Grenoble INP ENSE3
Electrical Engineering for Smart Grids and Buildings

Hardware-in-the-Loop Testing for Smart Charging Controller Development

Master Thesis

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Eindhoven, August 2023

STATEMENT OF ACADEMIC INTEGRITY

I, the undersigned, hereby declare and confirm that, this master thesis/end of study internship report is exclusively the result of my own autonomous work based on company experience, mentorship, research and the literatures used in the bibliography section.
I declare no part of the paper submitted has been made in an inappropriate way, whether by plagiarism or infringing on any third person's copyright.

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Introduction to Kropman B.V. and Avans Hogeschool

Kropman B.V.

Founded in 1934 in Nijmegen, the Netherlands, Kropman B.V. is one of the top Dutch installation companies with 13 regional branches throughout the country. With the mission to make buildings greener, healthier, and more efficient, Kropman specializes in design, realization, management, and operation of buildings installations. At Kropman, they are convinced that there is only one meaningful way to build and that is sustainable building.

As an integrated technical service provider, Kropman provides services from design and consultancy to execution and maintenance, and covers the fields of mechanical engineering, electrical engineering, measurement and control technology, contamination control, and prefabrication. They work with sectors of utilities, healthcare, pharmaceuticals, and industry.

As part of a multi-stakeholder project, Brains for Buildings (B4B), Kropman is working toward smart control technologies for building energy flexibility. This collaborative work involves several students, each contributing to different aspects of the project. This internship is also part of the project, with a specific focus on Electric Vehicle (EV) charging load flexibility.

Avans Hogeschool

Founded in 2004, Avans Hogeschool comprises 21 schools spanning fields like Economics and Business, Engineering, Health Care, Arts and Culture, and more. This diversity empowers Avans to provide a comprehensive range of practice-oriented education and research prospects.

Part of Avans Hogeschool's project for smart energy research and education, Smart Energy Delivery Lab (SEND Lab) is a hub for research in sustainable energy utilization. The lab focuses on integrating advanced technologies into energy systems, particularly in the context of energy conservation, sustainable energy incorporation, and practical applications for both consumers and businesses. The aim is to enhance the intelligence of energy networks, ensuring a harmonious balance between energy supply and demand.

The lab consists of a Net-zero Energy Classroom (NEC) and a Smart Grid setup, enabling a hands-on learning experience that bridges the gap between research and education. Guided by a comprehensive development plan and fostering collaboration between research, education, and industry, they have a vision to evolve it into a vibrant learning environment accessible to students and researchers. Also part of the B4B project, SEND lab focuses on the development of the hardware system for EV smart charging simulation, which is part of the objective of this assignment.

Abstract

With the trend of electrification, higher penetration of renewable energy in the grid, and increasing EVs, smart control strategies gain interest. From these strategies, EV smart charging is getting attention to provide demand side flexibility, reduce peak demands, and to provide support to the existing electricity grid for better system performance. The thesis is part of the Brains for Building's Energy Systems (B4B) multi-stakeholder project, focusing on the development of a smart EV charging controller for energy flexibility in buildings. The work carried out is a part of a continuation project that has an objective of establishing a testbed for bi-directional EV charging. In order to achieve that overall goal, this study is aiming to improve and test an EV charging controller and establish a Hardware-in-the-Loop (HIL) testbed at Avans' Smart Energy Lab. The objectives of the project include enhancing the controller, testing it through simulation, constructing the HIL testbed, and analyzing the controller with the testbed.
Following a thorough literature review, this thesis delivers a HIL testbed and a 1 directional (charging only) EV charge controller integrated with it. The simulation results confirmed the controller's ability to shift charging load (demand side management) for better energy performance with Key Performance Indicators (KPIs) values indicated. Also, the HIL testbed successfully emulates EV charging sessions, providing insights on charging efficiency.
In conclusion, the project brings the controller closer to the real system application and provides a testing environment for its future development. In addition, the built HIL testbed can serve as an accelerator for future research on a smart controller system.

French Version
Avec l'électrification croissante, la montée des énergies renouvelables dans le réseau et la multiplication des véhicules électriques (EV), les stratégies de contrôle intelligent gagnent en intérêt. Parmi elles, la recharge intelligente des EV se démarque pour sa capacité à offrir de la flexibilité du côté de la demande, à atténuer les pics de demande et à renforcer le réseau électrique existant en vue d'améliorer ses performances globales. Cette thèse s'inscrit dans le projet multi-acteurs "Brains for Building's Energy Systems" (B4B) et vise le développement d'un contrôleur intelligent de recharge pour les EV dans le but de gérer la flexibilité énergétique dans les bâtiments. Dans la continuité d'un projet préexistant visant à établir une plateforme de test pour la recharge bidirectionnelle des EV, cette étude a pour objectif d'améliorer et de tester un contrôleur de recharge pour les EV, tout en mettant en place une plateforme de test en boucle fermée (HIL) au sein du Smart Energy Lab d'Avans. Les objectifs incluent l'amélioration du contrôleur, sa validation par simulation, la création de la plateforme HIL et l'analyse du contrôleur au moyen de cette plateforme. Suite à un examen approfondi de la littérature, cette thèse propose une plateforme HIL ainsi qu'un contrôleur de charge unidirectionnel (recharge uniquement) pour EV intégré à celle-ci. Les résultats de simulation ont confirmé l'aptitude du contrôleur à décaler la charge de recharge (gestion du côté de la demande) pour améliorer la performance énergétique, avec des indicateurs clés (KPIs) démontrant cette capacité. En outre, la plateforme HIL simule avec succès des sessions de recharge des EV, fournissant des informations sur l'efficacité de la recharge. En résumé, ce projet rapproche le contrôleur de l'application réelle du système et offre un environnement de test pour son futur développement. La plateforme HIL établie peut également servir d'accélérateur pour les futures recherches sur un système de contrôle intelligent.

Preface

The journey from France to the Netherlands for this thesis was tougher than expected. I am sincerely grateful for the support that has paved the way for this project. Especially thanks to Prof. W. (Wim) Zeiler of TU/e and Dr. Ir. S.S.W. (Shalika) Walker from Kropman for providing me the opportunity and support on the administrative process. Thanks also extend to Prof. Vincent DEBUCHERE, our program director at Grenoble INP-ENSE3, for the encouragement and the trust in my journey.

The past 6 months have unfolded as a chapter full of growth and transformation. It was started with the struggling of understanding the topic and the work done before, but now I've gone through the way, being more familiar with smart charging strategies and feeling more comfortable with the hardware systems. I'm truly grateful to Roeland in 't Veld, the TU/e student who worked on the project before me. He patiently answered all my questions and helped me get on board smoothly. Also, a special thanks to Ir. R. (Redouane) Edeanne for guiding me through hardware setup and assisting me in the lab. In addition, appreciation extends to Ward Somers, Dr. ir. W. (Waqas) Khan, Dr. Ir. J.H.A. (Jobert) Ludlage, and Ir. Sander van Gameren for the provided discussions and answers to my questions. Thanks again to Shalika for the coordination, supervision, and understanding. It is your feedback that leads me out from the fog, and it is the space you left to me that allows me to walk in my pace. I sincerely hope the delivered results are helpful to the project.

Thanks to the friends back in Taiwan and all the incredible encounters during this two-year study, for making this journey in Europe possible and full of learning and joys.

Thanks to my family, my parents, my brother, and my grandma, for always trusting in me and supporting me in the pursuit of this study.

And finally, a big hug to my love, Tim, for being by my side all the time even when you are also fighting with your thesis. It is you that allows me to finish this report with a smile and confidence. Congratulations to both of us for making it!

Sincerely,
Jui-Lien (Rachel), HSIA
Eindhoven, August 2023

Contents

List of Figures

List of Tables

Abbreviations

AC Alternating Current. 4, 9

BMS Building Management System. 1

CAN Controller Area Network. 4, 9

CCS Combined Charging System. 8, 9

CHAdeMO Charge de Move. 8, 9

CHIL Controller Hardware-in-the-Loop. 4

CMS Continuous Monitoring System. 5

csv comma-separated values. 12

DC Direct Current. 9, 12

EV Electric Vehicle. 1–6, 8–13, 15, 22, 28, 29

EVSE Electric Vehicle Supply Equipment. 4, 8, 9, 29

HIL Hardware-in-the-Loop. 1–4

iPOPT Interior Point OPTimizer. 12

KPIs Key Performance Indicators. 15, 20, 22, 23

LDC Load Duration Curve. 20, 26

MPC Model Predictive Control. 4, 10, 11, 28

OF Objective Function. 13, 14, 20, 24

PFC Power Factor Correction. 9

PHIL Power Hardware-in-the-Loop. 4

PPR Power Peak Reduction. 11, 20, 23, 24

PV Photovoltaic. 2, 4, 6, 10, 18, 20, 28

Pyomo Python Optimization Modeling Objects. 12

SC Self-consumption. 20

SOC State of Charge. 10–12, 16

SS Self-sufficiency. 20, 23, 24

Chapter 1

Introduction

1.1 Background of the Project

The project is part of work package 2 (WP2) of the Brains for Buildings (B4B) multi-stakeholder project, aiming to explore "the development of smart control models to increase energy flexibility (heat, cold and electricity) within buildings". As an element getting increased attention within the Building Management System (BMS), EV charging load presents substantial potential for contributing to energy flexibility, which will be the scope of this thesis.
This project work is a continuation of Roeland in 't Veld, the student who also collaborated with Kropman for his graduation thesis [9]. The two stakeholders closely involved in my assignment are Kropman and Avans University. Kropman anticipated the improvement and testing of the EV charging controller initiated by the preceding student. On the other hand, Avans University seeks to establish a Hardware-in-the-Loop (HIL) testbed in its Smart Energy Lab.

1.2 Project Objectives

Considering the mutual interests of the company and the university lab, the aim of this assignment is to continue the development of the EV charging controller and build a testbed at Avans' Smart Energy Lab for its testing. The results expected in the end of the project include:

1. An improved controller integrated with the testbed.
2. Performance of the modified controller based on simulation.
3. A HIL testbed able to mimic an EV charging session.
4. Realtime emulation results using the testbed.

To reach the goals, this work is structured into three phases:

1. Improving and preparing the controller for the testbed testing.
2. Establishing a HIL testbed and integrating with the controller.
3. Controller testing on the testbed and result analysis.

1.3 Motivation

This section describes the background and reason why EV smart charging and a HIL testbed are of interests in general.

EV Smart Charging

The acceleration in EV adoption, coupled with the rapid development of renewable energy sources, reflects countries' collective commitment to combat climate change and promote sustainable practices. However, uncontrolled EV charging poses significant challenges, as vehicles are often charged at maximum power immediately upon plugging in until reaching full capacity. This charging pattern, combined with diverse charging behaviors, can lead to high-power peaks on the grid, straining various aspects of the energy system.

For instance, from the viewpoint of an asset owner who has EV chargers and Photovoltaic (PV) on the roof, the challenges could be: [6], [14]

1. Mismatch between EV charging demand and (green) energy supply, leading to curtailment and low self-sufficiency.

2. Overloading existing infrastructure capacity, imposing stress on the grid or bringing extra capacity cost.

3. Inducing grid stability issues, such as deteriorating grid characteristics or grid congestion.

A study conducted on Belgium's grid illustrates that a 30% EV penetration could result in a 10% increase in peak demand, highlighting the potential grid-related issues arising from the proliferation of EVs. [14] Alternatively, smart charging strategies provide an optimal means of utilizing existing infrastructure, averting challenges without extensive infrastructure upgrades.

Hardware-in-the-Loop Validation

To fully harness the potential benefits of EV smart charging within buildings, it is imperative to thoroughly evaluate the performance and impact of the developed charging controllers. While a pure software-based simulation offers convenience, it may fall short in replicating real-world conditions accurately. As a solution, the emergence of HIL testbeds has gained popularity across various research fields.

The significance of the HIL testbed lies in its integration of simulation models with real-world hardware. This enables researchers and developers to subject their smart charging controllers to realistic scenarios and dynamic grid conditions, all within a safe and limited laboratory environment. Recognizing the advantages of HIL testbeds, the establishment of a dedicated EV charging testbed at Avans' Smart Energy Lab presents opportunities.

1.4 Project Contributions and Outline

As mentioned, the main goal of this assignment is to continue the uncompleted smart charging controller and its testing in the Smart Energy Lab at Avans University. The previous student has done a case study on Kropman Breda office, proposed an algebraic model for the optimization, and initiated the controller algorithm. In this assignment, the controller is adapted, improved, and integrated with a HIL testbed also being built in the assignment. In addition, testing and simulation are done, followed by analysis and discussions.

The next chapter starts with a review of the literature on the topic and also the project status. Chapter 3 introduces the design of the system, including the testbed and the smart charging algorithm. Chapter 4 dives into the details of the integrated system including the system communication flow and the system configurations. Chapter 5 focuses on the testing scenarios and methodologies involved in the analysis. All the simulation and testing results are presented and discussed in chapter 6. Finally, the conclusion, recommendation for future work, and self assessment are drawn in chapter 7.

Chapter 2

Background Review

This chapter provides background information on both the topic and the project. The first part shortly introduces the state-of-the-art on the two topics: EV smart charging and HIL testbed. In the second part, previous student's work is summarized to recap the project and draw the starting point of this project.

2.1 Literature Review

2.1.1 EV Smart Charging

Review articles on EV charging present a wide range of benefits to charge EVs with control and integrate it with the power grid [2], [14], [15], [16], [3], [6].. They suggested that EV smart charging can enhance grid stability, reduce both energy and capacity cost, and promote sustainable development. In addition, the strategies enable EVs to provide ancillary services and frequency control, transforming EVs from potential grid stressors into active contributors to grid resilience and reliability. These benefits are not only shown in simulations but also in current practice as explored in [6].

State-of-the-Art

There are various strategies to achieve dynamic charging based on time-varying energy price or real-time load balancing. Literature with different system constraints and objectives applies different control manner and optimization methods. Instead of passively reacting to the real-time dynamics in the system, more and more strategies integrate advanced technologies to perform better controlled charging. Below shows some of the examples interesting for this project.

1) Schedule Optimization [1] suggests that proper scheduling EV charging can ensure grid stability. The control can be done in both centralizing or decentralizing manner, depending on the scale and communication infrastructure availability. The optimization can be implemented with various mathematical optimization methods, while more complicated approaches such as genetic algorithm and stochastic model, are also recommended since they allow decision-making under uncertainties.

2) Load prediction [13] presents an example of optimizing an office building's system performance by an automatic learning algorithm-based strategy based on the predicted available power. In this case, the charging power is limited to be either maximum or 0, which is indicated by a binary integer.

Instead of using binary charging power, the three-step strategy proposed in [18] can vary between 0 and maximum. The optimization is implemented with dynamic programming and considering the future horizons in a rolling manner. These allow diverse objective functions and

real-time control. Performing in a partially decentralized manner, this method offers an effective compromise between optimization and scalability.

Another predicting strategy that is getting attention is the charging load prediction. [7] displays a data-driven approach integrating machine learning (XGBoost) to predict arbitrary charge profiles in a smart charging algorithm. It concludes that such integration enhances infrastructure usage by showing a 21% increase in charged energy under limited infrastructure. Other examples making charging load prediction with different approaches can be found in [6] and [1].

3) Bi-directional Charging [10] shows the potential key role bi-directional charging could play in smart charging. A multi-objective optimization is utilized to minimize both the cost and the grid dependency. In this case, not only the predicted local load demand is considered but also the predicted PV power production. The results demonstrate a significant decrease of 167.71% in operating costs compared to the algorithm considering only one-directional charging, and a 28.85% higher peak reduction compared with conventional EV bi-directional charging.

This Project

This project focuses on a centralized scheduling optimization control strategy with Model Predictive Control (MPC). In this step, only single-directional charging is considered while bi-directional is the ultimate goal of the project. The system is formulated as a non-linear mathematical model without involving integer variables. Forecast building load and PV generation are utilized, while charging load prediction is not considered due to the small fleet presenting in the Kropman Breda Office.

2.1.2 Hardware-in-the-Loop Simulations

Introduction

HIL simulation is a testing method used for system development, which integrates real hardware into a simulation loop. [11] highlights its important role when it comes to safety requirements for testing, real-time simulation, cost, and unfeasible modeling. The technique was an essential part in the industry and research on flight and aerospace, not only due to the safety concerns but also the pressure to reduce the development cycles. As power electronic systems and electric drives become more complex and development speed is crucial, HIL simulation is increasingly used in areas such as power systems, vehicles, and system controllers, as demonstrated in this project.

The two types of HIL are presented in Figure 2.1. The difference between them is that Power Hardware-in-the-Loop (PHIL) includes actual power hardware and allows the testing with rated power corresponding to the actual electrical system. But for Controller Hardware-in-the-Loop (CHIL), only signals are simulated, which is usually used for model validation. [19] In this project, PHIL is applied for investigation of the power flow during the charging sessions.

Application Examples

One example for a HIL is presented in Figure 2.2, which is used to test the feasibility of the self-driving controller [4]. The structure is similar to the testbed setup in this project while in this case, it is signals and information that flow in the loop. Compared to our case, we have a charger module as the actuator directly connected with the controller via Controller Area Network (CAN)bus, and a battery model emulating the charging behavior of an EV.

Another example can be found in [5] and [20]. As two connected studies, they present a similar system setup where a real-time PHIL testbed is built for testing a smart charging algorithm. The charging algorithm is designed to charge EVs as much as possible with a minimal total charging cost. The testbed is built with a grid emulator, an EV emulator, a Electric Vehicle Supply Equipment (EVSE), a Alternating Current (AC) charger, and a real-time simulator. The author suggests that, for the charging algorithm, the delay caused by execution is more impactful compared with communication delay and recommends that the frequency of giving current setpoints could be 5

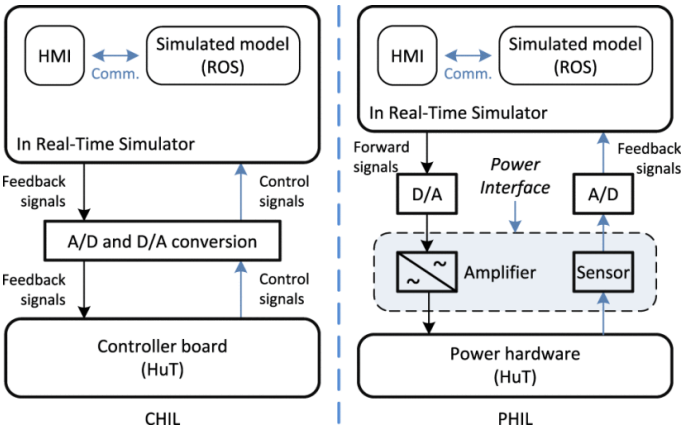


Figure 2.1: Two hardware-in-the-Loop setups [12]

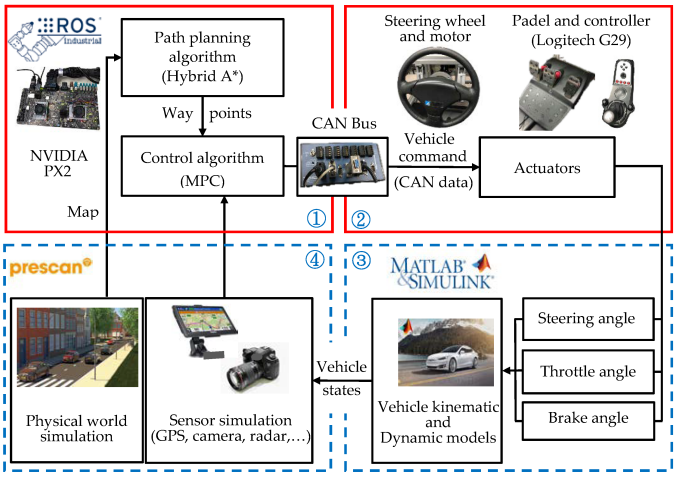


Figure 2.2: Example of a PHIL Experimental Structure for a Self-Driving Vehicle [4]

minutes instead of 1 minute. On the hardware side, it is noted that a real-time simulation enhances the reliability of the algorithm assessments while the simplicity of the system also needs to be considered.

2.2 Project Review

This section provides background of the project and the previous project status done by the student Roeland in 't Veld [9]. It will be started by an overview of the Kropman Breda Office and its current charging situation, followed by the system setup considered for this project.

2.2.1 Kropman Breda Office

The office is equipped with different loads and roof-top generation with an energy management system, allowing data collection, processing, and storage. Both the historical and forecasted data are processed by a Continuous Monitoring System (CMS) called InsiteSuite and stored in the database called InsiteReports, which is accessible for this project. The data has a minimum resolution of 5 minutes. Apart from this, an online application is used to collect EVs' presence data, where employees can fill in the information of the arrival time, expected departure time, and the required charged energy (kWh). The overview of the building system and data management is

shown in Figure 2.3.

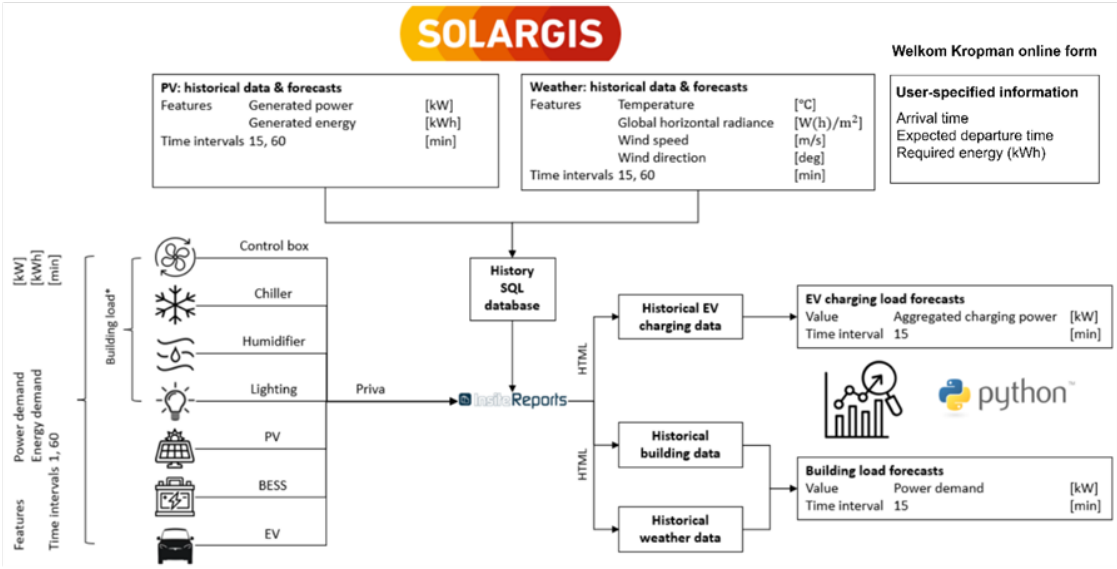


Figure 2.3: Overview of the Building Monitoring and Database

The office has two type 2 EV chargers (4 ports in total) with maximum power at 7.4 kW (1 phase/32A) or 22 kW (3 phase/32 A) and PV panels on the roof. The PV has a maximum capacity of 16.9 kW at the moment while there are still some spaces for the possibility to scale up the PV production.

2.2.2 Current Charging Situation

Currently, the EV charging is not controlled, meaning all the EVs start charging at the max power until full capacity is reached. The power curve under this condition is shown in Figure 2.4, as indicated 'EV historic' and 'Grid uncontrolled'. We can see that the demand in the morning is relatively high, which is caused when employees arrive and together start charging their EVs. Moreover, it is found that most of the EVs get a full charge before noon and then stay idled until the employees get off from work. Therefore, the idea of the project is to develop a charging controller which shifts and distributes the charging load based on the forecasted building load, PV generation, and EV information to shave the undesired power peaks. Considering only the office hours, this controller only schedules for hours during 6:00 to 18:00 during the weekdays.

2.2.3 Smart Charging Controller System

To flatten the power demand curves, this project focuses on the solution of adopting a smart charging controller to control the charging current of each EV. The controller used in this assignment was initiated by the previous student Roeland in 't Veld [9].

The considered system is formulated as shown in Figure 2.5. The charger charges according to the set current ($I_{\text{set},t}$) sent from the smart charging controller. The set current is determined by the smart charging controller, who implements optimization based on the latest known forecasted data, considering the best schedule for each present EV. Since the controller is set to run iteratively, each sent set current is the latest optimization result calculated by the updated data in the database.

Based on software-based simulation, the previous student concluded that the proposed controller concept is able to flatten the power curves and increase self-consumption. One of the simulation

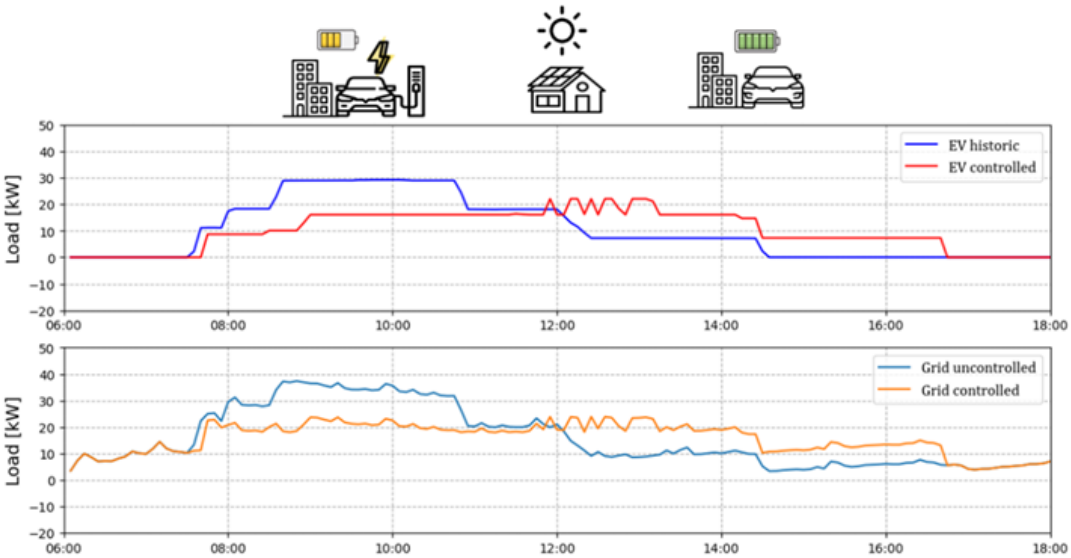


Figure 2.4: Controlled and uncontrolled charging scheme [9]

results is shown in the Figure 2.4, as indicated 'EV controlled' and 'Grid controlled', where the peak reduction is presented.

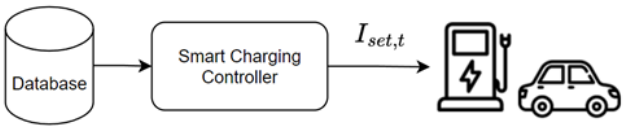


Figure 2.5: System setup

Chapter 3

System Design

The system overview is illustrated in Figure 3.1. Following, the testbed and the algorithm of the controller will be explained.

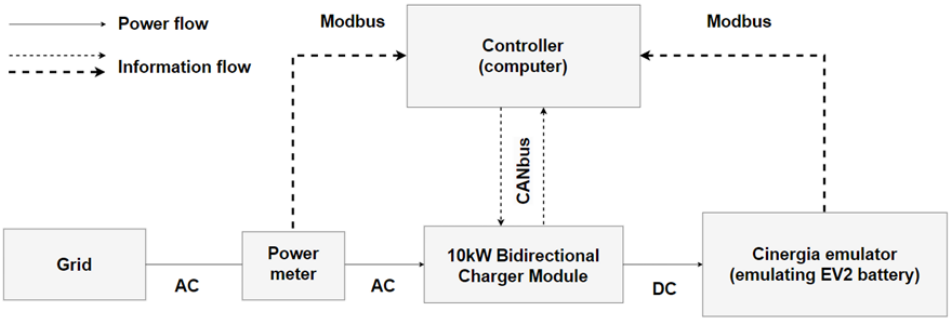


Figure 3.1: System overview

3.1 Hardware-in-the-loop Testbed

The aim of the testbed is to mimic the power flow during a charging session based on the system discussed previously (Figure 2.5). Since there is only one charger module available, the testbed can emulate the charging session for a single EV. Also noted that an EV-EVSE interface (such as Combined Charging System (CCS) or Charge de Move (CHAdeMO)) is not involved in the system so the control of the charger is fully based on the controller running on the host computer, which is connected with all the other components for data collection. The structure of the system is shown in Figure 3.1. The details on each component's specifications, purposes, and I/O interfaces are described below: (the interface figures can be found in Appendix A).

Power Monitoring Device (SENTRON PAC4200)

The power meter is placed between the grid and the charger, and is only connected when doing the power factor measuring. There are two supervision methods available: the monitoring screen and through Modbus protocol. Figure A.1 is the Modbus package on Matlab interface.

PRE Charger Module

The EV charger module used in the testbed is a 10kW bidirectional Direct Current (DC) power concept for EV chargers. During testing, the charger is directly connected to the grid and only charging mode is applied. In charging mode, the charger intakes 3 phase AC power and converts it to DC as output. According to the data sheet, the charger has a high efficiency, over 0.95, because of the use of active Power Factor Correction (PFC) technology. The charger is compatible with the CCS and CHAdeMO charging standards and can be fully controlled and monitored by CAN-open protocol or its in-built monitoring interface(Figure A.4). In our testing scenarios, no EVSE is integrated so the operational commands (enable/disable), the set charging current, and the set voltage are all assigned by the controller via CAN-bus.

Cinergia GE&EL+ vAC/DC Battery Emulator

The emulator is a regenerative converter, which can operate in different modes (for instance DC load, AC grid emulator, power amplifier, etc.) according to various experimental needs. In our case, it is used to emulate an EV battery, so it's working in the battery emulator mode. With its ability to replicate voltage and current characteristics of diverse batteries, we can investigate battery charging dynamics and performance. The battery characteristics and (initial) status can be specified and monitored via the Modbus/ethernet or its in-built monitoring interface (Figure A.3. The parameters present in Figure 3.2 are applied as the battery model for the testing, which is set according to the Nissan Leaf model. The emulator can work with up to 100kW and achieves up to 95% energy efficiency.

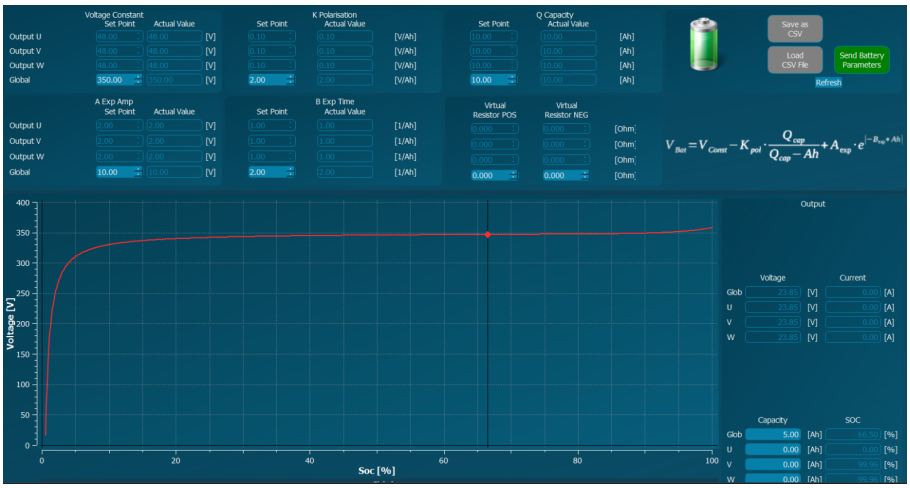


Figure 3.2: Parameters of the Battery model (Cinergia)

Controller (Host computer)

The host computer is where the smart charging controller is located. The host computer controls charger's charging according to the optimization result. The communication between the controller and charger is through CAN-bus, based on CAN-open library. The optimization process can be supervised via the controller terminal, where the new coming EV, leaving EV, and the present EV current status are all presented with the timing indicated. (Figure A.2.) The details of the control and optimization algorithm is followed in the next section.

3.2 Smart Charging Algorithm

The python-based smart charging algorithm of the controller is adopted from the previous student [9]. The modifications include considering dynamic pricing schemes, the optimization model, and integrating the I/O interface for hardware communication.

The role of the controller is determining the charging current set point for each EV and sending the set point to the charger. To achieve these, the controller consists of an algorithm performing schedule optimization, a MPC controller, and the communication interface with the charger. Figure 3.3 shows the structure of the algorithm. Following Table 3.1, where all the variables and parameters are listed, the MPC and optimization model will be explained.

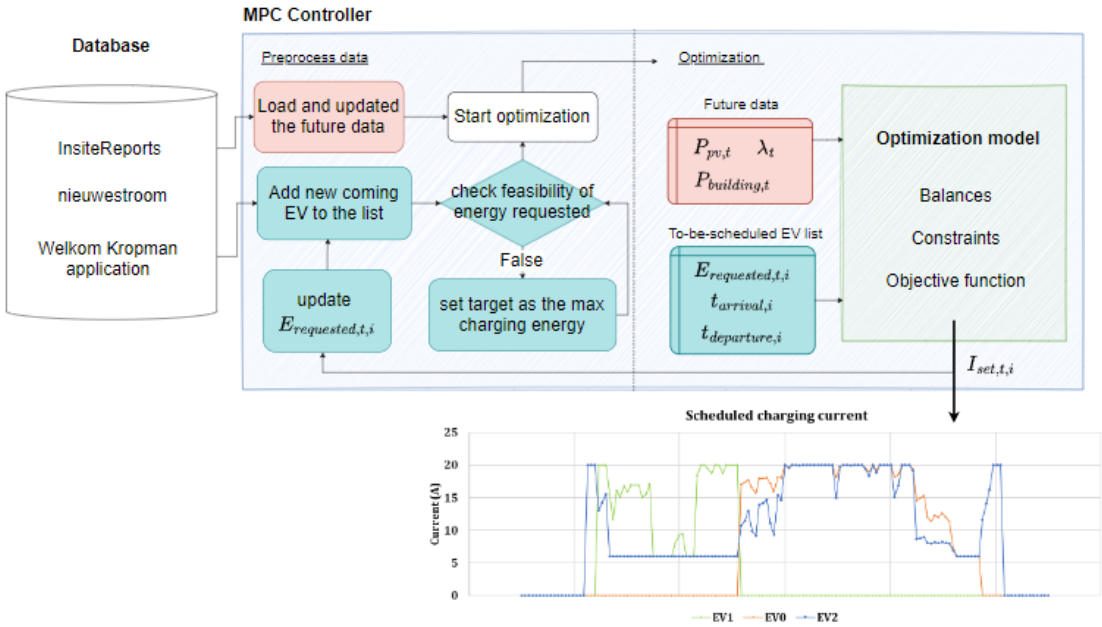


Figure 3.3: Structure of the Charging Algorithm

In Table 3.1, the input variables are the uncontrollable factors which will be loaded from the database and external data source. On the other hand, the set parameters are the settings corresponding to the real systems constraints or assumptions, which will be further explained in Chapter 4.

3.2.1 Input Variables

With the goal of matching the demand with PV generation and flattening the power demand from the grid while taking cost into account, the schedule optimization is made considering the building load power, PV generation, and electricity price (indicated as "future data" in the pink box in Figure 3.3). Since the current set point depends on the whole schedule in the future horizon, the decision requires the forecast future data. The load data are accessible from the InsiteReports database and the electricity price curve is obtained from the nieuwestroom website. Noted that a separate variable $\lambda_{t,\text{sign}}$ which indicates the positive or negative price is created to handle the possible negative price without involving complex integer programming. All the data are resampled to 5 minutes, as the minimum resolution for the data from the database.

Besides, the EV present time and request energy specified by the users are taken into account (they are included in the "To-be-scheduled EV list" shown in the Figure 3.3) . While the literature suggests that incorporating State of Charge (SOC) status and charging load predictions could yield improved outcomes, these factors are not considered in this instance due to the constraints

Table 3.1: Variables and Parameters

Input variables	Description	Unit
$P_{\text{building},t}$	Predicted building load at time t	kW
$P_{\text{pv},t}$	Predicted PV generation at time t (+ as generate)	kW
λ_t	Electricity market price at time t	Euros/MWh
$\lambda_{t,\text{sign}}$	The sign of electricity market price at time t	-1 or 1
$T_{\text{arrival},i}$	The arrival time of EV i	Datetime
$T_{\text{departure},i}$	The expected departure time of EV i	Datetime
$E_{\text{requested},i}$	The requested energy of EV i	kWh
Set parameters		
T_s	Set points resolution (Time between iteration)	5 minutes
η_{charger}	Charger efficiency	-
η_{battery}	Battery efficiency	-
i_{min}	Minimum charging current	6 A
i_{max}	Maximum charging current	20 A
v_{charger}	Charger voltage	380 V
$Weight$	The weight of the penalty term	40 for OF_1, 0.4 for OF_0
Decision variables		
$I_{\text{set},t,i}$	The charging current scheduled for EV i at time t	A
Dependent variables		
$P_{\text{grid,ev},t,i}$	The grid power for charging EV i at time t	kW
$P_{\text{charged},t,i}$	The charged power of EV i at time t	kW
$E_{t,i}$	The energy charged by EV i at time t	kWh
$E_{\text{arrival},t,i}$	The energy EV i has when $t = T_{\text{arrival},i}$	kWh
$E_{\text{departure},t,i}$	The energy EV i has when $t = T_{\text{departure},i}$	kWh
$E_{\text{requested},t,i}$	The remaining requested energy of EV i at time t	kWh

Note: t indicates time, whose range changes with the future horizon of each iteration, from the current time to the end of the future horizon. i indicates EV id, ranging from 0 to 4 for Kropman Breda office.

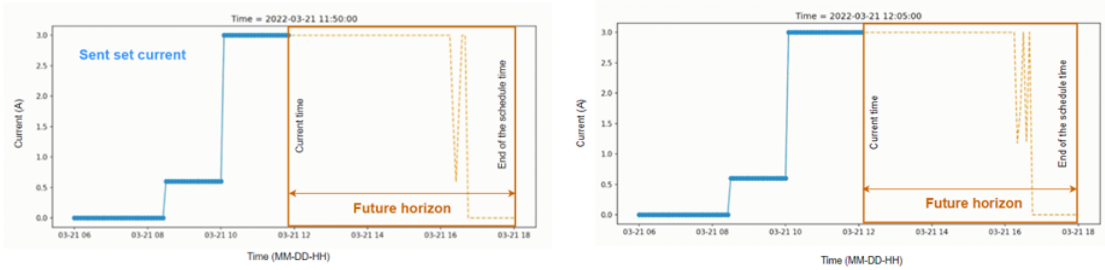
of the office. A former student, Somer, highlighted the challenge of capturing precise EV charging pattern for a relatively small-scale site in his research [17]. Furthermore, regarding the SOC information, given the constraints imposed by the charging infrastructure at Kropman Breda Office, the algorithm considers the charging status based on a predefined charging model, which will be elaborated in the next section.

3.2.2 Model Predictive Control (MPC)

To optimize the charging load for lower Power Peak Reduction (PPR) and the total energy cost, the charging current at each moment needs to be decided considering future system dynamics. Therefore, MPC is applied to specify the future horizon utilized by the optimization model. The future horizon in our case is bounded within the working hour, between 6:00 to 18:00, and is updated every iteration along with the shift of the current time. Considering the computation time and the possible resolution of the input variable, the controller time step is selected as 5 minutes [9], which is also suggested in [20]. In each step, MPC ensures the data within the corresponding future horizon is prepared for the optimization model, who will then predict the best charging schedule within the same horizon.

Two screenshots from the simulation on 21/03/2022 are presented in Figure 3.4, where the orange dashed line draws the predicted schedule at that moment, and the blue line out of the window indicates the past periods where the set currents had been sent to the charger. The mentioned future horizon in this context spans from the 'current time' to the 'end of the schedule time' (which is set to be 18:00). As we can observe from the screenshots, the predicted charging schedule might vary in each step. This could be due to the change of the forecast data or EV

presence, or there are multiple solutions for the minimization problem.



(a) screen shot at 11:50:00 (b) screen shot at 12:05:00

Figure 3.4: MPC simulation screen shots at different time

To address the missing real-time information on EVs' presence and their SOC status, a separated comma-separated values (csv) file is created to keep their approximated real-time status recorded. The file includes all present EVs' arriving/departure time and their remaining requested energy to be charged. In each iteration, the controller accesses the file and updates it by adding new arriving EV, removing the left ones and those finished charging, and adjusting the remaining requested energy for each car. The update of remaining requested energy is governed by the battery model considered in the optimization 3.3. After this status update, a feasibility check on the energy requests is done for each case before starting the optimization process. In cases where the requested energy exceeds the maximum deliverable energy before the planned departure, the request is modified as the maximum achievable charging energy.

3.3 Optimization Model

The purpose of the optimization model is to find the optimal charging schedules for all the present EVs considering overall charging cost, grid power consumption, and charging performance within the specified future horizon. The minimization problem is solved by the Interior Point OPTimizer (iPOPT) solver using the Python Optimization Modeling Objects (Pyomo) package, which was selected considering the possibility of a non-linear objective function [9]. The details of the model and the proposed alternative objective functions will be presented below, with the parameters shown in Table 3.1.

3.3.1 System Models

Charging Power

The charging model is modified to fit the DC charger on the testbed. Based on [8], η_{charger} is taken as a constant 88% and η_{battery} is considered as 97%, resulting in a total charging efficiency of around 85%. The charging power is model as:

$$P_{\text{grid,ev},t,i} \cdot \eta_{\text{charger}} = I_{\text{set},t,i} \cdot v_{\text{charger}} \tag{3.1}$$

$$P_{\text{charged},t,i} = I_{\text{set},t,i} \cdot v_{\text{charger}} \cdot \eta_{\text{battery}} \tag{3.2}$$

where $P_{\text{grid,ev},t,i}$ means the power requested from the grid for charging the EV and $P_{\text{charged},t,i}$ indicates the battery charged power.

Battery Model

$$E_{t,i} = \begin{cases} E_{\text{arrival},t,i} & \text{if } t = T_{\text{arrival},i} \\ E_{\text{arrival},t,i} + P_{\text{charged},t-1,i} \cdot \frac{T_s}{60} & \text{if } T_{\text{departure},i} > t > T_{\text{arrival},i} \\ E_{\text{requested},t,i} & \text{if } t = T_{\text{departure},i} \end{cases} \tag{3.3}$$

Power System Balance

$$P_{\text{grid},t} = P_{\text{building},t} + \sum_i P_{\text{grid,ev},t,i} - P_{\text{pv},t} \tag{3.4}$$

3.3.2 Constraints

Charging Current

The maximum charging current depends on the charger specification. In our case, it is limited by the hardware specification and stability. On the other hand, considering some types of EV require a minimum charging current to keep the connection between the charger and EVs, a lower bound is applied [5].

$$I_{\text{set},t,i} = \begin{cases} i_{\max} > I_{\text{set},t,i} > i_{\min} & \text{if } T_{\text{departure},i} > t > T_{\text{arrival},i} \\ I_{\text{set},t,i} = 0 & \text{if } T_{\text{departure},i} < t \text{ or } t < T_{\text{arrival},i} \end{cases} \tag{3.5}$$

Charging Current Difference Term

This variable indicates the switching level between each iteration. It is created to smoothen the charging profile.

$$\text{Idiff}_{t,i} = \sum_i (\sum_t ((I_{\text{set},t,i} - I_{\text{set},t-1,i})^2)) \tag{3.6}$$

3.3.3 Objective Function

The Objective Function (OF) is the key determining the quality of the optimization results. However, since there is no clear definition for the best charging schedule that we can follow, this is something that needs to be discussed and experimented. There are three OFs being investigated in this experiment:

Baseline Case (OF_0): With Penalty Term

OF_0 is proposed by previous student, Roeland in 't Veld, with modification to consider the dynamic price curve. To recap, the latter term of Eq 3.7 is a penalty function used to ensure better charging efficiency. And the square for the power terms is applied to penalize very high peaks to achieve a flatter load profile while also avoiding high prices. [9]

$$\text{OF}_0 = \sum_t (\lambda_{t,\text{sign}} \cdot (\lambda_t \cdot P_{\text{grid},t})^2 - Weight \cdot \sum_i (\frac{1}{1+\lambda_t} \cdot P_{\text{grid,ev},t,i})^2) \tag{3.7}$$

Adopted Version (OF_1): With Charging Current Difference Term

To smoothen the charging curve, the Charging Current Difference Term ($\text{Idiff}_{t,i}$) is included in the OF to minimize also the overall current difference. The $Weight$, therefore, works as the factor determining the balance between the smoothness of the charging profile and the overall charging efficiency.

$$\text{OF}_1 = \sum_t (\lambda_{t,\text{sign}} \cdot (\lambda_t \cdot P_{\text{grid},t})^2 - \sum_i (Weight \cdot (\frac{1}{1+\lambda_t} \cdot P_{\text{grid,ev},t,i})^2 - \text{Idiff}_{t,i})) \tag{3.8}$$

Basic Case ($\mathbf{OF}_2$): Pure cost function

When it comes to the robustness of an OF in this case, it means whether it fits different scenarios and system setups. In previous OFs presented, they all included the $Weight$, which is a parameter need to be defined based on trial and error. Since the trial and error are based on a certain dataset, the best value could be different from case to case. Also, the unclear definition of the 'best value' makes the determination even harder. Therefore, the Basic case, which considers only the cost and grid power, is also investigated.

$$\mathrm{OF}_2 = \sum_t (\lambda_{t,\mathrm{sign}} \cdot (\lambda_t \cdot P_{\mathrm{grid},t})^2) \tag{3.9}$$

Chapter 4

System Integration and Setup

The completed testing system is demonstrated in this chapter. The controller is adapted for connecting with the hardware and monitoring the data flow in the system. The data exchange in the hardware system is based on the physical buses. With the testbed prepared, the testing scenarios and KPIs are defined in the end of the chapter.

4.1 Hardware Integration and I/O

The hardware system is shown in Figure 4.1, with connections described in Figure 4.2. In reality, the power running in the system is just going as a loop. After the charger is enabled by the controller, it will draw 3-phase AC power from the grid, converting the power to DC, and charge the battery emulator according to the set current sent by the controller. The emulator will emulate the electrical characteristics of the battery based on the flown-in power and the set battery model, and then sends the power back to the grid.

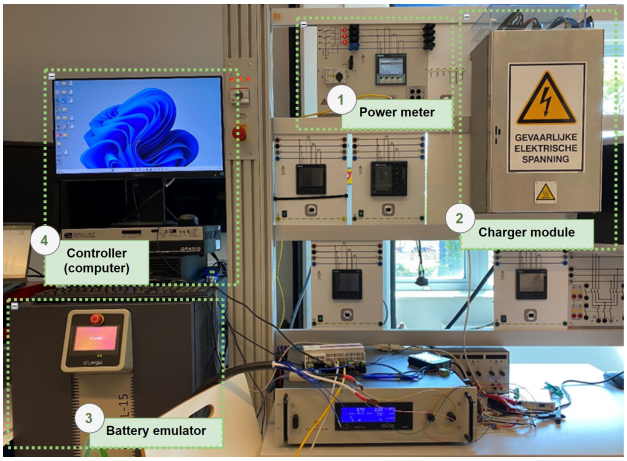


Figure 4.1: Testbed in the Smart Energy Lab

With the testbed able to mimic the communication behaviors of EV charging sessions, the next step is to replicating the simulated behaviors on the testbed to validate the functionality of the controller. To do this, the devices are made to return the desired measured values back to the controller, as shown in Figure 4.2. Noted that the measurements are not used for optimization purposes, but only for the later analysis. With measurements from a power meter, the charger, and the emulator, the dynamic of the charging power flow can be investigated. The details of the measurements are described below in Table 4.1.

Since the measurements are not synchronized, the time label and resolution of the returned data from different devices are not matched. For instance, each measurement point from the charger is returned right after a set point is sent to the charger. Therefore, the return frequency depends on the execution time of each iteration. The reason for not making measurement in a fixed frequency is to avoid the error that happens when two commends are sent to the charger. On the other hand, the measurement from the battery emulator is controlled by the emulator itself. It has a fixed resolution, but is not matching with the data label of the charger measurement. Therefore,

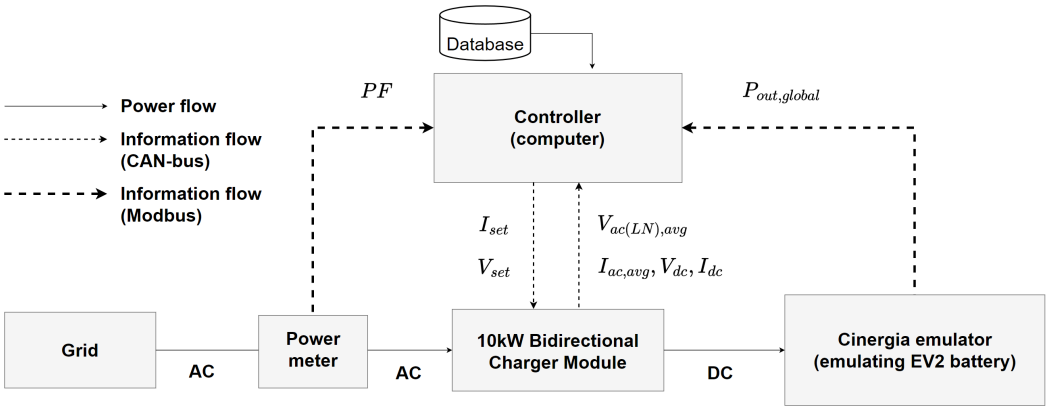


Figure 4.2: Testbed communication diagram

Measurement	Description	Device	Unit
PF	The power factor between grid and charger.	Power meter	-
$V_{\mathrm{ac(LN),avg}}$	Read value of the average input voltage of three AC phases (line-neutral), in 0.1 V steps.	Charger	V
$I_{\mathrm{ac,avg}}$	Read value of the average input current of three AC phases, in 0.1 A steps.	Charger	A
V_{dc}	Read value of the output voltage, in 0.1 V steps.	Charger	V
I_{dc}	Read value of the output current, in 0.1 A steps. (Positive: DC current delivered by module. Negative: DC current delivered to module.)	Charger	A
V_{battery}	Battery voltage measured by the battery emulator. (affected by SOC status)	Emulator	V
I_{battery}	Charging current measured by the battery emulator.	Battery emulator	A
$P_{\mathrm{out,global}}$	Read value of the active output power by the battery emulator. (Positive: power goes out. Negative: power goes into emulator (charging mode).)	Emulator	W

Table 4.1: Measurement Details

resampling and data matching is needed to make comparisons between the data. In this case, the data resampling is done by Excel and processed on separated segments. The process details will be explained in the next chapter.

4.2 Adapted Controller

To integrate the controller in the system, the I/O interface with the charger and other monitored devices needs to be added. The data exchange between the controller and the charger is done based on CANopen (Controller Area Network open), a high-level communication protocol based on the CANbus. Since the charger module requires CANbus messages on a regular basis, the controller is made to send a message at least every 0.5 seconds as recommended by the data sheet. To keep the connection alive, a thread sending the latest updated charging set current ($I_{\mathrm{set},i}$) is activated right after the initialization of the communication connection. The flowchart of the charging controller is presented in Figure 4.3.

4.3 System setup

The fixed system setup used in the following tests is described below: The schedule horizon considered during the day is between 6:00 to 18:00, which is the working hour. The battery's nominal voltage is set to be 350V and charger at 380V. The initial SOC is set to be 50%. The maximum charging current is set as 20A to have a maximum charging power of 7.6 kW theoretically. And the minimum current at 6A to keep the connection. [20] After every optimization iteration, there's

a brief 2-second delay to ensure new optimization iterations start after the last result is delivered to the charger. Noted that the actual time between iterations varies depending on the calculation time of the optimization model in each iteration.

With the system integrated and prepared, the controller was tested under various scenarios for functionality validation and performance evaluation.

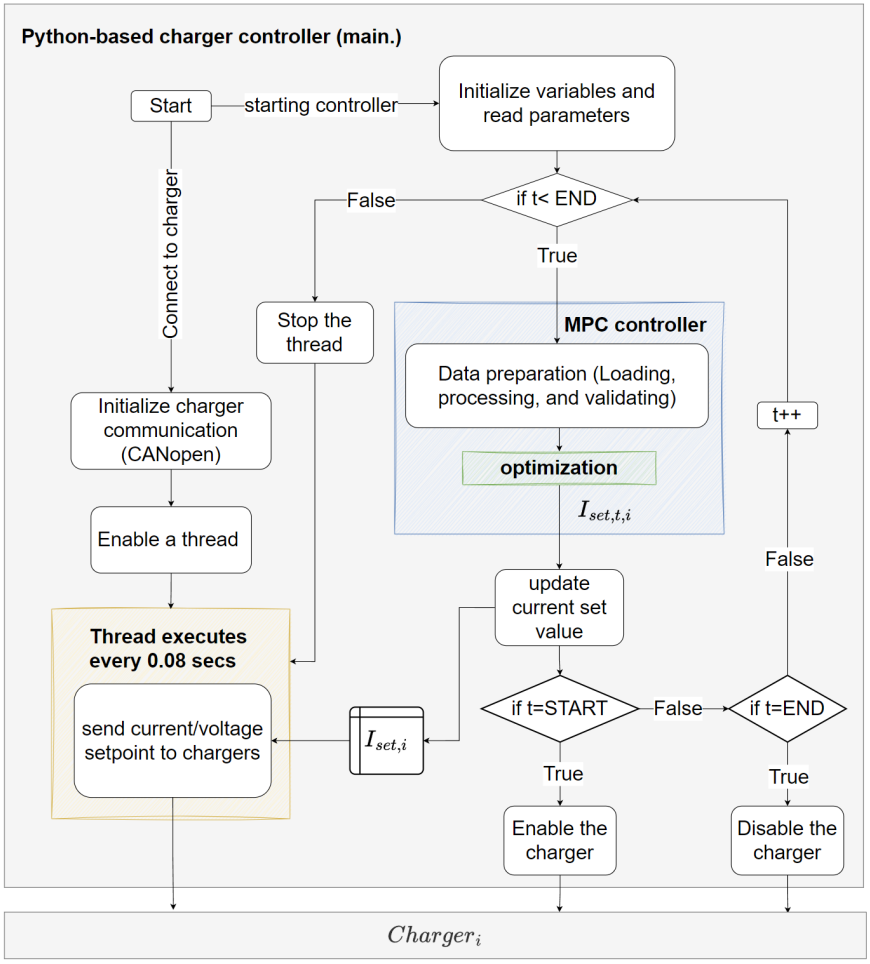


Figure 4.3: Flowchart of the controller

Chapter 5

Methodology

The aim for the testing is to validate the load shifting ability of the controller under different scenarios and investigate the performance when running on the testbed. This chapter starts with presenting the implemented testing scenarios, followed by the result analysis processes. The testing scenarios include the PV capacity and the control strategies, which are tested for 3 days in different seasons. The Key Performance Indicators (KPIs) of energy system performance are utilized to evaluate and compared the outcomes of the scenario testing. Furthermore, the process for investigating the results from the testbed is presented.

5.1 Testing Scenarios

The 3 days taken for simulation are 21st March, 22nd June, and 12th December in 2022, that can be seen as representations of different seasons during a year. The building load doesn't variate much on these three days as shown in Figure 5.1. The main difference is the PV production, whose profiles are illustrated in Figure 5.2. 12th December 2022 shows a low generation profile with the peak at around 8 kW. 21st March 2022, on the other hand, presents a higher generation profile, with the peak at around 12 kW. With a similar high peak production, 22nd June 2022 represents the day whose peak comes later in the early afternoon.

The EV information tested on the days is listed in Figure 5.4. To test the scenario where 4 chargers are all in use, one car's information is artificially.

Table 5.1: Testing scenarios

Scenario	Description
Control Strategy	Uncontrolled / Controlled with OF_0, OF_1, OF_2
PV Capacity	Current capacity (16.9 kW) / The scaled-up capacity (25.2 kW)

Control Strategy

Four charging strategies are investigated: uncontrolled and controlled with OF_0, OF_1, and OF_2. When uncontrolled, the EVs will be charged at the maximum power directly after they are plugged in until fully charged. When controlled, the three objective functions mentioned in Chapter 3 are all tested. OF_0 is used as the baseline for OF_1 to assess the functionality of the added Charging Current Difference Term ($Idiff_{t,i}$). OF_2, on the other hand, is used to evaluate the lowest cost the system can provide.

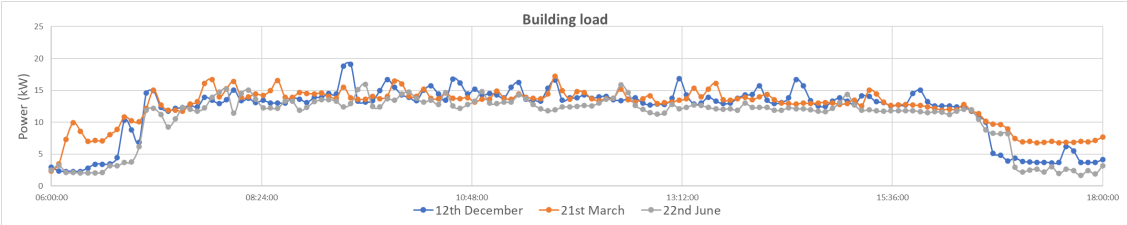


Figure 5.1: Building Load

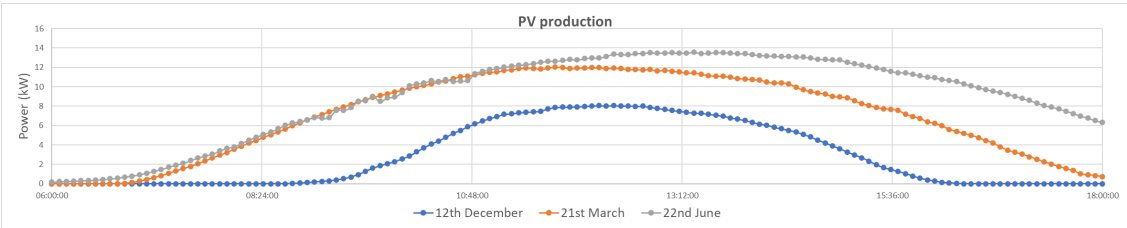


Figure 5.2: PV Production

Figure 5.3: System Profile on the Three Investigated Days

ID	Requested energy (kWh)	Arrival time	Departure time
2	36	7:40	14:15
0	46.74	7:45	14:30
3	46.74	7:55	14:30
1	39.03	8:30	16:45

(a) EV Information tested on 21st March 2022

ID	Requested energy (kWh)	Arrival time	Departure time
3	36.84	6:30	17:00
2	36.84	7:00	17:00
1	14.85	7:45	11:00
0	35.06	11:30	16:30

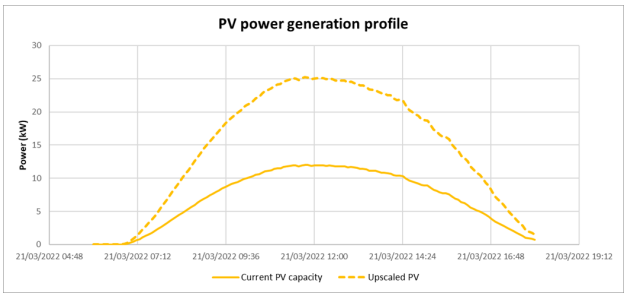
(b) EV Charging Data tested on 12th December and 22nd June 2022

Figure 5.4: EV Charging Data in Scenarios

PV capacity

Based on the free space on the rooftop of Kropman Breda office (orange area in Figure 5.5a), the PV capacity has a possibility to increase to around 25.2 kW (with factor of 1.49). [1] Figure 5.5 shows the solar profile on 21st March 2022 in the scenario of a doubled PV generation, having peak power close to 25.2 kW.

(a) Free rooftop space for PV upscale



(b) Current and upscaled PV profile

Figure 5.5: PV upscale scheme

5.2 Controller Evaluation KPIs

The comparison of controllers with different OF and the benefits of scaling up rooftop PV capacity are based on energy performance KPIss, as described below:

5.2.1 Power Peak Reduction (PPR)

The PPR quantifies the reduction in grid power peak achieved by the controller. A higher value indicates better performance.

$$PPR = P_{\text{max,uncontrolled}} - P_{\text{max,controlled}} \text{ (kW)} \tag{5.1}$$

Where $P_{\text{max,uncontrolled}}$ is the power peak without controller intervention, and $P_{\text{max,controlled}}$ is the power peak with a controller involved.

5.2.2 Self-sufficiency (SS)

Self-sufficiency (SS) represents the percentage of energy consumed covered by local generation. This value indicates system independence and the degree of match between local demand and supply. The ideal SS is 100%, reflecting complete independence. A lower solar capacity might limit the attainable maximum value.

$$SS = \frac{\text{daily consumption from solar generation (kWh)}}{\text{daily total consumption (kWh)}} \text{ (\%)} \tag{5.2}$$

5.2.3 Self-consumption (SC)

Self-consumption (SC) is the level of how much solar generation is used locally. This value indicates whether the solar generation is optimally used and could be used for evaluating the size of the solar capacity. The ideal value is 100, but it is more interesting when the solar capacity more closely matches the demand level.

$$SC = \frac{\text{daily solar generation consumed locally (kWh)}}{\text{daily total solar generation (kWh)}} \text{ (\%)} \tag{5.3}$$

5.3 Testbed Result Analysis

With collected data from the testbed, the functionality of the controller is validated by examining testbed reactions and behaviors. This process includes comparing set points from simulation with the actual charger output current, and investigating the charging efficiency based on the testbed simulation. Furthermore, the efficiency differences between low and high power charging are studied. Since the measurement from devices lacks synchronization and possesses varied resolution, the collected data cannot be compared directly. To compare the power dynamics within the system loop, the load duration curves (LDCs) of the charging sessions are built to enable the later efficiency analysis.

Load Duration Curve (LDC) is a load curve with data points in descending order. This project uses it to help synchronize data points for the calculation of charging efficiency. Therefore, in this case, the x and y axes represent data points and charging power, respectively. The step of building the LDC is illustrated in Figure 5.6.

To create the LDC at charger input/output and battery input, their load curves are required. Since the direct measurement of charger input/output power isn't feasible, their values are calculated as follows:

$$P_{\text{grid,ev2}} = \frac{3 \times V_{\text{ac(LN),avg}} \times I_{\text{ac,avg}} \times PF}{1000} \text{ (kW)} \tag{5.4}$$

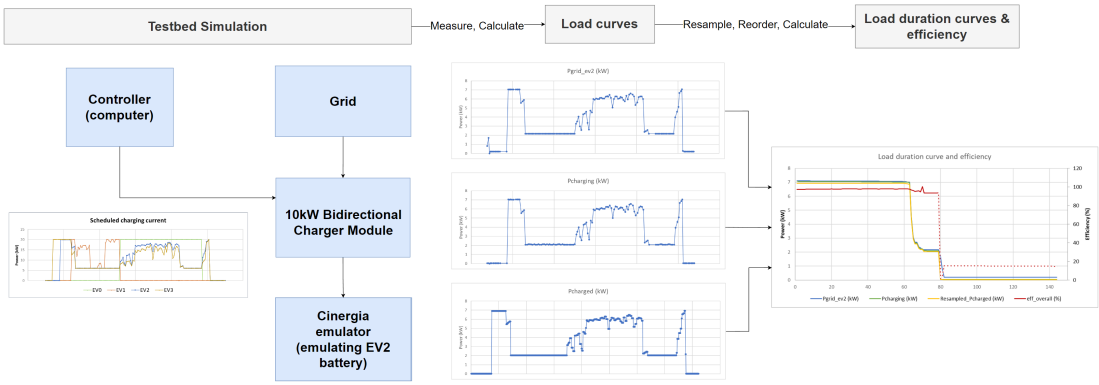


Figure 5.6: Steps of building LDC for the charging process

$$P_{\text{charging}} = \frac{V_{\text{dc}} \times I_{\text{dc}}}{1000} \text{ (kW)} \tag{5.5}$$

$$P_{\text{charged}} = \frac{P_{\text{out,global}}}{1000} \text{ (kW)} \tag{5.6}$$

After reordering the load curves in a descending manner, P_{charged} can be resampled to match the 144 data points of P_{charging} and $P_{\text{grid,ev2}}$ in terms of time.

With the power data, charger efficiency and overall charging efficiency (between the grid and battery) are calculated as follows:

$$\eta_{\text{charger}} = \frac{P_{\text{charging}}}{P_{\text{grid,ev2}}} \text{ (\%)} \tag{5.7}$$

$$\eta_{\text{overall}} = \frac{P_{\text{charged}}}{P_{\text{grid,ev2}}} \text{ (\%)} \tag{5.8}$$

Chapter 6

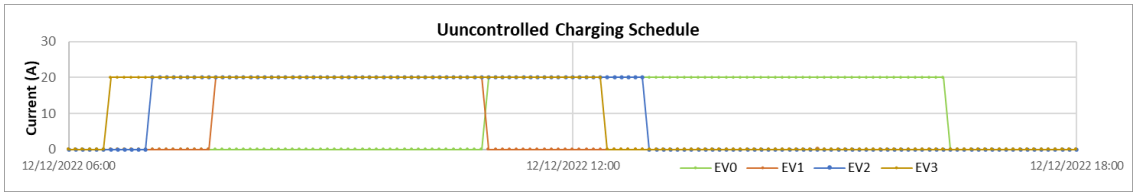
Results and Discussions

This chapter presents the simulation and testbed results. The first part focuses on the outcomes of controlled charging and the performance in different scenarios.The second part shows the testbed testing result with analysis following the steps mentioned in the previous chapter. The full result of individual charging curves in different scenarios can be found in the Appendix B.

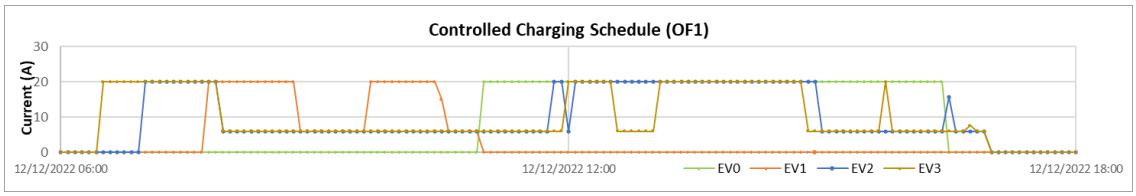
6.1 Controlled Charging Simulation

Load Shifting and Peak Shaving

With the controller, the EVs are charged in a coordinated manner as shown in Figure 6.1, in comparison to the uncontrolled charging scheme. The according system profiles are shown in Figure 6.2, illustrating that the controller ensures the aggregated charging load better aligns with the solar production pattern and leads to a flatter grid power profile. Same result can also be seen in the simulation on 22nd June 2022, presented in Figure 6.3.



(a) Uncontrolled

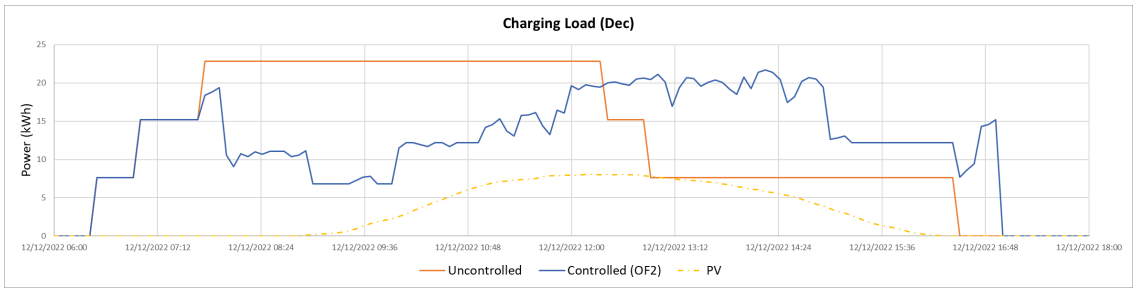


(b) Controlled

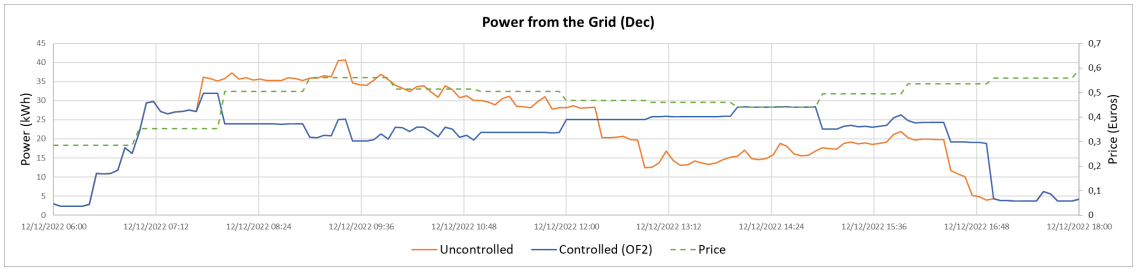
Figure 6.1: Charging Schedule under Controlled and Uncontrolled Charging

KPIs Evaluations

The utilization of defined KPIs enables a comparative assessment of system performance. Table 6.1, where the KPIs values are summarized, provides an avenue for contrasting various scenarios. It allows comparisons across seasons, levels of PV capacity, and the proposed control strategies.

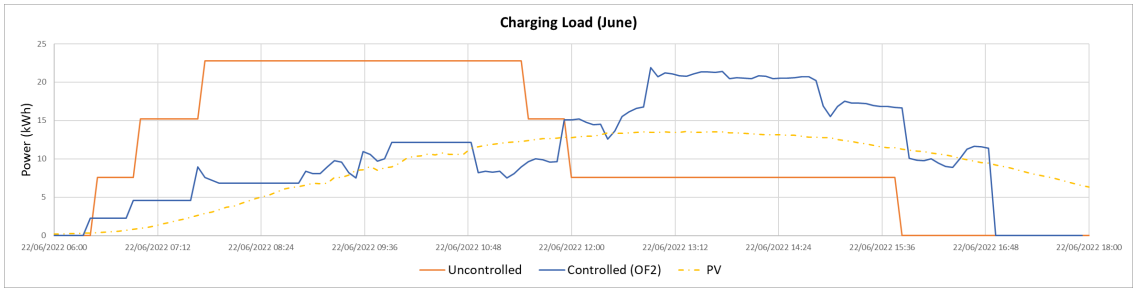


(a) Charging Load

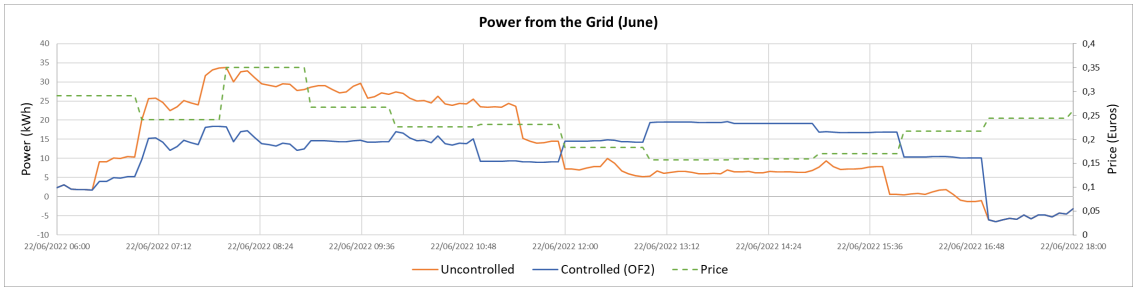


(b) Grid Power

Figure 6.2: System profile results on 12th December 2022



(a) Charging Load



(b) Grid Power

Figure 6.3: System profile results on 22nd June 2022

The results indicate that all proposed control strategies exhibit positive attributes, including improved PPR, reduced energy costs, and enhanced SS. Notably, the OF2 strategy showcases slightly superior KPIs scores. This can be attributed to the less constraints on the individual charging profiles within OF2, allowing the optimization process to focus on the power peak and cost performance.

Table 6.1: Scenario Comparison

Scenarios	Control Strategy	PPR (kW)	PPR (%)	Energy Cost (Euros/day)	SS (%)	SC (%)
December	Uncontrolled	-	-	126,025	11,953	100,000
	Controlled (OF0)	4,528	11,122	119,955	12,274	100,000
	Controlled (OF1)	4,528	11,122	119,810	12,274	100,000
	Controlled (OF2)	8,822	21,668	120,090	12,274	100,000
June	Uncontrolled	-	-	39,237	38,845	94,462
	Controlled (OF2)	14,266	42,177	31,423	40,481	94,796
June with Upscaled PV	Uncontrolled	-	-	19,759	61,169	80,950
	Controlled (OF2)	15,424	50,254	12,899	73,532	93,666
March	Uncontrolled	-	-	54,775	25,028	100,000
	Controlled (OF0)	6,173	15,105	52,791	25,086	100,000
	Controlled (OF1)	5,976	14,623	52,949	25,086	100,000
	Controlled (OF2)	6,173	15,105	52,784	25,086	100,000
March with Upscaled PV	Uncontrolled	-	-	36,550	51,037	97,106
	Controlled (OF1)	8,944	25,563	34,646	52,664	99,971

PV Upscaled Scenarios

While augmenting photovoltaic (PV) capacity stands as a potential strategy to mitigate grid power demand and elevate SS, the adaptation of controlled charging is still necessary to ensure the optimal use of the increased solar generation. This can be observed when comparing the grid usage shown in Figure 6.4. Using controlled charging results in a smoother power usage pattern and better use of solar energy, compared to just adding more solar panels. This is also shown in Figure 6.5, where presents how the controlled charging system optimizes power use from the solar panels.

In short, according to the data in Table 6.1, using a smart controller with the available rooftop space improves system performance. However, it is necessary to note that the optimal PV installation capacity requires further investigation in different seasons and weather conditions to avoid oversizing.

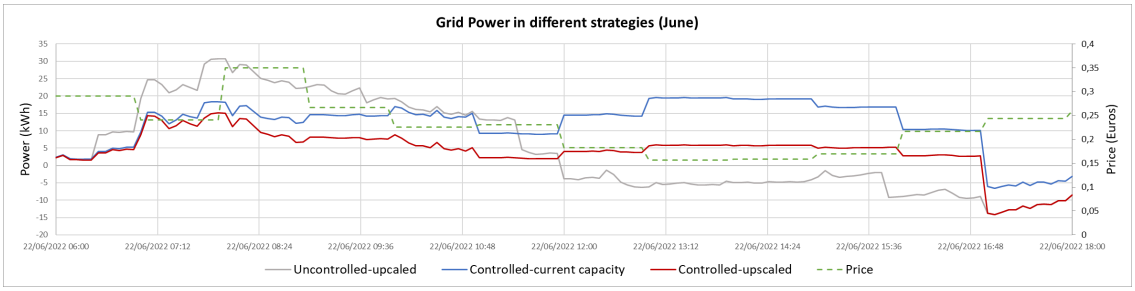
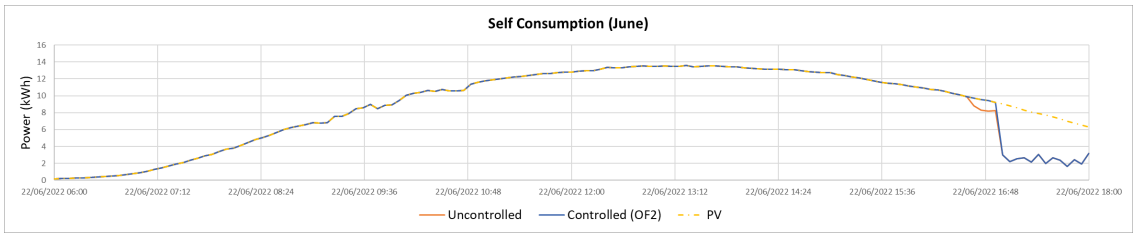


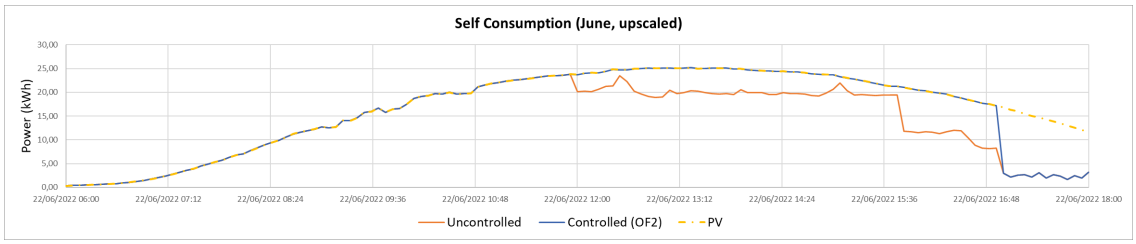
Figure 6.4: Gird Power Reduction with Upscaled PV Capacity on 22nd June 2022

Charging Curves

This section looks into the charging curves from the controlled strategies with various OFs. For the result on 21st March, OF0 works better than OF1 in terms of grid power reduction and stability. However, in the case of December (Figure 6.6), OF1 leads to a smoother charging curve while maintaining the same PPR as OF0. This inconsistency in performance could be due to the value set for the parameter $Weight$, which is determined through trial and error based on a certain dataset. It could also indicate that OF1 is not robust enough to handle a wide range of scenarios.



(a) Power from PV with current PV installation



(b) Power from PV with upscaled PV capacity

Figure 6.5: Comparison of SC in scenarios on 22nd June 2022

However, when comparing the results to those from OF2, both OF0 and OF1 manage to avoid lower charging power (lower efficiency), although the energy performance of the system is slightly sacrificed. The decision of which OF is a better practice in real cases requires further investigation, particularly it can depend on different definitions of good charging curves under different cases.

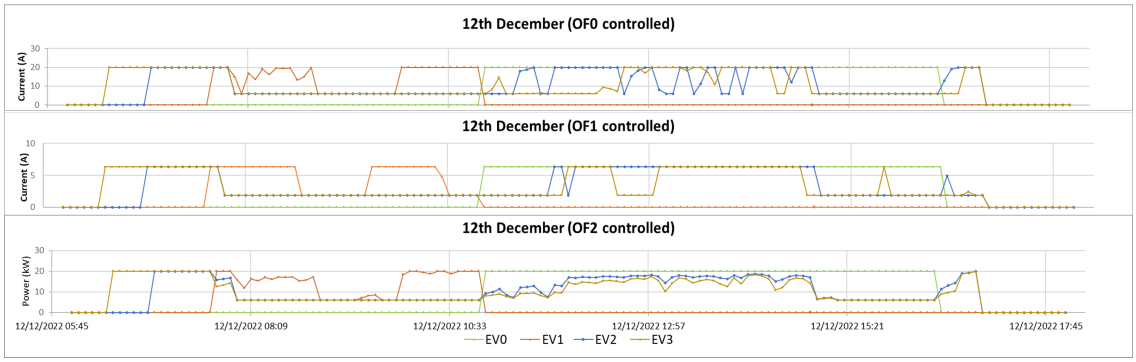


Figure 6.6: Simulated Charging Schedule on 12th December 2022

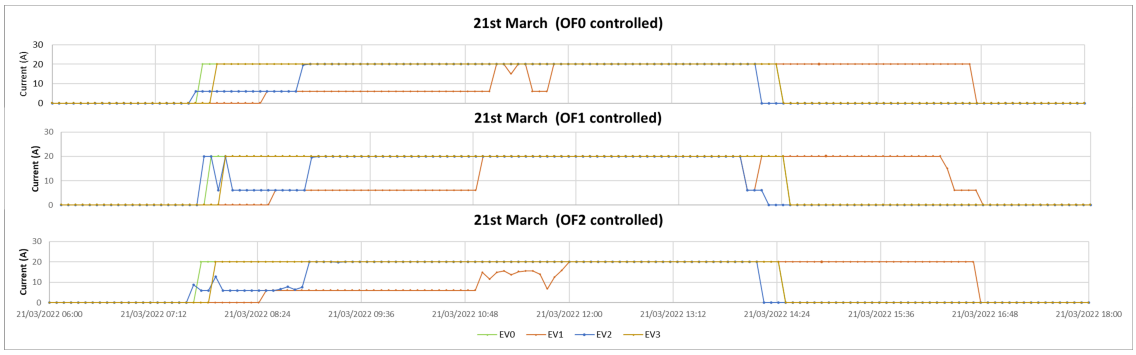


Figure 6.7: Simulated Charging Schedule on 21st March 2022

6.2 Testbed Results

Next, the results of the testbed simulation will be discussed.

6.2.1 Charger Performance

Figure 6.8 illustrates how the charger reacts to the set points sent from the controller. (More results in other scenarios can be found in Appendix C Figure C.1) The figure demonstrates that the charger closely follows the set points, with an error mostly within 2%.

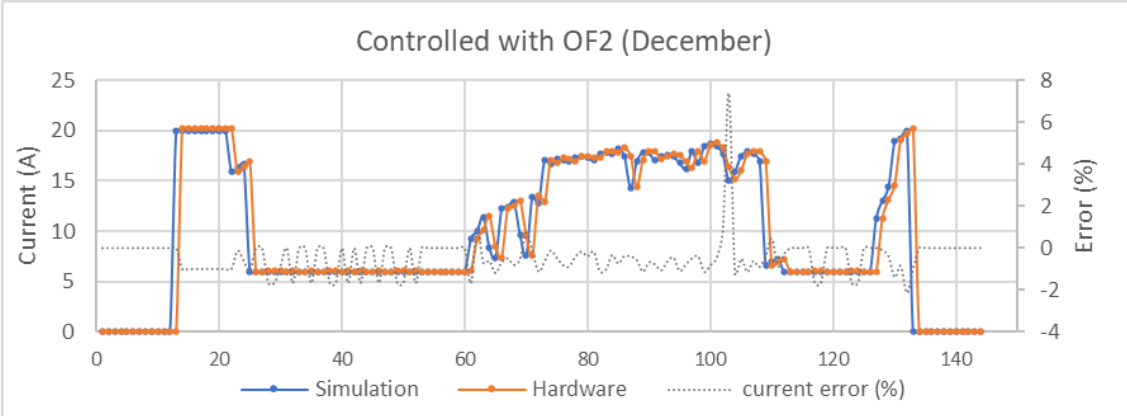


Figure 6.8: Current Error between Set Point and Charger Output

6.2.2 Testbed Efficiency

Load Duration Curves

Following the process described in Chapter 5, the load duration curves are obtained as Figure 6.9. Full results in other scenarios can be found in Appendix C.

Efficiency Calculation and Segmentation

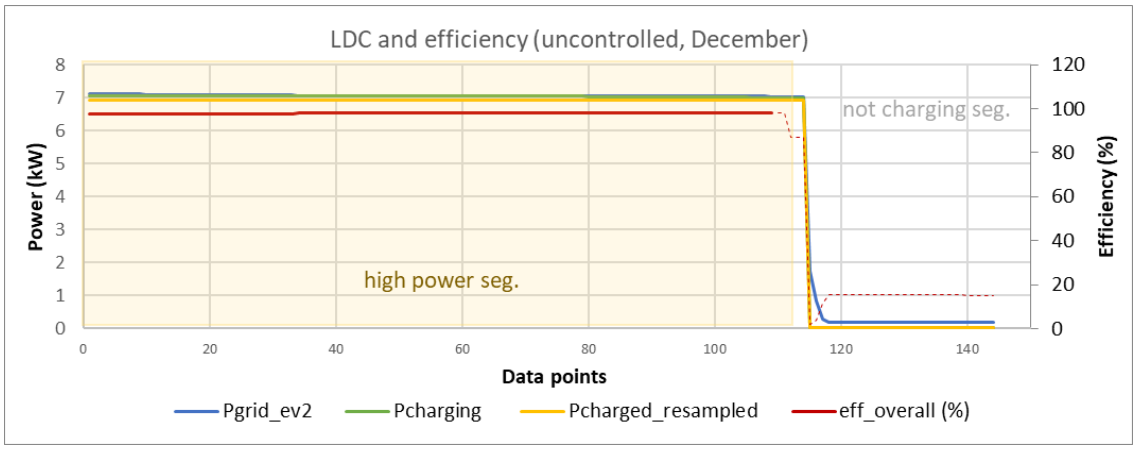
Due to mismatch caused by resampling, efficiency calculations are performed based on segments. The LDC are divided into segments: high-power charging, low-power charging, middle-power charging, and not charging, as indicated in Figure 6.9.

The high-power charging segment pertains to the moment charging with maximum current, while the low-power charging segment corresponds to instances of minimum power charging. The middle-power charging segment represents cases when the charging power falls in between. It's important to note that efficiency is only calculated for high and low power charging segments, as data points in the middle-power charging segment are not perfectly matched due to the resampling process. The nonzero measurements in the no charging segments might be due to the power requirements for system operation.

Efficiency Calculation Results

Based on Equation 5.7 and 5.8, the average overall and charger efficiency of the considered segments are calculated and summarized in Table 6.2. Noted that the overall efficiency in this context does not account for battery efficiency, only indicates the efficiency between the grid input and battery input.

It's observed that the overall efficiency of the testbed is higher than the literature reference [8], which is taken as the assumption in the optimization model. The higher efficiency could be



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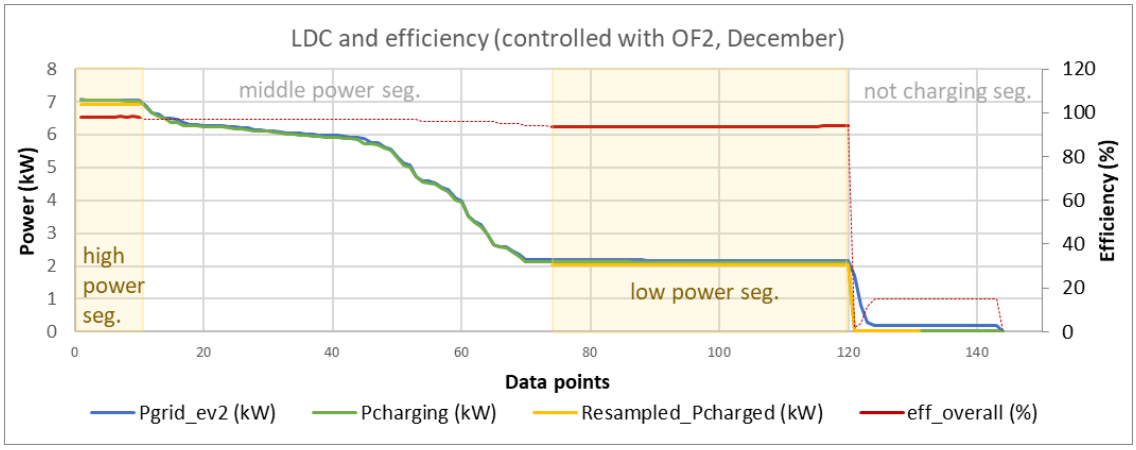

(b)

Figure 6.9: Load Duration Curves and Efficiency

attributed to the simple charger module setup, where no EV-EVSE interface is involved. When comparing the efficiency under different charging power, the results presents that a higher charging power (7 kW) demonstrates a better efficiency by around 4% comparing with charging at the lower power (around 2 kW). Such analysis allows evaluation of the overall charging efficiency of different charging curves.

Scenarios	Average values	High power segment		Low power segment	
		March	December	March	December
Uncontrolled	Power	7,031 kW	7,036 kW	-	-
	Charger eff	99,441%	99,598%	-	-
	Overall eff	97.871%	97.956%	-	-
Controlled with OF2	Power	7,037 kW	7,035 kW	2.085 kW	2.097 kW
	Charger eff	99.358%	99.791%	95.856%	96.353%
	Overall eff	97.792%	98.110%	93.497%	93.573%

Table 6.2: Charging Power and Efficiency

Chapter 7

Conclusions and future recommendation

7.1 Conclusions

Recapping the objectives outlined in Chapter 1, the conclusion is drawn based on the four expected results from this project.

An Improved Controller Integrated with the Testbed

The Python-based smart charging controller, rooted in the principles of MPC and an optimization model, has undergone further refinement and successful integration with hardware. The modified controller can either operate in standalone mode for pure simulation with output of the charging schedules for all the EVs present throughout the day, or in testbed mode to emulate one of the charging sessions for on a Hardware-in-the-Loop (HIL) testbed. The controller's MPC implementation has been completed, with dynamic price curves and a modified efficiency model applied in the optimization. In addition, the communication interface is integrated in the controller. Moreover, two alternative objective functions for the optimization model have been proposed and compared. The first incorporates the Charging Current Difference term ($Idiff_{t,i}$), which is used to smoothen the charging curve. The second one focuses solely on the system performance, considering only energy cost and grid power in the optimization process.

Performance of the Modified Controller based on Simulation

Simulation of the modified controller has been carried out to generate charging schedules and system power profiles in various scenarios. The results showcase the controller's ability to shift charging loads for improved energy system performance. Both proposed objective functions in the controller lead to a reduction in peak power demand from the grid, decreased overall energy cost, and enhancements in self-sufficiency and self-consumption metrics. Moreover, the simulation with a higher PV capacity emphasizes the advantage of controlled charging strategy for better system performance. While the definitive choice of the optimal objective function remains challenging within the scope of this assignment, the simulation results offer insights for future refinements. It is apparent that both objective functions with the penalty term and the Charging Current Difference term could be enhanced in terms of the generalizability and robustness. Otherwise, striking the right balance between curve smoothness and the overall charging efficiency under the particular scenarios and system constraint is required for determining the suitability.

A HIL Testbed Able to Mimic an EV Charging Session

The development of a HIL testbed capable of mimicking an EV charging session has been accomplished. This grid connected testbed comprises a host computer, a charger module, and a battery emulator. The controller, operating on the host computer, facilitates bi-directional communication with the charger using the CANopen protocol and the battery emulator via Modbus. Measured data returned from these devices and interfaces allows monitoring and analysis of charging sessions and system dynamics. In this assignment, the smart charging controller was tested on the testbed, by emulating one of the EV charging sessions. The controller sends a set charging current to the charger upon initiation of the emulated EV's charging session, controlling the power flowing to the battery. The battery emulator reacts in accordance with the predefined battery model.

Realtime Emulating Results Using the Testbed

Following simulations and testing on the HIL testbed, it has been demonstrated that the controller can offer an improved charging schedule through the utilization of MPC and the optimization model. The testing result reveals that the system achieves the goal of performing a controlled charging session as simulation. The measurement from the HIL testbed shows that the charger successfully follows the setpoint provided by the controller, with errors primarily within 2%. Investigation of charging efficiency has been undertaken through load duration curves of the devices to address the unsynchronized measurements. The charging efficiency on the testbed is higher than the literature reference, with an overall charging efficiency around 97% charging at high power (approximately 7 kW) and the charger efficiency exceeding 99%.This high efficiency can be attributed to the simplified system setup compared to a real-world scenario. Furthermore, charging at a lower power (around 2kW) leads to an approximately 4-5% lower efficiency compared to the high power scenarios. The analysis method could be applied to evaluate the efficiency performance of charging curves, allowing further investigation on the design of the optimization model.

7.2 Future Work and Recommendations

Objective Function

As highlighted, future investigations could delve into refining the optimization model, particularly regarding the objective function. While all proposed objective functions achieve the objective of shifting charging loads from morning to afternoon, enhancing their generalizability and robustness is imperative. One possible solution is applying Objective Function 2 (OF2) with charging power level and charging curve smoothness as soft constraints instead of direct objectives. Achieving this might necessitate a multi-objective or even integer programming optimization model. Due to time constraints, this solution is not implemented, though this step could be crucial, especially when bi-directional charging is involved.

Testing with EV-EVSE Interface and Real Car

With the development of the testbed, the controller can have another testing after the EV-EVSE interface is integrated to the system (which is now being implemented by another student). Furthermore, with the system able to connect to a real charger downstairs of the lab, a testing in a real system can be conducted, which would allow for deeper examination of efficiency and energy delivery.

Bidirectional Charging

Given the current limitations of the solver, the controller currently accommodates only one-directional charging. Realizing the final project objective of implementing bidirectional charging would be a focal point for the next student involved. Given the testbed's capacity for bi-directional

charging, testing with adjusted system configurations or controller design could be undertaken to accelerate the achievement of this objective.

7.3 Self Assessment

Participating in a project that combines software development and hardware implementation has been a rewarding journey, where I gained skills from various angles. On the software front, understanding others' code and building upon it are challenging. Making sense of the previously built controller took me a long time and a big effort. The challenge is that it is not easy to understand the purpose and logic behind each line of the code while also keeping questioning myself if this makes sense or is there a better way to do it? In addition, making modification in the controller is another challenge. Deciding between coming up with a solution to fit into the existing system or redoing part of the existing code for easier integration of a new feature is always not easy. There are many tries and errors throughout the process, but it is proven that everything encountered on the way is meaningful. "Trust the process" is the mindset I built on the way.

Same as working with hardware, which is also challenging but brings excitement from time to time. Shooting the bugs to make things work as expected is usually not just a few clicks – it's like going on an adventure, sometimes with a map, but it needs determination and perseverance. In addition, the testing process also makes me realize the importance of better planning for data flow and management, as they can have a huge influence on the efficiency and accessibility in the later process and future maintenance. For me, this opportunity to access such a testbed is valuable.

Finally, out of the technical objectives, this collaborative project developed my ability to work on an academic project in a professional setting. Learning how to be more communicative, precise, and straight forward as the people here brings my communication skill to another level, which I believe would be extremely crucial for my later career.

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Appendix A

Hardware Interfaces

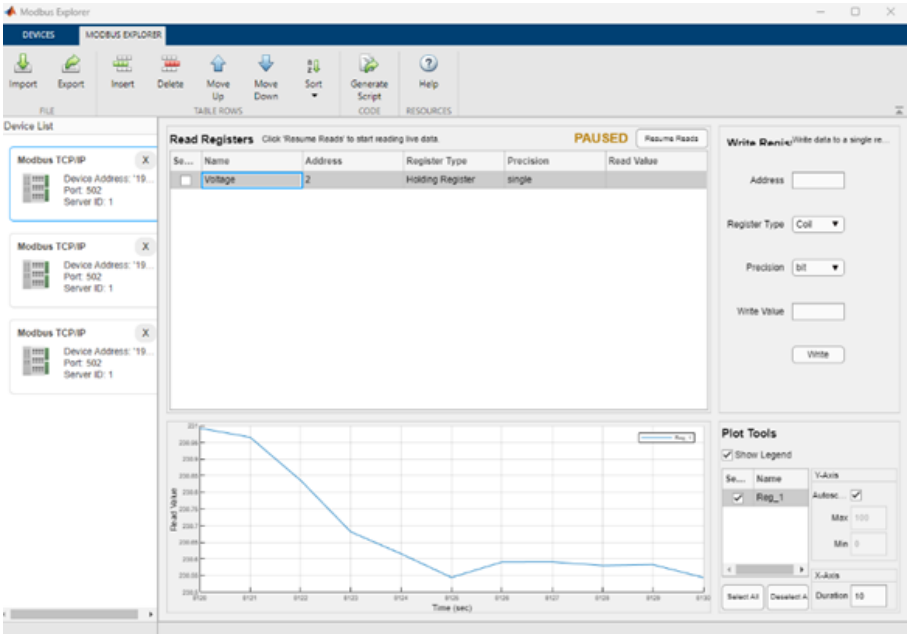


Figure A.1: Power meter monitoring with Matlab interface

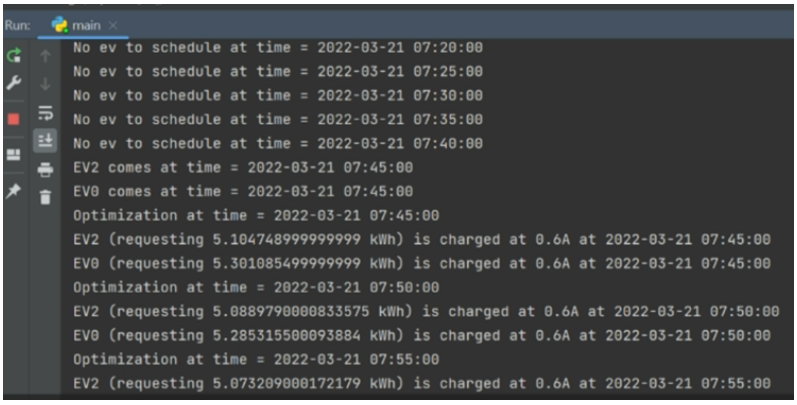


Figure A.2: Controller terminal

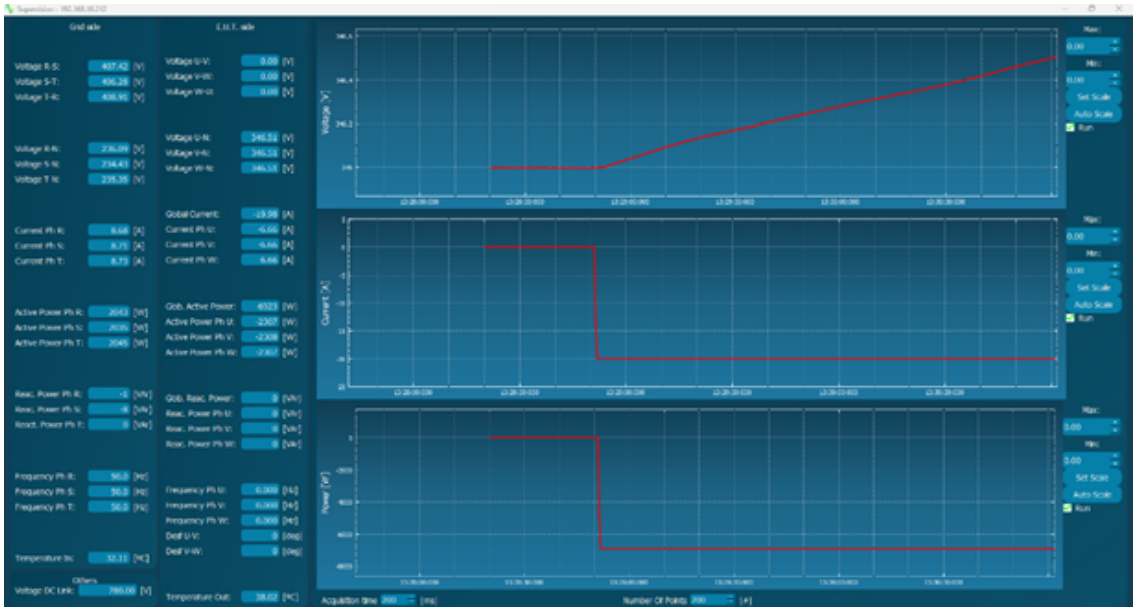


Figure A.3: Monitoring Interface of the Battery Emulator

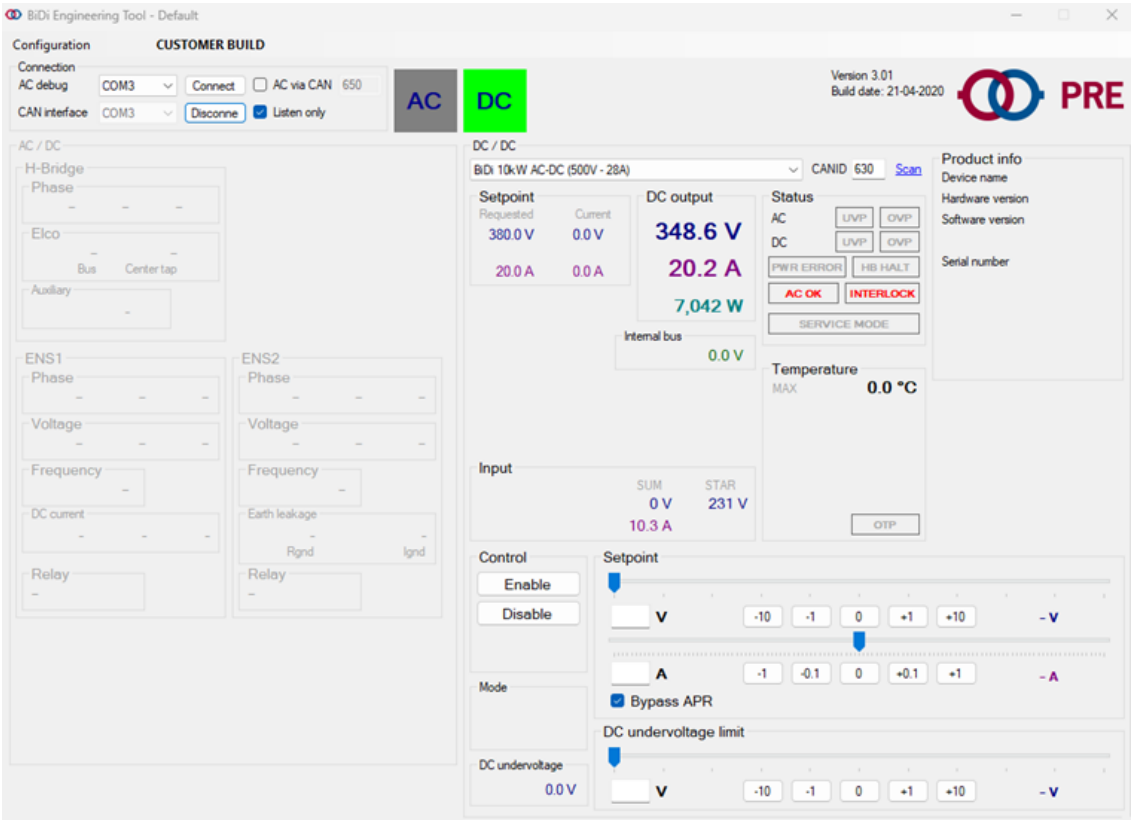
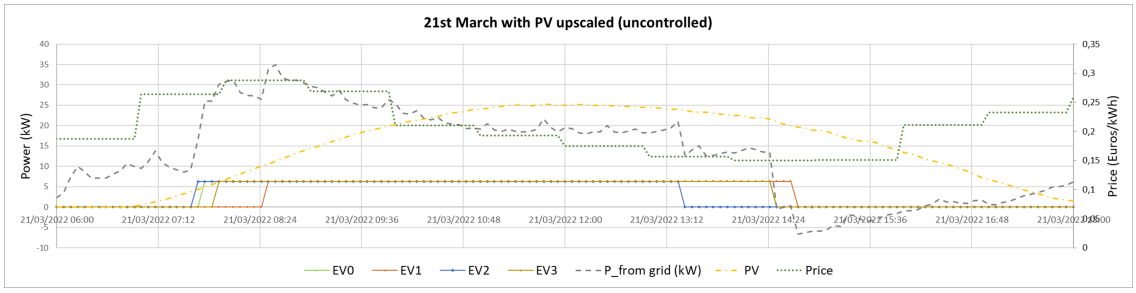


Figure A.4: Charger module interface

Appendix B

Simulation Results



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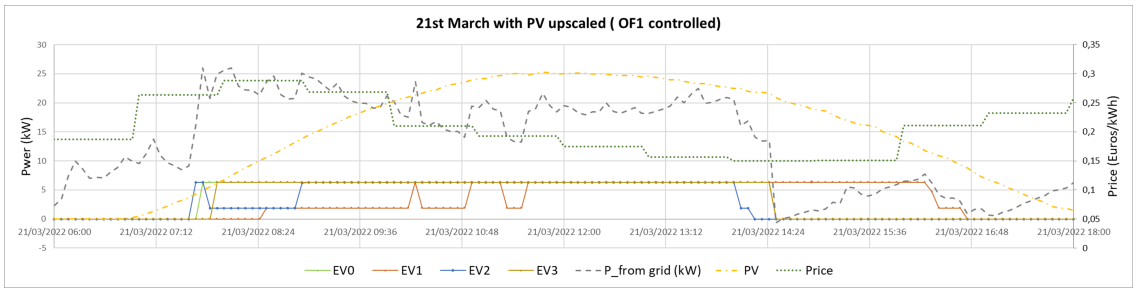
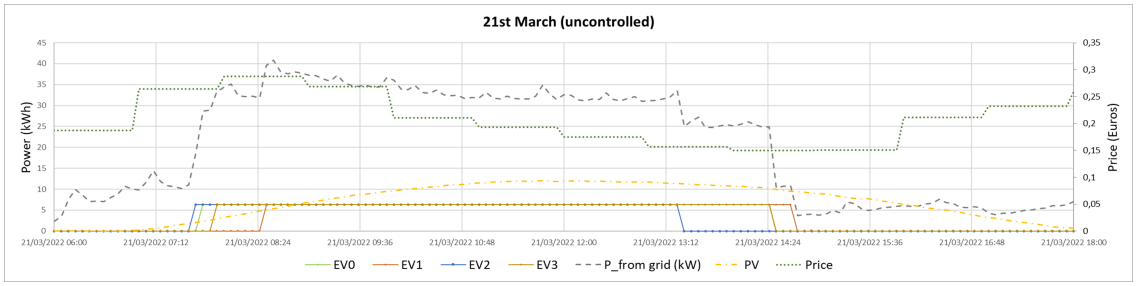


(b)

Figure B.1: System profile with upscaled PV capacity on 21st March 2022



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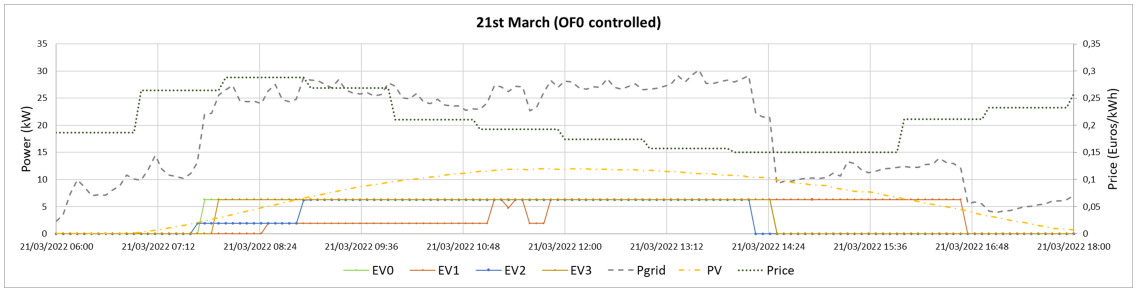

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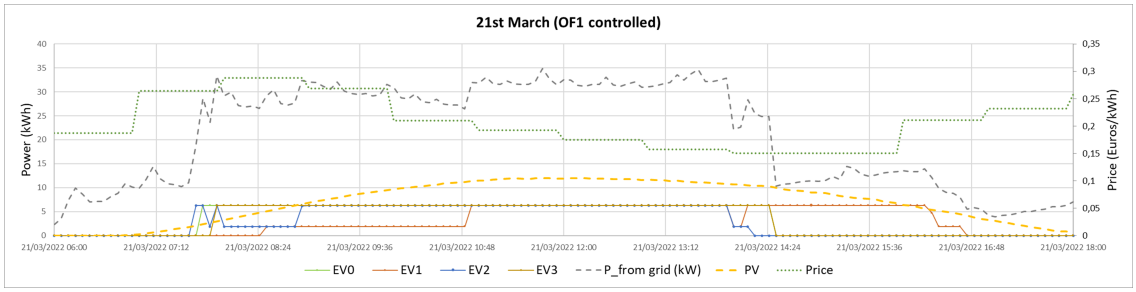

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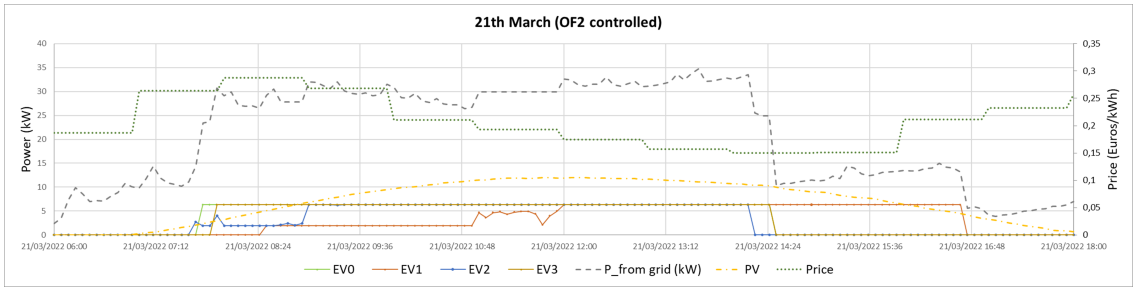

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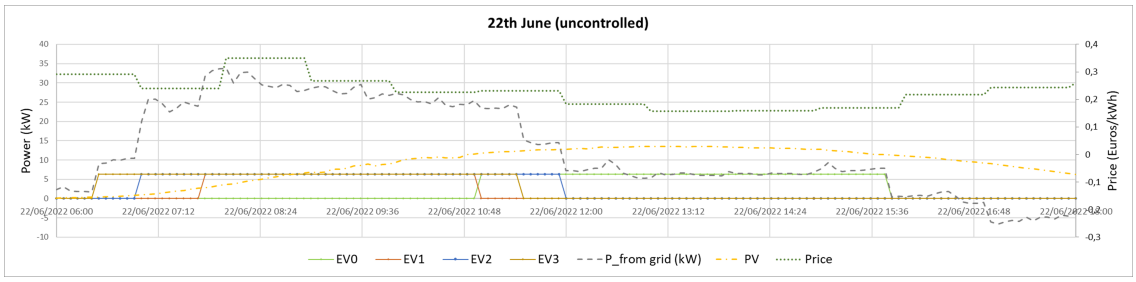
Figure B.2: System profile with different control strategies on 21st March 2022



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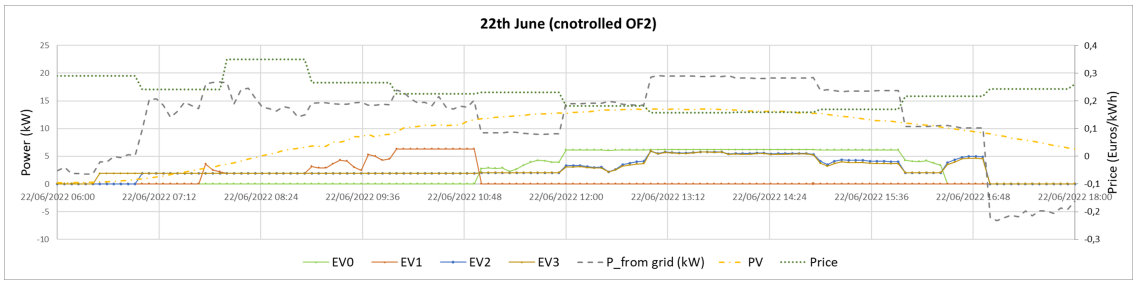

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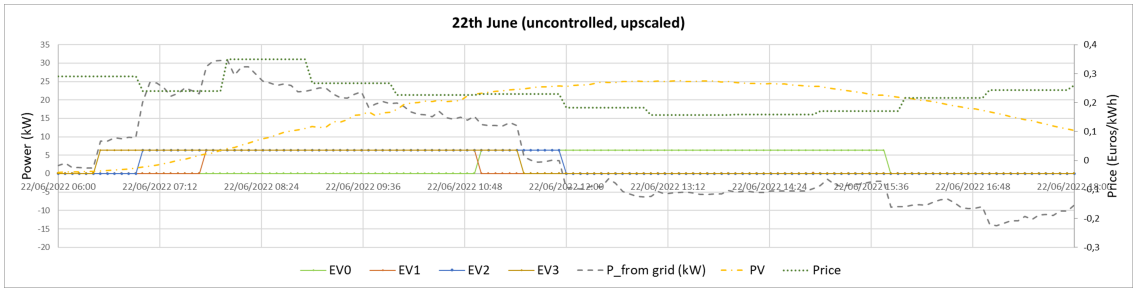

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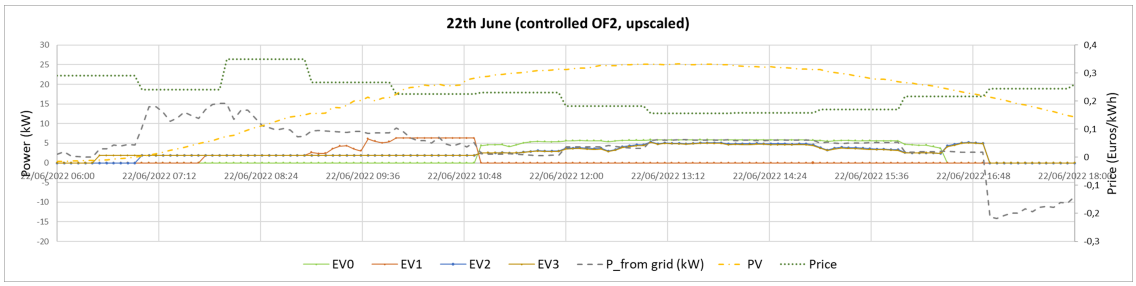

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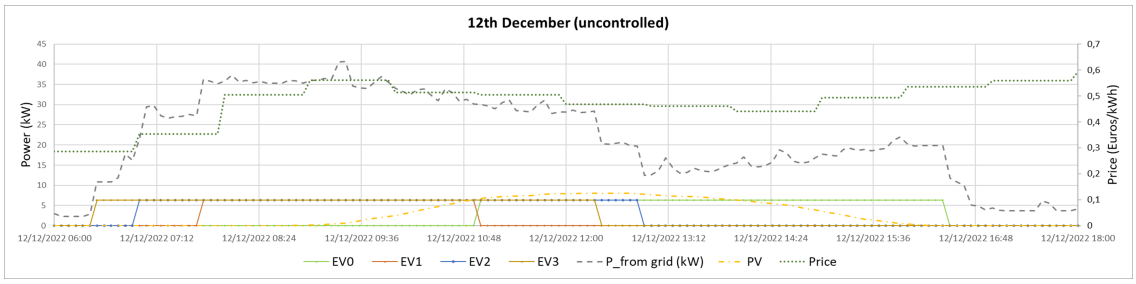
Figure B.3: Uncontrolled and controlled system profile in scenarios on 22st June 2022



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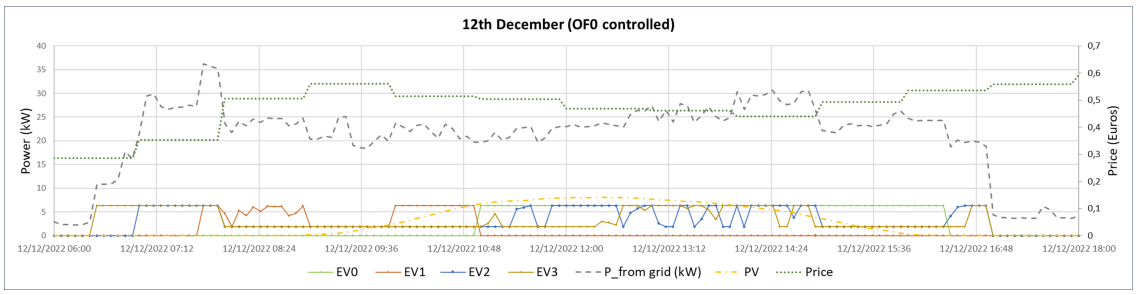

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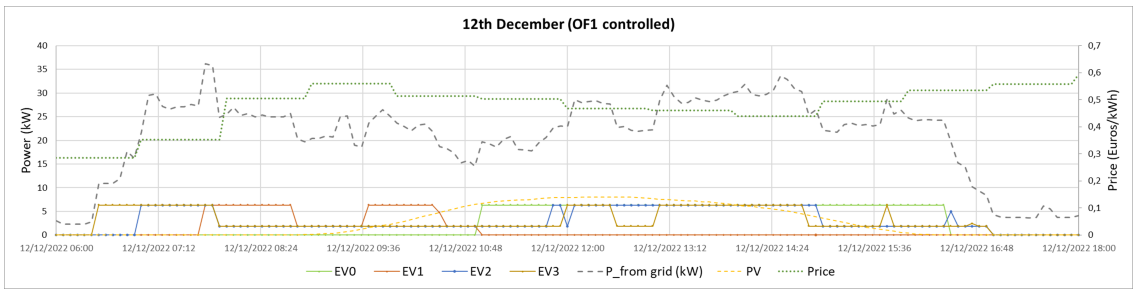

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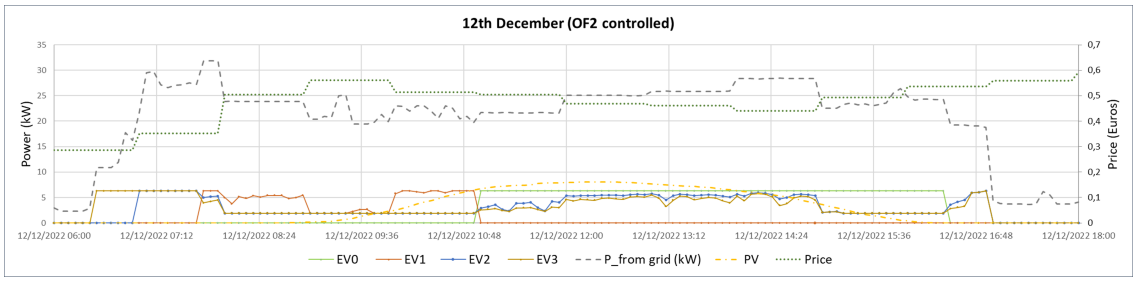

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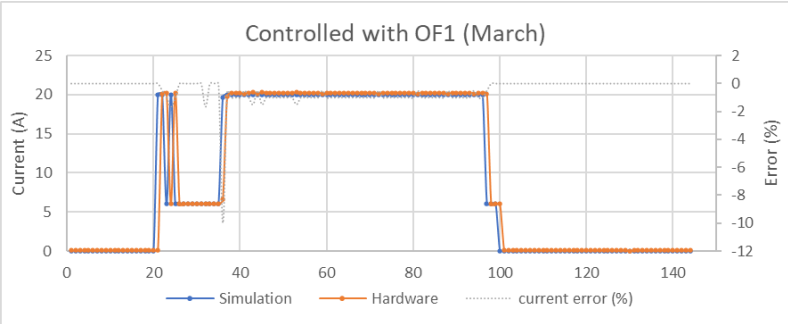
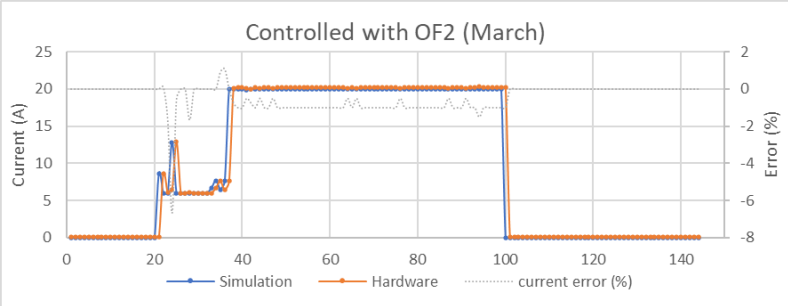
Figure B.4: System profile with different control strategies on 12nd December 2022

Appendix C

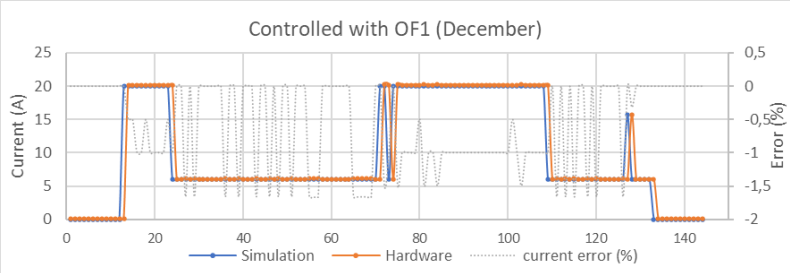
Testbed Results



(a)

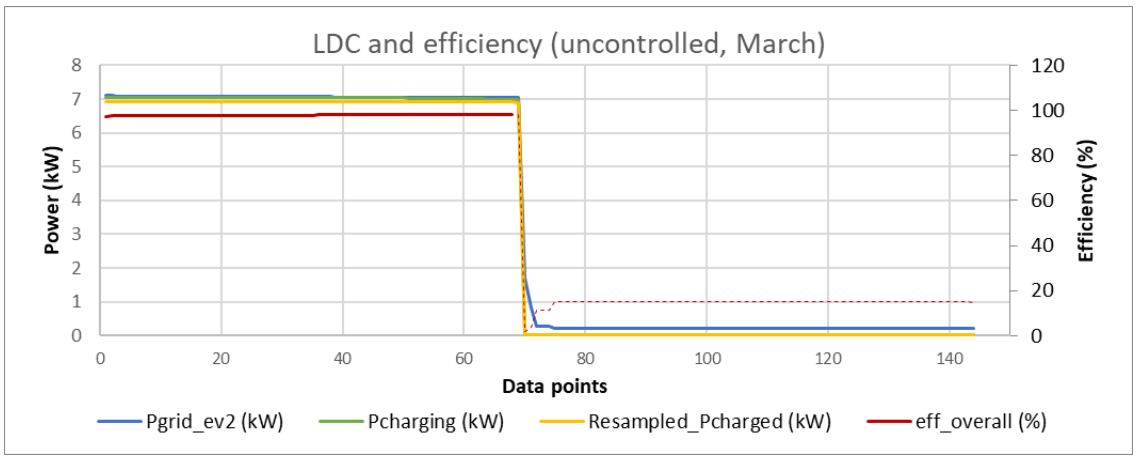


(b)

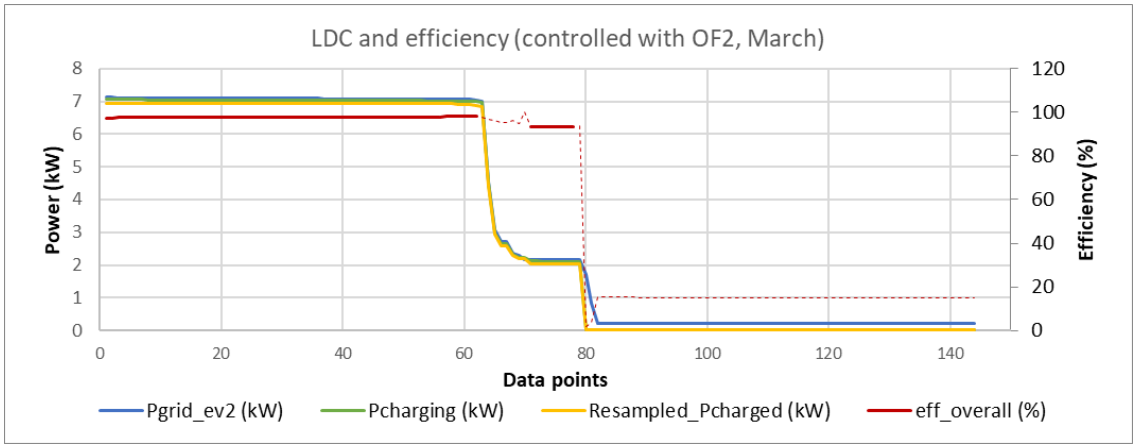


(c)

Figure C.1: Current Error



(a)



(b)

Figure C.2: Load Duration Curves and Efficiency in Scenarios