Behind the Meter: End-User Flexibility for Congestion Mitigation

An Agent-Based Exploration of Residential Behavior and Measures for Low-Voltage Congestion Relief

CoSEM Master Thesis

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TU Delft

“All models are wrong, but some are useful”
— George E. P. Box

“In every assumption, there lies a recommendation”
— Jorik Dekkers

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Preface

Almost two years ago, I started the Master's in Complex Systems Engineering and Management. I chose to specialize in the energy track, and throughout these two years, my passion for the energy transition has grown significantly. When I first learned about the issue of net congestion and how it is currently delaying the transition, I was immediately hooked. I believe that exploring short-term solutions to this problem is a key step in accelerating the energy transition in the Netherlands.

My thesis focuses on an area that I believe holds great potential but is currently overlooked by many experts and industry leaders: congestion on the low-voltage grid, and the potential to gain flexibility by changing household behavior. As this is a relatively new problem, the research came with its fair share of challenges. That's why my first thank you goes to the experts at Alliander, Enexis, and Stedin, who were open to having conversations with me and sharing valuable insights. Their input allowed me to fully dive into the topic, even though publicly available information on it was still quite limited.

I would also like to thank my TU Delft supervisors, Natalie van der Wal and Ivo Bouwmans, for the delightful meetings. Your optimism, cheerfulness, and of course your expertise made working on this thesis a joyful experience. From Accenture, I want to thank Jorik Dekkers for his endless knowledge on the topic of congestion. A special thank you goes out to Jens Backhausen, who sat with me every week, always asking the most difficult questions to keep me sharp and helping me reach my personal goals during this period.

I want to thank my parents, who supported me throughout my studies. During the thesis, I especially want to thank my dear roommates, who supported me through this sometimes challenging period and cooked me dinner when I was a little too busy to do so myself. My final thank you goes out to Carlo: thank you for all your support and your sometimes interesting insights into my topic. I promise I'll have time to hang out again now.

To the reader: I put a lot of effort into this research, and fortunately, I can proudly say that I'm happy with the end result. I wish you an insightful and inspiring read.

P.J. Treanor
Delft, June 2025

Summary

The energy transition is placing increasing pressure on the Dutch low-voltage electricity grid, leading to growing congestion that threatens grid reliability and slows the adoption of sustainable technologies. To address this, Distribution System Operators are exploring ways to unlock household flexibility. However, most current strategies treat households as a homogeneous group, overlooking the behavioral diversity that exists behind the meter. This research addresses that gap by investigating the differences in household profiles and how they respond to specific congestion mitigation measures. The main research question is: *Which low-voltage user profiles participate in specific congestion mitigation measures, and how does their participation impact demand and supply flexibility on the grid?*

To answer this, an Agent-Based Model was developed to simulate the behavior of five household profiles (*Conscientious Individuals*, *Structure Seekers*, *Status-Driven*, *Responsibles*, and *Self-Developers*) and their participation in three flexibility measures: smart charging for private EV chargers, flexibility contracts for curtailing residential solar energy, and flexibility contracts for all-electric heat pumps. Additionally, the model includes the influence of awareness campaigns as a communication-based congestion mitigation measure. In addition to private chargers, solar panels, and all-electric heat pumps, households can also own home batteries in the model. The household profiles were constructed through a literature review, and the selection of relevant congestion measures was informed by interviews with Dutch Distribution System Operators.

Scenarios were developed to represent both current conditions (base scenario) and two future situations: one in which the netting arrangements remain in place, and another in which they are abolished. The model ran over a two-year simulation period and tracked participation levels across household profiles, as well as the resulting effects on demand- and supply-side flexibility. Under current conditions, smart charging was the most favorable measure among households. The flex contracts for solar PV curtailment show high participation in the future scenarios with and without netting arrangements, enabling full mitigation of summer feed-in peaks. Home batteries also demonstrate strong potential for flattening both feed-in and demand peaks when paired with solar ownership. In contrast, participation in flexibility contracts for heat pumps remains limited unless the measure is made more financially attractive and widely promoted. The results also reveal strong variation in participation across household profiles. *Conscientious Individuals* and *Responsibles* emerge as early adopters, whereas *Status-Driven* are consistently the least likely to participate.

The findings suggest that summer feed-in peaks can be effectively mitigated through behavioral flexibility. Winter peak demand, however, remains a more difficult challenge due to lower participation in relevant measures and the broader diversity of electricity use during colder months. Nevertheless, the results indicate that significant potential exists and that this potential can be unlocked more effectively by accounting for the behavioral differences between households.

Theoretically, this study contributes to energy modeling by integrating behavioral heterogeneity into an agent-based framework. It shows how existing segmentation models can be used dynamically in simulations, and how the combination of qualitative and quantitative inputs enhances the realism of behaviorally informed models. Practically, the study supports Distribution System Operators and policymakers by offering insight into how different household types respond to specific incentives and interventions. It provides actionable recommendations for improving participation through more targeted engagement strategies, and it offers a broader understanding of how emerging flexibility measures could influence the electricity grid. In short, aligning grid flexibility with household behavior requires more than technical optimization: it demands a nuanced understanding of who is *behind the meter*.

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Nomenclature

Abbreviations

Abbreviation	Definition
ABM	Agent-Based Model
DSO	Distribution System Operator
EV	Electric Vehicle
Flex HP	Flexibility Contract for Heat Pumps
Flex PV	Flexibility Contract for Solar PV
HP	Heat Pump
HV	High Voltage
kWh	Kilowatt-hour
LV	Low Voltage
MV	Medium Voltage
OAT	One-At-a-Time (Sensitivity Analysis method)
PV	Photovoltaics / Solar Panels
SA	Sensitivity Analysis
ToU	Time-of-Use (tariff variant)

Model Variables

Table 2: Glossary of model variables (if no unit is given, the variable is unitless)

Variable Name	**Symbol**	**Description**
Comfort level	C_i	Inherent comfort tolerance of agent i.
Routine rigidity	R_i	Rigidity of daily schedule of agent i.
Household composition factor	w_i	Influence of household composition of agent i.
Financial sensitivity	F_i	Sensitivity to financial incentives of agent i.
Trust level	T_i	Baseline trust in external systems of agent i.
Knowledge level	K_i	Practical knowledge about energy systems and participation of agent i.
Environmental awareness	A_i	General concern for environmental impact of agent i.
Belief in personal impact	B_i	Belief that individual actions matter for larger outcomes of agent i.
Social norms	S_i	Sensitivity of agent i to peer influence.
Comfort requirement of measure	C_{m}	Minimum comfort flexibility required to participate in a measure.
Financial incentive of measure	F_{m}	Financial incentive offered by the measure.
Trust requirement of measure	T_{m}	Minimum trust score required to participate in a measure.
Familiarity of measure	K_{m}	Perceived familiarity of the measure in the population.
Comfort Choice	$C_{\text{choice},i}$	Determines how much comfort an agent is willing to give up.

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Variable Name	Symbol	Description
Financial Choice	$F_{\text{choice},i}$	Determines how financially sensitive an agent is.
Trust Choice	$T_{\text{choice},i}$	Determines how much trust an agent has in external parties.
Knowledge Choice	$K_{\text{choice},i}$	Determines how much knowledge an agent has.
Comfort score of agent	C_i, m	Score based on match between importance of comfort level for agent and perception of comfort loss of the measure.
Financial score of agent	F_i, m	Score based on match between financial sensitivity of the agent and financial incentive of the measure.
Trust score of agent	T_i, m	Score based on match between trust in external parties of the agent and trust required for the measure.
Knowledge score of agent	K_i, m	Score based on knowledge of the agent and familiarity of the measure.
Participation score	Score_i, m	Combined weighted score to determine agent's willingness to participate.
Participation threshold	θ	Minimum score required to trigger participation.
Knowledge weight	w_k	Weight of knowledge score in participation decision.
Comfort weight	w_c	Weight of comfort score in participation decision.
Financial weight	w_f	Weight of financial score in participation decision.
Trust weight	w_t	Weight of trust score in participation decision.
Social influence factor	λ_i	Strength of social influence on agent i.
Average neighbor value	$\bar{X}_{\text{neighbors}}$	Mean value of characteristic among neighbors.
Electricity profile of agent	$L_{i,h}$	Electricity profile (net load or generation) of agent i at hour h [kWh/h].
Annual base consumption	C_i	Annual base consumption of agent i [kWh/year].
Normalized load profile	p_h	Normalized load fraction at hour h (from profile data).
EV electricity usage	$\text{EV}_{i,h}$	EV electricity usage by agent i at hour h [kWh/h].
Heat pump electricity usage	$\text{HP}_{i,h}$	Heat pump electricity usage by agent i at hour h [kWh/h].
Solar PV generation	$\text{PV}_{i,h}$	Solar PV generation by agent i at hour h; negative value if supplying power [kWh/h].
Smart EV profile	SmartEV_h	Optimized EV charging load at hour h, applied when the agent participates in the smart charging measure [kWh/h].
Smart heat pump profile	SmartHP_h	Optimized heat pump usage profile at hour h, applied when the agent participates in the flexibility measure [kWh/h].
Curtailment threshold	γ_{curt}	Generation threshold below which curtailment is applied to PV output (PV curtailed to 0 if below this threshold) [kWh/h].
Social participation threshold	ϕ_m	Minimum fraction of neighboring agents participating in measure m to trigger social influence (default: 0.5).
Battery capacity	B_i^{cap}	Maximum energy capacity of agent i's battery [kWh].
Battery state of charge	B_i^{soc}	Current energy stored in battery [kWh].
Max charge rate	$B_{\max}^{\text{ch}}$	Maximum rate of battery charging [kWh/h].
Max discharge rate	$B_{\max}^{\text{dis}}$	Maximum rate of battery discharging [kWh/h].

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Variable Name	**Symbol**	**Description**
Charging increment	$\Delta B_{i,h}^{\text{ch}}$	Battery energy charged by agent i in hour h [kWh/h].
Discharging increment	$\Delta B_{i,h}^{\text{dis}}$	Battery energy discharged by agent i in hour h [kWh/h].
Final electricity load	$L_{i,h}^{\text{final}}$	Total electricity demand after accounting for all assets [kWh/h].
PV generation	$P_{i,h}$	Solar panel output of agent i at hour h (negative value if exporting) [kWh/h].
Exported PV	P_i^{exp}	Total PV energy exported to the grid by agent i [kWh/h].
Generated PV	P_i^{gen}	Total PV energy generated by agent i [kWh/h].
Self-consumption ratio	SelfUseRatio_i	Fraction of PV energy consumed directly by the agent.
Self-consumption target	ζ	Benchmark for desirable PV self-consumption.
Feedback sensitivity	α	Strength of feedback on financial sensitivity.
Knowledge learning rate	η	Learning rate for how fast measure becomes known.
Participation rate	$R_m(t)$	Participation rate for measure m at time t.

1 Introduction

The Dutch electricity grid is increasingly reaching its limits, as the volume of electricity being transported frequently exceeds the grid's available capacity [2]. In such cases, electricity can no longer be transported into or out of certain areas, leading to grid congestion [3]. The cause of this problem is that, in recent years, electricity generation and consumption patterns have shifted significantly due to the transition toward more sustainable systems [4]. This progress comes at a cost: electricity flows are increasing, leading to higher peak loads on the grid [5]. In many regions, these peaks are rising faster than the grid can be expanded [6].

Although congestion was initially concentrated in the high- and medium-voltage (HV and MV) networks, recent developments have exposed capacity limitations in the low-voltage (LV) grid as well [2]. This part of the grid serves households, small businesses, and other small-scale users, including prosumers who feed electricity back into the network [2, 4]. Three main trends are driving this increase in electricity flows [4]: (1) the rise in electric vehicle ownership [7], (2) electrification of household energy use [8], and (3) the widespread adoption of solar panels [9]. Originally designed to handle 1 to 1.5 kW per connection, the LV grid is now facing demands of 5 kW or more per household [10]. These developments have already led to congestion in various regions [11], and grid operators warn that simultaneous use of heat pumps during cold periods could lead to outages this coming winter [12].

The implications of LV congestion go beyond individual households. According to a study by Ecorys for the Ministry of Economic Affairs and Climate Policy, resolving congestion at the low- and medium-voltage levels could unlock €10 to €40 billion annually in societal and economic value [3]. The issue also limits industrial growth and delays the rollout of renewable energy technologies, thereby slowing national sustainability goals. Since the Dutch electricity system is highly interconnected, congestion on the lower voltage levels can contribute to congestion on MV and HV grids and vice versa [4].

Managing congestion in the LV grid poses unique challenges. Compared to the HV and MV levels, LV infrastructure has far more connection points and significantly less available data, limiting visibility and control [4, 11]. As the LV grid directly affects residential energy users, delays and limitations have become a visible societal issue [2, 4]. In November 2024, NOS reported waiting times of up to 1.5 years for grid connections for some Dutch households [13]. Without timely intervention, grid operators estimate that up to 1.5 million households may experience congestion-related issues by 2030 [2].

One of the main approaches to addressing congestion in low-voltage (LV) grids is grid reinforcement, meaning expanding the physical infrastructure. However, the scale and urgency of the required upgrades are such that they cannot be realized in a timely manner under the current approach. This is due to a combination of challenges, including labor shortages, material scarcity, financial limitations, and lengthy spatial planning procedures [4]. As a result, exploring alternative strategies beyond grid reinforcement is essential.

A January 2024 report by the Dutch government [2] outlines a strategy consisting of three key components to address LV congestion: (1) accelerating grid reinforcements, (2) improving grid efficiency through better coordination of supply and demand, and (3) encouraging energy conservation. Instead of solely expanding the grid to accommodate these peak electricity hours, optimizing the existing infrastructure is a more short-term and cost-effective approach. A key strategy to achieve this is adjusting energy consumption patterns among small-scale users to unlock flexibility: the ability to shift or reduce electricity consumption or generation in response to system needs [14].

However, grid operators currently lack sufficient insight into the behavior of individual LV users, which limits their ability to design targeted strategies for mitigating congestion (personal communication, February 10th, 2025). A deeper understanding of user behavior and flexibility potential is therefore essential [4, 14]. This study focuses on households, which comprise the majority of the approximately 8 million small-scale connections in the Netherlands [5]. Each household exhibits distinct consumption patterns and behavioral responses, making it complex and important to identify different user profiles that can inform differentiated interventions [8, 15].

This research seeks to support grid operators by analyzing the behavioral and technical characteristics of households in relation to specific congestion mitigation measures. Using these insights, the study explores how user engagement can contribute to more efficient and resilient grid operations. The central research question is:

> *What is the effect of different congestion mitigation measures on the participation of distinct household profiles in the low-voltage grid, and how does this participation affect supply- and demand-side flexibility?*

This question is addressed through the following sub-questions:

1. What are the key characteristics of the Dutch low-voltage grid, and how do household electricity demand and supply patterns contribute to its challenges?
2. Which congestion mitigation measures are currently in use or development, and where is household participation most critical?
3. How can household profiles be classified based on electricity usage behavior?
4. How do selected mitigation measures influence supply- and demand-side flexibility under different scenarios?
5. What is the effect of household profile characteristics on participation in these mitigation measures?

This research aligns with the Master's program in Complex Systems Engineering and Management (CoSEM) at Delft University of Technology, particularly within the Energy specialization. It addresses low-voltage grid congestion as a socio-technical challenge involving regulatory, technological, and societal factors. In line with the CoSEM approach, which emphasizes the interaction between technology, institutions, and society, the study enhances understanding of how operational and regulatory frameworks can support sustainable energy systems. By integrating technical, policy, and behavioral insights, it contributes to CoSEM's mission of developing multidisciplinary solutions to complex real-world problems. The research is supported by Accenture, a global leader in strategy consulting, which seeks deeper insights into the needs and behaviors of small LV grid users. Together, these perspectives inform strategies for more sustainable and adaptive grid management.

To answer the research questions, a mixed-method approach is applied. Chapter 2 presents a literature review to build an understanding of the characteristics of the LV grid and to identify key behavioral factors that influence household electricity use. These findings form the foundation for developing the household profiles. In Chapter 3, semi-structured interviews with the three largest Dutch grid operators (Stedin, Liander, and Enexis) are conducted to identify which congestion mitigation measures are currently in use or under development. Based on these insights, Chapter 4 introduces an agent-based modeling (ABM) approach to simulate the interaction between household behavior and selected mitigation strategies. Chapter 5 presents the simulation results, showing how different household profiles respond to various measures and how this affects the flexibility of the LV grid. Finally, Chapter 6 discusses the key findings, limitations, and directions for future research.

2 Background and Literature

This chapter addresses the first sub-question: *"What are the key characteristics of the Dutch low-voltage grid, and how do household electricity demand and supply patterns contribute to its challenges?"* To answer this, the chapter first outlines the structure and function of the Dutch LV grid and explores the growing issue of congestion at this level of the electricity network. It then clarifies the scope of this research and highlights the specific knowledge gap it aims to fill. Finally, a literature review is conducted to identify behavioral factors that influence how households consume and produce electricity.

2.1. Grid Congestion on the Low-Voltage Grid

The Dutch electricity grid is a highly interconnected system that facilitates the transport of electricity from generation sources to end-users [2]. It is considered one of the most reliable grids in the world, with customers experiencing an average of only 22.1 minutes of power outage in 2022 [11, 3]. High-voltage transport is managed by TenneT, while the distribution at medium and low voltage levels is the responsibility of regional grid operators such as Liander, Stedin, and Enexis [5]. This study focuses specifically on the low-voltage segment of the grid, which spans more than 240,000 kilometers across the Netherlands. Notably, only around 120 kilometers of this infrastructure is above ground; the vast majority is buried underground [11]. For a broader overview of the entire electricity system and the division of roles among key actors, refer to Appendix A.

The LV grid supplies electricity to small-scale users, such as households and small businesses, typically with connections up to 3x80A [2]. This research focuses specifically on residential households. Within this group, the ongoing energy transition has led to a sharp rise in electricity demand and increasingly volatile usage patterns, largely due to the growing adoption of technologies such as electric vehicles and rooftop solar panels [5]. As a result, household loads now exhibit sharper peaks and bidirectional flows. This effect is visualized in Image 2.1. The load curve on the left shows the base load of the household. To the right of this base load graph, there are load graphs that show how the adoption of energy-intensive assets changes this load. Despite these evolving dynamics, the LV grid remains under-monitored [2]. Limited measurement infrastructure and the large number of small-scale connections make timely detection and management of local grid stress particularly difficult [4]. As electrification continues and more power is both consumed and produced at the household level, grid capacity is reached more quickly, especially during peak periods [2]. This results in grid congestion, which occurs when electricity flows exceed the infrastructure's operational limits [6]. This trend is expected to accelerate in the coming years, further increasing the strain on the LV grid [4]. While congestion in the high- and medium-voltage networks has been acknowledged for several years, challenges in the LV grid have only recently become urgent [2, 4].

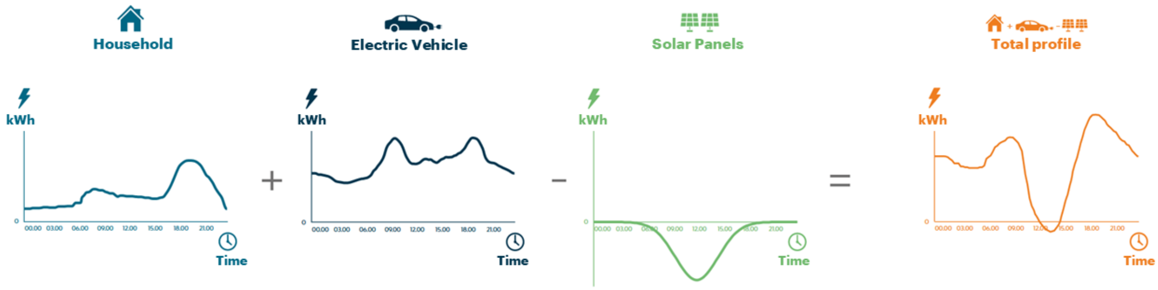


Figure 2.1: Changes in household electricity loads [5]

There are two types of grid congestion: congestion that arises when electricity demand exceeds transport capacity (*demand congestion*), and congestion that occurs when electricity supply exceeds grid capacity (*feed-in congestion*) [6, 16]. Due to the interconnected nature of the electricity system, congestion at one voltage level can influence other layers [4]. For instance, limitations in the MV grid may worsen issues in the LV grid. Conversely, reducing peak demand at the LV level can help alleviate pressure on MV or even HV infrastructure [2]. Since congestion on the LV grid has not yet been comprehensively mapped, Figure 2.2 presents the current state of congestion at the MV level. Because congestion can extend between voltage levels, this still provides a valuable indication of the overall magnitude of the issue and the regions in the Netherlands currently facing grid constraints.

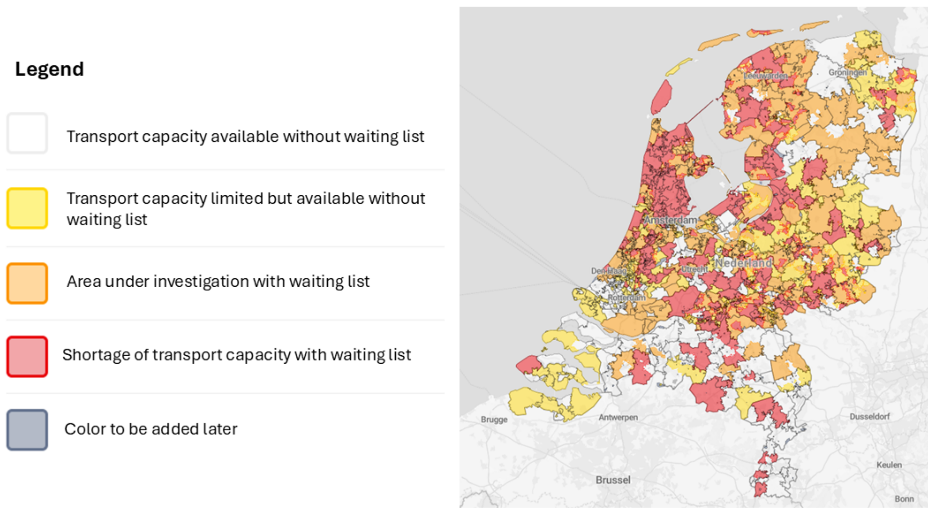


Figure 2.2: Congestion on the medium-voltage grid [17]

Grid congestion in the low-voltage network can lead to three main problems [4]:

1. **Capacity shortage**: Demand exceeds cable or transformer capacity, leading to overheating, outages, and delays in new or upgraded connections.
2. **Overvoltage**: Voltage exceeds 253V due to excess generation, such as from solar panels, limiting feed-in capacity.
3. **Undervoltage**: Voltage drops below 207V due to high demand, for example from heat pumps or electric vehicles, causing flickering lights, equipment malfunctions, or damage to appliances.

In contrast to the medium- and high-voltage networks, the low-voltage network is mostly single-lined and lacks redundancy. This means that disruptions typically lead to immediate power loss, and repair times are longer. In 2023, the low-voltage network accounted for over 24,500 unplanned outages, a 20.7 percent increase compared to the five-year average. These outages lasted 157 minutes on average, significantly longer than those in the medium-voltage (62.5 minutes) and high-voltage (19.5 minutes) networks [11]. Without intervention, grid operators estimate that up to 1.5 million households may experience congestion-related issues by 2030, such as overvoltage, outages, connection delays, or feed-in restrictions [4]. Figure 2.3 shows the expected distribution of these problems.

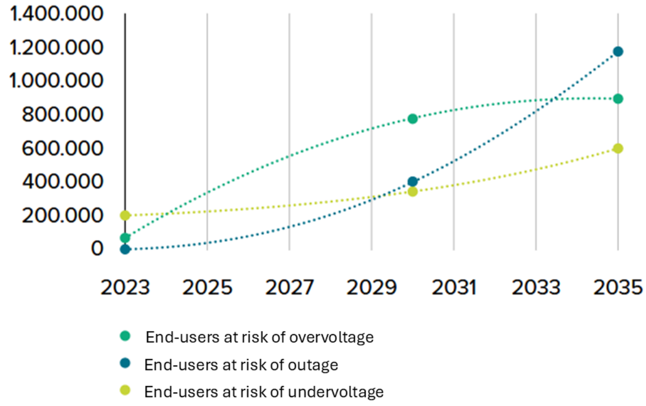


Figure 2.3: Projected future issues for households due to grid congestion [4]

Regional grid operators are tasked with managing these developments while maintaining grid reliability and affordability [5]. One important response is to reinforce the grid infrastructure [2, 4]. Although the original design capacity was around 1 to 1.5 kW per household connection, current demand in electrified homes often reaches up to 5 kW [4]. While the network can accommodate such high usage at the individual level, simultaneous consumption across neighborhoods rapidly exceeds capacity limits. However, the scale of the required reinforcements is so large that it cannot be realized within the necessary timeframe due to shortages in labor, materials, funding, and lengthy permitting processes [4]. As a result, grid operators must also implement congestion management strategies. Two essential approaches include better coordination between electricity supply and demand and encouraging energy conservation [2]. These strategies increase flexibility within the grid and help defer or reduce the need for physical infrastructure expansion.

Flexibility refers to the electricity system's ability to handle variability and uncertainty in supply, demand, and transport within the limits of grid capacity [18]. This flexibility is characterized by four dimensions: the amount of energy that can be shifted, the duration of the shift, the response speed, and the location in the network [19, 20]. Although each household has limited capacity to contribute, the aggregated effect of millions of small users can create a significant flexible resource [21]. Households can help reduce grid stress by shifting demand to off-peak times or, in the case of prosumers, by regulating the electricity they generate and supply [22]. This flexibility from small-scale users can be obtained in two primary ways: through demand-side adjustments [4] or supply-side management [23]. Demand-side flexibility addresses periods when consumption exceeds grid capacity, while supply-side flexibility can mitigate periods of excessive feed-in. These contributions not only help manage congestion at the LV level, but also support stability throughout the grid, including at the MV and HV levels [4]. Involving small-scale consumers and prosumers is therefore crucial for improving overall grid flexibility, reducing pressure on infrastructure, and enabling a more sustainable electricity system [22].

2.2. Electricity Behavior and Behavior Frameworks

Large-scale behavioral change among small-scale electricity users can significantly contribute to grid flexibility and reduce congestion on the LV grid [2, 4]. To enable such change, a clear understanding of how households consume electricity is essential. In this context, *electricity behavior* refers to all the factors that influence a household's electricity usage over time and ultimately shape their electricity bill. This section reviews earlier research on household electricity behavior and evaluates theoretical frameworks used to interpret this behavior.

As early as 1983, Van Raaij and Verhallen demonstrated that energy behavior could be meaningfully segmented into household profiles, and that interventions tailored to these profiles are more effective than generic interventions [24]. Despite these early insights, energy research has long focused primarily on technical and economic factors. Sovacool's 2014 review of 4,444 energy-related publications revealed that social and behavioral dimensions remained underrepresented in academic literature [25]. More recently, De Vries (2023) [26] emphasized that although behavior is often mentioned in transition plans, true behavioral expertise is still lacking. Engineers tend to overestimate public acceptance of new technologies, underlining the need for better integration of behavioral insights.

Despite this gap, recent studies highlight the relevance of bottom-up perspectives. Niamir et al. [27] highlighted the importance of psychological and socio-demographic factors in household decision-making, arguing that they should complement traditional top-down policy tools. In another study in the Dutch context, Bedir and Kara [8] identified four electricity consumption profiles based on income, education, household size, and working hours. These profiles showed statistically significant differences in electricity usage. Their study also pointed out that while much of the Dutch literature emphasizes heating behavior, electricity-specific behavior remains underexplored. Similarly, Muroni et al. [28] showed that modeling electricity use based on occupant behavior substantially improved prediction accuracy. Even in identical dwellings, different households display distinct consumption patterns.

Another key finding is that financial incentives alone are often insufficient to drive behavioral change. Niamir et al. [27] also found that decisions are shaped by personal norms, education, family composition, and especially peer behavior. Beunder et al. (2015) [29] found that household electricity consumption is influenced not only by financial incentives but also by social and cultural factors. Dijkstra [30] emphasized that to effectively promote sustainable energy practices, interventions must go beyond financial incentives and incorporate psychological and social factors such as social norms and intrinsic motivation.

The literature not only underscores the importance of integrating behavioral insights into energy research, but also highlights the wide variety of factors that influence household electricity use. These include both the way electricity is consumed and therefore, if a household owns solar panels, the extent to which households feed energy back into the grid. Changing such behaviors could create flexibility on both the demand and supply side. Looking more closely at demand-side flexibility, Poortinga et al. [31] found that households prefer technical solutions, such as energy-efficient appliances, over behavioral change. When behavioral changes do occur, they tend to focus on household electricity use rather than transportation. While this reveals untapped flexibility potential, it also reinforces the importance of user acceptance. Neuteleers et al. [32] found that dynamic pricing (charging more during peak hours) is often perceived as unfair, especially by lower-income households, and stressed that fairness should be a core principle in program design. On the supply side, prosumers (households that both consume and produce electricity) also offer untapped flexibility potential. Hubert et al. [33] found that low awareness, established routines, and perceived lack of impact limit their responsiveness. Georgarakis et al. [34] observed that prosumers are more motivated by environmental concerns than financial ones, and that ease of participation is essential. Bellekom [35], using Agent-Based Modeling, concluded that enabling prosumer flexibility depends on behavioral engagement, supportive policies, and accessible technologies.

In summary, although previouss studies have examined behavioral, technical, and social influences on household electricity use [8, 24, 28], past policy and modeling approaches have often treated electricity users as homogeneous, driven primarily by price signals [25, 28]. To unlock the full flexibility potential of households on the Dutch low-voltage grid, this heterogeneity must be acknowledged. Tailored strategies based on behavioral diversity can help grid operators implement more effective congestion mitigation. A structured approach that combines behavioral and technical insights could help operators develop more targeted, effective strategies for grid stability.

To interpret household electricity behavior in a structured manner and support the development of user profiles, it is important to apply a consistent behavioral framework. Such frameworks help identify the underlying drivers of sustainable energy practices and explain why households respond differently to interventions. They provide a lens to analyze behavior based on elements such as routines, social norms, values, and physical context [36]. Within this study, a behavioral framework serves as a guide to categorize influential factors in household electricity use, helping to structure and synthesize the wide array of variables found in literature. This is especially relevant given the diversity in household motivations, values, and perceptions emphasized by multiple researchers [37, 38]. Several studies analyzing energy or electricity behavior apply such frameworks to deepen behavioral understanding. One of the most commonly used is the Theory of Planned Behavior, which focuses on intention formation through attitudes, perceived behavioral control, and social norms [27, 33, 36, 39]. Other frameworks include Social Practice Theory, which emphasizes routines and shared practices [33], and the Norm Activation Model, which highlights the role of personal norms and awareness of consequences [27]. The COM-B model (Capability, Opportunity, Motivation—Behavior) offers an integrative perspective by linking behavioral drivers to context and capacity for change [36, 40]. Broader frameworks such as the Value-Belief-Norm theory [41] and the Energy Cultures Framework [42] connect individual behavior to technological and social influences. Of all the reviewed frameworks, the Energy Cultures Framework was selected to support this study. Introduced by Stephenson et al. in 2010 [42], it builds on classical behavioral theories such as the Theory of Planned Behavior but extends them by offering a specific focus on energy use, placing the individual at the center of analysis. The framework proposes that consumer energy behavior can be fundamentally understood through the interaction between three core elements: cognitive norms (e.g., beliefs, values, and understandings), material culture (e.g., technologies and infrastructure), and energy practices (e.g., routines and habits) [42]. It aims to identify factors that influence consumption behavior and to help recognize opportunities for behavioral change. As a flexible and adaptable framework, it has been applied in a wide range of case studies and research contexts, making it suitable for this research as well [43]. In the first phase of this study, the framework is used to structure and identify the most relevant factors that shape household electricity profiles. In later stages, its dynamic perspective (emphasizing how the three elements interact) will be applied to analyze how different households make decisions and how their adoption behavior influences grid flexibility. This next step is further elaborated in Section 4.2.

2.3. Creating Electricity Profiles of Households

As discussed in previous studies, household electricity behavior is shaped by a wide range of factors. According to the Energy Cultures framework, these patterns are influenced by technical infrastructure, psychological drivers, and habitual practices within a household [42]. One way to visualize electricity behavior is through a household load curve. An example of such a curve is shown in an earlier figure, Figure 2.1. A load curve can provide insights into the technical infrastructure of a household: as households adopt more appliances and technologies, their overall electricity demand typically increases [8]. It also reveals the magnitude and timing of electricity demand and generation. This visible consumption pattern and the technical elements that directly shape it, form what is referred to in this study as the *technical profile* of a household. In addition, there are behavioral characteristics that indirectly affect this curve. While not directly visible in the load profile, these characteristics nonetheless help shape it and are captured in what this study defines as the household's *behavioral profile*.

To define both the technical and behavioral profiles, a literature review was conducted to identify key influencing factors, using the Energy Cultures framework as a guiding structure. Since only a limited number of studies explicitly address low-voltage user profiles that combine both technical and behavioral elements, a snowballing approach was applied to broaden the scope. This method enabled the inclusion of relevant research on general energy-related household behavior, including electricity use, heating patterns, and broader sustainability actions. The goal was to capture a diverse set of motivations, routines, and contextual factors that shape energy behavior. An overview of the reviewed literature is presented in Table 2.1, and the most frequently identified behavioral factors are summarized in Table 2.2.

Citation Key	Author(s)	Year
[8]	Bedir & Kara	2017
[15]	Zhang et al.	2012
[24]	van Raaij & Verhallen	1983
[27]	Niamir et al.	2020
[28]	Muroni et al.	2019
[29]	Beunder & Groot	2015
[30]	Dijkstra	2020
[33]	Hubert et al.	2024
[34]	Georgarakis et al.	2021
[35]	Bellekom et al.	2016
[36]	Höpfl et al.	2024
[38]	Tijs et al.	2016
[41]	Sütterlin et al.	2011
[43]	Klaniecki et al.	2020
[44]	de Groot et al.	2008
[45]	Galvin	2020
[46]	Heinrich et al.	2022
[47]	Nyström et al.	2024
[48]	Abreu et al.	2012
[49]	van der Veen et al.	2024

Table 2.1: Overview of analyzed literature cited in Table 2.2.

Factor Influencing Energy Behavior	Cited in	Count
Environmental awareness	[15, 27, 34, 35, 38, 36, 46, 41, 44, 47]	10
Financial incentives	[29, 30, 34, 35, 36, 38, 43, 47, 44]	9
Practical knowledge	[15, 27, 30, 35, 36, 38, 41, 47, 49]	9
Motivation to save energy	[8, 15, 30, 36, 41, 43, 44, 46]	8
Routines	[8, 28, 33, 38, 46, 47, 48]	7
Household composition	[8, 15, 24, 29, 38, 46, 48]	7
Social norms/Community feeling	[27, 34, 35, 36, 41, 47, 49]	7
Appliance use	[8, 28, 44, 46, 47, 48]	6
Income	[15, 27, 29, 38, 43, 46]	6
Trust in external party	[27, 36, 38, 45, 47, 49]	6
Adoption of technology	[15, 27, 33, 35, 45, 47]	6
Belief in personal impact	[27, 33, 36, 38, 41, 47]	6
Education level	[8, 24, 27, 38, 43]	5
Metering abilities of electricity use	[28, 33, 35, 38, 49]	5
Importance of comfort levels	[28, 38, 41, 44, 46]	5
Presence at home	[8, 28, 48, 46, 15]	5
Dwelling type	[15, 27, 38, 46]	4
Ownership of dwelling	[15, 27, 35, 38]	4
Level of complexity of a system	[30, 34, 47, 49]	4
Age	[24, 38, 43, 44]	4
Ownership of appliance	[15, 35, 46]	3
Importance of hygiene levels	[8, 24, 46]	3
Cultural background	[27, 29]	2
Food equipment level	[8, 46]	2
Risk aversion	[30]	1
Feeling of unfairness	[30]	1
Choice overload	[30]	1

Table 2.2: Overview of significant factors influencing household energy behavior, sorted by frequency across the reviewed literature.

Tables 2.1 and 2.2 provide a foundation for constructing household electricity profiles. However, beyond identifying relevant influencing factors and organizing them within a behavioral framework, it is also necessary to define distinct household profiles. Specifically, there must be clarity about which types of households exhibit which technical and behavioral characteristics, and to what extent. There are various ways to structure such profiles.

One approach to structure household profiles is to adopt existing profiles developed in earlier studies. Several studies analyzed in the electricity behavior literature review proposed distinct user profiles. For instance, Van Raaij and Verhallen [24] distinguished five energy user types within the Dutch context: *Conservers*, *Spenders*, *Cool*, *Warm*, and *Average*. While valuable historically, these profiles are primarily focused on heating behavior. Similarly, Abreu et al. [48] used smart meter data from Dutch households to generate profiles based solely on usage patterns, such as *Unoccupied Baseline*, *Hot Working Days*, and *Cold Weekend Days*. However, these lacked behavioral or attitudinal dimensions. Bedir et al. [8], building on Van Raaij and Verhallen, aimed to identify patterns in electrical appliance use in Dutch households. They defined four data-driven profiles: *Energy Savers*, *Comfort Seekers*, *Tech-Oriented Users*, and *Passive Users*, based on 23 dwellings across two Dutch neighborhoods. These profiles offered insights into usage patterns, appliance ownership, and demographics. However, they focused primarily on energy awareness and did not include dimensions such as environmental values, openness to energy-saving actions, and social influence. A broader approach was taken by Nyström et al. [47], who developed fictional personas based on interviews with 16 Swedish households. These personas included both technical and behavioral aspects and captured themes such as daily routines, energy awareness, values (e.g., privacy and environmental concern), and technology use. While contextually useful, the personas were tailored to the Swedish setting and did not provide quantitative distribution for a Dutch population.

While previous studies provided valuable insights into household electricity behavior, none fully integrated psychological drivers, technical infrastructure, and habitual routines. One alternative method would be to first select a comprehensive set of behavioral factors and then construct distinct profiles based on those dimensions. While this approach supports clear segmentation for modeling purposes, it risks lacking empirical validity if not grounded in representative data. To address this, further research was conducted to find a suitable foundation. During interviews with Dutch DSOs, it became evident that two grid operators already apply the *Vijf Tinten Groener* ("Five Tints Greener") mental model by Motivaction [50] to better understand their end users. This segmentation study categorizes the Dutch population into five distinct groups based on values, beliefs, motivations, emotional drivers, and sustainability-related behaviors. Although not focused exclusively on energy use, the model offers highly relevant behavioral insights that can be mapped to electricity-related decisions, including participation in congestion mitigation measures. The profiles provide information on the likelihood of asset ownership, openness to innovation, financial sensitivity, trust in institutions, and social influence. The study also includes distributional data for each profile within the Dutch population. A comparable example can be found in the study by Schwarz and Ernst (2009) [51], which used Agent-Based Modeling to simulate the diffusion of environmental innovations using the Sinus-Milieus® model. This mental model is similar in structure to *Vijf Tinten Groener* but tailored to the German context. Like *Vijf Tinten Groener*, Sinus-Milieus® organizes the population based on social values and context. However, the Motivaction model is uniquely designed for the Dutch population. Given this existing use in practice and its conceptual alignment with behavioral modeling needs, the *Vijf Tinten Groener* model was selected as the foundation for building household profiles in this research. The detailed process for translating behavioral factors into profile characteristics is described in Section 4.3.

2.4. Modeling Behavior of Households Regarding Congestion Measures

After composing different profiles of households connected to the LV grid, the next step is to examine how these household profiles respond to net congestion mitigation measures. Capturing such responses requires a simulation method that reflects both the heterogeneity of individual behavior and how this behavior evolves over time through interaction with social and technical systems. Households do not make energy decisions in isolation; their choices are influenced by infrastructural conditions, access to information, and peer behavior within social networks [52]. Agent-Based Modeling is particularly well-suited to this task. It simulates decentralized decision-making by autonomous agents, each with unique attributes, preferences, and decision rules [53, 54]. Unlike traditional top-down models, ABM captures system-level outcomes as emergent from local, micro-level actions, offering a bottom-up framework that enables detailed modeling of both individual behavior and interaction dynamics [55, 53]. This makes ABM a powerful tool for testing adaptive strategies that support sustainable household behavior. Its strengths are multiple [55]: it reveals emergent system behavior from localized interactions; it allows for diversity in agent characteristics and behavior, reflecting real-world heterogeneity;

it enables dynamic scenario testing under behavioral or policy shifts; and it enhances interpretability through visual system evolution over time. ABM is especially relevant for studying innovation diffusion and behavioral change, where social influence and user diversity are critical drivers [54]. Furthermore, its flexible structure supports interdisciplinary energy research by integrating psychological, economic, and technological parameters [39].

Previous studies have developed agent-based models within the Dutch energy context at the household level. These models have addressed various aspects of the energy transition, including heat transition dynamics [56, 57, 58], the adoption of new energy technologies [59, 60], and household decision-making regarding energy-saving measures [61]. In addition, prosumer behavior and its impact on the electricity system have been studied been studied [35]. Across these studies, several recurring findings emerge: the possible influence of social norms on individual household decisions [35, 58, 56]; the significant role of policy measures in shaping household energy choices [56, 57, 59, 60]; the importance of spatial and agent-specific approaches to energy modeling [61]; and the central role of household preferences in driving energy behavior [57]. Common outcome measures across these ABMs include the share of households participating in certain technologies or policies, a metric that will also be adopted in this study. For example, in the ABM focused on energy-saving behavior [61], technology adoption rates were tracked but the actual energy saved was not measured. Since this research is particularly concerned with the potential of households to provide flexibility and reduce peak demand to alleviate grid congestion, it will not only assess participation rates, but also evaluate the resulting impact in terms of peak load reduction.

ABM also presents methodological challenges. Robustness and credibility depend on two key processes: verification and validation [55]. Verification ensures that the model has been implemented according to its conceptual framework, typically through debugging and internal consistency checks [62]. Validation involves comparing model outputs to real-world data or expert judgment to assess whether the simulation generates plausible results [62]. In this study, assumptions will be based on literature and refined through expert interviews. Importantly, ABM is not designed to produce precise forecasts but to explore system behavior under varying conditions [54]. Its value lies in identifying patterns, system vulnerabilities, and the implications of different strategies. This makes ABM highly relevant for grid operators, who can use such models to test interventions tailored to local contexts. The adaptability of ABM supports more data-informed decision-making and proactive congestion management.

Two Agent-Based Modeling platforms were considered for this study: NetLogo and Python Mesa. NetLogo is a mature and widely adopted platform, recognized for its intuitive interface, strong visualization capabilities, and extensive library of existing models. It is especially well-suited for simulations that rely on real-time, spatially explicit visual interaction and where computational complexity remains moderate. Although NetLogo uses a domain-specific language that can limit flexibility for advanced numerical operations or integration with external data pipelines, its accessibility and visual clarity make it highly effective for modeling behavioral dynamics [63]. Python Mesa, on the other hand, is a modular framework built in Python 3, offering high extensibility and seamless compatibility with scientific libraries such as NumPy and Pandas. While this makes Mesa more suitable for data-intensive simulations and custom analytics, it lacks native support for 3D environments and demands a higher level of programming expertise [63]. The choice between these platforms ultimately depends on the modeling context, including the importance of interactive visualization, model complexity, and computational requirements [64]. Given that this research focuses on household flexibility behavior and benefits from real-time spatial feedback rather than large-scale data processing, NetLogo was chosen as the most appropriate platform.

3 Interviews

This chapter addresses the second sub-question: *Which congestion mitigation measures are currently in use or development, and where is household participation most critical?* To answer this question, a series of interviews were conducted with professionals from the three largest Dutch regional grid operators. This chapter outlines the interview methodology and presents the resulting insights.

3.1. Methodology of the Interviews

Given that congestion on the LV grid is a relatively recent and rapidly evolving challenge [2, 4], many long-term strategies are still under development and not yet publicly available. Therefore, interviews were conducted with Dutch DSOs to gather up-to-date, practice-based insights. These interviews provided qualitative perspectives beyond what is covered in technical documentation or policy reports. They also helped identify which mitigation measures are perceived as realistic, scalable, and particularly reliant on behavioral engagement. To guide the interviews effectively, they were structured around three central themes:

1. The long-term vision of grid operators regarding congestion mitigation on the LV grid (discussed in Section 3.2.1).
2. The types of mitigation measures considered most promising, with particular attention to those that depend on active participation from end-users (discussed in Section 3.2.2).
3. The key barriers and bottlenecks that hinder participation from low-voltage users in these mitigation strategies (discussed in Section 3.2.3).

Interviewees were selected from the three major regional grid operators in the Netherlands: Stedin, Liander, and Enexis [65]. Although several smaller operators exist, these three serve the majority of the Dutch population and electricity demand, making them particularly relevant for this research (see Figure 3.1). The target was to conduct two interviews per grid operator. This approach enabled comparison of different perspectives, resulting in richer insights. To further diversify the insights, interviewees were selected from various professional backgrounds, including including strategic planning, operations, customer engagement, and LV grid management. This diversity provided a broad perspective on both current practices and future ambitions concerning congestion mitigation. In total, seven experts were interviewed. All participants were anonymized to encourage openness and ensure comparability across interviews.

Figure 3.1: Serving areas of Dutch regional distribution operators [65]

Grid Operator	Number of Interviewees
Liander	2
Enexis	3
Stedin	2

Table 3.1: Number of interviewees per grid operator

Interviewee	Interview Date
Interviewee 1	March 26, 2025
Interviewee 2	May 12, 2025
Interviewee 3	March 24, 2025
Interviewee 4	April 23, 2025
Interviewee 5	April 1, 2025
Interviewee 6	May 6, 2025
Interviewee 7	April 14, 2025

Table 3.2: Interview dates per interviewee

Each interview was scheduled for approximately 60 minutes and followed a semi-structured format. The format included in Appendix B served as a flexible interview guide designed to address the research objectives. The guide was not meant to be followed precisely but served to structure the conversation while allowing room for organic development based on each participant's responses [66, 67]. This approach enabled interviewees to provide open-ended responses and allowed the interviewer to explore emerging themes in more depth [66]. Therefore, the interviews followed a structured yet adaptable procedure, in line with Longhurst's methodological guidance [68]. Participants were selected for their relevance to the research topic based on their roles and expertise within the grid operators. Initial contact was established via email, during which the purpose of the study was explained and voluntary participation was requested. Interviews were held either online or in quiet, private settings to ensure participant comfort. Each session began with general warm-up questions and gradually transitioned to more specific topics tailored to the interviewee's area of expertise. This iterative method ensured consistency across interviews while allowing space for deeper insights.

To ensure ethical compliance, participants received an informed consent form prior to the interview, outlining the study's purpose, data handling protocols, and their rights as participants. With explicit consent, interviews were recorded using GDPR-compliant tools and transcribed shortly after completion to ensure accuracy. Within two weeks of the interview, an anonymized technical summary was shared with each participant, allowing them to provide corrections or clarifications. All data were securely stored in line with university policies. This study received approval from the TU Delft Human Research Ethics Committee (HREC), and all informed consent documentation is archived accordingly [69].

A potential limitation of semi-structured interviews is the risk of interviewer bias. For instance, leading questions may unintentionally guide participants toward certain responses [67]. To mitigate this, a neutral tone was maintained throughout the interviews, and care was taken to balance consistency with flexibility when using the interview guide. Additionally, the interview questions were pilot-tested and reviewed with the thesis supervisor to ensure alignment with the research objectives and to improve clarity and neutrality.

3.2. Results Interviews

Each interview was followed by a technical summary, providing an overview of the key takeaways. In addition to ensuring informed consent, these seven summaries were analyzed to extract contextual insights related to the three main research objectives.

3.2.1. The Long-Term Vision of Grid Operators on the Low-Voltage Grid

The first objective of the interviews was to gain insight into the long-term vision of grid operators regarding congestion mitigation measures on the LV grid. Since Dutch grid operators serve different types of areas across the country [65], they face distinct challenges depending on their service regions (interviewee 5). Urban and rural areas present different grid dynamics. For example, some regions experience high levels of solar feed-in, while others are primarily impacted by the electrification of heating and mobility, such as through heat pumps and electric vehicles (Interviewee 1). Despite the diversity in service areas, grid operators have initiated a joint action agenda with ministerial stakeholders to address congestion on the LV grid [2]. Interviewee 1 confirms this collaboration, explaining that operators work together through shared working groups and regular coordination meetings to exchange knowledge and align strategies.

All three major Dutch distribution system operators described their approach using a visual model commonly referred to as the “flexibility pyramid.” A simplified version of this concept has previously appeared in national publications and strategic documents [2, 70]. However, during the interviews, a more detailed and operational version of the pyramid was presented and discussed, particularly by Interviewees 3, 5, and 6. These interviewees elaborated on the structure and purpose of the pyramid, explaining how it guides the sequencing of congestion mitigation measures, from technical and infrastructural foundations to market-based contracts and direct control. While minor variations were observed in terminology and emphasis, the overall logic and layering of the pyramid were largely consistent across the operators. Their shared interpretation of this model is illustrated in Figure 3.2.

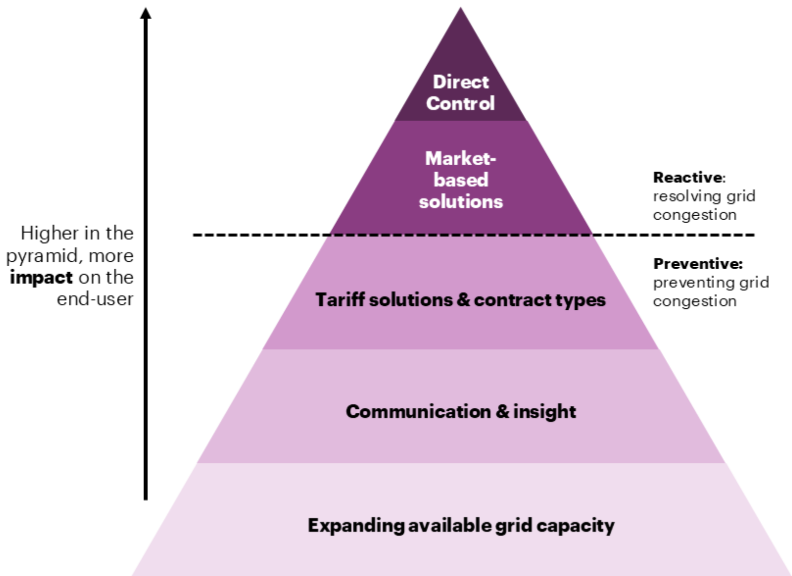


Figure 3.2: Overview of grid operators’ congestion mitigation vision

The pyramid structure reflects a strategic hierarchy of flexibility measures, as clearly explained by Interviewee 3. The foundation consists of expanding the electricity grid itself. As one moves up the pyramid, the measures become more intrusive for the end-user, progressing from communication and tariff solutions to market-based responses and ultimately direct control. Grid operators emphasize that their goal is to handle as much of the congestion mitigation as possible with measures from the lower layers. Moving to a higher layer is only considered when the measures below are insufficient to resolve or prevent grid congestion. The higher up the pyramid, the less scalable and socially accepted the measures become. A horizontal line separates preventive measures (below) from reactive ones (above), indicating whether a measure is aimed at preventing or resolving grid congestion. The layers are structured as the following:

1. The bottom layer focuses on expanding the physical capacity of the electricity grid, for example, by adding new cables or transformers. This is the most basic and reliable way to reduce congestion, but it is also the most expensive and slow to implement. It lays the foundation for all other strategies.
2. The second layer is about communication and insight. This involves tools and campaigns that help users understand how much stress the electricity grid is under. Examples include apps like the *Stroomnetchecker*, which shows whether a neighborhood is at risk of congestion. These tools raise awareness and aim to encourage people to adjust their electricity use voluntarily.
3. The third layer introduces financial incentives. For instance, grid operators and energy providers may offer cheaper rates during off-peak hours or give discounts to people who charge their electric vehicles at night. These price signals encourage users to spread out their energy use across the day, which helps reduce stress on the grid.
4. The fourth layer involves market-based solutions. These are systems where energy use can be automatically adjusted using smart technologies like home energy management systems or batteries. For example, a smart charger might delay charging your car if the grid is too busy. These services are usually organized by energy companies and require little effort from the user.
5. The top layer is direct control. This is only used in emergencies when there is a serious risk of overload. In such cases, the grid operator may temporarily limit how much electricity certain users can take from or feed into the grid. These interventions enable grid operators to act quickly, preventing outages when the system is at risk. However, the grid operators emphasize this is a last resort, only being utilized in case of an emergency.

Together, these five layers illustrate how grid operators combine long-term planning, public engagement, economic incentives, and technical solutions to manage congestion on the electricity grid, especially as more households electrify their energy use.

3.2.2. Most Promising Net Congestion Mitigation Measures

When asked which measures have the most potential to reduce or prevent low-voltage grid congestion, all interviewees emphasized that no single solution would suffice. Instead, they advocated for a layered strategy combining multiple approaches within a unified framework. However, they were still asked which single measure they believed had the most potential. The most frequently mentioned measures are listed in Table 3.2.2.

Measure	Pyramid Layer	Interviewee No.	Remarks
Time-of-Use tariffs	Layer 3: Tariff solutions & contract types	1, 2, 3, 5, 6, 7	Generic pricing mechanism for all small consumers to shift peak demand.
Awareness campaigns	Layer 2: Communication & insight	1, 3, 5, 7	Public campaigns to raise awareness and promote behavioral change.
Smart Charging (public)	Layer 3: Tariff solutions & contract types	1, 3, 5	Voltage control of public chargers to avoid peak hours.
Smart Charging (private)	Layer 4: Market-based solutions	1, 2, 3, 5, 6	Individual contracts via third parties for private chargers.
Curtailment of solar PV	Layer 4: Market-based solutions	1, 2, 3, 6	Curtailment via contract with third parties.
Flexible use of heat pumps	Layer 4: Market-based solutions	2, 3, 5, 6	Indirect control (e.g., pre-heating) via third parties.

Table 3.3: Overview of measures discussed by interviewees, their corresponding pyramid layers, and associated remarks.

Time-of-Use Tariffs

One frequently mentioned measure with high potential is the introduction of Time-of-Use (ToU) tariffs, which grid operators position in the third layer of their flexibility pyramid (tariff solutions and contract types). According to the grid operators, ToU tariffs aim to distribute the costs of grid use more fairly among consumers. For small-scale users, the electricity bill currently consists of the following main components: energy supply (from the provider), grid connection and transport fees (from the grid operator), and government taxes [71]. As Dutch households electrify their heating and mobility, pressure on the low-voltage grid increases, requiring significant grid reinforcement. This drives up the operational costs for grid operators. At present, all users pay a fixed connection fee (the price they pay to the DSOs), regardless of when or how intensively they use the grid. Because of this, these higher costs are currently being paid by all users connected to the grid, which is perceived as unfair by grid operators (Interviewees 1, 3, and 5). With ToU tariffs, this would change. Households would pay for their grid connection based on their actual grid usage, with rates varying depending on the time of consumption. Electricity consumed during peak hours would carry a higher network tariff than electricity used during off-peak periods. This pricing structure is designed to encourage users to shift consumption to less congested times, providing a financial incentive to align household energy behavior with available grid capacity. Interviewee 1 emphasized that ToU tariffs offer a scalable way to influence user behavior without the need for direct control over individual devices.

This measure is widely seen as having high potential to mitigate congestion, however, it also faces several challenges. ToU tariffs are considered a generic policy instrument, intended to apply to all small-scale electricity users in the Netherlands. However, current Dutch energy legislation does not yet permit their implementation. Lawmakers have expressed concerns that such pricing systems may be difficult for users to understand, could discourage electrification and sustainability efforts, and may disproportionately affect vulnerable groups, such as people with medically necessary electricity use [72]. Beyond these political limitations, interviewees also reflected on practical challenges associated with ToU tariffs. While Interviewee 1 viewed the measure as essential for unlocking demand-side flexibility, they also warned that its complexity could hinder user acceptance if not supported by clear and effective communication. Interviewee 2 highlighted the risk of rebound effects, where synchronized behavior in response to low-tariff periods could create new peaks in demand. Interviewees 3 and 5 stressed the importance of combining ToU tariffs with user insight tools such as the Buurtnet app, which can help households make informed decisions by visualizing local grid load. Interviewees 1 and 3 also questioned the short-term feasibility of the measure due to existing regulatory and political barriers.

While ToU tariffs are widely regarded as a cornerstone of future grid flexibility, interviewees agreed that complementary measures are necessary. These not only provide short-term alternatives in light of political delays but also function as essential reinforcements to the overall strategy. ToU tariffs alone are unlikely to fully mitigate congestion on the low-voltage grid. To address these limitations, the interviewees proposed a set of additional measures that could enhance user engagement and system flexibility in the near term, while also complementing ToU tariffs in the long run. These measures span multiple layers of the flexibility pyramid.

Awareness Campaigns

Public awareness campaigns were identified as essential to laying the groundwork for behavioral change. Interviewees 1, 3, 5, and 7 emphasized that awareness of grid congestion remains low and must be improved before other measures can be effective. They stressed the importance of explaining grid congestion in simple, relatable terms and linking the issue to concrete actions that residents can take. According to them, effective communication is critical to ensure that end-users understand not only the urgency of grid challenges, but also their own role in alleviating pressure on the system. Such campaigns are already being implemented. On March 28, 2025, the Dutch government officially launched a new national campaign, initiated by the Ministry of Climate and Green Growth [73]. The primary goal of this campaign is to raise public awareness about the limitations of the electricity grid and to encourage households to shift their electricity consumption away from peak hours, specifically between 16:00 and 21:00. This broad-based campaign targets all Dutch residents between the ages of 18 and 59 and is carried out across multiple media channels. It includes radio commercials, outdoor advertisements, online videos, display banners, and social media content. The overall strategy is to reach a wide audience with a consistent and actionable message: by slightly adjusting daily routines, residents can help prevent grid congestion and contribute to a more stable and affordable energy system.

Smart Charging

Interviewees 1, 2, 3, 5, and 6 discussed the role of private smart charging. The Netherlands is considered a front runner in the development and testing of smart charging technologies [74]. Mutliple pilot projects have been carried out across the country, involving both public and private charging infrastructure. It is, however, important to distinguish between public and private applications; therefore, they have been listed separately in Table 3.3. A key distinction lies in the ownership and control structure. For public charging stations, DSOs can coordinate directly with municipalities (as explained by Interviewees 3 and 5). In contrast, private charge points are owned by individuals and tied to the household. In these cases, DSOs rely on intermediaries, such as energy suppliers or mobility service providers, that offer smart charging apps or modules. Control is indirect, based on agreements between consumers and these market parties, placing them in layer 4 of the flexibility pyramid, rather than layer 3 as with public smart charging. Interviewees 3 and 5 noted that this fragmented setup adds complexity to scaling the measure nationally. In both cases, the main objective is to shift electric vehicle charging away from times of high grid congestion, particularly during the 16:00–21:00 window. While private smart charging offers greater flexibility through user-specific agreements, public charging provides opportunities for large-scale, location-based control. However, since this study focuses on measures where the participation of households is necessary for their effectiveness, private smart charging is considered a particularly relevant measure to examine.

Curtailment of Solar PV Through Contracts

Curtailing residential solar panel output was also discussed as a potentially valuable flexibility measure by interviewees 1, 2, 3, and 6. This strategy can be particularly helpful to DSOs during periods of high solar irradiation in the Netherlands, when local feed-in may exceed grid capacity. Since rooftop solar panels are privately owned, the implementation of this measure (similar to private smart charging) requires coordination with market parties. Residents can enter into so-called flexibility contracts with these intermediaries, granting permission to temporarily curtail their solar production during times of grid congestion. In return, participating households receive financial compensation, as they are unable to consume the electricity themselves or feed it back into the grid. This is because, under the current policy context of the netting arrangements, households are allowed to offset the electricity they supply to the grid against the electricity they consume from their energy supplier over the course of a year [9]. This arrangement is highly beneficial for solar panel owners, making voluntary curtailment financially unattractive without proper compensation.

A relevant pilot project was conducted in 2024 in the province of Zeeland [23]. During this pilot, DSOs requested residents to manually disconnect their solar installations during particularly sunny summer days, instead of coordinating this through a market party. In exchange, they received a small compensation. The pilot proved technically effective and successfully created headroom on the grid. However, it remained a temporary solution, and standardized flexibility contracts for solar PV curtailment are still under development.

Flexible Use of Heat Pumps Through Contracts

Lastly, flexible contracts for all-electric heat pumps were identified as a promising measure by Interviewees 2, 3, 5, and 6. These systems often include a buffer tank, which allows the heat pump to activate earlier or later while still maintaining a stable indoor temperature throughout the day (Interviewee 6). Similar to other privately owned assets, implementing this measure requires collaboration with market parties that can facilitate automated control through smart devices or service contracts. A pilot project involving this measure was carried out in cooperation with housing associations, focusing on the flexible control of all-electric heat pumps, including pre-heating strategies (Interviewee 2). However, interviewees noted that this flexibility option is still under development. Technical modifications are required to ensure that heat pumps can be reliably and user-friendly controlled remotely.Despite these challenges, it remains a potentially effective measure, as heat pumps are energy-intensive and typically operate during peak hours. Shifting their load outside of these times could significantly reduce pressure on the low-voltage grid. These flexibility contracts would also include financial compensation, offering consumers a direct economic incentive to participate.

Together, awareness campaigns, private smart charging, flexibility contracts for solar panels and heat pumps represent a practical and adaptable strategy for enhancing short-term flexibility on the low-voltage grid. Unlike Time-of-Use tariffs, which require national political approval and function as a generic measure, these contract-based solutions can be implemented through collaboration with market parties. As such, they offer an actionable bridge between the current situation of increasing grid congestion and the future introduction of ToU tariffs. While some of the measures are more developed than others, all show strong potential to reduce the use of energy-intensive assets during peak hours.

3.2.3. Key Barriers for Participation of Low-Voltage Users

With the vision of the grid operators established and the congestion mitigation measures selected for further analysis, it is also important to consider the barriers that may prevent low-voltage users from participating in or responding to these interventions. Understanding such barriers is essential for assessing how households make decisions about engaging in flexibility measures. Since many of these interventions rely on behavioral change at the household level, identifying potential obstacles is critical for realistic modeling. Due to the limited scope and timeframe of this study, it was not feasible to assess these barriers directly with end-users. Instead, interviews with grid operators were used to explore their perspectives on the most relevant obstacles to participation. Traditionally, Dutch grid operators have been technically oriented organizations. The need to actively involve end-users in congestion mitigation represents a relatively recent shift in practice (Interviewees 3, 5, and 7). Although their direct experience with user behavior is still evolving, this topic has received increasing attention over the past two years, resulting in several early insights. These reflections, though indirect, offer valuable perspectives on how low-voltage users may encounter behavioral or perceptual barriers when asked to contribute to flexibility strategies. Table 3.4 presents an overview of the barriers identified in the interviews. While the phrasing varied, several recurring themes were evident. Figure 3.3 groups these into four core categories: a general lack of awareness among small-scale users about grid congestion, the perception that participation compromises comfort, limited financial incentives to encourage behavioral change, and a degree of distrust toward the institutions or technologies involved in managing electricity use.

Barrier	Interviewee No.	Explanation
Lack of urgency / No direct inconvenience	1, 4, 5, 7	End-users only change behavior when facing blackouts or tangible inconvenience; no perceived urgency without direct impact.
Limited insight into grid load	1, 2, 3, 4, 5, 7	Lack of visibility into grid status at local level due to limited metering and data access.
Unawareness of personal contribution	1, 3, 5, 7	End-users are unaware of how their energy behavior affects grid load.
Loss of comfort	2, 5, 6	Users resist control that may affect heating or charging availability, even if comfort impact is minimal.
Complexity of tariffs and technology	1, 2, 3, 5, 6	Users find pricing models and technical systems confusing, which hinders engagement.
Lack of smart devices / Technical limitations	1, 3, 4, 5	Without compatible or automated devices, users must make manual changes, which costs effort and may affect comfort.
Insufficient financial incentives	1, 2, 5, 6, 7	Low compensation demotivates participation; several interviewees confirm money is a strong driver for behavior change.
Low trust in external parties	1	end-users question the motives and reliability of suppliers or commercial partners.
Loss of autonomy	1, 2, 6	Users want control over their own energy use and resist perceived external enforcement.

Table 3.4: Overview of which barrier is acknowledged by each interviewee

Main Barriers

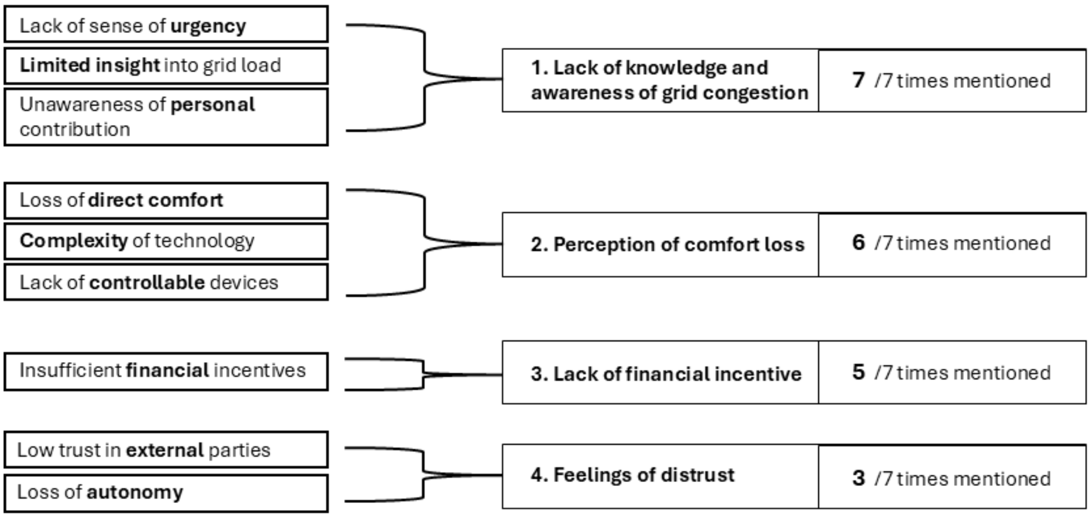


Figure 3.3: Construction of the main barriers

Knowledge and Awareness of Grid Congestion

A frequently mentioned barrier is the lack of user knowledge and awareness among households regarding grid congestion. According to the interviewees, many small-scale energy users are unfamiliar with the concept, do not understand its urgency, and feel little personal responsibility. Interviewee 1 noted that awareness typically arises only after a blackout or other visible impact. This was confirmed by interviewee 4, who stated that behavioral change often only follows direct inconvenience. In addition to lacking urgency, users also lack the insight needed to act. Interviewee 7 explained that many users are unaware of the actions they can take to support the grid. Interviewee 2 added that users often do not understand the basic functioning of their electricity connection, including capacity limits or what a kilowatt means, which limits rational energy-related decision-making. Interviewee 6 emphasized that while financial incentives or automation may trigger participation, many users prefer not to engage with the grid at all unless they are directly affected. Without a clear understanding of the problem or their role in addressing it, users are unlikely to contribute meaningfully to congestion mitigation.

Comfort

Comfort was another dominant theme across interviews. This barrier has both physical and practical components. Physically, users expect energy services such as home heating or electric vehicle charging to remain reliable and uninterrupted. Interviewees 1, 3, and 6 emphasized that users are only willing to engage with flexibility measures if their comfort is guaranteed. For instance, electric vehicles must be fully charged by the desired time, and indoor temperatures must remain stable. From a usability perspective, the effort required to participate in flexibility programs also influences user acceptance. Interviewees 1, 2, 4, and 7 stressed that if measures are not easy to understand or require manual intervention, users may be discouraged. Interviewee 2 highlighted that integrating flexibility into existing, trusted routines can reduce perceived hassle and improve participation. Across all interviews, it was clear that comfort is a decisive factor. If flexibility reduces comfort or imposes behavioral effort, user engagement will remain limited.

Financial Incentives

Financial incentives were frequently discussed, although views varied on their effectiveness. Several interviewees agreed that monetary rewards can influence user behavior, but only under certain conditions. Interviewee 5 noted that when the financial benefit is minimal, it may not be sufficient to justify the required effort or loss of comfort. As the interviewee phrased it, “What is in it for me?” is almost always the question end-users ask themselves. Interviewee 5 also referred to the Dutch netting arrangement policy as a historical example of how well-designed financial instruments can accelerate user adoption. Nevertheless, small incentives can still be effective. Interviewee 1 pointed to pilot programs in which modest rewards, such as a three-euro monthly discount for using smart charging with an electric vehicle, were sufficient to encourage participation.

Interviewees 2 and 6 observed that financial incentives are most successful when they are simple, fair, and linked to guaranteed outcomes. Interviewee 6 emphasized that combining financial rewards with comfort assurance can enhance both trust and willingness to participate. However, interviewee 4 noted that only a small segment of users appears to be highly responsive to financial incentives. Interviewee 7 added that while such incentives can be effective, they are not always perceived as customer-centric. In some cases, users feel less respected or valued when financial rewards are the sole motivator. In summary, although financial incentives can support user engagement, they should not be used in isolation.

Feelings of Distrust

A final barrier identified in the interviews concerns trust in external actors, such as the DSOs and energy suppliers. Interviewee 1 remarked that trust in market parties is relatively low in the Netherlands, which can hinder user participation. Interviewee 5 emphasized that users want to retain control over their electricity use, particularly when it comes to comfort-related aspects like heating or vehicle charging. Interviewee 3 observed that users are more likely to engage if the terms of participation are clear and transparent. This was reinforced by interviewee 2, who noted that users often respond negatively if control is taken away without their consent. Flexibility should therefore be offered in a way that maintains user agency, ideally through platforms and services that users already trust.

Framing also plays an important role. According to interviewee 6, telling users they are not allowed to charge at a specific time can feel restrictive. However, framing the same message in terms of guaranteed outcomes (such as having a fully charged car by morning) can make users more receptive to participation. Interviewee 7 added that the role of DSOs is changing. They are becoming more visible and more involved in daily energy decisions, which places additional pressure on them to build trust through transparent and consistent communication. As grid operators move closer to the end-user, credibility and clarity become essential.

3.3. Input for the Model

Based on the interview findings, there are two main aspects that will be incorporated into the ABM: (1) the measures that are considered high-potential by grid operators and for which household participation is crucial to their effectiveness, and (2) the potential barriers that may prevent households from participating in these measures. Four measures have been selected to continue with, as they were repeatedly highlighted by interviewees as feasible, potentially impactful, and relevant in the short term. The selected measures are:

1. Awareness campaigns;
2. Smart charging of electric vehicles at *private* charging stations;
3. Flex contracts for residential solar panel curtailment;
4. Flex contracts for the pre-heating of all-electric heat pumps.

The awareness campaigns in this study are not modeled as active measures that require direct participation from households. Instead, they operate as external influences that may affect household behavior without requiring deliberate engagement. In contrast, the next three interventions are implemented as ”active” measures, meaning they require conscious participation from households. These are therefore referred to as the *flexibility measures*. To evaluate the attractiveness of each measure for household participation, they are assigned specific characteristics linked to common participation barriers. Each measure is assessed on four criteria: perceived familiarity among residents, expected loss of comfort, the level of trust required in external actors, and the financial incentive offered. These assessments are based on the qualitative insights obtained from expert interviews. For implementation in the model, these qualitative evaluations are translated into quantitative values, scaled between 0 and 1. For instance, if a measure is widely recognized and thus favorable in terms of the familiarity barrier, it receives a score of 1. If it is entirely unknown to residents, it scores a 0. This scaling approach is applied across all characteristics for each of the flexibility measures.

Characteristics Smart Charging

Aspect	**Score**	**Reasoning / Source Interviews**
familiarity among residents	Medium high (0.7)	Interviewees 2, 3, and 6 noted that many users are already familiar with apps from suppliers like ANWB and Vattenfall, and smart charging pilots are running.
Perceived loss of comfort	Low (0.3)	Charging can happen overnight and is easily automated. As long as the car is ready by morning, users are unaffected, according to interviewee 6.
Financial incentive	Low (0.3)	Incentives are currently a few euros/month (interviewee 1), which some users accept, but others find insufficient unless combined with ease or ecological motivation (interviewee 2, 6).
Trust in external party required	Medium (0.4)	Users must trust their supplier or mobility provider to manage charging, but existing app relationships help (interviewee 2).

Table 3.5: Assessment of smart charging at home

The first flexibility measure to be assessed in terms of its four characteristics is smart charging at home. This is summarized in Table 3.5. As the Netherlands is considered a front runner in the development and testing of smart charging technologies [74], this is the most advanced of the three flexibility measures included in the model. It is also the only measure for which existing research is available on household perceptions. The *Nationaal Laadonderzoek 2024* [75] includes a section dedicated to different forms of smart charging, including options based on dynamic tariffs, net capacity, renewable generation, and bidirectional charging. On average, approximately 66% of respondents reported being familiar with these forms. This relatively high level of awareness among Dutch EV users suggests that smart charging is better understood than other household-based flexibility measures. For the model, this level of familiarity has been rounded up to 0.7 as an input parameter. Interviewee 6 noted that smart charging tends to involve minimal loss of comfort, particularly when framed in a user-friendly way. For example, messaging such as “your car will be fully charged by morning” is likely to be more effective than emphasizing temporary charging limitations during peak hours. This form of framing helps reduce the perceived sacrifice in convenience, making smart charging more acceptable to users. Assuming appropriate framing is applied, the perceived loss of comfort is expected to remain low. Therefore, this criterion is assigned a score of 0.3 in the model. The financial incentives associated with current smart charging pilots are generally modest. Interviewee 1 confirmed that compensation is limited, which may negatively influence willingness to participate. Based on this, the measure is assigned a score of 0.3 for financial incentive. The level of trust required in external actors (such as energy suppliers or service providers) is considered moderate. Interviewee 2 acknowledged that trust could be a barrier to adoption, particularly if users are unfamiliar with the third parties managing the charging process. However, they also noted that integrating smart charging into existing platforms already used by consumers could enhance trust and lower the threshold for participation. Assuming this integration is achieved, smart charging is assigned a score of 0.4 for trust in external parties required.

Characteristics Flexible Contract for Solar Curtailment

Aspect	Score	Reasoning / Source Interviews
familiarity among residents	Low (0.3)	Few residents are aware that curtailment can even happen. There has only been a small pilot in Zeeland (interviewee 1)
Perceived loss of comfort	Very Low (0.1)	Users do not feel a direct effect unless they monitor output. Several interviewees noted most users do not notice real-time power loss (interviewee 2, 6).
Financial incentive	Low (0.3)	Some compensation was offered. however, it was limited (interviewee 1).
Trust in external party required	Low (0.3)	Turning off a user's generation feels might not very invasive because the solar panels are outside of the house, however, might be sensitive since it conflicts with policy incentives (netting arrangements) (interviewee 1, 3, 6).

Table 3.6: Assessment of flex contract for solar panels (curtailment)

The second flexibility measure assessed is the use of flex contracts for curtailment of residential solar panels. This is summarized in Table 3.6. As of now, flex contracts for PV curtailment have not been realized at scale in the Netherlands, and no structured assessments of user perception are available in the academic or policy literature. As a result, the scores presented here are based solely on the perspectives of grid operators and pilot experiences, rather than direct user data. Only a few pilots have been conducted for curtailment of residential solar energy (interviewee 1)[23]. Therefore, awareness remains limited, and many residents might not even be aware that curtailment is technically possible. Based on this limited public exposure, familiarity is scored as 0.3 in the model. In terms of comfort, the impact is considered very low. Solar panels operate passively, and unless users are actively monitoring their energy production, they are unlikely to notice brief interruptions. Interviewees 2 and 6 emphasized that most users do not detect real-time power loss. Because of this passive nature, the perceived loss of comfort is minimal and is scored at 0.1 in the model. Financial incentives for participating in curtailment contracts are currently modest. Interviewee 1 confirmed that some compensation has been offered, but it remains limited. As a result, the financial incentive is considered low, resulting in a score of 0.3. The level of trust in external parties is also a relevant factor. While turning off a user's generation remotely may not feel highly invasive, since the equipment is typically located outside the home, it can still be a little sensitive. Interviewees 1, 3, and 6 noted that curtailment can conflict with existing policy incentives, such as the netting arrangements. This policy misalignment could reduce user willingness to participate, even if the direct user experience is unobtrusive. For this reason, trust in external parties is also scored at 0.3.

Characteristics Flex Contract for Heat Pumps

Aspect	Score	Reasoning / Source Interviews
familiarity among residents	Low (0.3)	Heat pump flexibility is a newer concept. Users are largely unaware of pre-heating or load-shifting methods (interviewee 2, 3).
Perceived loss of comfort	High (0.7)	Comfort (warmth) is critical; users are sensitive to any perceived control over temperature (interviewee 5, 6). Technology is also not uniformly compatible (interviewee 2).
Financial incentive	Medium (0.5)	Compensation is discussed, but exact incentive models are not widespread. There's potential, but uptake depends on trust and communication (interviewee 2, 6).
Trust in external party required	High (0.6)	External control of indoor climate requires high trust. Some pilots used control boxes placed by DSOs (interviewee 2), which signals low trust threshold.

Table 3.7: Assessment of Flex Contract for all-electric heat pump

The third flexibility measure assessed is the use of flex contracts for all-electric heat pumps. This is summarized in Table 3.7. Similarly to flex contract of solar panels, this measure has not yet been implemented at scale yet either. Consequently, there is currently no published research on how end-users perceive such contracts. The assessment in this study is therefore also informed exclusively by expert interviews. Among the three measures included in the model, heat pump flexibility is the least familiar to most residents. Interviewees 2 and 3 noted that users are largely unaware of the possibility of shifting heat pump operation through pre-heating or load-scheduling strategies. As a result, the familiarity score is set at 0.3. Perceived loss of comfort is a significant factor in this case. Comfort (particularly indoor temperature) is highly sensitive, and users tend to resist any external influence that could affect warmth levels. Interviewees 5 and 6 highlighted that users are more protective of thermal comfort than of other forms of energy flexibility. Additionally, Interviewee 2 noted that not all heat pump systems are compatible with centralized or remote control, which further increases the complexity. Based on this, the perceived loss of comfort is rated high, with a score of 0.7. Financial incentives for heat pump flexibility are still under development. While compensation has been discussed in some pilots, standardized incentive models are not yet widespread. Interviewees 2 and 6 emphasized that although the measure has potential, its uptake will depend heavily on how compensation is communicated and whether users trust that they are fairly rewarded for their participation. Given this uncertainty, the financial incentive score is set at 0.5. Finally, the level of trust required in external parties is relatively high. Heat pumps are directly linked to indoor comfort, and allowing third parties to influence their operation can feel intrusive. Interviewee 2 explained that some pilots attempted to mitigate this by installing control boxes through the DSO, which aimed to lower the trust threshold. However, the need for external control over a household's climate systems means that the trust burden remains high overall. Consequently, the score for trust in external parties is set at 0.6.

4 Agent-Based Model

In Chapter 3, potential measures for mitigating congestion on the low-voltage grid were discussed. Chapter 2 highlighted a gap in the literature concerning the limited inclusion of heterogeneity among electricity users in energy system models. It also introduced the potential of ABM as a method for studying such behavioral variation. This chapter describes the structure and implementation of the ABM developed to simulate diverse end-users in a low-voltage grid context and their responses to congestion mitigation measures. This chapter also addresses the following sub-question: *How can household profiles be classified based on electricity usage behavior?*

4.1. Modeling Approach and Components

The primary objective of the Agent-Based Model developed in this study is to simulate how different household profiles respond to specific congestion mitigation measures in the low-voltage electricity grid. By incorporating both technical and behavioral characteristics of households, the model explores how participation in flexibility measures (smart charging, solar curtailment, heat pump contracts) evolves under varying scenarios. This allows for a dynamic analysis of how behavioral heterogeneity among households impacts demand- and supply-side flexibility, offering valuable insights for grid operators aiming to design more targeted and effective congestion management strategies.

Agent-Based Models can generally follow two design paradigms: *phenomena-based modeling* and *exploratory modeling* [62]. The former focuses on reproducing known real-world phenomena, while the other aims to investigate emergent patterns resulting from the interaction of individual entities within a system. The goal of this model is exploratory: to analyze how diverse end-users might respond to different policy measures. Because of the visual interface of NetLogo, it is particularly well-suited for exploratory modeling. According to Wilensky and Rand [62], developing an ABM, especially within environments like NetLogo, typically involves the following conceptual steps:

1. **Choosing agents:** Agents are autonomous decision-makers in the model. In this study, agents represent households. Each agent can interact with its environment and with nearby agents to make behaviorally informed decisions [55].
2. **Defining agent properties:** Agents are assigned individual attributes, such as technology ownership and behavioral characteristics, which guide their responses to external incentives and peer behavior.
3. **Choosing environmental characteristics:** The model uses a grid-based environment. The world is structured as a grid of patches, each of which can host one or more agents. Agents interact with others on the same patch and in adjacent patches, simulating localized social influence within a neighborhood.
4. **Defining agent behavior:** Each agent follows decision rules based on their internal properties and external conditions, such as behavior of other agents or grid operator interventions.
5. **Designing the time step:** The model operates on discrete time steps. For this study, each tick

represents one hour of real time, enabling fine-grained modeling of daily and seasonal electricity behavior.

6. **Choosing model parameters:** Key parameters such as adoption thresholds, learning rates, and comfort sensitivities are defined to explore different behavioral dynamics.
7. **Defining measures for data collection:** Output metrics are determined to evaluate the effectiveness of each scenario.

The first four steps establish the basic components of the ABM, summarized in Table 4.1.

Table 4.1: Overview of the Conceptual Model Components

Category	Subcategory	Description
Agent	Stationary agent	Represents a household (a user of the low-voltage grid).
Agent Properties	Technical	Includes attributes such as asset ownership (EV, PV, HP, battery) and base electricity load.
	Behavioral	Includes traits such as comfort preference, financial sensitivity, trust in institutions, and environmental motivation.
Environment	Grid-based	The grid simulates a neighborhood. Patches represent spatial locations. Agents are randomly placed and can observe nearby agents.
Agent Behavior	Peer interaction	Agents influence and are influenced by others on neighboring patches.
	Grid interaction	Agents draw electricity from or feed electricity into the grid. Flexibility measures are offered by the environment, and agents decide whether to participate.

An overview of the model dynamics is presented in the conceptual model shown in Figure 4.1. Based on these dynamics, the model focuses on two key output metrics. These metrics are used to analyze both the behavioral responses of agents and their potential contribution to mitigating congestion in low-voltage grids:

- **Participation rates:** The proportion of eligible agents who adopt or engage with each flexibility measure.
- **Impact on grid load:** Visualization of electricity demand during the coldest and warmest weeks, comparing the situation without the measures to the situation with the measures, in order to assess the obtained flexibility.

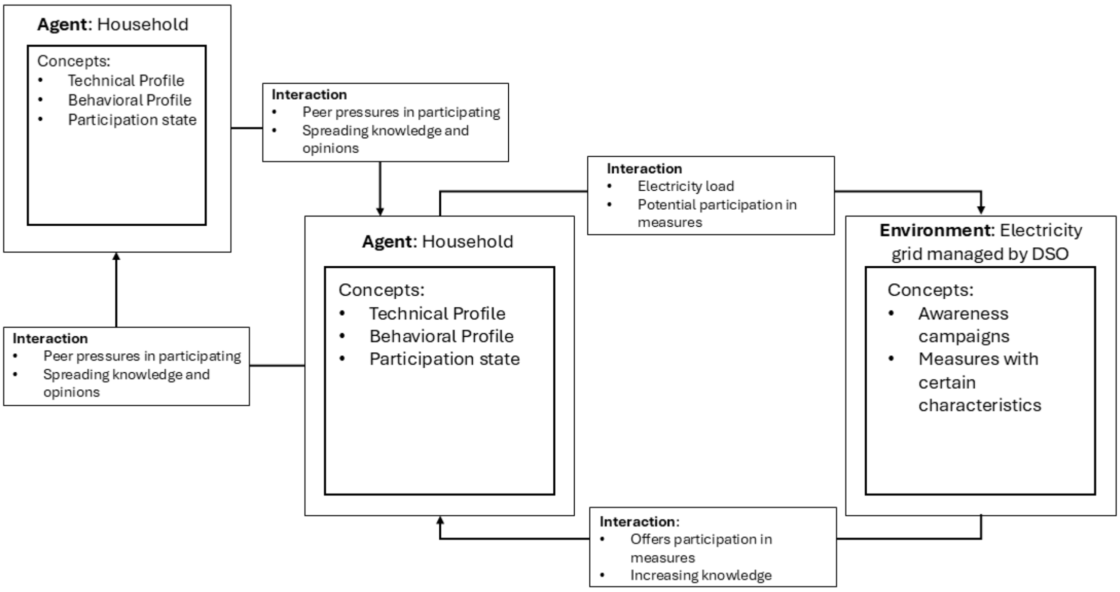


Figure 4.1: Conceptual model ABM

4.2. Constructing the Profile of the Agents

As discussed in Section 2.2, several behavioral frameworks exist for analyzing and understanding individual energy behavior. For this research, the Energy Cultures Framework was selected. This framework has been applied in multiple studies focused on energy end-user behavior [42, 43, 76]. In Section 2.2, the framework already served as a structuring tool to identify the most relevant factors that shape household electricity profiles. At this stage of the research, however, its dynamic perspective becomes essential. The framework highlights how the identified elements interact and how they collectively shape electricity behavior, influence household decision-making, and ultimately determine the responses to flexibility measures. Its core concept is illustrated in Figure 4.2.

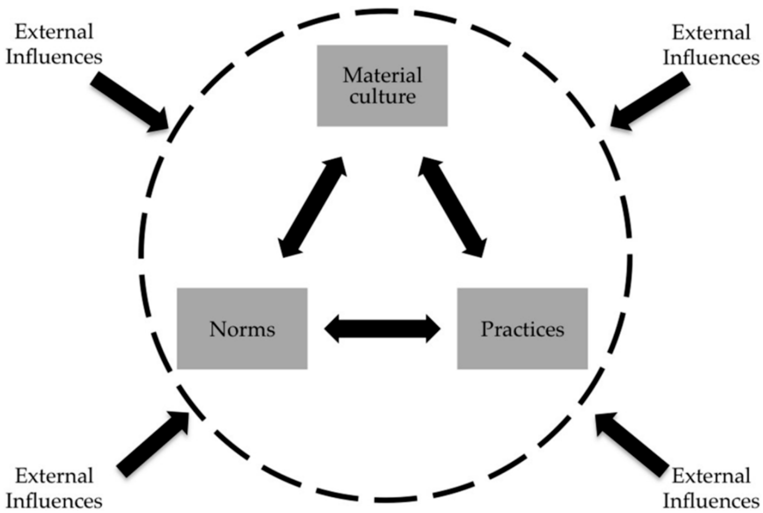


Figure 4.2: Core concept of the Energy Cultures Framework [42]

According to the framework, the elements that shape and sustain an individual's energy culture, and thereby enable or resist change, include the following components [42, 43, 76]:

1. **Cognitive norms**: Beliefs and understandings that influence choices about technologies and practices. Norms are defined as expectations and aspirations related to personal behavior and material culture.
2. **Material culture**: The technologies, building forms, and infrastructure that both constrain and shape behavior. Material culture not only facilitates certain practices but also influences values.
3. **Energy practices**: The recurring or incidental actions that determine how energy is used. Practices reflect day-to-day routines as well as infrequent but impactful energy decisions.
4. **External influences**: Contextual factors such as income, education, demographics, pricing structures, policy incentives, and technology availability.

These components are deeply interrelated. Cognitive norms influence the adoption and use of technology; material culture enables or constrains practices and shapes expectations; and energy practices both reflect and reinforce underlying norms and technology use. Unlike traditional cultural frameworks that segment populations by ethnicity or demographics, the Energy Cultures Framework defines culture as a distinctive pattern of knowledge, beliefs, behaviors, and material arrangements [42]. This allows for profiling based on behavioral logic rather than demographic attributes, aligning well with the objectives of Agent-Based Modeling. Before these behavioral dynamics can be analyzed within the framework, the relevant influencing factors must first be selected. This selection process is addressed in the following section.

4.3. Selecting Most Influential Factors for Electricity Behavior of the Households

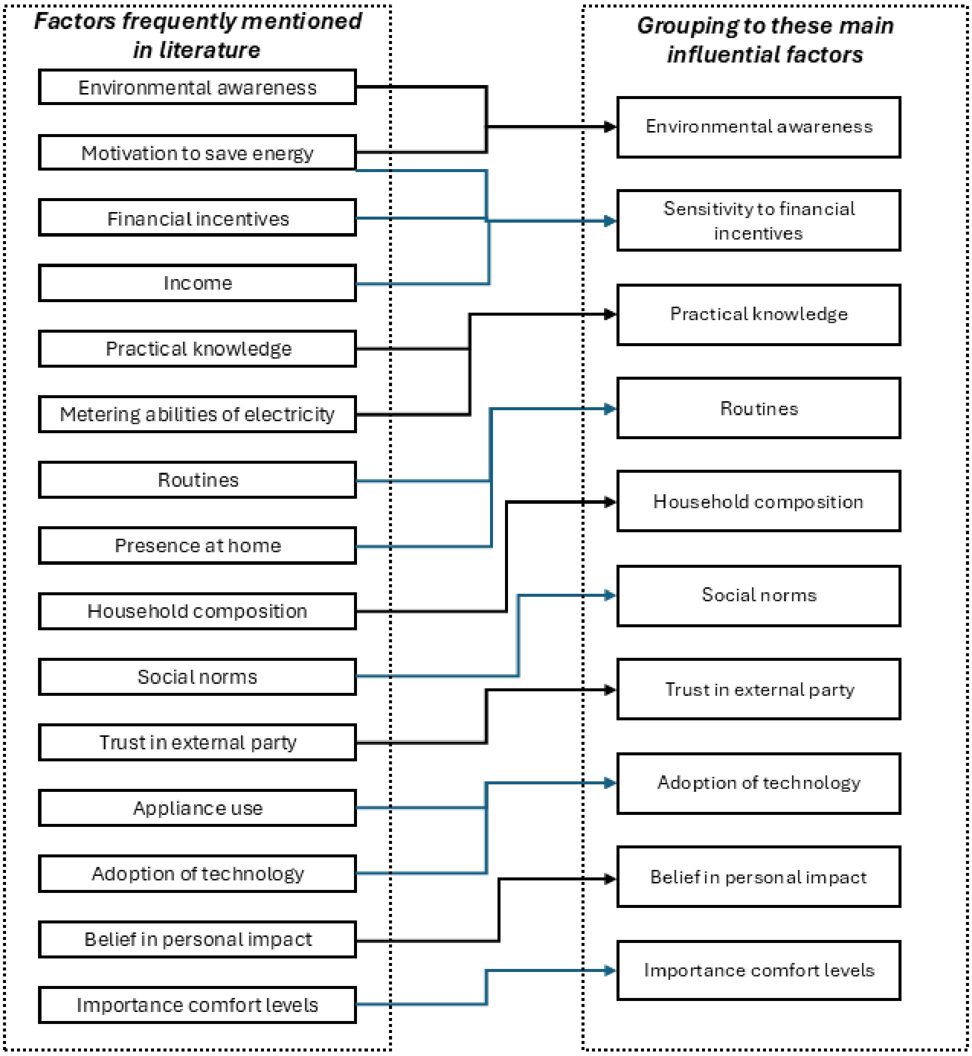


Figure 4.3: Mapping literature-based factors to key behavioral variables

As outlined in Section 2.3, a broad review of academic and applied research was conducted to identify the most frequently cited factors influencing household electricity behavior. Table 2.1 presents the reviewed sources, while Table 2.2 summarizes how often specific factors were mentioned across the literature. The most frequently named factors are listed in the left column of Figure 4.3. To avoid redundancy and better reflect conceptual overlap, some factors were grouped into broader behavioral dimensions. These groupings are shown by the arrows, leading to the summarized categories in the right column. For example, *financial sensitivity* includes both income level and general attitudes toward financial incentives. Although income is often cited on its own, it is usually an individual's sensitivity to price signals (rather than absolute income) that drives behavior. Some high-income households may still be financially cautious, while lower-income households may disregard incentives altogether. Grouping these under the broader dimension of financial sensitivity therefore captures both structural and psychological components. Similarly, *adoption of technology* encompasses a household's likelihood to adopt energy-related assets such as solar panels, heat pumps, or electric vehicles. This dimension also implicitly includes appliance usage and ownership, which are closely tied to technological openness. Lastly, *motivation to save energy* is conceptually represented through the combined influence of *environmental awareness* and *financial sensitivity*, both of which are already explicitly included. For this reason, motivation to save energy is not listed as a separate category in the right column of the figure.

Sociodemographic variables such as age, education level, and cultural background were mentioned in some studies but were not among the most frequently cited influencing factors. Moreover, these characteristics often serve as proxies for deeper behavioral traits—for example, education is frequently correlated with environmental awareness. Since this study aims to simulate household behavior directly, these background variables were excluded in favor of more proximate, behaviorally relevant predictors.

The selected variables reflect a balance between empirical relevance, conceptual clarity, and modeling feasibility. By aggregating some factors into broader categories, the resulting profiles remain diverse while ensuring the number of agent traits remains manageable for implementation in the ABM. These selected factors were then mapped onto the Energy Cultures Framework, as visualized in Figure 4.4. However, applying the framework in practice presents challenges. Due to its interactive nature, it is not always straightforward to assign a single factor to a specific pillar. In the end, technology adoption is the only one situated within the material culture dimension, as it directly influences the ownership and use of energy-related technologies. Household presence, routines, practical knowledge, financial sensitivity, and comfort preferences are best categorized as energy practices, as they manifest through recurring behavioral patterns. Cognitive norms include factors such as environmental awareness, social norms, belief in personal impact, and trust in external parties, which indirectly shape energy-related decision-making. Still, it is important to acknowledge that the framework does not imply strict separations; interactions between the pillars are central to its conceptual strength. Ultimately, the Energy Cultures Framework is used here as a structuring guide for identifying key behavioral dimensions and for understanding how their interplay shapes electricity use behavior in households.

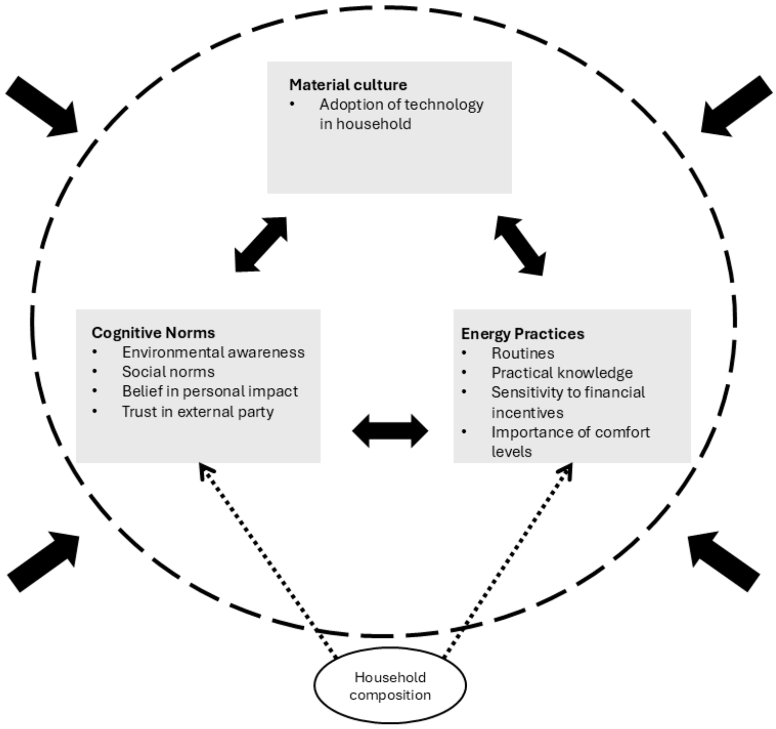


Figure 4.4: Factors placed in the Energy Culture Framework

4.4. Structuring the Profiles

In Section 2.3, various methods for constructing and quantifying household profiles were discussed. The study selected as the basis for quantifying these profiles is the Vijf Tinten Groener (Five Shades of Green) study by Motivaction [50], which categorizes Dutch residents according to their attitudes toward sustainability. This model distinguishes several mentalities based on core values and social position. The Motivaction study provides a detailed description of each mentality, offering qualitative assessments of how each group relates to the influencing factors identified in Section 4.3. Given that net congestion on the low-voltage grid is a relatively new issue, few studies have attempted to quantify behavioral responses to it. Although exact numerical representation of behavioral factors is not feasible, the model offers valuable insight into which profiles are likely to score relatively high or low on key dimensions. These qualitative insights are translated into quantitative values by assigning each profile a score between 0 (very low) and 1 (very high) for each behavioral factor. The descriptions in the study guide these estimations, and scores are determined relatively: if one profile is described as scoring extremely on a particular trait compared to others, it receives a correspondingly higher value. Figure 4.5 presents an overview of the Five Shades of Green mentality model. Table 4.2 shows the translation from qualitative insights to quantitative values.

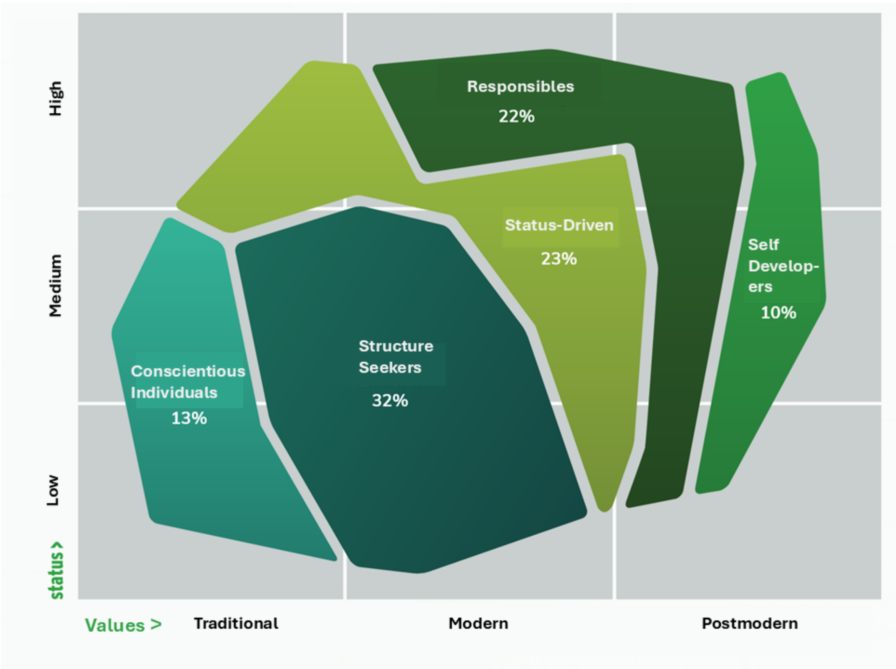


Figure 4.5: *Five Shades of Green* mentality model [50]

Profile A: Conscientious Individuals

This group is characterized by traditional, frugal, and often religious values. This strong attachment to traditional norms and values leads to the fact that they are socially engaged, but not driven by image or status. They show a strong sense of duty and are intrinsically motivated to contribute to a better world for future generations. Their lifestyles are structured and consistent, with a clear preference for order and routine. Behavioral changes are accepted only when they are gradual and aligned with their values of modesty and thrift, which are often inherited from upbringing. In terms of energy use, Conscientious Individuals are price-sensitive and generally willing to adjust their comfort levels if this aligns with their principles of restraint. While they do not actively seek out material possessions or technological upgrades, they are open to practical, trustworthy information that aligns with their worldview. Their trust in governmental and institutional authorities is relatively high, which makes them receptive to guidance from these entities. Despite having relatively low baseline knowledge regarding electricity use and sustainability measures, they are open to learning when the information is accessible and credible. They believe that their actions can have an impact at the local level but remain skeptical about their influence on larger, global issues. They are socially engaged, but their behavior is not driven by image or the opinions of others.

Profile B: Structure Seekers

Structure Seekers are oriented toward enjoyment, comfort, and ease, and tend to follow prevailing norms within their social environment. Sustainability is perceived as an abstract or distant issue, which results in low intrinsic motivation to act on it. Their daily routines are strongly driven by habit and convenience, and they prefer options that are straightforward and effortless. This group is highly sensitive to financial incentives and will adopt new behaviors primarily when these result in tangible savings or increased comfort. They are unwilling to sacrifice comfort unless there is clear and immediate personal benefit. Their openness to technology is limited, though they may accept new tools or systems if these clearly reduce effort or costs. Structure Seekers are responsive to social norms and often adopt sustainable behaviors only when these are widely practiced in their environment. While they do not have strong trust in external institutions, they may be guided by authority or peer behavior. Their knowledge about sustainability is generally low, and they often express uncertainty about the real-world significance of environmental issues. They tend to believe that their individual contribution has minimal impact.

Profile C: The Status-Driven

The Status-Driven group values success, luxury, comfort, and technological progress. Sustainability is not viewed as a moral obligation but rather as a means to enhance one's personal image or status. They are flexible in their routines, especially if adopting new habits helps reinforce their desired social identity. Comfort is a high priority for this group, and they are generally unwilling to compromise on convenience or luxury. While they are attentive to financial benefits, their primary motivators are visibility and prestige. As such, they are typically early adopters of innovative technologies, especially when they offer social recognition or competitive advantage. They are highly image-conscious and seek affirmation through external validation. Although their trust in institutions is selective, they are open to cooperation when it serves their interests. This group tends to be relatively well-informed about trends and developments and will engage with sustainability initiatives if they offer personal gain or increased status. Their belief in the personal impact of their actions is weak unless it translates into visible achievement.

Profile D: Responsibles

Responsibles are driven by strong ethical and environmental values. They exhibit a high level of intrinsic motivation to live sustainably and to contribute actively to global and local environmental solutions. They are generally open to adjusting their routines and behaviors to align with their values and are willing to sacrifice a certain level of comfort when this supports environmental goals. They are less concerned with personal image and more focused on collective responsibility, believing that citizens, businesses, and governments must work together to achieve sustainability. Financial incentives are not primary motivators for this group; they are willing to invest more if the outcomes are environmentally responsible. They adopt technology carefully and critically, with ethical considerations often playing a central role in their decision-making. Their trust in external institutions is moderate, they value collaboration but also expect accountability and transparency. They also value autonomy. Responsibles are highly informed and show awareness of both local and global sustainability challenges. They strongly believe that individual behavior can meaningfully contribute to environmental improvement.

Profile E: Self-Developers

Self-Developers prioritize personal freedom, creativity, and continuous self-growth. They value sustainability, but only when it aligns with their personal identity, curiosity, or social experiences. They are not bound by strict routines and are open to experimentation and change, provided these fit with their personal goals or lifestyle. This group places high importance on comfort and autonomy and is generally unwilling to compromise on pleasure or convenience. Financial incentives are of limited importance to them; they derive more value from unique, enriching experiences. They tend to adopt new technologies enthusiastically, particularly when these are innovative or align with forward-thinking values. While they are not driven by status, they are influenced by their peers and more likely to engage in sustainable behavior when it is part of a shared or meaningful group experience. Their trust in external institutions is low; they prefer independence and peer-to-peer initiatives. Their knowledge levels vary, often driven by momentary interest or engagement, but they are curious and open to new ideas. They wish to make a difference, but only under conditions that preserve their autonomy and allow for personal expression.

A summary of this information for each profile is presented in Table 4.2. Based on these qualitative insights, assumptions have been made to enable the quantification of behavioral characteristics.

Factor	Conscientious Individuals (A)	Structure Seekers (B)	Status Driven (C)	Responsibles (D)	Self-developers (E)
Importance of comfort levels	low (0.3)	high (0.8)	very high (0.8)	fairly high (0.4)	average (0.6)
Routines	(0.8)	(0.8)	(0.8)	(0.5)	(0.3)
Sensitivity to financial incentives	sensitive (0.8)	very sensitive (0.9)	sensitive (0.5)	fairly insensitive (0.3)	low (0.2)
Adoption of technology	low (0.3)	average (0.4)	high (0.9)	average/low (0.7)	average (0.8)
Social norms	medium (0.5)	high (0.7)	very high (0.9)	average (0.4)	average (0.6)
Trust in external party	high (0.9)	average (0.5)	fairly high (0.6)	fairly low (0.6)	moderate (0.4)
Belief in personal impact	fairly high (0.7)	low (0.2)	low (0.2)	average/high (0.7)	average (0.6)
Environmental awareness	fairly high (0.6)	low (0.2)	low (0.2)	high (0.8)	average (0.6)
Practical knowledge	below average (0.4)	low (0.3)	average (0.5)	high (0.8)	average (0.5)

Table 4.2: Combined qualitative and normalized (0–1) scores of behavioral profiles across energy behavior factors

4.5. Model Formalization

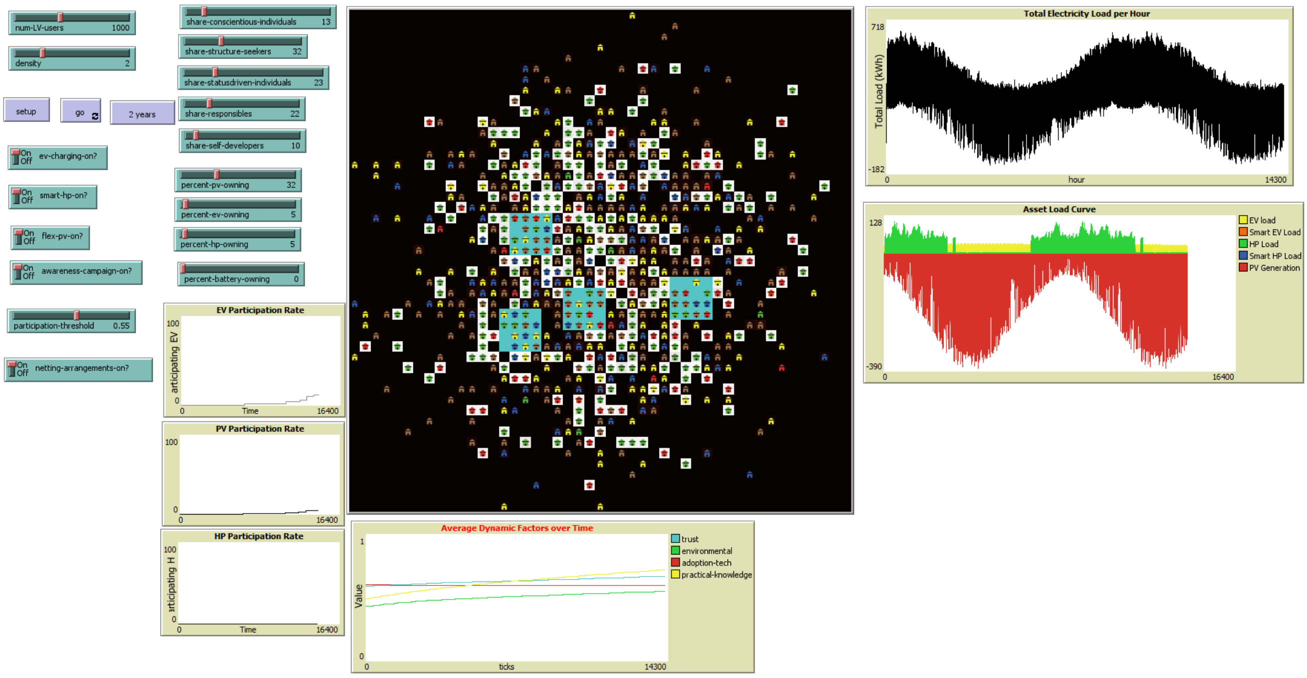


Figure 4.6: Interface of the Netlogo Model

After conceptualizing the Agent-Based Model in Section 4.1 and defining and quantifying the agent profiles in Section 4.4, the next step is to formally describe the model. Figure 4.6 presents the user interface of the ABM as developed in NetLogo. The model was built using the NetLogo Programming Guide and official documentation [77]. On the right side of the interface, system-level technical outputs are displayed. The “Total Electricity Load per Hour” plot shows the aggregate net load in kilowatt-hours per hour, while the “Asset Load Curve” presents the individual contributions of EVs, heat pumps, and solar panels. How these electricity loads are defined is further explained in Section 4.5.1. The plot labeled “Average Dynamic Factors over Time” displays how behavioral dimensions (trust in external parties, environmental awareness, adoption of technology, and practical knowledge) evolve throughout the simulation. The modeling of these behavioral factors is described in Section 4.5.2. On the left side, switches allow the user to activate specific flexibility measures. The logic behind these measures and their implementation is described in Section 4.5.3. Directly beneath these switches is the participation threshold slider, which determines the point at which agents decide to participate in a given measure. The composition of this threshold and the underlying decision logic are covered in Section 4.5.4. Participation in the three flexibility measures is visualized in the plots labeled “EV Participation Rate” (smart charging), “PV Participation Rate” (flex contract solar panels), and “HP Participation Rate” (flex contracts heat pumps). Finally, the user can simulate changes in the regulatory environment by toggling the *netting arrangements* on or off. This feature and its influence on agent behavior are discussed in Section 4.5.5.

The model operates using discrete time steps, with each step, referred to as a ”tick” in NetLogo, representing one hour. The model simulates a full year, totaling 8760 time steps. However, the simulation is designed to run indefinitely: while the seasonal cycle repeats annually, the agents’ characteristics and their participation in congestion mitigation measures continue to evolve over time. At the start of each simulation run, agents are randomly distributed across the grid, with a higher concentration near the center. Each simulation instance represents a newly generated hypothetical neighborhood, where spatial layout influences social interaction. Some households are centrally located and interact frequently with others, while others are positioned near the edges with fewer neighbors and less contact. Due to incomplete data availability for 2024, data from the year 2023 was used instead. This includes the baseline electricity load profiles of households, as well as profiles for solar PV production and heat pump demand, both of which are sensitive to weather conditions. While the model relies on 2023 weather patterns, adjustable input parameters such as asset ownership and awareness of measures allow the simulation to approximate future years. This enables the exploration of alternative scenarios based on the weather conditions of 2023.

Figure 4.7 provides a high-level schematic of the model's internal dynamics. It shows how each agent's profile type determines a set of behavioral characteristics, which influence their likelihood of participating in specific flexibility measures. These participation decisions then shape the overall electricity load in the system, allowing for the assessment of each measure's impact. The diagram also highlights two important feedback loops. First, participation can lead to increased trust, environmental awareness, and practical knowledge within the agent's network. Second, the more frequently a measure is adopted, the more familiar it becomes across the population, further lowering participation barriers. These reinforcing loops allow the model to simulate both behavioral diffusion and system-level effects over time.

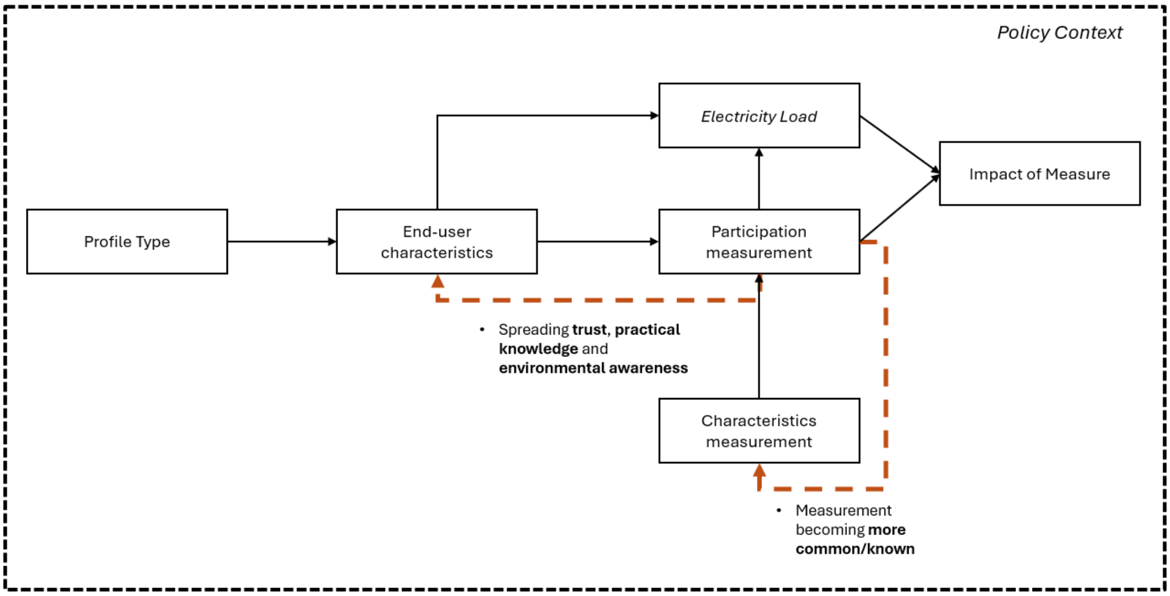


Figure 4.7: High-over system view

4.5.1. Technical Profile of the Agent

As outlined in Section 2.3, one way to visualize electricity behavior is through a household electricity profile. In the Agent-Based Model, each agent represents a household and has its own electricity profile over time. These individual profiles combine to form the total electricity profile of the system, which in this case represents a neighborhood. The model uses electricity load in units of kilowatt-hours per hour (kWh/h), representing average power consumption. The net electricity demand or supply of the system at hour h is computed by summing the electricity profiles $L_{i,h}$ of all N agents:

$$L_h^{\text{total}} = \sum_{i=1}^{N} L_{i,h} \tag{4.1}$$

Where:

- L_h^{total}: total electricity demand or supply of the system at hour h [kWh/h],
- $L_{i,h}$: electricity profile (net load or generation) of agent i at hour h [kWh/h],
- N: total number of agents in the system.

A positive value of L_h^{total} indicates that the system is drawing electricity from the grid (net demand), while a negative value indicates that it is feeding electricity into the grid (net supply). Figure 4.12 illustrates how the electricity profile of an individual agent is constructed. The profile is shaped by three key elements:

1. **Household composition**, which determines the base electricity consumption;
2. **Routines**, which define how consumption is distributed across time;
3. **Adoption of technology**, which influences the likelihood of owning energy-intensive assets such as electric vehicles (EVs), solar PV panels, or heat pumps (HPs).

Agents with higher levels of openness to innovation are more likely to own such assets. In the model, these assets are probabilistically assigned based on each agent's adoption score. Each asset has a predefined load curve, and the respective curves are added to the agent's base load if the agent owns the asset.

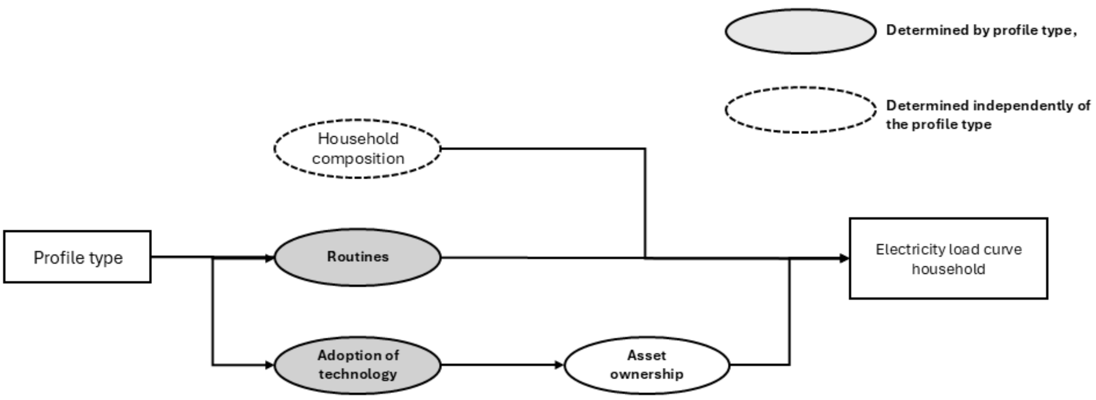


Figure 4.8: Constructing the technical profile of an agent

Household Compositions

In the Energy Cultures Framework, household composition is treated as an external factor, as it influences both daily routines and behavioral flexibility. A distinction is made between household size and the age structure of its members, as these factors have a non-linear relationship with total yearly electricity consumption [78]. For example, children generally contribute to lower overall per capita electricity use within households due to shared consumption patterns. Similarly, doubling the number of people in a household does not equate to doubling electricity use. Instead, electricity use per capita typically decreases as household size increases, due to the economies of scale that arise when appliances and activities are shared among more people [78]. Table 4.3 presents the total yearly electricity use for various household compositions. The table distinguishes between adults and children, reflecting differences in consumption behavior. In the model, agents are assigned a household composition and corresponding baseline electricity use according to the actual distribution of household types in the Netherlands (see the "Share" column). This is their yearly electricity usage, *excluding* potential assets. It is referred to as the *base load* of the households.

Household Type	#People	Frequency	Share	kWh/person/year	Total kWh/year
Living alone	1	3,340,560	32.25%	1,703	1,703
Couple without children	2	4,368,736	42.18%	1,227	2,453
Single parent + 1 child	2	381,700	3.69%	985	1,970
Two parents + 1 child	3	779,000	7.52%	898	2,693
Single parent + 2 children	3	177,200	1.71%	985	2,955
Two parents + 2 children	4	897,900	8.67%	898	3,590
Single parent + 3 children	4	59,100	0.57%	985	3,940
Two parents + 3 children	5	353,100	3.41%	898	4,488

Table 4.3: Electricity consumption by household type, representing Dutch distribution [79, 80]

Routines

As explained in the previous section, agents are assigned a yearly electricity consumption value at model initialization, referred to as their base load. However, the distribution of this base load over time depends on the agents' routines. To determine the actual hourly consumption of each agent, it is necessary to estimate their load profiles, representing electricity use in each hour of the year. Because the low-voltage grid in the Netherlands is part of a regulated infrastructure domain [5], detailed real-time consumption data from small-scale users is not publicly accessible. Therefore, an alternative approach was required to simulate household electricity consumption patterns. To this end, the model utilizes the *Verbruiksprofielen 2023*, published on the MFFBAS platform (Modelmatige Forecast Faciliteit Basis) [81]. These standardized profiles, developed by Netbeheer Nederland, estimate hourly electricity use across different user types and connection categories. They are based on aggregated historical consumption data and weather conditions, and are used by grid operators for forecasting, market analysis, and load allocation, particularly for households without smart meters or with infrequent meter readings. For this model, the selected load profile corresponds to category E1A (Residential, profile AZI), which represents households with a standard electricity connection. This implies no large-scale electricity use, such as charging an electric vehicle or operating an all-electric heat pump, and no electricity feed-in from sources like rooftop solar. The selected profile determines the household's load shape, defined as the distribution of total annual electricity consumption across the hours of the year. To derive the hourly load fraction for this household profile, the following steps were applied:

1. **Profile data import:** The profile data was downloaded in Excel format from MFFBAS. Each profile contains 35,040 entries (15-minute intervals for one year). These were aggregated into 8,760 hourly values, each representing a fraction of the total annual load. The sum of all fractions equals 1.
2. **Scaling to annual usage:** Each hourly fraction was multiplied by the agent's assigned annual electricity consumption (from Table 4.3) to calculate the hourly demand in kilowatt-hours.
3. **Scenario-based adjustments:** Two alternative load profiles were created based on the standard profile:
    - A version with *amplified evening peaks*, representing synchronized, routine-driven households.
    - A version with *flattened peaks*, simulating flexible behavior such as load shifting or increased self-consumption from solar energy.

Assignment of these profiles is based on household mentality types. Profiles A, B, and C are associated with households that follow strict routines and are less likely to adopt behavioral changes, thus receiving the high-peak load curves. In contrast, self-developer (Profile E) households value flexibility and independence. They are assigned the flattened load profiles, reflecting a more adaptive and potentially sustainable usage pattern. Households of profile D are generally open to adjusting their routines and behaviors, and will therefore get the default fraction profile.

Adoption of Technology

In the model, agents can own a private electric vehicle charger, solar panels, and/or an all-electric heat pump. These technologies were not only selected because they align with the flexibility measures, but also due to their significant contribution to pressure on the low-voltage grid, as identified in the Dutch government's *Problem Analysis Congestion on the Low-Voltage Grid* [4]. The report highlights that the Netherlands is a European frontrunner in solar PV adoption, the demand for heat pumps is rising rapidly, and electric transport is expanding quickly—particularly through private charging, which connects directly to the LV grid. The following sections explain how the electricity profiles of these technologies are constructed over the course of a year. In NetLogo, users can adjust the percentage of agents that own each technology via the model interface (see Figure 4.6). Each agent has a profile that reflects their likelihood of adopting new technologies. If an agent owns a specific asset, the corresponding electricity load is added to their base consumption profile, influencing the overall system load.

Private EV Charger (EV)

First, the hourly electricity consumption profile of a private EV charger was constructed. A single average demand profile is used, meaning that each agent who owns a private EV charger receives the same profile. To build this profile, the Low-Voltage Charging Profiles Generator developed by ElaadNL was used [82]. This tool generates historical charging profiles with similar characteristics based on user-defined parameters. The following parameters were applied:

- **Dataset type:** Private charging stations.
- **Location type:** Home.
- **Year:** 2023.
- **Maximum charging power:** 11 kW, representing a typical three-phase home charger (3x25A) [83].
- **Session configuration:** Only one charging session at a time.
- **Annual energy demand:** Set to 2500 kWh. This estimate is based on average driving behavior: Dutch cars drove 12,400 km in 2023 [84], and an electric vehicle consumes approximately 1 kWh per 5 km [85], resulting in 2480 kWh per year. It is assumed that households with a home charger perform most charging at home due to cost advantages [86].
- **Number of profiles:** A total of 150 profiles were generated to increase representativeness (50 profiles each using seeds 10, 20, and 30 (the tool's maximum per seed)), and the average load profile was taken.

This approach yielded a realistic weekly average electricity demand profile for a private home charging station. To construct a consistent annual load curve, the same weekly profile was repeated throughout the year. While applying a fixed weekly pattern is a simplification, it addresses the limited availability of detailed year-round load data. Moreover, the study by TNO [10] suggests that seasonal variation between summer and winter has minimal impact on private EV charging behavior, supporting the validity of this approximation.

Solar Panels (PV)

Second, the electricity generation profile of solar panels for each hour of the year 2023 was obtained. A single average generation profile is used, and each agent that owns solar panels receives this same profile. To create this profile, the European Commission Photovoltaic Geographical Information System (PVGIS) was used [87]. This is a tool that supplies hourly generation data for PV systems based on specific input parameters. The following settings were used to generate the PV profile:

- **Location:** De Bilt, the Netherlands (representing the central region of the country).
- **Timespan:** The year 2023, as it was the most recent year available in the database.
- **System size:** Based on the average Dutch household with PV, an installation of 10 panels was assumed [88], corresponding to approximately 3.3 kWp [89].
- **Mounting:** Fixed mounting system, typical for residential rooftops.
- **Tilt angle:** 40°, based on common Dutch roof slopes, which range between 30° and 45° [90].

- **Azimuth:** 180°, indicating a south-facing orientation.
- **PV technology:** Crystalline silicon, the most commonly used type in residential applications [91]
- **System losses:** 14%, accounting for inefficiencies such as inverter losses and shading [89].

Using these inputs, an hourly dataset was generated that reflects the electricity production of a typical residential PV system throughout the year 2023.

All-Electric Heat Pump (HP)

For the all-electric heat pump, it was more difficult to find a tool or dataset that represents the hourly load over an entire year. As a result, it had to be constructed using a calculation-based approach. The formulas used were obtained from the work of van der Holst et al. [92], which proposes a method for characterizing the downward flexibility of full-electric air-water heat pumps under congestion conditions. As input, the average daily temperature of 2023 was used [93]. An all-electric heat pump typically operates at two temperature levels:

- A lower set temperature of approximately 35–40°C for space heating,
- A higher set temperature of approximately 60°C for domestic hot water.

The electricity demand of the heat pump is dependent on the outside temperature. The colder it is, the more heat is required to maintain the desired indoor conditions. Furthermore, the efficiency of the heat pump (its COP) decreases as the outside temperature drops, making it less efficient during colder periods. To calculate the daily heat demand for space heating, the following equation was used [92]:

$$Q_{\text{HP, day, heating}} = HTC \cdot (T_{\text{set}} - T_{\text{outside}}) \cdot 24$$

Here:

- HTC is the Heat Transfer Coefficient (kW/K), set to 0.12 kW/K, representing an average Dutch home,
- T_{set} is the indoor setpoint temperature for space heating,
- T_{outside} is the daily average outside temperature,
- 24 represents the number of hours in a day.

For domestic hot water, the heat demand was assumed to be constant across the year. Based on an average household of two people, a fixed value of 4 kWh per day was used:

$$Q_{\text{HP, day, hotwater}} = 4$$

The efficiency of the heat pump, represented by its coefficient of performance (COP), was calculated based on the temperature difference between the setpoint and the outside temperature, as follows [92]:

$$COP = 8.74 - 0.190\Delta T + 0.00126\Delta T^2$$

Where $\Delta T = T_{\text{set}} - T_{\text{outside}}$.

Finally, the total electricity demand for each component (space heating and hot water) was computed as:

$$E_{\text{elec}} = \frac{Q_{\text{HP}}}{COP}$$

When the outside temperature was higher than or equal to the setpoint temperature, the heat pump was assumed to be off for space heating, only running for hot water provision. This calculation yields the daily electricity consumption of the all-electric heat pump. To construct an hourly profile, the daily electricity demand was distributed across 24 hours using a normalized hourly load profile specific to heat pumps.

Final Electricity Profile of Agents

In the model, each agent i has an *electricity profile* $L_{i,h}$ at hour h, which represents the net electricity exchanged with the grid. This includes both electricity consumption and potential generation. The total profile is defined as:

$$L_{i,h} = C_i \cdot p_h + \text{EV}_{i,h} + \text{HP}_{i,h} + \text{PV}_{i,h} \tag{4.2}$$

where:

- $L_{i,h}$: electricity profile (net load or generation) of agent i at hour h [kWh/h],
- C_i: annual base consumption of agent i [kWh/year],
- p_h: normalized load fraction at hour h (from profile data)
- $\text{EV}_{i,h}$: EV electricity usage at hour h [kWh/h],
- $\text{HP}_{i,h}$: heat pump electricity usage at hour h [kWh/h],
- $\text{PV}_{i,h}$: solar PV generation at hour h (negative value if supplying power) [kWh/h],

4.5.2. Behavioral Profile of the Agent

In addition to the technical profile, each agent is assigned a behavioral profile. These behavioral profiles are based on the quantification presented in Table 4.2. In the NetLogo model interface, sliders allow the user to adjust the distribution of behavioral profiles across the agent population. By default, this distribution follows the results of the Vijf Tinten Groener (Five Shades of Green) study by Motivaction [50], which segments the Dutch population into five groups: Conscientious Individuals (13%), Structure Seekers (32%), Status-Driven (23%), Responsibles (22%), and Self-Developers (10%). Figure 4.9 illustrates how the behavioral profile of each agent is structured. The diagram shows that, beyond the influence of the assigned profile type, household composition, which is randomly assigned to agents, also plays a role in shaping behavioral aspects. This means that behavior is not solely derived from profile type but is also partially influenced by demographic characteristics. Routines and technology adoption influence both the technical and behavioral aspects of the agent, and this interrelation is elaborated in the following section. The visual representation distinguishes three categories of behavioral factors:

- Light grey ovals represent factors determined by the agent's profile type and remain static over time.
- Dark grey ovals are also determined by the profile type but are dynamic and can change throughout the simulation.
- Dashed ovals represent variables that are independent of the agent's profile type.

Dynamic behavioral factors may evolve in response to two types of external influences: (1) interaction with the grid environment, and (2) social influence from other agents. Factors influenced by social dynamics are indicated by dotted arrows extending from the "Social Norms" component. The mechanisms through which these behavioral changes occur will be discussed in detail in the subsequent section.

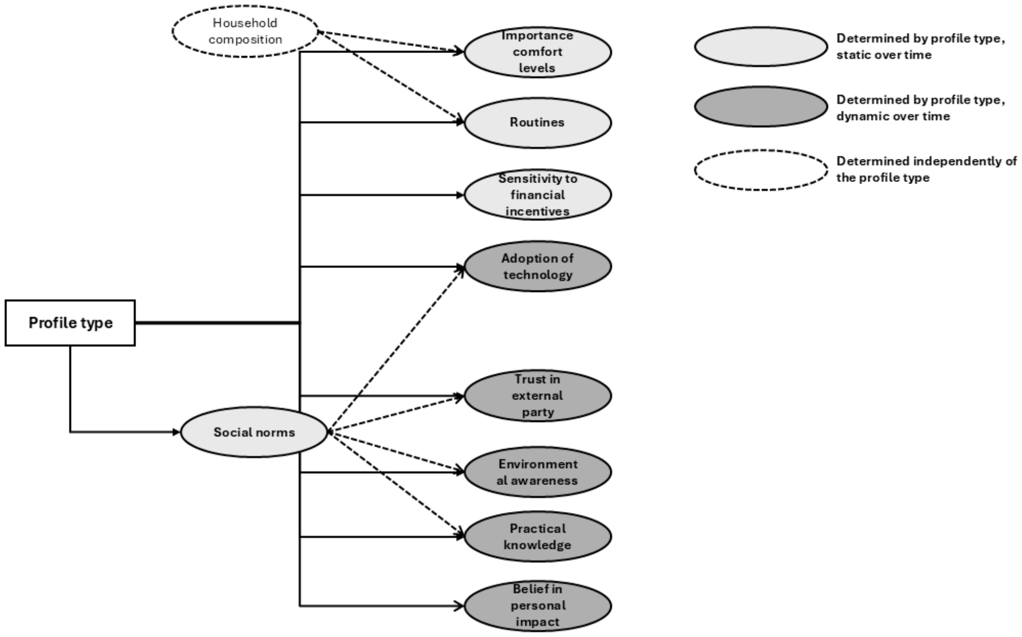


Figure 4.9: Constructing behavior profile of an agent

Dynamic Characteristics: Interaction Between Agents

When modeling consumer behavior and interactions, it is essential to reflect key micro-level factors and processes observed in real-world settings. Not only should the structure of social networks between agents be considered, but also the type of influence transmitted through these networks. As highlighted by García et al. (2011) [54], beyond understanding how consumers are connected, it is crucial to examine how different types of consumers influence each other, and which consumers are more susceptible to social norms or act as opinion leaders. Moglia et al. (2017) [94] also state that people may weigh the actions of their social peers when making a decision about adopting a new energy technology or having trust issues with the novel technology.

In this model, several individual attributes, including trust, environmental awareness, openness to innovation, and practical knowledge, are treated as dynamic factors that evolve over time through agent interactions. The extent to which these attributes change depends both on the influence exerted by connected peers and on each agent's sensitivity to social norms, which is determined by their profile characteristics. Social norms are patterns of behavior that are self-enforcing within a group: Everyone conforms, everyone is expected to conform, and everyone wants to conform when they expect everyone else to conform [95]. The higher an agent scores on the factor 'social norms', the stronger their desire to conform with what others expect the agent to do.

Trust

In 1998, trust was defined by Rousseau et al. as a "psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" [96]. Building on this, Composto et al. (2025) [97] developed a framework that explains how social norms shape the evolution of trust over time, particularly during periods of uncertainty. Their findings suggest that trust increases individuals' willingness to perform pro-social behaviors, such as participating in climate protection initiatives, by strengthening confidence in collective actions. Greater trust in institutions is associated with higher compliance with regulations and policies, leading to increased participation in measurement activities. Social norms serve as a critical mechanism in shaping trust, encoding collective experiences (descriptive norms) and moral judgments (injunctive norms) into shared expectations that individuals use when making interdependent decisions. Experimental evidence demonstrates that individuals exhibit higher levels of trust when they perceive trusting behavior to be socially normative.

A distinction can be made between horizontal trust (trust among individuals with equal power) and vertical trust (trust towards institutions or individuals in positions of authority). Trust norms are reinforced or weakened depending on whether individuals' experiences align with their expectations in interactions with others and institutions. Consequently, the willingness of individuals to participate in policies and measurement programs initiated by institutions is influenced by their level of trust. This level of trust is shaped by social norms and the dynamic interactions between horizontal and vertical trust. These feedback loops can either cause greater or diminished trust over time.

Environmental Awareness

Social norms play an important role in shaping environmental awareness and, therefore, influence an individual's overall energy behavior. Environmental awareness has been shown to positively influence pro-environmental behavior among community residents. Pro-environmental behavior, also referred to as environmentally friendly or environmental protection behavior, is defined as socially altruistic behavior characterized by positive attitudes and tendencies to care for the environment [98]. Social norms, as part of the broader concept of social capital, act as a key mechanism that can strengthen the relationship between environmental awareness and sustainable actions. Individuals with high environmental awareness are more likely to engage in environmentally responsible behavior when their social environment reinforces such behavior through supportive norms. Thus, pro-environmental behavior is shaped by the combined influence of internal (personal values), external (environmental conditions), and social (community norms) factors. Similarly, Verónica Sevillano and Pablo Olivos [99] emphasize the significant role of social norms in shaping environmental behaviors. They distinguish between descriptive norms, which are based on perceptions of what most people typically do (e.g., "most people recycle, so I recycle"), and prescriptive norms, which reflect societal expectations of what individuals should do (e.g., "please recycle" signs). Their research highlights that while descriptive norms can promote positive behavior, they can also backfire if they reveal widespread undesirable behaviors. Therefore, pointing out what others are doing regarding sustainability can motivate people to adopt similar behaviors. However, if others are not taking sustainable actions, individuals are also likely to be influenced by that and hold back from acting sustainably themselves.

Adoption of technology

Innovation diffusion critically depends on social interactions such as communication, influence, and the emergence of norms [54]. Jensen and Chappin (2017) [100] emphasized that incorporating *Word-of-Mouth (WOM) mechanisms* significantly improves the realism of innovation adoption in ABM frameworks. WOM models how individuals, households, or organizations learn about innovations through communication with others within their social networks. Schwarz and Ernst (2009) [51] further noted that many previous models incorrectly assumed homogeneity among agents in terms of their openness to innovation. In reality, individuals differ substantially in their propensity to adopt innovations early or late, reflecting the well-documented "early adopter" and "laggard" patterns [101]. These studies have shown that not only personal characteristics but also social networks and peer communication are critical determinants of adoption timing. Triggers for diffusion include communication in social networks, positive evaluation of innovations, and combinations of both approaches. Other previous research found that neighborhood cohesion and satisfaction are positively correlated with adoption likelihood [53]. Homeowners with a strong sense of belonging are more inclined to follow peers in adopting sustainable technologies. Visible retrofits, such as solar panels or upgraded insulation, act as social signals that encourage others to adopt similar measures [102].

Practical Knowledge

Si et al. (2022) identify environmental awareness as an important factor influencing pro-environmental behavior, and within their definition, knowledge is considered a component of environmental awareness [98]. In their view, being environmentally aware also entails possessing practical knowledge about related issues. They suggest that such knowledge can be shaped by social interactions, as individuals often learn from those around them. This perspective is supported by the Word-of-Mouth (WOM) mechanism described by Jensen and Chappin (2017) [100], which states that agents become capable of adopting new innovations only after being made aware of them, typically through social connections.

Practical knowledge spreads through networks when peers share their experiences. Therefore, in the model, practical knowledge is treated as a dynamic factor that can be influenced by social interaction between agents.

Social Influence Mechanism

In the model, the characteristics described above are allowed to evolve over time. It is assumed that agents are influenced by their peers on a weekly basis. The extent to which an agent is influenced depends on their individual sensitivity to social norms. The higher an agent scores on social norms, the more they care about what others expect from them and how they are perceived socially [95]. Agents are assumed to interact with their neighbors once per week. Neighbors are defined as agents located on the same patch or on the patch directly above, below, to the left, or to the right (i.e., Von Neumann neighborhood). This social influence mechanism is implemented in the model using the following equations:

$$X_i \in \{T_i, A_i, U_i\}$$

where:

- T_i: trust level of agent i,
- A_i: environmental awareness of agent i,
- U_i: adoption of technology by agent i.

The general update mechanism for each characteristic X_i is defined as follows:

$$\bar{X}_{\text{neighbors}} = \frac{1}{N} \sum_{j \in \text{neighbors}_i} X_j \tag{4.3}$$

$$\Delta X_i = \bar{X}_{\text{neighbors}} - X_i \tag{4.4}$$

$$X_i^{\text{next}} = X_i + \lambda_i \cdot \Delta X_i \tag{4.5}$$

$$X_i \leftarrow \max(0, \min(1, X_i^{\text{next}})) \tag{4.6}$$

Where:

- X_i: value of the characteristic for agent i,
- X_j: value of the characteristic of neighboring agent j,
- N: number of neighboring agents (can vary depending on spatial density),
- λ_i: agent-specific influence strength, calculated as the product of a configurable influence factor and the agent's social norm sensitivity S_i.

This rule enables convergence towards the local average behavior while ensuring values remain within the range $[0, 1]$. Agents more sensitive to social norms are influenced more strongly by their peers.

Unlike trust, environmental awareness, and adoption, *practical knowledge* K_i is treated as a cumulative factor. Agents do not share negative knowledge [103]. Its update mechanism allows only upward adjustments, meaning the value can increase but not decrease:

$$\bar{K}_{\text{neighbors}} = \frac{1}{N} \sum_{j \in \text{neighbors}_i} K_j \tag{4.7}$$

$$\Delta K_i = \max(0, \bar{K}_{\text{neighbors}} - K_i) \tag{4.8}$$

$$K_i^{\text{next}} = K_i + \lambda_i \cdot \Delta K_i \tag{4.9}$$

$$K_i \leftarrow \min(1, K_i^{\text{next}}) \tag{4.10}$$

4.5.3. Introduction of Net Congestion Measures in the Model

Now that the agents have been constructed with both a behavioral and a technical profile, the next step is to examine how these diverse agents respond to various congestion mitigation measures. As outlined in Section 3.2.2, the interviews identified several measures with high potential for unlocking flexibility from low-voltage users in the short term. This section explains how each of these measures is modeled within the Agent-Based Model.

Awareness Campaigns

As previously explained, this measure differs from the others. Unlike the flexibility measures where agents actively choose whether to participate, awareness campaigns do not require direct agent action. Instead, they aim to influence agents' behavioral characteristics indirectly. These campaigns are implemented periodically (once per month) and target specific spatial regions within the simulation environment.

Campaign Mechanics: Each campaign selects a fixed number of non-overlapping $n \times n$ patch grids. These grids are spatially distributed based on the same Gaussian distribution used for placing agents:

$$x \sim \mathcal{N}(\mu_x, \sigma_x), \quad \mu_x = \texttt{center-x}, \quad \sigma_x = \frac{\texttt{max-pxcor}}{4} \tag{4.11}$$

$$y \sim \mathcal{N}(\mu_y, \sigma_y), \quad \mu_y = \texttt{center-y}, \quad \sigma_y = \frac{\texttt{max-pycor}}{4} \tag{4.12}$$

The coordinates (x, y) are clamped to remain within the patch boundaries. Candidate grids are rejected if they overlap with previously selected ones in the same campaign cycle.

Agent Influence: Agents located on marked patches have a configurable probability p (default: $p = 0.8$) of being influenced. If selected, the agent receives a fixed increment δ (default: $\delta = 0.05$) to the following internal characteristics:

$$\texttt{trust} \leftarrow \min(1,\ \texttt{trust} + \delta) \tag{4.13}$$

$$\texttt{environmental\_awareness} \leftarrow \min(1,\ \texttt{environmental\_awareness} + \delta) \tag{4.14}$$

$$\texttt{practical\_knowledge} \leftarrow \min(1,\ \texttt{practical\_knowledge} + \delta) \tag{4.15}$$

$$\texttt{belief\_personal\_impact} \leftarrow \min(1,\ \texttt{belief\_personal\_impact} + \delta) \tag{4.16}$$

Timing: Campaigns are triggered every 720 ticks (monthly) if the `awareness-campaign-on?` switch is enabled.

Whereas the awareness campaign functions as a passive external intervention, the following three measures, referred to as the *flexibility measures*, require active behavioral responses from agents. Participation is voluntary, and the decision to adopt each measure depends on the agent's internal characteristics and profile.

Smart Charging at Home

When an agent participates in the smart charging measure, it agrees to allow its private electric vehicle charger to operate in a grid-conscious manner. This means that the standard charging profile is replaced by a "smart" profile designed to reduce stress on the grid. These smart profiles are generated using the same tool as the default EV load curves [82], which includes a feature for simulating smart charging behavior. According to grid operator interviews, grid-conscious charging involves reducing charging power during peak demand hours, typically between 17:00 and 21:00. To reflect this, the smart charging profile generated by the tool incorporates a static decrease in charging power during that window, effectively shifting a significant portion of the charging load to off-peak hours.

Curtailment of Residential Solar Panels

When an agent with solar panels agrees to the solar flexibility measure, it agrees to voluntarily curtail its solar energy production during periods of grid congestion or local overproduction. This is implemented by reducing the agent's PV generation to zero whenever production exceeds a specified threshold γ_{curt}. The curtailment threshold is set at 0.9 kWh per hour, which corresponds to solar irradiance levels of approximately 400 W/m^2, typical of warm, sunny days. This mechanism is intended to prevent excess electricity from being fed into the grid at times when local demand is low and solar output is high.

Flexible Use of All-Electric Heat Pumps

If an agent owns an all-electric heat pump and chooses to participate in this flexibility measure, its heat pump load is adjusted from the standard consumption pattern to a smart profile. In this smart profile, the electricity demand of the heat pump is shifted two hours earlier in the day, moving the load away from peak demand hours. This pre-heating strategy allows the household to maintain thermal comfort while reducing pressure on the grid during critical periods.

Characteristics of the Measures

In the NetLogo interface (see Image 4.6), each of these three measures is implemented as a toggle switch. When set to `on`, the measure is active; when set to `off`, it is inactive. The three flexibility measures in the model (smart charging, flexible contracts for solar panels and for heat pumps) require agents to make an explicit decision to participate. Whether an agent adopts a measure depends on both its internal characteristics and the attributes of the measure itself. Each measure is defined by four key parameters, all scaled between 0 and 1, based on the results of Section 3.3:

- **Comfort Requirement** (C_{m}): This parameter sets the minimum level of comfort flexibility an agent must possess to adopt the measure. It reflects the perceived disruption the measure may introduce into daily routines, such as delayed heating or reduced charging speed.
- **Trust Requirement** (T_{m}): This denotes the minimum trust level an agent needs to have in external systems or technologies to participate. A higher threshold implies that only agents with strong institutional or technological trust will engage.
- **Financial Incentive** (F_{m}): This represents the financial attractiveness of the measure. In the model, this value is used in conjunction with the agent's financial sensitivity to derive a financial compatibility score via a lookup table.
- **Familiarity** (K_{m}): This indicates how familiar or established the measure is within the population. This affects the interpolated knowledge score, which is based on the agent's practical understanding, environmental awareness, and belief in personal impact.

All these characteristics remain constant during the run, except for familiarity, which can increase. If the number of agents participating in the measure increases, the measure becomes more widely known. However, this growth will slow down once the measure is already very familiar. The formula of how the familiarity increasing looks like the following:

$$K_m(t+1) = K_m(t) + \eta \cdot (R_m(t) - R_m(t-1)) \cdot K_m(t) \cdot (1 - K_m(t)) \tag{4.17}$$

where:

- $K_m(t)$: current familiarity of measure m,
- $R_m(t)$: participation rate of eligible agents at time t,
- η: learning rate (default: 0.05), representing institutional or social responsiveness,
- $R_m(t) - R_m(t-1)$: the increase in participation since the previous time step.

4.5.4. Choice Model of the Agents

At this stage, two critical components have been introduced in the Agent-Based Model: agents with behavioral characteristics and flexibility measures with specific participation requirements. The next step is to define how agents decide whether to participate in a given measure. The Energy Cultures

Framework provides a theoretical foundation for identifying which factors influence energy-related behavior. By emphasizing the interplay between material culture, energy practices, and cognitive norms, it helps segment households into distinct behavioral profiles. This enables the classification of users based on shared patterns in how they use, understand, and relate to energy technologies and systems [42]. However, while the framework is well-suited for describing and clustering behaviors, it does not predict how those behaviors might evolve under new conditions. To bridge this gap, the model integrates a choice-based decision mechanism. Agent participation is determined through a dynamic scoring system that evaluates how an agent's internal attributes align with the characteristics of each measure. In this way, the Energy Cultures Framework provides the structural basis for behavior, while the choice model enables the simulation of behavioral change over time.

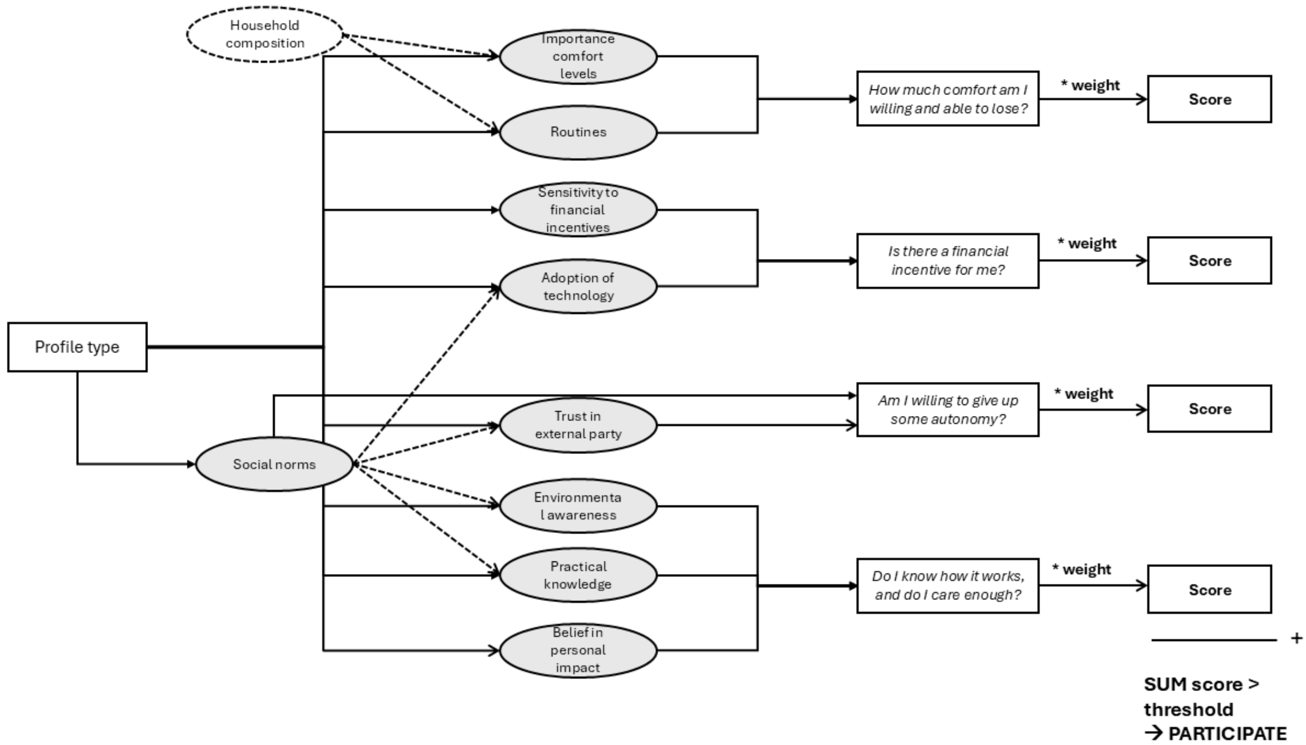


Figure 4.10: Decision model for agent participation in flexibility measures

Figure 4.10 represents how the agent makes the choice to participate or not. Put simply, the agent compares its own characteristics to those of the measure and asks itself the following four guiding questions:

1. *How much comfort am I willing and able to lose?*
2. *Is there a financial incentive for me?*
3. *Am I willing to give up some autonomy?*
4. *Do I know how it works, and do I care enough?*

These four questions reflect the primary barriers to participation identified by grid operators during the interviews presented in Chapter 3. Figure 4.10 illustrates how various agent characteristics influence each of these criteria. For each question, the agent receives a normalized score, which reflects how well the agent aligns with the requirements of the measure. The specific construction of these scores and the mathematical decision rule are explained in the following section.

Comfort Choice: How much comfort am I willing and able to lose?

An agent's comfort choice captures its flexibility in daily routines and sensitivity to disruptions. It is computed as the average of three behavioral attributes:

$$C_{\text{choice},i} = \frac{1}{3}\left(C_i + R_i + w_i\right) \tag{4.18}$$

where:

- C_i: the agent's inherent comfort level (0 to 1),
- R_i: the rigidity of the agent's daily routine (0 to 1),
- w_i: an adjustment factor based on household composition, set higher for agents with children (default: 0.5 if no children, 1.0 if children).

Empirical evidence suggests that families with children tend to follow more rigid routines, particularly in the evening [104]. The model accounts for this by increasing w_i for such agents, thereby lowering their comfort flexibility. The agent's comfort score is derived by comparing comfort choice with the comfort requirement of the measure, using bilinear interpolation in the comfort score matrix (Figure C.3).

Financial Choice: Is there a financial incentive for me?

The financial choice of an agent is only evaluated if the agent owns the asset required to participate in the measure. In such cases, the agent's financial sensitivity (determined by its behavioral profile) forms the basis for its financial choice. Similar to the comfort choice, a predefined financial score matrix (Figure C.1) is used to determine the resulting score by comparing the agent's financial sensitivity to the financial incentive level of the measure, using a direct lookup within the matrix.

$$F_{\text{choice,i}} = \begin{cases} F_i, & \text{if agent owns the applicable asset} \\ 0, & \text{otherwise} \end{cases} \tag{4.19}$$

where:

- F_i: the agent's financial sensitivity score (0 to 1).

Trust Choice: Am I willing to give up some autonomy?

The trust score reflects how confident the agent is in delegating control to external systems. This is influenced by both personal trust and social learning from neighboring agents.

$$T_{\text{choice,i}} = \begin{cases} \min(1, T_i + \lambda_i), & \text{if participation rate for measure } m \text{ among neighbors} \geq \phi_m \\ T_i, & \text{otherwise} \end{cases} \tag{4.20}$$

where:

- T_i: the agent's baseline trust score (0 to 1),
- λ_i: the influence strength, based on the agent's sensitivity to social norms (default: 0.5),
- ϕ_m: the social participation threshold for measure m (default: 0.5).

The resulting trust choice is then compared with the trust requirement of the measure using bilinear interpolation in the trust score matrix (Figure C.2).

Knowledge Choice: Do I know how it works, and do I care enough?

An agent's knowledge score represents both its awareness of the measure and its motivation to engage in sustainable energy behavior. It is calculated as the average of three internal values:

$$K_{\text{choice,i}} = \frac{1}{3}\left(K_i + A_i + B_i\right) \tag{4.21}$$

where:

- K_i: practical knowledge of energy systems and technologies (0 to 1),

- A_i: environmental awareness (0 to 1),
- B_i: belief in personal impact (0 to 1).

The knowledge score is derived by comparing knowledge choice with the familiarity level of the measure, using bilinear interpolation in the awareness matrix (Figure 4.11). How this is exactly done is explained in the next section.

Example of Bilinear Interpolation: Knowledge Score

Given the values of the agents' choices in the four given areas and the values of the characteristics of the measures in these areas, the agents will interpolate their overall score on this area through the matrices. All the matrices are given in Appendix C. The matrix for the knowledge score is given in image.

Awareness/ Familiarity	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
0.1	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55
0.2	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6
0.3	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65
0.4	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7
0.5	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
0.6	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8
0.7	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85
0.8	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
0.9	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95
1	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1

Figure 4.11: Example of one of the matrices: to calculate the knowledge score

The agent has access to this matrix, calculates their knowledge choice, looks at the familiarity of the measure, and follows the following steps:

Let:

- x: required knowledge threshold for a measure (0 to 1),
- y: agent's knowledge choice value (0 to 1),
- Q: an 11×11 matrix of awareness scores.

Define index and weight values:

$$x_1 = \lfloor 10x \rfloor, \qquad x_2 = x_1 + 1, \qquad w_x = 10x - x_1 \tag{4.22}$$
$$y_1 = \lfloor 10y \rfloor, \qquad y_2 = y_1 + 1, \qquad w_y = 10y - y_1 \tag{4.23}$$

Extract matrix values:

$$Q_{11} = Q[y_1 + 1][x_1 + 1], \qquad Q_{21} = Q[y_2 + 1][x_1 + 1] \tag{4.24}$$
$$Q_{12} = Q[y_1 + 1][x_2 + 1], \qquad Q_{22} = Q[y_2 + 1][x_2 + 1] \tag{4.25}$$

Interpolate row-wise:

$$R_1 = Q_{11} + w_y \cdot (Q_{21} - Q_{11}) \tag{4.26}$$
$$R_2 = Q_{12} + w_y \cdot (Q_{22} - Q_{12}) \tag{4.27}$$

Final interpolated score:

$$\text{Score}_{i,m} = R_1 + w_x \cdot (R_2 - R_1) \tag{4.28}$$

Participation Decision Formula

An agent reconsiders its decision to participate in each flexibility measure under the following conditions:

- The agent owns the asset associated with the measure.
- The agent is not already participating in the measure (participation is irreversible).
- It is the end of the month, simulating the moment when a household might reassess its energy use after receiving its electricity bill.

At the end of each month, the agent recalculates its comfort, financial, trust, and knowledge choices. These values may change over time due to evolving behavioral traits or external influences. Based on these updated scores, the agent computes a weighted decision score to determine whether to participate in a specific flexibility measure: smart EV charging, flex contract for solar panels, or for heat pumps. The decision formula is as follows:

$$\text{Score}_{i,m} = w_k \cdot K_{i,m} + w_c \cdot C_{i,m} + w_f \cdot F_{i,m} + w_t \cdot T_{i,m} \tag{4.29}$$

Where:

- $K_{i,m}$: knowledge score of agent i regarding measure m (0 to 1),
- $C_{i,m}$: comfort score of agent i regarding measure m (0 to 1),
- $F_{i,m}$: financial score of agent i regarding measure m (0 to 1),
- $T_{i,m}$: trust score of agent i regarding measure m (0 to 1),
- w_k, w_c, w_f, w_t: configurable weight parameters for each respective component. The default weight values are based on qualitative input from grid operator interviews. The more frequently a factor was mentioned by interviewees, the higher its weight: $w_k = 0.33$, $w_c = 0.28$, $w_f = 0.24$, $w_t = 0.14$.

An agent decides to participate if the total score exceeds a predefined participation threshold:

$$\text{Score}_{i,m} \geq \theta \tag{4.30}$$

where θ is the participation threshold, set by default to $\theta = 0.55$.

Change in Electricity Profile when Participating

These alternative electricity profiles for the measures add an extra component to the electricity profile of the agent:

$$L_{i,h} = C_i \cdot p_h + \text{EV}_{i,h} + \text{HP}_{i,h} + \text{PV}_{i,h} \tag{4.31}$$

Where:

- C_i: annual base consumption of agent i [kWh/year],
- p_h: normalized load fraction at hour h (from profile data),
- $\text{EV}_{i,h}$: EV electricity usage at hour h [kWh/year],
- $\text{HP}_{i,h}$: heat pump electricity usage at hour h [kWh/year],
- $\text{PV}_{i,h}$: solar PV generation at hour h (negative if supplying power) [kWh/year].

Each subcomponent depends on the agent's ownership of the asset and participation in the corresponding flexibility measure:

EV Load

$$\text{EV}_{i,h} = \begin{cases} \text{SmartEV}_h & \text{if agent owns EV and participates} \\ \text{EV}_h & \text{if agent owns EV and does not participate} \\ 0 & \text{otherwise} \end{cases} \tag{4.32}$$

Heat Pump Load

$$\text{HP}_{i,h} = \begin{cases} \text{SmartHP}_h & \text{if agent owns HP and participates} \\ \text{HP}_h & \text{if agent owns HP and does not participate} \\ 0 & \text{otherwise} \end{cases} \tag{4.33}$$

PV Generation

$$\text{PV}_{i,h} = \begin{cases} 0 & \text{if curtailment is active and PV}_h < \gamma_{\text{curt}} \text{ (default: } 0.9[kWh/h]) \\ \text{PV}_h & \text{if agent owns PV} \\ 0 & \text{otherwise} \end{cases} \tag{4.34}$$

4.5.5. Policy Context: the Netting Arrangements

The netting arrangements in the Netherlands are a financial policy that incentivizes small consumers, especially households, to install solar panels. It allows them to offset the electricity they feed into the grid with the electricity they consume from their energy supplier on an annual basis [9]. If this policy is discontinued, as currently proposed, households with solar panels will no longer receive full financial compensation for exported electricity. Instead, they will receive only a small feed-in payment. This shift creates a new financial incentive: to maximize self-consumption of generated solar power [105]. By default, the netting arrangement is active in the model. However, it can be deactivated to simulate its removal. In that case, the model introduces a behavioral feedback loop.

Self-Consumption Feedback Mechanism

When the netting arrangements are turned off, agents who own PV panels are no longer compensated for exported electricity. To simulate potential household adaptation, the model includes a feedback mechanism that gradually increases an agent's financial sensitivity if self-consumption is low. At the end of each month (every 720 ticks), each PV-owning agent calculates its self-consumption ratio, defined as:

$$\text{SelfUseRatio}_i = \frac{P_i^{\text{gen}} - P_i^{\text{exp}}}{P_i^{\text{gen}}} \tag{4.35}$$

where:

- P_i^{gen}: total PV electricity generated by agent i in the last month,
- P_i^{exp}: total PV electricity exported to the grid by agent i.

If the self-consumption ratio is lower than a target threshold ζ (e.g., 60%), the agent interprets this as a financial loss. The agent's financial sensitivity is then adjusted upward according to the following formula:

$$\texttt{financial\_sensitivity}_i \leftarrow \min\left(1,\ \texttt{financial\_sensitivity}_i + \alpha \cdot (\zeta - \texttt{SelfUseRatio}_i)\right) \tag{4.36}$$

where:

- ζ: the benchmark for desirable self-consumption (e.g., 0.60, so 60% self-consumption of total generated power),
- α: the sensitivity coefficient for feedback (default: 0.8).

As an agent's financial sensitivity increases, it becomes more likely to participate in future flexibility measures such as PV curtailment. This models real-world behavioral shifts in response to reduced compensation for electricity exports. This feedback mechanism is triggered by the model parameter `netting-arrangements-on?`. When this switch is set to `false`, the behavioral feedback loop is active. When set to `true`, the agent remains financially unaffected by their level of self-consumption.

Upcome of the Home Battery

With the option to deactivate the netting arrangements, it becomes highly relevant to include home batteries in the model. Currently, only a negligible number of households own a home battery [105], but once netting arrangements are abolished, a rapid increase in adoption is expected due to their ability to enhance self-consumption [106]. In the model, batteries store surplus solar power and discharge it during periods of high electricity demand. A slider in the NetLogo interface (Image 4.6) allows users to set the number of home batteries in the system, similar to how other assets are configured.

Battery Allocation: Only agents who own PV panels are eligible for battery assignment. Among these, the agents with the highest technology adoption scores receive the batteries first. Assigned agents are initialized with the following battery attributes:

- Battery capacity (default: $B_i^{\text{cap}} = 3$ [kWh]),
- Initial state of charge (default:$B_i^{\text{soc}} = 0$ [kWh]),
- Maximum charge rate (default: $B_{\max}^{\text{ch}} = 0.5$ [kWh/h]),
- Maximum discharge rate (default: $B_{\max}^{\text{dis}} = 1.5$ [kWh/h]).

Charging Logic: At each simulation tick h, if the net load of the household is negative (i.e., generation exceeds consumption), the battery absorbs the surplus:

$$\text{If } L_{i,h} < 0 : \quad \Delta B_{i,h}^{\text{ch}} = \min\left(L_{i,h}, B_{\text{max}}^{\text{ch}}, B_i^{\text{cap}} - B_i^{\text{soc}}\right) \tag{4.37}$$

$$B_i^{\text{soc}} \leftarrow B_i^{\text{soc}} + \Delta B_{i,h}^{\text{ch}} \tag{4.38}$$

$$L_{i,h}^{\text{adj}} = L_{i,h} + \Delta B_{i,h}^{\text{ch}} \tag{4.39}$$

Discharging Logic: When the net load is positive and the battery has stored energy, it discharges:

$$\text{If } L_{i,h} > 0 : \quad \Delta B_{i,h}^{\text{dis}} = \min\left(L_{i,h}, B_{\text{max}}^{\text{dis}}, B_i^{\text{soc}}\right) \tag{4.40}$$

$$B_i^{\text{soc}} \leftarrow B_i^{\text{soc}} - \Delta B_{i,h}^{\text{dis}} \tag{4.41}$$

$$L_{i,h}^{\text{adj}} = L_{i,h} - \Delta B_{i,h}^{\text{dis}} \tag{4.42}$$

Final Load Calculation: The final hourly electricity profile of agent i, accounting for battery charging and discharging, is:

$$L_{i,h}^{\text{final}} = L_{i,h}^{\text{adj}} \tag{4.43}$$

This ensures that solar power is first used to reduce consumption, then stored in the battery, and only exported when no storage capacity remains.

Model Assumptions: Batteries in the model are not optimized for financial returns (e.g., via time-of-use pricing) and do not account for battery degradation or energy losses. Instead, the battery serves solely as a passive buffer to increase the agent's solar self-consumption and reduce grid reliance.

4.6. Validation and Verification

Before analyzing the scenarios designed in this study, the Agent-Based Model must undergo a process of validation and verification to ensure its credibility and reliability. *Model verification* refers to the process of confirming that the model is implemented correctly according to its conceptual and formal specifications. It focuses on debugging, checking logical consistency, and verifying that all model components behave as intended [62]. *Model validation*, on the other hand, assesses whether the model accurately represents the real-world system it aims to simulate. This involves comparing model outputs with empirical data, expert opinion, or established theoretical expectations [62]. The verification and validation process includes the following components:

- Verification of individual agent behavior and electricity profile construction.
- Validation of adoption patterns against behavioral literature.
- Sensitivity analysis to assess the robustness of key parameters.

Technical Load

As a first step, a simplified simulation is run in which only one agent is placed in the environment. All asset ownership rates (electric vehicles, solar panels, and heat pumps) are set to 100%, and a random seed is applied to ensure reproducibility. The agent is assigned profile type E. This isolated simulation helps validate whether the model constructs electricity profiles correctly at the individual level, following the formal load equations introduced in Section 4.5.4. The resulting yearly load profile of the agent is shown in Figure 4.12.

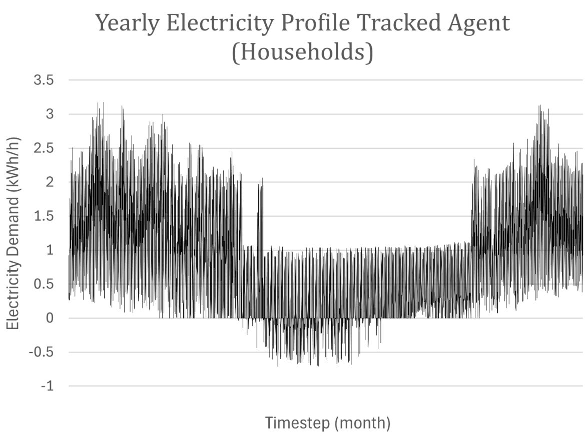


Figure 4.12: Electricity profile of a tracked single agent over the year

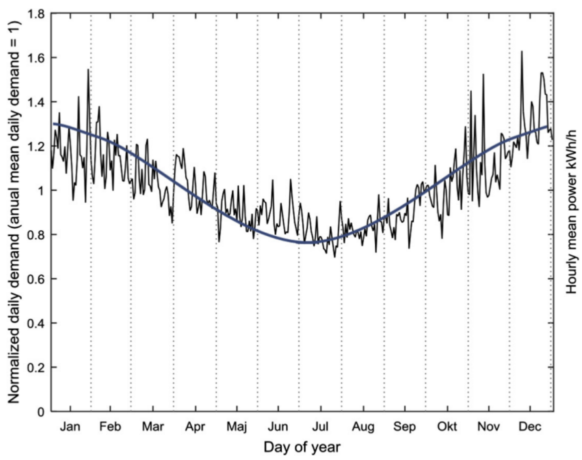


Figure 4.13: Average electricity profile of 35 households, without energy-intesive assets [107]

The electricity profile of the tracked agent (Figure 4.12) shows clear seasonal variation, primarily due to solar generation, which leads to negative net values during summer months as a result of PV export. The profile also reflects consistent base load consumption, along with distinguishable effects from a private EV charger and an all-electric heat pump. In comparison, Figure 4.13 presents the average yearly electricity use of 35 households based on measurement data [107]. While both profiles exhibit similar seasonal trends, the simulated agent's load in Figure 4.12 displays sharper peaks and higher overall demand. This difference is expected, as the simulated agent owns all energy-intensive assets, whereas the measurement data in Figure 4.13 includes households without explicit information on asset ownership, resulting in lower average peaks [107]. Although no empirical dataset was available showing real-world profiles for households with all these technologies combined, expert feedback confirmed that the shape and magnitude of the simulated profile are technically plausible, considering typical base load patterns alongside EV, PV, and heat pump usage (personal communication, May 15, 2025).

A more detailed breakdown of the component load curves, separating the baseline household demand, EV charging, heat pump load, and PV generation (is provided in Appendix D). This allows for manual verification that all individual components are combined logically and that the technical behavior of the agent aligns with model expectations.

Choice Model of the Agents and Overall Adoption

In addition to verifying the technical load profiles, the behavioral logic of the model must also be validated. As an initial test, all behavioral barriers are removed. The comfort and trust requirements for each measure are set to a minimum value of 0.1 (on a scale of 0 to 1), while the familiarity and financial incentive parameters are maximized to 1.0. In this configuration, all agents who own the corresponding asset adopt the measure immediately. This confirms that the participation logic is implemented correctly. When all criteria are satisfied, agents participate without hesitation.

Next, the model is tested under more realistic assumptions to examine the shape of the emergent adoption curve. This time, all measure characteristics are set to 0.5, making the flexibility options moderately attractive. In addition, all agents are assigned ownership of all relevant assets, removing asset availability as a limiting factor. This configuration enables all agents to potentially participate, allowing the model to simulate how behavioral heterogeneity and social influence alone shape adoption over time. Although no empirical adoption curves yet exist for the specific measures modeled, namely smart EV charging, flexible for solar panels and heat pump contracts, the resulting adoption trajectory can be qualitatively compared to the classic *Diffusion of Innovations* theory proposed by Rogers [101]. This theory describes how new technologies spread through a population over time, forming an S-shaped curve that reflects early adoption, social contagion, and eventual saturation. Figure 4.14 shows the theoretical S-curve and its decomposition into adopter categories: innovators, early adopters, early majority, late majority, and laggards. It is used here as a qualitative benchmark for validating the dynamics of the simulated adoption process.

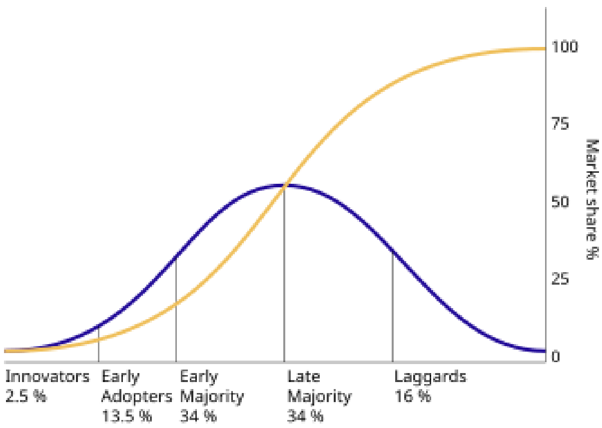


Figure 4.14: Diffusion of Innovation [108]

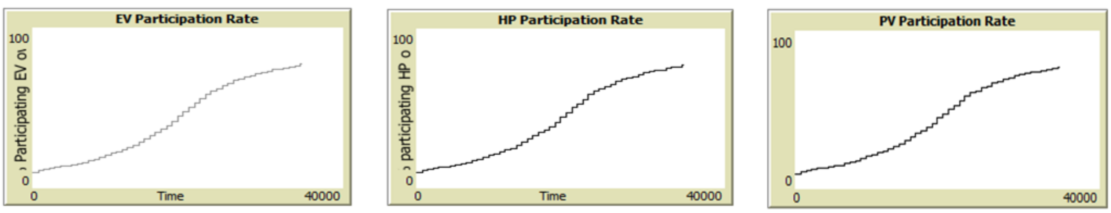


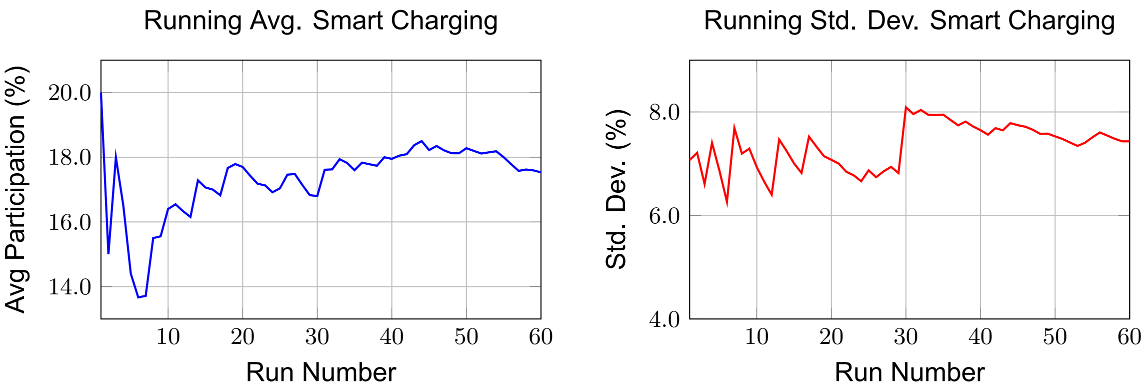
Figure 4.15: Adoption rates per measure over time

Figure 4.15 shows the adoption curves generated by the model for each measure. Each plot demonstrates a gradual uptake pattern driven by social influence. The curves exhibit S-shaped behavior consistent with the Diffusion of Innovations theory, with initial adoption by more receptive agents followed by social acceleration and eventual saturation. These results support the validity of the underlying behavioral model, demonstrating its sensitivity to both agent traits and peer influence.

4.6.1. Stability and Sensitivity Analysis

The last part of validating and verifying the model is to conduct a sensitivity analysis (SA). This method is widely accepted in the literature as essential for proper model evaluation and validation [109]. SA investigates how uncertainty in model outputs can be attributed to different sources of uncertainty in model inputs [109]. It is widely regarded as a powerful tool for understanding the behavior of numerical models [110]. Besides supporting model evaluation and validation, SAs also prioritize which variables are most influential and help to assess the robustness of model predictions [111]. In this study, a One-At-a-Time (OAT) sensitivity analysis is conducted. This approach involves systematically varying one parameter at a time while keeping all others fixed at their baseline values [110]. OAT is widely used in fields such as environmental science due to its simplicity, ease of implementation, and interpretability [110]. It offers a straightforward way to assess first-order sensitivities and to identify which parameters most directly influence model outcomes. However, a major limitation of OAT is that it assumes model responses to different inputs are independent, an assumption that may not hold in complex, nonlinear models [109]. While this method does not capture interactions between parameters, it remains appropriate for the purpose of this study: to identify dominant individual drivers of model behavior. Moreover, the analysis is applied systematically across all key parameters, offering a robust view of the model's primary sensitivities.

Because the agent-based model contains stochastic elements, such as the randomized assignment of agent characteristics, output variability is to be expected. Therefore, before conducting sensitivity analysis, a stability test was performed to ensure that the model produces consistent outcomes across multiple runs with identical input settings. The main output metrics used in the sensitivity analysis are the participation rates in: (1) smart charging for electric vehicles, (2) flexible contracts for solar PV curtailment, and (3) flexible contracts for heat pump usage. These same metrics were used to assess model stability. Both the stability test and the sensitivity analysis were conducted using the *BehaviorSpace* tool in NetLogo. BehaviorSpace is an integrated experiment manager that enables users to systematically explore the behavior of their models. It automates multiple simulation runs while varying specified parameters and records the outcomes of each run [77]. For the stability test, all input parameters were kept constant across repeated runs to observe how the model behaves under identical conditions and to assess the consistency of outcomes. This helps determine whether the model results converge or remain volatile due to stochastic processes. In the sensitivity analysis, by contrast, BehaviorSpace was used to systematically vary one parameter at a time while keeping all others fixed.



(a) Running average participation.

(b) Running standard deviation.

Figure 4.16: Convergence of smart charging participation metrics across 60 simulation runs. Values are shown in percentages.

The stability test was performed by running the model 60 times in total. In the base scenario, the running average and the standard deviation in participation rates for smart charging and flexible PV contracts stabilized after approximately 40 runs. Figure 4.16 shows the convergence of participation rates in smart charging. Notably, the participation rate in flexible heat pump contracts remained at 0% across all runs, indicating that this measure was not attractive under the base assumptions. The rest of the results of the stability test can be found in Appendix E.

4.6.2. Sensitivity Analysis

To conduct the one-at-a-time sensitivity analysis, each model parameter was independently varied by $\pm 10\%$ from its baseline value, while all other parameters were held constant. The resulting percentage change in participation rates for each flexibility measure, smart EV charging, flexible contracts for solar PV curtailment and flexible contract for heat pumps, was recorded. The results of this analysis are presented in Figures 4.17 and 4.18. The figures use conditional formatting to enhance interpretability. Cells shaded in dark red indicate that the variable change caused a substantial decrease in participation, whereas dark green signals a substantial increase. This visual aid allows readers to quickly identify which parameters are most influential. For a complete list of the analyzed model parameters, their associated symbols, and a brief explanation of their role in the model, refer to Table 2.

Sensitivity analysis is a key tool for assessing the robustness of simulation results when input variables are uncertain [112]. In this study, many behavioral parameters are derived from limited empirical literature, as residential decision-making in response to congestion mitigation strategies remains an emerging research area. This motivated a comprehensive sensitivity analysis to explore how uncertainty in these inputs may affect model outcomes.

				Smart Charging EV			Flex Contracts PV Panel			Flex Contracts Heat Pump		
Variable	**-10%**	**Base**	**10%**	**-10%**	**Base**	**10%**	**-10%**	**Base**	**10%**	**-10%**	**Base**	**10%**
num-lv-users	900	1000	1100	-6.20%	0.00%	-6.36%	3.94%	0.00%	-5.32%	0.00%	0.00%	0.00%
trust-required-smart-charging	0.36	0.4	0.44	17.41%	0.00%	-13.78%	-3.56%	0.00%	-3.49%	0.00%	0.00%	0.00%
familiarity-smart-charging	0.63	0.7	0.77	-61.45%	0.00%	79.79%	1.54%	0.00%	1.19%	0.00%	0.00%	0.00%
comfort-required-smart-charging	0.27	0.3	0.33	31.27%	0.00%	-25.37%	2.03%	0.00%	1.80%	0.00%	0.00%	0.00%
trust-required-smart-hp	0.63	0.7	0.77	-4.19%	0.00%	2.69%	7.79%	0.00%	2.28%	0.00%	0.00%	0.00%
familiarity-smart-hp	0.27	0.3	0.33	-2.73%	0.00%	-0.66%	-3.09%	0.00%	-1.97%	0.00%	0.00%	0.00%
comfort-required-smart-hp	0.63	0.7	0.77	-3.92%	0.00%	9.27%	-7.56%	0.00%	-8.53%	0.00%	0.00%	0.00%
trust-required-flex-pv	0.27	0.3	0.33	2.16%	0.00%	-4.91%	7.18%	0.00%	-16.70%	0.00%	0.00%	0.00%
familiarity-flex-pv	0.36	0.4	0.44	6.74%	0.00%	1.27%	-28.87%	0.00%	83.05%	0.00%	0.00%	0.00%
comfort-required-flex-pv	0.09	0.1	0.11	2.23%	0.00%	-1.05%	11.24%	0.00%	-5.29%	0.00%	0.00%	0.00%
participation-threshold	0.495	0.55	0.605	419.83%	0.00%	-100.00%	706.60%	0.00%	-99.56%	0.00%	0.00%	0.00%
social-influence-factor	0.09	0.1	0.11	-18.11%	0.00%	1.61%	2.24%	0.00%	23.33%	0.00%	0.00%	0.00%
trust-social-scaling	0.45	0.5	0.55	5.12%	0.00%	-7.71%	12.36%	0.00%	2.52%	0.00%	0.00%	0.00%
trust-social-threshold-ev	0.45	0.5	0.55	2.00%	0.00%	-2.31%	-8.97%	0.00%	-2.72%	0.00%	0.00%	0.00%
campaign-effect-size	0.045	0.05	0.055	-16.84%	0.00%	32.07%	-37.12%	0.00%	33.30%	0.00%	0.00%	0.00%
campaign-success-probability	0.72	0.8	0.88	-16.44%	0.00%	23.86%	-36.46%	0.00%	24.23%	0.00%	0.00%	0.00%
children-comfort-weight	0.9	1	1.1	11.65%	0.00%	7.33%	5.40%	0.00%	-2.18%	0.00%	0.00%	0.00%
knownness-learning-rate	0.9	1	1.1	-15.22%	0.00%	-5.07%	-4.53%	0.00%	-0.75%	0.00%	0.00%	0.00%

Figure 4.17: Sensitivity analysis base scenario

Figure 4.17 presents the results of the sensitivity analysis for the base scenario. Each parameter was varied by $+10\%$ and -10% relative to its baseline value, with all other inputs held constant. To address the model's stochastic nature, each configuration was simulated 40 times. Despite this, some output variability remains, up to approximately 10% in certain cases. This variation is not indicative of structural flaws in the model; rather, it reflects the embedded randomness in agent decision-making and social interaction dynamics. Repeated simulation runs filter out most of this stochastic noise, but the model is not entirely deterministic.

Number of Users and Social Influence. Modifying the number of agents (`num-lv-users`) in the model does not have a significant impact on participation metrics. This implies that increasing the size of the neighborhood, while maintaining the behavioral profile distribution, does not fundamentally alter agent decisions. In contrast, the `social-influence-factor` (which controls how strongly agents adjust their characteristics to align with their neighbors) has a measurable effect. When agents are more susceptible to peer influence, participation in flexibility measures increases. This highlights that the impact of social context depends more on the depth of influence than on the number of surrounding agents.

Measure Characteristics. The measure-specific variables show expected patterns of sensitivity. For smart-charging, three input parameters—`familiarity-smart-charging`, `comfort-required-smart-charging`, and `trust-required-smart-charging`—significantly affect participation. The strongest effect comes from familiarity, followed by comfort, with trust having the weakest influence. This aligns with the internal weighting of the agent decision model, where knowledge is the most important factor and trust the least. A similar pattern is seen in the participation for the flex contracts for solar PV measure. In contrast, the participation rate for the flex contracts of heat pumps does not respond significantly to any of the tested input variations. This suggests that, given the base case settings, most agents are already firmly below the decision threshold for this measure.

Participation Threshold. The most influential parameter across all measures is the `participation-threshold`, which sets the minimum score required for an agent to adopt a measure. Decreasing this threshold by just 10% (from 0.55 to 0.495) dramatically boosts adoption. Most notably, the uptake of the solar PV curtailment measure increases more than sevenfold. This result comes from the way compatibility scores are calculated. As seen in Appendix C, a score of 0.5 typically results when an agent's personal characteristic precisely matches the threshold of a measure. This 0.5 can be interpreted as a "sufficient" match. The base threshold of 0.55 reflects the idea that agents require more than just sufficiency to commit; they must perceive added benefit or security. When this requirement is relaxed to 0.5, many borderline agents participate. Conversely, raising the threshold eliminates nearly all participation, as very few agents achieve the higher required scores and participate in the measures. Yet again, the flex contract for heat pumps yields no participation, showing that agents are far below this threshold.

Impact of Awareness Campaigns. Two key variables determine the impact of awareness campaigns: `campaign-effect-size`, which defines the magnitude of change to internal characteristics when influenced, and `campaign-success-probability`, which is the likelihood that an agent will be influenced when exposed. In the model, awareness campaigns are deployed monthly at randomly selected locations. When agents are exposed, the default probability of being influenced is 0.8, based on expert input from interviewee 7, where the effectiveness of similar campaigns was reported as approximately 80%. The sensitivity results show that higher values for these parameters lead to notably increased participation in both smart charging and the flex contract for solar PV panels. This confirms the effectiveness of campaigns in driving adoption. The logic is as follows: campaigns incrementally raise four internal traits (trust, practical knowledge, environmental awareness, and belief personal impact) of an agent. Three of these traits are also diffused through peer interaction, enabling a snowball effect that spreads awareness and increases adoption beyond the initially affected agents.

Children's Impact on Comfort. The variable `children-comfort-weight` introduces a comfort penalty for households with children, based on findings by [104], which link young children to rigid household routines. While this factor slightly lowers the comfort score of such agents, its overall impact is limited. This is likely because agents can still achieve high overall scores through other dimensions (knowledge, financial incentive, trust), offsetting their reduced comfort compatibility with the measure. Therefore, small changes in this weight do not substantially affect participation decisions.

Knowledge Growth Rate. Lastly, the variable `familiarity-learning-rate` controls how quickly a measure becomes better known over time due to social diffusion. A 10% change in this parameter shows limited impact under the current settings. However, this is likely due to the short time window or relatively high default value. Since knowledge is the most heavily weighted decision factor, greater reductions in this variable would likely result in a noticeable decline in participation.

				Smart Charging EV			Flex Contracts PV Panel			Flex Contracts Heat Pump		
Variable		Base			Base			Base			Base	
weight-knowledge	0.25	0.33	0.4									
weight-comfort	0.25	0.28	0.3									
weight-financial	0.25	0.24	0.2									
weight-trust	0.25	0.14	0.1	72,06%	0,00%	144,07%	268,18%	0,00%	99,31%	0,00%	0,00%	0,00%
user-densitiy	1	2	3	-60,20%	0,00%	-8,99%	-49,72%	0,00%	20,72%	0,00%	0,00%	0,00%
num-campaigns	3	4	5	-60,44%	0,00%	60,78%	-51,27%	0,00%	85,23%	0,00%	0,00%	0,00%
campaign-size	3	4	5	-78,04%	0,00%	124,48%	-80,70%	0,00%	180,43%	0,00%	0,00%	0,00%
financial-incentive-smart-charging	0,2	0,3	0,4	-50,58%	0,00%	112,15%	1,18%	0,00%	-6,63%	0,00%	0,00%	0,00%
financial-incentive-smart-hp	0,4	0,5	0,6	-2,74%	0,00%	17,88%	-3,51%	0,00%	-12,71%	0,00%	0,00%	0,00%
financial-incentive-flex-pv	0,2	0,3	0,4	-1,50%	0,00%	-4,15%	-59,57%	0,00%	127,85%	0,00%	0,00%	0,00%

Figure 4.18: Sensitivity analysis base scenario discrete variables

A second sensitivity analysis was performed for the base scenario, focusing on discrete variables that are not suited for classical $\pm 10\%$ variation. These parameters were adjusted in logical steps, either by ± 0.1 or by 1 unit, depending on their nature, while all other inputs stayed consistent. This analysis also includes the financial incentive values of the flexibility measures, which are treated as discrete by the agents during decision-making.

Participation Decision Weights. The first four rows in Figure 4.18 represent the weights that agents assign to the decision criteria of `knowledge`, `comfort`, `financial`, and `trust`. In the base scenario, these weights were derived from interview results presented in Figure 3.3, with the most frequently cited barriers receiving the greatest weight: `weight-knowledge` = 0.33, `weight-comfort` = 0.28, `weight-financial` = 0.24, and `weight-trust` = 0.14. Adjusting these weights shows a clear effect on participation rates. Setting them to equal values (0.25 each) increases participation in both *Smart Charging EV* and *Flex Contracts PV*. Similarly, increasing the disparity between weights (0.4, 0.3, 0.2, 0.1) also yields higher participation. These results confirm the high sensitivity of the agent choice model to the weight parameters, which directly affect the total score used to determine agent participation.

Social Exposure and Spatial Density. Although the number of low-voltage users does not significantly influence outcomes in this scenario (as demonstrated in the continuous sensitivity analysis of Figure 4.17), the spatial proximity between agents, controlled by `user-density`, does. When `user-density` is reduced to 1, agents have fewer neighbors and experience less peer influence. This results in a noticeable drop in participation across the board. The result highlights the model's implementation of positive peer behavior: in more connected neighborhoods, behavioral adoption spreads more easily. This supports the validity of the peer learning dynamics implemented in the model, where exposure to active participants increases the likelihood of adoption.

Number and Size of Awareness Campaigns. The next set of variables, `num-campaigns` and `campaign-size`, relates to the design of awareness interventions. Increasing either the number or the spatial coverage of awareness campaigns yields strong increases in participation for *Smart Charging* and *Flex Contracts PV*. When these values are reduced, participation drops significantly. These findings mirror those observed in earlier sensitivity tests (see Figure 4.17) and reaffirm that awareness campaigns are powerful drivers of behavioral change, especially during early adoption phases.

Financial Incentives. The final group of variables relates to financial motivation. Increasing the `financial-incentive-smart-charging` from 0.2 to 0.3 more than doubles the participation rate for smart charging. Reducing the incentive by 0.1 leads to a decrease of nearly 50%, showing that participation in this measure is highly price-sensitive. Similar results are found for `financial-incentive-flex-pv`, though with slightly greater effect sizes. This is likely because a higher proportion of agents own solar panels (32%) compared to EVs (5%) in the base scenario, so changes to PV incentives affect a larger subpopulation. For heat pump flexibility (`financial-incentive-smart-hp`), changes to financial incentives alone are not sufficient to initiate agent participation. The measure remains unattractive under the current model configuration, suggesting that overcoming barriers to participation for heat pumps requires multiple simultaneous improvements, not just financial incentives. Interestingly, a minor negative impact on PV participation is observed when increasing the heat pump incentive, but this is considered stochastic noise rather than a causal relationship, as it lacks theoretical justification.

4.7. Scenarios

This section presents the simulation scenarios used to explore participation in flexibility measures and their effects on local electricity load and grid dynamics. Each scenario represents a stylized neighborhood composed of low-voltage users and is simulated over a period of 17,520 hourly timesteps, corresponding to two full years. This extended simulation time enables the model to capture the development of behavioral traits and interaction dynamics over time. While data such as household base load profiles, solar PV generation, and heat pump consumption are derived from the year 2023, the model is not designed to replicate any specific historical year. Instead, the 2023 data are used to provide realistic temporal patterns for electricity demand and generation. Using the remaining input variables, one current and two future scenarios are simulated. However, these are not intended to represent perfect predictions of reality.

The scenarios differ in terms of asset ownership and environmental/policy conditions and are grouped into three main categories. Sensitivity analyses revealed two key insights that are incorporated into scenario development. First, awareness campaigns have a significant positive impact on initial participation in net congestion mitigation measures. Second, the adoption of flexibility contracts for heat pumps remains persistently low, suggesting the presence of multiple participation barriers. Since the model output is highly sensitive to changes in measure characteristics, adjusting the parameters of this measure may yield valuable insights. To incorporate these findings, additional scenario variations are introduced, as shown in the second column of Table 5.1:

Scenario	Variant
Base (current-state approximation)	with effective campaigning
	without effective campaigning
Future *with* netting arrangements	with effective campaigning
	without effective campaigning
Future *without* netting arrangements	without extra incentives
	with additional incentives for flex contracts of heat pumps
	with every agent with solar panels owning a small home battery

Table 4.4: Scenarios and their variants to be analyzed

The base scenario reflects a current-state approximation and will therefore also be referred to as the current scenario. In addition to the base case, a forward-looking scenario is considered in which the netting arrangements remain active, allowing for continued financial incentives for solar export. Finally, a future scenario is analyzed where the netting arrangements are abolished, potentially leading to changes in asset adoption and behavioral responses.

The base scenario consists of two variants. The original base case assumes a relatively effective awareness campaign, the second version tests the impact of a weaker campaign. The same variations are applied to the future scenario *with* netting arrangements. For the future scenario *without* netting arrangements, the focus shifts to experimenting with the characteristics of flexibility contracts for heat pumps. Since this measure is the most challenging in terms of participation, the scenario explores what happens to participation rates when grid operators work on improving familiarity with the measure and increasing the associated financial incentives. A final variant includes the effect of agent participation in flexibility measures under the assumption that all agents own a battery. This is done because batteries enable agents to increase their level of self-consumption. As a result, battery ownership is likely to significantly affect participation in flexibility measures. If agents with solar panels are already self-consuming more of their electricity, they may have less need for additional flexibility measures designed to encourage this behavior.

Across all scenarios the size of the neighborhood will be the same. CBS data were analyzed to determine average Dutch neighborhood size. In 2023, the Netherlands had 13,342 neighborhoods and 8,270,244 households, giving an average of 616 households per neighborhood [113].

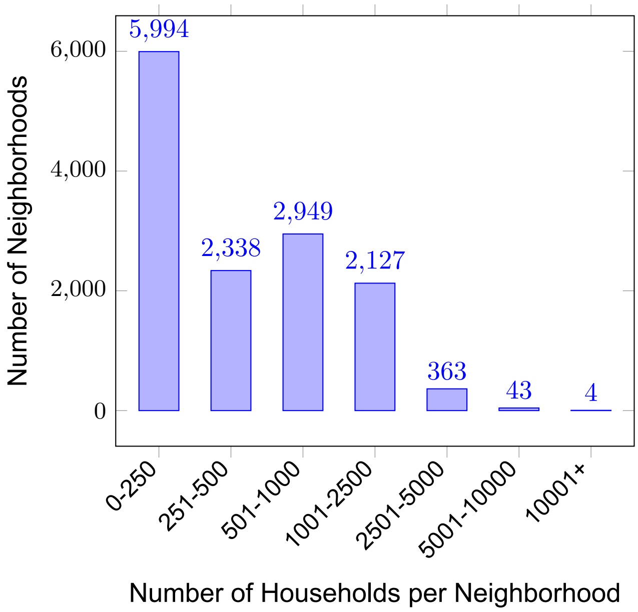


Figure 4.19: Distribution of Dutch neighborhoods by number of households (2023) [113]

To enhance social influence mechanisms, the base case assumes a larger-than-average neighborhood of 1,000 households. The density parameter is set to 2, resulting in agents having an average of five neighboring households. This means that a household maintains approximately five intimate social connections. In the model, these peers serve as sources of weekly behavioral influence.

4.7.1. Base Scenario

The base scenario reflects a stylized approximation of the current state of the Dutch energy system. It approximately simulates the years 2023 and 2024.

Asset Ownership: Asset ownership values are based on national statistics for Dutch households at the end of 2023. Percentages are calculated by dividing the number of assets by the total number of households in the Netherlands, which stood at approximately 8.3 million [113]:

- Approximately 2.6 million households (32%) had solar panels installed [9].
- Around 568,000 households had heat pumps, the majority of which were all-electric [114]. Assuming 75% were fully electric, this corresponds to roughly 5% of households.
- About 466,440 households (5%) had access to a private EV charging point [115].
- Home battery ownership was below 1% and is therefore excluded in the base case [105].

Table 4.5: Asset variables – base scenario

Asset Variable	Input Value
Private EV Charger	5%
Solar Panels	32%
All-Electric Heat Pump	5%
Home Battery	0%

User Profiles: Agents are initialized using the behavioral segmentation developed by Motivaction [50]. The study also reports the distribution of these profiles within the Dutch population. This distribution is applied consistently across all scenarios.

Table 4.6: User variables – base scenario

User Variable	Input Value
Number of LV Users	1000
Density	2
Conscientious Individuals	13%
Structure Seekers	32%
Status-Driven	23%
Responsibles	22%
Self-Developers	10%

External Environment: In the base scenario, all behavioral measures are assumed to be active, and the netting arrangements remain in place, consistent with policy conditions in 2023.

Table 4.7: External variables – base scenario

External Variable	Input Value
Smart EV Charging	Active
Smart Heat Pump Control	Active
Flexible PV Curtailment	Active
Awareness Campaigns	Active
Netting Arrangements	Active

Measure Characteristics: The characteristics of each flexibility measure used in the base case are summarized below. The quantification of these measures is based on the insights obtained from expert interviews, as discussed in Chapter 3. These findings are summarized in Tables 3.5, 3.7, and 3.6.

Table 4.8: Measure variables – base scenario

Measure Variable	Familiarity	Loss of Comfort	Trust Required	Financial Incentive
Smart Charging	0.7	0.3	0.4	0.3
Flex Contract for Solar Panels	0.3	0.1	0.3	0.3
Flex Contract for Heat Pumps	0.3	0.7	0.6	0.5

Variants: In the base scenario, an awareness campaign with an effectiveness probability of 80% is applied. This value is based on input from Interviewee 1, who reported that 80% of respondents in past campaigns indicated they had seen the campaign and that it influenced their behavior. In the model, this is operationalized as an 80% chance that exposure to a campaign modifies an agent's environmental awareness, practical knowledge, trust in external actors, and belief in personal impact. To explore a less optimistic case, a variant is included in which the campaign effectiveness is reduced to 40%.

4.7.2. Future Scenario with Netting Arrangements

This scenario simulates a future situation in which the netting arrangements remain active. Under this policy, households are allowed to offset the electricity they return to the grid against the electricity they consume from their supplier on an annual basis [116]. The netting arrangements are scheduled to be abolished on January 1st, 2027 [117]. Therefore, the future scenarios approximately simulate the years 2027 and 2028. As in the base case, this scenario assumes the continuation of the netting arrangements. However, several parameters differ to reflect developments expected in the near future.

Asset Ownership: A key aspect of simulating future conditions is adjusting the share of households that own flexible energy assets. This scenario uses projected asset ownership figures for 2027. The following estimates are based on growth forecasts, assuming that the netting arrangements are maintained:

- According to the 2021 Climate and Energy Outlook, the installed capacity of solar PV is expected to reach 25.2 gigawatt-peak by 2030 [118]. In 2021, 24% of Dutch households had solar panels. A doubling of this share suggests 48% adoption by 2030. Interpolating from 2023 results in an estimated 42% of households with solar panels in this scenario.
- Forecasts project approximately 1 million EV charging points in the Netherlands by 2027 [115]. Assuming the same private-to-public ratio as in 2023 (75% private), this corresponds to around 750,000 private chargers, or roughly 10% of households.
- The 2024 National Heat Pump Trend Report estimates that by 2029, around 1.9 million households will have a heat pump [114]. Assuming the hybrid-to-all-electric ratio remains unchanged, approximately 1.4 million households will own an all-electric heat pump—about 17% of the total.
- Home battery ownership remained negligible in 2023 (about 40,000 units) [106]. Because netting arrangements reduce the financial incentive for self-consumption, growth is expected to remain modest. Battery adoption is therefore set at 1.5%.

Table 4.9: Asset variables – scenario *with* netting arrangements

Asset Variables	Input Value
Private EV Charger	10%
Solar Panels	42%
All-Electric Heat Pump	17%
Home Battery	1.5%

The same neighborhood size and agent profile distribution as in the base scenario (Table 4.6) are used here. Likewise, all congestion mitigation measures are assumed to be available, and the netting arrangements remain active. Therefore, the external variables for this scenario are identical to those shown in Table 4.7.

Measure Characteristics Although the same flexibility measures are available as in the base case, their behavioral parameters are adjusted to reflect increased public familiarity and acceptance over time. It is assumed that by this future point, households are more aware of flexibility options and perceive them as more approachable. This is particularly relevant for contracts involving heat pump and solar PV flexibility.

Table 4.10: Measure variables – scenario *with* netting arrangements

Measure Variables	Familiarity	Loss of Comfort	Trust Required	Financial Incentive
Smart Charging	0.8 (+0.1)	0.3	0.4	0.3
Flex Contract for Solar Panels	**0.6 (+0.3)**	0.1	0.3	0.3
Flex Contract for Heat Pumps	**0.6 (+0.3)**	0.7	0.6	0.5

Variants: For this scenario, the same variants as in the base scenario are applied: one in which awareness campaigns have an effectiveness of 80%, and one in which the effectiveness is reduced to 40%.

4.7.3. Future Scenario without Netting Arrangements

The netting arrangements were introduced in the Netherlands in 2004 and have been under policy discussion since 2017, primarily due to the decreasing costs of solar panels and the rapid increase in household PV installations. The Dutch government has announced its intention to phase out the netting arrangements as of January 1, 2027 [117]. Removing the netting arrangements will have significant consequences for the financial return on solar investments. Households will no longer be able to offset self-generated electricity against their grid consumption, making strategies to maximize self-consumption increasingly relevant. The model reflects this shift through the introduction of a new behavioral feedback loop, as explained in Section 4.5.5. A target self-consumption ratio ζ is set at 0.6.

This is based on research indicating that, without netting arrangements, the average payback period for residential PV systems would increase from 7–9 years to 12–17 years, unless households raise their self-consumption share from around 30% to at least 60%. This finding supports the choice of $\zeta = 0.6$ as a behavioral benchmark in the model [119]. Just as in the previous scenario, this scenario approximately represents the years 2027 and 2028.

Asset Ownership: Ending the netting arrangements is also expected to reshape household investment behavior. Based on available studies, three assumptions are adopted for this scenario:

- Solar panel adoption is expected to slow. A 2017 study by ECN projected that replacing the netting arrangements with a feed-in subsidy would reduce the growth rate of residential PV adoption by approximately 20% [116].
- Battery adoption is expected to rise significantly, as households seek to increase self-consumption by storing surplus energy [106].
- Asset ownership levels for heat pumps and EV chargers are kept constant compared to the future scenario *with* netting arrangements.

The following table summarizes the asset input parameters for this scenario:

Table 4.11: Asset variables – scenario *without* netting arrangements

Asset Variables	Input Value
Private EV Charger	10%
Solar Panels	35%
All-Electric Heat Pump	17%
Home Battery	6%

External Environment: All flexibility measures remain available in this scenario, but the netting arrangements are turned off. This activates the self-consumption feedback mechanism described earlier. The external policy and intervention parameters are summarized in Table 4.12.

Table 4.12: External variables – scenario *without* netting arrangements

External Variables	Input Value
Smart EV charging	Active
Smart heat pump control	Active
Flexible PV curtailment	Active
Awareness campaigns	Active
Netting Arrangements	Not Active

Measure Characteristics: Due to increased public discourse and incentives to maximize local usage of generated electricity, flexibility measures, especially those involving solar PV, are expected to be more well-known and widely adopted. This is reflected in adjusted measure characteristics, as shown in Table 4.13:

Table 4.13: Measure variables – scenario *without* netting arrangements

Measure Variables	familiarity	Loss of Comfort	Trust Required	Financial Incentive
Smart Charging	0.8 (+0.1)	0.3	0.4	0.3
Flex Contract for Solar Panels	**0.7 (+0.3)**	0.1	0.3	0.3
Flex Contract for Heat Pumps	0.6 (+0.3)	0.7	0.6	0.5

Variants: This scenario includes three variants. The first is described in the main section above. The second variant increases the incentives for the flexible contract for heat pumps by making the measure more familiar (increasing familiarity from 0.6 to 0.8) and more financially attractive (raising the financial incentive from 0.5 to 0.7). The third variant tests the impact of universal home battery ownership among agents with solar panels, setting battery ownership to 100%. The battery is modeled as a small and simple storage device, but it increases agents' self-consumption. As a result, agents may become less inclined to participate in flexibility measures that aim to promote self-consumption.

Additional Sensitivity Analysis: Future Scenario Without Netting Arrangements

An additional sensitivity analysis was conducted to verify whether the participation mechanism for heat pump flexibility behaves as intended. This aspect was not assessed in the initial sensitivity analysis, as the participation rate remained at 0% across all runs. However, in the future scenario *without* the netting arrangements, participation in flexible heat pump use begins to emerge. This analysis explores whether the observed participation rates behave as expected or reveal notable deviations or extremes. It is important to note that, in this scenario, the average participation rate for heat pump flexibility remains low (around 1.5%), with a running standard deviation of nearly 2%. This implies that participation fluctuates between 0% and 4%, driven by minor behavioral shifts or stochastic variation within the simulation dynamics. These fluctuations do not indicate flaws in the model structure but rather reflect the inherent randomness of the system. To anticipate and account for this variability, a stability test was performed for this scenario prior to running the sensitivity analysis. Details are provided in Appendix F. Based on the results, consistent with the earlier stability test, model stability is achieved after approximately 40 simulation runs. Therefore, all results reported in the sensitivity analysis in Appendix F are based on 40 runs. Despite this number of runs, the sensitivity metric for heat pump participation can still vary by up to $\pm 20\%$ due solely to statistical noise. The interpretation of this variability is further explained in Appendix F. The additional SA showed that the participation mechanism for flexible heat pump contracts behaves as expected. Additionally, the high impact that awareness campaigns can have on participation rates is again clearly visible.

5 Results

This chapter addresses the final two sub-questions of this research: *How do selected mitigation measures influence supply- and demand-side flexibility under different scenarios?* and *What is the effect of household profile characteristics on participation in these mitigation measures?* To answer these questions, a series of scenarios were analyzed using NetLogo. As with the stability and sensitivity analyses (see Section 4.6.1), the simulations were conducted using NetLogo's *BehaviorSpace* tool. Each scenario was executed 40 times, and the average of the output runs was taken to ensure stable results. The setup of the scenarios is explained in detail in Section 4.7. An overview of the scenarios and their respective variants is provided again in the following table:

Scenario	Variant
Base (current-state approximation)	with effective campaigning
	without effective campaigning
Future *with* netting arrangements	with effective campaigning
	without effective campaigning
Future *without* netting arrangements	without extra incentives
	with additional incentives for flex contracts of heat pumps
	with every agent with solar panels owning a small home battery

Table 5.1: Scenarios and their variants to be analyzed

The first section of this chapter, Section 5.1, presents the evolution of participation rates over 17,520 time steps (representing two years) for each of the three flexibility measures across all scenarios. Section 5.2 examines the actual flexibility contribution of these measures under different scenarios. This section addresses the fourth sub-question. To enable a clear comparison between scenarios, the same representative hot summer week and cold winter week are used. Each scenario was also simulated with all flexibility measures turned off to provide a baseline for evaluating the actual contribution of each mitigation measure. Finally, Section 5.3 addresses the fifth sub-question by analyzing how household profile characteristics influence participation in the mitigation measures.

5.1. Participation Rates

This section will analyze the curves of the participation rates in each scenario per flexibility measure. First the participation rates of smart charging will be analyzed, then the ones from the flex contracts for solar panels, and lastly the flex contracts for heat pumps.

5.1.1. Smart Charging

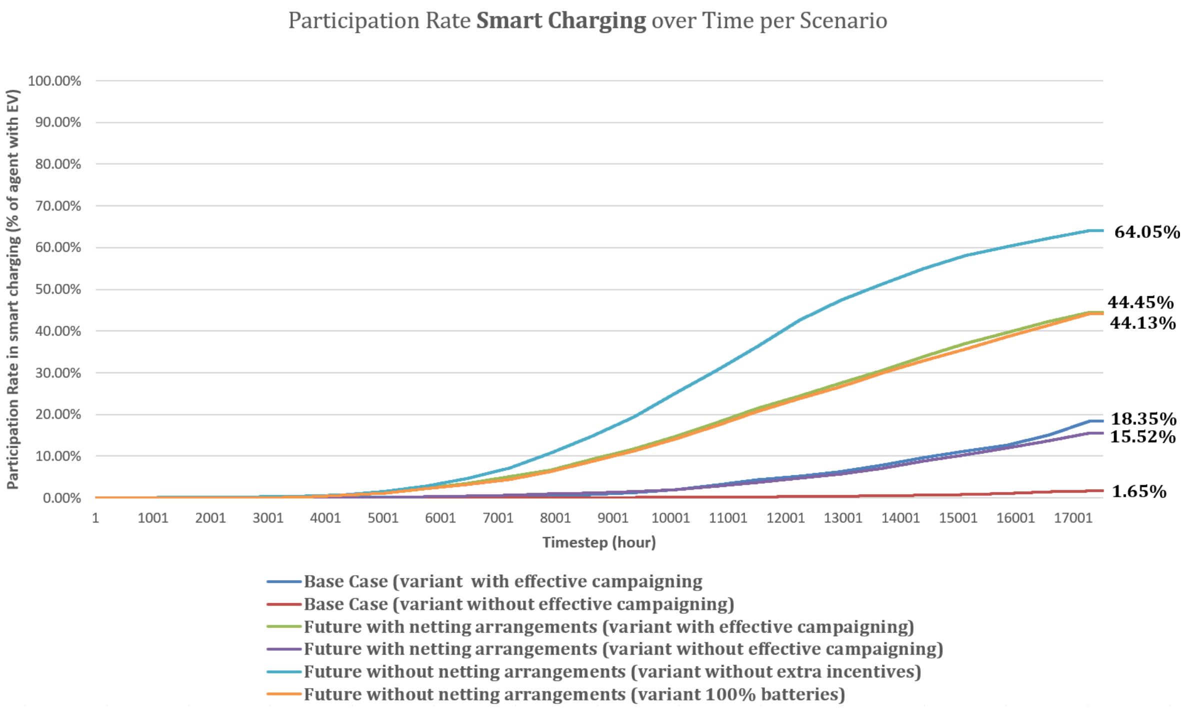


Figure 5.1: Smart Charging participation over time per scenario

Figure 5.1 presents the evolution of the participation rate in the smart charging flexibility measure across different scenario variants over the two-year simulation period. The graph reveals significant differences between scenarios. The lowest participation rate occurs in the base case *without* effective campaigning, while the highest is observed in the future scenario *without* the netting arrangements. This contrast highlights the impact of awareness campaigns: in the base scenario *with* effective campaigning, the participation rate is nearly 17 percentage points higher (18.35% versus 1.65%). This demonstrates that campaigns can significantly boost agent participation when successful. The highest participation rate, 64.05%, is found in the future scenario *without* netting arrangements. In this setting, agents become more financially sensitive if they fail to meet the 60% self-consumption threshold (the level needed to maintain a financially viable solar investment once netting is abolished [117]). As a result, they are more likely to adopt measures that support increased self-consumption. Smart charging can contribute to this goal by shifting EV charging outside of peak hours. However, it is not ideal: most households are likely to plug in their cars immediately upon arriving home. Therefore, smart charging is more likely to shift usage to nighttime off-peak hours rather than to afternoon hours, when solar production peaks. In addition to the incentive to self-consume, the model assumes that smart charging becomes more familiar in future scenarios. This increased familiarity is a second reason why participation rates are higher in the future scenario without netting arrangements.

Although the future scenario *without* netting arrangements shows a high participation rate, the alternative version of this scenario, where every agent with solar panels also owns a home battery, results in a lower rate. The home battery allows agents to increase their self-consumption by storing surplus solar energy for later use. As a result, they are less financially motivated to participate in additional flexibility measures. Nevertheless, participation remains relatively high at 44.45%. This can be explained by the fact that financial sensitivity is not the only factor influencing participation. In this scenario, the smart charging measure is also assumed to be more familiar to agents, increasing their likelihood of scoring high enough to adopt it. A similar participation rate of 44.13% is observed in the future scenario *with* netting arrangements and effective campaigning. This suggests that the increased self-consumption from battery ownership has a similar effect on participation as the presence of netting arrangements combined with awareness efforts. In contrast, the scenario with netting arrangements but without effective campaigning results in a much lower participation rate of only 15.52%. As seen in the other scenario versions, this again highlights the importance of strong awareness campaigns in encouraging participation in the smart charging measure.

5.1.2. Flex Contract PV

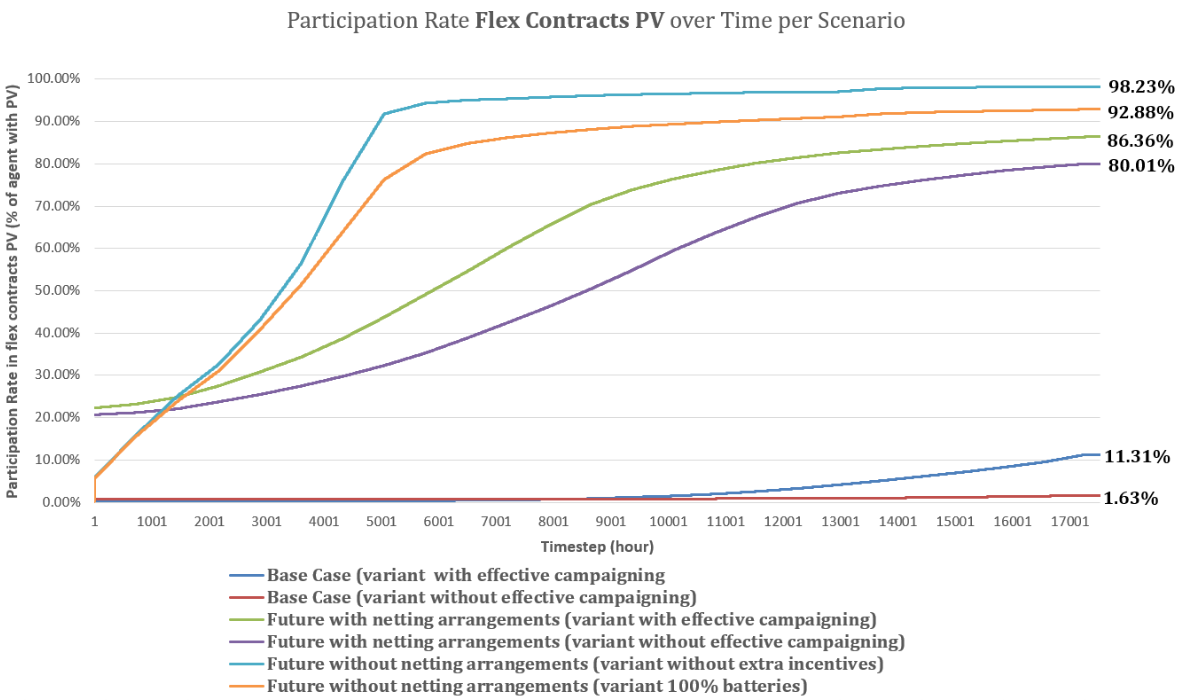


Figure 5.2: Flex contracts PV participation over time per scenario

Figure 5.2 shows the participation rate in flexible solar PV contracts across the different scenario variants. As with the smart charging measure, a clear distinction between scenarios is observed. The most notable outcome is that both base case variants (with and without effective campaigning) exhibit the lowest participation rates. Among these, there is a clear difference of nearly 10 percentage points (1.63% versus 11.31%), again highlighting the positive impact of effective awareness campaigns. Compared to the base scenario, the future scenario where netting arrangements remain active shows a substantial increase in participation in flexible solar PV contracts. This rise is attributed to two factors: increased familiarity with the measure and higher asset ownership, with 43% of agents owning solar panels. The latter factor plays a particularly important role. Assets are first assigned to agents with the highest innovation adoption scores based on their behavioral profiles. When more assets are available in the system, they are distributed among a broader range of profiles. These additional profiles may be more inclined to participate, which directly raises the participation rate. This broader adoption also triggers social influence, further encouraging others to follow. Together, these mechanisms help explain the high participation rates in the future scenarios with netting arrangements. However, an interesting observation emerges when comparing the two variants of this future scenario. The effect of effective campaigning is smaller than in earlier scenarios. With campaigning, the participation rate reaches 86.36%, compared to 80.01% without it. Although this is an absolute difference of around six percentage points, the relative impact is smaller because participation is already high. This suggests that the positive impact of campaigning on participation decreases as adoption approaches saturation.

Participation in flex contracts for PV is almost at 100% when the netting arrangements are abolished. This is a logical consequence: when the netting arrangement are abolished, households can no longer offset the electricity they feed into the grid with the electricity they use from their supplier over the year. As a result, flexibility contracts that offer a financial reward become more attractive, since agents can no longer rely on offsetting to recover their solar energy costs. Therefore, in the future scenario without netting arrangements and without extra incentives, participation is nearly 100%. In the variant where all agents with solar panels own a battery, the participation rate is slightly lower, around 93%. This lower rate was expected, as batteries help agents to self-consume. However, the participation rate is still very high. This can be explained by two factors: the battery is relatively small, so it likely cannot store all of a household's electricity generation; and financial sensitivity is, as mentioned before, not the only reason agents choose to participate in this measure. If they score well on the comfort, knowledge, and trust criteria, they are still likely to participate. Since the flex contracts for solar panels have high familiarity in this future scenario without netting arrangements (assumed because there are more incentives to maximize local usage of generated electricity), it is likely that even though agents have batteries and their financial sensitivity increases less due to higher self-consumption, they will still pass the participation threshold because they score high on knowledge and other criteria.

5.1.3. Flex Contract Heat pump

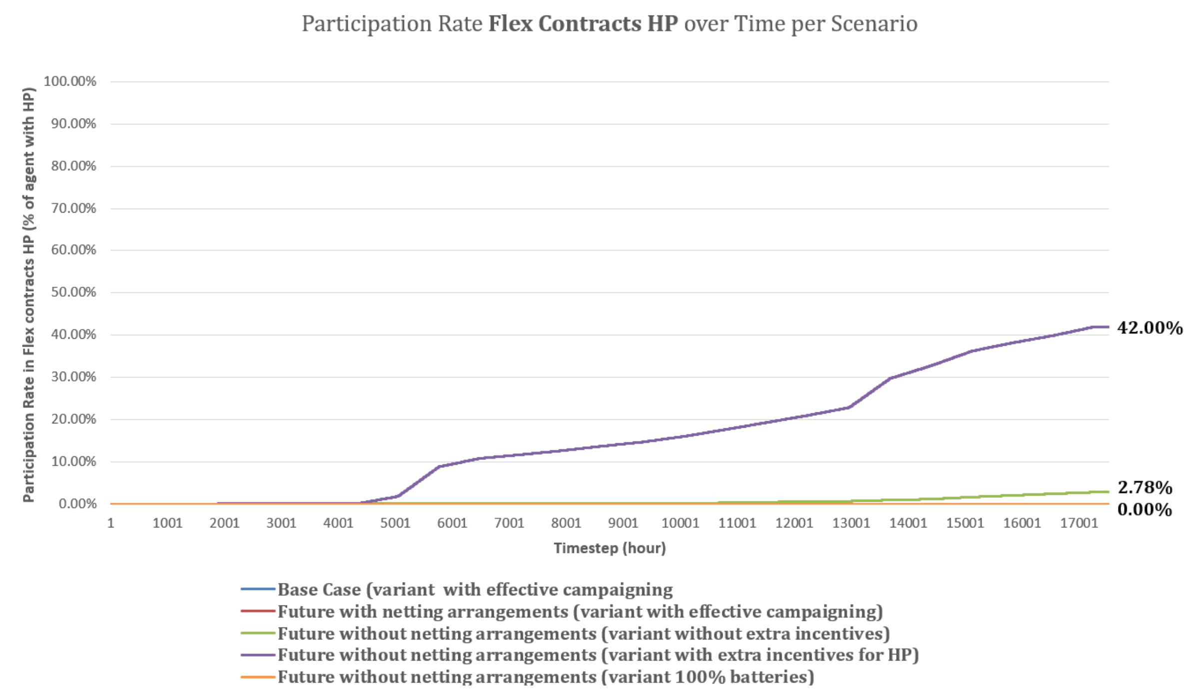


Figure 5.3: Flex contracts Heat Pump participation over time per scenario

Figure 5.3 illustrates the participation rate in flexible heat pump contracts across different scenario variants. Compared to the other two flexibility measures, adoption of this measure remains consistently low in all cases, except for two variations of the future scenario *without* the netting arrangements. In one of these variants, the heat pump flexibility contract receives increased attention through higher financial incentives and improved familiarity among agents. Therefore, it is logical that the participation rate increases; however, it does indicate that the financial and familiarity aspects of the flexibility measure are bottlenecks to participation in the other scenarios. The only other scenario variant that shows a slight participation rate at the end is the future scenario without the netting arrangements and without these extra incentives. Yet again, this is because agents are stimulated to self-consume their generated electricity if they have solar panels. This flexibility measure is a great way of stimulating self-consumption: it turns on the heat pumps two hours earlier in the model. However, this trigger is not large enough in the model to generate high participation rates in this scenario without the extra incentives for the heat pump flexibility measure. In the remaining scenario variants, the participation rate remains at 0% throughout the entire simulation. This indicates that, without substantial positive changes in the criteria of the measure (higher familiarity, higher financial incentives, less trust required, or less perceived comfort loss), participation will remain negligible.

5.2. Impact of the Measures

After analyzing the participation rates in the previous section, this section explores how these participation levels influence flexibility in the system. Rather than evaluating the full two-year simulation period, the analysis focuses on two specific weeks per scenario variant:

- A *summer week* in the second year of the simulation, selected based on the highest feed-in peak in the base scenario without flexibility measures.
- A *winter week* in the second year of the simulation, selected based on the highest demand peak in the base scenario without flexibility measures.
- For each of these two weeks, the *maximum absolute peak reduction* is analyzed, assuming that *all* available flexibility is fully utilized.

This analysis is carried out for each scenario variant. By selecting the same weeks across scenarios, the comparison becomes more consistent and insightful. The chosen peaks represent the highest stress moments on the grid, making them the most relevant from a congestion risk perspective. The focus is placed on the second year of the simulation, as participation rates generally begin to rise after the first year, making the impact of flexibility measures more visible. To clearly isolate and quantify the effect of the flexibility measures, each scenario variant is also simulated with all flexibility measures switched off. This allows for a direct comparison of grid behavior with and without the implemented interventions. In each plot, the absolute difference between the scenario variant with flexibility measures enabled and the same scenario variant with all measures disabled is shown in kWh/h, together with the corresponding percentage reduction at the peak (like this: $\Delta = \ldots$ kWh/h, $(\ldots\%)$).

5.2.1. Base Scenario

Since the alternative variant of this scenario, with *ineffective* awareness campaigns, resulted in very low participation rates for all measures, it was excluded from further analysis. As the aim of this analysis is to understand the potential impact of well-functioning flexibility interventions, the focus was placed on the more optimistic but still realistic scenario where awareness campaigns are effective and participation is substantial. As a result, only the base scenario with effective campaigning is considered in this section. At the end of the two-year simulation, the observed participation rates were as follows: participation in smart charging reached approximately 18%, while participation in solar PV curtailment via flexible contracts reached around 11%. Participation in the heat pump flexibility contracts remained negligible at 0%, and thus this measure is not expected to influence the aggregated electricity profile in this scenario.

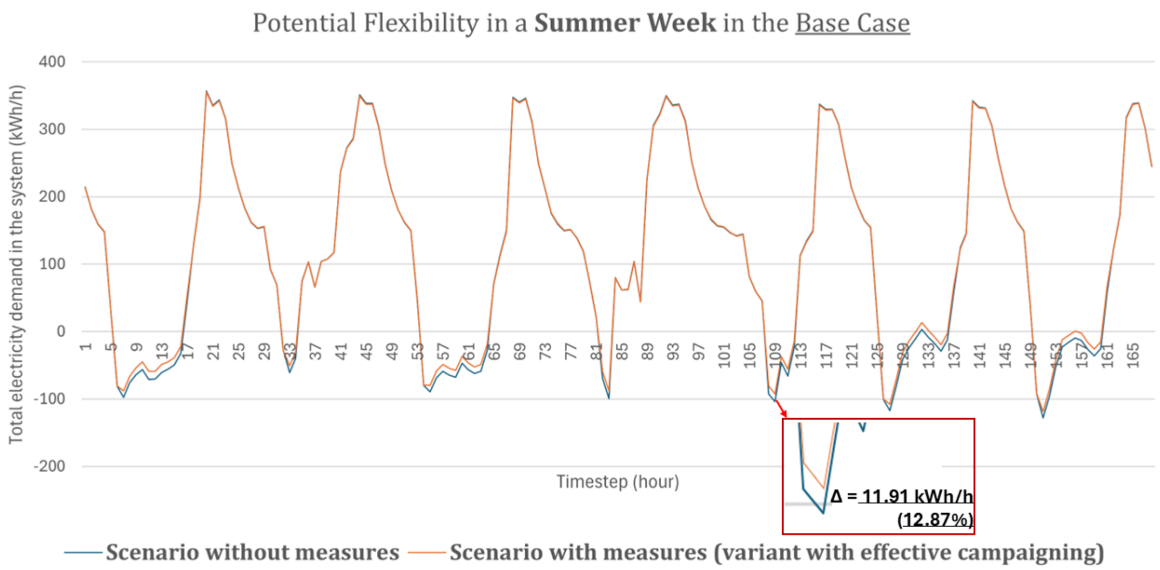


Figure 5.4: Obtained flexibility in a summer week in the base case

In Figure 5.4, a summer week in the base case is shown. The largest peak reduction in this graph occurs around hour 109 of the week. Here, an absolute peak difference of 11.91 kWh/h is visible, which corresponds to a 12.87% reduction of the feed-in peak. This already represents a significant reduction in peak feed-in. It indicates that the 11% of agents with solar panels who concluded a flexibility contract to curtail their solar energy above 400 W/m^2 can already help reduce grid stress for DSOs during summer peaks. However, smart charging may also contribute to this reduction, as charging is scheduled outside of peak hours. Still, it is more likely that these vehicles are charged during the night off-peak hours, since most households do not charge their cars at home during the day.

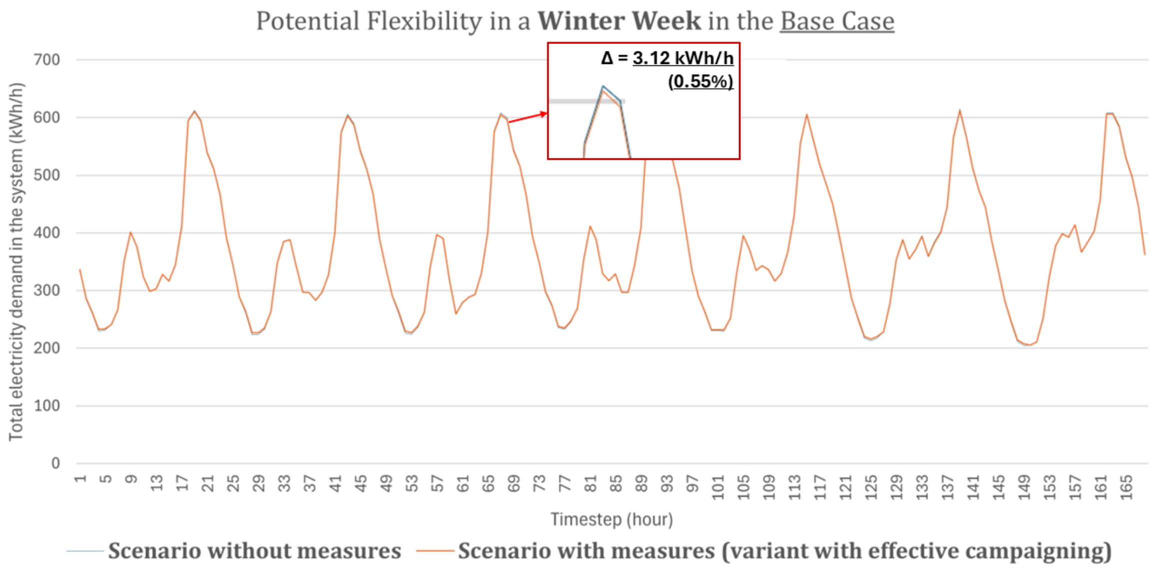


Figure 5.5: Obtained flexibility in a winter week in the base case

In contrast to the summer week in the base case, the winter week (Figure 5.5) shows limited demand-side flexibility. The total demand reduction is only 3.12 kWh/h during the most congested hour, corresponding to a decrease of just 0.55%. This reduction is entirely achieved through participation in the smart charging measure, as there are no participants in the heat pump flexibility contract. These results confirm that, under current conditions, flexibility measures have a reasonable effect on summer peak feed-in. However, their impact on winter peak demand remains limited due to low adoption rates and the inapplicability of solar-based measures.

5.2.2. Future Scenario with the Netting Arrangements

At the end of the two-year simulation in the future scenario *with* the netting arrangements, participation in smart charging reaches approximately 42–43%, while participation in the solar PV curtailment measure climbs to around 87%. In contrast, participation in the flexibility contract for heat pumps remains at 0%. As in the base case, the alternative variant of this scenario with ineffective awareness campaigns was excluded from further analysis. Since the aim of this section is to explore the potential impact of well-functioning flexibility interventions, the focus remains on the more optimistic variant where awareness campaigns are effective and participation is substantial.

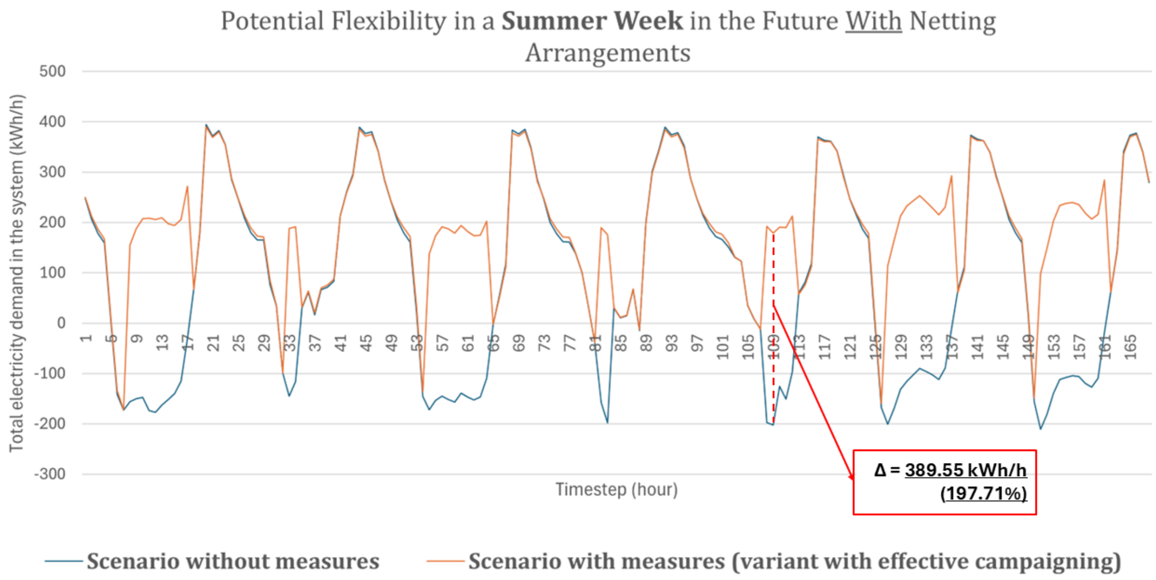


Figure 5.6: Obtained flexibility in a summer week in the future scenario with the netting arrangement still intact and effective awareness campaigns

The future scenario with the netting arrangements still intact shows high participation in the flexibility contracts for solar panels. The impact of this high participation rate is clearly visible in Figure 5.6. In this summer week, if all electricity generated by the solar panels were curtailed as allowed by the contracts, the DSO would not only be able to reduce peak feed-in but could even invert the peak into a net demand. However, this situation is not desirable and represents what can be described as a *rebound effect* of the measure: if curtailment is applied too extensively, a small demand peak may occur. It is important to note that this graph shows the theoretical potential flexibility. The key takeaway is that, if desired, the DSO would be capable of completely mitigating the feed-in peak in this scenario.

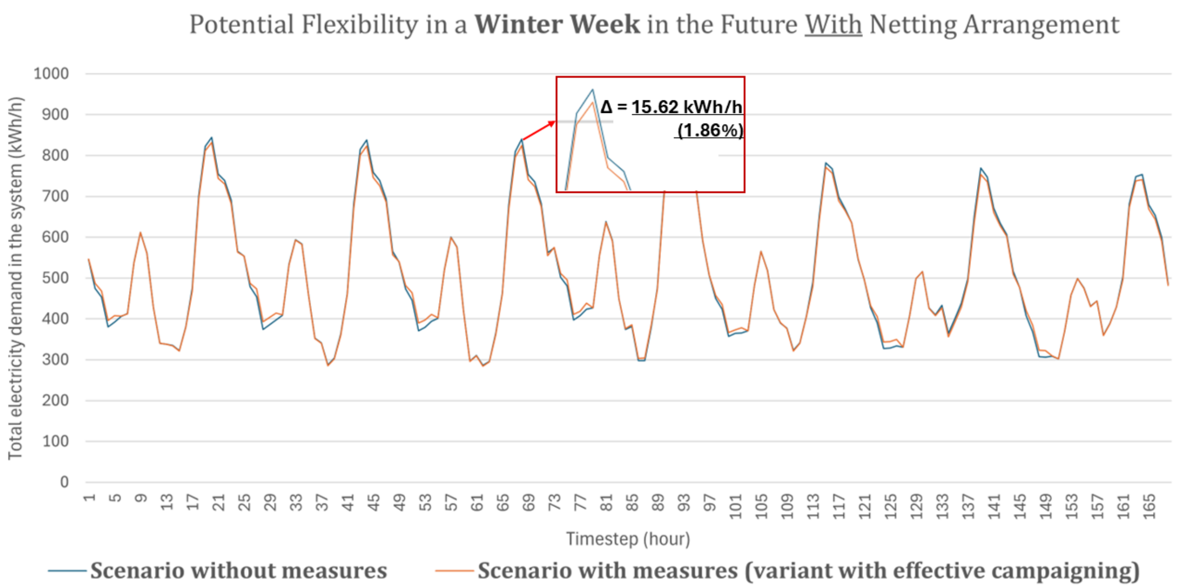


Figure 5.7: Obtained flexibility in a winter week in the future scenario with the netting arrangement still intact and effective awareness campaigns

Figure 5.7 shows once again that the impact of flexibility measures on winter demand peaks remains limited. In this case, a peak reduction of 15.62 kWh/h was observed if all available flexibility were utilized, accounting for a 1.86% reduction of the highest demand peak of the week. This already represents an improvement compared to the base scenario, where the peak reduction during winter was only 0.55%, but the amount of flexibility remains limited. This increase in peak reduction is entirely due to smart charging of electric vehicles, as participation in flexibility contracts for heat pumps remains at 0%.

5.2.3. Future Scenario without the Netting Arrangements

The final scenario explores the effectiveness of flexibility measures under future conditions in which the netting arrangements have been abolished. While in the previous two scenarios the additional variants were excluded from further analysis, here they have been included. For the winter week, the variant with extra incentives for the flexibility contracts of heat pumps is analyzed. This variant yields higher participation rates for heat pump flexibility, making it relevant to assess how much additional flexibility can be provided during a winter peak. For the summer week, the variant in which all agents with solar panels own a battery is examined. In this case, battery ownership does not lead to increased participation in flexibility measures, but the batteries themselves offer direct flexibility to the system. This makes it valuable to investigate their potential impact during a summer week.

At the end of the two-year simulation period, the participation rate in smart charging in the variant without extra incentives reaches approximately 64%, the participation in solar PV curtailment nearly saturates at 100%, and the heat pump flex contracts remain low, around 1.5%. For the scenario variant with the extra incentives, the participation rate for flex contracts of the heat pump is 43% after two years.

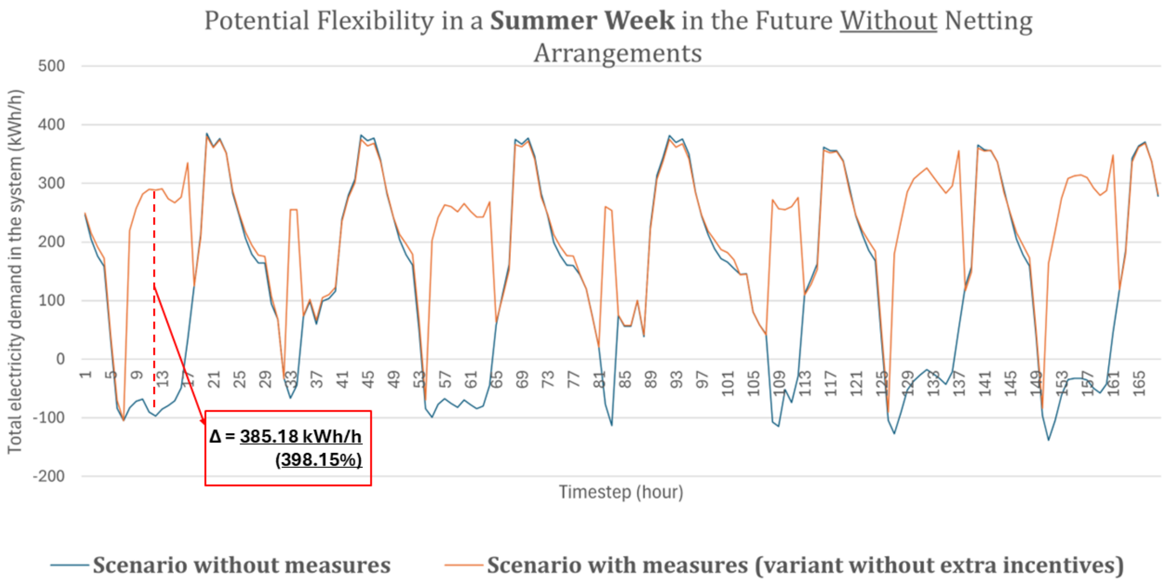


Figure 5.8: Obtained flexibility in a summer week in the future scenario with the netting arrangement abolished and no extra incentives

Figure 5.8 shows a summer week in the future scenario where the netting arrangements have been abolished and no additional incentives are present. In this scenario variant, almost 100% of the agents with solar panels participate in the flexibility contract for solar curtailment. This is clearly reflected in the plot, where the feed-in peaks can, just as in the previous scenario, be fully inverted. However, as mentioned earlier, this is not the desired operational outcome; it simply illustrates the maximum potential flexibility offered by the contracts. If needed, the DSO would have the capability to fully mitigate feed-in peaks in this scenario.

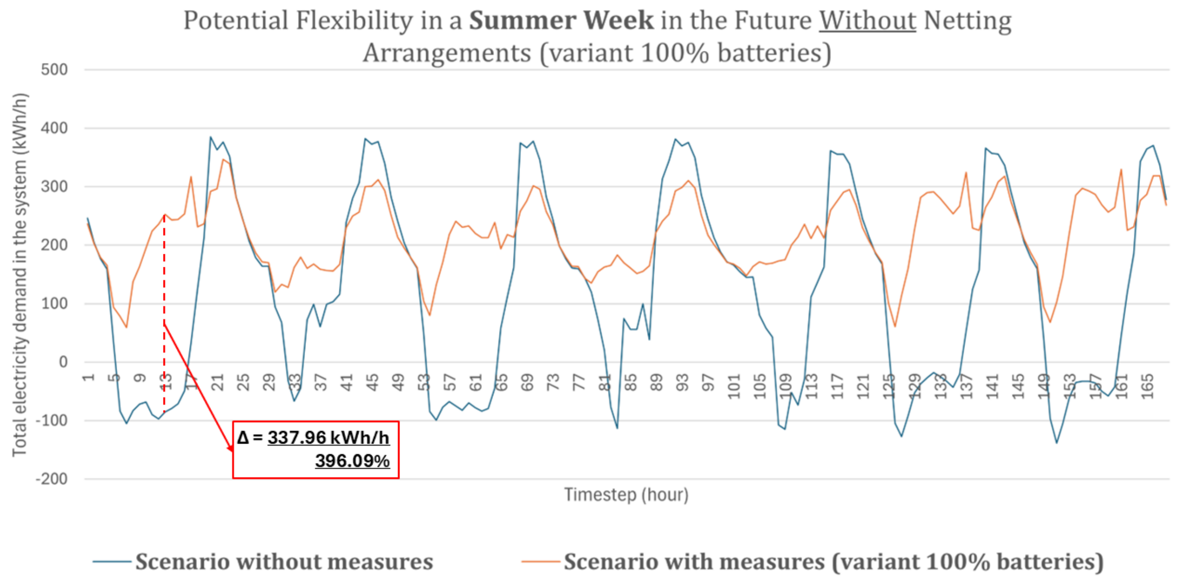


Figure 5.9: Obtained flexibility in a summer week in the future scenario without the netting arrangement and assumed that all households with solar panels have a home battery

Figure 5.9 shows the same summer week in the future scenario without netting arrangements, but now under the assumption that all agents with solar panels also own a home battery. This setup also provides substantial flexibility: the feed-in peaks can once again be fully mitigated. Compared to Figure 5.8, the presence of batteries results in smoother demand curves with less sharp peaks and more consistent load patterns throughout the week. This could represent a more desirable outcome for DSOs, as it reduces the need for active curtailment of residential solar energy. In this case, peak control is primarily managed behind the meter by the batteries themselves rather than through external grid interventions.

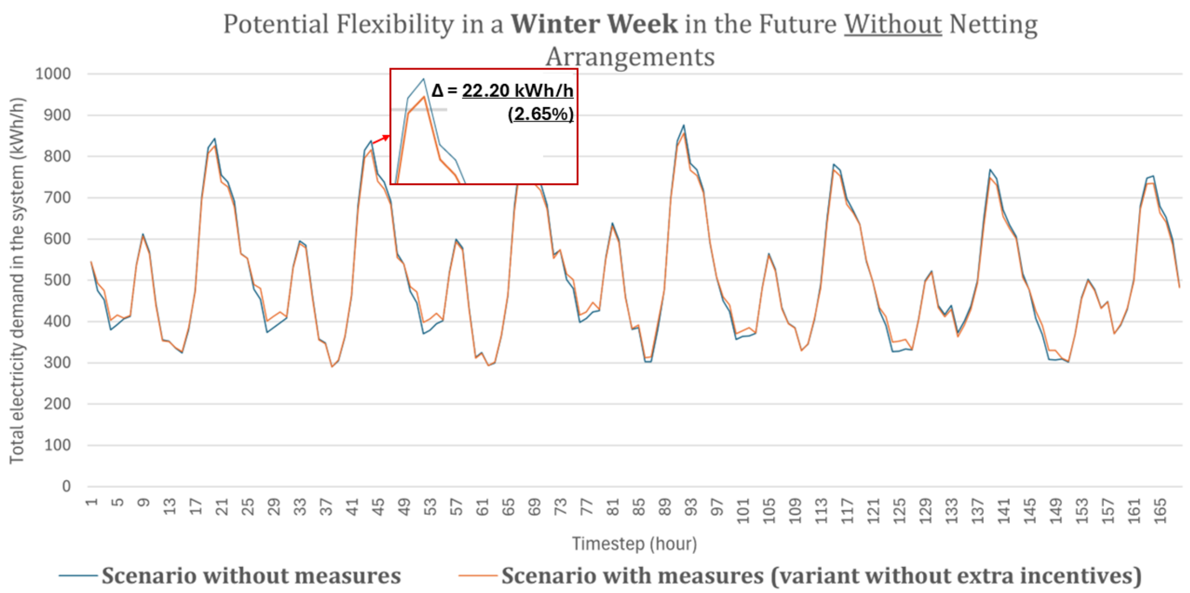


Figure 5.10: Obtained flexibility in a winter week in the future scenario without the netting arrangement and no extra incentive for flex contracts of heat pumps

Figure 5.10 shows the flexibility obtained in the scenario variant where the netting arrangement is abolished and no extra incentives are provided for the flexibility contracts of heat pumps. Once again, the reduction in winter peak demand remains minimal. Although there is a slight improvement compared to the winter week in the scenario with netting arrangements still intact (Figure 5.7, which showed a 1.86% reduction), no major progress is observed. This limited improvement is primarily due to an increase in participation in the smart charging measure (approximately 64% versus 44% in the earlier scenario). However, participation in the heat pump flexibility contracts improves only marginally, by about 1.5%. The small amount of flexibility obtained during winter weeks is likely still the result of these persistently low participation rates in heat pump flexibility contracts.

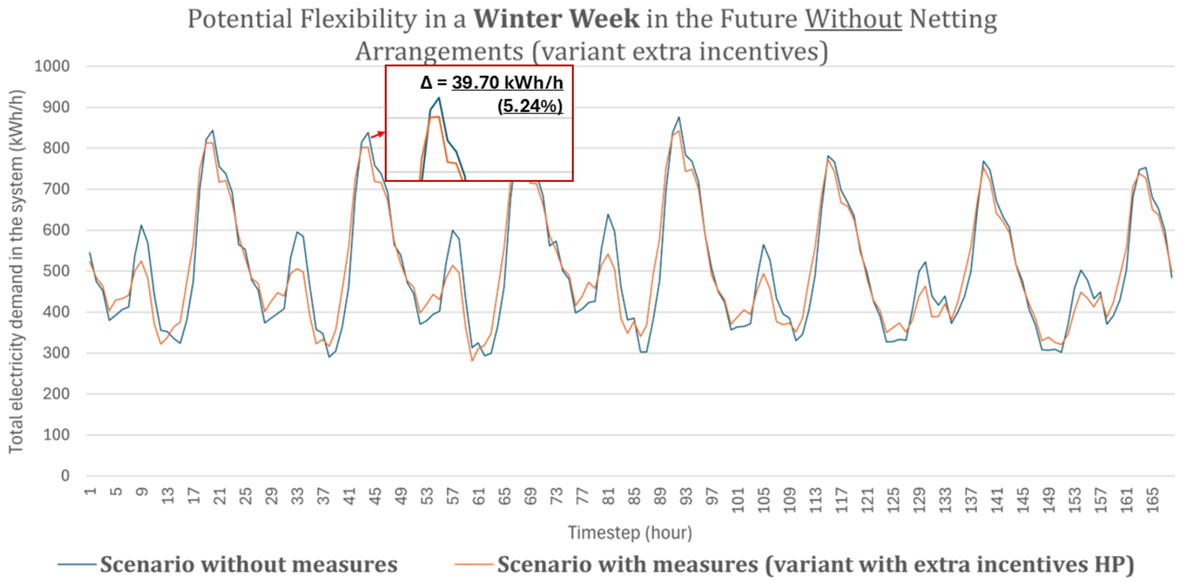


Figure 5.11: Obtained flexibility in a winter week in the future scenario without the netting arrangement and extra incentive for flex contracts of heat pumps

Because of the hypothesis that the potential reduction of winter peaks enabled by flexibility measures is limited due to the low participation rate in heat pump flex contracts, Figure 5.11 shows the impact on flexibility when this measure is made more attractive. In this scenario variant, the heat pump flex contracts achieved a participation rate of 40% (compared to 1.5% in the variant without these extra incentives). During the winter peak, this enables a flexibility gain of 5.24%. This is a significant improvement compared to the 2.65% in Figure 5.10, although the effect remains somewhat limited. The morning peak shows greater flexibility (e.g., at hour 8 and 9), but this analysis focuses on the afternoon peaks, as they are higher and more problematic from a grid management perspective. One explanation for the limited impact on this afternoon peak could be that only 17% of agents in this scenario own a heat pump. As a result, heat pumps may not be a major contributor to the overall peak, and shifting their demand to earlier hours has limited effect. However, this does not mean the measure is ineffective; more than 5% flexibility is still substantial and can help reduce peak demand sufficiently to mitigate the risk of power outages on cold days.

5.3. Participation per Profile

In this section, the differences in participation between agent profiles are examined. The goal is to gain insight into which profiles are more likely to participate in which flexibility measures. To enable this comparison, all asset ownership sliders in the model (private charging stations, solar panels, and electric heat pumps) are set to 100%. This is necessary because only agents who own the corresponding assets are eligible to participate in specific measures (e.g., only agents with private chargers can take part in smart charging). Since the focus here is on participation decisions per profile, the assumption is made that all agents own all assets, so every agent has the opportunity to choose whether or not to participate. Aside from this adjustment, the input settings from the base scenario (with effective campaigning), which roughly reflects the current situation on the electricity grid, are used. In this scenario, flexibility contracts for heat pumps do not gain traction: even when all agents own a heat pump, participation remains at 0%. In contrast, the smart charging and solar PV curtailment measures show increasing participation. The following figures present and analyze the participation rates for these two measures per profile.

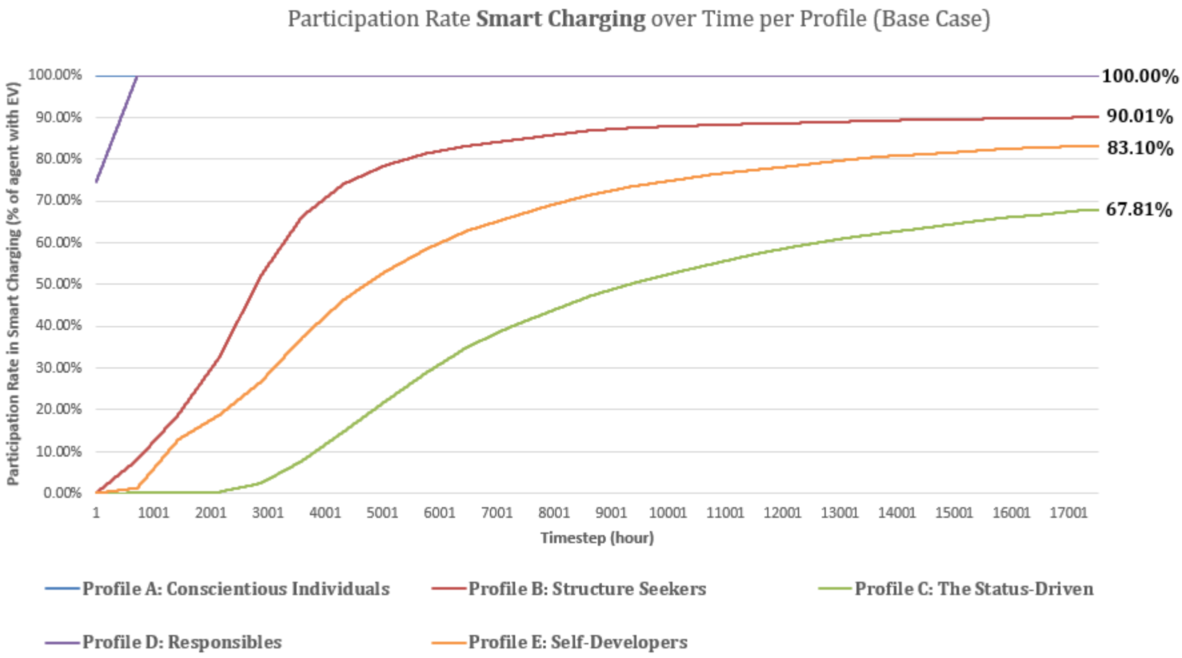


Figure 5.12: Smart Charging participation over time per profile

Figure 5.12 shows the participation rates per profile in smart charging. Notable is that everyone with Profile A participates immediately. These are the Conscientious Individuals. They hold traditional and often religious values. Normally, a barrier to their participation would be that they live minimally and are less likely to own assets. However, this barrier is removed here, since it is assumed that all agents own all assets. Besides this, they have a strong sense of duty and intrinsic motivation to contribute to a better world. If a powerful stakeholder emphasized the importance of flexibility and making the electricity system more reliable, this profile would likely respond and participate. Additionally, they are very sensitive to financial incentives, and since smart charging offers a small financial reimbursement, this can already trigger participation. They share this early and high participation rate with Profile D. This group, known as the Responsibles, is less driven by duty or financial benefits and more by a strong commitment to sustainability and high practical knowledge. They believe in their own impact, which makes them open to this measure and explains their consistently high participation rate.

Profile B, the Structure Seekers, join the participation later. These households value ease and comfort, and they are strongly influenced by peer behavior. So once the first two profiles begin participating, Profile B follows. Their motivation is not rooted in sustainability or belief in personal impact, but rather in the financial advantage and the influence of others. Moreover, smart charging does not imply a high loss of comfort, which is important to them. Profile E, the Self-Developers, follow after B. They value freedom, self-growth, and contributing to sustainability in their own way. Since they are also somewhat influenced by the behavior of others, their delayed participation is understandable. Smart charging suits their preference for autonomy, as the measure does not significantly restrict their freedom. Lastly, Profile C, the Status-Driven, are the slowest to participate. This group is primarily focused on luxury and comfort. They are not immediately triggered by smart charging, as it does not enhance their lifestyle. Nor are they strongly motivated by the financial benefits. The only reason they might participate is due to trend sensitivity; if many others adopt smart charging, they may perceive it as a trend worth following.

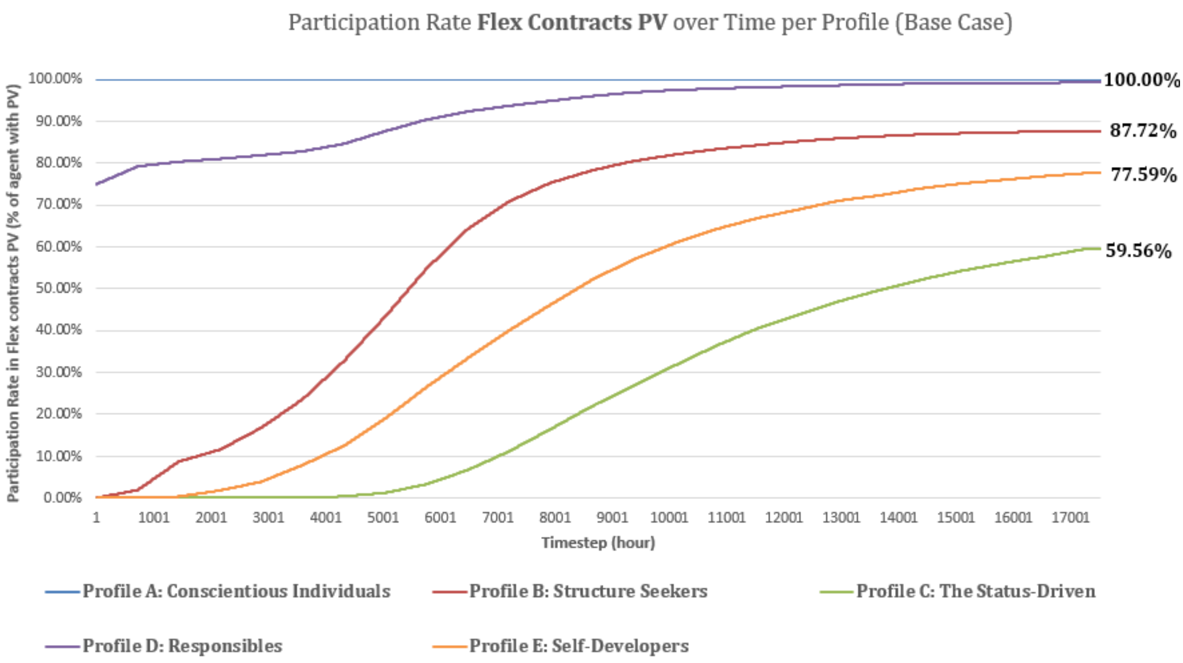


Figure 5.13: Flex contracts PV participation over time per profile

The first notable observation is that the distribution of participation rates for this measure closely resembles that of smart charging (Figure 5.12). This suggests that certain profiles are consistently more inclined to respond positively to flexibility measures in general, rather than each profile having a strong preference for a specific type of measure. However, the adoption curves in this case start to rise slightly later and level off at slightly lower rates. This delay and lower ceiling can be explained by the relatively low familiarity of the flexibility contract for solar curtailment within the system. Most profiles are less aware of this type of measure, which slows down early adoption.

Once again, Profiles A and D show steady and early participation, likely for the same reasons as with smart charging: Profile A (Conscientious Individuals) is driven by a strong sense of duty and is highly sensitive to financial incentives, while Profile D (Responsibles) is motivated by sustainability values and a strong belief in their ability to make a positive impact. Profiles B (Structure Seekers) and E (Self-Developers) follow later, as they are more likely to be influenced by the participation behavior of others. Profile C (the Status-Driven) shows the lowest adoption rate once again. Although a significant number may join if they perceive the measure as trendy, a large part of the group remains uninterested in participating.

5.4. Take-Aways of the Results

This chapter provided many figures. First, Section 5.1 presented the participation rates in the three flexibility measures across different scenario variants. In the base scenario with effective campaigning, representing more or less the current situation on the electricity grid, smart charging reached the highest participation rate of all three measures, indicating that it is currently the most favorable measure in the system. In the future scenarios, both with the netting arrangements still in place and with them abolished, the flex contract for solar panels became very popular among agents, showing the highest participation rates across all three measures. For the scenario with netting arrangements, this can be explained by the large number of agents owning solar panels (42%), creating a broad target group that includes agent profiles likely to adopt early and influence others. In the scenario without the netting arrangements, the high participation rate can be linked to financial logic: households can no longer offset the electricity they feed into the grid with the electricity they use from their supplier over the year. Without this financial advantage, participating in flex contracts becomes significantly more attractive. Participation in the flex contracts for heat pumps, on the other hand, remained low across all scenarios, suggesting this measure is not appealing to most households.

Section 5.2 showed the actual impact of these participation rates across different scenario variants, providing insight into the fourth sub-question: *How do selected mitigation measures influence supply- and demand-side flexibility under different scenarios?* This section illustrated the limited flexibility contribution to winter demand peaks across the various scenario variants, while the potential flexibility during summer peaks, particularly in future scenarios both with and without the netting arrangements, was found to be much higher. This difference is mainly due to the low participation in heat pump contracts, but also because heat pumps and EVs only account for a portion of the total electricity demand during peak hours. The base load also plays a role in these peaks, limiting the overall effect of shifting heat pump or EV demand. In contrast, solar panels directly contribute to the feed-in peaks, meaning that curtailing their output has a much more substantial impact. While the current contribution of heat pumps to flexibility is limited, the model results suggest that significant potential flexibility could be unlocked if participation in these contracts were to increase. Overall, the analysis demonstrated that mitigating winter peaks is more difficult than mitigating summer peaks.

Finally, Section 5.3 addressed the last sub-question of this research: *What is the effect of household profile characteristics on participation in these mitigation measures?* The main finding here was that the same household profiles tended to participate early across multiple measures, suggesting that profiles do not necessarily respond to specific types of measures, but rather have a general tendency toward (or against) participation. Differences between profiles are significant: some show immediate and near-universal participation, while others lag significantly or do not participate at all.

6
Discussion

6.1. Conclusion

The aim of this research was to answer the main research question: *What is the effect of different congestion mitigation measures on the participation of distinct household profiles in the low-voltage grid, and how does this participation affect supply- and demand-side flexibility?* Prior studies have shown that household electricity consumption varies considerably and is shaped by behavioral, technical, and contextual factors [8, 24, 28]. Tailored interventions have been found to be more effective than generic strategies for influencing household electricity use [24]. Despite this, existing research and energy system models often assume homogeneous users, overlooking this behavioral diversity [8, 25, 26, 28]. By answering the main research question, this study aimed to bridge that gap and support regional grid operators, who have indicated a lack of insight into household behavior behind the meter [4], with a model that captures both behavioral and technical diversity in the context of congestion mitigation on the low-voltage grid.

First, qualitative interviews with Dutch DSOs were conducted to identify congestion mitigation measures for the LV grid with high potential to obtain flexibility from LV users. A shared strategic vision was observed among the DSOs, although local grid characteristics led to differences in urgency and prioritization. All operators emphasized the high potential of time-of-use tariffs as a future congestion mitigation strategy (see Section 3.2.2), but recognized that political resistance may delay their implementation [72]. Consequently, this study modeled four shorter-term congestion mitigation options: awareness campaigns, smart EV charging, flex contracts for solar panels, and flex contracts for heat pumps. The last three required active participation from households and were referred to as *flexibility measures*.

Second, five user profiles were defined to represent Dutch households, based on lifestyle segmentation and behavioral traits [50]: Profile A (*Conscientious Individuals*), Profile B (*Structure Seekers*), Profile C (*Status-Driven*), Profile D (*Responsibles*), and Profile E (*Self-Developers*). Each profile was scored on nine factors identified in the literature as key to energy behavior (see Table 4.3). These factors contributed to constructing the behavioral and technical profiles of the households.

Third, an Agent-Based Model was developed to simulate the behavior of these five household profiles regarding the four congestion mitigation measures. The model tested participation rates and their impact under three main scenarios: a base case reflecting the current grid situation (approximately 2023 and 2024), and two future scenarios, one with and one without the netting arrangements (approximately 2027 and 2028). Each scenario ran for two simulated years (17,520 hours). Examining the simulated impact of the flexibility measures reveals clear differences in effectiveness across scenarios. The flex contracts for residential solar panels appear particularly promising. In the base scenario, participation in this measure leads to a reduction of the summer feed-in peak by 12.87%. In the future scenario where the netting arrangements remain in place, higher solar panel ownership and increased familiarity with the measure result in nearly full adoption among eligible agents, allowing DSOs to mitigate the feed-in peak entirely. This effect is even more pronounced in the scenario without netting arrangements, where participation in the PV flexibility contract approaches 100%, enabling full reduction of midday overproduction. A variant of the future scenario without netting arrangements assumes that every agent with solar panels also owns a home battery. This led to even more favorable electricity flows, since the feed-in peaks were fully prevented and the peak demand hours were also flattened, ensuring an overall steady electricity demand. In contrast, mitigating winter peak demand proves more challenging. Among the measures analyzed, smart charging and flexible heat pump contracts are the primary potential contributors to mitigating these peaks. While smart charging shows moderate participation across all scenarios, participation in heat pump flexibility contracts remains very close to 0% in most cases, unless the measure is actively promoted through increased familiarity and financial incentives. Therefore, the base and first future scenario yield only limited peak demand reductions during the most congested winter hour: 0.55% and 2.73%, respectively. However, when the heat pump measure is enhanced in this future scenario, a notable reduction of 39.70 kWh/h is achieved on the winter peak, corresponding to a 5.24% decrease. This decrease remains relatively small compared to the flexibility obtained in the summer weeks. This is also due to the fact that solar panels are the sole contributors to feed-in peaks, making the PV flex contract highly effective, whereas electric vehicles and heat pumps are only part of the overall winter demand peak (which also includes base load). These findings underscore the difference in flexibility potential between supply-side and demand-side measures, and the need for additional or more appealing congestion mitigation measures to reduce demand peaks during the winter.

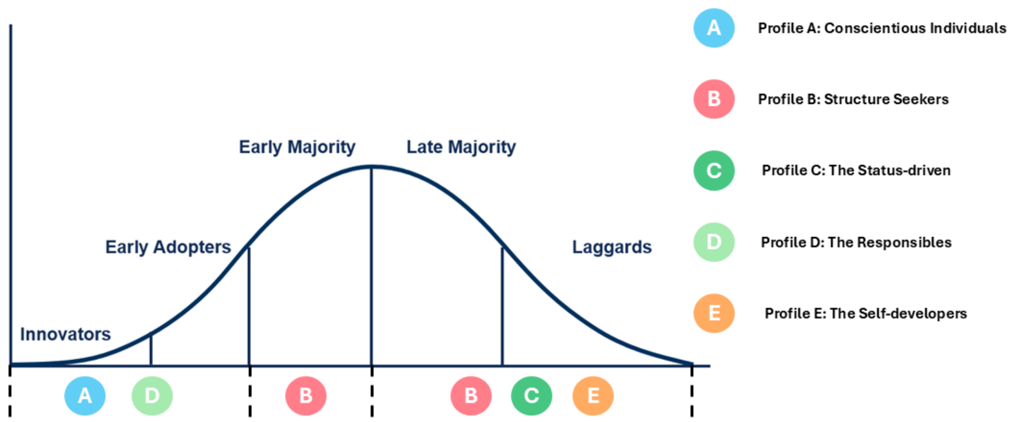


Figure 6.1: Synthesis of participation per profile

Lastly, the difference in participation rates among profiles was analyzed. If all profiles were to own all assets under the base scenario, and all were therefore able to participate, the adoption order for both smart charging and solar PV flexibility contracts appears similar. The timing of adoption per profile is summarized in Figure 6.1, where the profiles are mapped onto the distribution defined by Everett Rogers' *Diffusion of Innovation* theory [101]. Based on this figure, it can be observed that Profile A, the *Conscientious Individuals*, and Profile D, the *Responsibles*, are the earliest participants, also referred to as the *innovators* and *early adopters*. Profile A typically has low affinity with new technologies and a smaller chance of owning assets, but once in possession, they are open to trustworthy information, sensitive to financial incentives, and motivated by duty. Profile D joins early due to high practical knowledge, environmental awareness, and a strong belief in the impact of individual actions. Profile B, the *Structure Seekers*, forms the *early* to *late majority*. They are not intrinsically motivated by sustainability but are very responsive to financial incentives and peer behavior. Profile E, the *Self-Developers*, follows later as part of the *late majority*. This group values freedom and is skeptical of external institutions but can be influenced by social context and group experiences. Last to adopt is Profile C, the *Status-Driven*. They prioritize comfort and status above all and will only participate if a measure enhances their image. *Laggards* can be found among Profiles B, E, and especially C: households unwilling to change habits, unconvinced by peers, or simply not willing to sacrifice comfort.

6.2. Discussion

This section discusses the most notable findings presented in the results and their implications. First, the findings are examined per net congestion mitigation measure. An overview of these findings is summarized in Figure 6.2, which presents the key takeaways per measure. After elaborating on these takeaways, the discussion will address the implications of the observed participation trends across different household profiles. Lastly, the scope will broaden to consider what these findings suggest for the electricity system as a whole.

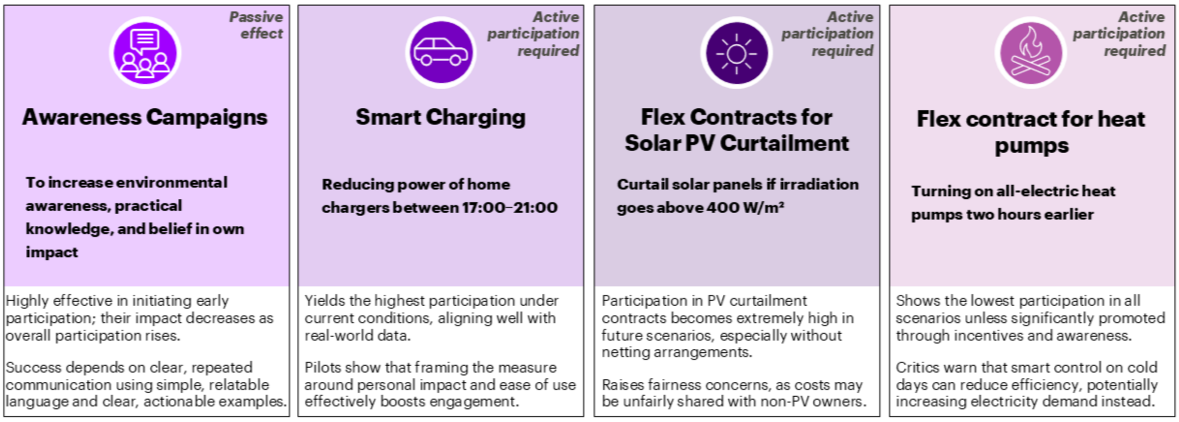


Figure 6.2: Key take-aways per net congestion mitigation measure

Awareness Campaigns

One noticeable observation is that, under current conditions (in the base scenario), households appear generally hesitant to participate in flexibility measures. However, the introduction of awareness campaigns in the model proves to be a highly effective catalyst in initiating participation. Interviewee 7 indicated an effectiveness rate of approximately 80% for such campaigns. This estimate was recently supported by Stedin in a network capacity update from June 2025 [120], which reported that “79% of respondents, after seeing the campaign, are willing to shift their energy consumption to moments when the grid is less burdened.” This dynamic was also integrated into the final scenarios that were analyzed: campaigns have a default effectiveness of 80%, meaning there is an 80% chance of influencing an agent when the campaign takes place at the location where the agent is stationed. The model demonstrates that these campaigns are particularly valuable in helping early adoption take off. Once participation increases due to favorable contextual conditions or improved characteristics of the measures, the impact of awareness campaigns decreases. In the current situation, their role in creating initial awareness is essential. Interviewees 1, 3, 5, and 7 emphasized that public awareness of grid congestion remains low and must be addressed before other mitigation measures can become effective. To be successful, campaigns must use simple language, relatable examples, and clearly link grid issues to individual behavior. Stedin also highlights the importance of repetition and suggests that municipalities can play a facilitating role in reinforcing campaign messages [120].

Smart Charging

Another important observation from the base scenario is that, among the three flexibility measures, smart charging yields the highest participation rate. By the end of the two-year simulation period, which roughly simulates 2023 and 2024, approximately 18% of agents with private EV chargers have adopted the smart charging measure. According to a report by the National Charging Infrastructure Agenda [121], around 20% of electric vehicle drivers had adopted dynamic electricity contracts for EV charging in 2024, a practice that closely resembles the modeled smart charging behavior (though using dynamic pricing rather than the modeled static control). This suggests that the model produces a reasonably accurate estimate of early-stage adoption. The same report also indicates that the proportion of smart charging with private chargers accounts for 68% of all sessions by May 2025. This rapid growth implies that participation is now entering the steep segment of an S-curve diffusion trajectory. The model reflects the initial slow adoption phase, but if extended beyond 2024, it could be expected to capture the accelerated growth phase as well.

In the future scenario where the netting arrangement is abolished, the participation rate in smart charging reaches approximately 65% after two simulation years. This scenario approximately simulates the years 2027 and 2028, meaning that by 2028 an adoption rate of 65% is reached among households with private charging stations. This is equal to the adoption rate reported in mid-2025 according to the National Charging Infrastructure Agenda (68%). This similarity suggests a possible underestimation of participation rates in the model and reveals two notable modeling limitations. First, all participation rates in the model are initialized at zero when a future scenario is simulated. This assumption was made because, at the time of model development, flexibility contracts for solar panels and heat pumps were not yet common or well-defined market products. To ensure comparability across all three flexibility measures, the same assumption was extended to smart charging. As a result, running the future scenario explores what would happen if implementation of each measure were to start from scratch under future conditions. This means that the model does not account for existing real-world adoption of smart charging technologies, leading to an underestimation of near-future participation rates. Second, the only measure characteristic that evolves during the simulation is familiarity, which increases solely as a function of observed adoption within the agent's social network. In reality, however, other characteristics, such as perceived comfort loss, trust in external actors, or financial attractiveness, can also improve over time due to broader societal developments, public campaigns, or improved technical designs. Since these evolving perceptions are not dynamically included in the model, some real-world accelerators of adoption may be overlooked.

In addition to the participation rate of smart charging, it is worth reflecting on how its impact is communicated publicly. Media outlets, grid operators, and campaign organizers often use statements such as "Charging your car at home outside of peak hours creates 68% more space on the grid" [122]. At first sight, such claims appear difficult to confirm using the results from this study. For instance, in the future scenario *with* the netting arrangements still intact, with a participation rate of around 45%, the observed peak load reduction during a winter evening was only 1.86%. This initially seems inconsistent with the magnitude of the claimed benefits. However, upon closer examination of external sources, it becomes clear that such statements refer specifically to the reduction of the *charging peak* of electric vehicles. It does not refer to the overall system peak [123]. This clarification is essential, as it reframes the perceived impact. In terms of public communication, this phrasing can be understood as a form of motivational messaging. If the public were told that even with half of EV owners adopting smart charging, the overall system peak would only decrease by less than 2%, it might discourage participation by reducing people's belief in their own impact. This *belief in their own impact* is also integrated into the model and is one of the characteristics that increases the chance that an agent decides to participate.

Flex contracts for Solar PV Curtailment

A striking outcome of the future scenarios is the very high participation rate in PV flexibility contracts, especially when the netting arrangements are abolished. In that case, nearly all agents with solar panels adopt the measure. This suggests that the measure becomes highly attractive under new regulatory and ownership conditions. However, the desirability of large-scale deployment of these contracts is disputed. According to interviewee 6, PV curtailment contracts are *fundamentally flawed*. Solar generation typically peaks around midday, when wholesale market prices are often very low or even negative. Paying households to reduce production during these hours implies compensating them for energy that has little or no economic value. These contracts are usually funded through socialized grid costs, meaning all users, regardless of whether they own PV systems, contribute. This is particularly problematic for vulnerable households in energy poverty who lack the means to invest in solar panels but are still effectively subsidizing wealthier, electrified households.

This issue parallels the fairness concerns raised around the introduction of time-of-use tariffs. These tariffs are designed not only to alleviate grid congestion but also to improve the equity of infrastructure cost distribution by moving away from fixed fees toward usage-based pricing schemes (Interviews 3, 5, and 6; [124]). As household electrification increases, driven by the adoption of solar panels, electric vehicles, and heat pumps, the need for costly grid expansions grows. Current cost allocation methods are socialized over all households, potentially placing an unfair burden on households without access to such technologies [124]. The high participation rate in the PV flexibility measure observed in the model may reflect this imbalance, as asset-owning households stand to benefit most from these interventions. While Interviewee 6 acknowledged that curtailment can be technically necessary (such as in cases of transformer overload at the low-voltage level or persistent congestion on the medium-voltage grid) its structural application could conflict with the long-term equity objectives held by DSOs.

In practice, solar feed-in is already curtailed under extreme voltage conditions: when the inverter voltage becomes too high due to excessive simultaneous generation, inverters are automatically shut down to protect grid stability (Interviewee 3). However, this is a safety mechanism, not a market-based flexibility solution. While Interviewee 6 emphasized that solar flexibility contracts could offer a preferable alternative to this automatic disconnection, their development is still in an early stage, unlike smart charging, which is already maturing in the market. The first private market actors are emerging. For example, Zonneplan now offers dynamic contracts that automatically disable inverters when electricity prices turn negative [125, 126]. This type of flexibility can then be monetized and offered to grid operators as a service. With the rise of such intermediaries between end-users and DSOs, these flexibility products are becoming increasingly viable. Nonetheless, this raises new questions about fairness and equity, especially when flexibility rewards disproportionately benefit already-electrified households, while lower-income households help fund them indirectly.

An alternative way to mitigate feed-in peaks was also observed in the model analysis. If every agent with solar panels owns a battery, not only do the feed-in peaks disappear, but demand peaks are reduced as well. This is a logical outcome, as batteries allow households to store their generated electricity and use it later. Research shows that home batteries can play a valuable role in energy balancing and congestion reduction. However, the business case for household batteries is not yet financially attractive for most consumers [106].

Flex contracts for Heat Pumps

The final flexibility measure examined in this study is the flex contract for heat pumps. Of all modeled interventions, this measure encountered the greatest difficulty in attracting participants. The low participation rates observed in the model can largely be attributed to three main barriers: the perceived loss of comfort, a reduced sense of autonomy, and general unfamiliarity due to the novelty of the intervention. As Interviewee 6 noted, flexible control of residential heat pumps is currently both technically and behaviorally complex and therefore still underdeveloped. Nonetheless, the potential of this measure should not be underestimated. Interviewee 3 described a successful pilot project in a newly built neighborhood that relied entirely on all-electric heat pumps. Due to a limited grid connection, residents adopted flexibility contracts, which proved effective in keeping the neighborhood within grid limits. While promising in such collective contexts, applying this form of flexibility at the level of individual households remains challenging. As Interviewee 6 emphasized, the viability of this measure depends on technical compatibility with remote and automated control. IT-based solutions must be implemented to automate the flexibility process, with user comfort as a primary condition.

According to Accenture et al. [127], achieving a scalable business case for this form of flexibility requires minimizing the cost and complexity experienced by end-users. This can be realized by simplifying the value chain and developing standardized protocols for information exchange. The future scenario in which the heat pump measure received additional promotion, through increased financial incentives and greater familiarity, demonstrated how participation could rise when these barriers are addressed. Although participation remained modest in absolute terms, the flexibility achieved during a cold winter day was substantial enough to meaningfully reduce peak demand and support local grid stability. This aligns with insights from Topsector Energie, which identifies heat pumps as one of the most promising sources of flexibility in the built environment, second only to smart EV charging [128]. However, not everyone agrees on the effectiveness of this measure. Spitters [12] argues that shifting heat pump operation out of peak hours can, under certain conditions, backfire. On cold days, limiting the operating hours of heat pumps from 24 to, for example, 16 hours, forces them to deliver the same amount of heat in a shorter time. This requires higher supply temperatures, which lowers efficiency (a reduced coefficient of performance, or CoP) and can increase electricity consumption by 30–50% on cold days. Moreover, this added consumption shifts to the off-peak hours, potentially overloading local transformers due to bulk buffering of thermal energy in buildings. If the heat pump cannot meet the heat demand within its reduced operating window, it may revert to its electric backup element, further increasing peak load and total electricity use. Thus, on cold days, the smart control of heat pumps could act as a boomerang, worsening rather than alleviating the problem.

Participation trends across different household profiles

The final sub-question of this research explored which household profiles are most likely to adopt specific flexibility measures. When analyzing the participation rates per profile in the base scenario, a surprising pattern emerged: both smart charging and the flex contracts for solar PV followed the same adoption sequence across profiles. This was unexpected, as both the agents and the measures differ in their characteristics, and it could reasonably be anticipated that some profiles would be early adopters of one measure while lagging in another. Nevertheless, the results highlight the importance of incorporating behavioral heterogeneity into energy system models. Although the adoption pattern was consistent across measures, the absolute participation rates varied substantially between profiles. This confirms that different household types respond differently to flexibility interventions and that tailored strategies are essential to engage certain groups. These insights will be further elaborated in the Recommendations Section 6.3.

Effects of the Dutch Electricity Grid

Some of the most compelling insights from this research emerge when zooming out from the agent-based modeling results and considering the broader system context. As previously discussed, the flexibility measures analyzed in this study are all still under development. These interventions typically require contractual arrangements between households and third-party providers who aggregate or manage flexibility on behalf of grid operators. Several interviewees expressed optimism about the increase of market actors willing and able to take on this intermediary role (Interviewees 1, 5, 6). With the planned phase-out of the netting arrangements, the business case for third-party flexibility services is expected to strengthen (Interviewee 2), particularly for assets such as home batteries and platforms like Zonneplan [125]. This signals the emergence of a new market focused on household-level flexibility, one that may experience rapid growth in the coming years. A look at the electricity market in the United Kingdom shows how such a flexibility market could evolve. There, household-based flexibility services are significantly more developed, led by energy supplier Octopus Energy, currently the largest energy provider in the UK [129]. Interviewee 1 referred to Octopus Energy as an inspiring example of how small consumers can be successfully guided through a smart and user-friendly approach. For example, the company allows users to input when their car needs to be charged via a mobile app, after which the supplier optimizes the charging schedule within that time window. However, the company goes far beyond smart charging. Octopus Energy offers household electricity contracts with innovative pricing schemes to encourage off-peak consumption, supplies 100% renewable electricity, and runs ”Octopus Outgoing”, one of the best feed-in tariffs for excess solar energy in the UK. It also provides digital tools to help users monitor and optimize their electricity use and generation [130]. According to Interviewee 1, this approach yields significant flexibility and could serve as a model for the Netherlands. Yet, this development may also come with risks. Octopus Energy has grown explosively in recent years. As of 31 October 2024, it held a 23.7% share of the domestic electricity and gas market in Great Britain [131]. The UK domestic electricity market has only a few major players, with Octopus rapidly becoming the dominant one, largely due to its advanced data and machine learning platform [129]. In addition, the company now serves over 60 million customer accounts worldwide. While this scale demonstrates the potential of data-driven flexibility markets, it also raises concerns about market concentration. Having such a powerful private actor alongside the regulated DSO could create power imbalances and governance challenges in the future.

Beyond the emergence of a flexibility market, all interviewed DSOs emphasized that no single solution will suffice to address the growing strain on the low-voltage grid. In the long term, a combination of strategies will be required: physical grid reinforcement, dynamic pricing mechanisms to discourage peak-hour consumption, and supplementary flexibility solutions to address moments of acute congestion. This means that even as grid capacity is expanded, flexibility measures will continue to play a crucial role in maintaining balance within the electricity system. These measures are more than just quick fixes; they are likely to become structural components of a resilient and adaptive energy infrastructure.

Strengths and Limitations

A key strength of this research lies in enabling the inclusion of behavioral aspects in a field traditionally dominated by technical considerations. By incorporating the needs, values, and motivations of households, this study addresses a dimension that is often overlooked in the formulation of energy policies. To include this social perspective, the research builds upon the *Vijf Tinten Groener* study by Motivaction [50], which offers a psychological segmentation of Dutch households based on their attitudes toward sustainability. While the original study presents these profiles as static archetypes, this research extends their application by embedding them within an Agent-Based Model to simulate behavioral dynamics over time. In doing so, the profiles are not only described but actively tested in a simulated environment, allowing for analysis of how different household types respond to policy interventions and influence one another through social interaction.

A second strength of this research is the use of expert interviews conducted prior to model development. Although these interviews required considerable time and may have limited the time available to increase model complexity, they contributed invaluable qualitative insights. In particular, they provided clarity on the current state of development, feasibility, and real-world relevance of the modeled flexibility measures. Since low-voltage grid congestion is a relatively new and under-documented challenge, publicly available data on grid operators' mitigation strategies was limited. The interviews helped bridge that gap by capturing operational perspectives and practical limitations, allowing the modeling effort to stay grounded in real-world concerns.

A final strength of this research lies in its close alignment with current policy debates. Rather than constructing a purely theoretical model, this study actively incorporates the expected effects of abolishing the netting arrangements and connects these to behavioral and technological transitions at the household level.

This research, while offering valuable insights into household participation in congestion mitigation, also has several limitations. A primary constraint lies in the limited availability of behavioral data specifically related to grid flexibility. Few studies have directly examined household attitudes and behaviors toward low-voltage congestion. Consequently, much of the behavioral modeling in the Agent-Based Model relied on insights from adjacent research areas, such as energy-saving behavior, sustainability perceptions, and general electricity use habits. Although these sources allowed for reasoned assumptions, many of which were logically supported by related literature, uncertainty remains regarding the exact strength and structure of behavioral relationships specific to grid-continuity behavior. Nonetheless, this does not mean that the model is ineffective. In many cases, the direction of relationships could be reasonably inferred, even if their magnitude remained uncertain. The Agent-Based Model served as a tool to integrate these various mechanisms and explore their interactions dynamically. Its outputs are not intended to deliver exact predictions, but rather to provide rough estimates that reveal whether majorities or minorities participate, how such participation might impact the system, and what behavioral insights can be drawn. As famously stated, *"All models are wrong, but some are useful."* This is exactly the case for this model. However, when certain exact data becomes available, it could be integrated into the model to obtain more precise results.

Second, the measures themselves were implemented in a static way. Smart charging was applied only during a fixed window (17:00–21:00), solar PV curtailment was triggered only when irradiation exceeded 400 W/m^2, and heat pump flexibility was modeled as a fixed 2-hour pre-shift. These implementations do not reflect the full operational potential of such technologies, which, in practice, could be dynamically controlled in response to real-time grid signals or optimized price settings. This simplification narrows the interpretation of the potential impact of flexibility. In addition, external grid-side constraints, such as transformer load, voltage deviations, or balancing requirements, were not modeled, further reducing the system realism.

Third, while the flexibility measures had evolving familiarity during the simulation (through social diffusion and campaigning), other attributes, such as financial attractiveness or comfort perception, remained fixed throughout each run. In practice, one would expect these characteristics to evolve as markets develop or as users gain direct experience. Restricting dynamic change to a single attribute may underrepresent key behavioral feedback effects.

6.3. Recommendations and Future Research

Based on the findings of this research, several actionable recommendations can be made for Dutch Distribution System Operators. However, the implementation of these recommendations goes beyond the responsibilities of regional grid operators alone. Municipalities can also play a crucial role in facilitating local adoption, while national-level coordination and regulatory support from the Dutch government will be essential to realize some of the recommended next steps.

Design personalized awareness campaigns

A key challenge for DSOs is the shift from being primarily technical organizations to also integrating social dimensions into their operations. To maintain a reliable grid, DSOs increasingly depend on the flexibility of households, yet achieving this requires an understanding of household values and behaviors. The results of this study showed that household profiles differ significantly in their likelihood to adopt flexibility measures. This indicates that some households are harder to engage and thus require tailored approaches. The simulations also confirmed the effectiveness of awareness campaigns. As mentioned in the discussion, grid operators have already begun implementing these campaigns [120]. However, most current efforts are generic: public posters, large-scale events, and general online messaging. Still, many residents have little to no understanding of what net congestion is (as emphasized by Interviewees 1, 3, 5, and 7), calling for a more targeted approach: one that informs and activates even the hardest-to-reach households. Therefore, awareness campaigns should not be one-size-fits-all but tailored to the behavioral profiles most common in a given neighborhood.

The *Vijf Tinten Groener* study [50] offers actionable guidance for reaching different household types:

- **Conscientious individuals:** Use simple, clear communication with concrete examples. Emphasize that participation requires little effort. Since they are sensitive to authority, institutional backing should be highlighted. Regional newspapers and trade magazines are effective channels.
- **Structure seekers:** Personal outreach is essential. Stress the financial benefits and ease of participation. Peer pressure can be effective—make it seem like everyone is doing it. Humor and endorsements from familiar figures can increase engagement, as can emphasizing the seriousness of the issue.
- **Status-driven:** Avoid sustainability messaging and instead highlight personal benefits such as comfort, innovation, and convenience. Position the measure as a smart, forward-thinking investment.
- **Responsibles:** Appeal to their intrinsic motivation and desire to contribute to society. Use facts, emphasize collective impact, and show how their actions make a real difference.
- **Self-developers:** Focus on social media. Avoid messaging that feels overly moralistic or collective. Instead, use bold, provocative content that stimulates curiosity and aligns with personal growth or lifestyle enhancement.

The implementation of personalized awareness campaigns could follow this structure: as DSOs become more customer-oriented, many have begun forming dedicated customer experience teams. These teams should assess the composition of target neighborhoods using available data, such as EV ownership, housing characteristics, and demographic trends, to infer which behavioral profiles dominate. Based on these insights, campaigns can be adjusted to resonate more deeply with the intended audience. Meanwhile, operational teams within the DSO must ensure follow-through. For example, if smart charging contracts are promoted, the DSO must guarantee that EVs are reliably charged overnight. A single failure can undermine trust and damage participation rates more than multiple successes can build them. Personalized awareness campaigns increase the likelihood of reaching and activating the least-informed households, ultimately contributing to a more resilient and flexible grid.

Prioritize the development and promotion of measures that help reduce winter demand peaks

The analysis showed that obtaining flexibility during winter weeks is more challenging than in summer weeks. This finding is particularly relevant because grid operators expressed greater concern about the risk of power outages in winter (Interviewees 4, 5). This research explored scenarios in which flex contracts for heat pumps were made more financially attractive and better known. This led to a significant increase in participation and a reduction of about 5% in peak winter demand. While this percentage may seem limited, it can be enough to prevent a power outage on a particularly cold day. Moreover, some neighborhoods have a much higher penetration of heat pumps. These areas are also the ones most at risk of outages, as noted by Interviewee 4: entire residential areas could lose power due to the simultaneous operation of all-electric heat pumps. There is also a risk of repeated outages during grid restoration, as heat pumps tend to restart at the same time and overload the system. Grid operators should therefore collaborate with market parties and policymakers to make flexible heat pump contracts technically feasible (which they currently are not), more user-friendly (to avoid perceived comfort loss), and financially attractive. In addition, appropriate promotion is necessary to build familiarity and trust in the measure.

Given recent criticism that preheating with heat pumps outside of peak hours could actually create a "boomerang effect," shifting rather than solving the problem [12], alternative or complementary solutions should also be considered. One such solution is to explore the role of home batteries in winter. In this study, batteries were modeled primarily for storing solar energy. However, they could also be used to charge during off-peak hours in winter and discharge during peak demand times. This would allow household batteries to reduce both summer feed-in peaks and winter demand peaks. As residential battery use is still emerging, now is the right time to explore these opportunities and communicate to households the broader value their batteries can provide.

Leverage the neighborhood effect

The scenarios demonstrated that when one agent begins to participate in a flexibility measure, nearby agents are likely to follow. This explains the diminishing impact of awareness campaigns once participation starts to rise. The behavior of peers can strongly influence household decision-making. This "neighborhood effect" could be strategically leveraged by DSOs to boost participation rates more efficiently. Interviewees 1, 3, and 5 mentioned the development of the *Buurtnet-app* (Neighborhood Grid App), a tool designed to provide households with real-time insight into local grid stress at the transformer level. By entering their postal code, users would be able to view expected electricity load in their neighborhood and receive tailored energy-saving tips. The app offers both localized transparency and actionable behavioral guidance. However, the product has not yet been released. Prioritizing the rollout of the Buurtnet-app could significantly enhance participation in flexibility measures. If the delay is due to financial or capacity constraints, either within DSOs or the companies to which the project is outsourced, collaborating with external partners could be a solution. For instance, involving university students with expertise in app development could offer both technical support and fresh perspectives.

Initiate the regulation of emerging flexibility markets

As discussed in the previous chapter, a new type of market is emerging in which third parties (often energy retailers) offer flexibility contracts to households. These contracts cover the smart use of energy-intensive assets such as private EV chargers, solar panels, and heat pumps, similar to the flexibility measures modeled in this study. Grid operators generally view this development as positive. For instance, Interviewee 1 cited Octopus Energy, a UK-based energy retailer and international frontrunner in this domain, as an inspiring example for the Netherlands. However, the rise of such flexibility markets also introduces new risks. Energy retailers may gain considerable influence over households' charging stations, solar panels, and electricity bills. Without proper regulation, this concentration of power could create risks for the fairness and reliability of the electricity system. It is therefore essential that DSOs initiate early dialogue with the Dutch government to develop appropriate regulatory frameworks for these markets. In addition to government involvement, Interviewee 1 stressed the importance of strong communication between grid operators and market players. To ensure that system-level stability and consumer interests are protected, DSOs must engage in proactive discussions on the risks associated with flexibility markets, how these risks can be mitigated, and how cooperation and trust between grid operators and market actors can be safeguarded in the long term.

Future Research

The first recommendation for future research comes from the idea that *in every assumption, there lies a recommendation*. Due to the lack of behavioral data on household contributions to grid flexibility, several assumptions had to be made in the agent decision-making process. This highlights the need for targeted empirical research. DSOs could, for example, conduct surveys to better understand which factors influence household decisions to participate in flexibility measures, where participation thresholds lie, and what values and motivations drive those decisions. The sensitivity analysis showed that variables such as participation thresholds and the weights agents use to make their decisions are highly sensitive. Obtaining more accurate values for these variables would therefore significantly improve the realism and reliability of future behavioral models.

An important avenue for future research is to examine how households respond to Time-of-Use tariffs. While DSOs see substantial potential in this form of dynamic pricing to alleviate grid congestion, they may be underestimating the social complexity of such measures. Because ToU tariffs apply uniformly across households, they assume that all users will be motivated to shift their electricity use outside of peak hours. However, this assumption may not hold for everyone. Key questions arise: How realistic is it to expect every household to actively engage with their electricity consumption? Which types of households are most responsive to price signals, and which are not? How should grid operators prepare for possible dissatisfaction when some users end up with unexpectedly higher electricity bills? To address these questions, a similar research approach as in this study could be applied. Instead of interviewing grid operators, future research could involve interviews with a diverse set of households to better understand their behavioral responses to ToU pricing. These insights could then be modeled using an Agent-Based Model to simulate how participation and behavioral change may evolve under different tariff designs. By exploring these dynamics in advance, DSOs would be better equipped to anticipate behavioral outcomes and strengthen their position in political and regulatory discussions surrounding ToU tariffs.

A valuable direction for future research is to explore how this Agent-Based Model can be made more location-specific by applying it to a real neighborhood and linking it to real-time or geographically accurate data, such as the number of energy assets per household or connection-level capacity. In doing so, the model could be enhanced by integrating it with a physical power flow model that accurately simulates the electricity network and identifies when and where congestion occurs. When technical congestion is detected in this coupled system, the ABM could then be used to simulate how local households might respond behaviorally and contribute to mitigating the issue. This combined approach would allow for more precise and context-aware insights into how behavioral flexibility can support grid stability in real-world settings.

6.4. Practical and Theoretical Implications

This research has both practical and theoretical implications that contribute to better alignment between household behavior and the evolving needs of the energy system.

Practical Implications

The practical value of this study lies in helping grid operators and policymakers better understand *who is behind the meter*. By moving beyond aggregated household load profiles and incorporating behavioral segmentation, this research provides insights into the motivations, values, and sensitivities that influence participation in congestion mitigation measures. The model results show that participation varies substantially across profiles. This underscores the value of targeted rather than one-size-fits-all strategies. Grid operators could use these findings to better address household diversity and engage end-users more effectively. For example, in a neighborhood with a high concentration of Structure Seekers, communication campaigns could highlight the long-term financial benefits of smart charging contracts. In areas with many Self-Developers, messaging could rely more on dynamic, attention-grabbing formats such as social media. DSOs could align these behavioral insights with internal organizational developments. As discussed in Section 6.3, emerging customer experience teams within DSOs could adopt these behavioral profiles to design and test more targeted pilot interventions. These teams might use available demographic data (e.g., EV ownership, housing type, or income levels) as indicators to estimate the dominant behavioral profiles in a given area. By identifying which user groups are most hesitant or least informed, such efforts can support a more inclusive and effective rollout of grid flexibility measures. Furthermore, if the DSO follows through on the recommended future research to distribute surveys aimed at identifying households' decision weights and participation thresholds, these insights could be incorporated into the model to simulate the resulting behavioral changes. This would support the identification of potential bottlenecks and opportunities to steer household behavior more effectively.

Taken together, these findings support a shift in the perspective of DSO operations: from managing infrastructure to managing behavior. Proactively incorporating social segmentation into planning tools would allow grid operators to anticipate not only where technical bottlenecks will emerge, but also where behavioral resistance may hinder the adoption of mitigation measures.

Theoretical Implications

From a theoretical perspective, this research contributes to narrowing the persistent gap between top-down energy policy design and the bottom-up dynamics of household behavior. While energy system models and policies often rely on assumptions of rational, average users, this study adds to the growing body of literature that emphasizes the importance of behavioral heterogeneity. Social and psychological factors play a critical role in shaping how—and to what extent—households respond to sustainability-oriented interventions.

This study offers three key contributions to the academic field. First, it demonstrates how existing behavioral segmentation models, such as *Vijf Tinten Groener*, can be translated into dynamic agent-based simulations. This enables analysis of how different household profiles behave and interact over time, rather than treating households as static entities. Second, the study highlights the added value of combining qualitative interview data with behavioral modeling to more accurately reflect real-world constraints and motivations. Third, it presents an Agent-Based Model applied to a topic that has received limited academic attention in the Dutch context: simulating household behavioral responses to net congestion measures. Beyond these contributions, the modeling approach offers a flexible and extensible framework that can inform future research. The model can be adapted to different regional contexts or types of interventions, and its structure provides a solid foundation for further development in academic applications. For example, the recommendation to investigate the impact of Time-of-Use tariffs on household behavior could build on this model's structure as a reliable starting point for such research.

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A

Background information Dutch electricity grid

A.1. The Dutch Electricity Grid

The electricity grid transports power from Dutch power plants, renewable generation sites, or foreign sources to the electricity connection of local end users, such as households or factories. To enable this, all electricity networks at the local, regional, and national levels are interconnected, forming a single integrated electricity system [5].

This grid boasts a reliability of over 99.99% [11]. For example, in 2022, the average customer experienced only 22.1 minutes without electricity. This makes the Dutch electricity grid one of the most reliable in the world [3].

A.1.1. Roles of the Electricity Market

Various actors play a role in ensuring the reliability of the Dutch electricity grid. These actors can be grouped into four general roles [5]:

1. **Production of Electricity**
   Energy production refers to the generation of electricity or gas from sources such as wind, solar, natural gas, or coal. In the Netherlands, this production can be centralized by major companies like Vattenfall, Essent, or NAM, or decentralized through local installations such as solar panels or wind turbines.
2. **Transportation of Electricity**
   The transportation of electricity across the Netherlands is managed by the national grid operator TenneT. TenneT is the independent operator responsible for the high-voltage transmission network (see A.1.2). From the national grid, electricity is delivered to most regional networks. TenneT also manages international connections with foreign grids and ensures the reliability and continuity of the Dutch electricity supply by maintaining a balance between production and consumption. Additionally, it conducts capacity auctions in which energy suppliers can participate. TenneT is fully owned by the Dutch government.
3. **Distribution of Electricity**
   Distribution refers to the delivery of electricity to end users via regional infrastructure. Regional grid operators such as Liander, Stedin, and Enexis are responsible for maintaining and operating these networks, ensuring a safe and continuous supply of energy. These operators are also fully owned by public authorities, specifically, Dutch provinces and municipalities.
4. **Supply of Energy**
   Energy suppliers are companies that provide electricity to households and businesses. In the Netherlands, there are approximately 50 suppliers, including major ones such as Essent, Eneco,

and Vattenfall (formerly Nuon). These companies operate in a free market, meaning that consumers are free to choose their supplier based on criteria such as price, service, and sustainability. In recent years, local energy cooperatives have grown in popularity, offering more community-based and green alternatives.

The national and regional grid operators function within a regulated domain. This means the government defines rules and tariffs, and consumers cannot choose between different operators. Grid operators have public tasks defined by law, including:

- Connecting producers and consumers to the electricity networks, and providing non-discriminatory access to ensure a functioning energy market;
- Managing the electricity infrastructure with a focus on safety and preventing outages or disruptions;
- Timely and cost-effective investment in network expansion to meet future demand;
- For the national grid operator: maintaining balance between energy supply and demand in the network.

An additional key player in this regulated framework is the Netherlands Authority for Consumers and Markets (ACM), which supervises the sector. Each regional grid operator is responsible for a designated area without competition, as building parallel infrastructure would be inefficient and prohibitively expensive. Nonetheless, the ACM benchmarks the performance of these operators to promote efficiency and sets maximum tariffs for electricity and gas transportation.

A.1.2. Components of the Electricity Grid

As discussed in the section on electricity transportation, TenneT is responsible for managing the national high-voltage grid. In addition to the high-voltage network, the electricity grid also includes medium-voltage and low-voltage components. These lower-voltage networks fall under the responsibility of regional grid operators. The higher the voltage level, the greater the amount of power that can be transported. Therefore, high-voltage networks primarily serve a transmission function, while low-voltage networks are used for distribution. Between these two lie the medium-voltage and sub-transmission networks, which act as a transition layer [5].

Each part of the electricity grid, high, medium, and low voltage, serves different types of users, based on the type of connection. There are two general categories of users. The first group is referred to as large-scale users, which includes companies and institutions, such as hospitals, with connections greater than 3 x 80 A. These users typically connect to the medium- or high-voltage networks.

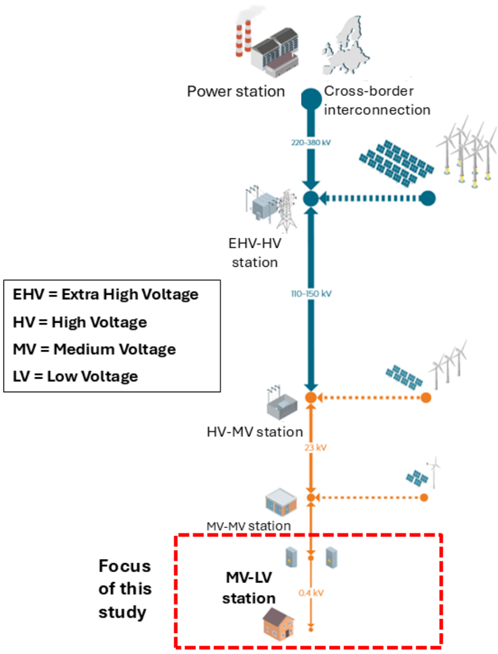


Figure A.1: Scope: Focus on low voltage grid [5]

The second category is small-scale users, which includes all households, small businesses, and community institutions such as schools. These users have a connection of up to 3 x 80 A and are exclusively connected to the low-voltage grid [2].

This study focuses on developments within the boundaries of the low-voltage network. This means that the main roles in this study are played by the regional grid operators, who own and manage the distribution networks, and the small-scale energy users, also referred to as low-voltage users, who are connected to these networks.

B

Interview Guide – Semi-Structured Interviews with Dutch Grid Operators

This appendix contains the semi-structured interview guide used for conversations with representatives from Dutch DSOs. The purpose of the interviews was to gain contextual insight into the challenges and opportunities surrounding low-voltage grid congestion and the role of end-user participation in mitigating it. While the interviews followed an open and adaptive structure, the following topics and questions were used as a guiding framework.

Interview Introduction

- Brief introduction of the interviewer and the purpose of the research.
- Explanation of recording, data use, anonymity, and right to withdraw.
- Consent confirmation (informed consent form)

Main Interview Topics and Example Questions

1. Background and Role

- Could you briefly introduce yourself and your role within the DSO?
- How are you involved in issues related to low-voltage congestion or flexibility?

2. Current and Expected Congestion on the LV Grid

- Is your organization currently experiencing congestion issues on the LV grid?
- How do you expect this to develop in the near future?

3. Vision and Strategy on Mitigating LV Congestion

- What is your organization's long-term vision for tackling LV congestion?
- What is the role of grid reinforcements vs. alternative strategies?

4. Congestion Mitigation Measures

- Which technical, contractual, or market-based congestion measures are currently being tested or deployed?
- In which types of measures do you see the most potential?

5. Role and Behavior of End Users

- How important is end-user behavior in mitigating congestion on the LV grid?

6. Challenges and Future Outlook

- What are the main implementation bottlenecks for LV congestion measures?

- How do you expect the role of the end user to evolve as the energy transition continues?
- What would you like to see happen (technically or institutionally) to enable more effective demand-side flexibility?

Closing

- Is there anything important I haven’t asked that you think should be included?

C

Score Matrices

Financial Sensitivity/ Financial Incentive	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
0.1	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55
0.2	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6
0.3	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65
0.4	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7
0.5	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
0.6	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8
0.7	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85
0.8	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
0.9	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95
1	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1

Figure C.1: Score matrix: to calculate financial score

Trust Level/ Trust Required	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1
0.1	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95
0.2	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85
0.4	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8
0.5	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
0.6	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7
0.7	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65
0.8	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6
0.9	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55
1	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5

Figure C.2: Score matrix: to calculate trust score

Importance Comfort/ Comfort Loss	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	1	0.95	0.9	0.85	0.8	0.75	0.7	0.65	0.6	0.55	0.5
0.1	0.95	0.9	0.85	0.8	0.75	0.7	0.65	0.6	0.55	0.5	0.45
0.2	0.9	0.85	0.8	0.75	0.7	0.65	0.6	0.55	0.5	0.45	0.4
0.3	0.85	0.8	0.75	0.7	0.65	0.6	0.55	0.5	0.45	0.4	0.35
0.4	0.8	0.75	0.7	0.65	0.6	0.55	0.5	0.45	0.4	0.35	0.3
0.5	0.75	0.7	0.65	0.6	0.55	0.5	0.45	0.4	0.35	0.3	0.25
0.6	0.7	0.65	0.6	0.55	0.5	0.45	0.4	0.35	0.3	0.25	0.2
0.7	0.65	0.6	0.55	0.5	0.45	0.4	0.35	0.3	0.25	0.2	0.15
0.8	0.6	0.55	0.5	0.45	0.4	0.35	0.3	0.25	0.2	0.15	0.1
0.9	0.55	0.5	0.45	0.4	0.35	0.3	0.25	0.2	0.15	0.1	0.05
1	0.5	0.45	0.4	0.35	0.3	0.25	0.2	0.15	0.1	0.05	0

Figure C.3: Score matrix: to calculate comfort score

Awareness/ Familiarity	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
0.1	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55
0.2	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6
0.3	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65
0.4	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7
0.5	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
0.6	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8
0.7	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85
0.8	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
0.9	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95
1	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1

Figure C.4: Score matrix: to calculate awareness score

D
Validation and Verification Model

To verify the correct implementation of household energy assets in the model, the technical load was broken down and analyzed for different seasonal conditions. A distinction was made between a typical winter day and a typical summer day, since the electricity profiles of three out of four assets (solar panels, heat pumps, and home batteries) are highly dependent on weather conditions.

Figure D.1 shows a typical daily load profile of a household without specific energy-intensive assets. This profile closely resembles the modeled winter day in Figure D.2, though the latter shows higher peaks due to the addition of a private EV charger and an all-electric heat pump.

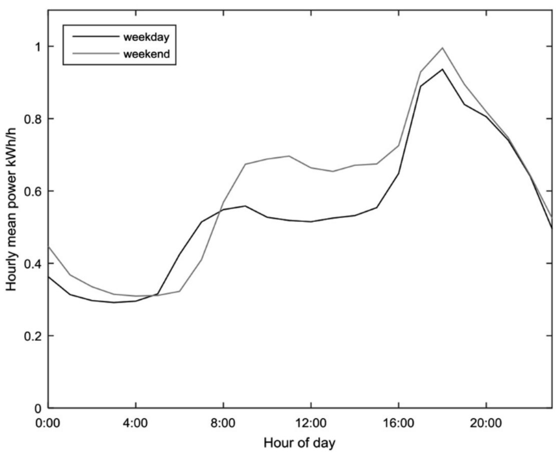


Figure D.1: Average load profile of a household without energy-intensive assets [107]

In contrast, the load profiles for summer days (Figures D.3 and D.4) look markedly different, which is expected. In these scenarios, the simulated agent owns solar panels, leading to midday electricity feed-in during sunny summer days. The impact of a home battery is clearly visible in Figure D.4: rather than feeding electricity back into the grid, the surplus solar generation is stored in the battery. This behavior confirms the correct functioning of the battery logic.

Lastly, the heat pump shows minimal electricity usage during the summer, which aligns with its intended operation, limited to domestic hot water production rather than space heating. Overall, these patterns confirm that the modeled asset behaviors are consistent with expectations and real-world energy usage patterns.

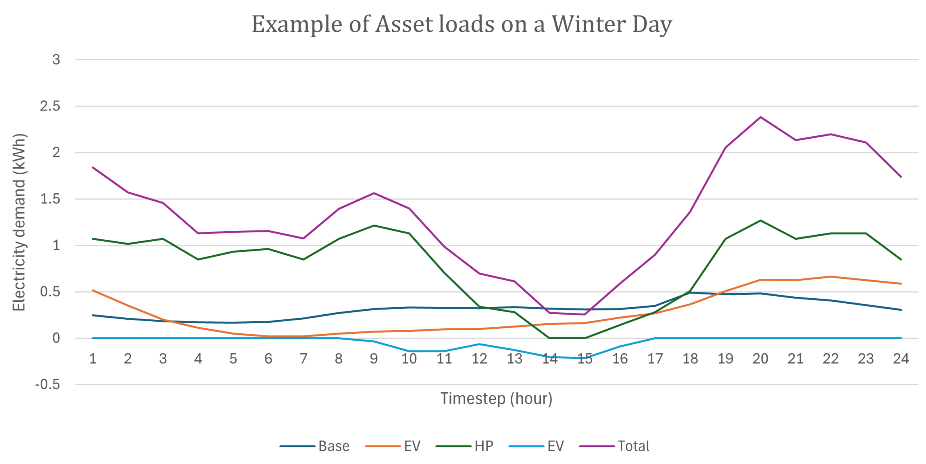


Figure D.2: Break down total load on a winter day (hour 745 - 768)

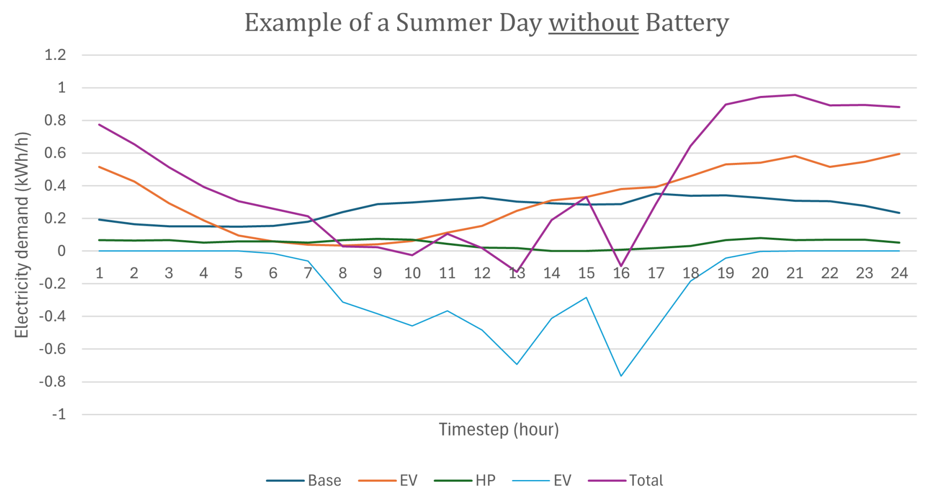


Figure D.3: Break down total load on a summer day (4345 - 4367)

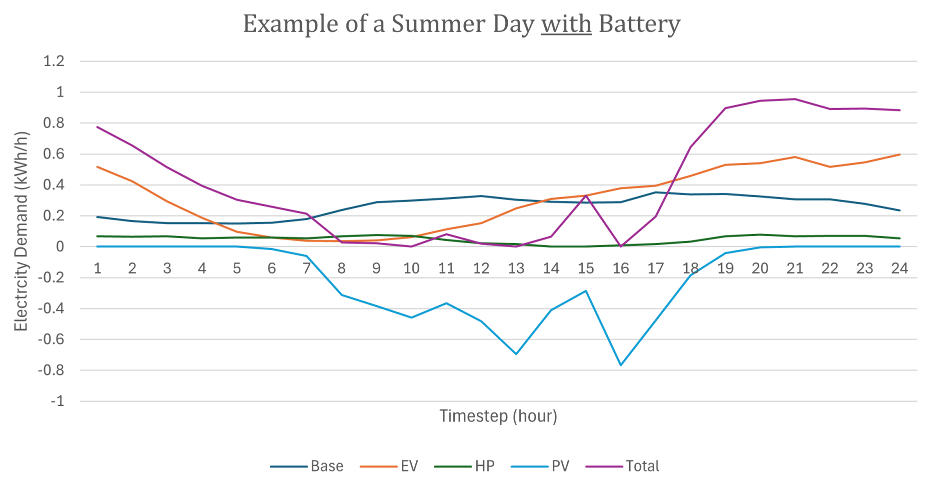
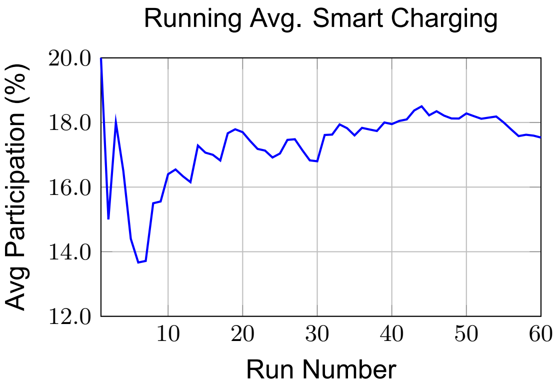


Figure D.4: Break down total load on a summer day (4345 - 4367) with battery

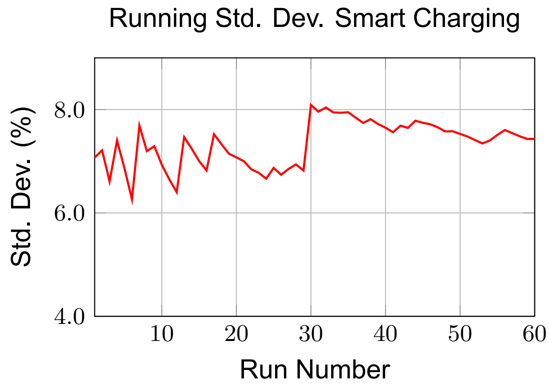
E

Results Stability Tests

E.1. Base Scenario

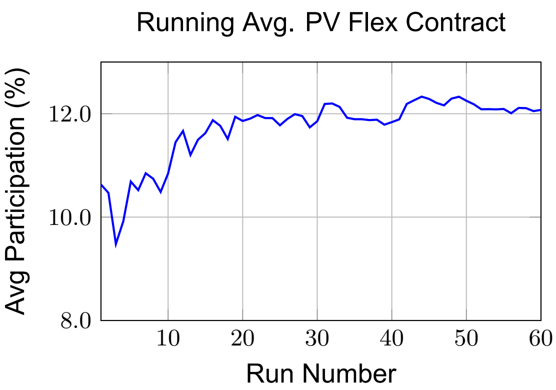


(a) Running average participation.

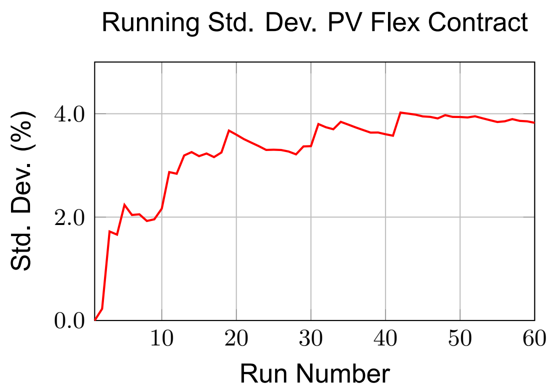


(b) Running standard deviation.

Figure E.1: Convergence of smart charging participation metrics across 60 simulation runs (base scenario)

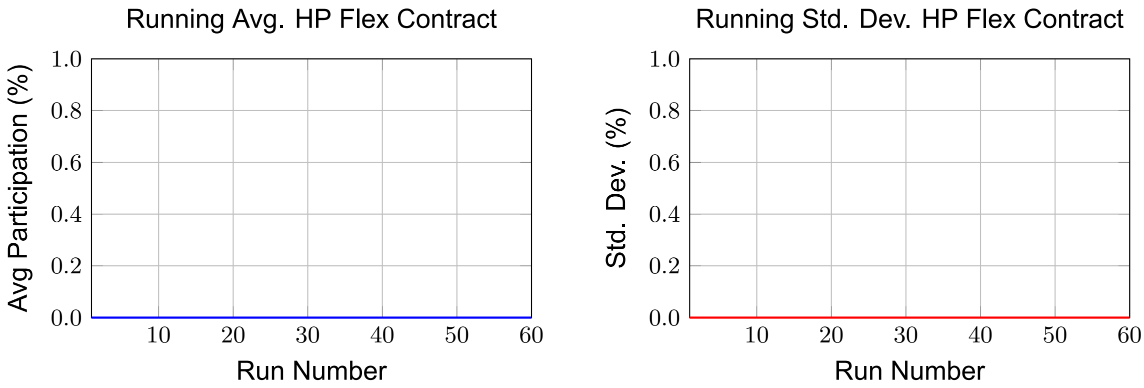


(a) Running average participation.



(b) Running standard deviation.

Figure E.2: Convergence of flex contract participation for solar panels across 60 simulation runs (base scenario)

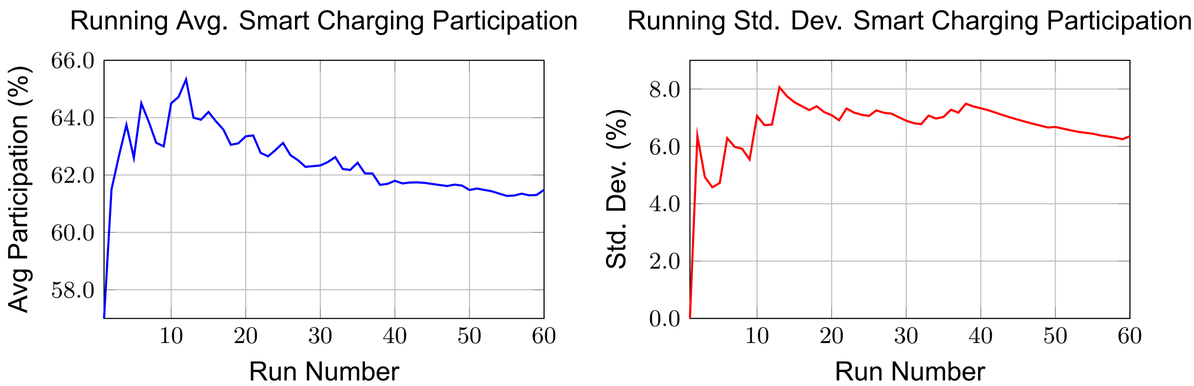


(a) Running average participation.

(b) Running standard deviation.

Figure E.3: Convergence of flex contract participation for all-electric heat pumps across 60 simulation runs: no participation was observed (base scenario)

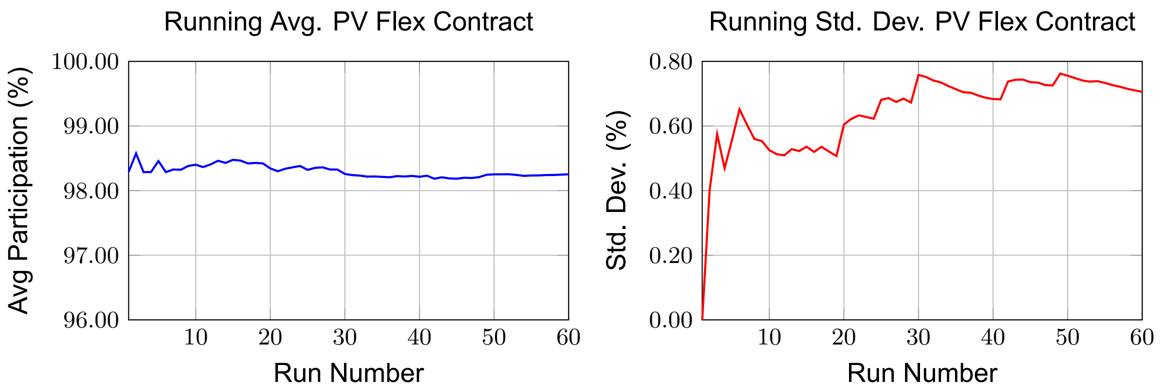
E.2. Future scenario without net metering scheme



(a) Running average smart charging participation.

(b) Running standard deviation of participation.

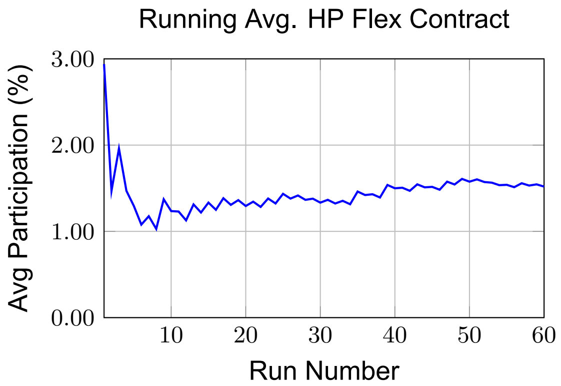
Figure E.4: Convergence of smart charging participation across 60 simulation runs (future scenario without netting arrangements)



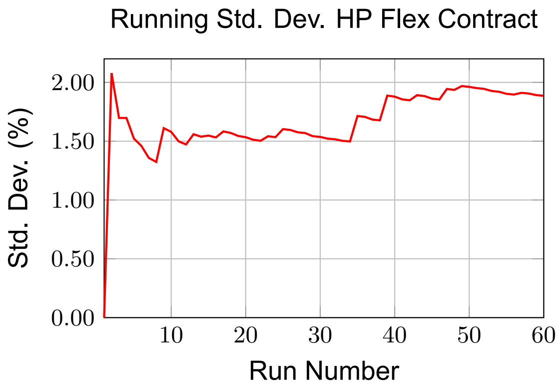
(a) Running average participation.

(b) Running standard deviation.

Figure E.5: Convergence of flex contract participation for solar panels across 60 simulation runs (future scenario without netting arrangements)



(a) Running average participation.



(b) Running standard deviation.

Figure E.6: Convergence of flex contract participation for all-electric heat pumps across 60 simulation runs (future scenario without netting arrangements)

F

Additional Sensitivity Analysis

Variable	-10%	Base	10%	-10%	Base	10%	-10%	Base	10%	-10%	Base	10%
num-lv-users	900	1000	1100	-3.57%	0.00%	-0.13%	-0.24%	0.00%	0.17%	-8.15%	0.00%	-14.84%
trust-required-smart-charging	0.36	0.4	0.44	10.01%	0.00%	-16.63%	-0.11%	0.00%	-0.11%	3.58%	0.00%	6.63%
familiarity-smart-charging	0.72	**0.8**	0.88	-41.82%	0.00%	20.53%	0.19%	0.00%	0.20%	10.98%	0.00%	4.57%
comfort-required-smart-charging	0.27	0.3	0.33	10.92%	0.00%	-20.49%	0.02%	0.00%	-0.09%	-8.41%	0.00%	-5.62%
trust-required-smart-hp	0.63	0.7	0.77	2.46%	0.00%	2.64%	0.08%	0.00%	0.05%	29.15%	0.00%	-26.29%
familiarity-smart-hp	0.54	**0.6**	0.66	8.44%	0.00%	4.04%	0.29%	0.00%	0.15%	-54.52%	0.00%	77.17%
comfort-required-smart-hp	0.63	0.7	0.77	-0.10%	0.00%	1.66%	-0.12%	0.00%	-0.29%	85.25%	0.00%	-53.24%
trust-required-flex-pv	0.27	0.3	0.33	-5.12%	0.00%	9.12%	0.11%	0.00%	-0.30%	-11.49%	0.00%	17.87%
familiarity-flex-pv	0.36	0.4	0.44	13.33%	0.00%	-21.52%	-0.68%	0.00%	0.71%	47.06%	0.00%	-6.05%
comfort-required-flex-pv	0.09	0.1	0.11	-7.67%	0.00%	3.52%	0.16%	0.00%	-0.08%	-1.80%	0.00%	17.28%
participation-threshold	0.495	0.55	0.605	58.35%	0.00%	-93.43%	1.57%	0.00%	-21.23%	1208.72%	0.00%	-100.00%
social-influence-factor	0.09	0.1	0.11	3.89%	0.00%	24.74%	-0.05%	0.00%	0.73%	6.75%	0.00%	26.57%
trust-social-scaling	0.45	0.5	0.55	-2.01%	0.00%	-1.84%	0.17%	0.00%	0.09%	-19.86%	0.00%	14.97%
trust-social-threshold-ev	0.45	0.5	0.55	-2.71%	0.00%	2.61%	0.04%	0.00%	0.06%	-5.07%	0.00%	1.61%
campaign-effect-size	0.045	0.05	0.055	-2.55%	0.00%	-0.48%	0.16%	0.00%	0.11%	-25.95%	0.00%	45.15%
campaign-success-probability	0.72	0.8	0.88	-5.44%	0.00%	2.13%	0.04%	0.00%	0.21%	-25.90%	0.00%	11.31%
children-comfort-weight	0.9	1	1.1	0.80%	0.00%	-1.11%	0.35%	0.00%	-0.30%	-8.89%	0.00%	3.72%
knownness-learning-rate	0.9	1	1.1	0.87%	0.00%	2.15%	0.08%	0.00%	0.33%	4.16%	0.00%	-6.99%
self-consumption-feedback	0.72	0.8	0.88	0.76%	0.00%	8.04%	-0.12%	0.00%	-0.11%	-4.48%	0.00%	12.94%
battery-capacity	2.7	3	3.3	0.55%	0.00%	-0.65%	0.11%	0.00%	0.18%	-11.27%	0.00%	-9.09%

Figure F.1: Sensitivity analysis: future scenario without netting arrangements

Number of Users and Social Influence. The `num-lv-users` variable does not have a consistent impact on participation outcomes. However, variability in the heat pump participation rate is clearly visible: even though the number of agents is not causally related to the measure, the output fluctuates between -8.15% and -14.84%. On the other hand, increasing the `social-influence-factor` shows a positive effect on participation across most measures, except for solar PV, which is already near saturation. This again supports the conclusion that agents positively influence one another in their participation decisions.

Measure Characteristics. According to the stability analysis in Appendix E, the participation rate for smart charging in this scenario is approximately 61–62%, while that for solar PV flexibility reaches 98.5%. The high adoption rate for PV contracts is expected: without netting arrangements, agents no longer benefit from offsetting grid exports, making the alternative flex contract relatively more attractive. Changes to `trust-required-flex-pv`, `familiarity-flex-pv`, or `comfort-required-flex-pv` have negligible influence. This implies that the measure is already appealing enough for nearly all eligible agents to participate. A similar, though slightly less pronounced, trend is visible in smart charging. The variables `familiarity-smart-charging`, `comfort-required-smart-charging`, and `trust-required-smart-charging` still affect outcomes, but their impact is less than in the base scenario. This is likely because smart charging now plays a greater role in increasing self-consumption, providing agents with an additional motivation beyond their individual trait alignment.

In contrast, for heat pump flexibility, even small changes in measure characteristics show relatively large effects. This is again due to the small base rate: a change from 1.5% to 3% still represents a 100% increase. As expected, `familiarity` has the strongest effect, followed by `comfort`, and then `trust`—matching their relative weights in the agent decision formula.

Participation Threshold. The `participation-threshold` remains the most sensitive parameter. Raising it from 0.55 to 0.605 causes adoption of smart charging to decrease. Interestingly, the participation rate for PV contracts drops by only around 20% in this case, showing that most agents already exceed even the elevated threshold. For heat pump flexibility, reducing the threshold from 0.55 to 0.5 increases participation tenfold (from 1.5% to nearly 15%). Conversely, increasing the threshold eliminates all participants. This confirms that the measure remains unappealing under current parameters, and participation is restricted to a narrow fringe of eligible agents.

Impact of Awareness Campaigns. As in the base scenario, `campaign-success-probability` and `campaign-effect-size` can meaningfully increase participation, but only when a measure is not already saturated. For smart charging (already over 60%) and PV curtailment (almost 100%), these inputs do not move the needle. For heat pump flexibility, however, the campaigns remain effective. This reinforces the insight that awareness campaigns are most valuable in encouraging participation in measures that agents are hesitant about, whereas more appealing measures rely less on external incentives.

Children and Knowledge Learning Rate. The variables `children-comfort-weight` and `familiarity-learning-rate` do not exert noticeable influence on participation in this scenario, just like in the base scenario. This is likely due to their indirect roles: the former affects comfort scoring through household composition, and the latter influences the speed at which familiarity increases. At $\pm 10\%$ change, these effects are too small to cause meaningful variation in participation outcomes.

Self-Consumption Feedback and Battery Capacity. Two new parameters are introduced in this scenario: `self-consumption-feedback` and `battery-capacity`. The former determines how strongly agents adjust their financial sensitivity when they underperform on self-consumption (target is set at 60%). Increasing this sensitivity yields a small positive effect on participation in the heat pump contract. However, the effect is modest and may fall within the model's stochastic margin of error. No meaningful changes are observed for the other two measures.

Altering `battery-capacity` by $\pm 10\%$ also has little effect. This is somewhat surprising, as batteries help agents self-consume more electricity, which should in theory reduce their need to participate in flexibility programs. The lack of effect may be due to the modest scale of the capacity change. Larger increases, such as doubling battery size, may yield more significant behavioral shifts, but such extreme values were beyond the scope of this analysis.

				Smart Charging EV			Flex Contracts PV Panel			Flex Contracts Heat Pump		
Variable		**Base**			**Base**			**Base**			**Base**	
weight-knowledge	0.25	0.33	0.4									
weight-comfort	0.25	0.28	0.3									
weight-financial	0.25	0.24	0.2									
weight-trust	0.25	0.14	0.1	-11,35%	0,00%	22,04%	0,94%	0,00%	1,03%	57,42%	0,00%	-38,46%
user-densitiy	1	2	3	-26,36%	0,00%	3,48%	-0,53%	0,00%	-0,14%	-45,70%	0,00%	23,61%
num-campaigns	3	4	5	-12,58%	0,00%	6,33%	-0,22%	0,00%	0,47%	-57,68%	0,00%	44,45%
campaign-size	3	4	5	-22,36%	0,00%	15,22%	-0,37%	0,00%	0,12%	-83,70%	0,00%	137,52%
financial-incentive-smart-charging	0,2	0,3	0,4	-46,90%	0,00%	29,83%	-0,11%	0,00%	-0,08%	-1,18%	0,00%	-4,22%
financial-incentive-smart-hp	0,4	0,5	0,6	-1,79%	0,00%	0,81%	-0,04%	0,00%	0,07%	-56,38%	0,00%	103,81%
financial-incentive-flex-pv	0,2	0,3	0,4	-1,65%	0,00%	-2,36%	0,01%	0,00%	0,16%	-10,01%	0,00%	9,52%

Figure F.2: Sensitivity analysis future scenario without netting arrangements discrete variables

This second part of the sensitivity analysis of Scenario 2 explores the effect of discrete input variables under the scenario where the netting arrangements have been abolished. As with the previous tests, a one-at-a-time approach is used: all parameters are held constant while a single variable is changed.

However, because the variables in this case are discrete rather than continuous, their values are incremented in fixed steps rather than by $\pm 10\%$. The results are given in Figure F.2

Decision Weight Distribution. The first four rows evaluate how different weightings of agent decision criteria influence participation rates. In the base scenario, adjusting these weights had a substantial effect on participation in *Smart Charging EV* and *Flex Contracts PV*. In this scenario, the effects are less pronounced. For solar PV flexibility, the measure is already extremely popular. Nearly all eligible agents participate, regardless of whether the weights are distributed equally (`weight-knowledge` = `weight-comfort` = `weight-financial` = `weight-trust` = 0.25) or more extremely (e.g., 0.4, 0.3, 0.2, 0.1). Therefore, adjusting the decision weights has minimal impact on this measure.

Smart Charging benefits from more extreme weight distributions, with participation increasing by over 20% when knowledge is prioritized. In contrast, for *Flex Contracts Heat Pump*, these same adjustments result in decreased participation. This suggests that agents scoring relatively low on knowledge or comfort are discouraged when those dimensions are weighted more heavily.

User Density. The variable `user-density`, which determines how many neighboring agents each agent interacts with, shows consistent effects. Lower density reduces participation across all measures, particularly for smart charging and heat pump flexibility. This confirms that peer interaction is a key mechanism in participation dynamics: more interactions generally lead to higher adoption, implying a positive social contagion effect in this scenario.

Number and Size of Awareness Campaigns. The parameters `num-campaigns` and `campaign-size` exhibit the same patterns observed in Figure F.1. For solar PV contracts, participation is already near 100%, so campaigns no longer contribute additional influence. For smart charging, a modest effect is still observed. For heat pump flexibility, both increasing the number of campaigns and expanding their spatial reach significantly boost participation, by up to 138%. This supports the view that awareness campaigns are most impactful during early adoption phases, especially for less popular or poorly understood measures.

Financial Incentives. Finally, the three rows evaluating financial incentive levels confirm model logic. Increasing the `financial-incentive-smart-charging` boosts participation by nearly 30%, while lowering it causes participation to collapse by almost 50%. For `financial-incentive-flex-pv`, no notable effects are observed, again, due to saturation.

The strongest result appears in the heat pump measure: increasing `financial-incentive-smart-hp` leads to a 104% jump in participation. This suggests that direct financial incentives can be a powerful lever for increasing adoption of less popular flexibility measures.