Effect of Dynamic Pricing

on the Low-voltage Grid

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by

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TU Delft

Abstract

The growing integration of renewable energy sources presents significant challenges for the reliability of the energy infrastructures in The Netherlands. To address these challenges, dynamic electricity pricing has been proposed as a potential solution to align the electricity demand with the variable supply. While dynamic pricing can incentivize the shifting of flexible loads, its impact on the low-voltage grid remains under-investigated. This thesis explores the impact of dynamic pricing on grid congestion, especially in combination with electric vehicle (EV) charging and Photo-Voltaic (PV) systems.

It is hypothesized that while dynamic pricing can effectively shift electricity consumption, it may also lead to concentrated periods of high demand. When consumers synchronize their electricity usage during low-price times, grid congestion can occur. The study creates a simulation model using Python and PowerFactory to analyse the effects of dynamic pricing on the low-voltage grid. The simulations are based on real-world data from 2023, making use of hourly intervals of loads, EV charging profiles, and solar energy generation across three representative weeks. The model evaluates the voltage levels and power flows to assess the potential for grid congestion under various scenarios of EV and PV adoption.

The results indicate that dynamic pricing can lead to concentrated EV-charging loads, resulting in voltage dips and power spikes. These findings show that the current low-voltage grid may not be equipped to handle the increased demand and variability caused by dynamic pricing schemes. Thus, while dynamic pricing can offer a promising tool for demand-side management, additional measures are necessary to ensure grid stability and to avoid future congestion issues.

In conclusion, the study underscores the dual nature of dynamic pricing as both a valuable tool and a potential risk for the low-voltage grid. Both the voltage and power limits of the grid were found to be causes of congestion, highlighting the need to investigate both. Future research should focus on optimizing dynamic pricing schemes and developing robust grid infrastructure to fully leverage the benefits of renewable energy integration while ensuring grid reliability and resilience.

Keywords: Dynamic pricing, grid congestion, low voltage grid, electric vehicles, flexible loads, photovoltaic systems, renewable energy integration, simulation modelling, grid stability.

Preface

To finalize their master's degree, all Sustainable Energy and Technology students of the Delft University of Technology have to complete a final graduation project, officially called the SET3901 Graduation Project. This particular project is carried out with the IEPG group of the EEMCS faculty, in collaboration with the distribution system operator Stedin.

The goal of this thesis is to investigate the effect of dynamic electricity pricing contracts on the low-voltage grid, especially in combination with electric vehicles and household solar panels. This is done by simulating and analysing the line voltage profiles and the power over the grid's transformer.

The results showed that dynamic pricing increases the number of simulations where grid congestion occurred. While the power limits were the most often crossed, the study showed that the voltage profiles cannot be ignored.

The past six years at the Delft University of Technology have proven to be both a challenge and an amazing adventure. I am grateful to all teaching and supporting staff of the university for guiding me through my bachelor and master program. Throughout past 9 months I had to use my technical knowledge in combination with my creativity and problem-solving skills to overcome the challenges I faced.

I would like to thank my supervisors, Simon Tindemans, Arjan van Voorden and Henk Fidder for all their help these past months. They were always willing to answer any questions I had and provided the necessary guidance to successfully complete this project. I also want to express my gratitude towards my colleagues from the Asset Management team and from the rest of Stedin for providing me with data and tools, and for giving me advice on my work.

And finally, I want to thank my friends and family for supporting me through the past six years of my studies. Without all of their support, I would have never been able to reach this goal.

Charlotte De Jonghe
Delft, August 2024

Acronyms

DSO Distribution System Operator.

EV electric vehicle.

EVSE electric vehicle supply equipment.

GO-e Gebouwde Omgeving Elektrificatie.

HEMS Home Energy Management Systems.

LV low-voltage.

PTU program time unit.

PV Photo-Voltaic.

SAC Standard Annual Consumption.

Contents

1 Introduction

To reach The Netherlands' climate goals, the energy infrastructure is undergoing a massive transformation. In the past years, grid operators have doubled their investments, with an expected annual investment of 8 billion euros from 2025 on. This will be used to construct over 1200 000 kilometres of cables, 50 000 new transformer stations and energy solutions like batteries. The grid operators want to accelerate the transition to sustainable energy sources, focusing on more efficient processes and increasing the production capacity. The goal of these investments is to address the growing demand for electricity and the shift towards renewable energy, ensuring a reliable, future-proof energy system for generations to come[1].

Our electricity sources are becoming more and more variable, the sun doesn't always shine, and the wind doesn't always blow. Yet our energy needs still have to be met, therefore, dynamic pricing might seem like a good solution. As a consumer, you pay more when the production is low, and less when the production is high. This will cause the demand to shift towards the high production times. However, dynamic pricing might have its drawbacks. If the electricity loads are shifted towards one point in time, can the capacity of the grid still be guaranteed?

This first chapter will provide and introduction for this thesis. First some background information is given on the low-voltage grid, solar energy, electric vehicle charging and dynamic pricing. Afterwards, the objective of this project is presented, including the research questions. Next, the scope of this thesis is explained. Section 1.3 will explain the prior work on this topic and what research gap this thesis aims to fill. Finally, an overview of the rest of the thesis will be given.

1.1. Background

1.1.1. The Current State of the Low-Voltage Grid

The electricity grid in The Netherlands is made up of three parts: the national, regional and local grids. The local grids exist of a medium voltage (MV) distribution grid and a low-voltage (LV) grid. The high voltage grid transports energy across the country, the medium voltage grid serves large consumers and small industrial loads, while the low voltage grid provides electricity to households[2]. The operation of the low and medium voltage grid is done by the different Distribution System Operator (DSO)'s, for the majority of the regions of Zuid-Holland, Utrecht and Zeeland this is grid operator Stedin[3].

Due to the electrification and the rise of variable electricity sources, a massive grid reinforcement is needed. New electric loads like electric vehicles and heat pumps create a much larger capacity need. At the same time, renewable energy sources like wind energy and PV power make the energy supply much more variable. As [4] highlighted, smart investments are needed to optimally expand the grid.

1.1.2. Solar Energy

Solar panels generate electricity by using the photovoltaic effect to convert sunlight into electricity, as illustrated in Figure 1.1. In this process, solar energy excites the electrons in the silicon cells, creating a negative charge, which results in a voltage difference. The hereby generated direct current is converted into an alternating current, using an inverter[5].

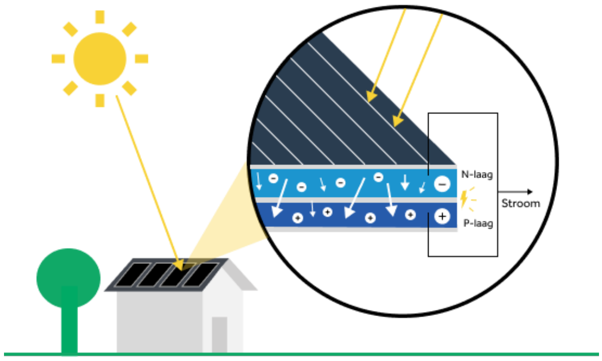


Figure 1.1: The working of PV panels illustrated[5].

Solar energy can help greatly to reduce the emission of greenhouse gasses, by providing a clean, renewable source of energy. However, its addition to the electricity network also complicates the energy balance. Solar power is variable, dependent on the weather and time of year. This creates periods with excess energy, but also periods with shortages. The challenge is now on how to deal with this variability and keep the energy supply reliable.

In recent years, there has been a massive growth of Photo-Voltaic (PV) systems in The Netherlands. The Dutch government wants the energy system to become carbon-neutral by 2050, to achieve this, a focus is put on both wind and solar energy. A part of this are the government stimulating policies, like grants and tax reductions, which have financially incentivized homeowners to invest in solar energy[6]. As a result, in 2023, over 2.5 million houses have solar panels on their roofs, which is over 30 % of all Dutch houses[7].

One heavily discussed policy is net metering. This financial scheme allows PV owners to subtract their electricity generation from their usage, allowing the household to save money on their electricity bill. This financial scheme is very usefully for households with solar panels as they only pay for their yearly net electricity usage. However, due to net metering, households have no incentive to use their own generated energy, which puts more strain on the grid. The Dutch government planned to phase out net metering by 2031, yet decision has recently been overruled[8].

1.1.3. EV Charging

Unlike traditional cars powered by internal combustion engines, electric vehicles make use of electric motors, drawing energy from an onboard battery. These batteries are charged by connecting the vehicle to a residential or public charging station. Charging an EV often requires high electrical powers, especially during fast charging sessions. As the EV adoption continues to rise, the power demands for charging have the potential to significantly impact grid stability, especially within the low-voltage network where most residential charging occurs[9].

On the other hand, electric vehicle charging could provide flexibility, when smart charging is optimally used. An example is given by [10], who addressed congestion issues by optimizing EV charging flexibility. According to this study, an optimal EV charging model could delay grid reinforcements by efficiently distribution the EV loads[10].

1.1.4. Electricity Market

The Dutch electricity market follows the framework of the European electricity market. Ever since the liberalization of energy sector in the late 1990s, the Dutch electricity market consist of the following components:[11][12]

- Wholesale market:
  - Day-ahead market: This is the most important part of the electricity market. Here the hourly electricity prices for following day are determined, based on the supply offers from generators and the demand bids from suppliers.
  - Intraday market: After the day ahead market closes, participants can keep trading here. This allows for adjustments because of updates and changes in the predicted demand or supply closer to the delivery time.
- Balancing market: Managed by the Transmission System Operator (TSO), the balancing market balances the supply and demand in real time.

The market price of electricity is determined by supply and demand. This so called price per program time unit (PTU) can be volatile, especially due to the varying wind and solar availability. Dutch consumers can choose their supplier out of a large range of companies. They can also choose which type of electricity contract suits their needs the best[12].

1.1.5. Dynamic Pricing

Households in the Netherlands can choose between a fixed, variable and dynamic contract. Traditional electricity contracts have a set the electricity price per kWh, either for the whole duration of the contract (fixed contract) or for each month, quarter, or year, dependent on the wholesale market price (variable contract)[13]. Dynamic contract on the other hand, have a price that changes hourly, following the day-ahead market price[14]. As this price varies, households could shift their electricity usage towards the low price times, which could significantly lower their electricity bill[14].

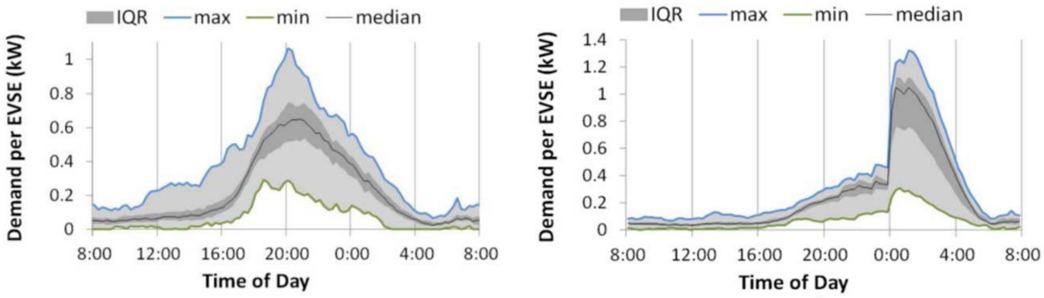
[15] shows an early study of 15 pilots and implementations of dynamic pricing conducted in the US. It concludes that, as expected, households will lower their electricity usage when the price is higher. The magnitude of this decrease is found to depend on three factors:

- Magnitude of price increase
- Presence of central air conditioning
- Availability of technologies that allow remote control

This study highlights the importance of relevant technologies, as without a remote control for their electricity usage, it is unlikely that households will adjust their consumption based on the pricing[15].

The shift of the demand peak towards a lower price period might seems advantageous at first. However, a so-called rebound peak can be created at the lower price periods, with the peak occurring at the lowest price point, when consumers plan their usage. This peak is found by [16] to be shorter in time, but with a higher peak load compared to the normal situation.

Figure 1.2 from [16] shows this by comparing the average electric vehicle supply equipment (EVSE) between two locations. Participants from location (a) did not have access to time varying tariffs, it can be seen that their demand peaks during the evening. Location (b) had a Time of Use tariff that lowered at midnight, at this time a large increase of the charging demand can be seen. The charging demand gets concentrated after midnight and a shorter, but larger peak takes place[16]. Consumers will focus as much of their demand as possible to the low-price periods, generating a higher demand peak, which could create more issue for the electricity grid.



(a) Flat electricity price

(b) Electricity price lowers at midnight

Figure 1.2: Average EVSE charging demand for two different pricing strategies investigated in [16].

1.2. Project Objective

The rapid increase in the integration of renewable energy sources, such as solar and wind, into the power grid presents a significant challenge for maintaining grid stability and reliability. Traditional grid infrastructures, designed for steady and predictable electricity flows, are now facing the variable and often unpredictable nature of renewable energy generation. This variability leads to mismatches between supply and demand, causing grid congestion and stability issues, particularly at the low-voltage level where residential and small commercial consumers are connected. The implementation of dynamic electricity pricing has been proposed as a solution to better align energy consumption with renewable generation. However, the impact of dynamic pricing on the low-voltage grid, specifically in terms of potential congestion and voltage stability, remains under explored. This thesis aims to address this gap by investigating how dynamic pricing influences grid performance, focusing on the implications for electric vehicle (EV) charging and Photo-Voltaic (PV) system integration.

The goal of this project is to analyse what the effect of dynamic pricing is on the low voltage grid. Different scenarios will outline potential grid issues that might occur. Simulations will be conducted to evaluate the impacts, with a focus on the line voltages and power flows over the transformer in the grid. PowerFactory will be used as a simulation tool, since it allows for a detailed analysis of the grid voltages.

The research question for this thesis is formulated as follows:

> What is the effect of dynamic electricity pricing on the low voltage grid, looking at the capacity requirements and voltage constraints in hourly intervals?

This question will be addressed by investigating multiple sub-questions:

- What will the electric vehicle charging profiles and solar panel power profiles look like under influence of dynamic pricing?
- What role does the integration of electric vehicles play for these results?

- How does the presence of solar panels affect the voltage and power profiles of the low voltage grid?
- What grid limit (voltage or power) in the most important to investigate when analysing grid congestion?

1.2.1. Scope

This thesis will focus on the modelling and analysis of EV charging and PV power in combination with dynamic pricing. Simulations will be done using over a residential area over a defined period, using a set of data parameters. PowerFactory will be the simulation tool, using hourly quasi-dynamic simulations.

The study will analyse the effect of dynamic pricing in combination with EV charging and PV generation. Other potentially flexible loads or generators like heat pumps or batteries will not be taken into account in the simulations.

1.3. Prior Work

1.3.1. Grid Congestion

A lot of papers have been written about the energy transition can create grid congestion. Especially the rise of eclectic vehicles has become a challenge for the grid. While the Dutch low-voltage grid is currently very reliable, experts expect a great influx in demand as the Netherlands moves away from a fossil-based society towards one that relies on electric sources.

One such example is [17], which investigated how replacing gas boilers with heat pumps in the majority of buildings would affect an 18-node low-voltage grid. The results showed voltage drops below the set constraints, even with the addition of solar energy[17].

[18] focused on creating a model to estimate EV charging sessions, which predicted weather blackouts took place for different EV penetration levels. This study showed that an EV penetration of 30 %, which is the expected number for 2030, already results in a 20 % increase in blackouts. For higher EV levels, the number of blackouts keeps increasing[18].

According to [2], installations have becoming more sensitive to power quality issues due to their non-linear operation characteristics. They thus conducted a detailed study about the power quality of the Dutch medium- and low-voltage grid, by looking at the grid impedance and the short circuit powers. The paper found that while at the time of writing, the minimum short circuit power requirement was met, large voltage changes are expected to cause power quality problems[2].

1.3.2. Proposed Solutions

Different papers have proposed many different solutions or mitigation methods for the expected grid congestion causes.

For example, [19] looked into solutions for the over voltages created by renewable energy sources and the under voltages from demand peaks. Peak shaving and power curtailment were proposed and found to have a technically feasible business model[19].

Another potential mitigation comes from [10], who focused on optimizing EV charging to address congestion in the low-voltage grid. The integration of dynamic pricing schemes, bidirectional charging and grid constraints were explored as potential benefits. The goal was to show how these measures could be used to delay grid reinforcements, while maintaining the grid stability. By analysing various scenarios, it was predicted that transformer reinforcements could be delayed until at least 2050, by implementing an optimally utilizing the flexibility of electric vehicles.

[20] explored different congestion management mechanisms, like smart network tariffs, local markets, and direct control methods. The study believes that while electric vehicles and hear pumps lead to congestion, their flexibility could be used as the solution. The benefits and drawbacks of each method were discussed, and an overarching framework for congestion management mechanisms was presented. The study classified congestion management approaches into categories, based on the load-controlling parties and the position of the grid operators. It emphasized the complexity of implementing the different methods and the challenges of coordinating them effectively to be able to optimize grid performance. It concluded that these mechanisms should be fitted to the exact problem that as to be solved, as there is no one size fits all solution[20].

1.3.3. Dynamic Pricing

The idea behind dynamic pricing is that households will shift their electricity usage when to prices are high towards low pricing times. This was investigated and proven by [15], who conducted a study on 15 pilot projects in 2010. These experiments and full-scale implementations showed that households respond to higher prices by lowering their usage. The magnitude of this load shift depended on the presence of central air conditioning and enabling technologies[15].

Different dynamic pricing models and algorithms have been analysed, for example by [21], [22], and [23]. In [21] it is explained how dynamic pricing in micro-grids has its challenges due to a lack of user-information and uncertainties. A reinforced learning algorithm is developed for service providers and consumers to independently strategize, without any prior knowledge[21]. The goal of [22] was to maximize social welfare by using dynamic energy pricing to improve how energy is managed. The authors created a method to determine dynamic energy prices and optimal strategies[22]. [23] focuses on the simultaneous charging of electric vehicles and the low voltage grid. Their dynamic pricing models show a significant impact on the voltage, highlighting the importance on taking these issues into account in the planning and control of the distribution system[23].

Dynamic electricity contracts are becoming more popular for households ever since the 2022 energy crisis. For example Elenia, a Finnish DSO, known as an early-adopter of smart metering, has noticed that more of their customers are interested in dynamic pricing contracts. As a response, the company has developed ”AinaLab”, a load control service that allows customers to alter their energy usage. It provides a free and easy way for households to utilize the cheap electricity times, without the need for investments into a separate system[24].

[25] explored the impact of dynamic energy pricing schemes on a home energy management system. It discussed the importance of energy management systems in optimizing residential energy usage, especially due to advancements in home appliance technologies. The paper presented a Home Energy Management Systems (HEMS) algorithm that monitors and controls household appliances based on various energy pricing models. The goal of the algorithm was to reduce greenhouse gas emissions, minimize the energy usage in response to increasing prices and demand, and decrease the waste of energy. By simulating different scenarios, the study showed which algorithms and pricing models led to a significant reduction in user payments and in the total energy consumption[25].

[26] analysed dynamic pricing models for electric vehicle charging using real data from Bosnia and Herzegovina. The authors noticed how the simultaneous charging of electric vehicles can significantly impact the network voltage and current, depending on the charging scenario. According to this study, a lack of user studies with real world data makes it difficult to quantify these issues and to investigate whether and what solutions are needed[26].

[16] discussed the effect of implementing a residential demand response program with time-varying electricity pricing. It stated that flexible demand is needed to reduce the strain on the power generators and to integrate renewable resources efficiently. Various electricity price structures, such as time-of-use tariffs and critical peak pricing, were analysed to assess their impact on the residential demand. One interesting finding of the study is that when consumers focus their energy consumption during the

low-price times, this can lead to large rebound peaks. These peaks can be higher and steeper than the original demand peaks, thus creating more grid issues while trying to eliminate them[16].

An extreme version of these low-price times are negative prices, when consumers can earn money based on their electricity usage. [27] conducted a study on how negative dynamic prices influence the Finish distribution grid. This was done by looking at the 24th of November 2023, when due to a faulty energy bid, households could earn over 0.40 euro/kWh of electricity usage. Since over 30 % of Finnish households have a dynamic pricing contract, this caused a large peak in consumption. As a result, 120 fuses were burned in the distribution system[27].

The NIST Technical Note 2261[28] also investigated the effect of dynamic prices on the power quality of the distribution grid, by comparing two price-responsive heat pump controllers. Results showed that larger prices changes caused significant power flow volatility, especially in already congested grids. A correlation is highlighted between price signals, temperature adjustments, power flow changes, and voltage variability. The study highlights the importance of managing price fluctuations to prevent grid instability[28].

On the other hand, [29] showed that dynamic pricing positively affects the grid and reduces the need for grid expansion. This study investigated the impact of dynamic pricing on the low voltage grid in Germany, in the case that households could choose their type of tariffs. Their model integrated both static and flexible consumption, where to goal of the model was to minimize household costs. The results showed that while dynamic pricing increased the peak demand, due to the other households without a dynamic contract, these peaks were spread out and did not create grid issues[29].

1.3.4. State of the Art Research

It can be seen that a lot of research has already been done on how load flexibility can influence the grid. A dynamic pricing scheme is often proposed as a solution for congestion ([15], [22], [23], [21], and [25]). Some studies have predicted that dynamic pricing could lead to more congestion ([26], [16], [27], and [28]), yet [29] does not agree. As [26] mentioned, little research has been done using actually simulations with real data, making some results, like [16] and [29], contradictory. Additionally, most of the research on grid congestion mentioned above focuses on the powers in the grid and the transformer limits. Often the line voltages are not taken into account, while these can also cause grid congestion.

This thesis will provide a study based on the Dutch low voltage grid, using actual dynamic prices, households electricity consumption data, and EV charging data. Both the line voltages and the transformer powers will be used to quantify the predicted grid congestion issues, and it will be investigated which constraint is the decisive factor for grid congestion.

1.4. Thesis Outline

This thesis will first go into more detail about base for the model, namely the concept of dynamic pricing, the analysed grid, and the different loads for the model. Then the model itself will be discussed, whereafter the results A more detailed overview of the thesis is described below:

First, chapter 2 will go into more detail about dynamic prices; what they are, what the expected consumer response is and what dynamic pricing profiles will be used for this project. In this chapter, it will also be explained what representative weeks are chosen for the simulations and why.

Chapter 3 will give some basic information about the low-voltage grid, what grid type is chosen and why, and about the boundaries of this grid. The model inputs, which are the Standard Annual Consumption (SAC), EV charging profiles and the Photo-Voltaic (PV) profiles, will be described in chapter 4. This chapter will elaborate on where the data was gathered from, how this data was processed, and what the resulting profiles look like.

The full model is discussed in chapter 5, going over the software used for the simulations and the full model set-up. This chapter will also go into detail about the assumptions that were made during the modelling.

The results are presented in the following three chapters. Chapter 6 presents the base scenario, using a fixed EV and PV penetration level based on current Dutch numbers. In chapter 7, the effect of the electric vehicle adoption is discussed, by performing simulations with different EV penetration levels. The last results chapter, chapter 8, analyses the effect of solar panels in combination with dynamic pricing. Multiple scenarios will be simulated, where there are either no solar panels, solar panels independent of dynamic pricing, and solar panels that are influenced by negative dynamic prices.

The more detailed discussion of the results will take place in chapter 9. This chapter talks about the limitations of the project, the occurrence of voltage versus power congestion, and the socio-economic impact of this thesis.

In chapter 10, this thesis will be concluded, and recommendations will be given for future work. The Appendices of this thesis include figures of the full results of all simulations.

2
Dynamic Pricing

Due to the variability of renewable energy sources, it has become possible for consumers to pay for their electricity based on the time of use market prices, determined in the day-ahead market. The hourly electricity prices are announced the day before to households with a dynamic pricing contract, allowing them to shift and plan their electricity usage. While this is positive for the balance of the energy market ([15], [22], [23], [21], and [25]), it might have some negative impacts on the grid. Households might shift their energy consumption towards low price times, causing grid congestion([26], [16], [27], and [28]).

This chapter will go more in depth about dynamic pricing for electricity and what the expected consequences for households are. First the concept of dynamic pricing will be explained, then the predicted consumer response to these prices will be analysed for different types of electricity components. At the end, the profiles of dynamic prices used for this thesis will be determined and explained.

2.1. Definition

Most renewable energy sources are variable, their output depending on the current time and weather conditions. Because of this, the market price of electricity will also vary. Many energy suppliers are starting to offer these changing tariffs to their customers, with dynamic pricing contracts. These allow energy users to pay the real time price of electricity, instead of a fixed price over multiple months or years. This could be beneficial for users, if they are able to shift their electricity consumption towards the low tariff times. This would focus the demand to the times where electricity is abundantly available.

A phenomenon that has been occurring more and more recently is a negative electricity price. This happens when the availability for electricity generation is higher than the demand (usually the generation in these cases is fully renewable), and the generators are willing to pay consumer to use their electricity[1]. [30][31]. This can be very beneficial to consumers, as instead of paying, they are now getting paid to for example charge their car. These negative prices have only started occurring since 2018, yet already over 300 negative hours took place in 2023. This is also shown in Figure 2.1, where the increase of negative pricing hours is clearly visible[32].

[1]The exact reasons as to why negative electricity prices occur are slightly more complex. Electricity generators could normally turn off their electricity sources when there is an excess availability, however, due to subsidies or predetermined contracts for example, it could be more beneficial for them to set a negative price[11]

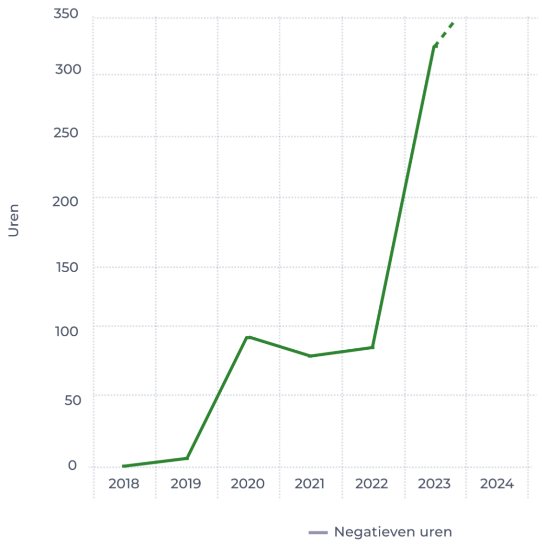


Figure 2.1: The occurrence of negative electricity prices over the years [32].

Energy suppliers have only recently started offering dynamic contracts, however, there has been an enormous growth. First a multitude of smaller suppliers started offering a dynamic contract and last year, Eneco became the first major supplier to follow[33]. As dynamic energy contract is often cheaper for households; they are becoming more and more common. In 2023, the portion of dynamic contracts already reached 6 %, a number that has tripled compared to the end of 2022. Predictions say that this number will keep growing, especially when HEMS enable households to schedule their consumption without having to track the prices[25][34] [35].

Important to note is that the term ”dynamic pricing” simply means pricing based on a flexible demand, it can thus also used for things like dynamic DSO tariffs, dynamic gas prices, or even prices in the tourism industry. In this thesis, unless otherwise specified, dynamic pricing will always refer to the electricity market based dynamic pricing.

2.2. Consumer Response

The amount of savings a household has due to dynamic prices heavily depends on how flexible they are with their demand. If a household cannot shift their electricity usage, they could be forced to pay the peak prices, possibly making their electricity bill a lot higher. On the other hand, when they are able to shift this usage towards the low-price times, their bill will become lower. It is thus important for households with a dynamic contract to be as flexible as possible, however, this is heavily dependent on which appliances and electricity consumers they have. A typical household's consumption can be divided into multiple components, as listed below, whose flexibility might differ.

- **Heat pumps and Water heating**: the heating and cooling of houses is becoming more and more electrified, using for example heat pumps. These can also be used to heat and store water, a technique far more energy efficient than traditional water heaters. Most types of heat pumps make use of outside air, making them more suited for warm climates. Geothermal heat pumps on the other hand, which make use of the underground heat, are very well suited for the Netherlands. Heat pumps have the capability to plan their electricity usage, based on the control system and the size of the heat storage. Likely, these control systems will be programmable, making it possible to shift their usage to low-cost times within relatively short time windows. This will allow households with a dynamic energy contract to be flexible, scheduling their electricity usage depending on the peaks in the electricity prices[36][37].

- **Electric vehicles**: Electric vehicles are on the rise; some predictions even expected that by 2044 almost all cars in the Netherlands will be electric[38]. These cars use electricity to drive, and thus need to be charged at times. While public chargers are becoming more common, many people will charge their car at home, often using a high-power EV charger. At home, cars are most of the time parked for long periods of time, longer than is necessary to fully charge their battery. This enables flexibility, as a smart charger can plan out the charging profile dependent on the electricity prices for example. The charging of electric cars will have large impacts on the grid, as this charging often happens at powers of 11 kW [39].
- **Dishwashers and Laundry**: Certain high consumption household machines, like dishwashers, washers, and dryers can also be flexibly used, by scheduling them during low price moments. However, these have some constraints. For example, one wants to avoid leaving wet laundry inside the washing machine while waiting for a cheap dryer time, neither is someone willing to wake up in the middle of the time to transfer laundry from one machine to the other. Probably, smart machines will become more common, where their algorithms will take both prices and user constraints into account[40].
- **Other Consumption**: this group consists of all the remaining electricity usage, including things like lights, appliances, cooking etc. Most of these have an inflexible demand, meaning their consumption will not be affected by dynamic prices.
- **Home Batteries**: Some households might choose to install a home battery, allowing them to store electricity to use at a later time. Especially in combination with PV systems, home batteries are expected to increase household's energy self-sufficiency. While this could potentially lead to a lower electricity demand, thus elevating grid congestion, it is also possible that home batteries lead to greater variability in the power loads, which could add more stress to the grid[41]. When used in combination with dynamic pricing, smart home batteries can store electricity when the supply is high and the prices are cheap. When the supply decreases and the prices go up, the household is able to used their stored electricity or even sell it back to the grid[42].
- **Solar**: In the past, different pricing schemes and tax benefits have made it very beneficial to inject excess power from solar panels into the grid, no matter when. However, this is coming to an end, with grid operators asking for a different system to relieve the pressure on the grid. Households with a dynamic pricing contract will also sell their excess power at a dynamic tariff. When there is plenty of energy generated by wind turbines or solar panels, this selling price will be low, while during times of shortage, energy can be sold for a high price. It is also possible for the market price to be negative, meaning that households would have to pay if they want to inject energy into the grid. It will thus be important for households to have a way to either turn their solar panels off or to optimize their consumption, to avoid being charged.

Out of all these components, the presence of electric vehicles will have the largest influence on a household's electricity usage. An EV's peak power consumption can be up to three times the regular peak power consumption of a household, making them a very important component. This thesis will focus on the effects of electric vehicle charging in combination with dynamic pricing. The flexibility of other components like heat pumps, batteries, or flexible appliances will not be simulated. For this thesis, the presence of EV's in combination with dynamic pricing scheme will also mean that it will be flexibly used. It is of course possible that a household has a dynamic contract but does not want to be flexible in their usage, however then the presence of the dynamic contract will then not make a difference. Thus, the percentage of households with a dynamic contract will be seen as the percentage of households that are flexible with their consumption due to their contract.

2.3. Set of Prices

The effect of dynamic pricing on the low voltage grid will depend on the dynamic price profile. It is expected that larger peaks will have a larger effect, as households will be more willing to shift their consumption. For this thesis, a list of hourly prices from the day ahead market of 2023 will be used. From this, three representative weeks will be chosen to compare the difference between high and low peaks.

The price a household pays for electricity does not only depend on the market price: there are also purchasing fees and taxes to keep in mind. The market price is determined the day-ahead, based on the predicted supply and demand. To this market price, the energy supplier adds a purchasing fee, usually around 2 cents per kWh. Next, there is a value added tax (VAT), or BTW in Dutch, of 21 % applied. Lastly, an energy tax has to be paid per kWh of electricity usage, in 2023 this tax was equal to 15 cents per kWh. Suppliers are quite vague about their method to go from the market price to the total price charged to their customers. For this thesis, Equation 2.1 was used, as this equation gave the closest results compared to the total prices seen on the website of electricity supplier Eneco[43].

$$\text{Total price} = (\text{market price} + \text{purchasing fee}) * (1+\text{VAT}) + \text{Energy tax} \tag{2.1}$$

The variables used in Equation 2.1[2] might differ based on the chosen electricity supplier and the current legislation for taxes. For this project the numbers shown in Table 2.1 will be used, the values from supplier Eneco in 2023[43]. Figure A.1, found in Appendix A shows the full year of dynamic prices, comparing the market price with the total price per kWh a household will pay.

Table 2.1: Values used for determining the dynamic energy prices[43].

	Value
VAT	21 %
Energy tax	0.15 €/kWh
Purchasing fee	0.02518 €/kWh

Out of this year worth of prices, three representative weeks were chosen for the simulations. The first week, shown in Figure 2.2 shows an average week, there are some fluctuations in the prices depending on the time of day, but no large peaks. The second week, seen in Figure 2.3, shows a couple of times with negative prices, most likely due to a combination of high solar and wind energy yields. The last week (Figure 2.4), has some large peaks, especially on the 25th of September at 19 o'clock. These three weeks give a good representation of year, enabling simulations with average, low, and high prices. These dynamic price profiles will be used in chapter 4 to determine the charging profiles of electric vehicles.

[2] When the sum of the market price and purchasing fee are negative, the VAT is subtracted in this equation.

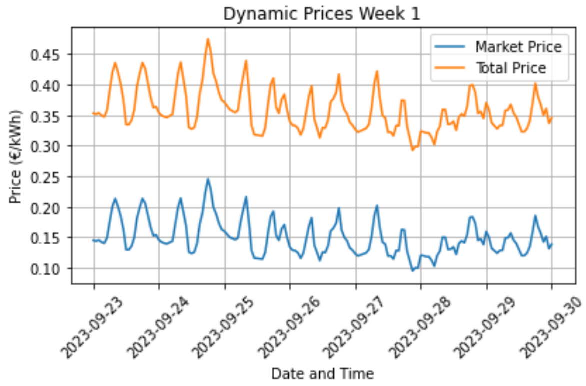


Figure 2.2: Dynamic prices representative week 1.

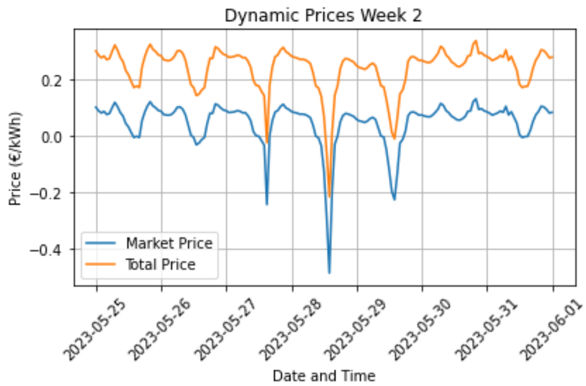


Figure 2.3: Dynamic prices representative week 2.

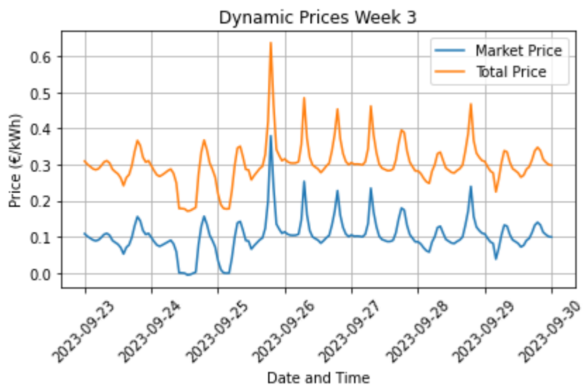


Figure 2.4: Dynamic prices representative week 3.

3

Low-voltage Grid

The low-voltage grid is an important element of the Dutch electricity network, connecting households to the broader power system. To maintain the reliability of the grid, constraints, like the EN50160 standard, are set on the line voltage. Similarly, each transformer of the grid has a rated power, which limits the capacity of the connection point. For this thesis, one neighbourhood will be selected for the simulations.

This chapter will go over some general information about the Dutch low voltage grid. First some characteristics will be explained. Then, a division of neighbourhoods into grid types will be given, where the grid type used for this project will be presented. Finally, the boundaries of the grid will be named, where the boundaries relevant for this report will be discussed.

3.1. Characteristics of the Grid

The Dutch electricity grid serves to provide power to over 8 million consumers, ranging from small households to large industrial sites. The grid can be divided into three parts, the high, medium and low voltage grids. The high voltage grid is used to transport energy over long distances across the country. To connect large consumer or small industrial loads, the medium voltage grid is used. The low voltage grid supplies electricity to households and small consumers, both in urban cities and rural areas[44]. This is done by over 240 000 km of cables, connected to the rest of the grid by over 95 000 low voltage stations [45].

The low voltage grid has a standard voltage of 230 V and a frequency of 50 Hz, compliant with the European standard. Most of the low voltage grid connections consist of three phases, each with a current of 25 A. Traditionally, each household is connected to the grid using a single phase, with each phase spread out over a neighbourhood to balance out the grid. Due to the rise of large household power components, like solar panels, heat pumps, or EV chargers, it is becoming more common to connect households using all three phases. This allows the household to utilize more power, or a voltage of 400 V, due to the line-to-line voltage of the three phases[46].

Despite its robustness, the Dutch voltage grid encounters some challenges, particularly with the renewable energy transition. The variability of renewable sources like wind and solar power requires a greater flexibility of the electricity grid. Additionally, the rise of electric vehicles and electric heating systems places more strain on the low voltage grid. As a result, an increase in capacity and efficiency is needed to accommodate these evolving energy demands. The Dutch grid operators have decided to work together on the biggest Dutch grid expansion to date, which includes increasing the grid's capacity and investing into a future proof grid[47].

3.2. Grid Types

The Gebouwde Omgeving Elektrificatie (GO-e), project is a collaboration between the regional grid operators, multiple universities, energy consumers, and many more. The goal of the project was to investigate flexibility as a potential solution for grid congestion[48][49]. While the Netherlands can be divided into over 13000 neighbourhoods, each with their own characteristics, the GO-e project has tried to group them into eight different archetypes.

The goal of these archetypes is to classify the many neighbourhoods into representative models, which for example be used to investigate the potential of flexibility in each neighbourhood type. The different types also facilitate academic research, since no reference to existing neighbourhoods has to be made[50].

Below, the eight different types of neighbourhoods are listed, together with a short explanation about each. Figure 3.1 show a map of the Netherlands, with the different neighbourhoods coloured by their archetype.

- **Archetype 1 Pre-housing bill:** These neighbourhoods consist mostly of old houses, build before 1920. It is densely populated, made up of multiple family apartments, since the houses are older, energy labels C and D are more common.
- **Archetype 2 Pre-war residences:** The houses in these neighbourhoods are mostly build between 1920 and 1946. Similarly to the first archetype the population density is high, however an A or B energy label is more present.
- **Archetype 3 Post-war terraced houses:** The neighbourhoods in this archetype consist of houses build between 1970 and 2010, and have a lower population density than the earlier archetypes. The houses are usually (semi)attached single family homes, some with private driveway and some with shared street parking.
- **Archetype 4 Post-war tenements:** Similarly to archetype 3, the houses stem from the 1970-2010 period. These houses are more likely rented, multiple family apartments.
- **Archetype 5 Corporation residences:** These neighbourhoods consist of attached houses, rented from housing corporations. The most common energy labels are C, D, and E.
- **Archetype 6 Detached houses:** This archetype consists of the neighbourhoods with mostly large, bought, detached houses, resulting in a low population density. Since most of the houses were built before the 1960's, the energy labels are often low, like F or G labels.
- **Archetype 7 Rural areas:** The most common type of neighbourhood across The Netherlands (over 25 %), the rural areas, consists of chained houses and apartments, located in the countryside. It has a medium population density, with mostly C, D, and E energy labels.
- **Archetype 8 Industry and limited population:** The final archetype consists of mostly industrial and commercial buildings. Since the population is so limited, this type of neighbourhood is not very relevant for this thesis

3.2.1. Chosen archetype

Looking at Figure 3.1, it can be seen that the seventh archetype, the rural areas, makes up the largest area of the Netherlands. However, as this thesis is made in collaboration with grid operator Stedin, a representative grid for their most common archetype was selected. Stedin is most active in the Randstad, and area where most people live in cities of various sizes. In these areas the Post-war terraced houses are the most common (as seen from the light blue colouring in Figure 3.1). Archetype 3 has thus been chosen as the grid type for this project.

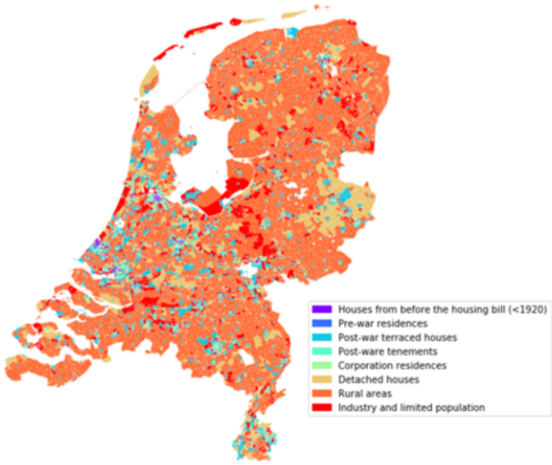


Figure 3.1: Map of the Netherlands, with the 8 archetypical neighbourhoods[50].

3.3. Constraints

As the low voltage grid provides electricity for the whole Netherlands, it is important to preserve its reliability. The grid needs to be reliable, with as little interruptions as feasible. To achieve this, constraints are put on the grid characteristics, to ensure that all connections can deliver the expected power quality.

One of these boundaries is the EN50160, a European standard specifying the voltage limits at the grid connection points. This standard has been created by the European Committee for Electrotechnical Standardization (or CENELEC), to ensure the reliability and compatibility of electrical supplies across the different European distribution systems[51]. The EN 50160 standard sets limits for multiple aspects of the voltage supplied by the grid. The values of parameters like the voltage levels, frequency variations or harmonic distortions are limited. Using EN50160, grid operators can monitor their grid performance, they can identify which areas are congested and which areas need strengthening.

The EN50160 standard is often the grid constraint used in research when investigating voltages, some examples include: [2], [10], [18], [17], and [19].

A few of the parameters limited by the EN50160 standard are listed below: [52]

- Voltage variation: increase or decrease of the voltage, cause by a variation of the loads
- Flicker: momentary variation in the voltage magnitude, often seen by dimming or brightening of lights, cause by sudden load changes
- Supply voltage dip: short, sudden dip in the supply voltage, lower than 90 % of the declared voltage, usually between 10 ms and 1 minute
- Supply interruption: voltage at supply terminal is lower than 1 % of the declared voltage
- Harmonic voltage: sinusoidal voltage with a frequency equal to a multiple of the base frequency
- Interharmonic voltage: sinusoidal voltage with a frequency between the harmonic frequencies.

Since hourly simulations are used for this project, only grid issues visible in such a time period will be simulated. Short time problems, like flickering or short voltage drops are not taken into account. The grid limits analysed for this thesis will be the power limit over the transformer and the line voltage over each branch.

One of the most important boundaries is maintaining the standard voltage of 230 V. High voltages can occur due to power supplies from sources, like PV's or batteries. Low voltages can have two potential causes; either due to high demands or due to long distances. When the demand is too high, the voltage will drop, due to an increase in the necessary current. As the grid is not ideal, internal impedances in all cables will result in losses. The longer the cable lengths, the higher these losses. Deviations from the standard voltage must be avoided, as they can cause appliances to malfunction[53].

With regards to the variations in the supplied line voltage, the EN50160 standard is as follows:

> Low-voltage and medium-voltage: maximal deviation of ±10% for 95% of a week, related to the mean rms values of 10 minutes intervals [52].

This means that for 95 % of the time, the voltage of each supply point on the grid can have a deviation of maximally 10 %. Important to note is that this percentage includes both deviations in the low voltage and medium voltage grids, the high voltage grid is not included in this standard and not investigated for this research. Similarly as to [10], for this project it is assumed that a 5 % voltage deviation is reserved for the medium-voltage grid. The voltage on the low-voltage grid thus has to remain between 0.95 p.u. and 1.05 p.u. for 95 % of the 10-minute intervals within a given week. The remaining time intervals, the voltage cannot deviate more than 15 % in total, which is seen as a deviation of 10 % caused by the LV loads.

Since the simulations for this project will be done in hourly intervals, it will be assumed that if the average voltage in such hourly interval is above/below the limit, the voltages during each 10 minute interval will also be above/below the limit, similarly as what [17] did. There will thus be grid congestion based on voltage whenever the deviation of the line voltage is more than more than 5 % during over 5 % of the hourly intervals. This assumption is accurate enough to compare the different scenario's, however, more detailed simulations might be needed to precisely quantify the number of congestion points.

Equations 3.1 and 3.2 show these voltage constraints translated into equations. Here, $v(t)$ is the measured line voltage and V the standard grid voltage, equal to 230 V for the Dutch low-voltage grid. t represents the one-hour time interval of the simulation time T of one week.

Grid congestion due to voltage occurs:

$$\text{If} \quad \tau > 5\,\%\text{ of }T \quad \text{where} \quad \tau \quad \text{is the size of} \quad \{t \in T \quad \text{such that} \quad |v(t) - V| > 5\,\%\text{ of }V\} \tag{3.1}$$

Or

$$\text{If} \quad \exists t \in T \quad \text{such that} \quad |v(t) - V| > 10\,\%\text{ of }V \tag{3.2}$$

Another, more well-known constraint on the grid, is the maximal power carrying capacity of the grid. This is currently the most common cause of grid congestion, although still mostly on the high voltage part of the grid. Each part of the low voltage grid has a maximal power capacity, determined usually by the rated power of the transformer between the low and medium voltage parts of the grid[54]. For the grid studied in this thesis, the transformer is rated at 0.25 MVA or 250 kVA.[1]

Equation 3.3 shows the constraint on the power over the transformer $p(t)$. P is the rated power over the transformer, equal to 0.25 MVA for the simulated grid. Again, t is the one-hour time interval and T the total simulation time.

Grid congestion due to power occurs:

$$\text{If} \quad \exists t \in T \quad \text{such that} \quad |p(t)| > P \tag{3.3}$$

For this thesis these two parameters will be used to define grid congestion. The first being the over- or under-voltage, the second the power supplied by the transformer. Both potential causes for congestion will be investigated and conclusions on which is the most suitable benchmark will be drawn.

[1] Data from the used grid file see section 5.2

4

Household Electricity Consumption

For this thesis, the electricity power profile of a household is split into three parts: the non-flexible loads, the EV charging loads, and the solar PV generation. The profiles of each will be assigned to a household at random, as explained in section 5.3. This chapter will explain how the data sets were obtained and what methods were used to process them to generate the necessary power profiles for the simulations.

First, a household's non-flexible consumption will be discussed. Afterwards, the power profiles of at-home electric vehicle (EV) charging will be generated using a simple optimization scheme. At the end, the power outputs of household solar PV panels will be presented. For each section, the resulting power profiles will be shown and briefly discussed.

Since dynamic prices are determined on an hourly basis, the simulations for this project will also be performed in hourly intervals. Often, the electricity consumption data is measured in fifteen-minute intervals, this data will be averaged out.

The electricity consumption data for this thesis stems from the GO-e project[48]. For this project, large sets of data of data related to household electricity consumption were collected and anonymized. The data sets related to household EV charging and the yearly electricity consumption of households provide a perfect base of the simulations performed in this thesis.

4.1. Non-flexible Consumption

While more and more parts of a household's electricity usage, like EV charging, heat pumps, etc, are becoming flexible, a large part remains inflexible. Things like for example lights or many appliances are constantly needed and will be consuming electricity, independent of its price. While the usage of some "inflexible" consumers, like electric stoves or TVs could be shifted, in reality these shifts will be minor in time and low in power, especially compared to the large flexible consumers. They will thus be seen as inflexible for this project.

The non-flexible loads of each households used for this project are Standard Annual Consumption (SAC) profiles of the GO-e project. A single person household has a yearly electricity usage of around 1500 kWh, this will go up by about 500 to 1000 kWh per person added. Table 4.1 shows the yearly electricity usage numbers used for this project, these numbers are taken from [55] and rounded of to be able to use the GO-e project files.

The GO-e project has collected power profiles of the 2013 electricity consumption of households, ranging from 500 kWh to 15000 kWh of average annual consumption. For each number of yearly usage, the

Number of people	Percentage of households	Yearly electricity usage
1 person	39%	1500 kWh
2 people	32%	2500 kWh
3 people	12%	3500 kWh
4 people	12%	4000 kWh
5 people	5%	4500 kWh

Table 4.1: Distribution of households and their yearly electricity consumption[56][55].

power consumption per 15 minutes was provided over the whole year. Since the data showed no clear differences between weekday and weekends[1], it was assumed that the 2013 data could be matched with the 2023 dynamic prices and thus could be used for the simulations of this thesis. This data was converted into hourly intervals, using a Python script. This script also combines the many different data columns for each yearly usage into a total of 495 households, made up according to the percentages in Table 4.1. Finally, the data set is divided up into the representative weeks explained in section 2.3.

The electricity usage plots for each of the three representative weeks can be found in Figures 4.1, 4.2, and 4.3, showing the average electricity consumption for each type of household. Generally, a households electricity consumption is lower at night than during the day. During the daytime, it can be observed that households mostly use electricity before and after going to work, their consumption is the highest especially in the afternoon.

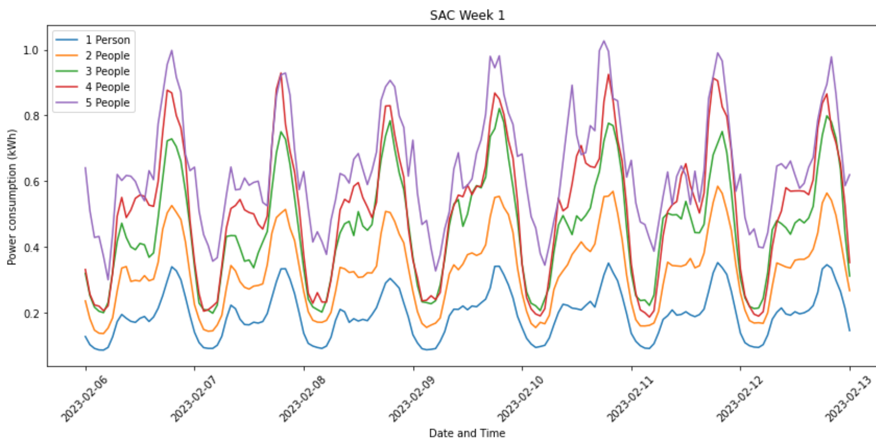


Figure 4.1: Average non-flexible electricity usage of each type of household during Week 1.

[1] Generally, week and weekend days will show differing electricity consumption profiles, however, while the GO-e data shows differing profiles for each day, no significant week/weekend pattern could be seen in the representative weeks.

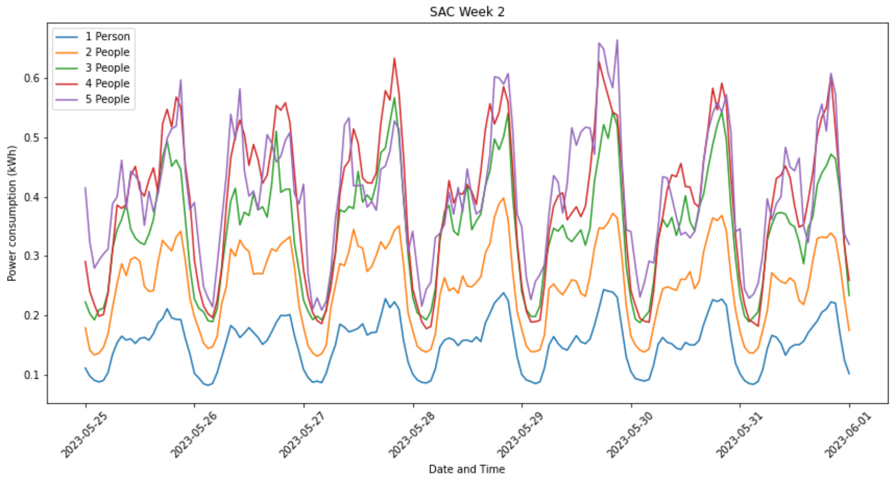


Figure 4.2: Average non-flexible electricity usage of each type of household during Week 2.

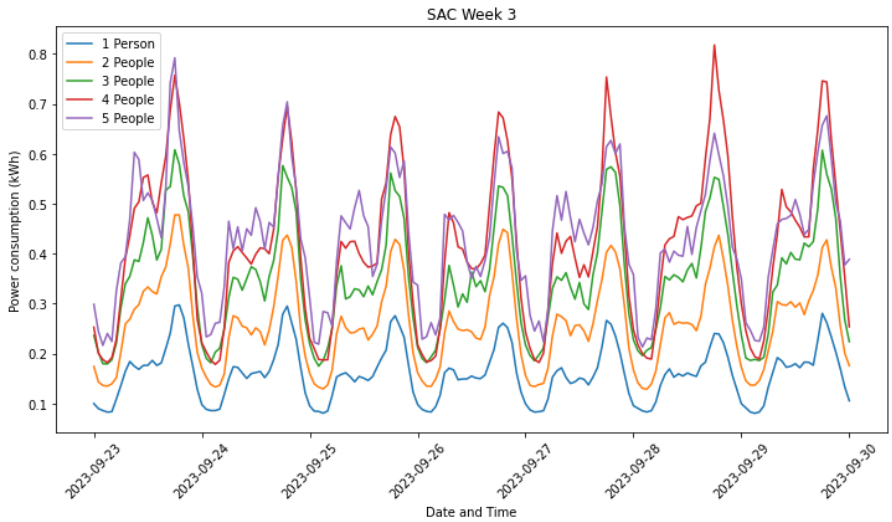


Figure 4.3: Average non-flexible electricity usage of each type of household during Week 3.

4.2. Electric Vehicle Charging

The flexible load investigated for this project is the charging of electric vehicles. Since electric vehicle charging often requires large amounts of power, it is very beneficial for households to charge their car at the cheapest moments. However, they also want their car to have enough battery capacity whenever they want to leave. An optimization model is thus needed, to find the most optimal charging profile for each household.

As part of the GO-e project, the EV charging behaviour of a large set of households was generated based on national charging records. From this, a set of 950 households were chosen for the electric vehicle charging data used in this project. During seven days time, a multitude of characteristics were generated, the ones used in this project are listed below:

- Household ID

- Arrival time
- Departure time
- Energy to be charged
- Maximal charging power

Without a dynamic pricing contract, it is assumed that households will charge their car upon arrival, until the battery is fully charged. The sum of resulting power profiles can be seen in Figure 4.4.

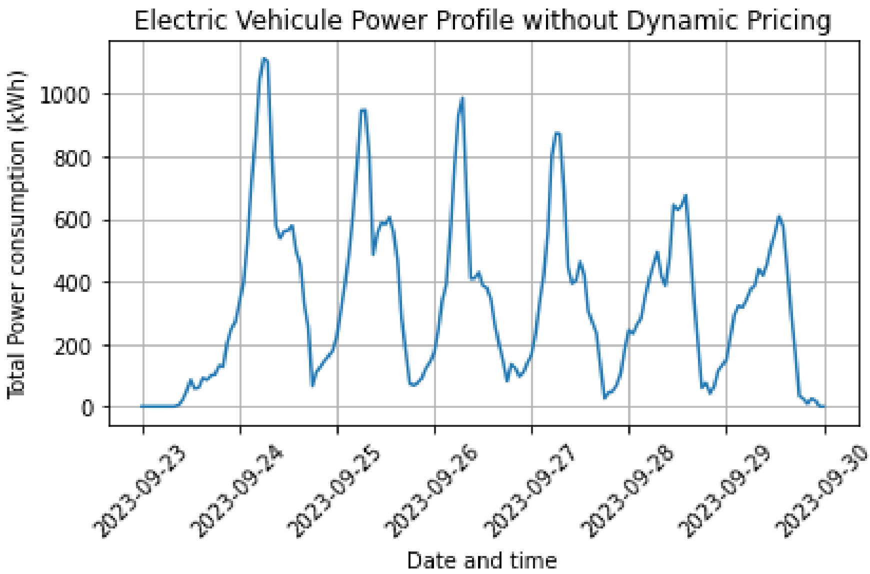


Figure 4.4: Sum of the 950 EV charging profiles without optimization.

4.2.1. EV Optimization

Many different optimization models exist to be able to plan out when and with how much power an EV should be charged. For this project, the model created by [57] was used. This is a relatively simple model, which chooses the optimal charging times between a predetermined arrival and departure time.

$$
\begin{aligned}
&\min_{p} \sum_{t \in T} c_t p_t \Delta t \\
&\quad \text{s.t.} \\
&\qquad e_t = 0, t \leq t; \quad e_t = e_{t-1} + p_{t-1}\Delta t, t^a < t < t^d; \qquad e_t = \overline{e}, t \geq t^d \\
&\qquad p_t = 0, t < t; \quad 0 \leq p_t \leq \overline{p}, t^a \leq t < t^d; \qquad p_t = 0, t \geq t^d
\end{aligned} \tag{4.1}
$$

Equation 4.1 shows the optimization model, combined with its constraints. The sets of dynamic prices, c_t, are described in section 2.3. t_a and t_d represent the arrival and departure times of the car, meaning it needs to be charged during this time. The charging power p is equal to zero outside of the charging window, during the charging time, p needs to remain below the maximal power, $\overline{p}$, for the battery. The energy e is the charged energy during the charging session, it is found by the difference between the initial charge left in the battery upon arrival and the maximal charge the battery can contain ($\overline{e}$). Before the arrival time the charged energy needs to be zero, and when the car leaves the car needs to be maximally charged. For this model, it is thus assumed that the car always needs to be fully charged upon departure. While charging the energy needs to be in balance with the power, according to energy = power * time.

This model was implemented using the *pyomo* package in Python. The model takes the dynamic prices and the inputs from the recorded EV charges and preforms the optimization to get the optimal power profile for each charging session. Using the unique ID's given for each household, the separate charging sessions are combined per household, to get the charging profile for a week.

Important to note is that this optimization model is quite simple. In reality, households might decide that the savings between two charging times are not large enough to change their schedule, or on the other hand, they can decide to not fully charge their car due to high prices. This is all not taken into account with this model.

4.2.2. Results

The resulting power profiles can be seen in Figures 4.5, 4.6, and 4.7, showing the profiles for Week 1, Week 2 and Week 3 respectively. The red line on each graph shows the dynamic prices for each week, showing how the charging sessions depend on the pricing peaks. When comparing the graphs, it can be seen that the profiles shift to avoid charging during peak pricing times. In all three graphs the charging profiles congregate to the ”cheap” times, while at the ”expensive” times, there is almost no charging taking place. It can thus be concluded that the EV optimization works as intended and that these profiles can be used to simulate a household's EV charging profile when having a dynamic pricing contract.

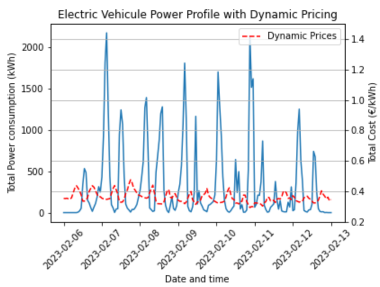


Figure 4.5: Week 1.

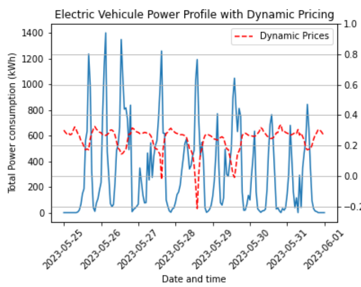


Figure 4.6: Week 2.

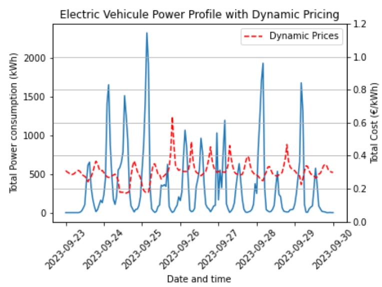


Figure 4.7: Week 3.

Sum of the 950 EV charging profiles for each week, combined with the shape of the dynamic prices.

4.3. Solar Panels

Household Photo-Voltaic (PV) systems have a potential to lessen grid congestion, however, they can also worsen the issue. Whenever a household is able to use their own generated energy, they are using a renewable source and avoid the transport of electricity, which both help with the energy transition. However, whenever there is an excess of solar energy, this gets injected into the grid, which can cause over-voltages and/or congestion at the transformer. It is thus important to include household PV systems when investigating the low voltage grid.

The past few years there has been a massive growth of household PV installations, partially due to subsidies and favourable policies. As a result, currently about 30 % of Dutch homes have solar panels. Interesting to note is that the growth has been slowing down[7]. Some potential reasons for this could be the abolishing of subsidies, the debate around net-metering, or that most interested households already have a PV system.

The PV data used for this project comes from Stedin's own collected data for the year 2023. This dataset has been created by collecting the normalized per 1 kWp, maximal PV outputs per fifteen-minute intervals over Stedin's full operational area. This profile is converted into hourly intervals and multiplied by 5, assuming that each household with a PV installation has 5 kWp worth of PV installed[58][59]. Since the simulations for this thesis are performed on one neighbourhood, it is assumed that the PV output profiles of each household will be the same. In reality, it is possible that due to clouds, solar panel orientations, or shading , there are small deviations in each households' profile, however this is not taken into account.

The power outputs of solar panels are generally not affected by dynamic pricing. A household might get compensated more when the electricity price is higher, but they cannot decide when the sun shines. The one thing households can do to change their solar output power profile, is turn off their solar panels output. Households with a dynamic contract might want to turn off their excess solar power when the market price of electricity is negative, as they would be charged for each kWh they inject into the grid. Newer PV systems often have ways to turn of the installation's inverter, thus turning off the solar generation[60][61].

It is possible that even with negative market prices it is profitable for a household to not turn off their PV system, like when they can use the generated electricity themselves, without injecting it into the grid. For the sake of simplicity, this will however not be taken into account for this thesis, as each household might have a different strategy to manage negative prices.

Figures 4.8, 4.9, and 4.11 show the resulting solar panel power output profile for all three representative weeks. The seven days each week are clearly marked with the non-zero values in each graph, while the nights of course result in no solar output. Figure 4.8 shows much lower PV outputs, as this week takes place in February. Weeks two and three show much higher PV powers, though at times clouds cause days with less sun. In these two weeks, negative market prices occur, as seen from Figures 2.3 and 2.4. Figures 4.10 and 4.12 show the PV profiles when the PV system is turned off with negative dynamic prices. It can be seen that at multiple times during the daytime the PV output is zero, especially in Figure 4.10.

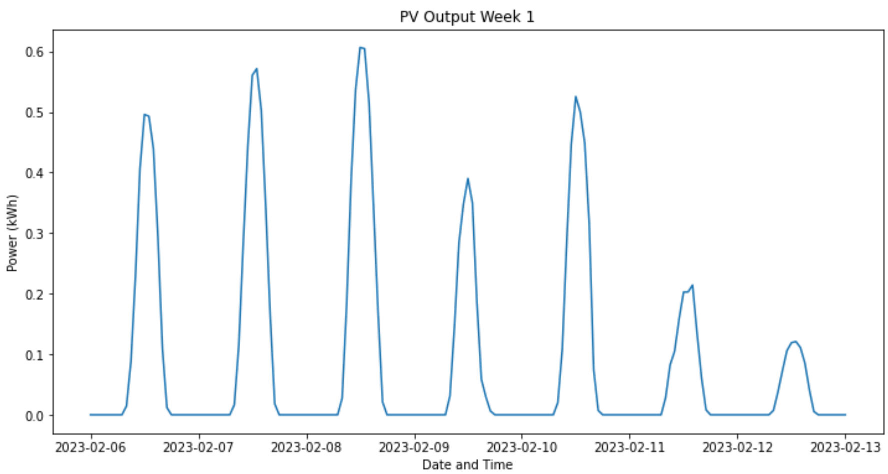


Figure 4.8: Power profile of the PV power output during Week 1.

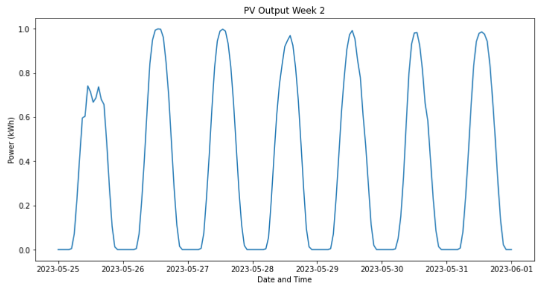


Figure 4.9: Without negative prices.

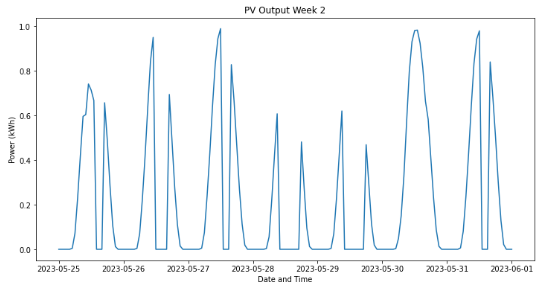


Figure 4.10: With negative prices.

Power profile of the PV power output during Week 2.

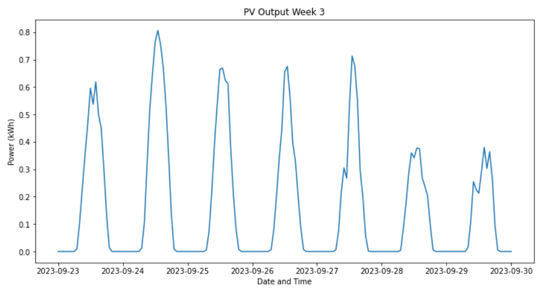


Figure 4.11: Without negative prices.

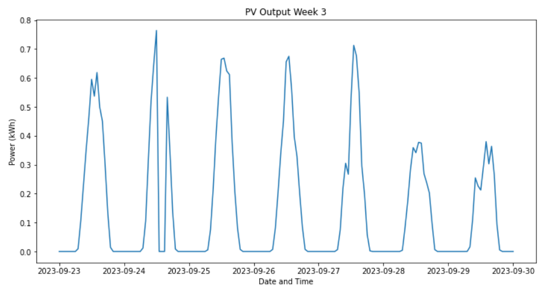


Figure 4.12: With negative prices.

Power profile of the PV power output during Week 3.

5 Model

After collecting all the necessary inputs in chapter 4, the model used for this thesis could be created. The model represents the low voltage grid of one neighbourhood, where each household has a non-flexible load, and potentially an EV charging load and a PV system. The simulations for this project will be performed using overarching Python simulations of a PowerFactory grid.

This chapter will first go into more detail about PowerFactory, the software used for the simulations. Then, the grid used for the model is described and converted from Gaia to PowerFactory. Section 5.3 will describe the full model, while section 5.4 explain the assumptions made for this model.

5.1. PowerFactory

PowerFactory is a power system analysis software developed by DIgSILENT, known for its advanced capabilities in analysing electrical power systems. The software is widely used by grid operators, utilities and researchers (like [2], [10], and [19]) for the planning, operation, and optimization of energy systems. PowerFactory has a broad range of functionalities, including load flow analysis, short-circuit calculations, and dynamic simulations. Its flexibility and robust analytical tools make it particularly suited for simulating the complexities of the integration of renewable energy sources and of advanced grid management strategies.

In this thesis, PowerFactory 2023 is used to perform quasi dynamic simulations, to simulate the effects of dynamic electricity pricing on the low-voltage grid. The software's ability to perform load flow analyses allows for the investigation of key parameters like the voltage levels and power flows. These simulations are crucial for understanding how dynamic pricing influences grid congestion.

5.2. Grid

As explained in section 3.2, the GO-e project divided the Dutch neighbourhoods into different archetypes. For this project, archetype 3 has been chosen as a base model for the low voltage grid. From the GO-e archetype grid files, grid *BU07360103 2030 anoniem 3* was selected. This is a large, meshed grid, with multiple external grid connections.

The GO-e grid files were designed in Gaia LV Network Design, a program for grid operators meant for the planning, design, and operation of low-voltage grids[62]. From the chosen grid file, one radial section was chosen for the simulations, which resulted in a grid similar in size to the one used in [29]. The selected grid consists of one external grid connection, with 5 branches springing from transformer.

The grid has 155 busbars, meaning there are 155 households in total.

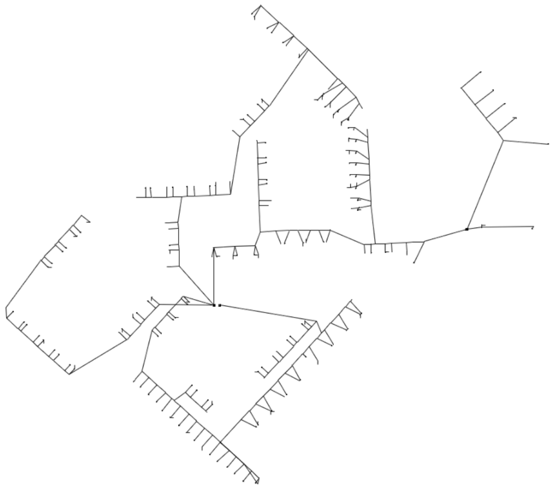


Figure 5.1: A screenshot of the layout of the Gaia grid.

The Gaia file of the grid was converted to a PowerFactory model using a Python script. The basis for this script is being made by *Rocio Revaliente Revuelta* and *Mark Boere*, to be able to convert Stedin's own Gaia files into PowerFactory. The original scrip is able to take Stedin's Gaia export files, read out the connections, and create the corresponding grid in PowerFactory, the script is not yet able to convert data about the loads. To be able to convert the GO-e Gaia grids, some adjustments to the code had to be made. These adjustments were related to column references and indices, and had no influence on to grid data.

A schematic overview of the conversion script can be found in Figure 5.2. This figure illustrates how the Gaia grid file is used to create the corresponding nodes, lines, transformers, loads, fuses, and sources. The *Cable and Transformer Types.xlsx* file, provided by Stedin, was used to convert the in Gaia defined component types to PowerFactory ones.

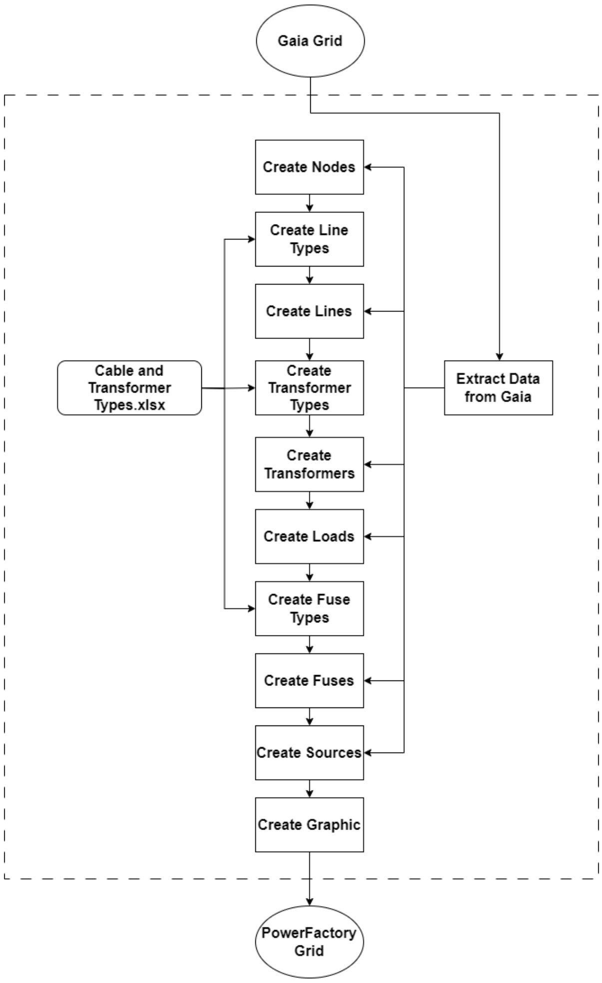


Figure 5.2: Overview of the Gaia to PowerFactory conversion.

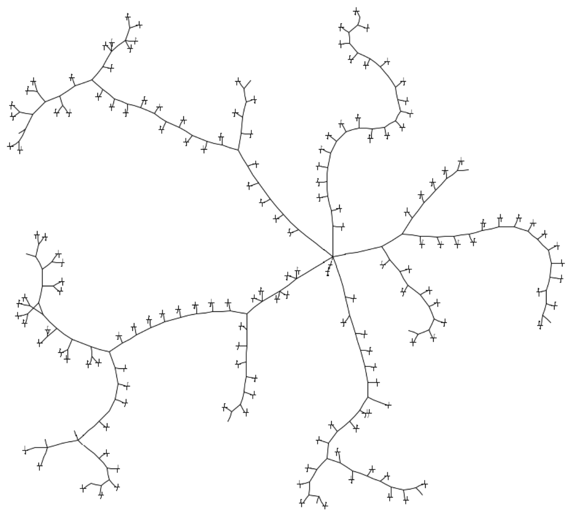


Figure 5.3: The PowerFactory grid.

Figure 5.3 show the to PowerFactory converted grid from Figure 5.1. When comparing the two figures it can be seen that their lay-outs look completely different. The reason for this is that the conversion only takes the different nodes and their distances into account, the coordinates and grid topology are ignored. This will have no effect on the results, as the cable lengths are not changed, even more, it makes the grid less recognizable, improving anonymity.

5.3. Full Setup

To make simulation of multiple scenarios easier, an overarching Python model is used. This model is capable of generating the necessary inputs based on the scenario, connecting the power profiles to the PowerFactory nodes, and retrieving the outputs from the PowerFactory simulations.

In the original grid, each node represents a household, with one load to represent the total power consumption. For this project, this existing load was be used to represent the non-flexible power usage, while extra loads were added for the flexible loads. These loads were added to each node using the Python script, representing the EV charging. The solar panels were added in a similar way, by adding a PV module to each household.

The profiles for each element were added by referencing the necessary data from csv files to the apparent power characteristic of each load. For each household, the load and EV charging profile are each randomly chosen from the large list of possible profiles. Whenever a household does not have an electric car or solar panels, as can be the case based on the simulated scenario, the element will become ”out of service”, a PowerFactory setting making its profile zero. Depending on the dynamic pricing penetration, the optimized EV charging profiles are assigned to a certain percentage of households, while the non-optimized profiles are assigned to all other households. A randomization is used when assigning the load profiles and when choosing which elements become ”out of service” in PowerFactory, to generate more general results, avoiding looking at outliers. The distribution of dynamic pricing, EVs and solar panels are completely independent.

Using the Python script, quasi dynamic simulations were run. Each simulation lasted for one of the representative weeks, using hourly intervals.

Figure 5.4 shows a simplified overview of the model and its inputs. First off, the EV charging inputs are optimized using the dynamic prices, and both SAC and PV profiles are converted into hourly intervals. The Gaia grid is converted into a PowerFactory one, where the three power profiles are used as inputs. On this PowerFactory grid quasi-dynamic simulations are performed, to generate the result files.

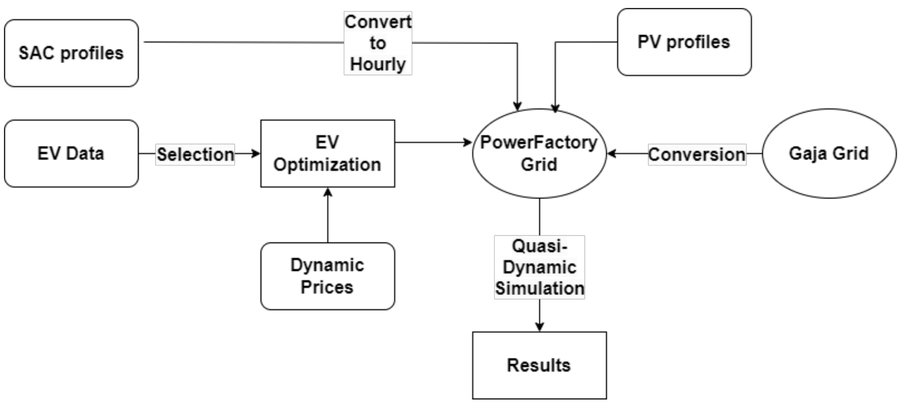


Figure 5.4: Overview of the different inputs for the simulations.

The results of multiple variables are exported from PowerFactory to Python. For this project, results concerning the bus voltages and transformer powers are of interest. These will be used to check whether the grid limits discussed in section 3.3 are crossed. The full list of extracted variables can be found below:

- Active power of each transformer
- Reactive power of each transformer
- Apparent power of each transformer
- Line voltage of each bus

Similarly to [29], multiple simulations with the same input parameters will be performed, to get more accurate results due to the randomization in the model. When showing the voltage and power profiles, the mean and standard deviation will be used. For making statements about the percentage of simulations where grid congestion occurs, confidence intervals will be used. For this, a Wilson Score interval is utilized, this is a method for creating a confidence interval for a binomial distribution[63].

5.4. Model Assumptions

While the goal of the model is to accurately represent reality, this is not always feasible. Due to time constraints and for simplicity's sake, certain choices had to be made to simplify the model and to be able to use the collected input data. The assumptions for this model are listed below:

- All households in the neighbourhood have the same PV output profile.
- When a household with and electric car has a dynamic pricing contract, they will charge their car such that their electricity costs are minimized, keeping in mind their arrival and departure times.
- EVs are always fully charged, when possible, before the departure time
- EV owners charge their electric car at home
- As hourly time steps are used, it is assumed that for the grid parameters, their 10-minute interval value is equal to their hourly value.
- Other than EVs, households do not have other flexible electrical loads.
- Out of the allowed 10% or 15% deviation for the grid's voltage limits, 5% is at all times reserved for the MV grid.
- Each household with solar panels has 5 kWp of PV installed.
- When negative market prices occur, all households will turn off their solar panels, unrelated to having a dynamic price contract or whether they could still use part of this generated electricity themselves. (For simulations where solar panels are turned off due to negative prices)
- Dynamic contracts and the presence of EVs are independent, households with no EV could still have a dynamic electricity contract, or the other way around.

6 Base Results

To show the general results and the effect of dynamic pricing alone, this chapter will focus on a base scenario. Using a fixed EV and PV percentage, the effect of dynamic pricing can be investigated for this set up.

For these simulations, a PV penetration level of 30 % was used, corresponding to the current Dutch average [7]. The current EV percentage in The Netherlands is still quite low, yet to be able to clearly see the effect of dynamic prices, an EV percentage of 30 % was chosen. For each dynamic pricing percentage, 50 runs were performed. Unless otherwise specified, all results show the average values of these runs, to eliminate the effect of outliers.

First, in section 6.1, the voltage over the different lines will be analysed, while keeping in mind the voltage limits discussed in section 3.3. Secondly, the power over the transformer is investigated in section 6.2, again in relation to the boundaries. section 6.3 draws conclusions about the grid congestion for the base scenario, due to the voltage and/or the transformer limits.

6.1. Voltage Analysis

The first potential cause for grid congestion analysed is the exceeding of the branch voltage limit. As described in section 3.3, both over and under voltages can be detrimental to appliances connected to the grid. It is thus important that the line voltage remains between the 0.95 and 1.05 p.u. limits.

For these results, a voltage of 1 p.u. corresponds to 230 V, or a line voltage of 398 V. From the simulations it was found that for this grid, the no load voltage is set at 225.3 V or 0.98 p.u..

Generally, independent of the dynamic pricing percentage, branches further from the external grid will have larger voltage variations, due to the internal resistance of each line. This can be seen by comparing Figures 6.1 and 6.2. Each shows the variations of the voltage over a branch for different levels of dynamic pricing. Figure 6.1 shows the voltage of *Tak_888*, a branch electrically located near the external grid. It can be seen that this voltage profile shows little variation. *Cbl_718*, located at the far end of one of the grid sections, shows a voltage profile with the same shape, but much more amplitude deviations, some even crossing the 0.95 p.u. boundary. The largest dip occurs on the night between the 10th and 11th of February.

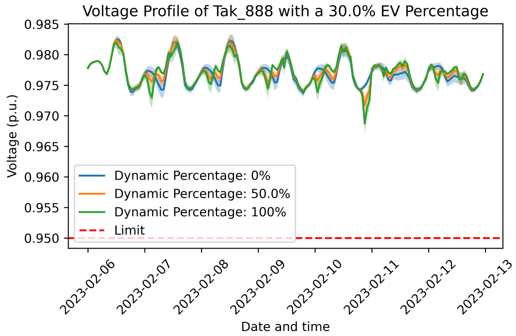


Figure 6.1: Tak_888, located close to the external grid

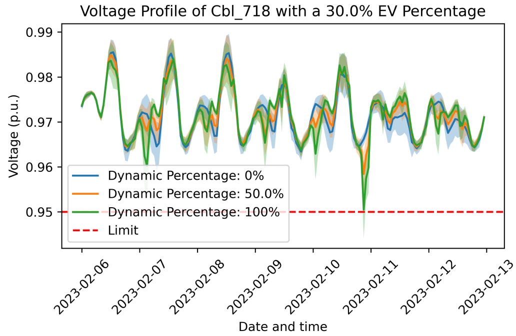


Figure 6.2: Cbl_718, located far from the external grid.

Average voltage profiles with standard deviation during Week 1 of the base scenario.

Since the more extreme voltage profiles are the most interesting to investigate, the profile of *Cbl_718* will be used in the further chapters to display the voltage profiles. The voltage variations for Week 2 and Week 3 can be seen in Figures 6.3 and 6.4 respectively. The second representative week takes place in May, where the large amounts of solar energy cause negative electricity prices.[1] In the resulting figures the PV profiles can be seen, as well when the solar panels are turned off during the negative market price moments. Due to the dynamic prices, the EV charging becomes more concentrated at negative pricing times. Since the solar panels are turned off during these times, large voltage dips occur, especially seen in Figure 6.3.

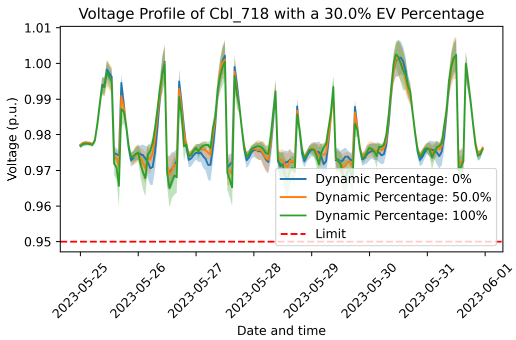


Figure 6.3: Week 2

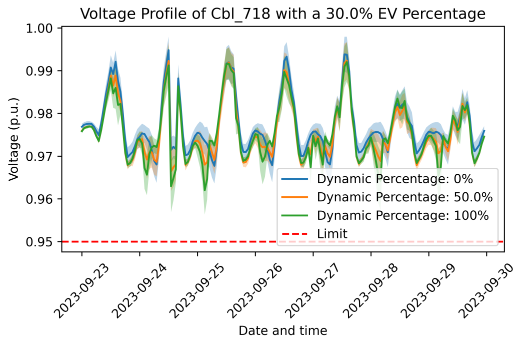


Figure 6.4: Week 3

Average voltage profiles with standard deviation of Cbl_718 for the base scenario.

The graphs show the shift in loads due to dynamic pricing. The high consumption times are more concentrated, creating low voltage dips. In Week 2, it can be seen that when the prices are negative (and the solar panels are turned off), the voltage dips due to dynamic pricing result in quite low voltages. The dynamic pricing caused the loads to be concentrated at the times when the PVs are turned off.

6.1.1. Under Voltage

For each simulation set up, the total measurements where the lower voltage limit of 0.95 p.u. was exceeded were counted and averaged over the 50 runs. Figure 6.5 thus shows how many times and at

[1] As explained in section 4.3, the solar panels are turned off whenever the market price is negative, unrelated to whether the household can use the generated solar energy themselves.

how many locations under voltages occurred for each week. Due to the high generation of solar power in Week 2, this week shows the least under voltage measurements. The results for Weeks 2 and 3 look very similar, as in both cases the solar power is high enough to elevate most voltage dips. Week 1, in combination with higher levels of dynamic pricing, shows the most under voltage measurements, as the concentrated EV loads cause larger voltage dips.

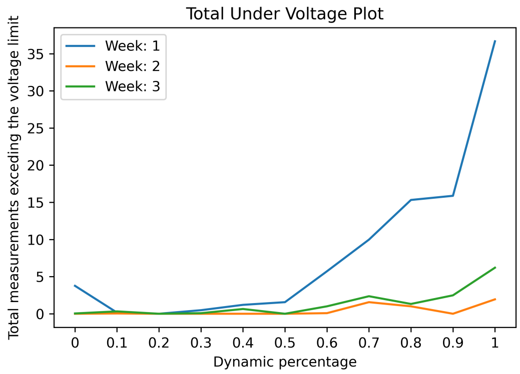


Figure 6.5: Average amount of measurements per run where the lower voltage limit was exceeded as a function of the consumers with a dynamic pricing contract.

6.1.2. Over Voltage

In these simulations, no over voltages occurred, since the level of households with solar panels is still low. It can be seen though, that the presence of PV causes the voltages to rise during the day.

6.1.3. Grid Congestion Due to Voltage

Since the simulations for this thesis were performed with hourly intervals, the European EN50160 voltage limit was adjusted, as explained in section 3.3. According to this adjusted EN 50160 limit, the voltage on each line needs to stay within the 95th percentile for 95 % of all hours and within the 90th percentile for all hours of one particular week. This means that under or over voltages do not necessarily cause grid congestion, as long as the voltage dip/spike is not too large, too long or too frequent in the week. Per branch, the number of measurements where the limit was crossed were counted. If this count was higher than the limit of 8 (5 % of 168 hours in one week), the run was indicated as congested.

For the base scenario, no voltage congestion occurred in any of the three representative weeks. While some under voltages did happen, as seen in Figure 6.5, there were not enough potential congestion measurements per branch to reach the EN 50160 limit.

6.2. Power Analysis

As discussed in section 3.3, the transformer in this grid has a limit of 250 kVA. Whenever the power over this transformer is higher, one can speak of grid congestion due to power. This limit is applicable both for the power delivered to the grid and the fed-in power to the external grid.

Figures 6.6, 6.7, and 6.8 show the power over the transformer, for Week 1, 2, and 3 respectively. As expected, the power profiles peak when the loads on the grid are high, which happens at the same times as when voltage dips occur. This can for example be seen the night from the 10th to the 11th of February, where a large peak occurs, at the same times as when there was a voltage drop.

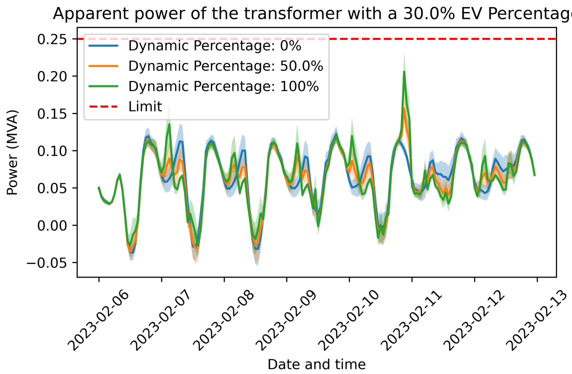


Figure 6.6: Average power with standard deviation over the transformer for the base scenario during Week 1.

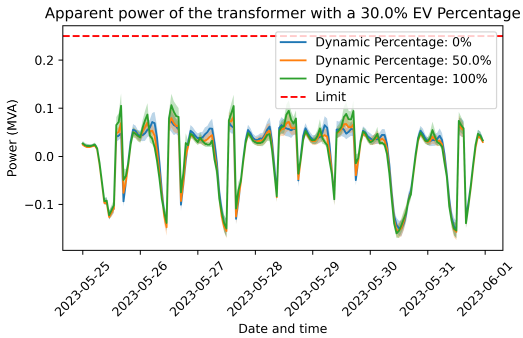


Figure 6.7: Week 2.

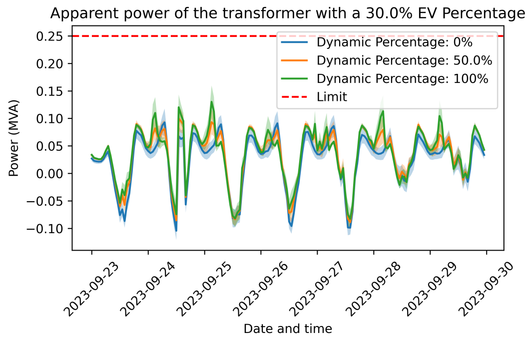


Figure 6.8: Week 3.

Average power with standard deviation over the transformer for the base scenario.

When comparing the profiles of the different levels of dynamic pricing (most notably in Figure 6.8), it is seen that some peaks are slightly shifted, causing lager power spikes. Higher percentages of dynamic pricing cause "high power" times which are short in time, yet high in power due to the shifted demand.

6.2.1. Grid Congestion Due to Power

Similarly as for the voltage analysis, the percentage of runs where grid congestion due to power occurred was calculated. Figure 6.9 shows the percentage of runs where the power limit was exceeded for each simulation set up. There are barely any runs with power congestion, only in Week 1, when nearly all households have a dynamic pricing contract, do a few runs cause the transformer limit to be crossed. These limit crossings cannot be seen in Figure 6.6, as each line in this figure shows the average over all 50 simulations, of which only a few crossed the transformer limit. Figure A.2, found in Appendix A, shows the power profiles of two of the simulations causing grid congestion, where it can be seen that the power limit is just crossed.

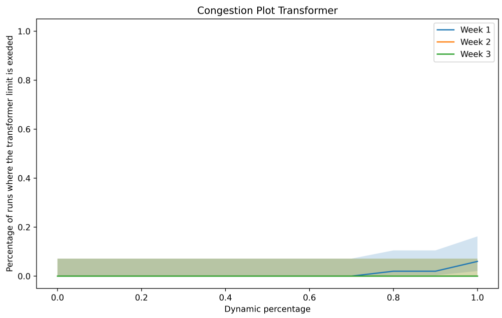


Figure 6.9: Percentage of runs with grid congestion due to power, bands show 95 % confidence levels.

6.3. Conclusion Base Scenario

When more households have a dynamic pricing contract, this will cause the electricity usages of these households to be more concentrated at the low pricing times. In some cases, this causes the grid boundaries to be exceeded, which can result in under voltages. Yet, due to the low levels of electric vehicles, grid congestion due to voltage does not take place in the base scenario. Congestion due to power only occurs in a few runs during Week 2, when the dynamic percentage is high. Thus, while congestion is rare for this base scenario, it can already be seen that dynamic pricing will most likely cause more congestion when there are more households with electric vehicles, which will be further investigated in chapter 7.

7 Effect of Electric Vehicle Adoption

From the results from the base scenario in chapter 6 it was predicted that with a higher EV percentage, dynamic prices will cause more grid congestion. This chapter will further investigate what the effect is of increasing the amount of households with an electric car

For these simulations, the EV penetration is taken to be 0, 30, 60, 80, and 100 %. As low numbers of EVs generally do not cause grid congestion, it was chosen to put a larger emphasis on the higher EV percentages. The dynamic percentage is again taken in 10 % increments, while performing 50 runs for each. Again, outliers due to the randomization are eliminated by averaging the results over these 50 runs.

Section 7.1 will show the voltage analysis of Weeks 1, 2 and 3. The power analysis for these weeks is shown in section 7.2. At the end, in section 7.3, conclusions about the effect of EV's are drawn.

7.1. Voltage analysis

Figure 7.1 shows the simulation results for Week 1, when no households have an electrical vehicle. It is clear that in the absence of flexible loads, there is no effect of dynamic pricing. The voltage remains nicely between the limits and there are no dips nor spikes.

When the EV percentage is higher, with more households having an electric car, the voltage profiles seen in Figures 7.2, 7.3, and 7.4 are generated. Under voltages take place in almost all of these combinations of EV and dynamic percentages. Due to the concurrency of the EV charging profiles, short but low voltage dips van be seen. A higher dynamic percentage causes these voltage dips to become lower, which can especially be seen on the evening of the 10th of February.

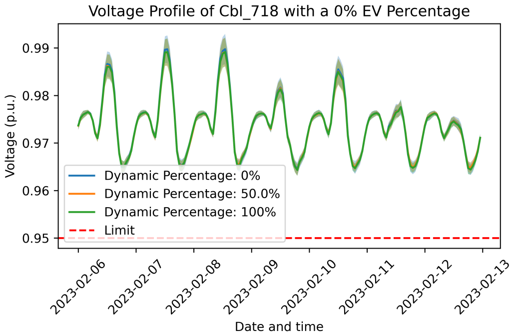


Figure 7.1: 0% EV

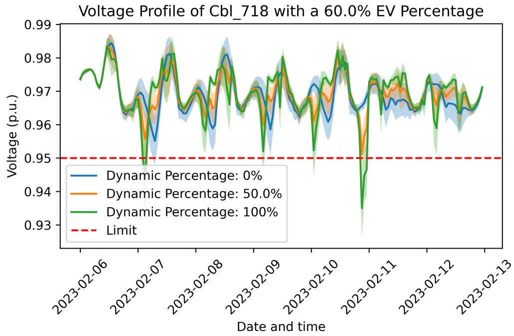


Figure 7.2: 60% EV

Average voltage profiles with standard deviation of Cbl_718 during Week 1.

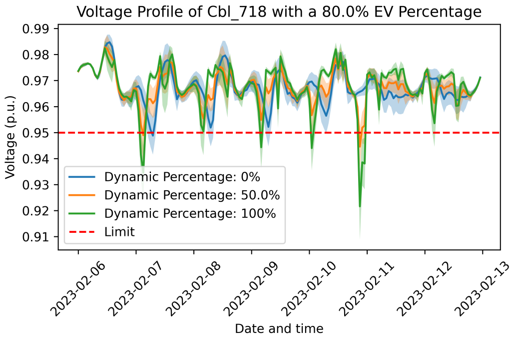


Figure 7.3: 80% EV

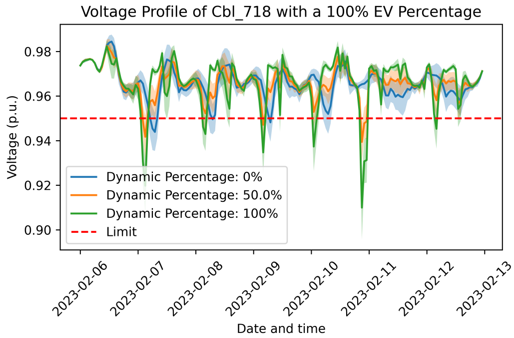


Figure 7.4: 100% EV

Average voltage profiles with standard deviation of Cbl_718 during Week 1.

In Week 2, the PV profiles can again be observed (Figures 7.5 and 7.6), yet higher levels of EV's cause the voltage profiles to drop and to have lower dips, similarly to Week 1. Due to the dynamic prices, the EV charging becomes more concentrated at negative pricing times. Since the solar panels are turned off during these times, large voltage dips occur.

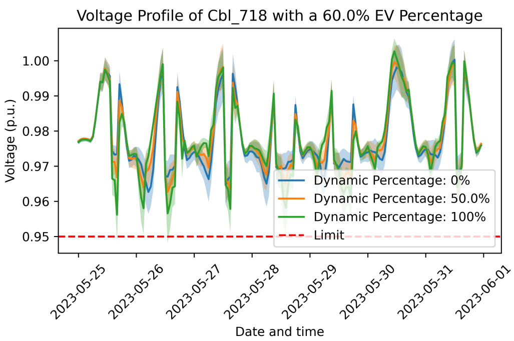


Figure 7.5: 60% EV

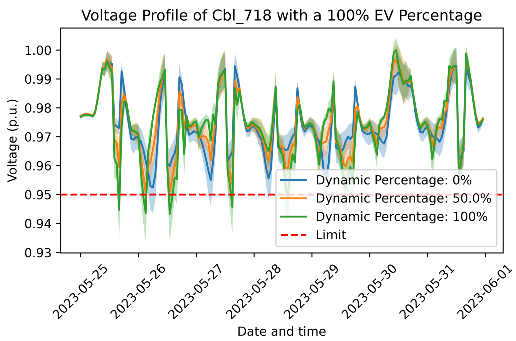


Figure 7.6: 100% EV

Average voltage profiles with standard deviation of Cbl_718 during Week 2.

Similarly as in Week 2, the presence of more electric cars will lower the voltages over each line, seen in Figures 7.7 and 7.8. The presence of high dynamic pricing percentages will cause low voltage dips, which cause under voltages for these high EV percentages.

In Figure 7.8, the evening of the 25th of September shows how due to higher percentages of dynamic pricing, a voltage ”peak” is created, since the power consumption at this time is lower. This shift in loads also causes a voltage dip right before, since all households with dynamic pricing contracts will have shifted their loads towards the time before and after the high peak.

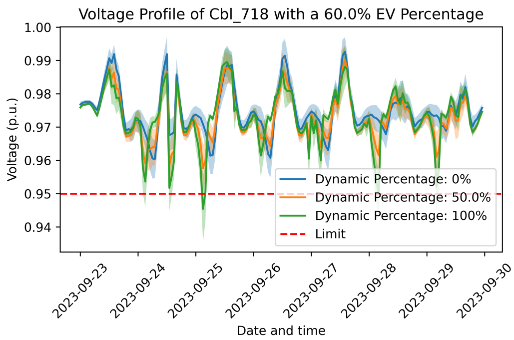


Figure 7.7: 60% EV

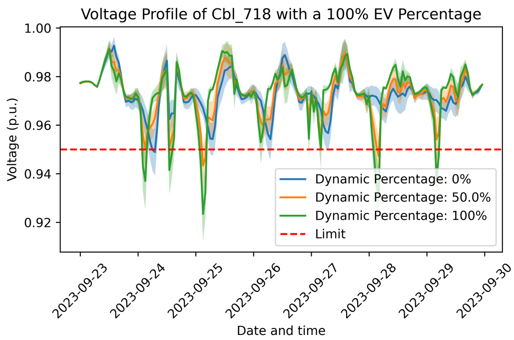


Figure 7.8: 100% EV

Voltage profiles of Cbl_718 during Week 3.

7.1.1. Concurrency non-flexible EV charging

An interesting phenomenon can be observed when comparing the voltage profiles when no households have a dynamic contract and all do. For example during Week 1, it can be seen in Figure 7.9 that the two profiles have some opposing peaks and dips.

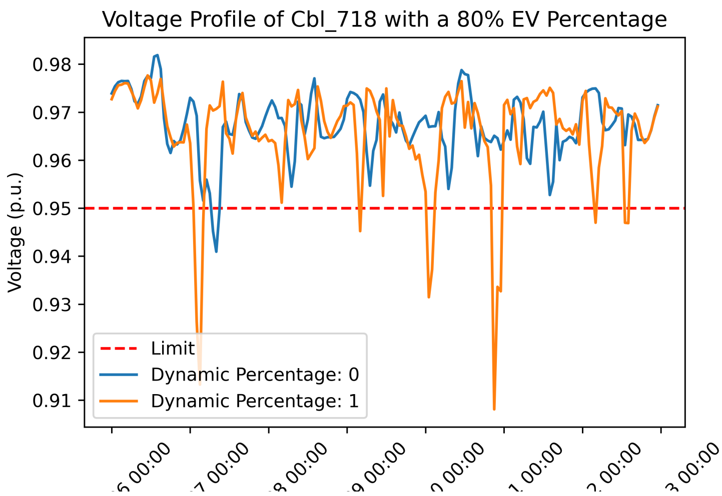


Figure 7.9: Voltage profiles during one day of Week 1 with 80 % EV, comparing 0 % and 100 % dynamic prices

Figure 4.4 shows that there is quite some concurrency in the non-flexible charging profiles. These concurrences occur at different times compared to the optimal charging profiles, which causes the difference in peak times. For the non-flexible charging profiles, EV owners mostly charge their car in the mornings and afternoons, which is often a more expensive time. Dynamic electricity prices are often the lowest at night and in the middle of the day, thus creating a difference between the optimized and non-optimized charging profiles. As a result, a mix of the dynamic and non-dynamic profiles will cause these peaks and dips to average out.

7.1.2. Under Voltage

The voltage profiles seen before show that the voltage limit of 0.95 p.u. is exceeded multiple times at *Cbl_718*. The question can now be asked, how many times exactly is this boundary crossed, and on how many of the branches of the grid does this happen?

For each combination of EV and dynamic pricing percentage, all measurements where the limit of 0.95 p.u. was exceeded were counted, which can be found in Figures 7.10, 7.11, and 7.12 for weeks 1, 2, and 3. These results show that a big factor to determine the number of these potential congestion measurements, is the EV percentage. More EV's cause much higher loads, creating lower voltage dips.

The dynamic percentage also has a very notable effect on the amount of potential congestion measurements. For example in Week 1, when all households have an electric car (purple line), it can be seen that the amount of potential congestion measurements increases by 500 for each 20 % increase of dynamic prices, starting from 40 %.

When comparing the three weeks it can be seen that due to the different PV powers, Week 2 generally has less under voltage measurements, while Week 1 has the most. The plots do have similar shapes, showing that the effects of EV's and dynamic pricing are the same for the different weeks.

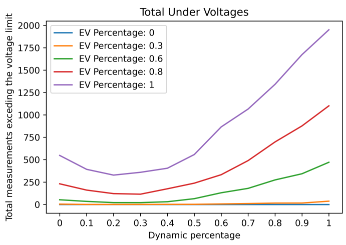


Figure 7.10: Week 1

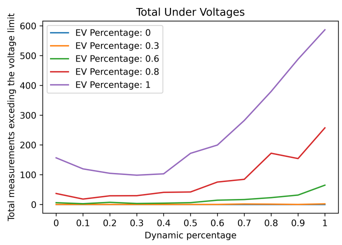


Figure 7.11: Week 2

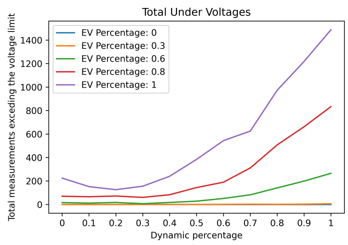


Figure 7.12: Week 3

Average amount of measurements per run where the lower voltage limit was exceeded.

7.1.3. Over Voltage

Similarly to the base scenario, no over voltages occur. Even more, the addition of more EV profiles causes the voltages to be lower.

7.1.4. Voltage Congestion

A voltage below the 0.95 p.u. limit does not necessarily cause grid congestion, as discussed in section 6.1. One can speak of voltage congestion when more than 5 % of the time steps on a branch show under voltages. A single under voltages lower than 90 % also directly causes congestion, however, this does not seem to take place in these simulations.

The results for each week can be seen in Figures 7.13, 7.14, and 7.15, showing the percentage of runs per scenario where voltage congestion occurred. These figures show how an increase in households with dynamic pricing causes more runs to be congested. Similarly, a higher EV percentage causes much more grid congestion.

Lower EV percentages, like the 0 % or the 30 % scenarios, don't result in grid congestion, independent of the dynamic percentage. This supports the idea that these simulations do not cause too large deviations on the voltage profiles, which is why more focus is put on the higher EV percentages.

In Week 1, it can be seen that there are more runs with grid congestion when the dynamic percentage is 0 % than when it is 20 %. This shows that a mix of households with and without dynamic pricing results in the least congestion.

For low percentages of dynamic prices in Week 2 and 3, there are almost no runs with voltage congestion due to the high solar powers. However, when the percentage of households with dynamic prices increases, so do the number of runs with voltage congestion. The influence of dynamic prices will cause the EV loads to shift to the times when the PV power is off, causing the congestion.

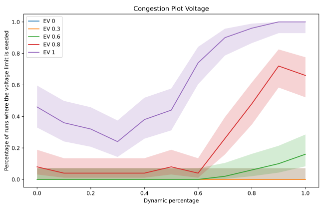


Figure 7.13: Week 1

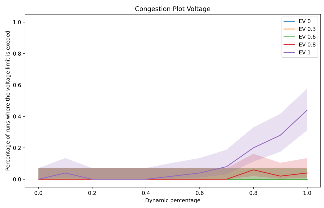


Figure 7.14: Week 2

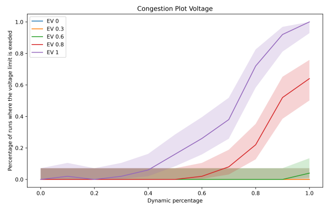


Figure 7.15: Week 3

Amount of runs with grid congestion due to voltage, bands show 95 % confidence levels.

7.2. Power Analysis

Figures 7.16, and 7.17 show the power supplied through the transformer during Week 1, with EV penetration limits of 60 %, and 100 % respectively. Over the graphs, it can be observed how an increase in EV's results in higher power peaks. More households with dynamic pricing will cause steeper power spikes. With no dynamic pricing, multiple small peaks occur, while a higher dynamic percentage causes fewer peaks, but these peaks have a much higher value.

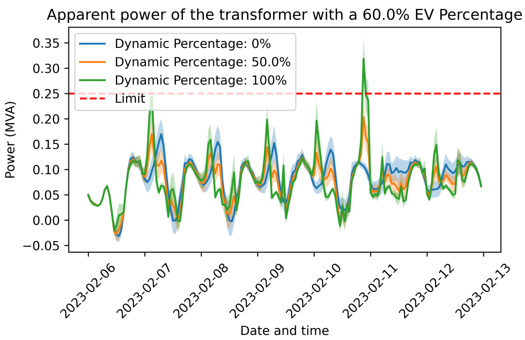


Figure 7.16: With an EV percentage of 60 %.

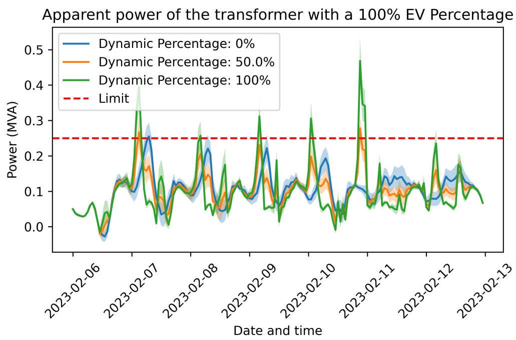


Figure 7.17: With an EV percentage of 100 %.

Average power with standard deviation over the transformer for Week 1

The power profiles seen in Figures 7.18 and 7.19 show the same trends as the for Week 1. The more households with an EV, the higher the overall power consumption and the more households with a dynamic pricing contract, the more concentrated power spikes. For Week 3, one of these spikes occurs on the 25th of September, right before the drop in power due to the high price of electricity at that time.

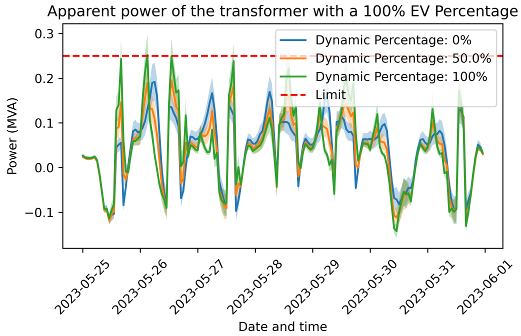


Figure 7.18: Week 2.

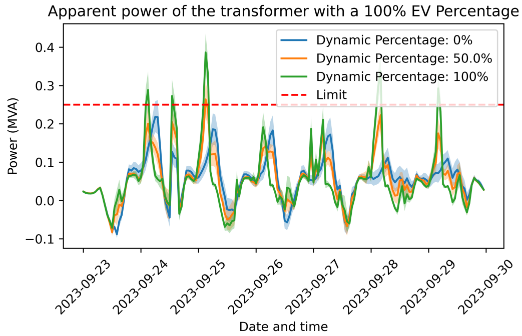


Figure 7.19: Week 3.

Average power with standard deviation over the transformer for an EV percentage of 100 %.

7.2.1. Congestion due to Power

In the previously shown power profiles, it can be seen that the 0.25 MVA limit is exceeded due to the power spikes. Similarly as with the voltage congestion, a graph was created to show the percentage of runs for each scenario where the transformer limit was crossed. The graphs in Figures 7.20, 7.21, and 7.22 show how an increase in dynamic percentage causes more runs to be congested.

For example, when 60 % of the households have an electric car, no transformer grid congestion occurs in combination with low dynamic percentages. When more than 40 % of the households have a dynamic pricing contract in Week 1, more runs start to show congestion, until at 80 %, almost all runs are congested. More households with an EV, cause this increase in congested runs to happen earlier. Similarly to the voltage plot, there is also a small congestion peak when the dynamic percentage is zero.

Similarly as with the voltage congestion, there are fewer runs with power congestion during Week 2. Yet, also for this week, when the level of dynamic pricing increases, so does the number of runs with congestion. When all households have an electric car and a dynamic pricing contract, power-based grid congestion takes place during each run.

The SAC loads are the lowest in week 2 (and the highest in week 1), however, as the SAC demand is relatively low, this does not influence the occurrence of grid congestion. The reason that week 2 shows the least simulations with grid congestion is that this week has the highest solar power yield. This solar power manages to slightly decrease the needed power, thus resulting in less cases where the transformer limit is crossed.

The number of runs where the transformer limits are crossed in Week 3 is quite higher than in Week 2, yet still lower than in Week 1. Power-based grid congestion starts happening at lower dynamic pricing percentages compared to voltage-based grid congestion. Especially for an EV percentage of 60 %; almost no voltage congestion occurs, while power congestion starts significantly happening in some runs when the dynamic percentage is about 60-80 %.

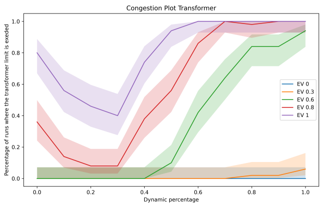


Figure 7.20: Week 1

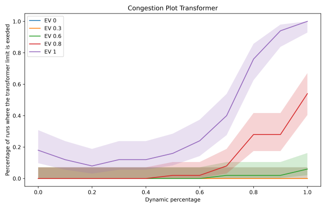


Figure 7.21: Week 2

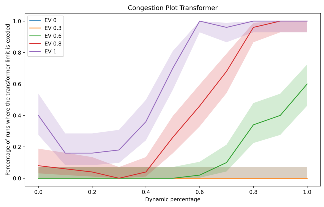


Figure 7.22: Week 3

Amount of runs with grid congestion due to power, bands show 95 % confidence levels.

7.3. Conclusion

From the Week 1, 2, and 3 simulations, it can be seen that grid congestion rarely occurs when there are few households with electric vehicles (0 - 30 %). Higher levels of electric vehicles will generally result in more grid congestion. When more households have a dynamic pricing contract, this will cause the electricity usages of the households to be more concentrated at the low pricing times. This causes the grid boundaries to be exceeded, which results in more congestion.

When comparing the results for the different weeks, it is seen that the height of the PV profiles has a large effect on the congestion in the grid. In general, more solar power results in less congestion measurements.

Even without dynamic pricing, some concurrency exists in the EV charging profiles, which could cause grid congestion. By having a small percentage of households with a dynamic contract, this concurrency is lower, causing less congestion measurements. It can thus be concluded that low percentages of dynamic pricing have a beneficial effect on this grid, while high dynamic percentages on the other hand cause much more congestion.

In general, the transformer limits are exceeded during more runs than when the voltage limits are. Yet it is important to point out that voltage congestion still occurs in most simulations with a high dynamic percentage and high dynamic pricing percentage.

8 Effect of Solar Panels

To better analyse the effect of household solar panels on the simulation results, more simulations were performed using different levels of PV penetration. Since the results of Week 2 are the most affected by the solar profile, due to the high peaks and negative prices, this week will be used to investigate the different levels of solar penetration. Similarly to earlier simulations, the dynamic pricing percentage is varied between 0 and 100 %, using steps of 10 %. EV percentages of 0, 30, 60, 80, and 100 % are used. For each combination of these dynamic and EV percentages, 50 simulations are run, to reduce the influence of the randomization. To keep a clear overview, the results of certain selected dynamic pricing and EV percentages will be shown, for a full overview of all results, Appendix B can be consulted.

First, in section 8.1, no households have solar panels. In section 8.2, all households will have solar panels, however, these will not be affected by dynamic prices, meaning that they are not turned off when the market price is negative. The results where the solar panels are turned off due to negative prices are seen in section 8.3. At the end of this chapter, in section 8.5, conclusions are drawn about the combined effect of solar panels and dynamic pricing.

8.1. No Solar Power

Figures 8.1 and 8.2 show the voltage and power profiles during Week 2, with no PV and no households with an electric car. These profiles are simply the sum of the SAC profiles. It is clear that these profiles are well between the grid limits.

The addition of electric vehicles causes a much higher load on the different grid branches, which creates voltage dips and power spikes. Since there is no Photo-Voltaic power in these simulations, there is no risk for over voltages, nor of the transformer limit being crossed due to feed-ins to the external grid. When the EV percentage is high, like for Figures 8.5 and 8.6, the grid limits are crossed, due to the high loads. When looking at the effect of dynamic pricing, it can be seen that a higher dynamic percentage results in higher peaks and lower dips.

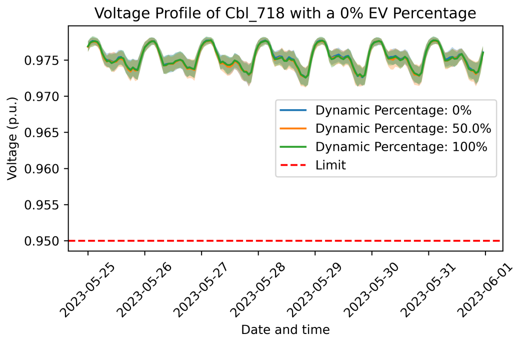


Figure 8.1: Voltage

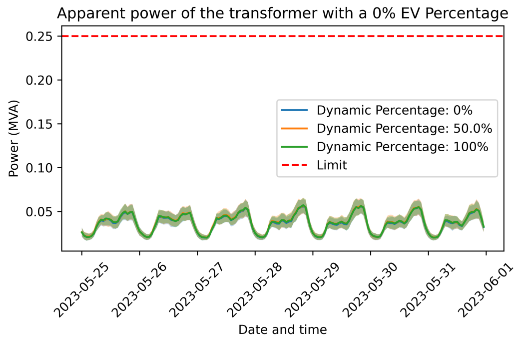


Figure 8.2: Power

Results for Week 2, with 0 % PV and no electric vehicles.

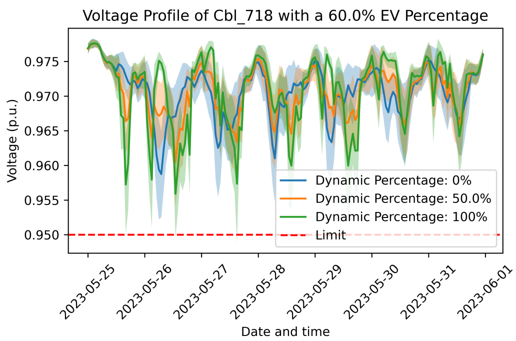


Figure 8.3: Voltage

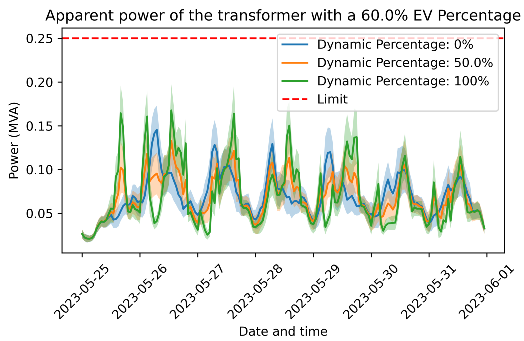


Figure 8.4: Power

Results for Week 2, with 0 % PV and 60 % EV penetration.

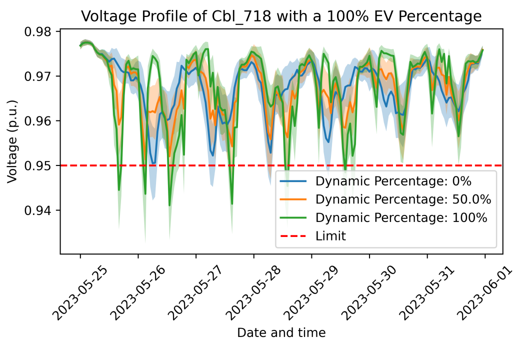


Figure 8.5: Voltage

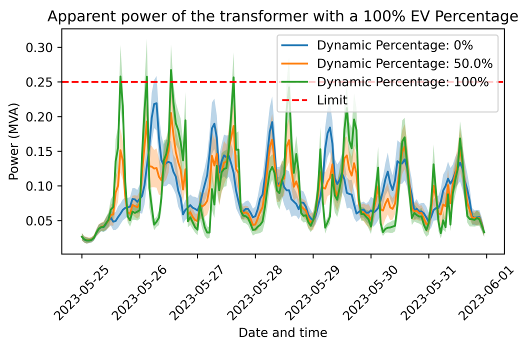


Figure 8.6: Power

Results for Week 2, with 0 % PV and 100 % EV penetration.

Figures 8.7 and 8.8 show the percentage of simulations with voltage or transformer congestion. It can be seen that transformer congestion occurs in more cases, especially for a combination of a high EV percentage with a high dynamic pricing percentage, there is almost 20 % more transformer congestion.

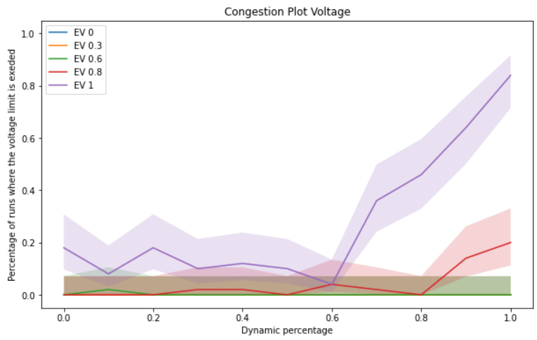


Figure 8.7: Voltage

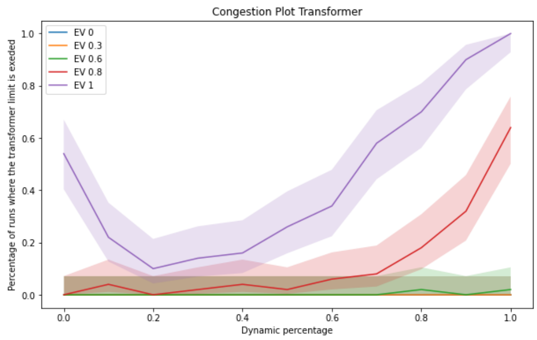


Figure 8.8: Power

Percentage of runs with grid congestion, bands show 95 % confidence levels.

8.2. All Households with Solar Power, not Affected by Negative Prices

For the next set of simulations, all households will have solar panels, which do not get turned off due to dynamic pricing. Figures 8.9 and8.10 show the resulting voltage and power profiles. Since the SAC profiles are small in comparison, these figures mainly show the PV profiles. It can be seen that both the voltage and the transformer limits are crossed by quite high margins, especially the minimal transformer powers are more than double the value of the limit.

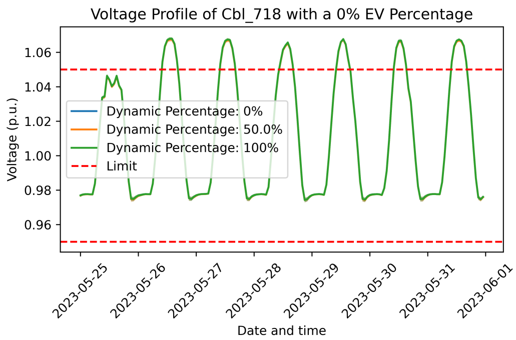


Figure 8.9: Voltage

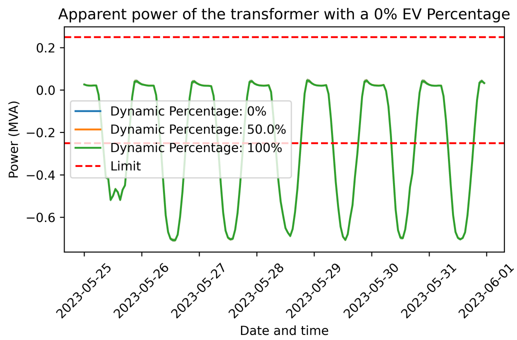


Figure 8.10: Power

Results for Week 2, with 100 % PV, not affected by negative prices and 0 % EV penetration.

The addition of electric vehicles causes the voltages to be lowered and power to be increased. Yet, since the PV powers are still much larger than the loads, the shape of the PV profiles remains. Figure 8.11 shows that dynamic pricing will concentrate the EV loads at the peaks of the solar profiles, since these times will coincide with the lowest prices. This causes the voltage profiles to dip, which can avoid crossing the voltage limit. However, the dynamic prices also cause some voltage drops at night, when there is no solar energy available. This can be observed in Figure 8.13, when under voltages occur due to the higher percentage of dynamic pricing. From Figures 8.12 and 8.14 it can be seen that even with the EV loads, the feed-in power cannot be decreased enough to avoid crossing the limits.

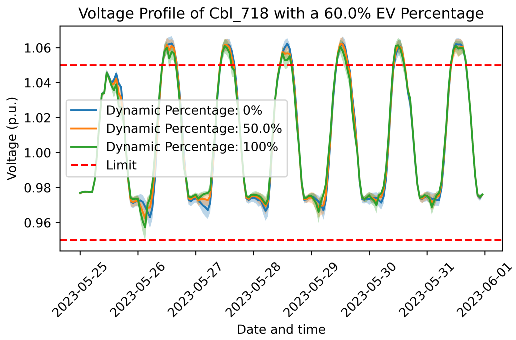


Figure 8.11: Voltage

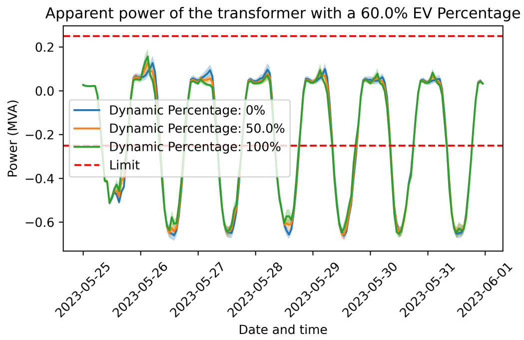


Figure 8.12: Power

Results for Week 2, with 100 % PV, not affected by negative prices and 60 % EV penetration.

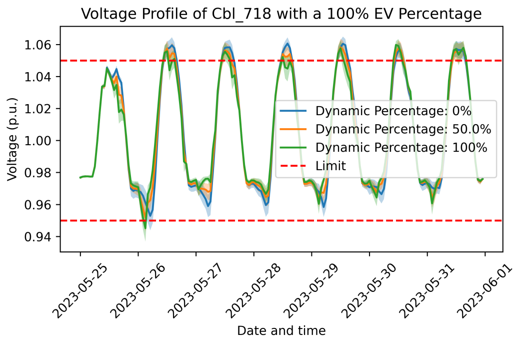


Figure 8.13: Voltage

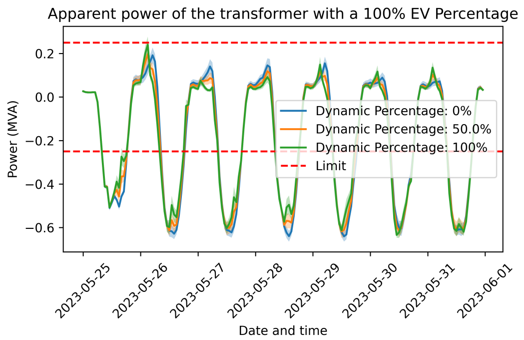


Figure 8.14: Power

Results for Week 2, with 100 % PV, not affected by negative prices and 100 % EV penetration.

Figure 8.15 shows the average amount of over voltages per simulation. it can be seen that higher levels of EV penetration cause a reduction in over voltages, as the EV loads will decrease the line voltage. When more households have a dynamic pricing contract, this will also decrease the amount of over voltages, since the EV loads will be concentrated at the voltage peaks. On the other hand, when looking at the under voltages in Figure 8.16, it is seen that more electric cars and more dynamic pricing causes more under voltages, although the amount of under voltage measurements is still much lower than in the simulations where less households have solar panels.

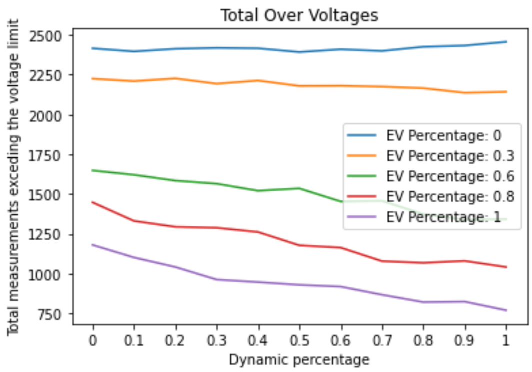


Figure 8.15: Over voltage measurements.

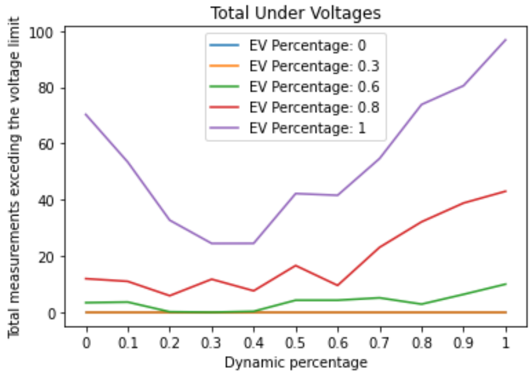


Figure 8.16: Under voltage measurements.

Average amount of measurements per run where the voltage limit was exceeded.

In all simulations the grid limits are exceeded such that both voltage and transformer congestion will always take place. Voltage congestion is caused by the large number of over voltage measurements, while transformer congestion is cause due to the high feed-in powers.

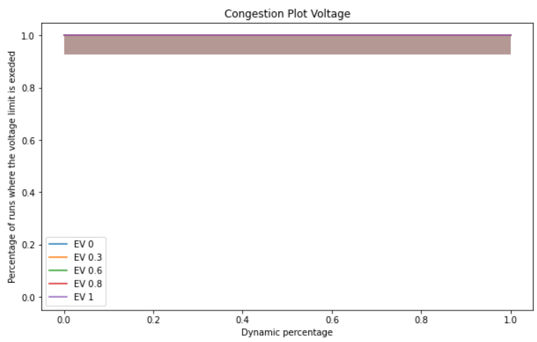


Figure 8.17: Voltage

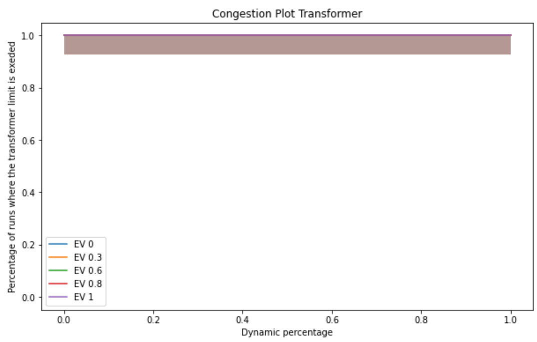


Figure 8.18: Power

Percentage of runs with grid congestion, bands show 95 % confidence levels.

8.3. All Households with Solar Power, Affected by Negative Prices

For the following simulations, again all households have solar panels, however this time, these get turned off during the negative market pricing times. Since the PV profiles dominate, their turning off can clearly be seen in all figures.

Households with a dynamic contract will focus their EV charging at the negative pricing times, yet since the PV panels are turned off during those times, this creates voltage dips, as seen in Figure 8.19. For high EV percentages, like in Figure 8.21, the high dynamic pricing percentages will cause under voltages during the negative pricing times. Similarly, power spikes can be observed for the power profiles in Figures 8.20 and 8.22.

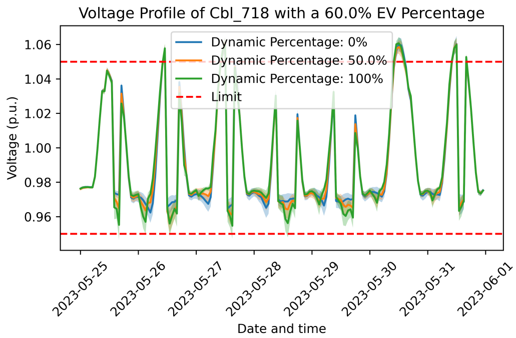


Figure 8.19: Voltage

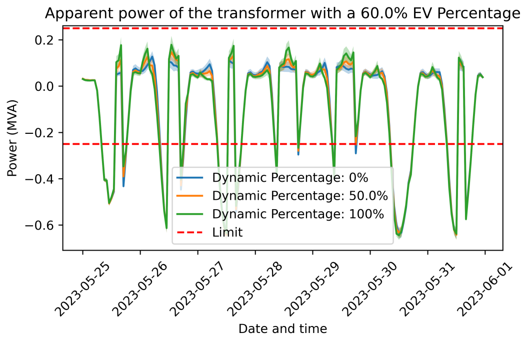


Figure 8.20: Power

Results for Week 2, with 100 % PV, affected by negative prices and 60 % EV penetration.

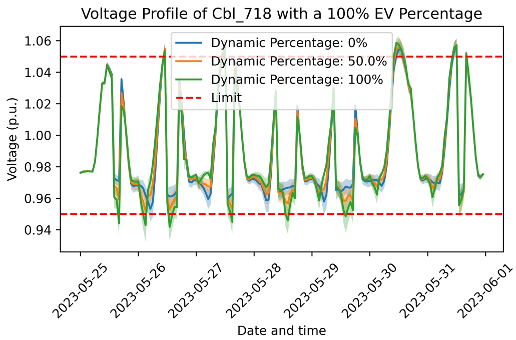


Figure 8.21: Voltage

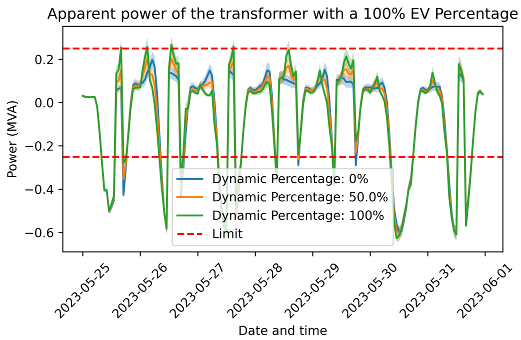


Figure 8.22: Power

Results for Week 2, with 100 % PV, affected by negative prices and 100 % EV penetration.

Figure 8.23 shows that the number of over voltage measurements has decreased significantly, compared to Figure 8.15. Since the solar panels are turned off during the peak solar times, there are less moments with over voltages. When the dynamic percentage increases, the amount of over voltage measurements increases slightly. This happens because the loads that would normally bring the voltage down, are shifted to the lowest pricing times.

The average number of under voltage measurements plot (Figure 8.24) looks very similar to that of the Week 2 simulations with a PV percentage of 30 % (Figure 7.11). This is quite logical, as the under voltages occur whenever the solar panels are turned off and during the night, thus the times when there is no solar energy generated. Since the combination of a high EV percentage and a high dynamic percentage causes the low voltage dips, this also causes the most under voltages.

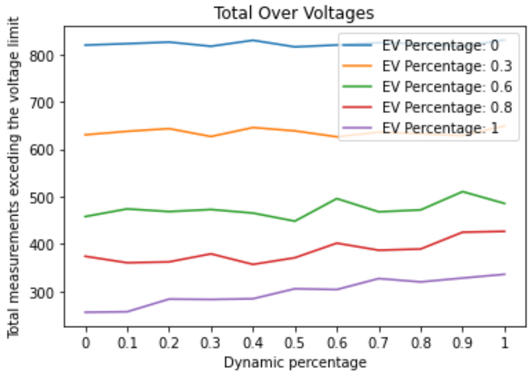


Figure 8.23: Over voltage measurements.

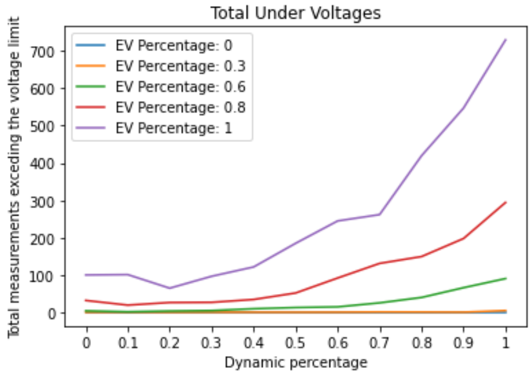


Figure 8.24: Under voltage measurements.

Average amount of measurements per run where the voltage limit was exceeded.

For most simulation runs, voltage congestion takes place, as seen in Figure 8.25. However, due to lower over and under voltages measurements at low dynamic pricing percentages, there are a few runs where there was no voltage congestion. Interesting to see here is that for the first time, a higher EV percentage is actually slightly beneficial for the grid. Due to the extremely high feed in powers, the transformer limits will always be crossed, causing transformer grid congestion (seen Figure 8.26).

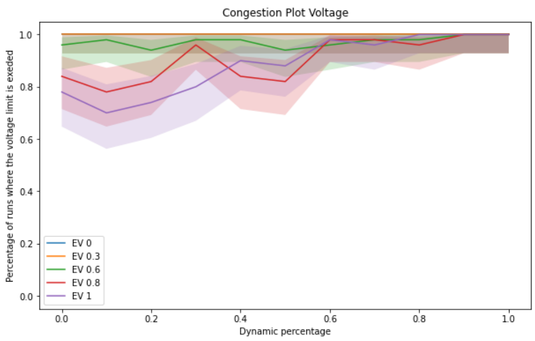


Figure 8.25: Voltage

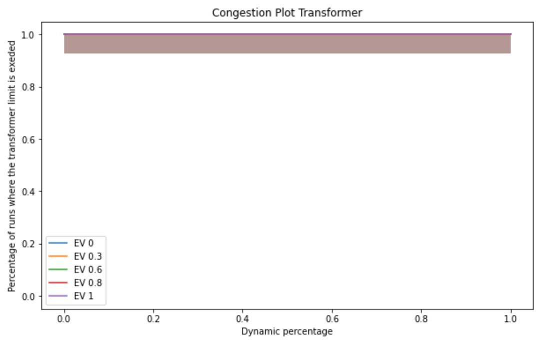


Figure 8.26: Power

Percentage of runs with grid congestion, bands show 95 % confidence levels.

8.4. Comparison Between Solar Panels Being Turned Off or Not

Figure 8.27 and Figure 8.28 show the voltage profiles during week 1 in a bit more detail, zoomed in on one day. Both figures show how due to dynamic pricing, the load in the grid is lower in the morning and higher around noon, when there are negative prices. When the solar panels are not turned off due to negative market prices (Figure 8.27), the increased loads around noon manage to lower the voltage, causing less over voltages. When the solar panels are turned off (Figure 8.28), the shifted loads cause under voltages

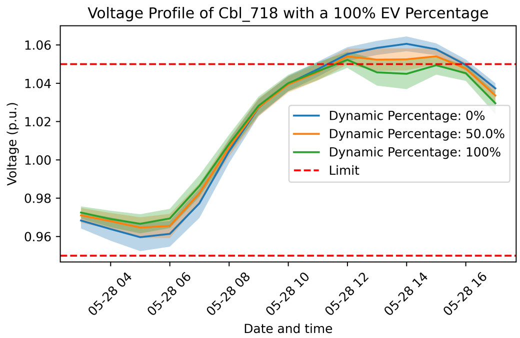


Figure 8.27: Not affected by negative prices.

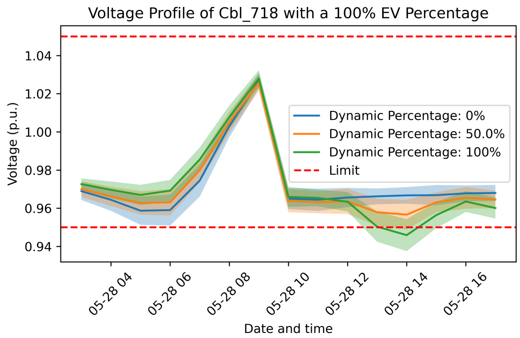


Figure 8.28: Affected by negative prices.

Zoomed in voltage profiles of Week 1 with 100 % PV.

8.5. Conclusion

When there are no households with solar panels, the influence of electric vehicles and dynamic prices on their own can be investigated. As expected, electric vehicles create higher loads, which get more concentrated in time due to higher levels of dynamic pricing.

The addition of solar panels for each household causes over voltages and high feed in powers that cross the grid limits. More electric cars lower the amount of over voltage measurements, since these higher loads lower the voltage. This effect is also caused by dynamic pricing, as the loads get concentrated at the peak solar times. However, this lowering of the voltage and the feed in power is not enough to avoid grid congestion.

When the solar panels are turned off at the negative pricing times, the amount of over voltage measurements is more than halved. On the other hand, the amount of under voltage measurements is massively increased, due to the voltage dips during the negative pricing times.

It can be concluded that a high PV percentage causes over voltages and too low transformer powers. To avoid these over voltages, the solar panels could be turned off during the negative pricing times. However, this causes high loads during these ”off times”, in turn causing under voltages.

Complex solutions are needed to solve the grid issues cause by higher levels of generated solar energy. Improved schemes for the turning off the solar panels can be used to better make use of the PV energy to avoid both types of congestion.

9

Discussion

This chapter will give a more detailed analysis of the results presented in chapters 6, 7, and 8. First, the limitations of the results will be discussed. In section 9.2 the results of the simulations are summarized. The relationship between the crossing of the voltage and power limits is discussed in section 9.3, whereafter a comparison is made between voltage and power grid congestion. Finally, the socio-economic impact of this thesis is presented.

9.1. Limitations

While the goal of the simulations was to be as accurate as possible, certain things were not feasible to implement. It is thus important to address the limitations of these simulations, to understand how the results can be translated to real-life situations.

First of all, since the simulations were performed on only one grid, the results can only be applied to this particular grid with absolute certainty. It is likely that a similar grid will show similar results, since most grids operate in the same fashion. Randomness was used when assigning the SAC loads, the EV loads and the solar panels, to minimize the effects of outliers on this specific grid.

The only flexible load taken into consideration for this thesis was the charging of electric cars. Other loads, like home batteries or heat pumps were not considered. These have the potential to influence the results significantly, as especially batteries can both be used for electricity generation and consumption. The EV charging method use is quite simple, only basing the charging profile on the lowest cost and the arrival/departure times. More complex charging schemes exist, where households base their charging on a combination of cost and desired battery SOC.

Another important consideration is that voltage results are in hourly intervals, while the EN50160 standard is based on 10-minute intervals. This thesis assumes that each 10-minute interval value is equal to the hourly value. It is thus possible that when looking at the 10-minute intervals more or less over/under voltage measurements occur.

For the household solar panels, the exact same profiles were used for all households. In reality each household will have different powers of solar panels installed, and the profiles will look slightly different due to clouds and shading.

Finally, the dynamic pricing profile is based on that of 2023, when very little households have dynamic energy contracts. The question could be raised how higher penetrations of dynamic contracts will influence the market prices. It is possible that a feedback loop will be formed, where the dynamic prices are updated based on load shifting predictions. It is thus possible that high pricing peaks and negative prices will occur far less often.

To conclude, there are quite some limitations to the research done for this project. The congestion results should thus not be used as exact values, but more as an indication of which grid issues can be expected for which scenarios.

9.2. Grid Problem Results

In chapters 6 and 7 it was analysed that when households will shift their energy consumption based on dynamic pricing, the demands can cause voltage dips and power spikes. The more households with a dynamic contract, the more likely it is that grid congestion occurs.

In general, when more households have an electric car, there will be more grid congestion, as these EV's cause higher loads. The combination with dynamic pricing, results in low under voltages and high peaks in the power demand.

It was found that for the EV charging data used for this project has some level of concurrency. The optimized and non-optimized EV profiles show opposing peaks and dips, and a combination of both resulted in the least amount of simulations with grid congestion. Thus, when a small percentage of households has a dynamic pricing contract, the EV loads are better spread out over the week, which resulted in less grid congestion for all scenario's. However, when the dynamic percentage increased over 40 %, the number of simulations with grid congestion increased

Chapter 8 also delved deeper into the effect of households' PV systems. When many households have rooftop solar panels, over voltages can happen. In these scenario's, electric vehicle charging can help lower the voltages, yet these EV's still cause under voltages during the night.

When the solar panels are turned off under the influence of negative prices, the amount of over voltages can be lowered, since the negative prices in most cases occur during the peak PV times. Similarly, if the solar panels are turned off under influence of negative prices, the shifted loads cause under voltages as well.

Another issue that occurs due to the high solar energy, is the high feed-in powers. The power delivered back to the grid crosses the transformer limits by a very large margin. When all households in the grid have solar panels, the feed in powers are even double the limit.

9.3. Extremities Versus Limits

Figures 9.1, 9.2, and 9.3 show the extreme voltage and power values for each simulation performed during a week. Each dot corresponds to the week's maximal power value and its minimum voltage value (measured over all different branches). In Figure 9.2, the maximal voltages and minimal powers are also shown. The grid limits are indicated by the red dashed lines. More figures for all the simulations can be found in section B.7.

The plots show an inverse relationship between the voltage and the power. When the line voltage decreases, the power over the transformer will rise. Generally, higher EV percentages will result in lower voltage dips and higher power spikes. For each level of EV, the more right under points correspond to simulations with higher dynamic pricing percentages.

It can be seen that generally, the lower voltage limit is crossed more than the upper power limit. One possible reason for this is that the grid's no-load voltage is set at 0.98 p.u., which automatically lowers the voltage by 0.2 p.u. compared to the transformer power.

Important to note about these results is that in contrary to crossing the transformer limit, crossing the voltage limit does not automatically cause grid congestion. According to the adjusted EN50160 standard, the voltage limit can be exceeded for up to 8 hours per branch in the simulated week. Many of the under and over voltage points shown, will not cause voltage congestion. The shown scatter plots can thus not be used to make any conclusions about congestion, only the trends of the voltages and powers can be discussed.

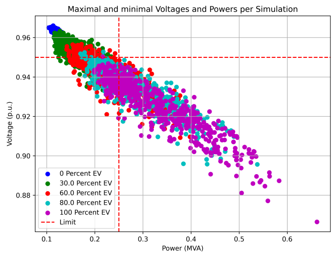


Figure 9.1: Week 1, with 30 % PV

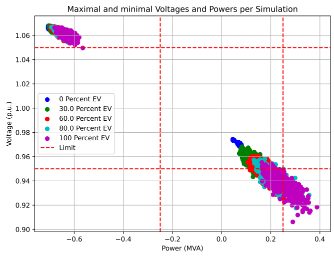


Figure 9.2: Week 2, with 100 % PV

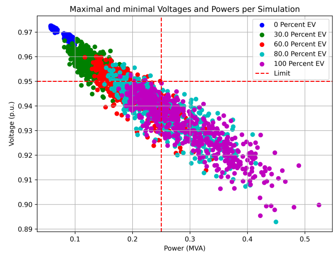


Figure 9.3: Week 3, with 30 % PV

Minimal and maximal voltage and power measurements for each of the simulations.

9.4. Voltage Versus Power Congestion

To be able to investigate which kind of congestion (voltage or power) occurs more often, congestion matrix plots were analysed. These plots show for how many of the simulations the transformer limit, the EN50160 limit, or both limits are crossed. From this data, it could be seen which limit is the most important cause of grid congestion for these scenarios.

From Figures 9.4 and 9.5 it can be seen that in most cases, whenever there is voltage congestion, there also is power congestion, while there are quite some cases where power congestion occurs without voltage congestion. From Figure 9.6, of the simulations with 100 % PV where over voltages and transformer feed-in problems also occurred, the same can be seen. This shows that the power limits are the biggest cause for grid congestion in this grid. However, the voltage limits are still crossed in many of the simulations, including a small few where the power limits are not crossed. The voltage limits can thus not be ignored, proving that load-flow simulations are important to investigate when looking at grid congestion.

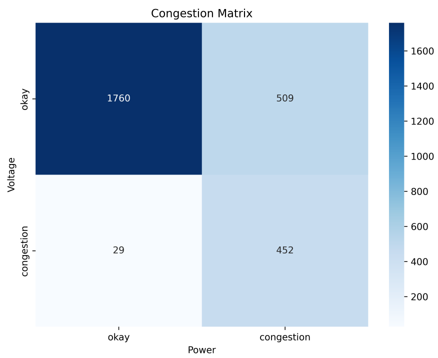


Figure 9.4: Week 1

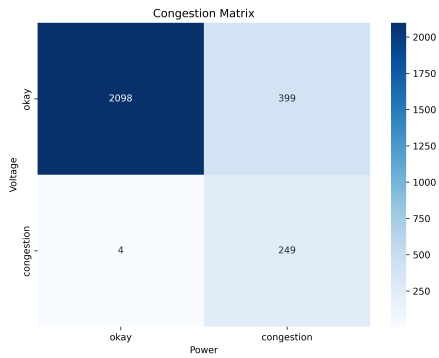


Figure 9.5: Week 3

Congestion matrix.

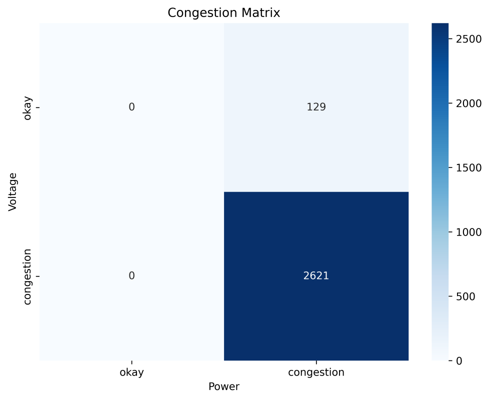


Figure 9.6: Congestion matrix of Week 2, with 100 % PV.

The use of software like PowerFactory is needed to simulate the detailed voltage profiles. More simple power calculations can be used in research to get a general idea about the predicted grid issues, however, sometimes load-flow calculations are needed. While more complex, it is important to use these load-flow simulations when making claims about grid congestion, especially in grids with long voltage lines and high transformer power ratings.

9.5. Socio-Economic Impact

Dynamic pricing provides economic incentives for consumers to shift their flexible loads to the off-peak hours, which can lower their electricity costs. Another advantage is that the available renewable energy is more efficiently used, eliminating the mismatch between supply and demand.

However, this load shift due to dynamic pricing also has an impact on the grid stability. Higher levels of EV adoption can lead to grid congestion during the peak charging times, especially due to low dynamic prices. There is thus a need for substantial investment in the grid infrastructure to handle this increased load. These results suggest that while dynamic pricing can provide economic benefits for households, regulatory and infrastructural adjustments are necessary to prevent grid failures.

While solar panels contribute to reducing electricity costs and promoting renewable energy usage, they can cause over-voltages during the periods of high solar generation. The addition of dynamic pricing schemes further complicates this, due to the shifting loads. Although the charging of electric cars can help mitigate some voltage spikes, the combined effect can still lead to under voltages, highlighting the need for more complex grid management solutions.

The combination of dynamic pricing with high levels of EV's and solar panels, has many advantages in terms of cost savings and environmental sustainability. However, these benefits must be matched with strategic investments in grid upgrades to maintain the grid stability. Policy makers should keep in mind the economic trade-off between consumer cost savings and expensive infrastructural reinforcements. By addressing these challenges, the transition to a more sustainable energy system can be accomplished.

10 Conclusion and Recommendations

The goal of this thesis was to investigate the effect of dynamic pricing on the low voltage grid, by analysing the impact of electric vehicles and solar panels, in combination with dynamic pricing. The goal was to create a deeper understanding of which scenarios result in grid congestion and to compare whether the grid congestion is caused by the line voltage limits or by the transformer power limits. With the help of DSO Stedin, the necessary input data was gathered, and simulations were performed using PowerFactory. This chapter will first provide the final conclusions of this project, and lastly, recommendations for future work will be given.

10.1. Conclusion

The variability of the different renewable energy sources has resulted in many challenges for the energy infrastructures all over the world. One possible solution for the mismatch between supply and demand is the introduction of dynamic electricity prices for households. However, this thesis predicts that dynamic pricing does not pose the perfect solution some might claim. While the shifting of flexible loads can solve the supply-demand mismatch, it is likely that the low voltage grid is not yet equipped to handle the resulting voltage and power spikes.

This thesis has created a model, which was used to study grid congestion for different scenarios. The impact of electric vehicles, Photo-Voltaic (PV) systems, and most importantly dynamic pricing on the low voltage grid was analysed. A Python model was created, which uses PowerFactory to perform a multitude of simulations.

The model made use of three different energy inputs, namely the non-flexible SAC loads, EV charging data and solar energy data. Both the inflexible consumption profiles and base EV charging data were taken from the GO-e data base, while the solar energy profiles are based on the by Stedin measured data from 2023. The dynamic prices were taken from the 2023 market prices, which were then scaled based on different taxes and fees, as explained in chapter 2. Using these prices, three representative weeks were chosen, to analyse the effect of different pricing profiles. A simple EV charging optimization scheme was used on the EV charging data to generate the charging profile based on the dynamic prices. The solar profile was set to zero (”turned off”) whenever the market priced became negative.

For the simulations, one grid was chosen from the GO-e archetypes, based on which kind of neighbourhood best fits Stedin’s customers. The grid file was converted from Gaia to PowerFactory, to enable more detailed simulations. In PowerFactory, quasi-dynamic simulations were performed during each of the three representative weeks, making use of hourly intervals. Different scenarios, meaning different combinations of the amount of dynamic pricing contracts, EV integration percentages, and solar panels installed, were run. For each scenario, 50 simulations were run, to eliminate the effects of the random assigning of the loads. From these, the power of the transformer and the line voltages were analysed and compared to the corresponding grid limits.

The goal of the model was for it to be as accurately as feasible within the thesis time constraints. However it is important to keep the limitations of the model in mind. First of all, since only one grid was used for the simulations, one must be careful when generalizing these results for other grids. The chosen archetype is quite electrically dense, with short distances between the households. A more rural grid could show different results, for example with more voltage issues due to the long voltage lines. Another limit of the model is its simplicity, especially the amount of flexible loads and the solar profiles provide a general idea, but do not entirely correspond to reality. The more detailed limitations can be found in section 9.1.

In the base scenario, seen in chapter 6, where the current PV percentage (30 %) and an EV percentage of 30 % was used, little grid congestion occurred. The simulations did show that dynamic pricing contracts will cause the EV charging loads to be more concentrated, causing voltage dips and power spikes. These results showed that the current grid infrastructure is generally sufficient for the present-day demands, however, future predictions suggest that more electric cars will result in more grid issues.

The introduction of more households with an electric car consistently resulted in more grid congestion, as analysed in chapter 7. Due to the higher load on the grid, under voltages occur , often in combination with too high powers over the transformer. The simulation results showed that even moderate levels of EV adoption can lead to congestion issues, as the charging times can coincide with peak demand times. This effect was amplified by the implementation of dynamic prices, which concentrated the charging loads whenever the prices were low.

More PV systems, while beneficial for reducing electricity costs and promoting renewable energy usage, introduced challenges of their own (chapter 8). High penetration of PVs caused over voltages and exceeded the feed-in power limit during the high solar generation periods. When the solar panels are turned off under influence of dynamic pricing, the amount of over voltages get lowered. However, during these ”off-times”, under voltages can take place due to the electric vehicle charging. This effect was further complicated by dynamic pricing, which shifted the EV charging loads towards these off-times, creating even more under voltages. Yet, while turning the solar panels off might have cause more under voltages, the amount of over voltages was greatly reduced.

Interestingly, the simulations consistently showed how low, but non-zero, dynamic pricing percentages resulted in the lowest occurrences of grid congestion. Due to the slight concurrency of the non-flexible EV charging profiles, it was shown to be beneficial to add some shifted profiles, to better distribute the loads over the week. However, when the dynamic percentage increased, the shifted loads overlapped again, causing even more grid congestion. These findings suggest that a mixed approach, incorporating both dynamic and regular pricing contracts, could offer a more balanced solution, utilizing the benefits of dynamic pricing while mitigating its risks. As a grid operator, Stedin is not able to control the amount of households with a dynamic contract, however it is still important information to have, when consulting with policy makers and suppliers.

The simulations showed that the crossing of the transformer’s power limits typically caused more grid congestion than the over and under voltages did. However, the voltage issues cannot be ignored, as voltage congestion does also occur in plenty of the simulations. While upgrading the transformer can temporarily alleviate power congestion and increase the grid’s capacity, voltage problems will persist unless also addressed. This highlights the importance of performing more detailed load flow simulations, with programs like PowerFactory, to be able to further analyse the voltage profiles.

This research demonstrated that dynamic pricing, despite its economic benefits and potential to enhance renewable energy utilization, must be carefully managed to avoid destabilizing the grid. While dynamic pricing encourages households to shift their electricity usage to times when power is cheaper, thus aligning demand with supply, it can also lead to more congestion on the low voltage grid. To effectively handle the increased loads from EVs and PVs, policymakers and grid operators analyse both power and voltage congestion. By addressing these challenges, the low-voltage grid can continue to support the increasing penetration of renewable energy sources and electric vehicles, paving the way for a more resilient and sustainable energy future.

10.2. Recommendations for Future Work

While this research already gave a general prediction about the effect of dynamic pricing on the low voltage grid, more extensive work could be done to improve the model. Solutions to the predicted problems could also be analysed, such that grid operations and policy makers have a better understanding on how to maintain the grid stability.

The first set of recommendations are improvement points for the model, to make it more accurate. These are mostly to correct the earlier discussed limitations. One such thing could be adding other flexible loads, like heat pumps, home batteries, and more, all with their own optimal power profiles, to see how these loads influence the grid's stability. Similarly, the EV charging optimization model could be improved. For example, a charging scheme could be used where the car's battery is not always fully charged, or where some charging is done upon arrival, which might be more desirable for households.

For the simulations it could be interesting to perform them om different grids, both from the same archetype and different ones, to see whether the results are similar. Performing more simulations will help determine how representative these results are to all Dutch low voltage grids. The simulations could also be done in smaller time steps, such as 10-minute interval to better investigate the EN50160 limit. Even smaller time steps could also be interesting to investigate other grid issues, such as voltage flickers or frequency deviations. It could also be interesting to analyse the probability of both voltage and transformer grid congestion when the transformer is upgraded.

The most interesting recommendation that should be further investigated would be the effect of different dynamic pricing models. Currently, the market price is based on the ratio between the predicted generation and the predicted demand, when the predicted demand is based on past data. Yet, as many investigations have showed, dynamic pricing will influence people's electricity usage, thus influencing the actual demand. Perhaps in the future, this will create a sort of feedback loop, when the market price is adjusted based on the predictions of the load shifts caused by households with a dynamic pricing contract. This would result in less extremities in the price profile, whether this is adverse or advantageous for the low voltage grid, remains to be seen.

Similarly, more research should be done on the disconnection of the solar panels. The question remains whether this is something all households will be incentivized to do, or only those with a dynamic contract. It is also possible that households are able to partially shut off their PV, allowing them to use their own generated energy, while not causing feed-in issues on the grid. Another option is a system that could automatically turn of the solar panels whenever over voltages occur, but again it remains to be investigated whether households would be interested in such system.

Finally, different solutions can be investigated to solve the predicted grid congestion. One such solutions could be based on powering off the solar panels based on the grid instead of only on the market price. By partially disconnecting the generated solar power, over voltages can be avoided, while some solar energy could still be used to prevent under voltages at peak EV charging times. This, however, does not eliminate all under voltage measurements, especially not those at night nor on cloudy winter days.

Some other solutions that could be analysed is the addition of different polity instruments, which can economically influence a household's energy profile. Policies like capacity tariffs or DSO based dynamic pricing could be used, which could shift the flexible loads away from the peak times.

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A
Figures

In this appendix, several figures that were not included in the main body text are presented.

A.1. Dynamic Prices of 2023

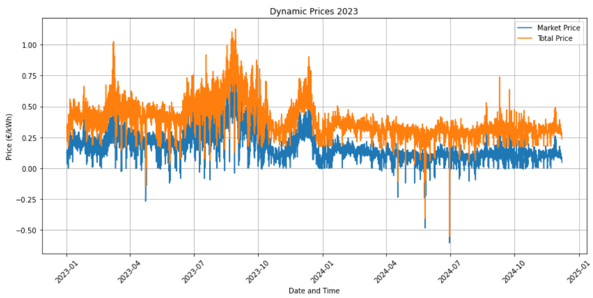

Figure A.1: Dynamic Prices 2023.

A.2. Crossing of the Power Limit Week 1 Base Scenario

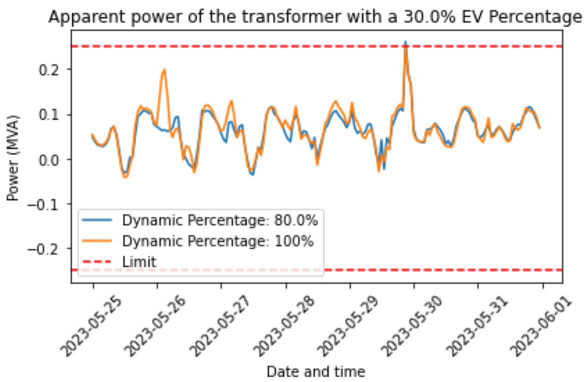

Figure A.2: The power profiles of two simulations were the transformer power limit was crossed

B
Full Results

B.1. Week 1

- Representative week: Week 1
- PV penetration: 30 %
- EV percentage: 0%, 30 %, 60 %, 80 %, and 100 %
- Dynamic percentage: 0%, 10% - 100%
- Number of runs: 50

B.1.1. Branch Voltages

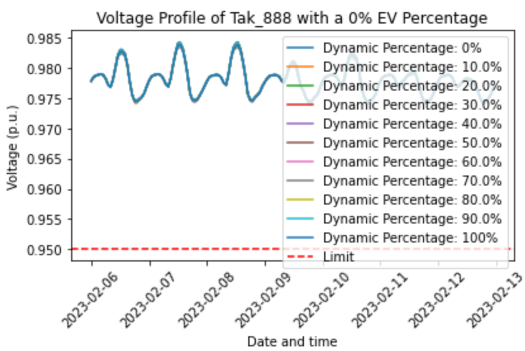

Figure B.1: Tak_888, located close to the external grid

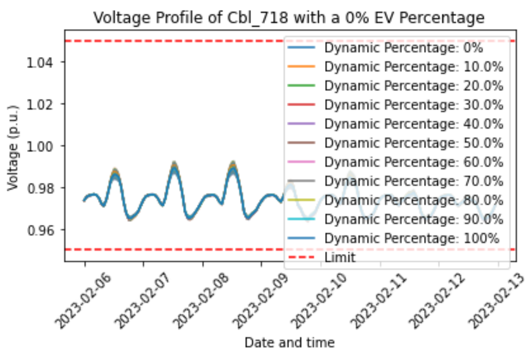

Figure B.2: Cbl_718, located far from the external grid.

Average voltage profiles with their standard deviation during Week 1, with 0 % EV penetration.

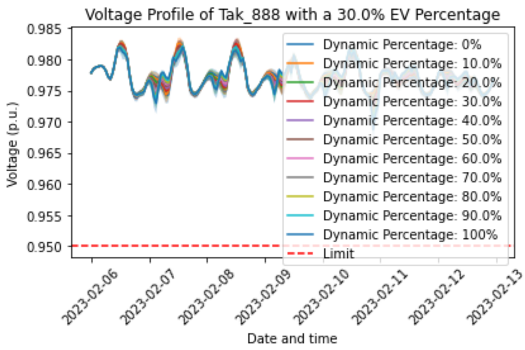

Figure B.3: Tak_888, located close to the external grid

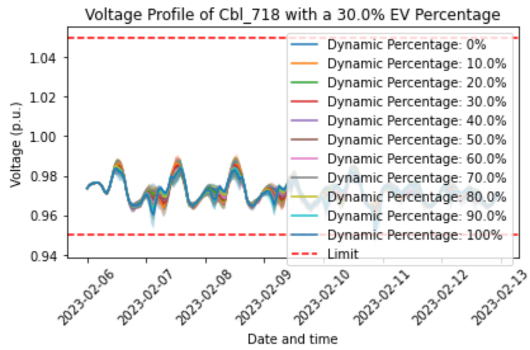

Figure B.4: Cbl_718, located far from the external grid.

Average voltage profiles with their standard deviation during Week 1, with 30 % EV penetration.

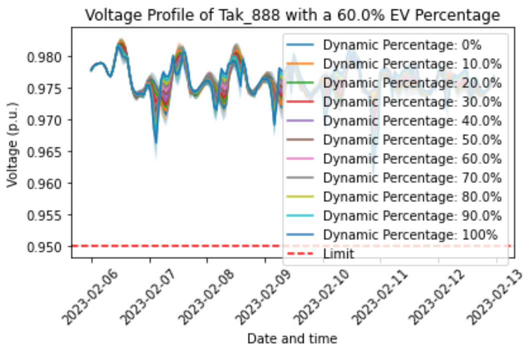

Figure B.5: Tak_888, located close to the external grid

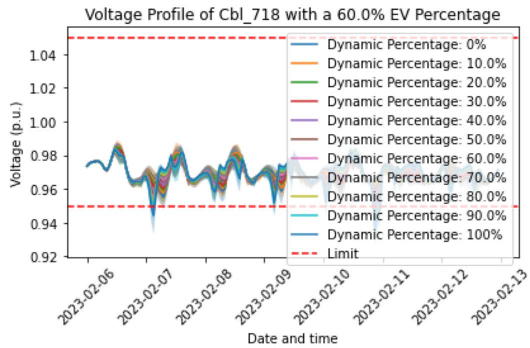

Figure B.6: Cbl_718, located far from the external grid.

Average voltage profiles with their standard deviation during Week 1, with 60 % EV penetration.

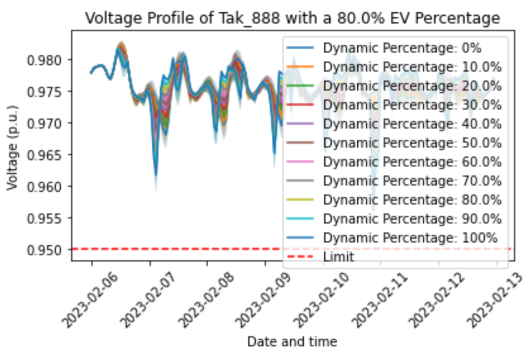

Figure B.7: Tak_888, located close to the external grid

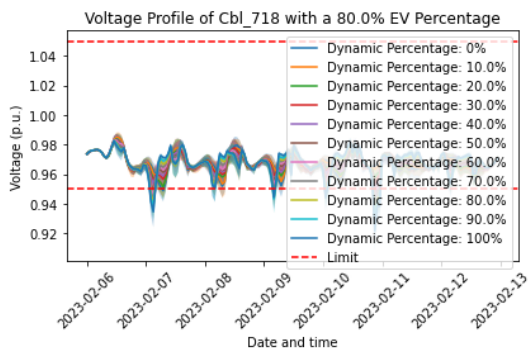

Figure B.8: Cbl_718, located far from the external grid.

Average voltage profiles with their standard deviation during Week 1, with 80 % EV penetration.

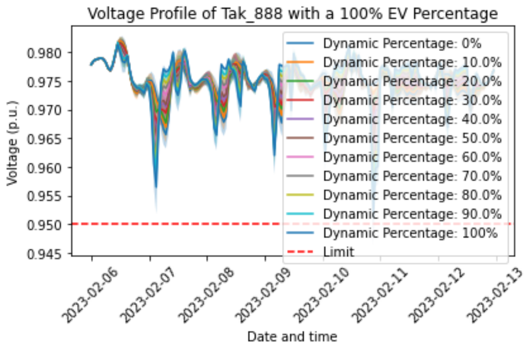

Figure B.9: Tak_888, located close to the external grid

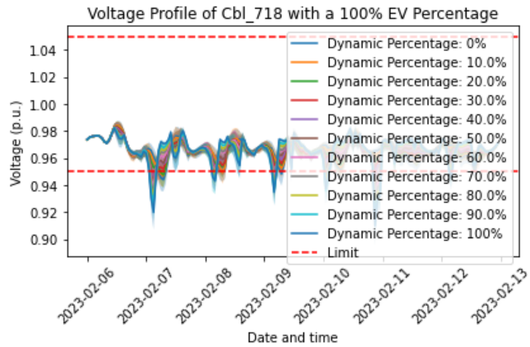

Figure B.10: Cbl_718, located far from the external grid.

Average voltage profiles with their standard deviation during Week 1, with 100 % EV penetration.

B.1.2. Transformer Power

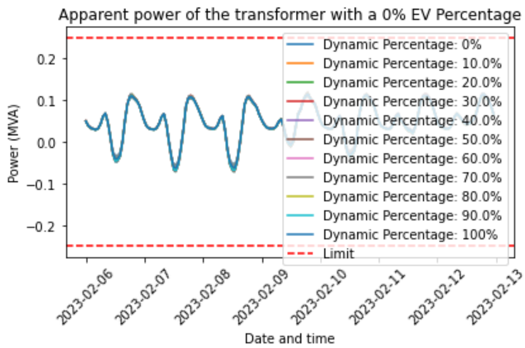

Figure B.11: With an EV percentage of 0 %.

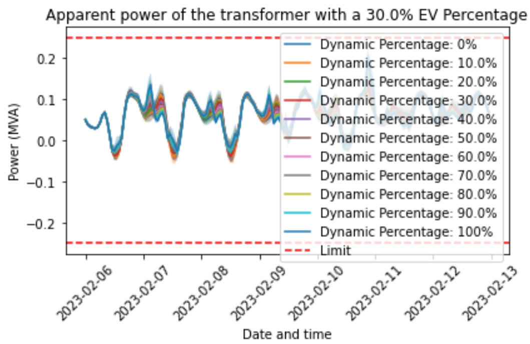

Figure B.12: With an EV percentage of 30 %.

Average power with standard deviation over the transformer for Week 1

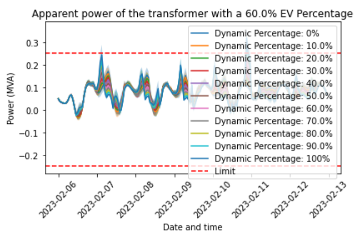

Figure B.13: With an EV percentage of 60 %.

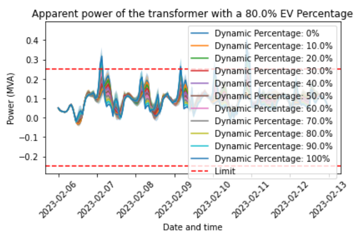

Figure B.14: With an EV percentage of 80 %.

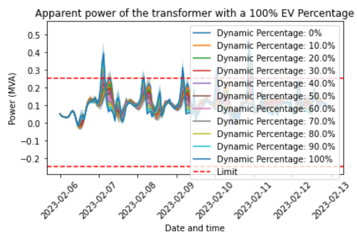

Figure B.15: With an EV percentage of 100 %.

Average power with standard deviation over the transformer for Week 1

B.2. Week 2

- Representative week: Week 2
- PV penetration: 30 %

- EV percentage: 0%, 30 %, 60 %, 80 %, and 100 %
- Dynamic percentage: 0%, 10% - 100%
- Number of runs: 50

B.2.1. Voltage

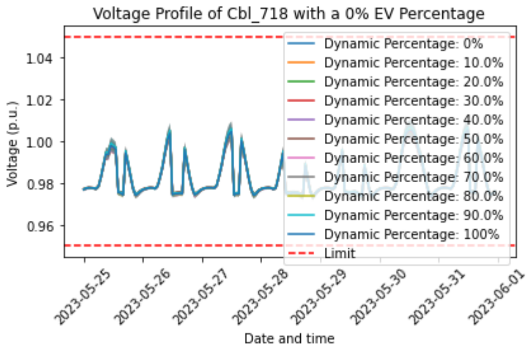

Figure B.16: With an EV percentage of 0 %.

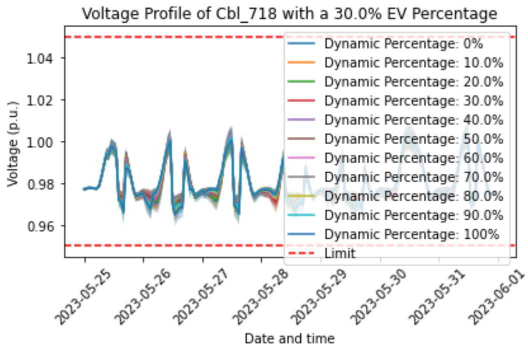

Figure B.17: With an EV percentage of 30 %.

Voltage profile of *Cbl_718* during Week 2.

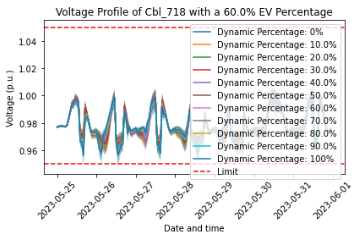

Figure B.18: With an EV percentage of 60 %.

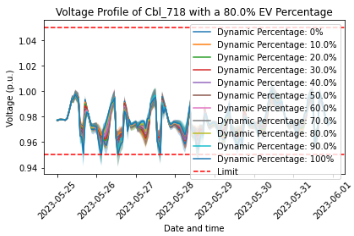

Figure B.19: With an EV percentage of 80 %.

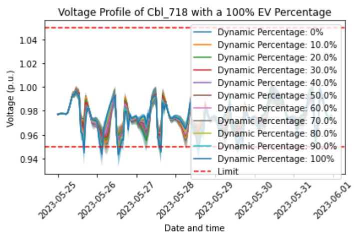

Figure B.20: With an EV percentage of 100 %.

Voltage profiles for *Cbl_718* during Week 2

B.2.2. Power

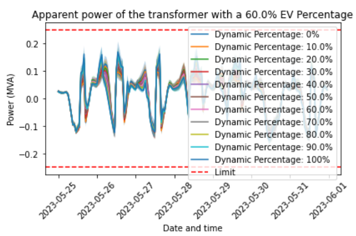

Figure B.23: With an EV percentage of 60 %.

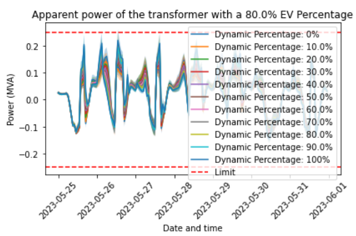

Figure B.24: With an EV percentage of 80 %.

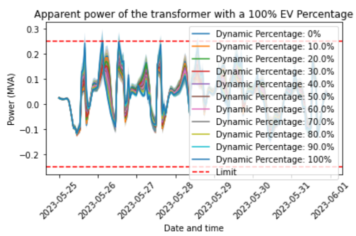

Figure B.25: With an EV percentage of 100 %.

Average power with standard deviation over the transformer for Week 2

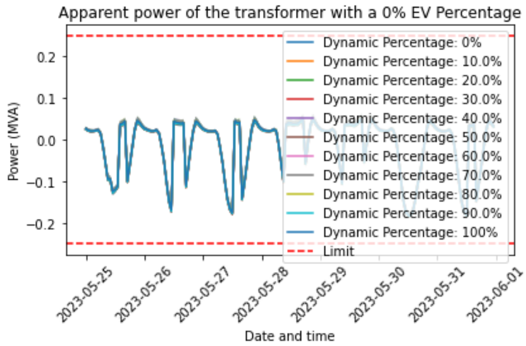

Figure B.21: With an EV percentage of 0 %.

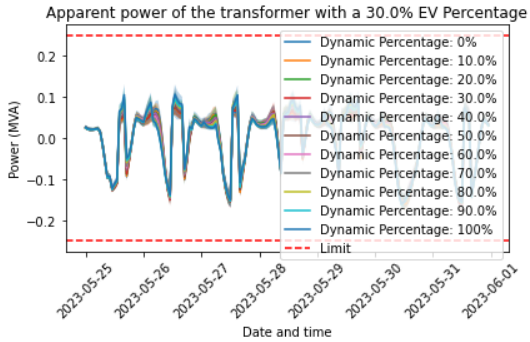

Figure B.22: With an EV percentage of 30 %.

Average power with standard deviation over the transformer for Week 2

B.3. Week 3

- Representative week: Week 3
- PV penetration: 30 %
- EV percentage: 0%, 30 %, 60 %, 80 %, and 100 %
- Dynamic percentage: 0%, 10% - 100%
- Number of runs: 50

B.3.1. Voltage

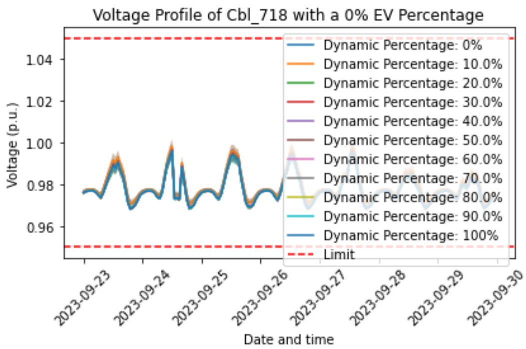

Figure B.26: With an EV percentage of 0 %.

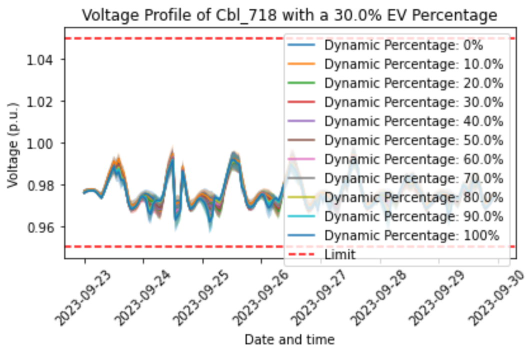

Figure B.27: With an EV percentage of 30 %.

Voltage profile of *Cbl_718* during Week 3.

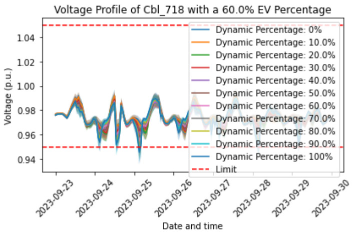

Figure B.28: With an EV percentage of 60 %.

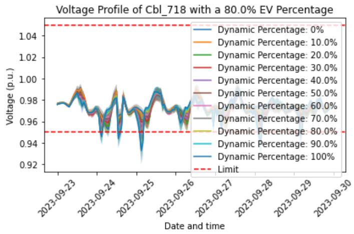

Figure B.29: With an EV percentage of 80 %.

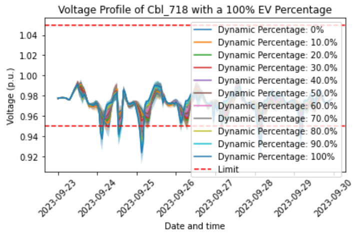

Figure B.30: With an EV percentage of 100 %.

Voltage profiles for *Cbl_718* during Week 3

B.3.2. Power

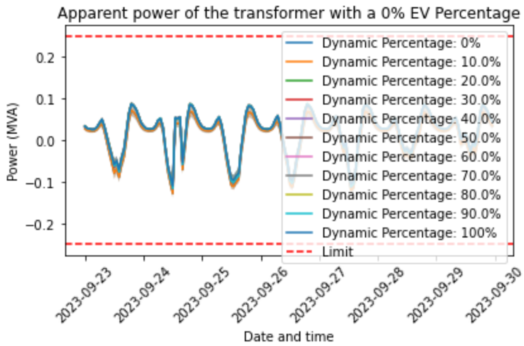

Figure B.31: With an EV percentage of 0 %.

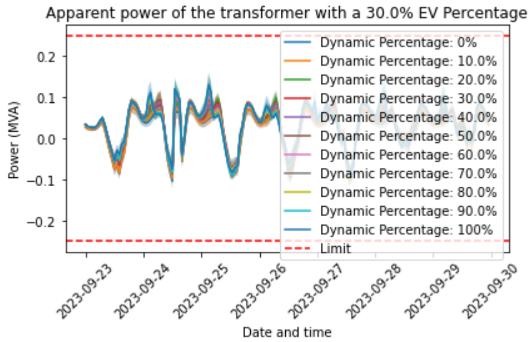

Figure B.32: With an EV percentage of 30 %.

Average power with standard deviation over the transformer for Week 3.

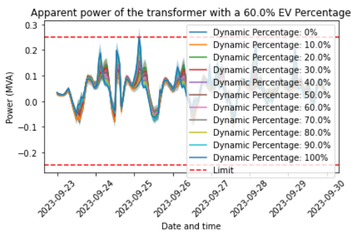

Figure B.33: With an EV percentage of 60 %.

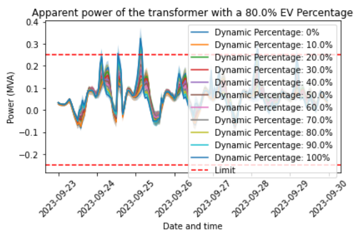

Figure B.34: With an EV percentage of 80 %.

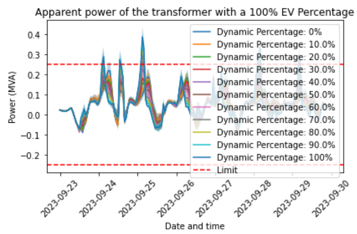

Figure B.35: With an EV percentage of 100 %.

Average power with standard deviation over the transformer for Week 3

B.4. No Solar Panels

- Representative week: Week 2
- PV penetration: 0 %
- EV percentage: 0%, 30 %, 60 %, 80 %, and 100 %
- Dynamic percentage: 0%, 10% - 100%
- Number of runs: 50

B.4.1. Voltage

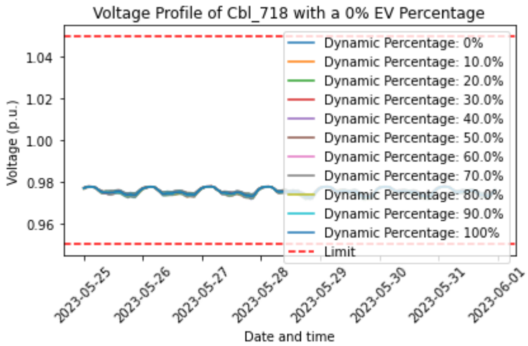

Figure B.36: With an EV percentage of 0 %.

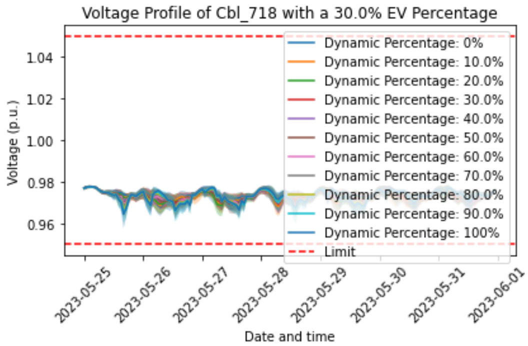

Figure B.37: With an EV percentage of 30 %.

Voltage profile of *Cbl_718* during Week 2.

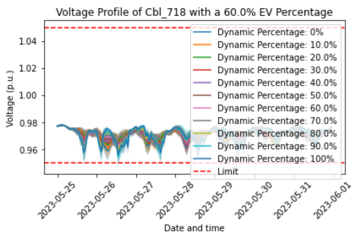

Figure B.38: With an EV percentage of 60 %.

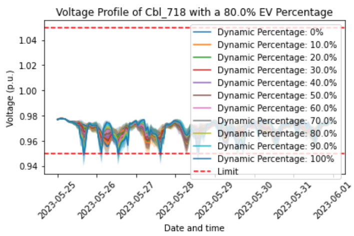

Figure B.39: With an EV percentage of 80 %.

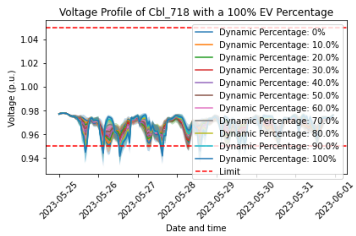

Figure B.40: With an EV percentage of 100 %.

Voltage profiles for *Cbl_718* during Week 2

B.4.2. Power

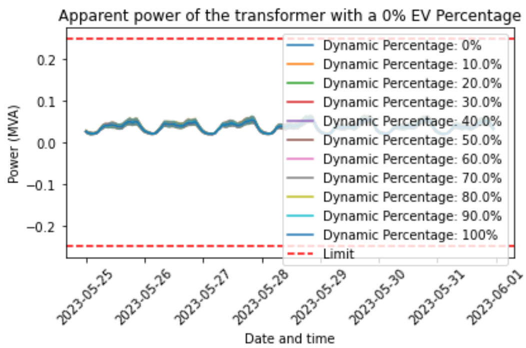

Figure B.41: With an EV percentage of 0 %.

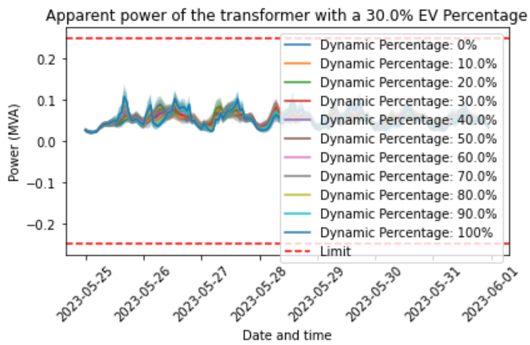

Figure B.42: With an EV percentage of 30 %.

Average power with standard deviation over the transformer for Week 2

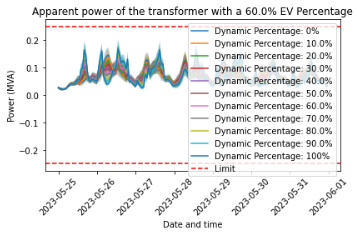

Figure B.43: With an EV percentage of 60 %.

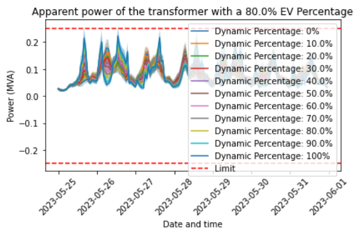

Figure B.44: With an EV percentage of 80 %.

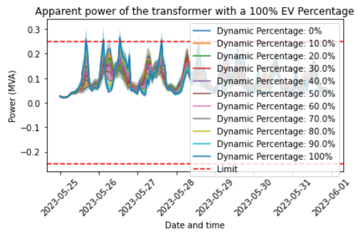

Figure B.45: With an EV percentage of 100 %.

Average power with standard deviation over the transformer for Week 2

B.5. 100% Solar Panels not Affected by Negative Market Prices

- Representative week: Week 2
- PV penetration: 100 %, not affected by negative market prices
- EV percentage: 0%, 30 %, 60 %, 80 %, and 100 %
- Dynamic percentage: 0%, 10% - 100%
- Number of runs: 50

B.5.1. Voltage

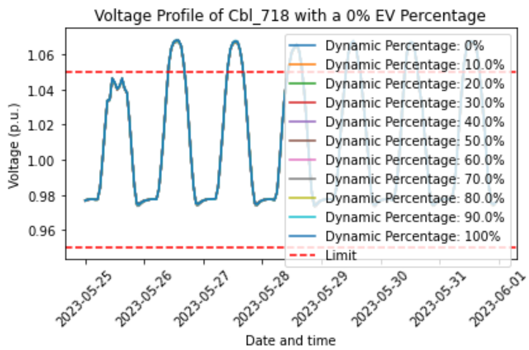

Figure B.46: With an EV percentage of 0 %.

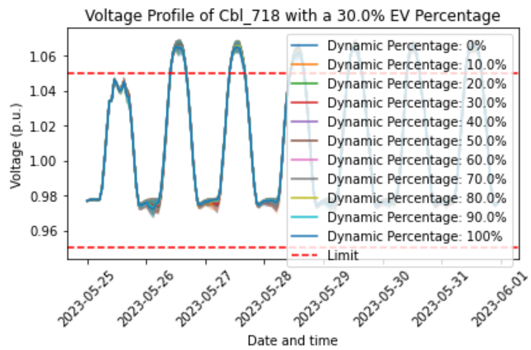

Figure B.47: With an EV percentage of 30 %.

Voltage profile of *Cbl_718* during Week 2, with 100 % PV, not affected by negative prices.

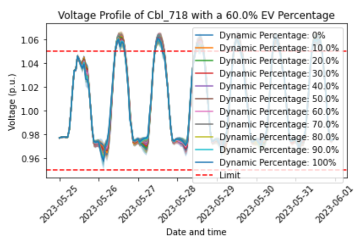

Figure B.48: With an EV percentage of 60 %.

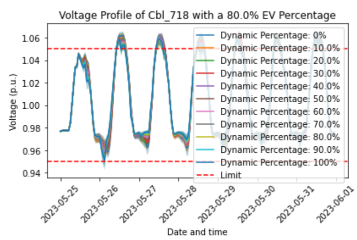

Figure B.49: With an EV percentage of 80 %.

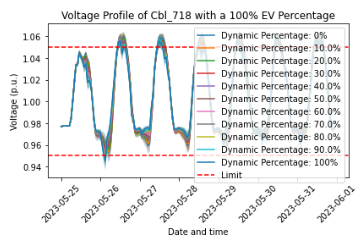

Figure B.50: With an EV percentage of 100 %.

Voltage profiles for *Cbl_718* during Week 2, with 100 % PV, not affected by negative prices.

B.5.2. Power

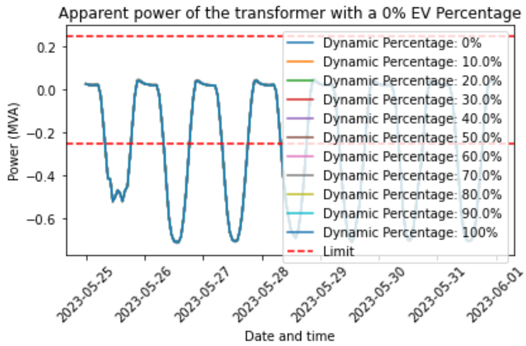

Figure B.51: With an EV percentage of 0 %.

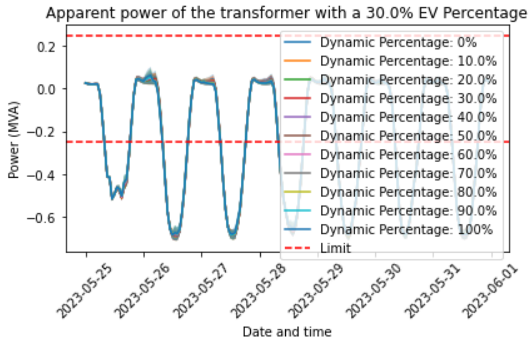

Figure B.52: With an EV percentage of 30 %.

Average power with standard deviation over the transformer for Week 2, with 100 % PV, not affected by negative prices.

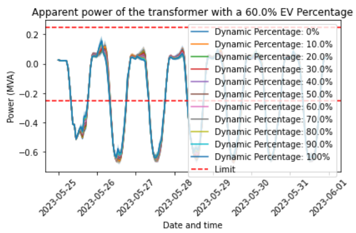

Figure B.53: With an EV percentage of 60 %.

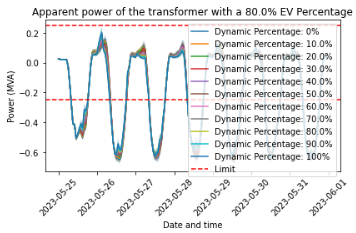

Figure B.54: With an EV percentage of 80 %.

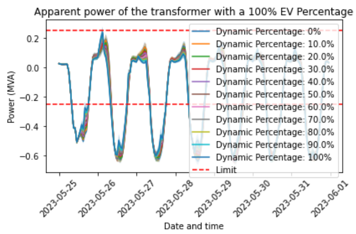

Figure B.55: With an EV percentage of 100 %.

Average power with standard deviation over the transformer for Week 2, with 100 % PV, not affected by negative prices.

B.6. 100% Solar Panels Affected by Negative Market Prices

- Representative week: Week 2
- PV penetration: 100 %, affected by negative market prices
- EV percentage: 0%, 30 %, 60 %, 80 %, and 100 %
- Dynamic percentage: 0%, 10% - 100%
- Number of runs: 50

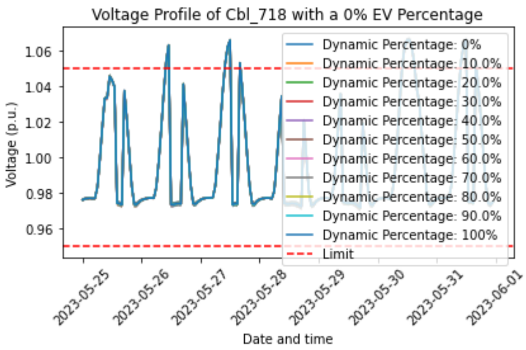

Figure B.56: With an EV percentage of 0 %.

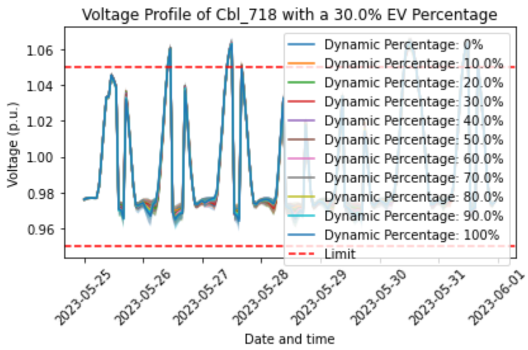

Figure B.57: With an EV percentage of 30 %.

Voltage profile of *Cbl_718* during Week 2, with 100 % PV, affected by negative prices.

B.6.1. Voltage

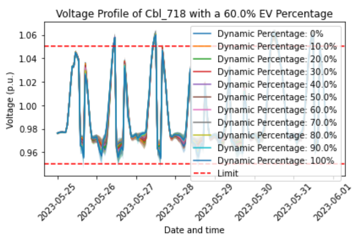

Figure B.58: With an EV percentage of 60 %.

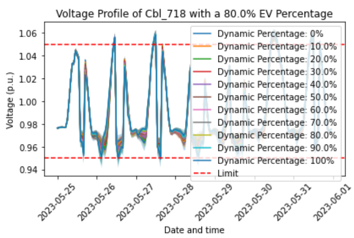

Figure B.59: With an EV percentage of 80 %.

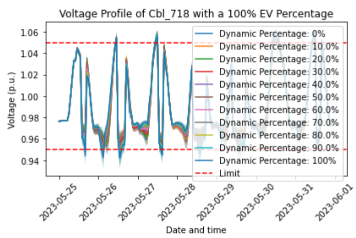

Figure B.60: With an EV percentage of 100 %.

Voltage profiles for *Cbl_718* during Week 2, with 100 % PV, affected by negative prices.

B.6.2. Power

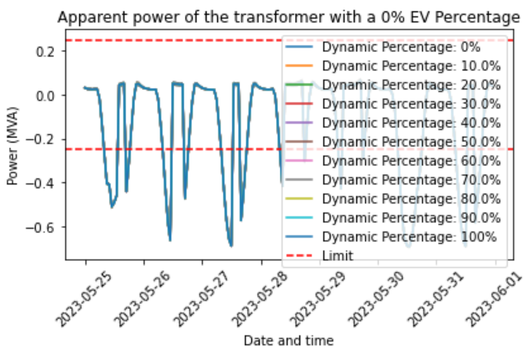

Figure B.61: With an EV percentage of 0 %.

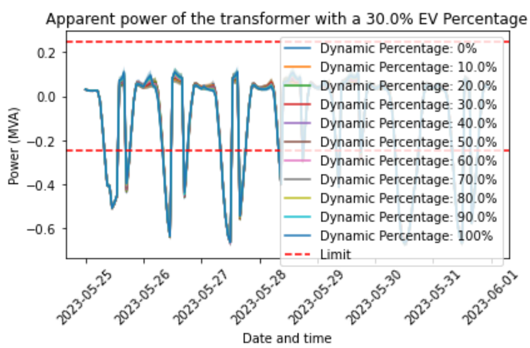

Figure B.62: With an EV percentage of 30 %.

Average power with standard deviation over the transformer for Week 2, with 100 % PV, affected by negative prices.

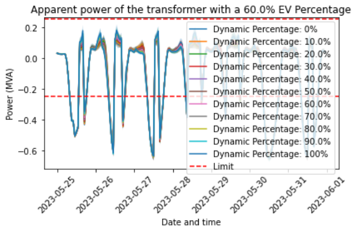

Figure B.63: With an EV percentage of 60 %.

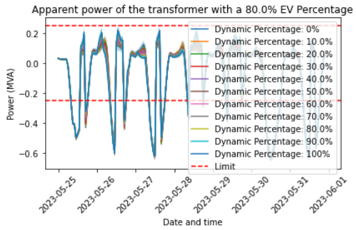

Figure B.64: With an EV percentage of 80 %.

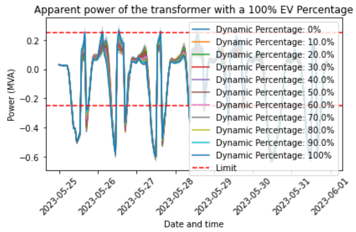

Figure B.65: With an EV percentage of 100 %.

Average power with standard deviation over the transformer for Week 2, with 100 % PV, affected by negative prices.

B.7. Extremities VS Limits

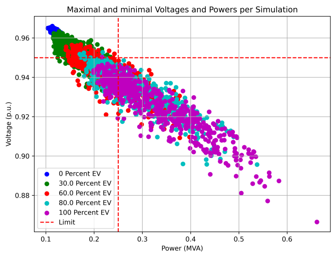

Figure B.66: Week 1, with 30 % PV

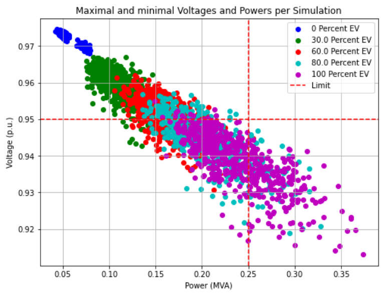

Figure B.67: Week 2, with 30 % PV

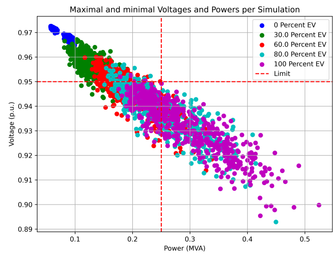

Figure B.68: Week 3, with 30 % PV

Minimal and maximal voltage and power measurements for each of the simulations.

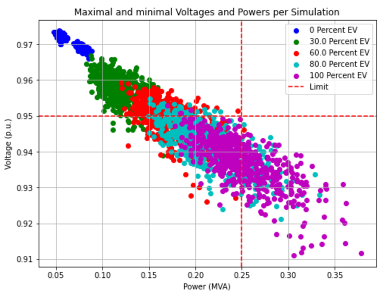

Figure B.69: Week 2, with 0 % PV

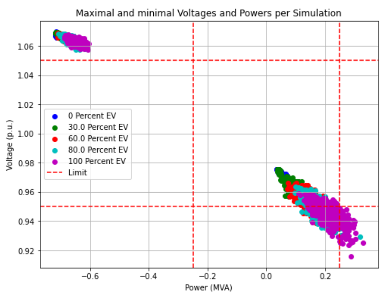

Figure B.70: Week 2, with 100 % PV, not affected by negative prices.

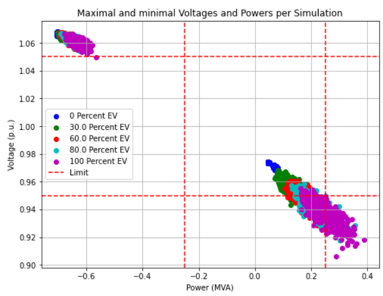

Figure B.71: Week 2, with 100 % PV, affected by negative prices.

Minimal and maximal voltage and power measurements for each of the simulations.

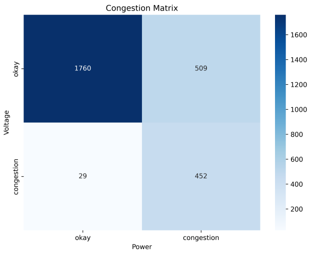

Figure B.72: Week 1, with 30 % PV

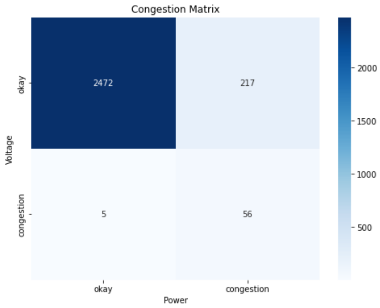

Figure B.73: Week 2, with 30 % PV

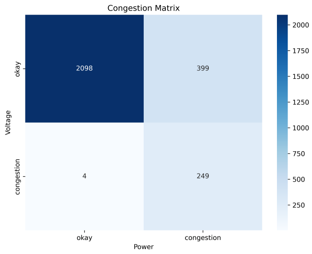

Figure B.74: Week 3, with 30 % PV

Congestion matrix.

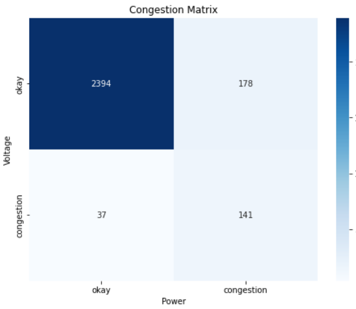

Figure B.75: Week 2, with 0 % PV

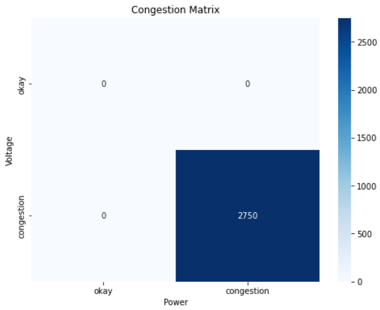

Figure B.76: Week 2, with 100 % PV, not affected by negative prices.

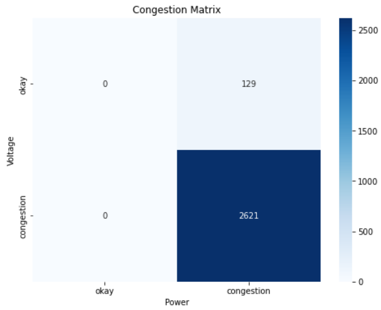

Figure B.77: Week 2, with 100 % PV, affected by negative prices.

Congestion matrix.