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Optimization of a Megawatt Truck Charging Station with Local Battery Storage

A study on cost optimization and peak load management in megawatt charging systems

Bachelor thesis in Electrical Engineering – EENX16

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Abstract

This thesis evaluates the design and economic feasibility of a megawatt charging station using a local battery energy storage system with a limited grid connection. The study investigates when local battery storage should be used, how the number of chargers should be dimensioned and which parameters have the largest impact on investment decisions. The conclusions are based on a linear optimization model, which minimizes system cost by sizing the system using connection and BESS, a simulation model that verifies the optimization and determines the number of chargers needed and an investment calculation that calculates the financial viability of the charging station.

The linear optimization results show that a higher battery cost leads to a smaller battery system and a larger grid connection as battery energy capacity and power capacity decrease. Additionally, with greater electricity price variation, it becomes more beneficial to have a larger battery capacity. For the base case, the optimal configuration under assumptions used in this study consisted of seven MCS chargers, two power distribution centers, a grid connection of approximately 642 kW, a battery energy capacity of 647 kWh and a battery power capacity of 264 kW. The simulation showed that eliminating queue time is not economically justified, since the additional reduction in waiting cost from installing another charger does not outweigh the additional investment cost. The investment calculation indicates that the charging station is profitable under the assumptions made in this study, with a positive NPV of 18.2 MSEK and a DPP below the assumed 10-year battery lifetime. Therefore, the results indicate that a local battery storage system is more beneficial when there are high charging peaks and a variation in electricity prices present. However, profitability is sensitive to demand level, battery cost, electricity price and retail price.

Nomenclature

Term	Explanation
AC (Alternating current)	Electric current that periodically reverses direction
BESS	Battery Energy Storage System
BEV	Battery Electric Vehicle
BMS	Battery Management System
CAPEX	Capital Expenditure (initial investment costs)
CCS2 (Combined Charging System Type 2)	European standard connector for fast charging of electric vehicles
Charging Station	A facility equipped to supply electric energy for charging electric vehicles
CPO	Charge Point Operator
DC (Direct current)	Electric current that flows in one direction
DPP	Discounted Payback Period
DSO	Distribution System Operator
EPC	Engineering, Procurement and Construction
HVAC	Heating, Ventilation and Air Conditioning
kW (Kilowatt)	Unit of electrical power, equal to 1,000 watts
kWh (Kilowatt-hour)	Unit of electrical energy, representing power consumed over time
MCS	Megawatt Charging System
NPV	Net Present Value
OPEX	Operational Expenditure (ongoing operating costs)
PDC	Power Distribution Center
ROI	Return on Investment
SoC (State of Charge)	The current battery charge level relative to its maximum capacity
SoH (State of Health)	A metric indicating the overall condition of a battery compared to a new one
SoP (State of Power)	The maximum power a battery can safely discharge or charge at a given moment
SSC	Supervisory System Control
TCO	Total Cost of Ownership

Contents

1

Introduction

The commercial road freight industry is the backbone of modern supply chains, operating in a highly competitive environment characterized by thin profit margins [1]. For transport operators, profitability relies heavily on maximizing vehicle uptime and maintaining strict logistical schedules. In this highly optimized sector, time is a critical financial asset. Unplanned halts or delays at any point in the logistic chain can quickly eliminate the profit margin of a delivery route [2].

Simultaneously, this heavily cost-driven industry is undergoing a historic transition toward battery electric vehicles (BEV). In part, motivated by the long-term economic advantages of electrification, such as lower operating costs and reduced dependence on fossil fuels [3]. However, integrating electric trucks into existing, time-sensitive logistics networks presents a formidable operational challenge. To maintain the thin margins of the industry, the efficiency of the route and the use of vehicles must be maximized [4]. This becomes particularly complex given that long-haul drivers must adhere to strict driving and resting time regulations, which require a 45-minute rest period after every 4.5 hours of driving [5]. To ensure profitability and avoid costly delays, battery electric vehicles must be sufficiently recharged precisely within these 45-minute windows, demanding a charging infrastructure capable of delivering power at the megawatt level [4].

Delivering several megawatts of power simultaneously to multiple trucks places an immense, burst-like strain on the local electricity grid. Upgrading existing grid connections to handle these extreme peak loads is often financially prohibitive and hampered by years-long construction lead times [6]. This is where the integration of local battery energy storage systems becomes highly beneficial and in many cases essential. By continuously drawing a lower steady stream of power from the grid and discharging it rapidly when trucks arrive, a local battery system acts as a high-power buffer. This capability allows station operators to bypass expensive grid capacity upgrades, drastically reduce peak demand grid tariffs and guarantee that the strict time constraints of the transport operators are met without queue-inducing power limitations.

1.1 Aim of the Project

This thesis aims to design a cost-effective megawatt charging station for long-haul electric trucks. Due to the high power requirements, there is a trade-off between investing in a large grid connection and implementing a local BESS.

The study seeks to answer the following questions:

- What should the size of the local battery system and grid connection be for a megawatt charging station?
- How should the number of chargers be dimensioned for a real megawatt truck charging station when balancing queue costs against infrastructure investment costs?
- What is the economic viability of implementing a megawatt charging station supported by a local battery energy storage system for electric trucks?

1.2 Scope

The thesis is made up of three primary parts: optimization of the station, simulation of the station and an economic evaluation based on the two.

The primary focus of this thesis is to evaluate the economic factors and study the profitability-driven design, with less emphasis on highly technical details such as battery chemistry, in-depth electrical design or circuit-level component sizing. Battery chemistry will therefore not be considered in the model. Elements such as power flows, capacity needs and costs are instead the main variables within the study.

1.2.1 Optimization

Optimizing the station aims to evaluate the operational strategy for the station regarding varying prices for electricity cost, grid tariffs, grid cost, queue, overall charging demand and varying investment-related costs. Battery degradation is also considered within the model, in order to prevent unnecessary usage. Within the optimization model the charging demand is modelled as a total demand for the station and no individual charging sessions are taken into account. The model uses varying costs for installation to simulate a base, worst and best case scenario to best replicate a real-world investment situation, ensuring that reasonable conclusions are made. Varied cost of battery is also evaluated in order to find out how the station distributes power from grid versus battery storage, based on the price of batteries. This is again used to compare different real-world cases to discuss and to conclude a reliable scenario to present.

1.2.2 Simulation

The simulation model aims to replicate the operational behaviour of the charging station over a year. The model will operate in two modes: either using recorded transaction data as direct input or generating synthetic data based on the properties of the raw data, such as arrival patterns, session duration and total energy charge.

The scope of the model is limited to the temporal boundary of one calendar year, with a resolution of 1 minute. It takes a fixed station configuration given by the optimization model and then sweeps across different amounts of chargers to see how many chargers are needed for that station. After determining the correct number of chargers, the simulation model produces time series outputs such as power flows, grid load, energy delivered and revenue, which will feed into the economic analysis.

1.2.3 Economics

The economic scope is divided into four parts, first capital expenditures, secondly operational expenditures, thirdly a financial evaluation and lastly a sensitivity and risk assessment of the investment.

Scope of Capital Expenditure (CAPEX)
When defining the scope of capital expenditures (CAPEX), it is essential to focus on the primary cost-driving factors. Attempting to incorporate every minor or highly site-specific expense into the calculation would overly complicate the model and severely reduce its generalizability. Therefore, to ensure that the economic model remains robust, objective and representative of the core infrastructure, the CAPEX scope in this study is restricted to the following fundamental components:

- Battery Energy Storage System (BESS): The battery modules required to buffer the grid, enable peak shaving and manage high-demand charging sessions.
- Power Conversion System (Converters/Inverters): The power electronics needed to convert alternating current (AC) from the grid to direct current (DC) for both the BESS and back to the chargers.
- Megawatt Chargers (MCS): The physical charging pedestals/dispensers, including the necessary liquid-cooling systems and heavy-duty cables.
- Substation & Grid Connection: The fixed costs associated with transformers, High-voltage switchgear and the regional utility interconnection.
- Power Distribution Center (PDC): The distribution module that manages AC power from the substation and BESS to DC power for the chargers.
- Installation Costs (EPC): The engineering, procurement and construction expenses, which encompass heavy civil groundworks, trenching, paving and system integration.

Scope of Operational Expenditure (OPEX)
The operational expenditure (OPEX) analysis in this thesis is limited to three cost components: grid fees, electricity costs, maintenance. The station operates as an unmanned facility with no on-site personnel, making administrative costs negligible compared to the other cost components. Insurance has also been excluded, as it is typically bundled across a company's entire property portfolio, making it difficult to obtain a site-specific rate.

Scope of Financial Evaluation
To assess the financial feasibility of the megawatt charging station, this study utilizes established, market-standard financial metrics that are of primary interest to investors and stakeholders [7]. Rather than incorporating an exhaustive array of theoretical formulas, the scope of the evaluation is intentionally restricted to the most critical indicators of profitability and risk: Capital expenditures (CAPEX), operating Expenses (OPEX), net present value (NPV), discounted payback period (DPP) and return on investment (ROI). By relying on these industry-standard equations, the project establishes a robust economic model that represents the investment's long-term viability, cash flow dynamics and expected return on investment. It should also be noted that all economic assessments in this project are conducted on a pre-tax basis, meaning that any implications of corporate or local taxes are excluded from the analysis.

Scope of Sensitivity and Risk Assessment
The sensitivity and risk assessment evaluates how the DPP is affected by changes in three key parameters: interest rate, installation cost and maintenance cost.
Each parameter is varied between two extreme values while the remaining parameters are held constant, resulting in a range of DPP outcomes that reflect the uncertainty of the investment. These three parameters were selected as they represent the primary sources of uncertainty across the investment calculation: installation cost captures uncertainty in CAPEX, maintenance cost captures uncertainty in OPEX and the interest rate captures uncertainty in the required return to investors. By isolating these parameters, the analysis provides insight into which aspects of the investment carry the greatest financial risk.

Time scope
When calculating the financial viability of a charging station, defining a clear time horizon is of great importance. The chosen time frame dictates the exact period over which the project must recover its initial capital investment and achieve a profitable net present value.

For this study, the economic model is restricted to a 10-year operational lifespan. This duration was chosen because the industry standard for a BESS is 10 years [8]. By limiting the calculation to this specific time frame, the model avoids speculative long-term assumptions and remains grounded in reliable, industry-standard data.

2

Theory

This section lays the theoretical foundation necessary for understanding the project.

2.1 Charging for Electric Trucks

In order to understand the concept of fast charging, multiple factors must be taken into account. A solid grid connection is important in order to ensure a stable source of electric power to the charging station. What type of charger is needed to deliver the correct amount of energy and what power distribution centre (PDC) is needed to divide up the energy between chargers. Lastly, the battery energy storage system is needed when the peak demand exceeds the available energy from the grid connection.

2.1.1 Grid Structure and Charging Station Connection

In Sweden, the power grid consists of the transmission grid and the distribution grid, where the latter is divided into the regional grid and the local grid [9]. The transmission grid forms the backbone of the Swedish power grid, while the distribution grids transport electricity from the regional to consumers using regional and local grid structures. The local grids are the last section of the power grid and is what most charging stations are connected to, using a maximum voltage of 40 kV [9]. The charging stations analysed in this thesis are connected to 10 kV and the voltage is converted by the station's own substation to the levels required to best suit the usage.

2.1.2 Charging Standards: CCS vs MCS

The standard for charging battery electric vehicles today is CCS2. With a typical maximum charging delivery of roughly 400 kW [10]. Figure 1 Shows how a Combined Charging System Type 2 looks like. One thing to note is that the CCS2 in the image has a maximum output of 360kW and not 400kW.

(a) CCS2 charging post. *(b) CCS2 connector.*

Figure 1: CCS2 charger, where the left image 1a shows the charging post for a DC fast charger (CCS2) and the right image 1b shows the outlet for a Combined Charging System Type 2.

Megawatt charging systems (MCS) are a new concept for fast charging, delivering more power when charging electric vehicles, enabling much faster charging. This newer type of charging is almost ten times faster, where MCS is able to produce roughly 3.75 megawatts, although in reality, the actual output of MCS when charging electric trucks will most likely be roughly 700 kW [10][11]. MCS is designed to be able to charge a truck from 20 to 80 percent in approximately 30 minutes. Given the 45-minute mandatory rest breaks for long-haul drivers, this charging window enables near seamless operations by aligning well with already existing schedules. This suggests that high-power charging can be integrated into existing long-haul schedules, provided that adequate infrastructure is available. Below in figure 2, an MCS charger can be seen and can be compare with the figure 1 for a CCS2 charger.

(a) MCS charging post. *(b) MCS connector.*

Figure 2: MCS charger, where the left image 2a shows the charging post for a Megawatt charger and the right image 2b shows the outlet for the charger.

2.2 Battery Energy Storage System

In the context of megawatt truck charging stations, the battery is modeled as a constrained energy storage unit capable of both charging and discharging within predefined power and state of charge (SoC) limits. Its primary function is to reduce peak grid power demand and adjust to varying charging patterns.

From a system point of view, the battery can be characterized in terms of its capacity in terms of energy rating, its power rating, as well as the chemistry used. These parameters affect the efficiency of the battery and the lifetime of the Battery Energy Storage System (BESS). In addition, the economic viability of the system depends on investment cost, cost savings from peak shaving and the optimal sizing of the storage unit.

2.2.1 Battery Structure and Internal Characteristics

In BESS, electrical energy is stored in the form of chemical energy through electrochemical reactions, where oxidations and reductions react, as called redox. When discharging the battery, electrons are transferred between the two electrodes via an external electrical circuit, which generates electricity. In a rechargeable battery, the process can be reversed by adding electrical energy to the system, which restores the chemical energy in the active materials [12]. Different battery technologies achieve this through different chemistries, including the well-established lead-acid battery and more modern options like lithium-ion and sodium-ion batteries. Each comes with its own benefits in energy density, cycle life and cost, which shape where and how they're used.

Despite the variety of different types, lithium-ion batteries have firmly established themselves as the dominant technology in both electric mobility and stationary energy storage, a position they're expected to hold well beyond the future. Stationary storage that stash energy with lithium-ion systems, is currently accounting for around 86% of the market [13]. Their attractiveness comes down to a strong combination of high energy density, excellent round-trip efficiency, long cycle life and fast response times. On top of that, the massive manufacturing scale driven by the electric vehicle industry has pushed costs down substantially, making lithium-ion an economically convincing choice across a wide range of applications.

State of Charge (SoC) is a central parameter for the state of a battery system. It describes the level of energy in the battery, in relation to its maximum capacity, often in percentage. A SoC value of 100% indicates the battery is fully charged, while 0% represents the opposite, a fully discharged state [14].

State of Health (SoH) is used to describe a battery's health and capacity to store energy compared to its original capacity. This helps to show how the battery performs over time. SoH is a percentage of the maximum charge available over the rated capacity of the cells, where 100% indicates that the battery is new, while 0% represents the opposite [15].

State of Power (SoP) shows how much power the battery can deliver or absorb at a given time interval. This helps with efficiency and ensure that the battery is in its safe operation range during peak charge and discharge spikes [16].

2.2.2 Battery Energy Storage Systems and Sizing

A BESS is a system designed to store electrical energy so that it can be saved and later used to meet future demand. In electric grid applications, a BESS is utilized to manage the imbalance between electricity generation and electricity consumption.

In the context of megawatt-based truck charging stations, a BESS works as a buffer by storing electrical energy that can later be used to meet high demand. In grid-connected applications, a BESS is used to balance load variations, reduce peak power demand and increase system flexibility. The most relevant aspect in this case is the high peak demands, since fast charging requires a very high instantaneous power outlet. BESS does not only consist of battery cells, but also includes a battery management system (BMS), power electronics for conversion between DC and AC, and a supervisory system control (SSC). The system is hierarchically structured, where individual battery modules are monitored by local BMS-units, which are coordinated by a superior control system that manages the power exchange with the power grid [17]. This structure enables safe operation, monitoring of state parameters such as SoC and SoH, as well as optimized power control.

The dimension of a BESS system is mainly determined by two central parameters, energy capacity and power capacity. Energy capacity, usually expressed in kWh or MWh, defines how much energy can be stored in the system. Power capacity, expressed in kW or MW, describes the maximum charging and discharging power. For high-power charging of heavy trucks, both parameters are critical. A high power capacity is required to support fast charging, while sufficient energy capacity is needed to manage repeated charging sessions without the battery quickly reaching its operational limits. Therefore, these dimensions are key aspects for both the technical performance of the system and its economic feasibility.

The sizing of a BESS is highly application dependent. The optimal size relies strongly on the load profile and the intended operational strategy is highly dependent. As conceptually illustrated in Figure 3, for peak shaving, the required power capacity is about determining the difference between the maximum charging demand and the allowed grid connection limit. The required energy capacity depends on the duration of peak events and how frequently they occur.

Oversizing the system can lead to increasing investment costs, while undersizing can lead to missing out on the achievable peak reduction. Therefore, sizing plays a crucial role in determining technical performance and economic feasibility.

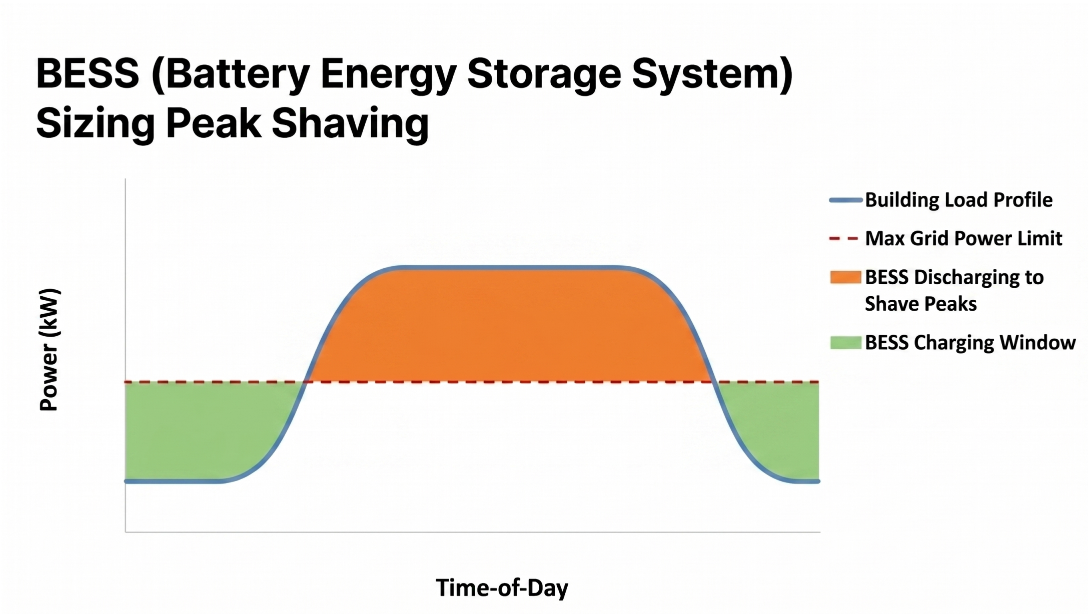


Figure 3: Conceptual illustration of peak shaving and BESS sizing. The required power capacity corresponds to the maximum difference between the load profile and the grid connection limit, while the required energy capacity corresponds to the energy above the grid limit over time.

As mentioned in Section 2.2.1, lithium-ion is the dominant technology for stationary energy storage. For grid-connected applications such as peak shaving and load balancing, specific lithium-ion chemistries are preferred. Lithium iron phosphate is the most commonly used chemistry in stationary BESS due to its high thermal stability, safety characteristics and long cycle life. Alternatively, nickel manganese cobalt batteries are also applied in certain BESS systems where a higher energy density might be prioritized [17].

2.2.3 Cost of the Battery Energy Storage System

When evaluating the cost of a BESS, a multitude of technical and economic variables can be considered. However, to construct a robust and solvable optimization model, this project focuses strictly on the primary cost-driving factors that determine the economic viability of the charging station. The parameters with the most significant impact on the total cost of ownership (TCO) are the following:

The initial investment represents the most significant financial hurdle for establishing the charging station. This capital expenditure encompasses all the physical hardware required to build the system. The primary cost drivers naturally include the battery cells, which dictate the total energy storage capacity. However, for a megawatt charging station, the power electronics, such as inverters capable of delivering massive, instant power to the trucks, could be equally critical and costly [18]. Additionally, supporting infrastructure like thermal management systems, safety equipment and general installation work contribute heavily to the final price tag. Since these upfront costs scale directly with the size and capability of the chosen system, estimating the overall component cost is a foundational step in evaluating the business case.

A battery is not a static asset; its capacity degrades continuously due to ageing. In a high-demand truck charging station, the battery will undergo frequent and intense cycles. As the capacity drops, the station loses its ability to buffer peak loads effectively [19]. Therefore, the economic model must account for the system's lifespan, which is expected to be at least 10 years, to maintain the station's performance over its intended lifetime.

No battery system is perfectly efficient. The round-trip efficiency of a BESS (the amount of energy retrieved compared to the energy put in) is typically around 85–90% [20]. The remaining energy is lost primarily as heat during the chemical conversion and within the inverters. Furthermore, as the battery ages, its internal resistance increases, which increases these efficiency losses [21]. From an economic perspective, this is a critical factor because the station operator must pay the grid provider for electricity that is lost as heat and can never be sold to the transport companies. This constitutes a continuous operational cost that scales with the utilization rate of the station.

2.3 Charging Station Cost Structure

The cost structure of a charging station is divided into CAPEX, representing the initial investment and OPEX, representing recurring costs during operation.

2.3.1 CAPEX Cost

The total capital expenditure of a megawatt charging station consists of the main upfront investment components required to establish the station. In this study, these components include the grid connection, MCS charging hardware, power distribution centers (PDC), battery energy storage system, converter/inverter capacity and installation work. Since exact component costs for emerging megawatt charging infrastructure are difficult to determine due to limited publicly available market data, several numerical cost values are treated as engineering assumptions. These assumptions are presented and motivated in Section 3.4.1.

2.3.2 OPEX Cost

To use the electrical grid in Gothenburg, the charging station operator must pay a network tariff to the local distribution system operator (DSO), in this case Göteborg Energi. The network tariff consists of a fixed fee based on the subscribed grid capacity (kW), which represents the maximum agreed power level that can be drawn from the grid. For customers connected at 10 kV in Gothenburg, the fixed subscription fee amounts to 1 100 SEK per month [22].

Furthermore, a transmission fee is charged based on the amount of electricity consumed. For customers connected at 10 kV, this transmission fee amounts to 0.055 SEK/kWh. This means that the total cost increases proportionally with energy usage [22].

The most substantial cost component for a high-power charging station is typically the demand charge. This fee is based on the maximum active power drawn from the grid during the billing period. For customers connected at 10 kV, the demand charge is determined by the highest hourly average active power (kW) measured during the month. In Gothenburg, this tariff amounts to 57.90 SEK/kW per month [22].

Finally, a reactive power fee of 16.6 SEK/kVAr may be charged if the reactive power (kVAr) during a given month exceeds 50 % of the highest measured active power (kW) during the same month for customers connected at 10 kV [22]. However, this aspect is not considered in the present study, assuming a power factor close to unity.

Maintaining the battery, chargers and PDCs is also an OPEX cost that is important to take in to count to see if a station can payback it self with the generated revenue or drown in operation cost. The maintenance cost has been estimated to be around 2 to 3 % of the hardware cost of each object, except the grid which the maintenance cost comes from the tariffs that are taken.

2.4 Optimization

Mixed-integer linear programming (MILP) is a mathematical optimization method used to find the best solution to a problem involving a mix of discrete variables, continuous variables and binary variables. The variables represent the choices the model has to make while being controlled by an objective function. For example: minimizing the cost given some constraints. MILP is therefore useful when trying to solve problems where resources will be dimensioned or distributed in an optimal way under constraints [23]. In this project, optimization is used to seek a cost-effective dimensioning of a charging-station grid connection and a local battery energy storage system.

2.5 Simulation Model

Simulation models can be used in both pre-production and in prototyping. It can help to visualize the model before a real-life version of it is made. It can also be used to test different scenarios that the model will face in the real world these different scenarios can later be analyzed to help designers and engineers to understand how the model will perform during its lifetime.

There are a lot of different types of simulation methods that can be used to build a simulation model, but two of these models are continuous and discrete simulation. These two simulation methods can be used to simulate an object over time and under that time, data can be simulated and then it can be analysed so see what happens to that object during the simulated time [24].

2.5.1 Continuous Simulation

Continuous simulation uses differential equations to describe how the model changes continuously over time. These differential equations are solved numerically with approximate algorithms that determine what the output variables should be over the set simulation time.

But these differential equations can be very hard or impossible to set up if the relations between the variables are not understood. Also, knowing what is the correct algorithms to use to solve the differential equations is can be hard to determine because of instabilities.

2.5.2 Discrete Simulation

This method uses distinct events/steps to show how the model changes over time. These events happen during a specific instant in time during the simulation. These events and or steps are when variables can changes states, this differs from continuous simulation where the variables could change states at any time.

This means that the resolutions of discrete simulation can not be as high as those of continuous simulation. This is because a continuous simulation can answer for any specific time in the simulation, where discrete simulation can only give results at some specific times. This can be somewhat negated by having the discrete simulation take smaller steps in time during the simulation, but this will make the simulation longer and it will take up more memory when it is running.

2.6 Economic Evaluation

This chapter introduces the different tools that will be used in this thesis to evaluate the economic viability of a megawatt charging station with local batteries.

2.6.1 Capital Expenditure

Capital expenditure refers to the initial financial investment required to acquire, construct and commission physical assets before a project can begin operations. In the context of establishing a megawatt charging station, it encompasses the upfront costs, such as hardware and installation.

The primary purpose of determining CAPEX in an economic analysis is to establish the baseline financial hurdle of an investment. In financial appraisal models, such as net present value (NPV) and discounted payback period (DPP), CAPEX serves as the initial capital outflow. It is used to evaluate the total capital exposure and financial risk of a project, enabling stakeholders to calculate exactly how much future discounted cash flow is required to break even and ultimately achieve profitability.

The total capital expenditure (CAPEX) is formulated as shown in (1), where C_i represents the cost of the i-th individual investment component and n denotes the total number of components.

$$CAPEX = \sum_{i=1}^{n} C_i \tag{1}$$

2.6.2 Operating Expenditure

Operational expenditure (OPEX) refers to the recurring financial costs required to run, maintain and manage physical assets once a project has commenced operations. In the context of operating a megawatt charging station, it encompasses the ongoing expenses such as electricity procurement, grid tariffs and system maintenance. Therefore, OPEX constitutes continuous operational outlays throughout the lifecycle of the project.

The primary purpose of determining OPEX in an economic analysis is to establish the annual financial burden of sustaining the investment. In financial appraisal models, such as NPV and DPP, OPEX is subtracted from the gross revenue to determine the net annual cash flow. It is used to evaluate the long-term operational efficiency and profitability margin of a project, enabling stakeholders to calculate the actual net income available to offset the initial capital exposure and generate a return.

The total $(OPEX_t)$ for a specific year t is formulated as in (2)

$$OPEX_t = \sum_{j=1}^{m} C_{j,t} \tag{2}$$

where $C_{j,t}$ represents the cost of the j-th individual operational component during that year and m denotes the total number of recurring operational components.

2.6.3 Return on Investment

Return of investment, often referred as ROI is a quick way to see if an investment is worthwhile. It expresses the expected return as a percentage of the total investment cost, providing a quick indication of profitability. It is calculated by dividing the net profit by the total cost of investment, as shown in equation (3).

$$ROI = \frac{\text{Net Profit}}{\text{Cost of Investment}} \cdot 100 \tag{3}$$

2.6.4 Net Present Value

Net present value is a method to assess if future amounts of money are worth more than the cost of investment made. It works by converting the expected/future revenue into present value where it evaluates if available funds is greater than the expected capital, available in the future. This to account for factors such as interest and inflation.

If the NPV is positive it will add value which says that the investment is worth it. A negative or zero value indicates that the investment fails to recover its cost and is not advisable.

NPV is calculated as the sum of the true revenue divided by the interest rate, with the power of time in years and the sum over the instalment period in years. The equation for the net present value can be seen below in equation (4).

$$NPV = \sum_{t=1}^{N} \frac{CF_t}{(1 + r_d)^t} - CAPEX \tag{4}$$

N is the instalment period in years, t is the present year, CF_t is the true revenue earned that year, which is given by the equation below (5), r_d is the interest rate and CAPEX is the total capital expenditure.

$$CF_t = R_t - OPEX_t \tag{5}$$

Where R_t is the revenue earned that year and $OPEX_t$ is the operating expenditures that year.

2.6.5 Discounted Payback Period

When further assessing the economic feasibility of the charging station, the discounted payback period (DPP) is calculated using equations (6) and (7). Where equation (6) is the theoretical way to calculate DPP, but because T is rarely a whole number, the equation is interpolated to (7).

This metric determines the precise timeframe required for the project's accumulated discounted cash flows to equal the initial capital expenditure. By factoring in the time value of capital.

$$\sum_{t=1}^{T} \frac{CF_t}{(1 + r)^t} - CAPEX = 0 \tag{6}$$

$$DPP = \text{Last negative year} + \left(\frac{|\text{Unrecovered cost at the end of that year}|}{\text{Discounted cash flow of the following year}} \right) \tag{7}$$

3
Method

The chapter outlines the approach for this project and describes the methods used, including statistical analysis, modelling and investment calculations.

3.1 Data Handling

This section describes the data collection and handling process used in this study. Data has been obtained from two sources. The first one is data from a charging station in the greater Gothenburg area, which provides historical charging data. While the second one is data from Nord Pool, which provides historical electricity prices. The collected charging data is filtered to remove outliers before processing both into a reference dataset used as input for the optimization and simulation models.

3.1.1 Filtering

To ensure that the data was accurate and relevant for electric truck charging, filtering of the dataset was performed. The filtering was done by removing outliers in charging times, charging capacity and charging sessions on weekends and holidays.

Regarding charging time filtering, sessions shorter than 5 minutes and longer than 6 hours were removed. This is done to exclude failed charging sessions where the charger or truck disconnected during start-up, as well as abnormally long sessions.

Charging sessions with a total energy below 75 kWh were also filtered out, as this roughly corresponds to the energy delivered from 20 to 80 percent state of charge for an electric car. As can be seen in Figure 4 below, there is nothing preventing cars from charging at truck chargers. Additionally, sessions with a total energy above 800 kWh were filtered out, as the largest truck battery found in the literature study was approximately 780 kWh.

Figure 4: Shows two electric cars and one electric truck charging using chargers intended for trucks.

Filtering criteria applied during weekends are the same as on regular weekdays, except with slightly stricter thresholds. This was done to maximise the removal of electric car charging sessions, since according to [25] an increase in electric car charging activity is expected on those days at this specific station.

Lastly, charging sessions during public holidays were also filtered out, as truck drivers tend to not work during this days.

By applying these filters, unwanted data could be removed. The filtered data included failed charging sessions, identified by short charging times and/or low charging energy, as well as corrupt data or malfunctioning charging stations, identified by excessively high charging times or energy values. However, it should be noted that this filtering may have also inadvertently remove genuine examples of truck charging, including trucks with battery capacities not yet common on the market. This may therefore have introduced an unintended bias.

3.2 Optimization Model

To determine the optimal size of BESS and grid a linear optimization was used. The model was built in the modelling language Pyomo [26]. The model was solved using GNU Linear Programming Kit.

The model aims to describe the important part of the system which is done in figure 5.

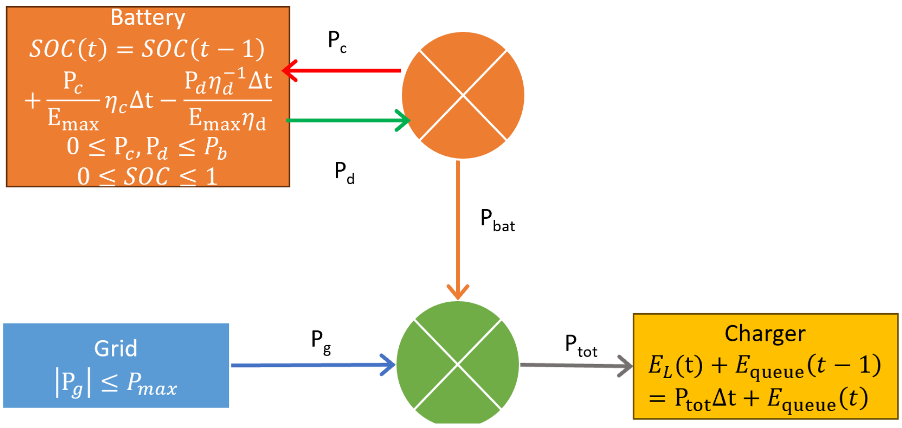


Figure 5: A chart of the model. Every process a set of constraints that govern how they work.

In the model, there is a battery that can store energy over time, but it has a set of constraints. The first describes how the battery can change its energy content.

$$SOC(t) = SOC(t-1) + \frac{P_c(t)}{E_{max}}\eta_c \Delta t + \frac{P_d(t)\Delta t}{E_{max}\eta_d} \tag{8}$$

where P_c, P_d are the energy charged respectively discharged, η_c, η_d is the efficiency in charging respectively discharging and Δt is the time between samples.

$$0 \leq P_c, P_d \leq P_b \tag{9}$$

limits the dis -and charging rate where P_b is the maximum charging rate.

$$0 \leq SOC \leq 1 \tag{10}$$

limits the battery between 0% and 100%.

The connection to the energy grid has one rule, which is

$$|P_g| \leq P_{max}\Delta t \tag{11}$$

where P_{max} is the capacity of the grid. The charger has the following rule

$$E_L(t) + E_{queue}(t-1) = P_{tot}\Delta t + E_{queue}(t) \tag{12}$$

The preset energy demand of all trucks (E_L) and the energy wanted to be consumed by the queue (E_{queue}) has to always match the energy from the grid and the battery and choose to increase or decrease the queue E_{queue}. The queue can not be negative, so $0 \leq E_{queue}$. The resolution Δt is set to 5 minutes, as it gives high enough resolution and is also a multiple of 15 minutes, which is the resolution of the energy prices.

$P_{bat} = P_d + P_c$ and $P_{tot} = P_b + P_g$ describe the energy flow between the systems in the model.

3.2.1 Electricity Prices

Electricity prices are important for the optimization model as they account for prices when buying or selling electricity. Electricity prices data are from Nord Pool [27]. The data used is from 2026-01-01 to 2026-04-10 and prices are set every 15 minutes.

3.2.2 Investment Costs

To obtain the correct values in consistent units, all input parameters were converted to a common basis. This section describes the unit conversions applied, as well as the inclusion of cost additions over the asset lifetime.

The CAPEX cost could not simply be used in the objective function; it needs to be in an equivalent operational cost. We choose to use the annuity method to spread the investment cost over the full lifetime. All investment cost was converted using the following equation:

$$C = \frac{rp}{1-(1+rp)^{-\frac{n}{p}}} \cdot C_{investment} \tag{13}$$

where r is the yearly interest rate, n is the expected lifetime in years of the investment, $C_{investment}$ is the investment cost and p is length of the optimization in years. The grid connection is the only investment considered over a longer time horizon, namely 30 years, whereas all other investments are evaluated over 10 years. A 20-day window was selected for all optimizations, as longer durations yielded negligible improvements that did not justify the increased computation time. This gives a p of 20/365.

3.2.3 Queue Calculations

In the optimization model, the queue had to be handled as a cost of energy within the queue. The cost of queue is therefore in SEK/kWh. The cost of the queue can be calculated using this simple model:

$$C_q = \frac{C_{qh}}{\bar{P}} \tag{14}$$

where C_{qh} is the cost for a waiting truck and is set to 1500 SEK/h. $\bar{P}$ is the mean power consumed and is calculated to 120 kW, which represent what an average truck would consume given it is charging. That gives a queue cost of C_q of 12.5 SEK/kWh.

3.2.4 Construction of Demand Vector

The demand vector E_L contain the energy demand for every truck for 5 minutes segments. The dataset of historical charging data are in transactional form where each record is an charging session. Every session is assumed to have constant power throughout the session and partition in to 5 minutes segments.

3.2.5 Battery Degradation

The use of batteries will degrade it and different use contribute to the degradation in different amount. The model uses two different penalties, the first one is a penalty of charging, where the cost is defined as:

$$C_c = \frac{cost\ of\ battery\ per\ kWh}{expected\ cycles \cdot DOD} \tag{15}$$

where the expected cycles is assumed to be 7300 as the expected battery life is 10 years and 2 cycles per day. DOD, depth of discharge is assumed to be 80% and the cost of battery is 1588 SEK/kWh. It gives a C_c of 0.27 SEK/kWh.

Charging to a high SoC or discharging to a low SoC will increase degradation. In this model, costs are linearly increasing as the SoC deviates from the safe bounds of 20% and 80%, as stated below:

$$C_{SOC}(t) = \begin{cases} (0,2 - SOC(t))C_{SOC\ low}, & SOC(t) < 0.2 \\ 0 & 0.2 \leq SOC(t) \leq 0.8 \\ (SOC(t) - 0.8)C_{SOC\ high}, & 0.8 < SOC(t) \end{cases} \tag{16}$$

where $C_{SOC\ high}$ are calculated using the following:

$$C_{SOC\ high} = C_{BEC} \cdot \tau_h / 0.2 \tag{17}$$

where τ_h is the differences in the decrease in state of health for a battery with 100% SoC and 50 % SoC over an hour. τ_h for a whole year is 3.15% and 3.54 ppm for an hour [28]. For the low SoC case, the cost is harder to estimate and is assumed to be the same as $C_{SOC\ high}$, so $C_{SOC\ low} = C_{SOC\ high}$.

3.2.6 Objective Function

The goal is to find the cheapest way construct the charging station give some information of demand and cost. The following equation, namely the objective function express the total cost of the station:

$$\begin{aligned} COST = (C_{grid,a} + C_{Fee})P_{max} + C_{BEC,a}E_{max} + C_{BPC,a}P_b + C_q \sum E_{queue} + \\ \sum (C_E + C_{Fee,t})P_g\Delta t + C_c \sum P_c\Delta t + \sum C_{SOC}\Delta t \end{aligned} \tag{18}$$

Where $C_{grid,a}$ is the annuity of the grid investment which can be calculated with equation 13. $C_{BEC,a}$ and $C_{BPC,a}$ are calculated using the annuity method but with investment cost for the BESS C_{BEC} and C_{BPC}. C_q is the cost of queue. C_E is price profile of energy and C_{Fee} is a transfer fee of energy.

3.3 Simulation Model

A simulation was developed to get a better picture and understanding of the given data and also too verify what was generated with the given data.

3.3.1 Simulation Environment

The simulation environment was developed in Python to replicate existing charging stations for both CCS2 and MCS charging and to validate the output of the optimization Model. Python was selected because of its enormously libraries and previous experience in the language.

The simulation is built with the use of NumPy for numerical computations and Pandas for data handling, Matplotlib for plotting simulated data and lastly random to be able to add variance in the dataset.

3.3.2 Model Overview

The simulation models is a discrete model that operates as a charging station over a fixed number of days using a time step of one minute. At each step, trucks arrive using either real or synthetic data and are assigned to an available charger or placed in a waiting queue. After that the power demand from all active chargers are calculated and compared to available grid capacity. If the calculated demand exceeds the grid limit, than a BESS can supplement the grid up to its rated discharge power and available SoC. But if the calculated demand does not exceed the grid limit, the simulation model may charge the battery depending on the SoC and the prices of the electricity.

Also during these time steps, the simulation tracks the different power flows, queue length and time of day, charger utilisation and charging revenue, providing a picture of station behaviour over the simulated period. All of this can be seen in the Figure 6, which is a flowchart of the simulation process.

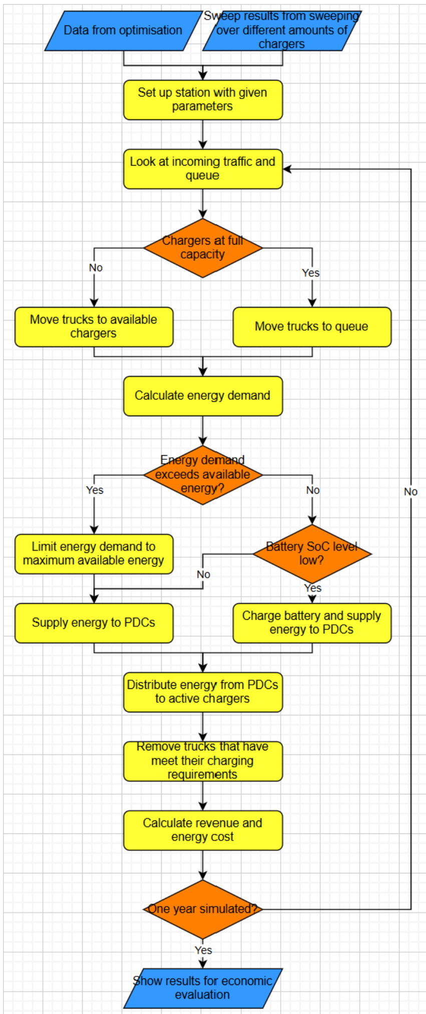


Figure 6: Flowchart of the simulation model, where the input parameters come from the optimisation model and a function called Sweep that goes over the station and sees how many chargers and PDCs are needed.

3.3.3 Simulation Execution

The model begins by reading the processed data and storing it in lists sorted by time. It then runs a sweep function that determines the optimal number of chargers for the station. This is done by calculating the total queue time over a ten year period and comparing the cost of the queue against the cost of adding another charger and if required, a power distribution centre. A PDC is added for every fourth charger, based on specifications from Kempower [29], where a power unit with a maximum output of 1,200 kW is stated to support up to 12 chargers. No specific charger type is stated, so a 360 kW CCS2 charger is used as a representative fast charger, giving a theoretical maximum of 4,320 kW across 12 chargers. Applying this ratio to MCS chargers yields approximately four MCS chargers per power unit.

Once the sweep is complete, the model selects the configuration where the cost of the remaining queue is lower than the cost of adding another charger or charger PDC pair. This configuration is then used to simulate a full year of operation. The simulation outputs key parameters for the economic evaluation, such as total electricity purchased and revenue generated and also produces plots of metrics such as average queue time and station power flow.

3.4 Economic Approach

The following section describes the investment calculation procedure, beginning with the assumptions required to define reasonable parameters in the coming table 2. It then presents the calculation of CAPEX, OPEX, ROI, NPV and DPP, followed by a sensitivity and risk assessment.

3.4.1 Engineering Cost Assumptions

Due to limited publicly available cost data for several components in the megawatt charging infrastructure, some cost parameters were treated as engineering assumptions. These assumptions are based on available literature and market indications where possible and is also supported by input from A.Grauers [30]. The assumed values are therefore used as indicative modelling inputs rather than exact market prices.

The investment required to connect a heavy-duty truck charging station to the electricity grid is high. In this study, the grid connection cost is assumed to be 2 million SEK per MW. This assumption is supported by indicative values reported in the literature [31], where medium- to low-voltage stations (0.2-1 MW) are estimated to cost 35.000 to 250.000 euros, although actual costs depend strongly on site-specific conditions and the required power level.

The battery energy storage system in this study is represented by two main cost components: an energy-related battery cost of 240.8 USD/kWh and a cost of 379.16 USD/kW, related to the power output of the battery system, and with a projection of a cost reduction of 28% to 2035 [32]. This leads to the cost of the battery system being 1588 SEK/kWh and 2501 SEK/kW with a 50% assumed investment cost.

Due to the limited publicly available cost data for MCS-specific charging hardware, the cost of one MCS charger is assumed to be 1 million SEK per unit in this study. This value should be interpreted as an indicative modelling assumption rather than a directly reported market price. The estimate is based on cost indications for conventional DC fast-charging stations and scaled to reflect the significantly higher power levels required for megawatt charging systems. Virta reports that DC charging stations in the 200 kW to 400 kW range cost at least 40 000 EUR, excluding costs such as charging cables, cable mounts, grid connection, installation, on-site cabling and other site-specific costs [33]. Since MCS chargers for heavy-duty trucks operate at substantially higher power levels, with ICCT reporting MCS charging capability between 440 kW and 3.75 MW and using 750 kW as an ultrafast charging level [34], the assumed value of 1 million SEK per charger is considered reasonable for the economic model.

The way maintenance has been calculated is with the help of some expected maintenance cost from [35] for fast DC chargers. In this report, it is stated that extended warranties for DC fast chargers can cost more than $ 800 per charger and that station owners should expect maintenance costs of up to $400 year per charger. So how the percentage was calculated was by taking these numbers and converting them to SEK and then comparing with the prices for a CCS2 charger, which gives the following equations (19) and (20).

$$Maintenance_{Low} = \frac{800 \cdot 9.16}{360000} \approx 0.02 \tag{19}$$

$$Maintenance_{High} = \frac{(800 + 400) \cdot 9.16}{360000} \approx 0.03 \tag{20}$$

Lastly, publicly available cost data for a power distribution center is very limited. Therefore, the cost of one PDC was treated as an engineering assumption and set to 1 million SEK per unit, based on input from A.Grauers [30].

CAPEX

The total capital expenditure (CAPEX) is calculated using Equation (1), which includes all individual investment components. To express the final CAPEX exclusively in Swedish kronor (SEK), certain investment components that are dependent on variables must be converted. This is achieved by multiplying them by the output values derived from the optimization and simulation models. Furthermore, to account for the installation costs, a 50% markup is applied, meaning the base hardware investment, excluding costs for grid connection, is multiplied by a factor of 1.5. The specific methodologies for these unit conversions and the calculation of the installation costs are detailed below in Equations (21) and (22).

$$
\begin{aligned}
C_{Grid} \cdot P_{Grid} &= \frac{SEK}{MW} \cdot MW = SEK \\
C_{MCS} \cdot N_{MCS} &= \frac{SEK}{unit} \cdot unit = SEK \\
C_{PDC} \cdot N_{PDC} &= \frac{SEK}{unit} \cdot unit = SEK \\
C_{BEC} \cdot P_{BEC} &= \frac{SEK}{kWh} \cdot kWh = SEK \\
C_{BPC} \cdot P_{BPC} &= \frac{SEK}{kW} \cdot kW = SEK
\end{aligned}
\tag{21}
$$

$$
C_{Install} = (CAPEX - C_{Grid} \cdot P_{Grid}) \cdot (1 + 0.50) \tag{22}
$$

OPEX

The total operational expenditure (OPEX) is calculated using Equation (2). In this formulation, the cost of the total electricity procured, denoted as $C_{Bought,t}$, is obtained directly from the simulation outputs. Furthermore, the annual maintenance cost is determined by multiplying the total hardware investment by a factor of 0.025, as detailed below in Equation (23).

$$
\begin{aligned}
C_{Maint,t} = (&C_{MCS} \cdot N_{MCS} + C_{PDC} \cdot N_{PDC} + C_{BEC} \cdot P_{BEC} \\
&+ C_{BPC} \cdot P_{BPC}) \cdot 0.025
\end{aligned}
\tag{23}
$$

Return on Investment

The return on investment (ROI) is determined based on the total net profit generated within a given year, as defined by Equation (5). In this formulation, the annual revenue, denoted as R_t, is derived from the simulation model, from which the corresponding operational expenditure (OPEX) for that year is deducted. This relationship establishes the final ROI calculation, which is presented below in Equation (24).

$$
ROI = \frac{CF_t}{CAPEX} \cdot 100 \tag{24}
$$

Net Present Value
Following the initial return on investment (ROI) assessment, the overall financial viability of the station is evaluated by calculating the net present value (NPV) using Equation (4). In this model, the economic appraisal period is primarily set to 10 years for the system components, with the exception of the grid connection, which is evaluated over a 30-year period in accordance with established industry standards [8].

Consequently, the comprehensive NPV calculation is strictly bound to a 10-year operational horizon. This limitation aligns with the 10-year performance warranty of the BESS, stipulating that the station must recover its initial capital outlay within the guaranteed lifetime of its core hardware to be considered a justifiable investment.

Discounted Payback Period
Once the net present value (NPV) has been established, the discounted payback period (DPP) is calculated to determine the exact point in time when the investment breaks even. This calculation is performed using Equations (6) and (7), in conjunction with the annual discounted cash flows derived from the NPV analysis. Together, these metrics provide a comprehensive evaluation of the station's total financial performance over its 10-year operational period.

Sensitivity and Risk Assessment
Upon completion of the primary economic calculations, a sensitivity and risk assessment is conducted to evaluate the extreme boundaries of the net present value (NPV) and discounted payback period (DPP). This analysis simulates a worst-case scenario by increasing the discount rate (r_d) to 10%, the installation cost markup ($C_{Install}$) to 80% and the annual maintenance cost ($C_{Maint,t}$) to 3%.

Conversely, a best-case scenario is modeled by decreasing these parameters to a discount rate of 7%, an installation cost markup of 30% and a maintenance cost of 2%. By evaluating these two extreme outcomes, a margin of error for NPV and DPP. This is established by calculating the average deviation between the scenarios, as shown below in Equation (25).

$$DPP_{MoE} = \frac{(DPP_{Upper} - DPP) + (DPP - DPP_{Lower})}{2} \tag{25}$$

4

Results

The following chapter presents the results from the optimization model, simulation model and economic analysis. The results are used to evaluate the station configuration, operational behaviour and economic viability of the proposed charging station

Table 2 shows all determined parameters from the optimization and simulation models that are used for the economic evaluation.

Table 2: Overview of determined parameters, categorised into station configuration, CAPEX, OPEX and revenue.

Parameter	**Symbol**	**Value**	**Unit**
Capital Expenditure (CAPEX)			
Interest rate	r_d	8	%
Grid connection	C_{Grid}	2 000	SEK/kW
Charger (CCS2)	C_{CCS2}	360 000	SEK/unit
Charger (MCS)	C_{MCS}	1 000 000	SEK/unit
PDC	C_{PDC}	1 000 000	SEK/unit
BESS energy capacity cost	C_{BEC}	1058	SEK/kWh
BESS power capacity cost	C_{BPC}	1667	SEK/kW
Installation	$C_{Install}$	50	%
Operating Costs (OPEX)			
Bought electricity	$C_{Bought,t}$	1 368 369	SEK/yr
Grid Subscription	$C_{Sub,t}$	13 200	SEK/yr
Grid tariff	$C_{Grid,t}$	700	SEK/kW/yr
Grid transfer fee	$C_{Fee,t}$	0.055	SEK/kWh
Maintenance	$C_{Maint,t}$	2.5	%/yr
Revenue			
Electricity sold	R_t	7 424 618	SEK/yr

4.1 Results from Optimization Model

This chapter presents the results obtained from the optimization model. Based on the input parameters listed in Table 3, the model determines the required battery size, grid connection capacity and the operational behaviour of the charging station over time.

Table 3: Optimization input parameters.

Parameter	Symbol	Value	Unit
Interest rate	r_d	8	%
Grid connection	C_{Grid}	2 000	SEK/kW
BESS energy capacity cost	C_{BEC}	1058	SEK/kWh
BESS power capacity cost	C_{BPC}	1667	SEK/kW
Installation cost for hardware	$C_{Install}$	30/50/80	%
Grid transfer fee	C_{Fee}	0.055	SEK/kWh
Grid tariff	$C_{Grid,t}$	700	SEK/kW/yr
Round trip efficiency for BESS	η	90	%

4.1.1 Optimization Depending on Different Cost Scenarios

Using the input parameters in Table 3, the optimization model yields the following results for battery size, battery power, grid capacity, total power and c-ratio. The results for the different installation cost cases (30%, 50% and 80%) are presented in Table 4.

Table 4: Presents the optimized battery size, battery power and grid capacity for different installation cost assumptions.

Parameter	30% install C	50% install C	80% install C
BESS energy capacity (kWh)	843.417	646.531	194.623
BESS power capacity (kW)	326.735	263.671	111.875
Grid capacity (kW)	596.000	641.841	761.812
Total power (kW)	922.734	905.512	873.687
c-ratio	0.390	0.410	0.570

The resulting c-ratio which is the ratio between BEC is close to 0.5C, indicating that the optimization model selects a balanced trade-off between battery power and energy capacity.

4.1.2 Optimized Charging Station Behaviour

Figure 7 shows the behaviour of the optimized charging station.

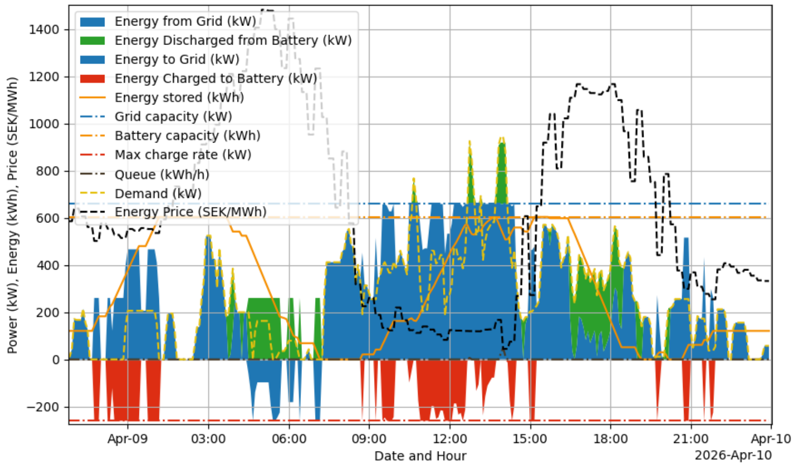


Figure 7: Optimized Charging Station Behaviour.

The figure includes fixed reference lines for grid capacity, battery capacity and maximum charging rate. The stored energy in the battery follows the electricity price pattern, especially around 04:00 and 17:00. When the electricity price is high, the station prioritizes using the battery in order to reduce grid consumption and improve profitability. Around 04:00, the charging load is low while the electricity price remains high, the station also sells energy back to the grid. Conversely, the battery is charged around 00:00 and 12:00, when the electricity price is lower. It is also clear that the battery is used in peak shaving around 13:00 and 14:00 where both the battery and the grid are used to maximum capacity.

4.1.3 Sensitivity Analysis

Figure 8 below, shows how the battery cost affects battery energy capacity, battery power capacity and the grid connection power.

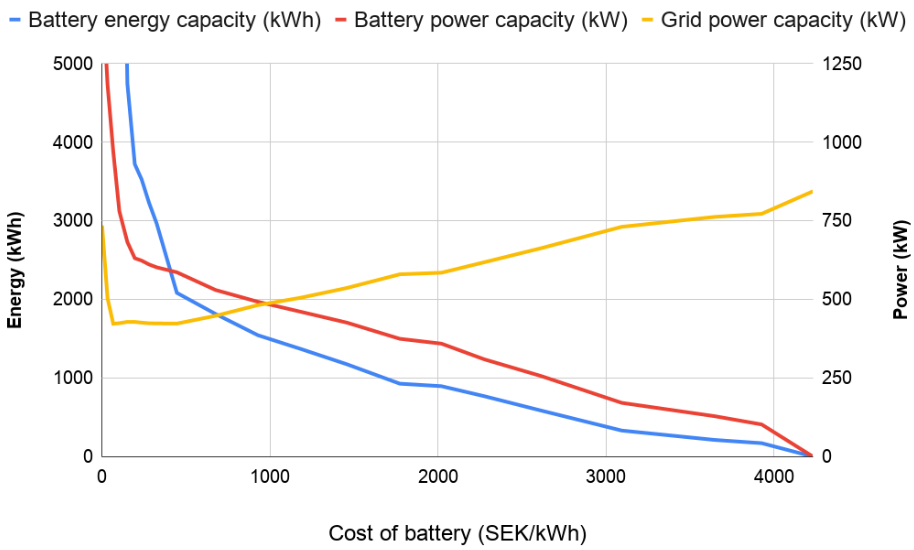


Figure 8: Battery price variation with constant grid cost.

At low battery cost, the battery storage is economically beneficial, where grid connection contributes less, resulting in a larger battery capacity and higher battery output. As battery cost increases the system uses less battery capacity, while relying more on grid electricity. At the highest battery cost, the battery capacity and power, approach zero, displaying that battery storage is no longer worth investing in and that the station relies almost entirely on the grid. At the lowest battery cost, grid capacity increases significantly. This is because it is possible to invest in excessive battery capacity at no cost, which in turn requires a larger grid connection.

4.1.4 Energy Price Correlation

At a constant electricity price, the model finds that no batteries and 833.28 kW was optimal. Real energy prices vary and the battery system can take advantage of that. Figure 9 shows how energy price variation correlate with optimal battery energy capacity.

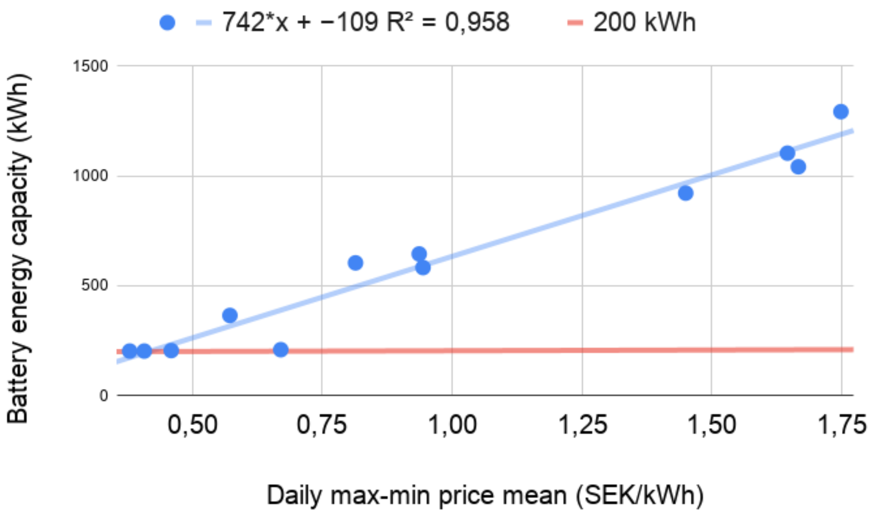


Figure 9: Correlation between energy price variation and optimal battery energy capacity.

The daily max-min mean is the mean of the difference of maximum and minimum energy prices per day. It depicts the maximum profit you can make by buying when the price is low and sell when the energy price is high during one day. Different price zones from different time periods are used in the optimizer with default values and 50% installation cost to generate the values in the figure. The figure clearly show that higher price variation makes batteries more economical. Four data point lie on the red 200 kWh line. The line shows the lower bound for battery energy capacity, where the price variation is low, but when a constant energy price is used, the battery size is zero.

4.2 Results from Simulation Model

The simulation model provided valuable insights into the operational dynamics of the charging station at various stages of charging demand. The simulation model gave an output on various parameters, such as charger requirement, PDC unit requirement, battery usage, load on grid and investment cost.

4.2.1 Infrastructure Requirements

Based on the simulated charging demand and the operational constraint of a maximum queue length of two vehicles, the physical infrastructure needed to maintain an acceptable service level was verified. The simulation model evaluates how the hardware configurations derived from the optimization affect station performance, confirming the optimal equipment setup shown in Table 5.

Table 5: Infrastructure requirements derived from simulation.

Parameter	Value	Unit
MCS chargers	7	units
Power Distribution Centers (PDC)	2	units
Grid connection capacity	642	kW
BESS capacity	647	kWh
BESS maximum power	264	kW

The configuration in Table 5 shows a balance between grid power and local energy storage. By using a 647 kWh battery energy storage system (BESS), the required grid connection can be kept at 642 kW, even though the seven megawatt charging system (MCS) dispensers create high power peaks. This infrastructure forms the technical basis for the following analysis of the operation and economic performance of the station.

4.2.2 Operational Behaviour

To evaluate the performance of the proposed infrastructure, the operation of the charging station was simulated over one full year. This made it possible to study how the station performs under different demand levels throughout the year, including periods with high charging activity. This section analyses the interaction between grid power, battery usage and vehicle demand to show how the battery supports the grid connection during peak loads and how the system can maintain an acceptable service level even during periods of high demand.

Determining the Optimal Number of Chargers
Figure 10 shows how the 10-year waiting cost changes as more chargers are installed. For the analysis, a 1 MSEK limit was set for the total acceptable waiting cost over the lifetime of the station. This was selected because of the prices for an MCS charger. Important to note is that installation cost is not taken into account when determining the number of chargers and PDCs that are needed.

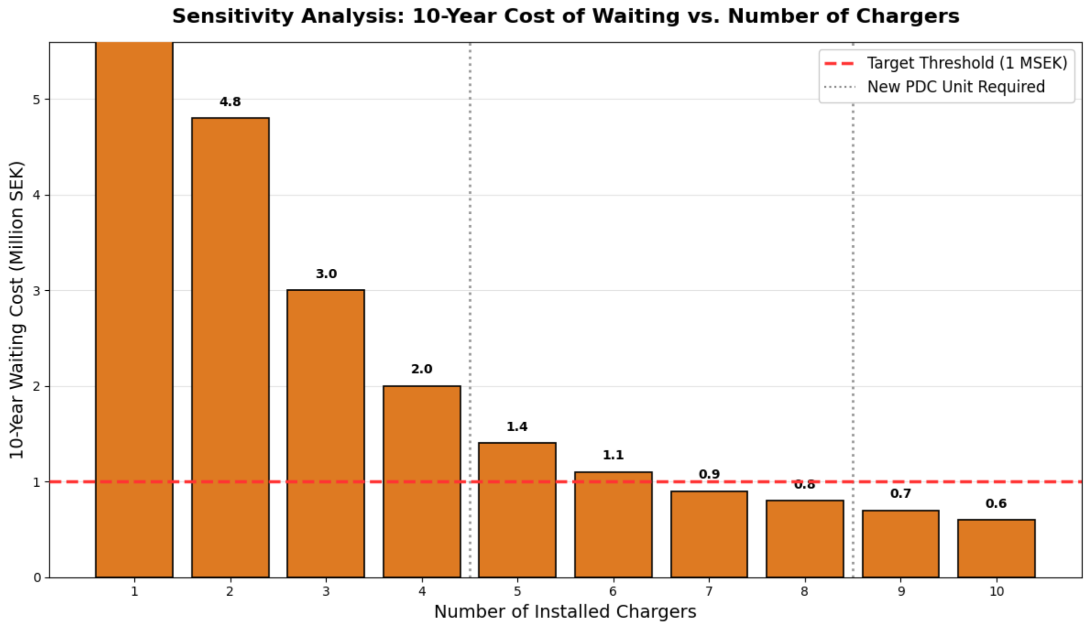


Figure 10: Sensitivity analysis of the 10-year waiting cost based on the number of installed megawatt chargers. Note that the cost for a single charger far exceeds the displayed limit. Instead, the graph is scaled to highlight the critical threshold dynamics between 6 and 7 chargers.

As the graph illustrates, with six chargers, the 10-year waiting cost sits at 1.1 MSEK, just above the target. Adding a seventh charger brings the cost down to 0.9 MSEK, successfully meeting the threshold and delivering the intended level of service. Additionally, adding an eighth charger reduces the waiting cost by merely an additional 0.1 MSEK. Given that the capital expenditure for a single MCS charger is 1 MSEK (as detailed in Table 2), this marginal operational savings does not justify the significant investment, confirming seven chargers as the economically optimal configuration. Therefore, this setup requires two power distribution centres (PDCs), as one unit can support up to four MCS chargers.

Queue Dynamics

To show how well the system prevents long waiting time for the trucks, a heatmap of the average truck waiting time (in minutes) per hour throughout the simulated year is presented in Figure 11. The figure highlights the time periods when the station is most active and shows how well the infrastructure prevents long waiting times for the trucks.

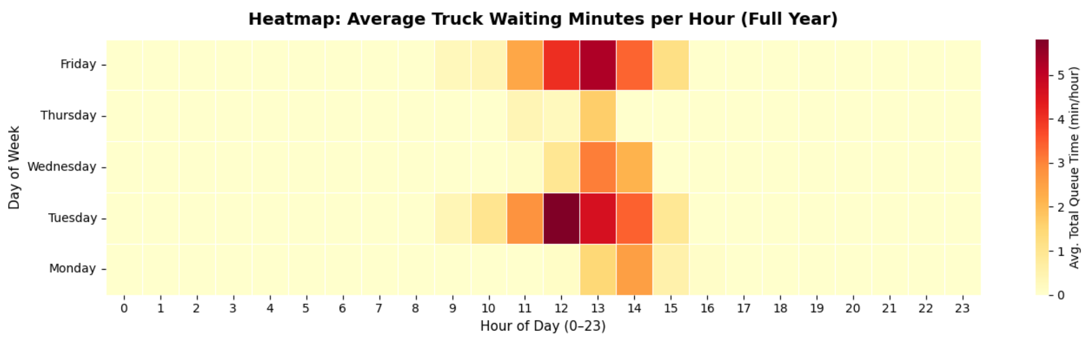


Figure 11: Heatmap of average total waiting time (in minutes) per hour over the full year. The results show that the average queue remains well below the constraint of two vehicles.

The heatmap illustrates when the station is busiest over a typical week. It should be noted that the simulation primarily focuses on regular working days, as weekends and public holidays are significantly lower traffic due to standard freight logistics schedules. During these working days, nights remain quiet, but significant peaks occur during weekday lunch hours. Tuesday midday stands out as the busiest time, followed closely by Friday.

Average waiting times stay low, usually just 5 or 6 minutes at their worst. Even so, the heatmap pinpoints exactly when the BESS and chargers face the most pressure. This data confirms that a configuration of 7 chargers is optimal for the current demand. If traffic rises in the future, Tuesday and Friday peaks are where trouble will show up first.

Power Flow Dynamics

To demonstrate how the BESS and the grid connection interact to supply the charging station throughout the day, the average power flow during a representative 24-hour period with relatively high charging demand is illustrated in Figure 12.

It is important to note that the data is smoothed using a 60-minute rolling average. Thus, periods where the graph displays the BESS charging and discharging simultaneously (e.g., between hours 11 and 12) are data smoothing. In physical reality, the battery operates strictly in one mode per time step. It indicates an hour of high traffic volatility, where the system rapidly cycled between discharging to support charging trucks and recharging during the brief pauses between arrivals. The rolling average effectively blends these rapid, sequential events into a broader trend of high system activity.

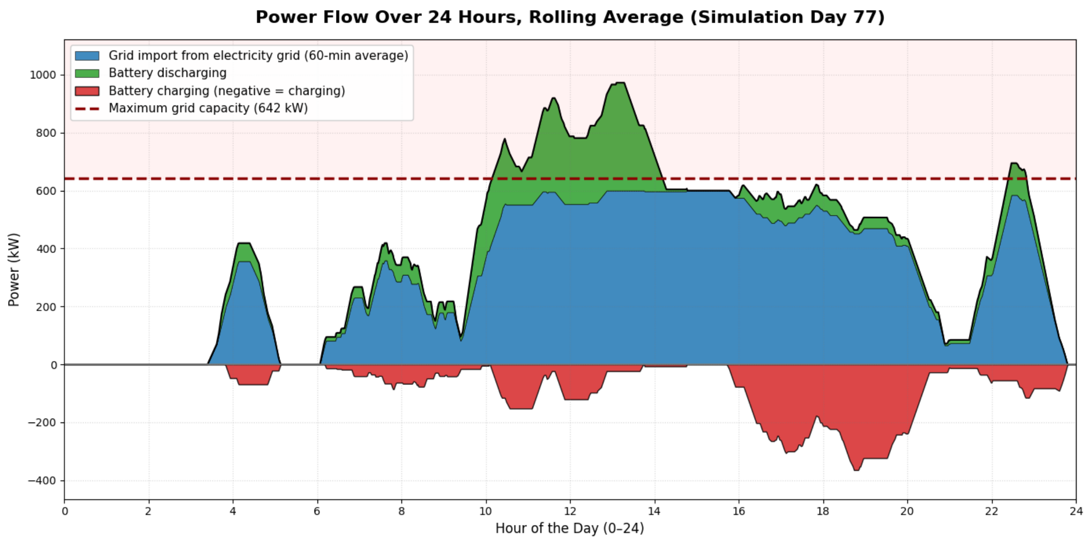


Figure 12: Average power flow over a 24-hour cycle (Day 77). Note that the data has been smoothed using a rolling average to show general dynamics rather than instantaneous fluctuations.

In the figure, the blue area marks what the electricity grid handles and that's the baseline power demand. But when demand spikes and jumps above the grid's 641 kW limit, the BESS kicks in. As seen in the green area on the chart, that's the battery system discharging, shaving those peaks so the chargers can keep running at max power without crossing what the grid can safely supply. When demand drops below 641 kW, the system utilizes the available grid capacity to recharge the battery, that's shown in red.

Battery Energy Management

Figure 13 shows the battery state of charge during the most demanding day of the simulation. The figure illustrates how the storage system is utilized in extreme conditions to ensure that the station can handle the highest traffic peaks.

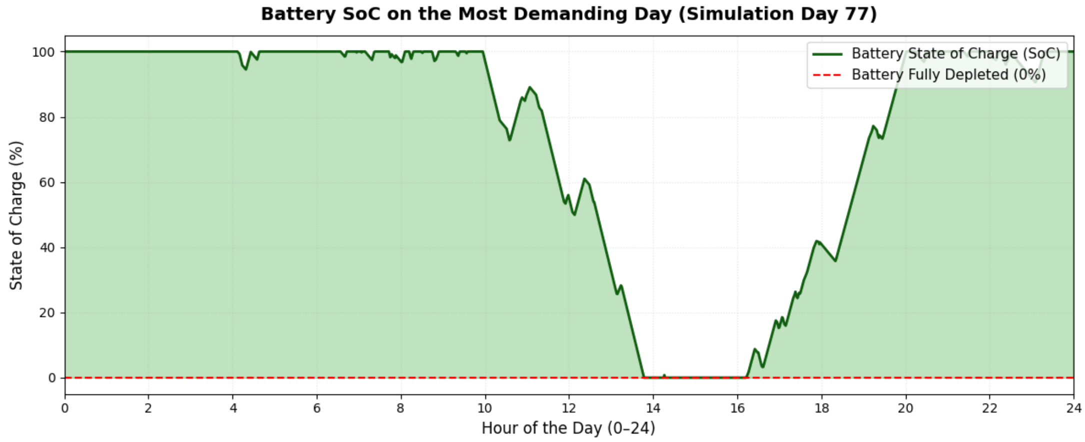


Figure 13: Battery state of charge during the most demanding simulation day (Day 77). The SoC reaches 0% during peak hours, showing full utilization of the storage capacity.

As illustrated in the figure the day unfolds with the battery starting off fully charged. Throughout the morning, the SoC remains close to 100%. As the traffic ramps up around hour 10, the station hits its busiest period. The battery steps in, discharging steadily to support the grid through the peak. This intense load drains the battery completely, by just before hour 14, the SoC drops to zero for a couple of hours. Every bit of grid power goes straight to charging trucks and the battery gets nothing. Once the traffic eases in the afternoon, the system seizes and recharging the battery slowly until it's back at 100%.

4.3 Investment Calculation Results

In this chapter, the economic viability of the charging station is evaluated. The results are derived from empirical data collected from a standard charging facility in the Gothenburg region, alongside the established baseline assumptions. This foundation allows for a comprehensive analysis of the projected revenues and the overall investment appraisal. Concluding the chapter, a sensitivity and risk assessment is presented to determine how fluctuations in key parameters impact the final profitability.

4.3.1 CAPEX Estimation

Following the procedures described in the methodology, the simulation and optimization models yielded the following result for the capital expenditure (26), where the different expenditures are divided in figure 14, where the leading cost is the MCS chargers, followed by the installation cost.

$$
\begin{aligned}
CAPEX = \sum_{i=1}^{n} C_i = P_{\text{Grid}} \cdot C_{\text{Grid}} + N_{\text{CCS2}} \cdot C_{\text{CCS2}} + N_{\text{MCS}} \cdot C_{\text{MCS}} + N_{\text{PDC}} \cdot C_{\text{PDC}} \\
+ P_{\text{BESS}} \cdot C_{\text{BESS}} + P_{\text{BPC}} \cdot C_{\text{BPC}} + C_{\text{Install}} = 16\,469\,502 \text{ SEK}
\end{aligned}
\tag{26}
$$

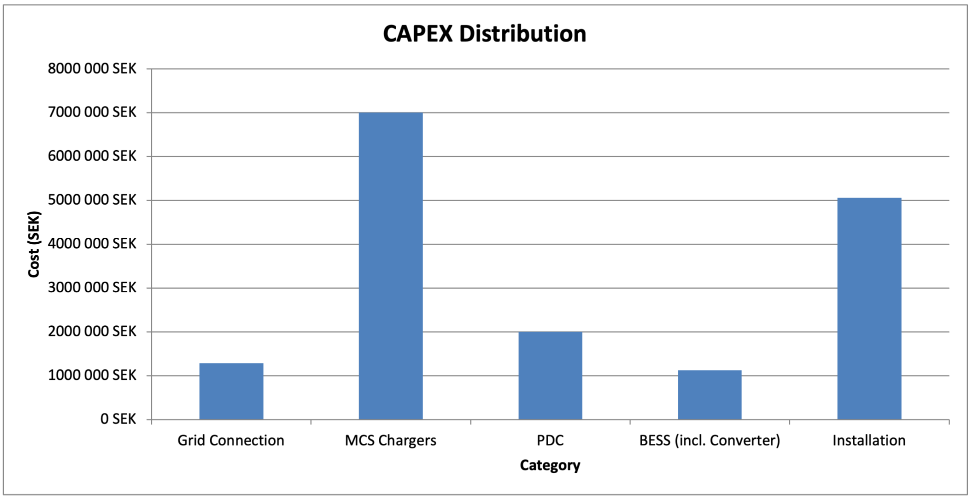


Figure 14: CAPEX distribution across the five cost categories. Grid Connection, MCS Chargers, PDCs, BESS and Installation.

4.3.2 OPEX Estimation

Following the procedures described in the methodology, the simulation and optimization models yielded the following results for the operational expenditure (27) and (28) for true revenue.

$$\text{OPEX}_t = \sum_{j=1}^{m} C_{j,t} = C_{Bought,t} + C_{Sub,t} + C_{Grid,t} + C_{Fee,t} + C_{Maint,t} = 2\ 251\ 021\ \text{SEK/yr} \tag{27}$$

$$\text{CF}_t = R_t - \text{OPEX}_t = 7\ 424\ 618 - 2\ 251\ 021 \ = 5\ 173\ 597\ \text{SEK/yr} \tag{28}$$

4.3.3 Investment Appraisal Outcomes

The following will show if whether investing in an MCS charging station with a local battery system is financially justified and if so, what the expected payback period is and what value the station will generate.

ROI

Given the values from (26) and (28) an ROI of 31.41 %/yr could be calculated, which indicates that it is worth looking further to see how profitable the station will be.

NPV

Based on the parameters presented in Table 2, the net present value is calculated using Equations (4) and (28). With this equation an NPV of 18 246 071 SEK could be calculated, the outcome of this calculation is visualized in Figure (15).

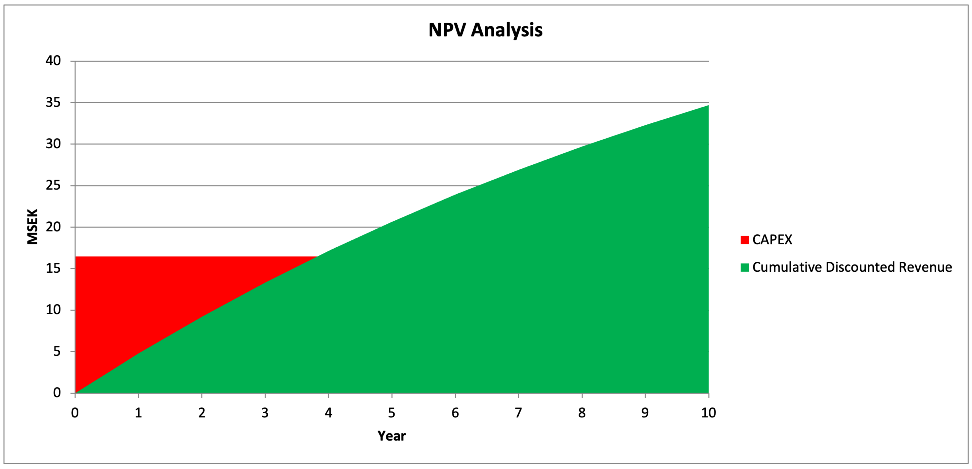


Figure 15: NPV Analysis.

DPP

Given the parameters presented in Table 2, the DPP was calculated using Equation (7), which gives a DPP of 3.82 years. The outcome of this calculation is visualized in Figure 16.

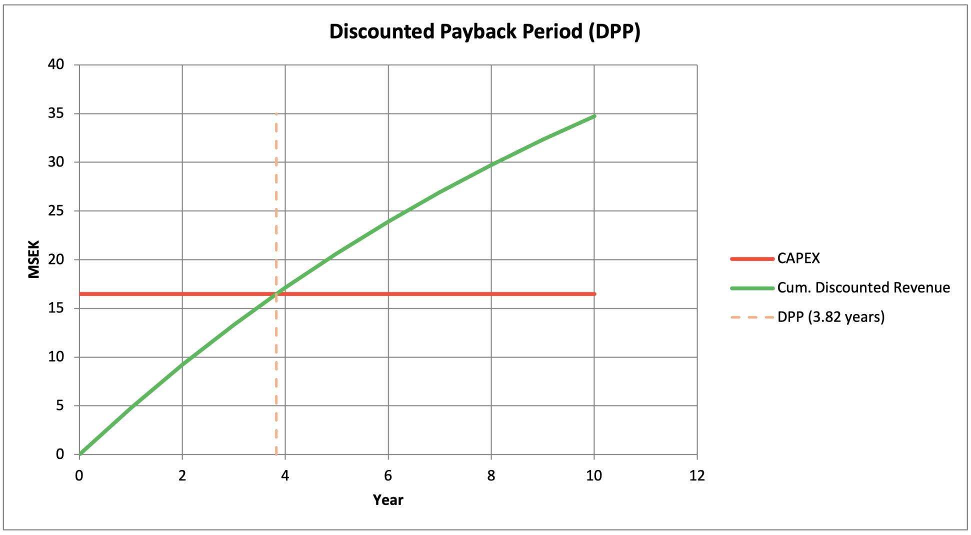


Figure 16: Discounted Payback Period.

4.3.4 Sensitivity and Risk Assessment

The following section presents the results of the sensitivity and risk assessment for both the upper and lower boundary scenarios, evaluating the impact on CAPEX, NPV and DPP.

Upper Boundary

With the given parameters from Table 2 and the new upper values that were presented in the method chapter, the following initial capital expenditure is shown below in Figure 17, with a sum of 19 506 299 SEK.

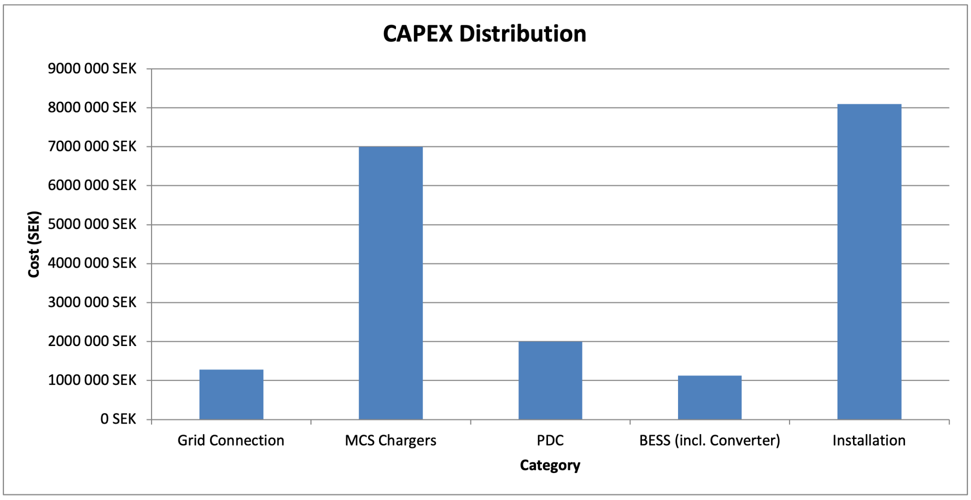
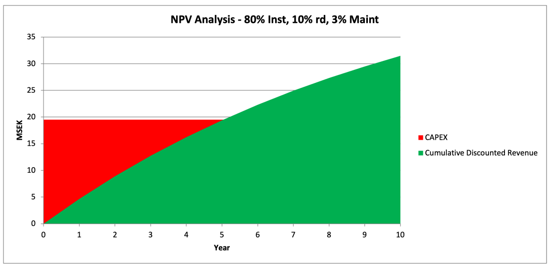
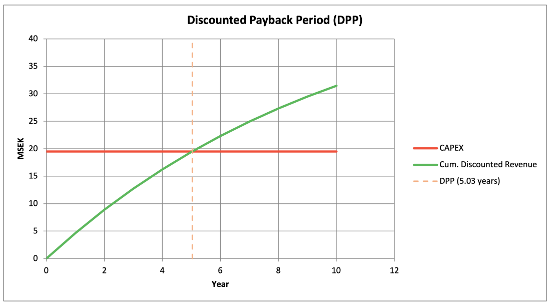


Figure 17: Upper - Capex Distribution.

With this new CAPEX, both a new NPV of 11 972 188 SEK and DPP of 5.03 years was calculated and can be seen in Figure 18 below.



(a) NPV Analysis.



(b) Discounted Payback Period.

Figure 18: Shows the upper NPV (18a) and DPP (18b) for the station.

Lower Boundary

The lower boundary gives a reduced CAPEX of 14 444 461 SEK, where the individual component costs can be seen in Figure 19. The more favourable installation and maintenance costs result in a higher annual cash flow, yielding a NPV of 22 248 243 SEK and a DPP of 3.18 years, as seen in Figure 20.

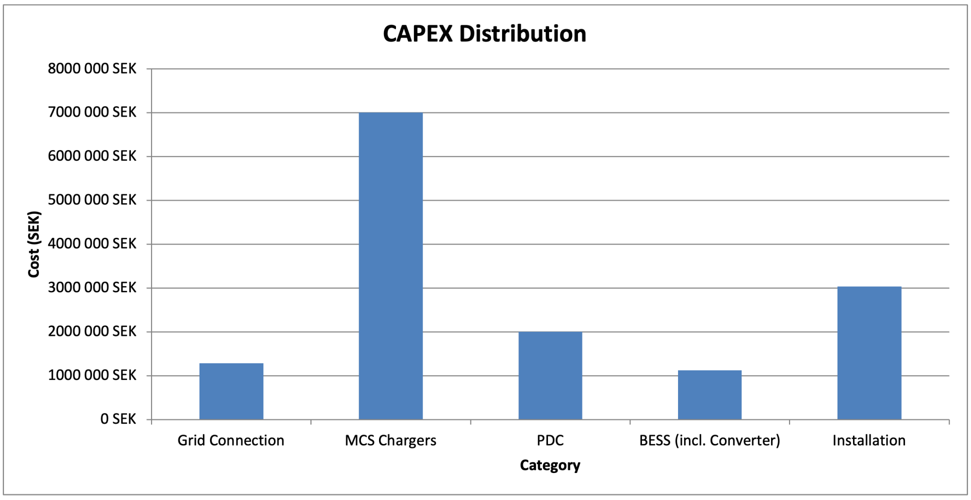
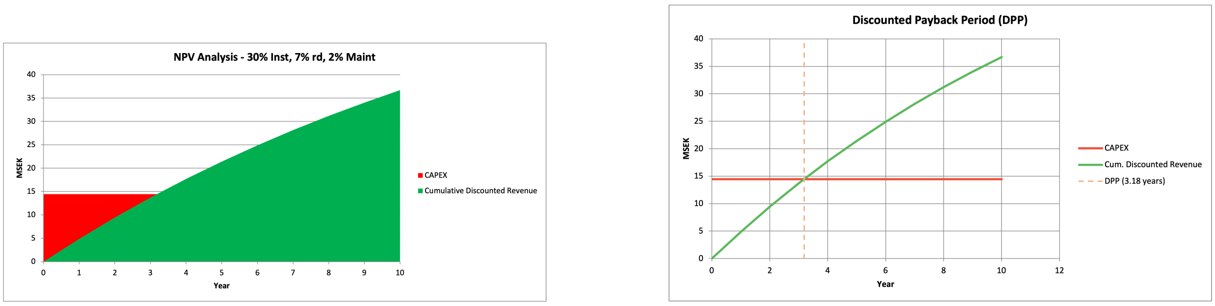


Figure 19: Lower - Capex Distribution.



(a) NPV Analysis. *(b) Discounted Payback Period.*

Figure 20: Shows the lower NPV 20a and DPP 18b for the station.

Risk

With both boundaries established, the NPV and DPP with margin of error can be calculated using Equation (25), yielding the results presented in Equations (29) and (30).

$$NPV \pm NPV_{MoE} = 18\ 246\ 071 \pm 5\ 138\ 027 \text{ SEK} \tag{29}$$

$$DPP \pm DPP_{MoE} = 3.82 \pm 0.925 \text{ years} \tag{30}$$

Even under the worst case assumptions, the station remains profitable with a positive NPV and the investment is recovered within the 10-year analysis period in all scenarios, indicating a robust business case.

5
Discussion

Chapter 5 discusses the results presented in the previous chapter and examines the factors that influenced them. The discussion is structured around the main objective of this thesis, to assess whether a megawatt charging station combined with a local BESS represents a viable investment.

5.1 Optimization

When examining Figure 8, it can be concluded that as battery price increases, the probability of using a BESS decreases. As battery cost rises, both battery capacity and output approach zero, where grid connection is instead utilized. Although the highest battery prices may be unrealistically high, the results still demonstrate the relationship between battery cost and economic benefit, indicating that a BESS is profitable only up to a certain point, after which profitability declines significantly. Table 4 supports the conclusions above by also displaying how the power from grid is prioritized when the battery cost is increased. Comparing the case of 30% in Table 4 with the increased battery cost of 50% instalment cost, shows that battery size decreases from 843 kWh to 647 kWh and down to 195 kWh for the instalment markup of 80%. Battery power also decreases, from 327 kW to 264 kW and to 112 kW, whereas grid capacity is 596 kW for the lower boundary and increases up to 762 kW for when battery instalment cost is at its highest.

5.1.1 The Model's Ideality

A limitation of the model is the fact that it has perfect knowledge of future events. It knows when the trucks arrive, how much energy they require and when the demand peak occurs. Therefore, the battery can be charged and discharged optimally in advance. In reality, the station would need to rely on forecasts when making operational decisions, which may lead to suboptimal decisions and require larger safety margins.

Since the model has access to more information than would be available in real operation, the results should be interpreted as a theoretical optimum. The total cost may therefore be lower and the battery utilization more efficient, than what could be achieved in practice. This is because the battery can be controlled perfectly and used exactly when it is most economically beneficial. In reality, battery control would be limited by uncertainties related to future demand, battery degradation, temperature variations, operational constraints and the need to maintain reserve capacity. A real station operator would therefore likely avoid discharging the battery as aggressively, since future demand is uncertain. Consequently, the results should be interpreted as an upper limit for system performance, rather than as an expected operational outcome.

Additionally, all charging sessions are assumed to occur at a constant power. In reality, the charging power varies depending on the truck's SoC, battery temperature, charging curve and vehicle limitations. This could result in a less predictable power profile, making the system harder to optimize. On the other hand, when several trucks charge simultaneously, individual variations may partly cancel each other out. Therefore, the constant-power assumption is considered an acceptable simplification at the system level, even though it does not fully represent individual charging behaviour.

Moreover, the queue is modelled as an amount of energy waiting to be charged, rather than individual trucks waiting for an available charger. This makes the model more mathematical and easier to solve, but it also simplifies how queues work in reality. In practice, trucks are discrete units that cannot be divided into continuous amounts of energy. This means that aspects such as the individual's waiting time, charger availability, truck prioritization and whether a specific truck can complete its charging session within a given time window are not fully captured. As a result, the model may underestimate some operational limitations related to queuing and service level.

The model also knows the electricity price in advance, which is relatively realistic since day-ahead prices are published the day before operation at 13:00. However, the model assumes demand is known at the same time, which is an idealization. It is the combination of perfect price information and perfect demand information that makes the optimization stronger than in reality. In practise, a real control system would need to combine known electricity prices with uncertain demand forecasts, which would likely reduce the economic performance compared to the modelled results.

Overall, the model's ideality means that the results should not be interpreted as exact design values but rather as an indication of the system's potential.

5.1.2 The Effect of Electricity Price

Figure 9 shows a clear positive correlation between battery energy capacity and electricity price variation. The results indicate that larger price variations make a BESS more economically attractive. This is expected, since a larger spread between low and high electricity prices increases the potential value of storing energy when electricity is cheap and using it, or selling it, when the electricity price is high. However, if more actors were to utilize this strategy, it could contribute to reducing the overall variation in electricity prices. Low-price periods would experience increased demand due to battery charging, while high-price periods would experience reduced demand or increased energy supply due to battery discharging. This would decrease the price spread and thereby reduce the economic potential of using the battery for trading purposes.

This behaviour is also illustrated in Figure 7, where the battery is charged during periods of lower electricity prices and discharged during periods of higher electricity prices. This shows that the optimization model not only uses the BESS for peak shaving, but also for price-based energy shifting and when beneficial, electricity trading. The battery, therefore, receives an additional value when electricity prices vary, as shown in Figure 9, which shows increasing battery capacity when the daily price spread increases.

5.2 Simulation

Building a comprehensive model to optimize the megawatt truck charging station is not achieved through a single, simple approach, rather, it is constructed from several interconnected parts. Among these, the simulation model plays a vital role. It serves as a foundation for understanding the dynamic behaviour of the station and bridges the gap between theoretical capacity and actual operational performance.

5.2.1 Sizing and Infrastructure Requirements

The simulation decided that seven MCS chargers and two PDCs was the optimal configuration. As shown in Figure 12, the decision is driven by the cost of waiting versus the cost of adding hardware. With six chargers the 10-year waiting cost sits at 1.1 MSEK, just above the 1 MSEK threshold, while a seventh charger reduces this to 0.9 MSEK. Adding an eighth charger only reduces waiting costs by a further 0.1 MSEK, which does not justify the 1 MSEK capital cost of an additional charger, confirming seven as the economically optimal number. This also show that trying to completely remove waited time for trucks is not economically available.

The two PDCs are directly related to the hardware constraint that one PDC supports a maximum of four chargers, making a second unit unavoidable with seven chargers. But it should be noted that connecting four MCS to one PDC in not based on any real-life data and is only a quest based on limited information.

It should however be noted that the 1 MSEK threshold is set equal to the hardware cost of a single MCS charger. The logic is straightforward, adding a charger is only justified if the reduction in waiting costs exceeds the cost of the charger itself. This is a reasonable assumption, but the result is sensitive to the assumed charger cost of 1 MSEK, which is an estimate rather than a confirmed market price and it also does not account for the installation cost of the charger. To get a better idea of exactly how many chargers are needed then installation cost should be taken into account and also how many trucks are waiting at a given time, to account for parking space, and how long they will wait for a free charger.

5.2.2 Queue Dynamics and Service Levels

The heatmap in Figure 11 shows a clear pattern of how the station is utilized throughout the day. During nighttime and early morning hours, there is virtually no queue, meaning trucks can arrive and begin charging immediately without any waiting time. Congestion is instead concentrated to weekday lunchtimes between roughly 11:00 and 14:00, where average waiting times peak at around 5–6 minutes. In the context of a 45-minute charging session, this is relatively modest and unlikely to cause significant disruption to transport schedules and can therefore be considered acceptable for the current demand level. This aligns well with the behaviour of long-haul truck drivers, who tend to cluster their mandatory 45-minute rest breaks around midday in accordance with EU driving time regulations. Tuesday and Friday stand out as the busiest days, which is likely a reflection of weekly freight patterns in the underlying data.

5.2.3 Power Flows and Battery Utilization

Both Figure 12 and Figure 13 illustrate the same simulation day and are best analysed together. Figure 12 shows the power flows through the system each hour, while Figure 13 shows the direct consequence for the battery. Each green area in Figure 12 corresponds to a decreasing SoC in Figure 13 and each large red area corresponds to a battery recovery.

During the nighttime the station is in principle unloaded and the battery stays at 100% SoC. Short periods of arrivals early morning, around hour 04:00 and also between hour 06:00 - 09:00, cause short discharges. The battery recovers between these sessions and enters the main demand period fully charged.

From hour 10:00 and onwards, simultaneous truck arrivals push the total demand beyond the grid limit of 642 kW, at times reaching close to 970 kW. The BESS responds by continuously discharging to compensate, with only a brief partial recovery around hour 11:00. Around hour 13:30–14:00, the SoC reaches zero and the battery is fully depleted, leaving the station running on grid power alone for approximately two hours. The full depletion on simulation day 77 confirms that the 647 kWh capacity is well dimensioned, large enough to handle demand peaks throughout the year, but not so oversized that it carries unused reserve capacity.

That the battery is fully charged every morning is a result of the simulation rather than a hard-coded assumption. During nighttime hours, truck traffic is in principle non-existent, meaning the grid capacity is not fully utilized. The simulation directs this surplus towards battery charging as long as the SoC is below 100%, which drives the battery to full capacity before the first trucks of the day arrive. It should however be noted that the simulation does not account for the SoH of the battery, which degrades over time. In reality, the battery capacity would gradually decrease over the 10-year lifespan, reducing its ability to handle peak loads in the following years. This is something to consider when further developing the simulation model. Also the simulation does not take in to account SoP, which says what the maximum power that can be delivered from the battery at a given time. The simulation model assumes that the battery can always deliver maximum power.

When the demand peaks diminish, the system switches to recharging the battery aggressively, drawing up to 350–400 kW below the grid limit through the evening. This behaviour is an emergent result of the control logic rather than a fixed rule. This is done because the simulation only knows what is happening during that specific time step and what has happened in previous time steps. So it is assuming the worst for the coming time step, which makes it so that it will always get ready to handle that by fully charging the battery. This is a limitation of the simulation model that should be looked into, where it should make guesses of what will happen based on what has happened during the simulation time. This will make it so it does not always need to charge the battery when it is possible.

Regarding the rolling average used in Figure 12, the 60-minute smoothing was chosen to illustrate the general dynamics of the system rather than showing each individual charging session as an isolated spike. A side effect is that periods of high traffic volatility, such as between hour 11:00 and 12:00, may appear to show the battery charging and discharging simultaneously, which is physically impossible. These are visual artefacts of the averaging, reflecting hours in which the battery rapidly alternated between the two operating modes in response to fluctuating truck arrivals.

5.3 Economic

When examining the results of the investment analysis, it can be concluded that a MCS charging station with a local BESS represents a financially viable investment under the given assumptions. The following reflects on the implications of these findings, the sensitivity of the results to key parameters and the limitations that should be considered when interpreting the conclusions.

5.3.1 Profitability and Investment Viability

The results indicate a strong business case for the charging station. With base results of NPV = 18 246 071 SEK, a DPP of 3.82 years and an annual ROI of 31.41%. However, it should be noted that these results are dependent on the assumption of a constant annual cash flow, which in reality may vary due to fluctuations in demand, electricity prices and operational costs. But is shows that the chosen markup of 5 SEK is a lot more than needed to hit the 10 payback period and a markup of about 2 SEK would be enough to get the payback period of 10 years with about one and half years to spare. The results should therefore be interpreted as indicative rather than definitive projections. It also assumes that electric truck market will stay the same during this 10 years evolutional thus the market will not grow nor will it shrink. Which is not what is expectation for the electric truck market, which is expected to grow during this time frame.

5.3.2 Sensitivity to Cost Parameters

The sensitivity analysis demonstrates that the economic results are robust across both boundary scenarios. Even under the worst case assumptions the station remains profitable with an NPV of 11 972 188 SEK and a DPP of 5.03 years. The margin of error for the NPV is 5 246 027 SEK and 0.925 years for the DPP suggests that while the cost parameters do influence the results, they do not fundamentally alter the viability of the investment. But important to take in to account only some cost parameters where change will the rest stayed fix which in not a full sweep of the cost sensitivity analysis.

5.3.3 Limitations and Real-World Uncertainty

While the economic model provides a solid foundation for evaluating the investment, several limitations should be acknowledged. First, the model assumes a constant electricity purchase price of 1 SEK/kWh and a fixed retail price of 6 SEK/kWh throughout the entire 10-year period. In reality, electricity prices are subject to significant market fluctuations, which could substantially impact the annual cash flow. Second, the model does not account for potential changes in grid tariffs or government policies regarding EV charging infrastructure, both of which could affect the operational costs. Third, the degradation of the BESS over time is not considered, which would gradually reduce its effectiveness and may require replacement within the analysis period, adding to the CAPEX. Finally, the assumption of constant annual demand does not reflect the expected growth in EV adoption, which could increase revenue over time, nor does it account for potential competition from other charging stations in the area. These limitations suggest that the actual economic performance of the station could deviate from the modelled results and future work should consider incorporating dynamic pricing, demand growth and component degradation into the economic model.

6
Conclusion

To answer the research question formulated in the introduction, a megawatt charging station should include local battery storage when the charging demand contains high-power peaks that are more cost-effectively handled by a BESS rather than by increasing the grid connection alone. Thus, implementing a BESS reduces the peak grid connection, supports high charging demand and makes the station more operationally flexible. Electricity price variation further increases the value of a BESS by allowing energy to be shifted from low-price periods to high-price periods, which explains why a larger battery capacity is wanted with a larger price spread shown in Figure 9. However, when the electricity price was set to a constant, the optimization model selected no battery storage, indicating that if many actors adopt similar battery strategies, the electricity price spread may decrease over time and reduce the economic benefit of local battery storage. Therefore, local battery storage should be included when the combined benefits from peak shaving, reduced grid capacity and electricity price arbitrage exceed the additional investment cost of the BESS.

For the analysed demand profile, the best trade-off between investment cost and waiting cost was achieved with seven MCS chargers and two PDC units. This was attained using a grid connection of approximately 642 kW, a 647 kWh battery capacity and a BESS power capacity of 264 kW taken from the optimization. The results show that it is not economically justified to eliminate all queuing, since adding an eight-MCS charger would only reduce the waiting cost by 0.1 MSEK while requiring an investment of another 1 MSEK for an additional MCS charger hardware, excluding installation costs and operational costs.

To conclude, this study presents a robust business case for implementing the megawatt charging station using a local battery storage system. The baseline economic indicators, including an NPV exceeding 18 MSEK and a payback period of under 4 years, highlight the investment's profitability. Crucially, the sensitivity analysis confirms that the project's viability remains robust to substantial increases in cost parameters. Although the model operates under static assumptions regarding electricity pricing, demand and hardware longevity, the financial margins are wide enough to absorb significant market fluctuations. Consequently, the investment is deemed both economically sound and strategically aligned with the ongoing transition to electric freight transport.

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