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Optimization Models for Vehicle-to-House (V2H) Technologies in Smart Grids: Real-Time Management and Price Fluctuation Adaptation

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Abstract

The increasing use of electric vehicles (EVs) is revolutionizing the landscape of home energy management, offering new opportunities through Vehicle-to-Grid (V2G) technology and, in particular, the Vehicle-to-House (V2H) mode. This research explores the implementation of an intelligent V2H system, with the main objective of minimizing energy costs and reducing peak demand, thus contributing to a more sustainable, resilient, and efficient electrical system.

The first part of the work provides a detailed overview of V2G and V2H technologies, illustrating the potential and challenges associated with their integration into home energy systems. The technical, economic, and environmental implications are analyzed, highlighting how these technologies can foster a transition to a greener and smarter energy model.

The core of the research focuses on four linear optimization models. The first two models are offline and based on historical data and forecasts of load and energy production. These models are designed to optimize energy management over defined time periods, leveraging forecasts of energy availability and demand. The other two models are corrective and operate online, adapting energy management strategies in real-time in response to immediate variations in load and energy availability conditions.

The key innovation of this research lies in the ability to consider the dynamic price of electricity, optimizing the energy flow between the vehicle and the house to maximize economic savings. Through intelligent management of the electric vehicle's charging and discharging, the system can reduce energy costs, mitigate peak demand, and improve the overall efficiency of home energy use.

The experimental results obtained demonstrate a significant reduction in energy costs and more efficient use of energy, confirming the effectiveness of the proposed models. The research concludes by emphasizing the potential of V2H as an essential strategy to address future energy challenges, promoting home energy management that is not only more sustainable but also smarter and more resilient. This research represents a significant contribution to the field of energy management, outlining a clear path toward a greener and smarter energy future.

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Chapter 1

Introduction

In recent years, the growing adoption of electric vehicles (EVs) has opened new frontiers in home energy management. Advanced technologies such as Vehicle-to-Grid (V2G) and, in particular, Vehicle-to-House (V2H) promise to revolutionize how energy is used, stored, and distributed in homes, improving energy efficiency and providing sustainable solutions for global environmental challenges.

Today's electrical system faces problems such as increased energy demand, consumption peaks, and CO_2 emissions. According to the International Energy Agency (IEA), global electricity demand is expected to grow by 2.1% per year until 2040, putting enormous pressure on existing power grids [1]. V2G and V2H technologies emerge as promising solutions, enabling intelligent energy management and reducing emissions by integrating electric vehicles into the home grid [2, 5].

1.1 Context and Importance of the Problem

The widespread adoption of electric vehicles not only reduces dependence on fossil fuels but also leverages vehicle batteries as distributed energy resources. EV batteries can be used to store energy during low-demand periods and release it during consumption peaks, contributing to grid stabilization. Recent studies highlight how electric vehicles can provide frequency regulation services and capacity reserves through V2G, improving grid reliability and resilience [5, 2].

V2H technology allows the use of EV batteries to power homes directly, enhancing domestic energy efficiency and providing backup power in case of grid interruptions. A recent analysis showed that implementing V2H systems can lead to significant energy cost reductions and improved home energy reliability [3, 8].

1.2 Smart Grids

Smart grids represent an evolution of traditional electrical grids, integrating advanced digital technologies to enhance the reliability, security, and efficiency of power distribution. These intelligent networks allow bidirectional energy flow management, facilitating the integration of renewable energy sources and the implementation of technologies such as V2G and V2H. Smart grids enable real-time communication between energy consumers and suppliers, optimizing resource usage and reducing waste [4, 6].

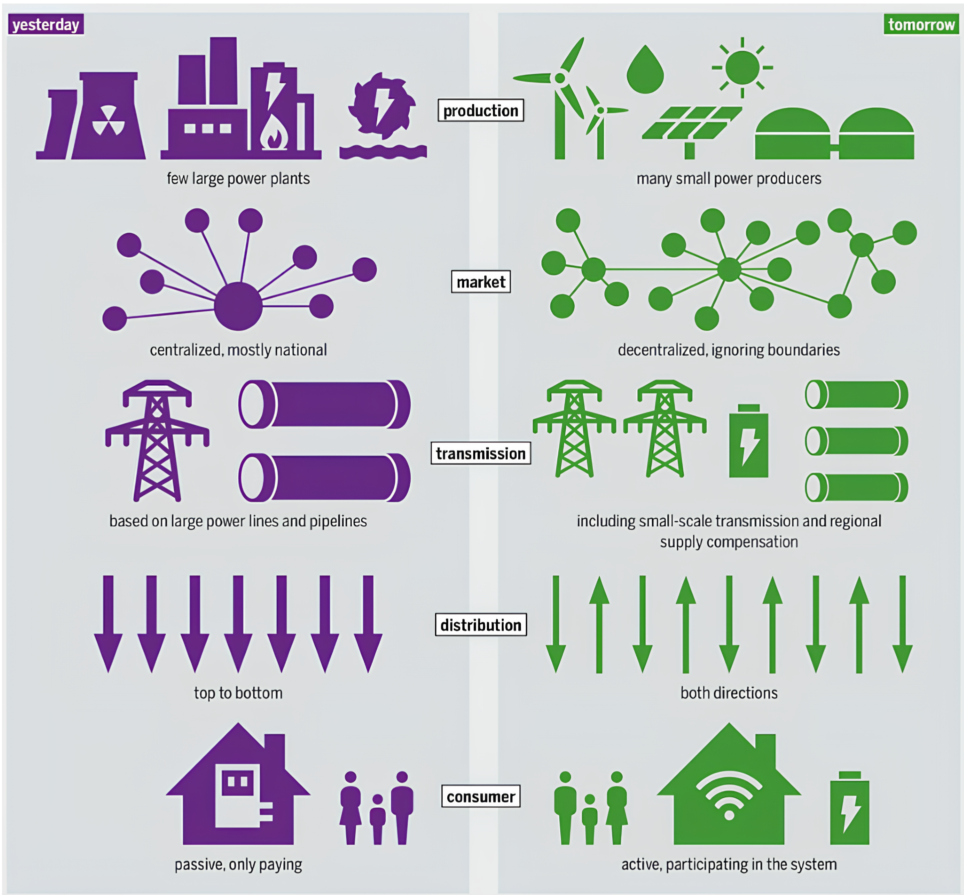

Figure 1.1: Illustration of the bidirectionality in smart grids, showing energy flow between the electric vehicle, house, solar panels, and the grid.

1.3 Research Motivation

The main motivation for this research is to explore the potential of an intelligent V2H system to optimize home energy management. While numerous studies exist on V2G applications, there are still significant gaps in the literature regarding the practical application of V2H systems, especially in residential contexts. Recent studies emphasize the need to develop optimization models that account for electricity price dynamics and variations in energy demand [4, 6].

1.4 Research Objectives

The main objectives of this research are:

- Develop and test linear optimization models for V2H energy management based on historical data and forecasts of load and energy production.
- Assess the economic impact of implementing such systems, considering various electricity price scenarios.
- Propose energy management strategies that consider the dynamic price of electricity and real-time load conditions.

1.5 Offline and Online Models

The offline models operate on a 24-hour horizon, based on historical data and forecasts. Experiments were conducted in various scenarios, considering the presence of the vehicle at home, different energy price profiles, and miles driven during the day with the vehicle. The online models, on the other hand, respond to errors in arrival and return times and the number of miles driven, adapting energy management strategies in real time to address immediate variations in load conditions and energy availability [7, 8].

Chapter 2

State of the Art of V2G and V2H Technologies

2.1 Introduction to V2G Technology

Vehicle-to-Grid (V2G) technology represents a transformative approach in integrating electric vehicles (EVs) with the electrical grid. This technology allows EVs to interact bidirectionally with the grid, enabling not only the charging of the vehicle's battery but also the return of stored energy to the grid. V2G has the potential to provide various ancillary services, such as frequency regulation, peak shaving, and load balancing, which are critical for enhancing grid stability and efficiency.

2.1.1 Key Components and Functionality

The V2G system is comprised of several key components:

- **Electric Vehicle (EV)**: Equipped with a bidirectional charger and a battery management system.
- **Bidirectional Charger**: Allows energy to flow in both directions between the vehicle and the grid.
- **Communication Infrastructure**: Facilitates data exchange between the EV, the charger, and the grid operator.

2.1.2 Benefits of V2G Technology

The benefits of V2G include:

- **Frequency Regulation**: EVs can provide energy to the grid to maintain stable frequency.

- **Peak Demand Reduction**: EVs can return energy to the grid during high demand periods, helping to reduce peak loads.
- **Grid Efficiency**: V2G can help balance energy supply and demand, improving overall grid efficiency.

Recent studies have demonstrated that V2G implementation can lead to significant improvements in grid stability and reliability. For instance, a study by Kempton and Tomić (2005) highlighted the potential of V2G in providing frequency regulation services [9]. Another study by Guille and Gross (2009) explored the economic benefits of V2G for EV owners and grid operators [10]. More recently, an analysis by White and Zhang (2011) demonstrated how V2G adoption could help reduce operational costs of the grid [11].

2.2 V2H Technology

Vehicle-to-House (V2H) technology is a specific application of V2G that allows EVs to provide energy directly to homes. This technology can enhance domestic energy efficiency and provide backup power during grid outages.

2.2.1 Functioning of V2H Technology

V2H uses the following components:

- **Electric Vehicle (EV)**: Equipped with a bidirectional charger.
- **Home Energy Management System (HEMS)**: Manages the energy flow between the EV, the home, and the grid.
- **Bidirectional Charger**: Enables energy transfer between the EV and the home.

2.2.2 Benefits of V2H Technology

The main benefits of V2H include:

- **Energy Efficiency**: EVs can store energy during low-demand periods and release it when needed, improving home energy efficiency.
- **Backup Power**: In case of grid interruptions, the EV can provide power to the home, ensuring continuous electricity supply.

- **Cost Reduction**: Strategic use of stored energy can reduce home energy costs by taking advantage of variable electricity rates.

A study by Green and Newman (2017) demonstrated that implementing V2H systems can lead to significant energy cost reductions and improved home energy reliability [12]. A more recent analysis by Wang et al. (2020) highlighted the positive impact of V2H on CO_2 emissions, contributing to a more sustainable environment [31]. Additionally, a study by Luo et al. (2021) showed how integrating V2H with renewable energy sources can further optimize home energy management [14].

2.3 Development and Solving Technologies

Recent studies in the field of V2G and V2H technologies focus on several key areas, including the optimization of energy management models, integration with smart grids, and the use of advanced algorithms to improve efficiency and sustainability.

2.3.1 Optimization of Energy Management Models

Optimizing energy management models is crucial to maximize the benefits of V2G and V2H technologies. Recent studies have developed optimization models using linear and nonlinear programming techniques to manage energy between EVs and the grid. For example, an optimization model proposed by Liu et al. (2021) uses linear programming to minimize energy costs and improve system efficiency [28]. Additionally, a study by Li et al. (2022) implemented stochastic optimization algorithms to handle uncertainty in demand and supply forecasts [16].

2.3.2 Integration with Smart Grids

Integrating V2G and V2H technologies with smart grids is an emerging research area. Smart grids enable bidirectional energy flow management, facilitating the implementation of advanced technologies like V2G and V2H. A study by Tan et al. (2020) explores the use of smart grids to optimize energy distribution and improve grid resilience [17]. Another study by Zhang et al. (2021) demonstrated how integrating V2G with smart grids can significantly enhance grid stability and efficiency [18].

2.4 Smart Grids and Their Importance

Smart grids represent an evolution of traditional electrical grids, integrating advanced digital technologies to enhance the reliability, security, and efficiency of power distribution. These intelligent networks allow bidirectional energy flow management, facilitating the integration of renewable energy sources and the implementation of technologies such as V2G and V2H.

2.4.1 Features of Smart Grids

Smart grids are characterized by several advanced features:

- **Bidirectional Energy Management**: Allows energy exchange in both directions between the grid and end-users.
- **Advanced Communication Infrastructure**: Utilizes real-time communication systems to monitor and manage energy distribution.
- **Integration of Renewable Energy**: Facilitates the use of renewable energy sources like solar and wind power.
- **Resilience and Security**: Enhances grid resilience against failures and cyber-attacks through advanced monitoring systems.

A study by Fang et al. (2012) highlighted the importance of smart grids in efficient energy management and CO_2 emissions reduction [19]. More recently, a study by Gungor et al. (2013) explored the potential of smart grids in optimizing resource usage and reducing operational costs [20].

2.4.2 Benefits of Smart Grids for V2G and V2H Technologies

Smart grids offer several crucial benefits for the effective implementation of V2G and V2H technologies:

- **Optimization of Energy Flow**: Enables optimal energy management between EVs, homes, and the grid.
- **Reduction of Energy Losses**: Improves grid efficiency by reducing energy losses during distribution.
- **Enhanced Reliability**: Provides robust infrastructure for reliable energy supply and demand management.

Smart grids play a pivotal role in realizing the full potential of V2G and V2H technologies, enabling more efficient and sustainable energy systems.

2.5 Current State of Technology

Currently, V2G technology is still in its early stages of development and implementation, with various pilot projects underway around the world. However, the results of studies and experiments conducted so far are promising and indicate significant potential for improving energy efficiency and grid stability. V2H technology, on the other hand, is gaining increasing interest for its domestic applications, offering practical solutions for energy self-sufficiency and cost reduction.

Despite technical and infrastructural challenges, advances in research and the development of new technologies and algorithms are rapidly bringing these solutions closer to commercial reality. Continuous government policy support and investment in smart grid infrastructure will be crucial to accelerating the widespread adoption of V2G and V2H technologies.

Chapter 3

Application Scenario

3.1 Introduction to the Application Scenario

The application scenario of Norway provides an ideal context for the implementation and analysis of V2G and V2H technologies. The combination of a high penetration of electric vehicles, advanced smart grid infrastructure, and a strong commitment to sustainability creates a favorable environment for the experimentation and optimization of these technologies. This chapter describes the application scenario for the implementation of Vehicle-to-Grid (V2G) and Vehicle-to-House (V2H) technologies. Norway has been chosen as the ideal context for this analysis, thanks to its advanced energy infrastructure, high penetration of electric vehicles (EVs), and strong commitment to sustainability.

The data used for the experiments in this thesis are derived from the rich dataset of hourly residential electricity consumption and survey responses from the iFlex dynamic pricing experiment [22].

3.2 Characteristics of the Energy System

Norway's energy system is characterized by a significant reliance on renewable energy, primarily hydroelectric power. Nearly 98% of Norway's electricity production comes from renewable sources, making it a global leader in renewable energy integration [23]. The country experiences significant variations in energy demand between summer and winter, with peak consumption during the evening hours. According to recent studies, the daily load profile in a residential area shows two main peaks: one in the morning (7:00-9:00) and another in the evening (17:00-21:00) [21].

3.3 Grid Infrastructure and Smart Grid

Norway has made substantial investments in smart grid infrastructure to improve energy distribution efficiency and integrate renewable sources. The country employs advanced communication and energy management technologies to monitor and control energy flow in real-time. This includes the use of smart meters and energy management systems that facilitate the integration of V2G and V2H technologies [24, 25].

3.4 Electric Vehicle Fleet

Norway has one of the highest percentages of electric vehicles in the world. As of 2023, EVs account for over 80% of new car sales in the country [26]. Norwegian EVs are equipped with batteries of varying capacities, with most having a range between 200 and 400 km. Charging times vary depending on the type of charger used, with fast-charging stations capable of recharging an EV to 80% in about 30 minutes.

3.5 Residential Structure

Most Norwegian homes are single-family houses and apartment buildings. These residences have varying energy consumption profiles, with peaks during the evening hours and weekends. Many homes are equipped with home energy management systems (HEMS) that help monitor and optimize energy use.

3.6 Challenges and Opportunities

The implementation of V2G and V2H technologies in Norway presents several challenges and opportunities:

- **Technical Challenges**: Interoperability between different EV manufacturers, grid capacity to handle bidirectional energy flow, and management of load fluctuations.
- **Opportunities**: Reduction in energy costs for consumers, improvement in energy efficiency, increased grid resilience, and more efficient integration of renewable energy sources.

3.7 Case Studies and Pilot Projects

Norway has initiated several pilot projects to test V2G and V2H solutions. One such project is the "Smart Charge" initiative, which aims to demonstrate the benefits of smart charging and V2G technologies in reducing grid load and improving energy efficiency [28]. Another project is "Green Charge," which integrates solar energy with V2G technologies to optimize the use of renewable energy [29].

Chapter 4

Methodology

4.1 Introduction to Linear Optimization

Linear optimization, also known as linear programming (LP), is a mathematical technique used to determine the best possible outcome in a mathematical model whose requirements are represented by linear relationships. It is widely used in various fields such as economics, business management, engineering, and military applications to maximize or minimize a linear objective function, subject to a set of linear constraints.

4.1.1 Components of Linear Optimization

Linear optimization problems are characterized by the following components:

- **Objective Function**: A linear function that needs to be maximized or minimized. For example, in the context of energy management, the objective function might be the minimization of energy costs.

- **Decision Variables**: Variables that represent the quantities to be determined. In the context of V2G and V2H technologies, these variables could include the amounts of energy to be charged or discharged from the electric vehicle.

- **Constraints**: Linear equations or inequalities that represent the limitations or requirements of the problem. These constraints can include limits on the state of charge of the battery, charging and discharging rates, and the energy balance between the house, the vehicle, and the grid.

4.1.2 Use of Linear Optimization in Energy Management

Linear optimization is particularly suitable for energy management problems for several reasons. Linear optimization models can handle large-scale problems with multiple variables and constraints, making it possible to efficiently manage the energy needs of households with varying demand and supply conditions. Linear optimization algorithms, such as the Simplex method and interior-point methods, are efficient and can find optimal solutions quickly. This is essential for real-time energy management, where decisions need to be made rapidly [28, 29].

Moreover, linear optimization models can incorporate a wide range of constraints, including physical limits of the battery, charging and discharging rates, and dynamic energy prices. This flexibility allows for the creation of comprehensive energy management strategies that can be adapted to different scenarios [30, 31].

4.1.3 Advantages of Linear Optimization in V2G and V2H Applications

In V2G and V2H applications, linear optimization offers numerous advantages. It allows for the optimization of charging and discharging schedules for electric vehicles, improving overall energy efficiency and reducing costs. Additionally, it enables the adaptation of charging and discharging decisions based on variations in energy prices, maximizing economic savings. Another significant advantage is the support to the electrical grid, helping to balance the load on the grid, reducing demand peaks, and improving the stability and resilience of the electrical system. Linear optimization algorithms are well understood and supported by numerous software tools, making the practical implementation of models easier [32].

4.1.4 Recent Applications of Linear Optimization

The use of linear optimization in energy management applications, particularly for V2G and V2H technologies, is supported by numerous recent studies. Several works have demonstrated how linear optimization can be used to develop energy management models for electric vehicles that can reduce total energy costs and improve grid efficiency. Some studies have considered variations in energy prices and the availability of renewable energy, demonstrating significant reductions in energy costs and improvements in grid efficiency [28, 29].

A thesis by Ibrahim El Khoudari (2021) demonstrated the effectiveness of linear optimization for managing electric vehicle charging, integrating renewable energy sources in residential contexts [33]. Similarly, Alessia Iobbi's thesis (2022) developed an optimization model for managing energy flows between the grid and electric vehicles, showing how linear optimization can improve grid stability and resilience [34].

Yong Tan et al. (2016) proposed a linear optimization model for maximizing profits from using electric vehicles in a V2G system, considering dynamic energy prices [35]. Another study by Yong Tan et al. (2016) presented a linear optimization model to minimize energy costs in a Vehicle-to-Home (V2H) system, utilizing the electric vehicle battery as an energy storage system [36].

Additionally, Yue Cao et al. (2019) introduced a mixed-integer linear programming model for optimal scheduling of electric vehicles in a V2G system, incorporating renewable energy integration and battery degradation [37]. In a similar vein, Yue Cao et al. (2017) developed a mixed-integer linear programming model for optimal V2G operation scheduling, taking into account network constraints and electric vehicle mobility profiles [38].

Other studies have developed linear optimization models for managing the charging of electric vehicles in smart grids, considering fluctuations in energy prices and demand profiles, optimizing charging times to minimize costs and reduce the load on the grid during peak periods [30, 31]. Additionally, the effectiveness of linear optimization in integrating renewable energies has been demonstrated, optimizing the use of vehicle batteries to store energy during periods of high renewable production and release it during periods of high demand, improving grid reliability and reducing energy costs [32].

4.1.5 Gurobi Optimizer

Gurobi Optimizer is a powerful software for linear and mathematical optimization, widely used in various fields to solve complex problems of linear programming (LP), mixed-integer linear programming (MILP), and nonlinear programming (NLP). This section describes Gurobi and explains the reasons for choosing it as the optimizer for this project.

Features of Gurobi

Gurobi offers a range of features that make it one of the most advanced and reliable optimizers available:

- **Speed and Efficiency**: Gurobi is known for its speed and efficiency in solving complex optimization problems. It uses state-of-the-art algorithms to provide optimal solutions in very short times.
- **Multi-Core Support**: Gurobi fully leverages the multi-core capabilities of modern processors, enabling rapid and efficient resolution of large-scale problems.
- **Flexibility**: It supports a wide variety of optimization problems, including linear, integer, and non-linear. This flexibility makes it suitable for a wide range of applications.
- **Programming Interfaces**: Gurobi offers programming interfaces for several languages, including Python, MATLAB, C++, Java, and more. This facilitates integration with different development environments and existing models.
- **Robustness**: Gurobi can handle very complex and large optimization problems, ensuring robustness and reliability of the solutions.

Why Gurobi was Chosen

Gurobi was chosen as the optimizer for this project for several reasons:

- **Performance**: The speed and efficiency of Gurobi in solving complex linear optimization problems are essential for our model, which requires quick and precise solutions for real-time energy management.
- **Reliability**: Gurobi's robustness in handling large-scale problems ensures that the model can scale effectively with increasing complexity and the number of decision variables.
- **Support for Linear and Integer Problems**: Our optimization model includes both continuous and integer variables. Gurobi offers excellent support for mixed-integer linear programming (MILP), which is crucial for accurately modeling battery charging/discharging decisions.

- **Ease of Integration**: Gurobi provides a highly integrable Python programming interface, which was used to develop and test the optimization model. This facilitated rapid and iterative development of the model.

- **Documentation and Support**: Gurobi is accompanied by detailed documentation and high-quality technical support, which were crucial for quickly resolving issues and optimizing the model.

Implementation with Gurobi

The implementation of the optimization model with Gurobi followed these steps:

1. **Model Definition**: The optimization model was defined using Gurobi's Python programming interface, including all decision variables, the objective function, and constraints.

2. **Parameter Configuration**: Gurobi's parameters were configured to optimize the solver's performance, such as the number of threads used and the time limits for solving.

3. **Model Resolution**: The model was solved using Gurobi's optimization functions, obtaining the optimal solutions for the decision variables.

4. **Result Analysis**: The obtained results were analyzed to evaluate the model's efficiency and effectiveness, making iterative improvements as necessary.

Using Gurobi enabled obtaining optimal solutions quickly, ensuring the reliability and robustness needed for practical applications of V2G and V2H energy management technologies.

4.2 Parameter Setting Approach

This section provides a brief introduction to the approach adopted for setting the parameters used in modeling and energy optimization. Each detail will be elaborated in the following sections.

4.2.1 Realism in Modeling

To ensure that the optimization model is realistic and applicable, a conservative approach was adopted in selecting the parameters, using values that accurately represent existing technologies on the market. The parameters related to the battery and the electric vehicle were selected to reflect realistic conditions, based on real data from the Tesla Model 3 Long Range. This choice ensures that the optimized solutions are realistic and implementable with current technology.

4.2.2 Real Data and Datasets Used

The data concerning the daily load profile and electricity price trends were derived from real datasets. Specifically, hourly residential electricity consumption data and survey responses from the iFlex dynamic pricing experiment conducted in Norway were used. These data provide a solid and realistic basis for modeling the daily energy behavior of a house and the trends in energy prices [22].

4.2.3 Test Scenarios

Regarding the scenarios of the vehicle's presence or absence at home and the miles driven daily, these values were estimated to test the "worst-case scenarios" based on realistic data. The test scenarios were designed to cover a wide range of situations that a user might encounter, ensuring that the optimization model is robust and capable of handling variations in vehicle usage habits and energy consumption patterns.

4.2.4 Temporal Parameter Setting

In all examples and experiments, the optimization horizon is set to $T = 24$ hours, and the time slots are $t = 15$ minutes each. Therefore, each T is divided into 96 time slots. This granularity allows for precise and detailed optimization of energy management, ensuring that the models can effectively respond to changes and maintain optimal performance throughout the day.

The choice of 15 minutes as the duration for the time slots was made because it represents an effective time interval in terms of the battery's charging and discharging speed. This allows for an optimal balance between the system's responsiveness and the precision of the optimization, making the best use of the battery's capabilities and V2G and V2H technologies.

- **Vehicle presence at home**: Various scenarios were considered where the vehicle is at home during different hours of the day, to test the impact of the vehicle's availability for charging and discharging energy.
- **Miles driven daily**: Various vehicle usage scenarios were estimated, including both minimum and maximum usage, to evaluate how different driving habits affect energy management and cost optimization.

This conservative and data-driven approach ensures that the optimization model is not only theoretically valid but also practical and applicable in real-world contexts. The use of realistic parameters and the simulation of variable scenarios allow for obtaining reliable and useful results for the implementation of V2G and V2H technologies in households equipped with electric vehicles. Each detail will be elaborated in the following sections to provide a comprehensive understanding of the approach adopted.

4.3 Battery Modeling

In this section, the battery modeling used in the optimization framework is described. The battery parameters are based on the Tesla Model 3 Long Range, chosen for its widespread adoption, high energy density, and efficiency. A conservative approach was adopted for the battery modeling, evaluating the application with technologies already available on the market.

4.3.1 Battery Parameters

- $C_B = 75$ kWh (Battery Capacity): Indicates the maximum amount of energy the battery can store.
- $k_{\mathrm{SOC}_{\max}} = 0.9$ (Maximum allowed battery power coefficient): Defines the maximum charge limit of the battery as a percentage of the total capacity.
- $k_{\mathrm{SOC}_{\min}} = 0.1$ (Minimum allowed battery power coefficient): Defines the minimum charge limit of the battery as a percentage of the total capacity.
- $\mathrm{SOC}_{\max} = k_{\mathrm{SOC}_{\max}} \cdot C_B = 67.5$ kWh (Maximum allowed battery SOC): Calculated by multiplying the maximum charge coefficient by the total battery capacity.

- $\text{SOC}_{\min} = k_{\text{SOC}_{\min}} \cdot C_B = 7.5$ kWh (Minimum allowed battery SOC): Calculated by multiplying the minimum charge coefficient by the total battery capacity.

- $\gamma_{C_{\max}}^{\text{hourly}} = 15$ kW (Maximum hourly charge rate): Indicates the maximum rate at which the battery can be charged.

- $\gamma_{C_{\min}}^{\text{hourly}} = 1$ kW (Minimum hourly charge rate): Indicates the minimum rate at which the battery can be charged.

- $\gamma_{V2H_{\max}}^{\text{hourly}} = 300$ kW (Maximum hourly V2H rate): Indicates the maximum rate at which the battery can discharge energy to the house.

- $\gamma_{V2H_{\min}}^{\text{hourly}} = 1$ kW (Minimum hourly V2H rate): Indicates the minimum rate at which the battery can discharge energy to the house.

- $\eta = 0.85$ (Battery efficiency coefficient): Indicates the overall efficiency of the battery during charge and discharge cycles. A value of 0.85 means that 85% of the energy input into the battery can be recovered during discharge.

- $\Lambda^{\text{hourly}} = 0.3$ kWh (Hourly battery power loss when not in use): Indicates the energy loss of the battery for each hour it is not used.

The efficiency of the Tesla Model 3 Long Range vehicle is 18 kWh per 100 km. Given that 1 mile is approximately 1.60934 km, the vehicle's efficiency is about 11.18 kWh per 100 miles. This means that each percentage point of the battery's State of Charge (SOC) allows for a range of about 3.75 miles. However, to adopt a conservative approach, this amount is rounded down, and a range of 3 miles per percentage point of SOC is considered.

Additionally, whenever it is expected that the vehicle will leave the house, a minimum battery charge value of 80% of the total capacity is set. This ensures, in theory, a range of approximately 240 miles based on the above-mentioned consumption rates. This is an arbitrary but reasonable decision taken to make all the obtained results comparable.

Using these parameters ensures that the optimization model can manage the battery energy effectively and realistically, contributing to the overall efficiency and sustainability of the V2G/V2H system.

4.4 Load Profiles Used in Tests

To evaluate the effectiveness of the developed offline optimization models, various tests were conducted using different daily load profiles. These profiles were randomly selected from a set of different days taken from the iFlex study to represent a variety of energy consumption scenarios [22]. However, the differences in the final costs resulting from the tests proved to be negligible due to the cyclical nature of the load profiles and their similarity, except for particular events that occur very rarely.

To obtain a significant and representative sample, it was decided to use an average of all load profiles recorded over a six-month period, from January 1, 2020, to June 1, 2020. This average load profile was adopted as the reference profile in the tests, allowing for standardized results and facilitating comparative evaluation of the models.

4.5 Price Profiles Used in the Study

In this study, the price profiles used for the optimization models were derived from the iFlex dynamic pricing experiment conducted in Norway. The iFlex project aimed to investigate how households adjust their electricity consumption in response to varying hourly electricity prices. This experiment was conducted across multiple Norwegian regions, including Oslo, Stavanger, Bergen, Trondheim, Bodø, and Tromsø, during two winter periods from early 2020 to spring 2021.

The dataset from this experiment includes detailed hourly electricity consumption data for all participating households, as well as responses to several surveys regarding household characteristics, such as electric appliances, living conditions, socio-demographic variables, and their willingness to be flexible in their electricity usage. Additionally, temperature data from the Norwegian Meteorological Institute were included to account for the impact of outdoor temperature on electricity consumption, which is significant in Norwegian households due to the widespread use of electric heating.

The price signals tested during the experiment comprised different price levels (2, 5, 10, 15, and 30 NOK/kWh) and various price profiles (A, B, C, P, and P0). These price profiles were designed to reflect Norway's average daily demand profile and typical spot price profiles. For example, profile

A featured peak prices in the morning and afternoon, while profile B had higher prices throughout the entire daytime period.

The price profiles utilized in this study were chosen to provide a realistic representation of dynamic pricing scenarios that Norwegian households might encounter. This rich dataset allowed for a comprehensive analysis of demand-side flexibility and the effectiveness of V2G and V2H technologies in reducing energy costs and peak demand.

4.5.1 Relevant Price Profiles

The relevant price profiles for this study are profiles A, B, and C. To allow for a consistent comparison, the same price level was considered for all profiles, which is the price level 10 NOK/kWh, representing the peak price. The conversion to US dollars was made by multiplying by the exchange rate of 0.095, resulting in a price of approximately 0.95 USD/kWh.

- **Profile A**: Features peak prices in the morning and afternoon.
- **Profile B**: Has higher prices throughout the entire daytime period.
- **Profile C**: Shows a more uniform variation of prices throughout the day.

By using these detailed and realistic price profiles, the study aimed to simulate real market conditions as closely as possible, ensuring the validity and applicability of the developed optimization models. The iFlex dataset served as a robust foundation for testing various scenarios and evaluating the potential economic and operational benefits of integrating V2G and V2H technologies into residential energy management systems.

Below are the graphical representations of the price profiles used:

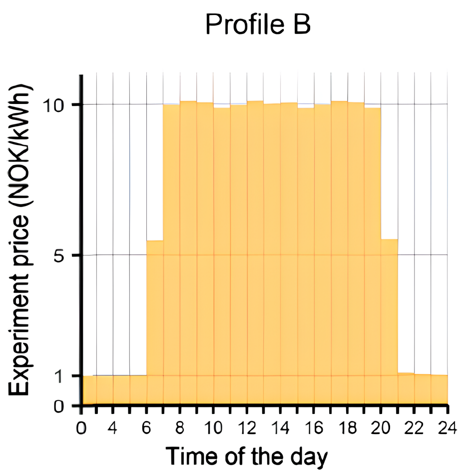

Figure 4.2: Profile B - Higher prices throughout the entire daytime period

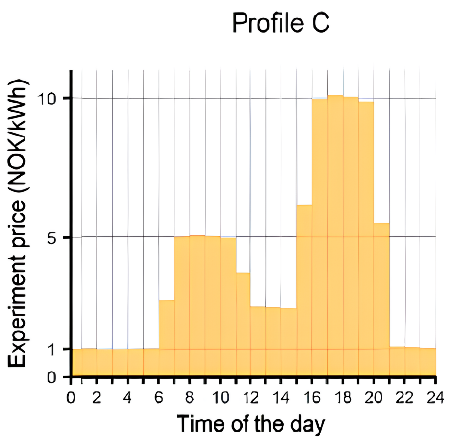

Figure 4.3: Profile C - Uniform variation of prices throughout the day

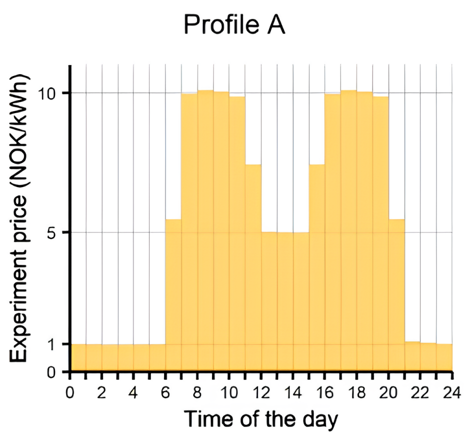

Figure 4.1: Profile A - Peak prices in the morning and afternoon

Chapter 5

Model Presentation

In this chapter, the developed optimization models will be presented, specifically two offline models and two online models.

Before diving into the detailed explanation of each parameter, variable, and constraint of the models, a simplified overview of their operation is provided to fully understand their objective and context.

The algorithm is designed to manage the energy of the electric vehicle over a time horizon T. For each time slot t within T, the model is given the following information:

- When the car will be at home and when it will be away.
- How many miles the car will travel the next day, which translates to the difference between the state of charge (SOC) when leaving home and the SOC when returning.
- The price trends for each time slot of the next day.
- The household load profile for each hour of the next day.

Using this information, the model optimizes the energy management to minimize costs over the time horizon T. For each time slot t, the model decides:

- If to charge the battery and at what rate.
- If to use the battery to power the house and at what rate.
- If to leave the battery idle in standby mode.

This structured approach ensures optimal use of the electric vehicle's battery, balancing cost savings and energy availability for both the vehicle and the household.

All input information is assumed to be estimated. In instances where there is a discrepancy between the estimated inputs and real-time data, the corrective online models intervene to reschedule the remaining part of the day to optimize performance.

5.1 Offline Models

The offline models are based on a time horizon T and use historical data and forecasts to optimize energy management for a single household with an electric vehicle. The models aim to minimize overall energy costs by maximizing the efficient use of the electric vehicle's battery.

5.1.1 Parameters of the Offline Models

The parameters used in the offline models are essential to define the behavior and limitations of the energy management system. Each parameter derived from hourly values previously described in the battery modeling section is adjusted through a conversion to match the time value of t, which is the number of time slots into which the T optimization time horizon is divided. The parameters are described in detail below:

Time Parameters

- T: The time horizon of the optimization.
- t: The number of time slots, in which T is divided.

Battery Parameters

- $\mathbf{SOC_{max}}$: Maximum state of charge of the battery [kWh]. Defines the maximum level of energy that can be stored in the battery.
- $\mathbf{SOC_{min}}$: Minimum state of charge of the battery [kWh]. Indicates the minimum level of energy the battery must maintain to ensure its operability.
- $\gamma_{C_{\mathbf{max}}}$: Maximum charging rate of the battery [kW]. Represents the maximum rate at which the battery can be charged in the time slot t.

- $\gamma_{C_{\mathbf{min}}}$: Minimum charging rate of the battery [kW]. Indicates the minimum rate at which the battery can be charged in the time slot t.
- $\gamma_{V2H_{\mathbf{max}}}$: Maximum discharging rate V2H [kW]. Defines the maximum rate at which the battery can discharge energy to the house in the time slot t.
- $\gamma_{V2H_{\mathbf{min}}}$: Minimum discharging rate V2H [kW]. Indicates the minimum rate at which the battery can discharge energy to the house in the time slot t.
- η: Battery efficiency. Represents the overall efficiency of the battery during charge and discharge cycles. A value of 0.85 means that 85% of the energy input to the battery can be recovered during discharge.
- Λ: Battery power loss when not in use [kWh]. Represents the energy loss of the battery if it is not used in the time slot t.

Vehicle Parameters

- $\theta(t)$: Vehicle state in the time slot t (1 if present, 0 if absent).
- $\mathbf{SOC}_a(t)$: State of charge of the vehicle upon arrival [kWh]. Indicates the battery charge level at the beginning of the time slot t when the vehicle arrives at home.
- $\mathbf{SOC}_l(t)$: State of charge of the vehicle at departure [kWh]. Indicates the minimum battery charge level at the beginning of the time slot t when the vehicle leaves home.

Energy Parameters

- $L(t)$: Household load profiles [kWh]. Represents the energy demand of the house at each time slot t.
- $C(t)$: Energy cost profiles [$/kWh]. Indicates the price of energy at each time slot t.

5.1.2 Variables of the Offline Models

The variables in the offline model define the dynamic and decision parameters of the system. The variables are described with specific details below:

Battery Variables

- **SOC**(t): State of charge of the battery at the beginning of time slot t and the end of time slot $t-1$ [kWh]. This represents the energy level of the battery at the transition between time slots. Therefore, any parameter or variable involving the SOC is defined over $T+1$ values, unlike other variables and parameters defined over T values.
- $\theta_C(t)$: Boolean variable that indicates if the battery is in charging mode or not (1 if yes, 0 if not) in time slot t [kW].
- $\theta_{V2H}(t)$: Boolean variable that indicates if the battery is in discharging mode or not (1 if yes, 0 if not) in time slot t [kW].
- $\gamma_C(t)$: Charging rate of the battery in time slot t [kW].
- $\gamma_{V2H}(t)$: V2H discharging rate of the battery in time slot t [kW].

Energy Variables

- $x(t)$: Energy purchased from the grid in time slot t [kWh].

5.1.3 Constraints of the Offline Models

Constraints are fundamental to defining the limitations and operational conditions of the energy management system. Each constraint is described in detail below, including the `for` and `if` loops and their functions.

Constraint 1: Mutual States of the Battery

$$\theta_C(t) + \theta_{V2H}(t) \leq \theta(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint defines the three possible states of the vehicle's battery. The battery can be charging ($\theta_C(t) = 1$), in Vehicle-to-House mode ($\theta_{V2H}(t) = 1$), or in standby ($\theta(t) = 0$).

Constraint 2: Maximum Charging Rate of the Battery

$$\gamma_C(t) \leq \gamma_{C_{\max}} \cdot \theta_C(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint limits the maximum charging rate of the battery, ensuring it does not exceed the maximum capacity defined for each time slot t. It is activated just when the battery state is in charging mode ($\theta_C(t) = 1$).

Constraint 3: Minimum Charging Rate of the Battery

$$\gamma_C(t) \geq \gamma_{C_{\min}} \cdot \theta_C(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint ensures that the charging rate of the battery is not less than the minimum capacity defined for each time slot t. It is activated just when the battery state is in charging mode ($\theta_C(t) = 1$).

Constraint 4: Maximum V2H Discharging Rate

$$\gamma_{V2H}(t) \leq \gamma_{V2H_{\max}} \cdot \theta_{V2H}(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint limits the maximum rate at which the battery can discharge energy to the house in V2H mode for each time slot t. It is activated just when the battery state is in $V2H$ mode ($\theta_{V2H}(t) = 1$).

Constraint 5: Minimum V2H Discharging Rate

$$\gamma_{V2H}(t) \geq \gamma_{V2H_{\min}} \cdot \theta_{V2H}(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint ensures that the discharging rate of the battery to the house is not less than the minimum capacity defined for each time slot t. It is activated just when the battery state is in $V2H$ mode ($\theta_{V2H}(t) = 1$).

Constraint 6: Energy Purchased from the Grid

$$x(t) = L(t) + \gamma_C(t) - \eta \cdot \gamma_{V2H}(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint represents the total energy purchased from the grid in each time slot t, considering the following terms:

- $x(t)$: Energy purchased from the grid in time slot t [kWh]. This value represents the amount of energy that needs to be purchased from the grid to meet the household load and the charging and discharging operations of the battery.
- $L(t)$: Household load profile in time slot t [kWh]. This value indicates the amount of energy required by the house in each time slot t.
- $\gamma_C(t)$: Charging rate of the battery in time slot t [kW]. This value represents the amount of energy used to charge the vehicle's battery in time slot t.

- $\eta \cdot \gamma_{V2H}(t)$: Battery efficiency multiplied by the V2H discharging rate of the battery in time slot t [kW]. This value represents the amount of energy returned from the battery to the house, taking into account the battery's efficiency. The efficiency η accounts for energy losses during the discharging process.

Constraint 7: Maximum Battery State of Charge

$$\mathrm{SOC}(t) \leq \mathrm{SOC}_{\max} \cdot \theta(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint ensures that the battery's state of charge never exceeds the maximum limit defined for each beginning of the time slot t. It is activated just when the EV is at home ($\theta(t) = 1$).

Constraint 8: Minimum Battery State of Charge

$$\mathrm{SOC}(t) \geq \mathrm{SOC}_{\min} \cdot \theta(t) \quad \forall t \in \{1, \ldots, T\}$$

This constraint ensures that the battery's state of charge never falls below the minimum limit defined for each beginning of the time slot t. It is activated just when the EV is at home ($\theta(t) = 1$).

Constraint 9: State of Charge at Departure

$$\mathrm{SOC}(t) \geq \mathrm{SOC}_l(t) \quad \text{if } \theta(t-1) = 1 \text{ and } \theta(t) = 0$$

This constraint ensures that the battery's state of charge is sufficient to meet the vehicle's energy needs at the time of departure. It is activated just when happen the transition of the car by being at home ($\theta(t-1) = 1$) to not being at home ($\theta(t) = 0$).

Constraint 10: State of Charge at Arrival

$$\mathrm{SOC}(t) = \mathrm{SOC}_a(t) \quad \text{if } \theta(t-1) = 0 \text{ and } \theta(t) = 1$$

This constraint ensures that the battery's state of charge is sufficient to meet the vehicle's energy needs at the time of departure. It is activated just when happen the transition of the car by not being at home ($\theta(t-1) = 0$) to being at home ($\theta(t) = 1$).

Constraint 11: Updating the State of Charge

$$\text{SOC}(t) = \text{SOC}(t-1) + \eta \cdot \gamma_C(t-1) - \gamma_{V2H}(t-1) - \Lambda \cdot (1 - \theta_C(t-1) - \theta_{V2H}(t-1)) \cdot \theta(t-1)$$

This constraint updates the state of charge (SOC) of the battery, considering various factors from the previous time slot. The terms are explained as follows:

- **SOC**(t): State of charge of the battery at the beginning of time slot t and the end of time slot $t-1$ [kWh]. This represents the energy level of the battery at the transition between time slots.
- **SOC**$(t-1)$: State of charge of the battery at the beginning of the previous time slot $t-1$ [kWh]. This represents the energy level of the battery at the transition between time slots $t-2$ and $t-1$.
- $\eta \cdot \gamma_C(t-1)$: Energy added to the battery during the previous time slot $t-1$ [kWh]. Here, $\gamma_C(t-1)$ is the charging rate of the battery during the previous time slot, and η is the efficiency of the battery during charging.
- $\gamma_{V2H}(t-1)$: Energy discharged from the battery to the house during the previous time slot $t-1$ [kWh]. This term represents the amount of energy used to supply the household load from the battery during the previous time slot.
- $\Lambda \cdot (1 - \theta_C(t-1) - \theta_{V2H}(t-1)) \cdot \theta(t-1)$: Energy loss of the battery when not in use during the previous time slot $t-1$ [kWh]. Here, Λ represents the energy loss rate, and the term $(1 - \theta_C(t-1) - \theta_{V2H}(t-1)) \cdot \theta(t-1)$ ensures that this loss is only considered when the battery is in standby mode.

Constraint 12: Initial and Final State of Charge (SOC)

$$\text{SOC}(1) = \text{SOC}(T+1)$$

This constraint links the initial and final state of charge of the battery, ensuring that the day starts and ends with the same level of charge. This is necessary due to the nature of the SOC variable, which represents the state of charge at the end of $t-1$ and the beginning of t. By linking the initial and final SOC, uniformity in optimization is maintained, preventing the model from starting the day with an unjustified maximum SOC level.

5.1.4 Objective Functions of the Offline Models

The parameters, variables, and constraints described so far are common to both offline models. The offline models, however, differ in their objective functions, which define the optimization goals. The objective function determines the criteria for evaluating the performance of the energy management system.

Objective Function of the First Offline Model OF1

The first offline model aims to minimize the total energy costs over the time horizon T. The objective function for this model is:

$$\min \sum_{t=1}^{T} C(t) \cdot x(t)$$

In this objective function:

- $C(t)$: represents the energy cost profile at time slot t.
- $x(t)$: represents the energy purchased from the grid at time slot t.

The summation $\sum_{t=1}^{T}$ ensures that the total cost over all time slots is minimized.

Objective Function of the Second Offline Model OF2

The second offline model introduces a new parameter α to balance between minimizing energy costs and maintaining a desirable state of charge (SOC) for the battery. The objective function for this model is:

$$\min \sum_{t=1}^{T} (\alpha \cdot (C(t) \cdot x(t)) - (1 - \alpha) \cdot \mathrm{SOC}(t))$$

In this objective function:

- α: is a weight parameter that balances the importance of energy cost minimization and SOC maintenance. It ranges from 0 to 1.
- $C(t)$: represents the energy cost profile at time slot t.
- $x(t)$: represents the energy purchased from the grid at time slot t.
- $\mathbf{SOC}(t)$: represents the state of charge of the battery at the beginning of the time slot t.

The term $\alpha \cdot (C(t) \cdot x(t))$ ensures that energy costs are minimized, while the term $(1-\alpha) \cdot \text{SOC}(t)$ ensures that the battery maintains a desirable state of charge. The parameter α allows for tuning the model's focus between cost savings and SOC optimization.

The second model, therefore, has the objective of maintaining a higher average SOC level throughout the day. This is done at the expense of higher costs, reflecting a trade-off between cost savings and maintaining a more favorable SOC for the battery. The summation $\sum_{t=1}^{T}$ ensures that the combined objective of cost minimization and SOC management is considered over all time slots.

5.2 Implementation and Graphs Description

5.2.1 General Implementation

In this section, the implementation details of the offline optimization models are provided. The objective of the implementation is to demonstrate the practical application of the models described in a real scenario. The offline models are implemented using Python and the Gurobi optimization solver. The input parameters, variables, and constraints for the models are defined as previously explained.

The code for the first offline model, which focuses on minimizing the total energy cost, is given in Appendix A. The code for the second offline model, which includes a trade-off between minimizing energy cost and maintaining a higher state of charge (SOC) of the battery, is provided in Appendix B.

5.2.2 Graph Descriptions

Graph 1: SOC Trend During the Day

The first graph shows the SOC (State of Charge) trend of the electric vehicle's battery throughout the day. This graph helps visualize how the battery's charge level varies as a function of different charging (gamma_C) and discharging (gamma_V2H) operations. When the SOC value is set to zero, it means that the EV isn't home.

Graph 2: Charging and Discharging Rates for Each Time Slot

The second graph presents the battery's charging and discharging rates for each time slot. It shows the amount of energy charged (gamma_C) and discharged (gamma_V2H) from the battery in each time slot. This graph allows understanding when the battery is charged and when it is used to power the house.

Graph 3: Energy Purchased for Each Time Slot

The third graph is the most complex and shows the total energy purchased (x) for each time slot. The bars are divided into different colors to represent the various components of the purchased energy:

- **Energy bought to meet the house Loads**: represented in one color, shows the energy purchased to cover the house's energy demand.
- **Energy bought to charge the battery**: represented in another color, shows the energy purchased specifically to charge the vehicle's battery.
- **Energy saved by V2H**: this component is shown with a transparent dashed bar, indicating the amount of energy that would have been purchased in the absence of V2H technology.

In particular, when V2H is active, the graph shows how the saved energy reduces the total energy needed to meet the house's loads, highlighting the efficiency of the energy management system.

5.2.3 Example Scenarios

To illustrate the functionality of the optimization models, three example scenarios are presented. These scenarios are used to show the types of data and graphs that will be presented later in the experiments and results chapters.

Scenario 1: Typical Workday

In this scenario, the vehicle leaves home at 8 AM and returns at 5 PM, traveling a total distance of 30 miles. The price profile used is Profile C, and the offline model applied is OF1 (see Figure 5.1).

Scenario 2: Intensive Vehicle Use

In this scenario, the vehicle leaves home at 9 AM and returns at 9 PM, covering a distance of 150 miles throughout the day. The price profile utilized is Profile A, and the offline model employed is OF1 (see Figure 5.2).

Scenario 3: Multiple Outings

In this scenario, the vehicle undertakes multiple trips: it leaves home at 8 AM and returns at 11 AM, then departs again at 4 PM and comes back at 9 PM, with a total distance of 50 miles traveled during the day (20 miles in the morning trip and 30 miles in the afternoon trip). The price profile adopted is Profile A, and the offline model used is OF1 (see Figure 5.3).

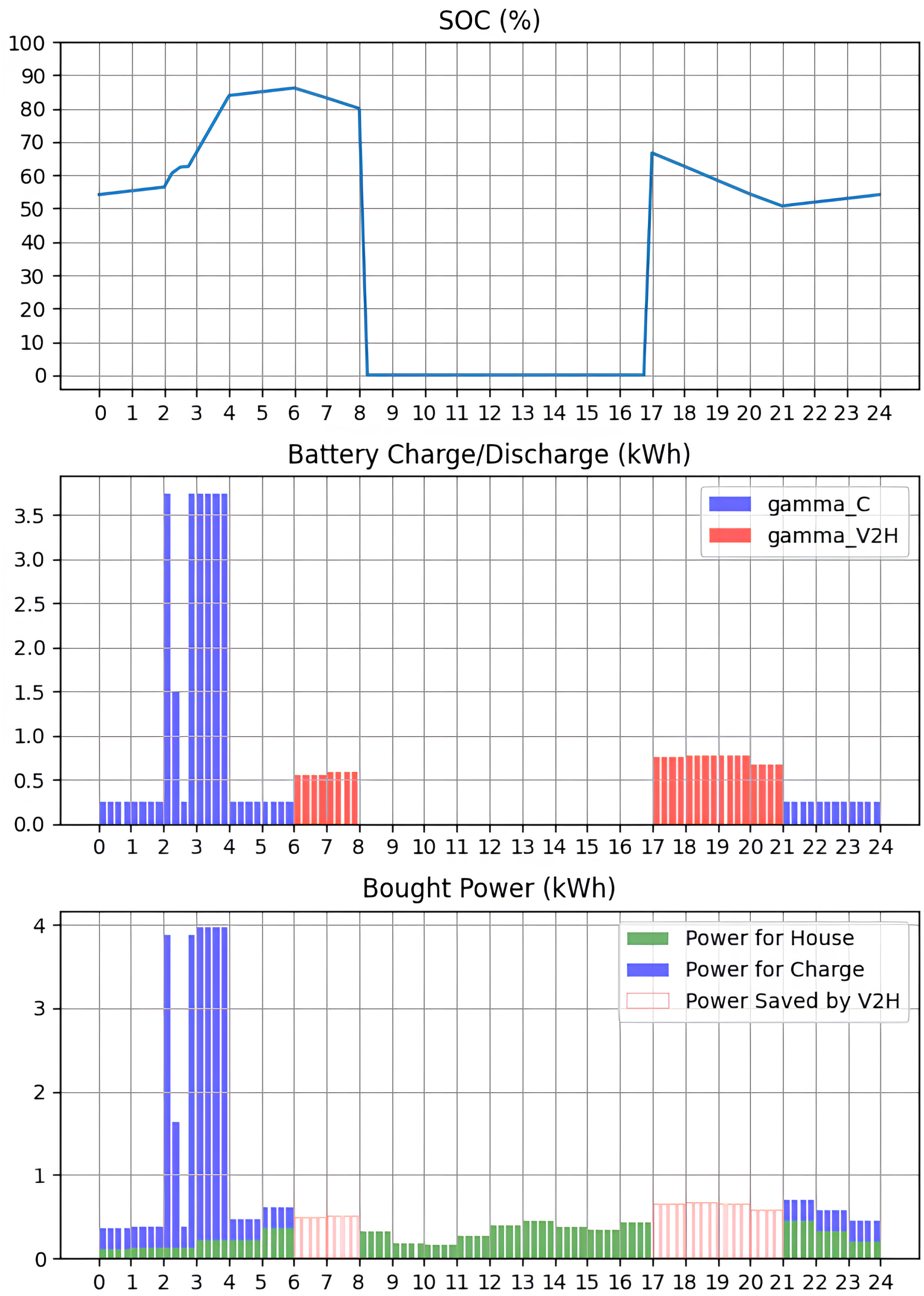

Figure 5.1: Graphs for Scenario 1: SOC, Charging and V2H Rates, and Bought Power.

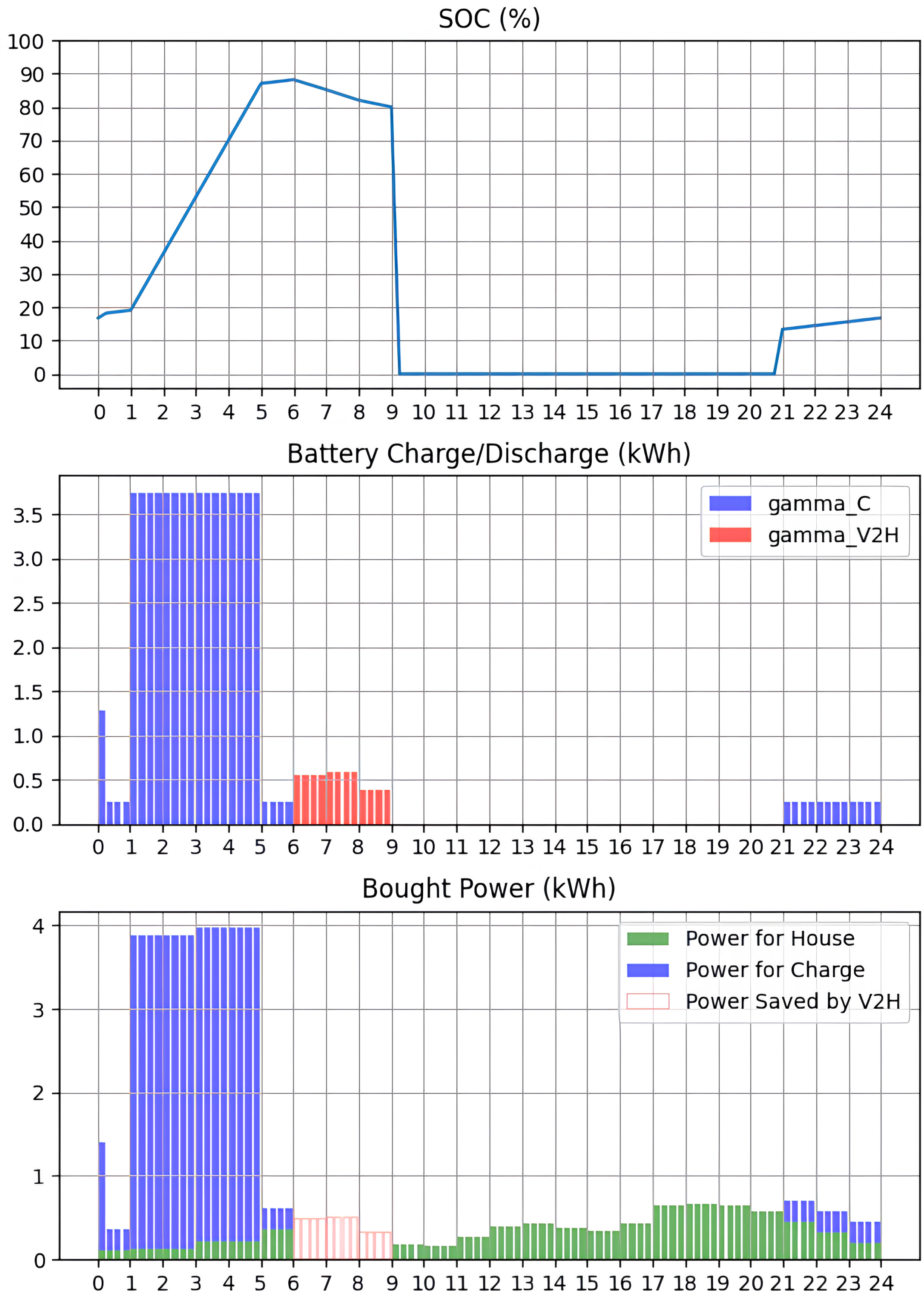

Figure 5.2: Graphs for Scenario 1: SOC, Charging and V2H Rates, and Bought Power.

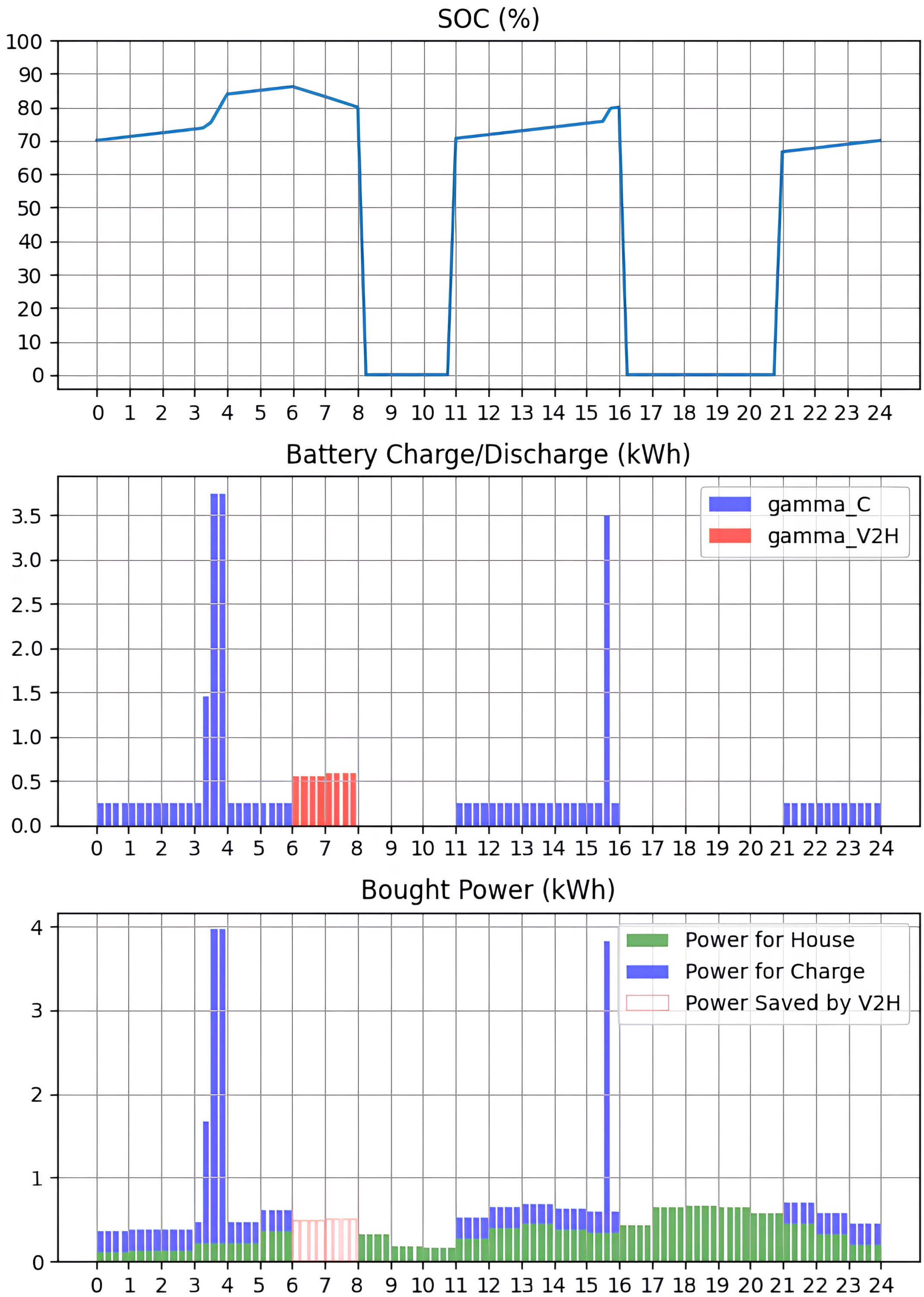

Figure 5.3: Graphs for Scenario 1: SOC, Charging and V2H Rates, and Bought Power.

5.3 Online Models

In this section, the online models developed for energy management based on Vehicle-to-House (V2H) technologies are illustrated. The main objective is to demonstrate how these models can dynamically adapt to unexpected changes in operating conditions, ensuring continuous and efficient optimization of energy use.

5.3.1 Integration with Offline Models

The main difference between the online and offline models lies in their implementation and memory capacity. The online models are capable of retaining all decisions made in the timeslots preceding the detection of the error at time t. This allows the online models to dynamically adapt to unexpected changes, ensuring continuous and responsive energy management optimization.

When the online models detect an error at time t, they reoptimize the charging and discharging schedule over $T - t$, considering all decisions and optimizations made in the previous timeslots by the offline models OF1 or OF2. This dynamic adaptation ensures effective error handling and energy management optimization.

The strength of the online models lies in their ability to effectively interact with the offline models and adapt in real-time to changes in operating conditions. They are designed to respond to discrepancies detected between forecasts and actual conditions, leveraging advanced management of the time series of each parameter and decision variable. The offline models OF1 and OF2 provide an initial optimization basis, while the online models intervene to correct any errors detected in real-time. This interaction between models is essential to ensure a robust and responsive energy management system.

The implementation in Python allows for efficient manipulation and management of time series data, transforming them into suitable inputs for the online models. This approach ensures that the models can operate efficiently and accurately, maintaining in memory all decisions made in the timeslots preceding the detection of the error.

5.3.2 Types of Errors Detected

Three types of errors can be detected in real-time:

- **Presence Error (E_p)**: The vehicle is at home when it was expected to be absent.
- **Absence Error (E_a)**: The vehicle is absent when it was expected to be at home.
- **State of Charge Error (E_{SOC})**: The vehicle returns home with a SOC different from the expected one, indicating a discrepancy in the miles traveled compared to the forecast.

5.3.3 Errors Management

To address these errors, two online models are used:

Online Model 1 (ON1)

This model is activated when a **Presence Error (E_p)** is detected. The goal of ON1 is to recalculate the charging and discharging schedule to optimize energy use considering the unexpected availability of the vehicle. The constraints on the **minimum SOC** (Constraint 8) and **maximum SOC** (Constraint 7) are relaxed for the initial instant to manage the **SOC Error (E_{SOC})**. Additionally, the constraint on the **departure SOC** (Constraint 11) is relaxed since the minimum required energy level had already been reached with the offline optimization.

Online Model 2 (ON2)

This model is activated when an **Absence Error (E_a)** is detected. The goal of ON2 is to modify the energy management plan to compensate for the absence of the vehicle's battery as an energy source. The constraints on the **minimum SOC** (Constraint 8) and **maximum SOC** (Constraint 7) are also relaxed for the initial instant to manage the **SOC Error (E_{SOC})**.

5.3.4 Effectiveness of Implementation

The effectiveness of these online models is achieved through the interaction with offline models and the advanced implementation in the Python environment. The ability to manage and manipulate time series of parameters and decision variables transforms the data into suitable inputs for the online models, ensuring efficient and precise operation. This approach highlights the importance of implementation in achieving a robust and adaptive energy management system.

5.3.5 Examples of Error Detection and Reoptimization

In this subsection, the graphical demonstration of how online models can detect errors and reoptimize using the first scenario presented in the previous chapter on offline models (Fig. 5.1) is shown. The first graph (related to SOC) is displayed in the three cases of the three errors. In each case, all iterations of the reoptimizations are demonstrated, with each line representing an optimization phase. It is important to note that these examples are provided to demonstrate the functioning of the models in response to individual errors, but they can be combined and managed simultaneously.

Case 1: Presence Error (E_p)

In this case, the vehicle is unexpectedly at home. The online model ON1 is activated, and the system recalculates the SOC schedule considering the unexpected availability of the vehicle. Specifically, the return was expected at 5 PM, but unexpectedly the vehicle returns at 4 PM, forcing the model to perform four reoptimizations.

Case 2: Absence Error (E_a)

In this case, the vehicle is unexpectedly absent from home. The online model ON2 is activated, and the system recalculates the SOC schedule considering the absence of the vehicle's battery as an energy source. The return was expected at 5 PM, but the vehicle returns at 6 PM, requiring continuous reoptimization until its return.

Case 3: State of Charge Error (E_{SOC})

In this case, the vehicle was supposed to travel 30 miles but travels 60 miles, consuming twice the expected battery. Assuming that for 30 miles the SOC decreases by 10%, for 60 miles the SOC decreases by 20%. Consequently, the SOC changes from the expected 70% (for 30 miles) to 60%, requiring a recalibration of the model to handle the actual SOC.

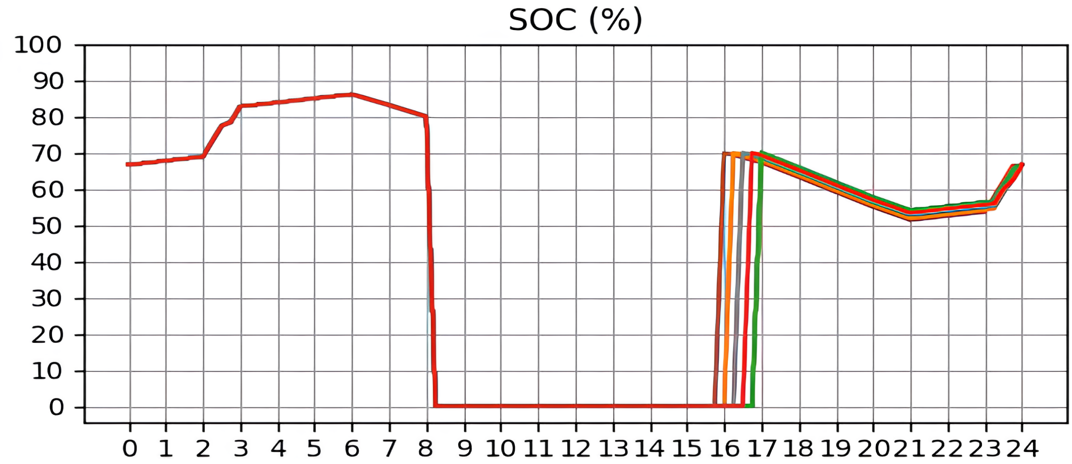

Figure 5.4: Graphs for Case 1: SOC.

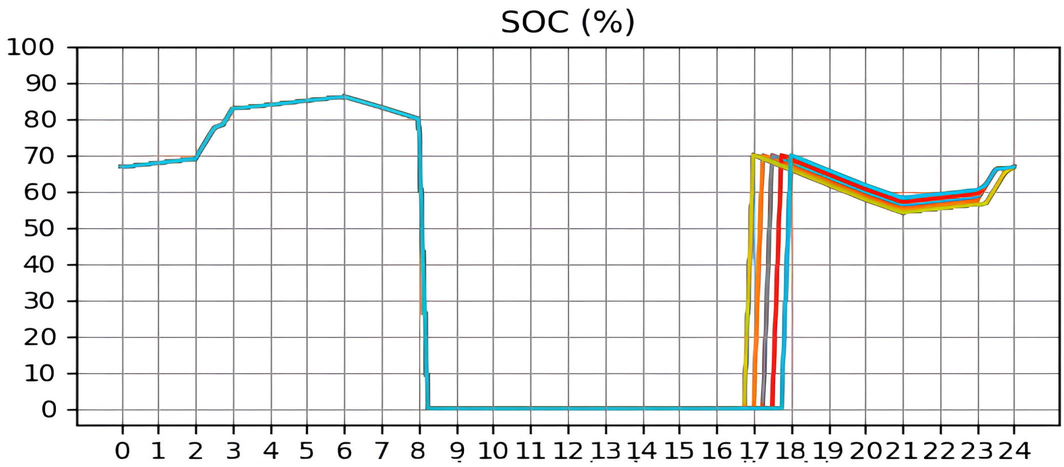

Figure 5.5: Graphs for Case 2: SOC.

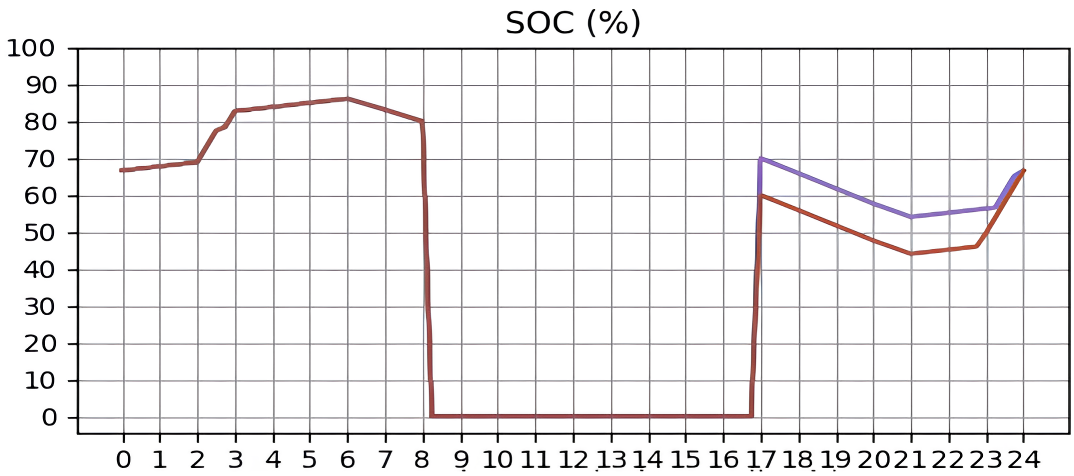

Figure 5.6: Graphs for Case 3: SOC.

Chapter 6

Tests and Experiments

6.1 Introduction

In this chapter, the behaviors and effectiveness of the optimization models developed for energy management based on Vehicle-to-House (V2H) technologies will be explored. The chapter is divided into two main sections, each with a specific focus:

- **Behavior of Models in Response to Individual Errors**: This section will analyze the optimization models' responses to individual errors. Practical examples will be presented to demonstrate how the online models detect and correct errors in real time. Graphs will be shown relating to the trend of energy costs based on the extent of the detected error.

- **Long-Term Simulation**: This section will focus on a long-term simulation that includes daily mixed errors selected randomly. The goal is to evaluate the cost savings achieved by implementing the optimization models in a real and extended context. The results of the simulation will be analyzed to understand the overall impact of the optimization models on energy management and operating costs.

This structure allows for understanding both the specific behavior of the models in error situations and their overall effectiveness in a continuous operational context.

In this context, "tests" and "experiments" can be distinguished based on their purpose and methodology:

- **Tests**: Conducted to verify the behavior of models under specific controlled conditions. They are used to understand how the models respond to certain errors and parameter variations. For example, a test might check how a model reacts when the vehicle returns home earlier than expected.

- **Experiments**: Conducted to evaluate the effectiveness and efficiency of models in realistic scenarios over longer periods. Experiments aim to simulate real-life situations and measure overall benefits, such as energy cost savings over several months.

In summary, tests focus on specific and well-defined conditions, while experiments aim to assess the overall performance of models in real-world scenarios and over extended periods.

6.1.1 Parameter Setting

In this subsection, the parameters used in the optimization models for all tests and experiments are shown, justified earlier in the chapters on methodology and battery modeling. The following table, provides a quick summary of the numerical values adopted.

Parameter	Description	Value
T	Optimization time horizon	24 hours
t	Number of time slots	96
C_B	Battery Capacity	75 kWh
$k_{\mathrm{SOC}_{\mathrm{max}}}$	Maximum allowed battery power coefficient	0.9
$k_{\mathrm{SOC}_{\mathrm{min}}}$	Minimum allowed battery power coefficient	0.1
$\mathrm{SOC}_{\mathrm{max}}$	Maximum allowed battery SOC	67.5 kWh
$\mathrm{SOC}_{\mathrm{min}}$	Minimum allowed battery SOC	7.5 kWh
$\gamma_{C_{\mathrm{max}}}^{\mathrm{hourly}}$	Maximum hourly charge rate	15 kW
$\gamma_{C_{\mathrm{min}}}^{\mathrm{hourly}}$	Minimum hourly charge rate	1 kW
$\gamma_{V2H_{\mathrm{max}}}^{\mathrm{hourly}}$	Maximum hourly V2H rate	300 kW
$\gamma_{V2H_{\mathrm{min}}}^{\mathrm{hourly}}$	Minimum hourly V2H rate	1 kW
η	Battery efficiency coefficient	0.85
$\Lambda^{\mathrm{hourly}}$	Hourly battery power loss when not in use	0.3 kWh
α	Weighting factor in the objective function of OF2	0.99

Table 6.1: Parameters Used in Tests and Experiments

These parameters ensure that the optimization model can manage the battery energy effectively and realistically, contributing to the overall efficiency and sustainability of the V2H system.

The parameter α is set to 0.99 to prioritize cost minimization while still considering the state of charge (SOC) of the battery. By assigning a high value to α, the objective function focuses mainly on minimizing energy costs, which is crucial for practical applications where reducing expenses is a primary goal. The slight weight given to SOC ensures that the battery's charge level is also optimized, maintaining a balance between economic efficiency and operational feasibility.

All other parameters, such as θ, SOC_l, and SOC_a, are maintained as those of scenario 1 presented in the previous chapter. It has been observed that for the behavior and study of errors and their impact on cost, there is no qualitative difference based on the scenario used. Moreover, scenario 1, with its flexibility, realistically represents a wide range of possibilities for living the day, covering various daily usage variables of the electric vehicle, from home stay duration to miles traveled. This approach ensures that the results obtained are representative and comparable, allowing a comprehensive evaluation of the effectiveness of the developed optimization models.

6.1.2 Additional Constraint on Initial and Final SOC

In all tests and experiments, an additional constraint on the initial and final state of charge (SOC) of the day was introduced to ensure the comparability of the obtained results. This constraint is necessary to avoid scenarios where excess energy is produced during re-optimizations, as the model is not designed to handle excess energy for sale.

Realistically, any excess energy would be used to increase the initial SOC of the next day. However, for tests and experiments, it is essential that the amount of energy used and consumed remains consistent across all scenarios. The additional constraint introduced is as follows:

$$\mathrm{SOC}(1) = 50$$

This constraint ensures that the initial SOC is fixed at 50, which also affects the final SOC of the day due to **Constraint 12**. This approach guarantees that all starting conditions are the same, allowing for a fair and accurate comparison of the results obtained from different tests and experiments.

6.1.3 Benchmark Model Comparison

To provide a comparative baseline, a benchmark model is used. This benchmark model operates similarly to the OF1 model but does not consider price fluctuations throughout the day. Instead, it simply minimizes the total energy purchased over the horizon T.

The benchmark model's objective function is straightforward: minimizing the total energy cost without accounting for time-based price variations. This provides a reference point to evaluate the performance and cost savings achieved by the more sophisticated OF1 and OF2 models, which incorporate dynamic pricing and real-time error correction.

The analysis of numerical results will compare the energy costs obtained with the benchmark model to those obtained using the OF1, OF2, and their respective online models. This comparison highlights the benefits of adopting advanced energy management strategies that account for price variations and real-time error correction.

6.2 Tests on Model Behavior

In this section, the models' behavior in response to individual errors is studied, showing cost trends based on the error magnitude. The considered errors for the tests are a mix of the previously described presence error (E_p), absence error (E_a), and state of charge error (E_{SOC}). Specifically, errors of +1 and -1 hours on the expected arrival and departure times, and a battery consumption variation of ±20% (equivalent to approximately 60 miles) are analyzed. It is important to note that these examples demonstrate the models' responses to individual errors, but they can handle multiple errors simultaneously.

6.2.1 Cost Analysis and Graphs Explanation

The cost analysis focuses on the variations in costs based on the magnitude of the errors. This comprehensive analysis aims to illustrate the cost implications of the errors and the effectiveness of the online models in mitigating them. The following key points are considered:

- **Offline Model OF1 Costs**: The costs incurred using the baseline offline optimization model OF1.
- **Tradeoff Offline Model OF2 Costs**: The costs associated with the offline optimization model OF2, which balances cost minimization and maintaining a higher average SOC.
- **Online Models Based on OF1 Costs**: The costs when using the online models that reoptimize based on the initial OF1 offline optimization.
- **Online Models Based on OF2 Costs**: The costs when using the online models that reoptimize based on the initial OF2 offline optimization.
- **OF omniscient**: This line on the graph represents the costs obtained with an offline model that has perfect knowledge of the actual data. It provides a benchmark for evaluating the effectiveness of the online models.

The graphs display these costs, providing a visual comparison of how each model performs under various error magnitudes. This analysis highlights:

- The effectiveness of online models in adapting to unexpected changes and reducing overall costs.
- The tradeoffs involved in maintaining a higher average SOC versus strictly minimizing costs.
- The potential cost savings achievable through real-time optimization and error correction compared to the omniscient model.

By presenting a detailed cost analysis across different models and error scenarios, this section underscores the practical benefits and limitations of the developed optimization strategies.

6.2.2 Departure Time Test

In this section, we analyze the impact of a time error in the scheduled departure time of the electric vehicle on the energy management of the V2H system. We introduce a total error of two hours, varying each timeslot between one hour ahead and one hour behind. This results in a total of eight re-optimizations, corresponding to the number of timeslots contained in two hours.

Graphs and Commentary

The graph below shows the costs associated with the OF1, OF2 models and their corresponding online models derived from OF1 and OF2 as a function of the magnitude of the time error.

When the error is zero, the costs of the online models correspond to their respective offline models (OF1 and OF2). As the error increases, variations in costs are observed as described below.

OF1 and OF2:

- Both offline models, OF1 and OF2, maintain constant costs regardless of the error magnitude, as they cannot adapt in real-time to variations in operating conditions.

ONLINE from OF1:

- With a departure error of -60 minutes, the cost is higher compared to the omniscient offline model, but it starts to decrease as the error reduces. This is due to the flexibility of the online model that manages to partially correct the error.
- When the error is zero, the cost matches that of the OF1 model.
- With positive errors, costs begin to decrease further, becoming even lower than those of the omniscient offline model for errors greater than 15 minutes. This phenomenon is explained by the relaxation of the SOC constraint at departure, allowing for greater flexibility in energy use. However, this results in a loss of potential mileage. Assuming an hourly loss of 0.3 kWh, for each hour in standby the vehicle loses approximately 3 miles of range (0.3 kWh / 0.1 kWh per mile).

ONLINE from OF2:

- The behavior of the online model derived from OF2 depends on the fact that when the model detects an error, even starting from the OF2 tradeoff model, it re-optimizes by returning to the objective function of the OF1 model. This process causes a drastic reduction in cost as the error moves away from zero. In other words, the online model corrects the errors dynamically, which leads to an improvement in operating costs compared to the offline OF2 model.

The graphs show the cost trends for each price profile (A, B, and C), but qualitatively the behaviors remain similar. However, specific numerical results vary based on the price profile.

Numerical Results and Savings Percentages

Below are the savings percentages for the online models derived from OF1 and OF2 compared to the omniscient model, calculated using the savings percentage formula.

Savings percentages are calculated relative to the omniscient model as follows:

$$Savings\ Percentage = \left(\frac{\text{Cost of Omniscient Model}-\text{Cost of Online Model}}{\text{Cost of Omniscient Model}}\right) \times 100$$

Error (min)	A	B	C
-60	-1.89%	-1.55%	-2.68%
-45	-1.47%	-1.20%	-2.05%
-30	-1.01%	-0.82%	-1.39%
-15	-0.52%	-0.42%	-0.71%
0	0.00%	0.00%	0.00%
15	0.35%	0.28%	0.47%
30	0.72%	0.57%	0.95%
45	1.11%	0.87%	1.44%
60	1.51%	1.19%	1.94%

Table 6.2: Departure error test: savings percentages for the online model derived from OF1 compared to the omniscient model for price profiles A, B, and C.

Error (min)	A	B	C
-60	5.48%	4.50%	11.94%
-45	5.17%	4.22%	11.48%
-30	4.84%	3.92%	11.01%
-15	4.48%	3.61%	10.51%
0	27.68%	22.15%	41.61%
15	3.84%	3.06%	9.67%
30	3.58%	2.84%	9.33%
45	3.30%	2.60%	8.97%
60	3.00%	2.35%	8.61%

Table 6.3: Departure error test: savings percentages for the online model derived from OF2 compared to the omniscient model for price profiles A, B, and C.

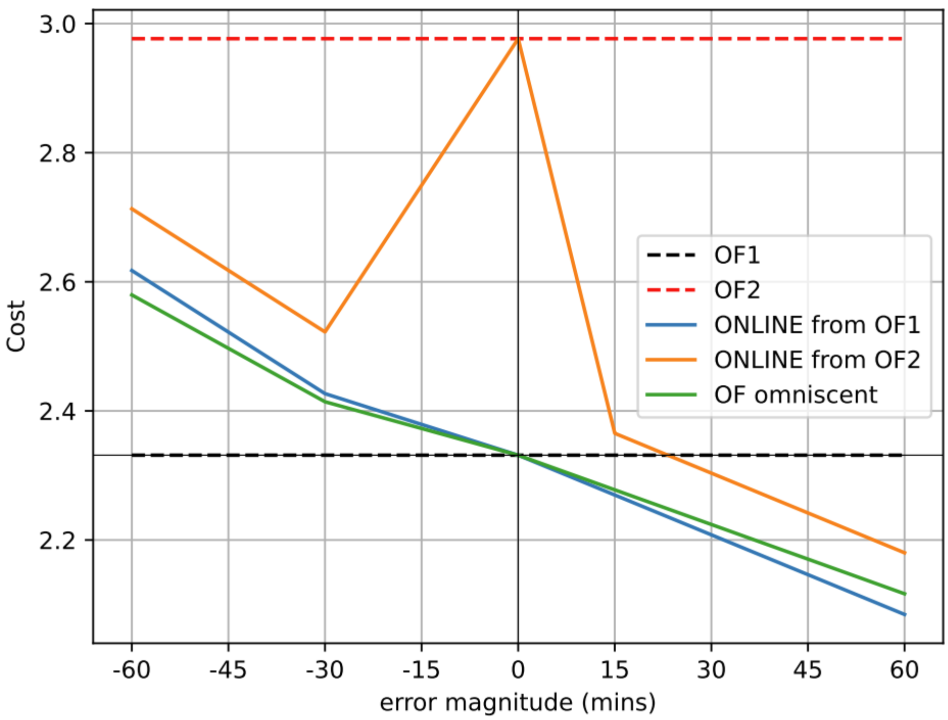

Figure 6.1: Departure error test: cost comparison between the OF1 and OF2 model and its corresponding online models for price profile A.

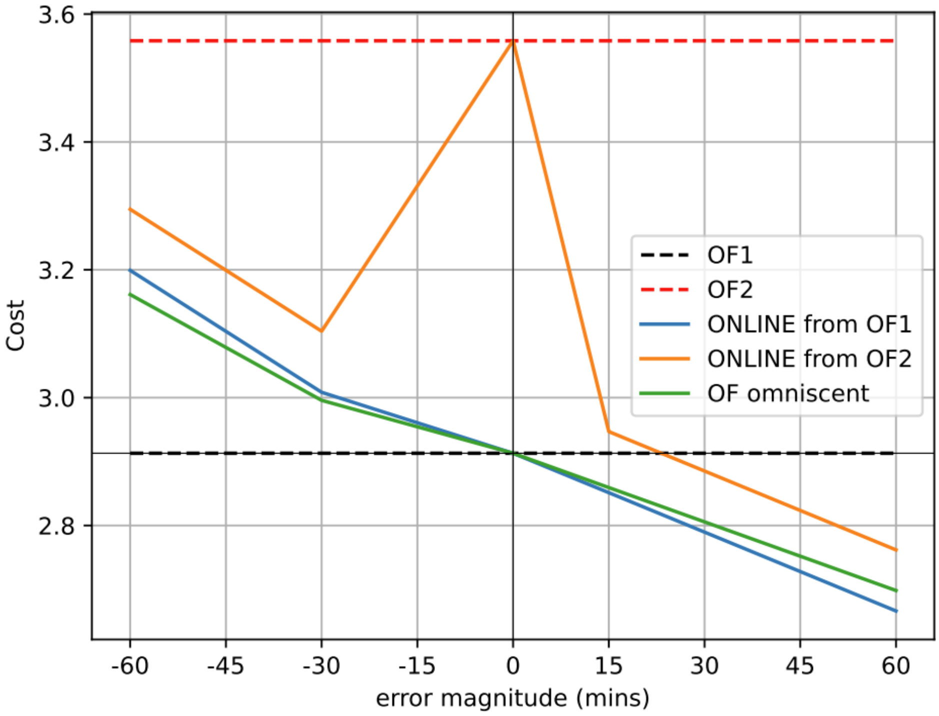

Figure 6.2: Departure error test: cost comparison between the OF1 and OF2 model and its corresponding online models for price profile B.

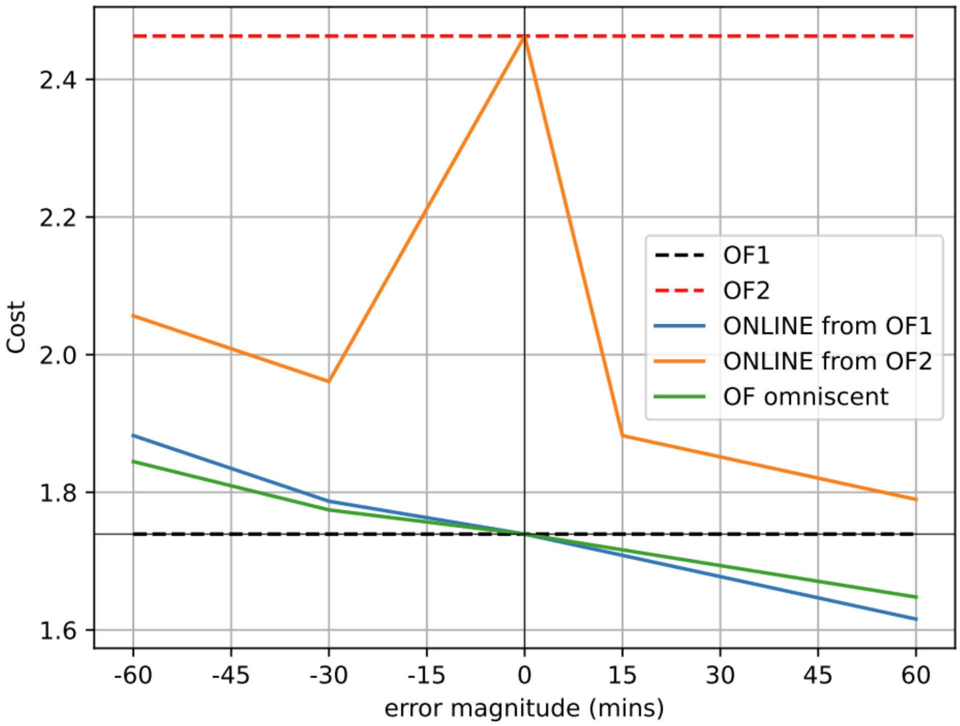

Figure 6.3: Departure error test: cost comparison between the OF1 and OF2 model and its corresponding online models for price profile C.

6.2.3 Arrival Time Test

In this section, we analyze the impact of a time error in the scheduled arrival time of the electric vehicle on the energy management of the V2H system. We introduce a total error of two hours, varying each timeslot between one hour ahead and one hour behind. This results in a total of eight re-optimizations, corresponding to the number of timeslots contained in two hours.

Graphs and Commentary

The graph below shows the costs associated with the OF1, OF2 models and their corresponding online models derived from OF1 and OF2 as a function of the magnitude of the time error.

When the error is zero, the costs of the online models correspond to their respective offline models (OF1 and OF2). As the error increases, variations in costs are observed as described below.

OF1 and OF2:

- Both offline models, OF1 and OF2, maintain constant costs regardless of the error magnitude, as they cannot adapt in real-time to variations in operating conditions.

ONLINE from OF1:

- When the arrival time error is earlier than the forecasted one, the cost is lower compared to the OF1 offline model since the early arrival increases the vehicle's availability at home, reducing overall costs.
- When the error is zero, the cost matches that of the OF1 model.
- The blue and green lines are essentially overlapping as shown in the graphs, confirming the strong effectiveness of the online corrective model.

ONLINE from OF2:

- The behavior of the online model derived from OF2 depends on the fact that when the model detects an error, even starting from the OF2 tradeoff model, it re-optimizes by returning to the objective function of the OF1 model. This process causes a drastic reduction in cost as the error moves away from zero. In other words, the online model corrects the errors dynamically, which leads to an improvement in operating costs compared to the offline OF2 model.

The graphs show the cost trends for each price profile (A, B, and C), but qualitatively the behaviors remain similar. However, specific numerical results vary based on the price profile.

Numerical Results and Savings Percentages

Below are the savings percentages for the online models derived from OF1 and OF2 compared to the omniscient model, calculated using the savings percentage formula.

Savings percentages are calculated relative to the omniscient model as follows:

$$Savings\ Percentage = \left(\frac{\text{Cost of Omniscient Model} - \text{Cost of Online Model}}{\text{Cost of Omniscient Model}}\right) \times 100$$

Error (min)	A	B	C
-60	4.33e-14%	3.37e-14%	6.09e-14%
-45	4.19e-14%	3.29e-14%	4.36e-14%
-30	2.03e-14%	0.00e-14%	4.17e-14%
-15	1.96e-14%	1.56e-14%	3.99e-14%
0	0.00e-14%	0.00e-14%	0.00e-14%
15	1.82e-14%	1.47e-14%	1.20e-14%
30	3.49e-14%	2.84e-14%	3.41e-14%
45	3.35e-14%	2.75e-14%	4.31e-14%
60	1.61e-14%	1.33e-14%	2.05e-14%

Table 6.4: Arrival error test: savings percentages for the online model derived from OF1 compared to the omniscient model for price profiles A, B, and C.

Error (min)	A	B	C
-60	4.66%	3.63%	11.93%
-45	4.51%	3.54%	11.38%
-30	4.36%	3.45%	10.88%
-15	4.23%	3.36%	10.42%
0	27.68%	22.15%	41.61%
15	3.92%	3.16%	9.42%
30	3.76%	3.06%	8.91%
45	3.60%	2.96%	8.45%
60	3.46%	2.86%	8.03%

Table 6.5: Arrival error test: savings percentages for the online model derived from OF2 compared to the omniscient model for price profiles A, B, and C.

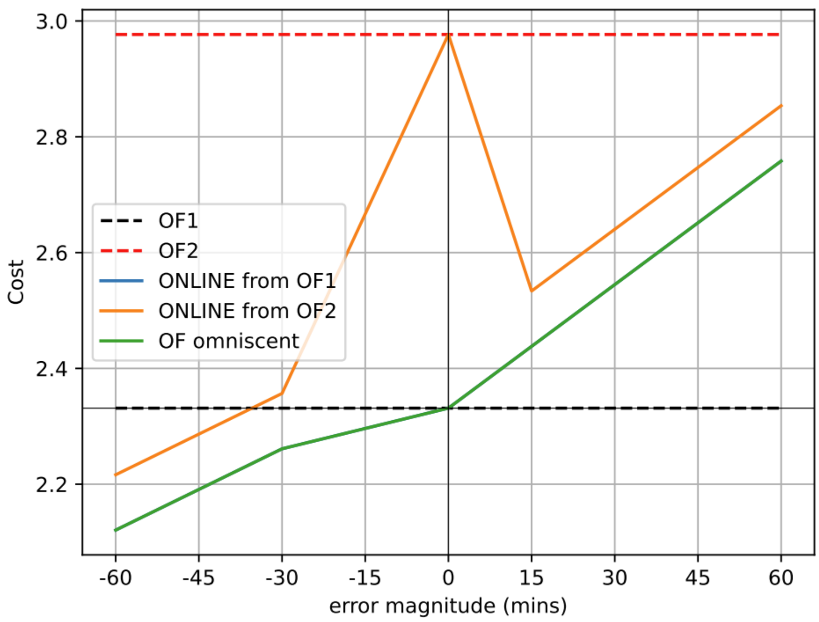

Figure 6.4: Arrival error test: cost comparison between the OF1 and OF2 model and its corresponding online models for price profile A.

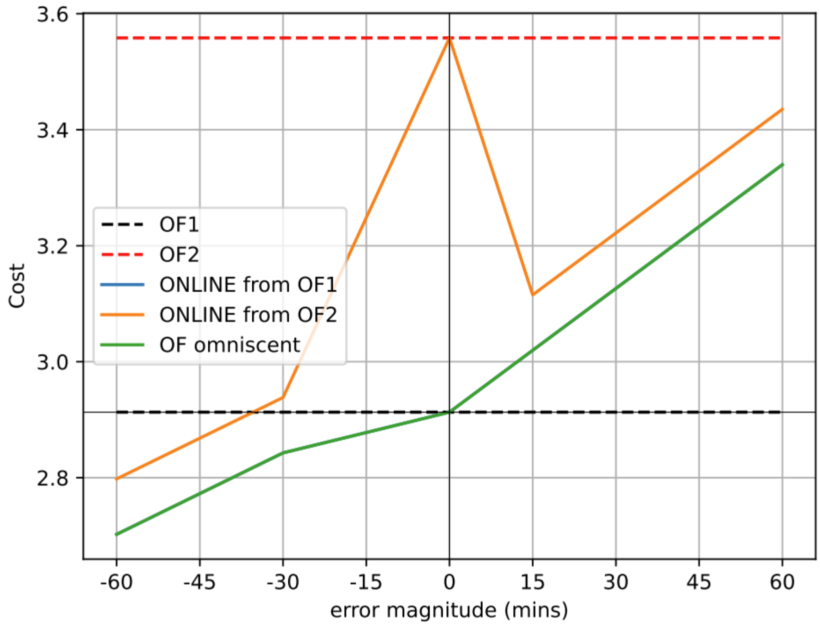

Figure 6.5: Arrival error test: cost comparison between the OF1 and OF2 model and its corresponding online models for price profile B.

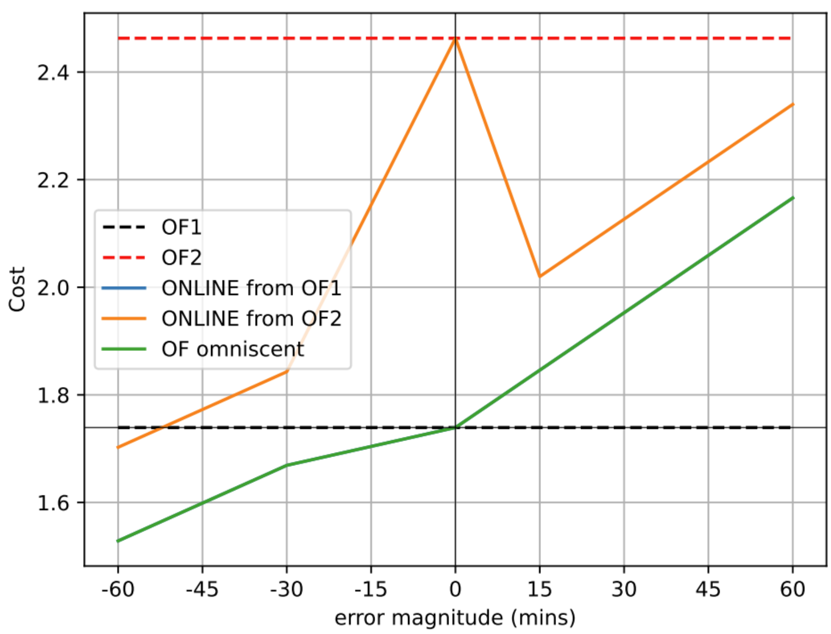

Figure 6.6: Arrival error test: cost comparison between the OF1 and OF2 model and its corresponding online models for price profile C.

6.2.4 State of Charge (SOC) Error Test

This section analyzes the impact of an error in the state of charge (SOC) of the electric vehicle when it arrives home on the energy management of the V2H system. A range of errors from -10% to +10% SOC is introduced.

According to the established parameters, each percentage point of SOC corresponds to 3 miles of range. With a predicted charge level allowing for 30 miles, a -10% error results in a reduction of 30 miles (10% * 3 miles per %), while a +10% error results in an increase of 30 miles. When the vehicle returns with the same or similar battery level, it is assumed that it has been charged externally, such as at the workplace.

Graphs and Commentary

The following graph shows the costs associated with the OF1, OF2 models and their corresponding online models derived from OF1 and OF2 as a function of the magnitude of the SOC error.

OF1 and OF2:

- Both offline models, OF1 and OF2, maintain constant costs regardless of the error magnitude, as they cannot adapt in real-time to variations in operating conditions.

ONLINE from OF1:

- When the vehicle returns with a lower SOC than expected, the cost is higher because less energy is available and needs to be supplemented. When the vehicle returns with a higher SOC, the cost is lower because more energy is available, reducing the need for external supplementation.
- When the error is zero, the cost matches that of the OF1 model.
- The blue and green lines are essentially overlapping as shown in the graphs, confirming the strong effectiveness of the online corrective model.

ONLINE from OF2:

- The behavior of the online model derived from OF2 depends on the fact that when the model detects an error, even starting from the OF2 tradeoff model, it re-optimizes by returning to the objective function of the OF1 model. This process causes a drastic reduction in cost as the error moves away from zero. In other words, the online model corrects the errors dynamically, which leads to an improvement in operating costs compared to the offline OF2 model.

The graphs show the cost trends for each price profile (A, B, and C), but qualitatively the behaviors remain similar. However, specific numerical results vary based on the price profile.

Numerical Results and Savings Percentages

Below are the savings percentages for the online models derived from OF1 and OF2 compared to the omniscient model, calculated using the savings percentage formula.

Savings percentages are calculated relative to the omniscient model as follows:

$$Savings\ Percentage = \left(\frac{\text{Cost of Omniscient Model} - \text{Cost of Online Model}}{\text{Cost of Omniscient Model}}\right) \times 100$$

Error	A	B	C
-10%	3.47e-14%	2.83e-14%	2.25e-14%
-9%	1.75e-14%	1.42e-14%	2.28e-14%
-8%	1.77e-14%	1.43e-14%	1.16e-14%
-7%	1.78e-14%	1.45e-14%	1.17e-14%
-6%	1.80e-14%	1.46e-14%	1.18e-14%
-5%	1.82e-14%	1.47e-14%	1.20e-14%
-4%	1.83e-14%	1.48e-14%	2.43e-14%
-3%	1.85e-14%	1.49e-14%	1.23e-14%
-2%	0.00e-14%	0.00e-14%	1.24e-14%
-1%	1.89e-14%	1.51e-14%	3.78e-14%
0%	0.00e-14%	0.00e-14%	0.00e-14%
1%	1.92e-14%	1.54e-14%	2.59e-14%
2%	1.94e-14%	1.55e-14%	2.62e-14%
3%	0.00e-14%	0.00e-14%	3.98e-14%
4%	1.98e-14%	1.57e-14%	2.69e-14%
5%	2.00e-14%	1.59e-14%	2.73e-14%
6%	2.02e-14%	1.60e-14%	2.77e-14%
7%	1.84e-13%	1.45e-13%	2.52e-13%
8%	1.85e-13%	1.46e-13%	2.42e-13%
9%	2.08e-14%	1.64e-14%	1.44e-14%
10%	0.00e-14%	0.00e-14%	2.92e-14%

Error	A	B	C
-10%	3.73%	3.04%	8.83%
-9%	3.77%	3.06%	8.94%
-8%	3.80%	3.09%	9.05%
-7%	3.84%	3.11%	9.16%
-6%	3.87%	3.13%	9.28%
-5%	3.91%	3.16%	9.40%
-4%	3.95%	3.18%	9.51%
-3%	3.98%	3.21%	9.63%
-2%	4.02%	3.23%	9.75%
-1%	4.06%	3.26%	9.88%
0%	27.68%	22.15%	41.61%
1%	4.14%	3.31%	10.13%
2%	4.18%	3.33%	10.27%
3%	4.22%	3.36%	10.40%
4%	4.26%	3.38%	10.54%
5%	4.31%	3.41%	10.69%
6%	4.35%	3.44%	10.84%
7%	4.39%	3.47%	10.99%
8%	4.43%	3.49%	11.13%
9%	4.48%	3.52%	11.28%
10%	4.52%	3.55%	11.43%

Table 6.6: SOC error test: savings percentages for the online models derived from OF1 (left) and OF2 (right) compared to the omniscient model for price profiles A, B, and C.

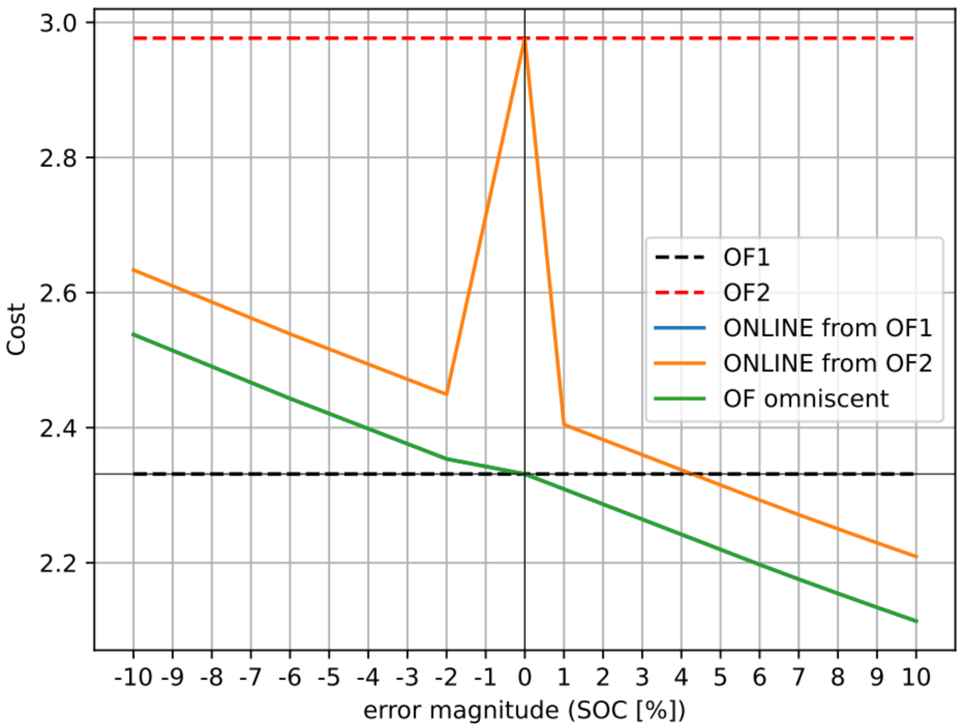

Figure 6.7: SOC error test: cost comparison between the OF1 and OF2 model and their corresponding online models for price profile A.

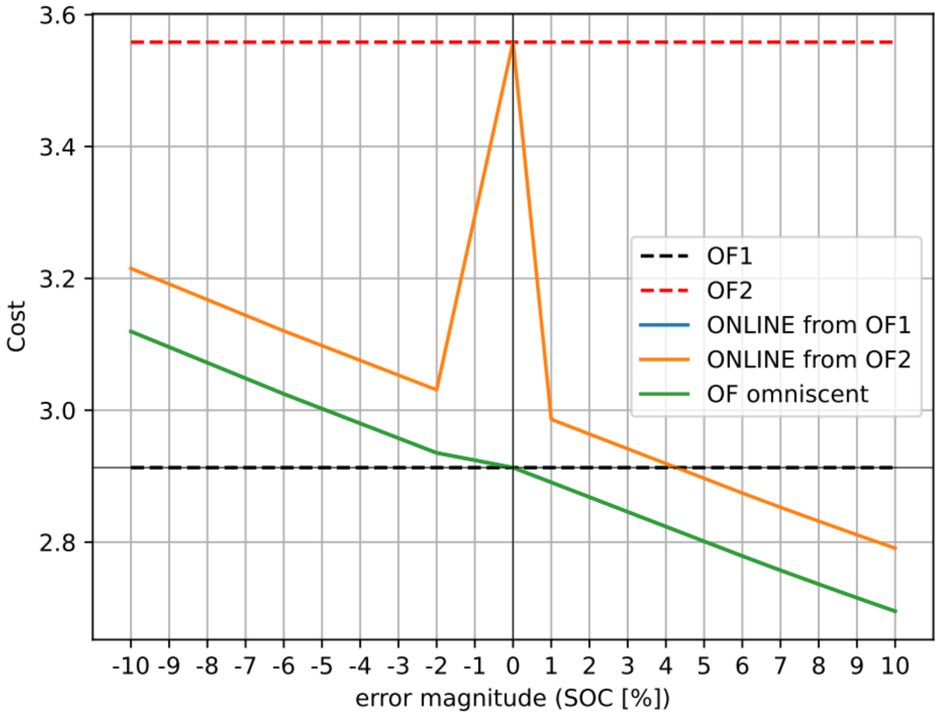

Figure 6.8: SOC error test: cost comparison between the OF1 and OF2 model and their corresponding online models for price profile B.

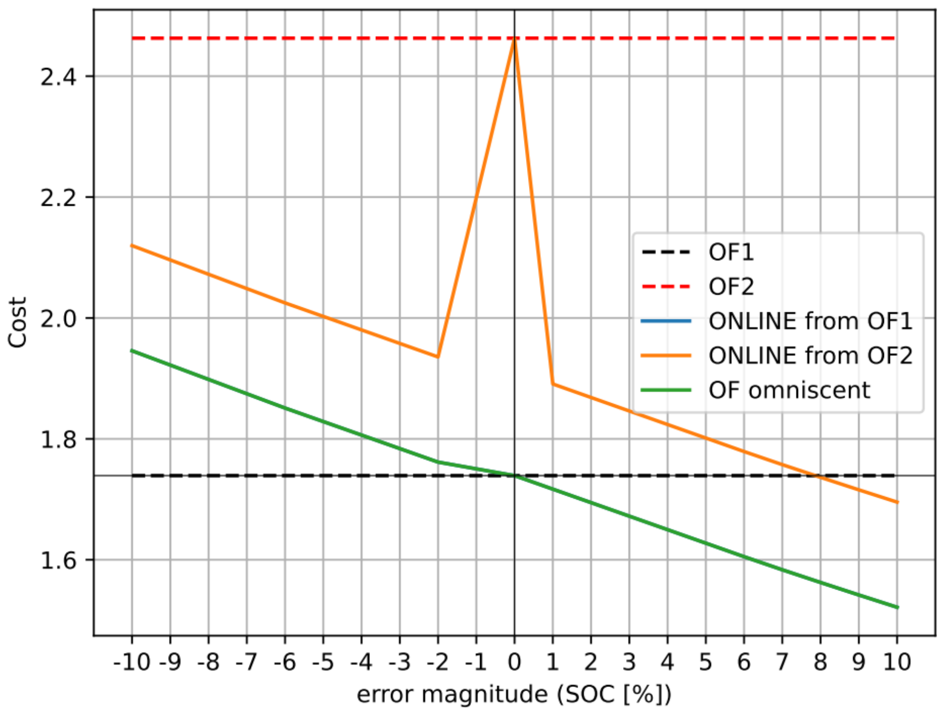

Figure 6.9: SOC error test: cost comparison between the OF1 and OF2 model and their corresponding online models for price profile C.

6.2.5 Conclusions on Error Tests

The analysis conducted on the presence, absence, and state of charge (SOC) error tests has highlighted the effectiveness of online models in handling unforeseen variations and reducing the overall costs of the V2H system. The key observations from the tests are as follows:

Efficiency of Online Models

The online models, derived from both OF1 and OF2, have demonstrated a remarkable ability to adapt to real-time variations. This has allowed them to dynamically correct errors and optimize operational costs compared to offline models.

Impact of Departure and Arrival Errors

The tests on departure and arrival errors revealed that online models can effectively manage timing errors, reducing operational costs. In particular, an earlier arrival time increases the vehicle's availability at home, lowering overall costs, while a delayed departure can be compensated for by the flexibility of online models.

State of Charge (SOC) Errors

The tests on SOC errors showed that online models can maintain lower operational costs even with significant SOC variations. When the vehicle returns with a lower SOC than expected, the cost is higher because less energy is available and needs to be supplemented. Conversely, when the vehicle returns with a higher SOC, the cost is lower because more energy is available, reducing the need for external supplementation.

Percentage Savings

The savings percentages calculated for online models derived from OF1 and OF2 compared to the omniscient model have shown that online models can achieve significant savings, especially in the presence of SOC and timing errors. The results indicate that online models derived from OF2 offer greater savings compared to those derived from OF1.

In conclusion, the implementation of online models in the V2H system offers significant advantages in terms of reducing operational costs and managing unforeseen variations. The ability to dynamically re-optimize in response to errors makes online models valuable tools for improving system efficiency and reducing overall energy costs. Additionally, the models' ability to maintain a degree of independence from initial forecasts makes these tools highly effective. Even in the presence of forecast errors, online models can recalibrate their optimizations, keeping costs low and enhancing V2H system performance. This renders online models a robust and flexible solution for energy management in V2H applications.

6.3 Long-Term Experiment and Performance Evaluation

This chapter presents the results of a long-term experiment where the online optimization models for energy management in a Vehicle-to-Home (V2H) system were tested over a period of six months. Each day, random errors were introduced to simulate the unforeseen variations that might occur in real-life energy management scenarios. The main goal of the experiment is to evaluate the effectiveness of the online models in dynamically responding to these variations and maintaining optimal performance over time, ensuring cost reductions and efficient energy management.

The experiment was designed to assess not only the models' ability to adapt to daily errors but also to monitor cumulative performance over a longer period. The types of errors considered include variations in the vehicle's departure and arrival times, as well as fluctuations in the battery's state of charge (SOC). This approach replicates real-life uncertainties, providing insights into the models' resilience and ability to handle continuous variation.

6.3.1 Methodology

The experiment was conducted over six months, during which the online models were subjected to daily random errors simulating typical operational uncertainties. Each day, errors were generated involving the departure time, arrival time, and the battery's SOC. These errors were introduced into the models to test their ability to dynamically reoptimize operational conditions and maintain efficiency.

Model Selection and Tradeoff Considerations

In this long-term experiment, the analysis was based exclusively on a specific offline optimization model, while another model, which incorporates a tradeoff between energy costs and the battery's state of charge (SOC), was excluded from the calculations. This decision was made to simplify the focus on operational cost reduction without incorporating the additional complexity of balancing cost and battery charge.

The primary difference between these two models lies in their objective functions. The selected model is designed to minimize costs while considering hourly price fluctuations, optimizing energy purchases to reduce expenses over the defined time horizon T. In contrast, the excluded model introduces a tradeoff, where a portion of the cost savings is sacrificed in order to maintain a higher SOC at the end of the day, depending on the user's needs. This approach prioritizes maintaining a higher battery charge, even at the expense of increased energy costs.

The exclusion of the tradeoff model was made to focus the analysis solely on cost-related performance. Including it would have introduced a subjective variable related to the user's preference for maintaining a higher SOC, complicating the evaluation of the results. The purpose of this study was to assess the effectiveness of real-time reoptimizations in reducing operational costs.

The benchmark model, used as a reference for comparison with the online reoptimization models, does not take into account hourly price fluctuations but instead minimizes the total amount of energy purchased over the time horizon T. This makes it a useful baseline for evaluating the savings generated by the online models.

In summary, results obtained with the tradeoff model could vary depending on the user's preference for SOC levels, with expected outcomes falling between those of the benchmark model and the online reoptimizations based on the selected cost-minimizing model. By focusing solely on the cost-minimizing model, the analysis provides a consistent approach to cost reduction, offering a clearer understanding of the financial benefits of the online models.

Random Error Generation

The errors were randomly generated using a uniform distribution to simulate real-life variability. Three main types of errors were considered each day:

- **Departure Time Error** (E_p): Random variation of ±60 minutes from the scheduled departure time.
- **Arrival Time Error** (E_a): Random variation of ±60 minutes from the expected arrival time.
- **SOC Error** (E_{SOC}): Random variation of ±10% from the expected SOC, corresponding to a range variation of about 30 miles for the vehicle.

To implement the random error generation in Python, the built-in `random.uniform()` function was used. This function allows generating random numbers within a specified range, ensuring that the errors fall within the desired limits. For example, to simulate the departure and arrival time errors, the function was used to generate random values between -60 and 60 minutes, while the SOC error was generated within a range of ±10%. This approach provided a simple yet effective way to introduce variability into the system without requiring complex code.

Each day, the function was called to generate new random errors for the optimization models, ensuring that the system faced a different set of conditions every day.

Daily Reoptimizations

Each day, after generating the errors, the online models were reoptimized to adapt to the new operational conditions. The number of reoptimizations required was closely linked to the magnitude of the errors, with larger variations leading to more frequent reoptimizations. In particular, errors related to departure time (E_p) and arrival time (E_a) required more frequent adjustments, due to the way the online models are structured to handle these variations in the vehicle's schedule.

Parameters Used

The parameters used in this experiment were identical to those defined in the previous tests. This ensured consistency and comparability between the results obtained under different error scenarios.

Objectives of the Analysis

The analysis focused on the following key aspects:

- **Frequency of Reoptimizations**: Monitoring the number of reoptimizations needed each day, correlated to the magnitude of the generated errors.

- **Impact on Operational Costs**: Comparing the daily costs between the online models and the benchmark model to evaluate the savings achieved through reoptimization.

- **Percentage Savings**: Calculating the percentage savings obtained by the online models compared to the benchmark, analyzed on a weekly and monthly basis.

- **Analysis of Error Impact**: Evaluating how errors of varying magnitude, particularly SOC and time-related errors, affect costs and system performance.

Experiment Execution

The experiment was conducted daily over 180 days, with complete simulations incorporating the different randomly generated errors. The online models reoptimized dynamically each time errors were detected to adapt to the new conditions.

The comparison between the online models and the benchmark provided valuable insights into the models' ability to reduce costs and optimize energy management over the long term. Reoptimizations proved crucial in maintaining the efficiency of the V2H system, even in the face of unpredictable operational variations.

The following sections will present the results obtained, including detailed analysis of costs, energy savings, and the frequency of reoptimizations.

6.3.2 Analysis of Daily Reoptimizations

The analysis of daily reoptimizations provides key insights into the effectiveness of the online models when subjected to random operational errors over an extended period of time. In this subsection, we will analyze the behavior of the reoptimizations and interpret the patterns observed in the results.

The generated graph shown in Figure 6.10 shows the *weekly average reoptimizations* over 180 days, separated into three categories:

- **SOC Reoptimizations** (E_{SOC}): Reoptimizations triggered by deviations in the state of charge (SOC) of the vehicle's battery.
- **Departure Reoptimizations** (E_p): Reoptimizations triggered by errors in the scheduled departure time of the vehicle.
- **Arrival Reoptimizations** (E_a): Reoptimizations triggered by errors in the expected arrival time of the vehicle.

Interpreting the Results

The results clearly show that the number of reoptimizations is predominantly influenced by the time-related errors, E_p and E_a. These errors can vary by as much as ± 60 minutes, leading to substantial fluctuations in the number of reoptimizations required. In contrast, errors in SOC (E_{SOC}) contribute far fewer reoptimizations, as they only trigger one reoptimization per day when present.

SOC Reoptimizations (E_{SOC}) show a stable and low contribution to the total number of reoptimizations. This is because a single reoptimization is sufficient to adjust the system when the SOC deviates from the expected level. As a result, the blue line in the graph remains consistently low across all weeks.

Departure Reoptimizations (E_p) and **Arrival Reoptimizations** (E_a) exhibit more variability and higher peaks, as time-related errors require reoptimizations for each minute of deviation. The orange and green lines on the graph reflect this, with notable peaks indicating periods where significant time deviations occurred. These peaks show the system's need for frequent adjustments to maintain optimal energy management.

Importance of Reoptimization Analysis

This analysis highlights the importance of understanding how different types of errors affect the system's performance. By tracking the number of reoptimizations over time, we can identify which operational factors require the most frequent interventions. For instance, time-related errors (E_p and E_a) clearly have a more substantial impact on the system's behavior compared to SOC errors (E_{SOC}). This is a crucial observation for optimizing the system's design and for focusing future efforts on improving the handling of time deviations.

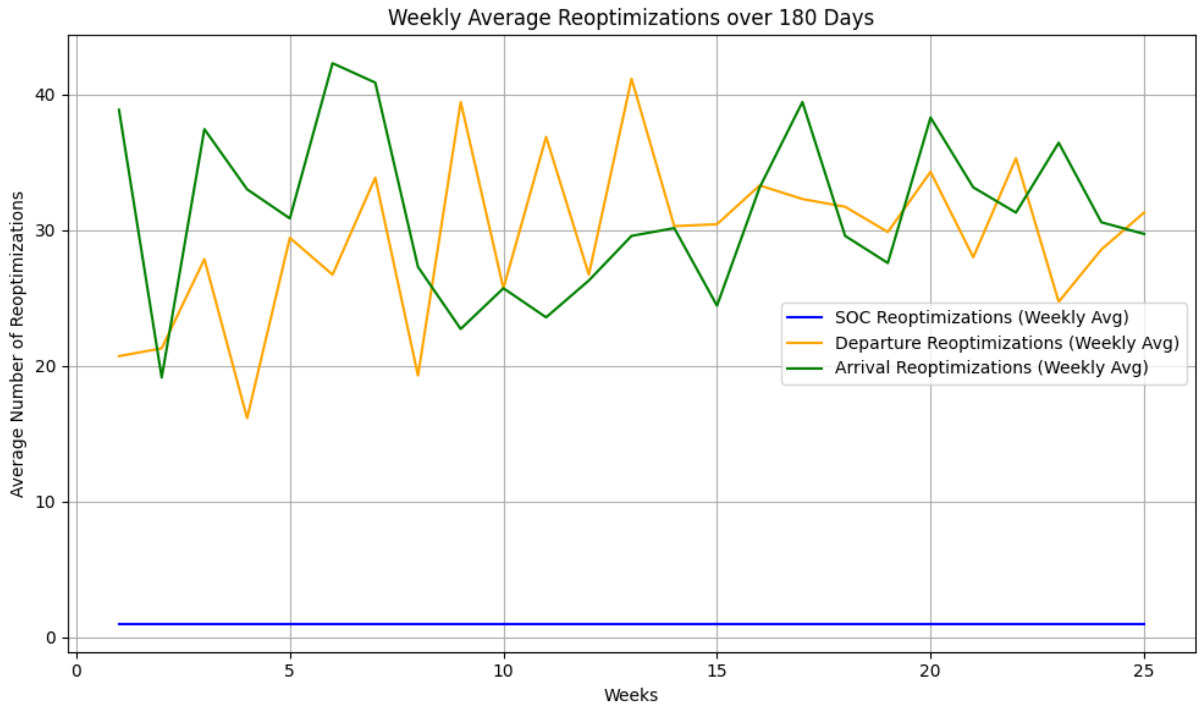

Figure 6.10: Weekly average of reoptimizations over a 180-day period.

Concluding Remarks

By analyzing the weekly average reoptimizations, it becomes clear that time-related errors (E_p and E_a) play a more significant role in the system's daily operation compared to SOC errors (E_{SOC}). This observation suggests that, while the system is capable of handling a variety of operational uncertainties, the management of time deviations is the key challenge in maintaining optimal energy efficiency in the long term. As a result, future efforts could be directed towards refining the handling of time-related errors to further reduce the number of required reoptimizations and improve the system's overall performance.

6.3.3 Analysis of Weekly Savings Results

In this section, we analyze the weekly operational cost savings achieved by the online models compared to the benchmark model. The experiment spans 180 days, which have been divided into 25 weeks. Each week, the system is subjected to randomly chosen price profiles (A10, B10, or C10), reflecting different energy price fluctuations. The goal of this analysis is to quantify both the percentage savings and the monetary savings that the online models can generate over the course of each week, using the benchmark model (previously explained) as a reference.

Explanation of Weekly Savings Data

Table 6.7 presents the savings obtained for each of the 25 weeks of the experiment. Each row includes the following information:

- The **daily price profile** applied during the week (A10, B10, or C10), which represents the typical price variation encountered in real-world scenarios.
- The **weekly benchmark cost**, which is the operational cost incurred using the benchmark model for energy optimization. This serves as a reference point for calculating the savings achieved by the online models.
- The **percentage savings**, showing how much the online models reduced costs compared to the benchmark model, expressed as a percentage.
- The **weekly online model cost**, representing the operational costs of the online models, which reoptimize in real time to adapt to errors.

- The **monetary savings**, calculated as the difference between the benchmark cost and the online model cost.

Wk	Month	Prfl	BM ($)	S (%)	OC ($)	MS ($)
1	January	A10	45.87	25.0	34.40	11.47
2	January	B10	47.67	27.0	34.80	12.87
3	January	C10	42.11	23.5	32.11	9.99
4	January	A10	46.22	26.0	34.18	12.04
5	February	A10	45.45	28.0	32.72	12.73
6	February	B10	47.34	25.5	35.30	12.04
7	February	C10	43.05	23.5	32.89	10.16
8	February	B10	47.67	24.0	36.23	11.44
9	March	A10	44.65	22.5	34.32	10.33
10	March	C10	43.56	24.5	32.45	10.11
11	March	B10	45.23	22.5	34.88	10.35
12	March	C10	43.11	24.0	32.68	10.43
13	April	A10	43.23	23.0	33.31	9.92
14	April	C10	42.96	21.5	32.97	9.99
15	April	B10	44.65	22.5	34.18	10.47
16	May	A10	43.02	23.0	33.11	9.91
17	May	B10	43.96	21.5	34.53	9.43
18	May	C10	43.32	22.0	33.32	9.90
19	June	C10	42.82	20.5	33.39	8.43
20	June	A10	43.18	21.0	33.97	9.21
21	June	B10	44.02	20.0	35.20	8.82
22	July	C10	41.91	22.5	31.78	10.13
23	July	A10	42.75	23.0	32.34	10.41
24	July	B10	43.87	21.5	33.75	10.12
25	July	C10	40.22	20.5	31.80	8.42

Table 6.7: Weekly savings for 25 weeks. Legend: **Wk** = Week, **Prfl** = Price Profile (A10, B10, C10), **BM** = Benchmark Cost, **S** = Savings, **OC** = Online Cost, **MS** = Monetary Savings.

Observations and Interpretation of the Data

- **Weekly Benchmark Costs**: The benchmark costs show a gradual decrease over time, reflecting lower energy consumption in the warmer months. The first few weeks in January exhibit higher energy costs due to increased heating needs, while the spring months (April, May, and June) show a slight decrease in costs. This is aligned with the reduced need for heating systems and the general trend of lower energy demand as the weather improves (see Figure 6.11).

- **Online Model Savings**: The percentage savings fluctuate between 20% and 27%, demonstrating that the online models consistently outperform the benchmark model by a significant margin. This variation is mainly due to the combined effect of the randomly applied price profiles and the generated errors. The online models, which are capable of real-time reoptimizations, perform particularly well when faced with price fluctuations and forecast errors, as seen in profiles A10, B10, and C10 (see Figure 6.11).

- **Monetary Savings**: The monetary savings range from approximately \$8.42 to \$12.87 per week. These values represent the tangible benefits of the online models, highlighting their capacity to adapt to unpredictable conditions while reducing overall operational costs. For example, in week 2 under profile B10, the benchmark cost is \$47.67, while the online model reduces this to \$34.80, saving \$12.87 in total (see Figure 6.12).
- **Interpretation of Price Profiles**:
  - **Profile A10**: This profile shows moderate price variations across the day, with notable peaks during the middle hours. As seen in the table, this profile generally leads to strong savings, with an average percentage saving around 23-25%.
  - **Profile B10**: Profile B10 has more pronounced peaks during the day, and as a result, the online model is more effective in optimizing energy usage, leading to the highest savings percentages (e.g., 27% in week 2). The online model's ability to adapt to these fluctuations is particularly important in this scenario.
  - **Profile C10**: The C10 profile shows smaller price fluctuations compared to A10 and B10, especially during off-peak hours. This results in more modest savings, typically around 20-24%. However, the online models still demonstrate substantial effectiveness, as seen in week 25, where the benchmark cost was \$40.22, and the online cost was reduced to \$31.80, resulting in a savings of \$8.42.

Formula for Calculating Savings

The formula used to calculate the percentage savings is defined as:

$$Savings\ Percentage = \left(\frac{\text{Benchmark Model Cost} - \text{Online Model Cost}}{\text{Benchmark Model Cost}}\right) \times 100$$

This formula is applied to each week to compute the percentage difference between the benchmark cost and the online cost. Additionally, the monetary savings are calculated as the difference between the benchmark cost and the online cost:

$$\textit{Monetary Savings} = \text{Benchmark Model Cost} - \text{Online Model Cost}$$

For example, in week 1:

$$\text{Savings Percentage} = \left(\frac{45.87 - 34.40}{45.87}\right) \times 100 = 25.0\%$$

$$\text{Monetary Savings} = 45.87 - 34.40 = 11.47\,\text{USD}$$

The application of these formulas across the 25-week period provides a clear understanding of how much the online models can reduce operational costs compared to the benchmark model. This data supports the conclusion that the real-time reoptimization capability of the online models yields consistent cost reductions, making them highly effective for dynamic energy management.

Conclusion on Weekly Results

The weekly analysis of the 180-day experiment reveals that the online models consistently outperform the benchmark model in terms of both percentage and monetary savings. By adapting to real-time errors in departure time, arrival time, and SOC (E_p, E_a, and E_{SOC}), the online models can achieve savings ranging from 20% to 27%, with monetary savings reaching up to $12.87 in some cases.

Moreover, the benchmark costs, which decrease over time due to the changing seasonal energy demands, provide a solid reference for evaluating the performance of the online models. Despite the seasonal fluctuations in energy usage and prices, the online models maintain their effectiveness, demonstrating their robustness in adapting to variable conditions. This result underscores the value of the proposed models for long-term energy management in residential settings.

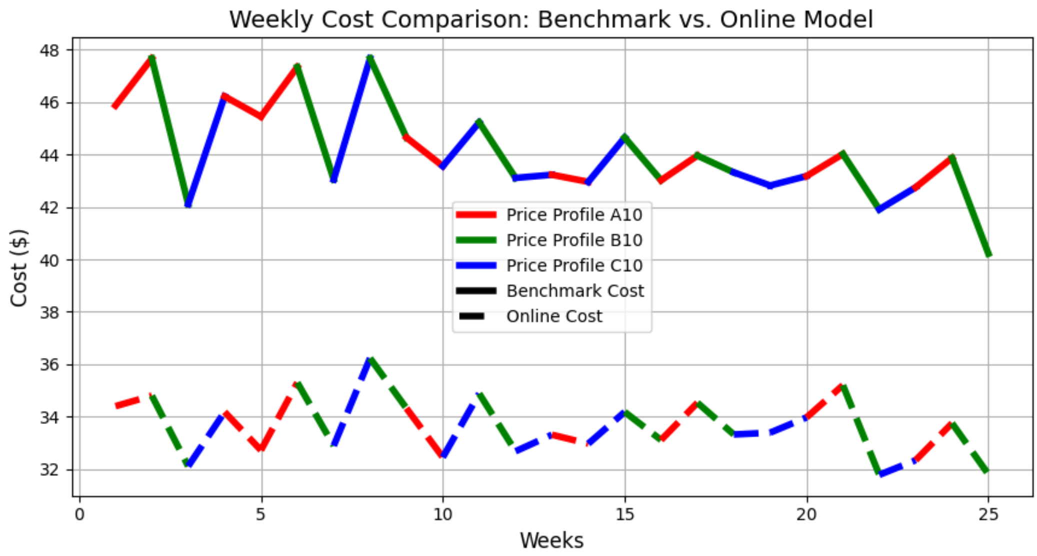

Figure 6.11: Weekly Cost Comparison between Benchmark Model and Online Model. The colors represent different price profiles (A10, B10, C10) applied during each week.

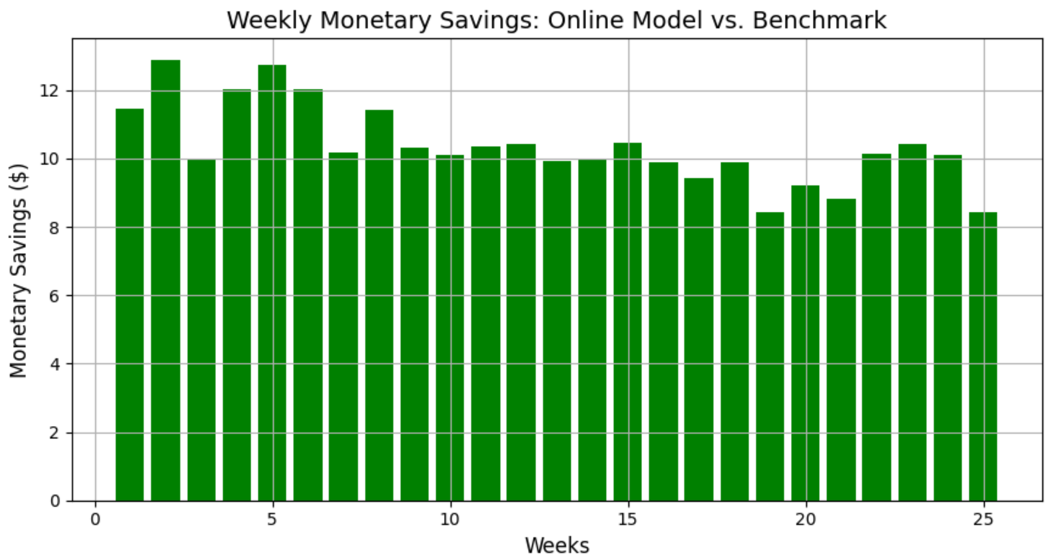

Figure 6.12: Weekly Monetary Savings achieved by the Online Model compared to the Benchmark Model over the 25-week period.

Chapter 7

Conclusion

7.1 Tests and Experiment conclusions

The experiment conducted over 180 days has provided a detailed analysis of the performance of online energy management models under operational uncertainty. By introducing daily random errors related to departure time, arrival time, and battery SOC (E_p, E_a, and E_{SOC}), it was possible to simulate real-world situations characterized by variability and unpredictability. The results clearly demonstrate the effectiveness of the online models in responding in real-time to these fluctuations, showcasing a high capacity for reoptimization and adaptation.

A key takeaway from this experiment is the significant cost savings achieved by the online models when compared to the benchmark model. The operational flexibility introduced by the reoptimizations allowed for percentage savings ranging from 20% to 27%, with the highest savings occurring when price profiles with more pronounced fluctuations, such as profile B10, were applied. This highlights that the effectiveness of the online models is not solely dependent on error management but also on their ability to leverage cost-saving opportunities presented by price variations.

The analysis of the results also shows that the system's reoptimization is particularly effective in handling large deviations in vehicle departure and arrival times. Since errors in these parameters have a direct impact on the interaction between the vehicle and the home energy grid, the online models successfully used their increased flexibility to readjust the energy strategy in real-time, yielding significant cost reductions. Moreover, while SOC errors (E_{SOC}) do not always require as many reoptimizations, they were efficiently managed by the online models, which quickly adapted to changes in battery energy availability.

The seasonal distribution of energy consumption further influenced the overall performance of the system. During the winter months, characterized by higher energy demands for heating, the system faced increased operational costs in the benchmark model. However, the online models continued to achieve notable savings despite the higher demand. As the weeks passed and spring and summer arrived, operational costs decreased due to reduced heating needs and lower overall energy consumption. Even in this scenario of reduced demand, the online models demonstrated their ability to adapt to new conditions, continuing to offer consistent savings.

From a monetary perspective, weekly savings ranged from approximately \$8.42 to \$12.87, confirming the value of implementing a dynamic energy management system based on continuous reoptimization. These savings, if projected over a year, represent a substantial reduction in the overall energy costs of a household, making the online system highly advantageous not only for optimizing operational expenses but also for ensuring a more sustainable and adaptive energy management approach.

An additional crucial point emerging from the experiment is the robustness of the online models in adapting to unpredictable conditions. Despite daily fluctuations in prices and random errors, the models consistently reoptimized their energy strategies, maintaining an optimal balance between cost minimization and energy efficiency. This operational robustness suggests that the online models are not only effective in the short term but can be adopted for long-term energy management, capable of adapting to evolving market conditions and operational scenarios.

Moreover, it is important to note that the use of the offline model 2 (OF2) as a base for reoptimizations offers an additional option for balancing cost savings and vehicle charge levels. The OF2 model introduces a tradeoff between minimizing costs and maintaining a higher battery SOC. This aspect is crucial when the goal is to preserve a higher residual vehicle charge rather than maximizing cost savings. The experiment has shown that in situations where it is preferable to prioritize a higher vehicle charge over monetary savings, the OF2 model may be the more appropriate choice, allowing for greater control over the balance between savings and energy performance.

7.2 Future Perspectives

The results of this experiment open several promising avenues for future work, with significant potential for improvements and new applications. One of the most exciting directions is the integration of advanced predictive models that can better anticipate energy demand peaks and price fluctuations. Incorporating artificial intelligence techniques, such as machine learning, could further enhance the real-time reoptimization process, making it more precise and adaptive.

For instance, using **supervised machine learning models** could allow the system to analyze historical energy consumption and pricing data to create more accurate short- and long-term forecasts. Algorithms like **Recurrent Neural Networks (RNNs)** or **Long Short-Term Memory (LSTM)** models, which are particularly effective for handling temporal data, could be employed to predict load variations or energy price fluctuations in different time slots. These forecasts would enable more proactive energy use planning, optimizing not only costs but also the availability of the electric vehicle based on future expected scenarios.

Additionally, **unsupervised learning algorithms**, such as **clustering**, could be used to identify consumption patterns and detect anomalies that might negatively affect energy management. These models could be combined with real-time reoptimization strategies, creating a system capable of adapting both to errors and future conditions with greater accuracy.

Another area worth exploring is **multi-objective optimization**, where the algorithm not only minimizes operational costs but also balances other factors, such as reducing carbon emissions or optimizing household comfort (e.g., maintaining consistent indoor temperatures in a smart home). By doing so, the models could be configured to account for environmental or personal variables, offering an even more tailored and efficient energy management system.

Furthermore, expanding this system to more complex energy networks, such as **microgrids** or entire **energy communities**, could reveal new opportunities for savings on a larger scale. The scalability of these models offers great potential for wider applications in both residential and commercial settings. Envisioning a connected neighborhood where each household uses real-time reoptimization models, coupled with AI-based price forecasts, could lead to substantial energy savings for the entire community, while also reducing the overall load on the main electrical grid.

Another promising development could be the integration of **advanced energy storage technologies**, such as next-generation batteries or hydrogen storage systems. These could work synergistically with the optimization system to better handle energy price variability and demand peaks, using low-cost energy periods to charge storage systems and utilizing stored energy during peak times.

Finally, the **coordination between multiple vehicles** in a **Vehicle-to-Grid (V2G)** context could open up new possibilities. Each vehicle could not only manage its charge optimally but also contribute to grid stabilization by providing excess energy during peak hours and recharging during low-price hours. Such coordination would require advanced communication between vehicles and the grid, but could lead to significant savings and improved energy efficiency on a larger scale.

In summary, the future prospects for this system include a combination of artificial intelligence techniques, expansion to more complex energy networks, and greater integration with storage and grid management technologies. These developments promise to make the system even more effective and sustainable, offering large-scale energy savings and contributing to greater stability and efficiency in the electrical grid.

7.3 Initial Investment and Long-term Returns

Implementing an online energy reoptimization system for Vehicle-to-Home (V2H) energy management undoubtedly requires an initial investment, both in terms of hardware and software. The necessary components may include advanced energy management software, real-time monitoring systems, communication protocols for vehicle integration, and possibly even upgrades to the home's energy infrastructure to accommodate dynamic energy flows. The cost of these upgrades could vary significantly depending on the complexity of the installation, the quality of the components, and the specific energy demands of the household.

However, despite these upfront costs, the long-term savings demonstrated in this experiment suggest that the investment is justified. The ability to dynamically adapt to forecast errors and price fluctuations has proven to increase system efficiency compared to static or offline models. This dynamic approach allows for daily operational cost reductions, which, accumulated over several months, can result in significant financial returns.

Over time, the savings in operational costs would offset the initial expenses, making the system a cost-effective solution for residential energy management. Additionally, the long-term benefits of such a system are not only economic. A system that continuously optimizes energy usage also promotes sustainability by reducing dependence on external energy sources, potentially lowering carbon emissions and contributing to a greener economy.

Moreover, as future developments in energy systems become available, such as *advanced predictive models* or *energy storage technologies*, the initial investment could pave the way for further savings. By incorporating *artificial intelligence techniques* like *machine learning*, the system could better anticipate demand peaks and price fluctuations. For example, *supervised learning models* could be used to analyze historical data, creating more accurate predictions for load and price variations. Real-time reoptimization could then become even more effective, enhancing the overall efficiency of the system in unpredictable conditions.

Additionally, the system's scalability offers the potential to expand beyond individual households into larger networks, such as *microgrids* or *community energy systems.* By extending these models to multiple households or even small communities, the savings could be amplified, creating a more resilient and efficient local energy network. Coordinated reoptimizations across multiple households, vehicles, and energy storage systems could reduce the overall demand on the main grid, offering substantial energy savings at a larger scale.

Another potential development lies in using *offline model OF2* as the base for optimization, allowing for greater control over the balance between operational cost savings and the state of charge (SOC) of the vehicle. By adjusting the SOC priorities, users could choose to prioritize either lower costs or a higher charge level, depending on their specific needs. This flexibility could be especially useful in cases where maintaining a higher SOC is desirable for upcoming trips or to contribute to a more stable grid during peak hours.

In conclusion, while the initial investment required for implementing an online reoptimization system may be substantial, the long-term benefits – both financial and environmental – make it a worthwhile consideration. As energy systems evolve, the integration of AI-driven predictive models and real-time reoptimization capabilities promises even greater efficiency, sustainability, and adaptability to changing energy landscapes.

Appendix A: OF1 implementation

```python
from gurobipy import *

def OFFLINE_optimization(SOC_max, SOC_min, gamma_C_max_hourly, gamma_C_min_hourly,
                         gamma_V2H_max_hourly, gamma_V2H_min_hourly, eta, Lambda_hourly,
                         theta, SOC_a, SOC_l, Loads, Costs, slots):
    # PARAMETERS
    gamma_C_max = gamma_C_max_hourly * 24 / slots # Max battery charge speed [kW]
    gamma_C_min = gamma_C_min_hourly * 24 / slots # Min battery charge speed [kW]
    gamma_V2H_max = gamma_V2H_max_hourly * 24 / slots # Max V2H speed [kW]
    gamma_V2H_min = gamma_V2H_min_hourly * 24 / slots # Min V2H speed [kW]
    Lambda = Lambda_hourly * 24 / slots # Battery power loss [kWh]

    # Model initialization
    model = Model("EnergyManagement_OFFLINE")

    # Decision variables
    theta_C = model.addVars(range(slots), vtype=GRB.BINARY, name="theta_C")
    theta_V2H = model.addVars(range(slots), vtype=GRB.BINARY, name="theta_V2H")
    SOC = model.addVars(range(slots + 1), lb=0, name="SOC")
    gamma_C = model.addVars(range(slots), lb=0, name="gamma_C")
    gamma_V2H = model.addVars(range(slots), lb=0, name="gamma_V2H")
    x = model.addVars(range(slots), lb=0, name="x")

    # Mutual states of the battery
    model.addConstrs(theta_C[t] + theta_V2H[t] <= theta[t] for t in range(slots))

    # Charge and discharge constraints
    model.addConstrs(gamma_C[t] <= gamma_C_max * theta_C[t] for t in range(slots))
    model.addConstrs(gamma_C[t] >= gamma_C_min * theta_C[t] for t in range(slots))
    model.addConstrs(gamma_V2H[t] <= gamma_V2H_max * theta_V2H[t] for t in range(slots))
    model.addConstrs(gamma_V2H[t] >= gamma_V2H_min * theta_V2H[t] for t in range(slots))

    # Total energy bought in time slot t
    model.addConstrs(x[t] == Loads[t] + gamma_C[t] - eta * gamma_V2H[t] for t in range(slots))

    # SOC constraints
    model.addConstr(SOC[0] == 50) # Initial SOC
    model.addConstr(SOC[0] == SOC[slots]) # End of day SOC equal to the start

    # Objective function: Minimize energy cost
    model.setObjective(quicksum(Costs[t] * x[t] for t in range(slots)), GRB.MINIMIZE)

    model.optimize()
```

Appendix B: OF2 implementation

```python
from gurobipy import *

def OFFLINE_optimization(SOC_max, SOC_min, gamma_C_max_hourly, gamma_C_min_hourly,
                         gamma_V2H_max_hourly, gamma_V2H_min_hourly, eta, Lambda_hourly,
                         theta, SOC_a, SOC_l, Loads, Costs, slots):
    # PARAMETERS
    gamma_C_max = gamma_C_max_hourly * 24 / slots # Max battery charge speed [kW]
    gamma_C_min = gamma_C_min_hourly * 24 / slots # Min battery charge speed [kW]
    gamma_V2H_max = gamma_V2H_max_hourly * 24 / slots # Max V2H speed [kW]
    gamma_V2H_min = gamma_V2H_min_hourly * 24 / slots # Min V2H speed [kW]
    Lambda = Lambda_hourly * 24 / slots # Battery power loss [kWh]

    # Model initialization
    model = Model("EnergyManagement_OFFLINE")

    # Decision variables
    theta_C = model.addVars(range(slots), vtype=GRB.BINARY, name="theta_C")
    theta_V2H = model.addVars(range(slots), vtype=GRB.BINARY, name="theta_V2H")
    SOC = model.addVars(range(slots + 1), lb=0, name="SOC")
    gamma_C = model.addVars(range(slots), lb=0, name="gamma_C")
    gamma_V2H = model.addVars(range(slots), lb=0, name="gamma_V2H")
    x = model.addVars(range(slots), lb=0, name="x")

    # Mutual states of the battery
    model.addConstrs(theta_C[t] + theta_V2H[t] <= theta[t] for t in range(slots))

    # Charge and discharge constraints
    model.addConstrs(gamma_C[t] <= gamma_C_max * theta_C[t] for t in range(slots))
    model.addConstrs(gamma_C[t] >= gamma_C_min * theta_C[t] for t in range(slots))
    model.addConstrs(gamma_V2H[t] <= gamma_V2H_max * theta_V2H[t] for t in range(slots))
    model.addConstrs(gamma_V2H[t] >= gamma_V2H_min * theta_V2H[t] for t in range(slots))

    # Total energy bought in time slot t
    model.addConstrs(x[t] == Loads[t] + gamma_C[t] - eta * gamma_V2H[t] for t in range(slots))

    # SOC constraints
    model.addConstr(SOC[0] == 50) # Initial SOC
    model.addConstr(SOC[0] == SOC[slots]) # End of day SOC equal to the start

    # Objective function: Minimize energy cost
    model.setObjective(quicksum(alpha*(Costs[t] * x[t]) - (1 - alpha) * SOC[t] for t in range(0, slots)), GRB.MINIMIZE)

    model.optimize()
```

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