Sustainable Energy Technology
MSc Thesis

Robust Online Electric Vehicle Control at a Charging Hub

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Abstract

The transportation and mobility sector is central to the energy transition from fossil fuels to sustainable sources. Given the European Union's impending ban on gasoline and diesel vehicles by 2035, electric vehicle (EV) sales are soaring, presenting challenges in charging infrastructure and power grid management. As EV adoption increases, so does the need for widespread charging infrastructure and strategies to manage the strain of EV charging on power grids. Moreover, the variable nature of energy prices introduces the need for optimizing energy consumption during cheaper rates, pushing businesses towards dynamic energy pricing.

Addressing these challenges, Energy Management Systems (EMS) have emerged, aiming to control EV charging, especially with increasing interest in photovoltaic (PV) systems integrated with charging facilities. The "Energy Scheduler" is a pioneering approach to determine optimal charging schedules, balancing costs, grid load, and EV user needs. However, the system, as it stands, doesn't account for real-time deviations from solar power predictions.

This thesis seeks to assess the performance of the Energy Scheduler and enhance it by integrating a Real-Time Control mechanism, making charging more adaptable to real-time conditions. The research also delves into gathering EV flexibility information, used for charging scheduling. It explores the potential of a charger integrated user interface (UIs). Additionally, to validate EV control strategies, a comprehensive Evaluation Framework is proposed, serving both simulated and real-world testing environments.

The Energy Scheduler demonstrated an effective EV charging schedule management based on PV power forecasts and EV flexibility. Significant achievements include a 67.47% reduction in summer electricity costs and a 40.97% reduction in peak grid loads. However, the system's efficiency waned during winter due to lower PV generation.

Implementing a real-time control mechanism provided an effective response to unforeseen solar power forecast fluctuations. Although costs slightly rose, the mechanism significantly reduced peak grid loads with an extra 5%, and improved self-consumption and self-sufficiency rates. While robust in simulated conditions, real-world complexities posed challenges to the mechanism's performance.

Simulations showed that an UI has potential for improved scheduling effectiveness, offering potential enhancements in self-sufficiency, self-consumption, cost-effectiveness, and grid stability. Challenges remain in user engagement and advocating the benefits of active UI use.

The Evaluation Framework enabled rigorous testing of solutions under various conditions. It ensures adaptability for simulation and real-world scenarios. However, limitations surfaced, including high-speed simulation challenges and the inability to perfectly replicate real-world hardware behaviors.

This research proposes enhancements to the EV charging system for a sustainable, cost-effective, and grid-protective future. Key recommendations include refining the Real-Time Control mechanism to consider grid load discrepancies, and reevaluating the Cost Optimization strategy to prevent grid strain. Furthermore, boosting user engagement with the UI, and leveraging sophisticated predictive modeling could be beneficial for EV scheduling. Extended real-world testing across seasons is advised to ensure system robustness. Implementing these measures promises a holistic improvement in EV charging infrastructure.

Keywords: energy transition, energy management, electric vehicles, smart charging

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Contents

Chapter 1

Introduction

1.1 Motivation

The transportation and mobility sector is a key factor in the current energy transition from fossil fuels to clean and sustainable energy sources, such as solar and wind energy. Therefore, different governments around the world are using policies to shift towards electrical mobility. The European Union has agreed on a complete ban on the sale of new gasoline and diesel vehicles starting in 2035 [1].

As a result, sales of electric vehicles (EVs) are increasing on a worldwide scale. They doubled in 2021 from the previous year to a new record of 6.6 million vehicles. In 2030, the market share of light duty cars in Europe that are electric is expected to be 80% [2]. This growing adoption of EVs has raised new challenges, particularly in terms of charging infrastructure and power grid management.

1.1.1 Charging Infrastructure

The first challenge involves the urgent need for augmenting charging infrastructure in numerous facilities. According to the IEA, this rise in EV sales "requires an adequate surge in chargers installed in buildings" [3]. Charge points will not only be installed at single-family homes but will continue to expand to several types of buildings. It will be crucial to include or increase charging points in buildings such as apartment complexes, offices, parking lots or commercial centers ([4], [5]). For EV owners, the preferred charging options are usually at home and workplaces.

A central element in this development is the concept of a *charging hub*. This is a centralized location equipped with multiple EV charging stations. It may also be integrated with renewable energy sources, such as photovoltaic (PV) panels for solar power generation and energy storage systems, providing a sustainable solution for EV charging.

1.1.2 Impact on Grid

The second challenge comes from the increasing strain of EV charging on the local electricity distribution grids due to widespread electrification initiatives. With more people making the transition from traditional fuel-based vehicles to electric ones, the demand for electricity soars. This leads to an increased usage of charging points, potentially resulting in synchronized electricity demand and high-power peaks on the grid. Such peaks significantly impact the power grid, escalating the risk of overload, congestion, and ultimately, service outages ([6], [7]).

Because existing grid infrastructure is not designed to accommodate the significant load increase, securing larger grid connections to accomodate the increasing power demands of EVs is a challenge. To tackle this problem, numerous businesses and organizations are combining the installation of EV charging stations with the deployment of PV panels (e.g. on their parking lots). Integrating PV systems directly with EV charging facilities presents a viable solution to meet the increasing power demands of EVs while alleviating pressure on the local grid [8]. This combination, however, calls for optimal control of EV charging to align with PV production times, leading to a necessity for effective EV charging management.

1.1.3 Dynamic Energy Pricing

An additional challenge emerges from volatility in dynamic day-ahead energy prices. With fluctuation in energy prices, businesses are increasingly interested to optimize the use of their self-generated energy and to shift their energy usage to periods of lower electricity prices in dynamic energy price contracts. This does not only maximize the use of self-generated and low-cost energy, it also induces the transition towards a decarbonized transportation sector [9]. Consequently, optimal control of EV charging and the utilization of dynamic energy pricing are becoming critical necessities for businesses, especially those required to achieve sustainability targets.

1.1.4 Energy Management Systems

In response to these challenges, alternative solutions have emerged, aiming to manage the increased demand from EVs without necessarily requiring extensive investments in transmission and distribution grids. One such solution is the application of *Energy Management Systems (EMS)*. EMS leverage the flexibility that EVs offer to move EV charging load from peak times to off-peak times. This not only relieves stress on the grid but, when combined with time-of-use electricity tariffs, allows EV users and charging hub operators to economically benefit from optimized charging strategies. Such an *EV scheduling strategy* must consider the practicalities of everyday EV use and provide solutions that can be applied within the typical charging locations, usually at home or at work. Numerous methods for optimal coordinated control of EV charging have been presented in recent years ([10], [11], [12], [13]). Applying these strategies in EMS aims to synchronize the EV charging process with (forecasted) PV production times and/or time of use electricity tariffs, leading to a more efficient and cost-effective use of energy, with less reliance on the grid. EMS and existing EV scheduling strategies are elaborated in more detail in Section 2.2.

An example of an innovative solution has been pursued by B. Nijenhuis [14] with the goal to balance multiple factors to create the best possible charging schedules. This system aims to keep costs low and prevent overloading the grid, while ensuring that the charging demand for the EV users are met before they leave. This strategy, which is called the *Energy Scheduler*, is explained in more detail in Section 2.3.

EV scheduling strategies often depend on available information regarding the adaptability of the EV's charging load. This information, referred to as *EV flexibility information*, can be used to adjust the charging process of the EV, i.e. being accelerated, decelerated, or temporarily halted, without compromising the user's need for a fully charged vehicle. The EV flexibility information consists of parameters regarding the charging constraints of the EV user, such as approximate departure times and energy demand. For more on 'EV flexibility information', see Section 2.2.3.

Nijenhuis et. al. [15] show that if the system is able to receive such information, grid peak load can be significantly reduced and PV self-consumption can be significantly increased compared to uncontrolled charging in an office parking scenario.

Therefore, it is important to research ways of gathering EV flexibility information. [16] shows that there is potential of gathering the information through a *User Interface (UI)*. Participants are willing to share their flexibility by using a smartphone application when starting their EV charging sessions. Although the quality of the data given by the users may be far from perfect (with over- and under estimations of both energy demand and departure time) their impact on the grid load and PV power self-sufficiency has been proven to be significant.

1.2 Research Problem

The Energy Scheduler is the base for this thesis. The aim is to explore further improvements for scheduling strategies and providing a framework in which the proposed solution and future solutions can be tested thoroughly, both in computer simulations and real-life field tests.

1.2.1 Real-Time Control

Currently, the Energy Scheduler is not designed to accommodate fluctuations in solar power predictions. It creates a charging profile for EVs upon arrival, taking into account the solar power prediction and the already scheduled loads (i.e., other EVs), and then optimizes for a flat grid load or low costs. These schedules typically come in durations ranging from 12 to 24 hours, depending on the available information. However, this approach does not take into account deviations from solar power forecasts, resulting in suboptimal utilization of available resources. Therefore, there is a need for short term corrections to these deviations.

There exist charging strategies that employ Real-Time Control without forecasting on PV output or EV charging demand ([17], [18]). A noticeable gap persists in the literature regarding methods that combine both predictive control and feedback control. In the case of EV charging, predictive control is represented by a scheduling strategy, which is designed to optimize EV charging schedules based on forecasted information, such as PV power generation and electricity prices. On the other hand, feedback control is a reactive measure, adjusting the charging schedule in real-time based on actual measured data, such as current PV power generation and EV load. The integration of these two control methods can offer a robust solution, enabling the system to schedule charging effectively based on predicted data and simultaneously make adjustments when actual data deviate from the forecasts.

This approach could potentially minimize energy-not-served, maximize the utilization of renewable energy, and reduce the cost of charging. By combining the foresight of predictive control (via the Energy Scheduler) with the adaptability of feedback control (via a real-time controller), this research seeks to enhance the robustness and efficiency of EV charging strategies.

With these challenges and potential solutions in mind, this thesis addresses the need for a more robust EV scheduling strategy. It proposes the integration of a *Real-Time Control mechanism* by creating a dynamic system that can respond to deviations and update the charging power as needed. Such a system better protects the grid, while the usage of renewable locally generated energy can be increased. Thereby the available energy flexibility of EV users could be utilized more effectively with this addition.

1.2.2 Acquisition of EV Flexibility Information

To further improve EV charging strategies, a key aspect that needs to be addressed is the collection and utilization of EV flexibility information. Many control solutions to coordinate EV charging depend on the availability of this EV flexibility information. The systems often rely on knowing the state of charge (SoC), energy demand, and departure time. However, in practice, often a lack of communication between the EV and the charging system is observed. Some information is not available to the charger, as the current standard of AC charging protocol (Open Charge Point Protocol (OCPP)) does not provide State of Charge (SoC) information for AC charging.

Based on this communication gap, researchers have been exploring alternative ways to collect EV flexibility information. Findings indicate that EV flexibility information can be collected through smartphone applications [16]. However, this method does have a notable constraint: users are required to install the relevant application on their mobile devices. Therefore, there is a pressing need to explore alternative UIs for the collection of EV flexibility information.

Notably, the effectiveness of the methods utilized in the [16] study to gather EV flexibility information may be somewhat skewed. This is because the research largely relies on tech-savvy users who are aware that a study is being conducted. Thus, there may be a potential bias in the data gathered from these informed users. To ensure the effectiveness of EV charging solutions, it is crucial that their interfaces cater to a wide array of users, not just those already familiar with or engaged in the research. Additional investigation is necessary, particularly regarding the efficacy of smart charging UIs for a more broad user group. This way, it can secure that more comprehensive and accurate data is available, which will better inform the development and implementation of robust online EV control systems.

1.2.3 Development of an Evaluation Framework

Next to the difficulties and possibilities in data acquisition, also an assessment of the performance of charging control solutions is relevant. Given the complexity and novelty of charging control solutions like the Energy Scheduler, an adaptable and robust evaluation tool becomes highly beneficial. Such an *Evaluation Framework* can provide an effective means to continuously refine and enhance these strategies. It allows to assess the performance of the system under a variety of conditions and circumstances and can be utilized in both computer simulations and real-life field tests. The framework thereby provides data that are critical to refine and improve the strategy. It finally can ensure that the strategy is not only theoretically sound but also practically viable.

1.3 Goals and Objectives

The primary goal of this research is to validate, test, and enhance the existing EV scheduling strategy of the Energy Scheduler for a smart charging hub equipped with solar PV panels. This strategy aims to optimize energy usage while protecting the grid and lower charging costs. For this, a Real-Time Control mechanism is implemented in this existing scheduling strategy to further optimize the charging process. Next to that, this thesis aims to provide a comprehensive framework for thoroughly testing the existing solution with and without a Real-Time Control mechanism, and testing future solutions, both through computer simulations and real-life field tests. The ultimate goal is to evaluate if the strategy is not only theoretically sound but also practically viable. Furthermore, a novel UI between EV user and EMS to acquire EV flexibility information is established. This UI is tested in a real environment with uninformed users. To achieve these objectives, the following specific aims have been established:

- To validate and test the existing Energy Scheduler approach that takes into account multiple factors, such as charging demand, grid limits, PV power production, and EPEX spot prices.
- To research, design, and evaluate a Real-Time Control Mechanism that can adjust the charging schedules based on deviations from forecasted values in charging profiles, solar energy, and grid load, to improve existing solutions.
- To research, design, and evaluate a UI that facilitates better communication between users and the EMS. This interface aims to improve the accuracy and effectiveness of scheduling by incorporating EV user flexibility information in a real-world environment.
- To develop a versatile Evaluation Framework that can effectively evaluate the performance of EV scheduling strategies by simulating a charging hub under varied conditions, while also allowing for real-life implementation and evaluation.

1.4 Research Questions

This research aims to address a series of research questions to enhance the current EV charging infrastructure. The initial question assesses the current Energy Scheduler:

> *"How does the existing Energy Scheduler approach perform under various conditions, and how can it be improved further?"*

Building upon the identified improvements, the next question explores the effectiveness of implementing a Real-Time Control Mechanism:

> *"What are the impacts and improvements achieved by the implementation of a Real-Time Control Mechanism in EV control?"*

The research then shifts to the user interface, examining how it could impact user-EMS interaction and scheduling effectiveness:

> *"How does an enhanced UI influence user-EMS interaction and EV scheduling effectiveness in a real-life environment?"*

The final question aims to establish an Evaluation Framework for testing the robustness of the EV scheduling strategies (with and without Real-Time Control component) under varied conditions:

> *"How can a comprehensive Evaluation Framework be designed that simulates various conditions to evaluate EV scheduling strategies, and allow for practical implementation?"*

These questions aim to systematically improve the EV charging system for enhanced sustainability and efficiency.

1.5 Approach

The research is structured into four primary phases, corresponding to the research questions.

The initial phase of the research is focused on validating the existing Energy Scheduler. Various conditions are created to test the system and its ability to adapt. The performance of the Energy Scheduler is analyzed using quantitative methods. Additionally, this phase involve a literature review to identify potential areas for improvement and further optimization.

The second phase of the research focuses on the development of a Real-Time Control Mechanism. This includes a rigorous exploration of feedback control and algorithms to adjust charging schedules to deviations from forecasts accordingly. The newly developed mechanism is validated through simulations under various scenarios and in a real environment.

The third phase of the research involves establishing a UI between users and the EMS. This phase includes prototyping and testing. User acceptance and interaction with the system is evaluated in a real-world setting.

A comprehensive Evaluation Framework for testing EV scheduling strategies is developed. It serves as the environment where the Real-Time Control mechanism, the Energy Scheduler and future solutions can be extensively tested and evaluated. The developed Evaluation Framework also has the capability to facilitate real-world testing, ensuring the practical validity of the proposed solutions. The framework provides a controlled setting for the iterative development, refinement, and evaluation of the Energy Scheduler and Real-Time Control Mechanism, while also allowing implementation of the UI.

1.6 Outline

The thesis is outlined as follows: The following chapter provides the necessary background on charging hubs, EMS, and the Energy Scheduler. Design decisions and the implementation of the research like Real-Time Control, User Interface, and Evaluation Framework are elaborated in Chapters 3 and 4. The method to assess their performance is explained in Chapter 5, with the results presented in Chapter 6. The findings are discussed and analyzed in Chapter 7, leading to the conclusions summarized in Chapter 8. The thesis concludes with Chapter 9, which offers recommendations for future research on improving the EV charging infrastructure.

Chapter 2

Background

This chapter provides a review of the fundamental concepts related to Electric vehicle (EV) charging. It expands on the general ideas introduced in the previous chapter, delving deeper into the specific topics important for understanding this thesis. Firstly, an overview of EV charging infrastructure, including its challenges and trends in today's energy landscape, is given. This includes the significance of charging hubs, discussing the transaction process at such hubs, and delving into the intricacies of Energy Management Systems (EMS). We focus on how EMS play a vital role in managing EV charging and discuss existing strategies and their limitations. Finally, we elaborate on the Energy Scheduler, an innovative approach that forms the basis of this research. We discuss its present performance, its potential shortcomings, and areas where enhancement is needed.

2.1 EV Charging

EV charging is the process of replenishing an EV's battery with electrical energy. Charging an EV can range from a few minutes to several hours, depending on the charging technology used and the capacity. This duration is influenced by various factors, including the state of charge (SoC) of the battery, its total capacity, the capabilities of the charging equipment, and the electrical infrastructure (i.e. the electricity grid) supporting the charging station. EV charging can be performed at multiple locations, including residential settings, workplaces, public charging stations, and dedicated EV charging hubs.

The energy transfer to the EV is controlled by both the charging station and the vehicle, whereby both have the capability to determine and regulate the maximum charging rate. A communication link between the charging station and the vehicle ensures safe and efficient charging.

EVs are quite specific loads in the electricity grid, because they are mobile and their power demand can be time-shifted to a certain extent without negatively affecting the user. Consequently, EVs may be charged during periods of low overall electricity demand (e.g., at night) or of high (sustainable) electricity production (e.g., when there is high local photovoltaic (PV) production) to level out the load profile and minimize the impact on the power grid. However, this requires intelligent charging strategies that can optimize the charging process based on the power system condition, the availability of renewable energy, and user requirements.

The following sections explore the EV charging process and landscape in more detail, discussing the challenges associated with EV charging and various types of charging stations.

2.1.1 Impact of Expanding EV Fleet on the Grid

The increasing market share of EVs introduces a new major consumer of electricity, which charging activities form an additional and substantial demand on the grid infrastructure [6]. This has considerable implications on the performance of the grid, particularly during peak periods. It is essential to assess the impact of EVs on power grid and the challenges they bring:

- **Increased Load Demand:** Charging EVs contributes to an overall increase in electricity demand, which can be substantial in areas with high EV adoption rates. If many EVs are charged during peak hours, they may cause an overload on the distribution grid. These synchronized load peaks significantly increase the risk of of overload, congestion, and ultimately, service outages ([6], [7]). [19] shows that at an EV penetration rate of 30%, the expected number of daily power outages in the Netherlands increases by 20%.

- **Voltage Drops and Instability:** The additional load from EV charging can lead to significant voltage drops and instability in the power grid, especially in local distribution networks that were not designed to accommodate such high power consumption levels [20].

- **Grid Infrastructure Upgrades:** If not properly managed, the growing EV load may necessitate costly infrastructure upgrades to distribution networks, including substations, transformers, and wiring.

In light of these challenges, it is clear that managing the integration of a large EV fleet into the power grid requires a multi-faceted approach. This includes considering the availability and sustainability of charging locations. Homes and workplaces are the primary locations for EV charging. These convenient charging locations are critical to supporting the growing EV market. However, charging dynamics vary across these locations, with daytime charging at workplaces being generally more sustainable than nighttime charging at homes [21]. It is also important to consider that lower-income households, renters, and residents of multi-unit dwellings (MUDs) are less likely to have access to home charging [22]. This lack of access emphasizes the importance of offering alternative, convenient, and sustainable charging solutions in the form of public charging hubs.

The issues raised, underline the need for effective strategies to manage the integration of an expanding EV fleet into the grid. This includes the integration of renewable energy sources to provide green power for EV charging, and the development of advanced charging strategies and EMS to control and optimize EV charging based on grid conditions and renewable energy availability. These solutions, which are discussed in more detail in the subsequent sections, not only mitigate the potential negative impacts of EV charging on the grid but can also bring several benefits, such as improving grid stability, reducing peak loads, and promoting the use of renewable energy.

2.1.2 Integration With Renewable Energy

Integrating PV systems directly with EV charging facilities presents a viable solution to meet the increasing power demands of EVs while alleviating pressure on the local grid [8]. Renewable energy, particularly wind and solar power, is variable and intermittent. The temporal mismatch between renewable energy production and electricity demand can be mitigated by using EVs as flexible loads.

In times of high renewable energy generation and low demand, instead of delivering the renewable power back to the grid or even curtailing it to protect the grid from overloading, this energy could be used to charge EVs. In contrast, during periods of low renewable energy generation and high electricity demand, the charging of EVs could be reduced or postponed. This would flatten the grid load.

By spreading out the EV charging demand over time and aligning it with periods of high renewable generation, the system load profile can be flattened. This has several benefits including reduced strain on the grid infrastructure, decreased reliance on grid power, and using more sustainable energy locally. To achieve this it is essential to develop "smart charging" and EMS that can coordinate the charging of a large number of EVs based on the availability of renewable energy.

2.1.3 Charging Hubs

One promising approach towards resolving the challenges associated with renewable energy integration and the growing EV fleet is the introduction of *Charging Hubs*. These hubs are centralized locations hosting multiple points for EV charging, thereby offering a critical infrastructure for the transition towards electric mobility by enabling EV users to conveniently charge their vehicles, especially for those who do not have access to home charging facilities. This complements workplace charging as a sustainable solution, ensuring the charging demand does not coincide with peak household electricity consumption and better utilizes PV power.

Charging hubs can be categorized based on their charging speed into three main types:

- **Level 1 charging stations:** These are the basic charging stations that offer slow charging, typically over several hours for one EV. They are often used for overnight or over day charging at homes or workplaces.
- **Level 2 charging stations:** Offering faster charging speeds than Level 1 stations. They are commonly used in public areas, shopping centers, and parking lots. They can fully charge an EV in a few hours.
- **DC Fast charging stations:** These are high-power charging stations designed to charge EVs rapidly, often within 30 minutes up to 80%. They are typically installed along highways or in areas with high traffic to provide quick charging for long-distance travelers.

Beyond providing the basic charging services to EV users, charging hubs have evolved to also adopt more integrated, intelligent and sustainable practices. Some charging hubs have started to incorporate renewable energy sources into their design. This could involve integrating solar PV panels or wind turbines to directly provide green energy for EV charging. Such renewable energy sources not only reduce the carbon footprint of EV charging but can also mitigate the increase of the load on the electricity grid.

In addition to renewable energy integration, energy storage systems, such as batteries, are often incorporated into these hubs. These systems store excess energy generated during periods of low demand or high renewable energy production, which later can be used to charge EVs during peak times or when renewable energy production is low. This further improves the energy efficiency and sustainability of the charging hub.

In line with the above, many contemporary charging hubs are equipped with advanced Energy Management Systems (EMS) that optimize energy usage, reduce peak load, and manage charging strategies of both the EVs and the added batteries. EMS and their state of the art are explained more thoroughly in Section 2.2.

The research within this thesis is conducted at a Level 2 charging hub at an office location. This particular charging hub serves as both the site for experimental studies and the basis for developing a simulation model. More information on the testing site is given in Section 5.2.

FIGURE 2.1: A Charging Hub in Hengelo [23].

2.1.4 Transaction Process

At public charge points (e.g. charging hub) several *transactions* take place. They refer to the process by which an EV is connected to a charging station, charged, and then disconnected. This process is managed and recorded to ensure transparency and efficiency. In the following a generalized flow of a transaction in a charging hub is given:

- **Initiation:** The transaction begins when an EV is plugged into a charging point, thereby the charger communicates with the vehicle to verify its readiness.
- **Identification and Authentication:** In this step, the users identify themselves, typically by using an RFID card or a mobile application linked to their user account. The system validates the credentials of the user and checks for available credit or membership status.
- **User Input of Flexibility Information (optional):** In some innovative charging hubs ([16]) employing smart charging strategies, users have the option to input their EV flexibility information (see Section 2.2.3 for an explanation) via a user interface (UI). This information may include their expected departure time and energy demand.
- **Charging:** Once the user has been authenticated, the charging process starts. The charging station communicates with the vehicle to manage the charging rate, ensuring it is within the capacity of the vehicle and the grid. Note, that the maximum charging rate of the charger may also be set by an external system.
- **Energy Metering:** Throughout the charging process, the amount of energy transferred to the EV is carefully monitored and recorded.
- **Completion:** The transaction is completed when the charging process is finished (either because the battery is fully charged, the user manually stops the charging, or

the charger suspends the charging) and the vehicle is unplugged. At this point, the final energy transfer is recorded.

In the context of this research, transaction data forms a critical component, providing necessary information for applying charging control, simulating realistic EV charging scenarios, and testing the performance of various EV scheduling strategies.

2.2 Energy Management Systems

Energy Management Systems (EMS) are integral to efficient energy utilization, particularly with the surge in the adoption of EVs. Although traditionally, EMS have been systems of software-tools used by operators of electric utility grids to monitor, control, and optimize the performance of the generation and transmission system, their role has significantly evolved. Today, EMS are extensively employed in homes, businesses, charging hubs, and other facilities to automate, manage, measure, and control their energy needs, including heating, ventilation, lighting installations, and EV charging.

In essence, an EMS is a computer system designed to automatically control and monitor electric facilities in a building that account for significant energy consumption. The inputs and outputs of EMS are derived from various data sources and can be tailored to the specific requirements of the site. Inputs into an EMS include:

- **Energy consumption data:** The EMS collects real-time or historical data about the energy usage of the connected devices or systems. This includes, for example, the energy usage of appliances, lighting, heating, and ventilation systems in a building, or charging needs of EVs at a charging station.

- **Energy production data:** If the system includes on-site energy generation facilities, such as solar panels or wind turbines, the EMS gathers data on the energy being generated.

- **Grid electricity prices:** Real-time or projected electricity prices, such as day ahead prices from the utility grid, can be fed into the EMS. This information is crucial for demand response strategies.

- **Weather forecasts:** Weather conditions significantly impact energy consumption and generation, particularly in the case of renewable energy sources, such as solar and wind. Hence, the EMS should also consider weather forecasts.

An EMS processes these inputs to generate useful outputs, such as:

- **Optimized energy usage schedules:** A schedule in the context of an EMS refers to a timetable that determines the start and end times for operating each controllable asset, such as an EV charger, heat pump, or battery system. It also specifies the rate or intensity at which each asset should be operated at any given time. Based on the input data, the EMS creates an optimized schedule for energy usage. For instance, it may schedule EV charging, heat pump operation, or battery charging during times when electricity prices are low or when renewable energy generation is high.

- **Real-time demand response signals:** In response to grid electricity prices or during periods of high demand, the EMS can adjust the energy consumption patterns of connected devices and systems to reduce load on the grid.

- **Energy savings and efficiency reports:** The EMS can provide reports on energy usage, potential savings, and efficiency measures. These insights can help users to make informed decisions and adjustments to further improve energy efficiency.

2.2.1 EV Charging Control Strategies

In the context of EV charging, EMS are especially valuable due to the flexible nature of EV charging, a process often referred to as 'smart charging'. To illustrate how this works, we consider a charging hub with several EVs plugged in at the same time. In an uncontrolled charging scenario, all EVs would begin charging immediately upon being plugged in, regardless of the current load on the power grid or the electricity prices. This could potentially overload the power grid during peak hours when many electrical devices are drawing power, leading to a power outage. Moreover, charging during peak hours when electricity prices are high results in higher charging costs.

With an EMS controlling the charging process, things may be different. The EMS, using real-time electricity prices, grid load data, and weather forecasts optimally schedules the EV charging. For example, it might delay the charging of some EVs to off-peak hours when electricity demand is low, and prices are cheaper. It could also distribute the available PV power among various EVs based on their individual energy needs and departure times. This smart management not only helps prevent overloading of the power grid but also optimizes energy usage, resulting in cost savings and more efficient use of energy resources.

This control of the charging process by an EMS can be done according to different strategies. Several strategies have already been explored to better manage EV charging. One approach involves decreasing the accessible charging power at charging stations. This technique commonly uses load-balancing, which ensures that the collective power usage of several charging stations remains within the limits set by local electrical installations [24]. However, researchers are examining more intricate methods [25], with some studies considering the impact on the wider electricity grid within built environments [26]. A detailed review of research focusing on PV production integrated with EV charging is presented in [27]. Van der Klauw [28] has designed scheduling algorithms tailored for different types of buffer devices. When integrated with decentralized optimization strategies, such as Profile Steering [29], these algorithms can promote the efficient management of a fleet of EVs. A novel scheduling approach is the Energy Scheduler [14]. This Energy Scheduler serves as a base for this research and is further explained in Section 2.3.

2.2.2 Openness To Smart Charging

According to a study conducted in the Netherlands involving EV drivers [30], the concept of smart charging can gain widespread acceptance if users are given the ability to 'override' the system. Although it is anticipated that this function may not be frequently used, the option to have it is appreciated by users.

Similar findings were given in a recent UK-based study [31] that interviewed 60 current and potential EV users. The study found that two-third of the participants preferred user-managed charging (UMC) over supplier-managed charging (SMC), citing improved personal control as the main reason.

In addition to the override feature, these studies underline the importance of considering user needs in the design of EV scheduling systems. Meeting energy demand of EVs before their departure is a crucial element of user satisfaction and system acceptance. By guaranteeing a high level of service to the EV user, a greater adoption of the technology can be expected.

2.2.3 EV Flexibility Information Acquisition

The effective operation of an EMS in managing EV charging greatly depends on its ability to acquire accurate *EV flexibility information*. This data includes parameters, such as the energy demand (i.e. the amount of electricity an EV user requests) and the expected departure time (i.e. the time at which the EV user plans to use their vehicle next). Energy demand reveals how much electricity is needed, and the expected departure time provides the window within which this demand must be met. By leveraging this information, the EMS can create more accurate and efficient charging schedules, thus ensuring optimal utilization of energy resources while fulfilling user requirements.

However, the acquisition of this data in real-world settings presents several challenges. The current standard of the AC charging protocol, Open Charge Point Protocol (OCPP), does not provide the SoC information for AC charging, a key parameter for charging control [32]. This lack of essential data prevents the EMS from gaining a comprehensive understanding of the charging state and needs of EVs, obstructing the creation of precise charging schedules.

Consequently, alternative ways of collecting EV flexibility information have been explored by researchers. One such method involves the use of smartphone applications [16]. While this approach provides a more direct and flexible option for data collection, it requires users to install the respective application on their mobile devices, creating a barrier to its widespread adoption.

Furthermore, the research on the efficacy of current methods of data collection may present a skewed picture of their true effectiveness. The study [16] primarily involved tech-savvy users who are often already aware of or engaged with the research, potentially introducing a bias in the collected data. This bias may undermine the applicability of the findings to a broader user base with varying levels of technical expertise.

As such, there is an increasing need for the development of user-friendly and universally accessible user interfaces (UIs) to effectively gather EV flexibility information. These UIs should be designed to cater to a wide spectrum of users, not just those already familiar with the concept of smart charging or engaged in research related to it.

Moreover, investigation of these new data collection methods is required, particularly in the context of a more generalized user group. By obtaining more comprehensive and accurate data from a broader user base, the control systems can be made more robust and effective, regardless of the technical proficiency of the user.

2.2.4 PV Power Forecasting and Uncertainty

Key to implementing an EMS based on renewable energy availability is the forecasting of PV power generation. PV power generation is highly dependent on weather conditions, particularly solar irradiance and temperature. The forecast of these weather parameters introduces a level of uncertainty into the PV power forecast.

The accuracy of PV power forecasting can be influenced by many factors, such as the forecast horizon, weather prediction errors, and inaccuracies in the model or methodology used for forecasting. For very short-term forecasts (minutes to a few hours), the most influential factor is often the rapidly changing weather conditions, particularly the movement of clouds. A sudden cloud cover can drastically reduce the solar irradiance reaching the PV panels, leading to a sharp drop in power output. On the other hand, the dissipation of cloud cover can result in a sudden increase in power generation.

In addition, many PV power forecasts typically provide output on a 15-minute basis, meaning they account for the average weather conditions and solar irradiance levels expected over each 15-minute interval. However, this approach does not capture the short-term fluctuations that can occur within these intervals.

For instance, a sudden cloud cover passing over the panels within the 15-minute interval may not be captured by the forecast, leading to an overestimation of the power output for that period. Conversely, if the sky clears unexpectedly within the 15-minute window, the power output could be underestimated.

Therefore, even with advanced forecasting techniques, the actual PV power output can exhibit high fluctuations and differ significantly from the forecasted values due to the dynamic and unpredictable nature of weather conditions. This discrepancy between forecasted and actual PV power output presents a significant challenge for the effective implementation of smart charging strategies based on renewable energy availability.

2.3 Energy Scheduler

This research builds on an integrated scheduling approach, the Energy Scheduler [14], that takes into account multiple factors, such as charging demand, grid limits, PV power production, and day ahead electricity prices. This approach, developed by B. Nijenhuis, serves as a foundation for this study. The focus of this research is on further exploring, enhancing, and assessing the performance of this approach under a variety of conditions and circumstances.

2.3.1 Description of the Energy Scheduler

The Energy Scheduler leverages the inherent flexibility of EVs, enabling the shifting of EV load from peak to off-peak times in sync with time-of-use electricity tariffs.

The Energy Scheduler employs the optimization capabilities of Mixed-Integer Linear Programming (MILP) solvers, such as CBC [33] or Gurobi [34]. It balances an array of inputs to generate optimal charging schedules for the various available assets. Such a charging schedule is refered to as a timetable that determines the start and end times for charging each EV. It also includes the rate at which each EV should be charged at any given time. The objective is to minimize costs and reduce peak loads, while maintaining a high level of service to the EV user, i.e. shifting EV charging load from peak to off-peak times in alignment with time-of-use electricity tariffs. Thereby, it takes into account forecasts, including electricity prices and PV energy generation predictions, to optimize the scheduling process. In addition, it considers the grid limit, ensuring that the grid is protected, and it respects the energy requirements of EV users, maintaining a high level of service. The system is designed to be able to adapt to ever-changing conditions in real-time. It is capable of incorporating new information, such as newly updated forecast data or new EV arrivals and departures, by constantly re-optimizing with the new information.

The Energy Scheduler utilizes an objective function to define the optimal characteristics of a scheduling solution. This function takes into account all relevant energy costs, from grid import/export to PV curtailment (i.e., the lost opportunity of generating free energy when the PV system is not fully utilized) and battery charging, as well as energy not served to the EVs. The end result is an optimal schedule for each controllable asset in the system that fulfills all demands, depending on the mode it is in. Thereby, the Energy Scheduler has 2 modes: cost optimization or peak shaving, explained in detail in the following sections.

Cost Optimization

In the Cost Optimization mode, the primary objective of the Energy Scheduler is to minimize the total cost of energy usage. The system not only takes into account the cost of energy imported from the grid, but also the cost associated with PV curtailment, and the cost of not serving energy demand to the EVs.

The scheduler uses its inputs, such as forecasts for energy prices and PV generation, along with known constraints, such as the grid limit and EV requirements, to generate an optimal schedule for each controllable asset. The optimization model hereby is designed to minimize the overall energy cost for the entire duration of the schedule, factoring in tariffs, PV generation, battery storage, and EV charging demands. If there is flexibility in when EVs can be charged (such as with overnight charging), the scheduler aims to do so at times when energy costs are at their lowest.

Peak Shaving

In Peak Shaving mode, the main objective of the Energy Scheduler is to reduce the maximum load placed on the power grid over time, while still providing the energy demand of the EVs. This not only safeguards the grid infrastructure from potential overloads, but also maximizes the effective utilization of existing power connections. By flattening the demand curve and mitigating peak usage, this strategy allows for a greater overall electricity usage without necessitating an upgrade to a higher capacity connection.

To achieve this, the scheduler aims to use energy from local storage (such as a battery system) or locally generated energy (such as PV) during times of peak demand. By doing so, the system effectively 'shaves off' the peaks in energy demand, reducing the maximum power drawn from the grid and thereby decreasing peak demand charges.

2.3.2 Current Performance and Limitations

The Energy Scheduler, at its current stage, demonstrates promising performance in managing EV charging schedules to optimize grid load, lower costs, and maximize the use of PV generation. However, there remain several challenges that need to be addressed.

Firstly, the Energy Scheduler is not designed to handle real-time adjustments effectively. It generates charging profiles based on PV power forecasts and other pre-known constraints. But this approach fails to accommodate unforeseen fluctuations or deviations from solar power forecasts, resulting in suboptimal usage of available resources.

Secondly, the Energy Scheduler currently relies on a limited set of data to generate schedules, primarily depending on solar power forecasts and known EV flexibility. However, in practice, the EV flexibility is often not readily available due to inadequate communication between EVs and the charging system. For instance, the current standard of AC charging protocol, Open Charge Point Protocol (OCPP), does not provide SoC information for AC charging. Also, the departure time of the EV is not known and can only be approximated.

Moreover, existing EV flexibility information collection methods, such as smartphone applications, may provide a barrier for EV users to provide their flexibility information, as they first have to install the application.

2.3.3 Areas for Enhancement

Based on the existing limitations, several key areas of improvement can be identified for the Energy Scheduler.

Primarily, there is a need for the integration of a Real-Time Control Mechanism. This enhancement allows the Energy Scheduler to dynamically respond to real-time deviations from forecasts, continually updating charging schedules to achieve optimal usage of available resources. This improved strategy can combine predictive control and feedback control, using forecasted data to plan charging schedules while adapting in real-time to actual measured data. The implementation of such a mechanism can potentially minimize energy-not-served, maximize the utilization of renewable energy, and reduce the cost of charging, leading to increased efficiency, reduced CO2 emissions, and lower costs.

Secondly, the Energy Scheduler could significantly benefit from better user integration. Currently, the lack of accurate EV flexibility information significantly hampers the optimization of the charging schedules. Thus, a more user-centric design could improve the overall performance. For instance, an intuitive and interactive UI could be developed to facilitate the exchange of information between EV users and the Energy Scheduler. This UI could collect data such as the State of Charge (SoC), the expected energy demand, the expected departure time, and other relevant user-specific data.

To evaluate these enhancements effectively, there is a need for a comprehensive Evaluation Framework. This framework should allow for thorough testing of proposed and future solutions under various conditions and scenarios, both in computer simulations and real-life field tests. This systematic evaluation can facilitate the ongoing development and refinement of the Energy Scheduler, ensuring it is robust, efficient, and widely applicable.

Chapter 3

Requirements & Design

This chapter explores the specific requirements and design considerations that have guided the development of the three key components of this research: the Real-Time Control mechanism, the User Interface (UI), and the Evaluation Framework. Each of these components plays a critical role in addressing the challenges outlined in Section 1.2 and contributing to the overall aim of enhancing the management of electric vehicle (EV) charging.

The chapter begins with a comprehensive discussion on the Real-Time Control mechanism in Section 3.1. The Real-Time Control mechanism is designed to adapt to real-time changes in energy production and demand, revising the charging schedules dynamically to enhance efficiency and reliability.

In Section 3.2, the UI is discussed. The UI has been designed to provide an intuitive and user-friendly platform to facilitate user-system interactions, enabling users to efficiently communicate their EV flexiblity information. The section details several key design considerations such as simplicity, information gathering, flexibility, reliability, and user control and choice.

Section 3.3 dives into the design considerations regarding the Evaluation Framework, which serves as the testbed. The design considerations for this framework revolve around its ability to test various scheduling strategies effectively and its adaptability for easy transition to real-world scenarios. This section also explains how the Evaluation Framework aligns with the principles of the Microservices Architecture Model for ease of implementation and scalability.

The requirements and design considerations detailed in this chapter are integral in solving the challenges outlined in Section 1.2. These design parameters set the stage for the subsequent chapters, which delve into the implementation. These requirements and design considerations not only guide the development process but also serve as benchmarks against which the effectiveness of the system can be evaluated.

3.1 Real-Time Control

The Real-Time Control mechanism has as aim to enhance the performance of EV scheduling strategies by accounting for deviations from forecasted values. A key requirement of the Real-Time Control mechanism is its ability to adapt to changes in real-time and revise the charging schedules accordingly. To effectively implement this mechanism, several aspects were considered during its design.

The following subsections go through the requirements and design considerations step by step, laying the groundwork for a detailed discussion of how the Real-Time Control mechanism was implemented to satisfy these essential characteristics. The specific implementation details are covered in Section 4.1.

3.1.1 Dynamic Responsiveness

The control mechanism was required to be dynamic, ensuring rapid and effective adjustments to the charging schedules in response to real-time data. This characteristic is crucial in addressing the uncertainty and variability associated with energy forecasts, as discussed in Section 2.2.4. The Real-Time Control mechanism should be capable of continually monitoring the system and making suitable adjustments to the charging power as required.

3.1.2 User Requirements

The control mechanism should take into account the EV user requirements, ensuring that the EVs are charged to the desired level by the time the user indicates to depart. While making adjustments to the charging schedule, it is important to ensure that these changes do not compromise the ability to meet EV user requirements. This requirement stems from the discussion in Section 2.2.2, where the importance of considering user needs in the design of EV scheduling systems was emphasized.

3.1.3 Utilization of Locally Produced Energy

The primary objective of the Real-Time Control mechanism is to optimize the utilization of locally produced solar energy and manage the load on the grid effectively. The grid load should be spread out across time and flattened. This would protect the grid load and works to lower the overall charging costs as well, as cheap locally produced solar energy is utilized more efficiently.

3.1.4 Simplicity and Computational Efficiency

The control mechanism has to be designed with the consideration of simplicity and computational efficiency. It is important that the control mechanism can be implemented in a practical setting without excessive computational requirements.

3.1.5 Timing Requirements

The Evaluation Framework, where the Real-Time Control mechanism is implemented, operates on a *time-tick* basis. This means the Evaluation Framework continuously measures and acts at regular intervals, called time ticks (e.g., every 10 seconds).

This approach has implications for the performance of the system. Specifically, in between time ticks, there is a possibility of changes in measured photovoltaic (PV) power values that the system is not aware of, potentially affecting the accuracy of the real-time control actions. As such, the accuracy of the control mechanism is inherently tied to the frequency of these time ticks. The design of the Real-Time Control mechanism should ensure it can effectively handle these inherent uncertainties.

To strike a balance between accuracy and performance, the length of the time tick needs to be chosen carefully. Short time ticks would allow the system to quickly respond to changes and enhance the accuracy of the control mechanism. However, this length should also not be so short that the chargers do not have sufficient time to react to changes in power settings.

On the other hand, longer time ticks might ease the computational burden and allow more time for the chargers to react, but this could lead to less accurate control as changes occurring between time ticks might not be accounted for. Therefore, it is crucial to determine a suitable time tick length that allows for rapid, accurate control adjustments, while also giving the chargers adequate time to respond to new power settings.

The detailed operation of the system on a time tick basis, including the determination of a proper tick length, is discussed further in Section 4.3.3.

3.2 User Interface

The User Interface (UI) plays a significant role in any system, which has to provide a communication bridge between users and the functionalities of the system. Given the complex nature of energy scheduling and real-time control, it is imperative that the UI is designed to provide clear, accessible, and concise information to users, regardless of their technical background.

To ensure that the UI effectively supports the functions of the Real-Time Control mechanism and the Evaluation Framework, the design incorporated several key considerations:

- **Simplicity:** As the primary interface between users and the system, the UI should be simple, uncluttered, and intuitive. This lowers the threshold for users to input their flexibility information.

- **Information Gathering:** One of the critical functions of the UI is to effectively gather flexibility information from users, including departure times and energy demands. To ensure broad user accessibility, it is essential to ask for this information in an easily understandable way. This approach reduces the technical complexity for the user. The UI should effectively accommodate users with varying degrees of technical expertise and facilitate accurate energy demand input.

- **Flexibility:** The UI design should be adaptable to accommodate future changes, additions, or updates to the system. It should be easy to add, remove, or modify components of the interface to adapt to the evolving system requirements.

- **Reliability:** The UI must be reliable. It should have a low error rate, handle exceptions gracefully, and always provide accurate information.

- **User Control and Choice:** In line with findings from Section 2.2.2, it is important for the UI to incorporate an element of control and choice for the users. Smart charging should be designed as the default, but it should be possible for users to override this when desired. This would not only enhance user experience but also support greater acceptance and adoption of the smart charging system.

- **Inviting Design:** The UI should not only be functional but also appealing and inviting to use. Recognizing that users might opt to start charging without utilizing the UI, it's crucial that interfacing with the system isn't perceived as cumbersome. The goal is a seamless, hassle-free user experience that encourages more consistent UI interaction.

3.3 Evaluation Framework

The design of the Evaluation Framework was driven by the primary objective of thoroughly testing various scheduling strategies and real-time control strategies for charging hubs before their implementation in real environments, while also allowing for easy implementation in real environments. The framework has to be versatile and adaptive, capable of accommodating charging hubs of different sizes and components, ranging from chargers, batteries, solar panels, to inverters. It is essential that the framework can adjust various settings to optimize for specific goals such as cost optimization and peak shaving. Also, real-time control has to be included, and it should be possible to set the system time tick frequency.

The framework's design aligns with the principles of the *Microservices Architecture Model* [35]. Microservices Architecture is a method of developing software systems that are made up of independently deployable, modular services. Each service runs a unique process and communicates through a well-defined, lightweight mechanism.

By following the Microservices Architecture Model, the framework can mirror real-world operations as closely as possible in simulations, and allows for easy implementation in practical scenarios. For this, only the simulated hardware services need to be replaced with actual hardware components, keeping the transition straightforward and efficient. The modularity inherent to this model enables a subdivision of the services, meaning some services can be hosted on centralized servers. This negates the need for expensive computational resources at each charging hub location. Computationally intensive calculations can be conducted at a central location, while tasks such as measuring and sending control signals can be managed locally at the charging hub. This efficient distribution of tasks enhances the scalability of the system and speeds up the transition to real-world applications while minimizing resource expenditure. This design encourages realistic testing, accelerates the transition to real-world applications, and simplifies the transition process.

Chapter 4

Implementation

This chapter delves into the practical side of our research, transforming the concepts and designs we detailed in the previous chapter into reality. We are focusing on three main components of this study: the Real-Time Control mechanism, User Interface (UI), and Evaluation Framework. Each serves a unique purpose in scheduling the charging of electric vehicles (EV) in response to solar power fluctuations.

Building on the design considerations and requirements elaborated in the previous chapter, we start by discussing the implementation of the Real-Time Control mechanism in Section 4.1. This mechanism combines predictive and feedback controls to adjust charging strategies dynamically and effectively based on real-time changes. Next, The implementation of the UI is discussed in Section 4.2. This is designed to be user-friendly and encourages users to share their flexibility information (i.e. estimated departure time and estimated departure time), which is critical for effective scheduling. Finally, we delve into the creation of the Evaluation Framework in Section 4.3. This framework acts as a realistic simulation and testing environment, bridging the gap between theoretical strategies and their practical applications.

4.1 Real-Time Control

This section describes the implementation of a Real-Time Control mechanism. The Real-Time Control mechanism is aimed at addressing the inability of the Energy Scheduler to adapt to real-time fluctuations in solar power. This lack of flexibility often results in suboptimal utilization of resources and increased costs. The Real-Time Control mechanism is designed to make corrections to charging schedules based on the deviations between forecasted PV power and measured PV power, with the objective to flatten the total grid load and increase the utilization of locally generated energy. The Real-Time Control implementation merges predictive and feedback control methods to achieve this.

We begin with an overview of the Real-Time Control mechanism in Section 4.1.1, explaining its purpose and basic function. This is followed by a discussion on the concept of Power Discrepancy, a central element to this control mechanism. Next, we delve into the method of distributing this Power Discrepancy among active chargers in Section 4.1.2. This method forms the basis for the charger adjustments made by the Real-Time Control mechanism. Sections 4.1.3 and 4.1.4 introduce more advanced considerations and strategies in charger adjustments to meet EV requirements and handle EV charging constraints, respectively. This way we illustrate the evolution of charger adjustments from simple to complex. After that, in Section 4.1.6, we discuss the handling of significant deviations induced by the Real-Time Controller. Finally, the core of this section provides a step-by-step description of the algorithm that drives the Real-Time Control mechanism.

4.1.1 Overview

The Real-Time Control mechanism is developed using a combination of predictive control and feedback control methods. Predictive control, derived from the Energy Scheduler, involves making predictions about the future and then taking action based on these predictions. On the other hand, feedback control involves continually measuring the state of the system and adjusting the control signals to achieve the desired outcomes. The flowchart in Figure 4.1 offers a view of the functional structure of this mechanism.

Initially, the cloud provides forecasts of power generation, consumption, and electricity prices. The Energy Scheduler receives these forecasts, along with EV flexibility information from the user interface (this User Interface is explained in Section 4.2), and processes these inputs to produce energy schedules for the chargers. This is used as input to the Real-Time Control mechanism to apply real-time adjustments based on the evolving power dynamics in the system, and is therefore referred to as *blueprint schedules*. These blueprint schedules represents a predictive control measure as it is developed based on future predictions.

The blueprint schedules then form the basis for the feedback control by the Real-Time Control mechanism. The Real-Time Control mechanism involves measuring the actual values of PV generation, grid load, and EV charging powers from the hardware, and comparing these with the forecasted values. Significant discrepancies between the forecasted and actual measured values results in positive (more power available than forecasted) or negative (less power available than forecasted) *Power Discrepancy*. The Real-Time Control mechanism operates on the principle of adjusting the charging rates of active chargers based on the Power Discrepancy. If there is Power Discrepancy, the charging schedule is adjusted by the Real-Time Controller to compensate for this. This means we are deviating from the blueprint schedule. After calculating the adjusted charging rates, the control signals are send to the chargers.

When the Real-Time Control mechanism identifies significant deviations from the blueprint schedules, it can send an optimization request back to the Energy Scheduler. This can then recalculate blueprint schedules based on new values. This is further elaborated on in Section 4.1.6.

Real-Time Control is applied at every time tick within the system. These time intervals are the frequency at which the system measures and reacts to changes in variables such as solar generation, grid load, and EV charging profiles. The proper length of these time-ticks is further elaborated on in Section 4.3.3. The subsequent sections describe how the Real-Time Control mechanism calculates the adjustments to the blueprint schedule at each time tick.

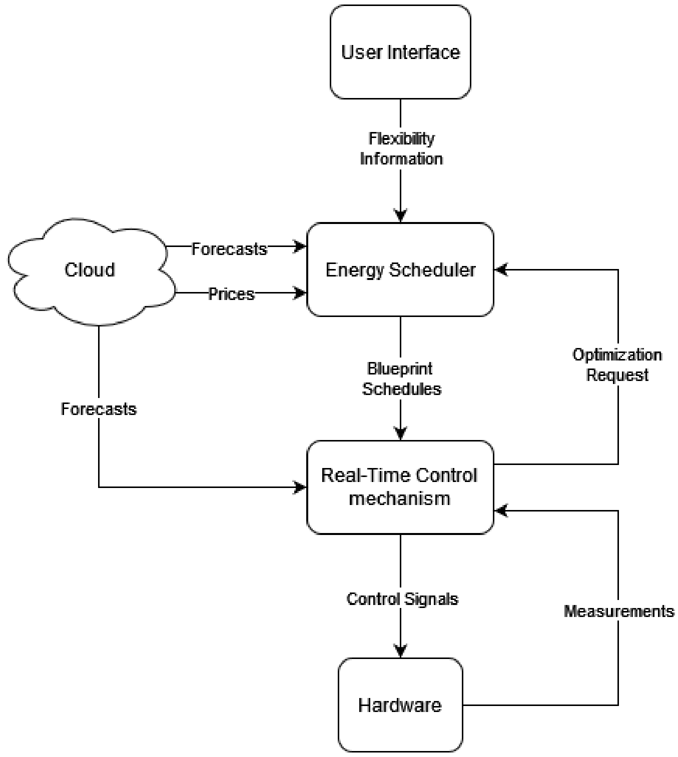


FIGURE 4.1: Flowchart illustrating the functional structure of the Real-Time Control mechanism. The mechanism sits in between the Energy Scheduler and the hardware and adapts the control signals from the blueprint schedules using a feedback algorithm.

4.1.2 Distributing Power Discrepancy Among Chargers

In essence, the Real-Time Control mechanism divides the Power Discrepancy among the active chargers. The Power Discrepancy can either be negative or positive. In case of a negative Power Discrepancy, the Real-Time Control mechanism attempts to decrease the charging rates of the active EV chargers, compared to their respective blueprint schedules, in order to compensate for the shortage. Conversely, when there is a positive Power Discrepancy, the mechanism increases the charging rates accordingly.

To achieve this balance, the mechanism aims to divide the Power Discrepancy at time interval t ($P_D(t)$) evenly among the number of active chargers at time interval t ($n(t)$). The adjustment for each charger at time interval t ($A_i(t)$) is computed as follows:

$$A_i(t) = \frac{P_D(t)}{n(t)}. \tag{4.1}$$

This computed adjustment, which can either be negative (when less power than forecasted is available) or positive (when more power than forecasted is available), is then applied to the charging rate of each charger.

However, while it might appear straightforward to evenly distribute the Power Discrepancy, the actual process is more nuanced. Various constraints and considerations come into play when applying these adjustments. The mechanism must account for the individual characteristics and states of each charger, the EV user requirements, as well as the broader conditions of the grid and the objectives of the overall energy management system. The subsequent sections delve deeper into these complexities, discussing the additional strategies employed to ensure the efficient use of available power and the fulfillment of EV charging requirements.

4.1.3 Fulfilling EV Requirements

The initial blueprint schedules are established by the Energy Scheduler considering two primary parameters: the energy demand of the EVs and their respective estimated or indicated departure times. When the system deviates from these blueprint schedules, it could potentially lead to an inability to meet the energy demand within the designated time, unless corrections are done later on in the schedule.

Therefore, an additional requirement is to ensure that despite any deviations, the total energy delivered by the end of the charging schedule is the same as or exceeds the energy demand. This responsive adaptation not only ensures energy requirements are met but also maintains a high level of service for the EV user. To handle this, three strategies are deployed: 'Maximum Charging Power', 'Urgency', and 'Cumulative Deviation'. These strategies collaboratively rectify deviations, prioritize energy distribution based on need, and align energy delivery with the original schedule, ensuring that service for EV users remains uninterrupted and efficient. Details of these strategies are outlined in the following sections.

Maximum Charging Power

A viable strategy to address time constraints involves utilizing the maximum charging power. Specifically, when the remaining time before the departure of the EV is less than the time required to fulfill the energy demand at the maximum power, the charging power is set to its highest level. First testings of this functionality revealed that this would often result in high power peaks just before EV users typically depart. Note, that this often is at times when PV generation is relatively low, in office scenarios. This results in higher than average grid load peaks, which are undesirable. Therefore, this strategy is only implemented as a fall-back mechanism that acts when the other mechanisms for compensation fail.

Urgency

To mitigate the high power peaks when utilizing the maximum charing power, and thus to better distribute the power, another solution has been implemented. If time until departure is also considered, it is possible to prioritize which chargers receive energy first based on both their remaining energy demand and the remaining time they have to charge. Chargers with a high energy demand and little remaining time would be prioritized. This is done by introducing the *Urgency* metric. This Urgency is based on the remaining energy demand and the remaining time before the estimated departure of the specific transaction, and it dictates the proportion of available excess energy which is allocated to each charger during each adjustment.

The Real-Time Control component identifies the active chargers and calculates the Urgency for each charger at the each time interval, represented as $U_i(t)$, as the remaining energy demand ($E_{\text{rem},i}(t)$) divided by the remaining time intervals, which can be calculated as the total charging time for each charger (T_i) minus the current time interval t:

$$U_i(t) = \frac{E_{\text{rem},i}(t)}{T_i - t} \tag{4.2}$$

Here, the Remaining Energy Demand is calculated as the initial energy demand indicated by the EV user minus the energy already served to that transaction. The Remaining Time Intervals is computed as the total number of time intervals from the current timestamp until the indicated departure time of the charger.

The Urgency represents the "pressure" to serve energy to each charger based on its remaining energy demand and the time left until its departure. A higher Urgency means that the charger has a high remaining energy demand and/or little time left to charge, so it gets prioritized during the adjustment of the charging schedules.

This Urgency metric is then used to distribute the Power Discrepancy among the active chargers. If the Power Discrepancy is positive (indicating excess PV production), chargers with a higher Urgency receive a larger share of the additional energy. If the Power Discrepancy is negative (indicating less PV production than expected), the system uses the Inverse Urgency (i.e. chargers with lower Urgency have higher inverse Urgency) to distribute the reduced energy allocation. The Inverse Urgency of each charger at each time interval, denoted as $U_{\text{inv},i}(t)$, is the reciprocal of the Urgency $U_i(t)$:

$$U_{\text{inv},i}(t) = \frac{1}{U_i(t)} \tag{4.3}$$

This way, chargers with lower Urgency (and therefore a lower need for immediate charging) receive a larger reduction in their charging schedule. With the introduction of the Urgency metric, the approach for adjusting the charging schedule for each active charger evolves. Instead of distributing the Power Discrepancy evenly, it is now weighted according to each charger's Urgency.

This is done by calculating the Urgency Proportion for each charger at each time interval, denoted as $U_{\text{prop},i}(t)$. It is calculated as the Urgency of the specific charger divided by the sum of Urgencies of all active chargers:

$$U_{\text{prop},i}(t) = \frac{U_i(t)}{\sum_{i=1}^{n(t)} U_i(t)} \tag{4.4}$$

where n is the number of active chargers. The Urgency Proportion represents the proportion of the total Urgency that each charger's Urgency represents.

Finally, we calculate the adjustment for each charger at each time interval, denoted as $A_i(t)$, as the product of Power Discrepancy ($P_D(t)$) and the Urgency Proportion of the charger $U_{\text{prop},i}(t)$:

$$A_i(t) = P_D(t) \times U_{\text{prop},i}(t) \tag{4.5}$$

This way, the chargers with higher Urgency receive a higher proportion of the Power Discrepancy, either positive or negative, depending on the real-time state of the energy system.

Note that if the Power Discrepancy is negative (indicating less PV production than expected), the system uses the inverse Urgency to distribute the reduced energy allocation. In this case it is denoted as $U_{\text{inv,prop},i}(t)$, and is calculated as the Inverse Urgency of the each charger divided by the sum of Inverse Urgencies of all active chargers:

$$U_{\text{inv,prop},i}(t) = \frac{U_{\text{inv},i}(t)}{\sum_{i=1}^{n(t)} U_{\text{inv},i}(t)} \tag{4.6}$$

The Adjustment for each charger then updates to the product of Power Discrepancy and the Inverse Urgency Proportion of the charger:

$$A_i(t) = P_D(t) \times U_{\text{inv,prop},i}(t) \tag{4.7}$$

This method ensures that chargers with a lower need for immediate charging (lower Urgency) receive a larger reduction in their charging schedule.

Cumulative Deviation

To further enhance the control over the charging process, the Real-Time Control system considers the *Cumulative Deviation* of the transactions. Cumulative Deviation, for a specific transaction, refers to the aggregate difference between the actual energy delivered to an EV and the energy that should have been delivered according to the blueprint schedule up to the current time interval. Mathematically, it is denoted as $D_{\text{cum},i}(t)$, and is the difference between the actual energy delivered for each charger until time interval t ($E_{\text{act},i}(t)$) and the scheduled energy until time interval t ($E_{\text{sch},i}(t)$):

$$D_{\text{cum},i}(t) = E_{\text{act},i}(t) - E_{\text{sch},i}(t) \tag{4.8}$$

A positive Cumulative Deviation indicates that an EV has received more energy than initially planned by the Energy Scheduler, while a negative Cumulative Deviation signifies less energy has been delivered.

The system integrates this Cumulative Deviation into its calculations to determine the adjustments needed to compensate for past deviations for each charger. To achieve this, the Cumulative Deviation is distributed over the remaining time intervals until the indicated departure time of the EV. This distributed deviation is referred to as the *Cumulative Adjustment Ratio*, denoted as $R_{\text{cum},i}(t)$, and is calculated as the Cumulative Deviation at the current time interval, $D_{\text{cum},i}(t)$, divided by the Remaining Time Intervals, which can be calculated as the total amount of time intervals (T) minus the current interval.

$$R_{\text{cum},i}(t) = \frac{D_{\text{cum},i}(t)}{T_i - t} \tag{4.9}$$

The Cumulative Adjustment Ratio gives an additional layer to fine-tune the charging schedule of each EV. It is added to the adjustment derived from the Power Discrepancy to form the total adjustment for each charger.

If we integrate this ratio into our original Adjustment formula, the Total Adjustment for each charger i at time interval t, denoted as $A_{\text{tot},i}(t)$, is the difference between the original Adjustment at time interval t, $A_i(t)$, and the Cumulative Adjustment Ratio at time interval t, $R_{\text{cum},i}(t)$:

$$A_{\text{tot},i}(t) = A_i(t) - R_{\text{cum},i}(t) \tag{4.10}$$

Incorporating the Cumulative Adjustment Ratio enables the Real-Time Control system to distribute the accumulated past deviations over the remaining charging period. This approach ensures corrections spread out over time, contrasting with methods such as the maximum charging approach, which might delay adjustments until the latest possible moment. As such, if an EV has received more energy than planned in the past (positive Cumulative Deviation), its charging rate will be reduced in the future and vice versa. By doing so, the system can ensure that the total energy delivered to each EV aligns as closely as possible with the original scheduled energy by the time of departure. This mechanism prevents the system from accumulating errors and being forced to make large corrections at the last possible moment. It contributes to a consistent and evenly distributed load on the grid.

Summary

In summary, the real-time control system leverages three strategies: Maximum Charging Power, Urgency, and Cumulative Deviation, to ensure energy requirements are met and to keep EV charging reliable. The Maximum Charging Power strategy serves as a fallback mechanism, while the Urgency strategy prioritizes power distribution based on the remaining energy demand and time left to charge. The Cumulative Deviation strategy provides a corrective mechanism for past deviations. Together, these strategies help in shaping an effective charging schedule for EVs.

The total adjustment for each charger is calculated using the following formula:

$$A_{\text{tot},i}(t) = P_D(t) \times U_{\text{prop},i}(t) - R_{\text{cum},i}(t) \tag{4.11}$$

This formula ensures the distribution of power adheres to the urgency of each charger and compensates for past deviations in energy distribution. This comprehensive approach ensures that the total energy delivered to each EV closely aligns with the original schedule, maintaining a high level of service for EV users and reducing stress on the grid.

4.1.4 EV Charging Constraints

The Real-Time Control component checks whether the current of the charger falls within certain bounds after the adjustment. Most EVs can only handle charging currents in between 6 and 16 amperes. If the adjusted charger value falls between 0 and 6 amperes, it is rounded up (6) or down (0). If the adjusted value exceeds the maximum allowed charging value, it is reset to this maximum value. Next to that, the considered AC chargers can only handle steps of 1 ampere. Due to this nature, it could happen that not all Power Discrepancy is used. To handle this, recursion is introduced.

4.1.5 Recursion

The Real-Time Control Component uses recursion to ensure that the total Power Discrepancy is properly distributed among all the active chargers. When the Real-Time Control component initially distributes this power discrepancy amongst the active chargers based on their Urgency and Cumulative Adjustment Ratios, it is possible that not all of the discrepancy can be used in that initial pass. This leftover or "unused" power discrepancy can occur under certain circumstances. For instance, if an adjustment would cause a charger to exceed its maximum or minimum permissible charging rate, the adjustment for that charger will be limited to keep it within those bounds. This limit may prevent the full Power Discrepancy from being allocated in the initial distribution.

Furthermore, the process of correcting past deviations (through cumulative adjustment ratios) might not fully utilize the Power Discrepancy. For example, if a charger was previously over-served and is now receiving less energy to compensate, it may not need its full share of any additional power available.

To handle this, the Real-Time Control component includes a check that determines whether there is any "remaining" Power Discrepancy and whether any adjustments have been made during the current iteration. If there is still Power Discrepancy and adjustments have been made, the function recalls itself, passing in the adjusted schedule values, active transactions, and the remaining Power Discrepancy.

The recursive calling of the Real-Time Control function will persist until one of the following conditions is met:

- All available Power Discrepancy has been allocated. This is determined when the remaining Power Discrepancy (in amperes) falls below the minimum step of 1 ampere that the chargers can handle. This implies that any remaining discrepancy cannot be further distributed among the chargers due to their operational constraints.
- No further adjustments can be made. This scenario occurs when a round of adjustments does not yield any changes to the charging schedules. This may happen when all chargers are already charging at their maximum capacity, while adjustments are positive, or when the remaining energy demand of the EVs has been met.
- The Power Discrepancy becomes worse after adjustments. This condition is included to prevent a potential infinite loop where the system keeps trying to optimize the distribution but instead worsens the Power Discrepancy due to various factors such as constraints in the charging process. This can occur when all chargers have reached their maximum or minimum allowable values, and no further adjustments can be made.

The above recursive mechanism is crucial, as it ensures that any remaining Power Discrepancy, whether excess or shortfall, is progressively distributed among the active chargers, adhering to their Urgency and Cumulative Adjustment Ratios. This results in a more accurate and efficient allocation of energy, taking into account both the Urgency and the past deviations for each charger.

4.1.6 Re-optimizations

Significant Power Discrepancies could diverge the served energy and scheduled energy by quite a lot. In such a case, a new optimization request could be sent to the Energy Scheduler, which then creates a new blueprint schedule considering the updated energy demand, (original energy demand minus the energy already served). This ensures that schedules are updated based on the updated energy demands.

The Cumulative Adjustment Ratio gives insight into the magnitude of the deviation from the blueprint schedule in relation to the remaining time to correct this deviation. Therefore is could serve as a good measure to trigger re-optimization of the blueprint schedules.

In detail, a high Cumulative Adjustment Ratio, even with a sufficient remaining charging time, indicates that the real-time charging process has deviated significantly from the initially planned blueprint schedule. On the other hand, a small remaining charging time, regardless of the size of the cumulative deviation would also increase the Cumulative Adjustment Ratio. This may indicate that there is insufficient time to adjust the charging rates and correct the deviation, without causing substantial disruptions in the charging schedules. Therefore the Cumulative Adjustment Ratio is a good indicator of the necessity for a re-optimization.

In either scenario, a re-optimization of the blueprint schedules could be beneficial to realign the actual energy delivery with the planned schedules. The re-optimization process involves sending a new optimization request to the Energy Scheduler, which then creates a revised blueprint schedule. This new schedule is based on the updated energy demand, which is the original energy demand minus the energy already served.

Importantly, the re-optimization process is triggered when the Cumulative Adjustment Ratio exceeds a pre-defined threshold. This threshold serves as an indicator of the acceptable level of divergence between the blueprint schedule and the realized schedule. If the Cumulative Adjustment Ratio exceeds this threshold, it signals that the blueprint and realized schedules have diverged excessively or there the remaining time to correct for the deviations is low, warranting re-optimization. It should be noted that this new blueprint schedule still relies on the original forecast values, reinforcing the necessity of the Real-Time Control component to handle any potential deviations for the new blueprint schedule as well.

The process of determining a corresponding threshold is a complex task that involves balancing the use of computational power and the quality of the scheduling solution. A too low threshold might cause frequent re-optimizations, increasing the computational load, while too high threshold might result in significant deviations from the blueprint schedule, requiring compensation at possibly inconvenient times, at which for example PV production is low. In practise, the threshold at which a new optimization is requested is chosen to be a pre-defined value set by trial and error.

4.1.7 The Algorithm

The Real-Time Control Component uses an algorithm that operates based on the principles and constraints previously discussed. The algorithm can be broken down into various steps to more clearly demonstrate its operation.

1. The algorithm begins by obtaining the blueprint charging schedule value from the Energy Scheduler, the current time, the grid load, PV power measurements and PV power forecasts.

2. It then computes the Power Discrepancy by comparing the forecasted PV power with the actual measurements.

3. The algorithm then retrieves all the active transactions. For each transaction, it calculates the remaining energy demand and remaining time intervals.

4. Using the remaining energy demand and remaining time intervals, it calculates the Urgency for each active transaction. The Urgency is reversed when the Power Discrepancy is negative.

5. The algorithm also calculates the Cumulative Deviation and Cumulative Adjustment Ratio for each active transaction.

6. The algorithm then uses the Urgency and Cumulative Adjustment Ratio to calculate the adjustment for each charger:

   $$A_{\text{tot},i}(t) = P_D(t) \times U_{\text{prop},i}(t) - R_{\text{cum},i}(t) \tag{4.12}$$

   This formula ensures that the adjustments made to each charger are based on both the urgency of their energy demand and the history of over- or under-supply of energy, while also taking into account the total Power Discrepancy available.

7. After computing the adjustments, the algorithm checks the constraints on the charging rates and adjusts the charging rates accordingly.

8. The algorithm then checks whether there is any remaining Power Discrepancy. If there is, and if any adjustments have been made, it repeats steps 6-7 with the new Power Discrepancy.

9. The algorithm continues to repeat these steps until all Power Discrepancy has been allocated, no further adjustments can be made, or the Power Discrepancy worsens after adjustments.

10. If at any time the Cumulative Deviation becomes too significant, the algorithm sends a request to the Energy Scheduler to create a new blueprint schedule.

4.2 User Interface

The UI is the connection between users and the EMS, it should be easy to use, and EV flexibility information should be gathered effectively. The UI enables users to input their expected departure time and desired travel distance, providing valuable data for both the Energy Scheduler, to schedule the loads, and the Real-Time Control algorithm, to know how much it can deviate. This section explores its development process and the underlying technology.

4.2.1 Development

The main feature of the UI is a straightforward, digital form for users to input their expected departure time and desired travel distance they want to charge. To make the process simple, users may provide their desired additional kilometers of range, instead of the more technical measure of energy in kWh. This approach aims to motivate non tech-savvy users to provide their flexibility information. The EMS converts these kilometers of range to kWh by a factor based on average kWh/km for EVs.

The designed UI is directly integrated into the charger, thereby simplifying the process of gathering user flexibility information. This approach encourages users to provide their data without the need for an additional smartphone application.

The developed UI uses a modern technology stack, consisting of JavaScript for dynamic functionality, HTML and CSS for structure and design, and a backend API for data storage and retrieval. These technologies were chosen for their ubiquity, simplicity, and robust support. The UI runs on a waterproof tablet installed above the charger. See Figure 4.2.

FIGURE 4.2: Integrated UI tablet on the EV charger facilitating ease of access for users to input their flexibility data.

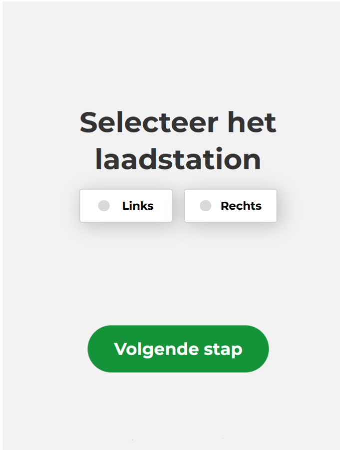
4.2.2 User Interaction

The UI supports three steps, shown in Figure 4.3. The first step informs the users about the benefits of Smart Charging (ZonLaden), which encourages them to drive sustainably. If the user wishes to proceed without Smart Charging, they can just swipe their charging card. This screen also displays the current cost of charging (€0.50 / kWh).

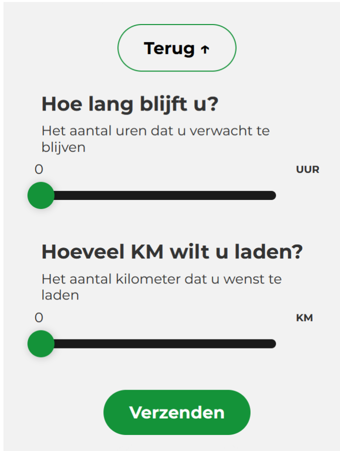
In the second step the user is able to select the charging station, here the two options for the left and the right charging plug are provided, as the charger has two plugs. For example, in Figure 4.2, the right charger plug is in use.

The third step allows users to input their flexibility information. They indicate their expected duration of their stay using a slider that ranges from 0 to 10 hours, and their desired travel distance (in kilometers) using another slider that ranges from 0 to 500 kilometers. This input is easy to adjust and visually intuitive, thereby aiding user accessibility. The conversion from kilometers to kWh happens in the EMS and uses an average kWh/km conversion factor.

(A) First screen shows benefits of ZonLaden (smart charging), offers standard charging, and shows kWh price.



(B) Second screen, where the user can select their charging station, choosing between the left or right socket.



(C) Third screen, asking the user for their stay duration in hours and the amount of km they want to charge.

FIGURE 4.3: Screenshots of the 3 steps of the form of the UI.

4.2.3 Backend

The UI already employs some error-checking algorithms to ensure that the given data is valid. It hereby provides visual feedback once the data is submitted and in case of inconsistencies, it guides the user where necessary.

The input data of the users is stored securely in the EMS database via a RESTful API. The EMS uses this data for energy scheduling. By providing an accessible interface for data input, the UI enables users to communicate their energy needs to the EMS easily, promoting efficient scheduling of the charging process.

4.3 Evaluation Framework

This Section presents the design and operations of the Evaluation Framework, providing a comprehensive understanding of the tools and methodologies adopted in this research to analyze EV scheduling strategies.

The Evaluation Framework has been instrumental in testing and evaluating EV scheduling strategies, providing a realistic simulation environment and practical implementation options. The framework is designed to to bridge the gap between theoretical strategies and their real-world applications.

4.3.1 Framework Design and Components

The Framework is constructed on a "*time tick*" principle. It operates by subdividing the simulation period into small time intervals (e.g., 10 seconds). During each time tick, a sequence of operations such as hardware measurements, optimization, application of live control, and signal transmission to the hardware are carried out.

The framework is designed to accommodate a multitude of variables, thereby broadening the range of its applications. Variables such as simulation time, frequency of time ticks, configuration of the charging hub, size of the PV installation, grid limit, battery capacity, building consumption, and electricity tariffs are taken into account. The framework also makes use of forecasted and measured PV power data, EV transaction data, and electricity price forecasts.

The framework has several components. An overview of these components and their dataflows can be found in Figure 4.4. The primary components of the framework include the *Livecontroller*, which coordinates the time ticks and subsequent operations, the *Hardware Model*, which can be either a simulation or physical hardware, a time-series database (*InfluxDB* [36]), a document-oriented database (*MongoDB* [37]), an *API-Gateway*, and the *Energy Scheduler*. The dataflows are further explained in Section 4.3.2.

The time ticks are handled by the *Livecontroller*, acting as the orchestrator of various activities, including measuring hardware, requesting and reading energy schedules, applying Real-Time Control, and sending control signals to different hardware components. The Livecontroller also accommodates user input, and forecasts, which can be used for Real-Time Control.

The hardware components, which can be either physical or simulated, encompass all the inverters, batteries, and chargers within the charging hub. The hardware has the capability to adjust power control values for the battery and chargers, and to curtail the inverter as needed. The hardware components can be measured, providing data on the actual power output. Additionally, these components can provide state information. For chargers, this includes transaction data, such as the energy charged (in kWh), the associated user ID and a unique transaction ID. For the battery, the state of charge (SoC) can be determined, providing information on the current capacity of the battery relative to its maximum capacity.

The Energy Scheduler is an event-based optimizer/solver, producing energy schedules for each asset in the system. These schedules are optimized energy schedules for each asset in the system for a horizon, set by the available forecast information. Due to the nature of PV power forecasts and electricity price forecasts, this horizon is typically between 12 and 24 hours. Energy schedules are calculated when the Energy Scheduler is triggered by the Livecontroller upon specific events (such as an EV arrival or departure), when new information becomes available, or other insights derived by the Real-Time Control mechanism, such as the Cumulative Adjustment Ratio, explained in Section 4.1. The Energy Scheduler uses user-input and state information from MongoDB and already scheduled loads and forecasts from InfluxDB to provide energy schedules for the different assets in the system. As such, the Energy Scheduler is the service that handles the energy scheduling approach explained in Section 2.3.

The API-Gateway is responsible for managing and directing user inputs, charger statuses, and forecasts to appropriate services.

4.3.2 Component Interactions and Dataflow

The flowchart in Figure 4.4 visualizes the interactions among the various components of the Evaluation Framework. It shows how the databases (InfluxDB and MongoDB), the Livecontroller, the Energy Scheduler, the API-Gateway, and the hardware components (either simulated or physical) communicate with each other.

Starting with the Livecontroller, it is shown that it receives inputs in the form of user input, forecasts and electricity prices and that it also measures the hardware. These measurements are stored in InfluxDB. It also fetches power schedules created by the Energy Scheduler from InfluxDB. The Livecontroller then requests an optimization from the Energy Scheduler when it deems it necessary. It also sends the control signal to the hardware.

The Energy Scheduler, which is responsible for producing optimized energy schedules, receives a variety of data; the forecasts and already scheduled loads achieved from the InfluxDB, are fetched and the user-input and state information is taken from MongoDB. The schedules are then stored in InfluxDB to be fetched by the Livecontroller when necessary.

The API-Gateway receives user inputs, charger statuses, and forecasts and saves them to the databases. These data can be stored in either MongoDB (for user inputs and state information) or InfluxDB (for PV power and price forecasts). The forecasts can come from a forecast API service such as Forecast.Solar [38] or ENTSO-e Transparency Platform [39] in case of real-world implementation, or from a file in case of simulations.

The hardware components receive control signals from the Livecontroller and provide measurements and state information back to the Livecontroller and the API-Gateway.

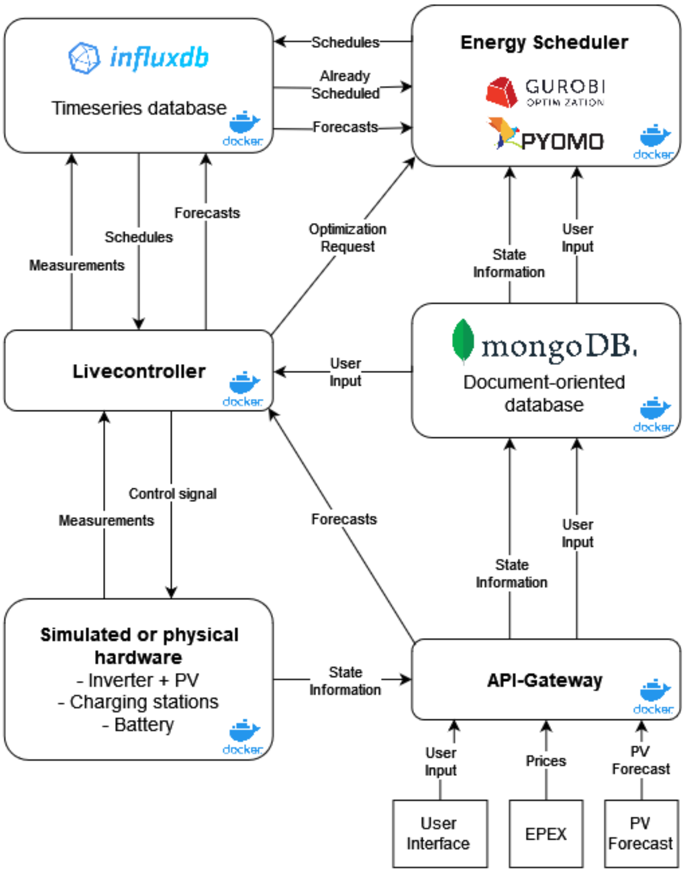


FIGURE 4.4: An overview of the different services and data flows of the Evaluation Framework.

4.3.3 Time Tick Operations

The operations of the Evaluation Framework revolve around the concept of "time ticks". These are discrete intervals of time that the framework uses to coordinate activities. Each time tick initiates a sequence of operations, such as gathering hardware measurements, optimization, Real-Time Control application, and signal transmission to the hardware.

In more detail, the operations happening each time tick are:

- **EV Arrivals and Departures:** Capturing real-time changes in the charging hub such as the arrival and departure of EVs, their energy demand, departure time, and charging status.

- **Active Transactions Update:** The framework keeps track of ongoing transactions, allowing for accurate data management and timely updates to the scheduling strategy.
- **Energy Price and PV Power Forecast Updates:** The framework incorporates real-time energy prices and PV power forecasts, improving the scheduling strategy's adaptability and efficiency.
- **Optimization Request:** Optimization requests are generated based on changes in the state of the charging hub, allowing for dynamic scheduling.
- **(Real-time) Control:** The framework executes Real-Time Control based on active transactions, further refining the energy schedules and their implementation.
- **Measurement Fetching and Storage:** Measurements from the assets are constantly retrieved and stored, aiding in real-time decision-making and future analysis.

The chosen frequency for the time tick in the Evaluation Framework is 10 seconds. This choice of time tick frequency is a balance between maintaining high-speed simulations, providing accurate Real-Time Control, and accurately reflecting fluctuations in PV production and charger response times.

In real-world environments, PV generation can fluctuate significantly due to changes in weather conditions. Having a time tick of 10 seconds allows the system to respond promptly to these rapid changes in solar output, providing more accurate control and optimization of charging schedules.

Charger response times are another critical factor to consider. Modern EV chargers can respond to control signals relatively quickly, often within a few seconds. By choosing a time tick of 10 seconds, the framework allows sufficient time for chargers to respond to control signals and for these changes to be measured and incorporated into the system, which is crucial for the effective implementation of Real-Time Control.

A shorter time tick would allow for even more precise control and could potentially handle faster fluctuations in variables such as PV output or charger state by the Real-Time Controller. However, this would come at the cost of significantly increasing the computational load. Also, chargers might not be able to respond in time to the changes in power as fast. In contrast, a longer time tick would reduce the computational load and allow enough time for hardware to react to control signals but might not be able to react to rapid changes in these variables effectively.

Finally, choosing a time tick frequency of 10 seconds aligns well with the communication protocols used by many energy assets, making the Evaluation Framework compatible with a wide range of potential real-world applications.

4.3.4 Implementation of the Framework

The Evaluation Framework is implemented using *Docker* [40], which facilitated a Microservices Architecture [35], where each microservice runs independently in isolated environments. This approach significantly reduced the complexity of managing multi-container Docker applications, thereby enhancing the effectiveness of the framework.

The Evaluation Framework is implemented using an asynchronous programming approach in *Python* [41], thereby utilizing the robust support for asynchronous Input/Output operations. The asynchronous nature of the tick method in the Livecontroller allows for concurrent execution of I/O-bound tasks such as data fetching and sending, resulting in significantly improved simulation speed.

For handling user inputs, charger statuses, and forecast APIs, the framework incorporated an API-Gateway, developed using *Flask* [42]. Data management is achieved using InfluxDB [36] for handling time-series data, and MongoDB [37] for handling non-time-series data. For visualization and analysis, *Grafana* [43] is employed, providing dynamic, real-time dashboards.

4.3.5 Implementation in Real Environment

The Evaluation Framework can be implemented for both simulated environments and actual real operation. The simulation mode uses theoretical data and emulated hardware to mimic real-world situations, whereas in the actual implementation, the framework interacts with physical hardware and utilises real-time data from the environment.

Firstly, the hardware models used in the simulations are replaced with actual hardware components, such as chargers, inverters, batteries, and solar panels. As these hardware components can receive and respond to control signals, they facilitate the transition from the simulation mode. They also offer the added advantage of providing real-time measurements and state information which can be integrated into the system for more accurate decision making.

Next, the forecast data for PV production and electricity prices, which are loaded from saved files in the simulation mode, are replaced with live data from APIs. The APIs, such as Forecast.Solar for PV power forecasts and ENTSO-e Transparency Platform for electricity prices, provide real-time and more accurate data for the Energy Scheduler to optimise the charging schedules.

To accommodate the difference in computation requirements between simulation and real-world operation, a distributed computing architecture may be adopted. The operations could be divided across a centralised location and the charging hub location. The centralised location, having robust computational power, would handle the computationally intensive tasks, such as optimising the energy schedules based on the current forecast and price data. On the other hand, the charging hub location, closer to the physical hardware, would take care of measuring the hardware, sending control signals, and implementing real-time control.

This distributed architecture can bring significant advantages. The computational load is efficiently divided, allowing for faster operation without overloading the hardware at the charging hub. Furthermore, real-time control and monitoring tasks could be performed with lower latency due to their proximity to the hardware.

4.3.6 Challenges and Limitations

One of the significant challenges encountered during the design was to ensure high-speed simulations while maintaining a high degree of realism. In simulations, where each 'time tick' does not represent actual elapsed time but is processed as quickly as possible, the initial design strategy of executing all steps at each time tick led to slower simulations, especially at lower time tick intervals. To enhance simulation speed, the Livecontroller was optimized to limit inputs and outputs to various services, only performing measurements and sending signals when necessary. However, in a real-world operation where each tick corresponds to an actual elapsed time, performance was not an issue. The system had ample time in between time ticks to complete necessary calculations, ensuring smooth real-time operation.

Creating accurate models for hardware, such as chargers, inverters, batteries, and solar panels is a non-trivial task. There may be a discrepancy between how the modelled hardware behaves in the simulation and their performance in the real world. Differences that can occur are hardware failures, measuring inaccuracies and slower reaction times on control signals.

Although this approach offers high speed and close-to-reality simulations, the accuracy of the results is dependent on the quality of the input data. While the design attempts to mirror real-world hardware as closely as possible, the unpredictable nature of real-world environments presents a significant challenge. Factors, such as unexpected user behavior or hardware failure, while hard to simulate accurately, can significantly impact the performance of EV scheduling strategies. Also, the power forecast data for PV need to be reliable.

Chapter 5

Test Setup

This chapter describes the comprehensive strategy employed for testing and evaluating the various components of our system, which include the Energy Scheduler, the Real-Time Control mechanism, the User Interface (UI), and the Evaluation Framework. The strategy revolves around a robust approach that ensures the evaluation of each component under various conditions. This includes the deployment of distinct scenarios and modes, the collection of real-world data from different seasons, and the investigation of user interaction through an enhanced UI.

A testing approach involving both simulation and field testing is employed. The simulations allow for systematic and controlled testing, while field testing provides an understanding of the performance of the system under real-world conditions. The testing site is a charging hub located at an office location, ensuring real-world applicability and reliability of the testing process.

The chapter is organized as follows: It starts with Section 5.1, where we introduce the evaluation metrics used to assess the performance of the components. Different quantitative performance metrics, including total electricity costs, peak grid loads, self-consumption, self-sufficiency, and energy not served, are used for evaluation.

This is followed by an explanation of the test location in Section 5.2. At this location the field test is performed and data gathered for input to the simulations.

Then Section 5.3 gives account of the how the simulations are done is given. The simulations are set up to evaluate how the existing Energy Scheduler approach performs under various conditions, and to investigate how it can be improved further. The simulations also seeks to understand the impacts and improvements resulting from the implementation of a Real-Time Control mechanism in electric vehicle (EV) control. For this, scenarios that incorporate the Real-Time Control mechanism are included. To highlight its impact, the performance under these scenarios with the performance under scenarios without this mechanism are compared. To address this, we have implemented a series of scenarios that encompass different operational conditions including different seasons and the two modes (peak shaving and cost-optimization, explained in Section 2.3).

Following that, Section 5.4 is dedicated to describing the real-world field testing and the strategies used therein. The influence of an integrated UI on user-EMS interaction and EV scheduling effectiveness in a real-world environment is evaluated. For this, the field test phase involves implementing the UI, allowing users to interact with it, and observing its influence on scheduling effectiveness. To evaluate the impact of the Real-Time Control mechanism in a real environment, additional simulations, mimicing the field test with inputs based on the field test, are conducted. These are used to compare the field test results with and see the effect of various dynamic variables that may emerge in a real-world environment. We conclude this chapter in Section 5.5 with an overview of how the different tests are compared with each other.

5.1 Performance Evaluation Metrics

Five performance evaluation metrics are used to assess the performance of the different scheduling techniques. These consist of the total electricity costs, the peak grid loads, the solar self-consumption, the self-sufficiency and the energy not served.

- **Total Electricity Costs:** This metric represents the overall expense incurred by the charging hub in consuming electricity from the grid over a (simulated) period. It directly reflects the economic efficiency of a scheduling strategy. An effective scheduling strategy should minimize the total electricity cost by making use of the available resources and electricity price dynamics. For example, it should aim to charge the EVs when the electricity prices are low, given the users' charging requirements are satisfied.

- **Peak Grid Loads:** This metric focuses on the highest power imports from the grid or exports to the grid during a period. In this work, the peak grid load is expressed as the mean of the top 1% of the highest grid loads during a certain period. A visual representation of peak grid loads is typically achieved through load duration curves. These curves effectively illustrate for how much time the system operates at particular load levels, enabling a better understanding of peak loads and their potential impact on the grid system.

  The Peak grid load is an important parameter as high peak loads can induce grid instability or even failure. Therefore, reducing the peak grid load is an important objective for energy scheduling strategies. A good scheduling strategy should be able to flatten the load by spreading the charging load across time and towards periods of high generation, thus reducing the peak demand. Also, it should be able to reduce peak PV production to protect the grid infrastructure.

- **Self-Sufficiency:** Self-sufficiency measures the percentage of the energy demand (from the EV chargers) that is met by the solar energy generated on-site. We define Self-Sufficiency (SS_{mean}) as the mean share of the total energy consumption by the EV charging stations that was sourced directly from the PV installation, calculated across all days. Each day, we calculate a daily self-sufficiency score by summing up the difference between the total energy consumed and the energy imported at each time interval within the day, and then dividing this sum by the total energy consumed that day, and finally multiplying by 100 to express the result as a percentage. Then the mean of these daily self-sufficiency scores is calculated to arrive at the SS_{mean}. This is mathematically represented as:

  $$SS_{\text{mean}} = \frac{1}{N} \left(\sum_{d=1}^{N} \left(1 - \frac{\sum_{t \epsilon t_{\text{d}}} E_{\text{imported}}(t)}{\sum_{t \epsilon t_{\text{d}}} E_{\text{consumed}}(t)} \right) \right) \cdot 100 \tag{5.1}$$

  where, N represents the total number of days, d is a specific day in $\{1, \ldots, N\}$, t_{day} are the time intervals within each day d and $E_{\text{consumed}}(t)$ is the energy consumed at time t and $E_{\text{imported}}(t)$ is the energy imported from the grid at time t.

A higher SS_{mean} implies that the hub is less reliant on the grid for its energy needs. Enhancing self-sufficiency is an important goal, given the environmental and economic benefits of using renewable energy sources. Higher self-sufficiency also results, on average, in lower grid load.

- **Self-Consumption:** This metric measures the percentage of solar energy produced by the PV panels that is directly consumed by the charging hub, rather than being fed into the grid.

  Like self-sufficiency, self-consumption (SC_{mean}) is calculated daily and then averaged across all days. The daily self-consumption score is derived by considering the energy consumed and imported at each time interval within a day, but now it is divided by the total energy generated that day.

  Mathematically, this is represented as:

$$SC_{\text{mean}} = \frac{1}{N}\left(\sum_{d=1}^{N}\left(\frac{\sum_{t\epsilon t_{\text{d}}}(E_{\text{consumed}}(t) - E_{\text{imported}}(t))}{\sum_{t\epsilon t_{\text{d}}} E_{\text{generated}}(t)}\right)\right)\cdot 100 \tag{5.2}$$

  Here, $E_{\text{generated}}(t)$ refers to the energy generated by the PV panels at time t.

  Higher self-consumption means that more of the solar energy produced is being effectively utilized at the spot. An efficient scheduling strategy should aim to maximize self-consumption by aligning charging schedules with periods of high solar generation, where possible.

- **Energy Not Served:** The energy not served is the energy demand minus the energy served to the EV at the end of a transaction. This is energy that the EV user expected, but did not receive. Energy not served due to a full battery is not taken into account. The energy not served of all transactions is a measure of how well a charging control system can satisfy the energy demand of EV users. A lower energy not served indicates a more reliable charging strategy. It is important to maintain a high level of service to the EV user while applying charging control.

5.2 Test Setting

The testing is performed at a charging hub located at an office location in Rijssen. An impression of this location is given in Figure 5.1. An office location was chosen for the field test and the simulations for several reasons. Firstly, this setting typically exhibits predictable patterns of EV arrivals and departures based on the work schedule of the office employees. This regularity allows the system to better manage the charging schedules based on expected vehicle availability. This makes an office location with charging hub a typical use case for employing an Energy Management system (EMS).

In addition to the predictable patterns, the choice of the office location was further influenced by the availability of historical data regarding the arrival and departure times of EVs. This data is valuable for the simulations, as it keeps the simulations closer to reality.

The chosen office location hosts, amongst other devices, 24 controllable AC charging stations (with a maximum power of 22 kW each) and a 73 kWp PV system. Two charging stations also have the UI (see Section 4.2 integrated to gather EV flexibility information.

At this location, transactions are tracked and EV users can be identified, by their ID tag. This enables us to use historical data (mean energy demand and mean stay duration) for scheduling per user if no departure time and energy demand is given by the user, further explained in Section 5.4. The time tick is set to 10 seconds for both the simulation and the real environment. This enables the use of Real-Time Control, while not performing too much redundant calculations. It also enables enough time for optimizations by the Energy Scheduler and for the EVs to react on changes in power supplied.

FIGURE 5.1: An impression of the test setup in Rijssen, The Netherlands.

5.3 Simulations

The simulations are conducted for specific periods, a week in summer and a week in winter, to account for the impact of seasonal variations on PV production. Furthermore, the performance of the Real-Time Control component is examined more closely on three particular days; one where PV production is fluctuating heavily, one where the PV production forecast is significantly lower than the actual measured value and one where the PV production is significantly higher than predicted. Here, no re-optimization is applied, to purely show how the Real-Time Control mechanism performs on its own.

The simulations are performed using the Evaluation Framework, of which the implementation has been explained in Section 4.3. The flexibility of this framework, resulting from the range of variables it can accommodate and its ability to utilize diverse data sources, facilitates the creation of diverse scenarios to test the performance of the system under different conditions.

5.3.1 Scenarios

Five primary scenarios are considered for the simulation testing.

1. Business As Usual
2. Cost Optimization
3. Cost Optimization and Real-Time Control
4. Peak Shaving

5. Peak Shaving and Real-Time Control

The simulations are conducted using distinct operational strategies of the Energy Scheduler: Peak Shaving and Cost Optimization. In Peak Shaving mode, the Energy Scheduler seeks to minimize the highest grid load, while in Cost Optimization mode, it tries to minimize the total cost of electricity.

The performance of the system under each scenario and strategy is evaluated based on the metrics defined earlier, including total electricity costs, peak grid loads, self-consumption, self-sufficiency and energy not served. This diverse set of scenarios and strategies provides comprehensive insights into performance of the system under various conditions and control strategies.

Business as Usual

This scenario represents the baseline case where there is no EMS or scheduling. This scenario simulates what would have happened if no charging control was applied. The EVs are charged according to a greedy strategy, meaning that it charges as much as possible as quickly as possible and that no scheduling or load-balancing is involved. It provides a reference point to compare the performance of the system when the Energy Scheduler approach and Real-Time Control mechanism are applied.

Cost Optimization

This scenario involves the Energy Scheduler, set to optimize for cost minimization. The EV charging sessions are scheduled upon arrival of the EV, on a first-come-first-serve basis and the EV follows the schedule. The scheduling is based on simulated user input. This scenario serves to understand the performance improvement achieved through the scheduling approach for cost minimization alone, while also providing a reference point for the performance of the Real-Time Control mechanism.

Cost Optimization and Real-Time Control

This scenario is similar to the Cost Optimization scenario but includes the Real-Time Control mechanism. Its purpose is to provide insights into the combined performance of the scheduling approach in Cost Optimization mode combined with Real-Time Control mechanism.

Peak Shaving

In this scenario, the Energy Scheduler is set to operate in Peak Shaving mode, aiming to minimize the highest grid load. The scenario is designed to study the performance of the system when peak grid loads were targeted for reduction.

Peak Shaving and Real-Time Control

This final scenario combined the Peak Shaving strategy with the Real-Time Control mechanism. The objective was to understand the performance of the system when the target is to reduce peak grid loads with the inclusion of the Real-Time Control mechanism.

5.3.2 Simulation Data and Assumptions

For the simulation, the EV arrivals and departures are generated based on actual patterns observed at the testing location during a typical week without holidays (April 3rd to 9th, 2023). This real-world data from the testing location is used to replicate typical EV arrivals and departures for both a summer and winter week at an office location.

Generated user input is intentionally designed to reflect the unpredictability and inherent inaccuracies in real-world predictions. In actual scenarios, the departure times and energy demands indicated by the user often do not align perfectly with the actual departure time and the actual charged energy, respectively. To simulate this discrepancy, an offset is introduced between the indicated and actual departure times, as well as between the indicated and actual energy demands.

The offsets are modeled using a normal distribution, with parameters drawn from the findings of a referenced study [16]. To simulate the time offset, a mean value of 33 minutes earlier than the indicated departure time is used. This suggests that, on average, the actual departure time is likely to be 33 minutes earlier than the time initially indicated by the user. The variation around this average is captured by a standard deviation of 107 minutes.

Similarly, the energy demand offset is simulated using a mean value of 8 kWh less than the indicated demand, with a standard deviation of 13 kWh. This reflects that the actual energy demand of EVs is, on average, likely to be 8 kWh lower than what is initially indicated by the user, with variations around this average captured by the standard deviation.

By simulating these offsets, the model can account for the deviations and uncertainties that typically occur in real-world EV usage and charging patterns.

The PV power data used in the simulation, both forecasted and actual measurements, is carefully sourced from historical data. Forecasted PV power data is obtained from a nearby weather station, ensuring that the predictions align closely with the potential weather conditions at the testing site.

Actual PV power data is gathered from a PV installation located in close geographical proximity and similar in setup to the testing location, namely at the SlimPark Living Lab at the University of Twente [44]. To align this data more closely with the specific parameters of the testing location, it is appropriately scaled to the PV system. This scaling accounts for any PV system size differences between the source of the measured data and the testing site, ensuring that the input data accurately reflects the potential power output of the PV installation at the testing location.

In terms of electricity pricing, EPEX day-ahead prices [45] for the periods being simulated are utilized. This represents a realistic and market-based price signal for both the import and export of electricity. The simulation assumes an equal price for both the import and export of electricity, as determined by the EPEX day-ahead prices.

5.4 Field Test

Next to the simulations, the system was also tested in a real-world field test. The field test involved the implementation of the system at the actual charging hub that is simulated in Section 5.3, with real EVs, solar panels, and grid connection. The user interface, described in Section 4.2, was also implemented to interact with EV users and gather their flexibility information.

In this charging hub, the UI is integrated at 4 of the 24 chargers. The energy scheduling is carried out based on the flexibility information provided through this UI when people use this UI. However, when an EV user does not park at a charger with UI or does not interact with the UI, we rely on historical transaction data to devise a charging schedule. In this case, schedules are based on the mean parking time and the mean energy demand from the user's past transactions, if available. These two variables enable the Energy Management System (EMS) to create a personalized and efficient charging schedule for each user, without the necessity of user interaction with the UI. Mean parking times under 4 hours are excluded. These cases typically involve visitors who cannot be reliably scheduled. In these case a "greedy" schedule is given, wherein maximum charging is provided until the EV user departs or the battery reaches full capacity.

The performance of the system in the field test is evaluated based on the metrics explained in Section 5.1. Doing a field test is important, as it takes into account the uncertainties and complexities of the real world.

One source of uncertainty could come from the behavior of the EV users. Although we have historical data to guide our predictions, individual behavior can vary greatly and is influenced by countless factors. For instance, EV arrival and departure times may be inconsistent due to changes in users' schedules. The state of charge of the EV upon arrival can also vary, affecting the charging requirements. Furthermore, users' responses to and interactions with the UI can be unpredictable. Next to that, unexpected technical issues or failures can have an effect on the results. Issues can range from minor glitches in the UI or the Energy Scheduler to more significant failures such as a malfunctioning EV charger. These occurrences can disrupt the planned charging schedules and affect the overall performance of the system.

Next to taking into account these uncertainties, the process of implementing and integrating the system into the existing infrastructure at the field test can also introduce complexities. This can include challenges related to compatibility with existing EV chargers or the power grid, compliance with regulations, and the successful implementation of the user interface.

Next to the field test, we run extra simulations (next to the ones explained in Section 5.3) using data measured at this field test at the time the field test was conducted, to ensure an accurate comparison between simulated and field test results. These include a Business As Usual scenario, a scenario without Real-Time Control, and a scenario with Real-Time Control. Comparing these extra simulations with the field test allow us to observe what would have happened if no control was applied, and how much influence uncertainties have on the performance of the charging control strategies. To run the simulations we use the same data (arrival times, departure times, measured PV power and forecasted PV power) from the real-world setting.

During the field test only the scenario with the Energy Scheduler in Peak Shaving mode and Real-Time Control was tested.

5.5 Comparison and Analysis

The results of the simulation and the field test are compared and analyzed to understand the performance of the system. This phase involves a systematic comparison of the results obtained from the simulation and field testing. The comparison between the simulations is made across the five scenarios: Business As Usual, Cost Optimization, Cost Optimization and Real-Time Control, Peak Shaving, and Peak Shaving and Real-Time Control. For the field test comparison, additional simulated scenarios are employed. These scenarios use measured data from the field test as inputs, providing a direct and fair comparison to the actual field test measurements.

The comparisons are done based on the defined metrics, including total electricity costs, peak grid loads, self-consumption, self-sufficiency, and energy not served. The evaluation provides a quantitative measure of the performance of the system and its potential for reducing electricity costs and grid load and increasing self-consumption and self-sufficiency.

The analysis is conducted in two distinct steps:

5.5.1 Comparison of Simulation Results

The first step involves comparing the results obtained from the simulations across the five scenarios. This comparison provides insights into the performance improvement achieved by implementing the Energy Scheduler and the Real-Time Control mechanism. It also helps to identify the strengths and weaknesses of each approach and their impact on the overall performance of the system.

5.5.2 Analysis of Field Test Results

The next step involves analyzing the results obtained from the field test with the Energy Scheduler (Peak Shaving) and Real-Time Control scenario. To enable an accurate comparison, we do three extra simulations where we mirror the real-world conditions of the field test in three specific simulation scenarios: a Business As Usual scenario, a scenario without Real-Time Control, and a scenario with Real-Time Control. To run these simulations, we use the exact same data, i.e. EV arrival times, departure times, measured PV power, and forecasted PV power, that we measured at the field test. This way we simulate what would have happened if either no control was applied and if no Real-Time Control was applied.

This parallel use of data ensures a fair comparison and a comprehensive understanding of how our system performs control strategies in the real world. To compare, we use the evaluation metrics explained in Section 5.1. This comparison helps understanding the differences in the performance of the system under controlled simulations and real-world conditions. It also provides insights into the robustness of the system and adaptability to real-world uncertainties and complexities, which may, among other things, occur due to the implementation of the UI.

Chapter 6

Results

This chapter provides a comprehensive presentation and analysis of the results obtained from the tests, explained in the previous chapter. Three primary aspects are examined: the Real-Time Control mechanism performance under varied conditions, the results of the simulation testing and the results of the real-world testing. The investigation of the Real-Time Control mechanism performance delves into its behavior under three distinctive situations: a day with high fluctuations in photovoltaic (PV) production (Section 6.1.1), a day with overestimated forecasts (Section 6.1.2) and a day with underestimated forecasts (Section 6.1.3). These scenarios offer valuable insights into the dynamic adjustment of the Real-Time Control mechanism in response to different forecast accuracies and fluctuations in photovoltaic (PV) production.

The Section 6.2 presents the results from the simulation testing, where the performance of the Energy Scheduler and Real-Time Control mechanism is evaluated under various scenarios, namely: 'Business As Usual', 'Cost Optimization', 'Cost Optimization + Real-Time Control (RTC)', 'Peak Shaving', and 'Peak Shaving + RTC'. The evaluation is based on performance metrics, including total electricity costs, peak grid loads, self-consumption, and self-sufficiency.

Finally, in Section 6.3 of this chapter, the field test results are analysed. Also the results of the effectiveness of the User Interface (UI) is discussed. This comparison further contextualizes the potential effectiveness and efficiency of the Real-Time Control mechanism and the Energy Scheduler, as well as their impact on cost, grid load, and self-sufficiency.

6.1 Real-Time Control Mechanism Under Varied Conditions

This section aims to give an understanding of how the Real-Time Control mechanism operates and performs in a charging hub hosting multiple chargers. To show this, only one charging schedule is shown. The analysis of the Real-Time Control mechanism performance under varied conditions focuses on its behavior under three distinctive situations: on a day with high fluctuations in PV production, a day with underestimated forecasts and a day with overestimated forecasts.

6.1.1 High Fluctuations in PV Production

Figure 6.1 illustrates the initial blueprint schedule for a particular charger versus actual charging values throughout a day with highly fluctuating PV production. These fluctuations are not reflected by the forecasts. On a day with high fluctuations in PV production, for example due to clouding, the benefits of the Real-Time Control mechanism showed to be evident. Even though the PV generation was highly fluctuating, the Real-Time Control mechanism was able to follow these fluctuations adjust the charging rate in real-time, allowing it to compensate for the deviations from the forecast effectively. As seen in Figure 6.1, the Real-Time Control mechanism decided to charge when the actual PV production was higher than the forecasted PV production, even if the Energy Scheduler had determined not to charge during that period (e.g. 9:00 till 12:00). It also reduced the charging rate significantly when the PV production decreased at times when the blueprint schedule determined to charge at the maximum rate (e.g. 12:00 till 15:00).

On this highly fluctuating day, the inclusion of the Real-Time Control resulted in both a notable increase in self-sufficiency and a decrease in the mean top 1% grid load. The self-sufficiency increased from 70.15% without Real-Time Control to 81.91% with Real-Time Control. Concurrently, the mean top 1% grid load significantly decreased from 57.6 kW to 30.5 kW, further highlighting the potential of the Real-Time Control mechanism to enhance system performance and manage grid load, especially during periods of high fluctuation in PV production.

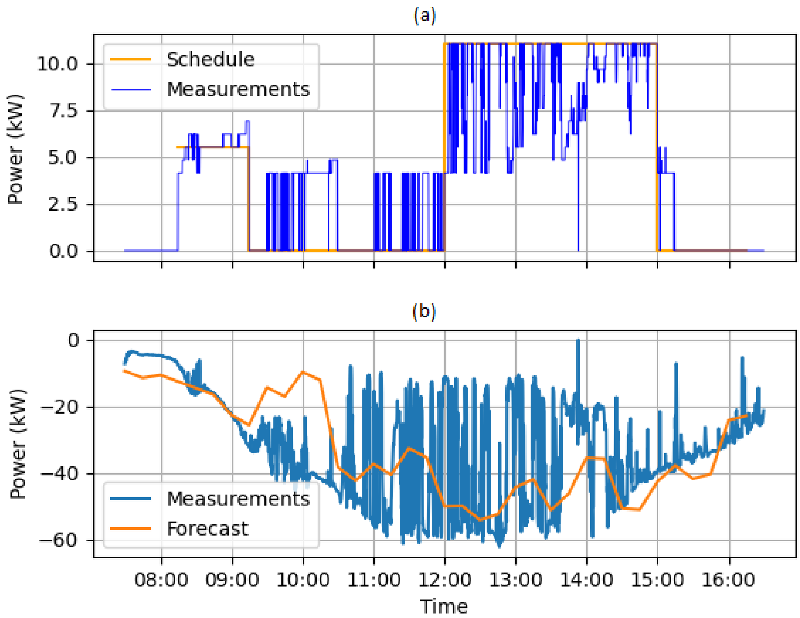


FIGURE 6.1: Illustration of the adaptability of the Real-Time Control mechanism during a day with high fluctuations in PV production. (a) The charging profile given by the Energy Scheduler and the measured charging power after real-time control adaptations. (b) The PV power forecast and the measured PV power.

Fluctuations in Charging Rate

An interesting dynamic observed during these periods of intense PV power fluctuation was a pattern of rapid oscillation in charger power. Specifically, the charger power was seen to quickly alternate between varying amperage levels in 10-second time ticks. It demonstrates the active engagement of the Real-Time Control mechanism in balancing the load in response to the highly fluctuating PV production. While these fluctuations can occur at all charging rates, the most striking pattern emerged between 0 and 6 amperes.

This oscillatory behaviour is primarily due to the operational constraints of the charger itself. The charger has a minimum charging rate set to 6 amperes and, therefore, when the adjusted charging rate falls in between 0 and 6, the charger would fluctuate between being fully off (0 amperes) and operating at the minimum allowed charging rate (6 amperes).

The influence of this behaviour on the system can be seen in the performance of the chargers. When the changes in the charging rate happen when the charger is already active (between 6 and 16 amperes), the chargers are able to respond to control signals quickly (within 10 second time ticks) and adjust their operation accordingly. This ensures a smooth flow of energy from the PV generation to the load, optimizing the use of renewable energy resources.

However, when faced with on/off oscillations, the system encounters challenges. The rapid oscillations between 0 and 6 amperes require the chargers to wake up from stand-by mode, which the chargers struggle to do within the 10-second time tick. This can lead to inefficiencies in the energy distribution, as the chargers may either under-utilize the available PV production or overdraw from the grid. Such situations underline the necessity for fine-tuning the control mechanisms and considering the operational constraints of the chargers in the real-time scheduling and control processes.

Impact on Grid Load

Figure 6.2 provides a depiction of the RTC mechanism's influence on the grid load during the day characterized by high fluctuations in PV production. The graph shows the result of the RTC acting on the multiple chargers on the grid.

An interesting pattern that can be observed is the significant reduction in the grid load at peak production times, when there are also multiple electric vehicles (EVs) charging. This illustrates the ability of the RTC mechanism to efficiently leverage the available PV power, mitigating grid stress during high-demand periods.

However, the introduction of RTC does introduce a trade-off. During periods of indicated EV departures (11:00, 14:15, 17:00), the grid load is often higher just before vehicle departures as compared to the scenario without RTC. This increase is a result of the compensation mechanism of the RTC compensating for past deviations, ensuring that the vehicles receive the energy they need before departure. Interestingly, shorter transaction durations sometimes result in higher peaks with the RTC mechanism, again attributable to the compensation mechanism. This mechanism tends to overcompensate during these short duration transactions, leading to these observed spikes.

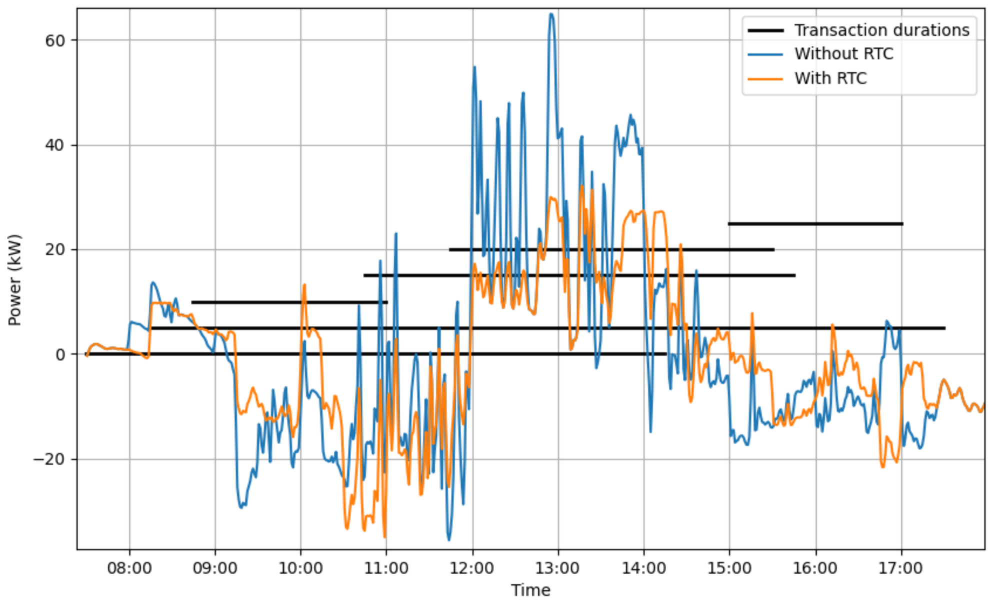


FIGURE 6.2: Illustration of the Real-Time Control mechanism's impact on grid load during a day with high fluctuations in PV production for the highly fluctuating PV production case.

6.1.2 Overestimated PV Power Forecasts

On a day with overestimated forecasts, the Real-Time Control mechanism does not follow the predetermined charging schedule when the power discrepancy between the actual and forecasted PV power becomes too large, as can be seen in Figure 6.3. The figure shows that, especially from 11:30 till 12:30, the Real-Time Control mechanism reduces the charging rate to compensate for the forecast error. Later on in the schedule (14:00), the charger follows the blueprint schedule again, even though there is still negative power discrepancy. This is part of the compensation mechanism. Starting from 17:00, shortly before departure of the EV, the Real-Time Control mechanism starts to compensate more for the earlier reduction in charging by applying a current of 6 amperes to the charger until the end of the schedule. This makes sure the requested energy demand is met before the EV departs. Unfortunately, this compensation occurs at a time when no PV power is available anymore, potentially leading to higher average power peaks.

Due to this, the inclusion of Real-Time Control resulted in a slight decrease of self-sufficiency, with values dropping from 11.66% without Real-Time Control to 11.42% with Real-Time Control. However, this reduction may be offset by days where the performance of the Real-Time Control mechanism is more significant. In terms of grid load, the mean top 1% grid load for this overestimated day remained consistent, showing no noticeable change with the introduction of the Real-Time Control.

For this simulation, no re-optimizations are performed by the Energy Scheduler troughout the schedule. The issue where compensation happens when no PV power is available could be mitigated by performing re-optimizations earlier in the day, allowing it to reschedule the remaining energy demand during periods when PV power is still available. For the summer week and winter week simulations in Section 6.2 this is done.

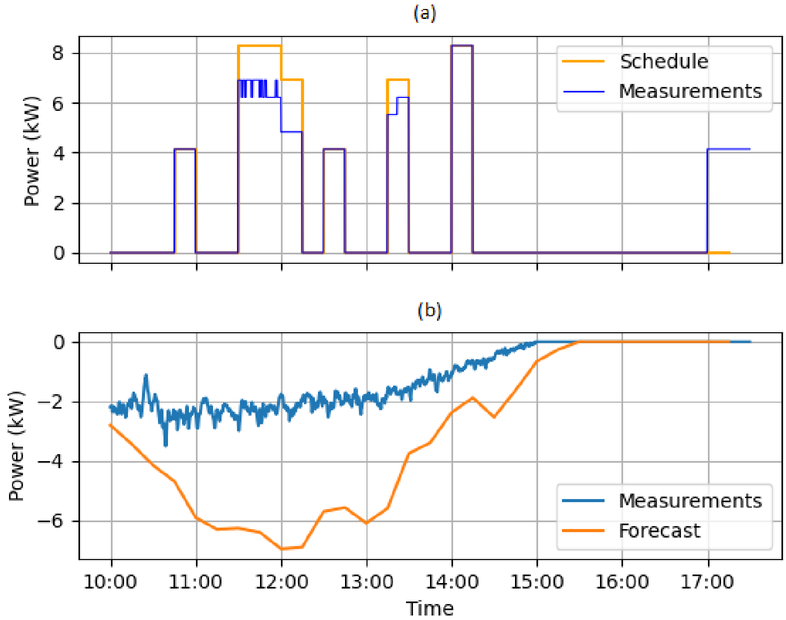


FIGURE 6.3: Comparison of the predetermined charging schedule and actual charging throughout the day on a day with overestimated forecasts. (a) The charging profile given by the Energy Scheduler and the measured charging power after real-time control adaptations. (b) The PV power forecast and the measured PV power.

6.1.3 Underestimated PV Power Forecasts

On a day with underestimated forecasts, where the forecasted PV power is lower than the actual PV power, the behavior of the Real-Time Control mechanism demonstrates a different pattern. At the beginning of the schedule, the Real-Time Control increased the power to a particular charger at periods when the PV discrepancy was positive, as shown in Figure 6.4. This strategy takes advantage of the surplus PV power that was not accounted for in the forecasts.

Towards the end of the schedule, specifically around 14:15 and 16:00, the Real-Time Control mechanism begins to compensate for these deviations by decreasing the power to the charger, even though the PV discrepancy remained positive. This reduction in power aligns with the objective of ensuring that the power supplied to the EV at the end of the day is equal to the energy demand, thereby preserving the balance between supply and demand.

Interestingly, the inclusion of the Real-Time Control mechanism resulted in a slight increase in self-sufficiency during this day with underestimated forecasts. The self-sufficiency values rose from 50.48% without Real-Time Control to 52.28% with Real-Time Control. Moreover, a slight decrease in the mean top 1% grid load was observed, which went from 43.3 kW to 42.2 kW. This decrease in grid load indicates a reduction in peak demand periods, further showcasing the potential benefits of integrating the Real-Time Control mechanism.

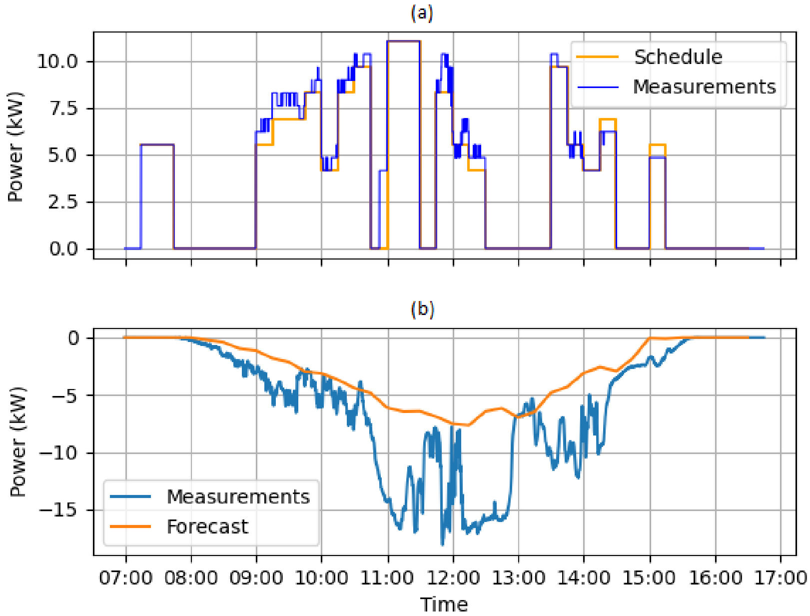


FIGURE 6.4: The Real-Time Control mechanism adjusts the charging schedule in response to underestimated PV forecasts. (a) The charging profile given by the Energy Scheduler and the measured charging power after real-time control adaptations. (b) The PV power forecast and the measured PV power.

6.2 Simulation Results

This section presents the results from the simulations of the testing location for a summer week and a winter week. This section assesses the performance of the Energy Scheduler alone and for the combination of the Energy Scheduler and the Real-Time Control mechanism in the two weeks. For this the performance of the Energy Scheduler and Real-Time Control mechanism is evaluated under different scenarios: Business As Usual, Cost Optimization, Cost Optimization + RTC, Peak Shaving, and Peak Shaving + RTC. Evaluation is done based on the performance evaluation metrics, including total electricity costs, peak grid loads, self-consumption, and self-sufficiency. The energy not served was the same over all scenarios. The Energy Scheduler and Real-Time Control mechanism do always reach the energy demand requested.

The performance results of the Energy Scheduler and the Real-Time Control Mechanism under different scenarios has been summarized for both summer and winter seasons in Tables 6.1 and 6.2, respectively. These tables provide a succinct overview of the comparative analysis for self-sufficiency (SS), self-consumption (SC), mean of the top 1% grid load (TG), and total cost under the different scenarios. The subsequent sections go over these result and each performance metric and draw conclusions.

Scenario	SS (%)	SC (%)	TG (kW)	Cost (EUR)
Business As Usual	49.25	45.86	80.713	95.39
Cost Optimization	51.26	47.75	81.917	30.95
Cost Optimization + RTC	56.7	51.63	72.222	34.48
Peak Shaving	57.44	51.42	47.651	44.80
Peak Shaving + RTC	64.66	56.78	35.871	46.94

TABLE 6.1: Overview of simulation results for different scenarios for a summer week (11-7-2022 till 17-7-2022).

Scenario	SS (%)	SC (%)	TG (kW)	Cost (EUR)
Business As Usual	7.94	70.54	84.586	340.34
Cost Optimization	8.14	69.13	78.635	302.20
Cost Optimization + RTC	8.14	68.69	77.481	301.19
Peak Shaving	9.14	71.43	42.203	296.57
Peak Shaving + RTC	9.12	71.43	43.337	297.24

TABLE 6.2: Overview of simulation results for different scenarios for a winter week (10-1-2022 till 16-1-2022).

6.2.1 Total Electricity Costs

The results of electricity costs for different scenarios across both summer and winter weeks are summarized in Table 6.3. This table highlights the differences in comparison to the Business As Usual scenario.

The total cost for the Business As Usual scenario in summer was 95.39 EUR, whereas in winter, it was significantly higher at 340.34 EUR. This clearly demonstrates the seasonality in electricity costs, presumably due to higher consumption and lower solar generation during winter.

Across all scenarios, the implementation of the Energy Scheduler, using either Cost Optimization or Peak Shaving strategies, results in notable reductions in total electricity costs. However, it is interesting to note the divergence between summer and winter costs.

With the implementation of the Energy Scheduler in Cost Optimization mode, the total electricity cost in summer was reduced to 30.95 EUR, a significant reduction of about 68% compared to the Business As Usual scenario. This reduction underscores the effectiveness of the Energy Scheduler in leveraging lower electricity rates and high solar energy generation for cost-efficiency. However, in winter, characterized by reduced solar generation, The Cost Optimization strategy still manages a decrease in total costs, albeit less significant at around 11%. This smaller reduction reflects the challenges of cost optimization in periods of reduced renewable energy generation.

The inclusion of the Real-Time Control mechanism with Cost Optimization mode resulted in a slight increase in total cost in both summer and winter scenarios. The total costs were 34.48 EUR and 301.19 EUR for summer and winter, respectively.

For the Peak Shaving strategy, the total cost was 44.80 EUR in summer, a 53% reduction from the Business As Usual scenario. In winter, the total cost was 296.57 EUR, representing a 13% reduction. When Real-Time Control was applied with the Peak Shaving mode, the total costs were 46.94 EUR and 297.24 EUR for summer and winter, respectively, similar to the Peak Shaving scenario.

It is noteworthy that the inclusion of the Real-Time Control mechanism leads to a slight increase in total costs in both seasons. Incorporating the Real-Time Control mechanism adds a dynamic layer to the energy scheduling process. Rather than being solely dependent on known electricity prices for cost reduction, the energy schedules now respond to real-time changes. This adaptability means the realized schedules are not optimally reducing costs anymore, whereas the schedules without Real Time Control would be optimal in reducing costs.

Scenario	**Summer**	**Winter**	**Average**	**Difference**
Business As Usual	95.39	340.34	217.87	-
Cost Optimization	30.95	302.20	166.58	-51.29 (-23.55%)
Cost Optimization + RTC	34.48	301.19	167.84	-50.03 (-22.97%)
Peak Shaving	44.80	296.57	170.69	-47.18 (-21.67%)
Peak Shaving + RTC	46.94	297.24	172.09	-45.78 (-21.00%)

Table 6.3: Cost in EUR for both the winter and the summer week, the average, and the difference compared to the Business As Usual Scenario.

6.2.2 Grid Loads

Grid loads significantly impact the overall longevity of the grid infrastructure and the power quality. Hence, strategies that effectively manage these loads can contribute to the long-term sustainability of energy systems.

Table 6.4 provides an overview of the top 1% grid loads across various scenarios, comparing summer and winter weeks and highlighting the difference relative to the "Business As Usual" scenario. The mean top 1% grid load under the Business As Usual scenario was 80.7 kW in summer, which was substantially reduced to 47.7 kW, a 41% reduction, with the Peak Shaving mode of the Energy Scheduler. The ability of the Peak Shaving strategy to flatten the grid load, thereby decreasing peak demand periods, can help reduce grid strain.

The addition of the Real-Time Control mechanism further decreased the mean top 1% grid load to 35.9 kW, a 24% reduction compared to the Peak Shaving scenario and a 56% reduction from the Business As Usual scenario. This indicates that a dynamic, responsive energy scheduling approach can offer even greater benefits in managing grid loads.

In winter, the Business As Usual scenario resulted in a mean top 1% grid load of 84.6 kW. The Peak Shaving scenario reduced this to 42.2 kW, a 50% reduction. The inclusion of the Real-Time Control mechanism did not significantly affect this, with the mean top 1% grid load slightly increasing to 43.3 kW. This shows that the Real-Time Control mechanism had to compensate a lot later on in schedules, which increased the grid load slightly.

In the winter week, the Cost Optimization strategy led to a decrease in the mean top 1% grid load by 7.0% compared to the Business As Usual scenario. However, the application of the Cost Optimization strategy in the summer led to a modest increase in the grid load compared to the Business As Usual scenario. Interestingly, this suggests that steering based solely on day-ahead prices may not always yield the most beneficial outcomes for grid load, while day-ahead prices are typically designed to signal periods of high and low demand, encouraging consumption shifts towards lower demand (and hence lower price) periods to balance the grid load. However, the time spent in higher grid loads is lower for the Cost Optimization strategy and even lower for the Cost Optimization strategy with Real-Time Control.

Scenario	**Summer**	**Winter**	**Average**	**Difference**
Business As Usual	80.713	84.586	82.6495	-
Cost Optimization	81.917	78.635	80.276	-2.3735 (-2.87%)
Cost Optimization + RTC	72.222	77.481	74.8515	-7.798 (-9.44%)
Peak Shaving	47.651	42.203	44.927	-37.7225 (-45.64%)
Peak Shaving + RTC	35.871	43.337	39.604	-43.0455 (-52.08%)

Table 6.4: Top 1% Grid Load (TG) in kW for both the winter and the summer week, the average, and the difference compared to the Business As Usual Scenario.

Figure 6.5 and Figure 6.6 show load duration curves of the simulated summer and winter week respectively at load hours with net electricity consumption. The load duration curves for both summer and winter show further differences between the performance of different scenarios. These curves effectively visualize how the load varies over time and how often it stays in high, medium, or low load zones. Long durations of high grid load are particularly unfavorable as they strain the grid infrastructure, leading to higher maintenance costs, increased likelihood of power outages, and potentially higher electricity tariffs during these peak periods.

In the summer, it can be observed that the Cost Optimization and the Cost Optimization + Real-Time Control scenarios experienced the highest peak loads. This is followed by the Business As Usual scenario, and significantly lower than that, we have the Peak Shaving scenario. The Peak Shaving + Real-Time Control scenario exhibited the lowest peak loads of all.

When it comes to the duration spent in high grid loads, the Business As Usual scenario spent the most time, reflecting less efficient use of energy resources. Comparatively, the Cost Optimization and Cost Optimization + Real-Time Control scenarios spent less time in high to medium grid loads, indicating their effectiveness in managing the system load.

The Peak Shaving scenario spents limited time in the high grid load zone, demonstrating its strength in reducing the strain on the grid and essentially flattening the grid load. This effectiveness was further amplified in the Peak Shaving + Real-Time Control scenario, which spent the least amount of time in the high grid load zone, thereby contributing to grid stability.

In the winter week, the flattened grid load by the Peak Shaving and Peak Shaving and Real-Time Control scenarios is even more evident. Time spent in high grid loads and peak grid loads are significantly lower than for the other scenarios. Both Cost Optimization and Cost Optimization and Real-Time Control show slightly lower peak loads and time spent in high grid loads than the Business As Usual scenario. The performance of the Real-Time Control mechanism is not evident, as the load duration curves of each scenario with and without Real-Time Control show no significant differences. This indicates a need for further investigation into its role in periods of low PV production.

The results strongly underline the benefits of both Cost Optimization and Peak Shaving scenarios in reducing the time spent in high grid loads, thereby reducing strain on the grid. The Peak Shaving strategy, in particular, demonstrates superior performance in maintaining lower peak loads, contributing significantly to grid stability.

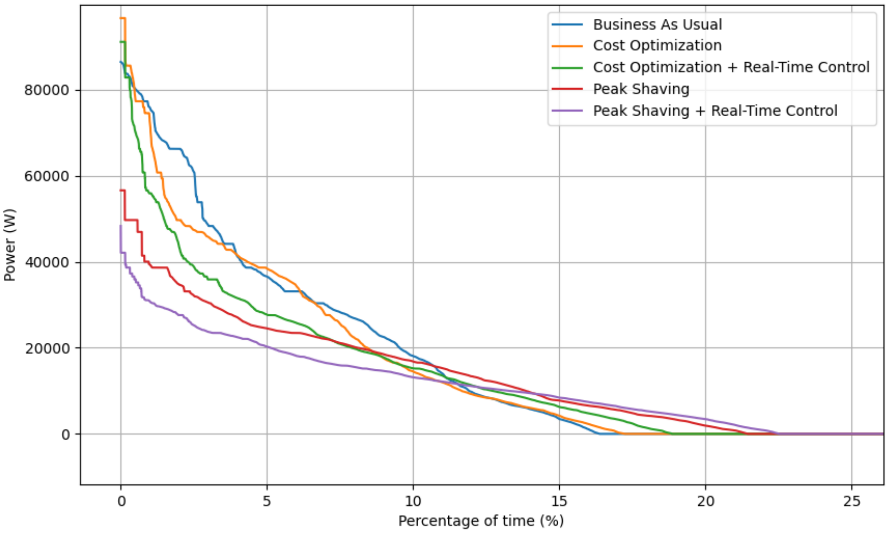


FIGURE 6.5: Load duration curves for the simulated summer week (11-7-2022 till 17-7-2022).

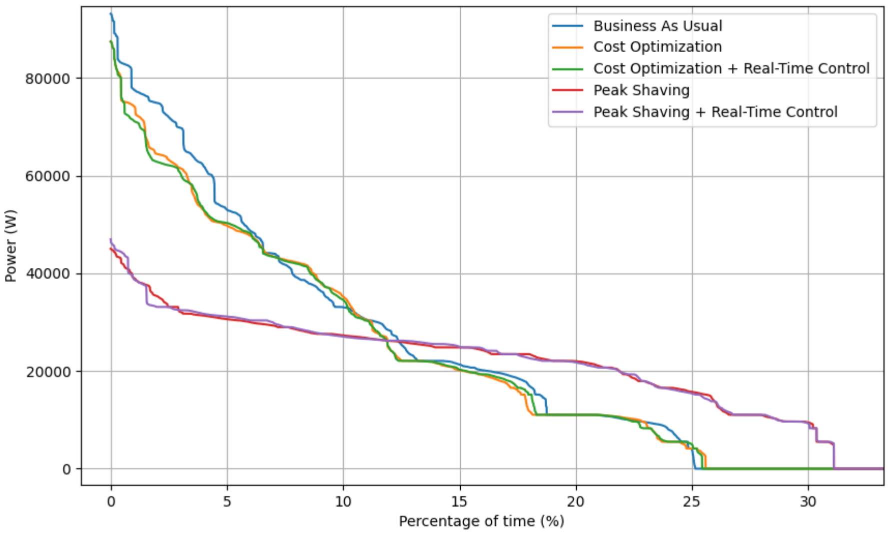


FIGURE 6.6: Load duration curves for the simulated winter week (10-1-2022 till 16-1-2022).

6.2.3 Self-Sufficiency

Table 6.5 provides a comparative summary of self-sufficiency percentages across different scenarios for summer and winter weeks. It highlighting the deviation from the "Business As Usual" scenario as well.

The Business As Usual scenario resulted in a self-sufficiency of 49.25% in summer and 7.94% in winter. When the Cost Optimization strategy was implemented, self-sufficiency slightly increased to 51.26% in summer and 8.14% in winter. Incorporating the Real-Time Control mechanism with the Energy Scheduler in Cost Optimization mode improved self-sufficiency to 56.7% in summer, but there was no change in winter (8.14%).

The Peak Shaving scenario resulted in self-sufficiencies of 57.44% and 9.14% in summer and winter, respectively. With the addition of the Real-Time Control mechanism, self-sufficiency increased significantly in summer to 64.66% but showed a negligible decrease in winter (9.12%).

Strategies involving the Energy Scheduler performed better than the Business As Usual scenario. The most significant improvement was observed in the Peak Shaving + Real-Time Control scenario during the summer, indicating an enhanced ability to cover electricity needs through solar generation. Particularly, this scenario simulated in the summer demonstrated an increased ability to cover electricity needs autonomously, signaling towards less dependence on the grid.

Scenario	**Summer**	**Winter**	**Average**	**Difference**
Business As Usual	49.25	7.94	28.595	-
Cost Optimization	51.26	8.14	29.7	+1.105
Cost Optimization + RTC	56.7	8.14	32.42	+3.825
Peak Shaving	57.44	9.14	33.29	+4.695
Peak Shaving + RTC	64.66	9.12	36.89	+8.295

TABLE 6.5: Self-sufficiency (SS) in % for both the winter and the summer week, the average, and the difference compared to the Business As Usual Scenario.

6.2.4 Self-Consumption

Table 6.6 summarizes the self-consumption rates across different scenarios for both summer and winter weeks, indicating the average values and differences when contrasted with the "Business As Usual" scenario.

In the Business As Usual scenario, self-consumption was 45.86% in summer and 70.54% in winter. With the implementation of the Cost Optimization strategy, self-consumption increased slightly to 47.75% in summer and decreased to 69.13% in winter.

The incorporation of the Real-Time Control mechanism with Cost Optimization increased self-consumption to 51.63% in summer, while it reduced further to 68.69% in winter.

For the Peak Shaving strategy, self-consumption was 51.42% in summer and 71.43% in winter. Adding the Real-Time Control mechanism led to self-consumption rates of 56.78% in summer and 71.43% in winter, showing a substantial increase in summer and no change in winter.

All scenarios involving the Energy Scheduler improved self-consumption rates compared to Business As Usual, particularly during the summer. This improvement implies a more efficient use of locally generated solar energy, contributing to sustainability and cost-efficiency. The combination of Peak Shaving and the Real-Time Control mechanism resulted in the highest self-consumption rate in the summer, highlighting the potential of these strategies to complement each other for optimal utilization of solar energy.

Scenario	Summer	Winter	Average	Difference
Business As Usual	45.86	70.54	58.2	-
Cost Optimization	47.75	69.13	58.44	+0.24
Cost Optimization + RTC	51.63	68.69	60.16	+1.96
Peak Shaving	51.42	71.43	61.425	+3.225
Peak Shaving + RTC	56.78	71.43	64.105	+5.905

TABLE 6.6: Self-consumption (SC) in % for both the winter and the summer week, the average, and the difference compared to the Business As Usual Scenario.

Seasonal Impact

Seasonality had a significant impact on all performance metrics. In winter, when solar generation is low, reductions in total cost and improvements in self-sufficiency were less pronounced. On the other hand, the potential of the Energy Scheduler, especially with the Peak Shaving strategy, to reduce grid loads was highly effective in both seasons.

6.2.5 Summary

A comparison of the various metrics - total electricity costs, peak grid loads, self-sufficiency, and self-consumption - in both summer and winter seasons reveals the strengths and limitations of each scenario.

Cost Optimization and Peak Shaving strategies of the Energy Scheduler demonstrated significant potential in improving the efficiency and sustainability of energy use. This was evident in the significant reductions in total electricity costs, particularly during the summer. Although the Real-Time Control mechanism did not notably decrease costs, its value becomes apparent in terms of grid load management and increased self-sufficiency and self-consumption, especially in the Peak Shaving + Real-Time Control scenario during summer.

The Peak Shaving scenario consistently delivered lower grid loads across both seasons. Notably, the addition of the Real-Time Control mechanism in this scenario further lowered the mean top 1% grid load. Such reduction in peak loads contributes significantly towards improved grid stability and longevity, indicating the potential of these strategies in enhancing the sustainability of energy systems.

Self-sufficiency and self-consumption rates were generally better in scenarios involving the Energy Scheduler compared to Business As Usual. Peak Shaving, combined with Real-Time Control, resulted in the highest self-sufficiency rate during summer, showcasing the potential of these strategies in achieving autonomous electricity needs coverage.

The seasonality effect was evident in all performance metrics. Reductions in total cost and improvements in self-sufficiency were less pronounced in winter due to lower solar generation. However, the potential of the Energy Scheduler, especially with the Peak Shaving strategy, to reduce grid loads was highly effective in both seasons.

In conclusion, while the individual benefits of both Cost Optimization and Peak Shaving strategies are apparent, their combination with the Real-Time Control mechanism showcases a significant opportunity for enhanced performance. Although the winter season presents certain challenges due to lower solar generation, the overall potential for cost savings, improved grid load management, and increased self-consumption and self-sufficiency demonstrates the viability of these strategies in improving the efficiency and sustainability of energy systems. Future work may involve refining these strategies to better tackle the challenges posed by seasonal variations and enhancing the performance of the Real-Time Control mechanism.

6.3 Field Test Results

The field test was conducted in a real-world environment, dealing with the complexities and unpredictability that come with real-world application. This environment provides crucial insights into the practical effectiveness of the implemented charging control strategies. An overview of the results of the field test and the corresponding simulations on the performance evaluation metrics is given in Table 6.7. The results presented in the following sections shed light on the impact of these strategies in a real-world setting, beyond their theoretical efficacy shown in simulations. First the results of the user interface (UI) are explained and the subsequent sections go over each performance metric. The results of the field test are compared with the corresponding simulations.

Scenario	**SS (%)**	**SC (%)**	**TG (kW)**	**Cost (EUR)**
Field Test	78.76	43.97	31.122	-0.24
Business As Usual Simulation	69.40	33.03	52.982	-0.12
Peak Shaving Simulation	83.01	35.32	25.283	-0.27
Peak Shaving + RTC Simulation	88.99	41.21	22.856	-0.26

Table 6.7: Overview of field test results and corresponding simulations, including the Self Sufficiency (SS), Self-Consumption (SC) Top 1% Grid Load (TG) and the Cost.

6.3.1 User Interface

The User Interface plays a crucial role in facilitating the interaction between the EV users and the charging infrastructure. However, during the period of the field test, the UI was not used by users. As such, all EV charging schedules were derived from the historical data of known users. In this case this data was the mean parking time and the mean energy demand from the user's past transactions, as explained in Section 5.4.

The absence of UI utilization during the field test could be attributed to several factors. It could be a result of users being unaccustomed to this new technology or being unaware of the benefits it could bring. Alternatively, it could be due to a lack of user engagement or understanding about how to utilize the UI to their advantage. This observation indicates that there is room for improving the usability of the UI and engagement of the users, as well as promoting its benefits to users more effectively.

Despite this limited use, the UI implementation in the field test provided important insights. For one, the results show that, despite this low UI use, the control strategies were still able to achieve significant improvements in self-sufficiency, self-consumption, cost, and grid load compared to the Business As Usual simulation. This success in real-world conditions, even with a less personalized and less accurate charging schedule, is a testament to the robustness of the control strategies. However, the simulations using the Energy Scheduler also highlight the potential of a more accurate charging schedule that could be achieved with active UI use. The UI, when fully utilized, could provide more precise and personalized data for scheduling, leading to optimized charging schedules that more accurately reflect the needs and habits of individual users.

In conclusion, the limited use of the UI during the field test indicates a clear opportunity for future improvement and refinement in the system. With a more effective UI design, user engagement, and communication of its benefits, the system could achieve even better results in terms of self-sufficiency, self-consumption, and cost. It could also result in a more user-friendly and personalized experience, thus fostering user satisfaction and the long-term success of the EV charging infrastructure.

6.3.2 Self-Sufficiency and Self-Consumption

An overview of the results of the field test for the self-sufficiency and the self-consumption is given in Table 6.8. In the real-world field test, we achieved a self-sufficiency of 78.76% and a self-consumption of 43.97%. Compared to the Business As Usual simulation, which had a self-sufficiency of 69.40% and a self-consumption of 33.03%, it is clear that the control strategies have significantly improved the use of locally generated renewable energy in a real-world scenario.

However, compared to the ideal conditions in the Peak Shaving + Real-Time Control simulation, which achieved a self-sufficiency of 88.99% and a self-consumption of 41.21%, the real-world setting saw a slight reduction in self-sufficiency. This confirms the impact of real-world complexities and uncertainties.

Scenario	**SS (%)**	**Diff. (%)**	**SC (%)**	**Diff. (%)**
Business As Usual Simulation	69.40	-	33.03	-
Field Test	78.76	+13.5	43.97	+33.1
Peak Shaving Simulation	83.01	+19.6	35.32	+6.9
Peak Shaving + RTC Simulation	88.99	+28.3	41.21	+24.8

TABLE 6.8: Difference and absolute values of Self Sufficiency (SS) and Self-Consumption (SC) compared to the Business As Usual Simulation.

6.3.3 Grid Load

The implemented control strategies were designed to manage and reduce the grid load. Table 6.9 gives an overview of the results of the mean top 1% grid load. The second column shows the differences compared with the Business As Usual scenario During the real-world field test this was 31.1 kW. This was significantly lower than the Business As Usual simulation, which had a mean top 1% grid load of 53.0 kW. This 41.2% decrease in peak grid load demonstrates the real-world efficacy of the implemented control strategies in managing grid load, thereby enhancing grid stability and reducing stress on infrastructure.

However, when compared to the ideal conditions in the Peak Shaving + Real-Time Control simulation, which had a mean top 1% grid load of 22.9, the real-world field test showed a higher peak load. This variation reflects the uncertainties and unpredictable aspects inherent in real-world scenarios, which impact grid load management.

The load duration curve shown in Figure 6.7 is consistent with these findings. It shows the Business As Usual simulation having the highest grid load, followed by the real-world field test, then the Peak Shaving and Peak Shaving + Real-Time Control simulations. This

Scenario	TG (kW)	Difference (kW)
Business As Usual Simulation	52.982	-
Field Test	31.122	-21.860 (-41.2%)
Peak Shaving Simulation	25.283	-27.699 (-52.3%)
Peak Shaving + RTC Simulation	22.856	-30.126 (-56.8%)

Table 6.9: Difference and absolute values of the top 1% Grid Load (TG) compared to the Business As Usual Simulation.

reinforces the real-world effectiveness of the control strategies in managing and reducing grid load.

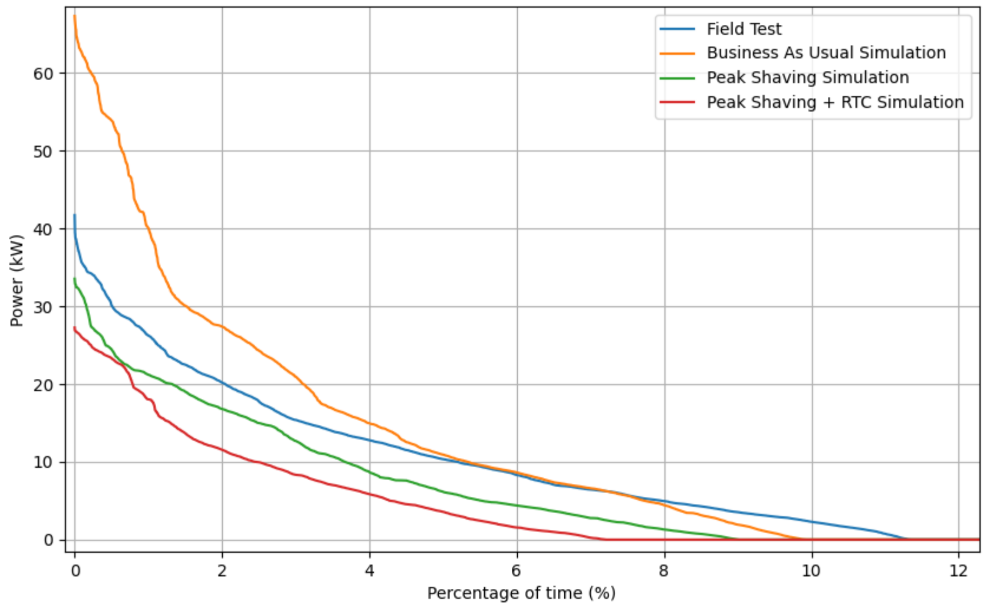


Figure 6.7: Load duration curves for the field test and the corresponding simulations.

6.3.4 Total Electricity Costs

Table 6.10 shows the cost for each scenario and the differences with the Business As Usual scenario. The negative values in these cost metrics typically indicate reimbursements due feeding surplus energy back into the grid. The total electricity cost in the real-world field test was -0.24 EUR. This was more favorable than the Business As Usual simulation, which yielded a total cost of -0.12 EUR.This result illustrates the cost-saving potential of the system when implemented in real-world scenarios, underlining the practical effectiveness of the control strategies.

It is important to note that while the field test showed a slightly less favorable result compared to the Peak Shaving + Real-Time Control simulation, which had a total electricity cost of -0.26 EUR, the difference is not substantial. This marginal difference demonstrates that, despite the variability and unpredictability of real-world factors, the control strategies of the system were effective in achieving cost savings.

In essence, the impact of real-world complexities and uncertainties on cost-effectiveness was minimal. This minor variation reinforces the robustness of the system, showing that it can successfully deliver significant cost savings in real-world applications, even when faced with inevitable environmental, user-related, and technical uncertainties.

Scenario	**Cost (EUR)**	**Difference (EUR)**
Business As Usual Simulation	-0.12	-
Field Test	-0.24	-0.12
Peak Shaving Simulation	-0.27	-0.15
Peak Shaving + RTC Simulation	-0.26	-0.14

Table 6.10: Difference and absolute values of electricity costs compared to the Business As Usual Simulation.

Chapter 7

Conclusions

This research addresses a series of research questions focusing on the improvement of electric vehicle (EV) charging infrastructure, specifically in the areas of Energy Scheduler performance, implementation of a Real-Time Control Mechanism, the User Interface (UI), and the development of a comprehensive Evaluation Framework. This chapter answers the research questions regarding the performance of the Energy Scheduler, the implementation of a Real-Time Control mechanism, improvements to the UI, and the construction of a comprehensive Evaluation Framework, as formulated in Section 1.4.

7.1 Energy Scheduler Performance and Improvements

The first research question, "*How does the existing Energy Scheduler approach perform under various conditions, and how can it be improved further?*", yielded a thorough understanding of the strengths and weaknesses of the current Energy Scheduler. It was found that the Energy Scheduler performs effectively in managing EV charging schedules based on photovoltaic (PV) power forecasts and EV flexibility information. It shows good results under various conditions, demonstrated by its ability to substantially lower total electricity costs, especially in summer, and its effective management of peak grid loads in both winter and summer.

The effectiveness of the Energy Scheduler is made evident by the Cost Optimization and Peak Shaving strategies, which both contribute significantly to enhanced energy use efficiency and sustainability. Simulations show that Cost Optimization could enable significant reductions in total electricity costs, which is particularly impactful during the summer, where a reduction of 67.47% compared to an uncontrolled scenario has been observed. This reflects the potential of the Energy Scheduler to strategically schedule EV charging based on cost and availability of renewable resources, leading to cost savings.

The Peak Shaving strategy of the Energy Scheduler consistently lowers grid loads across both summer and winter seasons, in both simulations and a field test. A reduction of 40.97% compared to uncontrolled charging is observed in the mean top 1% grid load in the summer week. By smoothing out the power demand and reducing peaks, the Energy Scheduler contributes to improved grid stability, potentially extending the lifespan of the grid infrastructure and reducing the need for costly grid upgrades.

Furthermore, the Energy Scheduler, especially when operating in the Peak Shaving strategy in summer, improves self-sufficiency and self-consumption rates by 17% and 12% respectively. This increased reliance on locally generated solar power contributes to the wider goal of energy autonomy, aligning with broader sustainability objectives.

However, simulations with only solar as energy source show that the performance of the Energy Scheduler is affected by seasonal variations, with reductions in total cost and improvements in self-sufficiency being less pronounced during winter due to lower PV generation. Despite this, the Energy Scheduler remains effective in managing grid loads across both seasons. Next to that, the challenges of real-time adjustments and inadequate EV flexibility information inputs were identified. EV flexibility information is needed to keep service to the EV user high by minimizing the energy not served. These challenges led to the recommendation of incorporating a Real-Time Control Mechanism and streamlining the flexibility data collection process, which became the focus of the following research questions.

7.2 Impact Real-Time Control Mechanism

The second research question, "*What are the impacts and improvements achieved by the implementation of a Real-Time Control mechanism in EV control?*", brought to light the significant value of a dynamic response mechanism in the Energy Scheduler. The Real-Time Control Mechanism proved essential in managing unforeseen solar power forecast fluctuations. While it did increase costs slightly compared to scenarios with only the Energy Scheduler, its impact was significant in managing grid load, particularly in the Peak Shaving + Real-Time Control scenario, while not reducing the energy not served. The service to the EV user is therefore kept high.

Simulations show that the mean top 1% grid load across both seasons can be reduced with an extra 15% when Real-Time Control is applied, compared to the Peak Shaving only scenario. This contributes to improved grid stability and longevity. In terms of self-sufficiency and self-consumption, the inclusion Real-Time Control increased these with an extra 14% and 11% respectively. This indicates the potential of these strategies in achieving autonomous electricity needs coverage.

In real-world application, the Real-Time Control Mechanism still made a significant impact. Field test results showed a significant reduction in peak grid load and improved cost-effectiveness compared to the Business As Usual scenario, even when faced with real-world uncertainties.

However, compared to ideal simulation conditions, slight reductions in self-sufficiency and increases in peak grid load were observed, underlining the challenges of real-world complexities. Overall, the Real-Time Control Mechanism significantly enhanced the performance of the Energy Scheduler, reducing peak loads, improving self-consumption and self-sufficiency rates, and proving its robustness in a real-world environment. Future work could focus on refining the Real-Time Control Mechanism to better adapt to real-world uncertainties and further improve its effectiveness.

7.3 User Interface

Addressing the third research question, "*How does an enhanced UI influence user-EMS interaction and EV scheduling effectiveness in a real-life environment?*", the field test has provided valuable insights. Even though the charging schedules during the field test were based on mean values derived from historical data, the system was still able to achieve substantial improvements compared to the Business As Usual scenario. This implies a significant potential for scheduling effectiveness when the UI would be actively used.

The role of a UI is hard to match in bridging the gap between the users and the Energy Management System (EMS). However, only having a UI does not mean people are going to use it. An enhanced UI could improve user-EMS interaction by facilitating the exchange of more accurate EV flexibility information, such as the expected energy demand and expected departure time of the user.

By allowing the EMS to gather this data, the UI can enable more effective scheduling that further boosts self-sufficiency, self-consumption, cost-effectiveness, and grid stability. This has been shown by the simulations involving the Energy Scheduler, where EV flexibility information was simulated to be available.

Therefore, an enhanced UI has the potential to substantially improve user-EMS interaction and EV scheduling effectiveness in real-life environments. However, realizing this potential requires overcoming the identified challenges in user engagement and promoting the advantages of active UI use.

7.4 Evaluation Framework

Finally, the last research question, "*How can a comprehensive Evaluation Framework be designed that simulates various conditions to evaluate EV scheduling strategies, and allow for practical implementation?*", resulted in the development of a robust and flexible Evaluation Framework. This framework, constructed based on the time tick principle, enables thorough testing of proposed and future solutions under a wide range of conditions. The architecture, which revolves around microservices, ensures a scalable system that can adapt to both simulation and real-world environments. It proved to be instrumental in the simulation and subsequent analysis of EV scheduling strategies, leading to meaningful insights for practical implementation.

Real-world field test results confirmed the effectiveness of the Energy Scheduler with Real-Time Control. While minor decreases in the performance metrics were noted when compared to simulations, the performance of the system in the real-world setting showcased its practicality and robustness.

While the Evaluation Framework provided valuable insights, it faced some limitations. A balance between high speed simulations and realism had to be found. High-speed simulations would sacrifice some realism. The behaviour of real-world hardware was not always accurately mirrored in simulations, which could impact fidelity.

The unpredictability of user behavior, hardware failure, and the reliability of PV power forecast data also presented challenges, making it hard to simulate real-world complexities. Despite these limitations, the research made significant strides towards enhancing the EV charging system. Future work should aim to further refine these strategies, addressing these limitations.

7.5 Summary

In conclusion, this research presented a methodical approach to enhancing the current EV charging system, specifically focusing on the Energy Scheduler, the Real-Time Control Mechanism, and the UI improvements. The results from this study, both from the simulation and the field tests, demonstrate that the proposed enhancements significantly contribute to sustainable and efficient energy management. Future research could build upon this work, refining these strategies, particularly to address user behaviour and engagement, and continue the exploration of efficient, sustainable, and user-friendly solutions for the EV charging infrastructure.

Chapter 8

Recommendations

The findings from this research have led to several recommendations to guide future efforts in enhancing electric vehicle (EV) charging systems. These insights form a series of recommendations, which, when implemented, could notably elevate the efficiency, efficacy, and user-friendliness of EV charging infrastructure. More importantly, the integration of these enhancements may significantly contribute to the broader goals of sustainability, cost reduction and grid protection.

An important aspect of the recommendations is the refinement of the Real-Time Control mechanism. At present, the mechanism is designed to manage discrepancies between forecasted and actual measured photovoltaic (PV) power. Nonetheless, this function can be further enhanced by incorporating the dicrepancy between forecasted and measured grid load instead of the PV discrepancy alone. Using grid load discrepancy, the system could not only account for PV variability, but also unexpected fluctuations in the EV load, such as malfunctioning chargers or EVs not adhering to prescribed schedules. By creating a more robust and inclusive Real-Time Control mechanism, the system could respond more effectively to the nuances of real-world operations.

Furthermore, currently, the Real-Time Control mechanism adjusts charging power further on in the schedule to compensate for earlier discrepancies, even when the energy demand has already been met. This process could be more effectively designed. Rather than decreasing charging power when there is surplus PV power, it would be more beneficial to continue channeling this excess energy to the EVs, as long as their batteries are not yet fully charged. This approach could lead to decreased grid exporting and an increase in PV self-consumption rates.

A notable observation during this research is that grid loads increased slightly in the Cost Optimizations setting of the Energy Scheduler. This is somewhat unexpected as energy prices are partly designed with the goal of mitigating grid strain; higher prices during peak demand periods are meant to disincentivize heavy power consumption, thus easing the load on the grid. This outcome is significant as it indicates that a strategy purely optimized for cost might inadvertently lead to higher loads on the grid, potentially contributing to peak demand issues. Therefore, it is advised to balance the Cost Optimization strategy with measures such as peak-shaving to prevent unintentional strain on the grid. Such a hybrid approach would not only optimize the cost but also maintain a healthy grid load.

The Evaluation Framework used in the project offers another area for improvement. The framework, as it stands, provides valuable insights but could benefit from more accurately mimicking real-world conditions. This could be achieved by integrating realistic hardware failures, measurement inaccuracies, and control signal response times into the framework. Additionally, the unpredictability of user behavior and the possibility of hardware failures, both significant challenges, could be better addressed through the use of more sophisticated models or simulation techniques. Another enhancement to the evaluation framework would involve augmenting the speed of simulations without compromising their realism, potentially achieved by employing advanced algorithms or leveraging more efficient hardware.

Next to that, given the absence of usage of the User Interface (UI) observed during the field test, it is clear that user education and engagement should be a priority. As with all emerging technologies, awareness and adoption of the UI are likely to grow over time. Users may not be fully aware of the benefits of active UI usage or understand how to utilize it effectively. To address this, a more comprehensive user guide could be developed and training sessions could be held to familiarize users with the system and its benefits. Additionally, making the use of the UI mandatory to charge an EV could drive more consistent engagement. As an incentive to further promote user engagement, rewards could be introduced, such as offering cheaper electricity rates for those who actively use the UI.

When the UI is not used, there are considerable opportunities to better utilize historical data in systems where the UI is not employed or in transactions where the user did not use the UI. In this research, only the mean of the energy demand and the mean of the stay duration of the historical transactions of a specific user are used for planning. While this approach yielded promising results, there is room for improvement. For example, more sophisticated predictive modeling techniques, such as machine learning algorithms, can be used to forecast future energy demand and stay durations based on historical data. These models can account for complex patterns and trends that are not captured when only the mean values are used.

Finally, the real-world implementation should be studied more extensively. The field test conducted in this research was only done for one summer week. As simulations show, the charging strategies could be less effective in winter scenarios. The field test as it stands should continue and gather data. Next to that, further field tests should be conducted to validate the robustness of the system in diverse conditions and over extended periods. By verifying the performance of the system outside of a controlled environment, we can build a compelling case for its practicality and robustness, underlining the viability of the improvements proposed in this research.

The above recommendations form a cohesive strategy to address the limitations identified in this study and set the course for future research. By integrating these improvements, we could continue to enhance EV charging infrastructure, creating a system that is not only efficient and user-friendly but also plays a key role in the broader push towards a more sustainable energy future.

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