

Balancing the Grid: Agent-Based Modelling for Congestion Management in Energy Hubs

Exploring the role of Social Value Orientation in
Energy Hubs

Master Thesis

Monique Shanaya Doerdjan

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by

Monique Shanaya Doerdjan

First Supervisor and Chair:	Dr.ir. I. Bouwmans, Energy and Industry
Second Supervisor:	Dr. A. Correljé, Economics of Technology and Innovation
External Supervisor:	Ir. J. Kluijtmans, Emmett Green
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Student Number:	5049881

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Preface

This thesis is the result of my Master's research at the Technology University of Delft, carried out within the faculty of Technology, Policy, and Management. It marks the conclusion of my academic journey in the master of Complex Systems Engineering and Management, and at the same time, it represents the beginning of my professional journey into the field of sustainable energy systems.

The process of writing this thesis has been both intellectually challenging and personally rewarding. It has required me to combine technical modelling, critical thinking, and practical considerations into one coherent study. I am grateful for the opportunity to explore a topic that I believe has real relevance for the future of the energy transition and to execute this at a company such as Emmett Green that prioritizes the energy transition.

I would like to express my sincere gratitude to my first supervisor, Ivo Bouwmans, for their guidance, constructive feedback, and continuous encouragement throughout the research process. The discussions I had with Ivo influenced my perspective on several aspects of the research process and provided reassurance during challenging moments. I also thank my second and external supervisors Aad Correljé and Joerie Kluijtmans for their valuable insights and support. Joerie gave me an excellent idea to use Agent-Based Modelling within the topic of Energy Hubs, so I am really grateful for his input because it inspired the core of my thesis and shaped the direction.

I would also like to thank the colleagues at Emmett Green for their support in my research process, as they also provided valuable insights. Their willingness to share their expertise and practical experiences greatly improved my understanding of Energy Hubs by bridging the gap between theoretical modelling and real-world application. Without their contributions, my practical knowledge in this field would have been far more limited.

Special thanks go to my family and friends for their support, patience, and understanding during the intense periods of research and writing. Without your encouragement, this work would not have been possible.

Finally, I would like to thank everyone who contributed, directly or indirectly, to this research. I hope that the findings presented here will not only contribute to academic understanding but also inspire further work in creating practical, sustainable solutions.

*Monique Shanaya Doerdjan
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Executive Summary

The Netherlands is going through a rapid electrification phase as a result of the National Climate Agreement of 2019. Industries, transport and households are shifting from fossil fuels to renewable electricity. However, the electricity grid struggles to accommodate the rising demand and supply. Congestion occurs when grid capacity is exceeded, leading to outages and delays for new connections which poses a challenge to the energy transition. Currently, large-scale consumers such as industrial companies (IC) are mostly affected. One potential solution for ICs are to join Energy Hubs (EH), where localized energy generation and distribution provide a reliable source, reduce dependency on the main grid, and lower costs for the IC.

Companies such as Emmett Green support these transition initiatives such as EH for IC by designing private grids, financing batteries, and developing Energy Management Systems (EMS). Emmett Green also plays a key role in EH projects by uniting these companies and act as Congestion Service Provider (CSP) that offers flexible capacity on behalf of the EH to the grid operator. In order to offer flexible capacity, Emmett Green uses an EMS that monitors, controls, and optimizes the generation, distribution, and consumption of energy within the EH. Additionally, Emmett Green is involved in Group Contracts (GTO), where the participants of the EH can share capacity through joint agreements. Yet, the success of EHs depends not only on the technical and contractual infrastructure but also on participants behaviour. While congestion management tools like Demand Response (DR) aim to shift electricity use to off-peak periods, behavioural diversity can make it more difficult to align individual incentives with the collective goals of the EH.

Existing frameworks for EHs mainly focus on techno-economic aspects using deterministic and stochastic models. These models often assume that the actors are rational, leaving out the bounded rationality and behavioural variability. There is a need for models that better include decentralized interactions, emergent system dynamics, and behavioural diversity. Also, empirical validation of consumer and prosumer behaviour is limited, especially for IC. From literature, it is clear that multi-actor collaboration is important but current models provide little insight into how informal communication develop.

To address the previous knowledge gaps, this research aims to explore the behavioural diversity and bounded rationality within an EH with a modelling tool such as Agent-Based Modelling (ABM). One approach to model consumer behaviour is to use the theory of Social Value Orientation (SVO), which divides humans into four categories: altruistic, pro-social, individualistic, and competitive. In the SVO theory the altruistic people prioritized social welfare, while individualistic people prioritized their own welfare. Pro-social people want to balance their self-interest with social welfare and competitive people pursue relative advantage. Literature also described some behavioural drivers in the context of DR, such as price sensitivity, trust, and expectations. When combining the SVO theory and behavioural drivers with ABM, the multi-actor collaboration within an EH under congestion management can be explored. Finally, with a survey the model can be compared with real-world data of participants in an EH.

By addressing these considerations, this research has the following research question:

What is the impact of diverse participant behaviour and Social Value Orientations on congestion management in an Energy Hub within a Group Contract?

To address this question, an ABM was developed to simulate an EH with ICs. Each IC was characterized by SVO, behavioural drivers such as load shift sensitivity, penalty sensitivity, and operational loss of load shifting. Also, each IC had a distinct demand profile and its own categorization of the four capacities which are fixed preferent, flexible preferent, fixed non-preferent, and flexible non-preferent. The model itself incorporated rotational load shedding, adaptive capacity allocation, PV panels, and a dashboard. The IC agents followed a daily planning cycle, where they receive and observe congestion forecast from the Collective Energy Management System (CEMS) via the dashboard, evaluate possible

penalties, and decide whether to shift their flexible preferent loads on the same day or accept penalties. The Key Performance Indicators (KPIs) to evaluate the performance of the model include total load shifting, total load shedding, total penalties, and total rewards.

Nine scenarios and a base case were simulated, ranging from homogenous populations (e.g. all altruistic) to heterogenous populations (e.g. altruistic and pro-social). The scenarios were run 50 times per scenario. The results across the four KPIs show clear trade-offs between the compositions, with no single populations excelling across all KPIs. All competitive populations achieve the highest long-term load shifting, but face very high load shedding and penalties which reduces reliability. All individualistic populations maximize their financial rewards, but contribute the least to load shifting which shows how they prioritize personal profit above collective performance. All pro-social populations show that they minimize load shedding, but face high penalties and low rewards. All altruistic populations did not contribute that much to load shifting, but just like pro-social population have a low number in load shedding. The mixed populations, such as moderate, equal, competitive dominant, cooperative dominants, and polarized, generally show balanced results and avoiding extremes. Cooperative dominants, competitive dominant, and polarized populations offer moderate benefits but have higher penalties and lower rewards. There are also seasonal patterns, because the results show that altruistic and pro-social populations perform the best in short-term, while the competitive populations adapt over time in long-term. However, it is important to note that competitive populations undermine reliability by a high load shedding number.

The survey explored the behaviour of real-life participants of EHs, focussing on the SVO type and decision factor for load shifting and capacity sharing. This survey was conducted anonymously via Google Forms and it combined multiple-choice, open-ended, and Likert-scale questions to understand the theoretical and new behavioural drivers, but also the SVO of participants. There were three situations presented as context for the questions: load shifting on the same day, sharing unused capacity, and approaching another company to lower their usage.

The survey results have shown that the respondents on average all have a pro-social SVO. They are mainly prioritizing fairness and cooperation in load shifting, capacity sharing, and approaching another company to lower their usage. Altruistic behaviour emerges in the situations of sharing unused capacity or load shifting, but is absent in conflict-prone situations such as asking others to reduce usage. Individualistic and competitive responses also emerged at a lower rate, which shows that self-interest emerges when operational stability or relative advantage is at stake. Overall, respondents value social and operational factors such as trust, reputations, continuity of business processes, and positive past experiences, more than financial incentives. This suggest that cooperation in EHs are less driven by short-term profit, but more by mutual recognition and long-term relationships. Compared to the ABM, the SVO composition of the respondents align with the all pro-social scenario. This would mean that the respondents in an EH were likely to perform well in load shifting and load shedding, but receive less rewards and moderate-high penalties.

Based on the survey results and the results from the ABM, this study proposed three strategies for improving EHs management with DR incentives: Time-of-Use (ToU) penalty pricing with dashboards, gamification, and proportional load shedding. ToU pricing in combination with dashboards target peak hours by signalling congestion in real-time to trigger pro-social and altruistic participants, while the variable pricing of ToU trigger competitive participants. The challenge with this strategy is that IC usually have limited flexibility of their processes which makes it harder for them to react to ToU signals. With gamification the social factors are used to engage diverse participants in interactive activities and support collaboration. The challenge with the gamification strategy is to design the game carefully, as it needs to be tailored to the needs and motivations of participants. Lastly, proportional load shedding is a fairer alternative than rotational load shedding as it reduces participants who have higher usage instead of the participants who have low usage. This load shedding approach is more equitable than equal.

For the generalizability of the results, it is important to know the model limitations. For example, it was difficult to determine the model validity since there is no existing real-world system to compare the model with. Also, stylized data was used as part of the model input and assumptions and simplifications were made in conceptualizing the model. Another important limitation was that the survey yielded a low response rate with a small sample size, so the results of the survey should be interpreted as exploratory

rather than robust evidence.

From this thesis, it can be concluded that an ABM simulation study is a successful way to integrate technical, economic, and behavioural aspects of EHs in one model. The model has provided a system-level perspective, showing how heterogeneous and homogeneous IC compositions influence demand response outcomes. This model can be used in future case studies to analyse collaboration patterns, test interventions, and the recommended strategies. Another future research suggestion would be to extend the model with adaptive learning, social networks of ICs, and to add additional flexibility assets to better reflect real-world EHs. Lastly, an extensive empirical data collection could validate the behavioural assumptions with using a larger target group.

The files created and used for this thesis are available in the 4TU Research Data repository (Doerdjan, 2025).

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Abbreviations and Glossary

Abbreviations

Abbreviation	Definition
ABM	Agent-Based Modelling
CEMS	Collective Energy Management System
CSP	Congestion Service Provider
DR	Demand Response
EH	Energy Hub
EMS	Energy Management System
GTO	Group Contract
GTV	Contracted Transport Capacity
G-GTV	Group Contracted Transport Capacity
IC	Industrial Company
kW	Kilowatt
kWh	Kilowatt hour
P2P	Peer-to-peer
PV	Photovoltaic
SVO	Social Value Orientation

Glossary

Term	Definition
(C)EMS	An (Collective) Energy Management System is a system that monitors, controls, and optimizes the generation, distribution, and consumption of energy within a facility, organization, or energy network. Its goal is to improve efficiency, reliability, and cost-effectiveness while reducing environmental impact (Emmett Green, n.d.-a).
Congestion Management	Strategies that aims at either steering the supply or demand of energy during peak periods, when the grid's capacity reaches its limit (Wampack, 2021).
CSP	A party that offers flexible capacity on behalf of one or more grid users to the grid operator in order to help resolve grid congestion (TenneT, n.d.).
DR	Balancing the demand on power grids by encouraging customers to shift electricity demand to times when electricity is more available (Arias et al., 2025)
Energy Hub	A small-scale decentralised energy production unit that utilizes locally available resources and distributes energy based on specific demand (Javid et al., 2021).
Fixed Non-Preferent Capacity	Capacity that should remain continuously available but does not have high priority.

Term	Definition
Fixed Preferent Capacity	Capacity that must remain continuously available and also has the highest priority. Examples include core business processes such as an oven that must always stay if the company is a bakery.
Flexible Asset	An asset is a physical energy installation that can be owned by an individual, company, or organization. A flexible asset is an installation that can quickly respond to changes in energy demand or supply. Examples of flexible assets include solar panels, batteries, charging stations.
Flexible Non-Preferent Capacity	Capacity that varies over time and can be steered without practical consequences.
Flexible Preferent Capacity	Capacity that varies over time and also has high priority. This means a device or process is turned on and off during the day by the control system, but the exact timing may vary. So, this capacity may be postponed, but it is necessary that eventually the process or device is turned on that day.

1

Introduction

1.1. Research Problem

The Netherlands has been electrifying for the past few years as a result of the National Climate Agreement of 2019 and therefore uses less gas than before (Klimaatkoord, 2019). Industries, homes, and transportation are rapidly transitioning from fossil fuels to electricity generated by renewable sources like wind and solar. According to the CBS, 2025, the bruto production of electricity in the Netherlands in December 2024 was 11.57 TWh while in October 2023 it was 9.76 TWh which is an increase of 1.81 TWh per year.

However, there is a major challenge: the current electricity grid is not ready for this large-scale electrification. The existing infrastructure was not designed to handle the huge increase in demand and supply of electricity. These peaks lead to problems during peaks, when either too much electricity is being consumed or generated (RVO, n.d.). This exceeds maximum capacity of the grid, causing delays or even power outages due to grid congestion.

With the electricity grid reaching its maximum capacity, an increasing number of new businesses can not be connected to the grid. This grid congestion poses a challenge to the energy transition as currently 22 TWh of electricity supply, mainly from solar and wind energy, is stuck in a waiting queue. At the same time, 63 TWh of electricity demand remains unfulfilled which shows that the energy needs can not be served at the moment (Energie Nederland, n.d.). This situation has serious social and economic consequences as delays in electrification slow the Dutch energy transition toward sustainable energy and limit companies with expanding or investing in sustainable technologies (Rooijers, 2023a, 2023b). Some businesses are even required to temporarily rely on fossil-fuelled back-up systems such as gas generators, making the whole energy transition less sustainable (Rooijers, 2023a).

Grid congestion mainly affects large-scale consumers, such as industrial companies (ICs) (Stedin, n.d.). One potential solution for ICs is joining an Energy Hub (EH), where a small-scale energy production unit utilizes locally available resources and distributes energy based on specific demand (Javid et al., 2021). An EH would benefit ICs because it allows them to secure reliable access to electricity for their business processes, reduce dependency on the main grid during peak congestion periods and potentially lower energy costs by optimizing local generation and consumption. In addition, EHs can improve collaborative energy sharing as demonstrated at Schiphol Trade Park and a business park in Nederweert (Rooijers, 2023a, 2023b). In the two previous examples, the companies within the park can jointly manage limited grid capacity and trade local solar generation to meet their needs. They also show that the energy transition is not only a technical challenge, but also a social challenge which requires coordination, cooperation, and trust among the stakeholders.

This social challenge is also illustrated by individual entrepreneur such as Jan Ros of La Coquerie (Westerveld, 2024). Ros faced delays in receiving grid capacity from Liander despite proactive planning after switching from gas to electric ovens. To manage this delay, he implemented evening and night shifts, installed batteries, and even developed his own Energy Management System (EMS). Ros's experi-

ence shows that the grid congestion challenges also require entrepreneurial problem-solving thinking, behavioural adaptation, and proactive energy management by businesses (Westerveld, 2024).

A company that has experiences with facilitating the energy transition for ICs is Emmett Green. Emmett Green facilitates the energy transition, among other things, by connecting stakeholders through services and technologies. These services and technologies include private grid design, battery financing and simulation, EMS development, and implementation of e-boilers and heating networks (Emmett Green, n.d.-b). By primarily helping ICs, Emmett Green plays a key role in EH projects by uniting these companies and act as congestion service provider (CSP). A CSP is a party that offers flexible capacity on behalf of one or more grid users to the grid operator in order to resolve grid congestion (TenneT, n.d.). This is partly done by the EMS that monitors, controls, and optimizes the generation, distribution, and consumption of energy within the party of grid users or user (Emmett Green, n.d.-a).

Additionally, Emmett Green is already involved in group contracts (GTO), where multiple industrial companies can share access to capacity through joint agreements (Enexis Netbeheer, n.d.). These agreements offer a contractual foundation for energy cooperations with EHs.

However, the successful operation of an EH relies not only on the physical infrastructure and the contractual foundation but also on the behavioural dynamics between its participants. Effective energy distribution requires coordination, yet individual members may have different priorities and objectives such as cost minimization or self-sufficiency. This creates a collective action problem where individual businesses may see limited direct gain by participating while the grid benefits if many companies adjust their consumption (Rooijers, 2023c).

These decentralized decisions introduce complexity into the systems behaviour, which can potentially lead to less optimal energy flows or stability. To handle these challenges, congestion management strategies are important because it aims to either steer supply or demand of energy during peak periods when capacity limits are reached (Wampack, 2021).

A component of congestion management is Demand Response (DR), where participants of the EH are encouraged to shift their electricity demand to off-peak times (Arias et al., 2025). Yet, in the context of EH where behavioural differences shape how decisions are made, implementing congestion management strategies such as DR may be challenging. The effectiveness of these strategies depend not only on technology and regulation, but also on aligning incentives and engaging participants so that businesses are willing and able to adjust their energy usage without compromising core operations. This can lead to resistance to cooperation or a situation where individual incentives conflict with collective goals of the EH.

1.2. Research Objective

The aim of this thesis is to analyse the different types of behaviour participants/IC can show in an EH, focussing on how cooperative and competitive dynamics influence the flow of energy distribution, operational reliability, and overall performance of the EH. The focus is also specifically on participants who stay in the EH and do not plan to leave or join the EH. The goal is to identify strategies that can optimize collaboration while managing the challenges posed by competitive incentives.

This research aligns with the Complex System Engineering and Management (CoSEM) program, as the EH is a complex system involving multiple internal and external factors, actors, and interactions. This thesis addresses technical challenges like grid congestion, energy distribution, and system stability, focusing on how EHs can optimize energy flow and address infrastructure limits. On the social side, this thesis explores how cooperative and competitive behaviours of participants impact energy sharing, system resilience, and long-term sustainability, highlighting the role of human decision-making in the EH's performance.

This thesis also aligns with Emmett Green's mission to enable and improve flexible energy systems. By analysing behavioural dynamics in EHs, this thesis can support Emmett Green's work at the level of stakeholder interaction and improve coordination, flexibility, and efficiency within EHs.

1.3. Research Scope

The scope of this research is specifically limited to participants who remain within the EH for the entire duration of the study, with no consideration for participant turnover. New participants are not allowed to join the Energy Hub, as the focus is not on membership dynamics or market entry and exit, but rather on the interactions and behaviours of a fixed group of participants.

The model focuses on indirect interactions between participants, where their decisions and actions influence each other through shared resources and system mechanisms, rather than through direct bilateral communication. Only internal EH operations are considered; interactions with the external energy market or other hubs are excluded.

1.4. Thesis Structure

This thesis consists of ten chapters, including the current one. Chapter 2 introduces some core concepts and synthesises the relevant literature, which leads to the identification of knowledge gaps and the formulation of the main research question. Chapter 3 outlines the research approach, which goes further into detail on the methods for each sub-question. Chapter 4 dives into the model conceptualization, where the aspects of the model is being conceptualized and discussed. Chapter 5 translates the conceptualization of Chapter 4 into an operational model. Chapter 6 describes the set-up of the experimental design and Chapter 7 presents the results from these experiments. Chapter 8 will analyse the model results from the previous chapter. Chapter 9 will discuss and present the survey design, results, and analysis. Chapter 10 presents the discussions and limitations, where the methodology is reflected upon and implications are discussed. Finally, the thesis ends with a conclusion in Chapter 11 where the research questions and sub-questions are answered. This chapter also presents managerial recommendations and future research recommendations as well as .

2

Literature Review

In this chapter, core concepts are introduced which are used for important background knowledge later in this research. Furthermore, an explanation of the methodology used to obtain and select literature is given. After this, the chosen literature will be synthesized and the knowledge gaps will be identified. Lastly, the main research question will be introduced based on the identified knowledge gaps.

2.1. Core Concepts

This section discusses some core concepts that are important for background knowledge of this research. These core concepts include information about the Social Value Orientation (SVO), Behavioural Drivers of Demand Response, and Group Contracts.

2.1.1. Social Value Orientation

The traditional economic models are based on the concept of homo economicus, which assumes that individuals act only out of self-interest and wants to maximize their profit. In addition, it is assumed that homo economicus is a rational being and also makes rational decisions (Mele & González-Cantón, 2014).

However, research in social psychology and behavioural economics of (Messick & McClintock, 1968) have shown that the concept of homo economicus fails to fully capture human motivation, particularly in contexts of social interdependence. They have provided empirical evidence that many individuals can display positive social concerns, which challenges the self-interested assumptions of homo economicus. Messick and McClintock, 1968 proposed that individuals have three dominant motivations which are maximizing joint outcomes (cooperative), relative advantage (individualistic), and one's own pay-off (competitive). These motivations are not fixed, but can shift depending on the context.

Building on the empirical evidence from Messick and McClintock, 1968, the term Social Value Orientation (SVO) was introduced through the research of Van Lange, 1999. Van Lange, 1999 defines SVO as the degree to which individuals value other's material outcomes alongside their own. In contrast to the homo economicus, individuals with a more prosocial SVO find value in outcomes that are fair or beneficial to both themselves and others.

Greiff et al., 2018 and Murphy and Ackermann, 2014 emphasized that SVO is a continuous spectrum which can be divided into four ranges: altruistic, prosocial, individualistic, and competitive. Altruistic individuals prioritize the other's pay-off above their own, while prosocial individuals seek fairness or maximize joint outcomes. Individualistic individuals are mainly concerned with their own outcome and competitive individuals aim to maximize the difference in their favour even at cost of themselves.

Expanding on Greiff et al., 2018 research, Moisan et al., 2018 showed that both intrinsic social preferences and the external incentive structure of the game influence cooperative behaviour. Their study use a set of Prisoner's Dilemma games with varying pay-off structures and showed that SVO can predict cooperation, but only under certain circumstances. Prosocial individuals are more likely to cooperate

and can even encourage individualistic individuals to do the same in games where mutual cooperation leads to rewards and rejection of cooperation leads losses. However, in games where cooperation is less advantageous or easily exploitable, prosocial individuals may receive lower pay-offs or even become targets of exploitation.

It can be concluded that the assumption of self-interested and rational decision-making as seen in the homo economicus model is not adequate for portraying the diversity of human motivations in social contexts. The integration of SVO into behavioural economic research offers a more nuanced understanding of cooperative behaviour. Individuals display varying degrees of concern for other's outcomes, which interacts with the external incentive structure. Recognizing this interplay between SVO and the external incentive structure may allow for a more accurate prediction of behaviour in social settings and can even help with designing institutions and policies.

2.1.2. Behavioural Drivers of Demand Response

While SVO provides a useful psychological framework for understanding how individuals value the outcomes of other's, it represents only one piece of a broader behavioural landscape. Real-world decision-making in complex systems such as EHs are shaped by a wide range of behavioural drivers.

According to Arias et al., 2025, DR refers to the adjustments electricity users make to their typical consumption patterns in response to electricity prices, financial incentives, or the need to support grid stability. Research by Hu and Jin, 2025 underline the significant role of DR within integrated energy systems such as EHs. They argue that DR strategies are an effective component of EHs to manage operational uncertainties, optimizing costs, and improve overall system flexibility.

Amini et al., 2019 and Carvalho et al., 2020 have shown that there are several drivers that affects consumer participation in DR programs. These drivers include economic and behavioural incentives. Economic incentives such as setting tariffs can motivate users to shift consumption, but its effectiveness depends on the user's price sensitivity and trust in the system. Behavioural incentives such as risks aversion, privacy concerns and consumption patterns play an important role in individual responses. Eslamizadeh et al., 2022 have shown that the reputation of one's company, positive experiences, and expectations of others can play a significant role in influencing and their willingness to participate in collaborative initiatives. Howard, 2024 have shown that providing users (specifically in residential context) with insight into capacity pressure and real-time grid conditions can increase the engagement in load shifting and other demand response action, because participants can see when their actions matter the most.

For an industrial user in particular, behavioural constraints are often closely tied to technological and operational limitations. While a company may theoretically benefit from shifting energy use to off-peak hours, practical constraints such as fixed production schedules, temperature control requirements, or quality assurance concerns may withhold such load shifts (Schwabeneder et al., 2019). It can be concluded that for some industrial users engaging in load shifting may result in additional operational costs (e.g.increased personnel expenses), reduced product quality requiring re-production, and other inefficiencies in the production process.

The study of Gerami et al., 2021 points out that many industrial processes fall into categories of either shiftable, controllable or non-shiftable loads which depends on their technological characteristics and operational constraints. Non-shiftable processes, such as continuous kiln operations in cement production must operate without interruption. Shiftable loads can be rescheduled within a certain time window. Controllable loads offer more flexibility by allowing both the timing and quantity of capacity to be adjusted. Emmett Green categorizes loads into four groups: fixed preferent, flexible preferent, fixed non-preferent, and flexible non-preferent (M. Wildschut, 2025). The distinction between fixed and flexible refers to the ability to reschedule a load: fixed loads are non-shiftable, while flexible loads can be shifted in time. The preferent versus non-preferent classification indicates the criticality of a process to the overall operation. For example, in the case of kiln operation within a cement production facility, the load would be classified as a fixed preferent load. This is because the kiln must operate continuously without interruption, and its operation is critical to the company's core production process.

In summary, while DR plays an important role in improving operational uncertainties, optimizing costs, and improve overall operational reliability, it also depends on understanding the behavioural and eco-

conomic drivers that influences stakeholders in the EH. Loads can be categorized into four main categories: fixed preferent, flexible preferent, fixed non-preferent, and flexible non-preferent.

2.1.3. Group Contracts

The minister of Climate and Energy of the Dutch government, Rob Jetten, had send a letter in October 2023 to the Speaker of the House of Representatives to announce the new measures to tackle grid congestion. These measures aim to decrease net congestion by focusing on faster grid reinforcement and for a smarter use of the electricity network (Ministerie van Economische Zaken en Klimaat, 2023a). One of the mentioned measures was the option for a flexible group contract for large-scale consumers, specifically the Group Transport Agreement in short the GTO.

The GTO is an agreement between the Distribution System Operator (DSO) and a group of connected parties such as the large-scale consumers (Wampack, 2024). In general, instead of each company having its own contracted transport capacity (GTV), the group jointly manage and optimize their shared group contracted transport capacity (G-GTV) by virtually linking their physical connections. The group can only be formed if the participating companies all are on the same substation and if they have the same type of connection, which are either low voltage, medium voltage, or high voltage (Enexis Netbeheer, n.d.) Large-scale consumers usually are on the medium voltage. This group appoints a single legal representative who acts as the contract holder and together they distribute the G-GTV among the participants based on mutual agreements (Netbeheer Nederland, 2024).

This group of companies is called an energy cooperation, which is a collaborative organizational form. Through an energy cooperation, its members can collectively invest in renewable energy technologies, such as solar panels, wind turbines, batteries and even an EH (Westland Woont Duurzaam, n.d.). By functioning as a cooperation, this legal entity can facilitate joint decision-making and shared ownership which enables making strategic investments. An example of this is the investment in batteries, which can be used to balance supply and demand or to make profits from market opportunities. These revenues can be redistributed among the members of the energy cooperation based on agreed upon principles (ACM, n.d.).

The advantages of a GTO is that it allows the participants of the group to optimally align their usage and avoid simultaneous peaks. Also, for the individual is that participation in the group allows him to use more GTV than his original GTV, as long as the group as a whole remains within the group's capacity (Netbeheer Nederland, 2024). Furthermore, the companies in the group are more enabled to jointly invest in renewable energy technologies, because the usage and costs can be shared in the group. The following figure 2.1 is a visualization of the GTO:

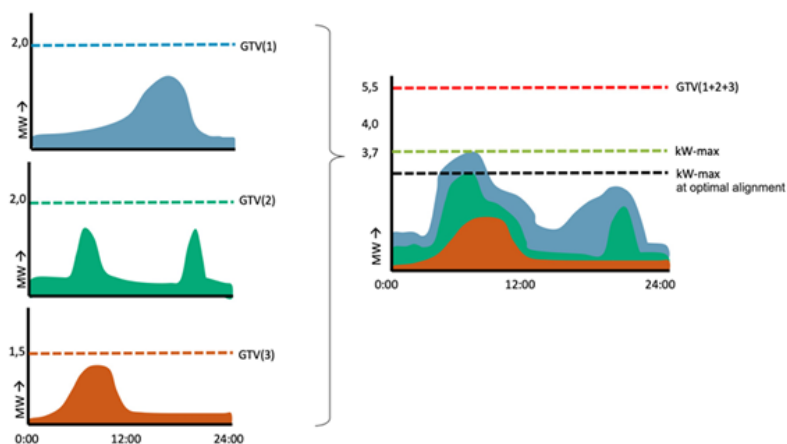


Figure 2.1: Visualization of GTO (Netbeheer Nederland, 2024)

The group capacity is decided by the aggregated profile of the group in the energy hub. Every company has its own usage profile, which can differ between companies. For example, company A might use more electricity during the morning and less during the afternoon, while company B uses more electricity

during the evening and less during the morning (see Figure X on the left). On the left, three user profiles of their electricity use have been displayed, along with their corresponding GTV. When you combine their electricity use and GTV, the G-GTV can be calculated (on the right). The G-GTV can be roughly calculated through determining the 95th percentile of the demand of the aggregated profile (ACM, 2025). The G-GTV can be calculated for both feed-in and feed-out. From this visualization, it becomes clear how much capacity is not used to its full potential.

Currently, the GTO is still under construction and is expected to be available sometime in 2025. However, the preparation for the GTO involves much coordination among participants to align their capacity use (Wampack, 2024). From a meeting with representatives with Stedin and Liander, it became clear that in reality this coordination is difficult to reach as participants have troubles with technical restraints of the location or being collaborative with each other. When participants reach a consensus, the next discussion is where to put the G-GTV as ideally from the distribution system operator's side this would be near the kW max (see Figure 2.1). The participants would ideally want to put the G-GTV near the GTV(1+2+3) line, as this gives them more space to grow in the future (Liander & Stedin, 2025).

In the meeting with Liander and Stedin, 2025 it also came forward that some founded that in reality some participants will use their GTV fully, so they can get a higher G-GTV. Here, the response of Liander and Stedin was that they will filter these peaks away from the rest of the historical profile.

This dynamic illustrates the tension between regulatory planning and market behaviour. As the representative from Liander summarized (Liander & Stedin, 2025):

"The market will always be smarter than the lawmaker that rushes behind it."

The quote highlights that despite rules and guidelines, participants often find ways to optimize their position which underlines the practical challenges of aligning incentives in a shared environment.

2.2. Literature Search Process

In this section, the process of how the literature for the state-of-art literature review was acquired. This includes where the literature has been retrieved, which keywords were used, what the criteria was for selecting literature, and what techniques were used to find more literature.

First of all, mainly one specific scientific database was used for the retrieval of the state-of-art literature which is ScienceDirect. ScienceDirect is a database from Elsevier that enables advanced research and provides peer-reviewed scientific literature (Elsevier, n.d.). Apart from ScienceDirect, the TU Delft repository was also used as scientific database. The TU Delft repository contains a range of academic publications, including theses, authored by TU Delft students and faculty.

Next, some combinations of key words were used to search for the papers. The searches on ScienceDirect are for example 'Energy AND Hub AND Behavio(u)r', and 'Energy AND Hub AND Consumer AND Behavio(u)r'. The searches on the TU Delft Repository was for example 'Energy AND Hub'. These searches together provided for 78,645 hits which is a lot, so it needed to be filtered by criteria. The first stage of screening involved reviewing the abstract and keywords off the identified papers to assess their relevance. After that, the literature was filtered based on the publication year and type of study. For example, the minimum publication year must be from 2016 and it must include something about behaviour or modelling frameworks within EHS. The third criterion assessed whether the technical context included for example only renewable energy or only fossil fuel based systems. Altogether, this refinement reduced the number of articles to 121.

Eventually some articles were found by backward snowballing and looking at recommended articles. Backward snowballing is looking at the reference list of an interesting article for articles that might be relevant (Sutherland, n.d.). Five articles were found by backward snowballing and looking at recommended articles. Finally, there were 11 relevant articles found that are included in the literature review.

2.3. Syntheses of Literature

In this section, the papers founded in the literature review process are compared and analysed. The state-of-art literature is categorised into three main themes: optimization of energy hubs, behaviour and decision-making, and multi-actor collaboration.

2.3.1. Optimization of Energy Hubs

The optimization of EH has become an important area of research as integrated energy systems have to balance efficiency, sustainability, and autonomy. EHs are the operational core of multi-energy systems which manage the conversion, storage and distribution of various energy forms. As the role of EHs expands, so does the complexity of optimizing their performance under economic, environmental, and technical constraints.

Mokaramian et al., 2025 provides a comprehensive review of optimization approaches of EHs where they are categorized into deterministic and probabilistic methods. Their focus lies primarily on the techno-economic dimension with methods such as linear and non-linear programming to improve operational efficiency and cost-effectiveness. At the same time, their review points out that other literature may need to include more social aspects as they are essential to optimize.

Darvishi et al., 2024 address this lack of social aspects by incorporating a multi-objective optimization framework within a centralized EH model. Their approach simultaneously minimizes operational costs, CO₂ emissions, and consumer dissatisfaction. They employ scenario-based methods to account for the uncertainties in renewable energy generation and incorporate load-shifting strategies as part of their demand response modelling. This research shows the importance of integrating both supply-side uncertainties and user-level flexibility in EH optimization.

Fan et al., 2018 shifts the optimization focus from single EHs to cooperative communities of EHs by using a game theoretic framework. They tried to enable decentralized EHs to coordinate energy exchanges in such a way that it is both economically fair and not intruding on any participants privacy. Their distribution optimization method ensures that each EH remains autonomous while still benefiting from the system-wide coordination and cost reductions. To be noted for this study is that the framework assumes that the players are rational, which may not always be the case in a real-world environment with bounded rationality and incomplete information.

Continuing on the concept of the cooperative model, Gan et al., 2024 proposed a joint energy and carbon rights trading mechanism among network-constrained EHs. These network-constrained EHs are EH that are dependent on the electricity grid or gas pipes. By modelling this interaction as a cooperative game with externalities, they account for both the physical infrastructure limitations and market-based incentives. While their two stage optimization approach proves to be effective in maintaining coalition stability and maximizing system-wide benefits, their model also assumes perfect cooperation and compliance with the agreed strategies. The model has simplified the behaviour of the players which not represent the behavioural variability actual end-users. In the real-world, players may deviate from the agreed strategies due to self-interest or lack of enforcement.

Earlier work by Dutta and Mitra, 2017 investigated dynamic electricity pricing as a demand-side management tool, which established the foundation for load shifting and price responsiveness. Their findings confirmed that pricing schemes could shift energy demand, but also highlighted that consumers are not very sensitive to price changes meaning that they a low elasticity. While this work laid the foundation for price-based optimization models, they noted that there is a need for a model that shows how consumers respond to dynamic tariffs.

To conclude this section, the optimization of energy hubs is evolving from cost-centric, single-agent models towards more integrated, cooperative, and environmentally conscious systems. However, there is a growing recognition that behavioural variability, decentralized interactions, and emergent system dynamics needs to be better represented.

2.3.2. Consumer Behaviour and Decision-Making

In a complex system such as the EH, uncertainty plays an important factor on many sides. In the previous section, it became clear that there is a need for recognition on behavioural variability and decision-making.

The challenge of modelling consumer behaviour and system responses under uncertainty becomes more clear in the paper of Lu et al., 2020 where the focus is on smart residential EHs. In this research, they introduced behavioural uncertainty into the optimization framework by simulating six types of user behaviour, which includes tolerance to comfort deviation and willingness to engage in demand

response. The inclusion of the behavioural factors results in notable differences in energy costs and comfort levels, which emphasizes how individual decision-making under uncertainty can significantly affect system outcomes. However, in this research they did not use empirical behavioural data to confirm the six types of user behaviour.

At a broader system scale, Gökçek et al., 2024 explores a decentralized P2P energy trading framework in a local energy community using a Multi-Agent System (MAS). Their model accounts for the autonomy and privacy of individual participants of the EH. The consumer behaviour here is modelled both as strategic and bounded, meaning that the consumers respond to the local price signals and grid conditions, but their actions are constrained by their limited information and their own energy goals. This research highlights the importance of decentralized decision making structures that can adapt to variability and uncertainty in consumers behaviour.

Li et al., 2025 extends the research in consumer behaviour by developing an extensive digital twin (EXDT) for interconnected multi EHs (MEHs) which also incorporates multi-agent reinforcement learning to capture local, autonomous, and stochastic decision-making processes of each EH. Here each EH in the MEHs acts as an agent that learns optimal behaviour in a decentralized setting. The EXDT allows for what-if scenario testing, including cooperative vs non-cooperative interactions and various P2P market designs. Their findings confirm that non-cooperative strategies, which reflects the real-world environment, result in reduced efficiency compared to cooperative models. What to note from this research is that they used EHs as agents and not the end-user which are consumers and prosumers in the EHs.

Boske, 2021 analyses how residential stakeholders with different preferences interact under various governance and market conditions. This thesis research uses Agent-Based Modelling (ABM) to evaluate energy policies, emphasizing the impact of behavioural uncertainty and the need for inclusive modelling that incorporates both individual and collective institutional responses.

In short, these studies illustrate the importance of looking beyond deterministic and scenario-based modelling. EHs are complex adaptive systems, where behaviour is dynamic, decentralized, and shaped by both individual preferences and institutional structures. Tools like ABM and digital twins can explore the complexity of this behaviour and can also bridge the gap between model-based insights and real-world decision-making.

2.3.3. Multi-Actor Collaboration

As mentioned in the previous section, consumer behaviour and decision-making is an important aspect when modelling EHs. Another important factor that influences an EH is multi-actor collaboration, because it enables diverse stakeholders to align their goals, share knowledge, and eventually co-develop solutions that build upon the dynamics of an EH.

The thesis research of Berkouwer, 2024 explores this complexity and focusses on the stakeholder collaboration and how it influences the deployment of local energy systems (LES) on Dutch business parks which are similar to EHs. Berkouwer concludes that the problem with EHs are not the technical feasibility, but rather the organizational collaboration. Factors such as having a shared vision, learning activities, and social network dynamics play an important role in actor alignment and trust development. Her research shows that understanding and managing these interdependencies is important for the broader adoption of energy systems.

Building on this, Fan et al., 2018 approach multi-actor collaboration from a systems optimization perspective. As said before, they proposed a game-theoretic, distributed optimization framework to enable autonomous EHs to participate in cooperative energy sharing. Their results show that even decentralized agents can reach collectively beneficial outcomes, if they follow rational decision-making principles. However, in a real-world setting the actors are not acting with full rationality but rather bounded rationality. This challenge is also noted by Berkouwer who points out that without the social and organizational foundation, the actors may misalign their goals or fail to cooperate. Similarly, Gökçek et al., 2024 emphasizes that effective multi-actor collaboration must balance autonomy with coordination, and flexibility with resilience.

In summary, the literature consistently highlights that while EH hold great promise for sustainable energy

transitions, their success heavily depends on effective multi-actor collaboration. Technical feasibility is no longer the primary challenge but instead the complexity lies in aligning diverse stakeholder interests, improving trust, and establishing shared goals across institutional, social, and technological domains.

2.4. Identified Knowledge Gaps

In this section, the knowledge gaps that are introduced in the previous sections are presented.

First of all, most optimization frameworks (e.g. Darvishi et al., 2024; Fan et al., 2018; Mokaramian et al., 2025) focus on techno-economic aspects using deterministic and stochastic methods. While these frameworks improve efficiency, these models often rely on assumptions of fully rational actors neglecting the bounded rationality, incomplete information, and variability of real-world consumers. There is a need for better representation of decentralized interactions, emergent system dynamics and behavioural diversity.

Furthermore, Lu et al., 2020 introduces behavioural types but it lacks empirical validation of those behaviours. Li et al., 2025 tries to refine the behaviour, but still comes short in modelling real consumer or prosumer behaviour. Boske, 2021 studies residential behaviour, but does not give insight into behaviour of industrial companies. It can be concluded that there is a need for empirically grounded, user-centric optimization model that reflects the real behaviour of consumers that are IC under uncertainty.

Lastly, while multi-actor collaboration is frequently acknowledged as a key factor in the functioning of EHs, current modelling provide limited insight into how this collaboration actually unfolds between diverse stakeholders. As Berkouwer, 2024 and Fan et al., 2018 emphasize that trust-building, goal alignment, and informal communication are central to effective cooperation but are not well represented in existing models. This leaves a knowledge gap in the understanding of the underlying processes that shape how multi-actor collaboration develops and changes over time.

2.5. Formulation of the Research Question

To shed more light on the first knowledge gap, this research should more accurately incorporate the decentralized interaction, emergent system dynamics, and behaviour diversity within an EH. To achieve this, a modelling tool such as ABM that can simulate individual actors and their interactions within a complex system can be used.

To address the second knowledge gap, this research should be empirically grounded in user-centric behaviour. This means that there needs to be more research into, and consideration for, the manner in which actual users interact with the system. This includes incorporating the bounded rationality and incomplete and asymmetrical information of real-world IC, but also another approach to the diversity of behavioural dynamics of humans. From Subsections 2.1.1 and 2.1.2, it can be said that the combination of SVO and behavioural drivers is a suitable approach to model more accurate behaviour.

Based on the third knowledge gap, this research will examine how participants behaviour influences multi-actor collaboration within an EH through congestion management. Specifically, it will analyse how individual behaviours, shaped by SVO and behavioural diversity, affect the formation and outcomes of collaborative interactions among each other under the constraint and rules of a GTO (Subsection 2.1.3).

Having discussed the considerations for formulating the research question, the main research question is formulated as the following:

What is the impact of diverse participant behaviour and Social Value Orientations on congestion management in an Energy Hub within a Group Contract?

3

Research Design

This chapter discusses the specific research objective based on the main research question presented in the Section 2.5. After that, the research approach is introduced which outlines its selection for this research. This is followed by an introduction of the sub-questions and the description of the research methods of how they are applied to address the sub-questions.

3.1. Research Objective

The objective of this research is to develop an empirically grounded, user-centric model for EHs that integrates the real-life behaviour of IC. Specifically, this research aims to represent how ICs with diverse SVOs and behavioural drivers interact with each other under bounded rationality and institutional constraints from the Group Contract. By bridging the gap between traditional techno-economic optimization models and socio-technical approaches, this research's goal is to understand how individual behaviours shape multi-actor collaboration and influence system-level outcomes in congestion management under a Group Contract.

Based on these objectives, the main research question is formulated as the following:

What is the impact of diverse participant behaviour and Social Value Orientations on congestion management in an Energy Hub within a Group Contract?

3.2. Research Approach

The objective of the main research question is to explore how diverse participants behaviours, shaped by SVO and behavioural drivers, influence congestion management and multi-actor collaboration within an EH under a Group Contract.

To achieve this objective, the most suitable approach is the modelling approach. This approach allows to simulate and evaluate various types of participants, which provides insights into the dynamics of their interactions, the resulting operational outcomes, and the overall performance of the EH under varying behavioural and system conditions (TPM, 2024). These interactions would be difficult to observe or test empirically as the EH are in their early stages. Through simulation, different types of participants can be evaluated without the cost and complexity of real-world experimentation.

According to Ghorbani et al., 2010, ABM is a modelling method that focuses on the behaviour and interactions of individuals agents rather than modelling the system a whole. ABM is frequently used for simulating socio-technical system, which are also called complex adaptive systems, where technical components and human behaviour are intertwined. A strength of ABM is its ability to capture how micro-level decision-making leads to emergent macro-level patterns, which is relevant when studying the institutional impact on system-wide performance.

Although the modelling approach is appropriate for this research, it also important to acknowledge its limitations. For instance, modelling will always be a simplification of the real-world meaning that they

are not absolutely truthful (Sterman, 2002). In this research, the representation of the EH is simplified to keep it within the available timeframe. As Robinson, 2004 points out, such simplifications are necessary because data collection and model development can be highly time consuming. Additionally, models rely on assumptions which means that the validity of the results depend on how accurate those assumptions are. Robinson, 2004 also notes that some data may not be available or too difficult to obtain, so it is sometimes necessary to make assumptions.

3.3. Formulation of Sub-Questions

In the previous section, the research approach was outlined highlighting the relevance of ABM for exploring agent behaviour within an EH. Based on this approach, a set of sub-questions has been formulated to structurally guide the research process towards answering the main research question.

First of all, in order to model the system in ABM, buildings blocks of the system and agents should be defined. These buildings blocks consist of the behavioural aspects of the participants, which includes the internal attributes, decision rules, and interaction rules (Dam et al., 2013). Conceptualizing both the agents and the environment is important, because it ensures that the ABM accurately represents the real-world dynamics of the EH. For this reason, the following sub-questions is formulated:

1. How can the Energy Hub be modelled as an Agent-Based Model?

According to Dam et al., 2013, the internal attributes of agents are properties that belong to the agent itself, for example the hourly energy usage or willingness to pay for capacity. The decision rules are the 'algorithms' that the agents use to make choices based on their internal attributes (state) and environment. Examples of decision rules are the consideration to load shift electricity consumption to another moment. Lastly, the interaction rules defines how agents interact with one another or the environment which represents the social dynamics. Examples of interaction rules is the way how agents can allocate their capacity to others.

Once the buildings blocks are established, the model can be built in ABM. Each agent will be programmed with the internal attributes, decision rules, and interaction mechanisms. The environment of the model will represent the technical, institutional, and organizational context of the EH, including energy exchange possibilities and the Group Contract.

Now the model is created, the Key Performance Indicators (KPIs) can be formulated to evaluate the model and results:

2. Which Key Performance Indicators are most suitable for evaluating the performance of the Agent-Based Model?

KPI's provide insight into the system's performance as they offer measurable benchmarks. In a complex system such as the EH, KPI's can translate abstract objectives into these measurable benchmarks to evaluate trade-offs and compare scenarios.

Now the KPI's are formulated, the simulation can be run with the following sub-question:

3. How do the different types of behaviours of agents influence the congestion management of the Agent-Based Model?

In this sub-question, the ABM will be run under multiple scenarios of different behaviour types to understand the influence of behaviour on congestion management. Congestion management in this case is mainly done by the EH operators with load shedding, however the participants could also apply demand response (which is part of congestion management) by load shifting. This is relevant, because it can explore which behaviours promote congestion management and which may lead to bottlenecks.

Now the results of the different types of behaviours are out and analysed, these can be evaluated with data of real-life participants with the following sub-question:

4. How do the survey results of real-life participants support the behavioural mechanisms implemented in the Agent-Based Model?

In this sub-question, empirical data is retrieved from the participants of a real EH and then compared to the results from the ABM. This comparison not only validates the model, but also provides insights into which behaviour types are currently present in real-life. This can point out discrepancies between predicted and actual behaviour.

Now all data from the model and survey is analysed, these insights can be translated into potential strategies with the following sub-question:

5. How can insights from the Agent-Based Model and survey be translated into potential strategies that influence system-level behaviour?

In this sub-question, the goal is to explore how insights derived from the ABM and survey can be translated into potential interventions that influence system-level behaviour within the EH. This sub-question links simulation results to recommendations for real-world implementation.

3.4. Research Methods

In the previous section, the sub-questions were introduced. This section outlines the research methods that is going to be used with each sub-question, detailing the specific approach and activities required to gather the necessary data and insights.

1. How can the Energy Hub be modelled as an Agent-Based Model?

As it says in the sub-question, this sub-question uses ABM as research method. The purpose of the model is to analyse the user behaviour. Each user (agent) represents a participant in the EH, which are ICs. The environment in which these agents live in is an EH.

To simulate this system, the model will be developed in Python which offers flexibility and efficiency for building and testing ABM. Python is particularly well-suited for ABM due to libraries like Mesa, which allow for scalable simulations and easy visualization of agent interactions (Ter Hoeven et al., 2025).

As mentioned before, the limitation of using ABM is that the EH will be simplified, because a more complex model would take more time to create and also would take a long time for running.

To make sure that the model is correctly simplified, expert interviews will be conducted to confirm that the model accurately represents the important dynamics of the EH without forgetting critical factors. These experts can provide feedback on the assumptions, structure, and level of detail to ensure the model remains both valid and practical for the research objectives.

Furthermore a desk research is conducted to explore the behavioural characteristics in literature.

2. Which Key Performance Indicators are most suitable for evaluating the performance of the Agent-Based Model?

In this sub-question, a closer look is taken at the KPI's which are needed to evaluate the performance of the model. The KPIs are selected based on logical reasoning from the model structure and the objectives of the simulation.

A limitation of this approach is that the KPIs are based on logical reasoning from the ABM instead of empirical validation, which may not include all relevant aspects of the real-world.

To address the limitations, the selection of KPIs are explicitly justified in relation to model outputs and behavioural mechanisms. The robustness of the KPIs are tested through scenario analysis across different agent compositions and system conditions. Expert feedback can validate the relevance of

these KPIs, while the extreme condition testing ensures that small changes in assumptions do not affect the interpretation of results.

3. How do the different types of behaviours of agents influence the congestion management of the Agent-Based Model?

In this sub-question, the model is run for multiple scenarios where some behavioural parameters are varied. Each scenario is going to be run multiple times to account for stochastic effects and to ensure robustness in the results.

A limitation of conducting a scenario analyses in ABM is that the results can be hard to interpret, because of the complexity of interactions between many agents (Ghorbani et al., 2014).

To minimize these limitations, an extreme condition test can be conducted to understand the causal relationship between the agents and the system-level outcomes. By varying individual parameters and observing their impact on the system, the test can help identify which behavioural factors are most influential. This not only improves the interpretability of the results but also supports the formulation of targeted interventions and policy recommendations.

4. How do the survey results of real-life participants support the behavioural mechanisms implemented in the Agent-Based Model?

The clients of Emmett Green that are in an EH will be approached and asked if they are willing to participate in the survey.

A survey is a fitting method for this sub-question, because it allows to collect data from a large group of EH participants. This approach makes it possible to identify preferences, and important factors that influence behaviour in a structured and quantifiable way while being time-efficient and scalable (Bryman, 2004).

However, the limitations of using a survey is that it gives a limited depth of the gathered information. Respondents may not be fully able to express their thoughts. Another limitation is that the respondent may misunderstand the questions if the questions are not clearly worded (Bryman, 2004).

To address the previous limitations, open questions and the Likert-scale will be included in the survey to allow for a more nuanced response and richer insight. A Likert scale measures respondents agreement with statements using multiple items, typically on a 5-point scale, such as strongly disagree, disagree, neutral, agree, or strongly agree (TU Delft, n.d.). Furthermore, to minimize the risk of misinterpretation, the questions will be written in simple and specific language together with examples of a situation or explanation of terms (Bryman, 2004).

5. How can insights from the Agent-Based Model and survey be translated into potential strategies that influence system-level behaviour?

In this sub-question, the simulation results will be interpreted and analysed to identify patterns, bottlenecks, and trade-offs that could lead to potential interventions.

However, there is a risk in misinterpreting the outcomes of the ABM and survey that may be context-dependent. To address this limitation, the interpretations will be discussed with experts to ensure that the interpretations are grounded in practicalities. This can also improve the validity and relevance of the interpretations derived from the model.

3.5. Ethical Considerations

As mentioned in the previous section, a survey will be conducted and data will from participants will be used. When conducting research with humans as research subjects, their safety and privacy should be guarded. For this reason an ethical plan will be submitted to the Human Research Ethics Committee

(HREC) of the TU Delft to ensure the ethical standards. This ethical plan includes a Data Management Plan, an informed consent form, and a risk assessment. The approval of the HREC will serve as confirmation that this study meets the ethical guidelines and respects the rights and privacy of the participants.

3.6. Research Flow Diagram

In this section, a Research Flow Diagram is presented to breakdown the research design into phases. In this visual representation, the research methods and sub questions are placed into these phases in such a way that there is a clear structure. Figure 3.1 shows this Research Flow Diagram.

As seen in the Figure 3.1, this research has six phases which are respectively: Research Design, Model Conceptualization, Model Operationalization, Experimental Design, Analysis and Synthesis, Conclusion and Discussion. In the first phase, the goal is to define the research with its background, objective, problem, and research questions. After the first phase is finished, the second phase can be started where the building blocks of the model are defined with relevant concepts, attributes, and rules. The building blocks of the model will lead to Model Operationalization, where the EH is modelled as ABM, the KPIs are determined, and the survey is designed. After that, the Experimental Design can be started where the experiments are setted-up and ran. The experiments results will be used in the Analysis and Synthesis phase, where it will be analysed together with the survey results. From this analysis, the implications and interventions are formulated. Finally, the conclusion and discussion can be written once the implications and interventions are formulated.

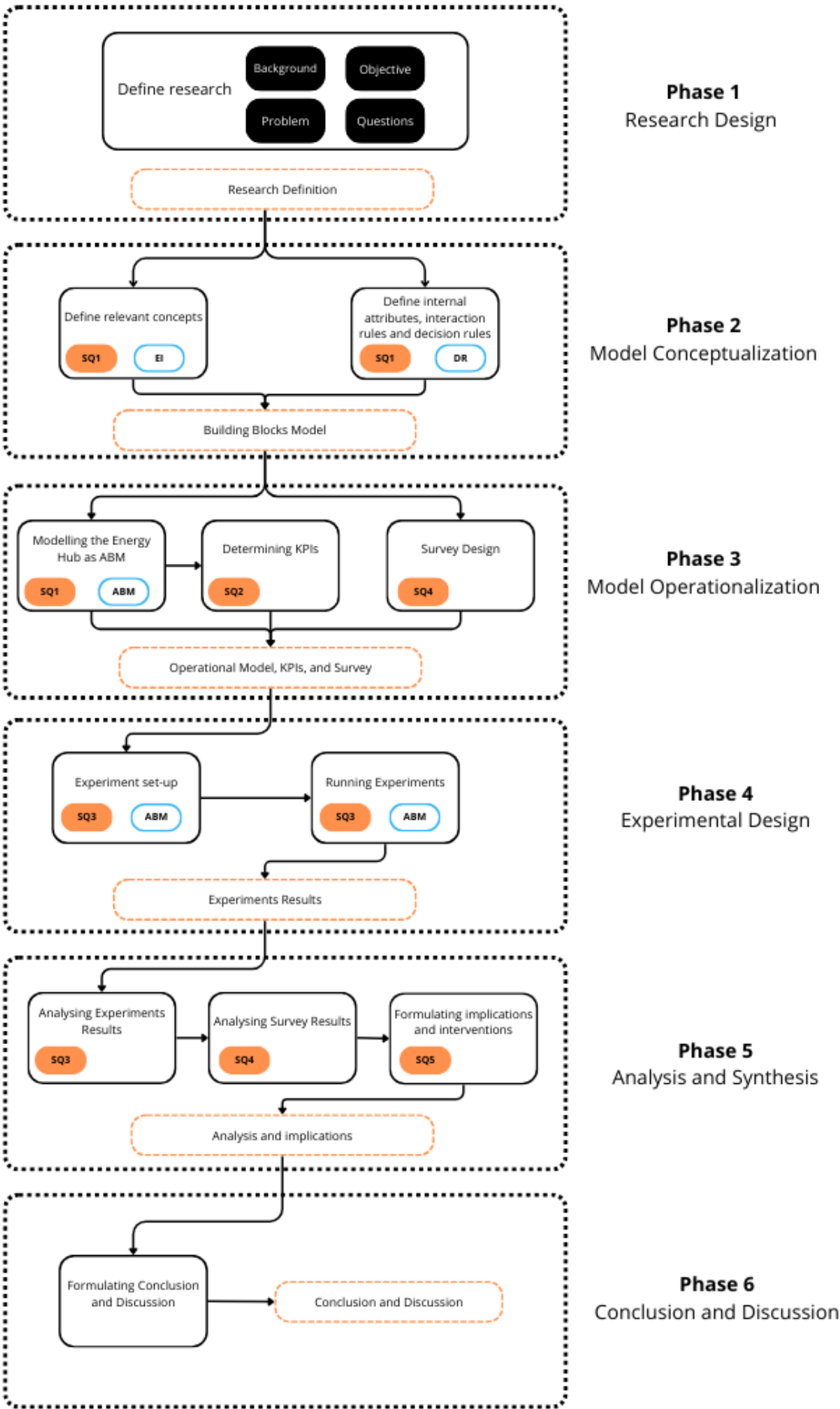


Figure 3.1: Research Flow Diagram

4

Model Conceptualization

This chapter focuses on the first phase of the modelling process: conceptualizing the model. It begins by outlining the primary objectives and provides a description of the agents and the environment within the system. Key components such as the creation of demand profiles and the implementation of G-GTV are examined. Additionally, the chapter explores the conceptualization of SVO and its integration into the model, alongside an explanation of the penalty and reward mechanisms. The role of collectively owned PV systems is also discussed. Furthermore, the chapter addresses the concept of bounded rationality and how it applies to agent behaviour. Finally, the chapter concludes with a summary of the key assumptions and simplifications made for the model.

4.1. Objectives of the Model

The objective of the model is to explore how agents (IC) with heterogeneous SVOs and demand profiles respond to day-ahead congestion signals in an EH environment. Specifically, the model will simulate how the agents make trade-offs between personal penalties and social costs when deciding whether to shift their load or accept penalties. The personal penalties include costs when exceeding their allocated capacity and operational costs of load shifting includes the costs when shifting their load. The social costs includes the costs the rest of the EH must pay of penalties.

Furthermore, another objective of the model is to capture the dynamics of individual decentralized decision-making and centralized control by the EMS. This dynamic will point out the emergent behaviour that appears in a complex system such as an EH, which can eventually help in making more effective policy decisions. An example of such emergent behaviour is the formation of load shifting patterns that unintentionally create new peaks in non-congested hours. These kind of effects are not directly programmed, but arise from the interactions between agent heterogeneity, penalty structures, and centralized control.

4.2. Description of Agents and Environment

In this section, a description is provided of the agents and the environment within the model. It outlines their characteristics, interactions, and the context in which they function. This model represents an EH as a system of interacting agents embedded in a shared technical and contractual environment. The agents resembles individual ICs, while the environment provides the operational context, constraints, and shared resources in which these agents make decisions. Together, they form a socio-technical system where individual behaviour and the system are tightly coupled.

4.2.1. Agents

The agents in the model are the ICs of the EH. Each IC is modelled as a distinct entity with its own preferences, priorities, and operational characteristics. While all agents share the same basic role (i.e. consuming electricity), they differ in their attitudes toward cooperation, their tolerance for operational adjustments, and their consumption patterns.

A key defining feature of each agent is its SVO (from Subsection 2.1.1, which determines how it balances self-interest against collective benefit. Four broad SVO categories are considered: altruistic, pro-social, individualistic, and competitive. These orientations guide how agents weigh the trade-off between their own consumption needs and the collective goal of avoiding congestion in the EH.

Each agent's electricity demand profile reflects variation over the day and year, as well as structural factors such as company size or the nature of industrial processes. Within this profile, certain loads are more flexible and critical than others, enabling agents to shift consumption in response to expected congestion. The core decision each agent faces in the model is whether to adjust its planned consumption to help avoid collective congestion, or to maintain its schedule and potentially incur a penalty.

Within the EH, ICs can theoretically perform a range of actions, such as load shifting, investing in renewable energy sources, or even coordinating with peers to redistribute demand. However, in the scope of this model the focus is limited to load shifting. Investment decisions fall under a longer-term scope, and peer-coordination is excluded due to differing interpretation and uncertainties brought up during expert interviews. Some experts predicted that ICs can call each other to ask another if they could lower their energy consumption, however other experts predicted that ICs do not have the time to do so (H. Spruijt, 2025; M. Wildschut, 2025).

Lastly, another interaction that the agents have is implicit capacity sharing. While each IC is assigned an individual capacity limit, the agents can exceed their own capacity limit if there is unused capacity within the EH from other agents. This implicit sharing creates a soft coupling between agents, influencing their decision-making around load shifting by providing a form of indirect flexibility.

4.2.2. Environment

The environment represents the shared technical and contractual infrastructure of the EH. It includes the CEMS, the physical connection to the electricity grid, collectively owned renewable assets, and an information interface (dashboard) available to all agents. The CEMS is the collective version of the EMS, which is practically the same but for the whole EH.

The EH operates under shared capacity constraints for both electricity consumption (off-take) and injection (feed-in) to the grid. These limits in the GTO apply collectively to all agents. The CEMS continuously monitors the aggregated demand and generation within the EH, ensuring these limits are adhered to. If the EH approaches its contractual capacity, the CEMS can intervene through actions such as rotational load shedding or curtailment of renewable generation (J. Bijl, 2025). Load shedding is the phenomenon of intentionally disconnecting power to certain areas or groups of users, which also happens in South-Africa (Nowakowska & Tubis, n.d.). Rotational load shedding means that there is a planned and cyclical distribution of intentional power outages among users, so that the burden is shared evenly among the participants. Curtailment refers to the intentional reduction or limitation of renewable energy (RE) generation, such as wind or solar power, even when the energy could potentially be produced (Laimon, 2025).

Collectively owned photovoltaic (PV) panels are integrated into the EH, providing RE generation that can help reduce grid overconsumption. However, high PV generation can also contribute to congestion on the feed-in side which requires the CEMS to occasionally curtail production. This collective ownership assumption simplifies the model by ensuring the CEMS has full operational control, avoiding the complexity of simulating competing EMS of the participants.

The dashboard interface serves as the informational link between the CEMS and the agents. It provides real-time data and forecasts on EH performance, including demand, renewable output, and expected congestion (J. Bijl, 2025). The day-ahead congestion forecast is a particularly important feature, as it forms the basis for the agents' planning decisions in the model. Both the forecast itself and the load shift opportunities of the agents are grounded in the functioning of the day-ahead electricity market, where supply and demand bids are cleared one day before operation to create a binding schedule of energy transactions (Helman et al., 2008). In reality, these schedules are later adjusted with real-time conditions which motivates participants to plan based on next-day forecasts. In the model, agents do not trade in a market but instead rely on the forecasted congestion signal as a indicator for day-ahead market outcomes. Their decision to adjust demand is conceptually aligned with how market participants reschedule consumption in anticipation of expected prices and constraints.

In addition to daily operations, the CEMS periodically reallocates capacity among agents based on historical usage patterns (J. Kluijtmans, 2025). This prevents persistent under-utilization of capacity of participants and ensures that the available capacity is distributed proportionally to need.

To summarize Section 4.2, the following Figure 4.1 is created. In this Figure, the distinction and the relation between the agents and environment is visible.

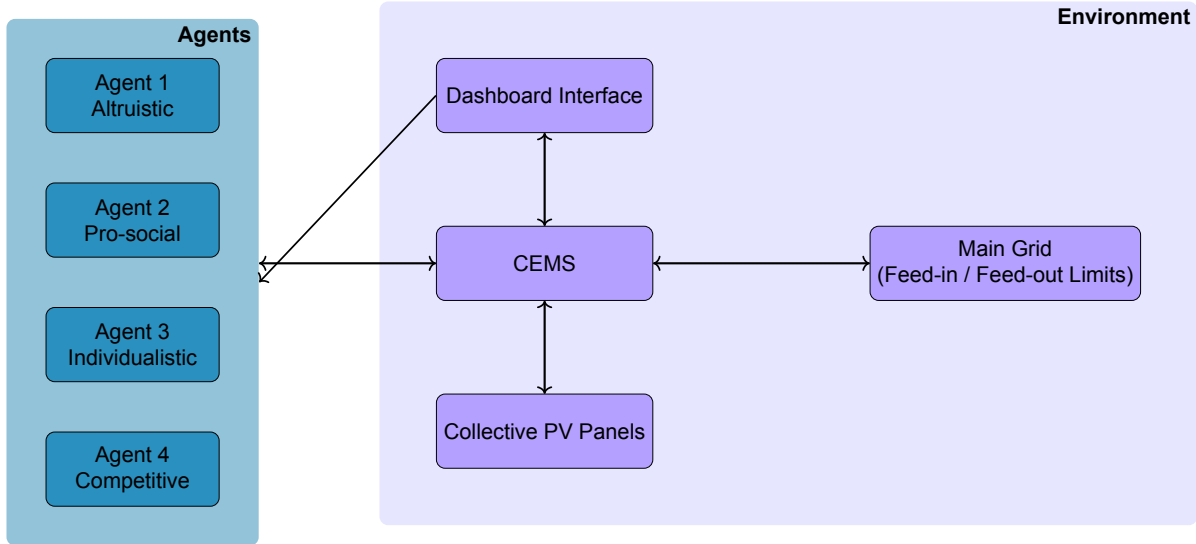


Figure 4.1: Conceptual Representation of the EH Environment and Agents.

4.3. Demand Profiles

In this section, an explanation is given of how the demand profiles of the agents in the model were set-up.

MeterInsight is a Dutch data platform that allows users to monitor the energy usage of clients. The platform retrieves energy data from diverse sources such as smart meters, submeters, solar panel inverters, and building management systems (MeterInsight, n.d.).

For this model, historical energy consumption data was retrieved from MeterInsight for a selection of companies. The raw data from MeterInsight included electricity usage at 15-minute intervals from the whole year of 2024. The year of 2024 is chosen, because the data is fully available for that year and it is the most recent year. The raw data with 15-minute intervals were converted to hourly intervals with Python code. The following figures represent the yearly and daily demand profiles of an anonymous company (Agent 5):

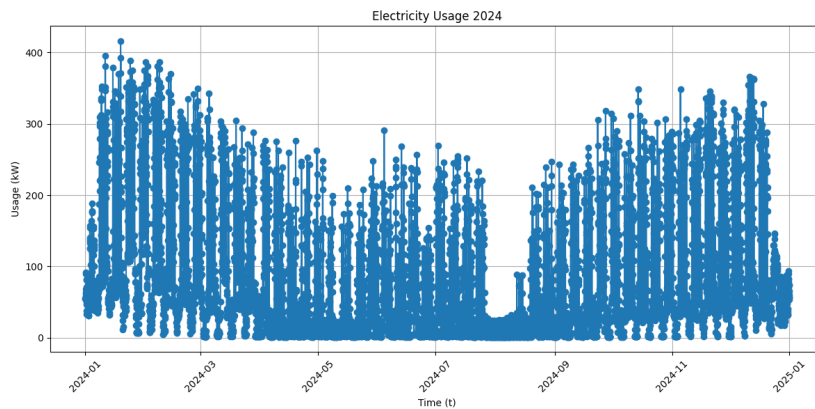


Figure 4.2: Electricity Usage of 2024 of an Anonymous Company (Agent 5)

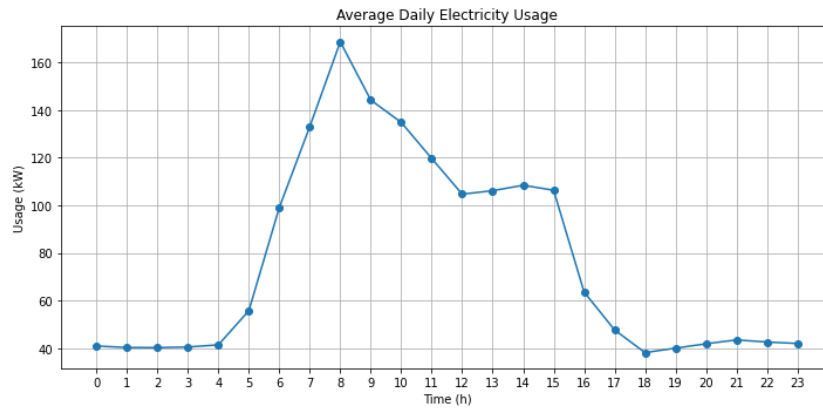


Figure 4.3: Average Daily Electricity Usage of an Anonymous Company (Agent 5)

The names of the companies are kept anonymous to ensure confidentiality and compliance with data privacy. However, the sector/specialization of each company was considered when processing the demand profiles. The sector/specialisation was used as guide to classify the total demand into four categories of capacity (Subsection 2.1.2) which is relevant for load shedding and load shifting. To continue with the previous demand profile, an example for this categorization is given below:

Table 4.1: Categorization of equipment preferences

Categorization	Detail	%
Sector/Specialization	Construction	
Fixed Preferent	Welding equipment	35%
Flexible Preferent	Sawing and drilling installations	30%
Fixed Non-Preferent	Dust suction	25%
Flexible Non-Preferent	Lights	10%

As seen from Table 4.1, the anonymous company specializes in construction which means that a big part of the electricity usage is from machinery and tools necessary for core production activities. It would be logical that the majority of the total demand originates from high-power critical equipment such as welding machines (Fixed Preferent) and sawing/drilling machines (Flexible Preferent). These categories reflect the essential production processes that either require constant operation or allow limited flexibility in scheduling.

Dust suction systems (Fixed Non-Preferent) are important for maintaining a safe and compliant working environment, but their timing is less critical to the production output and its electricity usage is not as much as sawing and drilling installations. Lastly, lights (Flexible Non-Preferent) are not particularly part of the production process, but are relatively low in power and have a higher degree of shiftability.

This reasoning and categorization is done for all agent's with their demand profiles. Agents could have different sector/specialization, which results in different types of capacity. If there is a bakery, their most important process is baking bread so an oven would be their Fixed Preferent capacity. Compared to all the other agents, Agent 5 also has a regular year demand and daily demand profile with a peak during the day and a dip in the summer. Appendix A represent the profiles and categorization of the agents. It shows the differences between the agent's profiles.

4.4. Group Contracted Transport Capacity

In this section, an explanation is given of how the Group Contracted Transport Capacity (in Dutch: Groeps Gecontracteerd Transport Vermogen, G-GTV) was determined for feed-in and off-take.

The choice to put a limit on both the feed-in and off-take is based on the fact that congestion not only occurs on the demand side, but also on the supply side (RVO, n.d.). For example, solar energy that is injected too much into the grid can lead to overloading the grid which forces grid operators (or in this

case EH operators) to implement curtailment. Since this happens in reality, including both the limits for feed-in and off-take makes the model more realistic with using operational constraints.

As said before in subsection 2.1.3, the G-GTV for both feed-in and off-take can be calculated through the aggregated profile of the group. The G-GTV can be calculated through determining the 95th percentile of the demand of the aggregated profile. The following figure portrays the aggregated profile of the demand profiles this model uses, with the maximum demand, the sum of the GTV of all demand profiles, and the G-GTV:

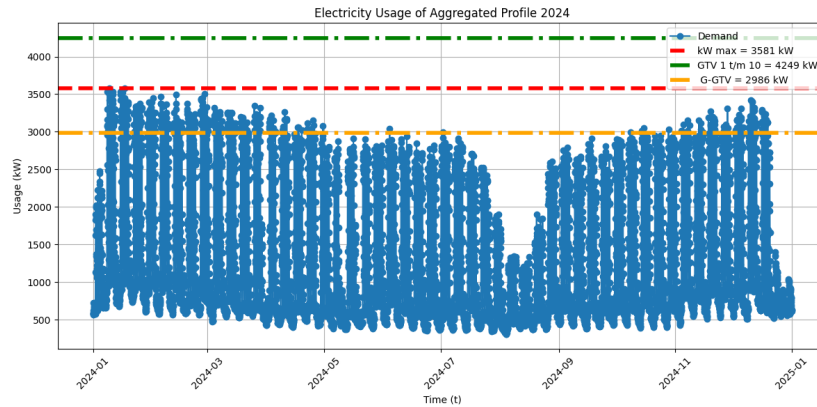


Figure 4.4: Aggregated Demand Profile

As seen in the previous figure, the maximum demand of the aggregated demand profile is around 3,581 kW (red line) which is reached around the first month of the year. This is likely due to the temperature during the winter months, meaning that the heating demand is higher than the summer months. Also, in the winter months there are shorter daylight hours meaning that the lights must be on for longer periods.

What to note is that there is also a decline in demand around the eight month of the year. This was also seen in Figure A.5a from Section 4.3. This could be explained by the fact that it is summer and some companies may have vacation, meaning that there are less processes going on. Furthermore, if the G-GTV for off-take would be calculated through summing up all the kW maxima of the demand profiles, it would be 4,249 kW (green line). This would be way higher than they actually need, meaning that there is too much capacity space left for the group.

So to actually calculate the G-GTV for off-take of the group the 95th percentile of the demand is taken, which is 2,986 kW (orange line). What is noticeable is that the actual G-GTV is a little lower than the kW max of the group. This is the case, because the G-GTV is designed to filter out extreme peaks such as the kW max that do not represent regular electricity usage. As noted by Joskow, 2008, designing energy systems based on infrequent peak values can lead to inefficiencies and over-investment in infrastructure.

The G-GTV for feed-in was calculated by first determining the ratio between feed-in of the EH and total electricity usage to which the demand profiles belong from MeterInsight. This ratio was then applied to the G-GTV for off-take to obtain a representative feed-in value. In this case, the ratio was 0.39, resulting in a G-GTV for feed-in of $0.39 \times 2,986 \text{ kW} = 1,179 \text{ kW}$.

4.5. Social Value Orientation Conceptualization

In this section, the conceptualization of SVO is given which explains how the SVO is implemented in the model and how the corresponding decision-making formulas are derived.

As said before in Subsection 2.1.1, there are four types of SVO individuals that can be distinguished from each other: Competitive, Individualistic, Pro-Social, and Altruistic. Starting with competitive individuals, they aim to maximize the difference between their own pay-off and other's pay-off in their favour.

Individualistic individuals aim to maximize their own pay-off and have little to no concern of other's pay-off. Pro-social individuals aim to maximize joint outcomes, while altruistic individuals prioritizes the other's pay-off above their own (Greiff et al., 2018; Murphy & Ackermann, 2014).

In this model, the context of the game is choosing to do nothing and just pay penalty or to load shift when congested hours are announced. However, for each decision there are social and individual costs attached, which affects the decision-making. The 'own' pay-offs in this context are the costs that an individual should make if they choose to pay penalty or load shift. The 'other's' pay-offs are the social costs that the rest of the EH must make if an agent chooses to pay penalty or load shift.

It can be said that the SVO types have their own self-interest weight, which determines the extent to which an agent prioritizes its own costs versus the social costs during decision-making. A higher self-interest weight means the agent gives more importance to minimizing its own costs, while a lower self-interest weight indicates a greater concern for the well-being of others. A categorization of self-interest weight could be formulated for the different SVO types:

Table 4.2: SVO types and their Self-Interest Weight

SVO Type	Self-Interest Weight
Competitive	0.9
Individualistic	0.7
Pro-Social	0.5
Altruistic	0.2

According to previous information given, two formulas could be created to capture the decision-making process:

$$\text{Score}(t) = W_{\text{self interest}} \cdot C_{\text{self}}(t) + (1 - W_{\text{self interest}}) \cdot C_{\text{social}}(t) \quad (4.1)$$

$$\text{Score}(t) = W_{\text{self interest}} \cdot C_{\text{self}}(t) - (1 - W_{\text{self interest}}) \cdot C_{\text{social}}(t) \quad (4.2)$$

Where:

- $C_{\text{self}}(t)$: the agent's own costs for penalty or load shifting
- $C_{\text{social}}(t)$: the cost imposed on others for penalty or load shifting
- $W_{\text{self interest}}$: the agent's weight on self-interest

The first formula 4.1 are for the altruistic, pro-social, and individualistic individuals as they do not aim to maximize the difference between their own pay-off and others. The second formula 4.2 is for the competitive individuals as they aim to maximize the difference between their own pay-off and others. If for example an altruistic individual must make a decision, their weight for self interest would be low meaning that they care less for themselves and more for the social costs.

According to this logic, a higher Score(t) implies a less preferred option, assuming that individuals aim to minimize cost. So agents choose the action with the lowest Score(t).

The agent's own costs for both penalties and load shifting are influenced by three main factors: the operational loss associated with load shifting, the agent's penalty sensitivity, and its load shift sensitivity. The social costs for load shifting are only influenced by the operational loss of shifting. In this calculation, it is assumed that agents have some information about the consumption of others with noise that mimics the agent estimate this amount. This assumption is made because there needs to some information available about others to 'know' the social costs. As discussed in Subsection 2.1.2, while a company

may theoretically benefit from shifting energy use to off-peak hours, practical constraints such as fixed production schedules, temperature control requirements, or quality assurance concerns can limit such shifts, leading to operational losses (Schwabeneder et al., 2019).

Price sensitivity plays a central role in this trade-off. It directly influences how strongly an agent reacts to both penalties and the potential savings from load shifting. In this research, it assumed that price sensitivity can be split into two categories for penalties and load shifting since the willingness to avoid penalties may not be the same as the willingness to load shifting. A highly penalty sensitive agent is more likely to avoid penalties by shifting loads, even if operational losses are present, whereas a less penalty sensitive agent may accept penalties as a cheaper or less disruptive option. As shown by Amini et al. (2019) and Carvalho et al. (2020), price sensitivity can significantly affect the effectiveness of price based demand response mechanisms.

Since the values for operational loss of load shifting, penalty sensitivity, and load shift sensitivity are not explicitly reported in the literature, there is no empirical basis to assign fixed values. These parameters are highly context-dependent and influenced by many factors. For instance, two companies with similar production processes may have different penalty sensitivities depending on their financial margins or contractual obligations.

Given this agent heterogeneity and the lack of concrete empirical data, these factors can be modelled as individual-specific attributes rather than uniform constants. To implement this variation in the model, these values are assigned randomly within predefined ranges (i.e. 0-1). This approach ensures that the simulation reflects a more realistic diversity of behavioural and operational profiles, rather than assuming that all agents respond identically to penalties or load shifting opportunities.

4.6. Penalty and Rewards

In this section, the mechanisms for penalties and rewards are discussed and an explanation is given for the origins of these prices.

Agents must pay a penalty if they are going over their allocated capacity and receive a money reward if they are under their allocated capacity and somebody else is using their capacity. The price for the penalty fee is derived from the electricity prices from 2024 and is assumed to be static: 0.3 €/kWh (CBS, n.d.). The choice to make the penalty price static is due to the fact that this research is only looking at the effects of behaviour and not a specific price incentive. If an agent uses too much then it would logically pay more penalty, so for the calculation of the penalty per hour the following formula could be used:

$$\text{Penalty}(t) = O(t) \cdot PF \quad (4.3)$$

Where:

- $O(t)$: overuse of capacity, the difference between their current demand and allocated capacity
- PF : penalty fee

Next, the rewards fee is derived from an actual agreement of Emmett Green and some anonymous EH where a fixed rewards fee was established. This rewards fee is intentionally set lower than the penalty fee to reflect the incentives in the system. While participants are encouraged to share unused capacity, the system places a stronger emphasis on avoiding congestion because it has to ensure that a system wide failure is avoided. Just as the penalty formula, if an agent uses too little capacity and someone else uses this, this agent would receive more rewards:

$$\text{Reward}(t) = U(t) \cdot RF \quad (4.4)$$

Where:

- $U(t)$: underuse of capacity
- RF : reward fee

4.7. Shared PV

This section explains how the PV generation profile was constructed.

As described before in subsection 4.2.2, the EH collectively owns the PV system which means that the CEMS has full access to those panels. For the purpose of this model, it is assumed that all PV panels are of a single type rated at 450 Wp, based on the average range of modern panels which typically falls between 400 and 500 Wp (Greenchoice, n.d.). The choice to assume that there is only a single type of PV panel is because this reduces complexity in the model. The surface area of a standard PV panel is approximately 2 m² (Zonnemarkt, n.d.).

According to the Dutch Ministry of Economic Affairs and Climate Policy (Ministerie van Economische Zaken en Klimaat, 2023b), the average roof surface area of Small and Medium-sized Enterprises (SME) ranges somewhere between 120 and 5,000 m². In this model, it is assumed that the combined available roof area for all agents totals in 8,000 m². This assumption is made, because 800 m² of roof surface area per company is randomly chosen and lies within the range. Since there are ten agents in the model, 800 m² is multiplied with ten which results in a total roof area of 8,000 m².

The amount of PV panels that could be placed on the roof area of 8,000 m² is 8,000 m² / 2 m² which results in 4,000 PV panels. It assumed that not all roof area is used for PV panels, because not all participants may have invested in PV panels and there are usually some structural constraints such as shading, roof load limits, and suboptimal slope angles further reduce the usable area. For this reason 30% of 4,000 PV panels is taken, which results in 1,200 installed PV panels.

The generation profile of one PV is based on general seasonal and daily patterns. In winter months, generation is lower due to shorter daylight hours, while in summer, output is higher due to longer days and increased solar intensity. Furthermore, generation is restricted to daytime hours only, with no production during the night.

4.8. Bounded rationality

This section describes how the model accounts for bounded rationality.

In the real-world, participants do not have perfect information about the behaviour or capacities of other participant's and their own capacity. Participants would also sometimes make non logical decisions due to personal reasons or other factors (Sovacool, 2014).

To take this into account in the model, uncertainty can be introduced and activated through a parameter. When this feature is activated, agents can estimate the available capacity from others and themselves using a noisy approximation instead of using an exact value. Also, when choosing an action the agents do not always choose the 'right' one as the noise influences their score of an action.

This noise is a stochastic distribution function that chooses a noise factor between certain values, such as the random uniform function.

4.9. Assumptions and Simplifications

In this model, certain assumptions and simplifications were made to focus on key dynamics, reduce complexity, and ensure computational feasibility while still capturing the important behaviours of the agents and their interactions within the environment. In this section, the most important assumptions and simplifications are given. The whole list of assumptions and simplifications can be found in Appendix B.

- The EMS has full operational control over shared assets.
- The EH only has PV as shared flexible asset.

- There is only one kind of PV panels of 450 Wp.
- The agents have 8,000 m² in total of roof space.
- The congested hours for the next day are assumed to be perfectly known and accurate.
- Agents know how much others are using.
- Each type of capacity is assumed to be one installation.
- Agents do not revise their strategies based on the outcomes.
- The decision-making formula assumes that the agents know how much others are using.
- The uncertainties of decision-making are covered by stochastic distribution functions.
- If there is no congestion the next day, the agents will not make a decision to load shift.
- Agents can only load shift their Flexible Preferent capacity.
- When rotational load shedding is activated, it will successively turn off the Flexible Non-Preferent, Fixed Non-Preferent, Flexible Preferent, and Fixed Preferent of an agent. If that is not enough, it will turn off the next agent on the rotation list.
- Agents can only choose to load shift; reducing their load is not included as a possibility.
- The agents have a GTO with each other and not another contract.

5

Model Operationalization

In the previous chapter, the conceptual model was discussed which included the model objectives, description of agents and environment, important concepts, and underlying decision-making structures. This chapter explains how these features are translated into a functioning and operational ABM. It will describe the Model Architecture, Model Parameterisation, KPI's, Base Case, and Model Verification.

5.1. Model Architecture

The model, input, and output files of this study for the operationalization can be found at the 4TU Research Data repository ¹.

This study models a day-ahead energy planning mechanism within an EH. The EH is composed of ten IC agents that operate within a shared infrastructure. The system was conceptualized with shared capacity constraints (G-GTV) and incorporates agent-based decision-making, which is formed by the SVO. The model simulates both the planning and execution phases of energy consumption, including bounded rationality and load shifting under constraints. The model runs for a whole year, which are 8784 steps or 8784 hours. Mesa uses discrete time steps (ticks) by default and during each time step the scheduler activates the agents, the agents performs its actions, the model state is updated, and eventually the step counter will go on to the next step. This process is visualized in the following Figure 5.1:

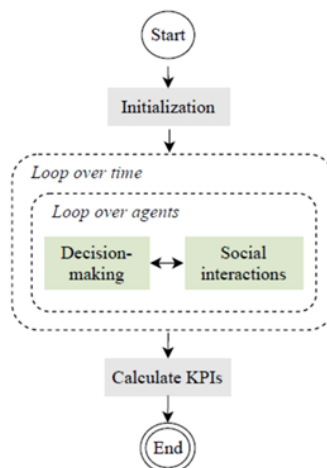


Figure 5.1: Simulation Flow of ABM (Werntges, 2020)

¹Accesible at: <https://doi.org/10.4121/1d4ad33a-1787-4057-8c1c-64a8ac47ef86.v1>

As mentioned before, at the core of the model there are ten heterogeneous agents, with each representing an IC with unique decision-making behaviours. These behavioural differences are modelled through SVO, a psychological and economic construct that describes how different types balance self interest against social welfare. These orientations can be categorized as the following:

- **Altruistic Agents:** Prioritize Social Welfare
- **Pro-Social Agents:** Balance Self-Interest with Social Welfare
- **Individualistic Agents:** Seek to maximize their own Welfare
- **Competitive Agents:** Actively pursue relative advantage on Welfare

Each agent is randomly assigned a SVO type with each run, when a certain distribution is implemented in the model.

Each agent has a portfolio of loads with different flexibilities and preferences. The loads consist of four types: fixed preferent, flexible preferent, fixed non-preferent, and flexible non-preferent. In short, the flexible loads can quickly respond to changes while the fixed can not quickly respond. The preferent loads have a higher priority than the non-preferent loads. In such way, the flexible preferent load can be shifted within the day but comes with operational cost.

The agent operates in a rolling, daily planning cycle which is structured into three phases: observe, decide, and action.

In the observe phase, the agents receive a 24-hour forecast of expected congestion for the whole EH. Agents will evaluate potential penalties for exceeding their allocated capacity and estimate the cost of shifting their flexible loads to non-congested hours. Under noisy conditions, agents estimate both forecasted demand and system constraints with potential errors which leads to suboptimal but human-like decision patterns. This simulates bounded rationality by introducing uncertainty into each agent's perception, which reflects real-world decision-making limitations. The agent will also look at which hours to shift their load to, if they eventually choose to load shift. The agent will examine all non-congestion periods within the same day, considering only time windows that fall within the agent's working hours, congestion conditions, and time proximity. If the agent chooses to load shift, it will choose the hours that are closer to now and that is the least congested.

In the decision phase, each agent selects a strategy based on their SVO. Agents weigh two options: paying a penalty for exceeding capacity allocations or shifting flexible demand to non-congested periods. The decision-making process is guided by utility functions that combine self-interest and social considerations, normalized to ensure fair comparison across cost components. Depending on the `use_noise` parameter, agents either make a deterministic choice of the action with the lowest normalized cost or a probabilistic choice, where actions with lower costs are more likely to be selected.

Next, in the action phase the agents will 'submit' their commitments for the next day with the assumption that they will be executed. As the planned day unfolds, the agents implement their predefined schedules. When the `use_noise` is on, unexpected behaviour may occur due to forecast errors or unanticipated events.

When the agents' actions all together threaten to exceed the EH's capacity, the centralized EMS will intervene. The EMS will apply rotational load shedding and curtailment of PV generation. These two mechanisms maintain the EH's stability and ensure that there is adherence to the contractual constraints. The rotational load shedding will turn off the loads in a certain order: the flexible non-preferent load, fixed non-preferent, flexible preferent, and at last the fixed preferent in urgent cases.

An important mechanism in the model is implicit capacity sharing. When one agent exceeds its allocated capacity while another underutilizes theirs, the system allows the surplus capacity to be reallocated in real time. The agent providing surplus capacity receives financial compensation, which serves as a natural economic incentive for capacity sharing.

The EH collectively owns 1,200 PV panels that can lead to some variability in the system. For example, on sunny summer days the panels may alleviate congestion. But when they generate more power than the EH uses, the excess must feed-in to the main grid. If this flow exceeds its limits, the CEMS will curtail the PV generation. On the other hand, in the winter when the days are shorter and it's not so

sunny the PV generation is reduced and will maybe help a little bit but not solve the whole congestion problem.

Every first day of each month, the CEMS learns from the consumption history of the agents and adjusts the allocated capacity for each agent. It will calculate the agents monthly desired capacity based on their historical consumption and calculates the average consumption with a 10% buffer above their actual average consumption. The 10% is for acknowledging that the energy demand can vary and gives some wiggle room. Afterwards, the CEMS uses an proportional allocation method which prevents any agent from hoarding unused allocated capacity. The agents have no choice in deciding how much capacity they want, because it is automatically distributed by the CEMS. This is due to model complexity reasons and the fact that agents could hoard unused capacity.

The following Figure 5.2 summarizes the Model Architecture into a flow chart:

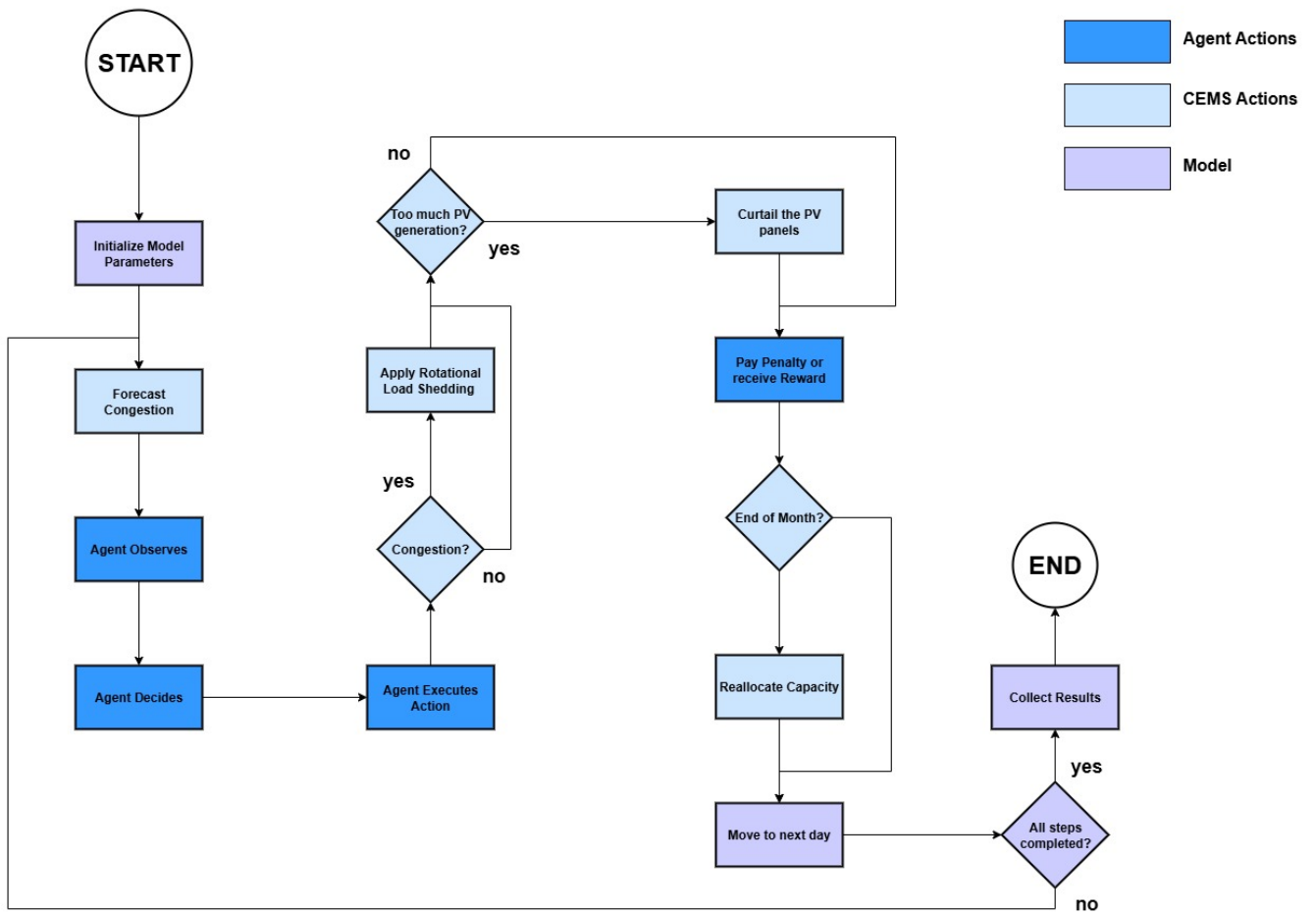


Figure 5.2: Flow Chart Model Architecture

As seen in Figure 5.2, the flow chart is divided into three colours/categories: Agent Actions, CEMS Actions, and the Model itself. From Forecast Congestion to Reallocate Capacity the timestep is one day, which is divided into 24 hours. The agent decide for the whole day and the CEMS will either load shed and/or curtail per hour.

5.2. Model Parameterisation

To operationalize the model, the model architecture from the previous section has been translated to code. This includes parametrization of the most important model variables. The model parameters that can be varied by the model and agent. The parameters and their ranges have been described in Table

5.1:

Table 5.1: Overview of Environment and Agent Parameters

Model Parameter	Range/Value	Description	Unit
Environment Settings			
Num_agents	10	The number of agents (IC) that are initialized in the model	[#]
Schedule	StagedActivation	The type of schedule the model adheres to. Agents are activated in a fixed order within each timestep.	[-]
Use_noise	True/False	If this is true, it will activate stochastic uncertainty to agent perceptions (e.g. estimating costs)	[-]
Load_shedding_method	Rotational	Load shedding will be rotational across the agents during congested events	[-]
Congestion_fee	0.3	The amount of penalty applied when an agent exceeds its allocated capacity	[€/kWh]
Reward_fee	0.2	The amount of compensation when an agent under-uses its allocated capacity and someone else uses this capacity	[€/kWh]
Max_capacity	2986	The collective maximum feed-out capacity based on the aggregated profile and 95th percentile	[kW]
Max_capacity_back	1179	The collective maximum feed-in capacity based on usage and generation ratio	[kW]
Rolling_horizon_hours	24	Number of hours the model evaluates looking ahead for scheduling load shifting	[h]
Amount_PV	1200	Total number of PV panels installed and collectively owned by the EH	[#]
Agent Settings			
ol_ls	0 – 1	Operational loss for load shifting: loss from example reduced product quality, increased personnel expenses, or other in-efficiencies	[€/kWh]
ps	0 – 1	Penalty sensitivity: how strongly an agent is influenced by paying penalty	[-]
ls	0 – 1	Load shift sensitivity: willingness of an agent to shift load	[-]
Has_shifted	True/False	Indicates whether an agent has already load shifted during a congestion event	[-]
Svo_type	Competitive, Individualistic, Pro-social, Altruistic	The type of an agent's SVO	[-]
Self_interest	0.2 – 0.9	Value depending on SVO type; determines how much weight an agent gives to its own vs. social costs	[-]
Shift_start_hour	5, 6	Hour at which the agent starts its working day and can shift its load	[h]

Model Parameter	Range/Value	Description	Unit
Shift_end_hour	18, 23	Hour at which the agent ends its working day and can no longer shift load	[h]

The values from Table 5.1 are found from data, interviews with experts, literature or based on assumptions. Behavioural aspects such as self-interest, penalty and load shifting sensitivity are linked to a random numeric value and are based on assumptions.

5.3. Key Performance Indicators

Key Performance Indicators (KPIs) are metrics used to measure the performance of the model and assess the success and effectiveness of its outcomes. They also help identify which scenarios produce the most favourable or unfavourable results. The KPIs used in this research are listed below with the reasoning:

- **Total Load Shifts:** This is the total number of times flexible preferent loads of agents is shifted to non-congested periods. This KPI is chosen, because it directly indicates how many times agents choose to load shift instead of doing nothing and just pay penalty. A higher number of load shifts suggests that agents are responsive to congestion signals and willing to adapt their consumption patterns to support system efficiency. It also reflects the operational feasibility of load shifting under the given constraints, including flexibility preferences, perceived costs, and behavioural factors. In this way, it serves as both a technical and behavioural indicator of demand side adaptability.
- **Total Penalties:** The total amount of fines imposed on agents when they exceed their allocated capacity limit. This KPI is chosen, because it reflects how many times an agent surpasses their allocated capacity limit, either due to insufficient flexibility in their load management or a thoughtful choice to prioritize demand over cost savings. It is possible that agents still have to pay a penalty, while they already have load shifted. The reason for this is that the amount of capacity that an agent has load shifted, may not be enough to keep their usage under allocated capacity limit.
- **Total Load Shedding:** The total number of times the CEMS had to reduce an agent's energy usage to prevent that the whole EH is going over the G-GTV. This KPI is chosen, because it shows how many times the CEMS had to interact with the EH and also reflects the EH's operational resilience and reliability. It also serves as an indirect measure of the effectiveness of an agent's planning and cooperation. In such way, fewer load shedding may suggest that agents are better at their demand response through load shifting or capacity sharing which reduces the need for a centralized CEMS action.
- **Total Rewards:** The total amount of compensation awarded to agents for giving up their capacity to another agent. This KPI is chosen, because it reflects the implicit capacity sharing of the agents. In the decision-making, agents take the reward fee into account when deciding to load shift or just pay penalty. So it is not only an economic but also a behavioural KPI as it captures how an agent's SVO and individual cost-benefit analysis influence cooperative behaviour. It could be said that a high total reward is equal to high amount of implicit capacity sharing, because it reflects the total implicit capacity sharing over all the agents.

5.4. Base Case

In this section, the base case is defined which serves as reference point. The base case is constructed by selecting representative values for key parameters. Table 5.2 provides an overview of these parameters, which includes the SVO composition of agents, the use of noise, load shedding strategy, congestion fee, and reward fee.

Table 5.2: Overview of Base Case

Parameter	Values
Num_agents	10
SVO composition	1 altruistic, 4 pro-social, 4 individualistic, 1 competitive
Use_noise	False
Load_shedding_method	Rotational
Amount_PV	1200
Congestion_fee	0.3
Reward_fee	0.2

As seen in Table 5.2, the SVO composition is set at 1 altruistic, 3 pro-social, 4 individualistic, and 1 competitive. This is based on the assumption that in real life, this composition follows a discrete distribution, because altruistic and competitive types are relatively rare in most populations, while pro-social and individualistic behaviours are more common.

The use_noise is set at false, as it serves as a reference point to a scenario where there is no bounded rationality. It shows the effect of the absence of bounded rationality in models by isolating the influence of the agent's decision-making with SVO and behavioural drivers. This allows for a comparison with scenario where use_noise is set at true, because it helps to understand how imperfect decision-making affects the KPIs.

5.5. Model Verification

According to Sargent, 2013, model verification is one of the crucial processes in developing a simulation model. Model verification is to ensure that the simulation model and its implementation are correct. The focus here is on the technical accuracy of the simulation model's implementation.

There are multiple possible ways to verify a model, however the verification in this study was inspired by van Dam et al., 2013 whereas two verification methods were chosen. The first method is the tracking of agent behaviour and has been performed during the iterative construction of the model. The second method consisted of checking the model under extreme conditions. The implementation of these model verification strategies and their results can be found in Appendix C, where the Base Case presented in Section 5.4 is used.

6

Experimental Design

The experimental design defines the structure and methodology used to evaluate the performance and behaviour of the developed model described in the previous Chapter 5. This chapter will specify the scenarios and its parameters implemented to test the model under various conditions. Furthermore, this chapter will discuss the methodology used to conduct the experiments.

6.1. Experimental Set-Up

This section discusses the type of scenarios and their implementation in the model. In the context of the EH, scenarios define the environmental and operational conditions under which the system is evaluated. For the experimental design, the focus is placed on varying the SVO compositions of the agents and using the noise parameter. This choice is motivated by the central role of agent heterogeneity in the model: each agent's SVO determines its decision-making strategy, balancing self-interest and social welfare. The noise parameter introduces bounded rationality, simulating uncertainty or imperfect perception of forecasts and system constraints.

By systematically varying the proportions of altruistic, pro-social, individualistic, and competitive agents, the experiments aim to reveal how differences in behavioural composition and bounded rationality affect the EH's operation. This approach isolates the influence of human-like behavioural diversity on system outcomes, providing insights into the resilience, efficiency, and coordination of the EH.

Table 6.1 provides an overview of the scenarios, the associated SVO compositions, noise usage, and the number of iterations per scenario. Each scenario is then described in detail, explaining the rationale behind its composition and the type of operational situation it represents.

Table 6.1: Overview of experimental scenarios

Scenario name	SVO composition	Use Noise	Runs
All altruistic	10 altruistic	Yes	50
All pro-social	10 pro-social	Yes	50
All individualistic	10 individualistic	Yes	50
All competitive	10 competitive	Yes	50
Equal mix	2 altruistic, 3 pro-social, 3 individualistic, 2 competitive	Yes	50
Cooperative dominant	5 altruistic, 5 pro-social	Yes	50
Competitive dominant	5 individualistic, 5 competitive	Yes	50
Polarized	5 altruistic, 5 competitive	Yes	50
Moderate	5 pro-social, 5 individualistic	Yes	50

6.1.1. Scenario: All Altruistic

This scenario includes ten altruistic agents, which is selected to explore the effects of a fully selfless population. The rationale behind this composition is to create a baseline in which collective welfare is the only guiding principle for all agents. By excluding any self-interest or competitive drive, this group serves as a clear reference point for understanding how purely cooperative motivations influence group composition in a simulated setting. Additionally, it serves as a comparative benchmark against more heterogeneous compositions.

6.1.2. Scenario: All Pro-Social

The pro-social scenario is composed entirely of ten pro-social agents, which is chosen to study a population where individuals consider both personal outcomes and the welfare of others. Unlike purely altruistic agents, pro-social agents balance self-interest with concern for others, making this composition a moderate expression of cooperative behaviour. The rationale for this composition is to understand how a homogeneous population with tempered social motivations interacts when no extreme selfishness or competitiveness is present. Just like the all altruistic scenario, it also serves as a benchmark to heterogeneous compositions.

6.1.3. Scenario: All Individualistic

This scenario includes ten individualistic agents, which is chosen to focus on the influence of pure self-interest. The composition isolates a population where personal priorities dominate over concern for others or competitive positioning compared to peers. By selecting a uniform group of self-interested agents, the scenario provides an environment to explore how a fully individualistic orientation shapes the social dynamics in the absence of cooperative or competitive pressures. Just like the all altruistic scenario, it also serves as a benchmark to heterogeneous compositions.

6.1.4. Scenario: All Competitive

This scenario includes ten competitive agents, which is selected to study the effects of prioritizing relative advantage above all else. The rationale for this composition is to observe a population in which competition is the sole guiding principle, providing a clear reference for understanding dynamics in a fully competitive setting. By focusing on a uniform competitive group, it is possible to distinguish the influence of less self-interested groups such as altruistic or pro-social. Just like the all altruistic scenario, it also serves as a benchmark to heterogeneous compositions.

6.1.5. Scenario: Equal Mix

This scenario consists of a balanced mix of agents: two altruistic, three pro-social, three individualistic, and two competitive. The rationale behind this composition is to represent a heterogeneous population that reflects multiple social motivations simultaneously. By including both cooperative and self-interested agents, the scenario allows for examining how diverse SVO can coexist within a group. The distribution emphasizes neither extreme altruism nor pure competitiveness, creating a population that integrates different priorities and perspectives. Overall, it can be said that it represents a realistic setting where multiple motivations are present.

6.1.6. Scenario: Cooperative Dominant

In this scenario, five altruistic and five pro-social agents form the population which creates a cooperative dominant group. The rationale for this composition is to emphasize collective welfare as the primary driver within the population while maintaining some diversity of cooperative orientations. Altruistic agents ensure full selflessness, while pro-social agents introduce a balance of self-interest and concern for others.

6.1.7. Scenario: Competitive Dominant

This scenario includes five individualistic and five competitive agents, which is designed to create a population where self-interest and relative advantage dominate. The rationale for this composition is to represent a group strongly oriented toward personal benefit, while excluding cooperative influences. Individualistic agents provide self-centred priorities, whereas competitive agents add a focus on relative positioning within the group.

6.1.8. Scenario: Polarized

The polarized scenario consists of five altruistic and five competitive agents, which is chosen to examine the effects of extreme divergence in SVO. The rationale behind this composition is to explore a population where motivations are at opposite ends of the cooperative-competitive spectrum, creating a sharply divided motivational landscape. Altruistic agents prioritize collective welfare without self-interest, while competitive agents focus entirely on relative advantage, establishing a clear contrast within the group.

6.1.9. Scenario: Moderate

This scenario includes five pro-social and five individualistic agents, forming a population characterized by moderate divergence in SVO. The rationale for this composition is to examine a population where motivations are neither fully cooperative nor purely competitive, but instead hold intermediate positions. Pro-social agents balance self-interest with concern for others, while individualistic agents focus solely on personal outcomes which creates a moderate contrast within the group.

6.2. Methodology

The experimental set-up builds on the base case defined in Section 5.4, which serves as a benchmark scenario. In the base case, the parameter `use_noise` is set to `False`, representing fully rational agents with perfect foresight. This configuration provides a reference point against which the impact of bounded rationality and behavioural diversity can be evaluated.

In the scenarios, `use_noise` is activated `True` to capture decision-making under imperfect information, introducing a more realistic representation of agent behaviour. Combined with different SVO compositions, the previously introduced scenarios allows to explore how heterogeneity and homogeneity of SVO and uncertainty affect system performance.

The experiments were implemented by using Python. While the Mesa framework's `Batchrunner` module can be used to run multiple scenarios and iterations (Mesa-Team, n.d.), it was not used here because from experience it does not allow easy observation of results over time. Instead, the simulations were executed using traditional `for-in` loops, providing direct control over each iteration.

Each scenario was simulated over a full year to capture potential seasonal and temporal variations in agent interactions. To account for stochastic effects and ensure representative results, 50 independent iterations were conducted per scenario.

This approach is consistent with the methodology used in the thesis by Vliet, 2022, which also applied ABM. Vliet, 2022 demonstrated that a single model run cannot reliably indicate the effect of parameter settings on the KPIs. Averaging outcomes over multiple runs provides a more accurate approximation of expected results. Her work shows that 50 iterations produce an outcome curve closely matching the average of 1000 runs, which confirms that this number of runs is sufficient to obtain representative results.

7

Model Results

This chapter presents the results generated by the simulations. The outcomes are shown without interpretation, providing a structured overview of how the model behaves under different experimental settings. The chapter begins with the base case, which serves as a point of reference and reflects a representative configuration of agents without bounded rationality. The base case establishes a consistent benchmark against which the outcomes of the experimental scenarios can later be compared. Afterwards, the experimental scenarios are presented individually. Each scenario corresponds to a distinct composition of SVOs among the agents, combined with bounded rationality.

7.1. Base Case Results

This section presents the results of the base case scenario. In this setup, the distribution of SVO types among agents was modelled using a discrete normal distribution. The cumulative outcomes over one year are shown in Figure 7.1, while the monthly distribution of KPIs is illustrated in Figure 7.2.

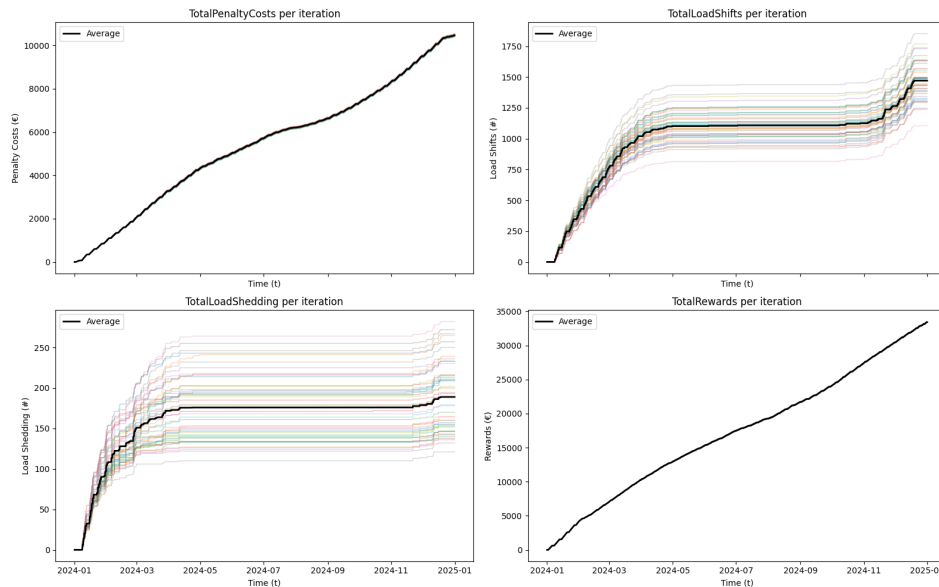


Figure 7.1: Base Case Result

The results from Figure 7.1 show that both load shedding and load shifting increase during the first months of the year, level off during the middle of the year, and rise again towards the end of the year. On average, the number of load shedding events reaches about 188, while load shifts average around

1,469. Penalties and rewards follow a more linear trend: rewards accumulate up to around €33,405, whereas penalties reach up to €10,468. It is also notable that the variation across runs is relatively large for both load shedding and load shifting.

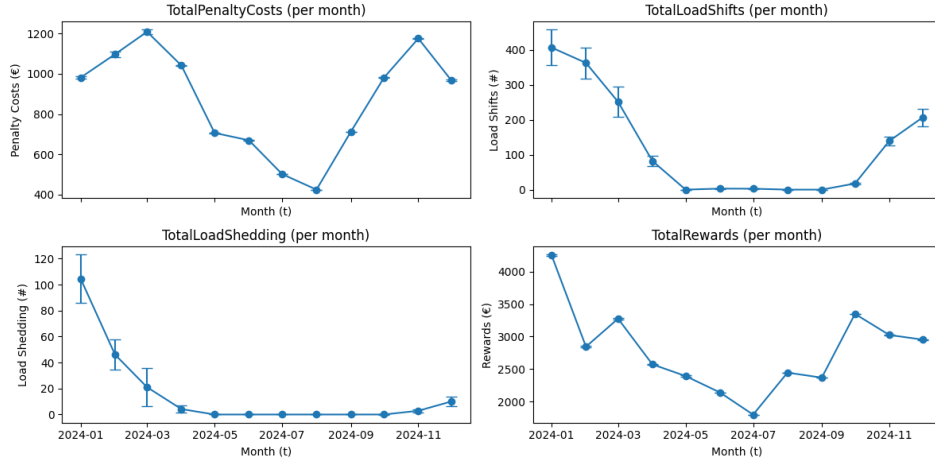


Figure 7.2: Base Case Monthly Result

From Figure 7.2 it can be seen that penalties and rewards show a clear seasonal pattern. Both are lowest during the summer months, while peaks occur in the early and late parts of the year. The highest monthly penalty of €1,209 is observed in March, whereas the largest monthly reward of €4,247 occurs in January. Load shedding peaks at around 104 events in January before dropping to nearly zero in summer, while load shifting reaches a maximum of about 406 events. Variability across runs is relatively small for most months, except during the first quarter, where the standard deviation is noticeably higher.

7.2. All Altruistic Results

In this scenario, the outcomes for the fully altruistic EH are reported. Figure 7.3 summarizes the cumulative development of the KPIs throughout the year, while Figure 7.4 depicts the monthly averages including their variation across runs. Both figures represent the system-wide totals.

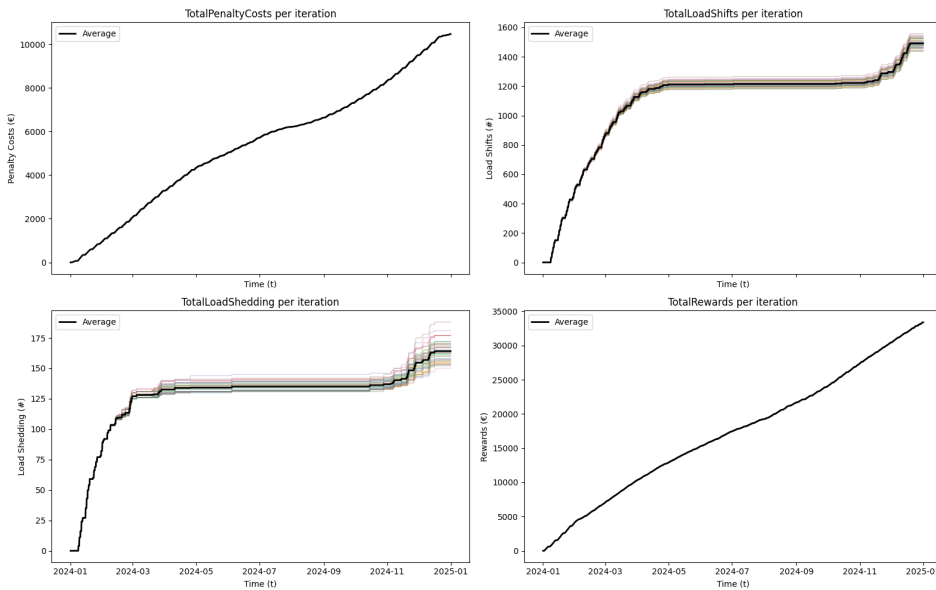


Figure 7.3: All Altruistic Yearly Result

What can be seen from Figure 7.3 is that both Load Shedding and Load Shifts increase rapidly in the beginning of the year, stagnates in the middle of the year, and increases again towards the end of the year. On average, annual load shedding stabilizes around 164 times, while load shifts accumulate to about 1491 times. Penalties and rewards follow a more linear trajectory, with rewards reaching up to €33,386 and penalties up to €10,470. The curves indicate that most runs remain close to the mean, though some divergence becomes visible for load shedding at the end of the year.

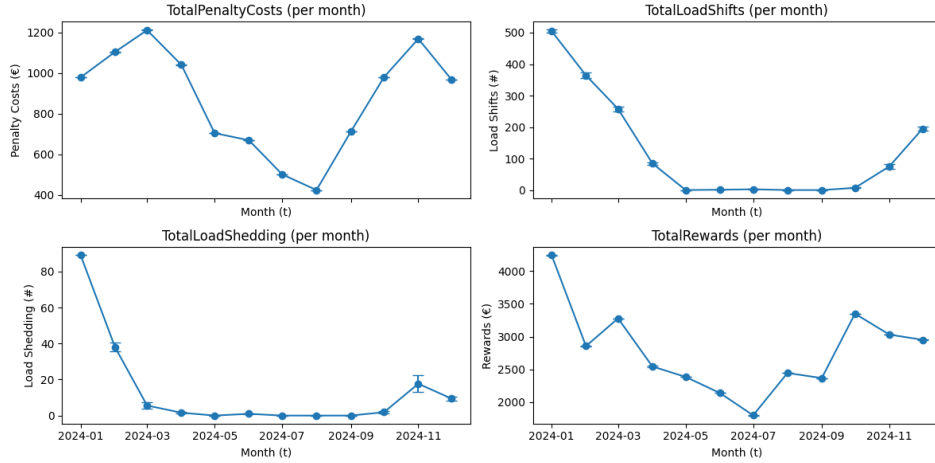


Figure 7.4: All Altruistic Monthly Result

Turning to Figure 7.4, a seasonal pattern emerges: both penalties and rewards are lowest in the summer months, while peaks occur in early and late months of the year. The maximum monthly penalty of €1,212 is recorded in month three, and the highest monthly reward of €4,239 occurs in month one. Load shedding peaks around 89 events in January before dropping to almost zero in summer, whereas load shifts reach about 504 at their maximum. Across runs, variability per month is minor, suggesting consistent outcomes.

7.3. All Pro-social Results

The second scenario explores an EH consisting entirely of pro-social agents. Cumulative annual results are displayed in Figure 7.5, and monthly averages with their spread in Figure 7.6.

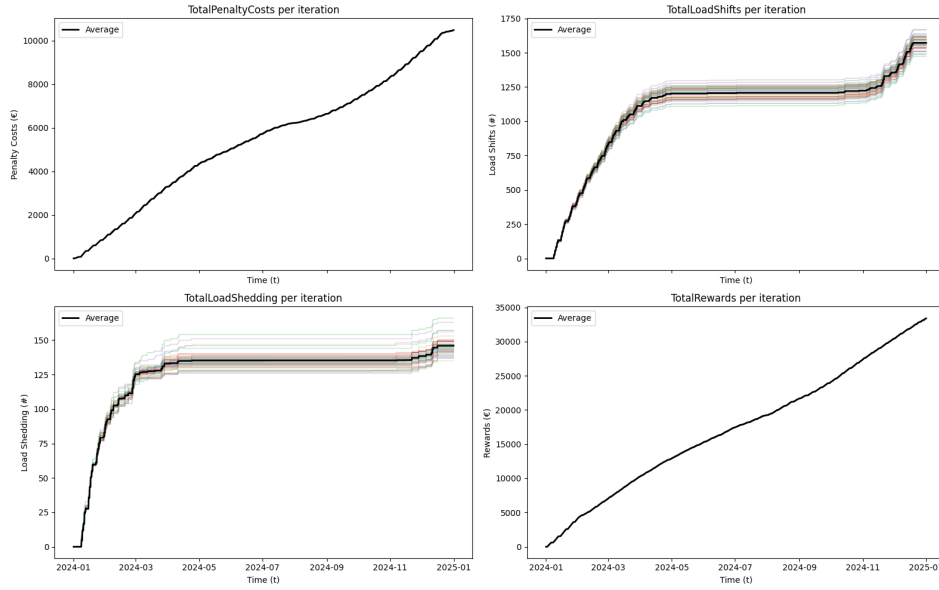


Figure 7.5: All Pro-Social Yearly Result

Figure 7.5 shows a growth pattern for load shedding and load shifting similar to the base case: a strong rise at the beginning, a plateau mid-year, and renewed increase towards December. Annual totals amount to about 146 load shedding events and roughly 1,572 shifts. Rewards again approach €33,382, with penalties much lower reaching around €10,483. Unlike the altruistic case, variation between runs becomes apparent after the second month, especially in load shedding.

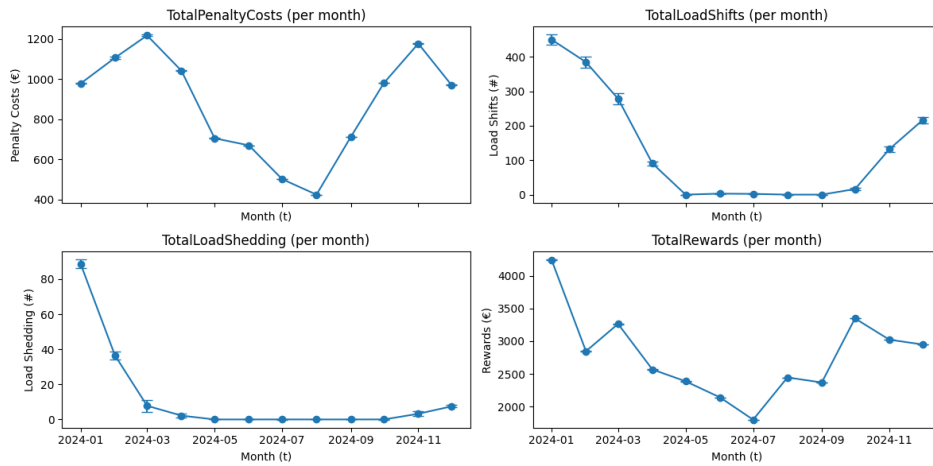


Figure 7.6: All Pro-Social Monthly Result

Monthly averages in Figure 7.6 show that summer months are less demanding for the EH, with reduced penalties and rewards. The third month records the highest penalties with €1,216, while the first month shows rewards exceeding €4,243. The maximum load shedding (89 events) and load shifting (449 events) both occur at the beginning of the year, followed by a steady decline. Deviations across runs remain limited, though slightly larger than in the altruistic scenario.

7.4. All Individualistic Results

Here, the focus shifts to the fully individualistic EH. Figure 7.7 presents cumulative KPIs, while Figure 7.8 gives average monthly outcomes and their variation.

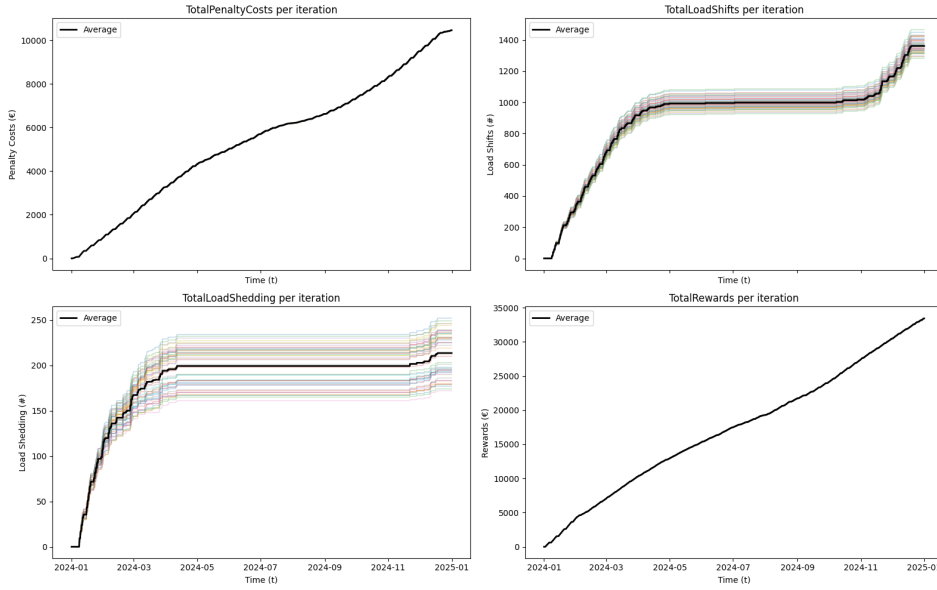


Figure 7.7: All Individualistic Yearly Result

As can be seen in Figure 7.7, cumulative load shedding and load shifting increase rapidly early in the year, then level off during summer, before rising again towards the end of the year. Compared to the pro-social scenario, load shedding is somewhat higher with 213 events annually, while load shifting stays closer to 1,361. Rewards once again trend towards €33,429 and penalties around €10,457. The spread between runs becomes more pronounced after the second month, with noticeable differences in the load shifting graph.

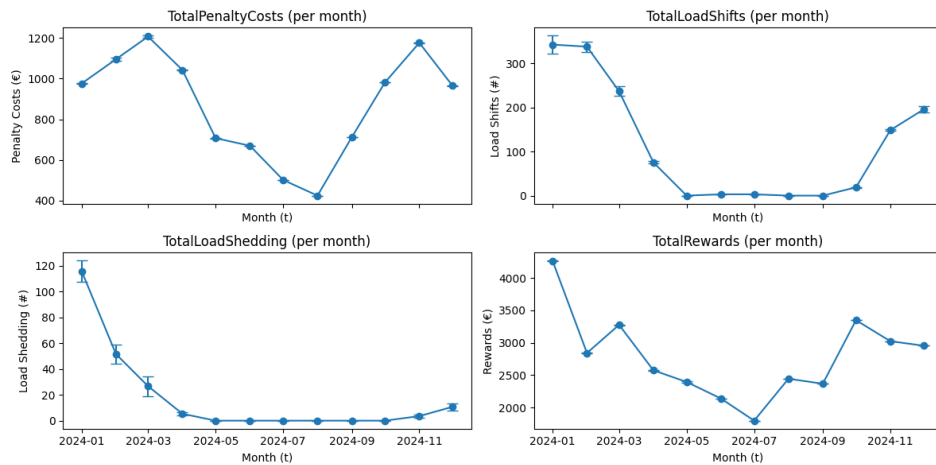


Figure 7.8: All Individualistic Monthly Result

Monthly dynamics in Figure 7.8 show clear peaks early in the year: about 115 load shedding events and 337 load shifts in January. Both KPIs drop significantly by summer, before slightly climbing again in the autumn months. Penalties reach around €1,206 in month three, while rewards top €4,260 in month one. While the standard deviation per month is generally small, the first quarter shows slightly higher variability, particularly in load shedding.

7.5. All Competitive Results

The final homogeneous case is the competitive EH. The annual cumulative numbers are shown in Figure 7.9, and monthly averages in Figure 7.10.

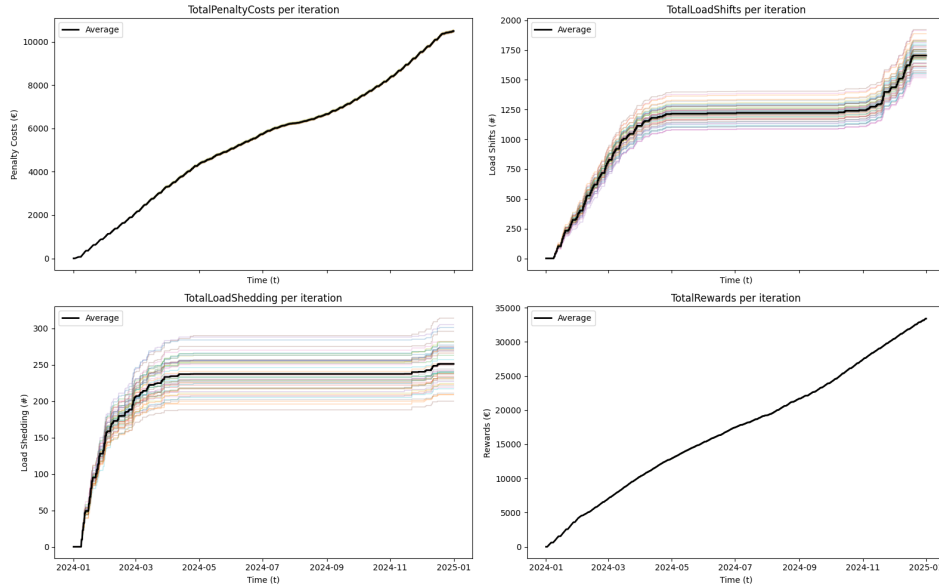


Figure 7.9: All Competitive Yearly Result

In Figure 7.9, load shedding and load shifting once more show a rapid start, a mid-year slowdown, and a renewed upward trend at the end. Here, shedding reaches 251 events annually, while shifting approaches 1,704. Rewards remain close to €33,404 with a relatively steady progression and the penalties also remain close to €10,488. Run-to-run variability is larger than in the previous cases, particularly after the first months.

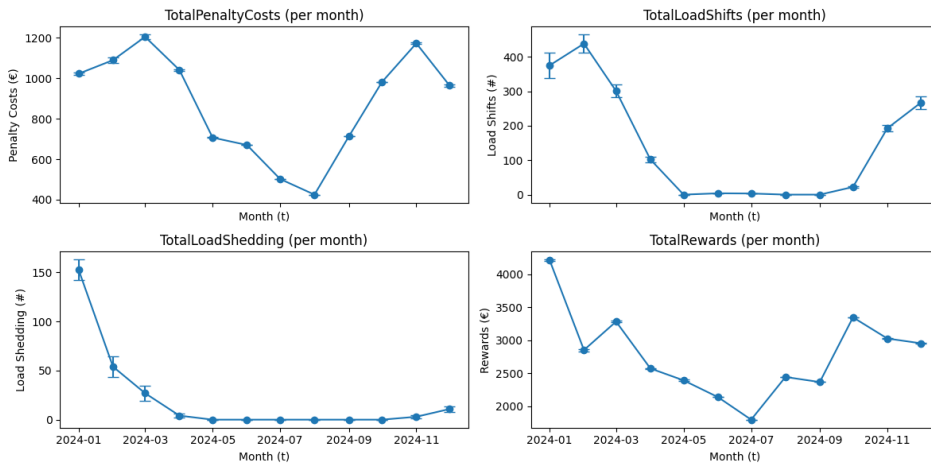


Figure 7.10: All Competitive Monthly Result

From Figure 7.10, penalties again peak around month three with €1,204, and the largest monthly reward close to €4,214 in January. Load shedding reaches about 152 events in the first month, while load shifting peaks around 438. Both indicators decline during summer before rising again towards the year's end. Although monthly variation is generally modest, the initial months show greater spread across runs, especially for shedding and shifting.

7.6. Equal Mix Results

In this section, the results of the scenario of equal mix is shown. Figure 7.11 shows the yearly cumulative results and Figure 7.12 shows the monthly averages.

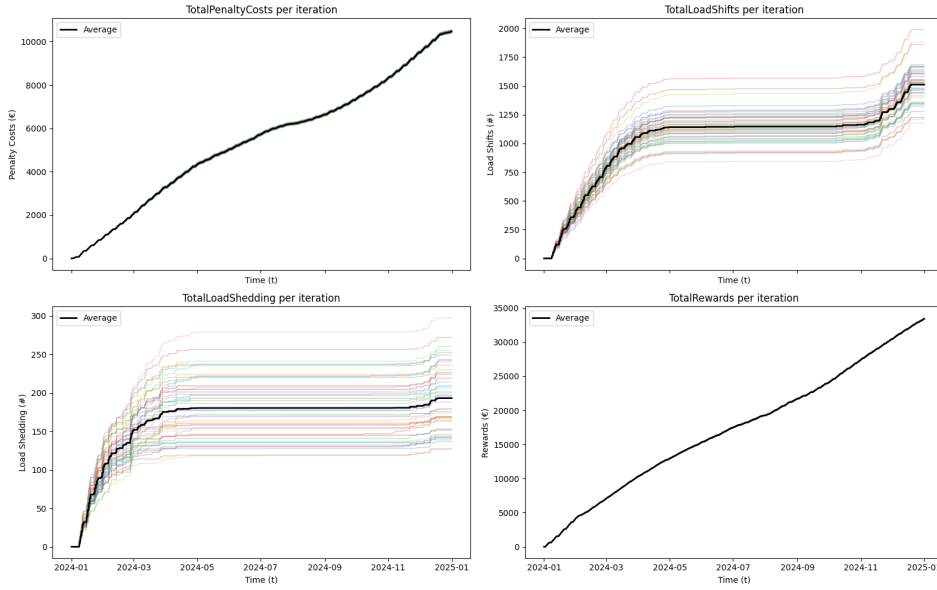


Figure 7.11: Equal Mix Yearly Result

What can be seen from Figure 7.11 is that once again the load shedding and load shifting graphs increases in the beginning, stagnates in the middle of the year, and slightly increase again towards the end of the year. For load shedding the average number reaches approximately 193 and for load shifts up to 1511 times. Just like all the other scenarios, the penalties and rewards stay linear, reaching €10,456 and €33,409 respectively. Here, the run variability is larger in comparison with the previous scenarios.

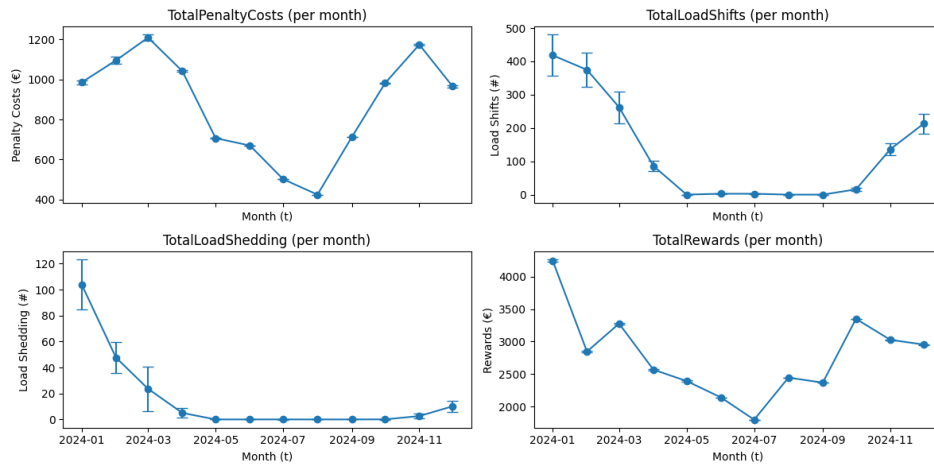


Figure 7.12: Equal Mix Monthly Result

From Figure 7.12, it can be noted that all the graphs follow the same trend as the homogenous scenarios. Penalties again peak around month three with €1,209, and the largest monthly reward close to €4,246 in January. Load shedding reaches about 104 events in the first month, while load shifting peaks around 418. Both load shedding and shifting decline during summer before rising again towards the year's end. Although monthly variation is generally modest, the initial months show greater spread across runs, especially for load shedding and shifting.

7.7. Cooperative Dominant Results

In the cooperative dominant scenario, the majority of agents are assigned altruistic or pro-social SVO types. Figure 7.13 presents the yearly cumulative results, while Figure 7.14 shows the monthly breakdown of KPIs.

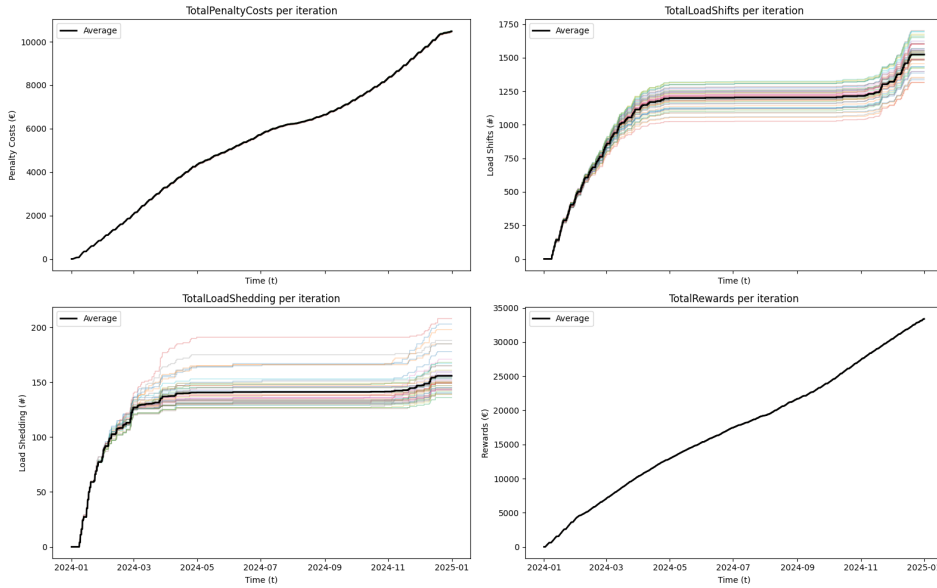


Figure 7.13: Cooperative Dominant Yearly Result

It can be seen that in Figure 7.13 load shifting is the dominant response in this scenario, averaging around 1,524 events by the end of the year, while load shedding remains relatively limited at about 156 events. Both shedding and shifting increase in the early months, stagnate during summer, and then rise again slightly in autumn. Rewards accumulate steadily, reaching nearly €33,390, while penalties stay low at around €10,477. Variability across runs is noticeable for load shedding, but for load shifting this is smaller.

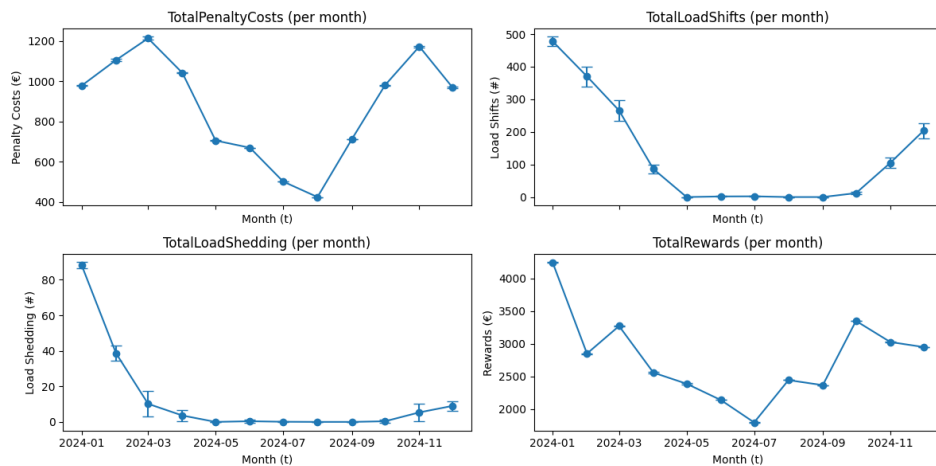


Figure 7.14: Cooperative Dominant Monthly Result

The monthly pattern in Figure 7.14 shows that load shifting is consistently present, peaking at around 477 in January. Load shedding is concentrated in the winter months but remains low during summer and its peak is around 88 in January. Rewards follow the same seasonal trend, with the highest monthly value slightly exceeding €4,241 in January, while penalties peaks at €1,213 in January.

7.8. Competitive Dominant Results

In this section, the results for the competitive dominant configuration is presented. Here, every agent either is individualistic or competitive. Figure 7.13 present the results throughout the year and Figure 7.14 present the results per month.

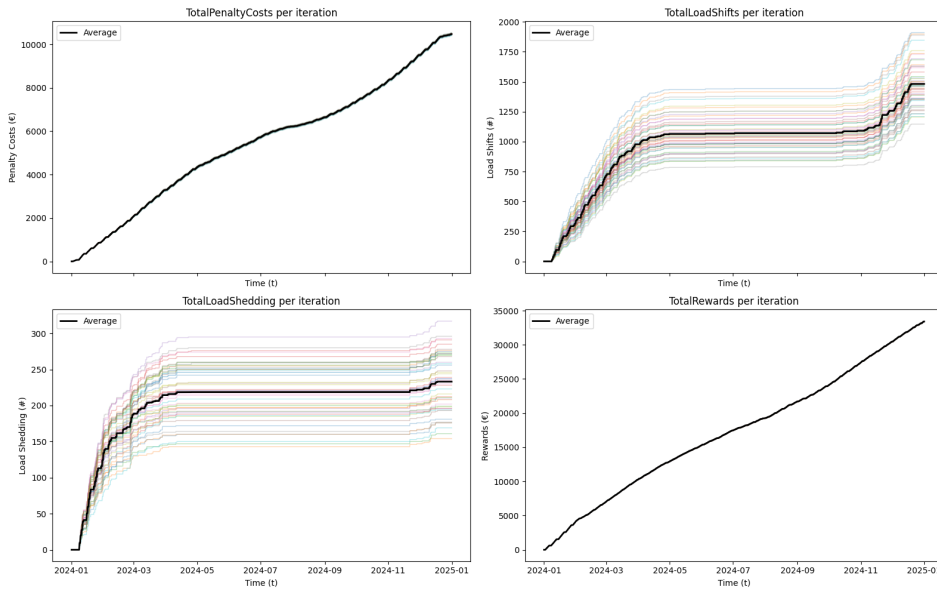


Figure 7.15: Competitive Dominant Yearly Result

From Figure 7.13 it can be seen that, once again, the load shifts and load sheds follow a trend that it increases in the beginning, stagnates in the middle, and slightly increase in the end of the year. The load sheds on average results in 246 and load shifting in 1517. For penalties and rewards the number is again €10,500 euros and for rewards €33,397. Load shedding and Load shifting are variable throughout all runs.

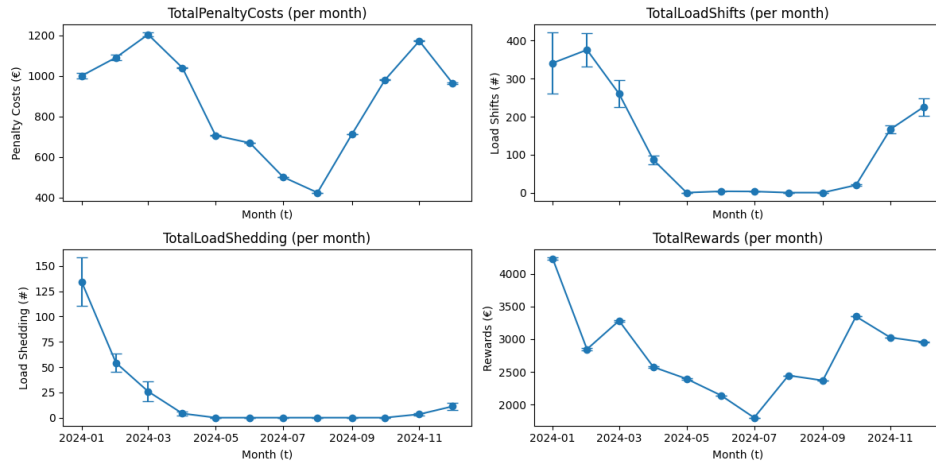


Figure 7.16: Competitive Dominant Monthly Result

From Figure 7.16 it can be seen that penalties are consistently higher across months, with a peak of €1,215 in March. Rewards are comparatively modest, rarely exceeding €4,237. Load shedding peaks at nearly 140 events in January, while load shifting reaches a maximum of about 387 in February. Summer months show reduced activity in both categories, though variability across runs is still visible in the first three months for load shedding and load shifting.

7.9. Polarized Results

In the polarized scenario, altruistic and competitive agents are present creating a divided agent population. Figure 7.17 reports the cumulative yearly outcomes, and Figure 7.18 provides the monthly results.

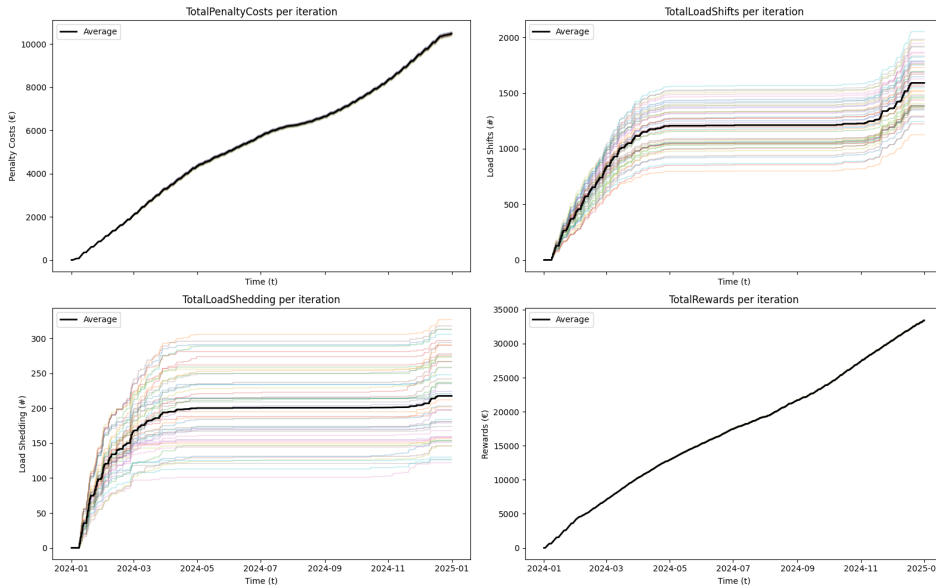


Figure 7.17: Polarized Yearly Result

Figure 7.17 show that both load shedding and shifting occur at notable levels: shedding ends with about 218 events, and shifting reaches nearly 1,591. Their trajectories show the same pattern of increase early in the year, stagnation in summer, and a small rise again at the end. Rewards reach about €33,404, while penalties accumulate to €10,475. Variability is high, especially in load shifting and load shedding where there are different outcomes across the runs.

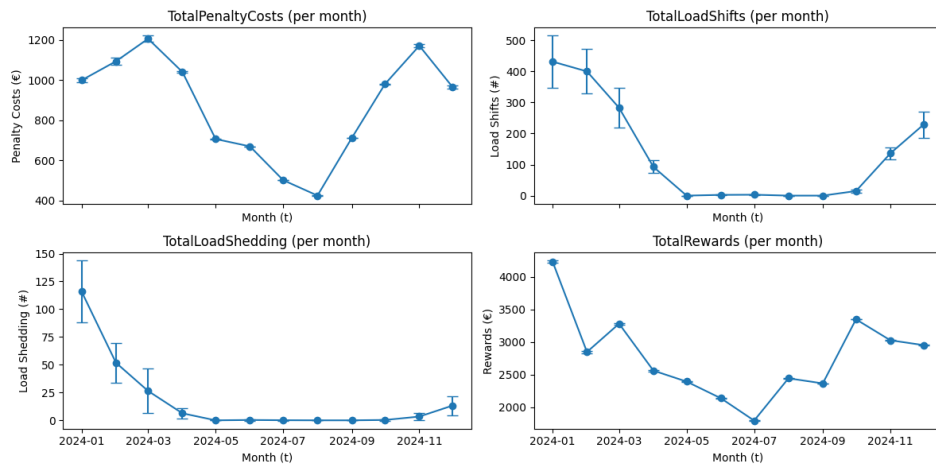


Figure 7.18: Polarized Monthly Result

From Figure 7.18 it becomes clear that the seasonal effect of load shedding is concentrated in the winter months with up to 115 events in January, whereas load shifting is follows almost the same pattern, with a maximum of around 431. Rewards peak in the early months, above €4,230 in January, while penalties show their maximum in March at around €1,206. Variation across runs is significant in the early part of the year but becomes less pronounced during summer for load shedding and load shifts.

7.10. Moderate Results

In this section, the moderate results are presented where only pro-social and individualistic agent occur. Figure 7.19 summarizes the cumulative yearly results, and Figure 7.20 shows the monthly KPIs.

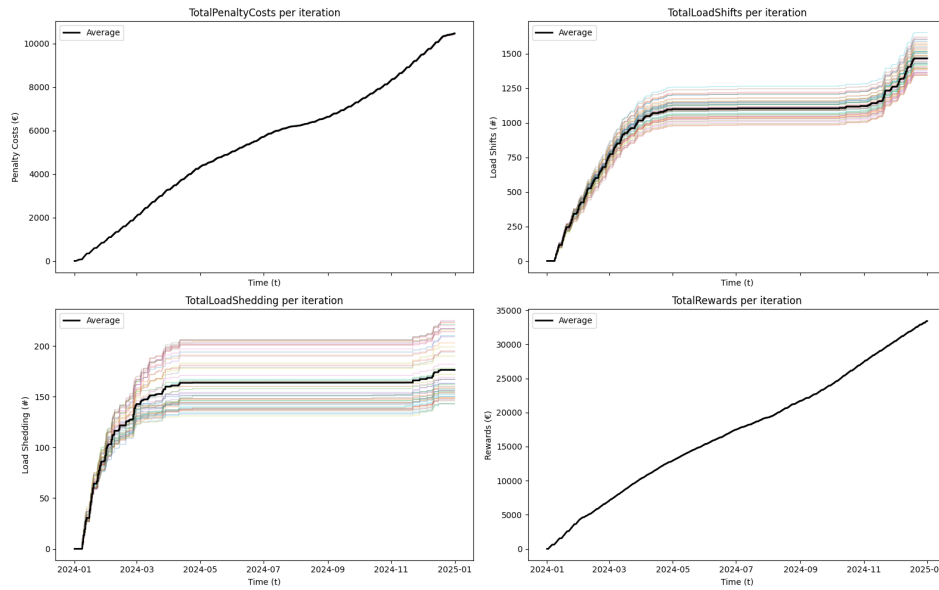


Figure 7.19: Moderate Yearly Result

The results from Figure 7.19 show a balanced outcome: load shedding averages around 176 events, while load shifting ends at 1,466. Both metrics rise at the beginning of the year, stagnate through the middle, and then climb slightly again in late months. Rewards accumulate to approximately €33,407, and penalties end around €10,468. Variability across runs is present but less compared to the polarized case.

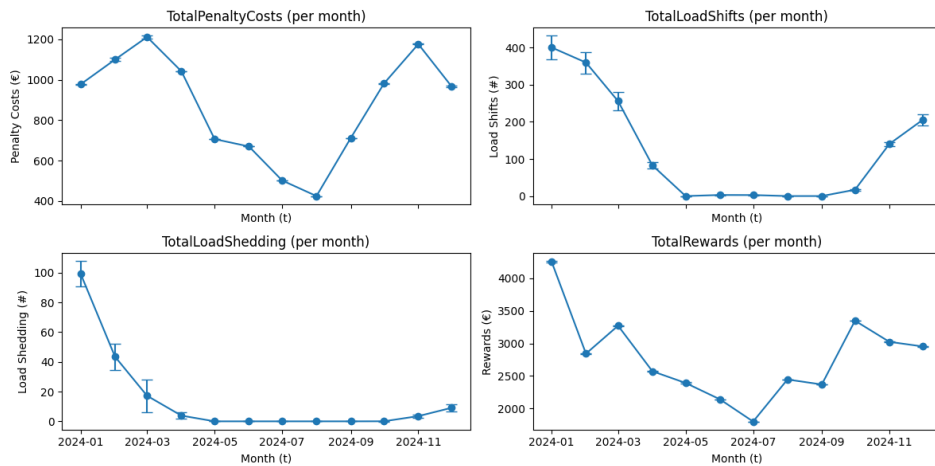
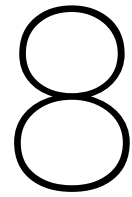


Figure 7.20: Moderate Monthly Result

Monthly from Figure 7.20 outcomes show the same seasonal trend as the base case: low penalties and rewards during summer and peaks in winter months. The maximum penalty of about €1,210 occurs in March, while the largest monthly reward, above €4,254, occurs in January. Load shedding is highest in January (around 99 events) and nearly disappears in summer, while load shifting peaks at about 400. Variability across runs is somewhat visible in the first months, but small for the rest of the year.



Model Analysis

This chapter interprets and compares the results presented in Chapter 7. While the previous chapter reported the outcomes of each scenario individually, this chapter analyses these findings to identify overarching patterns, differences, and implications. This chapter begins with validating the model and proceeds to the analysis of the model results.

8.1. Model Validation

Traditional model validation involves assessing whether a model accurately represents the real-world system and its behaviour (Dam et al., 2013). However, there is no real-world situation to compare this with, as this model represents a future EH with a GTO that is already running. When investigating a future scenario, the model validation should focus on whether it is useful and convincing in its system behaviour. The output values are in this case not as important as the insights provided by the model (Dam et al., 2013). According to Sargent, 2013, each model is created with a purpose and should be validated in relation to this purpose.

8.1.1. Model Validation in Relation to Model Purpose

The purpose of this study's model was to gain knowledge about the effects of SVO on participation in demand response. The model purpose can be validated by analysing the results of the experiments and asking to one's self if the results seem accurate and acceptable.

First of all the model input data is not empirical. Many assumptions and simplifications were made, which led to a simplified version of the real-world energy system. For this reason, the model does not accurately predict the actual values of penalties, load shifts, load sheds, and rewards if different SVO compositions would be implemented. However, the relative changes and range differences in the experiment results can be interpreted and validated.

When looking at load shedding, it becomes clear that it increases with every SVO composition throughout the year. This behaviour seems valid as it corresponds to the effects of less cooperative orientations found in the literature, where self-interested behaviour reduces willingness to load shift for the benefit of the system. In contrast, scenarios dominated by pro-social or altruistic agents show lower levels of shedding and higher levels of shifting, which is consistent with theoretical expectations. The relationship between penalties, rewards, and the SVO composition also appears logical, with competitive agents leading to higher penalties and individualistic agents achieving more rewards.

Overall, the model grasps the relative dynamics between different SVO compositions and their impact on demand response participation. While the absolute values should not be interpreted as real-world predictions, the patterns and relationships observed in the results correspond to expectations from the literature and therefore validate the model in relation to its intended purpose.

8.1.2. Extensive Model Validation Approach

Extensive model validation would require a high amount of resources and time, which were unfortunately not available within the scope of this thesis. A more traditional validation could be applied to this research, but would demand more effort. Nevertheless, a potential approach to validate the model can be proposed.

Even though there is no model available that compares with this model, cross-validation of model components could serve as a starting point. For instance, the simplified EH representation, and the pricing mechanism could be validated against existing models in the literature. Financial aspects such as the implementation of penalties, rewards, and operational loss of load shifting could also be compared to established models from energy economics or demand response studies. In addition, insights from models outside the energy sector that use financial incentives to influence behaviour could provide useful reference points, even if the applications are not directly comparable.

A particular challenge is the behavioural dimension of the model, which has not often been represented in quantitative simulations of energy systems. This makes it difficult to find directly comparable benchmarks. For this reason, expert validation could be an appropriate and effective method. Experts in energy policy, consumer psychology, and behavioural economics could provide feedback on whether the modelled agent responses to incentives and system conditions are realistic, and how the assumptions might be improved. Such expert assessment would also be valuable for evaluating the general assumptions underlying the future-oriented scenarios employed in this study.

Another widely used validation method is empirical validation, where model outcomes are compared to observed data or historical events. While this is challenging in this study due to the focus on a future scenario of EHs with different behaviours of agents, some aspects of the model could still be validated at a higher level. For example, empirical studies on congestion patterns, flexibility utilization, or load-shifting behaviour in existing energy systems can be used as benchmarks to assess whether the model produces logical behavioural responses.

Overall, while an extensive validation was not feasible in this thesis, a combination of cross-validation, expert validation, and partial empirical comparisons would provide a solid framework for further validating and improving the model in future work.

8.2. Analysis of Model Results

This analysis examines the four main KPIs: load shedding, load shifts, rewards, and penalties. General patterns and seasonal variations are discussed, followed by a discussion of homogeneous versus heterogeneous setups. Together, these analyses demonstrate how the behavioural heterogeneity of consumers can either stabilize or destabilize energy systems under DR schemes.

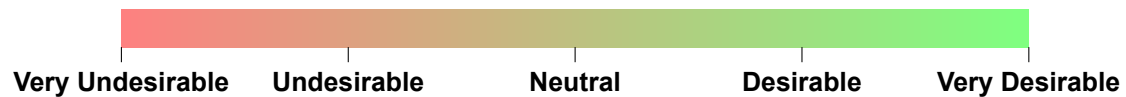
The following two Tables 8.1 and 8.2 summarize this section per KPI per scenarios. Table 8.1 provides an overview of the SVO composition per scenario and Table 8.2 shows the results of the trade-offs across the four KPIs by using colour coding to interpret the desirability of the results. Green is the most desirable, while the colours leaning toward red are less desirable.

Table 8.1: SVO compositions per scenario

Scenario	SVO Composition
All Altruistic	10 altruistic
All Pro-social	10 pro-social
All Individualistic	10 individualistic
All Competitive	10 competitive
Equal Mix	2 altruistic, 3 pro-social, 3 individualistic, 2 competitive
Base Case	1 altruistic, 4 pro-social, 4 individualistic, 1 competitive
Cooperative Dominant	5 altruistic, 5 pro-social
Competitive Dominant	5 individualistic, 5 competitive
Polarized	5 altruistic, 5 competitive
Moderate	5 pro-social, 5 individualistic

Table 8.2: Yearly Trade-offs across SVO Population Compositions and KPIs

Scenario	Load Shifting	Load Shedding	Rewards	Penalties
All Altruistic	Moderate-Low	Low	Low	Moderate
All Pro-social	Moderate-High	Very Low	Very Low	Moderate-High
All Individualistic	Very Low	Moderate-High	Very High	Low
All Competitive	Very High	Very High	Moderate	High
Equal Mix	Moderate	Moderate	High	Very Low
Base Case	Low	Moderate	Moderate-High	Moderate-Low
Cooperative Dominant	Moderate-High	Low	Moderate-Low	Moderate-High
Competitive Dominant	Moderate	High	Moderate-Low	Very High
Polarized	High	Moderate-High	Moderate	Moderate
Moderate	Low	Moderate-Low	Moderate-High	Moderate-Low



From Table 8.2, it could be said that with every scenario a trade-off could be made with the KPIs. Equal mix with heterogeneous SVOs is the most balanced outcome across all KPIs, while competitive dominant which consists only of self-interested agents got the least desirable outcomes across all KPIs. The following subsections will analyse these insights in more detail.

8.2.1. Load Shedding

This section discusses the results for load shedding. The following Figure 8.1 shows an overview of load sheds across all scenarios, comparing monthly results and results over the year with each other. Each bar presents the average load shed value distribution for a given scenario.

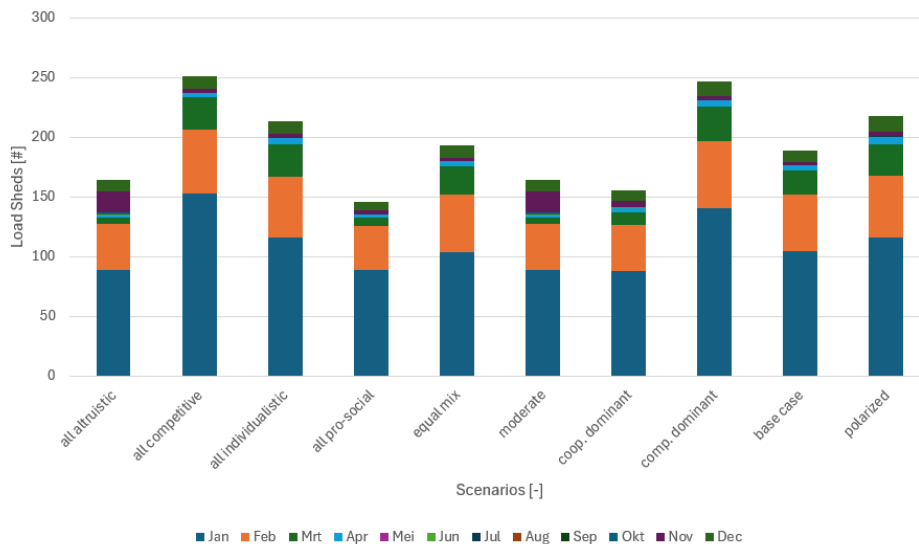


Figure 8.1: Load Shedding Monthly Distribution across the Year

As seen in Figure 8.1, the simulations have shown that load shedding is sensitive to the composition of the agent population. **In the monthly results for January, the ranking from highest to lowest load shedding was respectively: all competitive, competitive dominant, polarized, all individualistic, equal mix, base case, moderate, all altruistic, all pro-social, and cooperative dominant.** Fully competitive populations consistently display the highest levels of shedding, which reflects their prioritization of self-interest over system-level coordination. Competitive dominant and polarized populations also shed relatively more, but they are slightly mitigated by the presence of some altruistic agents. In contrast, all altruistic, all pro-social, and cooperative dominant populations show the lowest levels of load shedding, suggesting that their willingness to support the EH reduces the need to rely on load shedding as a response to congestion.

Seasonal demand and solar production have a clear effect during the high-demand winter months as the differences between the SVO types becomes more noticeable. Competitive and individualistic populations are shed more during the winter months, whereas altruistic and pro-social populations are shed less. At the same time, PV panels produce less in the winter as there is less sun, which reduces PV generation. The EH can rely less on available flexible capacity, so load shedding is the only way to not break the contractual limits. In lower-demand periods such as spring and summer, the combination of lower demand and higher PV production reduces overall shedding which leads to decreasing the differences between population compositions. **It can be said that the SVO is particularly influential during peak demand periods when both capacity margins and renewable production are constrained.**

The yearly results reveal a slightly different pattern, with the ranking from highest to lowest shedding as: all competitive, competitive dominant, polarized, all individualistic, equal mix, base case, moderate, all altruistic, cooperative dominant, and all pro-social. Over a longer period of time, all competitive populations continue to shed the most while all altruistic populations maintain the same low shedding observed in January. **Over time competitive populations persistently shed the most due to their self-interested behaviour across seasons, while altruistic populations maintain low shedding by consistently cooperating even during winter months with low PV generation.** Notably, cooperative dominant and all pro-social populations switch positions compared to the monthly ranking, suggesting that system behaviour over the year can reorder the relative performance of cooperative strategies depending on cumulative interactions and seasonal variations.

Comparing all scenarios to the base case shows how population extremes influence load shedding. The base case, which features a discrete distribution of SVOs and no noise, consistently occupies the middle of the ranking, serving as a reference for moderate system performance. Populations above the base case, particularly all competitive, competitive dominant, or polarized, demonstrate that the pres-

ence of self-interest amplifies reliance on shedding. Those below the base case, such as cooperative dominant, all altruistic, or all pro-social, show that pro-social and altruistic orientations can mitigate system pressure. **Scenarios with mixed compositions, like equal mix or moderate, are close to the base case which shows the balancing effect of heterogeneity.**

Overall, these results suggest that the system is most vulnerable to load shedding under competitive dominated populations, while altruistic or pro-social compositions provide greater resilience and reduce the need for interventions such as load shedding. Seasonal variations in solar production further intensify these effects, particularly in winter months when PV generation is limited and the system faces higher stress.

8.2.2. Load Shifting

This section discusses the results for load shifting. The following Figure 8.2 shows an overview of load shifts across all scenarios, comparing monthly results and results over the year with each other. Each bar presents the average load shift value distribution for a given scenario.

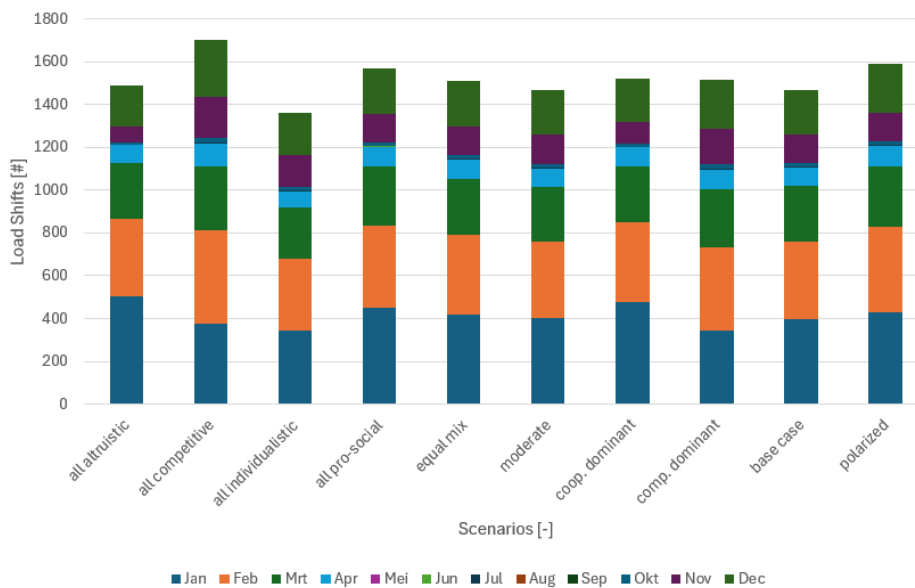


Figure 8.2: Load Shifts Monthly Distribution across the Year

As seen in Figure 8.2, the simulations have shown that load shifting also depends on the composition of the agent population. **In the monthly results, the observed ranking from highest to lowest number of load shifting in the month January was: all altruistic, cooperative dominant, all pro-social, all competitive, polarized, equal mix, base case, moderate, competitive dominant, and all individualistic.**

Altruistic and pro-social populations have shown the highest engagement in voluntary load shifts, which reflects a high willingness to support the community. In contrast, individualistic populations show lower levels of load shifting which shows that they prioritize self-interest over helping the community. Interestingly, fully competitive populations are fourth in the order for load shifting, likely because the presence of penalties constrain their behaviour. Mixed populations hold the intermediate positions in the order, which can be explained by the fact that the presence of altruistic and pro-social agents might increase the number of load shifting. The presence of individualistic agents would decrease this number of load shifting.

Seasonal demand also plays a role in load shifting. During high-demand winter months, the differences between SVO types become clear as altruistic and pro-social agents maintain high levels of load shifting while competitive or individualistic agents engage less. **In lower-demand periods such as spring and summer the gap narrows, which indicates that SVO are particularly influential during peak demand moments when capacity margins are tight.**

Solar production clearly affect load shifting. Limited PV production in winter reduces local generation, which increases system pressure and therefore shows the importance of cooperative behaviours. In spring and summer when demand is lower and PV production is higher, overall load shifting decreases and the differences between population compositions narrow. **This indicates that SVO is especially influential under periods of high system stress, when capacity margins and renewable generation is limited.**

In the yearly results, the observed ranking from highest to lowest number of load shifting differs: all competitive, polarized, all pro-social, cooperative dominant, competitive dominant, equal mix, all altruistic, base case, moderate, and all individualistic. **This suggests that over time, all competitive populations engage more in load shifting than might be expected from their monthly behaviour.** This could potentially be due to the presence of rewards, penalties, and repeating shifting opportunities which incentivized competitive agents to adapt their strategies over time and exploit flexibility whenever it benefits them. Meanwhile altruistic populations who rank highly in January, rank lower annually. This indicates that short-term willingness to shift may not always translate to sustaining that action over a full year. The behaviour of altruistic agents are less influenced by the rewards and penalties, which leads to a saturation point once their altruistic motivations are fulfilled.

When comparing all scenarios to the base case, it becomes clear that the base case consistently falls just below the middle of the rankings. This suggests that a balanced, discrete distribution of agent types with no noise produces moderate levels of load shifting. In the monthly results, all altruistic, cooperative dominant, and all pro-social scenarios rank above the base case. In the yearly results, this applies to fully competitive, polarized, and pro-social combinations. This shows that extreme population compositions can increase engagement in load shifting, which is either driven by strong cooperative tendencies or by penalties that limit high self-interest. On the other side, scenarios below the base case including moderate, competitive dominant, and all individualistic in the monthly results, reveal that insufficient pro-social motivation or excessive self-interest withholds participation. This comparison shows that the population composition and time interact with each other. **Populations that shift a lot in a given month do not always continue that behaviour over the whole year. Competitive populations may even perform more load shifting at the end of the year, as repeated opportunities and penalties push them to shift over time.**

Overall, the base case shows the moderating effect of heterogeneity while deviations above or below it illustrate how extremes in agent behaviour drive the variability in system-level outcomes. Pro-social and altruistic agents increase the number of load shifts, particularly during periods of high demand and low renewable production. Individualistic populations rely less on voluntary shifting and may require additional motivators to increase demand response.

8.2.3. Rewards

This section discusses the results for rewards. The following Figure 8.3 shows an overview of rewards across all scenarios, comparing monthly results and results over the year with each other. Each bar presents the average rewards value distribution for a given scenario.

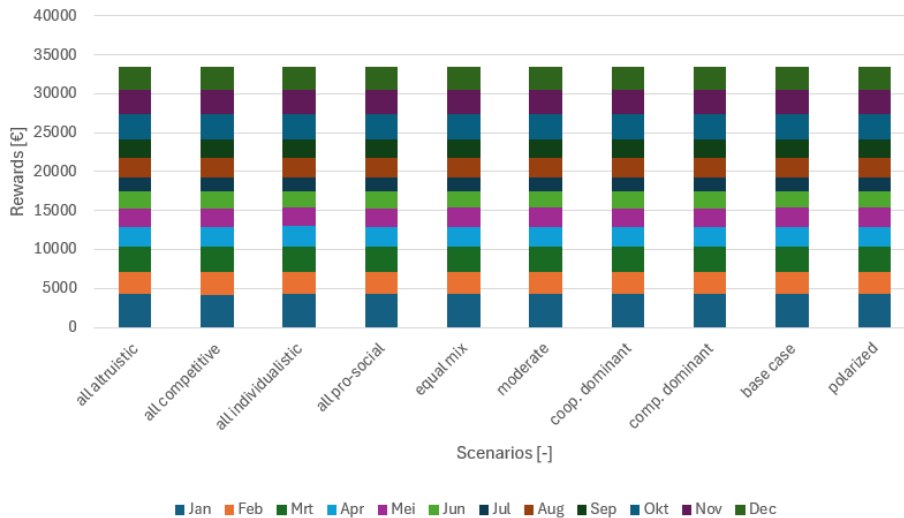


Figure 8.3: Rewards Monthly Distribution across the Year

As seen in Figure 8.3, the simulations have also shown that rewards (also implicit capacity sharing) are influenced by the composition of the agent population with small differences. **In the monthly results for January, the ranking from highest to lowest rewards is: all individualistic, moderate, base case, equal mix, all pro-social, cooperative dominant, all altruistic, competitive dominant, polarized, and all competitive.** All individualistic populations consistently achieve the highest rewards which reflects their focus on maximizing personal gain, while competitive populations rank the lowest positions due to their behaviour of a desire to outperform others rather than to optimize absolute gains. This shows that all individualistic agents will implicitly share more as long as they receive their monetary rewards. Mixed populations generally achieve intermediate outcomes, suggesting that a combination of self-interested and pro-social orientations produces moderate reward levels.

Seasonal effects are visible in the monthly results. Peaks occur in January, reflecting the high activity at the start of the year with smaller secondary peaks in March and October. **These peaks likely correspond to periods of increased energy demand or favourable system conditions for shifting and earning rewards. Furthermore, there is a dip in July which can be caused by lower energy demand during summer months and higher PV production reducing the need for participant action.** Across these seasonal variations, individualistic populations consistently exploit reward opportunities. Pro-social, cooperative, and altruistic populations prioritizes system balance over personal gain. Mixed and moderate populations show intermediate seasonal patterns, adjusting their engagement according to both population composition and seasonal system conditions.

In the yearly results, the ranking shifts somewhat: all individualistic remains at the top, followed by equal mix, moderate, base case, polarized (equal to all competitive), all competitive (equal to polarized), competitive dominant, cooperative dominant, all altruistic, and all pro-social. This indicates that over longer periods mixed and moderate populations can outperform some highly pro-social or competitive groups, as there more opportunities to load shifts. **Interestingly, polarized and all competitive populations have to the same reward level annually, showing that repeated interactions over time can equalize outcomes between extremes of SVO.**

Comparing all scenarios to the base case highlights that individualistic and moderately mixed populations consistently outperform it, while cooperative-dominated and altruistic populations tend to receive fewer rewards over time. **This suggests that strategies prioritizing personal gain or balancing self-interest with cooperation are more successful in maximizing cumulative rewards, whereas purely pro-social or highly cooperative strategies may trade-off individual reward for load shifting.**

Overall, the results demonstrate that both population composition and seasonal dynamics strongly influence rewards. Individualistic populations consistently maximize their cumulative rewards, while

pro-social, cooperative and altruistic populations achieve lower rewards due to their focus on support rather than personal gain. Mixed populations hold intermediate positions, benefiting from a balance of self-interest and cooperation. Seasonality intensifies these differences: winter and early autumn months offer more opportunities to earn rewards, while summer months show a general decline across all scenarios due to reduced demand and higher PV generation. This shows that both SVO and seasons must be considered when assessing strategies to optimize individual and collective outcomes in the EH.

8.2.4. Penalties

This section discusses the results for penalties. The following Figure 8.4 shows an overview of penalties across all scenarios, comparing monthly results and results over the year with each other. Each bar presents the average penalties value distribution for a given scenario.

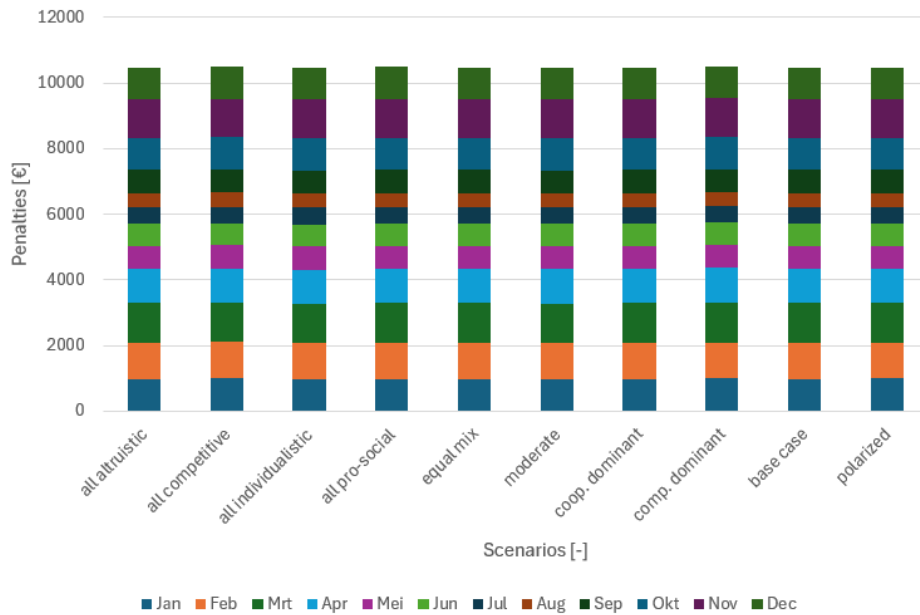


Figure 8.4: Penalties Monthly Distribution across the Year

As seen in Figure 8.4, the simulations indicate that penalties vary depending on the SVO of the agent population with small differences. **In the monthly results for January, the highest penalties were observed in the all pro-social scenario, followed by competitive dominant, cooperative dominant, all altruistic, moderate, equal mix, base case, all individualistic, polarized, and all competitive.** This outcome is somewhat counter-intuitive, as one might expect pro-social or altruistic populations to minimize penalties through cooperative behaviour. However, the higher penalties in these groups suggest that their strong willingness to shift load may also increase their exposure to penalty conditions in constrained system states. By contrast, fully competitive populations show the lowest penalties monthly, reflecting their unwillingness to participate in system-supportive actions that could otherwise result in penalty exposure.

Seasonal variations also have an impact on penalty outcomes across all scenarios. **Monthly results show that penalties tend to peak in March and November, periods that likely correspond with higher system demand and reduced renewable generation. However, penalties are lowest in August when there is reduced demand and higher PV generation.** Cooperative and pro-social populations are particularly sensitive to these seasonal dynamics: their willingness to engage in load shifting exposes them to higher penalties during the winter months. Equal mix and moderate populations generally experience intermediate seasonal fluctuations, which suggests that heterogeneity helps buffer the extremes caused by both altruistic and competitive behaviours. These patterns indicate that both the periods of high and low demand, PV generation, and the SVO of agents together drive the seasonal penalty trends.

In the yearly results, the ranking shifts from high to low are: competitive dominant, all competitive, all pro-social, cooperative dominant, polarized, all altruistic, base case (equal to moderate), moderate (equal to base case), all individualistic, and equal mix. Over time, pro-social and altruistic populations drop lower in the ranking, while competitive groups accumulate greater penalties. **This shift suggests that sustained self-interested behaviour leads to long-term inefficiencies that the system penalizes, whereas cooperative groups balance their participation in ways that mitigate penalties over time.**

When comparing scenarios to the base case, a clear pattern emerges. In the monthly results, the base case lies near the middle of the ranking, with only competitive, polarized, and individualistic populations performing better in terms of lower penalties. In the yearly results, the base case and moderate scenarios share the same middle position, outperforming both highly competitive groups and even some cooperative populations. **This indicates that the discrete distribution of agents in the base case produces a stabilizing effect that avoids the extremes of very high or very low penalty exposure.**

Overall, the results show that penalties are influenced by a combination of agent composition, seasonal demand fluctuations, and renewable generation. Populations dominated by pro-social or altruistic agents tend to face higher penalties during peak-demand months. Highly self-interested populations, such as competitive or individualistic agents, generally have lower penalties monthly, but over the course of the year the penalties accumulate more due to repeated suboptimal behaviours. Mixed and moderate populations consistently hold intermediate positions, which highlights the stabilizing effect of heterogeneity within the EH.

8.3. Trade-offs

The results across all four KPIs reveal some trade-offs between different SVO compositions. No single agent population performs best across all dimensions, meaning that the EH design must balance competing outcomes depending on whether the emphasis is on resilience, fairness, or individual incentives.

Competitive and individualistic populations show the sharpest contrasts. All competitive populations achieve the highest levels of load shifting in the yearly results, which indicates that **self-interested behaviour can still contribute to offering flexibility under strong constraints**. However, this comes at the cost of very high load shedding and penalties which makes these populations less reliable in maintaining operational reliability. **This counter-intuitive outcome can be explained by the fact that they load shift to optimize their own benefits and not the for the collective, so they are load shifting in such a way that it creates localized congestion that has to be shed.**

In contrast, **all individualistic populations rank highest in rewards as agents maximize opportunities for financial benefit**. Yet this group performs lowest in load shifting, which underlines the tension between individual profit and collective performance.

Altruistic and pro-social populations have a different type of trade-off. Over the year, all altruistic agents keep load shedding low but achieve only moderate to low levels of load shifting and rewards. Pro-social populations perform somewhat better with ranking moderate-high in load shifting and very low in shedding, but they obtain the lowest rewards and face moderate to high penalties. **This indicates that although both altruistic and pro-social orientations improve resilience by reducing load shedding and contributing to flexibility, it happens at the expense of maximizing their financial outcomes.**

Mixed populations, such as the equal mix, moderate, and base case scenarios, occupy middle positions across most KPIs. The equal mix population show moderate load shifting and shedding, but achieve high rewards while keeping penalties very low. This indicates that diversity in SVO can stabilize performance and maximize financial outcomes without creating systemic problems.

Moderate population rank low in load shedding but keeps load shifting, rewards, and penalties in the moderate range. This scenario makes the moderate population a somewhat 'steady' configuration by not excelling in any KPI.

The cooperative dominant population performs moderately high in load shifting and keeping load shedding low. However, this population faces higher penalties while earning moderate-low rewards. This

suggests that cooperation strengthens systemic stability, but also exposes the population to costs when incentives are misaligned.

Competitive dominant populations show moderate load shifting, but also experience high load shedding, low rewards, and very high penalties. These results underline the risks of dominance by self-interested behaviour, as operational reliability becomes harder to maintain and financial outcomes far are from optimal.

Next, polarized population perform well in load shifting but show relatively high load shedding and moderate results in rewards and penalties. This configuration shows both the benefits and disadvantages of a strong contrast population. While flexibility is achieved by high results in load shifting, the high amount of load shedding lowers their reliability.

Lastly, the base case consistently holds a balanced position across the KPIs. It performs low in load shifting, moderate in load shedding, moderate-high in rewards, and moderate-low in penalties. It can be said that the base case neither maximizes performance in any KPI or exposes the EH to vulnerabilities seen in more extreme population types. However, it is good to note that the base case does not account for uncertainty.

Seasonal patterns also reveal important trade-offs. In the short-term results which are represented by monthly data (e.g. January), all altruistic and all pro-social populations lead in load shifting and show reduced shedding. This shows that altruistic and pro-social agents prioritize the system when their actions align with their intrinsic motivations to support the collective. All competitive populations rank slightly lower in load shifting in the short-term results, because they prioritize self-interest over collective benefit. In the long-term results which is represented by the aggregated year results, the previous behaviour changes. All competitive populations move to the top in load shifting while all altruistic and all pro-social populations drop lower in the rankings. This change is due to cumulative effects of competitive agents repeatedly facing penalties and rewards, so their total strategic engagement across many events becomes significant. Pro-social agents hold a moderate-high positions, because they are trying to balance supporting the collective and their self-interest. This leads to consistent engagement in load shifting without overexposing themselves with load shifting. Altruistic agents consistently act to support the system, so their total grows steady but does not spike because they are not strategically shifting just as competitive agents. **This illustrates a trade-off between short-term benefits of cooperative agents (all altruistic and all pro-social) and long-term adaptability of competitive agents (all competitive).** While cooperative agents seek the best for the collective, their contribution remains steady and predictable. Competitive agents strategically respond to repeated opportunities that allows them to gradually increase their total load shifting over the year.

9

Survey

This chapter presents and discusses the design of the survey for real-life participants of an EH, which is followed by the survey results. After that, the analysis of the survey results are discussed. Lastly, this chapter ends with a comparison between the survey analysis and the ABM.

9.1. Survey Design

The purpose of the survey is to gain insights into the behaviour of real-life participants within an EH. Specifically, the survey aims to approximate the distribution of SVO types present in actual EHs and identify the factors that influence decisions regarding load shifting and capacity sharing.

The survey was distributed using Google Forms, a free and user-friendly tool. It was chosen because it allows easy access for all participants, anyone with the survey link can simply complete the questionnaire without the need for additional software or accounts.

The survey is completely anonymous, and no personal data of participants is collected. Participation is voluntary; respondents may join or leave the survey at any time. However, once the survey has been submitted, it cannot be exited or altered. This information is also explained in the first part of the survey, where the informed consent is discussed.

The survey questions were designed to test behavioural factors identified in literature to explore the alignment between theoretical insights and real-world data of ICs. They were also designed to uncover new behavioural factors directly from the experiences of real-life participants. To achieve this, multiple-choice questions were created around clearly described scenarios to ensure that respondents understand the question. Additionally, open-ended questions were included to identify any factors not previously considered. Furthermore, Likert-scale questions were used to measure the degree of agreement with specific factors, providing quantitative insight into participant attitudes.

Some survey answer options are designed to reflect the different SVO types, which describe how individuals prioritize their outcomes relative to others when making decisions. As mentioned before in Section 4.5, it can be assumed that competitive individuals aim to maximize their own pay-off and other's pay-off in their favour. Individualistic individuals aim to maximize their own pay-off and have little to no concern of other's pay-off. Pro-social individuals aim to maximize joint outcomes, while altruistic individuals prioritizes the other's pay-off above their own (Greiff et al., 2018; Murphy & Ackermann, 2014).

This means that individualistic individuals are represented by answer options that emphasize pursuing strategic self-interest. Competitive individuals are reflected in options that focus on maximizing the difference between their own outcomes and those of others. Prosocial individuals tend to prioritize balancing their own interests with the collective good, while altruistic individuals are characterized by answer options expressing a strong willingness to cooperate, share capacity, and contribute solely to collective solutions.

Several survey answer options include behavioural factors that influence consumer decision-making regarding load shifting. These factors correspond to those identified in the literature review (see Subsection 2.1.2), which are financial incentives, operational losses, expectations of other companies, the company's own reputation, and access to insights. In the survey, financial incentives are represented by both rewards and penalties within a single question.

Mind that the formulation of all these answer options are subjective and can be formulated in different ways.

The English version of the survey is provided in Appendix D. Since all participants are Dutch speakers, a Dutch version was created for their convenience. The Dutch survey can be accessed via the following link: [Google Forms Survey](#).

The answer options with the matching SVO types of Questions 1, 4 and 7 are given below in Tables 9.1, 9.2 and 9.3 respectively:

Answer option	SVO type
We see scarcity as an opportunity. If we can consume more than others, we might be able to gain a strategic advantage.	Competitive
We prefer to run our process at the time that is most efficient for us. If it is really necessary to shift due to the scarcity, we will only do so if it does not harm our own planning and objectives. Our priority lies in the optimal operation of our company.	Individualistic
We understand that there is scarcity and therefore want to contribute to a balanced solution. We are willing to shift our process, provided it fits within our operational capabilities.	Pro-Social
If scarcity is expected, we absolutely want to prevent our extra consumption from disadvantaging others. We will voluntarily shift our process to a quieter time during the day so that enough capacity remains available for the entire hub. The collective interest comes first.	Altruistic

Table 9.1: Answer options with matching SVO type of Question 1

The answer option of competitive should reflect that they prioritize maximizing their own outcomes relative to others. So, in first question the competitive sees the energy shortage as a chance to have a strategic advantage over others. An individualist only focusses on maximizing their own outcome, so the answer option of individuals should reflect that they are acting for their self-interest. This means that they will only load shift if it does not negatively affect their operation of the company. Next, pro-socials want fair outcomes for both themselves and others, so their answer option should reflect their willingness to adjust their processes while staying within their operational capabilities. Lastly, an altruistic prioritizes the well-being of others above their own, so their answer option should reflect that they voluntarily will load shift to ensure that the collective interest is met.

Answer option	SVO type
If another company runs into trouble due to a capacity issue while we have sufficient capacity, it strengthens our position in the hub. We see no reason to share our capacity; it is better that they manage their own affairs.	Competitive
As long as we do not urgently need the capacity, we keep it available for our own flexibility. We want to avoid getting into trouble ourselves later on.	Individualistic
We currently have available capacity and are willing to share it if that helps solve a problem for another company. As long as it does not disrupt our own.	Pro-Social
If another company urgently needs capacity and we do not need it at that moment, we will of course make it available to them.	Altruistic

Table 9.2: Answer options with matching SVO type of Question 4

In the fourth question, a competitive sees another company's capacity problem as an opportunity to strengthen their own position and also has no reason to share capacity because they do not gain from it. An individualist in this situation will keep their capacity to themselves, because they do not want to give it away in case they will need it. A pro-social wants what is best for both themselves and others, so their answer option shows again their willingness to share as long it does not affect themselves. Finally, an altruistic will only think about others and will have no second thought about giving the capacity to someone else.

Answer option	SVO type
No, unless they offer themselves. My process is important, but not more important than preventing strain on others	Competitive
Yes, absolutely. If I benefit from it and they can give way, then that's their problem	Individualistic
Yes, I can ask in a polite manner and it is reasonable. Together looking for the best solution for everyone.	Pro-Social
Yes, definitely. My process is important, and if I ask politely whether they can shift, that's fine.	Altruistic

Table 9.3: Answer options with matching SVO type of Question 7

In the seventh question, a competitive will not ask first unless others do it first because they want to minimize any risk or effort on their part. They are too focussed on their position and avoid taking action themselves. An individualist will only call if it benefits their own process, because they only care about themselves. A pro-social will think of others and ask in a polite manner to talk about the best solution for everyone, because they want the best for all. Lastly, an altruistic will not think twice about calling other because they think about the collective good and think that others will also voluntarily reduces or load shift for them.

9.2. Survey Results

In this section, the results from the online survey are presented. The survey's goal was to gain insights into the behaviour of real-life participants within an EH. In addition, the survey aims to approximate the distribution of SVO types from actual participants in an EH and identify factors that influence decisions regarding load shifting and capacity sharing. The questions of the survey with the answer options can be seen in Appendix D. Four respondents have reacted to the online survey. The statistical representativeness of this sample size is low, however it gives an impression of the real-world context.

Question 1

In the first question, the respondents were asked to choose from four options where each answer option

reflects a SVO type. The question talks about a situation where the company wants to consume more than agreed, but they still can shift to another moment on the same day. The following Figure 9.1 visualizes the answer in a pie chart, where each respondent corresponds with A, B, C and D:

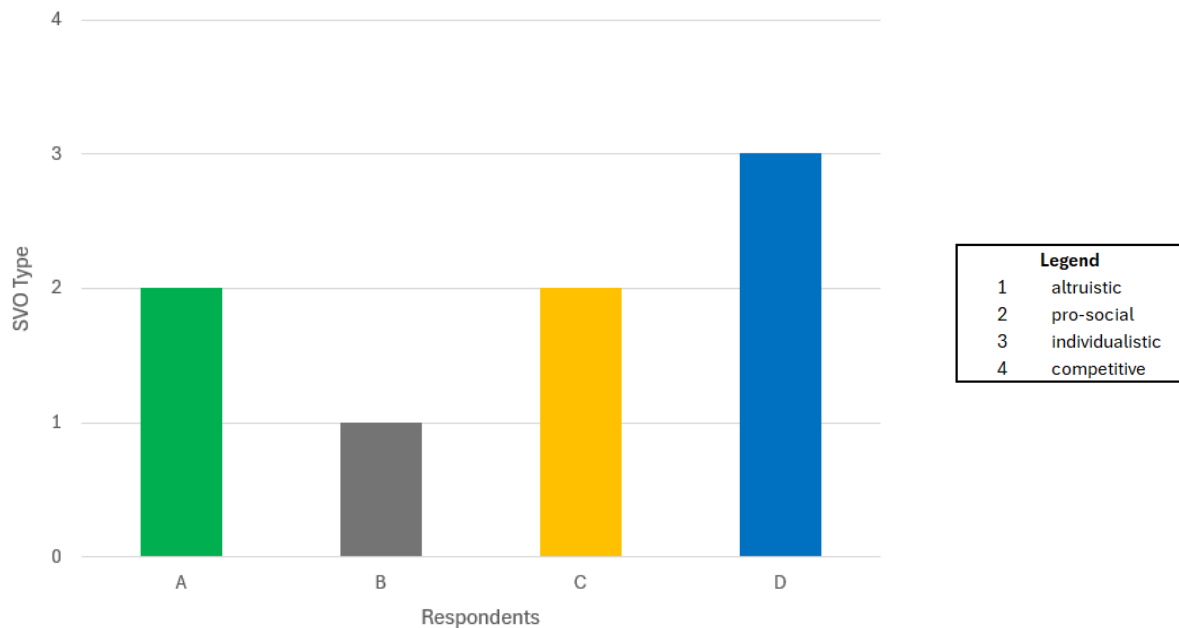


Figure 9.1: SVO type for load shifting on the same day

From Figure 9.1, it can be seen that respondent A and C react pro-social to this answer, while respondent B is altruistic. Respondent D have shown to agree with the competitive answer.

Question 2

In the second question, the respondents were asked to rate a couple of factors that influence load shifting on the same day. Again, the question talked about a situation where the company wants to consume more than agreed, but they still can shift to another moment on the same day. The following Table 9.4 summarizes the answers, where each respondent corresponds with A, B, C and D:

Table 9.4: Factors influencing load shifting on the same day

Factor	Very not important	Not important	Neutral	Important	Very Important
Financial rewards	B		A	C, D	
Penalty		A, C, D	B		
Cost of Production		B	A	C	D
Insight into Capacity			D	A, B, C	
Expectation of others				A, B, C, D	
Reputation		B	C	A, D	

From Table 9.4, it can be seen that respondent A finds insight into capacity, expectation of others, and reputation to be important. Penalty seem to be not important to respondent A. Financial rewards and cost of production is neutral to respondent A.

Respondent B finds insight into capacity and expectation of others to be important. Financial rewards, cost of production, and reputation seem to be (very) not important to respondent B. Penalty is neutral to respondent B.

Respondent C finds financial rewards, cost of production, insight into capacity, and expectation of others to be important. Penalty is the only factor to be not important to respondent C, while reputation remains neutral.

Respondent D finds financial rewards, expectation of others, and reputation to be important. Cost of production is even to be found very important to respondent D. Penalty is the only factor to be not important, while insight into capacity remains neutral.

Question 3

In the third question, the respondents were asked to give an answer to an open question which discusses other factors that influence load shifting on the same day.

There were two answers to this question, since it was optional to fill this in:

Respondent C: 'I assume that agreements have been made with the participants in the hub regarding how to handle grid congestion, and that everyone also adheres to the agreements'

Respondent A: 'Primary business processes should in principle continue as planned. Secondary business processes can if necessary be shifted (or cancelled) to a more favourable time'

Question 4

In this fourth question, the respondents were asked to choose from four options where each answer option reflects a SVO type. The question talks about a situation where the company has reserved capacity but does not necessarily need it while another company needs it. The following Figure 9.2 visualizes the answer in a pie chart, where each respondent corresponds with A, B, C and D:

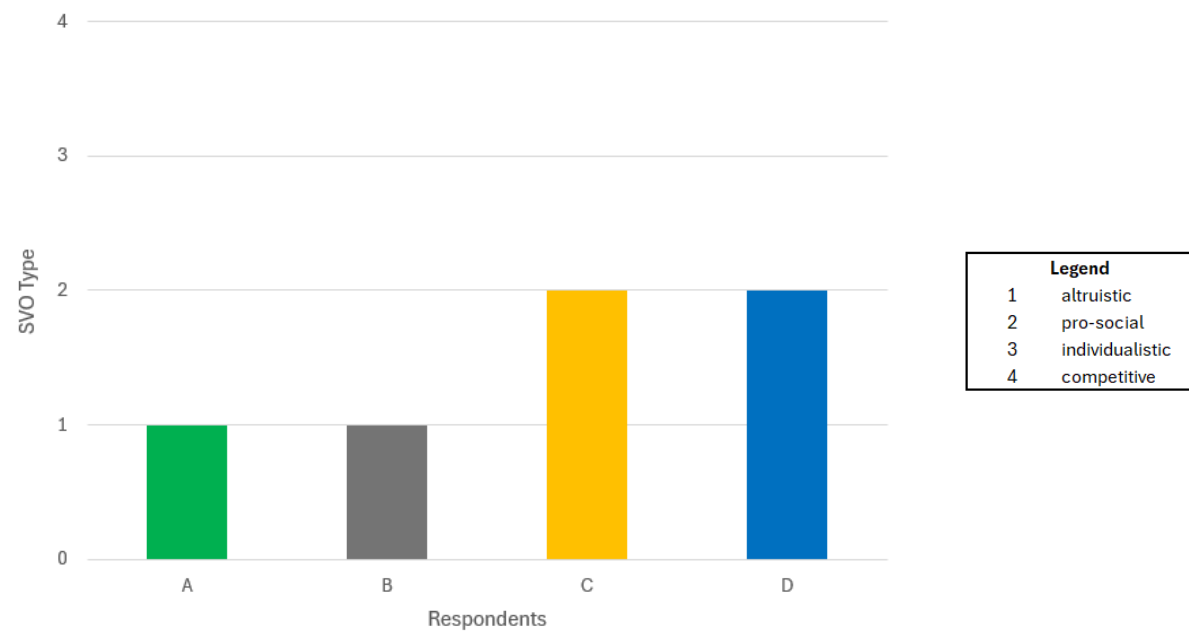


Figure 9.2: SVO type for load shifting on the same day

From Figure 9.2, it can be seen that respondents A and B chose the altruistic option. Respondents C and D chose the pro-social option.

Question 5

In the fifth question, the respondents were asked to rate a couple of factors that influence their decision to give reserved capacity away. Again, the question talked about a situation where the company has

reserved capacity but does not necessarily need it while another company needs it. The following Table 9.5 summarizes the answers:

Table 9.5: Factors influencing giving up capacity to others

Factor	Very not important	Not important	Neutral	Important	Very Important
Financial rewards	B		A	C, D	
Positive Experiences			D	A, C	B
Image			B	A, C, D	

From Table 9.5, it can be seen that respondent A finds positive experiences and image to be important. Financial rewards remains neutral.

Respondent B finds positive experiences to be very important, while image remains neutral. Financial rewards is even to be found very not important.

Respondent C finds financial rewards, positive experiences, and image to be equally important.

Respondent D finds financial rewards and image to be important, while positive experiences remains neutral.

Question 6

In this sixth question, the respondents were asked to give an answer to an open question which discussed factors that influence their decision to give reserved capacity away.

There was one answer to this question, since it was optional to fill this in:

Respondent A: 'We need to solve this together, so I expect the same from other participants where the continuation of business processes is more important than financial considerations.'

Question 7

In the seventh question, the respondents were asked to choose from four options where each answer option reflects a SVO type. The question talked about a situation where there is limited capacity in the EH and the company wants to continue their process, but that is only possible if another company lowers their usage. Here the question was about approaching another company to ask if they can make space for the company. The following Figure 9.3 visualizes the answers, where the respondents correspond with A, B, C, and D:

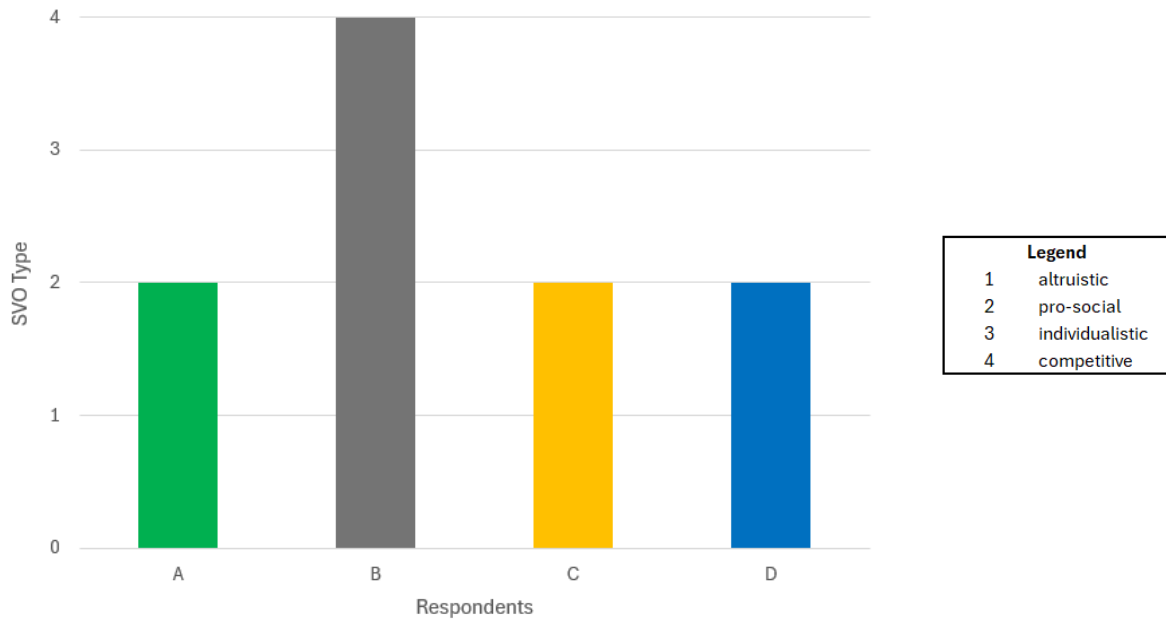


Figure 9.3: SVO type for load shifting on the same day

From Figure 9.3, it can be seen that respondents A, C and D agree with the pro-social option. Only respondent B agrees with the competitive option.

Question 8

In this last question, the respondents were asked to give an answer to the open question which discussed if there were other factors that influence their decision to approach another company. No one have reacted to this question.

9.3. Analysis of Survey

In this section, the survey results are analysed and the patterns/interpretations are discussed. There were three situations presented, where each time the SVO type is tested and the factors influencing decisions are examined.

Across these three situations an average could be calculated to determine the SVO type for each respondent. Respondent A chose the pro-social option (pro-social corresponds with number 2) two times and once the altruistic option (altruistic corresponds with number 1). The average for respondent A could be calculated as $(2 + 2 + 1) / 3 = 1.67$. This means that in general respondent A is somewhere between altruistic and pro-social, but leans more towards pro-social.

Respondent B chose the altruistic option (altruistic corresponds with number 1) twice and the competitive option (competitive corresponds with number 4) once. The average for respondent B could be calculated as $(1 + 1 + 4) / 3 = 2.00$. This means that in general respondent B is pro-social.

Respondent C chose in all three situations the pro-social option (pro-social corresponds with number 2). The average for respondent C could be calculated as $(2 + 2 + 2) / 3 = 2.00$. This means that in general respondent C is pro-social.

Respondent D chose the pro-social option (pro-social corresponds with number 2) twice and the individualistic option (individualistic corresponds with number 3) once. The average for respondent D could be calculated as $(2 + 2 + 3) / 3 = 2.33$. This means that in general respondent D is somewhere between pro-social and individualistic, but leans more towards pro-social.

It can be said that all respondents from the survey are pro-social or lean toward the pro-social behaviour.

Since most choices per situation were pro-social, it can be said that respondents prioritize fairness and cooperation when making decision about load shifting, capacity sharing, and approaching another company to lower their usage. The altruistic responses from respondents A and B emerge particularly in situations where unused capacity could be shared or where the respondent would load shift. This may suggest that in the case of capacity sharing when there is an excess, some respondents are willing to put the collective interest above their own because they do not need the excess anyway. Notably, there were no altruistic responses for approaching another participant to lower their energy usage. This may indicate that altruism can be more easily expressed in passive or voluntary moments than in actively requesting another to reduce or shift their usage.

One individualistic response from respondent D occurred in the situation where the company wants to consume more than agreed, but they can load shift to another moment on the same day. This shows that respondent D have decided in terms of their own operational stability rather than what is fair. Also, one competitive response from respondent B occurred in the situation to approach another participant to lower their energy usage. This might suggest that in a conflict-prone interaction such as asking another to reduce or load shift, a small part of the respondents may be acting more out of self-interest and viewing this situation as an opportunity to increase relative advantage.

From the factors, it can be said that respondents find different factors important. Respondent A mostly values social and operational factors such as insight into capacity, expectation of others, positive experiences, image and reputation. Respondent B finds insight into capacity, positive experiences and expectation of others to be most important. Respondent C finds financial rewards, cost of production, insight into capacity, positive experiences, image and expectation to be valuable. Respondent D finds financial rewards, cost of production, expectation of others, image and reputation important.

Overall, the respondents are mostly motivated by social and operational factors than by financial incentives. While there are some differences between respondent A, B and C, D with finding financial rewards important, the social and operational factors consistently appear across the respondents. This may suggest that in practice, cooperation in the EH are not primarily driven by short-term financial gain, but the desire to maintain operational reliability and build trusted long-term relationships. For example, the importance of reputations shows that participants care about how they are perceived by their peers because this may influence future opportunities for collaboration. This example can be verified by the fact that positive past experiences is also an important factor that is valued. Participants are more likely to give up capacity or shift their processes if they believe that others would do the same for them.

The answers to the open questions emphasize the importance of trust and cooperation. Respondent C have expressed the importance of having clear and shared agreements within the EH about handling scarcity and respondent A have expressed that primary business processes should always continue. Respondent A also said that secondary business processes can be adjusted if needed. Respondent A explicitly stated that the continuation of business processes is more important than financial incentives and that he expects the same attitude from others. This suggests that the participants should have a clear agreement of rules among them, where cooperation is expected not because of financial incentives but of mutual recognition of business continuity.

Since there are four responses to this survey which is a small samples size, the results of this survey should be interpreted as exploratory instead of robust evidence. The limitations of this survey can be found in Subsection 10.3.3 in the Discussion chapter.

In conclusion, the survey results show that the respondents all have a pro-social SVO type which emphasizes that their decision-making is more likely based on cooperation and fairness. Altruistic tendency may show when participants have unused capacity or have the ability to load shift. Individualistic and competitive SVO types are rare and only show in conflict-sensitive situations such as asking someone else to lower or shift their usage. Social and operational factors such as trust, reputation, and safeguarding core business processes are valued more than financial incentives. This suggests that collaboration in the EH depends primarily on mutual expectations and shared agreements rather than financial rewards or penalties. The results of this survey is more exploratory instead of robust evidence, because of the small sample size of the respondents.

9.4. Comparison with the Agent-Based Model

In general, the four respondents either are pro-social or lean to pro-social. Compared to the scenarios in the model, the configuration of SVO of the respondents corresponds exactly with the all pro-social scenario. In the all-pro-social scenario, every agent has a pro-social type. If the respondents were in an EH with each other, it would mean that they are likely to perform well in load shifting and load shedding. However, it is also likely that they receive less rewards and moderate-high penalties. Notably, the importance of factors from the survey corresponds with performing well on load shifting and load shedding. This is because the respondents and thus the pro-socials find social and operational factors much more important than financial incentives such as rewards and penalties. This means that in practice, the respondents are likely to cooperate and make decisions that benefit the collective even if there is lower individual financial gain or higher penalties.

The survey shows that there are some situations where the respondents can deviate from the pro-social typing depending on the situation. In the ABM model there is only situation where the agents could do something, which is the load shifting the company's process to another moment on the same day. Future research with a larger sample size should validate whether the observed behaviour and dominance of pro-social behaviour reflects the dynamics of real-world EHs. Additionally, future research could also implement the other two situations (capacity sharing and asking others to reduce their usage) in the model to explore the behaviour when other options are available.

Compared to the ABM, the factors are to some extent implemented in the model but could be extended. Currently, the model includes production costs, penalty and load shift sensitivity. However, social drivers such as reputation, expectations, and trust between participants are not included because there was no time. The survey suggests that these social dynamics are important drivers in practice and should be included in future versions of the model.

10

Discussion

This chapter reflects on the methodology and the interpretation of results. This is followed by a discussion of this research's limitations, where critical assumptions, model limitations, and survey limitations are addressed. Lastly, this chapter ends with implications for the design and management of an EH.

10.1. Reflection on Methodology

Using a modelling approach, specifically ABM, proved to be an effective way to combine behavioural, technical, and economic aspects in an EH. This method allowed the integration of different IC profiles and their decision-making, which offers insights into system-level outcomes that more traditional models would not seize. Alternative modelling approaches, such as techno-economic system models, behavioural psychology experiments, or optimization-based economic models, could each provide more precise information within their domain. However, none of these would combine all perspectives simultaneously. The chosen approach offered an advantage by capturing the interactions between diverse agents and their environment.

One methodological challenge was the formalization of behavioural aspects. SVO were modelled as discrete categories, which allows for a clear differentiation but at the same time it simplifies reality. In reality, these orientations are on a continuous spectrum and people can fall in between two SVOs. A continuous approach of the SVO could have captured this complex behaviour more realistically, but it would have required more model complexity and calibration. In the survey, it was also more practical to use discrete categories since the questions would otherwise have needed to be designed with finer scales. This will make the questions longer and potentially harder for respondents to interpret correctly. While this choice limited the psychological depth of the simulation, it allowed for behavioural diversity to be expressed in a quantifiable way.

Another consideration was computational intensity regarding running experiments. Each simulation run consisted of 8784 steps, which ensured that all seasons are included and real-time dynamics were preserved. However, this also produced large output files and limited the total number of scenarios that could be simulated. For this study, 50 runs per scenario was sufficient since another master thesis which used ABM proved that number to be enough (Vliet, 2022). However, incorporating more uncertainty or additional scenarios in the model would have significantly increased the computational burden. Reducing the time horizon could have helped this, but this would be at the cost of losing all seasons. Therefore, the chosen approach was well suited for the scope of this study.

10.2. Reflection of Results Interpretation

The interpretation of the results from this research comes with certain challenges. Since the model was not calibrated against a specific real-world EH, there was no direct benchmark available for validation of the absolute values. This limits the extent to which numerical outcomes, such as penalties or levels of load shifting, can be generalized. However, the goal of the model was not to provide precise forecasts but rather explore how interactions between IC and its environment would unfold. From this perspective,

the results are meaningful and valid in terms of capturing the system dynamics and its trends.

The exact numbers produced by the model should be treated cautiously, as they depend on a number of assumptions and simplifications. On the other hand, the relative changes across scenarios are generalizable. For instance, the simulations consistently showed that heterogeneous groups are much more stable than homogeneous groups on the KPIs. This effect is not dependent on a specific parameter value, but emerges from the structure of the model itself. Such results provide a useful indication for EH designers: diversity among participant's behaviour can improve resilience in demand response.

What can not be generalized directly are the exact tipping points or thresholds at which behavioural change occurs, since these are sensitive to assumptions made about consumer preferences such as penalty sensitivity. More precise knowledge on such thresholds could only be discovered by case studies with real-world data. In that context, the same model structure could be used but with empirically grounded input parameters.

10.3. Limitations

In this section, some critical assumptions and model limitations are discussed. An overview of all assumptions that were made can be found in Appendix B.

10.3.1. Critical Assumptions

This research did not aim to develop a fully detailed model, but rather to create a high-level framework capable of providing insights into demand response in EHs with diverse IC. Some model parameters are inherently uncertain, particularly those representing behavioural aspects which had to be quantified numerically. As a result, a number of simplifying assumptions were made regarding both the EH and the IC. While assumptions are an unavoidable part of simulation modelling, it is essential that they are supported by existing literature or grounded in clear reasoning. The following subsection discusses the most critical ones of these assumptions.

First of all, the representation of the flexible assets in the model are highly simplified. PV is the only type of flexible asset to be considered, without the inclusion of other technologies such as batteries, wind turbines, or thermal storage. The PV installations are assumed to be identical panels of 450 Wp, without efficiency variations or degradation over time. The agents are also assumed to have a fixed amount of roof space and installations, without the possibility to expand their roof space and installations over time. These assumptions may limit the realism of the EH representation as they simplify the technical challenges and opportunities of flexible assets in real-world EHs.

Next, the CEMS is assumed to have perfect foresight of congestion hours for the following day and to respond instantaneously. In reality, there will be forecasting errors and delays in response time. The CEMS is also assumed to perfectly redistribute the group capacity each month proportionally to each agent. In reality, this redistribution may not always be perfect and there may be a different distribution key. It is also assumed that all agents in the EH do not have other EMS for their own assets, but only have one CEMS for the whole EH. In real-life, this may not be always the case as participants already have an EMS before entering the EH. These assumptions may limit the realism of the CEMS as they simplify practical challenges such as imperfect forecasting and potential conflicts of interest between participants with the distribution key.

Lastly, the representation of agent behaviour is another important limitation. Agents in the model are restricted to load shifting as their only flexibility option, without the possibility to reduce their demand or invest in their own flexible assets. The SVO is modelled as four discrete categories, while in reality SVO exist on a continuous spectrum and can change over time. The agents can not adapt their strategies, learn from the past outcomes or each other. In the decision-making formulas, parameters such as penalty and load shifting sensitivity are included. These are quantified values, which are not empirically supported to be precisely that value. These assumptions may limit the realism of the agents as this representation simplifies important behavioural dynamics.

10.3.2. Model Limitations

A simulation is a simplification of reality, so not all aspects of a system such as an EH can be included in the model. The way certain features were included in the model directly influences how the results

can be interpreted.

This research does not represent a real-world case study as it relied on stylized and self-constructed data. Demand profiles were drawn from MeterInsight, where real-life data of potential participants from different EHs are registered. These profiles are not necessarily from one EH as some participants did not have data available from 2024. The PV profile of generation is self-constructed based on seasonally and daily patterns instead of measured data. The model outcomes can not be generalized, because the input data does not correspond with one specific EH.

The results should instead be interpreted as indicative trends rather than exact forecasts. In reality, there are many configurations of EHs: some have a lot of flexible assets, while others may have more participants and different types of flexible assets. Each of these configurations could have different results and implications, which indicates that future research could explore these configurations to a specific case.

10.3.3. Survey Limitations

In addition to the critical assumptions and the model limitations, the design and outcomes of the survey also comes with limitations that affect the reliability of the findings.

First of all, the sample size of the survey was very small as only four participants responded. In context of behavioural or social science research, this sample size is far below the recommended thresholds. Memon et al., 2020 suggested that behavioural studies typically require a sample size between 30 and 500 respondents. With such a limited number of four responses, it is not possible to identify patterns or make statistically meaningful claims. The results of the survey should therefore be interpreted as exploratory input rather than robust evidence. Future research could conduct larger-scale survey with a more representative sample size to obtain statistically meaningful insights.

Another limitation is the fact that the survey was conducted online. While online surveys are convenient and cost-effective as there are no costs to visit the respondents (DeCarlo, 2018), they also come with disadvantages. As mentioned before in Section 3.4, the limitations are that it gives a limited depth of gathered information and respondents may not fully be able to express their thoughts. Also respondents may misinterpret the questions. To tackle these limitations, the survey was deigned with examples, open questions, and the Likert-scale (Bryman, 2004). However, the answers to open questions could not be more clarified because there was no direct communication which limits the depth of the answers. Future research could conduct a complementary interview with respondents as a follow-up to the survey, which would help to better understand the respondents answers.

10.4. Implications

The findings from this study have several implications for the design and management of EH with demand response incentives. In the following subsections, three strategies are discussed. These three strategies are Time-of-Use pricing with dashboard, gamification, and rotational load shedding.

10.4.1. Time-of-Use pricing with dashboard

Seasonal variations in load shedding, load shifting, rewards, and penalties indicate that targeted time-sensitivity interventions can improve overall performance. Altruistic and pro-social agents are most effective during peak demand periods or times of low renewable generation. Their cooperative orientation ensures that they engage in load shifting, but this often plateaus over time since their actions are less responsive to financial incentives. In contrary, competitive agents show great strengths in long-term adaptability. Over time the competitive agents face repeated rewards and penalties that influence their decision-making, which leads to taking better advantages of shifting opportunities.

The survey have shown that all respondents on average have a pro-social SVO type, which means that they are willing to cooperate. Their actions are not primarily driven by financial incentives, but rather social and operational factors such as having insight into capacity pressure within the EH. Competitive and individualistic types are less common in the survey results, but from the model is can be said that they are driven by financial incentives.

It can be said that a combined strategy is needed that encourages cooperation during peak hours while

still providing triggers for competitive and individualistic agents.

An example of such a strategy is a Time-of-Use (ToU) penalty scheme combined with a dashboard. ToU is a pricing scheme where the electrical prices vary between predefined periods of the day, with higher prices during peak demand hours and low prices during off-peak times. By providing predictable financial incentives, ToU encourages consumers to shift their electricity use from expensive peak hours to cheaper off-peak hours (Wang & Li, 2015). According to the extreme condition test from Section 5.5, the pricing must stay between the 0 and 1 €/kWh. The reason for this is that system boundary is 1 €/kWh, so in the model agents already have shifted their maximum flexible capacity.

In research by Zhang et al., 2000 into dynamic ToU pricing for Electric Vehicle (EV) charging, the authors propose a strategy in which the EV cluster aggregator (could also be the EH operator) first collects the charging plans and the schedules of its participants. Then, based on the collected charging plans and expected output of renewable generation, the price could be determined for each time period and continuously be updated. The price adjustment is based on the difference between supply and demand in each time slot with the goal to minimize imbalance. To ensure practicality for its users and economic efficiency, the price is constrained. The price can not exceed the peak-valley price, so that users remain incentivized. The price may also not drop below the generation and transmission costs of renewable energy. If the dynamic pricing does not achieve the desired load adjustment, the pricing goes back to safe prices so that non-responding EVs are charged normally.

In this combined strategy, the dashboard provides real-time signals of congestion moments, while penalties have a higher number for peak moments particularly in the winter or low renewable generation moments. For altruistic and pro-social agents, the dashboard shows when their actions are most needed which allows them to target load shifting in critical hours. Altruistic and pro-socials are less responsive to penalties or rewards, so factors such as transparency and insight into the capacity pressure within the EH would help to encourage cooperation. For competitive agents, the combination of information from the dashboard and higher penalties during critical hours encourages them to adapt more and increase load shifting.

However, there are some challenges when using ToU for IC. According to Normasari et al., 2025 who conducted a systematic literature review about ToU schemes, the main issue is the limited flexibility in operational processes as production and maintenance schedules are often fixed. This makes it difficult to shift energy without affecting efficiency or output. Next, optimizing energy consumption under ToU requires integrating production planning, maintenance, and energy costs which can be a complex operational and technical task. Therefore, it requires careful planning and coordination across the EH to balance operational constraints with peak-demand hours. Also, successful implementation depends on the IC understanding and responding correctly to the signals which requires transparent dashboard and communication.

10.4.2. Gamification

The results also highlight the value of heterogeneous populations. Mixed compositions, such as moderate or equal mix, consistently produce balanced outcomes across all KPIs which decreases the extremes observed in the pure homogenous compositions. In this way, heterogeneity reduces extremes and risks while maintaining reasonable financial outcomes.

From the survey results, it was clear that participants can be influenced by social factors such as reputation, positive experiences, expectations, and trust. These factors should therefore be encouraged within the EH to strengthen long-term engagement. Also, all respondents have on average a pro-social type and in some situations altruistic, individualistic, or competitive responses which affects the diversity in the group.

This suggests that EH designers should encourage diversity in user behaviours to stabilise performance and use the social factors in this incentive.

According to Galeote et al., 2025 who reviewed gamification for sustainability transitions, gamification can improve this diversity and trust in users by engaging different participants in structured, interactive, and playful activities.

To quote Baptista and Oliveira, 2019, gamification is the use of game-design elements in non-gaming

contexts, in a process of enhancing a service with game-related features that support users' overall value creation. Gamification seeks to unite functionality and engagement, to increase usability, productivity, and satisfaction, to create more enjoyable experiences, to drive behaviours, and to produce positive business impact.

The research of Galeote et al., 2025 proves that gamified interventions can increase awareness, stimulate creativity, and encourage collaboration among diverse stakeholders. By providing a safe environment, gamification helps participants explore complex system dynamics, understand how individual actions impact collective outcomes, and build emotional and cognitive engagement.

A gamified approach in the case of the EH could be that there are cooperative challenges where participants can earn (gamified) rewards when everybody contributes to load shifting. This way the participants can build trust, improve reputations and expectations and have positive experiences with each other. With this implementation, gamification can bring different participants together while also strengthening the social dynamics.

An example of gamification in the context of demand response is the Jeju Island pilot project (Lee et al., 2024) from Korea. The project implemented game-based incentives via a mobile application to increase participation in demand response events. Here, participants could earn points for connecting their electric vehicles during demand response events, engage in subgames such as quizzes, lotteries, or badge collections, and compete via a leader board. These elements balanced intrinsic motivations like achievements, recognition, and competition, while also encouraging engagement over time. What important is to note, the design allowed participants with different behavioural tendencies to contribute.

Another example of gamification is the game 'Rethinking Users'. According to Youngblood and Chesluk, 2022, 'Rethinking Users' can offer a new perspective that embeds all users in a framework of complex, linked experiences. This game is designed to make abstract system interactions tangible, allowing participants to experiment with different roles, explore trade-offs, and see the consequences of their choices in a simulated environment. This game can encourage collaboration across heterogeneous populations by allowing the different types of participant to explore how their behaviours impact individual- and system-level outcomes. This shared perspective can reduce the reliance on penalties, improve engagement in load shifting, and helps align the individual with collaborative objectives.

According to Becka et al., 2019, gamification elements should not be added randomly when designing an app. It should be aligned with the user's needs, motivations, and the overarching system objectives. Poorly designed gamification can otherwise lead to confusion, disengagement, or even frustration which undermines the intended behavioural change. In addition, gamification in the energy domain is still relatively underdeveloped compared to other domains such as health. Most existing apps use only a limited number of basic components and rarely use advanced elements such as narratives, or immersive environments. Therefore, the success of gamification in the context of EH depends on moving beyond superficial into a developed design, where each component is purposefully aligned with the user's needs, motivations, and overarching system objectives.

10.4.3. Proportional Load Shedding

Lastly, it was noticed from the runs that rotational load shedding might not be the fairest approach. In the current implementation, some agents are shed even though their energy usage is relatively low, while other agents that exceed their capacity limits do not pay the price of being shed. This could eventually lead to perceived inequalities among participants and reduced trust in the EH. The observation suggests that another load shed method may be more fair and better to implement.

An example of a new method could be proportional load shedding with the priority order that already is implemented in the model. In proportional load shedding, each agent's reduction would be scaled according to its actual energy consumption. This ensures that an agent with a high energy usage are more affected than the agents with a lower energy usage. According to Valiev et al., 2017 proportional load shedding, in particular Active Proportional Strategies, are recommended for practical implementation because they lower total interruptions, fairly distribute the shortage among participants, and help identify weak points in the network. With this method, the focus is more on equity instead of equality as agents are shed relative to their actual demand rather than being treated identically.

11

Conclusion

This chapter concludes this study by answering the main research question and sub-questions, which presents a concise answer for each of them based on this research. Next, the scientific and societal contribution are discussed after which the final section presents recommendations for further research. Lastly, this chapter will end with managerial recommendations.

11.1. Main Research Question

In this research, an Agent-Based Model (ABM) simulation was created and a survey was conducted to gain more insight in the effect of different Social Value Orientation (SVO) types in an Energy Hub (EH) and bounded rationality. The main research question was the following:

What is the impact of diverse participant behaviour and Social Value Orientations on congestion management in an Energy Hub within a Group Contract?

ABM can be used to assess the impact of participants behaviour on congestion management in an EH. This can be done by representing each Industrial Company (IC) as an autonomous agent with its own energy demand and decision-making rules based on SVO. ABM allows these agents to interact with each other and with the shared EH infrastructure, which is managed by the Collective Energy Management System (CEMS).

By using ABM, it was possible to simulate the interactions between the four different SVO types and explore how these influence load shifting and cooperation. The model also includes bounded rationality, which mimics the fact that agent make decisions on limited information and do not always make the right decisions because humans are not perfect. This approach shows how system-level outcomes, such as total load shifts, penalties, load shedding, and rewards, are affected by different compositions of agent types.

When comparing homogenous and heterogenous populations with each other, the model have demonstrated that behavioural diversity in an EH can balance the system-level outcomes and mitigate the extreme outcomes. Behavioural diversity also balances short-term and long-term Demand Response (DR). Different trade-offs could be made among homogenous populations if there is a specific emphasis on resilience, fairness, or other values.

The survey results have provided additional insights that complement the findings from the ABM. In practice, participants are mostly motivated by social and operational factors such as trust, reputation, positive past experiences, and adherence to shared agreements, instead of purely financial incentives. Most respondents can be typed as pro-social, with sometimes altruistic, individualistic, or competitive tendencies depending on the context.

Combining the insights from the ABM and survey, it becomes clear that strategies for the EH should not only rely on financial incentives but also the social and operational drives. From these results, several potential strategies could be formulated such as Time-of-Use penalty pricing with real-time dashboards,

gamification, and proportional load shedding technique. These strategies can help align individual actions with collective goals, improve balance in the system, and stimulate the social dynamics within the EH.

11.2. Sub-Questions

1. How can the Energy Hub be modelled as an Agent-Based Model?

The EH can be modelled as an ABM by representing each IC as an autonomous agent with its own portfolio of energy demands, decision-making behaviour, and bounded rationality. The behavioural diversity of these IC agents are based on SVO, which categorizes people into altruistic, pro-social, individualistic, or competitive types:

- **Altruistic Agents:** Prioritize Social Welfare
- **Pro-Social Agents:** Balance Self-Interest with Social Welfare
- **Individualistic Agents:** Seek to maximize their own Welfare
- **Competitive Agents:** Actively pursue relative advantage on Welfare

The agents follow a daily planning cycle, where they receive and observe congestion forecasts from the Collective Energy Management System (CEMS) via a dashboard, evaluate possible penalties, and decide whether to shift their flexible preferential loads or accept penalties. The penalties are the amount of money that the agents have to pay if they exceed their capacity limit. Their decision-making is influenced by their SVO and bounded rationality, which mimics human-like heterogeneous responses. This daily planning cycle is based on the day-ahead market, where agents make commitments for the following day and execute them. The environment of the model is defined by the shared EH infrastructure, which includes collective capacity constraints, a CEMS, and photovoltaic (PV) panels.

The actions of the agents altogether interact with the shared EH infrastructure, which is managed by the CEMS. The CEMS enforces operational reliability through mechanisms such as rotational load shedding, curtailment of PV generation, adaptive capacity allocation, and implicit capacity sharing. In the latter, unused capacity of an agent can be reallocated to another that exceeds its allocated capacity. Financial compensation is then given if implicit sharing happens.

For this ABM of the EH certain assumptions and simplifications were made. The whole list can be found in Appendix B, but the important ones are the following:

- The EMS has full operational control over shared assets.
- The EH only has PV as shared flexible asset.
- The congested hours for the next day are assumed to be perfectly known and accurate.
- Agents know how much others are using.
- Each type of capacity is assumed to be one installation.
- Agents do not revise their strategies based on the outcomes.
- The decision-making formula assumes that the agents know how much others are using.
- If there is no congestion the next day, the agents will not make a decision to load shift.
- Agents can only load shift their Flexible Preferential capacity.
- Agents can only choose to load shift; reducing their load is not included as a possibility.
- The agents have a GTO with each other and not another contract.

2. Which Key Performance Indicators are most suitable for evaluating the performance of the Agent-Based Model?

For this research, four Key Performance Indicators (KPI) were chosen to evaluate the results of the ABM with. These KPIs are total load shifts, total penalties, total load shedding, and total rewards.

First of all, the total load shifts is the total number of times flexible preferential loads of agents is shifted to non-congested periods. This KPI is chosen, because it directly indicates how many times agents choose to load shift instead of doing nothing and just pay penalty. A higher number of load shifts suggests that agents are responsive to congestion signals and willing to adapt their consumption patterns to support system efficiency. It also reflects the operational feasibility of load shifting under the given constraints, including flexibility preferences, perceived costs, and behavioural factors. In this way, it serves as both a technical and behavioural indicator of demand-side adaptability.

Next, the total penalties is the total amount of fines imposed on agents when they exceed their allocated capacity limit. This KPI is chosen, because it reflects how many times an agent surpasses their allocated capacity limit, either due to insufficient flexibility in their load management or a deliberate choice to prioritize demand over cost savings.

Then, the total load shedding is the total number of times the CEMS had to reduce an agent's energy usage to prevent that the whole EH is going over the Group Contracted Transport Capacity (G-GTV). This KPI is chosen, because it shows how many times the CEMS had to interact with the EH and also reflects the EH's resilience. It also serves as an indirect measure of the effectiveness of an agent's planning and cooperation. In such way, fewer load shedding may suggest that agents are better at their DR through load shifting or capacity sharing which reduces the need for a centralized CEMS action.

Lastly, the total rewards is the total amount of compensation awarded to agents for giving up their capacity to another agent. This KPI is chosen, because it reflects the implicit capacity sharing of the agents. In the decision-making, agents take the reward fee into account when deciding to load shift or just pay penalty. So it is not only an economic but also a behavioural KPI as it captures how an agent's SVO and individual cost-benefit analysis influence cooperative behaviour.

3. How do the different types of behaviours of agents influence the congestion management of the Agent-Based Model?

The different behaviours of agents with varying SVO strongly influence how congestion is managed within the EH. All altruistic and pro-social agents contribute most effectively during peak demand periods or moments of low renewable generations, since they are more willing to load shift for the collective. However, their total load shifts plateaus over time, because their behaviour is less responsive to repeated penalties or rewards. On the other hand, all competitive agents are more strongly driven by financial incentives. Over time, it becomes clear that they adapt to repeated penalties and rewards which enables them to exploit load shifting opportunities more effectively in the long run. Individualistic agents consistently contribute the least to congestion management and thus not load shifting. Since these agents prioritize their own welfare, their load shifting levels remain the lowest of all agent types.

Looking at the mixed groups, agent heterogeneity in an EH plays an important role in balancing short-term and long-term congestion management. The presence of a mixed population prevents extreme outcomes, because they balance the behaviour of the less self-interested ones and the highly self-interested.

4. How do the survey results of real-life participants support the behavioural mechanisms implemented in the Agent-Based Model?

The survey have shown that the participants are primarily motivated to load shift or give capacity away by social and operational factors such as trust, reputation, positive experiences, adherence to shared agreements instead of financial incentives. This matches the assumptions made for the ABM, where specifically the pro-social and altruistic agents handle based on collective well-being.

The survey also have shown the diversity in participant behaviour in certain situations as all respondents are in general pro-social, but sometimes altruistic, individualistic, and even competitive tendencies occur depending on the situation. For example, more altruistic tendencies occur when there is excess capacity left while another company needs it. This may suggest that respondents are willing to put the collective interest above their own because they do not need the excess anyway. Competitive tenden-

cies appeared in conflict-prone situations such as asking another company to reduce or shift their load, which reflects that a small percentage may act out of self-interest under pressure. Individualistic tendencies emerged in scenarios involving load shifting, where respondents emphasized the importance of maintaining the operational stability of their own business process.

The survey shows that all four respondents are either pro-social or lean toward pro-social behaviour, which matches with the all pro-social scenario in the ABM. This suggests that in practice the respondents from the survey in an EH are likely to cooperate and make decisions that benefit the collective, even if it results in lower individual rewards or higher penalties. This behaviour observed from the scenarios corresponds with the respondents prioritizing social and operational factors over financial incentives. As said before, there are some deviations from behaviour depending on the situation which can suggest that there can be some level of heterogeneity in real-world EHs. Also, only a limited number of respondents participated in the survey, which means that the evidence is not sufficient to make strong claims about the actual distribution of behavioural types in practice. Future research should test with larger sample sizes and validate the all pro-social behaviour. In addition, future research should include the other two situations and additional social factors from the survey in the model.

5. How can insights from the Agent-Based Model and survey be translated into potential strategies that influence system-level behaviour?

The insights from the ABM and survey can be translated into potential interventions that influence system-level behaviour in the EH by tailoring strategies to agent behaviour, timing, and heterogeneity.

The ABM emphasizes the role of agent types in congestion management. Altruistic and pro-social agents respond strongly to collective needs, especially during peak demand periods or low renewable generation but their responsiveness plateaus over time. Competitive agents are highly adaptive to repeated incentives and penalties, which encourages them to exploit load shifting opportunities more effectively in the long term. However, individualistic agents consistently contribute the least to congestion management.

One practical intervention to balance the strengths of each group and mitigate weaknesses, is a Time-of-Use (ToU) pricing scheme combined with a real-time dashboard. ToU pricing provides predictable financial incentives, encouraging load shifts from peak to off-peak periods. The dashboard communicates congestion signals in real-time, giving altruistic and pro-social agents insight into capacity pressure within the EH and motivating competitive agents to adapt strategically to penalties and rewards.

The ABM also shows the value of heterogeneous populations. Mixed agent compositions consistently produce balanced outcomes across all KPIs, which balances the extremes observed in homogeneous populations. This suggests that interventions should aim to maintain or encourage behavioural diversity, as it stabilizes system performance while preserving financial incentives. From the survey it was clear that social factors are important for most participants so these should be encouraged. Also, the responses seem to be pro-social with some other SVO type tendencies. This indicates that there is a need to promote more diversity.

Gamification can be an effective intervention to maintain or encourage behavioural diversity. By engaging participants in interactive and playful activities, gamified systems can increase awareness, encourage collaboration and trust, update expectations of everyone, and provide a safe space for participants to explore the effects of their actions on the system. Examples include the Jeju Island pilot project, where EV owners earned points, participated in subgames, and competed via leader-boards. Another example is the “Rethinking Users” game, which allows participants to experiment with different roles and see how behaviours affect system-level outcomes. Gamification helps with aligning individual actions with collective objectives and sustains engagement over time.

Proportional load shedding is another intervention that can be included in future EHs as rotational load shedding might not be the fairest approach. The reason for this is that some agents in the model are shed even though they are not using as much as others who are not shed. According to literature it seems that proportional load shedding may be the fairest focussing more on equity instead of equality.

11.3. Scientific Contribution

A lot of research has already been done in the field of DR or the optimization of EHs. However, previous research focussed mainly techno-economic aspects such as improving the operational efficiency and cost-effectiveness (e.g. Darvishi et al., 2024; Fan et al., 2018; Mokaramian et al., 2025). Most of these studies disregarded the heterogeneity of irrational actors and their bounded rationality. Behavioural diversity was researched by some studies (e.g. Boske, 2021; Li et al., 2025; Lu et al., 2020), but there was a need for empirically grounded, user-centric model that reflects the real behaviour of industrial consumers. Next, while multi-actor collaboration is acknowledged as a key factor in the functioning of EHs (e.g. Berkouwer, 2024; Fan et al., 2018), current modelling provide limited insight into how this collaboration actually unfolds between the industrial consumers.

Based on former research and the identified knowledge gaps, this thesis analysed how the collective behaviour of heterogeneous or homogeneous groups of participants in an EH shapes technical, economic, and behavioural aspects of the system. Scientific contributions were made to three parts of literature, which are optimization of EH models, behavioural diversity of consumers, and multi-actor collaboration within the EH.

First of all, this thesis contributes to the optimization of EH models by integrating both technical, behavioural, and economic aspects into a single model. Unlike previous studies that primarily focused only on the operational efficiency and cost-minimization, this model also considers flexible load shifting and behavioural diversity. Here, participants can choose to shift their load themselves instead of the energy producer (e.g. Boske, 2021). This research has contributed to optimizing EH models by including real-world operational constraints and demand-side flexibility. It can be said that the model itself is a scientific contribution, as it can be reused in future studies to evaluate interventions and explore behavioural compositions.

The second scientific contribution is the understanding of behavioural diversity among IC. By incorporating SVO and bounded rationality into ABM, the study captures heterogeneous and homogeneous decision-making patterns. This method is an approach to allow more realistic simulation of the decision-making of load shifting. Additionally, this approach has introduced a new way to represent decision making about DR in a quantitative manner and incorporate this in a quantitative agent-based model. The final simulation model was able to provide comprehensive insights about participation in DR on a system level.

Lastly, the final scientific contribution to the literature on multi-actor collaboration by modelling indirect interactions between the different ICs within the EH. The agent-based approach captures how shared infrastructure, penalties, rewards, and informational dashboards influence collective behaviour. The findings of this research show how heterogeneous populations can stabilize the system, while homogeneous groups may intensify extremes. This highlights the importance of diversity in DR. By linking individual-level behaviour to system-level performance, this research provides valuable insights for designing intervention strategies for future EHs.

11.4. Societal Contribution

The energy transition is one of the challenges of this century and IC are expected to play an active role in balancing their demand with supply. As the demand of energy is growing, the reliability of energy supply becomes uncertain. This requires mechanisms for DR to ensure grid stability. EHs offer a promising solution by coordinating multiple ICs within a shared infrastructure. However, the dynamics of such a collaboration remains hard to predict. This thesis provides insights into how heterogeneous behaviours influence system-level outcomes and reasons which interventions can support more effective DR. In doing so, the results offer valuable lessons for both policy makers and practitioners involved in the energy transition.

Firstly, the research shows that purely homogenous populations produce extreme outcomes. In contrast, heterogeneous populations achieved a more balanced system performance across economic, technical, and behavioural aspects. This has social relevance, because it shows that supporting behavioural diversity within EHs can stabilize the collective outcomes.

Next, the strategies that were recommended in this research offer practical pathways for improving

engagement. A combination of dashboards that provide real-time congestion signals and seasonal ToU penalties can be an effective strategy. Such tools allow ICs to see when their actions matter most and align their decisions with system needs. Furthermore, gamified interventions offer opportunities to engage participants in a more collaborative and sustainable way, which shifts the perception of DR from an imposed burden to a shared responsibility. By encouraging transparency, engagement, and cooperation these strategies contribute to the societal goals of promoting fair participation in the energy transition.

Lastly, this research shows the societal implications of encouraging ICs to actively participate in the energy transition. This study emphasizes that the energy transition is not only a technical or economic challenge but also a social challenge. While advances in technology and market mechanisms are important, their effectiveness eventually depends on how people engage with them. The importance of factors such as behavioural diversity, trust, and cooperation among participants underline that achieving collective energy goals relies on aligning individual incentives with shared societal benefits. Behavioural diversity allows for a more balanced system performance, trust encourages the IC's willingness to share resource, and cooperation is the backbone of coordinating with other IC's. By encouraging these factors, ICs may see the energy transition not as a burden that can not be helped but rather a chance to evolve their operations, behaviour and eventually contribute to a more resilient energy system. This way the energy transition also becomes a catalyst for social innovation, empowerment, and long-term community well-being.

11.5. Managerial Recommendations

The findings of this research contribute to several insights for managers and policymakers involved in the design and operation of EHs under congestion management. Based on the results of this thesis, three recommendations can be made.

A ToU pricing scheme for penalties paired with a real-time dashboard can provide advantages for the participants of the EH as it allows for transparent information and gives predictable financial incentives. Altruistic and pro-social participants are less sensitive to financial penalties and rewards, but can be motivated by social factors such as insights into the pressure of the system. A dashboard that shows real-time capacity pressure helps them to target load shifting at the peak moments. Competitive and individualistic participants are more responsive to financial triggers, so predictable penalties during peak hours can encourage adaptive decision-making over time. However, manager and policymakers must also account for limitations of ICs such as that they have rigid production and maintenance schedules. This may make it harder for ICs to react to ToU signals as they have limited flexibility.

Next, survey results have shown that potential participants have a pro-social SVO type, which makes them less motivated by financial incentives such as penalties and rewards. At the same time, the model have shown that heterogenous populations with a mix of different SVO types have more balanced outcomes across the KPIs. For this reason, managers and policymakers should encourage diversity, trust, and engagement. A game such as 'Rethinking Users' can offer new perspectives for participants and allows let the participants see the consequences of their choices in a simulated environment. Gamified interventions such as cooperative challenges, recognition systems, or leader-boards can engage different behavioural types and encourage long-term cooperation and trust. What to note is that gamification should not be applied superficially, because to be effective it must be tailored to the needs and motivations of participants.

Lastly, implementing proportional load shedding instead of rotational load shedding can increase fairness. Rotational load shedding may unfairly penalize low consuming participants while high consuming participants are spared. With the proportional load shedding method, the reductions are scaled according to each participant's actual usage. This method actually stimulates fairness by prioritizing equity rather than equality.

11.6. Further Research

This research has focussed on the interplay between IC, their behaviour, and the functioning of EHs. However, the model and its findings can be improved for future research to deepen the understanding of EHs.

First of all, this research's goal was to explore the collective behaviour of IC in an EH by using an ABM that included technical, economic, and behavioural aspects. Due to the limited scope and time frame of this research, several assumptions and simplification were made as discussed in Chapter 10. Nevertheless, the model was able to provide valuable insights into how heterogeneous and homogeneous populations influence DR. The model is suitable for exploratory purposes and can be applied in small-scale case studies, where real data on consumer profiles is available. The future research recommendation is to apply the model to more specific case studies, which allows for empirical validation of the behavioural parameters.

Next, this research's main focus was comparing the effects of different SVO group compositions within the EH. While this provided valuable insights into how behavioural diversity influences DR, the model did not test a range of potential interventions. Future research could explore interventions that were mentioned earlier, such as ToU pricing schemes for penalty with dashboards, gamified mechanisms, and proportional load shedding. By implementing these interventions in the model with the heterogeneous agent populations, it becomes possible to explore how the interventions affect the collective outcomes and how different agent types respond to those interventions.

Thirdly, in the model the agents follow behavioural rules throughout the simulation which is implemented via SVO. In reality, people and thus also IC learn from experience and adapt their behavioural rules. Agents could for example switch from SVO throughout the time as indicated by Moisan et al., 2018, which can change the whole social dynamic. Future research can incorporate adaptive learning mechanisms, such as reinforcement learning, into the model. This implementation would allow researchers to study how behaviours evolve over repeated interactions and whether cooperation can emerge without external enforcement.

Another future research recommendation is including additional flexibility assets in the model. The model only included PV panels as part of the shared EH infrastructure, which means that agents could only contribute to DR through behavioural adjustments such as load shifting. However, real-world EHs are expected to include a broader portfolio of flexible assets. Future research could extend the model to include flexible assets such as batteries, thermal energy storage, or hydrogen systems. For example, researcher could evaluate whether battery systems reduce the dependency on behavioural DR.

Also, future research could include active capacity sharing and approaching another agent to reduce their usage. Active capacity sharing means that agents could ask another to use the unused capacity. The model only included the option to load shift, since experts do not agree with each other if the ICs will have more option. In the model it, means that the agents only can contribute to DR through shifting their load. In practice, participants may have more options to cooperate or negotiate with others.

Then, future research could include social networks between the IC. As mentioned before, research has shown that people are influenced by their peers through reputation or benchmarking. Introducing a social network structure into the ABM would make it possible to study how peer influences choices made by others in an EH. For example, IC may be more likely to implement load shifting if others are seen to benefit from it. From the survey, it was clear that there are more social dynamics factors to be included in future models such as trust, expectations, positive past experiences, and reputation. Incorporating these into future models would help to make a more realistic representation of how behavioural drivers influence outcomes in an EH.

In addition, future research could explore the effects of different EMS of agents in an EH. This includes scenarios where individual agents have their own EMS that interacts with the CEMS, which could give more insights of potential conflicts or synergies challenges within the EH. It would allow for more a realistic approach for an EH, because participants often have their own EMS.

Lastly, this research was limited by the empirical data available to check behavioural assumptions. While a survey was conducted, the response rate was low which restricted the ability to fully capture the diversity of perspectives. This leads to not accurately validating the observed SVO behaviour of the survey and correctly comparing it with the scenarios of the ABM. Future research could use the same approach in more extensive data collection using larger target group or targeted interviews. Using the same approach from this study ensures methodological consistency and allows the new findings to be directly compared with the results from this study. Such bigger dataset would increase the statistical representativeness of the survey and allows for a more preciser identification of patterns

across the respondents. This bigger dataset would also form a stronger empirical basis that could reveal more behavioural drivers and validate the assumptions made in the model. Also, the observed SVO behaviour of the respondents from the survey could be validated and compared with the scenarios of the model.

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Disclosure of AI

While preparing this work, I used NotebookLM to summarise papers that I selected. I copied certain parts of the paper and asked NotebookLM if it could bullet point or summarise in words the selected text. I used ChatGPT to help with ideation of the model, structure the text that I have written and to add missing links between sentences. Also, ChatGPT and Claude were used for ideating how to structure the code for the ABM. After using this tool/service, I reviewed and edited the content as needed and I take full responsibility for the content of my research report.

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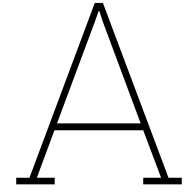
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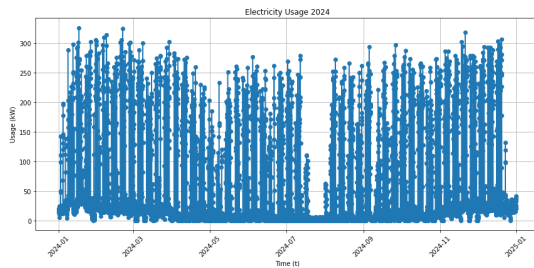
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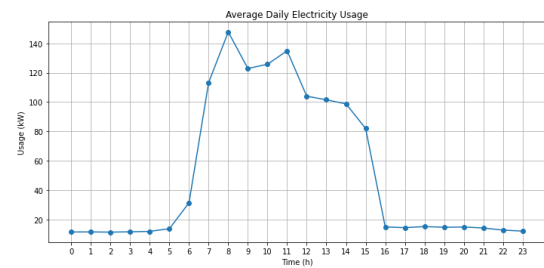


Profiles and Categorization of Agents

This Appendix will show the ten agents with corresponding demand profiles and categorization. The first graph (a) shows the demand in kW over a year and the second graph (b) shows the average demand in kW over a day. The table (c) shows the categorization of the four types of capacities for the total demand.



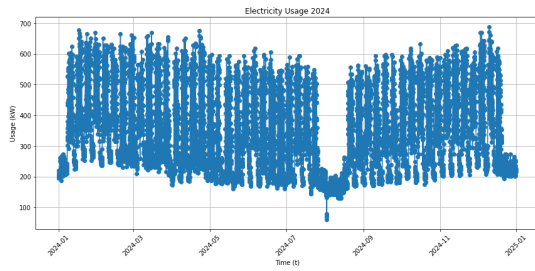
(a) Electricity Demand Profile of 2024 Agent 1



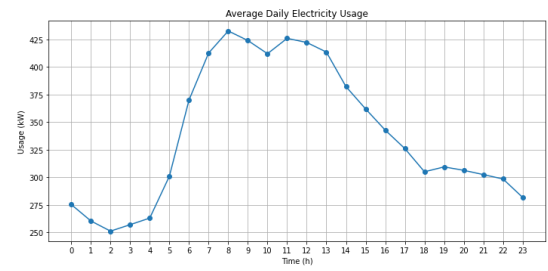
(b) Daily Demand Profile of Agent 1

Type	Aluminium Manufacturer
Fixed Preferent	Potlines
Flexible Preferent	Cool Water Pumps
Fixed Non-Preferent	Waste Disposal Installations
Flexible Non-Preferent	Lights

Figure A.1: Demand Profiles and Categorization of Agent 1



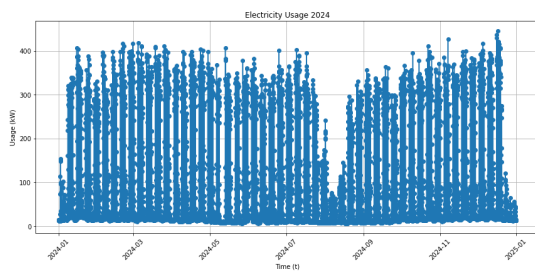
(a) Electricity Demand Profile of 2024 Agent 2



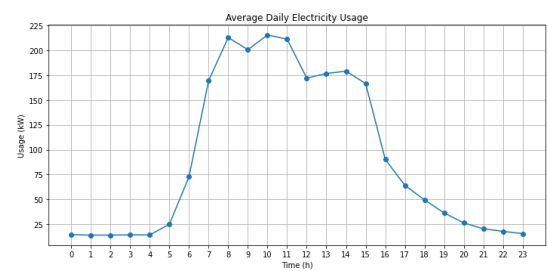
(b) Daily Demand Profile of Agent 2

Type	Prefab Concrete Producer
Fixed Preferent	Concrete Mixers
Flexible Preferent	Ventilation Systems
Fixed Non-Preferent	Conveyer Belts
Flexible Non-Preferent	Cooling Machines

Figure A.2: Demand Profiles and Categorization of Agent 2



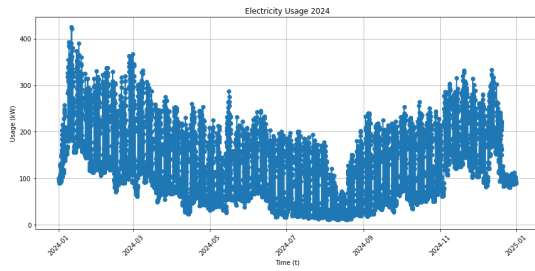
(a) Electricity Demand Profile of 2024 Agent 3



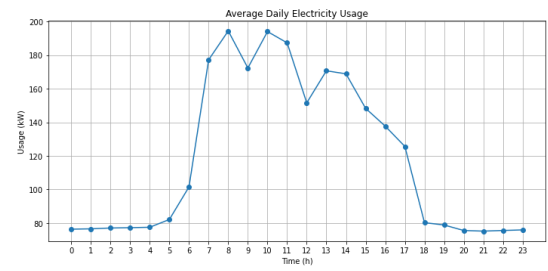
(b) Daily Demand Profile of Agent 3

Type	Timber Trader
Fixed Preferent	Climate Control
Flexible Preferent	Sawing and Drilling Installations
Fixed Non-Preferent	Wood dryer
Flexible Non-Preferent	Lights

Figure A.3: Demand Profiles and Categorization of Agent 3



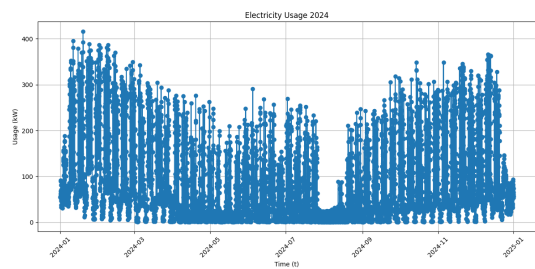
(a) Electricity Demand Profile of 2024 Agent 4



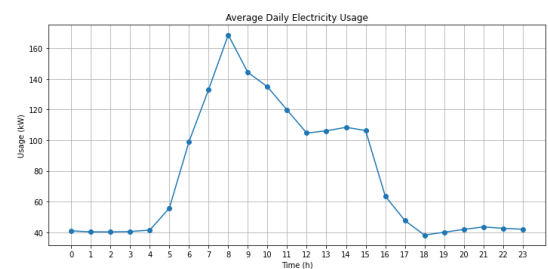
(b) Daily Demand Profile of Agent 4

Type	Shipyards
Fixed Preferent	Cool Water Pumps
Flexible Preferent	Ventilation and Extraction Systems
Fixed Non-Preferent	Welding and Cutting Equipment
Flexible Non-Preferent	Lights

Figure A.4: Demand Profiles and Categorization of Agent 4



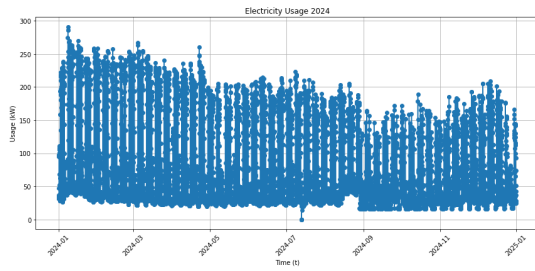
(a) Electricity Demand Profile of 2024 Agent 5



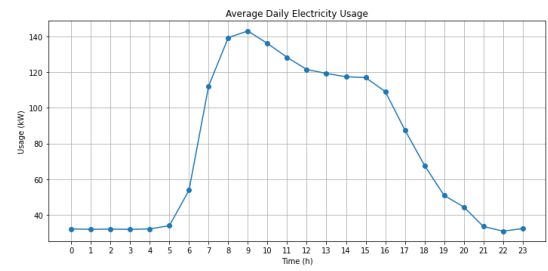
(b) Daily Demand Profile of Agent 5

Type	Construction
Fixed Preferent	Welding Equipemnt
Flexible Preferent	Sawing and Drilling Installations
Fixed Non-Preferent	Dust Extraction
Flexible Non-Preferent	Lights

Figure A.5: Demand Profiles and Categorization of Agent 5



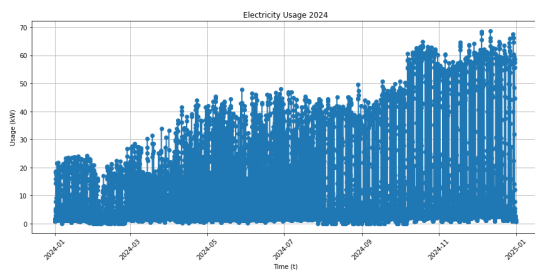
(a) Electricity Demand Profile of 2024 Agent 6



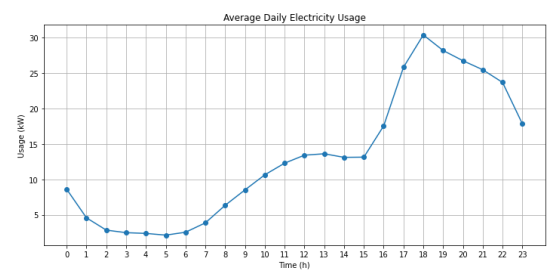
(b) Daily Demand Profile of Agent 6

Type	Industrial Services and Producer
Fixed Preferent	CNC Machines
Flexible Preferent	Charging Stations for Electric Vehicles
Fixed Non-Preferent	Cooling Systems
Flexible Non-Preferent	Lights

Figure A.6: Demand Profiles and Categorization of Agent 6



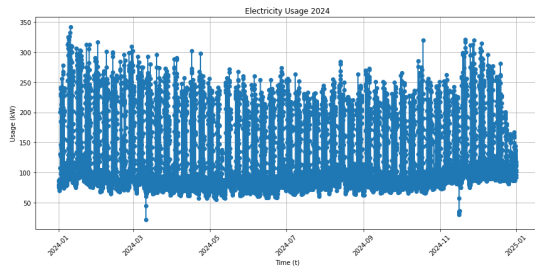
(a) Electricity Demand Profile of 2024 Agent 7



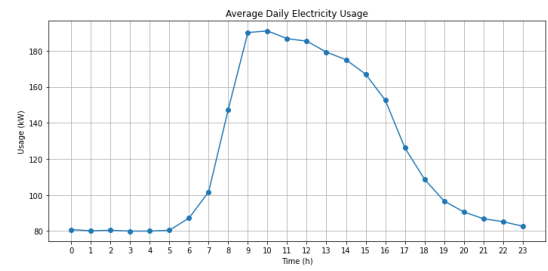
(b) Daily Demand Profile of Agent 7

Type	Bakery
Fixed Preferent	Oven
Flexible Preferent	Cooling Systems
Fixed Non-Preferent	Moisture Control
Flexible Non-Preferent	Lights

Figure A.7: Demand Profiles and Categorization of Agent 7



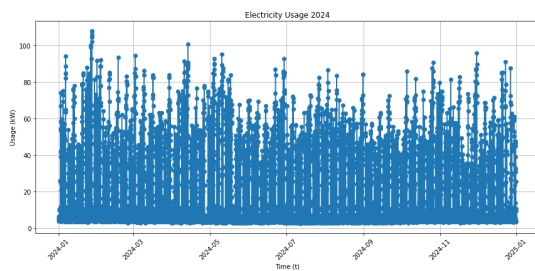
(a) Electricity Demand Profile of 2024 Agent 8



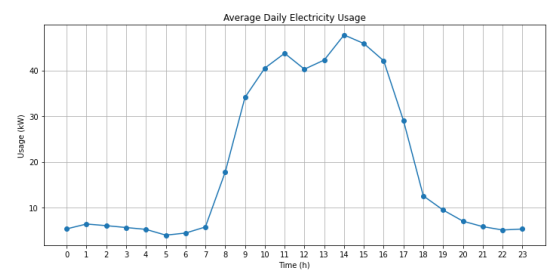
(b) Daily Demand Profile of Agent 8

Type	Real Estate
Fixed Preferent	Servers
Flexible Preferent	Server Cooling
Fixed Non-Preferent	Heating
Flexible Non-Preferent	Lights

Figure A.8: Demand Profiles and Categorization of Agent 8



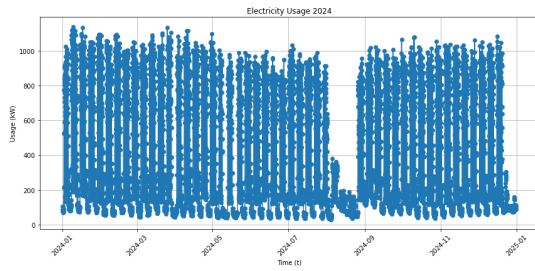
(a) Electricity Demand Profile of 2024 Agent 9



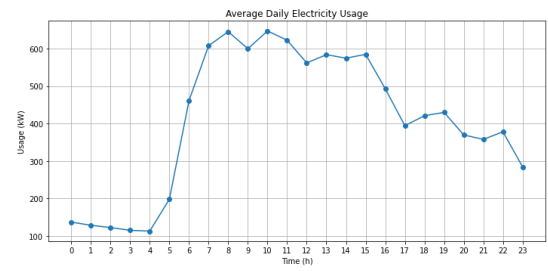
(b) Daily Demand Profile of Agent 9

Type	Car Wash
Fixed Preferent	Water Pumps
Flexible Preferent	Drying Installation
Fixed Non-Preferent	Boiler
Flexible Non-Preferent	Advertising Lights

Figure A.9: Demand Profiles and Categorization of Agent 9



(a) Electricity Demand Profile of 2024 Agent 10



(b) Daily Demand Profile of Agent 10

Type	Industrial Producer
Fixed Preferent	CNC Machines
Flexible Preferent	Oven
Fixed Non-Preferent	Extraction Systems
Flexible Non-Preferent	Heating

Figure A.10: Demand Profiles and Categorization of Agent 10

B

Overview of Model Assumptions and Simplifications

In this Appendix, an overview is given of the model assumptions and simplifications. Each assumption or simplification is categorized into either three categories, which are Electricity Supply and Demand, CEMS, and Agent Behaviour and Decision-Making.

B.1. Electricity Supply and Demand

- The EMS has full operational control over shared assets.
- The EH only has PV as shared flexible asset.
- The agents do not have their own flexible asset.
- There is only one kind of PV panels of 450 Wp.
- The PV generation is from one PV panel and in the model the amount of PV panels is multiplied by the generation of that hour.
- In the summer there are more PV generation hours than in the winter.
- PV generation only happens during the day and not the night.
- There are no energy losses caused by transportation and transmission.
- The G-GTV for feed-in is based on a ratio from real-life usage versus feed-in.
- The agents have 8,000 m² in total of roof space.
- Each type of capacity is assumed to be one installation, while in real-life this could be multiple.
- The type of installation is assumed to be typical in accordance to the type of company.
- Agents do not plan to expand their company or processes

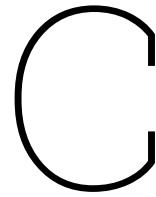
B.2. CEMS

- The CEMS applies rotational load shedding if there is congestion
- When rotational load shedding is activated, it will first turn off the Flexible Non-Preferent, Fixed Non-Preferent, Flexible Preferent, and then Fixed Preferent of an agent.
- If one agent is fully load shed and it is not enough, the load shedding will continue with the next agent on the list.
- When curtailment happens, the EMS curtails the excess PV panels.
- The congested hours for the next day are assumed to be perfectly known and accurate.
- Everybody uses the CEMS and nobody has their own EMS.

- The monthly reallocation is based on proportional redistribution which is deterministic and memory-based.
- The desired capacity of an agent in proportional redistribution is simplified as the monthly average consumption plus a 10% buffer.
- The 10% buffer of proportional redistribution is assumed to account for fluctuations in energy use.
- The CEMS has a fast and direct response.
- The congestion and reward fees are fixed, while in real-life these can be dynamic.

B.3. Agent Behaviour and Decision-Making

- Agents can only choose to load shift; reducing their load is not included as a possibility.
- The agents have a GTO with each other and not another contract.
- The SVO composition of the base case has discrete distribution, because altruistic and competitive are assumed to be relatively rare in populations.
- Price sensitivity is split up into two parameters: penalty and load shifting sensitivity.
- Behavioural parameters such as self-interest, penalty and load shifting sensitivity have made up numerical values to simplify the concept.
- An agent that has a high probability for an action will likely choose that action, but the chance that it will choose another action with a lower probability can still happen.
- An agent will stay the same SVO type and can not become another type.
- An agent can not fall in between two SVO types, while in real-life this can be the case.
- The implementation of the pay-off game in the model is assumed to be one vs. the rest instead of one vs another.
- The number of EH participants does stay the same throughout the whole simulation, the participants can not leave or enter the EH.
- The model operates in discrete time steps, while real energy consumption and decision-making happens in continuous time.
- Agents do not revise their strategies based on the outcomes.
- The decision-making formula assumes that the agents know how much others are using.
- The uncertainties of decision-making can be covered by stochastic distribution functions.
- If there is no congestion the next day, the agents will not make a decision to load shift.
- Agents can only load shift their Flexible Preferent capacity
- The base case follows a discrete distribution for the SVO composition.
- With each new run, the agents are distributed another SVO type if there is a particular SVO configuration.



Model Verification

In this Appendix, model verification is implemented to ensure that the simulation model and its implementation are correct. Van Dam et al. (2013) have proposed multiple methods to verify the model, but in this research two verification methods were chosen. The two verification methods are tracking of agent behaviour, and the extreme condition test.

C.1. Tracking of Agent Behaviour

As the model started rather simple and was enriched with more complexity along the way, verification happened during multiple stages of the model construction process. When the final model version was finished, a structured walk-through was implemented to check if all steps were executed correctly. This was done by printing variable values during the simulation, studying short periods of simulation time and analysing the agent and model variables over time. For the tracking of agent behaviour, a number of agents were followed throughout the simulation, to verify if the values of the agent variables were correct over time and if they had changed as expected. To do this, the different procedures and processes were tracked over time starting from the model and agent initialization.

The initialization of the agents consisted of multiple functions, including initializing the demand profiles, operational loss of load shifting, penalty sensitivity, and load shift sensitivity, working time, and self-interest weight.

```
Agent 1 initialized: SVO = individualistic, PenaltySens = 0.8, LoadShiftSens = 0.6, OperationalLossLS = 0.2, WorkingTime = 6 to 18, Self-InterestWeight = 0.7801222453171592, InitialDemandFirstHour = 13.6
Agent 2 initialized: SVO = pro-social, PenaltySens = 0.9, LoadShiftSens = 0.7, OperationalLossLS = 0.4, WorkingTime = 6 to 23, Self-InterestWeight = 0.4684989967372121, InitialDemandFirstHour = 210
Agent 3 initialized: SVO = individualistic, PenaltySens = 0.9, LoadShiftSens = 0.8, OperationalLossLS = 0.1, WorkingTime = 6 to 23, Self-InterestWeight = 0.7931834072796023, InitialDemandFirstHour = 13.169
Agent 4 initialized: SVO = pro-social, PenaltySens = 0.9, LoadShiftSens = 0.6, OperationalLossLS = 0.2, WorkingTime = 6 to 18, Self-InterestWeight = 0.44681544656138444, InitialDemandFirstHour = 94.875
Agent 5 initialized: SVO = pro-social, PenaltySens = 0.8, LoadShiftSens = 0.7, OperationalLossLS = 0.1, WorkingTime = 6 to 23, Self-InterestWeight = 0.4345417189515291, InitialDemandFirstHour = 56.0
Agent 6 initialized: SVO = individualistic, PenaltySens = 0.4, LoadShiftSens = 0.7, OperationalLossLS = 0.7, WorkingTime = 6 to 23, Self-InterestWeight = 0.6052380943467137, InitialDemandFirstHour = 32
Agent 7 initialized: SVO = individualistic, PenaltySens = 0.5, LoadShiftSens = 0.8, OperationalLossLS = 0.7, WorkingTime = 6 to 23, Self-InterestWeight = 0.6729227630597898, InitialDemandFirstHour = 0.75
Agent 8 initialized: SVO = altruistic, PenaltySens = 0.7, LoadShiftSens = 0.9, OperationalLossLS = 0.8, WorkingTime = 6 to 18, Self-InterestWeight = 0.2174987277744643, InitialDemandFirstHour = 76.384
Agent 9 initialized: SVO = pro-social, PenaltySens = 0.3, LoadShiftSens = 0.7, OperationalLossLS = 0.8, WorkingTime = 6 to 18, Self-InterestWeight = 0.5643272314599646, InitialDemandFirstHour = 6.279999999999999
Agent 10 initialized: SVO = competitive, PenaltySens = 0.3, LoadShiftSens = 0.8, OperationalLossLS = 0.9, WorkingTime = 5 to 23, Self-InterestWeight = 0.921881610902903, InitialDemandFirstHour = 78.525
```

Figure C.1: Code Snippet of Initializing Agents

The initialization of the model consisted of initializing the congestion fee, reward fee, the maximum feed-out capacity, the maximum feed-in capacity, the amount of PV panels.

Other interesting time steps to verify are the fact that when a congestion period is announced, the agents will use the functions observe, decide, and act accordingly. In the function observe, the agent estimates the congestion for tomorrow and calculated the variables used for the decide function. Next, in the decide function the agent evaluates the actions it could take (either accept penalty or load shift) for tomorrow and chooses the best one. Lastly, in the act function the agent implements the chosen plan for each congestion hour during the day. To check if the three functions are executed, printing statements were used to verify this which is shows in the following figure.

```

=== Model initialized with parameters ===
Congestion fee: 0.3
Reward fee: 0.2
Max feed-out capacity: 2986 kW
Max feed-in capacity: 1179 kW
Number of PV panels: 1200
=====

```

Figure C.2: Code Snippet of Initializing Model

```

==== HOUR 2024-01-06 09:00:00 ====
Agent 1 OBSERVE: Estimating congestion for tomorrow...
Agent 2 OBSERVE: Estimating congestion for tomorrow...
Agent 3 OBSERVE: Estimating congestion for tomorrow...
Agent 4 OBSERVE: Estimating congestion for tomorrow...
Agent 5 OBSERVE: Estimating congestion for tomorrow...
Agent 6 OBSERVE: Estimating congestion for tomorrow...
Agent 7 OBSERVE: Estimating congestion for tomorrow...
Agent 8 OBSERVE: Estimating congestion for tomorrow...
Agent 9 OBSERVE: Estimating congestion for tomorrow...
Agent 10 OBSERVE: Estimating congestion for tomorrow...
Agent 1 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 2 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 3 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 4 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 5 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 6 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 7 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 8 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 9 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 10 DECIDE: Evaluating actions (penalty vs load shift)...
Agent 1 ACT: Implementing chosen plan for congestion hours.
Agent 2 ACT: Implementing chosen plan for congestion hours.
Agent 3 ACT: Implementing chosen plan for congestion hours.
Agent 4 ACT: Implementing chosen plan for congestion hours.
Agent 5 ACT: Implementing chosen plan for congestion hours.
Agent 6 ACT: Implementing chosen plan for congestion hours.
Agent 7 ACT: Implementing chosen plan for congestion hours.
Agent 8 ACT: Implementing chosen plan for congestion hours.
Agent 9 ACT: Implementing chosen plan for congestion hours.
Agent 10 ACT: Implementing chosen plan for congestion hours.

```

Figure C.3: Code Snippet of Agent's Three Main Functions

C.2. Extreme Condition Test

The extreme condition test is used to evaluate if the model code works as expected under different extreme conditions. The goal is not only to confirm that the model works as expected, but also to understand its boundaries. The model boundaries are important to understand because they provide insight into the range within which the model delivers reliable results, and beyond which the results may no longer be credible.

For this sensitivity analysis, three variables were tested which are congestion fee, ol_{ls} , and amount pv . These were chosen, because congestion fee and amount pv are two fixed parameters of the model and ol_{ls} is a fixed parameter of the agent self. By testing these parameters, it can be assessed how both system-wide and agent-specific constraints affect the model's behaviour. These variables were tested against the KPI's, which are total load shifts, total penalties, total EMS load sheds, and total rewards.

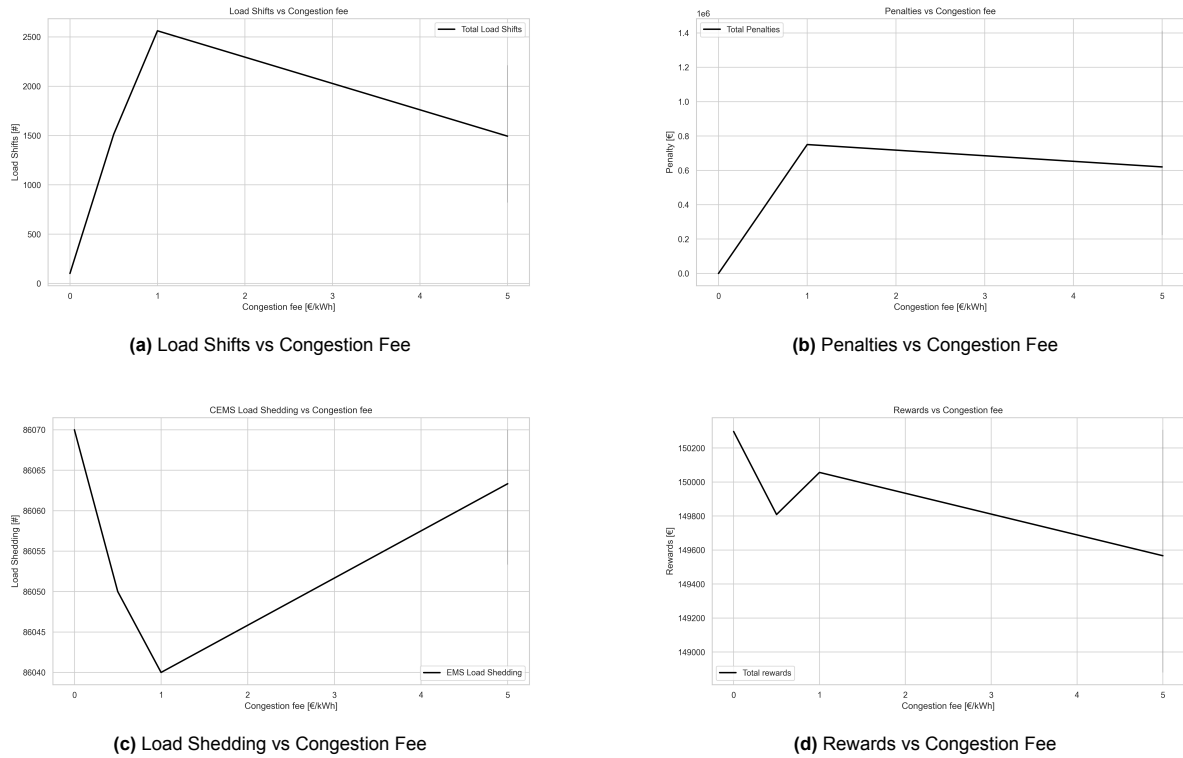


Figure C.4: Congestion Fee Extreme Condition Test

What can be seen from Figure C.4 is that as congestion fees increase, the amount of load shifts and penalties rise until the congestion fee reaches 1 €/kWh, after which they both decrease. This behaviour can be explained by the system boundary at 1 €/kWh: for values above this threshold, agents have already shifted their maximum flexible capacity and cannot shift any further, which reduces both load shifts and penalties. For values below 1 €/kWh the system behaves as expected, as agents are more incentivized to shift load when the congestion fee rises.

For load shedding, higher congestion fees initially lead to fewer residual congestion events because more agents actively shift load. This reduces the need for EMS interventions, resulting in lower load shedding. With more flexible capacity used efficiently, there is also more available space for other agents to shift load which increases the rewards received by agents who participate in load shifting. Conversely, if agents choose not to shift and instead pay the penalty, total penalties rise more sharply as the congestion fee increases.

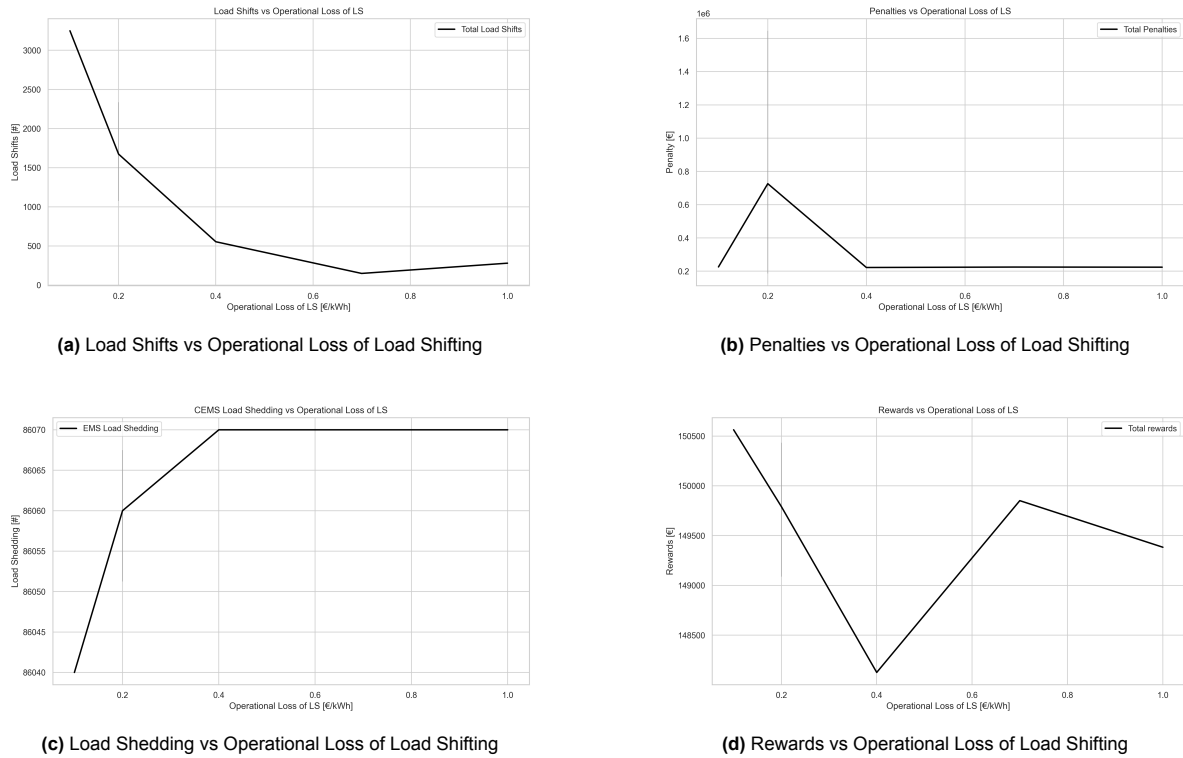


Figure C.5: Operational Loss of Load Shifting Extreme Condition Test

What can be seen from Figure C.5 is that both the number of load shifts and the rewards decrease as the operational loss of load shifting increases. This follows from the fact that shifting becomes less attractive when it comes with higher losses. As a result, fewer agents choose to shift and consequently the rewards also decline because less flexibility is deployed.

The amount of load shedding on the other hand increases with the operational loss. Since fewer agents are willing to shift voluntarily, more residual congestion remains in the system which must then be solved by CEMS load shedding. This continues until it reaches a limit, which reflects the maximum number of time steps in which congestion occurs — beyond this limit, load shedding cannot increase further.

The penalties show a different pattern: they peak around 0.2 €/kWh and remain relatively flat after 0.4 €/kWh. This can be explained by the balance between shifting and paying the penalty. At very low operational loss most agents prefer to shift, so penalties remain relatively low. As the operational loss increases more agents stop shifting and accept penalties instead causing the penalty costs to rise. Once a critical threshold (around 0.4 €/kWh) is reached almost all agents who are willing to shift have already dropped out and penalty levels stabilize. This is because further increases in operational loss no longer change agent behaviour significantly.

The rewards follow a specific pattern: they decline until 0.4 €/kWh, then increase slightly until 0.7 €/kWh before declining again. This fluctuation is likely due to the interplay between fewer agents shifting at higher operational losses and the concentration of rewards among the smaller group that still engages in shifting. In other words, when only a few agents remain willing to shift, they may capture relatively more rewards for the flexibility they provide. This is until eventually even this residual flexibility disappears as losses rise further.

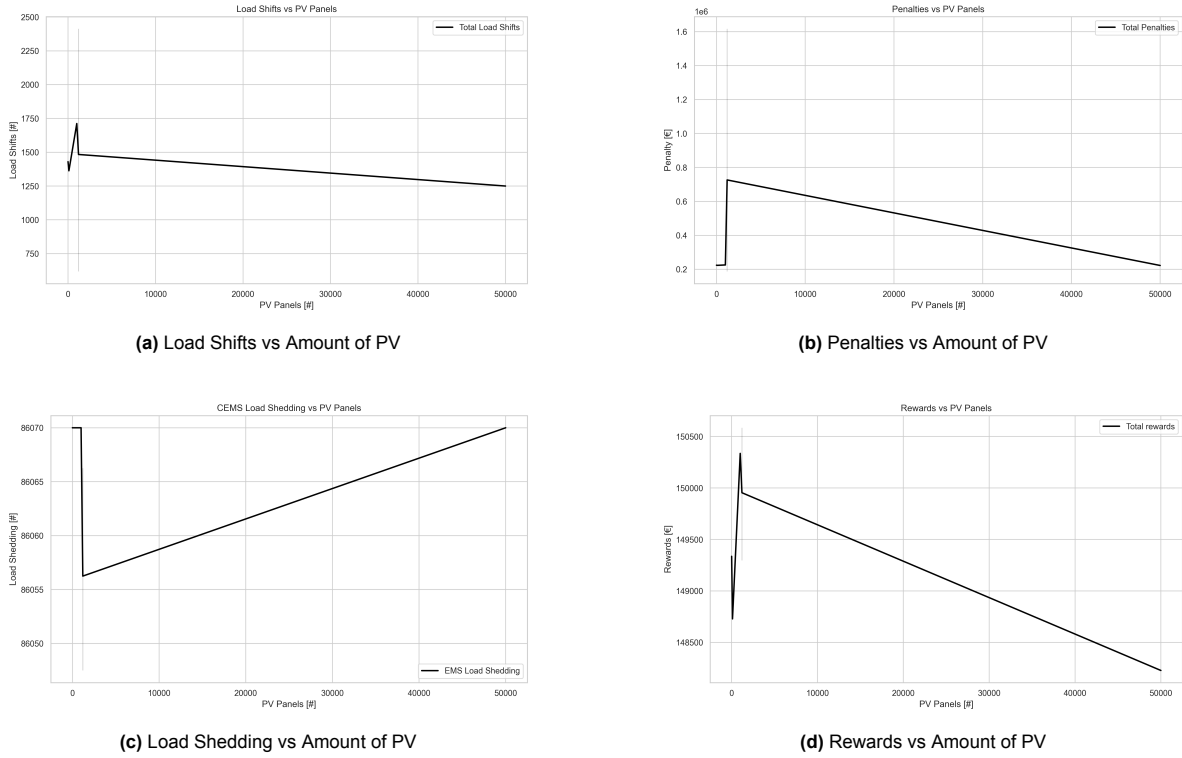
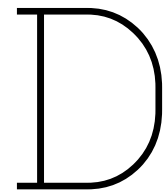


Figure C.6: Amount of PV Extreme Condition Test

What can be seen from Figure C.6 is that both the number of load shifts and the rewards follow a similar non-linear pattern: they first decrease, then increase, and finally decrease again around the point of 100 PV panels. After this threshold, both values gradually decline as the number of PV panels continues to rise. This indicates that the integration of additional PV initially reduces flexibility needs, but around 100 panels new congestion points emerge that temporarily increase load shifting and rewards after which the system saturates and flexibility becomes less effective.

Load shedding remains stable at lower PV levels and then rapidly decreases as the number of panels approaches 100. This can be explained by the fact that additional PV initially alleviates residual congestion, lowering the need for forced EMS interventions. However, after surpassing this point load shedding increases again due to new imbalances caused by excess PV generation that cannot always be matched with flexible demand.

Penalties remain relatively stable until just before 100 PV panels, after which they increase sharply. At the 100-panel threshold, penalties reach their peak and then decrease again. This pattern reflects the tipping point where the added PV shifts the system from being slightly under-supplied to occasionally over-supplied, which increases penalties temporarily until flexibility and saturation effects dampen further penalty growth.



Survey

This appendix shows the survey in English that has been send to the real-life participants of Emmett Green of various EHs. The participants will remain anonymous together with the EH they are involved in. The survey was conducted in Dutch, because all of the participants speak Dutch and not English. So for the sake of this research, the English translation of the survey is given below. The link of the Dutch survey that has been send can be found here: [Google Forms Survey](#)

Dear participant,

Thank you very much for your time and effort in participating in this survey. This survey is part of my graduation research and focuses on decision-making within local energy hubs. The aim of my research is to better understand how different participants can collaborate and which factors influence this process, particularly in situations where energy capacity is limited.

This research is part of my Master's thesis at the Faculty of Technology, Policy and Management at TU Delft, under the supervision of academic mentors and in collaboration with Emmett Green.

The survey consists of 9 questions and will take approximately 5–10 minutes to complete. The questions focus on your preferences, attitudes, and potential decisions within hypothetical energy hub scenarios. Your participation will help me gain insight into how companies make investment and operational decisions.

Confidentiality and data handling

Your responses will be treated with strict confidentiality and used solely for academic research purposes. The survey is anonymous; no personal information such as your name, IP address, or organization will be collected. This means that no one will be able to trace your responses back to you.

- The data will be securely stored on TU Delft servers.
- Only I, as the researcher, and my academic supervisors will have access to the raw data.
- Data will not be shared with third parties without your explicit consent.
- The results may be published in anonymized and aggregated form in academic or professional contexts. Only the responses to multiple-choice and closed questions will be published.
- Please do not include your name or any other identifying information in the open text fields. These fields are meant solely for general insights and should not contain any personal data.

- The anonymized dataset may also be included in open-access repositories for future academic reuse.
- In accordance with TU Delft's data management policy, research data will be retained for a period of 10 years. Your rights and potential risks

Participation in this study poses no physical, emotional, or reputational risks. You are completely free to skip any question you do not wish to answer. You may also stop filling out the survey at any time, as long as you have not yet submitted your responses. Once submitted, withdrawal is unfortunately no longer possible, as the data will be fully anonymized. No financial compensation or reimbursement is offered for your participation.

Questions or contact

If you have any questions about the research or your participation, please feel free to contact:

Research contact:

Shanaya Doerdjan

TU Delft – Faculty of Technology, Policy and Management

By clicking "Next" to begin the questionnaire, you confirm that you have read the above information and voluntarily agree to participate in this anonymous study.

Question 1 Suppose: within the energy hub, a shortage has been announced at a certain point in the future. Your company wants to consume more than agreed at that time, but that process can still be shifted to another moment on the same day.

Which of the options below best matches how you would act in that situation?

- ☐ We see scarcity as an opportunity. If we can consume more than others, we might be able to gain a strategic advantage.
- ☐ We prefer to run our process at the time that is most efficient for us. If it is really necessary to shift due to the scarcity, we will only do so if it does not harm our own planning and objectives. Our priority lies in the optimal operation of our company.
- ☐ We understand that there is scarcity and therefore want to contribute to a balanced solution. We are willing to shift our process, provided it fits within our operational capabilities.
- ☐ If scarcity is expected, we absolutely want to prevent our extra consumption from disadvantaging others. We will voluntarily shift our process to a quieter time during the day so that enough capacity remains available for the entire hub. The collective interest comes first.

Question 2 Suppose: within the energy hub, a shortage has been announced at a certain future moment. Your company wants to consume more than agreed at that time, but that process can still be shifted to another moment on the same day.

To what extent do the factors below influence your choice to consume at a different time on the same day?

Please indicate how important you find each factor.

- Financial rewards if you do not consume during peak moments
- A penalty if you still consume during peak moments
- Costs of production interruption during peak moments (lost revenue, additional labour costs)
- Insight into capacity pressure within the hub
- Expectation that other companies will also be flexible with shifting

- Reputation of your company compared to other companies in the energy hub

Scale: Not very important, Not important, Neutral, Important, Very important

Question 3 Suppose: within the energy hub, a shortage has been announced at a certain future moment. Your company wants to consume more than agreed at that time, but that process can still be shifted to another moment on the same day.

Are there any other factors that influence your choice to consume at a different time on the same day?

Please enter your answer. If there are no other factors, you may skip this question.

Question 4 Suppose: your company has reserved energy capacity at a certain time that is not urgently needed, while another company in the energy hub urgently needs capacity.

Which of the options below best matches how you would act in that situation?

- ☐ If another company runs into trouble due to a capacity issue while we have sufficient capacity, it strengthens our position in the hub. We see no reason to share our capacity; it is better that they manage their own affairs.
- ☐ As long as we do not urgently need the capacity, we keep it available for our own flexibility. We want to avoid getting into trouble ourselves later on.
- ☐ We currently have available capacity and are willing to share it if that helps solve a problem for another company. As long as it does not disrupt our own.
- ☐ If another company urgently needs capacity and we do not need it at that moment, we will of course make it available to them.

Question 5 Suppose: your company has reserved energy capacity at a certain time that is not urgently needed, while another company in the energy hub urgently needs capacity.

To what extent do the following factors influence your choice to share capacity?

Please indicate how important you find each factor.

- Financial compensation
- Positive experiences with other companies
- Reputation

Scale: Not very important, Not important, Neutral, Important, Very important

Question 6 Suppose: your company has reserved energy capacity at a certain time that is not urgently needed, while another company in the energy hub urgently needs capacity.

Are there any other factors that influence your choice to share capacity?

Please enter your answer. If there are no other factors, you may skip this question.

Question 7 Suppose: your company has an important process scheduled at a certain time that requires a lot of energy. However, there is limited capacity in the energy hub, and if all companies proceed with their planned consumption, the grid will become overloaded.

You see that you can only run your process if another company voluntarily reduces or shifts their consumption temporarily.

Would you personally approach this other company (via WhatsApp or phone call) to ask them to make room for your process?

- ☐ No, unless they offer themselves. My process is important, but not more important than preventing strain on others.
- ☐ Yes, I can ask in a polite manner and it is reasonable. Together looking for the best solution for everyone.
- ☐ Yes, definitely. My process is important, and if I ask politely whether they can shift, that's fine.
- ☐ Yes, absolutely. If I benefit from it and they can give way, then that's their problem.

Question 8 Suppose: your company has an important process scheduled at a certain time that requires a lot of energy. However, there is limited capacity in the energy hub, and if all companies proceed with their planned consumption, the grid will become overloaded.

You see that you can only run your process if another company voluntarily reduces or shifts their consumption temporarily.

Are there any other factors that influence your choice to personally approach another company with the request to make room for your process?

Please enter your answer. If there are no other factors, you may skip this question.