration for every session since 2013.

The connection and charging durations at the charging stations are shown in Figures 4.15 and 4.16, at an interval of one hour. From Figure 4.15, it is observed that many connection durations, 26.8 %, are five hours or more, with an average connection time of 9.86 hours. In contrast, Figure 4.16 shows that most of the charging durations are less than five hours, with only 6.2 % greater than five hours. The average charging duration is 2.34 hours. On average, individual connection durations are 7.53 hours longer than charging durations. This idle time could potentially prevent other users from charging their vehicles as EV usage increases.

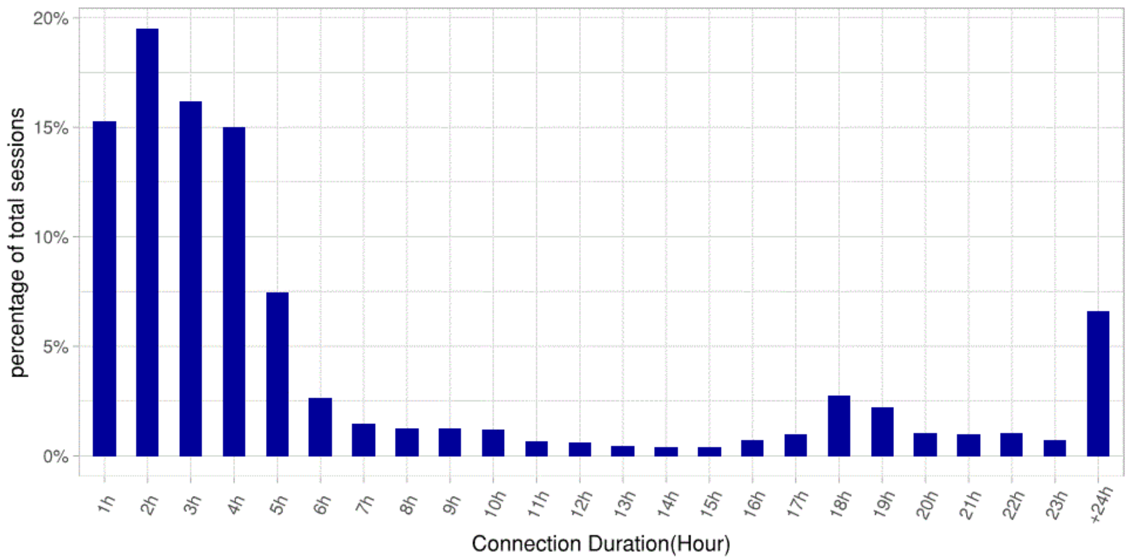


Fig. 4.15 Percentage of sessions versus a given connection duration.

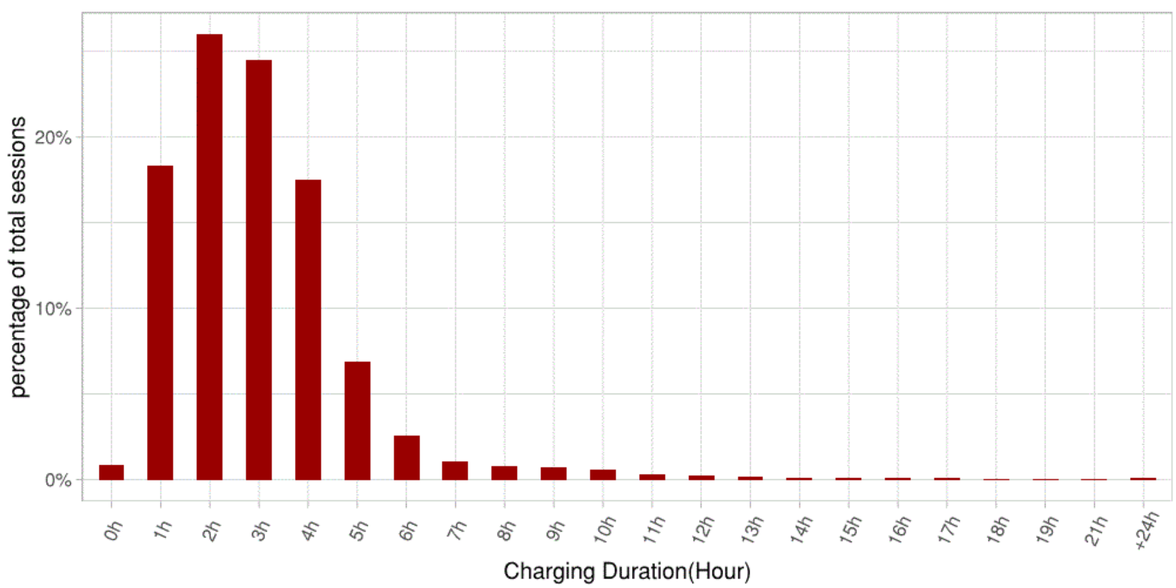


Fig. 4.16 Percentage of sessions versus a given charging duration.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Connection Duration

While planning to support electric vehicles with appropriate charging infrastructure, it is extremely crucial to understand the length of time those charging infrastructures are occupied by a unique user on a specific day and time [116], which is called the connection duration—the duration between the beginning and the end of the session. Predicting the specific duration of these sessions is fundamentally difficult because of the combination of refueling and parking behavior. The subsequent analysis in this section focuses on modeling this relationship.

5.1.1 Data Treatment

For a detailed analysis, the connection duration is divided into time intervals. Figures 5.1 and 5.2 show the percentage of sessions within the six time intervals considered. After organizing the data by time of day and day of the week, trends in connection time at public charging stations are analyzed. Time of day is classified into four categories: morning is considered the time between 5 a.m. and 10 a.m.; afternoon is considered the time between 10 a.m. and 3 p.m.; evening is considered the time between 3 p.m. and 10 p.m.; and, night is considered the time between 10 p.m. and 5 a.m. To explore the parking and charging behavior, a binning technique is used to divide the connection duration into four different ranges.

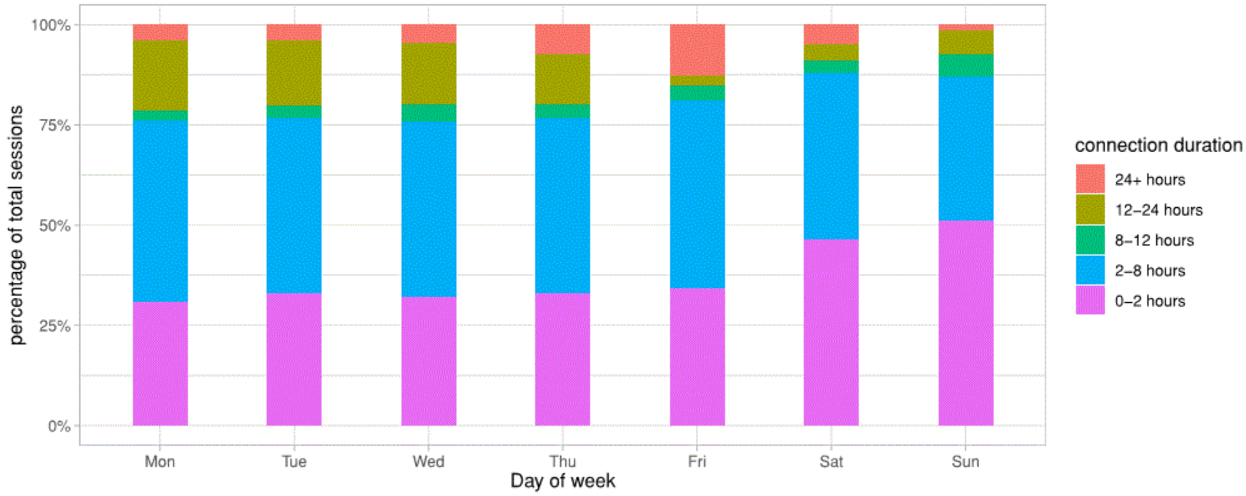


Fig. 5.1 Percentage of sessions with a given connection duration, for each day of the week.

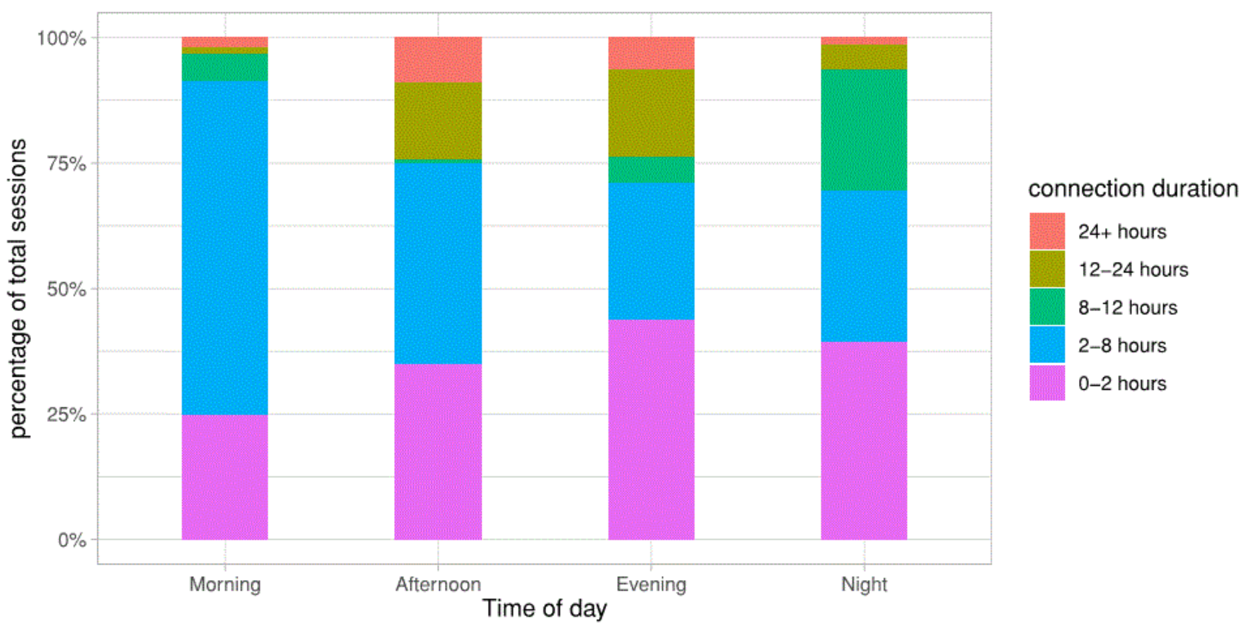


Fig. 5.2 Percentage of sessions with a given connection duration, for each category of start time.

Figures 5.3 and 5.4 show the percentage of sessions over a given location category and fees, respectively.

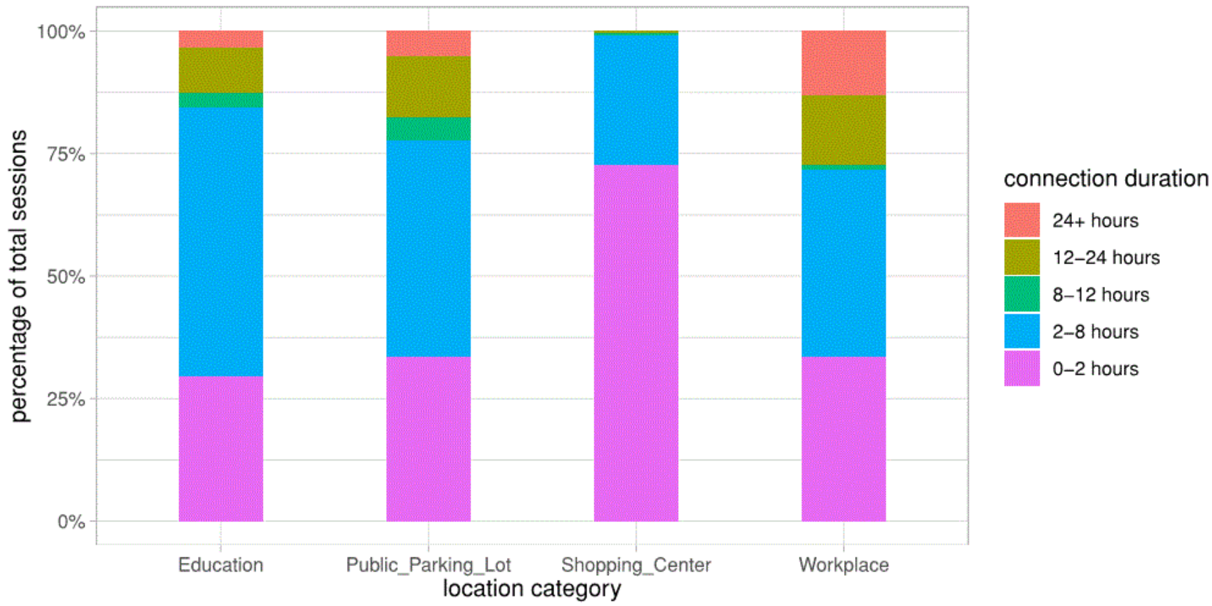


Fig. 5.3 Percentage of sessions versus connection duration over a given location.

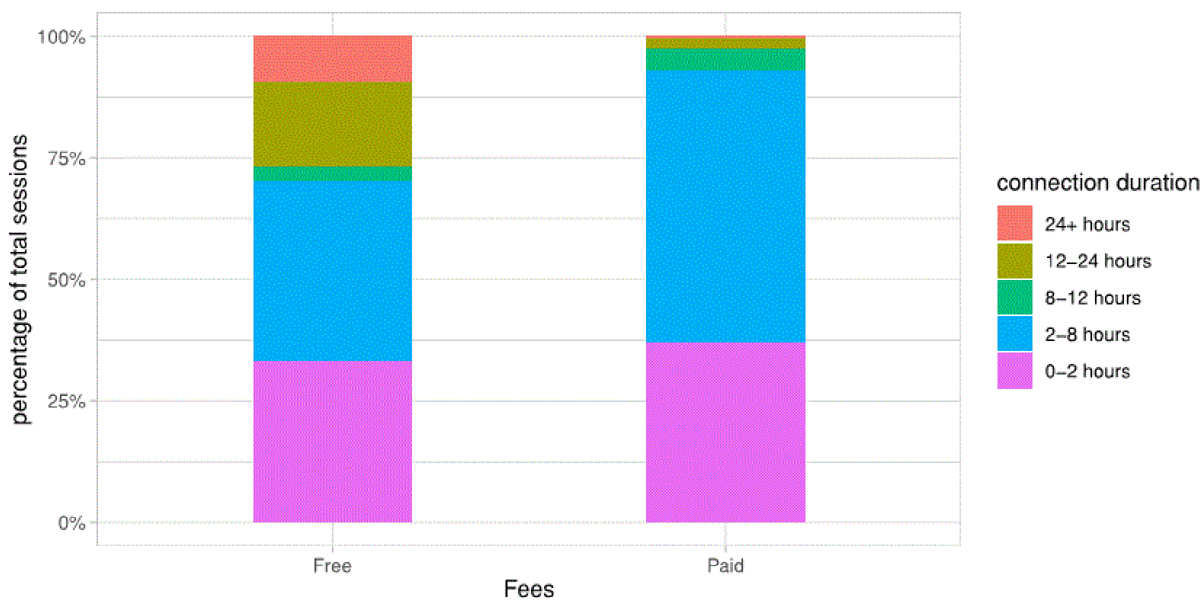


Fig. 5.4 Percentage of sessions versus connection duration over fees.

These ranges are picked as follows: 0-2 hours, stop and charge; 2-8 hours, park and charge; 8-12 hours, work and charge; 12-24 hours, home and charge. Also included are “long sessions” that lasted more than 24 hours. Since the distribution of connection duration is highly non-normal, linear regression is not suitable for the analysis. As seen in previous research conducted in the Netherlands [90], multinomial logistic regression is an effective way to model the results.

5.1.2 Results and Discussion

TABLE VI
MULTINOMIAL LOGISTIC REGRESSION MODEL ESTIMATION RESULTS

	Stop & Charge [0-2 Hours]	**Park & Charge [2-8 Hours]**	**Work & Charge [8-12 Hours]**	**Home & Charge [12-24 Hours]**	**Home & Charge [24+ Hours](ref)**
(Intercept)	2.9491***	3.8987***	2.2094***	0.5567***	
Day of Week					
Mon	0.0862	0.1184	-0.4196**	0.3614**	
Tue	0.1507	0.1509	-0.2790	0.2499*	
Wed (ref)					
Thu	-0.4804***	-0.5084***	-0.8995***	-0.6873***	
Fri	-1.1663***	-1.1296***	-1.6156***	-2.8992***	
Sat	-0.5900***	-0.7423***	-1.5787***	-1.8206***	
Sun	1.1602***	0.8145**	0.7602*	-0.1252	
Time of Day					
Morning(ref)					
Afternoon	-1.4833***	-2.2926***	-4.0350***	0.7494***	
Evening	-1.4374***	-2.9262***	-2.0724***	1.2088***	
Night	-0.2297	-1.5597***	0.8080	1.4857**	
Location Category					
Shopping Center	11.5338	10.5970	8.9225	6.1580	
Public Parking Lot(ref)					
Education	-1.4643***	-1.1841***	-1.6638***	-0.2495	
Workplace	-0.4189***	-0.7153***	-1.9820***	-0.7836***	
Fees					
Free (ref)					
Paid	4.4461***	4.6824***	4.1606***	1.5045***	

* Significant at 0.05
** Significant at 0.01
*** Significant at 0.001

The table above shows the model estimation. Long connection sessions (greater than 24 hours) are used as a reference for the categorical outputs. The time-of-day variable is dummy-coded using Morning as a reference. The day of week is dummy-coded using Wednesday as a reference. Finally, the location is dummy-coded using Public Parking Lot as a reference.

The model results show a high correlation between the variables. Short sessions (Stop & Charge and Park & Charge) are equally likely to happen across workdays. Significant negative parameters are obtained for Friday and Saturday, along with an unexpected positive parameter for Sunday. In terms of time of day, short sessions are more likely to occur in the morning and night than during the afternoon and evening, as suggested by parameters for the afternoon and evening dummy variables, which are significant and negative. The timing parameters for (Work & Charge) are somehow equally likely to happen across workdays. Significant negative parameters are obtained for Friday and Saturday. Regarding time of day, sessions with a duration between 8-12 hours (Work & Charge) are more likely to occur in the morning and night than during the afternoon and evening, as suggested by parameters for the afternoon and evening dummy variables, which are significant and negative. For sessions with a duration between 12-24 hours (Home & Charge), a negative parameter is found for the Friday dummy, indicating that this behavior is replaced by long sessions (+24 hours); positive dummies are obtained for the evening and night, indicating that these sessions mainly start after working hours.

In analyzing the parking and charging behavior of PEV users, it is observed that the location and the time of the charging session have the greatest influence on the connection duration due to the parking behaviors aligned with charging behaviors.

5.2 Idle Time

Most electric vehicle users plug in and leave their vehicles for an extended time in the public parking lots, which are usually specified for plug-in electric vehicles. Some users even leave their vehicles for longer than 24 hours. Prolonged idle time is a concern for other PEV users who need to charge their vehicles to be able to complete their planned trip. Previous study shows that 23% of the connection duration is used for charging, while the remaining 77% is used for parking [91]. Therefore, several well-known regression methods are applied using 25,291 charging sessions obtained from existing public charging stations in Nebraska to predict the idle time in order to help policymakers minimize irregular charging behaviors. The performance of different regression methods for predicting the idle time is characterized using metrics such as R^2, RMSE, and MAE. The results show that XGboost can acceptably predict the idle time in the public charging stations in a certain area with RMSE equal to 0.9552 and R^2 equal to 40.80%. The relative importance of the input variable is also discussed. The proposed data-driven strategy in predicting the idle time in the public charging stations can be a useful tool for PEV users to decide whether to wait or approach a different charging station.

5.2.1 Data Treatment

For each of the charging sessions, the following information was collected: ID of the station, city, location category (Education, Shopping Center, Workplace, or Parking Lot), port number (1 or 2), start time, connection duration, charging duration, kWh consumed, unique driver ID, and fee. Sessions from the charging point data that lasted less than five minutes without charging were excluded, reducing the dataset to 25,291. Because of the vast range of times, it would be quite difficult to develop a model that could be trained to estimate the idle time with acceptable accuracy. For this reason, only idle times under seven hours were considered, bringing the dataset to 20,628.

Removing the null values reduces the dataset to 20,059 observations. As there are many users who do not frequently use charging stations, we omitted data from users who charged less than 10 times to get a more realistic prediction of long-term use, reducing the dataset to 17,595 observations and 222 unique PEV users. The final dataset was formed with the ten variables, including: three numeric independent variables—total energy, charging duration, and time of day; six categorical independent variables—location, city, Nbr. port, EVSE ID, fee, and weekday; and, idle time, the numeric response variable. Equation (4) expresses that the dependent variable shown in Table VII (idle time or I_t) is a function of the nine independent variables, with the abbreviations specified in Table VIII.

$$(I_t) = \int E_s + Ch_s + T_d + D_w + L_c + C_s + P_n + s_i + F_s \qquad (4)$$

TABLE VII

NUMERIC DEPENDENT VARIABLE

Dependent Variable	**Symbol**	**Type**	**Description**
Idle Time	(I_t)	Numeric	The difference between connection and charging durations in h

TABLE VIII

NUMERIC AND CATEGORICAL INDEPENDENT VARIABLES

Independent Variables	**Symbol**	**Type**	**Description**
Total Energy	(E_s)	Numeric	The energy consumed during the charging session in kWh
Charging Duration	(Ch_s)	Numeric	The time required to charge EVs fully or partially in h
Time of Day	(T_d)	Numeric	The time of day when the electric vehicle plugs in for EVSE
Weekday	(D_w)	Categorical	Mon, Tue, Wed, Thu, Fri, Sat, and Sun

Location Category	(L_c)	Categorical	The location category of the EVSE used in every session
City	(C_s)	Categorical	The city where the session happened
Port Number	(P_n)	Categorical	The port number used each session
EVSE ID	(s_i)	Categorical	The unique ID for the stations used in every session
Fee	(F_s)	Categorical	The fee required to charge, either required fee or free
User ID	(U_i)	Categorical	The unique ID for the drivers

Table IX presents the summary of the numeric variables used in this study.

TABLE IX

SUMMARY OF NUMERIC VARIABLES

PARAMETER	IDLE TIME (H)	ENERGY CONSUMPTION (KWH)	CHARGING DURATION
MIN.	0	0	0
1ST QU.	0.1236	4.056	1.131
MEDIAN	0.4689	6.766	2.026
MEAN	0.9524	9.152	2.201
3RD QU.	1.5692	11.827	2.999
MAX.	6.9933	103.118	20.234

The R programming language was used for all steps that follow, from cleaning to data modeling. Also, Rstudio was the integrated development environment (IDE) utilized to organize the R code [117]. The MLR is also the major machine-learning library used in this study as the standardized interface to interact with the various supervised machine-learning methods [118].

Results and Discussion

The goal of this research is to apply several different regression methods to our dataset in order to predict the idle time and evaluate the performance of each to determine which regression method produces the most accurate results. As can be seen from Figure 5.5, the 17,595 observations are randomly divided into two parts—a training set containing three-fourths of the data points (14,076 observations) and a test set containing the remaining 3,519 data points. The training set is then used to fit a regression model, and its performance is evaluated using the test set.

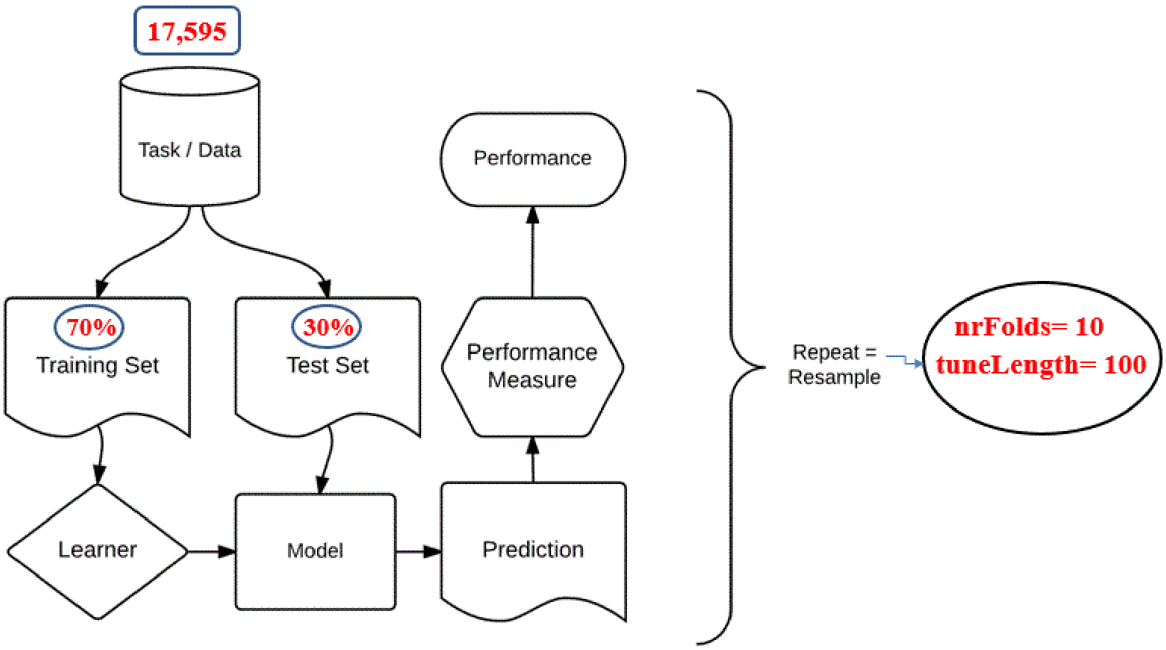


Fig. 5.5 Machine-learning algorithm framework.

As discussed above, an accurate model is one with a higher R^2 and lower RMSE and MAE. Table X shows the results for each model. The XGBoost method yielded the highest R^2 score with 40.8%, as well as the lowest mean absolute error and root mean squared error of 0.575 and 0.955, respectively.

TABLE X

MACHINE-LEARNING ALGORITHMS' ACCURACY EVALUATIONS, IDLE TIME PREDICTION

	R^2 %	RMSE	MAE
XGboost	40.8	0.9552	0.5751
Random Forest	34.9	1.0011	0.6365
Rpart	30.5	1.0354	0.6508
SVM	29.9	1.0392	0.5793

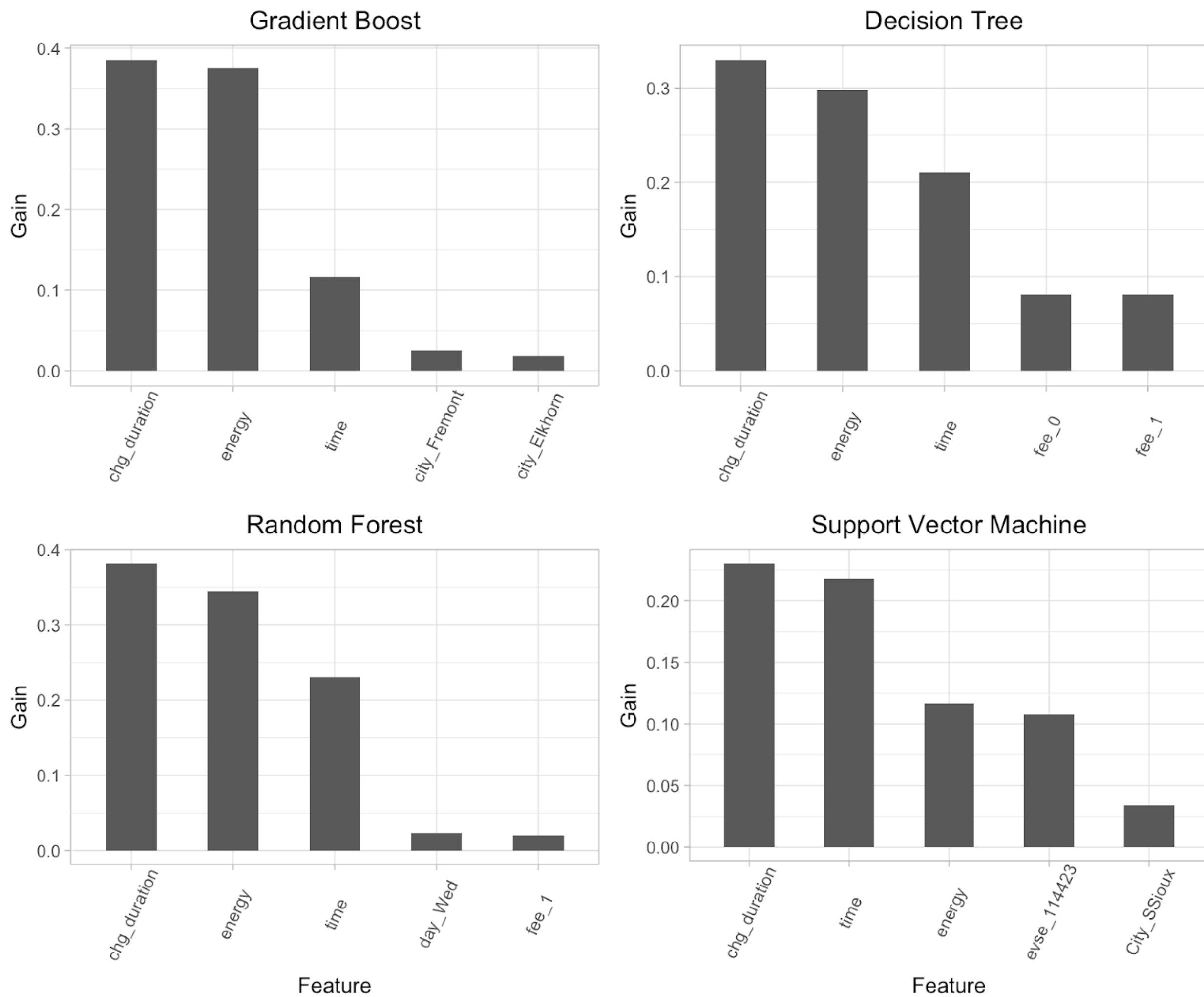
Each regression method may have several tuning parameters. Proper tuning parameter selection is an important issue for good predictive performance. Tuning parameters are usually selected by k-fold cross-validation (CV) technique [119], [120]. A tenfold CV technique is used to select tuning parameters for different regression methods. The tuning parameters for the four algorithms used are shown in Table XI.

TABLE XI

MACHINE-LEARNING ALGORITHMS' TUNING PARAMETERS, IDLE TIME PREDICTION

Regression Method	Function	Tuning Parameters	Package
XGB	xgboost ()	Eta = 0.00685 max depth = 46 Nrounds = 1024 lambda = 0.526	MLR
Rpart	rpart()	Minsplit = 50 Minbucket = 6 Cp = 0.0015	MLR
RF	randomForest ()	Mtry = 6 ntree = 814 Nodesize = 12	MLR
SVM	svm ()	C = 1 sigma = 1	MLR

Fig 5.6 shows a graphical representation of the importance of the five most significant predictor variables in each regression task. Based on the results obtained from these four regression methods, charging duration, energy, and time of the day are the most important predictor variables in predicting the idle time in each session.



To evaluate the performance of the regression models in predicting the idle time, we predicted the idle time for several samples for a specific user by means of different regression models. The comparison of the actual and predicted values for the idle time is shown in Figure 5.7, which illustrates that XGboost outperforms other models.

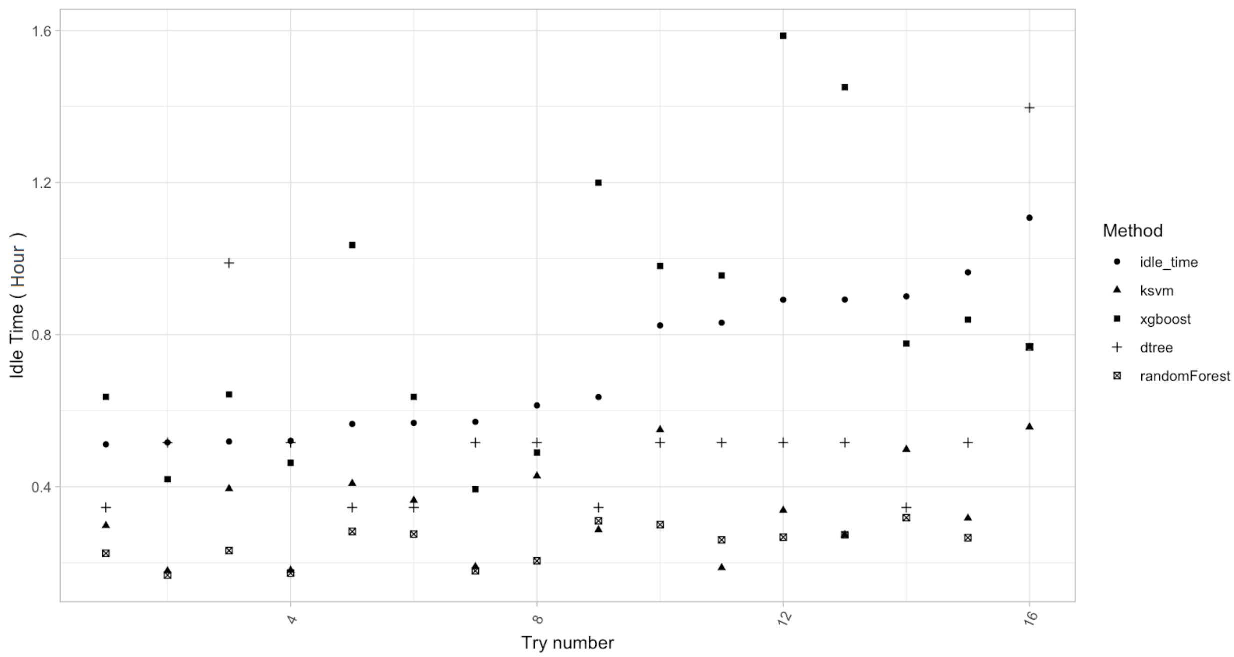


Fig. 5.7 Idle time predictions of each method over several trials.

Conclusions

A data-driven idle time prediction is presented in this research. The proposed strategy formulates the idle time prediction as a multiple regression problem. Several statistical machine-learning regression methods are applied to predict when the PEV users will leave the parking spot after charging their vehicles using nine input variables. This approach is validated using a dataset collected from public charging stations in the state of Nebraska. The results show that the regression algorithm XGboost outperforms the other models in predicting the idle time in public charging stations.

It gives a beneficial message for PEV users to observe the availability of the public charging stations and plan their use. EV users can use the tool to decide if they want to wait for a charging station in use or to find another one. Also, local management authorities and those who own and build charging infrastructure could use certain variables, like changing demand and focusing on load scheduling, power reduction, or complete load shifting, to reduce total idle time and to efficiently manage the power grid. They could also change or create policies such as requiring minimum energy usage per charging session, restricting free parking at EV charging points during certain hours, or allowing such parking spaces to be used by non-EV users.

5.3 Energy Consumption

The PEV user charging behavior has a significant influence on the distribution network and its reliability. Generally, monitoring the energy consumption has become one of the most important factors in green and micro grid [121], [122]; therefore, predicting the energy consumption (the energy consumed during the charging session) could help to efficiently manage the electric grid. Consequently, four machine-learning algorithms were applied in this research to predict the energy consumption in order to help the utility companies manage the electric grid accordingly.

5.3.1 Data Treatment

The research is based on the charging sessions, and for each charging session the following information is considered: ID and location of the station, location city and category, Nbr. port, start time, connection duration, charging duration, kWh consumed, unique driver ID, and fee. Sessions from the charging point data that lasted less than five minutes without charging were excluded, reducing the dataset to 25,291. Furthermore, the null value lines were removed, reducing the dataset to 24,654 observations. Most sessions consumed less than 20 kWh, so we only included the data between 1-20 kWh, reducing the dataset to 21,591. Since there are many users who do not frequently use the charging stations, we only included the data from users who charged at least 50 times to get a more realistic prediction of long-term use, reducing the dataset to 16,698, which corresponds to 68 different PEV users. The final dataset is formed of eight variables, including one numeric independent variable, time of day, and six categorical independent variables—location, city, Nbr. port, EVSE ID, fee, and weekday; and, energy, the numeric response variable. Equation (5) expresses the relationship between the dependent variable (energy) and seven independent variables:

$$(E_s) = \int T_d + L_c + C_s + P_n + s_i + F_s + D_w \qquad (5)$$

5.3.2 Results and Discussion

The goal is to apply several different regression methods to our dataset in order to predict energy. It is an important task to find which regression method produces the most accurate results. We randomly divide the 16,698 observations into two parts, a training set containing three-fourths of the data points (12,523 observations) and a test set containing the remaining 4,175 observations. Then we fit a regression model using the training set and evaluate its performance on the test set. A good regression method is the one with higher R^2 and lower RMSE.

Table XII shows the results for the metrics assessed by each model. The XGBoost was the one with the highest R^2 score of 41.18%, which also obtained the lowest mean absolute error and root mean squared error of 2.63 and 3.50, respectively.

TABLE XII

MACHINE-LEARNING ALGORITHMS' ACCURACY EVALUATIONS, ENERGY PREDICTION

	R^2%	RMSE	MAE
XGboost	41.18	3.50	2.63
Random Forest	35.9	3.65	2.85
Rpart	30.8	3.79	2.97
SVM	35.1	3.68	2.37

Each regression method may have several tuning parameters. Proper tuning parameter selection is an important issue for good predictive performance. Tuning parameters are usually selected by k-fold cross-validation (CV) techniques [119], [120]. We used a tenfold CV technique to select tuning parameters for different regression methods, shown in Table XIII.

TABLE XIII

MACHINE-LEARNING ALGORITHMS' TUNING PARAMETERS, ENERGY PREDICTION

Regression Method	Function	Tuning Parameters	Package
XGB	xgboost ()	Eta = 0.0498 max depth = 50 Nrounds = 243 lambda = 0.483	MLR
Rpart	rpart ()	Minsplit = 30 Minbucket = 25 Cp = 0.00326	MLR
RF	randomForest ()	Mtry = 10 ntree = 872 Nodesize = 19	MLR
SVM	svm ()	C = 1 sigma = 1	MLR

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Thesis Summary

The main objective of this thesis was to understand the charging behavior at public charging stations in Nebraska by collecting data from existing charging stations in the state and analyze those data. This thesis analyzed the parameters correlated with charging behavior, and the analysis will aid policymakers in amending regulations for using charging infrastructure more efficiently.

While planning to support electric vehicles with appropriate charging infrastructure, it is extremely crucial to predict the length of time those charging infrastructures are occupied by a unique user at a specific day and time. Predicting the specific duration of these sessions is fundamentally difficult because of the combination of charging and parking behavior. The thesis proposes a multinomial logistic regression model to study trends in both charging and parking duration to facilitate forming effective policies to optimize charging.

Most electric vehicle users plug in and leave their vehicles for an extended time at public parking lots that are usually specified for plug-in electric vehicles. Some users even leave their vehicles for longer than 24 hours. Prolonged idle time is a concern for other PEV users who need to charge their vehicles to be able to complete their planned trip. This thesis also proposes several well-known regression methods to predict the idle time in order to help the policymakers minimize irregular charging behaviors. The performance of different regression methods for predicting the idle time is characterized using established metrics such as R^2, RMSE, and MAE.

Additionally, the PEV users' charging behavior has a significant influence on the distribution network and its reliability. Monitoring the energy consumption has become one of the most important factors in green and smart grids. This thesis suggests several well-known regression methods to predict the energy consumption, the energy consumed during the charging session, when a specific user plugs in, which could help to efficiently manage the electric grid.

6.2 Conclusions

In analyzing the parking and charging behavior of PEV users, it is observed that the location, fee policy, and time of the charging session have the greatest influence on the connection duration due to the parking behaviors aligned with charging behaviors. However, dealing with many random data leads to difficulties in finding the fit model that describes the charging and parking behaviors. Nevertheless, in applying machine-learning methods to predict the idle time, it is observed that XGBoost outperforms the other methods used in this thesis. However, the prediction is not yet good enough to be used in real applications. In a similar conclusion regarding predicting energy consumption, XGBoost has the best performance compared with the other methods. However, there is still room for improving this prediction.

6.3 Future Work

It was confirmed that applying machine-learning algorithms could predict the idle time and energy consumption but with low accuracy. The randomness of charging behavior makes it difficult to apply a machine-learning method; however, to provide better prediction and accuracy, an artificial neural network method could be applied.

An extension to this work can be done by analyzing the charging behavior in both public and home charging stations to generate a charging profile for each PEV user. This analysis will aid policymakers in amending the regulations for using the charging infrastructure more efficiently by placing the charging infrastructure in optimal locations as well as increasing the utilization rate of the charging stations by applying the most suitable price policy.

The electric vehicle is no longer simple transportation. It becomes one of the most important mobile power plants. Vehicle-to-grid (V2G) technology is an emerging technology used nowadays to support the electric grid in the peak demand. Predicting the idle time with an acceptable accuracy will facilitate applying the V2G technology in public charging infrastructure. Therefore, our future research will be focusing on studying the impact of V2G on the electric grid in terms of harmonic distortion and the voltage stability.

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