Time-of-Use-Aware Priority-Based Multi-Mode Online Charging Scheme for EV Charging Stations

by

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M.Sc., RWTH Aachen University, 2013
B.Sc., American International University - Bangladesh, 2011

A Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

in the Department of Computer Science

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ABSTRACT

Electric vehicle charging stations (EVCS) play a vital role in providing charging support to EV users. In order to facilitate users in terms of charging speed and price, two different charging modes (L2 and L3) are currently available at public charging stations. L3 mode provides quick charging with higher power, whereas L2 mode offers moderate charging speed with low power. The integration of an EVCS into the power grid requires coordinated charging strategies in order to reduce the electricity bill for a profitable operation. However, the effective utilization of the multi-mode charging strategy to serve the maximum number of EVs for a small charging station with limited charging capacity and spots is an open issue. To this end, we propose a priority-based online charging scheme, namely PBOS, which is based on real-time information and does not depend on future knowledge. The objective is to serve as many vehicles as possible in a day while fulfilling their charging requirements under a multi-mode EVCS setting and reducing the charging costs by utilizing the time-of-use pricing based demand response strategy. Extensive simulation is done while considering two different demand response strategies under various settings. The results show that the proposed algorithm can increase profit for the EVCS by up to 48% with a 22% lower rejection rate. In addition, it can serve EVs with a low battery charge, known as state of charge (SOC), up to 11% higher than most of the other schemes and can save up to 81.75 minutes to attain the same SOC when compared with other schemes.

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List of Symbols

i	Index of time step
n	Index of EV
ΔT	Duration of each time step
$w_{n,i}$	Priority weight at time step i for EV n
$t^a_{n,i}$	Arrival time at time step i for EV n
$t^d_{n,i}$	Departure time at time step i for EV n
$t^r_{n,i}$	Remaining charging time at time step i for EV n
B_n	Battery capacity for EV n
$m_{n,i}$	Charging mode selection at time step i for EV n
$\mathrm{SOC}_{n,i}$	Initial SOC at time step i for EV n
$\mathrm{SOC}^{\max}_q$	Maximum allowed SOC in L3 mode
$\mathrm{SOC}^{\max}_r$	Maximum allowed SOC in L2 mode
$\mathrm{SOC}^{\mathrm{exp}}_{n,i}$	Expected SOC at time step i for EV n
$\mathrm{SOC}^{\mathrm{req}}_{n,i}$	Required SOC at time step i for EV n
P^q	Charging power in L3 mode
P^r	Charging power in L2 mode
P^{total}	Total charging capacity of the charging station
α, β	Charging priority regulator parameters
$x_{n,i}$	Charging decision at time step i for EV n
C	Time of use electricity price set
c_i	Electricity cost at at time step i
$c^{\max}$	Maximum electricity price
$c^{\min}$	Minimum electricity price
M	Total number of charging spots

$\mathcal{L}_i$	Charging request set of EV at time step i
L_i	Total number of EVs in $\mathcal{L}_i$ at time step i
$\mathcal{N}_i$	Feasible set of EV
N_i	Total number of EVs in $\mathcal{N}_i$ at time step i

ACKNOWLEDGEMENTS

I would like to thank:

Dr. Jianping Pan for selecting me as a member of his excellent research lab. I want to express my gratitude to him for his guidance, support, and encouragement in every step of my master's program. Despite the fact that I began my study program during a pandemic, which kept me thousands of miles away from my research lab during my first year, he never let me feel the distance. Instead, he always maintains close communication virtually and provides me with all kinds of suggestions, from course selection to research ideas. He helped me to enhance my research skills and achieve my goals. It is really difficult for me to describe all his efforts in just a few lines. I am always thankful to him.

My wife for being my constant source of motivation and encouragement during this journey. She not only served delicious hot meals on my plate every day, but also took care of my child almost with a single hand. During financial hardship, she stood by beside me and provided financial support by working a part-time job. Because of her, I was able to keep focused on my academic work and finally managed to come to an end successfully.

My Parents for always being supportive whenever it is needed. Without their tremendous support, love, and encouragement, I would never be where I am today.

Finally, I would like to thank all of my research group members for their assistance and inspiration throughout my master's program.

"So, verily, with every difficulty, there is relief"
The Quran (94:5)

DEDICATION

To my beloved wife, Fatema Shamain Chowdhury and only daughter, Zunaira Binte Navid.

Chapter 1

Introduction

Electric vehicles (EVs) are considered as a critical technology for minimizing significant amounts of carbon emissions and efficiently dealing with the fossil fuel scarcity problem [45]. In 2021, the sales of global electric cars increased by 108% from 2020, and 198% from 2019. According to [36], we see the rapid growth and high penetration rate of EVs on the market. Despite numerous advantages, EVs encounter many challenges, such as frequent charging requirements because of limited cruising range, long charging duration, and significant power consumption during the charging process [10]. Therefore, in order to provide the charging facilities for this rising rate of EV adoption effectively, it is important to design efficient charging control algorithms with smart strategies for a charging station [26].

A standard public charging station currently offers two charging modes: i) Level 2 (L2), known as regular charging mode, with a charging power range of 10 to 22 kW; and ii) Level 3 (L3), known as direct current fast charging (DCFC) mode, with a charging power range of 50 to 120 kW [48]. In the L2 mode, an empty battery can be refilled within 8 hours, whereas L3 requires less than 1 hour [28]. Although L3 charging is more expensive compared to the L2 one, it facilitates users who require urgent charging. On the other hand, L2 is more suitable for users who are not sensitive to the charging duration but the battery lifetime or charging expense [28]. Thus, by introducing both charging modes in a charging station, not only flexibility is achieved but also the requirements of multi-class customers are fulfilled.

Despite numerous works available on the scheduling of EVs at charging stations, they are oblivious about the multi-mode functionality, demand of EVs and the limitation of charging station capacity. To this end, we propose an efficient real-time charging algorithm for EV charging stations (EVCSs) while considering two different charging modes. The proposed scheduling scheme always selects the maximum number of EVs at each charging time slot based on the priority of EVs and capacity of the station. The priority is determined by user's urgency in terms of departure time, charging demand, battery's state of charge (SOC), charging mode and capacity of the battery. To be more relevant in a real-time environment, all the charging information, such as the arrival time of EVs, charging demand, battery capacity, selection of charging mode and departure time, will only be revealed once an EV user submits a charging request to the EVCS.

In order to maintain a profitable operation for the charging station, the influence of electricity prices also needs to be considered. To incorporate this, a time-of-use (TOU) pricing scheme is used in this proposed charging algorithm. TOU is a well-known strategy for assisting the charging station operators in maintaining their operations economically [41], [43]. The price of electricity rises in a proportional manner with the increase in demand during the peak period of a day.

Therefore, in order to lower the electricity bill, two different TOU-based demand response (DR) strategies are considered in this work, in which EVCSs voluntarily reduce their load during peak periods by utilizing the TOU scheme [43]. In the first strategy, EVCS reduces the charging load sharply to a certain level and keeps it constant for a long period of time, whereas in the second strategy, the load is reduced gradually over time and then restored while the price goes down. The bidirectional communication capabilities of the smart grid can be used to implement a TOU scheme. It helps EVCS to set the charging cost of the EVs at a particular time of a day in real time based on the price offered by the electricity utility authority [26].

1.1 Main Contributions

The main aspects and contributions of this thesis are as follows:

1. We formulate an EV charging scheduling problem while considering L2 and L3 charging modes together in an online setting.

2. We study the problem with a small charging station setting where the charging capacity and spots are limited. Each charging spot is equipped with both types of chargers, and an EV user can select only one charging mode at a time. The EVCS takes charging decision based on the current information.

3. We propose an efficient online charging scheme by utilizing a TOU-based DR strategy and historical EV arrival data. The objective of the formulated optimization problem is to select the maximum number of EVs at each time slot for charging while keeping the charging load under the total capacity of the EVCS and fulfilling the minimum charging requirements of the EV users before they depart. In addition, it limits the charging by a maximum allowable SOC level depending on the charging mode to protect the EVs from getting overcharged and the battery's lifetime.

4. In the proposed method, PBOS, it considers not only the user's urgency in terms of departure time but also the user's SOC status. According to the proposed method, EV users with low SOC and low charging demand have higher priority. Similarly, it ensures L3 users have more priority than L2 users because of the small charging duration.

5. The formulated optimization problem for real time charging scheduling is essentially a binary programming problem because of the binary nature of the decision variables. This causes the problem to be NP-hard, which is hard to solve and often suffers from the dimensionality problem. Therefore, a sophisticated state-of-the-art Gurobi MIP solver is used to find the optimal outcome based on the current information.

6. We compare the proposed scheme with other existing state-of-the-art scheduling algorithms, namely, first come first serve (FCFS), real-time charging scheme (RTCS) [43] and SOC-based priority (SBP) [37] in three different cases. Through extensive simulation, we show that the proposed scheme has a lower rejection rate of up to 22% and can increase the profit by up to 48% compared to other schemes. Additionally, it can serve EVs with a lower SOC up to 11% higher than most of the other schemes, and can satisfy the charging demand of the EVs up to 81.75 minutes faster than other schemes.

7. We utilize two different publicly available datasets on EV arrival patterns and charging behavior to evaluate the performance of the proposed scheme under various use cases while considering EVs with various battery capacities.

8. To the best of our knowledge, this is the first work in EVCS scheduling by considering two different charging modes together while utilizing historical EV arrival data and TOU-based DR strategy.

1.2 Thesis Overview

The rest of the thesis is organized as follows. We briefly discuss the background information and related work in Chapter 2. In Chapter 3, we describe the system model, formulate the corresponding charging scheduling problem, and propose an online charging scheduling scheme. We evaluate the performance of the proposed online charging scheduling scheme in Chapter 4. Finally, we draw the conclusion about this thesis work in Chapter 5.

1.3 Accepted Research Article based on the Thesis

Part of this research work has already been published at the IEEE International Conference on Smart Grid Communications (SmartGridComm 2022) [4]. As the main author, I did the work in collaboration with my supervisor, lab member, and alumni lab member during my Master's program at the University of Victoria.

At the beginning, we worked on formulating an EV charging scheduling problem by considering L2 and L3 charging modes together in an online setting. Then an online charging scheme is proposed by considering a TOU-based demand response (DR) strategy and a historical dataset of EV arrivals and charging behavior. We showed that the performance of the proposed scheme works better than other existing schemes, such as FCFS and RTCS. This work has been accepted at the SmartGrid-Comm 2022 conference.

Later, as part of the thesis, we extended the work by considering two different DR strategies and EVs with various battery capacities. We reduce the number of regulator parameters to one, and formulate the value of this parameter in such a manner that the scheme can change it dynamically at each time step. It ensures that L3 users always have a higher priority weight, even for EVs with different battery capacities. As a result, the strategy is more reliable and avoids ambiguity. In addition, we also evaluate the performance of the scheme against another recent scheme, SBP, from the literature with another real-world dataset. The results show that the proposed scheme is not dependent on a particular dataset but can perform well with other datasets as well. Lastly, more numerical results are included in this thesis that reflect the better performance of the proposed scheme.

Chapter 2

Background and Related Work

In this chapter, we first discuss the background of various components associated with EVCS and charging scheduling. After that, we review the existing work related to the scheduling problem.

2.1 Electric Vehicles (EVs)

An electric vehicle is powered fully or partially by an electric motor and battery pack [21]. It is classified into three categories: battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs) as shown in Fig. 2.1 [44]. In a BEV, the batteries provide all of the vehicle's power to run. It is driven by one or more electric motors that are powered by rechargeable battery packs. Regenerative braking is used in BEVs to recharge the batteries. This implies that by using the brakes, the electric motor(s) slows down the car, collects that energy, and supplies it back into the battery [8]. Hybrid electric vehicles (HEVs) combine an internal combustion engine with electric motors that are driven by a battery pack. An HEV's batteries cannot be recharged by an external source. Plug-in hybrid electric vehicles (PHEVs) also use batteries to power an electric motor and can recharge from an external power source, but they also include a smaller internal combustion engine that can recharge the battery to enable longer driving ranges [47].

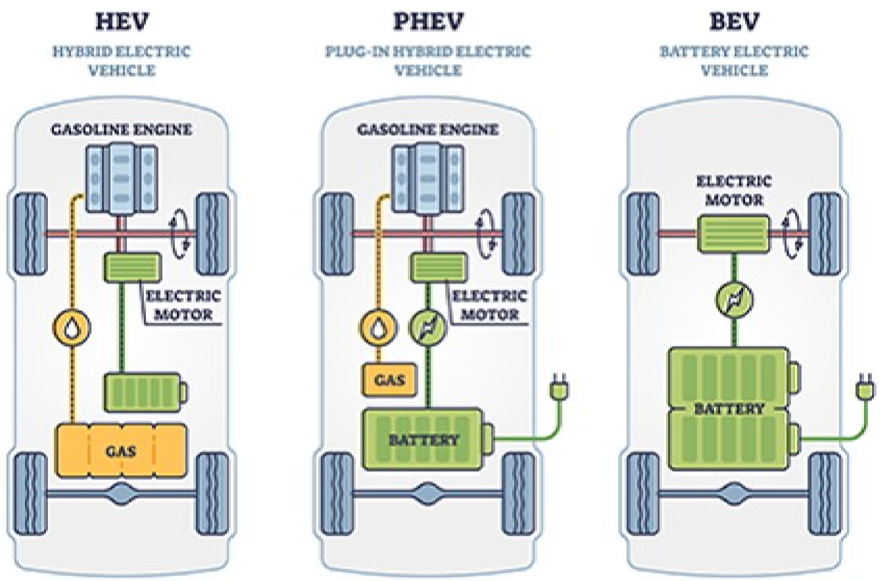

Figure 2.1: Different types of EVs [39].

2.2 State of Charge (SOC)

The state of charge (SOC) of a battery represents the available capacity as a function of the rated capacity. The SOC's value ranges from 0% to 100% as shown in Fig. 2.2. A battery is considered to be fully charged if the SOC is 100%, whereas 0% denotes a totally discharged battery [1].

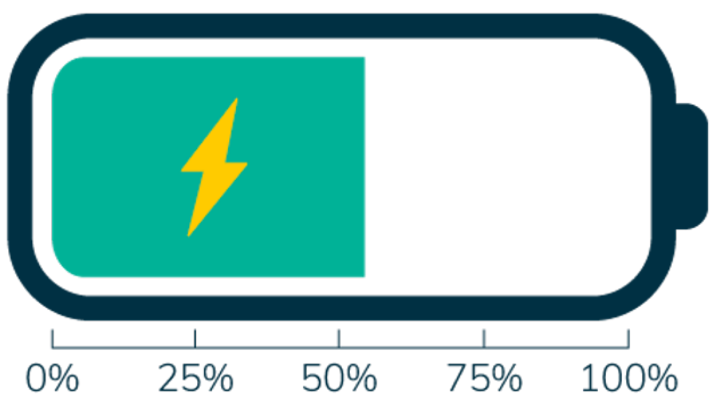

Figure 2.2: State of charge (SOC) of an EV battery [13].

SOC is a crucial factor in calculating an EV's driving range, or how far it can travel on a fully charged battery before running out of useable energy. EV users often experience range anxiety when traveling, which is the concern about running out of battery energy. EV users with low SOC (below 20%) suffer from range anxiety most of the time and keep looking for charging stations to recharge the battery as soon as possible [38].

2.3 Time-of-Use Pricing

Time-of-use (TOU) pricing is a technique for monitoring and billing a utility customer's energy usage depending on when the energy is consumed [7]. Utility companies charge more when there is greater daily demand for electricity. Rates for TOU vary by utility and location. Numerous utilities around the countries are using TOU pricing to reduce grid load by altering consumer behavior [19]. Power outages are more likely to occur when the grid is under too much energy demand. Customers of utilities are encouraged to utilize energy at times of the day when power demand is lower by charging them more during statistically higher demand periods.

There are three different periods that exist in the TOU scheme [2]:

- Off-peak: This is the period when the electricity prices are lowest. In Ontario, nearly two-thirds of the power is consumed by homes and small businesses during this period.
- Mid-peak: In this period, demand for electricity is moderate. Even though these hours are during the day, they are not the busiest ones.
- On-peak: During this period, the electricity demand goes higher. These are the busiest periods of the day since people are typically cooking, turning on their laptops, and using the heating or cooling system.

Fig. 2.3 shows an example of TOU pricing rates in Ontario during the summer period offered by the electricity utility.

2.4 Demand Response (DR) Strategy

The Department of Energy (DOE) defines demand response (DR) as: "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [31].

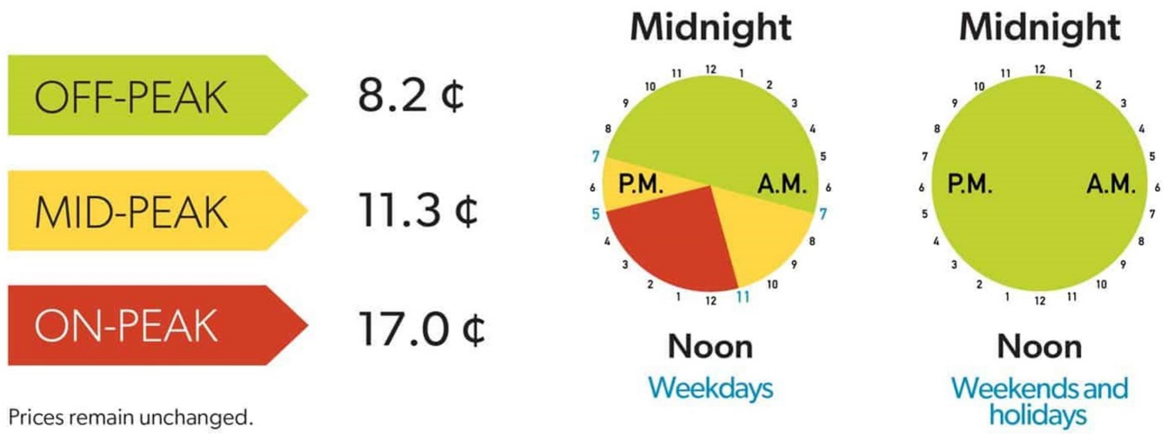

Figure 2.3: Time-of-use pricing periods for electricity [11].

DR has recently made strides in sensing and control technologies, and is seen as a crucial tool for addressing the issue of insufficient power supply compared to demand. Due to time-based pricing, such as TOU, DR enables energy customers to alter or reduce their electricity consumption during peak hours. Different DR schemes were suggested for residential households to offer load shifting and appliance curtailment [14], [30], [16]. Since the regulation of low power appliances has minimal effects on total power usage, the advantages of DR programs in these studies may be insignificant. Additionally, because some high power appliances' activities cannot be interrupted or shifted, the load flexibility they offer may be limited.

Due to the following factors, coordinating extensive EVCS appears to be a more viable option for a utility's demand response program than residential households [34]. First, if the combined charging loads of EVs in charging stations are well-coordinated, they could supply a significant amount of demand capacity and have a noticeable influence on the DR program. Second, the increased load flexibility of these EV charging loads with shifting and interrupting properties guarantees that scheduling of EV charging coordinated with the utility's DR programs may fulfill all charging requirements of EVs while completing committed demand curtailment for DR.

An EVCS can participates in a DR program either by its own (i.e., self-dispatch) or by a third party [27]. Self-dispatch DR is also known as TOU-based DR, in which customers voluntarily shift or reduce their load in response to TOU pricing signals from the grid. Fig. 2.4 shows different types of TOU-based DR strategies.

In load curtailment, electricity consumers, such as EVCS, reduce their load during on-peak time. Load shifting is a mix of peak-clipping and valley-filling procedures in

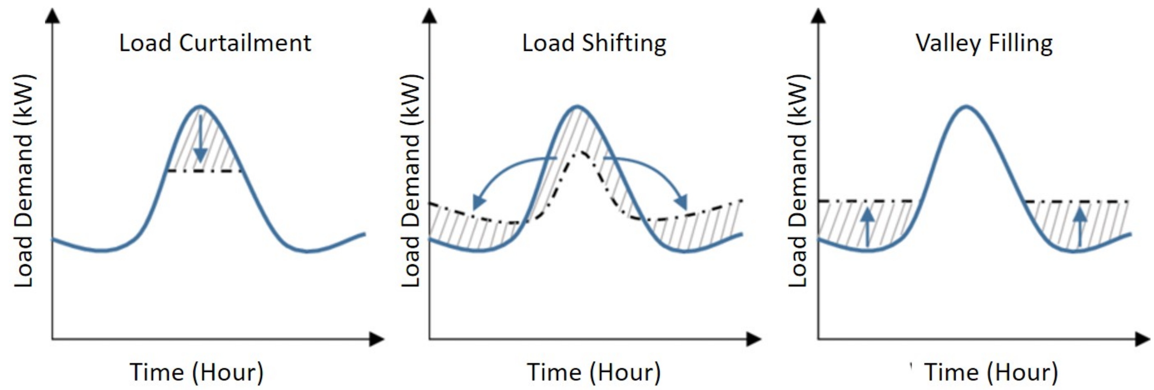

Figure 2.4: Types of TOU-based DR strategies [27].

which loads are cut during the on-peak time and restored during the off-peak period. Valley filling entails adding loads throughout the off-peak load curve phase.

2.5 EV Charging Modes

EV charging units typically fall into one of the three levels listed below in North America and Japan [5].

- Level 1: In Level 1 (L1) charging mode, charging equipment requires a dedicated circuit and charges using a 120 volt (V) alternating current (AC) socket. In general, Level 1 charging refers to the usage of a regular household outlet. Since level 1 charging equipment is already included in cars, it is portable and does not require additional installation. A typical three-prong home plug is located at one end of the supplied cord. The other end has a connection that connects to the car. A totally discharged battery may be fully charged with Level 1 charging in 8 to 12 hours, depending on the battery technology utilized in the vehicle. Due to the slow charging rate, Level 1 charging is more suitable for at-home charging. It is most frequently done overnight at the residence of the car owner. A typical L1 charging equipment is shown in Fig. 2.5.
- Level 2: In Level 2 (L2) charging mode, additional installation of home charging or public charging equipment is required. It offers charging using a 240V AC plug. These devices need their own 40 amp circuit. All types of EVs can use L2 charging infrastructure. The same connector used for L1 equipment is utilized for the wire that connects L2 chargers to the car. A totally discharged battery

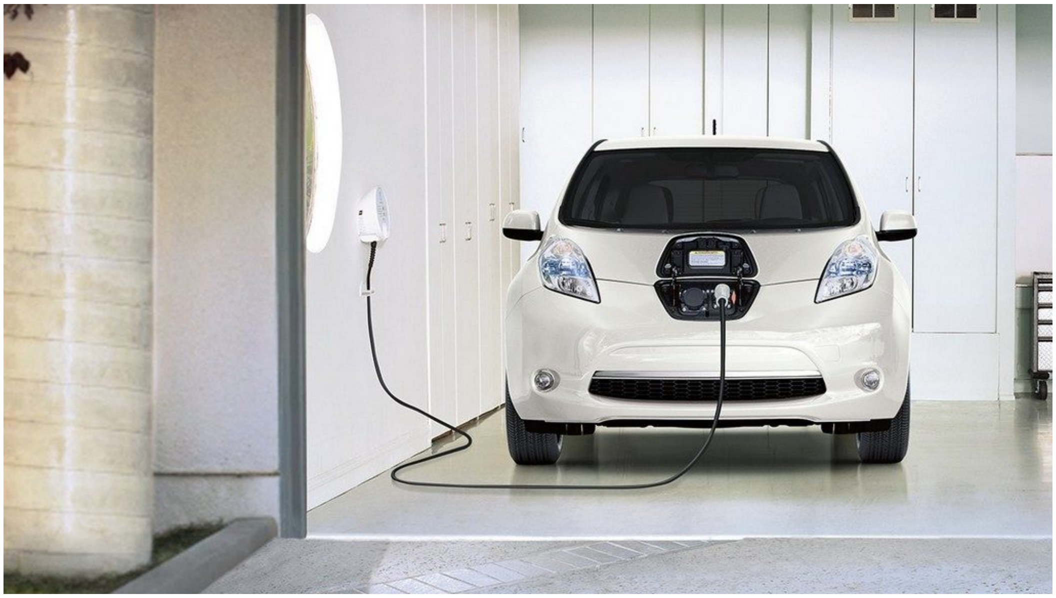

Figure 2.5: Level 1 charging stations [15].

may be fully charged with L2 charging in 4 to 8 hours, depending on the battery technology used in the vehicle. In cold weather, charging time may increase. Residential environments, public parking lots, workplaces, and business settings all frequently include L2 chargers. Fig. 2.6 shows a public L2 charging station.

Figure 2.6: Level 2 charging stations [9].

- Level 3: As mentioned earlier, Level 3 (L3) is also known as direct current fast charging (DCFC). This is the fastest charging mode. Because direct current charging can provide substantially higher amounts of electrical power since it bypasses an EV's inbuilt inverter to charge the battery directly. This kind of charger is normally exclusively utilized in business settings, such as public charging stations. Because studies have shown that frequent usage of L3 may accelerate the deterioration of battery capacity over time, most EVCS limits the maximum charging by using L3 to 80% [20]. Fig. 2.7 shows a public L3 charging station.

Figure 2.7: Level 3 charging stations [29].

In this thesis, we consider only the two charging modes (L2 and L3), which are used in most of the public charging stations. The comparison of these two levels of charging modes is summarized in Table 2.1.

Table 2.1: Comparison of L2 and L3 Charging Modes

Components	**Level 2 (AC Charging)**	**Level 3 (DC Fast Charging)**
Suitability	The best balance of charging speed, cost, and time—whether at home, work, or a public spot.	This is best for EV users who need quick charging and go.
Use case	Best for destination charging when EV drivers can leave their cars for a short time (such at work) or if the station operator prefers drivers to stay on site (e.g. shopping mall).	Best suited for en-route charging, when the primary aim is to charge rapidly so EV users may resume driving as soon as possible.
Charge times and ranges*	About 100 km of range can be gained with 2.5 hours of Level 2 charging.	Typically, 100 km of range can be achieved in 30–40 minutes using a DC fast charger. When the battery is 80% full for many EVs, the speed of charge will eventually slow to a trickle.
Customer experience & driver obligations	Four to eight hours is the maximum charging period permitted for a public Level 2 charger. This indicates that it is permissible for drivers to leave their cars unattended while they go shopping, to a movie, or to the gym. To avoid overstaying, EV drivers are advised to set a timer or turn on message notifications from the charging network provider.	At busy places and when others are waiting, the maximum allowed charging time at a public DC fast charger is 30-40 minutes. Drivers should keep close to the charger in case there is a problem with it or if they need to relocate their vehicles to enable the next driver to charge. Clear signage is useful for reminding drivers of proper driving etiquette.

*Charge periods can vary based on a variety of factors, such as the type of EV, battery state of charge, power output, temperature, etc.

As discussed above, L2 chargers do not require a power converter and instead rely on the on-board vehicle charger to charge the vehicle. On the other hand, L3 chargers run at a high-power DC voltage and require an off-board AC-DC converter to charge the battery. Therefore, two different types of chargers are required to charge the EVs in different modes [40]. The type of EV we consider in this work is battery EVs (BEVs), as they are compatible with both charging modes. In order to protect the battery, it is recommended to charge an EV up to 80% in the L3 mode. However, in the L2 mode, the maximum allowed SOC level is 100% [40]. Although in this work, two available charging modes are considered, it can be easily extended to multiple charging modes using the proposed method herein.

2.6 Charging Scheduling

Although EVs are emerging as a promising solution to the developing ecological concerns, the high penetration rate of EVs and their intermittent charging demands have an influence on the public power grid's operation [6]. As a result, designing charging scheduling scheme to alleviate the peak demand imposed by EVs and reduce their electricity bills is critical. The EV charge scheduling problem takes as input a set of EVs and their charging requirements, as well as utility-side parameters, and outputs a charging schedule. It is an optimization problem that aims to optimize certain parameters of different parties (or a combination of them) under various restrictions. There is no one universal mathematical formulation for the issue since the range of parameters, constraints, and objective functions under consideration leads to a variety of optimization problems.

In general, EV charging strategies are classified as centralized or decentralized method.

- Centralized method: In the centralized method, each EV's charging schedule is decided by an aggregator, such as CRS. The aggregator collects the charging requirements from all EVs and solves an optimization problem while considering the constraints, such as energy capacity, maximum charging limit, and charging spots, to determine which EVs it can serve. Finally, it relays the optimization-based charging schedule to the EV owners.

- Decentralized method: Unlike centralized method, in decentralized approach, each EV makes its own small-scale decisions independently. In a decentralized charging control system, each EV has some computational power, and it decides whether or not to charge in consultation with the aggregator. Each EV transmits its energy demands to the aggregator, which utilizes some of the data gathered there to pick the optimum schedule.

In this thesis, we mainly focus on the centralized method, where all the EVs send their charging requests to the EVCS, and the aggregator, CRS, computes the optimization problem and makes the final charging decision.

2.7 Related Works

In an EV charging scheduling problem, it would be ideal to know the future charging demand in advance, so that the EV charging can be scheduled to serve the maximum number of EVs, flatten the total load, or maximize the profit of an EVCS [6]. However, an EVCS faces significant uncertainties in EVs' behaviors, including travel patterns and charging demands. Online charge techniques have become a potential paradigm to determine the best charging for EVs in the face of uncertainty [6]. The online EV charging problem is more realistic since it simply uses past and present EV characteristics, such as arrival and departure times and charging demands, and makes no assumptions about the future.

There have been a considerable number of studies conducted on designing online charging scheduling strategies for EVCSs, such as an online social welfare maximization model for EVCSs developed in [3] that takes charging station capacity, stochastical EV arrival patterns, and on-arrival commitment into consideration. The station operator uses a best-effort approach to meet EV charging requests, while drivers prefer an on-arrival commitment, which informs them of a guaranteed amount of energy to be given upon their arrival. However, on-arrival commitment makes theoretical guarantees difficult to design due to the significant temporal dependency of each EV's schedule, particularly when a charging rate constraint is also enforced. As a result, in order to reduce temporal dependency, this work focuses on a strategy that achieves on-arrival commitment by generating a committed schedule upon arrivals.

A prediction-based charging method is proposed in [42] that takes expected future demand over a look-ahead period into account. In this paper, two different objectives are considered. The first objective is to minimize the peak demand, and the second one is to minimize the total charge cost. For the first objective, a greedychoice property was applied, which suggests that a globally optimum solution may be obtained by making locally optimal greedy choices. In order to reach the global optimum for the second objective, it proposed a non-myopic charging technique that takes future demands into consideration. A bisection search algorithm and a multi-commodity network flow model combined with a rolling horizon framework are used in a heuristic solution to solve this problem.

To study an energy scheduling problem for distributed data centers and EVs, a distributed online approach is suggested in [46]. To deal with uncertainties in data center workloads, power costs, and EV energy demands, it formulated a stochastic programming problem. Then it proposed a distributed online algorithm based on the Lyapunov optimization approach and an enhanced alternating direction method to solve the specified issue because these uncertain system parameters are time-varying and the size of the problem is very large.

A framework for online energy management of EVs using an evolutionary algorithm is presented in [32]. The framework employs a self-adaptive technique in order to control the vehicle's SOC in a rolling horizon fashion for real-time execution.

There are also some existing works on online charging algorithms. For example, an innovative spot price-based centralized EV charging approach that takes into account charging priority and location is offered in [18]. To reduce the operating cost of utilities while taking into account time-varying demand responses and customer responses, a combined online learning and pricing algorithm is proposed in [22]. In [17], a novel multiobjective evolutionary algorithm is presented to reduce the load and operational cost differences from peak to valley. With certain practical restrictions, a two-stage stochastic programming approach to optimize the power flow of commercial buildings and EV charging stations is suggested in [33].

While coordinating charging at EVCSs, some works place a greater emphasis on lowering charging costs or maximizing profit. For example, authors in [43] proposed a binary programming-based method for online charging while considering a real-time pricing-based demand response program. The proposed method aims to maximize the number of EVs selected for charging and reduce the cost of electricity paid to the utility. In the proposed study, the on-off technique is used to accomplish the fast charging speed for EVs.

An optimal charging scheduling scheme is proposed in [23] to minimize the charging cost with a limited number of chargers while considering the TOU pricing concept. It investigated the serviceability of charging stations and compared the charging costs among different numbers of charging EVs and chargers. In [41], an admission control mechanism and TOU pricing scheme are adopted for scheduling EVs at charging stations to maximize the profit of charging stations.

In all of these previous studies, only a single charging mode is considered with different types of distributions, scenarios, and queuing models to characterize the EV arrival pattern without historical data and realistic assumptions, such as unlimited charging capacity and charging spots of the stations. Furthermore, these studies primarily focus on the benefits of EVCSs or grids while ignoring or only partially considering user demand. To the best of our knowledge, this is the first study to use historical EV arrival data and TOU-based DR strategy to address the online charging scheduling problem while taking dual charging modes into consideration, focusing not only on the profit of EVCSs, but also satisfying the EV users by fulfilling their charging requirements.

Chapter 3

Priority-based Online Charging Scheduling

In this section, we describe the system model, formulate the online EV charging problem and propose an efficient priority-based online algorithm, namely PBOS.

3.1 System Model

There are three major parties involved when considering the EV charging problem at a public charging station [35]. The parties are EV users, EVCSs, and electric utilities. EV users are typically EV drivers. Like gasoline-fueled cars, EV users are often required to charge their vehicles to keep them running. An electric utility produces electricity from different energy sources, such as power plants and renewable energy sources, and sells it to its consumers, such as EVCS. The EVCS provides charging services to the EV users. It acts as an interface between the utilities and a large number of EV users. As a result, its profit is ultimately linked to the other two parties. The price difference between purchasing energy from utilities and selling energy to EVs can make EVCSs profitable in many cases [35]. Fig. 3.1 shows the basic interaction among the three parties and flow of electricity.

EV charging issues have primarily been investigated from three perspectives: electricity utilities, EVCS, and EV users [35]. In this thesis, we study the problem from the EVCS perspective.

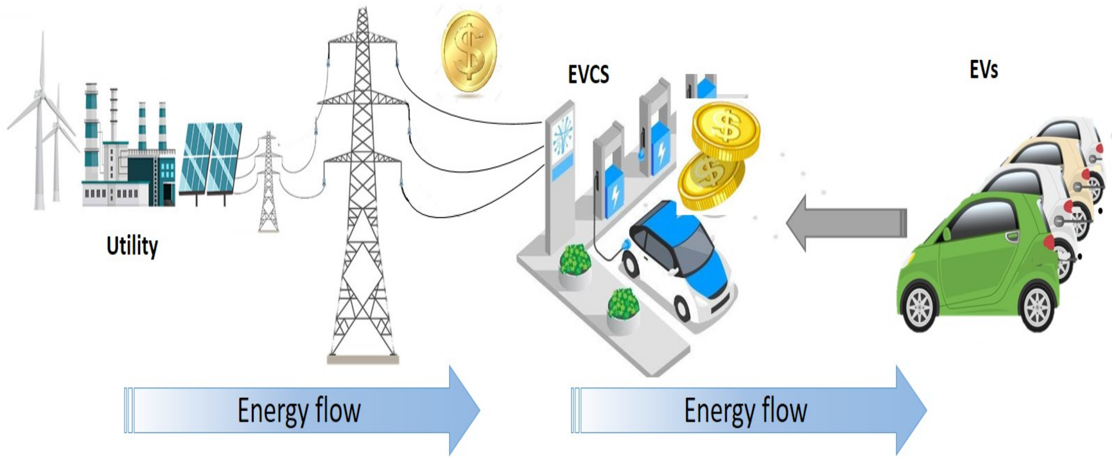

Figure 3.1: Interactions between utility, EVCS, and EVs.

3.1.1 EVCS Model

We consider a small charging station scenario in an urban area (e.g., downtown) with a limited number of charging spots and power capacity. Therefore, only selected EVs are permitted to go inside the charging station, and they need to depart immediately after finishing charging to make space available for the next EV user. In order to facilitate EV users, we further consider that each charging spot is equipped with both types of chargers (L2 and L3) as shown in Fig. 3.2. This is similar to how conventional gasoline and diesel pumps operate. Although currently most of the EVCS have only one type of charger at each charging spot, considering the high EV penetration rate, this might not be enough to facilitate multi-class EV users in the future [24]. EVCS with multiple charging modes, including wireless charging, at the same charging spot are now becoming a reality [24]. This assumption also makes sense when an EV user requires 100% of SOC but selects L3 charging. Because the maximum charging limit in the L3 charging mode is up to 80%, the remaining 20% can be charged by using the L2 charger in the same location without moving the EV.

As discussed in Section 2.5, L2 and L3 need different types of changers because the working principles of these two modes differ and they have different electrical configurations and constraints. Furthermore, each EV has only one charging port. So, we further assume that a single EV user can only use one charging mode at a time, not both at the same time. Considering a real-time scenario, the charging information of each EV will only be available to the charging station once it receives the request at the current time. Other than this, it has no prior knowledge regarding the future incoming EVs. Users can send the request by smartphone applications before coming to the station. Due to the limited number of charging spots and charging capacity, charging requests may not be all accepted. As a result, a charging scheduling method is required to coordinate charging among all incoming EVs and the existing charging process in order to keep the charging load below the total charging capacity P^{total} while fulfilling the charging demands of connected EVs before their departure.

In this work, a slotted time-based optimization framework is considered in which the entire charging period of a day is divided evenly into I time steps, where $i = 1, 2, 3, \cdots, I$ is the index of each time step, and the duration of each time step is ΔT. The decision of charging scheduling is made at the beginning of each time step ΔT to achieve a certain goal. The objective of this work is to select the maximum number of EVs based on user priority while minimizing the charging cost and fulfilling the minimum charging requirements of the EV users before they depart.

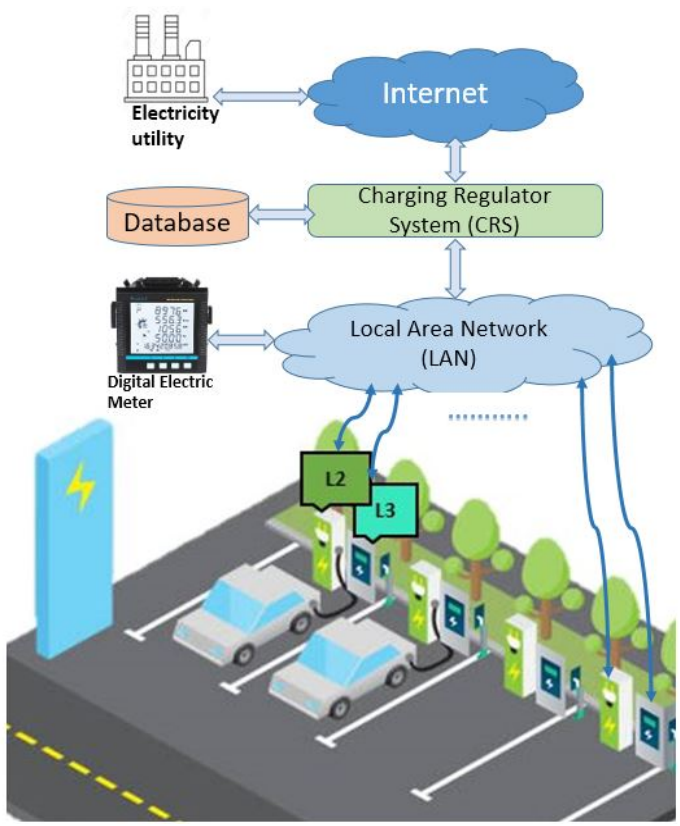

Figure 3.2: An illustration of EVCS with dual-mode charging capabilities.

The total number of EVs that request for charging at the i-th time step is L_i, and the set containing all these EVs is denoted by $\mathcal{L}_i$. Note that if the total number of EVs coming to the EVCS is denoted by L, we can write $L = \sum_{i=1}^{I} L_i$. When the n-th EV requests at a charging station at the i-th time step, it reports its charging requirement to the charging regulator system (CRS), which includes the arrival time $t^a_{n,i}$, departure time $t^d_{n,i}$, charging mode $m_{n,i}$ and minimum required energy $\mathrm{SOC}^{\mathrm{req}}_{n,i}$. The scheduler in the CRS keeps track of the requests of each incoming EV, and it schedules the charging operation based on the optimization decision before starting the next charging slot. A local area network (LAN) is used to create two-way communication among the CRS, chargers and database by using conventional communication channels, such as Wi-Fi, RS-485 or Ethernet.

According to the application scenario of such a dense traffic area, EV users are unlikely to stay in the charging station. Moreover, the limited number of charging spots can only allow the selected users to enter the charging station. Therefore, it is legitimate to assume that when an EV is selected for charging, it cannot be stopped until the charging is done or the maximum allowed SOC level is reached.

3.2 Feasibility Test

In an EVCS, EVs are continually send requests for charging or depart the charging station. The sample duration is set to ΔT i.e., every ΔT minutes, the CRS updates the charging schedule. The arrival time step, $t^a_{n,i}$, of a requested n-th EV at the i-th time step is calculated by converting the real value ratio, $t^a_{n,i}/\Delta T$, onto the smallest subsequent integer using the ceiling rounding operator $\lceil\cdot\rceil$. The expected real-valued departure time, $t^d_{n,i}$, of a requested n-th EV at the i-th time step is calculated by converting the real value ratio, $t^d_{n,i}/\Delta T$, onto the largest previous integer using the floor rounding operator $\lfloor\cdot\rfloor$.

At the i-th time step, when the n-th EV requests for charging, the CRS first determines the feasibility of the minimum charging demand $\mathrm{SOC}^{\mathrm{req}}_{n,i}$ to check whether or not the desired charging mode and departure time will attain the required SOC level. The expected SOC level that can be achieved within a given duration is computed as follows.

$$\mathrm{SOC}^{\mathrm{exp}}_{n,i} = \begin{cases} \mathrm{SOC}_{n,i} + \frac{\eta * P^r * t^r_{n,i}}{B_n}, m_{n,i} = 0, \ \forall i \in I, \forall n \in \mathcal{L}_i \\ \mathrm{SOC}_{n,i} + \frac{\eta * P^q * t^r_{n,i}}{B_n}, m_{n,i} = 1, \ \forall i \in I, \forall n \in \mathcal{L}_i \end{cases} \tag{3.1}$$

where $\mathrm{SOC}^{\mathrm{exp}}_{n,i}$ represents the expected SOC, η is charging efficiency, B_n is battery capacity, and P^r and P^q are the L2 and L3 charging power, respectively. The charging mode is indicated by a binary variable $m_{n,i} \in \{0, 1\}$, where $m_{n,i} = 0$ denotes the L2 mode and $m_{n,i} = 1$ denotes the L3 mode. The remaining charging time before the EV departs and initial SOC level are represented by $t^r_{n,i}$ and $\mathrm{SOC}_{n,i}$, respectively. $t^r_{n,i}$ is determined as

$$t^r_{n,i} = t^d_{n,i} - t^a_{n,i}, \ \forall i \in I, \forall n \in \mathcal{L}_i. \tag{3.2}$$

In order to consider a request viable, $\mathrm{SOC}^{\mathrm{req}}_{n,i} \leq \mathrm{SOC}^{\mathrm{exp}}_{n,i}$ must be met, and it is rejected otherwise. The SOC level of the battery is updated whenever an EV is selected for charging as follows.

$$\mathrm{SOC}_{n,i+1} = \begin{cases} \mathrm{SOC}_{n,i} + \frac{\eta * P^r * \Delta T}{B_n}, m_{n,i} = 0, \ \forall i \in I, \forall n \in \mathcal{L}_i \\ \mathrm{SOC}_{n,i} + \frac{\eta * P^q * \Delta T}{B_n}, m_{n,i} = 1, \ \forall i \in I, \forall n \in \mathcal{L}_i \end{cases} \tag{3.3}$$

In Algorithm 1, we provide the pseudo code of the feasibility test method. It selects the feasible requests from all the incoming charging requests at each time step. Let $\mathcal{N}$ be the set of all EVs after passing the feasibility test, where $\mathcal{N} \subset \mathcal{L}$ holds, and the set of feasible requests at the i-th time step is denoted by $\mathcal{N}_i$.

Algorithm 1: FT (Feasibility Test)

Input: $\mathrm{SOC}_{n,i}, B_n, P^r, P^q, \mathrm{SOC}^{\mathrm{req}}_{n,i}, \mathrm{SOC}^{\mathrm{exp}}_{n,i}, m_{n,i}$ for all EVs arrive at any time step i

Output: Feasible set of requested EVs, $\mathcal{N}_i$

for Any EV n arrives at current time step i **do**
    $t^r_{n,i} \leftarrow t^d_{n,i} - t^a_{n,i}$
    if $m_{n,i} = 0$ **then**
        $\mathrm{SOC}^{\mathrm{exp}}_{n,i} \leftarrow \mathrm{SOC}_{n,i} + \frac{\eta * P^r * t^r_{n,i}}{B_n}$
    else
        $\mathrm{SOC}^{\mathrm{exp}}_{n,i} \leftarrow \mathrm{SOC}_{n,i} + \frac{\eta * P^q * t^r_{n,i}}{B_n}$
    end
end
if $\mathrm{SOC}^{\mathrm{req}}_{n,i} < \mathrm{SOC}^{\mathrm{exp}}_{n,i}$ **then**
    Update $\mathcal{N}_i$
else
    Reject the charging request
end

3.3 Ranking of Charging Priority

At every time slot, multiple EVs can send requests for charging. In order to ensure priority-based fairness, a priority weight is introduced that integrates $\mathrm{SOC}_{n,i}$, $t^r_{n,i}$, $\mathrm{SOC}^{\mathrm{req}}_{n,i}$ and B_n based on $m_{n,i}$. From the feasible set $\mathcal{N}_i$, the priority weight $w_{n,i}$ for the n-th EV at the i-th time step is defined as follows.

$$w_{n,i} = \begin{cases} \dfrac{B_n((\mathrm{SOC}^{\max}_r - \mathrm{SOC}_{n,i}) + (\mathrm{SOC}^{\max}_r - \mathrm{SOC}^{\mathrm{req}}_{n,i}))}{P^r t^r_{n,i}}, \\ m_{n,i} = 0,\ \forall i \in I, \forall n \in \mathcal{N}_i \\ \\ \dfrac{\alpha B_n((\mathrm{SOC}^{\max}_q - \mathrm{SOC}_{n,i}) + (\mathrm{SOC}^{\max}_q - \mathrm{SOC}^{\mathrm{req}}_{n,i}))}{P^q t^r_{n,i}}, \\ m_{n,i} = 1,\ \forall i \in \{1, 2, \cdots, I\}, \forall n \in \mathcal{N}_i, \end{cases} \tag{3.4}$$

where $\mathrm{SOC}^{\max}_r$ and $\mathrm{SOC}^{\max}_q$ are the maximum SOC levels allowed by the L2 and L3 modes, respectively. The numerator of (3.4) considers the required level of energy and the requested level of energy to fill the battery given the maximum allowed SOC in any of the charging modes. In another word, EVs with low SOC and small charging demand have higher priority. The denominator of (3.4) represents the energy level that can be delivered to fill the battery within the remaining charging time $t^r_{n,i}$. A smaller value of $t^r_{n,i}$ denotes that the EV needs to be charged as early as possible. Since the charging time in the L3 mode is much shorter than that in the L2 mode, an EVCS can charge more vehicles in a day by choosing more L3 users. It is also important to note that users who pick the L3 charging option pay more money compared to the L2 users. However, as the charging power of the L3 mode is much higher compared to the L2 one, under the charging requests by multiple users with the same or different battery capacity, SOC status and charging demand, L2 users may always have a higher priority compared to the L3 ones.

To resolve this issue and ensure the L3 users have higher priority compared to the L2 ones in such cases, a regulator parameter, α, is used, where α is defined as follows.

$$\alpha = \frac{\max\{w_{n,i}\}, m_{n,i} = 0,\ \forall i \in I, \forall n \in \mathcal{N}_i}{\min\{w_{n,i}\}, m_{n,i} = 1,\ \forall i \in I, \forall n \in \mathcal{N}_i} + \epsilon \tag{3.5}$$

The numerator of (3.5) defines the maximum priority weight among all the EVs in the L2 mode, and the denominator defines the minimum priority weight among all the EVs in the L3 mode at the same time step. As the L3 users' priority weights are multiplied by α, the highest priority weight among the L2 users will always be equal to the lowest priority weight of an L3 user. To avoid this ambiguity, an additional parameter, ϵ, is added, where ϵ is a non-zero positive constant.

The value of α in (3.5) converted into the next largest integer using ceiling rounding operator $\lceil\cdot\rceil$, i.e., $\lceil\alpha\rceil$. However, when all the EVs request the same charging mode, the value of α is set to 1. A pseudocode of the Priority Ranking (PR) method is presented in Algorithm 2.

Algorithm 2: PR (Priority Ranking)

Input: $t^r_{n,i}, t^a_{n,i}, t^d_{n,i}, t^r_{n,i}, m_{n,i}, B_n, \mathrm{SOC}^{\max}_r, \mathrm{SOC}_{n,i}, \mathrm{SOC}^{\max}_q, \mathrm{SOC}^{\mathrm{req}}_{n,i}, P^r, P^q, \mathcal{N}_i$

Output: $w_{n,i}$

for Any EV n within the feasible set $\mathcal{N}_i$ at time step i **do**

  $t^r_{n,i} \leftarrow t^d_{n,i} - t^a_{n,i}$

  if $m_{n,i} = 0$ & $t^r_{n,i} \neq 0$ **then**

    $w_{n,i} \leftarrow \left(\frac{B_n((\mathrm{SOC}^{\max}_r - \mathrm{SOC}_{n,i}) + (\mathrm{SOC}^{\max}_r - \mathrm{SOC}^{\mathrm{req}}_{n,i}))}{P^r t^r_{n,i}}\right)$

  else if $m_{n,i} = 1$ & $t^r_{n,i} \neq 0$ **then**

    $w_{n,i} \leftarrow \left(\frac{\alpha B_n((\mathrm{SOC}^{\max}_q - \mathrm{SOC}_{n,i}) + (\mathrm{SOC}^{\max}_q - \mathrm{SOC}^{\mathrm{req}}_{n,i}))}{P^q t^r_{n,i}}\right)$

  else

    $w_{n,i} \leftarrow 0$

  end

end

3.4 Time-of-Use (TOU) Pricing Scheme

In order to consider the profitability of EVCSs, we take into account a real-time electricity pricing scheme, time-of-use (TOU), offered by the electricity utility [7]. During the peak period, the electricity prices go higher, and hence less number of EVs should be selected, and more EVs should be scheduled during the off-peak period. Let the hourly electricity price set by the utility authority for a specific day be C, with the maximum and minimum electricity prices are denoted by $c^{\max}$ and $c^{\min}$, respectively, where $\{c^{\max}, c^{\min}\} \in C$. An ancillary parameter, γ_i, is defined to quantify the charging preference as follows.

$$\gamma_i = \frac{(c^{\max} - c_i)}{(c^{\max} - c^{\min})},\ \forall i \in I, \tag{3.6}$$

where c_i is the electricity price at the i-th time step. As per (3.6), the parameter γ_i generates a higher value when the electricity price is lower and vice versa. The resultant value is normalized, i.e., $\gamma_i \in [0, 1]$.

3.5 Optimization of Online Scheduling

In an online scheduling strategy, the charging station only knows the charging requirements of EV users at current time step i or before i. Therefore, the scheduler in the CRS needs to select EVs dynamically at every time step by coordinating with the existing charging tasks at the corresponding EVCS.

Based on the charging priority $w_{n,i}$ and real time electricity price c_i, we propose an efficient charging scheduling algorithm, PBOS, to coordinate the charging process. It selects the maximum number of EVs for charging based on priority weight $w_{n,i}$ at each time step and keeps the overall charging load within the total charging capacity P^{total} and spot capacity of the EVCS. If there are N_i number of EVs in set $\mathcal{N}_i$ ($\mathcal{N}_i = \{1, 2, ...N_i\}$) at the i-th time step, the priority weight is set to $\sigma_i = \{w_{1,i}, w_{2,i}, w_{3,i}, ..., w_{N,i}\}$.

The scheduling optimization process searches through the set $\mathcal{N}_i$, and selects the best suitable number of EVs to maximize the objective function while satisfying all the constraints. The search process is conducted in the descending order of weights $w_{n,i}$ using the sort$(\cdot)$ operator. All the elements within $\mathcal{N}_i$ are rearranged in the same order at every i-th time step. The new set of EVs ϕ_i at any time step after rearranging is defined as

$$\phi_i = \text{sort}(\mathcal{N}_i)|_{\sigma_i}. \tag{3.7}$$

The objective function is formulated to maximize the sum of weighted cost benefit $w_{n,i}\gamma_i$ as follows.

$$\max_{\{x_{n,i}\}_{n\in\phi_i}} \sum_{n\in\phi_i} x_{n,i} w_{n,i} \gamma_i \tag{3.8}$$

In (3.8), the decision variable $x_{n,i}$ is a binary parameter, i.e., $x_{n,i} \in \{0, 1\}$. $x_{n,i} = 1$ implies that EV n is selected for charging, whereas EV n is not selected under the other case. Any EV that is rejected at the current time step can wait until the next time slot or can send request to another nearby EVCS. The total charging load at the i-th time step is defined as

$$\sum_{n\in\phi_i} x_{n,i}(1-m_{n,i})P^r + x_{n,i}m_{n,i}P^q, \quad \forall i \in I, \forall n \in \mathcal{N}_i \tag{3.9}$$

According to the system model, at each charging spot, one EV can be charged in a single charging mode. Any charger in either mode cannot serve multiple users simultaneously, but can serve more than one EV throughout the day. Let the total number of charging spots be M, and then the maximum load $P^{\max}$ of an EVCS is defined as

$$P^{\max} = \sum_{n\in\phi_i} MP^q, \forall n \in \mathcal{N}_i. \tag{3.10}$$

As $P^q > P^r$ holds, according to (3.10), the maximum charging load at any time step is considered when all the selected EVs at each charging spot use L3 mode simultaneously. Therefore, the maximum capacity limit of an EVCS at any time step is $P^{\text{total}} = P^{\max}$. In order to consider the DR event, a load curtailment P_i^{tou} is used. Therefore, at the i-th time step, the total charging load is constrained by demand limit $(P^{\text{total}} - P_i^{\text{tou}})$. Therefore, we can write

$$\begin{aligned}&\sum_{n\in\phi_i} x_{n,i}(1-m_{n,i})P^r + x_{n,i}m_{n,i}P^q \le P^{\text{total}} - P_i^{\text{tou}},\\ &\forall i \in I, \forall n \in \mathcal{N}_i\end{aligned} \tag{3.11}$$

The total number of EVs that a charging station can serve at each time slot is restricted by the total number of charging spots. Therefore, the following relation holds.

$$\sum_{n\in\phi_i} x_{n,i} \le M, \quad \forall i \in I, \forall n \in \mathcal{N}_i \tag{3.12}$$

As discussed earlier, EVs can only be charged to a maximum allowed SOC level depending on the charging mode. Therefore, the upper limit SOC^{up} is formulated as

$$\begin{aligned}&\text{SOC}^{\text{up}} = \text{SOC}_r^{\max}(1-m_{n,i}) + \text{SOC}_q^{\max}m_{n,i},\\ &\forall i \in I, \forall n \in \mathcal{N}_i\end{aligned} \tag{3.13}$$

In order to ensure that the vehicles do not exceed the maximum allowable SOC level throughout the charging process, the SOC level is restricted to $\mathrm{SOC}^{\mathrm{up}}$. Similarly, it is also important to fulfill the minimum charging demand $\mathrm{SOC}_{n,i}^{\mathrm{req}}$ before the departure. By considering these upper and lower limits, we can have the following constraints.

$$\begin{aligned}&\mathrm{SOC}_{n,i}B_n + \eta(x_{n,i}(1-m_{n,i})P^r +\\ &x_{n,i}m_{n,i}P^q)\Delta T \leq \mathrm{SOC}^{\mathrm{up}}B_n, \forall i \in I, \forall n \in \mathcal{N}_i\end{aligned} \tag{3.14}$$

$$\begin{aligned}&\mathrm{SOC}_{n,i}B_n + \eta(x_{n,i}(1-m_{n,i})P^r +\\ &x_{n,i}m_{n,i}P^q)\Delta T \geq \mathrm{SOC}_{n,i}^{\mathrm{req}}B_n,\ \forall i \in I, \forall n \in \mathcal{N}_i\end{aligned} \tag{3.15}$$

The formulated optimization problem in (3.8), (3.11), (3.12), (3.14) and (3.15) is a binary programming problem because of the binary nature of the decision variables $x_{n,i} \in \{0,1\}$, $n = 1,2,...,N_i$, $i = 0,1,...,I$. This causes the problem to be NP-hard, which is usually intractable to solve as it suffers from the dimensionality problem. A sophisticated state-of-the-art Gurobi MIP solver is used to find the optimal outcome based on the current information. However, obtaining the global optimal solution may be possible if we would have knowledge about the future arrival information. Since obtaining the future information is usually unrealistic, we consider an online scheduling scheme in this work, which is developed based on the currently available information.

Chapter 4

Performance Evaluation

In this section, we evaluate the performance of the proposed PBOS algorithm through extensive simulation. In the following results, a significant number of simulation runs (i.e., 1000 times) have been conducted. The average of these runs corresponds to each data point.

4.1 Simulation Setup

For the simulation, we consider an EVCS with M=10 total charging spots. The entire available charging time $I = 24$ hours is divided into 96 time steps, while the size of each time step is $\Delta T = 15$ minutes.

The L3 mode charging power P^q is set to 50 kW and the L2 mode charging power P^r is set to 20 kW. In this thesis, the following four different battery capacities of EVs are taken into account: 16 kWh, 25 kWh, 33 kWh, and 60 kWh, with proportions of 20%, 30%, 30%, and 20%, respectively.

We model the unpredictable behavior of user charging mode selection as a random discrete uniform distribution, where $m_{n.i} \in [1, 0]$ holds. The dwelling time of the EVs follows a uniform distribution throughout the scheduling period $i \in \{1, 2, \ldots, I\}$ depending on $m_{n,i}$. The users with the L3 mode follow the distribution with the mean value spanning between 15 min and 2 hours, and this range varies between 1 and 8 hours for the L2 users.

To make the scenario realistic, the initial SOC level, $\mathrm{SOC}_{n,i}$, is generated through a normal distribution with a mean of 50%, a standard deviation of 15%, and a positive skewness of 15%. The positive skewness indicates that the initial SOC of incoming vehicles will probably have less than 50% of its maximum battery capacity. The charging efficiency of each charger is set to $\eta = 90\%$, and the capacity of the EVCS P^{total} at each time step is set to 500 kW. To simulate the DR event, a load curtailment $P_i^{\text{tou}} = 300$ kW is considered. An hourly-basis TOU electricity price offered by RTE [12], a French electricity transmission system operator, is used for the simulation as shown in Fig. 4.1. The EV charging prices offered by the EVCSs for the L2 and L3 modes are set to 27 and 35 cents/kWh, respectively.

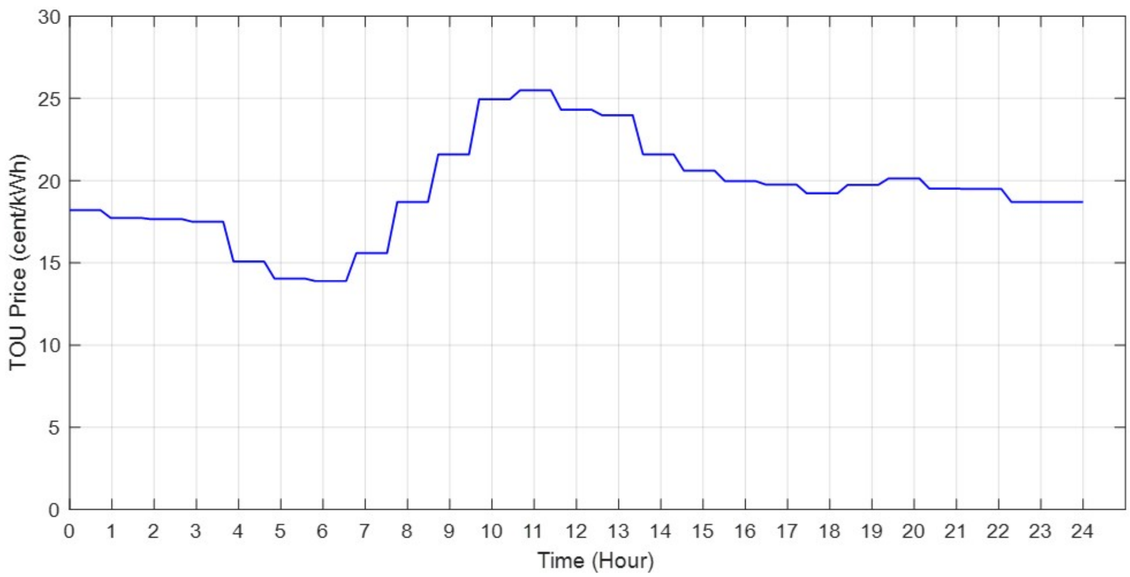

Figure 4.1: Time-of-Use (TOU) electricity rate [12].

4.2 Simulation Results with Historical Dataset

The Gaussian distribution of EV arrivals at the charging station is generated using a historical dataset [26], where the mean value of the number of incoming vehicles at each time slot is taken from the true dataset and a standard deviation is varied between 0.5% and 2%. Note that this distribution is truncated, where only the positive values taken into account when generating arrival data for the EVs. Fig. 4.2 shows historical information about the number of charging requests received by an EVCS throughout the day.

We compare the performance of the PBOS method with the other existing methods. The other schemes are summarized as follows,

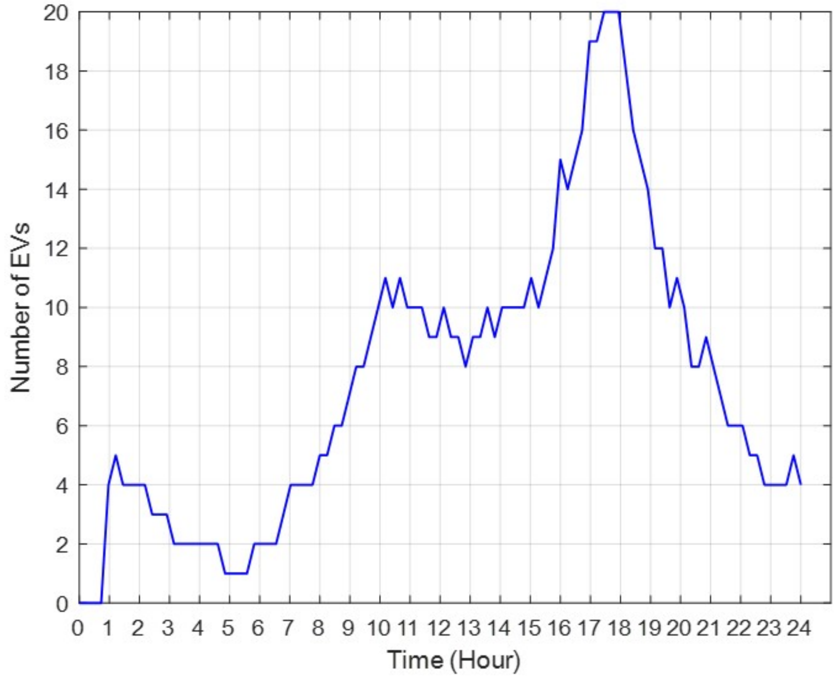

Figure 4.2: The number of EVs arrive at the EVCS throughout the day [26].

- First come first serve (FCFS): In the FCFS scheme, the charging requests of EVs are ranked according to their arrival time. The scheduler provides service to the EV that comes first to the EVCS and this process continues. It allows the vehicles to begin charging as soon as they arrive, which reduces the charging waiting time and prevents the charger from sitting idle. It is widely used in the current EVCS scheme [42].

- Real time charging schedule (RTCS): In the RTCS, EVs are sorted based on the priority weight for scheduling in real time. In this scheme, the initial SOC level and remaining charging time are considered while determining the priority along with the membership level. According to [43], RTCS provides a near-optimal solution to the single-mode charging scheduling scheme. In an online scheduling problem, it may not be possible to obtain a global optimal solution without having future arrival information. Therefore, RTCS is considered as the benchmark scheme. This method is built on charging EVs in the shortest amount of time and at the lowest feasible cost.

- SOC-based priority (SBP): The SBP algorithm takes into account the SOC level at real charging time [37]. In this scheme, EVs that have a lower SOC get more priority to be charged at the lowest feasible cost. The process begins by allocating all EVs to the charging stations in increasing order so that the charging can be finished as soon as possible. Up until all of the EVs are charged, the same procedure is repeated.

To evaluate the performance, three cases are studied based on different proportions of L3 and L2 user penetration. In Case 1, the proportions of both charging modes remain equal (50%). In Case 2, the proportion of L3 users is 70% and L2 users is 30%, and in Case 3, the proportions of L3 and L2 users are 30% and 70%, respectively. In each of these cases, three different incoming traffic scenarios, i.e., 500, 700, and 900 EVs, are considered.

Two different DR programs, DR1 and DR2, are taken into consideration to simulate participation in a DR event. DR1 takes into account a steady load reduction over a longer time period, while DR2 takes into account time-varying load shedding. During the DR1 event, a constant load curtailment of 300 kW is considered during the peak period (i.e., 9:00 – 14:00). In the DR2 event, a more complicated simulation is performed, in which time-varying load shedding is considered from 9:00 to 14:00. The DR1 and DR2 events are shown in Fig. 4.3 and Fig. 4.4, respectively, with the distribution of 900 EVs arriving at the station and the hourly varying day-ahead electricity pricing.

We study the charging rejection rate incurred by the proposed scheme as well as the benchmark ones in Fig. 4.5. The percentage of EVs that the EVCS can not serve is defined by the rejection rate. It is obtained by the total number of charging requests rejected by the EVCS over the total number of charging requests received by the EVCS from the feasible set within a day.

It can be seen in Fig. 4.5 that FCFS has the largest rejection rate during the DR1 event, with a range of 28% to 56%, followed by RTCS with a range of 24% to 53% and SBP with a range of 23% to 54%. For PBOS, the values are just between 18% and 36%. Fig. 4.6 shows the rejection rate of different schemes during the DR2 event. During this event, FCFS has a rejection rate ranging from 26% to 53%, whereas RTCS has a range of 21% to 51% and SBP has a range of 21% to 51%. While the rejection rate for PBOS varies from 15% to 31%.

This implies that PBOS has a lower rejection rate of up to 22% compared to other schemes. In another word, PBOS can serve more EVs compared to other schemes by rejecting a lower number of charging requests. This is due to the fact that the

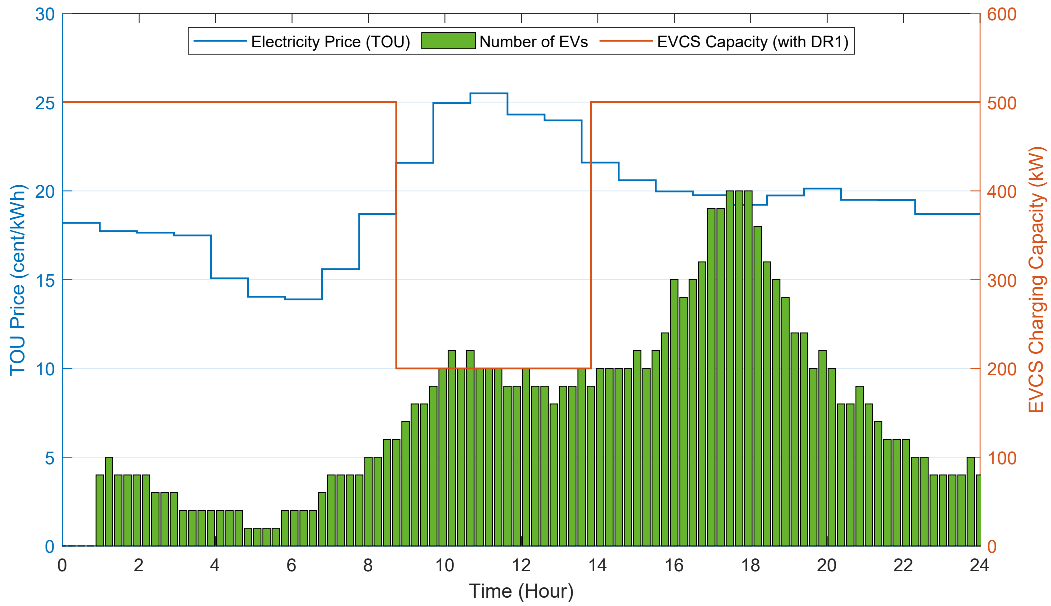

Figure 4.3: TOU electricity prices, charging station capacity, and the number of EVs arriving at an EVCS at various times of a day considering the DR1 event.

proposed method selects EVs with low charging demand in addition to prioritizing L3 over L2. So, it can serve more EVs than FCFS, RTCS, and SBP, which ignore charging demand and choose EVs based on arrival time, membership, or charging status, respectively.

For the DR1 and DR2 events, the total number of EVs selected by each algorithm in a day where the initial SOC is less than 20% is evaluated. An EV user with a battery SOC level below 20% suffers from range anxiety and looks for charging whenever it is possible. Fig. 4.7 shows that PBOS selects up to 7.6% more EVs compared to FCFS and 11% more EVs compared to RTCS while having an initial SOC below 20% during the DR1 event. But, this rate is 6.7% lower compared to the SBP. During the DR2 event, the selection rate of EVs with an initial SOC below 20%, PBOS selects almost 11% higher EVs than FCFS and 8% higher than RTCS, however the rate is 5% lower when compared to the SBP as shown in Fig. 4.8.

This demonstrates clearly that the proposed scheme, in contrast to FCFS and RTCS, can service more EVs with greater urgency in terms of low SOC condition. This is because other schemes select EVs based on the arrival time (e.g., FCFS) or membership status with initial SOC only (e.g., RTCS). The results also show that the selection rate of PBOS is lower than SBP in both DR events. Since SBP only

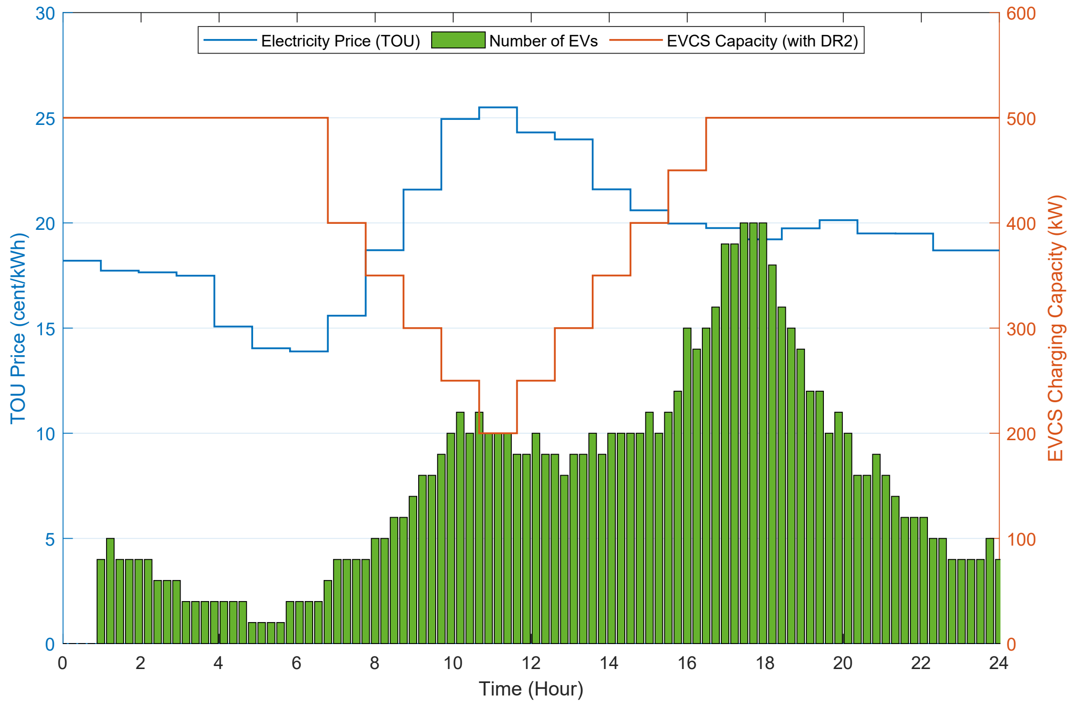

Figure 4.4: TOU electricity prices, charging station capacity, and the number of EVs arriving at an EVCS at various times of a day considering the DR2 event.

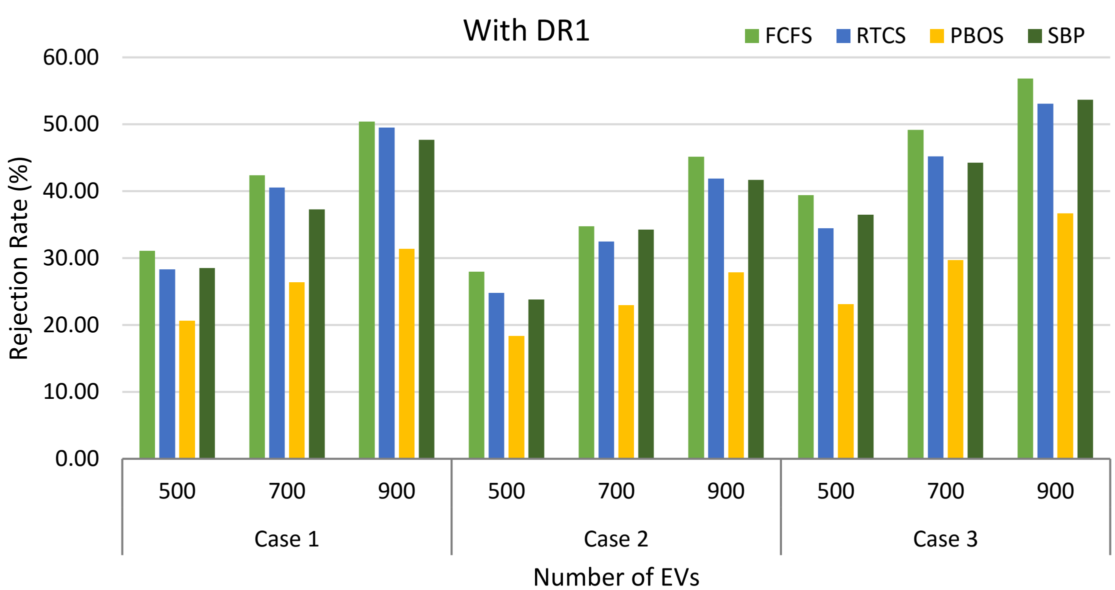

Figure 4.5: Comparisons of rejection rates under various traffic conditions and use cases during the DR1 event.

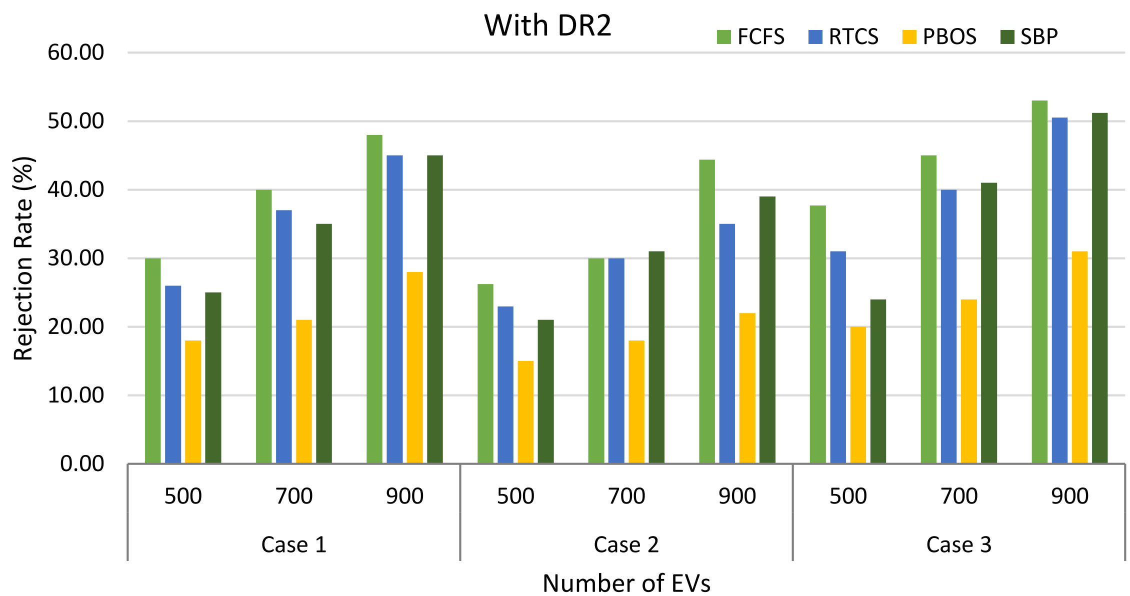

Figure 4.6: Comparisons of rejection rates under various traffic conditions and use cases during the DR2 event.

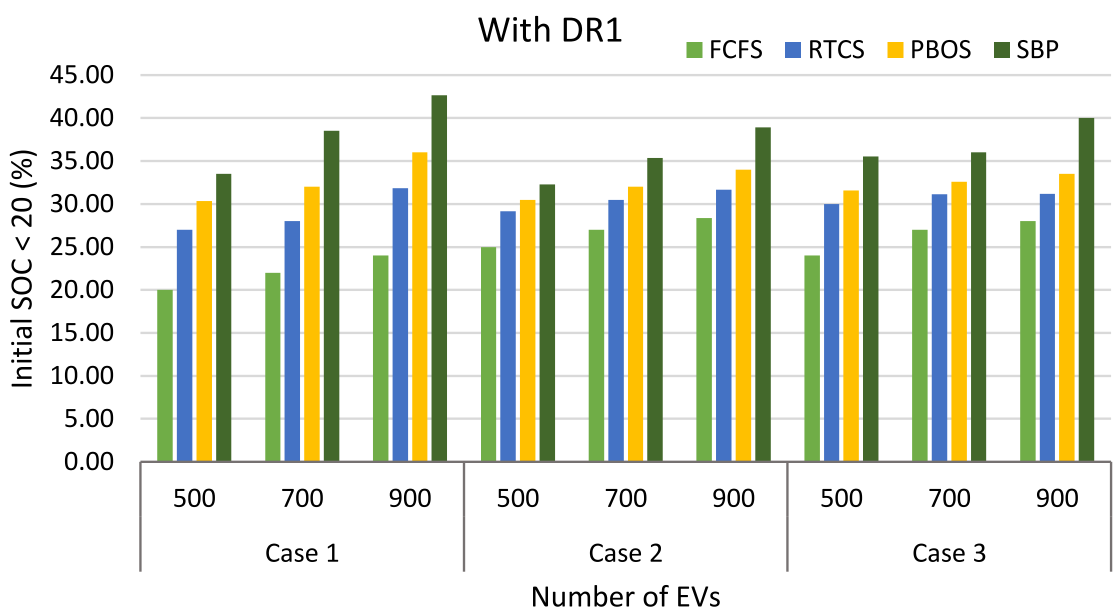

Figure 4.7: Comparisons of average selected EVs under various traffic conditions and use cases (initial SOC is less than 20%) during the DR1 event.

selects EVs with low SOC, while the proposed scheme prioritizes not only the user's low SOC status but also charging demands and charging mode. Therefore, this result should be quite obvious.

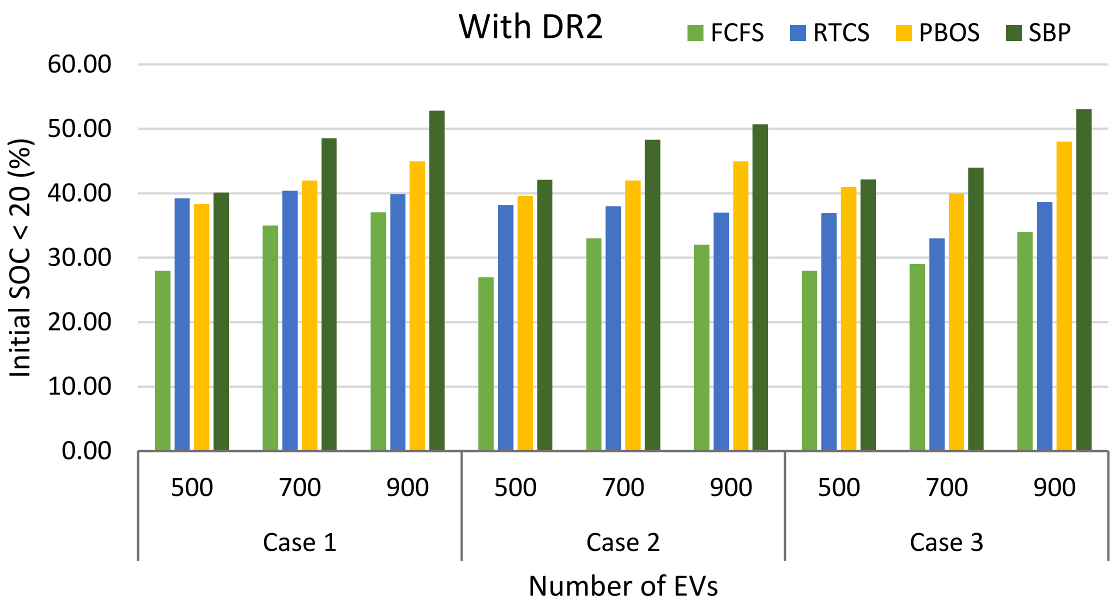

Figure 4.8: Comparisons of average selected EVs under various traffic conditions and use cases (initial SOC is less than 20%) during the DR2 event.

One of the goals of the proposed scheme is to serve EVs as early as possible by prioritizing EVs with low SOC requirements. This is because the sooner the charging is finished, the more charging spaces are accessible and more EVs can be charged. Therefore, the average charging time to attain SOC is compared across all schemes and DR events. A small value of time step means the EVCS can complete the charging quickly, while a larger value means it needs more time to complete the charging.

The average number of time steps required by various schemes to achieve the required SOC is shown in Table 4.1 under the DR1 event. It can be seen that the average charging time of PBOS is always lower than the other schemes in all cases. In Case 1, the maximum time step differences compared to FCFS, RTCS, and SBP are 2.54, 1.68, and 1.40, respectively. In Case 2, the differences are 4.30, 3.34, and 3.76, while in Case 3, the differences are 5.45, 2.27, and 1.53. So, the proposed scheme can serve EVs by up to 5.45 time steps less than other schemes. This means PBOS can save up to 81.75 minutes to attain the same SOC compared to the other schemes when each time step, $\Delta T = 15$ minutes, holds.

The average number of time steps needed by various schemes to achieve the required SOC is shown in Table 4.2 under the DR2 event. It can be seen that the average charging time of PBOS is also shorter than the other schemes in all cases.

Table 4.1: Comparisons of Average Required Time Steps to Attain the Requested SOC During the DR1 Event

	Case 1			Case 2			Case 3		
# of EVs	500	700	900	500	700	900	500	700	900
PBOS	6.36	6.03	5.70	4.67	4.63	4.27	8.05	7.72	7.28
FCFS	8.30	8.27	8.24	8.97	8.84	7.89	13.50	11.20	9.80
RTCS	6.90	7.20	7.38	6.47	6.88	7.61	8.37	9.05	9.55
SBP	7.29	7.25	7.10	5.77	5.85	8.03	8.62	8.77	8.81

The maximum time step differences during Case 1 compared to FCFS, RTCS, and SBP are 1.95, 1.31, and 1.76, respectively. In Case 2, the differences are 2.79, 1.93, and 1.51, while in Case 3, the differences are 3.41, 1.22, and 2.22. Therefore, compared to other schemes, the PBOS can save up to 3.41 time steps, or 51.15 minutes, in the DR2 event to achieve the same required SOC.

Table 4.2: Comparisons of Average Required Time Steps to Attain the Requested SOC During the DR2 Event

	Case 1			Case 2			Case 3		
# of EVs	500	700	900	500	700	900	500	700	900
PBOS	6.09	6.84	5.86	4.52	4.49	4.23	7.37	6.97	6.66
FCFS	8.04	7.45	7.18	7.31	6.91	5.43	10.78	9.80	8.65
RTCS	6.09	7.04	7.17	5.17	6.04	6.16	7.39	7.45	7.88
SBP	7.85	7.51	7.36	5.57	5.67	5.74	7.98	8.27	8.89

In summary, the proposed scheme can meet an EV user's charging needs up to 81.75 minutes faster than other schemes. This is because, in contrast to existing schemes, the proposed approach prioritizes both small charging demands and the L3 charging mode.

The economic benefit of the PBOS compared with FCFS, RTCS, and SBP is presented in Table 4.3 and Table 4.4 in terms of revenue and profit gain for both DR events. The following equation is used to calculate the profit gain that PBOS has over a benchmark scheme.

$$\text{Profit Gain} = \frac{\text{Revenue of Proposed Scheme - Revenue of Benchmark Scheme}}{\text{Revenue of Benchmark Scheme}} \times 100$$

The result shown in Table 4.3 proves that PBOS achieves a higher profit compared to FCFS, RTCS, and SBP under all three cases with different traffic intensities during the DR1 event. It can be seen that the maximum profit gain over FCFS can be up to 48.03%, 44.69% over RTCS, and 30.40% over SBP.

Table 4.3: Comparisons of Revenues ($/Day) and Profit Gain (%) under Various Traffic Conditions and Use Cases During the DR1 Event

	Case 1			Case 2			Case 3		
# of EVs	500	700	900	500	700	900	500	700	900
PBOS	3,522	4,613	5,594	3,734	5,034	6,143	3,609	4,224	4,916
FCFS	2,995 (−17.60)	3,582 (−28.78)	3,923 (−42.59)	3,302 (−13.08)	4,031 (−24.88)	4,570 (−34.42)	2,581 (−39.83)	3,087 (−36.83)	3,321 (−48.03)
RTCS	3,128 (−12.60)	3,512 (−31.33)	3,866 (−44.69)	3,468 (−7.65)	4,246 (−18.56)	4,635 (−32.54)	2,752 (−31.17)	3,188 (−32.53)	3,523 (−39.52)
SBP	3,135 (−12.34)	3,862 (−19.45)	4,290 (−30.40)	3,466 (−7.73)	4,367 (−15.27)	4,931 (−24.58)	3,281 (−10.00)	3,439 (−22.83)	3,816 (−28.83)

The comparison of revenue and profit gain among all the schemes is presented in Table 4.4 under the DR2 event. The results also show that the proposed scheme, PBOS, achieves better performance compared to FCFS, RTCS, and SBP. The maximum profit gain over FCFS can be up to 47.20%, 43.20% over RTCS, and 36.57% over SBP.

This is due to prioritizing L3 over L2 mode in addition to selecting EVs with small charging demand in the proposed scheme. On the other hand, in FCFS, EVs are selected by following the sequence of charging requests. In RTCS, EVs are ranked

Table 4.4: Comparisons of Revenues ($/Day) and Profit Gain (%) under Various Traffic Conditions and Use Cases During the DR2 Event

	Case 1			Case 2			Case 3		
# of EVs	500	700	900	500	700	900	500	700	900
PBOS	3,623	4,621	5,549	3,802	4,814	6,057	3,266	4,229	4,993
FCFS	3,009 (−20.41)	3,546 (−30.32)	3,986 (−39.21)	3,256 (−16.77)	4,021 (−19.72)	4,592 (−31.90)	2,663 (−22.64)	3,113 (−35.85)	3,392 (−47.20)
RTCS	2,992 (−21.09)	3,640 (−26.95)	3,875 (−43.20)	3,503 (−8.54)	4,160 (−15.72)	4,415 (−37.19)	2,763 (−18.20)	3,180 (−32.99)	3,503 (−42.53)
SBP	3,185 (−13.75)	3,865 (−19.56)	4,330 (−28.15)	3,459 (−9.92)	4,246 (−13.38)	4,889 (−23.89)	2,918 (−11.93)	3,398 (−24.46)	3,656 (−36.57)

based on their membership and SOC status while ignoring the charging mode and demand, and in SBP, EVs are sorted based on only low SOC.

4.3 Simulation Results with NHTS Dataset

In order to evaluate the performance of the proposed scheme based on real-world users' charging behaviour in the EV charging stations, we also use a publicly available parking dataset from the National Household Travel Survey (NHTS) [25]. Fig. 4.9 shows the distribution of EVs arriving at the charging station according to the NHTS dataset under the DR1 event. According to the NHTS, the peak charging times are 08:00–10:00, 12:00–14:00, and 18:00–20:00. The distribution of EV arrivals to the charging station is generated using the NHTS dataset [25], where the mean value of the number of incoming vehicles at each time slot is taken from the true dataset and a standard deviation is varied between 0.5% and 2%.

Fig. 4.10 shows the rejection rate of different schemes during the DR1 event. During this event, FCFS has a rejection rate ranging from 26% to 48%, whereas RTCS has a range of 24% to 47% and SBP has a range of 25% to 46%. However, the rejection rate for PBOS varies from 20% to 34%. Therefore, the proposed scheme can always serve more EVs compared to other existing schemes.

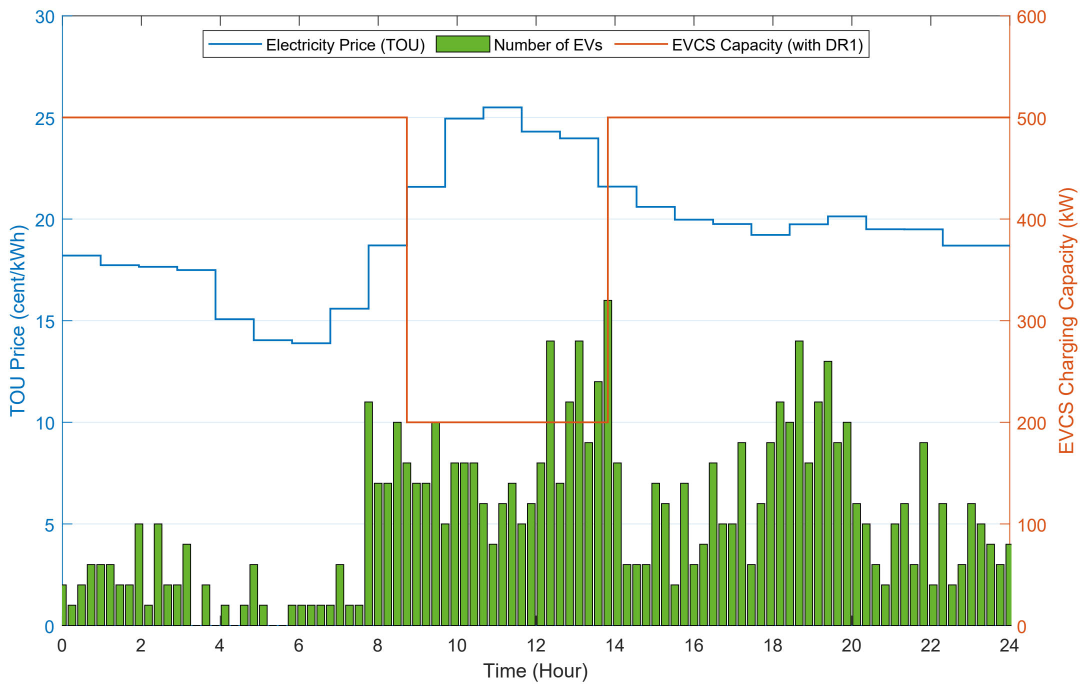

Figure 4.9: TOU electricity prices, charging station capacity, and the number of EVs arriving at an EVCS at various times of a day while considering the DR1 event and the NHTS dataset.

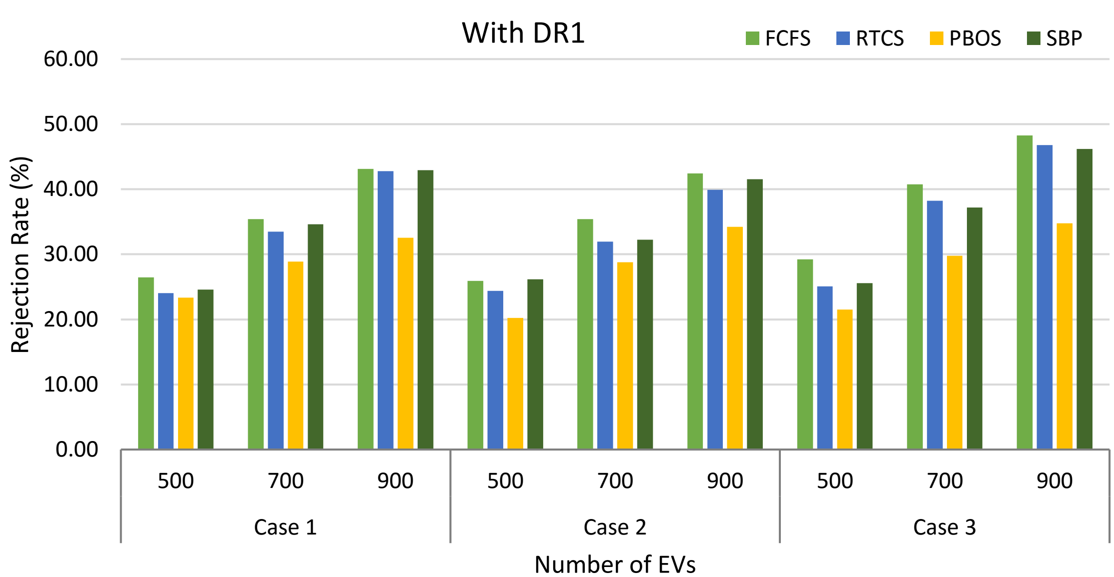

Figure 4.10: Comparisons of rejection rates under various traffic conditions and use cases while considering the DR1 event and the NHTS dataset.

The selection of EVs with lower SOC (less than 20%) by different schemes is shown in Fig. 4.11. By analyzing different cases, it can be seen that PBOS selects 13.57% more EVs compared to FCFS and almost 7% more EVs compared to RTCS while the EVs have an initial SOC below 20% during the DR1 event. However, this rate is 4.46% lower compared to the SBP one. This is because SBP only gives priority to EVs with lower SOC, not taking into account user demand or charging mode.

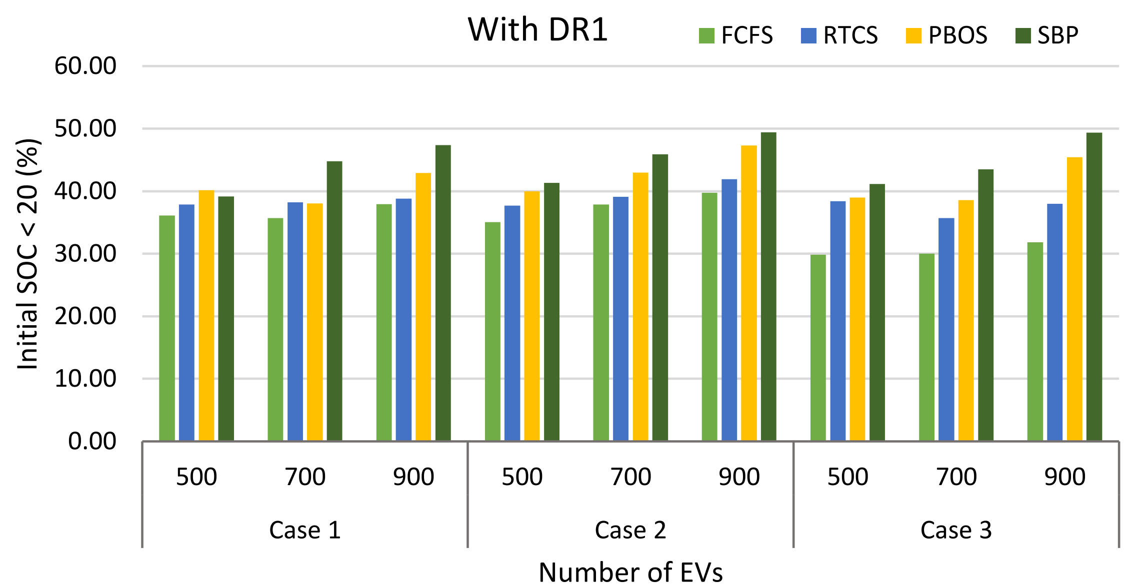

Figure 4.11: Comparisons of average selected EVs under various traffic conditions and use cases (initial SOC is less than 20%) while considering the DR1 event and the NHTS dataset.

In Table 4.5, the average number of required time steps to attain the requested SOC by different schemes is presented for the DR1. It can be seen that the average charging time of PBOS is always lower compared to the other schemes under all cases. In Case 1, the maximum time step differences compared to FCFS, RTCS, and SBP are 1.66, 1.25, and 0.83, respectively. In Case 2, the differences are 2.30, 2.11, and 1.89, respectively, while in Case 3, the differences are 4.36, 2.40, and 2.46, respectively. Therefore, the proposed scheme can serve EVs by up to 4.36 time steps less compared to other schemes. In another word, it can save up to 65.4 minutes to attain the same SOC compared to the other schemes when each time step, $\Delta T = 15$ minutes holds.

The revenue and profit gain of all the schemes are presented in Table 4.4 under the DR1 event. The results show that the proposed scheme, PBOS, achieves higher revenue and profit gains compared to FCFS, RTCS, and SBP. The maximum profit gain over FCFS can be up to 51.55%, over RTCS it is 31.36%, and 19.48% over SBP.

Table 4.5: Comparisons of Average Required Time Steps to Attain the Requested SOC while Considering the DR1 Event and the NHTS Dataset

	Case 1			Case 2			Case 3		
# of EVs	500	700	900	500	700	900	500	700	900
PBOS	6.58	5.90	5.78	4.35	4.43	4.12	6.75	6.86	6.65
FCFS	7.69	7.56	6.83	6.38	5.93	5.82	11.11	10.11	9.50
RTCS	6.74	6.93	7.03	5.90	6.01	6.23	8.22	9.08	9.05
SBP	6.69	6.73	6.46	5.87	5.70	6.01	9.07	9.18	9.12

Table 4.6: Comparisons of Revenues ($/Day) and Profit Gain (%) under Various Traffic Conditions and Use Cases while Considering the DR1 Event and the NHTS Dataset

	Case 1			Case 2			Case 3		
# of EVs	500	700	900	500	700	900	500	700	900
PBOS	2,814	3,686	4,811	3,062	4,162	4,932	2,639	3,193	4,057
FCFS	2,470 (−13.93)	3,223 (−14.37)	3,555 (−35.33)	2,845 (−7.63)	3,537 (−17.67)	3,996 (−23.42)	2,413 (−9.37)	2,135 (−49.56)	2,677 (−51.55)
RTCS	2,665 (−5.59)	3,307 (−11.44)	3,663 (−31.36)	2,819 (−8.64)	3,620 (−14.98)	3,947 (−24.95)	2,411 (−9.46)	2,669 (−19.64)	3,109 (−30.52)
SBP	2,698 (−4.30)	3,311 (−11.33)	4,053 (−18.70)	2,901 (−5.55)	3,575 (−16.42)	4,128 (−19.48)	2,538 (−3.98)	2,788 (−14.53)	3,486 (−16.38)

In summary, it can be seen that the proposed scheme can perform better than other existing schemes even with different dataset.

Chapter 5

Conclusions

In this thesis, we investigate the real-time EV charging scheduling problem of an EVCS in an urban area with dual charging modes. The proposed charging scheduling scheme, PBOS, aims to maximize the number of scheduled EVs based on priority while minimizing the electricity bill by utilizing a TOU-based DR strategy. We solved the optimization problem by using a standard MILP solver and used two well-known public datasets to evaluate the performance of PBOS. In comparison to other benchmark schemes, such as FCFS, RTCS, and SBP, the simulation results showed that PBOS achieves a significantly lower rejection rate, a shorter charging time, and a higher profit gain. In addition, PBOS serves more EVs with a lower initial SOC compared to FCFS and RTCS. However, compared to SBP, this number is lower due to the fact that SBP sorted EVs based on SOC only while ignoring other important parameters such as charging demand and modes. As part of future work, this work can be further extended in various directions, such as the prediction of future load and the scheduling of more EVs, considering the flexible nature of some EV users in terms of charging time and requirements.

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