EXPLORING DEMAND RESPONSE OPPORTUNITIES IN ENERGY COMMUNITIES

An agent-based modeling approach for attaining self-sufficiency in mixed energy communities in the Netherlands.

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Master Thesis: M.Sc. Engineering and Policy Analysis

Exploring demand response opportunities in energy communities

An agent-based modeling approach for attaining self-sufficiency in mixed energy communities in the Netherlands

by

Anmol Soni

to obtain the degree of Master of Science in Engineering and Policy Analysis at the Delft University of Technology. This thesis will be defended publicly on Thursday August 11, 2022 at 15:00.

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The GitHub repository of this project is available at https://github.com/SoniAnmol/Modelling-Dutch-Energy-Communities

Preface

The eighteen-year-old version of me living in an Indian village never imagined studying abroad. Ten years later, I am defending my master thesis at the TU Delft in the Netherlands. This wouldn't have been possible without immense love and support from my parents, Vinod and Jyotsna Soni. Thank you to my brother and sisters for lighting up the gloomy days through long video calls. I am grateful to all my friends, family, and especially my girlfriend for being my emotional pillar and support system. I would also like to thank my mentor Simran for encouraging me and inspiring me to embark on this journey.

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Lastly, this study program and thesis have been a truly rewarding experience for me. I am proud of this report and I hope it helps energy communities and fellow researchers.

Anmol Soni
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Executive Summary

Amidst the discourse regarding the decentralization of urban energy systems, energy community has emerged as a solution for optimizing the electricity demand and distributed generation. Community energy projects also facilitate collaboration amongst local prosumers. An energy community is a collective of residential electricity consumers (or prosumers) and non-energy small and medium-sized enterprises (SMEs) formulating a social network involved in decentralized energy production. This study is focused on exploring demand response opportunities in community energy projects located in the Netherlands to reduce their dependence on the grid. Existing studies on community energy projects are primarily focused on residential members, and have little to no inclusion of non-residential community members. However, recent studies regarding demand response in the energy community highlight the benefits of having a mixed configuration of residential and non-residential members. Introducing non-residential community members such as SMEs, offices, and schools with a complementary demand profile can help the community in attaining self-sufficiency through demand response. Formulating energy communities with a mixed configuration (i.e. including residential and non-residential community members) optimizes local electricity generation and consumption thus avoiding congestion in the distribution network.

This research focuses on evaluating the role of demand response in reducing the grid dependence of energy communities. The community setups studied in this research are inspired by communities located in the Netherlands. The scope of this study is limited to the low voltage electricity distribution network of the modeled communities. Since this study is based in the Netherlands, key social, financial, institutional (policy & regulation), and technical aspects characterizing a Dutch energy community are studied. These characteristics are used to reproduce the real-life behavior of residential and non-residential community members through a model. Furthermore, the effect of introducing a time-of-use tariff in the modeled energy community is studied. Lastly, the effect of demand flexibility by residential and non-residential community members on the efficacy of demand response is evaluated.

Demand response in energy communities is driven by actor perception and individual behavior. Agent-based modeling (ABM) effectively captures the complex adaptive behavior of energy communities. Agents make informed decisions regarding energy transactions along with social activities like cooperation, coordination, and negotiation. This study conceptualizes the community coordinator and members (both residential and non-residential) as agents. A community coordinator is the service provider appointed by the community to balance the internal electricity network and facilitate demand response by preparing the time-of-day schedule. The agent-based model developed for this study takes electricity consumption data and weather data from the Netherlands. This model is simulated for the year 2021 and has three policy levers. The first policy lever is the participation of community members in demand response. The second policy lever is the demand flexibility of residential community members and the third policy lever is the demand flexibility of non-residential community members. Demand flexibility of a community member refers to the proportion of connected load that can be switched on or off during demand response. Usage of behind-the-meter storage is recommended as an intervention in this study for increasing the demand flexibility of community members. Furthermore, this model has three uncertainties. The first uncertainty is the availability of residential flexible demand and the second uncertainty is the availability of non-residential flexible demand. Availability of flexible demand is a behavioral function that signifies whether a flexible load is available for operation on a particular day. Lastly, the accuracy of demand and generation forecast for preparing a time-of-day schedule is also conceptualized as an uncertainty. The model experimentation is performed with two community configurations. These configurations are inspired by Groene Mient (Den Haag) and GridFlex (Heeten) energy communities. Currently, these communities do not have any non-residential community members. Therefore, a non-residential community member is assumed for both community configurations.

The results obtained from the experimentation concluded that active participation of community members in demand response helps in reducing grid dependence. Demand flexibility plays a critical role in defining the efficacy of demand response in modeled energy communities. Using behind-the-meter storage to extend the flexible demand further reduces the grid dependency of residential community members. The two community setups used for the experimentation attained electricity autonomy through the captive generation and behind-the-meter storage from March to September. However, grid import is required for these community setups from October to February because of their dependency on solar PV generation. Including a non-residential community member, with a relatively higher yet complementary demand profile resulted in a dampening effect to absorb the irregularities in the consumption curve of the community. Moreover, non-residential community members have a larger floor area to house substantial shared generation and storage capacities in their vicinity. Furthermore, the cost of importing electricity is directly proportional to the amount of grid import as it uses a linear function for cost computation. Feed-in tariffs or electricity trading in short-term markets is not considered in the financial calculations. Therefore, savings from demand response are directly proportional to the load shifted through demand response.

Lastly, this study recommends a sequential approach for implementing demand response in the modeled energy communities. Two policies are formulated based on the analysis of experiment outcomes. These policies are named 'realistic' and 'optimistic' based on the ease of implementation. In the first stage, implementation of 'realistic' policy is recommended. This policy implies 50% participation in the demand response along with 50% demand flexibility of community members. The recommended demand flexibility can be achieved through automation and installing smart appliances. In the second stage, 'optimistic' policy can be implemented by increasing participation in demand response to 75%. Along with this, behind-the-meter storage is recommended for residential community members to enhance their demand flexibility to 90%.

The academic contribution of this study is threefold. Firstly it contributes to the body of literature regarding the use of ABMs in community energy research. Secondly, this study contributes to research focusing on demand response in energy communities. Lastly, it adds to the academic discourse about leveraging mixed energy configuration through demand response in community energy projects. Moreover, this research creates a platform for virtual experimentation on mixed energy communities to further explore demand response opportunities. This research and model developed during this study can propagate further community energy research in the Netherlands using agent-based modeling. Lastly, this model can be further extended to heat networks and can incorporate other renewable generation sources.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
ABM	Agent-based modelling
CBS	Centraal Bureau voor de Statistiek
CE	Community Energy
DR	Demand Response
DSO	Distribution Service Operator
EC	Energy Community
EU	European Union
EV	Electric Vehicles
IEMC	Internal Electricity Market Directive
KNMI	National knowledge institute for weather, climate and seismology
kWh	Kilowatt hour
kWp	Kilowatt peak
LCOE	Levelized cost of electricity
NREL	National Renewable Energy Laboratory
PV	Photo-voltaics
RED-II	Renewable Energy Directive - II
SME	Small and Medium Enterprise
ToD	Time of Day
ToU	Time of Use
UML	Unified Modeling Language

List of Figures

List of Tables

1 Introduction

As the world is moving towards cleaner, sustainable, and smarter energy sources, urban energy systems are evolving into complex systems (Pagani & Aiello, 2013). This is attributed to an exponential growth of distributed renewable energy sources (like solar PV and wind turbines) in the last decade. The widespread distributed renewable generation among residential households has converted many electricity consumers into ”prosumers” (An electricity consumer involved in the generation of electricity) whilst transforming the unidirectional electricity grid into a bidirectional network. Amidst this, the energy community has emerged as a promising solution to facilitate collaboration among prosumers and meet the energy demand locally. An energy community is a collective of residential electricity consumers (or prosumers) non-energy small and medium-sized enterprises (SMEs) formulating a bottom-up social-economic network involved in decentralized energy production (van der Schoor & Scholtens, 2015).

1.1. Background

The European Commission in its Renewable Energy Directive - II (RED-II) has acknowledged the potential of energy communities. RED-II enables households and non-energy SMEs (Small and Medium Enterprises) with local authorities to operate individually or as a part of the energy community to consume, trade, and store the energy generated from renewable sources (EU, 2021). The RED-II will be adopted by the EU countries and will be transposed into the national legislation of the Netherlands. Currently, the process is delayed because of challenges related to the integration of directives into the Dutch legislature.

However, the complex and multifaceted nature of energy communities makes decision-making regarding investments and asset ownership challenging. In addition to this, most of the existing studies and financial models limit energy communities to residential members and have limited inclusion of non-residential members and functionalities like EV charging. This is an untapped opportunity for leveraging the complementing demand profiles of non-residential community members through demand response. Both residential households and offices have flexible loads (such as heating, cooling, lighting, and ventilation for offices whereas washing machines, dishwashers, etc.) that can be coordinated for maximizing the self-sufficiency of the community (Reis et al., 2020). Moreover, the directive mentions the inclusion of non-energy small and medium enterprises and local authorities (EU, 2021) in the energy community.

According to Elena and Andreas (2020), the Netherlands stands third in the number of community energy projects in the EU. However, the difference between the number of projects in Germany (leader on the list) and the Netherlands is over threefold. Although Germany has over four times more residents than the Netherlands, the true potential of community energy projects in the Netherlands is still untapped. Apart from this, none of the studies implementing demand response in community energy projects is conducted or tested in the Netherlands. Some community energy projects like Groene Mient and GridFlex Heeten are planning to conduct these studies in near future. Thus, this research will also serve as a baseline for these energy communities. Thus, this research is focused on the Netherlands to provide relevant insights and expand the knowledge base required for making mixed community energy projects self-sufficient through demand response.

1.2. Literature Review

To further explore the academic milieu of energy communities, a literature review was conducted. The literature scan was conducted through search engines like Scopus, PubMed, Google Scholar and ScienceDirect. Apart from this, Leiden University Library and TU Delft Library were also used to access additional journals and articles. The following keywords were used in permutation and combination to search for the relevant literature. *Keywords: "Energy Community", "Smart Local Energy Grid", "Energy community modeling", "RE Community in the Netherlands", etc.* Additionally, forward and reverse snowballing was done to find the previous and derivative research work of selected papers. This snowballing was done using a web application called Research Rabbit and the figure 1.1depicts the cluster of papers reviewed. Over 60 articles/papers from different platforms/journals were initially selected and filtered using the following criteria:

- Language: Articles published in English were considered for this review. Because of the linguistic constraints of the author, limited Dutch articles were included. However, critical articles and policy papers were considered after translation using google translate.
- Relevance to research topic: Articles and research papers focused on energy communities and modeling were selected for the review.
- Date of publishing: As this is a recent and growing field, 20 papers are published after 2018. The oldest paper selected for review is from the year 2016.
- Credibility of the research journal: All the journals and sources selected are accredited in the scientific community.

As the research is focused on energy communities in the Netherlands, most of the selected literature is based in Europe and studies conducted in (or around) the Netherlands. However, to understand the global perspective of technology, three articles discussing the global take on Energy Communities are included in the literature review.

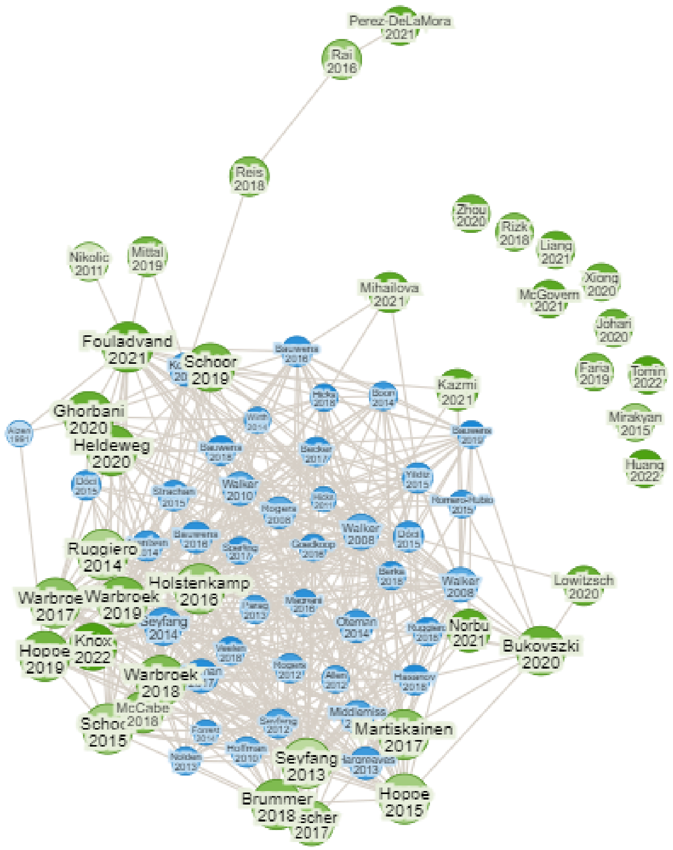


Figure 1.1: Literature Snowballing: Green bubble indicates literature included and the blue bubble indicates literature excluded from the study. The excluded papers are filtered out as per the criteria. These papers are either focused on thermal energy projects or represented through subsequent literature.

1.2.1. Transition of Energy Clusters to Energy Communities and their Policy Prominence

The notion of clustering the energy assets or networks is not new in energy systems. Traditionally islands and remote energy clusters were operated as autonomous energy systems. However, the energy flow in these clusters was predominantly unidirectional. With increased penetration of distributed renewable energy, the flow of electricity in the distribution network became bidirectional and clusters evolved into micro-grids and mini-grids (Marnay et al., 2015). Energy clusters were formulated by collating the local demand or consumption patterns of an area whereas, energy communities necessarily include the energy generation profile of the area. This theoretically positions both concepts differently but approaching them as mirror concepts provide an opportunity to evolve urban energy clusters into energy communities. Brummer (2018) provided a literary comparison of community energy projects in the UK, Germany, and the USA highlighting the benefits and barriers of these projects. These projects are citizen-driven and hugely impact the sustainability and energy transition discourse in the society (Fischer et al., 2017). The level of citizen participation and engagement in the community energy projects are driven by trust, awareness, personal gain, and affinity towards sustainability (Kalkbrenner & Roosen, 2016), (Koirala et al., 2018). van der Schoor and Scholtens (2015) emphasizes the need for a shared vision for strengthening the network and aligning the interests in community energy projects.

Energy communities rose to the pinnacle of prominence in the scientific literature and policy discourse recently after the European Union (EU) introduced a framework for prosumers in Renewable Energy Declaration - II (RED -II) (EU, 2021) and directive on common rules for the Internal Market in Electricity Directive (IEMD). The EU (2021) provides legal rights to households and SMEs in the EU states to operate individually or form a renewable energy community on a non-profit basis to consume, sell and/or store renewable energy. Hoppe et al. (2019) highlight the importance of renewable energy cooperatives for simulating household energy savings. The transposition of RED-II in the Dutch national governance system will enable energy communities to trade electricity (1) within the energy community, (2) among different energy communities, and (3) between energy communities and markets. Whereas IEMD provides additional power to enable distribution, aggregation, and efficiency along with other energy services. Busch et al. (2021) performed a detailed literature review for policies and regulations regarding energy communities in the EU. Furthermore, Renata Leonhardt et al. (2022) provide an overview of global policy discourse around community energy projects.

These community energy projects require support from local authorities and intermediaries. The role of local authorities in supporting citizen-driven initiatives is discussed by Hoppe et al. (2015). Apart from local authorities, intermediaries (or community coordinators) also play a critical role in bridging the technology gap for the communities by providing necessary infrastructural and technical support (Warbroek et al., 2018). However, the level of involvement and motives of intermediaries in community projects vary widely based on the socio-political setting (Holstenkamp & Kahla, 2016).

1.2.2. Literature on Community Energy Projects in the Netherlands

The case study conducted by (Warbroek & Hoppe, 2017) for Dutch community energy projects in Overijssel and Frisian regions provides a governance model for local authorities to support citizen-driven low carbon initiatives. The social, organizational, and governance factors characterizing Dutch community energy projects are highlighted by Warbroek et al. (2019) and Fouladvand, Ghorbani, et al. (2022). Community energy projects require the implementation of smart grid features for enabling demand response and active monitoring (Knox et al., 2022). Lammers and Hoppe (2019) conducted a study for analyzing the 'rules of the game' governing the decision-making regarding smart-grid projects in the Netherlands and concluded that not all stakeholders actively participate in the decision-making. No separate legal permit is required to operate an energy cooperative. However, energy cooperatives require legal permits for starting and implementing renewable energy projects. Moreover, a permit is required for conducting an experimental (smart grid and demand response) project, like Groene Mient or GridFlex Heeten as an exemption from the Dutch 1998 Electricity Act (Milchram et al., 2020).

1.2.3. Demand Response in Energy Communities

Demand response is a price or incentive-based policy instrument used to shift the demand curve and energy consumption behavior of electricity consumers (Faria et al., 2019). Demand response is crucial for energy communities because of three reasons.

First, to manage the intermittency of renewable energy sources. Solar and wind are the most accessible renewable energy sources and act as the most common generation sources for energy communities (Schiera et al., 2019). These energy sources are intermittent and energy storage is not enough to attain self-sufficiency, particularly during peak hours. Reis et al. (2018) mention demand response as the most effective measure for attaining self-sufficiency in the energy community and refers to it as the ”democratization of energy”.

Second, to reduce dependence on energy storage systems. Existing business models used by community energy projects do not account for battery degradation costs in the expenses and heavily depend on energy storage for meeting the peak demands (Huang et al., 2022). This is unrealistic and reduces the life of energy storage further adding to the overall energy cost. Thus, demand response can reduce the dependency on energy storage for managing electricity generation and consumption.

Lastly, to optimize the utilization of energy assets in the energy community. All the developed countries discourage the export of renewable energy back to the grid for avoiding congestion in the grid. This is evident through the recent reduction in feed-in-tariffs. In addition to this, the European Commission (2018) indicate the non-profit behaviour of energy communities to curb the electricity feed into the grid (Xiong et al., 2020). As a result, the price of exporting electricity is getting much lower than the price of importing electricity from the grid. Therefore, it is critical for energy communities to optimize the generation assets and become self-sustaining by reducing grid dependence (Huang et al., 2022).

1.2.4. State-of-the-art Literature and Knowledge Gaps

Community energy projects involve multiple stakeholders such as community members (both residential and non-residential), DSO (Distribution Service Operators), Community Coordinator, and Municipality. Independent decision-making and interaction of these agents lead to unpredictable outcomes in the long term. The actors involved in these projects learn from their previous decisions and adapt. Thus, community energy projects fit the requirements of complex adaptive systems enlisted by Nikolic and Ghorbani (2011). Agent-based modeling (ABM) effectively captures the complex adaptive behavior of community members along with social activities like cooperation, coordination, and negotiation capabilities (Reis et al., 2020). ABM involves multiple agents representing the actors in the system acting and reacting to each other’s actions. These agents make informed decisions to fulfill their respective objectives (Dam et al., 2012). In addition to this, Perez-DeLaMora et al. (2021) highlights the effectiveness of ABMs in developing strategies for energy communities.

Unfortunately, existing ABM models used for community energy research do not capture all the dynamics of energy communities (particularly in the Netherlands) and therefore are not suitable for performing experiments. Following are the two knowledge gaps identified during the literature study.

Firstly, most of the studies using agent-based models are limited to residential community members. Recent literature like Guimaraes et al. (2021), Mittal et al. (2019), Schiera et al. (2019) and Tomin et al. (2022) consider only residential members for studying energy communities. Whereas, European Commission (2018) explicitly recommends the inclusion of non-residential members like SMEs for the formulation of an energy community. Additionally, most of the neighborhoods have non-residential buildings with significant potential for generation and energy storage assets available in the proximity of residential communities. Reis et al. (2020) highlights the need for including non-residential agents (i.e. SMEs, offices, and EV charging) in the energy community and utilizing their potential for achieving self-sufficiency in energy communities. Therefore, the models above are not capable of testing policies involving non-residential members of the community.

Secondly, as an extension of the above-mentioned gap, demand response opportunities are not sufficiently explored in the energy communities. Introducing non-residential members and EV charging stations (having complementing energy consumption profiles) creates opportunities for demand response in the community. Reis et al. (2020) explore demand flexibility by introducing non-residential members to the energy community but does not consider Electric Vehicle (EV) charging in the analysis. In addition to this, the economic analysis does not address the role of intermediaries and service providers required to manage and maintain the infrastructure. Another analysis by Tomin et al. (2022) explore the demand flexibility for energy communities but the load profiles considered are limited to residential consumers ignoring the benefit of complementary load profiles of non-residential members.

1.3. Research Questions

The Literature review Section 1.2highlights the knowledge gaps in the recent research around energy communities. In a nutshell, the first knowledge gap is the exclusion of non-residential members in energy communities. The second knowledge gap is the limited exploration of demand response opportunities for attaining self-sufficiency in the energy community. This research envisages bridging these knowledge gaps in the context of the Dutch socio-political and technical setting. The following research question is formulated to address these knowledge gaps:

"How does demand response by residential and non-residential[1] community members affect the self-sufficiency and expenditure on grid import of electricity for modeled Dutch energy communities?"

Following sub-questions are derived to answer the main research question:

1. What are the key social, financial, institutional (policy & regulation), and technical aspects characterizing a Dutch energy community?
2. How can an ABM reproduce the current real-life behavior of residential and non-residential community members in the chosen energy community?
3. What effect does a time-of-use tariff have on the grid dependence and energy costs in the modeled energy community?
4. How does the demand flexibility by residential and non-residential community members affect the efficacy of demand response?

1.4. Research Objective

The objective of this research is twofold. First, this research identifies the key social, institutional, and technical attributes of a Dutch energy community regarding demand response (time-of-use tariff in this case). This information is used for building an agent-based model to get a better understanding of the transactive behavior of Dutch energy communities. This study will also include small and

[1] Non-residential members, in this case, refer to SMEs (not trading in energy for profit), Schools, Office buildings, and EV charging stations as community members.

medium enterprises and local authorities as non-residential members of the energy community as per the directive released by European Commission (2018). Including non-residential members with complimenting energy demand profiles provide the opportunity for better peak management through demand response policies and reducing the dependence on energy storage. Demand response and its relevance for energy communities are further discussed in Section 1.2.3. The scope of this model is limited to the electricity distribution network (low voltage) of the modeled energy community. However, this model can be extended to include heat and gas networks in future versions. Two real-life inspired energy community configurations are modeled with additional non-residential members for experimentation. Additionally, behind-the-meter storage for community members is introduced as a policy lever to augment the demand flexibility for the energy community.

1.5. Relevance of this Research for the Study Program

This research is conducted as a master thesis project for MSc. Engineering and Policy Analysis (EPA) at the faculty of Technology, Policy, and Management of TU Delft. EPA is a unique program designed to prepare future leaders for tackling complex problems located at the interface of technology, politics, and society using a data-driven approach. This research supports decision-making using a data-driven modeling and simulation approach while considering socio-technical aspects of the problem. This study uses agent-based modeling as the research approach which is an EPA method for modeling complex adaptive systems and incorporating a multi-actor perspective. This research is done in association with an external organization Croonwolter&dros and the findings of this research will inform decision-makers on the interface of public and private domains. Thus, this research fits all the requirements of a thesis project for MSc. Engineering and Policy Analysis.

1.6. Report Overview

The remaining of this report has the following structure. Chapter 2 describes the research approach and methods used for answering the research questions. This involves model conceptualization, formalization, implementation along with verification and validation. Furthermore, the experiment design and community setup used for experimentation are discussed. Chapter 3 curates the important insights from the experiment outcomes and documents the key results of this study. These results are further interpreted in Chapter 4along with key assumptions and a brief discussion on the validity of the results. Lastly, the findings of this research are concluded with recommendations in Chapter 5. Additionally, added academic and social value of this research are discussed.

2
Methods

This chapter explains the research approach selected for answering the research questions. Based on the selected research approach, the research method is adopted for answering research sub-questions, and eventually, the main research question is discussed and explained. The research steps indicated in this chapter are followed to obtain the results in subsequent chapters.

Energy communities are complex socio-technical systems involving multiple stakeholders such as community members, coordinators, and service operators making informed decisions while interacting and influencing each other (Dam et al., 2012). Every energy community is unique in its composition and functioning and ABMs can effectively capture the unique characteristics of community members (Mihailova et al., 2022). These parameters can be easily tweaked to reproduce the model for a different community setting. Agent-based modeling involves encoding actors as agents making autonomous choices based on decision drivers whilst learning from their previous decisions (Nikolic & Ghorbani, 2011). Agents are assumed to make rational decisions for attaining their personal goals based on the principle of distributed artificial intelligence (Rizk et al., 2018). These agents can not only decide for themselves but also can communicate, coordinate and negotiate with each other (Wooldridge, 2009). Therefore, because of the autonomous decision-making capability of agents, ABM is selected over other modeling approaches for modeling the socio-technical systems of the energy community. In chapter , the literature review further highlights the suitability of agent-based models for studying energy communities.

The following research methods are designed to answer all the sub-research questions and eventually the main research question mentioned in Section 1.3. These research methods are taken from Van Dam et al. (2012) and adapted for this study. The methods used in this research are shown in the Figure 2.1. These steps capture all the steps involved in the agent-based modeling of the energy community as a socio-technical system. Though the entire process is explained linearly however the process is more iterative in practice.

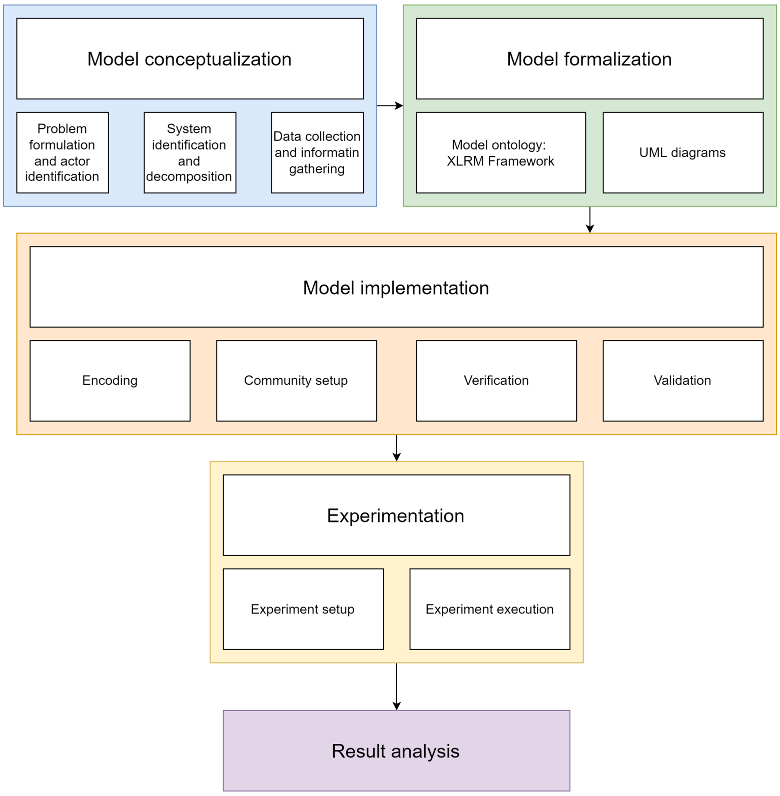


Figure 2.1: Steps for modeling energy community as a socio-technical system. These steps are adapted from Van Dam et al. (2012)

2.1. Conceptualization

This is the first step in modeling the energy community as a socio-technical system. The findings of this step will help in answering the first research sub-question by identifying key social, financial, institutional (policy & regulation), and technical aspects characterizing Dutch energy communities. This step formalizes the problem and identifies the key actors involved in the decision arena. The outcome of model conceptualization will serve as the foundation stone for the next step in modeling the energy communities.

Model conceptualization is done in three steps. Firstly, "key players" are identified to be modeled as agents, and their relationships are established. Secondly, the interaction of agents and the scope of this model are defined by system identification and decomposition. Lastly, a conceptual model is derived and depicted in form of a systems diagram. Additionally, all the input data points required for simulation are enlisted along with their source.

2.1.1. Problem Formulation and Actor Identification

Problem formulation and agent identification define the scope and purpose of the model. This step also identifies the key actors influencing the decision arena for achieving desired outcomes. These actors are modeled as agents and the decision arena is modeled as agent interaction space(i.e. model).

The problem formulation for this research is taken from the main research question mentioned in Section 1.3. The problem is focused on understanding the mechanisms within an energy community

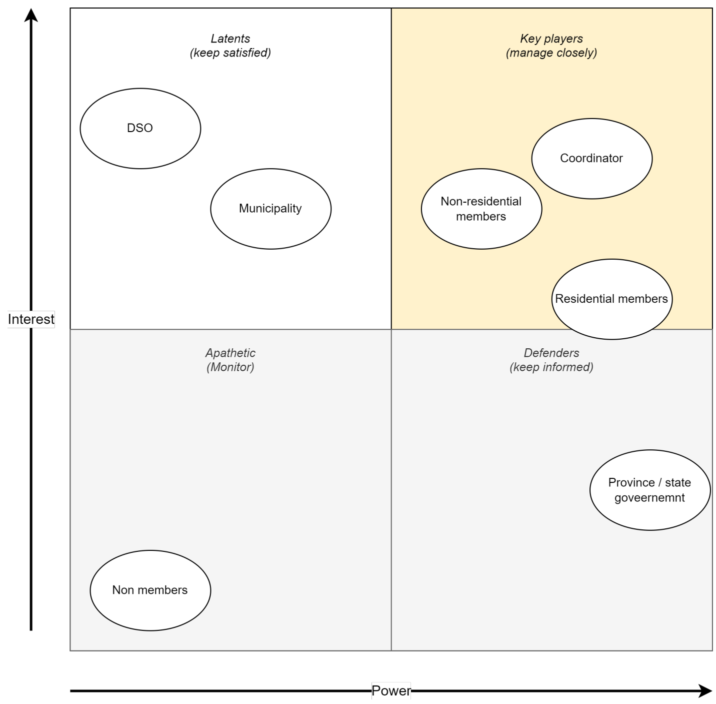


Figure 2.2: Power interest matrix of actors involved in a typical energy community

to unlock the potential of demand response with active participation from both residential and non-residential members. To identify the key actor influencing demand response within a community energy project, an actor scan was performed. Since every energy community is unique in its actor configuration and power dynamics, a generic scan was performed based on two interviews with Mr. Willie Berentsen - cooperative Sterk op Stroom, and Mr. Dominique Doedens - GridFlex Heeten energy community. Additionally, inputs from Rob Roodenburg, Senior Consultant Smart Grid at Croonwolter&dros were taken to create a generic actor-network scan. Actors identified through the actor-network scan are plotted on the power-interest matrix based on their relative interest level and (relative) power to influence the decision-making for the community. The power interest matrix of actors involved in the decision arena (energy community) is shown in Figure 2.2. The decision arena depicted in the figure is a representation of a typical energy community project. The power perception shown in Figure 2.2 is based on the power to influence demand response (internally) and electricity consumption within the energy community. Although regulatory bodies have higher governance power, community members have a direct influence on electricity consumption, generation, and demand response. Therefore community members are shown on the right-hand side of the power interest matrix.

Defenders are the most powerful actors in the decision arena but with relatively lower interest levels. In this case, the province has high regulatory and financial power to support a project however their interests are also distributed across multiple projects and governance matters. This project aligns with the sustainability goals of the province however it does not have any direct influence on the everyday functioning of the province.

The actors with the least interest levels and influence on decision-making are apathetic or crowd. Other residents of the neighborhood who are not part of the energy community are labeled as apathetic. These actors do not associate with the energy community either positively or negatively and do not engage in decision-making.

Latent are the actors with relatively higher interest levels but lower power to directly influence the decision-making in the decision arena i.e. energy community. Distribution Service Operators (such as Enexis) want to reduce energy congestion by promoting local consumption of electricity generated from renewable sources (Enexis, 2021). On the other hand, local municipalities also have sustainability targets set by the province and national government that can be realized through community energy and demand response projects. Therefore, the interests of both DSOs and local municipalities align with the community projects implementing demand response.

Key players have the highest interest and influence on decision-making within the community regarding demand response. Both residential and non-residential members want to reduce their expenditure on electricity cost and utilize locally generated renewable energy. The community coordinator can expand their service portfolio by facilitating demand response in the community and have an additional revenue source by managing the demand response in the community. Community members and coordinators have their interests aligned with implementing demand response in the community and can directly influence the decision-making within the community. Therefore, the coordinator and community members (both residential and non-residential) are modeled as agents in the socio-technical model of energy community to study demand response. In addition to community members, their assets (such as solar PV, and wind turbines) are also modeled as agents owned by respective community members. Modeling assets as agents maintain the autonomy of these assets (autonomy of operation as a generation asset) and make data collection during model simulation easier.

2.1.2. System Identification and Decomposition

System identification and decomposition further delve into the system and decision arena to define the scope of the model. This step determines what aspect (or subsystem) of reality is relevant for the problem and what portion will be left out. Figure 2.3 showcases the conceptualized model in form of a systems diagram adapted from Enserink et al. (2010). The dotted line represents the system boundary. All the components shown within the system boundary will be modeled for this research. The levers on the left-hand side are the interventions (or measures), the box on the top of the system boundary contains the uncertainty parameters and lastly, the metrics mentioned on the right side of the system boundary are the performance matrix for the conceptualized model. The grid shown at the bottom of the system diagram showcases that a single electricity connection connects the energy community with the grid. The internal electricity network and balance of demand and supply are managed by the community coordinator. The inputs data used by the conceptual model shown at the bottom of the figure are are 1. weather data used for simulating solar and wind assets, and 2. electricity consumption data for simulating the electricity consumption of agents in the model. The model has both residential and nonresidential agents and all of them are electricity consumers. This entails that all the community members consume electricity (consumers) and some of them also have generation assets to generate renewable energy (prosumers). These community members (or agents) are connected to a community coordinator responsible for balancing the supply and demand in the community and trading energy on behalf of the energy corporation. The coordinator also analyses the historical demand and weather forecast to prepare a day-ahead schedule for demand response based on the availability of electricity from local generation. Some of the community members have demand flexibility and hence can participate in the demand response by adhering to the ToD schedule.

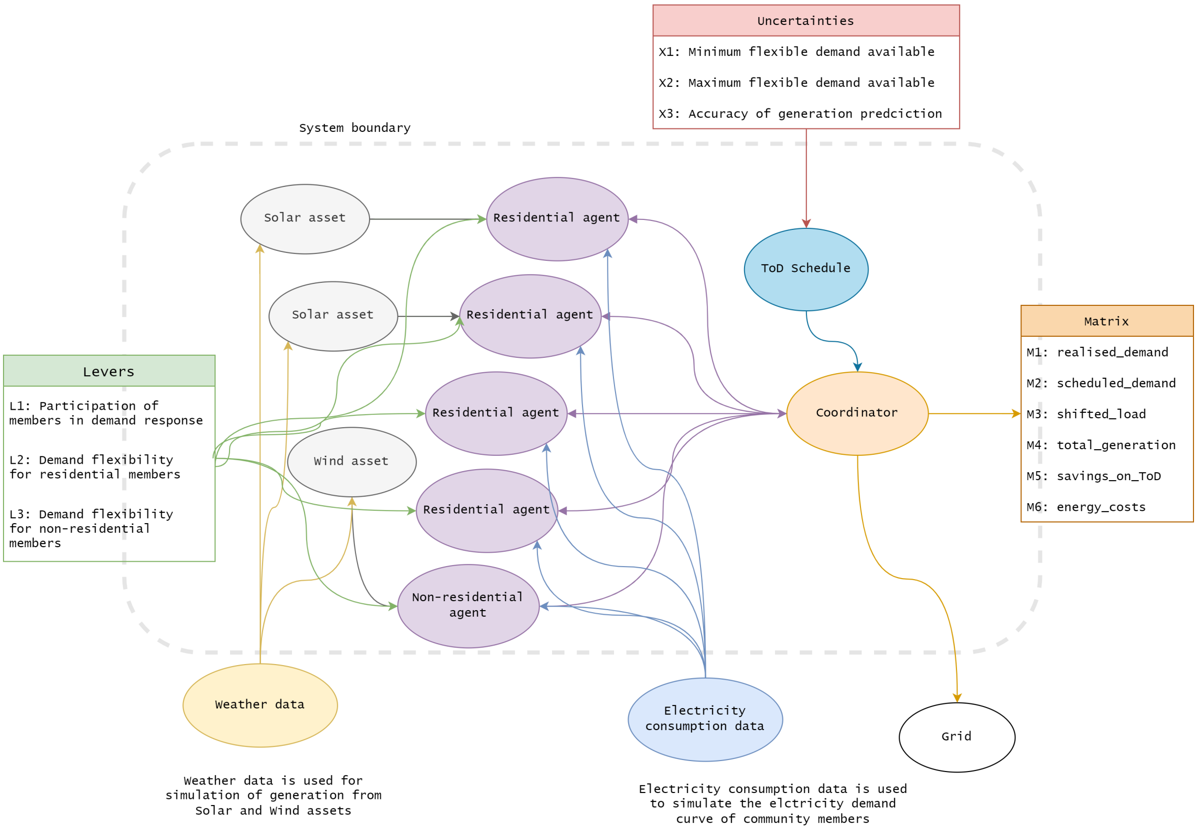


Figure 2.3: Conceptualized model showcased as a systems diagram adapted from (Enserink et al., 2010)

The participation of a community member depends on two aspects. First, is the flexible load that can be moved without causing discomfort for the community member. (For example, using a dishwasher or laundry machine in the case of residential consumers can be considered a flexible load.) Second is the availability of flexible demand. For example, if a residential consumer owns a dishwasher or laundry machine that can be switched on/off to suit the demand response schedule, the number of dishes or laundry to be washed on that particular day determines the actual load shift possible that day. Additionally, community members can have behind-the-meter energy storage to further augment the demand flexibility of community members. Lastly, not all agents with demand flexibility would follow the demand response. This way, the system shown in the dotted box represents an energy community encoded into the agent-based model.

2.1.3. Data Collection and Information Gathering

Data collection and information gathering is the last step of model conceptualization. This step involves defining and collecting data required to replicate the real-life system behavior through the model with a "good-enough" accuracy to derive useful results from it. The conceptualized model shown discussed in Section 2.1.2 is based on qualitative data regarding the social structure of energy communities based on interviews enlisted in Table 2.1. Apart from qualitative data, simulating an energy community requires three major quantitative data inputs. Firstly, a high-resolution hourly consumption data for simulating the load profile of community members including both residential and non-residential members. Secondly, hourly weather data (solar irradiance and wind speed) for simulating generation from solar and wind assets. Lastly, electricity cost per unit for the entire year to simulate the expenditure on importing electricity from the grid. The data points along with sources are enlisted in Table 2.1.

Table 2.1: Data points used for simulating an energy community along with its respective source

S.No	Data point	Source
1.	Hourly energy consumption data for residential consumers	GreenVillage
2.	Hourly energy consumption data for Offices	Croonwolter&Dros, Smart Buildings
3.	Hourly energy consumption data for EV-Charging station	Croonwolter&Dros, Smart Buildings
4.	Hourly energy consumption data for School	Croonwolter&Dros, Smart Buildings
5.	Weather data (hourly solar irradiation and wind speed)	KNMI
6.	Electricity pricing data	CBS database
7.	Social, technical, institutional, and financial characteristics of community	Expert interviews and literature such as Koirala et al. (2018) and Fouladvand, Ghorbani, et al. (2022)
8.	Organizational structure of energy community	Expert interviews (Willie Berentsen - cooperative Sterk op Stroom and Dominique Doedens - GridFlex Heeten energy community former smart-grid pilot)

These aforementioned data sets are anonymized, cleaned, checked for completeness, and then processed for model input using Jupyter Notebooks (Python). Only anonymous data sets are uploaded to the GitHub repository and acquired data with traceable information is deleted after anonymizing the data sets.

Moreover, the electricity consumption and weather data used in this model are from the year 2021. Electricity consumption is dependent upon weather conditions. The electricity consumption data for non-residential community members (i.e. school and office buildings) include electricity consumption for indoor heating and cooling. Thus, extreme weather conditions result in increased electricity consumption. These temperature variations should be taken into consideration while interpreting the model outcomes. Figure 2.4 showcase the temperature variation for the year 2021 as compared to the last 20 years. The temperature variation for the year 2021 follows the common trend of the last 20 years.

2.2. Formalization

Model formalization helps in translating the conceptualized model into the encoded model in Python. This step involves the translation of the conceptual model defined in the previous step into pseudo-codes, flow charts, and UML diagrams. These formalized representations of the conceptual model are encoded in the next step. The flow charts and UML diagrams prepared during formalization also serve as a blueprint during model verification and validation. Model formalization is done in two

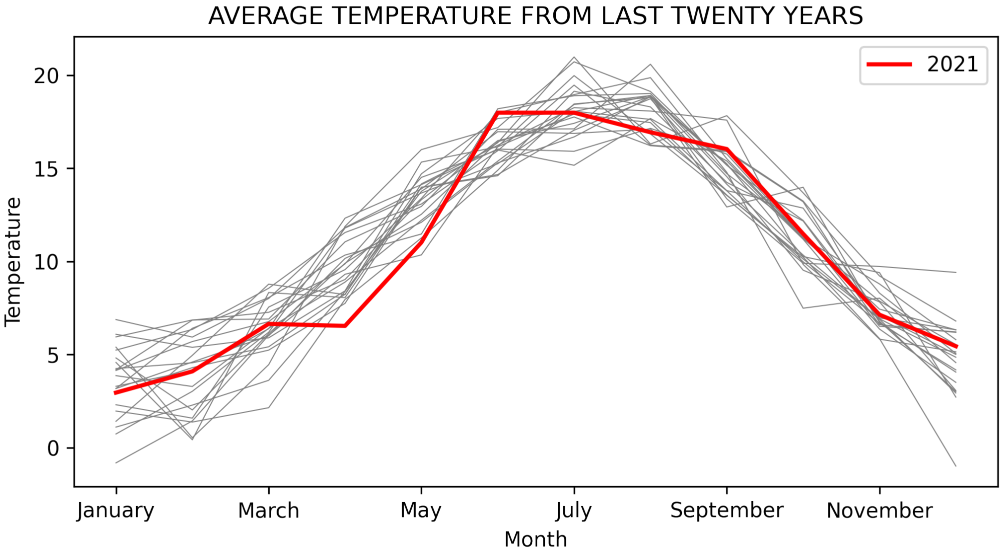


Figure 2.4: Temperature variation for the year 2021 compared to the last 20 years

steps. Firstly, the conceptual model is adapted to the XLRM framework for its python implementation. Secondly, Model and Agents ontology are discussed through UML diagrams and explanatory figures prepared to depict agents' behavior and interaction.

2.2.1. XLRM Framework Adaptation

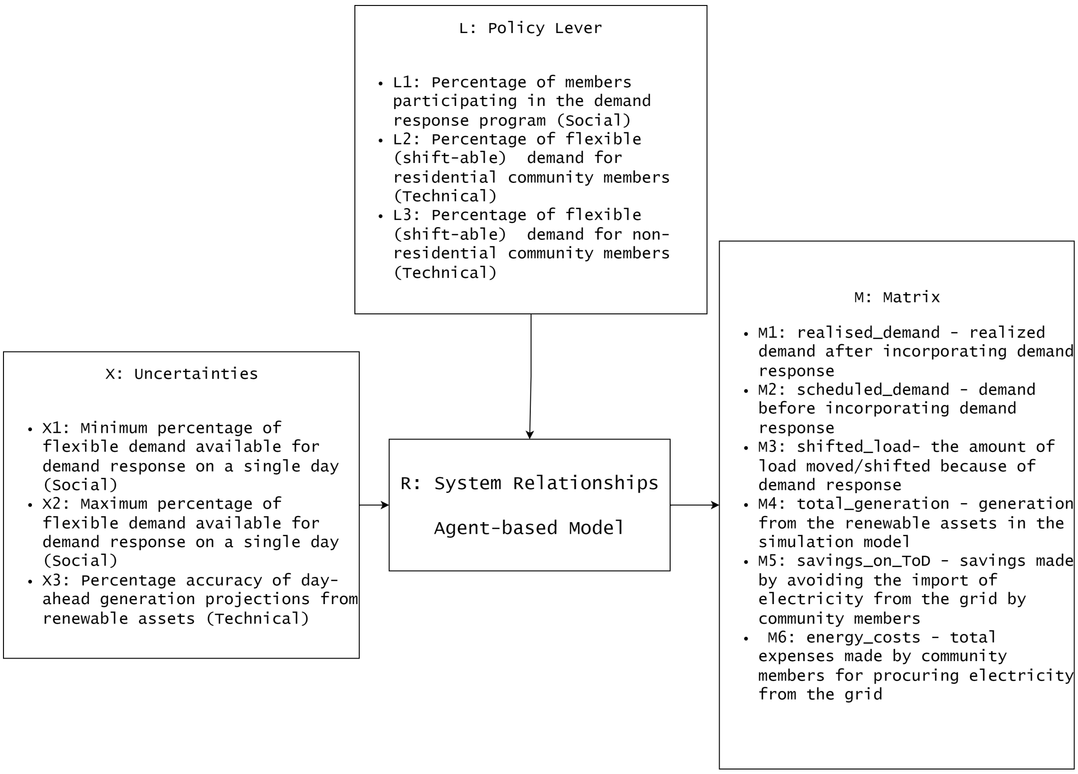


Figure 2.5: XLRM framework adapted for the model

The model is set up using the XLRM framework provided by Lempert et al. (2003) where the model is represented as system relationships (R), and model inputs are divided into two categories i.e. Uncertainties (X) and Policy Levers (L) or interventions. Lastly, model outcomes are measured in performance matrices (M). This framework facilitates experimentation setup by specifying the range of Uncertainties (X) and Policy Levers (L) to study their impact on model performance matrices (M). Figure 2.5 showcases the XLRM framework adapted for this model. Each block of this framework is further explained below:

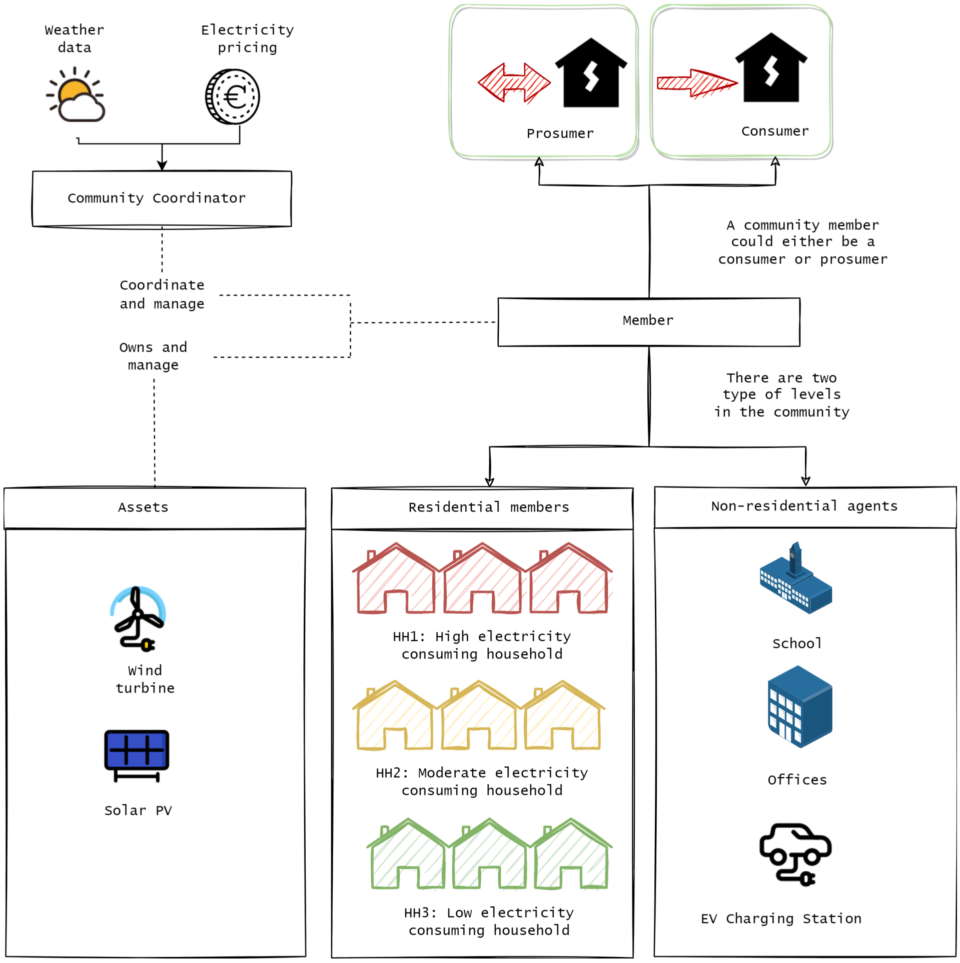


Figure 2.6: Agent relationships modeled for the research

System relationships (R) in this context are represented by the model. The model is a scaled-down replica of system relationships in an energy community and the formalized representation of the model is shown in Figure 2.6. The community members are agents and they are all connected to the community coordinator. Some community members are prosumers and own generation assets which are also modeled as agents. All agents can participate in demand response based on the availability of flexible demand. The system relationships and model are further discussed in detail in Section 2.1.2.

This model is conceptualized to have three uncertainties (X). The community coordinator takes the availability of generation assets and base demand for the next day into account for preparing the demand response (ToD) schedule. However, both of these values are uncertain and can differ from the historical trend resulting in unforeseen energy shortages or excess. Therefore these two uncertainties are programmed as a percentage value that can be specified in the python implementation of the model. Additionally, the accuracy of demand forecast and day-ahead generation from renewable assets is conceptualized as the third uncertainty.

The policy levers (L) are the intervention in the model that can be controlled or modified to obtain a desirable result. Based on the interview with community operators in the Netherlands, it is deduced that highly motivated people join these community initiatives. Thus, it is assumed that the participation of community members in demand response can be increased by encouraging community members subjected to the availability of flexible loads. Therefore, the participation of community members in ToD is modeled as the policy lever (L1). This value can range from zero i.e. no agent participating in the demand response to 100 percent participation by members. In addition to this, the amount of flexible load (or movable load) as a percentage of total load for community members is also modeled as a policy lever. The flexible load percentage for a community member is calculated with the following formula. flexible load percentage $=$ movable load without causing any discomfort $/$ total connected load $*$ 100 Flexible load percentages are separately defined for residential (L2) and non-residential community members (L3) in the model levers.

Lastly, the outcomes of the model simulation are captured using the performance matrix (M) shown on the right-hand side of Figure 2.3 and Figure 2.5. This model has five performance matrices to evaluate the performance of the community to answer the research question and they are as follows:

- *M1: Electricity consumption* is the total electricity consumption for residential and non-residential members.
- *M2: Electricity demand* is the total electricity demand for residential and non-residential members.
- *M3: Shifted load* is the amount of load moved/shifted because of demand response.
- *M4: Total generation* is total generation from the renewable assets in the simulation model of the energy community.
- *M5: Savings on ToD* is the amount saved on electricity purchase through demand response by community members.
- *M6: Energy costs* is total expenses made by community members for procuring electricity from the grid.

2.2.2. Model and Agents Ontology

Model ontology describes the general structure of model encoding such as time step, duration of the model run, structure of code, etc. This step defines all the input parameters and model performance parameters. Agent-based models act as an interaction space for agents to interact and exchange information. In this case, the energy community is the interaction space for models to act and react to the information. An energy community is constituted of community members (along with their respective generation assets) and a community coordinator. These agents act/react to each other based on the information available to them and decision drivers. This model is run (or simulated) for the duration of a year for incorporating seasonal variation in solar irradiance, wind speed, and electricity consumption. Since most data sets are complete for the year 2021, it is selected as the year for the simulation run. One tick is equal to one day, thus the model runs for 365 ticks. The focus of this research is to evaluate the impact of demand response on the everyday functioning of an energy community in short term.

The overall agent structure of the model is depicted in the Figure B.1. Mesa is the python library used for agent-based modeling and contains a model and an agent class by default. As shown in Figure 2.8, the community energy model has three types of agents class members, assets, and coordinators all derived from the agent class of the mesa library.

Asset class represents generation assets such as solar PV plants or wind turbines in the model. This class is further detailed in the Section 2.2.2. The coordinator class represents the community coordinator that is responsible for balancing the supply and demand of electricity in the energy community.

Member agent class represents a member of the community who can participate in community activities involving consuming the community energy and opting to participate in the demand response program. The properties and methods of a member are shown in the Figure B.1. On a broader level, A Member can be a consumer or a prosumer based on their role in the community. As the name suggests, the consumer can only consume electricity, whereas a prosumer is also involved in the generation of electricity. Primarily a prosumer generates electricity for self-consumption and shares the excess

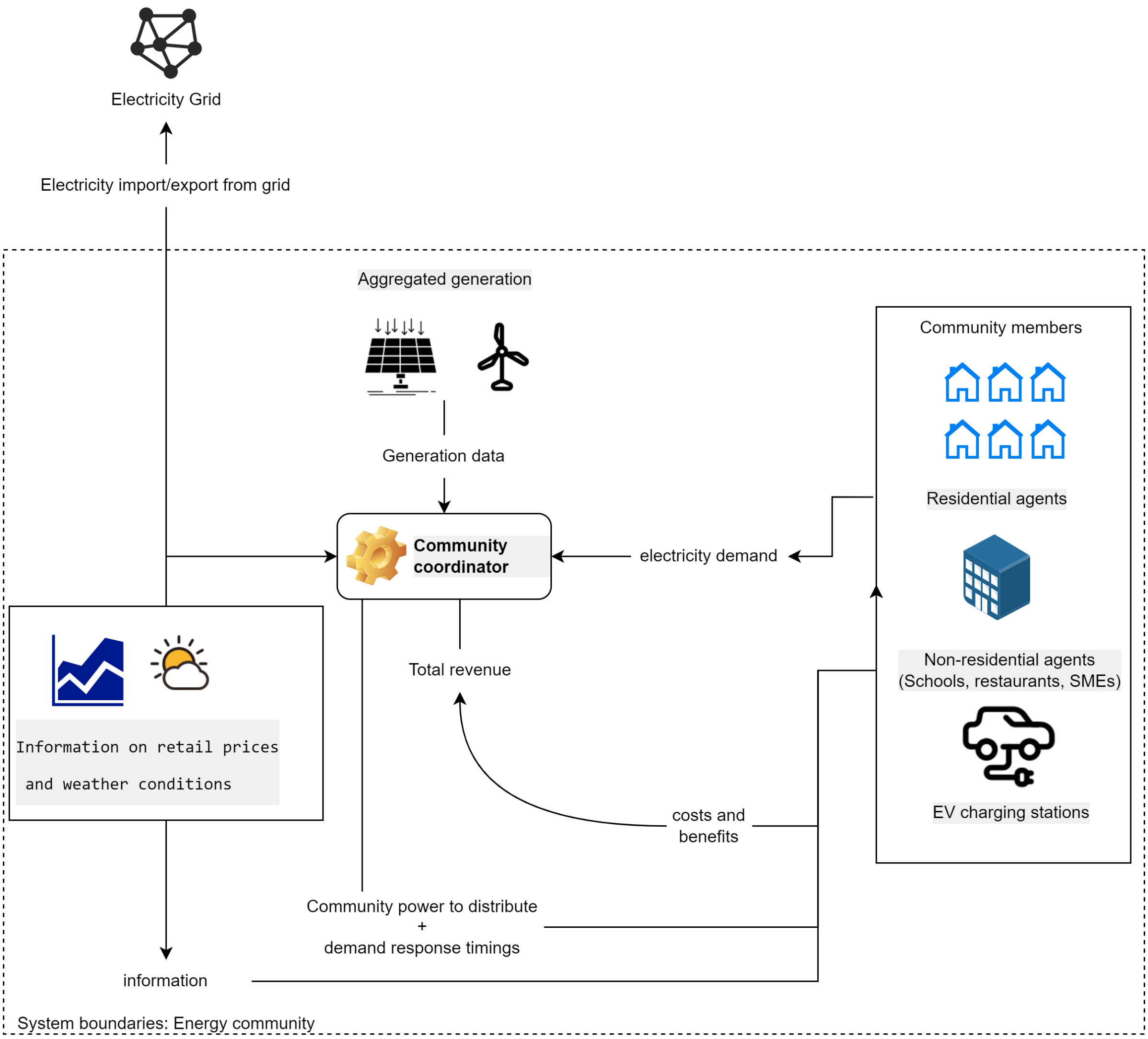


Figure 2.7: Community energy model setup

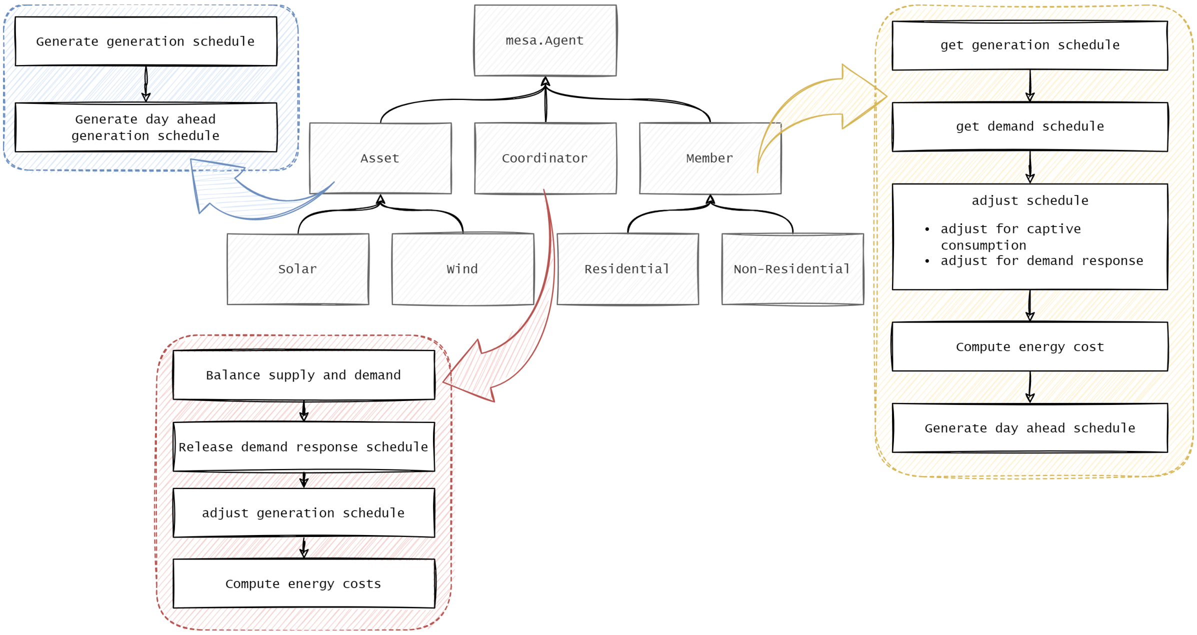


Figure 2.8: Agent ontology in the model

generation with other community members. The conceptualization of assets owned by prosumers in the community is further explained in the Section 2.2.2. The number of community members and their respective connected load and generation capacity remain constant for a simulation run of the model. The members can also be classified based on their load profile. Currently, the model has a demand profile for the following user groups. These demand profiles belong to real locations and can be scaled and mixed-matched to create different community energy archetypes for experimenting with different community configurations.

Residential community members represent a member of the community that is a residential household. The current version of the model has data for three typical households based in Delft, the Netherlands. Figure 2.9 showcases the annual averaged hourly load profile and depicts the average annual consumption of residential members in the model. These data sets include load profiles for the following types of households.

- Household type I: Low consumption household (average hourly consumption 17 kWh)
- Household type II: Medium consumption household (average hourly consumption 20 kWh)
- Household type III: High consumption household (average hourly consumption 35 kWh)

This model has three types of agent subgroups in non-residential community members. The number of sub-agent groups in this category is limited by the unavailability of the hourly energy consumption data of different sectors and SMEs. In the future, further diverse energy profiles can be added to this model to evaluate the pairing of the energy communities with small and medium enterprises. Figure 2.11 showcases the annual averaged hourly load profile of non-residential members in the model.

One of the highlights of this study is the inclusion of non-residential members as community members. Since the hourly energy consumption of office buildings or industrial players is private, Croonwolter&Dros has shared the energy profile of four anonymous office buildings along with their

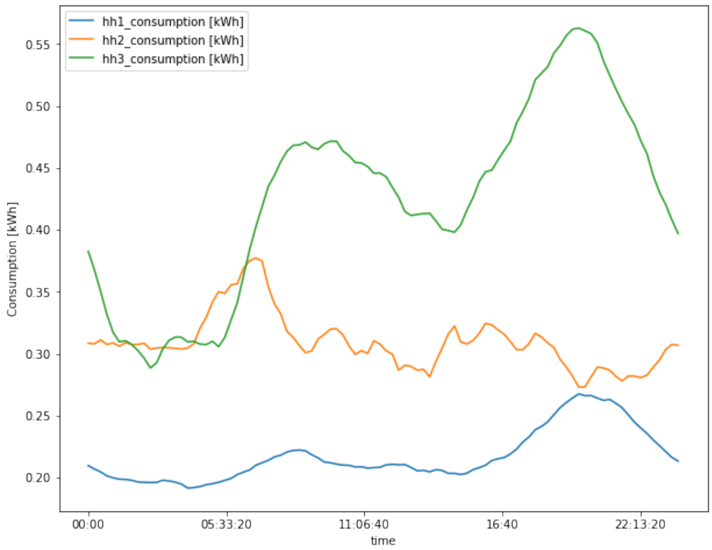


Figure 2.9: Annual average hourly load profile of residential members in the model

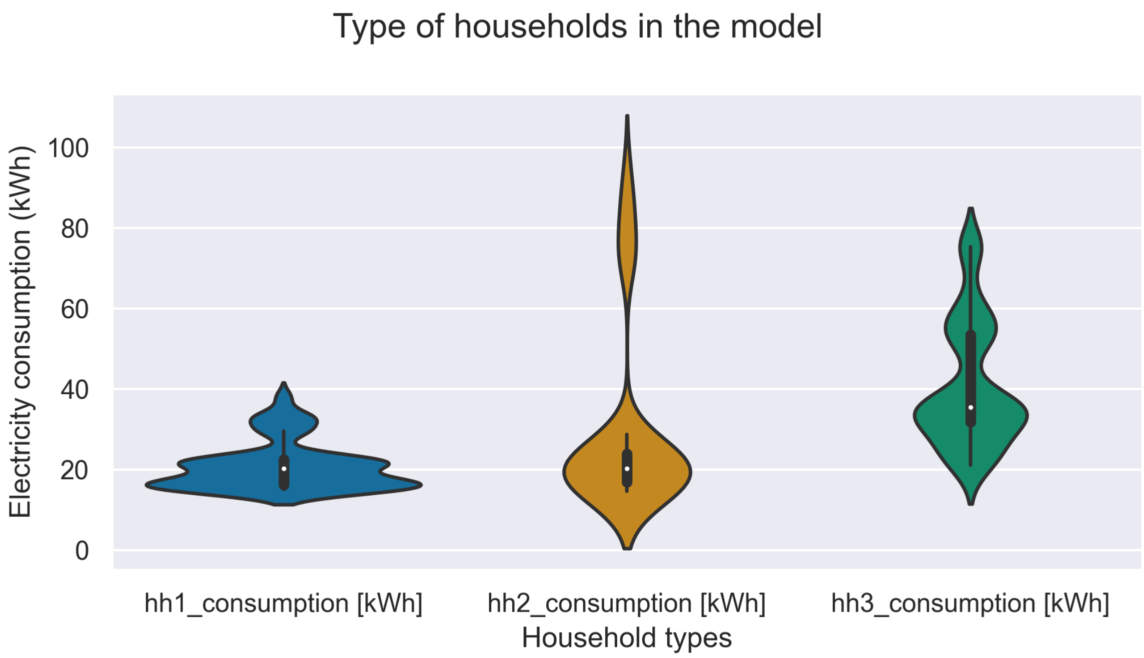


Figure 2.10: Type of households used in the model

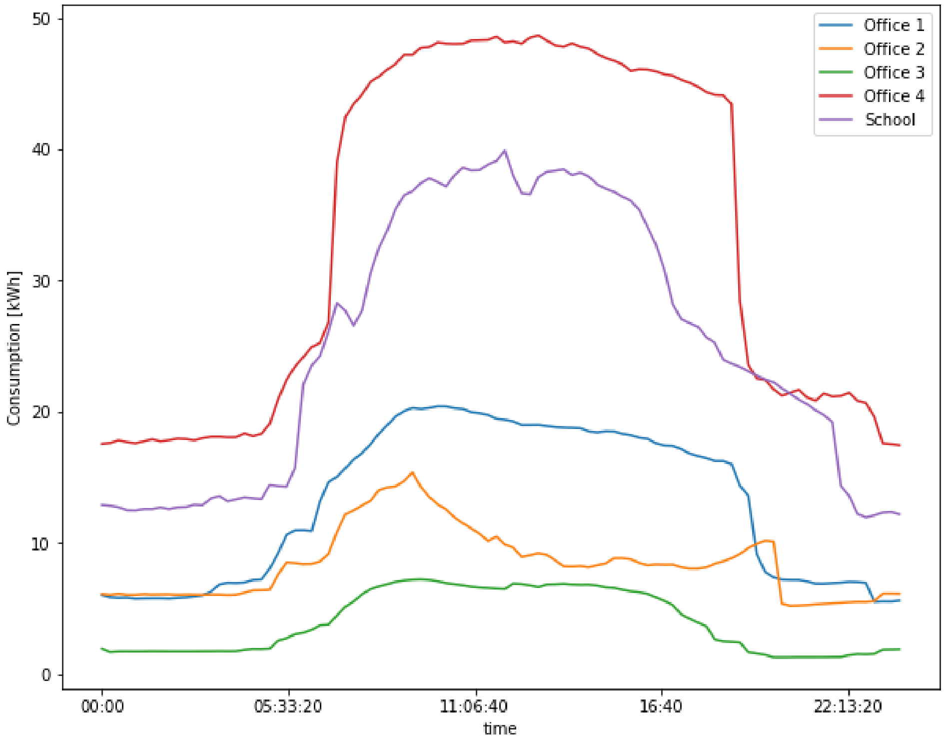


Figure 2.11: Annual average hourly load profile of non-residential members in the model

floor area. Table 2.2 contains the details of hourly consumption data sets for office buildings. The school represents the load profile of a typical MBO building. Further information about this building is shown in the Table 2.2. With increased penetration of EVs in public and private transport, a provision of an EV charging station is added to the model database. This load profile is based on the EV charging station calculations provided by Croonwolter&Dros. The load profile is computed considering three slow chargers of 60 kWh rating . Further details of the charging station are available in the Jupyter notebook "Data cleaning" in the GitHub repository. These profiles can be modified based on the number of chargers and their ratings for future experiments.

Table 2.2: Details of non-residential profiles in the model database

Building	Area (square meters)	Location
Office 1	9375	Handelsweg
Office 2	8808	Eindhoven
Office 3	3500	Maastricht
Office 4	13500	Heeerlen
School	27000	Heerhugowaard

The coordinator is the agent that balances the supply and demand of electricity within the energy community. Every community has only one coordinator. The coordinator is responsible for aggregating the day ahead of schedule and releasing the ToD schedule based on excess generation within the community. In addition to this, a coordinator is also responsible for distributing the earnings from energy export to prosumers within the community. It is assumed that the energy generated within the community will always be cheaper than the grid import and the coordinator will first optimize the demand by prioritizing the self-generation. The properties and methods of the coordinator class are shown in the Figure B.1. In practice, community coordinators are the external ESCO commissioned by the energy community for availing the aforementioned services. These coordinators coordinate with local aggregators and DSOs for trading electricity on behalf of the energy community.

Prosumers in the model own assets. These assets include Solar PV and Wind Plant. The generation from these assets depends upon the weather data obtained from KNMI. Figure B.1 showcase the methods used in the class. Assets are derived from the agent class for easy monitoring of parameters but are initialized by the Member class, particularly if a community member is a prosumer. At the initialization of the instance, an asset computes lifetime generation and LCOE (Levelized Cost of electricity) for the asset to determine the cost at which the generated electricity will be sold by the asset owner. Since energy corporations work on a non-profit basis, no additional profits are added to the price of electricity. If a member owns multiple assets, LCOE from all assets is averaged out for the simplicity of the model. An asset generates its supply schedule at every tick based on the weather data and its generation capacity. The generation from the assets is determined using the following formulas provided by NREL (National Renewable Energy Laboratory). The calculation of electricity generation from a wind turbine is taken from Burton et al. (2011). The efficiency, performance, and LCOE of an asset do not change during a simulation run.

Daily kWh from a solar PV asset = solar system size $*$ *capacity factor* $*$ *total hours*

Daily kWh from Wind turbine = $0.01328 * (rotordiameter(feet))^2 * (averagewindspeed(mph))^3$

2.3. Model Implementation

In this step, the conceptualized model is translated into a python model with the help of formalized flowcharts and UML diagrams. This answers the second research sub-question by successfully modeling the energy community as a socio-technical system using agent-based modeling. After encoding, the model is first verified to check if all the components of the conceptual model are translated accurately. After verification, the model is validated to check if the model and output generated are suitable for answering the research question. Model implementation involves the following steps:

2.3.1. Model Encoding

Model encoding means coding the conceptualized and formalized model into the python code. The model is encoded in the python programming language using mesa, a python library designed for agent-based modeling. Figure B.2 showcases the model setup in the python using mesa library through a UML diagram. Mesa uses schedulers for sequencing the agent activation in the model. Based on the scheduler, agents are activated to perform their tasks at every time step. The energy community model uses ”BaseScheduler” to activate the agent in the sequence they are initialized. This setup allows the last activation of the coordinator so that the coordinator can compile the demand and supply for community members at the end of every time step and prepare a demand response schedule for the next time step (i.e. day). This model is a skeleton of an energy community that takes community configuration to take shape of the specified energy community and simulate the results. The community configuration includes a list of all residential and non-residential community members along with their respective generation assets (for example solar PV plant). This community configuration along with others specified in the later section of this report fed to the model is used to simulate an energy community. The model skeleton encoded in Python takes ”agent_list” as an input parameter to simulate an energy community. This list specifies all the community members and their respective assets to be initialized in the model as assets. The agent list can be created by mixing residential and non-residential community members specified in Section 2.2.2 along with their respective assets. The model has two community configurations enlisted in the code for "Groene Mient inspired community" and "GridFlex Heeten inspired community" already defined in the code. These community setups are further explained in Section 2.4.1. In addition to this, a custom community setup can be created by specifying the configuration in the "community_setup.py" script in the model directory.

2.3.2. Model Verification

The model verification is performed after successful python implementation of the conceptualized model. The objective of this verification method is to ensure that the conceptualized agent interaction and behaviors are successfully translated to the python implementation. The methods adopted for model verification are taken from Van Dam et al. (2012) and are explained in the Section 2.3.2. The verification tests performed are explained below and are recorded in the validation evidence file.

1. **Tracing the agent behavior**

   Tracing the agent's behavior entails embedding prompts and pop-ups if the agent performs a certain action. These prompts ensure that the agent is performing the tasks as expected in the model conceptualization without fail. These checks are integrated into the initial model implementation and are removed in the later stage to avoid unnecessary spamming of prompts. The agent tracking was integrated into the encoding stage of the modeling. The tracking flags were removed after the successful implementation of the model. A few examples of text prompts used for agent tracking are shown below:

   - Printing 'agent created' while agent initialization
   - Printing 'asset initialized' for asset initialisation
   - Printing 'demand updated' when ToD is implemented and demand is revised

2. **Single agent testing**

   Single-agent testing was only performed for community members and coordinators. In this test, a single agent is created in the model and its behavior is monitored for a small number of iterations of the simulation. The parameters and behavior of the agent are checked for anomaly or unexplained behavior. Single-agent testing consists of sanity checks to ensure all agent methods are functional and behave as per conceptualization. These checks also check if the agent parameters are in the permissible range. Figure 2.12 showcase that a single residential agent is initialized. The y-axis of the plot showcases the electricity demand of the agent in kWh and the x-axis of the plot represents time blocks of 15 minutes intervals. This agent is simulated for three days and therefore different demand curves of the agent can be seen in the plot. The demand curves generated by the agent are similar in shape and do not exhibit an anomaly. Thus, it can be deduced that the single-agent test for the residential agent confirms the conceptualized behavior. Similarly, Figure 2.13 showcases the demand curve for a non-residential agent. The non-residential agent selected for this test is a school. As shown in the plot, the demand curve for three days follows a similar trend and does not deviate significantly from each other. Therefore, it can be concluded that the single-agent testing has been conducted successfully for the model.

3. **Interaction testing in a minimalist model**

   In this model, not all agents interact with each other directly. There are two types of agent interactions in this model which are verified in this step using a minimalist model of minimum agents required to initiate the model. Firstly, the interaction between the coordinator and the members to collect the total generation and total demand of the community is verified. Secondly, the interaction between members and their respective assets is verified. This is verified by checking if captive generation is considered during calculating the electricity consumption of an agent. For performing interaction testing in the model, an agent with a solar asset is initialized.

   As per the conceptualization, the agent owns the asset and initializes the asset class. Figure 2.14 depicts that the agent has both demand and generation curves. This indicates that the asset has been initialized by the agent as the generation curve is a property of the Solar asset. The x-axis of the plot indicates 15 minutes time blocks for a day and the y-axis indicates the generation and consumption of electricity in kWh. This interaction testing simulation is run for three days

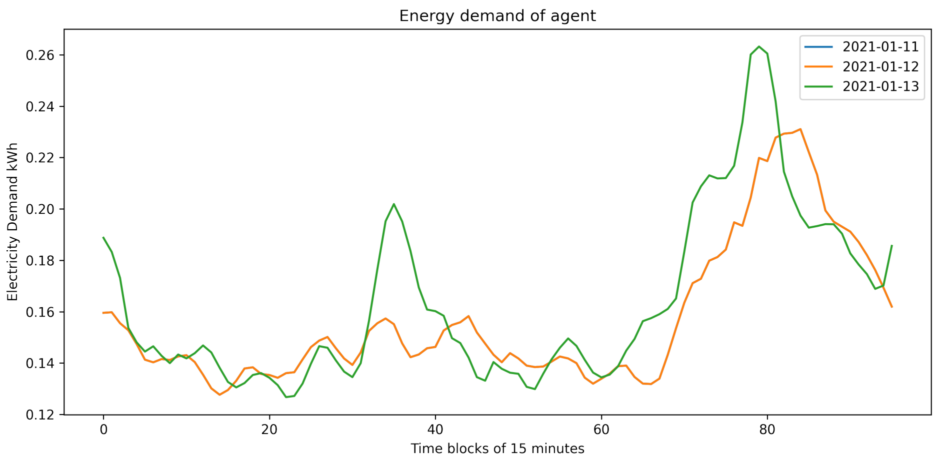


Figure 2.12: Verification check: Single-agent testing on a residential agent

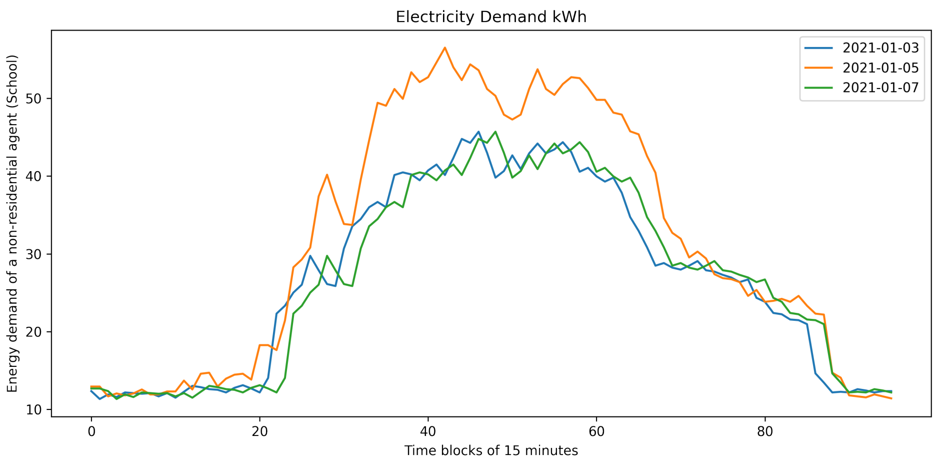


Figure 2.13: Verification check: Single-agent testing on a non-residential agent

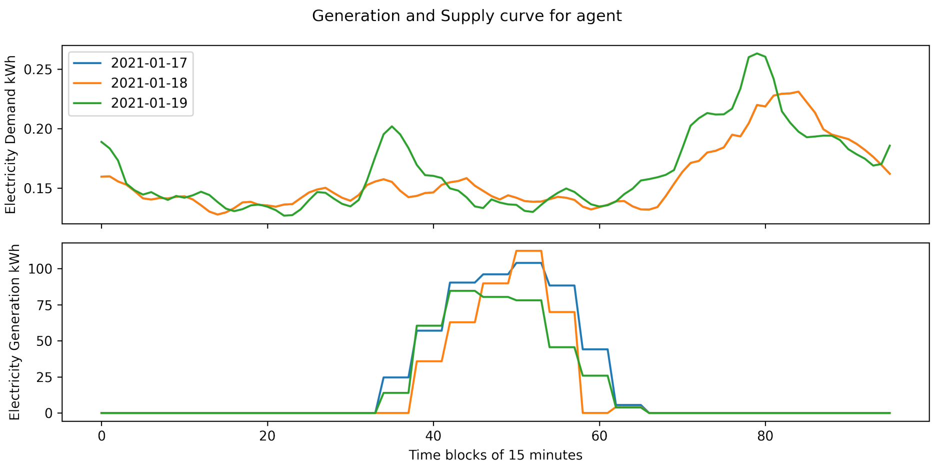


Figure 2.14: Verification check: Interaction testing

therefore three demand and generation curves are shown in the graph. As an agent initialized a solar asset and generation by solar asset is accounted as the generation for the agent, it can be concluded that the agents (community member and respective asset) are interacting as per the model conceptualization. Thus, the agent interaction test is also performed successfully for the model.

4. **Multi-agent testing**

   All the previous tests are performed at the agent level to verify agent behavior and interaction. Multi-agent testing is performed to verify the overall model behavior when all agents are active in the model. For this test, the model is initialized with minimal agents and a simulation run of thirty steps is performed and the model behavior is compared with the model conceptualization. Multi-agent testing is performed by initializing two agents, one with a solar asset and another without any assets. The demand curve and generation curve of these agents are generated for a day. The conceptualized model has two types of demand curves, Scheduled demand and Realized demand. Scheduled demand is the actual electricity consumption of the agent, whereas realized demand is electricity consumption after subtracting the captive generation for the agent. It can be seen in Figure 2.15 that agent 1 has a reduced realized demand indicated by the orange line plot. This indicates that the generation by a solar asset owned by agent 1 is subtracted from the electricity demand of agent 1. On the other hand, the scheduled and realized demand for agent 2 is the same as it has no captive assets. The x-axis of the plot indicates 15 minutes time blocks for a day and the y-axis indicates the consumption of electricity in kWh. Thus, the agent behavior is as per the conceptualized model in the multi-agent setup and multi-agent testing has been conducted successfully.

The verification tests concluded that agents were exhibiting the conceptualized behavior and agent interaction in the model was happening as per the conceptualization. Thus, the model conceptualization is successfully encoded in python.

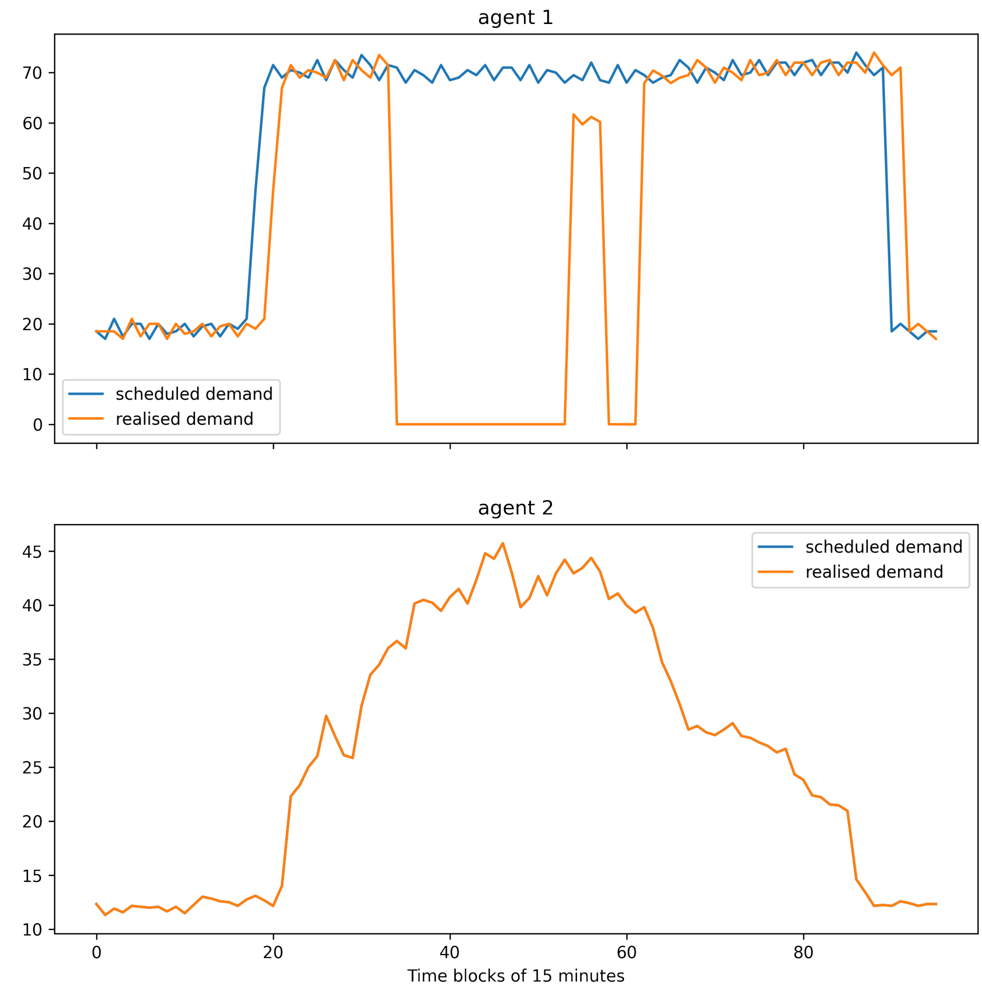


Figure 2.15: Verification check: Multi-agent testing

Extreme low	Extreme policy levers	Extreme high
0	L1: Percentage of members participation in demand response	100%
10%	L2: Percentage of total demand that can be shifted during demand response by residential community members	90%
10%	L3: Percentage of total demand that can be shifted during demand response by non-residential community members	90%

Extreme low	Extreme uncertainty values	Extreme high
10%	X1: Minimum percentage of flexible demand available for demand response on a single day	80%
50%	X2: Maximum percentage of flexible demand available for demand response on a single day	90%
10%	X3: Percentage accuracy of electricity demand forecast and day-ahead generation projections from renewable assets	90%

Figure 2.16: Extreme policy levers and uncertainty values used for the validation tests

2.3.3. Model Validation

The objective of model validation is to evaluate its suitability to answer the research question. Following validation tests taken from Van Dam et al. (2012) are performed for the model. The tests used for validation are also referred to as "robustness tests" in some literature. However the term "extreme value test" is used in this report to signify that the purpose of these tests is to validate the model and not to evaluate the robustness. Each validation test enlisted below consists of two steps called Micro validation and Macro validation. Micro validation is the validation test performed at the agent level. These tests evaluate the agent's behavior and interaction under extreme uncertainty and policy levers. Test results are considered to be positive when the agent properties and agent behavior is pragmatic and explainable under these extreme conditions. Macro validation is the validation test performed at the model level. These tests evaluate the model behavior and model relations under extreme uncertainty and policy levers. Test results are considered to be positive when the system properties and model behavior is plausible and explainable under these extreme conditions.

The validation tests are performed on a simple energy community setup with ten residential members out of which eight are consumers and two are prosumers having a solar-PV plant of 5 kWp generation capacity. The household electricity consumption profiles are randomly picked from the data bank for each household during model initialization. The community has a school as a non-residential community member with a solar-PV plant of 200 kWp generation capacity. The model is simulated for 365 time steps amounting to one year of community simulation to evaluate the results.

1. **Validation test for extremely low policy levers**

   The first test was conducted by setting extremely low policy levers for the model. This setup entails that no community member will participate in the demand response. The percentage of

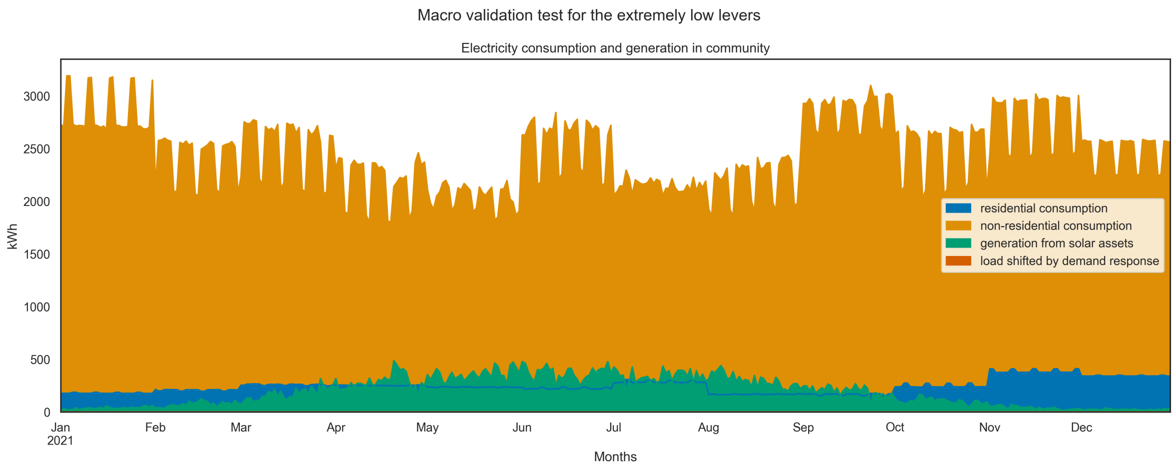


Figure 2.17: Community demand, generation, and shifted load under extremely low policy levers (macro validation)

community members participating in the demand response (L1) was set to zero, the percentage of total demand that can be shifted during demand response by residential community members (L2) was set to 0.1, and the percentage of total demand that can be shifted during demand response by non-residential community members (L3) was set to 0.1 as well. The uncertainty values are kept at default for the extreme policy lever tests. The minimum availability of flexible demand (X1) and maximum availability of flexible demand (X2) are set to 0.3 and 0.75 respectively. Lastly, the accuracy of day-ahead generation projections from renewable assets and electricity demand forecast was set to 0.80. The model is run for 365 steps and the following model and agent behavior are observed.

The results of macro validation can be seen in the Figure 2.17. This figure showcases the model level parameters for a simulation run of one year. Since no community member participated in the demand response, the load shift for the demand response is set to zero. Thus, the model exhibited expected behavior under extremely low policy levers.

Figure C.1 (of Appendix C) showcases individual agents' electricity demand and generation from solar assets during the simulation run of one year. As no agent participated in the demand response, the shifted load for individual agents during demand response amounts to zero and can be seen in the Figure 2.18. The individual agents also exhibited the expected behavior thus micro validation test for extremely low levers is conducted successfully.

2. **Validation test for extremely high policy levers**

   The second test was conducted by setting extremely high policy levers for the model. This setup entails that all the community members will participate in the demand response. The percentage of community members participating in the demand response (L1) was set to 1, and flexible demand for residential community members (L2) and non-residential community members (L3) was set to 0.9. The uncertainty values are kept the same as that of the previous test. Minimum availability of flexible demand (X1) and maximum availability of flexible demand (X2) at a time-step (day in this case) are set to 0.3 and 0.75 respectively. The accuracy of day-ahead generation projections from renewable assets and electricity demand forecast was set to 0.80.

   The model behavior for extremely high policy levers is captured in the Figure 2.19. The demand

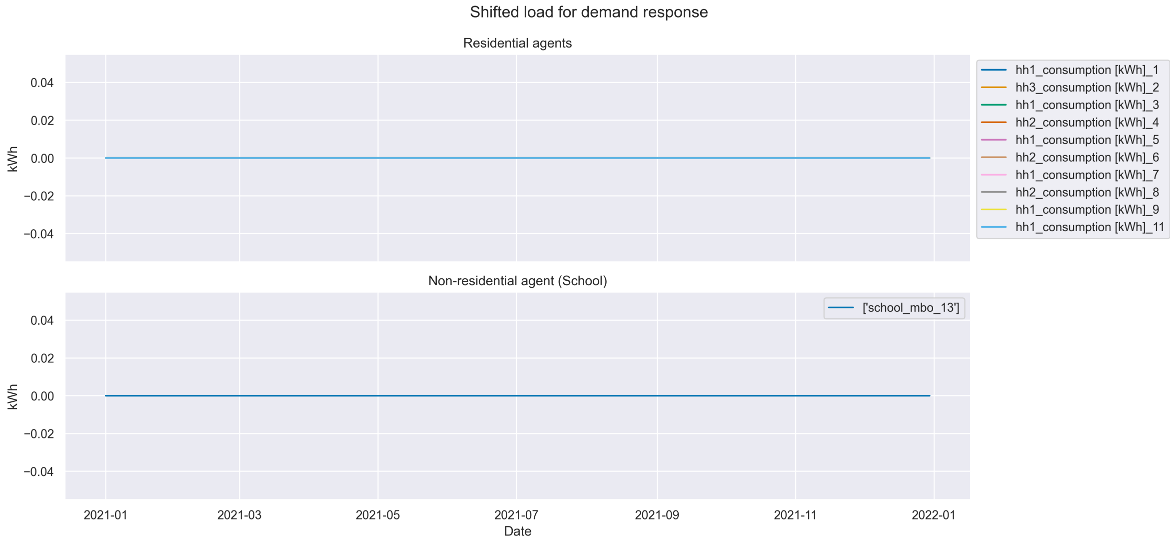


Figure 2.18: Load shifted by community members under extreme low lever settings (micro validation)

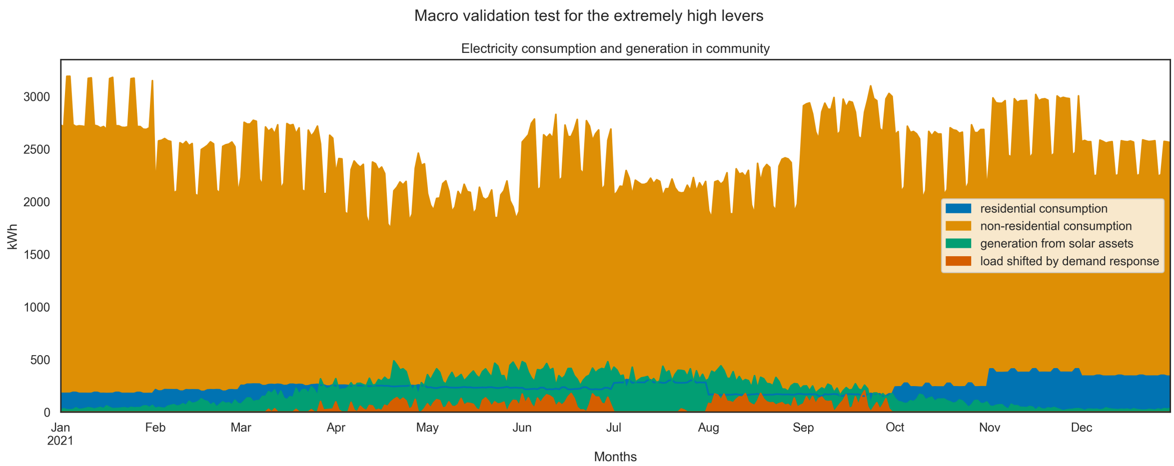


Figure 2.19: Community demand, generation, and shifted load under extremely high policy lever (macro validation)

curves and generation curves for the community are the same as in the previous test. However, since all community agents are participating in the demand response, a total shift in the demand because of demand response can be seen in the Figure 2.19. Thus, the model exhibit expected behavior and macro validation check for extremely high policy levers conducted successfully.

The individual electricity demand under extremely high policy levers is shown in Figure C.2 (of Appendix C). Figure 2.20 confirms participation from all community members. This shift is facilitated by the excess generation from the solar plant and therefore the demand response is active during the peak summers and spring from March to October. The agents exhibited the expected behavior under extremely high policy levers thus the micro validation is conducted successfully.

3. **Validation test for extremely low uncertainty parameters**

   The third test was conducted by setting extremely low uncertainty parameters for the model. This setup entails that the availability of flexible demand for the demand response is extremely

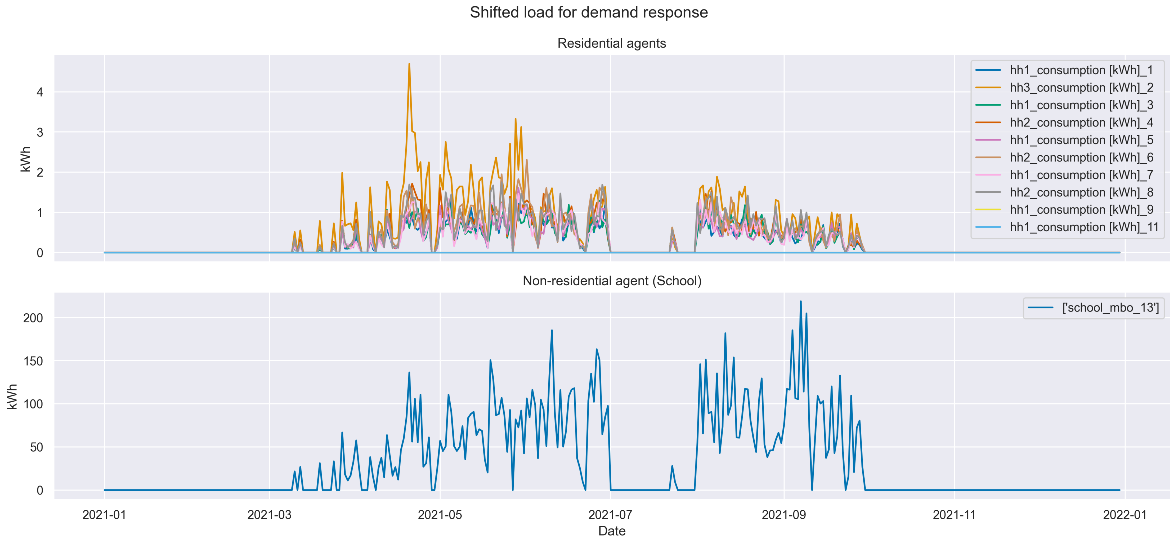


Figure 2.20: Load shifted by community members under extremely high policy levers(micro validation)

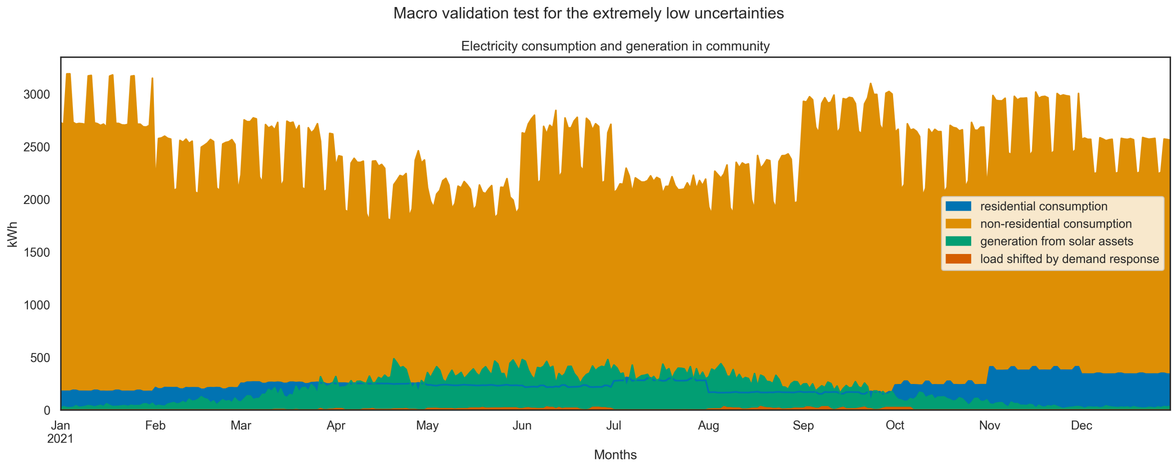


Figure 2.21: Community demand, generation, and shifted load under extremely low uncertainty(macro validation)

low and the accuracy of the ToD scheduling for demand response is also very poor. Minimum availability of flexible demand (X1) and maximum availability of flexible demand (X2) at a time-step (day in this case) are set to 0.1 and 0.5 respectively. The accuracy of day-ahead generation projections from renewable assets and electricity demand forecast was set to 0.1. Policy levers are set to their default values for the extreme uncertainty test. The percentage of community members participating in the demand response (L1) was set to 0.5, and flexible demand for residential community members (L2) and non-residential community members (L3) was set to 0.2 and 0.3 respectively.

Figure 2.21 showcases the overall electricity demand, electricity generation, and shifted demand by demand response during the simulation run of one year. As the availability of demand response is very low and the accuracy of projection for preparing the ToD scheduling for demand response is very poor, the shifted load is significantly lower than the previous test in Figure 2.19. Since the overall model behavior is explainable, the macro validation test for extremely low uncertainties is conducted successfully.

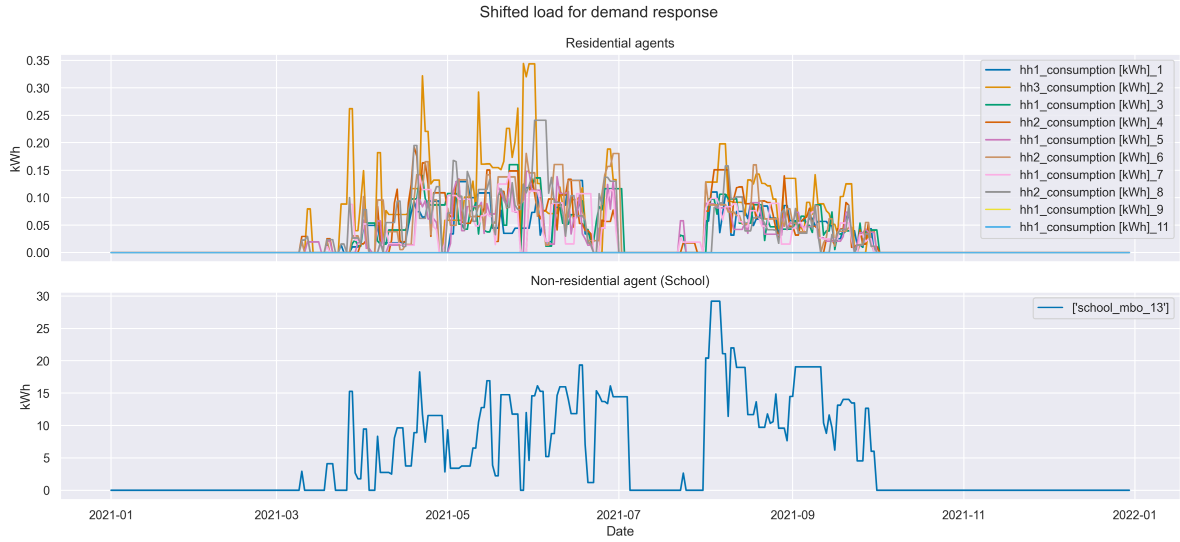


Figure 2.22: Shifted load of community members for demand response under extremely low uncertainty values(micro validation)

The individual electricity demand of community members and generation from solar PV assets under extremely low uncertainty parameters are shown in Figure C.3 (in Appendix C). Figure 2.22 showcases the load shift by community members as a part of demand response. The maximum load shift by a residential member is 0.35 kWh and for a non-residential member (School) is 30 kWh for the entire year. These figures are significantly lower than the previous test shown in the Figure 2.20. Thus, lower availability of flexible demand and poor prediction of demand response schedule lead to reduced load shift by agents despite the availability of excess supply from solar PV plants. Therefore, agents exhibit plausible behavior under extremely low uncertainty values and the micro validation test is successfully conducted.

4. **Validation test for extremely high uncertainty parameters**

   The last validation test was conducted by setting extremely high uncertainty parameters for the model. This setup entails that the availability of flexible demand for the demand response is extremely high and the ToD schedule for demand response is also very accurate. Minimum availability of flexible demand (X1) and maximum availability of flexible demand (X2) at a time-step (day in this case) are set to 0.8 and 0.9 respectively. The accuracy of day-ahead generation projections from renewable assets and electricity demand forecast was set to 0.9. Policy levers are set to their default values same as the previous test setup. The percentage of community members participating in the demand response (L1) was set to 0.5, and flexible demand for residential community members (L2) and non-residential community members (L3) was set to 0.2 and 0.3 respectively.

   The overall model behavior under extremely high uncertainty parameters is shown in Figure 2.23. The increase in total load shift caused by demand response is visibly increased from the previous test shown in the Figure 2.21. Since the availability of flexible load is increased, the total shifted load for the model is increased. Thus, the model has exhibited expected behavior under extremely high uncertainty parameters and the macro validation test is successfully conducted.

   The individual electricity demand and generation from solar PV are depicted in Figure C.4 (in

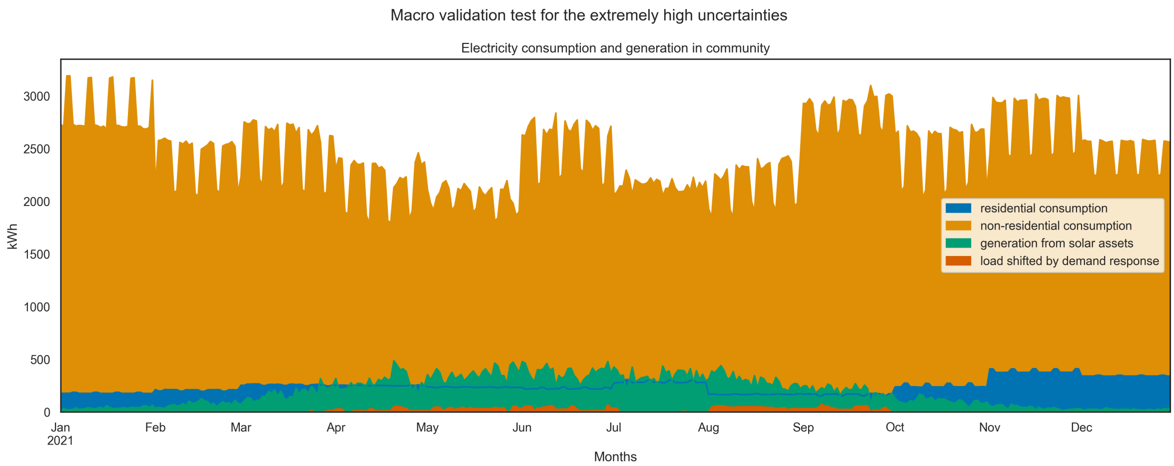


Figure 2.23: Community demand, generation, and supplied load under extremely low uncertainty(macro validation)

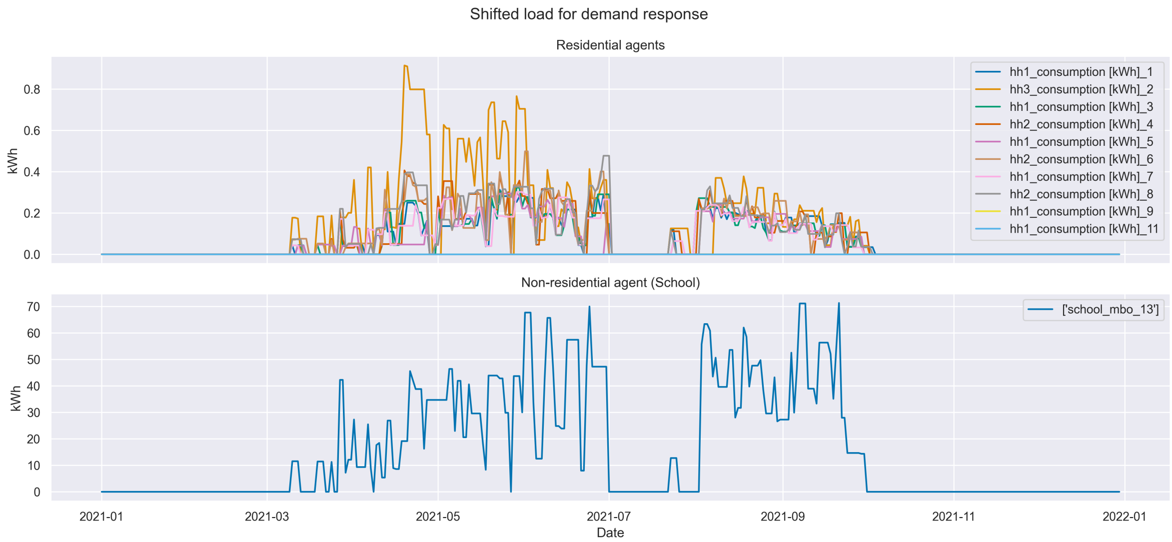


Figure 2.24: Load shifted by agents under extreme high uncertainty values(micro validation)

Appendix C). The agent's participation in demand response and shifted load is higher than in the previous test as the availability of flexible demand and accuracy of demand response schedule is set to the highest extreme. The load shifted by each agent through demand response is shown in the Figure 2.24. Thus, agents exhibit expected behavior under extremely high uncertainty and the micro validation test is successfully conducted.

5. **Face validation**

   Face validation is the validation of the model behavior by field experts and professionals. Model outcomes and validation checks performed are documented and shared with the field experts and experienced modelers for validation. Experts evaluate the model outcomes for any abnormal or unexplained behavior and compare the model outcomes with real projects. The validation tests performed on this model and its respective results are shared with the Croonwolter&dros team and reviewed by the experienced energy modelers. The Croonwolter&dros team has evaluated the results and validated the model outcomes to be realistic and plausible. Moreover, the behavior exhibited by the model during the validation test aligns with the system description provided by the problem owners (Willie Berentsen - cooperative Sterk op Stroom and Dominique Doedens - GridFlex Heeten energy community former smart-grid pilot) during the interview.

2.4. Experimentation

After successful model implementation, experiments are performed using the model to answer the main research question. The experimentation involves simulating an energy community multiple times while varying the input parameters. Experimentation answers the last two research sub-questions by evaluating the impact of demand response and flexible demand on self-sufficiency and energy cost for the modeled community.

These experiments are performed on two community configurations that are inspired by existing energy communities with some assumptions. The overall experiment design has two components. First, to define the community configuration to perform experiments. Second, selecting uncertainties and policy lever values from uncertainty and policy space. The model records the performance matrices at every step of simulation to evaluate and compare different policy alternatives.

2.4.1. Community Setup for Experimentation

The experiments are performed on two hypothetical energy communities inspired by existing energy corporations. Both these energy communities have residential members therefore non-residential community members are assumed for these communities to create a community configuration with a mix of residential and non-residential members. It is assumed that the non-community members will not participate in the community affairs for profit generation as specified in the EU (2021). Following are the communities configured for performing the experiments:

The first community configuration is inspired by the Groen Mient community energy project located in The Hague. As part of this research, a semi-structured and informal interview was conducted with Willie Berentsen cooperative Sterk op Stroom (Manager of energy community) to understand the current organizational structure and plans of the cooperation. The cooperation has various plans to expand the existing community of 33 households to 300 and eventually 3000 households while piloting features like demand response through ToD. Since this cooperation is considering the implementation of demand response and expanding its member base, it is chosen for performing this experimentation. For experimenting demand response in a mixed community consisting of both residential and non-residential members is created and is shown in the Table 2.3. A school (MBO) is introduced in the community configuration with a Solar PV plant with an installed capacity of 300 kW. Apart from residential and non-residential enlisted below, a community coordinator is also included in the community configuration.

The second configuration is inspired by GridFlex-Heeten, an energy community with 48 households and renewable electricity generation and storage (battery) assets. This was originally a smart-grid pilot project located in the Veldegge neighborhood of Heeten in the Dutch province of Overijssel, currently functioning as an energy corporation. A semi-formal interview with Dominique Doedens - GridFlex Heeten energy community was conducted to know about the plans of the community. This project is a consortium of organizations including ICT Group, Enexis, University of Twente, Enpuls, Endona, Buurkracht, and Dr Ten, a sea-salt batteries manufacturer. This community is serving as a testing ground for forthcoming technologies like renewable integration through smart grid application and Vehicle to Grid through demand response. Therefore, the opportunities for demand response by including a non-residential community member are explored by conducting this experiment. Community configuration is shown in is designed to perform the demand response experiments for GridFlex-inspired communities having non-residential community members. For this purpose, an office building and centralized EV charging station with three slow chargers are introduced to the community of 48 households. Both non-residential members are assumed to have a Solar PV system of installed capacity of 400 kWp and 100 kWp respectively. Apart from the agents listed in a community coordinator is also assigned to the community configuration.

2.4.2. Experiment Design

Each experiment is conducted for one complete simulation run of the model for 365 ticks or time steps. This amounts to the simulation of the energy community for one year. Since agent-based models are path-dependent (i.e. their outcome depends on the decision path taken by all agents during the simulation), the model outcome may vary for every simulation run despite the same input parameters (Van Dam et al., 2012). Therefore, each experiment is replicated ten times. This provides a "good enough" sample size to evaluate and compare results from different experiments considering the time constraints of this study. Each simulation takes on average 120 seconds to perform the simulation for one year. Since every experiment is replicated for ten simulations, each experiment takes around twenty minutes of the simulation run (i.e. 120 seconds times 10).

Simulation experiments are performed by running the model for an energy community with a different set of input parameters and recording the simulation outcome for each input value. As shown in Figure 2.5, this model has two types of input parameters i.e. uncertainty values and policy levers. A unique combination of input parameters is called experiment condition. Three points are selected for each policy lever. Thus, unique experiment conditions are created by combining different values for uncertainty and policy levers.

Uncertainty parameters used in the model are discussed in Section 2.2.1. Two values are selected for each uncertainty parameter for designing the experiment setups. The first value is a "moderate value" and a medium value range for each parameter is selected for this value. The optimistic value entails that the availability of flexible demand for community members is in the range of 40% - 50%. Moreover, accuracy of forecasting demand and generation from renewable assets is capped at 50%.

Number of residential prosumers (owning a rooftop solar-PV system)	23
Installed capacity of residential rooftop solar PV system	20 kWP per household
Demand profile of residential consumers	Randomly picked for each household from low and mid-energy consumption households shown in Figure 2.9
Non-residential consumer	School building (MBO)
The asset of non-residential member	Solar PV system with an installed capacity of 300 kWp
Electricity demand profile of non-residential agents	Demand profile of MBO-school shown in Figure 2.11

Table 2.3: Configuration for Groene Mient inspired energy community

The second value is an ”optimistic value” and a favorable (higher) value of uncertainty parameters is selected in this case. Optimistic value entails that the availability of flexible demand for community members is in the range of 80% - 100%. Additionally, the accuracy of forecasting day ahead demand and generation for deriving demand response is capped at 90%. Table 2.5 showcases the values defined for each uncertainty.

Policy levers used in the model are discussed in Section 2.2.1. Three points are selected from the policy space for each policy lever to create experiment setups. The first point is the ”baseline value” with all policy levers set to the minimum values. The second point is the ”optimistic value” with moderate values of policy levers that is relatively attainable. Lastly, the third point is a ”very optimistic value” and has policy levers set to the maximum. The value for all three policy levers is shown in Table 2.6.

2.4.3. Implementation of Experiments Using Python

All the aforementioned experiment design, setup, and execution are facilitated by defining a dedicated Experiment class. This class is encoded as an extension of the model and is not connected to the model code directly. The attributes and methods of the Experiment class are shown in Figure B.3 of Appendix B. This class has attributes for time tracking and storing results in addition to the input parameters like community configuration, uncertainties, and policy levers. The methods in the class include experiment setup to specify the policy levers and uncertainty values and prepare the experiment setup as specified in the above sections. Run experiments method performs the experiments for the defined number of replications and saves the result at the end of the experiment run. Additionally, methods are defined to divide the experiment setup into multiple segments for distributed computing and loading results.

The simulations for experiments are performed through distributed computing. Distributed computing means dividing the experiment setup into multiple segments and simulating them separately on multiple machines individually. This distributes the total simulation load on multiple computers and after simulation, all the results are conjoined together and analyzed to derive results. This method is easy to implement and is adapted to the model for performing experiments.

Since the total number of unique combinations for uncertainty values is eight (i.e. 2^3) and the total number of unique combinations of policy levers are twenty-seven (i.e. 3^3). Therefore, the total number of unique experiment setups is 216 (i.e.27 times 8). Thus one experiment (with ten replications) takes around twenty minutes to run and conducting all experiments for an energy community takes approximately 70 hours (i.e. 216 experiments times 20 minutes) on a single machine. Running the same experiment set up on two machines of the same specifications will take approximately half of the estimated time. These experiments are performed on three computers and one virtual machine on Google cloud. Several segments required for distributed computing can be specified in the Experiment class. The entire simulation can also be performed on a single machine by specifying the number of segments as zero while initializing the Experiment class.

Lastly, results are collected for every experiment setup simulation. All the model and agent performance matrices are elaborated in Section 2.2.1. These performance matrices are recorded at every time step of the simulation run. Once a simulation run is finished, the model returns a data frame of metrics with the time step (date in this case) as an index.

Number of residential prosumers (owning a rooftop solar-PV system)	40
Installed capacity of residential rooftop solar PV system	20 kWP per household
Number of residential consumers (not owning any generation asset)	9
Demand profile of residential consumers	Randomly picked for each household from low and mid-energy consumption households shown in Figure 2.9
Non-residential members	Office building and EV charging station)
The asset of non-residential member (Office building)	Solar PV system with an installed capacity of 400 kWp
The asset of non-residential member (EV charging station)	Solar PV system with an installed capacity of 100 kWp
Electricity demand profile of non-residential agents	Demand profile of Office building 1 and EV charging station shown in Figure 2.11

Table 2.4: Configuration for GridFlex inspired energy community

Uncertainty parameter	Neutral Scenario	Optimistic Scenario
X1: Minimum (lower cap) availability of flexible demand	40%	80%
X2: Maximum (upper cap) availability of flexible demand	50%	100%
X3: Accuracy of demand response schedule	50%	90%

Table 2.5: Uncertainties used for experiment design

Policy levers	Baseline	Optimistic	Very optimistic
L1: Percentage of community members participating in demand response	0%	50%	75%
L2: Flexible demand as percentage of total demand for residential members	10%	50%	100%
L3: Flexible demand as percentage of total demand for non-residential members facilitated by behind-the-meter storage	10%	45%	90%

Table 2.6: Policies used for experiment design

3
Results

This chapter showcases and discusses the results obtained by experiments performed on two energy community configurations i.e. Groene Mient inspired energy community and GridFlex-Heeten inspired energy community setup. Experimental setups created by combining policy levers and uncertainty parameters are described in Section 2.4.2. The results of the experiments are discussed in two steps in this chapter. Firstly, the overall performance of modeled energy communities under all twenty-seven unique policies is discussed. Secondly, a quantitative analysis is performed on the experiment outcomes using a python library called Exploratory Modeling and Analysis (EMA) Workbench. EMA Workbench is designed for supporting exploratory modeling and has tools for analyzing experiment results. The quantitative analysis of the experiment outcomes is done for identifying important linkages between input parameters and model outcomes. These linkages are used to formulate policies and derive recommendations for the modeled energy communities.

For the first discussion part of the results, all the experiment outcomes are grouped over the same policy lever combination and visualized as a time series. Grouping results on a unique policy lever combination showcases the change in the performance matrix subjected to a unique combination of policy levers (i.e. a unique policy). The experiments are designed by selecting three points in the policy space for each lever. These points correspond to a baseline (B), optimistic (O), and very optimistic (V) value for the policy lever respectively. For example, participation of community members in demand response (L1) has a baseline value representing zero participation, an optimistic value representing 50% participation, and the very optimistic value representing 75% participation from community members. All three values (baseline, optimistic, and very optimistic) for each policy lever are shown in Figure 3.1.

Reiterating the experiment setup, three policy levers with three possible values result in twenty-seven unique policies (i.e. $3^3 = 27$). For each unique policy, the experiment setup has eight different scenarios (since two uncertainty parameters have two possible values i.e. 2^3). Every unique combination of policy and scenario is called an experiment setup. This study performs experiments using 216 unique experiment setups (i.e. 27 unique policies $*$ 8 unique scenarios = 216 experiment setups). Simulation for every experiment setup is replicated ten times. Following are the results and key insights from the experiments performed on both community configurations.

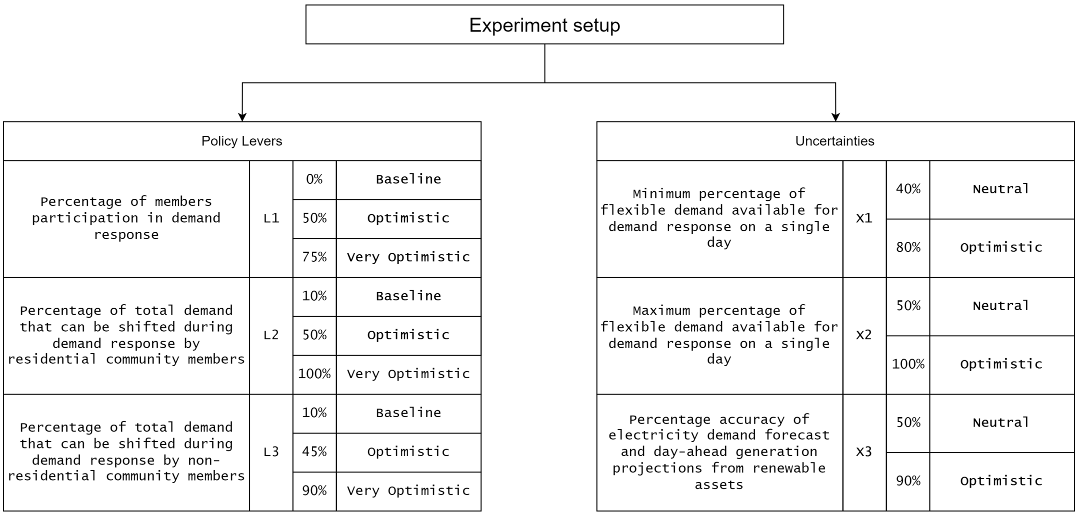


Figure 3.1: Value of policy levers and uncertainties used for designing experimentation setup

3.1. Results for Groene-Mient Inspired Energy Community Setup

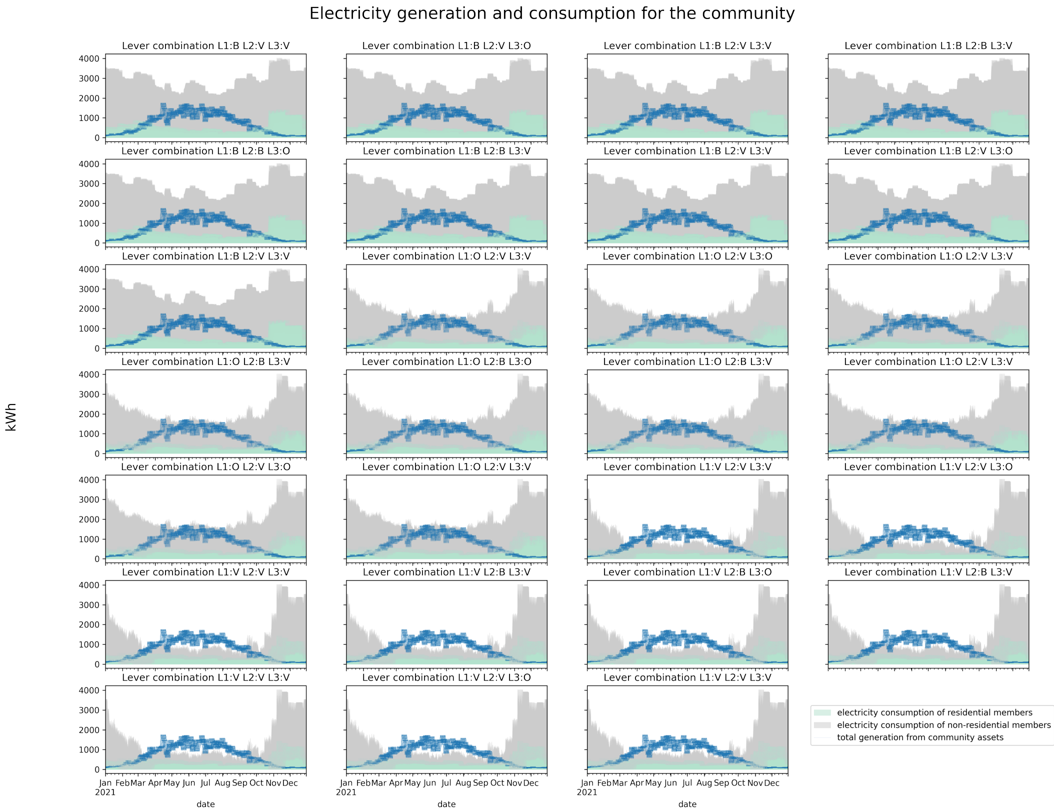


Figure 3.2: Overview of simulation results of Groene Mient inspired energy community

This section of the results describes the outcomes of experiments performed on the Groene-Mient inspired energy community setup. This community setup has 23 residential households each having a solar rooftop generation capacity of 20 kWp. The energy intensity of every household is randomly picked from the residential load profiles shown in Figure 2.10. Apart from residential members, this community is assumed to have a secondary vocational education (MBO) school with an installed solar rooftop capacity of 300 kWp. The community setup is further explained in Section 2.4.1.

Figure 3.2 showcases the overall performance of the energy community under the experimental setup. The plot depicts electricity consumption for both residential and non-residential community members along with total electricity generation from community assets. The first nine plots represent the baseline policy for community participation i.e. no participation from community members in demand response. This implies that excess solar PV generation from the community will be fed into the grid and does not contribute to peak shaving through demand response. Excess generation is the additional electricity (in kWh) for each community member that can not be used for self-consumption and is fed into the grid. In a short term, this may provide some earnings through feed-in tariffs or trading in short-term energy markets with the help of the community coordinator. The feed-in to the grid is not accounted for earning from the grid in this model as feed-in tariffs are reducing and DSOs (such as Enexis) discourage feed-in to avoid grid congestion at the distribution network. Subsequent plots with optimistic participation of community members (i.e. participation from community members is set to 50%), showcase a reduction in peak demand for both residential and non-residential members. Excess solar generation from the solar PV assets in the community is being utilized within the community through demand response. The last nine subplots in the figure with L1 set to 'V' represent very optimistic participation (i.e. 75% participation) from community members in the demand response. This leads to a reduction in the overall electricity demand of the community. The flexible demand available for residential and non-residential community members also influences the outcomes of the simulation run for the energy community. Participation of residential community members in demand response contributes to peak shaving significantly (subplots with L2: 'O' i.e. optimistic or 50% participation in demand response from community members). Similarly, the load flexibility of non-residential consumers (L3) also influences the shifted load and contributes to peak shaving. The flexibility of non-residential community members results in lower electricity imports from the grid since the installed capacity and flexible load of non-residential members is much higher than the residential members. However, the extent of load shift achieved by augmenting load flexibility through behind the meter storage is not visible in these plots.

Moreover, electricity demand and electricity consumption are analyzed under different policies for Groene-Mient inspired community. In this model, electricity demand is the aggregated electricity demand of community members without incorporating captive generation and demand response. Whereas, electricity consumption is the aggregated metered electricity consumption after incorporating captive consumption (from renewable generation assets) and demand response for the energy community. Electricity demand and electricity consumption of residential community members are shown in Figure D.2 and for non-residential community members is shown in Figure D.1 of Appendix D. The electricity consumption is same as the electricity demand in the experiment setups with zero participation of community members in demand response (i.e. L1 set to baseline policy scenario 'B'). The minor deviation in the consumption curve from the demand curve in the summer months (from March to September) is caused by captive generation without any demand response. Since solar power plants are generating electricity at their full potential from March to September, deflection from electricity demand is maximum during this period without any demand response. As participation of community members is increased to optimistic (i.e. 50% participation from community members) and very optimistic (75% participation from community members) values, an increase in the deviation of the consumption curve from the demand curve is observed. This deviation of the consumption curve from the demand curve is the load shift caused by the demand response. The deviation of electricity consumption from electricity demand is quite evident under demand response. Particularly, when behind-the-meter storage is used to augment the flexible load i.e. optimistic and very optimistic policies respectively. However, this deviation from electricity demand is because of two factors. Firstly, self-consumption of electricity generated from the renewable generation assets, and secondly demand response by community members. Therefore, shifted load is analyzed separately to investigate the role of demand response in reducing grid dependence of the modeled community.

Shifted load is the electricity demand (in kWh) avoided or moved through demand response. The community coordinator analyses the electricity demand (based on historical electricity consumption data) and generation forecast (using weather data) to prepare a time-of-day (ToD) tariff schedule. This ToD schedule has timings when electricity is in abundance (through generation from renewable assets) and timings for electricity shortage when electricity is being imported from the grid. These ToD schedules have price incentives associated with it. Electricity generated within the community (from generation assets) is cheaper than the electricity imported from the grid. Community members signed up for the demand response adhere to the ToD schedule based on their load flexibility and availability of demand. Shifted load by residential and non-residential community members under different policies is shown in Figure D.3 of Appendix D. Since, participation from community members is set to zero (baseline) for the first nine experiment setups, shifted load for the respective nine sub-plots is zero. The flexible load for non-residential members is much higher than that of residential members because the MBO school has a higher rating for flexible load appliances such as ventilators and air conditioners.

The demand response potential of non-residential members is achieved with optimistic (50%) participation of community members in demand response. Therefore, in this case, using behind-the-meter storage for additional demand flexibility does not show a significant improvement in shifted load for non-residential consumers. On the other hand, for residential consumers, an increase in consumer participation (L1) and demand flexibility (L2) increase the peak shaving and load shift. The use of behind-the-meter storage for increasing the flexible demand significantly increases the shifted load during the winter months (November to February) since generation from solar assets is comparatively lower during those months. In a nutshell, behind-the-meter storage helps in peak shaving when generation from solar assets cannot propagate the demand response.

The expenditure of the energy community on importing electricity from the grid and savings on grid import through demand response is shown in Figure D.4 of Appendix D. The cost of importing electricity from the grid mimics the electricity consumption curve for residential and non-residential community members since they are directly proportional to each other. In this model, a linear pricing function of electricity is used. Therefore, an increase in the electricity consumption from the grid results in an increase in the cost of importing electricity from the grid and vice versa. Similarly, the savings curve through demand response mimics the behavior of shifted load for the community shown in Figure D.3. The similarity in the behavior of these curves is because electricity consumption and the cost of electricity for the community are directly proportional to each other and no financial incentives are included for feeding excess electricity to the grid. Therefore, with zero participation in demand response, the savings from demand response are zero, and the total cost of electricity is in the range of 1000 to 1500 Euros for residential members (i.e. L1 is set to 0). As more community members participate in the demand response, electricity import from the grid is reduced through demand response during the optimistic (50%) and very optimistic (75%) participation from community members. The reduced consumption is represented as the shifted load in Figure D.3 of Appendix D and contributes to savings on electricity expenditure. The savings on electricity import are maximized with an increase in demand flexibility facilitated by behind-the-meter storage. However, to evaluate the financial feasibility of behind-the-meter storage for propelling demand response, a detailed fiscal analysis incorporating investment costs is recommended.

3.2. Results for GridFlex Inspired Energy Community Setup

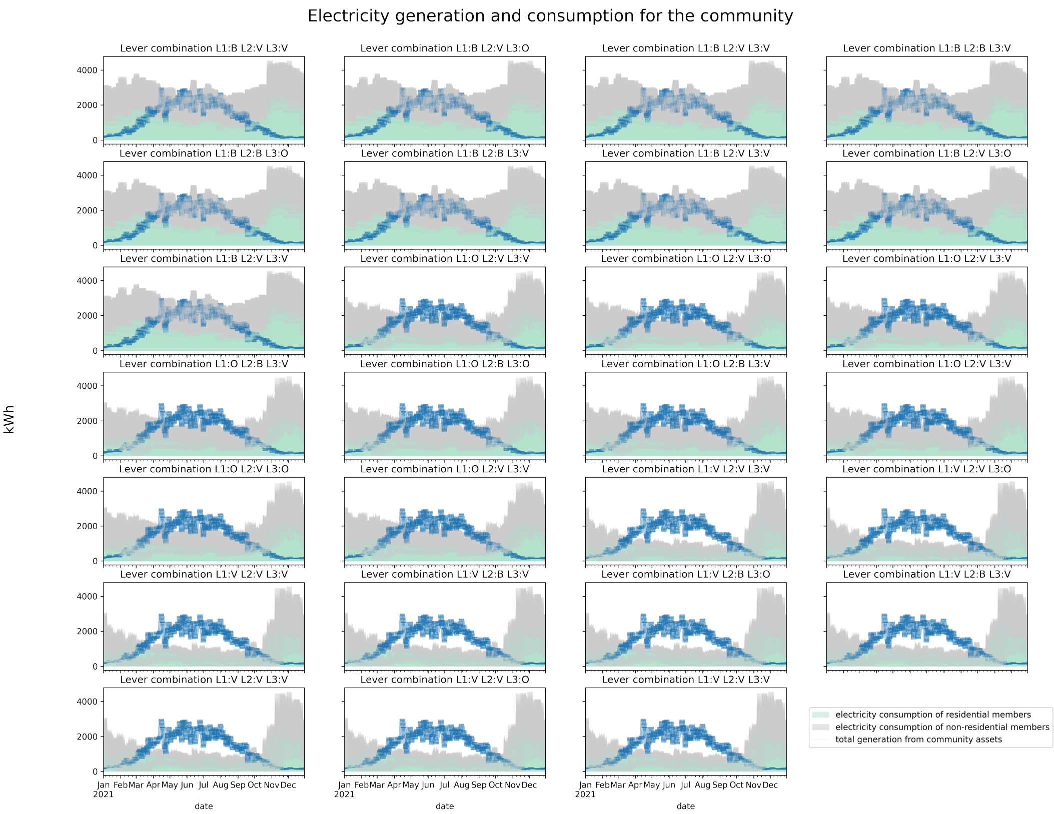


Figure 3.3: Overview of simulation results of GridFlex inspired energy community

This section of results discusses the outcomes of experiments performed on the GridFlex-Heeten inspired energy community setup. This setup has 49 households. 40 of these households are assumed to have a solar rooftop system of 20 kWp each. The energy intensity of every household is randomly picked from the household load profiles shown in Figure 2.10. Apart from residential community members, this setup assumes an office building with a load profile shown in Figure 2.11 as 'Office 1' and three slow EV chargers. The office building is assumed to have a solar rooftop system of 400 kWp. The community setup is further explained in Section 2.4.1.

Total electricity consumption and electricity generation from renewable assets within the community are shown in Figure 3.3. Light grey and green color depict the daily electricity demand for the GridFlex inspired energy community. The blue line plot represents electricity generation from the community generation assets. Participation in demand response is set to zero (L1 set to baseline participation 'B' i.e. zero participation) for the first nine plots and electricity consumption is comparatively higher in the corresponding subplots. The subsequent nine plots in the sequence (with L1 set to optimistic participation 'O') showcase results for optimistic community participation i.e. 50% participation in demand response. Lastly, the last nine plots (with L1 set to 'V' or very optimistic participation) exhibit a significant reduction in electricity demand particularly for residential members during the summer months (from March to September) when generation from solar PV assets is maximum. The impact of flexible demand is visible in when demand flexibility levers are set to the optimistic value of 45% of the installed load (i.e. plots with L2 and L3 set to the optimistic value 'O'). The maximum potential of demand response is exploited with the very optimistic values of policy levers with the use of behind-the-meter storage for extending flexible demand. However, the flexible demand potential is limited by the energy storage capacity of behind-the-meter storage.

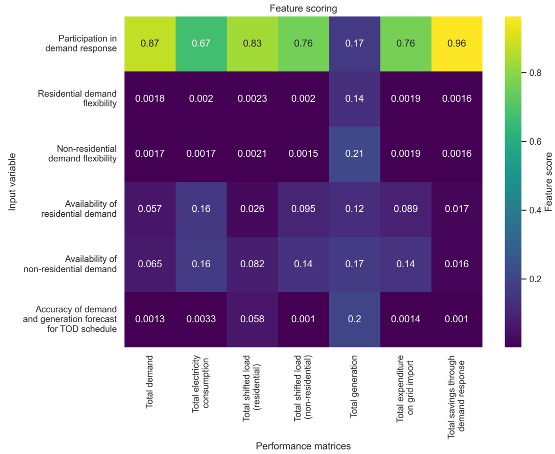
Demand response in the community is evaluated by comparing the projected electricity demand with the actual electricity consumption by the community members. Electricity demand and electricity consumption of residential and non-residential community members are shown in Figure D.5 and Figure D.6 of Appendix D respectively. Electricity demand and electricity consumption exhibit similar behavior for both residential and non-residential community members subjected to the same policy lever combination. The deviation of electricity consumption from electricity demand is most influenced by the policy lever controlling the participation of community members in demand response (L1). Electricity consumption and electricity demand are quite identical in experiments having baseline participation of community members in demand response i.e. zero participation in demand response. The minor deviation from electricity demand in these subplots is because of the captive consumption of electricity generated from solar PV plants. Whereas, the shift from electricity demand is significantly more under optimistic participation (75%) of community members in demand response. The maximum offset of electricity demand is achieved through very optimistic policy participation in demand response from March to July. This shift in consumption from the demand curve is supported by surplus generation from the solar PV assets of the community during peak sunny months. Residential community members do not show a significant difference when behind-the-meter storage is used to increase the flexible load because optimistic load flexibility (45% of installed load) is enough to exploit the residential demand response potential. However, non-residential community members have a significant reduction in electricity consumption from March to October. This shows that behind-the-meter storage aids the demand response when generation from renewable assets is comparatively lower. The deviation of electricity consumption from the projected demand is attributed to demand response and self-consumption of electricity generated from self-owned generation assets (such as rooftop solar PV plants). Therefore, shifted load is analyzed to evaluate the contribution of demand response in the deviation of electricity consumption from the electricity demand.

Shifted load for residential and non-residential members of GridFlex inspired energy community setup is shown in Figure D.7. Since load shift is caused by demand response, shifted load for experiment setup having zero participation in demand response is zero. In the optimistic (i.e. 50%) participation of community members, an increase in the shifted load for both residential and non-residential community members is observed. An increase in flexible demand through behind-the-meter storage further increases the shifted load under the very optimistic lever values (i.e. L2 and L3 set to 'V' very optimistic values). The maximum shifted load for non-residential community members is achieved through the optimistic value of the demand flexibility lever (i.e. L3 set to 'O' and demand flexibility set to 50% of installed load) without incorporating behind-the-meter energy storage. This is caused because of the higher volume of flexible demand of non-residential community members as compared to residential community members. However, behind-the-meter storage is utilized by non-residential members to facilitate demand response from November to February when Solar PV generation is comparatively lower.

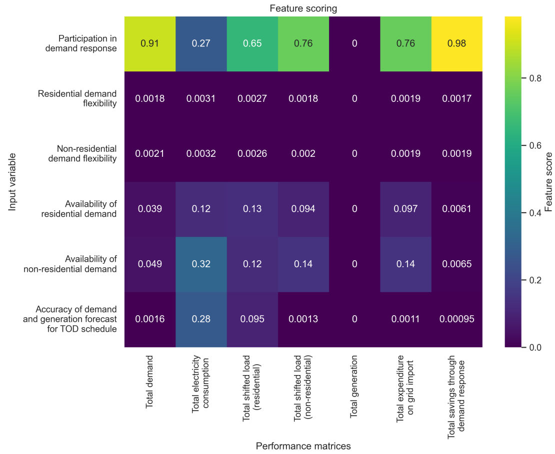
Since the cost of electricity is a linear function of electricity consumption, electricity cost is proportional to electricity consumption for the energy community. Similarly, savings made by avoiding the import of electricity from the grid is directly proportional to shifted demand. The overall community expenses for importing electricity from the grid are around 1000-2000 Euros (per day) without demand response. The expenditure is significantly reduced to around 500 Euros per day when 50 percent of community members participate in the demand response (i.e. L1 set to 'O' optimistic policy scenario). Expenditure for electricity import significantly dropped from March to October under very optimistic (75%) participation of community members in demand response. During this period, the solar PV assets of the community also generate electricity at the maximum potential. From November to February the generation from solar assets is not sufficient to support the electric autonomy of the community. Therefore, during this period electricity is imported from the grid resulting increase in expenditure on grid import of electricity. The winter of 2021 was colder than that of the previous year (see Figure 2.4), therefore electricity demand and eventually expenditure on electricity import is higher in December 2021 compared to January 2021. Moreover, behind-the-meter storage effectively reduced the grid dependence of the energy community from March to October in combination with surplus generation from solar assets. However, the storage capacity is not sufficient to maintain the electricity autonomy of the community from November to February.

3.3. Analysis

Previous sections reflect upon the overall change in the key performance matrix of energy communities under different policies. This analysis is done to further investigate the influence of input parameters on the model outcomes for formulating recommendations for the energy communities. The experiment outcomes are analyzed using the EMA-Workbench library through an open exploration inspired approach. Conventionally, systematic sampling of uncertainty and policy space is done for open exploration. Whereas in this case, instead of systematic sampling, the model is simulated with selected points from the uncertainty and policy space (i.e. values of policy lever and uncertainties used in experiment setup). An open exploration with a systematic sampling of uncertainty and policy space is recommended for future research using this model. For this analysis, the experiment outcomes are aggregated annually and formatted in the EMA-Workbench's result format. This analysis is performed on results from both energy community setups separately. However, as highlighted in previous sections, because of similar configurations, the outcomes of the analysis are similar for both communities. The analysis is done in three steps. Firstly feature scoring is done to identify the most influential policy levers and uncertainties. Secondly, a scenario discovery is done to identify the quantitative range of policy levers helping in reducing the grid dependence of energy communities. Lastly, outcomes from the first and second steps are used to formulate two policies and key outcomes are visualized for both the energy communities.



(a) Feature scores for GridFlex inspired energy community



(b) Feature scores for Groene Mient inspired energy community

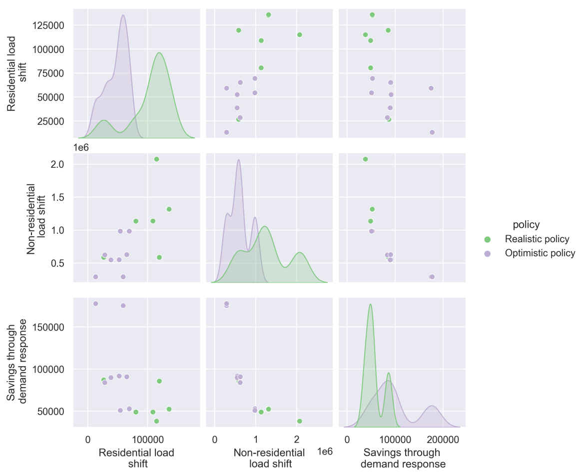
Figure 3.4: Feature Scoring

To identify the most influential input parameters of the model, feature scoring analysis is performed for all the performance matrices of the energy community. Feature scoring is done in regression mode in this case since all the output matrix is quantitative and not categorical. Figure 3.4a and Figure 3.4b showcases feature scoring for GridFlex and Groene Mient inspired energy community setup respectively. Both the plots showcase that participation of community members (L1) in demand response has the highest influence on model outcomes. Moreover, overall electricity generation in the energy community is not influenced by any policy levers as it is only dependent on the weather. Availability of residential and non-residential load flexibility has a direct influence on shifted load. Shifted load is directly proportional to the cost of importing electricity from the grid for the energy community. Lastly, the accuracy of demand and weather forecast has a relatively lower influence on the overall shifted load of the energy community.

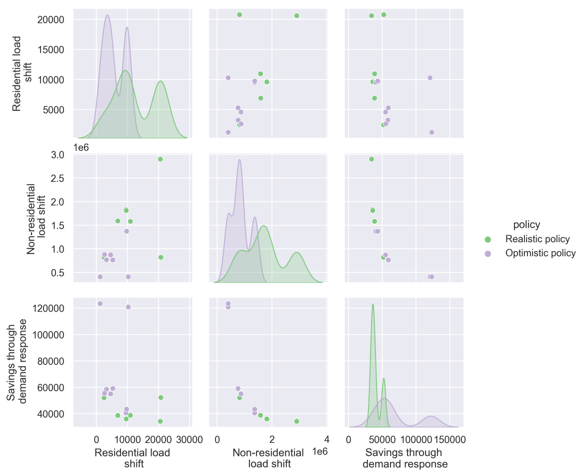
After feature scoring, scenario discovery is performed to find input parameters resulting in favorable outcomes. This is done to identify the quantitative range of policy levers and uncertainties leading to favorable outcomes. The scenario discovery, in this case, is done with the set of selected points from uncertainty and policy space. A detailed exploration of uncertainty and policy space is recommended for future studies using this model. The scenario discovery is done through 'prim' analysis used by the EMA-Workbench library and is conducted for two sets of outcomes. First for the experiments resulting in the eighty percentile value of shifted load by residential community members. Secondly, for the experiments resulting the eighty percentile value of overall shifted load for the entire energy community. The results of scenario discovery were in accordance with the results of feature scoring. For maximum load shift by residential community members, participation of members in demand response (L1) should be more than 75%. Additionally, the availability of flexible load for residential community members should be in the range of 60% - 80% of the flexible load. Furthermore, for maximizing the load shift by residential community members, the availability of non-residential community members should be capped at 62% - 75%. Capping the availability of non-residential community members insures that the flexibility of residential community members is utilized as non-residential community members have a higher load flexibility. For maximum load shift by the entire energy community, participation of community members should be more than

62% and availability of flexible demand should be more than 75% of non-residential load flexibility. This indicates that a non-residential flexible load with a complementary usage pattern is utilized for maximizing the load shift and reducing the expenditure on importing electricity from the grid. To further highlight the most influential policy levers and uncertainties, dimensional stacking is done and shown for the Groene Mient inspired energy community in Figure E.2 and Figure E.4 and for the GridFlex inspired energy community in Figure E.1 and Figure E.3 of Appendix E.

Based on feature scoring and scenario discovery, two policies are formulated for both energy community setups. These policies are selected from the policies used for running the experimentation and have the lever values matching with the result of scenario discovery. Based on the practicality of implementation, these policies are termed 'realistic' and 'optimistic' policies. The realistic policy recommends 50% participation of community members in demand response with 50% of load flexibility for residential community members and 45% of load flexibility for non-residential community members. Whereas, the optimistic policy recommends 75% participation from community members through behind-the-meter storage for residential community members and 45% load flexibility for non-residential community members. The key matrices with both realistic and optimistic policies are shown in Figure 3.5. The plot showcases that optimistic policy results in higher load shift resulting in more savings through demand response. However, implementing these interventions incurs additional costs for installing behind-the-meter storage for residential community members. Therefore, a step-wise approach to implementing these policies is recommended. In the first stage, the realistic policy can be implemented. Once the implementation of the first stage is done, the model can be calibrated based on the outcomes. The calibrated model should be used to re-conduct an open exploration for implementing behind-the-meter storage in the second stage. Based on the outcomes of open exploration, the optimistic policy can be implemented. The implications of these results and recommendations are further elaborated in Section 4.1.



(a) Pair-plot of GridFlex inspired energy community



(b) Pair-plot of Groene Mient inspired energy community

Figure 3.5: Pair plots with realistic and optimistic policies

4
Discussion

In this chapter, the results described in the previous chapter are further interpreted and reflected upon. Furthermore, the key assumptions used in the model and for this study are discussed. Lastly, the impact of these assumptions on the validity of results is explored.

4.1. Implications of the Findings

The outcomes of the experiments showcase that participation of community members in demand response has the highest influence on reducing the grid dependence of modeled energy communities. This implies that having 50% participation from community members in demand response significantly shifts the load during peak hours and optimizes the local consumption of electricity in the modeled communities. For the simplicity of this model, energy trading in short-term markets is not incorporated into the financial calculations. This model uses a linear cost function therefore cost of grid import for the community is directly proportional to the metered energy consumption. Therefore, increasing participation in demand response increases the load shift and eventually reduces the expenditure on the grid import of electricity for the modeled community. This study considers participation in demand response as a policy lever however ensuring fixed participation from community members is challenging in practice. Therefore, a robustness test is advised to evaluate the impact of fluctuations in member participation on the energy costs of the community.

Demand flexibility is a critical factor for successful demand response in the modeled energy communities. Demand flexibility is the proportion of installed load that can be switched on or off during demand response without causing significant discomfort for the end users (i.e. community members in this case). Flexible loads for residential members include appliances like laundry machines, dryers, dishwashers, etc. On the other hand, flexible loads of non-residential community members (office buildings and schools) include EV chargers, ventilation machines, etc. The flexible load for non-residential members is much higher as compared to residential members because the appliances used at the domestic level are much smaller than commercial appliances. Additionally, non-residential community members can coordinate multiple appliances in a more centralized manner through building energy management systems. Therefore, the demand flexibility of non-residential community members dominates the overall demand flexibility of the energy community. On the other hand, coordination of all residential flexible demands can not be done centrally as every household makes independent decisions. Therefore, automating the demand flexibility through behind-the-meter storage and smart appliances is a suitable solution for residential community members. However, upgrading the appliances and installing behind-the-meter storage require significant upfront investments. A detailed financial analysis should be performed to further investigate the financial feasibility of smart appliances and behind-the-meter storage for residential members in the community energy setting.

Ensuring minimum availability of flexible demand is required for the implementation of demand response in the energy community. The availability of flexible demand defines the extent to which a load can be shifted during demand response. For instance, consider a community member with a smart laundry dryer that can be used as a flexible load when electricity is cheaper. Apart from having a smart appliance, having enough laundry to dry is also required for utilizing cheaper electricity. The availability of flexible demand is a behavioral function conceptualized as uncertainty in this model. Alternatively, behind-the-meter storage can be used to further improve the availability of flexible demand.

In a nutshell, the participation of community members in demand response is most important for reducing the grid dependence of modeled energy communities. Smart appliances and behind-the-meter storage can be used by the residential community members to further reduce the expenditure on grid import of electricity. Furthermore, including a non-residential community member improves the overall demand flexibility of the modeled energy communities. The higher demand flexibility of non-residential community members acts as a cushion to dampen the sudden peaks and falls in the demand curve of modeled communities. All the results and recommendations presented in this report require high upfront investments. Therefore a step-wise approach to implementing these interventions is recommended. Two policies are formulated based on the analysis of the results. Based on the ease of implementation and expected outcomes, these policies are named 'realistic' and 'optimistic' respectively. The realistic policy is implemented in the first stage of implementation. This policy recommends 50% participation from community members in demand response. Along with this, the demand flexibility for community members is recommended as 50% of the installed load. After implementing the realistic policy, the outcomes of implementation can be used to calibrate the model. In the second phase, the optimistic policy can be implemented. This policy recommends 75% participation of community members in demand response. In addition to this, residential community members are recommended to install behind-the-meter storage to further extend the demand flexibility to 90% of the installed load. The implementation details and implications are further elaborated in the final recommendations discussed in Section 5.2.

Lastly, the results of this study align with the existing literature regarding demand response in energy communities. As recommended by Knox et al. (2022), this study also implies smart grid features for enabling active monitoring and demand response in the modeled energy communities. The experiment outcomes align with the finding of Reis et al. (2018) by confirming that demand response is an effective way of attaining self-sufficiency in the modeled energy communities. Furthermore, the results also confirm the findings of Huang et al. (2022) by showcasing that the optimization of energy consumption within the community helps in reducing grid dependence significantly.

4.2. Key Assumptions

The model conceived for this study is based on multiple assumptions to replicate an abstract of real-world system behavior with limited complexity. These assumptions simplify the system so that it can be encaptured into a model for research and performing experiments. Following are the key assumptions shaping up this study:

- The real-life energy communities are used as an inspiration for the community setup in this study. The properties mentioned in community setup (Section 2.4.1) should be considered while evaluating the results. The community setup is simplified and altered to suit the research interests of this study. Therefore, the simulation results and recommendations of this study are not directly applicable to the original energy communities.

- All the residential and non-residential members are assumed to either have (or be connected to) the distributed generation of solar and wind assets. It is assumed that the infrastructure required for electricity sharing along with smart grid functions (such as monitoring and demand response) are already present in the modeled energy communities.

- It is assumed that all the community members participating in the formulation of energy community are driven and motivated to participate in demand response. All of them are assumed to be (driven) members of the community who actively participate in community initiatives. However, in practice, the motivation and participation of community members depend upon multiple factors. This model assumes that community members can be convinced to participate in demand response.

- This study assumes that for implementing recommended interventions, community members will either invest themselves or will receive support from the government (through grants or subsidies) for installing flexible loads and behind-the-meter storage. However, subsidies and government grants are quite limited and often community energy projects are delayed because of financial constraints. This study recommends exploring innovative business models involving non-residential community members to tackle this issue in the future.

- It is assumed that all the renewable generation assets (such as solar PV and wind), storage assets (including behind-the-meter storage), and flexible loads considered in this model do not undergo any wear or tear during the simulation run. Thus, maintenance, degradation, or breakdown cost and downtime are not taken into account in this study.

- The Levelized Cost of Electricity (LCOE) generated from the local renewable assets owned by community members is assumed to be much lower than the cost of importing electricity from the grid. Therefore, community members always prefer electricity generated through the community assets over grid import. However, in practice, there could be instances when electricity from the grid or short-term energy market is much cheaper.

- Moreover, no feed-in tariff or inter-community trading of electricity is considered for calculating electricity cost for the energy community. For the simplicity of this model, energy trading in short-term markets is not incorporated into the financial calculations. However, both inter and intra-trading of electricity are being explored for energy communities at the moment and should be considered for future research on this topic.

- Lastly, this model is limited to the low voltage electricity distribution network of the modeled energy community. This study does not include other energy sources such as gas for heating. The residential load profiles considered in this study do not include electricity consumption for domestic heating in residential members. However, the non-residential load profiles of office buildings used in this study have heat pumps and air conditioners. Therefore, the load profile of non-residential community members includes electricity consumption for heating and cooling.

4.3. Validity of the Results

The results and recommendations of this study are based on the assumptions listed in Section 4.2. Therefore, these assumptions should be taken into account while interpreting the key findings of this report. This section further explores the threats to the validity of the results of this research.

The results described in this study are based on the simulation runs for the year 2021. These results, particularly electricity consumption patterns are dependent on the weather conditions. A colder winter results in increased electricity consumption in winters because of excessive use of heaters (electric heaters are assumed in this case). Whereas, heat waves during summer further increase electricity consumption by ventilators and air conditioners. Figure 2.4 showcase the temperature change throughout the year 2021 compared to other years. It can be deduced from Figure 2.4 that 2021 follows the pattern of a typical year shown in the plot. For the years with more extreme temperatures, higher electricity consumption is expected. To further study the influence of temperature on overall model outcomes, a sensitivity analysis is recommended for future research.

This study considers participation in demand response as a policy lever however ensuring participation from a fixed number of community members can be challenging in practice. The participation in demand response is expected to be more dynamic in real life. Furthermore, minimum availability of flexible demand can not be ensured in the real-life implementation of interventions. Therefore a detailed analysis of the robustness of recommended policies should be done in future studies.

It is assumed that the local DSO will support this project as demand response in energy communities can help in reducing the congestion in distribution networks. However, technical or regulatory constraints can prevent DSOs from sharing their distribution assets with the energy community. This can significantly increase investment costs and negatively affect the validity of recommendations.

The recommendation made in this study assumes that successful integration of RED-II in the national legislation will be carried out. This research does not take any policy disruption or further delay into account. The current regulations still have a lot of grey areas regarding the functioning of energy communities and the role of intermediaries particularly regarding demand response. Thus, regulatory challenges are not taken into consideration and can affect the validity of results and recommendations made in this report.

5 Conclusion

This chapter compiles the key findings of this research to answer the research sub-questions and eventually the main research question. Thereafter, recommendations for implementing these findings for modeled energy communities are discussed. This is followed by highlighting the key limitations of this study. Lastly, the scientific and social contributions of this research are discussed.

5.1. Addressing The Research Questions

The first research sub-question is *What are the key social, financial, institutional (policy & regulation), and technical aspects characterizing a Dutch energy community?* To answer this research sub question, literature delving into socio-technical dynamics of energy community such as Koirala et al. (2018) and Ghorbani et al. (2020) were referred. Semi-structured interviews with problem owners including Willie Berentsen, cooperative Sterk op Stroom (Manager of energy community), and Dominique Doedens from GridFlex Heeten energy community were conducted. These interviews and literature review provided information about the social dynamics of a typical Dutch energy community. Additionally, the policy-related news articles and directives were consulted to understand the institutional aspect of demand response in energy communities. The policy framework for energy communities is being transposed into the Dutch legislature whilst this report is drafted. Existing energy communities considered in this study were initially pilot projects and therefore are functioning on an experimental license. Moreover, these energy communities are highly reliant on subsidies and state funding for formulation and expansion.

To conceptualize energy communities as a complex-adaptive system, an actor-network scan was conducted. The network scan was followed by a power interest analysis of the decision arena to identify the key actors involved in the decision-making. The power interest analysis helped in segregating all the identified actors into four categories. The Province has the highest regulatory power but low-interest levels in the internal functioning of an energy community. Therefore, the province is categorized as a 'defender' in the decision arena. Other residents of the neighborhood who are not part of the energy community are labeled as 'apathetic' as they have low-interest levels and influence in the decision-making. Distribution Service Operators (DSOs) and municipalities have relatively higher interest levels in these projects but have no direct influence on the internal decision-making regarding demand response in the energy community. Therefore, DSOs and local municipalities are categorized as 'latent'. Lastly, members of the energy community (including residential and non-residential community members) and community coordinators are categorized as 'key players' in the decision arena. Community coordinators are typically a third party hired by the community to balance the supply and demand within the community and facilitate demand response. Both members and coordinators are directly involved in the decision-making regarding demand response in the energy community. Thus, members and coordinators of the energy community are modeled as 'agents' in the agent-based model adaptation of the energy community.

Community members are primarily classified as residential and non-residential community members. Furthermore, community members can also be classified as consumers and prosumers based on their technical profiles. Community members with renewable generation assets (such as rooftop solar PV) are called 'prosumers' and members without any generation assets are called as 'consumers'. A prosumer is the electricity consumer involved in the generation of electricity through a captive renewable generation asset. The coordinator aggregates the total electricity consumption and generation from the community members. Apart from this, the coordinator also analyses the historical demand and generation forecast from renewable assets to prepare a time-of-day (ToD) tariff schedule. As per the ToD schedule, electricity is cheaper when surplus generation from the captive renewable assets is available and vice versa. Thus, ToD is used as a policy instrument to shift the load curve of community members. Every community member in this model is assumed to have some flexible load that can be switched on and off based on the ToD schedule. This demand flexibility is expressed as the percentage of the total installed load for a community member. Every day, a community member decides to participate in the demand response based on the ToD schedule and availability of flexible demand. Additionally, community members can further increase their demand flexibility by installing behind-the-meter storage. This is usually a lithium-ion battery to store electricity when it is available in abundance and consume when electricity from the grid is expensive. Using behind-the-meter storage is proposed as an intervention in the study. Moreover, having flexible demand does not guarantee the participation of community members in demand response. The availability of flexible demand defines the extent of load shift through demand response. For example, if a residential community member has a laundry machine that is used as a flexible load when electricity is in surplus in the community. This laundry machine functions if the user has dirty clothing to be washed when electricity is available for cheaper. Thus, the availability of flexible demand is dependent on the behavior of community members. These key institutional, social, and technical aspects helped in modeling an archetypical energy community located in the Dutch landscape. The conceptual model is further described in Section 2.1 in detail.

The second research sub-question is *How can an ABM reproduce the current real-life behavior of residential and non-residential community members in the chosen energy community?* The adaptation of the energy community as a complex system is discussed in Section 2.1.2. The conceptualized model is then encoded into python code in Section 2.3.1 and its outcome is verified and validated in Section 2.3.2 and Section 2.3.3 respectively to answer the second research sub-question. The encoded model is adapted to the XLRM framework. According to this framework, the model takes uncertainty parameters and policy levers as inputs. These input parameters are processed through the simulation of the agent-based model as per the system relationships established in the model conceptualization. Lastly, the model outcomes are recorded as matrices using a data collection mechanism encoded in the model. This model has three policy levers. The first lever denoted by L1 is the percentage participation of community members in the demand response program. The second lever denoted by L2 is demand flexibility for residential community members. Lastly, the third lever denoted by L3 is demand flexibility for non-residential community members. All these levers have three values selected from the policy space each representing a baseline, optimistic, and very optimistic value. Additionally, this model has three uncertainty parameters used to formulate different scenarios. The first uncertainty denoted by X1 is the availability of residential flexible demand expressed as a percentage value of flexible demand. Similarly, the second uncertainty denoted by X2 is the availability of non-residential flexible demand. Lastly, the accuracy of demand and electricity generation forecast used for preparing the ToD schedule is denoted as X3. These uncertainties have two values each selected from the uncertainty space representing moderate and optimistic values respectively. The model outcomes are represented by performance matrices. These matrices include electricity consumption, electricity demand, shifted load, and overall generation in the community. Apart from technical details, performance matrices also include financial parameters like total expenditure on grid import of electricity and savings done through demand response. The model is verified and validated to make sure that the simulation outcomes represent the real-life situation and are suitable to answer the research question. Moreover, the model behavior and outcomes are further validated by problem owners including the technical team of Croonwolter&dros. These were the salient features of the agent-based model created to answer the second research sub-question. The model encoding and validation are further discussed in Section 2.3.1 and Section 2.3.3 respectively.

The third research sub-question is *What effect does a time-of-use tariff have on the grid dependence and energy costs in the modeled energy community?* This research sub-question is answered through experimentation performed on two real-life inspired energy community configurations. The energy community setups used for experimentation are inspired by the Groene Mient energy community and GridFlex-Heeten energy community. These setups and experiment designs are discussed in detail in Section 2.4.2 and the outcomes of the experiments are described in Chapter 3. The impact of demand response on energy communities is observed by changing the policy lever controlling the participation of energy community members in demand response. The impact of demand response on-grid dependence of energy communities is evaluated by comparing the model outcomes with the baseline participation scenario i.e. no community member participated in demand response. Both the community setups used for experimentation exhibit a significant reduction in grid dependence under optimistic (50%) and very optimistic (75%) participation of community members in demand response. The energy community under very optimistic participation attains electric autonomy from March to September as surplus generation from solar assets is used locally. However, electricity is imported from the grid from October to February since the community setups used for experimentation rely on solar PV plants which have comparatively lower generation in the winter months (because of fewer sunshine hours). It can be concluded that the time-of-day schedule and participation of community members in demand response significantly reduce the grid dependence. Moreover, ToD and demand response helped energy communities in attaining electric autonomy when a surplus generation from local community assets is available.

The last research sub-question is *How does demand flexibility by residential and non-residential community members affect the efficacy of demand response?* Demand flexibility along with available flexible demand is the driving factor for demand response in the energy community. Availability of flexible demand is a behavioral function of community members that signifies whether and to what extent a community member operates the flexible load during demand response. Therefore it is encoded as uncertainty in the experiment setup. To further exploit the potential of demand response, flexible demand for a community member is extended by using behind-the-meter storage. This storage capacity for behind-the-meter storage is assumed to be 90% of the connected load for a community member with one day of backup (or autonomy). An increase in demand flexibility facilitates peak shaving and excess energy generated by local community assets is stored in behind-the-meter storage. This stored electricity is utilized when generation from local assets is not available and reduces the grid dependence of community members. Experimental results further reveal that the savings on electricity import from the grid are maximum when behind-the-meter storage is used by the community members and more than 75% of community members participate in demand response. However, electricity import from the grid is required from October to December because of two reasons. Firstly, due to lower sunshine hours in winter, generation from solar assets is reduced and is not sufficient to support the autonomy. Secondly, the weather is colder in November and December as compared to January therefore the storage capacity of behind-the-meter storage is not sufficient to support the heating requirements of community members. Thus, it can be concluded that flexible demand by residential and non-residential community members directly influences the efficacy of demand response. Increasing demand flexibility via behind-the-meter storage helps the community members to save on electricity imported from the grid and reduce their dependence on the grid.

The main research question for this research is *"How does demand response by residential and non-residential community members affect the self-sufficiency and expenditure on grid import of electricity for modeled Dutch energy communities?"* This question is answered by answering all the derived research sub-questions in the previous section. The impact of demand response on typical energy community configurations was studied and discussed. The results of experiments revealed that demand response by community members (both residential and non-residential) can help an energy community in reducing its dependence on the grid. Additionally, having behind-the-meter storage augments the demand flexibility of community members, further reducing the grid dependence. This helps in attaining autonomy when the excess generation from generation assets is not available. Having non-residential community members supported the communities in attaining self-sufficiency in two ways. Firstly, non-residential community members have more connected load and eventually more demand flexibility to dampen the intermittency in the demand curve. Secondly, since non-residential community members are usually larger in floor area as compared to residential community members, they can house a large capacity of both renewable generation and storage assets. Because of these two factors combination of having a non-residential community member and demand response helps energy communities reduce their dependence on the electricity grid and save on electricity costs. However, both the communities in this study failed to stay autonomous in the months of November to February because of an increase in electricity consumption for heating purposes and a lack of generation from solar assets. Therefore, other renewable generation sources (such as wind turbine/hydrogen) and inter-community trading can be explored in future research to attain electricity autonomy for the entire year. The energy expenses on grid import of electricity are directly proportional to electricity consumption in the energy community. Since, the price calculation mechanism used by the DSOs is linear, a reduction in grid import results in the reduction of expenditure on grid import of electricity and vice versa.

5.2. Recommendations

This research highlighted the role of demand response in reducing the grid dependence of energy communities with a mixed configuration (having both residential and non-residential community members). Through demand response, consumption of locally generated electricity is optimized by modeled energy communities. Implementing demand response further helps in reducing the expenditure on grid import of electricity.

This study recommends a two-step policy plan for implementing demand response in the modeled communities to reduce their dependence on grid import. In the first stage, 50% participation from community members is recommended. Along with this, the demand flexibility of community members should be equivalent to 50% of the connected load. The recommended demand flexibility can be attained by replacing the existing appliances with smart appliances and installing behind-the-meter storage. After implementing and monitoring the outcomes of stage one, the second stage can be implemented. Outcomes of the first stage can be used for calibration of the model and performing an open exploration to adjust the further course of actions. In the second stage, 75% participation from community members is recommended. Moreover, residential community members are recommended to install behind-the-meter storage of capacity equivalent to 90% of installed load with one day of autonomy. This will further increase the demand flexibility to 90% for residential community members. Furthermore, installing behind-the-meter storage for residential community members will reduce their grid dependence and can provide opportunities for energy trading and ancillary services in the future.

There are three major takeaways for policymakers that can be taken into consideration while formulating policies regarding demand response in energy communities. Firstly, demand response through a time-of-day schedule can help in peak shaving of the demand curve and optimize the local consumption of electricity generated from renewable sources. The minimum member participation required for the smooth functioning of demand response can be further investigated by modeling different community configurations and evaluating the results. Secondly, the implementation of behind-the-meter storage for residential community members is a long-term solution for improving their demand flexibility. This further optimizes the local consumption of electricity and reduces the grid dependence of the overall community. Improved demand flexibility of energy communities can facilitate storage (through behind-the-meter storage) of locally generated electricity from renewable generation assets and avoid grid congestion in a long term. Lastly, the inclusion of non-residential community members helps in reducing the grid dependence of an energy community by dampening the sudden peak and fall in the demand curve. Since non-residential community members usually have a higher volume of connected load and therefore higher demand flexibility, their participation in demand response further supports the flattening of the demand curve. Additionally, non-residential community members also have a larger floor area to house generation and storage assets. Mostly residential communities are reliant on subsidies and state funding for investments. Therefore non-residential community members can invest in the shared generation and storage assets. However, detailed research in formulating a fair and inclusive business plan which incorporates non-residential community members is recommended to explore this option further.

The energy communities used as inspiration cases in this study are exploring demand response opportunities and can use this study as a road map. The outcomes of this study can help these communities in preparing plans for the community regarding the inclusion of non-residential members and exploring behind-the-meter storage. The methods used in this study can be replicated by the communities to test and evaluate different scenarios for reducing grid dependence through demand response. Furthermore, the impact of introducing assets like community storage, and generation assets like wind turbines can be explored through this model.

Moreover, methods showcased in this report can be used by CroonWolter&dros for providing consultation regarding demand response to energy communities and municipalities. The primary interest of CroonWolter&dros in this study was twofold. First, to understand the impact of demand response in an energy community to avoid congestion in the electricity distribution network. Second, to study the impact of introducing a non-residential community member to the community configuration. Both these questions are answered through this study. To summarise, implementing demand response through a time-of-day schedule with 50% participation in the demand response significantly reduces the grid dependence of modeled energy communities. Implementing demand response optimized the local consumption of electricity and effectively managed congestion in the local distribution network. Furthermore, including non-residential community members in the modeled energy communities improved the demand flexibility of the energy community. The two-part policy plan recommended in this report can be adapted for other communities and clients by simulating the model with updated configurations and carefully examining the outcomes. CroonWolter&dros can further expand this model by including other load profiles. Thus, the methods and model prepared during this study can serve as input to support the decision-making of energy communities and future projects of CroonWolter&dros.

5.3. Limitations and Future Research

The results and recommendations of this study should be interpreted with the assumption and validity threats mentioned in Section 4.2 and Section 4.3 respectively. Following are the main limitations of this study.

- This study assumes the participation of community members in demand response as a policy lever. However, it is quite challenging to ensure the participation of community members in practice due to multiple technical and behavioral factors. Therefore, a detailed analysis to study the sensitivity of consumer participation on model outcomes is recommended.

- The socio-technical system in the model is a simplified version of two real-world energy communities (i.e. GridFlex and Groene Mient community projects). The load profiles for households in these communities are assumed to be same as that of the Green Village (Delft). However, the electricity consumption pattern of a household depends on multiple factors such as the floor area, number of members in the household, behavioral aspects, etc. Thus, the electricity consumption pattern assumed for the residential consumers of modeled communities is not an accurate depiction of the real-life situation.

- The generation and storage assets in the modeled community are assumed for creating a suitable configuration for performing experiments. The generation assets shown in the experiment such as behind-the-meter storage are not commonly used in any of these communities and are used to showcase their applicability for improving demand flexibility. To highlight the functioning of behind-the-meter storage, existing neighborhood batteries (shared storage) are not included in this model.

- Moreover, this study assumes that the modeled communities have resources and support to implement the intervention such as time-of-day tariff and behind-the-meter storage. These applications require smart grid functionality in the community for monitoring and controlling the energy flow. Enabling these smart grid functionality in practice may take a significant amount of time and initial investments. These initial investments and delays are not considered in the results and recommendations.

- The actor-network scan performed for this study is very generic. Every community is unique in its configuration and social dynamics. Therefore, the social dynamics depicted in the modeled energy community may not apply to other energy communities. Thus, a detailed actor network scan along with power interest analysis should be performed for replicating this study for other energy communities.

- Implementing the interventions recommended in this study requires policies for regulating demand response in these energy communities. The existing policies regulating energy communities are not enough to address specificities like demand response and behind-the-meter storage. It is assumed that RED-II will be transposed in the Dutch legislature in the near future and the effect of further delay in this process is not considered. Thus, the results and recommendations of this study do not take these policy challenges into account.

- Another major limitation of the agent-based model is the quality and diversity of electricity consumption data used by the model. Primarily, this model assumes only three types of electricity consumption profiles for households that are limited by the availability of residential consumption data. Likewise, four types of office buildings are considered for non-residential community members. Whereas, a more diverse profile of residential and non-residential community members is expected in practice.

- Furthermore, the electricity consumption and generation calculations are oversimplified to keep the computational requirements of the model in check. Similarly, financial calculations used in this model are also oversimplified. The calculations for the cost of importing electricity from the grid and savings made through demand response are simplified for the model adaptation.

- Moreover, the agent-based models are path-dependent therefore multiple simulations run under the same input parameters can lead to different model outcomes. Therefore, multiple iterations of the same experiment setups are required. Because of the limitation of time and computational resources, each experiment setup is run for 10 iterations leading to sufficient results but at least 30 iterations of each experiment setup are recommended.

- Another intrinsic limitation of agent-based models is their dependence on assumptions and the quality of input data. To address this limitation this model is validated. However, further face validation by field experts and scholars is recommended to improve this model.

Lastly, energy communities are not limited to electricity and often extend to other energy sources. Therefore, this research can be extended in the future to incorporate a thermal (gas) network of the energy community. Furthermore, other renewable generation and storage assets such as hydrogen should be added to the assets library. This research considers office buildings, schools, and EV charging stations as non-residential community members. Other SMEs, restaurants, and other non-residential community members with complementary demand profiles should be incorporated in future research. The financial calculations used in this study are oversimplified. Therefore, a detailed financial analysis on savings made through demand response versus returns on the investment of behind-the-meter storage should be conducted in the future. The policy levers used in this study are much harder to control in real life. Therefore, a detailed analysis to discover the minimum value range for the availability of flexible demand is recommended for future studies. Furthermore, detailed research on the technical and financial feasibility of interventions mentioned in this study is recommended. To further test the robustness of interventions under deep uncertainties, an open exploration study using systematic sampling of uncertainty and policy space is recommended. Moreover, this study does not consider the policy and regulatory support required for implementing the recommended interventions. Thus, a study for analyzing existing policies and regulations in the EU for the governance of demand response in energy communities should be done.

5.4. Scientific Contribution

The academic contribution of this study is threefold.

First of all, this research contributes to the use of agent-based modeling for community energy research. Existing literature like Perez-DeLaMora et al. (2021) and Reis et al. (2020) highlight the suitability of agent-based modeling for community energy research. A novel agent-based model is created based on the the dutch social, technical, organisational and governance characteristics highlighted by Warbroek and Hoppe (2017), Warbroek et al. (2018) and Fouladvand, Aranguren Rojas, et al. (2022). Existing studies like Ghorbani et al. (2020) also developed an agent-based model for dutch energy communities but these models are focused on studying the dynamics behind the formulation of an energy community. Whereas, the model developed in this research is focused on performing experimentation regarding optimization of local electricity generation and consumption. Lastly, this model uses the load profiles of residential and non-residential electricity consumers from the Netherlands that can be used for future community energy research based in the Netherlands.

Secondly, this research contributes to the literature focused on studying demand response and in particular load shifting in community energy projects. The findings of this research align with Knox et al., 2022 and advocate the use of smart-grid features for enabling monitoring and demand response in energy communities. The results of model experimentation confirm the findings of Reis et al. (2018) and Xiong et al. (2020) by showcasing the effectiveness of demand response for reducing the grid dependence of energy communities. Moreover, as suggested by Huang et al. (2022), this study signifies the importance of optimizing local consumption of electricity generated from community assets (such as solar PV and wind turbines) for a community to become self-sustaining and reduce grid dependence.

Lastly, this research contributes to the body of literature on leveraging complementary demand profiles of residential and non-residential consumers through demand response. As recommended by Reis et al. (2018) and Reis et al. (2020), this study showcase that introducing a non-residential community member with a complementary load profile can help in optimizing local consumption of electricity. The existing studies on mixed configuration communities like Reis et al. (2020) and Huang et al. (2022) are conducted on community setups located in Germany and China. However, this research performed virtual experimentation on two real-life inspired community configurations based on socio-technical settings of the Netherlands. Moreover, this study contributes to the academic discourse regarding demand flexibility such as Faria et al. (2019), Schiera et al. (2019) and Xiong et al. (2020) by exploring the applicability of behind-the-meter storage for residential community members.

5.5. Social Contribution

Energy communities are promising citizen-driven initiatives taking the bottom-up path to transcend towards accessible, sustainable, efficient, and low-carbon urban energy systems (Bomberg, 2012). Stewart (2021) suggests that community energy projects successfully propagate the benefits of low-carbon technologies to the deprived and low-income areas of society. Therefore, this project has a significant place in the societal discourse regarding energy transition. This research helps energy communities by supporting their decision-making through a model-based and data-driven approach. The use of this model-based approach can help in robust energy planning and investments regarding demand response for energy communities under uncertainties.

Moreover, this research can help organizations like Croonwolter&dros to work closely with municipalities and DSOs to map potential energy communities in the Netherlands and explore demand response opportunities for them. This research and recommendations can be used as a blueprint for existing energy communities (such as Groene Mient and GridFlex-Heeten) for implementing demand response and introducing non-residential members to the communities. However, the limitations and assumptions of this study are mentioned in Section 5.3 and Section 4.2 should be considered respectively before adopting these recommendations for any community energy project.

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A
Data Cleaning and Preparation

This appendix encapsulates methods used for data cleaning and preparation. Data preparation for this model is done in two steps:

A.1. Data Cleaning

In this step, the data acquired from the source is cleaned and checked for syntactical and semantic errors. The steps for checking and rectifying the data are further elaborated in the Jupyter notebook available on the GitHub repository.

Data cleaning notebook:
https://github.com/SoniAnmol/Modelling-Dutch-Energy-Communities/blob/main/data/data_cleaning.ipynb

A.2. Data Preparation

The cleaned data is then formatted and sliced for the required time-span of the model run. In this case, since data is most complete for the year 2021, all data sets are sliced for the year 2021. Lastly, all the time-series data are aligned and combined into a single file and saved as a ".csv" file for model input. Detailed description of data preparation is available in the data preparation notebook hosted in the GitHub repository of the project.

Data preparation notebook:
https://github.com/SoniAnmol/Modelling-Dutch-Energy-Communities/blob/main/data/data_prep.ipynb

B UML Diagrams

This appendix contains additional UML diagrams created during model formalisation.

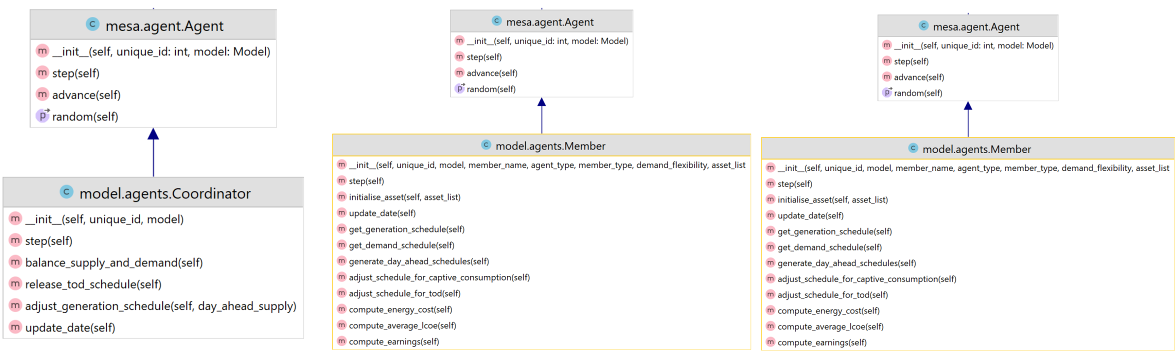

Figure B.1: UML diagram of Asset class. 'm' stands for methods in the class.

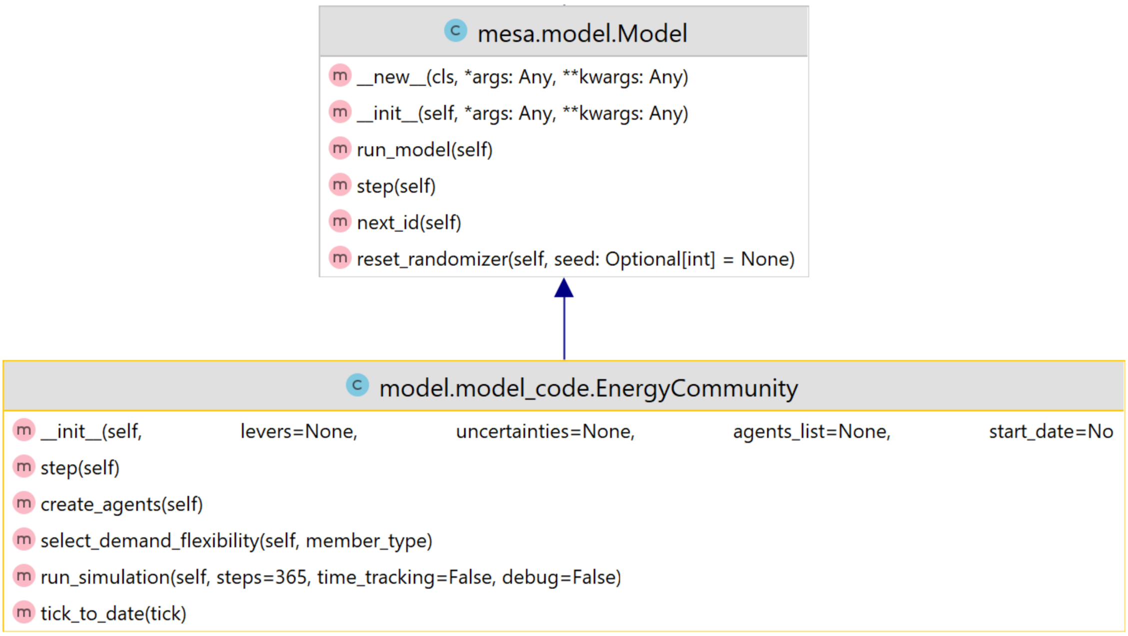

Figure B.2: UML diagram of the model setup in python. 'm' stands for methods in the class.

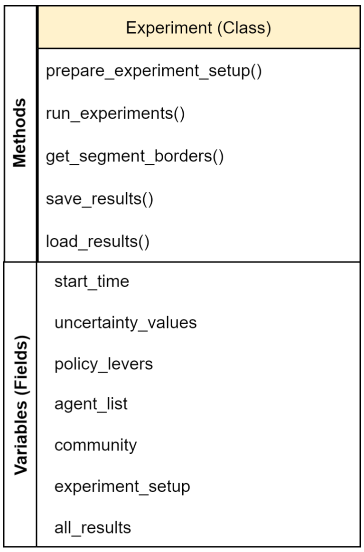

Figure B.3: UML diagram of Experiment class

C
Validation Plots

This appendix contains additional plots generated during model validation.

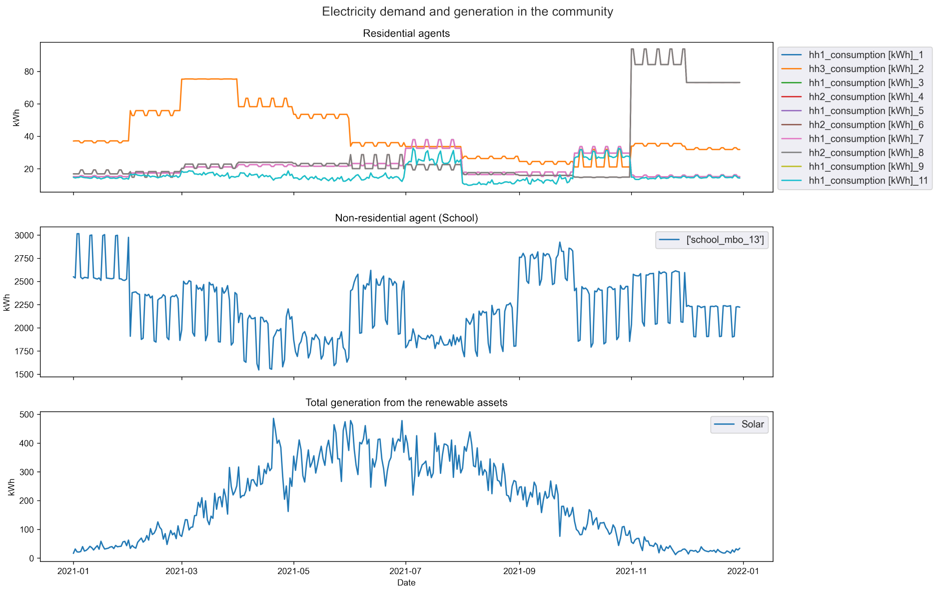

Figure C.1: Community members' demand and generation under extremely low policy levers

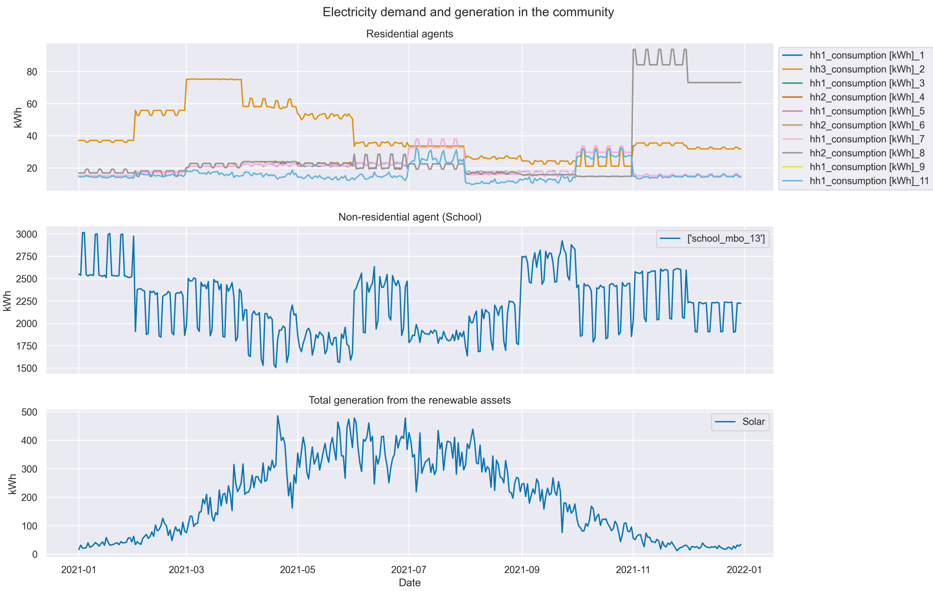

Figure C.2: Community members' demand and generation under extremely high policy levers

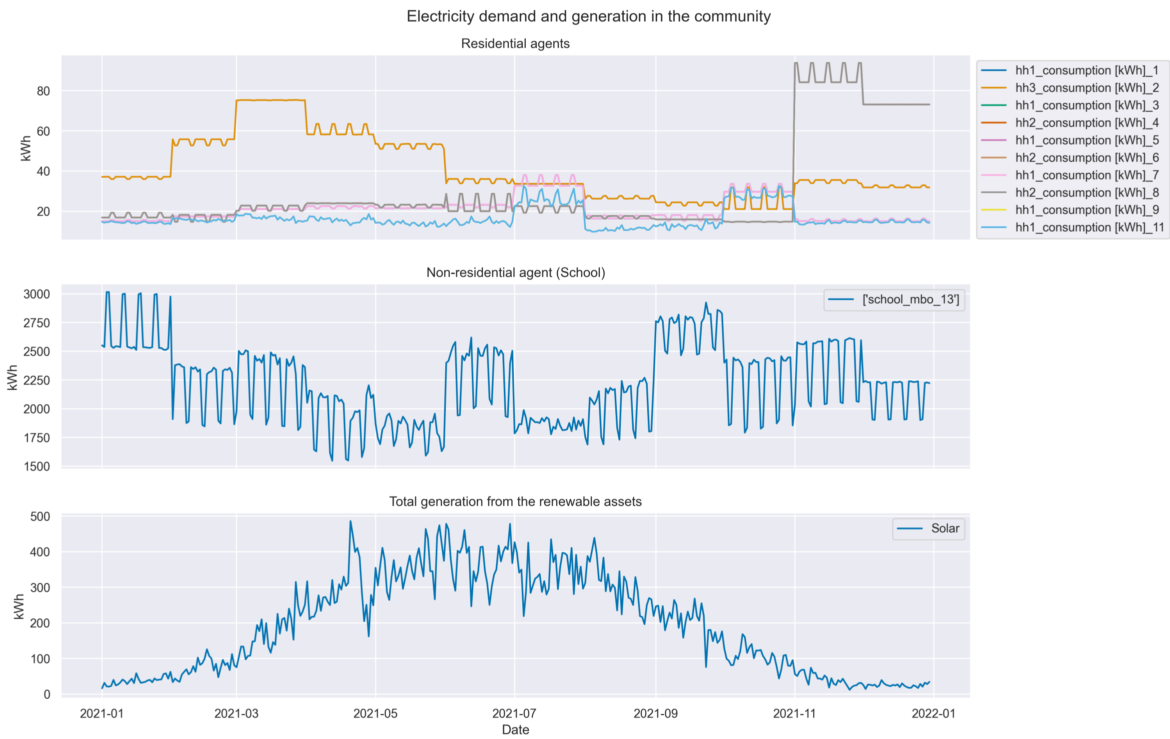

Figure C.3: Community members' demand and generation extremely low uncertainty parameters

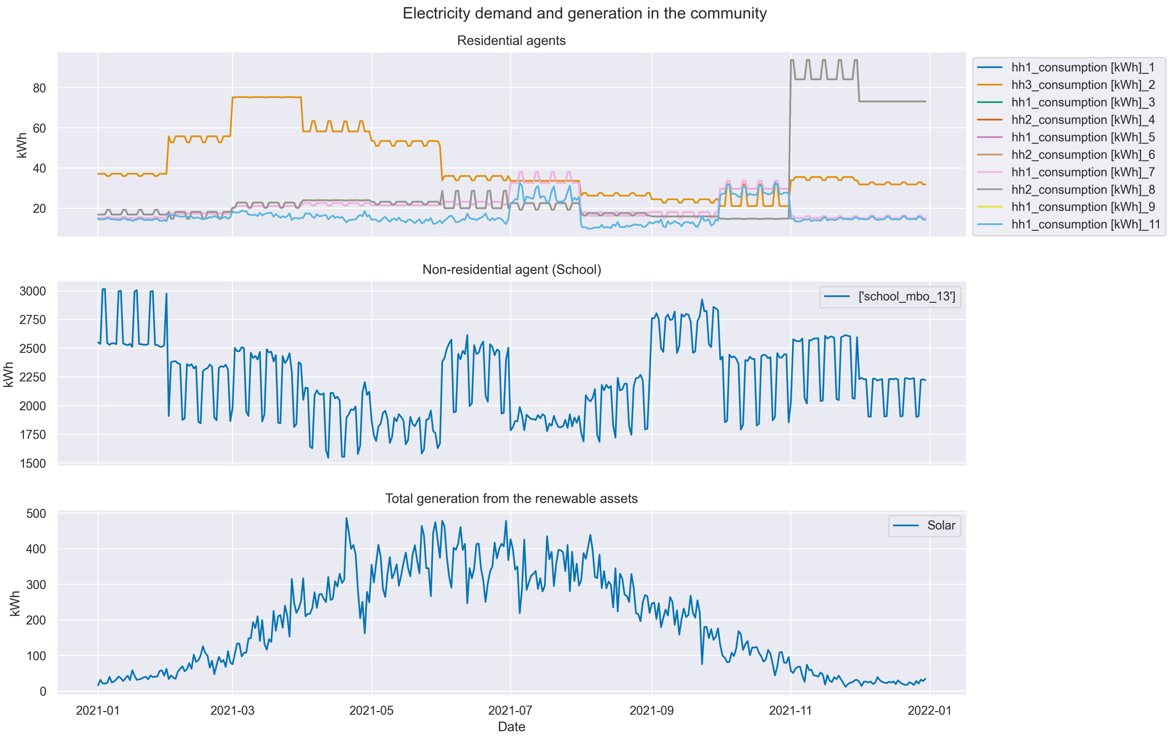

Figure C.4: Community members' demand and generation under extremely high uncertainty parameters

D
Experiment Outcomes

This appendix contains additional plots generated from experiment outcomes.

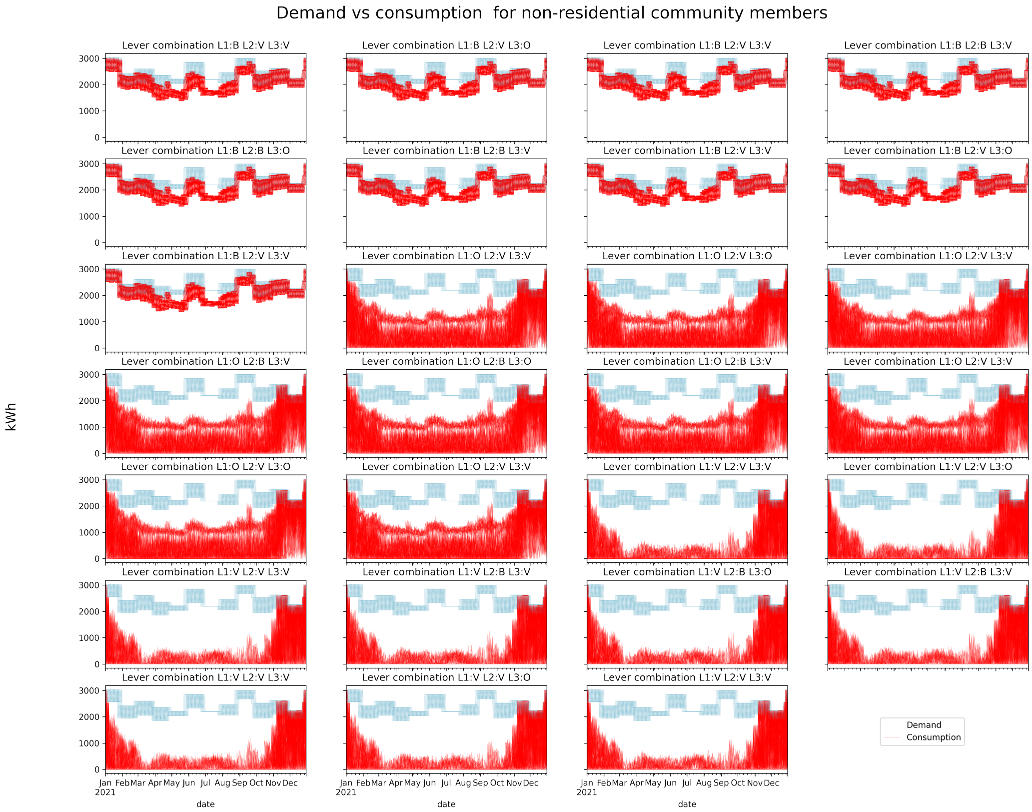

Figure D.1: Electricity demand vs electricity consumption for non-residential community members of Groene Mient inspired community setup

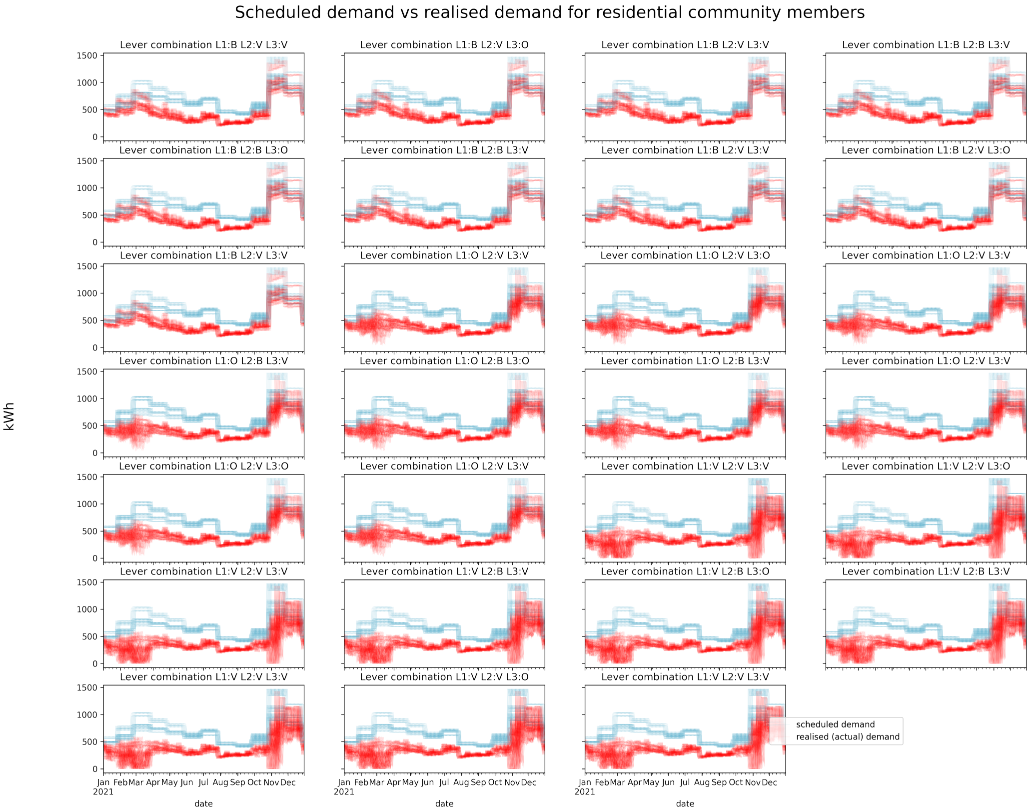

Figure D.2: Electricity demand vs electricity consumption for non-residential community members of Groene Mient inspired community setup

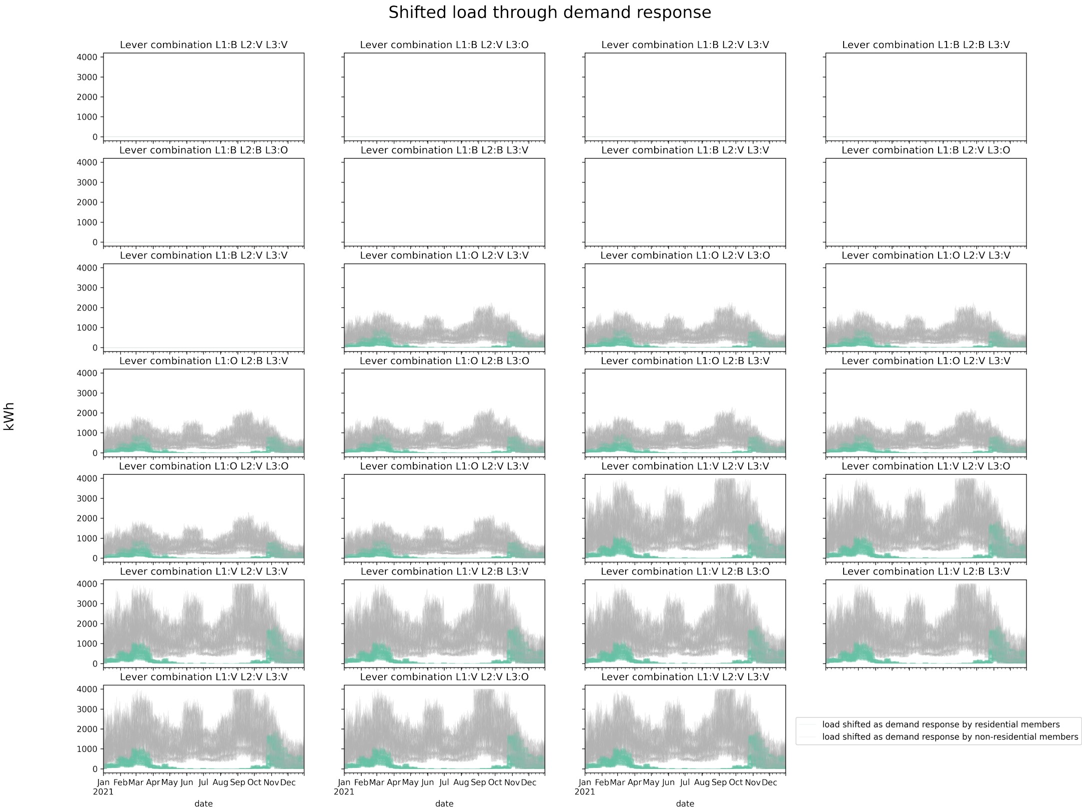

Figure D.3: Load shifted by residential and non-residential community members through demand response for Groene Mient inspired community setup

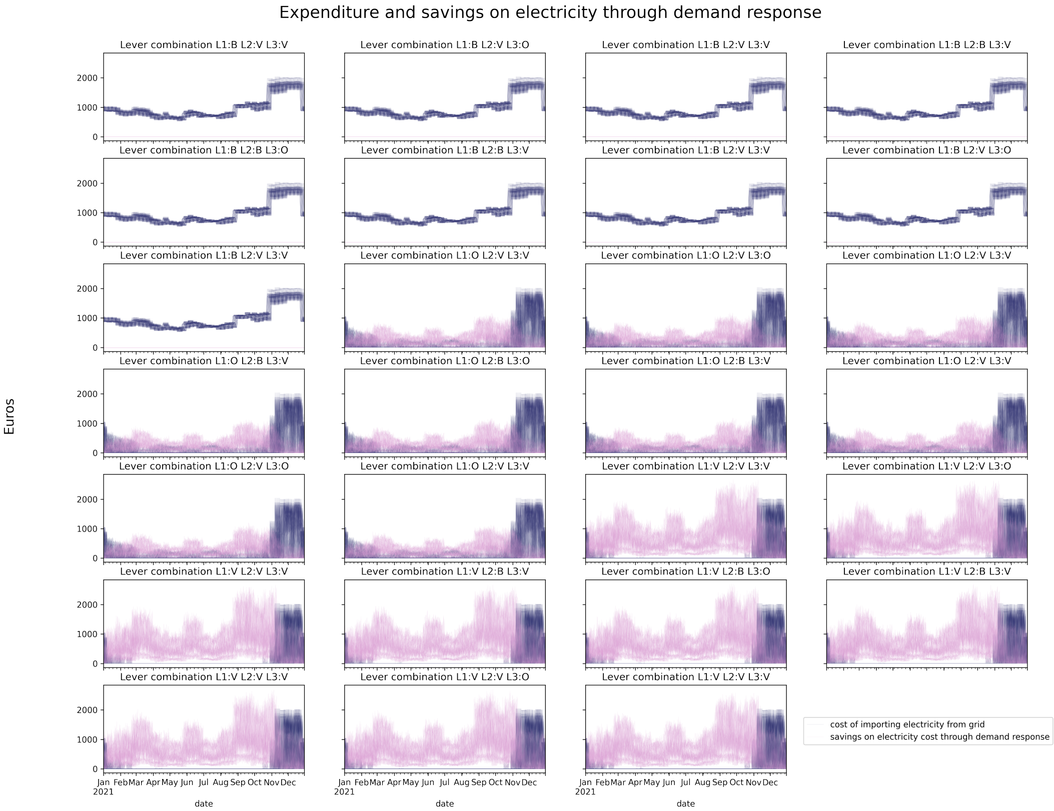

Figure D.4: Expenditure on import of electricity from grid vs savings incurred through demand response for Groene Mient inspired community setup

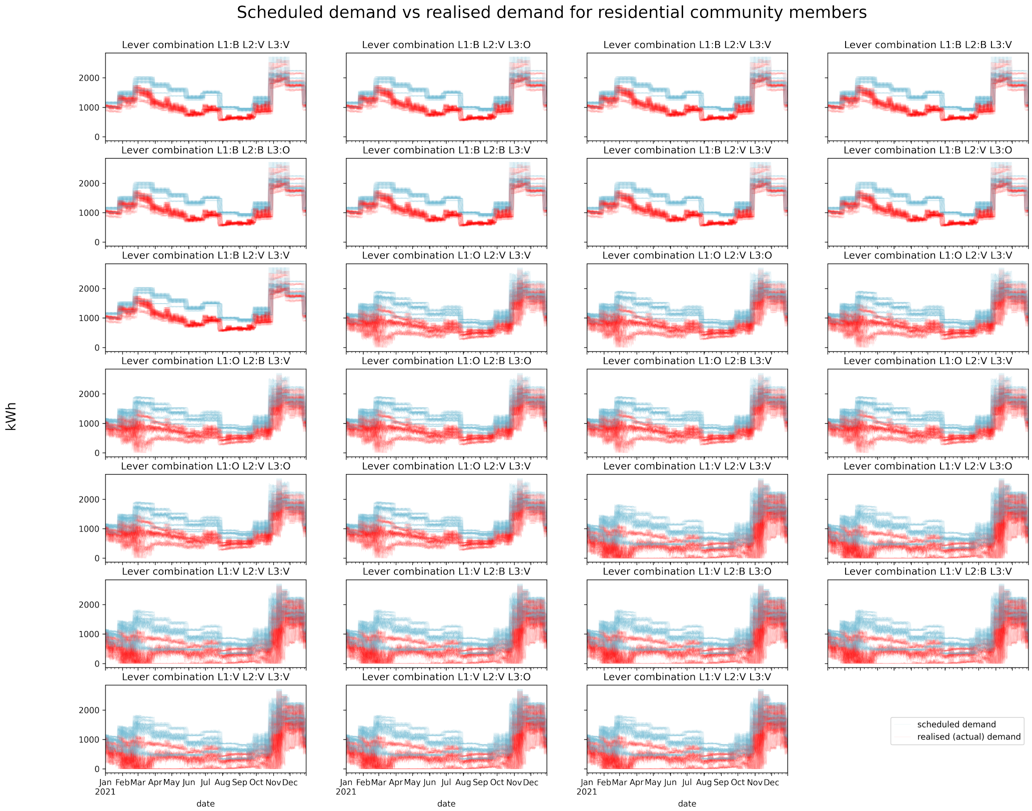

Figure D.5: Electricity demand vs electricity consumption for residential community members of GridFlex inspired community setup

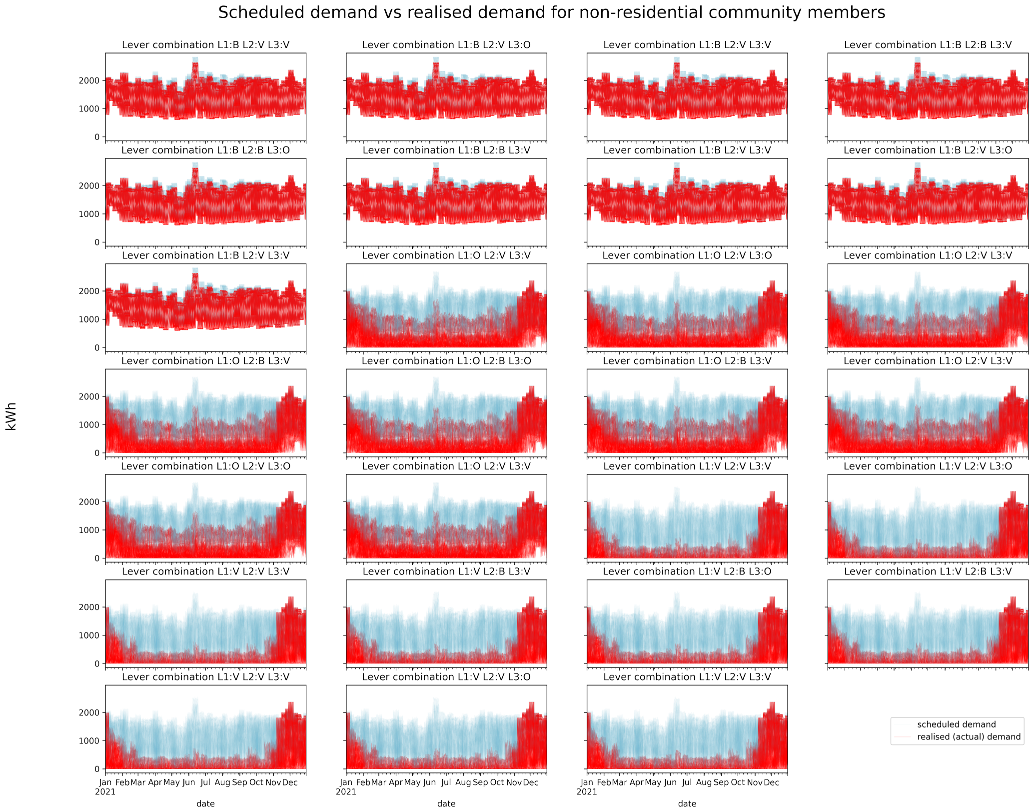

Figure D.6: Electricity demand vs electricity consumption for non-residential community members of GridFlex inspired community setup

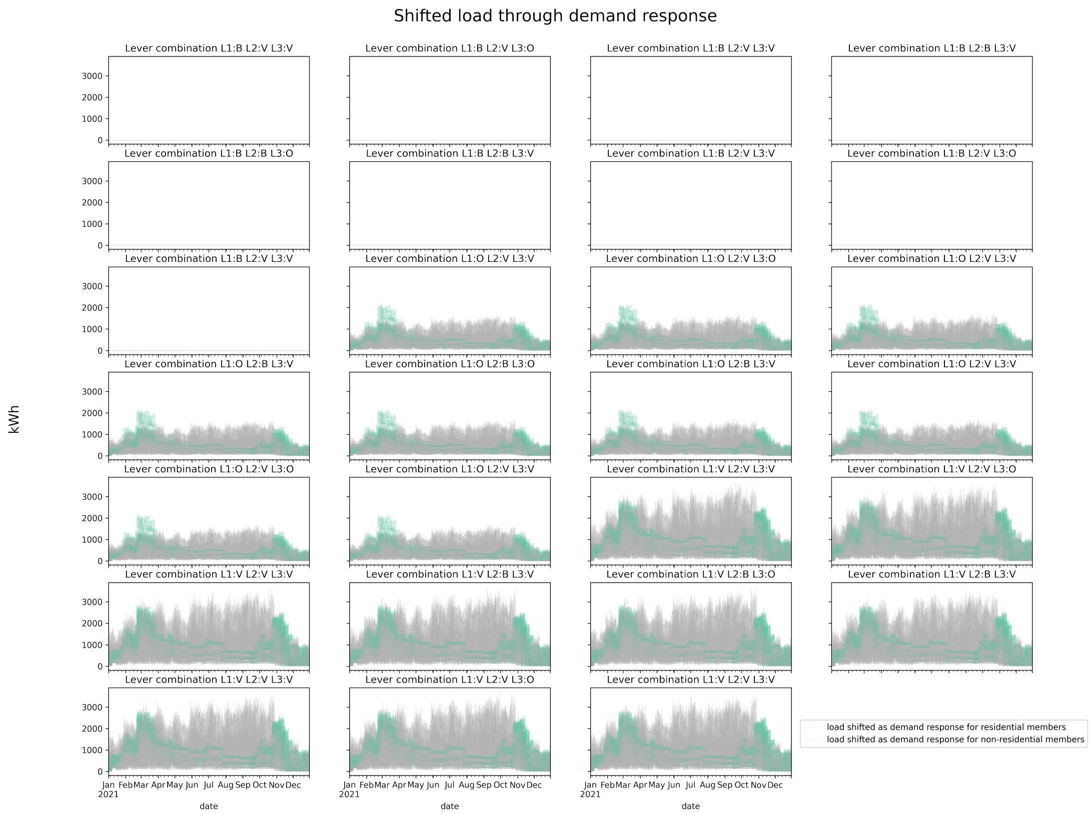

Figure D.7: Shifted load by community members through demand response

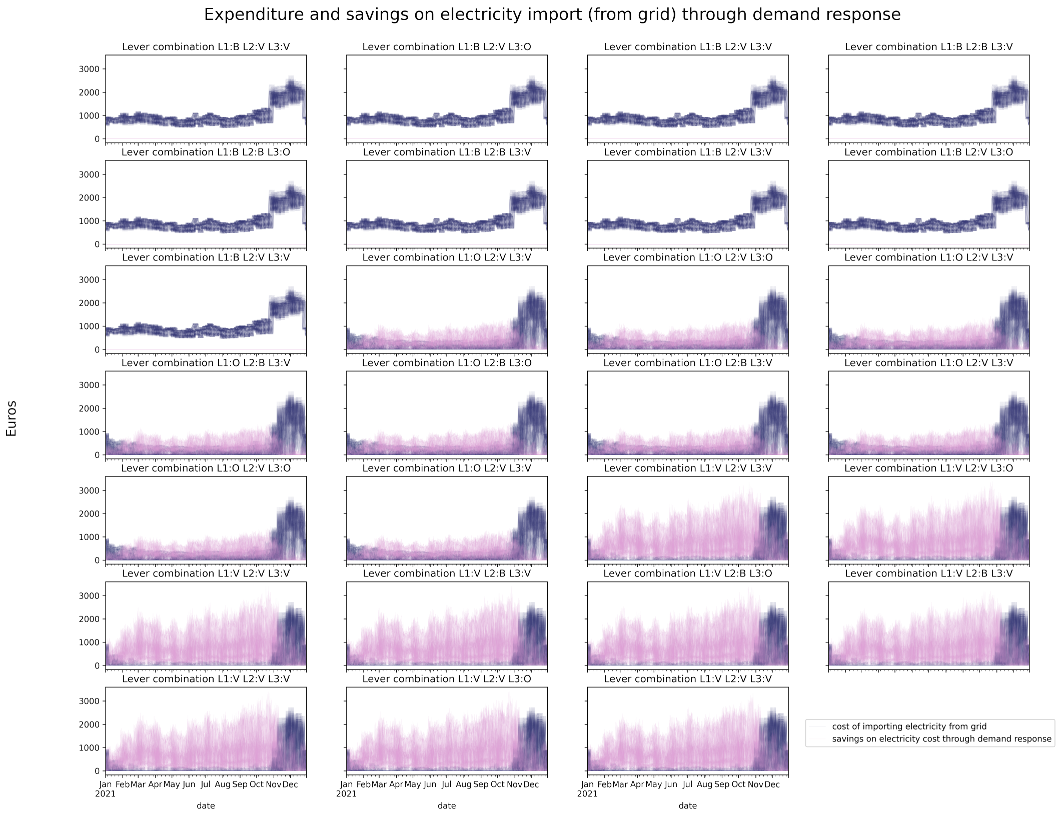

Figure D.8: Expenditure on import of electricity from grid vs savings incurred through demand response for GridFlex inspired community setup

E Analysis of Experiment Outcomes

This appendix contains plots generated during analysis of experiment outcomes.

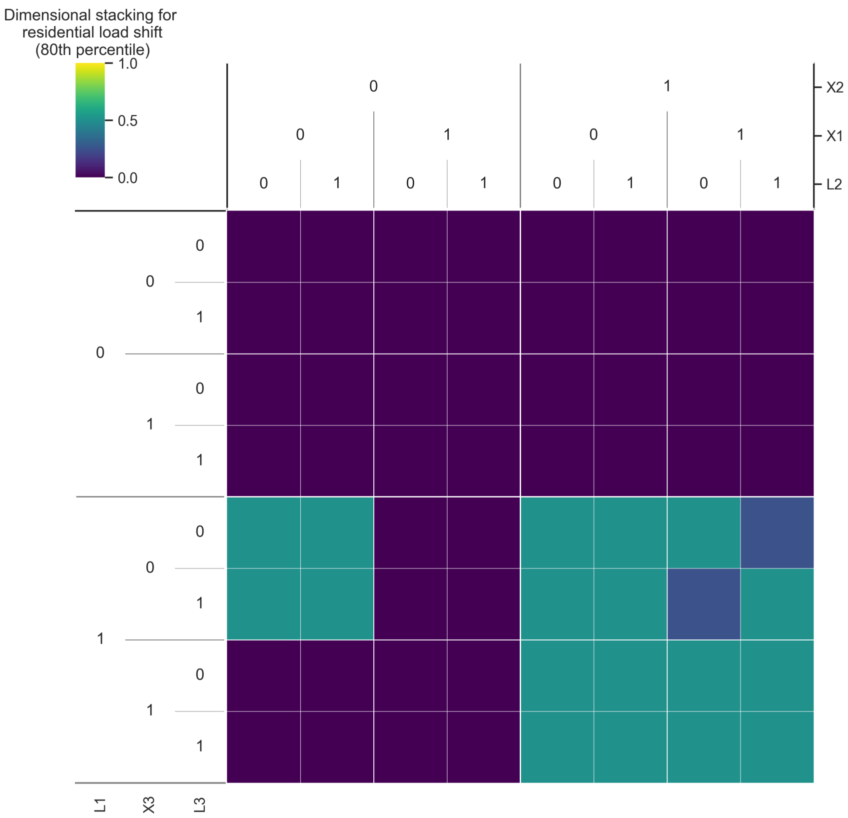

Figure E.1: Dimensional stacking for GridFlex inspired energy community

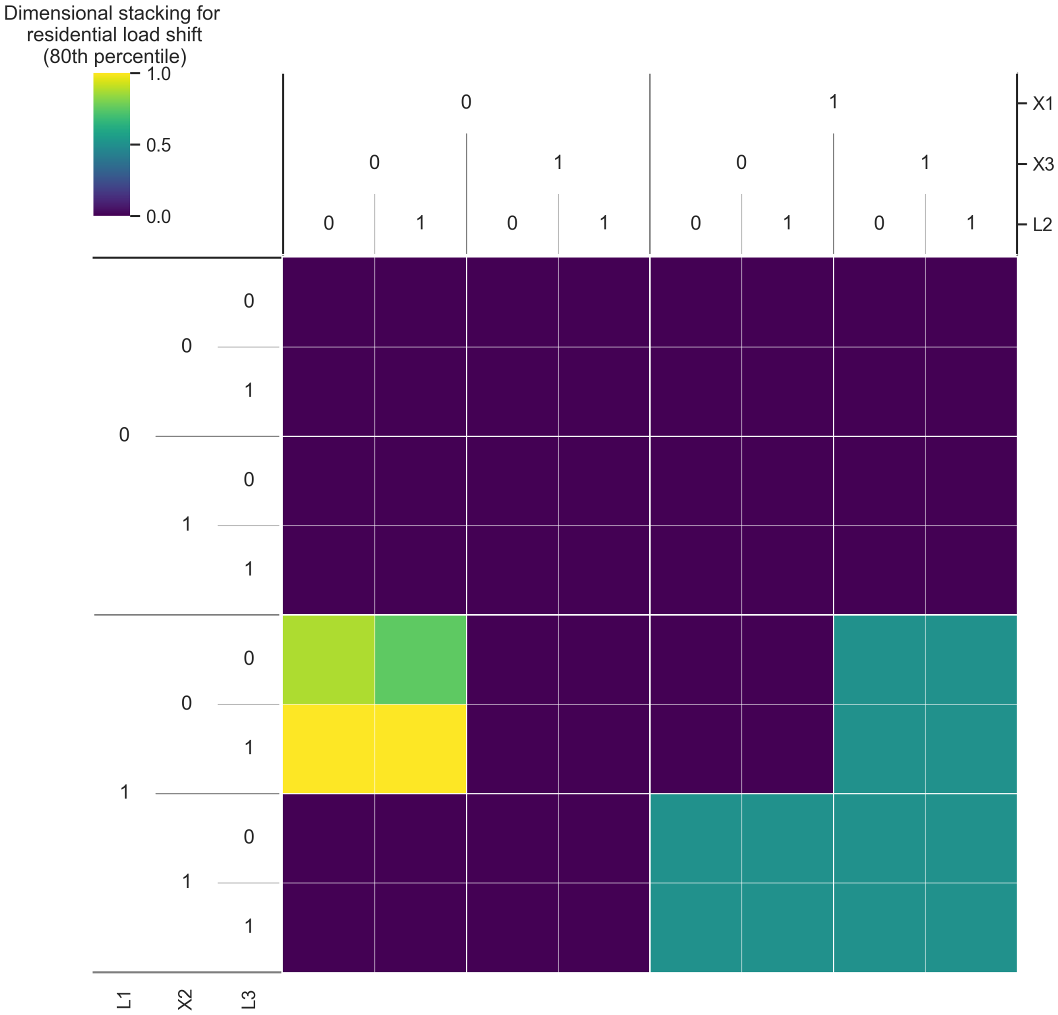

Figure E.2: Dimensional stacking for Groene Mient inspired energy community

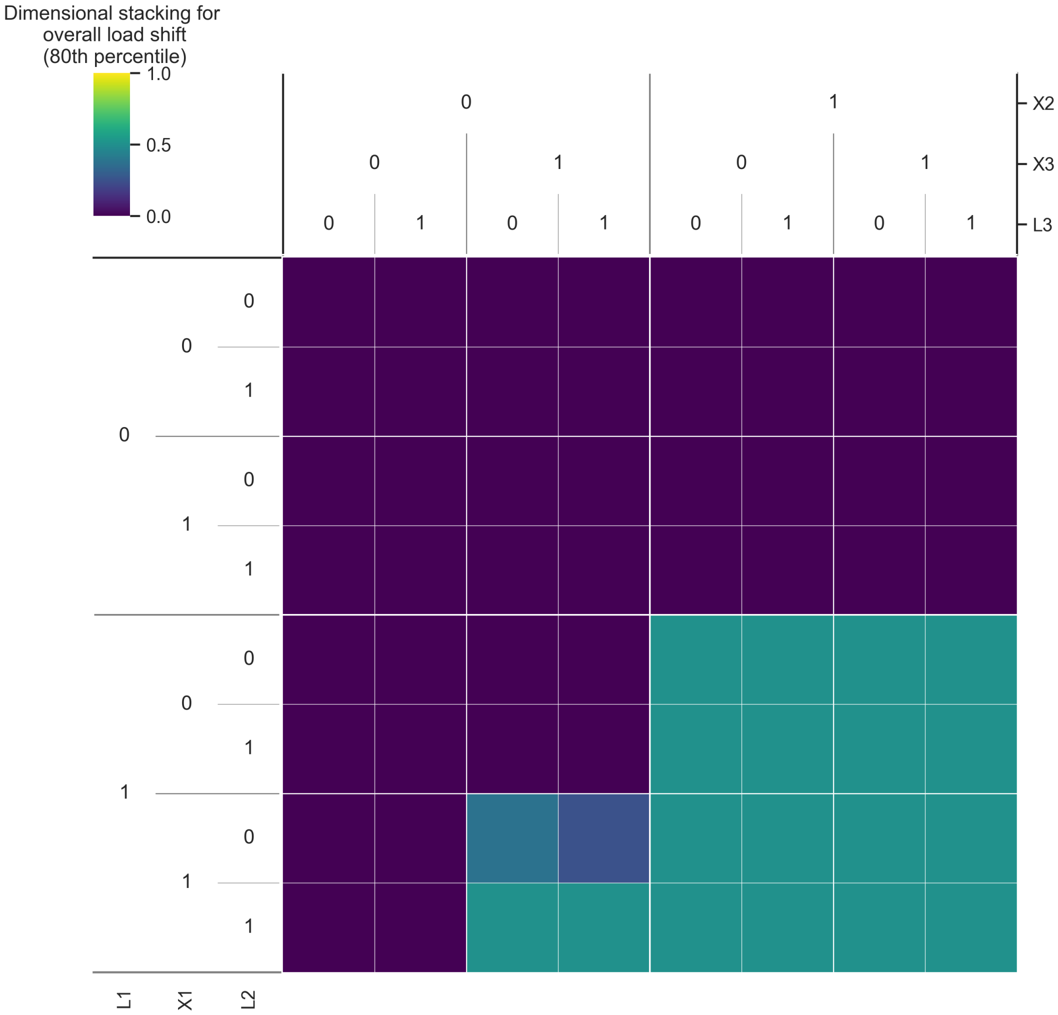

Figure E.3: Dimensional stacking for shifted load of GridFlex inspired energy community

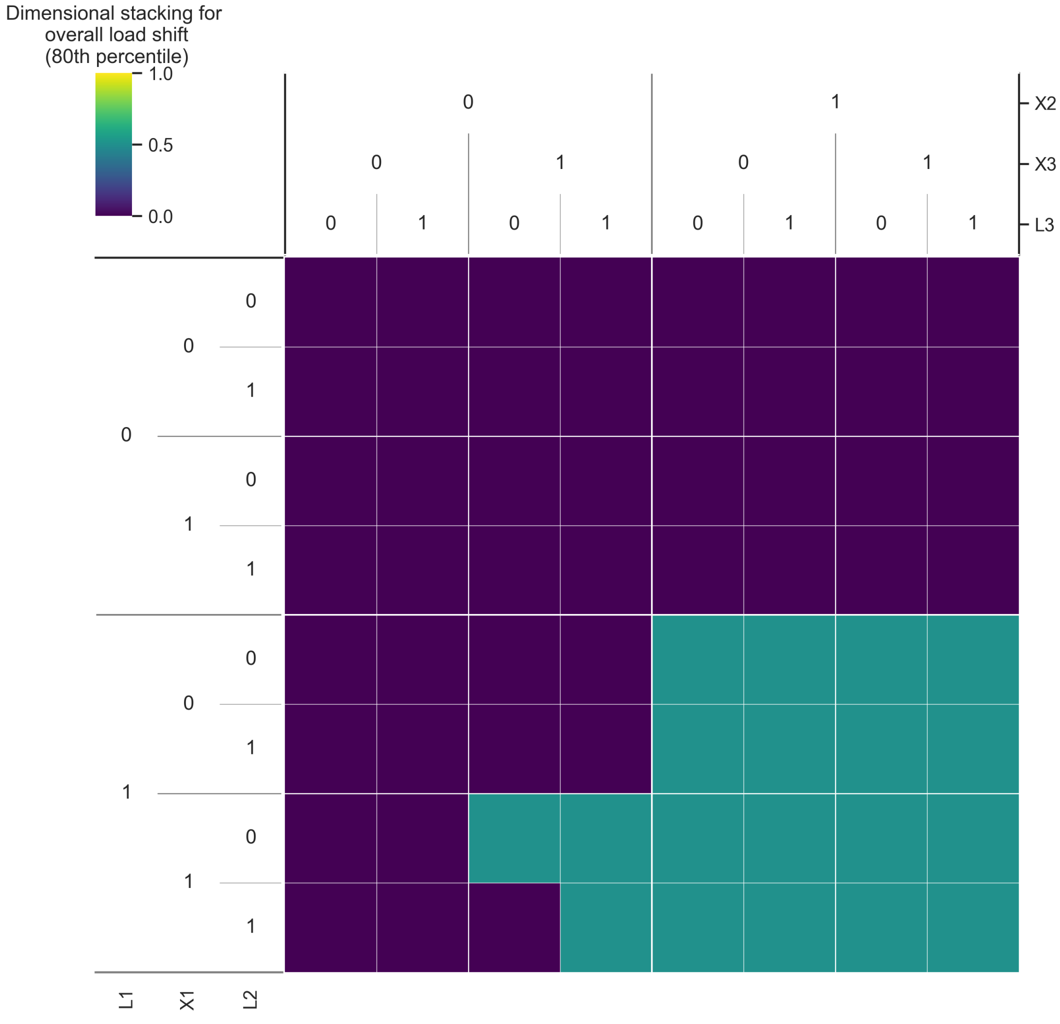

Figure E.4: Dimensional stacking for shifted load of Groene Mient inspired energy community

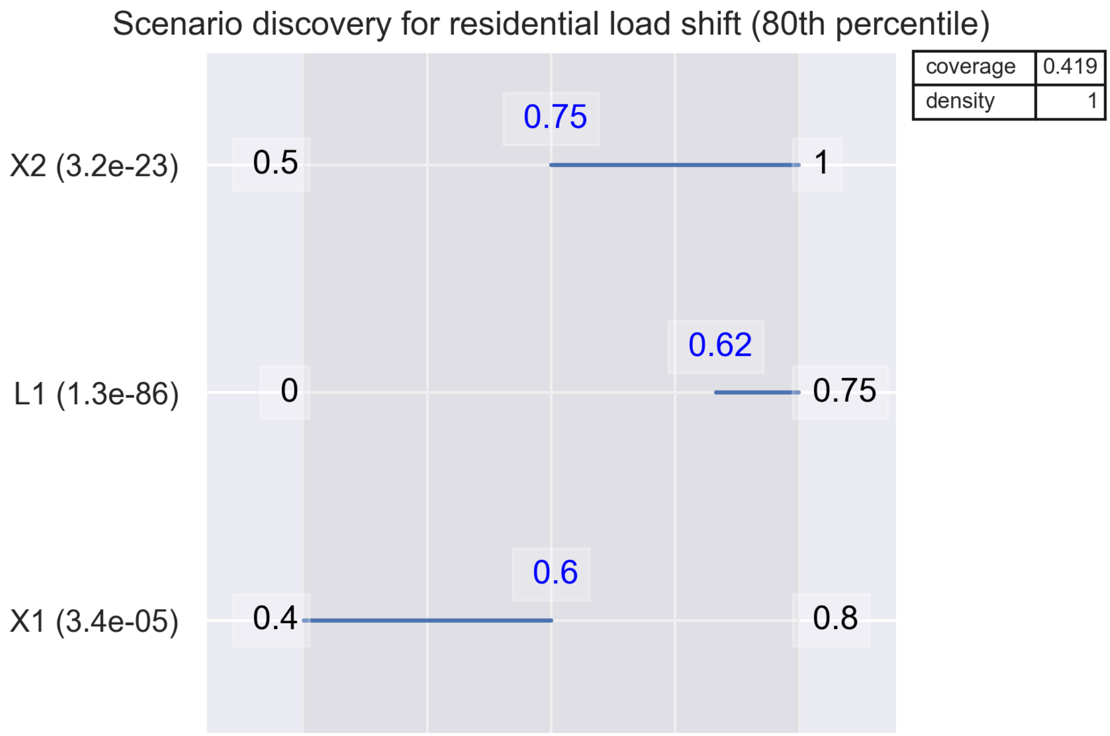

Figure E.5: Prim analysis box for maximum residential load shift for GridFlex inspired energy community

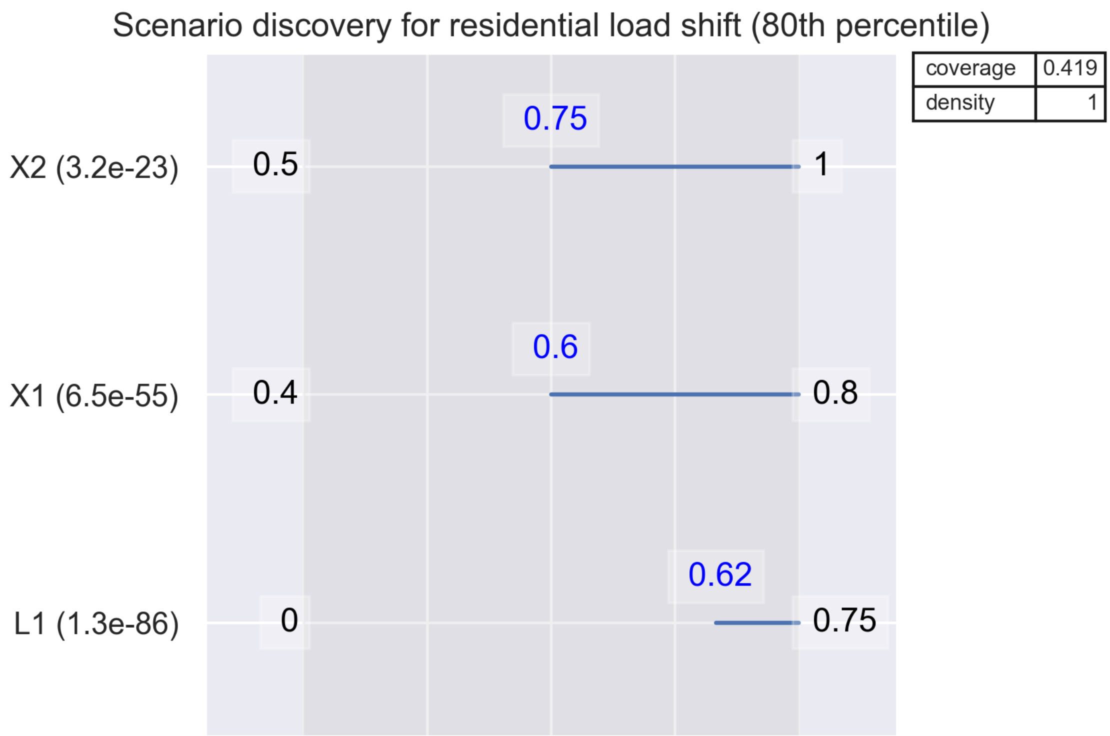

Figure E.6: Prim analysis box for maximum residential load shift for Groene Mient inspired energy community

Figure E.7: Prim analysis box for maximum load shift for GridFlex inspired energy community

Figure E.8: Prim analysis box for maximum load shift for Groene Mient inspired energy community