MASTER THESIS

COMBINING SMART CHARGING AND ENERGY STORAGE FOR PEAK REDUCTION AT EV-FAST CHARGING STATIONS

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PREFACE

Dear reader,

Before you lies the report of the research that I have worked on for the past months, containing my research and findings regarding energy peak reduction at charging stations in the Netherlands. I started my research at this company in November 2020, 10 months into the Covid-19 crisis in the Netherlands. After months of applying at different companies, it became clear that during this crisis, companies were not ready to take in new employees and especially graduates due to the uncertainties surrounding the virus. I was overjoyed when, with the help of my cousin Joost, this company reached out to me for an interview, after which I was accepted to start my graduation. I want to thank Joost for his help in introducing me to this company during this time where the entire professional world seemed closed for newcomers.

At this company, I was placed in the Products-team, nowadays called Solutions & Services, where I was given a very warm welcome by the entire team. Bas would become my lead supervisor and Frank would become the key stakeholder of my research. In a crash course, they shared with me the most important information about the company, the team I would become part of, and the EV market with all its complexities. Together with them, we gave direction to the research and its objective. During my research, they helped me stay on track and working towards the end goal. I want to thank them both for their help and support. I think our talks have always contributed to a better end product. Thank you for guiding me through the research. I also want to thank the Products-team in general, for their warm welcome and always being available for questions or helping me otherwise. I want to thank Guillaume in special, for taking me along some field trips to see and discuss the inner workings of charging locations. He has helped me greatly with understanding the technical aspects of EV-charging, for which I am very grateful.

I would also like to thank my supervisors Peter and Martijn from the University of Twente for guiding me through the process of conducting and reporting an academic research. Their insights and their often critical questions helped me in shaping my research and keeping me on the right track to successfully complete the research. Our talks, while unfortunately digital, were always not only insightful but also very fun. We could easily spend half of the appointment talking about the Covid-19 situation, discussing a scheme for occupying a family member's gaming room for use as an office, or simply discussing a recent tennis match. This really helped in setting the informal tone of our meetings, which however never interfered with the valuable feedback you provided. Thank you for your help and the great talks.

Furthermore, I want to thank my parents for their unwavering support, who can rest easy now knowing their son successfully finished his studies. Finally, I want to thank my girlfriend Amy, who has always been there to help me clear my mind, proofread my report, and calm me down when anxiety and stress about looming deadlines got the better of me. You have had to endure countless hours of me discussing problems I ran into, and helped me restructure my thoughts and overcome these problems. Thank you for being there for me.

With a research connected to the new developing EV market, I feel privileged to have worked towards improvements on this company's operations, and in the process maybe even help relieve some of the load currently imposed on the Dutch energy grid. In my months at this company, besides working on my research, I have contributed in a side-project by developing a dashboard and tool to control and monitor an industrial battery system, which has then been successfully used for peak-shaving at a charging location during a two month pilot run, which I am very proud of. Most importantly, I have learned more than I could have ever imagined about the inner workings of charging locations and all the interesting developments in the EV(-charging) market. I can only hope my research will contribute to this exciting field.

I hope you enjoy reading my thesis.

Koos Sipma
Amersfoort, August 17th, 2021

MANAGEMENT SUMMARY

This report presents an exploratory research on options for reducing peak demand at fast charging locations, in particular by means of Smart Charging, the installation of batteries or the combination of both. The current working context of company X is analyzed, after which a model has been built that incorporates the proposed solutions. A tool has been built that provides easy access to simulating the built model. A total of 18 scenarios have been simulated, which provide promising results, with possible savings spanning between €5,000 and €70,000 per fast-charging location over a 10-year time-period.

The height of the peak demand on fast-charging locations determines the equipment needed for supporting that peak, as well as the monthly costs associated with that peak. Initial analysis reveals that all Dutch fast-charging locations of company X have observed a peak 10x-50x higher than the average load. Literature suggests the solution of integrating a battery at the charging locations, providing a buffer whenever the demand is exceptionally high, and recharging whenever demand is low. Little has been written about Smart Charging at fast-charging locations, while studies are available where additional customer data (arrival times, departure times, target battery charge) is available before the start of a charging session. This report assumes no prior knowledge other than the expected demand for a certain day. This leads the main research question for this report to be: *How can peak-related costs be reduced at fast-charging locations for EVs in the absence of customer arrival- and charging information, and what is the impact of the possible solutions?* The report further distinguishes itself from the available literature by combining two peak-reduction techniques.

A model has been made to combine the use of batteries with Smart Charging. The Smart Charging algorithm in this implementation distributes the available energy to customers proportional to their contribution to the total demand. Unfulfilled demand is penalized, introducing costs to the model whenever Smart Charging is applied. The report defines the mathematical functions behind the model. Simulations are used to analyze different experiments.

A tool has been built using Apache Spark, providing company X easy access to the simulations and allowing the model to be scalable through parallel computing. The tool has been used to run the simulations and gather results. The tool requires input-parameters with which the simulation can be customized to the desired configuration. For the configuration used in the experiments in this report, an explanation is given in the report substantiating the choices made. The true value of certain inputs are not yet known. For those, a sensitivity analysis is done in the experiments to determine the influence of these inputs on the results. It should therefore be noted that the results present a range on which the true value is expected to be. Further research should investigate the actual value of these inputs as to create more precise results.

The experiments investigate three different fast-charging locations in the Netherlands, differing in number and type of chargers, and thus differing in expected demand profiles. For these three locations, six experiments are run with some differing input parameters for sensitivity analysis, for a total of 18 experiments. These experiments show that it is almost always profitable to apply peak-reduction techniques, with additional profits ranging between €5,000 and €70,000

per location over a 10-year time-period. The exception is for locations with only a single fast-charger and low expected demand growth. While some additional profit is generated through lower monthly costs for peak demand, the majority of the profit is realized through being able to use smaller -and cheaper- grid connections, easily reducing the total investment costs for a fast-charging location with €20,000. One especially interesting case is for locations that can drop below a peak of 160 kW, where not only the expenses for the grid connection drop with €26,000 total, but also the need for a transformer is removed further reducing the investment cost by €50,000. Note that these values and prices are specific to the Netherlands (and even differ slightly inside the Netherlands) and that for other countries other rates and limits may apply. The created tool offers the possibility to define those values for analysis of charging locations in other countries.

The majority of the experiments has the best solutions not using any battery at all, while the experiments that do recommend batteries only use fairly small ones. This presumably indicates that batteries are on the verge of becoming cost-effective tools of combating demand peaks.

This research recommends that Smart Charging is introduced to new charging locations, or to charging locations where the demand would normally warrant an upgrade of grid connection. Charging locations that narrowly exceed the maximum limit of a certain grid connection are especially interesting candidates for peak-reduction techniques given the possible cost reductions.

Further research should focus on defining currently unknown input parameters as to increase the accuracy of the results. Mainly the penalty function for unmet demand should be further investigated. Furthermore, improvements to the model can be made to include a better implementation of demand growth. Finally, the influence of lower battery prices can be researched for more insight in when the batteries are expected to become cost-effective.

CONTENTS

Acronyms

AC Alternating Current.

CPO Charge Point Operator.

DC Direct Current.

EAN European Article Number.

EV Electric Vehicle.

HPCs High Power Chargers.

kW Kilowatt.

kWh Kilowatt-hour.

NPV Net Present Value.

1 INTRODUCTION

With the introduction of Direct Current (DC) Fast Chargers and High Power Chargers (HPCs) (see Section 2.1.2 for descriptions of these types of chargers), the Electric Vehicle (EV) market has overcome one of the main concerns for consumers to switch to EVs by supplying time-efficient ways of recharging an EV. However, increased charging speeds comes with higher fluctuations in the energy demand, with severely increased peaks in demand when several cars are charging simultaneously. These peaks require more expensive hardware and furthermore increase the monthly cost of energy. This report presents an exploratory research investigating the possibilities for lowering the energy related costs at these fast-charging locations. Real life data for this report has been made available by company X.

1.1 Problem Statement

company X experiences intermittent demand at their charging locations, causing high initial and monthly recurring expenses. They want to know what steps they can take to decrease these costs. This section briefly discusses the main components of this problem: what are the consequences of the intermittent demand, and which factors drive up company X's costs? Finally, a problem cluster is presented to visualize the problem at hand.

1.1.1 Investment costs

The main driver of the initial investment costs is the height of concurrent power that the infrastructure must be able to support. The expected peak power usage dictates the type of grid connection and the need for auxiliary equipment like, for example, a transformer. The choice for any connection limits the maximum power draw from the grid accordingly. In different countries, different limits and options apply. Section 2.2.1 elaborates upon the different investment costs that are incurred.

1.1.2 Intermittent demand

On company X's Fast-charging locations, while there is historical data, there is no information on currently occurring customer arrivals. Furthermore, once a customer has arrived, no information is available on their demands. Combining this with the intermittent demand creates a situation where scheduling arrivals or pre-allocating resources is hard. There is a clear seasonality over the day, which increases the variance in load even further. The grid operator uses the observed peak demand as their metric to decide how much capacity they must reserve (see Section 2.1.1). This means that the height of the peak directly correlates with the monthly energy costs. Section 2.2.2 goes into more detail about the way these costs are structured, and what monthly costs to expect.

1.1.3 Problem Cluster

In order to get a better overview of the problem at hand, a problem cluster has been made, which is displayed in Figure 1.1.

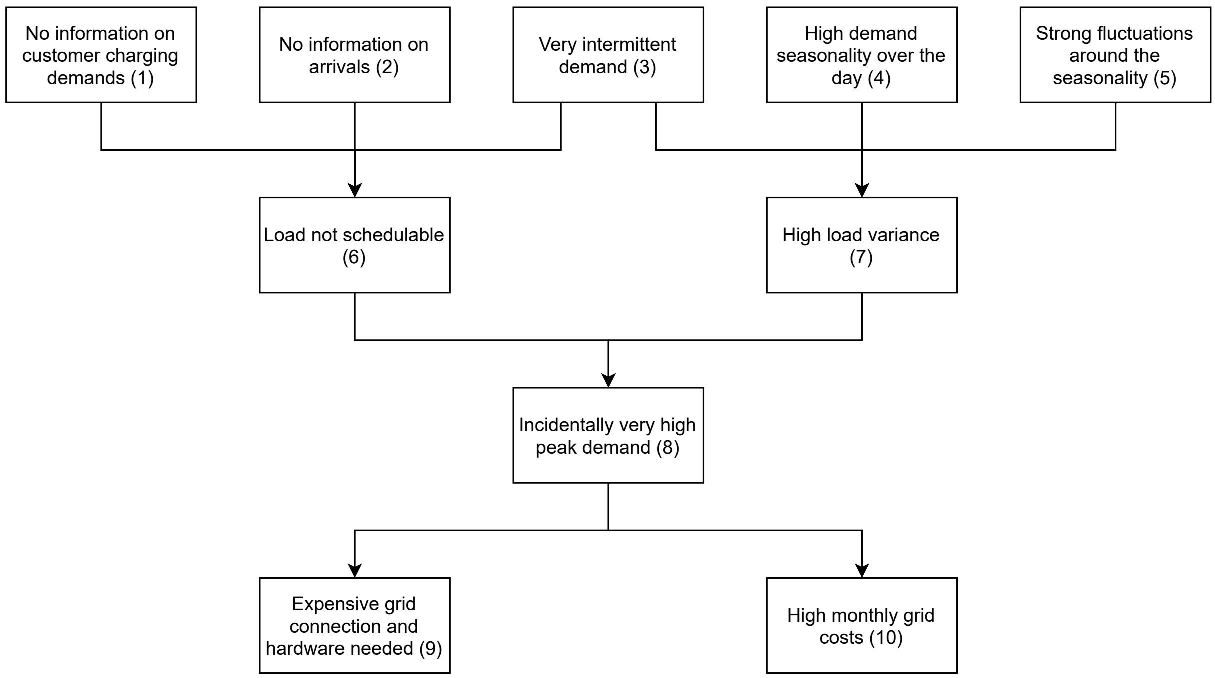

Figure 1.1: Problem Cluster

First of all, there is *no information on customer charging demands (1)*; most of the time there is no information how long an EV driver wants to wait before leaving the charging locations again, or how much battery charge they need before being able to arrive at their destination. Furthermore, *there is no information on when an EV driver will arrive (2)*, as they do not have to place a reservation on a charging spot. Finally, the nature of fast-charging locations is to have a *very intermittent demand (3)*. These three factors combine into an encapsulating problem, which is that *the required load is not schedulable (6)*, which in turn *incidentally causes very high peaks in the required load (8)*.
Furthermore, the *very intermittent demand (3)* also causes a high load variance. This is further increased by having a *high seasonality over the day (4)* and *strong fluctuations around this seasonality (5)*. These factors cause a *high load variance (7)*. Having a high load variance implicitly tells us that, again, *there will occasionally be very high demand peaks (8)*.
Finally, as elaborated in Section 1.1.1, *incidentally having a very high peak demand (8)* requires *expensive grid connections and hardware (9)* in order to be able to support those peaks. Furthermore, *these high demand peaks (8)* also *increases the monthly grid costs (10)*.

1.2 Research Questions and Deliverables

The main objective of this research is to explore options to maximizing the profits of company X's Fast-Charging operations, by optimizing the peak energy demand from the grid. Looking at the problem cluster presented in Section 1.1.3, it is clear that solving the main problem, *incidentally very high peak demand*, will reduce the expenses for the charging location. Solving this problem can either be done by solving underlying problems, or by implementing solutions that solve the problem despite the underlying problems still being present. As for the underlying problems, the *high load variance* is implicit with the market in which company X operates, and thus it is not subject to change in this research. The other underlying problem, the fact that the *load is not schedulable*, can possibly be solved if company X implements some sort of system in which customers present their arrival times and charging demands. However, this research will focus on solving the main problem as to provide solutions even if there is no customer information available. The main research question will therefor be defined as:

> **Main Research Question.** *How can peak-related costs be reduced at fast-charging locations for EVs in the absence of customer arrival- and charging information, and what is the impact of the possible solutions?*

1.2.1 Research Sub-questions

In order to answer the main research question, multiple sub-questions will have to be answered first. The sub-questions are categorized by the logical step they belong to and display the section in which the research question is discussed.

I. Analysing Current Situation

The first step is to create a benchmark to which we can compare proposed solutions. Multiple questions will have to be answered to create a overview of the current situation.

Research Sub-question 1*. What are the amounts of costs involved in operating a fast-charging location? (Section 2.2)*

Research Sub-question 2*. How does the current demand behave over different time periods? What are the current demand peaks? How often do those peaks occur? (Section 2.4)*

II. Generating Possible Solution Ideas

After quantifying the problem by analysing the current situation, we need solutions to solve the problem. A literature research conducted in this step will present possible solutions.

Research Sub-question 3*. What kind of solutions are proposed in the literature for reducing peak energy demand? (Section 3.1)*

Research Sub-question 4*. Which solutions are applicable for company X's situation? How would they be applied? To what extend can they be combined and how? (Section 3.2)*

III. Creating Methodologies

Knowing which solutions are valuable to test out, methodologies have to be created on how to approach setting up experiments using the solution, and how to gain meaningful results out of them.

Research Sub-question 5*. How can the proposed solutions be modeled? How should the proposed solutions be evaluated? (Chapter 4)*

Research Sub-question 6*. How should the experiments be designed? (Section 5.2)*

IV. Result Analysis

When the experiments are finished, the results have to be analysed on the impact they would have, both in customer experience and in decrease of operating costs.

Research Sub-question 7*. How do the proposed solutions perform? What impact do the solutions have on company X's profit? (Section 5.3)*

Research Sub-question 8*. What are the drawbacks of the proposed solutions? What impact do the solutions have on customer experience? (Section 4.1.1, Section 4.2.1, Section 4.3.1 and Section 5.3.3)*

1.2.2 Research Scope

Now that the research questions are defined, it is important to define a scope in which they will be investigated. Below, an overview is found defining the scope of this research.

Countries

company X is active in many European Countries. Each country has different rules and associated costs to high energy usage. While the model aims to be generic enough to include a wide range of countries, this report will focus on the data originating from the Netherlands.

Charging Stations

Of all the charging locations, fast-charging locations are the main driver when it comes to energy-related expenses for reasons explained in Section 1.1. This research will therefor focus on this group of locations.
Note that these locations will often still house Alternating Current (AC) Chargers as well (see Sections 2.1.2 and 2.3), which are taken into account in the location's demand models in this report.

Input Variables

This report will focus solely on lowering energy-related costs, given a certain location configuration. This means that geographical location allocation, as well as demand forecast, location design (types and amounts of chargers) and other types of input parameters will *not* be subject to optimization or investigation. These kinds of variables will be treated as input variables and the accuracy and efficiency of these variables are thus not discussed in this report.

Tool

In order to provide company X with the means to analyse these problems not only now but also in the future, a tool will be created that can help company X make decisions on their Peak Reduction measures. This tool will implement the proposed model and provide easy access to performing simulation experiments.

1.3 Report Outline

Chapter 2 will present an analysis of the working context, giving an overview of the workings of the field, explaining the different stakeholders and equipment, as well as present an overview of the current data on company X's Fast-Charging locations. Chapter 3 presents the current literature on relevant topics, and discusses where this report will fit into the current literature. Chapter 4 discusses the selected solutions and describes the methodology and model used for each of the solutions. Chapter 5 presents the results of the experiments with the proposed solutions and presents findings on these results. These findings will be used to create conclusions and recommendations in Chapter 6, where also the limitations of this research and possibilities for further research will be discussed.

2 CONTEXT OVERVIEW

This chapter focuses on the working context of the project. Section 2.1 introduces the actors and terminology of EV-charging, Section 2.2 presents an overview of the costs associated to operating a Fast-Charging location. Section 2.3 visualizes an overview of the connections and interactions at a fast-charging site. Section 2.4 provides data insights into the current situation. Finally, Section 2.5 concludes the chapter.

2.1 EV Charging

This section will go over the different terminology and actors in the EV charging branch.

2.1.1 Actors

It is important to understand the different actors in the EV-Charging context in this report. We will discuss Charge Point Operators (CPOs), Mobility Service Providers (MSPs), Grid Operators and EV-drivers.

Charge Point Operators

A Charge Point Operator (CPO) is a company that is responsible for installing, maintaining and operating the charge poles. While the exact business models of CPOs differ, their main cash flow comes from selling the installation of charge poles and auxiliary services like maintenance, as well as fees from MSPs (see below). The CPO is responsible for connecting the charge pole to the grid and they pay the energy fees to the Grid Operators and Energy Suppliers (energy costs as well as connection and transportation fees).

Mobility Service Providers

Mobility Service Providers (MSPs) are parties that mediate between the CPO and the EV-driver (consumer). They provide services for payment and provide products like charging-subscriptions as well as payment cards. Alternatively, they handle payments via an smartphone app. The MSPs have contracts with CPOs allowing the MSP to be able to use the charge poles owned by the CPO. While many pricing constructions can be imagined, often the CPO receives some margin per sold kWh, with the MSP determining what the price per kWh would be for the EV-driver. While the contracts can differ greatly, it can be speculated that the CPO might impose additional restrictions on the contract such as for example a maximum consumer-price per kWh.

Grid Operator

The Grid Operator is responsible for maintaining a healthy energy grid in the area where they are active. They sell grid connections and reserve grid capacity for high-usage customers.

Their focus lies on ensuring that all energy demand can be transported over the grid. The grid operator is not responsible for supplying the energy, which is done by an Energy Supplier.

EV-Driver

The EV-driver is the end consumer who uses the charge pole maintained by the CPO and pays for the charging sessions through their MSP.

2.1.2 Charge Poles

Their exist many types of charge poles, with differing amounts of charge speeds and charge methods. These charge poles can be categorized based on their charging method.

AC-Chargers

AC-Chargers provide Alternating Current (hence the ”AC”) to the EV. However, in order to charge the battery of the EV (or any battery for that matter), Direct Current (DC) is required. This means that the EV needs to convert the current, for which it has a AC-DC converter installed. This converter is however small and thus often cannot take high amounts of current, resulting in large charging times. This earns this type of charger its unflattering nickname ”Slow-Charger”. These kinds of chargers are often found in consumer homes, large charging plaza’s and at public urban charging spots. These kinds of chargers are mostly fit for overnight charging due to their low currents. The maximum amount of energy that can be supplied to an EV through an AC-charger is 19.2 kW [1]. Ultimately, the amount of energy that the EV can actually take is determined by its transformer and battery.

DC-Chargers

DC-Chargers circumvent the need for the transformer in the EV by providing Direct Current by converting the AC current from the grid before supplying it to the EV. This allows the charger to supply the energy straight into the battery without getting bottle-necked by the converter inside the EV. For DC-charging, the definition in the J1772 standard defines a level 1 DC charger with a maximum energy throughput is 48 kW, and a level 2 DC charger with a maximum energy throughput of 400 kW [1]. Nowadays, most DC-chargers implement the level 2 DC charging, with chargers currently ranging from 50kW to 350kW. The term ”Fast Charging” (also confusingly named ”DC-charging”) is used for DC charging with 50 kW or lower energy throughput, while everything above 50 kW is coined ”Ultra-Fast Charging”, also named ”HPC-charging” (High Power Charger). For this report, we will use the term ”Fast-Charging” to span all types of DC-chargers. These kinds of chargers are found at in-transit charging locations. Their high charging speeds make them excellent for recharging during a trip.

2.2 Cost Components

The introduction of DC Fast Chargers (50 kW) on public charging locations has introduced more erratic demand on the grid, with higher demand peaks. Recently, new fast chargers have become capable of delivering higher power amounts, increasing the problem even further. These chargers are called High-Power Chargers (HPCs), currently going up to 350 kW. This causes two obstacles for the CPO to overcome, as discussed in Section 1.1. First, in order to assure the peak demand can be met, the hardware on the charging site has to be able to handle the large amounts of energy. Second, the grid operator needs to reserve capacity for this site. In this section we will discuss the costs associated with the hardware and the energy contract respectively. The elaborated costs are calculated individually per European Article Number (EAN). An EAN is a code specific to the grid connection of a location. Theoretically multiple EANs can be present on a single location, however, this only occurs in very specific circumstances. In practice, the relation between a location name and an EAN code is one-on-one. As such, this report will be using the two terms interchangeably.

2.2.1 Investment Costs

When thinking about investment costs for Fast-Charging locations, many different elements can come to mind. For this report however, we will only look at two elements that have a direct connection to the expected peak power: grid connections and transformer costs. One could argue that the number and types of charge poles also has a direct connection with the peak power, and one would be right. However, as stated in the research scope (Section 1.2.2), the types and amounts of chargers will be treated as input variables and are thus not subject to optimization. As such, in analyzing different scenarios these charge poles -and thus the associated costs- remain constant and can therefore be left out of the equation.

Grid Connection

The choice for a certain grid connection determines the maximum concurrent power that can be supported. The exact costs and limits of different connections differ over the grid operators. Table 2.1 shows example investment costs of different grid connection sizes, based on the pricing of Liander in 2021 [2]. As can been seen from the table, these investment costs increase significantly with each step up. Moreover, these costs are incurred not only for connecting a site to the grid, but also again on disconnecting from the grid, for example when upgrading the grid connection or decommissioning a site. Finally, there is also a difference in the associated time-to-market. Experts say that with a bigger connection, the time needed to install the connection increases. This means that a site can be operational (and generating revenue) earlier when choosing a smaller sized connection.

Example of grid connection prices (Liander 2021 [2])	
Max. Capacity (in kW)	Costs (in €)
100	4,522.00
160	5,037.00
630	18,508.00
1,000	25,179.00
2,000	36,406.00
5,000	237,731.00
10,000	282,321.00

Table 2.1: Example costs for grid connections

Transformer

Charging poles are operating on low voltage alternating current (400Vac [1]). When the grid connection increases, the supplied voltage may be too high, requiring a transformer to change the voltage down to the required amount. Such a transformer results in significant costs, with prices in the range of €50.000, required whenever the peak energy usage exceeds 160 kW [2]. Furthermore, the transformer has a power loss, which further increases the monthly energy

[1] 400 Volts Alternating Current
[2] Limit for the Netherlands, other countries may apply different limits

costs. Finally, a transformer takes up space at the charging location which also introduces costs, either in the form of contracted costs per square meter or in the form of opportunity costs, as there could have been more chargers in the same allocated area providing additional revenue. The power loss and costs per square meter will not be implemented in the model, but will be additional benefits for locations without the need for a transformer.

2.2.2 Energy Contract

In order to assure the demand can be met, the grid operator reserves a certain amount of energy transport capacity, determined in the contract between grid operator and the CPO (in this case company X) as the Contracted Value. Naturally, this reservation of capacity costs money, which gets charged to the CPO. The way the Contracted Value is determined differs per country. In the Netherlands, whenever the 15-minute demand exceeds the contracted value, the Contracted Value is upgraded to the new peak. The Contracted Value has to be manually adjusted down, and can never be reduced below the highest observed peak demand in the past 12 months. The implications of such contracts are that a single time period of 15 minutes with exceptionally high demand can dictate the costs of the Contracted Value for the coming 12 months. In addition to the Contracted Value, depending on the size of your contract, there can also be additional monthly costs for the observed peak energy usage for that month specifically. Table 2.2 provides an example of energy transportation costs from Liander in 2021 [3].

Example of monthly grid operator energy transport prices (Liander 2021 [3])		
Max. Peak (in kW)	Contracted Value (in €/kW)	Monthly Peak (in €/kW))
50	0.76	-
136	1.93	1.74
2,000	1.23	1.74
>2,000	2.01	2.50

Table 2.2: Example costs for energy contracts

2.3 Overview Charging Site

Now that the most important elements of a charging location are discussed, it may be helpful to visualize a charging site. Figure 2.1 presents a simplified overview with the components discussed in the previous Sections. In this Figure, multiple chargers of different types can be seen, with DC-Chargers ("Ultra-Fast-Chargers" [A] and "Fast-Chargers" [B]) and AC-Chargers [C]. The chargers all connect to the transformer [D] which in turn is connected to the grid [F]. Somewhere between the grid [F] and the transformer [D], the amount of energy is measured [E]. As can be seen from this Figure, the energy usage from the combined chargers is measured at this point, including possible energy losses in the transformer. Note that this Figure is a generalization, as the way the energy drawn from the grid is measured differently in varying countries and even differs within a country depending on different factors including the type of grid connection. Discussing all the different variations and nuances is beyond the goal of this report, and the purpose of the Figure is to create a visualization of the connections at an average charging site. This Figure will be adopted later in the report when discussing solution proposals to illustrate the differences in site configuration.

2.4 Data Analysis

Before implementing any solutions, it is useful to investigate what the current situation is, which provides insights and creates a benchmark for later analysis to compare to. This section

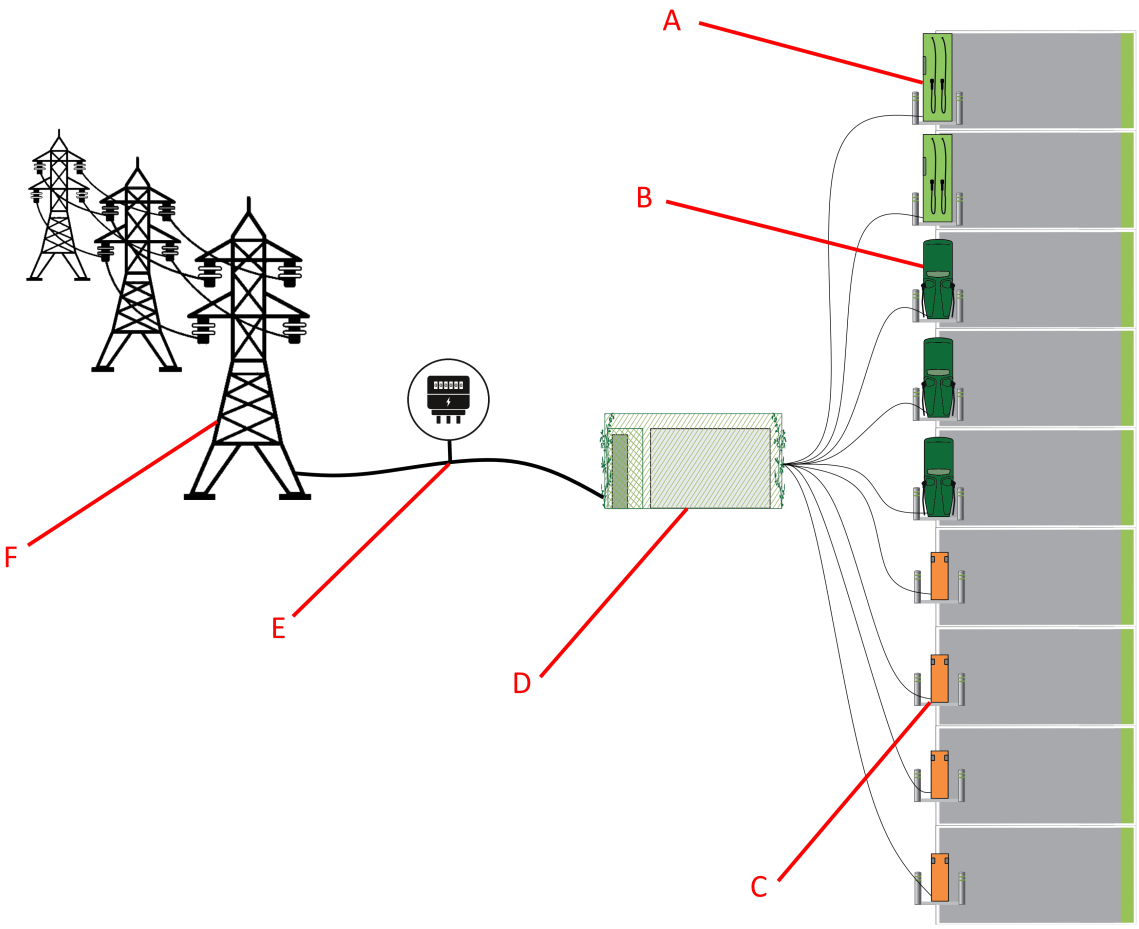

Figure 2.1: Overview Charging Station

presents multiple figures representing the data, providing different viewpoints and information. Each subsection presents a question which that is answered by the presented data. In some cases, it might prove useful to additionally look at a single EAN (location) to get a better feel for what the data on EAN-level looks like. In those cases, the charging location 'Location Y' will be used.

2.4.1 Seasonality

It is useful to recognize the patterns in daily and weekly power consumption. Below, an overview can be found of these seasonalities.

Daily seasonality

Question. What is the average energy demand at a certain time during the day on company X's chargers at fast-charging locations?

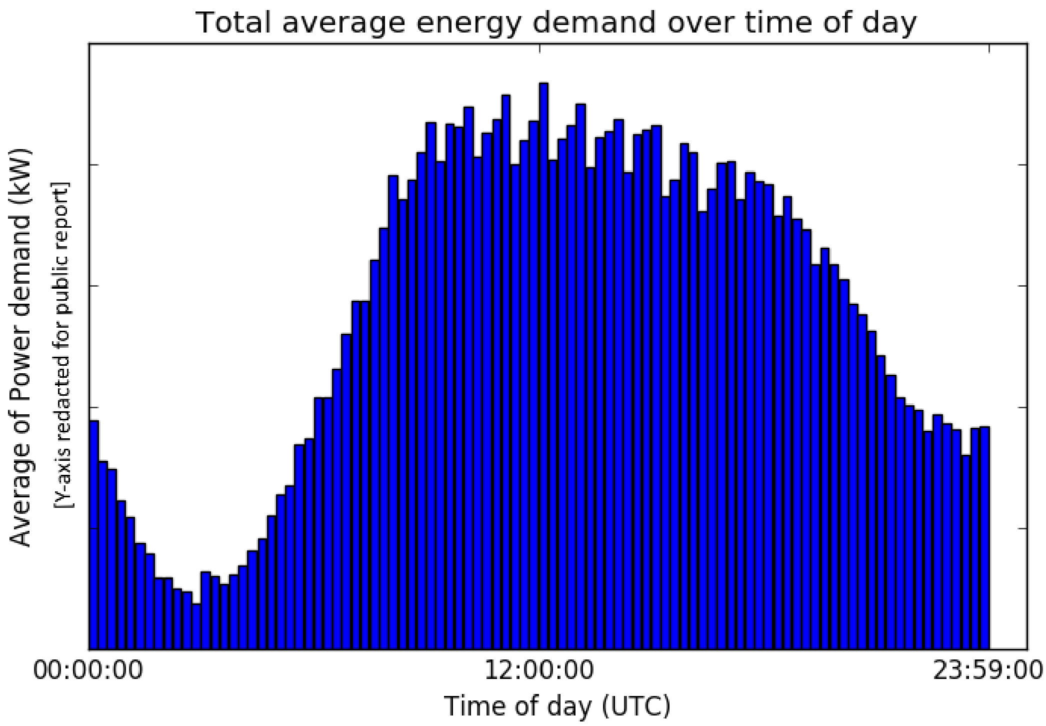

Figure 2.2: Average Energy Usage over the Day

Figure 2.2 shows that there are large differences between nighttime charging at Fast-Charging locations, and charging during the day. A peak is observed somewhere between 11:00 and 13:00 (UTC).

Weekly seasonality

Question. What is the average energy demand at a certain time during the week on company X's chargers at fast-charging locations?

Figure 2.3 shows that the weekdays have similar demand patterns, whereas the weekends show a significantly smaller energy demand.

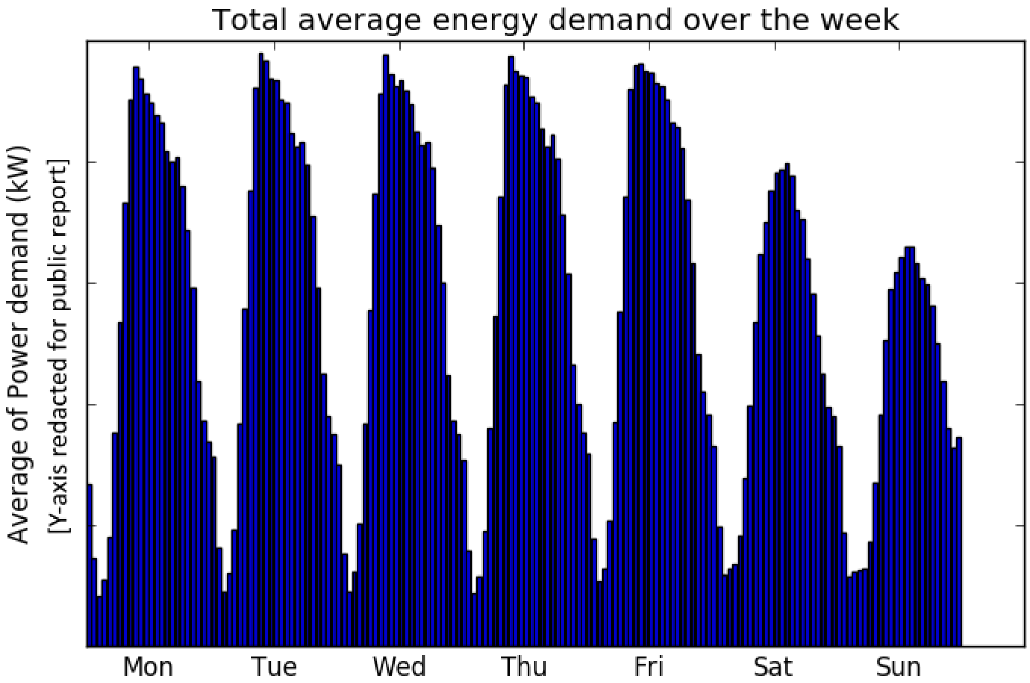

Figure 2.3: Average Energy Usage over the Week

2.4.2 Load Factors

It is important to know how much of the reserved capacity is actually used, and how much is 'thrown away'. A good metric to indicate how much of the reserved capacity is utilized is the Load Factor. Let t be a 15-minute time slot for $t = 1, \ldots, n$. The demand in time slot t is denoted by d_t. The Load Factor L is described by the equation:

$$L = \frac{\bar{d}}{d^+} \tag{2.1}$$

where

$$\bar{d} = \sum_{t=1}^{n} \frac{d_t}{n} \tag{2.2}$$

and

$$d^+ = max(d_1, \ldots, d_n) \tag{2.3}$$

.
As follows from equation 2.1, the Load Factor L will be in the range $L \in [0, 1]$ and represents the fraction of the reserved capacity actually utilized. When trying to increase L, we can either try to increase the mean demand $\bar{d}$, or decrease the peak demand d^+. As this report does not look at ways to increase (or decrease) the daily demand, our only option is to somehow decrease the peak demand d^+.

Load Factor Distribution

A central question that arises regarding Load Factor is what the current distribution of Load Factors over the different locations is. Figure 2.4 shows the distribution of the Load Factors across all researched EANs. Notice that the majority of the locations have a Load Factor below 0.05, which means that only one twentieth of the reserved capacity is actually utilized.

Question. How are the Load Factors of company X's fast-charging locations distributed?

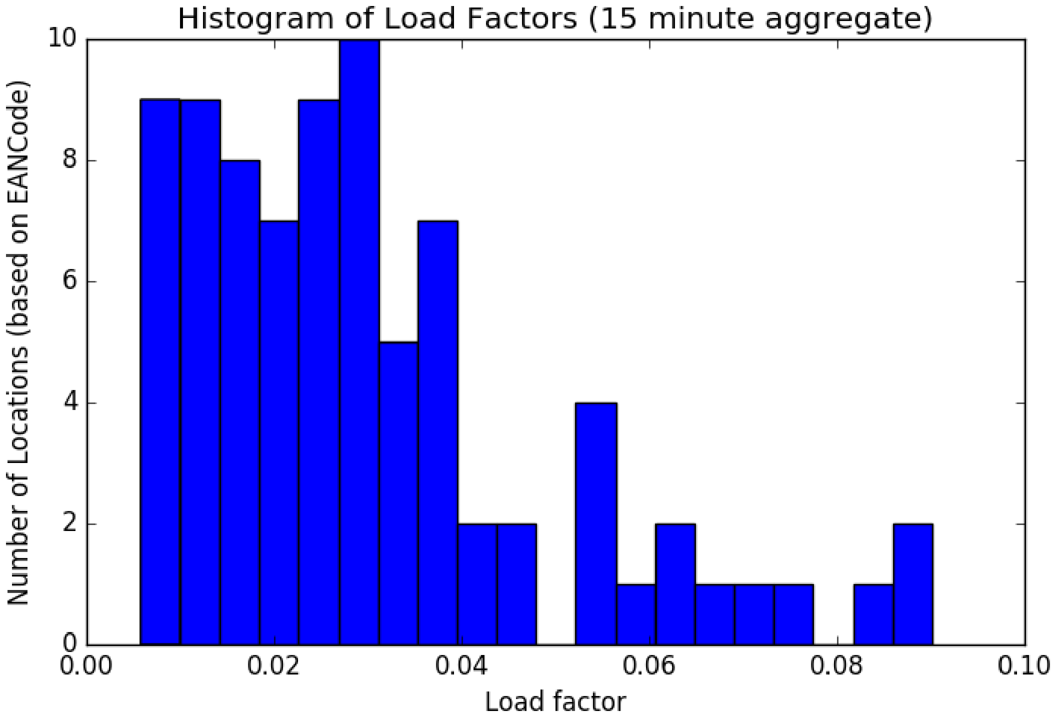

Figure 2.4: Distribution of Load Factors

Load Factor versus Peak Demand

It might be useful to determine if there exists a correlation between the Load Factor and the maximum peak demand. Figure 2.5 shows the distribution of Load Factors given their Peak Load. This figure indicates no such correlation.

Question. Is there a correlation between Peak Power and Load Factor at company X's fast-charging locations?

2.4.3 Example of energy demand at a location

Given the data found in Section 2.4.2, it might be useful to get a feeling what a time window of loading sessions looks like. Figure 2.6 shows the data from Location Y over a 3-day time period in November 2020. Each vertical line represents a 15-minute time interval, with the height indicating the amount of kW demanded. Recall from equation 2.1 that the Load Factor is influenced by the maximum demand in the time window. This means that a single outlier can have a big impact on the Load Factor. From this figure it can be seen that the contracted value would have been at least 250 kW, while the rest of the time no peak comes close, if there is any demand to begin with.

Question. What does the energy demand over time at a given location look like?

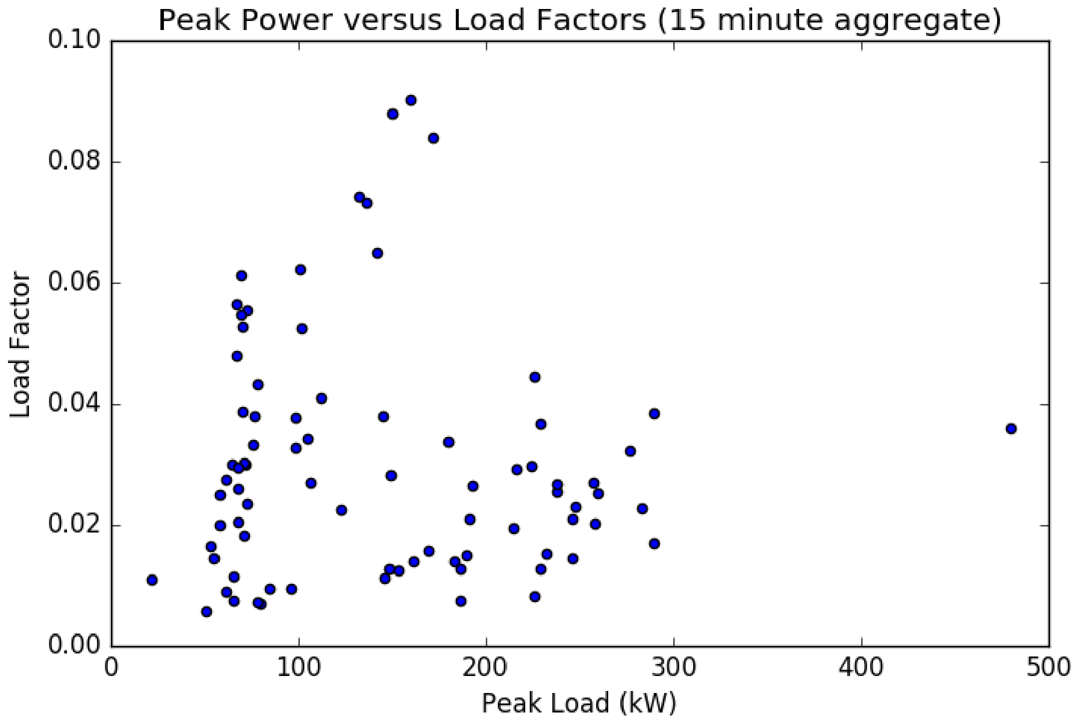

Figure 2.5: Peak demand vs Load Factor

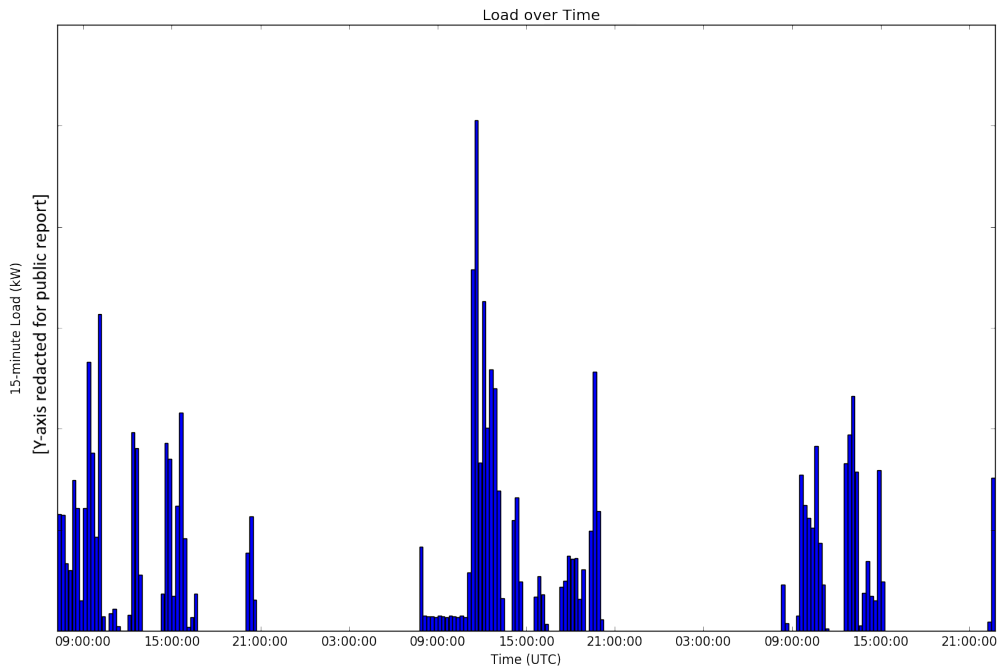

Figure 2.6: Example of energy demand at a location

2.5 Chapter Summary

This chapter has presented the different actors in the EV charging market, and elaborated on the different types of chargers and hardware found at an EV charging site. An simplistic overview of the connections at a charging site has been provided. We have presented the types of costs a CPO has to account for and how these costs are influenced. Finally, data has been presented to give an overview of the current performance of company X's charging locations in the Netherlands, and the term Load Factor was introduced as an indicator to how much of the reserved energy transport capacity is actually used by the charging site.
Summarizing, the CPO has to pay initial investments in the form of grid connections and auxiliary hardware like transformers. Furthermore, the CPO also has to pay monthly expenses to the grid operator for the transportation of the energy. Both the investment costs and monthly costs are highly dependent on the height of the energy peak that the charging location needs to be able to draw from the grid. The data analysis showed that the Load Factor is low over all fast-charging sites, with most values ranging between 0.01 and 0.05, meaning that only 1-5% of the total reserved transport capacity is utilized.

3 LITERATURE RESEARCH

This chapter presents an overview of the available literature concerning EV charging (Section 3.1). Furthermore, Section 3.2 reflects on how the current literature is applicable for fast charging locations and explains where this report tries to fit in within the current literature.

3.1 Literature

Recently, a lot of research has been conducted on the topic of charging electric vehicles, spanning a wide variety of topics associated with it. Daina [4], Wang [5], Weldon [6], Lin [7] and Shun [8] have modeled the usage and charging patterns of EV-drivers. Furthermore, research has been conducted on location-allocation of fast charging sites by Morro-Mello [9] and Motoaki [10]. More societal focused research is presented by Zheng [11] with research on the topic of Vehicle-to-Grid, using electric vehicles to help balance energy grids, and Fang [12] who focuses on the societal costs of EV charging.

Many papers have focused on reducing the peak demand in urban locations caused by EV home charging. Kang [13] and Jian [14] present concepts of real-time scheduling techniques for EV charging, with the goal of minimizing impact to the power grid. These techniques make use of the fact that EVs are charged at night and only have to be done charging when the EV driver wants to depart in the morning. This creates the opportunity to cleverly allocate the available energy and reduce the peak energy demand. For Fast-Charging locations, EV drivers want their EV to charge up quickly as they are in-transit and want to continue their journey as soon as possible. This creates a new problem of how to reduce peak demand on Fast-Charging locations.

Reducing the peak power on a Fast-Charging location is not only needed for grid stability, but also for financial feasibility for the CPO. Flores [15] and Muratori [16] outline the financial factors that can influence the decision of placing High-Power Chargers at charging locations and assesses the cost of electricity at Fast-Charging locations. They both show that the marginal costs of electricity demand goes down when the utilization of a Fast-Charging location goes up.

One of the solutions for reducing peak power is to not always meet the demand. Choices can be made to deliver less power to the EV driver in periods of high demand. This approach becomes a trade-off between customer satisfaction and financial gain. Many different approaches exist to optimize this trade-off, which make use of additional customer information like expected arrival time, preferred departure time or required state-of-charge of the battery. Casini [17] uses a receding horizon approach for minimizing peak power while guaranteeing customer satisfaction, by forcing the EV driver to select upon arrival a desired amount of energy to be charged at departure. Şengör [18] uses an LP model to maximize the Load Factor, using customer data on required state-of-charge at a certain specified departure time to optimize allocation of the available energy.

Another solution is to steer demand to lower demand time-periods. Xydas [19] presents a scheduling algorithm based on Multi-agent systems, where EV driver agents place bids for available electricity with the goal of minimizing the costs, while energy supplier agents set prices of electricity to push energy demand towards low-demand time periods. Zhang [20] uses a

game-theoretic approach to find the optimal allocation of energy given the departure deadlines of EV drivers and the cost of electricity as factors in each driver's willingness to charge. These methods require dynamic pricing towards the EV driver.
A third solution is presented in the form of storing energy during low demand time periods for later use during high demand. Muratori [21] and Elma [22] outline the benefits of adding energy storage to a Fast-Charging location and propose the deployment of microgrids for these locations, with a battery as a buffer between the supply and demand of energy. Batteries can reduce the peak demand and the associated demand charges, and increase efficiency of local energy generation by being able to store the surplus of energy whenever there is more supply than demand. Johnson [23] presents a methodology to determine the optimal battery size for a given demand.
Finally, a more visionary approach to solving the EV charging problem is discussed by Sarker [24] and Tan [25], who present the idea of battery-swapping stations where a depleted EV battery gets swapped out for a charged battery, theoretically minimising the lead-time of re-energising the EV while also creating opportunities for optimally recharging the depleted batteries. At the time of writing this report, the company NIO is planning to roll out these kinds of swapping stations and has presented its deployment plan [26].

3.2 Literature Reflection

The current literature contains many papers about energy distribution and peak shaving in the presence of EV charging. Most of the literature concerned with lowering demand peaks focuses on nighttime peak shaving in urban environments, where optimization can take place as cars will only have to be charged by morning, and they are connected longer than needed to reach that goal. In the case of fast-charging locations, this problem has not yet been extensively researched, presumably due to the fast-charging locations being a relatively new concept. The literature that does discuss peak shaving at fast-charging locations mainly uses dynamic pricing in order to sway customers to accept longer waiting times or change their behaviour to charge in low-demand periods of the day. Other literature uses ahead-of-time information on demand for optimally scheduling sessions. For this report, company X is interested in what other solutions can be used for peak shaving where pricing is not dynamic, and no session information is available prior to the EV driver arriving at the station. This report will use existing solutions for home smart charging and try to adapt them for fast-charging locations. More specifically, two concepts are chosen and additionally combined to see if that would further improve results. The first chosen concept is 'Smart Charging', where the maximum amount of grid-draw is capped at some value and the available energy is distributed in some way to the charging EVs. The second concept is the idea of integrating a battery into the micro-grid, creating a buffer for when peaks occur. This battery would be configured to store energy whenever the demand is below a certain threshold, and to supply additional energy to the chargers whenever the demand would be above the specified threshold to decrease the load on the grid. This report proposes a novel model where the two concepts are combined and used in fast-charging locations. Table 3.1 gives an overview of what kind of charging scenario (home-charging or fast-charging) is discussed and what the solutions are that the literature provides, and compares them with what this report presents.

	[13][14]	[17][18]	[19][20]	[21][22]	[23]	This work
Home Charging	✓				✓	
Fast-Charging		✓	✓	✓		✓
Dynamic Pricing			✓			
Smart Charging with Prior Info		✓				
Smart Charging without Prior Info	✓					✓
Energy Storage				✓	✓	✓
Combining Solutions						✓

Table 3.1: Literature Comparison

4 POSSIBLE SOLUTIONS & MODELS

From the literature, two solutions have been selected to be analyzed in detail to see how much they could reduce the peak-related costs in fast charging locations: Local Energy Storage and Smart Charging solutions. A third solution is added in the form of a combination of the two solutions. This chapter discusses the justifications for proposing the different solutions and presents the methodologies and functions that are used to build the model. The implementation of the model, and the exact implementations for the input functions and parameters can be found later in Chapter 5.

4.1 Local Energy Storage

This Section discusses the solution of Local Energy Storage, which introduces a battery in between the charge poles and the grid at an EV-charging site. Subsection 4.1.1 discusses the concept and the goals of this solution. Subsection 4.1.2 presents a mathematical model of this solution.

4.1.1 Justification

As shown by the literature (see [21], [22], [23]), local energy storage (a battery) can be used to decrease the peak grid demand by storing energy in periods of low demand and supplying energy from the storage system during peaks. Furthermore, it increases effectiveness of local energy generation, for example from solar panels or other renewable energy sources as energy generated in periods of low demand will not go to waste but can instead be stored for later use. Finally, the expected decrease in peak power can also lead to smaller (and cheaper) grid connections and auxiliary hardware, as discussed in Section 2.2.1. One positive effect from this solution is that the end-user will not experience any difference from their original charging experience. However, a downside is that initial investments have to be made to purchase and install the battery. Also, an extra point-of-failure is introduced, possibly increasing average maintenance costs. While maintenance costs are out-of-scope for this report, it is important to evaluate if the reduced costs from lower peaks justify the initial investment of the battery.
Figure 4.1 presents an adaptation of Figure 2.1, with the introduction of the battery into the system. Again, there are different types of chargers ([A], [B] and [C]) which are now connected to the battery [D]. In turn, the battery is connected to the transformer [E]. The transformer is connected on the grid [G], where somewhere along this connection an energy meter is installed [F]. Note that, as explained in Section 2.2.1, the transformer may be omitted if a small grid connection is used. In this case, the battery is directly connected to the grid, with the energy meter somewhere along that connection. The blue lines in the Figure show the tunable parameters, with the Battery Size b^+ [X] and the maximum grid draw g^+ [Y]. Section 4.1.2 will discuss these parameters in detail.

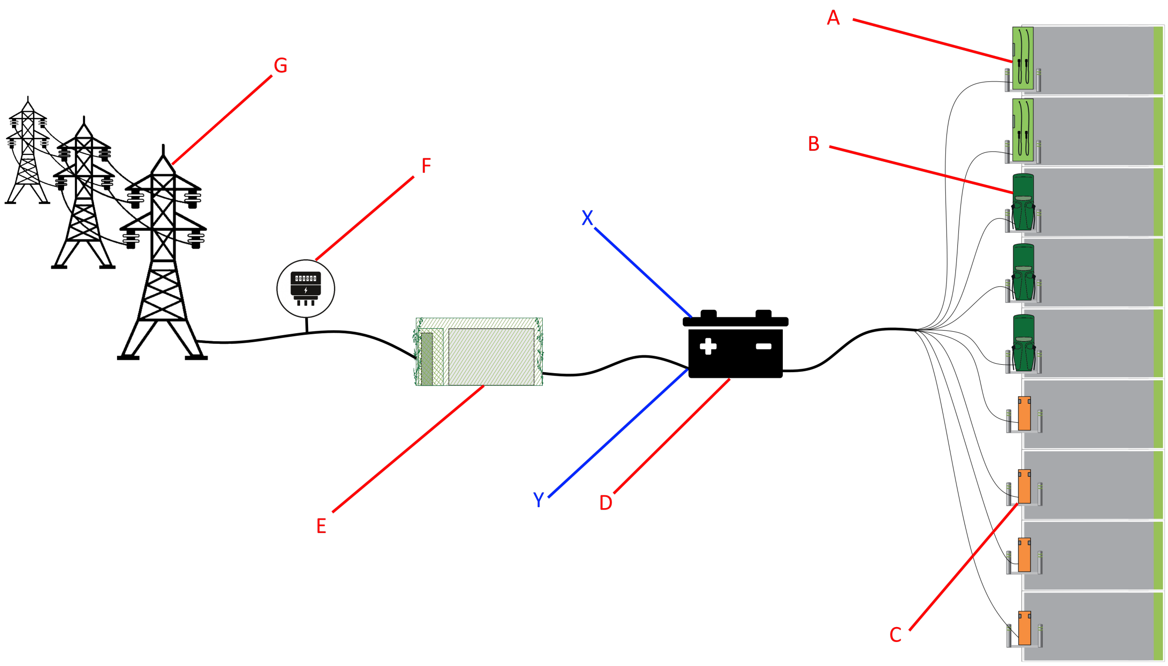

Figure 4.1: Overview Charging Station

4.1.2 Methodology & Model

A model of the state of the battery is needed in order to analyze this solution. As inputs for this model, a battery size b^+ in kWh and a maximum power draw from the grid g^+ in kWh per time-step t are defined. For each time-step t with corresponding charger demand d_t, the battery will either store the energy in a battery whenever a surplus of energy is available, or draw from the battery the difference between the demand and the specified max power draw from the grid, bounded by the capacity of the battery. The amount of stored energy at any time-step b_t is described by equation 4.1.

$$b_t = min(b^+, \quad b_{t-1} - d_t + g^+) \tag{4.1}$$

The amount of power drawn from the grid on a certain time-step g_t is given by equation 4.2 . It describes that the amount of energy taken from the grid is either the maximum allowed grid draw g^+ or the amount of energy needed to fill the battery, whichever is lower.

$$g_t = min(g^+, b^+ - b_{t-1}) \tag{4.2}$$

It can be observed from equation 4.1 that the battery charge b_t can be negative. This does not concern our model as it allows for freedom to choose what happens whenever the battery charge b_t drops below 0.

4.1.3 Battery Costs

In order to analyze the profitability of implementing local energy storage, a cost function is required to calculate the investment costs of a battery with a certain size. This battery cost function will be defined as $B(b^+)$, which is some function that returns a value B depending on a given battery size b^+. The implementation of this function for the experiments in this report will be done in Section 5.2 discussing the experimental setup.
When investigating the battery solution with a certain battery size b^+, max grid demand g^+ and battery cost B, we can calculate the total savings by first calculating the peak-related costs per

time-step if no battery was present and compare it to the peak-related costs after introducing a battery to the system. Subtracting those two from each other offers a list of savings A per time-step t for the entire time-frame. We can now subtract the initial costs for the battery at $t = 0$ and using a certain discount rate r we can find the Net Present Value (NPV) by applying the data to equation 4.3.

$$NPV = \frac{A_t}{(1+r)^t} \tag{4.3}$$

4.2 Smart Charging

This section discusses the second proposed solution: Smart Charging, which limits the amount of energy the chargers can collectively draw from the grid. Subsection 4.2.1 presents the concepts and goals behind the solution. Subsection 4.2.2 presents a mathematical model of the solution.

4.2.1 Justification

Smart Charging is the name given to the practice of distributing a limited amount of electricity load to multiple customers. Given that the highest peaks only occur rarely, the idea is to limit the available energy in such a way that it normally would not have an impact on the end-user, but at the same time does flatten out the highest outliers. Company X assumes this approach requires no additional investments to implement, but will have a negative impact on the end-user as they will not always be able to charge as fast as they normally could, which is why evaluating this solution should account for that.
Figure 4.2 shows a representation of a site implementing Smart Charging. The chargers of different types [A], [B] and [C] are all connected to some controller [D] which controls the amount of energy each individual charger can draw. The controller is connected to the transformer [E] which in turn is connected to the grid [G], where an energy meter [F] is placed somewhere along this connection. In case the transformer is not present, the Smart Charging controller [D] is connected directly to the grid [G] with the energy meter [F] somewhere along that connection. The amount of energy available for the chargers s^+ [Z] is able to be tuned. Section 4.2.2 will discuss this parameter in more detail.

4.2.2 Methodology & Model

As discussed in Section 1.1.2, there is currently almost no information available to deploy effective scheduling methods based on existing algorithms. While there is information available about the 'present' situation of a charging site, like for example the amount of currently charging EVs, or the time that the EVs have been charging, this model assumes no prior knowledge as to provide a worst-case analysis of the possibilities of deploying this solution. Even so, Smart Charging can still be useful in reducing the peak load, albeit with a very simplistic energy distribution algorithm. Given a demand $d_{c,t}$ for each customer c at time-step t, and a maximum grid draw g_t^+, where the total demand is $d_t = \sum_c d_{c,t}$, the amount of energy supplied to customer c, $s_{c,t}$ is determined by equation 4.4.

$$s_{c,t}(d_{c,t}, d_t, g_t^+) = \begin{cases} d_{c,t}, & \text{if } d_t \leq g_t^+ \\ (d_{c,t} * g_t^+)/d_t, & \text{otherwise} \end{cases} \tag{4.4}$$

The total charger draw s_t at time t can be computed easily by computing the sum over all customers c.

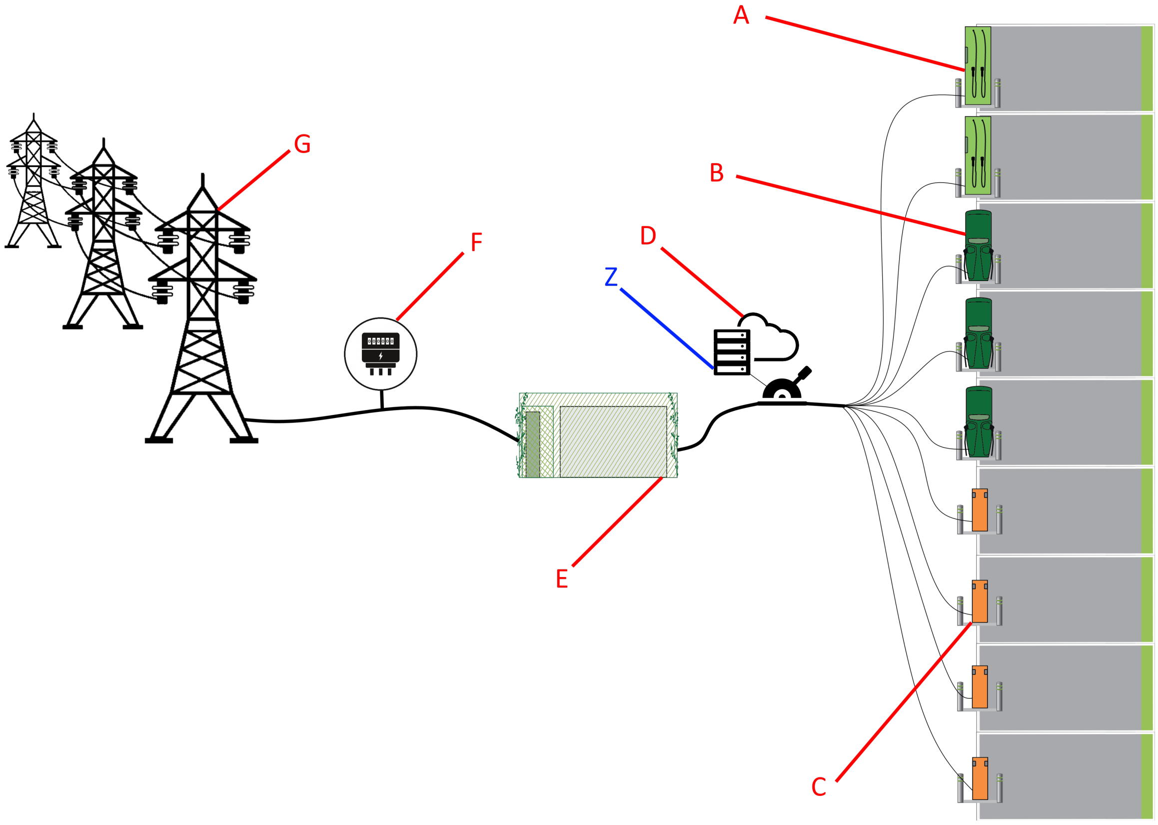

Figure 4.2: Overview Charging Station

$$s_t(d_{c,t}, d_t, g_t^+) = \sum_c s_{c,t}(d_{c,t}, d_t, g_t^+) = min(d_t, g_t^+) \tag{4.5}$$

It follows that the total charger draw s_t is always less or equal to the maximum grid draw g_t^+:

$$s_t \leq g_t^+ \quad \forall t \tag{4.6}$$

In the implementation specific for this report, the available energy from the grid at time-step t, g_t^+ will be constant over t, which is to say that $g_t^+ = g^+ \quad \forall t$.
Note that the distribution algorithm described by equation 4.4 is by no means the only way of distributing the available energy, nor is it necessarily the best way. Other algorithms, possibly taking into account more information, can be used to find a more optimal way of distributing the energy over the chargers. Further research can be conducted in order to analyze and compare other distribution algorithms.

Financial Impact

In order to calculate the negative financial impact due to unfulfilled demand, a function needs to be designed that represents these incurred costs at time-step t, given the demand d_t and provided energy to the chargers s_t at that time-step. While the exact implementation of this function for the experiments in this report will be presented in Section 5.2.1, let us assume we have a function $E_t(d_t, s_t)$ that describes the costs, we can then compute the total incurred costs E by summing E_t over t.

$$E(g^+) = \sum_t E_t(d_t, s_t) \quad \text{, where } s_t = min(d_t, g^+) \tag{4.7}$$

The financial impact can also be positively influenced by the lower demand peak, which causes lower peak-related costs towards the grid-operator. Let t_{hours} be the amount of hours in a single time-step. Given an original peak grid draw $g_O^+ = max(d_t)/t_{hours}$ (in kW) and a 'new' peak when applying Smart Charging $g_S^+ = g^+/t_{hours}$ (in kW), the associated grid operator costs can be used to calculate the cost savings F based on some function $GridOperatorCosts(kW)$ taking as a parameter the highest grid draw amount observed. While the implementation of this function will be defined in Section 5.2.1, let us assume there is a function $GridOperatorCosts(kW)$, we can then state the following:

$$F(g_O^+, g_S^+) = GridOperatorCosts(g_O^+) - GridOperatorCosts(g_S^+) \tag{4.8}$$

The net financial impact can now be computed by subtracting the additionally incurred costs E from the cost savings F. It should be noted that the cost savings F are based on a monthly peak, where the incurred costs E are expressed for an undefined period of time, as such, either E or F should be scaled accordingly to match in time-span.

$$FinancialImpact(g_O^+, g_S^+) = F(g_O^+, g_S^+) - E(g_S^+) \tag{4.9}$$

Affected Time-slots

Besides financial impact, another metric for investigating the impact of Smart Charging is the amount of affected time-slots. Given a demand d_t for time-slots t and a maximum grid draw g^+, the amount of affected time-slots is trivially computed by counting the amount of time-slots where $d_t > g^+$.

Simulation replications

Over multiple simulation replications, an average-, minimum- and maximum financial impact and count of affected time-slots are stored for analysis. As it is assumed that no additional investments are needed for Smart Charging, we can use the financial impact as a sole financial indicator on the expected net result per time-step t.

4.3 Combined Solution

4.3.1 Justification

As shown in the literature, both local energy storage and Smart Charging solutions can decrease the peak power used by fast charging locations. It would be interesting to know what the impact would be when combining both solutions. The idea behind this approach is that by combining both solutions, a smaller battery would be required, as well as a less-strict maximum charger draw. This would both decrease the initial investment compared to solely using a battery, and decrease the amount of unfulfilled kWhs to the end-user, resulting in lower costs for unfulfilled demand.
Figure 4.3 shows the combined solution setup. Like the Smart Charging solution, all types of chargers [A], [B] and [C] are connected to a controller [D] that decides how much energy is available for the individual chargers. The controller is connected to a battery [E] which is connected to a transformer [F] which in turn is connected to the grid [H]. Somewhere between the transformer [F] and the grid [H] is the energy meter [G], unless the transformer is not present, in which case the energy meter is placed between the battery and the grid. The combined setup has three tunable parameters; the battery size b^+ [X], the maximum grid draw g^+ [Y] and the maximum charger draw s^+ [Z]. These parameters will be discussed in more detail in Section 4.3.2.

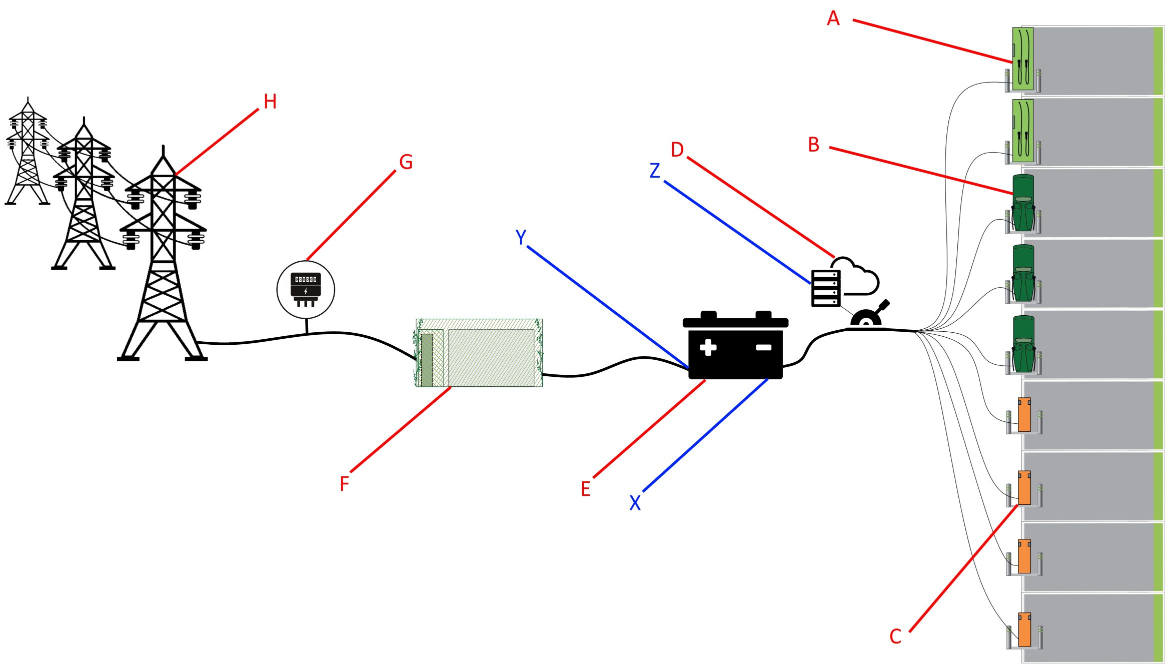

Figure 4.3: Overview Charging Station

4.3.2 Methodology & Model

While the Smart Charging solution required as parameters only a maximum grid draw g^+, the battery solution used two parameters; maximum grid draw g^+ and battery size b^+. For the combined solution, we need to introduce a third parameter; maximum charger draw s^+. This maximum indicates how much energy can be drawn by the chargers, which in this solution is a distinct metric from how much energy can be drawn from the grid, as we also include a battery in between the grid connection and the chargers. This maximum charger draw is only a limit, and not necessarily always the amount provided to the chargers as there might not be enough charge in the battery to reach this limit, or there might simply not be as much charging demand d_t at that time. The actual amount of energy provided to the chargers at time t is denoted as s_t. The maximum grid demand g^+ determines how high the peak demand on the grid-side can be. This ultimately decides the size (and costs) of the grid-connection, as well as the need for a transformer. The maximum available energy s^+ dictates the maximum concurrent power draw from the chargers at the fast-charging location, and thus ultimately dictates the amount of kWh not delivered to customers. With the battery, there is also a buffer between these two points, where the battery can fill the gap between what comes into the system via the grid, and what goes out into the chargers, while being limited in its ability to fill the gap based on its State-of-Charge b_t (amount of kWh stored at time-step t). Whenever there is a surplus, the battery is filled to a maximum b^+. These parameters have time-step associated values in the form of grid draw (g_t), State-of-Charge of the battery (b_t) and energy delivered to the chargers (s_t). The actual demand per time-step t is described as d_t. These three parameters are described in equations 4.10, 4.11 and 4.12.

The energy delivered to the chargers at some timestep s_t is equal to the demand at that timestep d_t, bounded by the maximum charger draw s^+, and the available energy in the system (grid and battery combined) $g^+ + b_t$:

$$s_t = min(d_t, \quad s^+, \quad g^+ + b_t) \tag{4.10}$$

The State-of-Charge of the battery at some time-step is determined by the amount of energy coming into the system from the grid g_t and the amount of energy going out of the system towards the chargers and EVs s_t, bounded by the capacity of the battery b^+:

$$b_t = min(b^+, \quad b_{t-1} + g_t - s_t) \tag{4.11}$$

The amount drawn from the grid at some time-step is equal to the maximum grid draw g^+, bounded by the amount of energy the system can use, either by storing it in available battery capacity $b^+ - b_{t-1}$ or by supplying it to the charge poles s_t:

$$g_t = min(g^+, \quad b^+ - b_{t-1} + s_t) \tag{4.12}$$

For the incurred costs E for not fulfilling all demand, the equations 4.4, 4.5 and 4.7 are reused. For the cost savings F due to lowering peak, equation 4.8 is reused. The financial impact is redefined in equation 4.13.

$$FinancialImpact(g_O^+, g_S^+, s^+) = F(g_O^+, g_S^+) - E(s^+) \tag{4.13}$$

If we want to know whether the investments on the battery are worth it for the Financial Impact, we need to take into account the time-period T over which the Financial Impact is calculated. We can now calculate the Net Present Value (NPV) by applying equation 4.3 to the Financial Impact, with A_t equal to the calculated Financial Impact for all time-steps $t = 1..T$. For $t = 0$ we need to take the initial investment of the battery $B(b^+)$ into account, as well as the possible decrease in costs for the grid connection and auxiliary hardware, $C(g_O^+, g_S^+)$, based on a lower observed (and supported) peak grid draw.

$$A_t(g_O^+, g_S^+, b^+, s^+) = \begin{cases} FinancialImpact(g_O^+, g_S^+, s^+) - B(b^+) + C(g_O^+, g_S^+), & \text{if } t = 0 \\ FinancialImpact(g_O^+, g_S^+, s^+), & \text{otherwise} \end{cases} \tag{4.14}$$

The NPV will be calculated according to equation 4.3 for many different combinations of (g_S^+, b^+, s^+) with the observed value of the original maximum grid draw g_O^+, where the highest NPV will provide the recommended setting.

4.4 Chapter Summary

This Chapter has presented three solutions for solving the high peak-related costs at fast charging locations. First of all, batteries were proposed as a solution to the incidental high peaks, where the battery would provide additional energy to the charge poles whenever a high peak would occur, in order to lessen the amount of energy that needed to be drawn from the grid. Placing a battery does however require additional investments, but the solution will not have any impact on the EV-driver.

Secondly, the solution of Smart Charging has been proposed, where a certain energy limit is introduced that the combined charge poles cannot exceed. The available energy gets distributed in some predetermined way to the EV-drivers. While no additional investments are needed for Smart Charging, additional costs do arise like for example missed income, loss of goodwill and brand value.

Finally, a solution in the form of a combination of the first two solutions is proposed. A battery is placed at the site and a energy limit are introduced. When the combined chargers exceed a certain energy threshold the battery starts supplying energy, while the total amount of demanded energy cannot be higher than the decided limit, in which case the Smart Charging tactic would throttle the amount of supplied energy to that limit. This solution tries to combine the advantages of both solution while reducing the disadvantages: A smaller battery would be needed reducing

the investment costs, while the EV-driver experiences less impact on their charging, as some of the demand can now be fulfilled by the battery.
Definitions and formulas have been presented to create a model of the three solutions, which will be implemented in the experiments in Chapter 5.

5 TOOL, EXPERIMENTS & RESULTS

This chapter will go over the setup of the experiments that have been run and their corresponding results. In order to run the experiments, a tool has been built that makes use of simulations to gather information on the viability and impact of the proposed solutions, based on the methodology and model proposed in Chapter 4. The tool also helps company X to easily run simulations in the future when the input parameters might have changed. First, this tool and its functions will be discussed in Section 5.1. Then, the parameters used for the experiments are presented in Section 5.2. Finally, the results from the outlined experiments are discussed in Section 5.3.

5.1 Tool

A tool has been created to provide company X with easier access to simulating the solutions following the models proposed in Chapter 4. The tool is using Apache Spark, allowing for scalable parallel execution. With a few lines of code, simulations can be run while giving the user a lot of freedom in defining their parameters and cost functions. The simulations and analysis are based on the methodologies discussed in Sections 4.1.2, 4.2.2 and 4.3.2. The tool provides functions that fully autonomously give the user recommendations for implementing solutions with information on which setup to use and what additional profit to expect compared to the current situation. Furthermore, the tool provides graphing functionalities for manual analysis of different proposed solutions. This section briefly goes over the supported functionalities. Examples of graphs generated by the tool are shown as well. A more hands-on manual for how to use the tool can be found in appendix A.

5.1.1 Data Generation

All analysis is done on a set of demand-values, where the time-interval is 15 minutes. For an accurate analysis, the tool supports analysing multiple replications of data. To get this data prepared in the right form, the tool defines two different ways of preparing this data. The first function takes historical 15-minute demand data, a list of EAN Codes, and a number of required replications of the simulations. This function will then create the specified number of replications, where each replication contains a single week of demand data, created by random sampling from the historical data. This random sampling is done by taking into account the time of day and the day of the week that it is sampling for. For instance, for each replication, the sampled demand data for Monday 2 P.M. will be the demand seen on any of the Mondays 2 P.M. contained in the historical data for that specific EAN. This results in a data set containing the specified amount of replications for each specified EAN, with each replication containing a uniquely generated list of 15-minute demand aggregates spanning a single week. The process described above can take some time to execute, and thus a second function is created for when pre-generated replications are available. In this case, the user only has to specify where the pre-generated replications are stored (in one or multiple files) and the program will easily load them in.

5.1.2 Battery analysis

The tool supports analysis for battery solutions. A single command can be called to prepare all simulation scenarios. First, this command takes the generated replications (each containing 15-minute aggregated demand values, like specified above). The command then takes a list of battery sizes to analyse, as well as a list of maximum grid draw amounts. Optionally, a list of demand-multipliers can be specified, where a multiplier would take the 15-minute values in a replication and increase them by the specified multiplier. The Cartesian product between these 2 (or 3) lists spans the solution space that will be simulated for later analysis, where each element of the resulting set uses the entire set of replications, ensuring the use of the same data for all different solutions. This function returns the object that contains the instructions for simulating all options in the solution space. As Spark execution is 'lazy', it will not actually execute the instructions till this object is used for analysis in displaying the results (either in graph or list form). Each simulation results in either a 'fail' or a 'success', depending on whether the analyzed battery size and maximum grid draw setup would be sufficient to always fulfill all demand, as denoted in equation 5.1. A simulation run (replication) r_i will mark itself as successful whenever there is not a single time-step t where a negative battery charge occurs. Given a number of replications, the success fraction $\bar{r}$ can easily be computed by taking the mean of results r_i over the replications i. The success fraction can be used as an indicator whether or not the proposed setup would be sufficient for a given location.

$$r_i = \begin{cases} 1, & \text{if } b_t \geq 0 \quad \forall t \\ 0, & \text{otherwise} \end{cases} \tag{5.1}$$

The created object can be viewed from different viewpoints. Multiple functions have been created which take this object and visualize it in different ways. One function displays the percentage of successes over the maximum grid draw, with the different battery sizes as distinct lines inside the graph, shown in Figure 5.1. In this Figure it can be seen that a higher success-expectancy is achieved when the maximum allowed grid draw d^+ grows. For instance, if one would wonder what maximum grid draw d^+ would be required for a success-rate of 1 using a battery of 50 kWh for the specific charging site analyzed in this Figure, it shows that $d^+ >= 50$ kW would suffice.

Another function flips this around and plots the success-percentage over the specified battery sizes, with each distinct line representing a different maximum grid draw, as can be seen in Figure 5.2. Here you can see that the success expectancy for a given maximum grid draw d^+ grows with larger battery sizes b^+. For example, Figure 5.2 shows that if a maximum grid demand $d^+ = 50$ kW is desired at the specific charging site analyzed in the graph, the battery size b^+ needs to be a little over 100 kWh big (purple line in the graph).

A third function plots the success-percentage over specified multipliers, with each distinct line representing a unique combination of battery size and maximum grid draw (Figure 5.3).This graph illustrates how the site configuration would perform if all demand d_t was scaled by the factor on the x-axis. For example, if the site analyzed in this graph would use a maximum grid draw of $g^+ = 50$ and a battery capacity of $b^+ = 100$ (blue line), it would not be sufficient at a growth factor of 2, with a success fraction of almost 0. A battery capacity of $b^+ = 300$ (red line) would perform much better with a success fraction of more than 90%.

Finally, the tool also contains two functions that lets you analyze the profitability of the battery solution. The first function again takes the object with the simulation instructions. Additionally, it requires a cost structure for the investment costs, including grid connection costs and transformer costs, as well as battery costs and any other investment costs the user wants to specify. Furthermore, it needs a cost-reduction function, providing the weekly cost-reduction based on the 'original peak' and the newly realized peak. Finally, it needs a time-period for which we want to analyze the profitability. Optionally, a weekly demand-growth factor and a

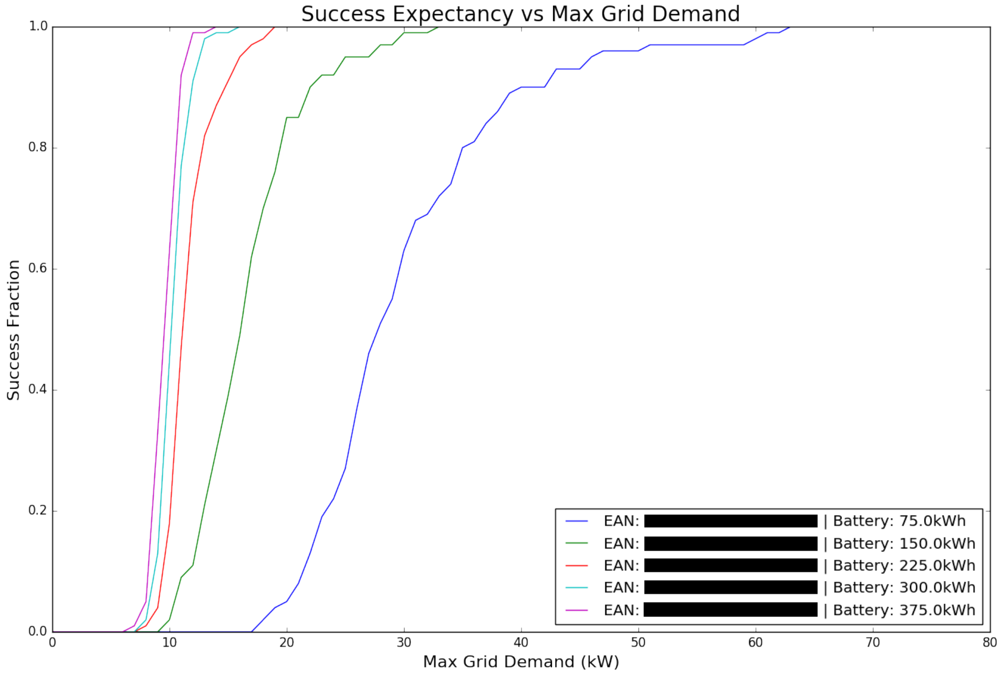

Figure 5.1: Example Graph: Success over Maximum Grid Draw

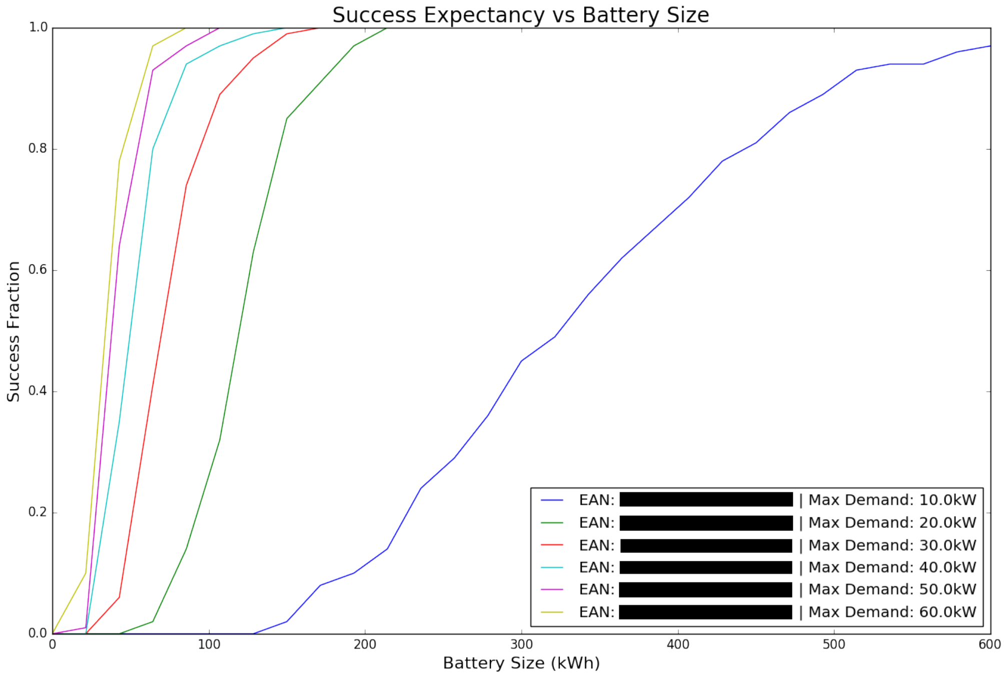

Figure 5.2: Example Graph: Success over Battery Size

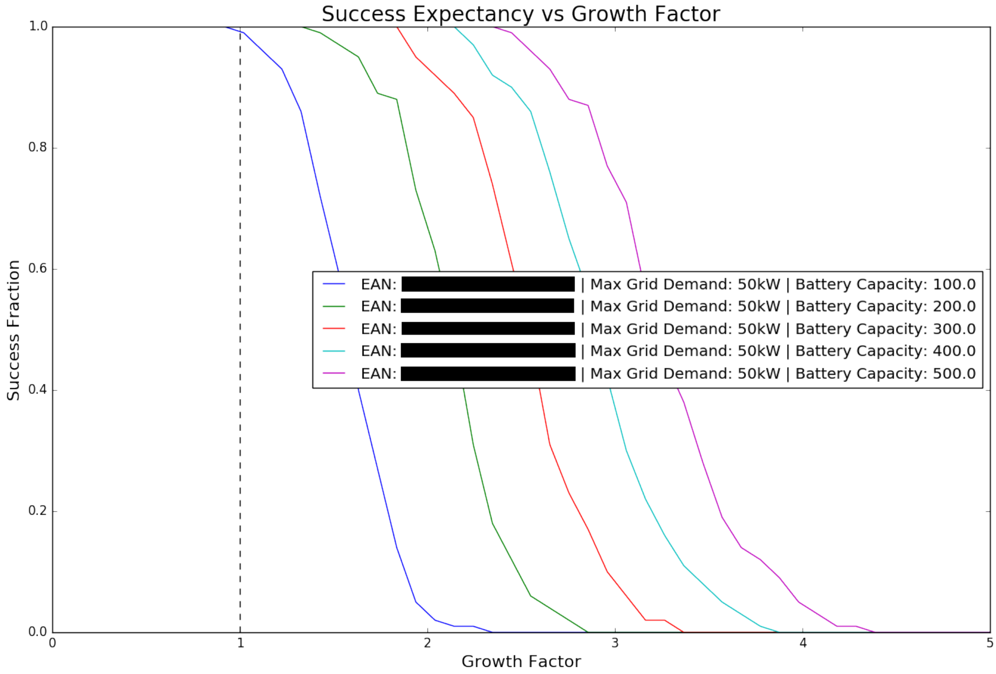

Figure 5.3: Example Graph: Success over Growth Factor

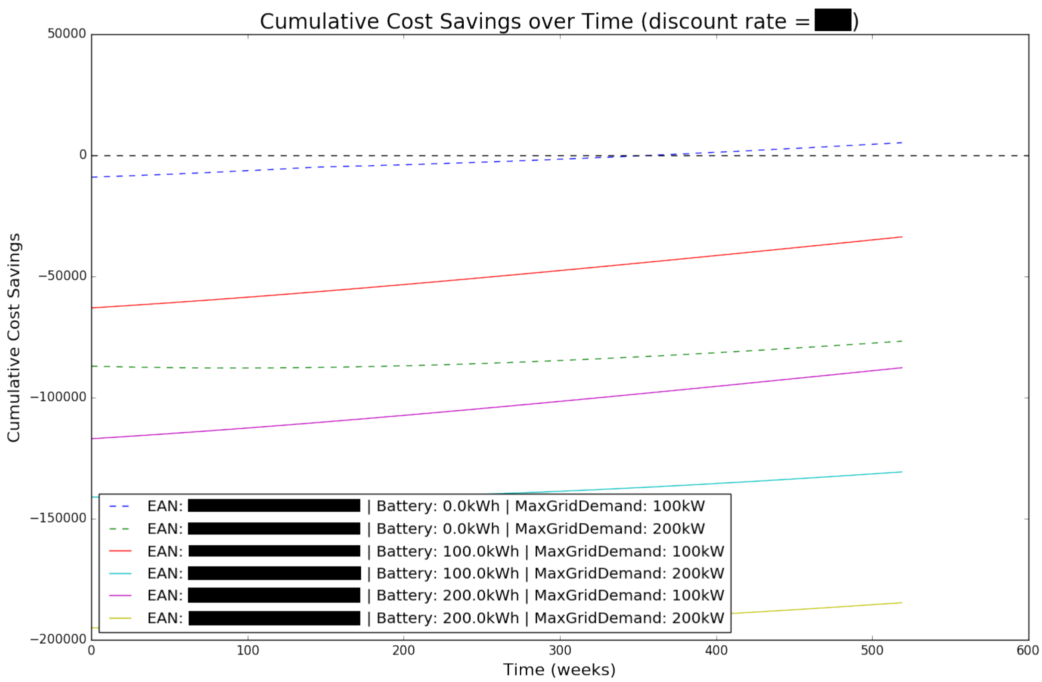

Figure 5.4: Example Graph: Battery profitability over time

discounting rate can be specified. This function will then plot the Net Present Value (NPV) over the amount of weeks specified, as shown in Figure 5.4. The function takes into account the growth factor over the weeks, and will calculate if the configuration would have a success factor of 100%. The continuous lines represent the configurations that have a success factor of 100%, while the dashed lines (blue and green in the Figure) represent configurations that would have a success factor lower than 100%. Figure 5.4 shows that from the 6 analyzed options, no feasible option would be profitable for this specific charging site, with the specified cost functions. The blue line indicates that there is a configuration that would generate a positive NPV, but that the configuration will not be sufficient to meet all demand in the future.
The second function is a simple 'advice' function, using the first function and selecting the configuration with the best (highest) NPV, unless the best configuration still provides a negative NPV in which case it will return no result. This function does not create a graph.

5.1.3 Smart Charging Analysis

The tool also has functions built-in for Smart Charging analysis. First, similar to the battery analysis, a simulation instruction object is needed containing the Smart Charging simulation instructions. This object is created by calling a method contained in the tool, which takes the previously created 15-minute aggregated replication data, as well as a list of maximum grid draw amounts that we want to analyze. Optionally, a list of demand multipliers can be specified, which multiply the aggregated demand values by the specified amounts.
After creating the simulation instruction object, a method is defined to simultaneously analyze the simulations from two different standpoints, which only needs the instruction object as a parameter. This function creates two graphs (Figure 5.5), the first being the amount of kWhs of demand not fulfilled over the specified list of grid draw amounts, the second graph showing in how many time-steps the Smart Charging solution actually had impact on the amount of energy delivered ($g_t < d_t$). The blue area show the range found over the number of analyzed replications, with the red line indicating the average over these replications. The Figure shows that both the amount of unmet demand and the amount of affected time-slots decrease similarly when the maximum grid demand g^+ increases.
A second method instead plots the amount of unfulfilled demand and affected time slots over the specified demand-multipliers (Figure 5.6). It shows that the average amount of unmet demand grows linearly with the growth factor, while the amount of time-slots in which Smart Charging is applied follows some inverse exponential distribution for the specific charging site analyzed in the Figure.
Finally, a third method plots the expected weekly cost savings for the specified maximum grid draws. This method takes the simulation-instruction-object, as well as a cost function for unfulfilled demand and a function for calculating the weekly costs associated with the peak (figure 5.7). Additionally, the tool provides a method to get advice on how to setup the smart charging solution. This method uses the results from the cost-savings graph to find the optimum and prints the results. As can be seen from the Figure, the cost savings reach some optimum after which the cost savings trend towards 0 when the maximum grid draw increases. This is expected, as from some point onward, the maximum allowed grid draw g^+ is larger or equal to the current situation, which means no extra costs are saved or incurred compared to the current situation. Small bumps in the graphs can be observed at 50 kW and 136 kW maximum grid draw, which occur when transport prices change for different maximum grid draws (see Table 2.2).

5.1.4 Combination Solution Analysis

While the previously discussed functions discuss the solutions if applied individually, the tool also supports analyzing a combination of the two solutions. In practice, this would probably be

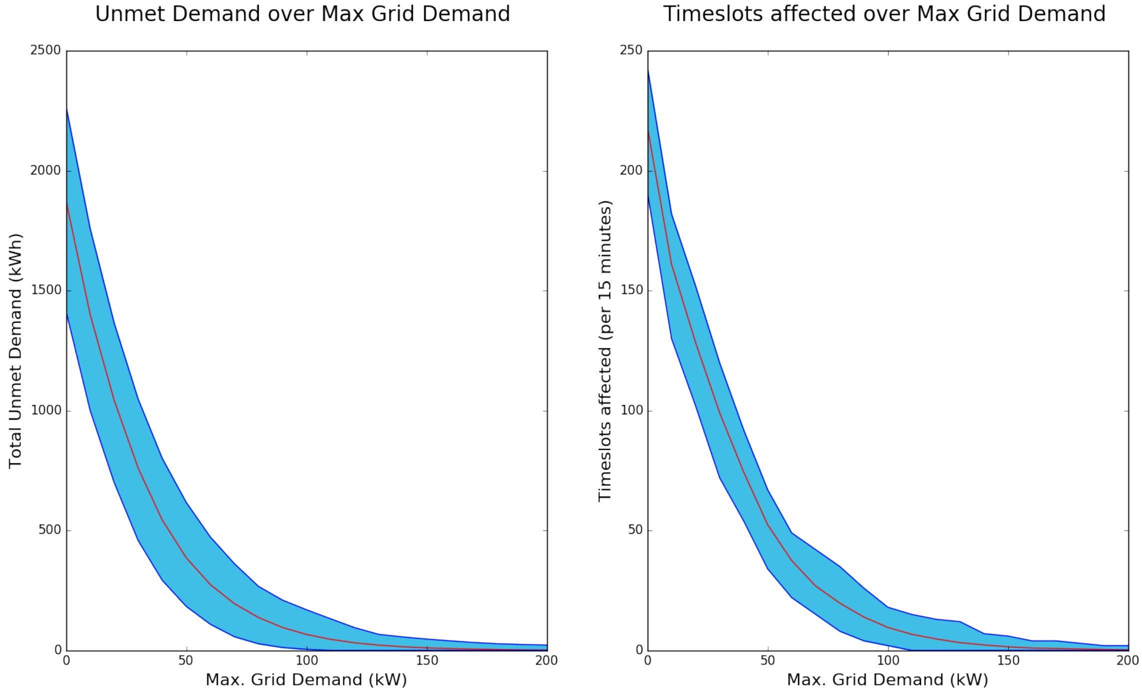

Figure 5.5: Example Graph: Smart Charging - Impact

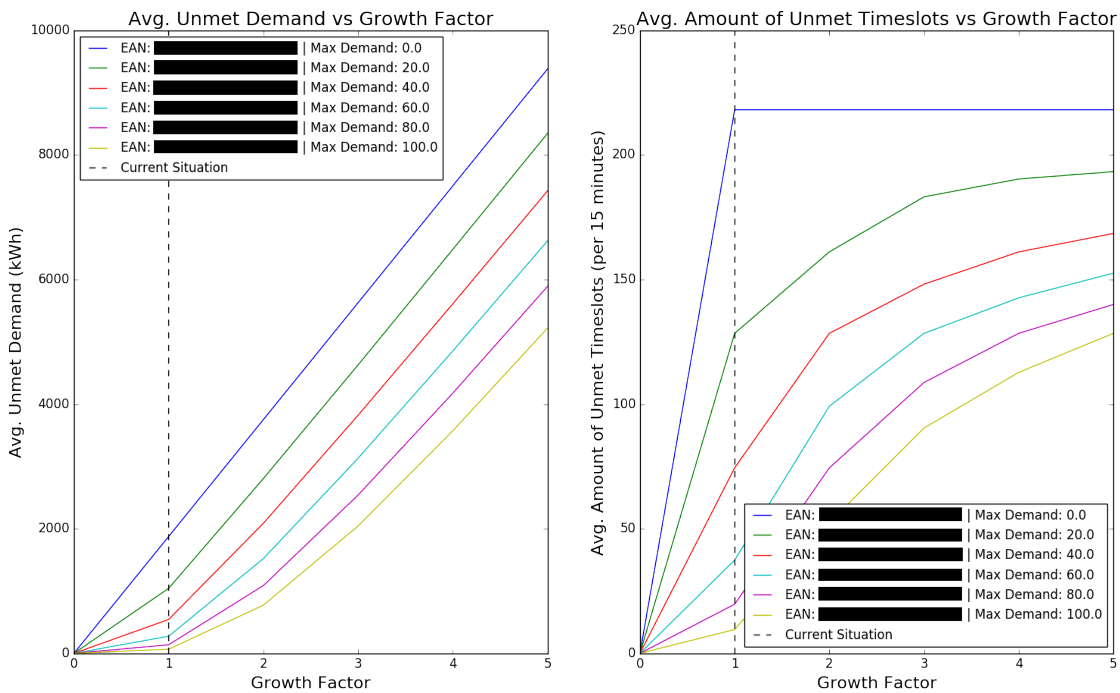

Figure 5.6: Example Graph: Smart Charging - Impact over growth

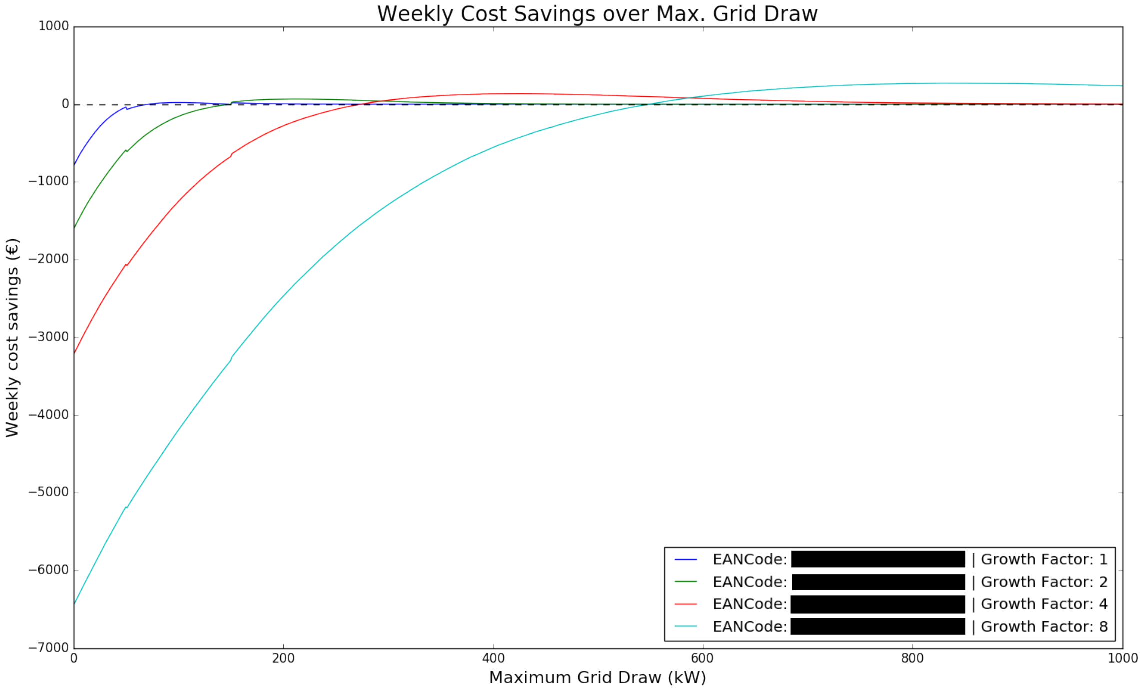

Figure 5.7: Example Graph: Smart Charging - Profitability

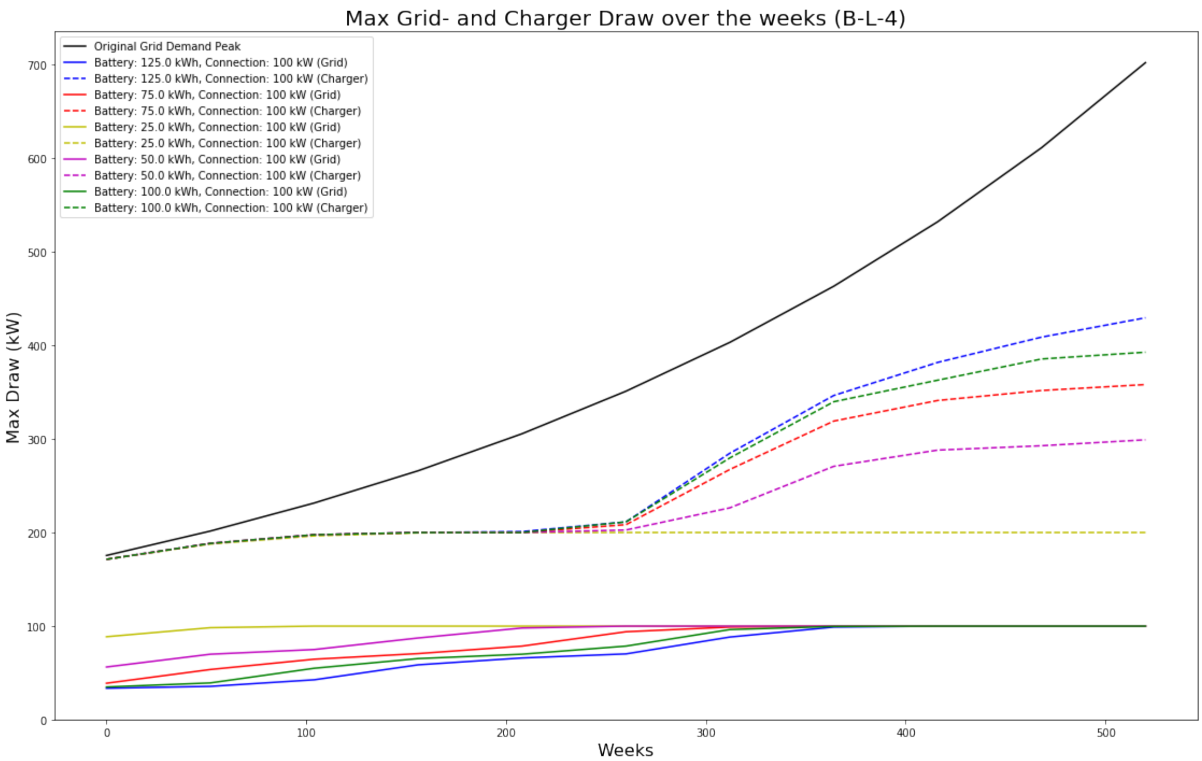

Figure 5.8: Example Graph: Combined Solution - Draw limits per week

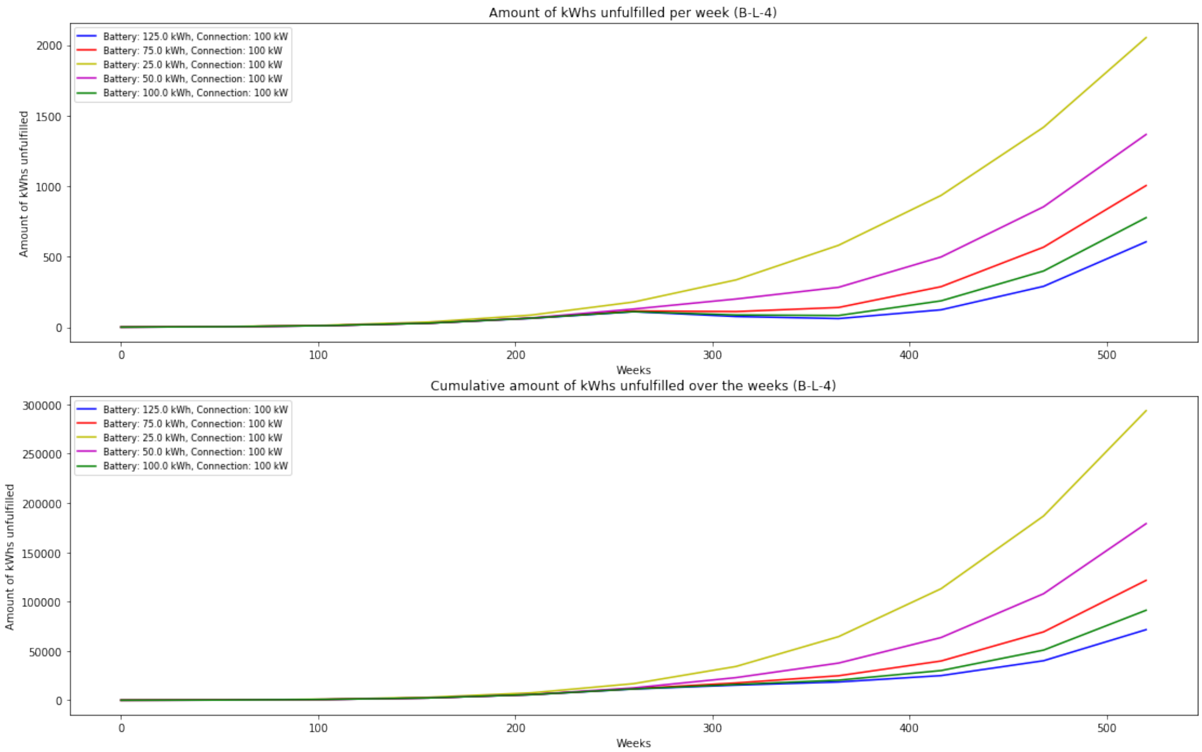

Figure 5.9: Example Graph: Combined Solution - Unfulfilled demand per week

the most used functions as these functions can also be used to compare the combined solution to the individual solutions. In fact, the results of the experiments later in this report are based on these functions.
The methods associated with the combined solution work slightly different in that there is no function to create a simulation-instruction object. Instead, all input parameters are directly passed to the desired analysis function which internally creates a simulation-instruction object. The parameters for the functions are listed below:

- The generated replications of 15-minute aggregated demand data
- A list of battery sizes for which to test
- A list of maximum grid draw amounts for which to test
- A list of grid draw boundaries for grid-connections
- A list of maximum energy supplied (per 15 minutes) to the chargers for which to test
- An initial investment cost structure
- A function for calculating the lost-value per 15 minutes for unfulfilled demand
- A function for calculating the costs associated with the peak grid draw
- A weekly demand growth rate
- The number of weeks for which to simulate
- A re-calibration period (in weeks)
- A yearly discount rate (used for calculating NPV)

Many of these parameters are already explained previously, with the exception of the grid draw boundaries and the re-calibration period. The grid draw boundaries (grid-connection sizes) are used to create scenarios where a certain grid-connection is used. This means that the maximum grid draw cannot exceed the maximum grid draw boundary for that scenario. The re-calibration period is a speed-improvement metric that defines an amount of weeks for which we assume the demand not to differ too greatly, as to only calculate the optimal levels of grid draw and available energy for the charger once for the specified re-calibration period. This means that normally when simulating a period of 500 weeks, the optimal level of maximum grid draw and maximum charger draw are normally calculated for each week. When using the re-calibration period, for example with a value of 50, the simulation will only calculate the optimal levels of grid draw and charger draw every 50 weeks, decreasing the number of calculations for these optimal levels of grid draw and charger by a factor 50, increasing the simulation speed by this same factor.

The stand-alone solutions (only using a battery or Smart Charging) can be analyzed by this function as well by adding the possibility of '0' battery capacity (thus only smart charging can be applied) and by adding an infinitely big maximum charger draw (thus no Smart Charging will take place) to the associated parameters.

The first of the three methods associated to the combined solution returns for each possible setup in the solution space the average expected NPV over the replications, as well as different confidence intervals of this value. This function creates no Figure.

A second method takes the same parameters as the previous method, and in addition take a parameter x. This method executes the first method, but then selects only the top x solutions based on the average NPV over the replications, and then returns for each of those selected solutions the weekly setup for maximum charger draw s^+. These values are then plotted on a graph to visualize these results (figure 5.8). This Figure shows with the black line what the grid draw peaks would be if no improvements were implemented. The colored lines show the values of the maximum grid draw g^+ (continuous line) and maximum charger draw s^+ (dashed line) for different configurations of grid connection and battery size. The figure provides a guide to how much grid draw and charger draw should be allowed on a per-week basis. The difference between the black line and the colored continuous lines represents the difference in peak grid draw between no solution and some configuration of the combined solution. The difference between the black line and the colored dashed lines shows the maximum impact on the EV driver during a peak demand moment.

A third method graphs out the amount of unfulfilled demand, both per week and with a cumulative sum over the weeks (Figure 5.9), providing insight into how much impact the proposed solutions have on the customer charging experience. The top graph shows the amount of unfulfilled demand on a per week basis, while the bottom graph shows the same data in cumulative form.

5.2 Experiment Setup

The experiments will run using the provided tool described in section 5.1, specifically the 'combined solution' methods will be used, where the parameters will be set up in such a way that also the individual solutions are analyzed. This section will discuss how the required parameters are determined and which experiments will be run.

5.2.1 Input Functions and Parameters

Generated Replication Data

For generating the data, the functions defined in section 5.1.1 are used to create 100 replications of one-week's worth of 15-minute aggregated demand data for a certain charging location.

Maximum Grid Draw and Charger Draw Amounts

To define the range for maximum grid- and charger draw, we first look at the observed highest peak in the historical data. Depending on the growth factor and amount of weeks we want to simulate for a certain experiment, we take a peak higher than the demand would be in the final week of the simulation (recall from section 5.1 that the simulation uses the demand growth to multiply the generated 15-minute demand values). The range for the draw amounts spans from 0 to the calculated peak in equal steps. Table 5.2 displays the ranges that have been selected for the experiments. In selecting the amount of steps on the selected range, a trade-off is made between simulation execution speed and result accuracy. The amount of steps used for the experiments in this report is set on 31. Note that a maximum grid draw and charger draw of 0 is also analysed, which essentially calculates if providing charging infrastructure is profitable at all.

Maximum Grid Limits, Battery Capacities and Investment Cost Structure

The maximum grid limits defined for these simulation are based on the grid connection sizes defined by Liander (see table 2.1). The costs associated with these limits are used for the investment cost structure. While the exact costs do vary between grid operators, they do not vary by much. Furthermore, as experiments are defined for different types of locations, this would provide an honest comparison to how different types of locations are applicable for peak-reduction techniques by using a constant cost-model. Note that the prices from the referenced table are doubled, as this price is paid both for installing the connection and also for removing the connection at the end of the term.

$$ConnectionCosts(g^+) = \begin{cases} 0, & \text{if } g^+ = 0kW \\ 2 * 4,522.00, & \text{if } 0 < g^+ \leq 100kW \\ 2 * 5,037.00, & \text{if } 100 < g^+ \leq 160kW \\ 2 * 18,508.00, & \text{if } 160 < g^+ \leq 630kW \\ 2 * 25,179.00, & \text{if } 630 < g^+ \leq 1000kW \\ 2 * 36,406.00, & \text{if } 1,000 < g^+ \leq 2,000kW \\ 2 * 237,731.00, & \text{if } 2,000 < g^+ \leq 5,000kW \\ 2 * 282,321.00, & \text{otherwise} \end{cases} \quad (5.2)$$

Besides grid connection costs, the investment costs in these experiments also compromise of transformer costs and battery costs. For the transformer costs, an expert within company X provided the investment cost function defined by equation 5.3, which takes the peak grid draw g^+ as parameter.

$$TransformerCosts(g^+) = \begin{cases} 50,000.00, & \text{if } g^+ > 160kW \\ 0, & \text{otherwise} \end{cases} \quad (5.3)$$

The possible decrease in hardware costs can be described by a function $C(d^+, g^+)$.

$$C(d^+, g^+) = ConnectionCosts(d^+) + TransformerCosts(d^+) - \\ ConnectionCosts(g^+) - TransformerCosts(g^+) \quad (5.4)$$

Supplier prices for industrial batteries differ and are typically not publically available. To create a cost model, an approximation has been made on cost per kWh, based on available pricing information. In table 5.1 an overview is given of the consulted sources. From this table a battery cost B of €540 / kWh is deemed an acceptable approximation by company X.

$$B(b^+) = b^+ * 540 \tag{5.5}$$

Name	Capacity (in kWh)	Costs (in €)	Costs per kWh (in €)	Source
ECPC-10KWH-Solar-ESS	10	7,060	706.00	[27]
ECPC-15KWH-Solar-ESS	15	10,240	682.67	[27]
ECPC-25KWH-Solar-ESS	25	13,430	537.20	[27]
Tesla Powerpack	232	125,793	542.21	[28]
company X Owned Battery	430	250,000	581.40	-

Table 5.1: Available pricing information for batteries

For the experiments in this report, the tested battery capacities will be ranging from 0 to 200 kWh, in 25 kWh increments.

Lost Demand Cost Function

Determining the financial impact of not fulfilling all demand is not an easy task. Many factors can negatively influence this value, including missed income of unmet demand, goodwill of customers, lost brand value, et cetera. Determining the exact value or function of those factors is beyond the scope of this research. However, as no definite cost function is currently known, we will run two scenarios per experiment to assess the impact of this cost-function, namely a 'lenient' cost-function and a 'harsh' cost-function, where the first function would not penalize unfulfilled demand by much, while the second function penalizes unfulfilled demand by a lot. These two approximating cost-functions will use the mean gross-profit margin per kWh m, which is provided by company X, as well as a penalty factor p_t determined per time-slot by the percentage of unfulfilled demand in order to incorporate additional costs, like for example goodwill. The lenient function uses the penalty factor described by equation 5.6, and the harsh function uses the penalty function described by equation 5.7. Further research should determine the exact cost-function for more accurate results.

$$p_t(d_t, s_t) = \begin{cases} 1, & \text{if } s_t/d_t \geq 0.9 \\ 1.25, & \text{if } 0.7 \leq s_t/d_t < 0.9 \\ 1.50, & \text{if } 0.5 \leq s_t/d_t < 0.7 \\ 2, & \text{otherwise} \end{cases} \tag{5.6}$$

$$p_t(d_t, s_t) = \begin{cases} 1, & \text{if } s_t/d_t \geq 0.9 \\ 5, & \text{if } 0.7 \leq s_t/d_t < 0.9 \\ 10, & \text{if } 0.5 \leq s_t/d_t < 0.7 \\ 1000, & \text{otherwise} \end{cases} \tag{5.7}$$

The incurred costs at time-step t, denoted by E_t, can be described by equation 5.8.

$$E_t(d_t, s_t) = p_t(d_t, s_t) * (d_t - s_t) * m \tag{5.8}$$

Peak Cost Savings Function

The prices between grid-operators vary but not by much. As such, an approximation based on the prices of Liander is used for the experiments, for the same reasons as stated with the implementation of the investment cost structure: the prices do not vary by much and taking a constant price function for all experiments creates the most objective view of how much different types of locations would benefit from the proposed solutions. The prices used for the experiments were presented earlier in this report in table 2.2, and are expressed in equation 5.9.

$$GridOperatorCosts(kW) = \begin{cases} 0.76 * kW, & \text{if } kW \leq 50 \\ (1.93 + 1.74) * kW, & \text{if } 50 < kW \leq 136 \\ (1.23 + 1.74) * kW, & \text{if } 136 < kW \leq 2,000 \\ (2.01 + 1.74) * kW, & \text{otherwise} \end{cases} \tag{5.9}$$

Simulation Length and Weekly Demand Growth

For the simulation length, a period of 10 years (10*52 weeks) is used for the simulation. This figure is given by company X as an acceptable time-span to look ahead for charging locations based on contract length for location usage and equipment depreciation times.
For determining the weekly demand growth, a drawback of the design-choices for the simulation becomes apparent. As the simulation simply scales up the originally generated demand values per 15 minutes in order to implement demand growth, the highest observed peak will linearly grow along with the total demand growth. These scaled values very likely do not give a truthful representation of what demand would look like after growth has taken place. Still, the simulation can be used as to assess what happens when the peak demand and total demand grow by some factor, and how that would have impact on the optimal strategy of deploying batteries and/or Smart Charging. Therefore, three different growth rates are investigated to assess the impact of growth rate on the optimal strategy. However, we recommend to do further research on how to better generate future demand aggregates when taking demand growth into account. That said, the three scenarios that will be investigated are:

- No demand growth
- A demand growth of factor 4 over 10 years (520 weeks)
- A demand growth of factor 10 over 10 years (520 weeks)

These demand growth scenarios can easily be converted to weekly demand growth rates by applying equation 5.10.

$$WeeklyGrowthRate = Factor^{(1/NumWeeks)} \tag{5.10}$$

Given the factors and number of weeks, we get weekly growth factors of 1, $4^{(1/520)}$ and $10^{(1/520)}$ for our scenarios.

Re-calibration Period and Discount Rate

The re-calibration period is used to speed up the execution of the simulation, possibly at the expense of the accuracy of the results. Instead of calculating the optimal values for maximum grid draw g^+ and maximum charger draw s^+, the model will only calculate it once for every re-calibration period, and assume that g^+ and s^+ are still optimal. When taking a time-period where the demand does not change drastically, the optimal values will still be close to the earlier determined optimal values. Moreover, even when the optimal values do significantly differ from what was taken by this re-calibration tactic, if anything, this will undershoot the amount of costs saved by the setup, which is why this is not seen as a problem for interpreting the results. For the experiments in this report, the re-calibration period is set to 52 weeks.
For the discount rate, an expert within company X provided the value of this variable (which is undisclosed in the public version of this report), with which the scenarios will be run.

5.2.2 Experiments

As the simulations can take some time to run, a small selection of EAN-codes (locations) is made for the experiments to run on. Three locations are selected that differ in the amounts and types of chargers on the location, as to provide a feeling for what the impact can be on different types of locations. Furthermore, as discussed in section 5.2.1, both the lost demand cost function and the growth rate will be subject to sensitivity analysis. Two scenarios will be run for the cost function and three scenarios will be run for the demand growth. The experiments will be labeled as displayed by table 5.2. For the Weekly Growth Factor, ranges are defined on which the optimal value for the maximum Grid Draw and Charger Draw will be searched for. Both parameters share these ranges. For example, the label **A-H-4** will correspond to the experiment for location A, with the Harsh cost demand function and a weekly growth factor of $4^{(1/520)}$, with the values for Grid Draw and Charger Draw being somewhere on the range $[0, 1000]$.

Label	Location Name	EAN
A	[Redacted]	[Redacted]
B	[Redacted]	[Redacted]
C	[Redacted]	[Redacted]
Label	Lost Demand Cost Function	
L	Lenient	
H	Harsh	
Label	Weekly Growth Factor	Grid Draw & Charger Draw Ranges
1	1	[0,250]
4	$4^{(1/520)}$	[0,1000]
10	$10^{(1/520)}$	[0,2500]

Table 5.2: Label legend

5.3 Results

This section will present the results of the experiments defined in section 5.2. With the many experiments that are run, discussing all experiments individually might prove of little added value compared to only discussing the results. However, in order to provide more insight into the results of an individual experiment and how these results should be interpreted, Section 5.3.1 discusses one of the experiments in depth. Section 5.3.2 will discuss the overall results, while a detailed overview of the results per experiments can be found in Appendix B, including graphs visualizing each individual experiment. Section 5.3.3 will compare the results and try to find similarities between the experiments in order to present global conclusions.

5.3.1 Example Experiment Explained (B-L-4)

In this section, we will discuss a single experiment in depth, for which experiment **B-L-4** is chosen. The experiments yields as the best options and corresponding the five setups displayed in Table 5.3. As shown in the table, all five options expect a positive NPV even when taking a 99 percent confidence interval. All five options use a 100 kW grid connection, indicating that using this size of grid connection is very much advised for this location in the case of a cost function similar to the Lenient cost function (Equation 5.6) an expected growth factor of 4. Furthermore, every setup uses a battery ($b^+ > 0$), with the most profitable setup uses a 50 kWh battery size. Figure 5.8 shows the values of the maximum grid draw g^+ and maximum charger draw s^+ over the weeks of the total time-span. Taking for example the purple line representing the most

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
50	100	42682.03	40334.94-45029.11	39575.31-45788.74
25	100	38642.26	35953.60-41330.91	35083.42-42201.09
75	100	38063.38	35855.56-40271.19	35141.01-40985.75
100	100	29350.03	27240.00-31460.07	26557.09-32142.98
125	100	18772.98	16730.17-20815.79	16069.02-21476.95

Table 5.3: Best options for B-L-4

profitable setup, the Figure shows the recommended configuration for the two variables, with the maximum grid draw in week 100 being around 75 kW, and the maximum charger draw around 180 kW. Whenever a peak occurs higher than the maximum grid draw, additional power is supplied from the battery. As the chosen grid connection allows only for a maximum of 100 kW energy draw, the grid draw values will not surpass this value. Whenever a peak higher than the maximum charger draw occurs, Smart Charging will throttle the amount of supplied energy back down to the maximum charger draw. The difference between the black line and the dotted lines represents the amount of kW shaved from the highest expected demand peak. The actual amounts of unmet demand is represented in Figure 5.9, where it can be observed that the majority of unmet demand is incurred in the later weeks of the time-span, when supposedly the demand and demand peaks have grown by almost a factor 4. For this experiment, it can be concluded that for charging locations similar to the one in this experiment, around €40,000 can be saved over the time-span of 10 years if the combined solution of Smart Charging and energy storage is used, where the total amount of unmet demand of this same time-span would be around 175,000 kWh.

5.3.2 Overview of results

After running the experiments, the best option based on highest NPV is selected for each experiment. The metrics associated with the solution are displayed in table 5.4 and 5.5. Table 5.4 provides an overview of the average NPV that has been achieved by the best solution over the 100 replications. Additionally, confidence intervals are provided for confidence levels of 95 and 99 percent respectively. Table 5.5 provides the configuration of the best solution, providing the used battery size and grid connection. The table also contains some additional columns. The ‘Current Peak’ column provides the average demand peak that was observed in the data at $t = 0$. The ‘Future Peak’ column shows what the peak demand would be in the last week of the specified time-frame ($t = 519$). Finally, the column ‘Missed Demand’ specifies the amount of demand that has not been fulfilled in the time-frame (10 years), and the ‘%’ column specifies how much that is compared to the total amount of demand. Note that the maximum charger draw limits are not included in these tables as they change per week. Appendix B contains graphs per experiment detailing the weekly values for the maximum charger draw.

5.3.3 Result Analysis

Upon inspection of the results, multiple things stand out. First of all, each scenario provides a positive average NPV (except for C-L-1 and C-H-1 which we will discuss shortly). Also the confidence intervals show predominantly positive values, indicating that it is very likely for the true mean NPV to be positive. By running multiple experiments for different unfilled demand cost functions and demand growths, it became clear that even though the exact values and functions for these inputs still have to be researched, the peak reduction techniques covered in these experiments can be cost-effective.
Secondly, using batteries does not seem to be the best options for each scenario. Moreover,

Label	Average NPV (in €)	NPV CI(0.95) (in €)	NPV CI(0.99) (in €)
A-L-1	16,715	10,584 - 22,847	8,600 - 24,831
A-L-4	59,948	58,391 - 61,505	57,887 - 62,009
A-L-10	34,449	23,121 - 45,778	19,455 - 49,444
A-H-1	5,941	-476 - 12,358	-2,553 - 14,435
A-H-4	5,381	4,341 - 6,422	4,004 - 6,759
A-H-10	13,301	2,786 - 23,815	-615 - 27,218
B-L-1	52,561	46,008 - 59,113	43,887 - 61,234
B-L-4	45,536	43,194 - 47,878	42,436 - 48,636
B-L-10	54,410	33,782 - 75,039	27,105 - 81,716
B-H-1	54,593	38,780 - 52,405	36,576 - 54,610
B-H-4	11,013	9,739 - 12,287	9,327 - 12,700
B-H-10	29,622	9,311 - 49,932	2,738 - 56,506
C-L-1	0	0 - 0	0 - 0
C-L-4	70,888	70,581 - 71,195	70,482 - 71,294
C-L-10	32,648	31,528 - 33,768	31,166 - 31,130
C-H-1	0	0 - 0	0 - 0
C-H-4	64,169	63,952 - 64,387	63,881 - 64,458
C-H-10	101	64 - 138	52 - 149

Table 5.4: NPV best solution per experiment

Label	Bat. Capacity	Grid Connection	Current Peak	Future Peak	Missed demand
A-L-1	0	100	148	148	16,144 (3.0%)
A-L-4	25	100		594	133,520 (6.1%)
A-L-10	0	1,000		1,485	36,919 (0.7%)
A-H-1	25	100		148	109 (0.0%)
A-H-4	0	630		594	4,544 (0.2%)
A-H-10	25	1000		1,485	15,721 (0.3%)
B-L-1	0	100	181	181	37,616 (3.9%)
B-L-4	50	100		724	175,602 (4.6%)
B-L-10	0	1,000		1,811	67,165 (0.7%)
B-H-1	25	100		148	895 (0.1%)
B-H-4	0	630		724	7,538 (0.2%)
B-H-10	0	2,000		1,811	7,270 (0.1%)
C-L-1	0	100	52	52	0 (0.0%)
C-L-4	0	100		209	54,883 (5.0%)
C-L-10	50	100		524	128,149 (4.6%)
C-H-1	0	100		52	0 (0.0%)
C-H-4	25	100		209	1,676 (0.2%)
C-H-10	0	630		524	752 (0.0%)

Table 5.5: Setups best solution per experiment

when batteries are used they will most often be of a small size, often smaller than what you would find in a modern EV. This probably would indicate that the prices of batteries are currently on the verge of becoming cost-effective. Further research could indicate at what price-point batteries would be present in all optimal solutions.

A third point of interest is the difference in expected profitability between scenarios. Most notably, A-H-1 and A-H-4 have a significantly lower NPV. It can be observed however that the demand peaks they would expect at the end of the time-frame are just below the point where a bigger grid connection would have been needed (160 and 630 kW respectively). This means that they would need to lower the peak significantly more to realize a smaller grid connection, compared to other solutions. Take for example B-L-1 and B-H-1, which has a future peak just above the grid limit of 160 kW. This means that with just a small bit of peak reduction a big financial impact can be made, especially as dropping below 160 kW not only enables the

use of a smaller connection, but removes the need for a transformer (costing €50,000 in these experiments) as well. It can be stated that, possibly unsurprisingly, peak reduction techniques have the largest financial impact on locations where the expected peak demand would be just a tiny bit too high for using a smaller grid connection.
Finally, it can be observed that the best solutions for C-L-1 and C-H-1 provide no value. This is quite intuitive, as those scenarios have only a single fast charger at the location. As this single charger can only output a maximum of 50kW, it cannot reduce the investment costs as it already uses the cheapest connection and does not require a transformer. Moreover, applying peak reduction techniques would probably not prove useful as these techniques mostly tackle the rare outliers in demand. Having just a single fast charger would not create these outliers as the 'peak' of 50kW will probably be reached quite often. The results from these experiments are therefore not surprising.

5.4 Chapter Summary

A model had been created in Chapter 4 in order to analyze the possible financial impact of Smart Charging and/or battery usage in grid demand peak reduction. A tool has been developed with which the impact can be assessed, which is discussed in this Chapter and has been used to analyze scenarios with three different location types with differing charger amounts and demand profiles, two different cost functions, and three different demand growth rates. The experiments show that applying these peak reduction techniques lead to higher profits compared to always meeting all demand straight from the grid. While a small amount of additional profit comes from the lower monthly peak-related costs, the majority of additional profit is realized by using a smaller grid connection than otherwise needed. The results show that the financial impact of peak-reduction techniques is, not surprisingly, highest whenever a location would expect a peak just a tiny bit larger than a certain grid connection limit. The peak reduction allows the location to then use a smaller grid connection, easily saving €20,000 or more on the investment costs. A particular interesting grid connection change in the experiments in this report is the change from higher than 160kW to below 160kw, saving two times €13,500 (deploying and removing) and an additional €50,000 from not requiring a transformer. It very much recommended that any future location should be investigated using the built model and tool to see if a 160kW grid connection could lead to substantial cost savings.

6 CONCLUSIONS, DISCUSSION & FURTHER RESEARCH

The following chapter concludes the report. Section 6.1 summarizes the goals and findings of the report, and in doing so answers the main research question. Section 6.2 goes into detail about the limitations of the research and how future research could build further on this report.

6.1 Conclusions & Recommendations

This report set out to answer the following research question:

> **Main Research Question.** *How can peak-related costs be reduced at fast-charging locations for EVs in the absence of customer arrival- and charging information, and what is the impact of the possible solutions?*

In the report, we have identified the different peak-related costs for operating a fast-charging location with investment costs in the form of grid connections and transformers, and monthly recurring costs in the form of energy transport costs *(Sub-question 1)*. The current behaviour of the charging demand has been investigated and both daily and weekly seasonalities in the data were identified *(Sub-question 2)*. From the literature multiple techniques were found for reducing peak energy usage at charging locations *(Sub-question 3)*, of which two solutions were further investigated: Smart Charging and local energy usage *(Sub-question 4)*. Advantages and disadvantages have been identified for these solutions *(Sub-question 8)*, with the main advantage of the Smart Charging being that it can be implemented without incurring any investment costs. Smart Charging does however have an impact on the charging solution of the EV-driver, with possibly longer charging times, resulting in costs in the form of missed sales, lost customer goodwill or brand value. For the local energy storage solutions, it is exactly the other way around: this solution will not have any effect on the charging experience of the EV-driver, but does require an hefty initial investment in purchasing a battery of sufficient size. A third solution has been created combining Smart charging and local energy usage, aiming to mitigate the disadvantages of the individual solutions, where Smart Charging would enable a smaller and cheaper battery to be used, while the battery can provide additional energy instead of drawing it directly from the grid, increasing the limit where Smart Charging would be activated, in turn decreasing the impact on the EV-driver. Models have been created and experiments have been designed for investigating these solutions *(Sub-question 5)*. Experiments have been designed *(Sub-question 6)*, with the experiments yielding promising results, with clear indications for possible cost savings of €5,000 to €70,000 over a 10-year period *(Sub-question 7)*. Battery usage is limited with predominantly small batteries used in the combined solution, where there are even cases where no battery is recommended at all and a 'pure' Smart Charging solution is most profitable instead. The majority of the reduced costs come from the smaller grid connection needed and the possible removal of the transformer. The smaller grid connection (and possibly the removal of a transformer) not only lead to higher profits, it possibly also opens up opportunities to open new fast charging locations in areas where it normally would not have been possible due to the grid being too congested. Moreover, the time-to-market might decrease as the lead-time of building a charging location with a smaller grid connection is supposedly shorter than with a bigger grid connection. The possibility of using these peak reduction techniques is very much recommended to further investigate as this study has proven the possible savings. With the current pricing, the usage of batteries is only recommended when using small batteries, with a size less than 50kWh. The impact of bigger batteries currently do not (yet) weigh up to the associated costs. Smart Charging on the other hand does prove to allow significant cost savings, and it is recommended to move towards hardware (such as chargers) that support Smart Charging.

6.2 Discussion & Further Research

This research has limitations which are important to be aware of. First of all, the simulation technique implements demand growth by simply scaling a generated time-set by the demand growth factor for that week compared to the current situation. It is however likely that demand would balance itself out more when demand increases, and the peaks would comparatively not grow as much as the total demand. A better method can be implemented to more accurately represent demand profiles in the future. Attempts during this research have led to significantly longer simulation times and less accuracy on demand expectancy over the day. Further research could dive into this problem to see if the demand growth representation can be improved.
Furthermore, the experiments in this research have used two different Lost Demand functions, as to assess the impact of different implementations of this function ('Lenient' and 'Harsh') on the results. While the comparison between these two implementations show that in both cases costs can be significantly reduced, further research is needed to determine the actual cost function as to provide a more definitive answer as to how much money it really is going to save. As a third point, the batteries in these experiments are modeled to have an infinite charge and discharge rate. While the delivered tool does support limiting these rates, the actual value differs greatly between battery producers, models and sizes. Further research could improve the model by implementing these values in the experiments. Moreover, more research can be done on the impact of lower battery prices on the suggested optimal location setup. Finally, the model currently leaves out certain parameters like temperature or grid stability, both of which can have impact on how the battery behaves. Further research could focus on researching the behaviour of the battery under changing conditions and implementing this into the model.
Furthermore, the majority of the peak reduction is currently being done by Smart Charging. However, possibly the profits can be increased further when changing the Smart Charging algorithm to not balance the load by reducing each charger by the same percentage, but to use some other load-balancing method, perhaps by taking into account for example the amount of cars currently charging, the time cars have been charging or even what type of cars are charging. A research into the possibilities to optimize this load-balancing function is advised.
Finally, this report only discusses the usage of Smart Charging and/or battery usage for peak reduction. However, as outlined in the literature research (section 3.1), there are also other opportunities for peak reduction. Further research could investigate how those solutions interact with the combined solution discussed in this report.

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A TOOL MANUAL

Here you can find the instructions for using the built tool. Examples of code will be given for the available functions. We will first go over the types of objects specific to the tool, after which we will go over the different functions grouped by solution type.

A.1 Objects

There are a few objects that are key to understand before we dive into the functions.

A.1.1 Generated Data Object

First, there is a Generated Data Object which is a Apache Spark RDD Object consisting of Python Tuples. Each Tuple is a key-value pair, with the key being a Spark Row object containing a field for the EAN Code and a field containing the replication identifier. The 'value' in the key-value pair is a list of Spark Rows where each row contains a Python DateTime specifying the date and time (rounded to nearest 15 minutes) and an amount specifying the Consumed Energy for that timeslot.
- Generated Data Object
- - List of [Tuple]
- - - key = Row(EANCode, Replication)
- - - value = List of [Row]
- - - - DateTime
- - - - ConsumedEnergy

A.1.2 Simulation Instruction Object

When the Generated Data Object is passed through Simulation Preperation functions (discussed later), a Simulation Instruction Object is returned. This object contains the instructions for which simulations need to be run including the parameters that are used for the simulations. This object can be passed to graphing functions to create visualizations of the simulation results. We distinguish three different Simulation Instruction Objects:
- Battery Simulation Instruction Object
- Smart Charging Simulation Instruction Object
- Combined Solution Simulation Instruction Object

Note that while there is a Combined Solution Simulation Instruction Object, this object is only used in the back-end of the tool, and the user should not have to worry about interacting with it. It will therefore also not be a part of this manual.

A.1.3 Investment Cost Structure

An Investment Cost Structure is a structure which holds one or more cost functions defining the amount of investment needed for a certain setup. The first function passed to this structure on its creation should be some function $f(kWh)$ which takes a single parameter kWh and returns the costs for a battery of kWh capacity. Any further functions passed to this object should be functions of type $f(kW)$ where kW is the maximum peak that should be supported, and returns the costs associated with this amount of kW.

A.2 Loading in the Tool

Before we can use the tool, it needs to be loaded in. This process is made very easy by a single line of code. This code uses the file-location of the tool and imports all dependencies and functions. A relative or absolute path to the tool must be provided in this function.

```
%run "./Multi-Simulation Tool"
```

Running this code imports the Tool's methods as described in Section 5.1 and uses the following dependencies:

```
from datetime import datetime, date, time, timedelta
from pyspark.sql import Row
from pyspark.sql.types import StructType, StructField, IntegerType, StringType,
    DateType, TimestampType
from math import inf, log
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats
```

A.3 Data Generation

Before any analysis can take place, a Generated Data Object should be created. Two different functions are in place to make this possible. The first method 'GeneratedTimeframesRDD' takes data from the data-lake, and provides parameters where the specific EAN codes, the amount of replications and the time frame can be defined. This function returns a Generated Data Object. This function can take some time to execute, and thus might be prepared beforehand and saved to some file location. The method 'LoadGeneratedTimeframesFromFiles' takes a list of file-location and can be used to reload an earlier created Generated Data Object.

```
GeneratedDataObject = GeneratedDemandData(HistoricalData, ListOfEANs,
   date_start, date_end, numReplications)
```

```
GeneratedDataObject = LoadGeneratedTimeframesFromFiles(ListOfFileLocations)
```

A.4 Creating Simulation Instruction Objects

Now that we have a Generated Data Object, we can start specifying the simulations we want to run.

A.4.1 Battery Simulation Instruction Object

When creating a Battery Simulation Instruction Object (BSIO), we need to define the list of battery sizes we want to analyze, as well as the different maximum grid demands we want to analyze. Optionally, a list of demand growth factors can be specified. The function 'getRDD_BatterySimulation' is then used to create a BSIO. Using the numpy library we can use the 'linspace' function to create a list of evenly spaced numbers. The definition of 'ListOfBatterySizes' in the code below will create a list of 6 evenly spread numbers between 0 and 100 (thus [0, 20, 40, 60, 80, 100]).

```
ListOfBatterySizes = numpy.linspace(0,100,6).tolist()
ListOfMaxGridDemands = numpy.linspace(0,200,41).tolist()

BSIO = getRDD_BatterySimulation(GeneratedDataObject, ListOfBatterySizes,
   ListOfMaxGridDemands)
```

```
ListOfBatterySizes = numpy.linspace(0,100,6).tolist()
ListOfMaxGridDemands = numpy.linspace(0,200,41).tolist()
ListOfDemandGrowthFactors = numpy.linspace(0,20,21).tolist()

BSIO = getRDD_BatterySimulation(GeneratedDataObject, ListOfBatterySizes,
   ListOfMaxGridDemands, ListOfDemandGrowthFactors)
```

A.4.2 Smart Charging Simulation Instruction Object

If we want to create a Smart Charging Simulation Instruction Object (SCSIO), we can call the method 'getRDD_SmartChargingSimulation'. Besides the Generated Data Object, this method takes only a list with maximum grid limits as an argument, and optionally a list of demand growth factors.

```
ListOfMaxGridDemands = numpy.linspace(0,200,41).tolist()

SCSIO = getRDD_SmartChargingSimulation(GeneratedDataObject,
   ListOfMaxGridDemands)
```

```
ListOfMaxGridDemands = numpy.linspace(0,200,41).tolist()
ListOfDemandGrowthFactors = numpy.linspace(0,20,21).tolist()

SCSIO = getRDD_SmartChargingSimulation(GeneratedDataObject,
   ListOfMaxGridDemands, ListOfDemandGrowthFactors)
```

A.5 Graphing Functions

In this section the available graphing functions will be explained, grouped by the peak shaving solution they belong to.

A.5.1 Battery Solution

The battery solution defines four graphing functions, three of which take only the created BSIO as input, the fourth taking more arguments.

The first function plots the Success Expectancy from a configuration over the maximum grid demand (see Figure 5.1). A configuration in this case means a maximum battery size and possibly demand growth factor. The second function turns this around and plots the Success Expectancy over the maximum battery size, where the configuration is maximum grid demand with possibly a demand growth factor (see Figure 5.2). The third function plots the Success Expectancy over the demand growth factors, with a configuration begin the combination of a certain battery size and a certain grid demand limit (see Figure 5.3).

```
plot_BatteryRDD_Over_MaxGridDemand(BSIO)
plot_BatteryRDD_Over_BatterySize(BSIO)
plot_BatteryRDD_Over_DemandMultiplier(BSIO)
```

Note that for the different plots, different BSIOs work best (with different lists of parameters). It is advised to tailor the BSIO to the graphing function the user wants to execute.
The fourth graphing function creates a graph of the expected profit over time, and takes additional parameters (see Figure 5.4). Besides the BSIO, it takes a Investment Cost Structure (see "Objects" earlier in this manual), a function (1), the number of weeks we want to calculate the profit for, a discount rate and finally a weekly demand growth rate. The function (1) should be a function taking in two parameters detailing the old peak in kW and the new peak in kW, and return the weekly savings of transportation costs based on the two peaks specified. An example is given below.

```
def weeklyCostReduction(oldPeak, newPeak):
  #example function based on Liander Grootzakelijke Tarieven
  if newPeak <= 50:
    c_new = 0.76
  elif newPeak <= 150:
    c_new = 1.93+1.74
  else:
    c_new = 1.23 + 1.74

  if oldPeak <= 50:
    c_old = 0.76
  elif oldPeak <= 150:
    c_old = 1.93+1.74
  else:
    c_old = 1.23 + 1.74

  return (c_old * oldPeak - c_new * newPeak) / 4

numWeeks = 520 #10 years
yearlyDiscountRate = 0.1
weeklyGrowthRate = pow(2,1/(52*10)) # a doubling in demand every 10 years

plot_BatteryRDD_Profit_Over_Time(BSIO, InvestmentCostStructure,
    weeklyCostReduction, numWeeks, yearlyDiscountRate, weeklyGrowthRate)
```

A.5.2 Smart Charging Solution

For the smart charging solution, three different graphing functions are available. The first two functions require only the created SCSIO, the third function requires additional parameters.
The first function provides a double graph, where the first graph plots the amount of unfulfilled demand for different grid demand limits, and the second graph plots the amount of 15-minute

time-steps in which there was more demand then was ultimately provided to the chargers, i.e. the number of time-steps the Smart Charging was active (see Figure 5.5). The second function provides these same two graphs but plotted over the different demand growth factors (see Figure 5.6).

```
plot_SmartChargingRDD_Over_MaxGridDemand(SCSIO)
plot_SmartChargingRDD_Over_DemandMultiplier(SCSIO)
```

The third function creates a graph displaying the expected weekly cost savings over the different grid draws. Besides the created SCSIO, this function also requires a function describing the costs of unmet demand, as well as a function describing the cost savings due to a lower peak grid demand. The unmet demand cost function takes two parameters which hold the value of the amount of energy of demand, and the amount of energy supplied to the chargers, on a 15-minute basis (see Figure 5.7). The cost savings function also takes two parameters: the original peak grid demand, and the 'new' grid demand when applying Smart Charging.

```
def DemandCostFuncLenient(d,s):
  if d == 0:
    return 0

  fraction_unfilled_demand = 1 - s/d
  if fraction_unfilled_demand <= 0.1:
    factor = 1
  elif fraction_unfilled_demand <= 0.3:
    factor = 1.25
  elif fraction_unfilled_demand <= 0.5:
    factor = 1.5
  else:
    factor = 2

  return (d-s)*0.25*factor

def weeklyCostReduction(oldPeak, newPeak):
  #example function based on Liander Grootzakelijke Tarieven
  if newPeak <= 50:
    c_new = 0.76
  elif newPeak <= 150:
    c_new = 1.93+1.74
  else:
    c_new = 1.23 + 1.74

  if oldPeak <= 50:
    c_old = 0.76
  elif oldPeak <= 150:
    c_old = 1.93+1.74
  else:
    c_old = 1.23 + 1.74

  return (c_old * oldPeak - c_new * newPeak) / 4

plot_SmartChargingRDD_Value_over_MaxGridSize(SCSIO, DemandCostFuncLenient,
    weeklyCostReduction)
```

A.5.3 Combined Solution

For the combined solution, no graphing functions are currently implemented in the tool. However, this section will discuss the available function for getting simulation results, and propose graphing functions for visualizing these results. The function take a large list of parameters which will be discussed below, and returns two variables. The first returned variable is a list of the top x setups based on NPV with their corresponding NPV and confidence intervals, where x can be specified in the parameters (see below). The second returned variable is a Apache Spark RDD-object containing the top x setups based on NPV, each containing a list of y^* weeks with each week containing information on the height of the old grid demand peak as well as the new optimal grid demand maximum and the optimal charger draw maximum. The value of y^* is determined dividing the amount of weeks for which will be simulated by the speed-improvement metric, which are both parameters in calling the function (see below for both these parameters). In order to call this function, no Simulation Instruction Object is needed, as it will create this object itself based on the parameters given to the function. The total list of parameters is given below. Refer to Section 5.1 and in particular Section 5.1.4 for details about the individual parameters.

- The generated replications of 15-minute aggregated demand data
- A list of battery sizes for which to test
- A list of maximum grid draw amounts for which to test
- A list of grid draw boundaries for grid-connections
- A list of maximum energy supplied (per 15 minutes) to the chargers for which to test
- An initial investment cost structure
- A function for calculating the lost-value per 15 minutes for unfulfilled demand
- A function for calculating the costs associated with the peak grid draw
- A weekly demand growth rate
- The number of weeks for which to simulate
- A re-calibration period (in weeks)
- A yearly discount rate (used for calculating NPV)

```
def DemandCostFuncLenient(d,s):
  if d == 0:
    return 0

  fraction_unfilled_demand = 1 - s/d
  if fraction_unfilled_demand <= 0.1:
    factor = 1
  elif fraction_unfilled_demand <= 0.3:
    factor = 1.25
  elif fraction_unfilled_demand <= 0.5:
    factor = 1.5
  else:
    factor = 2
```

```
  return (d-s)*0.25*factor

def weeklyCostReduction(oldPeak, newPeak):
  #example function based on Liander Grootzakelijke Tarieven
  if newPeak <= 50:
    c_new = 0.76
  elif newPeak <= 150:
    c_new = 1.93+1.74
  else:
    c_new = 1.23 + 1.74

  if oldPeak <= 50:
    c_old = 0.76
  elif oldPeak <= 150:
    c_old = 1.93+1.74
  else:
    c_old = 1.23 + 1.74

  return (c_old * oldPeak - c_new * newPeak) / 4

BATTERY_CAPACITIES = np.linspace(0,200,9).tolist()
MAX_GRID_DEMANDS = numpy.linspace(0,200,41).tolist()
MAX_GRID_LIMITS = [0,100,160,630,1000,2000,5000,10000]
MAX_CHARGER_DRAW = numpy.linspace(0,200,41).tolist()
BATTERY_COST_STRUCTURE = InvestmentCostStructure
LOST_DEMAND_FUNC = DemandCostFuncLenient
COST_SAVE_FUNC = weeklyCostReduction
WEEKLY_GROWTH = WEEKLY_GROWTH = pow(4,(1/520)) # multiply by 4 every 520 weeks
NUM_WEEKS = 52*10+1
CALIBRATE_NUM_WEEKS = 52
YEARLY_DISCOUNT_RATE = 0.1

best_options, results_rdd = get_CombinedSolutionRDD_Advice_Fast_New3(
    GeneratedDataObject, BATTERY_CAPACITIES, MAX_GRID_DEMANDS,
    MAX_GRID_LIMITS, MAX_CHARGER_DRAW, BATTERY_COST_STRUCTURE,
    LOST_DEMAND_FUNC, COST_SAVE_FUNC, WEEKLY_GROWTH, NUM_WEEKS,
    CALIBRATE_NUM_WEEKS, YEARLY_DISCOUNT_RATE, NUM_BEST = 5
)
```

Now that the results are loaded into the variables ‘best_options’ and ‘results_rdd’, we can analyse the results using a user-defined function. Proposed functions for the analysis are given below.

Visualizing the maximum grid draw and maximum charger draw per week

The function below is proposed to visualize the maximum grid draw and maximum charger draw. The resulting graph has been presented in the main report in Figure 5.8.

```
def plotMaxDraw(results, experiment, recalibrationWeeks):
  fig, ax = plt.subplots()
  colors = ['b','r','y','m','g']
  c = 0
```

```
  first = True
  for setup in results:
    x = [i['Week'] for i in setup[1]]
    y = [i['AvgOldPeak'] for i in setup[1]]
    z = [i['AvgNewPeak'] for i in setup[1]]
    z2 = [i['AvgMaxGridDemand'] for i in setup[1]]
    if first:
      ax.plot(x,y,color='k',linestyle='-', label = 'Original Grid Demand Peak')
      first = False
    labeltext = 'Battery: ' + str(setup[0]['BatteryCapacity']) + ' kWh,
       Connection: ' + str(setup[0]['MaxGridLimit']) + ' kW'
    ax.plot(x,z2,color=colors[c],linestyle='-', label = labeltext + " (Grid)")
    ax.plot(x,z,color=colors[c],linestyle='--', label = labeltext + " (Charger)
       ")
    c = (c + 1) % 5

  fig.set_size_inches([16., 10.])
  fig.tight_layout(pad=3.0)
  ax.legend(loc='best')
  ax.set_title('Max Grid- and Charger Draw over the weeks (' + experiment + ')'
     , fontsize = 20)
  ax.set_ylabel('Max Draw (kW)', fontsize = 16)
  ax.set_xlabel('Weeks', fontsize = 16)
  display(fig)
```

Visualizing the amount of lost demand

The function below is proposed to visualize the amount of lost demand due to applying the combined solution. The resulting graph has been presented in the main report in Figure 5.9.

```
def plotMissedDemand(results, experiment, recalibrationWeeks):
  fig, ax = plt.subplots(2,1)
  colors = ['b','r','y','m','g']
  c = 0
  for setup in results:
    x = [i['Week'] for i in setup[1]]
    y = [i['AvgUnmetDemand'] for i in setup[1]]
    z = np.cumsum([i['AvgUnmetDemand'] for i in setup[1]])
    z = [a*recalibrationWeeks for a in z]
    labeltext = 'Battery: ' + str(setup[0]['BatteryCapacity']) + ' kWh,
       Connection: ' + str(setup[0]['MaxGridLimit']) + ' kW'
    ax[0].plot(x,y,color=colors[c],linestyle='-', label = labeltext)
    ax[1].plot(x,z,color=colors[c],linestyle='-', label = labeltext)
    c = (c + 1) % 5

  fig.set_size_inches([16., 10.])
  fig.tight_layout(pad=3.0)
  ax[0].legend(loc='best', fontsize='small')
  ax[1].legend(loc='best', fontsize='small')
  ax[0].set_xlabel('Weeks')
  ax[0].set_ylabel('Amount of kWhs unfulfilled')
```

```
ax[0].set_title('Amount of kWhs unfulfilled per week (' + experiment + ')')
ax[1].set_xlabel('Weeks')
ax[1].set_ylabel('Amount of kWhs unfulfilled')
ax[1].set_title('Cumulative amount of kWhs unfulfilled over the weeks (' +
    experiment + ')')
display(fig)
```

B ALL EXPERIMENT RESULTS

B.1 Results per Experiment

B.1.1 A-L-1

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	100	15941.11	9690.68-22191.53	7667.74-24214.47
25	100	5337.51	-1208.40-11883.42	-3326.97-14002.00
50	100	-8162.49	-14708.40–1616.58	-16826.97-502.00
75	100	-21662.49	-28208.40–15116.58	-30326.97–12998.00
0	160	-32310.86	-38808.45–25813.26	-40911.39–23710.33

Table B.1: Best options for A-L-1

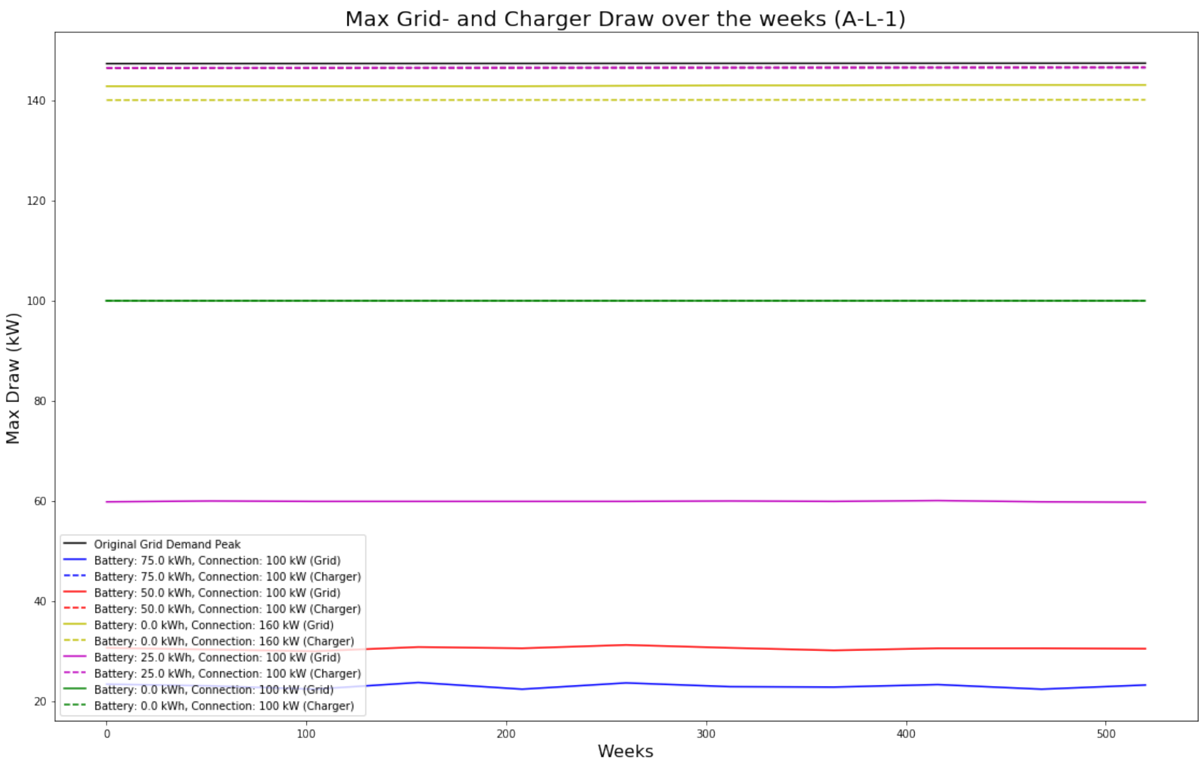

Figure B.1: Optimal Charger Draw Limit A-L-1

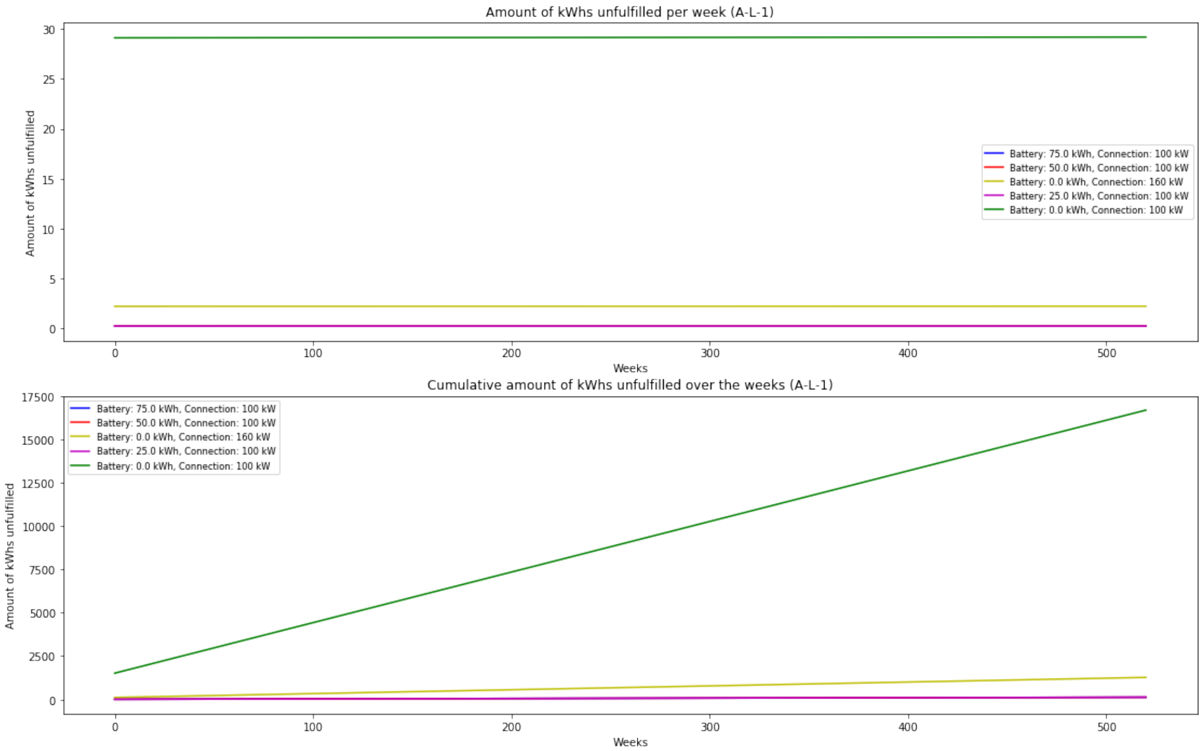

Figure B.2: Unmet demand A-L-1

B.1.2 A-L-4

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
25	100	59568.05	57639.92-61496.18	57015.89-62120.22
50	100	53989.90	52319.68-55660.12	51779.11-56200.68
75	100	43936.32	42314.61-45558.03	41789.75-46082.89
100	100	31892.38	30302.50-33482.25	29787.94-33996.82
0	100	19584.39	16315.83-22852.95	15257.96-23910.82

Table B.2: Best options for A-L-4

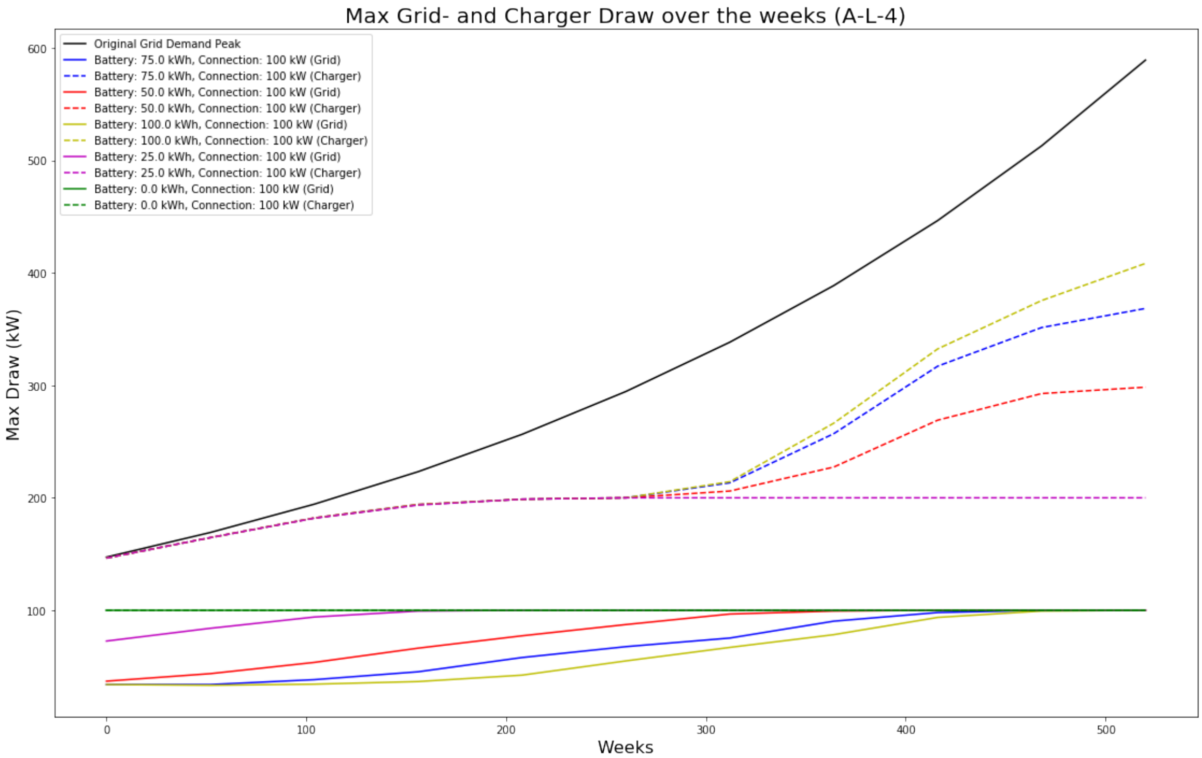

Figure B.3: Optimal Charger Draw Limit A-L-4

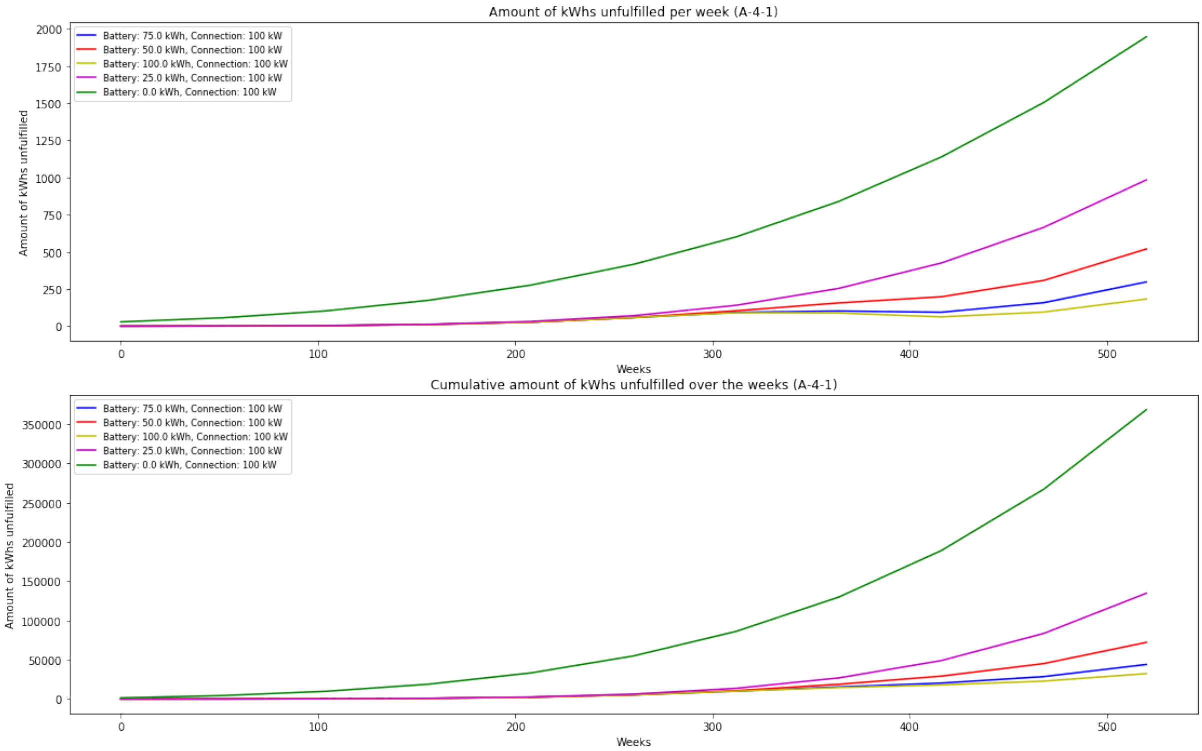

Figure B.4: Unmet demand A-L-4

B.1.3 A-L-10

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	1000	33335.34	21857.94-44812.74	18143.30-48527.38
0	630	31036.41	19602.99-42469.82	15902.59-46170.22
25	630	26480.51	15025.62-37935.40	11318.26-41642.76
25	1000	20595.28	9076.42-32114.13	5348.36-35842.19
50	630	16381.01	4927.83-27834.19	1221.03-31540.99

Table B.3: Best options for A-L-10

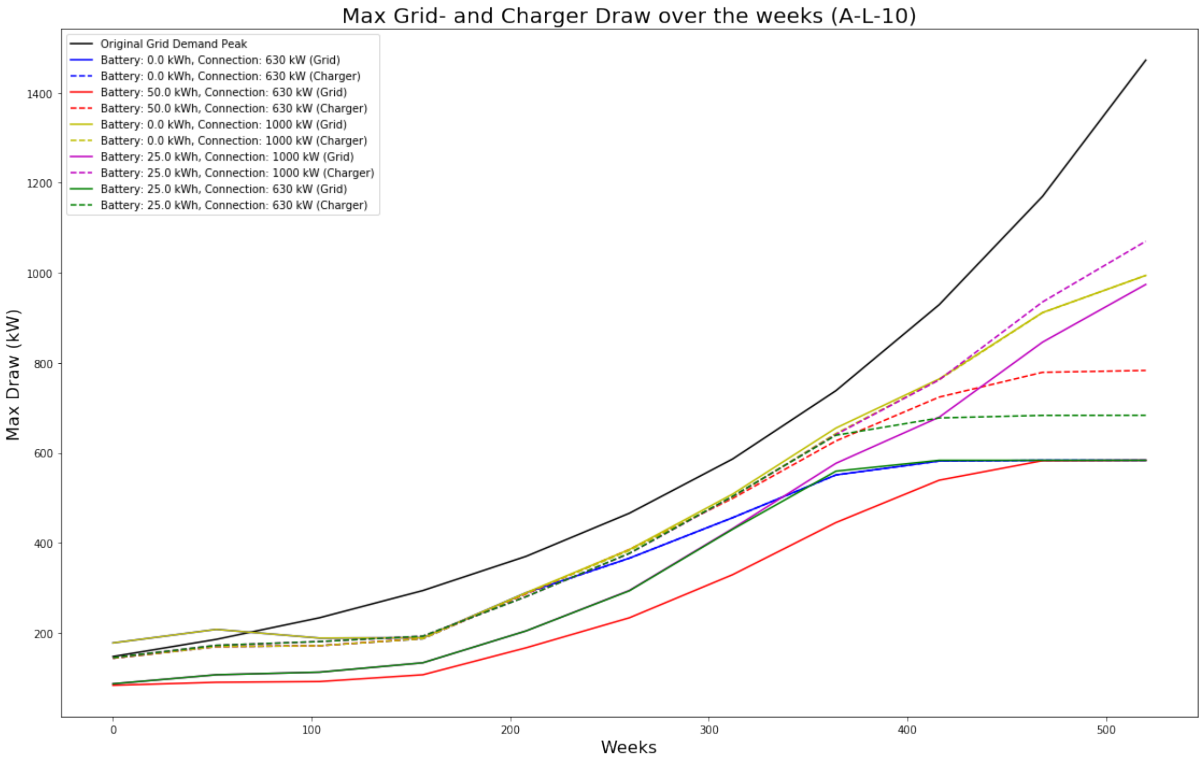

Figure B.5: Optimal Charger Draw Limit A-L-10

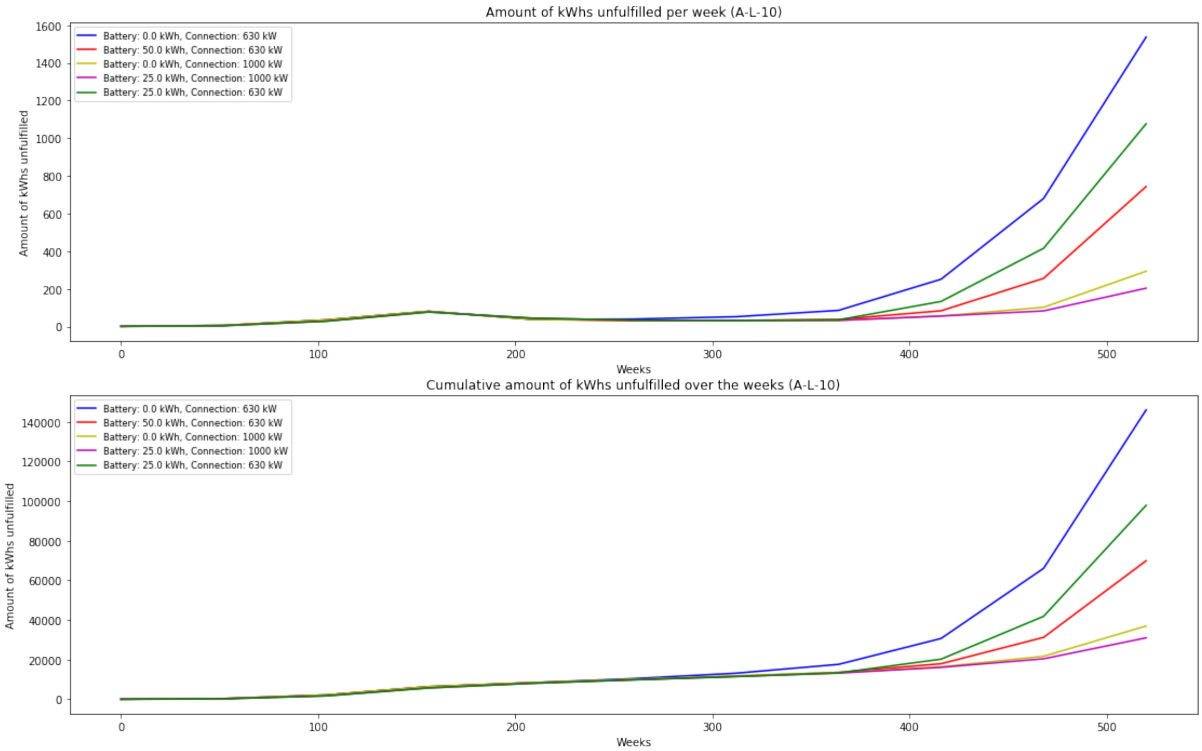

Figure B.6: Unmet demand A-L-10

B.1.4 A-H-1

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
25	100	5337.51	-1208.40-11883.42	-3326.97-14002.00
50	100	-8162.49	-14708.40–1616.58	-16826.97-502.00
0	100	-21401.75	-34352.52–8450.98	-38544.01–4259.48
75	100	-21662.49	-28208.40–15116.58	-30326.97–12998.00
0	160	-33010.43	-39218.51–26802.35	-41227.75–24793.12

Table B.4: Best options for A-H-1

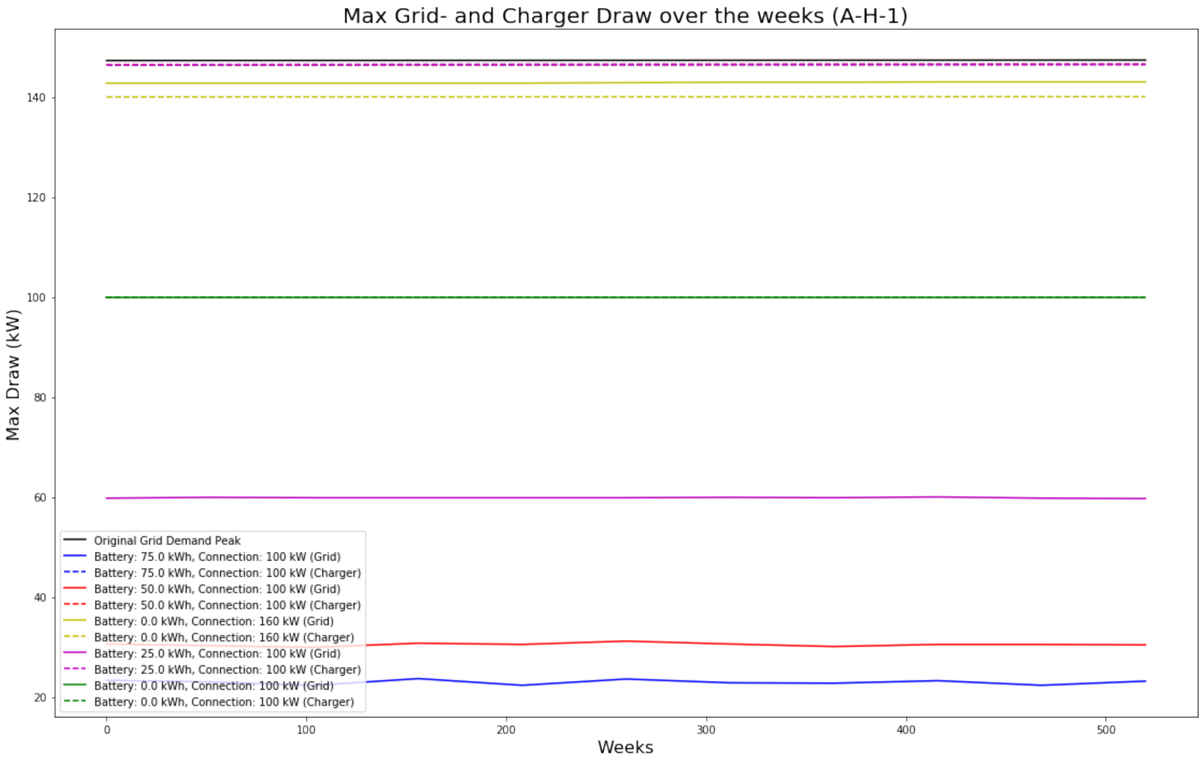

Figure B.7: Optimal Charger Draw Limit A-H-1

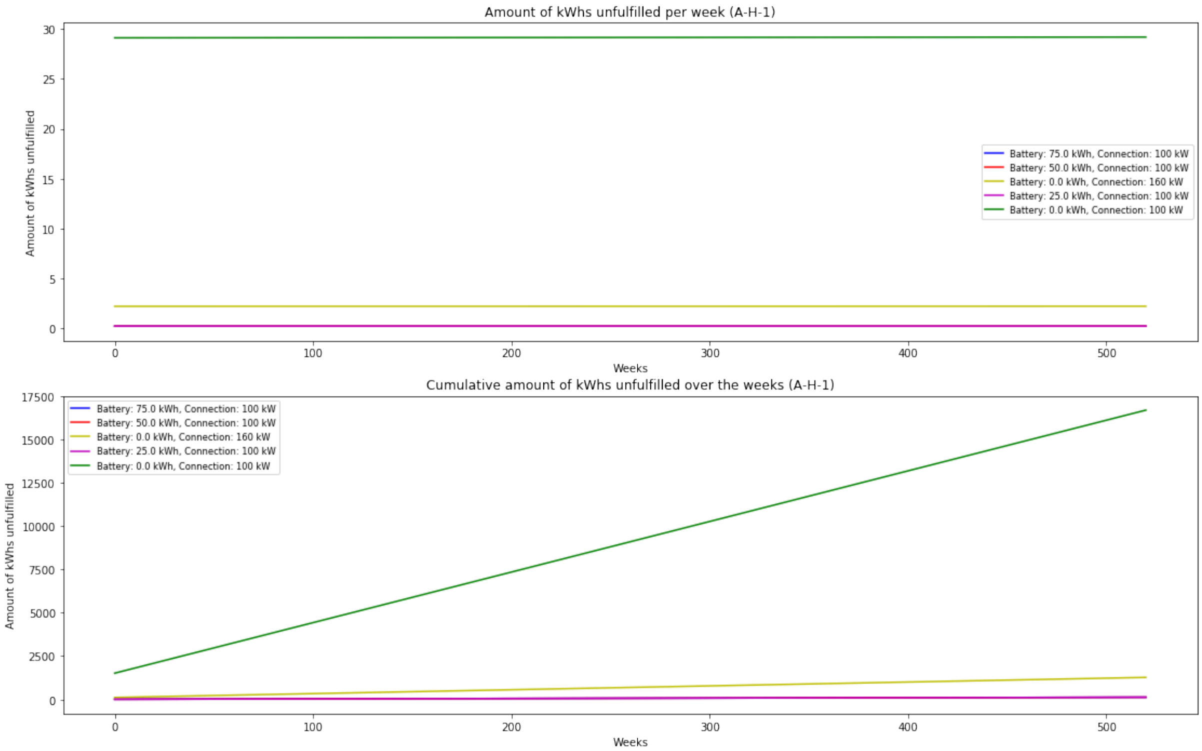

Figure B.8: Unmet demand A-H-1

B.1.5 A-H-4

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	630	5381.88	4341.46-6422.30	4004.73-6759.03
125	100	62.61	-7080.84-7206.06	-9392.81-9518.03
100	100	-4301.87	-15501.15-6897.41	-19125.78-10522.04
150	100	-5104.58	-9208.00–1001.15	-10536.06-326.91
0	1000	-7431.11	-8638.65–6223.57	-9029.47–5832.75

Table B.5: Best options for A-H-4

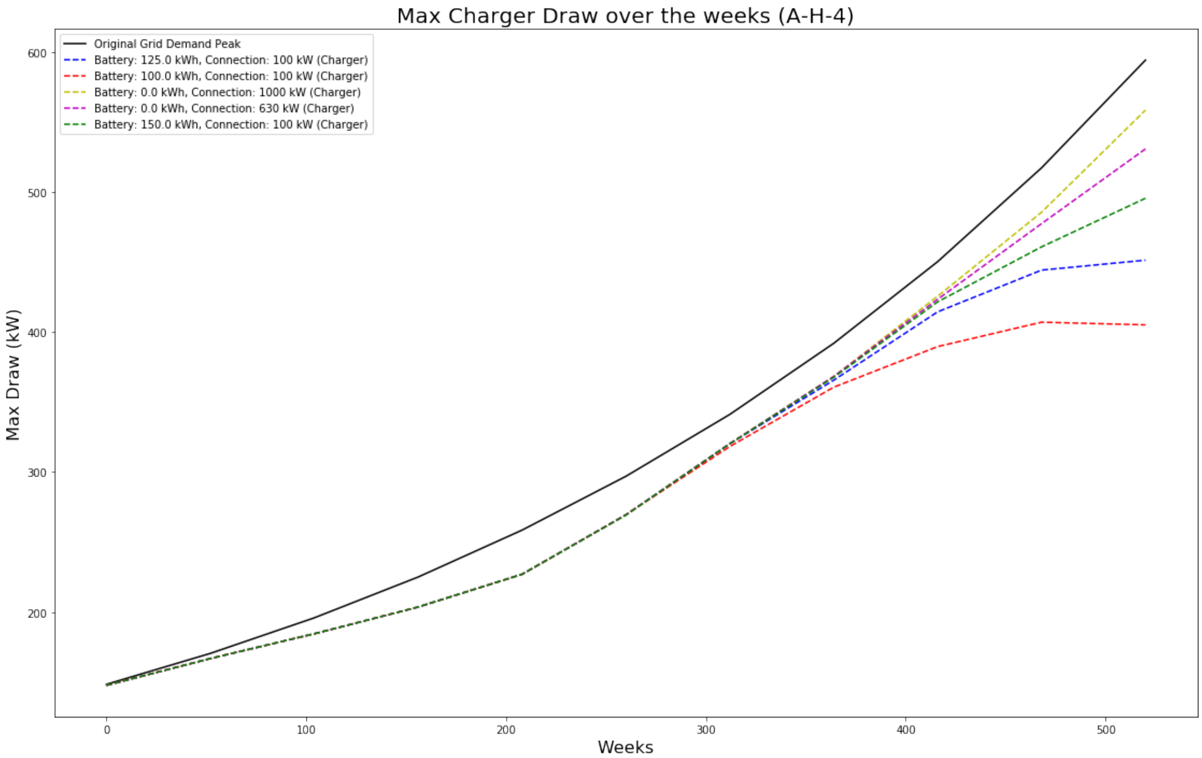

Figure B.9: Optimal Charger Draw Limit A-H-4

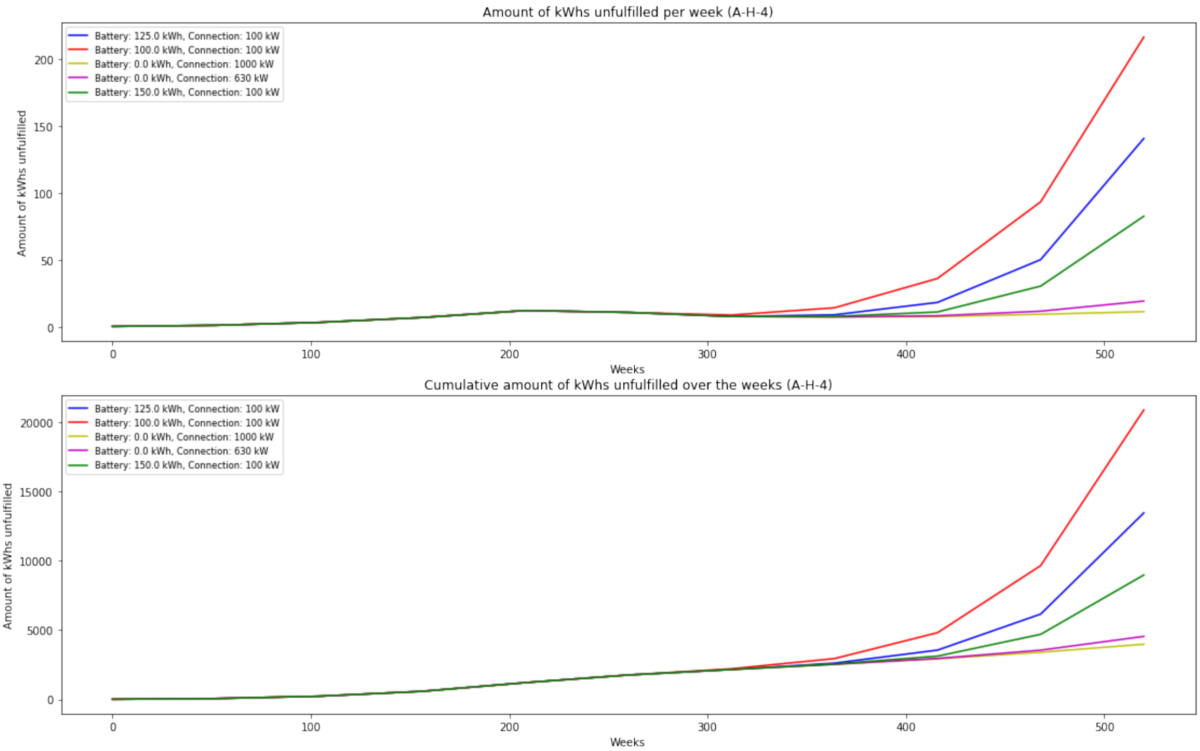

Figure B.10: Unmet demand A-H-4

B.1.6 A-H-10

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
25	1000	13301.43	2787.00-23815.85	-615.98-27218.83
0	1000	12971.78	5163.10-20780.46	2635.84-23307.73
0	2000	9022.06	-2294.69-20338.80	-5957.33-24001.44
50	1000	1716.36	-8996.74-12429.46	-12464.01-15896.74
25	2000	-3868.29	-15178.70-7442.12	-18839.29-11102.71

Table B.6: Best options for A-H-10

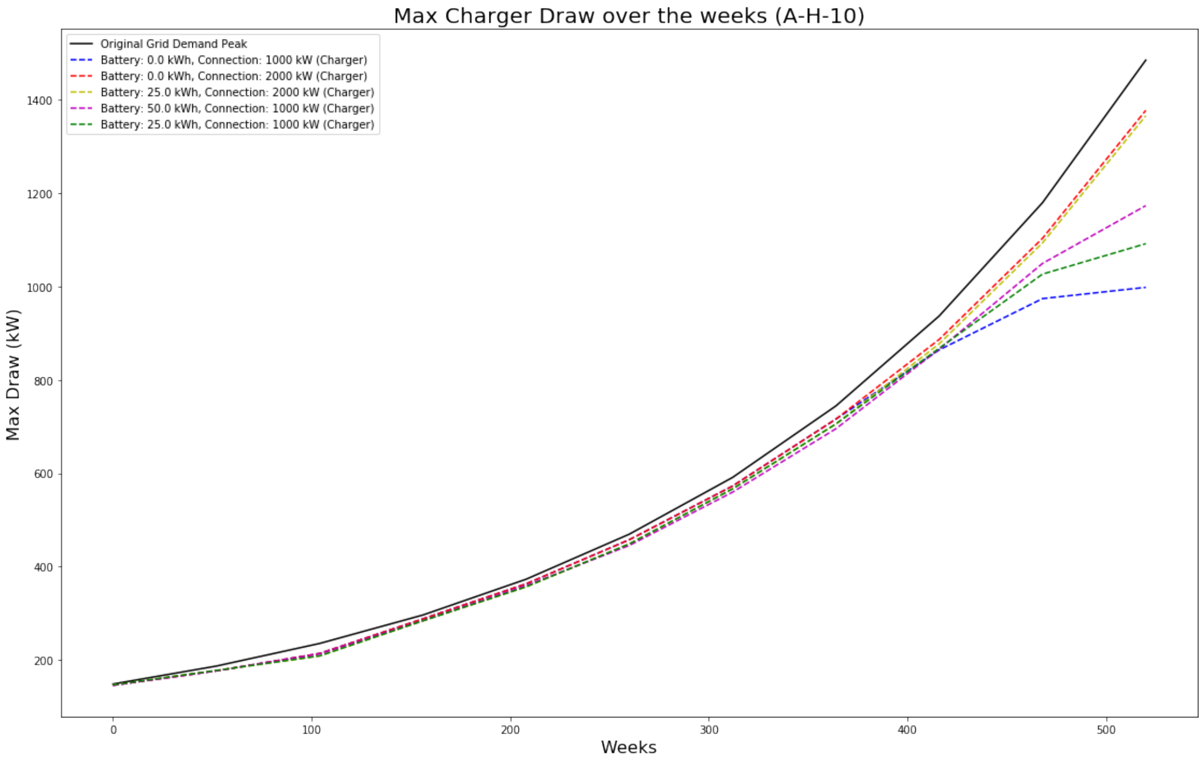

Figure B.11: Optimal Charger Draw Limit A-H-10

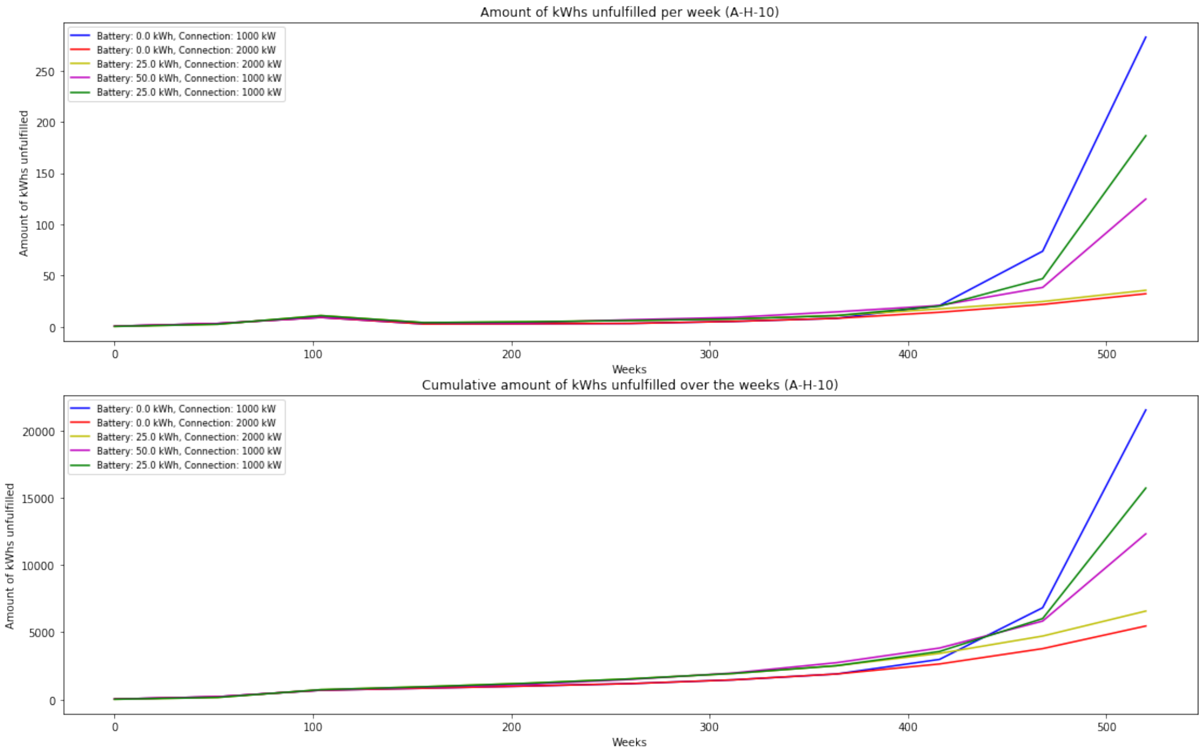

Figure B.12: Unmet demand A-H-10

B.1.7 B-L-1

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	100	42666.93	35662.90-49670.97	33396.05-51937.82
25	100	36209.40	28876.58-43542.22	26503.32-45915.47
50	100	22743.13	15402.27-30083.98	13026.41-32459.84
75	100	9243.13	1902.27-16583.98	-473.59-18959.84
0	160	-1646.79	-8920.36-5626.77	-11274.43-7980.85

Table B.7: Best options for B-L-1

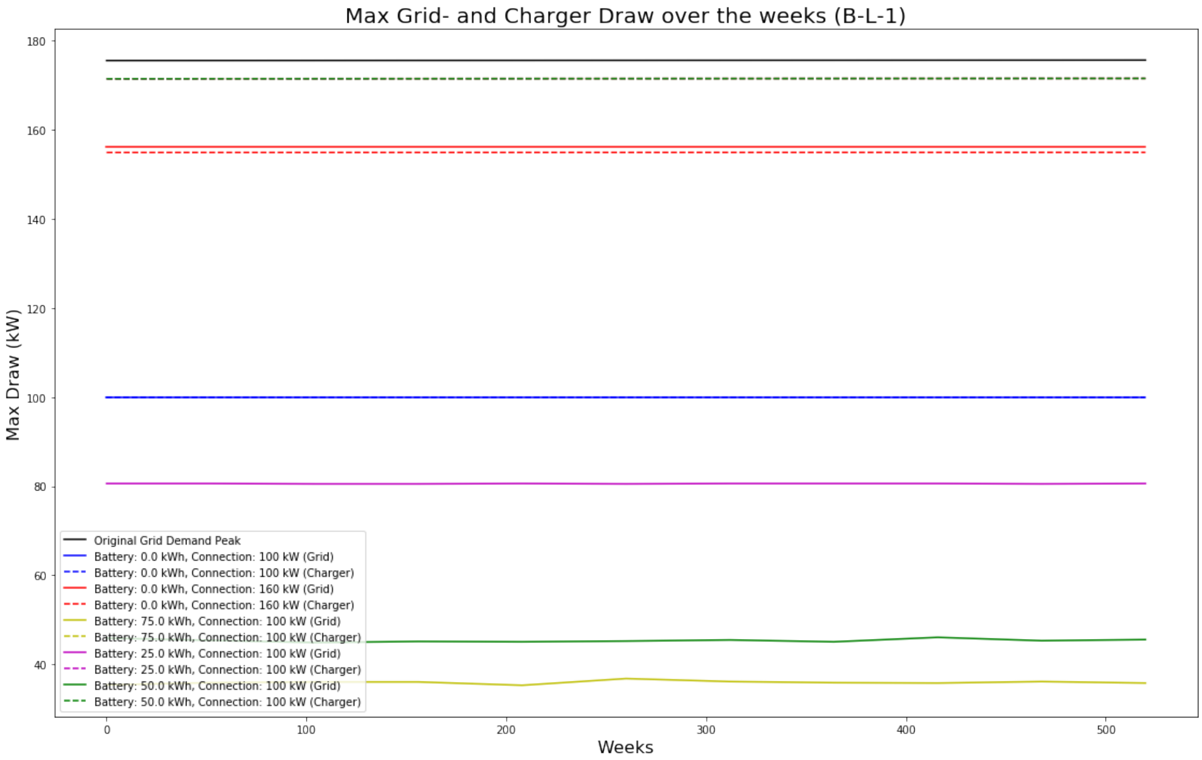

Figure B.13: Optimal Charger Draw Limit B-L-1

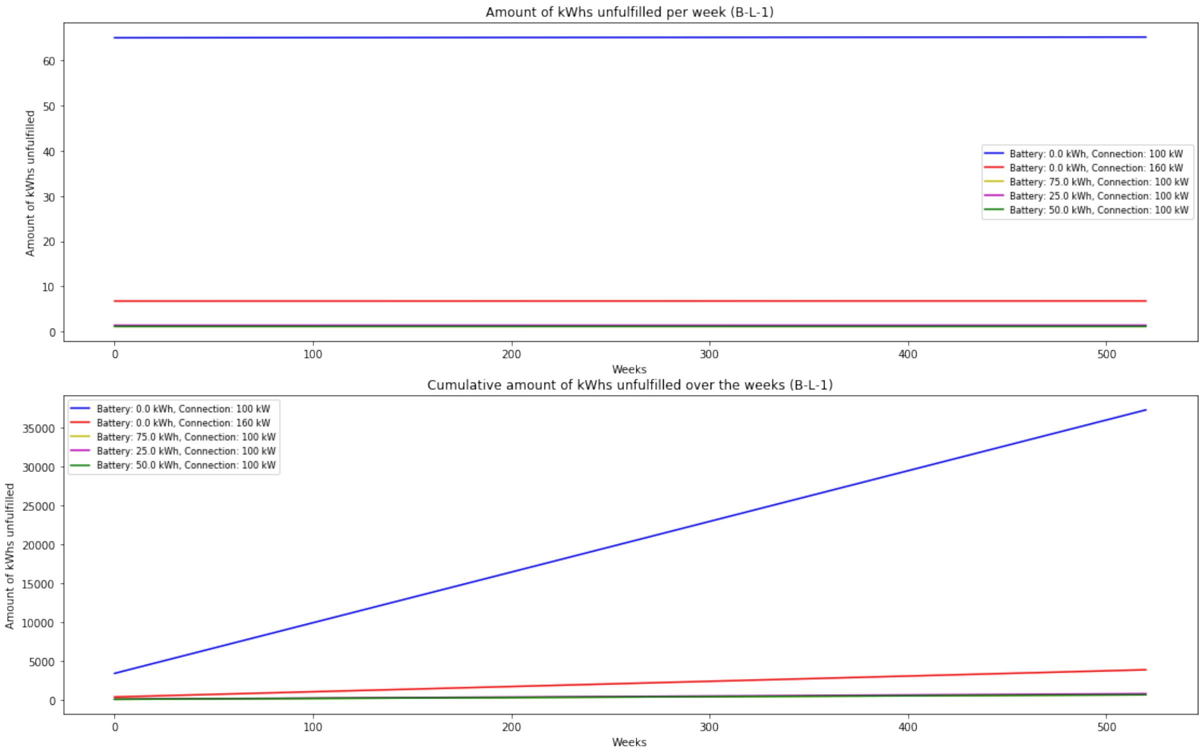

Figure B.14: Unmet demand B-L-1

B.1.8 B-L-4

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
50	100	42682.03	40334.94-45029.11	39575.31-45788.74
25	100	38642.26	35953.60-41330.91	35083.42-42201.09
75	100	38063.38	35855.56-40271.19	35141.01-40985.75
100	100	29350.03	27240.00-31460.07	26557.09-32142.98
125	100	18772.98	16730.17-20815.79	16069.02-21476.95

Table B.8: Best options for B-L-4

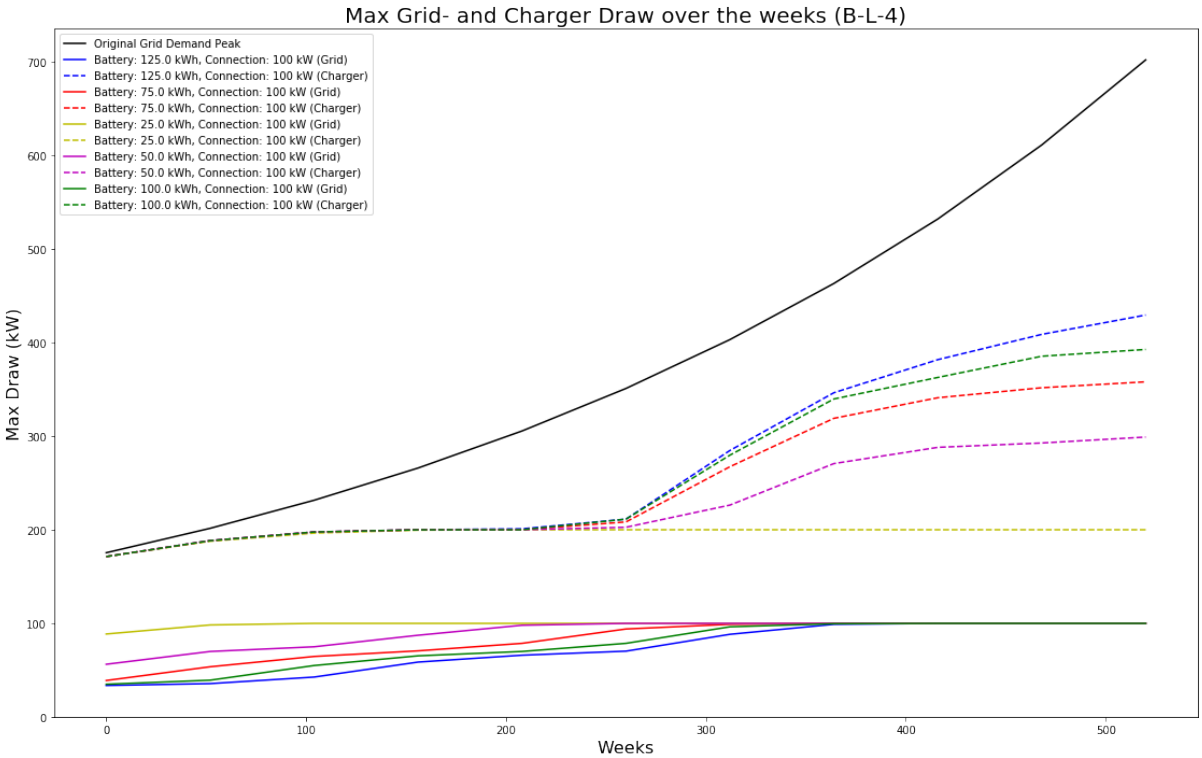

Figure B.15: Optimal Charger Draw Limit B-L-4

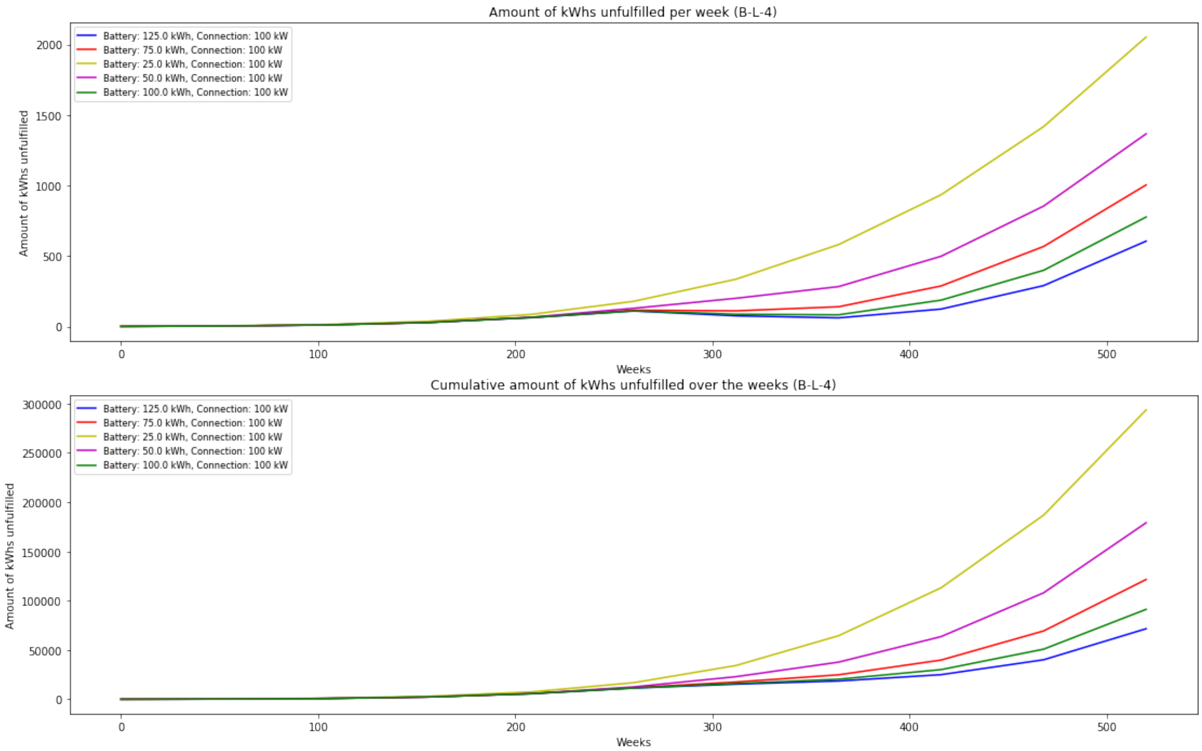

Figure B.16: Unmet demand B-L-4

B.1.9 B-L-10

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	1000	61670.69	38351.33-84990.05	30804.06-92537.33
25	1000	49704.32	26356.72-73051.93	18800.30-80608.34
25	630	45015.70	21758.71-68272.68	14231.63-75799.77
0	630	43065.36	19780.38-66350.34	12244.24-73886.48
0	2000	41917.50	18463.83-65371.17	10873.09-72961.91

Table B.9: Best options for B-L-10

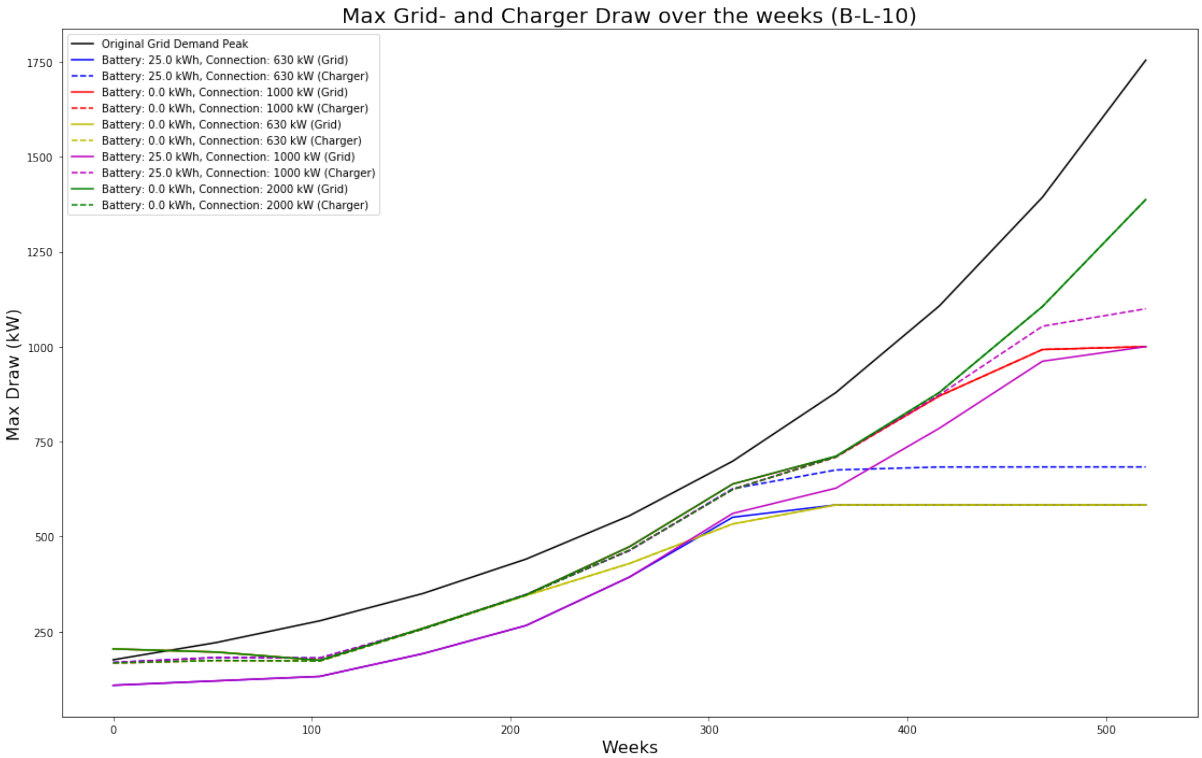

Figure B.17: Optimal Charger Draw Limit B-L-10

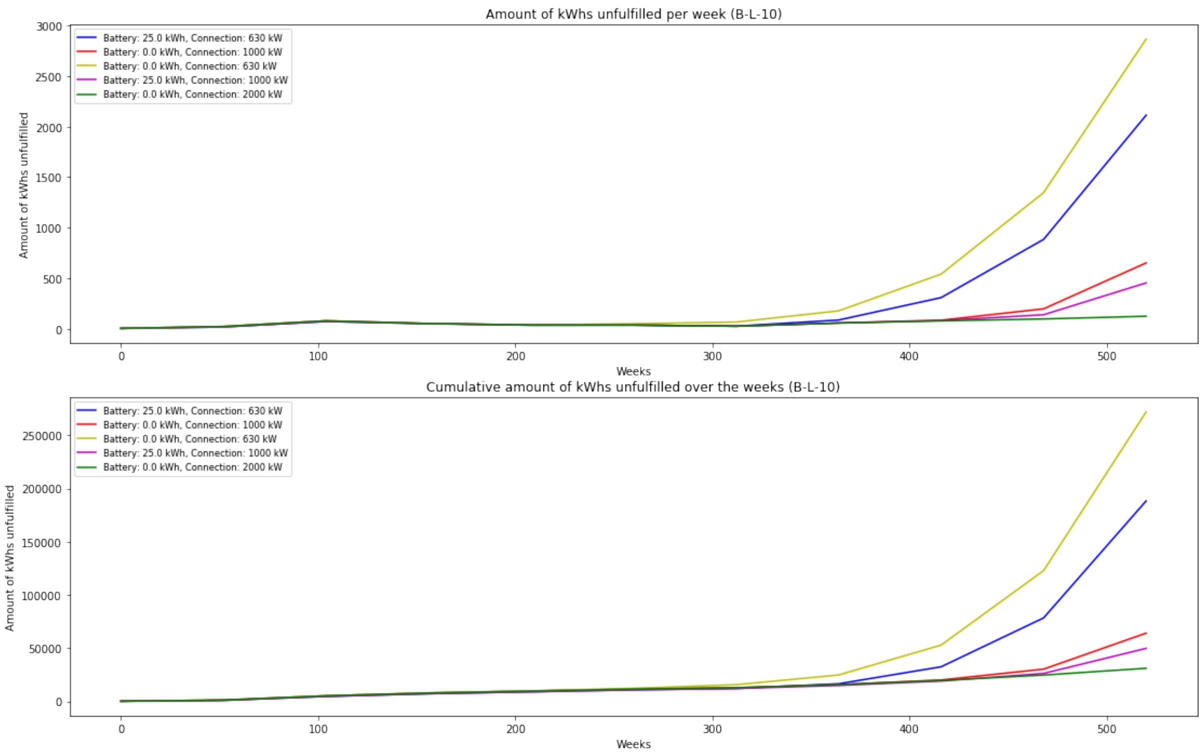

Figure B.18: Unmet demand B-L-10

B.1.10 B-H-1

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
25	100	35527.08	28319.36-42734.80	25986.60-45067.57
50	100	22231.80	14999.88-29463.72	12659.29-31804.32
75	100	8731.80	1499.88-15963.72	-840.71-18304.32
0	160	-4189.46	-11000.17-2621.26	-13204.45-4825.54
100	100	-4768.20	-12000.12-2463.72	-14340.71-4804.32

Table B.10: Best options for B-H-1

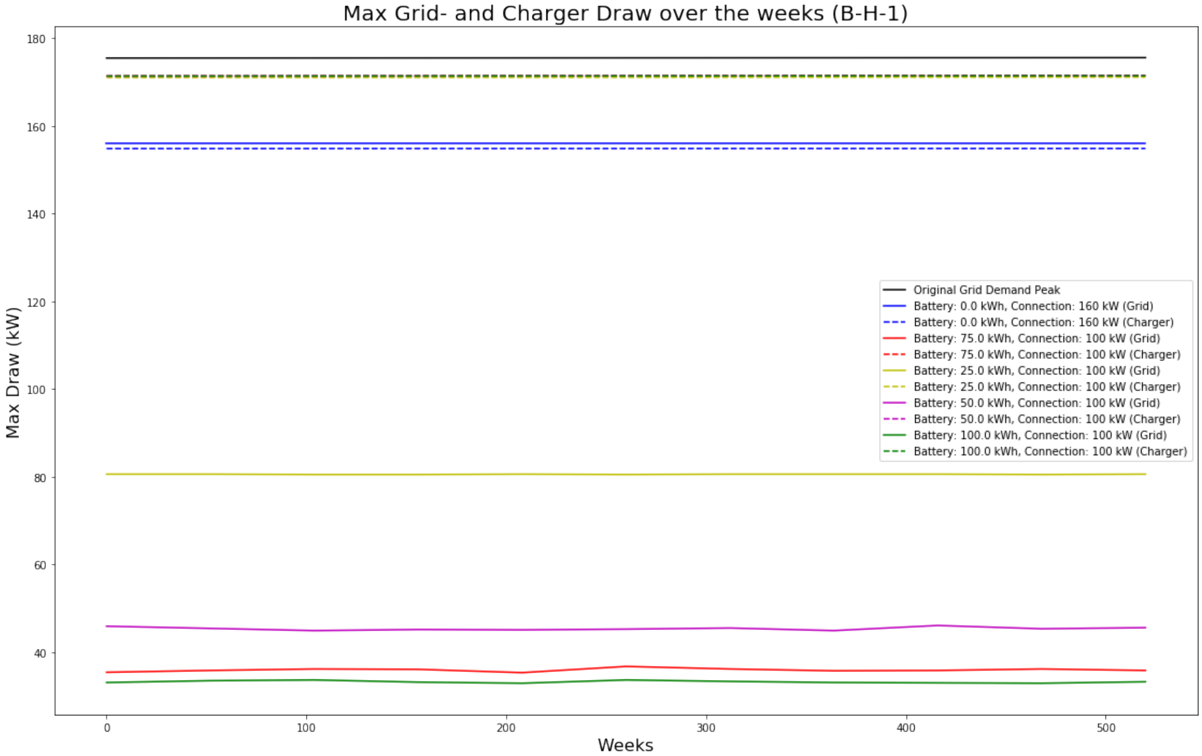

Figure B.19: Optimal Charger Draw Limit B-H-1

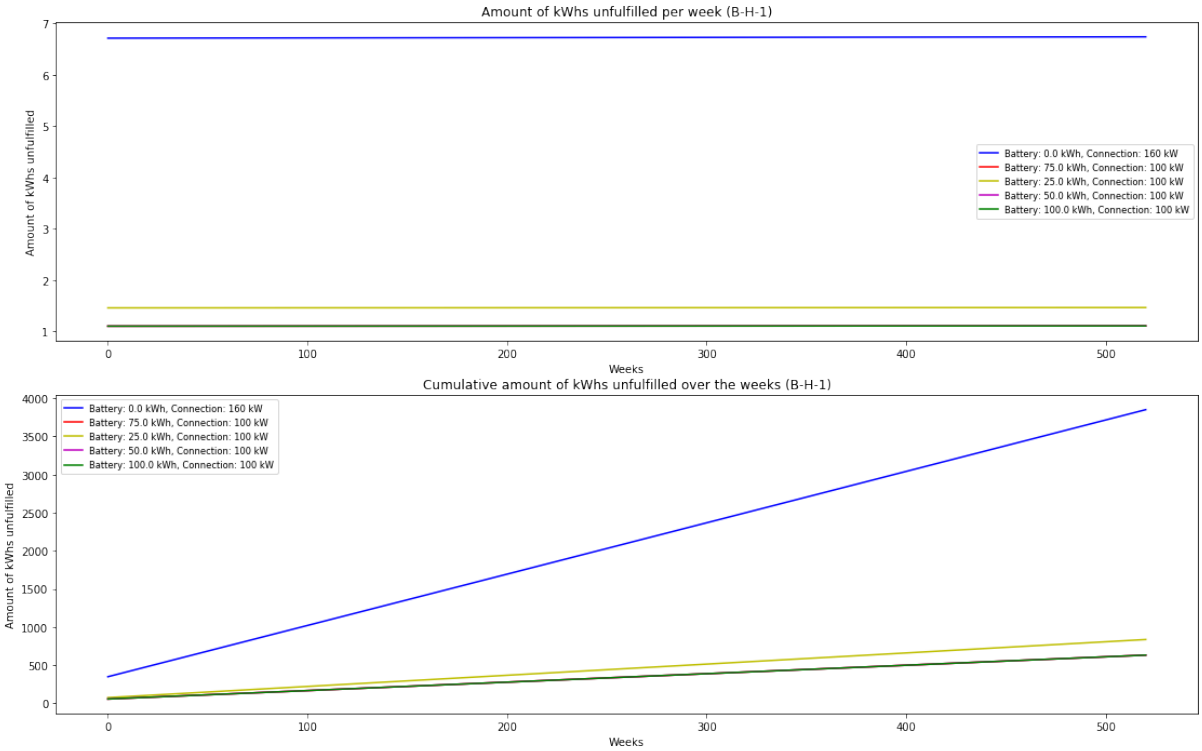

Figure B.20: Unmet demand B-H-1

B.1.11 B-H-4

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	630	11013.79	9739.64-12287.94	9327.26-12700.32
0	1000	-24.51	-1557.96-1508.94	-2054.26-2005.24
25	630	-596.70	-2028.56-835.16	-2491.98-1298.58
25	1000	-13523.71	-15057.28–11990.15	-15553.61–11493.81
50	630	-13793.51	-15282.39–12304.63	-15764.26–11822.76

Table B.11: Best options for B-H-4

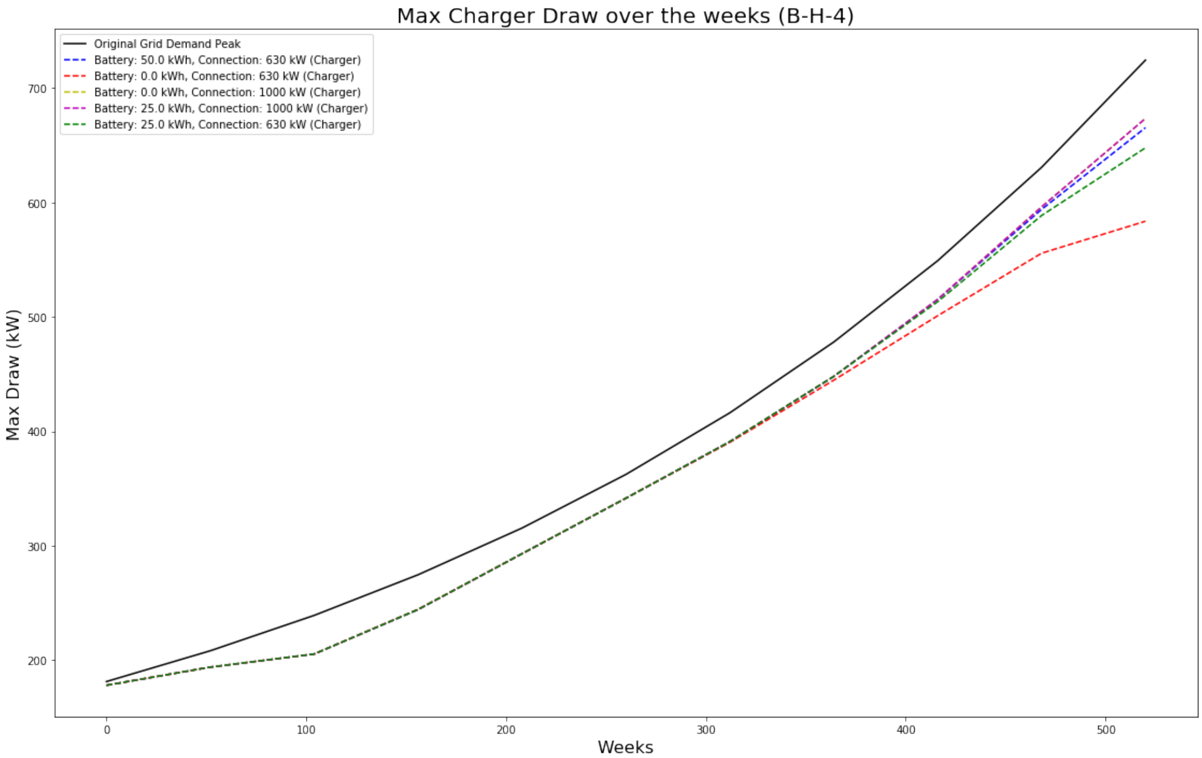

Figure B.21: Optimal Charger Draw Limit B-H-4

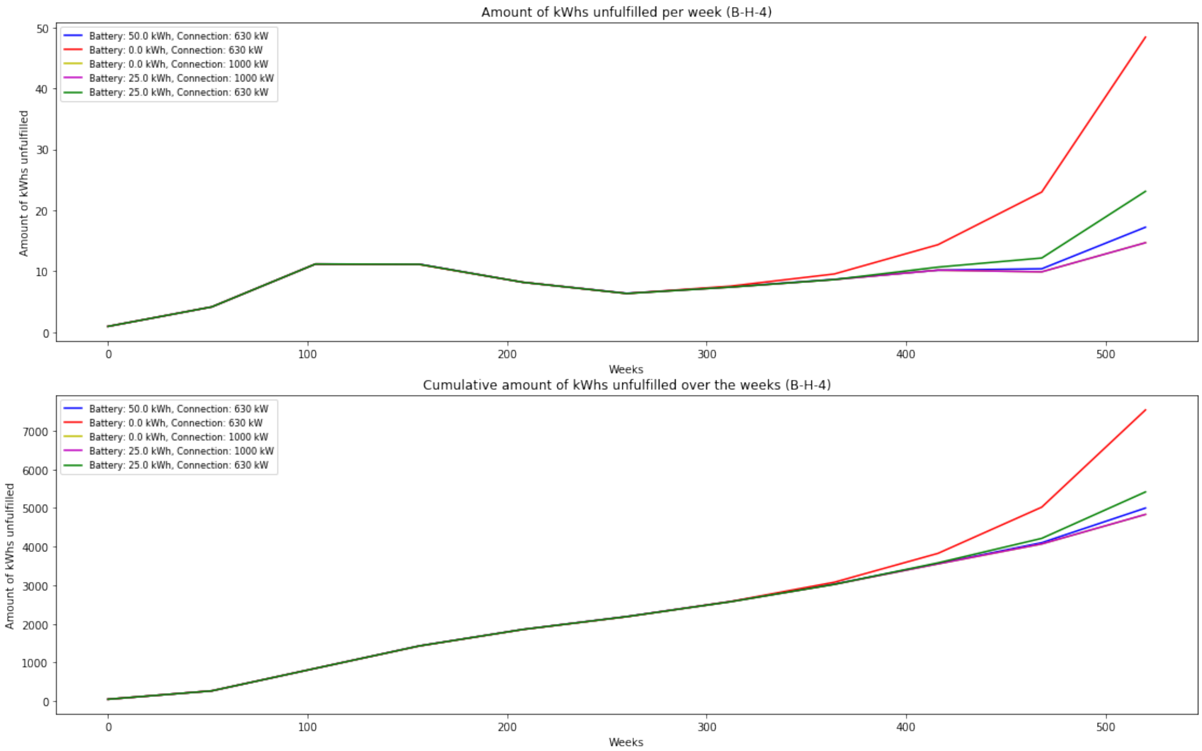

Figure B.22: Unmet demand B-H-4

B.1.12 B-H-10

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	2000	29622.22	9311.66-49932.78	2738.18-56506.26
25	2000	17079.99	-3355.35-37515.33	-9969.21-44129.20
50	2000	3312.76	-17165.21-23790.74	-23792.88-30418.40
50	1000	2525.70	-9536.97-14588.36	-13441.03-18492.42
25	1000	2356.33	-6615.78-11328.43	-9519.59-14232.24

Table B.12: Best options for B-H-10

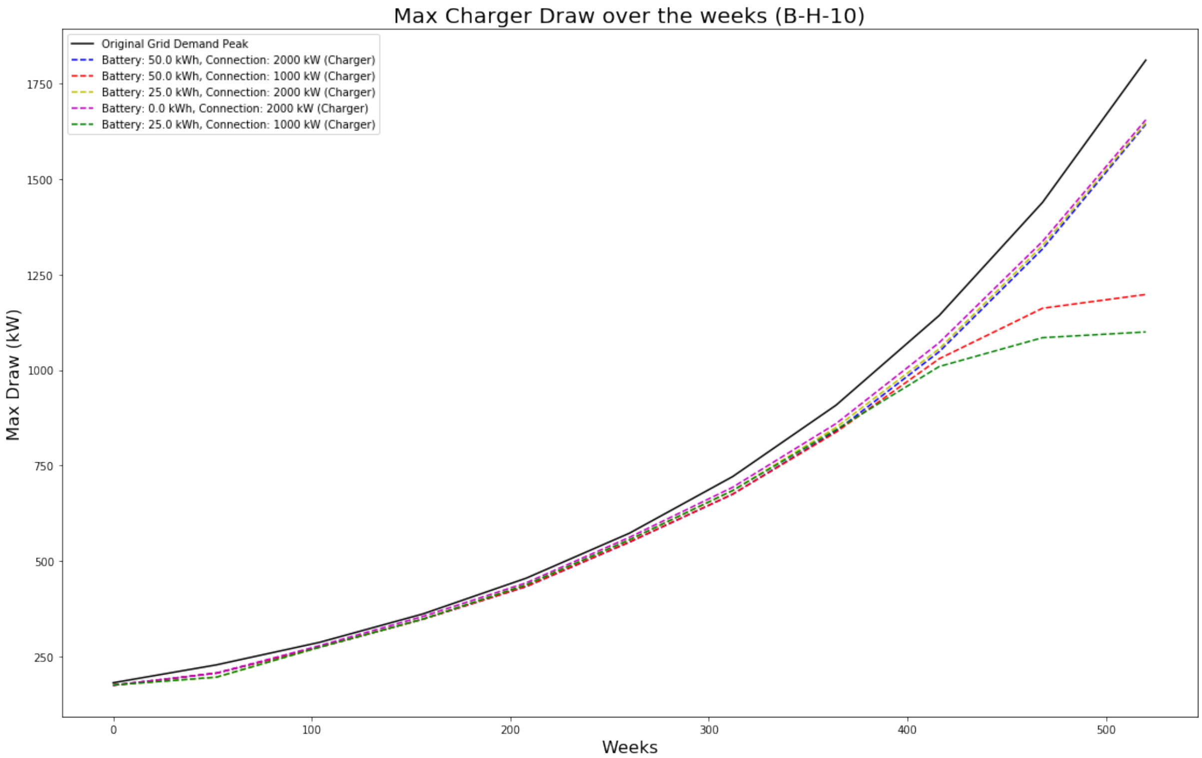

Figure B.23: Optimal Charger Draw Limit B-H-10

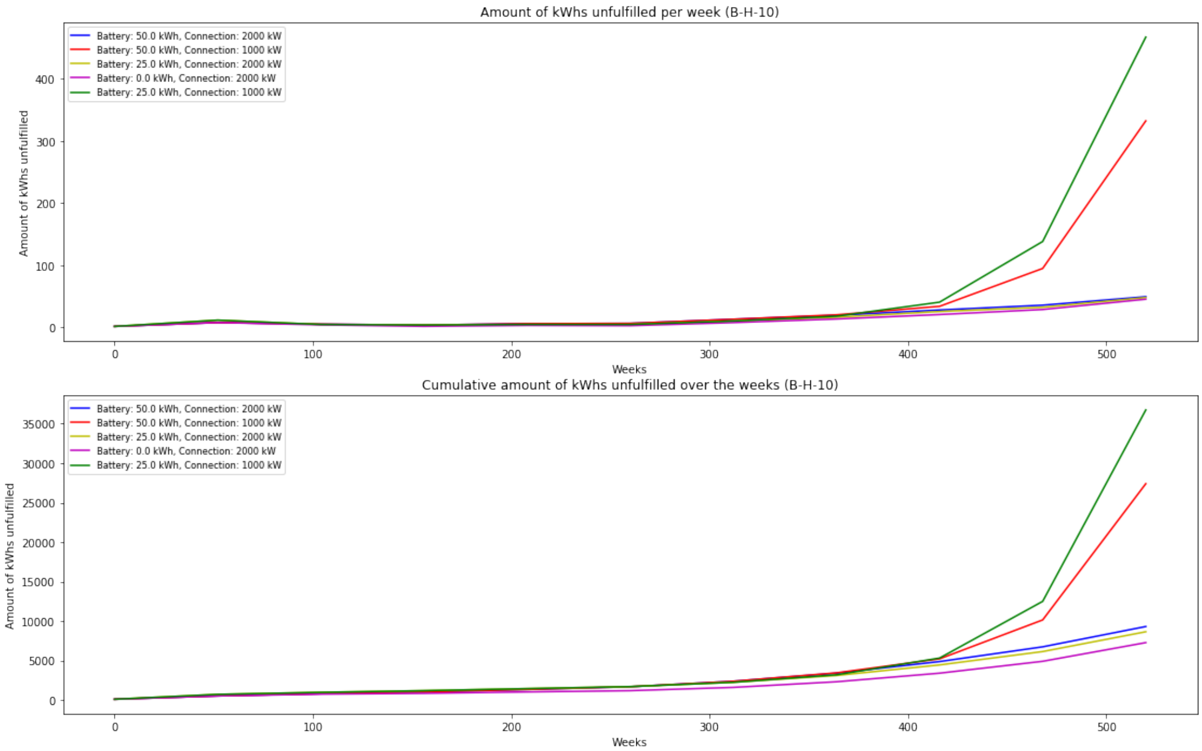

Figure B.24: Unmet demand B-H-10

B.1.13 C-L-1

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	100	0.00	0.00-0.00	0.00-0.00
25	100	-13500.00	-13500.00–13500.00	-13500.00–13500.00
50	100	-27000.00	-27000.00–27000.00	-27000.00–27000.00
75	100	-40500.00	-40500.00–40500.00	-40500.00–40500.00
0	160	-51030.00	-51030.00–51030.00	-51030.00–51030.00

Table B.13: Best options for C-L-1

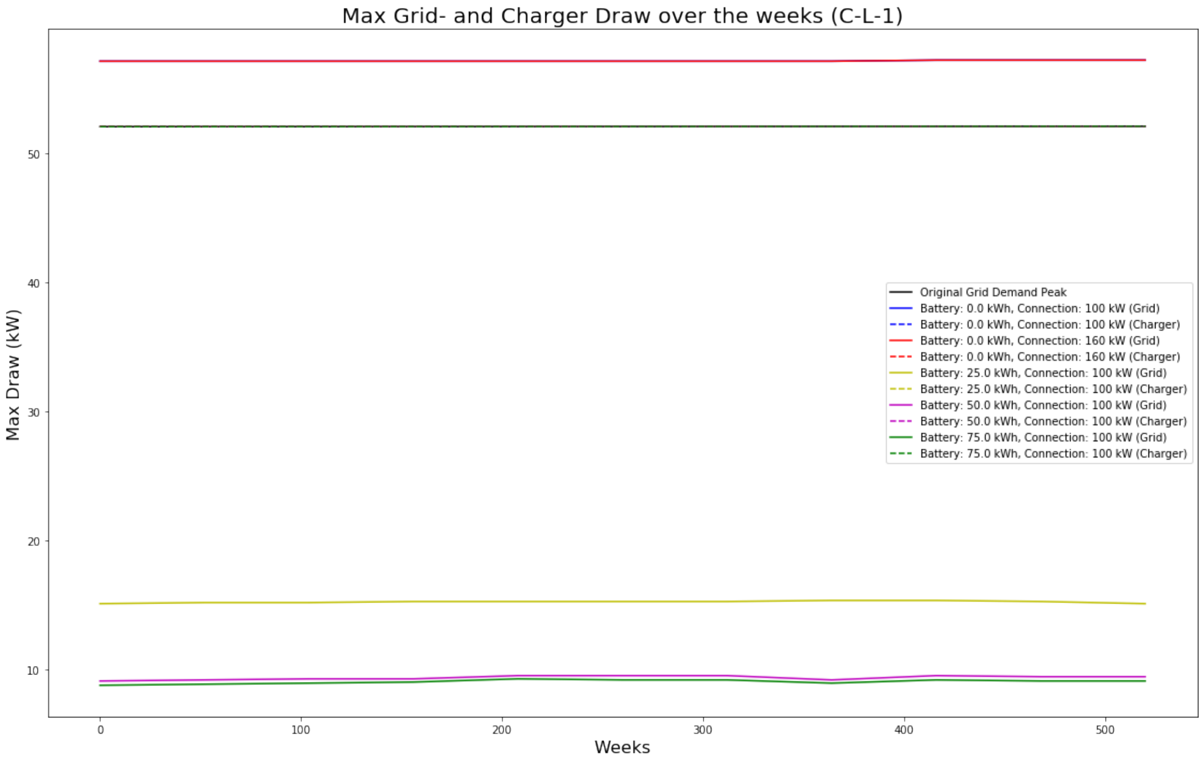

Figure B.25: Optimal Charger Draw Limit C-L-1

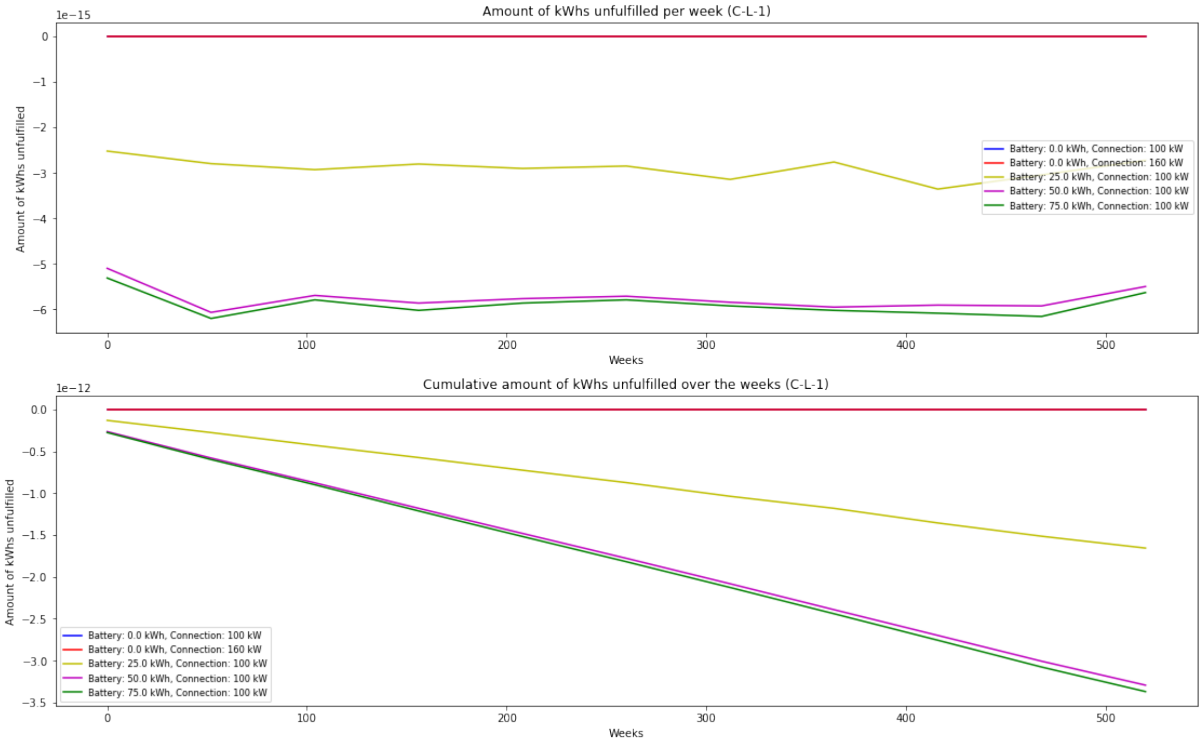

Figure B.26: Unmet demand C-L-1

B.1.14 C-L-4

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	100	70948.66	70650.90-71246.41	70554.54-71342.78
25	100	65005.38	64888.75-65122.01	64851.01-65159.75
50	100	51681.31	51570.08-51792.55	51534.08-51828.55
75	100	38188.10	38077.00-38299.19	38041.05-38335.14
0	160	25637.25	25515.14-25759.35	25475.62-25798.87

Table B.14: Best options for C-L-4

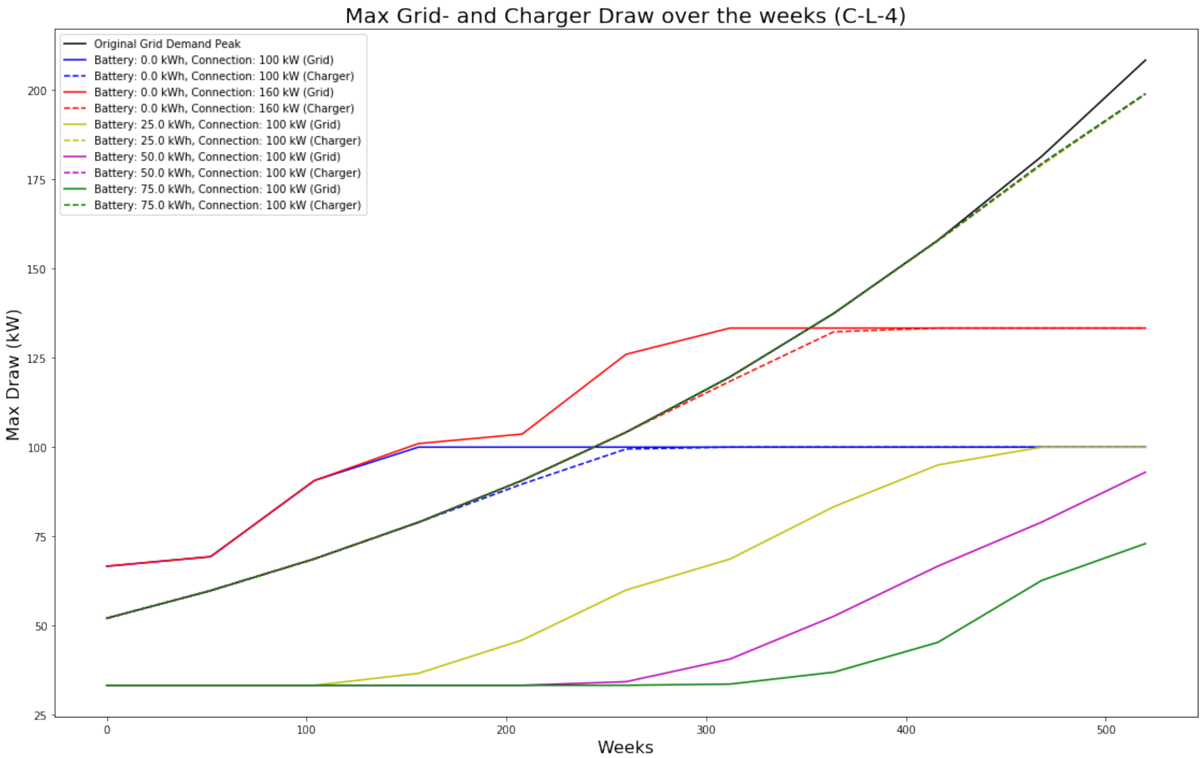

Figure B.27: Optimal Charger Draw Limit C-L-4

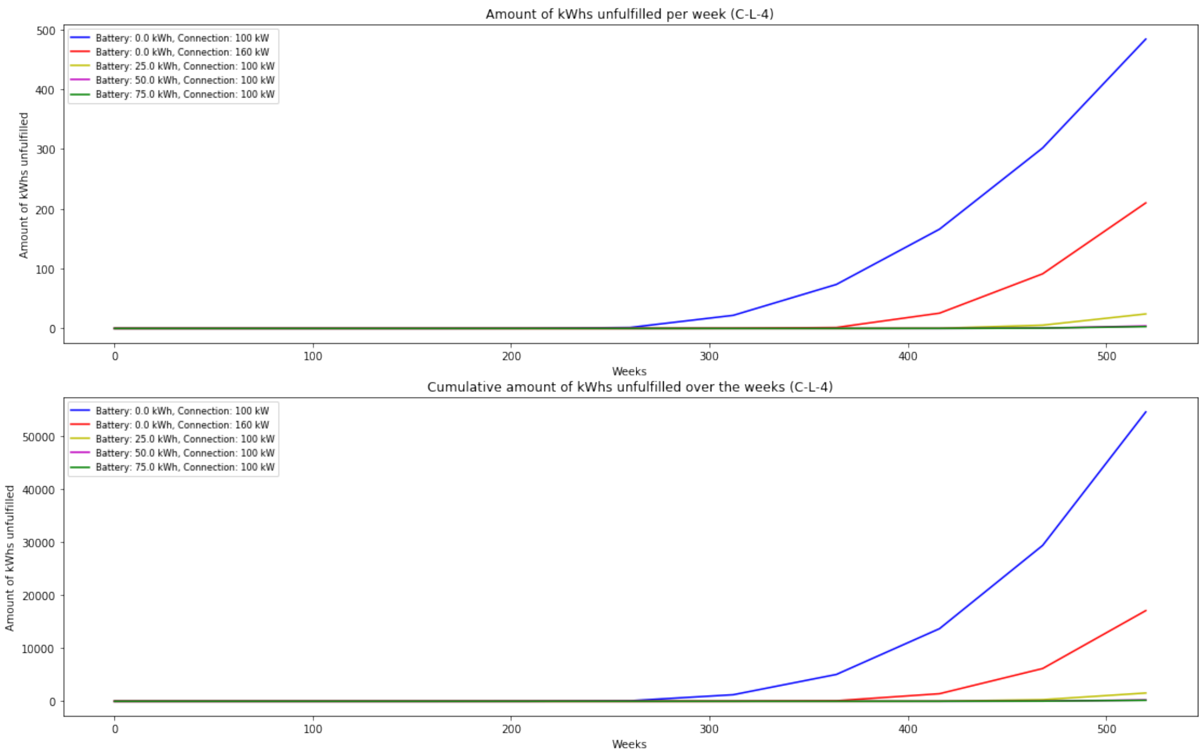

Figure B.28: Unmet demand C-L-4

B.1.15 C-L-10

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
50	100	32164.96	30964.74-33365.17	30576.29-33753.62
25	100	28451.55	26749.63-30153.47	26198.81-30704.30
75	100	26563.41	25616.90-27509.92	25310.56-27816.25
100	100	17247.13	16499.15-17995.10	16257.07-18237.18
125	100	6236.24	5623.40-6849.07	5425.06-7047.41

Table B.15: Best options for C-L-10

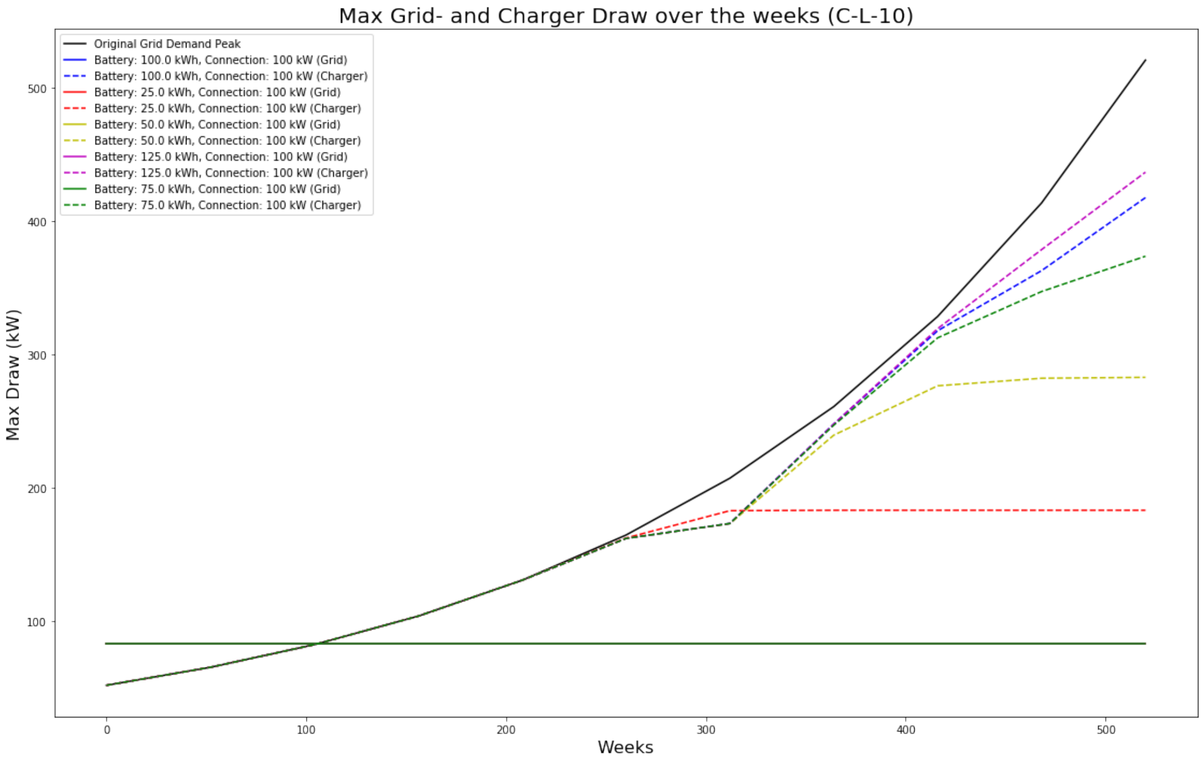

Figure B.29: Optimal Charger Draw Limit C-L-10

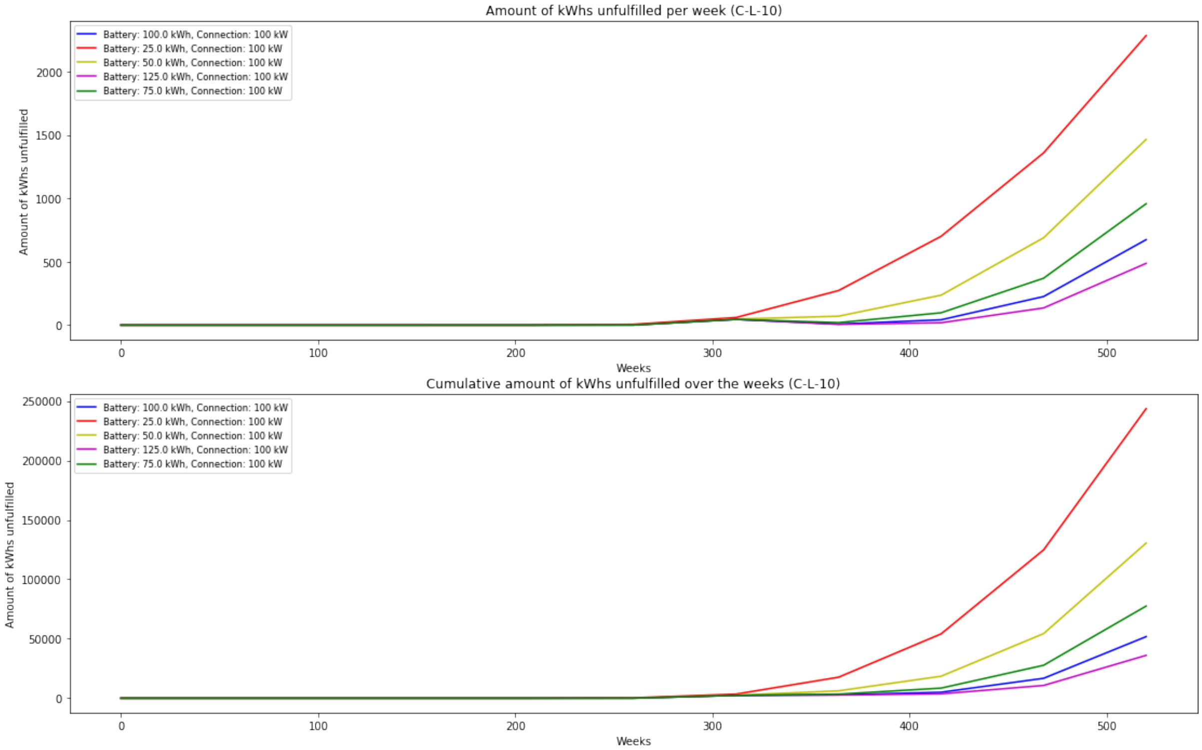

Figure B.30: Unmet demand C-L-10

B.1.16 C-H-1

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	100	0.00	0.00-0.00	0.00-0.00
25	100	-13500.00	-13500.00–13500.00	-13500.00–13500.00
50	100	-27000.00	-27000.00–27000.00	-27000.00–27000.00
75	100	-40500.00	-40500.00–40500.00	-40500.00–40500.00
0	160	-51030.00	-51030.00–51030.00	-51030.00–51030.00

Table B.16: Best options for C-H-1

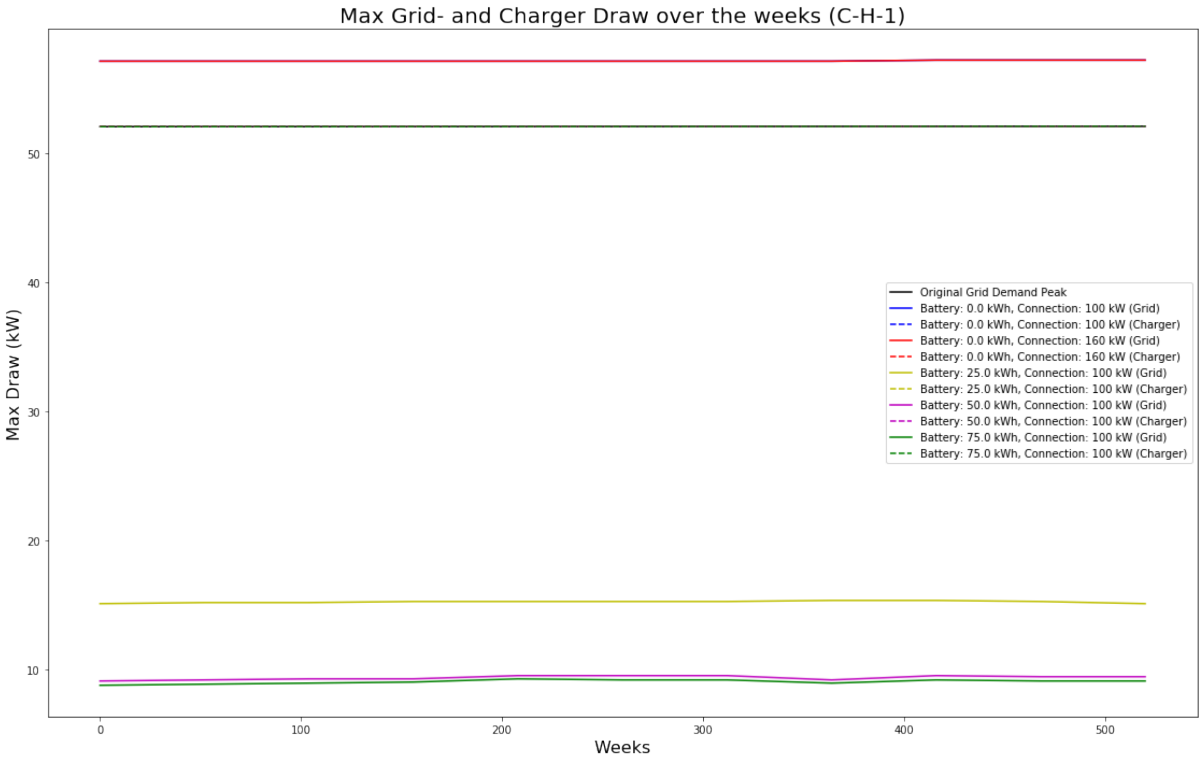

Figure B.31: Optimal Charger Draw Limit C-H-1

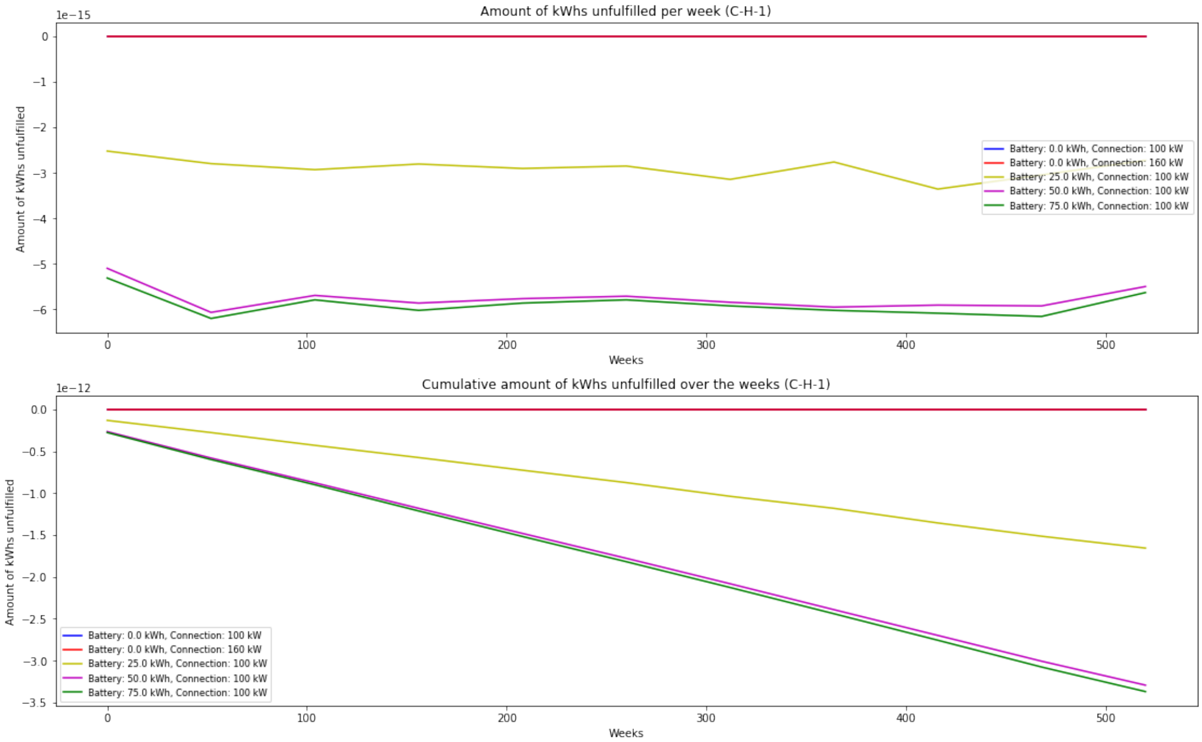

Figure B.32: Unmet demand C-H-1

B.1.17 C-H-4

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
25	100	64173.07	63940.01-64406.13	63864.57-64481.56
50	100	51613.97	51518.28-51709.66	51487.31-51740.62
75	100	38143.31	38050.45-38236.17	38020.40-38266.22
100	100	24643.31	24550.45-24736.17	24520.40-24766.22
0	160	18276.21	17770.97-18781.44	17607.45-18944.96

Table B.17: Best options for C-H-4

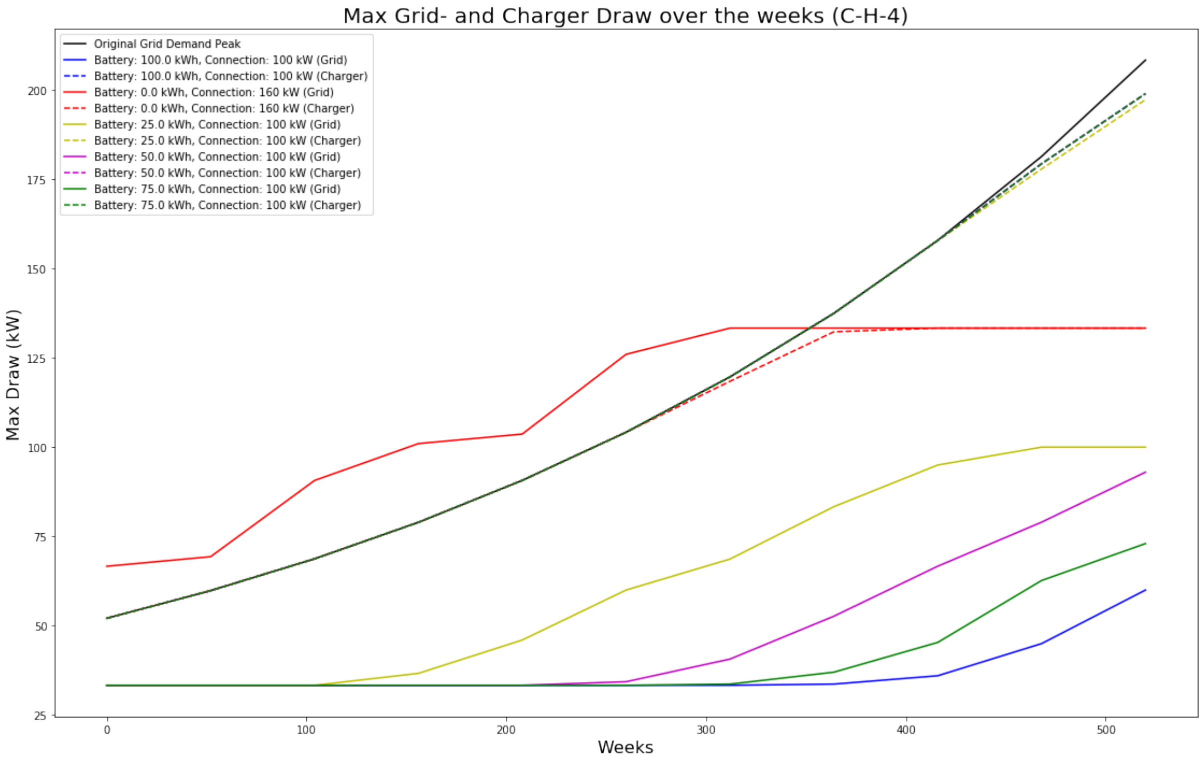

Figure B.33: Optimal Charger Draw Limit C-H-4

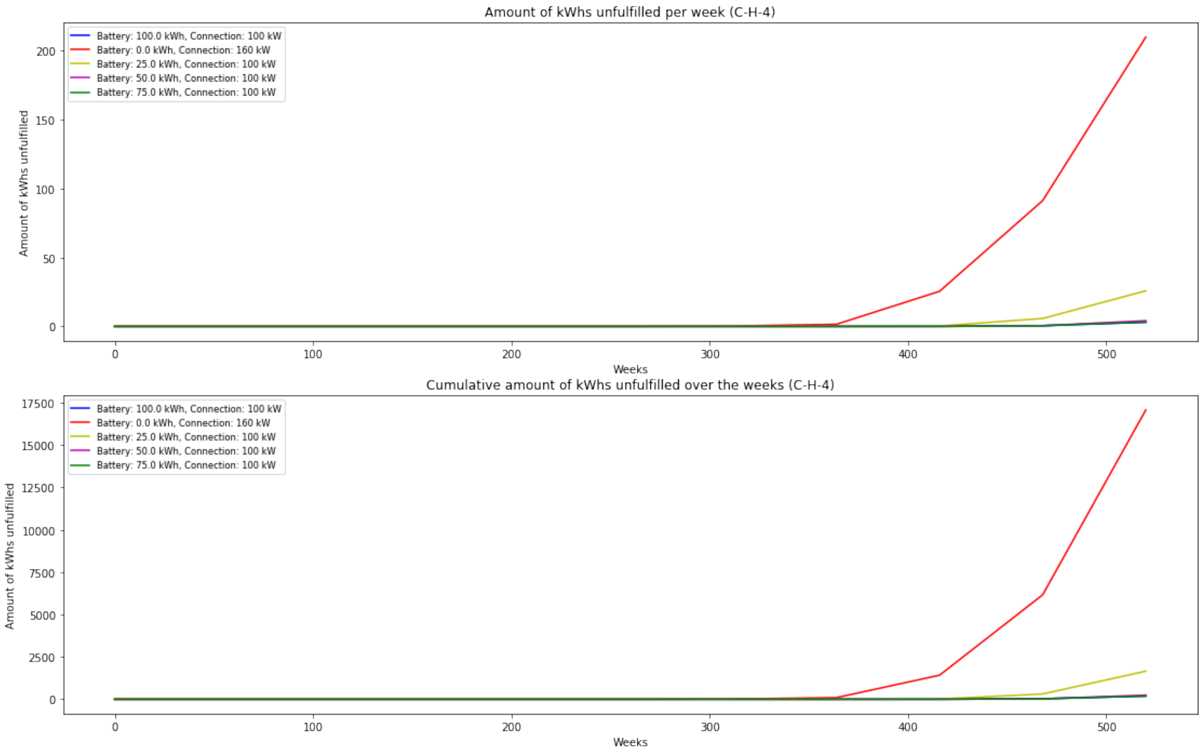

Figure B.34: Unmet demand C-H-4

B.1.18 C-H-10

Bat. Capacity	Grid Connection	NPV	CI 0.95	CI 0.99
0	630	83.18	47.91-118.45	36.50-129.87
0	1000	-13207.60	-13251.57–13163.64	-13265.79–13149.42
25	630	-13264.47	-13329.01–13199.93	-13349.90–13179.04
25	1000	-26606.47	-26671.01–26541.93	-26691.90–26521.04
50	630	-26825.94	-26881.50–26770.39	-26899.48–26752.41

Table B.18: Best options for C-H-10

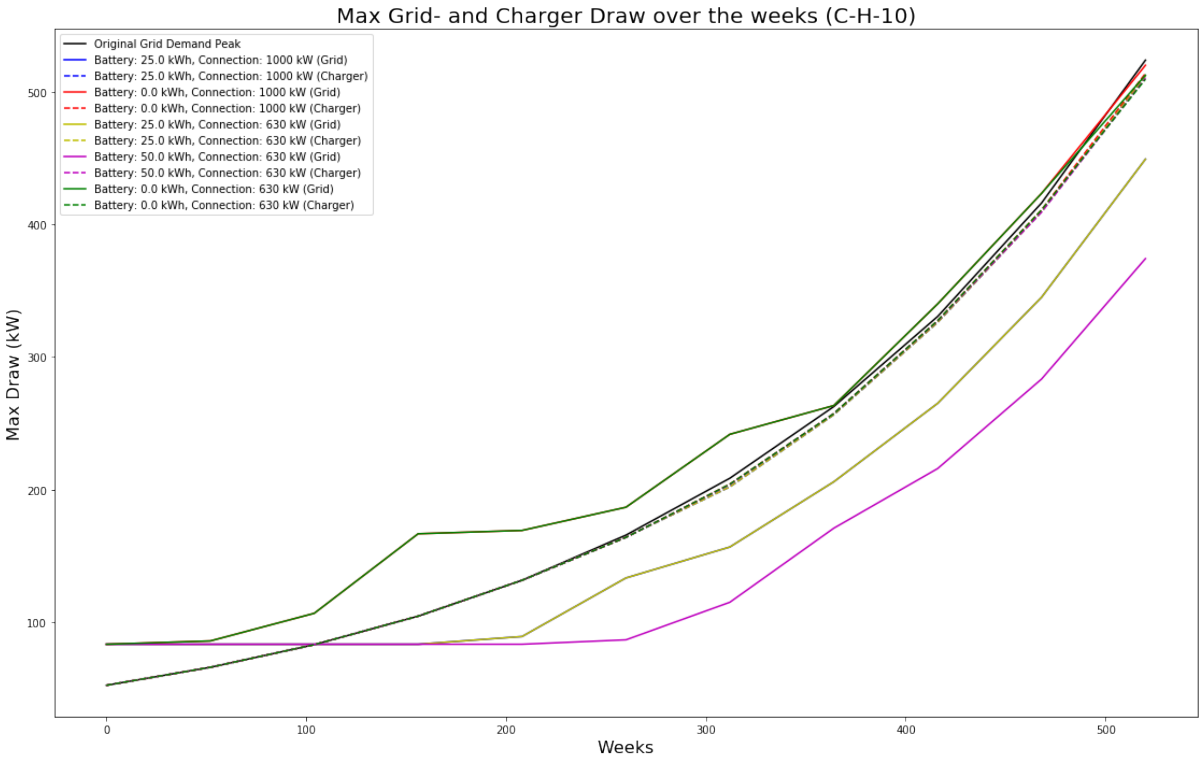

Figure B.35: Optimal Charger Draw Limit C-H-10

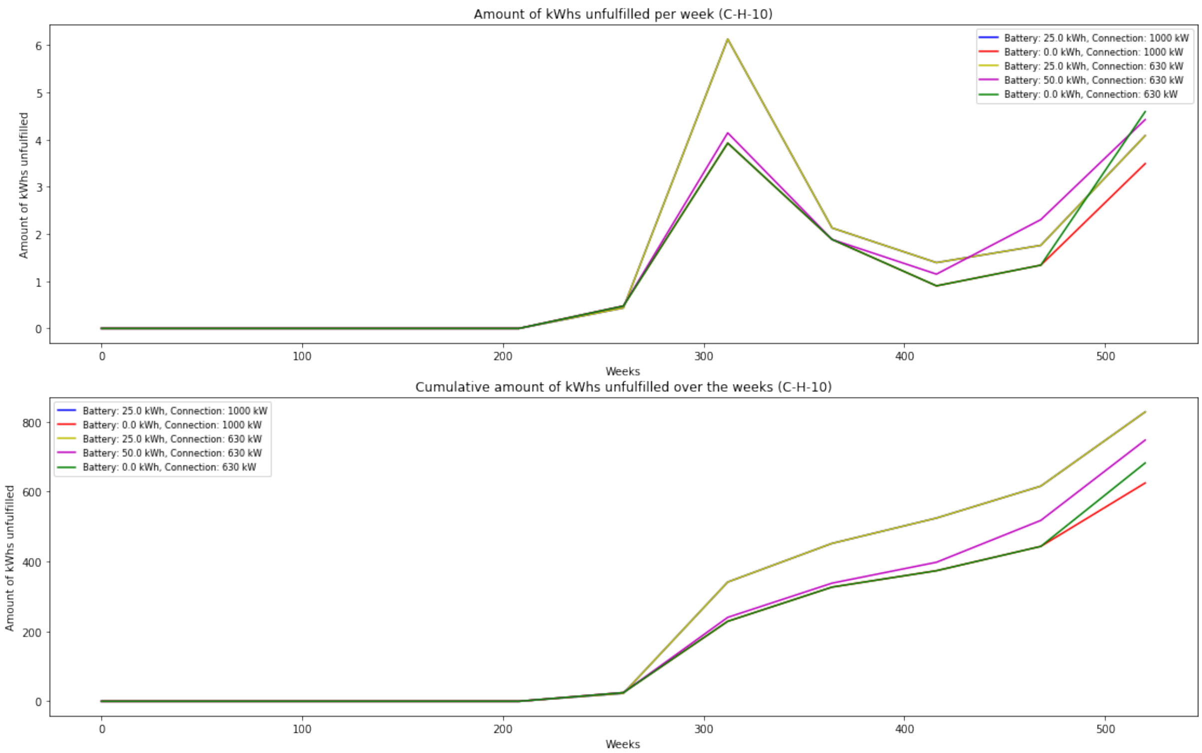

Figure B.36: Unmet demand C-H-10