Alleviating low-voltage network congestion using electric vehicles and heat pumps: an agent-based modeling approach

Master's thesis Energy Science (GEO4-2510)

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1 Abstract

This thesis investigates the integration of multiple explicit and implicit flexibility incentives at the household level to identify a cost-effective solution to mitigate congestion on low-voltage (LV) networks using electric vehicles and heat pumps. Explicit flexibility allows for real-time adjustments in energy usage during periods of congestion, while implicit flexibility involves shifting demand based on price signals such as Time-of-Use tariffs and the Day-ahead market. An agent-based modeling approach is used to simulate household energy consumption patterns and responses to these flexibility incentives.

The findings showed that implicit flexibility is effective up to a 20% participation rate in reducing congestion and resulted in the highest cost savings. However, beyond this participation point effectiveness diminished eventually creating more congestion. Explicit flexibility provided more consistent congestion relief. The combination of both flexibility types enhances congestion mitigation and also increases cost savings for households compared to explicit flexibility, while comfort can be maintained using comfort limits. This integrated approach promotes a more efficient LV network system, benefiting both network operators and residents.

Contents

Acronyms

ABM Agent-Based Modelling.

COP Coefficient of Performance.

CPC Critical Peak Control.

DLC Direct Load Control.

DoD Depth of Discharge.

DSO Distribution System Operator.

EV Electric Vehicle.

HEMS Home-Energy Management Systems.

HP Heat Pump.

LV Low Voltage.

RE Renewable Energy.

SOC State of Charge.

ToU Time-of-Use.

VAT Value Added Taxes.

Nomenclature

η_{charging} Charging efficiency [%]

η_{solar} Solar efficiency [%]

A_{panel} Area of a solar panel [m^2]

C_{bat} Battery capacity [kWh]

C_{IN} Indoor thermal mass [J/K]

C_{OUT} Outdoor thermal mass [J/K]

COP Coefficient of Performance

DoD Depth of Discharge [%]

f_{r} Fraction rate conduction

$F_{agent,ev}$ Flexibility provided with electric vehicle [W]

$F_{agent,hp}$ Flexibility provided with heat pump [W]

G Solar irradiance [kW/m^2]

N_{ev} Number of houses with flexibility of electric vehicle

N_{hp} Number of houses with flexibility of heat pump

N_{panels} Number of solar panels per house

P_{charging} Charging power [W]

P_{hp} Heat pump power [W]

P_{total} Total transformer load [kW]

P_{trafo} Maximum load of the transformer [kW]

Q_{hp} Internal heat gain heating of heat pump [W]

Q_{internal} Internal heat gain appliances [W]

Q_{solar} Internal heat gain solar radiation [W]

R_{cond} Thermal resistance conduction [K/W]

R_{floor} Thermal resistance floor [K/W]

$R_{\mathrm{vent\ +\ inf}}$ Thermal resistance ventilation and infiltration [K/W]

SOC State of Charge [%]

T_{amb} Ambient temperature [°C]

T_{crawl} Crawling space temperature [°C]

$T_{\text{in, desired}}$	Desired inside temperature [°C]
T_{in}	Inside temperature [°C]
T_{out}	Building envelope temperature [°C]
T_{sink}	Sink temperature [°C]
V	Volume of the building [m^3]

2 Introduction

2.1 Problem description

The global transition from fossil fuels to renewable energy sources requires a substantial overhaul of the energy system. As households and businesses transition towards renewable electricity, the Low Voltage (LV) grid is expected to face significant challenges such as congestion and grid capacity reduction in distribution networks (Damianakis et al., 2023). Without intervention, these challenges are projected to impact approximately one and a half million small consumers by the year 2030 in the Netherlands (Actieagenda Netcongestie Laagspanningsnetten, 2024).

Electrification is one of the causes of these challenges. Households are increasingly adopting induction cooking, Electric Vehicle (EV) charging, and Heat Pumps (HPs) resulting in increased electricity consumption and peak demands (Actieagenda Netcongestie Laagspanningsnetten, 2024). This increased demand often leads to congestion, a situation wherein the supply or demand of electricity surpasses the network's capacity, particularly during peak periods of electricity demand (Verzijlbergh et al., 2014).

Another cause is the strong correlation between social routines and a morning and evening peak in electricity demand. In the morning, there is an increase in energy consumption as people wake up and use appliances, to prepare for work or school. Similarly, in the evening, there is another surge in demand as people return home and use various electrical devices. Additionally, households adhere to routines such as charging EVs after returning from work and adjusting heating devices according to school and work schedules (Hanmer et al., 2018; Zarnikau et al., 2015). These social routines lead to peak periods of energy demand in the morning and evening, potentially surpassing the network's capacity and leading to congestion.

Finally, an increase in solar power generation is anticipated, particularly on sunny summer days when the supply of solar power is much higher than electricity demand. This imbalance occurs when the supply of solar energy to the grid surpasses the grid's capacity. However, the generated energy from solar panels can only be fed back into the electricity grid if the voltage from the inverter is higher than the grid voltage. As a result, solar energy gets curtailed during over-voltage situations, preventing excess energy from being efficiently utilized (Actieagenda Netcongestie Laagspanningsnetten, 2024; Maharjan et al., 2021).

Flexibility is an important tool to effectively mitigate congestion issues on the LV grid. These incentives can encourage consumers to adjust their energy consumption in response to grid conditions. Flexibility can take various forms, including flexibility from batteries, smart charging, or direct control of HPs. The flex-pyramid of Figure 2.1 summarises the main focus of achieving flexibility, sorted from least to most impact on individuals (VREG, 2022).

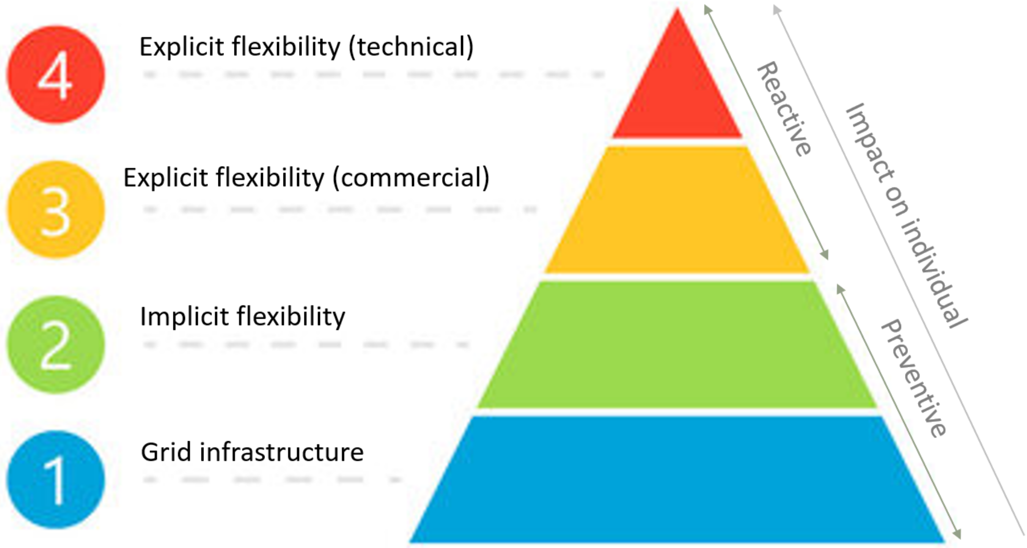


Figure 2.1: Flex-pyramid (Adapted from VREG (2022))

In the flex-pyramid model, the initial focus on achieving flexibility corresponds to the first layer, which is preventive measurements through enhanced grid infrastructure. This involves implementing various technical solutions within the grid infrastructure to enhance its resilience and adaptability. These solutions typically include upgrading transmission and distribution lines and enhancing substation capabilities.

Not all grid reinforcements can be finished on time due to the significant scale of the process. Grid reinforcements are time-consuming due to the required procedures and face challenges such as insufficient availability of materials, labor, and finances (Actieagenda Netcongestie Laagspanningsnetten, 2024).

The second layer of the flex-pyramid is referred to as implicit flexibility and can be in the form of tariffs. This type of flexibility is implicit as it influences the behavior of market participants in response to changing conditions within the market (SEDC, 2016). An example of this is Time-of-Use (ToU) tariffs, which is described in more detail in Section 3.1.1.

The last two layers of the flex-pyramid use a reactive approach and are referred to as explicit flexibility (SEDC, 2016; Freire-Barceló et al., 2022). This can be in the form of financial compensation for the usage of flexibility incentives such as Direct Load Control (DLC) and smart charging. This type of flexibility intends that it is voluntary and not mandatory, but during critical peak moments, mandatory flexibility can be used as a last resource in the form of Critical Peak Control (CPC).

2.2 Modelling approaches

In the literature, several methods to study flexibility have been used. Jin et al. (2020) identified four main modelling approaches for flexibility: centralized optimization models, game theory-based models, auction theory-based models, and simulation models.

Centralized optimization models use an objective that has to be optimized, using technical and financial constraints. An example of this is a cost-optimization model used by Wesseh and Lin (2022). The study showed that ToU pricing contributes to a reduction of peak load electricity consumption, while off-peak consumption remains stable or only has a slight increase.

Game theory-based models are a mathematical methodology used to analyze strategic interactions among participants, where decisions made by each participant are influenced by the actions of others, particularly in competitive scenarios (Tushar et al., 2018). Stute and Kühnbach (2023) used a game-theory approach to model the strategic decision-making of households regarding different ToU tariffs. The ToU tariffs caused an increase in peak demand at the individual household level but also resulted in a more evenly distributed peak load across the grid, consequently reducing the need for extensive grid expansions.

Auction theory-based models can be used to model auctions such as balancing the supply and demand of electricity. Zaidi and Hong (2017) used an auction mechanism to model energy trading between two micro-grids. The goal of an auction is to minimize costs with maximum economic efficiency.

Finally, simulation models can be used to model innovations in complex systems by exploring different scenarios and can help in understanding system behavior (Jin et al., 2020).

2.2.1 Agent-Based modelling

A simulation model used to model the impact of various flexibility incentives is through Agent-Based Modelling (ABM). An ABM is used to study complex systems by representing agents and their interactions within an environment. Wilensky and Rand (2015) describe an agent as "an autonomous individual or object with particular properties, actions, and possibly goals". An advantage of using an ABM-approach over other modelling methods is that it can model individual agents and thus represents a heterogeneous population instead of making assumptions of homogeneity (Wilensky and Rand, 2015).

When considering LV grids, ABM can be used to model the varied energy consumption patterns and responses among households in reaction to flexibility incentives and pricing signals. By using an ABM-approach, flexibility is provided in modelling different scenarios for the implications of flexibility incentives. This can be done by adjusting or modifying the agent behaviors or parameters (Mehdizadeh et al., 2022).

In the literature various ABM-approaches were used to study complex energy systems.

Van Der Kam et al. (2019) used ABM to explore the impact of different policy interventions among which financial incentives, automated smart charging, information campaigns, and social charging on EV charging patterns. Results showed that automated smart charging resulted in lower grid capacity requirements compared to the other policy interventions. A limitation of the research was that it only looked at maximizing Renewable Energy (RE) consumption and did not look specifically at mitigating congestion and peak load reduction.

Reis et al. (2018) utilized an ABM-approach to analyze energy trading dynamics within a community, focusing on end-users behaviors and demand-side flexibility in response to renewable generation and automation changes in power systems. Similarly, Nunna et al. (2016) employed an ABM to study smart micro grids, emphasizing management strategies for price-sensitive consumers.

Vellei et al. (2021) used an ABM-approach to model how individual residents interact with the thermostat based on their thermal comfort needs and presence. However, no studies were found that specifically use an ABM approach to model the flexibility of both HPs and EVs in mitigating LV congestion.

2.3 Scientific background

Several studies have been conducted on the impact of flexibility. Enrich et al. (2024) observed that ToU tariffs contributed to a 1 - 9% consumption reduction in Spain, during peak periods. Price-elasticity of households ranges between 0 and -0.4 according to Wesseh and Lin (2022), while empirical research from Khanna et al. (2016) found a price-elasticity of -0.51 in Chinese households. This means that a 1% price increase leads to a 0.51% decrease in demand. Enrich et al. (2024) stated that pre-determined pricing increases awareness and price-elasticity and that responsiveness is income-dependent.

In terms of smart charging, Sadeghian et al. (2022) highlighted its potential benefits, such as a 10% reduction in grid operational costs, a 40% decrease in renewable energy curtailment, and a 30% reduction in charging costs. Simulations by Crozier et al. (2020) showed that smart charging reduced the need for grid reinforcements from 28% to 9%. Research from Chen and Wu (2018) showed similar results, stating that 1 million EVs with smart charging in Guangzhou, China could reduce peak load by 43 to 50%. A real-world case study in Amsterdam illustrated that smart charging impacts the charging of consumers 4% of the time positively and 5% of the time negatively (Bons et al., 2020).

Moreover, a proof of concept model from Brus et al. (2023) showed that hybrid HPs significantly reduced the degree and duration of grid overload in 8 out of 9 instances of grid congestion, when DLC was implemented. Barani et al. (2023) stated that ambitious participation of DLC, of multiple appliances such as EV, HPs and refrigeration, can contribute to about 1% cost savings for households versus not introducing DLC, excluding compensation. According to Yılmaz et al. (2022), the acceptance of DLC ranges between 33 and 71%. For heat pumps, financial incentives were the factor with the highest impact, while for EVs it was the option to have an overriding option.

2.4 Research gap

While existing research has examined the impacts of individual flexibility incentives, several areas remain unexplored. Existing research has primarily focused on isolated flexibility measures, such as ToU tariffs or DLC strategies for specific appliances like EVs and HPs. However, the integrated impact of combining different types of flexibility incentives and their aggregate effects on the LV grid, particularly when considering user comfort constraints, is not well understood.

Faria and Vale (2023) has researched the technical and economic viability of flexible heat pump operations under real-time pricing, using control strategies. The findings indicate that while flexible heat pumps can offer operational cost savings and enhance demand-side management, the economic benefits are highly dependent on specific technical setups and market conditions.

Van Der Kam et al. (2019) used ABM to explore the impact of policy interventions like financial incentives and smart charging on EV charging behaviors, aligning them with renewable energy production. The study concluded that while these interventions can significantly enhance the alignment of EV charging with renewable energy availability, the effectiveness of these policies varies, with automated smart charging demonstrating the most potential. The research didn't focus on congestion mitigation and the impact of comfort constraints.

Shi et al. (2022) analyzed different HP control strategies for flexibility while remaining at a constant temperature. However, it did not examine the effects of varying the temperature within comfort limits and didn't consider costs. Srithapon and Månsson (2023) modeled the flexibility of a combination of HPs, EVs, and thermal energy storage and found that it can enhance energy flexibility while reducing operational costs. The study didn't research how it can be combined to mitigate congestion and focused solely on cost savings as a flexibility strategy.

Van Den Berg et al. (2021) investigated the impact of EV charging demand on transformers in an office area. The study highlighted that strategic placement of charging stations and utilizing the flexibility of EV demand could mitigate transformer overloads. However, the research focused on office areas and did not explore the integrated impact of multiple flexibility strategies in residential settings.

This research aims to fill these gaps by examining the integrated impact of various flexibility incentives on the LV grid while considering user comfort constraints. By investigating how different strategies can be combined to optimize both flexibility and economic benefits, my study provides a comprehensive understanding of the potential of alleviating grid congestion.

2.5 Research question

This observation mentioned in Section 2.4 prompts the following research question:

How can the integration of multiple explicit and implicit flexibility incentives at the household level effectively mitigate congestion on low voltage networks while optimizing costs for both the network operator and residents?

This main research question is broken down to the following sub-questions:

- *How can explicit flexibility for electric vehicles and heat pumps be integrated effectively, while accounting for constraints like minimum driving distance and temperature, to minimize their impact on the grid?*
- *How do different combinations of implicit and explicit flexibility incentives interact and complement each other in mitigating congestion on low voltage networks?*
- *What are the optimal set-points and recommendations for implementing a combination of implicit and explicit flexibility incentives to effectively alleviate congestion on low voltage networks while optimizing costs for both the network operator and residents?*

The first question sub-question focuses on the practical implementation of explicit flexibility incentives. In this question, the impact of comfort constraints will be examined by comparing scenarios with and without the constraints.

In the second sub-question, the synergistic effects of various incentive mechanisms will be explored, which is crucial for understanding the overall effectiveness of congestion mitigation strategies. During this research question, combinations of both implicit and explicit will be examined and compared to see the impact of different combinations of these flexibility incentives.

The final sub-question focuses on actionable insights that can inform decision-making for both network operators and residents. Specifically, the aim is to identify the most cost-effective solution with minimal congestion.

2.6 Research Scope

The scope of the research is the LV grid in the Netherlands. This will consist of a single transformer and multiple households connected to the transformer, representing a typical Dutch neighborhood. Data from Distribution System Operator (DSO) Alliander is used for the model. The households can provide flexibility through EVs and HPs when installed. By integrating adoption rates of EVs and HPs, different years can be simulated by using the expected adoption rates of that particular year. The goal of the model is to make it adaptable to different scenarios. In this research, the adoption rates of 2030 are used for analysis and the climate year of 2023 is used.

3 Literature review

In this section, the concepts of implicit and explicit flexibility that are the foundation of this research will be explained in more detail based on the literature review.

3.1 Implicit Flexibility

An electricity bill in the Netherlands is composed of three elements: energy costs, taxes, and grid fees, from which the latter accounts for around 25% of the total price (Rodriguez et al., 2022). Grid fees are used to finance the capital and operational costs of the electricity network. In exchange for a fixed tariff, the grid operator ensures that there is always enough capacity available to serve the peak load of the connection (Alliander, nd). Under the traditional flat-rate tariff currently used in the Netherlands, there is no incentive to reduce electricity usage during peak periods (Yang et al., 2013). Implicit flexibility can be used to incentivize behavior change in energy consumption.

3.1.1 Time-of-Use tariffs

A ToU tariff is a grid fee, which varies during the day based on grid availability and is a form of implicit flexibility. The goal of ToU tariffs is to encourage households to reduce their electricity consumption during periods of high demand and limited grid availability, typically by raising prices during peak hours and lowering them during off-peak times. Conversely, during periods of low demand and sufficient grid supply, prices are decreased to incentivize consumption (Nicolson et al., 2018). Examples of ToU tariffs are visualized in Figure 3.1.

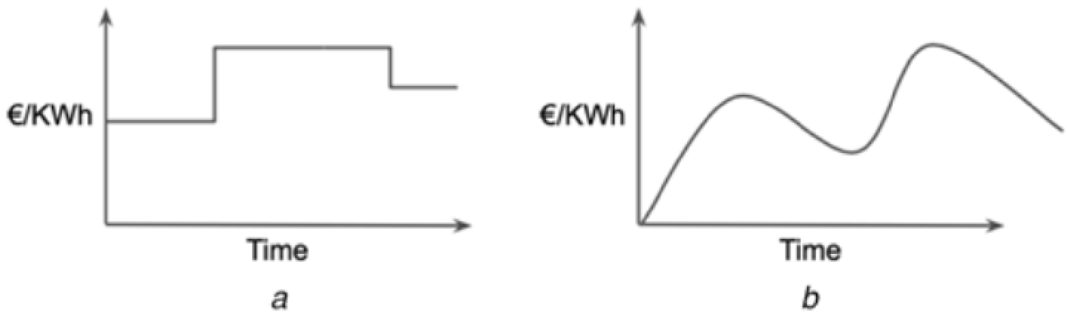


Figure 3.1: Static ToU (a) and Real-time ToU tariff (b) (Alliander, nd).

There are many different types of ToU tarrifs, some examples include (Nicolson et al., 2018):

- Static ToU: Prices follow a consistent pattern during the day, with fixed fluctuations. For example a fixed increase in price during the morning and evening, with a lower price during the remaining hours.

- Dynamic ToU: Fixed prices, with fluctuating times at which the prices are applied. For example a high, medium, and low price tariff for fluctuating times of the day.
- Real-time ToU: Fluctuating prices for fluctuating times of the day. Prices can vary hourly based on wholesale prices or grid availability.
- Critical peak ToU: Prices typically remain stable for the majority of the time, resembling a flat-rate tariff. However, occasionally prices are increased during critical peaks, which are communicated to customers in advance.

To effectively optimize the efficiency and sustainability of ToU tariffs different constraints to the implementation of ToU are needed. Wesseh and Lin (2022) stated that ToU models mainly used the following three constraints:

- Mutual benefit of ToU tariffs: The end result of ToU tariffs has to be beneficial for both consumers and producers.
- Demand constraint: The ToU tariffs lead to more stability of the LV grid.
- Renewable energy integration constraint: ToU effectively promotes the utilization of RE sources like wind and solar.

These constraints underscore the importance of carefully designing and implementing ToU tariffs to achieve optimal outcomes for all stakeholders involved.

3.2 Explicit flexibility

Explicit flexibility refers to a situation where a consumer is committed to providing flexibility in return for a financial reward (Rodriguez et al., 2022). Explicit flexibility can be delivered through various device types, yet with the rapid expansion of electrification, particularly in EVs and HPs, emphasis will be placed on these two technologies. In this thesis also referred to as smart charging and DLC.

3.2.1 Smart Charging

Sales of EVs are growing rapidly due to among others increasing environmental awareness, advancements in technology, and government incentives (ElaadNL, 2021). An outlook of expected EV and charging stations is visualized in Figure 3.2.

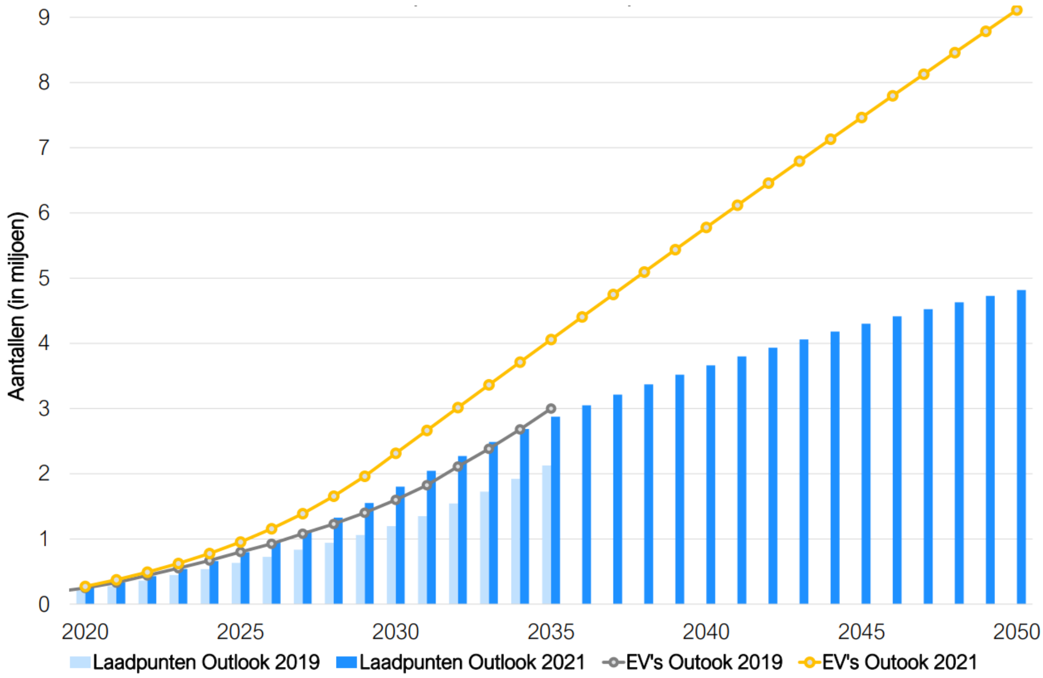


Figure 3.2: Projected growth of EVs and charging points in the Netherlands (2020-2050). Yellow and grey lines represent EV outlooks for 2021 and 2019. Blue and light blue bars show charging point outlooks for 2019 and 2021. Y-axis shows numbers in millions (ElaadNL, 2021).

Smart charging can offer a solution for the increasing grid impact of EVs and RE. Smart Charging involves shifting charging, through direct control, from peak loads to times of the day when there is sufficient capacity on the electricity grid (Daina et al., 2017). While smart charging typically extends charging time, it can usually be implemented without the EV driver noticing, as parking time usually exceeds charging time. In the Netherlands, for instance, the average car is stationary 95% of the time (Flexpower, 2022).

In the literature, a distinction is made between centralized and decentralized smart charging (Daina et al., 2017). In a centralized framework, EV load aggregators serve as middlemen between electric vehicle owners and grid markets. A typical approach to do this is by direct control without the involvement of EV owners (Galus et al., 2019). The aggregator has to identify in such case the charging requirements of the EV owner. Sundström and Binding (2011) highlighted two key requirements in the context of EV charging: the energy needed to reach a desired distance upon completion of charging, and the time by which the charging process must be completed.

In the decentralized framework EV owners adapt their charging behavior based on market information (Daina et al., 2017; Galus et al., 2019). An example of this is ToU pricing as described in Section 3.1.1.

One smart charging approach involves implementing load shedding with a guaranteed capacity of 4kW during peak hours. A downside of this is that after load shedding, a new power peak can be formed when the charging restriction is revoked, as can be seen in Figure 3.3 (Flexpower, 2022).

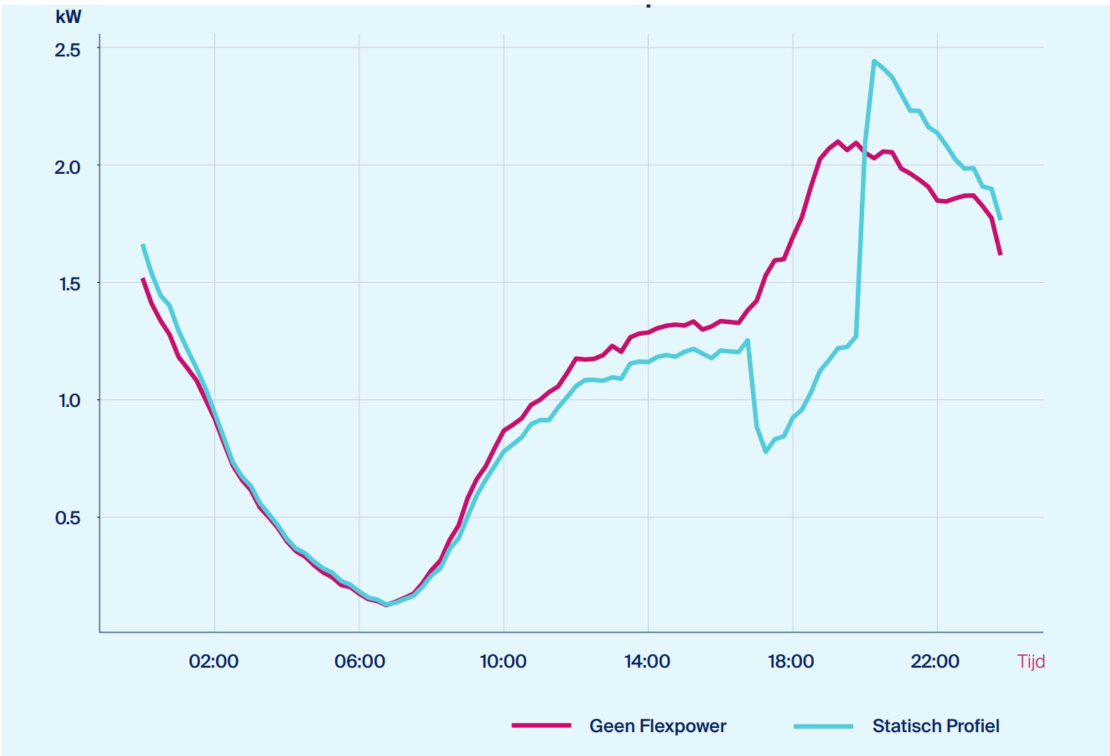


Figure 3.3: Charging using load shedding can lead to a new peak load after charging restrictions are revoked (blue line). The graph compares load profiles with (red line) and without (blue line) flexibility over 24 hours (Flexpower, 2022).

To solve this EV chargers have to be turned on and off in different time steps. As a result, the charging sessions extend further into the night, creating a flatter overall profile and utilizing the available power for the charging stations more effectively compared to if no smart charging is applied.

3.2.2 Direct Load Control Heat pumps

Similar to EVs, sales of HPs are expected to grow rapidly, as can be seen in figure 3.4.

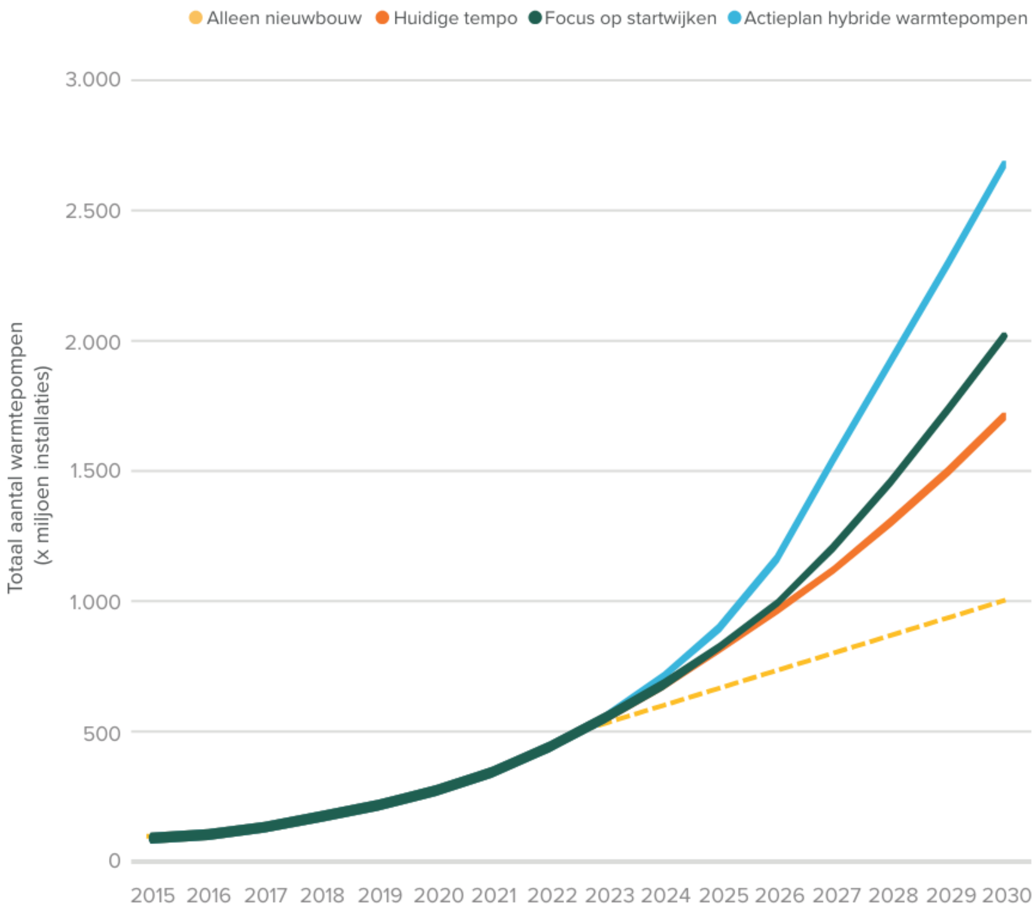


Figure 3.4: Annual heat pump sales in the Netherlands from 2015 to 2022 with forecasts until 2030. The lines represent different scenarios: new buildings only (yellow), current pace (orange), focus on starting districts (green), and action plan for hybrid heat pumps (blue). The y-axis shows the total number of heat pump installations in millions (DNE Research, 2021)

The surge in popularity in HPs provides opportunities for leveraging flexibility. Yılmaz et al. (2022) identified three different types of flexibility provided by HPs:

- Manually: households shift the device on and off manually, which requires significant behavior changes.
- Home-Energy Management Systems (HEMS): automated control of the device which involves setting up rules to operate based on factors such as time of day, energy prices, or user preferences.
- DLC: is typically implemented through agreements between companies and consumers who allow remote control of their devices in exchange for lower rates.

The advantage of DLC is that it can reduce peak loads more accurately, as well as make it effortless for households. While HEMS systems also collect data on energy usage within a household, the scope is typically limited to the devices and appliances connected to the system, while DLC can optimize the system more holistically using data from participating households (Goulden et al., 2018).

Shi et al. (2022) conducted a comparison of various HP control strategies, specifically focusing on peak shaving and power flow control, while remaining thermal comfort. The peak shaving strategy requires no coordination between households and turns the HP off when the baseload of a household is higher than a certain threshold value. During the power flow control strategy, the DSO operator dispatches the HPs of multiple households to find the optimal solution. The results can be seen in Figure 3.5.

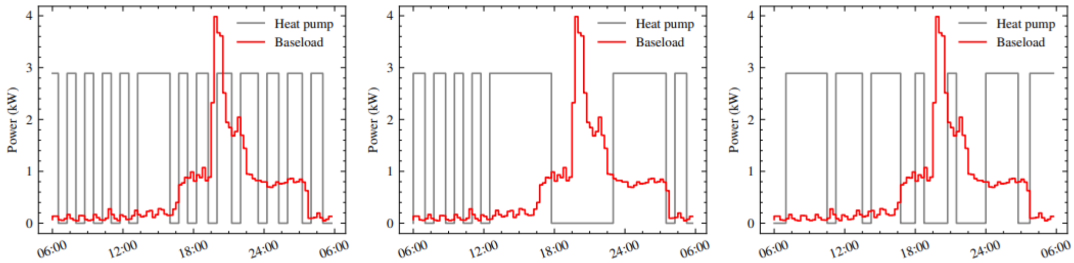


Figure 3.5: Heat pump profile compared to baseload. From left to right: reference scenario, peak shaving, and power flow control (Shi et al., 2022)

From Figure 3.5 can be concluded that the peak shaving strategy forces the HP to be turned off during a high baseload while maintaining a level of thermal comfort by staying on longer before and after the peak load. The power flow control strategy also results in lower HP energy consumption during peak moments. This is compensated for during the morning when the baseload consumption is negligible.

The peak shaving scenario resulted in a 2% increase of HP-hosting capacity compared to 49% in the reference scenario. The power flow control strategy resulted in 100% hosting capacity without causing grid congestion, an increase of 51% (Shi et al., 2022). The power flow control strategy however requires more advanced real-time smart meters and forecast algorithms, compared to peak shaving.

3.2.3 Critical Peak Control

CPC is a type of explicit flexibility which applies DLC during critical peak moments (Aghaei and Alizadeh, 2013). This can be achieved by taking control of a large number of electrical appliances while maintaining a level of comfort. Wang and Li (2016) defined a critical peak as an event where electricity consumption is exceptionally high for a certain amount of time. By applying much higher prices during critical peaks, consumers can be stimulated to reduce energy consumption during these periods or potentially make dispatch mandatory for appliances with DLC.

4 Methodology

This research investigates the integration of multiple explicit and implicit flexibility incentives at the household level to address congestion mitigation on low-voltage networks. The methodology to explore these aspects is structured around the three sub-questions outlined in Section 2.5. The following sections describe the methodology, beginning with a simplified overview of the model in Section 4.1.

4.1 Simplified model overview

A simplified overview of the model is visualized in Figure 4.1.

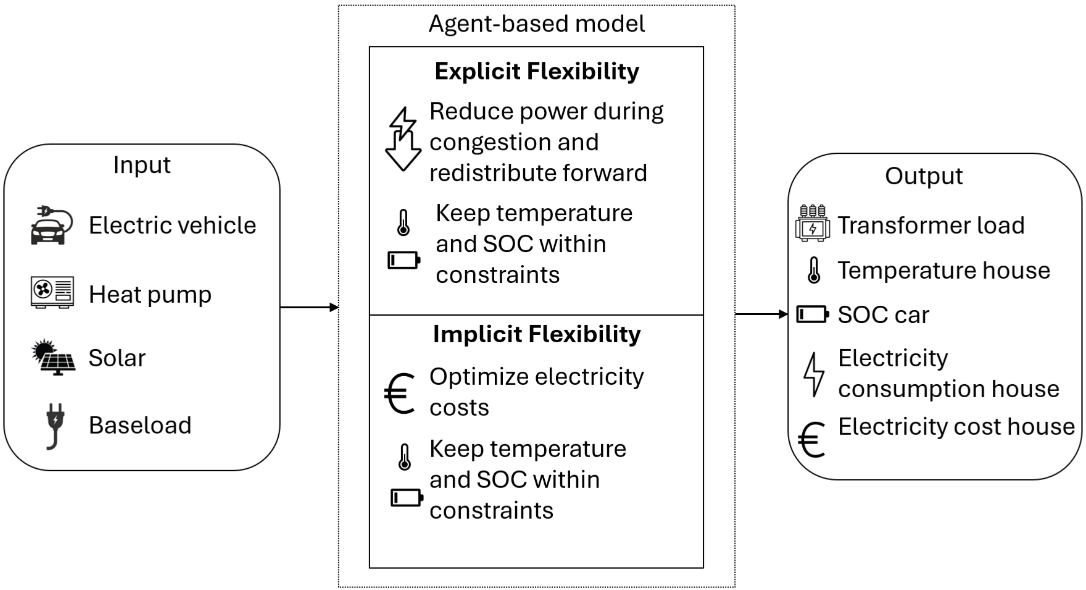


Figure 4.1: Simplified model design.

The model is constructed as an ABM using Python Mesa, comprising 300 individual 'household agents' and a single 'transformer' agent. Each household agent has a unique energy consumption pattern, which includes a baseload profile, and when adopted, a HP profile, EV charging profile, and a solar profile. These profiles are generated in 15-minute intervals over a full year (detailed descriptions of these profiles are provided in Sections 4.3, 4.4, and 4.5). The transformer agent calculates the total load by summing all individual energy consumption patterns. The transformer experiences congestion when the total load exceeds its maximum capacity.

This model addresses the three sub-questions. First, it demonstrates how explicit flexibility systems for EVs and HPs can be integrated effectively considering minimum driving distance and temperature, addressing the first sub-question. Explicit flexibility is achieved by adjusting the energy consumption profiles of EVs and HPs during periods of congestion. The model limits flexibility with the constraints of a minimum State of Charge (SOC) for EVs and minimum temperature for HPs, thereby minimizing the impact on the grid while maintaining comfort for household agents. This is explained more in detail in Section 4.6.

Second, the model demonstrates how combinations of implicit and explicit flexibility incentives can interact and complement each other in mitigating congestion, addressing the second research sub-question. Implicit flexibility is achieved through optimization based on prices, explained in more detail in Section 4.7. By modelling scenarios where implicit flexibility is applied first, followed by explicit flexibility during periods of congestion, the model allows for a comparison of the individual and combined effects of implicit and explicit flexibility on grid stability and costs.

Third, the model helps to identify the optimal set-points and recommendations for implementing a combination of implicit and explicit flexibility incentives, addressing the third research sub-question. By simulating various scenarios, the model offers insights into the most effective strategies for implementing flexibility through EVs and HPs, ensuring a balance between cost savings and grid stability.

4.2 Detailed model overview

Building on the simplified model, a more detailed model design is illustrated in Figure 4.2. This figure highlights the steps performed by the transformer agent in green and those performed by the household agents in yellow.

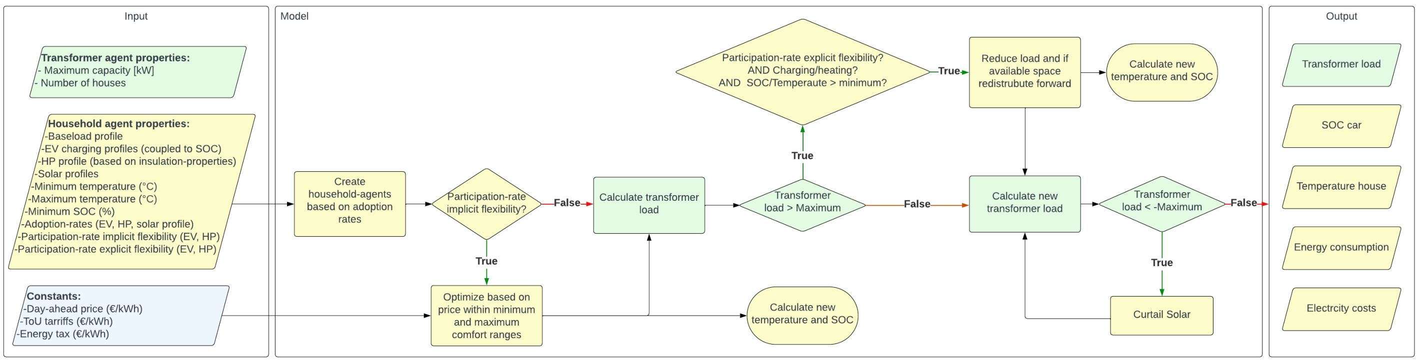


Figure 4.2: Detailed overview of the final model design, highlighting the steps performed by the transformer agent in green and those performed by the household agents in yellow.

Initially, household agents are created based on adoption rates, generating baseload, solar, EV, and HP profiles for each agent. If agents have a positive participation rate for implicit flexibility, their HP and/or EV profiles are re-generated based on price optimization. For EVs, charging is constrained to periods when the vehicle is connected to a charging station, ensuring a 100% SOC by the end of the session. For HPs, the temperature is maintained within the specified minimum and maximum temperature.

The transformer agent calculates the total load by summing all individual profiles from each household agent. If the transformer load exceeds the maximum power capacity, explicit flexibility is applied for agents with a positive participation rate for explicit flexibility. For EVs, explicit flexibility can only be applied when the vehicle is connected to a charging station and the SOC is above the minimum required level. Similarly, for HPs, flexibility can be applied as long as the temperature remains above the minimum temperature. If these conditions are not met, explicit flexibility cannot be applied to the respective agent. The power for all agents applying flexibility is reduced, and the reduced power is redistributed while preventing new congestion. New temperature and SOC values are calculated based on the adjusted profiles.

Finally, the new transformer load is recalculated. If the load exceeds the minimum capacity, solar panels for each agent will be curtailed. The model provides outputs including transformer load, costs, SOC, temperature, and energy profiles.

4.3 Heat pump

To generate a profile of a heat pump, the heat demand of a house is needed. This is generated by calculating the temperatures and heat losses of a building, using the method described in Koene et al. (2022) and Koene and Eslami-Mossallam (2023). The building model consists of two thermal masses and four thermal resistances and is visualized in Figure 4.3.

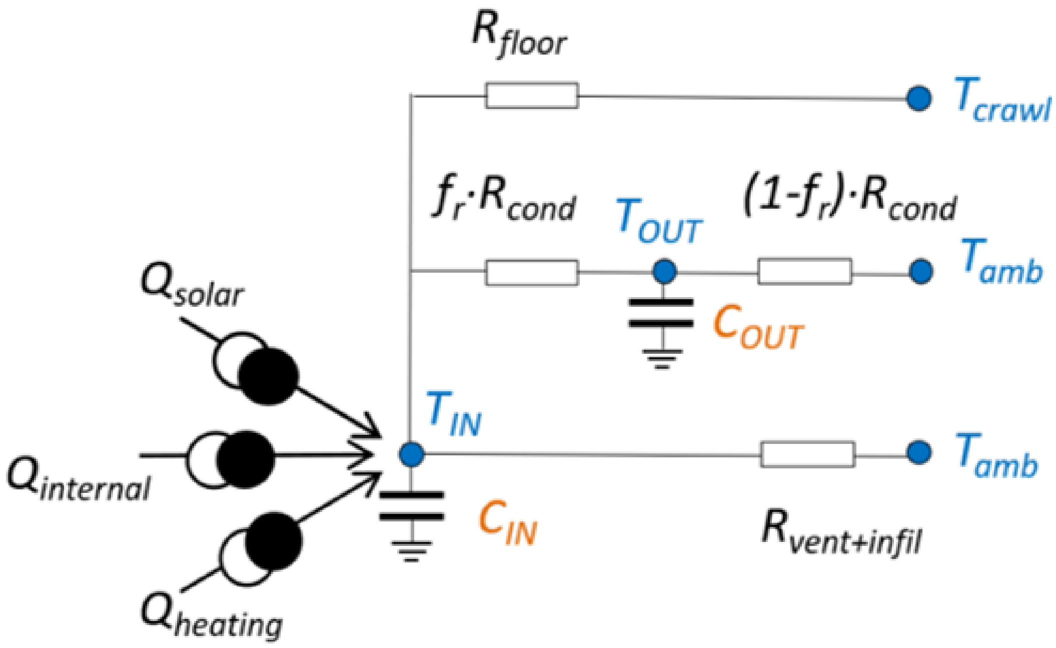


Figure 4.3: Visualization of thermal model used for a house, showing how temperatures, heat flows, and thermal resistances interact within the system (Koene et al., 2022).

4.3.1 Building model parameters

This section describes the parameters used as input for the building model described in Figure 4.3.

The building model has two thermal masses C_{IN} and C_{OUT}. C_{IN} [J/K] is the thermal mass of the indoor area, furniture, and a few centimeters of the walls, roof, and floor's inner layer. C_{OUT} [J/K] is the remaining part of the building envelope, which is found to be three times larger than C_{OUT} (Koene et al., 2022). C_{IN} and C_{OUT} is calculated using the following equations:

$$C_{IN} = (0.055 \cdot V + 0.8) \cdot 10^6 \tag{4.1}$$

$$C_{OUT} = 3 \cdot C_{IN} \tag{4.2}$$

V [m^3] is the Volume of the building, which is assumed to be a random value between 380 and 420 m^3 for each house (Alliander, nd).

C_{IN} and C_{OUT} are dependent on each other through conduction between the inside and outside of the building through the windows, roof and walls, represented as thermal resistance R_{cond} [K/W]. R_{cond} is assumed to be a random value in the range 0.002 - 0.03

K/W for each house, based on houses built in 1970 with different sizes and levels of insulation (Alliander, nd).

The thermal resistance of the floor R_{floor} is set as a random value between 0.003 and 0.07 K/W and for the thermal resistance of infiltration and ventilation $R_{\text{vent + inf}}$ a random value in the range 0.01 and 0.03 K/W is used (Alliander, nd). The method used to calculate the individual thermal resistance of each house is described in Appendix A.1.

f_{r} represents the fraction rate between heat losses from C_{IN} to C_{OUT}, which is 0.35 (Koene and Eslami-Mossallam, 2023). This is used to calculate which fraction of heat losses from R_{cond} is between C_{IN}, C_{OUT} and ambient.

The internal heat gain of the building consists of three factors Q_{internal}, Q_{solar} and Q_{hp}.

Q_{internal} [W] is the internal heat gain of the building, caused by appliances, lighting, and residents. This is assumed to remain constant at 5 W/m^2 floor area throughout the year (Koene et al., 2022).

Q_{solar} [W] is the internal heat gain through solar radiation. For simplicity, this factor is assumed to be zero, as it depends on many factors such as window area, angle of the sun, solar radiance, and cloud coverage. This will result in a higher energy usage of the heat pumps.

Q_{hp} [W] is the internal heat gain through the heating of a full-electric heat pump. The heat input of the heat pump is calculated by calculating how much heat is required to bring the building back to the desired temperature.

4.3.2 Temperatures

The building model can be written using Equation 4.3 and 4.4:

$$C_{\text{in}}\frac{dT_{\text{in}}}{dt} = \frac{1}{R_{\text{floor}}}(T_{\text{crawl}} - T_{\text{in}}) + \frac{1}{f_r \cdot R_{\text{cond}}}(T_{\text{out}} - T_{\text{in}}) + \frac{1}{R_{\text{vent+infil}}}(T_{\text{amb}} - T_{\text{in}}) + Q_{\text{internal}} \tag{4.3}$$

$$C_{\text{out}}\frac{dT_{\text{out}}}{dt} = \frac{1}{f_r \cdot R_{\text{cond}}}(T_{\text{in}} - T_{\text{out}}) + \frac{1}{(1-f_r) \cdot R_{\text{cond}}}(T_{\text{amb}} - T_{\text{out}}) \tag{4.4}$$

T_{in} is the inside temperature of the building, which was assumed to be 19°C as an initial value. T_{out} is the temperature of the building envelope. For the initial value, it was assumed that the building was in steady-state, calculated using Equation 4.5.

$$T_{\text{out}} = T_{\text{amb}} + \frac{(1-f_r) \cdot R_{\text{cond}}}{(1-f_r) \cdot R_{\text{cond}} + f_r \cdot R_{\text{cond}}} \cdot (T_{\text{in}} - T_{\text{amb}}) \tag{4.5}$$

T_{amb} represents the ambient temperature, as reported by KNMI (2024). The data was sourced from the De Bilt weather station, using hourly observations from 2023, which were then interpolated to 15-minute intervals. T_{crawl} is the crawling space temperature which is assumed constant at 12 °C (Koene et al., 2022).

Finally, Equation 4.3 and 4.4 could be rewritten using the forward difference method to calculate the inside and envelope temperature for each time step i, using Equation 4.6 and 4.7.

$$\begin{aligned} T_{\text{out}[i]} = T_{\text{out}[i-1]} &\left(1 - \frac{\Delta t}{C_{\text{out}}}\left(\frac{1}{f_r \cdot R_{\text{cond}}} + \frac{1}{(1-f_r)\cdot R_{\text{cond}}}\right)\right) \\ &+ \frac{\Delta t}{C_{\text{in}}}\left(\frac{1}{f_r \cdot R_{\text{cond}}} \cdot T_{\text{in}[i-1]} + \frac{1}{(1-f_r)\cdot R_{\text{cond}}} \cdot T_{\text{amb}[i-1]}\right) \end{aligned} \tag{4.6}$$

$$\begin{aligned} T_{\text{in}[i+1]} = T_{\text{in}[i]} &\left(1 - \frac{\Delta t}{C_{\text{in}}}\left(\frac{1}{R_{\text{floor}}} + \frac{1}{f_r \cdot R_{\text{cond}}} + \frac{1}{R_{\text{vent\_inf}}}\right)\right) \\ &+ \frac{\Delta t}{C_{\text{in}}}\left(\frac{1}{R_{\text{floor}}} T_{\text{crawl}} + \frac{1}{f_r \cdot R_{\text{cond}}} T_{\text{out}[i]} + \frac{1}{R_{\text{vent+infil}}} T_{\text{amb}[i]} + Q_{\text{internal[i]}}\right) \end{aligned} \tag{4.7}$$

Δt is in this case 900 seconds (15 minutes).

The inside temperature (T_{in}) allows for the calculation of the necessary heat input from the heat pump (Q_{hp}) [W] to restore the temperature to the desired level, in this case 19 °C. For each time step, this was calculated using Equation 4.8.

$$Q_{hp[i]} = (T_{in,desired} - T_{in[i]}) \cdot \frac{C_{\text{in}}}{\Delta t} \tag{4.8}$$

The inside temperature could then be updated using Equation 4.9.

$$T_{in[i]} = T_{in[i]} + Q_{hp[i]} \cdot \frac{\Delta t}{C_{\text{in}}} \tag{4.9}$$

4.3.3 Power Heat Pump

It is assumed that all HPs are fully electric, air-sourced, and modulating. Additionally, the heat pumps are utilized exclusively for heating purposes, with no cooling functionality.

The efficiency of these HPs depends on the temperatures and heat transfer conditions at both the heat source and the heat sink, influenced by the pump's technical properties and weather conditions. Ruhnau et al. (2019) used quadratic regression to find Equation 4.10 for the Coefficient of Performance (COP) under different temperature conditions:

$$\text{COP} = 6.09 - 0.09 \cdot \Delta T_{\text{sink-amb}} + 0.0005 \cdot \Delta T_{\text{sink-amb}} \tag{4.10}$$

$\Delta T_{\text{sink-amb}}$ is the difference between the sink temperature of the central heating system and the ambient temperature. The sink temperature is assumed to be 55°C for all buildings, corresponding to a medium temperature central heating system (Alliander, nd). The resulting COP of the HP under different ambient temperatures can be seen in Figure 4.4.

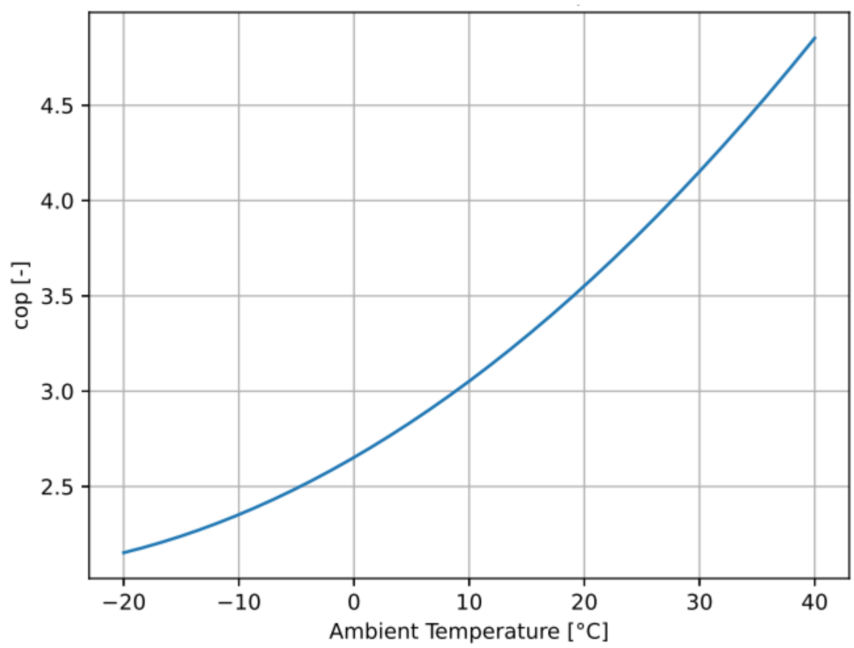
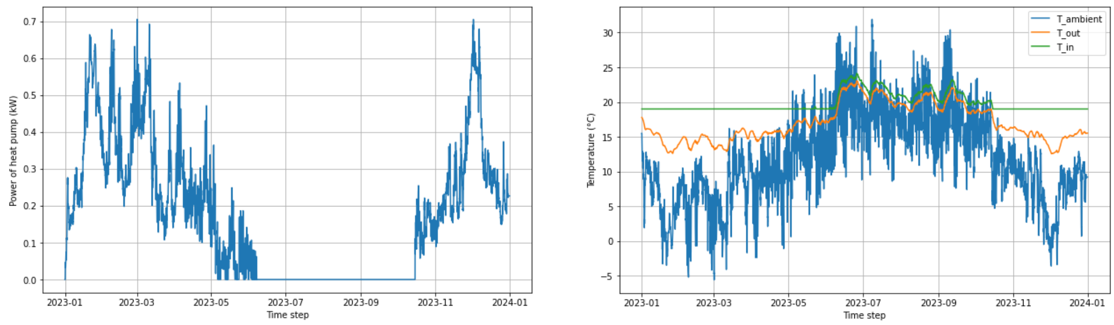


Figure 4.4: The coefficient of performance of the heat pump as a function of ambient temperature.

The COP is used to calculate the power of the HP [W] for each time step using Equation 4.11.

$$P_{hp}(t) = \frac{Q_{hp}(t)}{COP} \tag{4.11}$$

The resulting HP profile and temperatures of a single house are visualized in Figure 4.5.



(a) Heatpump profile.

(b) Temperature variation over time.

Figure 4.5: Heatpump and temperature profile of a house for a full year.

The temperature will be maintained at 19°C unless it naturally increases, as no cooling is assumed. The results were compared with Matthijssen et al. (2022) and simulated HP-profiles from Alliander (nd), which showed similar results.

4.4 Electric Vehicle

To acquire the electric vehicle loads, the load profile generator from ElaadNL (nd) was used. A total of 100 different charging profiles for home charging stations, each with a maximum power of 11 kW, were utilized. The data contained both the power of each time step and the arrival and departure times of the EV. In the generator, the EV starts charging immediately when connected to a charging station.

4.4.1 Battery size

The battery size (C_{bat}) of each car was determined using the following Equation 4.12, based on the assumption that the car traveled the maximum possible distance during its longest charging session:

$$C_{\text{bat}} = \frac{\sum_{t=1}^{T_{max}} P_{charge}(t) \cdot \Delta t \cdot \eta_{\text{charging}}}{\text{DoD}} \tag{4.12}$$

where:

- C_{bat} is the battery capacity [kWh].
- $\sum_{t=1}^{T_{max}} P_{charge}(t)$ the total power used during the longest charging session, where $P_{charge}(t)$ is the power [kW] at each time step t, and T_{max} is the total duration of the longest charging session.
- Δt is the time step duration [hours]
- η_{charging} is the charging efficiency, assumed to be 95% (Chakraborty et al., 2022).

- DoD is the Depth of Discharge, assumed to be 80% (Rastgoo et al., 2022).

4.4.2 State of Charge

To determine the starting SOC of each car, it was assumed that the SOC is always 100% at the end of each charging session.

First, the initial SOC [%] of each charging session was determined using Equation 4.13.

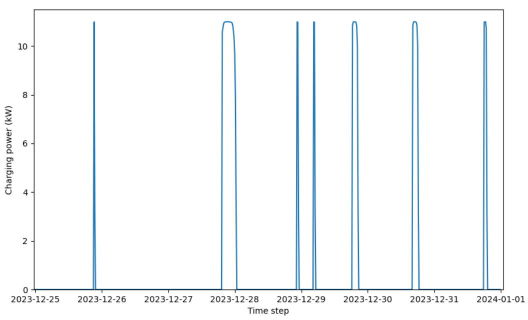
$$SOC_{\text{initial}} = 100 - \frac{\sum_{t=1}^{T} P_{\text{charge}}(t) \cdot \Delta t \cdot \eta_{\text{charging}}}{C_{\text{bat}}} \cdot 100 \tag{4.13}$$

Here, T represents the total duration of each charging session. This calculation results in an initial SOC of 20% for the longest charging sessions, given that the DoD is assumed to be 80% and the battery size is based on the longest charging session.

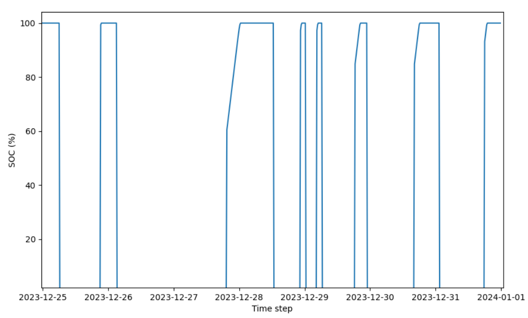
This initial SOC value is then used to calculate the SOC for each time step using Equation 4.14.

$$SOC(t) = SOC_{initial} + \frac{\sum_{t=1}^{t} P_{charge}(t) \cdot \Delta t \cdot \eta_{\text{charging}}}{C_{\text{bat}}} \cdot 100 \tag{4.14}$$

The SOC was used to compare the SOC under various flexibility strategies compared to the reference scenario. The SOC and power output of the charging station over a week for the reference scenario are presented in Figure 4.6. The SOC remains at 100% when the car is connected to the charging station but not actively charging. Discharge is not considered.



(a) Charging profile of an EV for a week.



(b) SOC of an EV for a week.

Figure 4.6: Charging and SOC profile of a house for a week.

4.5 Baseload and Solar

Finally, the profile of the baseload and solar energy was generated. The baseload profile was generated based on the average baseload profile of a Dutch neighborhood in 2022 (Alliander, nd). For every household, the same baseload profile was used. This approach may oversimplify household energy consumption patterns by not accounting for variability between different households, potentially leading to more extreme cases of congestion as all baseloads will exhibit the same aggregated power peaks.

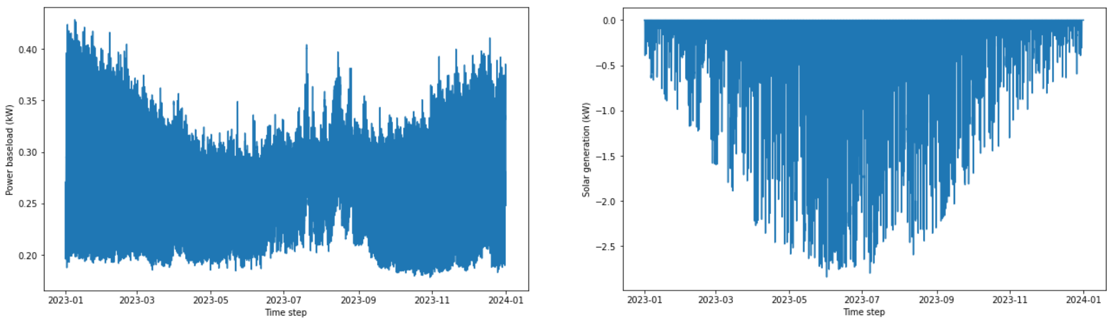
The solar profile was developed based on the measured solar irradiance data from the weather station in De Bilt, using hourly observations from 2023. This data was then interpolated to 15-minute intervals to meet the required data points (KNMI, 2024). To determine the power generated by the solar panels at each time step, Equation 4.15 was used.

$$P_{solar}(t) = G(t) \cdot A_{panel} \cdot N_{panels} \cdot \eta_{solar} \tag{4.15}$$

where:

- G is the solar irradiance [kW/m^2].
- A_{panel} is the area of a single solar panel [m^2], which was assumed to be 1.7 m^2 (Svarc, 2024).
- N_{panels} is the number of solar panels, for each house a random value was used in the range 6 to 12.
- η_{solar} is the efficiency of the solar panels, which was assumed to be 20% (Svarc, 2024).

Solar production is measured as negative power consumption in this model. A solar and baseload profile of a house is visualized in Figure 4.7.



(a) Baseload profile house for full year.

(b) Solar profile house for full year.

Figure 4.7: Baseload and Solar profile of a house for a full year.

When the amount of solar energy fed back into the grid exceeds the transformer's total load capacity, the excess solar energy is curtailed.

4.6 Explicit Flexibility

During explicit flexibility, the goal is to mitigate congestion by reducing the load during congestion and redistributing the load to a period with more available load. The methodology used for this is described in more detail in the following section.

4.6.1 Transformer load

First, all individual profiles of each household agent were combined to calculate the total transformer load. The adoption rates were determined based on the Climate Ambition Scenario for 2030 from NetbeheerNederland (2023), which reflects the Dutch government's energy and climate policies.

For solar panels, an adoption rate of 55% was used. EVs were assumed to have an adoption rate of 26%. NetbeheerNederland (2023) distinguishes between hybrid heat pumps and fully electric HPs, with adoption rates of 15% and 12% respectively. According to Milieu Centraal (2024c), hybrid HPs use electricity 60% of the time and gas 40% of the time. Since all HPs in this model are fully electric, it was assumed that 60% of the hybrid HPs would be considered as fully electric, resulting in an overall adoption rate of 21% for fully electric HPs.

The maximum active load was set at 250 kW. When the total loads exceed this threshold, explicit flexibility is applied. This means that every agent capable of providing explicit flexibility will shift its production forward until the congestion is resolved. It is assumed that 50% of the HPs and 50% of the EVs can offer this flexibility.

4.6.2 Flexibility provision and constraints

For EVs and HPs, the flexibility provided per household at each time step was calculated using Equation 4.16 and Equation 4.17.

$$F_{\text{agent,ev},n}(t) = \frac{P_{\text{charge,min},n}(t)}{\sum_{n=1}^{N} P_{\text{charge,min},n}(t)} \cdot (P_{\text{total}}(t) - P_{\text{trafo}}) \tag{4.16}$$

$$F_{\text{agent,hp},n}(t) = \frac{P_{\text{hp},n}(t)}{\sum_{n=1}^{N} P_{\text{hp},n}(t)} \cdot (P_{\text{total}}(t) - P_{\text{trafo}}) \tag{4.17}$$

where:

- $F_{\text{agent,ev},n}(t)$ and $F_{\text{agent,hp},n}$ are the amounts of flexibility that the individual agent n provides [kW].
- N is the total number of houses with the flexibility source.

- P_{total} is the total load of the transformer [kW].
- P_{trafo} is the maximum load of the transformer [kW].
- $P_{\text{charge,min},n}$ is the power of the EV when the SOC is higher than the minimum [kW].
- $P_{\text{hp},n}$ is the power of the HP [kW].

As a result, each household with an EV or HP will provide a proportional share of flexibility based on the extent to which they contribute to congestion. This ensures that all HPs and EVs reduce their load by the same proportion, distributing the effort evenly across all participating households.

For the EVs a minimum SOC is used as a constraint to provide flexibility, which is set at 50% in the reference scenario. When the SOC is lower than 50% an EV will not provide flexibility. For the HPs the minimum temperature constraint is assumed to be 18 °C, as recommended by WHO (2018).

Finally, the required flexibility for each household agent is subtracted from its power consumption. If the required flexibility exceeds the power consumption, the power consumption is set to zero, resulting in unresolved congestion.

4.6.3 Redistribution of flexibility

The redistribution of the reduced load relies on the available capacity in the transformer. Each agent iterates over a series of time steps to shift the reduced load to periods with available capacity. A visualization of this process is shown in Figure 4.8.

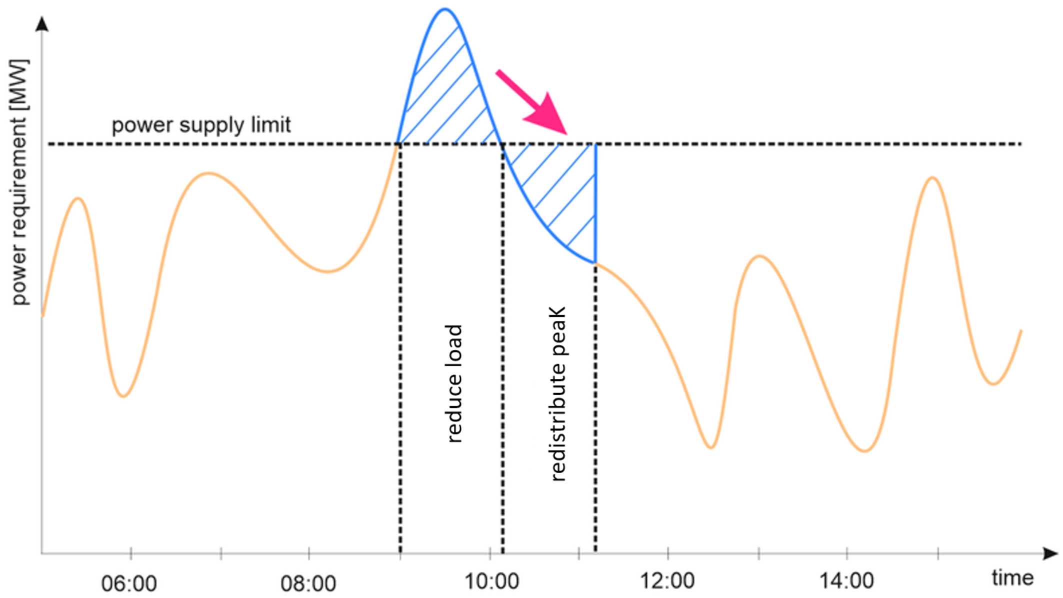


Figure 4.8: Redistribution of flexibility (Adapted from BeXema (nd)).

When available capacity is identified, the maximum possible amount of flexible load is shifted to that time step. In Figure 4.8 this is shown with the arrow shifting the blue area forward in time. The shifted load is subtracted from the load to be redistributed, and the available capacity for that future time step is reduced accordingly. This process continues until all possible flexibility is utilized. Finally, the new energy profiles for the HPs and charging stations are calculated by adding the shifted energy profile to the original HP and charging profile. This approach ensures that energy demand is redistributed to better align with the available capacity.

4.7 Implicit Flexibility

To model the effect of implicit flexibility an optimization approach was used, using linear programming and the Pulp library. During the optimization, the electricity costs of the HP and EV were minimized based on price. The way the optimization works is explained using Figure 4.9.

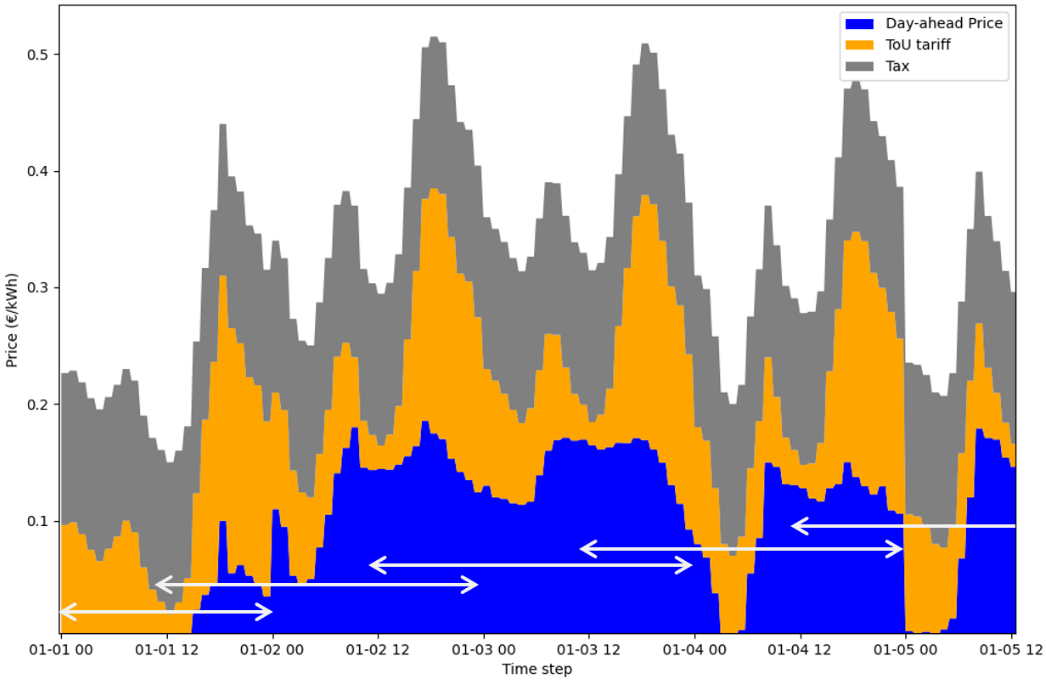


Figure 4.9: Total electricity price breakdown and optimization periods (arrows).

The total electricity price is divided into three components: the Day-ahead Price, ToU tariffs, and the energy tax. Most recent prices were used, including the projected ToU tariffs for 2030 (Alliander, nd). The Day-ahead prices of the Netherlands for 2023 were sourced from ENTSO (2024). The energy tax for 2024, is 13.2 cents per kWh including Value Added Taxes (VAT) (CBS, 2024).

The Day-ahead prices in the Netherlands are released every day at 12:00 PM [1](TenneT, nd). Consequently, the model's optimization occurs every day at 12:00 PM based on the prices known at that time, as indicated by the white arrows.

EVs are constrained to charge only when connected to the charging station and must reach 100% SOC by the end of each charging session. For HPs, the temperature must be maintained within a set range, specifically between 18°C and 22°C. The energy consumption of both EVs and HPs is optimized for each period by shifting the load to times when electricity prices are lower, thereby minimizing costs. When an overlap in optimization periods takes place, the numbers from the latest optimization are used.

The ToU tariffs consist of summer and winter tariffs with fixed prices that vary each hour, offering an alternative to the regular flat-rate grid tariff, as seen in Figure 4.10.

[1]Just before the deadline for this thesis, it was brought to attention that the Day-ahead prices are released at 12:40 PM. This slight discrepancy does not affect the core results and conclusions of the model, but it is important to acknowledge the correct release time for accuracy.

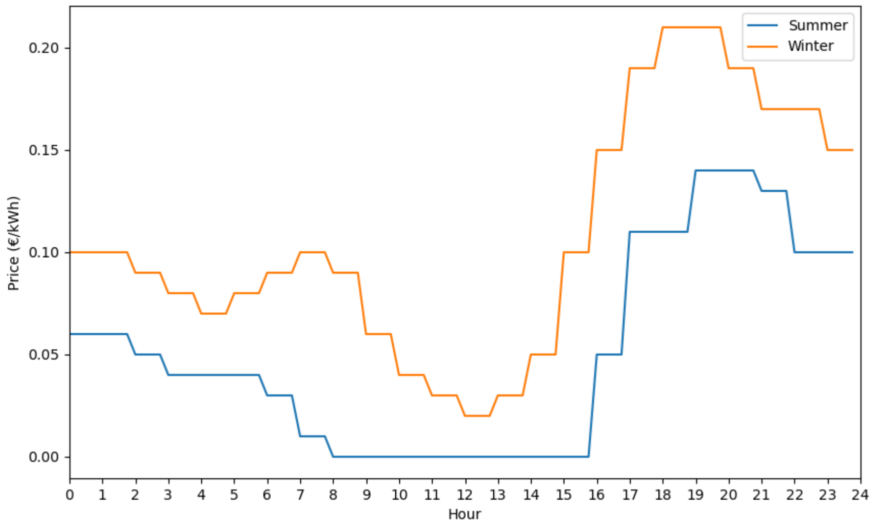


Figure 4.10: Time of Use Tariffs summer and winter.

The switch from summer to winter tariffs takes place when the clock is switched from summer to winter time in the Netherlands. The total price of electricity for the full year is seen in Figure 4.11.

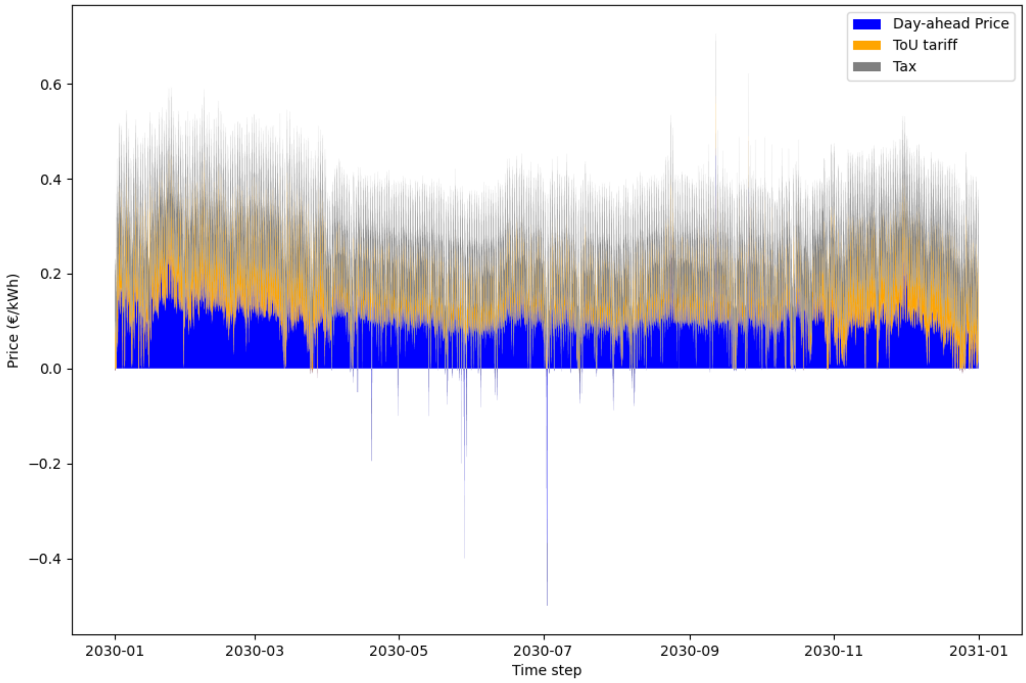


Figure 4.11: Total electricity price for a full year.

4.8 Scenarios

In the reference scenario for this research, the neighborhood comprises 300 households. According to the Climate Ambition Scenario for 2030 by NetbeheerNederland (2023), 55% of the households have solar panels, 21% have HPs, and 26% have EVs. The nominal capacity of the transformer is assumed to be 250 kW.

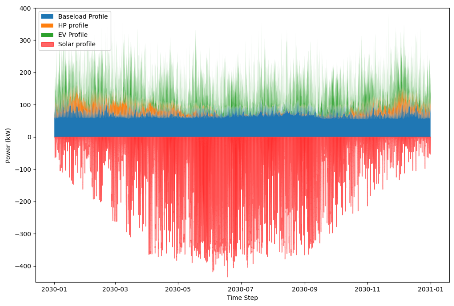
In all scenarios, it is assumed that 50% of the HPs and EVs are capable of providing flexibility. The scenarios include a reference scenario with no flexibility, a scenario with explicit flexibility, a scenario with implicit flexibility, and a scenario combining both implicit and explicit flexibility. Additionally, a sensitivity analysis is performed to assess the impact of varying comfort constraints, price sensitivity, and the proportion of households applying flexibility.

5 Results

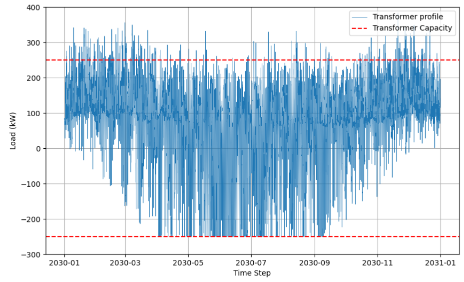
This section investigates the effects of implicit and explicit flexibility, as well as a combination of both. First, the results for the reference scenario are presented in Section 5.1, followed by the results of explicit flexibility in Section 5.2 and the results of implicit flexibility in Section 5.3. Section 5.4 covers a combination of implicit and explicit flexibility after which a comparison is made between all scenarios in Section 5.5. Additionally, a sensitivity analysis evaluates the effects of varying comfort constraints, price sensitivity, and the proportion of households applying flexibility. The findings of these analyses are detailed in the subsequent subsections.

5.1 Reference Scenario

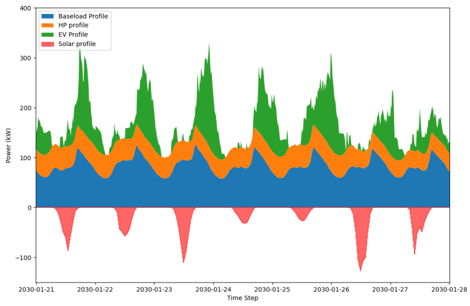
The resulting combination of all profiles and the net transformer profile of the reference scenario is visualized in Figure 5.1.



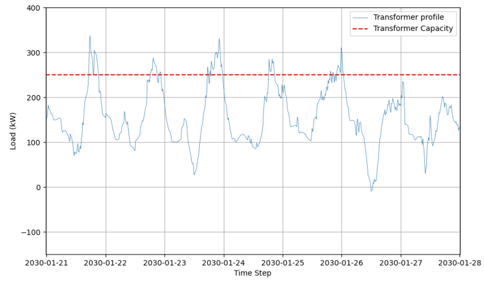
(a) Combined profiles for a year.



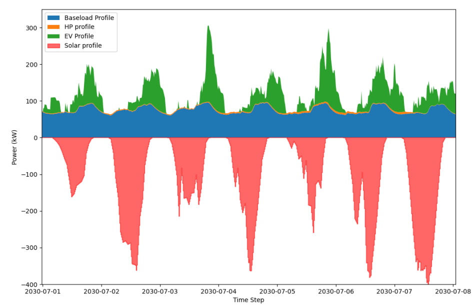
(b) Transformer profile for a year.



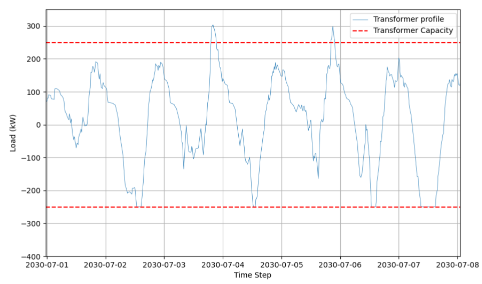
(c) Combined profiles for a week in winter.



(d) Transformer profile for a week in winter.



(e) Combined profiles for a week in summer.



(f) Transformer profile for a week in summer.

Figure 5.1: Combined and transformer power profiles over a year and week in summer and winter in the reference scenario.

Figure 5.1a, 5.1c and 5.1e visualize the combined power profiles of the baseload, HPs, EVs, and solar panels of all individual households. Figure 5.1b, 5.1d and 5.1f display the sum of these profiles, representing the transformer load. The dashed lines indicate the maximum capacity of the transformer. In this scenario, congestion is experienced for 255.75 hours throughout the year, while solar energy curtailment occurs for 283.5 hours.

Figure 5.1c and 5.1e highlight the difference between a week in summer and winter. In the summer, there is generally more solar production, which often leads to increased solar curtailment as the grid's capacity is exceeded by the excess energy generated. During this time, HPs use little to no energy, thus contributing minimally to the overall load.

In contrast, winter weeks are marked by higher energy consumption from HPs and the baseload. This is due to the increased need for heating and the fact that people tend to stay indoors longer, leading to more usage of lighting and electrical devices. As a result, winter experiences more instances of curtailment caused by the transformer's maximum capacity being exceeded. Therefore, while summer mainly deals with solar curtailment, winter is characterized by more congestion due to higher overall energy usage, as can be seen in Figure 5.1b

For a clearer visualization, the figures used for further analysis focus on the week of January 21, as shown in Figures 5.1c and 5.1d. This particular week is selected because it represents a typical period during which congestion is experienced caused by the usage of HPs and EVs.

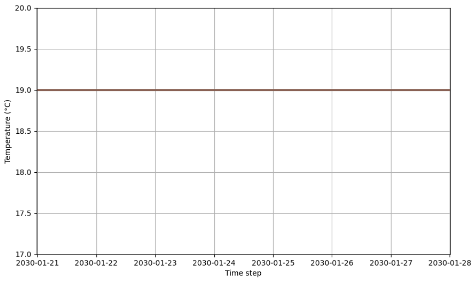
The average energy consumption and production of the baseload, HPs, EVs, and solar panels in the reference scenario are 2238, 2356, 4346, and 3397 kWh.

5.2 Explicit Flexibility

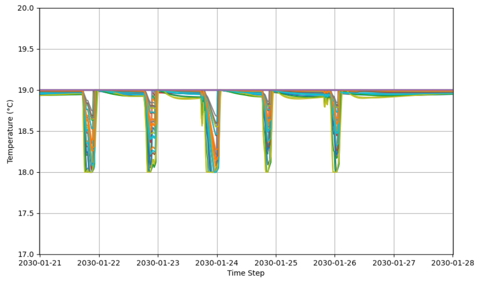
First, the effect of explicit flexibility for HPs and EVs was analyzed separately to facilitate a clear comparison between the two. This analysis helps in understanding the individual impact of each asset on mitigating congestion.

5.2.1 Explicit Flexibility Heat Pumps

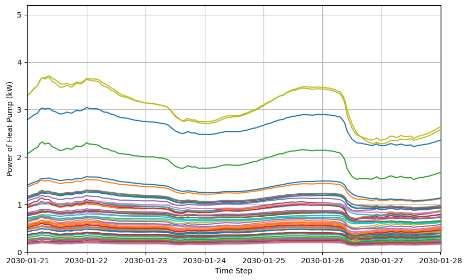
For HPs, the flexibility constraint includes maintaining a minimum temperature of 18°C to ensure comfort. In the reference scenario, it was assumed that the temperature is maintained at a constant 19°C without active cooling, allowing it to naturally rise but not fall below this point due to heating. The maximum power for all HPs was assumed to be 5 kW. The effect of explicit flexibility for HPs is visualized in Figure 5.2



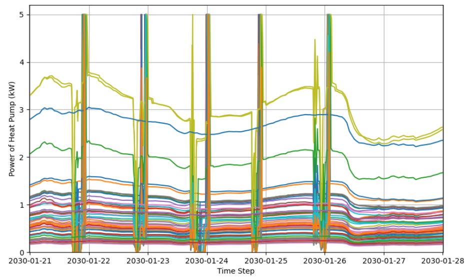
(a) Temperature houses for a week in the reference scenario.



(b) Temperature houses for a week after explicit flexibility.



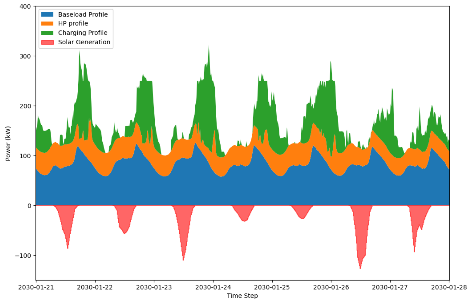
(c) HP profile houses for a week in the reference scenario.



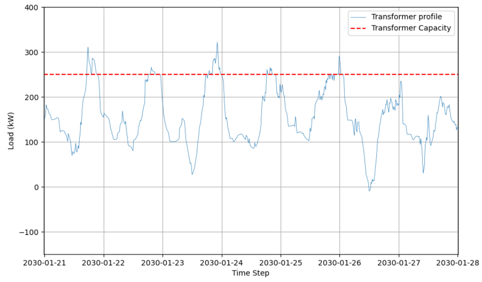
(d) HP profile houses for a week after explicit flexibility.

Figure 5.2: Temperature and HP profiles before and after explicit flexibility.

Figure 5.2 visualizes the temperature and power output of the HP before and after explicit flexibility. In the reference scenario, it is assumed that a constant temperature of 19°C is maintained, as shown in Figure 5.2a. Figure 5.2c shows the HP profiles used to maintain a constant temperature of 19°C, with variations based on different levels of insulation. After flexibility is provided the temperature and power of the houses and HPs that apply flexibility will be reduced until congestion is solved. In Figure 5.2b can be seen that the minimum temperature of 18 °C serves as a limiting factor for flexibility. When capacity becomes available in the grid, the temperature is increased back to the original 19 °C. This causes peaks in power consumption as seen in Figure 5.2d. The effect this will have on the transformer load is shown in Figure 5.3.



(a) *Combined profiles for a week after explicit flexibility HPs.*



(b) *Transformer profile for a week after explicit flexibility HPs.*

Figure 5.3: Combined and transformer power profiles over a week after explicit flexibility HPs.

Figure 5.3 shows a reduction in peak loads and shorter periods of load exceeding of the transformer's nominal capacity compared to Figure 5.1. However, despite the applied flexibility, the HPs were unable to fully resolve the congestion during any of the days in this week. The total hours of congestion was reduced from 225.75 hours to 186.25 hours over the year.

Furthermore, the average electricity consumption of HPs decreased from 2356 kWh to 2351 kWh per year. However, the HPs that applied flexibility experienced an average cost increase from 790 € to 873 € per year.

5.2.2 Sensitivity Analysis Heat Pumps

A sensitivity analysis was conducted on the minimum temperature constraint and the number of HPs applying flexibility to evaluate their impact on the reduction of total congestion. The maximum amount of flexibility of the HPs was achieved when the temperature constraint was reduced to 14.9 °C or lower, as can be seen in Figure 5.4. In this case, total congestion could be reduced to 169.25 hours. In this case, energy consumption of the HPs was reduced to zero, indicating that HPs are not responsible for congestion during these hours.

The limiting constraint of the minimum temperature, however, depends on the insulation level of the house. Houses with poorer insulation will cool down faster than those with better insulation. The results of the sensitivity analysis for minimum temperature are shown in Figure 5.5.

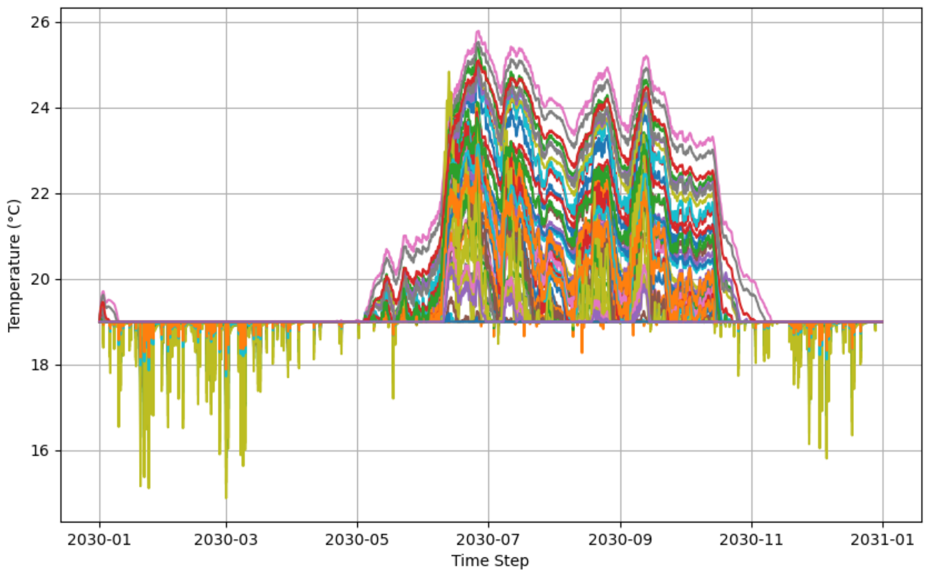


Figure 5.4: Temperature profile houses for a full year after explicit flexibility HPs with no temperature constraint.

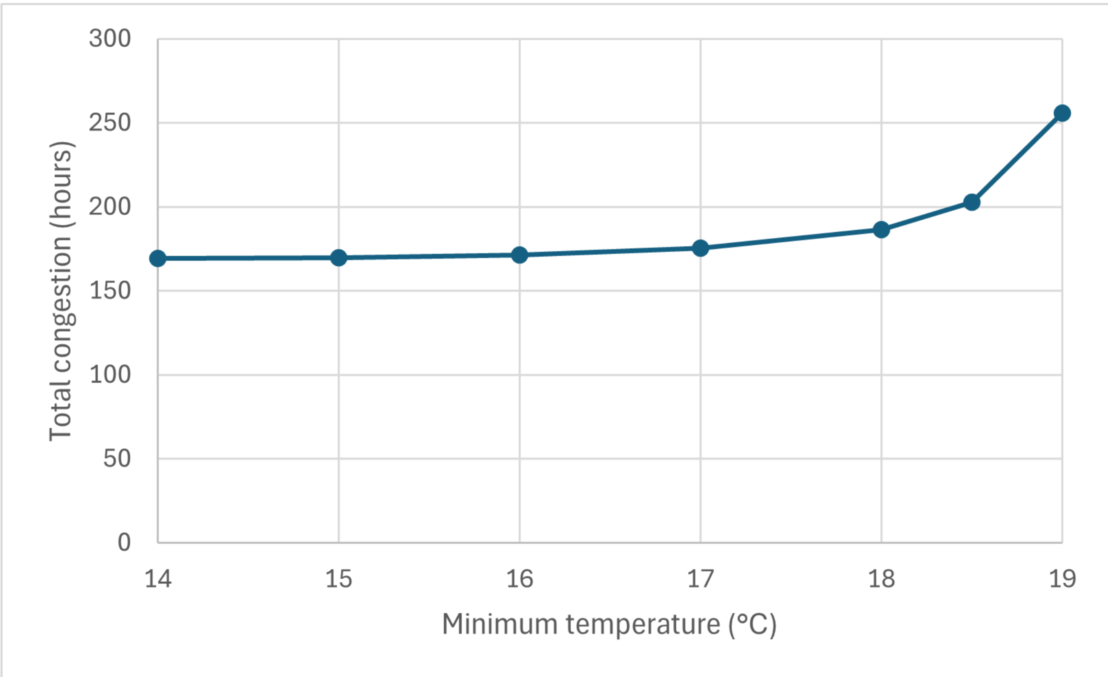


Figure 5.5: Sensitivity analysis minimum temperature.

Figure 5.5 illustrates that reducing the minimum temperature constraint helps resolve more congestion. The most significant impact occurs when the temperature is lowered from 19 °C to 18 °C, resulting in a reduction of congestion hours from 225.75 to 186.25. Further reductions in the minimum temperature have a smaller effect, with congestion hours decreasing from 186.25 to 169.25 when the temperature is lowered from 18 °C to the minimum of 14.9 °C.

A sensitivity analysis was also performed on the percentage of HPs that apply flexibility. The results of this are shown in Figure 5.6.

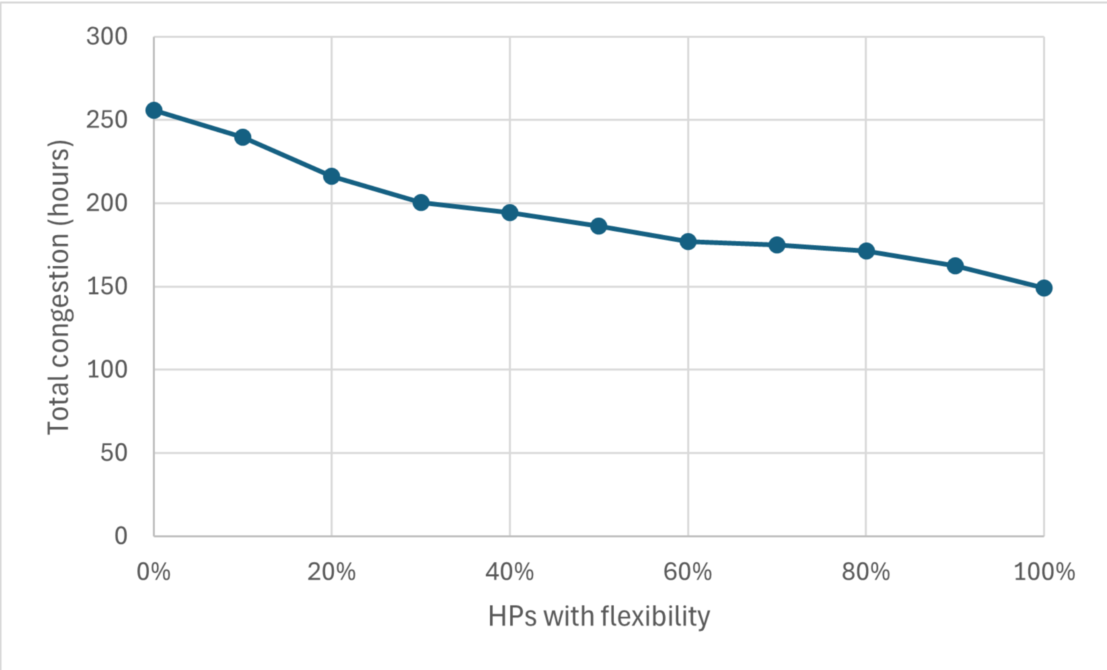
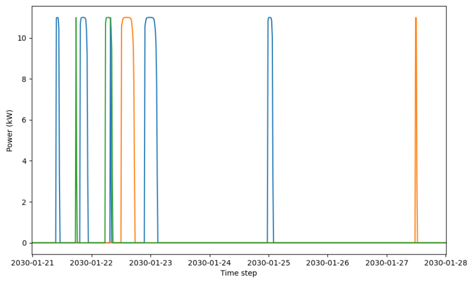


Figure 5.6: Sensitivity analysis percentage of HPs with flexibility.

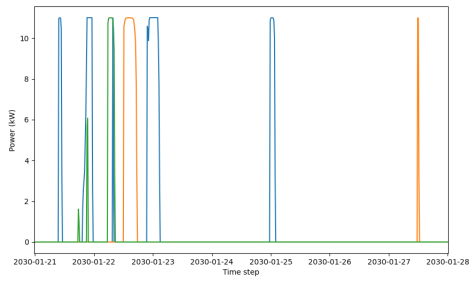
Figure 5.6 demonstrates that increasing the number of HPs applying explicit flexibility results in a greater reduction of congestion. The effect of adding more HPs remains relatively consistent in terms of resolving congestion. The effectiveness of each HP in reducing congestion is linked to its contribution to the overall electrical load; HPs that consume more electricity have a higher impact. However, since all HPs operate similarly, with heat output dependent on the ambient temperature, the overall effect remains fairly constant.

5.2.3 Explicit Flexibility Electric Vehicles

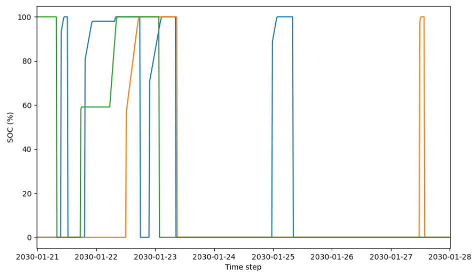
EVs have the constraint that explicit flexibility can only be applied when the SOC of the car is higher than 50%, ensuring the car can always drive a minimum distance. This means that the car will be charged to a SOC of 50% as quickly as possible before any flexibility can be applied, resulting in a guaranteed SOC of 50% or higher. In the reference scenario, it is assumed that the SOC must be 100% at the end of the charging session. The maximum power output of the charging station is set at 11 kW. It is again assumed that 50% of the EVs can apply explicit flexibility. The effect of applying explicit flexibility to EVs is visualized in Figure 5.7. For a clearer visualization, the power and SOC of only three cars that apply flexibility are shown.



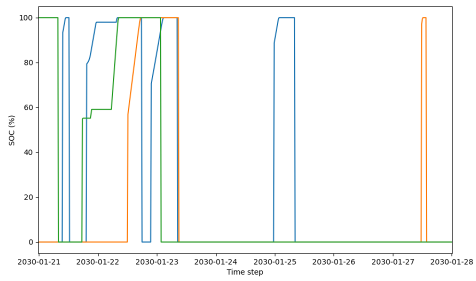
(a) EV profile houses for a week in the reference scenario.



(b) EV profile houses for a week after explicit flexibility.



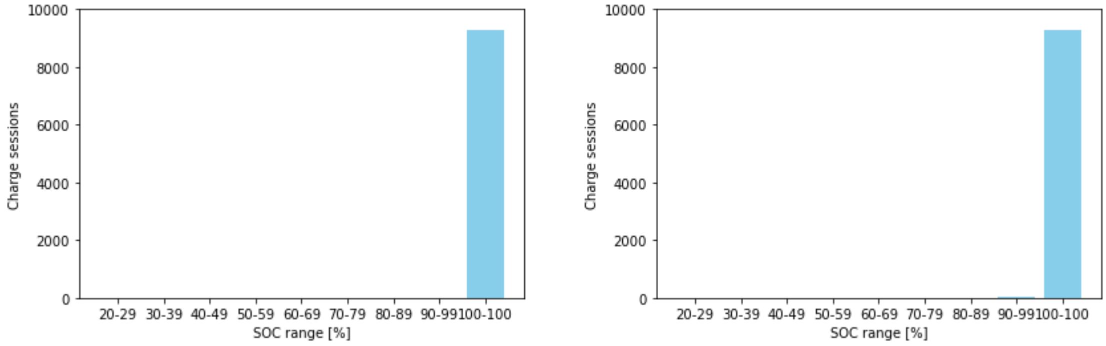
(c) SOC houses for a week in the reference scenario.



(d) SOC houses for a week after explicit flexibility.

Figure 5.7: EV profiles and SOC before and after explicit flexibility.

Figure 5.7a and 5.7b illustrate the differences in charging power before and after the application of explicit flexibility. Most charging sessions remain unaffected as they occur during periods without congestion. The first green charging session demonstrates how the power output of the car is reduced during a congestion period and subsequently shifted forward. In the reference scenario is was asumed that at the end of each charging session the final SOC would achieve a 100% SOC as seen in Figure 5.7c. After applying explicit flexibility as shown in Figure 5.7d, the car still achieves a full SOC by the end of the charging session, despite the adjustments. The effect of applying explicit flexibility on the final SOC for cars that apply flexibility is shown in Figure 5.8.

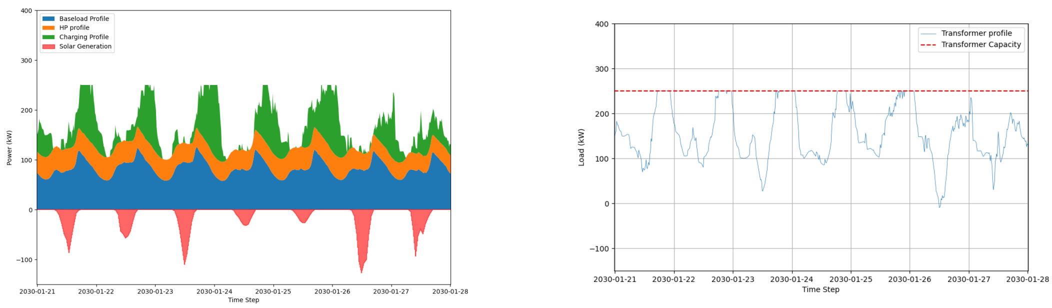


(a) Final SOC of cars before flexibility. *(b) Final SOC of cars after explicit flexibility.*

Figure 5.8: Final SOC of cars before and after explicit flexibility.

Figure 5.8 shows that applying flexibility can result in a final SOC that is not 100%. Out of the cars that used explicit flexibility, 9269 out of 9303 charging sessions achieved a full SOC, which equates to 99.6%. When considering all cars in the neighborhood, 15032 out of 15066 charging sessions ended up with a full SOC, meaning that 99.8% of all charging sessions achieved a full SOC. The lowest final SOC was found to be 67.9%.

The impact of explicit flexibility from EVs on mitigating congestion is shown in Figure 5.9.



(a) Combined profiles for a week after explicit flexibility EVs. *(b) Transformer profile for a week after explicit flexibility EVs.*

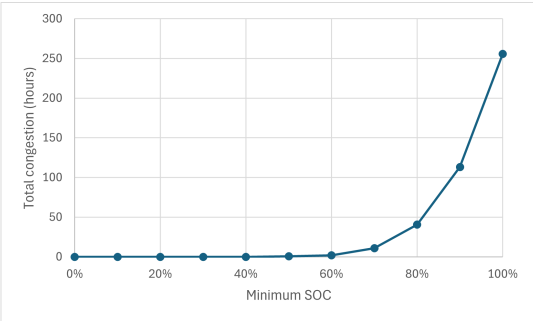
Figure 5.9: Combined and transformer power profiles over a week after explicit flexibility HPs.

Figure 5.9 shows that in all cases, congestion was fully resolved. This effect was consistent throughout the year, with the total hours of congestion being significantly reduced from 255.75 hours to 0.5 hours.

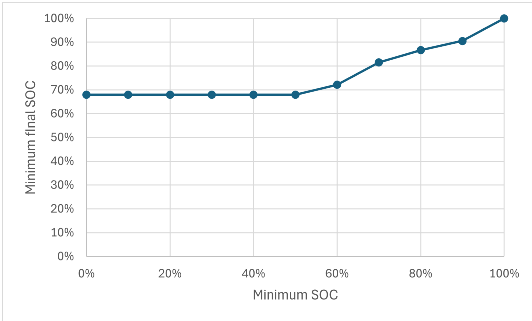
The average electricity consumption for all EVs slightly decreased from 4346 kWh to 4344 kWh. Additionally, EVs that applied flexibility saw a reduction in annual costs, from 1517 € to 1508 €.

5.2.4 Sensitivity Analysis Electric Vehicles

The impact of the minimum SOC constraint before applying explicit flexibility was also analyzed using a sensitivity analysis. The sensitivity analysis was conducted on the total hours of congestion per year, and the minimum final SOC. The results are shown in Figure 5.10.



(a) Total hours of congestion for different minimum SOC constraints.



(b) Minimum final SOC for different minimum SOC constraints.

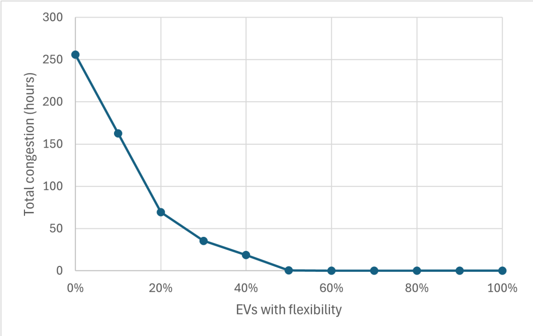
Figure 5.10: Sensitivity analysis minimum SOC constraint.

In Figure 5.10a illustrates how varying the minimum SOC threshold, after which flexibility can be applied, impacts the total hours of congestion that can be resolved. The graph shows that as the minimum SOC constraint increases, the ability to resolve congestion decreases.

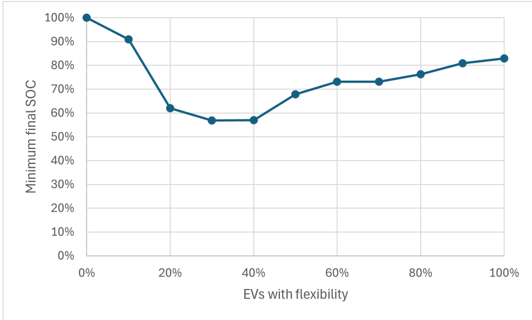
At lower SOC thresholds (0% to 60%), the total congestion remains low, at 0 hours and 2 hours respectively. However, beyond a minimum SOC of 60%, there is a noticeable rise in congestion hours. The trend shows an exponential increase, indicating that higher minimum SOC constraints significantly limit the flexibility to reduce congestion.

Figure 5.10b demonstrates that increasing the minimum SOC constraint positively impacts the minimum final SOC. This effect becomes noticeable when the constraint is raised above 60%. If the constraint is set below 60%, the cars end up with the minimum final SOC of 67.9%.

A sensitivity analysis was also performed for the number of electric vehicles that apply flexibility, as illustrated in Figure 5.11.



(a) Total hours of congestion for different percentages of EV providing flexibility.



(b) Minimum final SOC for different percentages of EV providing flexibility.

Figure 5.11: Sensitivity analysis EVs with flexibility.

Figure 5.11a illustrates the relationship between the percentage of EVs providing flexibility and the total hours of congestion. As the percentage of EVs providing flexibility increases, there is a significant reduction in total congestion hours. Notably, when 50% or more of the cars provide flexibility, congestion is reduced to 0.5 hours or less. Beyond this point, additional reductions in congestion are minimal. The majority of the benefits from flexibility in this scenario are realized once half of the EVs participate.

Figure 5.11b shows the relation between the percentage of EVs providing flexibility and the minimum final SOC. As the proportion of EVs providing flexibility increases up to 50%, the minimum final SOC decreases. When more than 50% of EVs provide flexibility, an increase in the minimum final SOC is seen.

5.2.5 Explicit Flexibility Electric Vehicles and Heat Pumps

A comparison was also made between the explicit flexibility provided by HPs and EVs, as well as a combination of both. In the model, priority was given to EVs for providing flexibility, as the comfort constraint of having a lower final SOC is less impactful than the discomfort caused by a lower temperature from HPs. The results are shown in Figure 5.12.

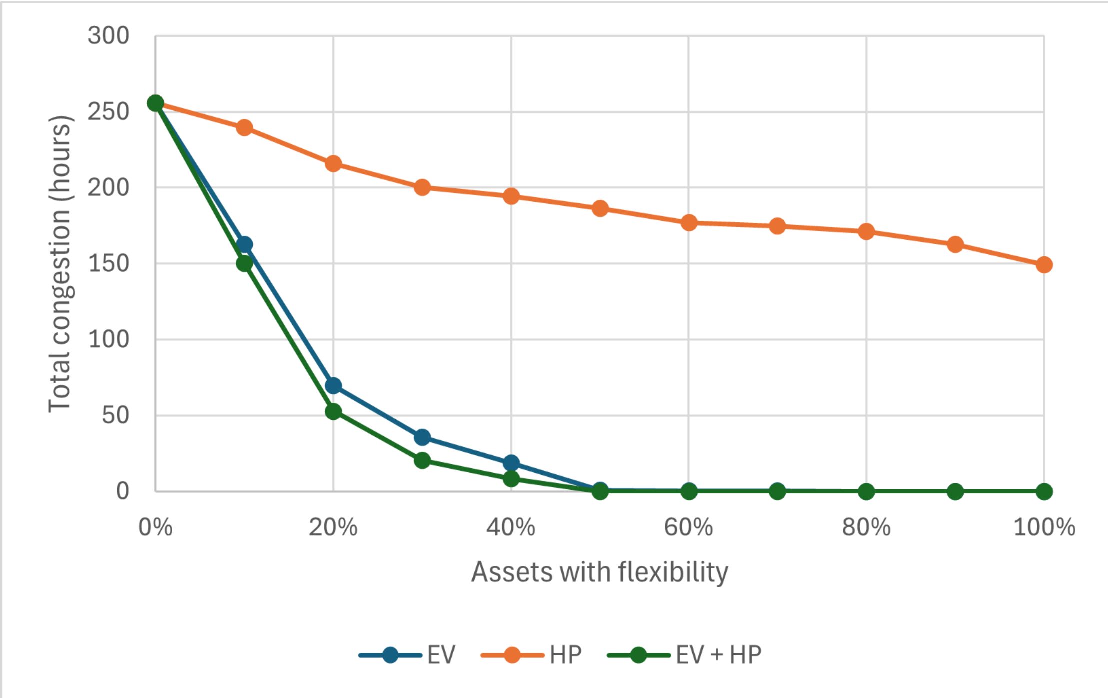


Figure 5.12: Sensitivity analysis percentage of assets with explicit flexibility.

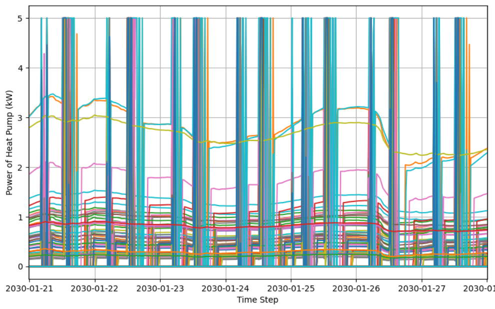
The comparison highlights the difference between the explicit flexibility provided by EVs and HPs, as well as a combination of both. EVs are demonstrated to be more effective in providing flexibility compared to HPs.

5.3 Implicit Flexibility

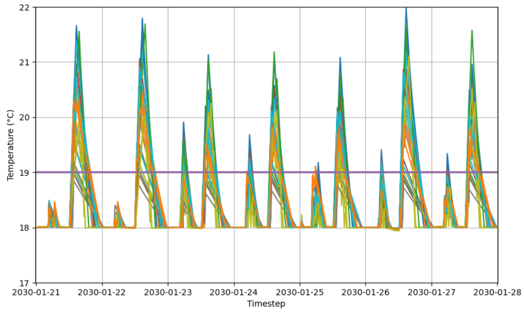
This section begins with an analysis of the effect of implicit flexibility on HPs and EVs in Section 5.3.1. This is followed by a sensitivity analysis on the impact of ToU tariffs in Section 5.3.2.

5.3.1 Implicit Flexibility Heat Pumps and Electric Vehicles

The HP profiles and temperature after implicit flexibility can be seen in Figure 5.13.



(a) HP profiles after price optimization.



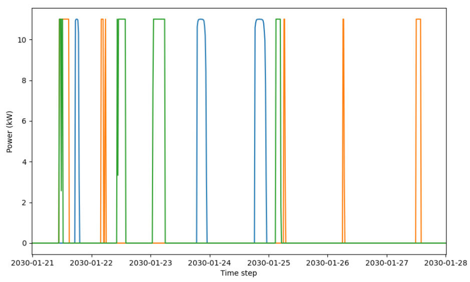
(b) Temperature houses after price optimization.

Figure 5.13: Temperature and HP profiles after implicit flexibility.

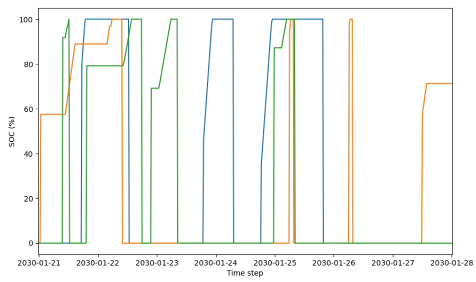
Figure 5.13a shows the power output of HPs after applying implicit flexibility. During periods of the lowest electricity prices, HPs are turned on at maximum power. This allows the HPs to reduce the power consumption to a minimum while maintaining the indoor temperature above the minimum threshold of 18°C. As shown in Figure 5.13b, the temperature increases during these low-price periods and then gradually decreases until it reaches 18°C. This cycle usually occurs twice daily in the winter, once with a small increase in temperature at 4 AM and once with a bigger increase at 12 PM, which aligns with the lowest ToU tariffs during the winter.

The average annual electricity cost for a HP after applying implicit flexibility is 665 €, a reduction of 125 € compared to the reference scenario where the average cost was 790 € per year.

The EV profiles and SOC for three cars with flexibility are seen in Figure 5.14.



(a) Charging profiles after price optimization.

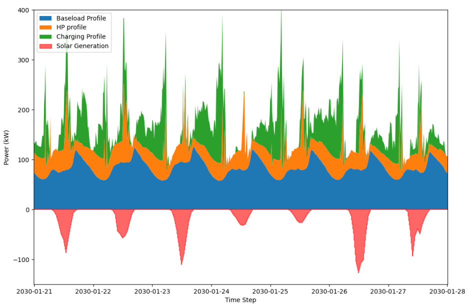


(b) SOC cars after price optimization.

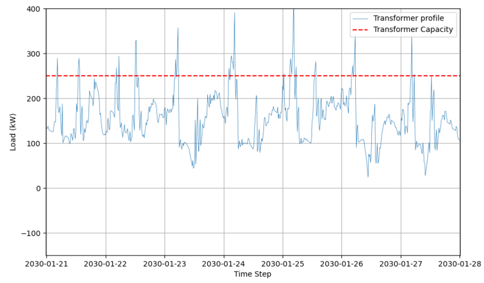
Figure 5.14: SOC and EV profiles after implicit flexibility.

A similar effect to the HPs is seen for the EVs in Figure 5.14. The cars will charge at maximum power during the cheapest price periods and charge until a SOC of 100% is reached. For the EVs, this usually takes place once a day, during the cheapest period when the car is connected to the charging station. The average price an EV pays after implicit flexibility is 1112 €, compared to 1517 € a year in the reference scenario.

The effect of implicit flexibility on the transformer load for a combination of HP and EV flex is seen in Figure 5.15.



(a) *Combined profiles after price optimization.*



(b) *Transformer load after price optimization.*

Figure 5.15: Combined and transformer power profiles over a week after explicit flexibility HPs

After implementing implicit flexibility, congestion was reduced from 255.75 hours to 205 hours. This reduction occurs as demand is shifted to periods with higher solar energy supply or to times of low baseload consumption in the morning or at night. However, since 50% of the HPs and EVs are using implicit flexibility, new peaks were created during low-cost periods, leading to new periods of congestion. These new peaks are generally shorter and occur at the lowest price points. The maximum peak load tends to increase with higher participation rates due to greater concurrency.

Finally, a sensitivity analysis was done on the percentage of EVs and HPs that apply implicit flexibility as seen in Figure 5.16.

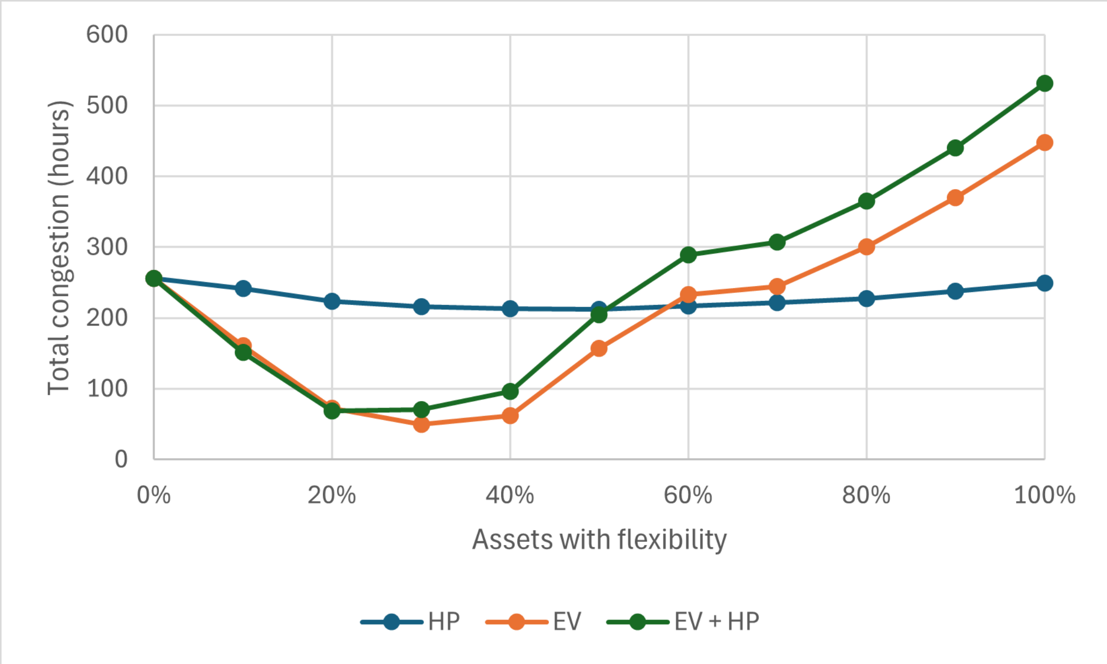


Figure 5.16: Sensitivity analysis percentage of assets with implicit flexibility.

Figure 5.16 shows that congestion initially decreases when implicit flexibility is applied but later increases. This trend occurs because, initially, demand is shifted to periods with lower demand and cheaper prices, reducing congestion. However, as more households adopt this strategy, the combined demand during these low-cost periods increases, leading to new congestion.

5.3.2 Implicit Flexibility Price Sensitivity

A sensitivity analysis was also conducted on the expected ToU tariffs for 2030 by comparing the effects of having higher or lower ToU tariffs. Additionally, prices were compared to the current situation without ToU tariffs and a scenario combining ToU tariffs with a fixed energy contract instead of a variable one.

The results of the sensitivity analysis of ToU prices are shown in Figure 5.17.

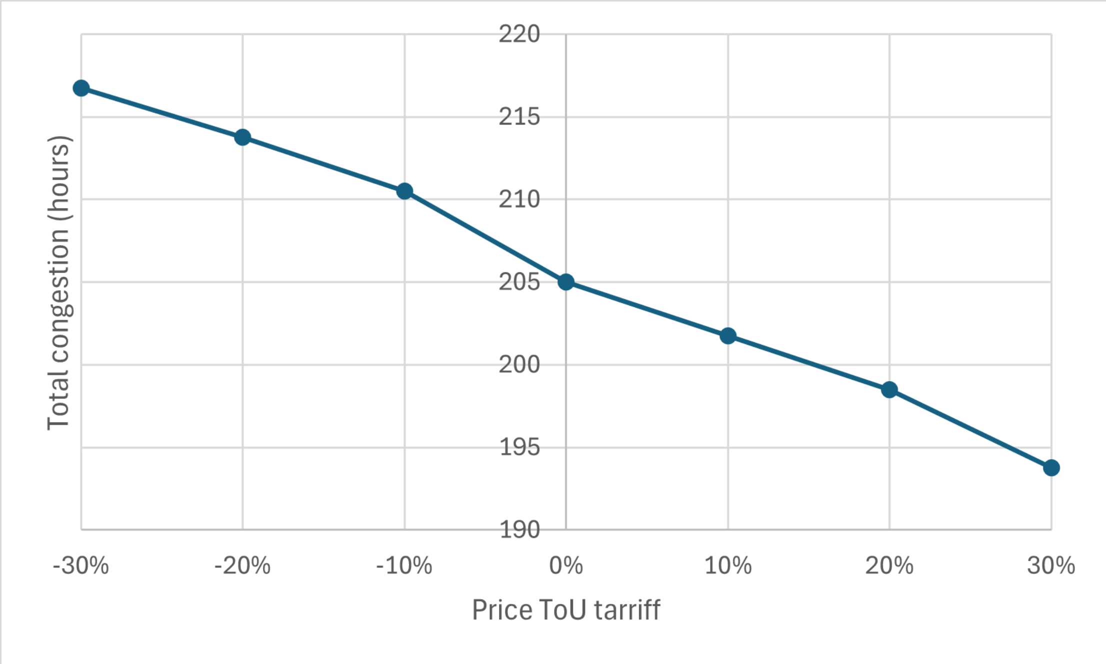


Figure 5.17: Sensitivity analysis ToU price.

Figure 5.17 illustrates that increasing the ToU price leads to reduced congestion while decreasing the ToU price results in increased congestion. The relationship appears to be nearly linear. On average, a 1% increase in price corresponds to a reduction of 0.38 hours of congestion in the reference scenario.

Instead of using Day-ahead market prices, a scenario with a fixed energy contract combined with ToU tariffs was modelled. The prices in this scenario depend on the energy provider, the timing of the contract, and previous energy usage. In this model, a price of 0.40 €/kWh was used. This represents the maximum price cap in the Netherlands, which was paid by 6% of households with a fixed contract (Milieu Centraal, 2024b). A scenario was also used with a combination of the Day-ahead market and with a regular flat-rate tariff. The cost savings and total congestion in each scenario are shown in Table 1.

Table 1: Total congestion and cost savings under different scenarios.

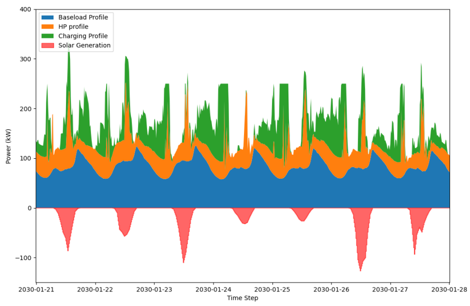
Scenario	**Total congestion (hours)**	**EV cost savings**	**HP cost savings**
ToU + Day-ahead	205	€ 406	€ 125
ToU only	112	€ 296	€ 116
Day-ahead only	286.5	€ 162	€ 60

Table 1 demonstrates that the scenario with a ToU tariff and a fixed energy contract achieved the greatest reduction in congestion. Conversely, the highest total congestion occurred in the absence of a ToU tariff. The reference scenario that combined both ToU tariffs and day-ahead price variation yielded the highest cost savings. The results show that the ToU tariff not only provides additional incentives for implicit flexibility but also contributes to reducing congestion.

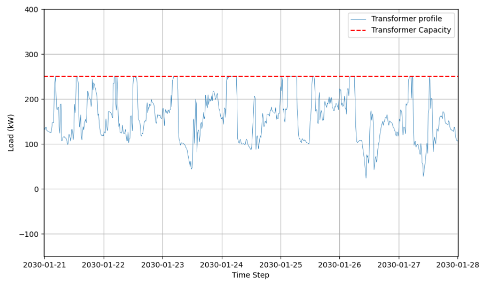
5.4 Implicit and Explicit Flexibility

Finally, a scenario combining implicit and explicit flexibility was modeled. In this scenario, HPs and EVs first applied implicit flexibility to achieve cost savings and then utilized explicit flexibility during periods of congestion.

As a result, congestion was reduced from 205 hours, when 50% of the EVs and HPs provided implicit flexibility, to 0 hours when explicit flexibility was subsequently applied. The effect this had on the transformer load and combined power is shown in Figure 5.18.



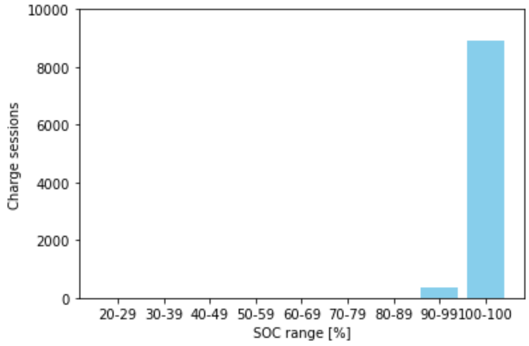
(a) Combined power after implicit and explicit flexibility.



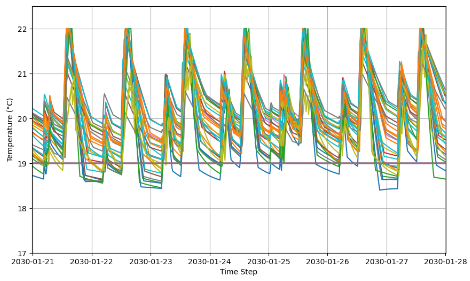
(b) Transformer load after implicit and explicit flexibility.

Figure 5.18: Combined and transformer power profiles over a week after implicit and explicit flexibility.

Figure 5.18 illustrates how the power peaks created by implicit flexibility are shifted forward to mitigate congestion. The impact of this adjustment on comfort constraints was also modeled, as shown in Figure 5.19.



(a) Final SOC after implicit and explicit flexibility.



(b) Temperature houses after implicit and explicit flexibility.

Figure 5.19: Final SOC and Temperature after implicit and explicit flexibility.

Of the EVs that applied a combination of implicit and explicit flexibility, 8928 out of 9303 charging sessions (96.0%), resulted in a full final SOC, as shown in Figure 5.19a. The lowest final SOC observed was 86.9%. The average power consumption of EVs decreased from 4346 kWh to 4314 kWh compared to only implicit flexibility. Consequently, average electricity costs declined from 1112 € to 1102 € after applying explicit flexibility, despite implicit flexibility being optimized for cost. This reduction is attributed to some cars not charging to 100% in this scenario.

For HPs the average energy consumption increased from 2225 to 2444 kWh, and costs increased from 665 € to 776 € per year. The energy consumption and costs of the HPs are higher than optimal because pre-heating was used to overcome increased congestion resulting from maintaining comfort limits. The impact this has on the temperature is shown in Figure 5.19b.

5.5 Comparison of Scenarios

The final results found in each scenario, when 50% of the assets provide flexibility are summarized in Table 2.

Table 2: Comparison results of each type of flexibility.

Category	**No flexibility**	**Explicit flexibility**	**Implicit flexibility**	**Implicit & Explicit flexibility**
Total congestion (hours)	255.5	0	205	0
Peak load (kW)	383	250	468	250
Total curtailment (hours)	283.5	283.5	225	223.75
Cost savings per EV	0 €	9 €	406 €	416 €
Cost savings per HP	0 €	-83 €	125 €	19 €
Comfort impact EV	No impact	Medium	Low	High
Comfort impact HP	No impact	Low	Medium	High
Total compensation DSO	0 €	300 €	0 €	3300 €

Table 2 demonstrates that explicit flexibility, or the combination of implicit and explicit flexibility, is most effective in mitigating congestion and reducing peak load. While implicit flexibility is more effective than having no flexibility at all, it increases the maximum peak load.

Total solar curtailment was reduced the most when both implicit and explicit flexibility were utilized. This is primarily due to implicit flexibility shifting demand to periods with higher solar energy.

The highest average cost savings for HPs were achieved when implicit flexibility was applied, while explicit flexibility negatively impacted cost savings. For EVs, the greatest cost savings were realized when both implicit and explicit flexibility were applied. This increased savings partly stemmed from EVs not always being charged to a 100% final SOC under explicit flexibility, resulting in lower overall charging costs.

Comfort was most impacted when both implicit and explicit flexibility were applied to both EVs and HPs. This led to the highest number of cars not achieving a full SOC and the greatest deviation from maintaining a constant temperature of 19°C. Less comfort was impacted when only implicit flexibility was applied, as it primarily increased charging time but still ensured a final SOC of 100%. For HPs, explicit flexibility resulted in the least comfort impact, with temperature drops occurring during periods of congestion. In contrast, implicit flexibility caused high-temperature fluctuations, frequently bringing the temperature closer to the minimum threshold.

Finally, the total compensation for the DSO to offset the cost losses from households applying explicit flexibility was calculated. The combined use of implicit and explicit flexibility resulted in the highest total compensation costs of 3300 €, averaging 11 € per household. In contrast, applying only explicit flexibility led to lower compensation costs of 300 €.

A comparison of the sensitivity analyses between the different types of flexibility using both EV and HP flexibility is given in Figure 5.20.

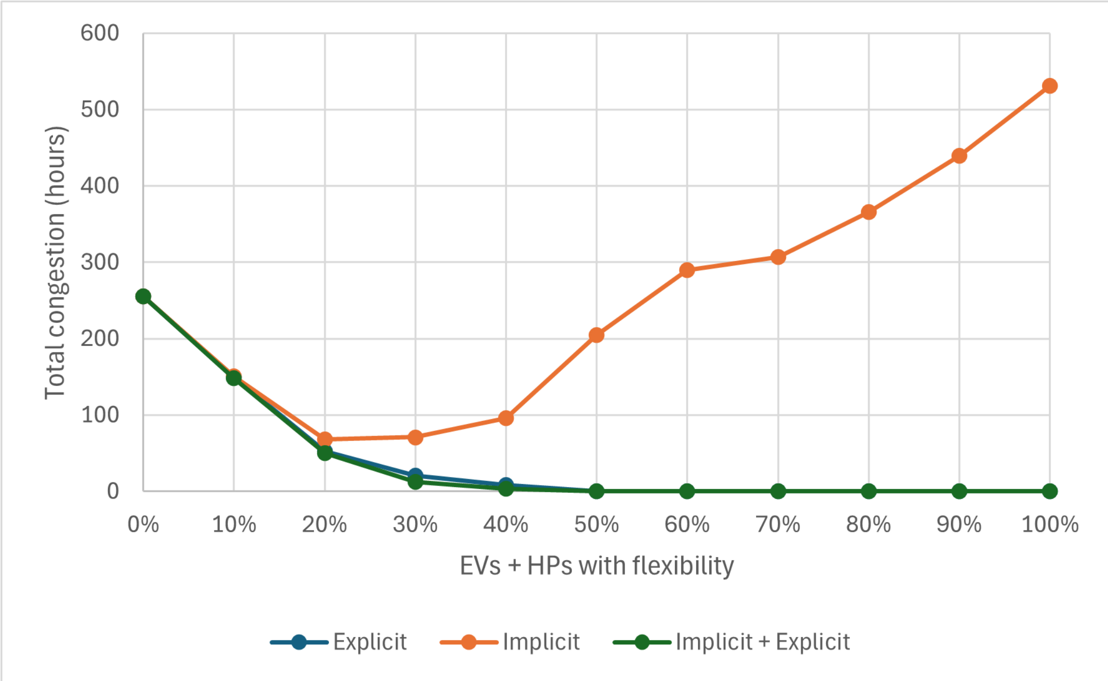


Figure 5.20: Sensitivity analysis percentage of EVs and HPs with flexibility for different types of flexibility.

Figure 5.20 shows that there is little difference in mitigating congestion when using participation rates up to 20% across all three flexibility strategies. Beyond this point, implicit flexibility starts to increase congestion, while both variants of explicit flexibility result in a sustained decrease in congestion.

5.6 Validation

In this section, results are compared with empirical data for validation of the model.

The energy usage of an HP depends on the matter of insulation of a house, the ambient temperature, and the type of HP. vanhetgasafgegaan.nl (2024) reported that a fully electric HP used 2039 kWh of electricity for heating only between December 1, 2022, and November 30, 2023, in the Netherlands. This is comparable to the average electricity usage of 2356 kWh for HPs in this model.

Refa et al. (2023) reported that EVs are expected to drive an average distance of 16,890 km per year in 2030, with an average energy usage of 0.2 kWh per km, resulting in an average annual usage of 3378 kWh. In contrast, data from ElaadNL (nd) used in this model showed an average usage of 4346 kWh per EV, potentially resulting in higher levels of congestion from EVs in this model than in practice. This can be due to higher assumed usage rates or lower charging efficiency assumed by ElaadNL (nd).

The solar panels in this model produced an average of 3397 kWh, while Milieu Centraal (nd) reported that 10 solar panels facing south produced an average of 3500 kWh. Additionally, Milieu Centraal (2024a) reported an average household electricity usage of 2497 kWh in the Netherlands in 2023. In comparison, the baseload consumption in this model was 2238 kWh per year.

A pilot project in Houten where HPs were used to apply flexibility, reported that the pilot houses cooled down by 0.3 °C per hour when no heating was applied (GO-E, 2024). These findings align with the cooling rate observed in this model, with variations depending on insulation quality and ambient temperature.

In addition to the empirical data comparison, results were visually compared with models used by Alliander (nd) and by colleagues. However, validation using actual transformer congestion data has not been performed. These results suggest that the model provides a reasonable representation of real-world outcomes, despite the simplifications and assumptions made. Further validation with actual transformer congestion data would be a valuable addition to enhance the model's accuracy and reliability.

6 Discussion

In this section, the results will be discussed and interpreted, followed by an outline of the limitations of this research and recommendations for future research and extensions to the model.

6.1 Explicit Flexibility

In section 5.2, the effectiveness of explicit flexibility in reducing grid congestion was examined. EVs were more effective in reducing grid congestion compared to HPs. A reduction from 255.75 hours to 0.5 hours was seen when 50% of the EVs were providing explicit flexibility. In contrast, the same percentage of HPs providing explicit flexibility resulted in a more modest reduction from 255.75 hours to 186.25 hours. The sensitivity analysis further highlighted the difference. Only 10% of EVs providing flexibility achieved a reduction in congestion to 162.75 hours, which is comparable to the 162.5-hours reduction attained by 90% of HPs.

There are several reasons why EVs are more effective than HPs in providing flexibility in the model. Firstly, the anticipated number of EVs in 2030 is higher, with 26% of households expected to own EVs compared to 21% for HPs. Additionally, EVs consume more electricity, averaging 4346 kWh per EV annually, compared to 2238 kWh for HPs.

The profiles of HPs and EVs also differ significantly. HPs have a relatively constant profile throughout the day, driven by ambient temperature, with a maximum power output of 5 kW that is only reached during extremely cold periods for poorly insulated homes. In contrast, EVs exhibit more variability and concurrency, as their charging patterns depend on human behavior, with a peak typically occurring when people return home from work. Furthermore, EVs have a higher maximum power output of 11 kW, which is utilized as soon as they are connected to the charging station to charge the vehicle as quickly as possible. These factors combined make EVs more effective in mitigating grid congestion compared to HPs.

6.1.1 Comfort contraints

Furthermore, the impact of the comfort constraints of minimum temperature and driving distance was analyzed. In the reference scenario, the lowest temperature found was 14.9 °C when no minimum temperature constraint was used. For EVs, the lowest final SOC was found to be 67.9%.

The sensitivity analysis in Figure 5.5 showed how the minimum temperature for HPs impacts congestion reduction. Lowering the minimum temperature from 19 °C to 18 °C led to the highest decrease in congestion hours, from 225.75 to 186.25. However, further reductions in the minimum temperature showed less effect. Lowering the temperature from 18 °C to 14.9 °C only resulted in an additional decrease in congestion hours, from 186.25 to 169.25 hours. The maximum potential for mitigating congestion with HPs is thus up to 169.25 hours when temperature constraints are ignored. In this scenario, HPs would be completely turned off during congestion periods, thus not contributing to it. This demonstrates that the HPs providing flexibility are not responsible for this remaining congestion.

The minimum temperature constraint closest to the assumed constant temperature of 19 °C has the highest impact, as this threshold is reached more frequently. As the minimum temperature constraint is lowered, it becomes less of a limiting factor. In Figure 5.4 where no constraint is used, the temperature to which the house drops differs as it depends on the matter of insulation of the house, the ambient temperature, and the duration of congestion. Poorly insulated houses experience faster temperature drops, and during colder periods, heat losses are greater, causing the temperature to drop more quickly. Additionally, the longer the congestion period, the more the temperature can drop, as the HPs are providing flexibility longer during these times.

A similar effect was seen in the sensitivity analysis for the minimum SOC after which explicit flexibility was applied, as shown in Figure 5.10. The constraint closest to a SOC of 100% had the greatest impact in limiting flexibility. When the constraint was lowered to 60% or below, little to no effect was observed. This occurs because most charging sessions begin when the SOC is already close to 100%, as cars often do not drive far enough distances to significantly reduce the SOC. There are a few instances when a car's SOC drops below 60% due to longer trips. Therefore, the impact of this comfort constraint diminishes, as it rarely comes into play.

When 50% of the cars used explicit flexibility, 99.8% of all charging sessions still resulted in a full state of SOC by the end of the session. This is because vehicles are often connected to a charging station but not actively charging. With explicit flexibility, the charging time is deferred to a later period, but in most cases, the final SOC still reaches 100%. The lowest final SOC was found to be 67.9%.

The relationship between cars that apply flexibility and minimum final SOC was also analyzed, as seen in Figure 5.11. Initially, as the proportion of EVs providing flexibility increases up to 50%, the minimum final SOC decreases. This decline occurs because more cars are simultaneously adjusting their charging schedules and redistributing flexibility, which strains the grid to its maximum load for a longer period. This increases the likelihood that some vehicles will not fully charge within the desired time frame, as not all flexibility can be redistributed. However, when more than 50% of EVs provide flexibility, the minimum SOC starts to increase. This improvement is because as more cars reduce their load simultaneously, the overall flexibility required to be redistributed per car decreases, leading to a more evenly distributed load and higher minimum SOC levels for each vehicle.

6.2 Implicit Flexibility

The effect of implicit flexibility was examined in Section 5.3. In the reference scenario, the flexibility for EVs decreased from 255.75 hours to 156.75 hours, while for HPs, congestion hours were reduced to 211.75. When combining HPs and EVs, the congestion hours further decreased to 205 hours.

The sensitivity analysis in Figure 5.16 demonstrated that implicit flexibility initially reduces total congestion, followed by an increase. For EVs, the greatest reduction was achieved when 30% of the EVs used implicit flexibility, resulting in 50 hours of congestion. However, when more EVs began to apply flexibility, congestion increased again. For HPs, the most significant reduction occurred when 50% of the HPs used implicit flexibility, reducing congestion to 211.75 hours. A combination of HPs and EVs showed the best results when 20% of the assets provided flexibility, resulting in 68,25 hours of congestion.

When comparing implicit and explicit flexibility, EVs showed similar results when up to 20% of the assets provided flexibility. Explicit flexibility resulted in 69.5 hours of congestion, compared to 72.25 hours for implicit flexibility. Interestingly, when 10% of the EVs provided flexibility, implicit flexibility slightly outperformed explicit flexibility, with 161 hours of congestion versus 162.75 hours. This difference can be attributed to implicit flexibility's ability to shift the charging session to any moment during the cheapest price periods. In contrast, explicit flexibility shifts power forward to the first possible future moment, only when the SOC is higher than 50%.

As more assets begin to use implicit flexibility, the effectiveness diminishes compared to explicit flexibility, eventually leading to increased congestion. This occurs because all assets shift power consumption to periods with lower prices, creating new congestion during these times. This trend was observed in the sensitivity analysis, where congestion began to rise again at a certain point.

In contrast, explicit flexibility resulted in a sustained decrease in congestion because the assets communicate with each other to avoid creating new congestion. This coordination among assets using explicit flexibility helps manage the load more effectively, preventing the shifting of congestion to different periods.

6.2.1 ToU tariffs

The impact of ToU tariffs on mitigating congestion was also analyzed in Section 5.3.2. The reference scenario, which combined the Day-ahead market with ToU tariffs, resulted in the highest cost savings through the use of implicit flexibility and reduced congestion to 205 hours. In the scenario where only ToU tariffs were applied, congestion was reduced to its lowest level of 112 hours. Conversely, the scenario with only the Day-ahead market and no ToU tariffs demonstrated the least effective mitigation of congestion and the lowest cost savings. These results indicate that ToU tariffs contribute significantly to both cost savings and congestion mitigation.

The sensitivity analysis of ToU prices also revealed that increasing ToU tariff prices leads to a greater reduction in congestion. This aligns with the scenarios, as higher ToU tariffs reduce congestion more effectively when they constitute a larger portion of the overall price. The relationship appeared nearly linear, with a reduction of 0.38 hours of congestion for every 1% increase in ToU prices. However, it is anticipated that this relationship will reach saturation, as the scenario with only ToU tariffs still resulted in 112 hours of congestion. This indicates that the relationship cannot be entirely linear. Additionally, the extent of congestion reduction depends on various factors, such as the number of assets providing flexibility, ambient temperature, and the concurrency of EV usage at a given time step.

The reason ToU tariffs are more effective in reducing congestion compared to Day-ahead prices is that Day-ahead prices do not accurately reflect congestion on the LV grid. For example, during periods of high offshore wind production, prices may be low even when electricity demand on the LV grid is high. This discrepancy can negatively impact congestion mitigation on the LV grid due to increased demand during these times. In contrast, ToU tariffs are more representative of this type of congestion, as their prices are based on the time of day when congestion on the LV grid is expected.

However, ToU tariffs are not a perfect solution, as congestion is not fully resolved. New congestion can emerge when more assets shift demand to periods with lower prices, a phenomenon known as the rebound effect. This effect was observed in the sensitivity analysis shown in Figure 5.16 as more assets provided implicit flexibility.

6.3 Implicit Flexibility and Explicit Flexibility

In Section 5.4, the combination of implicit and explicit flexibility was modeled. This approach reduced congestion from 205 hours, when only implicit flexibility was used, to 0 hours with the subsequent application of explicit flexibility. The peaks initially created by implicit flexibility were effectively mitigated by shifting them forward with explicit flexibility.

Combining implicit and explicit flexibility overall has the highest impact on comfort. For EVs, 96.0% of the cars that applied flexibility achieved a full SOC, whereas only applying explicit flexibility resulted in 99.6% of the cars reaching a full SOC. This difference occurs because implicit flexibility increases the charging time, as cars now charge during the cheapest periods instead of starting immediately when connected to a charging station. Consequently, there is less charging time available to redistribute demand, leading to a higher likelihood of not achieving a full SOC.

For HPs, the minimum temperature constraint becomes more limiting when combining implicit and explicit flexibility. During implicit flexibility, the temperature often drops to the minimum threshold of 18°C, with spikes of maximum power usage during cheaper price periods, allowing for reduced power consumption during more expensive periods. This limits the flexibility of HPs, as explicit flexibility will require additional power to maintain the temperature above the minimum 18°C during certain periods if flexibility is applied, thus increasing power usage during those times.

To overcome this issue pre-heating was applied during the redistributing to still reach optimal results, resulting in 0 hours of congestion instead of 94 hours without using pre-heating. This was however not done using the most cost-effective approach as described as a limitation in more detail in Section 6.3. Combining implicit and explicit flexibility has the most negative impact on comfort, as it deviates further from the original situation without comfort impact.

6.4 Comparison Flexibility

Finally, a comparison was made between all different types of flexibility in Section 5.5 as seen in Table 2. A comparison was made based on congestion mitigation, cost savings, and comfort impact.

6.4.1 Congestion mitigation

A scenario that includes explicit flexibility is the most effective in mitigating congestion, resulting in 0 hours of congestion with 50% participation. While there is little difference between the effectiveness of explicit flexibility alone and the combination of implicit and explicit flexibility, the primary distinction lies in the comfort constraints. However, this difference had minimal impact on the overall outcomes, as was seen in Figure 5.20.

The effectiveness of implicit flexibility in mitigating congestion depends on the participation rate. Up to a 20% participation rate, the effectiveness of implicit flexibility is comparable to that of explicit flexibility. However, beyond this participation rate, the effectiveness diminishes and eventually leads to more congestion than the original scenario. This occurs because as the participation rate increases, the concurrency of assets also increases, which ultimately causes more congestion at different periods. Additionally, this will result in higher peak power compared to no flexibility, as the increased concurrency of assets leads to higher simultaneous power demand.

Implicit flexibility had the most positive effect on reducing solar curtailment. Although this was not directly considered in the price optimization, the lowest prices usually occur during periods of high solar irradiance, leading to increased demand during these periods and ultimately reducing solar curtailment. When explicit flexibility was applied after implicit flexibility, curtailment was further reduced as the redistribution of peaks forward now occurred during periods with higher solar production.

6.4.2 Cost Savings

Cost savings were highest for HPs with implicit flexibility, as this approach is optimized based on cost. In contrast, explicit flexibility led to increased costs. This outcome is expected for the combination of implicit and explicit flexibility since it deviates more from the optimal cost solution. Surprisingly, a cost increase was observed when only explicit flexibility was applied, despite a decrease in energy consumption. This primarily occurs because explicit flexibility results in high power peaks for HPs rather than a more distributed profile. If these peaks occur during more expensive periods, the overall costs will rise. However, this doesn't always have to be the case, as the costs depend on the period to which flexibility is redistributed.

A different result was observed for EVs, where the most cost-effective solution was the combination of implicit and explicit flexibility, with costs decreasing when explicit flexibility was applied. This occurred because explicit flexibility led to a reduction in energy consumption, as cars did not always charge to 100%, thereby reducing overall costs. However, this comparison is not entirely fair, as it does not account for the increased cost of charging during subsequent sessions, which was not considered in this research.

In addition to cost savings, the total costs that the DSO would have to compensate for the additional expenses of explicit flexibility were also calculated. Applying explicit flexibility alone resulted in a total compensation cost of 300 € per year, averaging 1 € per household. For the combination of implicit and explicit flexibility, this cost rose to 11 € per household. This increase was primarily due to HPs causing more congestion during implicit flexibility, necessitating more intervention to mitigate congestion. Since the additional costs associated with HPs were higher than those for EVs, this led to higher overall costs. However, this comparison is not entirely fair, as the costs associated with the loss of SOC for EVs were not accounted for. Given that the combination of implicit and explicit flexibility resulted in more cars with an incomplete SOC compared to only explicit flexibility, it is expected that this cost difference would be even greater if SOC losses were considered.

6.4.3 Comfort impact

All forms of flexibility impacted comfort levels. Without flexibility, EVs would charge immediately when connected to a charging station, and HPs would consistently maintain the desired temperature. Introducing flexibility deviates from these conditions.

For EVs, implicit flexibility had the least impact on comfort as it still ensured a 100% final SOC, although charging time increased. Explicit flexibility didn't have this guarantee but with a 99.6% chance of having a full SOC this was still high. The combination of implicit and explicit flexibility had the highest impact on comfort, resulting in both the longest charging times and the lowest likelihood of achieving a full SOC of 96.0%.

For HPs, the least impact on comfort was observed when only explicit flexibility was applied. In this scenario, the temperature deviated from the desired level only during periods when flexibility was applied. Implicit flexibility, however, had a much higher impact on comfort, as it consistently deviated from the desired temperature to minimize costs. Most of the time, the temperature remained close to the minimum constraint of 18°C, with occasional spikes in temperature during cheaper periods. Combining implicit and explicit flexibility made the temperature even more unpredictable and showed the highest fluctuation thus impacting comfort the most.

6.5 Limitations

To make this model several assumptions and simplifications were made. The main limitations are discussed in this section.

6.5.1 Limitations Heat Pump profile

To model the profile of an HP, several simplifications were made. Firstly, it was assumed that all HPs in this model are fully electric, air-sourced, and modulating. In practice, there are various types of HPs, such as hybrid HPs and groundwater HPs, each with different efficiencies and use-cases. Additionally, while the model assumes modulating HPs that can continuously adjust their power output to maintain a constant temperature, many real-world HPs are on-off types, operating only at minimum and maximum power levels.

Further simplifications were made by randomizing the R-values for a neighborhood consisting of houses from the 1970s with different levels of insulation. For a more accurate representation, the R-values of each house should be specifically defined and calculated based on individual house properties, as explained in Appendix A.1. Typically, houses with good insulation are more likely to adopt HPs, as they result in greater cost savings. As well-insulated homes have lower heat losses, this will result in lower energy output of the HPs.

The temperatures of the house and crawl space were also assumed to be constant at 19°C and 12°C, respectively. In reality, these temperatures vary based on personal preferences and, for the crawl space, based on seasonal temperatures, ground temperatures and heat losses.

Lastly, the heat input from the sun was not considered, resulting in a higher energy consumption profile than what would occur in reality. This omission affects both the envelope temperature and the heat losses of the house. On the contrary, the model used climate data from 2023, which was the hottest year ever recorded in the Netherlands (Klimaatadaptatie, 2023). Selecting a different climate year with a colder winter would therefore result in higher energy consumption for the HP.

6.5.2 Limitations Charging profile

To model the SOC of an EV, two simplifications were made. First, the battery size was determined based on the longest charging sessions of each year, assuming a DOD of 80%. This implies that each car's SOC will drop to 20% at least once per year. Secondly, it was assumed that all cars would achieve a final SOC of 100% in the reference scenario. In reality, cars may charge for shorter periods, resulting in less than a full SOC.

When flexibility was applied a car could achieve a final SOC that is not 100%. This would result in more charging for the next charging session to compensate for this loss. However, this was not considered in the model, as the SOC starting values were predetermined, and charging could also occur at different locations.

Finally, all charging stations in this model had a maximum power of 11 kW, while many home charging stations have a maximum power of 3.7 or 7.4 kW (ENGIE, nd). Because of this the EVs might have caused higher peaks in consumption than in practise.

6.5.3 Limitations Transformer Load

To model the load on the transformer, the projected average adoption rates for the Netherlands in 2030 were used. In practice, some neighborhoods will experience higher adoption rates, leading to increased congestion. For example, an adoption rate of 21% was used for HPs, reflecting the national average expected in 2030. However, some neighborhoods may have district heating networks, resulting in few to no HPs, while others may have significantly higher adoption rates. For more accurate results, using the actual adoption rates of specific neighborhoods would provide a better understanding of where congestion is likely to occur.

The modeled neighborhood consisted of 300 houses, with the transformer's maximum active load assumed to be 250 kW. Varying the number of houses or the maximum load capacity will affect the overall congestion levels. Additionally, this model focused solely on transformer congestion, neglecting transmission line losses and congestion, which could further impact the results.

6.5.4 Limitations Flexibility

To model the flexibility of the HPs and EVs, technical constraints were neglected. HPs have a constraint that they should not be turned on or off too frequently in a short period, as this can cause short cycling and shorten compressor lifetime. Using a buffer cylinder can minimize this issue, but this was not considered in this research (Magloff, 2024).

Charging of EVs cannot be fully turned on and off from 11 kW to 0 kW during flexibility periods due to several technical and safety reasons. Completely stopping the charge can lead to temperature fluctuations within the battery, which can affect its performance and lifespan. Maintaining a minimal charging level can mitigate these issues, though this was not considered in the model (Li et al., 2023). Ortiz et al. (2024) highlighted that new advancements in thermal management strategies can potentially address these challenges. Ignoring these technical constraints may overestimate the flexibility potential of HPs and EVs.

6.5.5 Limitations Implicit and Explicit Flexibility

To correctly model the combination of implicit and explicit flexibility, a simplification was made in the redistribution of heat pumps, leading to higher costs and energy consumption than necessary. Due to implicit flexibility minimizing costs, the temperature constraint of 18°C became a more significant limiting factor compared to the reference scenario, where the temperature was assumed to be constant at 19°C. As a result, total congestion increased significantly. When the temperature approached 18°C and explicit flexibility was applied, additional power consumption was needed to maintain the temperature above 18°C, leading to new congestion during periods when the heat pump was not consuming energy, compared to the scenario with only implicit flexibility. This resulted in 94 hours of congestion.

To address this issue, pre-heating was modeled for more optimal results. In this scenario, instead of restoring the temperature to its original level during redistribution, it was maintained within the minimum and maximum temperature bounds. Normally, redistributing power would decrease energy consumption due to the absence of heat losses, however, this function was now omitted, resulting in a higher overall temperature. This can be seen in Figure 5.19b where the temperature now doesn't reach its minimum temperature constraint. Consequently, this approach did not reduce energy consumption and thus led to increased costs, but it did reduce congestion, bringing the results closer to optimal and resulting now in 0 hours of total congestion. To further enhance optimization, a new optimization process should be conducted after applying explicit flexibility. However, this step was not applied in the current model, resulting in higher overall costs than the optimal solution.

6.6 Potential extension and future research

In this research, the analysis focuses on a single scenario using the average adoption rates projected for 2030 in the Netherlands. For future research, it is recommended to explore different years, various adoption rates, different price years, and diverse climate conditions. Additionally, moving beyond the national average for the Netherlands to examine neighborhood-specific adoption rates and transformer data would be beneficial. This approach would help predict how congestion might increase over time and identify the necessary adoption rates of flexibility to mitigate these issues. Moreover, the model can be adapted for use in other countries if data from those regions are included. Such insights could guide decisions on deferring investments in new grid infrastructure and determining times for transformer replacements. It is also recommended to run the model with multiple simulations instead of using a single seed for scenario comparisons, enhancing the internal validity of the results.

For future extensions of the model, several additional applications could be incorporated to provide a more accurate picture of congestion mitigation. These include batteries, hybrid HPs, vehicle-to-grid technology, and AC cooling systems. The model could also be adapted to explore other flexibility strategies such as real-time pricing, ancillary services, and critical-peak pricing. Additionally, it is recommended to expand the focus beyond transformer congestion to include transmission-line congestion and losses.

7 Conclusion

This section addresses the research questions defined in Section 2.5 and provides corresponding recommendations.

7.1 Answers sub-questions

First, the sub-question "*How can explicit flexibility systems for electric vehicles and heat pumps be integrated effectively, while accounting for constraints like minimum driving distance and temperature, to minimize their impact on the grid?*" was explored.

The analysis showed a trend concerning the balance between flexibility provision and user comfort. When more assets, such as EVs and HPs, are providing flexibility, the initial effect is a decrease in comfort. This is due to the increased competition among assets to redistribute flexibility, making it harder to shift a reduction in load forward to meet desired comfort levels. This specifically results in reduced driving distance for EVs and lower temperature comfort for HPs.

However, a turning point was observed. As more assets participate in providing flexibility, grid congestion decreases. This reduction in congestion means that each asset has to provide less flexibility. As a result, comfort levels begin to improve again.

The comfort constraints, of maintaining a minimum temperature and ensuring a minimum final SOC, were the most limiting factors when closest to the desired temperature and final SOC of 100%. When the comfort constraints were lowered more, the limitation in providing flexibility was reduced.

The second sub-question explored was "*How do different combinations of explicit and implicit flexibility incentives interact and complement each other in mitigating congestion on LV networks?*"

Implicit flexibility proved effective in providing flexibility up to a 20% participation rate. However, beyond this point, increased participation led to greater congestion. In contrast, explicit flexibility effectively sustained a decrease in congestion. Combining implicit and explicit flexibility resulted in greater cost savings, but comfort levels were lower compared to scenarios with only explicit flexibility. However, in all cases, comfort losses were minimized due to the minimum comfort limits ensuring an acceptable level of comfort.

EVs were found to be more effective in mitigating congestion compared to HPs. The adoption of 50% or more explicit flexibility for EVs demonstrated that congestion could be fully resolved. Comfort was also impacted less for EVs as in most cases a full final SOC was still achieved. For HPs comfort is impacted more directly as in all cases the temperature will be reduced when flexibility is applied.

7.2 Recommendations

The sub-question "*What are the optimal setpoints and recommendations for implementing a combination of flexibility incentives to effectively alleviate congestion on low voltage networks while optimizing costs for both the network operator and residents?*" will be addressed in this section. Based on the results the following recommendations are given:

- *Implement ToU tariffs effectively.*

ToU tariffs were found to be effective up to 20% participation. Beyond this point, the effectiveness diminishes eventually resulting in increased congestion. It is recommended to create a new incentive that can effectively mitigate congestion beyond this participation threshold. This approach ensures that initial benefits are maximized and prepares for continued effectiveness as participation grows.

- *Facilitate asset communication.*

To mitigate the rebound effect, which can occur when multiple assets shift their usage simultaneously, assets providing flexibility must communicate with each other. Implementing a communication protocol or system that allows assets to coordinate will lead to more efficient network operation.

- *Prioritize EV flexibility.*

Prioritizing the flexibility of EV charging over HP flexibility is recommended. EV flexibility has been found to be more effective in alleviating network congestion while having a lesser impact on comfort. This prioritization can optimize network performance and maintain higher levels of resident satisfaction.

- *Mandate flexibility for social effectiveness.*

From a social perspective, obliging flexibility participation will be the most effective approach. By mandating certain levels of participation in flexibility, network operators can ensure a consistent and reliable level of congestion mitigation. This approach also minimizes the impact on individual comfort by distributing the flexibility requirement across a larger number of assets, thereby reducing the amount of flexibility each asset needs to provide.

- *Quantify loss in comfort to ensure fair compensation.*

It is important to quantify any potential loss in comfort experienced by residents due to participation in flexibility programs. This quantification allows for fair compensation, ensuring that residents are adequately compensated for any discomfort caused by participation. This can increase willingness to participate and maintain a positive relationship between network operators and residents.

- *Design price incentives aligned with LV congestion.*

By developing a price incentive structure that closely aligns with LV congestion, implicit flexibility can be achieved more effectively. This approach results in better congestion mitigation and delays the rebound effect. The pricing strategy should be transparent and easy to understand, ensuring that residents can manage their electricity usage without encountering unexpected costs.

7.3 Final conclusion

Finally, the main research question "*How can the integration of multiple explicit and implicit flexibility incentives at the household level effectively mitigate congestion issues on low-voltage networks while optimizing costs for both the network operator and residents?*" will be answered.

The integration of multiple explicit and implicit flexibility incentives at the household level can effectively mitigate congestion problems on LV networks by using the strengths of both types of flexibility. Implicit flexibility, driven by price signals from ToU tariffs and the Day-ahead market, encourages households to shift their energy use to off-peak times, helping to reduce congestion. This type of flexibility is shown effective up to a 20% participation rate and resulted in the highest costs savings. Beyond this point, using implicit flexibility alone becomes less effective as it can create new peaks in demand as more households shift their energy use to the same low-price periods.

Explicit flexibility is more effective at higher participation rates, as it allows for a sustained reduction in congestion. It provides real-time adjustments to energy use during peak periods, offering immediate relief to grid congestion.

Combining implicit flexibility with explicit flexibility not only reduces congestion but also results in more cost savings for households. Ensuring resident comfort through proper limits and compensation makes these flexibility programs more acceptable and effective.

In short, using both explicit and implicit flexibility, supported by communication between assets and well-designed financial incentives and comfort limits, can significantly reduce congestion, lower costs for network operators, and reduce energy costs for residents, creating a more efficient LV network system.

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A Appendix A

A.1 Equations thermal resistance

This subsection describes how thermal resistance R_{cond}, R_{floor} and $R_{\text{vent+inf}}$ can be calculated and is based on Koene et al. (2022) and Koene and Eslami-Mossallam (2023).

R_{cond} [W/K] represents the thermal resistance of the floor, walls and windows of a building and can be calculated with the corresponding R_{C}-values [m^2*K/W] and area's (A) [m^2] using Equation A.1.

$$R_{\text{cond}} = \frac{1}{\frac{1}{R_{\text{c,roof}} \cdot A_{\text{roof}}} + \frac{1}{R_{\text{c,wall}} \cdot A_{\text{wall}}} + \frac{1}{R_{\text{c,glass}} \cdot A_{\text{glass}}}} \tag{A.1}$$

Similarly, thermal resistance R_{floor} can be calculated using Equation A.2

$$R_{\text{floor}} = \frac{R_{c,\text{floor}}}{A_{\text{floor}}} \tag{A.2}$$

For ventilation, a distinction can be made between mechanical ventilation (A), natural ventilation (B), and a balanced ventilation system (C) (Koene et al., 2022). The thermal resistance of ventilation and infiltration $R_{\text{vent+inf}}$ [W/K] can be calculated using the following Equations:

$$H_{\text{vent+inf}}(A) = \frac{C_p \cdot (0.383 \cdot qv_{10} + 91)}{3600} \tag{A.3}$$

$$H_{\text{vent+inf}}(B) = \frac{C_p \cdot (0.349 \cdot qv_{10} + 53)}{3600} \tag{A.4}$$

$$H_{\text{vent+inf}}(C) = \frac{C_p \cdot (0.349 \cdot qv_{10} + 21)}{3600} \tag{A.5}$$

$$R_{\text{vent+inf}} = \frac{1}{H_{\text{vent+inf}}} \tag{A.6}$$

qv_{10} [l/s] is the infiltration flow rate during a pressure difference of 10 Pa and C_p is the heat capacity of air (1230 J/m^{3}K).