Relocation Strategies For Shared Electric Vehicles To Transport Energy And Provide Vehicle-to-Grid Services

Empowering Mobility: Innovative Approaches to Energizing the Grid with Shared Electric Vehicles

Master Thesis

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by

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Preface

This thesis addresses one of the pressing challenges of our time: the need for sustainable urban mobility while contributing to the decarbonization of the transport and energy sectors. The combination of Electric Vehicles (EVs), Vehicle-to-Grid (V2G) technology, and Car Sharing Systems (CSS) presents an opportunity to significantly reduce greenhouse gas (GHG) emissions and improve energy efficiency. The focus of this research is on optimizing vehicle relocation strategies for Electric Car Sharing Systems (ECSS) by integrating V2G technology. In this study, a mathematical model is developed and applied to case studies to optimize financial profits while addressing relocation, charging, and grid-related challenges. However, like all models, it operates within certain assumptions and limitations. By addressing these, the research aims to clarify both the strengths and the constraints of the findings presented.

The study is relevant given the growing push for the integration of renewable energy and the increasing popularity of shared mobility services. It is my hope that this research contributes to the ongoing discussion around sustainable transportation and inspires further exploration of the synergies between shared mobility, smart energy management, and grid support.

Cas Oudijk
Delft, January 2025

Summary

This research explores the potential of integrating V2G technology with ECSS to enhance Car Sharing Operator (CSO) profits while incorporating active peak reduction strategies. The study focuses on a station-based ECSS with a fleet of EVs and evaluates the operational and economic impacts of enabling V2G functionality across various case studies.

The mathematical model developed for this study aims to maximize the financial profit of a CSO managing five stations with 24 EVs. Key factors considered include driving, relocation, charging, and the discharging of EVs via V2G technology. The model explores scenarios with and without V2G, accounting for both uniform time-varying and location-dependent time-varying electricity prices. It also considers summer and winter conditions, as well as the impact of peak-reducing measures.

The results demonstrate that V2G technology boosts overall profit by allowing energy to be sold back to the grid during periods of low driving demand and high electricity prices, particularly when electricity prices vary across different stations. Additionally, peak-reducing measures effectively reduce peak load demand without substantially compromising overall profit. However, the integration of V2G increases the complexity of vehicle relocation, which can lead to higher relocation costs. This highlights the importance of developing optimized vehicle management strategies to balance the trade-offs between V2G implementation and operational efficiency.

The findings have significant implications for the design of Electric Vehicle Sharing Systems (EVSS) and related policies, particularly in the context of dynamic electricity pricing and incentives for grid participation. Additionally, the study highlights key limitations, such as the simplification of real-world factors, and provides recommendations for future research aimed at refining the model using real-world data and advanced vehicle relocation algorithms.

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Abbreviations

Abbreviation	Definition
EV	Electric Vehicle
V2G	Vehicle-to-Grid
CSS	Car Sharing System
GHG	Greenhouse Gas
ECSS	Electric Car Sharing System
CSO	Car Sharing Operator
EVSS	Electric Vehicle Sharing System
ICE	Internal Combustion Engine
ICV	Internal Combustion Vehicle
SCA	Smart Charging Algorithm
EVReP	Electric Vehicle Relocation Problem
DECRP	Dynamic Electric Car Relocation Problem
MILP	Mixed-Integer Linear Programming
VSS	Vehicle Sharing System
SOC	State of Charge
DES	Distributed Energy Storage
G2V	Grid-to-Vehicle
CC	Constant Current
CV	Constant Voltage
MIP	Mixed-Integer Programming
PV	Photovoltaic
MPC	Model Predictive Control

1

Introduction

Reducing GHG emissions is crucial to mitigate the adverse effects of climate change, including extreme weather events, rising sea levels, and loss of biodiversity [1]. These changes pose significant threats to global ecosystems, human health, and economies [2]. Immediate and sustained action to reduce emissions can help stabilize the climate, protect natural resources, and ensure a sustainable future for all. Therefore, transitioning to renewable energy sources and improving energy efficiency are essential steps to reduce our carbon footprint [3].

The transport sector contributes approximately 25% of global CO2 emissions from fuel combustion, with road transport being responsible for nearly 75% of these emissions. Cars alone account for about 45% of road transport emissions, making their decarbonization critical [4].

Mitigating transport emissions involves exploring alternatives such as cycling and public transport [5]. However, these options are not universally viable. Therefore, it is necessary to enhance the environmental sustainability of automobile transportation as it currently exists.

1.1. Decarbonizing Car Transport

1.1.1. Electrification

The transition to EVs is considered one of the key strategies for decarbonizing the transport sector [4, 6]. EVs are driven by electric motors that are powered by electricity instead of internal combustion engines (ICE) that are powered by fossil fuels, such as traditional internal combustion vehicles (ICV). The potential of EVs to combat GHG emissions is significant as they have the potential to run on electricity that is generated in a renewable manner [7]. However, switching from ICVs to EVs is not a straightforward transition. EVs are typically more costly than ICVs, limiting their accessibility and adoption rate. In addition, the production of EVs, particularly the extraction of rare metals for batteries, presents significant environmental challenges. Furthermore, the infrastructure demands of EVs, such as the need for charging stations and parking facilities, strain existing resources [8]. Hence, to handle the increased load on the electricity grid, the grid must be expanded [9]. Moreover, increasing the share of renewable energy in the overall energy mix is essential, as reducing emissions through car electrification relies on a substantial portion of renewable electricity in the power supply [4].

The intermittent nature of renewable energy sources and the increased load demand caused by EVs challenge the balance between energy supply and demand, increasing the need for flexibility services within the electricity system [10, 11].

To address this issue, several solutions have been developed. Smart Charging Algorithms (SCA) determine the optimal time for EVs to charge based on energy market conditions and requirements set by the vehicle owner. SCAs primarily aim to reduce charging costs by scheduling charging sessions when electricity prices are low, which typically occurs during off-peak hours when demand is low or when there is a high share of renewable energy in the mix [12]. Additionally, SCAs can stop charging, (partially) delay charging, and reduce charging power during periods of high demand, a practice known as demand response [13]. Consequently, SCAs enable cost-effective and renewable energy-based charging while assisting the grid with reducing peak demand [14].

V2G technology, while relatively new in practical applications, has been extensively studied in academic circles and is regarded as a major breakthrough in the fields of electricity and EVs. V2G technology enables bidirectional electricity flow between EVs and the electrical grid. This means that EVs can not only draw electricity from the grid to charge but also discharge electricity back into the grid when needed [4]. V2G supports the integration of renewable energy and EVs into the grid by providing flexibility services as EVs can absorb electricity when there is a surplus and supply it back during shortages, helping with congestion management and frequency regulation [9].

1.1.2. Carsharing

Increasing the prevalence of CSS is regarded as another key strategy for decarbonizing the transport sector [4, 6]. Car-sharing improves vehicle efficiency by ensuring cars are utilized more frequently and makes transportation more affordable and accessible by eliminating the high costs associated with car ownership.

Car-sharing significantly reduces the need for private car ownership. According to Rijkswaterstaat, one shared car can replace four to eight private cars [15]. In addition, each shared car provides a space saving of 36–38 square meters [15]. Also, since shared cars decrease the demand for private vehicles, fewer cars need to be produced, which reduces the pollution associated with car manufacturing, particularly for EVs.

An intriguing finding is that adopting car-sharing may also reduce the total distance traveled by car. A study from the Netherlands revealed that, on average, car sharers drive 1,600 kilometers less per year after switching from private car ownership [15]. Another Dutch study found that car travel distances decrease by 20% [16]. Both studies attribute this behavior to increased awareness of mobility choices. Breaking habitual reliance on private cars encourages people to consider alternative modes of transportation, such as walking, cycling, and using public transport.

CSSs exist in various forms with increasing user flexibility, including two-way station-based, one-way station-based, and free-floating systems respectively, [7, 17, 18]. Two-way station-based CSS require rented vehicles to be returned to their departure station, similar to traditional car rental models. One-way station-based CSS allows users return the rented vehicle to the same station or to a different station belonging to the CSO [4]. Free-floating CSS offers users the flexibility to pick up and park vehicles within designated zones.

In this context, combining vehicle sharing with EVs, offers a compelling and renewable alternative to current day to day car transport. Together, these approaches promote sustainable, efficient, and equitable urban mobility. Notably, in the Netherlands, companies like Greenwheels (two-way station-based) [19], Felyx [20], and Check [21] (free-floating) have pioneered such services.

1.2. The Electric Vehicle Relocation Problem

A common challenge faced by both one-way station-based and free-floating CSS is the imbalance in vehicle distribution. Vehicles tend to be picked up in high-demand areas (hot zones) and returned in low-demand areas (cold zones), decreasing the likelihood of the vehicle being picked up again and profitability [17, 18]. Additionally, vehicles are often returned with low battery levels, requiring dedicated staff to recharge them and relocate them to hot zones to better serve customers and enhance revenue [17, 18].

This issue, often referred to in the literature as the Electric Vehicle Relocation Problem (EVReP) [18, 22, 23] or the Dynamic Electric Car Relocation Problem (DECRP) [17], revolves around optimizing vehicle relocation strategies to optimize financial outcomes while taking into account charging requirements. To address this, research has focused on developing digital models capable of effectively solving the relocation problem and maximizing overall profitability within CSS networks.

1.3. Contribution

This study presents a mathematical Mixed-Integer Linear Programming (MILP) model that integrates V2G functionality with optimal vehicle relocation strategies for a centralized station-based fleet of shared EVs. The primary aim is to demonstrate how the incorporation of V2G capabilities can enhance the profitability of EVSS while simultaneously supporting the electricity grid by alleviating peak load demand.

Research Objectives

- **Financial Analysis**
  To analyze the financial implications of enabling SEVs to participate in energy markets.
- **Impact of Electricity Prices**
  To investigate the impact of location-dependent time-varying electricity prices on the economic outcomes of V2G-enabled ECSS.
- **Peak Load Reduction**
  To explore the impact of peak reduction on the performance of V2G-enabled ECSS.
- **Seasonal Dynamics**
  To assess the effect of seasonal variation on the performance of V2G-enabled ECSS.

Research Questions

- How do ECSS benefit financially from integrating V2G technology?
- How do location-dependent time-varying electricity prices affect the profitability of V2G-enabled ECSS?
- How do vehicle relocation and energy procurement contribute to the overall costs of implementing V2G in ECSS?
- How do peak reducing measures help with mitigating peak load demand?

1.4. Thesis Structure

This thesis report is organized as follows: First, Chapter 2 reviews and discusses the existing literature. Next, Chapter 3 provides a detailed explanation of the mathematical model. Chapter 4 discusses the model inputs that are common to all case studies and simulations. Chapter 5 presents the case studies used to test the model. The results are analyzed and presented in Chapters 6, 7, and 8. Chapter 9 provides a discussion of the findings and presents recommendations for future research. Finally, Chapter 10 concludes the study with a summary of key insights.

2

Literature Review

This chapter provides a comprehensive review of the current literature on the EVReP, V2G, and their integration. It begins with Section 2.1, which addresses the imperative of decarbonizing car transport and evaluates the most promising approaches to achieve this goal. Section 2.2 then reviews the literature on ECSS, including operational challenges and modeling strategies. Following this, Section 2.3 explores V2G technology and its potential benefits. Section 2.4 examines the integration of V2G with ECSS, summarizing the latest research in this area. Finally, Sections 2.5 and 2.6 identify research gaps and outline the contributions of this study.

2.1. Car Transport Decarbonization

The transport sector is a major contributor to global CO2 emissions, accounting for approximately 25% of emissions from fuel combustion. Within this sector, road transport is responsible for nearly 75% of these emissions, with cars alone contributing to about 45% of road transport emissions. Thus, decarbonizing cars is crucial for reducing overall emissions [4].

In urban environments, the negative impacts of car emissions are significantly exacerbated due to a variety of factors. High traffic density in cities leads to increased tailpipe emissions, which tend to linger longer in the air because of phenomena such as street canyons—narrow streets lined with tall buildings that trap pollutants [24]. This lack of air circulation prevents the dispersion of harmful gases, leading to concentrated levels of air pollution [25]. As a result, air quality deteriorates rapidly, posing serious health risks such as respiratory illnesses, cardiovascular diseases [26], and an increased incidence of asthma [27], particularly in vulnerable populations like children and the elderly [28]. Beyond the direct expenses related to treating these pollution-induced diseases, there are indirect costs such as reduced worker productivity and lost school days for children [29].

In addition to air pollution, cities also suffer from the urban heat island effect, where large concentrations of buildings, vehicles, and paved surfaces absorb and retain heat. This contributes to higher temperatures compared to surrounding rural areas, which further intensifies the negative impacts of car emissions. Warmer conditions speed up the chemical reactions that form ground-level ozone, exacerbating smog formation and worsening the health effects of pollution [30]. Moreover, the combination of heat and pollution creates an environment that can increase the frequency of heat-related illnesses, compounding the public health burden [31, 32].

Urban areas also face challenges such as congestion and the need for vast parking spaces, which further strain already crowded environments and contribute to the cycle of pollution and inefficiency. Noise pollution from vehicles is another significant issue in cities, contributing to stress, sleep disturbances, and overall reduced quality of life for urban residents [33].

Therefore, addressing car transport emissions is not only critical for improving air quality but also for mitigating the broader environmental, economic, and health impacts that disproportionately affect urban areas.

Gschwendtner [4] and Suel [6], among others, have identified electrification and the increased adoption of CSS as some of the most promising solutions to the aforementioned challenges.

2.1.1. Electrification

EVs are a key solution for improving urban air quality and addressing environmental challenges. Unlike ICVs, EVs produce no tailpipe emissions, and their environmental impact can be further minimized when powered by renewable energy sources. This transition to EVs, driven by growing environmental awareness and advancements in renewable energy technologies, offers a significant opportunity to reduce GHG emissions and air pollution in cities [22]. Moreover, the quieter operation of EVs reduces noise pollution, enhancing the quality of life in densely populated urban areas. As the adoption of EVs and their integration with renewable energy systems accelerate, substantial improvements in urban air quality and environmental sustainability are expected.

2.1.2. Vehicle Sharing Systems

Vehicle Sharing Systems (VSS) have advanced significantly, with the support of the internet and driven by technological innovations and increasing environmental awareness [17]. VSS encompass bikes, scooters, and cars, and they differ in terms of flexibility. VSS are generally categorized into three models:

- **Two-Way Station-Based**
  A vehicle must be returned to the station at which it was picked up. Hence, this system is also called 'round-trip'. This model provides the least amount of flexibility.
- **One-Way Station-Based**
  A vehicle can be returned to any station that belongs to the CSO. This model provides more flexibility.
- **Free-Floating**
  A vehicle must be returned anywhere within an area specified by the CSO. This model provides the highest degree of flexibility.

Each model presents its own set of advantages and challenges [34, 18].

VSS are increasingly viewed as key components of the 'smart city' concept. They help reduce the reliance on personal vehicle ownership, alleviate parking congestion, and contribute to lower transportation costs. They also help reduce traffic congestion and the emission of GHGs. [18, 7].

However, despite their growing popularity, managing vehicle distribution and ensuring availability, particularly in one-way station-based and free-floating systems, remains a significant challenge [17].

2.2. Electric Car-Sharing Systems (ECSS)

Combining EVs with CSS offers an optimal solution for advancing sustainable urban mobility. This integration is becoming increasingly prevalent as car-sharing programs adopt EVs to leverage their zero emissions and reduced noise, thereby enhancing environmental benefits and urban livability [22, 8, 18].

2.2.1. Operational Challenges in Car Sharing Systems

CSS face several operational challenges, including fleet management, parking station placement, and the complexities introduced by short-term vehicle use, which often involves multiple users per day [23].

A primary challenge in vehicle distribution, especially within one-way station-based and free-floating CSS, is the relocation of vehicles. Vehicle distribution fluctuates as cars are used, leading to imbalances where some stations may have too many vehicles while others have too few. This, together with uneven vehicle demand, can result in users abandoning the system if they cannot find a car or parking space near their destination [17, 34, 22]. Vehicle relocation strategies aim to address these imbalances by redistributing vehicles from areas of high accumulation to areas of high demand.

Relocation can be managed through two main approaches: user-based and operator-based [23]. User-based strategies incentivize customers to adjust their behavior, while operator-based strategies involve redistributing vehicles either during low-demand periods (static relocation) or throughout the day (dynamic relocation). Although both approaches involve personnel costs, these can be offset by increased revenue from higher user satisfaction.

The integration of EVs adds further complexity due to the need for managing battery levels and charging infrastructure [8, 34, 7]. This leads to what is known in the literature as the EVReP or the DECRP, which is extensively studied.

2.2.2. Modelling Relocation Strategies

In recent years, researchers have focused on developing optimization models to determine the most effective routing for vehicle relocation and charging schedules. These models incorporate continuous updates on vehicle locations, battery levels, and demand patterns throughout the planning horizon [17].

Several innovative strategies have been proposed to address the EVReP. Notable contributions include the works of Xiaonong Lu [7] and Zhaoming Wang [8].

Lu [7] developed a model for optimizing one-way ECSS to enhance operational income. This model involves multiple SEV stations distributed across various city areas (residential, office, commercial), each equipped with parking and charging facilities. The primary objective is to maximize profit by efficiently scheduling SEVs for charging, user service, and relocation. The system divides the city into grids, with up to one SEV station per grid. SEVs must return to their starting or another designated station after use, with parking reservations required. Idle SEVs connect to charging stations, and a State of Charge (SOC) protection level prevents their use when the battery is too low. Decisions on charging or relocating SEVs are based on real-time electricity pricing, SOC, grid load, and user requests.

Wang [8] employs a different approach to determine optimal routes and schedules for vehicle relocation. This model aims to balance vehicle distribution across stations, minimize the number of vehicles with low battery levels, and adhere to battery constraints and route time limits. The study also accounts for employee constraints: each employee must start and end their shifts at a central depot, use folding bicycles for relocation, and complete each relocation within a specified time. Additionally, the study addresses the management of non-charging poles.

2.3. V2G

V2G technology enables EVs to participate in bidirectional energy exchanges with the power grid [35]. This technology transforms EV batteries into Distributed Energy Storage (DES) units, allowing them to both draw electricity from and supply power to the grid. Unlike the previous unidirectional flow, known as Grid-to-Vehicle (G2V), V2G facilitates a two-way energy flow [36]. This shift not only allows EVs to charge during low-demand periods but also to return electricity to the grid during peak demand. Efficient implementation of V2G requires smart charging systems and aggregators to coordinate multiple EVs as a unified energy resource [35].

Research has investigated the integration of EVs with the power grid, highlighting how V2G technology can enhance grid management and support the transition to renewable energy [36, 37]. Technically, V2G provides several benefits, including flexibility services such as voltage regulation, spinning reserve, peak load shifting, and frequency regulation [36, 37]. Environmentally, V2G can aid in decarbonizing the electricity sector, especially when combined with renewable energy sources like solar and wind, by improving grid flexibility and offering backup storage [36, 37]. Economically, V2G presents opportunities for various stakeholders. EV owners can earn income by selling stored electricity during high-demand periods when prices are elevated and purchasing energy when prices are lower. For grid operators and society, V2G can reduce electricity costs [36, 35]. Although individual vehicle profits might be modest, these can accumulate significantly across a large fleet of EVs. However, the exact profitability can vary greatly depending on specific market conditions, regulatory frameworks, and technological implementations.

2.4. V2G coupled with ECSS

While extensive research has been conducted on the EVReP and V2G technology, there is surprisingly little research on the integration of these elements. This gap is especially notable, since ECSS offer substantial cumulative benefits due to their extensive fleets of EVs.

Recently, however, there has been growing interest in combining V2G technology with E-carsharing, prompting research into its potential benefits, challenges, and adoption factors. This body of work highlights both the opportunities and complexities associated with this innovative approach.

Integrating V2G technology into carsharing systems offers a promising way to enhance the sustainability of both the transportation and electricity sectors.This approach leverages EVs not only for mobility but also as mobile energy storage units that can provide electricity back to the grid when not in use.This dual-functionality could create additional revenue streams for carsharing operators, who often face financial challenges, while simultaneously supporting the integration of renewable energy sources into the grid.

At the start of this thesis, three key studies were identified that examine the integration of V2G technology within E-carsharing. The first study, by Prencipe [9], presents a MILP model designed to optimize both the start-of-day EV distribution and their charging/discharging schedules in a one-way station-based ECSS. This model aims to maximize profits from both car-sharing operations and V2G activities. The other two studies, conducted by Suel [6] and Gschwendtner [4], explore societal willingness to adopt V2G-enabled carsharing through stated-choice experiments.

2.4.1. Customer Preferences and Willingness to Adopt V2G Carsharing

Research into customer preferences for V2G CSS reveals significant insights. A stated-choice experiment conducted in Germany and Switzerland reveals that customers exhibit a clear preference for V2G-enabled car-sharing over conventional CSS in 74.2% of cases and over electric car-sharing in 56.1% of cases [4]. This preference is primarily driven by the environmental benefits associated with V2G technology, which aligns with the growing consumer demand for sustainable mobility solutions. However, cost remains the most significant factor influencing customer decisions, even among environmentally conscious early adopters [4]. To enhance the appeal of V2G services, CSOs should consider offering cost-effective discounts or financial incentives into the cost structure. Moreover, improving access and egress times through robust charging infrastructure, especially in one-way station-based and free-floating systems, will enhance the appeal [4].

Further research using an integrated choice and latent variable model estimates the financial incentives needed for users to shift their booking slots and examines how socio-demographic factors, latent attitudes, and trip characteristics influence these incentives [6]. A stated preference survey conducted with car-sharing users in Switzerland revealed that the value of time flexibility ranged from 22.4 CHF/h to 35.5 CHF/h [6].The study identified that older adults, lower-income individuals, those in employment, and those with higher education levels showed less flexibility in changing their booking slots. Additionally, trips related to work, leisure, social interactions, and those occurring during weekdays and peak morning hours were less adaptable to changes [6]. These findings are crucial for designing V2G initiatives and understanding user behavior. This research is notable for being among the first to focus on the willingness of car-sharing users to offer time flexibility in exchange for financial incentives, contrasting with the focus on car owners in existing literature [6].

2.4.2. Impact of Socio-Demographic Factors and Infrastructure on V2G Adoption

Gschwendtner [4] indicates that socio-demographic factors, such as prior EV ownership and familiarity with V2G technology, positively impact the likelihood of adopting V2G CSS. This finding underscores the potential role of policy interventions in raising awareness and educating the public about V2G technology. Furthermore, customers demonstrated a preference for longer driving ranges, which CSOs must take into account when developing their charging strategies. This suggests that V2G functionality might be more suitable for vehicles with lower utilization rates to ensure availability for mobility needs.

2.4.3. Economic, Environmental and Operational Benefits

The integration of V2G technology into E-carsharing systems offers significant economic, environmental, and operational benefits. According to Prencipe [9], V2G technology can create additional revenue streams for both CSOs and grid operators by enabling EVs to return stored energy to the grid during peak demand periods. This capability can offset charging costs and higher investment costs associated with EVs. For example, a case study in Delft, Netherlands, demonstrated that V2G operations could cover daily charging costs and generate additional profits, with a fleet of 50 EVs earning an average of 36.04 €/day in V2G profits [9].

Environmentally, V2G in E-carsharing can contribute to the integration of renewable energy sources into the grid [4] and support grid operators in managing peak loads and frequency regulation [9]. This dual benefit underscores V2G's potential to aid in the decarbonization of both the transportation and energy sectors, making it an attractive option for large-scale implementation as EV demand grows [9].

2.4.4. Conclusion

In summary, the integration of V2G technology into CSS presents a promising but complex opportunity. While the potential economic and environmental benefits are significant, challenges such as battery degradation, customer behavior, and the early-stage nature of V2G in the market require careful consideration. Future research should focus on empirical studies, cost-benefit analyses, and the exploration of synergies between V2G and other sustainable technologies to fully realize the potential of this innovative approach to mobility and energy management.

2.5. Research Gap

The primary research gaps in the existing literature on the potential of V2G integrated with ECSS are outlined below:

- There is a lack of accurate and dynamic mathematical models that fully capture the operational aspects of an ECSS, including vehicle driving, relocation, charging requirements, and particularly V2G functionality and peak reduction.
- There is a lack of quantitative simulation-based results that evaluate the operational impacts of V2G in ECSS.

2.6. Contribution

This thesis offers a novel addition to the existing body of literature on the potential of V2G-enabled ECSS, with its key contributions summarized as follows:

- Development of a mathematical model that describes the integration of V2G in ECSS.
- Simulations showing optimal vehicle driving, relocation, charging, and particularly V2G activities and grid interactions.
- Empirical validation of V2G integration in ECSS, addressing operational complexities.
- Empirical validation of the effectiveness of peak reducing measures on peak load demand.
- Emphasizes real-world system performance and provides practical, implementable outcomes, helping bridge the gap between theoretical concepts and practical application.
- Enhances understanding of synergies between V2G and ECSS operations.

3
Model

To assess whether integrating V2G into relocation strategies for an EVSS can enhance overall profitability, while simultaneously using peak-reducing measures to minimize peak load demand, a mathematical model is needed to simulate the real-world scenario.

The following model describes a one-way, station-based EVSS over a single day, divided into half-hour time steps. During each time step, SEVs can either be driven by consumers, relocated by staff, or (dis)charged. Each station features location-dependent time-varying load demand and photovoltaic (PV) generation profiles. Additionally, the electricity price is time-varying and may vary by location, depending on the test scenario.

The model requires inputs such as electricity price, station load demand, and PV generation (all continuous values), as well as driving demand (binary values). It is characterized by a linear objective function and constraints, classifying it as a MILP. The model is solved using the CPLEX solver developed by IBM ILOG, which was selected due to its widespread use in prior studies modeling the EVReP, including [22, 23, 9].

This chapter delves into the development of the MILP model used in this study.

Firstly, Section 3.1 explores the mathematical framework of the model. Section 3.2 presents a summary of the model. Lastly, Section 3.3 enlists model simplifications.

3.1. Model Mathematics

3.1.1. Indices & Variables

For a list of all indices, see Table 3.1.

Index	Definition
T	Timesteps
I	Set of departure stations
J	Set of arrival stations
K	Set of EVs

Table 3.1: List of indices and definitions.

For a list of all decision variables, see Table 3.2.

Symbol	Definition	Type	Indices	Unit
D	Driving	boolean	[t][i][j][k]	-
R	Relocation	boolean	[t][i][j][k]	-
M	Movements	boolean	[t][i][j][k]	-
C	Connected	boolean	[t][i][j][k]	-
PreMD	Pre Movements Distribution	boolean	[t][i][k]	-
PMD	Post Movements Distribution	boolean	[t][i][k]	-
BC	Battery Charge	float	[t][k]	kWh
P^{ch}	Charging Power	float	[t][i][k]	kW
P^{dch}	Discharing Power	float	[t][i][k]	kW
P^{EV}	Electric Vehicle Power	float	[t][i][k]	kW
P^{buy}	Buying Power	float	[t][i]	kW
P^{sell}	Selling Power	float	[t][i]	kW
P^{grid}	Grid Power	float	[t][i]	kW
E^{ch}	Charging Energy	float	[t][i][k]	kWh
E^{dch}	Discharging Energy	float	[t][i][k]	kWh
P^{peak}	Peak Power	float	[i]	kW
P^{sur}	Surpassed Power	float	[i]	kW

Table 3.2: List of decision variables and definitions.

For all other variables, see Table 3.3.

Symbol	Definition	Type	Indices	Unit
Δt	Timestep Duration	float	-	h
F^i	Initial Fee	float	-	€
F^d	Per Distance Fee	float	-	€/km
F^w	Worker Fee	float	-	€
C^E	Energy Cost	float	[t][i]	€/kWh
SD	Station Distance	float	[i][j]	km
P^{ch}_{max}	Maximal Charging Power	float	[i]	kW
P^{dch}_{max}	Maximal Discharging Power	float	[i]	kW
P^{LD}	Load Demand	float	[t][i]	kW
P^{PV}	PV Generation	float	[t][i]	kW
P^{net}	Net Station Demand	float	[t][i]	kW
p^{max}	Maximal Parking Spaces	float	[i]	-
OED	Optimal End Distribution	float	[i]	-
SF	Selling Factor	float	-	-
P^{GC}	Grid Capacity	float	-	kW
C^P	Penalty Cost	float	-	€/kW
P^{limit}	Power Limit	float	[i]	kW
η	Vehicle Energy Efficiency	float	[k]	kWh/km
BC^{max}	Maximal Battery Charge	float	[k]	kWh
BC^{min}	Minimal Battery Charge	float	[k]	kWh
BC^i	Initial Battery Charge	float	[k]	kWh
η^{ch}	Charging Efficiency	float	[k]	%
η^{dch}	Discharging Efficiency	float	[k]	%
v^{avg}	Average Car Velocity	float	-	km/h
DD	Driving Demand	float	[t][i][j]	-
IPreMD	Initial Pre Movements Distribution	boolean	[i][k]	-

Table 3.3: List of input variables and definitions.

3.1.2. Objective Function

For CS: Summer (see Section 5.1) the objective function aims to maximize the difference between the revenue generated by consumers driving the SEVs and providing V2G services and the cost of relocation and charging, as shown in Equation 3.1. In CS: Summer + Peak Reduction (see Section 5.2) the objective function (see Equation 3.2) includes a penalty for exceeding a certain power limit, which is used to stimulate peak reduction.

$$\text{maximize Driving Revenue - Relocation Costs + Energy Sold Revenue - Energy Bought Costs} \tag{3.1}$$

$$\begin{aligned}\text{maximize Driving Revenue} - \text{Relocation Costs} + \text{Energy Sold Revenue} - \text{Energy Bought Costs} \\ - \text{Peak Exceedance Penalty}\end{aligned} \tag{3.2}$$

For all fulfilled driving demand (D_{tijk}) the total driving revenue is shown by Equation 3.3 and consists of a fixed initial fee (F^i) and a per-distance fee (F^d) that is proportional to the distance between the departure and arrival station (SD_{ij}).

$$\text{Driving Revenue} : \sum_{t \in T} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} D_{tijk} * (F^i + SD_{ij} * F^d) \tag{3.3}$$

The relocation costs are calculated by multiplying the total number of relocation trips, R_{rijk}, by a fixed per-relocation worker fee (F^w) (see Equation 3.4).

$$\text{Relocation Costs} : \sum_{t \in T} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} R_{rijk} * F^w \tag{3.4}$$

The V2G revenue is calculated as the discharging energy (E^{sold}) multiplied with the energy price (C^E), the timestep duration (Δt = 24/48) and the selling factor (SF) (see Equation 3.5).

$$\text{Energy Sold Revenue} : \sum_{t \in T} \sum_{i \in I} \sum_{k \in K} P^{sell}_{tik} * C^E_{ti} * \Delta t * SF \tag{3.5}$$

The charging cost is calculated as the charging energy (E^{bought}) multiplied with the energy price (C^E) (see Equation 3.6).

$$\text{Energy Bought Costs} : \sum_{t \in T} \sum_{i \in I} \sum_{k \in K} P^{buy}_{tik} * C^E_{ti} * \Delta t \tag{3.6}$$

In CS: Summer + Peak Reduction (see Section 5.2, peak reduction is stimulated by factoring in a penalty for exceeding a power limit (P^{limit}_i). P^{sur}_i denotes the amount by which P^{limit}_i is surpassed by P^{buy}_{ti} and C^P denotes the penalty cost in €/kW (see Equation 3.7).

$$\text{Peak Exceedance Penalty} : \sum_{i \in I} P^{sur}_i * C^p \tag{3.7}$$

3.1.3. Constraints

The model constraints can be divided into four groups: movement constraints, charging constraints, battery charge constraints and grid constraints. In that order, this section provides an overview and elaboration of all constraints .

Movement Constraints

$$PreMD_{[1]ik} = IPreMD_{ik} \qquad \forall i \in I, \forall k \in K \tag{3.8}$$

$$PreMD_{tik} = PMD_{(t-1)ik} \qquad \forall t \in 2..T, \forall i \in I, \forall k \in K \tag{3.9}$$

Equation 3.8 and Equation 3.9 ensure that the pre-movements distribution of t=1 is equal to the initial pre-movements distribution and that the pre-movements distribution of sequential timesteps are equal to the post-movements distribution of the previous timesteps respectively.

$$\sum_{k \in K} D_{tijk} \leq DD_{tij} \qquad \forall t \in T, \forall i \in I, \forall j \in J \tag{3.10}$$

Equation 3.10 ensures that no more cars are driven than there is demand for.

$$M_{tijk} = D_{tijk} + R_{tijk} \qquad \forall t \in T, \forall i \in I, \forall j \in J, \forall k \in K \tag{3.11}$$

Equation 3.11 introduces decision variable Movements, containing all of the car moves.

$$\sum_{i \in I} M_{tijk} \leq 1 \qquad \forall t \in T, \forall j \in J, \forall k \in K \tag{3.12}$$

$$\sum_{j \in J} M_{tijk} \leq 1 \qquad \forall t \in T, \forall i \in I, \forall k \in K \tag{3.13}$$

$$\sum_{i \in I} M_{tiik} = 0 \qquad \forall t \in T, \forall j \in J, \forall k \in K \tag{3.14}$$

Equation 3.12, 3.13 and 3.14 ensure that cars can only be moved to and from one station and cannot be moved to a station equal to the departure station.

$$\sum_{i \in I} M_{tijk} \leq PreMD_{tjk} \qquad \forall t \in T, \forall i \in I, \forall k \in K \tag{3.15}$$

Equation 3.15 ensures that there cannot be more cars leaving a station than there are located at that station pre-movements.

$$PMD_{tjk} = PreMD_{tjk} + \sum_{i \in I}(M_{tijk} - M_{tjik}) \qquad \forall t \in T, \forall j \in J, \forall k \in K \tag{3.16}$$

Equations 3.16 ensures that the post-moving distribution is equal to the pre-moving distribution plus cars going from any station i to the j station studied minus cars going from the j stations studied to any station i.

$$C_{tijk} = PreMD_{tik} - \sum_{j \in J} M_{tijk} \qquad \forall t \in T, \forall i \in I, \forall k \in K \tag{3.17}$$

$$C_{tijk} = 0 \qquad \forall t \in T, \forall i \in I, \forall j \in J : i \neq j, \forall k \in K \tag{3.18}$$

Equations 3.17 and 3.18 ensure that Connected is defined as all cars that do not move. Hence, they are stationary and connected to a charger. Parking spots are limited by p_i^{max}, but all parking spots have chargers.

$$\sum_{k\in K} PMD_{Tik} = OED_i \qquad \forall i \in I \tag{3.19}$$

Equation 3.19 ensures that the vehicle distribution at the final time step aligns with the optimal end distribution. This optimal end distribution is an input provided by the CSO and represents the most favorable start-of-day vehicle distribution for the following day.

$$\sum_{k\in K} PMD_{tik} \leq p_i^{max} \qquad \forall t \in T, \forall i \in I \tag{3.20}$$

Equation 3.20 ensures that at no timestep t, there are more cars parked at a station than there are parking spots.

Charging Constraints

$$P_{tik}^{ch} \leq P_i^{ch,max} * \sum_{i\in I} C_{tiik} \qquad \forall t \in T, \forall i \in I, \forall k \in K \tag{3.21}$$

$$P_{tik}^{dch} \leq P_i^{dch,max} * \sum_{i\in I} C_{tiik} \qquad \forall t \in T, \forall i \in I, \forall k \in K \tag{3.22}$$

Equation 3.21 and 3.22 ensure that a car can only (dis)charge when it is connected and that the (dis)charging power must be equal to or lower than the maximum (dis)charging power.

$$E_{tik}^{ch} = P_{tik}^{ch} * \Delta t \qquad \forall t \in T, \forall i \in I, \forall k \in K \tag{3.23}$$

$$E_{tik}^{dch} = P_{tik}^{dch} * \Delta t \qquad \forall t \in T, \forall i \in I, \forall k \in K \tag{3.24}$$

Equation 3.23 and 3.24 ensure that the energy that is taken from or fed into the grid to (dis)charge vehicle k is equal to the product of the (dis)charging power and the timestep duration.

$$P_{ti}^{buy} - P_{ti}^{sell} = \sum_{k\in K} (P_{tik}^{ch} - P_{tik}^{dch}) + P_{ti}^{LD} - P_{ti}^{PV} \qquad \forall t \in T, \forall i \in I \tag{3.25}$$

Equation 3.25 ensures that, for all stations, the net power purchased and sold equals the difference between charging and discharging power, plus the station load, minus the station's PV generation.

$$P_{ti}^{grid} = P_{ti}^{buy} - P_{ti}^{sell} \tag{3.26}$$

$$P_{tik}^{EV} = P_{tik}^{ch} - P_{tik}^{dch} \tag{3.27}$$

$$P_{ti}^{net} = P_{ti}^{LD} - P_{ti}^{PV} \tag{3.28}$$

$$P_{ti}^{grid} = \sum_{k\in K} P_{tik}^{EV} + P_{ti}^{net} \qquad \forall t \in T, \forall i \in I \tag{3.29}$$

To simplify the equation and enhance clarity, Equations 3.26, 3.27, 3.28, and 3.29 are introduced to make the interpretation of the power balance easier (see Equation 3.25).

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Battery Charge Constraints

$$BC_{(1)k} = BC_k^i \qquad \forall k \in K \tag{3.30}$$

$$BC_{(T+1)k} = BC_k^i \qquad \forall k \in K \tag{3.31}$$

Equations 3.30 and 3.31 ensure that the battery charge at t=1 and t=T+1 is equal to the initial battery charge levels (which is set to 100% (see Section 4)).

$$BC_{tk} \geq BC_k^{min} \qquad \forall t \in T, \forall k \in K \tag{3.32}$$

$$BC_{tk} \leq BC_k^{max} \qquad \forall t \in T, \forall k \in K \tag{3.33}$$

Equations 3.32 and 3.33 ensure that battery charge levels always remain within their minimum (10% SOC) and maximum values (100% SOC) respectively.

$$BC_{tk} = BC_{(t-1)k} - \sum_{i \in I} \sum_{j \in J} M_{(t-1)ijk} * \frac{SD_{ij}}{\eta_k} + \sum_{i \in I} (\eta_k^{ch} * E_{(t-1)ik}^{ch} - \frac{1}{\eta_k^{dch}} * E_{(t-1)ik}^{dch}) \\ \forall t \in 2..T+1, \forall k \in K \tag{3.34}$$

Equation 3.34 ensures that the battery charge at the start of the timestep is equal to the battery charge of the previous timestep, minus the energy used during moving, plus the energy added during charging or minus the energy removed during discharging of the previous timestep.

Grid Constraints

$$P_{ti}^{sell} \leq P^{GC} \qquad \forall t \in T, \forall i \in I \tag{3.35}$$

$$P_{ti}^{buy} \leq P^{GC} \qquad \forall t \in T, \forall i \in I \tag{3.36}$$

Equations 3.35 and 3.36 limit the power that is being fed into and taken from the grid by the grid capacity. Equation 3.36 is only applicable in *Case Study: Summer* and *Case Study: Winter*.

To enable peak reduction, the following equations are applied exclusively in *Case Study: Summer + Peak Reduction*.

$$P_{ti}^{buy} \leq P_i^{peak} \qquad \forall t \in T, \forall i \in I \tag{3.37}$$

$$P_i^{peak} \leq P^{GC} \qquad \forall i \in I \tag{3.38}$$

Equations 3.37 and 3.38 limit P_i^{peak} to be larger than P_{ti}^{buy} and smaller than P^{GC}, allowing P_i^{peak} to be used as a measure to minimize P_{ti}^{buy} while respecting the grid capacity.

$$P_i^{sur} \geq 0 \qquad \forall i \in I \tag{3.39}$$

$$P_i^{sur} \geq P_i^{peak} - P^{limit} \qquad \forall i \in I \tag{3.40}$$

Equations 3.39 and 3.40 ensure proper calculation of the amount of power by which P_i^{limit} is surpassed.

3.2. Model Summary

The model is a dynamic MILP problem that optimizes the driving, relocation, charging, V2G functionalities while minimizing peak load demand of a one-way station-based ECSS to maximize financial profit for the CSO.

The system comprises of a set of SEVs, stations, and operators. All SEVs have unique battery capacities, driving efficiencies and (dis)charging efficiencies. All stations have location-dependent time-varying load demand and PV generation. Electricity prices are time-varying and can be location-dependent depending on the test scenario. Revenue is generated by renting out SEVs to consumers, who pay an initial fee plus a per-distance fee, and by selling electrical energy to the grid. Conversely, the system incurs costs from paying operators a fixed cost for each vehicle relocation, for buying electricity from the grid and for exceeding a certain load demand.

The model operates in 48 half-hour timesteps, starting at 6 AM and ending at 6 AM the following day. From midnight to 6 AM (Δt = 37 - 48) there is no driving demand, ensuring all vehicles have sufficient time to charge fully for the next timestep.

The model logistics are visualized in Figure 3.1. The model is a discrete model that has 48 half-hour timesteps, starting at 6 AM and ending at 6 AM the following day. From midnight to 6 AM (Δt = 37 - 48) there is no driving demand, ensuring all vehicles have sufficient time to charge fully for the next timestep. Per timestep, all cars can perform the following actions: they can be driven by customers, be relocated by staff, be charged or discharged.

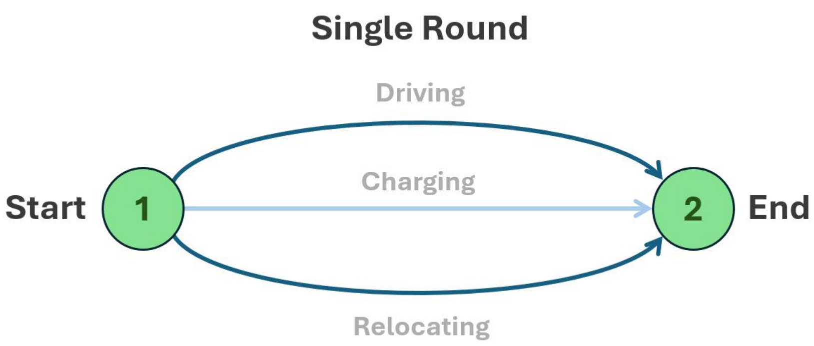


Figure 3.1: Model logistics.

3.3. Model Simplifications

To simplify the model and reduce computational load, several simplifications have been made.

Energy Management

- Energy costs (C^E) are assumed to be known for the entire day at the start of the model. In reality, energy prices are dynamic, influenced by real-time market conditions, and might vary within a timestep.
- The model assumes no energy losses during power transmission, while in reality, power grids experience losses depending on distance and load.
- A single grid capacity constraint (P^{GC}) applies uniformly to all stations. Real-world grid capacities are likely station-specific and influenced by infrastructure and location.
- PV generation (P^{PV}) is treated as deterministic, while real solar power depends on weather conditions, which are stochastic.

Vehicle and Battery Dynamics

- Vehicle energy efficiency (η) is simplified to a fixed value. Real vehicles have varying efficiencies due to driving conditions, age, and load.

- Battery performance is assumed to remain constant over time, with no degradation effects considered during the constant current (CC) and constant voltage (CV) phases or during discharging, which would apply in the real world.
- The model does not account for battery degradation, which affects (dis)charging efficiency (η^{ch}) and (η^{dch}), capacity (BC^{max}), and longevity over time.

Fleet Management

- All stations are assumed to have an unlimited supply of operators to fulfill relocation needs.
- The model assumes the optimal vehicle distribution at the end-of-day (OED) is known and fixed. In practice, determining this distribution requires forecasting and may vary with changing demand or events.
- Vehicles are assumed to always be operational, ignoring downtime for maintenance or unexpected failures.

Driving and Relocation

- Driving demand (DD) is treated as deterministic, while in practice, demand is uncertain and influenced by stochastic factors such as weather, traffic, and user behavior.
- Travel times and energy consumption are not affected by traffic, weather, or road conditions, which would influence the real-world performance.
- Each vehicle is allowed only one movement per timestep, assuming simplified operations and ignoring scenarios where vehicles could perform multiple trips within a timestep.

Cost Structures

- Costs for relocation (F^w) is constant, ignoring nonlinear factors like time-dependant rates.
- Revenue from driving (F^i and F^d) is linear based on distance traveled, ignoring linear factors like time-dependent rates.

Grid Interaction

- The model assumes a clear distinction between power buying and selling, with no simultaneous bidirectional flow at a station. Real-world systems might allow for dynamic power exchanges with time-based net metering.

4

Baseline Inputs

This chapter discusses the baseline inputs that are consistent throughout all case studies. For an overview of the index values and all model input variables see Table 4.1 and Table 4.2 respectively. See Table 3.1 and 3.3 for the definitions of the indices and variables.

Multidimensional variables are discussed in great detail in this chapter. Section 4.1 covers station data, including locations, the number of parking spots, and (dis)charging power capacities. Section 4.2 addresses the input driving demand. Next, Section 4.3 outlines the initial vehicle distribution at $\Delta t = 1$. Finally, Section 4.4 provides detailed information on the vehicle data.

Station load demand (P^{LD}), PV generation (P^{PV}) and cost of electricity (C^E) differ per case study or model scenario, so their values are elaborated upon in Chapter 5.

Index	Set Size
T	48
I	5
J	5
K	24

Table 4.1: List of index sizes.

Symbol	Type	Value or Indices	Unit
Δt	float	**24/48**	h
F^i	float	**5**	€
F^d	float	**0.38**	€/km
F^w	float	**3**	€
C^E	float	[t][i]	€/kWh
SD	float	[i][j]	km
P^{ch}_{max}	float	[i]	kW
P^{dch}_{max}	float	[i]	kW
P^{LD}	float	[t][i]	kW
P^{PV}	float	[t][i]	kW
P^{net}	float	[t][i]	kW
p^{max}	float	[i]	-
OED	float	[i]	-
SF	float	**0.8**	-
P^{GC}	float	**100**	kW
C^P	float	-	€/kW
P^{limit}	float	[i]	kW
η	float	[k]	kWh/km
BC^{max}	float	[k]	kWh
BC^{min}	float	[k]	kWh
BC^i	float	[k]	kWh
η^{ch}	float	[k]	%
η^{dch}	float	[k]	%
v^{avg}	float	**30**	km/h
DD	float	[t][i][j]	-
IPreMD	boolean	[i][k]	-

Table 4.2: List of input variables.

4.1. Station Data

4.1.1. Station Location Data

Station location data is organized into a dataset created in Excel, as shown in Figure 4.1. A fictional map is designed, placing five stations on an X-Y coordinate system at integer coordinate values. Travel distances between stations are calculated as Cartesian distances, represented as straight lines derived from the Pythagorean Theorem.

In the model, these station distances are denoted as SD. A color gradient from green to red is used to visualize the distances, where green represents shorter distances and red indicates longer distances.

4.1.2. Parking Spot and Charger Data

As shown by Table 4.3 all stations have a limited number of parking spots (p^{max}). All parking spots have chargers, but the maximum charging power (P^{ch}_{max}) and discharging power (P^{dch}_{max}) varies across stations.

Coordinates

Station	X	Y
1	-6	-4
2	8	0
3	-4	4
4	2	-6
5	2	8

Station

Station	1	2	3	4	5
1	0.000	14.560	8.246	8.246	14.422
2	14.560	0.000	12.649	8.485	10.000
3	8.246	12.649	0.000	11.662	7.211
4	8.246	8.485	11.662	0.000	14.000
5	14.422	10.000	7.211	14.000	0.000

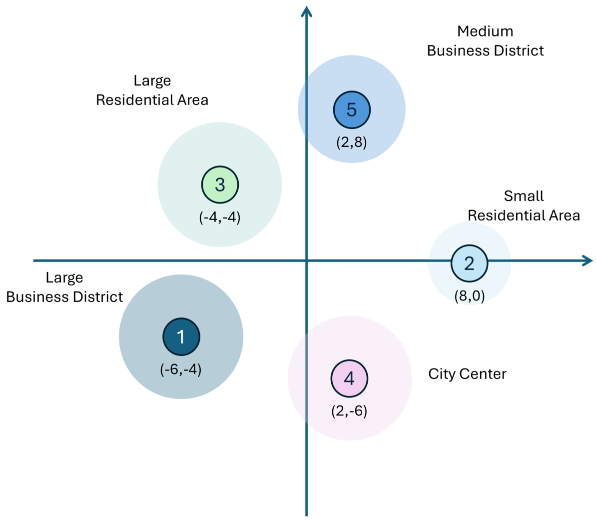


Figure 4.1: Station map, coordinates and distances in kilometers.

Station	p^{max}	P^{ch}_{max} [kW]	P^{dch}_{max} [kW]
1	20	3.7	3.7
2	14	7.4	7.4
3	14	7.4	7.4
4	24	11	11
5	18	11	11

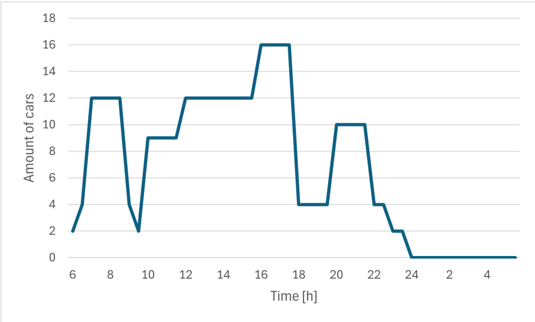
Table 4.3: Station parking spots.

4.2. Input Driving Demand

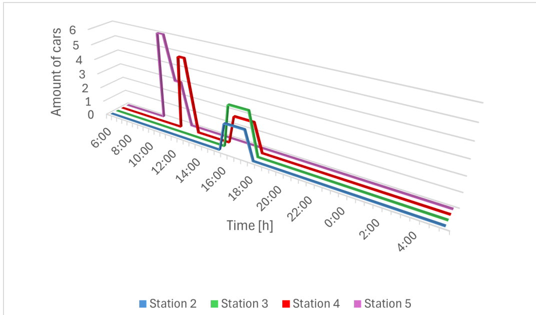
The model uses hypothetical driving demand based on typical real-life driving patterns, as summarized in Table 4.4. In the model, driving demand is represented by DD and is assumed to be known for the entire day. Figure 4.2b, 4.2c, 4.2d, 4.2e, and 4.2f illustrate the driving demand of station 1, 2, 3, 4, and 5, respectively, while the overall driving demand is shown in Figure 4.2a.

Timestep	Time	Explanation
1	06:00-06:30	Early risers start their commutes to work
2	06:30-07:00	
3	07:00-07:30	Peak rush hour as people drive to work or drop off their kids at school
4	07:30-08:00	
5	08:00-08:30	
6	08:30-09:00	
7	09:00-09:30	Late risers start their commutes to work
8	09:30-10:00	
9	10:00-10:30	Business people go for business appointments within the other business area
10	10:30-11:00	
11	11:00-11:30	
12	11:30-12:00	
13	12:00-12:30	People head home or to the city centre to have lunch
14	12:30-13:00	
15	13:00-13:30	
16	13:30-14:00	
17	14:00-14:30	Home carers go for errands in the city centre
18	14:30-15:00	
19	15:00-15:30	
20	15:30-16:00	
21	16:00-16:30	Evening rush hour begins as people pick up children from school and leave work to go home or to the city centre
22	16:30-17:00	
23	17:00-17:30	
24	17:30-18:00	
25	18:00-18:30	Home carers go to the city centre to enjoy the nightlife
26	18:30-19:00	
27	19:00-19:30	
28	19:30-20:00	
29	20:00-20:30	People are heading home returning from events in the city centre.
30	20:30-21:00	
31	21:00-21:30	
32	21:30-22:00	
33	22:00-22:30	People are heading home from late-night events in the city centre.
34	22:30-23:00	
35	23:00-23:30	
36	23:30-24:00	
37	00:00-00:30	**Charging Window**
38	00:30-00:10	
39	01:00-01:30	
40	01:30-02:00	
41	02:00-02:30	
42	02:30-03:00	
43	03:00-03:30	
44	03:30-04:00	
45	04:00-04:30	
46	04:30-05:00	
47	05:00-05:30	
48	05:30-06:00	

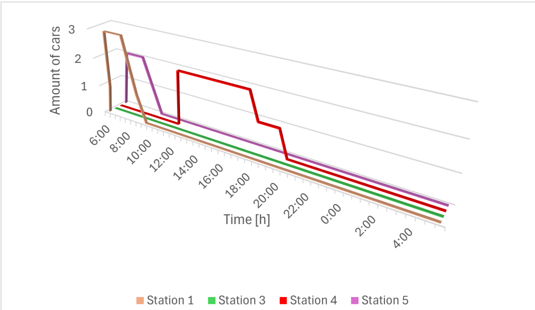
Table 4.4: Driving demand behavior.



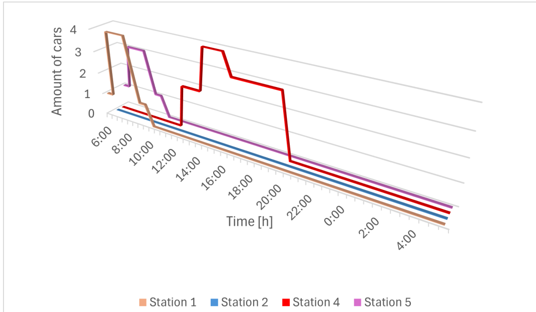
(a) Overall driving demand.



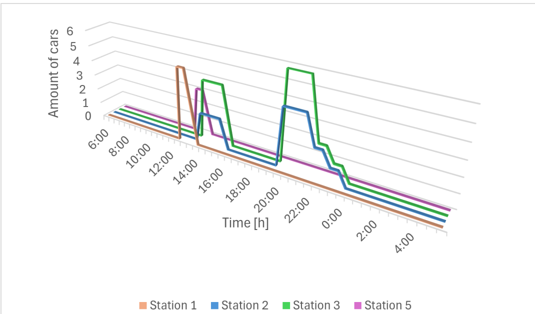
(b) Driving demand from Station 1.



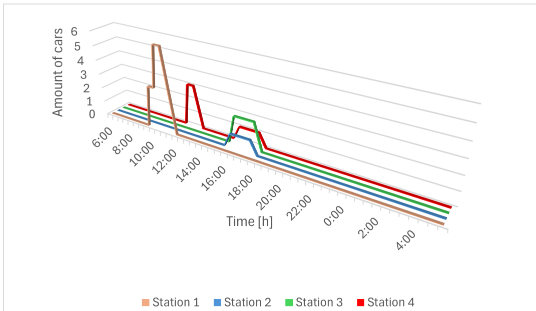
(c) Driving demand from Station 2.



(d) Driving demand from Station 3.



(e) Driving demand from Station 4.



(f) Driving demand from Station 5.

Figure 4.2: Driving demand from Station 1 (a), 2 (b), 3 (c), 4 (d) and 5 (e).

4.3. Vehicle Distribution

The initial car distribution, referred to in the model as the Initial Pre-Movements Distribution ($IPreMD$), is based on the driving behaviour described in Section 4.2. At the start of the day, most vehicles are parked at Station 2 and 3, which are designated as residential areas. This setup is ideal for consumers, allowing them to easily pick up cars in the morning for their commute to work or the city.

Conversely, at the end of the day, the model incorporates an Optimal End Distribution (OED), which represents the most optimal vehicle distribution for the following morning.

Table 4.5 presents both $IPreMD$ and OED. The table shows that cars 1-8 are located at Station 2, cars 9-22 are at Station 3, and cars 23-24 are parked at Station 4. By the end of the day, the model ensures that 8, 14, and 2 cars are stationed at Station 2, 3 and 4, respectively.

Station

Vehicle	1	2	3	4	5
1	0	1	0	0	0
2	0	1	0	0	0
3	0	1	0	0	0
4	0	1	0	0	0
5	0	1	0	0	0
6	0	1	0	0	0
7	0	1	0	0	0
8	0	1	0	0	0
9	0	0	1	0	0
10	0	0	1	0	0
11	0	0	1	0	0
12	0	0	1	0	0
13	0	0	1	0	0
14	0	0	1	0	0
15	0	0	1	0	0
16	0	0	1	0	0
17	0	0	1	0	0
18	0	0	1	0	0
19	0	0	1	0	0
20	0	0	1	0	0
21	0	0	1	0	0
22	0	0	1	0	0
23	0	0	0	1	0
24	0	0	0	1	0

Station	OED
1	0
2	8
3	14
4	2
5	0

Table 4.5: Initial car distribution and optimal end distribution.

4.4. Vehicle Data

The model includes four distinct EV models, namely the *KIA e-Soul 64 kWh*, *Tesla Model 3*, *Renault Zoe ZE50 R110* and the *Volkswagen ID.4 Pro*, as shown in Table 4.6. All vehicle models are characterized by unique energy efficiencies and battery capacities, based on data from the *EV Database* [38]. The charge and discharge efficiencies are assumed to be the same for all models, with a minimum battery charge level set at 10% of the total battery capacity.




VehicleID	1 to 6	7 to 12	13 to 18	19 to 24	
Vehicle Model	KIA e-Soul 64 kWh	Tesla Model 3	Renault Zoe ZE50 R110	Volkswagen ID.4 Pro	
η	5.78	7.19	6.06	5.78	km/kWh
BC^{max}	64	57.5	52	77	kWh
BC^{min}	6.4	5.75	5.2	7.7	kWh
BC^{i}	64	57.5	52	77	kWh
η^{ch}	90	90	90	90	%
η^{dch}	90	90	90	90	%

Table 4.6: Vehicle data.

5

Case Studies

The primary objective of this research is to assess the potential benefits of integrating V2G technology into ECSS. Specifically, the study investigates whether V2G can generate additional revenue for CSOs by enabling EVs to sell electricity back to the grid. Beyond the potential for increased revenue, V2G could also contribute to grid balancing.

To explore these possibilities, four simulations were conducted. Each simulation was evaluated using IBM ILOG CPLEX, using a mixed-integer programming (MIP) gap of 0.1 to achieve a balance between computational efficiency and solution accuracy. The primary focus of the simulations is on total revenue generation, encompassing earnings from both car rentals and potential V2G services. Additionally, relocation and charging costs are factored into each scenario. The simulations are outlined below.

- **Smart charging & same prices (SC-SP)**
  This simulation provides a baseline scenario where V2G is disabled, and all charging stations offer electricity at the same time-varying (TV) price. This test case simulates typical shared EV operations without any grid interaction.
- **V2G & same prices (V2G-SP)**
  This simulation builds on this by enabling V2G, while maintaining equal time-varying electricity prices across stations. This will highlight the revenue potential of V2G services in a uniform price environment.
- **Smart charging & location-dependent prices (SC-LDP)**
  This simulation examines the impact of location-dependent (LDP) and time-varying electricity prices across charging stations, without V2G. This allows us to observe how price differences alone affect overall revenue, with no grid services provided by the EVs.
- **V2G & location-dependent prices (V2G-LDP)**
  This simulation introduces both V2G services and location-dependent time-varying electricity prices across stations, providing a comprehensive view of how both factors—V2G and price variation—work together to maximize revenue for the CSO.

See Table 5.1 for a summary of the simulations.

Simulation	TV Electricity Prices	LDP Electricity Prices	V2G
SC-SP	Yes	No	Disabled
V2G-SP	Yes	No	Enabled
SC-LDP	Yes	Yes	Disabled
V2G-LDP	Yes	Yes	Enabled

Table 5.1: Overview of the simulations.

By comparing the results from these simulations, we can better understand how V2G, location-dependent time-varying electricity prices, peak reduction and seasonal variation influence the overall profitability of shared EV systems.

The data used in the simulations varies depending on the specific case study. The model was tested using three distinct case studies: *Case Study: Summer* (see Section 5.1), *Case Study: Summer + Peak Reduction* (see Section 5.2) and *Case Study: Winter* (see Section 5.3).

5.1. Case Study: Summer

This case study explores model behavior during the summer months, characterized by relatively low station load demand due to minimal heating and lighting requirements, coupled with high PV generation driven by abundant sunlight.

An overview of the data used in *Case Study: Summer* is shown in Table 5.2. Station load demand (P^{LD}) and PV generation (P^{PV}) data are elaborated in Section 5.1.1 and electricity price (C^P) data is elaborated upon in Section 5.1.2.

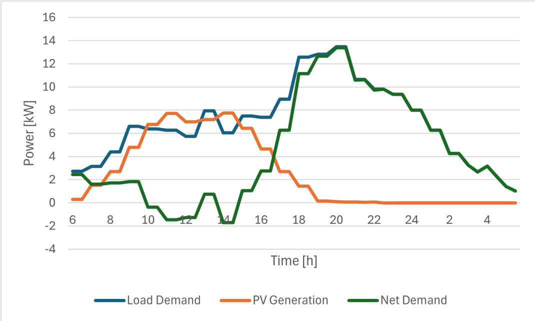
				Electricity Price	
		Load Demand	PV Generation	SP	LDP
Station	**1**	**+100%**	Normal	Normal	Normal
	2	Normal	Normal	Normal	**+200%**
	3	Normal	**-50%**	Normal	**+100%**
	4	Normal	**+100%**	Normal	**0.6**
	5	Normal	**0**	Normal	**-20%**

Table 5.2: Overview of station load demand (P^{LD}), PV generation (P^{PV}) and electricity price (C^P) for all stations.

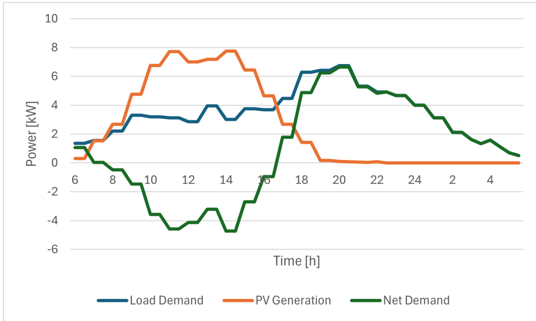
5.1.1. Station Load and PV Data

The stations have the same location-dependent time-varying load demand and PV generation profiles. Station 2 (see Fig. 5.1b) is considered to have a 'normal' load demand and PV generation profile. The other stations have profiles that are scaled versions of these profiles:

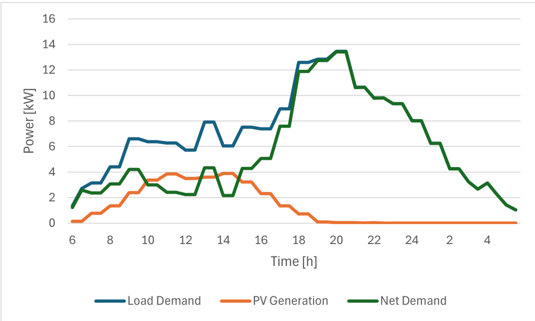
- Station 1 has twice as much load and the same amount of PV generation (see Fig 5.1a);
- Station 3 has the same amount of load but half as much PV generation (see Fig 5.1c);
- Station 4 has the same amount of load but twice as much PV generation (see Fig 5.1d);
- Station 5 has the same amount of load but no PV generation (see Fig 5.1e).



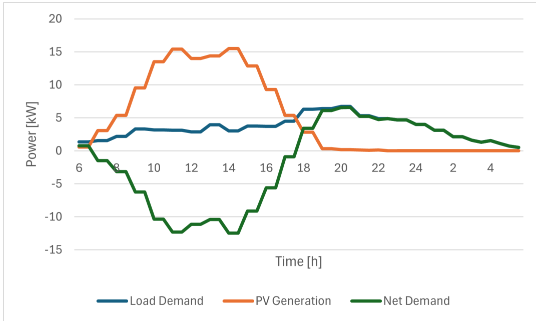
(a) Station 1 power profiles.



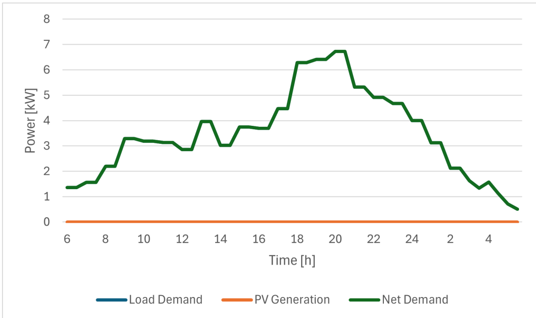
(b) Station 2 power profiles.



(c) Station 3 power profiles.



(d) Station 4 power profiles.



(e) Station 5 power profiles.

Figure 5.1: Load demand (P^{LD}), PV generation (P^{PV}) and net demand (P^{net}) profiles for all stations throughout the day.

5.1.2. Electricity Price

Electricity prices differ per simulation.

Same electricity prices

For *SC-CP* and *V2G-SP*, all stations have the same time-varying electricity price profile as shown by Figure 5.2. The price profile is based on real day-ahead electricity price data from the ENTSO-E Transparency Platform [39]. The electricity price has a minimum of 0.42 €/kWh at t = 19-20 (15:00-16:00) and a maximum of 0.87 €/kWh at t = 29-30 (20:00-21:00).

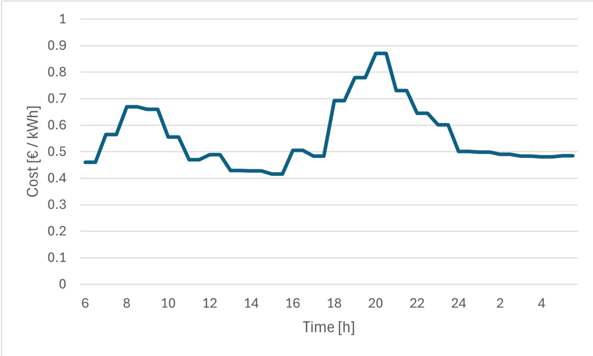


Figure 5.2: Electricity prices for all stations throughout the day.

Location-dependent electricity prices
For *SC-LDP* and *V2G-LDP*, station load demand and PV generation profiles remain identical to those of *SC-CP* and *V2G-SP* (see Figure 5.1). However, unlike for *SC-CP* and *V2G-SP*, electricity prices are now location-dependent and time-varying, meaning that each station now has a distinct time-varying electricity price. Station 1 is assigned a 'normal' price profile (see Fig 5.2), with prices reaching a minimum of 0.42 €/kWh at t = 19-20 (15:00-16:00) and peaking at 0.87 €/kWh during t = 29-30 (20:00-21:00).

The other stations have price profiles that are scaled versions of the price profile of Station 1 or have a fixed electricity price.

- At Station 2 electricity is sold at +200% the price at Station 1;
- At Station 3 electricity is sold at +100% the price at Station 1;
- At Station 4 electricity prices are fixed at 0,6 €/kWh;
- At Station 5 electricity is sold at -20% the price at Station 1.

5.2. Case Study: Summer + Peak Reduction

This case study examines the model's behavior during the summer months with active peak-reduction methods enabled. This case study focuses exclusively on the *V2G-SP* simulation.

For station load demand (P^{LD}), PV generation (P^{PV}), and electricity prices (C^{P}) the same data as in *Case Study: Summer* is used (see Section 5.1.1 and 5.1.2).

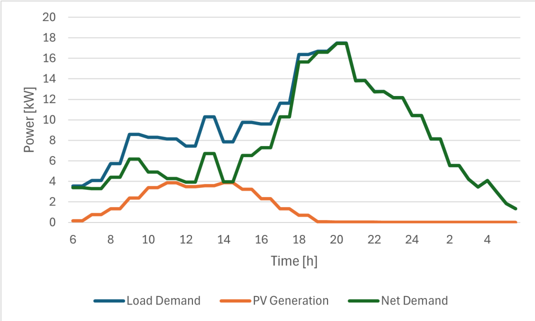
5.3. Case Study: Winter

This case study examines model behavior during the winter months, marked by elevated station load demand driven by significant heating and lighting needs, alongside reduced PV generation due to limited sunlight. This case study focuses exclusively on the *V2G-SP* simulation.

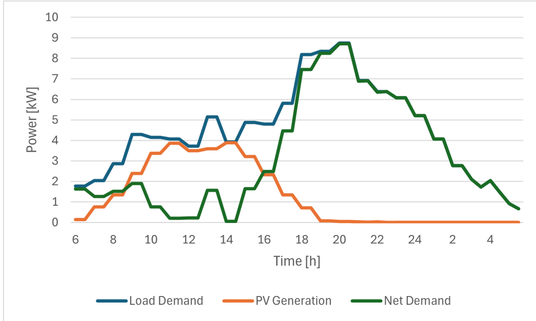
Station load demand (P^{LD}) and PV generation (P^{PV}) data are elaborated in Section 5.3.1 and electricity price (C^{P}) data is elaborated upon in Section 5.3.2.

5.3.1. Station Load and PV Data

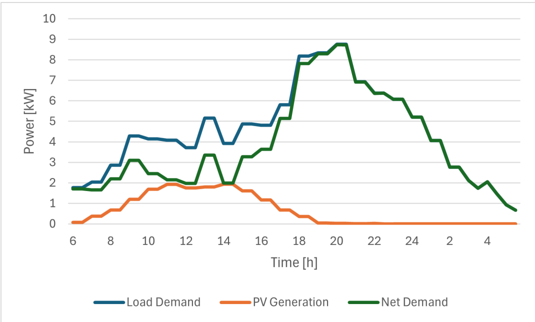
In *Case Study: Winter*, the same power profiles are used as in *Case Study: Summer* (see Section 5.1.1). However, station load demand has increased by 30% due to higher energy requirements for heating and lighting during winter. Additionally, PV generation has decreased by 50% because of reduced sunlight.



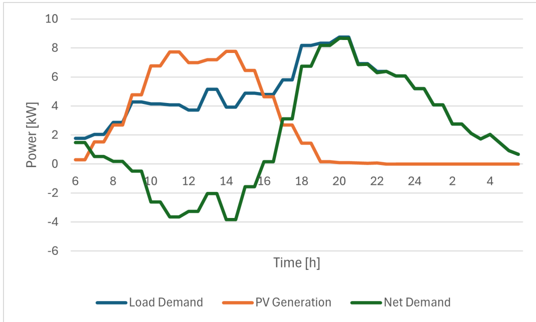
(a) Station 1 power profiles.



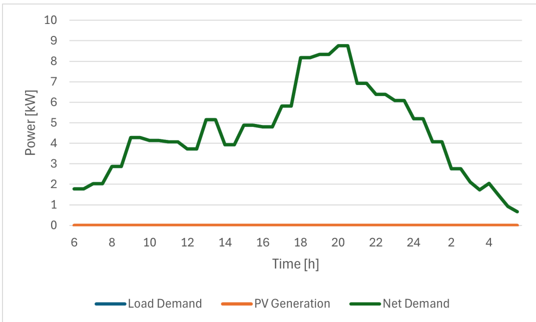
(b) Station 2 power profiles.



(c) Station 3 power profiles.



(d) Station 4 power profiles.



(e) Station 5 power profiles.

Figure 5.3: Load demand (P^{LD}), PV generation (P^{PV}) and net demand (P^{net}) profiles for all stations throughout the day.

5.3.2. Electricity Price

All stations share the same time-varying electricity price profile, as shown in Figure 5.2. This price profile is derived from real day-ahead electricity price data provided by the ENTSO-E Transparency Platform [39]. The electricity price ranges from a minimum of 0.24 €/kWh at t = 42 (02:30-03:00) to a maximum of 1.18 €/kWh at t = 26 (18:30-19:00).

In comparison to the electricity prices in *Case Study: Summer SC-SP* (see Section 5.1.2), the average, maximum, and minimum electricity prices have all increased. This rise is primarily driven by higher demand in the winter, which typically results in elevated prices. However, during the night, electricity prices tend to decrease due to the abundance of wind power generation.

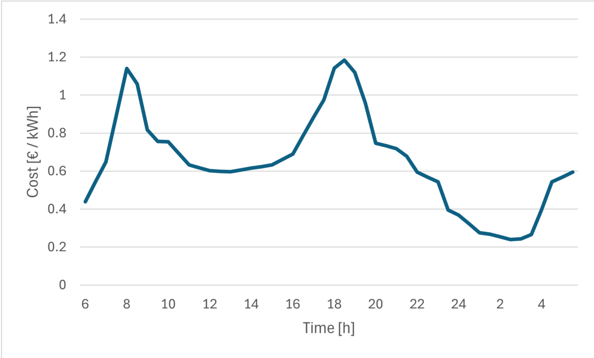


Figure 5.4: Electricity prices for all stations throughout the day.

6

Results Case Study: Summer

This chapter presents the results from *Case Study: Summer*. The results of simulations *SC-SP*, *V2G-SP*, *SC-LDP*, and *V2G-LDP* are presented and discussed in Sections 6.1, 6.2, 6.3, and 6.4, respectively.

The results of *V2G-SP* and *SC-LDP* are compared to those of *SC-SP* and the results of *V2G-LDP* are compared to those of *V2G-SP* and *SC-LDP*. *V2G-SP* highlights the impact of V2G in a system with uniform time-varying electricity prices, while *SC-LDP* demonstrates the effects of location-dependent time-varying electricity prices in a system where V2G is disabled. Lastly, *V2G-LDP* demonstrates the impact of location-dependent time-varying electricity prices in a system with integrated V2G.

6.1. Smart charging & same prices

All results of *SC-SP* are plotted in Appendix 11.1.1.

Objective Values
As illustrated in Table 6.1, Driving Revenue constitutes the largest share of total revenue. With 315 out of 324 drives successfully completed, 97.2% of driving demand is fulfilled (see Tables 6.2 and 6.3a). In contrast, Energy Sold Revenue contributes only a small portion (1.14%) of total revenue because V2G is disabled. Energy is sold infrequently, occurring only when P^{PV} exceeds P^{LD} and selling directly to the grid is more profitable than charging vehicles.

Driving and Relocation
Table 6.3a and Figure 6.2 illustrate the fulfilled driving demand, showing that most drives occur between Station 4 and Stations 2 or 3, in both directions. This pattern corresponds to the input driving demand (see Figure 4.2), which predominantly consists of drives between the residential areas (Stations 2 and 3) and the city center (Station 4).

The remaining fulfilled drives consist primarily of work-to-home and home-to-work trips, as well as inter-business area meetings and lunch trips.

Table 6.3b reveals that the majority of relocations occur from Station 1 to Station 3, to and from Station 4, and from Station 5 to Station 2. These relocation patterns are also visualized in Figure 6.3.

The high volume of relocations from Station 1 to Station 3 is driven by the substantial demand for home-to-work trips at Station 3. To meet this demand, cars used for trips from Station 1 to Station 3 are frequently relocated back to Station 1 in the subsequent round to continue fulfilling similar trips (see Figure 6.3a). A similar pattern explains the significant relocations from Station 5 to Station 2, as shown by Figure 6.3e.

The large number of relocations to and from Station 4 is attributed to its role as the city center, which remains a popular destination throughout the day.

Power and Energy
Table 6.2 shows that Station 3 purchases two to three times more energy than the other stations. This

is due to a significant peak in charging power occurring between 3 and 5 AM, as shown in Figure 6.4c. The peak is driven by Station 3's role as a large residential area. By the end of the day, 14 out of 24 vehicles are located at Station 3 due to the OED. Since electricity prices are relatively low during these hours, vehicles are charged, resulting in the peak station charging power.

Station 4 sells the most energy, as shown by Table 6.2 and the largest amount of negative P^{grid} in Figure 6.4d compared to other stations. This is because the PV generation of Station 4 is twice as large as that of the other stations, making Station 4 responsible for the peak selling power.

A closer look at Figure 6.4 reveals several other significant power peaks in the plots:

- For the same reason, Station 2 experiences a similar peak between 3 and 5 AM (see Figure 6.4b) as Station 3. This is because Station 2 is a small residential area where 8 out of 24 vehicles are parked due to the OED (see Figure 6.1).
- Station 4 has a peak at 5 AM, which is caused by high driving demand to and from Station 4 in the preceding hours, leaving vehicles with no earlier opportunity to charge. Vehicles that remain at Station 4 attempt to charge as much as possible before the cost of electricity rises starting from 18 PM.
- Stations 1 and 5 show peaks between 2 and 4 AM. These peaks occur because driving and relocation demand is minimal during these hours, and electricity prices are low.

It is worth noting that the model strategically schedules vehicle charging during periods of low electricity prices, as illustrated in Figure 6.4.

Driving Revenue	€ 2,859.30
Relocation Costs	€ 360.00
Energy Sold Revenue	€ 33.08
Energy Bought Costs	€ 616.68
Profit	€ 1,915.70

Table 6.1: *SC-SP* objective values.

	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
Station	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	157.42	0.64	4.41	13.38	8:30:00 PM	2.12	22.20	2:00:00 PM	6.56	23.26	3:00:00 PM	0.03	1.27	12:30:00 PM
2	178.30	18.04	0.93	6.65	8:30:00 PM	5.75	59.20	4:30:00 AM	7.43	60.33	4:30:00 AM	0.75	4.74	2:00:00 PM
3	446.34	0.00	5.66	13.42	8:30:00 PM	12.94	97.74	4:30:00 AM	18.60	100.00	4:00:00 AM	0.00	0.00	6:00:00 AM
4	172.32	63.98	-1.62	6.56	8:30:00 PM	6.14	50.07	5:30:00 PM	7.18	49.16	5:30:00 PM	2.67	12.49	2:00:00 PM
5	221.69	0.00	3.48	6.73	8:00:00 PM	5.75	66.00	3:00:00 PM	9.24	69.75	3:00:00 PM	0.00	0.00	6:30:00 AM
Sum	1176.06	82.66												
Fulfilled Driving Demand	97.2%													

Table 6.2: *SC-SP* KPIs.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	12	13	18	51
2	14	0	0	28	10	52
3	19	0	0	47	16	82
4	10	30	45	0	6	91
5	18	4	7	10	0	39
	61	42	64	98	50	**315**

(a) *SC-SP* driving routes.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	0	27	0	0	27
2	0	0	0	14	2	16
3	0	0	0	16	4	20
4	17	8	9	0	3	37
5	0	18	2	0	0	20
	17	26	38	30	9	**120**

(b) *SC-SP* relocation routes.

Table 6.3: All driving and relocation routes in *SC-SP*.

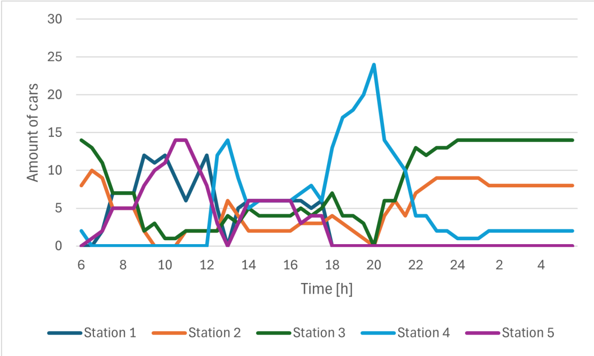
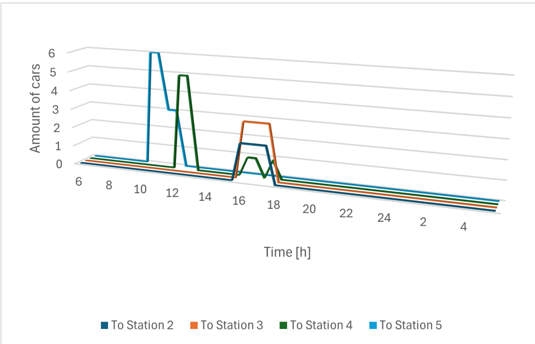
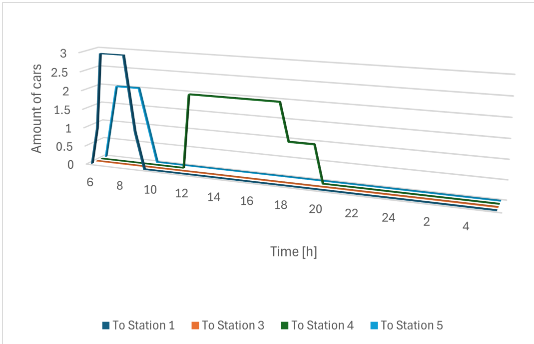


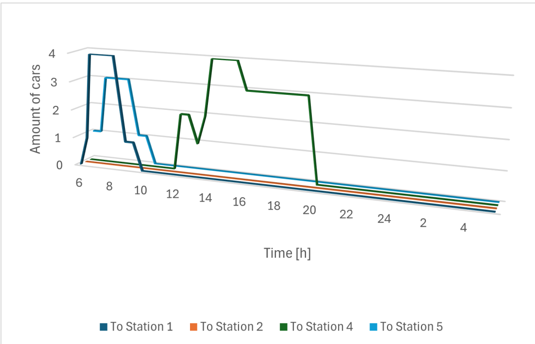
Figure 6.1: *SC-SP* amount of cars throughout the day.



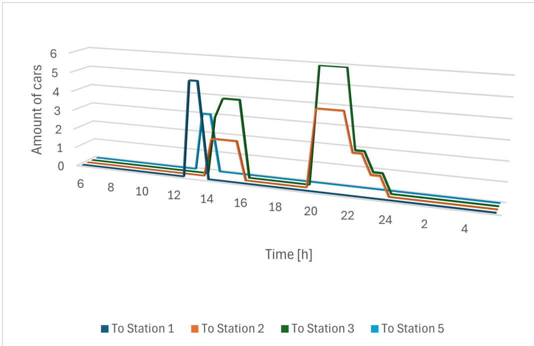
(a) Drives from Station 1.



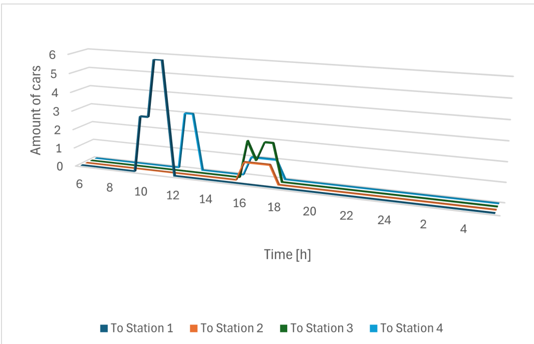
(b) Drives from Station 2.



(c) Drives from Station 3.

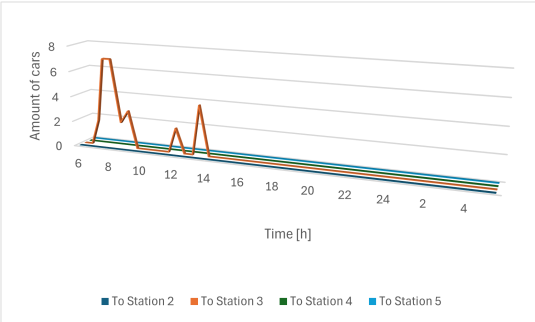


(d) Drives from Station 4.

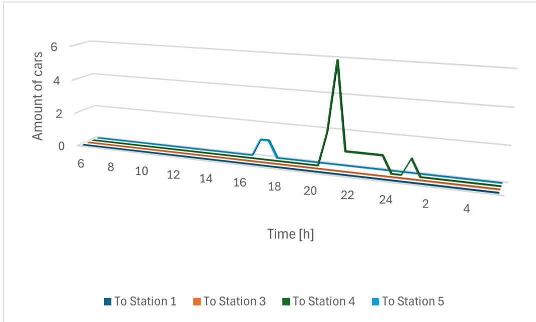


(e) Drives from Station 5.

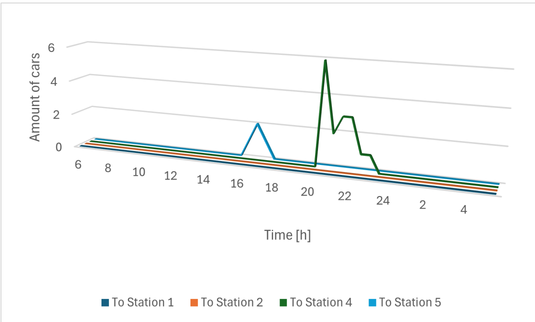
Figure 6.2: Drives from all stations in *V2G-LDP*.



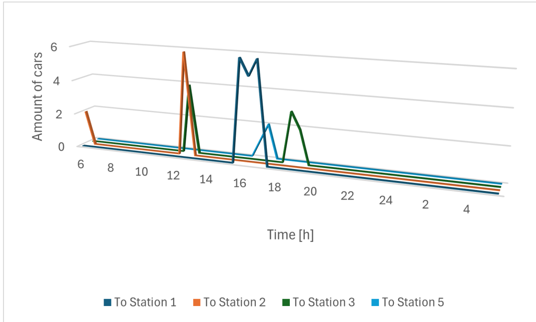
(a) Relocations from Station 1.



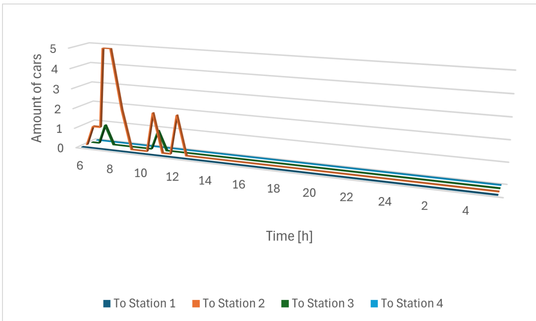
(b) Relocations from Station 2.



(c) Relocations from Station 3.

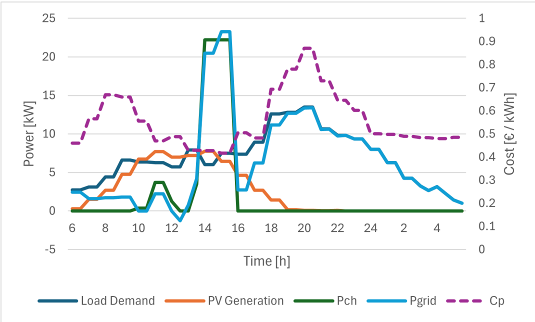


(d) Relocations from Station 4.

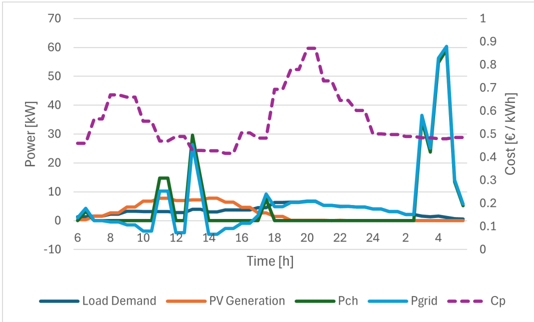


(e) Relocations from Station 5.

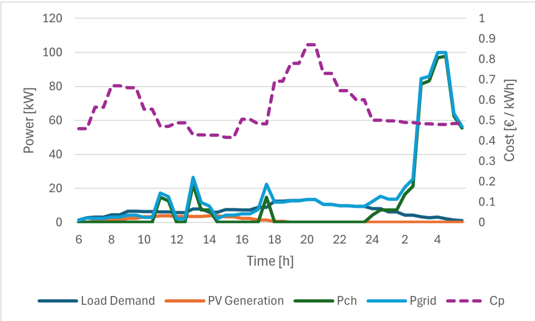
Figure 6.3: Relocations from all stations in *SC-SP*.



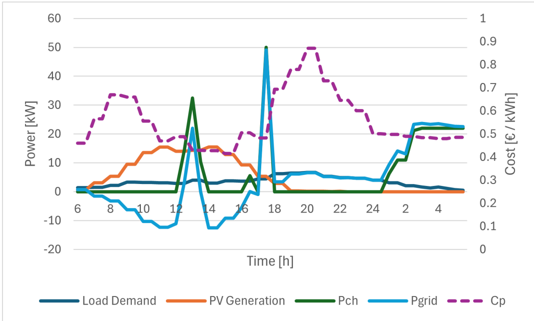
(a) Power profiles for Station 1.



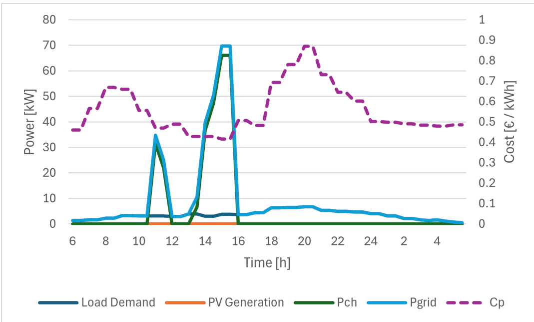
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 6.4: P^{LD}, P^{PV}, P^{ch}, P^{grid} and C^{P} for all stations in *SC-SP*.

6.2. V2G & same prices

All results from *V2G-SP* are presented in Appendix 11.2.

Objective Values

Compared to *SC-SP*, overall profit has increased by 2.25%, as shown in Table 6.4. While the increase is modest, it is not unexpected. This growth is primarily driven by a significant rise in Energy Sold Revenue, which has increased by 371.5% following the introduction of V2G (see Table 6.5). The impact of V2G activity is evident in the greater occurrence of negative P^{EV} values across all stations in Figure 6.5. However, Energy Bought Costs have also risen, as vehicles are charged more frequently to maintain higher energy levels in anticipation of discharging back to the grid during periods of elevated electricity prices.

Driving and Relocation

A comparison of the drives and relocations from *V2G-SP* (see Figures 11.2 and 11.3) with those from *SC-SP* reveals negligible differences in movement patterns. Consequently, both Driving Revenue and Relocation Costs remain largely unchanged.

Since driving generates more revenue in this scenario than selling energy, it is unsurprising that the number of fulfilled drives has remained consistent with *SC-SP*.

The minimal changes in relocations can be attributed to the apparent lack of benefit in adjusting relocation patterns following the integration of V2G.

Power and Energy
In addition to charging during times of low electricity prices — a behavior already observed in *SC-SP* — vehicles in *V2G-SP* now discharge during periods of relatively high prices. This behavior is particularly noticeable when comparing the power profiles of Stations 2 and 3, and even more so for Stations 5 and 4.

In *SC-SP*, Stations 3 and 5 sold little to no energy due to minimal or no PV generation. However, in *V2G-SP*, these stations sell energy during periods of peak electricity prices (see Figures 6.5c and 6.5e). Station 4 remains the largest contributor to energy sales. As shown in Figure 6.5d, it capitalizes on peak electricity prices, low vehicle demand (see Figure 4.2a) and having a relatively high share of vehicles available for discharging.

Regarding peak demand, there are notable changes at Stations 2, 3, and 4. The charging peaks at Stations 2 and 3 have increased in duration, and Station 2 now exhibits a discharging peak between t=19 and t=21.

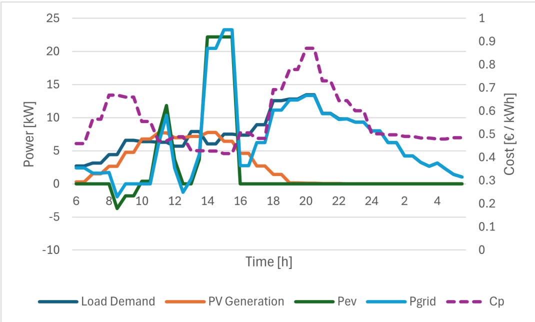
Driving Revenue	€	2,886.30
Relocation Costs	€	363.00
Energy Sold Revenue	€	155.96
Energy Bought Costs	€	720.60
Profit	€	1,958.66

Table 6.4: *V2G-SP* objective values.

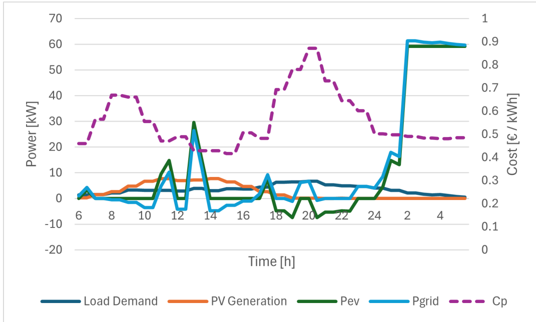
Station	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	161.97	1.62	4.41	13.38	8:30:00 PM	2.27	22.20	2:00:00 PM	6.75	23.26	3:00:00 PM	0.07	1.97	8:30:00 AM
2	311.54	18.99	0.93	6.65	8:30:00 PM	11.26	59.20	2:00:00 AM	12.98	61.33	2:00:00 AM	0.79	4.74	2:00:00 PM
3	541.89	9.11	5.66	13.42	8:30:00 PM	16.54	98.98	5:30:00 AM	22.58	100.00	2:00:00 AM	0.38	9.45	7:00:00 PM
4	189.12	232.70	-1.62	6.56	8:30:00 PM	-0.19	-106.55	8:00:00 PM	7.88	57.46	5:30:00 PM	9.70	100.00	7:00:00 PM
5	236.89	10.15	3.48	6.73	8:00:00 PM	5.96	66.00	2:30:00 PM	9.87	69.75	3:00:00 PM	0.42	20.31	8:30:00 AM
Sum	1441.42	272.58												

Fulfilled Driving Demand	98.1%

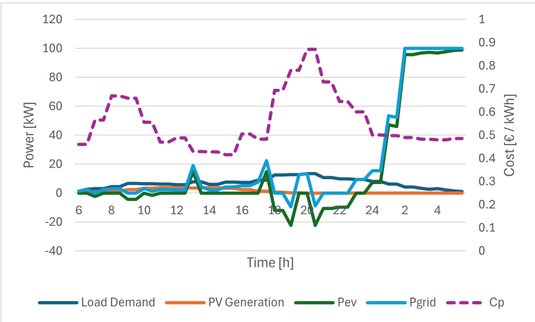
Table 6.5: *V2G-SP* KPIs.



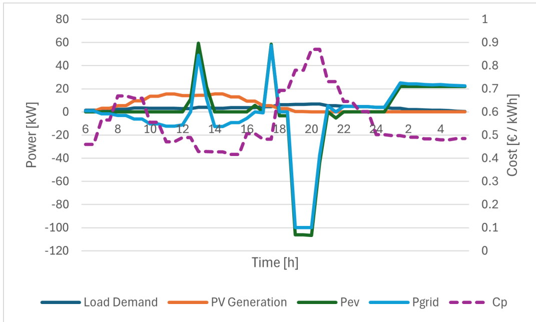
(a) Power profiles for Station 1.



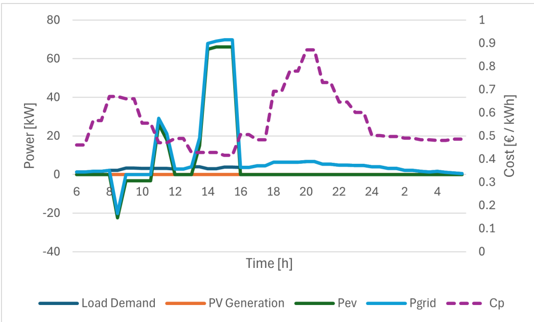
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 6.5: P^{LD}, P^{PV}, P^{EV}, P^{grid} and C^{P} for all stations in *V2G-SP*.

6.3. Smart charging & location-dependent prices

All results from *SC-LDP* are presented in Appendix 11.3.

Objective Values

As shown in Table 6.6, total profit decreased by 9.24% compared to *SC-SP*. This decline is primarily due to increase in Relocation Costs (+15%) and Energy Bought Costs (+28%).

Driving and Relocation

The change in Driving Revenue remains negligible, as only one single drive has changed (see Figure 11.10). Driving revenue continues to be the primary source of income, making it essential to fulfill as much driving demand as possible, just as in *SC-SP*.

Relocation Costs grew because the variation in electricity prices across stations led the model to move vehicles more frequently to optimize charging and vehicle availability (see Figure 6.8 and 11.11).

Power and Energy

Energy Bought Costs increased due to higher average electricity prices compared to *SC-SP*.

The amount of energy sold remains unchanged from *SC-SP*, as station load demand and PV generation have not varied. Consequently, the instances where P^{PV} exceeds P^{LD} remain the same. Energy Sold

Revenue has increased slightly, driven by a marginal rise in average electricity prices, resulting in a proportional increase in revenue.

For Stations 1, 2, and 3, the power profiles show minimal variation compared to *SC-SP*. However, Station 4 displays a significant and broad spike in charging power between t=18 and t=20, as illustrated in Figure 6.7c. This spike occurs because, during this period, a large number of vehicles are located at Station 4 (see Figure 6.6), and driving demand is low (see Figure 4.2a). Furthermore, unlike in *SC-SP*, where electricity prices at Station 4 peak after t = 18, *SC-LDP* features stable and relatively low electricity rates for Station 4, making it more cost-effective to charge during this window.

At the end of the day, most vehicles remain parked at Stations 2 and 3 due to the OED. In *SC-SP*, all vehicles were positioned by t = 1 and charged at Stations 2 and 3. However, in *SC-LDP*, the dynamics change significantly with electricity prices at Station 2 tripling and at Station 3 doubling. As a result, a notable portion of vehicles now charge at Station 5, where electricity costs are 20% lower than the "normal" rate. These vehicles are subsequently relocated to Stations 2 and 3 later in the day, as illustrated in Figures 11.11e and 6.7d.

There are some notable changes in peak demand. The peak buying power has shifted from Station 3 to Station 5, as Station 5 now offers the lowest electricity prices (see Table 6.7). Previously, the charging load at the end of the day was distributed across Stations 2, 3, and 4 (see Figure 6.7a, 6.7b and 6.7c), but it is now primarily handled by Station 5 (see Figure 6.7d).

Regarding peak selling power, no changes have been observed. This is because the instances and durations when P^{PV} exceeds P^{LD} remain unchanged.

Driving Revenue	€ 2,885.90
Relocation Costs	€ 414.00
Energy Sold Revenue	€ 56.84
Energy Bought Costs	€ 789.83

Profit	€ 1,738.91

Table 6.6: *SC-LDP* objective values.

	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
Station 1	153.48	0.64	4.41	13.38	8:30:00 PM	1.96	22.20	3:00:00 PM	6.39	23.26	3:00:00 PM	0.03	1.27	12:30:00 PM
2	74.52	25.85	0.93	6.65	8:30:00 PM	1.10	34.15	4:30:00 AM	3.11	35.28	4:30:00 AM	1.08	4.74	2:00:00 PM
3	178.84	0.00	5.66	13.42	8:30:00 PM	1.79	30.98	4:30:00 AM	7.45	33.25	4:30:00 AM	0.00	0.00	6:00:00 AM
4	204.26	55.56	-1.62	6.56	8:30:00 PM	7.82	69.11	6:30:00 PM	8.51	72.55	6:30:00 PM	2.32	12.31	11:00:00 AM
5	597.38	0.00	3.48	6.73	8:00:00 PM	21.41	94.32	11:00:00 AM	24.89	97.45	11:00:00 AM	0.00	0.00	6:30:00 AM

Sum	1208.48	82.04

Fulfilled Driving Demand	98.1%

Table 6.7: *SC-LDP* KPIs.

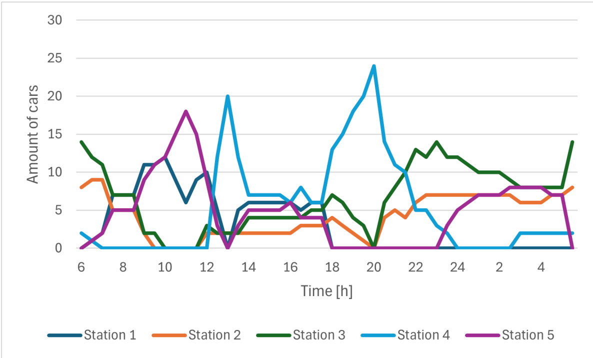
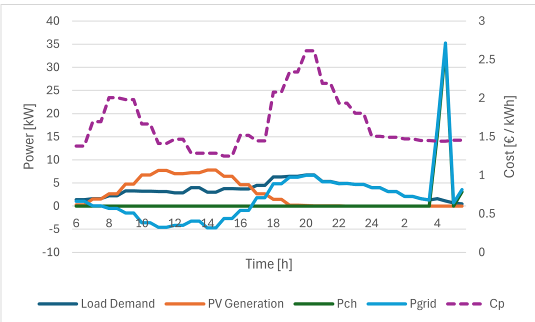


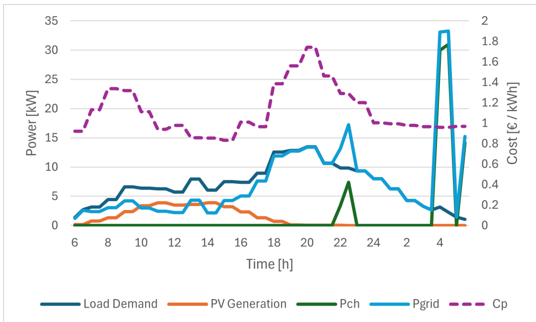
Figure 6.6: *SC-LDP* amount of cars throughout the day.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	1	27	0	0	28
2	0	0	0	14	4	18
3	0	0	0	16	10	26
4	16	7	9	0	5	37
5	0	20	9	0	0	29
	16	28	45	30	19	**138**

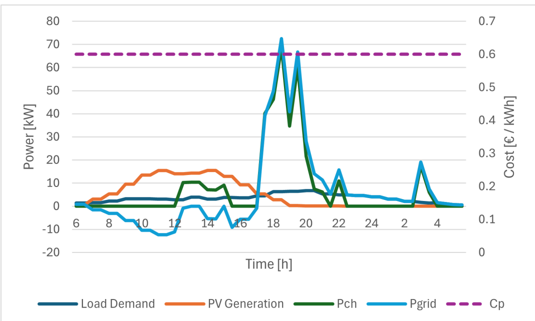
Table 6.8: *SC-LDP* relocation routes.



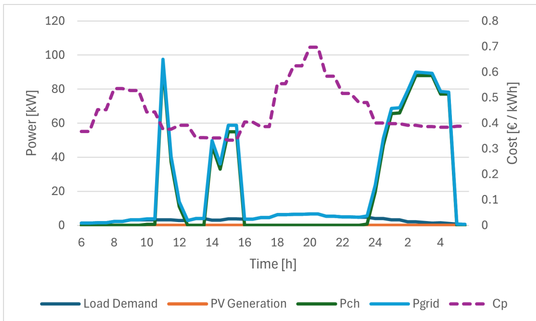
(a) Power profiles for Station 2.



(b) Power profiles for Station 3.



(c) Power profiles for Station 4.



(d) Power profiles for Station 5.

Figure 6.7: P^{LD}, P^{PV}, P^{ch}, P^{grid} and C^P for station 4 and 5 in *SC-LDP*.

6.4. V2G & location-dependent prices

All results from *V2G-LDP* are presented in Appendix 11.4.

6.4.1. Same prices versus location-dependent prices with V2G enabled

Objective Values

Compared to *V2G-SP*, which also included V2G functionality, the impact of location-dependent time-varying electricity prices is significant. As shown in Table 6.9, Driving Revenue remains the largest contributor to total revenue. However, Energy Sold Revenue has become a major revenue stream, now accounting for approximately 36.8% of the total revenue.

Relocation Costs, Energy Bought, and Energy Bought Costs have all increased compared to *V2G-SP* (see Table 6.10).

Driving and Relocation

It is important to note that Driving Revenue has decreased compared to *V2G-SP* (see Table 6.9). This decline is attributed to a reduction in the number of drives (see Figure 6.11a) and, consequently, a lower percentage of fulfilled demand (see Table 6.10). This shift occurs because driving is no longer always the most profitable option. In some scenarios, keeping vehicles stationary to perform V2G generates higher revenue than fulfilling driving demand.

The increase in Relocation Costs is modest compared to the rise in Energy Sold Revenue. This is because the model opts to perform more relocations to optimize not only charging and vehicle availability but also discharging. However, the primary change lies in the selection of different relocation routes compared to *V2G-SP* (see Figure 11.15. In earlier simulations, relocations were primarily driven by the need to meet driving demand. In this case, however, relocations for V2G play a significant role, as variations in time-varying electricity prices across stations enhance the revenue potential from V2G operations.

Supporting the increased use of V2G requires vehicles to charge more often, resulting in more bought energy and associated costs.

Power and Energy

The power profile of Station 1 shows minimal change, as its electricity price remains unchanged from *V2G-SP*. In contrast, the power profiles of the other stations have shifted significantly, as shown in Figure 6.9.

As depicted in Table 6.10, Station 2 accounts for 90% of all energy sold. This is due to its electricity price being the highest, at +200%, prompting the model to prioritize vehicle discharging at this location to maximize revenue.This behavior is clearly reflected in Figure 6.9a, which shows a high volume of negative P^{EV}. While Station 2 experienced relatively low vehicle traffic in previous simulations, Figure 6.8 demonstrates that it is now heavily frequented for discharging operations.

Station 3's power profile, compared to *V2G-SP*, shows slightly more discharging and significantly less charging toward the end of the day (see Figure 6.9b). This change is attributed to its electricity price, which has doubled relative to the ”normal” rate.

Stations 4 and 5 collectively account for 87% of all energy purchased. This outcome aligns with their electricity prices, which remain constant at the ”normal” average and -20%, respectively. The high P^{EV} values for these stations, shown in Figures 6.9c and 6.9d, reflect this charging activity.

The model continues to optimize charging and discharging by leveraging periods of low electricity prices for charging and high electricity prices for discharging (see Figure 6.9). Additionally, it strategically relocates vehicles to stations with low electricity prices for charging and to stations with high prices for discharging, as illustrated in Figure 6.8.

Peak demand has increased significantly in *V2G-LDP*. The frequency of peaks reaching grid capacity P^{GC} has risen. Power peaks have worsened at Stations 2, 4, and 5, driven by their respective electricity price variations: +200%, 'normal' average, and -20%. The model seeks to capitalize on these pricing differences, amplifying peak demand at these stations.

6.4.2. Smart charging versus V2G with location-dependent prices

In *SC-LDP* (see Section 6.3), overall profit decreased compared to *SC-SP* due to the implementation of location-dependent time-varying electricity prices. These prices had a higher average than the uniform time-varying pricing scheme used in *SC-SP*, leading to increased operational costs.

Objective Values

The integration of V2G in *V2G-LDP*, however, results in a significant improvement, with overall profit increasing by 28.43% compared to *SC-LDP*. In this simulation, Energy Sold Revenue becomes a major revenue stream, accounting for 36.8% of total revenue, while Driving Revenue contributes the remaining 63.2%.

Driving and Relocation

Driving revenue decreased by 17.5%. Again, this decline is attributed to a strategic shift: fulfilling driving demand is no longer always the most profitable approach. In certain scenarios, selling energy yields higher revenue, leading to a reduction in the amount of fulfilled driving. This trend is illustrated in Figure 6.10 and Figure 6.11a.

An aspect that might seem unusual is the decrease in relocation costs compared to *SC-LDP*. This is, once again, linked to the fact that fulfilling driving demand is not always the top priority. The model appears to optimize profits by keeping cars more stationary on average to facilitate discharging. Relocation decisions are therefore more influenced by charging and discharging requirements rather than solely focusing on meeting driving demand.

Power and Energy

The improvement in Energy Sold Revenue is attributed to the model's ability to optimize not only charging but also discharging, leveraging the pronounced differences in electricity prices. This is evident from the substantial amount of energy sold at Station 2 (see Table 6.10 and Figure 6.9a) and the high volume of energy purchased at Station 5 (see Table 6.10 and Figure 6.9d).

Again, peak demand has increased significantly in *V2G-LDP*. Compared to *SC-LDP*, power peaks have worsened at Stations 2, 4, and 5, driven by their respective electricity price variations.

Driving Revenue	€ 2,379.70
Relocation Costs	€ 381.00
Energy Sold Revenue	€ 1,383.60
Energy Bought Costs	€ 1,149.00

Profit	€ 2,233.30

Table 6.9: *V2G-LDP* objective values.

	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Peak [t]	Average [kW]	Peak [kW]	Peak [t]	Average [kW]	Peak [kW]	Peak [t]	Average [kW]	Peak [kW]	Peak [t]
Station 1	152.23	1.56	4.41	13.38	8:30:00 PM	1.86	18.50	12:00:00 PM	6.34	17.23	12:00:00 PM	0.06	1.45	11:00:00 AM
Station 2	21.86	845.65	0.93	6.65	8:30:00 PM	-35.26	-103.60	4:00:00 AM	0.91	11.80	4:00:00 AM	35.24	98.33	9:00:01 PM
Station 3	113.59	27.77	5.66	13.42	8:30:00 PM	-2.08	43.27	5:30:00 AM	4.73	44.30	5:30:00 AM	1.16	13.17	7:00:00 AM
Station 4	695.13	67.23	-1.62	6.56	8:30:00 PM	27.78	98.38	3:00:00 AM	28.96	100.00	7:30:00 PM	2.80	12.49	2:00:00 PM
Station 5	1195.13	0.00	3.48	6.73	8:00:00 PM	46.31	98.87	4:30:00 AM	49.80	100.00	11:30:00 PM	0.00	0.00	6:30:00 AM

Sum	2177.94	942.21

Fulfilled Driving Demand	80.2%

Table 6.10: *V2G-LDP* KPIs.

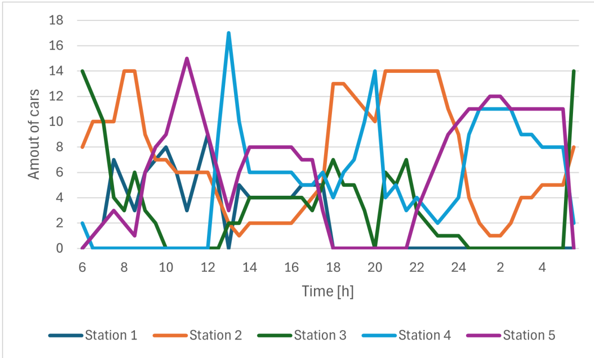


Figure 6.8: *V2G-LDP* amount of cars throughout the day.

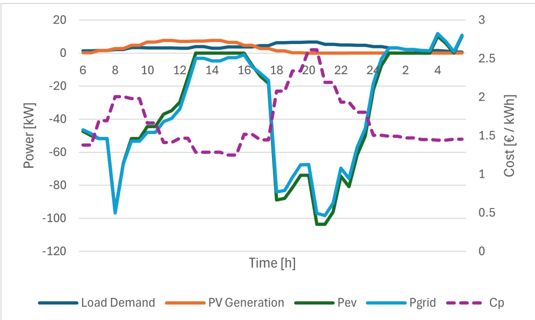
Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	11	9	18	46
2	12	0	0	25	4	41
3	15	0	0	44	13	72
4	9	16	35	0	6	66
5	18	4	6	7	0	35
	54	28	52	85	41	**260**

(a) *V2G-LDP* driving routes.

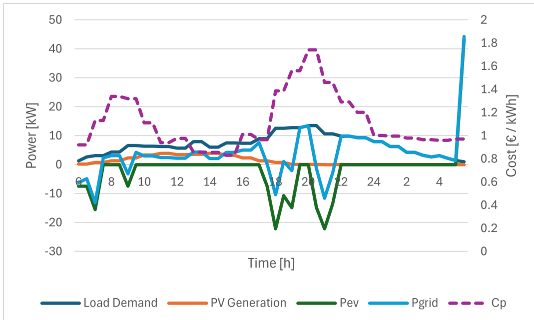
Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	16	0	0	24
2	1	0	0	12	5	18
3	0	0	0	12	9	21
4	15	14	13	0	1	43
5	0	9	12	0	0	21
	16	31	41	24	15	**127**

(b) *V2G-LDP* relocation routes.

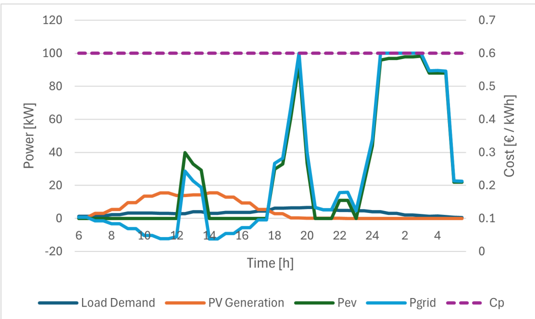
Table 6.11: All driving and relocation routes in *V2G-LDP*.



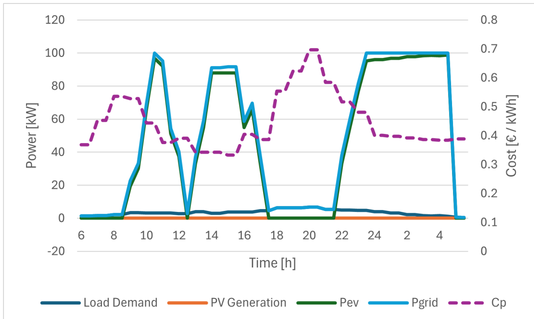
(a) Power profiles for Station 2.



(b) Power profiles for Station 3.



(c) Power profiles for Station 4.



(d) Power profiles for Station 5.

Figure 6.9: P^{LD}, P^{PV}, P^{EV}, P^{grid} and C^P for all stations in *V2G-LDP*.

7

Results Case Study: Summer + Peak Reduction

This chapter presents the results from *Case Study: Summer + Peak Reduction*, in which peak reduction is enabled by Equations 3.37, 3.38, 3.39 and 3.40 (see Section 3.1.3). In this study, only *V2G-SP* was conducted, using the data outlined in Section 5.1. The results are compared with Simulation 1 and 2 from *Case Study: Summer* (refer to Section 11.2).

7.1. V2G & same prices

All results from *V2G-SP* of *Case Study: Summer + Peak Reduction* are presented in Appendix 12.1.

For this simulation, P^{limit} is set at the average value of P^{grid} in *V2G-SP* of *Case Study: Summer* (9.74 kW). To begin, the penalty (C^P) was initially set at the average electricity cost (0.56 €/kWh). However, through trial and error, this penalty was found to be excessively high, resulting in no V2G activity and even less energy sold compared to Simulation 1. A revised penalty value of 0.2 €/kWh proved to be effective, as it maintained the profitability of V2G while substantially reducing charging peaks seen previously in *V2G-SP* of *Case Study: Summer* without peak reduction.

Objective Values
Compared to *V2G-SP* of *Case Study: Summer*, the overall profit has decreased slightly by 0.44% (see Table 7.1). Considering the MIP gap, this error is negligible. Driving revenue and relocation costs have remained largely unchanged. However, energy sold revenue and energy bought costs have decreased by 46% and 15%, respectively. This reduction reflects a strategy of minimizing charging, which in turn limits opportunities for discharging.

As shown in Table 7.2, P^{limit} has been exceeded at every station. The amount by which the peak limit is exceeded is penalized, and results in the Peak Exceedance Penalty.

Driving and Relocation
Since driving remains the primary source of revenue, there is minimal to no change in driving activity and relocation movements compared to *V2G-SP* of *Case Study: Summer*.

Power and Energy
A comparison of the power profiles (see Figure 7.1) with those from *V2G-SP* of *Case Study: Summer* reveals that the (dis)charging peaks remain in the same locations. However, the charging peaks exhibit significantly reduced amplitudes, most of the large peaks have nearly halved. While discharging activity has generally decreased, it is still present.

Driving Revenue	€	2,861.70
Relocation Costs	€	363.00
Energy Sold Revenue	€	84.64
Energy Bought Costs	€	611.28
Peak Exceedance Penalty	€	22.03

Profit	€	1,950.03

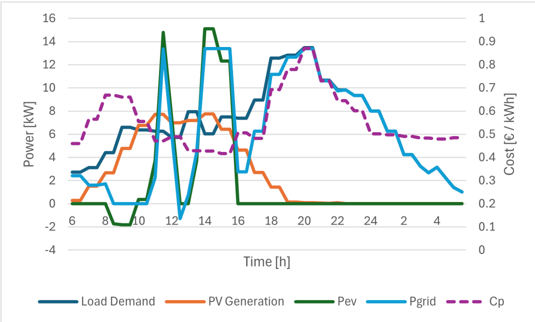
Table 7.1: *V2G-SP* objective values.

	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
Station	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	146.47	0.64	4.41	13.38	8:30:00 PM	1.66	15.10	2:00:00 PM	6.10	13.38	2:00:00 PM	0.03	1.27	12:30:00 PM
2	271.64	20.18	0.93	6.65	8:30:00 PM	9.55	33.64	5:30:00 AM	11.32	34.15	12:00:01 AM	0.84	15.55	8:30:00 PM
3	429.78	1.53	5.66	13.42	8:30:00 PM	15.64	59.78	5:30:00 AM	17.91	60.29	12:00:01 AM	0.06	0.86	2:00:00 PM
4	165.34	132.70	-1.62	6.56	8:30:00 PM	2.98	-106.55	8:00:00 PM	6.89	20.58	1:00:00 PM	5.53	100.00	8:00:00 PM
5	187.68	0.00	3.48	6.73	8:00:00 PM	4.34	27.59	12:00:00 PM	7.82	30.45	11:00:00 AM	0.00	0.00	6:30:00 AM

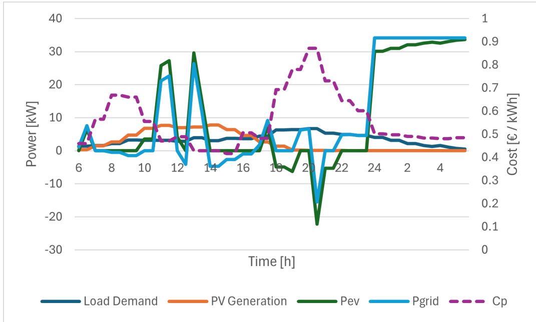
Sum	1200.90	155.04

Fulfilled Driving Demand	97.2%

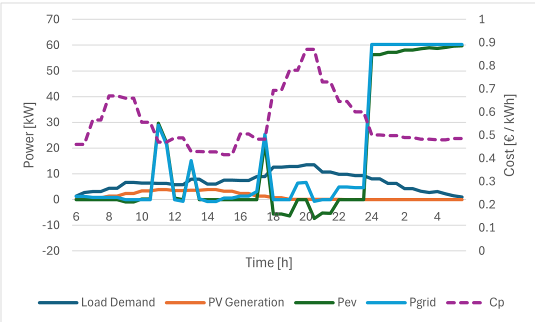
Table 7.2: *V2G-SP* KPIs.



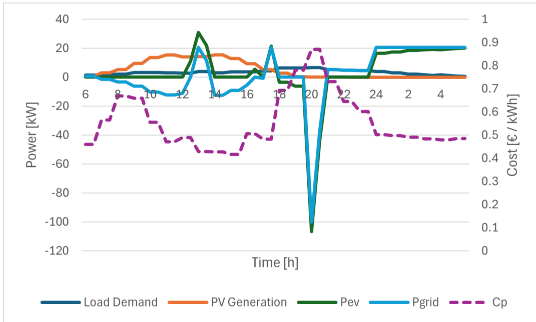
(a) Power profiles for Station 1.



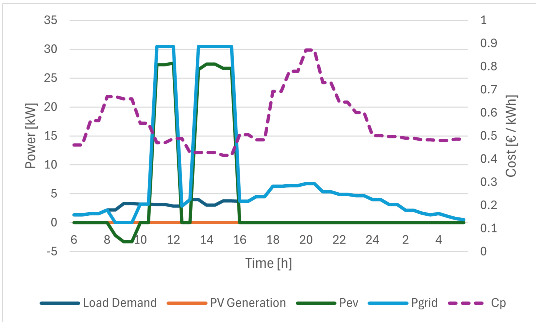
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 7.1: P^{LD}, P^{PV}, P^{EV}, P^{grid} and C^{P} for all stations in *V2G-SP*.

8

Results Case Study: Winter

This chapter presents the results from *Case Study: Winter*. In this study, only *V2G-SP* was conducted, using the data outlined in Section 5.3. The results are compared with *V2G-SP* from the *Case Study: Summer* (refer to Section 11.2).

8.1. V2G & same prices

All results from *V2G-SP* are presented in Appendix 13.1.

Objective Values
Compared to *V2G-SP* of *Case Study: Summer*, overall profit has increased very slightly by 1.95% (see Table 8.1). This is due to the increase in Energy Sold Revenue, which increased by 84.5%. Driving Revenue decreased as less driving demand is fulfilled (see Table 8.2). Relocation Costs decreased as less relocation moves have been performed (see Table 8.2) and Energy Bought Costs increased.

Driving and Relocation
Since the driving demand is identical for both simulations and neither involves location-dependent time-varying electricity prices, the relocation and driving moves remain largely identical.

Power and Energy
When comparing the power profiles, significant changes can be observed. These differences can be attributed to the uniform but time-varying electricity prices, which differ from those observed in *Case Study: Summer*.

In *Case Study: Summer* (see Section 5.1), vehicles were predominantly charged between 12:00–16:00 and 02:00–06:00, coinciding with the lowest electricity prices during those periods. However, in this case, midday charging peaks have disappeared, shifting instead to later in the day. To accommodate this redistribution, the evening charging peaks now exhibit a longer duration.

Regarding discharging, the timing of the peaks remains consistent with those observed in *Case Study: Summer* during peak electricity demand periods. However, the intensity of discharging peaks has increased due to higher electricity prices, making V2G operations more profitable. Additionally, the sharper spikes in electricity prices have led to more centralized discharging patterns.

Driving Revenue	€	2,830.40
Relocation Costs	€	348.00
Energy Sold Revenue	€	287.75
Energy Bought Costs	€	773.17

Profit	€	1,996.98

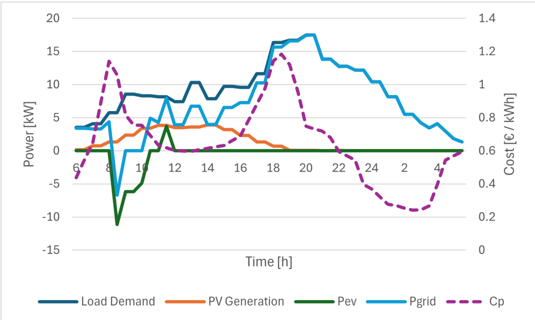
Table 8.1: *V2G-SP* objective values.

Station	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	177.70	3.35	7.78	17.46	8:30:00 PM	-0.51	-11.10	8:30:00 AM	7.40	17.46	8:30:00 PM	0.14	6.71	8:30:00 AM
2	474.10	12.50	3.25	8.71	8:30:00 PM	15.98	59.20	12:00:01 AM	19.75	64.40	12:00:01 AM	0.52	14.73	6:00:00 PM
3	786.74	62.70	3.89	8.73	8:30:00 PM	26.28	99.07	5:00:00 AM	32.78	100.00	11:30:00 PM	2.61	51.38	6:00:00 PM
4	179.36	230.35	1.98	8.67	8:30:00 PM	-4.10	-108.18	7:30:00 PM	7.47	33.08	11:00:00 PM	9.60	100.00	6:30:00 PM
5	97.95	26.07	4.53	8.75	8:00:00 PM	-1.53	-55.00	8:30:00 AM	4.08	8.75	8:00:00 PM	1.09	52.13	8:30:00 AM

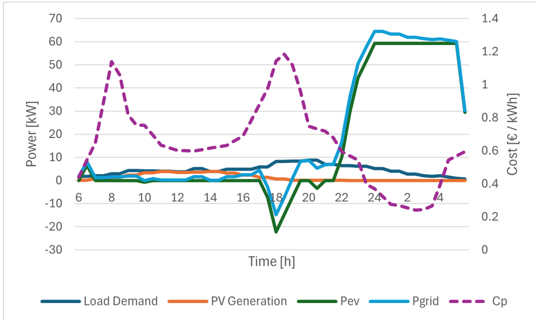
Sum	1715.85	334.97

Fulfilled Driving Demand	96.3%

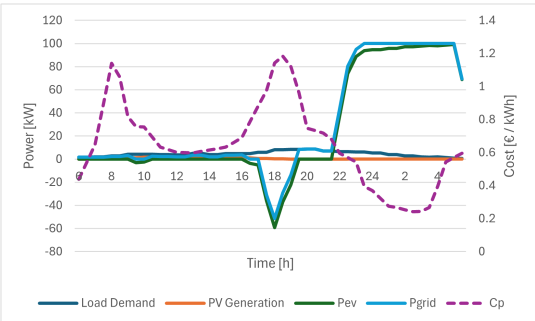
Table 8.2: *V2G-SP* KPIs.



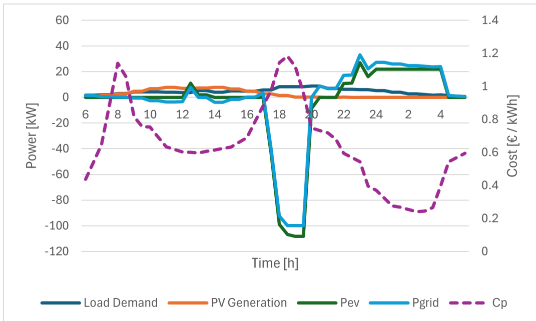
(a) Power profiles for Station 2.



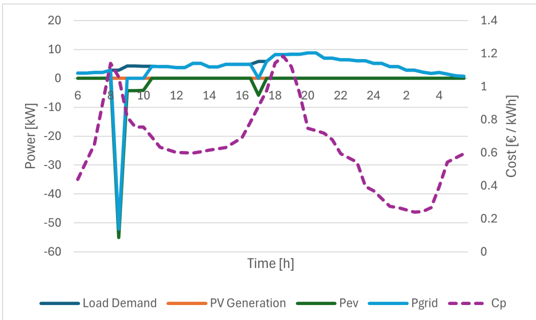
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 8.1: P^{LD}, P^{PV}, P^{ch}, P^{grid} and C^{P} for all stations in *V2G-SP*.

9

Discussion

The primary aim of this study is to evaluate the operational and economic impacts of enabling V2G functionality in a station-based EVSS. Specifically, scenarios have been studied with and without V2G, with and without location-dependent time-varying electricity prices, and with and without peak reducing measures. The key metrics for comparison were Driving Revenue, Relocation Costs, Energy Sold Revenue, Energy Bought Costs, and Peak Exceedance Penalty.

All simulations are compared to each other to illustrate key differences. For *Case Study: Summer*, *V2G-SP* versus *SC-SP* and *V2G-LDP* versus *SC-LDP* highlight the impact of V2G in a system with uniform time-varying electricity prices and location-dependent time-varying electricity prices respectively (see Section 6.2 and Section 6.4.2). *SC-LDP* versus *SC-SP* and *V2G-LDP* versus *V2G-SP* demonstrate the effects of location-dependent time-varying electricity prices in a system where V2G is disabled (see Section 6.3 and Section 6.4.1).

A comparison between *V2G-SP* of *Case Study: Summer* (see Section 6.2) and *Case Study: Summer (Peak Reduction)* (see Section 7.1) highlights the significant impact of peak reduction on the system's charging behavior.

V2G enhances profitability of EVSS
As demonstrated in the results presented in Section 6.2 and 6.4.2, integrating V2G into the ECSS enhances overall profitability. This improvement arises from the model's ability to capitalize on high electricity prices during periods of low driving demand, thereby introducing a valuable additional revenue stream.

However, the increase in Energy Sold Revenue observed in Section 6.2 was minimal. This prompts the question of whether integrating V2G into a system with uniform time-varying electricity prices across stations justifies the added model complexity and extended computational time. Furthermore, it is crucial to highlight that V2G operations increase battery cycling, which can accelerate battery degradation. Since the impact of V2G on total profit is relatively negligible, the faster degradation of batteries due to increased cycling could potentially outweigh any minor gains in energy revenue.

Location-dependent electricity prices enhance V2G profitability
As highlighted in the result comparisons in Section 6.4.1 and 6.4.2, the introduction of location-dependent time-varying electricity prices significantly impacts overall system performance and dynamics. These prices amplify the potential benefits of V2G by increasing price variability not only over time but also across locations. This creates stronger incentives to strategically charge during low-cost periods and locations and to sell during high-cost periods and locations, optimizing profitability.

As demonstrated in Section 6.4.1, *V2G-LDP* maximized profits by reducing fulfilled driving demand in favor of using vehicles for discharging, which generates higher revenue. Depending on the objectives of the CSO, a penalty could be introduced into the model to prioritize fulfilling driving demand over V2G operations. While this may result in lower profits, it could enhance customer satisfaction — consistent with the traditional goals of a CSS.

It is important to note that the model used in *Case Study: Summer* did not account for peak reduction. Instead, it focused solely on maximizing profit through V2G optimization, leading to a high frequency of electricity peaks reaching grid capacity P^{GC}, particularly under location-dependent time-varying electricity prices. In reality, this can pose significant challenges, as it may overload certain parts of the electricity grid due to uneven distribution of (dis)charging demand.

Peak reduction reduces charging peaks without significantly affecting revenue
As demonstrated in *V2G-SP* of *Case Study: Summer + Peak Reduction* (see Section 7.1), peak reduction significantly lowers the amplitudes, nearly halving them, with minimal impact on profit. However, determining the optimal buying power limit (P^{limit}) and penalty (C^P) remains a challenging task.

9.1. Contribution

These results are consistent with prior research highlighting the economic benefits of integrating V2G into the EVReP, particularly in leveraging grid support to generate additional revenue from stored energy [9, 6, 4]. This study adds to this by presenting a MILP model that combines V2G with EVReP. In addition, this study demonstrates that location-dependent time-varying electricity prices further enhance the revenue potential from V2G, as opposed to systems with uniform time-varying electricity prices.

9.2. Implications

The findings of this study have several implications for the design of EV-sharing systems. First, enabling V2G clearly enhances revenue potential, particularly in regions with location-dependent time-varying electricity prices. Operators of EV fleets should prioritize V2G integration to capitalize on grid service opportunities. However, the increase in relocation costs suggests that system operators will need to develop more sophisticated vehicle management algorithms to optimize energy pricing and vehicle availability simultaneously. From a policy perspective, the success of V2G integration depends heavily on dynamic electricity pricing structures, suggesting that regulatory bodies should encourage or maintain price variability across regions to incentivize grid participation. Furthermore, energy policies that reward grid contributions from EVs could make such systems even more economically viable.

9.3. Limitations

There are several limitations to this study that should be considered. First, regarding SEVs, the model assumes no battery degradation and that vehicles do not experience breakdowns. It also simplifies driving conditions by assuming cars travel at fixed speeds, directly from point A to point B without detours. In reality, these factors affect vehicle availability and reliability. In terms of driving logistics, the model assumes fixed demand throughout the day, with no accounting for variations in user behavior or potential booking cancellations. In practice, fluctuations in demand and user unpredictability could influence vehicle availability, particularly for V2G services. In terms of cost structure, the relocation model employs a simplified version that may not adequately reflect the complexities of real-world logistics. The relocation dynamics and costs are likely more intricate than what is captured in the study. Overall, the study relies on hypothetical data, limiting the applicability of the results to real-world situations. Finally, the model's solving time is highly influenced by the provided inputs. While incorporating location-dependent time-varying electricity prices and V2G capabilities boosts revenue, it also significantly increases complexity and extends computation time. This trade-off requires careful consideration.

9.4. Research recommendations

Future research should focus on validating the model using comprehensive and temporally consistent real-world data. While the electricity prices and PV generation data in this study are based on real data, the driving demand and station location data were synthesized. Addressing these limitations would improve the model's accuracy and practical applicability. Investigating user behavior and demand variability, such as changes during rush hours or special events, will help refine the model's predictions.

Studying a Model Predictive Control (MPC) approach for this model could enhance its applicability in real-world scenarios. MPC accounts for variability in inputs such as vehicle demand, vehicle availability, and electricity prices, which are subject to change throughout the day. Aiming for a framework that adapts to unknown conditions and evolving information provides a more realistic and practical approach, as real-world systems rarely have full, upfront knowledge of all conditions.

Additionally, studying the impact of V2G on battery degradation and vehicle maintenance is essential, as frequent charging and discharging may affect battery longevity and costs. Incorporating real-world grid constraints, such as congestion and voltage deviations, would provide insights into how ECSS can support grid stability.

Exploring how dynamic pricing and regulatory policies, like time-of-use tariffs or carbon credits, impact the profitability of V2G services is also crucial. Different regions' regulatory frameworks should be compared to assess their influence on the adoption of V2G-enabled CSS. Furthermore, evaluating the effect of fleet size and vehicle composition on operational efficiency and grid interaction could provide insights into optimizing fleet performance. Larger fleets or heterogeneous vehicle types may present unique challenges and opportunities for balancing driving demand and grid support.

Finally, developing advanced relocation algorithms that account for energy pricing and vehicle demand could help operators reduce costs while maximizing V2G revenues.

10 Conclusion

In conclusion, this study presents a novel approach to integrating V2G technology with ECSS to enhance the profitability of transportation services. The results show that V2G can improve financial outcomes by enabling EVs to participate in energy markets, particularly in scenarios where time-varying electricity prices fluctuate across different locations. Additionally, peak load demand can be significantly reduced without substantially impacting overall profit. However, this added complexity increases vehicle relocation costs, highlighting the need for more sophisticated vehicle management strategies.

The integration of V2G not only provides economic benefits but also supports the broader goal of decarbonizing the transport sector by optimizing the use of renewable energy. The findings align with existing literature on the potential of V2G technology but also extend it by demonstrating the importance of location-based price differentiation in enhancing profitability.

Nevertheless, this study has limitations, including simplified assumptions regarding vehicle operation, user behavior, and grid conditions. Future research should address these limitations by incorporating real-world data and developing more advanced and realistic models that account for dynamic pricing, as well as variations in user demand, vehicle availability, and other relevant factors. Additionally, further exploration of policy incentives for V2G participation and the development of more efficient vehicle relocation algorithms could enhance the practical application of these systems.

By combining car-sharing with V2G, this research contributes to the growing body of knowledge on sustainable urban mobility and renewable energy integration, providing a promising direction for future innovation in transportation and energy systems.

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11

Simulation Plots Case Study: Summer

11.1. Smart charging & same prices

11.1.1. Objective and KPIs

Driving Revenue	€	2,859.30
Relocation Costs	€	360.00
Energy Sold Revenue	€	33.08
Energy Bought Costs	€	616.68

Profit	€	1,915.70

Table 11.1: *SC-SP* objective values.

	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
Station	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	157.42	0.64	4.41	13.38	8:30:00 PM	2.12	22.20	2:00:00 PM	6.56	23.26	3:00:00 PM	0.03	1.27	12:30:00 PM
2	178.30	18.04	0.93	6.65	8:30:00 PM	5.75	59.20	4:30:00 AM	7.43	60.33	4:30:00 AM	0.75	4.74	2:00:00 PM
3	446.34	0.00	5.66	13.42	8:30:00 PM	12.94	97.74	4:30:00 AM	18.60	100.00	4:00:00 AM	0.00	0.00	6:00:00 AM
4	172.32	63.98	-1.62	6.56	8:30:00 PM	6.14	50.07	5:30:00 PM	7.18	49.16	5:30:00 PM	2.67	12.49	2:00:00 PM
5	221.69	0.00	3.48	6.73	8:00:00 PM	5.75	66.00	3:00:00 PM	9.24	69.75	3:00:00 PM	0.00	0.00	6:30:00 AM

Sum	1176.06	82.66

Fulfilled Driving Demand	97.2%

Table 11.2: *SC-SP* KPIs.

11.1.2. Driving and Relocating

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	12	13	18	51
2	14	0	0	28	10	52
3	19	0	0	47	16	82
4	10	30	45	0	6	91
5	18	4	7	10	0	39
	61	42	64	98	50	**315**

(a) *SC-SP* driving routes.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	0	27	0	0	27
2	0	0	0	14	2	16
3	0	0	0	16	4	20
4	17	8	9	0	3	37
5	0	18	2	0	0	20
	17	26	38	30	9	**120**

(b) *SC-SP* relocation routes.

Table 11.3: All driving and relocation routes in *SC-SP*.

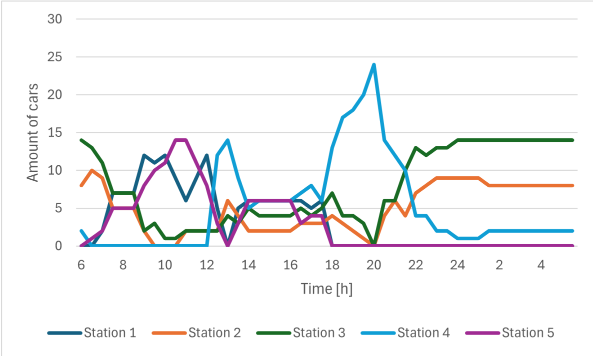
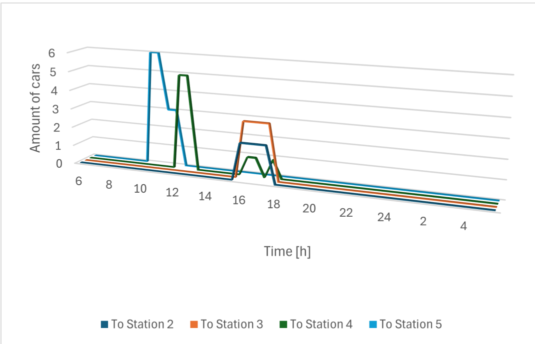
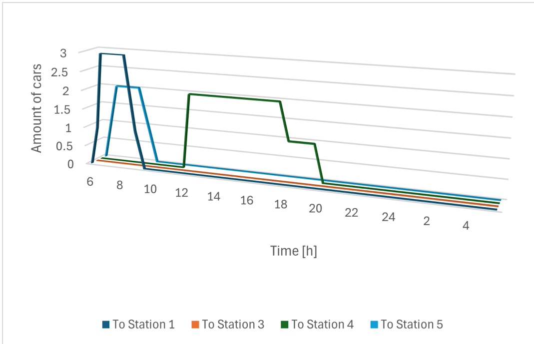


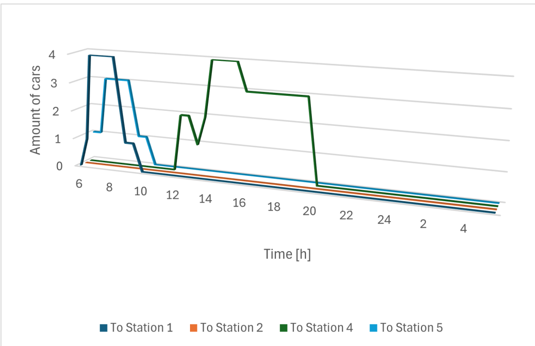
Figure 11.1: *SC-SP* number of cars per station throughout the day.



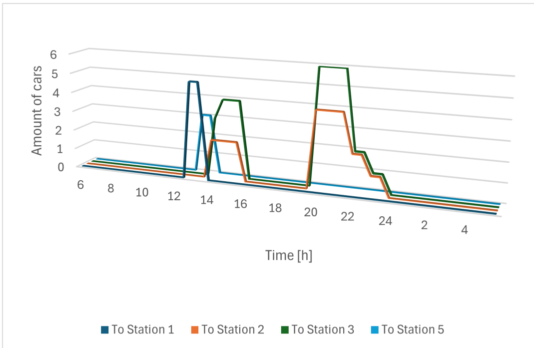
(a) Drives from Station 1.



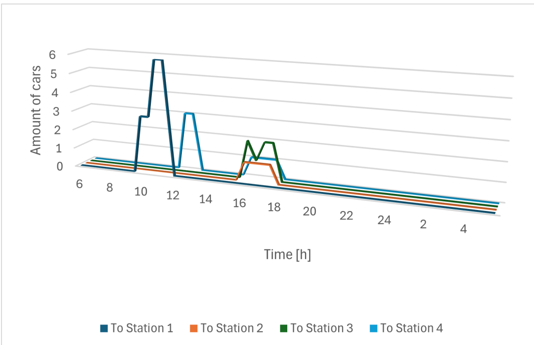
(b) Drives from Station 2.



(c) Drives from Station 3.

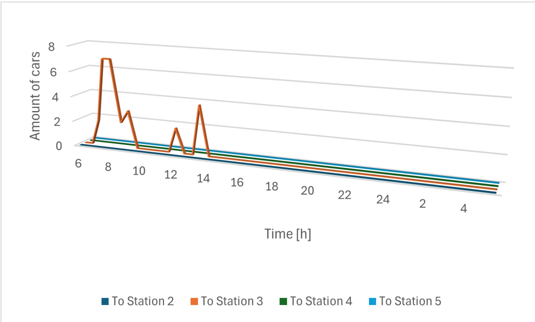


(d) Drives from Station 4.

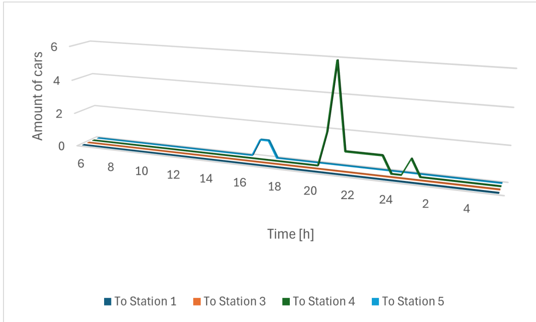


(e) Drives from Station 5.

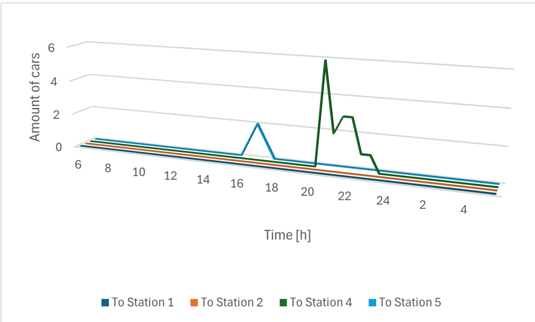
Figure 11.2: Drives from all stations in *SC-SP*.



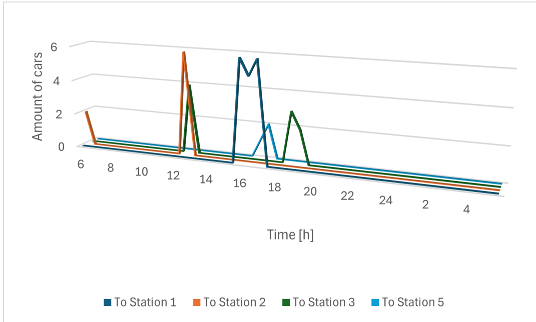
(a) Relocations from Station 1.



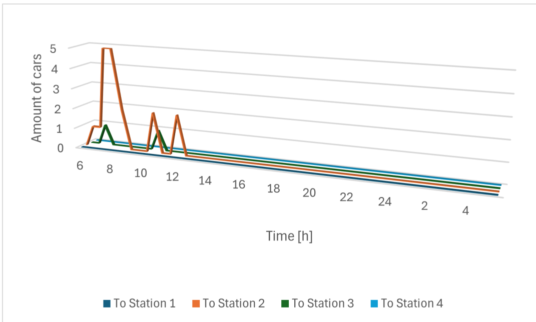
(b) Relocations from Station 2.



(c) Relocations from Station 3.



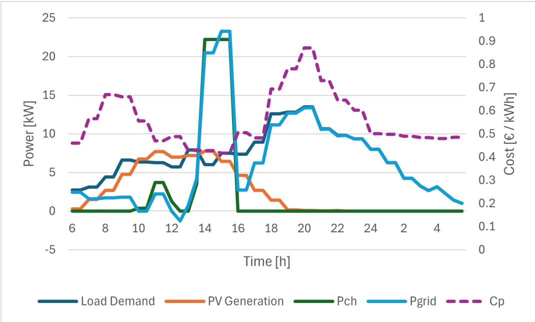
(d) Relocations from Station 4.



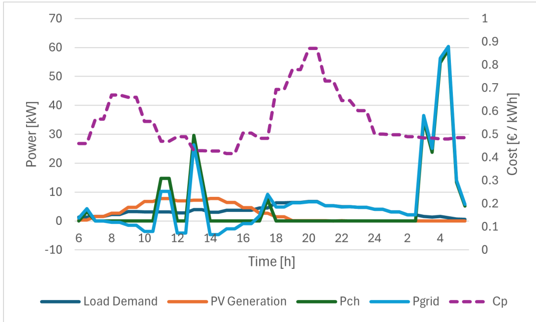
(e) Relocations from Station 5.

Figure 11.3: Relocations from all stations in *SC-SP*.

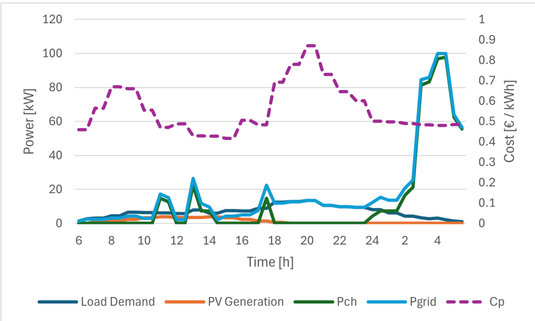
11.1.3. Power Profiles



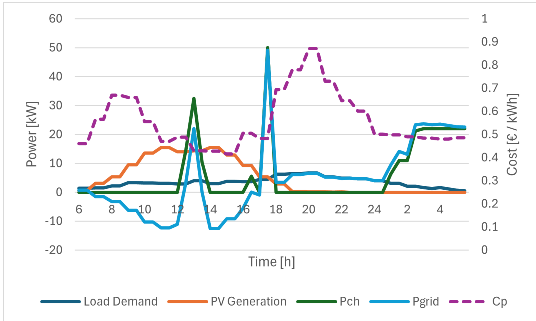
(a) Power profiles for Station 1.



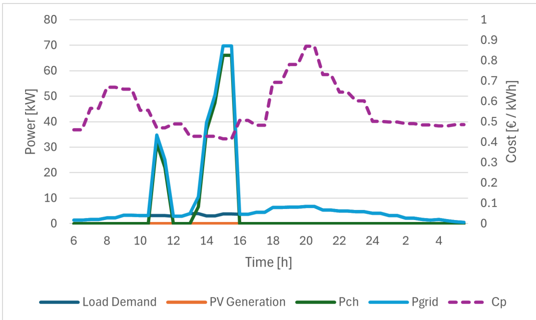
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 11.4: P^{LD}, P^{PV}, P^{ch}, P^{grid} and C^{P} for all stations in *SC-SP*.

11.2. V2G & same prices

11.2.1. Objective and KPIs

Driving Revenue	€ 2,886.30
Relocation Costs	€ 363.00
Energy Sold Revenue	€ 155.96
Energy Bought Costs	€ 720.60

Profit	€ 1,958.66

Table 11.4: *V2G-SP* objective values.

Station	Total Energy Bought [kWh]	Total Energy Sold [kWh]	Station Net Demand Average [kW]	Station Net Demand Peak [kW]	Station Net Demand Time [t]	Charging Power Average [kW]	Charging Power Peak [kW]	Charging Power Time [t]	Buying Power Average [kW]	Buying Power Peak [kW]	Buying Power Time [t]	Selling Power Average [kW]	Selling Power Peak [kW]	Selling Power Time [t]
1	161.97	1.62	4.41	13.38	8:30:00 PM	2.27	22.20	2:00:00 PM	6.75	23.26	3:00:00 PM	0.07	1.97	8:30:00 AM
2	311.54	18.99	0.93	6.65	8:30:00 PM	11.26	59.20	2:00:00 AM	12.98	61.33	2:00:00 AM	0.79	4.74	2:00:00 PM
3	541.89	9.11	5.66	13.42	8:30:00 PM	16.54	98.98	5:30:00 AM	22.58	100.00	2:00:00 AM	0.38	9.45	7:00:00 PM
4	189.12	232.70	-1.62	6.56	8:30:00 PM	-0.19	-106.55	8:00:00 PM	7.88	57.46	5:30:00 PM	9.70	100.00	7:00:00 PM
5	236.89	10.15	3.48	6.73	8:00:00 PM	5.96	66.00	2:30:00 PM	9.87	69.75	3:00:00 PM	0.42	20.31	8:30:00 AM
Sum	1441.42	272.58												

Fulfilled Driving Demand	98.1%

Table 11.5: *V2G-SP* KPIs.

11.2.2. Driving and Relocating

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	12	13	18	51
2	14	0	0	28	10	52
3	20	0	0	48	16	84
4	10	30	46	0	6	92
5	18	4	7	10	0	39
	62	42	65	99	50	**318**

(a) *V2G-SP* driving routes.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	0	28	0	0	28
2	0	0	0	14	2	16
3	0	0	0	16	4	20
4	17	8	9	0	3	37
5	0	18	2	0	0	20
	17	26	39	30	9	**121**

(b) *V2G-SP* relocation routes.

Table 11.6: All driving and relocation routes in *V2G-SP*.

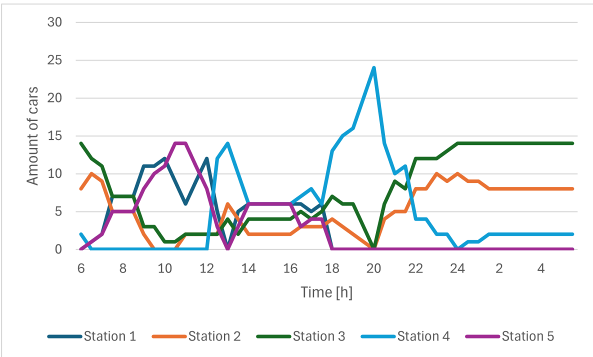
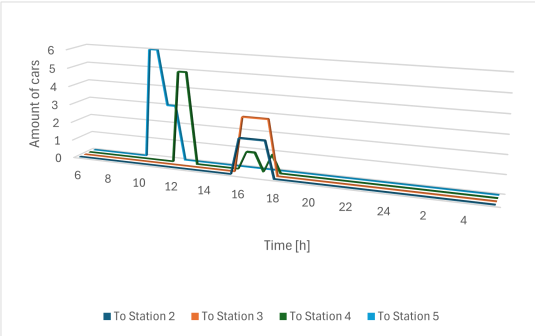
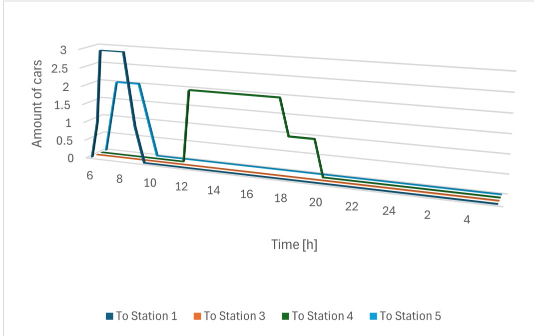


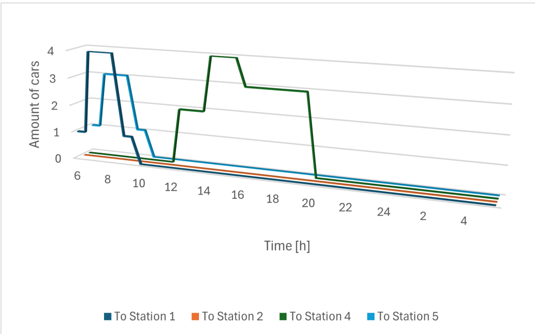
Figure 11.5: *V2G-SP* number of cars per station throughout the day.



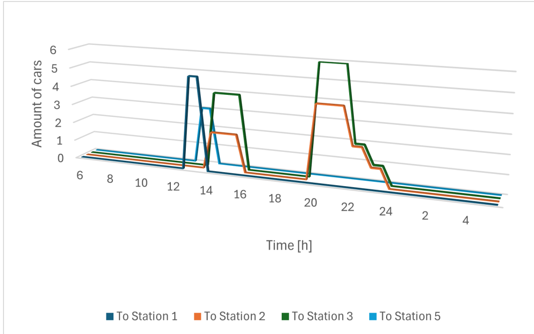
(a) Drives from Station 1.



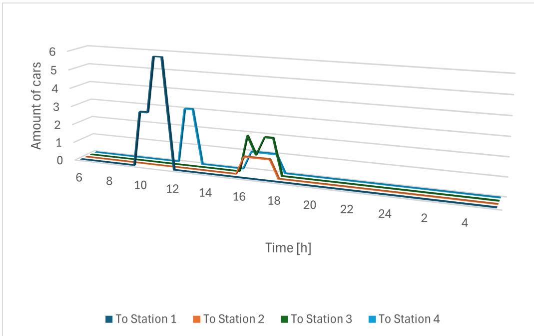
(b) Drives from Station 2.



(c) Drives from Station 3.

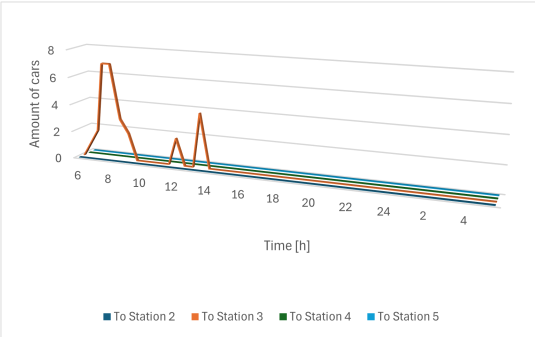


(d) Drives from Station 4.

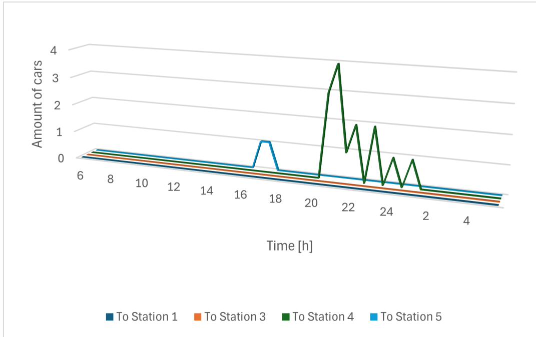


(e) Drives from Station 5.

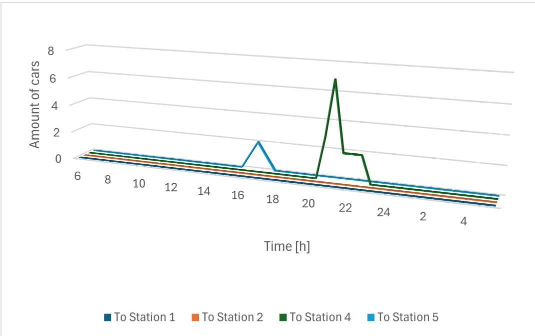
Figure 11.6: Drives from all stations in *V2G-SP*.



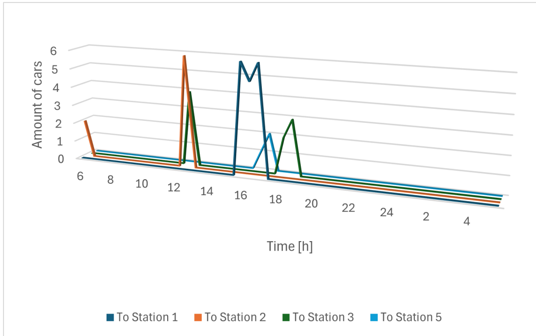
(a) Relocations from Station 1.



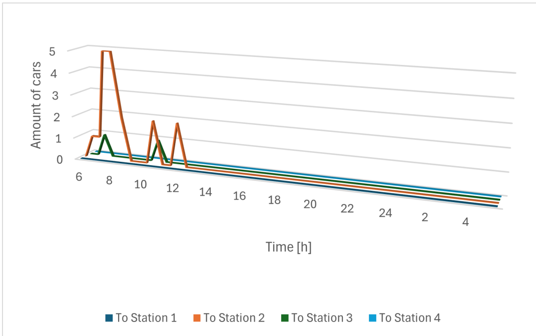
(b) Relocations from Station 2.



(c) Relocations from Station 3.



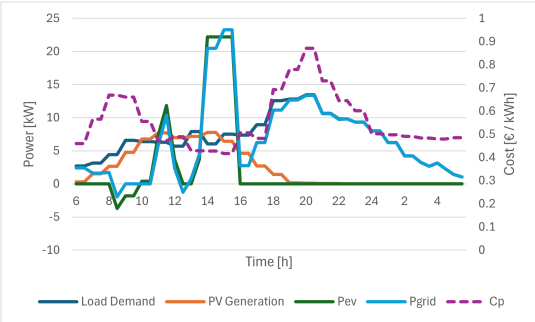
(d) Relocations from Station 4.



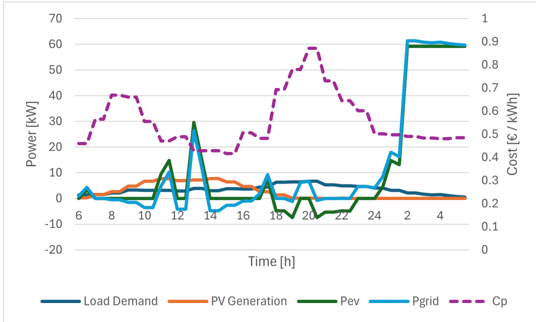
(e) Relocations from Station 5.

Figure 11.7: Relocations from all stations in *V2G-SP*.

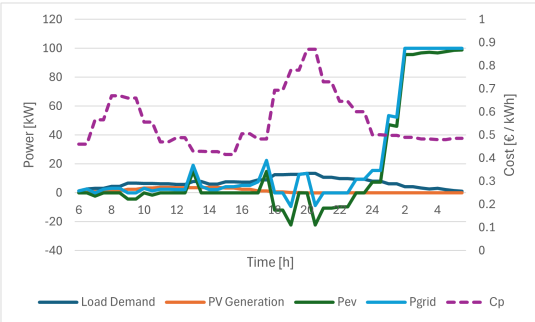
11.2.3. Power Profiles



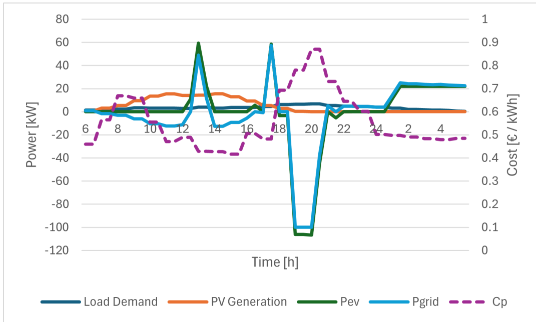
(a) Power profiles for Station 1.



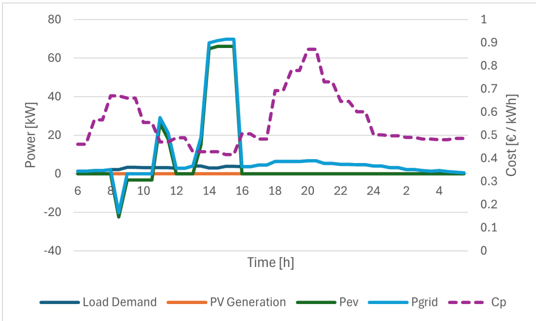
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 11.8: P^{LD}, P^{PV}, P^{EV}, P^{grid} and C^P for all stations in *V2G-SP*.

11.3. Smart charging & location-dependent prices

11.3.1. Objective and KPIs

Driving Revenue	€ 2,885.90
Relocation Costs	€ 414.00
Energy Sold Revenue	€ 56.84
Energy Bought Costs	€ 789.83

Profit	€ 1,738.91

Table 11.7: *SC-LDP* objective values.

Station	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	153.48	0.64	4.41	13.38	8:30:00 PM	1.96	22.20	3:00:00 PM	6.39	23.26	3:00:00 PM	0.03	1.27	12:30:00 PM
2	74.52	25.85	0.93	6.65	8:30:00 PM	1.10	34.15	4:30:00 AM	3.11	35.28	4:30:00 AM	1.08	4.74	2:00:00 PM
3	178.84	0.00	5.66	13.42	8:30:00 PM	1.79	30.98	4:30:00 AM	7.45	33.25	4:30:00 AM	0.00	0.00	6:00:00 AM
4	204.26	55.56	-1.62	6.56	8:30:00 PM	7.82	69.11	6:30:00 PM	8.51	72.55	6:30:00 PM	2.32	12.31	11:00:00 AM
5	597.38	0.00	3.48	6.73	8:00:00 PM	21.41	94.32	11:00:00 AM	24.89	97.45	11:00:00 AM	0.00	0.00	6:30:00 AM
Sum	1208.48	82.04												

Fulfilled Driving Demand	98.1%

Table 11.8: *SC-LDP* KPIs.

11.3.2. Driving and Relocating

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	11	13	18	50
2	14	0	0	28	10	52
3	20	0	0	48	16	84
4	10	30	46	0	6	92
5	18	4	8	10	0	40
	62	42	65	99	50	**318**

(a) *SC-LDP* driving routes.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	1	27	0	0	28
2	0	0	0	14	4	18
3	0	0	0	16	10	26
4	16	7	9	0	5	37
5	0	20	9	0	0	29
	16	28	45	30	19	**138**

(b) *SC-LDP* relocation routes.

Table 11.9: All driving and relocation routes in *SC-LDP*.

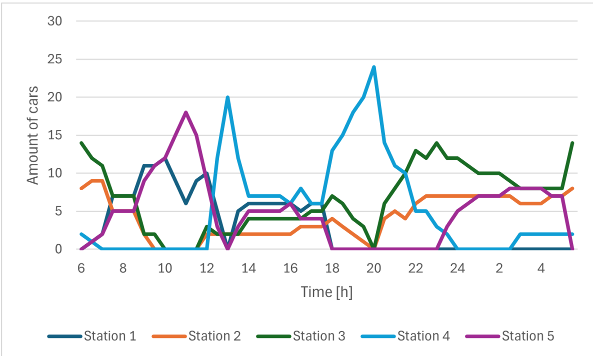
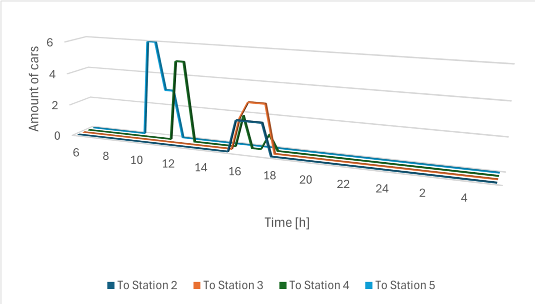
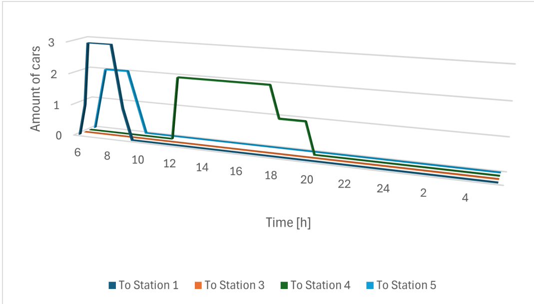


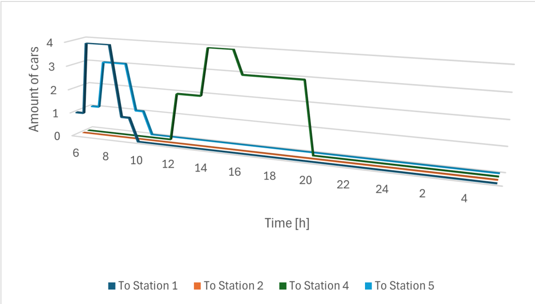
Figure 11.9: *SC-LDP* number of cars per station throughout the day.



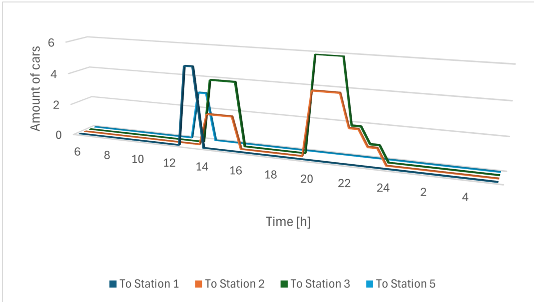
(a) Drives from Station 1.



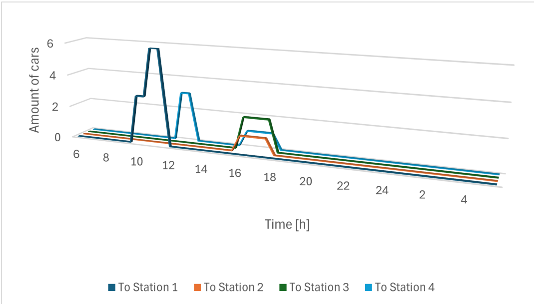
(b) Drives from Station 2.



(c) Drives from Station 3.

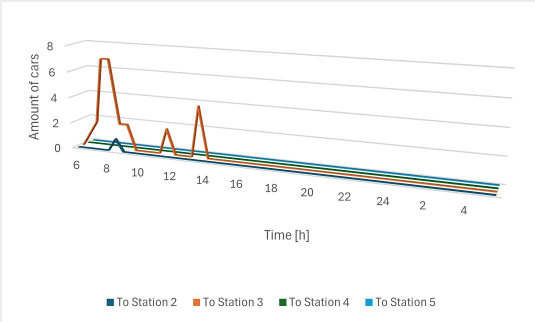


(d) Drives from Station 4.

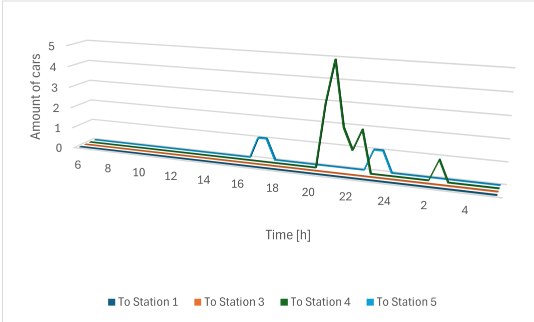


(e) Drives from Station 5.

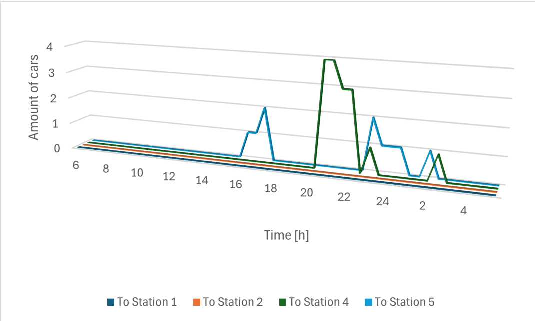
Figure 11.10: Drives from all stations in *SC-LDP*.



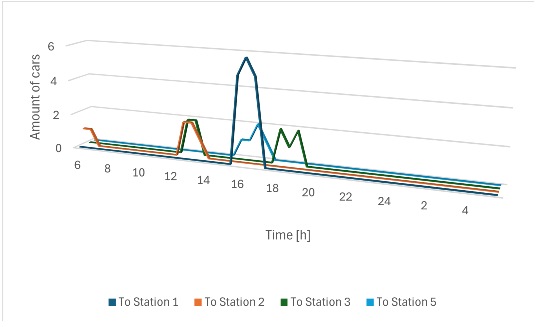
(a) Relocations from Station 1.



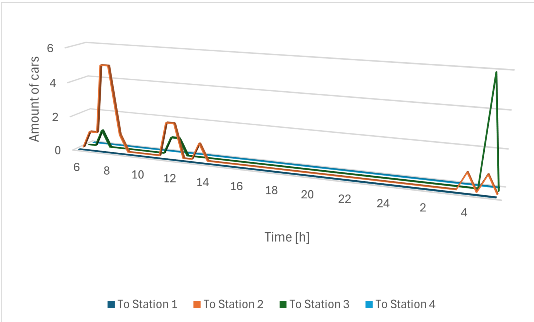
(b) Relocations from Station 2.



(c) Relocations from Station 3.



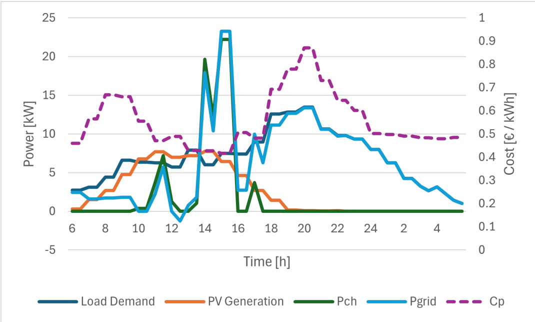
(d) Relocations from Station 4.



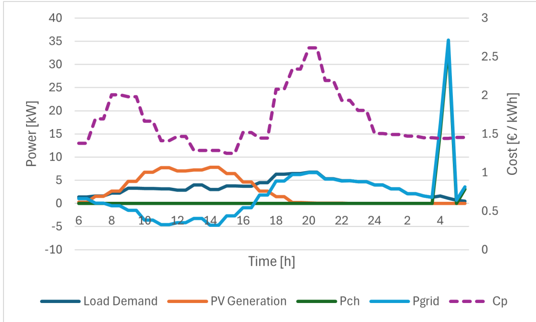
(e) Relocations from Station 5.

Figure 11.11: Relocations from all stations in *SC-LDP*.

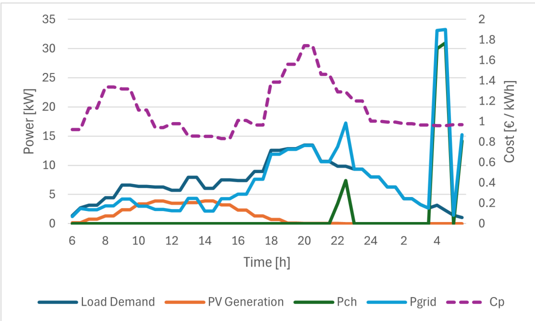
11.3.3. Power Profiles



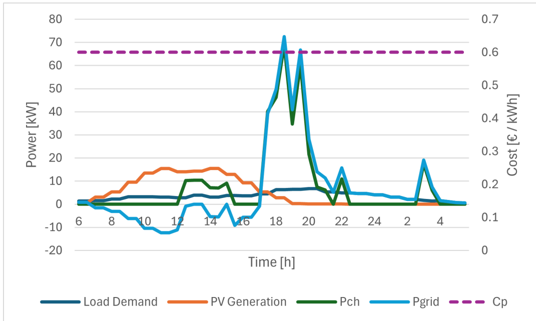
(a) Power profiles for Station 1.



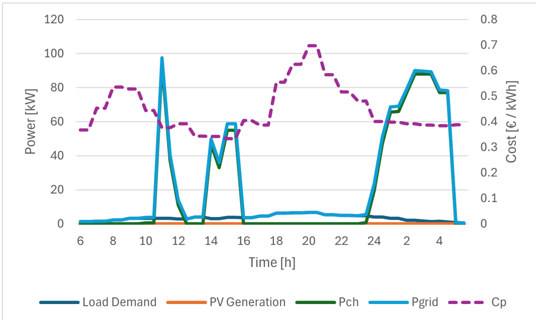
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 11.12: P^{LD}, P^{PV}, P^{ch}, P^{grid} and C^{P} for all stations in *SC-LDP*.

11.4. V2G & location-dependent prices

11.4.1. Objective and KPIs

Driving Revenue	€ 2,379.70
Relocation Costs	€ 381.00
Energy Sold Revenue	€ 1,383.60
Energy Bought Costs	€ 1,149.00

Profit	€ 2,233.30

Table 11.10: *V2G-LDP* objective values.

Station	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Peak [t]	Average [kW]	Peak [kW]	Peak [t]	Average [kW]	Peak [kW]	Peak [t]	Average [kW]	Peak [kW]	Peak [t]
1	152.23	1.56	4.41	13.38	8:30:00 PM	1.86	18.50	12:00:00 PM	6.34	17.23	12:00:00 PM	0.06	1.45	11:00:00 AM
2	21.86	845.65	0.93	6.65	8:30:00 PM	-35.26	-103.60	4:00:00 AM	0.91	11.80	4:00:00 AM	35.24	98.33	9:00:01 PM
3	113.59	27.77	5.66	13.42	8:30:00 PM	-2.08	43.27	5:30:00 AM	4.73	44.30	5:30:00 AM	1.16	13.17	7:00:00 AM
4	695.13	67.23	-1.62	6.56	8:30:00 PM	27.78	98.38	3:00:00 AM	28.96	100.00	7:30:00 PM	2.80	12.49	2:00:00 PM
5	1195.13	0.00	3.48	6.73	8:00:00 PM	46.31	98.87	4:30:00 AM	49.80	100.00	11:30:00 PM	0.00	0.00	6:30:00 AM

Sum	2177.94	942.21

Fulfilled Driving Demand	80.2%

Table 11.11: *V2G-LDP* KPIs.

11.4.2. Driving and Relocating

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	11	9	18	46
2	12	0	0	25	4	41
3	15	0	0	44	13	72
4	9	16	35	0	6	66
5	18	4	6	7	0	35
	54	28	52	85	41	**260**

(a) *V2G-LDP* driving routes.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	16	0	0	24
2	1	0	0	12	5	18
3	0	0	0	12	9	21
4	15	14	13	0	1	43
5	0	9	12	0	0	21
	16	31	41	24	15	**127**

(b) *V2G-LDP* relocation routes.

Table 11.12: All driving and relocation routes in *V2G-LDP*.

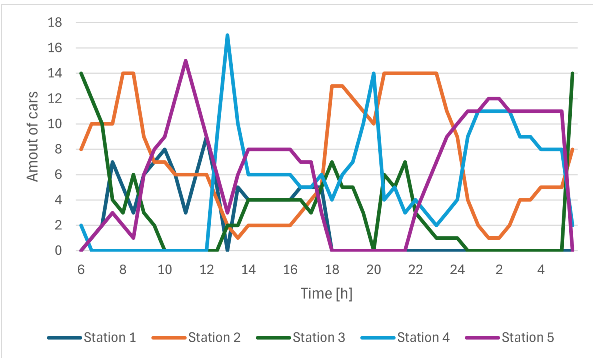
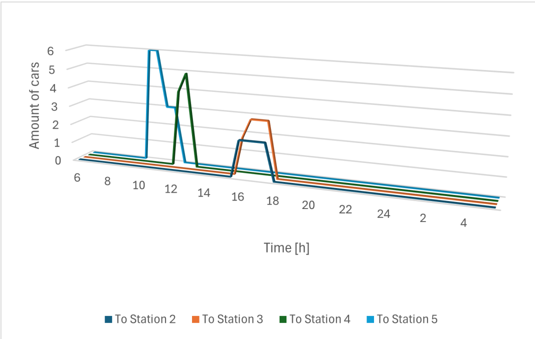
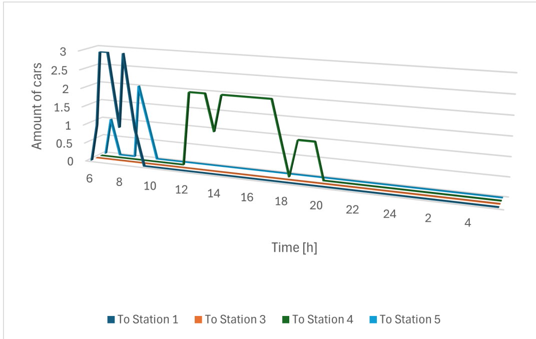


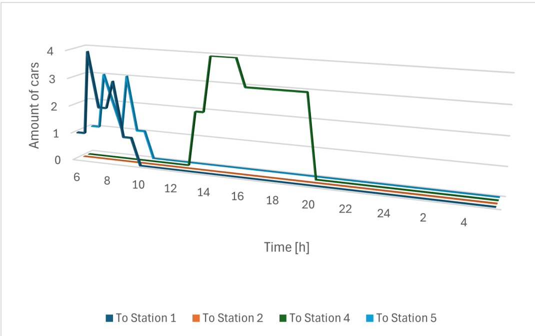
Figure 11.13: *V2G-LDP* number of cars per station throughout the day.



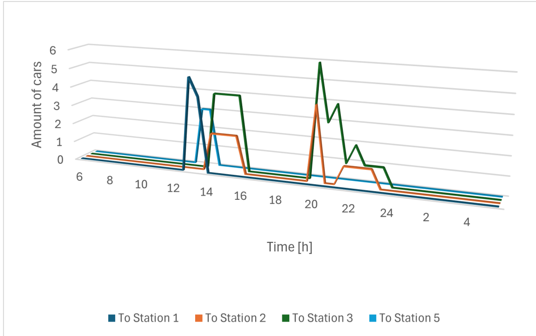
(a) Drives from Station 1.



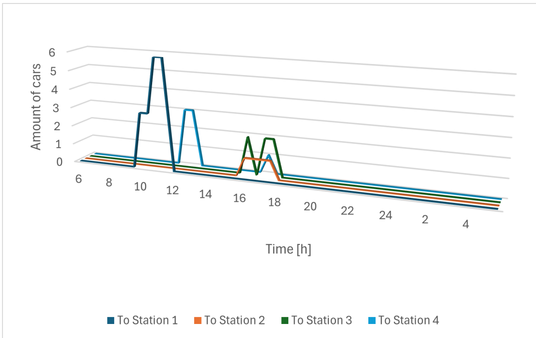
(b) Drives from Station 2.



(c) Drives from Station 3.

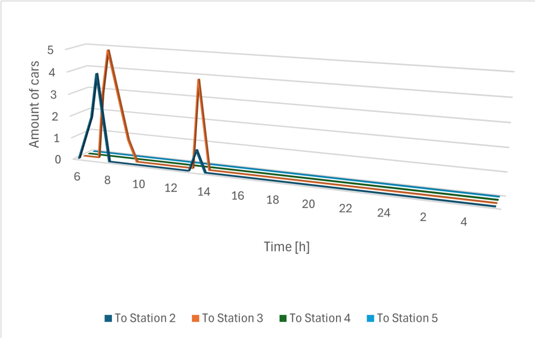


(d) Drives from Station 4.

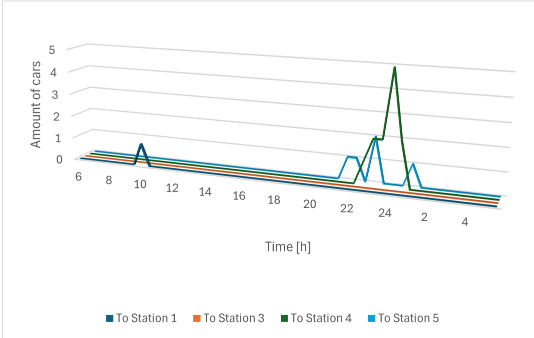


(e) Drives from Station 5.

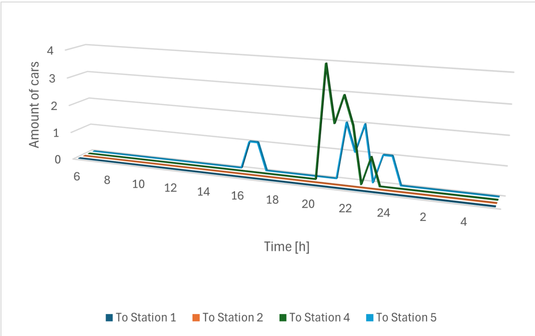
Figure 11.14: Drives from all stations in *V2G-LDP*.



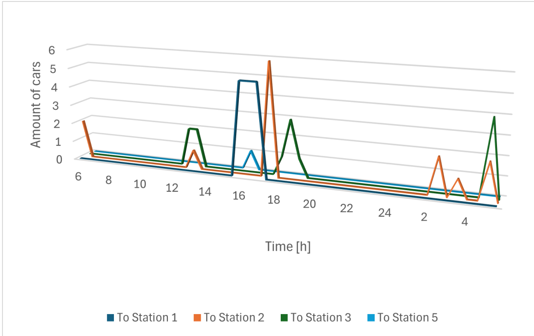
(a) Relocations from Station 1.



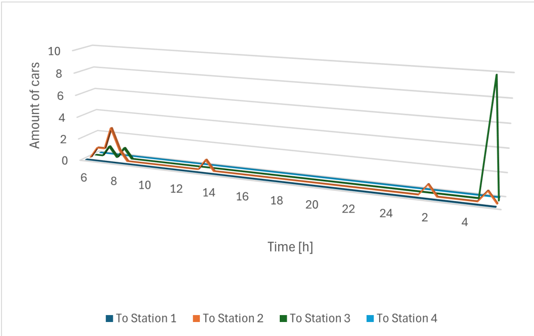
(b) Relocations from Station 2.



(c) Relocations from Station 3.



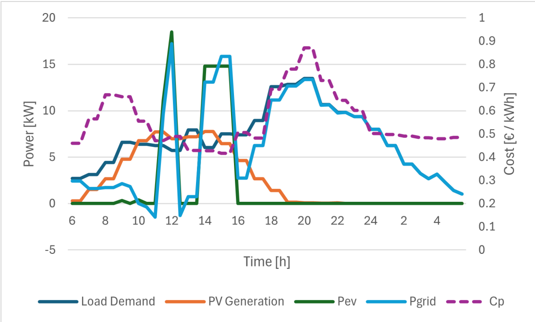
(d) Relocations from Station 4.



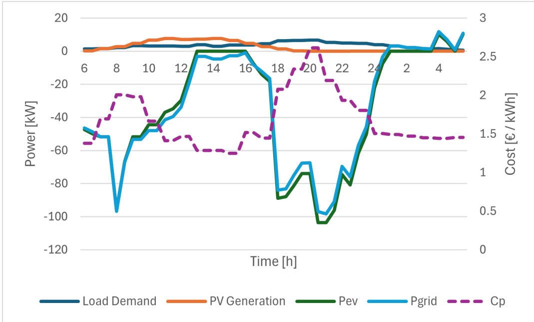
(e) Relocations from Station 5.

Figure 11.15: Relocations from all stations in *V2G-LDP*.

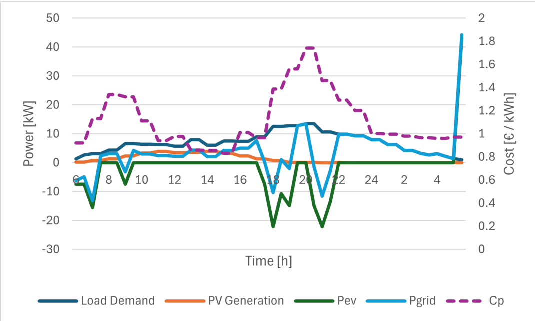
11.4.3. Power Profiles



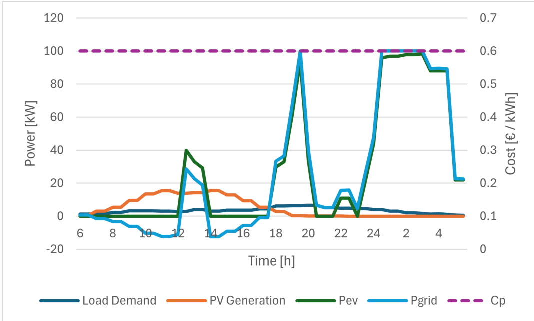
(a) Power profiles for Station 1.



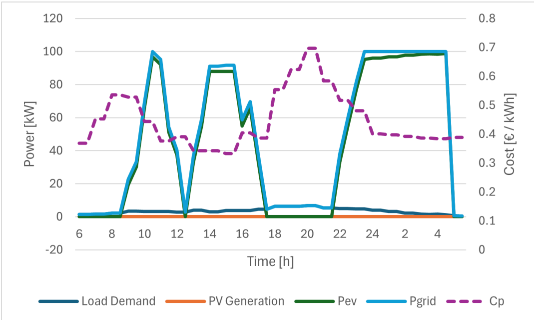
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 11.16: P^{LD}, P^{PV}, P^{EV}, P^{grid} and C^{P} for all stations in *V2G-LDP*.

12

Simulation Plots Case Study: Summer + Peak Reduction

12.1. V2G & same prices

12.1.1. Objective and KPIs

Driving Revenue	€ 2,861.70
Relocation Costs	€ 363.00
Energy Sold Revenue	€ 84.64
Energy Bought Costs	€ 611.28
Peak Exceedance Penalty	€ 22.03

Profit	€ 1,950.03

Table 12.1: *V2G-SP* objective values.

	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
Station	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	146.47	0.64	4.41	13.38	8:30:00 PM	1.66	15.10	2:00:00 PM	6.10	13.38	2:00:00 PM	0.03	1.27	12:30:00 PM
2	271.64	20.18	0.93	6.65	8:30:00 PM	9.55	33.64	5:30:00 AM	11.32	34.15	12:00:01 AM	0.84	15.55	8:30:00 PM
3	429.78	1.53	5.66	13.42	8:30:00 PM	15.64	59.78	5:30:00 AM	17.91	60.29	12:00:01 AM	0.06	0.86	2:00:00 PM
4	165.34	132.70	-1.62	6.56	8:30:00 PM	2.98	-106.55	8:00:00 PM	6.89	20.58	1:00:00 PM	5.53	100.00	8:00:00 PM
5	187.68	0.00	3.48	6.73	8:00:00 PM	4.34	27.59	12:00:00 PM	7.82	30.45	11:00:00 AM	0.00	0.00	6:30:00 AM

Sum	1200.90	155.04

Fulfilled Driving Demand	97.2%

Table 12.2: *V2G-SP* KPIs.

12.1.2. Driving and Relocating

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	8	11	13	18	50
2	14	0	0	28	10	52
3	20	0	0	48	16	84
4	10	28	46	0	6	90
5	18	4	7	10	0	39
	62	40	64	99	50	**315**

(a) *V2G-SP* driving routes.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	1	27	0	0	28
2	1	0	0	11	2	14
3	0	0	0	17	4	21
4	15	8	10	0	4	37
5	0	17	4	0	0	21
	16	26	41	28	10	**121**

(b) *V2G-SP* relocation routes.

Table 12.3: All driving and relocation routes in *V2G-SP*.

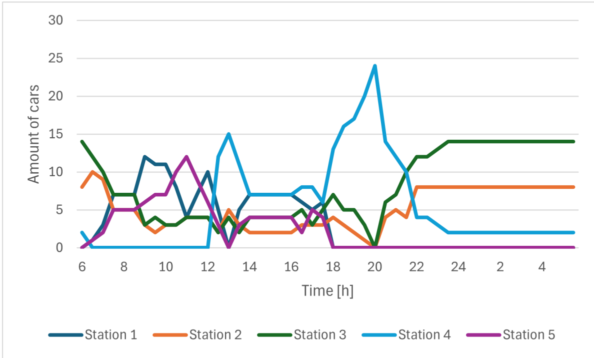
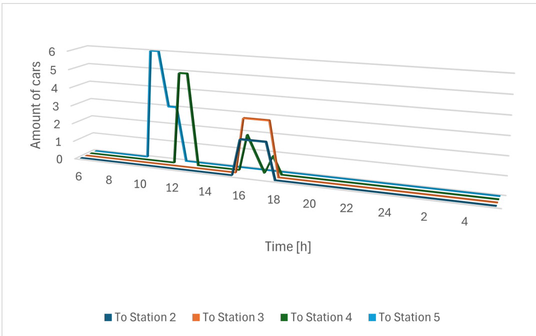
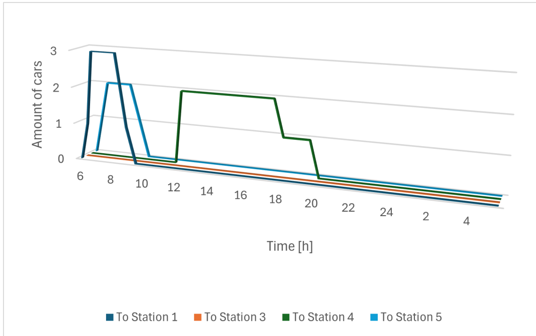


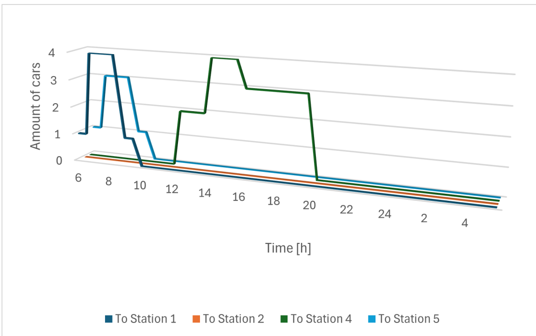
Figure 12.1: *V2G-SP* number of cars per station throughout the day.



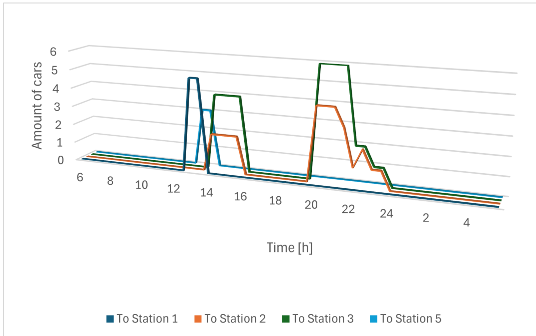
(a) Drives from Station 1.



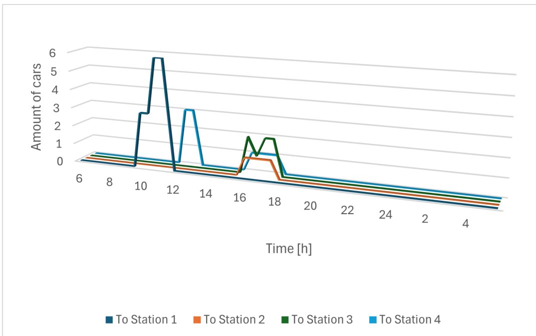
(b) Drives from Station 2.



(c) Drives from Station 3.

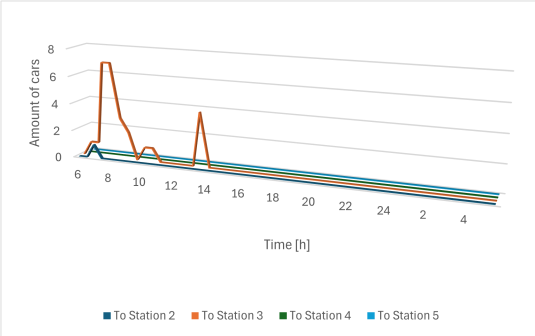


(d) Drives from Station 4.

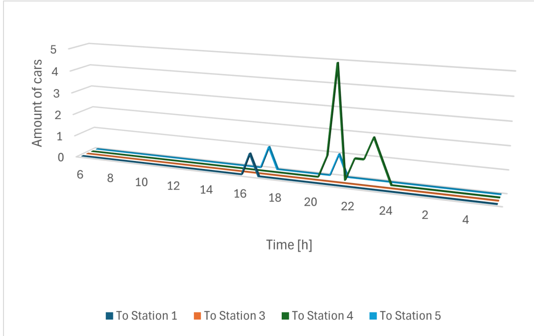


(e) Drives from Station 5.

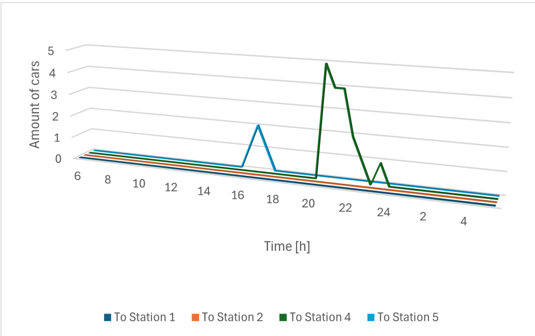
Figure 12.2: Drives from all stations in *V2G-SP*.



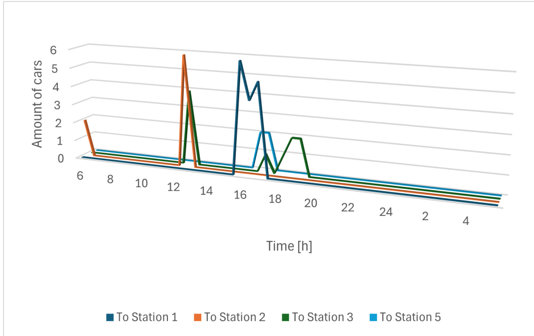
(a) Relocations from Station 1.



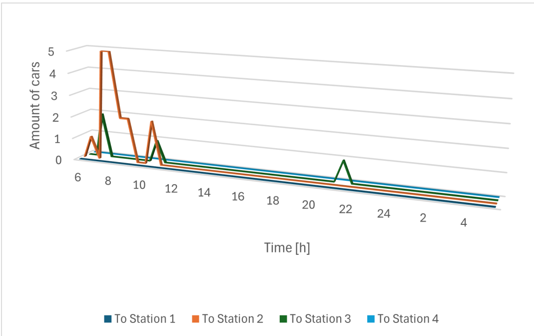
(b) Relocations from Station 2.



(c) Relocations from Station 3.



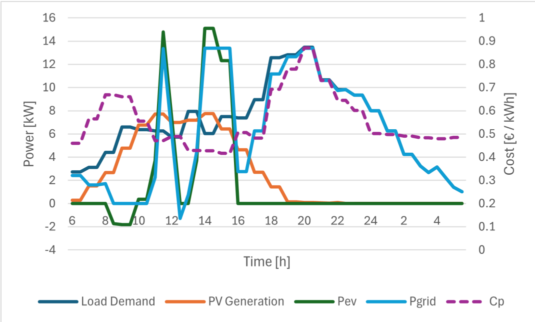
(d) Relocations from Station 4.



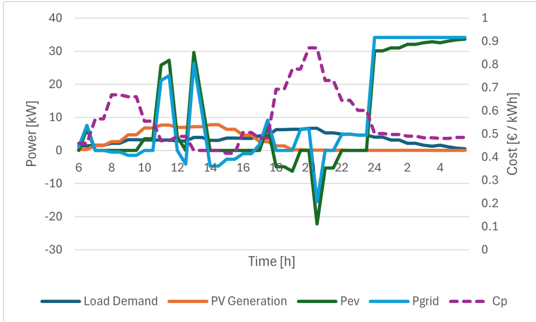
(e) Relocations from Station 5.

Figure 12.3: Relocations from all stations in *V2G-SP*.

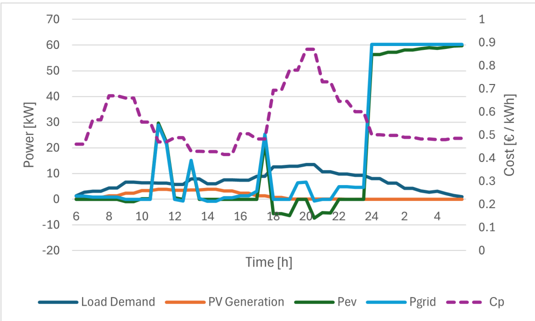
12.1.3. Power Profiles



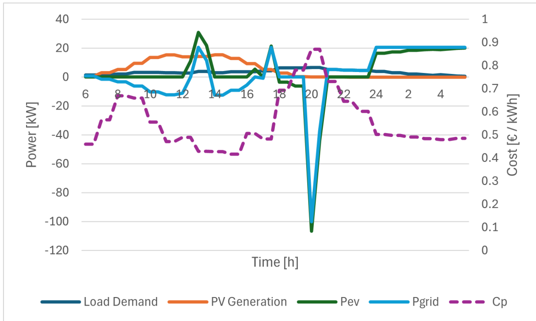
(a) Power profiles for Station 1.



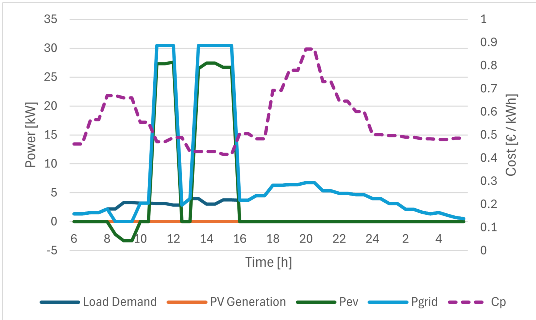
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 12.4: P^{LD}, P^{PV}, P^{EV}, P^{grid} and C^{P} for all stations in *V2G-SP*.

13

Simulation Plots Case Study: Winter

13.1. V2G & same prices

13.1.1. Objective and KPIs

Driving Revenue	€ 2,830.40
Relocation Costs	€ 348.00
Energy Sold Revenue	€ 287.75
Energy Bought Costs	€ 773.17
Profit	€ 1,996.98

Table 13.1: *V2G-SP* objective values.

	Total Energy		Station Net Demand			Charging Power			Buying Power			Selling Power		
Station	Bought [kWh]	Sold [kWh]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]	Average [kW]	Peak [kW]	Time [t]
1	177.70	3.35	7.78	17.46	8:30:00 PM	-0.51	-11.10	8:30:00 AM	7.40	17.46	8:30:00 PM	0.14	6.71	8:30:00 AM
2	474.10	12.50	3.25	8.71	8:30:00 PM	15.98	59.20	12:00:01 AM	19.75	64.40	12:00:01 AM	0.52	14.73	6:00:00 PM
3	786.74	62.70	3.89	8.73	8:30:00 PM	26.28	99.07	5:00:00 AM	32.78	100.00	11:30:00 PM	2.61	51.38	6:00:00 PM
4	179.36	230.35	1.98	8.67	8:30:00 PM	-4.10	-108.18	7:30:00 PM	7.47	33.08	11:00:00 PM	9.60	100.00	6:30:00 PM
5	97.95	26.07	4.53	8.75	8:00:00 PM	-1.53	-55.00	8:30:00 AM	4.08	8.75	8:00:00 PM	1.09	52.13	8:30:00 AM
Sum	1715.85	334.97												

Fulfilled Driving Demand	96.3%

Table 13.2: *V2G-SP* KPIs.

13.1.2. Driving and Relocating

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	7	11	13	18	49
2	14	0	0	26	10	50
3	20	0	0	47	16	83
4	10	30	46	0	6	92
5	18	3	8	9	0	38
	62	40	65	95	50	**312**

(a) *V2G-SP* driving routes.

Departure Station \ Arrival Station	1	2	3	4	5	
1	0	2	26	0	0	28
2	0	0	0	14	2	16
3	0	0	0	16	3	19
4	15	8	7	0	3	33
5	0	16	4	0	0	20
	15	26	37	30	8	**116**

(b) *V2G-SP* relocation routes.

Table 13.3: All driving and relocation routes in *V2G-SP*.

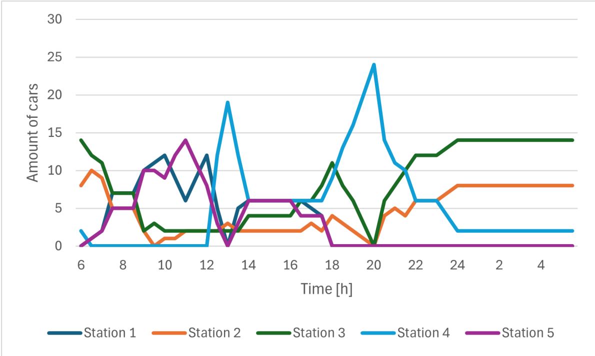
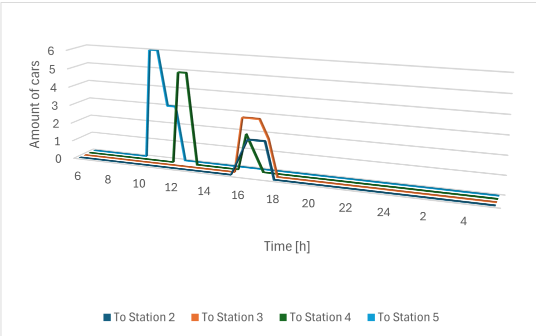
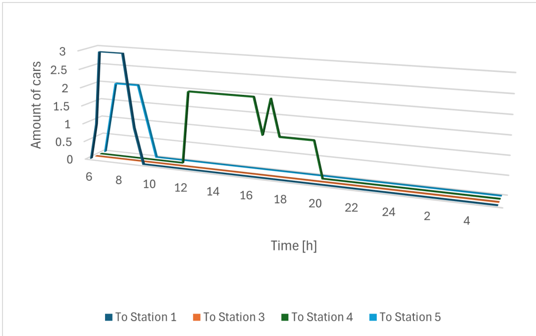


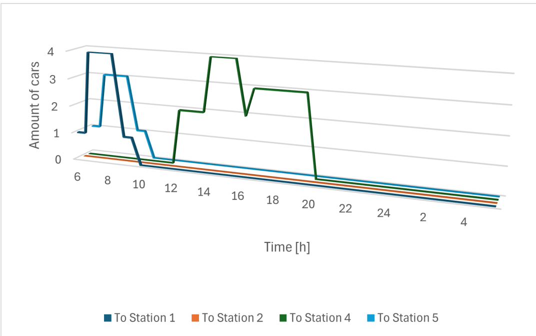
Figure 13.1: *V2G-SP* number of cars per station throughout the day.



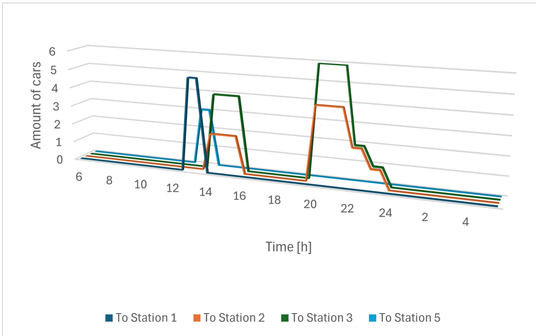
(a) Drives from Station 1.



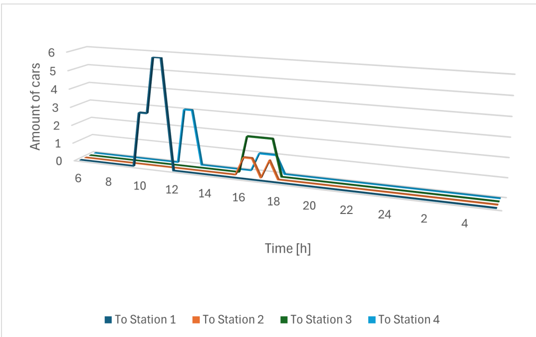
(b) Drives from Station 2.



(c) Drives from Station 3.

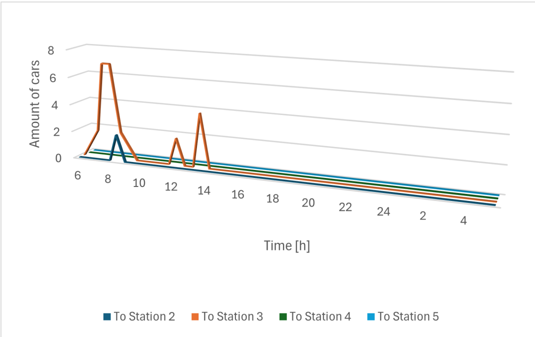


(d) Drives from Station 4.

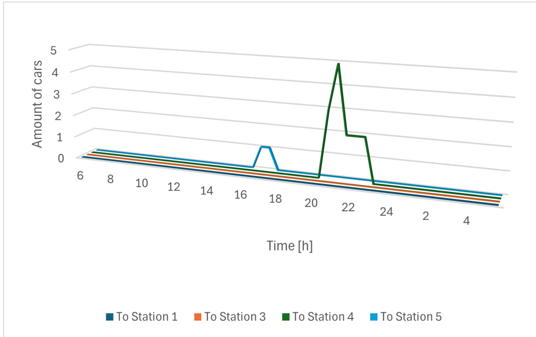


(e) Drives from Station 5.

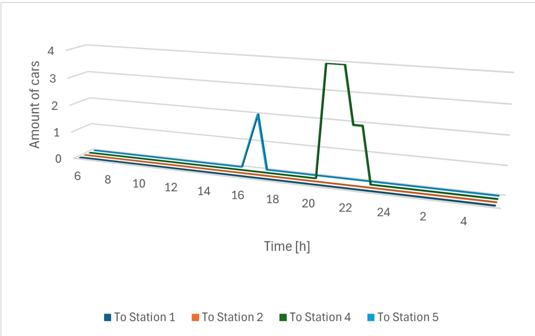
Figure 13.2: Drives from all stations in *V2G-SP*.



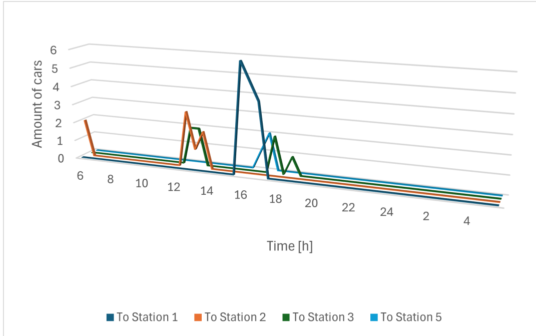
(a) Relocations from Station 1.



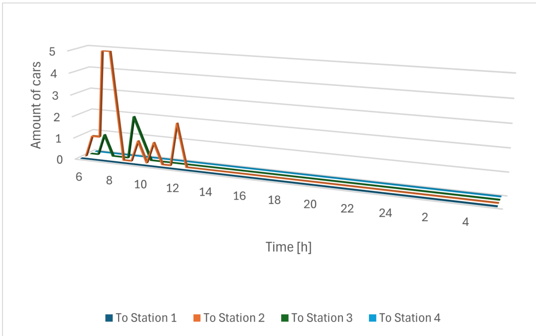
(b) Relocations from Station 2.



(c) Relocations from Station 3.



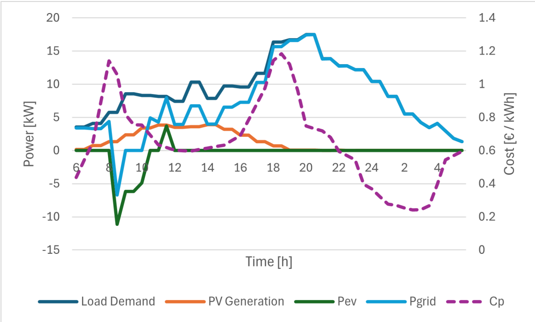
(d) Relocations from Station 4.



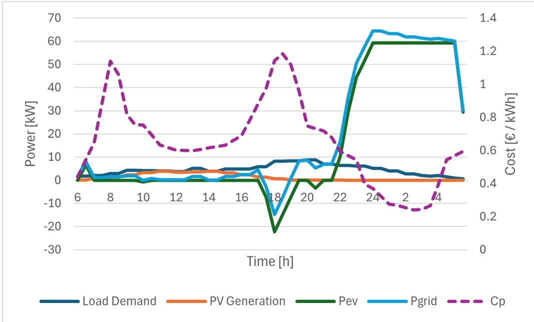
(e) Relocations from Station 5.

Figure 13.3: Relocations from all stations in *V2G-SP*.

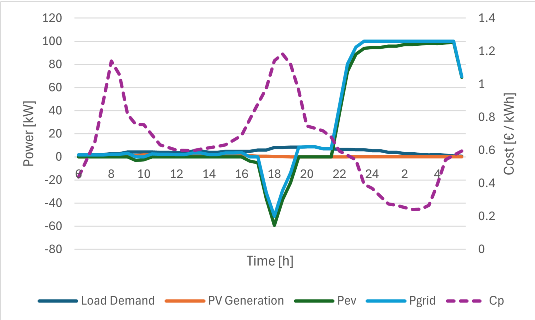
13.1.3. Power Profiles



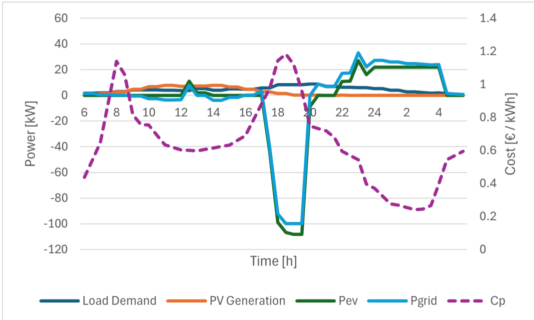
(a) Power profiles for Station 2.



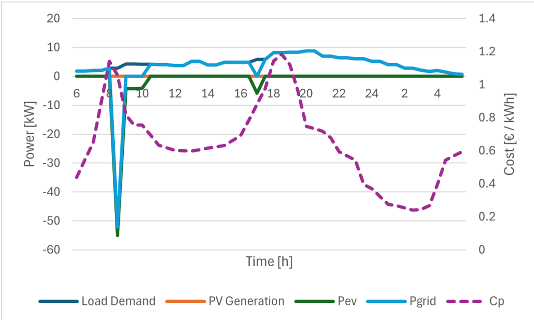
(b) Power profiles for Station 2.



(c) Power profiles for Station 3.



(d) Power profiles for Station 4.



(e) Power profiles for Station 5.

Figure 13.4: P^{LD}, P^{PV}, P^{ch}, P^{grid} and C^{P} for all stations in *V2G-SP*.