Optimal Day-Ahead Scheduling Frameworks for E-Mobility Ecosystem Operation with Drivers Preferences under Uncertainties

Mahsa Bagheri Tookanlou

A thesis submitted in partial fulfilment of the requirements of the University of Northumbria at Newcastle for the degree of Doctor of Philosophy

Research undertaken at the Faculty of Engineering and Environment

Department of Mathematics, Physics and Electrical Engineering

May 2022

To my beloved family

Abstract

Distribution networks are envisaged to host significant number of electric vehicles (EVs) and potentially many charging stations (CSs) in the future to provide charging as well as vehicle-to-grid (V2G) services to the electric vehicle owners. A high number of electric EVs in the transportation sector necessitates an advanced scheduling framework for e-mobility ecosystem operation as a whole in order to overcome range anxiety and create a viable business model for CSs. Thus, the future e-mobility ecosystem will be a complex structure with different stakeholders seeking to optimize their operation and benefits. The main goal of this study is to develop a comprehensive day-ahead grid-to-vehicle (G2V) and V2G scheduling framework to achieve an economically rewarding operation for the ecosystem of EVs, CSs and retailers using a comprehensive optimal charging/discharging strategy that accounts for the network constraints. To do so, a non-cooperative Stackelberg game, which is formed among the three layers, is proposed. The leader of the Stackelberg game is the retailer and the first and second followers are CSs and EVs, respectively. EV routing problem is solved based on a cost-benefit analysis rather than choosing the shortest route. The proposed method can be implemented as a cloud scheduling system that is operated by a non-profit entity, e.g., distribution system operators or distribution network service providers, whose role is to collect required information from all agents, perform the day-ahead scheduling, and ultimately communicate the results to relevant stakeholders. To facilitate V2G services and to avoid congestion at CSs, two types of trips, i.e., mandatory and optional trips, are defined and formulated. Also, EV drivers' preferences are added to the model as cost/revenue threshold and extra driving distance to enhance the practical aspects of the scheduling framework. The stochastic nature of all stakeholders' operation and their mutual interactions are modelled by proposing a three-layer joint distributionally robust chance-constrained (DRCC) framework. The proposed stochastic model does not rely on a specific probability distribution for stochastic parameters. To achieve computational tractability, the exact reformulation is implemented for double-sided and single-sided chance constraints (CCs). Furthermore, the impact of temporal correlation of uncertain PV generation on CSs operation is considered. To solve the problem, an iterative process is proposed to solve the non-cooperative Stackelberg game and joint DRCC model by determining the optimal routes and CS for each EV, optimal operation of each CS and retailers, and optimal V2G and G2V prices. Extensive simulation studies are carried out for a e-mobility ecosystem of multiple retailers and CSs as well as numerous EVs based on real data from San Francisco, the USA. The simulation results shows the necessity and applicability of such a scheduling method for the e-mobility ecosystem.

keywords - Distributionally robust chance constraints, E-mobility ecosystem, EV drivers' preferences, G2V and V2G operation, optional trips, temporal correlation of uncertain PV generation, three-layer optimization problem.

Acknowledgments

First and foremost, I would like to express my thanks to the Northumbria University for sponsoring me and providing an opportunity for me to study PhD. Second, I would like to thank my principle supervisor, Dr. Mousa Marzband, for his advice, patience, and support throughout this PhD journey.

I owe a deep sense of gratitude to my external supervisor, Dr. Ali Pourmousavi Kani from the University of Adelaide, for his enthusiasm, support, and guidance for this study. It has been a chance for me to work with him and benefited greatly from his wealth of knowledge and meticulous editing.

I would like to thank all my friends and colleagues in the Northumbria University for their kind assistance and times in all aspects.

Finally, very special thanks to my family for their support and unconditional love.

Declaration

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work. I also confirm that this work fully acknowledges opinions, ideas and contributions from the work of others.

Any ethical clearance for the research presented in this thesis has been approved. Approval has been sought and granted by the Faculty Ethics Committee / University Ethics Committee / external committee.

I declare that the Word Count of this Thesis is 50,934 words

Name: Mahsa Bagheri Tookanlou

Date: 1st of May 2022

Signature:

Contents

List of Figures

List of Tables

List of Acronyms

AC Alternating Current
ACO Ant Colony Algorithm

BEV Battery Electric Vehicle
BNEF BloombergNEF

CC Chance-Constrained
CGU Conventional Generation Unit
CS Charging Station

DC Direct Current
DNO Distribution Network Operator
DOE Department of Energy
DRCC Distributionally Robust Chance-Constrained

ERCOT Electric Reliability Council of Texas
ESS Energy Storage System
EV Electric Vehicle

G2V Grid-2-Vehicle
GHG Greenhouse Gas

HEV Hybrid Electric Vehicles

IEA	International Energy Agency
IRENA	International Renewable Energy Agency
KKT	Karush–Kuhn–Tucker
MILP	Mixed Integer Linear Programming
MIQCP	Mixed Integer Quadratically Constrained Programming
MIQP	Mixed-Integer Quadratic Programming
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PSO	Particle Swarm Optimisation
PV	Photovoltaic
QP	Quadratic Programming
RES	Renewable Energy Source
RMSE	Root Mean Square Error
SOC	State of Charge
SPIDERS	Smart Power Infrastructure Demonstration for Energy Reliability and Security
SSA	Salp Swarm Algorithm
SwRI	Southwest Research Institute
V2G	Vehicle-2-Grid
VCS	Virtual Charging Station

1 | Introduction

1.1 Background

Electrification of the transport system first emerged in mid-19th century, when electricity was found as a propulsion for automobiles [1]. However, the low top speed, exorbitant cost, battery depletion, and short driving range of electric vehicles (EVs) confined the use of EVs to public transport, especially electric locomotive. At the beginning of the 21st century, by developing the modern chargers and advances in battery storage technologies for EVs, together with the potential of EVs to reduce greenhouse gas (GHG) emissions, the general public's interest grew in purchasing EVs. In the past few years, in industrialised and developing countries, interest in EVs has grown and measurements have been undertaken to facilitate the electrification of the greater transportation sector. For instance, in the first half of 2019, the sales of internal combustion engine cars were dropped by 5%, while the sales of plug-in hybrid electric vehicles (PHEVs) were increased by 36% [2].

The rising trend of using EVs could be seen mostly in China, Europe, the US, Japan, and South Korea, which collectively share 97% of EV manufacturing and sale capacity in the world [3], as shown in Figure 1.1. The global sales of EVs and PHEVs reached more than 3.2 million unites in 2020 compared to 2.26 million units in 2019. By comparing Figure 1.1 and Figure 1.2, it can be seen that, in 2020, Europe has passed China and become pioneer in EV and PHEV sales with a 137% growth compared to registered vehicles in 2019 [4].

One of the major advantages of EVs is the contribution that they can make towards reducing the air pollution in urban areas due to zero tailpipe emissions. The internal combustion engine car emits around 3.4 times more GHG per passenger mile

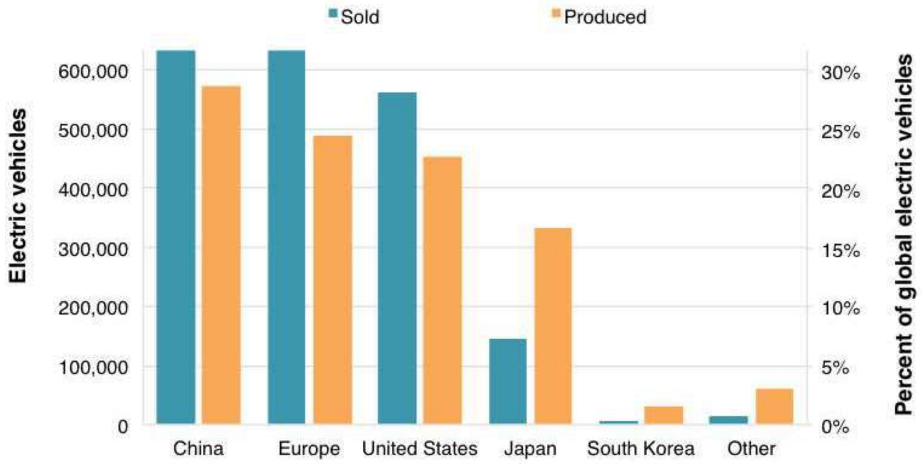

Figure 1.1: EVs sold and manufactured by countries and percentage in 2016 [3].

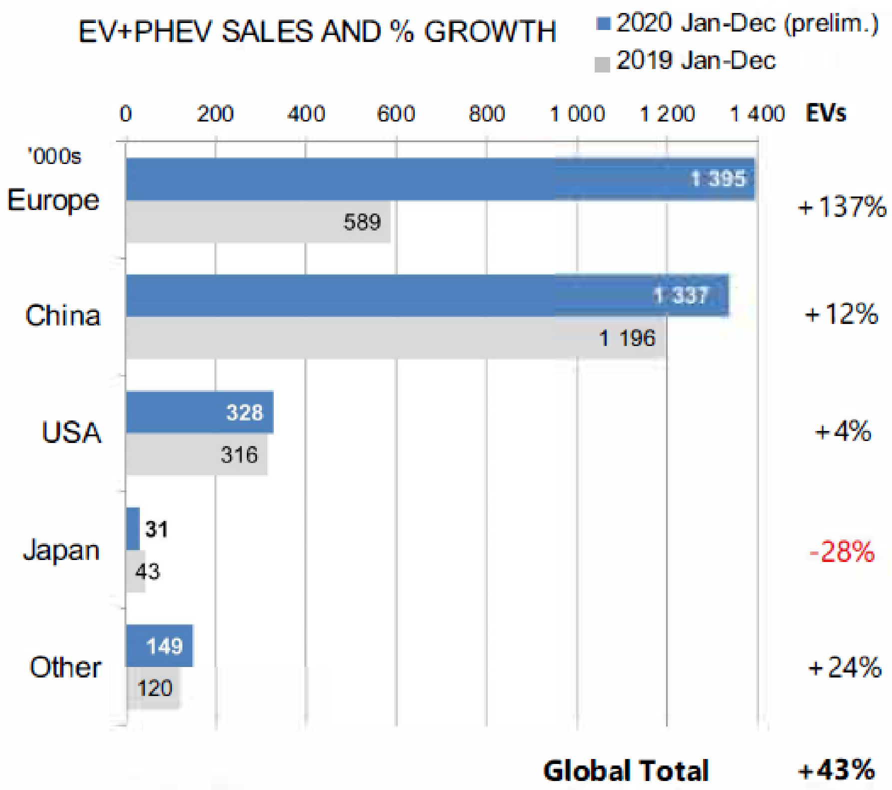

Figure 1.2: The number and percentage growth of EV and PHEV sales [4]

emitted by the EV. In 2019, the UK's domestic transport emitted 122 million tonnes of carbon dioxide (27%) from the total emissions. By increasing the penetration of transportation electrification, the UK's domestic transport GHG emissions in 2020 have been dropped by 19.6% since 2019 [5]. Thus, transportation electrification is an assuring option to reach decarbonisation targets and improve urban air quality. In fact, electrification of transportation sector was one of the main talking points at the COP 21 UN Climate Change Conference in Paris in 2015 on the grounds that transportation system makes a significant contribution to the current GHG emissions (23%) and it is predicted that it will be on the rise by 20% by 2030 and nearly 50% by 2050 [6]. Therefore, there is a general consent between the participants of the conference to develop e-mobility infrastructure and implement policies and consumer incentives to limit the global warming to two degrees or less. These factors have been catalysts for the transition of the transportation sector towards electric technologies.

Besides the environmental advantages, the wider adoption of EVs leads the charging demand increase, which means that additional electricity generation will be required to meet extra demand due to the EV uptake. According to the UK Department for Transport study [7], the accessibility of charging infrastructure is an important factor to support the higher uptake of e-mobility technologies. The report further states that the inadequate charging infrastructure and the range anxiety are the biggest deterrents for adopting EVs in the domestic transportation sector [7]. To tackle this issue, many countries have financed the roll-out of fast chargers by building charging infrastructure. For example, the UK government has dedicated substantial budget to design zero emission vehicles and develop the EV charging infrastructure to terminate producing and selling of petrol and diesel cars by 2030 and hybrid vehicles by 2035 [8]. Furthermore, the UK government set out Road To Zero Strategy to boost the transition to zero emission road transport, thereby diminishing GHG emissions during the transition [9]. Figure 1.3 summarises the UK's EV deployment plan to meet the target of Road To Zero Strategy [10]. In November 2020, the UK government announced that £1.9 billion will be invested in charging infrastructure which support the turn out of fast charging stations (CSs), the manufacture of the EVs, vans, taxis, and motorcycles, as well as installation of more charging points. As depicted in Figure 1.4, the registration of EVs in the UK has been on the rise from 2010. Since it is impossible to meet the zero GHG emission transportation target without having easy and plentiful access to fast charging points, the number of different types of public charging points installed in UK is increasing as shown in Figure 1.5. Thus, continued investment in charging infrastructure sets the stage to overcome consumers' anxiety and concerns regarding accessibility of charging points.

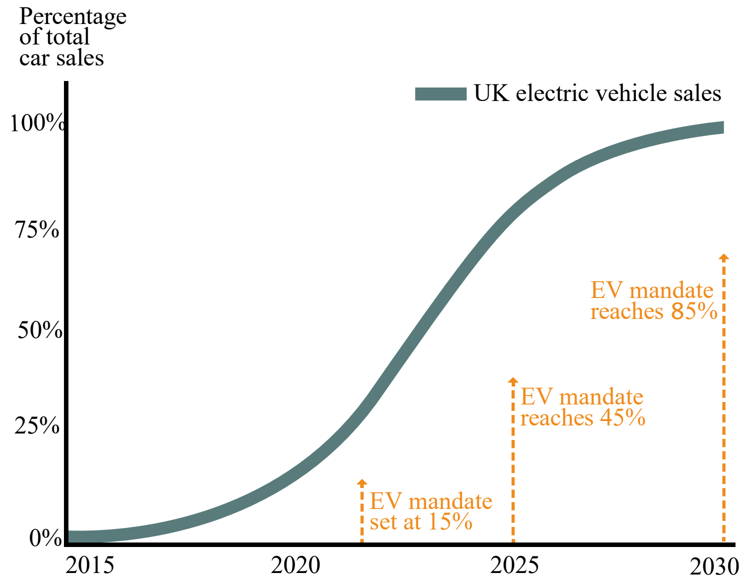

Figure 1.3: UK market share of electric vehicles to 2030 [10].

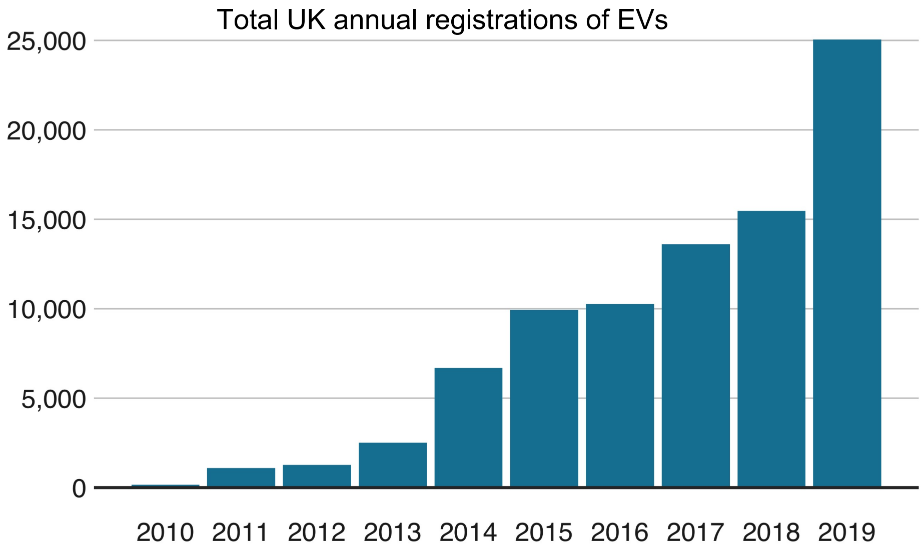

Figure 1.4: Increase in the total UK annual registrations of EVs from 2010 to 2019 [11].

Furthermore, financial incentives, e.g., tax credits, tax exemptions and registration fee reduction, play an important role in decreasing the upfront cost of EVs and encouraging the EVs' adoption in the transportation sector. The United States, the third largest EV market after China and Europe, has implemented a wide range of policies including financial incentives and charging infrastructure development to foster the

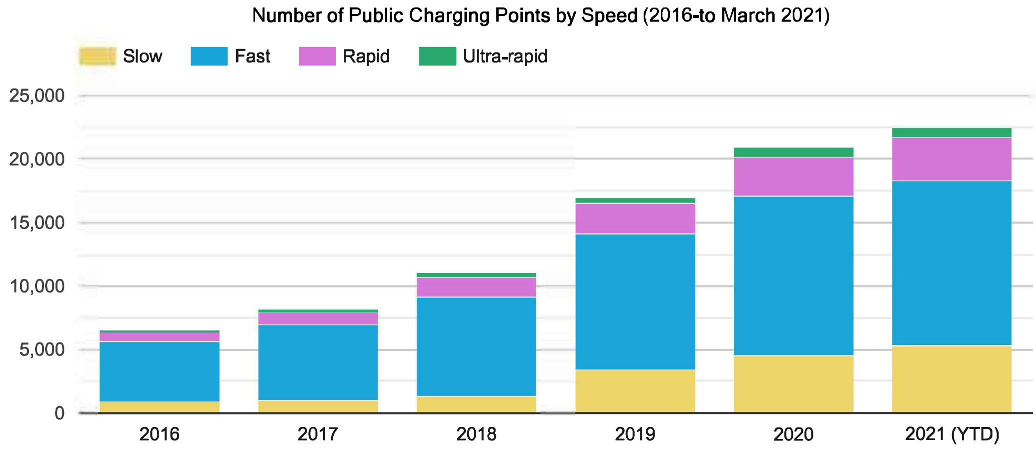

Figure 1.5: Increase in number of public charging points by charging speed (2016-March 2021) [11].

far-reaching commercialisation of EVs and overcome the barriers regarding high costs of EVs and range anxiety of consumers. The US federal government has entitled a tax credit ranges from \$2,500 to \$7,500 for each plug-in electric vehicle (PEV) purchased after 2009. In November 2020, at least 45 states and the District of Columbia developed incentives to accelerate e-mobility deployment, which are high-occupancy vehicle lane exemptions, financial aids for purchasing EVs and their equipment, emissions inspections exemptions, and price reductions for grid-2-vehicle (G2V) operation during off-peak hours [12].

China has laid the major groundwork for EV's adoption. The government has announced tax exemption on EV purchase since 2014 and initiated a consumer subsidy program since 2010 which covers up to 60% of the costs of EVs [13].

1.2 Deployment of Renewable Energy Resources in E-mobility Ecosystem

Electric transportation offers opportunities for the wide integration of renewable energy sources (RESs) to the transport sector. By 2050, the gross electricity consumption will be doubled and RESs can compensate the increase in power demand [14]. The main part of increase in power demand will be derived from increased use of EVs [15], which cause significant impact on the power grid. In order to mitigate the impact, the distributed generators, such as RESs, are used in the local charging infrastructure [16]. In fact, if the EV electricity demand is fulfilled by fossil fueled generators, the EV could become significant GHG emitter in the environment. Thus, integration of RESs into charging infrastructure is an effective solution to mitigate GHG emissions and reduce charging cost. Supplying EVs from RESs leads to true decarbonisation of the transportation sector, and consequently, helps to meet the goal of 80-95% reduction in GHG emissions by 2050. On account of RES intermittency, the difficulty associated with coordinating EV charging with other grid load and RES becomes challenging for distribution network service providers [16]. Recently, the RES-powered CSs that can work in parallel with the grid are becoming a popular technology to provide reliable and clean charging infrastructure.

In addition to the advantages of this transition on reducing GHG emissions and air pollution, e-mobility has a significant impact on how RESs are used to produce efficient and green energy. According to the International Renewable Energy Agency (IRENA), at the end of 2020, global renewable generation capacity reached 2,799 GW (261 GW or 10.3% increase), as shown in Figure 1.6. The joint share of solar and wind energy is 91% of total RES in 2020. In addition, the growth in solar, wind, and hydropower energy has led to an increase in renewable generation capacity [17].

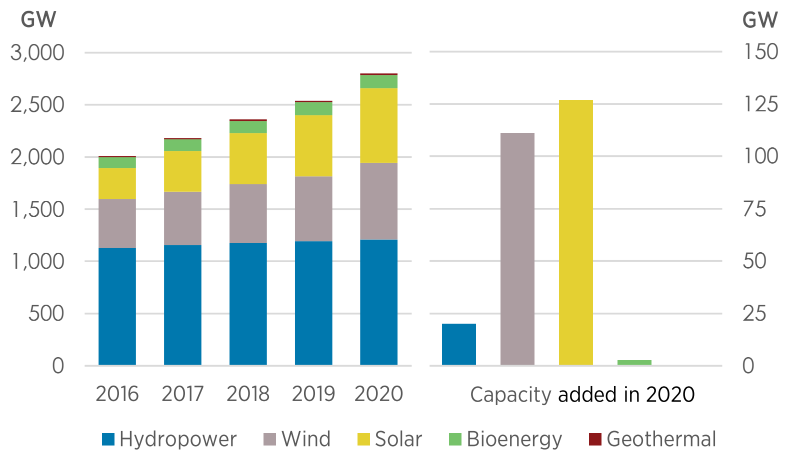

Figure 1.6: Renewable power capacity growth [17].

RESs participate in producing more than 20% of the UK's electricity and wind is the biggest contributor of RES in the UK. Furthermore, there has been an increase in solar power integration into the power grid. In 2020, 545 MW of new photovoltaic

(PV) capacity was installed in UK, which is a 27% increase compared with 2019. As depicted in Figure 1.7, 70% of total installations of PV panels in the UK accounts for ground-mounted plants and there is a 14% year-on-year increase for installed PV belongs to rooftop solar panels [18].

Figure 1.7: UK PV deployment to March 2021 [18].

1.3 Vehicle-2-grid Service

From one perspective, EVs can be seen as distribution energy storage devices under the concept of vehicle-2-grid (V2G). They can supply electricity to the grid when needed, e.g., during generation shortfall. This capability allows a larger integration of renewable energy resources in the weak grid without network upgrade, which leads to avoiding investment in the infrastructure.

Improvement in battery lifetime, advanced bi-directional chargers, higher adoption of EVs and higher prices of ancillary services in many electricity markets have provided true economic opportunities for the car manufacturers, retailers, service providers/aggregators and EV owners to pursue the idea of V2G. In response to the changing landscape, many research studies have focused on V2G operation of full/hybrid EVs to provide services to the grid (accompanied by remuneration for the EV owners). The V2G concept has been trialed in many projects around the world. For instance, Nissan Leaf is the first full EV that is capable of providing V2G service [19]. In 2016, Nissan announced a major V2G project with Enel, a multinational power company in the UK. Nissan and Enel installed and connected 100 V2G units for Nissan Leaf and e-NV200 owners in order to sell the excess energy back to the National Grid [20]. In 2017, V2G technology provider Nuvve launched a pilot program at the University of California, San Diego, called INVENT, which was funded by the California Energy Commission, with the installation of 50 V2G bi-directional CSs around the campus [21]. The program expanded in 2018 to include a fleet of EVs for its free night-time shuttle service, Triton Rides [22]. In Amsterdam, V2G CSs have been installed for the public at locations to supply stored energy back to the company's grid network in 2008 [23]. In 2019, Nissan and EDF announced that they will co-develop V2G technology as part of a new agreement in France, Italy, the UK and Belgium [24]. Western Power in Australia started a V2G program where EV owners can join the program and they will be called for services and get paid for it [25]. In 2014, southwest research institute (SwRI) developed the first V2G aggregation system qualified by the electric reliability council of Texas (ERCOT). The system allows for owners of electric delivery truck fleets to make money by assisting in managing the grid frequency. The system was originally developed as part of the Smart Power Infrastructure Demonstration for Energy Reliability and Security smart power infrastructure demonstration for energy reliability and security (SPIDERS) Phase II program, led by Burns and McDonnell Engineering Company, Inc. The goals of the SPIDERS program are to increase energy security in the event of power outage from a physical or cyber disruption, provide emergency power, and manage the grid more efficiently [26, 27]. Thus, there is a global consensus on the benefit and possibility of V2G services that should be fully exploited. It is believed that the true value of V2G will be unlocked by introducing aggregators, appropriate market products, availability of fast bi-directional chargers as well as robust and scalable scheduling platforms.

The entities that are involved in the V2G service are EV drivers, CSs, the aggregator, and distribution network operator (DNO). A review of motivation for V2G service of each entity is presented in the following subsections [28].

1.3.1 Motivations for DNO

The V2G service would be attractive for DNOs because it can be a storage system for intermittent RESs. If a sufficient number of EVs offers the V2G service at the right times, it would pave the way for faster adoption of RESs and tackling the issues regarding the inconsistent and limited predictability of RESs. In fact, if EVs connect to the grid during the times when they are not driven, the EV batteries can be operated as the distributed storage system and support RESs. Thus, V2G can bring environmental benefits and reduce GHG emissions. The ancillary services which are provided by the V2G service include providing peak power and the operating reserve. EVs can help the DNO to supply reliable electricity for the customers during peak period. EVs could be charged during off-peak period and then discharged during peak period to supply peak loads in order to waive the need to start up the peaking power plants, which reduces the maintenance and operation costs and leads to environmental benefits.

1.3.2 Motivations for the Aggregator

The aggregator's responsibility is to accumulate battery sources and provides various services, e.g., fast regulation or energy arbitrage, for the electricity network. The aggregator manages the total flexibility in terms of consumption and/or generation and certifies the participation level. Participation of a single EV in the V2G service does not have significant impact on electricity network operation but when a large number of EVs offer the V2G service, the aggregator can guarantee the provision of sufficient electricity which is contracted.

1.3.3 Motivations for EV Drivers

The V2G service can provide revenues for EV drivers to reduce their overall cost through energy arbitrage between the electricity network and EV drivers. During the V2G service, the battery degradation is quantified to avoid excessive and uneconomical V2G operation. To do so, the battery degradation cost is formulated into the cost of EV operation during V2G and considered in the objective function of the optimisation problem. The battery degradation cost considers the most important cycling degradation factors in optimal scheduling. In fact, the battery degradation cost is considered to ensure benefits of the services outweigh degradation cost. For instance, EVs will be scheduled for V2G services only if they can recover the cost of battery degradation and make a profit.

1.3.4 Motivations for CSs

The CSs provide the required infrastructure to link EVs and the distribution network during the V2G and G2V services. The CSs must be designed for bi-directional flow and make the communications between EVs and the aggregator to allow access and control of the discharge of EVs during V2G operation. CSs will purchase the V2G service offered by the EV drivers and sell it to the aggregator to make a profit.

1.4 Charger and Plug Types

EVs can be charged using either alternating current (AC) or direct current (DC) chargers. Typically, DC chargers are able to charge faster than AC chargers. The capacity of the most common DC fast chargers is 50 kW. However, three different charging levels (Level 1, 2 and 3) exist in the market based on their power and charging speeds.

- **Level 1 Charging** - These types of chargers provide charging through 120 volt (V) single phase AC up to 16 amps, and a slow charging rate (up to 1.9 kW). That equals to about 4 to 5 miles per hour. The fully charging time takes 8 to 12 hours depending on the EV's battery capacity. EV owner's house is the common place to install Level 1 chargers.

- **Level 2 Charging** - These chargers offer charging through 240V single phase AC up to 80 amps and 19.2 kW charging rate, which provides 12 to 60 miles per hour charging speed. The fully charging time varies from 4 to 6 hours depending on the EV battery. Level 2 chargers can be installed at commercial buildings, workplaces and public parking lots.

- **Level 3 Charging** - These chargers are typically Known as DC fast chargers and they charge through a 480 V DC plug. The charging rate is up to 140kW, which provides 170 miles per hour. It takes about 30 minutes to charge an EV for 80%. Level 3 chargers are mainly installed at public CSs.

Furthermore, the chargers could be categorised based on the plug types as follows. In particular, type 1 and 2 are AC and type 3 (Combined Charging System) and 4 (CHAdeMo) are for DC.

- **Type 1 plugs** - These types of chargers allow charging at a speed up to 7.4 kW, depending on the charging power of the EV and the grid capability. Most of these types of plugs are used by Asian manufacturers, such as Nissan and Mitsubishi and they are rare in Europe.

- **Type 2 plugs** - These types of chargers are the European standard and utilised mainly by European car manufacturer such as Audi, BMW, and Mercedes. Type 2 plugs provide faster charging for EVs. The highest charging power rate is 22 kW at home and up to 43 kW at public CSs.

- **Type 3 plugs: Combined Charging System** - These types of chargers are used by most manufacturers for rapid charging and commonly seen in Europe. Two additional DC power lines have been added to the Type 2 plug in order to boost the voltage. Type 3 connectors can supply between 25 kWh and 350 kWh power.

- **Type 4 plugs: CHAdeMO** - These types of chargers consist with rapid-charging DC connectors up to 50 kW. CHAdeMO chargers can be bi-directional chargers for V2G technology in order to send back the energy stored in EV batteries to the main grid.

Considering the nature of fast chargers (Level 3), the limited time that EV owners have to charge during a trip, and the limited number of CSs relative to the higher number of EVs on the road in the future, it is anticipated that only CSs with fast chargers can make economic sense in the e-mobility ecosystem. In other words, CSs are expected to have fast chargers in order to attract EV drivers to their service and fulfil their charge requirements in a timely manner. Otherwise, EV owners would prefer to charge their cars at home or workplaces. In addition, CSs primary customers will be the EV drivers in rush. Therefore, they obviously need fast chargers if they are going to sell services to the majority of EV drivers. In fact, fast charging has become the main trend in the EV industry during the last couple of years. From the car manufacturers' perspective, e.g., Tesla, BMW and Hyundai, fast charging is inevitable for e-mobility ecosystem operation. As a result, they indicated supports for fast charging in their electric cars by charging up to 80% in an hour in fast CSs [29–31]. Following the EV manufacturers, a revolution in fast DC chargers have been rolled out in the market. For instance, Nissan recently announced installation of 8,000 public fast CSs across Europe [32]. Another example is Tesla, which installed 16,585 fast chargers in Asia, North America, Europe and Middle East up to this day [29]. As one of the biggest chargers provider in the world, ABB has sold more than 13,000 fast DC chargers across 80+ countries until 2019 [33]. According to the international energy agency (IEA) Global EV Outlook 2019 report [34], 140,000 fast chargers have been installed only in 2018. Further, EVSE has sold 111,333 fast chargers only in China until 2020 [35]. As one can see, the future of EV ecosystem is envisaged with fast chargers at different locations and CSs as one of the solutions to overcome range anxiety and encourage people to purchase EVs. This way, CSs are expected to have fast chargers in order to compete in the market or they won't have a chance to attract EV owners to use their services.

1.5 Barriers to the Transit

The transportation landscape has been changing quickly after the introduction of EVs. However, there are major barriers to EV adoption in the transportation sector as follows:

- **Infrastructure** - Lack of enough fast and ultra-fast charging points is one of the major concerns of EV drivers. There have been concerns among EV drivers if there are enough charging points available close to interstate roads and highways, or they can recharge in a reasonably short time. The CSs with fast- and ultra-fast chargers provide an opportunity for EV drivers to limit the time of charging/discharging during a trip, and consequently, reduces the EV drivers range anxiety in an e-mobility ecosystem.

- **Battery Range** - The increasing rate of urbanization of EVs puts new demands on the battery. The lithium-ion battery is a rechargeable battery that has a high potential for the e-mobility application due to its low self-discharge rate, high energy density, and lack of memory effect. Using the existing energy storage technologies, which determines the driving range of EVs, is the main economical and technical constraints for the commercialisation and wide spread adoption of EVs [36]. The battery range restricts the driving distance of an EV that can travel on a single charge. The battery range problem is more critical for battery electric vehicle (BEV), compared to PHEV and hybrid electric vehicles (HEV) due to the lack of flexibility of energy source [37]. The typical battery range of Evs are 8kWh, 12kWh, 14.5kWh, 16kWh, 22kWh, 28kWh, 30kWh, 40kWh, 50kWh, 64kWh, and 100kWh.

- **Battery Cost** - The major economic bottleneck of large-scale integration of EVs in transportation sector is the battery cost. In 2015, the price of the battery of an EV accounted for about 57% of the vehicle's production cost [38]. Thus, due to battery cost, EVs are significantly more expensive than conventional vehicles [37]. Therefore, one of the main factors which will boost e-mobility adoption is the reduction of the total cost of EV batteries. The growth in the EV market leads to significant improvements in battery technology and reduction in battery costs as depicted in Figure 1.8. Over the last ten years, battery prices have been decreased as production has increased the economy of scale. Further, in 2010, the U.S. department of energy (DOE) investigated to decrease cost of batteries from 1200 $/kWh in 2008 to 300 $/kWh by 2014 according to Vehicle Technology Program [39]. In 2020, it costs below $137/kWh, which is 85% drop from 2010. According to BloombergNEF (BNEF) forecast, the average EV battery prices will be close to $100/kWh by 2023. Therefore, the major obstacle to e-mobility integration has been resolving by reducing battery cell production costs and improving battery performance.

- **Battery Degradation** - The battery degradation reduces the driving range and battery efficiency. Thus, enhancing the battery lifetime gives confidence to EV drivers. Thus, prolonging battery lifetime, and consequently, reducing the degradation process of the battery during EV operation are essential factors to increase the EV market share [40]. Most new EV battery lifetime is around eight years [41].

- **Battery Recycling** - The significant safety, environmental and commercial issue of integration of EVs in transportation sector is to recycle dead EV batteries. EV batteries have a limited operational life and the recyclable materials need to be used to have safe and environmentally desirable batteries. Recycling batteries is expensive and leads the high operational costs for recyclers who do it properly.

- **Electrical Network** - While electrification of transportation sector has undeniable and significant environmental impacts, a large uptake of EVs introduces new challenges for the grid operation, the biggest of which is uncoordinated EV charging in G2V mode. Also, distribution network service providers are expected to face extreme voltage violations, increased power losses and overload of power lines and transformers due to significant increase in demand by uncoordinated EV charging [42]. The system's operation will become more challenging when EVs operate in V2G mode supporting the upstream grid operation. It has been investigated in several studies [43–46] by showing that a proper coordinated operation of EVs in both G2V and V2G modes can be beneficial for the grid operation.

It should be noted that considering other entities/agents involved in the future electrified transportation sector, e.g., CSs and energy providers (retailers), the e-mobility ecosystem will be faced with an unprecedented level of operational complexity. As a result, optimal scheduling of CSs and EVs as well as determining V2G and G2V prices by accounting for EVs driving needs are deemed as one of the significant challenges to facilitate transportation electrification. Therefore, a comprehensive optimal scheduling framework is needed to overcome the outstanding economic and technical challenges by minimising the cost of EVs operation while fulfilling their requirements, and maximising the profit of CS operators and other entities/agents while respecting technical limitations of the network.

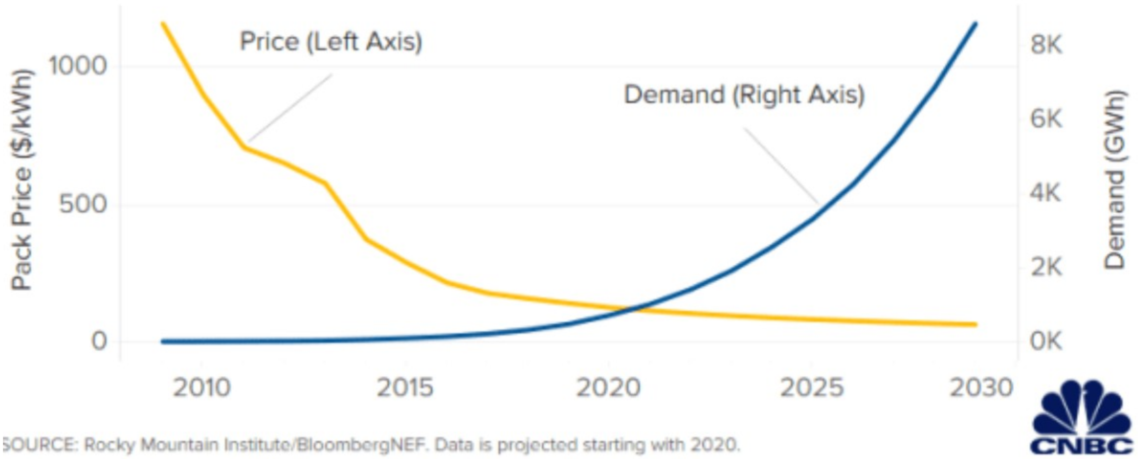

Figure 1.8: Li-ion battery market development for EVs [15].

1.6 Stochastic Nature of E-mobility Ecosystem

With the increasing adoption of EVs in the transportation sector and the rising number of CSs equipped with renewable generation resources, application of a coordinated V2G and G2V operation of e-mobility ecosystems under inherent uncertainties has become inevitable. While day-ahead scheduling can reduce range anxiety of the drivers, using a deterministic model to do so might not fulfil the actual driving requirements of the EV drivers due to inaccurate estimation of stochastic parameters for the next day; hence leading to ineffective outcomes and drivers' disappointment. In fact, ignoring the impact of underlying uncertainties in an e-mobility ecosystem might result in significant losses for all stakeholders/agents and might introduce concerns and challenges for power system operation. This indicates the importance of a scheduling framework that accounts for the different source of uncertainty in the e-mobility ecosystem operation. Thus, the major sources of uncertainty in the future e-mobility ecosystem originate from the EV drivers behavior, unpredictable nature of RESs at the CSs and the wholesale electricity market prices [47, 48].

1.7 Problem Statement

In this study, it is supposed that the future e-mobility ecosystem consists of three stakeholders namely EVs, CSs, and retailers. Retailers purchase electricity from the wholesale electricity market and sell it to CSs who deal with EVs. The CSs are charging stations with DC fast bidirectional chargers and known location throughout an area and operate at the distribution system level. In other words, CSs are the point of connection for the EVs to the grid in both G2V and V2G services. Both CSs and EVs are qualified to decide their energy suppliers based on their economic benefits. At the same time, CSs might supply electricity to EVs by onsite sources including a conventional generation unit (CGU), PV, and energy storage system (ESS). Thus, a framework for an e-mobility ecosystem which includes all entities is proposed to represent the interaction between EVs, CSs, and retailers during V2G and G2V operation. The framework is developed to solve EV day-ahead scheduling problem based on a non-cooperative Stackelberg game (the leader is the retailer and the first and second followers are CSs and EVs, respectively). In fact, instead of optimising one or two stakeholders (as in the existing literature) which may lead to sub-optimal solutions, a comprehensive model is developed in this study to consider the operation of all stakeholders in the future e-mobility ecosystem as a three-layer optimisation problem. In the proposed problem, through the iterative process, economical scheduling of EVs and CSs operation is determined and the collective social welfare of all agents in the e-mobility ecosystem is maximised, which means that the profits of EVs, CSs, and retailers are optimised collectively instead of individually. Furthermore, the proposed method offers a way to determine the optimal electricity prices in both V2G and G2V modes such that the collective benefit of all three agents are guaranteed simultaneously. Additionally, CSs are assigned to EVs based on their travel plans, driving routes, and cost/benefit of V2G and G2V operation considering the energy consumed on the routes in the proposed method. The proposed scheduling system is offered as a cloud service to the stakeholders, which is scalable and well-developed industry-level solution for massive computation. The operator of the cloud scheduling system will receive required information from all stakeholders in order to solve the scheduling problem. It should be noted that in this study, most of EV drivers are daily commuters with the same driving plan for weekdays. Also, many CS-related parameters in the model will not change on a daily basis and can be updated when required. Therefore, most of the parameters do not change every day and the amount of data which is exchanged by the scheduling operator on a daily basis is limited. The scheduling model is designed in such a way that allows EVs not to be scheduled for charging or discharging throughout a day. The rationale behind this is that some of the EVs might be fully charged at home over the night and they may not travel too far in a day. As a result, they may not need to be charged or discharged according to the G2V and V2G prices, drivers' preferences, etc. Therefore, every EV is not expected to use CSs on a daily basis, which can be verified by the simulation results. This consideration leads to a more practical scheduling system that can handle a variety of situations in a real world implementation. Furthermore, the e-mobility ecosystem is designed in such a way that the practical aspects of EV scheduling problem is considered to lead to facilitate higher participation in the G2V and V2G services, and to enhance convenience and flexibility in EV scheduling. In order to provide an opportunity for EV drivers to take advantage of cheaper G2V prices and more expensive V2G prices outside of the mandatory trips, optional trips as opposed to mandatory trips are introduced to provide a chance to EV drivers to take advantage of cheaper G2V prices or more V2G prices (for the purpose of making money). Also, the economically-irrational decisions that may be taken by the EV drivers is modeled. This is based on the fact that EV drivers (similar to other consumers and producers) respond differently to economic incentives. To consider economically-irrational decisions, driver's cost/revenue threshold and driver's route preference constraints are modeled. Finally, a three-layer joint distributionally robust chance-constrained (DRCC) framework is proposed to schedule day ahead V2G and G2V operation in an uncertain environment with unknown probability distribution. The mutual impacts of stochastic behaviours of the three stakeholders of the ecosystem are explored in the proposed model. To achieve computational tractability, the exact reformulation is implemented for double-sided and single-sided chance constraints (CCs). Furthermore, the impact of temporal correlation of uncertain PV generation on CSs operation is considered. Eventually, the simulation studies are carried out for an ecosystem of three retailers, nine CSs, and 600 EVs based on real data from San Francisco, the USA.

1.8 Aims and Objectives of the Research Work

Aim: The aim of this study is to develop a holistic day-ahead scheduling framework for the most comprehensive e-mobility ecosystem including EVs, CSs, and retailers, where the operation of different agents/entities is optimised collectively.

Research Objectives:

A list of research objectives could be outlined as follows:

- Developing a non-cooperative Stackelberg game to model a day-ahead scheduling framework, which is formed as a three-layer optimisation problem;
- Proposing an e-mobility ecosystem to model the interaction between all stakeholders (EVs, CSs, and retailers) during EV's V2G and G2V operation and optimise the collective welfare of all agents;
- Determining optimal day-ahead electricity prices for all agents during V2G and G2V operation;
- Improving the practical aspects of EV scheduling problems to facilitate higher participation in G2V and V2G services, and to enhance convenience and flexibility in EV scheduling.
- Proposing a strategy to alleviate the congestion at CSs;
- Modelling economically-irrational decisions which are made by the EV drivers to consider the different responses of EV drivers towards economic incentives;

- Developing a stochastic model to account for the stochastic nature of all stakeholders' operations and their mutual interactions in the future e-mobility ecosystem.

1.9 Main Contributions

The main contributions of the proposed research could be highlighted as follows:

- **C1: Formulating a three-layer optimisation problem:** A comprehensive day-ahead scheduling model based on a non-cooperative Stackelberg game is developed to evaluate the operation of all stakeholders in the future e-mobility ecosystem as a three-layer optimisation problem. The interaction between EVs, CSs, and retailers during EVs' V2G and G2V operation is considered while optimising the collective welfare of all stakeholders. In addition, the proposed three-layer optimiation problem is solved iteratively to obtain the optimal solutions of the ecosystem operation.

- **C2: Considering the effects of optimal operation of CSs and retailers:** The effects of optimal operation of CSs and retailers are investigated in the coordinated EVs' V2G and G2V operation through an iterative process.

- **C3: Day-ahead pricing:** Optimal day-ahead electricity prices of all stakeholders are obtained by solving the proposed equilibrium problem iteratively such that the benefit of all three stakeholders are achieved collectively and simultaneously.

- **C4: Combining cost/benefit and energy-efficient-routing problem for choosing CSs:** Selection of the best CS by each EV based on combined cost/benefit and energy-efficient-routing problems instead of choosing the shortest route;

- **C5: Optional trips:** Optional trips (besides mandatory trips) are proposed in this research for the first time to improve the practical aspects of EV scheduling problem, to facilitate higher participation in the G2V and V2G services, and to enhance convenience and flexibility in EV scheduling. EV drivers can take advantage of cheaper G2V prices or more expensive V2G prices in optional trips. The results show that the optional trips can decrease the cost of EVs, increase revenue of CSs, help to eliminate congestion at CS, and reduce CSs' PV spillage. Moreover, CSs have a chance to sell more energy from onsite PV at a cheaper prices.

- **C6: Modelling economically-irrational decisions taken by the EV drivers.:** Since EV drivers respond differently to economic incentives, new constraints are added to the optimisation problem in order to model economically-irrational decisions by the EV drivers. Therefore, driver's cost/revenue threshold and driver's route preference constraints are introduced in this study. Driver's cost/revenue threshold represents the drivers' expectation regarding minimum cost reduction of G2V and minimum revenue increase of V2G operation.

- **C7: Formulating and solving a stochastic problem:** A three-layer joint DRCC model is proposed in this research to provide the day-ahead V2G and G2V scheduling framework for an e-mobility ecosystem in an uncertain environment considering the mutual interactions of the stochastic behaviour of all stakeholders.

- **C8: Independency of stochastic programming to specific probability distribution functions:** A three-layer joint DRCC model proposed in this research is for a family of probability distributions with the same mean and covariance matrix without relying on a specific probability distribution function.

- **C9: Exact reformulation of double-sided DRCC in EV's G2V and V2G scheduling:** An exact second order cone programming reformulation of joint DRCC day-ahead scheduling framework is developed which ensures that violation of both the upper and lower limit of a constraint for the worst-case probability under the ambiguity set is small.

- **C10: Temporal correlation of PV generation in CSs:** The temporal correlation of the PV system generation in each time interval is considered in joint DRCC model.

1.10 Thesis Structure

The rest of the thesis is organised as follow: Chapter 2 outlines a literature review. Particularly, the existing studies are categorised into five groups and caveats of the corresponding studies are mentioned at the end of each category. In addition, the major drawbacks in the existing literature are highlighted categorically in the list of gaps. Chapter 3 proposes a comprehensive day-ahead scheduling strategy for EVs' V2G and G2V operation to guarantee economic and energy-efficient routing of EVs. A three-layer optimisation problem is formulated and solved by salp swarm algorithm (SSA) through an iterative process to model the interaction between all stakeholders including EVs, CSs, and retailers in an e-mobility ecosystem. Moreover, the simulation results are verified by particle swarm optimisation (PSO) algorithm. Optimal day-ahead electricity prices of all stakeholders during V2G and G2V operation is obtained in this chapter. In Chapter 4, a non-cooperative Stackelberg game is proposed as a three-layer optimisation problem to model a day-ahead scheduling framework. A mixed-integer quadratic programming (MIQP) problem is developed and solved using Gurobi® solver in Python. Furthermore, two kinds of trips including mandatory trip and optional trip during a typical day are introduced in this chapter. The optional trip (aside from mandatory trips) is introduced to improve the practical aspects of EV scheduling problem. Two new constraints are added to the optimisation problem to model economically-irrational decisions. Chapter 5 focuses on the stochastic programming of the proposed e-mobility ecosystem. A three-layer joint DRCC model is developed to provide the day-ahead V2G and G2V scheduling framework under uncertain behaviours of all stakeholders. Finally, Chapter 6 summerised the proposed work and recommends the future works on the e-mobility ecosystem.

1.11 Publications, Scholarships, and Awards

1.11.1 Journal Papers

1. **Mahsa Bagheri Tookanlou**, S. Ali Pourmousavi, Mousa Marzband, "An Optimal Day-Ahead Scheduling Framework for E-Mobility Ecosystem Operation with Drivers Preferences", *IEEE Transactions on Power Systems*, 36, 2021.

2. **Mahsa Bagheri Tookanlou**, S.Ali Pourmousavi Kani, Mousa Marzband, "A comprehensive day-ahead scheduling strategy for electric vehicles operation", *International Journal of Electrical Power & Energy Systems*, 131, 2021, 106912.

1.11.2 Book Chapter

1. **Mahsa Bagheri Tookanlou**, Mousa Marzband, Ameena SaadAl-Sumaiti, Somayeh Asadi, "Energy vehicles as means of energy storage: impacts on energy markets and infrastructure", *Energy Storage in Energy Markets, Elsevier*, 2021, pp. 131–146.

1.11.3 Conference Papers

1. **M. Bagheri Tookanlou**, M. Marzband, A. Al Sumaiti, and A. Mazza, "Cost-benefit anal-ysis for multiple agents considering an electric vehicle charging/discharging strategy and grid integration", *2020 IEEE 20th Mediterranean Electrotechnical Conference (MELECON)*, 2020, pp. 19–24.

2. **M. Bagheri Tookanlou**, M. Marzband, J. Kyyrä, A. Al Sumaiti, and K. A. Hosani, "Charg-ing/discharging strategy for electric vehicles based on bi-level programming problem: San francisco case study," *2020 IEEE 14th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG)*, 2020, pp. 24–29.

1.11.4 Scholarships and Awards

1. Received a Ph.D. full-fund scholarship and tuition-waver from Northumbria University (2018-2021).

2. Received three conference travel grant from Northumbria University.

References

[1] A. Martínez, "Energy innovation and transport: The electrification of trams in spain, 1896–1935," *Journal of Urban Technology*, vol. 19, no. 3, pp. 3–24, 2012.

[2] "Internal combustion engines (ice) counted for over 90% of global car sales in h1 2019, available at: https://www.jato.com/internal-combustion-engines-ice-counted-for-over-90-of-global-car-sales-in-h1-2019/," 2019.

[3] "The internation council on clean transportation, available at: https://theicct.org/."

[4] "The electric vehicle world sales database, available at: http://www.ev-volumes.com/."

[5] "Transport and environment statistics 2021 annual report, available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/984685/transport-and-environment-statistics-2021.pdf," 2021.

[6] "Paris declaration on electro-mobility and climate change & call to action, available at: https://unfccc.int/media/521376/paris-electro-mobility-declaration.pdf," 2015.

[7] T. Seymour, "Ev charging infrastructure 'biggest barrier' to adoption, available at: https://www.fleetnews.co.uk/," 2020.

[8] D. Hirst, "Electric vehicles and infrastructure," *House of Comments Library*, 2020.

[9] "The road to zero: Next steps towards cleaner road transport and delivering our industrial strategy, available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads_data/file/739460/road-to-zero.pdf," 2015.

[10] "How the UK can lead the electric vehicle revolution, available at: https://www.green-alliance.org.uk/resources/How_the_UK_can_lead_the_electric_vehicle_revolution.pdf."

[11] "SMMT, available at: https://www.smmt.co.uk/vehicle-data/evs-and-afvs-registrations/."

[12] "State policies promoting hybrid and electric vehicles, available at: https://www.ncsl.org/research/energy/state-electric-vehicle-incentives-state-chart.aspx," *National Conference of State Legislatures*, 2021.

[13] "Comparing U.S. and Chinese electric vehicle policies, environmental and energy study institute, available at: https://www.eesi.org/articles/view/comparing-u.s.-and-chinese-electric-vehicle-policies," 2018.

[14] "Global power consumption to almost double by 2050, available at: https://www.energylivenews.com/2021/01/18/global-power-consumption-to-almost-double-by-2050/," 2021.

[15] "BloombergNEF electric vehicle outlook , available at: https://about.bnef.com/electric-vehicle-outlook/," 2021.

[16] L. Liu, F. Kong, X. Liu, Y. Peng, and Q. Wang, "A review on electric vehicles interacting with renewable energy in smart grid," *Renewable and Sustainable Energy Reviews*, vol. 51, pp. 648–661, 2015.

[17] "Renewable capacity highlights, international renewable energy agency (IRENA), available at: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2021/Apr/IRENA_-RE_Capacity_Highlights_2021.pdf?la=en&hash=1E133689564BC40C2392E85026F71A0D7A9C0B91," 2021.

[18] "Solar Media Ltd , available at: https://solarmedia.co.uk/," 2021.

[19] "Power system ecosystem, available at: https://www.nissan-global.com/EN/ZEROEMISSION/APPROACH/COMPREHENSIVE/ECOSYSTEM."

[20] "Nissan to launch a new vehicle-to-grid project with Enel in the UK, available at: https://electrek.co/2016/05/11/nissan-vehicle-to-grid-enel-uk/," 2016.

[21] "Startup pioneers EV-to-grid technology in pilot at UC San Diego, available at: https://xconomy.com/san-diego/2017/06/16/startup-pioneers-ev-to-grid-technology-in-pilot-at-uc-san-diego/," 2017.

[22] "The V2G -technology: Electrical car's charger, available at: https://www.sciencetechniz.com/2020/01/the-v2g-technology-electrical-vehicle.html," 2020.

[23] "Amsterdam pilots V2G under smart city initiative, available at: https://www.smart-energy.com/industry-sectors/energy-grid-management/v2g-technology-amsterdam/," 2018.

[24] "Nissan and EDF group partners to accelerate electric vehicle adoption and grid integration across Europe, available at: https://europe.nissannews.com/en-GB/releases/nissan-and-edf-group-partners-to-accelerate-electric-vehicle-adoption-and-grid\-integration-across-europe," 2019.

[25] "Electric vehicle to grid system, available at: https://westernpower.com.au/connections/solar-batteries-electric-vehicles/electric-vehicle-to-grid-system/."

[26] "SWRI develops first ERCOT-qualified vehicle-to-grid aggregation system, available at: https://www.swri.org/press-release/swri-develops-first-ercot-qualified-vehicle-grid-aggregation-system#.VO66HfldWLY."

[27] "SPIDERS: The smart power infrastructure demonstration for energy reliability and security, available at: https://energy.sandia.gov/wp-content//gallery/uploads/SPIDERSFactSheet2012-1431P.pdf," 2012.

[28] A. Briones, J. Francfort, P. Heitmann, M. Schey, S. Schey, and J. Smart, "Vehicle-to-grid (v2g) power flow regulations and building codes review by the avta," *Idaho National Lab., Idaho Falls, ID, USA*, vol. 1, 2012.

[29] "Tesla superchargers in urban areas, available at: https://www.tesla.com/supercharger," 2020.

[30] "Hyundai ioniq electric, available at: https://www.hyundai.co.uk/electric-cars," 2020.

[31] "BMW i3 charging basics, available at: https://www.pluglesspower.com/learn/bmw-i3-charging-ultimate-guide/," 2017.

[32] "Nissan leaf - 50kw chademo rapid charger quick charge, available at: https://www.nissan.co.uk/vehicles/new-vehicles/leaf/range-charging.html," 2020.

[33] "ABB powers e-mobility progress in chile with innovative charging solution, available at: https://new.abb.com/news/detail/57902/abb-powers-e-mobility-progress-in-chile-with-innovative-charging-solution," 2020.

[34] "Global EV outlook, available at: https://www.iea.org/reports/global-ev-outlook-2019," 2019.

[35] "Public EVSE chargers by country and type, available at: https://www.statista.com/statistics/571564/publicly-available-electric-vehicle-chargers-by-country-type/," 2020.

[36] M. Anderman, "Status and prospects of battery technology for hybrid electric vehicles, including plug-in hybrid electric vehicles," *Advanced Automotive Batteries*, 2007.

[37] O. Egbue and S. Long, "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions," *Energy policy*, vol. 48, pp. 717–729, 2012.

[38] "The price of an electric car battery, available at: https://easyelectriclife.groupe.renault.com/en/day-to-day/charging/what-is-the-price-of-an-electric-car-battery/," 2020.

[39] "U.S. department of energy vehicle technologies program, vehicle technologies program: Goals, strategies, and top accomplishments, available at: http://www1.eere.energy.gov/vehiclesandfuels/pdfs/pir/vtp_goals-strategies-accomp.pdf," 2010.

[40] V. Nimesh, R. Kumari, N. Soni, A. K. Goswami, and V. M. Reddy, "Implication viability assessment of electric vehicles for different regions: An approach of life cycle assessment considering exergy analysis and battery degradation," *Energy Conversion and Management*, vol. 237, p. 114104, 2021.

[41] "How long do electric car batteries last? ev battery recycling, available at: https://www.rac.co.uk/drive/electric-cars/charging/how-long-do-electric-car-batteries-last/."

[42] N. Neyestani, M. Y. Damavandi, M. Shafie-Khah, J. Contreras, and J. P. Catalão, "Allocation of plug-in vehicles' parking lots in distribution systems considering network-constrained objectives," *IEEE Transactions on Power Systems*, vol. 30, no. 5, pp. 2643–2656, 2014.

[43] Y. R. Rorigues, A. C. Z. de Souza, and P. F. Ribeiro, "An inclusive methodology for Plug-in electrical vehicle operation with G2V and V2G in smart microgrid environments," *International Journal of Electrical Power & Energy Systems*, vol. 102, pp. 312–323, 2018.

[44] P. Jain, A. Das, and T. Jain, "Aggregated electric vehicle resource modelling for regulation services commitment in power grid," *Sustainable Cities and Society*, vol. 45, pp. 439–450, 2019.

[45] L. Wang, S. Sharkh, and A. Chipperfield, "Optimal decentralized coordination of electric vehicles and renewable generators in a distribution network using A^*

search," *International Journal of Electrical Power & Energy Systems*, vol. 98, pp. 474–487, 2018.

[46] M. R. Mozafar, M. H. Amini, and M. H. Moradi, "Innovative appraisement of smart grid operation considering large-scale integration of electric vehicles enabling V2G and G2V systems," *Electric Power Systems Research*, vol. 154, pp. 245–256, 2018.

[47] J. Zhao, Z. Xu, J. Wang, C. Wang, and J. Li, "Robust distributed generation investment accommodating electric vehicle charging in a distribution network," *IEEE Transactions on Power Systems*, vol. 33, no. 5, pp. 4654–4666, 2018.

[48] A. Hajebrahimi, I. Kamwa, M. M. A. Abdelaziz, and A. Moeini, "Scenario-wise distributionally robust optimization for collaborative intermittent resources and electric vehicle aggregator bidding strategy," *IEEE Transactions on Power Systems*, vol. 35, no. 5, pp. 3706–3718, 2020.

2 | Literature Review

2.1 Introduction

The uncoordinated EVs' G2V and V2G operation results in several issues and challenges in distribution network due to excessive load consumption, such as voltage violations, power loss increase, and overloads. Recently, as governments have shifted their focus towards environmental aspects and energy saving in the transportation sector, EV has been developed expeditiously in terms of both technical advances and market expansion. For instance, Nissan Leaf increased the driving range of EVs from 84 miles in the 2015 EV model to 220 miles in the 2019 EV model by upgrading their battery performance [1]. With the commercialization of EVs, large-scale EV charging may negatively impact drivers (they need to wait in long queues for a long time for charging their vehicles), the electrical distribution network operation, and traffic congestion at CSs. Although increasing market share of EVs reduces fuel consumption to a certain degree, the random arrival times of EVs in the CSs may cause traffic congestion at CSs which are located at city centers. Further, the system's operation will become more challenging when EVs operate in V2G mode supporting the upstream grid operation. Therefore, a proper scheduling strategy for EVs plays an important role to have a secure e-mobility ecosystem.

Researchers have put forward different algorithms for EV charging/discharging scheduling problem from different perspectives. In this chapter, a review of the existing studies on EV's G2V and V2G scheduling algorithm is presented. Considering the fact that EV scheduling literature is quite crowded, the existing studies have been categorised into five groups in this chapter as follows:

- Coordinated G2V and V2G operation algorithm;
- Game theory in e-mobility ecosystem;
- Multi-objective optimisation problem;
- Pricing in e-mobility ecosystem;
- Stochastic programming in e-mobility ecosystem;

Then, the drawbacks of the corresponding studies are mentioned at the end of each category. In addition, at the end of this chapter, the major cons in the existing literature are highlighted categorically in the list of gaps. Helpful definitions are provided for the context of this chapter.

Bi-directional chargers: Bi-directional chargers allow EV drivers to not only charge the EV batteries but to also send energy back to the main power grid.

Chance-constrained optimisation: It is a kind of stochastic optimisation problem that certifies that the probability of meeting a certain constraint is more than a confidence level.

Charging station (CS): An infrastructure that supplies electricity to recharge EVs or connect to the power grid to send energy back through bi-directional chargers.

Day-ahead scheduling algorithm: It is defined as an algorithm which schedules a system one day prior to or one day earlier.

E-mobility ecosystem: It represents the concept of a system which includes all stakeholders/agents participated in charging and discharging of EVs, as well as their mutual interaction between them.

Grid-2-Vehicle (G2V): It is defined as a technology in which an EV is connected to the grid to store energy in its battery.

Hierarchical control system: It is a control system which includes hierarchy of control levels and formed as a hierarchical tree. Each control level consists of an optimisation problem, with the formulation regarding a multilevel programming problem [2].

Plug-in hypbrid electric vehicle (PHEV): A type of vehicle which is able to swap between the internal combustion engine and electric motor. It has EV benefits for the short drives and have the support of the diesel or petrol engine for long drives.

Stackelberg game: A sequential game in economics which involves two types of players with asymmetric roles which are called leader and follower. The leader makes a decision and the follower chooses a policy with the knowledge of leader's strategy [3].

State of charge (SOC): It is defined as the level of charge of the EV's battery capacity which is expressed as a percentage of the capacity.

Stochastic programming: It is a framework for modeling optimisation problems including uncertainties. In the optimisation problem, some or all problem parameters uncertain. The framework is compared with deterministic model, in which all problem parameters are supposed to be certain.

Vehicle-2-Grid (V2G): A technology which enables the EV to send back energy to the main grid through bi-directional chargers.

2.1.1 Literature regarding coordinated G2V and V2G operation algorithm

Most of the literature have proposed coordinated G2V and V2G operation mechanisms to minimise their impact on the grid as the coordination of EVs' operation is necessary to determine optimal charging/discharging schedule for EVs in order to attain the economical and technical operation in the e-mobility ecosystem. Since behaviour of EV drivers is unpredictable, regulated operation of EVs in charging/discharging mode is challenging. Therefore, different algorithms for coordinated G2V and V2G operation have been proposed in the literature. In [4], mixed integer linear programming (MILP) was proposed for an economic scheduling strategy to coordinate energy exchanged between distribution network operators and EVs in order to satisfy cost-effective targets considering uncertainty of wholesale electricity prices and random EV charging behaviours. In that study, the model is not comprehensive because only the operation of the EVs and grid were considered in the e-mobility ecosystem. Furthermore, electricity prices were considered as given parameters. In [5], a quadratic programming (QP) was proposed to develop EV charging/discharging scheduling algorithm to minimise EV operational costs and mitigate voltage violation. EV arrival and departure times were considered as stochastic parameters to investigate the presence of uncertainties on the voltage level. The impact of the CS operation on the EV charging/discharging scheduling was not considered in [5]. In [6], a regulated charging scheduling algorithm was proposed for microgrid to minimise the difference between load demand during peak period and valley period. In the proposed algorithm, the urgency of EV charging demand and the uncertainty of EV charging behaviour were considered to improve the actual aspects of the scheduling method. The proposed algorithm was not comprehensive because the V2G service was not investigated. A mixed integer quadratically constrained programming (MIQCP) was formulated in [7] to coordinate the planning of electrical network, transportation system, energy storage systems, fast CSs, and a large number of EVs. In the proposed problem, the fast CS siting module and traffic congestion were considered to decrease the investment cost of the transportation network and improve the efficiency of driving. In that study, the economically-irrational decisions taken by the EV drivers were not modeled and their role was not investigated. Optimal day-ahead V2G and G2V scheduling scheme was proposed in [8] to determine the optimal charging power and minimise the total cost for a large number of EVs. The operation of CSs and the grid was not investigated on V2G and G2V scheduling and the V2G and G2V prices were considered as known parameters and were not determined. In [9], a MILP model was proposed for developing EV charging coordination problem under unbalanced distribution system. The proposed problem minimised the energy cost of EV considering the requested priorities of EV drivers. In that study, the impact of CSs operation was not considered in the EV charging coordination problem. In addition, the electricity prices were considered as known parameters. Authors of [10] have developed EV charging schedules framework to minimise the charging cost considering the distribution network constraints including voltage magnitude limit, power line rating, DC power flow, and the transformer capacity limitation. In that study, the V2G service and the revenue obtained from selling electricity by the EV were not considered in the schedules framework. A hierarchical framework, which was presented in [11] as a three-level model, coordinated real-time and day-ahead PEV charging to deal with the PEV drivers requirement. The proposed mathematical three-level model, which included provincial level, municipal level, and CS level, optimised system load profile and charging costs. The economically-irrational decisions taken by the EV drivers were not modeled and the electricity prices were considered as given parameters in the model. In [12], a convex mathematical model was proposed to coordinate DC fast charging of a group of EVs. The model accounted for the nonlinear relationship between maximum charging power, battery voltage, and SOC of battery. The maximum charging power was constrained by battery voltage in the model. However, the impact of CSs operation and the preferences of the EVs were not considered in the coordination problem. In [13], a hierarchical mixed-variable optimisation problem was developed for EV charging scheduling, which included multiple optimisation objectives and considered the different charging options and charging amounts at CSs. The total time, charging cost, and the SOC gap were minimised in the proposed optimisation problem. The total time included the driving time, the waiting time, and the charging time at CSs. The SOC gap was considered as the difference between the final SOC of EVs and the expected SOC. The limitations of the distribution network were not implemented in the optimisation problem. A scheduling problem based on a decentralised method was developed in [14] to coordinate the charging schedules of a large number of EVs. The plug-in and plug-off times were considered in the proposed strategy to enhance the practical aspects of EV charging scheduling. The EV drivers' convenience (charging time and desired SOC at the departure time) and the grid operator benefits (load valley filling) were considered in the proposed model. The different responses of the EV drivers to economic incentives were not modeled, and also, the electricity prices during G2V operation were considered as the given parameters.

Two optimal scheduling models were proposed in [15] to obtain the scheduling single EV and an EV fleet in public CS and home-charging patterns with regard to minimise the cost of EV owners based on dynamic pricing. The inconvenience of EV owners was considered as a part of the cost of EV owners which improved the satisfaction of EV owners. The operation of two stakeholders including CSs and the distribution network was ignored in that study. In [16], a distributed algorithm was proposed to schedule EVs and optimise the usage of CSs in G2V operation in a highway. The queues among the CSs were coordinated considering the traffic network and the status of CSs. The distribution network constraints were not taken into account in the scheduling model and the electricity prices were not calculated and they were considered as known parameters. The authors of [17] developed a coordination algorithm based on fuzzy method for charging PEVs, which decreased the total cost of energy generation and loss of electricity network while sustaining constraints of the network operation including the voltage and maximum load limitations. The algorithm considered random PEVs, Time-of-Use electricity prices, and preferences of PEV drivers for charging time. The algorithm was not considered economically-irrational decisions that may be taken by the EV drivers. In addition, the electricity prices during charging PEVs were know parameters and the optimal prices were not calculated as a part of the algorithm. In [18] a more realistic model was developed to coordinate EV, which considered discrete charging levels in the distribution network and the grid capacity limitation. The proposed model optimised the total load variations and total number of switching in EV's G2V operation. In that study, the operation of CSs was ignored in the EV coordination problem. In [19], a real-time scheme for EV's G2V operation was brought forward to coordinate EV charging with respect to the dynamic electricity price, and implementation of the demand response program in the parking station. The proposed optimisation problem was maximisation of the number of EVs charged and the EV owner's convenience and minimisation of the charging cost. A bi-level optimisation problem, which was MILP programming was developed in [20] to determine the optimal day-ahead charging strategy for PEVs. The peak load which consisted of charging load of PEVs and the load fluctuation, were minimised in the first and the second level, respectively. In addition. a social welfare approach was presented to determine the revenue and cost of a PEV in V2G and G2V operation. In [19, 20], the V2G service, the impacts of CSs operation and the distribution network were neglected. In [21], an energy management and charging scheduling system were proposed for CSs and PEVs based on battery control units. The system provided facilities for the EV drivers to make the optimal decision for EV charging. ,The distribution network constrains and the V2G operation were ignored in that study. Authors of [22] proposed the multi-objective energy management problem to minimise total cost of EVs and obtain real-time energy management control. The proposed energy management optimisation was based on the direct multiple shooting method and sequential QP algorithm. The proposed algorithm reduced the total operating cost. The impacts of two stakeholders operation including CSs and the distribution network were not be taken into account in the energy management problem.

In [23], an EV charging/discharging scheduling and control framework have been proposed to provide grid services considering EV drivers travel requirements. The economically-irrational decisions that may be taken by the EV drivers were not considered in the scheduling. Further a charging algorithm has been proposed for allocating power to a large-scale PHEVs at a parking station in [24]. In that study, the operation of only EVs was taken into account and other stakeholders including CSs and retailers were neglected. The EV management and charging/discharging scheduling model have been developed for an intelligent parking lot in [25] considering economical and technical aspects of EV operation, simultaneously. The proposed model considered desired charging electricity prices, remaining battery capacity, remaining charging time and age of the battery as EV owners' preferences. The prices were considered as given parameters and the optimal desired charging prices were not obtained in the model. In [26], a bi-level optimisation algorithm was developed based on multi-agent systems to optimise the performance of an EV aggregator and to generate optimal bids for participation in the energy markets. The effects of EV's V2G and G2V operation on the power system demand profile as well as the stability and reliability of the power system were investigated in [27]. Various power levels for V2G and G2V operation were considered to estimate its impact on the system reliability.

In [28], a coordination algorithm for EVs' V2G and G2V operation was proposed considering the impact of penetration of EV fleets into the power system. In [27, 28], the operation of CSs were not considered and the prices for G2V and V2G services were considered as given parameters.. In [29], a multi-variant route optimisation model was presented for EVs operation incorporating G2V and V2G options in the travel path. The impacts of retailers were not investigated in operation of EVs and CSs in that study. A steady-state analysis of a distribution network was introduced in [30] to determine the nodal voltage variations considering different EVs' charging strategies. A smart charging strategy of EVs at CSs has been introduced offering multiple charging options. In [31], a combination of EV routing and charging/discharging scheduling strategy was proposed to operate an EV fleet. A MILP was formulated to maximise the revenue of EV owners subject to EV and distribution network constrains. In [30, 31], the operation of CSs as one of the main stakeholders in e-mobility ecosystem was ignored. In addition the optimal charging/discharging prices were not obtained and the prices were considered as given parameters in the model. In [32], a mathematical model is developed for integration of EVs and distributed generation units in energy market under a joint aggregator. Also, the performance of the EV aggregator under the uncertainty of electricity market prices was studied through an stochastic optimisation formulation. A two-stage scheduling framework at the distribution level was proposed in [33]. In the first stage, the charging/discharging schedules of EVs were obtained. In the second stage, the resource were scheduled, i.e., usage profiles of the distributed generation units, strategy of buying electricity from the market, and final charging/discharging patterns of the EVs were obtained. The operation of CSs was ignored in the proposed framework. In [34], a framework was presented to develop the network equilibrium traffic and charge patterns in an electric transportation network. In that study, the effects of individual CS on aggregate congestion and electricity costs were investigated. However, the impacts of retailers were not studied. In [35], the optimal traffic-power flow model was reformulated as a mixed integer second-order cone program to optimise coordinated operation of transportation and electricity networks.

A two-step EV scheduling methodology was proposed in [36] to minimise EVs' charging impact on the distribution network. The optimal number of EVs to be charged during each hour was determined in the first step and the maximum number of EVs that should be charged during the next hour was obtained in the second step. An iterative two-layer optimisation model was proposed in [37] based on a mixed-integer programming to alleviate the negative impact of uncoordinated charging/discharging of a large number of EVs on the grid. The operation of retailers and economically-irrational decisions that may be taken by the EV drivers were not investigated in [36, 37]. A decentralised algorithm was proposed to optimally schedule EV charging and discharging to fulfil load shifting in [38, 39]. Only the operation of EVs were investigated in those studies and the impacts of CSs and retailers as two significant stakeholders in the e-mobility ecosystem were ignored completely. In [40], an energy management problem was formulated using dynamic programming to minimise the daily energy cost of PHEVs. In that study, an optimal charging scheme for PHEVs was developed to shave the peak load and flatten the overall load profile from the distribution system operator's perspective. In [41], an optimal V2G and G2V control mechanism was offered to reduce the negative impact of EVs on the grid while minimising EV charging cost and losses of the power system. The authors in [42] developed a two-stage scheduling optimisation model including EVs, thermal power units and load demand. The day-ahead schedules of charging and discharging EVs and thermal units were determined in the first step, and charging and discharging schedules of the EVs were obtained afterwards considering demand uncertainties. A smart charging approach was presented in [43] for EV aggregator's operation to optimise power delivered to EVs during G2V mode. Three different options were considered based on electricity prices and charging power rates, and the final decision was made by the EV owners based on their waiting time preferences.

As summarised in Table. 2.1, in the proposed algorithms only one or two stakeholders were considered by neglecting the impact of other players in the future e-mobility ecosystem. Moreover, the prices were treated as given parameters as opposed to obtaining them in the solutions. Also, a careful review of the literature shows that the proposed algorithms find the best CS based on the EV drivers' preferences such as minimum driving distance , minimum cost of G2V, maximum revenue of V2G , and minimum waiting time in CSs without considering diverse attitude of EV drivers to economic incentives. In addition, the EV drivers may react differently to extra driving distances required for cheaper (more expensive) G2V (V2G) services. In other words, EV drivers are modelled fully rational in the literature, which may jeopardise the EV drivers' welfare because considering EV drivers' preferences, drivers would accept a longer route to save any amount of money. However, in this thesis, a whole system approach is adopted to optimise major stakeholders (EVs, CSs, and retailers) operation in the ecosystem. Also, the mutual impacts of the stakeholders are considered by optimising stakeholders' operation collectively. Furthermore, two significant preferences of EV drivers (driver's cost/revenue threshold and driver's route preference) are considered to model economically irrational decisions taken by the EV drivers in response to economic incentives. Furthermore, the G2V and V2G prices are investigated for all stakeholders.

Table 2.1: The comparison of works relevant to coordinated G2V and V2G operation algorithm proposed in the literature and the model proposed in this thesis.

Ref.	Which stakeholder is considered?	Pricing	Preferences
[8, 15, 19, 20, 22, 24, 25, 38, 39]	EVs	✗	✗
[7, 13, 16, 21, 29, 34]	EVs & CSs	✗	✗
[4–6, 9, 10, 12, 14, 17, 18, 27, 28, 30, 31, 33, 35–37, 40, 41, 43]	EVs & Grid	✗	✗
[26]	EV Aggregator & Retailers	✗	✗
[32, 42]	EV Aggregator, & Generation Units	✗	✗
[11, 23]	EVs, CS, & Grid Constraints	✗	✗
This thesis	EVs, CSs, & Retailers	✓	✓

2.1.2 Literature regarding game theory in e-mobility ecosystem

Since there are distinct entities/stakeholders in the e-mobility ecosystem, competition between the stakeholders exists to give services to EVs in V2G and G2V operation. Game theory has been used in several studies on this subject, which facilitates analysis of the interactions between the stakeholders and price calculation. In [44], a game was developed to minimise the total cost of the utility company which controls the load supplied to CSs and maximise the profit of each CS, considering uncertainty of EV demand and renewable energy generation. In that study, CSs and utility company were considered as the game players and the role of other stakeholders including EVs and retailers were neglected in the game.

In [45], a stackelberg game was formulated as a bi-level optimisation problem to provide energy and reserve management of the fast CS as the leader of the game. The fast CS managed electricity and determined energy/reserve prices for EVs considering the uncertainty of renewable energy sources. Charging and reserve strategies were determined in the follower level of the game which belongs to EVs. In that study, only the optimal electricity prices during G2V operation were determined and the V2G service was not considered. In addition, the operation of retailers as one of the key players in the Stackelberge game was not taken into account. In [46], a bi-level non-cooperative game was developed to model the competition among multiple EV aggregators who deal with the coordination of EV charging, while considering the response of the aggregators are not rational. In the developed model, charging costs of aggregators were minimised by choosing optimal start times for G2V operation and energy profiles. In [47], a Stackelberg game was presented for EV charging scheduling. The leader was the smart grid, which maximised its revenue and decided the electricity price. The followers in the game were EVs and charging strategy was determined in the followers' level by minimising the charging cost. The G2V prices were determined in that study but the V2G services and V2G prices were not investigated. The competition between CSs with renewable energy generation to attract EVs was analysed using a supermodular game in [48]. The electricity price and the revenue of CSs were determined considering the limitations of power line capacity, the distance between EVs and CSs, and the number of chargers at CSs. The impacts of EVs and retailers operation were not investigated in the competition between Css. The authors of [49] proposed a non-cooperative and cooperative game. The interaction between the EV aggregator and EVs was modeled using non-cooperative stackelberg game, in which the EV aggregator was the leader and EV drivers were the followers. The electricity price was determined in the leader's level and V2G and G2V mode was decided in the followers' level. In addition, the cooperative game was developed to investigate the social welfare of the entities in the V2G service. However, in that study, the economically-irrational decisions that may be taken by the EV drivers were not modeled as part of the game. In [50], a hierarchical game was presented to model the competition between PHEVs in the frequency regulation. The prices of frequency regulation were obtained in the upper level as the non-cooperative game model. Then, the regulation capacity of the aggregator was optimised in the cooperative game of the lower level to improve the ability of the aggregator in frequency regulation bidding. The V2G service was ignored in that study. In [51], a non-cooperative game model was developed for the parking-lot EV charging scheduling. The utility function of each EV as a player was maximised considering SOC, the transformer capacity, and the electricity price. In that study, only EVs were the players of the non-cooperative game and the comprehensive game which includes CSs and retailers were not studies. In [52], a non-cooperative game framework which is based on charging control method was developed to coordinate the charging schedule of PEV fleet, while minimising the cost of PEV drivers without jeopardising the constraints of the power grid constraints. In the proposed game, the V2G services and operation of CSs and retailers were neglected and the economically-irrational decision that may be taken by PEV drivers was not considered as one of the preferences of the PEVs. A Stackelberg game between EVs and CSs was proposed with multiple leaders and followers in [53]. In the developed model, the charging scheme was obtained, which includes selection of CSs for G2V operation and pricing strategy for EVs and CSs. The selection of CSs by EVs was based on the charging prices and the distance between EVs and CSs, while maximising the revenue of CSs. The pricing strategy was developed only for G2V and the V2G pricing was neglected. In addition, the retailers were not considered as players of the game and only CSs and EVs partecipated in the game. In [54], a graphical game was proposed for the charging scheduling of EVs to minimise the charging time, which includes driving time to CSs, waiting time and charging time at CSs. In that study, only EVs participated in the graphical game and other players (CSs and retailers) were ignored. A framework linking power network with transportation system was proposed in [55] to navigate EVs to CSs using a hierarchical game approach considering reliability of the distribution network and profit of CSs. A day-ahead G2V scheduling was proposed in [56] based on an aggregative game model accounting for the interaction between the EV charging demand and its impact on the electricity prices. In [57], a Stackelberg game was developed, where CSs (as leaders) offered their G2V prices to EVs (as followers), who then select CSs based on prices, travel distances, and expected waiting times at CSs. In [58], an optimisation framework based on non-cooperative game was developed using mixed-integer linear programming to allocate CSs to EVs for G2V operation in order to minimise EV waiting times.

As summarised in Table. 2.2, in the literature, the proposed algorithms can only solve the scheduling problem for a subset of the players in future e-mobility ecosystem, which may lead to sub-optimal solutions, thus lower public acceptance. However, in this thesis, a comprehensive non-cooperative stackelberge game is proposed which includes all major stakeholders (EVs, CSs, and retailers) operation in the ecosystem. The new added constraints (i.e., drivers' preferences) represent economically-irrational drivers as opposed to fully rational users assumed in the literature, where the drivers would accept a longer route to save any amount of money. Also, both G2V and V2G prices are determined.

2.1.3 Literature regarding multi-objective optimisation problem

Numerous studies offered approaches based on a multi-objective optimisation for the EV scheduling problem. In [60], a multi-objective optimisation problem was de-

Table 2.2: The comparison of works relevant to game theory in e-mobility ecosystem proposed in the literature and the model proposed in this thesis

Ref.	Game Players (Type of Game)	Pricing		Preferences
		G2V	V2G	
[44]	CSs	✗	✗	✗
[45]	EVs and CSs (Stackelberge game)	✓	✗	✗
[46]	EV aggregators	✗	✗	✗
[47]	EVs and smart grid (Stackelberge game)	✓	✗	✗
[48]	CSs	✓	✗	✗
[49]	EVs and EV aggregator (Stackelberge game)	✓	✓	✗
[50]	Non-cooperative game between aggregators and Markov game between PHEVs	✓	✗	✗
[51]	EVs (non-cooperative game)	✗	✗	✗
[52]	PEVs (non-cooperative game)	✓	✗	✗
[53]	EVs and CSs (Stackelberge game)	✓	✗	✗
[54]	EVs (graphical game)	✗	✗	✗
[55]	EVs and CSs (hierarchical game)	✓	✗	✗
[56]	EVs (aggregative game)	✓	✗	✗
[57]	PEVs and CSs (Stackelberg game)	✓	✗	✗
[58]	EVs (non-cooperative game)	✗	✗	✗
[59]	EVs and aggregator (Stackelberge game)	✓	✗	✗
This thesis	EVs, CSs, Retailer (Non-cooperative Stackelberge game)	✓	✓	✓

veloped for scheduling EV's V2G and G2V operation. Simultaneous optimisation of electricity cost, battery degradation, grid net exchange, and CO_2 emissions have been performed. In that study, the electricity prices for G2V and V2G service were not determined and the optimisation problem was not considered CSs and retailers costs. Another multi-objective optimisation problem was developed in [61] to consider both power grid and EV drivers' concerns. The stochastic modelling was proposed to take into account the inherent uncertainty of EV driving activities and renewable energy output power. In [62], a day-ahead co-optimisation problem was developed to minimise the negative impacts of PEVs on the power system operation by minimising the cost of energy losses and the transformer operation cost while managing active and reactive powers. In [61, 62], the optimisation problems were not comprehensive and the operation of CSs was not part of the optimisation problems. In [63], a multi-objective framework was proposed to schedule EVs' charging and discharging in a smart distribution network, where total operation cost of the distribution network, including EVs and CO_2 emission from distributed generation units and the main grid, was minimised. The charging and discharging prices were considered as given parameters and were not determined as part of the optimisation problems. A multi-objective optimisation problem was proposed in [64] to find optimal charging schedule of a large EV fleet considering the operation of the transportation network, power network, and CSs where the nearest CS was selected as the best option regardless of the electricity prices. In that study, the operation of the stakeholders including EVs, CSs, and grid were considered in the optimisation problem but no strategy was proposed for determining the electricity prices. A two-stage multi-objective optimisation problem was offered in [65], where the driving needs of EV owners were considered in the first stage. In that study, total energy and emission costs were optimised in the second stage under the uncertainty of solar irradiation and wind speed.

On a relevant subject, a CS selection method was presented in [66] to minimise the travel time, waiting time, and charging cost for an EV. However, the operation of retailers was not considered in the optimisation problem. In [67], a multi-objective optimisation problem was proposed to co-optimise customer and system operator objectives. The proposed model controlled the peak load from the system operator's perspective and optimised EVs' costs/revenues and the battery degradation cost from the EVs' perspective. In [68], a real-time multi-objective optimisation problem was developed to schedule charging/discharging EVs, while performing the co-optimisation of the end-user cost, battery degradation and grid stress. In [69], a scheduling strategy was proposed for a system including EVs, distributed energy resource, and grid load to minimise the variance of total power load and the maximise dispatching cost simultaneously. In [70], a bi-objective optimisation problem was developed for EV charging scheduling to optimise the operation of two stakeholders including CSs and EV drivers. The proposed centralised scheduling algorithm minimised the charging cost and reduce the charging time. In [71], a multi-objective optimisation problem as MILP was developed for charge scheduling and route management of EVs considering the traffic network to minimise the energy usage and the travel time which includes driving time on roads, waiting time at the CS, and charging time at the CS. Scheduling of a large-scale EVs was developed in [72] to flatten the electricity duck curve by proposing a multi-objective optimisation problem, whereas the ramp-up requirement system and the quality of service were optimised. In [73], a 24-hour charging profile of a PHEV was optimised by minimising the electricity, fuel, and battery degradation cost concurrently. A multi-objective model was proposed in [74], to schedule electric vehicles by optimising the convenience and cost of users, along with the load fluctuation of grid using PSO algorithm.

It can be seen in Table. 2.3, that the proposed multi-objective methods only optimise one or two stakeholders' operation without accounting for the impact of optimal operation of the other ones. Also, the G2V and V2G prices for different stakeholders have not been obtained in the proposed multi-objective frameworks.In addition, economically-irrational drivers' behaviour were not modelled in the literature which may reduce the EV drivers' interests. Moreover, other potential challenges related to multi-objective problems are the dilemma over determining appropriate weights for different objectives and the tractability of a larger optimisation problem that should be solved in a single shot [75].

Table 2.3: The comparison of works relevant to multi-objective optimisation problem in e-mobility ecosystem proposed in the literature and the model proposed in this thesis

Ref.	Which stakeholder is considered?	Pricing		Preferences
		G2V	V2G	
[60, 68]	EVs and microgrid	✗	✗	✗
[61–63, 65, 67, 69, 74]	EVs and grid	✗	✗	✗
[64]	EVs, CSs and grid	✗	✗	✗
[66, 70, 72]	EVs and CSs	✗	✗	✗
[71, 73]	EVs	✗	✗	✗
This thesis	EVs, CSs, and retailers	✓	✓	✓

2.1.4 Literature regarding pricing in e-mobility ecosystem

Another group of studies focused on optimal pricing of G2V and/or V2G services in the future e-mobility ecosystem. For example, an optimal pricing scheme was proposed in [76] to coordinate the charging processes of EVs. Another model was developed in [77] for managing EVs in a public CS network through differentiated services including optimal pricing and routing. In the method, CSs were assigned to EVs based on the energy demand and the traveling preferences (i.e., which stations they are willing to visit) to manage waiting time and electricity prices. In [78], a pricing scheme for charging an EV was proposed including two optimisation problems to maximise the profit of CSs and EV owners. In [79], a pricing methodology for CSs was developed to facilitate consumption of renewable generation. The selection of CSs by EV owners was modeled based on the charging prices, driving distance to CSs and traffic congestion information. In [80], an algorithm was proposed to schedule EVs for G2V and V2G services according to EV driving demand while planning the time and location of the services. The scheduling was based on Time-of-Use pricing. In [81], a CS operation mechanism was developed that jointly optimised pricing, charging scheduling and admission of a single CS to maximise the CS's profit. In [82], pricing for G2V operation was developed to improve the coordination between CSs and EVs in order to obtain the equilibrium strategies of those entities. The uncertainties of PV system generation, traffic conditions and electricity prices were investigated. Pricing policy for G2V considering power of PV system and internal distributed generation and power purchased from the grid were determined in the proposed CS model. In the EV model, the optimal travel-route selection and G2V scheduling were determined with regard to the pricing policy. The distribution locational marginal pricing method was proposed in [83] to mitigate congestion in the grid which was caused by EVs' G2V operation. A nonlinear optimisation problem was developed to maximise the social welfare of the distribution system and the electricity price was determined for EV aggregators.

As illustrated in Table. 2.4, the impact of retailers' operation and prices is disregarded in this group of literature, which is quite important as the major provider of electricity and thus a price maker. Also, V2G prices have not been determined in the proposed algorithms.

Table 2.4: The comparison of works relevant to pricing in e-mobility ecosystem proposed in the literature and the model proposed in this thesis

Ref.	Which stakeholder is considered?	Pricing		Preferences
		G2V	V2G	
[76, 79, 81, 82]	EVs and CSs	✓	✗	✗
[78, 80]	EVs and CSs	✓	✓	✗
[77]	EVs, CSs, and grid	✓	✗	✗
[83]	EV aggregators and grid	✓	✗	✗
This thesis	EVs, CSs, and retailer	✓	✓	✓

2.1.5 Literature regarding stochastic programming in e-mobility ecosystem

To consider sources of uncertainties in the scheduling problem, various approaches have been proposed in the literature including robust optimization and scenario-based stochastic programming, which are commonly used to characterise the uncertainties in transportation sector [84–86]. However, each of these approaches poses certain challenges. For scenario-based methods, an adequate number of scenarios must be considered to sufficiently represent the stochasticity of the parameters. This is because the performance of stochastic models highly depends on the assumed scenarios. More than often, it requires extra computational time and sometimes results in computational intractability. In robust optimisation approaches, the worst-case scenario is considered, which may lead to the most conservative solutions [87]. Also, it is challenging to define a proper probability distribution function for stochastic parameters.

Numerous research papers in the literature focused on EVs' G2V and V2G scheduling in an uncertain environment in recent years. The existing studies have been categorised based on different methods used, namely (1) scenario-based methods, (2) robust optimisation-based methods, and (3) Chance-constrained (CC) optimisation-based approaches. The first group of studies focused on scenario-based methods using stochastic programming for e-mobility ecosystem operation. For instance, a scenario-based stochastic approach was proposed in [88] to obtain optimal scheduling of PEVs for aggregators by maximising their profit in day-ahead and reserve markets. To consider uncertainties, the risk-constrained stochastic optimisation model was proposed in that paper. In [89], a scenario-based two-stage stochastic problem was offered based on a rolling window approach for scheduling EVs in G2V operation for different grid requirements. The goal was to minimise the distance between the actual and SOC over a given time span. The arrival and departure times, and the initial and target SOC of EV batteries were considered as uncertain parameters. A two-stage stochastic model was developed in [90] to optimise the investment decision and the operational cost of EVs in the first and second stage, respectively, considering energy consumption and available charging times as the sources of uncertainties. The stochastic study was investigated based on different scenarios, which was generated by a hidden Markov model. In [91], an EV charging scheduling model was presented to minimise the mean waiting time of EVs at a CS with multiple charging points equipped with RES. The EV arrival, the intermittency of the RES, and the electricity price were considered as uncertain parameters and described as independent Markov processes. In [92], optimal control of a CS with a PV system was investigated based on a finite-horizon Markov decision model under uncertainties of EV drivers' behaviors and dynamic electricity prices. Then, the total operation cost of the CS was minimised considering the V2G service and battery degradation. In [93], a two-stage scenario-based stochastic framework was developed for modeling the optimal network of CSs aiming to find the optimal CS for PHEVs. In that study, stochastic parameters were the battery demand, initial SOC, preferences for charging, and RES generation. In the first stage, the deterministic problem was solved leading into the second stage, where the decision was made considering the uncertainties. In [94], a dynamic stochastic optimisation problem was solved to determine optimal EV charging cost considering electricity prices, RES production, and load as stochastic parameters. The authors in [95] proposed a predictive framework by accounting for the uncertainties of EV drivers' behaviors to achieve cost-efficient solutions, whereas a kernel-based method was used to estimate uncertain parameters in G2V operation.

The second group of studies explored the application of robust optimisation in the e-mobility ecosystem. For example, in [96], a bi-level robust optimisation model was formulated to optimise the design of a CS considering uncertainties in real-time operation of the CS including the electricity prices, RES, and the number of EVs.

In [84], a robust day-ahead scheduling approach was developed for EV charging in a stochastic environment in order to simultaneously deal with EV drivers' requirements and distribution network constraints. Several uncertainties were considered including daily trip distances and arrival and departure times. Furthermore, conservative day-ahead assumptions were considered in the proposed model to address the negative effects of uncertainties. In [97], a robust optimisation-based unit commitment model was developed for a system with thermal generators and EV aggregators in day-ahead V2G planning problem. The robust optimisation model was then reformulated as a deterministic mixed-integer quadratic program using explicit maximisation method. The uncertain parameter was the available energy capacity of each EV aggregator. In [59], a robust Stackelburg game was used to investigate the interaction between an aggregator as the leader and several plug-in hybrid EVs as the followers for charging scheduling under energy demand uncertainty. Cooperative and non-cooperative games were investigated to analyse charging scheduling in that study, and selling electricity price to EVs was determined by maximising the utility of the aggregator. Then, the EV schedules were obtained by optimising the utility function of EVs. A deterministic optimisation problem for optimal charging schedules and its robust counterparts under uncertainty of electricity prices were compared in [98]. Trade-offs between optimality of the cost function and robustness of charging scheduling were investigated and stability of robust charging schedules were obtained with respect to uncertain electricity prices. In [99], robust scheduling of EV aggregators operation was investigated under uncertainty of electricity prices to maximise its profit. In [100], a Stackelberg game was proposed for the EV aggregator (as the leader) and EVs (as followers) to determine optimal day-ahead charging and frequency reserve scheduling aiming to balance the benefits of the players in the game. The robust optimisation approach was used to investigate EVs' optimal schedules under uncertain frequency regulation signals. In [101], a bi-level stochastic framework was developed for day-ahead scheduling for PHEV fleets and wind farm system. In the upper level, the total cost and operational emission of GHG were minimised. Arrival/departure times and their driving distance were considered as stochastic parameters for PHEV fleets were modelled through scenarios-based stochastic programming. The wind power production was modelled based on robust optimisation problem. The proposed bi-level problem was solved using Karush–Kuhn–Tucker (KKT) and the PHEV fleets were categorised into five clusters via K-means clustering.

The application of CC optimisation has been investigated in several studies in this field. For instance, to consider the stochastic features of the EV driving patterns in [102], a CC optimisation problem of EV aggegators and the distribution system operator were developed as a mixed-integer quadratic program. The goal was to reduce the congestion in the distribution network with a large amount of EVs. In [103], the CC programming was used to develop a day-ahead scheduling strategy for an EV battery swapping station. EV's battery swapping and PV generation were considered as the source of uncertainties, described by a probabilistic sequence. In [104], a two-stage program for energy management system of the distribution networks with EVs and RES was presented. In the first stage, a CC model was developed to obtain the optimal operation of CSs and battery swapping stations under uncertainties of RES generation. In the second stage, the regulated EV charging was determined to meet the EV's charging demand following the optimal operation of CSs.

There are several concerns about existing studies regarding stochastic programming of EV scheduling in e-mobility ecosystem. As mentioned in Table. 2.5, in the existing studies, the interactions between stochastic parameters originated from different stakeholders in an e-mobility ecosystem was ignored by optimising each stakeholder's operation individually. Also, the stochastic programming has been investigated based on a specific type of probability distribution functions which may be different for a certain stochastic parameter [105]. In other words, the uncertain parameters do not follow a specific type of probability distribution in reality and a family of probability functions needs to be considered. In addition, the proposed CC models in the literature have considered the lower and upper-bound constraints separately as two single-sided CCs, which makes error in the simulation because it is an inexact approximation when the lower and upper- bound are treated separately in two single-sided CCs. Furthermore, the impacts of temporal correlation of PV generation uncertainty on CSs operation has not been investigated in a CC formulation in this field. To properly address these concerns in stochastic programming, in this thesis, a three-layer joint DRCC model is proposed to G2V and V2G operation in day-ahead for e-mobility ecosystems. The proposed stochastic model does not rely on a specific probability distribution for stochastic parameters. The model considers an ambiguity set, which encompasses a family of probability distributions with the first- and second-order moments. Also, the ambiguity set with mean and covariance matrix obtained from empirical data can perfectly describe the temporal correlation of uncertainties. To achieve computational tractability, the exact reformulation is implemented for double-sided and single-sided CCs. Furthermore, the impact of temporal correlation of uncertain PV generation on CSs operation is considered.

Table 2.5: The comparison of works relevant to stochastic programming in e-mobility ecosystem proposed in the literature and the model proposed in this thesis

Ref.	Which stakeholder is considered?	Stochastic modeling method	Correlation of PV	Preferences
[88]	PEV aggregators	Scenario-based method	✗	✗
[89, 90]	EVs	Scenario-based method	✗	✗
[91]	EVs, CSs, and grid	Scenario-based method	✗	✗
[92–95]	EVs and CSs	Scenario-based method	✗	✗
[96]	EVs and CSs	Robust optimisation	✗	✗
[84]	EVs and grid	Robust optimisation	✗	✗
[97]	EV aggregators and grid	Robust optimisation	✗	✗
[98]	EVs	Robust optimisation	✗	✗
[99]	EV aggregator	Robust optimisation	✗	✗
[100]	EVs and EV aggregator	Robust optimisation	✗	✗
[101]	EVs and CSs	Scenario-based and robust optimisation	✗	✗
[102]	EV aggregators and grid	CC optimisation	✗	✗
[103]	EVs and CS	CC optimisation	✗	✗
[104]	EVs, CS, and grid	CC optimisation	✗	✗
This thesis	EVs, CSs, and retailers	DRCC optimisation	✓	✓

2.2 Conclusion

This chapter has presented the different algorithms proposed for EVs' G2V and V2G scheduling in five groups. A review of the existing literature indicates several gaps in research related to G2V and V2G operation as well as CSs operation, which are outlined in the following.

- **G1:** The proposed strategies have not optimised the profit of all agents including retailers, CSs, and EVs (major stakeholders in the future e-mobility ecosystem) participating in charging/discharging scheduling, whether collectively or individually. In other words, a comprehensive ecosystem has not been considered in these studies to address different aspects of the G2V and V2G operation considering the effects of optimal operation of CSs and retailers through an iterative process. That is to say, the mutual impacts of the stakeholders have been ignored by optimising each stakeholder's operation individually (**Dealt with by C1 and C2**);
- **G2:** V2G and G2V prices have been considered as known parameters as opposed to calculating the equilibrium prices as a part of the optimisation problem. Also, they have not offered a mechanism to determine V2G prices (**Dealt with by C3**);
- **G3:** The nearest CSs were selected as the optimal option without considering the cost-benefit of the services offered by CS operators (**Dealt with by C4**);
- **G4:** The role of retailers on the operation of the EV's scheduling system and the prices have not been investigated (**Dealt with by C2 and C3**);
- **G5:** In the proposed algorithms, some of the practical aspects of EV scheduling, e.g., EV drivers' preferences and G2V and V2G operation outside of declared trips, were not considered (**Dealt with by C5 and C6**);
- **G6:** The interactions between stochastic parameters originated from different stakeholders in an e-mobility ecosystem was ignored by optimizing each stakeholder's operation individually (**Dealt with by C7**);
- **G7:** Specific probability distribution functions were assumed for modelling of stochastic parameters, which mostly are just an estimation of true underlying

model (**Dealt with by C8**);

- **G8:** The proposed CC models treated the lower and upper bounds as two single-sided CCs, which may lead to over or under-estimation of the parameters; hence violating the constraints in reality (**Dealt with by C9**);
- **G9:** The impacts of temporal correlation of PV generation uncertainty on CSs operation have not been investigated in a chance-constraint formulation in this field (**Dealt with by C10**).

References

[1] H. Wang, Q. Meng, J. Wang, and D. Zhao, "An electric-vehicle corridor model in a dense city with applications to charging location and traffic management," *Transportation Research Part B: Methodological*, vol. 149, pp. 79–99, 2021.

[2] S. Sieniutycz, "Chapter 5 - systems design: Modeling, analysis, synthesis, and optimization," *Complexity and Complex Thermo-Economic Systems*, pp. 85–115, 2020.

[3] M. Ferrara, M. Khademi, M. Salimi, and S. Sharifi, "A dynamic stackelberg game of supply chain for a corporate social responsibility," *Discrete Dynamics in Nature and Society*, vol. 2017, 2017.

[4] J. Su, T. Lie, and R. Zamora, "A rolling horizon scheduling of aggregated electric vehicles charging under the electricity exchange market," *Applied Energy*, vol. 275, p. 115406, 2020.

[5] N. I. Nimalsiri, E. L. Ratnam, C. P. Mediwaththe, D. B. Smith, and S. K. Halgamuge, "Coordinated charging and discharging control of electric vehicles to manage supply voltages in distribution networks: Assessing the customer benefit," *Applied Energy*, vol. 291, p. 116857, 2021.

[6] K. Zhou, L. Cheng, L. Wen, X. Lu, and T. Ding, "A coordinated charging scheduling method for electric vehicles considering different charging demands," *Energy*, vol. 213, p. 118882, 2020.

[7] W. Gan, M. Shahidehpour, M. Yan, J. Guo, W. Yao, A. Paaso, L. Zhang, and J. Wen, "Coordinated planning of transportation and electric power networks

with the proliferation of electric vehicles," *IEEE Transactions on Smart Grid*, vol. 11, no. 5, pp. 4005–4016, 2020.

[8] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE transactions on smart grid*, vol. 3, no. 3, pp. 1095–1105, 2012.

[9] J. F. Franco, M. J. Rider, and R. Romero, "A mixed-integer linear programming model for the electric vehicle charging coordination problem in unbalanced electrical distribution systems," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2200–2210, 2015.

[10] L. Hua, J. Wang, and C. Zhou, "Adaptive electric vehicle charging coordination on distribution network," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2666–2675, 2014.

[11] Z. Xu, W. Su, Z. Hu, Y. Song, and H. Zhang, "A hierarchical framework for coordinated charging of plug-in electric vehicles in China," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 428–438, 2015.

[12] T. Morstyn, C. Crozier, M. Deakin, and M. D. McCulloch, "Conic optimization for electric vehicle station smart charging with battery voltage constraints," *IEEE Transactions on Transportation Electrification*, vol. 6, no. 2, pp. 478–487, 2020.

[13] W.-L. Liu, Y.-J. Gong, W.-N. Chen, Z. Liu, H. Wang, and J. Zhang, "Coordinated charging scheduling of electric vehicles: A mixed-variable differential evolution approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 12, pp. 5094–5109, 2019.

[14] G. Binetti, A. Davoudi, D. Naso, B. Turchiano, and F. L. Lewis, "Scalable real-time electric vehicles charging with discrete charging rates," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2211–2220, 2015.

[15] K. Zhou, L. Cheng, X. Lu, and L. Wen, "Scheduling model of electric vehicles charging considering inconvenience and dynamic electricity prices," *Applied Energy*, vol. 276, p. 115455, 2020.

[16] A. Gusrialdi, Z. Qu, and M. A. Simaan, "Distributed scheduling and cooperative control for charging of electric vehicles at highway service stations," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 10, pp. 2713–2727, 2017.

[17] A. S. Masoum, S. Deilami, A. Abu-Siada, and M. A. Masoum, "Fuzzy approach for online coordination of plug-in electric vehicle charging in smart grid," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 3, pp. 1112–1121, 2014.

[18] B. Sun, Z. Huang, X. Tan, and D. H. Tsang, "Optimal scheduling for electric vehicle charging with discrete charging levels in distribution grid," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 624–634, 2016.

[19] L. Yao, W. Hong Lim, and T. Shih Tsai, "A real-time charging scheme for demand response in electric vehicle parking station," *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 52–62, 2017.

[20] Z. Luo, Z. Hu, Y. Song, and H. Xu, Zhiwei Lu, "Optimal coordination of plug-in electric vehicles in power grids with cost-benefit analysis—part I: Enabling techniques," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3546–3555, 2013.

[21] K. N. Qureshi, A. Alhudhaif, and G. Jeon, "Electric-vehicle energy management and charging scheduling system in sustainable cities and society," *Sustainable Cities and Society*, vol. 71, no. 3, pp. 1789–1798, 2015.

[22] J. Li, X. Wu, M. Xu, and Y. Liu, "A real-time optimization energy management of range extended electric vehicles for battery lifetime and energy consumption," *Journal of Power Sources*, vol. 498, no. 3, p. 229939, 2021.

[23] D. Wu, N. Radhakrishnan, and S. Huang, "A hierarchical charging control of plug-in electric vehicles with simple flexibility model," *Applied Energy*, vol. 253, pp. 1–9, 2019.

[24] W. Su and M.-Y. Chow, "Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm," *IEEE Transactions on Smart Grid*, vol. 3, pp. 308–315, June 2011.

[25] M. Honarmand, A. Zakariazadeh, and S. Jadid, "Optimal scheduling of electric vehicles in an intelligent parking lot considering vehicle-to-grid concept and battery condition," *Energy*, vol. 65, pp. 572–579, February 2014.

[26] M. Shafie-Khah, M. Moghaddam, M. Sheikh-El-Eslami, and J. Catalão, "Optimised performance of a plug-in electric vehicle aggregator in energy and reserve markets," *Energy Conversion and Management*, vol. 97, pp. 393–408, 2015.

[27] M. R. Mozafar, M. H. Amini, and M. H. Moradi, "Innovative appraisement of smart grid operation considering large-scale integration of electric vehicles enabling V2G and G2V systems," *Electric Power Systems Research*, vol. 154, pp. 245–256, 2018.

[28] F. Safdarian, L. Lamonte, A. Kargarian, and M. Farasat, "Distributed optimization-based hourly coordination for v2g and g2v," *2019 IEEE Texas Power and Energy Conference (TPEC)*, pp. 1–6, 2019.

[29] A. Ahmed, M. H Cintuglu, S. Asfour, and M. Osama A, "Solving the multivariant ev routing problem incorporating v2g and g2v options," *IEEE Transactions on Transportation Electrification*, vol. 3, pp. 238–248, 2016.

[30] A. G. Anastasiadis, G. P. Kondylis, A. Polyzakis, and G. Vokas, "Effects of increased electric vehicles into a distribution network," *Energy Procedia*, vol. 157, pp. 586–593, January 2019.

[31] A. Triviño-Cabrera, J. A. Aguado, and S. de la Torre, "Joint routing and scheduling for electric vehicles in smart grids with V2G," *Energy*, vol. 175, pp. 113–122, 2019.

[32] S. S. Barhagh, B. Mohammadi-Ivatloo, A. Anvari-Moghaddam, and S. Asadi, "Risk-involved participation of electric vehicle aggregator in energy markets with robust decision-making approach," *Journal of Cleaner Production*, vol. 239, p. 118076, 2019.

[33] M. Shafiee, R. Ghazi, and M. Moeini-Aghtaie, "Day-ahead resource scheduling in distribution networks with presence of electric vehicles and distributed generation units," *Electric Power Components and Systems*, vol. 47, pp. 1450–1463, 2019.

[34] A. Moradipari, N. Tucker, and M. Alizadeh, "Mobility-aware electric vehicle fast charging load models with geographical price variations," *IEEE Transactions on Transportation Electrification*, 2020.

[35] W. Wei, S. Mei, L. Wu, M. Shahidehpour, and Y. Fang, "Optimal traffic-power flow in urban electrified transportation networks," *IEEE Transactions on Smart Grid*, vol. 8, pp. 84–95, Jan 2016.

[36] V. Aravinthan and W. Jewell, "Controlled electric vehicle charging for mitigating impacts on distribution assets," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 999–1009, 2015.

[37] Y. Li and B. Hu, "An iterative two-layer optimization charging and discharging trading scheme for electric vehicle using consortium blockchain," *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 2627–2637, 2019.

[38] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 940–951, 2012.

[39] H. Xing, M. Fu, Z. Lin, and Y. Mou, "Decentralized optimal scheduling for charging and discharging of plug-in electric vehicles in smart grids," *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 4118–4127, 2015.

[40] X. Wang and Q. Liang, "Energy management strategy for plug-in hybrid electric vehicles via bidirectional vehicle-to-grid," *IEEE Systems Journal*, vol. 11, no. 3, p. 102990, 2021.

[41] R.-C. Leou, "Optimal charging/discharging control for electric vehicles considering power system constraints and operation costs," *IEEE transactions on power systems*, vol. 31, no. 3, pp. 1854–1860, 2015.

[42] X. Wang, C. Sun, R. Wang, and T. Wei, "Two-stage optimal scheduling strategy for large-scale electric vehicles," *IEEE Access*, vol. 8, pp. 13 821–13 832, 2020.

[43] J.-M. Clairand, J. Rodríguez-García, and C. Álvarez-Bel, "Smart charging for electric vehicle aggregators considering users' preferences," *IEEE Access*, vol. 6, pp. 54 624–54 635, 2018.

[44] Y. Zhou, R. Kumar, and S. Tang, "Incentive-based distributed scheduling of electric vehicle charging under uncertainty," *IEEE Transactions on Power Systems*, vol. 34, no. 1, pp. 3–11, 2018.

[45] T. Zhao, Y. Li, X. Pan, P. Wang, and J. Zhang, "Real-time optimal energy and reserve management of electric vehicle fast charging station: Hierarchical game approach," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 5357–5370, 2017.

[46] C. P. Mediwaththe and D. B. Smith, "Game-theoretic electric vehicle charging management resilient to non-ideal user behavior," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 11, pp. 3486–3495, 2018.

[47] W. Tushar, W. Saad, H. V. Poor, and D. B. Smith, "Economics of electric vehicle charging: A game theoretic approach," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1767–1778, 2012.

[48] W. Lee, L. Xiang, R. Schober, and V. W. Wong, "Electric vehicle charging stations with renewable power generators: A game theoretical analysis," *IEEE transactions on smart grid*, vol. 6, no. 2, pp. 608–617, 2014.

[49] X. Chen and K.-C. Leung, "Non-cooperative and cooperative optimization of scheduling with vehicle-to-grid regulation services," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 114–130, 2019.

[50] J. Tan and L. Wang, "A game-theoretic framework for vehicle-to-grid frequency regulation considering smart charging mechanism," *IEEE Transactions on Smart Grid*, vol. 8, no. 5, pp. 2358–2369, 2016.

[51] L. Zhang and Y. Li, "A game-theoretic approach to optimal scheduling of parking-lot electric vehicle charging," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 4068–4078, 2015.

[52] J. Li, C. Li, Y. Xu, Z. Y. Dong, K. P. Wong, and T. Huang, "Noncooperative game-based distributed charging control for plug-in electric vehicles in distribution networks," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 301–310, 2016.

[53] A. Laha, B. Yin, Y. Cheng, L. X. Cai, and Y. Wang, "Game theory based charging solution for networked electric vehicles: A location-aware approach," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 7, pp. 6352–6364, 2019.

[54] C. Sun, X. Wen, Z. Lu, J. Zhang, and X. Chen, "A graphical game approach to electrical vehicle charging scheduling: Correlated equilibrium and latency minimization," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 1, pp. 505–517, 2020.

[55] J. Tan and L. Wang, "Real-time charging navigation of electric vehicles to fast charging stations: A hierarchical game approach," *IEEE Transactions on Smart Grid*, vol. 8, pp. 846–856, March 2015.

[56] Z. Liu, Q. Wu, S. Huang, L. Wang, M. Shahidehpour, and Y. Xue, "Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 5173–5184, 2017.

[57] W. Yuan, J. Huang, and Y. J. A. Zhang, "Competitive charging station pricing for plug-in electric vehicles," *IEEE Transactions on Smart Grid*, vol. 8, no. 2, pp. 627–639, 2015.

[58] R. F. Atallah, C. M. Assi, W. Fawaz, M. H. K. Tushar, and M. J. Khabbaz, "Optimal supercharge scheduling of electric vehicles: Centralized versus decentralized methods," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 9, pp. 7896–7909, 2018.

[59] H. Yang, X. Xie, and A. V. Vasilakos, "Noncooperative and cooperative optimization of electric vehicle charging under demand uncertainty: A robust stackelberg game," *IEEE Transactions on vehicular technology*, vol. 65, no. 3, pp. 1043–1058, 2015.

[60] R. Das, Y. Wang, G. Putrus, R. Kotter, M. Marzband, B. Herteleer, and J. Warmerdam, "Multi-objective techno-economic-environmental optimisation of electric vehicle for energy services," *Applied Energy*, vol. 257, p. 113965, 2020.

[61] L. Wang, S. Sharkh, and A. Chipperfield, "Optimal decentralized coordination of electric vehicles and renewable generators in a distribution network using A^* search," *International Journal of Electrical Power & Energy Systems*, vol. 98, pp. 474–487, 2018.

[62] S. S. K. Madahi, H. Nafisi, H. A. Abyaneh, and M. Marzband, "Co-optimization of energy losses and transformer operating costs based on smart charging algorithm for plug-in electric vehicle parking lots," *IEEE Transactions on Transportation Electrification*, 2020.

[63] A. Zakariazadeh, S. Jadid, and P. Siano, "Multi-objective scheduling of electric vehicles in smart distribution system," *Energy Conversion and Management*, vol. 79, pp. 43–53, 2014.

[64] Y. Luo, G. Feng, S. Wan, S. Zhang, V. Li, and W. Kong, "Charging scheduling strategy for different electric vehicles with optimization for convenience of

drivers, performance of transport system and distribution network," *Energy*, vol. 194, p. 116807, 2020.

[65] M. Shafiee, R. Ghazi, and M. Moeini-Aghtaie, "A multi-objective framework for energy resource scheduling in active distribution networks," *International Journal of Ambient Energy*, vol. 40, pp. 504–516, 2019.

[66] Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung, "Smart charging strategy for electric vehicle charging stations," *IEEE Transactions on Transportation Electrification*, vol. 4, pp. 76–88, March 2017.

[67] M. L. Crow *et al.*, "Electric vehicle scheduling considering co-optimized customer and system objectives," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 1, pp. 410–419, 2017.

[68] R. Das, Y. Wang, K. Busawon, G. Putrus, and M. Neaimeh, "Real-time multi-objective optimisation for electric vehicle charging management," *Journal of Cleaner Production*, vol. 292, p. 126066, 2021.

[69] N. Wang, B. Li, Y. Duan, and S. Jia, "A multi-energy scheduling strategy for orderly charging and discharging of electric vehicles based on multi-objective particle swarm optimization," *Sustainable Energy Technologies and Assessments*, vol. 44, p. 101037, 2021.

[70] H.-M. Chung, W.-T. Li, C. Yuen, C.-K. Wen, and N. Crespi, "Electric vehicle charge scheduling mechanism to maximize cost efficiency and user convenience," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 3020–3030, 2018.

[71] N. Chakraborty, A. Mondal, and S. Mondal, "Intelligent charge scheduling and eco-routing mechanism for electric vehicles: A multi-objective heuristic approach," *Sustainable Cities and Society*, vol. 69, p. 102820, 2021.

[72] R. Jovanovic, S. Bayhan, and I. S. Bayram, "A multiobjective analysis of the potential of scheduling electrical vehicle charging for flattening the duck curve," *Journal of Computational Science*, vol. 48, p. 101262, 2021.

[73] S. Bashash, S. J. Moura, J. C. Forman, and H. K. Fathy, "Plug-in hybrid electric vehicle charge pattern optimization for energy cost and battery longevity," *Journal of power sources*, vol. 196, no. 1, pp. 541–549, 2011.

[74] Y. Zhang, H. Hou, J. Huang, Q. Zhang, A. Tang, and S. Zhu, "An optimal subsidy scheduling strategy for electric vehicles in multi-energy systems," *Energy Reports*, vol. 7, pp. 44–49, 2021.

[75] G. Chiandussi, M. Codegone, S. Ferrero, and F. E. Varesio, "Comparison of multi-objective optimization methodologies for engineering applications," *Computers & Mathematics with Applications*, vol. 63, no. 5, pp. 912–942, 2012.

[76] Y. Zhang, P. You, and L. Cai, "Optimal charging scheduling by pricing for ev charging station with dual charging modes," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 9, pp. 3386–3396, 2018.

[77] A. Moradipari and M. Alizadeh, "Pricing and routing mechanisms for differentiated services in an electric vehicle public charging station network," *IEEE Transactions on Smart Grid*, vol. 11, 2019.

[78] A. Ghosh and V. Aggarwal, "Menu-based pricing for charging of electric vehicles with vehicle-to-grid service," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 10 268–10 280, 2018.

[79] S. Zhou, Y. Qiu, F. Zou, D. He, P. Yu, J. Du, X. Luo, C. Wang, Z. Wu, and W. Gu, "Dynamic EV charging pricing methodology for facilitating renewable energy with consideration of highway traffic flow," *IEEE Access*, vol. 8, pp. 13 161–13 178, 2019.

[80] D. Said and H. T. Mouftah, "A novel electric vehicles charging/discharging management protocol based on queuing model," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 1, pp. 100–111, 2019.

[81] S. Wang, S. Bi, Y.-J. A. Zhang, and J. Huang, "Electrical vehicle charging station profit maximization: Admission, pricing, and online scheduling," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 4, pp. 1722–1731, 2018.

[82] Z. Ding, Y. Lu, K. Lai, M. Yang, and W.-J. Lee, "Optimal coordinated operation scheduling for electric vehicle aggregator and charging stations in an integrated electricity-transportation system," *International Journal of Electrical Power & Energy Systems*, vol. 121, p. 106040, 2020.

[83] R. Li, Q. Wu, and S. S. Oren, "Distribution locational marginal pricing for optimal electric vehicle charging management," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 203–211, 2013.

[84] W. Sun, F. Neumann, and G. P. Harrison, "Robust scheduling of electric vehicle charging in LV distribution networks under uncertainty," *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5785–5795, 2020.

[85] Y. Zhou, D. K. Yau, P. You, and P. Cheng, "Optimal-cost scheduling of electrical vehicle charging under uncertainty," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4547–4554, 2017.

[86] O. Fallah-Mehrjardi, M. H. Yaghmaee, and A. Leon-Garcia, "Charge scheduling of electric vehicles in smart parking-lot under future demands uncertainty," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 4949–4959, 2020.

[87] E. Roos and D. den Hertog, "Reducing conservatism in robust optimization," *INFORMS Journal on Computing*, vol. 32, no. 4, pp. 1109–1127, 2020.

[88] M.-W. Tian, S.-R. Yan, X.-X. Tian, M. Kazemi, S. Nojavan, and K. Jermsittiparsert, "Risk-involved stochastic scheduling of plug-in electric vehicles aggregator in day-ahead and reserve markets using downside risk constraints method," *Sustainable Cities and Society*, vol. 55, p. 102051, 2020.

[89] Z. Wang, P. Jochem, and W. Fichtner, "A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand," *Journal of Cleaner Production*, vol. 254, p. 119886, 2020.

[90] M. Schücking and P. Jochem, "Two-stage stochastic program optimizing the cost of electric vehicles in commercial fleets," *Applied Energy*, vol. 293, p. 116649, 2021.

[91] T. Zhang, W. Chen, Z. Han, and Z. Cao, "Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 6, pp. 2600–2612, 2013.

[92] Y. Wu, J. Zhang, A. Ravey, D. Chrenko, and A. Miraoui, "Real-time energy management of photovoltaic-assisted electric vehicle charging station by markov decision process," *Journal of Power Sources*, vol. 476, p. 228504, 2020.

[93] S. Faridimehr, S. Venkatachalam, and R. B. Chinnam, "A stochastic programming approach for electric vehicle charging network design," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 5, pp. 1870–1882, 2018.

[94] S. Liu and A. H. Etemadi, "A dynamic stochastic optimization for recharging plug-in electric vehicles," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4154–4161, 2017.

[95] B. Wang, Y. Wang, H. Nazaripouya, C. Qiu, C.-C. Chu, and R. Gadh, "Predictive scheduling framework for electric vehicles with uncertainties of user behaviors," *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 52–63, 2016.

[96] B. Zeng, H. Dong, R. Sioshansi, F. Xu, and M. Zeng, "Bi-level robust optimization of electric vehicle charging stations with distributed energy resources," *IEEE Transactions on Industry Applications*, 2020.

[97] X. Bai and W. Qiao, "Robust optimization for bidirectional dispatch coordination of large-scale V2G," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1944–1954, 2015.

[98] N. Korolko and Z. Sahinoglu, "Robust optimization of EV charging schedules in unregulated electricity markets," *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 149–157, 2015.

[99] Y. Cao, L. Huang, Y. Li, K. Jermsittiparsert, H. Ahmadi-Nezamabad, and S. Nojavan, "Optimal scheduling of electric vehicles aggregator under market price uncertainty using robust optimization technique," *International Journal of Electrical Power & Energy Systems*, vol. 117, p. 105628, 2020.

[100] Y. Cui, Z. Hu, and H. Luo, "Optimal day-ahead charging and frequency reserve scheduling of electric vehicles considering the regulation signal uncertainty," *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5824–5835, 2020.

[101] S. Zeynali, N. Nasiri, M. Marzband, and S. N. Ravadanegh, "A hybrid robust-stochastic framework for strategic scheduling of integrated wind farm and plug-in hybrid electric vehicle fleets," *Applied Energy*, vol. 300, p. 117432, 2021.

[102] Z. Liu, Q. Wu, S. S. Oren, S. Huang, R. Li, and L. Cheng, "Distribution locational marginal pricing for optimal electric vehicle charging through chance constrained mixed-integer programming," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 644–654, 2016.

[103] H. Liu, Y. Zhang, S. Ge, C. Gu, and F. Li, "Day-ahead scheduling for an electric vehicle PV-based battery swapping station considering the dual uncertainties," *IEEE Access*, vol. 7, pp. 115 625–115 636, 2019.

[104] B. Wang, P. Dehghanian, and D. Zhao, "Chance-constrained energy management system for power grids with high proliferation of renewables and electric vehicles," *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 2324–2336, 2019.

[105] F. Pourahmadi, J. Kazempour, C. Ordoudis, P. Pinson, and S. H. Hosseini, "Distributionally robust chance-constrained generation expansion planning," *IEEE Transactions on Power Systems*, vol. 35, no. 4, pp. 2888–2903, 2019.

3 | A Comprehensive Day-Ahead Scheduling Strategy for Electric Vehicles Operation

Nomenclature

Indices	
a, b	Index of buses in the distribution network
h	Index of number of cycles of EV's battery
h	Index of hours of a day
i	Index of CS
it	Number of iterations
j	Index of chargers
k	Index of EV
m	Branch of the distribution network
n	Dimension of search space
r	Index of trip
s	Index of retailer
Parameters	
A_i^{PV}	Area of PV in CS i (m^2)
B_{ba}	Susceptance of overhead line between bus b and a (mho)
$c_{p.u}^{\mathrm{BAT}}$	Per-unit capacity cost of battery

$c_{p.u,i}^{\mathrm{PQ}}$	Per-unit capacity cost of the active power filtering and reactive power compensation in CS i
$Cp_{h,i,j}^{\mathrm{AV,CH}}$	Capacity of available charger j in CS i (kWh)
$Cp_{h,i,j}^{\mathrm{CH}}$	Capacity of charger j in CS i at time h (kWh)
Cp_{i}^{ESS}	Capacity of ESS of CS i (kWh)
Cp_{k}^{EV}	Capacity of EV's battery k (kWh)
Cp_{i}^{GU}	Capacity of CGU of CS i (kWh)
Cp_{k}^{nom}	Nominal capacity of EV k (kWh)
Cp_{k}^{re}	Real capacity of EV k (kWh)
Cp^{TR}	Substation transformer capacity (kWh)
$D_{h,k,r}^{\mathrm{EV^{OR}\rightarrow CS^{SE}}}$	Shortest driving distance of EV k between its origin and the selected CS in trip r at time h (km)
$D_{h,k,r}^{\mathrm{CS^{SE}\rightarrow EV^{DE}}}$	Shortest driving distance of EV k between the selected CS and its destination in trip r at time h (km)
$D_{h,k,r}^{\mathrm{EV^{OR}\rightarrow EV^{DE}}}$	Shortest driving distance of EV k between its origin and destination in trip r at time h (km)
G_{ba}	Conductance of overhead line between bus b and a (mho)
HV	Heat value fuel on the operation of gas turbine-generator (kWh/m^3)
$\overline{it}$	Maximum number of iterations
N^{b}	Number of distribution network nodes
N^{CS}	Number of charging stations
N^{CYC}	Number of cycles of EV's battery
N^{EV}	Number of electric vehicles
N^{Re}	Number of retailers
N^{T}	Number of trips
$P_{i}^{\mathrm{PV,nom}}$	Nominal power of PV system of CS i
$PF_{i,j}^{\mathrm{CH}}$	Power factor of charger j in CS i
R_{m}	Resistance of overhead line (Ω)
Ra_{h}	Solar radiation at time h (W/m^2)
$S_{D_0,b}$	Nominal apparent electrical load of the distribution network (kVA)

$SOC_{h,k,1}^{in}$	Initial SOC of EV k at the beginning of first trip (%)
$\overline{SOC}_i^{\text{ESS}}/\underline{SOC}_i^{\text{ESS}}$	Maximum/Minimum SOC of ESS in CS i (%)
$\overline{SOC}_k^{\text{EV}}$ / $\underline{SOC}_k^{\text{EV}}$	Maximum/ Minimum SOC of EV k (%)
$\underline{SOC}_{h,k,r}^{EV^{DE}}$	Minimum SOC of EV k at the destination of trip r (%)
Tm_h^{am}	Ambient temperature at time h (°C)
Δt	Time step (s)
ub_n/lb_n	Upper/Lower bound of variables in SSA
$\underline{V}_b/\overline{V}_b$	Minimum/Maximum nodal voltage of the distribution network (V)
$WT_{h,k,r}$	Waiting time of EV k for trip r at time h (s)
X_i^{CS}	Longitude of CS i
$X_{h,k,r}^{EV^{DE}}$	Longitude of destination of EV k in trip r at time h
$X_{h,k,r}^{\text{EV}^{\text{OR}}}$	Longitude of origin of EV k in trip r at time h
Y_i^{CS}	Latitude of CS i
$Y_{h,k,r}^{\text{EV}^{\text{OR}}}$	Latitude of origin of EV k in trip r at time h
$\alpha_{i,j}$	Harmonic current containing rate in the AC power input terminal of the charger j of CS i
$\beta_{i,j}$	Reliability coefficient of the charger j of CS i
γ_k	Power consumed by EV k per km (kWh/km)
η_i^{PV}	Efficiency of PV system of CS i at time h
$\eta_{i,j}^{\text{CH}}$	Efficiency of charger j of CS i
$\eta_{h,i}^{\text{GU}}$	Efficiency of CGU of CS i at time h
$\eta^{\text{ESS+}}$	Efficiency of ESS in charging period
$\eta^{\text{ESS}-}$	Efficiency of ESS in discharging period
$\eta^{\text{Bat+}}$	Efficiency of EV's battery in G2V operation
$\eta^{\text{Bat}-}$	Efficiency of EV's battery in V2G operation
κ_i	Overall correction coefficient of CS i
λ_i	Simultaneity coefficient of the chargers of CS i
ρ_h^{gas}	Natural gas price at time h
$\rho_{h,s}^{\text{Re+,WM}}$	Electricity price purchased from wholesale market by retailer s at time h ($/kWh)

$\overline{\rho}^{\text{Re}-,\text{CS}}/\underline{\rho}^{\text{Re}-,\text{CS}}$	Maximum/Minimum electricity price sold to CSs by retailers (\$/kWh)
σ_1,σ_2,σ_3	Fitting parameters for cycling degradation related to DOD
ϕ_1,ϕ_2,ϕ_3, ϕ_4	Fitting parameters for cycling degradation related to discharge rate

Variables

$c_{1,it}$	Coefficient for balancing exploration in SSA for iteration it
$c_{2,it}, c_{3,it}$	Random number generated uniformly between 0 and 1 in SSA for iteration it
$\mathbb{C}^{\text{CS+,EV}}$	Cost of energy purchased from EVs (\$)
$\mathbb{C}^{\text{CS+,Re}}$	Cost of energy purchased from retailers (\$)
$\mathbb{C}^{\text{D}}$	Battery degradation cost (\$)
$\mathbb{C}^{\text{EV}}$	The net cost of EVs operation (\$)
$\mathbb{C}^{\text{EV+,CS}}$	The cost of electricity purchased from CSs by EVs (\$)
$\mathbb{C}^{\text{Op,CS}}$	Operation cost of CSs (\$)
$\mathbb{C}^{\text{Re+,WM}}$	Cost of electricity purchased from the wholesale market by retailers (\$)
$\mathbb{D}^{\text{EV}}_{h,k,r}$	Battery degradation of EV k in trip r at time h
$DOD^{\text{EV}}_{h,k,r}(T)$	Depth of charge of EV's battery k in trip r
$DR^{\text{EV}}_{h,k}(T)$	Discharging rate of EV's battery k in trip r
$F_{n,it}$	Position of food source in SSA for iteration it
$I_{h,m}$	Current of overhead line m at time h (A)
it	Number of iterations
$it^{\text{EV}}/it^{\text{CS}}/it^{\text{Re}}$	Number of iterations in EV/CS/retailer layer
$M_{h,k,r}$	Mode of electric vehicle k in trip r at time h
$N^{\text{AV,CH}}_{h,i}$	The number of available chargers in CS i
$P^{\text{CS+,EV}}_{h,i,k,r}$	Power purchased from EV k by CS i in trip r at time h (kW)
$P^{\text{CS}-,\text{EV}}_{h,i,k,r}$	Power sold to EV k by CS i in trip r at time h (kW)
$P_{D_b,h}$	Calculated active electrical load at bus b of the distribution network at time h (kW)
$P^{\text{DN}}_{L_h}$	Power loss of distribution network at time h (kW)
$P^{ESS+}_{h,i}$	Charging power of ESS of CS i at time h (kW)

$P_{h,i}^{ESS-}$	discharging power of ESS of CS i at time h (kW)
$P_{G_b,h}$	Power generation at bus b of the distribution network at time h (kW)
$P_{h,i}^{\mathrm{PV}}$	PV generation of CS i at time h (kW)
$P_{h,i}^{\mathrm{CS-,AG}}$	Power sold to the aggregator by CS i at time h (kW)
$P_{h,s,i}^{\mathrm{CS+,Re}}$	Power purchased from retailer s by CS i at time h (kW)
$P_{h,i,k,r}^{\mathrm{EV+,CS}}$	Power purchased from CS i by EV k in trip r in trip r at time h (kW)
$P_{h,i,k,r}^{\mathrm{EV-,CS}}$	Power sold to CS i by EV k in trip r at time h (kW)
$P_{h,i}^{\mathrm{GU}}$	Power produced by CGU of CS i at time h (kW)
$P_{h,s,i}^{\mathrm{Re-,CS}}$	Power sold to CS i by retailer s at time h
$P_{h,s}^{\mathrm{Re+,WM}}$	Power purchased from wholesale market by retailer s at time h (kW)
$PF_{h,b}$	Power factor at bus b and time h
$Q_{D_b,h}$	Calculated reactive electrical load at bus b of the distribution network at time h (kVar)
$Q_{L_h}^{\mathrm{DN}}$	Reactive power loss of distribution network at time h (kVar)
$\mathbb{R}^{\mathrm{CS}}$	Net revenue of CS operators (\$)
$\mathbb{R}^{\mathrm{CS-,AG}}$	Revenues of CSs from selling energy to the aggregators (\$)
$\mathbb{R}^{\mathrm{CS-,EV}}$	Revenues CSs from selling energy to EVs (\$)
$\mathbb{R}^{\mathrm{EV-,CS}}$	Revenue of EVs from selling electricity to CSs (\$)
$\mathbb{R}^{\mathrm{Re}}$	Net revenue of retailers (\$)
$\mathbb{R}^{\mathrm{Re-,CS}}$	Revenue of retailers obtained by selling electricity to CSs (\$)
$S_{D_b,h}$	Calculated apparent electrical load at bus b of the distribution network at time h (kVA)
$SOC_{h,k,r}^{\mathrm{DP,EV}}$	SOC of EV k in trip r at time h (%)
$SOC_{h,i}^{ESS}$	SOC of ESS of CS i at time h (%)
$SOC_{h,k,r}^{\mathrm{EV}}$	SOC of EV k in trip r at time h (%)
$SOC_{h,k,r}^{\mathrm{EV^{DE}}}$	SOC of EV k at its destination in trip r at time h (%)
$SOC_{h,k,r}^{\mathrm{in}}$	Initial SOC of EV k at the beginning of trip r and time h (%)

$SOC_{h,k,r}^{\mathrm{R,EV+}}$	Required SOC of EV k in trip r at time h during charging period (%)
$SOC_{h,k,r}^{\mathrm{R,EV^{OR}\rightarrow CS^{SE}}}$	Required SOC of EV k in order to reach the selected CS from its origin in trip r at time h (%)
$SOC_{h,k,r}^{R,EV^{\mathrm{OR}}\rightarrow EV^{\mathrm{DE}}}$	Required SOC of EV k in order to reach its destination from its origin in trip r at time h (%)
$SOC_{h,k,r}^{R,CS^{\mathrm{SE}}\rightarrow EV^{\mathrm{DE}}}$	Required SOC of EV k in order to reach its destination from the selected CS in trip r at time h (%)
T^{CYC}	Period of cycle
$V_{h,b}$	Voltage at bus b and time h (V)
$x_{n,it}^{\mathrm{f}}$	Position of the follower f in the dimension n in SSA
$\theta_{b,h}$	Voltage angle of the bus b at time h
$\rho_{h,i}^{\mathrm{CS-,AG}}$	Electricity price sold to the aggregator by CS i at time h (\$/kWh)
$\rho_{h,i}^{\mathrm{CS+,EV}}$	Electricity price purchased from EVs by CS i at time h (\$/kWh)
$\rho_{h,s}^{\mathrm{Re-,CS}}$	Electricity price sold to CSs by retailer s at time h (\$/kWh)
$\rho_{h,i}^{\mathrm{CS-,EV}}$	Electricity price sold to EVs by CS i at time h (\$/kWh)
$\rho_{h,s}^{\mathrm{CS+,Re}}$	Electricity price purchased from retailer s by CS i at time h (\$/kWh)
$\rho_{h,i}^{\mathrm{EV+,CS}}$	Electricity price purchased from CS i by EVs at time h (\$/kWh)
$\rho_{h,i}^{\mathrm{EV-,CS}}$	Electricity price sold to charging station i by EVs at time h (\$/kWh)

3.1 Introduction

The goal of this chapter[1] is to develop a comprehensive day-ahead scheduling framework to guarantee economic and energy-efficient routing of EVs, where each EV finds the best CSs for V2G and G2V operation based on a cost-benefit analysis. It is done by proposing an ecosystem including three stakeholders (EVs, CSs and retailers) and a three-layer optimisation problem. It is formulated and optimised as an equilibrium problem such that the collective benefits of all three stakeholders are guaranteed simultaneously. Numerous studies have proposed various EV's charging/discharging strategies considering customers' preferences which are presented in Chapter 2. As stated in Chapter 2, a review of the existing literature indicates several gaps in research related to G2V and V2G operation as well as CSs operation, which are outlined in G1, G2, and G3 of Section 2.2 of Chapter 2. In this chapter, the proposed framework has dealt with the gaps.

The main contributions of this chapter can be summarised as follows:

- Proposing a comprehensive day-ahead scheduling strategy that represents an ecosystem including the interaction between EVs, CSs, and retailers during EVs' V2G and G2V operation whilst optimising the collective welfare of all agents;
- The coordinated EVs' V2G and G2V operation is formulated and solved such that the effects of optimal operation of CSs and retailers are considered through an iterative process;
- Obtaining optimal day-ahead electricity prices of all agents during V2G and G2V operations such that the collective benefit of all three stakeholders are achieved simultaneously by solving an equilibrium problem iteratively;
- Combining cost/benefit and energy-efficient-routing problems (instead of choosing the shortest route) for each EV to select the best CS, which is integrated with the CSs operation in purchasing electricity from retailers.

[1] This chapter is published on International Journal of Electrical Power Energy Systems: Mahsa Bagheri Tookanlou, S.Ali Pourmousavi Kani, Mousa Marzband, "A comprehensive day-ahead scheduling strategy for electric vehicles operation", *International Journal of Electrical Power Energy Systems*, 131, 2021, 106912.

This chapter is organized as follows. Section 3.2 describes the structure of the proposed EV charging and discharging strategy incorporating the three agents. Section 3.3 presents the proposed three-layer optimisation formulation. In this chapter, SSA is used for solving optimisation problems (and compared with PSO, which is explained in Section 3.4. The case study is introduced in Section 3.5. The simulation results are presented and discussed in Section 3.6. Finally, in Section 3.7, conclusion is given.

3.2 The Structure of the Proposed Ecosystem

In this chapter, a comprehensive ecosystem is envisaged for the future electrified transportation sector by considering all three agents, as shown in Figure 3.1. In this ecosystem, retailers purchase electricity from the wholesale market and sell it to CSs aiming to maximise their profit. The CSs are charging stations with known locations in a given area and operate at the distribution system level as the point of connection of EVs to the main grid in G2V and V2G modes. Similar to retailers, CS operators are looking to maximise their profit in this framework. CSs and EVs are entitled to choose retailers and CSs, respectively, based on their economic benefits. For the sake of completeness, the CSs are assumed to have onsite CGU, PV, and ESS, which might be used to supply electricity to EVs. An CGU could be a small gas turbine-generator. In this study, conventional retailers are assumed; thus they are not able to sell energy back to the wholesale market by purchasing it from CS operators. Therefore, V2G service is purchased from EVs by CS operators and sold in the wholesale market through an aggregator. Please note that the aggregator optimal operation has not been considered in this study to avoid further complexity and will be considered in the future work.

EVs are the end-users, as shown in Figure 3.1. During a typical day, EVs might have multiple trips with different waiting times between each trip. EVs with known location and initial SOC plan their charging/discharging depending on the shortest driving route and a cost/benefit analysis based on the CSs prices. Please note that each EV can only be charged or discharged during each trip if there is an economic benefit to do so while respecting the EV's constraints. In this case, EVs require an algorithm to select proper CSs for G2V and V2G operation to minimise their cost.

In order to satisfy the objectives of different agents, a top-to-bottom coordinated method is proposed that solves a day-ahead scheduling problem for all agents. The formulated problem is an equilibrium one that is solved in three layers sequentially and iteratively, where the leader is the retailer agent. The solution to the equilibrium problem is inspired by Walrasian tâtonnement, which leaves the price invariant if and only if it is an equilibrium price [1, 2]. Through the iterative three-layer optimization problem, the operation of each player in the framework is changed by receiving new information from other players to reach the equilibrium point. The proposed solution can be offered to the agents as a cloud scheduling system, which is operated by a non-profit entity (aka price-setter). Its role is to collect required information from all agents, as shown in Figure 3.2, run the top-to-bottom coordinated scheduling method, and ultimately dispatch the results to relevant agents. Since power system topology is needed to ensure the feasibility of the solutions against network constraints, distribution system operators or distribution network service providers could be the best candidates to take on this role. Since the scheduling system operator does not seek any profit in the proposed framework, accessing to the information of the three stakeholders does not compromise fair operation of the scheduling system. It is assumed that all agents have communication links with the cloud scheduling system. All information exchanged between the stakeholders and the scheduling operator can be end-to-end encrypted, so that it becomes more difficult to compromise the information. The information exchanged between three agents and the cloud scheduling system are detailed in Figure 3.2. The following assumptions are made in developing the proposed strategy:

- All agents are economically rational within their personal preferences and limitations, which means that they change their behaviour in response to economic incentives;
- It is assumed that each EV can only be charged or discharged during each trip if there is an economic benefit to do so while respecting the EV's constraints. Therefore, there is an implicit constraint in the optimisation formulation that

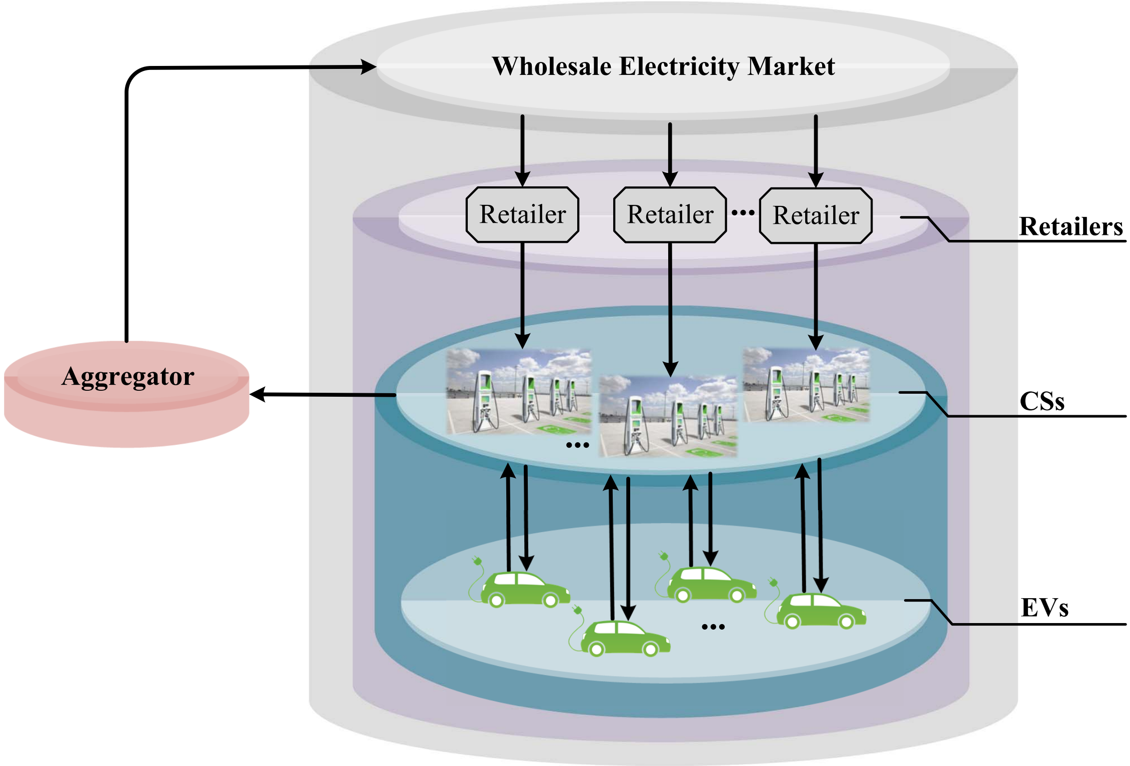

Figure 3.1: Conceptual structure of the proposed ecosystem including interactions between wholesale electricity market, retailers, aggregator, CSs, and EVs.

is limiting the number of charge/discharge events, which is based on the EV owner's preferences (as in their day-ahead plan);

- In order to consider EV owners' preferences, a minimum SOC level is specified by the EV owner as the minimum battery SOC at the end of the day;
- All CSs have fast DC charger (22kW and 50kW). This is to ensure that the scheduled G2V or V2G operation will be fulfilled within an hour for any type of EVs;
- In each hour, the number of EVs assigned to a CS is smaller or equal to the number of EV chargers in that station. Therefore, no queuing is required.

There are four steps to implement the proposed strategy, as depicted in Figure 3.3, that should be followed:

Step 1: At the beginning of the scheduling period, the cloud scheduling system collects required parameters and data from each agent for every hour of the next day. The input parameters that should be communicated to the cloud scheduling system from each agent and decision variables of each agent are summarized in Table 3.1. It

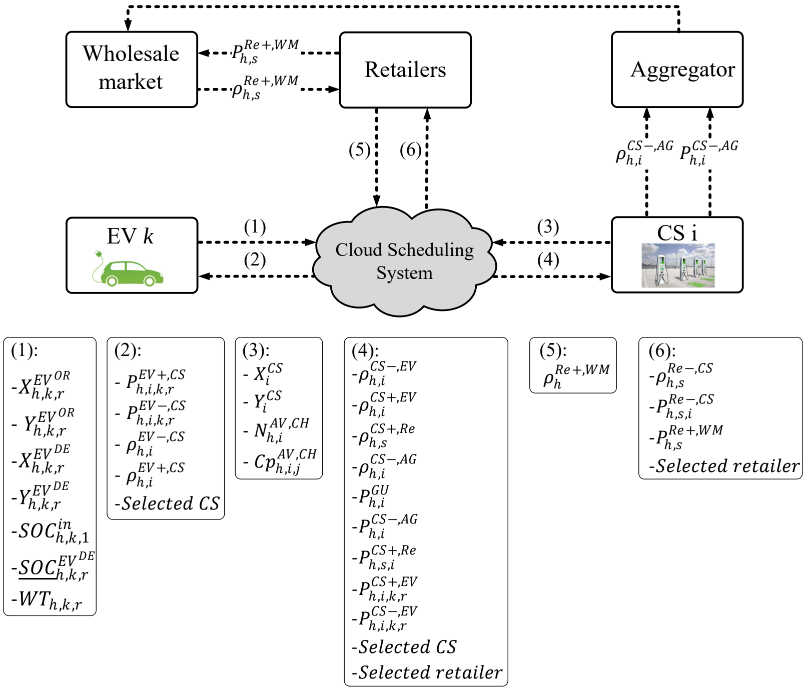

Figure 3.2: The cloud scheduling system and the required communication links with other agents.

is worth mentioning that some of the parameters do not change on a daily basis; they will be updated when needed by the agent, e.g., number and capacity of available EV chargers in each CS. This way, the amount of required communication bandwidth can be reduced significantly.

Table 3.1: Input parameters and decision variables for each agent

Agent	Input Parameters	Decision Variables
Retailers	$\rho_{h,s}^{Re+,WM}$	$\rho_{h,s}^{Re-,CS}$
CSs	X_i^{CS}, Y_i^{CS} $N_{h,i}^{AV,CH}$, $Cp_{h,i,j}^{AV,CH}$	$P_{h,i}^{GU}$, $P_{h,s,i}^{CS+,Re}$, $P_{h,i}^{CS-,AG}$
EVs	$X_{h,k,r}^{EV^{OR}}$, $Y_{h,k,r}^{EV^{OR}}$, $X_{h,k,r}^{EV^{DE}}$, $Y_{h,k,r}^{EV^{DE}}$ $SOC_{h,k,1}^{in}$, $WT_{h,k,r}$, $\underline{SOC}_{h,k,r}^{EV^{DE}}$	$P_{h,i,k,r}^{EV-,CS}$, $P_{h,i,k,r}^{EV+,CS}$

Step 2: Let's assume that each EV is allowed to plan T trips per day where each trip $r \in \{1, \ldots, r, r+1, \ldots, T\}$ (in this chapter, it is assumed that each EV has two trips per day). The shortest driving route for each trip is determined by a network analyst toolbox called ArcGIS [3] as a navigation platform in the cloud scheduling

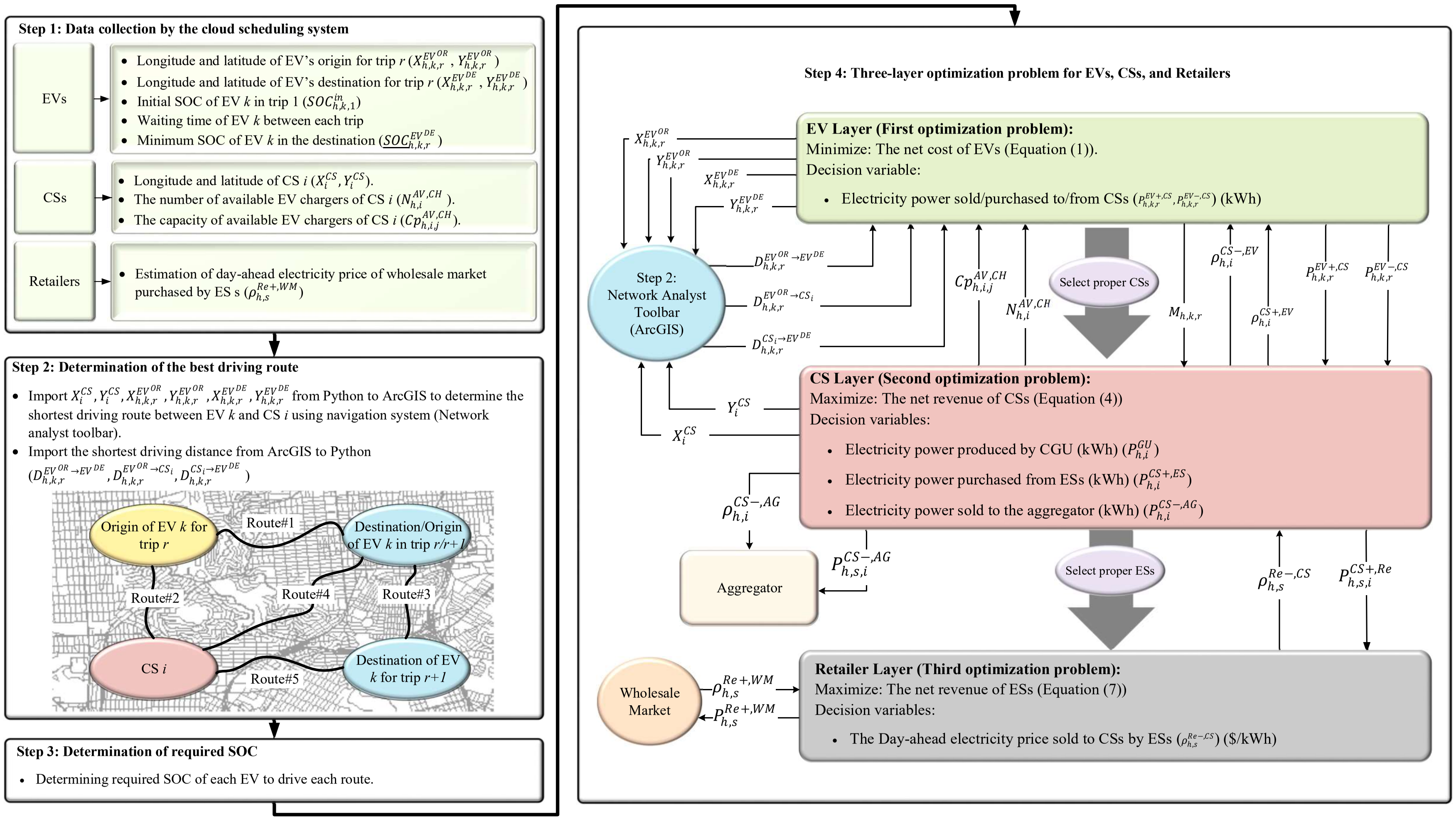

Figure 3.3: Step-by-step process of implementing the proposed strategy

system. For each hour, the longitude and latitude of each CS, origin and destination of each EV for each trip are used to determine the shortest route considering the traffic pattern in each hour. Five potential shortest driving routes will be identified in step 2: **Route#1**: the shortest driving route between the origin and destination of EV k for trip r; **Route#2**: the shortest driving route between the origin of EV k and the location of CS i for trip r/trip $r+1$; **Route#3**: the shortest driving route between the destinations/origin of EV k for trip r/trip $r+1$ and destination of EV k for trip $r+1$; **Route#4**: the shortest driving route between the location of CS i and destination of EV k for trip r; **Route#5**: the shortest driving route between the location of CS i and the destination of EV k for trip $r+1$. As shown in Figure 3.3, the driving distances corresponding to the five possible driving routes will be used in Step 3.

Step 3: Required energy (in terms of battery SOC changes) to drive each set of the five routes will be calculated in this step for each EV.

Step 4: The framework of the three-layer optimisation problem for EVs, CSs, and retailers is implemented in this step, as shown in Figure 3.3. Three layers in the framework correspond to the optimisation problem that should be solved for each of the three agents. As shown in Figure 3.2, parameters are received by the cloud scheduling system, as explained in Table 3.1. The three optimisation problems are solved iteratively for 24 hours ahead, which is summarised in Algorithm 1. The optimisation problems formulation and the optimisation technique are explained in Section 3.3 and 3.4, respectively. Through the iterative three-layer optimization problem, the profit of all agents are optimised as an equilibrium problem. It essentially leads to collective optimisation which can be called social welfare optimisation of the ecosystem. In the equilibrium problem, the iterative algorithm is used to solve, and consequently, update the position of each player in the framework by receiving new information (e.g., new prices) from other players to find the equilibrium point in which the prices do not change. This way, the prices of V2G and G2V at different level of the system are obtained. Since the scheduling system is operated in day-ahead, wholesale market price estimation is needed for the entire next day.

In the first iteration, retailers generate the prices that they would like to offer to

CSs based on their profit margin. Then, the prices will be passed on to CS layer in this iteration. The prices increase in CS layer considering their profit margin. Then, CSs communicate the prices to EV layer where the first optimisation problem, i.e., Eqs. (3.1)-(3.2c) with the constraints in Eqs. (3.9a)-(3.14), will be solved for the first time. The optimisation solutions, i.e., energy sold/purchased to/from CSs in each trip, will be sent to the CSs layer, where the operation of CSs will be scheduled by solving the optimisation problem in Eqs. (3.4)-(3.6c) with the constraints given in Eqs. (3.15a)-(3.19c). Ultimately, the optimisation solutions including energy produced by CGUs as well as the electricity traded with retailers and aggregators will be used in retailer layer to obtain optimal operation of the retailers using the optimisation problem in Eqs. (3.7)-(3.8b) and the constraints in Eqs. (3.20a)-(3.26). As a result, the optimal day-ahead electricity prices sold to CSs by retailers is determined in retailer layer. The newly generated prices will then be used in the second iteration to repeat the optimisation problems of the EV and CS layers. This iterative process will go on until a certain convergence criterion is met. In this study, the convergence criterion is defined as the change in the objective function in the two consecutive iterations, which should be less than 10^{-3} for all three optimisation problems.

The cloud scheduling system finds the charging/discharging schedules of all EVs at once, which depends on the V2G and G2V prices in each trip throughout a day and the minimum expected SOC level of EVs by the owners. To identify V2G and G2V mode of each EV during a day, a rule-based approach is developed in this study as follows:

- If G2V prices in trip r is less than V2G prices in trip $r+1$, EV k will be charged in trip r and discharged in trip $r+1$ with regards to the minimum expected SOC level of EV k throughout a day;

- If V2G prices in trip r is more than G2V prices in trip $r+1$, EV k will be discharged in trip r and charged in trip $r+1$ with regards to the minimum SOC level of EV k at the end of the trip.

Algorithm 1 **Three-layer optimisation problem for EVs, CSs, and Retailers**

▷ **retailer layer**
$it^{Re} = 1$
while $it^{Re} \leq \overline{it}^{Re}$ **do**
  Initialize the decision variables in retailer layer.
  ▷ **CS layer**
  $it^{CS} = 1$
  while $it^{CS} \leq \overline{it}^{CS}$ **do**
    $it^{CS} = 1$
    Initialize the decision variables in CS layer.
    ▷ **EV layer**
    $it^{EV} = 1$
    while $it^{EV} \leq \overline{it}^{EV}$ **do**
      if $it^{EV} = 1$ **then**
        Initialize the decision variables in EV layer.
        Calculate the objective function in EV layer (Eq. (3.1))
      else
        Determine the best value of decision variables in EV layer
        Solving optimisation problem of EV layer
        $it^{EV} = it^{EV} + 1$
    Import the optimal value of decision variables from EV layer.
    Calculate the objective function in CS layer (Eq. (3.4)).
    Determine the best value of decision variables in CS layer
    Solving optimisation problem of CS layer
    $it^{CS} = it^{CS} + 1$
  Import the optimal value of decision variables from CS layer
  Calculate the objective function in retailer layer (Eq. (3.7)) for each salp
  Determine the best value of decision variables in retailer layer
  Solving optimisation problem of retailer layer
  $it^{Re} = it^{Re} + 1$

3.3 Mathematical Modeling

In this section, objective functions and technical constraints for each layer in Step 4 of Figure 3.3, namely EVs, CSs, and retailers, are presented and explained. For the sake of clarity, objective functions and constraints are presented in separate subsections for the three agents.

3.3.1 Objective function of EV layer

The net cost of EV operation must be minimised in this layer, which is the difference between the cost of EVs (including electricity purchased from CSs, $\mathbb{C}^{\mathrm{EV+,CS}}$, and battery degradation cost during V2G operation, $\mathbb{C}^{\mathrm{DEG,EV}}$) and the revenue from selling electricity to CSs, $\mathbb{R}^{\mathrm{EV-,CS}}$, as per below equation:

$$\mathbb{C}^{\mathrm{EV}} = \mathbb{C}^{\mathrm{EV+,CS}} + \mathbb{C}^{\mathrm{DEG,EV}} - \mathbb{R}^{\mathrm{EV-,CS}} \tag{3.1}$$

The individual cost and revenue terms can be computed as follows:

$$\mathbb{C}^{\mathrm{EV+,CS}} = \sum_{h=1}^{24} \sum_{k=1}^{N^{\mathrm{EV}}} \sum_{r=1}^{N^{\mathrm{T}}} \frac{1}{2} \times M_{h,k,r} \times (M_{h,k,r} + 1) \times P_{h,i,k,r}^{\mathrm{EV+,CS}} \times \rho_{h,i}^{\mathrm{EV+,CS}} \tag{3.2a}$$

$$\mathbb{C}^{\mathrm{DEG,EV}} = \sum_{h=1}^{24} \sum_{k=1}^{N^{\mathrm{EV}}} \sum_{c=1}^{N^{\mathrm{CYC}}} \sum_{r=1}^{N^{\mathrm{T}}} \frac{1}{2} \times M_{h,k,r} \times (M_{h,k,r} - 1) \times c_{p.u}^{\mathrm{BAT}} \times Cp_k^{\mathrm{nom}} \times \frac{\mathbb{D}_{h,k,r}^{\mathrm{EV}}(T^{\mathrm{CYC}})}{Cp_k^{\mathrm{nom}} - Cp_k^{\mathrm{re}}} \tag{3.2b}$$

$$\mathbb{R}^{\mathrm{EV-,CS}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\mathrm{CS}}} \sum_{k=1}^{N^{\mathrm{EV}}} \sum_{r=1}^{N^{\mathrm{T}}} \frac{1}{2} \times M_{h,k,r} \times (M_{h,k,r} - 1) \times P_{h,i,k,r}^{\mathrm{EV-,CS}} \times \rho_{h,i}^{EV-,CS} \tag{3.2c}$$

To avoid uneconomical V2G operation, battery degradation should be quantified and its cost should be included in the objective function. As a result, EV owners will be remunerated for V2G services only if they can recover the cost of battery degradation and make some profit. In Eq. (3.2b), the battery degradation cost is considered for EVs during discharging period, which is obtained from the cycling degradation for a given discharge profile using the following equations [4]. The cost considers cycle number, depth of discharge, and discharge rates in optimal scheduling:

$$Cp_k^{\mathrm{re}} = 0.8 \times Cp_k^{\mathrm{nom}} \tag{3.3a}$$

$$\begin{aligned}\mathbb{D}_{h,k,r}^{\mathrm{EV}}(T_c^{\mathrm{CYC}}) =& (\sigma_1 \times [DOD_{h,k,r}^{\mathrm{EV}}(T_c^{\mathrm{CYC}})]^2 + \sigma_2 \times DOD_{h,k,r}^{\mathrm{EV}}(T_c^{\mathrm{CYC}}) + \sigma_3) \\ &\times (\phi_1 \times [DR_{h,k}^{\mathrm{EV}}(T_c^{\mathrm{CYC}})]^3 + \phi_2 \times [DR_{h,k}^{\mathrm{EV}}(T_c^{\mathrm{CYC}})]^2 + \phi_3 \times DR^{\mathrm{EV}}(T_c^{\mathrm{CYC}}) + \phi_4)\end{aligned} \tag{3.3b}$$

3.3.2 Objective function of CS layer

As it was explained in Section 3.2, it is assumed that CS operators purchase electricity from retailers only if the onsite generation and storage is not sufficient to meet EVs charging demand, or the onsite generation is more expensive compared to the electricity supplied from retailers. In addition, to provide services to the upper grid for added revenue, CS operators are allowed to purchase electricity from EVs and sell to the wholesale market through aggregators. Therefore, the objective function in this layer is defined as the net revenue of CS operators, which has to be maximised. The net revenue (profit) of CS operators can be calculated by subtracting revenues of selling energy to the aggregators, $\mathbb{R}^{\mathrm{CS-,AG}}$, and EVs, $\mathbb{R}^{\mathrm{CS-,EV}}$, from the expenses including onsite operational costs, $\mathbb{C}^{\mathrm{Op,CS}}$, cost of energy purchased from retailers, $\mathbb{C}^{\mathrm{CS+,Re}}$, and EVs, $\mathbb{C}^{\mathrm{CS+,EV}}$, expressed by:

$$\mathbb{R}^{\mathrm{CS}} = \mathbb{R}^{\mathrm{CS-,AG}} + \mathbb{R}^{\mathrm{CS-,EV}} - \mathbb{C}^{\mathrm{Op,CS}} - \mathbb{C}^{\mathrm{CS+,Re}} - \mathbb{C}^{\mathrm{CS+,EV}} \tag{3.4}$$

The revenue terms in Eq. (3.4) can be calculated as follows:

$$\mathbb{R}^{\mathrm{CS-,AG}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\mathrm{CS}}} \sum_{s=1}^{N^{\mathrm{Re}}} P_{h,i}^{\mathrm{CS-,AG}} \times \rho_{h,i}^{\mathrm{CS-,AG}} \tag{3.5a}$$

$$\mathbb{R}^{\mathrm{CS-,EV}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\mathrm{CS}}} \sum_{k=1}^{N^{\mathrm{EV}}} \sum_{r=1}^{N^{\mathrm{T}}} \frac{1}{2} \times M_{h,k,r} \times (M_{h,k,r} + 1) \times P_{h,i,k,r}^{\mathrm{CS-,EV}} \times \rho_{h,i}^{\mathrm{CS-,EV}} \tag{3.5b}$$

Various cost terms are calculated by:

$$\mathbb{C}^{\mathrm{Op,CS}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\mathrm{CS}}} \frac{P_{h,i}^{\mathrm{GU}} \times \rho_{h}^{\mathrm{gas}}}{\eta_{h,i}^{\mathrm{GU}} \times HV} + \sum_{i=1}^{N^{\mathrm{CS}}} c_{p.u,i}^{\mathrm{PQ}} \times \lambda_i \times \kappa_i \sum_{j=1}^{N_i^{\mathrm{CH}}} \beta_{i,j} \times \alpha_{i,j} \times \frac{P_{i,j}^{\mathrm{CH}}}{\eta_{\mathrm{i,j}}^{\mathrm{CH}} \times PF_{i,j}^{\mathrm{CH}}} \tag{3.6a}$$

$$\mathbb{C}^{\mathrm{CS+,Re}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\mathrm{CS}}} P_{h,i,s}^{\mathrm{CS+,Re}} \times \rho_{h,s}^{\mathrm{CS+,Re}} \tag{3.6b}$$

$$\mathbb{C}^{\mathrm{CS+,EV}} = \sum_{h=1}^{24} \sum_{i=1}^{N^{\mathrm{CS}}} \sum_{k=1}^{N^{\mathrm{EV}}} \sum_{r=1}^{N^{\mathrm{T}}} \frac{1}{2} \times M_{h,k,r} \times (M_{h,k,r} - 1) \times P_{h,i,k,r}^{\mathrm{CS+,EV}} \times \rho_{h,i}^{\mathrm{CS+,EV}} \tag{3.6c}$$

The operation cost of each CS in Eq. (3.6a) includes the operation costs of the CGU and chargers related to active power filtering and reactive power compensation cost, as given in [5–7]. Charger efficiency is considered because of the internal conversion losses, where input power to the charger is more than the power sold to EVs. For the other terms, the cost is simply the product of the traded energy by the prices obtained from previous optimisation layer.

3.3.3 Objective function of retailer layer

The net revenue of retailers in this layer must be maximised, which is defined as the difference between the revenue obtained by selling electricity to CSs and the cost of electricity purchased from the wholesale market, as given by:

$$\mathbb{R}^{\mathrm{Re}} = \mathbb{R}^{\mathrm{Re-,CS}} - \mathbb{C}^{\mathrm{Re+,WM}} \tag{3.7}$$

The collective daily revenue and cost of retailers are expressed in the following equations:

$$\mathbb{R}^{\text{Re}-,\text{CS}} = \sum_{h=1}^{24} \sum_{s=1}^{N^{\text{Re}}} \sum_{i=1}^{N^{\text{CS}}} P_{h,s,i}^{\text{Re}-,\text{CS}} \times \rho_{h,s}^{\text{Re}-,\text{CS}} \tag{3.8a}$$

$$\mathbb{C}^{\text{Re}+,\text{WM}} = \sum_{h=1}^{24} \sum_{s=1}^{N^{\text{Re}}} P_{h,s}^{\text{Re}+,\text{WM}} \times \rho_{h}^{\text{Re}+,\text{WM}} \tag{3.8b}$$

3.3.4 Constraints of EV layer

The SOC evolution after each charge and discharge and each trip for hour h can be determined by Eq. (3.9a), while Eq. (3.9b) ensures that the battery SOC level is maintained within a lower and upper bound for EV k for the safety and longevity of the battery:

$$SOC_{h,k,r}^{\text{EV}} = SOC_{h-1,k,r}^{\text{EV}} + \frac{P_{h,k,r}^{\text{EV}+,\text{CS}} \times \eta^{\text{BAT}+} \times \Delta \text{t}}{Cp_k^{\text{EV}}} - \frac{P_{h,k,r}^{\text{EV}-,\text{CS}} \times \Delta \text{t}}{Cp_k^{\text{EV}} \times \eta^{\text{BAT}-}} \tag{3.9a}$$

$$\underline{SOC}_k^{\text{EV}} \le SOC_{h,k,r}^{\text{EV}} \le \overline{SOC}_k^{\text{EV}} \tag{3.9b}$$

Charging and discharging power of the chargers at each CS are limited, which is enforced by Eqs. (3.10a) and (3.10b). At each hour h, an EV can only adopt one of the charging or discharging mode, which is achieved by Eq. (3.10c).

$$0 \le P_{h,k,r}^{\text{EV}+,\text{CS}} \le Cp_{h,i,j}^{\text{CH}} \tag{3.10a}$$

$$0 \le P_{h,k,r}^{\text{EV}-,\text{CS}} \le Cp_{h,i,j}^{\text{CH}} \tag{3.10b}$$

$$P_{h,k,r}^{\text{EV}+,\text{CS}} \times P_{h,k,r}^{\text{EV}-,\text{CS}} = 0 \tag{3.10c}$$

During charging period, the required energy (in terms of battery SOC) is calculated by Eq. (3.11) in a way to guarantee the minimum SOC level, $\underline{SOC}_{h,k,r}^{EV^{DE}}$, at the next destination, which is specified by the EV owner. The required SOC of EV is determined by the minimum driving distance obtained in Step 2 of Section 3.2.

$$
\begin{aligned}
SOC^{\mathrm{R,EV+}}_{h,k,r} &= SOC^{\mathrm{R,EV^{OR}\to CS^{SE}}}_{h,k,r} + SOC^{R,CS^{\mathrm{SE}}\to EV^{\mathrm{DE}}}_{h,k,r} + SOC^{R,EV^{\mathrm{OR}}\to EV^{\mathrm{DE}}}_{h,k,r} \\
&\quad + \underline{SOC}^{EV^{DE}}_{h,k,r} - SOC^{in}_{h,k,r} \\
&= \frac{(D^{\mathrm{EV^{OR}\to CS^{SE}}}_{h,k,r} + D^{\mathrm{CS^{SE}\to EV^{DE}}}_{h,k,r} + D^{\mathrm{EV^{OR}\to EV^{DE}}}_{h,k,r}) \times \gamma_k}{Cp^{\mathrm{EV}}_k} \\
&\quad + \underline{SOC}^{EV^{DE}}_{h,k,r} - SOC^{\mathrm{in}}_{h,k,r}
\end{aligned} \tag{3.11}
$$

Similarly, the maximum available energy of an EV that can be sold to a CS, depends on the EV's travel plan and the distance of the routes, which is calculated in Eq. (3.12).

$$
\begin{aligned}
SOC^{\mathrm{R,EV-}}_{h,k,r} &= SOC^{\mathrm{in}}_{h,k,r} - SOC^{\mathrm{R,EV^{OR}\to CS^{SE}}}_{h,k,r} - SOC^{R,CS^{SE}\to EV^{DE}}_{h,k,r} \\
&\quad - SOC^{\mathrm{R,EV^{OR}}\to EV^{\mathrm{DE}}}_{h,k,r} - \underline{SOC}^{\mathrm{EV^{DE}}}_{h,k,r} \\
&= SOC^{in}_{h,k,r} - \frac{(D^{\mathrm{EV^{OR}\to CS^{SE}}}_{h,k,r} + D^{\mathrm{CS^{SE}\to EV^{DE}}}_{h,k,r} + D^{\mathrm{EV^{OR}\to EV^{DE}}}_{h,k,r}) \times \gamma_k}{Cp^{\mathrm{EV}}_k} \\
&\quad - \underline{SOC}^{EV^{DE}}_{h,k,r}
\end{aligned} \tag{3.12}
$$

For EV k in both charging or discharging mode, the SOC at the departure time from selected CS must be higher than the required SOC of the EV to reach the next destination, as expressed in Eq. (3.13):

$$
SOC^{\mathrm{DP,EV}}_{h,k,r} \geq SOC^{\mathrm{R,EV\pm}}_{h,k,r} \tag{3.13}
$$

At the final destination, the SOC of EV k must be more than the final SOC level that is specified by the EV owner, which is achieved by:

$$
SOC^{EV^{\mathrm{DE}}}_{h,k,r} \geq \underline{SOC}^{EV^{\mathrm{DE}}}_{h,k,r} \tag{3.14}
$$

3.3.5 Constraints of CS layer

Balance between supply and demand within a CS should be maintained at all times during charging and discharging, which is achieved by Eq. (3.15a). Charger efficiency is considered for the sake of accuracy. Equation (3.15b) ensures that the number of operational chargers in a CS does not exceed the number of existing chargers in that station.

$$
P^{\mathrm{PV}}_{h,i} + P^{\mathrm{GU}}_{h,i} \pm P^{\mathrm{ESS\pm}}_{h,i} + \sum_{k=1}^{N^{\mathrm{EV}}} P^{\mathrm{CS+,EV}}_{h,i,k,r} + \sum_{s=1}^{N^{\mathrm{Re}}} P^{\mathrm{CS+,Re}}_{h,s,i} = \frac{P^{\mathrm{CS-,AG}}_{h,i}}{\eta^{\mathrm{CH}}_i} + \sum_{k=1}^{N^{\mathrm{EV}}} \frac{P^{\mathrm{CS-,EV}}_{h,i,k,r}}{\eta^{\mathrm{CH}}_i} \tag{3.15a}
$$

$$N_{h,i}^{\mathrm{AV,CH}} \leq \overline{N}_i^{\mathrm{CH}} \tag{3.15b}$$

The onsite PV generation is estimated by Eq. (3.16a) from meteorological data and PV panel specifications. Equation (3.16b) ensures that the PV dispatch at time h is lower than or equal to the maximum available PV at the same time. Therefore, PV curtailment is allowed in the CS operation.

$$P_{h,i}^{\mathrm{PV}} = \eta_i^{\mathrm{PV}} \times A_i^{\mathrm{PV}} \times Ra_h \times (1 - 0.005 \times (Tm_h^{\mathrm{am}} - 25)) \tag{3.16a}$$

$$P_{h,i}^{\mathrm{PV}} \leq P_i^{\mathrm{PV,nom}} \tag{3.16b}$$

In Eq. (3.17a), onsite stationary ESS operation and its SOC evolution is characterised. The SOC upper and lower limits are enforced by Eq. (3.17b). Moreover, simultaneous operation of the ESS in the two modes (i.e., charge and discharge) is prohibited by Eq. (3.17c).

$$SOC_{h,i}^{\mathrm{ESS}} = SOC_{h-1,i}^{\mathrm{ESS}} + \frac{P_{h,i}^{\mathrm{ESS+}} \times \eta^{\mathrm{ESS+}} \times \Delta \mathrm{t}}{Cp_i^{\mathrm{ESS}}} - \frac{P_{h,i}^{\mathrm{ESS-}} \times \Delta \mathrm{t}}{Cp_i^{\mathrm{ESS}} \times \eta^{\mathrm{ESS-}}} \tag{3.17a}$$

$$\underline{SOC}_i^{\mathrm{ESS}} \leq SOC_{h,i}^{\mathrm{ESS}} \leq \overline{SOC}_i^{\mathrm{ESS}} \tag{3.17b}$$

$$P_{h,i}^{\mathrm{ESS+}} \times P_{h,i}^{\mathrm{ESS-}} = 0 \tag{3.17c}$$

Equation (3.18a) ensures that electricity produced by a CGU at time h does not exceed its nominal capacity [8]. Moreover, based on Eq. (3.18b), it is not reasonable to operate the CGU below 30% of its rated power due to low efficiency and high greenhouse gas emission at the lower operating ranges. Therefore, the CGU will be turned off, as in [8].

$$P_{h,i}^{\mathrm{GU}} \leq Cp_i^{\mathrm{GU}} \tag{3.18a}$$

$$P_{h,i}^{\mathrm{GU}} = \begin{cases} P_{h,i}^{\mathrm{GU}} & P_{h,i}^{\mathrm{GU}} \geq 0.3 \times Cp_i^{\mathrm{GU}} \\ 0 & P_{h,i}^{\mathrm{GU}} < 0.3 \times Cp_i^{\mathrm{GU}} \end{cases} \tag{3.18b}$$

Total charge/discharge capacity of CS i is calculated by Eq. (3.19a) [9]. Electricity purchased from retailers by CS i at the point of common coupling is limited by

Eq. (3.19b). Based on Eq. (3.19c), CS i is not allowed to sell CGU power to the aggregator. In other words, the power sold to the aggregator should be equal or lower than the power purchased from EVs. This is because of the existing regulations in many electricity markets and the desire to limit emissions from CGU.

$$Cp_i^{\mathrm{CS}} = \lambda_i \times \sum_{j=1}^{N^{\mathrm{CH}}} \frac{P_{i,j}^{\mathrm{CH}}}{\eta_{i,j}^{\mathrm{CH}} \times PF_{i,j}^{\mathrm{CH}}} \tag{3.19a}$$

$$P_{h,s,i}^{\mathrm{CS+,Re}} \leq Cp_i^{\mathrm{CS}} \tag{3.19b}$$

$$P_{h,i}^{\mathrm{CS-,AG}} \leq \sum_{k=1}^{N^{\mathrm{EV}}} P_{h,i,k,r}^{\mathrm{CS+,EV}} \times \eta_i^{\mathrm{CH}} \tag{3.19c}$$

3.3.6 Constraints of retailer layer

Active and reactive power should be balanced at all times. Therefore, sum of the electricity purchased from the wholesale electricity market through retailers must be equal to the sum of the electricity purchased by CSs from retailers, load demand and power losses of the distribution network for active and reactive power at hour h:

$$\sum_{s=1}^{N^{\mathrm{Re}}} P_{h,s}^{\mathrm{Re+,WM}} = \sum_{s=1}^{N^{\mathrm{Re}}} \sum_{i=1}^{N^{\mathrm{CS}}} P_{h,s,i}^{\mathrm{Re-,CS}} + \sum_{b=1}^{N^{\mathrm{b}}} P_{D_b,h} + P_{Lh}^{\mathrm{DN}} \tag{3.20a}$$

$$\sum_{s=1}^{N^{\mathrm{Re}}} Q_{h,s}^{\mathrm{Re+,WM}} = \sum_{s=1}^{N^{\mathrm{Re}}} \sum_{i=1}^{N^{\mathrm{CS}}} Q_{h,s,i}^{\mathrm{Re-,CS}} + \sum_{b=1}^{N^{\mathrm{b}}} Q_{D_b,h} + Q_{Lh}^{\mathrm{DN}} \tag{3.20b}$$

Active and reactive power demands at bus b and hour h are determined by:

$$P_{D_b,h} = \frac{S_{D_0,b}}{\sum_{b=1}^{N^{\mathrm{b}}} S_{D_0,b}} \times P_{D_0,h} \tag{3.21a}$$

$$Q_{D_b,h} = tan(\cos^{-1}(PF_{h,b})) \times P_{D_b,h} \tag{3.21b}$$

The power factor of bus b is extracted from [10].

Active power losses are given by:

$$P_{L_h}^{\mathrm{DN}} = \sum_{m=1}^{N^{\mathrm{M}}} \mid I_{h,m} \mid^2 \times R_m \tag{3.22}$$

Total electricity purchased from the wholesale electricity market must not exceed substation transformation capacity [11]:

$$\sum_{s=1}^{N^{\mathrm{Re}}} P_{h,s}^{\mathrm{Re+,WM}} \leq Cp^{\mathrm{TR}} \tag{3.23}$$

Voltages of all buses must be within permissible range in order to guarantee a secure operation of the distribution network while maintaining power quality at a standard level:

$$\underline{V_b} \leq | V_{h,b} | \leq \overline{V_b} \tag{3.24}$$

Active and reactive power balance are maintained for bus b at hour h by [12]:

$$P_{G_b,h} - P_{D_b,h} = V_{b,h} \sum_{a=1}^{N^{\mathrm{b}}} V_{a,h}(G_{ba}cos(\theta_{b,h} - \theta_{a,h}) + B_{ba}sin(\theta_{b,h} - \theta_{a,h})) \tag{3.25a}$$

$$Q_{G_b,h} - Q_{D_b,h} = V_{b,h} \sum_{a=1}^{N^{\mathrm{b}}} V_{a,h}(G_{ba}sin(\theta_{b,h} - \theta_{a,h}) + B_{ba}cos(\theta_{b,h} - \theta_{a,h})) \tag{3.25b}$$

The electricity price offered by retailers to CSs is limited by minimum and maximum bounds for the optimisation problem at this layer.

$$\underline{\rho}^{\mathrm{Re-,CS}} \leq \rho_{h,s}^{\mathrm{Re-,CS}} \leq \overline{\rho}^{\mathrm{Re-,CS}} \tag{3.26}$$

3.4 Optimisation Model

Despite the fact that evolutionary algorithms might not be able to guarantee global optimal solutions and that they might only reach near-optimal solutions, an evolutionary algorithm, called SSA, is preferred in this study because of the non-linear nature of the three optimisation problems. SSA is an evolutionary computation technique that is inspired by swarming behaviour of salps when they navigate in deep oceans within chains of salp searching for a food source as the swarm's target. In literature, the most popular swarm-inspired algorithms are PSO and ant colony algorithm (ACO) [9, 13–15]. However, it was discovered in a few studies. e.g., [16, 17], that the SSA is able to explore the search space more effectively, and that the optimisation technique benefits from high exploration and convergence speed to obtain the true global solutions [16]. In order to obtain a mathematical model of salp chains, the population of salps is divided into two groups: the first group is the leader where the salp at the front of the chain guides the swarm and the second group includes the followers, as the rest of salps, chasing the leader. In every iteration, the leader changes its position around the food source and the followers chase the leader. The position of salps is defined as an n-dimensional search space, where n is the number of decision variables of the optimisation problem at hand. The position of all salps are stored in a two-dimensional matrix, $x_{n,it}$. The position of the first salp as the leader is updated with respect to the food source, $F_{n,it}$, based on [16, 18]:

$$x_{n,it}^{\mathrm{L}} = \begin{cases} F_{n,it} + c_{1,it}\left(\left(ub_n - lb_n\right)c_{2,it} + lb_n\right) & c_{3,it} \geq 0 \\ F_{n,it} - c_{1,it}\left(\left(ub_n - lb_n\right)c_{2,it} + lb_n\right) & c_{3,it} < 0 \end{cases} \tag{3.27}$$

where $c_{1,it}$ is a variable that will exponentially decrease throughout the iterations, as obtained by Eq. (3.28); and $c_{2,it}$ and $c_{3,it}$ are random numbers uniformly distributed on the interval of [0,1] at iteration it.

$$c_{1,it} = 2e^{-\left(\frac{4 \times it}{\overline{it}}\right)^2} \tag{3.28}$$

The position of the follower f in the dimension n is updated by:

$$x_{n,it}^{\mathrm{f}} = \frac{1}{2}\left(x_{n,it}^{\mathrm{f}} + x_{n,it}^{\mathrm{f}-1}\right) \tag{3.29}$$

To determine optimal day-ahead electricity prices sold to CS operators by retailers, there are $N^{\mathrm{Re}} \times 24$ decision variables to optimise in retailer layer. The number of decision variables in the CS layer is $3 \times N^{\mathrm{CS}} \times 24$ considering three sets of variables that correspond to the power produced by CGU, power purchased from retailers, and power sold to the aggregator for 24 hours ahead. In the EV layer, the optimisation problem includes $2 \times 24 \times N^{\mathrm{EV}}$ decision variables that correspond to the power sold/purchased to/from EVs.

3.5 Simulation Study

In order to examine the performance of the proposed method, a comprehensive simulation study is carried out, as shown in Figure 3.4, using a selected area of San Francisco [19]. The IEEE 37-bus distribution test system [10] is mapped over the area to represent the CSs connection to the distribution system. It is assumed that there are three retailers to provide electricity to CSs and one aggregator is considered to sell energy back to the wholesale market by purchasing it from CSs. The nominal voltage of the network is 480 V and the minimum and maximum voltage limits are 0.95 and 1.05 p.u., respectively. Node 1 is connected to the distribution transformer as the slack bus. Total active and reactive power demand (without EV) at the peak hour are equal to 8.7 MW and 4.3 MVAr, respectively. As depicted in Figure 3.4, the CSs are randomly placed at nodes 2, 8, 10, 11, 16, 22, 29, 32, and 35. The origin and destination of EVs in each trip is assumed to be contained in this area. 600 EVs are randomly situated over the area, each of which is assumed to complete two trips per day with different waiting times between each trip, without loss of generality. Furthermore, four types of EVs with battery capacity of 14.5kWh, 16kWh, 28kWh, and 40kWh are considered. In this study, the base case is defined in such a way that no optimisation is carried out for scheduling and every EV selects the closest CS without considering prices. Also, V2G and G2V prices in the base case strategy are equal to the initial prices in the first iteration of the proposed three-layer optimisation problem for each agent.

Input parameters and their corresponding values for the distribution network, CSs, and EVs are given in Table 3.2. Due to lack of daily load profile at each node in the IEEE 37-bus distribution test system, the daily hourly load profile of California ISO [20] is used by re-scaling the values in proportion to the test network load demand using Eqs. (3.21a) and (3.21b). Also, day-ahead electricity prices of the wholesale electricity market for a typical day are extracted from California ISO [20], which are used in the simulation studies.

In order to take into account ancillary services costs, network maintenance costs, taxes, and etc. (which are normally included in the retail electricity tariffs), the day-ahead electricity prices of the wholesale market is multiplied by 4.5 homogeneously. The new prices will serve as the electricity prices that is paid by CS operators to the retailers. The electricity prices sold to EVs by CSs and electricity prices purchased from EVs by CSs are obtained by:

$$\rho_{h,i}^{CS-,EV} = rand(1.1, 1.5) \times \rho_{h,i}^{Re-,CS} \tag{3.30}$$

In Eq. (3.30), it is assumed that CSs' asking prices are 10–50% more than what

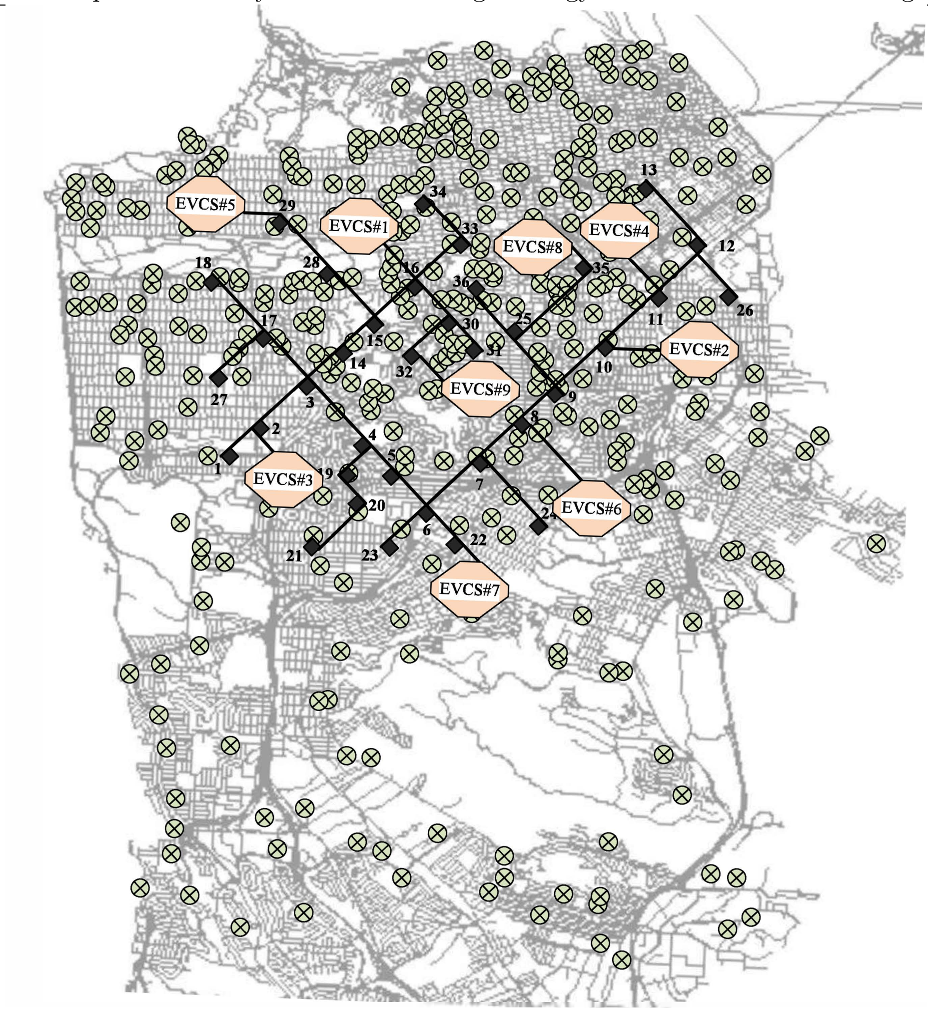

Figure 3.4: IEEE 37-bus distribution test network and location of some of the EVs and all CSs in San Francisco, the USA [19] and [10].

Table 3.2: Input parameters of distribution network, CSs, and EVs [7, 21, 22]

Parameter	Value	Parameter	Value
$M_{h,k,r}$	± 1(+1: G2V, -1: V2G)	Cp^{EV}	14.5, 16, 28, 40 (kWh)
Δt	1 hr	$\underline{V}_b/\overline{V}_b$	0.95/1.05
$c_{p.u}^{\text{PQ}}$	10.16 ($/kVA)	HV	0.7 (kWh/m^3)
η^{CH}	0.9	η^{PV}	0.157
PF^{CH}	0.95	A^{PV}	800 (m^2)
Cp^{GU}	65 (kW)	Cp^{ESS}	50 (kWh)
$\overline{N}_i^{\text{CH}}$	5	ρ^{gas}	13.07 (cents/m^3)
α	0.03	β	1.05
κ	0.61	λ	1
$\underline{SOC}^{\text{ESS}}$/ $\overline{SOC}^{\text{ESS}}$	0.1/0.9	γ	0.2 (kWh/km)

they pay to the retailers in order to make profit. In addition, CS operators offer prices to EVs for V2G services that will be sold to the wholesale market through aggregators. The performance of a CS in this case depends on the prices offered to the EVs. Therefore, a sensitivity analysis is carried out using the following three scenarios:

Scenario I (Low-price scenario): $\rho_{h,i}^{CS+,EV} = \dfrac{1}{4.5} \times \rho_{h,i}^{Re-,CS} \times rand(0.1, 0.9)$

Scenario II (Medium-price scenario): $\rho_{h,i}^{CS+,EV} = \rho_{h,i}^{Re-,CS} \times rand(0.6, 0.85)$

Scenario III (High-price scenario): $\rho_{h,i}^{CS+,EV} = \rho_{h,i}^{Re-,CS} \times rand(1.05, 1.3)$

It can be seen that the optimal day-ahead electricity prices for discharging EVs increase from scenario I to scenario III. In fact, in scenario I to scenario III, V2G prices are getting closer to G2V prices to encourage more EVs in V2G operation, and consequently, determine the range of V2G prices in which the collective benefit of all agents is maximised. In all scenarios, $\rho_{h,i}^{CS-,AG} = 1.1 \times \rho_{h,i}^{CS+,EV}$ where the aggregator expects maximum of 10% profit based on the price offered by CSs.

It is assumed that different retailers are looking for up to 30% profit. As a result, the minimum and maximum value of the day-ahead electricity prices sold to CSs by retailers are expressed as:

$$1.05 \times 4.5 \times \rho_{\mathrm{h}}^{\mathrm{Re+,WM}} \leq \rho_{\mathrm{h,s}}^{\mathrm{Re\text{-},CS}} \leq 1.3 \times 4.5 \times \rho_{\mathrm{h}}^{\mathrm{Re+,WM}} \tag{3.31}$$

The cloud scheduling system specifies the charging/discharging plan of all EVs at once. Four plans can be expected for EV charging and discharging with two trips. The flowchart for choosing a proper plan for EVs is shown in Figure 3.5, which are explained below:

- **Plan 1**: The initial SOC of EV k at the beginning of trip 1 is not sufficient to complete this trip. Therefore, EV k must be charged in trip 1. If it is profitable, it will be discharged in trip 2.
- **Plan 2**: The initial SOC of EV k at the start of trip 1 is more than the total energy needed to finish trip 1 and the minimum SOC of the EV at the end of

the trip. If charging prices in trip 1 are less than discharging prices in trip 2, EV k will be charged in trip 1 and discharged in trip 2. EVs will be scheduled for discharging only if they can recover the cost of battery degradation and make a profit.

- **Plan 3**: The initial SOC of EV k at the beginning of trip 1 is more than the total energy required for the trip and the minimum SOC of EV at the end of the trip. If discharging prices in trip 1 are more than charging prices in trip 2, EV k will be discharged in trip 1 and charged in trip 2.
- **Plan 4**: The initial SOC of EV k at the beginning of trip 1 is more than the required energy to complete the trip and minimum SOC of EV at the end of the trip. However, charging prices in trip 1 are more than discharging prices in trip 2. In addition, discharging price in trip 1 is less than charging price in trip 2. In this case, EV k will not be charged nor discharged. However, if the initial SOC of EV k at the beginning of trip 2 is not more than the required energy to complete the trip and minimum SOC of EV at the end of the trip, the EV k must be charged in trip 2.

3.6 Simulation Results and Discussion

In this section, simulation results for a typical day will be presented and explained for the case study introduced in Section 3.5.

3.6.1 V2G and G2V operation and prices

The optimal day-ahead electricity prices offered by the most and least profitable CS are shown in Figure 3.6. It can be seen that the most profitable CS is CS#8 in scenario II and the the least profitable CS is CS#1 in scenario I. The number of EVs charged and discharged in each scenario for each hour is depicted in Figure 3.7. No EVs is planned for V2G service in Scenario I due to the extremely low prices offered by the CSs. However, by increasing the V2G prices (assuming that the cost of ancillary services, taxes, etc. are reduced or prices in the wholesale market are high), the number of EVs participating in V2G increases and reaches its maximum in

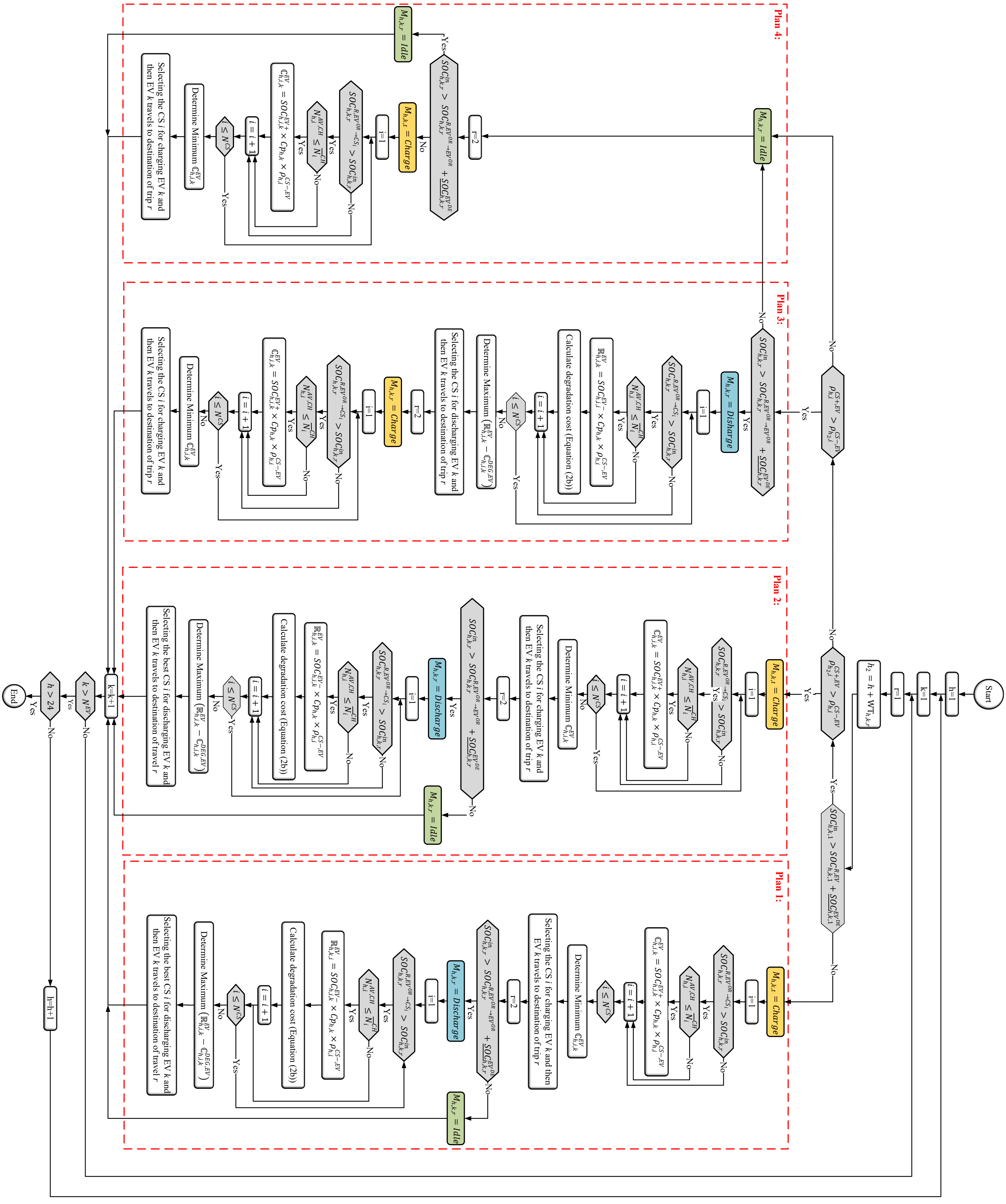

Figure 3.5: Flowchart of the rule-based process to determine the charging/discharging modes at the end of each trip.

Scenario III. Also, it can be seen from Figure 3.7 that the number of EVs in charging mode has increased substantially because it is economically beneficial for the EVs to charge in one trip and discharge in the next one (i.e., energy arbitrage).

The number of EVs in each charge and discharge mode in each scenario for **Plan 1**, **2**, and **3** is depicted in Figure 3.8. For **Plan 1**, the number of EVs planned for V2G service in the second trip is raised by increasing V2G prices because it is economically rewarding for EVs to make profit from the high SOC level of batteries in the second trip. For **Plan 2**, the results show that by increasing V2G prices, when G2V prices in the first trip is lower than V2G prices in the second trip, the number of EVs that prefer to charge in the first trip and discharge in the second trip increases because they can make more profit. As explained in Section 3.5, for **Plan 1**, EVs must be charged in trip 1, and if it is profitable, they will be discharged in trip 2. However, for **Plan 2**, EVs are charged in trip 1 and discharged in trip 2 to make profit if the prices are right. Furthermore, in **Plan 3**, more EVs discharged in the first trip with higher prices and charge in the second trip with lower prices.

Figure 3.9 depicts the routes for an EV that is specified by ArcGIS in the base case and the proposed strategy in this study. In this example, EV k selects the nearest CSs (CS#8 and CS#3) in the base case without running a cost-benefit analysis, which leads to $4 extra cost for EV k in comparison with the proposed three-layer optimal strategy.

3.6.2 CS and retailers operation

In Table 3.3, optimal day-ahead electricity prices offered by three retailers to CSs are reported. The cheapest retailer is selected in each hour, which are specified in the Table. Off-peak and peak periods with minimum and maximum electricity prices occur in hours 10 and 19, respectively, and Retailer#1 is selected by CSs in both off-peak and peak periods.

As reported in Table 3.4, by increasing the number of EVs participating in V2G program from scenario I to III, the net cost of EVs decreases and the net revenue of CS operators and retailers increases. However, in Scenario III, while more EVs participated in the V2G program, the net revenue of retailers and CS operators as

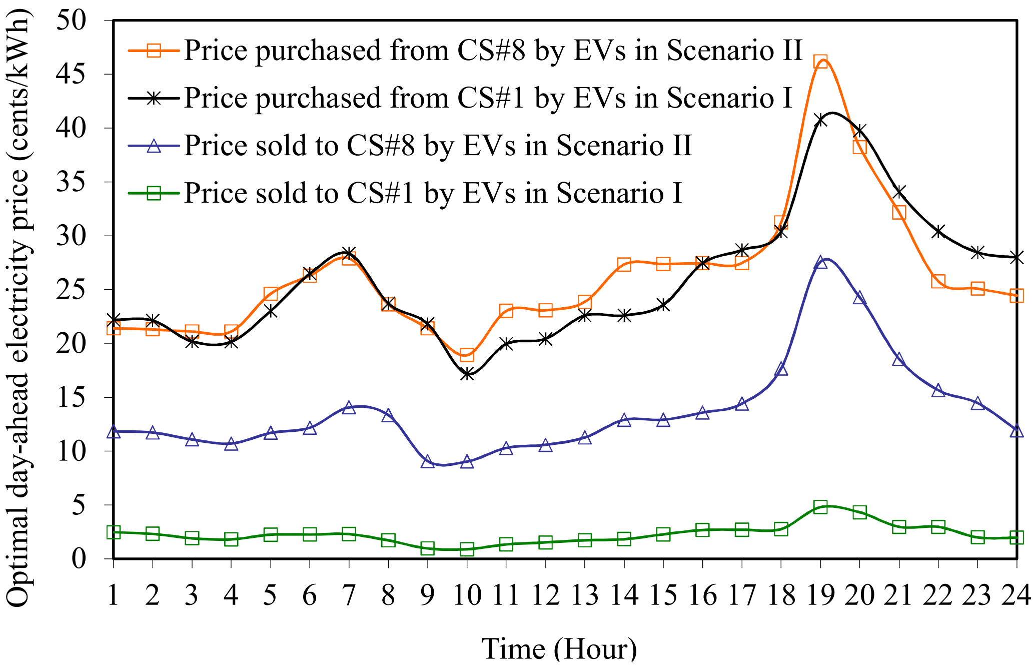

Figure 3.6: Optimal day-ahead electricity prices offered by the least (CS#1) and the most profitable CS (CS#8) during charging and discharging of EVs among all Scenarios.

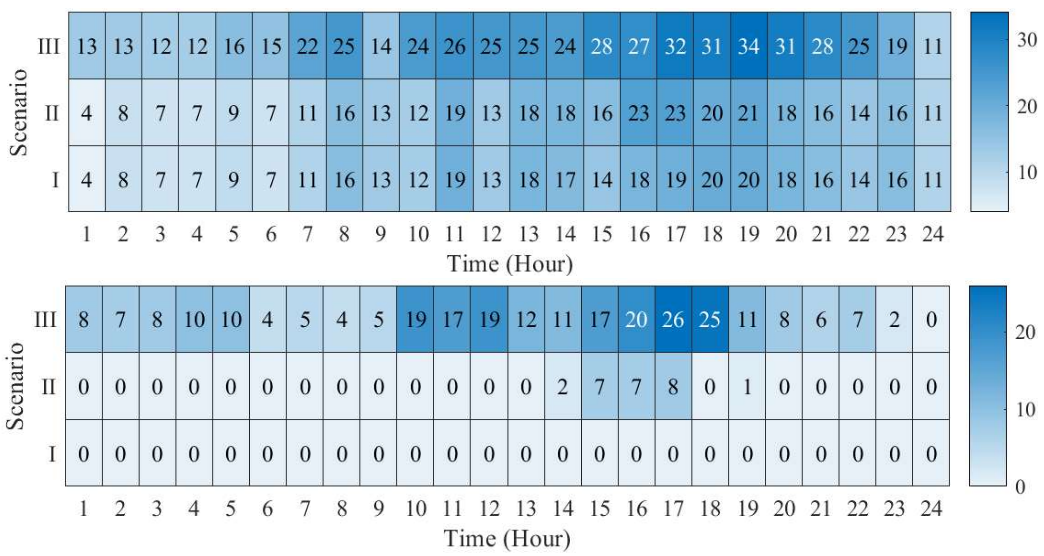

Figure 3.7: Number of EVs planned to participate in (a) G2V and (b) V2G in each scenario.

Table 3.3: Optimal day-ahead electricity prices offered by retailers and the selected retailer in each hour (cents/kWh)

Time (Hour)	Retailer#1	Retailer#2	Retailer#3	Selected retailer
t=1	18.74	19.35	21.12	Retailer#1
t=2	18.66	17.48	19.96	Retailer#2
t=3	16.74	17.46	16.43	Retailer#3
t=4	16.73	17.39	16.33	Retailer#3
t=5	17.73	18.24	18.13	Retailer#1
t=6	20.62	18.75	19.25	Retailer#2
t=7	24.34	24.42	22.51	Retailer#3
t=8	20.03	19.49	22.31	Retailer#2
t=9	16.58	15.16	16.72	Retailer#2
t=10	14.25	15.11	16.03	Retailer#1
t=11	16.52	15.55	16.12	Retailer#2
t=12	16.60	18.53	16.20	Retailer#3
t=13	18.06	18.62	17.38	Retailer#3
t=14	18.78	21.16	19.68	Retailer#1
t=15	19.93	21.16	19.96	Retailer#1
t=16	21.56	22.1	21.00	Retailer#3
t=17	22.73	22.19	21.94	Retailer#3
t=18	25.16	27.39	27.81	Retailer#1
t=19	35.64	38.03	39.52	Retailer#1
t=20	32.75	35.15	33.59	Retailer#1
t=21	28.69	29.07	25.67	Retailer#3
t=22	25.22	22.96	25.27	Retailer#2
t=23	22.48	21.57	21.51	Retailer#3
t=24	21.74	19.45	19.00	Retailer#3

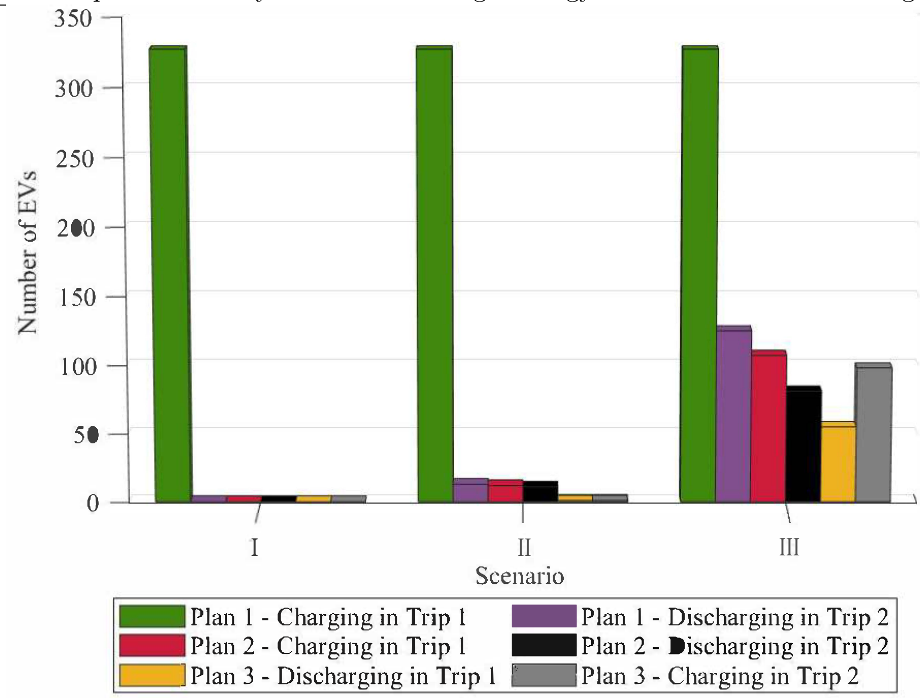

Figure 3.8: Total number of EVs for **Plan 1**, **Plan 2**, and **Plan 3** in each scenario.

Table 3.4: Objective function values in three layers and the number of EVs discharged in all scenarios

Scenario	Total net cost of EVs ($)	Total net revenue of CSs ($)	Total net revenue of retailers ($)	No. of EVs discharged
Scenario I	1835.1	291.7	643.9	0
Scenario II	1800.4	453	654.7	25
Scenario III	1219.3	378.1	639.7	261

well as the net cost of EVs decreased compared to Scenario II. The main reason is that the cost of electricity purchased by CS operators from EVs participating in V2G services increased while the electricity purchased from retailers by CS operators decreased. Based on the results presented in Table 3.4, the most profitable operation is achieved in Scenario II for all three agents, i.e., EV, CS, and retailer.

3.6.3 The proposed algorithm performance and convergence

To verify the simulation results obtained by SSA, the three-layer optimisation problem is also solved by PSO approach. The optimisation algorithms convergence rates of prices for both optimisation techniques are shown in Figure 3.10 for each scenario in the three layers, where optimal results are reached after about 70 and 75

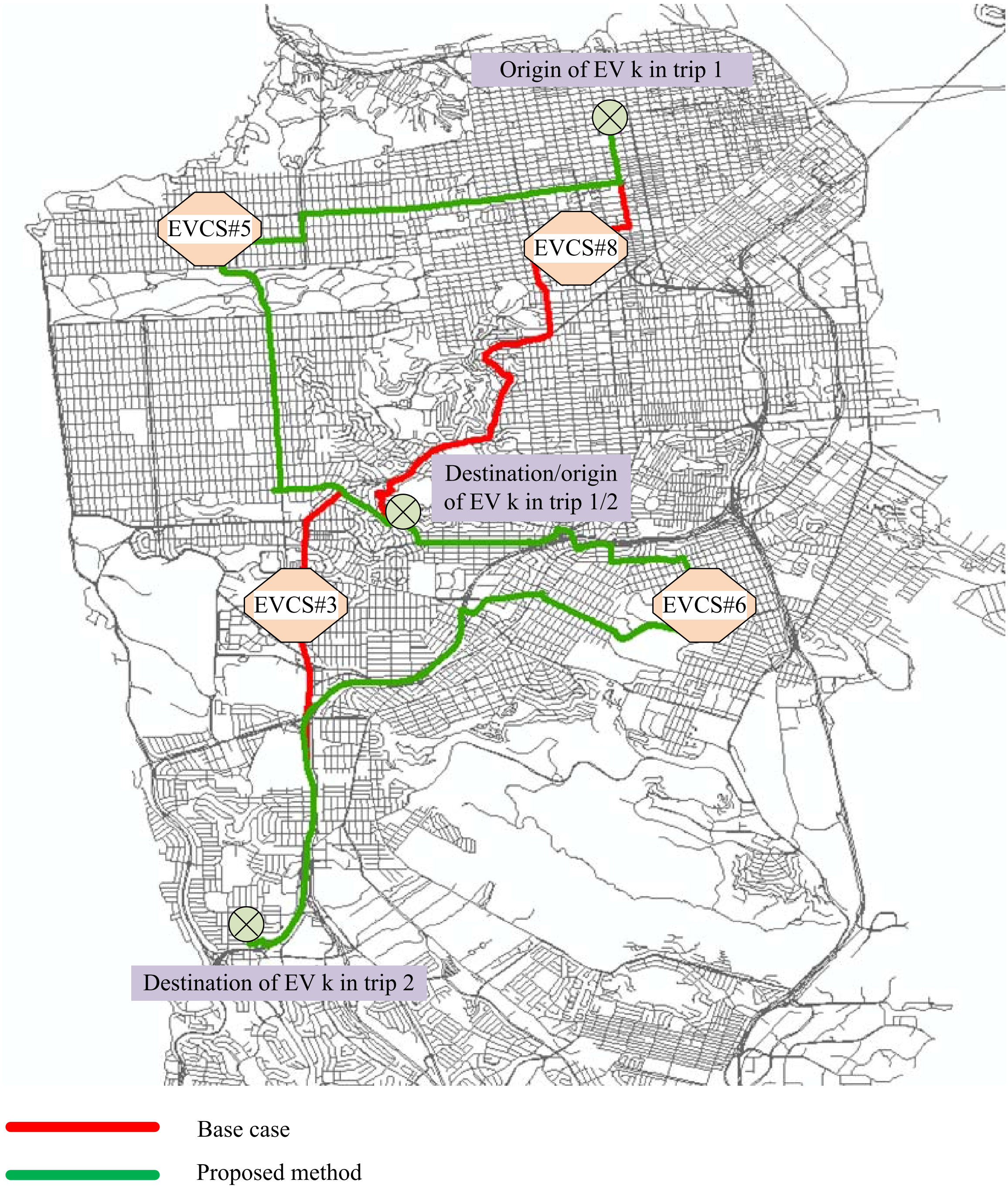

Figure 3.9: Scheduling results for a sample EV in the base case (red line) and the proposed strategy (green line).(If the preferences proposed in Chapter 4 are considered, the green line may not be chosen).

Table 3.5: Comparing the simulation results for the base case, the proposed three-layer optimisation problem and the individual optimisation problems in Scenario II

Parameters		Optimal Value	
		SSA	PSO
$\mathbb{C}^{EV}$ (\$)	Three-layer optimisation problem	1800.4	1801.3
	Base case	2185.7	2185.7
	Individual optimisation problem	2005.7	2006.2
$\mathbb{R}^{CS}$ (\$)	Three-layer optimisation problem	453	453.7
	Base case	374.1	374.1
	Individual optimisation problem	382.6	382.9
$\mathbb{R}^{Re}$ (\$)	Three-layer optimisation problem	654.7	655.2
	Base case	534.1	534.1
	Individual optimisation problem	550.2	550.8

iterations in most cases using SSA and PSO, respectively. The optimal values are obtained by SSA and PSO in 1,683 and 1,829 seconds, respectively. Therefore, it shows that SSA is outperforming PSO in terms of computational time. All computations are executed on a laptop with Intel Core i7 CPU with 1.80GHz processor and 8GB RAM.

In Table 3.5, the cost/revenue of EVs, CS operators, and retailers are reported for the base case and the proposed three-layer optimisation problem in scenario II, obtained by SSA and PSO. It can be seen that the cost of EVs decreased by 17.6%, and the revenue of CS operators and retailers raised by 21.1% and 22.6%, respectively, in the proposed method solved by SSA in comparison with the base case. The results obtained by SSA and PSO are quite close, with SSA performing slightly better in most instances. It shows the effectiveness of SSA in solving these complex optimisation problems in a reasonable time.

To better show the effectiveness of the proposed method, another simulation study is performed, called "Individual optimisation problem", in which the optimisation problem of each stakeholder is solved individually without iterative process. It can be seen from Table 3.5 that if the the proposed method yields 10.2% reduction in EVs operation cost and 18.4% and 19% increase in revenue of CSs and retailers, respectively, compared to "Individual optimisation problem" in scenario II.

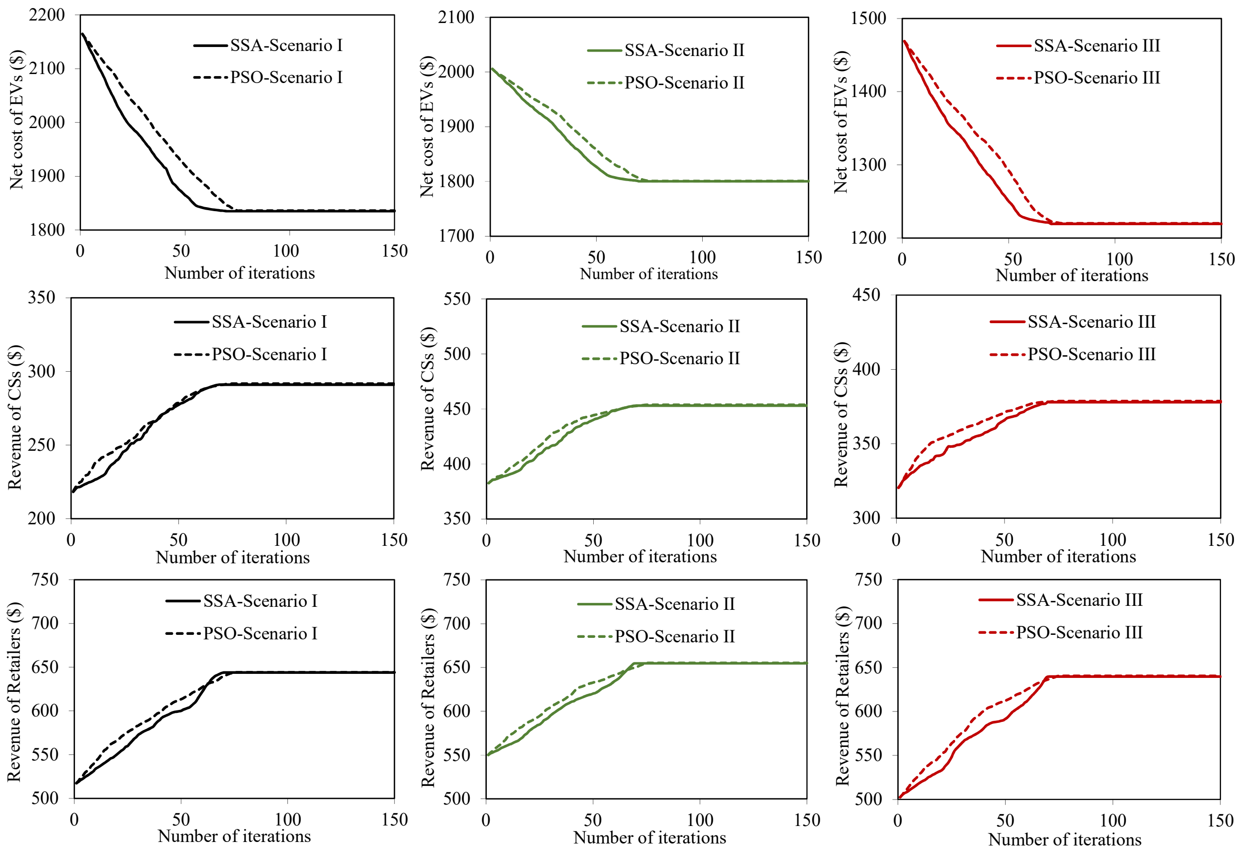

Figure 3.10: Convergence of the optimisation problems in (a-c) EV layer, (d-f) CS layer, and (g-i) retailer layer for all scenarios.

3.7 Conclusions

In this chapter, a day-ahead scheduling framework is presented to guarantee economic and energy-efficient routing of EVs. Based on the proposed strategy, each EV and CS finds optimal CSs and retailers, respectively, for V2G and G2V services by solving an equilibrium problem. The proposed method can be offered as a cloud service to all stakeholders, which facilitates day-ahead EV scheduling considering objectives and preferences of all stakeholders. In this method, EVs independently plan their charging/discharging depending on the minimum driving routes and cost/benefit analysis based on the prices offered by CSs. Also, CSs select optimal retailers to purchase energy while utilising onsite generation and stationary storage in the most economic way. In addition, CSs are able to facilitate V2G operation by purchasing energy from EVs and selling back to the wholesale market through aggregators. Comprehensive simulations are conducted on a real test system.The results are obtained by SSA. To verify the simulation results, the three-layer optimisation problem is also solved by PSO approach. The results obtained by SSA and PSO are quite close. Simulation results confirm that the cost-effective operation is achieved for all agents, and it is highly dependant on the level of participation of EVs in the V2G program and the cost of energy in the wholesale market. The optimal solutions are obtained for all stakeholders by respecting physical limits of the network, avoiding queuing at the CSs, and preserving EV owners comfort and preferences during the scheduling.

In the next chapters, the practical aspects of EV scheduling problem are improved to facilitate higher participation in the G2V and V2G services, and to enhance convenience and flexibility in EV scheduling. EV owners' preferences, and unpredictable and economically-irrational behavior taken by EV drivers are considered. Also, various sources of uncertainty will be added to the model and stochastic optimisation will be used to deal with the uncertainties.

References

[1] V. Dvorkin, J. Kazempour, and P. Pinson, “Chance-constrained equilibrium in electricity markets with asymmetric forecasts,” *arXiv preprint arXiv:2005.11749*, 2020.

[2] H. Uzawa, “Walras' tatonnement in the theory of exchange,” *The Review of Economic Studies*, vol. 27, no. 3, pp. 182–194, 1960.

[3] “"ArcGIS 10.5.1 desktop." Available: https://desktop.arcgis.com/en/ .[{A}ccessed:01-Oct-2018].” 2019.

[4] A. Ahmadian, M. Sedghi, B. Mohammadi-ivatloo, A. Elkamel, M. A. Golkar, and M. Fowler, “Cost-benefit analysis of V2G implementation in distribution networks considering PEVs battery degradation,” *IEEE Transactions on Sustainable Energy*, vol. 9, pp. 961–970, 2017.

[5] W. Wei, S. Mei, L. Wu, M. Shahidehpour, and Y. Fang, “Optimal traffic-power flow in urban electrified transportation networks,” *IEEE Transactions on Smart Grid*, vol. 8, pp. 84–95, Jan 2016.

[6] X. Chen, H. Lei, R. Xiong, W. Shen, and R. Yang, “A novel approach to reconstruct open circuit voltage for state of charge estimation of lithium ion batteries in electric vehicles,” *Applied Energy*, vol. 255, p. 113758, 2019.

[7] Z. Liu, F. Wen, and G. Ledwich, “Optimal planning of electric-vehicle charging stations in distribution systems,” *IEEE Transactions on Power Delivery*, vol. 28, pp. 102–110, November 2013.

[8] S.G.Tichi, M.M.Ardehali, and M.E.Nazari, "Examination of energy price policies in Iran for optimal configuration of CHP and CCHP systems based on particle swarm optimization algorithm," *Energy Policy*, vol. 38, pp. 6240–6250, Oct 2010.

[9] Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung, "Smart charging strategy for electric vehicle charging stations," *IEEE Transactions on Transportation Electrification*, vol. 4, pp. 76–88, March 2017.

[10] K. Shaloudegi, N. Madinehi, S. H. Hosseinian, and H. A. Abyaneh, "A novel policy for locational marginal price calculation in distribution systems based on loss reduction allocation using game theory," *IEEE Transactions on Power Systems*, vol. 27, pp. 811–20, 2012.

[11] A. Algarni and K. Bhattacharya, "A generic operations framework for discos in retail electricity markets," *IEEE Transactions on Power Systems*, vol. 24, pp. 356–367, 2009.

[12] J. Zhang, Y. Wu, Y. Guo, B. Wang, H. Wang, and H. Liu, "A hybrid harmony search algorithm with differential evolution for day-ahead scheduling problem of a microgrid with consideration of power flow constraints," *Applied Energy*, vol. 183, pp. 791–804, 2016.

[13] S. P. Simon, N. P. Padhy, and R. Anand, "An ant colony system approach for unit commitment problem," *International Journal of Electrical Power & Energy Systems*, vol. 28, pp. 315–323, 2006.

[14] Z. Chen, R. Xiong, and J. Cao, "Particle swarm optimization-based optimal power management of plug-in hybrid electric vehicles considering uncertain driving conditions," *Energy*, vol. 96, pp. 197–208, 2016.

[15] B. Amirhosseini and S. H. Hosseini, "Scheduling charging of hybrid-electric vehicles according to supply and demand based on particle swarm optimization, imperialist competitive and teaching-learning algorithms," *Sustainable cities and society*, vol. 43, pp. 339–349, 2018.

[16] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and M. Mirjalili, "Salp swarm algorithm: A bio-inspired optimizer for engineering design problems," *Advances in Engineering Software*, vol. 114, pp. 163–191, 2017.

[17] R. A. El Sehiemy, F. Selim, B. Bentouati, and M. Abido, "A novel multi-objective hybrid particle swarm and salp optimization algorithm for technical-economical-environmental operation in power systems," *Energy*, vol. 193, p. 116817, 2019.

[18] H. Faris, M. M. Mafarja, A. A. Heidari, I. Aljarah, A. M.Al-Zoubi, S. ali Mirjalili, and H. Fujita, "An efficient binary salp swarm algorithm with crossover scheme for feature selection problems," *Knowledge-Based Systems*, vol. 154, pp. 43–67, 2018.

[19] "San francisco map, available at: https://www.arcgis.com/home/item.html?id=e66bb5dac376457b9f721b083572712c."

[20] "California ISO, available at: http://www.oasis.caiso.com," 2019.

[21] "U.S. environmental protection agency combined heat and power partnership, catalog of CHP technologies section 5. technology characterization - microturbines," 2015.

[22] J. Jannati and D. Nazarpour, "Optimal performance of electric vehicles parking lot considering environmental issue," *Journal of cleaner production*, vol. 206, pp. 1073–1088, 2019.

4 An Optimal Day-Ahead Scheduling Framework for E-Mobility Ecosystem Operation with Drivers' Preferences

Nomenclature

Indices	
e,i,r	Index for EVs, CSs, and retailers, respectively
m, n	Index of buses of distribution network
t	Index for hours
Parameters	
Δt	Time step (s)
η_i^{GU}/η_i^{CH}	Efficiency of CGU/chargers at CS i (p.u.)
η_e^{+}/η_e^{-}	Efficiency of EV e's battery in G2V/V2G mode (p.u.)
γ_e	Power consumed by EV e per km (kWh/km)
$\mathcal{D}_{t,e,i}$	Shortest driving distance between CS i and destination of EV e at time t, (km)
$\mathcal{G}_e$	EV e's driver preference for minimum revenue increase in V2G operation ($)
$\mathcal{K}_e$	EV e's driver preference for maximum extra distance to lower the cost compared to minimum route (in km)

$\mathcal{O}_{t,e,i}$	Shortest driving distance between origin of EV e and CS i at time t (km)
$\overline{\rho}^{-}/\underline{\rho}^{-}$	Maximum/Minimum electricity prices offered by CSs for V2G service ($\$/kWh$)
$\overline{\rho}^{re}/\underline{\rho}^{re}$	Maximum/Minimum electricity prices offered by retailers to CSs ($\$/kWh$)
$\overline{E}_i^{\text{CGU}}/\overline{E}_i^{\text{PV}}$	Capacity of CGU/PV system at CS i (kW)
$\overline{E}_i^{\text{ESS}}$	Capacity of ESS at CS i (kW)
$\overline{E}_e$	Capacity of EV e's battery (kWh)
$\overline{E}_i$	Capacity of CS i (kW)
$\overline{E}_i^{\text{CH}}$	Capacity of chargers at CS i (kW)
$\overline{N}_i^{CH}$	Maximum number of chargers in CS i
$\overline{P}_{m,n,t}/\underline{P}_{m,n,t}$	Maximum/Minimum active power flow between bus m and n (kW)
$\overline{Q}_{m,n,t}/\underline{Q}_{m,n,t}$	Maximum/Minimum reactive power flow between bus m and n (kVar)
$\overline{SOC}_e/\underline{SOC}_e$	Maximum/Minimum SOC of EV e (p.u.)
$\overline{SOC}_i^{ESS}/\underline{SOC}_i^{ESS}$	Maximum/Minimum SOC of ESS at CS i (p.u.)
ρ_t^{gas}	Natural gas price at time t ($\$/m^3$)
ρ_t^{WM}	Wholesale electricity market price at time t (\$/kWh)
$\underline{\Delta V}/\overline{\Delta V}$	Lower/Upper limit of voltage deviation at bus m
ϑ_e	EV e's driver preference for minimum cost reduction in G2V operation (\$)
$\widehat{\mathcal{DO}}_{t,e}$	Driving distance of EV e to closest CS at time t (km)
$\widehat{SOC}_{t,e}$	SOC of EV e at time t if EV e charged or discharged at the closest CS (p.u.)
a	SOC target
b, c, d, f	Cost of battery degradation parameters
$b_{m,n}/g_{m,n}$	Susceptance/conductance of transmission line between bus m and n
HV	Heat value of fuel on the operation of gas turbine-generator (kWh/m^3)

$N^{\mathrm{EV}}/N^{\mathrm{CS}}/N^{\mathrm{re}}$	Number of EVs/CSs/retailers
SOC_e^{end}	SOC of EV e at the end of the day (p.u.)
$\zeta_{t,e}$	Shortest driving route to reach the destination directly from origin of EV e at time t without stopping at any CS (km)
VCS	Virtual charging station
Sets	
B, E, R, S, T, F	Sets of Buses, EVs, retailers, CSs, hours, and optional trip times, respectively
Variables	
$\beta_{t,i,r}$	Binary variable for retailer r by CS i at time t
$\Delta\theta_{m,t}$	Voltage angle deviation on bus m at time t
$\Delta V_{m,t}$	Voltage magnitude deviation on bus m at time t
$\Delta\hat{V}_{m,t}$	Voltage magnitude deviation obtained from the lossless power flow solution on bus m at time t
$\Gamma_{t,e,i}/\Pi_{t,e,i}$	Binary variable for CS i for charging/discharging EV e at time t
$\psi_{t,i}$	Binary variable for charging/discharging ESS at CS i
$\rho^{+}_{t,i}/\rho^{-}_{t,i}$	Electricity price offered by CS i at time t for charging/discharging EVs (\$/kWh)
$\rho^{AG}_{t,i}$	Electricity price sold to the aggregator by CS i at time t (\$/kWh)
$\rho^{re}_{t,r}$	Electricity price sold to CSs by retailer r at time t (\$/kWh)
$\theta_{m,t}$	Voltage angle of bus m and time t
$\widehat{\rho}^{+}_{t,e}/\widehat{\rho}^{-}_{t,e}$	Electricity price offered by the closest CS to EV e at time t in G2V/V2G mode (\$/kWh)
$P_{m,n,t}/Q_{m,n,t}$	Active/Reactive power flow between bus m and n at time t (kW/kVar)
$Y^{re}_{t,i,r}/Q^{re}_{t,i,r}$	Active/Reactive power purchased/provided from/by retailer r by CS i at time t (kW/kVar)
$SOC_{0,e}$	Initial SOC of EV e (p.u.)
$SOC_{T,e}$	SOC of EV e at the end of the day (p.u.)

$SOC_{t,e}$	SOC of EV e at time t (p.u.)
$V_{m,t}$	Voltage magnitude of bus m and time t
$X^{+}_{t,e,i}/X^{-}_{t,e,i}$	Charging/Discharging power of EV e at CS i at time t (kW)
$Y^{+}_{t,i}/Y^{-}_{t,i}$	Charging/Discharging power of ESS of CS i at time t (kW)
$Y^{GU}_{t,i}$	Power produced by CGU/PV system of CS i at time t (kW)
$Y^{PV}_{t,i}$	Local PV generation of CS i at time t (kW)
$P^{\mathrm{WM}}_{t,r}/Q^{WM}_{t,r}$	Active/Reactive power purchased/provided from/by the wholesale market by retailer r at time t (kW/kVar)

4.1 Introduction

In this chapter[1], a comprehensive day-ahead scheduling framework is developed for an e-mobility ecosystem including EVs, CSs, and retailers (as the three major stakeholders) for V2G and G2V operation. In an attempt to improve the practical aspects of the EV scheduling formulation, two major improvements are proposed. First, the optional trips (besides mandatory trips) are introduced in the formulation to provide opportunities for G2V and V2G services beyond mandatory trips, explained in Section 4.2.1. As it can be seen in the simulation studies in Section 4.4.1, it will enhance convenience and flexibility in EV scheduling and provide an opportunity to encourage more G2V and V2G participation. Second, two new parameters, namely driver's cost/revenue threshold and driver's route preference, are defined and formulated to model diverse reaction of EV drivers to economic incentives, as described in Section 4.2.2. The G2V and V2G prices are also obtained by considering the mutual impact of the stakeholders through an iterative process, which is presented in Section 4.2.3.

A careful review of the literature are presented in Chapter 2. As stated in Chapter 2, a review of the existing literature indicates the several gaps, which are outlined in G1, G2, G4, and G5 of Section 2.2 of Chapter 2. In this chapter the proposed

[1] This chapter is published on IEEE Transactions on Power Systems journal: Mahsa Bagheri Tookanlou, S. Ali Pourmousavi, Mousa Marzband, "An Optimal Day-Ahead Scheduling Framework for E-Mobility Ecosystem Operation with Drivers Preferences", *IEEE Transactions on Power Systems*, 36, 2021.

framework has been dealt with the gaps. The main contributions of this study are:

1. **Formulating and solving a three-layer optimisation problem:** A comprehensive model is developed to consider the operation of all stakeholders in the future e-mobility ecosystem as a three-layer optimisation problem. An iterative solution is proposed to solve the problem as a non-cooperative Stackelberg game.

2. **Optional trips:** This provision is expected to improve the practical aspects of EV scheduling problem and provides an opportunity for EV drivers to take advantage of cheaper G2V prices and more expensive V2G prices beyond mandatory trips' timeframe. The effect of optional trips on the cost/revenue of three stakeholders, CS congestion and PV spillage are investigated.

3. **Preferences of EV drivers:** Two important practical aspects of the EV scheduling problem are considered by adding new constraints in order to model economically-irrational decisions taken by the EV drivers in response to economic incentives. These constraints are driver's cost/revenue threshold and driver's route preference.

The rest of the chapter is organised as follows: Section 4.2 presents problem definition and describes the structure of the proposed G2V and V2G framework including the three stakeholders. It is followed by the proposed three-layer optimisation formulation in Section 4.3. In Section 4.4, two ecosystems are proposed for simulation and a series of studies are carried out to show the effectiveness of the proposed framework. Simulation results are discussed and the chapter is concluded in Section 4.5.

4.2 Problem Definition

This chapter presents a day-ahead scheduling framework for e-mobility ecosystems including EVs, CSs, and retailers as three major players. In the proposed ecosystem, illustrated in Fig 4.1, there are multiple retailers selling electricity to CSs from the wholesale electricity market. The CSs are the charging stations located in the scheduling area. They operate at the distribution system to serve EVs during G2V and V2G operation. For the sake of completeness, each CS is assumed to own and operate an onsite small gas turbine/diesel generator as a CGU, PV, and ESS, which can be used to supply electricity to EVs during G2V operation. Also, CSs purchase V2G services from EVs and sell it in the wholesale electricity market through aggregators. It is assumed that conventional retailers are not allowed to sell electricity to the wholesale market (i.e., simultaneous buying and selling energy are prohibited).

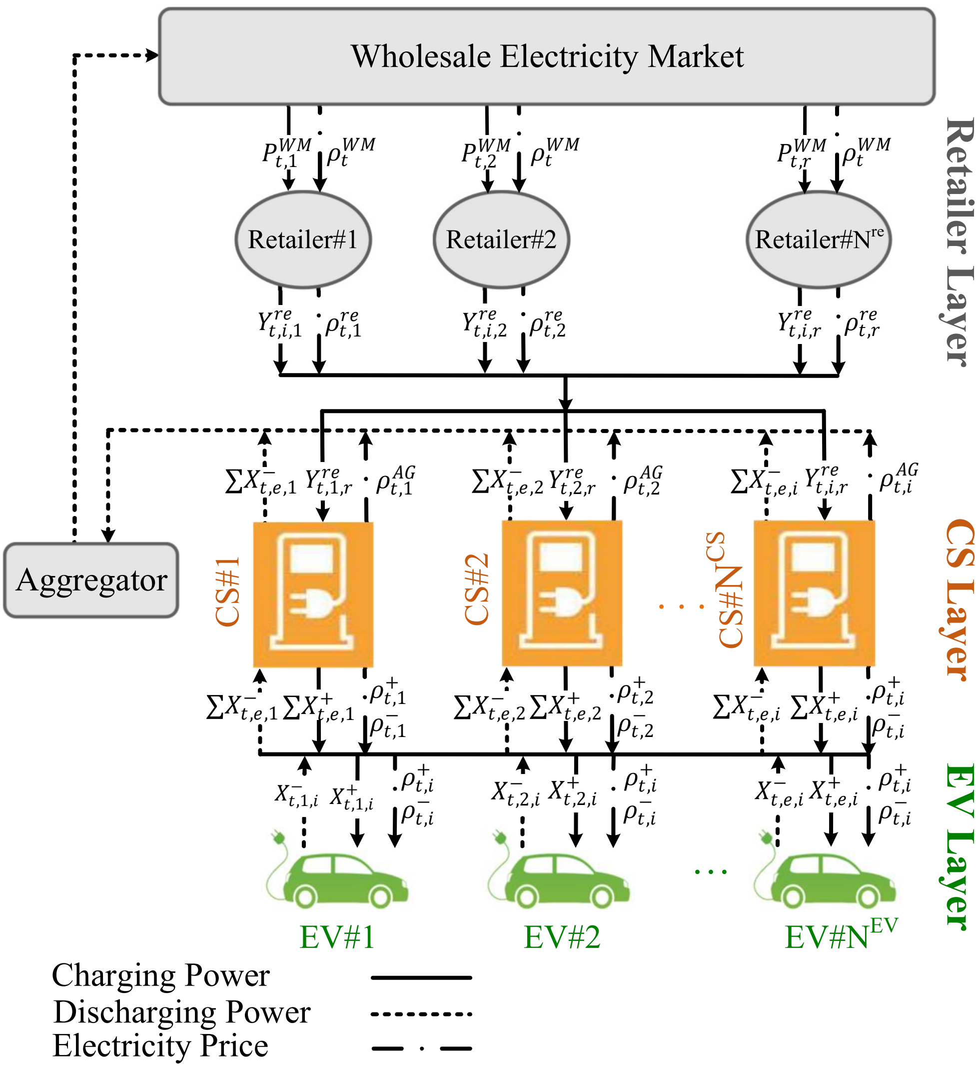

Figure 4.1: Schematic diagram of the future e-mobility ecosystem.

In order to facilitate cost-effective operation of the stakeholders, to mitigate congestion and PV curtailment at CSs, and to consider EV drivers' preferences, two kinds of trips and extra constraints are defined and formulated in this chapter, which are explained in detail in Sections 4.2.1 and 4.2.2, respectively. It should be noted that the reduction in PV curtailment leads reduction in loss of PV power generation.

4.2.1 Different Types of Trips

As shown in Figure 4.2, EVs can have two kinds of trips during a typical day: mandatory trip and optional trip. Each EV can have multiple mandatory trips with known departure time, origin, and destination for each trip. These trips will be fulfilled at any cost. In other times, e.g., between two mandatory trips, EV drivers may have time for G2V and/or V2G services if the prices are right. This is the basis for what is called optional trip in this study. An optional trip, as opposed to mandatory trip, provides a chance for EV drivers to take advantage of cheap G2V or expensive V2G services outside of the mandatory trip time frame; thus reduce their overall cost. Overall, EVs with a known location and initial SOC seek a G2V and V2G plan for the combined mandatory and optional trips such that it minimises their overall cost while respecting their preferences. The optional trips also help CSs to sell their excess energy, to provide services to the upper grid that generates revenue for EVs, and to enable CSs to alleviate congestion.

The scheduling problem is solved for the entire day ahead. EV drivers submit their plans for mandatory and optional trips to the scheduling centre (which could be a cloud platform with monthly subscription fee) a day before the scheduling day. As shown in Figure 4.2, there are N^{CS} real CSs with known driving routes from EV origin in each trip, only one of which might be scheduled for EV e. Therefore, each CS is represented by two binary variables in the EV e problem for G2V and V2G operation at each time interval (as shown in Figure 4.3).

As mentioned before, a mandatory trip should always be accomplished. Let's consider a mandatory trip in which the most economic decision for EV e is not to be charged nor discharged. In this case, none of the actual CSs should be selected and yet, the battery SOC values should be updated at the end of the trip and the shortest route should be selected. For this purpose, Virtual CS (virtual charging station) is introduced in the model that represents the shortest route to reach the destination directly from EV's origin, as shown in Figure 4.2. When VCS is selected, EV e arrives at the destination from its origin without charging or discharging, while it is ensured that the EV's preferences and constraints are satisfied. Hence, G2V and V2G power of a VCS in a mandatory trip are equal to zero for EV e. A VCS is also needed for EV e in an optional trip to correctly model the solution in which neither G2V or V2G services are recommended. The only difference between VCS in optional and mandatory trips is that the driving route of a VCS is zero in the optional trip. Thus, the EV will be idle for that optional trip.

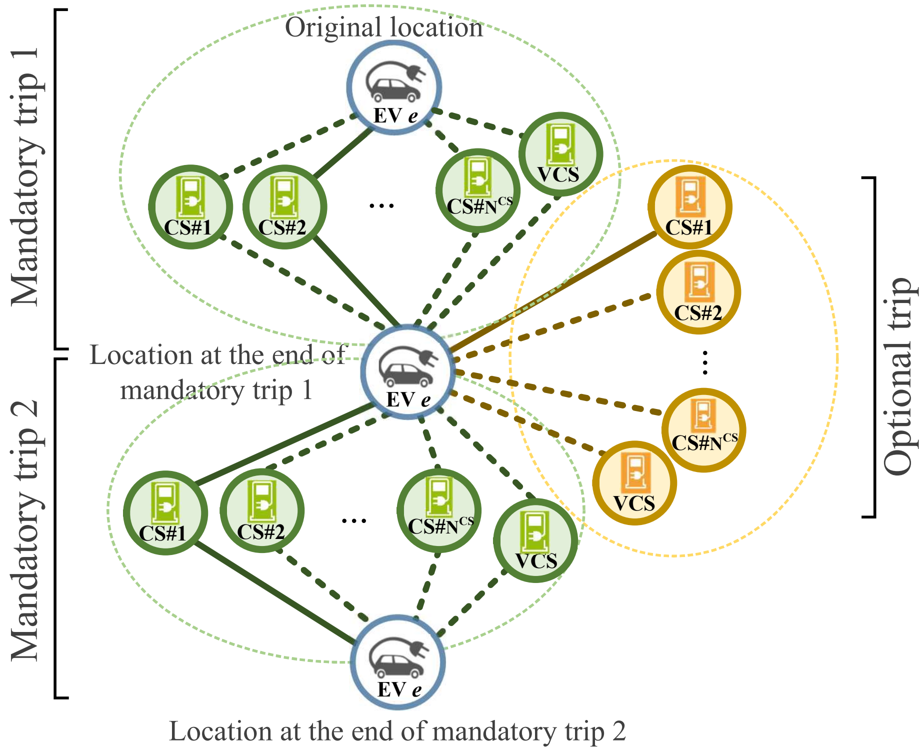

Figure 4.2: A schematic of two mandatory trips and one optional trip for EV e.

4.2.2 EV Drivers Preferences

In this study, two practical aspects of the EV scheduling problem are modeled by defining "driver's cost/revenue threshold" and "driver's route preference" constraints. They represent economically-irrational decisions of the EV drivers, as explained in the following.

Driver's cost/revenue threshold: It is assumed that EV drivers accept an alternative route (instead of the shortest route) only if there is an economic incentive

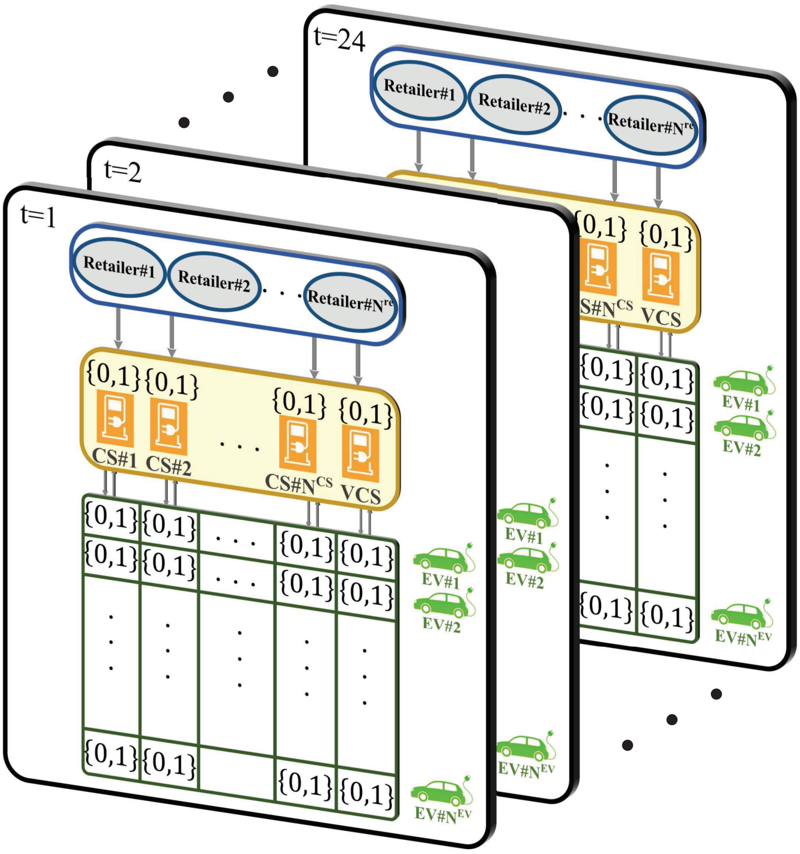

Figure 4.3: The proposed framework for day-ahead G2V and V2G scheduling for all stakeholders.

greater than or equal to the drivers' expectation. When a CS offers a lower price than the nearest CS for G2V service, the EV driver accepts it only if the charging cost reduction is equal to or more than the driver's cost threshold. Otherwise, the EV driver would prefer to charge at the nearest CS although it may be a bit more expensive. The same argument can be made during the V2G services, where a driver chooses a CS with higher V2G prices over the nearest CS only if the increase in revenue is equal to or more than the driver's revenue threshold.

Driver's route preference: In addition to the cost/revenue threshold, an EV driver may accept a CS other than the nearest CS only when the required extra driving distance is equal to or less than "driver's route preference". In other words, the driver's route preference ensures that not only selecting an alternative route makes sense economically to the driver, but also the driver's desire for not being on the road for more than "driver's route preference" is fulfilled in the scheduling process.

Let's see the two preferences in an example. Consider an EV driver whose "cost/revenue threshold" and "route preference" are \$5 and 2 km, respectively. An alternative route will be selected only if the cost-benefit of the alternative route is at least \$5 **AND** the extra driving distance does not go beyond 2 km, both in comparison with the nearest CS.

4.2.3 The Proposed Day-Ahead Scheduling Framework/Solution

The proposed scheduling framework is a non-cooperative Stackelberg game, which is formed among the three layers [1]. The leader of the Stackelberg game is the retailer and the first and second followers are CSs and EVs, respectively. Typically, three- or n-level non-cooperative games are solved using KKT optimality condition or strong duality theorem by replacing the lower level problem with a set of constraints in the upper level problem. In this study, however, the lower level problem is a mixed-integer quadratic program, which doesn't satisfy the KKT optimality condition. Even if there was a differentiable objective function and constraints in the lower level, formulating the complementarity conditions of the lower level in the middle-level problem would result in a non-convex optimisation problem [2, 3]. In this study, an iterative approach is adopted to solve the Stackelberg game, which is common in three-level games in the literature [2, 4]. The solution of this formulation provides a Nash equilibrium, although the uniqueness and existence of Nash equilibrium cannot be guaranteed [2, 3].

As shown in Figure 4.4, the electricity prices, estimated using historical wholesale market prices, are generated by retailers in the first iteration. Then, the prices will be given to the CS layer. In this iteration, the prices will be modified by adding CSs' profit margin. Afterwards, CSs' prices will be passed on to EV layer where the first optimisation problem will be solved in the first iteration. Please note that the prices for V2G services are also estimated by the CS layer in the first iteration. In the EV layer, the decision variables are EVs' power during G2V and V2G operation, and CS selection for each trip (as shown in Figure 4.3). The optimal solutions (i.e., G2V and V2G power of EVs and optimal CSs) for this iteration are sent back to the

CS layer, where its optimisation problem is solved. The optimal solutions in the CS layer are electricity prices for V2G service, power generation of onsite CGU and PV system, power purchased from retailers, charging/discharging power and operation mode of stationary ESS and optimal retailers for each CS. Afterwards, the EV layer problem will be solved with the updated V2G prices and new EV and CS schedules will be obtained. The inner loop (see Fig 4.4) will continue between CS and EV layers until the convergence criterion of the optimisation problems in the CS layer is satisfied for the given retailers' prices. Since the aggregator operation is not modelled in this study, the same V2G prices from the first iteration will be used in the inner loop. Upon convergence of the inner loop in the first iteration (of the outer loop), optimal solutions (i.e., selected retailers and power purchased from each) are passed on to retailer layer. Then, an optimisation problem is solved to identify new electricity prices offered by retailers to CSs according to the reactions of CSs and EVs to original prices. Second iteration of the outer loop starts with the new Retailers' prices (see Fig 4.4). The iterative process will be terminated when the change in the relevant objective functions in the last two iterations for both inner and outer loops is less than or equal to 0.001.

4.3 Mathematical Modeling

4.3.1 Optimisation Problem in the EV Layer

The objective function of EV e is the net cost of EV operation to be minimised. It is the difference between cost of EV e and the revenue from selling electricity to CS i in V2G mode. The cost of EV e comprises electricity purchased from CS i in G2V mode and battery degradation cost (the term inside the bracket of Eq. (4.1)). The battery capacity degradation model is used from [5], which works for any arbitrary battery charging/discharging profile and captures the impact of battery SOC and charge/discharge power levels. As a result, EVs will be scheduled for V2G services only if they can recover the cost of battery degradation and make a profit. During G2V operation, the battery degradation model ensures that EVs won't be charged

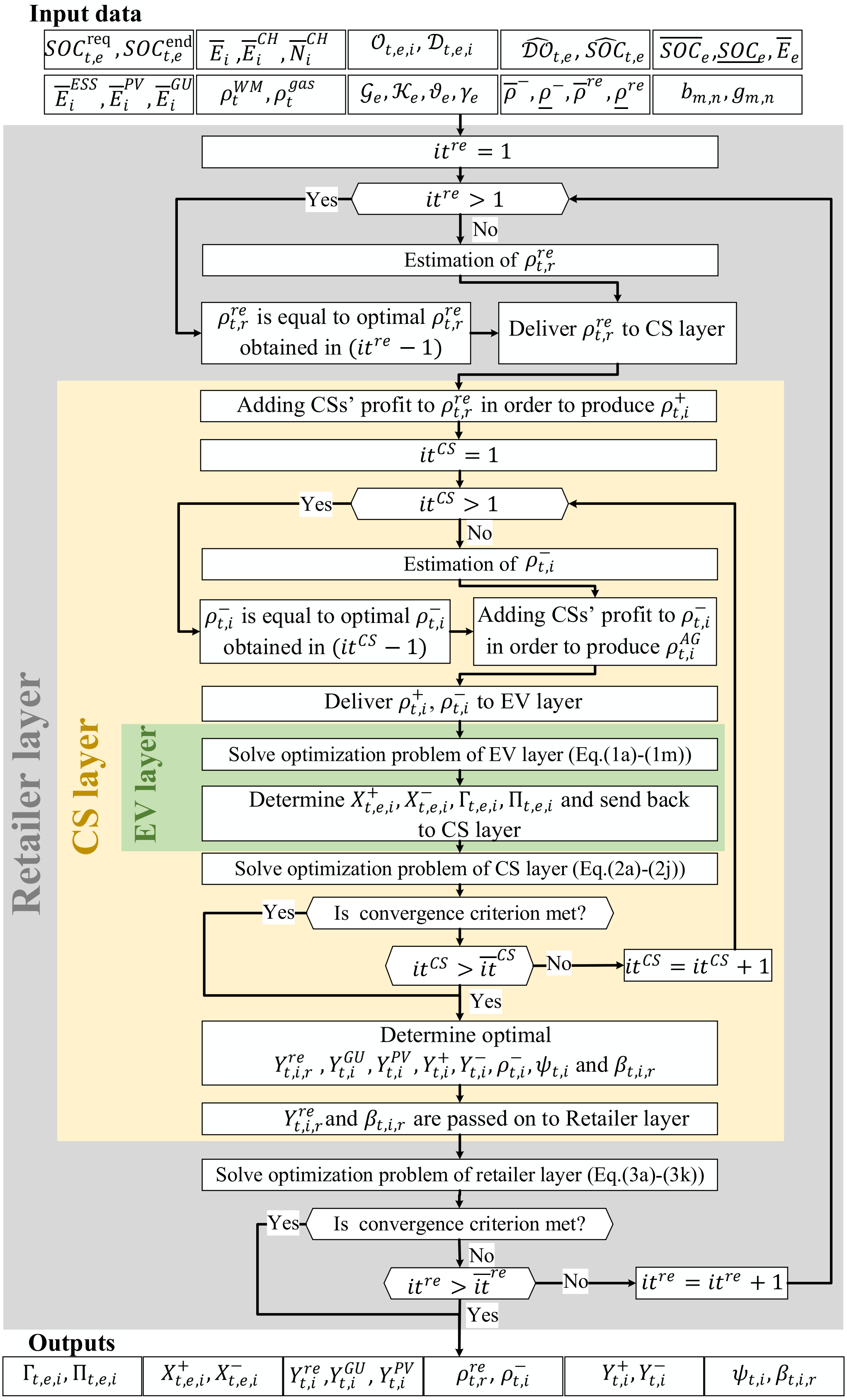

Figure 4.4: Flowchart of the three-layer optimisation problem.

excessively unless the benefits of low G2V prices exceed the extra degradation cost of the battery. Please note that the objective is sum of the objective functions of all EVs in this layer [2].

$$\min_{\substack{X^+_{t,e,i}, X^-_{t,e,i},\\ \Gamma_{t,e,i}, \Pi_{t,e,i}}} \quad \sum_{t=1}^{T}\sum_{e=1}^{E} X^+_{t,e,i}\cdot\rho^+_{t,i} + \Big[b\cdot\big(SOC_{t,e} - a\cdot(\Gamma_{t,e,i}+\Pi_{t,e,i})\big)^2 + c.X^+_{t,e,i} - d.X^-_{t,e,i} + f.X^{-2}_{t,e,i}\Big] - X^-_{t,e,i}.\rho^-_{t,i} \qquad \forall i \in S \tag{4.1a}$$

s.t.

$$SOC_{t,e}{=}SOC_{0e} + \frac{\eta^+_e\cdot\sum_{t=1}^{t} X^+_{t,e,i}.\Delta t}{\overline{E}_e} - \frac{\sum_{t=1}^{t} X^-_{t,e,i}\Delta t}{\eta^-_e\overline{E}_e} - \sum_{t=1}^{t}\frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}.(1-\Gamma_{t,e,i}-\Pi_{t,e,i}) - \frac{(\mathcal{O}_{t,e,i}{+}\mathcal{D}_{t,e,i}).\gamma_e}{\overline{E}_e}(\Gamma_{t,e,i}+\Pi_{t,e,i}) \quad \forall t\in T, \forall e\in E, \forall i\in S \tag{4.1b}$$

$$\underline{SOC}_e \le SOC_{t,e} \le \overline{SOC}_e \quad \forall t\in T, \forall e\in E \tag{4.1c}$$

$$SOC_{T,e} \ge SOC^{\text{end}}_e \quad \forall e\in E \tag{4.1d}$$

$$0 \le X^+_{t,e,i} \le \overline{E}^{\text{CH}}_i.\Gamma_{t,e,i} \quad \forall t\in T, \forall e\in E, \forall i\in S \tag{4.1e}$$

$$0 \le X^-_{t,e,i} \le \overline{E}^{\text{CH}}_i.\Pi_{t,e,i} \quad \forall t\in T, \forall e\in E, \forall i\in S \tag{4.1f}$$

$$\sum_{i=1}^{S}(\Pi_{t,e,i}+\Gamma_{t,e,i}) \le 1 \quad \forall t\in T, \forall e\in E \tag{4.1g}$$

$$\textstyle\sum_{e\in E}(\Gamma_{t,e,i}+\Pi_{t,e,i}) \le \overline{N}^{CH}_i \quad \forall t\in T, \forall i\in S \tag{4.1h}$$

$$\rho^+_{t,i}.X^+_{t,e,i} \le \big(\vartheta_e + \widehat{\rho}^+_{t,e}.\widehat{SOC}_{t,e}.\overline{E}_e\big).\Gamma_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{4.1i}$$

$$\rho^-_{t,i}.X^-_{t,e,i} \ge \big(\mathcal{G}_e + \widehat{\rho}^-_{t,e}.\widehat{SOC}_{t,e}.\overline{E}_e\big).\Pi_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{4.1j}$$

$$\Gamma_{t,e,i}.(\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i}) \le (\widehat{\mathcal{DO}}_{t,e}+\mathcal{K}_e).\Gamma_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{4.1k}$$

$$\Pi_{t,e,i}.(\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i}) \le (\widehat{\mathcal{DO}}_{t,e}+\mathcal{K}_e).\Pi_{t,e,i} \qquad \forall t\in T, \forall e\in E, \forall i\in S \tag{4.1l}$$

$$X^+_{t,e,i}{=}\ 0 \qquad \forall t\in T, \forall e\in E, \forall i = VCS \tag{4.1m}$$

$$X^-_{t,e,i}{=}\ 0 \qquad \forall t\in T, \forall e\in E, \forall i = VCS \tag{4.1n}$$

$$\mathcal{O}_{t,e,i}+\mathcal{D}_{t,e,i}{=}\ \zeta_{t,e}\forall t\in(T-F), \forall e\in E, \forall i = VCS \tag{4.1o}$$

[2] Due to complexity of the proposed problem, cost sharing study in the cooperative game has not been investigated. In the future work, it is recommended to study cost sharing in a cooperative game to determine a proper and stable coalition in which players stay together and cooperate

$$\mathcal{O}_{t,e,i} + \mathcal{D}_{t,e,i} = 0 \quad \forall t \in F, \forall e \in E, \forall i = VCS \tag{4.1p}$$

SOC of EV e after each charge and discharge is calculated by Eq. (4.1b), while Eq. (4.1c) ensures that the SOC level is maintained within a lower and upper bound at all times. The SOC of EV e must be greater than or equal to the desired SOC level specified by the driver at the end of the day, as expressed in Eq. (4.1d). Maximum and minimum charging and discharging capacity of the chargers at CS i are enforced by Eqs. (4.1e) and (4.1f). Sum of the binary variables of CSs must be less or equal to one for EV e in order to select one CS for either G2V or V2G operation at time t, imposed by Eq. (4.1g). Equation (4.1h) ensures that the number of used chargers in a CS during G2V and V2G operation does not exceed the number of existing chargers. Equations (4.1i) and (4.1j) enforce drivers' cost/revenue preferences. Based on Eq. (4.1i), an EV will be assigned an alternative CS from the nearest CS only if the driver's cost reduction is greater than or equal to her/his expected cost reduction. In V2G mode, Eq. (4.1j) guarantees a minimum incentive greater than or equal to drivers' revenue expectation for a CS that is not on the shortest route. Equations (4.1k) and (4.1l) enforce the driver's route preference in G2V and V2G mode, respectively. In this case, an alternative route will be selected only if the extra driving distance (in comparison with the shortest route) is less than or equal to the specified value. Equations (4.1m) and (4.1n) set the VCSs' G2V and V2G power to zero. Based on Eq. (4.1o), the driving route assigned to VCS for the mandatory trip is equal to the shortest route to reach the destination directly from EV's origin. Equation (4.1p) set the driving route distance to zero between the EV and VCS in the optional trips.

4.3.2 Optimisation Problem in CS Layer

The objective function of CS i is the net revenue of the CS. The revenue of CS i comes from selling electricity to EV e and aggregator during G2V and V2G operation, respectively. It is assumed that the electricity purchased from EV e is equal to the electricity sold to the aggregator. The expenses of CS i consists of onsite operational costs [6] and cost of energy purchased from retailer r and EV e during G2V and V2G services, respectively. The overall objective function is the sum of the individual CSs' objective functions [3].

$$\max_{\substack{Y^{re}_{t,i,r},Y^{GU}_{t,i},Y^{\mathrm{PV}}_{t,i}\\ Y^{+}_{t,i},Y^{-}_{t,i},\rho^{-}_{t,i},\\ \beta_{t,i,r},\psi_{t,i}}} \sum_{t=1}^{T}\sum_{i=1}^{S} \sum_{e\in E}(X^{+}_{t,e,i}.\rho^{+}_{t,i}+X^{-}_{t,e,i}.\rho^{\mathrm{AG}}_{t,i}) - \underset{r\in R}{Y^{re}_{t,i,r}.\rho^{re}_{t,r}} - \sum_{e\in E} X^{-}_{t,e,i}.\rho^{-}_{t,i} - \frac{Y^{GU}_{t,i}.\rho^{\mathrm{gas}}_{t}}{\eta^{\mathrm{GU}}_{i}.HV} \tag{4.2a}$$

s.t.

$$Y^{\mathrm{PV}}_{t,i}+Y^{GU}_{t,i}+Y^{re}_{t,i,r}+Y^{-}_{t,i}+\sum_{e\in E}X^{-}_{t,e,i} = \frac{\sum_{e\in E}X^{-}_{t,e,i}}{\eta^{\mathrm{CH}}_{i}}+\frac{\sum_{e\in E}X^{+}_{t,e,i}}{\eta^{\mathrm{CH}}_{i}}+Y^{+}_{t,i} \tag{4.2b}$$

$\forall t\in T, \forall i\in S, r\in R$

$$0\le Y^{GU}_{t,i}\le \overline{E}^{\mathrm{GU}}_{i} \quad \forall t\in T,\forall i\in S \tag{4.2c}$$

$$0\le Y^{PV}_{t,i}\le \overline{E}^{\mathrm{PV}}_{i} \quad \forall t\in T,\forall i\in S \tag{4.2d}$$

$$0\le Y^{re}_{t,i,r}\le \overline{E}_{i}.\beta_{t,i,r} \quad \forall t\in T,\forall i\in S, r\in R \tag{4.2e}$$

$$\sum_{r=1}^{R}\beta_{t,i,r}\le 1 \quad \forall t\in T,\forall i\in S \tag{4.2f}$$

$$0\le Y^{+}_{t,i}\le \overline{E}^{\mathrm{ESS}}_{i}.\psi_{t,i} \quad \forall t\in T,\forall i\in S \tag{4.2g}$$

$$0\le Y^{-}_{t,i}\le \overline{E}^{\mathrm{ESS}}_{i}.(1-\psi_{t,i}) \quad \forall t\in T,\forall i\in S \tag{4.2h}$$

$$\underline{SOC}^{\mathrm{ESS}}_{i}\le \frac{\sum_{t=2}^{t}(Y^{+}_{t,i}-Y^{-}_{t,i}).\Delta t}{\overline{E}^{ESS}_{i}}\le \overline{SOC}^{\mathrm{ESS}}_{i} \quad \forall t\in T,\forall i\in S \tag{4.2i}$$

$$\underline{\rho}^{-}\le \rho^{-}_{t,i}\le \overline{\rho}^{-} \quad \forall t\in T,\forall i\in S \tag{4.2j}$$

During G2V and V2G operation, the power balance between supply and demand at CS i will be maintained at all times by Eq. (4.2b). Therefore, the total power produced by PV system, CGU, stationary ESS during discharging, and power purchased from retailer r and EVs must be equal to the total power demand, including power of stationary ESS in charging mode, power sold to the aggregator and EVs during V2G considering chargers' efficiency. CGU and PV upper and lower capacity limits

[3]Due to complexity of the proposed problem, cost sharing study in the cooperative game has not been investigated. In the future work, it is recommended to study cost sharing in a cooperative game to determine a proper and stable coalition in which players stay together and cooperate

at CS i are enforced in Eqs. (4.2c) and (4.2d), respectively. The power purchased from retailer r is limited by Eq. (4.2e). $\beta_{t,i,r}$ is a binary variable showing if retailer r is selected by CS i. Equation (4.2f) ensures that only one retailer is selected by CS i at time t. Charging and discharging power of the stationary ESS at CS i are enforced by Eqs. (4.2g) and (4.2h). The upper and lower limits of ESS' SOC in CS i at time t are guaranteed by Eq. (4.2i). The electricity prices offered by CS i to EV e for V2G services are confined by Eq. (4.2j).

4.3.3 Optimisation Problem in Retailer Layer

The objective function in this layer is the net revenue of all retailers to be maximised. It includes the difference between revenue obtained by selling electricity to CS i, and the cost of electricity purchased from the wholesale market, as given by [4]:

$$\max_{\rho^{\text{re}}_{t,r}} \quad \sum_{t=1}^{T}\sum_{r=1}^{R}\sum\nolimits_{i\in S} Y^{re}_{t,i,r}.\rho^{\text{re}}_{t,r} - P^{\text{WM}}_{t,r}.\rho^{\text{WM}}_{t} \qquad \forall i \in S \tag{4.3a}$$

s.t.

$$P^{\text{WM}}_{t,r} = \sum\nolimits_{i\in S} Y^{re}_{t,i,r} \tag{4.3b}$$

$$Q^{\text{WM}}_{t,r} = \sum\nolimits_{i\in S} Q^{re}_{t,i,r} \tag{4.3c}$$

$$P_{m,n,t} = g_{m,n}.(1+\Delta\hat{V}_{m,t}).(\Delta V_{m,t} - \Delta V_{n,t}) - b_{m,n}.(\theta_{m,t} - \theta_{n,t}) \quad \forall m,n \in B, \forall t \in T \tag{4.3d}$$

$$Q_{m,n,t} = -b_{m,n}.(1+\Delta\hat{V}_{m,t}).(\Delta V_{m,t} - \Delta V_{n,t}) - g_{m,n}.(\theta_{m,t} - \theta_{n,t}) \quad \forall m,n \in B, \forall t \in T \tag{4.3e}$$

$$V_{m,t} = 1 + \Delta V_{m,t} \quad \forall m \in B, \forall t \in T \tag{4.3f}$$

$$\theta_{m,t} = 0 + \Delta\theta_{m,t} \quad \forall m \in B, \forall t \in T \tag{4.3g}$$

$$\underline{\Delta V}_m \le \Delta V_{m,t} \le \overline{\Delta V}_m \quad \forall m \in B \tag{4.3h}$$

$$\underline{P}_{m,n} \le P_{m,n,t} \le \overline{P}_{m,n} \quad \forall m,n \in B, \forall t \in T \tag{4.3i}$$

[4]Due to complexity of the proposed problem, cost sharing study in the cooperative game has not been investigated. In the future work, it is recommended to study cost sharing in a cooperative game to determine a proper and stable coalition in which players stay together and cooperate

$$\underline{Q}_{m,n} \le Q_{m,n,t} \le \overline{Q}_{m,n} \quad \forall m,n \in B, \forall t \in T \tag{4.3j}$$

$$\underline{\rho}^{\text{re}} \le \rho^{\text{re}}_{t,r} \le \overline{\rho}^{\text{re}} \quad \forall t \in T, \forall r \in R \tag{4.3k}$$

Equations (4.3b) and (4.3c) maintain the balance of active and reactive power at all times. Thus, sum of the electricity purchased from wholesale electricity market through retailer r must be equal to the electricity purchased by CS i from retailer r for active and reactive power at time t. Equations (4.3d) and (4.3e) represent real and reactive power flows in the network based on voltage magnitude and angle deviations [7]. Voltages and angles deviations are obtained by Eqs. (4.3f) and (4.3g). Equation (4.3h) guarantees that bus voltages are within permissible range. Active and reactive power of the line are constrained by Eqs. (4.3i) and (4.3j). The electricity prices offered by retailers are limited by Eq. (4.3k) based on their profit margin.

4.4 Simulation Results

To assess the effectiveness of the proposed model and the impact of new practical constraints and optional trips on the solutions, a comprehensive simulation study is carried out. The first simulation model contains three retailers, nine CSs, and 600 EVs in San Francisco, the USA, and IEEE 37-bus distribution test system. Without loss of generality, all CSs are assumed to have 30 bidirectional fast DC chargers (50kW). Other simulation parameters are:

- A 65 kW CGU for each CS;
- 16kW, 19.2kW, 24kW, 27.2kW, and 32kW of PV systems randomly assigned to CSs;
- Five one-hour ESS with the capacity of 45kW, 50kW, 65kW, 70kW, and 85kW randomly assigned to CSs;
- Four types of EVs with battery capacity of 14.5kWh, 16kWh, 28kWh, and 40kWh are considered; and

Table 4.1: Different simulation scenarios

Scenario	Optional trip?	EV drivers' preferences?
s_1	Yes	Yes
s_2	Yes	No
s_3	No	Yes
s_4	No	No

- The initial SOC of EVs is randomly generated between 10% and 95% with mean value of 28%; and
- The desired SOC of EVs at the end of day specified by the drivers is randomly selected between 70% and 90%.

Without loss of generality, it is assumed that each EV plans two mandatory trips and one optional trip in a typical day. The first mandatory trip of 90% of EVs in the fleet is randomly scheduled between 06:00 to 10:00. The optional trip of 90% of EVs is randomly planned between 11:00 to 15:00. Finally, the second mandatory trip of 90% of EVs is assumed to take place between 16:00 to 20:00. The shortest routes between origin of EV e, location of CS i, and destination of EV e for each trip are determined by ArcGIS® prior to optimisation. Since end-users should pay network maintenance costs, ancillary services costs, taxes, and etc., the day-ahead electricity prices of the wholesale market (California ISO [8]) is multiplied by 4.5 homogeneously to obtain the prices offered to the CS operators by the retailers. The profit margin of the retailers is assumed to be 5-30%, while the CSs profit margin is varied between 10% to 30%. In addition, electricity prices offered for the V2G service is between 60-85% less than prices offered by retailers. The electricity prices sold to the aggregator by CSs is 10% more than what CSs pay for V2G service to the EV owners. Four simulation scenarios are defined, see Table 4.1, to assess the impact of optional trips and EV drivers' preferences on the cost/revenue of all stakeholders, explained in subsections 4.4.1 and 4.4.2. The optimisation problems are solved by Branch-and-Bound method using Gurobi® solver in Python on a laptop with Intel Core i7 CPU with 1.80GHz processor and 8GB RAM. The MIP optimality gap is set to 0.0001 for all optimisation problems.

A larger ecosystem with 1000 EVs, 18 CSs, and three retailers on IEEE 69-bus distribution test system is also simulated, where the simulation parameters and results are explained in Section 4.4.5.

4.4.1 The Impact of Optional Trips

In order to quantify the significance of optional trips on the net cost of EVs and the net revenue of CSs and retailers, s_1 and s_2 can be compared with s_3 with s_4, respectively. Table 4.2 shows the cost/revenue of each stakeholder obtained in each scenario, where the total net cost of EVs decreased from \$1240.5 to \$1153.4 and the total revenue of CSs increased from \$238.0 in s_3 to \$256.4 in s_1. The reduction in retailers' revenue is due to less PV curtailment at CSs (see Figure 4.8) in s_1 and thus less energy purchase from the retailers by the CSs. Also, it can be seen from Table 4.3 that the number of EVs participated in G2V (V2G) increased from 566 (27) in s_3 to 688 (32) in s_1, and from 556 (297) in s_4 to 739 (327) in s_2.

The impact of optional trips on the congestion can be seen in Figure 4.5, where more EVs are scheduled to charge in the middle of the day rather than early morning. A similar pattern has been observed by comparing scenarios s_1 and s_3. It shows that the consideration of optional trips can eliminate/reduce G2V congestion during the hours of mandatory trips, which consequently affect power system operation as a whole by avoiding new peaks and voltage issues, although its impact on V2G is negligible. The optimal hourly averaged electricity prices offered by retailers and CSs during V2G and G2V operation for scenario s_1 are shown in Figure 4.6. Since unique prices will be obtained for each stakeholder in this framework, only stakeholders with non-zero prices in an hour are considered in the hourly average calculation. Zero price in an hour shows that no G2V or V2G activity was scheduled in that hour. The prices in Figure 4.6 are aligned with the G2V and V2G operation in Figure 4.5. Note that the higher G2V prices of CSs from 18:00 to 21:00 is consistent with high V2G prices of CSs and zero prices of retailers to encourage services to the grid by EVs.

The number of EVs who selected VCS during V2G and G2V operation in the mandatory and optional trips is shown in Figure 4.7 in s_1. EVs selected VCS 347 times during optional trips, which means that they didn't participate in either G2V or V2G program in those hours. Also, EVs are not scheduled for G2V or V2G 766 times during mandatory trips (176 EV in the first mandatory and 590 in the second

Table 4.2: Total daily net cost and revenue of the stakeholders with MIP optimality gap

Scenario	Total net cost of EVs [$] (relative MIP gap)	Total net revenue of CSs [$] (relative MIP gap)	Total net revenue of retailers [$] (relative MIP gap)
s_1	1153.4 (0.0097%)	256.4 (0%)	958.1 (0%)
s_2	1000.1 (0.002%)	418.9 (0%)	1333.9 (0%)
s_3	1240.5 (0%)	238.0 (0%)	1040.5 (0%)
s_4	1118.8 (0.0044%)	389.4 (0%)	1382.6 (0%)

Table 4.3: Total number of charged and discharged EVs

Scenario	Total # of EVs		# of EVs charged (*discharged*)	
	Charged	Discharged	Mandatory trips	Optional trip
s_1	688	32	434 (*30*)	254 (*2*)
s_2	739	327	448 (*320*)	291 (*7*)
s_3	566	27	566 (*27*)	–
s_4	556	297	556 (*297*)	–

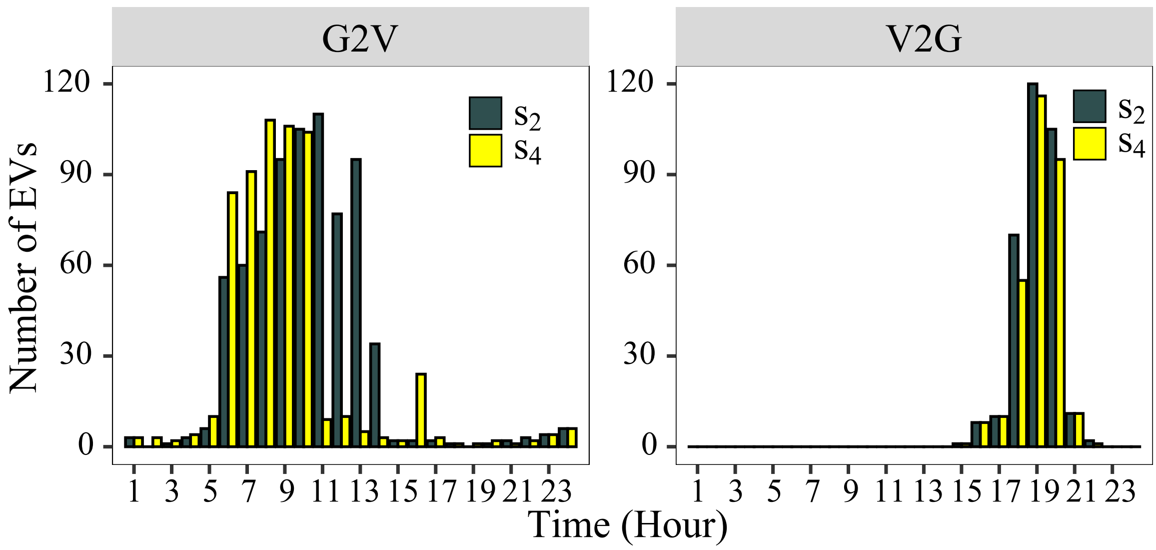

Figure 4.5: Number of EVs charged and discharged under s_2 and s_4.

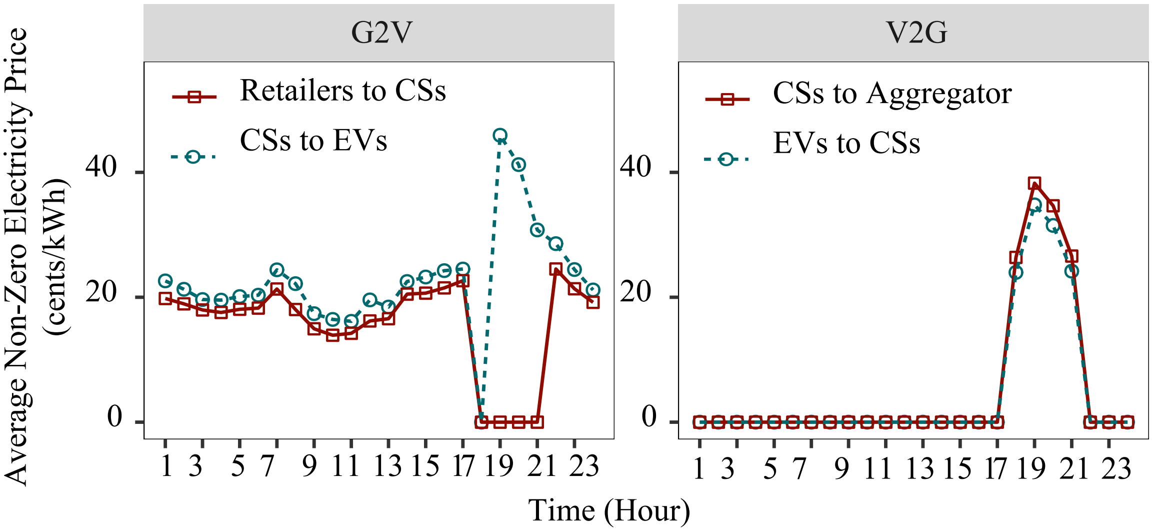

Figure 4.6: Optimal hourly average electricity prices of the stakeholders in s_1

mandatory trip) in a day of simulation. In the remaining 687 times, EVs have been scheduled for either G2V or V2G operation.

The impact of optional trips on the total PV curtailment is shown in Figure 4.8 for CS#1, CS#2, and CS#6, where considering optional trips led to significant reduction (49.8%, 16.3%, and 13%, respectively,) in PV curtailment. In other CSs, no PV generation was curtailed in the four scenarios.

4.4.2 The Impact of EV Drivers' Travel Preferences

In this subsection, the impact of drivers' cost/revenue and extra driving distance preferences are investigated. The simulation results in Table 4.2 show that when the constraints in Eqs. (4.1i), (4.1j), (4.1k), and (4.1l) are enforced, the total net cost of EVs increased from \$1000.1 in s_2 to \$1153.4 in s_1. Also, the total net revenue of CSs and retailers decreased from \$418.9 and \$1333.9 in s_2 to \$256.4 and \$958.1 in s_1, respectively. Also, Figure 4.9 shows that significantly fewer EVs participated in the V2G program due to drivers' preferences. In particular, the number of EVs participated in V2G increased from 32 in s_1 to 327 in s_2, and from 27 in s_3 to 297 in s_4. Therefore, eliminating these preferences leads to significant overestimation of the G2V and V2G services and revenue of retailers and CS, and underestimation of EV's costs.

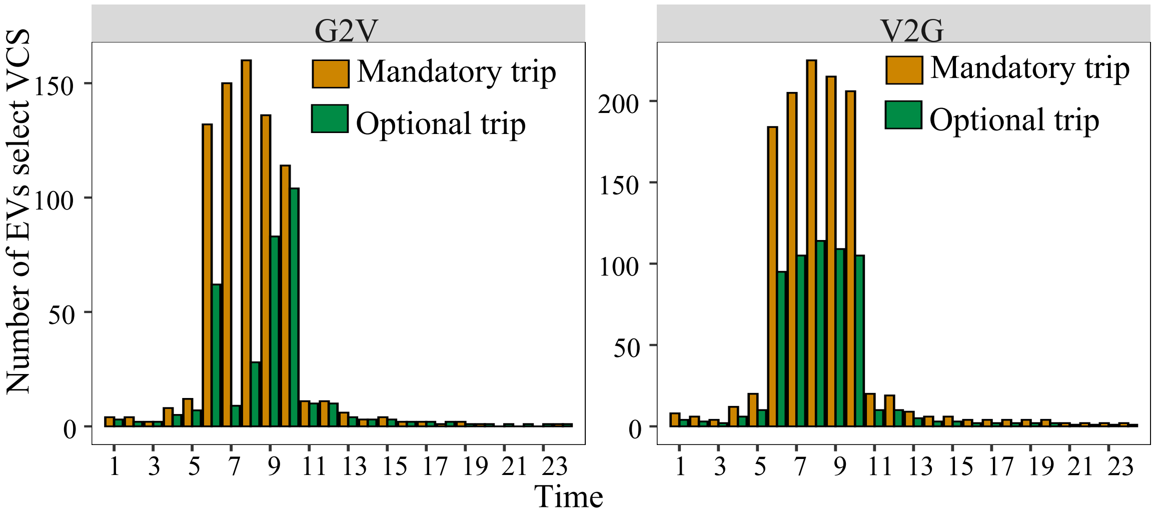

Figure 4.7: Number of EVs selected VCS during V2G and G2V operation in s_1.

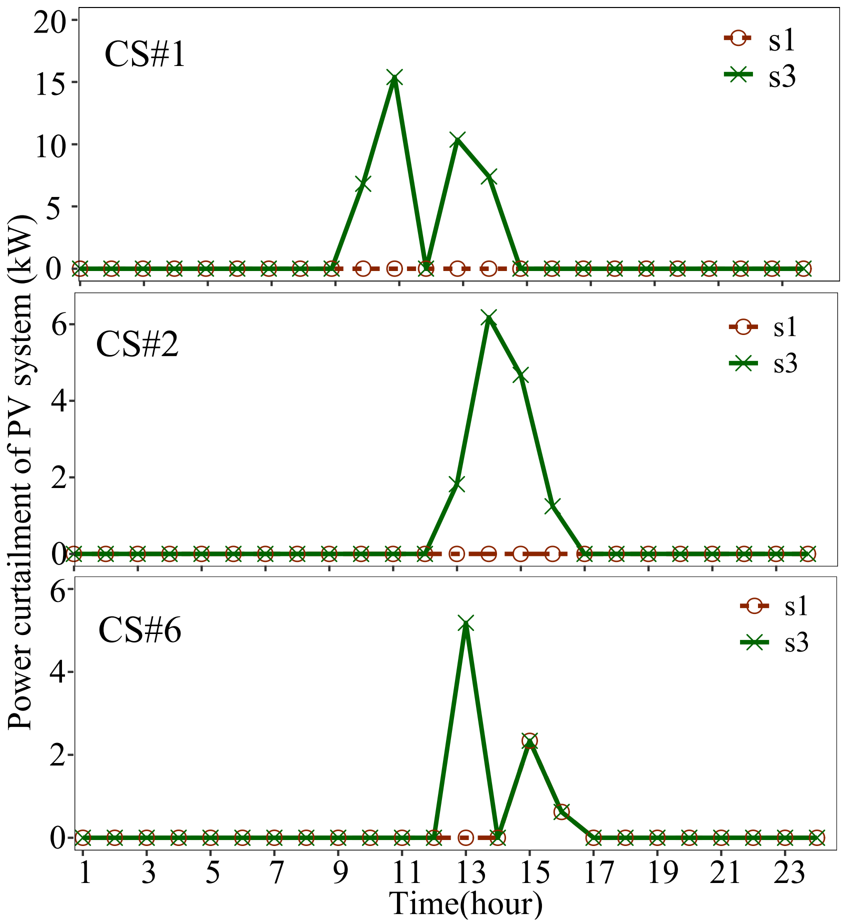

Figure 4.8: CS#1, CS#2, and CS#6 PV curtailment in scenario s_1 and s_3.

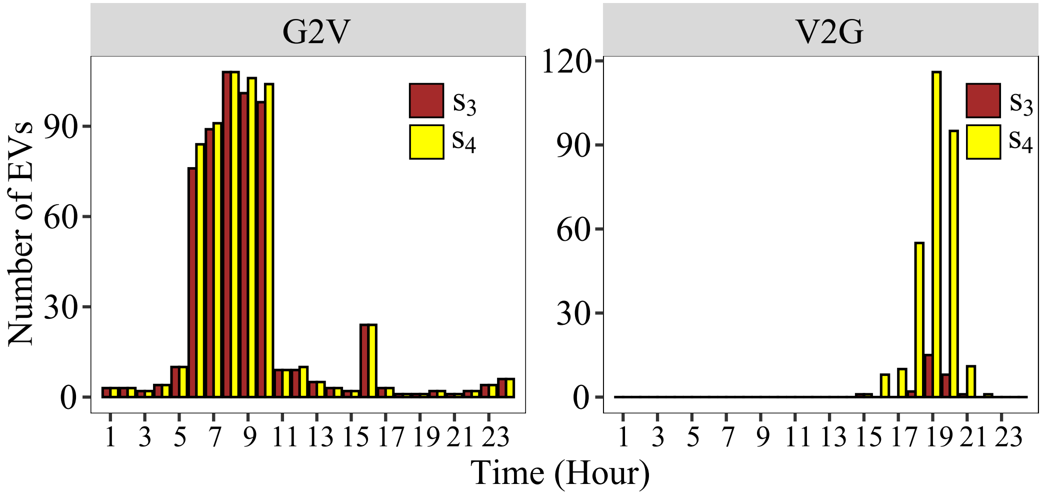

Figure 4.9: Number of EVs in G2V and V2G operation in s_3 and s_4.

Table 4.4: Total daily net cost and revenue of the stakeholders after eliminating V2G service

Scenario	Total net cost of EVs [$]	Total net revenue of CSs [$]	Total net revenue of retailers [$]
s_1	1166.1 (0%)	245.8 (0%)	941.3 (0%)
s_2	1154.7 (0.007%)	242 (0%)	933.7 (0%)
s_3	1250 (0%)	235.1 (0%)	1037.4 (0%)
s_4	1249 (0%)	234.1 (0%)	1037.7 (0%)

4.4.3 The Impact of V2G Services

To show the impact of V2G services, the iterative three-layer optimisation problems is solved in all scenarios by eliminating V2G services from the framework. A comparison between Table 4.2 and Table 4.4 reveals 6.8% increase in the total net cost of EVs on average, and 26.5% and 16.2% decrease in the total net revenue of CSs and retailers on average, respectively, in the absence of V2G services. It depicted the sheer magnitude of V2G impact on the financial interests of all stakeholders in the ecosystem.

Table 4.5: Total net cost and revenue of all stakeholders in s_1

Cost/Revenue	Case I	Case II
Total net cost of EVs ($)	1153.4	1172.4
Total net revenue of CSs ($)	256.4	198.7
Total net revenue of retailers ($)	958.1	920.3

4.4.4 The Impact of Three-Layer Iterative Optimisation

Table 4.5 shows a comparison between cost/revenue of three stakeholders for two different cases as defined below:

- Case I: This the case in which the proposed three-layer optimisation problem is solved iteratively to find equilibrium based on the flowchart in Figure 4.4.
- Case II: The optimisation problems in the three layers are solved individually, not iteratively. Thus, G2V and V2G prices are not updated and the impact of G2V prices offered by retailers and V2G prices offered by CSs are not considered.

Similar optional trips and EV drivers' preferences are considered in both cases. It can be observed in Table 4.5 that the total net cost of EVs in Case II increased by 1.65% and the total net revenue of CSs and retailers decreased by 22.5% and 3.95%, respectively, compared to Case I. It should be mentioned that when the optimisation problems in the three layers are solved individually, fewer EVs participated in G2V and the V2G program, which led to significant decrease in the total net revenue of CSs.

The optimisation algorithms convergence for the three layers is shown in Figure 4.10 in scenario s_1, where optimal results are obtained after 18 iterations of the outer loop in 37 minutes.

4.4.5 Scalability and Convergence of the Proposed Solution

In this section, a larger e-mobility ecosystem with 1000 EVs, 18 CSs, three retailers on the IEEE 69-bus distribution test system is designed to show the scalability of the proposed solution. In this simulation study, the first mandatory trip of 88.5% of EVs in the fleet is randomly scheduled between 06:00 to 10:00. The optional trip of 85%

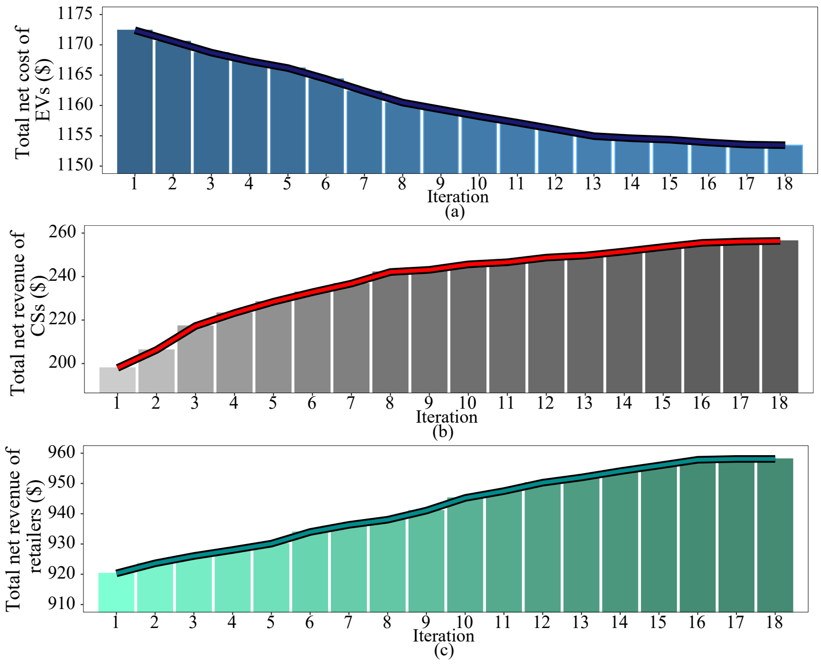

Figure 4.10: (a) EV layer, (b) CS layer, and (c) retailer layer objective function values at different iterations

of EVs is randomly planned between 11:00 to 15:00. Finally, the second mandatory trip of 76.8% of EVs is assumed to take place between 16:00 to 20:00. Simulation parameters of CSs and EVs are identical to the first simulation study with 600 EVs. The optimal results are obtained after only 19 iterations of the outer loop in 113 minutes on average. The total net cost of EVs and total net revenue of CSs and retailers for all scenarios are given in Table 4.6. It shows that the proposed solution can manage to solve scheduling problem of a larger ecosystem in a reasonable time. The trends in the cost and revenue changes of the stakeholders from one scenario to another are similar to those observed in the smaller ecosystem in Section 4.4.1.

Furthermore, a sensitivity analysis is performed for 10 cases with different simulation parameters to demonstrate the convergence of the proposed iterative algorithm. The simulation parameters (# of EVs and CSs and trips planning) are presented in Table 4.7. The total net cost of EVs and total net revenue of CSs and retailers as well as the corresponding relative MIP Gap are reported in Table 4.7 for s_1. In Figure 4.11, the convergence rates for total net cost of EVs and optimal total net revenue of CSs and retailers are illustrated. The average computation time for c_1-c_6 and c_7-c_{10} was 39 and 115 minutes, respectively. It can be seen that the proposed

Table 4.6: Total daily net cost and revenue of the stakeholders for larger e-mobility ecosystem

Scenario	Total net cost of EVs [$] (relative MIP gap)	Total net revenue of CSs [$] (relative MIP gap)	Total net revenue of retailers [$] (relative MIP gap)
s_1	1653.2 (0%)	400.8 (0.0015%)	1422.61 (0%)
s_2	1413.3 (0.0083%)	649.3 (0%)	1960.8 (0%)
s_3	2050.1 (0.0096%)	375.5 (0.0016%)	1545.5(0%)
s_4	1986.7 (0.0041%)	417.2 (0%)	1612.1 (0%)

solution solved all cases in a reasonable time with a near-zero relative MIP gap.

4.5 Conclusion

In this chapter, a comprehensive day-ahead scheduling framework is proposed for the future e-mobility ecosystem including EVs, CSs, and retailers by considering both G2V and V2G operation. Two kinds of trips, namely mandatory and optional trips, as well as EV drivers' preferences are formulated to enhance practical aspects of the proposed algorithm. The proposed tool finds the best CS for EV's G2V and V2G operation and the best retailers for CSs to purchase electricity. Also, electricity prices offered by CSs for G2V and V2G services and optimal charging and discharging scheduling of EVs are determined considering the impacts of prices offered by retailers through a three layer optimisation problem. An iterative solution is proposed to solve the three-level Stackelberg game. Simulation results confirm the value of optional trips to reduce total cost of EVs and congestion at CSs during early morning peak. Furthermore, the proposed scheduling system helped to reduce the cost of EVs and to increase the revenue of CSs and retailers. The drivers' preferences are proven to have an immense impact on the solutions and financial benefits of the stakeholders. In the next chapter, different sources of uncertainties are modeled, e.g., EV drivers and PV generation, and solve a stochastic optimisation.

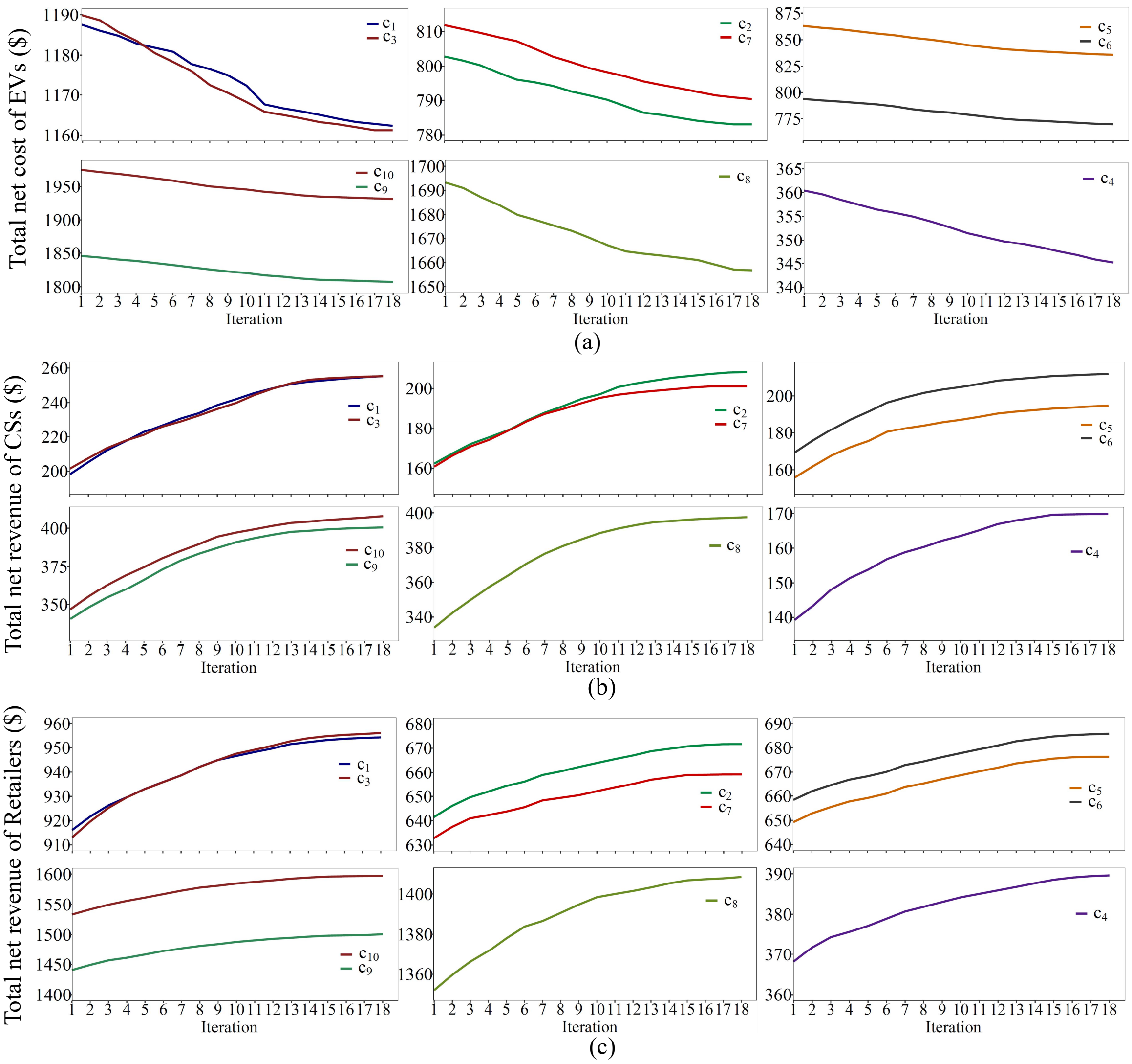

Figure 4.11: Objective function values of (a) EV layer, (b) CS layer, and (c) retailer layer for cases c_1 to c_{10}

Table 4.7: Simulation parameters and the total daily net cost and revenue of the stakeholders for cases c_1 to c_{10}

Cas	Total # of		% of EVs		Distribution network	Initial SOC (Mean value)	Total net cost of EVs [$] (relative MIP gap)	Total net revenue of CSs [$] (relative MIP gap)	Total net revenue of retailers [$] (relative MIP gap)
	EVs	CSs	Option Trip (11:00-15:00)	Second Manda-tory Trip (16:00-20:00)					
c_1	600	9	90%	70%	37-bus system	10-95% (28%)	1162.3 (0%)	255.3 (0%)	954.3 (0%)
c_2	600	9	65%	80%	37-bus system	25-95% (38%)	783.0 (0.0072%)	208.1 (0%)	671.7 (0%)
c_3	600	9	94%	80%	37-bus system	10-95% (28%)	1161.2 (0%)	255 (0%)	956.1 (0%)
c_4	600	9	90%	70%	37-bus system	15-100% (56%)	345 (0%)	169.8 (0%)	389.6 (0%)
c_5	600	9	94%	60%	37-bus system	15-86% (36%)	835.8 (0.0078%)	194.8 (0.0089%)	676.3 (0%)
c_6	600	9	70%	90%	37-bus system	10-74% (37%)	769.3 (0%)	211.6 (0%)	685.8 (0%)
c_7	600	9	60%	60%	37-bus system	25-95% (38%)	789.9 (0%)	201 (0%)	659.2 (0%)
c_8	1000	18	75%	65%	69-bus system	10-100% (33%)	1655.5 (0.009%)	397.5 (0.0015%)	1408.4 (0%)
c_9	1000	18	65%	55%	69-bus system	10-80% (30%)	1806.2 (0.0082%)	400.5 (0%)	1500.6 (0%)
c_{10}	1000	18	55%	45%	69-bus system	10-70% (27%)	1930.4 (0.0077%)	407.9 0.0056%	1597.1 (0%)

References

[1] W. F. Bialas and M. N. Chew, "Coalition formation in n-person stackelberg games," in *1982 21st IEEE Conference on Decision and Control*, 1982, pp. 669–672.

[2] A. Vafamehr, M. E. Khodayar, and K. Abdelghany, "Oligopolistic competition among cloud providers in electricity and data networks," *IEEE Transactions on Smart Grid*, vol. 10, number=2, pages=1801-1812, year=2017, publisher=IEEE.

[3] D. Pozo, E. E. Sauma, and J. Contreras, "A three-level static MILP model for generation and transmission expansion planning," *IEEE Transactions on Power systems*, vol. 28, no. 1, pp. 202–210, 2012.

[4] Z. Feng, G. Ren, J. Chen, X. Zhang, Y. Luo, M. Wang, and Y. Xu, "Power control in relay-assisted anti-jamming systems: A bayesian three-layer stackelberg game approach," *IEEE Access*, vol. 7, pp. 14 623–14 636, 2019.

[5] P. Fortenbacher, J. L. Mathieu, and G. Andersson, "Modeling, identification, and optimal control of batteries for power system applications," in *2014 Power Systems Computation Conference*. IEEE, 2014, pp. 1–7.

[6] S.G.Tichi, M.M.Ardehali, and M.E.Nazari, "Examination of energy price policies in Iran for optimal configuration of CHP and CCHP systems based on particle swarm optimization algorithm," *Energy Policy*, vol. 38, pp. 6240–6250, Oct 2010.

[7] M. Alturki, A. Khodaei, A. Paaso, and S. Bahramirad, "Optimization-based distribution grid hosting capacity calculations," *Applied Energy*, vol. 219, pp. 350–360, 2018.

[8] "California ISO, available at: http://www.oasis.caiso.com," 2019.

5 Three-Layer Joint Distributionally Robust Chance-Constrained Framework for Optimal Day-Ahead Scheduling of E-mobility Ecosystem

Nomenclature

Indices	
e,i,r	Index for EVs, CSs, and retailers, respectively
m, n	Index of buses of distribution network
t	Index for hours
Parameters	
Δt	Time step (s)
$\epsilon_{th}^{\text{EV}}/\epsilon_{th}^{\text{CS}}/\epsilon_{th}^{\text{re}}$	Theoretical risk parameter in each layer
η_i^{GU}/η_i^{CH}	Efficiency of CGU/chargers at CS i (p.u.)
η_e^{+}/η_e^{-}	Efficiency of EV e's battery in G2V/V2G mode (p.u.)
γ_e	Power consumed by EV e per km (kWh/km)
$\mathbb{P}$	Probability distribution
$\mathcal{D}_{t,e,i}$	Shortest driving distance between CS i and destination of EV e at time t, (km)

$\mathcal{O}_{t,e,i}$	Shortest driving distance between origin of EV e and CS i at time t (km)
$\overline{\alpha}/\underline{\alpha}$	Profit margin of the retailer
$\overline{\rho}^{-}/\underline{\rho}^{-}$	Maximum/Minimum electricity prices offered by CSs for V2G service ($\$/kWh$)
$\overline{\rho}^{re}/\underline{\rho}^{re}$	Maximum/Minimum electricity prices offered by retailers to CSs ($\$/kWh$)
$\overline{E}_i^{\mathrm{GU}}/\overline{E}_i^{\mathrm{PV}}$	Capacity of CGU/PV system at CS i (kW)
$\overline{E}_i^{\mathrm{ESS}}$	Capacity of ESS at CS i (kW)
$\overline{E}_e$	Capacity of EV e's battery (kWh)
$\overline{E}_i$	Capacity of CS i (kW)
$\overline{E}_i^{\mathrm{CH}}$	Capacity of chargers at CS i (kW)
$\overline{N}_i^{CH}$	Maximum number of chargers in CS i
$\overline{P}_{m,n,t}/\underline{P}_{m,n,t}$	Maximum/Minimum active power flow between bus m and n (kW)
$\overline{Q}_{m,n,t}/\underline{Q}_{m,n,t}$	Maximum/Minimum reactive power flow between bus m and n (kVar)
$\overline{r}_i^{\mathrm{PV}}/\underline{r}_i^{\mathrm{PV}}$	Maximum/Minimum ramping rates of PV generation
$\overline{SOC}_e/\underline{SOC}_e$	Maximum/Minimum SOC of EV e (p.u.)
$\overline{SOC}_i^{ESS}/\underline{SOC}_i^{ESS}$	Maximum/Minimum SOC of ESS at CS i (p.u.)
ρ_t^{gas}	Natural gas price at time t ($\$/m^3$)
Σ_e	Covariance of initial SOC of EV e
$\Sigma_{t,i}^{\mathrm{PV}}$	Covariance of PV generation in CS i at time t
τ_t	Covariance of wholesale electricity market prices at time t
$\underline{\Delta V}/\overline{\Delta V}$	Lower/Upper limit of voltage deviation at bus m
ϑ_e	EV e's driver preference for minimum cost reduction in G2V operation ($)
$\widehat{X}^{+}_{t,e,i}/\widehat{X}^{-}_{t,e,i}$	Charging/discharging power of EV e in the nearest CS at time t
$\widehat{\mathcal{DO}}_{t,e}$	Driving distance of EV e to closest CS at time t (km)

$\mathcal{O}_{t,e,i}$ Shortest driving distance between origin of EV e and CS i at time t (km)

$\widetilde{\rho}_t^{\mathrm{WM}}$	Mean wholesale electricity market price at time t (\$/kWh)
$\widetilde{SOC}_{0_e}$	Mean of initial SOC of EV e
$\Xi^{EV}/\Xi^{CS}/\Xi^{re}$	Ambiguity set in EV/CS/retailer layer
$\zeta_{t,e}$	Shortest driving route to reach the destination directly from origin of EV e at time t without stopping at any CS (km)
a	SOC target
b, c, d, f	Cost of battery degradation parameters
$b_{m,n}/g_{m,n}$	Susceptance/conductance of transmission line between bus m and n
HV	Heat value of fuel on the operation of gas turbine-generator (kWh/m^3)
it^{CS}/it^{re}	Number of iterations in CS/retailer layer
SOC_e^{end}	SOC of EV e at the end of the day (p.u.)
VCS	Virtual charging station
Sets	
B, E, R, S, T, F_1, F_2	Sets of Nodes, EVs, retailers, CSs, hours, first optional trip time, and second optional trip time, respectively
Variables	
$\beta_{t,i,r}$	Binary variable for retailer r by CS i at time t
$\Delta\theta_{m,t}$	Voltage angle deviation on bus m at time t
$\Delta V_{m,t}$	Voltage magnitude deviation on bus m at time t
$\Delta\hat{V}_{m,t}$	Voltage magnitude deviation obtained from the lossless power flow solution on bus m at time t
$\Gamma_{t,e,i}/\Pi_{t,e,i}$	Binary variable for CS i for charging/discharging EV e at time t
$\kappa_{t,r}$	A random variable with zero mean and covariance matrix τ_t for retailer r at time t
ω_e	A random variable with zero mean and covariance matrix Σ_e for EV e
$\psi_{t,i}$	Binary variable for charging/discharging ESS at CS i
$\rho_{t,i}^{AG}$	Electricity price sold to the aggregator by CS i at time t (\$/kWh)

$\rho^{+}_{t,i}/\rho^{-}_{t,i}$	Electricity price offered by CS i at time t for charging/discharging EVs (\$/kWh)
$\theta_{m,t}$	Voltage angle of bus m and time t
$\theta_{m,t}$	Voltage angle of bus m and time t
$\widehat{\rho}^{+}_{t,e}/\widehat{\rho}^{-}_{t,e}$	Electricity price offered by the closest CS to EV e at time t in G2V/V2G mode (\$/kWh)
$\widetilde{Y}^{\mathrm{PV}}_{t,i}$	Mean local PV generation of CS i at time t (kW)
$\xi_{t,i}$	A random variable with zero mean and covariance matrix $\Sigma^{PV}_{t,i}$ for CS i at time t
$A_{t,e,i}$	Sum of charging and discharging power of EV e in CS i at time t
$P_{m,n,t}/Q_{m,n,t}$	Active/Reactive power flow between bus m and n at time t (kW/kVar)
$P^{\mathrm{WM}}_{t,r}/Q^{WM}_{t,r}$	Active/Reactive power purchased/provided from/by the wholesale market by retailer r at time t (kW/kVar)
$SOC_{t,e}$	SOC of EV e at time t (p.u.)
$V_{m,t}$	Voltage magnitude of bus m and time t
$X^{+}_{t,e,i}/X^{-}_{t,e,i}$	Charging/Discharging power of EV e at CS i at time t (kW)
$Y^{+}_{t,i}/Y^{-}_{t,i}$	Charging/Discharging power of ESS of CS i at time t (kW)
$Y^{GU}_{t,i}$	Power produced by CGU/PV system of CS i at time t (kW)
$Y^{re}_{t,i,r}/Q^{re}_{t,i,r}$	Active/Reactive power purchased/provided from/by retailer r by CS i at time t (kW/kVar)
$\rho^{re}_{t,r}$	Electricity price sold to CSs by retailer r at time t (\$/kWh)

5.1 Introduction

In this chapter, a three-layer joint DRCC framework is proposed to schedule V2G and G2V operation in the day ahead for an e-mobility ecosystem including EVs, CSs, and retailers in an uncertain environment with unknown probability distributions. In order to investigate an uncertain e-mobility ecosystem, the interactions between stochastic nature of the three stakeholders are considered in the proposed model. In fact a family of probability distributions with the same mean and covariance matrix is defined, called a moment-based ambiguity set, to solve a stochastic program without relying on a specific distribution function. Furthermore, an exact second-order cone programming reformulation of joint DRCC day-ahead scheduling framework is developed to ensure that violation of both upper and lower limits of a constraint remains small for the worst-case probability under the ambiguity set. Moreover, the temporal correlation of the PV system generation in each time interval is applied in the joint DRCC model. The temporal correlation is considered between PV power generation at t and $t-1$.

Based on the comprehensive literature review presented in Chapter. 2, four gaps in knowledge concerning EV scheduling in an e-mobility ecosystem are identified (G6, G7, G8, and G9). In this chapter the proposed framework has been dealt with the gaps.

The rest of this chapter is structured as follows: Section 5.2 presents problem definition and describes the stochastic G2V and V2G framework including the three stakeholders, followed by the proposed three-layer joint DRCC formulation in Section 5.3. In Section 5.4, an ecosystem based on 600 EVs, nine CSs, and three retailers is devised for simulation study and the results are discussed. The conclusion remarks are expressed in Section 5.5. In addition reformulation of the single-sided and double-sided CCs in EV, CS, and retailer layers is explained and demonstrated in Appendix of this paper.

5.2 Problem Definition

This chapter offers a three-layer joint DRCC scheduling framework in the day ahead, where the DRCC model of each stakeholder is developed in each layer. In particular the uncertainty of each player is modelled by means of an ambiguity set, which consists of a family of probability distributions of each uncertain parameter with the first- and second-order moments, i.e, mean and covariance of available historical data. In this proposed ecosystem, R number of retailers is considered, indexed by $r \in \{1, 2, ..., R\}$. Retailers sell electricity to CSs from the wholesale electricity market. Therefore, the wholesale electricity price at time t is the major source of uncertainty in this layer. Further, there are S number of CSs in the ecosystem, indexed by $i \in \{1, 2, ..., S\}$, physically located in the scheduling area. They operate at the distribution network level and provide V2G and G2V services to EVs. Without losing the generality, it is assumed that each CS possesses small gas turbine/diesel generator as a CGU, PV, and ESS to supply electricity to EVs during G2V operation. In addition, the CSs purchase electricity from EVs and sell it to the wholesale electricity market through aggregators. PV generation is the main source of uncertainty in the CS layer. During a typical day, it is assumed that EVs can have multiple mandatory trips and optional trips, which are explained in detail in Chapter 4. In this study, EVs have two mandatory trips, which must be fulfilled at any cost. However, as opposed to mandatory trips, an optional trip is selected if it offers a possibility for EV drivers to benefit from cheap G2V or expensive V2G services outside of the mandatory trip hours. Each EV driver may select only one or two optional trips during a day to reduce its cost. In addition, EVs with a known location and initial SOC, which is the source of uncertainty in EV layer, seek G2V and V2G plans for the combined mandatory and optional trips, such that it minimises their overall cost while fulfilling their preferences. A day before the scheduling day, EV drivers send their trip plans to the scheduling centre. Then, the scheduling problem is solved for the entire day ahead. The driving routes between CS i and origin of EV e in each trip are known and only one of CSs might be selected for EV e. Thus, two binary variables are assigned to each CS for G2V and V2G operation of the EV e at each time interval. The VCS is considered when the most economic decision for EV e is not to be charged nor discharged in a trip. Thus by selecting a VCS, EV e reaches to the destination from its origin without charging or discharging, while the EV's preferences and constraints are satisfied. Therefore, in a mandatory trip, charging and discharging power of a VCS are equal to zero for EV e. The only difference between mandatory and optional trips is that, the driving route of a VCS is considered zero for the optional trips. Please see Chapter 4 for further details on this modelling approach.

5.3 Modeling Framework

In this section, the day-ahead joint DRCC V2G and G2V scheduling framework, which includes several uncertain and deterministic constraints, is presented for each layer based on the deterministic model developed in Chapter 4. A general formulation is expressed in Eq. 5.1, which finds minimisers x to $f : \mathbb{R}^n \longrightarrow \mathbb{R}$ as the objective function of a CC program subject to a set of deterministic constraints (D) and stochastic constraints $(H(x, \lambda) \leq 0, H : \mathbb{R}^n \times \Lambda \longrightarrow \mathbb{R}^m)$. H satisfies any probability distribution $(\mathbb{P})$ from the ambiguity set (Ξ) at a given confidence level $(1 - \epsilon) \in (0, 1)$.

$$c^* = min\left\{ f(x) : x \in D, \inf_{\mathbb{P} \in \Xi} \mathbb{P}\Big[\lambda \in \Lambda : \{ H(x, \lambda) \leq 0 \} \Big] \geq 1 - \epsilon \right\}. \tag{5.1}$$

In the joint DRCC, the uncertain parameter is modeled by $\mu + \omega$, where μ is the first-order mean of the uncertain parameter and ω is a random variable with zero mean and covariance matrix Σ. The ambiguity set is defined by

$$\Xi = \left\{ \mathbb{P} \in \Xi(\mathbb{R}^v) : \mathbb{E}_{\mathbb{P}}[\omega], E_{\mathbb{P}}[\omega \omega^T] = \Sigma \right\}. \tag{5.2}$$

The DRCC models for EV, CS, and retailer layers are presented in Section 5.3.1, 5.3.2, and 5.3.3, respectively. The exact reformulation of the single-sided and double-sided CCs are defined by in Theorem 1 and Theorem 2 in [1]. The reformulation of the problem are described in Appendix.

The proposed three-layer scheduling framework is solved by an iterative approach shown in Fig. 5.1. Particularly the retailers estimate wholesale electricity prices by historical data in the first iteration. The prices are passed on to the CS layer. In this iteration, the prices are only inflated to consider the CSs' profit margin. Then, the CSs' will determine their prices accordingly and pass them on to the EV layer, where the first DRCC problem will be solved in the first iteration. In addition, the V2G prices are estimated by the CS layer in the first iteration. In the EV layer, under the uncertainty of the EV's initial SOC, the decision variables including EVs' charging and discharging power and CS selection for each trip will be determined by solving the joint DRCC problem. The inner loop, which is between CS and EV layers, will continue until the convergence criterion of the DRCC problem in the CS layer under PV generation uncertainty is satisfied. Afterwards, the selected retailers and the amount of purchased power from each retailer will be communicated back to the retailer layer. Then, the DRCC problem in the retailer layer is solved considering the uncertainty of the wholesale electricity prices. Further, in retailer layer, new electricity prices offered by retailers to CSs will be determined according to the reactions from the CSs and EVs to the original prices. Second iteration of the outer loop starts with the new retailers' prices. The iterative process will be terminated once the difference between the relevant objective functions in the last two iterations for both inner and outer loops is less than or equal to 0.001.

5.3.1 Joint DRCC Model in EV Layer

The proposed DRCC model in EV layer has included Eqs. (5.3)-(5.3r) to minimise the net cost of EV operation during V2G and G2V services. The proposed problem restricted by a set of distributionally robust chance constraints in Eqs. (5.3d), (5.3e), (5.3j), and (5.3k). Equations (5.3b) and (5.3c) indicate sum of the charging and discharging power of EV e in CS i and the nearest CS, respectively, at time t. Equation (5.3d) signifies that under the worst distribution in ambiguity set for EV layer (Ξ^{EV}), the probability of maintaining the SOC level of EV e within a lower and upper bound at all times must be greater than or equal to a given confidence level. Further the DRCC in Eq. (5.3e) is expressed to fulfil target SOC of EV e at the end of the day within a permissible range (i.e., between the target and maximum SOC). Permissible charging and discharging capacity of the chargers at CS i are imposed by Eqs. (5.3f) and (5.3g). In order to select one CS for either G2V and V2G services by EV e at time t, sum of the binary variables of CSs must be less than or equal to one, as in by Eq. (5.3h). Furthermore, Eq. (5.3i) guarantees that the number of used chargers at a CS for charging and discharging does not exceed the number of existing chargers. The DRCC in Eqs. (5.3j) and (5.3k) impose driver's cost/revenue threshold limitations for selecting alternative route instead of the shortest route during V2G and G2V operation. Further, the driver's route preferences for charging/discharging EV

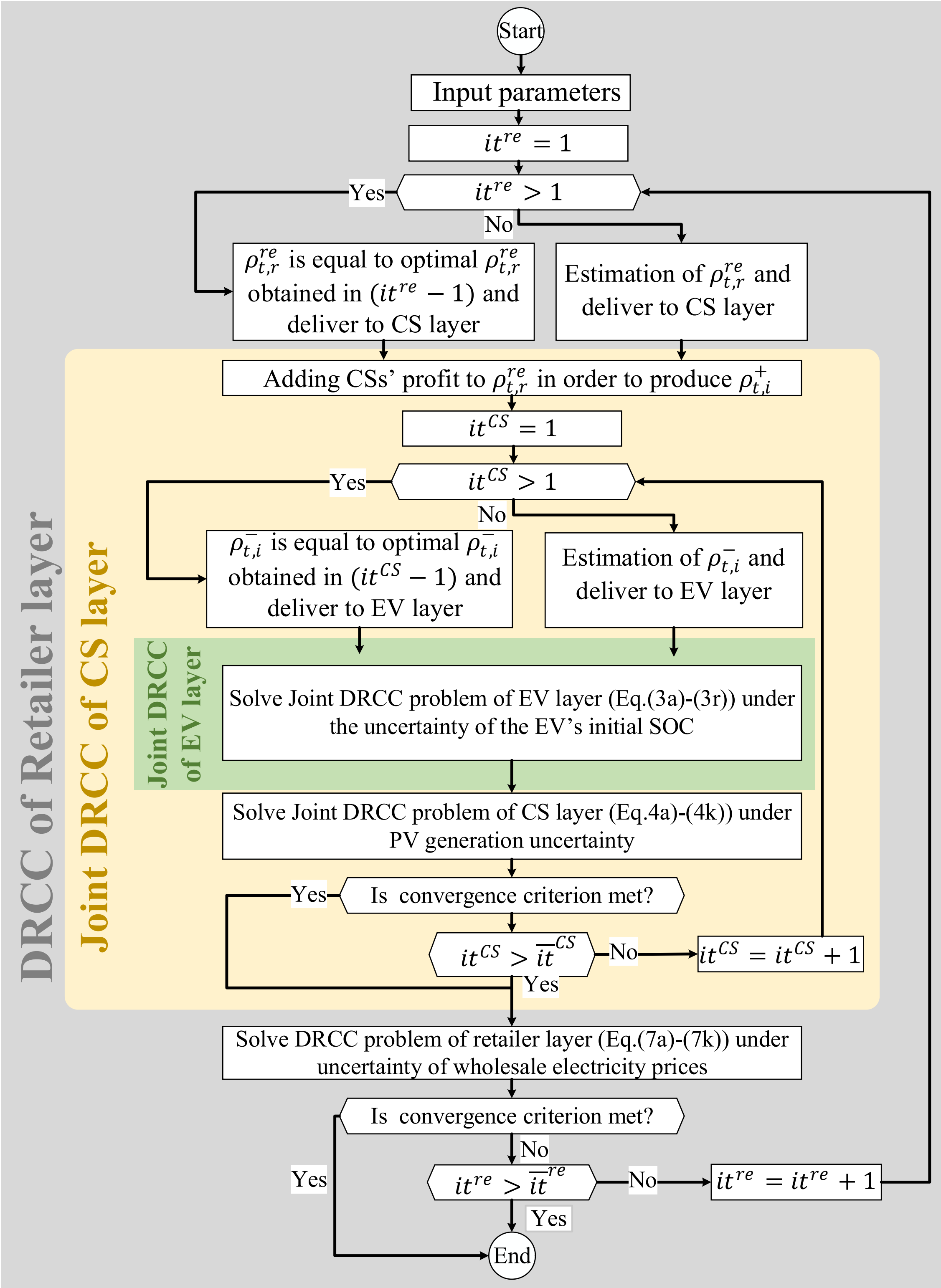

Figure 5.1: Flowchart of the three-layer joint DRCC problem

e at time t in an alternative CS other than the nearest CS are ensured by Eqs. (5.3l) and (5.3m). The zero power of charging and discharging at a VCS must be set to zero, which is achieved by Eqs. (5.3n) and (5.3o). Moreover, Equation (5.3p) sets the driving route allocated to VCS for the mandatory trip, which is equal to the shortest route to reach the destination directly from origin of EV e. In addition, the driving route distance between EV and VCS in the first and second optional trips are set to zero by Eqs. (5.3q) and (5.3r).

$$\min_{\substack{X^+_{t,e,i}, X^-_{t,e,i},\\ \Gamma_{t,e,i}, \Pi_{t,e,i}}} \quad \sup_{\mathbb{P}\in\Xi^{EV}} \mathbb{E}_{\mathbb{P}}\Bigg[\sum_{t=1}^{T}\sum_{e=1}^{E} X^+_{t,e,i}\cdot\rho^+_{t,i} \tag{5.3a}$$

$$+\Big(b\cdot\big(SOC_{t,e} - a\cdot(\Gamma_{t,e,i}+\Pi_{t,e,i})\big)^2$$

$$+ c.X^+_{t,e,i} - d.X^-_{t,e,i} + f.X^{-2}_{t,e,i}\Big)$$

$$- X^-_{t,e,i}.\rho^-_{t,i}\Bigg] \qquad \forall i \in S,$$

s.t.

$$A_{t,e,i} = \frac{\eta^+_e\cdot\sum\limits_{t=1}^{t} X^+_{t,e,i}.\Delta t}{\overline{E}_e} - \frac{\sum\limits_{t=1}^{t} X^-_{t,e,i}\Delta t}{\eta^-_e\overline{E}_e}, \tag{5.3b}$$

$$\widehat{A}_{t,e,i} = \frac{\sum\limits_{t=1}^{t}\eta^+_e.\widehat{X}^+_{t,e,i}\Delta t}{\overline{E}_e} - \frac{\sum\limits_{t=1}^{t}\widehat{X}^-_{t,e,i}\Delta t}{\overline{E}_e.\eta^-_e}, \tag{5.3c}$$

$$\inf_{\mathbb{P}\in\Xi^{EV}} \mathbb{P}\Bigg[\underline{SOC}_e \le \widetilde{SOC}_{0_e} - e^T\omega_e + A_{t,e,i} \tag{5.3d}$$

$$-\sum_{t=1}^{t}\frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}.(1-\Gamma_{t,e,i}-\Pi_{t,e,i}) - \frac{\mathcal{O}_{t,e,i}\cdot\gamma_e}{\overline{E}_e}.$$

$$(\Gamma_{t,e,i}+\Pi_{t,e,i}) \le \overline{SOC}_e\Bigg] \ge 1-\epsilon^{EV}_{th}$$

$$\forall t\in T, \forall e\in E, \forall i\in S,$$

$$\inf_{\mathbb{P}\in\Xi^{EV}} \mathbb{P}\Bigg[SOC^{\text{end}}_e \le \widetilde{SOC}_{0_e} - e^T\omega_e + A_{T,e,i} \tag{5.3e}$$

$$-\sum_{t=1}^{T}\frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}(1-\Gamma_{t,e,i}-\Pi_{t,e,i}) - \frac{\mathcal{O}_{T,e,i}\cdot\gamma_e}{\overline{E}_e}.$$

$$(\Gamma_{T,e,i}+\Pi_{T,e,i}) \le \overline{SOC}_e\Bigg] \ge 1-\epsilon^{EV}_{th}$$

$$\forall t\in T, \forall e\in E, \forall i\in S,$$

$$0 \le X^+_{t,e,i} \le \overline{E}^{\text{CH}}_i.\Gamma_{t,e,i} \quad \forall t\in T, \forall e\in E, \forall i\in S, \tag{5.3f}$$

$$0 \le X^{-}_{t,e,i} \le \overline{E}^{\text{CH}}_i . \Pi_{t,e,i} \quad \forall t \in T, \forall e \in E, \forall i \in S, \tag{5.3g}$$

$$\sum_{i=1}^{S} (\Pi_{t,e,i} + \Gamma_{t,e,i}) \le 1 \quad \forall t \in T, \forall e \in E, \tag{5.3h}$$

$$\textstyle\sum_{e \in E} (\Gamma_{t,e,i} + \Pi_{t,e,i}) \le \overline{N}^{CH}_i \quad \forall t \in T, \forall i \in S, \tag{5.3i}$$

$$\begin{aligned} \inf_{\mathbb{P} \in \Xi^{EV}} \mathbb{P}\Bigg[& \rho^{+}_{t,i}.X^{+}_{t,e,i} \le \vartheta_e.\Gamma_{t,e,i} + \widehat{\rho}^{+}_{t,i}.\overline{E}_e.\Gamma_{t,e,i} \\ & .\left(\widehat{SOC}_e - e^T \omega_e + \widehat{A}_{t,e,i} - \frac{\widehat{\mathcal{O}}_{t,e,i}.\gamma_e}{\overline{E}_e} \right) \\ & - \widehat{\rho}^{+}_{t,i}.\overline{E}_e.(1 - \Gamma_{t,e,i}). \sum_{t=1}^{t} \frac{\zeta_{t,e}.\gamma_e}{\overline{E}_e} \Bigg] \ge 1 - \epsilon^{EV}_{th} \\ & \forall t \in T, \forall e \in E, \forall i \in S, \end{aligned} \tag{5.3j}$$

$$\begin{aligned} \inf_{\mathbb{P} \in \Xi^{EV}} \mathbb{P}\Bigg[& \rho^{-}_{t,i}.X^{-}_{t,e,i} \ge \mathcal{G}_e.\Pi_{t,e,i} + \widehat{\rho^{-}_{t,i}}.\overline{E}_e.\Pi_{t,e,i} \\ & .\left(\widehat{SOC}_e - e^T \omega_e + \widehat{A}_{t,e,i} - \frac{\widehat{\mathcal{O}}_{t,e,i}.\gamma_e}{\overline{E}_e} \right) \\ & - \widehat{\rho^{-}_{t,i}}.\overline{E}_e.(1 - \Pi_{t,e,i}). \sum_{t=1}^{t} \frac{\zeta_{t,e}.\gamma_e}{\overline{E}_e} \Bigg] \ge 1 - \epsilon^{EV}_{th} \\ & \forall t \in T, \forall e \in E, \forall i \in S, \end{aligned} \tag{5.3k}$$

$$\begin{aligned} \Gamma_{t,e,i}.(\mathcal{O}_{t,e,i} + \mathcal{D}_{t,e,i}) & \le (\widehat{\mathcal{DO}}_{t,e} + \mathcal{K}_e).\Gamma_{t,e,i} \\ & \forall t \in T, \forall e \in E, \forall i \in S, \end{aligned} \tag{5.3l}$$

$$\begin{aligned} \Pi_{t,e,i}.(\mathcal{O}_{t,e,i} + \mathcal{D}_{t,e,i}) & \le (\widehat{\mathcal{DO}}_{t,e} + \mathcal{K}_e).\Pi_{t,e,i} \\ & \forall t \in T, \forall e \in E, \forall i \in S, \end{aligned} \tag{5.3m}$$

$$X^{+}_{t,e,i} = 0 \quad \forall t \in T, \forall e \in E, \forall i = VCS, \tag{5.3n}$$

$$X^{-}_{t,e,i} = 0 \quad \forall t \in T, \forall e \in E, \forall i = VCS, \tag{5.3o}$$

$$\mathcal{O}_{t,e,i} + \mathcal{D}_{t,e,i} = \zeta_{t,e} \forall t \in (T - F_1 - F_2), \forall e \in E, \forall i = VCS, \tag{5.3p}$$

$$\mathcal{O}_{t,e,i} + \mathcal{D}_{t,e,i} = 0 \quad \forall t \in F_1, \forall e \in E, \forall i = VCS, \tag{5.3q}$$

$$\mathcal{O}_{t,e,i} + \mathcal{D}_{t,e,i} = 0 \quad \forall t \in F_2, \forall e \in E, \forall i = VCS. \tag{5.3r}$$

5.3.2 Joint DRCC Model in CS Layer

The DRCC model in the CS layer is presented in this section the net revenue of all CSs. As in Eq. (5.4) the sum of the CSs' revenue is the objective function of the DRCC problem in the CS layer. Furthermore, the revenue of CS i is derived from selling electricity to EV e and the aggregator during G2V and V2G operation, respectively. In addition, the costs of CS i include the operational cost of CGU, cost of electricity purchased from retailer r and EV e in G2V and V2G services, respectively.

$$\max_{\substack{Y^{re}_{t,i,r}, Y^{GU}_{t,i}, \widetilde{Y}^{\mathrm{PV}}_{t,i} \\ Y^{+}_{t,i}, Y^{-}_{t,i}, \rho^{-}_{t,i}, \\ \beta_{t,i,r}, \psi_{t,i}}} \quad \sup_{\mathbb{P}\in\Xi^{CS}} \mathbb{E}_{\mathbb{P}}\Bigg[\sum_{t=1}^{T}\sum_{i=1}^{S}\sum\nolimits_{e\in E}(X^{+}_{t,e,i}.\rho^{+}_{t,i} + X^{-}_{t,e,i}.\rho^{\mathrm{AG}}_{t,i}) - Y^{\mathrm{re}}_{t,i,r}.\rho^{\mathrm{re}}_{t,r} - \sum\nolimits_{e\in E} X^{-}_{t,e,i}.\rho^{-}_{t,i} - \frac{Y^{\mathrm{GU}}_{t,i}.\rho^{\mathrm{gas}}_{t}}{\eta^{\mathrm{GU}}_{i}.HV}\Bigg] \quad \forall r \in R, \tag{5.4a}$$

s.t.

$$\inf_{\mathbb{P}\in\Xi^{CS}} \mathbb{P}\Bigg[\widetilde{Y}^{\mathrm{PV}}_{t,i} - \mathbf{1}^{\mathrm{T}}\xi_{t,i} + Y^{\mathrm{GU}}_{t,i} + Y^{\mathrm{re}}_{t,i,r} + Y^{-}_{t,i} + \sum\nolimits_{e\in E} X^{-}_{t,e,i} + \varepsilon \geq \frac{\sum_{e\in E} X^{-}_{t,e,i}}{\eta^{\mathrm{CH}}_{i}} + \frac{\sum_{e\in E} X^{+}_{t,e,i}}{\eta^{\mathrm{CH}}_{i}} + Y^{+}_{t,i}\Bigg] \geq 1 - \epsilon^{CS}_{th} \quad \forall t \in T, \forall i \in S, \forall r \in R, \tag{5.4b}$$

$$0 \leq Y^{\mathrm{GU}}_{t,i} \leq \overline{E}^{\mathrm{GU}}_{i} \quad \forall t \in T, \forall i \in S, \tag{5.4c}$$

$$\inf_{\mathbb{P}\in\Xi^{\mathrm{CS}}} \mathbb{P}\Big[0 \leq \widetilde{Y}^{\mathrm{PV}}_{t,i} - \mathbf{1}^{\mathrm{T}}\xi_{t,i} \leq \overline{E}^{\mathrm{PV}}_{i}\Big] \geq 1 - \epsilon^{CS}_{th} \quad \forall t \in T, \forall i \in S, \tag{5.4d}$$

$$\inf_{\mathbb{P}\in\Xi^{\mathrm{CS}}} \mathbb{P}\Bigg[\underline{r}^{\mathrm{PV}}_{i} \leq \frac{\widetilde{Y}^{\mathrm{PV}}_{t,i} - \widetilde{Y}^{\mathrm{PV}}_{t-1,i} - \widehat{\xi}_{t,i}}{\Delta t} \leq \overline{r}^{\mathrm{PV}}_{i}\Bigg] \geq 1 - \epsilon^{\mathrm{CS}}_{th}, \tag{5.4e}$$

$$0 \leq Y^{\mathrm{re}}_{t,i,r} \leq \overline{E}_{i}.\beta_{t,i,r} \quad \forall t \in T, \forall i \in S, \forall r \in R, \tag{5.4f}$$

$$\sum_{r=1}^{R} \beta_{t,i,r} \leq 1 \quad \forall t \in T, \forall i \in S, \tag{5.4g}$$

$$0 \leq Y^{+}_{t,i} \leq \overline{E}^{\mathrm{ESS}}_{i}.\psi_{t,i} \quad \forall t \in T, \forall i \in S, \tag{5.4h}$$

$$0 \leq Y^{-}_{t,i} \leq \overline{E}^{\mathrm{ESS}}_{i}.(1 - \psi_{t,i}) \quad \forall t \in T, \forall i \in S, \tag{5.4i}$$

$$\underline{SOC}^{\mathrm{ESS}}_{i} \leq \frac{\sum_{t=2}^{t}(Y^{+}_{t,i} - Y^{-}_{t,i}).\Delta t}{\overline{E}^{ESS}_{i}} \leq \overline{SOC}^{\mathrm{ESS}}_{i} \quad \forall t \in T, \forall i \in S, \tag{5.4j}$$

$$\underline{\rho}^{-} \leq \rho^{-}_{t,i} \leq \overline{\rho}^{-} \quad \forall t \in T, \forall i \in S. \tag{5.4k}$$

A set of DRCC is presented in Eqs. (5.4b), (5.4d), (5.4e) in this layer. The probability of maintaining power balance between supply and demand at CS i under the worst distribution in ambiguity set for CS layer (Ξ^{CS}) is imposed by Eq. (5.4b). Moreover, the lower and upper capacity limit of CGU are enforced by Eq. (5.4c). In Eq. (5.4d), the DRCC for ensuring the lower and upper capacity limit of PV generation at CS i is given. Equation (5.4e) represents temporal correlation between renewable energy generation uncertainty by restricting the ramping of PV generation. For this constraint, the uncertainty parameter contains both $\xi_{t,i}$ and $\xi_{t-1,i}$ as:

$$\widehat{\xi}_{t,i} = \begin{bmatrix} \xi_{t,i} \\ \xi_{t-1,i} \end{bmatrix}. \tag{5.5}$$

In order to consider the effect of temporal correlation on Eq. (5.4e), covariance matrix should be defined as [2]:

$$\widehat{\Sigma}^{\mathrm{PV}}_{t,i} = \begin{bmatrix} \Sigma^{\mathrm{PV}}_{t,i} & \Upsilon^{\mathrm{PV}}_{(t,t-1),i} \\ \Upsilon^{\mathrm{PV}}_{(t,t-1),i} & \Sigma^{\mathrm{PV}}_{t-1,i} \end{bmatrix}. \tag{5.6}$$

The electricity purchased from retailer r is constrained by Eq. (5.4f). Equation (5.4g) guarantees that only one retailer is selected by CS i at time t. The limitation of charging and discharging power of ESS at CS i are established by Eqs. (5.4h) and (5.4i). Furthermore, the SOC of ESS must be within a permissible range, which is enforced by Eq. (5.4j). Equation (5.4k) ensures that the electricity prices in V2G services is limited by minimum and maximum bounds for the DRCC problem in CS layer.

5.3.3 DRCC Model in Retailer Layer

The DRCC model in retailer layer is presented in this section to maximise the net revenue of all retailers. In fact, it consists of the difference between revenue obtained by selling electricity to CS i, and the cost of electricity purchased from the wholesale electricity market, as given in Eq. (5.7). Moreover, the wholesale electricity prices is the stochastic parameter in this layer.

$$\max_{\widetilde{\rho}^{\mathrm{re}}_{t,r}} \quad \sup_{\mathbb{P}\in\Xi^{CS}} \mathbb{E}_{\mathbb{P}}\Bigg[\sum_{t=1}^{T}\sum_{r=1}^{R}\sum\nolimits_{i\in S} Y^{re}_{t,i,r}.\rho^{\mathrm{re}}_{t,r} - P^{\mathrm{WM}}_{t,r}.(\widetilde{\rho}^{\mathrm{WM}}_{t} - \mathbf{1}^{T}\kappa_t)\Bigg] \quad \forall i \in S, \tag{5.7a}$$

s.t.

$$P^{\mathrm{WM}}_{t,r} = \sum\nolimits_{i\in S} Y^{re}_{t,i,r}, \tag{5.7b}$$

$$Q^{\mathrm{WM}}_{t,r} = \sum\nolimits_{i\in S} Q^{re}_{t,i,r}, \tag{5.7c}$$

$$P_{m,n,t}= g_{m,n}.(1+\Delta\hat{V}_{m,t}).(\Delta V_{m,t}-\Delta V_{n,t}) -b_{m,n}.(\theta_{m,t}-\theta_{n,t}) \quad \forall m,n\in B, \forall t\in T, \tag{5.7d}$$

$$Q_{m,n,t}= -b_{m,n}.(1+\Delta\hat{V}_{m,t}).(\Delta V_{m,t}-\Delta V_{n,t}) -g_{m,n}.(\theta_{m,t}-\theta_{n,t}) \quad \forall m,n\in B, \forall t\in T, \tag{5.7e}$$

$$V_{m,t} = 1 + \Delta V_{m,t} \quad \forall m \in B, \forall t \in T, \tag{5.7f}$$

$$\theta_{m,t} = 0 + \Delta\theta_{m,t} \quad \forall m \in B, \forall t \in T, \tag{5.7g}$$

$$\underline{\Delta V}_m \leq \Delta V_{m,t} \leq \overline{\Delta V}_m \quad \forall m \in B, \tag{5.7h}$$

$$\underline{P}_{m,n} \leq P_{m,n,t} \leq \overline{P}_{m,n} \quad \forall m,n \in B, \forall t \in T, \tag{5.7i}$$

$$\underline{Q}_{m,n} \leq Q_{m,n,t} \leq \overline{Q}_{m,n} \quad \forall m,n \in B, \forall t \in T, \tag{5.7j}$$

$$\inf_{\mathbb{P}\in\Xi^{re}} \mathbb{P}\Big[\underline{\alpha}_t \times \widetilde{\rho}^{\mathrm{WM}}_t - \mathbf{1}^T\kappa_t \leq \rho^{\mathrm{re}}_{t,r} \leq \overline{\alpha}_t \times \widetilde{\rho}^{\mathrm{WM}}_t - \mathbf{1}^T\kappa_t\Big] \geq 1-\epsilon^{re}_{th}. \tag{5.7k}$$

Equations (5.7b) and (5.7c) enforce the active and reactive power balance at all times, respectively. Thus, the electricity purchased from the wholesale electricity market through retailer r must be equal to sum of the electricity purchased by CSs from retailer r for active and reactive power at time t. Equations (5.7d) and (5.7e) satisfy real and reactive power flows in the network considering voltage magnitude and angle deviations determined by Eqs. (5.7f) and (5.7g). Equation (5.7h) enforces the node voltages between minimum and maximum bounds. Equations (5.7i) and (5.7j) guarantee that active and reactive power are maintained within a standard range. In addition, the probability of maintaining the electricity prices offered by retailers between maximum and minimum bounds under the worst distribution ambiguity set in Retailer layer (Ξ^{re}) is imposed by Eq. (5.7k).

5.4 Simulation Results

The simulation is carried out with the proposed day-ahead DRCC scheduling framework along with three retailers, nine CSs, and 600 EVs in an small area of San Francisco, the USA, deploying IEEE 37-node distribution test system to assess its performance under different conditions. Here, 30 bidirectional fast DC chargers with the capacity of 50 kW are considered in all CSs. Each CS is equipped with a 65 kW CGU, a PV system with the capacity of $\{16, 19.2, 24, 27.2, 32\}$ kW and one-hour ESS with the capacity of $\{45, 50, 65, 70, 85\}$ kW. Furthermore, the mean value of the initial SOC of 600 EVs is between 10% and 95% and the standard deviation of initial SOC of each EV is equal to 5%. It is assumed that each EV plans two mandatory trips and two optional trips in a typical day. As depicted in Fig. 5.2, the first mandatory trip of 88.3% of EVs in the fleet is randomly scheduled between 06:00 to 10:00. The first optional trip of 93.5% of EVs is randomly planned between 11:00 to 15:00, while the second optional trip of 88.8% of EVs is assumed to occur between 13:00 to 18:00. Finally, the second mandatory trip of 89.7% of EVs is supposed to take place between 16:00 to 20:00. Before solving the scheduling problem, the shortest driving routes between the origin of EV e, the location of CS i, and the destination of EV e for each trip are determined by ArcGIS®. The ambiguity sets for PV generation and wholesale electricity prices, which include a family of probability distribution functions with the same mean and covariance, are constructed from historical data. The mean value of PV generation ($\widetilde{Y}_{t,i}^{PV}$) and the covariance matrix of PV generation ($\xi_{t,i}$ and $\widehat{\xi}_{t,i}$) for each hour are calculated from data of 100 days extracted from Renewables.ninja for the same area in San Francisco [3]. In addition, for calculating the mean value ($\widetilde{\rho}_t^{\mathrm{WM}}$) and covariance ($\kappa_t$) of the wholesale electricity prices, 100 days worth of prices are utilised from California ISO [4]. To obtain the prices offered to CSs by the retailers, the day-ahead electricity prices of the wholesale market is multiplied by 4.5 homogeneously in order to consider network maintenance costs, ancillary services costs, taxes etc. Moreover, the profit margin of the retailers ($\underline{\alpha}$ and $\overline{\alpha}$) is assumed to be 5-50% in the G2V operation, while the CSs seek profit in the range of 10% to 30% of the true energy prices. Furthermore, during the V2G service, electricity prices offered by CSs are between 60-85% less than the prices offered by the retailers. The electricity prices sold to the aggregator by CSs is 10% greater than what CSs offered to EV drivers during V2G service.

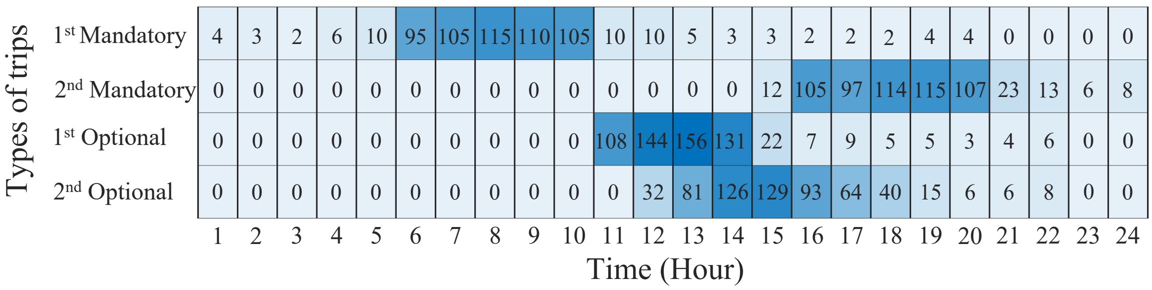

Figure 5.2: Number of EVs in different trips

5.4.1 Evaluation of Low- to High-Risk Cases

First, the DRCC problem in different layers for various confidence levels ($\nu = 1 - \epsilon$) is solved to investigate the changes in cost and profits of the stakeholders. For the low-risk (conservative) case study, the confidence level is high and the constraints in Eqs. (5.3d), (5.3e), (5.3j), and (5.3k) in EV layer, and Eqs. (5.4b), (5.4d), and (5.4e) in CS layer will be satisfied 95% of the time or more. In the same case study, Eq. (5.7k) in retailer layer will be considered with a probability that is higher than or equal 90% because the DRCC model will not be converged at 95% confidence level. It means that the retailers cannot supply CSs under the most conservative condition of the entire ecosystem. It shows the importance of the proposed sequential framework to capture the impact of different layers on each other.

The total net cost of EVs, and the total net revenue of CSs and retailers are illustrated in Fig. 5.3 for different confidence levels. By increasing the confidence level from 0.5 (high-risk case study) to 0.95 (low-risk case study), the total net cost of EVs increased from \$231 to \$803 while the total net revenue of CSs and retailers decreased from \$678 and \$852 to \$498 and \$762, respectively. This is because that at the lower confidence levels, constraints are relaxed for all stakeholders resulting more options

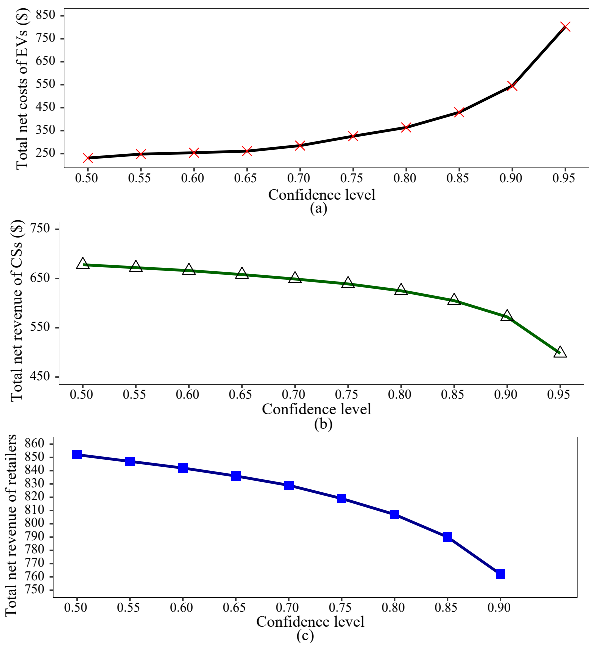

Figure 5.3: (a) Total net cost of EVs, (b) total net revenue of CSs, and (c) total net revenue of retailers for different confidence levels from 0.5 (high-risk case) to 0.95 (low-risk case)

are available to choose the most optimal V2G and G2V operation. Consequently, the risk of failing the day-ahead commitment for all stakeholders is comparatively higher in this case in the real-time operation. However, at higher confidence levels, the feasible solution space is much smaller for all stakeholders. This way, they pay a premium for a higher confidence (lower risks) at the time of delivery of services. Since the DRCC problem for the three layers are solved iteratively, the impact of conservative operation of one layer leads other players to behave more conservatively, which resulted in disproportionately higher prices. The number of EVs scheduled for G2V and V2G operations in each trip is shown in Fig. 5.4 for 0.95 confidence level in EV and CS layer, and 0.9 in retailer level.

5.4.2 Validation of DRCC Formulation

In this subsection, the quality of the proposed three-layer joint DRCC framework and the solutions are investigated. The DRCC solutions are valid when the actual confidence level ($\nu_{ac} = 1 - \epsilon_{ac}$) is more than or equal to the theoretical confidence level ($\nu_{th} = 1 - \epsilon_{th}$). For this investigation, as shown in Fig. 5.5(a), firstly it is needed to consider a theoretical confidence level, ν_{th}, to solve the DRCC problems at different

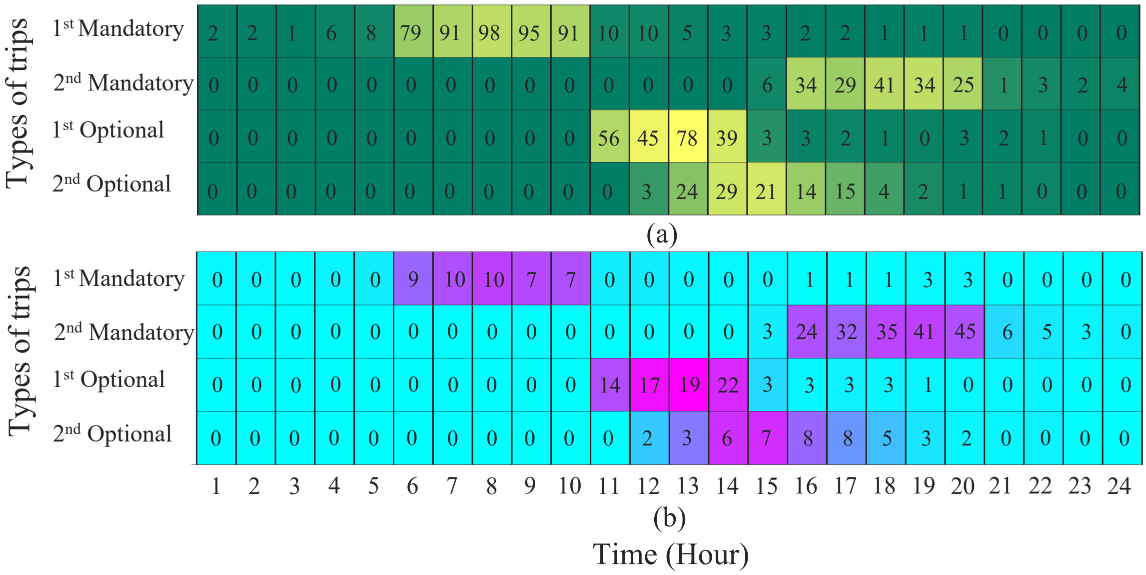

Figure 5.4: Number of EVs schedule for (a) G2V and (b) V2G operation layers iteratively based on the mean value and covariance of stochastic parameters.

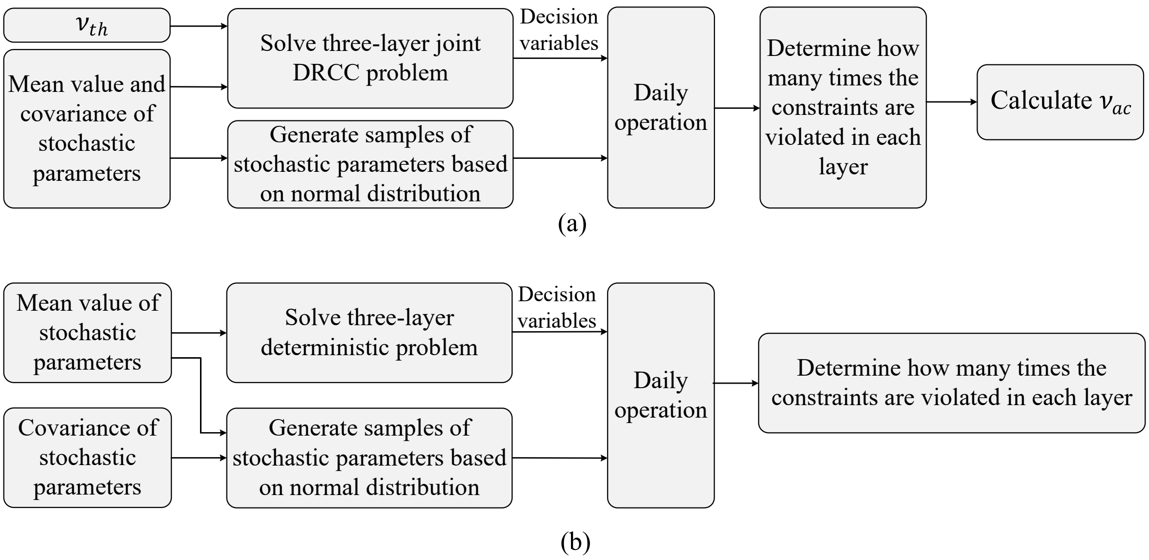

Figure 5.5: Flowchart of determining actual confidence level in (a) the DRCC problem and (b) the deterministic problem

Afterwards, the optimal solutions jointly used with the samples created for the stochastic parameters (representing the realised value of the parameters in real-time operation) to run a daily operation of the ecosystem. Then, the number of times in which the CCs (Eqs. (5.3d), (5.3e), (5.3j), and (5.3k) in EV layer, Eqs. (5.4b), (5.4d), and (5.4e) in CS layer, and Eq. (5.7k) in retailer layer) have been violated is checked to obtain the actual confidence level, ν_{ac}. This process is repeated for different values of theoretical confidence level in each layer, i.e., $\nu_{th} \in [0.5, 0.9]$, to obtain the mean values of the actual confidence level, ν_{ac}. While normal distribution is used in this part of the simulation study, it should be noted that the reformulation of the single-sided and double-sided CCs, presented in Appendix, is independent of the type of probability distribution function. Also, the CCs violations in a deterministic day-ahead scheduling framework are calculated using the process shown in Fig. 5.5(b).

The actual confidence levels obtained by the proposed stochastic framework are illustrated in Fig. 5.6 for each layer in comparison with the theoretical ones. Please note that for determining the actual confidence level of each layer, the theoretical confidence level of other layers are kept constant at 0.9. It can be seen from the figure that the actual confidence level is always higher than the theoretical one. In addition, Fig. 5.6 shows that the DRCC programming is more conservative on the lower range of theoretical confidence levels. The simulation results for the deterministic scheduling framework show actual confidence levels of 0.71, 0.79, and 0.75 for EV, CS, and retailer layer, respectively, which are lower than the lowest actual confidence level of the proposed stochastic framework.

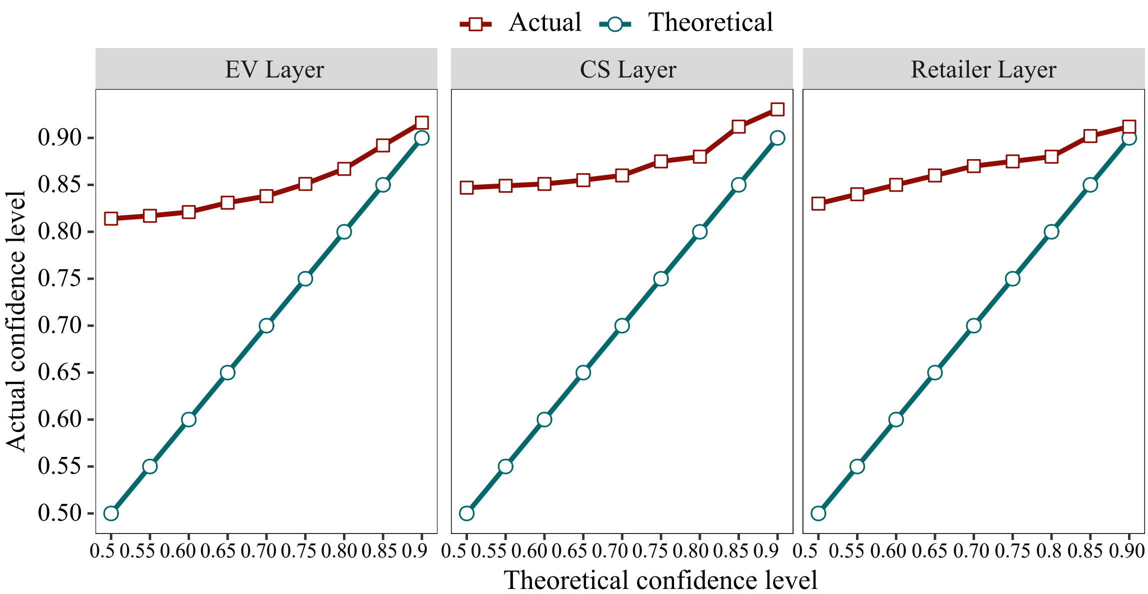

Figure 5.6: DRCC validation for EV, CS, and Retailer layers

In addition, the number of unique EVs that violated the CCs (Eqs. (5.3d), (5.3e), (5.3j), and (5.3k)) in the proposed DRCC framework are shown for different confidence levels in Fig. 5.7. According to the figure, the number of unique EVs with constraint violation is decreased by increasing the confidence level in EV layer. Furthermore, Fig. 5.8 depicts the number of unique EVs that have not reached their destination (due to lower SOC limit violation) at different confidence levels, which expectantly decreases by increasing the confidence level. It shows the importance of the proposed framework in reducing the EV drivers frustration, which contributes to lowering range anxiety. In addition, 272 unique EVs could not reach their destination in the deterministic problem, which is more than the one obtained at the lowest confidence level, 0.5, in the proposed DRCC framework.

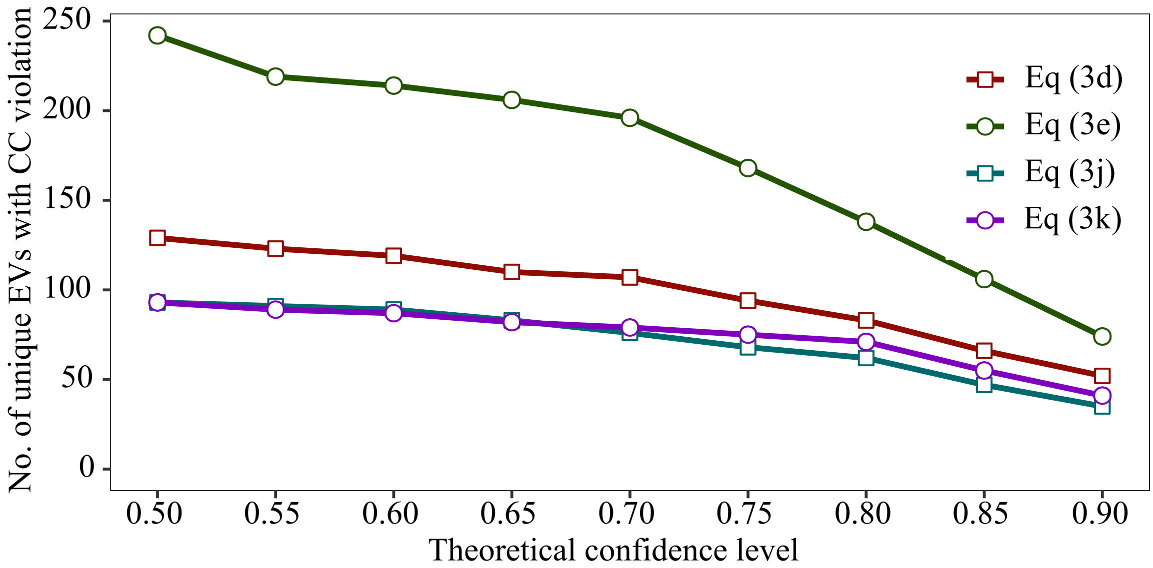

Figure 5.7: Number of unique EVs violating their CCs at least once a day at different confidence level in EV layer in the proposed DRCC framework.

5.4.3 Impact of Temporal Correlation of PV Generation

In this section, the impact of considering the temporal correlation of PV generation in CSs are investigated. First, the root mean square error (RMSE) of PV generation with and without considering the temporal correlation is calculated in Eq. (5.4e) for all CSs. It shows that the RMSE has improved from 17.8% to 16.3% by considering PV temporal correlations. In addition, the number of unique EVs that could not fulfill their mandatory trip due to violating lower SOC limit at different confidence levels

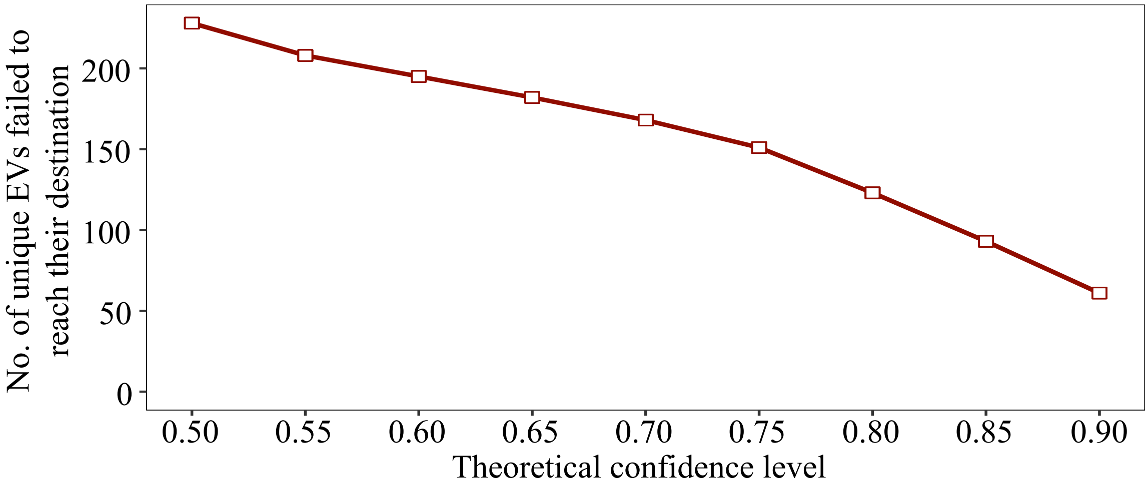

Figure 5.8: Number of unique EVs which does not fulfill their mandatory trips in the proposed DRCC framework at different confidence level.

is calculated after removing the PV correlation effect in CS layer, which are shown in Fig. 5.9. It can be seen that an additional 2 EVs won't reach their destination at 0.95 confidence level. By decreasing the confidence level in the CS layer from 0.95 to 0.5 in the absence of PV correlation, the number of EVs that cannot fulfill their mandatory trips increases to 9. It shows the impact of PV temporal correlation on the successful scheduling of the ecosystem.

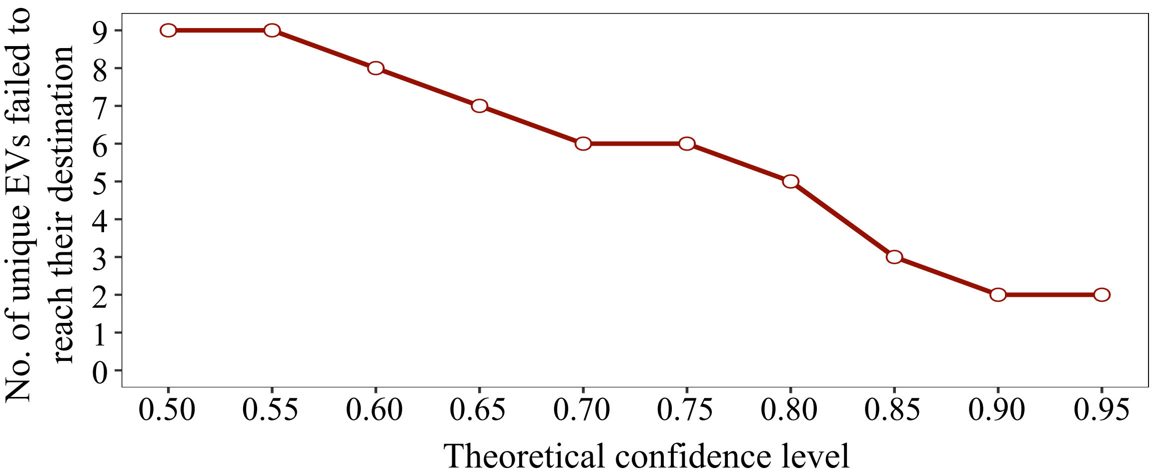

Figure 5.9: Number of unique EVs that could not reach their destination in the absence of PV correlation constraint at the CS layer.

5.5 Conclusion

This chapter proposes a three-layer joint DRCC model for the future e-mobility ecosystem including EVs, CSs, and retailers to schedule V2G and G2V services in the day ahead system under an uncertain environment with unknown probability distribution functions. In particular, the interactions between stochastic parameters of the three stakeholders are considered in the proposed iterative model to improve the performance of the scheduling system for the entire e-mobility ecosystem. Further, second-order cone programming reformulation of the DRCC model is implemented to reformulate the double-sided CCs. In addition, the impact of temporal correlation of uncertain PV generation on the CSs operation is considered. The simulation results confirm that the choice of confidence level significantly affects the cost and revenue of the stakeholders as well as the accuracy of the schedules in real-time operation. For a low-risk case study, the model estimates 247.3% increase in the total net cost of EVs compared to a high-risk case study, and a 26.6% and 10.6% reduction in the total net revenue of CSs and retailers, respectively. In addition, the number of unique EVs failed to reach their destination has decreased from 272 in deterministic scheduling model to 61 in low-risk case study. The simulation results prove the necessity of such planning frameworks to reduce the risks for all stakeholders, which in turn facilitates higher adoption of EVs by the end-users and investors.

References

[1] W. Xie and S. Ahmed, "Distributionally robust chance constrained optimal power flow with renewables: A conic reformulation," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 1860–1867, 2017.

[2] F. Pourahmadi, J. Kazempour, C. Ordoudis, P. Pinson, and S. H. Hosseini, "Distributionally robust chance-constrained generation expansion planning," *IEEE Transactions on Power Systems*, vol. 35, no. 4, pp. 2888–2903, 2019.

[3] "Renewables.ninja for san francisco, available at: https://www.renewables.ninja/."

[4] "California ISO, available at: http://www.oasis.caiso.com," 2019.

6 | Conclusions and Future Works

The future e-mobility ecosystem will be a complex structure with different stakeholders seeking to optimise their operation and benefits. This thesis highlighted the technical challenges, motivations behind conducting this study and the contributions made to knowledge in Chapter 1. A comprehensive literature review has been performed in five groups in Chapter 2 and the gaps in knowledge and the comparison between the existing literature and this study have also been highlighted at the end of each group.

In Chapter 3, a comprehensive day-ahead G2V and V2G scheduling framework is proposed including EVs, CSs, and retailers to achieve an economically rewarding operation for the ecosystem of EVs, CSs and retailers using a comprehensive optimal charging/discharging strategy that accounts for the network constraints. To do so, an equilibrium problem is solved using a three-layer iterative optimisation problem for all stakeholders/agents in the ecosystem. EV routing problem is solved based on a cost-benefit analysis rather than choosing the shortest route. The proposed method can be implemented as a cloud scheduling system that is operated by a non-profit entity, e.g., distribution system operators or distribution network service providers, whose role is to collect required information from all agents, perform the day-ahead scheduling, and ultimately communicate the results to relevant stakeholders. To evaluate the effectiveness of the proposed framework, a simulation study, including three retailers, one aggregator, nine CSs and 600 EVs, is designed based on real data from San Francisco, the USA. The simulation results show that the total operating cost of electric vehicles including battery degradation cost decreased by 17.6%, and the total revenue of charging stations and retailers increased by 21.1% and 22.6%, respectively, in comparison with a base case strategy.

An iterative process is proposed in Chapter 4 to solve the non-cooperative Stackelberg game by determining the optimal routes and CS for each EV, optimal operation of each CS and retailers, and optimal V2G and G2V prices. To facilitate V2G services and to avoid congestion at CSs, two types of trips, i.e., mandatory and optional trips, are defined and formulated. Also, EV drivers' preferences are added to model economically-irrational decisions that may be taken by the EV drivers. This is based on the fact that EV drivers (similar to other consumers and products) respond differently to economic incentives. The EV drivers' preferences are modelled as cost/revenue threshold and extra driving distance. Driver's cost/revenue threshold represents the drivers' expectation regarding minimum cost reduction during G2V and minimum revenue increase during V2G operation. Additionally, using driver's route preference as a constraint, a CS other than the nearest CS would be selected only when the extra required driving distance is equal to or less than what is specified by the driver in driver's route preference. Therefore, driver's route preference is a constraint in the economic benefit problem, which is aiming to respect driver's welfare in the decision-making process. Extensive simulation studies are carried out for two different e-mobility ecosystems of multiple retailers and CSs as well as numerous EVs. The simulation results show that the optional trips not only reduces the cost of EVs and PV curtailment by 8.8-24.2% and 26.4- 28.5% on average, respectively, in different scenarios, but also mitigates congestion during specific hours while respecting EV drivers' preferences. Moreover, the simulation results revealed the significant impact of EV drivers preferences on the optimal solutions and cost/revenue of the stakeholders.

In Chapter 5, the proposed framework accounts for the stochastic nature of all stakeholders' operation and their mutual interactions. In this chapter, a three-layer joint DRCC model is developed to plan G2V and V2G operation in day-ahead for mobility ecosystems. The proposed stochastic model does not rely on a specific probability distribution for stochastic parameters. To solve the problem, an iterative process is proposed using joint DRCC formulation. To achieve computational tractability, the exact reformulation is implemented for double-sided and single-sided CCs. Furthermore, the impact of temporal correlation of uncertain PV generation on CSs operation is considered. The simulation results shows the necessity and applicability of such a scheduling method for the e-mobility ecosystem in an uncertain environment.

The application of the proposed framework is to develop a mobile app for the EV drivers. An EV driver with access to the mobile app can find a CS easily such that the collective social welfare of all agents in the e-mobility ecosystem is maximised.

6.1 Future Works

Even though the goals mentioned in Chapter 1 have been accomplished, the following future work is recommended in order to improve and extend the work reported in this thesis.

- It is recommended to study cost sharing in a cooperative game to determine a proper and stable coalition in which players stay together and cooperate;
- It is recommended to explore different reformulation of DRCC in each layer that is less conservative at lower confidence levels;
- It is recommended to make the scheduling problem more flexible for the EV drivers, a new formulation will be developed to automatically select the best time for optional trips within a pre-defined range of time by the EV drivers.

Appendix

Reformulation of Three-Layer Joint Distributionally Robust Chance-Constrained Framework for Optimal Day-Ahead Scheduling of E-mobility Ecosystem

In this appendix, the reformulation of the single- and double-sides CCs of EV, CS, and retailer layers are presented based on the two ***Theorems*** developed in [1].

Nomenclature

Indices

e,i,r	Index for EVs, CSs, and retailers, respectively
t	Index for hours
Parameters	
$\epsilon_{th}^{\mathrm{EV}}/\epsilon_{th}^{\mathrm{CS}}/\epsilon_{th}^{\mathrm{re}}$	Theoretical risk parameter in each layer
η_i^{CH}	Efficiency of chargers at CS i (p.u.)
γ_e	Power consumed by EV e per km (kWh/km)
$\mathbb{P}$	Probability distribution
$\mathcal{G}_e$	EV e's driver preference for minimum revenue increase during V2G operation (\$)
$\mathcal{O}_{t,e,i}$	Shortest driving distance between origin of EV e and CS i at time t (km)
$\overline{\alpha}/\underline{\alpha}$	Profit margin of the retailer
$\overline{E}_i^{\mathrm{PV}}$	Capacity of PV system at CS i (kW)
$\overline{E}_e$	Capacity of EV e's battery (kWh)
$\overline{r}_i^{\mathrm{PV}}/\underline{r}_i^{\mathrm{PV}}$	Maximum/Minimum ramping rates of PV generation
$\overline{SOC}_e/\underline{SOC}_e$	Maximum/Minimum SOC of EV e (p.u.)
Σ_e	Covariance of initial SOC of EV e

$\Sigma_{t,i}^{\mathrm{PV}}$	Covariance of PV generation in CS i at time t
τ_t	Covariance of wholesale electricity market prices at time t
ϑ_e	EV e's driver preference for minimum cost reduction during G2V operation (\$)
$\widehat{\mathcal{O}}_{t,e,i}$	Shortest driving distance between origin of EV e and the nearest CS at t (km)
$\widetilde{\rho}_t^{\mathrm{WM}}$	Mean wholesale electricity market price at time t (\$/kWh)
$\zeta_{t,e}$	Shortest driving route to reach the destination directly from origin of EV e at time t (km)
SOC_e^{end}	SOC of EV e at the end of the day (p.u.)
Sets	
B, E, R, S, T, F_1, F_2	Sets of Nodes, EVs, retailers, CSs, hours, first optional trip time, and second optional trip time, respectively
Variables	
$\Gamma_{t,e,i}/\Pi_{t,e,i}$	Binary variable for CS i for charging/discharging EV e at time t
$\kappa_{t,r}$	A random variable with zero mean and covariance matrix τ_t for retailer r at time t
ω_e	A random variable with zero mean and covariance matrix Σ_e for EV e
$\rho_{t,i}^{+}/\rho_{t,i}^{-}$	Electricity price offered by CS i at time t for charging/discharging EVs (\$/kWh)
$A_{t,e,i}$	Sum of charging and discharging power of EV e in CS i
$\widehat{A}_{t,e,i}$	Sum of charging and discharging power of EV e in the nearest CS at time t
$\widehat{\rho}_{t,i}^{+}/\widehat{\rho}_{t,i}^{-}$	Electricity price offered by the closest CS to EVs at time t in G2V/V2G mode (\$/kWh)
$\widetilde{Y}_{t,i}^{\mathrm{PV}}$	Mean local PV generation of CS i at time t (kW)
$\xi_{t,i}$	A A random variable with zero mean and covariance matrix $\Sigma_{t,i}^{PV}$ for CS i at time t

$P_{t,r}^{\mathrm{WM}}/Q_{t,r}^{\mathrm{WM}}$	Active/Reactive power purchased/provided from/by the wholesale market by retailer r at time t (kW/kVar)
$q_{t,e,i}/I_{t,e,i}$	Additional variables for double-sided CC reformulation in EV layer
$SOC_{t,e}$	SOC of EV e at time t (p.u.)
$X_{t,e,i}^{+}/X_{t,e,i}^{-}$	Charging/Discharging power of EV e at CS i at time t (kW)
$x_{t,r}/l_{t,r}$	Additional variables for double-sided CC reformulation in retailer layer
$Y_{t,i}^{+}/Y_{t,i}^{-}$	Charging/Discharging power of ESS of CS i at time t (kW)
$Y_{t,i}^{\mathrm{GU}}$	Power produced by CGU system of CS i at time t (kW)
$z_{t,i}/\mu_{t,i}/U_{t,i}/V_{t,i}$	Additional variables for double-sided CCs reformulation in CS layer
$\rho_{t,r}^{\mathrm{re}}$	Electricity price sold to CSs by retailer r at time t (\$/kWh)

A. Reformulation of single-sided and double-sided chance constraints

As mentioned before, the aim is to reformulate the single-sided and double-sided CCs of EV, CS, and retailer layer based on the two ***Theorems*** developed in [1].

Theorem 1. Suppose the ambiguity set defined as Ξ in Eq. (5.2) in colorred-Chapter 5, then the equivalents of single-sided chance constraints in Eqs. (1a) and (1b) are as Eqs. (2a) and (2b), respectively.

$$\inf_{\mathbb{P}\in\Xi} \mathbb{P}\left[a(x)^T\Omega + b(x) \le L\right] \ge 1 - \epsilon, \tag{1a}$$

$$\inf_{\mathbb{P}\in\Xi} \mathbb{P}\left[a(x)^T\Omega + b(x) \ge -L\right] \ge 1 - \epsilon, \tag{1b}$$

$$b(x) + \sqrt{\frac{1-\epsilon}{\epsilon}}\sqrt{a(x)^T\Sigma a(x)} \le L, \tag{2a}$$

$$-b(x) + \sqrt{\frac{1-\epsilon}{\epsilon}}\sqrt{a(x)^T\Sigma a(x)} \le L, \tag{2b}$$

where $a(x)$ and $b(x)$ are affine mappings, and Ω is a random variable with zero mean and covariance matrix, Σ.

Theorem 2. Suppose the ambiguity set defined as Ξ in Eq. (5.2) in Chapter 5, then the equivalent of a double-sided chance constraint in Eq. (3) can be reformulated as in Eqs. (4) with two additional variables (y and π).

$$\inf_{\mathbb{P}\in\Xi} \mathbb{P}\Big[|a(x)^T\Omega + b(x)| \le L\Big] \ge 1 - \epsilon. \tag{3}$$

$$\left\{\begin{array}{l} y^2 + a(x)^T\Sigma a(x) \le \epsilon(L-\pi)^2, \\ |b(x)| \le y + \pi, \\ L \ge \pi \ge 0, y \ge 0 \end{array}\right\}. \tag{4}$$

A.1: Reformulation of Chance Constraints of EV layer

According to reformulation of single-sided and double-sided chance constraints explained in Eqs. (1a)-(4), the reformulation of the constraints in Eq. (5.3d) in Chapter 5 will be as of Eqs. (5a), (5b), and (5c).

For example, in Eq. (5.3d):

$a(x) = \mathbf{1}^T$,

$b(x) = \widetilde{SOC}_e + A_{t,e,i} - \sum_{t=1}^{t} \frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}.(1 - \Gamma_{t,e,i} - \Pi_{t,e,i}) - \frac{\mathcal{O}_{t,e,i}\cdot\gamma_e}{\overline{E}_e}.(\Gamma_{t,e,i} + \Pi_{t,e,i}) - \frac{\overline{SOC}_e + \underline{SOC}_e}{2}$,

$L = \frac{\overline{SOC}_e - \underline{SOC}_e}{2}$.

In Eq. (5.3e):

$a(x) = \mathbf{1}^T$,

$b(x) = \widetilde{SOC}_e + A_{T,e,i} - \sum_{t=1}^{T} \frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}.(1 - \Gamma_{t,e,i} - \Pi_{t,e,i}) - \frac{\mathcal{O}_{T,e,i}\cdot\gamma_e}{\overline{E}_e}\cdot(\Gamma_{T,e,i} + \Pi_{T,e,i}) - \frac{SOC_e^{end} + \underline{SOC}_e}{2}$,

$L = \frac{\overline{SOC}_e - SOC_e^{end}}{2}$

In Eq. (5.3j):

$a(x) = \mathbf{1}^T \cdot \overline{E}_e \cdot \Gamma_{t,e,i} \cdot \widehat{\rho}^+_{t,i}$,

$b(x) = \rho^+_{t,i}.X^+_{t,e,i} - \vartheta_e \cdot \Gamma_{t,e,i} - \widehat{\rho}^+_{t,i} \cdot \overline{E}_e \cdot \Gamma_{t,e,i} \cdot \left(\widetilde{SOC}_e + \widehat{A}_{t,e,i} - \frac{\widehat{\mathcal{O}}_{t,e,i}\cdot\gamma_e}{\overline{E}_e}\right) + \widehat{\rho}^+_{t,i} \cdot \overline{E}_e \cdot (1 - \Gamma_{t,e,i}) \cdot \sum_{t=1}^{t} \frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}$

$L = 0$

In Eq. (5.3k):

$a(x) = \mathbf{1}^T.\overline{E}_e.\Pi_{t,e,i}.\widehat{\rho^-_{t,i}}$,

$$b(x) = \rho_{t,i}^{-}.X_{t,e,i}^{-} - \mathcal{G}_e.\Pi_{t,e,i} - \widehat{\rho_{t,i}^{-}}.\overline{E}_e.\Pi_{t,e,i}.\left(\widetilde{SOC}_e - \widehat{A}_{t,e,i} + \frac{\widehat{\mathcal{O}}_{t,e,i}.\gamma_e}{\overline{E}_e}\right) + \widehat{\rho_{t,i}^{-}}.\overline{E}_e.(1 - \Pi_{t,e,i}).\sum_{t=1}^{t}\frac{\zeta_{t,e}.\gamma_e}{\overline{E}_e},$$

$$L = 0$$

In addition, Eq. (5.3e) in Chapter 5 is converted to Eqs. (5d), (5e), and (5f), as well as Eq. (5.3j) and (5.3k) is converted to (5g), and (5h), respectively.

$$q_{t,e,i}^2 + 1^T\Sigma_e 1 \le \epsilon_{th}^{EV}\left(\frac{\overline{SOC}_e - \underline{SOC}_e}{2} - I_{t,e,i}\right)^2, \tag{5a}$$

$$\left|\widetilde{SOC}_e + A_{t,e,i} - \sum_{t=1}^{t}\frac{\zeta_{t,e}.\gamma_e}{\overline{E}_e}\cdot(1 - \Gamma_{t,e,i} - \Pi_{t,e,i}) - \frac{\mathcal{O}_{t,e,i}\cdot\gamma_e}{\overline{E}_e}.(\Gamma_{t,e,i} + \Pi_{t,e,i}) - \frac{\overline{SOC}_e + \underline{SOC}_e}{2}\right| \le q_{t,e,i} + I_{t,e,i}, \tag{5b}$$

$$\frac{\overline{SOC}_e - \underline{SOC}_e}{2} \ge I_{t,e,i} \ge 0, \quad q_{t,e,i} \ge 0, \tag{5c}$$

$$q_{T,e,i}^2 + 1^T\Sigma_e 1 \le \epsilon_{th}^{EV}\left(\frac{\overline{SOC}_e - SOC_e^{end}}{2} - I_{T,e,i}\right)^2, \tag{5d}$$

$$\left|\widetilde{SOC}_e + A_{T,e,i} - \sum_{t=1}^{T}\frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e}.(1 - \Gamma_{t,e,i} - \Pi_{t,e,i}) - \frac{\mathcal{O}_{T,e,i}\cdot\gamma_e}{\overline{E}_e}\cdot(\Gamma_{T,e,i} + \Pi_{T,e,i}) - \frac{SOC_e^{end} + \underline{SOC}_e}{2}\right| \le q_{T,e,i} + I_{T,e,i}, \tag{5e}$$

$$\frac{\overline{SOC}_e - SOC_e^{end}}{2} \ge I_{T,e,i} \ge 0, \quad q_{T,e,i} \ge 0, \tag{5f}$$

$$\rho_{t,i}^{+}.X_{t,e,i}^{+} - \vartheta_e\cdot\Gamma_{t,e,i} - \widehat{\rho}_{t,i}^{+}\cdot\overline{E}_e\cdot\Gamma_{t,e,i}\cdot\left(\widetilde{SOC}_e + \widehat{A}_{t,e,i}, - \frac{\widehat{\mathcal{O}}_{t,e,i}.\gamma_e}{\overline{E}_e}\right) + \widehat{\rho}_{t,i}^{+}\cdot\overline{E}_e\cdot(1 - \Gamma_{t,e,i})\cdot\sum_{t=1}^{t}\frac{\zeta_{t,e}\cdot\gamma_e}{\overline{E}_e} + \sqrt{\frac{1 - \epsilon_{th}^{EV}}{\epsilon_{th}^{EV}}\cdot\Sigma_e\cdot\mathbf{1}^T\cdot\overline{E}_e\cdot\Gamma_{t,e,i}\cdot\widehat{\rho}_{t,i}^{+}} \le 0, \tag{5g}$$

$$-\rho^{-}_{t,i}.X^{-}_{t,e,i} + \mathcal{G}_e.\Pi_{t,e,i} + \widehat{\rho_{t,i}}.\overline{E}_e.\Pi_{t,e,i}.\Bigg(\widetilde{SOC}_e + \widehat{A}_{t,e,i} \tag{5h}$$

$$-\frac{\widehat{\mathcal{O}}_{t,e,i}.\gamma_e}{\overline{E}_e}\Bigg) - \widehat{\rho_{t,i}}.\overline{E}_e.(1-\Pi_{t,e,i}).\sum_{t=1}^{t}\frac{\zeta_{t,e}.\gamma_e}{\overline{E}_e}$$

$$+\sqrt{\frac{1-\epsilon^{EV}_{th}}{\epsilon^{EV}_{th}}.\Sigma_e.\mathbf{1}^T.\overline{E}_e.\Pi_{t,e,i}.\widehat{\rho_{t,i}}} \leq 0.$$

A.2: Reformulation of chance constraints of CS layer

Using ***Theorem 1***, Eq. (5.4b) in Chapter 5 is reformulated as Eq. (6a). Also, Eqs. (5.4d) and (5.4e) in Chapter 5 are converted to Eqs. (6b)-(6d) and Eqs. (6e)-(6g), respectively, based on ***Theorem 2***.

In Eq. (5.4b):

$a(x) = \mathbf{1}^T,$

$b(x) = \widetilde{Y}^{\text{PV}}_{t,i} + Y^{GU}_{t,i} + Y^{re}_{t,i,r} + Y^{-}_{t,i} + \sum_{e\in E} X^{-}_{t,e,i} - \frac{\sum_{e\in E} X^{-}_{t,e,i}}{\eta^{\text{CH}}_i} - \frac{\sum_{e\in E} X^{+}_{t,e,i}}{\eta^{\text{CH}}_i} - Y^{+}_{t,i},$

$L = \varepsilon$

In Eq. (5.4d):

$a(x) = \mathbf{1}^T,$

$b(x) = \widetilde{Y}^{PV}_{t,i} - \frac{\overline{E}^{PV}_i}{2},$

$L = \frac{\overline{E}^{PV}_i}{2}$

In Eq. (5.4e):

$a(x) = \mathbf{1}^T,$

$b(x) = \widetilde{Y}^{PV}_{t,i} - \widetilde{Y}^{PV}_{(t-1),i} - \frac{\underline{r}^{PV}_i + \overline{r}^{PV}_i}{2},$

$L = \frac{\overline{r}^{PV}_i - \underline{r}^{PV}_i}{2},$

$$-\widetilde{Y}^{\text{PV}}_{t,i} - Y^{GU}_{t,i} - Y^{re}_{t,i,r} - Y^{-}_{t,i} - \sum\nolimits_{e\in E} X^{-}_{t,e,i} + \frac{\sum_{e\in E} X^{-}_{t,e,i}}{\eta^{\text{CH}}_i} \tag{6a}$$

$$+\frac{\sum_{e\in E} X^{+}_{t,e,i}}{\eta^{\text{CH}}_i} + Y^{+}_{t,i} + \sqrt{\frac{1-\epsilon^{CS}_{th}}{\epsilon^{CS}_{th}}.\Sigma^{PV}_{t,i}} + \leq \varepsilon$$

$$\forall t \in T, \forall i \in S, \forall r \in R,$$

$$z^2_{t,i} + \mathbf{1}^T.\Sigma^{PV}_{t,i}.\mathbf{1} \leq \epsilon^{CS}_{th}\left(\frac{\overline{E}^{PV}_i}{2} - \mu_{t,i}\right)^2, \tag{6b}$$

$$\left|\widetilde{Y}^{PV}_{t,i} - \frac{\overline{E}^{PV}_i}{2}\right| \leq z_{t,i} + \mu_{t,i}, \tag{6c}$$

$$\frac{\overline{E}_i^{PV}}{2} \geq \mu_{t,i} \geq 0, \quad z_{t,i} \geq 0, \tag{6d}$$

$$U_{t,i} - \mathbf{1}^T \widehat{\Sigma}_{t,i} \mathbf{1} \leq \epsilon_{th}^{CS} \left(\frac{\overline{r}_i^{PV} - \underline{r}_i^{PV}}{2} - V_{t,i} \right)^2, \tag{6e}$$

$$\left| \widetilde{Y}_{t,i}^{PV} - \widetilde{Y}_{(t-1),i}^{PV} - \frac{\underline{r}_i^{PV} + \overline{r}_i^{PV}}{2} \right| \leq U_{t,i} + V_{t,i}, \tag{6f}$$

$$\frac{\overline{r}_i^{PV} - \underline{r}_i^{PV}}{2} \geq V_{t,i} \geq 0, \quad U_{t,i} \geq 0, \tag{6g}$$

A.3: Reformulation of chance constraints of retailer layer

Based on ***Theorem 2***, the double-sided CC in Eq. (5.7k) in Chapter 5 is reformulated as Eqs. (7a)-(7c).

In Eq. (5.7k): $a(x) = \frac{1}{\widetilde{\rho}_t^{\mathrm{WM}}}$,

$b(x) = \frac{\rho_{t,r}^{re}}{\widetilde{\rho}_t^{\mathrm{WM}}} - \frac{\overline{\alpha}_t + \underline{\alpha}_t}{2}$,

$L = \frac{\overline{\alpha}_t - \underline{\alpha}_t}{2}$,

$$x_{t,r}^2 + \frac{1}{\widetilde{\rho}_t^{\mathrm{WM2}}} . \tau_t \leq \epsilon_{th}^{re} \left(\frac{\overline{\alpha}_t - \underline{\alpha}_t}{2} - l_{t,r} \right)^2, \tag{7a}$$

$$\left| \frac{\rho_{t,r}^{re}}{\widetilde{\rho}_t^{\mathrm{WM}}} - \frac{\overline{\alpha}_t + \underline{\alpha}_t}{2} \right| \leq x_{t,r} + l_{t,r}, \tag{7b}$$

$$0 \leq l_{t,r} \leq \frac{\overline{\alpha}_t - \underline{\alpha}_t}{2}, \quad x_{t,r} \geq 0. \tag{7c}$$

References

[1] W. Xie and S. Ahmed, "Distributionally robust chance constrained optimal power flow with renewables: A conic reformulation," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 1860–1867, 2017.