Economic operation of electric vehicle parking lot based on vehicle-to-grid function

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Certificate of Authorship / Originality

I, Jiwen Qi, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Electrical and Data Engineering at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

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Abstract

In recent years, the rapid development of electric vehicles (EVs) has drawn increasing attention to the field, particularly in relation to the vehicle-to-grid (V2G) function and its economic operation challenges. This research aims to delve into the V2G function and the economic operation and planning of EV parking lots.

A model is developed for an EV parking lot equipped with V2G, renewable energy sources, and energy storage system. Various charging modes and uncertainties, such as electricity market prices and solar radiation, are considered. The model classifies EVs based on parking duration and adjusts charging prices dynamically using a linear price-demand relationship. Scenario generation in MATLAB validates the model's effectiveness, demonstrating superior profitability compared to two alternative models across multiple cases.

Further analysis incorporates distributed energy resources and examines the parking lot's participation in spot and Frequency Control Ancillary Services (FCAS) markets. Uncertainty in market prices, solar irradiance, and wind speed is forecasted using long short-term memory models. EV behavior, including arrival times and state of charge, is simulated via Monte Carlo methods. An Information Gap Decision Theory-based approach is proposed to optimize V2G incentives under uncertain conditions, yielding the highest profit when participating in both FCAS and spot markets.

A hybrid multi-agent bi-level optimization framework integrates a deep reinforcement learning (DRL)-based virtual power plant (VPP) with lower-level EV parking lot models, using mixed-integer linear programming. The VPP dynamically adjusts prices in response to market conditions, with lower-level models maximizing profits and providing feedback to the upper-level for enhanced learning. Results highlight the sensitivity of the pricing strategy to changes in the lower bounds, with significant impacts on system profitability.

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List of Publications

- Jiwen Qi, Li Li, and Gang Lei. "Economic Operation of a Workplace EV Parking Lot under Different Operation Modes." 2021 31st Australasian Universities Power Engineering Conference (AUPEC). IEEE, 2021.
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- Jiwen Qi, Li Li, Jahangir Hossain, and Gang Lei. "Optimizing EV Parking Lot Profitability through IGDT-based V2G Incentive Decision-Making in Multiple Energy Markets." *Under review by Sustainable Energy, Grids and Networks.*

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Nomenclature

$\tau^{l}_{t,j}$ Randomly generated variable representing the bidding success of lower contingency markets

$\tau^{r}_{t,j}$ Randomly generated variable representing the bidding success of raise contingency markets

η^{ESS}_{ch} ESS charging efficiency

η^{EV}_{ch} EV charging efficiency

η^{ESS}_{dis} ESS discharging efficiency

η^{EV}_{dis} EV discharging efficiency

$\lambda^{c,max}$ Price upper bound

$\lambda^{c,min}$ Price lower bound

$\lambda_{1,t,s}$ Electricity feed-in price at time t in scenario s

$\lambda_{1,t}$ Electricity feed-in price at time t

$\lambda_{2,t,s}$ Electricity purchase price at time t in scenario s

$\lambda_{2,t}$ Electricity purchase price at time t

λ_{inc} V2G incentive rate

λ^{c}_{i} Charging price for the i-th EV

λ_{pv} Operating cost coefficient of PV panels

$\lambda_{q,i}^{c}$ Charging price in the q-th EVPL for the i-th EV

$\lambda_{t,j}^{r}$ J-th FCAS raise market price at time t

$\lambda_{t,k}^{l}$ k-th FCAS lower market price at time t

$\lambda_{t}^{l,max}$ Maximum offered power reserve for lower market price at time t

$\lambda_{t}^{l,min}$ Minimum offered power reserve for lower market price at time t

λ_{t}^{ls} Power reserve base line price for lower markets price at time t

$\lambda_{t}^{r,max}$ Maximum offered power reserve for raise market price at time t

$\lambda_{t}^{r,min}$ Minimum offered power reserve for raise market price at time t

λ_{t}^{rs} Power reserve base line price for raise market price at time t

$\lambda_{t}^{vpp,l}$ Upper-level offered power reserve for lower market price at time t

$\lambda_{t}^{vpp,r}$ Upper-level offered power reserve for raise market price at time t

$\lambda_{t}^{Feed-in}$ The energy feed-in price at time t

$\lambda_{t}^{fvp,max}$ Maximum offered energy purchase price at time t

$\lambda_{t}^{fvp,min}$ Minimum offered energy purchase price at time t

λ_{t}^{fvp} Upper-level offered energy purchase price at time t

λ_{t}^{grid} Electricity purchase price from anther source at time t

$\lambda_{t}^{vf,max}$ Maximum offered energy feed-in price at time t

$\lambda_{t}^{vf,min}$ Minimum offered energy feed-in price at time t

λ_{t}^{vf} Upper-level offered energy feed-in price at time t

λ_{t}^{whole} The spot market electricity purchase price at time t

λ_{w} Operating cost coefficient of WT

$\mu_{i,t,s}$ Binary variable of EV charging/discharging status for the i-th EV at time t in scenario s

$\mu_{i,t}$ Binary variable of EV charging/discharging status for the i-th EV at time t

$\mu_{q,i,t}$ Binary variable of EV charging/discharging status in the q-th EVPL for the i-th EV at time t

ω_1 Weighting factor of upper-level profit in Rewards function

ω_2 Weighting factor of lower-level profit in Rewards function

ρ_s Possibility of scenario s

$\tau_{q,t}^{l}$ Binary variable indicating dispatch or not in the lower market

$\tau_{q,t}^{r}$ Binary variable indicating dispatch or not in the raise market

φ_i Binary variable of EV parking status

$\varphi_{q,i}$ Binary variable of EV parking status in the q-th EVPL

$a_{q,t}$ Binary variable of ESS charging/discharging status in the q-th EVPL at time t

$a_{t,s}$ Binary variable of ESS charging/discharging status at time t in scenario s

a_t Binary variable of ESS charging/discharging status at time t

B Unit battery degradation cost

$b_{q,t}$ Binary variable of grid export/import status in the q-th EVPL at time t

B_q Unit battery degradation cost in the q-th EVPL

$b_{t,s}$ Binary variable of grid export/import status at time t in scenario s

b_t Binary variable of grid export/import status at time t

$c_{q,t}$ Binary variable of FCAS raise/lower market participation status in the q-th EVPL at time t

$C_q^{ESS,de}$ ESS battery degradation cost in the q-th EVPL

$C_s^{ESS,de}$ ESS battery degradation cost in scenario s

c_t Binary variable of FCAS raise/lower market participation status

$C^{ESS,de}$ ESS battery degradation cost

e^{ESS} Square root of the roundtrip efficiency of the battery

$E_i^{de,max}$ Maximum required energy of EV

E_i^{de} Demand energy of EV

$E_{0,s}^{ESS}$ Initial energy of ESS in scenario s

E_0^{ESS} Initial energy of ESS

$E_{i,max}^{EV}$ Upper bounds of the EV energy

$E_{i,min}^{EV}$ Lower bounds of the EV energy

$E_{i,t,s}^{EV}$ Energy of i-th EV at time t in scenario s

$E_{i,t}^{EV}$ Energy of i-th EV at time t

E_{max}^{ESS} Upper bounds of the ESS energy

E_{min}^{ESS} Lower bounds of the ESS energy

e_{pv} PV panel efficiency

$E_{q,0}^{ESS}$ Initial energy of ESS in the q-th EVPL

$E_{q,i,max}^{EV}$ Upper bounds of the EV energy of the q-th EVPL

$E_{q,i,min}^{EV}$ Lower bounds of the EV energy of the q-th EVPL

$E_{q,i,t}^{EV}$ Energy of i-th EV in the q-th EVPL at time t

$E_{q,i}^{de,max}$ Maximum required energy of EV in the q-th EVPL

$E_{q,i}^{de}$ Demand energy of EV in the q-th EVPL

$E_{q,max}^{ESS}$ Upper bounds of the ESS energy in the q-th EVPL

$E^{ESS}_{q,min}$ Lower bounds of the ESS energy in the q-th EVPL

$E^{ESS-}_{q,t}$ ESS of the q-th EVPL discharged energy at time t

$E^{ESS}_{q,t}$ ESS energy in the q-th EVPL at time T

$E^{ESS}_{q,t}$ Energy of ESS in the q-th EVPL at time t

e^{ESS}_{q} Square root of the roundtrip efficiency of the battery in the q-th EVPL

e^{pv}_{q} PV panel efficiency of the q-th EVPL

$E^{ESS-}_{t,s}$ ESS discharged energy at time t in scenario s

$E^{ESS}_{T,s}$ ESS energy at time T in scenario s

$E^{ESS}_{t,s}$ Energy of ESS at time t in scenario s

E^{ESS-}_{t} ESS discharged energy at time t

E^{ESS}_{t} ESS energy at time t

E^{ESS}_{t} Energy of ESS at time t

i Index of EV

j Index of FCAS raise markets

k Index of FCAS lower markets

L Battery lifetime throughput

L_q Battery lifetime throughput in the q-th EVPL

N Total number of EVs

N_l Total number of FCAS lower markets

N_r Total number of FCAS raise markets

N_s Total number of scenarios

$P^{EV+}_{i,max}$ Maximum EV charging power

$P^{EV-}_{i,max}$ Maximum EV discharging power

$P^{EV+}_{i,t,s}$ EV charging power at time t in scenario s

$P^{EV-}_{i,t,s}$ EV discharging power at time t in scenario s

$P^{EV+}_{i,t}$ EV charging power at time t

$P^{EV-}_{i,t}$ EV discharging power at time t

P^{ESS+}_{max} Maximum ESS charging power

P^{ESS-}_{max} Maximum ESS discharging power

$P^{EV+}_{q,i,max}$ Maximum EV charging power in the q-th EVPL

$P^{EV-}_{q,i,max}$ Maximum EV discharging power in the q-th EVPL

$P^{l,ev}_{q,i,t}$ Power reserve from i-th EV of the q-th EVPL for lower market at time t

$P^{t,ev}_{q,i,t}$ Power reserve from i-th EV of the q-th EVPL for raise market at time t

$P^{EV+}_{q,i,t}$ EV charging power in the q-th EVPL at time t

$P^{EV-}_{q,i,t}$ EV discharging power in the q-th EVPL at time t

$P^{l}_{q,max}$ Maximum reserve power of the q-th EVPL for lower market

$P^{r}_{q,max}$ Maximum reserve power of the q-th EVPL for raise market

$P^{ESS+}_{q,max}$ Maximum ESS charging power in the q-th EVPL

$P^{ESS-}_{q,max}$ Maximum ESS discharging power Binary variable of EV charging/discharging status

$P^{l,ess}_{q,t}$ Power reserve from ESS of the q-th EVPL for lower market at time t

$P^{l,res}_{q,t}$ Power reserve of the q-th EVPL for lower market at time t

$P^{r,ess}_{q,t}$ Power reserve from ESS of the q-th EVPL for raise market at time t

$P^{r,res}_{q,t}$ Power reserve of the q-th EVPL for raise market at time t

$P^{ESS+}_{q,t}$ ESS charging power in the q-th EVPL at time t

$P_{q,t}^{ESS-}$ ESS discharging power in the q-th EVPL at time t

$P_{q,t}^{Feed-in}$ Feed-in power of the q-th EVPL at time t

$P_{q,t}^{fvp}$ Import power of the q-th EVPL at time t from VPP

$P_{q,t}^{Grid}$ Import power of the q-th EVPL at time t from alternative purchasing source

$P_{t,j}^{vpp,r}$ Upper-level power trade with j-th FCAS raise market at time t

$P_{t,k}^{vpp,l}$ Upper-level power trade with k-th FCAS lower market at time t

$P_{t,s}^{ESS+}$ ESS charging power at time t in scenario s

$P_{t,s}^{ESS-}$ ESS discharging power at time t in scenario s

$P_{t,s}^{Feed-in}$ Grid feed-in power at time t in scenario s

$P_{t,s}^{Grid}$ Grid import power at time t in scenario s

P_{t}^{ESS+} ESS charging power

P_{t}^{ESS-} ESS discharging power

$P_{t}^{Feed-in}$ Grid feed-in power at time t

P_{t}^{Grid} Grid import power at time t

Q Total number of EVPLs

q Index of EVPL

R Battery purchase cost

$r_{q,t}$ Solar radiation of the q-th EVPL at time t

R_q Battery purchase cost in the q-th EVPL

$r_{t,s}$ Solar radiation at time t in scenario s

r_t Solar radiation at time t

s Index of scenario

s_{pv}	Surface area of PV panels
s_q^{pv}	Surface area of PV panels of the q-th EVPL
T	Simulation time
t	Index of time step
$t_{a,i}$	EV's arrival time
$t_{a,q,i}$	EV's arrival time in the q-th EVPL
$t_{d,i}$	EV's departure time
$t_{d,q,i}$	EV's departure time in the q-th EVPL
V_{ci}	Cut-in wind speed
V_{co}	Cut-out wind speed
V_r	Rated wind speed
$v_{t,s}$	Wind speed at time t in scenario s
v_t	Wind speed at time t
Z_q^{evpl}	Total profit of the q-th EVPL
z_q^{EV}	Profit of the q-th EVPL from EV charging
z_q^{res}	Profit of the q-th EVPL from power reserve
$P_{q,t}^{PV}$	Power generated by the PV panel of the q-th EVPL at time t
P_r	Rated power output of wind turbine
$P_{t,s}^{PV}$	Power generated by the PV panel at time t in scenario s
$P_{t,s}^{W}$	Power generated by the wind turbine at time t in scenario s
P_t^{PV}	Power generated by the PV panel at time t
P_t^{W}	Power generated by the wind turbine at time t

Chapter 1

Introduction

1.1 Background

The increasing urgency to address climate change has accelerated the global transition toward electrification in the transportation sector, with electric vehicles (EVs) playing a pivotal role in this shift. As a cleaner alternative to internal combustion engine vehicles, EVs offer the potential to reduce emissions and support the broader goal of decarbonization significantly [1] [2].

However, the rise of EVs presents new opportunities and challenges, particularly when considering their interaction with the power grid. The potential for EVs to contribute to energy systems through vehicle-to-grid (V2G) functionality has garnered increasing attention, as EVs have the capacity to not only consume energy but also provide services back to the grid [3]. This dual role introduces both operational complexities and economic opportunities [4] [5].

In this context, EV parking lots—especially those equipped with V2G technology—represent a key point of interaction between EVs, energy markets, and the grid. Optimizing the operation of these parking lots to maximize their economic benefits requires addressing a range of uncertainties and dynamic factors.

1.1.1 The Rise of EVs

The global push towards decarbonization has intensified the focus on reducing greenhouse gas emissions, especially in industries like transportation, which is a major contributor to environmental degradation. As part of this transition, EVs have emerged as a promising alternative to traditional internal combustion engine vehicles. Their ability to reduce emissions and reliance on fossil fuels makes them critical components in the broader efforts to mitigate climate change [1] [6].

The adoption of EVs has accelerated in recent years, driven by advancements in battery technology, government incentives, and the growing availability of charging infrastructure. According to the International Energy Agency (IEA), by the end of 2020, the global EV stock exceeded 10 million vehicles, and this figure is projected to rise dramatically to 230 million by 2030 [7]. This exponential growth reflects the increasing recognition of EVs as a vital solution to achieving carbon reduction targets in the transportation sector.

In Australia, the average annual distance travelled by vehicles is 12.1 thousand kilometers, which equates to less than 35 kilometers per day [8], [9]. However, as of 2020, the median range of EVs was approximately 416.8 kilometers, meaning that over 90% of the energy stored in EV batteries typically remains unused during daily commutes. This surplus energy represents a significant opportunity for EVs to contribute to power grid support through the V2G function. Aggregating the energy stored in EV batteries at parking lots or charging stations could offer a substantial resource for grid stabilization, peak shaving, and renewable energy integration.

Thus, the rapid rise in EV adoption, coupled with the inherent energy storage potential of their batteries as energy storage systems (ESS), sets the stage for leveraging V2G technology. This capability transforms EVs from mere transportation devices into key components of a flexible and resilient power system, ready to provide ancillary services to the grid. As the number of EVs continues to grow, the role of V2G-enabled parking lots in supporting the grid becomes increasingly critical, creating a natural transition to the next key discussion on the potential of the V2G function.

1.1.2 V2G Potential

As EVs continue to grow in number, their potential to support the power grid through V2G technology is becoming increasingly apparent. V2G allows for bidirectional energy flow between EVs and the power grid, enabling EVs not only to charge their batteries but also to discharge stored energy back into the grid. This transformation of EVs into mobile energy storage units opens up new opportunities for enhancing grid flexibility, stability, and resilience, particularly in systems with a growing share of renewable energy sources (RESs)[10][11].

The surplus energy remaining in EVs can be tapped to provide critical grid services. V2G enables EVs to contribute to frequency regulation, voltage control, and peak load shaving, effectively balancing energy supply and demand across the grid [12] [13]. By aggregating the energy storage potential of EVs at parking lots or charging stations, where vehicles are often idle for extended periods, these hubs can serve as centralized points of energy storage and distribution. This aggregation amplifies the impact of V2G by coordinating the collective energy capacity of multiple vehicles, enhancing the grid's ability to manage fluctuations in demand and supply [14].

Moreover, the financial incentives associated with V2G participation provide significant economic benefits for EV owners. By charging their vehicles during off-peak periods when electricity prices are low and discharging energy back to the grid during peak periods when prices are higher, EV owners can optimize their electricity usage and generate additional income. This dynamic interaction between EVs and the power grid creates a mutually beneficial relationship, wherein EV owners, parking lot operators, and grid operators all stand to gain from the implementation of V2G technology.

V2G's potential becomes even more pronounced as renewable energy penetration increases. The intermittent nature of renewable energy sources like solar and wind poses challenges for grid operators, as periods of excess generation can lead to curtailment, while periods of low generation can strain the grid. EVs, through V2G, offer a flexible solution by storing excess renewable energy and discharging it back into the grid when needed, helping to smooth out these fluctuations [15] [16]. This not only enhances the integration of renewables into the energy mix but also reduces the need for fossil fuel-based peaking plants, further contributing to the decarbonization of the power system [17].

As the number of EVs continues to rise globally, the role of V2G in providing essential grid services and supporting renewable energy integration will only grow. EV parking lots, equipped with V2G-enabled chargers, are poised to become critical nodes in this evolving energy landscape, serving as both transportation hubs and valuable energy resources.

1.1.3 RES and ESS Integration

The global energy transition is closely tied to the increasing integration of RESs like solar and wind power, which are crucial for reducing reliance on fossil fuels and mitigating climate change. However, the inherent variability and intermittency of renewable energy present significant challenges to grid stability and reliability. Solar and wind power are weather-dependent, leading to periods of excess generation when conditions are favourable and periods of low output when they are not. This unpredictability can cause fluctuations in power supply that need to be managed effectively to ensure a stable grid [18].

In this context, ESSs play an essential role by providing the flexibility needed to store excess renewable energy during periods of high generation and discharge it back into the grid during times of low generation or high demand. Traditional ESSs, such as large-scale battery installations, have already proven effective in smoothing out the variability of renewable energy [19]. However, the rise of EVs introduces a new form of distributed energy storage that can complement conventional ESSs [20].

EVs, equipped with the V2G function, can act as mobile ESSs, offering a flexible and scalable solution to support the grid. When aggregated in parking lots or charging stations, EVs can provide significant energy storage capacity, helping to balance the intermittency of renewable energy sources [21]. By storing surplus energy generated from solar or wind power and feeding it back into the grid when needed, EVs can effectively reduce the need for fossil fuel-based peaking plants, thereby contributing to the decarbonization of the electricity system [22].

Moreover, the integration of RESs into the grid can benefit from the distributed nature of EVs and their mobility. EVs can provide localized energy support in areas with high renewable energy penetration, reducing transmission losses and enhancing the overall efficiency of the energy system [23]. For instance, an EV parked at a charging station equipped with solar panels can directly charge from on-site renewable generation, reducing strain on the grid and maximizing the use of clean energy. In this way, EVs not only offer transportation solutions but also become an integral part of the renewable energy ecosystem.

Energy storage is also critical for enabling the broader adoption of renewables, particularly in markets with high levels of solar and wind energy. By smoothing out the generation profiles of these sources, ESSs and V2G-enabled EVs can facilitate the shift towards a cleaner energy mix, making it easier for grid operators to manage supply and demand [24]. This synergy between EVs, V2G, and RESs will be instrumental in advancing the transition to a sustainable energy system, where electricity is generated and consumed more efficiently and cleanly [25].

As the penetration of renewable energy increases, the role of EVs as flexible, distributed energy storage units becomes increasingly important. The combination of V2G technology, renewable energy integration, and ESSs presents a powerful tool for enhancing grid resilience, reducing emissions, and optimizing the use of clean energy. EV parking lots, in particular, can act as hubs where renewable energy, storage, and transportation meet, driving both economic and environmental benefits.

1.1.4 EV Parking Lot Operations

While EV parking lots equipped with V2G functionality present significant opportunities for grid support and renewable energy integration, their economic operation introduces a range of challenges. Managing these parking lots requires navigating uncertainties related to electricity market prices, renewable energy generation, and the behavior of EV users. Successfully optimizing the operation of EV parking lots to maximize profitability while maintaining grid support is a complex, multi-faceted problem that requires advanced decision-making and forecasting tools.

One of the key challenges lies in the variability of electricity prices in different energy markets. Prices in these markets fluctuate based on real-time supply and demand dynamics, making it difficult to predict the optimal times for EVs to charge or discharge energy. Moreover, the unpredictable nature of RESs further complicates the decision-making process. These fluctuations can impact both the availability of renewable energy for charging EVs and the potential profits from discharging stored energy back to the grid [26].

In addition to market uncertainties, the operational diversity of EV users presents another challenge. EVs in parking lots may have different arrival and departure times, varying energy requirements, and different states of charge upon arrival. Accounting for this diversity is critical to ensuring efficient energy management. A dynamic pricing mechanism, which adjusts based on real-time demand and the state of the grid, is essential to incentivize EV owners to participate in V2G services [27]. This requires accurate forecasting of both user behavior and energy market conditions to optimize charging and discharging schedules [28].

Another significant factor to consider is the degradation of ESSs. The frequent cycling of ESSs, including the batteries in EVs, leads to gradual degradation over time, reducing their capacity and efficiency. This degradation must be factored into the economic model to ensure that the financial benefits of participating in V2G services outweigh the costs associated with reduced battery life [29]. Understanding the trade-offs between energy usage, ESS degradation, and profitability is crucial for optimizing the operation of V2G-enabled parking lots [30].

While the economic operation of EV parking lots with V2G capabilities presents complex challenges, the economic opportunities for EV parking lots are substantial. By participating in various energy markets, parking lots can generate revenue from both charging EVs and providing grid services through V2G. During periods of high renewable energy generation, parking lots can charge EVs at lower prices, taking advantage of cheaper, cleaner energy. As the market for EVs and renewable energy continues to expand, the role of EV parking lots in providing both transportation and energy services will become increasingly critical, offering new avenues for economic growth and sustainability.

1.1.5 Virtual Power Plants (VPPs)

The concept of VPPs has emerged as a crucial mechanism to integrate and manage distributed energy resources (DERs), such as renewable energy systems, energy storage, and EV fleets, particularly in parking lots and charging stations. VPPs leverage advanced communication and control technologies to aggregate multiple energy assets, including EVs, to participate in energy markets and provide grid services such as frequency regulation, load balancing, and peak shaving.

VPPs serve as aggregators that coordinate the operation of EVs, RESs, and ESS in parking lots to maximize energy efficiency and profit. The study of [31] examines how EV parking lots can be used as frequency containment reserve providers, highlighting the potential for additional revenue through VPP integration. EV charging stations within VPPs can actively participate in grid services, balancing electricity demand and supply through coordinated charging and discharging schedules. Similarly, the research of [32] discusses the role of VPPs in integrating smart charging stations and parking lots to provide global and local power system support. Their study emphasizes the importance of VPPs in smoothing the uncertainties introduced by renewable energy sources, such as solar panels, and how aggregated EVs can be dispatched as virtual storage plants to stabilize the grid during peak demand.

In terms of economic and operational benefits, the integration of EV parking lots into VPPs presents numerous economic benefits. The study of [33] investigates solar-powered EV charging stations managed within a VPP structure, showing that such setups can provide clean energy while also participating in energy trading markets. These parking lots can also serve as flexible energy hubs that adjust charging schedules based on energy prices and market conditions, contributing to the overall profitability of the VPP. Further, the study of [34] analyzes how EV fleets parked in VPP-enabled charging stations interact with electricity markets. Their research indicates that VPPs help optimize the participation of EVs in energy markets by ensuring that vehicles can provide grid support during times of high electricity prices, thereby generating profit for both parking lot operators and the VPP.

Moreover, the integration of EV parking lots with renewable energy resources, such as solar and wind, introduces operational uncertainties related to intermittent generation. To address these challenges, the research of [35] proposes a grid-interactive charging strategy that uses VPPs to manage uncertainties while enhancing profitability. The study highlights the role of real-time data and predictive models in dynamically adjusting the charging/discharging schedules of EVs in response to grid conditions, thereby optimizing energy flows and minimizing energy costs. In addition, the study of [36] explores how virtual battery models can reduce computational complexity and improve the efficiency of charging stations in EV parking lots. Their research shows that VPPs, coupled with advanced energy management systems (EMS), can better predict renewable energy output and adjust EV operations to support grid stability during periods of high uncertainty.

1.1.6 Optimization and Decision-Making

The successful operation of EV parking lots with V2G functionality requires more than just technical infrastructure; it demands advanced decision-making processes to handle the inherent complexity of energy markets and the evolving nature of grid interactions. As these parking lots act as both energy consumers and providers, operators must navigate a variety of dynamic factors to ensure optimal performance and profitability.

To manage the uncertainties associated with electricity prices, renewable energy output, and EV user behavior, sophisticated optimization frameworks are essential. It must be capable of responding to real-time changes in market conditions, adapting to fluctuations in renewable energy availability, and ensuring efficient energy use across the system. Moreover, the decision-making process must balance short-term operational gains with long-term sustainability, accounting for potential impacts on ESS and EV battery life.

Optimization strategies need to be flexible enough for dynamic adjustment as conditions evolve. Energy market prices and RESs can be highly variable, so decision-making frameworks must incorporate reliable forecasts and data analytics to make the most of available energy. Scenario-based and machine learning-based approaches are valuable for planning in such uncertain environments to handle fluctuations in market prices or renewable energy availability [37]. In addition, these decision-making frameworks must integrate the evolving role of EVs in the energy ecosystem. As EVs become more widespread, parking lots will need to consider not only the immediate charging and discharging decisions but also the broader implications for revenue generation in various energy markets [38]. This includes optimizing when and how to participate in ancillary services markets, setting dynamic pricing, and adjusting energy dispatch strategies to capture the most profit from market opportunities [39]. Hence, by efficiently managing the flow of energy between EVs, parking lots, and the grid, these frameworks help ensure that parking lots operate profitably, leveraging V2G services, dynamic pricing, and energy market participation to achieve the highest possible economic returns [40].

1.2 Research Questions

Having established the context and challenges associated with the economic operation of EV parking lots, it is essential to investigate how these challenges can be addressed to maximize profitability. The following research questions aim to explore the potential for optimizing EV parking lots equipped with V2G functionality while managing uncertainties and enhancing economic performance:

- In parking lots with EV charging stations, does the V2G function have any potential for profit? What about short-term parking EVs? Is there any strategy for them to increase profits for the parking lot?

- How can an EV parking lot manage uncertainties such as solar irradiance, wind speed, market prices, or EV behaviors? If we consider EV owners' willingness to participate in V2G, how can we set V2G incentives to increase the profitability of parking lots? Given these factors, what is the overall profit potential for EV parking lots in the market?

- For multi-EV parking lots or charging stations, how can they achieve or enhance potential profits under an upper-level pricing strategy, such as VPP? How does the pricing strategy impact their profits and the profits at the upper level?

It should be noted that battery degradation of ESS needs to be considered in the above questions. On the other hand, as energy storage technology continues to evolve, the price keeps decreasing while battery performance improves. The cost and performance problems of EV batteries will likely be better resolved in the near future. Thus, EV battery degradation will not be directly considered in the above research questions. From the EV parking lot's perspective, upper and lower bounds for EV charging and discharging will be set to prevent over-charging and over-discharging of EVs. Furthermore, V2G incentives and EV owners' willingness will be taken into account to limit EV battery discharging during the optimization in certain scenarios or to provide more reasonable monetary rewards to EVs.

1.3 Research Methodology

1.3.1 Aims

- To investigate methods for managing uncertainties in EV parking lots and charging stations.

- To explore the V2G profit potential across different operational and business models.

1.3.2 Objectives

- To explore methods for managing uncertainty factors using data generation, machine learning, and historical data analysis.
- To investigate methods for managing EV behavior uncertainties using data generation and deep reinforcement learning (DRL), considering different parking periods.
- To explore the profit potential of the V2G function in EV parking lots and charging stations under various operational and business models, including different market conditions such as Frequency Control Ancillary Service (FCAS) and spot markets.
- To analyze V2G incentive pricing by considering EV owners' willingness to participate, discussing the profitability potential under a comprehensive operational model.
- To assess the profit potential of multi-EV parking lots or charging stations with V2G functions under an upper-level market-centralized model, analyzing the impact of pricing strategies under multiple market conditions.

1.3.3 Research Methods

This research adopts a multi-method approach to address the economic operation of EV parking lots with V2G functionality. The methods selected aim to explore how uncertainties can be managed and how V2G potential can be optimized to maximize profitability.

- Scenario-Based Modelling: To address the uncertainties related to market prices, solar irradiance, and wind speed, scenario-based modeling is employed. Scenarios are generated using the scenred toolbox in MATLAB, providing a range of potential future conditions. These scenarios help explore how different combinations of market and environmental factors affect the operation of EV parking lots. By testing operations against these scenarios, optimal solutions can be identified to maximize profits.
- Monte Carlo Simulation: To simulate the diverse behavior of EV users, including their arrival and departure times and initial state of charge (SoC), Monte Carlo simulations are utilized. This method helps capture the variability in user behavior, ensuring that the optimization process reflects reliable scenarios. By incorporating a wide range of possible

user behaviors, this approach provides a more robust solution to managing EV parking lot operations.

- Information Gap Decision Theory (IGDT): To account for the uncertainty in V2G participation willingness and market conditions, IGDT is used. It allows for robust decision-making by evaluating strategies across a range of uncertain outcomes. This approach helps parking lot operators determine the optimal V2G incentives that maximize profits while minimizing the financial risks associated with unpredictable market conditions and user participation willingness.

- Machine Learning and Data Analysis: Machine learning techniques, particularly Long Short-Term Memory (LSTM) networks, are applied to predict key variables like electricity market prices and renewable energy availability. LSTM models are well-suited for time-series forecasting, enabling accurate predictions of renewable energy output and market price fluctuations. This predictive capability informs the charging and discharging schedules for EVs, allowing for more informed decision-making.

- DRL: DRL is employed to optimize the upper-level pricing strategies of the VPP. The VPP uses DRL to learn and adjust dynamic pricing strategies based on real-time market conditions and feedback from the lower-level EV parking lot operations. By continuously adapting, DRL helps to identify pricing strategies that achieve the best overall profit for the entire bi-level system, rather than solely maximizing the VPP's revenue, which could lead to an unsustainable business model.

- Normalizing Flows: Normalizing flows are utilized in this research to model the complex behaviors of EV users more effectively. By applying this machine learning technique, the joint probability distributions of EV arrival, departure times, and SoC can be modeled in a flexible and tractable way. Normalizing flows allow for more realistic simulations of user behavior by capturing the inherent variability and uncertainty in EV actions. This, in turn, helps to optimize decision-making in scenarios involving multiple EVs with varying behaviors.

1.4 Research Contributions

This research presents several key contributions to the optimization of EV parking lots. First, an energy management strategy is proposed to maximize the benefits of EV parking lots across multiple charging modes, addressing the uncertainties of RESs, ESS degradation, and varying EV parking statuses. EVs are classified based on their parking duration to determine eligibility for V2G participation, with tailored charging and reward strategies designed accordingly. Dynamic charging prices are introduced based on EV demand and parking status, ensuring economic charging and rewards for EV owners while securing satisfactory profits for the parking lot. Additionally, the project develops a comprehensive EV parking lot model that integrates RESs and V2G functions, effectively managing the uncertainties of smart grid operations, including market price volatility, RES variability, and unpredictable EV user behavior. A simple yet efficient EV allocation method is proposed to optimize the use of limited charging infrastructure. A modified IGDT-based method is also introduced to determine V2G incentives, accounting for EV owners' willingness to participate in grid support services. Furthermore, a hybrid optimization framework combines DRL and mixed integer linear programming (MILP) framework to enhance decision-making in a bi-level system, with the VPP operating at the upper level and EV parking lots at the lower level. Finally, normalizing flows are employed to model complex EV behavior patterns, improving the robustness and accuracy of simulations under market and grid uncertainties.

1.5 Thesis Organization

This thesis is organized into six chapters, each addressing different aspects of the economic operation of EV parking lots, with a focus on the V2G function.

Chapter 1: Introduces the research background, outlining the research aims, questions, and methodology. It also summarizes the key contributions of the thesis.

Chapter 2: Presents a literature review related to the operation of EV parking lots, examining existing research and identifying gaps that this thesis seeks to address.

Chapter 3: Explores the economic operation of an EV parking lot equipped with V2G, RESs, and ESS, focusing on profit maximization and addressing market and environmental uncertainties. The proposed optimization model is validated through scenario generation using MATLAB.

Chapter 4: Examines EV parking lots integrated with DERs, participating in both spot and FCAS markets. Forecasting is conducted using LSTM models, and an IGDT-based approach is employed to optimize V2G incentives, demonstrating profitability across multiple scenarios.

Chapter 5: Presents a hybrid bi-level optimization framework that integrates DRL for dynamic pricing in VPPs and EV parking lots. The chapter also analyzes the effect of pricing bounds on profitability and introduces normalizing flows for modeling EV behavior.

Chapter 6: Concludes the thesis, discussing the main findings and outlining potential directions for future research.

Chapter 2

Literature Review

The economic operation of EV parking lots, particularly those utilizing V2G functions, is a rapidly evolving research area. This chapter reviews the existing literature to establish a foundation for this thesis. Key topics covered include the integration of RES and ESS, the development of EMS, and the operation of EV parking lots in electricity markets. The chapter also examines the role of VPPs, uncertainties in market conditions, and the challenges associated with optimizing economic performance. Reviewing these critical areas, this chapter identifies the research gaps and sets the stage for the subsequent analysis.

2.1 Electric Vehicle

With the rising need for sustainable energy solutions, EVs have gained significant penetration as a promising response to environmental challenges such as carbon emissions and reliance on fossil fuels. Beyond their role as eco-friendly transportation options, EVs offer additional benefits in energy management and grid support, especially when integrated with RESs and ESS. This literature review explores the multifaceted contributions of EVs, focusing on their integration with RES, energy management strategies, and participation in market trading, positioning EVs as a crucial component in modern power systems.

The rapid development of EVs, coupled with the increased adoption of RESs, has shown considerable feasibility for power grid support and EV charging applications. Renewable energy, particularly solar power, is increasingly integrated into EV charging infrastructures, such as parking garages equipped with photovoltaic (PV) panels, which can provide a sustainable source of energy for EVs [41]. In addition, V2G technology enables bidirectional energy flow, allowing EV batteries to not only consume but also supply energy back to the grid, optimizing power generation scheduling and improving grid stability [42]. A key focus of recent research has been on combining ESS with EV batteries to mitigate the intermittency and instability of PV systems. Several studies propose controllable optimized charging and discharging strategies to stabilize PV systems using limited EV battery capacity [43]–[46]. This approach enhances the efficiency of renewable energy utilization, reduces the stress on the grid, and contributes to overall system stability. For example, one study demonstrated that using EV batteries as responsive demand could improve renewable energy utilization by 7.9% [46]. Moreover, the integration of EVs into EMS further emphasizes their role as distributed energy storage units in parking lots and charging stations. By treating EVs as virtual power plants or distributed storage systems, these facilities can actively participate in local and global power system support [32]. Intelligent scheduling models ensure that EV batteries are charged and discharged optimally, contributing to grid stability while taking into account battery conditions and V2G operations [47], [48]. This dual role of EVs as both energy loads and sources enhances utility company operations and enables effective demand-supply balancing.

Beyond their role in energy management, EVs in parking lots and charging stations are increasingly recognized as valuable participants in energy markets. Studies have proposed optimization models that allow EVs to engage in market trading, such as day-ahead energy markets [49], and manage charging demand in a cost-effective manner [50]. These models integrate EVs with renewable energy resources like solar and wind, further positioning them as key assets in the transition to a more decentralized and sustainable energy system. However, several challenges remain, particularly in ensuring the reliability and availability of EV charging infrastructure. Issues such as random charging patterns, distribution losses, and power quality degradation must be addressed, and coupling ESS with EV charging stations has been proposed as an effective solution [51]. Despite these challenges, the potential of EVs to support both the grid and renewable energy integration through intelligent management strategies, market participation, and technological innovations continues to grow.

2.2 Energy Storage System

The growing adoption of RESs EVs is reshaping modern power systems, driving the need for efficient energy management and storage solutions. ESS plays an essential role in addressing the challenges posed by the intermittent nature of RESs while enabling the integration of EVs into the grid. In particular, ESS enhances the reliability and stability of both renewable energy generation and EV charging infrastructure, providing a critical bridge between sustainable energy use and grid stability.

RESs such as PV systems are increasingly used to reduce grid power demand and greenhouse gas emissions. However, due to the intermittent and unstable nature of RESs, ESS has become a vital component for ensuring power quality and maintaining the reliability and stability of renewable power supplies [52]. ESS plays a crucial role by storing excess energy generated during peak production periods and supplying power during times of insufficient renewable generation. This dynamic allows ESS to support grid operations, especially in applications such as smart homes and charging stations. In the context of EV parking lots and charging stations, ESS serves as an essential energy reserve, helping balance supply and demand. Several studies have explored the integration of ESS with EVs and RESs to create sustainable charging environments. For example, parking lots can function as virtual storage plants, leveraging both EV batteries and ESS to provide power system support during peak demand [32]. Furthermore, integrating regenerative braking energy and ESS with RES in EV parking lots contributes to a more sustainable and efficient energy ecosystem [53].

In addition, energy management strategies for EV charging stations integrated with ESS and RES play a vital role in optimizing energy use and enhancing profitability. Various approaches, such as real-time scheduling and intelligent energy management systems, are designed to synchronize EV charging with peak renewable energy generation, effectively utilizing ESS to buffer intermittent power supply [54]. Stochastic and multi-objective optimization models further refine the charging and discharging schedules for both EVs and ESS, ensuring cost-effective operation while maintaining reliable service [55], [56]. For instance, time-of-use pricing strategies can maximize profitability by managing energy flow between the grid, ESS, and RES during periods of fluctuating electricity prices [57]. Similarly, VPP models integrating EV parking lots, ESS, and RES demonstrate how these systems can improve overall energy efficiency, minimize grid dependency, and enhance sustainable energy management [58].

Beyond energy management, ESS integrated with EV parking lots and charging stations can participate in energy markets through V2G programs and demand response services. Studies have shown that ESS in EV parking lots can offer valuable services such as frequency regulation and demand response, thereby improving grid reliability and enhancing profitability for parking lot operators [59]. The resource allocation frameworks that integrate ESS into residential parking lots further underscore the potential for optimizing market participation. The integration of RES, particularly solar PV, with ESS in EV parking lots is also a growing area of research. Studies have explored how ESS can buffer the intermittency of renewable generation, ensuring a stable and reliable energy supply for EV charging stations. By optimizing the charging schedules of EVs based on solar energy availability, ESS helps to reduce grid dependency and enhance renewable energy utilization [56], [60].

2.3 Energy Management System

EMS is critical to the efficient operation of EV parking lots and charging stations, particularly in managing the integration of RES, scheduling charging, and interacting with the power grid. With the rise of V2G services, EMS plays a crucial role in balancing energy flow while addressing challenges such as battery degradation and ensuring cost-effective, sustainable energy management.

One key challenge for EMS in EV charging stations is managing the integration of renewable energy, especially PV systems, with real-time charging schedules. For example, the study of [54] proposes a real-time EMS for PV-assisted EV charging stations, ensuring EVs are charged when solar energy is available. The inclusion of ESS helps buffer excess energy and reduces stress on EV batteries, extending their lifespan. While battery degradation remains a significant concern for V2G operations, efficient EMS can mitigate this issue by coordinating charging and discharging events, reducing unnecessary battery cycling. Studies such as [61] and [62] propose optimization strategies to minimize degradation while still supporting grid services.

Another essential function of EMS is ensuring fairness and cost-effective management of EV charging in parking lots. For instance, in [63] presents an EMS that distributes charging power equitably among multiple EVs based on fairness indices, while also managing operational costs. This approach ensures EVs are charged efficiently without disproportionately draining resources, promoting a balanced energy management system. The integration of transactive energy models into EMS enables EVs in parking lots to actively participate in energy markets. For example, the research of [64] introduces an EMS that allows EVs to contribute energy back to the grid during high-demand periods. This transactive model not only improves the utilization of available energy but also provides economic incentives for parking lot operators and EV owners through market participation. Given the inherent uncertainties in renewable energy generation and fluctuating EV demand, predictive and stochastic EMS models have been developed to address these complexities. For instance, a real-time EMS that integrates renewable energy forecasts with predictive models is proposed in [65] for EV demand. This system allows for optimal EV charging scheduling, reducing peak loads and minimizing grid reliance while ensuring that EVs are charged during periods of high renewable energy availability. Hybrid renewable energy systems, such as those combining solar PV and biogas, are also gaining attention in the context of EV charging stations. The study of [66] develops an EMS that maximizes the use of hybrid renewable energy resources while minimizing grid dependency. By managing EV charging schedules to capitalize on available renewable energy, the system ensures both sustainability and efficiency. EMS can also incorporate demand-side management strategies to optimize energy use based on time-of-use pricing and energy availability. An EMS that dynamically adjusts EV charging schedules according to energy prices and grid demand is proposed in [67], which reduces operational costs for EV parking lots while ensuring that vehicles are adequately charged when needed.

2.4 EV Parking Lots and Charging Stations

EV charging stations and parking lots offer a promising opportunity to act as centralized ESS and participate in energy markets. The study of [68] examines bidding strategies in energy and reserve markets for aggregators managing multiple EV fast charging stations with battery storage. This study emphasizes the importance of using ESS in charging stations to buffer energy supply and demand, facilitating effective market participation and enhancing grid stability. An energy management approach is proposed in [58] for VPP that includes commercial loads and EV parking lots integrated with solar PV units and ESS. Their strategy focuses on market participation of PV and EVs, demonstrating how EV charging infrastructure can support grid services and energy storage needs.

In [69], an optimal operation model is presented for aggregated EV charging stations coupled with ESS, considering market participation and ESS degradation costs. The study emphasizes the economic benefits of coordinated energy management between EV parking lots and smart grid systems. Additionally, a probabilistic capacity planning methodology is provided in [70] for EV charging lots with on-site ESS. The objective is to optimize energy storage and market participation while managing uncertainties in energy demand and supply. In [71], an EV parking lot EMS is designed to integrate hydrogen storage and demand-side management. The strategy aims to optimize energy usage and market participation, demonstrating the potential for new energy storage technologies in EV charging infrastructure.

The comprehensive energy management strategies have been discussed in [72]–[74]. The study of [72] develops a real-time energy management strategy for EV charging stations integrated with local renewable generations and ESS. Their approach incentivizes EV owners to participate in V2G operations, enhancing the flexibility and reliability of the energy grid. A hybrid optimization framework is presented in [73] for deploying ESS in PV-integrated EV charging stations. This study focuses on time-of-use (TOU) based energy management to encourage consumer participation and optimize energy storage utilization. The study of [74] reviews various mechanisms for energy storage and charging stations, highlighting the impact of EVs as mobile ESS on the power system. Their work underscores the potential of EV charging infrastructure in providing ancillary services and participating in energy markets.

These studies demonstrate the potential of EV charging stations and parking lots to serve as ESSs, contributing to grid stability and market participation. By integrating renewable energy sources and employing advanced energy management strategies, EV infrastructure can significantly enhance the efficiency and sustainability of the power grid.

To offer optimal energy management for EV parking lots and charging stations, handling uncertainties is a significant challenge. These uncertainties primarily focus on RESs and EV behavior. Many studies, such as [75], [76], [77], [78], and [79], focus on handling uncertainties in EV behaviors, including stochastic EV charging behaviors, EV load variability, and unpredictable EV arrival times. Additionally, the studies of [80], [81], [82], [83], and [84] address uncertainties in renewable energy sources, such as variability in wind and solar power generation, and the impact of these uncertainties on the energy management of EV charging infrastructure. The study of [55] focuses on integrated energy management strategies that consider uncertainties in both RESs and EV behaviors, aiming to optimize the performance and reliability of EV charging stations with renewable energy and storage systems.

In terms of methods to deal with uncertainty, stochastic modeling and scenario-based approaches have been used in [75], [80], [81]. A unified planning model that incorporates stochastic processes is proposed in [75] to handle uncertainties in renewable energy and load demand. Their objective is to accurately predict PV output and manage stochastic EV charging behaviors in parking lots. The study of [80] utilizes scenario-based analysis to address the variability in renewable resources and load demands. The objective is to generate multiple scenarios to better predict the behavior of RESs and EV charging demands. Stochastic models are integrated in [81] for EV charging stations with wind energy, aiming to effectively model the probabilistic nature of renewable energy generation and EV charging needs.

The studies of [76], [82] discuss robust optimization. Robust optimization in [76] aims at placing and sizing EV charging stations, considering uncertainties in EV load and renewable power sources. Their objective is to optimize the placement and capacity of EV charging infrastructure under uncertainty. A hybrid robust-stochastic optimization framework is developed in [82] for managing energy in EV parking lots, taking into account uncertainties in wind and solar power generation and EV behaviors. The objective is to enhance energy management strategies.

Probabilistic methods are used in [77], [83]. The study of [83] focuses on probabilistic modeling of RESs and demand response for designing EV fast charging stations. The objective is to predict the variability in renewable energy output and optimize charging station performance under uncertainty. A Markov chain model is proposed in [77] to handle the uncertainty in EV charging loads, guiding EV users to optimize their charging schedules. The objective is to minimize the impact of unpredictable EV arrival times on the charging infrastructure.

Besides, game-theoretic approaches in [79] explore energy pricing strategies using game-theoretic models under vehicle uncertainty. The objective is to optimize energy pricing and utilization in EV parking lots equipped with charging stations and photovoltaic systems. An integrated energy management strategy is proposed in [55] for large EV charging stations incorporating RESs and ESSs to handle uncertainties and reduce prediction errors. Their objective is to improve the overall efficiency and reliability of the charging infrastructure.

2.5 Virtual Power Plants

One thing that must be mentioned here is VPP, which integrates various DERs, including RESs, ESSs, and EVs to enhance grid stability and efficiency. The studies of [32], [85]–[87] discuss integrating EVs and ESSs for power support. The study of [32] investigates the role of VPP in parking lots of EVs, providing both local and global power system support. The study emphasizes the use of EVs as mobile storage units to mitigate power system intermittency and volatility. The research of [85] proposes an energy trading model for technical VPPs, considering various RESs, ESSs, and EVs. The expanded VPP model addresses the operational challenges of DERs in distribution systems. In [86], the authors develop a genetic algorithm for managing residential VPPs with EVs, focusing on providing ancillary services. The coordinated management system optimizes energy generation and storage to support grid operations. The study of [87] reviews control techniques for VPPs that integrate RESs, ESSs, and smart loads, highlighting the role of EVs in enhancing grid stability and demand response.

In terms of scheduling and optimization in VPPs, the study of [88] introduces scheduling strategies for VPPs containing EVs based on DRL. The model optimizes the charging and discharging schedules of EVs to enhance VPP performance. In [89], the authors present a case study on DERs and ESSs within a VPP, focusing on the economic aspects. The study explores the integration of EVs and ESSs to improve the profitability of VPPs. The research of [90] discusses VPP control concepts with EVs, emphasizing the aggregation of EV battery storage to provide grid support and enhance the flexibility of power systems.

Furthermore, economic and technical dimensions of VPPs are explored in several studies [49], [91], [92]. The study of [91] provides a comprehensive review of VPPs integrating EVs, covering V2G concepts, interface topologies, and market prospects. The economic and technical benefits of using EVs as part of VPPs are highlighted. A self-scheduling optimization model for a hybrid solar-wind VPP that aggregates EV charging and discharging power for participation in electricity markets is proposed by [49]. In [93], a bi-level optimal planning model for ESSs in VPPs is developed, addressing the challenges of trading characteristics and optimal location and capacity planning for ESSs. A comprehensive review on EVs integrated in VPPs is conducted by [92], discussing the coordinated control methods and intelligent management systems that enable efficient integration of EVs and ESSs.

The studies of [94], [95] discuss VPPs and demand response. The optimal integration of demand response programs and EVs in the coordinated energy management of industrial VPPs is investigated by [94], with a focus on enhancing operational efficiency and economic benefits. The study of [95] explores the optimal operation of VPPs considering demand response and EVs, proposing strategies to integrate flexible loads and storage systems to operate as independent power units.

2.6 Uncertainties

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In addition to the above methods, Machine learning offers powerful tools to handle the complexities of EV behavior. Data-driven tools and machine learning algorithms play a pivotal role in forecasting EV charging behaviors. By cleaning data and addressing outliers, these methods offer predictive insights into charging patterns [96]. Advances in systematic reviews and meta-analyses further validate the efficacy of deep learning and ensemble learning techniques in this domain [97]. Moreover, the application of Grey Wolf Optimizer-based algorithms exemplifies the capability to predict charging durations amidst noisy data [98].

Strategic frameworks that integrate EVs as mobile battery ESSs within smart grids benefit significantly from machine learning. These models manage both charging and discharging behaviors, thereby enhancing grid stability and reducing operational costs [99]. Furthermore, model-free real-time scheduling methods, developed using DRL, optimize electricity costs and bolster grid reliability [100]. This optimization also extends to continuous charging control, adapting seamlessly to dynamic user behaviors [101].

In the realm of transportation systems, deep learning methods model EV travel behaviors to improve system integration [102]. These methods support the development of control strategies for plug-in hybrid EVs and optimize energy usage at charging stations, thus facilitating effective demand-side management [103], [104]. Additionally, machine learning algorithms aid in tuning parameters of EV charging behaviors to mitigate congestion and reduce investment costs at charging stations [105]. Reinforcement learning further enhances the management of EV charging systems by effectively handling the dynamic and uncertain nature of EV behaviors [106]. Moreover, machine learning-based intrusion detection systems ensure the safety and reliability of IoT-enabled EV charging stations [107].

Additionally, generative adversarial networks (GANs) have been proposed as a data-driven approach to generate EV charging scenarios [108]. This method enables the generation of realistic and diverse EV charging data, which is crucial for understanding and optimizing charging infrastructure. GANs have also been utilized to generate synthetic PMU data [109], creating synthetic data for power management units and demonstrating the versatility of GANs in generating various types of synthetic data, including EV data. Additionally, a conditional tabular GAN-based method has been developed for two-stage data generation [110]. This approach is applied to generate electric load data, which can be used to train forecasting models, showcasing the potential of GANs in enhancing predictive analytics for EV data. In another study, adversarial networks were developed to learn distributions of EV charging sessions and generate synthetic data, known as EVGen, highlighting the effectiveness of GANs in modeling and simulating EV charging behavior [111].

On the other hand, variational autoencoders (VAEs) combined with GANs have been employed to generate synthetic datasets for smart home energy management, including EV load and PV power generation [112]. This hybrid approach benefits from the strengths of both VAEs and GANs, producing more accurate and realistic data. Furthermore, a novel GAN-based synthetic data training model has been proposed to generate synthetic data for various applications, including EV data [113]. This model demonstrates the continuous evolution and application of GANs in generating high-quality synthetic data.

2.7 Electricity Markets

As mentioned, a group of EVs can be treated as a large ESS, with both participating in the electricity market to generate profit. In addition to contributing to grid stability and optimizing energy management, they can also provide ancillary services. Many researchers have widely discussed these benefits.

In terms of day-ahead markets, the study of [114] explores the participation of EVs and ESS in the day-ahead frequency regulation market. They propose a risk-averse optimal bidding strategy for an aggregator managing a fleet of EVs and ESS, focusing on unidirectional participation to optimize bidding strategies. Also, the study of [115] assesses the impact of grid-scale electricity storage and EVs on renewable energy penetration in Italy, discussing how participation in day-ahead and reserve markets influences renewable energy integration. A self-scheduling optimization model is proposed in [49] for a solar-wind VPP, considering the participation of EVs in day-ahead energy and reserve markets. Sustainable energy system planning is presented in [116] for industrial zones by integrating EVs as energy storage, highlighting their role in day-ahead market scheduling and aggregator implementation.

Furthermore, frequency regulation and reserve markets have been widely discussed in [49], [114], [115], [117]–[119]. Specifically, the study of [114] explores the participation of EVs and ESS in the day-ahead frequency regulation market. They propose a risk-averse optimal bidding strategy for an aggregator managing a fleet of EVs and ESS. The study of [117] discusses the integration of ESS in energy markets and balancing services, emphasizing the participation of EVs in ancillary services markets such as fast reserve and frequency services. In [118], the authors review the integration of renewable energy sources, ESS, and EVs with smart power distribution networks, highlighting their participation in frequency regulation markets. In addition, the study of [119] develops a stochastic bidding strategy for EVs and ESS in uncertain reserve markets, focusing on optimizing market participation by leveraging the cooperation between EVs and ESS. The research of [115] assesses the impact of grid-scale electricity storage and EVs on renewable energy penetration in Italy, discussing how participation in reserve markets influences renewable energy integration. In [49], the authors propose a self-scheduling optimization model for a solar-wind VPP, considering the participation of EVs in day-ahead energy and reserve markets.

The studies of [117], [120]–[122] discuss the ancillary services markets. To be more specific, the integration of ESS is discussed in [117] in energy markets and balancing services, emphasizing the participation of EVs in ancillary services markets such as fast reserve and frequency services. The study of [120] evaluates the eco-environmental management of electricity markets among micro-grids with high penetration of smart homes, plug-in EVs, and ESS, discussing their impact on market flexibility and reliability. In [121], the authors discuss the potential of EVs as ESS, emphasizing their participation in ancillary services markets based on V2G concepts. The research of [122] proposes an optimal energy storage allocation strategy by coordinating EVs participating in auxiliary service markets. This study focuses on the aggregated response capacity and market strategies for EVs and ESS.

Additionally, Ref. [123] investigates the coordination of wind power producers with ESS for optimal participation in wholesale electricity markets, discussing the role of EVs in meeting energy requirements and reducing costs.

Intraday markets are explored in [124], where the participation of an EV aggregator in the intraday and balancing markets are modelled as a multistage stochastic programming problem. The study focuses on utilising the demand-side flexibility of EVs to reduce charging costs and optimize participation in these markets.

In terms of demand response markets, the study of [125] investigates the market potential for residential ESS from repurposed EV batteries, developing a service-centered business model that facilitates participation in energy consumption and demand response markets. The research of [126] analyzes the participation of an energy storage aggregator in electricity markets, including the aggregation of EV fleets for demand response.

These mentioned studies demonstrate the significant potential of EVs and ESS in actively participating in various electricity markets.

2.8 Research Gaps

As previously discussed, V2G technology allows EVs to discharge stored energy back to the grid during periods of high demand, offering financial incentives for both EV owners and parking lot operators. While much research has documented the revenue potential of long-term parked EVs participating in V2G, the opportunities and strategies for short-term parked EVs remain underexplored.

In this context, integrating V2G into parking lots holds significant potential for generating new revenue streams. For instance, Ref. [127] demonstrates that EV parking lots equipped with

V2G can provide ancillary services, such as frequency regulation and peak shaving, by offering flexible storage that can be dispatched on demand. Their study estimates that EV parking lots participating in these markets can earn substantial revenue, particularly when large numbers of EVs are aggregated and managed via a central EMS. However, the challenge lies in the timing of EV availability and parking patterns. Most V2G strategies assume that EVs remain parked for extended periods, allowing time for both charging and discharging, a scenario more typical of workplace or residential parking than short-term parking.

The introduction of short-term parking, such as in shopping centers, airports, or urban garages, complicates the effective use of V2G. EVs parked for short durations may not have sufficient time to participate meaningfully in V2G services, as these operations require time to transfer energy and turn a profit. Ref. [128] emphasizes that limited EV availability in short-term parking reduces the profitability of V2G. Moreover, the battery cycling required for V2G may not align with the parking habits of short-term users. Despite these obstacles, some strategies, such as dynamic pricing models that reward drivers for leaving their vehicles plugged in during peak demand periods, have been proposed to extract value from short-term parked EVs [129]. These approaches incentivize participation even in short stays by capitalizing on strategically timed intervals.

While V2G offers considerable potential for profit generation in EV parking lots, integrating short-term parked EVs into these systems remains a challenge. Strategies like dynamic charging fees and incentives [130], aggregation of short-term EVs [131], battery-friendly V2G cycles [61], and peak-time targeting for short stays [129] have been proposed to increase profitability. However, comprehensive discussions that fully consider short-term EVs within the broader context of entire parking lot operations are still lacking. Additionally, short-term EV users may prioritize charging over participating in V2G, further complicating potential profitability.

The integration of V2G technologies alongside RES in EV parking lots presents another layer of opportunity. Studies have shown that parking lots can manage uncertainties related to solar irradiance, wind speed, market prices, and EV behavior using stochastic and scenario-based optimization models [132], [133]. These EMS can enhance profitability by incentivizing long-term parked EVs to engage in V2G operations [82]. Furthermore, hybrid renewable energy sources, such as solar PV and ESS, enable more efficient energy use and market participation, thereby improving economic returns [54], [134]. Financial incentives also play a crucial role in encouraging EV owners to participate in V2G programs, with flexible contracts and battery-friendly strategies designed to address concerns about battery degradation [61], [82]. However, uncertainties related to renewable energy variability and user behavior must be effectively managed to maximize profits.

Despite these advancements, gaps remain in our understanding of long-term user engagement with V2G programs, especially as user preferences evolve, battery technologies advance, and market conditions change [133]. There is also a lack of empirical studies on the profit potential of short-term parked EVs in V2G operations, which is particularly relevant given the increasing prevalence of short-term parking in urban settings [54]. Further research is needed to explore how parking lots can optimize participation in various energy markets, such as demand response and frequency regulation [82], [132]. Additionally, integrating advanced machine learning models into EMS could significantly enhance energy flow predictability and optimization, but this area remains underexplored.

Multi-EV parking lots and charging stations integrated with VPPs offer another promising opportunity for profit maximization, particularly through advanced pricing strategies like time-of-use tariffs, demand response participation, and dynamic pricing models. These pricing strategies allow parking lots to manage their energy flows more effectively by charging or discharging EVs during peak demand periods when energy prices are highest. Studies indicate that aggregating multiple EVs under a VPP improves load balancing, enhances market participation, and boosts revenues for both parking lots and the VPP [135]–[137]. Moreover, VPP pricing strategies can be tailored to accommodate both long-term and short-term parked EVs, enabling short-term parkers to contribute to energy markets during high-demand periods [133], [134]. The use of dynamic pricing, combined with efficient communication between EVs, parking lots, and the VPP, ensures that energy is dispatched at optimal times, further enhancing profitability.

However, despite the clear potential, several gaps remain in the literature. While long-term parked EVs' role in V2G operations is well-covered, optimizing the profit potential of short-term parked EVs is less understood. Additionally, while VPP aggregation and time-of-use pricing strategies have demonstrated the potential to increase revenues, in-depth studies exploring how these strategies impact individual parking lot operators and the overall VPP are still lacking.

Managing the uncertainty associated with EV parking lots and charging stations continues to be a significant challenge. Several factors, such as the unpredictability of RES, the available energy for V2G, and the random behavior of EVs, influence how these facilities can be configured to maximize profit. As previously discussed, machine learning-based methods like GANs and VAEs are commonly used to generate EV data from historical patterns. GANs utilize a generator and discriminator network that compete to produce realistic data samples, while VAEs use a probabilistic approach to encode data into a latent space and decode it back, producing smoother and more structured outputs. However, VAEs can produce blurry results due to approximate inference, and both methods face challenges with loss balancing and training stability.

While GANs are powerful, they often encounter challenges such as unstable training and mode collapse, making them less reliable for EV data modeling [138]. VAEs, despite their strengths, can suffer from blurry outputs and constraints related to latent space complexity and loss term balancing [139]. To address these limitations, a more robust approach, such as Normalizing Flows (NFs), should be considered. NFs offer stable training dynamics and exact likelihood estimation, avoiding common issues seen in GANs and VAEs. Additionally, NFs generate sharper, more accurate samples and outperform classical statistical methods by capturing complex, non-linear dependencies in the data. Although NFs come with computational and design challenges, their ability to model high-dimensional datasets makes them an ideal choice for the next stage of EV data modeling [140].

2.9 Summary

This chapter has reviewed the literature on the economic operation of EV parking lots, with a particular focus on V2G functionality. The integration of RES, ESS, and EMS was discussed as a critical aspect of optimizing the energy flows within EV parking lots. Moreover, EVs' participation in various energy markets, such as day-ahead, intraday, and ancillary services markets, was discussed, emphasizing their potential for grid support and profitability. The review also highlighted the emerging role of VPPs and the challenges posed by uncertainties in renewable energy generation and EV behavior. Lastly, key research gaps were identified, including the underexplored potential of short-term parked EVs in V2G operations and the need for advanced optimization techniques to handle the inherent uncertainties of these systems. The insights gained from this chapter provide a foundation for the methodology and analysis in the subsequent chapters.

Chapter 3

Economic Operation Strategy of an EV Parking Lot with Vehicle-to-Grid and Renewable Energy Integration

3.1 Introduction

EV parking lots and charging stations offer significant potential to support power grids through V2G technology, which allows bidirectional energy flow. This enables EVs not only to charge but also to return power to the grid, contributing to grid stability and integrating RESs. By utilizing the collective energy stored in EV batteries, parking lots can serve as valuable DERs, providing both economic and technical benefits.

Smart charging or parking lot profits have been explored in many studies [141]–[144]. However, the above studies only consider grid-to-vehicle (G2V) interaction. Studies in [145]–[147] take V2G into account while considering EV charging. A management strategy considering the behaviour of EV owners is proposed in [145], focusing on the impact of their behaviour, including arrival and departure time, initial SoC, and energy demand, on the profits of the parking lots. In [146], an EV charging strategy for workplace charging stations is proposed by maximising the energy usage of RESs to reduce EV charging costs. However, the above studies focus mainly on EV charge and discharge or operating cost reduction, and they need a holistic consideration of the EV parking lot or charging station. The study in [147] proposes an energy management system that includes EV parking lots and PV. Four charging modes with different priorities are proposed, aiming to improve the efficiency of microgrids. However, it is more appropriate to treat all EVs equally rather than prioritising charging by charging mode. Ref. [148] presents a hybrid stochastic information gap decision theory method to handle uncertainties and propose a two-stage scheduling framework for the EV parking lot. The results prove the importance of the optimal sizing of the EV parking lot and the ability of EVs to improve the economy of energy communities. Ref. [149] discusses the optimal sizing and location of the EV parking lot, considering EVs' charging and discharging behaviour, and applies the analytical model to estimate the number of EVs in the EV parking lot at different times.

The study in [150] proposes an energy management algorithm for a large-scale EV parking lot with 100 charging points. By using the decentralized optimization framework and the scheme of moving sliding-window method to minimize the random aspects of user charging habits, the optimization problem complexity of large EV parking lots is simplified. However, the operation and management strategies in EV parking lots have been explored less or neglected in those studies.

As mentioned in the study [151], different charging modes have different advantages. Under the same RES size, EVs can be charged for free, but they must participate in V2G services to receive free charging. Compared with the paid charging mode, it still has considerable development potential. Based on the study in [151], this chapter will further improve the charging mode of EV parking lots. Specifically, instead of free charging, EVs participating in V2G services need to pay a minimum charging fee due to their longer connection. However, they will receive V2G incentives to offset this fee. Considering many EVs entering parking lots may not be able to get fully charged or participate in V2G services due to insufficient charging time, the following study will divide EVs into two categories: EVs with sufficient charging time for V2G participation and insufficient charging time for non-V2G participation. Different charging models will be adopted and assessed for these two categories. It should be noted that this chapter mainly explores the profit of the charging station set up in the parking lot, so the parking fee is not considered at this stage.

In general, the main features and contributions of this chapter are as follows:

1. An energy management strategy is proposed to maximise the benefit of the parking lot

under multiple charging modes by considering the uncertainty of RESs, ESS degradation, and different parking status of EVs;

2. EVs connected to chargers are classified by different parking times to indicate whether they can participate in V2G services. Different charging or reward strategies are determined accordingly;

3. Dynamic charging price is proposed based on the charging demand and parking status of EVs, which ensures that EVs will get economic charging/parking/reward while the parking lot can have satisfactory profit as well.

3.2 Problem Formulation

The case of a parking lot with EV charging stations, including PV, wind turbine (WT), and ESS, is considered. EV parking lots will determine whether EVs can participate in V2G services based on the information collected by the EMS: arrival/departure time, initial SoC, etc. This data collection will happen once they are connected to the bi-directional charger. Additionally, EVs will be divided into two categories: participation in V2G and non-participation in V2G, depending on the parking time. Based on realistic considerations, it is assumed that all EVs with insufficient charging time want to charge to the maximum possible SoC. If the charging fee is too high, many EVs will choose not to charge. Therefore, to make the idea more realistic and attract more EVs to be charged and bring profits to the parking lots, the charging demand of such EVs will generate different charging prices, which are between the maximum and minimum market prices, while more requests will get cheaper charging fees. Therefore, for a vehicle with insufficient charging time and cannot participate in V2G services, its charging demand will determine the charging price. For a vehicle with a sufficiently long charging time, it is assumed that it has agreed to participate in the V2G service when choosing the parking lot. Due to the long connecting time, their charging price will always be the minimum. On this basis, the V2G service is carried out to ensure no overcharge and discharge, and the energy participating in the V2G service will further lead to reducing the charging cost. Based on these two modes, the parking lot can profit by providing grid support, storing energy from the grid during off-peak hours, and delivering power to the grid during peak hours. The detailed model is shown as follows.

3.2.1 RESs Modelling

In this chapter, electricity market price, solar radiation and wind speed are considered as uncertain factors because of their randomness and uncertainty. The scenred toolbox of Matlab is used to generate uncertainty factors [152]. This toolbox is based on scenario generation and reduction method. This is also thoroughly discussed in [153]–[155].

The WT output is mainly determined by wind speed. The power output of WT can be calculated as follows:

$$P_{t,s}^{W} = \begin{cases} 0 & v_{t,s} \leq V_{ci} \\ P_r(A + B * v_{t,s} + C * v_{t,s}^2) & V_{ci} < v_{t,s} \leq V_r \\ P_r & V_r < v_{t,s} \leq V_{co} \\ 0 & v_{t,s} \geq V_{co} \end{cases} \tag{3.1}$$

where $P_{t,s}^{W}$ is the power generated by the wind turbine at time t in scenario s; $v_{t,s}$ is the wind speed; P_r indicates the rated power output; A, B, C are constant coefficients of the wind turbine [156]; V_{ci},V_r,V_{co} represent the cut-in, rated and cut-out wind speed, respectively.

The power output of PV can be calculated by (3.2).

$$P_{t,s}^{PV} = r_{t,s} * s_{pv} * e_{pv} \tag{3.2}$$

where $P_{t,s}^{PV}$ is the power generated by the PV panel; $r_{t,s}$ is the solar radiation; s_{pv} is the surface area of PV panels; e_{pv} is the PV panel efficiency.

3.2.2 EV Modelling

It is assumed that the parking lot knows the arrival and departure time of all the EVs in advance. The available energy of the EV at charging point i for the parking lot to use is shown in (3.3). Before EV's arrival and after EV's departure, the available energy to the charging point the EV is connected to is zero. When the EV arrives, the available energy to the charging point i is the initial energy of the EV, E_i^{ini}. In the following time, between the time of EV's arrival and departure, the EV energy variation depends on the energy at the previous time step and the charging or discharging energy at the current time step. Then the EV will be charged to the allowed maximum energy at the departure time, which is normally not 100% of the EV battery capacity, to prevent the adverse effects of overcharging, as shown in (3.4).

A binary variable $\mu_{i,t,s}$ is defined in (3.5) and (3.6) to indicate that EVs cannot charge and discharge simultaneously. The minimum and maximum energy in the charging and discharging process are also essential factors in determining the degradation of EV batteries [157]. Eq. (3.7) presents the lower and upper bounds of the EV energy, represented by $E^{EV}_{i,min}$ and $E^{EV}_{i,max}$, respectively. If EVs are not in the charging station, charging and discharging will not occur, which is reflected in (3.8).

$$E^{EV}_{i,t,s} = \begin{cases} 0, & t < t_{a,i} \\ E^{ini}_{i}, & t = t_{a,i} \\ E^{EV}_{i,t-1,s} + \left(\eta_{ch} * P^{EV+}_{i,t,s} - \dfrac{1}{\eta_{dis}} * P^{EV-}_{i,t,s}\right)\triangle t, & t_{a,i} < t \leq t_{d,i} \\ E^{EV}_{i,max}, & t = t_{d,i} \\ 0 & t > t_{d,i} \end{cases} \tag{3.3}$$

$$E^{EV}_{i,max} = E^{ini}_{i} + \sum_{t=t_{a,i}+1}^{t_{d,i}} \left(\eta^{EV}_{ch} * P^{EV+}_{i,t,s} - \frac{1}{\eta^{EV}_{dis}} * P^{EV-}_{i,t,s}\right)\triangle t \tag{3.4}$$

For $t_{a,i} < t \leq t_{d,i}$,

$$0 \leq P^{EV+}_{i,t,s} \leq \mu_{i,t,s} * P^{EV+}_{i,max} \tag{3.5}$$

$$0 \leq P^{EV-}_{i,t,s} \leq (1 - \mu_{i,t,s}) * P^{EV-}_{i,max} \tag{3.6}$$

$$E^{EV}_{i,min} \leq E^{EV}_{i,t,s} \leq E^{EV}_{i,max} \tag{3.7}$$

For t otherwise

$$P^{EV+}_{i,t,s} = P^{EV-}_{i,t,s} = 0 \tag{3.8}$$

where $E^{EV}_{i,t,s}$ is the available energy of the EV at charging station i for the parking lot to use at time t in scenario s. $t_{a,i}$ and $t_{d,i}$ are the EV's arrival and departure time; $P^{EV+}_{i,t,s}$ and $P^{EV-}_{i,t,s}$ are the

EV charging and discharging power; η_{ch}^{EV} and η_{dis}^{EV} represent the EV charging and discharging efficiency; $\triangle t$ is the time interval. $P_{i,max}^{EV+}$ and $P_{i,max}^{EV-}$ indicate the maximum EV charging and discharging power.

For some EVs, although staying at the charging station, their charging time is not long enough to use V2G and get fully charged when leaving; so a binary variable φ_i is defined to indicate the V2G participating status of the EV at the charging station i, as shown in (3.9). Therefore, If EVs satisfying the condition $(t_{d,i} - t_{a,i}) \leq \frac{E_{i,max}^{EV} - E_i^{ini}}{\eta_{ch}^{EV} * P_{i,max}^{EV+}}$, $\varphi_i = 0$, indicating non-V2G participation as the short parking period cannot make these EVs get fully charged; otherwise, $\varphi_i = 1$, indicating that the charging time is long enough to participate in V2G.

Under the non-V2G participation scenarios ($\varphi_i = 0$), it is assumed that all EVs will charge at the maximum charging power because of the lack of charging time, as shown in (3.10). Based on this assumption, the charging price is then determined by the energy required by the EVs, as shown in (3.12) [141]. It can also encourage EV owners to charge at the maximum demand.

In contrast, under the V2G participation scenarios ($\varphi_i = 1$), as mentioned above, this will give the participating EVs the lowest charging price. Besides, it is assumed that all such EVs participate in V2G services, so in addition to paying for charging, they will also be rewarded for participating in V2G. In summary, the charging cost under these two charging schemes can be expressed as (3.14).

$$\varphi_i = \begin{cases} 1\,, & (t_{d,i} - t_{a,i}) > \frac{E_{i,max}^{EV} - E_i^{ini}}{\eta_{ch}^{EV} * P_{i,max}^{EV+}} \\ \\ 0\,, & (t_{d,i} - t_{a,i}) \leq \frac{E_{i,max}^{EV} - E_i^{ini}}{\eta_{ch}^{EV} * P_{i,max}^{EV+}} \end{cases} \tag{3.9}$$

$$E_i^{de} = \left(\eta_{ch}^{EV} * P_{i,max}^{EV+}\right) * (t_{d,i} - t_{a,i}) \tag{3.10}$$

$$E_{i,t_{d,i}}^{EV} = E_i^{ini} + E_i^{de} \tag{3.11}$$

$$E_i^{de} = \frac{E_i^{de,max}}{\lambda^{c,max} - \lambda^{c,min}} (\lambda^{c,max} - \lambda_i^c) \tag{3.12}$$

$$\lambda^{c,min} \leq \lambda_i^c \leq \lambda^{c,max} \tag{3.13}$$

$$\begin{aligned} z_s = & \left[\sum_{i=1}^{N} \sum_{t=t_{a,i}}^{t=t_{d,i}} (1-\varphi_i)(P_{i,t,s}^{EV+} * \lambda_i^c) \triangle t \right] \\ & + \sum_{i=1}^{N} \varphi_i \left[\left(E_{i,max}^{EV} - E_i^{ini} \right) * \lambda^{c,min} - \sum_{t=1}^{T} (P_{i,t,s}^{EV-} * \lambda_{inc}) \triangle t \right] \end{aligned} \tag{3.14}$$

where T is the simulation time. N is the total number of EVs. E_i^{de} indicates the demand energy under V2G participation. $E_i^{de,max}$ represents the maximum required energy for charging the EV to the maximum SoC, λ_i^c, $\lambda^{c,max}$ and $\lambda^{c,min}$ indicate the charging price for the i-th EV, the price upper and lower bound, respectively. λ_{inc} is the V2G incentive rate provided to EVs. Eq. (3.11) means that the energy when the i-th EV leaves the charging station is composed of its initial and charged power, that is, the demand power. Eq. (3.13) shows the upper and lower bound of the charging price.

3.2.3 ESS Modelling

Similar to the EV part, Eq. (3.15) shows the energy dynamic of ESS. The constraint (3.16) is to ensure that at the end of the day, the ESS has the same energy as the initial energy to ensure that it can be put into use quickly the next day. Eq. (3.17) presents the lower and upper bounds of the ESS energy. A binary variable $a_{t,s}$ is also defined in (3.18) and (3.19) to make sure ESS cannot charge and discharge simultaneously.

$$E_{t,s}^{ESS} = E_{t-1,s}^{ESS} + \left(\eta_{ch}^{ESS} * P_{t,s}^{ESS+} - \frac{1}{\eta_{dis}^{ESS}} * P_{t,s}^{ESS-} \right) \triangle t \tag{3.15}$$

$$E_{T,s}^{ESS} = E_{0,s}^{ESS} \tag{3.16}$$

$$E_{min}^{ESS} \leq E_{t,s}^{ESS} \leq E_{max}^{ESS} \tag{3.17}$$

$$0 \leq P_{t,s}^{ESS+} \leq \ a_{t,s} * \ P_{max}^{ESS+} \tag{3.18}$$

$$0 \leq P_{t,s}^{ESS-} \leq (1 - a_{t,s}) * \ P_{max}^{ESS-} \tag{3.19}$$

where $E_{t,s}^{ESS}$ indicates the energy for the ESS at time t in scenario s; $P_{t,s}^{ESS+}$ and $P_{t,s}^{ESS-}$ represent ESS charging and discharging power, respectively; $E_{0,s}^{ESS}$ and $E_{T,s}^{ESS}$ represent ESS's initial energy and the energy in the end of the simulation time T. E_{min}^{ESS} and E_{max}^{ESS} indicate the lower and upper bounds of the ESS energy, respectively. P_{max}^{ESS+} and P_{max}^{ESS-} indicate the upper and lower bound of ESS charging power, respectively; η_{ch}^{ESS} and η_{dis}^{ESS} are the charging and discharging efficiency, respectively.

3.2.4 Battery Degradation Cost

The battery degradation cost of the ESS in the parking lot is also a factor to be considered, as it is charged and discharged in daily operations. To minimize the degradation cost of ESS, the method considered in this study is to control the discharging power flow in ESS. It is assumed that the battery pack will need to be replaced once its total throughput reaches its lifetime throughput. Based on this point of view, the unit battery degradation cost B is defined as (3.20), where R is the battery purchase cost, L indicates the battery lifetime throughput, and e^{ESS} is the square root of the roundtrip efficiency of the battery [158]. According to the total discharged energy in ESS and degradation cost per kWh, the ESS degradation cost can be obtained, which is expressed in (3.21), where $E_{t,s}^{ESS-}$ represents the discharged energy of ESS.

$$B = \frac{R}{L * e^{ESS}} \tag{3.20}$$

$$C_s^{de} = \sum_{t=1}^{T} E_{t,s}^{ESS-} * B \tag{3.21}$$

As for EV battery degradation, some studies do not consider it when discussing EV parking lot profits [148], [159]. As this chapter stands from the perspective of the EV parking lots and charging stations, EV battery degradation is not directly modelled, but indirectly considered by the compensation to EVs through V2G reward; see (3.14). It is worth mentioning that the proposed strategy tries to reduce EV battery degradation during V2G as much as possible. As mentioned in the modelling part, the upper and lower bound of charging and discharging are set in (3.7) to avoid battery degradation caused by excessive charging and discharge of EVs. Also, incentive rewards are paid to V2G participants based on the discharging energy, which also limits the V2G discharge of EVs in subsequent optimization calculations to avoid excessive discharge. A similar technique can be found in [157] by limiting the depth of battery charging and discharging to reduce the degradation of EV batteries.

3.2.5 Constraints for the Grid

Like the ESS and EV parts, the parking lot cannot simultaneously buy electricity from the grid and feed it into the grid. The binary variable $b_{t,s}$ in (3.22) and (3.23) is used to ensure this.

$$0 \leq P_{t,s}^{Feed-in} \leq b_{t,s} * P_{max}^{Feed-in} \tag{3.22}$$

$$0 \leq P_{t,s}^{Grid} \leq (1 - b_{t,s}) * P_{max}^{Grid} \tag{3.23}$$

where $P_{t,s}^{Feed-in}$ and $P_{t,s}^{Grid}$ are the feed-in power to and purchasing power from the grid, respectively; $P_{max}^{Feed-in}$ and P_{max}^{Grid} are the maximum feed-in and purchased power, respectively.

3.2.6 Balance Equation

Eq. (3.24) represents the power balance. The EV charging, $\sum_{i=1}^{N} P_{i,t,s}^{EV+}$, ESS charging, $P_{t,s}^{ESS+}$, and the grid feed-in power, $P_{t,s}^{Feed-in}$ are satisfied by the power from PV, $P_{t,s}^{PV}$, wind turbine, $P_{t,s}^{W}$, grid, $P_{t,s}^{Grid}$, ESS discharging, $P_{t,s}^{ESS-}$ and EV discharging, $\sum_{i=1}^{N} P_{i,t,s}^{EV-}$.

$$\begin{aligned} \sum_{i=1}^{N} P_{i,t,s}^{EV+} \quad & + P_{t,s}^{ESS+} + P_{t,s}^{Feed-in} \\ & = P_{t,s}^{PV} + P_{t,s}^{W} + P_{t,s}^{Grid} + P_{t,s}^{ESS-} + \sum_{i=1}^{N} P_{i,t,s}^{EV-} \end{aligned} \tag{3.24}$$

3.2.7 Objective Function

The objective function in the following is to maximize the profit of the parking lot by buying electricity in low-price periods and selling electricity in high-price periods through managing the charge and discharge of EVs and ESS. It consists of the following parts: feed-in income, EV charging income, V2G payment, grid electricity purchase cost, PV and wind turbine operating cost, and ESS degradation cost.

$$\begin{aligned} Maximize\ Z = \sum_{s=1}^{N_s} \rho_s \Bigg[& \sum_{t=1}^{T} (P_{t,s}^{Feed-in} * \lambda_{1,t,s}) \triangle t - \sum_{t=1}^{T} (P_{t,s}^{Grid} * \lambda_{2,t,s}) \triangle t + z_s \\ & - \sum_{t=1}^{T} (P_{t,s}^{PV} * \lambda_{pv} + P_{t,s}^{W} * \lambda_{w}) \triangle t \ - C_s^{de} \Bigg] \end{aligned} \tag{3.25}$$

where N_s is the total scenarios in the simulation; ρ_s is the possibility of scenario s; $\lambda_{1,t,s}$ and $\lambda_{2,t,s}$ indicate the power purchase and feed-in price, respectively; λ_{pv} and λ_w represent the operating cost coefficient of PV panels and WT, respectively.

Compared with other methods, the scenarios generation method generates many scenarios based on different assumptions of market price uncertainty, which can be used to estimate the deficit and profit of different pricing or investment strategies. The objective of this chapter is to identify the range of possible market prices and then apply the management strategy to obtain more profit. Therefore, the scenario generation method is appropriate to use here. It also has the advantages such as fast computation time (with scenario reduction), less modelling complexity, available toolbox, etc.

3.3 Case Study

3.3.1 Parameter and Case Settings

This section will compare the proposed model with the other two models under three cases. To comprehensively discuss the economic operation strategy, the selection of cases will also need to cover as many EV parking states as possible. Therefore, mixed, long-term and short-term parking periods will be selected as three cases. These models and cases are defined as follows:

- Case 1: EVs consist of long-term and short-term parking EVs. The arrival and departure times of EVs and the initial energy are shown in Figs. 3.1 and 3.2.

- Case 2: All the EVs park for a long time and have less initial energy. The data are shown in Figs. 3.3 and 3.4.

- Case 3: Contrary to the previous case, all the EVs park for a short period in this case, as shown in Figs. 3.5 and 3.6.

The energy information shown in Figs. 3.2, 3.4 and 3.6 are directly tied to the EV arrival and departure times, as all data points come from the same practical dataset provided in [160]. Each record in the dataset includes an EV's arrival time, departure time, and corresponding energy data. For each case, the EVs were selected based on their arrival and departure times, and their corresponding energy data was inherently included without modification or additional assumptions. This approach ensures that the analysis remains consistent and grounded in real-world data, as no artificial data was created or adjusted during the process.

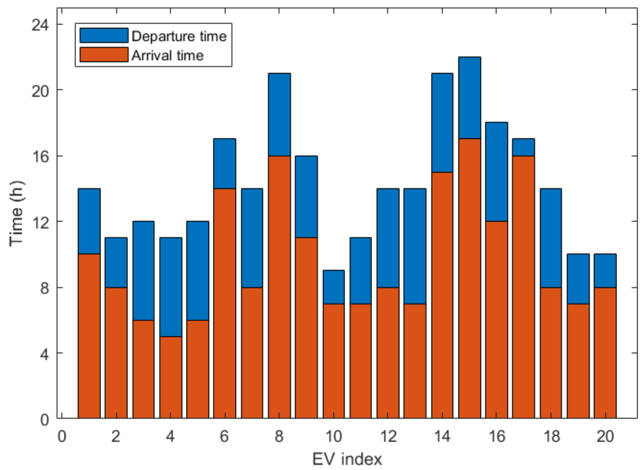


Figure 3.1: EV's departure/arrival time (Case 1).

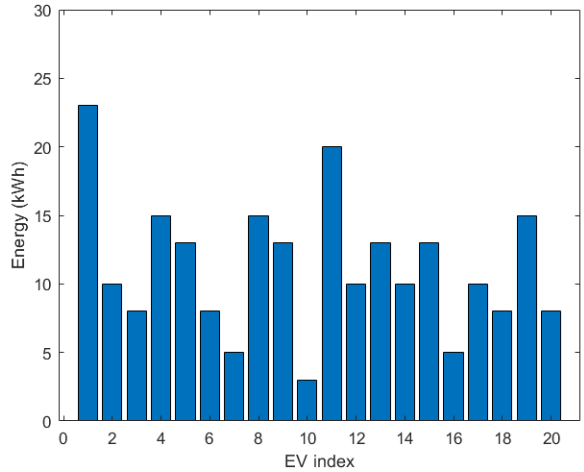


Figure 3.2: EV's initial energy (Case 1).

The models under assessment are as follows:

- Proposed model: This is the proposed model. EVs will use the parking lot and its charging stations with corresponding charging costs. For long-term parking EVs, they will offer V2G service in return for getting a charging price discount or may even get monetary reward payback. The charging price of short-term parking EVs is dynamic and determined by their charging demand.

- Comparison model 1: The pricing strategy of this model is based on [151], [161]. Both long-term and short-term parking EVs will pay the same fixed rate for their charging. Also, V2G is considered as feed-in power to provide profit for the parking lot, and the participating EVs will receive incentive payments from the parking lot. It is assumed that

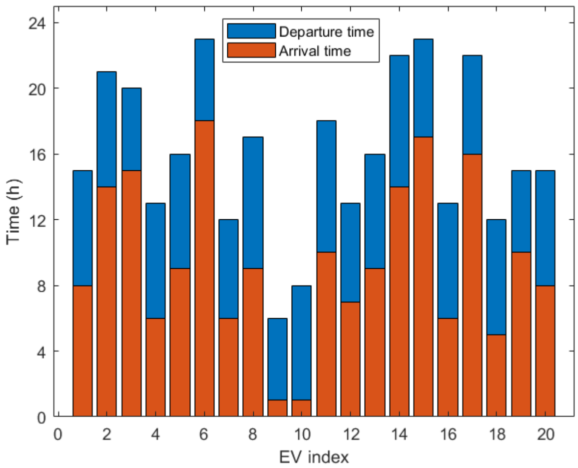


Figure 3.3: EV's departure/arrival time (Case 2).

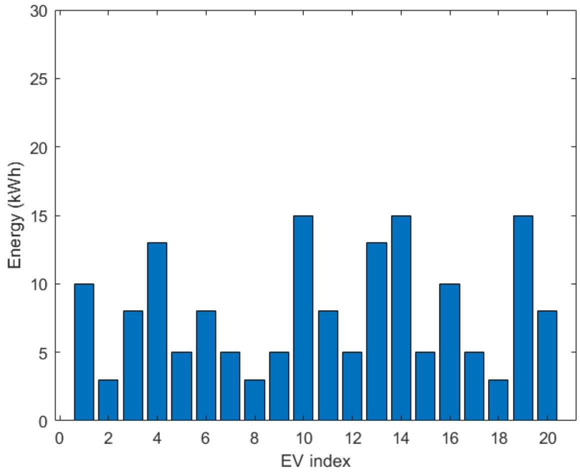


Figure 3.4: EV's initial energy (Case 2).

all short-term parked EVs will charge as much as they can.

- Comparison model 2: This model does not consider V2G services. The pricing strategy is based on [141], where the charging price of EVs is determined by their required charging energy.

All the EVs will be charged to the maximum allowable energy when departing from the charging station. The maximum and minimum charging price are 0.35 \$/kWh and 0.2 \$/kWh [162], respectively. The efficiency of the PV panel is set as 0.16, and the total surface area is 40 m^2. The wind turbine cut-in, rated, and cut-out wind speeds are set as 3.5 m/s, 9 m/s, and 22 m/s, respectively. Note that in this case study, PV and wind turbine operating costs are neglected, and thus λ_{pv} and λ_w are set to zero [163]–[165]. The capacity of EV and ESS is 30 kWh and 31.5 kWh, respectively. The simulation time T is set as 24 h. The uncertainties of the electricity price, solar irradiation, and wind speed are considered in this chapter. Historical weather data are imported from [166]. Ten scenarios have been implemented based on the scenario generation and reduction method by using the scenred toolbox of Matlab [167]. The electricity prices are shown in Fig. 3.7. The feed-in price $\lambda_{1,t,s}$ is considered lower than the electricity purchase price $\lambda_{2,t,s}$, which is set as $\lambda_{1,t,s} = 0.9\lambda_{2,t,s}$ [163]. According to the V2G projects around the world [168], the V2G reward coefficient λ_{inc} and maximum EV charging/discharging power will be considered as 0.1 \$/kWh and 10 kW, respectively.

The simulation is done in MATLAB R2021a using a laptop with Intel(R) Core(TM) i7-11850H

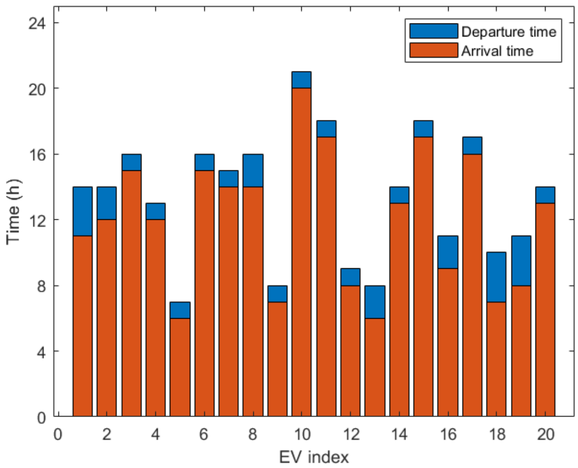


Figure 3.5: EV's departure/arrival time (Case 3).

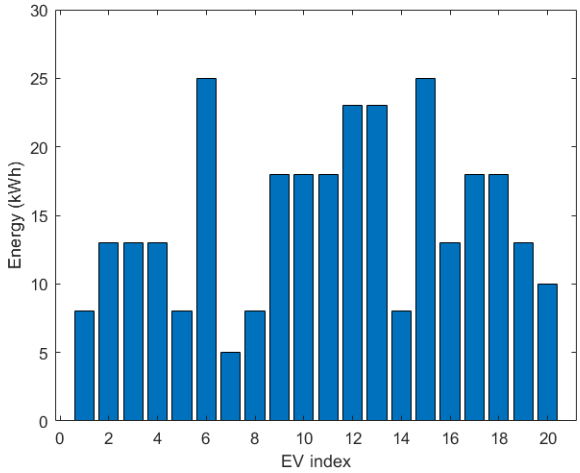


Figure 3.6: EV's initial energy (Case 3).

processor and 32.0 GB RAM. The computation times of the proposed model are 24.97 s, 18.53 s, and 18.19 s in cases 1–3, respectively. In comparison model 1, these times are 31.82 s, 34.96 s and 29.72 s, respectively. The computation times of comparison model 2 are 38.75 s, 29.22 s, and 29.64 s in cases 1–3, respectively.

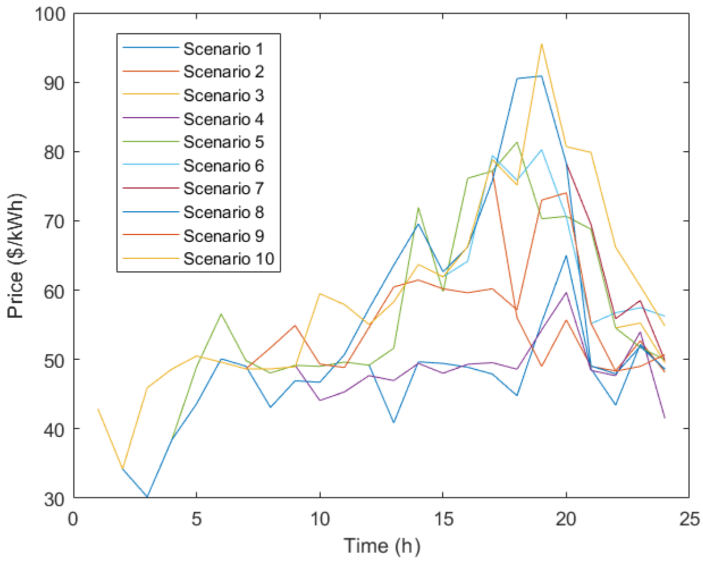


Figure 3.7: Electricity market price in 10 scenarios.

3.3.2 Results and Comparison

It should be noticed that, in the figures below, the charging and import energy are positive, and the discharging and export energy are negative.

In Case 1, a mixture of long-term and short-term parking EVs are considered. According to Fig. 3.8, although the lowest electricity price is in the period between 00:00–05:00, there are no EVs connected to the charger, and this makes all three models' EV charging time mainly distributed in the middle of the day when the electricity price is low. In the proposed model and comparison model 1, V2G occurs when the electricity price increases to obtain more significant benefits, i.e., around 04:00–06:00. The highest feed-in price is between 18:00–20:00. However, almost all the EVs depart from the parking lot, so there is no V2G participation during this period. At 21:00, the electricity price drops sharply. All three models do their final charging at that point for the departing EVs.

Fig. 3.9 shows the feed-in energy to and purchased energy from the grid, which follows the same pattern as in Fig. 3.8. They all buy electricity when the electricity price is low and make profits by selling the surplus RES energy, the ESS discharging energy, and the V2G energy when the electricity price is high. The charging and discharging strategy for ESS and EVs is optimized according to the electricity market price and EV parking status so that the ESS can sell the energy that is charged during the lower-price periods, or charge the EVs when the electricity price is higher.

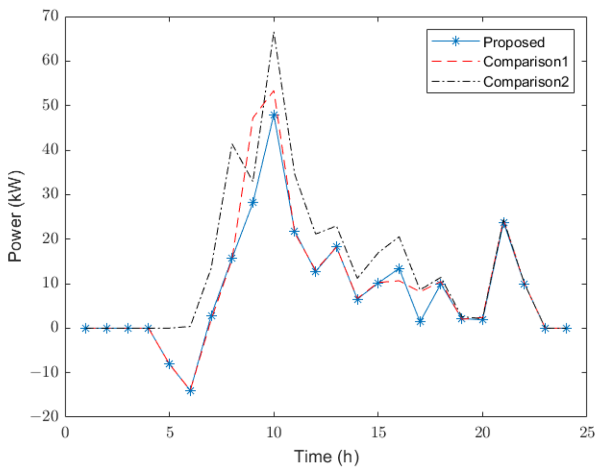


Figure 3.8: EVs charging/discharging energy (Case 1).

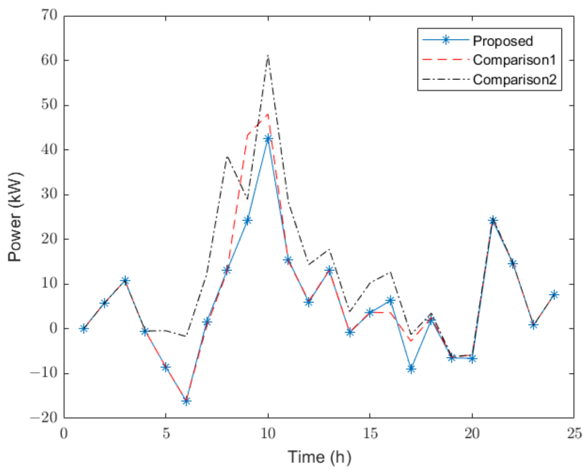


Figure 3.9: Export/import energy (Case 1).

The profits of different models under different cases are shown in Table 3.1. It can be seen that comparison model 2, in which V2G is not provided, has an operating deficit of \$1.48 in Case 1. On the other hand, the proposed model and comparison model 1, both of which have V2G services, have more significant profits. Because of the dynamic charging price for short-term parking EVs in the proposed model, the overall profit is $27.08, which is the most prominent of the three models.

For Case 2, the charging/discharging energy of the EVs and export/import energy of the parking lot are shown in Figs. 3.10 and 3.11, which have a similar trend to those in Case 1. Because of the long parking time of all the EVs, the adopted pricing strategy of the proposed model and comparison model 1 is to charge the EVs at the minimum charging price and provide V2G services when necessary. Hence, they have the same profit of $21.06, as shown in Table 3.1. Since V2G cannot be used to offset operating costs in comparison model 2, it needs to pay more for the higher energy demand, incurring a larger operation deficit of $12.55.

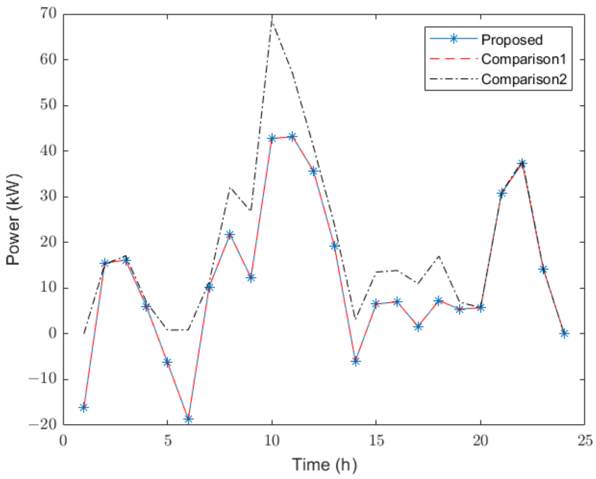


Figure 3.10: EVs charging/discharging energy (Case 2).

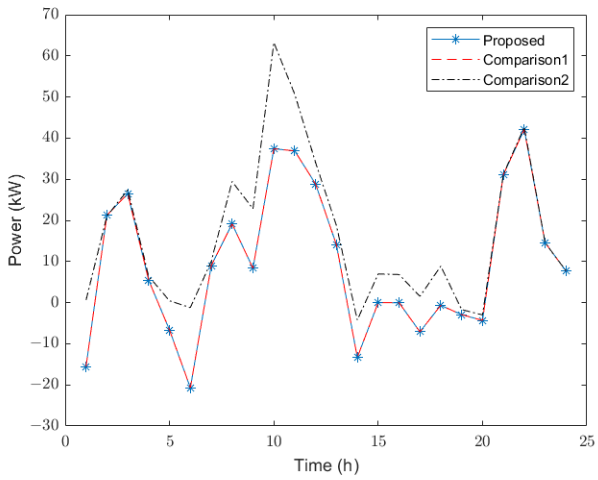


Figure 3.11: Export/import energy (Case 2).

Table 3.1: Profit in each case.

	Proposed model	Comparison model 1	Comparison model 2
Case 1	$27.08	$21.11	$-1.48
Case 2	$21.06	$21.06	$-12.55
Case 3	$36.90	$17.60	$22.06

Contrary to the previous case, in Case 3, where all EVs are short-term charging, the impact of V2G on the profits is not as significant as that in the first two cases, as shown in Fig. 3.12. Due to short-term charging, the remaining energy of the ESS and the surplus energy of the RES can be used more for grid feed-in to obtain the maximum profit. In this case, the demand for grid power is also the smallest among all cases; see Fig. 3.13. As seen in Table 3.1, the profit obtained by the proposed model is still the highest at \$36.90 because of a small amount of V2G feed-in energy. Compared with the previous cases, the proposed model has the highest profit in Case 3. With only a small amount of V2G energy, more dynamic charging fees are paid by the higher numbers of short-term charged EVs, which is the key factor making the model more profitable. Comparison model 2 has a better profit of \$22.06 than comparison model 1 as the dynamic charging price mechanism gives it an advantage over comparison model 1 with a fixed charging price for the short-term parking EVs. Even with the V2G service, the profit of model 1 is still the smallest at \$17.60.

It can be seen from the comparison that dynamic charging prices for EVs without V2G and with short-term parking can bring more significant profits to the parking lot. With EVs parking for a relatively long time and participating in V2G, the profit of the parking lot is greater than that of the traditional charging-only model, even if the parking lot needs to pay the V2G rewards to EVs. Although a high fixed charging price would make the fixed charging fee model gain more profits, it is impractical because the high charging price will result in fewer EV charging users.

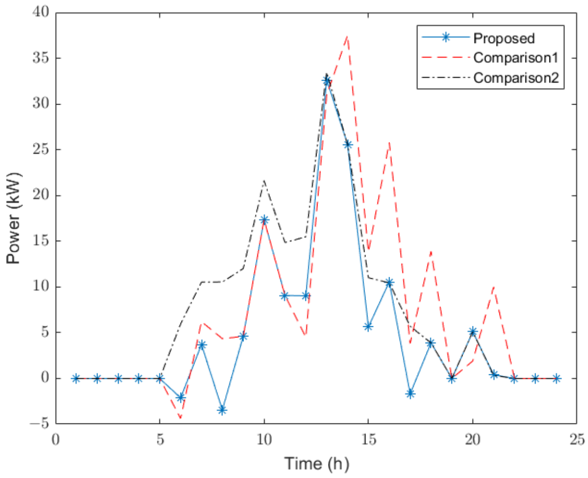


Figure 3.12: EVs charging/discharging energy (Case 3).

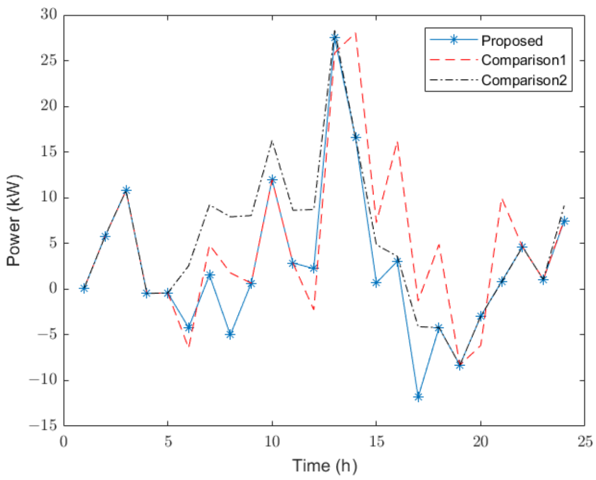


Figure 3.13: Export/import energy (Case 3).

3.4 Summary

In this chapter, the economic operation strategy of the EV parking lot was modelled. The underlying parking lot is equipped with EV charging stations, PV, WT, and ESS. Electricity market price, solar radiation and wind speed are considered as uncertainty factors, and scenarios are generated by MATLAB scenred toolbox. All EVs connected in the parking lot are classified into V2G and non-V2G groups depending on the length of parking. Dynamic charging price is provided for EVs that do not participate in V2G according to their charging demands. EVs participating in V2G will receive the lowest charging price and incentive reward based on the discharged energy through V2G. The profit of the parking lot considered in this chapter comes from the charging fees for the EVs and the feed-in energy into the grid.

The proposed model was compared with the other two models. Comparison model 1 has V2G services and fixed charging rates for EVs; comparison model 2 has no V2G services but applies dynamic charging prices for all EVs. All models were tested under three cases: EVs with mixed parking conditions, long-term parking, and short-term parking. The proposed model can obtain the most significant profit in all three cases. After comparing the earnings of the three models, it is found that dynamic charging prices can bring greater profits for the parking lot with EVs that park for a short time and do not participate in V2G services. In the case of EVs with long parking times and participating in V2G, even if the V2G incentive needs to be paid, the profit is still greater than that obtained by charging without V2G.

Chapter 4

Optimizing EV Parking Lot Profitability through IGDT-based V2G Incentive Decision-Making in Multiple Energy Markets

4.1 Introduction

The penetration of EVs globally is increasing rapidly, driven by the need for mitigating climate change and reducing greenhouse gas emissions. With this trend, EV parking lots and charging stations are seen as potential assets to the power grid by providing V2G capabilities, utilizing the energy stored in EV batteries.

Emerging markets that leverage EVs to support the power grid, especially in services maintaining grid frequency stability, demonstrate considerable potential. The study in [169] examines these support services, classifying them and highlighting the critical role of EV charging stations. They point out the capabilities of advanced chargers that can schedule and adjust charging, which are vital for providing these grid services. Their research provides a clear picture of how EV charging infrastructure can be used by grid operators. The study in [170] proposes a new method for managing the charging and discharging of EVs that considers the preferences of EV owners, allowing for energy sharing between EVs and enabling EVs to support the grid. This method not only aims to reduce charging costs for EV owners but also helps with efficient operation of the power grid. The focus on the EV owner's needs and the practical application of the method are significant, as they show how EVs can realistically be part of the energy market. These studies extend previous research in [171] and [172], which looked into optimizing home energy resources, like solar panels and batteries, and the strategic sharing of battery storage in energy and grid support markets. The first study uses a method to ensure that the energy resources meet the grid's rules, while the second presents a sharing strategy that aims to increase profits for battery companies and reduce costs for customers. Furthermore, the research in [173] suggests a strategy for a power plant that combines solar energy and battery storage, including a way to split profits that takes into account the lifespan of the batteries. This strategy is designed to increase profits while also keeping the storage systems in good condition for as long as possible. However, while these studies collectively underscore the transformative potential of EVs and battery storage in FCAS markets, they do not provide a comprehensive model that encompasses the full scope of V2G interactions, particularly the incentives for EV owners and their willingness to participate in V2G or discharging activities.

The integration of EVs into the grid through V2G services is a critical area of research, with studies exploring various dimensions of this integration. While V2G technology holds significant potential in FCAS markets, it has yet to be widely implemented thus far. One reason is the lack of knowledge about V2G technology [174], but an even more critical barrier is the concern that V2G may accelerate the degradation of EV batteries. Hence, it is necessary to study EV owners' willingness to participate in V2G. The research in [157] delves into the optimization of energy resources for prosumers, including EVs, highlighting the economic benefits of market participation, yet without a specific focus on the V2G participation willingness of EV owners. The study in [175] proposes cost-minimizing V2G models that consider EV driving patterns and real-time pricing, indirectly touching upon user behavior but not explicitly addressing the willingness to participate in V2G services. The study [176] quantifies the impact of V2G on battery degradation, providing valuable insights into the technical feasibility of V2G services, while Ref. [177] discusses optimized bidirectional V2G operation strategies, suggesting potential cost reductions for EV ownership through grid service participation. The research in [178] also presents a strategy for optimal EV charging/discharging within a DC Microgrid, focusing on technical efficiency and battery preservation in V2G services. Collectively, these studies contribute to the body of knowledge on V2G integration but also highlight a significant research gap: the absence of a detailed examination of EV owners' willingness to participate in V2G and discharging activities, a factor critical to the practical implementation of V2G services.

In this chapter, we will investigate the willingness of EV owners to participate in V2G services. We will approach this issue from the perspective of EV parking lots, where V2G incentives are employed to encourage discharging, as discussed in our previous study [179]. Balancing incentives is critical; while lower incentives may reduce costs for EV parking lots, they could also discourage V2G participation. On the other hand, higher incentives may encourage more EVs to engage in V2G, but at the expense of the parking lot's profit. Assuming that V2G willingness can be represented by the energy that EV owners are willing to discharge, zero incentives would result in no desire. The challenge lies in finding the optimal V2G incentives that not only benefit EV owners by offsetting their charging fees or generating profit but also motivate V2G participation and ensure parking lot profitability. Existing studies, such as [180], explore the impact of fluctuating charging costs and discharging incentives on EVs participating in V2G, while the study in [181] introduces an EV economic dispatch optimization model designed to reduce regional V2G system operating costs. Although both studies propose strategies for optimizing charging and discharging processes and scheduling approaches, neither specifically addresses the challenge of determining the optimal V2G incentive.

To bridge this gap, we propose an IGDT-based method, which has been extensively discussed in [182]–[186]. The study in [182] has been instrumental in this progress, offering a sophisticated energy procurement model that allows large consumers to navigate the volatile landscape of energy prices with greater confidence. Their model leverages IGDT to provide a robust framework that accounts for the unpredictable nature of energy markets, enabling consumers to make informed decisions despite price uncertainties. Building on the concept of robust energy management, an innovative two-stage model that harnesses the potential of EVs as a collective energy storage mechanism within intelligent parking lots is introduced in [183]. This model not only optimizes the operational efficiency of energy communities but also underscores the strategic role that EVs play in balancing supply and demand in energy systems. The research in [184] expands the scope of robust scheduling to encompass renewable energy hubs, addressing the challenge of integrating diverse energy demands and storage options. Their model is particularly noteworthy for its comprehensive approach to managing uncertainties in both energy demands and market prices, thereby ensuring the resilience of energy hubs in a fluctuating market environment. In the context of virtual power plants, a bilevel decision-making framework that is designed to optimize participation in both day-ahead and balancing markets is proposed in [185]. This framework is distinguished by its incorporation of demand response programs and financial transmission rights, with IGDT applied to manage the uncertainties associated with renewable energy production. Additionally, the study in [186] contributes to the literature with an optimal energy management strategy for multi-energy microgrids. Their strategy is particularly relevant for microgrids integrated with hydrogen refuelling stations and EV parking lots, employing an IGDT-based approach to manage the uncertainties in the wind and PV power generation effectively.

Despite these significant contributions, the literature reveals a gap in the simultaneous application of robust and opportunistic decision-making within these models. We propose a refined IGDT-based method, one that not only provides robustness in the face of uncertainties but also harnesses the potential opportunities presented by the dynamic energy markets. This method will be explored in depth in Section 4.2.5, while additional uncertainties such as solar irradiance, wind speed, and EV user behaviors will be examined in Sections 4.2.5 and 4.2.1.

In general, the main features and contributions of this chapter are as follows:

- We develop a sophisticated EV parking lot model that synergistically incorporates RESs and V2G functionalities. This model is adept at managing the uncertainties associated with smart grid operations, such as the volatility of FCAS and spot market prices, variability in solar irradiance and wind speed, and the unpredictable patterns of EV user behavior.

- In response to the limited availability of charging infrastructure, a straightforward EV allocation method is proposed. This method effectively assigns EVs to available charging stations, ensuring a simplified yet efficient use of the parking lot's charging capabilities.

- A modified IGDT-based method is introduced to determine V2G incentives optimally. This novel method considers the willingness of EV owners to participate in V2G services, thereby enhancing decision-making robustness under uncertain conditions and increasing the appeal for EV owners to contribute to grid support activities.

4.2 Problem Formulation

The parking lot equipped with bi-directional chargers, PV panels, WTs, and an ESS is considered. It is assumed that all EVs in the parking lot intend to charge, and all EVs connected to the chargers want to charge to the maximum possible SoC. An allocation method is considered to allocate multiple EVs into the limited available V2G chargers. As our previous study [179] proposed, depending on each EV's parking period and initial SoC, the management system in the charging station will divide them into V2G and non-V2G groups, with different charging modes and pricing schemes applied. It is worth noting that a significant challenge for the broad application of V2G services is EV battery degradation. Therefore, considering the V2G participation willingness with incentive price sensitivity, an IGDT-based optimal decision-making method will determine the V2G incentives, motivating EV owners to discharge more power through V2G willingly. Regarding the charging price, the EVs not joining V2G will have a dynamic price depending on their charging demand, and the V2G-participating EVs could incur the minimum charging price and receive the monetary reward. The focus of this chapter does not include parking fees for EVs. Consequently, EV parking costs have not been taken into account. The subsequent sections provide a detailed description of the model.

4.2.1 System Modelling

The system model used in this study aligns with the one we previously proposed, as outlined in [179]. Thus, we'll briefly summarize its main components and mechanisms here. Please refer to our previous study for all related definitions.

RESs modelling

This study also takes into account WTs and PV systems, as indicated in (4.1) and (4.2), respectively.

$$P_t^W = \begin{cases} 0 & v_t \leq V_{ci} \\ P_r(A + B * v_t + C * v_t^2) & V_{ci} < v_t \leq V_r \\ P_r & V_r < v_t \leq V_{co} \\ 0 & v_t \geq V_{co} \end{cases} \tag{4.1}$$

$$P_t^{PV} = r_t * s_{pv} * e_{pv} \tag{4.2}$$

EV modelling

In this study, we have enhanced our model to handle increasingly complex scenarios. Considering the behavior of EVs, their arrival and departure times and initial SoC will be randomly generated by the widely used Monte Carlo method [187][188]. Based on practical cases, EV parking lots with parking spaces and limited charging spaces are considered here. Assume that all EVs entering the parking lot already have the willingness to park within their parking period (from arrival to departure time). When an EV arrives at the parking lot, it will start to find an available charger and get connected. If all the chargers are occupied, this EV will park in a parking space to wait in the parking lot until any chargers become available or it is time to depart. The logic flow chart is shown in Fig. 4.1. Based on the practical situation in the parking lot, the EV queuing problem is unrealistic in our case and is not considered here.

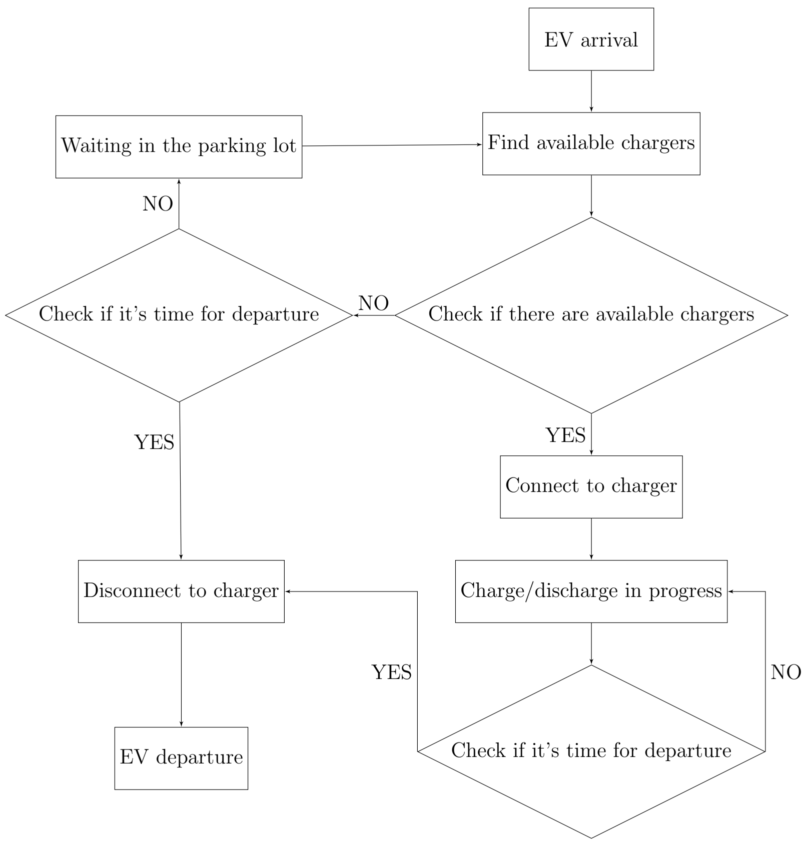


Figure 4.1: EV allocating.

After the EV allocation process, the EV charging and discharging models are defined as follows.

Eqs. (4.3)-(4.4) illustrate the variation in EV energy and ensure that EVs will have their required energy upon departure. Before arrival and after departure, the energy available from the EV is zero, reflecting its absence from the parking lot. Upon arrival, the EV's energy is initialized to its current state. During the parking period, the battery energy evolves based on the previous time step and the charging or discharging operations performed. To ensure the EV departs with the required energy level, it is charged to a maximum allowed level when departure, typically below full capacity to preserve battery health and avoid overcharging. Constraints (4.5)-(4.6) are introduced to ensure that charging and discharging do not occur simultaneously. Throughout the charging process, the energy state of each EV is kept within a reasonable range to protect the batteries from overcharging or over-discharging, hence reducing potential battery degradation, as shown in (4.7). Eq. (4.8) stipulates that both charging and discharging power will be zero when EVs disconnect.

$$E_{i,t}^{EV} = \begin{cases} 0, & t < t_{a,i} \\ E_i^{\text{ini}}, & t = t_{a,i} \\ E_{i,t-1}^{EV} + \left(\eta_{ch} * P_{i,t}^{EV+} - \dfrac{1}{\eta_{dis}} * P_{i,t}^{EV-}\right) \triangle t, & t_{a,i} < t \leq t_{d,i} \\ E_{i,max}^{EV}, & t = t_{d,i} \\ 0 & t > t_{d,i} \end{cases} \tag{4.3}$$

$$E_{i,max}^{EV} = E_i^{ini} + \sum_{t=t_{a,i}+1}^{t_{d,i}} \left(\eta_{ch}^{EV} * P_{i,t}^{EV+} - \frac{1}{\eta_{dis}^{EV}} * P_{i,t}^{EV-}\right) \triangle t \tag{4.4}$$

For $t_{a,i} < t \leq t_{d,i}$,

$$0 \leq P_{i,t}^{EV+} \leq \mu_{i,t} * P_{i,max}^{EV+} \tag{4.5}$$

$$0 \leq P_{i,t}^{EV-} \leq (1 - \mu_{i,t}) * P_{i,max}^{EV-} \tag{4.6}$$

$$E_{i,min}^{EV} \leq E_{i,t}^{EV} \leq E_{i,max}^{EV} \tag{4.7}$$

For t otherwise

$$P_{i,t}^{EV+} = P_{i,t}^{EV-} = 0 \tag{4.8}$$

$$\begin{aligned} z^{EV} = & \left[\sum_{i=1}^{N}\sum_{t=t_{a,i}}^{t_{d,i}}(1-\varphi_i)(P_{i,t}^{EV+} * \lambda_i^c)\triangle t\right] \\ & + \sum_{i=1}^{N}\varphi_i\left[\left(E_{i,max}^{EV} - E_i^{ini}\right) * \lambda^{c,min} - \sum_{t=1}^{T}(P_{i,t}^{EV-} * \lambda_{inc})\triangle t\right] \end{aligned} \tag{4.9}$$

The modeling of the conditions that determine whether an EV can participate in V2G services follows the same approach as outlined in Chapter 3, as seen in Eqs. (3.9)-(3.13). Eq. (4.9) represents the total profit from these two groups. The profit for non-V2G EVs is determined by their charging energy and the dynamic charging price. On the other hand, for V2G participant EVs, the profit includes the minimum charging price required to charge them to their maximum allowed energy, while the cost of the V2G incentive is also accounted for. λ_{inc} in (4.9) is the optimal V2G incentive provided to EVs, and the method to determine it will be explored in Section 4.2.5.

ESS modelling

Eqs. (4.10)-(4.14) describe the ESS model in the EV parking lot system. Eq. (4.10) illustrates the energy dynamics of the ESS. Similar to the EV modelling, the ESS energy evolves based on the energy level from the previous time step and the charging or discharging operations performed. The study also accounts for battery degradation costs, which calculated based on the total discharged energy and the degradation cost per kWh, as shown in (4.15), where the unit battery degradation cost B is defined in (3.20).

$$E_t^{ESS} = E_{t-1}^{ESS} + \left(\eta_{ch}^{ESS} * P_t^{ESS+} - \frac{1}{\eta_{dis}^{ESS}} * P_t^{ESS-}\right)\triangle t \tag{4.10}$$

$$E_T^{ESS} = E_0^{ESS} \tag{4.11}$$

$$E_{min}^{ESS} \leq E_t^{ESS} \leq E_{max}^{ESS} \tag{4.12}$$

$$0 \leq P_t^{ESS+} \leq \ a_t * \ P_{max}^{ESS+} \tag{4.13}$$

$$0 \leq P_t^{ESS-} \leq (1 - a_t) * \ P_{max}^{ESS-} \tag{4.14}$$

$$C^{ESS,de} = \sum_{t=1}^{T} P_t^{ESS-} \triangle t * B \tag{4.15}$$

4.2.2 Market Constraints

The FCAS market comprises two regulation markets and six contingency markets. At this stage, aside from the spot market, given the extremely low likelihood of contingency events occurring, our focus is limited to the six contingency markets and their reserve participation situation. According to their response time, these markets can be categorized as 6-second raise and lower, 60-second raise and lower, and 5-minute raise and lower markets [171]. Eq. (4.16) represents the profit obtained from the FCAS market. It comprises earnings from both the raise and lower markets. C_t^{FCAS} denotes the transactional cost for FCAS market participation, which is paid to EV owners for reserving the capacity of their EVs. Distinctly separating from EV incentives and the degradation of ESS, it underscores the financial implications of continuous market engagement. $P_{t,j}^r$ and $P_{t,j}^l$ represent the power from different raise and lower markets, respectively. N_r and N_l are the number of raise and lower markets, which are both equal to 3 in this study. The binary variable $\tau_{t,j}^r$ and $\tau_{t,j}^l$ are randomly generated to represent the bidding success of each contingency market. The bidding strategy is not considered.

Similar to the parts of the ESS and EVs, the parking lot cannot simultaneously import and export power. Additionally, energy trading cannot occur simultaneously in both the FCAS raise and lower markets. Therefore, the binary variable b_t and c_t is utilized in (4.17)-(4.20). Eqs. (4.21)-(4.24) define auxiliary variables used for the upper bound of the raise and lower markets. The constraints (4.25) - (4.26) define the upper bounds for reserve power in the FCAS market. To convert (4.21)-(4.24) to equivalent mixed integer linear constraints, the big-M method is employed, as illustrated in (4.27)-(4.42)[189]. The binary variables $d_{evr,i}$, $d_{evl,i}$, d_{esr} and d_{esl} are employed within this method. It should be noted that only V2G-participating EVs can join the FCAS markets. As detailed in the EV modeling section, the primary focus for short-term parking EVs is to charge as much as possible.

$$z^{FCAS} = \sum_{t=1}^{T} \left[\sum_{j=1}^{N_r} \left(P_{t,j}^{r} * \tau_{t,j}^{r} * \lambda_{t,j}^{r} \right) + \sum_{k=1}^{N_l} \left(P_{t,j}^{l} * \tau_{t,j}^{l} * \lambda_{t,j}^{l} \right) - C_t^{FCAS} \right] \tag{4.16}$$

$$0 \leq P_t^{Feed-in} \leq b_t * P_{max}^{-} \tag{4.17}$$

$$0 \leq P_t^{Grid} \leq (1 - b_t) * P_{max}^{+} \tag{4.18}$$

$$0 \leq \sum_{j=1}^{N_r} P_{t,j}^{r} * \tau_{t,j}^{r} \leq c_t * P_{max}^{R} \tag{4.19}$$

$$0 \leq \sum_{k=1}^{N_l} P_{t,k}^{l} * \tau_{t,k}^{l} \leq (1 - c_t) * P_{max}^{L} \tag{4.20}$$

$$P_{i,t}^{r,ev} = min \left(\frac{\left(E_{i,t}^{EV} - E_{i,min}^{EV} \right) \cdot \varphi_i}{\triangle t} , P_{i,max}^{EV-} \cdot \varphi_i \right) \tag{4.21}$$

$$P_{i,t}^{l,ev} = min \left(\frac{\left(E_{i,max}^{EV} - E_{i,t}^{EV} \right) \cdot \varphi_i}{\triangle t} , P_{i,max}^{EV+} \cdot \varphi_i \right) \tag{4.22}$$

$$P_t^{r,ess} = min \left(\frac{E_t^{ESS} - E_{min}^{ESS}}{\triangle t} , P_{max}^{ESS-} \right) \tag{4.23}$$

$$P_t^{l,ess} = min \left(\frac{E_{max}^{ESS} - E_t^{ESS}}{\triangle t} , P_{max}^{ESS+} \right) \tag{4.24}$$

$$\sum_{j=1}^{N_r} P_{t,j}^{r,res} \leq \sum_{i=1}^{N} P_{i,t}^{r,ev} + P_t^{r,ess} \tag{4.25}$$

$$\sum_{k=1}^{N_l} P_{t,k}^{l,res} \leq \sum_{i=1}^{N} P_{i,t}^{l,ev} + P_t^{l,ess} \tag{4.26}$$

$$P_{i,t}^{r,ev} \leq \frac{\left(E_{i,t}^{EV} - E_{i,min}^{EV}\right) \cdot \varphi_i}{\triangle t} \tag{4.27}$$

$$P_{i,t}^{r,ev} \leq P_{i,max}^{EV-} \cdot \varphi_i \tag{4.28}$$

$$\frac{\left(E_{i,t}^{EV} - E_{i,min}^{EV}\right) \cdot \varphi_i}{\triangle t} - M \cdot d_{evr,i} \leq P_{i,t}^{r,ev} \tag{4.29}$$

$$P_{i,max}^{EV-} \cdot \varphi_i - M \cdot (1 - d_{evr,i}) \leq P_{i,t}^{r,ev} \tag{4.30}$$

$$P_t^{r,ess} \leq \frac{E_t^{ESS} - E_{min}^{ESS}}{\triangle t} \tag{4.31}$$

$$P_t^{r,ess} \leq P_{max}^{ESS-} \tag{4.32}$$

$$\frac{E_t^{ESS} - E_{min}^{ESS}}{\triangle t} - M \cdot d_{esr} \leq P_t^{r,ess} \tag{4.33}$$

$$P_{max}^{ESS-} - M \cdot (1 - d_{esr}) \leq P_t^{r,ess} \tag{4.34}$$

$$P_{i,t}^{l,ev} \leq \frac{\left(E_{i,max}^{EV} - E_{i,t}^{EV}\right) \cdot \varphi_i}{\triangle t} \tag{4.35}$$

$$P_{i,t}^{l,ev} \leq P_{i,max}^{EV+} \cdot \varphi_i \tag{4.36}$$

$$\frac{\left(E_{i,max}^{EV} - E_{i,t}^{EV}\right) \cdot \varphi_i}{\triangle t} - M \cdot d_{evl,i} \leq P_{i,t}^{l,ev} \tag{4.37}$$

$$P_{i,max}^{EV+} \cdot \varphi_i - M \cdot (1 - d_{evl,i}) \leq P_{i,t}^{l,ev} \tag{4.38}$$

$$P_t^{l,ess} \leq \frac{E_{max}^{ESS} - E_t^{ESS}}{\triangle t} \tag{4.39}$$

$$P_t^{l,ess} \leq P_{max}^{ESS+} \tag{4.40}$$

$$\frac{E_{max}^{ESS} - E_t^{ESS}}{\triangle t} - M \cdot d_{esl} \leq P_t^{l,ess} \tag{4.41}$$

$$P_{max}^{ESS+} - M \cdot (1 - d_{esl}) \leq P_t^{l,ess} \tag{4.42}$$

where P_{max}^{+} and P_{max}^{-} are the maximum import and export power, respectively. $P_{t,j}^{r}$ and $P_{t,j}^{l}$ represent different FCAS raise and lower markets, respectively, while $P_{t,j}^{r,res}$ and $P_{t,k}^{l,res}$ signify the power reserved for these markets. $P_{i,t}^{r,ev}$ and $P_{i,t}^{l,ev}$ indicate the reserve power of EVs for the raise and lower market at time step t, respectively. In a similar vein, $P_t^{r,ess}$ and $P_t^{l,ess}$ stand for the ESS reserve power for the raise and lower market at time step t, respectively.

4.2.3 Balance Equation

The system power balance is presented in (4.43). The power drawn from the PV system, P_t^{PV}, the WT, P_t^{W}, the grid, P_t^{Grid}, the ESS discharging, P_t^{ESS-}, and the EV discharging $\sum_{i=1}^{N} P_{i,t}^{EV-}$, is distributed to the EV charging, $\sum_{i=1}^{N} P_{i,t}^{EV+}$, the ESS charging, P_t^{ESS+}, and the grid feed-in power $P_t^{Feed-in}$.

$$\begin{aligned} &\sum_{i=1}^{N} P_{i,t}^{EV+} + P_t^{ESS+} + P_t^{Feed-in} \\ &\qquad = P_t^{PV} + P_t^{W} + P_t^{Grid} + P_t^{ESS-} + \sum_{i=1}^{N} P_{i,t}^{EV-} \end{aligned} \tag{4.43}$$

4.2.4 Objective Function

The objective function delineated below seeks to maximize the parking lot's profit by strategically managing the charging and discharging of EVs and ESS to purchase electricity in low-price periods and sell it during high-price periods. It comprises several components: feed-in revenue, EV charging revenue, FCAS market revenue, V2G payment, cost of grid electricity purchase, PV and WT operating cost, and the cost associated with ESS degradation.

$$\begin{aligned} Maximize\ Z = &\sum_{t=1}^{T}(P_t^{Feed-in} * \lambda_{1,t})\triangle t - \sum_{t=1}^{T}(P_t^{Grid} * \lambda_{2,t})\triangle t + z^{EV} + z^{FCAS} \\ &- \sum_{t=1}^{T}\left(P_t^{PV} * \lambda_{pv} + P_t^{W} * \lambda_{w}\right)\triangle t - C^{ESS,de} \end{aligned} \tag{4.44}$$

4.2.5 Uncertainty

In this section, we delve deeper into the uncertainty factors associated with the proposed model, specifically focusing on market price prediction and the determination of V2G incentives. These elements are forecasted using LSTM and addressed using the IGDT-based method, respectively. It's worth noting that, although EV behavior also constitutes an uncertainty factor, it has been thoroughly discussed in the preceding section on the EV model.

Long short-term memory prediction

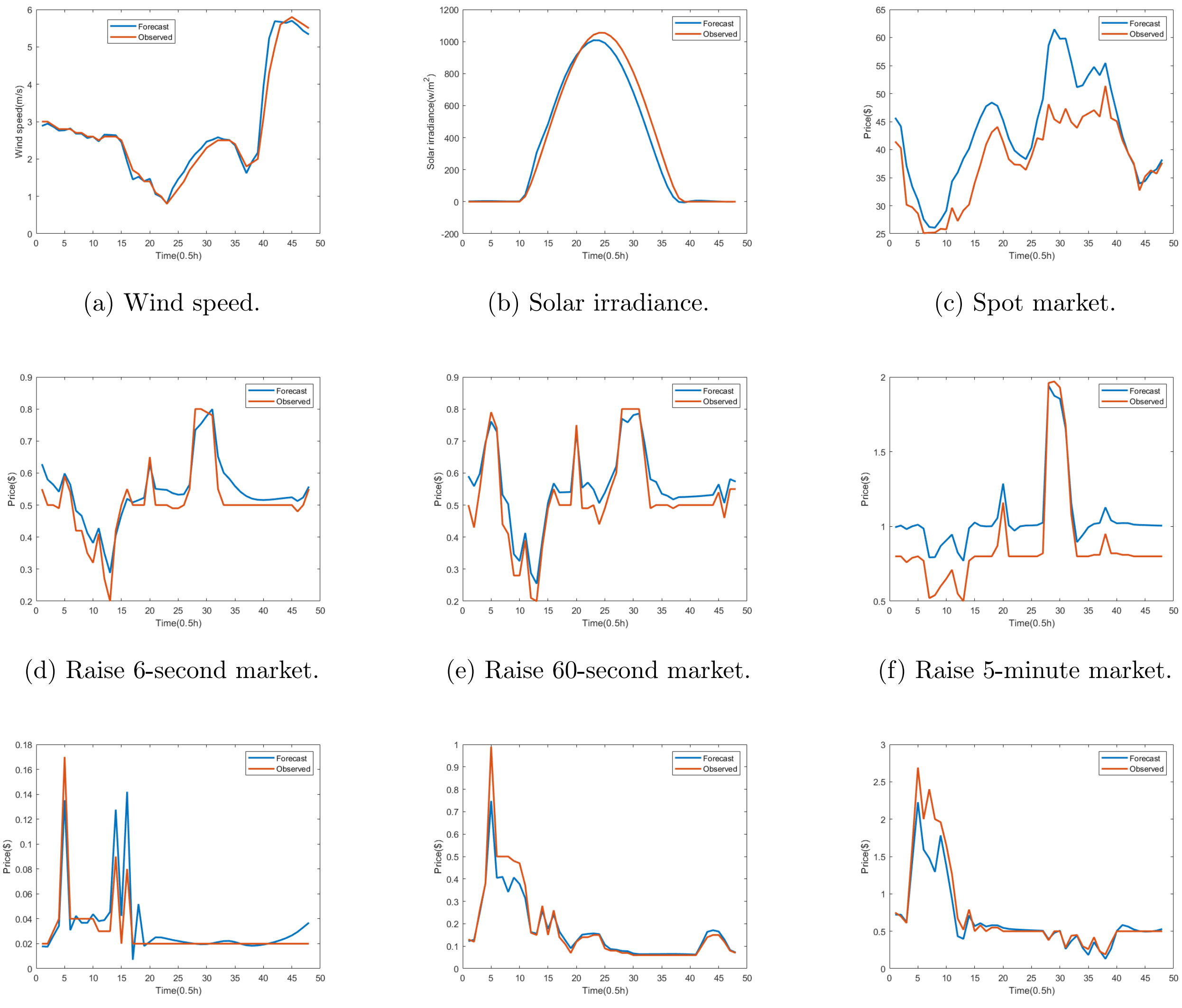
LSTM networks, a type of recurrent neural network (RNN), excel at predicting variables characterized by high degrees of randomness and uncertainty [190]. One of their main advantages is their capacity to capture long-range dependencies and complex patterns in sequential data due to their unique memory cell architecture [191], [192]. This architecture effectively stores and manages information from past observations, enabling the model to learn intricate temporal relationships and enhance forecasting accuracy. LSTM has proven effectiveness in time series forecasting. Using LSTM-based methods for renewable energy and market price prediction has yielded promising results in numerous studies [191], [193]–[195]. Given the inherent randomness and uncertainty, LSTM is employed in this chapter to predict the uncertainty factors of solar irradiance, wind speed, and market prices. In this chapter, explicit consideration of weather conditions was not included in the predictive modelling approach. However, the LSTM model was trained on a dataset spanning an extensive time period, inherently encompassing variations in weather conditions. These variations are embedded within the historical data, captured by the trained model, and subsequently reflected in the prediction results. While this approach leverages the inherent variability in the training data, incorporating specific weather data as additional input features could further enhance the accuracy of the model's predictions. Although the method may not fully account for certain sudden market shifts, these patterns align well with the historical data and are consistent with their trends, as illustrated in Fig. 4.2.

While there are observable differences between the predicted and practical market prices in the spot and raise 5-minute markets, these discrepancies fall within an acceptable range. All market data are expressed in energy and power units of MWh and MW. When scaled down to operational levels (kWh and kW), the prediction gaps become negligible, making them suitable for practical calculations. Furthermore, the predicted trends align closely with practical market data, which is crucial as optimization models rely on trends rather than absolute values to guide decision-making effectively. The optimization framework is also designed to be resilient, consistently identifying profitable opportunities for V2G participation despite variability in market price predictions. Thus, these differences do not undermine the validity of the V2G optimization model, as the alignment of trends ensures reliable and profitable operation under real-world conditions.

Information gap decision theory

One of the major challenges for the widespread adoption of V2G technology is the concern among EV owners that it could accelerate their EV battery degradation. To address this issue, incentives can be offered to EV owners who participate in V2G, along with upper and lower bounds to prevent overcharging or over-discharging of EVs at parking lots and charging stations.

An optimal V2G incentive can indirectly limit the discharge of the EV during the optimization process, reducing EV battery degradation in some cases. However, excessive incentives can negatively impact the parking lot's profit. To determine the optimal value of the incentive, IGDT [196] is considered here. Before applying IGDT, we first need to explore the willingness that is triggered by the price [197]. It is assumed that no one will participate in V2G without any rewards. The relationship between incentives (in dollars) and V2G willingness (in kWh) is shown in (4.45), where ω_{γ}^{v2g} is the willingness corresponding to the current incentive γ, ζ indicates the price sensitivity of EV owners, and C_{EV} represents the capacity of the EVs.



(a) Wind speed. (b) Solar irradiance. (c) Spot market.

(d) Raise 6-second market. (e) Raise 60-second market. (f) Raise 5-minute market.

(g) Lower 6-second market. (h) Lower 60-second market. (i) Lower 5-minute market.

Figure 4.2: LSTM forecast result.

The IGDT method has two modes - the robustness mode (4.46) and the opportunity mode (4.47). The robustness mode represents the highest uncertainty level to ensure that the profit is greater than the critical profit f_r. In contrast, the opportunity mode represents the lowest uncertainty level to gain a windfall profit as large as f_o, which should be greater than the critical profit in any case. Eq. (4.48) shows the envelope bound [185][186], representing the uncertainty values of V2G incentives γ within their expected value $\hat{\gamma}$, where α is the uncertainty radius of V2G incentives.

The decision-making policy is shown as (4.49). A baseline model F^{base} serves as a reference point against the current model's performance F_γ^{perf}. F^{base} is calculated as the minimum profit without any uncertainty and is usually less than or equal to f_r. F_γ^{perf} is calculated by (4.50), where e_γ^w is the weighting factor for the current γ in balancing the robustness and opportunity decision-making. As shown in (4.51) and (4.52), the weighting factor will be increased by v_p when the gap G_γ between $\hat{\alpha}_\gamma(Z, f_r)$ and $\hat{\beta}_\gamma(Z, f_o)$ is greater than d, and decrease by v_p when the gap is less than or equal to d. v_p and d are constants. The γ of the best performance which optimizes (4.49) will be the optimal incentive λ_{inc} used in (4.9).

$$\omega_\gamma^{v2g} = C_{EV}\left(1 - \exp\left(-\zeta * \gamma\right)\right) \tag{4.45}$$

$$\hat{\alpha}_\gamma(Z, f_r) = \underset{Z,\gamma}{max}\left\{\alpha : \underset{\gamma\in U}{min}\ F(Z,\gamma) \geq f_r\right\} \tag{4.46}$$

$$\hat{\beta}_\gamma(Z, f_o) = \underset{Z,\gamma}{min}\left\{\alpha : \underset{\gamma\in U}{max}\ F(Z,\gamma) \geq f_o\right\} \tag{4.47}$$

$$U(\alpha, \hat{\gamma}) = \left\{\gamma : \left|\frac{\gamma - \hat{\gamma}}{\hat{\gamma}}\right| \leq \alpha\right\} \tag{4.48}$$

$$Max\ C(\gamma, \omega_\gamma^{v2g}) = \frac{F_\gamma^{perf} - F^{base}}{F^{base}} \tag{4.49}$$

$$F_\gamma^{perf} = \left(1 - e_\gamma^w\right) * \hat{\alpha}_\gamma(Z, f_r) + e_\gamma^w * \hat{\beta}_\gamma(Z, f_o) \tag{4.50}$$

$$G_\gamma = \left(1 - e_\gamma^w\right) * \hat{\alpha}_\gamma(Z, f_r) - e_\gamma^w * \hat{\beta}_\gamma(Z, f_o) \tag{4.51}$$

$$e_\gamma^w = \begin{cases} e_\gamma^w + v_p \,, & G_\gamma > d \\ \\ e_\gamma^w - v_p \,, & G_\gamma \leq d \end{cases} \tag{4.52}$$

4.3 Case Study

4.3.1 Parameter and Case Settings

This section will compare two cases with scenarios of 10 EVs, 15 EVs, and 20 EVs, respectively, to explore the parking lot profit variation. The cases are defined as follows:

- Case 1: EV parking lot participates in both the spot market and 6 FCAS contingency market;
- Case 2: EV parking lot only joins the spot market.

These two cases have the same parameter setting and are controlled by the same EMS. The simulation time step is set to 48 with $\triangle t = 0.5h$, and the total number of chargers equipped is 10. Additional settings for the EV parking lot can be found in [179]. Solar irradiance and wind speed data are imported from [198], and market data are imported from [199]. The LSTM is based on the MATLAB deep learning toolbox [200]. It should be noted that the randomly generated $\tau_{t,j}^r$ and $\tau_{t,j}^l$ are the same in all scenarios. Because the bidding strategy is not within the scope of this chapter, the results of the FCAS market bidding are randomly generated. It is assumed that energy bidding commitments will always be fulfilled. The bidding strategy may be further explored in our future research.

In order to further verify the selection of V2G incentives, the range of V2G incentives is set from 0 to 0.1, with an interval of 0.01. Based on the comparison of the above cases, in addition to the optimal incentives cases, the comparison will also be made with the V2G incentives at a minimum value of 0 and maximum value of 0.1, respectively.

4.3.2 Results and Analysis

In this section, we will examine the two mentioned cases under varying numbers of EVs. As mentioned before, lower incentives may reduce costs for EV parking lots but could also deter V2G participation. Conversely, higher incentives might encourage more EVs to participate in V2G, but this may negatively impact the parking lot's profit. Finding the optimal balance between these two factors is significant. In the following analysis, the IGDT method will be employed to determine the optimal incentives within the range of potential incentives for both cases. The minimum and maximum incentive values will be established and compared to the optimal V2G incentives to evaluate the impact on profit. This comparison will provide valuable insights into the variations in profit under different incentive conditions. Consequently, we present the following results.

Optimal V2G incentives

Figs. 4.3 - 4.11 depicts the behavior under optimal incentives. In case 2, EVs mainly discharge between time steps 15 and 30 due to a rising market price, charging at lower spot market price points to maximize profit. In contrast, case 1 exhibits an opposite trend during the same time steps. Anticipating a rise in FCAS contingency market prices, the parking lot initiates EV charging to reserve capacity for the FCAS market and delays discharging to a later period when spot market prices are higher. This strategy increases participation and profitability in case 1. Although the charging and discharging activities exhibit similar trends in both cases as the number of EVs increases, the ESS in case 1 shows more frequent energy fluctuations. This ESS also participates in the FCAS market through periodic charging and discharging to secure additional profits. On the other hand, in case 2, which only engages in the spot market, frequent charging and discharging fail to offset the associated costs, thereby diminishing profits.

The optimal V2G incentives derived from the proposed IGDT method are detailed in TABLE 4.1. Notably, monetary rewards for V2G-participating EVs in case 1 are higher compared to those in case 2. This discrepancy stems from the parking lot's participation in the FCAS market, which allows for more substantial incentives to be offered to EV owners, thereby boosting its own profits as well. Because of the revenue from the raise markets and the additional income from reserved capacity in lower markets, the entire parking lot system engages in more frequent energy exchanges in case 1, thereby justifying higher V2G incentives to encourage participation.

Profits for each case, featuring varying numbers of EVs, are summarized in TABLE 4.2. While the profits in case 1 significantly exceed those in case 2, the growth rate tends to plateau as the number of EVs increases. This flattening growth is attributed to the limited charging space, which restricts the number of EVs participating in V2G activities. As the primary goal of the EV parking lot is to fully charge all EVs to their maximum SoC before departure, the amount of releasable energy does not proportionally increase with more EVs connecting to the system.

Table 4.1: The optimal incentives in each case.

	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	\$0.06	\$0.05	\$0.05
Case 2	\$0.04	\$0.03	\$0.02

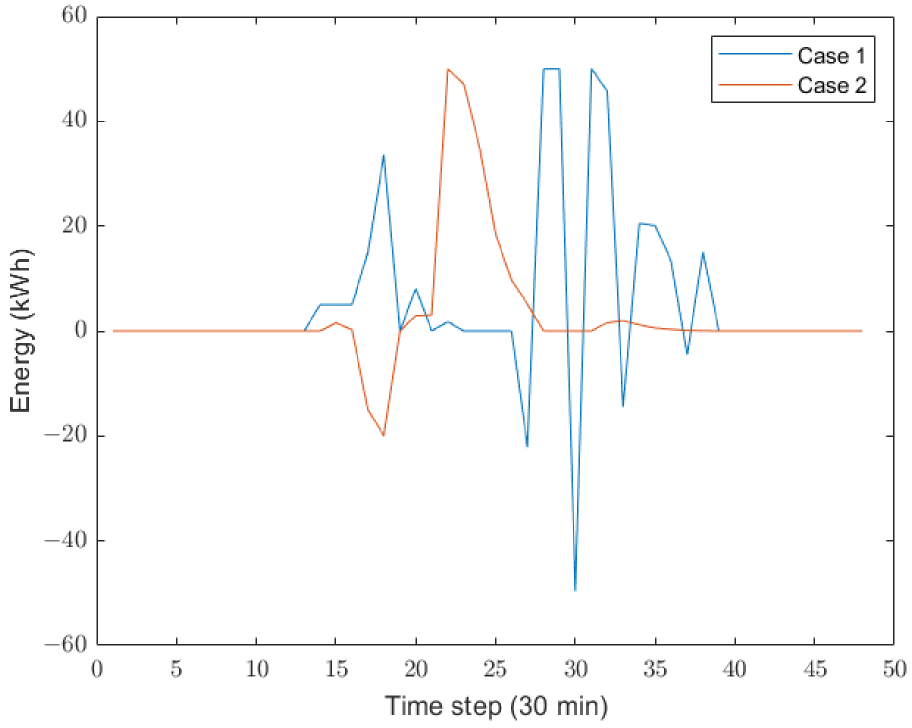


Figure 4.3: EVs charging/discharging energy with optimal incentives (10 EVs).

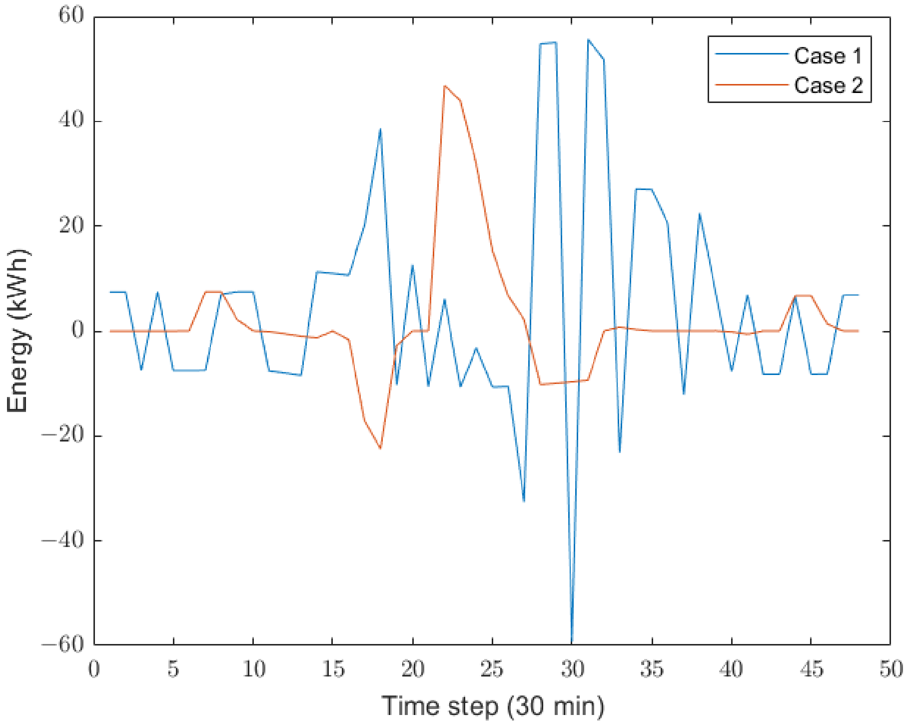


Figure 4.4: Export/import energy with optimal incentives(10 EVs).

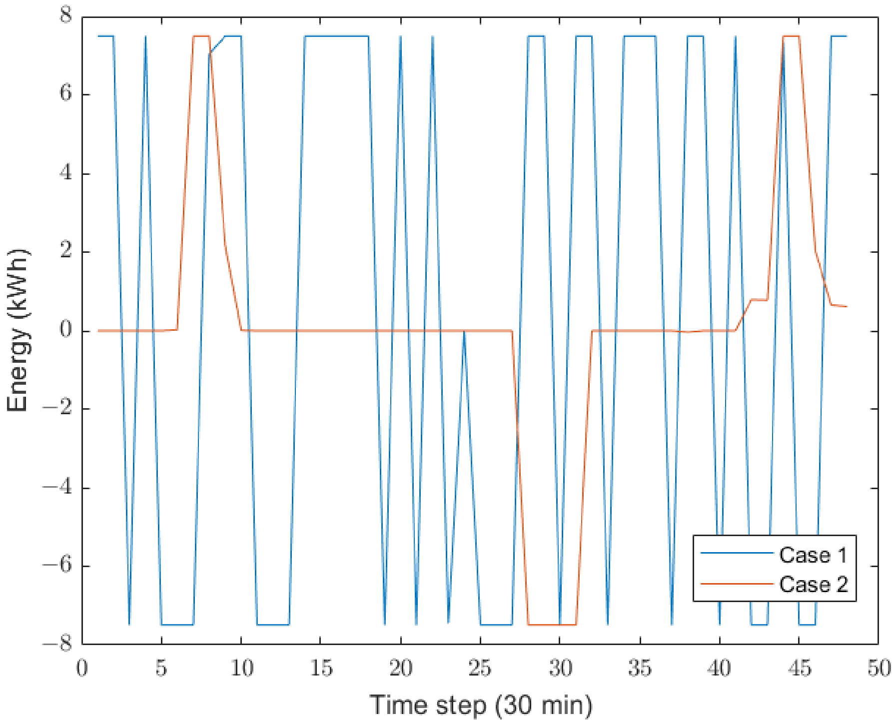


Figure 4.5: ESS charging/discharging energy with optimal incentives (10 EVs).

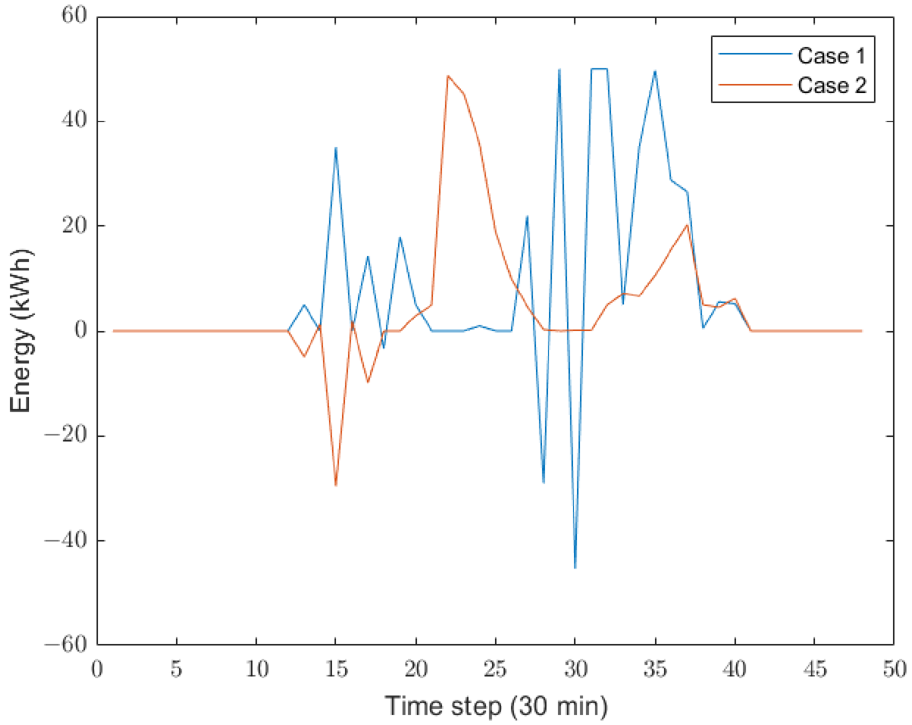


Figure 4.6: EVs charging/discharging energy with optimal incentives (15 EVs).

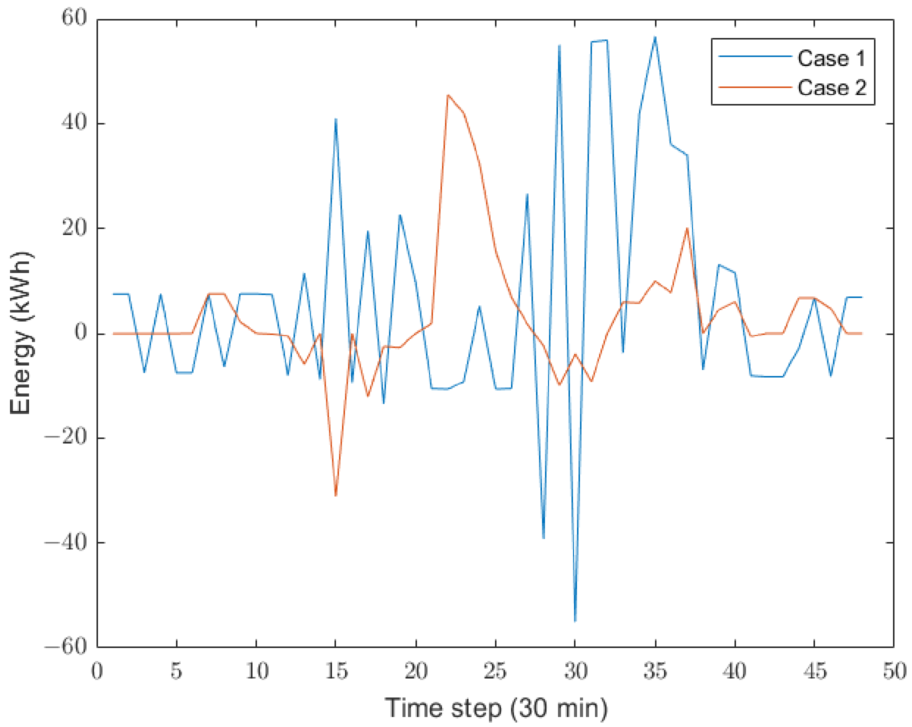


Figure 4.7: Export/import energy with optimal incentives (15 EVs).

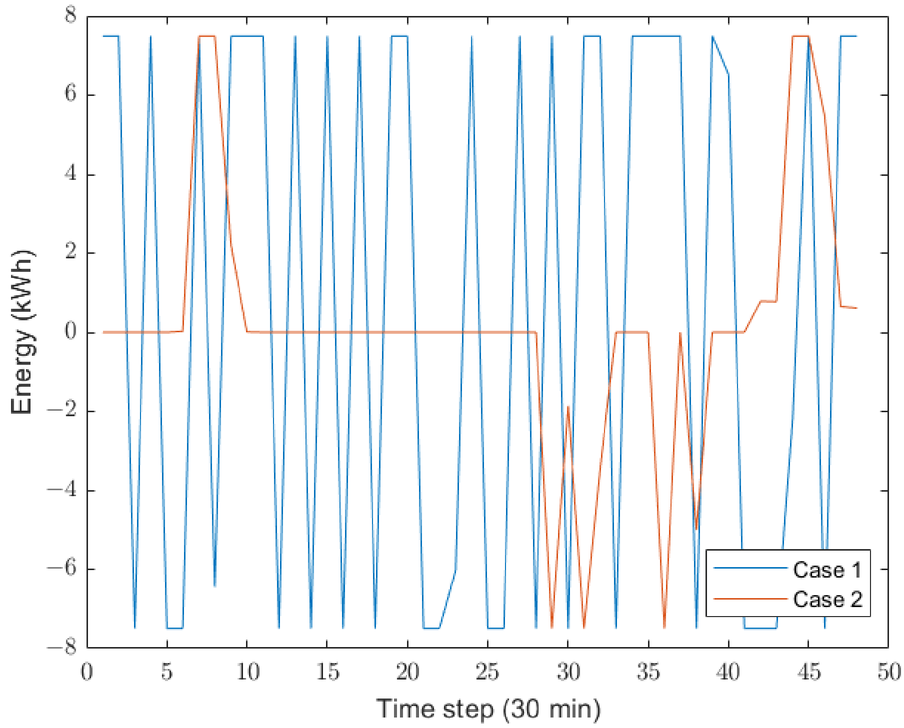


Figure 4.8: ESS charging/discharging energy with optimal incentives (15 EVs).

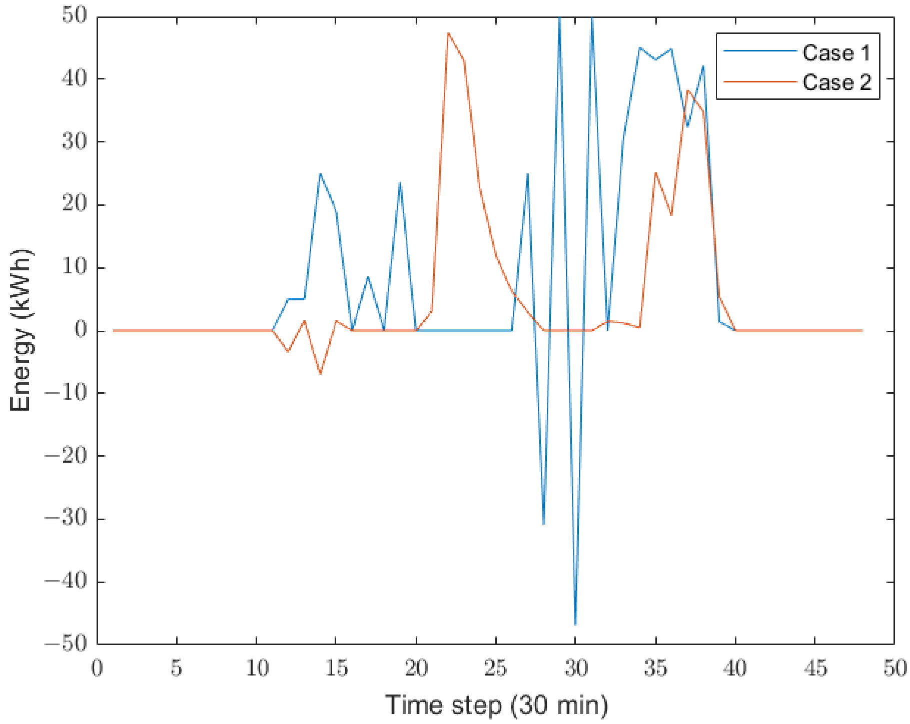


Figure 4.9: EVs charging/discharging energy with optimal incentives (20 EVs).

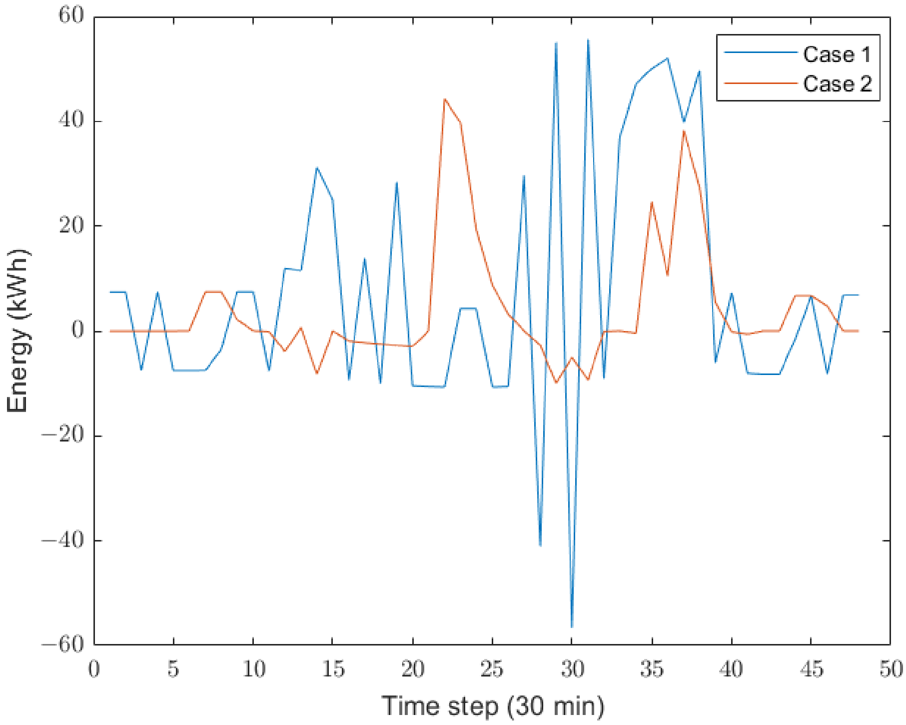


Figure 4.10: Export/import energy with optimal incentives (20 EVs).

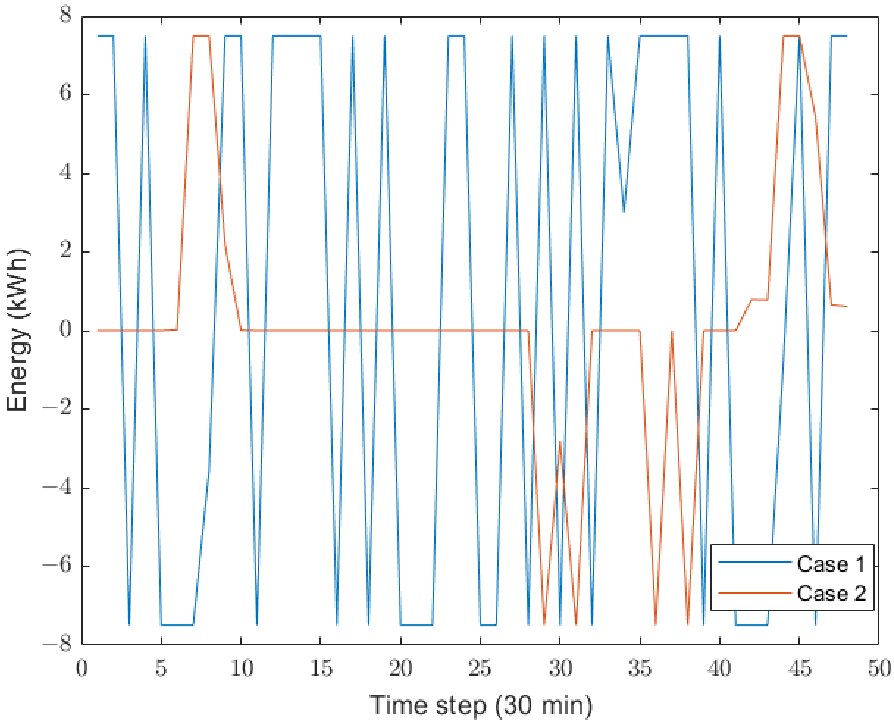


Figure 4.11: ESS charging/discharging energy with optimal incentives (20 EVs).

Without V2G incentives

When the V2G incentives are set to 0, as illustrated in Figs. 4.12 - 4.20, the willingness to participate in V2G drops to 0 for all cases, attributed to concerns about battery degradation resulting from EV discharge. In case 1, the trend remains similar to that of the optimal incentive scenario. To maximize profits, the ESS energy fluctuates frequently, adjusting its capacity to reserve for the FCAS contingency markets. Conversely, in case 2, charging still occurs at low spot market prices. The ESS is charged when prices are low and discharged at high electricity prices to minimize charging costs or generate profits.

Table 4.2 reveals that, even without EV participation in V2G, profits in case 1 are still substantially higher than in case 2. However, when compared to the scenario with optimal incentives, the difference in profits slightly decreases as the number of EVs increases.

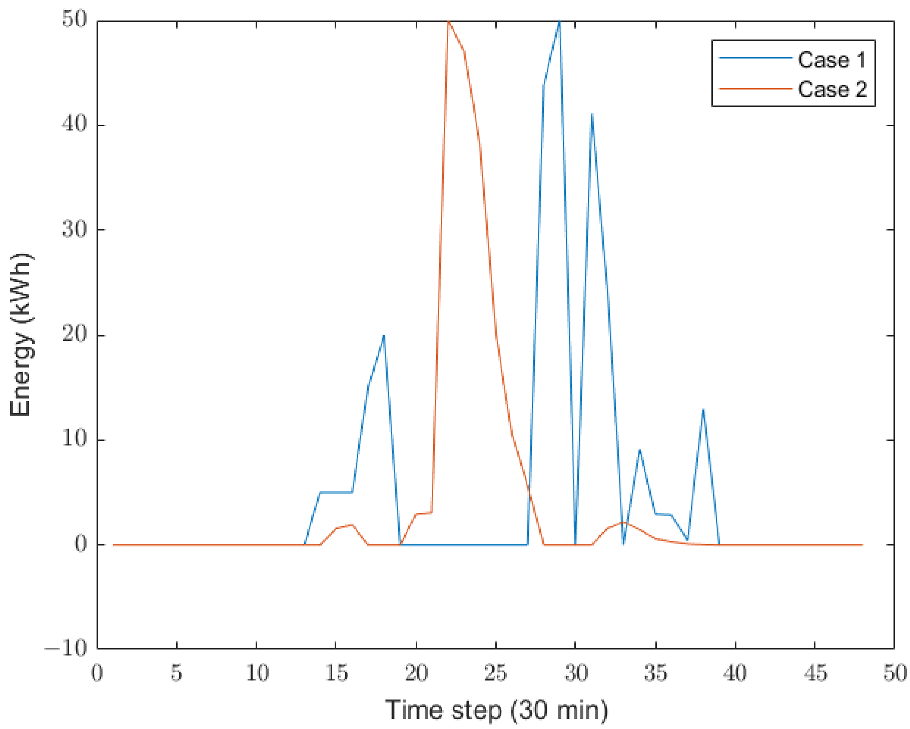


Figure 4.12: EVs charging/discharging energy without incentives (10 EVs).

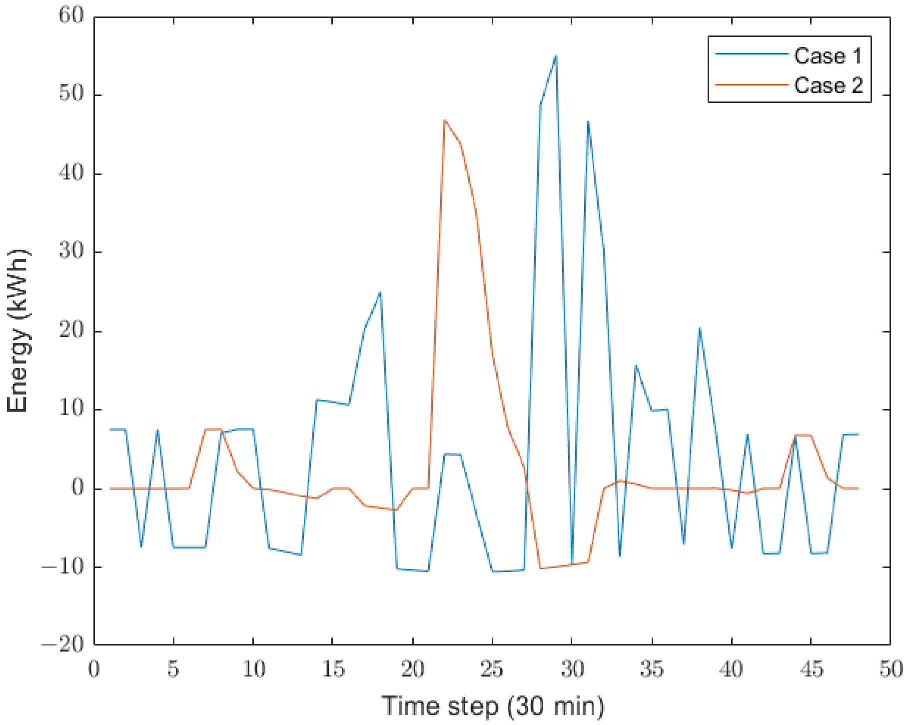


Figure 4.13: Export/import energy without incentives (10 EVs).

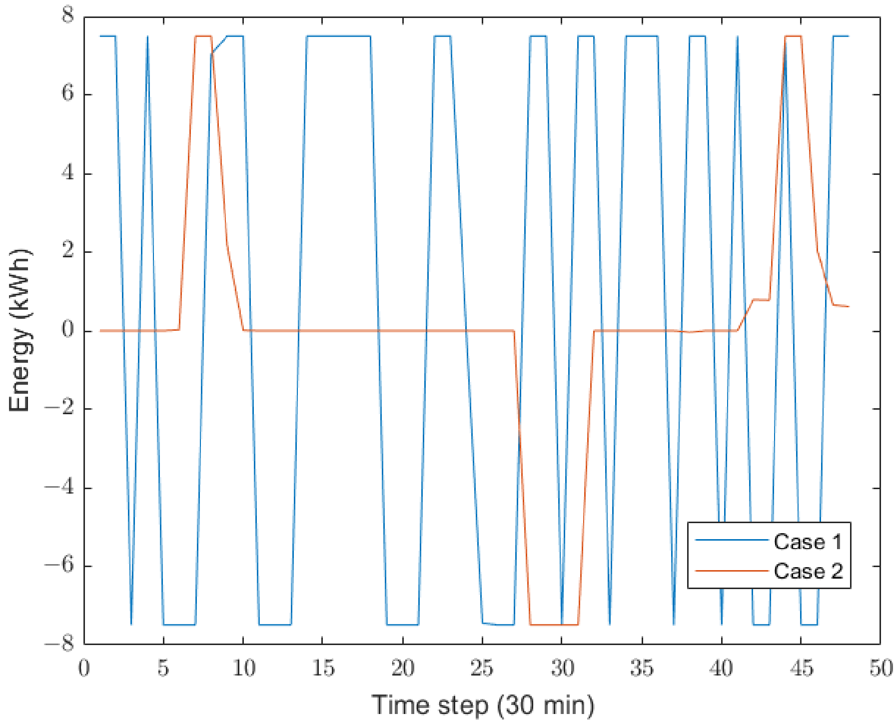


Figure 4.14: ESS charging/discharging energy without incentives (10 EVs).

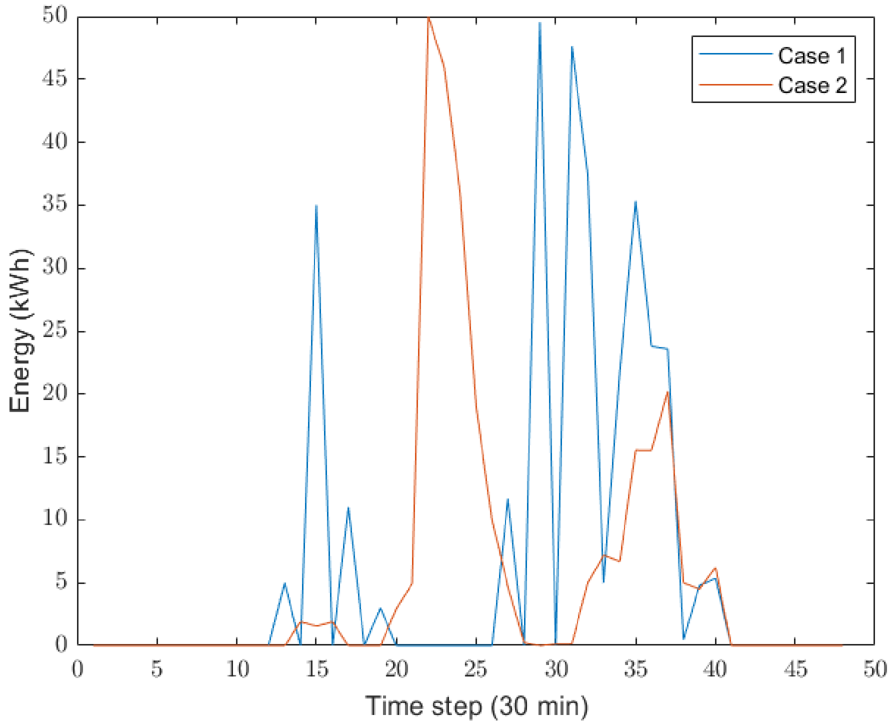


Figure 4.15: EVs charging/discharging energy without incentives (15 EVs).

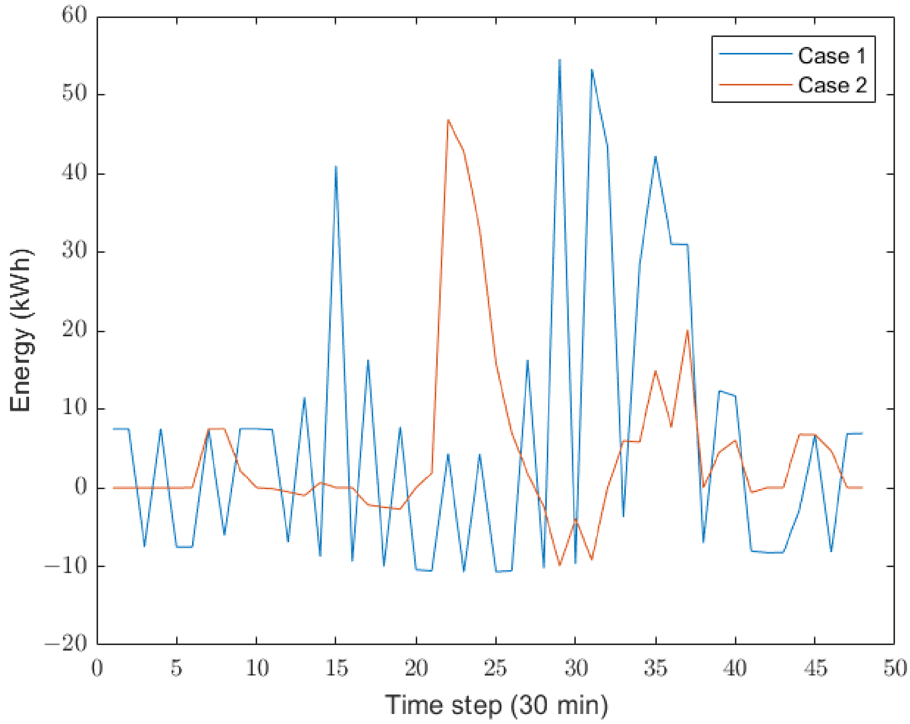


Figure 4.16: Export/import energy without incentives (15 EVs).

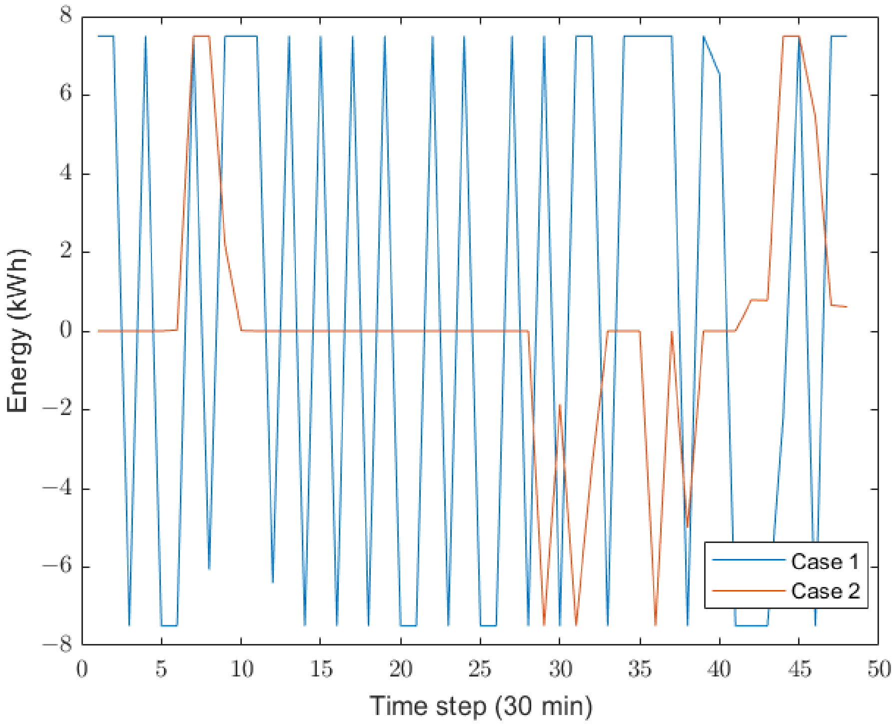


Figure 4.17: ESS charging/discharging energy without incentives (15 EVs).

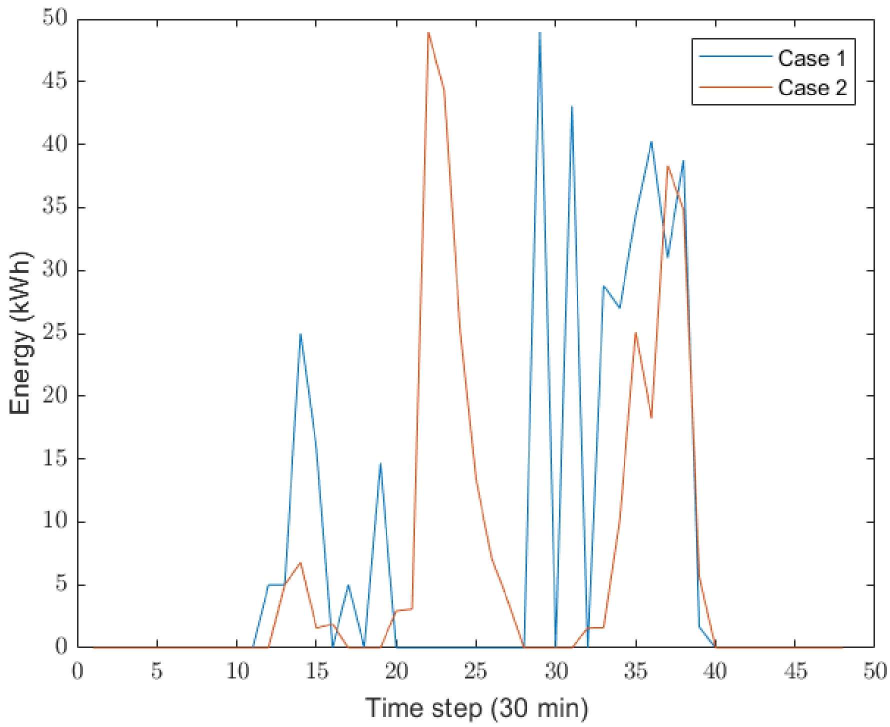


Figure 4.18: EVs charging/discharging energy without incentives (20 EVs).

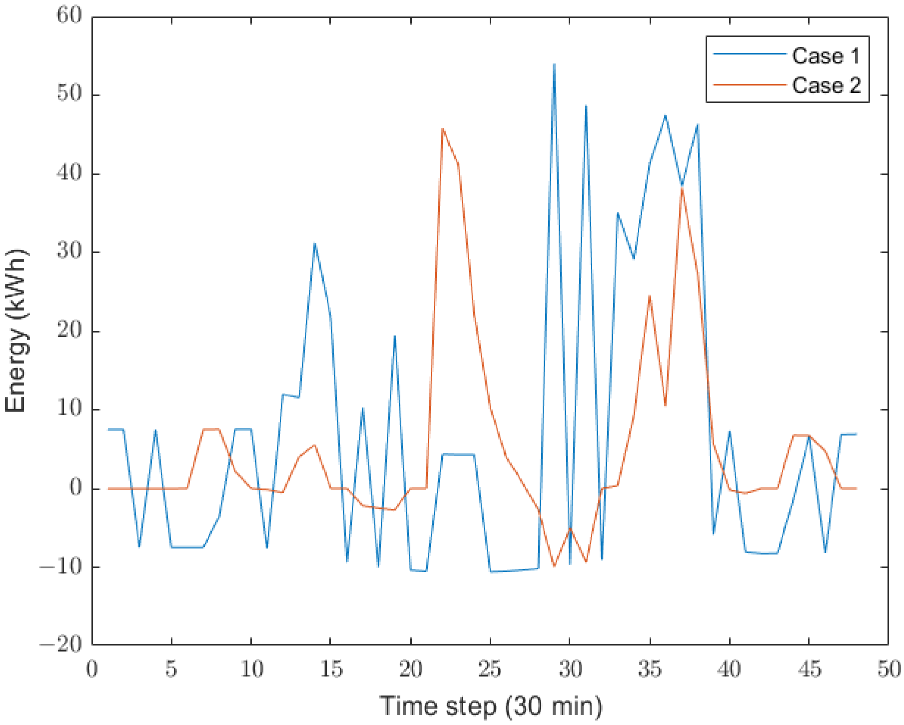


Figure 4.19: Export/import energy without incentives (20 EVs).

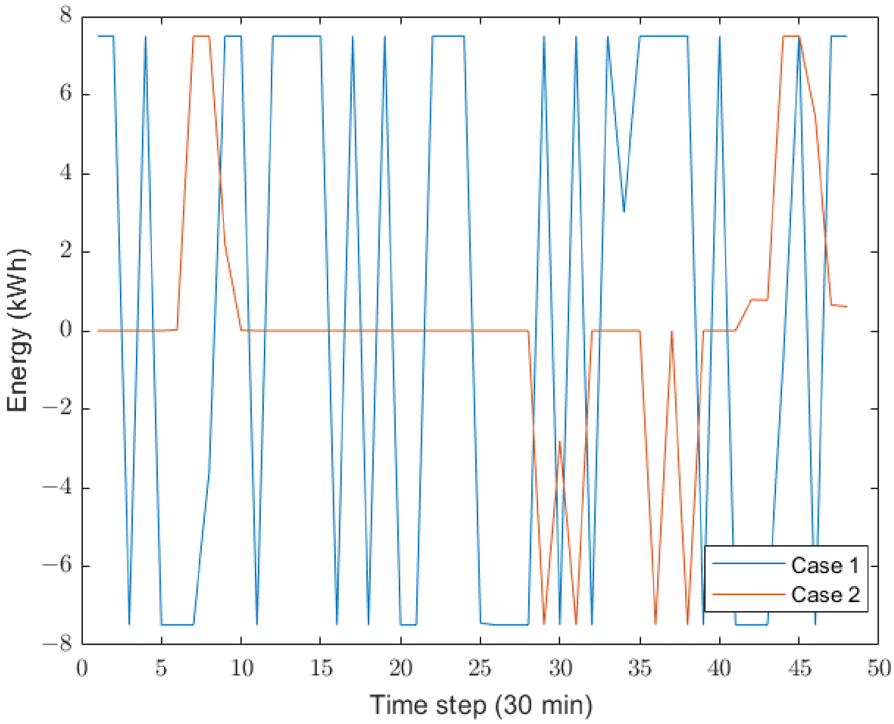


Figure 4.20: ESS charging/discharging energy without incentives (20 EVs).

With the maximal V2G incentives

When the V2G incentive is set to \$0.1, as illustrated in Figs. 4.21 - 4.29, the elevated incentive causes the EMS to entirely suspend V2G operations in case 2 as a cost-saving measure, despite the increased willingness from EVs to engage in V2G. The charging and discharging patterns of the ESS are consistent with the zero-incentive scenario. In contrast, in case 1, the frequency of energy import and export activities increases, resembling the trends observed in the optimal incentive scenario. Even with these higher incentives, V2G in case 1 continues to operate, capitalizing on the higher returns from multiple markets to maximize profits. Profits in case 2 remain consistent with those in previous incentive scenarios, but the difference in profits is slightly higher compared to the zero-incentive scenarios.

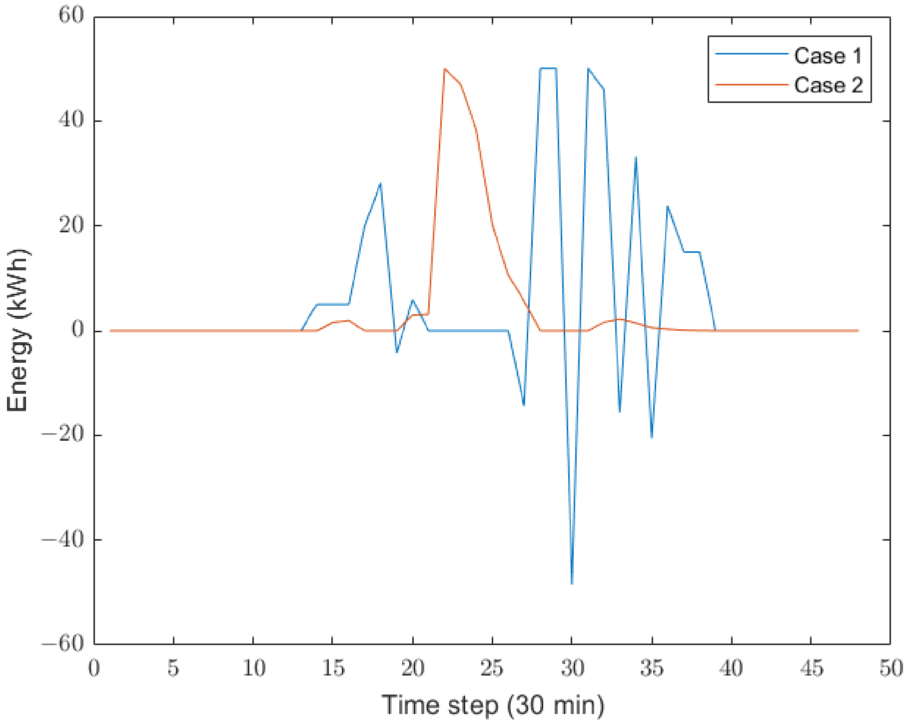


Figure 4.21: EVs charging/discharging energy with maximal incentives (10 EVs).

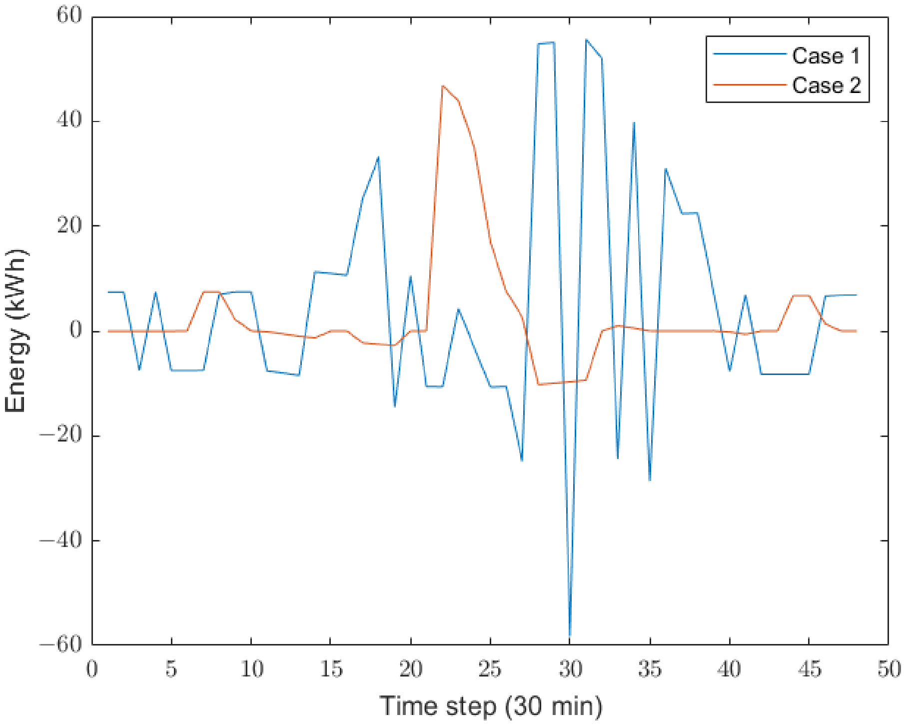


Figure 4.22: Export/import energy with maximal incentives (10 EVs).

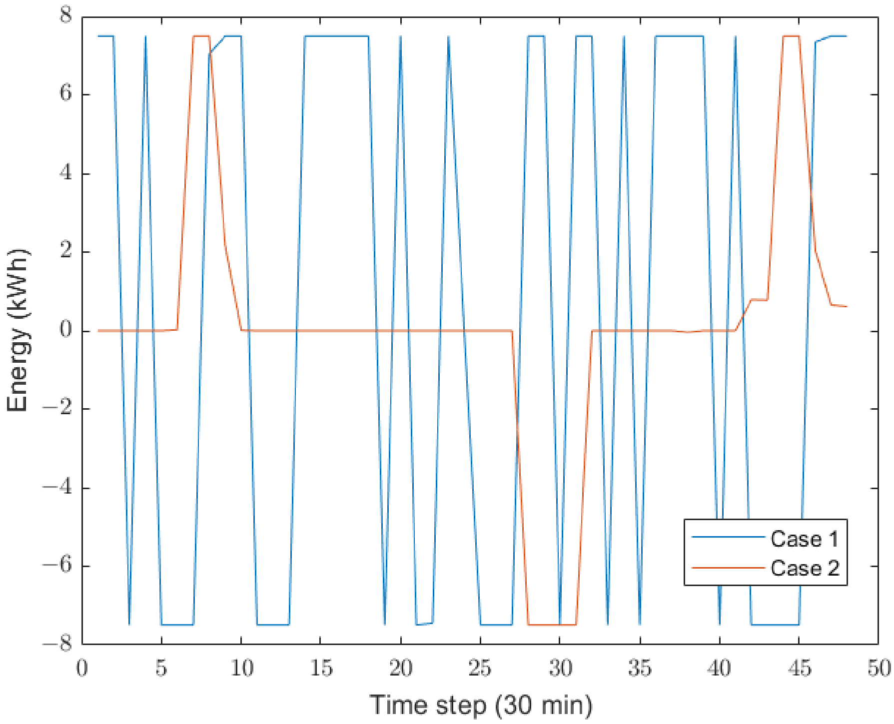


Figure 4.23: ESS charging/discharging energy with maximal incentives (10 EVs).

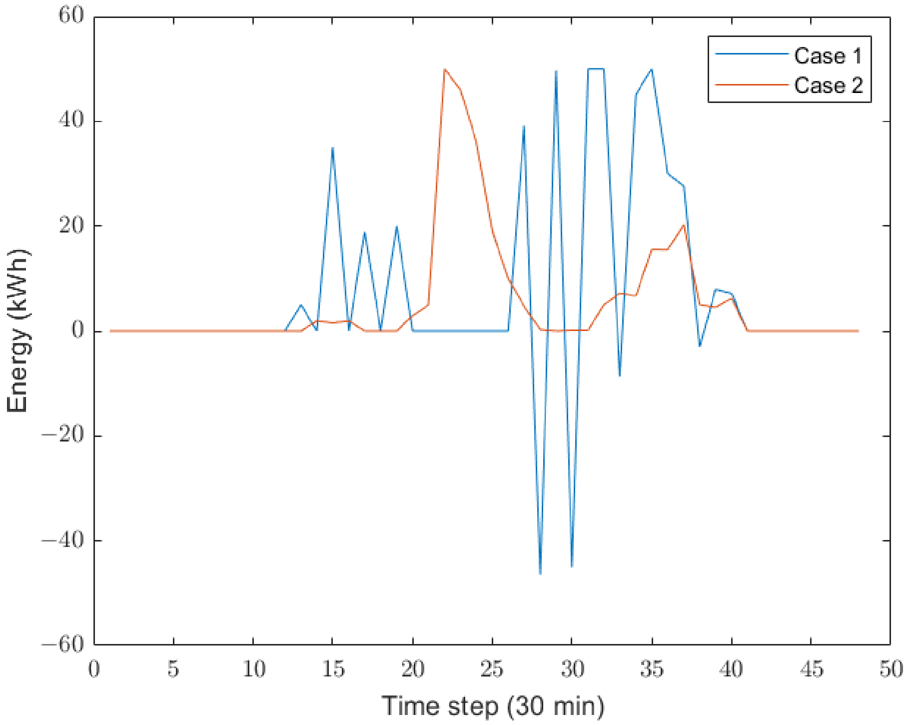


Figure 4.24: EVs charging/discharging energy with maximal incentives (15 EVs).

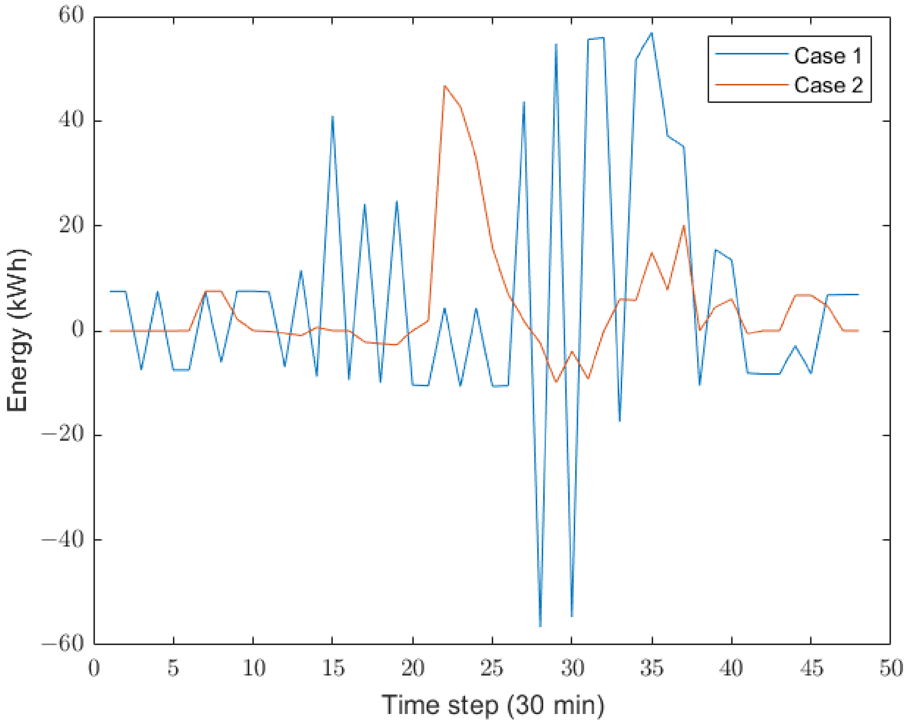


Figure 4.25: Export/import energy with maximal incentives (15 EVs).

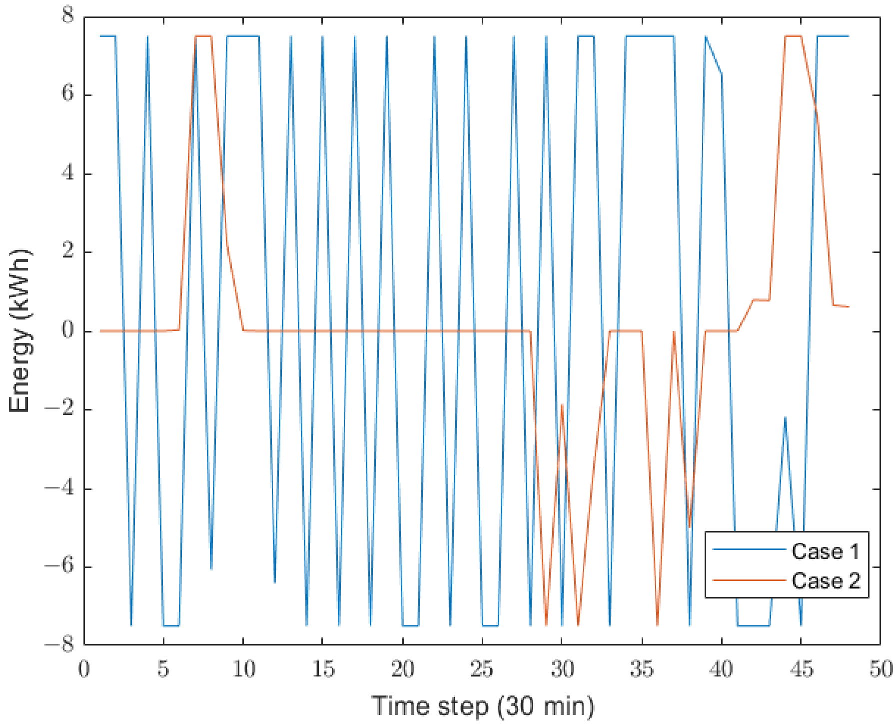


Figure 4.26: ESS charging/discharging energy with maximal incentives (15 EVs).

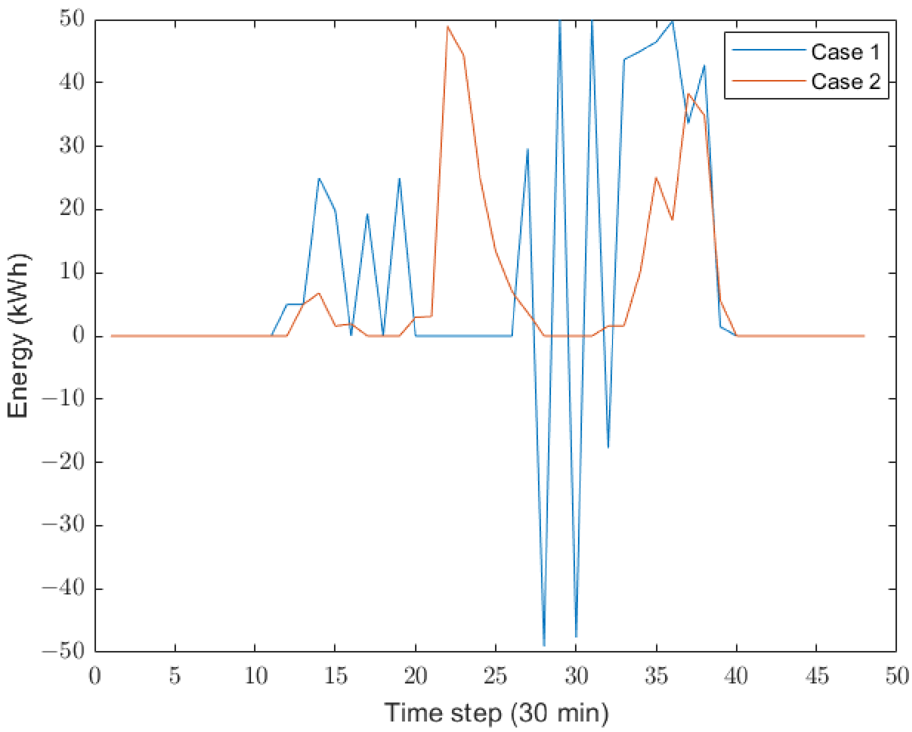


Figure 4.27: EVs charging/discharging energy with maximal incentives (20 EVs).

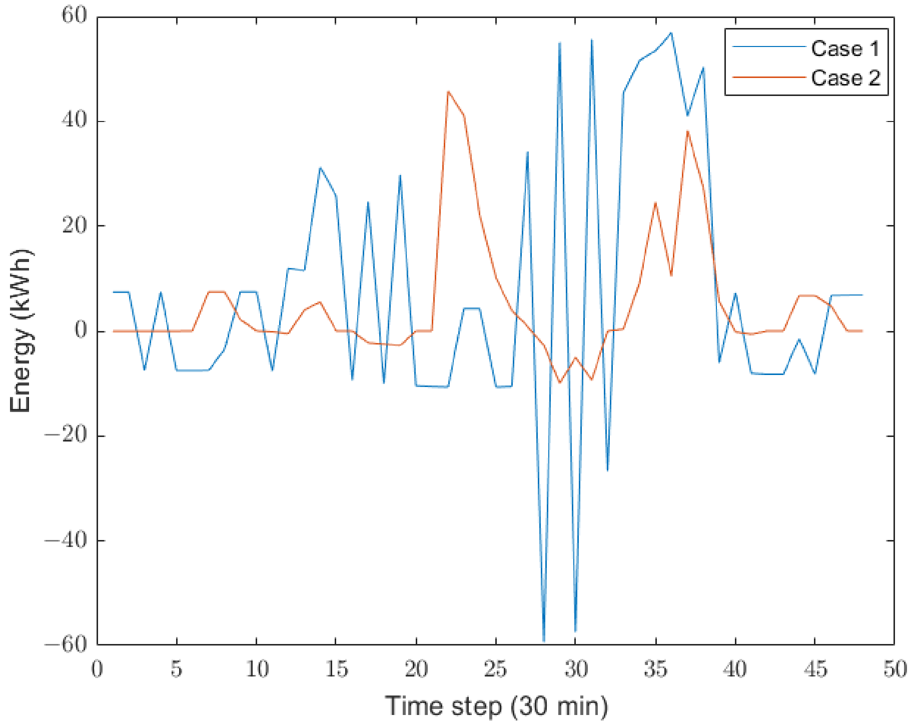


Figure 4.28: Export/import energy with maximal incentives (20 EVs).

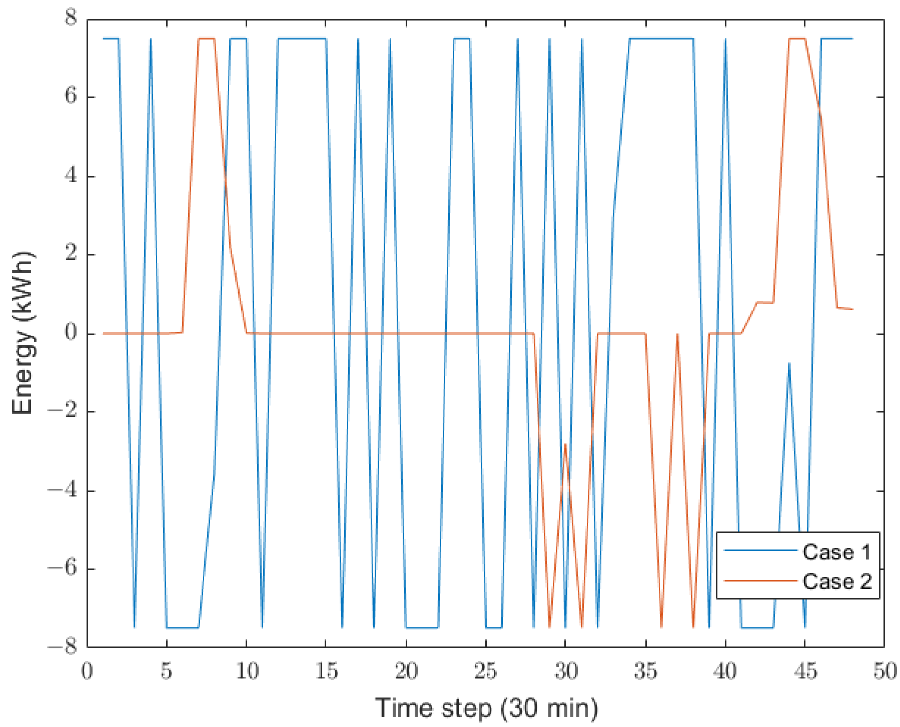


Figure 4.29: ESS charging/discharging energy with maximal incentives (20 EVs).

In general, irrespective of the V2G incentive setting, the profit in case 1 consistently exceeds that in case 2 under randomly generated bidding results. However, excessively high monetary rewards can reduce or even stop V2G operations in the parking lot to minimize costs. On the flip side, insufficient incentives may deter EV owners from participating in V2G, or even not participating altogether. These challenges are mitigated by identifying an optimal incentive value through the proposed IGDT-based method.

Table 4.2: Profit in each case.

Optimal V2G incentives			
	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	\$ 65.56	\$ 88.77	\$ 102.33
Case 2	\$ 29.08	\$ 45.19	\$ 53.39
Difference	125.45%	96.44%	91.67%
\$0 V2G incentives			
	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	\$ 61.31	\$ 84.90	\$ 97.14
Case 2	\$ 28.95	\$ 44.61	\$ 52.44
Difference	111.78%	90.32%	85.24%
\$0.1 V2G incentives			
	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	\$ 62.33	\$ 85.90	\$ 98.23
Case 2	\$ 28.95	\$ 44.61	\$ 52.44
Difference	115.3%	92.56%	87.32%

4.4 Summary

An EV parking lot model, including RES, was proposed in this chapter. By considering the uncertainties, the FCAS and spot market prices, solar irradiance, and wind speed were forecasted using LSTM based on the MATLAB deep learning toolbox. In addition, the Monte Carlo method was used to generate EV behaviors, including arrival/departure times and initial SoC. EVs are allocated to a limited number of bi-directional chargers in the EV parking lot using the proposed allocation method. It is considered that the parking lot can participate in both the FCAS and spot markets through the V2G function. In order to increase the profit for the parking lot and reduce the cost of EV owners, an IGDT-based method was proposed to decide on V2G incentives.

Two cases were compared with different EV numbers, under \$0, \$0.1, and IGDT-decided optimal value of incentives. Case 1 considers both the FCAS and spot markets, while Case 2 only engages in the spot market. Both cases achieved the highest profit under the optimal V2G incentives. It was found that incentives of \$0 and \$0.1 would cause V2G to cease in Case 2. In Case 1, even with high incentives paid to EVs, the V2G still operates and can gain profit in the FCAS market. Case 1 has the highest profit in all situations.

Chapter 5

Analyzing Pricing Strategy in Virtual Power Plants and Electric Vehicle Parking Lots: A Bi-Level Hybrid DRL-MILP Framework

5.1 Introduction

As the integration of EVs into the power grid continues to expand, VPPs have become increasingly crucial. VPPs aggregate DERs along with controllable loads, such as EVs, to enhance grid stability and efficiency. VPPs integrate DERs like solar panels, WTs, and EV batteries to function as a single power plant. EVs and EV parking lots (EVPLs) act as energy storage units, absorbing excess energy during low demand and supplying it during peak times. This not only enhances grid stability and renewable energy integration but also optimizes energy use, reduces operational costs, and facilitates higher penetration of renewable energy, thereby contributing to environmental sustainability [201]–[206]. The adoption of VPPs is driven by the need for efficient, reliable, and environmentally friendly energy solutions, supported by advancements in smart grid technologies [207]–[209].

Various strategies and models have been proposed in recent studies to optimize the operation of VPPs. The study in [210] proposes a DRL-based Stackelberg game model to optimize the scheduling of EVs in VPP. They employ a soft actor-critic (SAC) algorithm for the VPP agent and a twin delayed deep deterministic policy gradient algorithm for the EV charging station agent. This method effectively handles stochastic and non-convex challenges, thereby improving operational efficiency. However, market-induced price adjustments could affect the learning stability of the agents. In [211], a Stackelberg game model is also presented to manage the orderly charging of EVs by setting a reasonable power sales price. They transform the game model into a robust MILP problem to handle uncertainties in wind power output, allowing the VPP operator's bidding scheme to adjust flexibly, enhancing economic reliability and robustness. A two-level optimization model is proposed in [212], employing a master-slave game to optimize energy transactions between distribution network operators and VPPs. They use dynamic pricing to encourage energy sharing, which improves both operator income and VPP operational efficiency. In [213], a self-scheduling model is presented that integrates EV storage capacity and wind power production, using a roulette wheel mechanism to generate scenarios that capture uncertainties in market prices, wind production, and EV behaviors. The study in [214] introduces a four-level robust MILP model to optimize VPP participation in multiple markets. It addresses multi-stage uncertainties by integrating robust optimization approaches to hedge against the worst-case scenarios. A DRL-based model for economic dispatch in VPPs is presented in [215], optimizing the dispatch of DERs in real-time to improve efficiency and cost-effectiveness. This model adapts to dynamic changes but requires real-time data. The study in [216] introduces a reinforcement learning (RL) approach to optimize VPP operations, focusing on maximizing the economic benefits of VPPs by learning optimal strategies for energy dispatch and trading. The model is able to learn and adapt to market conditions over time, thereby increasing profitability. In [217], a bi-level optimization model is proposed to design tariff schemes that balance the economic benefits of utility companies and the satisfaction of EV users. The upper level maximizes the utility company's revenue, while the lower level maximizes consumer satisfaction by minimizing charging costs, creating a balanced tariff scheme that benefits both parties.

However, despite extensive research in multi-layer optimizing in VPPs, none of the mentioned studies combines machine learning with mathematical models like MILP for bi-level or multi-level optimization in VPP and EVs. Machine learning methods like DRL can handle large, dynamic, and uncertain environments efficiently. DRL is particularly useful for making high-level decisions or policies, such as pricing strategies. However, when analyzing pricing strategies, it is crucial to consider that the lower-level models are independent and equipped with comprehensive management and control mechanisms to optimize profits. While DRL can identify optimal or near-optimal policies over time, it may not always find the precise optimal solution due to approximation errors or computational limits. Therefore, a framework like MILP, which can handle complex constraints and provide optimal solutions within them, is better suited for the lower-level models. In addition, integrating MILP as the lower-level model can offer more accurate feedback to the upper level, enhancing overall system performance and training progress. This hybrid approach leverages the strengths of both methods, potentially offering a more balanced and efficient solution for managing bi-level VPP and EV systems.

Moreover, the behavior of EV owners is a critical focus in EV-related research and is extensively explored in many studies, such as [218]–[224]. In [218], Cumulative Prospect Theory is leveraged to understand the charging decisions of EV drivers, using data to simulate various scenarios and focusing on factors like the SoC at the beginning of charging, timing, location choices, and charging power demand. This method effectively captures risk attitudes, providing insights into how risk-seeking behavior influences charging decisions and grid demand. Moreover, in [219], machine learning models are utilized to predict EV behavior by integrating features such as traffic data, charging currents, and connection-disconnection events into the adaptive charging network dataset, achieving higher accuracy in predicting session duration and energy consumption. A discrete choice model is employed in [220] to analyze EV owners' decision-making at charging stations, using a stated preference survey with 18 hypothetical scenarios to capture socio-demographic influences on charging behavior. In [221], a cumulative prospect theory-based model is adopted using a real traffic travel dataset to simulate EV driving and charging decisions, accounting for psychological factors and limited rationality to provide a realistic portrayal of behavior through comprehensive data analysis. An ensemble machine learning approach is proposed in [222] to predict EV user behavior, reducing prediction errors for stay duration and energy consumption compared to single algorithms and improving prediction accuracy by adapting to different data scenarios. A probabilistic, data-driven approach is presented in [223] to model EV charging behavior by clustering charging data, providing insights into driver patterns and their impact on the power grid. This model's scalability and modularity enable efficient simulation of large-scale charging scenarios, beneficial for infrastructure planning. Unsupervised clustering is used in [224] to identify driving patterns from battery management system data, helping to understand individual and fleet driving behaviors and aiding in product improvement for automakers.

Nevertheless, due to the high uncertainty of EV users, the distribution of behavioral data is significantly influenced by various factors, resulting in considerable fluctuations, making it challenging to effectively simulate the randomness of EV data through prediction or simple generation methods.

To address this complexity, normalizing flows provide a powerful solution [225]. Normalizing flows are generative models that transform simple probability distributions into complex ones through a series of invertible mappings. This allows for capturing intricate patterns and dependencies in EV behavior more accurately. By modeling the data distribution precisely, It generates realistic synthetic data, enhancing the robustness and reliability of simulation.

As mentioned, for an effective pricing strategy analysis, a comprehensive approach involving lower-level models with complex management to optimize profit is necessary. Therefore, the EV system in this study will be modeled as multiple EVPLs or EV charging station models acting as lower-level models. For clarity, the rest of the chapter will use EVPLs to represent these models.

In general, the main features and contributions of this chapter are as follows:

- A hybrid optimization framework is introduced to combine the DRL algorithm SAC with MILP for bi-level and multi-agent systems, with VPP as the upper level and EVPLs as the lower level. This combination leverages the adaptive decision-making capabilities of machine learning and the precise optimization of MILP, enhancing overall system performance.

- A detailed pricing strategy analysis is conducted for the bi-level system, focusing on lower-level models equipped with a comprehensive management system designed to optimize their own profits. This analysis examines how changes in offer prices influence overall profitability within the system, providing key insights into the financial dynamics of VPP operations.

- Innovative use of normalizing flows for EV behavior modeling is proposed. This approach transforms simple probability distributions into complex ones, capturing intricate patterns and generating realistic synthetic data, thereby improving the robustness and reliability of simulations.

5.2 Problem Formulation

In this section, a hybrid multi-agent bi-level system is proposed, as shown in Fig. 5.1. In this system, the VPP, as the upper-level model, sets prices based on the SAC algorithm. Upon receiving these price signals, the lower-level models, which are EVPLs equipped with their own PV panels, ESS, and comprehensive EMS, optimize their operations to maximize profit. The EVPL models also take short-term charging EVs into consideration. In practical situations, these EVs only charge and do not provide reserve power, as they could lose their energy instead of charging if the dispatch is enabled. The uncertainty of EV behaviour is also considered and handled by normalizing flows, as mentioned previously.

During the operation of the bi-level system, the VPP will provide four distinct prices through its pricing strategy to the lower level: λ_t^{fvp}, λ_t^{vf}, $\lambda_t^{vpp,r}$, and $\lambda_t^{vpp,l}$, which correspond to the offered energy purchase price, offered energy feed-in price, the offered power reserve price for the raise market, and the offered power reserve price for the lower market, respectively. In response, the EVPLs will optimize their profit based on these price signals. If the energy purchase price from the VPP becomes unacceptably high at any given time step, the EVPLs may choose to purchase energy from another source using the real-time electricity price, denoted as $\lambda_{q,t}^{grid}$, to avoid operational cost increases. Furthermore, in addition to the dynamic charging price $\lambda_{q,i}^{c}$, the EVPLs offer a V2G incentive λ_{inc} to EVs that participate in discharging through V2G. Detailed descriptions are provided in this section.

5.2.1 Lower-level System Modelling

EVPLs act as lower-level agents in our bi-level system. In the lower-level modelling, each agent operates within the same framework but with its own operational controls and parameters, including the behaviour of EVs at each EVPL and strategies to maximize profit. Details of the model and the specific behaviours of EVs will be presented in Sections 5.2.1 and 5.2.3, respectively.

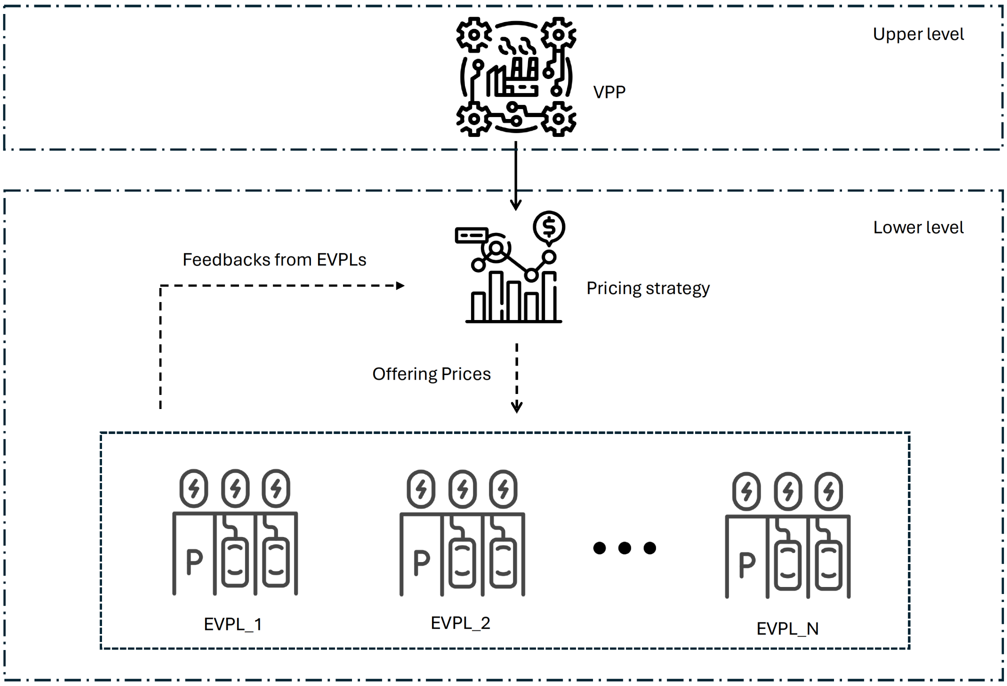


Figure 5.1: System layout.

EVPL modelling

EVPLs play a significant role in our proposed bi-level system by acting as flexible energy storage units. They provide exhaustive optimized EMSs that respond to pricing signals from the upper-level model during pricing strategy analysis. Additionally, EVPLs offer precise feedback during the DRL training process, enhancing the effectiveness of the policy. The modeling details will be presented as follows. Q and q represent the total number of EVPLs and the index of each individual EVPL, respectively. Each EVPL model is described by (5.1) - (5.34). Eq. (5.1) describes the energy dynamics of EVs within the EVPL during their period of stay, from arrival to departure. It is assumed that the priority for all EVs upon connection to the charger at the EVPLs is charging to ensure that each EV can reach its maximum allowed energy level. Hence, Eq. (5.2) is introduced to address this. Eqs. (5.3) - (5.6) define the charging and discharging logic to ensure proper operation of the EVPL and an energy bond to prevent overcharging or over discharging of the EVs. Moreover, not every EV can participate in the V2G service due to the limited connection time. Following the determination of eligible EVs for V2G using (3.9), those not participating in V2G are subjected to a dynamic charging price that varies within a defined range depending on the amount of energy charged, as outlined in (5.7) - (5.10). On the other hand, EVs that participate in V2G are charged the minimum price and receive incentives for the energy they discharge. The profits from the EVs' charging fees are represented by (5.11).

Additionally, Eq. (5.12) represents the PV output, while Eqs. (5.13)-(5.19) describe the ESS model within the EVPL. Eq. (5.13) describes the energy dynamics of the ESS. Eq. (5.14) ensures that the energy level at the end of the day is equal to the initial level. The constraints for charging, discharging, and energy bounds are specified in (5.15)-(5.17). Furthermore, the cost associated with battery degradation is considered in (5.18) and (5.19).

In addition to participating in the general spot market, the VPP also sets reserve power prices for both the raise and lower FCAS markets. These details are further explored in Section 5.2.2. It is important to note that the EVPLs choose to reserve power exclusively for these markets. The associated trading constraints are presented from (5.20) - (5.31). Eqs. (5.20)-(5.21) represent the relationship between reserve power and dispatch power for the upper level's raise and lower markets, which depend on the probability of dispatch occurring. The constraints for power export and import are listed as (5.22)-(5.23), followed by the reserved power constraints (5.24)-(5.25). Eqs. (5.26)-(5.29) describe the reserve power capabilities of the ESS and EVs within the EVPL. It should be noted that these constraints employ the big M method for linearization, as discussed in [189]. Furthermore, constraints specific to the reserve power for the raise and lower markets are presented in (5.30) and (5.31), respectively. Eq. (5.32) quantifies the profits derived from the reserved power.

Power balance is detailed in (5.33), followed by the objective function presented in (5.34). In this context, $P_{q,t}^{Grid}$ represents the power obtained from the grid, which is associated with a retail purchase price. This ensures that the EVPL can obtain power from an alternative source if the VPP's offered price is excessively high. The objective function (5.34) aims to maximize the profit of the q-th EVPL. It incorporates multiple revenue and cost components to ensure a comprehensive optimization framework. In addition to the profit gained from energy feed-in, it includes the cost of energy purchased from the VPP or grid. The equation also accounts for the previously mentioned profit from reserve power, calculated using (5.32), and the income from EV charging services, determined by (5.11). Furthermore, it considers the cost of battery degradation, as derived from (5.19). By integrating these elements, the objective function provides a comprehensive optimization framework for the lower-level EVPLs.

$$E^{EV}_{q,i,t} = \begin{cases} 0, & t < t_{a,q,i} \\ E^{ini}_{q,i}, & t = t_{a,q,i} \\ E^{EV}_{q,i,t-1} + \left(\eta_{ch} * P^{EV+}_{q,i,t} - \dfrac{1}{\eta_{dis}} * P^{EV-}_{q,i,t}\right)\triangle t, & t_{a,q,i} < t \le t_{d,q,i} \\ E^{EV}_{q,i,max}, & t = t_{d,q,i} \\ 0 & t > t_{d,q,i} \end{cases} \tag{5.1}$$

$$E^{EV}_{q,i,max} = E^{ini}_{q,i} + \sum_{t=t_{a,q,i}+1}^{t_{d,q,i}} \left(\eta^{EV}_{ch} * P^{EV+}_{q,i,t} - \frac{1}{\eta^{EV}_{dis}} * P^{EV-}_{q,i,t}\right)\triangle t \tag{5.2}$$

For $t_{a,q,i} < t \le t_{d,q,i}$,

$$0 \le P^{EV+}_{q,i,t} \le \mu_{q,i,t} * P^{EV+}_{q,i,max} \tag{5.3}$$

$$0 \le P^{EV-}_{q,i,t} \le (1 - \mu_{q,i,t}) * P^{EV-}_{q,i,max} \tag{5.4}$$

$$E^{EV}_{q,i,min} \le E^{EV}_{q,i,t} \le E^{EV}_{q,i,max} \tag{5.5}$$

For t otherwise

$$P^{EV+}_{q,i,t} = P^{EV-}_{q,i,t} = 0 \tag{5.6}$$

$$E^{de}_{q,i} = \left(\eta^{EV}_{ch} * P^{EV+}_{q,i,max}\right) * (t_{d,q,i} - t_{a,q,i}) \tag{5.7}$$

$$E^{EV}_{q,i,t_{d,q,i}} = E^{ini}_{q,i} + E^{de}_{q,i} \tag{5.8}$$

$$E^{de}_{q,i} = \frac{E^{de,max}_{q,i}}{\lambda^{c,max} - \lambda^{c,min}}(\lambda^{c,max} - \lambda^{c}_{q,i}) \tag{5.9}$$

$$\lambda^{c,min} \leq \lambda_{q,i}^{c} \leq \lambda^{c,max} \tag{5.10}$$

$$\begin{aligned} z_q^{EV} = & \left[\sum_{i=1}^{N} \sum_{t=t_{a,q,i}}^{t_{d,q,i}} (1-\varphi_{q,i})(P_{q,i,t}^{EV+} * \lambda_{q,i}^{c}) \triangle t\right] \\ & + \sum_{i=1}^{N} \varphi_{q,i} \left[\left(E_{q,i,max}^{EV} - E_{q,i}^{ini}\right) * \lambda^{c,min} - \sum_{t=1}^{T} (P_{q,i,t}^{EV-} * \lambda_{inc}) \triangle t\right] \end{aligned} \tag{5.11}$$

$$P_{q,t}^{PV} = r_{q,t} * s_q^{pv} * e_q^{pv} \tag{5.12}$$

$$E_{q,t}^{ESS} = E_{q,t-1}^{ESS} + \left(\eta_{ch}^{ESS} * P_{q,t}^{ESS+} - \frac{1}{\eta_{dis}^{ESS}} * P_{q,t}^{ESS-}\right) \triangle t \tag{5.13}$$

$$E_{q,T}^{ESS} = E_{q,0}^{ESS} \tag{5.14}$$

$$E_{q,min}^{ESS} \leq E_{q,t}^{ESS} \leq E_{q,max}^{ESS} \tag{5.15}$$

$$0 \leq P_{q,t}^{ESS+} \leq a_{q,t} * P_{q,max}^{ESS+} \tag{5.16}$$

$$0 \leq P_{q,t}^{ESS-} \leq (1 - a_{q,t}) * P_{q,max}^{ESS-} \tag{5.17}$$

$$B_q = \frac{R_q}{L_q * e_q^{ESS}} \tag{5.18}$$

$$C_q^{ESS,de} = \sum_{t=1}^{T} P_{q,t}^{ESS-} \triangle t * B_q \tag{5.19}$$

$$P_{q,t}^{r,disp} = \tau_{q,t}^{r} \cdot P_{q,t}^{r,res} \tag{5.20}$$

$$P_{q,t}^{l,disp} = \tau_{q,t}^{\ l} \cdot P_{q,t}^{l,res} \tag{5.21}$$

$$0 \leq P_{q,t}^{Feed-in} + P_{q,t}^{r,disp} \leq b_{q,t} * P_{q,max}^{-} \tag{5.22}$$

$$0 \leq P_{q,t}^{Grid} + P_{q,t}^{fvp} + P_{q,t}^{l,disp} \leq (1 - b_{q,t}) * P_{q,max}^{+} \tag{5.23}$$

$$0 \leq P_{q,t}^{r,res} \leq c_{q,t} * P_{q,max}^{r} \tag{5.24}$$

$$0 \leq P_{q,t}^{l,res} \leq (1 - c_{q,t}) * P_{q,max}^{l} \tag{5.25}$$

$$P_{q,i,t}^{r,ev} = min\left(\frac{\left(E_{q,i,t}^{EV} - E_{q,i,min}^{EV}\right) \cdot \varphi_{q,i}}{\triangle t}\ ,\ P_{q,i,max}^{EV-} \cdot \varphi_{q,i}\right) \tag{5.26}$$

$$P_{q,i,t}^{l,ev} = min\left(\frac{\left(E_{q,i,max}^{EV} - E_{q,i,t}^{EV}\right) \cdot \varphi_{q,i}}{\triangle t}\ ,\ P_{q,i,max}^{EV+} \cdot \varphi_{q,i}\right) \tag{5.27}$$

$$P_{q,t}^{r,ess} = min\left(\frac{E_{q,t}^{ESS} - E_{q,min}^{ESS}}{\triangle t}\ ,\ P_{q,max}^{ESS-}\right) \tag{5.28}$$

$$P_{q,t}^{l,ess} = min\left(\frac{E_{q,max}^{ESS} - E_{q,t}^{ESS}}{\triangle t}\ ,\ P_{q,max}^{ESS+}\right) \tag{5.29}$$

$$P_{q,t}^{r,res} \leq \sum_{i=1}^{N} P_{q,i,t}^{r,ev} + P_{q,t}^{r,ess} \tag{5.30}$$

$$P_{q,t}^{l,res} \leq \sum_{i=1}^{N} P_{q,i,t}^{l,ev} + P_{q,t}^{l,ess} \tag{5.31}$$

$$z_q^{res} = \sum_{t=1}^{T} \left[\left(P_{q,t}^{r,res} \cdot \lambda_t^{vpp,r}\right) + \left(P_{q,t}^{l,res} \cdot \lambda_t^{vpp,l}\right)\right] \tag{5.32}$$

$$\sum_{i=1}^{N} P_{q,i,t}^{EV+} + P_{q,t}^{ESS+} + P_{q,t}^{Feed-in} + P_{q,t}^{r,disp} = P_{q,t}^{PV} + P_{q,t}^{Grid} + P_{q,t}^{fvp} + P_{q,t}^{ESS-} + \sum_{i=1}^{N} P_{q,i,t}^{EV-} + P_{q,t}^{l,disp} \tag{5.33}$$

$$Maximize\ Z_q^{evpl} = \sum_{t=1}^{T}(P_{q,t}^{Feed-in} * \lambda_t^{vf})\triangle t - \sum_{t=1}^{T}(P_{q,t}^{Grid} * \lambda_t^{grid})\triangle t - \sum_{t=1}^{T}(P_{q,t}^{fvp} * \lambda_t^{fvp})\triangle t + z_q^{EV} + z_q^{res} - C_q^{ESS,de} \tag{5.34}$$

5.2.2 Upper-level Modeling

The VPP functions as the upper-level model, using a DRL-based pricing strategy to send price signals to the lower-level EVPLs. Upon receiving feedback from the optimized lower-level models, the VPP maximizes its profit based on the feedback and market prices. The interaction between the VPP and EVPLs, along with the training of the DRL-based pricing strategy, will be detailed in the following sections.

FCAS markets

Before presenting the VPP modeling, the FCAS market should be briefly introduced here. The FCAS market is segmented into two regulation markets and six contingency markets. These markets are organized based on their response times: 6-second, 60-second, and 5-minute services, each available in both raise and lower capacities. Additionally, the very fast contingency FCAS, capable of responding within 1 second, was introduced recently. Despite its rapid response capability, we do not currently focus on this 1-second market due to its disproportionately high enabled prices compared to other services [226]. Therefore, our analysis is concentrated on the original six contingency markets and two regulation markets at this stage. For the raise regulation and contingency markets, N_r and j are used to represent their total number and index. Similarly, for the lower regulation and contingency markets N_l and k are used for their total number and their index. Eqs. (5.35)-(5.36) show the constraint of the powers which join the FCAS markets.

$$\sum_{j=1}^{N_r} P_{t,j}^{vpp,r} = \sum_{q=1}^{Q} P_{q,t}^{r,res} \tag{5.35}$$

$$\sum_{k=1}^{N_l} P_{t,k}^{vpp,l} = \sum_{q=1}^{Q} P_{q,t}^{l,res} \tag{5.36}$$

Upper-level profit optimization

The objective function of VPP is shown as (5.37), which consists of the price difference between FCAS markets enabled price and offered price, the difference between wholesale market and offered buying price for EVPLs, and the price difference between offered feed-in price and market feed-in price. The offered prices will be determined by the proposed DRL pricing strategy and will be further explored in Section 5.2.2.

$$\begin{aligned} Maximize\ Z^{vpp} = \sum_{t=1}^{T} \Bigg[& \sum_{j=1}^{N_r} P_{t,j}^{vpp,r}(\lambda_{t,j}^{r} - \lambda_{t}^{vpp,r}) + \sum_{k=1}^{N_l} P_{t,k}^{vpp,l}(\lambda_{t,k}^{l} - \lambda_{t}^{vpp,l}) \\ & + \sum_{q=1}^{Q} P_{q,t}^{fvp}(\lambda_{t}^{whole} - \lambda_{t}^{fvp})\triangle t + \sum_{q=1}^{Q} P_{q,t}^{Feed-in}(\lambda_{t}^{vf} - \lambda_{t}^{Feed-in})\triangle t \Bigg] \end{aligned} \tag{5.37}$$

Deep reinforcement learning

In this study, the VPP operates as the upper-level model in our bi-level system layout, offering four distinct prices to the lower-level EVPLs. These prices include the energy buying price, the feed-in price, and power reserve prices for both the raise and lower markets, allowing the VPP to participate in the FCAS market as well. To set these prices, we utilize the SAC algorithm, a model-free, off-policy actor-critic method based on DRL. This approach employs a maximum entropy framework to navigate complex action spaces effectively [227]. The objective function of SAC is given as (5.38).

$$J(\pi) = \mathbb{E}_{(s_t,a_t)\sim\rho_\pi} \left[\sum_{t} \gamma^t (r(s_t, a_t) + \alpha\mathcal{H}(\pi(\cdot|s_t))) \right] \tag{5.38}$$

where ρ_π is the state-action marginal of the trajectory distribution induced by policy π, γ is the discount factor, r is the reward function, α is the temperature parameter that determines the relative importance of the entropy term $\mathcal{H}$ against the reward, and $\pi(\cdot|s_t)$ is the policy. The algorithm optimizes both a policy network (actor) and a value network (critic), with the actor policy being adjusted to maximize the expected return and entropy, thereby promoting exploration. The SAC model is configured with a multi-layer perceptron for both the actor and critic networks, adapted to our continuous action space. In this setup, four prices are defined as actions, and SAC dynamically adjusts the pricing strategy. The upper and lower bounds for these actions are detailed in (5.39) - (5.42). Upon receiving these price signals, EVPLs optimize their profits and provide feedback to the VPP, including total energy demand, total feed-in energy, and total reserved power for both the raise and lower markets. Those are also set as the state space of the environment. Moreover, feedback from the lower-level models is integral to the learning process, enabling the continuous refinement of the pricing strategy. To ensure that the feedback signal functions correctly and does not excessively reduce agent profits, it is incorporated into the reward function, as shown in (5.43). This integration allows the SAC to optimize long-term profitability through precise and adaptive pricing decisions, which are crucial in the volatile energy markets. The baseline reserve prices for both the raise market, λ_t^{rs}, and the lower market, λ_t^{ls}, are determined by taking the minimum value across all considered FCAS markets at each time step t. These prices serve as the baseline for the proposed DRL-based pricing strategy to decide the reserve power prices. Additionally, we deploy the SAC using Stable Baselines 3, a framework for training and implementing reinforcement learning models [228]. The training process is illustrated in Fig. 5.1.

$$\lambda_t^{fvp,min} \leq \lambda_t^{fvp} \leq \lambda_t^{fvp,max} \tag{5.39}$$

$$\lambda_t^{vf,min} \leq \lambda_t^{vf} \leq \lambda_t^{vf,max} \tag{5.40}$$

$$\lambda_t^{r,min} \leq \lambda_t^{vpp,r} \leq \lambda_t^{r,max} \tag{5.41}$$

$$\lambda_t^{l,min} \leq \lambda_t^{vpp,l} \leq \lambda_t^{l,max} \tag{5.42}$$

$$
\begin{aligned}
Reward = \sum_{q=1}^{Q}\sum_{t=1}^{T}\Big[& P_{q,t}^{Feed-in}(\lambda_t^{vf} - \lambda_t^{Feed-in})\triangle t + P_{q,t}^{fvp}(\lambda_t^{whole} - \lambda_t^{fvp})\triangle t \\
&+ P_{q,t}^{r,res}(\lambda_t^{rs} - \lambda_t^{vpp,r}) + P_{q,t}^{l,res}(\lambda_t^{ls} - \lambda_t^{vpp,l})\Big] \cdot \omega_1 + \sum_{q=1}^{Q} Z_q^{evpl} \cdot \omega_2
\end{aligned}
\tag{5.43}
$$

5.2.3 Implementation of Normalizing Flows

Normalizing flows is a powerful class of statistical models that allows for complex transformations of simple distributions into more intricate ones while maintaining differentiability and invertibility [225]. This characteristic makes normalizing flows particularly suitable for modeling intricate phenomena, such as EV behaviors in our study, including initial SoC and arrival and departure times.

The foundation of this approach involves transforming a simple base distribution into a distribution that captures complex patterns, like EV behaviors. Specifically, the density of the random variable $x = F_\theta(z)$ can be computed from (5.44), where $x = F_\theta(z)$, and F_θ is a bijective map parameterized by θ. J_{F_θ} is the Jacobian matrix of F_θ. Then, a complex probability distribution $p(x)$ can be constructed from our base distribution $p(z)$. The variable z is randomly taken from the g-dimensional real dataset $\mathbb{R}^g$. The base Gaussian distribution used in this study is shown in (5.45), where $\mu \in \mathbb{R}^g$ and Σ is a diagonal covariance matrix. To train the model, we minimize the Kullback-Leibler divergence between the transformed complex probability distribution of the data and the target density distribution, as described in (5.46). The settings and training details will be presented in Section 5.3.1.

$$
p(x) = p(z)\left|\det(J_{F_\theta}(z))\right|^{-1} \tag{5.44}
$$

$$
p(z) = \mathcal{N}(\mu, \Sigma) \tag{5.45}
$$

$$
KLD(\theta, \phi) = \mathbb{E}_{p(x)}[\log p(x)] - \mathbb{E}_{p(x)}[\log p^*(x)] \tag{5.46}
$$

5.3 Case Study

5.3.1 Configuration

As mentioned, the normalizing flows method has been adopted for generating EV behaviour, including arrival and departure times and initial SoC. The architecture utilizes a three-dimensional Gaussian as the base distribution, divided into a two-dimensional distribution covering arrival and departure times, and a one-dimensional part for the initial SOC, to enhance model accuracy and ensure distinct treatment of the variables for optimal results. The configuration includes a series of 32 flow layers; each layer is an affine coupling block that transforms the base distributions. These blocks are implemented using neural networks with two hidden layers, each comprising 64 units. The model is trained using the Adam optimizer, with a learning rate of 5×10^{-4} and a weight decay of 1×10^{-5}. Fig. 5.2 presents the training progress, showing a sharp reduction in error during the early stages of training, followed by gradual adjustments in performance until it stabilizes. To validate that the generated EV behaviours reflect real-world EV behaviours, we performed a comparison between the generated data and the historical dataset used to train the model, as illustrated in Fig. 5.3. The results show that the generated data perfectly falls within the range of the historical data, indicating that the generated behaviours align well with the real behaviours of EVs. This demonstrates that the generated data can be used in the same manner as actual EV data for the purpose of analytics. Moreover, this approach highlights the robustness of the EVPL model, as it can handle any reasonable real EV behaviour dataset to perform optimization. The historical dataset was obtained from a practical EV operating database [160], ensuring that the model was trained on realistic and representative data.

In addition to the normalizing flows component, the reinforcement learning pricing strategy implemented using the OpenAI Gym framework generates prices based on market rates and feedback signals from the EVPLs [229]. The time step is set at 288 to accommodate the 5-minute intervals throughout the day. It should be noted that the bounds of actions will not exceed the market prices and maximum acceptable levels from agents, making the strategy more relevant. The Stable Baselines3 library is utilized here, employing the SAC algorithm with the *MlpPolicy*, and the training step will be detailed in the training process figures. The agents, which are the EVPLs, optimize using the Gurobi solver, and the model's operational parameter settings can be referenced from our previous study [179].

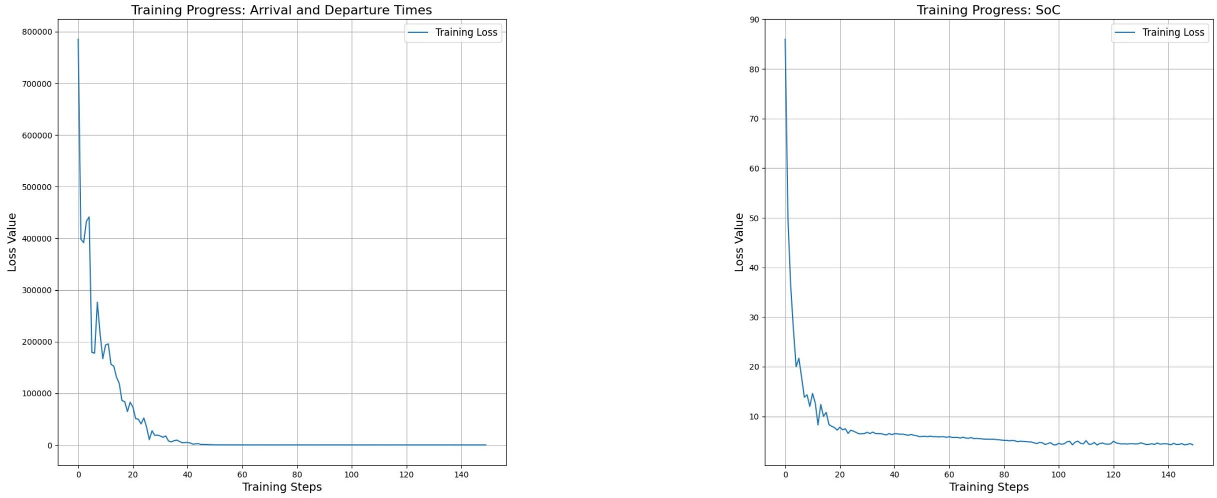


Figure 5.2: Training progress of normalizing flow.

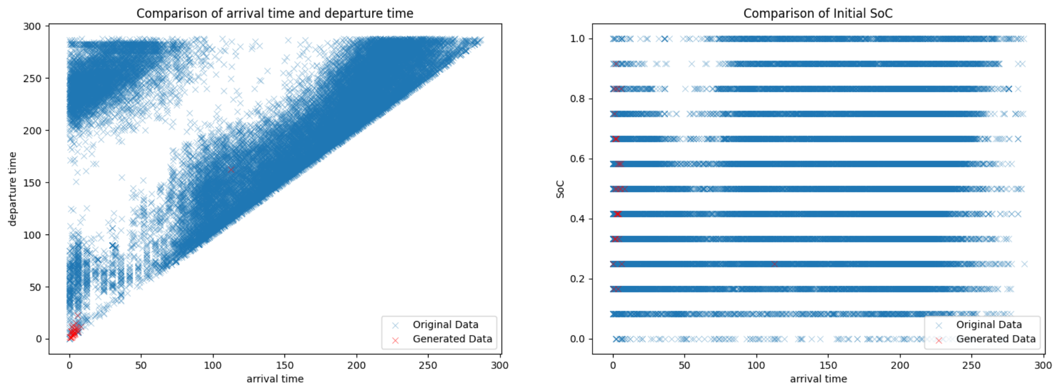


Figure 5.3: EV behavior from normalizing flows.

Before conducting the pricing strategy analysis, we propose a comparison model to validate our method, which follows the method described in [230] to employ an iterative pricing strategy for a bi-level system. Thus, our comparison model will utilize an iterative method adapted to our bi-level configuration using the same parameter settings. This approach allows for the specification of particular weighting ranges. Once the optimal result is achieved within these weighting settings, the iteration stops, and the offering prices are determined. Additionally, the iterative method tracks the result closest to the setting ranges if the algorithm completes its iterations without finding an optimal solution.

To explore the changes in profits within the bi-level system, we will set different upper and lower bounds in various cases. As previously mentioned, the lower-level models employ complex optimization strategies in response to the prices offered by the upper-level model. The original range will be set from 0 to 0.8 [231] to ensure sufficient space for exploring changes and to make differences more apparent. In addition to setting this range, to prevent algorithm overfitting or the offering of excessively high constant values, the lower-level model is also assumed to have an alternative energy purchasing source at a constant value of 0.8.

5.3.2 Establishing the Base Case

In this case, to evaluate the pricing strategy's ability to maintain equilibrium and stability among agents in the bi-level system, the strategy will be designed to balance the profits of both VPPs and EVPLs. Therefore, ω_1 and ω_2 are set as 1 during the training, and the weighting in the comparison model will be set within the range between 1 and 1.5.

The training process is shown in Fig. 5.4, which illustrates the rewards rapidly increase and stabilize around 10000 steps. The y-axis represents the total reward obtained during training steps. The reward values are dimensionless and do not have specific units, as they are determined by the reward function, which aggregates various objectives relevant to the problem being solved. Since the rewards are not normalized, the scale reflects the absolute cumulative values resulting from the training process. This approach is consistent with reinforcement learning practices, as discussed in [232], which highlights the flexibility of reward functions in tailoring learning to domain-specific tasks. After this initial phase, the rewards maintain a consistent level with occasional fluctuations. Although there are two significant dips around 18000 and 36000 steps, the model quickly recovers and returns to a stable reward level. During these phases, the SAC algorithm likely engages in exploratory actions that occasionally reach the lower-level agents' acceptable price bound, resulting in a temporary decrease in rewards. However, instead of presenting the result within the set range, the iterative comparison model provides a strategy with the closest weighting range result.

The profit for this case is shown in Table 5.1. As we can see, the profit distribution in the proposed method is more balanced, with profits of $42.72, $37.32, and $36.02 for each EVPL, respectively. The income variation under the same offer prices can be observed due to the different EV statuses in each EVPL. Although the comparison method provides a strategy that shows higher income for the VPP, $66.52 compared to $42.19 in the proposed method, the income for all EVPLs and the total profit in the system are lower than those in the proposed method, with the total profits being $158.25 and $152.2 for the proposed method and the comparison method, respectively.

Figure 5.4: Base case training process.

5.3.3 Results and Analysis

Upper-bound setting exploration

a) With upper-bound of $ 0.4

For the purpose of strategy analysis, we set the upper-bound energy price at $ 0.4. Under this

Table 5.1: Base case profit comparison.

	Proposed method	Comparison method [230]
EVPL1	\$42.72	\$30.51
EVPL2	\$37.32	\$27.25
EVPL3	\$36.02	\$27.91
VPP	\$42.19	\$66.52
Total	\$158.25	\$152.2

setting, stable training convergence can be observed after 10000 training steps, as shown in Fig. 5.5. The system status variation presented in Figs. 5.6 - 5.14 demonstrates that, despite the reduction in the offered price bound to \$ 0.4, the profits in the bi-level system show no significant changes. This stability is attributed to the lower-level EVPLs being equipped with comprehensive management systems that continually track dynamic prices and optimize their own profits. Therefore, they may not react to higher offered energy prices, even though they must charge EVs to the maximum allowed energy level upon departure. As depicted in Figs. 5.9 - 5.11, the focus shifts to charging at lower offered price points and discharging when the feed-in price increases. The timing of discharging across different EVPLs may vary due to the duration of EV stays. Overall, as the upper-level model, altering the maximum offered prices in the pricing strategy for the VPP does not decrease its income. This leads to a new setting: further reducing the maximum offered price, as shown next.

Table 5.2: Profit of \$ 0.4 upper-bound setting.

	Original bounds	Upper-bound \$ 0.4
EVPL1	\$42.72	\$40.87
EVPL2	\$37.32	\$36.62
EVPL3	\$36.02	\$35.57
VPP	\$42.19	\$40.82
Total	\$158.25	\$153.89

b) With upper-bound of \$ 0.1

After reducing the upper-bound of the offered energy price to \$ 0.1, the training process,

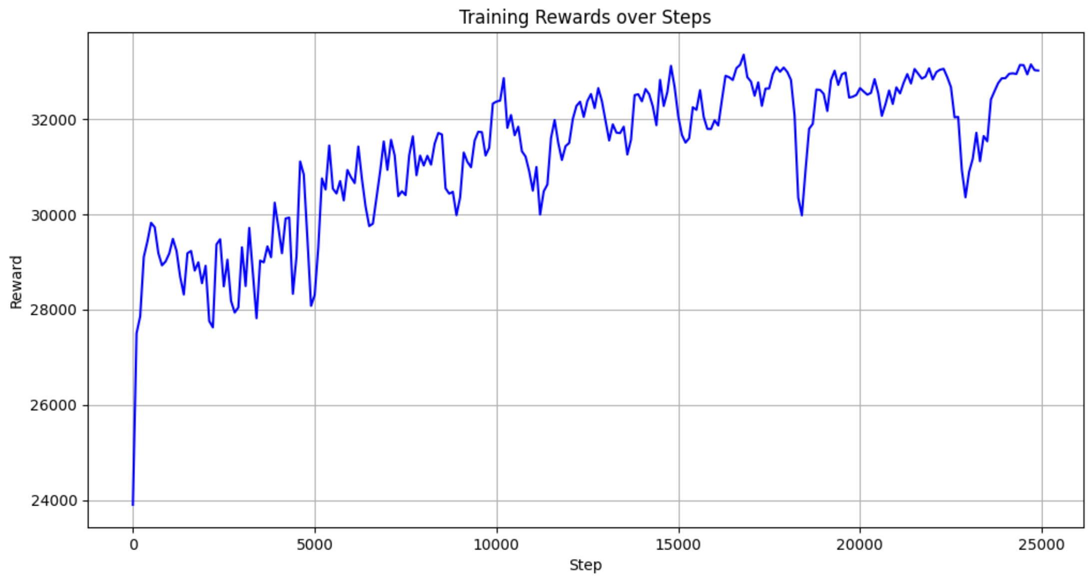


Figure 5.5: Upper-bound 0.4 training process.

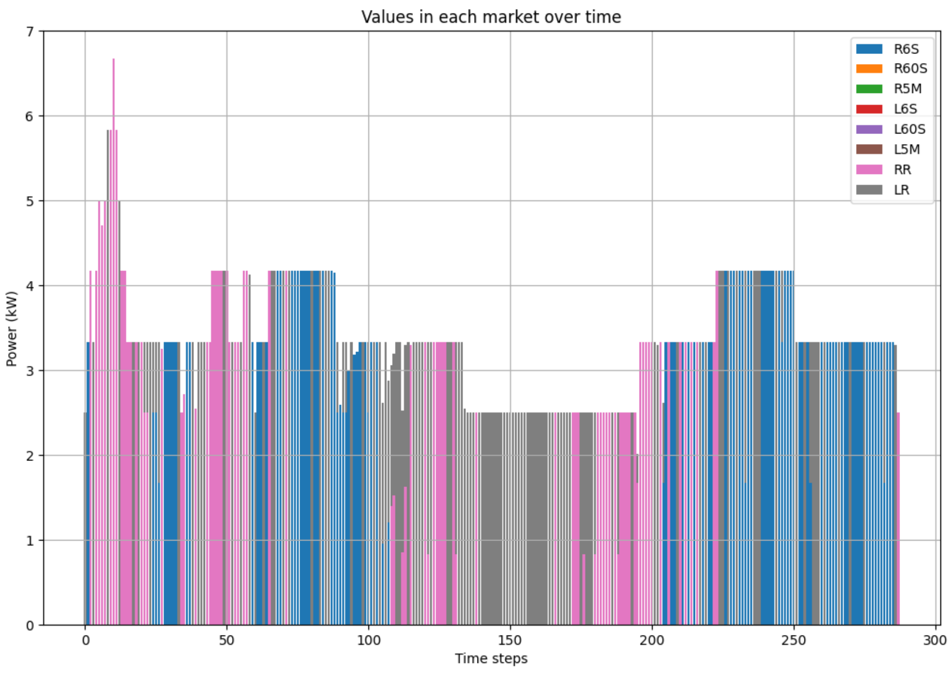


Figure 5.6: Power in each FCAS market over time with the upper-bound of 0.4.

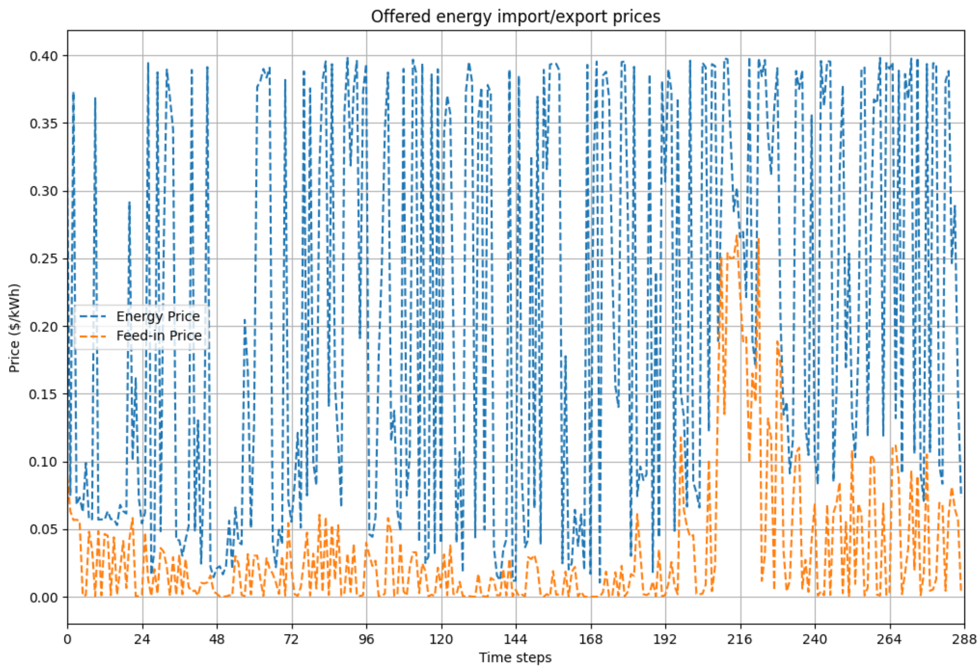


Figure 5.7: Offered energy import/export prices with the upper-bound of 0.4.

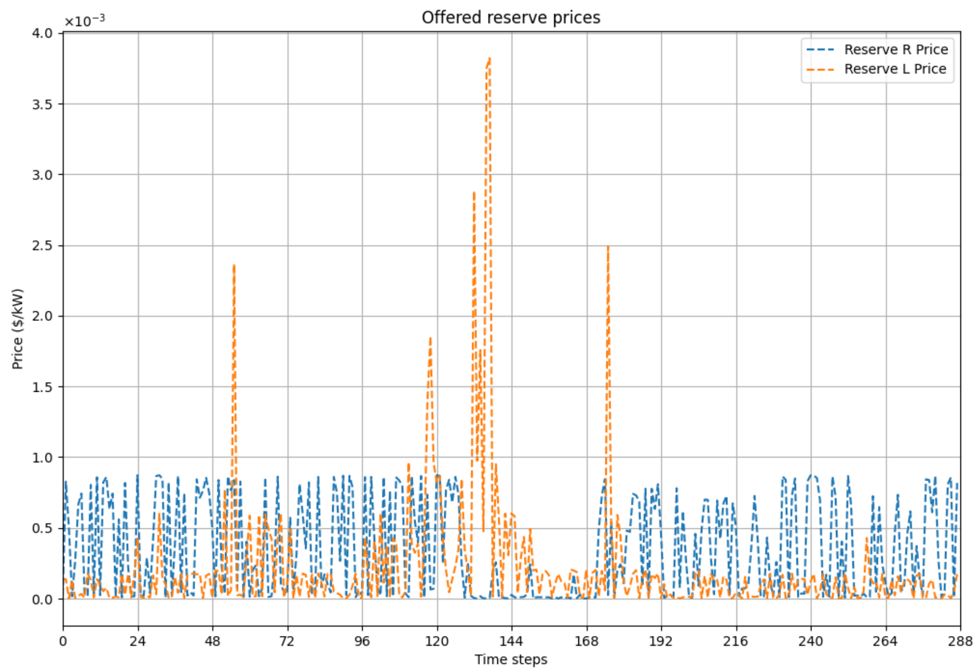


Figure 5.8: Offered reserve prices with the upper-bound of 0.4.

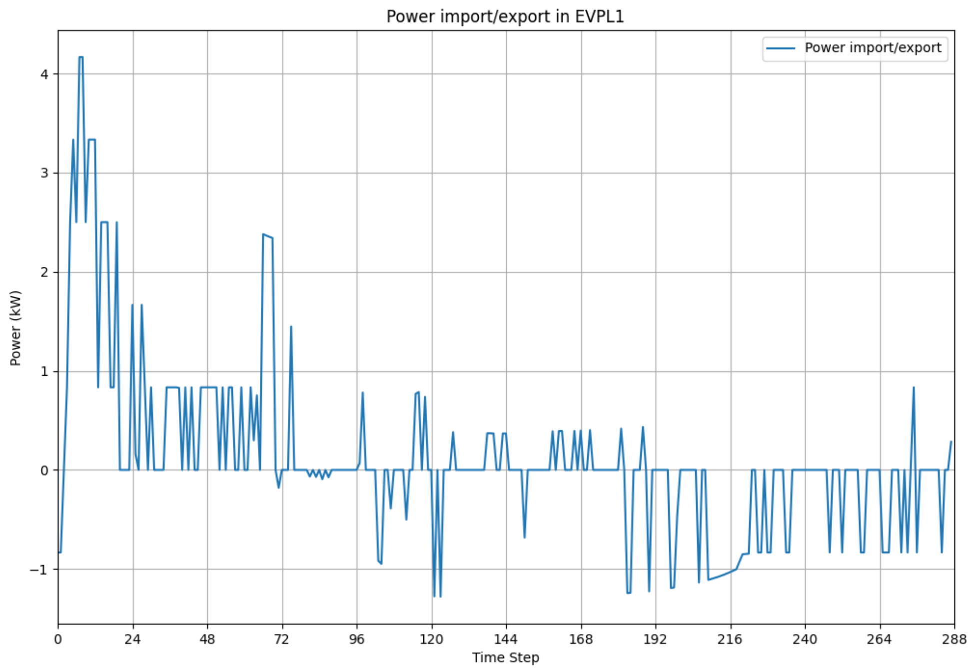


Figure 5.9: Power import/export in EVPL1 with the upper-bound of 0.4.

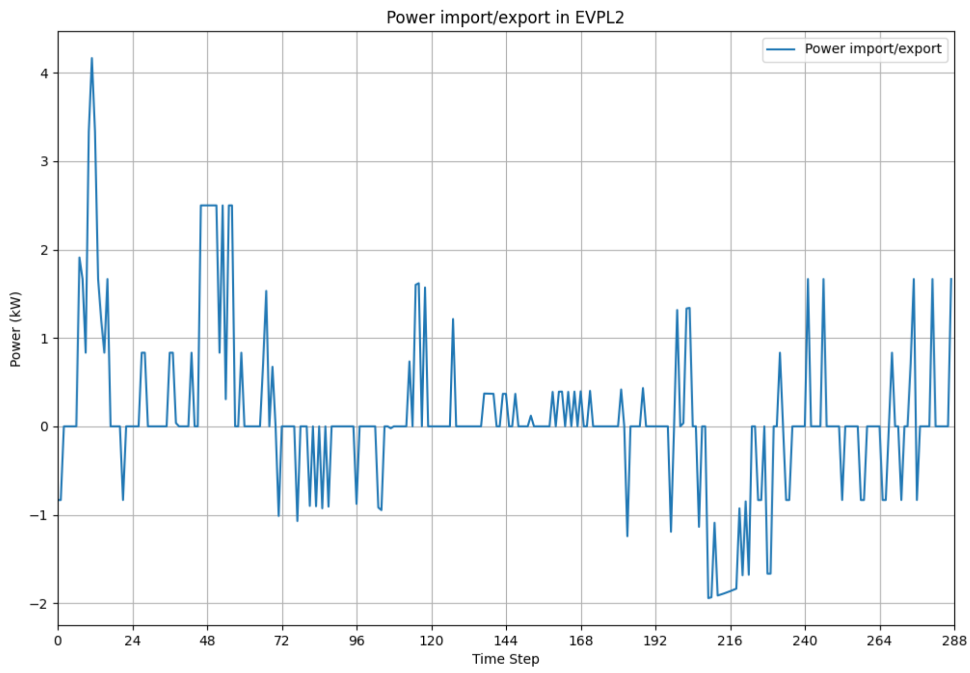


Figure 5.10: Power import/export in EVPL2 with the upper-bound of 0.4.

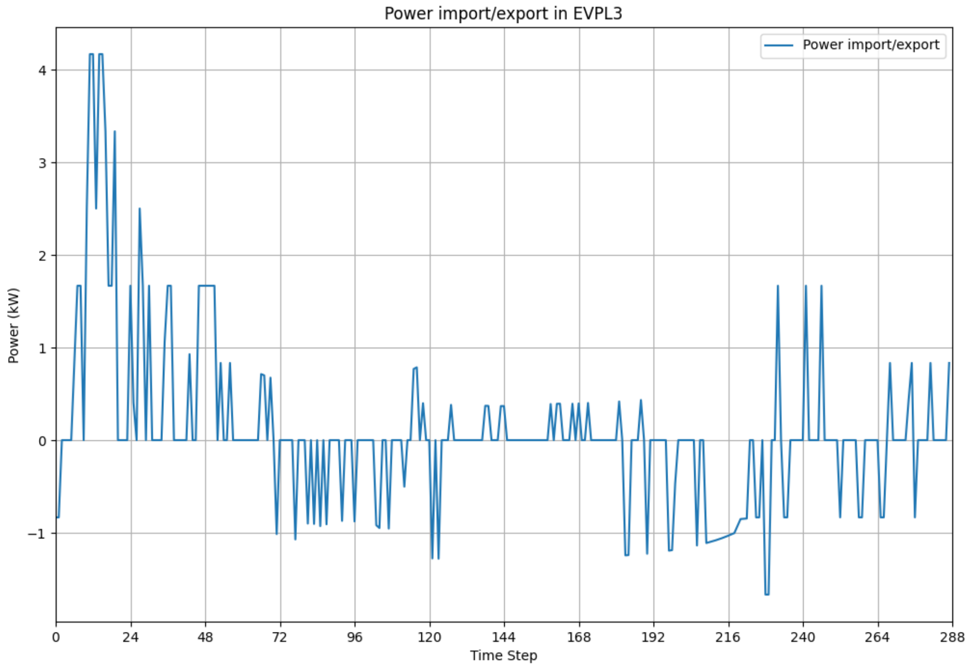


Figure 5.11: Power import/export in EVPL3 with the upper-bound of 0.4.

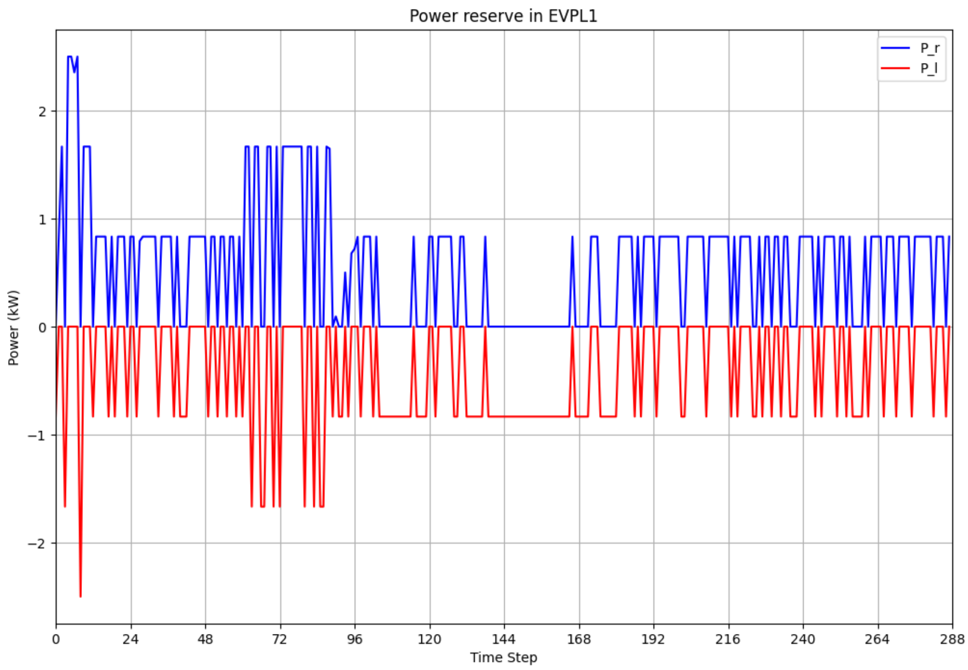


Figure 5.12: Power reserve in EVPL1 with the upper-bound of 0.4.

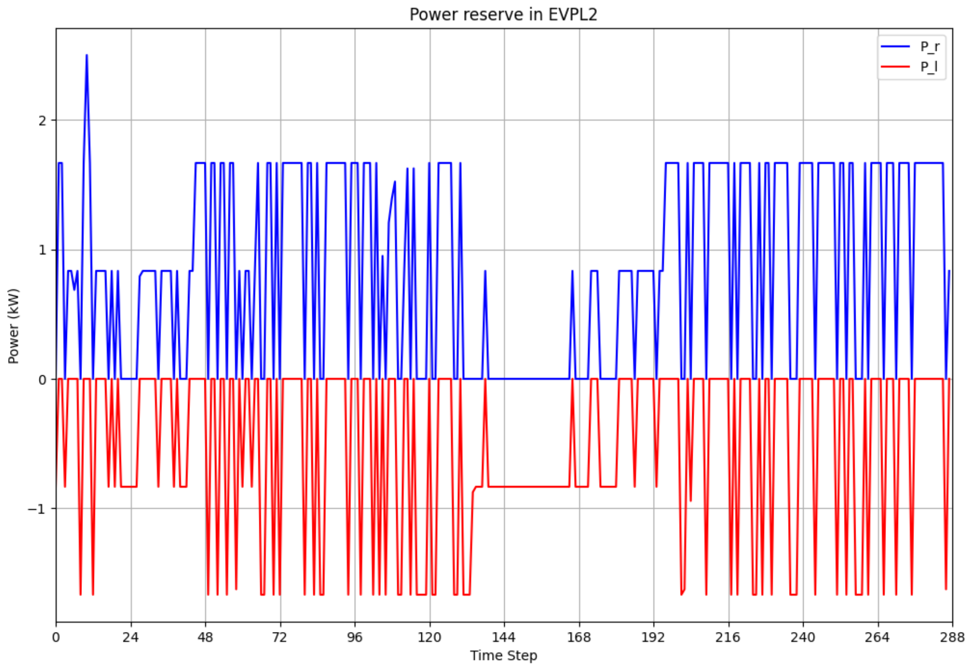


Figure 5.13: Power reserve in EVPL2 with the upper-bound of 0.4.

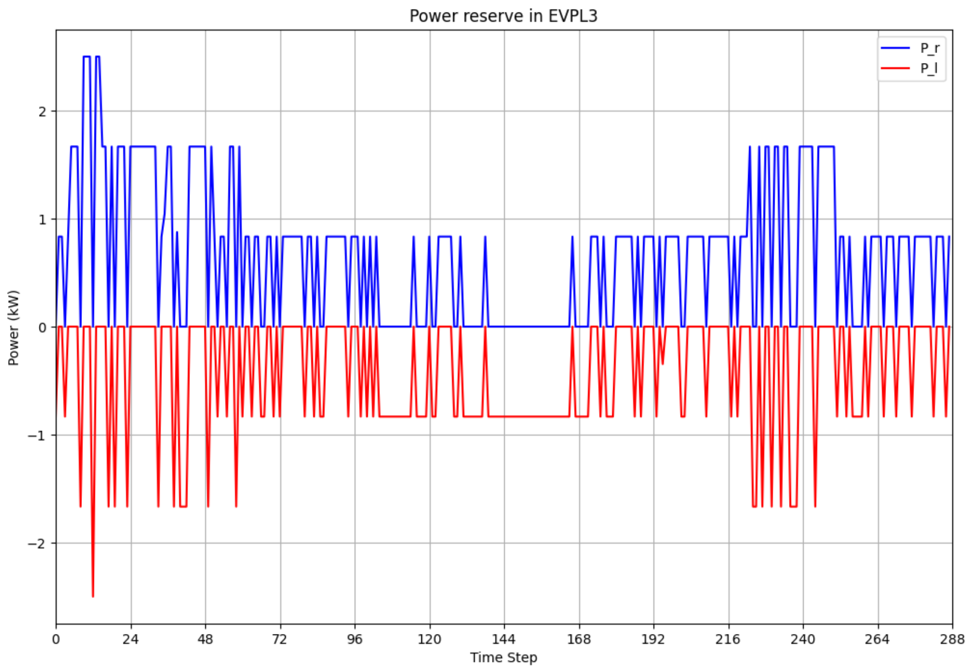


Figure 5.14: Power reserve in EVPL3 with the upper-bound of 0.4.

as depicted in Fig. 5.15, shows a more minor overall change compared to previous sessions. Following 13000 training steps, although the strategy continues to explore and optimize rewards, a relatively convergent result has begun to emerge. Despite the profit of VPP dropping by half, the total profit only shows a slight decline, as the profits of lower-level EVPLs increase, as demonstrated in Table 5.3. Besides, Figs. 5.16 - 5.24 highlights the pattern of profitability among EVPLs, which experience the most intense power exchange fluctuations. With the further decrease in offered energy price, lower-level participants gain more operational flexibility. This increased frequency of charging and discharging enhances EVPLs' profits due to low operational costs. However, even though the profits of EVPLs have increased, they have not offset the significant decline in VPP's profit.

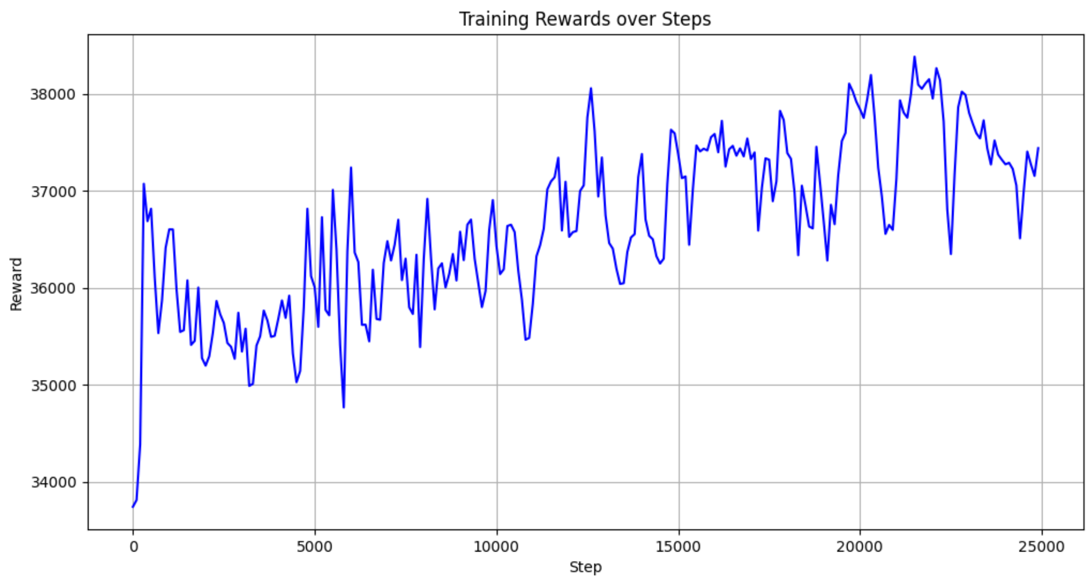


Figure 5.15: Upper-bound 0.1 training process.

Table 5.3: Profit of \$ 0.1 upper-bound setting.

	Original bounds	Upper-bound \$ 0.1
EVPL1	\$42.72	\$47.07
EVPL2	\$37.32	\$42.45
EVPL3	\$36.02	\$40.88
VPP	\$42.19	\$20.28
Total	\$158.25	\$150.70

According to the results from various upper-bound settings, the profits of lower-level models

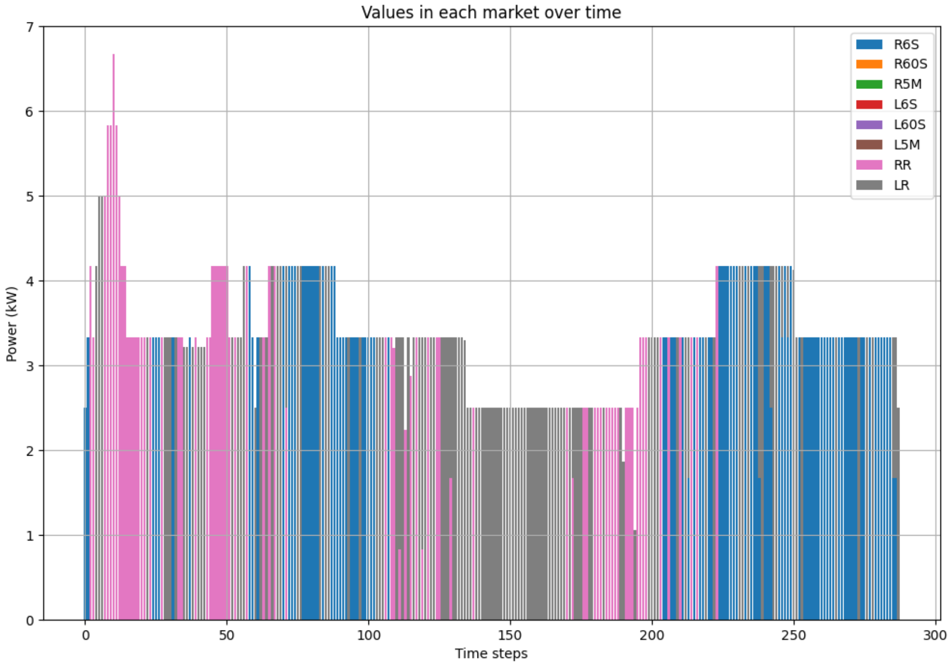


Figure 5.16: Power in each FCAS market over time with the upper-bound of 0.1.

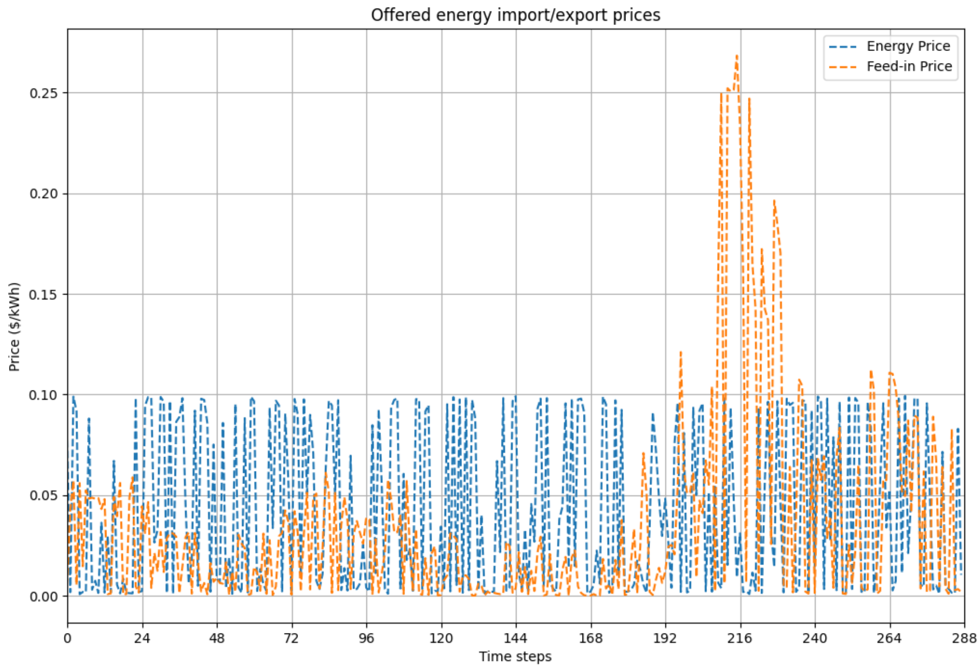


Figure 5.17: Offered energy import/export prices with the upper-bound of 0.1.

Figure 5.18: Offered reserve prices with the upper-bound of 0.1.

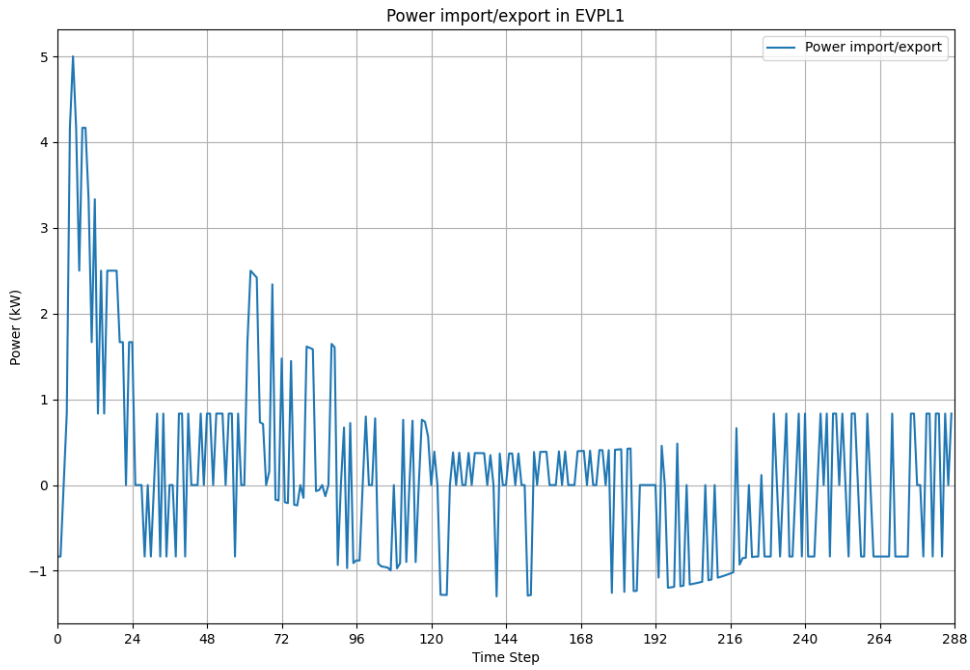


Figure 5.19: Power import/export in EVPL1 with the upper-bound of 0.1.

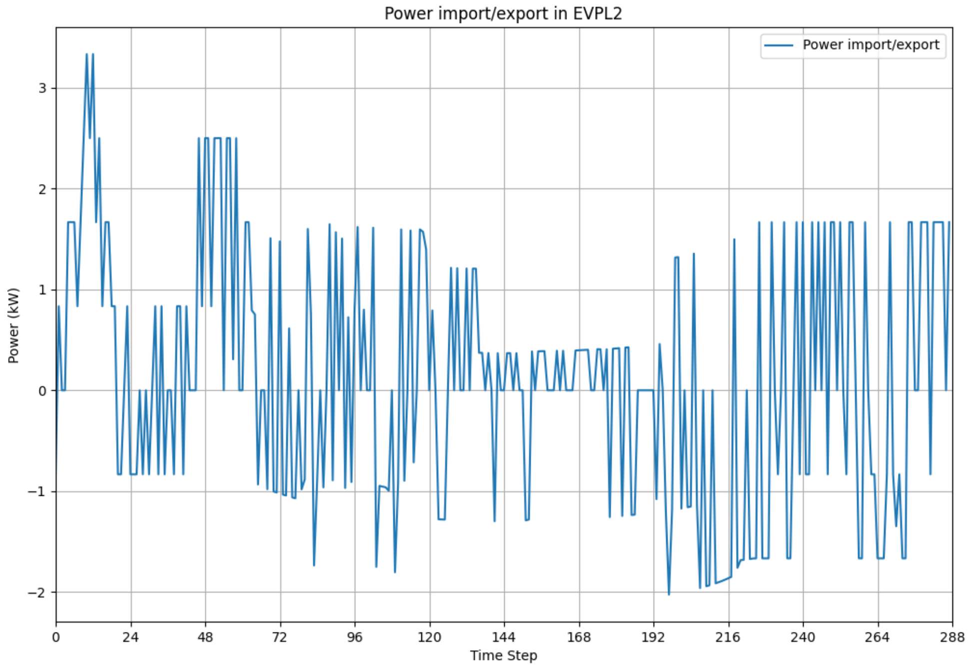


Figure 5.20: Power import/export in EVPL2 with the upper-bound of 0.1.

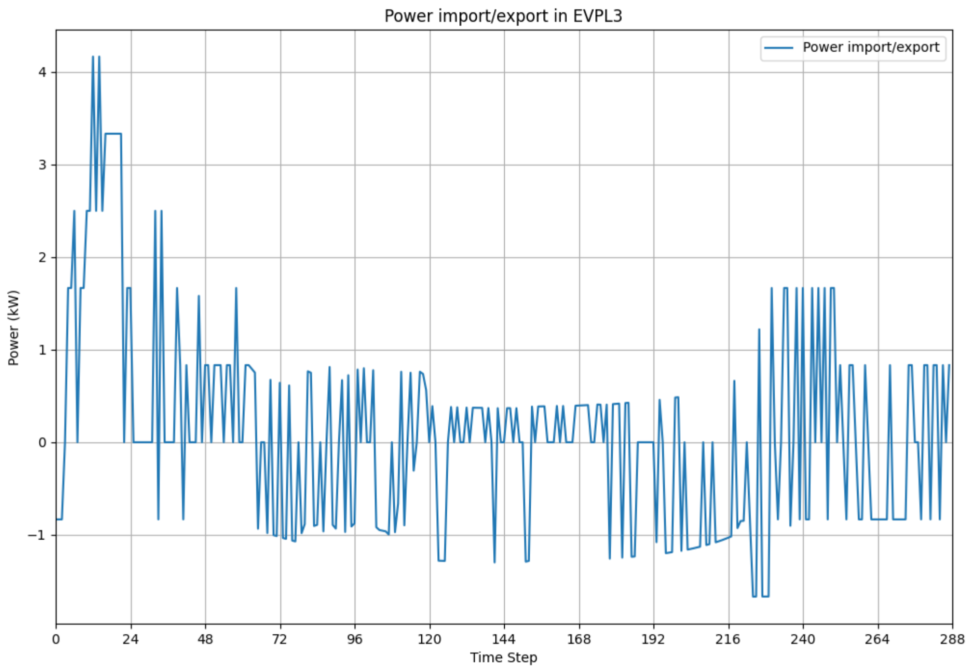


Figure 5.21: Power import/export in EVPL3 with the upper-bound of 0.1.

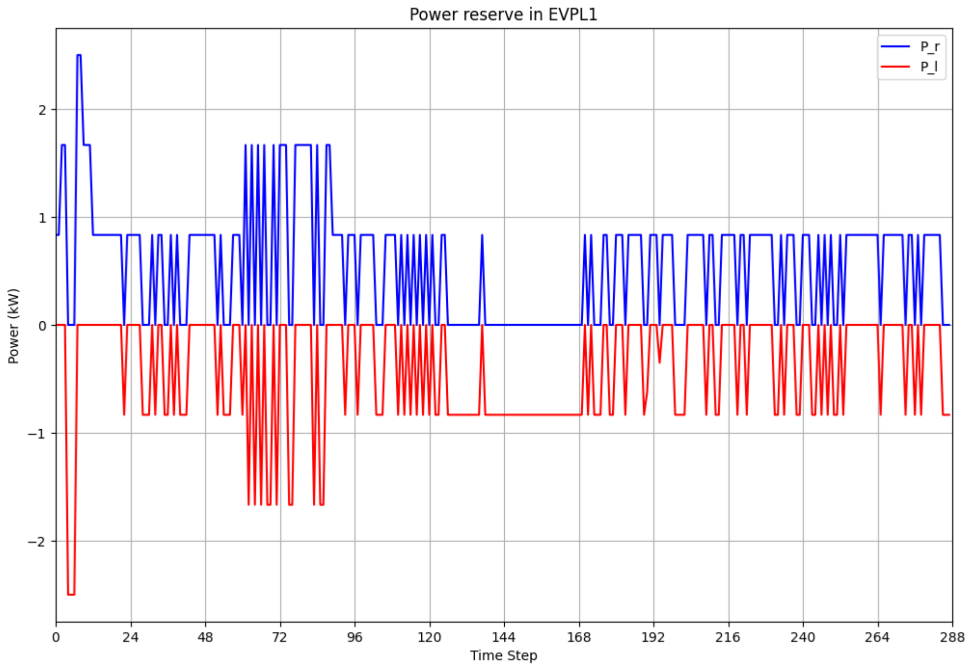


Figure 5.22: Power reserve in EVPL1 with the upper-bound of 0.1.

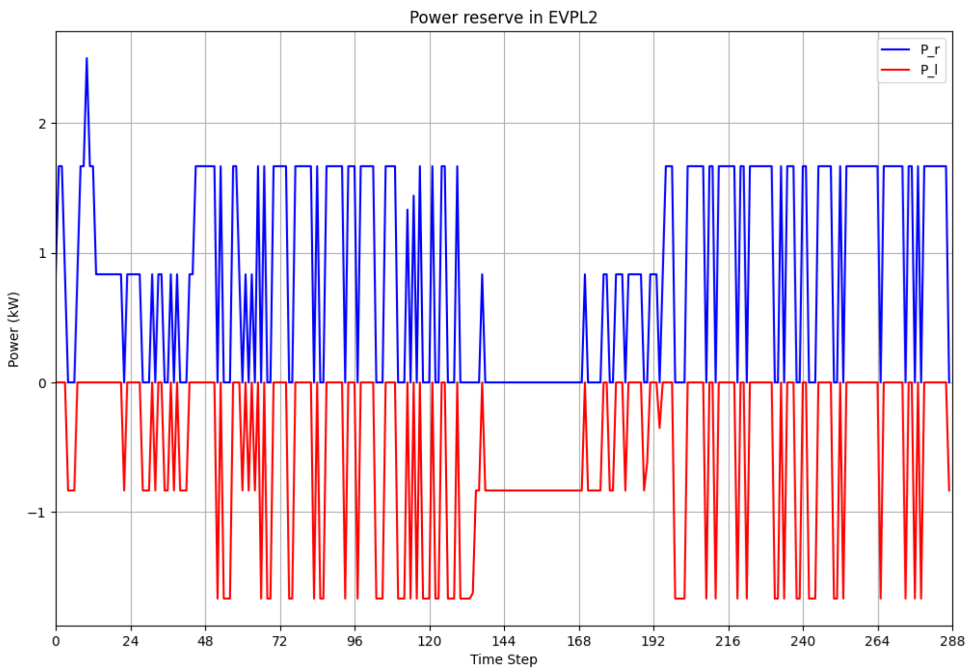


Figure 5.23: Power reserve in EVPL2 with the upper-bound of 0.1.

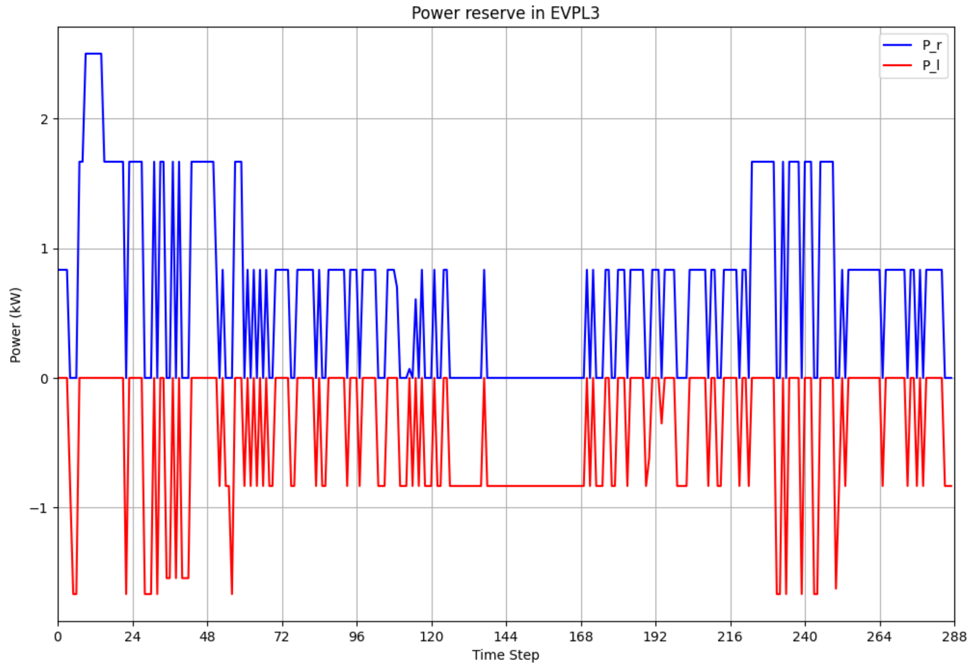


Figure 5.24: Power reserve in EVPL3 with the upper-bound of 0.1.

exhibit only minor variations and generally remain stable. This observation leads to a new setting: rather than adjusting the upper-bound of the offered energy price, different lower-bound settings will be used to restrict the optimization range and further investigate the consequences of different pricing strategy settings, which will be shown next.

Lower-bound setting exploration

a) With lower-bound of $ 0.4

In this case, the lower-bound of the energy offer price is set at $ 0.4, mirroring the upper-bound setting to halve the range. The VPP pricing strategy training process is illustrated in Fig. 5.25, demonstrating stable convergence after a brief exploratory period at approximately 5000 training steps. Unlike the upper-bound scenarios, the price response here is more obvious. Although the overall system profit remains relatively stable, the profit for VPP is considerably higher than in previous scenarios, as indicated in Table 5.4. Consequently, a predictable profit decrease is observed in EVPLs. As shown in Figs. 5.26 - 5.34, fluctuations in power import and export are smaller. Despite the limited pricing range in both cases, setting a higher lower-bound forces the optimization of lower-level models to select relatively higher prices, thereby reducing charging costs and maximizing income. To build on these findings, the next step will involve further narrowing the lower-bound to explore variations in profit.

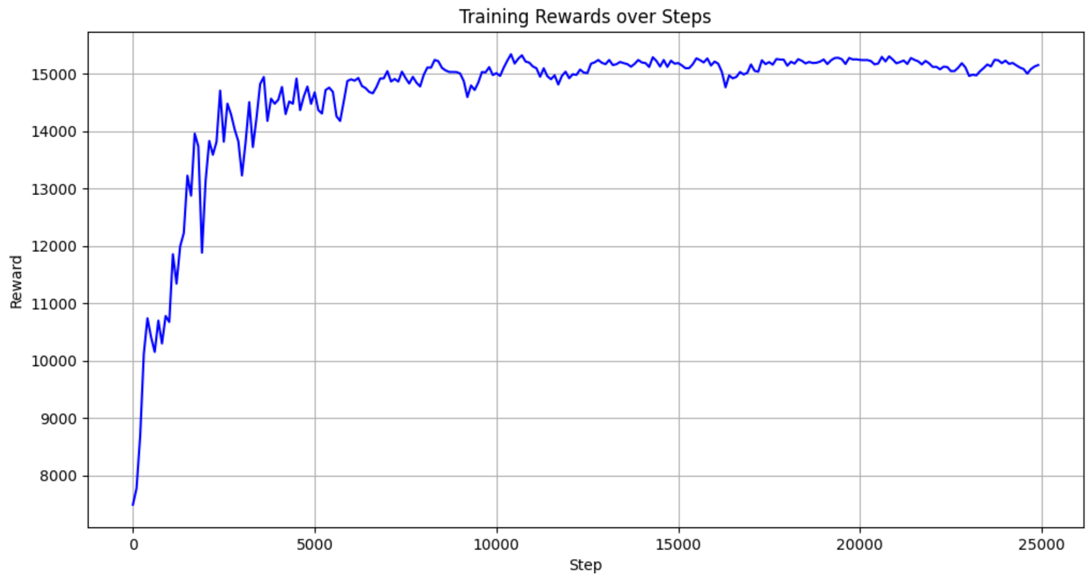


Figure 5.25: Lower-bound 0.4 training process.

Table 5.4: Profit of \$ 0.4 lower-bound setting.

	Original bounds	Lower-bound \$ 0.4
EVPL1	\$42.72	\$17.09
EVPL2	\$37.32	\$19.56
EVPL3	\$36.02	\$16.02
VPP	\$42.19	\$98.71
Total	\$158.25	\$151.40

b) With lower-bound of \$ 0.7

After applying the new setting, the pricing strategy training process converged rapidly at around 2500 training steps and then maintained a smooth and consistent level, as shown in Fig. 5.35. According to the previous cases, decreasing the lower-bound of the energy price typically reduces the profits of lower-level models by narrowing their optimization range due to the relatively higher price options. However, contrary to expectations, the profit of the

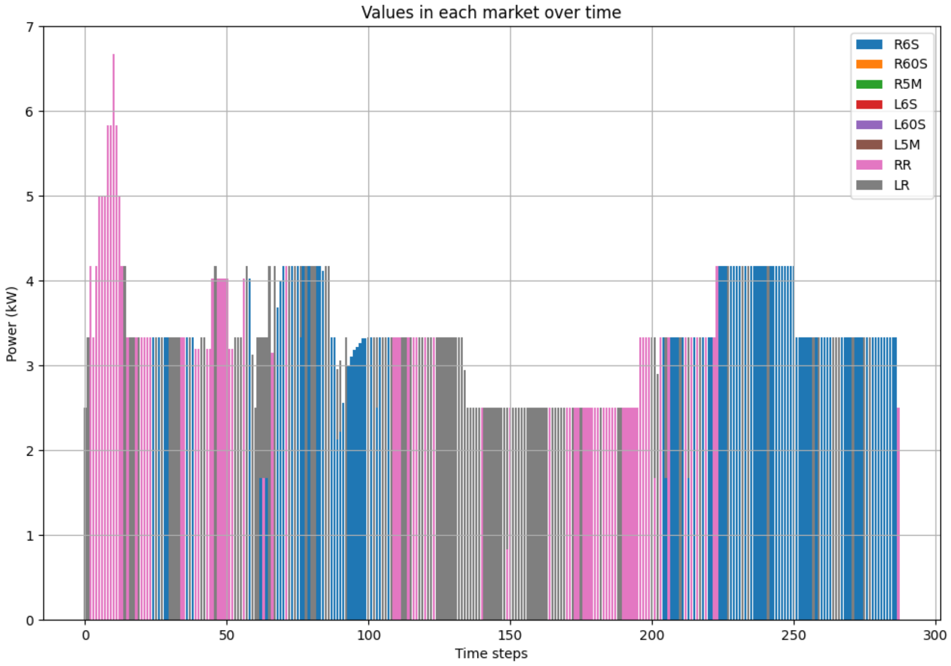


Figure 5.26: Power in each FCAS market over time with the lower-bound of 0.4.

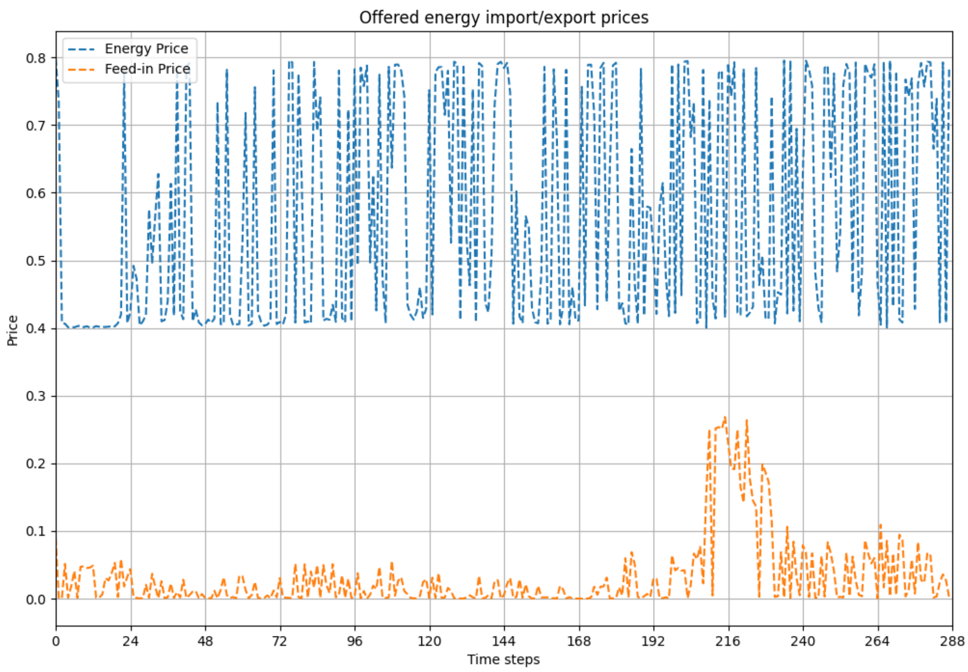


Figure 5.27: Offered energy import/export prices with the lower-bound of 0.4.

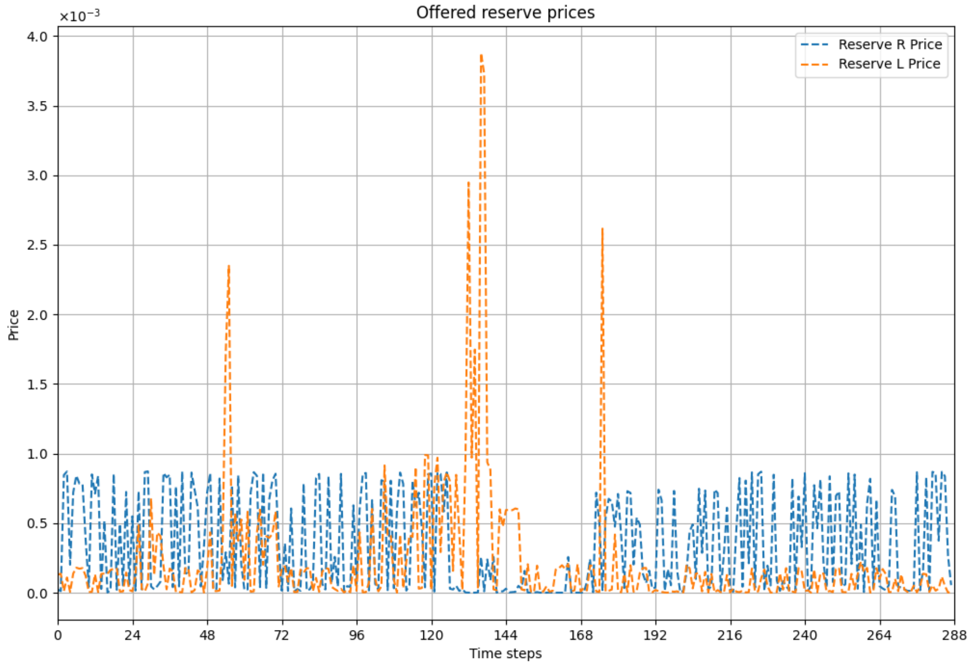


Figure 5.28: Offered reserve prices with the lower-bound of 0.4.

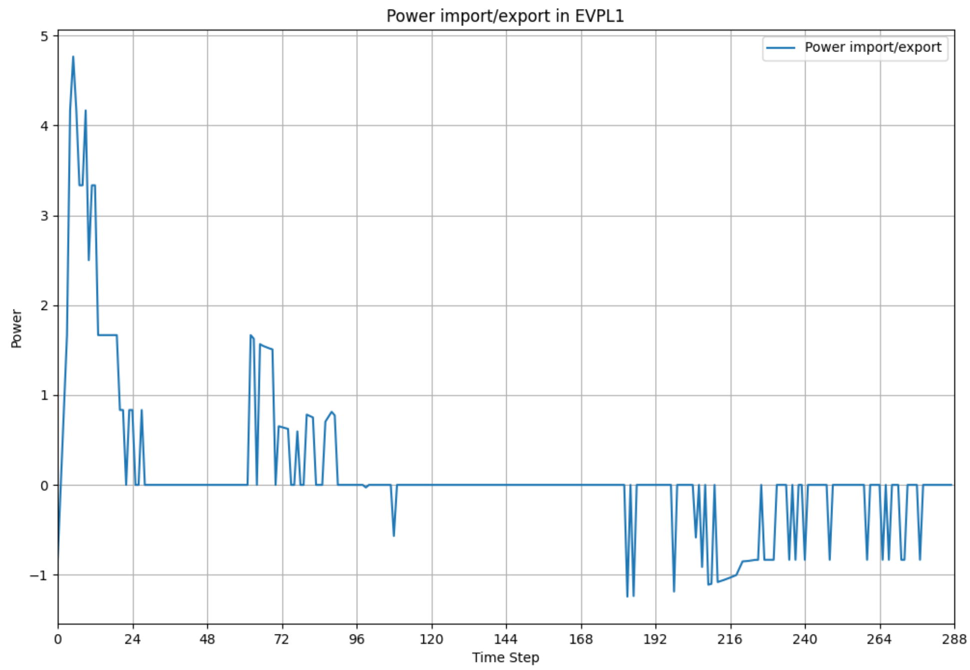


Figure 5.29: Power import/export in EVPL1 with the lower-bound of 0.4.

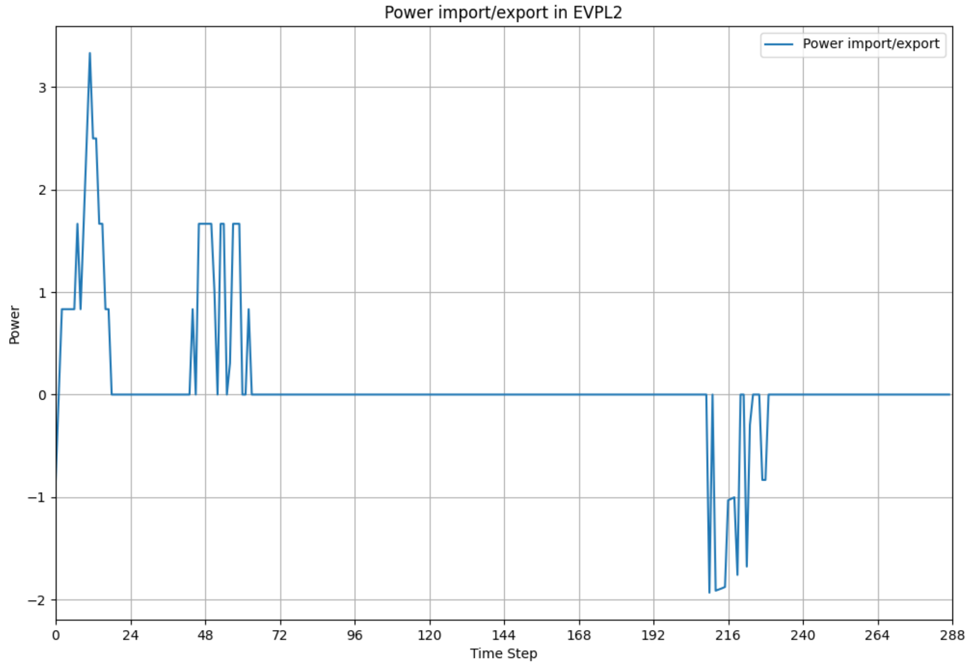


Figure 5.30: Power import/export in EVPL2 with the lower-bound of 0.4.

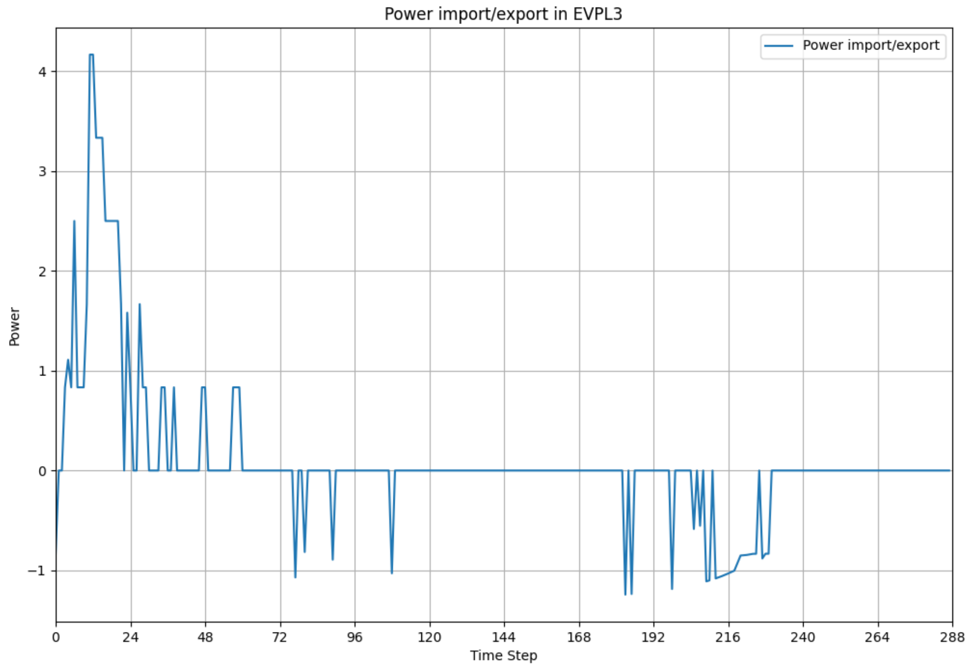


Figure 5.31: Power import/export in EVPL3 with the lower-bound of 0.4.

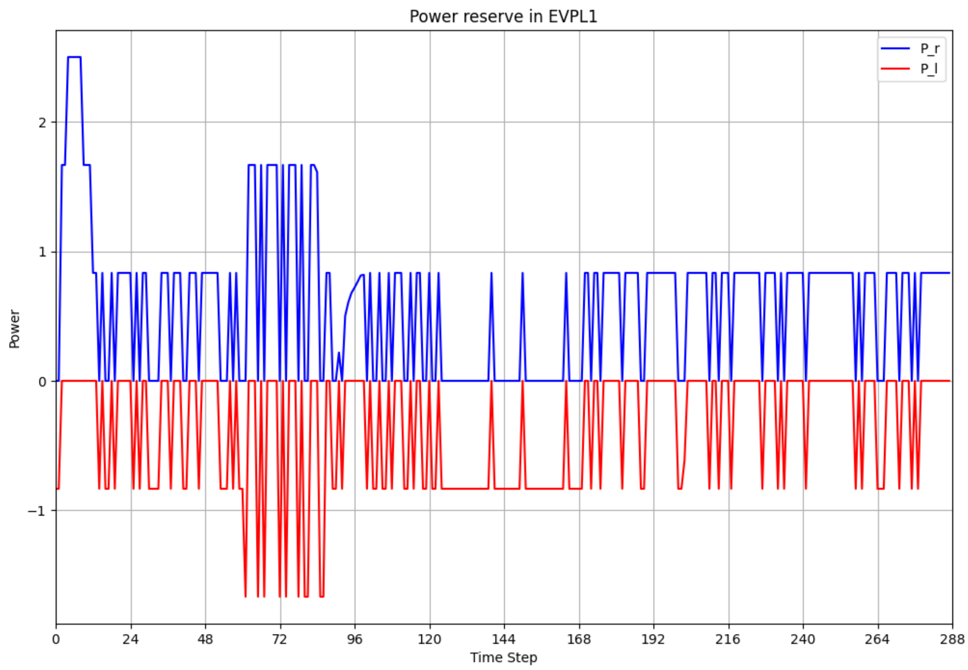


Figure 5.32: Power reserve in EVPL1 with the lower-bound of 0.4.

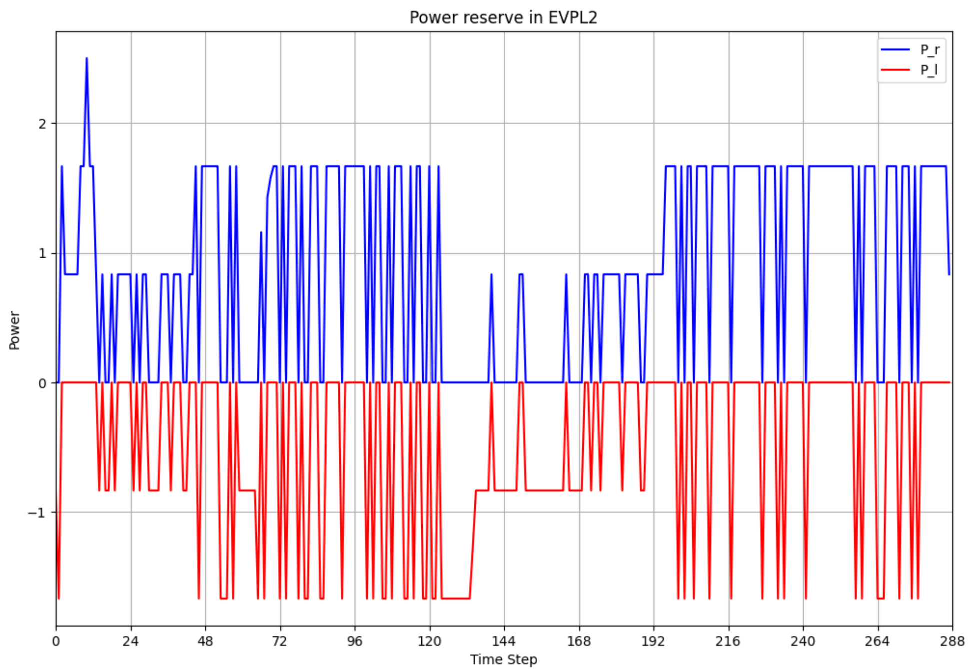


Figure 5.33: Power reserve in EVPL2 with the lower-bound of 0.4.

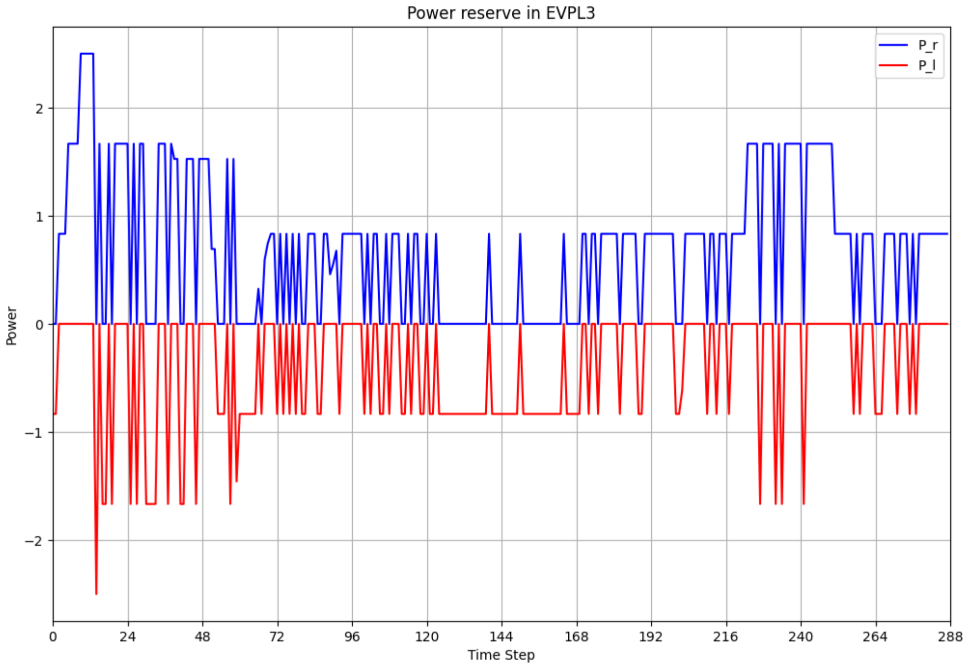


Figure 5.34: Power reserve in EVPL3 with the lower-bound of 0.4.

VPP did not increase. Specifically, Figs. 5.36 - 5.44 illustrates minimal fluctuations in power import and export. Due to the high energy purchase prices offered by VPP, the profits of some EVPLs become very small, or even negative. This is because they are required to charge the connected EVs to the maximum allowed SoC upon departure. Additionally, reduced power exports from the EVPLs often result in lower power demand, as they must recharge the EVs at a significantly higher energy purchase price after feed-in. Consequently, a decrease in power exchange is expected. Table 5.5 shows a very sharp decline in total system profit, presenting the worst case across all settings, with a profit of just \$ 44.95. This outcome contrasts sharply with previous adjustments, which increased VPP's income; in this setting, the profit of the VPP is close to the base case. While some EVPLs may achieve profitability, the profits are minimal or even negligible compared to other scenarios. In general, increasing the lower-bound of the offering energy price will trigger more noticeable variations in profit values within the bi-level system and is a beneficial strategy for the upper-level model to increase its profits. However, excessive adjustment will not only fail to make the upper level more profitable but will also significantly decrease the profits of lower-level models, leading to an unhealthy system pricing configuration.

In all the cases discussed above, the capabilities of the lower-level model are constrained by the number of EVs and the ESS capacity of the EVPLs. Consequently, the power fluctuations involved in the reserve market are relatively uniform, leading to consistent participation by the upper-level model in the FCAS market. Notably, to maximize profits, activities in all eight FCAS markets are concentrated primarily on the contingency raise 6-second market and both the raise and lower regulation markets.

Figure 5.35: Lower-bound 0.7 training process.

Table 5.5: Profit of $ 0.7 lower-bound setting.

	Original bounds	Lower-bound $ 0.7
EVPL1	$42.72	$-3.06
EVPL2	$37.32	$6.67
EVPL3	$36.02	$0.46
VPP	$42.19	$40.87
Total	$158.25	$44.95

5.4 Summary

In this chapter, we introduced a hybrid multi-agent bi-level optimization system that integrates a DRL-based upper-level VPP model and a lower-level EVPL model within the MILP frame-

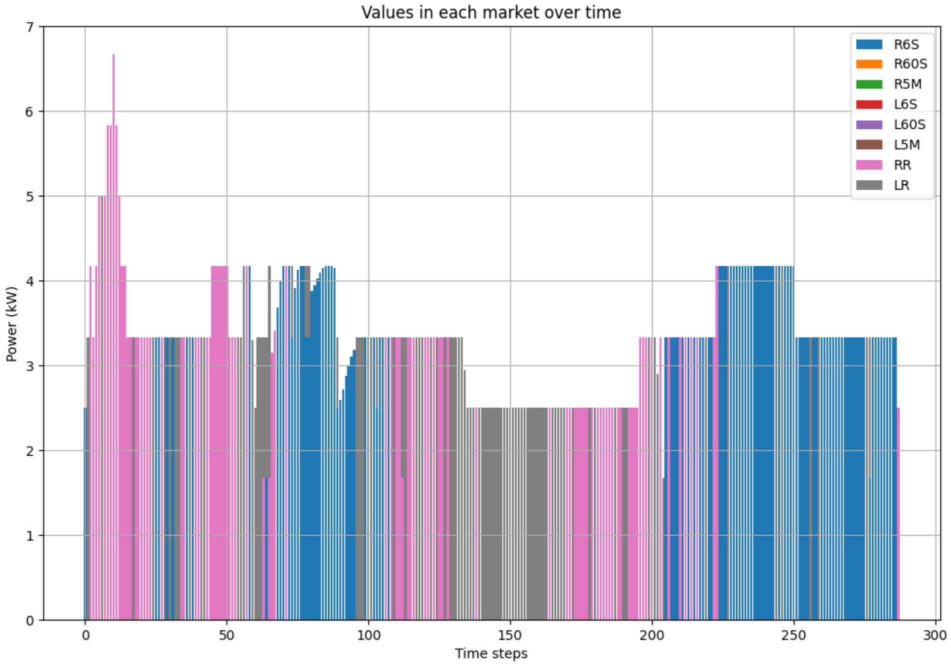


Figure 5.36: Power in each FCAS market over time with the lower-bound of 0.7.

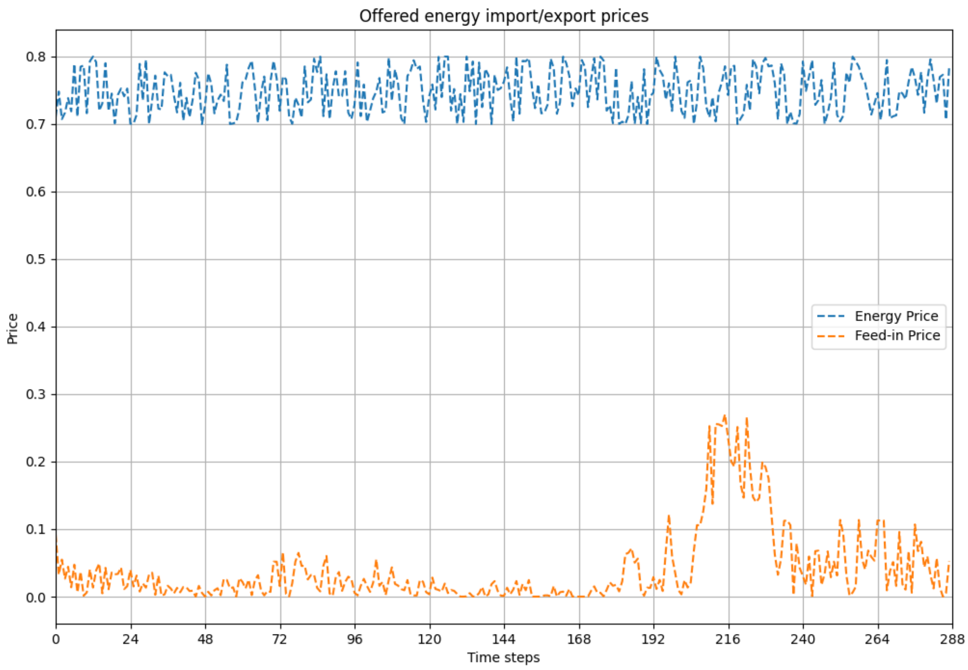


Figure 5.37: Offered energy import/export prices with the lower-bound of 0.7.

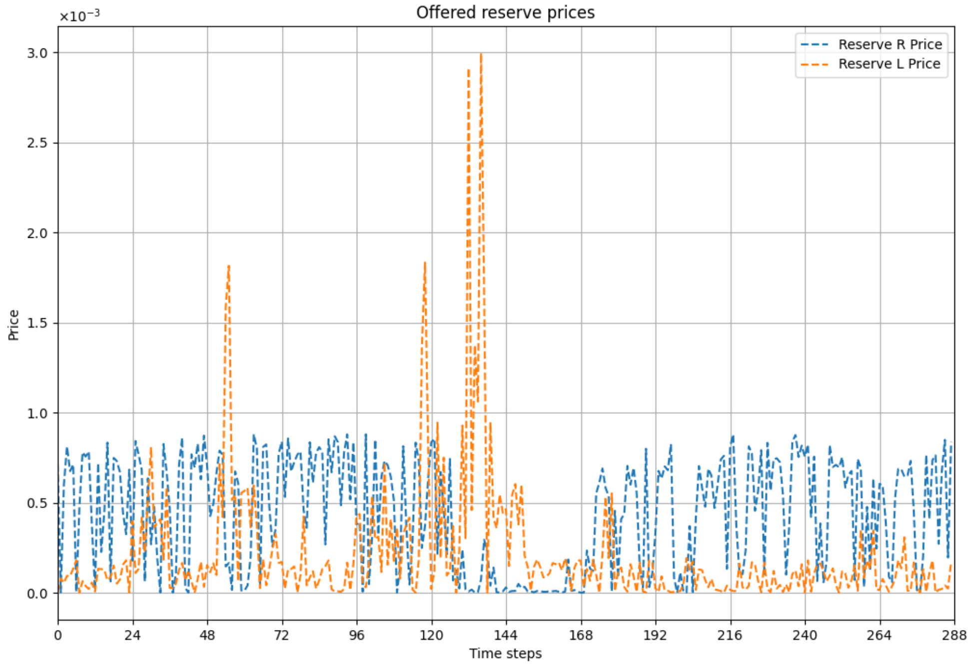


Figure 5.38: Offered reserve prices with the lower-bound of 0.7.

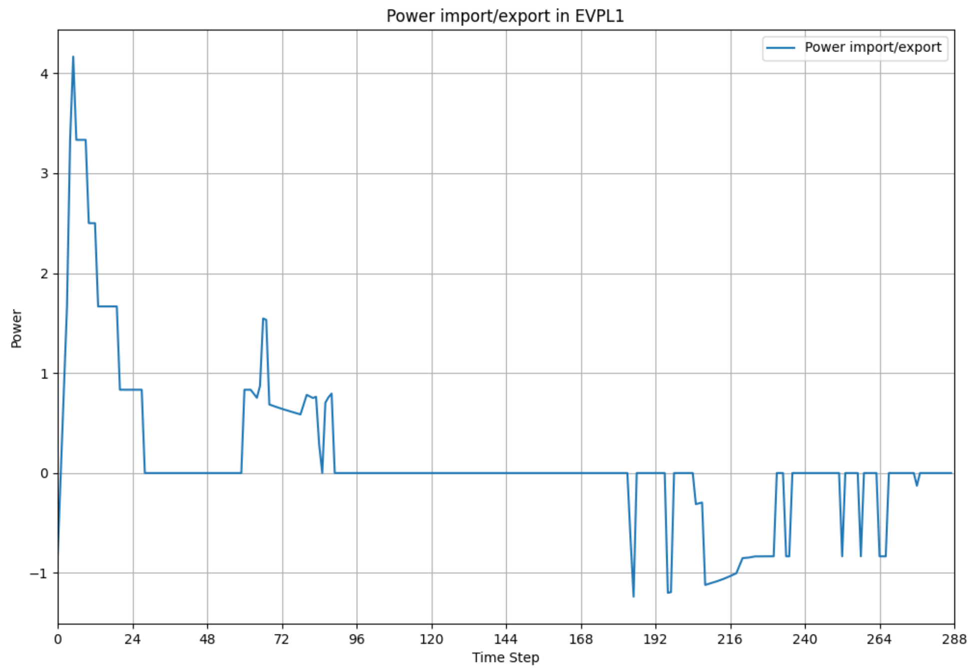


Figure 5.39: Power import/export in EVPL1 with the lower-bound of 0.7.

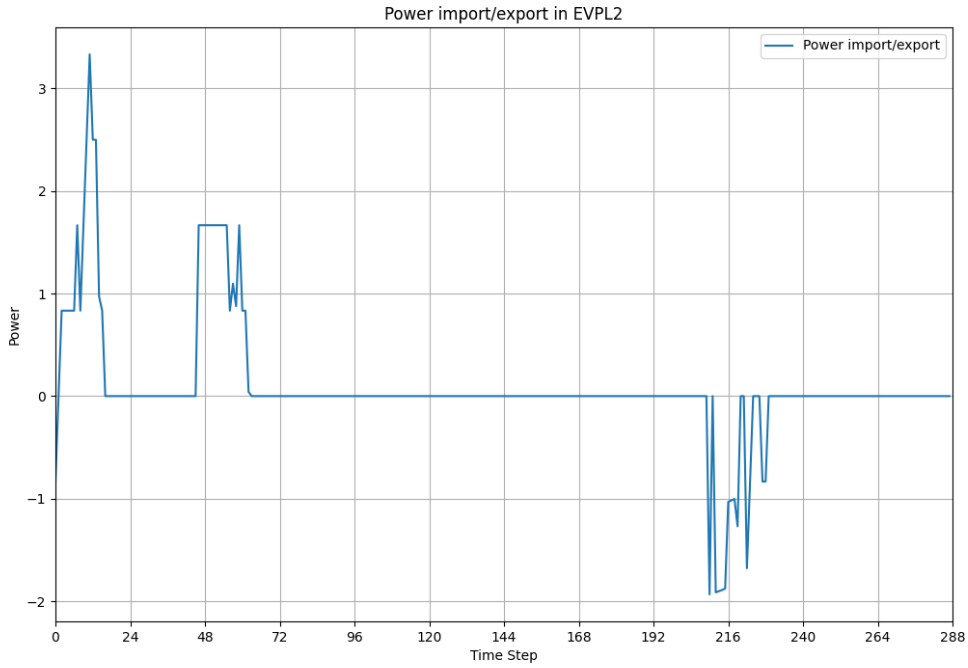


Figure 5.40: Power import/export in EVPL2 with the lower-bound of 0.7.

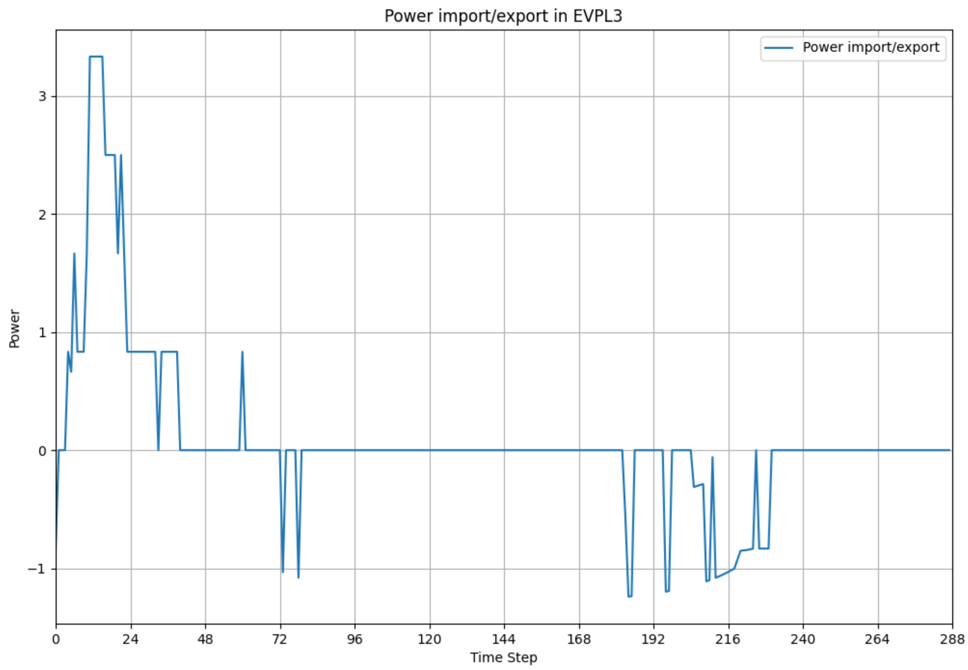


Figure 5.41: Power import/export in EVPL3 with the lower-bound of 0.7.

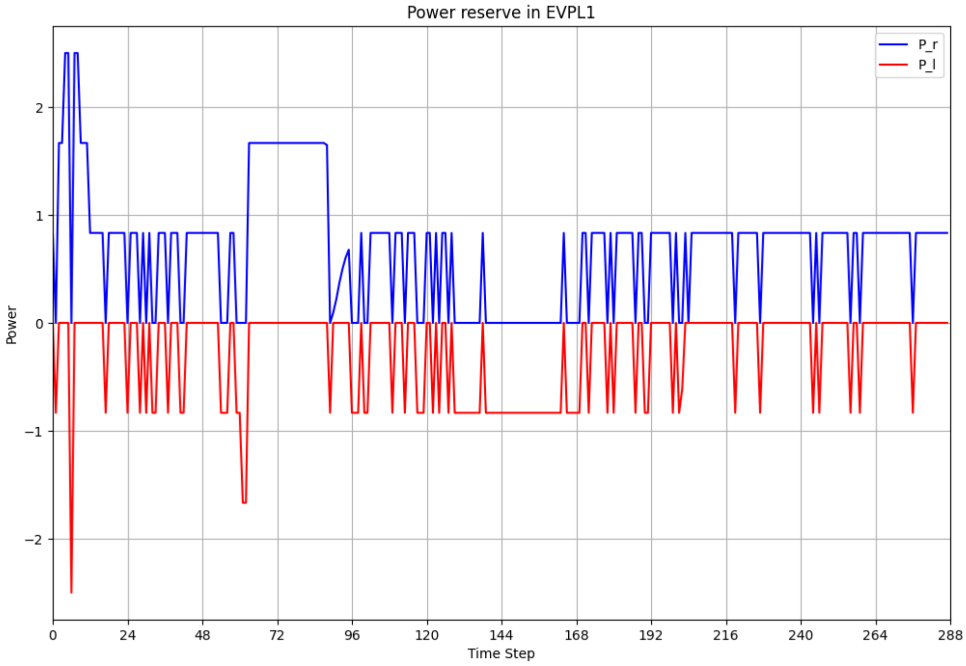


Figure 5.42: Power reserve in EVPL1 with the lower-bound of 0.7.

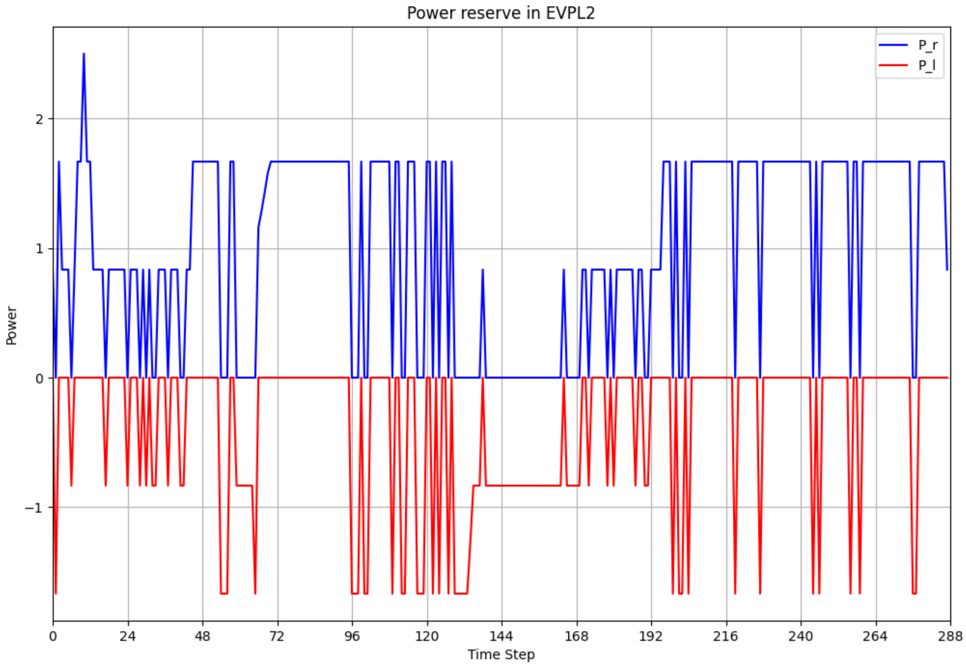


Figure 5.43: Power reserve in EVPL2 with the lower-bound of 0.7.

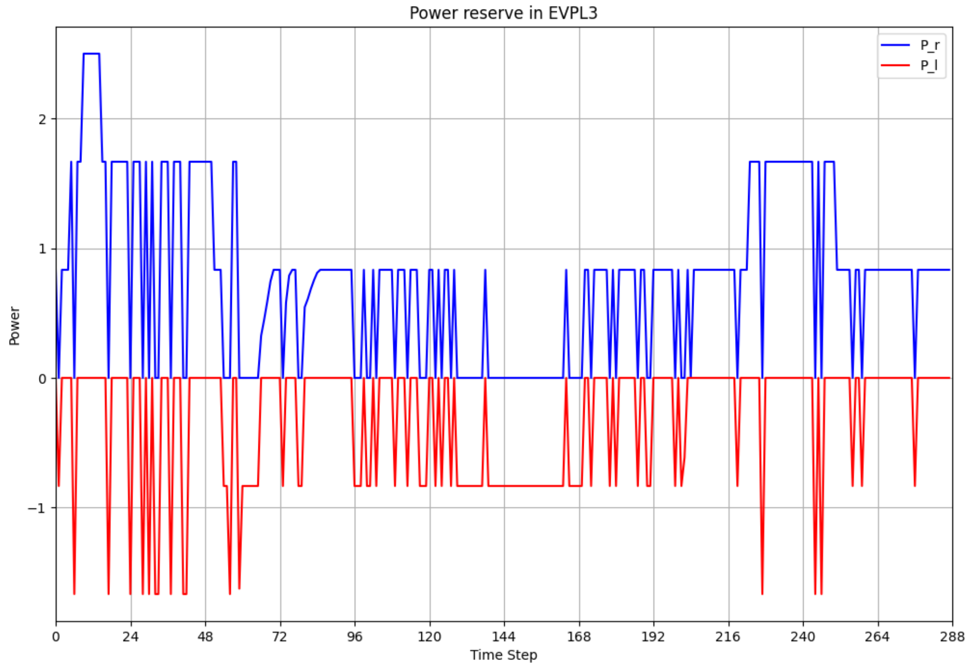


Figure 5.44: Power reserve in EVPL3 with the lower-bound of 0.7.

work. The VPP employs the SAC algorithm to set prices under multiple market conditions, including spot and the 8 FCAS markets. The comprehensive MILP frame enables the lower-level EVPL agents to maximize their profits based on the prices provided and to offer feedback to the upper-level VPP to enhance strategic training. EV behaviour, including SoC, arrival time, and departure time, is modelled through the first use of normalizing flows.

Furthermore, after comparing the results between the proposed method and an iterative method used to establish the base case, various settings were applied to analyze the pricing strategy. With the continuous decrease in the upper-bound, the profits at the lower-level show only a slight increase, and the total profit of the bi-level system remains stable with minor changes, even though the profit of VPP drops by half in the 0.1 upper-bound setting. In contrast, when the lower-bound setting is increased, the VPP records the highest profit among all cases at the \$ 0.4 setting. However, the system's profits collapse when the setting reaches \$ 0.7, with the worst total of \$ 44.95 compared to \$ 158.25 in the base case. Much like the two sides of a coin, setting the upper-bound of the offered energy price is more likely to achieve a win-win situation. To increase the profits of the upper-level model, adjusting the lower-bound of the price is one option. However, excessive adjustment may cause the entire system to collapse, leaving no party beneficial.

Moreover, throughout the cases analyzed, the performance of the lower-level models in responding to the offered reserve prices is consistently influenced by the number of EVs and the ESS capacity within the EVPLs. This limitation leads to uniform power fluctuations in all cases, which in turn makes the activity remain consistent with the upper-level model in the FCAS market. To optimize profit generation, strategic focus across all eight FCAS markets is predominantly directed towards the contingency raise 6-second market, as well as the raise and lower regulation markets.

Chapter 6

Conclusion and Recommendation for Future Research Work

6.1 Conclusion

This study explores the economic operation strategies and optimization of EV parking lots integrated with RES, ESS, and V2G technology. Across three stages, we have developed and analyzed models to maximize the profitability and efficiency of EV parking lots under varying conditions and market scenarios.

In Chapter 3, a comprehensive economic operation strategy for an EV parking lot equipped with EV charging stations, PV systems, WT, and ESS was developed. The model accounted for uncertainties in electricity market prices, solar radiation, and wind speed. Scenarios were generated using MATLAB's scenred toolbox, classifying EVs into V2G and non-V2G groups based on parking duration. Dynamic charging prices were implemented for non-V2G EVs, while V2G-participating EVs benefited from lower charging rates and incentives. The model demonstrated superior profitability compared to models with fixed charging rates or without V2G services, particularly in scenarios with short-term parking EVs benefiting from dynamic pricing and long-term parking EVs from V2G incentives. Future research will focus on the impact of V2G on EV behavior and market conditions.

Chapter 4 introduced an EV parking lot model incorporating RES and participating in both the FCAS and spot markets. Forecasts of market prices, solar irradiance, and wind speed were generated using LSTM within MATLAB's deep learning toolbox. Monte Carlo methods simulated EV behaviours, and an IGDT-based method optimized V2G incentives. Comparing two cases, the study found that engaging in both FCAS and spot markets (Case 1) consistently yielded higher profits, especially under optimized V2G incentives. Case 2, limited to the spot market, showed diminished V2G activity with lower incentives, highlighting the profitability of multi-market participation.

Chapter 5 presented a hybrid multi-agent bi-level optimization system integrating a DRL-based VPP model and several MILP lower-level EVPL models. The VPP used the SAC algorithm to set prices across multiple market conditions, including the spot and eight FCAS markets. The system allowed lower-level agents to maximize profits and provide feedback for upper-level strategic training. Results indicated that while adjusting upper and lower price bounds could influence profitability, extreme adjustments risked destabilizing the system. Optimal profit generation required balancing these bounds, with a significant focus on strategic markets like the contingency raise 6-second market.

Throughout the chapters, this study highlighted the importance of integrating dynamic pricing, multi-market participation, and advanced optimization techniques to enhance the profitability and efficiency of EV parking lots. The proposed models consistently demonstrated that well-designed V2G incentives and strategic market engagement could significantly boost profits. However, balancing the system's parameters is significant to avoid instability.

In addition, by applying advanced modelling, optimization, and market participation strategies, this study contributes valuable insights into the sustainable and profitable operation of EV parking lots, leading to more efficient integration of EVs and RESs into the power grid.

6.2 Recommendation for Future Research Work

Future research will delve deeper into the behavioral impact of V2G technology on EV owners and explore the scalability of the proposed models under different market conditions and practical environments. This includes understanding the implications of V2G on revenue generation, refining optimization techniques to adapt to real-time market fluctuations, and developing more sophisticated models for selecting an appropriate V2G reward coefficient, which is crucial for the successful implementation of the developed model.

Moreover, we aim to expand the scope of research to include more diverse RESs and storage technologies to enhance the resilience and profitability of EV parking systems. Addressing the issue of EV battery degradation will also be a key focus, as well as exploring alternative methods for managing uncertainties in market prices and RESs. Future studies will apply more reliable and precise techniques to manage these fluctuations effectively in EVPLs.

Additionally, we plan to investigate the bidding strategy for the FCAS market and associated penalties, examining their effects on revenue outcomes. This will involve developing a more comprehensive system configuration with an optimal bidding strategy. Determining the optimal pricing strategy range, particularly for lower-level models using comprehensive optimization algorithms, remains a significant challenge that will be tackled in subsequent research.

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