Spatial-temporal domain charging optimization and charging scenario iteration for EV

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A thesis submitted for the degree of
Doctor of Philosophy

May, 2023

Declaration

I declare that the work presented in this thesis is, to the best of my knowledge and belief, original and my own work. The material has not been submitted, either in whole or in part, for a degree at this, or any other university. This thesis does not exceed the maximum permitted word length of 80,000 words including appendices and footnotes, but excluding the bibliography. A rough estimate of the word count is: 34513

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Abstract

Environmental problems have become increasingly serious around the world. With lower carbon emissions, Electric Vehicles (EVs) have been utilized on a large scale over the past few years. However, EVs are limited by battery capacity and require frequent charging. Currently, EVs suffer from long charging time and charging congestion. Therefore, EV charging optimization is vital to ensure drivers' mobility. This study first presents a literature analysis of the current charging modes taxonomy to elucidate the advantages and disadvantages of different charging modes. In specific optimization, under plug-in charging mode, an Urgency First Charging (UFC) scheduling policy is proposed with collaborative optimization of the spatial-temporal domain. The UFC policy allows those EVs with charging urgency to get preempted charging services. As conventional plug-in charging mode is limited by the deployment of Charging Stations (CSs), this study further introduces and optimizes Vehicle-to-Vehicle (V2V) charging. This is aim to maximize the utilization of charging infrastructures and to balance the grid load. This proposed reservation-based V2V charging scheme optimizes pair matching of EVs based on minimized distance. Meanwhile, this V2V scheme allows more EVs get fully charged via minimized waiting time based parking lot allocation. Constrained by shortcomings (rigid location of CSs and slow charging power under V2V converters), a single charging mode can hardly meet a large number of parallel charging requests. Thus, this study further proposes a hybrid charging mode. This mode is to utilize the advantages of plug-in and V2V modes to alleviate the pressure on the grid. Finally, this study addresses the potential problems of EV charging with a view to further optimizing EV charging in subsequent studies.

Publications

The following publications have been generated while developing this thesis, and to an extent has guided the thesis into what it has become:

Journal and Conference

1. (Journal) **Shuohan Liu**, Qiang Ni, Yue Cao, Jixing Cui, et al. "A Reservation-Based Vehicle-to-Vehicle Charging Service under Constraint of Parking Duration", IEEE System Journal, 2022.

2. (Conference) **Shuohan Liu**, Yue Cao, Wenjie Ruan, Qiang Ni, et al. "EV Charging Recommendation Concerning Preemptive Service and Charging Urgency Policy". IEEE VTC Fall 2020.

3. (Journal) **Shuohan Liu**, Xu Xia, Yue Cao, Xu Zhang, Qiang Ni et al. "Reservation-Based EV Charging Recommendation Concerning Charging Urgency Policy". Elsevier Sustainable Cities and Society, vol. 74, 103150, November 2021.

4. (Journal) **Shuohan Liu**, Yue Cao, Qiang Ni, Lexi Xu, et al. "Towards Reservation-based E-Mobility Service via Hybrid of V2V and G2V Charging Modes". Elsevier Energy, 2023.

5. (Conference) Yue Cao, **Shuohan Liu**, Ziming He, Xuewu Dai, et al. "Electric Vehicle Charging Reservation Under Preemptive Service", IEEE IAI, Shenyang, China, 2019.

6. (Journal) Xu Zhang, Linyu Peng, Yue Cao, **Shuohan Liu**, et al. "Towards Holistic Charging Management for Urban Electric Taxi via a Hybrid Deployment of Battery Charging and Swap Stations". Elsevier Renewable Energy. vol. 155, pp. 703-716, August 2020.

7. (Conference) Jie Zhang, Qiang Tang, **Shuohan Liu**, Yue Cao, et al. "Deadline-based V2V Charging under Spatial Resource Constraints", IEEE ICCAIS, Xi'an, China 2021.

8. (Journal) Xu Zhang, Fang Yuan, Yue Cao and **Shuohan Liu**. "Reservation Enhanced Autonomous Valet Parking Concerning Practicality Issues". IEEE Systems Journal, vol. 16, no. 1, pp. 351-361, March 2022.

9. (Journal) Xu Zhang, Xu Xia, **Shuohan Liu**, Yue Cao, et al. "An Integrated Framework on Autonomous-EV Charging and Autonomous Valet Parking (AVP) Management

System”. IEEE Transactions on Transportation Electrification, vol. 8, no. 2, pp. 2836-2852, June 2022.

10. (Conference) Jixing Cui, **Shuohan Liu**, Yue Cao, Xu Zhang, et al. “A Hybrid Electric Vehicle Energy Supply System via Direct and Asynchronous V2V Charging Modes”. IEEE SMC, Prague, Czech Republic, 2022.

11. (Journal) Yue Cao, Jixing Cui, **Shuohan Liu**, Xinyu Li, et al. ”An Review of E-Mobility Service Management via Digitalization”. Elsevier eTransportation (submitted)

12. (Journal) Xinyu Li, Yue Cao, Shaohua Wan, **Shuohan Liu**, et al. ”A Coordinated Battery Swapping Service Management Scheme Based on Battery Heterogeneity”. IEEE Transactions on Transportation Electrification, Early Access, 2023.

Book Chapter

1. **Shuohan Liu**, Xu Xia, Jixing Cui, Yue Cao and Qiang Ni. “Vehicle-to-Vehicle Enabled EV Charging Scenario Iteration”. CRC Press - Secure and Digitalized Future Mobility: Shaping the Ground and Air Vehicles Cooperation, 2022.

2. Xinyu Li, Yue Cao and **Shuohan Liu**. “Navigation Service Optimization for Electric Vehicle”. Springer - Automated and Electric Vehicle: Design, Informatics and Sustainability, 2022.

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List of Abbreviations

AC	Alternating Current
AHP	Analytic Hierarchy Process
B2G	Battery to Grid
BES	Battery Energy Storage
BSCS	Battery Swapping and Charging Station
BSS	Battery Swapping Station
CA	Central Aggregator
CC-CV	Constant-Current/Constant-Voltage
CS	Charging Station
DC	Direct Current
DTN	Delay Tolerant Networks
DWC	Dynamic Wireless Charging
ET	Electric Taxis
EV	Electric Vehicle
G2V	Grid to Vehicle
GA	Genetic Algorithm
GC	Global Controller
GIS	Geographic Information System
ICT	Information and Communications Technology
ICV	Intelligent Connected Vehicle
LTE	3G/Long Term Evolution
MCT	Mobile Charging Truck
MDP	Markov Decision Process
MEC	Mobile Edge Computing
MILP	Mixed Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
MQN	Mixed Queueing Network
ONE	Opportunistic Network Environment
PCS	Portable Charging Station
PL	Parking Lot
PSO	Particle Swarm Optimization
PSS	Power Storage Station
PV	Photovoltaic
QoE	Quality of Experience
RES	Renewable Energy Sources
SOC	State of Charge
SWC	Static Wireless Charging
TOU	Time-of-Use
UFC	Urgency First Charging
V2G	Vehicle to Grid
V2V	Vehicle to Vehicle
V2V	Vehicle to Everything
WKT	Well Known Text

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Chapter 1

Introduction

The global climate is experiencing significant changes with warming as the main feature, which has become a major challenge faced by the international community today. With the degradation of the cryosphere and the beginning of environmental degradation, climate warming has profoundly affected human survival and development and is triggering a global energy revolution. Meanwhile, the global energy crisis is also getting worse, especially in terms of demand for oil. The latest data published by the International Energy Agency for 2018 [1] show that the global demand for oil continues to grow, with an increase of more than 15% over the same level in 2016. The transport sector, however, consumes about 60% of the total oil consumed.

The development of modern intelligent transportation systems cannot be achieved without safe and efficient transportation energy technologies. Technological changes in the field of transportation energy are also an important way to protect the energy system of society, and even in the global climate. Energy and transportation are the two cornerstones of modern human society, and the change in energy and transportation is naturally the most fundamental change in modern society. Electric Vehicles (EVs) use electricity instead of traditional fuel as a means of energy replenishment, effectively achieving low carbon and environmental protection. Thus, EVs are regarded as an important means of solving energy and environmental problems. With the tightening of fuel resources and the development of battery technology, EVs are approaching or even outperforming traditional internal combustion vehicles in terms of performance and economy. Recently, EVs are beginning to be used gradually around the world. It has become a general consensus that EV is an inevitable approach in the development of the automotive industry. The charging system provides an important basic support system for EVs, as well as an important link in the process of commercialisation and industrialisation of EVs. In the charging system, the construction of charging infrastructures needs to be planned and designed accordingly according to the charging demand of EVs and combined with the charging mode of EVs.

1.1 Importance of EV charging

Recently, a large number of countries regard the deployment of EVs as a core environmental strategy. The UK government announced in 2020 that internal combustion vehicles will cease to be sold in 2035. At the same time, the UK government requires new production of vehicles to be completely zero-emission from 2035 onwards. In contrast, China released a development plan for its EVs industry in 2020. China has set a goal that EVs ratio reaches about 20% of total new vehicle sales by 2025. By 2035, EVs will become the mainstream of new vehicle sales in China.

To ensure the widespread adoption of EVs, it is necessary to break through current charging infrastructure constraints, and actively promote key technology and mode innovations. Meanwhile, in order to achieve the goal of net greenhouse gas emissions, EVs need to be effectively integrated into the charging system for the transition to a decarbonisation society in the near future. Here, EV charging optimization focuses on spatial domain optimization and temporal domain optimization:

- **Spatial domain optimization:** Taking the current EV situation in China as an example. The current EV charging network includes dedicated Charging Stations (CS), intercity and urban public charging networks, and personal charging infrastructures. Here, the EV charging network in China suffers from unbalanced regional development. EV charging network is unable to meet the scale of the private vehicle market. The current oil-to-electricity ratio (ratio of the petrol station to charging infrastructures) in China's major first-tier cities has reached 2.8. However, the fuel-to-electricity ratio in regions with poor development is less than 0.3. The limited deployment of EV charging infrastructures places a higher demand on EV charging optimization. Moreover, combined with the penetration of vehicles in different levels of cities, the oil-to-electricity ratio indicator has a high correlation with the penetration of operating vehicles (buses, etc.). However, there is a low correlation with the regional penetration of private vehicles, which means that there are greater difficulties in charging private EVs.

- **Temporal domain optimization:** EV charging optimization involves the flexible use of time latitude for charging services, such as at night when demand on the power system is low, or when renewable energy generation is high. This helps to reduce the need for costly electrical network reinforcement and increased generation capacity. Here, EV drivers can adopt different charging strategies to reduce charging congestion and avoid high charging price.

1.2 Challenges in EV Charging

1.2.1 Range Anxiety in EV Travelling

Range anxiety refers to the mental distress or anxiety caused by the fear of sudden loss of power while driving an EV [2]. Here, range anxiety is mainly caused by limited battery capacity and the difficulty of finding charging infrastructures. Factors such as vehicle speed, driving habits, road conditions, and temperature would have a non-negligible impact on range. There is even an exaggerated situation where the actual range of EVs is only half of the summer range in winter below freezing temperatures, and the instability is far beyond consumer expectations, which leads to mileage anxiety among EV drivers. The core of solving the range anxiety problem lies in improving the deployment of charging infrastructures and optimizing EV charging management.

1.2.2 Concern on Charging Infrastructures

A major difficulty in optimizing EV charging is the deployment of charging infrastructures. In contrast to the large number of EVs, charging infrastructures built are struggle to meet a large number of parallel charging requests, with the following constraints:

- **Unbalanced distribution of charging infrastructures:** Currently, charging infrastructures are mainly located in urban areas, while the coverage of suburban areas is insufficient. The location of charging infrastructures needs to consider factors such as customer flow density and utilization rate, which makes public areas such as superstores, schools, hospitals and tourist attractions become high deployment areas. At the macro level, some local governments have provided significant funding for CS deployment to promote infrastructure development, while some areas lack funding.
- **Low utilization of charging infrastructures:** Due to cost considerations, some operators choose to deploy charging infrastructures in suburban areas to reduce land and operating costs. This brings the problem of low utilization of charging infrastructures. During the peak hours of electricity consumption, the queuing of public charging infrastructures is more prominent in some hotspots.
- **Difficulty in grid capacity:** With the rapid growth of EVs, the charging behaviour of EVs poses a great challenge to the stability and load of the grid in charging network. Considering the limited load capacity of the power system, the deployment of charging infrastructures are with a huge challenge. In addition, the service capacity of the grid is required to be continuously improved to meet the rapidly growing demand for EV charging. In addition to the hardware infrastructures mentioned above, Information and Communication Technology (ICT)-based navigation systems are also important to facilitate the development of EVs.

1.2.3 Inconsistent Stakeholders Requirement

In the charging network, the interests of various stakeholders are inconsistent. For example, if the charging facility operators increase their investment, EV users will get higher quality charging services (e.g., shorter charging waiting time and more available charging slots). Nevertheless, the charging infrastructures may have lower revenue due to excessive idle rate and operation and maintenance costs. Conversely, EV users will not get reliable charging services, such as the insufficient number of charging infrastructures or the charging distance being too far. Therefore, this places higher demands on EV charging optimization, including overall energy utilization efficiency and distribution network security.

1.2.4 Evaluation Metrics

- **Average Charging Waiting Time:** It indicates the average waiting time for EVs between arriving at a charging infrastructure and receiving a charging service.
- **Average Charging Trip Duration:** It indicates the average trip duration for EVs from their location to their destination via an intermediate charging service.
- **Average Charging Price:** It indicates the average charging price of EVs charged at CS.
- **Average Energy Charging:** It indicates the average energy of EVs charged per charging service.
- **Number of Fully Charged EVs:** It indicates the total number of EVs being fully charged.
- **Number of Not Fully Charged EVs:** It indicates the total number of EVs that can not get fully charged although they have arrived at a charging infrastructure.

1.3 Research Motivation of EV Charging Optimization

1.3.1 Spatial- Temporal Domain Optimization

Due to the increasing amount of EVs, it is extremely problematic for the driver to make charging decisions solely through the EV side. Therefore, a systematic optimization of EV charging can significantly address the EV charging challenges mentioned in the above section. Previous studies on EV charging optimization seldom focused on both the temporal domain and the spatial domain, e.g., solving the problem of where to charge by optimizing charging recommendations (spatial domain) and solving the charging scheduling problem by charging scheduling (temporal domain). Therefore, integrated optimization of the spatial-temporal domain and optimization of the management of differentiated charging requests are particularly important.

1.3.2 Charging Scenario Iteration

EV charging has evolved with technology to benefit from novel charging mode, while a large number of previous studies have focused on a single plug-in charging mode. Less research considers battery swapping mode. Battery swapping mode is effective in reducing the time required to charge an EV. Therefore, the optimization of the battery swapping mode can improve the effectiveness of EV charging. Meanwhile, with the improvement of battery technology, the V2V charging mode has started to be studied. In this mode, the EV as energy Providers (EV-Ps) can transfer electrical energy directly via a converter to the EV as energy Consumers (EV-Cs), in the form of a V2V-Pair. The V2V charging mode resolves the limitations of fixed charging infrastructures.

However, optimization under a single charging mode is difficult to accommodate a large number of parallel EV charging requests. This means that EV charging optimization can be done by combining the advantages of each mode for targeted EV charging allocation. For example, plug-in charging mode has the advantage of stable electrical energy replenishment, while swapping mode has the advantage of rapid battery replacement. By combining and optimizing the different charging modes, EV charging can be effectively improved. Even during peak charging times, the hybrid charging mode would achieve a more stable charging service.

1.4 Contributions in This Thesis

1.4.1 Research Aim

EVs emit great greenhouse gases and do not rely on non-renewable energy. Thus, they have huge application potential in achieving green transportation. However, the current limitations of battery charging technology and the unreasonable allocation of Charging infrastructures lead to long EV charging time and charging congestion, which degrades the travel experience of EVs. Here, charging scheduling (when-to-charge) and CS-Selection (where-to-charge) become key optimization points under the plug-in charging mode. Therefore, this research aims to optimize EV charging under spatial-temporal domain. Furthermore, a novel flexible V2V charging mode can be applied as a supplement to the plug-in charging mode as it alleviates CS deployment and charging peak hour problems. This research further alleviates EV charging congestion, improves EV charging efficiency, and explores the benefits of iterative EV charging scenarios (V2V charging and hybrid charging modes).

1.4.2 Research Methodology

In this research, a corresponding EV charging simulation platform and evaluation system are built using an Opportunistic Networks Environment (ONE). ONE is an opportunity network environment simulation software based on a discrete-event simulation engine, which can achieve simulation results that approximate real-city scenarios.

1.4.3 Research Objectives

The objectives are to optimize EV charging experience, as follows:

- Adopt a flexible charging scheduling strategy and CS selection scheme to improve charging efficiency.
- Iterate charging mode (V2V charging) to suit different temporal and spatial requirements of EV charging.

1.4.4 Research Achievements

- The first achievement concentrates on optimizing the plug-in charging mode. Here, a preemptive charging scheduling strategy that considers the EVs' charging urgency (urgency-first charging policy) is proposed [3]. It allows EVs with high charging urgency, calculated by charging demand and remaining parking time, to get preemptively charged, optimizing EV charging in the temporal domain [4]. Based on the proposed charging scheduling strategy, a CS selection scheme is further proposed, jointly considering the anticipated charging reservation information [5]. This scheme selects the CS with the shortest charging trip duration including one charging process. Meanwhile, EVs are required to report their charging reservation information, helping to accurately predict the congestion status of CSs and efficiently allocate charging resources in the spatial domain [6]. The charging network simulation is carried out through the urban traffic scenario of Helsinki. The results show that the proposed charging management scheme (scheduling policy and reservation-based CS selection scheme) can effectively shorten the EVs' average charging waiting time and allow more EVs to get fully charged within a limited parking duration.
- The second achievement introduces an emerging V2V charging mode to solve the problems encountered in the plug-in charging mode, such as charging congestion at peak hours due to the fixed locations of CSs. Urban areas are nearly saturated recently, and CSs suffer from high costs in deployment and operation, which restricts further EV charging optimization in the CS charging mode. In the V2V charging mode, EV-Ps transfer their surplus energy to EV-Cs in the form of V2V-Pairs via V2V charging converters deployed at Parking Lots (PLs). However, this brings the

matching problem of V2V-Pairs and the PL selection problem. A distance-based V2V-Pair matching algorithm is proposed to reduce energy costs in travelling, and a PL selection scheme to maximize the use of constrained parking resources within the parking duration limitation [7]. As the occupation status of PLs is difficult to estimate, EVs are asked to send V2V charging reservations for accurate estimation [8].

- Finally, the V2V charging mode still has certain limitations (the power provided by EV-Ps is limited, and the V2V charging power is low). In the work [9], a holistic EV charging management via cooperative deployment (CSs and battery switching stations) is considered, improving convenience for EV charging. Therefore, introducing the V2V charging mode as a supplement to the CS charging mode can improve the flexibility and effect of EV charging. A cooperative charging system by simultaneously considering CS and PL in the charging network is proposed. This cooperative charging system maximizes the comprehensive utilization of CS charging (flexible charging scheduling and high charging power) and V2V charging (flexible charging location selection). This cooperative charging system finds the optimal charging provider among CSs and PLs and recommends the optimal provider to the EV as the charging selection, thereby shortening the charging service time. In addition, the joint optimization of user travels and charging also improves the convenient charging and parking management for EV drivers [10].

1.5 Structure of This Thesis

The rest of this thesis is as follows:

In Chapter 2. I provide a survey on different charging modes, where objectives, risks and optimization approaches under different modes are discussed. This work has been submitted to Elsevier eTransportation.

Chapter 3 provides an introduction to the EV charging network simulation tool, the Opportunistic Networks Environment (ONE) simulator. It includes EV movement model, EV routing model (for charging purpose) and auxiliary models (reporting and visualization model).

Chapter 4 provides an EV charging scheduling policy named the "Urgency First Charging" policy. It considers the charging urgency of EVs (calculated by estimated charging time and remaining parking time). Based on this policy, EVs can be scheduled efficiently (time domain optimization). As EVs would park at CSs for a limited duration, based on this policy and the introduction of reservation, we propose an EV charging recommendation scheme to utilise CSs efficiently (spatial domain optimization). This work was accepted at the IEEE-VTC 2020 Fall conference and the work was further refined and accepted by Elsevier Sustainable Cities and Society in 2021.

Chapter 5 provides a V2V charging mode optimization under constrained parking duration and locations. It is designed to optimize V2V-Pair matching and charging location selection, to reduce charging waiting time and allow more EVs to be fully charged. This work was accepted at the ICCAIS 2021 conference and the work was further refined and accepted by IEEE System Journal in 2021.

Chapter 6 provides an optimization approach to hybrid charging mode. Since a single charging mode faces some limitations (e.g. location limitation under plug-in charging and low charging stability under V2V charging), my research considers the cooperative optimization of multiple charging modes. This part of the work designs the switching between the various charging modes and how to select the charging facilities (CSs etc.) according to the requirement of the EV. This work has been accepted by Elsevier Renewable Energy (hybrid under plug-in and battery swapping modes). Meanwhile, another paper based on this part of the work has been submitted to Elsevier Energy for revision (hybrid under plug-in and V2V charging modes).

Finally, Chapter 7 concludes contributions together with the highlighted future research directions.

Chapter 2

Survey on EV Charging Modes

2.1 Taxonomy on EV Charging Modes

With the continuous development of EV industry and the increasing number of EVs, the EV charging problem becomes an important factor that affects EV development. The construction of charging infrastructures affects the utilization of EVs. Limited by battery capacity, EVs need frequent charging to replenish their driving range. The existing charging methods of EV include plug-in charging mode (AC plug-in charging, DC plug-in charging), and battery swapping mode. Since the batteries used in EVs are mostly fused in the vehicle body, the plug-in charging mode was the previous mainstream EV charging mode. With the progressed battery technology and introduction of split battery design, the battery swapping mode has gained more attention these years. However, plug-in charging mode and battery swapping mode both face the problem of restricted locations of charging infrastructures. Therefore, the V2V charging mode has been proposed in recent years. Furthermore, wireless charging and portable charging modes are also introduced as novel charging solutions.

2.2 Plug-in Charging Mode

2.2.1 Introduction of Plug-in Charging Mode

Plug-in charging mode, due to its convenience and economy, has become the mainstream charging mode for EVs. Therefore, the study of the plug-in mode is of great importance. Here, plug-in charging mode is usually divided into AC plug-in charging and DC plug-in charging.

2.2.1.1 AC plug-in charging

AC charging includes private home charging and public charging. Home AC charging generally uses a fairly low charging current to charge the battery. EV drivers simply plug the vehicle charger into an electrical outlet. In addition, because AC charging at home is usually processed at night or during low electricity periods, it facilitates the efficient use of electricity and EV charging can enjoy more price discounts. Public AC charging is one of the most important charging methods for EVs, with chargers set up on the street, in supermarkets, office buildings, etc. Regular charging current is used for charging. EV drives only need to park the car at CSs and connect the wire to start charging.

AC charging current is generally not large, with a charging time of more than 6 hours. The advantage of AC charging is that it has less impact on the battery life of EVs and the impact on the power grid. The disadvantage of AC charging is that the charging time of EVs is longer, which is difficult to meet when there is an urgent demand for power replenishment. AC charging adopts the traditional charging method of constant voltage and current to charge EVs.

2.2.1.2 DC plug-in charging

The purpose of DC plug-in charging is to fully charge EVs in a short period of time, and the charging time could be close to the refuelling time of the internal combustion vehicle. Most CSs apply DC plug-in charging. This is mainly for long-distance travel or the need for rapid range replenishment. Here, the typical charging time is 10-30 min. The key to the fast CSs is the non-vehicle fast charging component, which is capable of outputting 35 KW or even higher power. Because of the high power and current ratings, DC charging method has high requirements on the power grid and is widely applied for service.

DC charging current are high, thus it is called fast charging. The advantage of DC charging is that it improves the charging efficiency of EVs and saves time. The disadvantage of DC charging is that it produces a huge current shock to the power battery pack, which will reduce the cycle life of the power battery pack. Meanwhile, the cost of the battery pack is relatively high.

2.2.2 Optimization under Plug-in Charging Mode

The following methods are most often adopted in optimization problems about plug-in charging mode:

- **Mathematical optimization:** Typical methods include linear programming, Mixed-Integer Linear Programming (MILP), quadratic programming and robust optimization.

- **Operational research:** Typical methods include queuing theory and game theory. Considering the computational complexity with a large density of EVs and CSs in practical case, the above solve tools of mathematical optimization are not always applicable. With regard to the characteristic of the large-scale optimization problems, solving methods related to operation research are thus applied.

- **Meta-heuristic algorithms:** Typical methods include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and evolutionary algorithms. Since traditional optimization algorithms are hard to deal with large-scale mobile scenarios, meta-heuristic algorithms have thus been applied to obtain an approximate optimal solution.

Here, reasonable decision-making control manners can improve the optimization performance given demands constraints [11]. The benefit of cooperative control over the charging decision-making between EVs and the system operator has also been depicted in the literature [12]. There are two main types of decision-making frameworks as follows.

- **Centralized control:** The centralized control method is the most common optimization scheme under plug-in charging mode [13]. The centralized control framework aggregates the global information, including the charging demand of all EVs and the service capability of all CSs [14, 15]. Based on comprehensive information, the centralized method can thus obtain the optimal solution. Besides, a central node that aggregates and deals with all global information is necessary to implement centralized decision-making [16, 17]. The node is usually called the Central Aggregator (CA) or the Global Control (GC). As for the intelligent traffic scenario, the CA or GC plays the role of the city brain to manage the traffic flow [18, 19, 20, 21]. Compared to the decentralized control framework, centralized control is efficiently executed in practical applications due to lower communication costs and time delays. This is because CSs and EVs can connect with the central node directly without intermediate transmission.

- **Decentralized control:** As discussed above, the centralized control framework can obtain the global optimal solution, but it also faces some problems, such as robustness and privacy issues. This is because the centralized approach aggregates all information to the central node, making it vulnerable and fragile. The decentralized control framework has been proposed as an essential supplement to the centralized framework [22, 23, 24]. The advantage of the decentralized method is that it can share information only with local infrastructure rather than aggregating all data at a central node [25, 26]. Therefore, it only requires minimal computational resources on the local side. However, it should also be noted that the decentralized control framework is limited by the availability of global information, making it difficult to obtain the global optimal solution [26, 27].

2.2.3 Objectives and Risks under Plug-in Charging Mode

2.2.3.1 Objectives of Plug-in Charging

The objective of EV charging determines the optimization problem formulation and decision behavior for different service stakeholders. The objective from the perspective of multi-party stakeholders in charging service is further discussed.

- From the power grid's perspective, it mainly concerns peak load shifting, voltage fluctuations and power system load variance to maintain the stability of electricity service network. Renewable energy such as wind, hydro, solar, and geothermal is also important energy sources that can be fully utilized. Based on these, the power grid can alleviate dependence on fossil fuels and reduce power generation cost. Therefore, environmental friendliness and lower power generation cost can be achieved.

- From EV drivers' perspective, the Quality of Experience (QoE), namely the service waiting time, is the primary concern. Besides, charging cost is another crucial factor they consider. The cost usually consists of two aspects: the battery degradation cost caused by charging and the charging expense paid to CSs.

- From CSs' perspective, the operating profit is the determinant for long-term running. To maximize the profit, the CS operator should improve the charging revenue from EVs and reduce the expenditure on purchasing electricity. Additionally, the departure deadline is normally taken into account so as to address the user tolerance on charging service.

2.2.3.2 Potential Risks of Plug-in Charging

The objective and benefits of EV charging under plug-in mode are presented in section 2.2.3.1. The primary control frameworks for plug-in charging is introduced. Besides, the potential risks of above control frameworks are summarized.

- **Infrastructure construction:** To support communication among entities, primary infrastructures over networks are necessary. Therefore, the construction of communication facilities is the fundament of EV charging.

- **Privacy issues:** Regardless of centralized or decentralized frameworks, EVs send information about IDs, locations and destinations to a third party. Private information should be protected and prevented for commercial purposes.

- **Coordinated management:** Different service stakeholders tend to make decisions that benefit their interests. A coordinated management scheme that balances the demand of various entries is thus essential for long-term operation.

2.2.4 Optimization under Plug-in Charging Mode

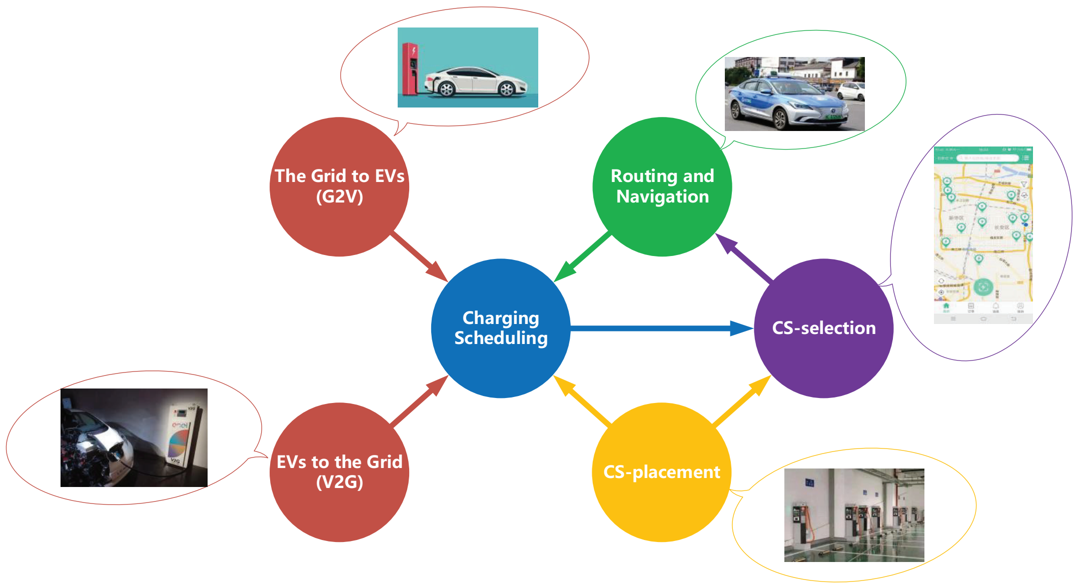


Figure 2.1: The optimization under plug-in charging mode.

2.2.4.1 CS Operation Optimization:

The optimal decision is mainly concerned with the perspective of CSs. With a focus on these scenarios, operation optimization can be achieved at CSs from construction to charging scheduling. Therefore, optimization objectives from the perspective of CSs are eventually realized based on these analyses.

- **Charging scheduling:** The optimization problem of charging scheduling is usually formulated as allocating each time slot for optimal charging/discharging. Under plug-in charging mode, EVs are usually parked at a building and connected to the power grid with a wired connection. The problem is defined as "when/whether to charge", where EVs are regarded as static consumers without considering the property of mobility.

  For a plug-in EV charging scenario, EVs are parked at CSs or parking lots with plugging into charging slots. EVs set the target State of Charge (SOC) and the departure time to the CS operator. Based on the demand for serviced EVs, the CS operator determines an optimal charging scheduling with respect to each EV.

Han et al. [13] designed an optimal aggregator by providing frequency regulation service to the power grid. In this scenario, apart from the energy demander, EVs are also regarded as the supplier of frequency regulation services. Considering the constraint of battery energy, the optimization problem is formulated based on the EV charging cost and the frequency regulation revenue. Then, a dynamic programming-based approach is accordingly developed to solve the optimization problem. Therefore, the optimal charging scheduling in terms of charging rate, charging sequence and charging duration is derived from revenue maximization.

Erol-Kantarci and Mouftah [14] developed a prediction-based charging method to determine the suitable charging time achieving low operation cost. Specifically, the CS receives real-time electricity price with the help of Information and Communication Technologies (ICT). Then, the data is saved for training a K-Nearest Neighbor classification to forecast the future electricity price. If the predicted price exceeds the set threshold, the charging process is delayed until an acceptable price emerges. Finally, the electricity cost of EV charging is significantly reduced based on the proposed algorithm.

Apart from centralized charging scheduling, decentralized charging is also an important component of static mode. Gan et al. [22] proposed a decentralized EV charging scheduling algorithm, applying broadcast control signals and asynchronous computation to satisfy the valley-filling electricity demand. To be specific, the charging scheduling problem is reformulated as an optimal control process. Then, EVs update their charging choice according to the price signal broadcast from the power grid in each iteration.

- **CS-placement:** The CS is an essential infrastructure to supply electrical energy for EVs' recharging. A reasonable planning scheme for CS-placement can improve the QoE of EV drivers and benefit the CS's long-term operation. Considering different

Table 2.1: Literature Related to Charging Scheduling under Plug-in Mode

Reference	Methods & Techniques	Objectives	Advantage & Disadvantage
[13]	Dynamic programming	Revenue maximization; Frequency regulation	Make efficient use of the distributed power; Consider the transport properties and charge loads of EVs
[14]	K-nearest neighbor	Reduce electricity cost	Provide simple classification technique; Show prediction-based charging providing less operating cost
[22]	Optimal control process	Peak-load shifting	Consider PV farm transactive energy; Achieve higher revenue by the private investor
[23]	Convex relaxation optimization	Maximize user convenience	Work even meeting predefined circuit-level demand limits; Online, decentralized and robust against various uncertainties
[15]	Look-ahead dispatch	Maximize CS profits	Model power system on stochastic differential-algebraic equations
[24]	Four-stage optimization and control	Reduce operation cost	Use a chance-constrained optimization objective; Propose an optimized operational cost reduction

charging modes for EVs, the CS-placement optimization problem is accordingly divided into two categories: slow and fast charging.

1) AC charging station: Here, slow charging is usually related to AC charging. EV drivers can spend 6-10 hours recharging the EV at home, in buildings and in workplaces, which has a negligible impact on the power grid. Considering the low power of this mode, EV charging is regarded as household electrical equipment.

Frade et al. [16] investigated the deployment of slow charging facilities around Lisbon, where the utilization of residential and commercial is mixed. The proposed method is developed from the prediction of charging demand on the basis of census data. Besides, considering the mixing characteristic of the district, a nighttime factor related to residences and a daytime factor related to workplaces are both analyzed. Finally, the placement of CSs aims to best cover the predicated demand based on a maximal covering model.

2) DC charging station: Fast charging stations provide a public charging service to EV drivers. Due to a higher power, the charging duration can thus be significantly reduced. Recent research has extensively focused on the placement and planning of fast charging stations. The majority of these works are mainly formulated from the field of economic benefit. However, the security of the power grid can not be guaranteed if operation profit is the only determinant factor for CS-placement. Therefore, the optimization problem of placement and planning of fast charging stations should also consider power grid impacts.

Liu et al. [18] comprehensively investigated the impact of geographic information, construction and running cost. Then, an objective function is mathematically formulated based on the above factors. Since the optimization problem is with the characteristic of non-convex, non-linear and combinatorial optimization, the optimal planning of CSs is determined with the proposed adaptive particle swarm optimization algorithm. The convergence and effectiveness of the proposed algorithm are also validated by examples.

Wang et al. [19] proposed a multi-objective CS planning scheme to ensure the satisfaction of customers and the stability of the power grid. With the constraint of traffic system, the proposed algorithm is developed based on data analysis and cross-entropy method to obtain the optimal location of CSs. The simulation with a 33-node power system and a 25-node traffic network confirms the reasonability of proposed scheme.

2.2.4.2 EV Drivers' QoE Optimization:

The above analysis of application scenarios has been derived from the concerns of CSs. Besides, EV drivers are another indispensable part of the plug-in charging service.

Considering the essential role of EV drivers, the following application scenario from their perspective is introduced.

- **EVs to Grid (V2G):** The optimization problem of charging scheduling from the view of CSs is mainly based on the Grid to Vehicles (G2V). Based on the application of bidirectional power flow, EVs can sell the residual energy to the grid for profit. In a G2V scenario, an EV only acts as an energy demand side. By contrast, an EV can supply energy to the grid in a V2G scenario. Apart from an energy supplier, it can provide ancillary services such as frequency regulation and peak-load shifting. Although EVs can participate in the bidirectional power flow, the battery degradation on EV batteries due to frequent discharging should also be studied.

  Sortomme and El-Sharkawi [20] proposed a unidirectional regulation algorithm for an aggregator. The aggregator combines many EVs for transacting energy in the market and uses several smart algorithms to determine the discharging rate. Finally, it is proven that the energy demand of EVs can be maximally satisfied with minimum charging cost.

  Ota et al. [25] developed an autonomous distributed V2G control strategy. In this scenario, large-scale Renewable Energy Sources (RES) and battery energy storage are integrated into the power system. Besides, a smart charging control algorithm is proposed to satisfy the convenience of EV drivers and ensure the frequency stability of the power grid. To be specific, if the frequency deviation is below a minimum threshold, the EV discharge to the power grid. Otherwise, the EV is charged from the power grid.

- **CS-selection:** Since most works focus on the static mode, the mobility characteristic of EVs should be taken into account. Compared to the charging scheduling problem about "when/whether to charge", the optimization problem under the on-the-move mode is defined as "where to charge". When an EV requires a charging service, it will drive toward the optimal CS under recommendation. Based on the above analysis, it can observe that the optimization problem under the on-the-move mode is formulated as a "CS-selection" problem. In recent years, the EV charging optimization problem related to "CS-selection" has been attracting increasing attention. Combining the

Table 2.2: Literature Related to CS-selection under Plug-in Mode

Reference	Methods & Techniques	Objectives	Advantage & Disadvantage
[21]	Data mining	Minimize recharging time	Provide real-time recommendations for CSs; Reduce downtime of EV taxis; Rely on up-to-date data on CS availability
[26]	Service protocol framework	Minimize service waiting time; Improve communication efficiency	Enable on-the-move EV charging management ; Use reliable vehicular-publish/subscribe (V-P/S) communication

mobility characteristic of EVs, research is usually derived from the perspective of EV drivers. Besides, load balance over the network is another main focus in this field.

Tian et al. [21] proposed a real-time CS recommendation system for Electric Taxis (ETs). The solution framework of the real-time recommendation system combines historical recharging events and real-time taxi GPS. Based on the above information, the recharging intentions of ET drivers are predicated. Then, for ET drivers with recharging demand, an optimal CS is recommended for the ET drivers, so as to minimize charging cost and total charging time.

Cao et al. [26] developed a vehicular-publish/subscribe communication framework for on-the-move EV selecting the optimal CS. The framework is integrated with public transportation buses. Based on the infrastructure, considering low privacy sensitivity, the charging management scheme is implemented in a fully distributed manner. Simulations based on the city scenario of Helsinki verify the desirable performance of the proposed framework in improving EV drivers' QoE and communication efficiency.

- **Routing and navigation:** The optimization problem of routing and navigation aims to find a desirable route from the current location towards the selected CS. Besides, it also aims to design an optimal tour route so that EVs can experience the shortest additional distance for recharging.

  Lee and Park [27] proposed a distance-based heuristic algorithm to design a tour schedule for EVs selecting CSs during a trip with better QoE. The work in [27] considers the increasing time complexity caused by the large density of CSs. To deal with the disadvantage, the literature [27] adjusts the optimal CS selecting from all CSs in the area to the candidate subset. Moreover, the candidate subset is determined by the proposed heuristic algorithm picking CSs close to selected destination points.

2.3 Battery Swapping Mode

2.3.1 Introduction of Battery Swapping Mode

The battery swapping mode uses battery pack replacement, where a fully charged battery pack is used to replace a depleted battery pack when the battery is depleted. The concept of battery swapping can be traced back to 1896 [28]. Moreover, the battery swapping technology was applied into practice by Hartford Electric Light Company in the early 1900s [29]. The battery is owned by the service station or battery manufacturer, and the EV user simply rents the battery. The EV user parks the vehicle in a specific area and then uses a battery pack replacement machine to remove the depleted battery and replace it with a fully

Figure 2.2: Battery Swapping Mode for EVs.

charged battery pack. The replaced uncharged batteries can be charged at the service station or collected centrally for recharging later. Since the battery replacement process includes mechanical replacement and battery charging, it is sometimes referred to as mechanical "refuelling" or mechanical charging. The battery replacement station has the advantages of both a normal charging station and a fast charging station, which means that the battery can be charged by low valley electricity while the "refuelling" process can be completed in a very short time. Through the use of mechanical equipment, the entire battery replacement process can be completed within 10min, and the existing fuel car refuelling time is roughly equivalent. However, there are still a number of problems with this method that need to be solved. First, the initial cost of this battery replacement system is high, including expensive mechanical devices and a large number of batteries. Second, because of the large amount of space required to store a large number of uncharged and charged batteries, the space required to build a battery replacement station is much larger than the space required to build a normal charging station or a fast charging station. Also, uniform standards for the physical size and electrical parameters of batteries need to be developed before automatic battery replacement systems can be applied. As a result, the battery exchange model is more widely used in the public sector. However, in recent years, the battery exchange mode has also seen a major development in the private mode. EV producers like NIO [30] have established more than 900 Battery Swapping Stations (BSSs).

2.3.2 Benefits of Battery Swapping Service

The dramatic increment in BSSs has promoted the application of battery swapping service, which can be summarized as follows:

- From EV drivers' perspective, the battery swapping service can effectively reduce the energy supplement duration, alleviate range anxiety and improve QoE. Moreover, EV drivers will no longer concern about the battery degradation problem. This is mainly due to the business model of battery swapping, where both EV manufacturers and battery operation share market by separating the battery and the vehicle.

- From the BSS operator's perspective, the battery swapping mode can reduce the operation cost, by charging batteries in advance at the valley electricity price periods. Differing from the plug-in charging mode with uncertain charging behavior, the battery swapping service can balance service demand and charging process by providing inventory batteries. Therefore, the demand of EV drivers can be guaranteed and the operation cost can be reduced.

- From the power grid's perspective, depleted batteries are managed by the BSS operator. The disordered charging behavior of individual users under plug-in charging mode can thus be avoided. Therefore, the stability of power grid can be achieved with the cooperation of BSSs. Besides, depleted batteries are regarded as a static load connected to the power grid. The battery swapping mode can further help to implement peak-load shifting through charging and discharging behaviors of depleted batteries.

- From the government's perspective, the battery lifetime can be extended by regular testing and maintenance. Besides, the battery swapping mode facilitates recycling of batteries. Moreover, it can improve the public acceptance of EVs, thus promoting EV popularization.

2.3.3 Potential Risks of Battery Swapping Service

Although the battery swapping service mode indeed exhibits great excellence, potential risks should also be noticed.

- **Users convenience:** Compared with the plug-in charging mode, the battery swapping service can significantly reduce the waiting time. However, it is based on the ideal assumption that there are adequate inventory batteries for incoming EVs. Otherwise, long charging waiting time is still inevitable for depleted batteries becoming available. Besides, considering the land value, BSSs are usually deployed in suburban districts. Thus, users have to drive a long distance for energy supplements. Moreover, considering congestion at BSSs, a reasonable BSS-selection mechanism is necessary to achieve load balance.

- **Initial investment:** The battery swapping mode can indeed reduce electricity costs through battery charging optimization. However, the expensive BSS construction cost is inevitable, such as expenditure on batteries and equipment.

2.3.4 Optimization under Battery Swapping Mode

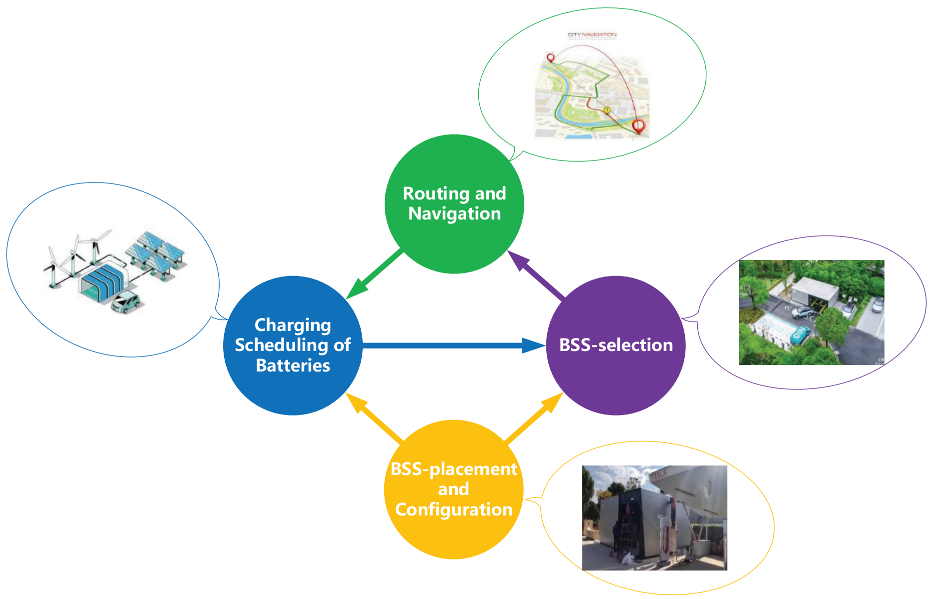


Figure 2.3: The optimization under battery swapping mode.

2.3.4.1 BSS Operation Optimization:

Compared to plug-in charging mode, stakeholders under battery swapping mode include BSS operators and EV drivers. Then, the operation optimization at BSSs is presented from the construction to charging scheduling.

- **Charging scheduling of batteries:** Batteries at each BSS can be regarded as a static load connecting to the power grid. Therefore, the scheduling can be achieved through battery charging regulation.

  1)BSS Operation Scheduling: As for BSS operation scheduling, the BSS operator arranges an optimal charging scheduling based on the service requirements of incoming EVs and the availability of batteries. The target is to maximize the profit for BSS operation and satisfy the demand for EV drivers.

  The first method to achieve the BSS operation scheduling is to allocate charging slots with different charging rates on depleted batteries. Different types of chargers, i.e., slow charge, fast charge and ultra-fast charge, may cause different battery degradation cost on batteries. Considering this characteristic, the BSS determines the optimal charging scheduling based on the local status information, such as requirements for EV drivers, BSS status, battery cost and Time-Of-Use (TOU) electricity price.

Wu et al. [31] developed an optimal charging scheduling method for batteries in BSSs. It aims to maximize the number of available batteries, and minimize the average battery degradation cost caused by different rates of charger. Then, a multi-objective optimization problem integrating the above two factors is formulated. Accordingly, the GA, differential evolution algorithm and three versions of PSO algorithms have been applied to solve the optimization problem. Combining the advantages of above algorithms, the varied population genetic algorithm and varied population differential evolution algorithm are thus proposed to achieve optimal charging scheduling with low time complexity.

Apart from the different types of chargers in [31], authors in [32] further considered the Constant-Current/Constant-Voltage (CC-CV) model to depict the actual charging process. The optimal charging scheduling based on different kinds of charging rates is to minimize BSS operation cost, including the number of batteries removed from inventory, battery degradation cost caused by different types of chargers and electricity cost. Inspired by GA, PSO and differential evolution algorithm, an integrated algorithm with desirable characteristics of the above algorithms is accordingly proposed. Simulations verify the effectiveness of proposed algorithm in optimal scheduling facing large-scale swapping demands during the day.

The second method to achieve the BSS operation scheduling is assigning a specific charging time slot for depleted batteries. In this situation, the difference among chargers is neglected. By contrast, the BSS can assign a different charging time slot for each depleted battery according to the current battery capacity. Therefore, the individual demand related to battery energy for EV drivers can be satisfied.

Based on an arrival rate at BSSs, SOC of serviced EVs and target SOC, Wang and Pedram [33] predicated the future service demands, so as to guide the optimal charging scheduling in terms of charging time and rate. Considering the dynamic energy price, a battery swapping charging algorithm is proposed to implement online charging scheduling of batteries at BSSs. Eventually, the electricity cost during BSS operation can be reduced while the QoE of EV drivers is guaranteed. Besides, a heuristic algorithm is proposed to solve the offline optimization problem about the optimal number of inventory batteries.

Considering the stochasticity of requirements and real-time energy price, Mohsen et al. [34] investigated the optimal scheduling problem based on the constraint of BSS operation. Since the charging scheduling includes the charging and discharging process, the BSS operation cost is formulated from electricity and battery degradation cost. Then, a robust optimization method is developed to find the optimal solution with the aim of minimizing cost function, so as to achieve the optimal BSS scheduling.

2) Interactive Charging Scheduling With the Power Grid: Considering the high power demand of BSSs and the energy storage characteristic of batteries, a reasonable charging scheduling method interacting with the power grid is necessary. Accordingly, depleted batteries can be charged at the valley electricity price to reduce operation cost. Besides, BSSs can transmit battery energy back to the grid at peak periods. Through above interaction, the profit of BSSs and the stability of power grid can both be improved.

Benefiting from the rapid development of deep Q-network, Wang et al. [35] developed a dynamic scheduling strategy at BSSs for providing fast frequency regulation services to the power grid. Specifically, a cost function is formulated to evaluate the revenue for BSS providing fast frequency regulation services. Due to the non-convex and random characteristics of the optimization problem, a well-trained deep Q network (DQN) is thus proposed for optimal scheduling. Simulation results present the effectiveness of proposed scheme in improving fast frequency regulation services and profits of the BSS.

Yang et al. [36] utilized the energy storage property of batteries in the BSS, providing auxiliary services with the Battery to Grid (B2G) method. Then, an operation strategy is proposed based on the SOC of each battery to determine the candidate battery set for B2G. Besides, considering the power fluctuation and QoE of battery swapping service, a coordinated charging mechanism for the BSS in a microgrid is proposed to minimize electricity costs. An actual example investigates the impact of free parameters and verifies the desirable performance of proposed service strategies.

- **BSS Construction:** This part mainly analyzes the BSS initial operation planning, including BSS placement and configuration.

  1) BSS-placement: The BSS placement problem is defined as locating and deploying a BSS at a certain place over the city district. Since the location of BSS is fixed but with increased investment cost, the construction of BSS should be determined with the sufficient investigation based on the quantity of EV, land price, distance and power grid.

  Since BSS-placement plays an important role in subsequent operations, Wang et al. [37] proposed a BSS-placement framework based on multi-criteria decision making. Firstly, three criteria are considered, including up-front investment, impact on power grid and QoE of EV drivers. The criteria system is further developed. Then, considering a lack of information in the decision scenario, triangular fuzzy numbers are applied to handle uncertainties. Besides, a decision making trial and evaluation laboratory method is developed to determine the weights of three criteria. Finally, a fuzzy-based approach is applied to rank the candidate position.

Considering the prevalence of internal combustion engines and data science, Zeng et al. [38] developed a data-driven BSS-placement method based on large-scale GPS data. The proposed BSS-placement scheme includes three parts: a Hidden Markov Model for map matching and trajectory extraction, an electricity consumption rate model for demand estimation, and a clustering strategy for location determination. An example case in Shanghai present that the proposed scheme outperforms related benchmarks.

2) Configuration: After a BSS is deployed, the matched configuration is an essential factor for BSS's long-term operation. It includes the service strategy, the number of charging slots and the initial number of batteries.

Schneider et al. [39] investigated the configuration optimization problem of BSSs with charging slots and batteries. The aim is to obtain the optimal equipment configuration of BSS operation, considering the battery swapping requirements and electricity price. Whereas, the optimization problem is hard to be solved in practice due to large time complexity. Therefore, a near-optimal solution heuristic based on Monte Carlo sampling is developed to obtain the solution. Finally, the proposed algorithm can simultaneously determine the optimal configuration of BSSs and charging scheduling strategy.

With the aim of reducing carbon emission and operation cost, Liang et al. [40] proposed a BSS configuration and operation model with three charging strategies. Based on dynamic and historical data, the authors derive the optimal number of chargers, swappers and inventory batteries. Besides, annual battery rental fees are taken into account to satisfy battery swapping demand and improve BSS profits. Then, the profit of BSSs is analyzed from the aspect of battery technology, policy, and BSS planning. Finally, it is concluded that battery cost and swapping pricing are crucial factors for BSS profits.

2.3.4.2 EV drivers' QoE Optimization:

From the perspective of EV drivers, the optimization problem is usually formulated from the aspect of service waiting time and servicing expense.

- **BSS-selection:** EV drivers move toward an optimal BSS for battery swapping service when the service requirement occurs due to extending driving range anxiety, known as the BSS-selection problem. In charging scheduling part, the optimization strategy on BSS operation is presented, with concern on when and which battery to charge. By contrast, the BSS-selection problem is devoted to recommending the optimal BSS to EV drivers. Here, the optimal BSS is selected according to various criteria, such as minimum service waiting time, lowest service cost and shortest travelling distance.

1) Optimization Theory: Due to the limited available batteries and charging slots of BSSs, incoming EVs usually have to wait until a depleted battery becomes available. Considering the arrival rate of EV flows and the service ability of BSSs, the service process can thus be transformed as a queuing theory problem. Besides, since the optimization objective function is usually formulated with waiting time and service cost, the optimization problem can thus be solved from the field of mathematical optimization.

Based on the battery swapping and charging process, Tan [41] et al. proposed a queuing theory method to assess the service performance of a Battery Swapping and Charging Station (BSCS). To be specific, a Mixed Queuing Network (MQN) model consisting of an EV queue and a battery queue is designed. Then, the balance equations and steady-state distribution is derived. Besides, the EVs' blocking probability (a criterion related to waiting time) is adopted to evaluate the battery swapping service performance. Moreover, the influence of crucial configurations of BSCS (e.g., the number of parking spaces, swapping islands, chargers, and batteries) on the blocking probability is also depicted.

You et al. [42, 43] investigated the optimal BSS assignment based on the current location and SOC in a centralized and distributed manner. It aims to minimize a weighted sum of EVs' travel distance and electricity generation cost. For centralized implementation, a solution based on second-order cone programming relaxation of optimal power flow and generalized Benders decomposition is proposed with global information [42]. Since the power grid, EVs and BSSs may be operated independently, the global scheduling information is unable to be obtained.

2) Service Framework: Many works are developed based on mathematical optimization. Although a globally optimal solution can be achieved, they are usually derived with the ideal assumption that the global demand information is known in advance. Considering this disadvantage, the service framework is thus proposed in practical application scenarios.

With the development of ICT, Cao et al. [44] developed a Mobile Edge Computing driven battery swapping service management scheme. In this work, the optimal BSS decision process is implemented by EVs in a distributed manner. Besides, the public transportation bus integrated with MEC server collects EVs' reservations and transmits BSS status to EVs. Based on the number of batteries at BSSs and reservation information, the GC can predicate the waiting time at each BSS. Therefore, the EV driver can move toward the optimal BSS with the shortest waiting time.

Apart from the waiting time for EV drives, Li et al. [45] also considered the impact of battery degradation cost from the perspective of BSS operator. In the paper, a CC-CV charging model is applied to depict the recharging process of depleted batteries. Based on the CC-CV model, the battery degradation cost is accordingly derived. Then, combining the reservation mechanism, a demand balance battery swapping service framework is proposed. Finally, the joint optimization between EV drivers and the BSS operator can be achieved through the optimal BSS selection.

- **Routing and Navigation:** The routing and navigation optimization problem is mainly derived from the optimal path planning when a target BSS is selected. Considering the route limitation, EVs aim to find a BSS for energy supplement. This is common for ETs service process that drivers should achieve fast battery swapping service to meet seamless journey demand for customers, in order to maximize profit.

  Due to the limited battery capacity, ETs have to select a BSS for energy supplement during pickup and drop-off tours. Based on above scenario, Sayarshad et al. [46] developed a dynamic routing method based on Markov Decision Process (MDP) with elastic demand. The proposed non-myopic routing scheme considers battery SOC, detours of the ET moving toward a BSS, customers delay and system cost to maximize social welfare. Then, the optimization problem is formulated and solved as a Traveling salesman problem with pickup and drop-off to obtain the optimal route planning. An example case based on taxi trip data in New York City proves the proposed method's effect on improving social welfare.

  Masmoudi et al. [47] defined an EV Dial-a-Ride Problem. The optimization problem considers the interaction between EVs and BSSs. Besides, it focuses on scheduling a fleet of EVs to satisfy pre-specified service requests during a certain planning period. Then, three Evolutionary Variable Neighborhood Search algorithms are proposed, including population-based, diversification and advanced local search method. The simulation presents that the proposed algorithm efficiently combines the advantage of evolutionary meta-heuristics and Variable neighborhood search.

- **Multiple BSSs and CSs:** Under multiple BSSs and CSs service mode, BSSs and CSs are operated independently. A station can only support battery swapping or charging services. A certain number of BSSs and CSs are located around the city. EV drivers with energy supplement demand, will move toward a BSS or a CS according to the recommendation.

  Utilizing MATLAB and MATPOWER, Luo et al. [48] developed a simulation platform for a large-scale traffic flow and proposed an EV charging scheduling scheme for different types of EVs. Considering the deployment of BSSs and CSs over the city, choosing a charging or battery swapping service depends on service waiting time, travelling distance and real-time road condition information. Then, a multi-objective optimization operation function related to traffic, power grid and CSs/BSSs, is constructed. Finally, the optimal charging scheduling strategy is solved with the weight coefficient method.

2.4 Vehicle-to-Vehicle Charging Mode

2.4.1 Introduction of Vehicle-to-Vehicle Mode

Unlike the traditional plug-in mode, a flexible V2V charging mode is proposed in [49] to allow a pair of EVs to transfer energy between each partner other than plug-in charging at CS/ battery swapping at BSS. The V2V charging mode allows EVs' energy transfer from EVs as energy Providers (EV-Ps) to those EVs as energy Consumers (EV-Cs), in a convenient and economic energy transfer manner. Besides, the V2V charging mode does not occupy grid resources during the peak charging period. Therefore, the V2V charging mode can also be used to balance the load of the grid and reduce the adverse impact of the grid during peak hours. Due to the V2V charging mode, the optimization of charging service is normally modelled as a constrained MILP. In the work [49], through dual decomposition and benders decomposition, the distributed algorithm was used to solve the problem. Chakraborty et al. [50] introduced a cloud-based control system to match V2V charging pair and optimize charging service. At the hardware level, Ucer et al. [51] investigated the potential of bidirectional DC-DC converters for V2V charging. Meanwhile, by deploying converters, traditional PLs can be facilitated for V2V charging [52].

There are mainly two V2V charging modes, direct V2V charging and asynchronous V2V charging. The direct V2V charging mode provides adaptability for EVs on-the-move. Usually, under the direct V2V charging mode, EVs are divided into energy providers and energy consumers. Through energy transfer devices (such as DC-DC converters [53]), energy can be transferred from energy providers to energy consumers [54, 55]. Besides, the accumulators at Power Storage Stations (PSSs) can store the energy of energy providers, and transmit energy to energy consumers that needed charging. Thus, under the asynchronous V2V charging mode, the charging and discharging services do not require both parties to start at the same time.

The dual-input single-output DC-DC converter geography is proposed in [53] for the integration of the two information sources. This converter works in six distinct kinds of activity, it can utilize the power delivered by sun-based Photovoltaic (PV) and the power accessible in the battery. Likewise, it performs V2V or V2G activity when the vehicle is in leaving mode without the necessity of any outer DC converter.

Roberts et al. [54] proposed a progression of confirmation protocols to be utilized for V2V charging applications. The fundamental inspiration is to get EVs charged using existing norms like dedicated short range communication, Wi-Fi Direct or Bluetooth. Authors utilized a common key trade convention that doesn't depend on testaments for confirmation. Then, they proposed conventions utilizing cell phones and Wi-Fi Direct conventions.

2.4.2 Objectives and Risks under V2V Charging Mode

2.4.2.1 Objective of EV Charging under V2V Charging

The objective of the V2V charging determines the optimization problem consensus and decision-making behavior of different service participants. This objective from the perspective of both the provider and the consumer is further analyzed.

- From the perspective of energy consumers, range anxiety and QoE are major concerns. Besides, charging cost is another key factor that energy consumers consider. Here, the cost typically includes two aspects: travel costs and fees paid to the energy provider.
- From the perspective of energy providers, they want to sell their excess energy to energy consumers. Therefore, selling price and travel costs are key issues for them to consider.
- From the perspective of PL/PSS, when EVs reach the PL/PSS, an effective scheduling strategy is required to plan the charging/discharging sequence of EVs.

2.4.2.2 Potential Risks of V2V Charging Service

In this section, the potential risks of above V2V charging mode are summarized.

- **The mismatch of V2V-Pairs:** The V2V charging may fail due to mismatch of charging protocol among heterogeneous EVs in the market.
- **Privacy issues:** The V2V charging mode requires sensitive information of EVs including location and driving route. The leaking of information will affect the security of users.
- **Slow charging:** The V2V charging is flexible in the temporal domain and avoids the problem of long charging waiting time at CSs. However, it is noted that the charging power, between energy consumers and energy providers under V2V charging mode, is much lower compared to that under the plug-in mode.

2.4.3 Optimization under V2V Mode

The V2V charging mode is flexible in the temporal domain (depends on the available time of EVs other than the available time of charging infrastructures), avoids the charging time of EVs not matching the free time of CSs/BSSs. Besides, the V2V charging mode is flexible in the spatial domain (depending on choosing a parking lot with available parking space), avoiding selecting fixed-position CSs. Thus, the V2V charging mode can avoid the problem of long waiting time at CSs.

However, it is a significant problem for optimization of temporal and spatial domain.

- In the temporal domain, the distance between energy consumers and energy providers should normally not be too far, so that they can reach the target PL at a certain time to perform V2V charging services. Otherwise, the energy transfer may suffer from a long time to wait for any one of V2V pair reaches the PL. Thus, in order to allocate resources, it is necessary to collect the current information of both energy consumers and energy providers.

- In the spatial domain, the matching optimization is performed according to the distance of energy consumers, energy providers and PLs. The optimality of spatial domain problem is limited by the high mobility of EVs and the complexity of PLs locations. Thus, it is important to match energy consumers and energy providers that are not too far. At the same time, it is also necessary to consider the distance between both V2V charging parties and the target PL.

Here, optimization approaches are reviewed under V2V application scenarios (direct and asynchronous V2V charging modes). A typical procedure for on-the-move EVs V2V charging is structured. The system is controlled centrally by a GC, including information collection and global planning. Based on global planning, energy consumers and energy providers can travel to PLs for V2V charging services according to their respective preferences.

Under the direct V2V charging mode, when an EV customer requests for charging, it requires an adequate energy provider to match for a maximized charging utility and minimized charging cost.

- **V2V-pair matching:** During V2V-pair matching, the following constraints should be noted: (a) If the subsequent travel of energy providers is considered, the residual energies of energy providers need to meet the minimum requirement of completing their travels. (b) The transferring of EVs providers' energy will cause additional energy loss.

  1) Maximum weighted diplot matching algorithm: Bulut et al. [55] proposed a V2V charging system to permit V2V energy transferring. EV drivers with range anxiety can purchase energy from EVs with excess energy to sell. A mobility model is developed for EVs during their trips. EVs communicate with each other in proximity through a location based social networking system. Besides, this work uses a maximum weighted diplot matching algorithm to optimize pair matching between EVs.

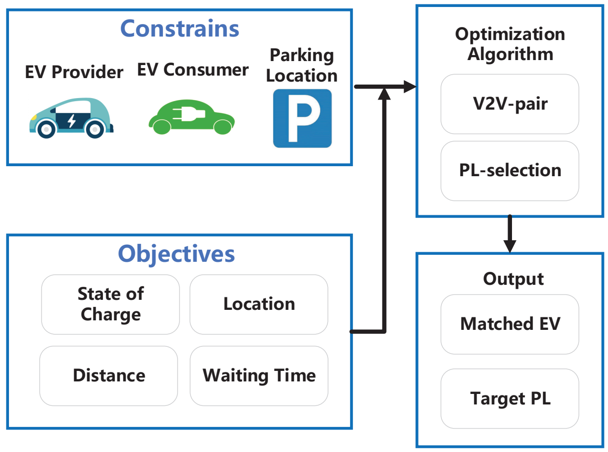


Figure 2.4: The optimization under direct V2V charging

2) Trucks with batteries: Kabir et al. [56] assumed a company having a number of V2V enabled charging trucks equipped with a larger battery and a fast charger. The company intends to maximize the served number of EVs been fully charged. The work also considers that all trucks should return to the depot after serving EVs. Kabir et al. formulate a MILP to maximize the number of served EVs by determining the optimal trajectory of each truck.

3) Cooperating V2V charging and plug-in charging: In the work [57], energy consumers are allocated to the optimal energy supplier (CS or energy provider) to minimize the total charging cost. The matching problem is described as a mixed integer optimization problem which is NP-hard, and then this work develops an algorithm based on a stable marriage algorithm.

4) The stable marriage matching algorithm: The work [57] proposed a stable marriage matching algorithm for the given preferences of EVs. It is proven by the classical deferred acceptance algorithm [58] that at least one stable matching exists. Then, the problem comes with how to find a stable matching effectively and efficiently. The Gale-Shapley algorithm [59] has been proposed as an efficient method to find a stable one-to-one matching in the stable marriage problem. Note that although the provided EV-consumer-oriented and EV-provider-oriented V2V matching algorithms can both realize stable matchings, they have significant consequences. The EV-consumer-oriented algorithm yields an EV-consumer optimal stable matching, in which each EV as energy consumer has the best matched partner that it can have in any stable matching, whereas the EV-provider-oriented algorithm leads to an EV-consumers output. This property is referred to as the polarization of stable matchings [59].

5) Subsystems of V2V charging Scenario: Zeng et al. [60] proposed a hierarchical bipartite graph matching method to facilitate power exchange in power distribution systems. The power distribution system is divided into a series of subsystems according to the location of the EVs. The V2V power exchange is optimized to schedule charge/discharge cycles between trading EVs in each subsystem. The energy surplus and deficit of each subsystem will be regulated by the exchange of electricity between adjacent subsystems and the utility grid. The proposed hierarchical bipartite graph algorithm adopts charging models in EVs to facilitate transactional V2V power exchange. In addition, by adaptively adjusting the respective energy transaction targets, the energy transaction price of a single EV can track the price of the subsystem. Several case studies demonstrate the effectiveness of the approach, in which interactive V2V power exchange is improved to increase the energy efficiency of power distribution systems.

6) Price model: Wang et al. [61] presented a novel smart grid architecture with enhanced communication capabilities for mobile EVs, via a heterogeneous wireless network-enhanced smart grid. The authors proposed an online V2V energy swapping strategy based on price control. Specifically, EVs with surplus energy are motivated by getting paid to contribute to a V2V energy swapping transaction. Based on the gathered information from both EVs and the power grid, the aggregators determine the energy price for EVs. The price control strategy is modeled as an Oligopoly game [62] with competition among EVs. Using the announced price, a mobility-aware spatio-temporal coordinated V2V energy swapping strategy is designed to enable energy exchange among EVs at the aggregators. The proposed strategy is modelled as a time-coupled MILP, which is decoupled into a series of sub-MILPs through Lagrange duality [63]. To evaluate the performance of the proposed V2V energy swapping strategy, a realistic suburban scenario is developed in VISSIM [64] to track the EVs' mobility using the generated simulation traces. Extensive simulation results are given to demonstrate the efficacy of the proposed V2V energy swapping strategy.

7) V2V energy sharing framework: Shurrab et al. [65] proposed a novel holistic V2V energy sharing framework. It consists of four layers including vital modules, models, and technologies to develop efficient and effective V2V solutions. This framework focuses on building an all inclusive V2V solution, which is not only cost effective, but also maintains high user satisfaction, social welfare, and energy demands fulfillment. Besides, this framework can simultaneously protect users' privacy and secure their sensitive data. This is possible with the support of evolutionary technologies, such as AI, IoT, blockchain, and game theory, which are the building blocks of the proposed framework. The aim of the framework is to build a comprehensive V2V system. It can integrate all the necessary modules at various stages of the V2V process and introduces new ideas, such as user behavior profiling, AI models, etc., that can enhance the system.

- **PL-selection:** Any V2V-pairs need to select a PL as common place to operate energy transfer. Once the GC has conducted a feasibility analysis of PL-Selection for V2V-pairs, the core factors are based on trajectory driving time, energy consumption, charging time and charging comfort quality. When energy consumers and energy providers establish the charging matching of V2V-pairs, they will face the problem of PL-selection. In practice, EVs requires an optimized PL-selection algorithm due to the scarcity of parking resources. Besides, PLs provide the equipment for V2V charging and EVs may cause congestion. However, only a few previous studies have considered the problem of PL-selection after V2V pairing [66], [67].

  1) Travel energy cost and charging pleasure degree models: Li et al. [66] designed a VANETs-based communication framework to enable data transmissions between CSs and EVs in a real-time manner. By means of the derived travel energy cost and charging pleasure degree models, EVs firstly reserve the corresponding optimal parking place to minimize the charging cost.

  2) Intelligent V2V charging navigation strategy: Li et al. [67] proposed an intelligent V2V charging navigation strategy for mobile EVs under VANET communication. Firstly, an efficient Mobile Edge Computing (MEC) based semi-centralized charging navigation structure has been established. It ensures reliable charging information dissemination and feasible charging coordination with a low cost of communication and computation. After that, based on the travelling time prediction model, Li et al. designed an effective local charging navigation scheme and global charging navigation mechanism, to dynamically choose the optimal travelling route as well as stopping location for V2V charging operations.

2.4.3.1 The Asynchronous V2V Charging:

Since the majority of the direct V2V charging approaches are with low charging rates under 20 kW [51, 52], the charging time through direct V2V charging is extremely long. Meanwhile, the V2V charging mode suffers from the uncertainty of EV charging demand. Therefore, by introducing an asynchronous V2V charging mode, the above problem can be alleviated by decoupling the requirement in spatial and temporal dimensions.

Fig. 2.5 shows the asynchronous V2V charging scenario. The asynchronous V2V charging method is different from the direct V2V charging [66], under asynchronous V2V charging mode, an energy consumer and an energy provider do not have to start V2V charging at the same moment. energy providers deliver energy to the Power Storage Station (PSS) equipped with condensers [68], which can store energy. The PSS can transfer energy to energy consumers that have energy demand.

- **GC**: It is responsible for coordinating EVs information, and calculating the waiting time of V2V charging to arrange EV charging/discharging services.

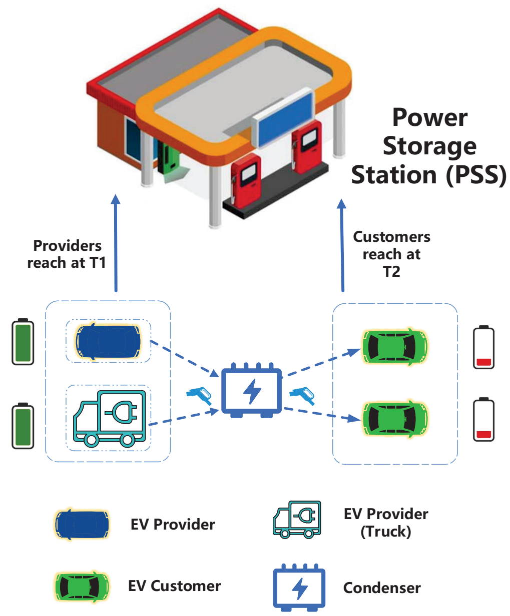


Figure 2.5: Asynchronous V2V Charging Scenario

- **PSS**: PSSs can provide V2V charging services as charging places. They are equipped with batteries to store energy discharged by energy providers and provide asynchronous charging services to energy consumers.
- **EV-Cs**: When the SOC of an energy consumer is under the threshold, it will send a charging request to the GC and waits for the result of charging arrangement.
- **EV-Ps**: An energy provider sends its discharging request to the GC when its SOC is higher than the threshold. Then, the energy will transfer from the energy provider to the target PSS.

Under the asynchronous V2V charging mode, when an EV customer requests for charging, it requires a suitable PSS for a maximized charging utility and minimized charging time. Therefore, optimization problems for asynchronous V2V charging are divided into two main categories as asynchronous V2V charging and synchronous V2V charging. At present, there are few pieces of literary work on asynchronous V2V charging.

- **PSS-selection:** During PSS-selection, the following constraints should be noted: From the perspective of energy consumers, they want to recharge with a short charging service time. In addition, the charging price also needs to be considered. From the perspective of energy providers, they want to sell excess energy at a high price. Besides, the energy consumption for travel also needs to be considered.

1) Cooperation between V2G and V2V modes: Kim et al. [69] tackled range anxiety and limited charging spots, based on the matching theory (choosing sufficient energy supplier for energy consumers). In this paper, the authors proposed a matching based method that can cooperate between V2G and V2V charging modes, then it can decrease range anxiety and increase the number of charged EVs. Then, Kim et al. investigated the proposal numerically by comparing V2G and V2V charging mechanisms. Results show that the algorithm can improve in terms of range anxiety and the number of charged EVs.

- **PSS-scheduling:** During PSS-scheduling, scheduling algorithms should be applied to efficiently schedule EVs to charge/discharge. It is important to prioritize charging for EVs. In addition, EVs in urgent need of charging should be given high priority.

  1) An online auction mechanism: Yuan et al. [70] researched the EV charging scheduling problem with V2V auction and local generation under demand response. To incentivize EVs to participate in energy supply, authors proposed an online auction mechanism based on a primal-dual approximation algorithm, which decomposes the long-term social cost minimization problem into a series of single-round auctions. Furthermore, to avoid the cost caused by excessive switching of local generators, Yuan et al. designed an online algorithm based on the idea of delayed switching, which guarantees provable polynomial running time, authenticity, and individual rationality for each auction. Finally, real-world data is used tu track and verify the practical superiority of the method over multiple existing algorithms.

  2) Cooperation between G2V and V2V modes: Koufakis et al. [71] proposed an optimal EV charging scheduling scheme considering the cooperation between G2V and V2V modes. This work formulates the optimization using integer linear programming and for problem solving in off-line manner. Furthermore, it introduces three different ideal arrangements for the EV charging planning problem, which support the movement of energy between EVs. Through a number of trials, authors demonstrated the efficiency of energy storage devices (i.e., EV batteries, or batteries at the CS) towards the higher use of energy and higher EV satisfaction. Additionally, the authors showed that all calculations have generally low execution times and great adaptability.

2.5 Mobile Charging Mode

2.5.1 Introduction of Mobile Charging

Considering that EVs are with high mobility, there is a great potential for EVs to be charged via mobile charging. Mobile charging involves MCSs (as opposed to fixed charging

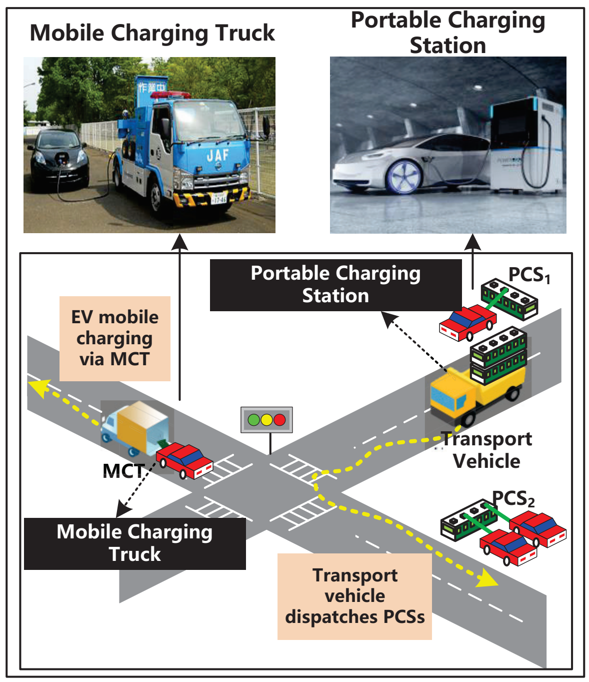


Figure 2.6: Mobile Charging

infrastructure) and in-motion EV charging by Mobile Charging Truck (MCTs) or other private EVs. As such, mobile charging has greater potential for application in temporary charging or emergency roadside assistance. There are currently two categories of mobile charging:

Mobile Charging Station (MCS): Unlike Fixed location Charging Stations (FCSs) deployed at fixed locations, MCSs can be dispatched by transport vehicles to changing addresses for charging. Battery Energy Storages (BESs), the main component of MCSs, are towed or carried by transport vehicles.

In-motion EV Charging: When an EV determines that it needs to get charging service as soon as possible, it sends a charging request. Other EVs (MCTs or other private EVs) that are aware of this signal can provide the service. EVs are continuously charging by wired or wireless approach while driving.

2.5.2 Benefits and Risks under Mobile Charging

2.5.2.1 Benefits of Mobile Charging Service

Mobile charging is more flexible than FCS in terms of location. The MCS mode is designed to relieve energy pressure in 'hot spot' areas, while the in-motion EV charging mode provides differentiated charging services specifically for EVs (e.g. roadside assistance).

- From EV driver's perspective, the lack of charging infrastructure in most remote areas (suburban or rural) makes it difficult for EVs to find charging facilities. However, the MCS mode allows temporary deployment and increases the supply of charging infrastructure in remote areas.

- From the grid perspective, the use of MCS can effectively reduce the investment cost of grid charging facilities. On the one hand, as a flexible mobile charging mode, mobile charging can effectively reduce the driving time of EVs. On the other hand, mobile charging can be used in emergency charging scenarios such as roadside assistance (charging EVs with depleted batteries). In addition, MCS with storage capacity can be recharged during off-peak hours, allowing them to provide energy during peak hours, thereby relieving pressure on the grid [72].

2.5.2.2 Potential Risks of Mobile Charging

Although mobile charging has a huge application potential, it is still subject to a number of constraints:

- **Operational Management:** The current EV penetration rate is not high enough, the economic benefits of deploying and operating MCSs will be smaller than those of FCSs [73]. Meanwhile, as some MCSs are dispatched to remote areas, it is difficult to carry out periodic checks on them at short frequencies. This leads to susceptible physical uncertainties, making MCSs more difficult to manage. Furthermore, MCSs still face the impact of battery degradation levels on BES life expectancy [74].

- **Privacy Protection:** Due to high frequency data interaction in mobile charging management, this places a high demand on privacy protection during communication. A large amount of private EV data (e.g. location, vehicle ID) is included, thus MCSs operator needs to ensure that the data is protected during transmission and utilization.

2.5.3 Mobile Charging Operation Optimization

The V2V charging optimization focuses on the requirement for users to optimize EV drivers' QoE, while the mobile charging optimization focuses on service providers. Therefore, the operational deployment of MCSs is crucial.

2.5.3.1 MCS Operation

There are currently two issues for MCS research. To ensure the QoE of EV drivers, the deployment of MCSs needs to be optimised. To minimise the operating costs of MCS operators, optimisation of MCS scheduling, charging station reservation and charging pricing need to be considered.

- **MCS-Placement:** The deployment of MCS can alleviate charging pressure in 'hotspot' areas and provide flexible charging options in locations that are not suitable for permanent FCS deployment. The work in [75] proposed a nomadic MCS concept, it looked at the impact of the number of MCSs in a region and the ratio of EVs to MCSs on the probability of outages and charging delays. The EV charging waiting time was reduced by MCSs deployment through a proposed mobile charging information management system in [76]. It allocates MCSs based on information about the charging density of FCSs. This allocation takes into account EV arrival queues, request queues. In [76], a multi-queue scenario is applied to optimise the mobile charging service provided to EVs. The work in [77] modelled the dispatch of MCSs as a constrained optimization problem and proposes a heuristic solution. Here, a meta-heuristic solution based on an ant colony optimization algorithm is considered. A greedy algorithm was proposed in [78] to allocate MCSs. Here, the MCS with the most excess energy is allocated to the locations where the energy demand is highest, helping to maintain load balance in the grid.

- **MCS Operation Optimization:** On the operational side, optimizing the energy use of MCS requires balancing supply and demand [79]. The work in [80] modelled the stochastic and dynamic behaviour of charging demand. This is to reduce operating costs while improving mobile charging service levels. Out of consideration for the benefits of MCSs, the work in [81] proposed an optimization on transport vehicle routing problem with time windows, which is optimized by MILP. The maintenance of MCSs to complete grid line rehabilitation was considered in [82], with the dispatch of mobile battery-carried vehicles to stabilise the grid load. A recovery model for distribution systems based on MCSs is proposed. Ding et al. modelled it into a MILP optimization problem and solved it by an algorithm based on auxiliary induced functions. The work in [83] presented an energy trading system involving multiple MCSs and EVs. The system formulates the incentives between MCS and EV as an auction game, where MCSs act as the auctioneers and EVs as the bidders. Experimental results demonstrate the fairness guarantee of the system for mobile charging. The work in [84] modelled MCSs as a queuing process. It developed mathematical models to characterize the placed MCSs, for minimizing operating costs and battery capacity of MCSs with efficient mobile charging services provided.

- **MCS Scheduling:**In contrast to First In First Serve (FIFS), an approach based on Nearest Job Next (NJN) policy was proposed in [85]. Here, MCSs serve the next closest EV after the completion of the previous charging service. The work in [86] modelled MCSs path planning as a MILP problem, considering different possible service allocations and constrained operating range. This is to minimise the total distance travelled of transport vehicles. In order to increase the number of EVs that obtain charging services, the work in [87] applied an ILP to determine the optimal driving path of transport vehicles. For more accurate information, the work in [88] proposed a reservation-based intelligent scheduling scheme for efficient MCS utilisation. The proposed scheme is suitable for charging on demand with pre-charging reservation at MCSs. Nazari-Heris et al. proposed a smart parking self-scheduling model for EVs [89]. MCSs are involved in the planning of energy production and storage in RES system, as interim BESs. The work in [89] aims to quantify the equity implications of MCS operation, the optimal siting of RES system.

2.5.3.2 In-motion EV Charging Decision

In-motion EV Charging can be regarded as V2V charging on the move, or accompanying charging. This convenient mobile charging mode has been in the spotlight in recent years as battery technology has evolved. Cisco Technologies also filing a patent for In-motion EV Charging in 2019 [90].

The work in [91] investigated the technical aspects of in-motion EV charging and proposed a novel structure for V2V wireless charging technology to increase the possibilities of wireless charging services. In [92], EV fleets are used as a collaborative system where EVs in the fleet can share batteries with other EVs while driving to optimise the distribution of power across the EV fleet.

2.6 Wireless Charging Mode

2.6.1 Introduction of Wireless Charging

Wireless charging converts electrical energy into a form of energy that can be transmitted wirelessly. Converters then receive energy (wirelessly) and convert it into electrical energy, enabling wireless EV charging. Wireless charging, also known as inductive charging or contactless inductive charging, is a technology for the wireless transfer of electrical energy in space based on the principle of electromagnetic induction. With wireless charging technology, electric or dual-energy vehicles on the road can be quickly recharged using transmitters mounted on utility poles or other tall buildings [**DUARTE2021102952**]. Current wireless charging technologies include inductive coupling [93] and magnetic resonance coupling [94]. Both are efficient over medium distances and can be used to charge EVs wirelessly (as opposed to wired in the traditional plug-in charging mode) [95].

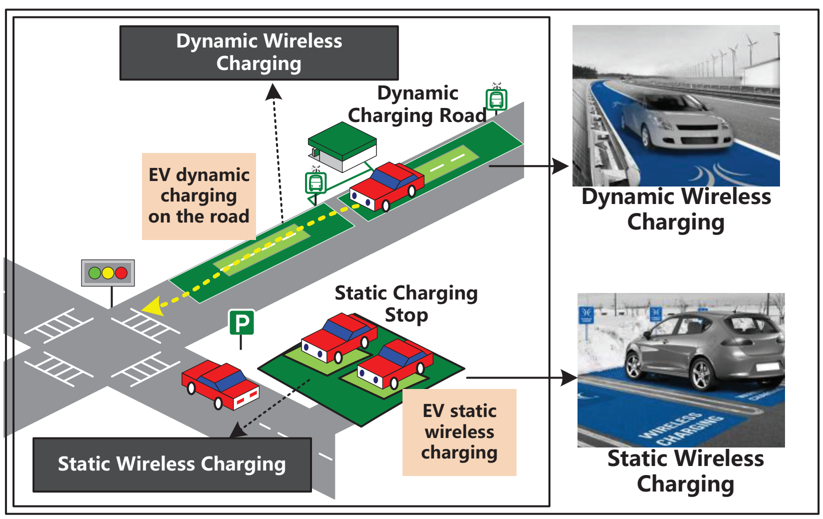


Figure 2.7: Wireless Charging

Fig.2.7 demonstrates the scenario of wireless charging. Depending on whether an EV is static during the wireless charging process, there are two main categories: Static Wireless Charging (SWC) and Dynamic Wireless Charging (DWC). Under SWC mode, EVs park in user-friendly areas (e.g., supermarkets, parking lots) and perceive direct charging services via ground wireless charging assembly. Under DWC mode, EVs perceive charging service during driving through the road sections covered with an energy transfer loop.

2.6.2 Benefits and Risks under Mobile Charging

2.6.2.1 Benefits of Wireless Charging

The wireless charging mode avoids the involvement of wired devices during the charging process, and therefore guarantees a relatively close and safe system. In addition, wireless charging reduces the maintenance pressure of the charging providers.

- From EV driver's perspective, the wireless charging mode allows EVs to charge on the move, saving the time EVs need to drive exclusively to the FCS. With two minutes of waiting time at each stop and 20 minutes at the terminal, the electric bus could gain one hour of wireless charging time. This can effectively extend the range of buses.

- From the security protection perspective, wireless charging does not require an external wired device and therefore avoids security threats (e.g., illegal access at the software level) during the wireless connection.

2.6.2.2 Potential Risks of Wireless Charging

Wireless charging technology has rapid development in recent years and is being applied in some cities. Literature works have assessed the application prospects and significant economic benefits of wireless charging [96, 97]. However, there are still concerns about the mass adoption of wireless charging services.

- **Insufficient Charging:** The low charging conversion rate is still the major gap for large-scale commercialization of wireless charging. Inherently, wireless charging is less efficient than traditional charging methods, as there is a significant amount of energy loss in transition. Meanwhile, the wireless charging rate is not fast enough, with most wireless charging powers below 11kW under wireless charging standards [98].

- **Safety Concerns:** The safety of electromagnetic radiation is widely concerned. Firstly, electrical energy is transmitted in the form of electromagnetic waves. Here, metal obstacle detection between EVs and transmitters is mandatory, to avoid overheating and fire. Secondly, when a high-powered wireless charging device is in operation, it has an impact on the surrounding biological and electronic equipment. Therefore, how alleviating people's concerns about health is also crucial.

- **Road Renovation:** Although DWC can effectively extend the driving range of EVs, it requires the modification of roads for pilot operation, a large upfront cost investment and human resource extensive cost on maintenance if applied for large-scale operation.

2.6.3 Optimization under Wireless Charging

The previous mobile charging mode focused on optimization at the operational level. In contrast, QoE for EV drivers is a key optimisation target for wireless charging services. The following therefore addresses wireless charging optimization from a driver charging service perspective.

2.6.3.1 Adaptation and Navigation

SWC technology is applied when EVs are parked. This technology is of potential for applications in parking lots, supermarkets and residential areas. Recently, the power and efficiency of SWC is increasing as technology advances, some manufacturers (like Audi [99], Qualcomm [100], etc.) are already able to achieve stable SWC for commercial applications. Meanwhile, SWC for electric buses staying at stops is currently being implemented in public transport systems in Barcelona [101]. Meanwhile, dynamic charging and driving can be processed simultaneously, which eliminates the charging waiting time and helps to reduce range anxiety for EV drivers [102].

Under DWC mode, how to facilitate the deployed wireless charging road sections for path planning is of importance. In addition, the communication between the road and EVs is crucial for bridging the seamless and optimal energy transfer. Here, when an EV enters a dynamic wireless road segment, the EV should be informed so that the EV could slow down in order to obtain sufficient charging time [103]. An online coordination strategy is proposed in [104], it allows EVs to maximise the use of a dynamic wireless road, thus achieving grid load balance and maximising charging capacity. Meanwhile, DWC has commercial benefits for EVs, where battery costs can be significantly reduced when wireless road segments are large-scaled [96].

2.6.3.2 Charging Reliability

SWC does not require substantial human involvement during charging service and avoids some of the potential safety issues, such as the danger of electric shock in plug-in charging [105].

The work in [106] controls the wireless charging rate to balance energy supply, and demand to facilitate the integration of SWC with the grid. In contrast to SWC, DWC allows EVs to charge while they are on-the-move [107]. Under DWC mode, charging panels are laid on the road, for EVs charging while on-the-move. This provides continuous energy transfer to EVs without much concern for the capacity of batteries.

2.7 Cooperated and Hybrid Charging Mode

2.7.1 Introduction of Hybrid Charging Mode

EV charging modes are usually investigated separately. Thus, in most research, only plug-in charging mode and battery swapping mode are considered in a scenario, with optimization targeting a single type of stakeholder. Nevertheless, it is difficult for a single charging mode to solve the flexible charging requirements of EVs, and optimizing EV charging through hybrid mode synergy can ensure the QoE of EV charging more efficiently.

2.7.2 Hybrid Battery Swapping and Plug-in Charging Mode

In this section, a hybrid coordinated consideration of CSs and BSSs is introduced. Hybrid stations are integrated with the function of battery swapping and plug-in charging under this service mode. When an EV arrives at the station, the driver can choose the battery swapping or charging service based on the personalized demand, such as waiting time and service cost.

Zhong et al. [108] investigated a cooperative mechanism for a CS and a BSS in a microgrid to reduce operation costs. Considering the important role of CS and BSS in electricity and carbon trading, the optimization problem related to operation revenue is formulated based on Nash bargaining theory. Moreover, the optimization problem is modelled as an electricity and carbon scheduling subproblem. With a linearization method, the subproblem is further converted into a MILP optimization problem and solved. Simulation results present the effectiveness of the proposed cooperative strategy compared with a non-cooperative method.

Sun et al. [109] proposed an optimal operation strategy for a BSCS to simultaneously reduce the electricity cost and ensure QoE of EV drivers. Based on a queuing model, the optimization problem of charging scheduling is modelled as a constrained MDP. Then, the optimal strategy is obtained by the standard Lagrangian and dynamic programming methods. Moreover, considering the problem of dimension curse in practical application, the dynamic programming process is transformed into an equivalent threshold optimization problem with a discrete separable convex objective function for real-world applications.

2.7.3 Hybrid V2V and Plug-in Charging Mode

Although plug-in charging is stable and fast [110], the deployment of CS is costly and rigid in location, which still leads to higher electricity prices and longer charging waiting time. The V2V charging mode is flexible in terms of location [67], however with limitations in slow charging power and uncertain energy supply from EV-Ps. The shortcomings under single plug-in and V2V charging modes limit further user QoE enhancements. Thus, a hybrid plug-in and V2V charging could flexibly utilise the advantages of both charging modes [111]. However, the above two charging modes differ in their application scenarios. The plug-in charging mode is used for deterministic charging as the charging place is fixed and public, while V2V charging is used for opportunistic charging as the charging place is flexible and uncertain [112, 57]. It is crucial to figure out how to combine the advantages of V2V charging (high flexibility) and plug-in charging (high stability).

Koufakis et al. [113] consider the cooperation of plug-in and V2V charging mode, via dispatched by offline and online algorithms. Plug-in charging benefits from cheap electricity prices from RES, but energy availability is limited. Thus, EVs are capable and willing to participate in V2V energy transfer to reduce charging costs and increase the utilization of RES. This work minimizes the total charging cost of EVs via a formulated problem of MILP problem. Meanwhile, it optimizes EV charging with full knowledge of EV demand and energy production.

2.8 Research Gaps

At present, plug-in charging, battery-swapping charging and V2V charging are the most mature and widely used charging methods. Plug-in charging and battery-swapping charging have the advantages of fast charging speed and low cost, while V2V charging can realize energy sharing between vehicles and further improve charging efficiency. Therefore, the research on these charging methods is also more in-depth and mature.

In contrast, wireless charging and mobile charging technologies are still in the early stages of development, and there are many technical difficulties and limitations in application scenarios. For example, wireless charging has problems such as low energy transmission efficiency and distance limitations between devices. Mobile charging needs to fully consider factors such as the vehicle's driving path and road conditions to achieve effective charging. These technical difficulties and limitations make the research on wireless charging and mobile charging relatively less. Therefore, this study only conducts a small amount of literature analysis on these two modes in Chapter 2.

My research focuses on plug-in charging optimization (Chapter 4), V2V charging optimization (Chapter 5), and hybrid optimization of V2V and plug-in charging (Chapter 6), because these charging methods have been widely used and researched, and have practical application scenarios and implementation possibilities. Through the optimization research on these charging methods, the charging efficiency can be further improved, the cost can be reduced, and the popularization and development of electric vehicles can be promoted. At the same time, the research on these charging methods can also provide reference for the development of people's EV travel in the future.

Chapter 3

Introduction of Simulation Tool

My research uses Opportunistic Network Environment (ONE) [114] as a simulation environment for EV charging networks to test different optimization approaches. ONE is written in Java by the University of Helsinki, Finland. ONE uses different routing protocols to simulate the sending and receiving of messages in Delay Tolerant Networks (DTN) and generate records of node movement trajectories. Node movement events can be generated in ONE based on different movement models, displaying messages between nodes with various DTN routing algorithms, senders and receivers (types) and real-time graphical display of node movements and messages. The movement of nodes in ONE is implemented by the movement model (definable) and the communication between nodes is based on the node's location, communication range and transmission rate. In addition, the routing function of ONE is determined by the routing model and messages are created by the event generator. Considering that ONE is a discrete event-based simulation engine, simulation effects similar to real city scenarios can be achieved. Therefore, this project flexibly applies ONE to reproduce EV charging information interaction and EV node movement information. In addition, ONE can introduce real-world information (e.g., importing WKT format files of city roads through OpenStreetMap as simulation scenarios and setting EV nodes by modifying parameters), simulate node motion patterns, and generate various result reports (applied to charging management scheme evaluation).

3.1 Core Architecture of ONE Simulator

The ONE simulation platform consists of six core packages: UI, GUI, core, movement, routing and report. As shown in Fig.3.1, the core components of ONE (e.g., nodes defining DTNs and classes for simulation) are contained in the core package, while interface-related classes are contained in the GUI package. the GUI package also contains the playfield sub-package, which defines the program classes displayed in the playfield view. The basic interface classes and the text-based output classes can be found in the UI package. The

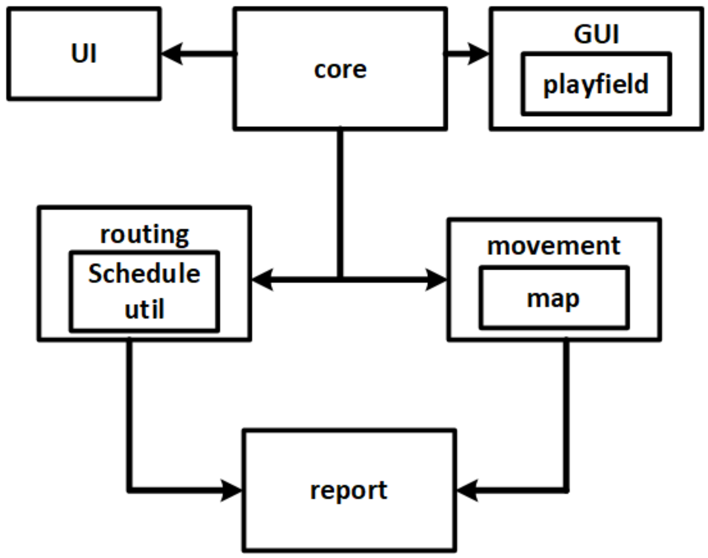


Figure 3.1: Core Architecture of ONE Simulator

routing module can be built from classes in the routing package, and the movement module is built from the movement package. In addition, the report module is implemented through the report package. Among them, the routing module and the movement module provide data sources for the report module. The functionality of each package is independent. For example, the GUI class instantiates the simulator environment from the core package.

3.2 Modules Related to EV Charging

3.2.1 Movement Module

The Movement Model (Fig.3.2) provides the way the node (EV) moves during the simulation, and the definition of coordinates, velocity, and other parameters is done through the model. All the movement models in the simulation are inherited from the MovementModel parent class. Note here that the MovementModel class provides an interface for nodes to request new paths and ask for new paths, and implements the above functions through different subclasses.

The map-based movement model controls node movement in the core road path. the ONE simulator version includes three map-based movement models. 1) Map-based Stochastic Movement (MBM), 2) Shortest Path Map-Based Movement (SPMBM), and 3) Routed Map-Based Movement (RMBM). Here, movement models are able to understand arbitrary map data defined in Well Known Text (WKT). Such data is usually converted from real-world map data or created manually using a Geographic Information System (GIS)

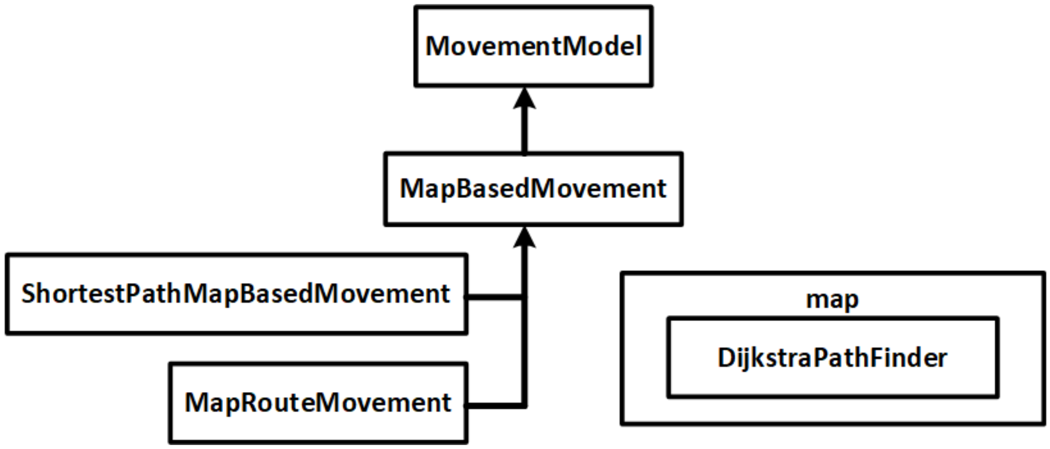


Figure 3.2: Movement Model in ONE

program (e.g. OpenJUMP). The ShortestPathMapBasedMovement model, which inherits from the MapBasedMovement class, is mainly used in this thesis. This model ensures that EVs will only travel in the road topology and find the shortest path between two random map nodes and the end point using the Dijkstra algorithm, which can find the shortest path to travel to the destination in complex urban areas.

3.2.2 Routing Module

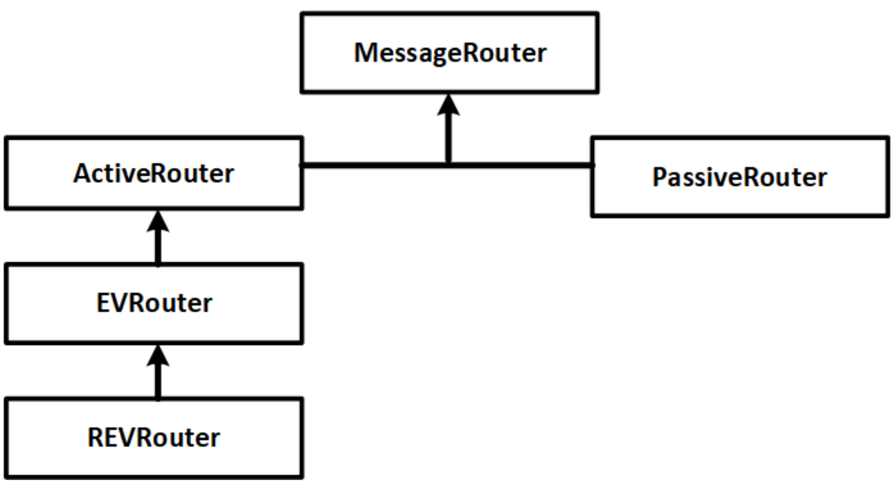


Figure 3.3: Routing Model in ONE

As shown in Fig.3.3, the Routing package in the ONE project provides the routing module, which defines how messages are handled during the entire environment simulation.

MessageRouter class is divided into ActiveRouter and PassiveRouter classes according to active and passive routing, where the ActiveRouter class provides functions such as neighboring node messaging.

The implementation of the message routing module is similar to the movement model: the simulator includes a framework for defining the algorithms and rules used in routing and comes with ready-made implementations of known DTN routing protocols. In order to restore the EV charging network, the tuples in the charging network (e.g., EVs, charging infrastructures, etc.) use active routing protocols. Here, EV router class (charging behavior logic is implemented within specific routing classes) completed in this thesis inherits from ActiveRouter. EV router class inherit ActiveRouter Basic functionality such as simple buffer management and callbacks for various message related events.

3.2.3 Reporting Module

ONE includes reporting modules for message statistics, statistics on the time period of node contacts, etc. The Report class is an abstract superclass of all reporting module classes, and all settings defined therein can be used for all report classes. The report module can be registered to the node's connectivity, message forwarding, movement, and other related events. Thus, when a relevant event of a node occurs, the registered report module can generate data corresponding to the relevant event that occurred. This helps to record the evaluation of the effectiveness of the EV charging network. When the EV charging network is simulated, the reporting module collects charging performance data (charging wait time, charging energy), which facilitates the evaluation of EV charging optimization effects.

3.2.4 Visualization Module

ONE can generate a real-time screen during the simulation through the GUI. Fig3.4 displays a simulation GUI of EV charging network: it includes EV node location, charging infrastructures location, current EV path, etc. Also, the GUI of this EV charging network generates a filter for monitoring the charging status of EVs and charging infrastructures. The simulation GUI allows selecting a node from the EV list for a specific review, facilitating an intuitive understanding of the real-time status of the EV charging network.

3.2.5 Summary

ONE simulator, designed to evaluate routing and application protocols for DTNs. It allows users to create scenes based on different synthetic motion models and real-world traces, and provides a framework It allows users to create scenes based on different synthetic motion models and real-world traces. ONE is used as the simulation platform in this thesis and a large number of functions are rewritten using java to achieve the goal of EV

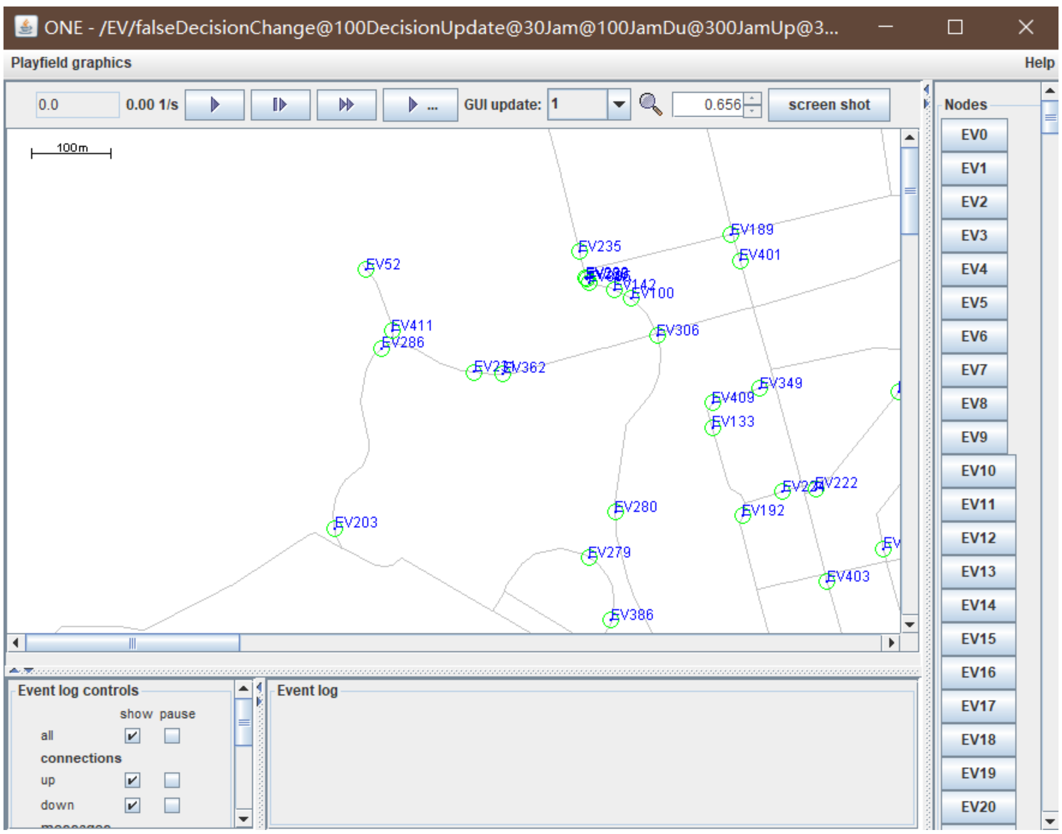


Figure 3.4: GUI of EV Charging Simulator

charging optimization. Here, the advantages of ONE as an EV charging network simulation are presented. The following advantages can be achieved by rewriting ONE to build EV charging simulation:

- ONE includes movement and routing modules that can revert to simulate the EV movement and program the EV action logic.
- ONE can obtain real-time data through simulation. This allows for better reproduction of realistic EV charging optimization problems compared to simulations using offline data.
- ONE can extract background data and analyze the results through report classes. This can be of great help to optimize EV charging.
- ONE supports visualization interface. This can help more third parties or industries to get convenient EV charging optimization analysis.

Chapter 4

Reservation-based EV Charging Recommendation Concerning Charging Urgency Policy

For coping with long charging time and uneven distribution of CSs in urban city, CS-Selection scheme (which/where to charge) and charging scheduling (when/whether to charge) are key solutions. In this chapter, an Urgency First Charging (UFC) scheduling policy is proposed, which orders EV charging via their charging urgency (calculated by their charging demand and remaining parking duration). With the underlying UFC policy, this chapter further proposes a reservation-based CS-Selection scheme that selects the optimal CS with the minimum trip duration (summation of travelling time through CS, and the charging time spent at CS). Meanwhile, EVs would further report their reservations to help anticipate the service congestion status of CSs.

These approaches aims to reduce the charging congestion problems that exists under plug-in charging mode. Technically:

1. Firstly, this chapter proposes a UFC scheduling policy, which calculates charging urgency by EVs' charging demand and parking duration. Here, the charging urgency is enabled as a metric for prioritized scheduling. The EV with higher charging urgency is allowed to be preempted charged. The UFC policy is different from previous works without considering the parking duration (like in works [115, 116, 117]) and those without providing preempted charging (like in works [115, 118]), instead, it guarantees as many EVs as possible to get fully charged before their departure.

2. Further to UFC scheduling policy, this chapter proposes a reservation-based CS-Selection scheme via a total trip duration estimation (based on the summation of time spent at CS and travelling time towards and departs from the CS). Here, the

estimation of the time spent at CS applies the UFC scheduling policy. Many previous CS-Selection schemes are based on historic data (like in works [119, 120]), it is novel in this proposed CS-Selection which is based on real-time charging status at CSs. Meanwhile, in this proposed scheme, EVs are asked to send their charging reservations. Such reservations would benefit the overall allocation of EVs in the network and would significantly improve the user's QoE.

4.1 System Model

4.1.1 Urgency First Charging

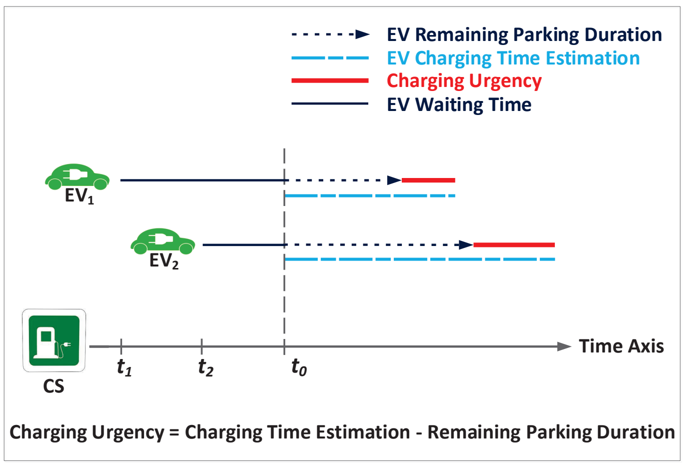


Figure 4.1: Urgency First Charging

This chapter proposes a UFC policy as an underlying scheduling policy (concerning when to charge EVs). The UFC takes into account EVs' parking duration, charging energy demand and allows preempted charging for those EVs with higher "charging urgency". Here, the charging urgency is given by the difference that EV's remaining parking duration minus EV's charging time estimation.

In Fig.4.1, charging urgency is a metric used to determine which EVs should receive priority charging service when multiple EVs are waiting for charging slots. The higher the charging urgency of an EV, the more priority it should receive for charging.

Even though EV_1 arrived earlier than EV_2 and has a shorter remaining parking duration, it will not receive preemptive charging service because EV_2 has a higher charging urgency. The charging algorithm will prioritize EV_2 and charge it first to ensure that it has enough energy to reach its destination. Once EV_2 is fully charged, the charging slot will be made available for EV_1 to charge.

This charging scheduling algorithm is designed to optimize the charging process for all EVs and ensure that they have enough energy to complete their journeys. By prioritizing the EV with the highest charging urgency, the algorithm minimizes the risk of EVs running out of energy and maximizes the efficiency of the charging infrastructure.

If an EV is with higher charging demand and a shorter remaining parking duration, the UFC policy scheduling will improve the possibility that the EV gets a charging service. Meanwhile, the UFC policy can reduce the number of EVs that miss fully charging (due to that some EVs may need to depart before being fully charged). It is worth mentioning that the preempted charging will only occur between EVs plan to be charged, the UFC policy will not interrupt EVs being charged.

4.1.2 Assumption

In this chapter, CSs are distributed in different locations over the city scenario. The GC globally manages EV charging and is equipped with communication module for wireless information exchange with CSs and EVs. EVs' on-board system can communicate with the GC with the equipped wireless devices such as 3G/Long Term Evolution (LTE). EVs request/reply to the GC for CS-Selection. Here, the GC processes the charging requests on the cloud in a centralized manner to optimize the distribution of charging facilities. When an EV is on-the-move and its SOC is lower than the preset threshold, the EV sends its charging request to the GC. The GC processes EV's charging request and starts ranking CSs through which the EV perceive the minimum trip duration (mainly influenced by waiting time). To fully recharge more EVs, the GC jointly considers EVs charging demand and CSs charging status. Here, the UFC scheduling policy is applied to provide preempted charging service for EVs with charging urgency. With this, the GC estimates total trip duration that the EV charges at each CS and selects the CS with the minimum total trip duration. Table 4.1 lists the notations covered in this chapter. It should be noted that some of the parameters are named in line with other chapters, but the notations in this table are only applicable to this chapter.

4.1.3 Problem Formulation

To achieve a better usage of CSs and alleviate charging congestion, the CS-Selection optimization is formulated in this subsection, starting with the notations and following with the objective functions. To facilitate problem formulation, this work has the notations as follows:

- $\delta_{l_{cs}}$: Number of EVs being fully charged at a CS.
- υl_{cs}: Average trip duration for each EV being fully charged at a CS l_{cs}.

Table 4.1: List of Notations of Chapter 4

LIST	Output including available time per charging slot at CS
T_{ev}^{arr}	EV's arrival time at CS
T_{ev}^{tra}	EV's travelling time to reach CS
T_{ev}^{cha}	Estimated charging time upon arrival of EV
T_{ev}^{sta}	Time EV has stayed at the CS after its arrival
T_{cur}	Current time in network
S_{ev}	Moving speed of EV
α	Electric energy consumed per meter
D_{ev}	Parking duration of EV
β	Charging power at CS
N_C	Queue of EVs under charging at CS
N_W	Queue of EVs waiting for charging at CS
N_R	Queue of EVs reserved for charging at CS
V_{ev}	Charging urgency of EV
δ	Number of charging slots at CS
E_{ev}^{max}	Full volume of EV battery
E_{ev}^{cur}	Current volume of EV battery
T_{ev}^{fin}	Charging finish time of EV
EACT$_{cs}$	Estimated available charging time at CS
N_{cs}	Queue of CSs
l_{cs}	Location of a CS
$T_{cs,d}^{min}$	Travelling time from a CS to EV's trip destination
$T_{ev_{(r)}}^{cs,d}$	Trip duration of EV$_r$ through charging at a CS
LIST	Available charging time list of the charging slots at a CS

- N_{CS}: Queue of CSs.
- M: Total trip duration for all EVs being fully charged in the network.
- X: Total number of all EVs being fully charged in the network.

Then the objective functions are as follows:

$$\text{Maximize} \quad X = \sum_{l_{cs} \in N_{cs}} \delta_{l_{cs}} \tag{4.1}$$

$$\text{Minimize} \quad M = \sum_{l_{cs} \in N_{cs}} \delta_{l_{cs}} \times \upsilon l_{cs} \tag{4.2}$$

Here, the time an EV could stay at a CS is constrained by the parking duration. An EV has to depart from the CS after its departure deadline. The objective function (4.1) is set to maximize the total number of all EVs get fully charged, which could better reflects charging scheduling efficiency. To fully charge more EVs in the network, $\delta_{l_{cs}}$ at each CS needs to increase. The objective function (4.2) aims to minimize the total trip duration for all EVs being fully charged in the network. As $\delta_{l_{cs}}$ increases in objective function (4.1), υl_{cs} needs to decrease. υl_{cs} and $\delta_{l_{cs}}$ are related to N_{cs}, a larger N_{cs} enables a small υl_{cs}, this is because EVs could be distributed at more CSs. Since N_{cs} is immutable as it refers to number of total CSs, υl_{cs} can only be reduced by distributing EVs equally among the CSs as an ideal situation.

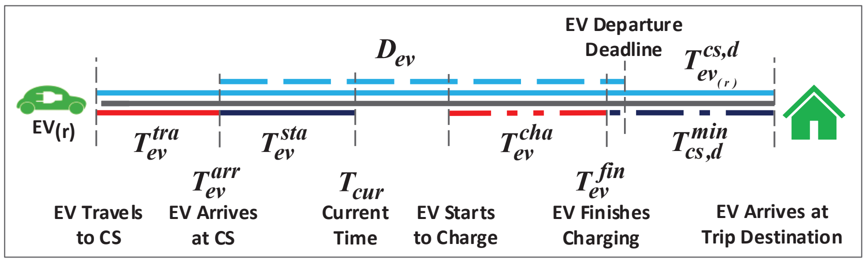


Figure 4.2: T-variables on time axis

Fig.4.2 illustrates T-variables in a timeline from EV$_r$'s original location to its destination with an intermediate charging at a CS.

4.2 System Design

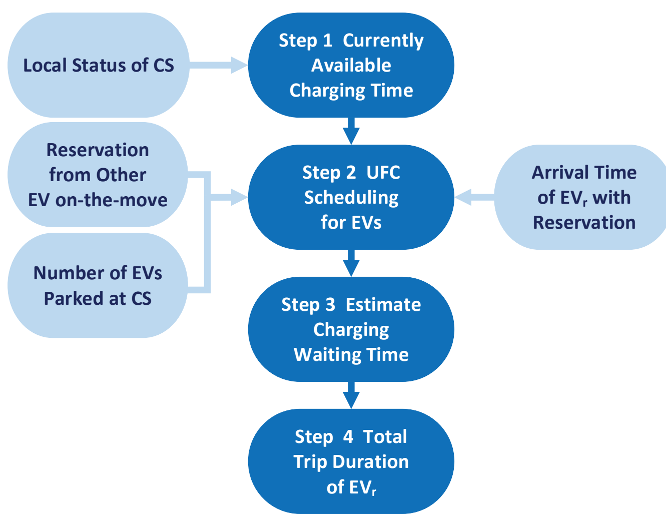


Figure 4.3: Flow Chart of Computation Logic

EV drivers want to shorten their trip durations. Therefore, the GC calculates EV's total trip duration at each CS with an intermediate charging and select the optimal CS. Referred to Fig.4.3, the total trip duration of an incoming EV with reservation (EV$_r$) is obtained through the follow steps:

Step 1: Through the local charging status, the GC estimates the available time at charging slots.

Step 2: When EV$_r$ requests, the output of **Step 1**, the queue of parked EVs and reservations of on-the-move EVs are aggregated to estimate the charging scheduling (via UFC policy) when EV$_r$ arrives.

Step 3: The GC calculates charging waiting time through the scheduling estimated by **Step 2**.

Step 4: Through the charging waiting time estimation by **Step 3** and the EV$_r$'s trip time drives to/departs from the CS, the total trip duration is estimated.

4.2.1 Estimation of CS Charging Status

Algorithm 4.1 Estimation of CS Charging Status

1: **if** no EV is under charging **then**
2:     add T_{cur} in LIST with δ times
3:     **return** LIST
4: **end if**
5: **for** $(n = 1; n \leq N_C; n++)$ **do**
6:     **if** $((T_{cur} + \frac{E^{max}_{ev_{(n)}} - E^{cur}_{ev_{(n)}}}{\beta}) \leq (T^{arr}_{ev_{(n)}} + D_{ev_{(n)}}))$ **then**
7:         LIST.ADD$(\frac{E^{max}_{ev_{(n)}} - E^{cur}_{ev_{(n)}}}{\beta} + T_{cur})$
8:     **else**
9:         LIST.ADD$(T^{arr}_{ev_{(n)}} + D_{ev_{(n)}})$
10:     **end if**
11: **end for**
12: **if** $(N_C < \delta)$ **then**
13:     **for** $(m = 1; m \leq (\delta - N_C); m++)$ **do**
14:         LIST.ADD(T_{cur})
15:     **end for**
16: **end if**
17: sort LIST with ascending order
18: **return** LIST

Considering that CS has several charging slots to charge multiple EVs in parallel, the EVs under charging is characterized in the queue of N_C. The current time in the network is denoted as T_{cur}. If no EV currently parking at the CS for charging, T_{cur} will be added into the LIST (available charging time list of the charging slots) with δ (number of charging slots) times to indicate the CS is available, and the available charging time of all charging slots is T_{cur}, as line 2 in Algorithm 4.1 demonstrated. Lines from 5 to 11 present the charging process of EV$_n$ (EVs in the queue of N_C). Line 6 compares parking duration

$D_{ev_{(n)}}$ and time $(\frac{E^{max}_{ev_{(n)}} - E^{cur}_{ev_{(n)}}}{\beta})$ to fully charge EV$_n$. If EV$_n$ could get fully charged before its departure, given by the condition $((T_{cur} + \frac{E^{max}_{ev_{(n)}} - E^{cur}_{ev_{(n)}}}{\beta}) \leq (T^{arr}_{ev_{(n)}} + D_{ev_{(n)}}))$, its charging finish time $(\frac{E^{max}_{ev_{(n)}} - E^{cur}_{ev_{(n)}}}{\beta} + T_{cur})$ will be added to the LIST. Otherwise, the charging finish time will be given by $(T^{arr}_{ev_{(n)}} + D_{ev_{(n)}})$ instead, which indicates that EV$_n$ has to leave after the departure deadline.

The lines between 12 and 16 consider the situation that not all charging slots are occupied, T_{cur} will be added to the LIST with $(\delta - N_C)$ times (number of available charging slots). Here, T_{cur} will be the available charging time for these unoccupied charging slots. Followed by lines 17 and 18, Algorithm 4.1 returns the LIST with ascending order. The LIST indicates the charging status for each charging slot in the order of their available time.

4.2.2 Estimation of Available Charging Time

To alleviate charging congestion at CSs, the CS-Selection scheme attempts to allocate EVs evenly across CSs. In practice, EVs have different charging urgency requirements and some EVs may need to be preempted charged. Therefore, the GC estimates charging status of CSs when the on-the-move EV that sends charging request (EV$_r$) arrives. Algorithm 4.2 and Algorithm 4.3 calculate the Estimated Available Charging Time (EACT) at the CS underlying the UFC policy charging scheduling. There are two cases separately introduced in Algorithm 4.2 and Algorithm 4.3:

- **Case-1:** Algorithm 4.2 considers the incoming EVs (EV$_r$ and other EVs made reservations) have chance to be preempted charged upon their arrival (only with high charging urgency), comparing with EVs in the queue of N_W.

- **Case-2:** Algorithm 4.3 considers the incoming EVs will be charged, in which case, all EVs in the queue of N_W have been charged or the CS has no parked EV.

4.2.2.1 Case-1

Initially, the queue of N_W is sorted with the UFC policy, EV$_r$ is added into the queue of N_R (sorted with the UFC order). Lines between 4 and 6 refer to the condition that EV$_r$ arrives at a CS with no other EVs waiting for charging, then the EACT will be further calculated in Algorithm 4.3. The LIST has been sorted in Algorithm 4.1 with the earliest available order of charging slots. Thus, LIST.GET(0) represents the first available charging time. When the first charging slot is available, EV$_i$ (the EV in the queue of N_W) and EV$_j$ (the EV in the queue of N_R) will be compared to decide their charging priority. The comparison is indicated in loop operation starts from line 7. Here, the charging urgency (V_{ev}) will be the indicator to determine the charging order among the EVs, given by:

Algorithm 4.2 EACT Case-1$\langle$LIST, $N_R\rangle$

sort the queue of N_W according to UFC order
add EV$_r$ into the queue of N_R
sort the queue of N_R according to UFC order
if no EV is waiting for charging **then**
    return EACT Case-2$\langle$LIST, $N_R\rangle$
else
    for $(i = 1; i \leq N_W; i++)$ **do**
        for $(j = 1; j \leq N_R; j++)$ **do**
            if (LIST.GET(0) $> T^{arr}_{ev_{(j)}}$) $\cap$ $(V_{ev_{(j)}} > V_{ev_{(i)}})$ **then**
                if (EV$_j$ equals to EV$_r$) **then**
                    return LIST.GET(0)
                else
                    if (($T^{cha}_{ev_{(j)}}$ + LIST.GET(0)) $<$ ($D_{ev_{(j)}}$ + $T^{arr}_{ev_{(j)}}$)) **then**
                        $T^{fin}_{ev_{(j)}}$ = LIST.GET(0) + $T^{cha}_{ev_{(j)}}$
                    else
                        $T^{fin}_{ev_{(j)}}$ = $D_{ev_{(j)}}$ + $T^{arr}_{ev_{(j)}}$
                    end if
                    replace the LIST.GET(0) with $T^{fin}_{ev_{(j)}}$
                    sort LIST with ascending order
                    record EV$_j$ into DELETESET
                end if
            end if
        end for
        remove EVs recorded in DELETESET, from the queue of N_R
        if (($T^{cha}_{ev_{(i)}}$ + LIST.GET(0)) $<$ ($D_{ev_{(i)}}$ + $T^{arr}_{ev_{(i)}}$)) **then**
            $T^{fin}_{ev_{(i)}}$ = LIST.GET(0) + $T^{cha}_{ev_{(i)}}$
        else
            $T^{fin}_{ev_{(i)}}$ = $D_{ev_{(i)}}$ + $T^{arr}_{ev_{(i)}}$
        end if
        replace the LIST.GET(0) with $T^{fin}_{ev_{(i)}}$
        sort LIST with ascending order
    end for
end if
return EACT Case-2$\langle$LIST, $N_R\rangle$

$$V_{ev} = T_{ev}^{cha} - (T_{ev}^{arr} + D_{ev} - T_{ev}^{sta}) \tag{4.3}$$

In this equation, T_{ev}^{arr} reflects the time slot an EV arrives at CS, T_{ev}^{cha} reflects the charging time. T_{ev}^{sta} reflects the time that the EV has stayed at the CS after its arrival (the time at which the algorithm is called minus the time at EV arrives), calculated by $(T_{cur} - T_{ev}^{arr})$. Here, (T_{ev}^{arr} + D_{ev} − T_{ev}^{sta}) refers to the remaining parking duration of a EV. Line 9 refers to the condition that EV$_j$'s charging urgency $V_{ev_{(j)}}$ is higher than EV$_i$'s charging urgency $V_{ev_{(i)}}$, and EV$_j$ has arrived at the CS when the first charging slot is available (LIST.GET(0) $>$ $T_{ev_{(j)}}^{arr}$), then EV$_j$ can preempt charging before EV$_i$. However at line 10, there are two different conditions.

On the one hand, if EV$_j$ (the EV in the queue of N_R being processed in current loop operation) is the EV$_r$. This implies that EV$_r$ is able to be preempted charged upon its arrival, Algorithm 4.2 will return the EACT as LIST.GET(0) at line 11.

On the other hand, lines from 13 to 18 consider the other condition that EV$_j$ could preempt charging prior to EV$_i$, but EV$_j$ is other than EV$_r$. EV$_j$'s charging finish time $T_{ev_{(j)}}^{fin}$ will take place LIST.GET(0). As EV$_j$ is currently travelling and has not yet arrived the CS, its charging time $T_{ev_{(j)}}^{cha}$ is estimated by:

$$T_{ev_{(j)}}^{cha} = \frac{E_{ev_{(j)}}^{max} - E_{ev_{(j)}}^{cur} + (S_{ev} \times T_{ev_{(j)}}^{tra} \times \alpha)}{\beta} \tag{4.4}$$

Here, extra energy is consumed due to EV$_j$'s travelling from its current location to the CS, which is calculated as $(S_{ev} \times T_{ev_{(j)}}^{tra} \times \alpha)$. Under the condition that meets line 13, EV$_j$ can get fully charged within its parking duration ($D_{ev_{(j)}}$ + $T_{ev_{(j)}}^{arr}$), then $T_{ev_{(j)}}^{fin}$ is estimated as (LIST.GET(0) + $T_{ev_{(j)}}^{cha}$). If EV$_j$ can not get fully charged, line 16 estimates $T_{ev_{(j)}}^{fin}$ as EV$_j$'s departure deadline ($D_{ev_{(j)}}$ + $T_{ev_{(j)}}^{arr}$).

Because the charging slot is occupied by EV$_j$, the LIST will be updated in the ascending order so that LIST.GET(0) will still be the earliest available charging time. Since EV$_j$ has been scheduled, it will be removed from the queue of N_R which is given at line 24. EV$_j$ will not be scheduled to get preempted charged when it does not meet the preempt charging condition ($V_{ev_{(j)}}$ is higher than $V_{ev_{(i)}}$ and there is an available slot when EV$_j$ arrives). Therefore, only EV$_i$ could get charged. Lines from 25 to 28 calculate EV$_i$'s charging finish time $T_{ev_{(i)}}^{fin}$. Considering the parking duration, If EV$_i$ could be fully charged (($T_{ev_{(i)}}^{cha}$ + LIST.GET(0)) $<$ ($D_{ev_{(i)}}$ + $T_{ev_{(i)}}^{arr}$)), $T_{ev_{(i)}}^{fin}$ will be calculated as (LIST.GET(0) + $T_{ev_{(i)}}^{cha}$). Otherwise, $T_{ev_{(i)}}^{fin}$ will be calculated as ($D_{ev_{(i)}}$ + $T_{ev_{(i)}}^{arr}$). Lines 30 and 31 update the LIST to ensure that LIST.GET(0) is the first available charging time. Eventually, if EV$_r$ is still not scheduled for charging within the loop operation, Algorithm 4.3 is applied to schedule the rest EVs in the queue of N_R at line 34.

4.2.2.2 Case-2

Algorithm 4.3 EACT Case-2$\langle$LIST, $N_R\rangle$

insert all EVs (in the queue of N_R) into N_R^f
sort the queue of N_R^f according to FIFS order
for $(k = 1; k \leq N_R; k++)$ **do**
  for $(l = 1; l \leq N_R^f; l++)$ **do**
    if $(($LIST.GET(0) $> T^{arr}_{ev_{(l)}}) \cap ($LIST.GET(0) $> T^{arr}_{ev_{(k)}}) \cap (V_{ev_{(l)}} > V_{ev_{(k)}}))$ **then**
      if (EV$_l$ equals to EV$_r$) **then**
        return LIST.GET(0)
      else
        if $((T^{cha}_{ev_{(l)}}$ + LIST.GET(0)) $< (D_{ev_{(l)}} + T^{arr}_{ev_{(l)}}))$ **then**
          $T^{fin}_{ev_{(l)}} =$ LIST.GET(0) $+ T^{cha}_{ev_{(l)}}$
        else
          $T^{fin}_{ev_{(l)}} = D_{ev_{(l)}} + T^{arr}_{ev_{(l)}}$
        end if
        replace the LIST.GET(0) with $T^{fin}_{ev_{(l)}}$
        sort LIST with ascending order
        record EV$_l$ into DELETESET
      end if
    end if
  end for
  remove EVs recorded in DELETESET, from the queues of N_R and N_R^f
  if (EV$_k$ is not EV$_r$) **then**
    if (LIST.GET(0) $> T^{arr}_{ev_{(k)}}$) **then**
      if $((T^{cha}_{ev_{(k)}}$ + LIST.GET(0)) $< (D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}))$ **then**
        $T^{fin}_{ev_{(k)}} =$ LIST.GET(0) $+ T^{cha}_{ev_{(k)}}$
      else
        $T^{fin}_{ev_{(k)}} = D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}$
      end if
    else
      if $((T^{arr}_{ev_{(k)}} + T^{cha}_{ev_{(k)}}) < (D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}))$ **then**
        $T^{fin}_{ev_{(k)}} = T^{arr}_{ev_{(k)}} + T^{cha}_{ev_{(k)}}$
      else
        $T^{fin}_{ev_{(k)}} = D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}$
      end if
    end if
    replace the LIST.GET(0) with $T^{fin}_{ev_{(k)}}$
    sort LIST with ascending order
  else
    if (LIST.GET(0) $> T^{arr}_{ev_{(r)}}$) **then**
      return LIST.GET(0)
    else
      return $T^{arr}_{ev_{(r)}}$
    end if
  end if
end for

If the queue of N_W is empty or EV$_r$ fails to get preempted charged, the GC only needs to consider charging priority among EV$_r$ and the other EVs in the queue of N_R. The inputs of Algorithm 4.3 (the LIST and the queue of N_R) have been updated by Algorithm 4.2. All EVs in the queue of N_R are added into the queue of N_R^f at line 1. The queue of N_R^f is then sorted as a queue scheduled in FIFS order. The loop operation from line 3 goes through EV$_l$ (the EV in the queue of N_R^f), meanwhile loop operation from line 4 goes through EV$_k$ (the EV in the queue of N_R). If EV$_l$ has arrived at the CS before LIST.GET(0), EV$_k$ has arrived at the CS before LIST.GET(0) and EV$_l$ is with a higher charging urgency ($V_{ev_{(l)}} > V_{ev_{(k)}}$), EV$_l$ is allowed to be charged prior to EV$_k$. Under the conditions specified in line 5, there are two cases:

- At lines 6 and 7, if the EV$_l$ in the current loop is EV$_r$, the EACT will be returned as LIST.GET(0).
- Lines 8 to 16 refer that EV$_l$ could get charged before EV$_k$, however EV$_l$ is other than EV$_r$. LIST.GET(0) will be replaced with EV$_l$'s charging finish time $T^{fin}_{ev_{(l)}}$. Note that if EV$_l$ could get fully charged before its departure, $T^{fin}_{ev_{(l)}}$ will be calculated as (LIST.GET(0)+$T^{cha}_{ev_{(l)}}$). If EV$_l$ could not get fully charged, $T^{fin}_{ev_{(l)}}$ will be calculated as ($D_{ev_{(l)}}$ + $T^{arr}_{ev_{(l)}}$). Then line 15 sorts the LIST to ensure the LIST is with available time order.

As EV$_l$ has been scheduled for charging, it will be removed from the queues of N_R and N_R^f at line 20. It should be mentioned that EV$_l$ and EV$_k$ are EVs in the initial queue of N_R, the queues of N_R and N_R^f have same EVs but sorted with two different scheduling policy. Any EV$_l$ mapping to EV$_k$ that is excluded at line 20, will no longer appear in subsequent loop operations. After EV$_l$ that meets the above condition has been scheduled, Algorithm 4.3 only needs to schedule the rest EV$_k$. There are two different cases depends on whether EV$_k$ is EV$_r$:

- Lines from 21 to 36 process the condition that EV$_k$ is other than EV$_r$. Depending on whether EV$_k$ arrives before LIST.GET(0) and whether EV$_k$ could be fully charged, there are four different sub-cases. Firstly, if EV$_k$ arrives before LIST.GET(0) and could be fully charged within its parking duration (($T^{cha}_{ev_{(k)}}$ + LIST.GET(k)) $<$ ($D_{ev_{(k)}}$ + $T^{arr}_{ev_{(k)}}$)), $T^{fin}_{ev_{(k)}}$ will be calculated as (LIST.GET(0)+$T^{cha}_{ev_{(k)}}$) at line 24. Secondly, if EV$_k$ arrives before LIST.GET(0) but could not be fully charged within its parking duration, $T^{fin}_{ev_{(k)}}$ will be calculated as ($D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}$) at line 26. Thirdly, if EV$_k$ arrives later than LIST.GET(0) but could be fully charged within its parking duration, $T^{fin}_{ev_{(k)}}$ will be calculated as ($T^{arr}_{ev_{(k)}} + T^{cha}_{ev_{(k)}}$). In the last sub-cases, if EV$_k$ arrives later than LIST.GET(0) and could not be fully charged within its parking duration, $T^{fin}_{ev_{(k)}}$ will be returned as ($D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}$). Then $T^{fin}_{ev_{(k)}}$ will take place LIST.GET(0) at line 35 and the LIST will be sorted with ascending order at line 36.

- Lines from 37 to 43 consider the final condition that EV_k in current loop is EV_r. EV_r's arrival time will be compared with LIST.GET(0) concerning when EV_r could get charged. LIST.GET(0) is returned as the EACT at lines 39 if EV_r arrives before the first available charging slot. In the other condition under line 41, its arrival time ($T^{arr}_{ev_{(r)}}$) is returned as the EACT.

4.2.3 CS-Selection Decision Making

Algorithm 4.4 CS-Selection Decision Making

```
1: for ∀l_cs ∈ N_cs do
2:     calculate T^min_{cs,d}
3:     calculate EACT_cs via Algorithm 4.3
4:     if ((T^cha_{ev(r)} + EACT_cs) ≤ (D_{ev(r)} + T^arr_{ev(r)})) then
5:         T^{cs,d}_{ev(r)} = T^cha_{ev(r)} + EACT_cs + T^min_{cs,d}
6:     else
7:         T^{cs,d}_{ev(r)} = T^arr_{ev(r)} + D_{ev(r)} + T^min_{cs,d}
8:     end if
9: end for
10: l^min_cs ← arg min(T^{cs,d}_{ev(r)})
11: return l^min_cs
```

As to select the CS with the minimum time spent through an entire charging process (total trip duration $T^{cs,d}_{ev_{(r)}}$), the CS-Selection scheme calculates total trip duration ($T^{cs,d}_{ev_{(r)}}$) at each CS. Here, $T^{cs,d}_{ev_{(r)}}$ is calculated with the following three inputs:

1. The duration EV_r spends at the selected CS, which is given by the lines between 5 and 7 in Algorithm 4.4. It refers to the EV's charging and waiting time (duration before the EV gets charging service). Here, the EACT at CS (with location l_{cs}) has been estimated by the Algorithm 4.3.

2. The travelling time from the selected CS to EV_r's trip destination, given by $T^{min}_{cs,d}$.

Considering the parking duration, $T^{cs,d}_{ev_{(r)}}$ is calculated in two cases to refer that EV_r to be fully/not fully charged respectively. Firstly, if EV_r could get a fully charged service before it departure deadline $((T^{cha}_{ev_{(r)}} + \mathrm{EACT}_{cs}) \leq (D_{ev_{(r)}} + T^{arr}_{ev_{(r)}}))$, $T^{cs,d}_{ev_{(r)}}$ is given by:

$$T^{cs,d}_{ev_{(r)}} = T^{cha}_{ev_{(r)}} + \mathrm{EACT}_{cs} + T^{min}_{cs,d} \tag{4.5}$$

In the other case, EV_r could not get a fully charged because it has to depart at its departure deadline ($T^{arr}_{ev_{(r)}} + D_{ev_{(r)}}$), $T^{cs,d}_{ev_{(r)}}$ is calculated by the following calculation at line 7:

$$T^{cs,d}_{ev_{(r)}} = T^{arr}_{ev_{(r)}} + D_{ev_{(r)}} + T^{min}_{cs,d} \tag{4.6}$$

When loop operation finished at line 9, $T^{cs,d}_{ev_{(r)}}$ for each CS is obtained. The GC will select the CS with the minimum $T^{cs,d}_{ev_{(r)}}$ together with its location l^{min}_{cs} back to EV$_r$ as the CS-Selection decision. Then, the CS-Selection scheme calculates the total trip duration ($T^{cs,d}_{ev_{(r)}}$) at each CS. Here, $T^{cs,d}_{ev_{(r)}}$ is calculated with the following inputs:

1. The duration EV$_r$ spends at the selected CS, which is given by the lines between 5 and 7 in Algorithm 4.4. It refers to the EV's charging and waiting time (duration before the EV gets charging service). Here, the EACT at CS (with location l_{cs}) has been estimated by the Algorithm 4.3.

2. The travelling time from the selected CS to EV$_r$'s trip destination, given by $T^{min}_{cs,d}$.

Considering the parking duration, $T^{cs,d}_{ev_{(r)}}$ is calculated in two cases to refer that EV$_r$ to be fully/not fully charged respectively. Firstly, if EV$_r$ could get a fully charged service before it departure deadline $((T^{cha}_{ev_{(r)}} + \text{EACT}_{cs}) \leq (D_{ev_{(r)}} + T^{arr}_{ev_{(r)}}))$, $T^{cs,d}_{ev_{(r)}}$ is given by:

$$T^{cs,d}_{ev_{(r)}} = T^{cha}_{ev_{(r)}} + \text{EACT}_{cs} + T^{min}_{cs,d} \tag{4.7}$$

In the other case, EV$_r$ could not get a fully charged because it has to depart at its departure deadline ($T^{arr}_{ev_{(r)}} + D_{ev_{(r)}}$), $T^{cs,d}_{ev_{(r)}}$ is calculated by the following calculation at line 7:

$$T^{cs,d}_{ev_{(r)}} = T^{arr}_{ev_{(r)}} + D_{ev_{(r)}} + T^{min}_{cs,d} \tag{4.8}$$

When loop operation finished at line 9, $T^{cs,d}_{ev_{(r)}}$ for each CS is obtained. The GC will select the CS with the minimum $T^{cs,d}_{ev_{(r)}}$ together with its location l^{min}_{cs} back to EV$_r$ as the CS-Selection decision.

4.3 Performance Evaluation

This work applies ONE to build a city charging system simulation scenario. In Fig.4.4, a 4500×3400 m^2 area scenario demonstrates the urban area of Helsinki city in Finland. EVs are configured using Coda Automotive [121] with 33.8 kWh maximum electricity capacity, 193 km max travelling distance and average energy consumption of 0.1751 kWh/km. All EVs' batteries are with full volume at the beginning of the simulation.

To classify different EVs types, three SOC thresholds 30%, 40% and 50% are set. EVs are initialized in the scenario with variable moving speed from $30km/h$ to $50km/h$. The speed of EVs change upon each path to reflect the impact of traffic. Each EV would randomly select its destination. Whenever the destination is reached, a new destination will be randomly selected by the GC, until its SOC reaches the preset threshold. Besides, 7 CSs are deployed in the city scenario and provide fast charging. CSs are equipped with 5 charging slots. This work applies the centre manner for communication between EVs,

Figure 4.4: Simulation Scenario of Helsinki City

CSs and the GC. The GC processes all charging requests from all EVs and make CS-Selection decision to EVs whenever EVs request CS-Selection. The EV with request then would travel towards the decided CS for charging with the shortest road path underlying the Helsinki road topology.

The simulation lasts for a 12 hours' duration with updating per 0.1s, where EVs' positions, speeds and energies are updated every 0.1s, no matter EVs are on the road or parked at CSs. Unless mentioned, incoming EVs are scheduled underlying the UFC policy, as detailed in Section 4.1.1. The following CS-Selection schemes are evaluated for comparison:

- **Proposed**: The GC returns the decided CS with the minimum total trip duration by the Algorithm 4.4, indicated as UFC with reservation.

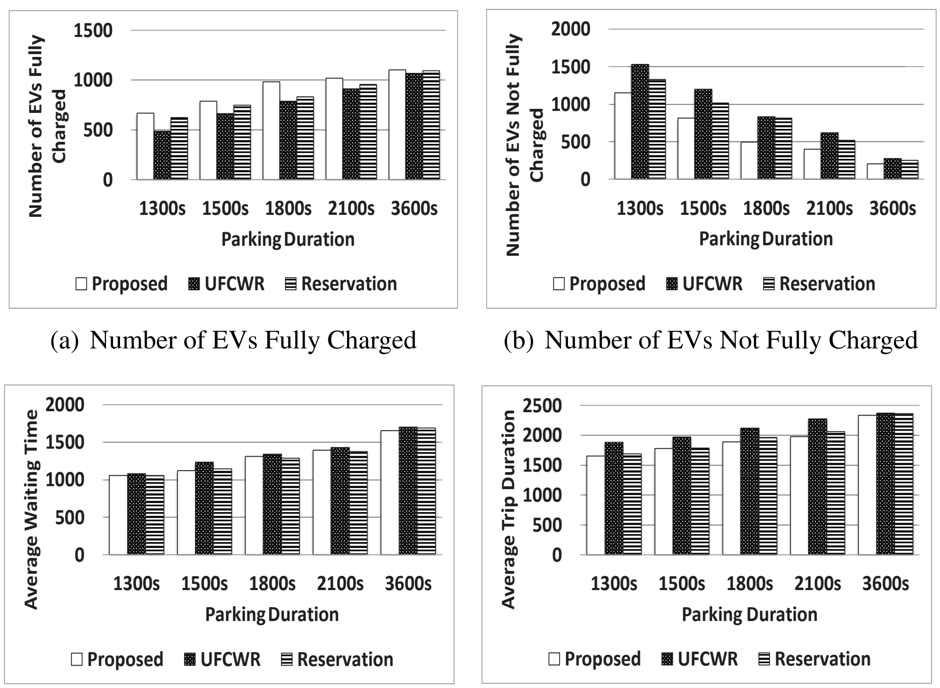
- **Urgency First Charging Without Reservation (UFCWR) [4]**: Literature work that the GC selects the CS with the EACT which is detailed in Algorithm 4.2, but does not ask EVs making reservations to CSs. The EVs' charging scheduling in simulation is based on the UFC policy.

- **Reservation**: The reservation scheme is based on FIFS charging scheduling [122]. The GC returns the CS-Selection decision by the EACT which considers both parked EVs and EVs made reservations.

To compare different simulation results, the following performance metrics are evaluated:

- **Number of EVs Fully Charged**: It is a performance metric at the CS side, which refers to the total number counting of EVs get fully charged service in the network within the simulation duration (each EV can be fully charged and counted for several times).
- **Number of EVs Not Fully Charged**: Number of EVs not fully charged although they have arrived at a CS. In the extreme case, an EV could not get charging service within its parking duration, which degrades user QoE, and the EV needs to continuously find a new CS for charging.
- **Average Waiting Time**: It is a performance metric at the EV side, which represents the average time costs that an EV get fully charged after it arrives at a selected CS.
- **Average Trip Duration**: The average trip duration sums the travelling time that an EV travels through the decided CS and its charging time the EV spends at the CS.

4.3.1 Influence of Parking Duration



(a) Number of EVs Fully Charged (b) Number of EVs Not Fully Charged

(c) Average Waiting Time (d) Average Trip Duration

Figure 4.5: Influence of Parking Duration (EV Density: 330 EVs & Charging Power: 62kWh)

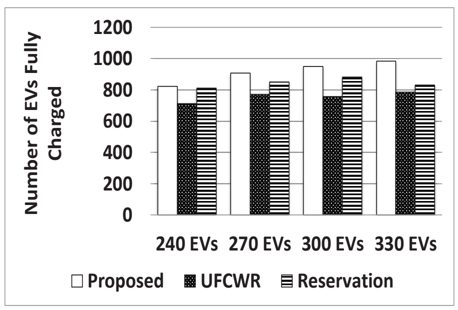
In the first group of simulations, EV density and charging power are fixed. Here, the parking duration are set to 1300s, 1500s, 1800s, and 2100s respectively. In 1800s, an EV could complete a fully charging from empty battery volume to full battery volume. Here, charging slots would terminate EVs' charging service after their departure deadline. It refers that with a higher parking duration, all of the three CS-Selection schemes achieve a higher number of EVs get fully charged in Fig. 4.5(a). However, as both the proposed scheme and the reservation scheme allow EVs making reservations, they have more accuracy in the EACT than the UFCWR scheme. Thus the GC can allocate EVs towards a CS with lower congestion level. Since the proposed scheme takes into account the charging urgency and would allow preempted charging, it avoids some EVs having to leave CS when the parking duration expires after a long wait but not getting fully charged. With the benefit of the UFC policy, more EVs could get fully charged comparing with the reservation scheme.

In Fig.4.5(b), the proposed scheme has an obvious advantage over the reservation scheme and the UFCWR scheme. Especially when the parking duration is the primary constrain, congestion would occur at CSs, EVs with higher charging urgency would require preempted charging, thus charging scheduling becomes significant. In Fig.4.5(c), the UFCWR scheme suffers from the longest average waiting time among the three schemes, no matter how parking duration changes. The average waiting time of the proposed scheme and the reservation scheme are at a similar level. Because both the reservation scheme and the proposed scheme enable the GC to estimate CSs charging status more accurate, it can prevent EVs from driving to a CS with a high level of congestion. However the proposed scheme has certain advantages as the proposed scheme achieves a larger number of EVs fully charged (in Fig.4.5(a)). The proposed scheme achieves a shorter average trip duration than the UFCWR scheme and the reservation scheme in Fig.4.5(d). With the increasing parking duration, the advantage of the proposed scheme becomes more significant. Because in Algorithm 4.4 the proposed CS-Selection scheme jointly considers the time from the EV's current location to the CS and the time from the CS to EV's destination, so the proposed scheme performs better than the other two schemes in average trip duration.

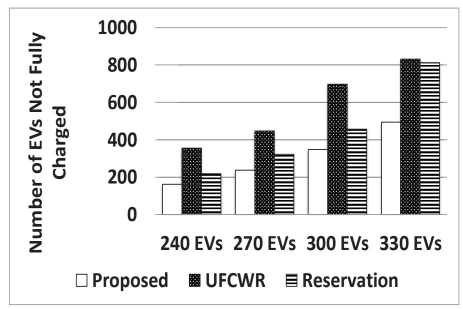
The parking duration are set to 3600s in the last set of simulations. As there are not many EVs in the network, most EVs can be fully charged in Fig.4.5(a) and only a few EVs can not fully charged in Fig.4.5(b). Meanwhile, the average waiting time and trip duration fail to reflect the difference between the three schemes. This is because the advantages of schemes can be better reflected when congestion occurs.

4.3.2 Influence of EV Density

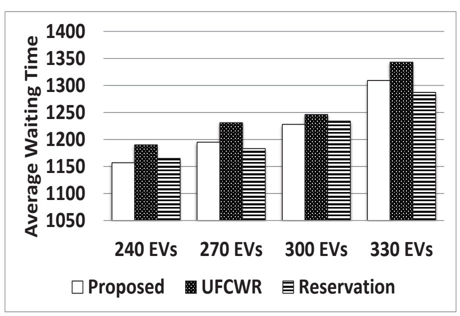
In the second group of simulations, EV's parking duration is set to 1800s and charging power to 62kW. Then the results of three different CS-Selection schemes are evaluated when changing number of EVs. In Fig.4.6(a), the result shows that the proposed scheme



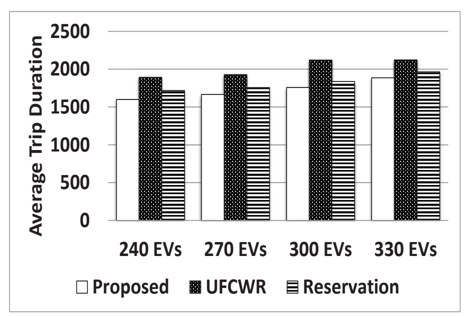
(a) Number of EVs Fully Charged



(b) Number of EVs Not Fully Charged



(c) Average Waiting Time



(d) Average Trip Duration

Figure 4.6: Influence of EV Density (Parking Duration: 1800s & Charging Power: 62kWh)

Table 4.2: Influence of EV Density (EV Density: 660 & Parking Duration: 3600s & Charging Power: 62kWh)

Performance Metrics\CS-Selection Schemes	Proposed	UFCWR	Reservation
Number of EVs Fully Charged	1401	883	870
Number of EVs Not Fully Charged	1844	2973	2922
Average Waiting Time (s)	2031	2377	2242
Average Trip Duration (s)	4288	4883	4743

achieves the highest number of EVs fully charged. Especially when the total number of EVs increases, the proposed scheme performs much better than the reservation scheme and the UFCWR scheme. Here, the proposed scheme achieves the higher number of EVs fully charged because it considers the charging urgency of EVs and allows preempted charging.

The result in Fig.4.6(b) also proves the advantage of the proposed scheme. It is worth mentioning that when the number of EVs increased by 330, the difference between the proposed scheme and the reservation scheme has a huge increase, this is because more congestion occurs when the number of EV increases and charging scheduling becomes significant. As the total number of EVs increases, the average waiting time and the average trip duration in Fig.4.6(c) and Fig.4.6(d) increase as well. This is due to the more charging congestion happens. The average waiting time of the proposed scheme and the reservation scheme are at a similar level as shown in Fig.4.6(c), shorter than the UFCWR scheme. This is because the UFCWR scheme calculates the EACT without considering EVs' reservations, thus the CSs charging status are not able to be accurately predicted and the GC may select a CS with charging congestion. Due to the difference of number of EVs fully charged, the proposed scheme has an advantage over the reservation scheme as it allows more EVs get fully charged (in Fig.4.6(a)). In Fig.4.6(d), the proposed scheme achieves the shortest average trip duration among the three schemes. This is because Algorithm 4.4 jointly considers travelling time and charging time, which is different from the reservation scheme and the UFCWR scheme.

In Table 4.2, the number of EVs is increased and the parking duration is set to 3600s (otherwise most EVs cannot be fully charged). This setting reflects that when the number of vehicles increases and congestion occurs, the proposed scheme increases the probability of EV getting fully charged within the limited parking duration. This scheme also reduces the total trip time as it considers the charging urgency.

4.3.3 Influence of Charging Power

In the third group of simulations, the parking duration is fixed to 1800s and EV density is set to 330 EVs to observe the influence of charging power. In this chapter, DC charging (fast charging technology) is applied to supplement EV energy. Fast charging reduces

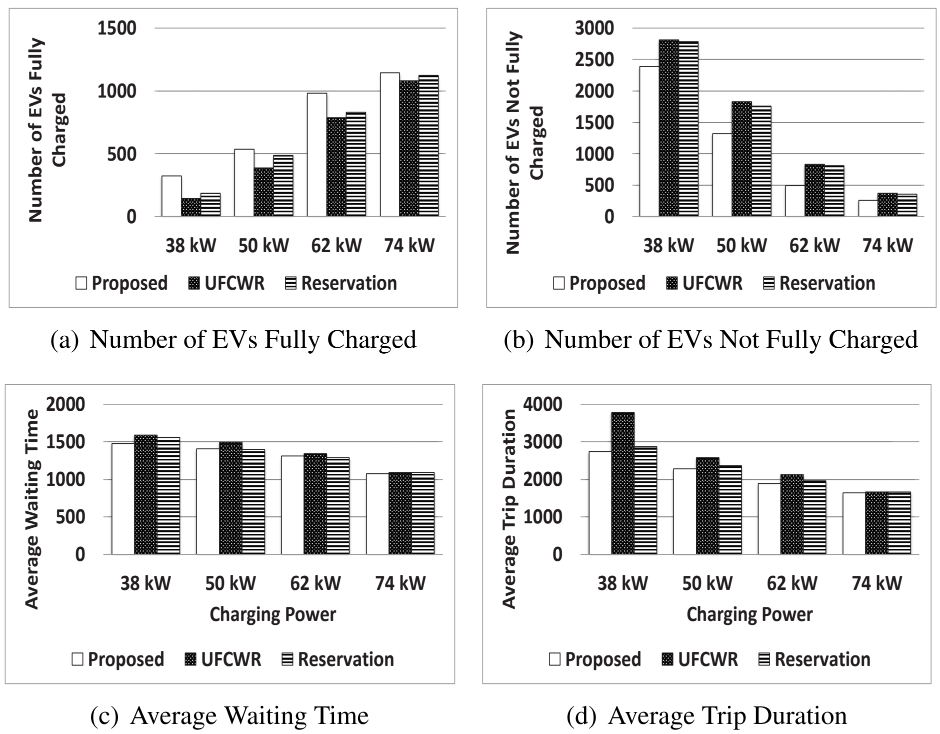


Figure 4.7: Influence of Charging Power (EV Density: 330 EVs & Parking Duration: 1800s)

the charging time of EVs, which is more convenient for drivers to travel. In Fig.4.7(a), the proposed scheme achieves the highest number of EVs get fully charged. Especially when the charging power is at 38kW, the proposed scheme has an obvious advantage over the other CS-Selection schemes. This is because the proposed scheme allows preempted charging and sends reservations to the GC, which benefits overall EVs charging allocation. The result in Fig.4.7(a) also shows that, with the increase of charging power, more EVs get fully charged in all three schemes. The proposed scheme achieves the least number of EVs not fully charged in Fig.4.7(b). Because the proposed scheme considers the charging urgency of EVs, it prevents EVs from waiting at one CS without charging before its departure. When the charging power increases by 74kW, EV's charging time is shortened at all CSs, and all the three schemes decrease the number of EVs not fully charged.

The UFCWR scheme suffers from the longest average waiting time in Fig.4.7(c), this is because the UFCWR scheme does not ask EVs to send their reservations. Thus estimation of CSs charging status are uncertain, and it causes CS hotpots. Both the proposed scheme and the reservation scheme achieve shorter average waiting time comparing with the UFCWR scheme, however the proposed scheme allows more EVs get fully charged (Fig.4.7(a)) and thus it proves the importance of considering charging urgency. In Fig.4.7(d), the average trip duration decreases when the charging power increases. Here, the result shows that if charging power at CSs is increased, EVs would adequately avoid charging congestion, thereby reducing the overall trip duration. Among the three CS-Selection schemes, the proposed scheme considers the influence of the trip time in Algorithm 4.4, and thus achieves the shortest average trip duration.

4.4 Remaining Challenges

The proposed UFC charging scheduling policy orders EVs charging priority by their charging urgency (jointly considering their charging demand and parking duration). Based on the UFC scheduling policy, this work further proposed a reservation-based CS-Selection scheme to minimize the EVs' trip duration, which also guarantees more EVs to get fully charged within the parking duration. Results show the proposed CS-Selection scheme achieves a shorter EVs' trip duration through an intermediate charging, higher number of EVs get fully charged as well as a shorter average waiting time.

While the UFC policy and the associated recommendation scheme have shown promising results in improving the efficiency of EV charging scheduling and spatial optimization, there are still several challenges that need to be addressed. One major challenge is to improve the accuracy of estimating charging urgency, which can help in better predicting the optimal charging duration for each EV. Additionally, integrating renewable energy sources into the charging process can pose a challenge due to their intermittent nature, traditional plug-in charging modes will be limited to fixed locations, challenges that will be addressed in the next chapter, where we present the flexible application of V2V charging mode optimization in synergy with time and space.

Chapter 5

Reservation-Based V2V Charging Service under Constraint of Parking Duration

The traditional plug-in charging mode is limited by fixed location and peak hours. Therefore, a flexible V2V charging mode is considered in this chapter. Here, PLs widely dispersed in cities can be reused as a common place for V2V charging. EVs are divided into EVs as energy consumers and EVs as energy providers to form as V2V-Pairs.

A V2V charging management scheme is proposed, which includes a distance-based V2V-Pair matching algorithm and a PL-Selection scheme. As the occupation status at PLs is difficult to predict, to achieve high PL utilization and evenly PL-Selection, V2V charging reservation is introduced. Meanwhile, since EV drivers usually park at PLs within a limited duration, this proposed V2V charging scheme introduces the parking duration to optimize V2V charging under a temporal constraint. This chapter simulates V2V charging scheme under the Helsinki city scenario. The results prove the proposed V2V charging scheme achieves great charging efficiency (minimized charging waiting time and maximized fully charging times). Technically:

1. This chapter proposes a distance-based V2V-Pair matching scheme to reduce the EVs' energy consumed on-the-move before the charging of V2V-Pairs starts. Major previous works in V2V-Pair matching rely on preset static data (like in works [113, 123]), nevertheless, the real-time status of EVs is considered in this chapter.

2. Furthermore, this chapter proposes a PL-Selection scheme. This is different from previous works that focus on V2V charging optimization in a single parking area without considering on-the-move EVs (like in works [49, 57]).

3. As the occupation status at PLs is difficult to predict, EVs are asked to send

reservations (different from the work [124]). This helps to predict the occupation status at PLs and evenly allocate V2V-Pairs.

4. Previous works ignore the parking duration constraint (like in works [67, 60]), which is contrary to the reality (drivers park a PL within a limited duration). It is novel in this chapter that introduces the parking duration to refer the upper limitation that EVs park at a PL. This allows the GC to intelligently allocate V2V charging requests within the limited parking duration.

5.1 Preliminary

5.1.1 Assumption

Table 5.1: List of Notations of Chapter 5

δ_{V2V}	Number of V2V converters at PL
β_{V2V}	V2V Charging power via converters
α_{V2V}	Electric energy consumed per meter
T_{cur}	Current time in the network
T_{ev}^{tra}	EV's travelling time to reach PL
E_{ev}^{max}	Full volume of EV battery
E_{ev}^{cur}	Current volume of EV battery
T_{ev}^{arr}	EV's arrival time at PL
T_{pair}^{arr}	Later EV's arrival time at PL in a V2V-Pair
DIS_{ev}^{ev}	Distance between two EVs (an EV-C and another EV-P)
LIST	List includes available charging time for converters at PL
N_C	Queue of EV-Cs under V2V charging at PL
N_W	Queue of EV-Cs waiting for V2V charging at PL
N_R	Queue of EV-Cs sending reservation to PL
N_P^{ev}	Queue of EV-Ps
N_{PL}	Queue of PLs providing V2V charging
T_{ev}^{fin}	Charging finish time of EV-C
D_{ev}	Parking duration of EV
S_{ev}	Speed of EV
EACT	Estimation of Available Charging Time

This chapter considers V2V charging under an urban scenario as follows. Table 5.1 lists the notations covered in this chapter. It should be noted that some of the parameters are named in line with Chapter 4, but the notations in this table are only applicable to this chapter. A GC is deployed to communicate with EVs and PLs. The GC manages V2V charging in a centralized manner. Multiple PLs are geographically distributed in the scenario. Each PL is equipped with multiple DC-DC converters (δ) to allow parallel energy transfer. EVs are divided into EV-Cs and EV-Ps, an EV-C can only receive energy from a paired EV-P. Here, the energy transfer via an EV-P to an EV-C is under a rate of β_{V2V} (constrained by converters).

The freshness of occupation status information is determined by the communication architecture [125]. Such information is particularly important in V2V charging [126]. Therefore, the GC and EVs are equipped with a wireless communication module so that they can communicate through the cellular network with a low delay. Additionally, the encrypted communication between EV and GC is applied to ensure the message will not be eavesdropped on by others and to protect drivers' privacy.

5.1.2 Network Entity

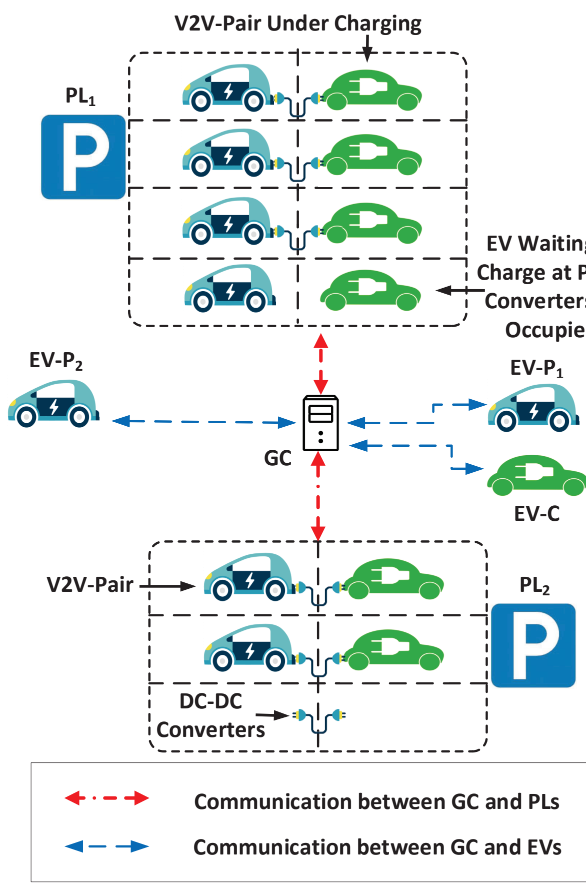


Figure 5.1: System Procedure

An urban scenario is illustrated in Fig.5.1. Network entities involved are as follow:

EV as energy Consumer (EV-C): An EV-C seeks for V2V charging if its State of Charge (SoC) is below the threshold. Here, the EV-C requires a suitable EV-P to match. Once an EV-C has been matched to an EV-P (in the form of a V2V-Pair) by means of centralized optimization, they both will travel towards the determined PL to enable V2V charging service. Here, this chapter considers EV-Cs would leave the service due to limited parking duration.

EV as energy Provider (EV-P): It is EV with surplus energy providing and transferring energy to EV-C. Each EV-P is assumed to have enough energy to provide multiple times V2V services, deemed as an alternative to the grid.

Parking Lot (PL): Each PL has space for EVs to park. Meanwhile, it provides additional DC-DC converters to allow energy transfer between a V2V-Pair. Multiple V2V-Pairs are allowed to transfer energy in parallel at a PL, but it depends on the number of DC-DC converters. In the worst case, EVs need to wait if all DC-DC converters are occupied.

Global Controller (GC): The GC communicates with PLs and EVs simultaneously in a centralized manner. Here, the GC monitors the local occupation status of V2V-Pairs at PLs. If the GC receives a V2V charging request from an EV-C, it matches a suitable EV-P and arranges the PL-Selection for the V2V-Pair.

5.1.3 Proposed V2V Charging Management System

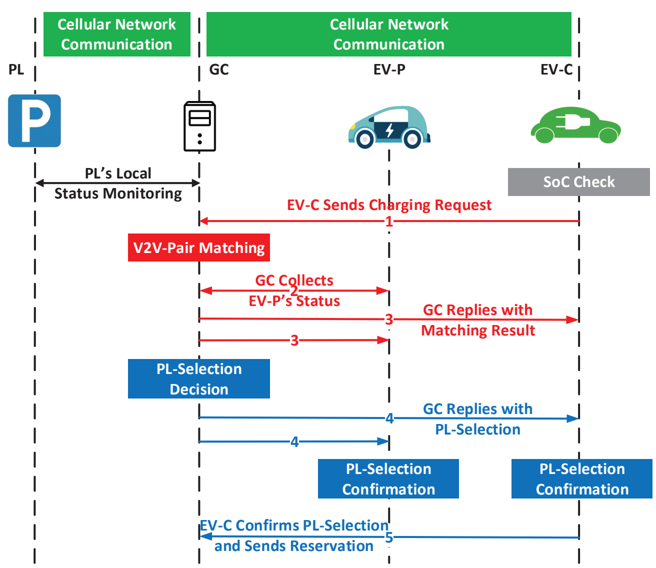


Figure 5.2: Time Sequence of V2V Charging

Fig.5.2 illustrates the procedure for the proposed V2V charging scheme. Here, the GC monitors the local occupation status of V2V-Pairs of all PLs in the charging network. Here, the V2V charging management scheme contains two parts: the V2V-Pair matching process (steps 2,3) and the PL-Selection decision process (steps 4,5).

Step 1: Once an EV-C (EV$_r$) is driving on the road and its SoC is below the preset threshold, EV$_r$ sends its V2V charging request (contains its location and energy request) to the GC.

Steps 2: When the GC receives the charging request from EV$_r$, it communicates with EV-Ps to aggregate their current status.

Steps 3: The GC matches an appropriate EV-P for EV$_r$ according to the collected real-time location of EV-Ps, and then it replies to the V2V-Pair matching result to EV$_r$ and EV-Ps.

Step 4: The GC estimates the V2V charging availability at each PL. This estimation jointly considers PLs' local occupation status of V2V-Pairs, EVs parked at PLs waiting for energy transfer and EVs sending charging reservations. Here, the GC replies to the PL-Selection decision (the PL with the shortest trip duration) to the matched V2V-Pair of EV$_r$.

Steps 5: The V2V-Pair (EV$_r$ and the matched EV-P) then confirms the selected PL by reporting the reservation to the GC.

5.1.4 V2V Charging Reservation Format

The GC accurately estimates the Earliest Available Charging Time (EACT) at each PL. Here, the GC replies to the PL with the minimum trip duration (influenced by the EACT) as PL-Selection to EVs. An EV-C is asked to confirm and send a reservation once it receives the PL-Selection decision from the GC. Such reservation is beneficial to analyse PL's occupation status in the near future and prevent EVs from driving towards potential PL hotspots.

The reservation is reported via the cellular network and includes the following information:

⟨**EV-C ID:**⟩ The ID of EV-C which needs charging.

⟨**EV-P ID:**⟩ The ID of matched EV-P in EV-C's V2V-Pair.

⟨**Arrival Time:**⟩ Here, the estimated arrival time T_{ev}^{arr} is given by the travelling time (T_{ev}^{tra}) from EV's current location towards the selected PL plus the current time in the network (T_{cur}):

$$T_{ev}^{arr} = T_{cur} + T_{ev}^{tra} \tag{5.1}$$

⟨**Expected Charging Time:**⟩ The estimated charging time T_{ev}^{cha} of the EV-C, is given by:

$$T_{ev}^{cha} = \frac{E_{ev}^{max} - E_{ev}^{cur} + (S_{ev} \times T_{ev}^{tra} \times \alpha_{V2V})}{\beta_{V2V}} \tag{5.2}$$

$(S_{ev} \times T_{ev}^{tra} \times \alpha_{V2V})$ calculates the energy consumption in EV's travelling, where S_{ev} refers speed of EV-C and α_{V2V} refers to energy consumption per meter.

Here, Table 5.2 displays a sample reservation message of EV_{22} sent to the GC.

Table 5.2: Reservation of EV-C_{22}

EV-C ID	Matched EV-P	Selected PL	Arrival Time	Expected Charging Time
EV-C_{22}	EV-P_{85}	PL_{26}	8676s	3043s

5.1.5 Problem Formulation

This chapter proposes a V2V charging management solution to alleviate potential charging congestion. To facilitate the problem formulation, the following notations are listed:

(a) ξ_l: The V2V charging service time for an EV-C being fully charged at PL l.

(b) ω_l: The average waiting time for each EV-C being fully charged at PL l.

(c) N_{PL}: The queue of PLs in the network.

(d) ϕ_l: The number of EV-Cs that arrive at PL l and require V2V charging services.

(e) Ω: Overall V2V charging service time for all EV-Cs taken V2V charging in the network.

Here, the V2V charging service time (ξ_l) is summed by the waiting time (before an EV-C get charged) and charging time. It is worth mentioning, an EV waiting at a PL is due to either the other EV (EV-P/EV-C in the V2V-Pair) not arrived (arrival latency) or the PL has no converter available (charging congestion). To reduce the V2V charging service time and improve drivers' Quality of Experience (QoE), the problem is formulated as follows:

$$\text{Minimize } \Omega = \sum_{l \in N_{PL}} \phi_l \cdot \xi_l \tag{5.3}$$

Since the charging time depends on the charging power (determined as a constant by converters), reducing the average waiting time (ω_l) has become the core in the optimization. Ω is minimized if charging EV-Cs (ϕ_l) are evenly across all PLs (N_{PL}). Due to the uncertainty in the city scenario, a practical approach is to achieve local optimization for each EV-C. Therefore, the problem of Equation (5.4) is formulated as follow:

$$\arg\min_{l \in N_{PL}} \omega_l := \{l | l \in N_{PL} \wedge \forall i \in N_{PL} : \omega_i \geq \omega_l\} \tag{5.4}$$

Here, this chapter aims to find the optimized PL-Selection for EVs, which minimizes the EV's average waiting time. This will be discussed in detail in Section 5.2.5.

5.2 V2V Charging Management

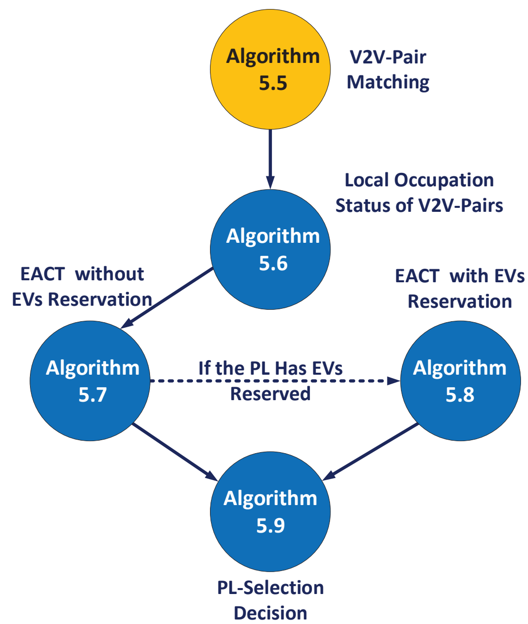


Figure 5.3: Computation Logic of V2V Charging Management

Fig.5.3 illustrates the logic of the proposed V2V charging management scheme. To reduce energy consumed on-the-move before the charging of V2V-Pairs starts, the GC matches V2V-Pairs in Algorithm 5.5.

There are three types of EVs in V2V charging process:

(a) EVs under V2V charging at PLs (in the queue of N_C)

(b) EVs waiting for V2V charging at PLs (in the queue of N_W)

(c) EVs send reservations to PLs (in the queue of N_R)

In Algorithm 5.6, the GC calculates the PLs' local occupation status of V2V-Pairs by considering EV-Cs in the queue of N_C, and further sorts the converters in the order of their charging availability in time. Here, the cases a PL without or with receiving EVs' reservations are concerned respectively, as detailed in Algorithm 5.7 and Algorithm 5.8. Algorithm 5.7 and 5.8 estimate the Earliest Available Charging Time (EACT) at a PL. Algorithm 5.9 further aggregates the EACT at each PL and selects the most suitable PL for selection.

Algorithm 5.5 Pair Matching Algorithm

```
1: for (p = 1; p ≤ N_P^{ev}; p++) do
2:     if (EV-P_p is not matched) then
3:         calculate DIS_{ev_(r)}^{ev-p_(p)}
4:     end if
5: end for
6: EV-P_p ← arg min(DIS_{ev_(r)}^{ev_(p)})
7: return EV-P_p
```

5.2.1 Distance-Based V2V-Pair Matching

When an EV-C (EV$_r$)'s SoC is below the preset threshold, it sends a charging request to the GC. Here, the GC matches the most suitable EV-P (with the minimized energy cost on-the-move) as the EV$_r$'s V2V-Pair. This energy cost calculation is according to the location and availability of EV-Ps.

In the Algorithm 5.5, the GC communicates with EV-Ps to aggregate their locations. The GC confirms whether an EV-P (EV-P$_p$) has been matched with other EV-C at line 2. If EV-P$_p$ has not been matched, then EV-P$_p$ is determined available, and the distance between EV$_r$ and EV-P$_p$ is calculated at line 3. EV-P$_p$ with the minimum distance is returned as the most suitable EV-P, thanks to the minimum energy consumed on-the-move (line 6). Then the GC matches EV-P$_p$ as the V2V-Pair result of EV$_r$ at line 7. This pair matching result is replied to EV$_r$ and EV-Ps to ensure the stability of V2V-Pair matching.

5.2.2 Local Occupation Status of V2V-Pairs at PLs

Algorithm 5.6 calculates the local occupation status of V2V-Pairs at a PL. Meanwhile, it further returns a list (LIST) that indicates the available time for V2V charging at each DC-DC converter. Here, an EV-C's V2V charging refers to the energy transferring from its V2V-Pair. If there's no EV-C under charging at the PL, the current time in the network (T_{cur}) is added into the LIST with δ_{V2V} to indicate all converters are available from T_{cur}.

The loop operation from line 5 to 11 considers the condition that the PL has EVs under charging. Therefore, a number of converters (size of N_C) are occupied until EV$_n$ (in the queue of N_C) finishes charging. From lines 6 to 10, Algorithm 5.6 calculates the charging finish time of EV$_n$. Note that, EV$_n$'s charging time is limited by the parking duration (D_{ev}). If EV$_n$ can get fully charged before its departure deadline, the EV$_n$'s charging finish time ($\frac{E_{ev_{(n)}}^{max} - E_{ev_{(n)}}^{cur}}{\beta_{V2V}} + T_{cur}$) is added into the LIST at line 7. Otherwise, EV$_n$ has to depart at its departure deadline ($T_{ev_{(n)}}^{arr} + D_{ev}$).

The condition from 12 to 16 indicates that not all converters have EV-Cs under charging. Here, the converters with availability are added to the LIST to indicate they are available from T_{cur}. At line 17, the LIST is sorted in the order of the available time at each converter. Algorithm 5.6 further returns the LIST at line 18 as the local occupation status at the PL.

Algorithm 5.6 Local Occupation Status of V2V-Pairs at PLs

1: **if** no EV is under charging **then**
2: add T_{cur} in LIST with δ_{V2V} times
3: **return** LIST
4: **end if**
5: **for** $(n = 1; n \leq N_C; n++)$ **do**
6: **if** $((T_{cur} + \frac{E^{max}_{ev_{(n)}} - E^{cur}_{ev_{(n)}}}{\beta_{V2V}}) \leq (T^{arr}_{ev_{(n)}} + D_{ev}))$ **then**
7: LIST.ADD$(\frac{E^{max}_{ev_{(n)}} - E^{cur}_{ev_{(n)}}}{\beta_{V2V}} + T_{cur})$
8: **else**
9: LIST.ADD$(T^{arr}_{ev_{(n)}} + D_{ev})$
10: **end if**
11: **end for**
12: **if** $(N_C < \delta_{V2V})$ **then**
13: **for** $(m = 1; m \leq (\delta_{V2V} - N_C); m++)$ **do**
14: LIST.ADD(T_{cur})
15: **end for**
16: **end if**
17: sort LIST with ascending order
18: **return** LIST

5.2.3 Estimation of EACT without Reservation

EV-Cs waiting at the PL are scheduled to charge. At line 1, the waiting queue of N_W is sorted with the FIFS order to ensure more EVs can finish V2V charging within their D_{ev}.

The lines from 2 to 14 consider the condition that there are EVs waiting for V2V-Pair at the PL. Those EVs are scheduled to charge once a converter becomes available. Here, the estimated charging time of EV$_i$ (the EV-C in the queue of N_W) is calculated by:

$$T^{cha}_{ev_{(i)}} = \frac{E^{max}_{ev_{(i)}} - E^{cur}_{ev_{(i)}}}{\beta_{V2V}} \tag{5.5}$$

To consider whether EV$_i$ is able to be fully recharged before its departure, lines 5 and 7 calculate EV$_i$'s charging finish time ($T^{fin}_{ev_{(i)}}$) respectively. If EV$_i$ is able to be fully recharged (meets the condition at line 4), its $T^{fin}_{ev_{(i)}}$ is calculated as ($T^{cha}_{ev_{(i)}}$ + LIST.GET(0)). Otherwise, EV$_i$ has to depart at (D_{ev} + $T^{arr}_{ev_{(i)}}$). LIST.GET(0) is replaced by $T^{fin}_{ev_{(i)}}$ to imply the first available converter is occupied by EV$_i$ until $T^{fin}_{ev_{(i)}}$. Then the LIST is sorted in ascending order at line 10. EV$_i$ is recorded into DELETESET and removed at line 13 to indicate that all EVs in the queue of N_W have been scheduled to charge.

If the PL has not received any reservation for charging as the condition at line 15, EV$_r$ will be the first charging sequence when it arrives. However, a necessary condition of starting V2V charging is both EVs in a V2V-Pair have arrived. Therefore, the arrival time ($T^{arr}_{pair_{(r)}}$) is determined of EV$_r$'s V2V-Pair as the later EV's arrival time in the pair. If EV-P$_r$ (EV$_r$'s energy provider in its V2V-Pair) arrives later than EV$_r$, $T^{arr}_{pair_{(r)}}$ is recorded as

Algorithm 5.7 EACT without EVs Reservation $\langle$LIST$\rangle$

sort the queue of N_W according to the FIFS order
if contains EVs waiting for charging **then**
  for $(i = 1; i \leq N_W; i++)$ **do**
    if (($T^{cha}_{ev_{(i)}}$ + LIST.GET(0)) $<$ (D_{ev} + $T^{arr}_{ev_{(i)}}$)) **then**
      $T^{fin}_{ev_{(i)}}$ = $T^{cha}_{ev_{(i)}}$ + LIST.GET(0)
    else
      $T^{fin}_{ev_{(i)}}$ = D_{ev} + $T^{arr}_{ev_{(i)}}$
    end if
    replace the LIST.GET(0) with $T^{fin}_{ev_{(i)}}$
    sort LIST with ascending order
    record EV$_i$ into DELETESET
  end for
  remove EVs recorded in DELETESET, from the queue of N_W
end if
if no EV reservation for charging **then**
  if $(T^{arr}_{ev_{(r)}} < T^{arr}_{ev-p_{(r)}})$ **then**
    $T^{arr}_{pair_{(r)}} = T^{arr}_{ev-p_{(r)}})$
  else
    $T^{arr}_{pair_{(r)}} = T^{arr}_{ev_{(r)}}$
  end if
  if ($T^{arr}_{pair_{(r)}}$ $<$LIST.GET(0)) **then**
    return LIST.GET(0)
  else
    return $T^{arr}_{pair_{(r)}}$
  end if
else
  return EACT with EVs Reservation $\langle$LIST$\rangle$
end if

$T^{arr}_{ev-p_{(r)}}$ at line 17. If EV$_r$ arrives later than EV-P$_r$, $T^{arr}_{pair_{(r)}}$ is recorded as $T^{arr}_{ev_{(r)}}$ at line 19.

Considering that the PL may have no available converter when EV$_r$ arrives (all converters are occupied by EVs in the queue of N_W), it is necessary to compare $T^{arr}_{pair_{(r)}}$ with LIST.GET(0). If EV$_r$ arrives with the first available converter occupied ($T^{arr}_{pair_{(r)}}$ <LIST.GET(0)), then Algorithm 5.7 returns LIST.GET(0) at line 22 for PL-Selection purpose in Algorithm 5.9. In the other case, $T^{arr}_{pair_{(r)}}$ is returned at line 24.

If the PL has received V2V charging reservations, the further EACT estimation will be processed in Algorithm 5.8.

5.2.4 Estimation of EACT with Reservation

Algorithm 5.8 EACT with EVs Reservation $\langle$LIST$\rangle$

1: sort the queue of N_R according to the FIFS order
2: **for** $(j = 1; j \leq N_R; j++)$ **do**
3:     **if** (($T^{cha}_{ev_{(j)}}$ + LIST.GET(0)) $<$ (D_{ev} + $T^{arr}_{ev_{(j)}}$)) **then**
4:         $T^{fin}_{ev_{(j)}}$ = $T^{cha}_{ev_{(j)}}$ + LIST.GET(0)
5:     **else**
6:         $T^{fin}_{ev_{(j)}}$ = D_{ev} + $T^{arr}_{ev_{(j)}}$
7:     **end if**
8:     replace the LIST.GET(0) with $T^{fin}_{ev_{(j)}}$
9:     sort LIST with ascending order
10:     record EV$_j$ into DELETESET
11: **end for**
12: remove EVs recorded in DELETESET, from the queue of N_R
13: **if** ($T^{arr}_{ev_{(r)}} < T^{arr}_{ev-p_{(r)}}$) **then**
14:     $T^{arr}_{pair_{(r)}} = T^{arr}_{ev-p_{(r)}}$)
15: **else**
16:     $T^{arr}_{pair_{(r)}} = T^{arr}_{ev_{(r)}}$
17: **end if**
18: **if** ($T^{arr}_{pair_{(r)}}$ <LIST.GET(0)) **then**
19:     **return** LIST.GET(0)
20: **else**
21:     **return** $T^{arr}_{pair_{(r)}}$
22: **end if**

Based on the output from Algorithm 5.7, Algorithm 5.8 further calculates the EACT with reservations generated from EV-Cs. Here, N_R is sorted according to the FIFS order. This is the estimated arrival order of EV-Cs in the queue of N_R.

If EV$_j$ (EV-C in the queue of N_R) could be fully charged before its departure (($T^{cha}_{ev_{(j)}}$ + LIST.GET(0)) $<$ (D_{ev} + $T^{arr}_{ev_{(j)}}$)), Algorithm 5.8 calculates $T^{fin}_{ev_{(j)}}$ as ($T^{cha}_{ev_{(j)}}$ + LIST.GET(0)) at line 4. Otherwise, $T^{fin}_{ev_{(j)}}$ is calculated as (D_{ev} + $T^{arr}_{ev_{(j)}}$) at line 6.

Line 8 replaces LIST.GET(0) with $T^{fin}_{ev_{(j)}}$ to indicate the first available converter is occupied until $T^{fin}_{ev_{(j)}}$. Then line 9 updates the LIST in ascending order to make sure that LIST.GET(0) is still the first available charging time at converters. All EVs that have been scheduled to charge are recorded into DELETELIST and removed from the reservation queue of N_R.

As the V2V charging can only start when both EVs in a V2V-Pair have arrived, the lines from 13 to 17 compare the arrival time of EVs in a V2V-Pair. If EV$_r$ arrives later than EV-P$_r$, $T^{arr}_{pair_{(r)}}$ is recorded as $T^{arr}_{ev-p_{(r)}}$. Otherwise, $T^{arr}_{pair_{(r)}}$ is recorded as $T^{arr}_{ev_{(r)}}$.

If all converters are occupied when EV$_r$ arrives ($T^{arr}_{ev_{(r)}}$ <LIST.GET(0)), Algorithm 5.8 returns LIST.GET(0) as the EACT at the PL at line 19. In the other case, EV$_r$ can get direct energy transfer service once it arrives, the EACT at the PL is returned as $T^{arr}_{pair_{(r)}}$ at line 21.

5.2.5 PL-Selection Decision

Algorithm 5.9 PL-Selection Decision Making

1: **for** $\forall l_{pl} \in N_{PL}$ **do**
2: calculate $T^{min}_{pl,d}$
3: calculate EACT$_{pl}$ via Algorithm 5.7 & 5.8
4: **if** $((T^{cha}_{ev_{(r)}} + \text{EACT}_{pl}) \leq (D_{ev} + T^{arr}_{ev_{(r)}}))$ **then**
5: $T^{pl,d}_{ev_{(r)}} = T^{cha}_{ev_{(r)}} + \text{EACT}_{pl} + T^{min}_{pl,d}$
6: **else**
7: $T^{pl,d}_{ev_{(r)}} = T^{arr}_{ev_{(r)}} + D_{ev} + T^{min}_{pl,d}$
8: **end if**
9: **end for**
10: $l^{min}_{pl} \leftarrow \arg\min(T^{pl,d}_{ev_{(r)}})$
11: **return** l^{min}_{pl}

Algorithm 5.9 selects the PL for EV$_r$ with the minimum time spent with an intermediate V2V charging (total trip duration $T^{pl,d}_{ev_{(r)}}$). Here, $T^{pl,d}_{ev_{(r)}}$ is the summation of the duration EV$_r$ spends at the selected PL and the travelling time from the selected PL to EV$_r$'s trip destination ($T^{min}_{pl,d}$).

Here, $T^{min}_{pl,d}$ is calculated at line 2, which refers to the time EV$_r$ travels from the PL to its destination via the shortest path. The EACT at PL (with location l_{pl}) is estimated by Algorithm 5.7 & 5.8. There are also two cases considering whether EV$_r$ can be fully charged before its departure.

(a) At line 5, EV$_r$ can be fully charged before its departure, thus $T^{pl,d}_{ev_{(r)}}$ is calculated by ($T^{cha}_{ev_{(r)}} + \text{EACT}_{pl} + T^{min}_{pl,d}$).

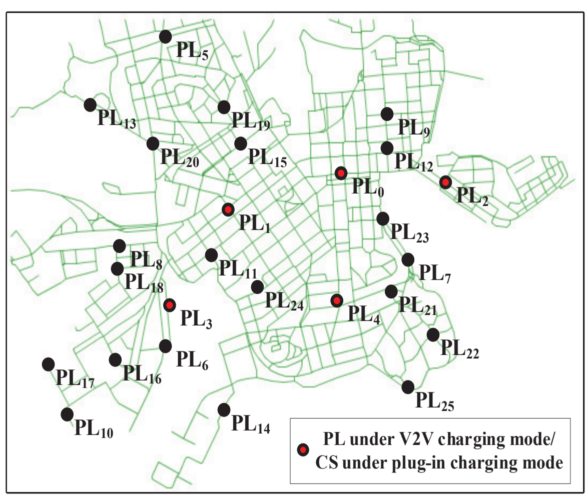
(b) At line 7, due to the D_{ev} limitation, EV$_r$ has to depart from the PL no matter whether it is fully charged or not. Thus $T^{pl,d}_{ev_{(r)}}$ is calculated by ($T^{arr}_{ev_{(r)}} + D_{ev} + T^{min}_{pl,d}$).

In the loop operation at line 10, Algorithm 5.9 calculates $T^{pl,d}_{ev_{(r)}}$ at each PL. The PL with the minimum $T^{pl,d}_{ev_{(r)}}$ will be returned as PL-Selection decision to EV_r.

5.3 Performance Evaluation

5.3.1 Simulation Configuration

(a) The Helsinki City



(b) Deployment of PLs

Figure 5.4: Simulation Scenario

This chapter applies ONE to build V2V charging management scenario. The ONE is initially designed for mobile networks. Here, the system is modified to simulate the V2V charging process. In Fig.5.4(a), the simulation demonstrates the urban area of Helsinki city (Fig.5.4(a)) with a 4500×3400 m^2 scenario. 26 PLs are geographically deployed in the urban area and each PL is equipped with 4 DC-DC converters. One DC-DC converter allows V2V charging for a V2V-Pair with an energy transferring rate of 15 kW.

Meanwhile, to examine the efficiency of V2V charging mode as compared with the plug-in charging mode. Another scenario is considered under plug-in charging mode where 5 CSs are deployed in this urban scenario. Each CS is provided with 5 charging slots, using the fast charging rate of 62 kW.

EVs in the scenario are using Coda Automotive [121] with the following configuration: Maximum electricity capacity: 33.8 kWh; Max travelling distance: 193 km; Average energy consumption: 0.1751 kWh/km.

To enrich EV differences in the scenario, three SoC thresholds (30%, 40% and 50%) are set. All EV-Cs' batteries are at full volume when the simulation starts. To simplify the simulation and exam the optimality of V2V-Pair matching, PL-Selection and reservations, EV-Ps are set with a super power, EV-Ps are able to provide repeatedly charging services without intermediate charging. The numbers of EV-Cs and EV-Ps are set equally to avoid a large number of EV-Cs competing with a few number of EV-Ps.

Here, EVs are with $[30 \sim 50]$ km/h variable moving speed, the speed fluctuation reflects the impact of traffic. The EV's destination is randomly selected from a location on the map. Once an EV arrives at its trip destination, it will travel towards the next randomly selected destination again. If the EV's SoC is below the threshold, it travels towards the selected PL via the shortest path, which is formed considering the Helsinki road topology. The simulation lasts for 12 hours. Here, EVs' location, speed and energy are updated per 0.1s, no matter whether EVs are at a PL or on-the-move.

5.3.2 Comparison Configuration

A reservation-based V2V charging management scheme is proposed in this chapter. To compare the efficiency of different V2V charging schemes, the following V2V schemes are evaluated for comparison:

- **MD-V2V**: The benchmark scheme with distance-based V2V matching and distance-based PL-Selection.
- **MWT-V2V [7]**: The benchmark scheme with distance-based V2V matching and waiting time-based PL-Selection (without reservation).
- **R-V2V**: The proposed scheme with a distance-based matching scheme and a reservation-based PL-Selection scheme.

This chapter evaluates two other CS charging schemes for comparison. In CS charging schemes, the number of EVs is set as the same number of EV-Cs in V2V schemes.

- **MWT-CS [120]**: Literature work applies the plug-in charging mode for EVs. The GC allocates EVs to the CS with the minimum waiting time.
- **R-CS [118]**: Literature work applies the plug-in charging mode for EVs and considers charging reservation. The CS allocates EVs to the CS with the earliest EACT.

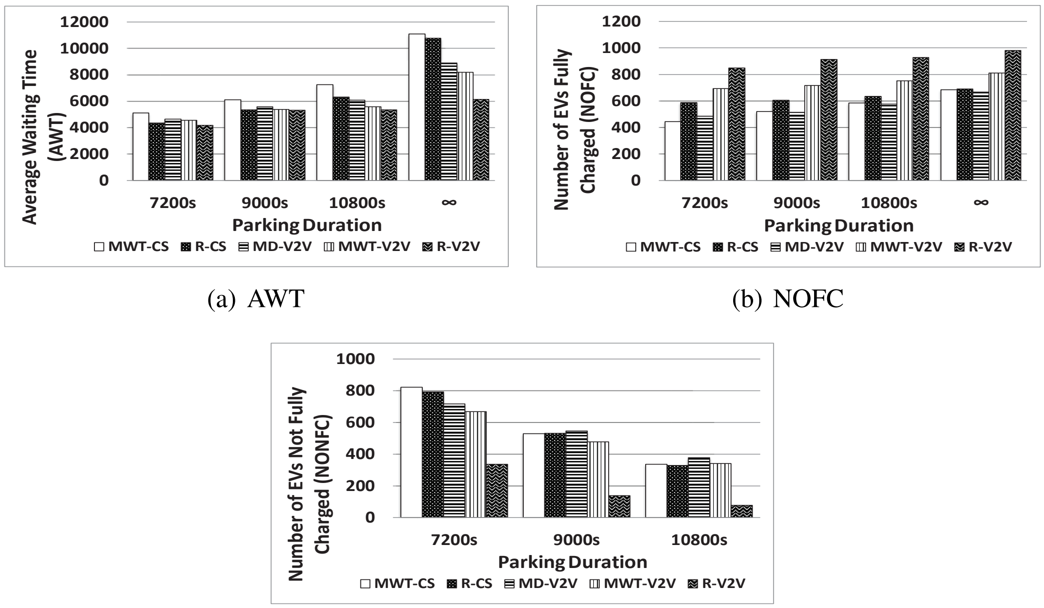
The key differences between the existing work and the proposed work lie in the PL-Selection scheme and the reservation mechanism as listed in Table 5.3.

Table 5.3: Comparison of Existing and Proposed Schemes

Characteristics	MD-V2V	MWT-V2V [7]	R-V2V	MWT-CS [120]	R-CS [118]
V2V Matching Scheme	Distance-based	Distance-based	Distance-based	N/A	N/A
PL-Selection Scheme	Distance-based	Waiting time-based (without reservation)	Waiting time-based (with reservation)	Waiting time-based	Waiting time-based (with reservation)
Reservation Mechanism	N/A	N/A	Proposed with fixed and adaptive reservation windows	N/A	Proposed with fixed reservation windows
Charging Mode	V2V	V2V	V2V	Plug-in	Plug-in

The following performance metrics are evaluated:

- **Number of EVs Fully Charged (NOFC)**: It indicates the total number of EV-Cs get fully charged. Here, within the simulation duration, each EV-C can be charged for several times.
- **Number of EVs Not Fully Charged (NONFC)**: It indicates the total number of EV-Cs can not get fully charged although EV-Cs have arrived at a PL. In extremity, an EV-C may not receive V2V charging before its departure, thus it needs another PL-Selection for charging.
- **Average Waiting Time (AWT)**: It indicates the average queuing time for EV-Cs before they get charging service at the selected PL.



(a) AWT

(b) NOFC

(c) NONFC

Figure 5.5: Influence of Parking Duration

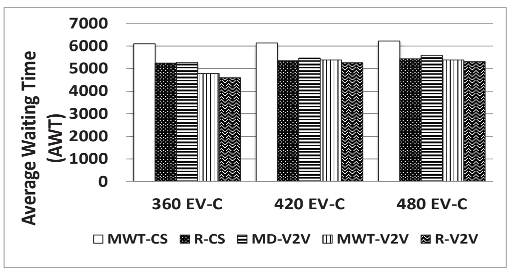
5.3.3 Influence of Parking Duration

In the first group of simulations, the EV density is set to 840 (420 EV-Cs and 420 EV-Ps) and observe the influence of the parking duration. Here, the parking durations are set to 7200, 9000, and 10800s respectively. To further observe the upper limit of charging schemes, the results are added without considering the parking duration (the results with ∞ symbol in the figures).

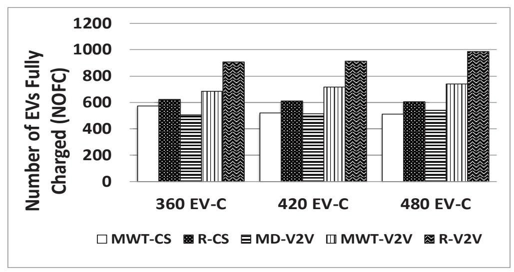
In Fig.5.5(a), due to the lack of prediction at PLs/CSs, MWT-CS, MD-V2V and MWT-V2V schemes are unable to prevent EVs from selecting the PL/CS hotspots and suffer from a longer AWT. Here, V2V charging schemes (based on flexible utilization of PLs), with a far lower charging power (15 kW), are able to achieve better charging efficiency than 5 CSs with 62 kW charging power (MWT-CS and R-CS schemes). In the three V2V schemes, the MD-V2V scheme suffers from the longest AWT. This is because the MD-V2V scheme lacks global planning and only considers the location of EV-Cs. This inevitably leads to charging congestion at PL hotspots. As the R-V2V scheme enables the GC to estimate PLs' occupation status accurately (with the benefit of reservations), it is able to better allocate V2V charging among PLs and achieves the shortest AWT. If the parking duration is not limited, the AWT of MD-V2V and MWT-V2V schemes are obviously increased, which also reflects the importance of reservation to charging efficiency.

In Fig. 5.5(b), under V2V charging mode, a longer parking duration reduces the proportion of arrival latency (time waiting for EV-C/EV-P in a V2V-Pair) in one entire charging process. Here, an EV-C has a longer time waiting for its matched pair to get fully charged and thus the NOFC increases. As R-CS and R-V2V schemes ask EVs to send reservations, then the GC has more accuracy in the estimation of EACT than the other schemes. The GC is able to select the CS/PL with a lower congestion level. Therefore, R-CS and R-V2V schemes achieve higher NOFC than other schemes. In Fig.5.5(c), the R-V2V scheme achieves a lower NONFC than the other schemes. This benefits from the prediction of potential occupation status at PLs. When the parking duration is extended to 10800s, almost all EV-Cs charging requests can be satisfied.

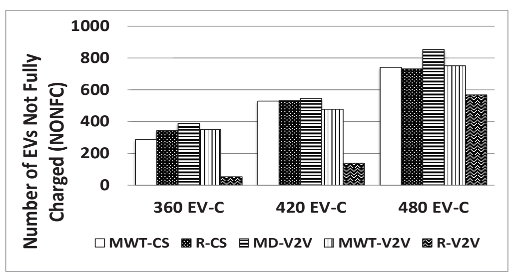
5.3.4 Influence of EVs Density



(a) AWT



(b) NOFC



(c) NONFC

Figure 5.6: Influence of EVs Density

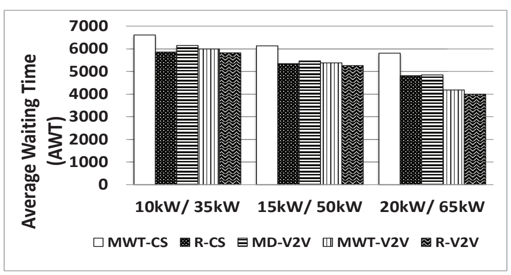
In the second group of simulations, EV's parking duration is set to 9000s and further vary the number of EVs to reflect the scalability of management schemes. Here, the EV density refers to the number of EV-Cs. The numbers of EV-Cs and EV-Ps are set equally to avoid a large number of EV-Cs competing with a few numbers of EV-Ps.

The result in Fig.5.6(a) shows that the MWT-CS scheme suffers from the longest AWT. However, the AWT can be significantly reduced with the help of reservation in the R-CS scheme. Among three V2V schemes, the MD-V2V scheme suffers the longest AWT. This is because the distance-based PL-Selection would centralize charging requests at PLs in the city centre and thus cause charging congestion. By considering the local occupation status of V2V-Pairs at PLs, EVs are able to avoid PL hotspots. Here, when the number of EV-Cs is 360, MWT-V2V and R-V2V schemes can effectively reduce the AWT. When the number of EV-Cs increases by 480, the R-V2V scheme still achieves the shortest AWT as it considers the potential charging flow.

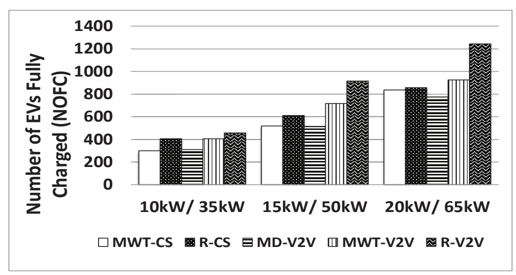
In Fig.5.6(b), it shows that the R-V2V scheme achieves the highest NOFC. In CS schemes, charging congestion occurs when the number of EVs increases and thus NOFC decreases. However, in V2V schemes, the V2V-Pair matching becomes more flexible when the number of EVs increases. Therefore, the NOFC increases in V2V schemes.

The result in Fig.5.6(c) also proves the advantage of the R-V2V scheme. When the number of EVs is at a low level (360 and 420 EV-Cs), the R-V2V scheme benefits from the reservations as the GC could accurately estimate EACT at PLs. This effectively avoids EV-Cs charging at PLs with high charging congestion. When the density of EV-Cs increases by 480, reservations still help the GC evenly allocate EVs at PLs and thus maximize the PLs' charging utility.

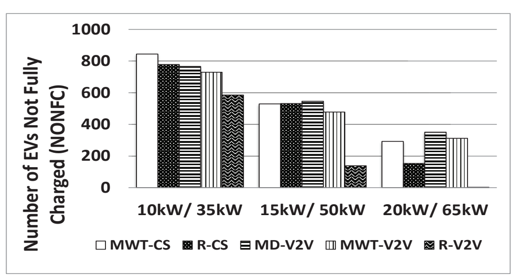
5.3.5 Influence of Charging Power



(a) AWT



(b) NOFC



(c) NONFC

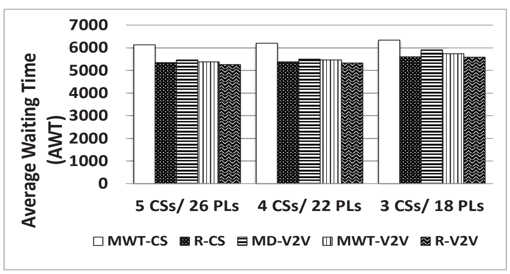
Figure 5.7: Influence of Charging Power

By adjusting the charging power at CSs and PLs, this chapter observes the utility of each charging scheme. Here, the parking duration is set to 9000s and EV-Cs density to 420.

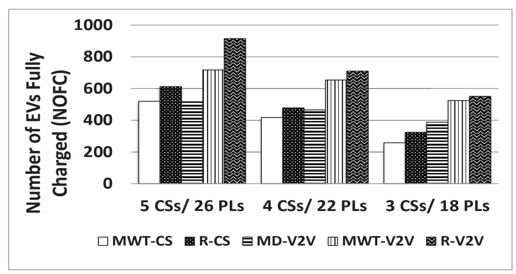
The R-V2V scheme achieves the shortest AWT in Fig.5.7(a). The increment of charging power reduces the AWT in all charging schemes. However, under V2V charging mode, charging power with a small increase (5 kW) can significantly shorten the AWT. This is because the number of PLs is large, and a small increase of charging power can effectively improve the overall charging performance in V2V charging. Considering the bottleneck in charging technology, V2V charging schemes take great charging efficiency improvement with less charging power increment.

In Fig.5.7(b), when the charging power increases, the NOFC is significantly increased under V2V charging schemes. And the R-V2V scheme achieves the highest NOFC, because it considers the reservations and efficiently allocates the charging requests at each PL. Note that with the increase of charging power, the NONFC decreases significantly in all schemes in Fig.5.7(c), and this decreasing trend is more obvious in V2V schemes. When the charging power at PL reaches 20 kW, the R-V2V scheme can ensure that all EV-Cs can be fully charged once they arrive at PLs.

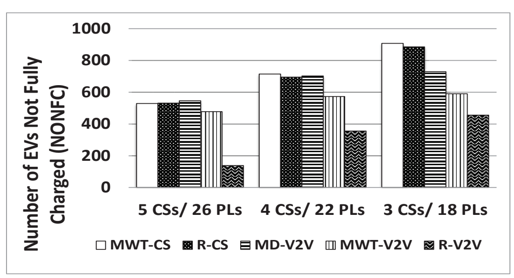
5.3.6 Influence of Charging Facility Deployment



(a) AWT



(b) NOFC



(c) NONFC

Figure 5.8: Influence of Charging Facility Deployment

To simulate the EV charging under different charging facility deployment, the number of PLs and CSs are adjusted in the scenario for simulation:

(a) In the first group of comparison, the number of CSs is reduced to 4. Here, CS_0 to CS_3 in Fig.5.4(a) can continue to provide charging services. Meanwhile, the number of PLs is reduced to 22. Here, PL_0 to PL_{21} in Fig.5.4(a) can continue to provide V2V charging services.

(b) In the second group of comparison, the number of CS is further limited to 3. Here, CS_0 to CS_2 can continue to provide charging. The number of PLs is limited to 18. Here, PL_0 to PL_{17} can can continue to provide V2V charging.

In Fig.5.8(a), a less number of charging facilities means that EV charging is further limited by constrained locations. Therefore, the MD-V2V scheme suffers a significant increase in the AWT. This is because distance-based PL-Selection further aggravates charging congestion at PL hotspots. MWT-CS and MWT-V2V schemes consider the local charging status/occupation status of CSs/PLs and select the CS/PL with the minimum waiting time. To some extent, the charging requests are evenly distributed among CSs/PLs. However, R-CS and R-V2V schemes further consider the reservation information to predict potential charging requests. Therefore, these two reservation-based schemes achieve a lower AWT.

In Fig.5.8(b), the NOFC reduces with less number of charging facilities. This reflects the dilemma faced by plug-in charging mode when a small number of CSs deployed. Since V2V charging mode can flexibly use preset PLs, V2V schemes can still ensure relatively high NOFC. In particular, the R-V2V scheme achieves the highest NOFC, with the benefit of reservations. In Fig.5.8(c), V2V schemes achieve a lower NONFC. However, limited by the number of CSs, more EVs depart with not fully charged in plug-in charging mode.

5.3.7 Charging Distribution at PLs

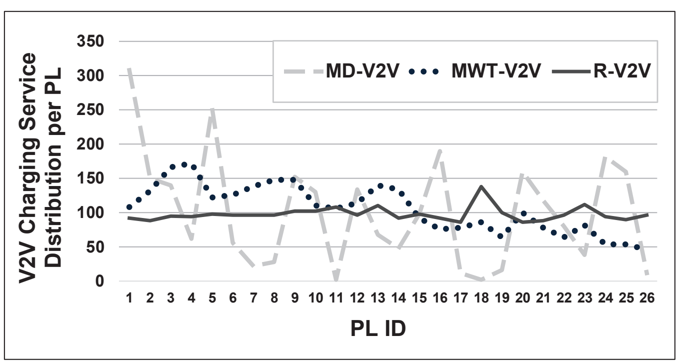


Figure 5.9: Charging Distribution at PLs

Fig. 5.9 shows the distribution of V2V charging at each PL under V2V charging schemes. Here, the parking duration is set as 9000s and the number of EV-Cs is set to 420.

The even distribution of V2V charging at each PL can maximize the V2V charging efficiency. Since the MD-V2V scheme selects PL based on EV's local information (distance from each PL), V2V charging requests are easy to concentrate at some PLs (especially PLs at the city centre). This leads to charging congestion and reduces EV drivers' QoE. In the MWT-V2V scheme, the GC calculates the EACT of each PL. But due to the lack of reservations, the GC cannot accurately predict the potential charging requests. Here, it's inevitable that several V2V-Pairs are allocated to the PL hotspots and thus cause charging congestion.

The R-V2V scheme avoids the above problems. In Fig. 5.9, the V2V charging distribution at each PL is relatively average under the R-V2V scheme. Therefore, converters at each PL are able to be highly utilized. This guarantees a higher charging efficiency in large-scale EVs deployment.

5.3.8 Summary Discussions of V2V Charging

Based on the above evaluations, the proposed V2V charging mode proves its advantages over CS charging mode.

- When the number of EVs participating in V2V charging increases (from 360 to 480 EV-Cs), the more EVs get fully charged. This is because V2V-Pair matching optimizes with more EV participators. However, the increase number of EVs in CS charging mode leads to the decrease of charging results (less fully charged EVs and longer charging waiting time).

- The V2V charging mode flexibly use PLs under a low charging power (10-20 kW) to achieve a charging result of CSs under a high charging power (35-65 kW). Meanwhile, a small charging power increase (5 kW) in V2V charging mode achieves a large improvement in V2V charging result. Currently, charging power is limited by battery technology, V2V charging mode is conducive to improving the EV drivers' charging experience.

- In V2V charging schemes, the introduction of reservation optimizes the PL-Selection. This proposed V2V charging scheme proves its advantage over simply considering the local PL occupation at PLs. EVs distributes evenly among PLs thanks to V2V charging reservations, which maximizes the use of V2V charging resources in the city.

5.4 Remaining Challenges

Since range anxiety and spatial limitation of public charging facilities hinder EVs' large-scale application, this chapter proposes a reservation-based V2V charging management scheme. It is applied as an alternative to the traditional plug-in charging mode. Here, the V2V charging mode is able to effectively reduce grid fluctuation as it allows directly transfer among EVs.

By means of V2V charging technology, PLs widely distributed in urban areas can be reused as V2V charging places. Here, an EV-P transfers surplus energy to another EV-C (in the form of a V2V-Pair) through the DC-DC converters deployed. To reduce energy consumed on-the-move before the charging of V2V-Pairs starts, the GC monitors EVs' status and global matches V2V-Pairs considering their locations. Meanwhile, to solve where to charge problem for V2V-Pairs, this chapter proposes a reservation-based PL-Selection algorithm. Here, the GC selects the PL with the highest charging availability (jointly considers parking V2V-Pairs and reservations).

This chapter further evaluates the EVs' charging performance under the plug-in and V2V charging modes. The results show that the V2V charging mode provides more flexibility in urban scenarios, which shortens the AWT and achieves a higher NOFC within the constrained parking duration. The V2V charging mode optimization proposed in this chapter has demonstrated significant improvements in reducing charging waiting times and increasing the number of fully charged EVs. However, there are still several challenges that need to be addressed to make V2V charging more efficient and scalable. One key challenge is to improve the matching algorithm for V2V-Pair selection, which can help in reducing the overall charging time. Additionally, the limited availability of V2V charging infrastructure in certain regions can pose a challenge for widespread adoption. These challenges will be addressed in the next chapter, where we propose an optimization approach to hybrid charging mode that considers the cooperative optimization of multiple charging modes.

Chapter 6

Towards Reservation-based E-Mobility Service via Hybrid of V2V and G2V Charging Modes

The shortcomings of plug-in and V2V charging modes limit further user QoE enhancements. Thus, a hybrid charging management is proposed to flexibly utilise the advantages of both charging modes [111]. Generally, plug-in and V2V charging modes differ in their application scenarios. The plug-in charging mode is used for deterministic charging as CSs fixed and public, while V2V charging is used for opportunistic charging as PLs are flexible and uncertain [112, 57]. It is crucial to figure out how to combine the advantages of V2V charging (high flexibility) and plug-in charging (high stability). Although the plug-in charging is stable and fast [110], the deployment of CS is costly and rigid in location, this still leads to higher electricity price and longer charging waiting time. The V2V charging mode is flexible in terms of location [67], however with limitation in slow charging power and uncertain energy supply from EV-Ps.

With vision to integrate both charging modes into sustainable eco-system for future smart city, this chapter proposes a hybrid charging management in this chapter. The proposed management recommends the most suitable charging mode (CS/PL-Selection) with aim to minimize charging cost for EV. The charging cost is calculated with consideration of charging price, charging waiting time (time spent from arrival at CS/PL to the start of charging service) and charging energy factors. The contributions of this chapter are as follows. Technically:

1. *Hybrid plug-in & V2V charging management framework:* In previous works, EV charging optimization has been solely considered under a single charging mode (those [8, 67] under V2V charging and that [127] under plug-in charging). Although, some literature applied V2V charging as a replacing of grid when the grid stops supplying energy ([113, 128, 129]). This chapter proposes a hybrid

charging management in this chapter, which allows EV charging via two different charging modes. This framework alleviates charging congestion and flexibly utilizes heterogeneous charging infrastructures across city.

2. *Collaborative optimization in price-time-energy dimensions:* In this chapter, a charging cost optimization function is proposed, which is jointly calculated by expected charging price, charging waiting time and charging energy (price-time-energy dimensions). Here, the weights of each dimension are innovatively assigned based on the AHP. By selecting the charging service with the lowest charging cost, EV charging can be optimized across above three dimensions.

3. *Hybrid real-time recommendation system:* Unlike previous literature that utilized offline data (historical price data [130], fixed energy requirement [60]), real-time data is considered in this chapter. Real-time data better represents complexities of the real-world conditions, but changes in real-time data are more difficult to predict. This chapter therefore introduces charging reservation, including EV arrival time and expected charging energy, to effectively alleviate this problem and improve the charging recommendation by accurate information.

6.1 Preliminary

6.1.1 Assumption

In this chapter, a hybrid framework is considered between the plug-in charging and V2V charging modes, aiming to take advantages of both modes under a holistic manner. In this framework, GC, CSs/PLs and EVs are equipped with wireless communication modules so that they can communicate charging information over the cellular network. To protect the privacy of EVs, encrypted communication is applied between EVs and GC. Table 6.1 lists the notations covered in this chapter. It should be noted that some of the parameters are named in line with other chapters, but the notations in this table are only applicable to this chapter.

6.1.2 Problem Formulation

The charging quality of EV-Cs is affected by the charging decision (charging mode selection and CS/PL-Selection). To achieve an optimal hybrid charging management, a comprehensive consideration of factors under different dimensions is required. The proposed hybrid charging management aims to: 1) minimize the unit price of energy for charging services. 2) minimize the charging waiting time. 3) maximize charging energy per service. To formulate above objectives, it has follow sub-questions:

Table 6.1: List of Notations of Chapter 6

δ	Number of charging slots at CS / Number of V2V converters at PL
β	CS charging power at slot / V2V charging power via converters
α	Electric energy consumed per meter
λ	Charging rate at converter
ω_{γ}	Charging rate at converter
ω_{ϵ}	Charging rate at converter
ω_{λ}	Charging rate at converter
E_{ev}^{max}	Full volume of EV battery
E_{ev}^{cur}	Current volume of EV battery
E_{ev}^{req}	Required charging volume of EV battery
E_{ev}^{cha}	Actual charging volume of EV battery
E_{ev}^{tra}	EV's energy consumption in travelling to CS/PL
T_{ϕ}^{arr}	EV's arrival time at CS / V2V-Pair's arrival time at PL
T_{cur}	Current time in the network
T_{ϕ}^{cha}	EV's charging time at CS / V2V-Pair's charging time at PL
T_{ϕ}^{wait}	EV/V2V-Pair's waiting time at CS/PL before it been charged
T_{ϕ}^{fin}	Charging finish time of EV / V2V-Pair
DIS_{ev}^{ev}	Distance between two EVs (an EV-C and another EV-P)
LIST	List includes available charging time for slots at CS / converters at PL
N_C	Queue of EVs under CS charging at CS / V2V charging at PL
N_W	Queue of EVs waiting for CS charging at CS / V2V charging at PL
N_R	Queue of EVs sending reservation to CS/PL
N_P^{ev}	Queue of EV-Ps
N_{PL}	Queue of PLs providing V2V charging
N_{CS}	Queue of CSs providing CS plug-in charging
D_{ev}	Parking duration of EV
S_{ev}	Speed of EV
$Cost_{ev}^{\Phi}$	Charging cost for EV / V2V-Pair to be charged at CS / PL
Note:	Φ and ϕ differs under plug-in/V2V charging modes, which is replaced by CS/PL or EV/V2V-Pair respectively.

1. *Minimize Charging Price:* EV wants to be charged at providers with lower energy price, the total charging price for EVs is defined as R. The optimization objective is as follow:
$$Minimize \quad R = \sum_{l \in L} \sum_{s_l \in S_l} P_{s_l} \times E_{s_l}^{cha} \tag{6.1}$$
Here, L is the list of all EVs in the network. Considering that each EV may receive charging service for several times, each EV is with a charging service list S_l. The price of each charging service ($s_l \in S_l$) is calculated as the unit price of energy (P_{s_l}) multiplied by the amount of energy it charged ($E_{s_l}^{cha}$).

2. *Minimize Charging Waiting Time:* EV requires a reduced charging waiting time to shorten time spent at a CS/PL, the total charging waiting time for EVs is defined as W. The optimization objective is as follow:
$$Minimize \quad W = \sum_{l \in L} \sum_{s_l \in S_l} T_{s_l}^{wait} \tag{6.2}$$
Here, $T_{s_l}^{wait}$ represents the waiting time of an EV charging service.

3. *Maximize Charging Energy:* EV wants to receive more charging energy, thus avoids frequent charging in the subsequent travelling. Here, the ratio of overall EVs' received charging energy is defined as Ω, the optimization objective is given as:
$$Maximize \quad \Omega = \sum_{l \in L} \sum_{s_l \in S_l} \frac{E_{s_l}^{cha}}{E_{s_l}^{req}} \tag{6.3}$$
EVs want to maximize the ratio of actual charging energy ($E_{s_l}^{cha}$) to the energy required ($E_{s_l}^{req}$).

Considering there exist repulsion, a charging cost ($Cost_{ev}^{\Phi}$) is proposed to balance each factor, which is given as follow:

$$Cost_{ev}^{\Phi} = \omega_{\gamma} * \frac{P_{local}}{P_{max}} + \omega_{\epsilon} * \frac{T_{\phi}^{wait}}{D_{ev}} - \omega_{\lambda} * \zeta * \frac{E_{ev}^{cha}}{E_{ev}^{req}} \tag{6.4}$$

Here, $Cost_{ev}^{\Phi}$ optimizes charging QoE in a joint consideration of three factors:

- **Charging Price Factor:** ($\omega_{\gamma} * \frac{P_{local}}{P_{max}}$) calculates the price factor. $\frac{P_{local}}{P_{max}}$ represents the ratio of the local energy price at a CS/PL (P_{local}) to the maximum energy price in the network (P_{max}). ω_{γ} represents the charging price coefficient. A lower charging price means that a CS/PL has a more significant advantage in terms of price.

- **Charging Waiting Time Factor:** ($\omega_{\epsilon} * \frac{T_{\phi}^{wait}}{D_{ev}}$) calculates the charging waiting time factor. ω_{ϵ} represents charging waiting time coefficient, $\frac{T_{\phi}^{wait}}{D_{ev}}$ calculates the ratio of charging waiting time (T_{ϕ}^{wait}) to the EV_r's parking duration (D_{ev}). In case CS/PL is highly congested, this value may be greater than 1.

- **Charging Energy Factor:** ($\omega_\lambda * \zeta * \frac{E_{ev}^{cha}}{E_{ev}^{req}}$) calculates the charging energy factor. ω_λ represents charging energy coefficient. ζ indicates the rate of energy transfer through the converter (energy is lost during the transfer), which differs between V2V and plug-in charging modes. ζ is set as 86% under V2V charging mode [113] and 95% under plug-in charging mode. A higher charging energy factor means that EVs have a higher probability of receiving a fully charging service.

The calculation of $Cost_{ev}^{\Phi}$ is influenced by the predefined coefficients of ω_γ, ω_ϵ and ω_λ. The primary objective for EV charging is to replenish the driving range of EVs, therefore, ω_λ is weighted as the most important. The impact of energy price is weighted higher than the charging waiting time, provided that the charging service is guaranteed [131]. Based on the AHP [132], to determine the relative importance of the criteria, it calculates the weights for each factor based on the judgement matrix construction in Table 6.1.2.

Table 6.2: AHP Judgement Matrix Construction

Criteria	ω_λ	ω_γ	ω_ϵ
ω_λ	1	2	3
ω_γ	1/2	1	2
ω_ϵ	1/3	1/2	1

Weights ω_γ, ω_ϵ and ω_λ are then calculated as 0.2970, 0.1634 and 0.5396 respectively, thus $Cost_{ev}^{\Phi}$ is normalized as:

$$Cost_{ev}^{\Phi} = 0.2970 * \frac{P_{local}}{P_{max}} + 0.1634 * \frac{T_{\phi}^{wait}}{D_{ev}} - 0.5396 * \zeta * \frac{E_{ev}^{cha}}{E_{ev}^{req}} \tag{6.5}$$

6.2 Hybrid Charging Management Framework

Fig.6.1 demonstrates the framework of proposed hybrid charging management. Once the SOC of an EV-C falls below the preset threshold, it sends a charging request to the GC, the hybrid management is as follow:

- **V2V Charging Mode:** It contains V2V-Pair matching process and V2V charging process. The GC is responsible for V2V-Pair matching by referring EVs' current location (Algorithm 1). In the V2V charging process, PL schedules its charging queue, including the current occupancy queue (V2V-Pairs under charging), the subsequent queue for V2V-Pairs waiting and reservation queue for V2V-Pairs that have sent charging reservations. The V2V charging cost at a PL is calculated at Algorithms 2 and 3.

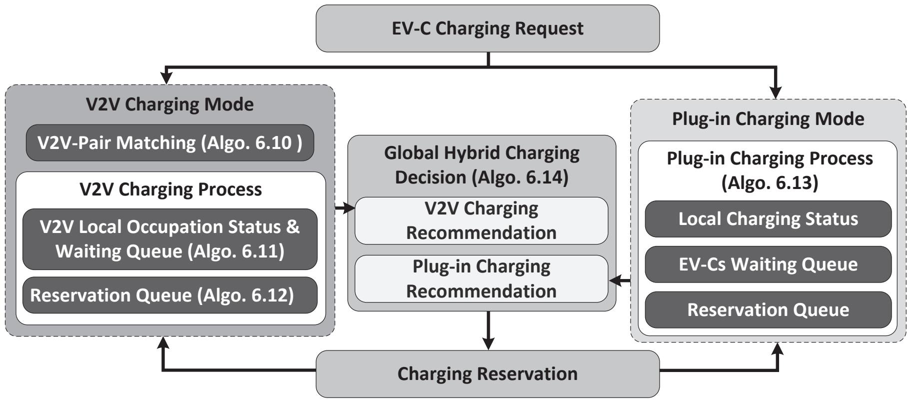


Figure 6.1: Hybrid Charging Management Framework

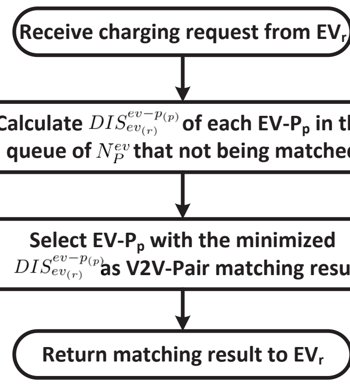
- **Plug-in Charging Mode:** It contains a CS charging process. CS schedules the charging order of EV-Cs, which includes the current charging queue of EV-Cs, the waiting queue and the reservation queue of EV-Cs. Subsequently, the EV-C's charging cost at the CS can be calculated (Algorithm 4).
- **Global Hybrid Charging Decision:** The charging cost at overall CSs/PLs are aggregated to the GC for global decision making (Algorithm 5). This decision is then sent to the EV-C. Once the EV-C confirms the charging reservation, the information in hybrid charging management system is updated.

6.2.1 V2V Charging Mode

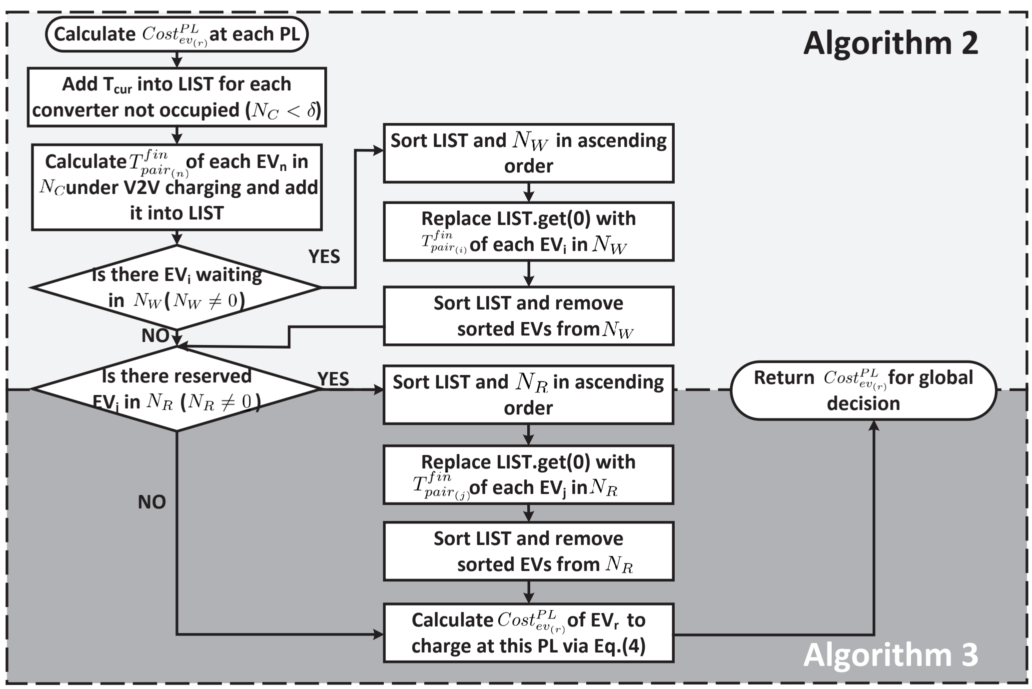
Algorithm 6.10 Pair Matching Algorithm

for $(p = 1; p \leq N_P^{ev}; p++)$ **do**
  if (EV-P$_p$ has not been matched) **then**
    calculate $DIS_{ev_{(r)}}^{ev-p_{(p)}}$
  end if
end for
EV-P$_p \leftarrow \arg\min(DIS_{ev_{(r)}}^{ev-p_{(p)}})$
return EV-P$_p$

Flowchart in Fig.6.2(a) demonstrates V2V-Pair matching process in Algorithm 6.10. When EV-C (EV$_r$) sends charging request to the GC, the GC matches the most suitable EV-P (with the minimised energy cost on-the-move) as the V2V-Pair of EV$_r$. Flowchart in Fig.6.2(b) demonstrates that all PLs are traversed in the charging network to obtain the V2V charging cost at each PL.



(a) Algorithm 6.10



(b) Algorithms 2 and 3

Figure 6.2: Flowcharts of algorithms. (a) Algorithm 6.10. (b) Algorithms 6.11 and 6.12.

6.2.1.1 V2V-Pair Matching

In the Algorithm 6.10, the GC communicates with EV-Ps to aggregate their locations. The GC confirms whether an EV-P (EV-P_p) has been matched with other EV-C (line 2). If not, EV-P_p is considered with service availability, then the distance between EV_r and EV-P_p is calculated at line 3. The EV-P_p with the minimum distance is returned as the most suitable EV-P, thanks to the minimum energy consumed on-the-move (line 6). At line 7, the GC matches EV-P_p as the result of V2V-Pair for EV_r. This pair matching result is replied to EV_r and EV-Ps to ensure the stability of V2V-Pair matching.

6.2.1.2 V2V Charging Process

Lines from 2 to 13 in Algorithm 6.11 process PL local charging occupation status. If there is no converter at the PL currently occupied by V2V-Pairs, the current time in the network (T_{cur}) will be added to LIST with δ time at line 3. It indicates all converters (with number of δ) are available from T_{cur}. Here, LIST represents the available V2V charging time at each converter.

If there is EV (EV_n) in the queue of charging EVs at PL (N_C), the charging finish time of its V2V-Pair ($T^{fin}_{pair_{(n)}}$) will be added into LIST at line 6. This represents the converter is occupied by a V2V-Pair till $T^{fin}_{pair_{(n)}}$. It should be noted that the calculation of $T^{fin}_{pair_{(n)}}$ includes two cases:

- If the EV-C in a V2V-Pair can be fully charged, as the condition $((T_{cur} + T^{cha}_{pair_{(n)}}) \leq (T^{arr}_{pair_{(n)}} + D_{ev}))$, $T^{fin}_{pair_{(n)}}$ is given as the fully charging time of V2V-Pair ($T^{cha}_{pair_{(n)}} + T_{cur}$).
- If the EV-C in a V2V-Pair cannot be fully charged, $T^{fin}_{pair_{(n)}}$ is calculate as the V2V-Pair's departure deadline ($T^{arr}_{pair_{(n)}} + D_{ev}$). Then the V2V-Pair has to leave the PL at the upper limit of parking duration.

$$T^{arr}_{pair_{(n)}} = \begin{cases} T^{arr}_{ev-p_{(n)}} & \text{if } (T^{arr}_{ev_{(n)}} \leq T^{arr}_{ev-p_{(n)}}) \\ T^{arr}_{ev_{(n)}} & \text{else} \end{cases} \tag{6.6}$$

Here, the arrival time of a V2V-Pair depends on the pair with later arrival time. Due to the difference in arrival times of EV-C and EV-P as V2V-Pair, EVs inevitably incur extra waiting time at PLs, and this would cause those EVs in the queue of N_W to wait.

To ensure LIST is with the earliest available charging time, it is sorted in ascending order at line 13. Lines from 14 to 21 process EV (EV_i) in the queue of N_W (EVs waiting to be charged). The for-loop from lines 16 to 20 updates the LIST by scheduling converters occupation of waiting V2V-Pair of EV_i. Line 17 replaces LIST.GET(0) with $T^{fin}_{pair_{(i)}}$ to indicate the first available converter would be occupied by EV_i until $T^{fin}_{pair_{(i)}}$. Then LIST

Algorithm 6.11 V2V Charging of Local V2V-Pairs

for each PL in N_{PL} **do**
    if no EV is under charging **then**
        add T_{cur} in LIST with δ times
    end if
    for $(n = 1; n \leq N_C; n++)$ **do**
        LIST.ADD$(T^{fin}_{pair_{(n)}})$
    end for
    if $(N_C < \delta)$ **then**
        for $(m = 1; m \leq (\delta - N_C); m++)$ **do**
            LIST.ADD(T_{cur})
        end for
    end if
    refine LIST with ascending order
    sort the queue of N_W
    if contains EVs waiting for charging **then**
        for $(i = 1; i \leq N_W; i++)$ **do**
            replace the LIST.GET(0) with $T^{fin}_{pair_{(i)}}$
            refine LIST with ascending order
            remove EV$_i$ from the queue of N_W
        end for
    end if
    if no EV's reservation for charging **then**
        $E^{req}_{ev_{(r)}} = E^{max}_{ev_{(r)}} - E^{cur}_{ev_{(r)}} - E^{tra}_{ev_{(r)}}$
        $T^{cha}_{pair_{(r)}} = \frac{E^{req}_{ev_{(r)}}}{\beta}$
        if $((T^{cha}_{pair_{(r)}} +$ LIST.GET(0)$) < (D_{ev} + T^{arr}_{pair_{(r)}}))$ **then**
            $E^{cha}_{ev_{(r)}} = E^{req}_{ev_{(r)}}$
        else
            $E^{cha}_{ev_{(r)}} = (D_{ev} + T^{arr}_{pair_{(r)}} -$ LIST.GET(0)$) * \beta$
        end if
        if $(T^{arr}_{pair_{(r)}} <$ LIST.GET(0)$)$ **then**
            $T^{wait}_{pair_{(r)}} =$ LIST.GET(0) $-T^{arr}_{pair_{(r)}}$
        else
            $T^{wait}_{pair_{(r)}} = 0$
        end if
        calculate $Cost^{PL}_{ev_{(r)}}$
        return $Cost^{PL}_{ev_{(r)}}$
    else
        return Algorithm 3 with input LIST
    end if
end for

is sorted in ascending order at line 18 to make sure that LIST.GET(0) remains the first available charging time among converters. EV$_i$ that has been scheduled is removed from N_W at line 19. Subsequently, the remaining EVs in the queue of N_W, continue to be scheduled for V2V charging until all EVs in the queue of N_W have been ordered.

Based on whether the PL has V2V charging reservations, Algorithm 6.11 is divided into two cases:

- **Case 1 - No Reservation:** If the PL has not been reserved, LIST.GET(0) becomes the first available V2V charging time, after the scheduling of N_C and N_W queues. The charging cost for V2V charging through this PL can be calculated at line 35.

- **Case 2 - With Reservation:** If the PL has been reserved, then LIST is passed to Algorithm 6.12 for V2V charging scheduling with the reservation queue N_R at line 38.

6.2.1.3 Case 1 - No Reservation

At line 23 in Algorithm 6.11, the V2V charging energy requirement of EV$_r$ ($E^{req}_{ev_{(r)}}$) is calculated. Considering whether the EV$_r$ can be fully charged, the actual charging energy ($E^{cha}_{ev_{(r)}}$) is calculated between lines 24 and 28. If EV$_r$ can be fully charged, $E^{cha}_{ev_{(r)}}$ is equal to $E^{req}_{ev_{(r)}}$ at line 26. Conversely, at line 28, $E^{cha}_{ev_{(r)}}$ is calculated as the product of its actual charging time and charging power at the PL (($D_{ev} + T^{arr}_{pair_{(r)}}$ −LIST.GET(0)) $* \beta$).

Lines from 30 to 34 calculate the charging waiting time ($T^{wait}_{pair_{(r)}}$). If the V2V-Pair of EV$_r$ arrives earlier than the earliest available charging converter ($T^{arr}_{pair_{(r)}}$ <LIST.GET(0)), $T^{wait}_{pair_{(r)}}$ is calculated as (LIST.GET(0) $-T^{arr}_{pair_{(r)}}$). Otherwise, $T^{wait}_{pair_{(r)}}$ equals 0, which means that EV$_r$ is able to directly receive V2V charging upon its arrival.

As core parameters ($E^{req}_{ev_{(r)}}$, $E^{cha}_{ev_{(r)}}$ and $T^{wait}_{pair_{(r)}}$) for calculating the charging cost have been obtained, Algorithm 6.11 calculates the charging cost at the PL at line 35. The charging cost calculation is detailed in section 6.1.2. Line 36 returns the charging cost for EV$_r$ to charge at the PL ($Cost^{PL}_{ev_{(r)}}$). This charging cost is then aggregated to further determine the optimal V2V charging PL.

6.2.1.4 Case 2 - With Reservation

If a PL receives V2V charging reservations (at line 37 in Algorithm 6.11), it is necessary to sort the charging scheduling of other EVs (and their corresponding V2V-Pairs) in the queue of N_R with EV$_r$. Thus, at line 38, LIST is passed to Algorithm 6.12 for further V2V charging scheduling and charging cost calculation.

In Algorithm 6.12, EV$_r$ is added into the queue of N_R at line 1. EV (EV$_j$) in the queue of N_R is sorted in ascending order. This is to ensure EV$_j$ can receive V2V charging in the order of their arrival time. The for-loop operation from lines 3 to 16 schedules the V2V

Algorithm 6.12 V2V Charging of Reservation V2V-Pairs $\langle$LIST$\rangle$

1: add EV$_r$ into the queue of N_R
2: sort the queue of N_R
3: **for** $(j = 1; j \leq N_R; j++)$ **do**
4:     **if** EV$_r$ equals to EV$_j$ **then**
5:         break
6:     **else**
7:         **if** $((T^{cha}_{pair_{(j)}} +$ LIST.GET(0)$) < (D_{ev} + T^{arr}_{pair_{(j)}}))$ **then**
8:             $T^{fin}_{pair_{(j)}} = T^{cha}_{pair_{(j)}}$+LIST.GET(0)
9:         **else**
10:             $T^{fin}_{pair_{(j)}} = D_{ev} + T^{arr}_{pair_{(j)}}$
11:         **end if**
12:         replace the LIST.GET(0) with $T^{fin}_{pair_{(j)}}$
13:         sort LIST in ascending order
14:         remove EV$_j$ from the queue of N_R
15:     **end if**
16: **end for**
17: calculate $Cost^{PL}_{ev_{(r)}}$
18: **return** $Cost^{PL}_{ev_{(r)}}$

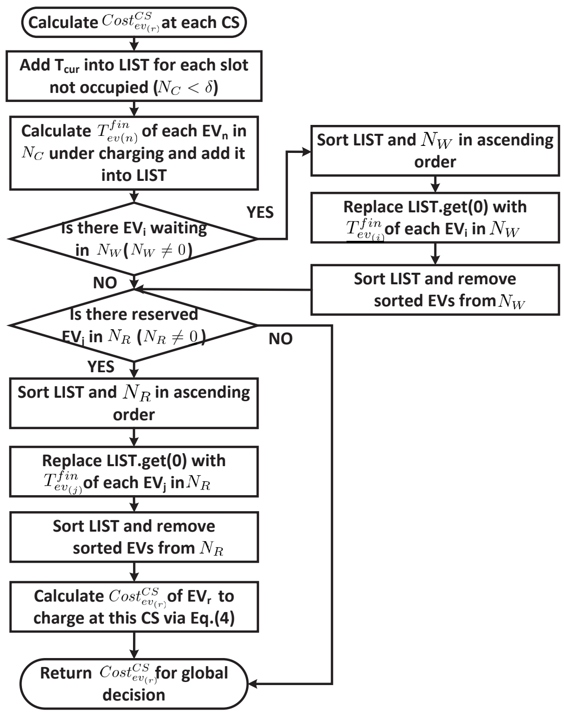
charging of EV$_j$ in N_R. At line 5, the for-loop would break if EV$_j$ in that loop is equal to EV$_r$. Otherwise, EV$_j$ would charge prior to EV$_r$. $T^{fin}_{pair_{(j)}}$ is calculated separately at lines 8 and 10, corresponding to the fully charged and not fully charged cases. Then LIST.GET(0) is replaced by $T^{fin}_{pair_{(j)}}$, meaning that the earliest available converter is occupied by the V2V-Pair of EV$_j$ till its charging finished. EV$_j$ been scheduled is removed from N_R at line 14.

When the for-loop is finished, parameters for EV$_r$ to charge at that PL ($E^{req}_{ev_{(r)}}$, $E^{cha}_{ev_{(r)}}$ and $T^{wait}_{pair_{(r)}}$) can be calculated. With above parameters, Algorithm 6.12 calculates $Cost^{PL}_{ev_{(r)}}$ at line 17 and outputs this value as the charging cost of EV$_r$ to have V2V charging at this PL.

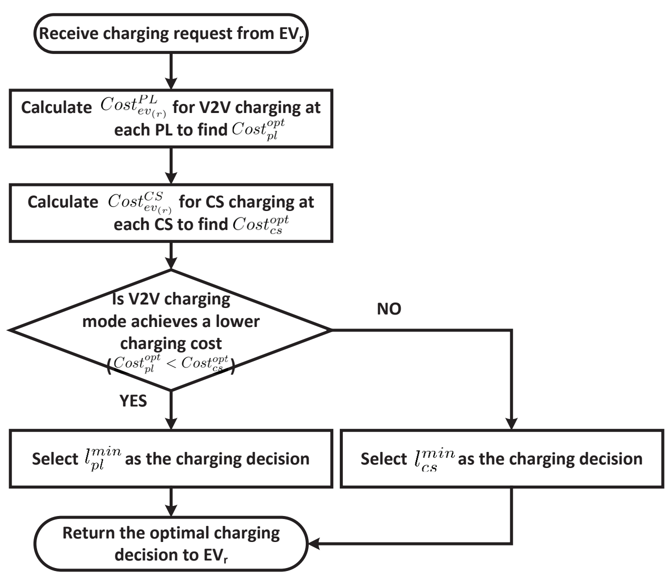
6.2.2 CS Charging Mode

In Algorithm 6.13, a global for-loop traverses all CSs in the charging network, to obtain the charging cost at each CS under the CS charging mode. Such process is demonstrated in Fig.6.3(a).

The EVs under charging is characterized in the queue of N_C. Here, T_{cur} will be added into the LIST with δ times to indicate that all slots are available from T_{cur}. Lines from 5 to 7 update the LIST by traversing charging service of EV$_n$ (EV in the queue of N_C). $T^{fin}_{ev(n)}$ is added into LIST at line 6 to indicate that a charging slot is providing service to EV$_n$ until $T^{fin}_{ev(n)}$. Lines between 8 and 12 consider the situation that not all charging slots are



(a) Algorithm 6.13



(b) Algorithm 6.14

Figure 6.3: Flowcharts of algorithms. (a) Algorithm 6.13. (b) Algorithm 6.14.

Algorithm 6.13 CS Charging of Local EV-Cs

for each CS in N_{CS} **do**
  if no EV is under charging **then**
    add T_{cur} in LIST with δ times
  end if
  for $(n = 1; n \leq N_C; n++)$ **do**
    LIST.ADD$(T^{fin}_{ev(n)})$
  end for
  if $(N_C < \delta)$ **then**
    for $(m = 1; m \leq (\delta - N_C); m++)$ **do**
      LIST.ADD(T_{cur})
    end for
  end if
  refine LIST with ascending order
  sort the queue of N_W
  if contains EVs waiting for charging **then**
    for $(i = 1; i \leq N_W; i++)$ **do**
      replace the LIST.GET(0) with $T^{fin}_{ev_{(i)}}$
      refine LIST with ascending order
      remove EV$_i$ from the queue of N_W
    end for
  end if
  if no EV's reservation for charging **then**
    calculate $Cost^{CS}_{ev_{(r)}}$
    return $Cost^{CS}_{ev_{(r)}}$
  else
    add EV$_r$ into the queue of N_R
    sort the queue of N_R
    for $(j = 1; j \leq N_R; j++)$ **do**
      if EV$_r$ equals to EV$_j$ **then**
        break
      else
        replace the LIST.GET(0) with $T^{fin}_{ev_{(j)}}$
        sort LIST in ascending order
        remove EV$_j$ from the queue of N_R
      end if
    end for
    calculate $Cost^{CS}_{ev_{(r)}}$
    return $Cost^{CS}_{ev_{(r)}}$
  end if
end for

occupied, T_{cur} will be added to the LIST with $(\delta - N_C)$ times. Followed by lines 13 and 14, Algorithm 6.13 schedules the LIST in ascending order.

Lines from 14 to 21 process EVs parked at the CS waiting for charging. To obtain the occupation status of converters, EV$_i$ in the queue of N_W is calculated. For each EV$_i$, its $T^{fin}_{ev_{(i)}}$ would replace LIST.GET(0) to indicate its occupancy status for the charging slot. Then LIST is sorted in ascending order at line 18, to make sure that LIST.GET(0) remains the first available charging time among converters. EV$_i$ that has been scheduled is removed from N_W at line 19. Those EVs not been removed, continue to be scheduled until they have been ordered.

If the CS has no charging reservation received, EV$_r$ is scheduled with the top charging order after EV$_i$ been charged. The charging cost ($Cost^{CS}_{ev_{(r)}}$) of EV$_r$ at this CS can be calculated at line 23. This $Cost^{CS}_{ev_{(r)}}$ is return for the global hybrid charging decision making. Lines from 25 to 38 consider the condition that this CS has charging reservation received. If EV$_j$ (the EV in the queue of N_R being processed in current loop operation) is the EV$_r$. This implies that EV$_r$ is able to be charged upon its arrival. If not, EV$_j$'s charging finish time $T^{fin}_{ev_{(j)}}$ will take place LIST.GET(0). Then LIST is sorted in ascending order and EV$_j$ that has been scheduled is removed from N_R. Once EV$_r$ has been determined its charging order, $Cost^{CS}_{ev_{(r)}}$ can be calculated. Such $Cost^{CS}_{ev_{(r)}}$ is returned to Algorithm 6.14 at line 38 for final charging decision making.

Algorithm 6.14 Global Hybrid Charging Decision Making

1: **for** $\forall l_{pl} \in N_{PL}$ **do**
2: calculate $Cost^{PL}_{ev_{(r)}}$ via Algorithm 6.11 and 6.12
3: **end for**
4: $Cost^{opt}_{pl} \leftarrow \arg\min(Cost^{PL}_{ev_{(r)}})$
5: **for** $\forall l_{cs} \in N_{CS}$ **do**
6: calculate $Cost^{CS}_{ev_{(r)}}$ via Algorithm 6.13
7: **end for**
8: $Cost^{opt}_{cs} \leftarrow \arg\min(Cost^{CS}_{ev_{(r)}})$
9: **if** $Cost^{opt}_{pl} < Cost^{opt}_{cs}$ **then**
10: **return** l^{min}_{pl}
11: **else**
12: **return** l^{min}_{cs}
13: **end if**

6.2.3 Global Hybrid Charging Decision

In order to serve EVs with desire QoE, in Algorithm 6.14, the GC aggregates $Cost^{\Phi}_{ev}$ via Algorithm 6.11, 6.12 and 6.13, and determines the global hybrid charging decision selection. Here, the process of Algorithm 6.14 is demonstrated in Fig.6.3(b).

The for-loop from lines 1 to 3 traverses all PLs in the charging network to calculates their $Cost^{PL}_{ev_{(r)}}$. Then the PL with the lowest $Cost^{PL}_{ev_{(r)}}$ would be selected as optimal V2V charging selection. This PL-Selection determines the minimum charging cost ($Cost^{opt}_{pl}$) under V2V charging mode.

All CSs in the charging network are traversed between lines 5 and 8. Their charging cost ($Cost^{CS}_{ev_{(r)}}$) are calculated. The CS with the lowest $Cost^{opt}_{cs}$ will be determined as CS-Selection for global hybrid selection at line 8.

Based on the minimized charging cost, the optimal PL-Selection and CS-Selection are identified at line 5 and line 8 respectively, which takes into account the charging price, the charging waiting time and the actual charged energy. Therefore, if the condition ($Cost^{opt}_{pl} < Cost^{opt}_{cs}$) holds, the optimal PL (l^{min}_{pl}) will be recommended for EV$_r$ as its allocated charging decision; Otherwise, the optimal CS (l^{min}_{cs}) will be recommended for EV$_r$.

6.3 Performance Evaluation

6.3.1 Simulation Configuration

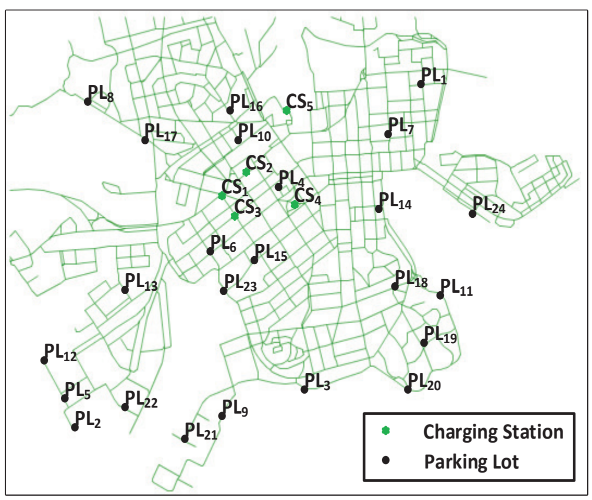
The Opportunistic Network Environment (ONE) [114] is applied to simulate EV charging network scenario. In Fig.6.4(b), the simulation demonstrates the urban area of Helsinki city (Fig.6.4(a)) with a 4500×3400 m^2 scenario. 24 PLs are geographically deployed in the urban area and each PL is equipped with 4 DC-DC converters. The DC-DC converter allows charging for a V2V-Pair with an energy transfer power of 15 kW. Meanwhile, 5 CSs are deployed in this urban scenario, and each is provided with 4 charging slots using the fast charging power of 52 kW. The benchmark price in the network is set as plug-in charging price with €0.25 /kWh [133]. To represent the price variation of V2V charging and the impact of PL availability on the price, a grading price is introduced in simulation as listed in Table 6.3.

Table 6.3: V2V Charging price at PL (€/kWh)

	Urban Areas	Suburban Areas
All Converters Available	0.10	0.12
Half Converters Available	0.15	0.16
All Converters Occupied	0.20	0.20

EVs in the scenario are divided into three types, with the following configuration: Maximum Electricity Capacity (MEC), Max Travelling Distance (MTD), Average Energy Consumption (AEC) and SOC threshold. Table 6.4 lists configuration of EVs.

(a) Google Map of Helsinki City



(b) Deployment of CSs/PLs

Figure 6.4: Simulation Scenario

Table 6.4: EV configuration under hybrid mode

	Coda [121]	Wheego whip [134]	BlueOn[135]
MEC (kWh)	33.8	30.0	16.4
MTD (km)	193	161	140
AEC (kWh/km)	0.1751	0.1863	0.1171
SOC threshold	30%	40%	50%

EV-C battery is with full volume at the beginning. Meanwhile, the number of EV-Ps is set as the same number of EV-Cs (to ensure stable V2V-Pair matching). EV-Ps are set to have enough energy to provide multiple V2V charging service, thus they don't require intermediate charging.

EVs are with moving speed from 30 to 50 km/h, to reflect situation of roads and traffic. Here, destinations of EVs are set randomly. If the SOC of an EV-C is below the threshold, it sends charging request to the GC for charging decision. When the EV receives CS/PL-Selection and confirms the charging reservation, it travels to the selected CS/PL along the Helsinki city road topology. The real-time location and energy information of EVs are updated at a frequency of 0.1s. The simulation lasts for a duration of 12 hours.

6.3.2 Comparison Configuration

A hybrid charging management scheme is proposed in this chapter. The following charging schemes are evaluated for comparison:

- **Reservation-based Hybrid Charging Management (R-Hyb)**: The proposed scheme with hybrid charging management that selects the CS/PL with the minimized charging cost, with reservation.
- **Hybrid Charging Management without Reservation (Hyb)**: The benchmark scheme with hybrid charging management that selects the CS/PL with the minimized charging cost, without reservation.

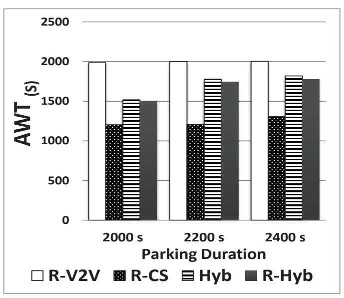
Two other schemes under single plug-in or V2V mode are evaluated.

- **Reservation-based V2V Charging (R-V2V) [8]**: Literature work applies the V2V charging mode with reservation. The GC allocates V2V-Pairs to the PL with the earliest available charging time.
- **Reservation-based plug-in Charging (R-CS) [122]**: Literature work applies the plug-in charging mode with reservation. The GC allocates EVs to the CS with the earliest available charging time.

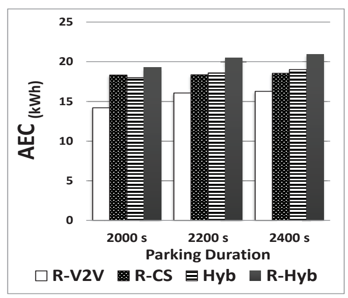
The following performance metrics are evaluated:

- **Average Charging Price per unit (ACP)**: It indicates the average charging price of EV-Cs charged at CS/PL.
- **Average Waiting Time (AWT)**: It indicates the average waiting time for EV-Cs between they arrive at CS/PL and receive charging service.
- **Average Energy Charging (AEC)**: It indicates the average energy of EV-Cs charged per charging service.
- **Charging Cost**: It indicates the average charging cost of each EV during the entire duration of simulation. Here, lower charging cost refers better QoE.

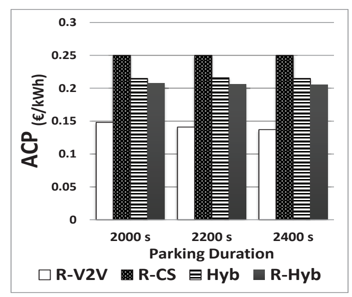
6.3.3 Influence of Parking Duration



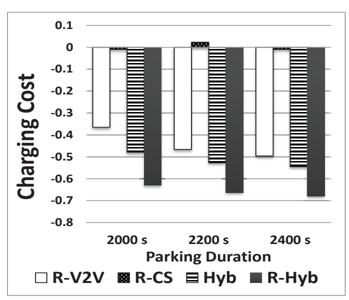
(a) AWT



(b) AEC



(c) ACP



(d) Charging Cost

Figure 6.5: Influence of Parking Duration

In the first group of simulations, the EV density is set to 150 (including 150 EV-Cs and 150 EV-Ps) and observe the influence of parking duration.

R-Hyb scheme achieves a shorter AWT comparing with Hyb scheme in Fig.6.5(a). As the parking duration increases, there is a significant increase of AWT under both hybrid modes. Since charging cost is considered, the increase of parking duration means that hybrid modes accept a longer waiting time in exchange for sufficient charging energy (ω_λ = 0.5396).

When the parking duration increases in Fig.6.5(b), AEC increase under R-Hyb scheme is most significant. Hyb scheme suffers with a lower AEC than that of R-Hyb scheme by 14%, due to the lack of a priori information. In Fig.6.5(c), R-V2V scheme achieves the lowest ACP as it only allows V2V charging (with a lower charging price). The ACP under R-CS scheme, on the other hand, is fixed at €0.25 /kWh. The ACP of R-Hyb and Hyb schemes are concentrated around €0.2 /kWh. This is because their optimization jointly consider both charging modes. In addition, parking duration have low influence on the ACP, as the coefficients of charging price is low (ω_ϵ = 0.1634).

The charging cost of EVs is illustrated in Fig.6.5(d). Here, the charging cost of R-Hyb scheme decreases when the parking duration increases. Meanwhile, R-Hyb scheme achieves the lowest charging cost. The improvement in charging cost for R-Hyb compared to Hyb is about 33%. The improvement in charging cost for R-Hyb compared to R-V2V is about 65%, which is most significant when the parking duration is short (meaning higher charging congestion). This indicates that R-Hyb scheme ensures EV-Cs receiving services with high QoE, thanks to the consideration of hybrid charging mode, as well as charging reservation.

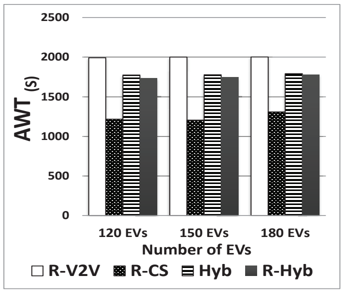
6.3.4 Influence of EV Density

In the second group of simulations, the parking duration is set to 2200s and observe the influence of EV density.

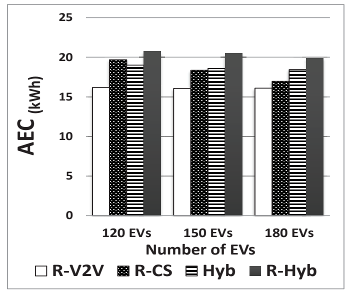
In Fig.6.6(a), R-CS scheme achieves the shortest AWT above all schemes. However, it is worth noting that there is a significant increase in AWT of R-CS scheme when the number of EVs increases. This reflects that, limited by the rigid deployment of CSs, R-CS scheme can not avoid charging congestion when it faces with large concurrent charging requests. In comparison, R-Hyb scheme maintains a lower level of AWT when the number of EVs increases.

As the number of EVs increases, AEC under each of the schemes decreases (Fig.6.6(b)). Here, R-Hyb achieves the highest AEC due to the introduction of charging cost as an optimization objective. Meanwhile, R-Hyb scheme considers hybrid charging, thus allowing for a maximized utilization of charging resources. As R-Hyb avoids allocating EVs to CSs/PLs with high charging congestion and considers hybrid charging, it helps R-Hyb scheme to maximized utilize charging resources. This results in that the ACP under R-Hyb scheme decreases even when the number of EVs increases (Fig.6.6(c)).

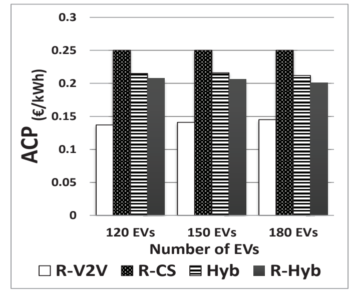
In Fig.6.6(d), both R-CS and R-V2V schemes have significant increase in charging cost when the number of EVs increases, which means that the QoE of EV charging can not be guaranteed. This is due to a longer charging waiting time caused by charging congestion. However, R-Hyb scheme still achieves the lowest charging cost, due to the



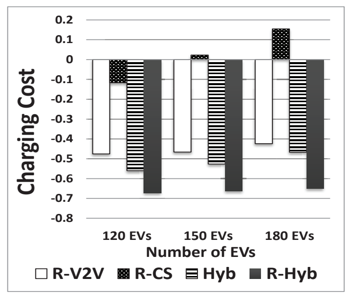
(a) AWT



(b) AEC



(c) ACP



(d) Charging Cost

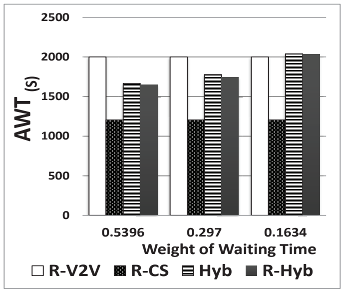
Figure 6.6: Influence of EV Density

consideration of hybrid charging and charging reservation. Even if the number of EVs increases significantly, the increase in charging cost under R-Hyb is about only 3%. This refers that R-Hyb can guarantee QoE by flexibly utilizing charging resources in the network.

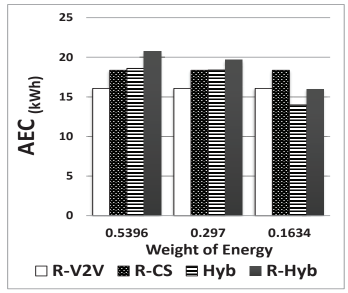
6.3.5 Influence of AHP Coefficients Weight

In Eq.(6.5), the coefficient weight in the judgement matrix is assigned according to AHP. Due to that the coefficient of charging energy (ω_λ = 0.5396) is the highest, AEC among all metrics varies the most significant. Therefore, in this group of simulation, the weight of each coefficient are adjusted. Here, the parking duration is set to 2200s and the number of EVs is set to 150. The results of changing weight for ω_γ, ω_ϵ and ω_λ respectively are shown in Fig.7(a-c). This is to see how each coefficient has an effect on performance metrics under different levels of weight.

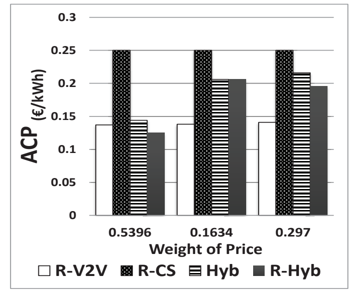
In Fig.6.7(a), ω_ϵ is set to 0.5396, 0.2970 and 0.1634 respectively. The results reflect that AWT of R-Hyb increases as ω_ϵ decreases. When ω_ϵ is 0.5396, both hybrid schemes achieve lower AWT than R-V2V scheme, while still higher than R-CS scheme. However, Hyb scheme suffers a higher AWT comparing with R-Hyb scheme, which reflects the importance of reservation. In Fig.6.7(b), ω_λ is changed. It should be noted that AEC under R-Hyb is even lower than that under R-V2V scheme, when ω_λ is set to 0.1634. This reflects the



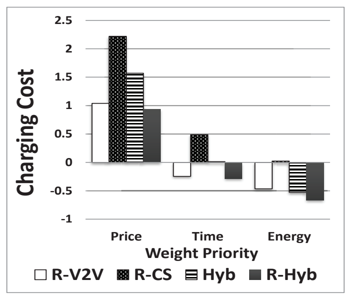
(a) AWT



(b) AEC



(c) ACP



(d) Charging Cost

Figure 6.7: Influence of AHP Coefficients Weighting

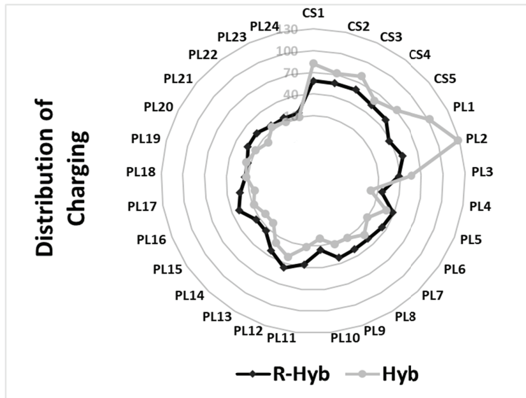
importance of individual coefficient weight settings. Meanwhile, in Fig.6.7(c), ACP under R-Hyb is the lowest when the weight of ω_γ is the highest.

In Fig.6.7(d), results show charging cost when each coefficient is set with the highest weight priority. Here, the density of EVs and the parking duration are set same. When ω_λ's weight is set as the highest ($\omega_\lambda = 0.5396$), the charging cost of all schemes are at the lowest level. This illustrates the improvement of overall EV charging QoE when charging energy is given priority. Nevertheless, for the purpose of optimizing EV charging, coefficient weights could be adjusted by EV charging network operators to suit different charging scenarios.

6.3.6 Distribution of Charging at CSs/PLs

Fig.6.8(a) illustrates the charging distribution at different CSs/PLs under R-Hyb and Hyb schemes. Here, the simulation is set with 150 EVs and 2200s parking duration.

An even distribution among CSs/PLs could maximise the utilization of charging resources. As Hyb scheme makes charging decision without reservation, CSs/PLs in urban centre would be selected frequently. This inevitably causes charging congestion and reduces the QoE of EV drivers. However, R-Hyb scheme ensures a relatively even distribution of charging among all CSs/PLs. This reflects that R-Hyb makes better utilization of charging resources in the network. When the charging network is faced with



(a) Distribution

Figure 6.8: Distribution of Charging at CSs/PLs

a large number of concurrent EV charging requests, R-Hyb can still guarantee a high QoE.

6.4 Summary

Currently, a single charging mode cannot handle a large number of concurrent EVs charging requests. Therefore, this chapter proposes a hybrid charging management scheme to flexibly utilise both plug-in charging and V2V charging modes. To improve the QoE of EV charging, the proposed hybrid management introduces a charging cost based on a collaborative optimization of price-time-energy dimensions. When determining the charging allocation for EVs, the proposed hybrid management selects the CS/PL with the lowest charging cost. Considering the high mobility of EVs, the hybrid charging management further introduces charging reservation. This allows a more accurate assessment of charging availability of each CS/PL, to make optimal utilization of charging resources in the network. In this chapter, a EV charging network is simulated under Helsinki urban scenario. The results show that the proposed reservation-based hybrid scheme can effectively improve the EV charging QoE, with higher charging energy, lower charging waiting times and charging price.

Chapter 7

Conclusions

This chapter provides a summary of this thesis' contributions and discusses how the proposed algorithms in this thesis contributed to the field of EV charging optimization. The perspective regarding future works is further discussed.

7.1 Summary of Contributions

In Chapter 2, different modes of EV charging are discussed methodologically. Optimization under plug-in charging mode focuses on CS deployment problem, charging scheduling problem, and charging recommendation problem (where-to-charge). In contrast, under the battery swapping mode, charging optimization focuses on battery scheduling, BSS deployment, and BSS-Selection. Here, V2V charging mode, as a novel approach, requires optimization of V2V-Pair matching and PL-Selection problem. Considering the advantages and disadvantages of the above three modes, hybrid modes would have a greater application prospect. It avoids uneven allocation of charging infrastructures and charging congestion under a single mode, achieving higher EV charging flexibility. Meanwhile, the hybrid mode could improve the efficiency of charging infrastructure utilization. Following this taxonomy, a better perception of the overall framework of EV charging can be achieved.

In Chapter 4, a spatial-temporal domain co-optimization approach, UFC policy, under plug-in charging mode is proposed. It takes into account the user charging demand as well as the remaining available parking duration. Based on the UFC policy, an EV with high charging urgency obtains a higher chance to be fully charged, which improves the overall charging efficiency of the charging network. In addition, this work applies to queue theory to optimize CS-Selection. As EV drivers lack global awareness in making charging decisions, this optimization method manages to charge globally via the GC. Moreover, this optimization approach introduces a reservation method. This is to guide EV charging allocation through prior information, thus alleviating the charging congestion problem. Based on the ONE introduced in Chapter 3, simulation results show the improvement of

EV charging by applying the UFC policy. There is a significant reduction in the average charging waiting time, and average charging trip duration, and a significant increase in the number of EV fully charged.

In chapter 5, EV charging is optimized by introducing a novel V2V charging mode. Here, EV-Ps transfer surplus energy to EV-Cs. This reduces the stress on the grid while maximizing the flexibility of EV charging. Since in the V2V charging mode, EV charging takes place in the form of V2V-Pair, V2V-Pair matching needs to be optimized. For the consideration of minimizing energy consumption, the shortest distance V2V-Pair matching method is proposed. Meanwhile, the mobility of EVs in V2V mode presents higher requirements on the PL-Selection. Thus, the V2V charging reservation method is introduced in this work. This approach perceives the PL occupation status in different areas of the city and improves the PL-Selection allocation. Considering factors such as parking duration, EV density, and charging power, this V2V charging optimization is evaluated under simulations (based on the ONE). The results under different scenarios show that the proposed V2V charging achieves a higher percentage of EV fully charged and a shorter charging waiting time compared to the traditional plug-in charging mode.

In Chapter 6, a hybrid charging mode is proposed by taking advantage of the algorithms presented in Chapters 4 and 5. This hybrid mode flexibly exploits the advantages and overcomes the disadvantages under each single charging mode. For example, plug-in charging mode is stable but limited by CS deployment, and V2V charging is flexible but does not guarantee fast charging. The proposed hybrid charging mode integrates the charging infrastructures in the network. It is emphasized that the charging reservation approach is introduced in this mode to avoid charging congestion, considering the high mobility of EVs. Aware of the difficulty of selecting different charging modes in the same dimension, this hybrid mode introduces AHP to analyze the charging cost under different CS and PL. The simulations of EV charging network show that this mode is effective in reducing charging waiting time by up to 30% and minimizing charging cost compared with single charging modes.

7.2 Future Direction

7.2.1 EV Charging and Autonomous Driving

Autonomous driving technology provides convenience for people in their daily travels. Considering that EVs would become the main branch of future mobility, there leads to a huge challenge in combining EV charging with autonomous driving. Specifically, such a combination suffers from the following problems:

- Precise navigation technology in charging space: In order to accommodate large-scale cluster autonomous driving, some EVs need to travel to CSs for charging while autonomous driving. Therefore, it is necessary to confirm the charging position at the parking space by means of a precise navigation system.

- Construction of a supporting communication platform: Autonomous driving EVs require communication between the on-board system and charging system. Autonomous EV notifies CSs via communication for advance docking, to facilitate charging scheduling.

- Application of wireless charging technology: With wireless charging technology, EVs can be charged without human involvement. The combination of wireless charging and autonomous driving enables automated EV charging. Meanwhile, automated charging would automatically break at the departure deadline.

7.2.2 Integration of Multi-energy in EV Charging

The main difference between EVs and traditional fuel vehicles is the source of energy. Here, EVs utilize electricity as a clean source of energy to supplement driving range. However, as electricity generation still relies heavily on thermal power, there is currently controversy over the level of carbon emissions from EVs. Optimizing EV charging, therefore, requires consideration of the renewable energy sources:

- PV system: The utilization of PV systems for EV charging is a popular recently. However, PV system requires high upfront deployment cost. In addition, considering the practical charging scenario, plenty of EVs request charging services during night periods (e.g., in residential areas). The staggered timing of energy generation and charging makes PV charging system more inconvenient.

- Wind power systems: Currently, there is considerable installed wind power capacity worldwide, but relatively few applications apply wind power as a source of EV energy. This is because wind power does not provide a steady supply of electricity, and thus cannot meet a large number of EV charging requests. In addition, wind power is mostly established in suburban locations, where the wind is stronger at night than during the day, but the night period is with a low charging request level in suburban. Therefore, there are challenges in integrating wind power systems with EV charging.

7.2.3 Information Security

The vehicle-mounted system faces a risk of information security, and it may be attacked by hackers causing serious threats to society. This is because the number and types of external interfaces of ICVs have increased rapidly. Thus, ICVs have become highly integrated information system equipped with large-scale software. Accordingly, utilizing existing vulnerabilities of software and system, hackers can attack the vehicle-mounted system for the purpose of in-vehicle information theft, driving system failure, remote control of the braking system etc. Therefore, the security of vehicle-mounted system needs to be concerned.

Apart from the above security problem of in-vehicle, the information security of V2X (Vehicle to Everything) communication is another focus. If the attacker always sends fake messages, the driver will be disturbed and ignore various warnings from the cloud controller, causing unreasonable decision-making behaviors. Besides, privacy protection is an important field of V2X communication. When a message containing personal information is sent from the ICV to the outside, it is easy to be tracked. It causes a serious privacy problem for the driver.

7.2.4 The Binding between the ICV and the Metaverse

The technology usage of the metaverse fits in a lot with ICV. In the future, ICVs will become an important terminal in people's daily life. Many people in the industry even believe that this will become a more important terminal device than mobile phones. The combination of ICV and metaverse will produce many colorful and brand-new application scenarios.

- The Virtual Reality and Augmented Reality technologies in the metaverse have been applied to ICVs to become AR-HUD.
- Connecting virtual and reality will make ICVs' service, brand communication, etc. easier.
- The display form of car virtual projection will also derive more diverse and humanized functions. It will promote communication between drivers and ICVs, pedestrians, and even other vehicles, making driving safe and comfortable.
- Metaverse creates an immersive experience space, trying to replicate a parallel world in the digital world.

Appendix A

Introduction

A.1 Running Simulation

ONE comes with a default settings.txt file. It is important to note here that this file is read (used) for every simulation. Thus, we would, in general, be modifying this file to suit this research. It is needed to specify names of these files while running the simulation, as shown below:

Listing A.1: ONE simulation execution

```
one.bat -b 1 V2V.txt
```

A.2 Scenario Configuration

Next, an example of the configuration file using for V2V charging under EV charging simulation in Chapter 5 is presented:

Listing A.2: V2V.txt

```
######################
## Scenario settings##
#IEEE Systems Journal#
######################

Scenario.name = /V2VJournal/
Scenario.simulateConnections = [true]
Scenario.updateInterval = [0.1]
Scenario.endTime = [43210]

##############################
```

```
##Transmission Configuration##
################################
/****EV Radio Range****/
btInterface.type = SimpleBroadcastInterface
btInterface.transmitSpeed = [500k]
btInterface.transmitRange = [15]
Scenario.nrofHostGroups = [23]

Group.router = [RVEVRouter]
#SpeedEVRouter;REVRouter;

##############################
#RSU-EVRouter Configuration#
##############################
EVRouter.StreamingModel = [false]
EVRouter.StreamRecordTime = [1]

##################################################
##RSU-EVRouter Reservation/Changing Decision##
###########"false" For CentralisedEV##########
##################################################
EVRouter.RSULabel = [false]

############################
####CS Update Interval####
############################
EVRouter.CSUpdateInterval = [300]

##########################################
#####Change Decision Configuration#####
##########################################
EVRouter.ChangeDecision = [false]

###########################################
##True, For Directly Moving Towards CS##
###########################################
Group.TripPlanning = [true]

##########################################
##Update Period For Changing Decision##
```

```
######0 Means No Updating Process######
#######################################
Group.TripUpdating= [100]

#####################################
######Consider Trip Destination######
#####################################
Group.ContinuousTrip = [true]

####################
##Traffic Accident##
####################
Group.MotionChangeInterval=[300]
Group.JamDuration = [100]
Group.JamNumber = [30]
Group.JamDistance = [300]


Group.nrofInterfaces = [1]
Group.interface1 = [btInterface]

Group.movementModel = [ShortestPathMapBasedMovement]
Group.speed = [8.333,13.9]

Group.nrofHosts = [140]

Group1.groupID = [EV-C]
Group2.groupID = [EV-C]
Group3.groupID = [EV-C]
Group4.groupID = [EV-P]
Group4.nrofHosts = [210]
Group5.groupID = [EV-P]
Group5.nrofHosts = [210]


#########################
####Deployment of CS ####
#########################
Group6.movementModel = [PLPlacementMovement]
Group6.groupID = [PL]
```

```
Group6.speed = [0,0]
Group6.nrofHosts = [1]
Group6.nodeLocation = [2637,940]

Group7.movementModel = [PLPlacementMovement]
Group7.groupID = [PL]
Group7.speed = [0,0]
Group7.nrofHosts = [1]
Group7.nodeLocation = [1552,1301]

Group8.movementModel = [PLPlacementMovement]
Group8.groupID = [PL]
Group8.speed = [0,0]
Group8.nrofHosts = [1]
Group8.nodeLocation = [3592,1151]

Group9.movementModel = [PLPlacementMovement]
Group9.groupID = [PL]
Group9.speed = [0,0]
Group9.nrofHosts = [1]
Group9.nodeLocation = [1092,2001]

Group10.movementModel = [PLPlacementMovement]
Group10.groupID = [PL]
Group10.speed = [0,0]
Group10.nrofHosts = [1]
Group10.nodeLocation = [2492,1801]

Group11.movementModel = [PLPlacementMovement]
Group11.groupID = [PL]
Group11.speed = [0,0]
Group11.nrofHosts = [1]
Group11.nodeLocation= [1152,307]

Group12.movementModel = [PLPlacementMovement]
Group12.groupID = [PL]
Group12.speed = [0,0]
Group12.nrofHosts = [1]
Group12.nodeLocation = [991,2401]
```

```
Group13.movementModel = [PLPlacementMovement]
Group13.groupID = [PL]
Group13.speed = [0,0]
Group13.nrofHosts = [1]
Group13.nodeLocation = [3171,1701]

Group14.movementModel = [PLPlacementMovement]
Group14.groupID = [PL]
Group14.speed = [0,0]
Group14.nrofHosts = [1]
Group14.nodeLocation = [876,1801]

Group15.movementModel = [PLPlacementMovement]
Group15.groupID = [PL]
Group15.speed = [0,0]
Group15.nrofHosts = [1]
Group15.nodeLocation = [2871,701]

Group16.movementModel = [PLPlacementMovement]
Group16.groupID = [PL]
Group16.speed = [0,0]
Group16.nrofHosts = [1]
Group16.nodeLocation = [201,2682]

Group17.movementModel = [PLPlacementMovement]
Group17.groupID = [PL]
Group17.speed = [0,0]
Group17.nrofHosts = [1]
Group17.nodeLocation = [1560,1604]

Group18.movementModel = [PLPlacementMovement]
Group18.groupID = [PL]
Group18.speed = [0,0]
Group18.nrofHosts = [1]
Group18.nodeLocation = [2884,801]

Group19.movementModel = [PLPlacementMovement]
Group19.groupID = [PL]
Group19.speed = [0,0]
Group19.nrofHosts = [1]
```

```
Group19.nodeLocation = [571,688]

Group20.movementModel = [PLPlacementMovement]
Group20.groupID = [PL]
Group20.speed = [0,0]
Group20.nrofHosts = [1]
Group20.nodeLocation = [1601,2756]

Group21.movementModel = [PLPlacementMovement]
Group21.groupID = [PL]
Group21.speed = [0,0]
Group21.nrofHosts = [1]
Group21.nodeLocation = [1860,860]

Group22.movementModel = [PLPlacementMovement]
Group22.groupID = [PL]
Group22.speed = [0,0]
Group22.nrofHosts = [1]
Group22.nodeLocation = [701,2456]

Group23.movementModel = [PLPlacementMovement]
Group23.groupID = [PL]
Group23.speed = [0,0]
Group23.nrofHosts = [1]
Group23.nodeLocation = [302,2326]

Group24.movementModel = [PLPlacementMovement]
Group24.groupID = [PL]
Group24.speed = [0,0]
Group24.nrofHosts = [1]
Group24.nodeLocation = [888,1888]

Group25.movementModel = [PLPlacementMovement]
Group25.groupID = [PL]
Group25.speed = [0,0]
Group25.nrofHosts = [1]
Group25.nodeLocation = [1666,666]

Group26.movementModel = [PLPlacementMovement]
Group26.groupID = [PL]
```

```
Group26.speed = [0,0]
Group26.nrofHosts = [1]
Group26.nodeLocation = [999,999]

Group27.movementModel = [PLPlacementMovement]
Group27.groupID = [PL]
Group27.speed = [0,0]
Group27.nrofHosts = [1]
Group27.nodeLocation = [2991,1901]

Group28.movementModel = [PLPlacementMovement]
Group28.groupID = [PL]
Group28.speed = [0,0]
Group28.nrofHosts = [1]
Group28.nodeLocation = [3204,2301]

Group29.movementModel = [PLPlacementMovement]
Group29.groupID = [PL]
Group29.speed = [0,0]
Group29.nrofHosts = [1]
Group29.nodeLocation = [2837,1240]

Group30.movementModel = [PLPlacementMovement]
Group30.groupID = [PL]
Group30.speed = [0,0]
Group30.nrofHosts = [1]
Group30.nodeLocation = [1837,1758]

Group31.movementModel = [PLPlacementMovement]
Group31.groupID = [PL]
Group31.speed = [0,0]
Group31.nrofHosts = [1]
Group31.nodeLocation = [3233,3330]

Group32.movementModel = [PLPlacementMovement]
Group32.groupID = [PL]
Group32.speed = [0,0]
Group32.nrofHosts = [1]
Group32.nodeLocation = [1405,2920]
```

```
Group33.movementModel = [PLPlacementMovement]
Group33.groupID = [PL]
Group33.speed = [0,0]
Group33.nrofHosts = [1]
Group33.nodeLocation = [708,2870]

Group34.movementModel = [PLPlacementMovement]
Group34.groupID = [PL]
Group34.speed = [0,0]
Group34.nrofHosts = [1]
Group34.nodeLocation = [1708,1920]

Group35.movementModel = [PLPlacementMovement]
Group35.groupID = [PL]
Group35.speed = [0,0]
Group35.nrofHosts = [1]
Group35.nodeLocation = [3408,1920]

Group36.movementModel = [PLPlacementMovement]
Group36.groupID = [PL]
Group36.speed = [0,0]
Group36.nrofHosts = [1]
Group36.nodeLocation = [3208,520]

Group37.movementModel = [PLPlacementMovement]
Group37.groupID = [PL]
Group37.speed = [0,0]
Group37.nrofHosts = [1]
Group37.nodeLocation = [208,3520]

Group38.movementModel = [PLPlacementMovement]
Group38.groupID = [PL]
Group38.speed = [0,0]
Group38.nrofHosts = [1]
Group38.nodeLocation = [2408,3320]

Group39.movementModel = [PLPlacementMovement]
Group39.groupID = [PL]
Group39.speed = [0,0]
Group39.nrofHosts = [1]
```

```
Group39.nodeLocation = [109,1376]

Group40.movementModel = [PLPlacementMovement]
Group40.groupID = [PL]
Group40.speed = [0,0]
Group40.nrofHosts = [1]
Group40.nodeLocation = [1109,1876]

Group41.movementModel = [PLPlacementMovement]
Group41.groupID = [PL]
Group41.speed = [0,0]
Group41.nrofHosts = [1]
Group41.nodeLocation = [1999,1999]

###############################
#####Report Configuration#####
###############################
Report.nrofReports = [3]
Report.warmup = [0]
Report.reportDir = reports/

Report.report1 = [EVEnergyReport]
Report.report2 = [EVEncounterReport]
Report.report3 = [EVInformationReport]

EVEncounterReport.granularity = [43210]
EVEnergyReport.granularity = [43210]
EVInformationReport.granularity = [43210]


###############################
####Mobility Configuration####
###############################
MovementModel.rngSeed = [1]
MovementModel.worldSize = [4500,3400]
MovementModel.warmup = [0]

MapBasedMovement.nrofMapFiles = [4]
MapBasedMovement.mapFile1 = data/roads.wkt
MapBasedMovement.mapFile2 = data/main\_roads.wkt
```

```
MapBasedMovement.mapFile3 = data/pedestrian\_paths.wkt
MapBasedMovement.mapFile4=   data/shops.wkt


###########################
####Energy Configuration###
###########################
Group.chargeInterval = [0.1]
Group.SOC = [0.6]

###########################
###########################
Group.departureDeadline = [9000]

################################
#Configuration of Charging Slot#
################################
Group.chargeSlot = [8]


##############################
#####Energy Configuration#####
##############################
/*----108000KJ=30KWh----*/
Group1.intialEnergy = [108000]

/*----108000KJ/161000Meters=0.67801KJ/Meters ----*/
Group1.movingEnergy = [0.67081]
Group1.SOC=[0.4]

Group2.intialEnergy = [121680]
Group2.movingEnergy = [0.63046]
Group2.SOC=[0.3]

/*----3600000KJ=1000KWh----*/
Group3.intialEnergy = [59040]
Group3.movingEnergy = [0.42171]
Group3.SOC = [0.5]

/*----3600000KJ=1000KWh----*/
```

```
/*----Let Group 4-5 be charging provider----*/
Group4.intialEnergy = [108000000]
Group4.movingEnergy = [0.67081]
Group4.SOC = [0.01]

Group5.intialEnergy = [108000000]
Group5.movingEnergy = [0.67081]
Group5.SOC = [0.01]


Group6.intialEnergy = [108000000]
Group6.chargeEnergy = [15]

Group7.intialEnergy = [108000000]
Group7.chargeEnergy = [15]

Group8.intialEnergy = [108000000]
Group8.chargeEnergy = [15]

Group9.intialEnergy = [108000000]
Group9.chargeEnergy = [15]

Group10.intialEnergy = [108000000]
Group10.chargeEnergy = [15]

Group11.intialEnergy = [108000000]
Group11.chargeEnergy = [15]

Group12.intialEnergy = [108000000]
Group12.chargeEnergy = [15]

Group13.intialEnergy = [108000000]
Group13.chargeEnergy = [15]

Group14.intialEnergy = [108000000]
Group14.chargeEnergy = [15]

Group15.intialEnergy = [108000000]
Group15.chargeEnergy = [15]
```

```
Group16.intialEnergy = [108000000]
Group16.chargeEnergy = [15]

Group17.intialEnergy = [108000000]
Group17.chargeEnergy = [15]

Group18.intialEnergy = [108000000]
Group18.chargeEnergy = [15]

Group19.intialEnergy = [108000000]
Group19.chargeEnergy = [15]

Group20.intialEnergy = [108000000]
Group20.chargeEnergy = [15]

Group21.intialEnergy = [108000000]
Group21.chargeEnergy = [15]

Group22.intialEnergy = [108000000]
Group22.chargeEnergy = [15]

Group23.intialEnergy = [108000000]
Group23.chargeEnergy = [15]

Group24.intialEnergy = [108000000]
Group24.chargeEnergy = [15]

Group25.intialEnergy = [108000000]
Group25.chargeEnergy = [15]

Group26.intialEnergy = [108000000]
Group26.chargeEnergy = [15]

Group27.intialEnergy = [108000000]
Group27.chargeEnergy = [15]

Group28.intialEnergy = [108000000]
Group28.chargeEnergy = [15]

Group29.intialEnergy = [108000000]
```

```
Group29.chargeEnergy = [15]

Group30.intialEnergy = [108000000]
Group30.chargeEnergy = [15]

Group31.intialEnergy = [108000000]
Group31.chargeEnergy = [15]

Group32.intialEnergy = [108000000]
Group32.chargeEnergy = [15]

Group33.intialEnergy = [108000000]
Group33.chargeEnergy = [15]

Group34.intialEnergy = [108000000]
Group34.chargeEnergy = [15]

Group35.intialEnergy = [108000000]
Group35.chargeEnergy = [15]

Group36.intialEnergy = [108000000]
Group36.chargeEnergy = [15]

Group37.intialEnergy = [208000000]
Group37.chargeEnergy = [15]

Group38.intialEnergy = [108000000]
Group38.chargeEnergy = [15]

Group39.intialEnergy = [108000000]
Group39.chargeEnergy = [15]

Group40.intialEnergy = [108000000]
Group40.chargeEnergy = [15]

Group41.intialEnergy = [108000000]
Group41.chargeEnergy = [15]


#####################################
```

```
Selection PL: 1 = MinWaitingTime
                7 = Distance;
######################################
Schedule EV: 0 = Shortest Charging Time;
             1 = Longest Charging Time;
             2 = Earliest Departure
             other = FIFO;
######################################
EVRouter.SelectModel = [1]
EVRouter.ScheduleModel = [3]
```

A.3 Output of Result Report

An example of the output report for V2V charging optimization in Chapter 5 is presented. Here, EV-C is set to 180, and parking duration is set to 7200s. The result displays charging services encountered at each PL, together with AWT, NOFC and NONFC.

Listing A.3: 360C-EV-Reservation-EVEncounterReport.txt

```
[43210]
----------------------------
PL720 Number of Encountered by EVs: 94.0000
PL720 Number of Times for Update: 0.0000
PL721 Number of Encountered by EVs: 80.0000
PL721 Number of Times for Update: 0.0000
PL722 Number of Encountered by EVs: 74.0000
PL722 Number of Times for Update: 0.0000
PL723 Number of Encountered by EVs: 88.0000
PL723 Number of Times for Update: 0.0000
PL724 Number of Encountered by EVs: 106.0000
PL724 Number of Times for Update: 0.0000
PL725 Number of Encountered by EVs: 86.0000
PL725 Number of Times for Update: 0.0000
PL726 Number of Encountered by EVs: 84.0000
PL726 Number of Times for Update: 0.0000
PL727 Number of Encountered by EVs: 104.0000
PL727 Number of Times for Update: 0.0000
PL728 Number of Encountered by EVs: 80.0000
PL728 Number of Times for Update: 0.0000
PL729 Number of Encountered by EVs: 90.0000
```

```
PL729 Number of Times for Update: 0.0000
PL730 Number of Encountered by EVs: 66.0000
PL730 Number of Times for Update: 0.0000
PL731 Number of Encountered by EVs: 96.0000
PL731 Number of Times for Update: 0.0000
PL732 Number of Encountered by EVs: 86.0000
PL732 Number of Times for Update: 0.0000
PL733 Number of Encountered by EVs: 80.0000
PL733 Number of Times for Update: 0.0000
PL734 Number of Encountered by EVs: 82.0000
PL734 Number of Times for Update: 0.0000
PL735 Number of Encountered by EVs: 80.0000
PL735 Number of Times for Update: 0.0000
PL736 Number of Encountered by EVs: 84.0000
PL736 Number of Times for Update: 0.0000
PL737 Number of Encountered by EVs: 70.0000
PL737 Number of Times for Update: 0.0000
PL738 Number of Encountered by EVs: 86.0000
PL738 Number of Times for Update: 0.0000
PL739 Number of Encountered by EVs: 84.0000
PL739 Number of Times for Update: 0.0000
PL740 Number of Encountered by EVs: 88.0000
PL740 Number of Times for Update: 0.0000
PL741 Number of Encountered by EVs: 90.0000
PL741 Number of Times for Update: 0.0000
PL742 Number of Encountered by EVs: 94.0000
PL742 Number of Times for Update: 0.0000
PL743 Number of Encountered by EVs: 88.0000
PL743 Number of Times for Update: 0.0000
PL744 Number of Encountered by EVs: 80.0000
PL744 Number of Times for Update: 0.0000
PL745 Number of Encountered by EVs: 81.0000
PL745 Number of Times for Update: 0.0000
---------------------------
PL720 Number of Queued EVs: 10.0000
PL721 Number of Queued EVs: 8.0000
PL722 Number of Queued EVs: 6.0000
PL723 Number of Queued EVs: 8.0000
PL724 Number of Queued EVs: 6.0000
PL725 Number of Queued EVs: 4.0000
```

PL726 Number of Queued EVs: 8.0000
PL727 Number of Queued EVs: 8.0000
PL728 Number of Queued EVs: 6.0000
PL729 Number of Queued EVs: 8.0000
PL730 Number of Queued EVs: 8.0000
PL731 Number of Queued EVs: 8.0000
PL732 Number of Queued EVs: 8.0000
PL733 Number of Queued EVs: 8.0000
PL734 Number of Queued EVs: 4.0000
PL735 Number of Queued EVs: 6.0000
PL736 Number of Queued EVs: 8.0000
PL737 Number of Queued EVs: 8.0000
PL738 Number of Queued EVs: 10.0000
PL739 Number of Queued EVs: 6.0000
PL740 Number of Queued EVs: 6.0000
PL741 Number of Queued EVs: 6.0000
PL742 Number of Queued EVs: 8.0000
PL743 Number of Queued EVs: 4.0000
PL744 Number of Queued EVs: 10.0000
PL745 Number of Queued EVs: 7.0000
———————————————————————————
PL720 Average Waiting Time: 4235.6500
PL720 Total Waiting Time: 160954.7000
PL720 Number of Charged EVs in History: 38.0000
PL720 Maximum Waiting Time of EV: 6672.0000
PL720 Number of Missed Charged EVs: 4.0000
——————————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@@
PL721 Average Waiting Time: 4947.0000
PL721 Total Waiting Time: 173145.0000
PL721 Number of Charged EVs in History: 35.0000
PL721 Maximum Waiting Time of EV: 6901.0000
PL721 Number of Missed Charged EVs: 1.0000
——————————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@@
PL722 Average Waiting Time: 4679.8630
PL722 Total Waiting Time: 126356.3000
PL722 Number of Charged EVs in History: 27.0000

```
PL722 Maximum Waiting Time of EV: 6980.8000
PL722 Number of Missed Charged EVs: 7.0000
--------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL723 Average Waiting Time: 4090.1031
PL723 Total Waiting Time: 130883.3000
PL723 Number of Charged EVs in History: 32.0000
PL723 Maximum Waiting Time of EV: 6857.4000
PL723 Number of Missed Charged EVs: 8.0000
--------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL724 Average Waiting Time: 4185.8833
PL724 Total Waiting Time: 175807.1000
PL724 Number of Charged EVs in History: 42.0000
PL724 Maximum Waiting Time of EV: 6398.1000
PL724 Number of Missed Charged EVs: 8.0000
--------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL725 Average Waiting Time: 4391.6405
PL725 Total Waiting Time: 162490.7000
PL725 Number of Charged EVs in History: 37.0000
PL725 Maximum Waiting Time of EV: 6477.8000
PL725 Number of Missed Charged EVs: 4.0000
--------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL726 Average Waiting Time: 4454.4882
PL726 Total Waiting Time: 151452.6000
PL726 Number of Charged EVs in History: 34.0000
PL726 Maximum Waiting Time of EV: 6978.1000
PL726 Number of Missed Charged EVs: 4.0000
--------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL727 Average Waiting Time: 3823.8556
PL727 Total Waiting Time: 137658.8000
PL727 Number of Charged EVs in History: 36.0000
```

PL727 Maximum Waiting Time of EV: 7080.9000
PL727 Number of Missed Charged EVs: 12.0000
—————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL728 Average Waiting Time: 4420.8586
PL728 Total Waiting Time: 128204.9000
PL728 Number of Charged EVs in History: 29.0000
PL728 Maximum Waiting Time of EV: 6479.9000
PL728 Number of Missed Charged EVs: 8.0000
—————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL729 Average Waiting Time: 5126.0143
PL729 Total Waiting Time: 179410.5000
PL729 Number of Charged EVs in History: 35.0000
PL729 Maximum Waiting Time of EV: 6865.2000
PL729 Number of Missed Charged EVs: 6.0000
—————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL730 Average Waiting Time: 4427.2458
PL730 Total Waiting Time: 106253.9000
PL730 Number of Charged EVs in History: 24.0000
PL730 Maximum Waiting Time of EV: 6720.0000
PL730 Number of Missed Charged EVs: 5.0000
—————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL731 Average Waiting Time: 4309.2105
PL731 Total Waiting Time: 163750.0000
PL731 Number of Charged EVs in History: 38.0000
PL731 Maximum Waiting Time of EV: 6777.3000
PL731 Number of Missed Charged EVs: 6.0000
—————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL732 Average Waiting Time: 4811.2031
PL732 Total Waiting Time: 153958.5000
PL732 Number of Charged EVs in History: 32.0000

```
PL732 Maximum Waiting Time of EV: 6448.4000
PL732 Number of Missed Charged EVs: 7.0000
-------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL733 Average Waiting Time: 4520.1437
PL733 Total Waiting Time: 144644.6000
PL733 Number of Charged EVs in History: 32.0000
PL733 Maximum Waiting Time of EV: 7027.8000
PL733 Number of Missed Charged EVs: 4.0000
-------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL734 Average Waiting Time: 4582.6421
PL734 Total Waiting Time: 174140.4000
PL734 Number of Charged EVs in History: 38.0000
PL734 Maximum Waiting Time of EV: 7055.4000
PL734 Number of Missed Charged EVs: 1.0000
-------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL735 Average Waiting Time: 4922.6061
PL735 Total Waiting Time: 162446.0000
PL735 Number of Charged EVs in History: 33.0000
PL735 Maximum Waiting Time of EV: 6937.5000
PL735 Number of Missed Charged EVs: 4.0000
-------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL736 Average Waiting Time: 4411.5125
PL736 Total Waiting Time: 141168.4000
PL736 Number of Charged EVs in History: 32.0000
PL736 Maximum Waiting Time of EV: 6708.9000
PL736 Number of Missed Charged EVs: 6.0000
-------------------------
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL737 Average Waiting Time: 4543.7043
PL737 Total Waiting Time: 104505.2000
PL737 Number of Charged EVs in History: 23.0000
```

PL737 Maximum Waiting Time of EV: 7083.8000
PL737 Number of Missed Charged EVs: 8.0000
—————————————————————————
@@@@@@@@@@@@@@@@@@@@@@@@@@
@@@@@@@@@@@@@@@@@@@@@@@@@@
PL738 Average Waiting Time: 4355.5969
PL738 Total Waiting Time: 139379.1000
PL738 Number of Charged EVs in History: 32.0000
PL738 Maximum Waiting Time of EV: 6393.7000
PL738 Number of Missed Charged EVs: 6.0000
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PL739 Average Waiting Time: 4482.1937
PL739 Total Waiting Time: 143430.2000
PL739 Number of Charged EVs in History: 32.0000
PL739 Maximum Waiting Time of EV: 7057.5000
PL739 Number of Missed Charged EVs: 7.0000
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PL740 Average Waiting Time: 4592.0371
PL740 Total Waiting Time: 160721.3000
PL740 Number of Charged EVs in History: 35.0000
PL740 Maximum Waiting Time of EV: 6780.3000
PL740 Number of Missed Charged EVs: 6.0000
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PL741 Average Waiting Time: 4568.4314
PL741 Total Waiting Time: 159895.1000
PL741 Number of Charged EVs in History: 35.0000
PL741 Maximum Waiting Time of EV: 6656.0000
PL741 Number of Missed Charged EVs: 7.0000
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PL742 Average Waiting Time: 4384.0051
PL742 Total Waiting Time: 170976.2000
PL742 Number of Charged EVs in History: 39.0000

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PL742 Maximum Waiting Time of EV: 6389.8000
PL742 Number of Missed Charged EVs: 4.0000
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PL743 Average Waiting Time: 4400.7622
PL743 Total Waiting Time: 162828.2000
PL743 Number of Charged EVs in History: 37.0000
PL743 Maximum Waiting Time of EV: 6853.8000
PL743 Number of Missed Charged EVs: 5.0000
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PL744 Average Waiting Time: 4852.6937
PL744 Total Waiting Time: 155286.2000
PL744 Number of Charged EVs in History: 32.0000
PL744 Maximum Waiting Time of EV: 7033.5000
PL744 Number of Missed Charged EVs: 3.0000
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PL745 Average Waiting Time: 4194.8853
PL745 Total Waiting Time: 142626.1000
PL745 Number of Charged EVs in History: 34.0000
PL745 Maximum Waiting Time of EV: 6435.2000
PL745 Number of Missed Charged EVs: 3.0000
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**************************
 All PL Total Average Waiting Time: 4481.5273
 All PL Total Waiting Time: 3912373.3000
 All PL Number of Charged EVs in History: 873.0000
 All PL Maximum Waiting Time: 7083.8000
 All PL Total Missed Charged EVs: 144.0000
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 Total Trip Duration 10429802.7999
 Average Trip Duration 5251.6630
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