Demand response in the Dutch energy communities

An agent-based modelling approach to explore demand response opportunities for energy communities having residential and non-residential members in the Netherlands

Masters Thesis project

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by

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Preface

This is the draft copy of the thesis and is still a work in progress. A preface will be included in the final version of the report.

Anmol Soni (5290228)
Delft, June 2022

Summary

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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

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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 and Wind) in the last decade. The widespread distributed renewable generation among residential households has converted many electricity consumers into ”prosumers” (An electricity consumer who is also involved in the generation process) 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 or cooperation 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 EU countries and will be transposed into the national legislation of the EU countries including the Netherlands. Currently, the directive transposition process is delayed because of challenges related to integration into the Dutch legislature.

However, the complex nature of transactions and uncertainties regarding policy and business model makes decision-making regarding investments and asset ownership challenging for energy communities. 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 through demand response. Both residential households and offices have flexible loads (such as heating, cooling, lighting, and ventilation for offices whereas washing machine, dishwasher, and heating for households) which can coexist for maximizing the self-sufficiency of the community (Reis et al., 2020). The directive mentions the inclusion of non-energy small and medium enterprises and local authorities (EU, 2021).

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 three folds. Although Germany has over four times more residents than the Netherlands, the true potential of community energy projects in the Netherlands is still untapped as there are many households yet to be connected to a community. 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 Groen Mient and GridFlex Heeten are planning to conduct these studies in near future thus this research will also serve as a baseline for them. Therefore, this research is focused on the Netherlands to provide relevant insights and expand the knowledge base required for making 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 and web tools 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 modelling", "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 1.1 depicts the cluster of papers reviewed.

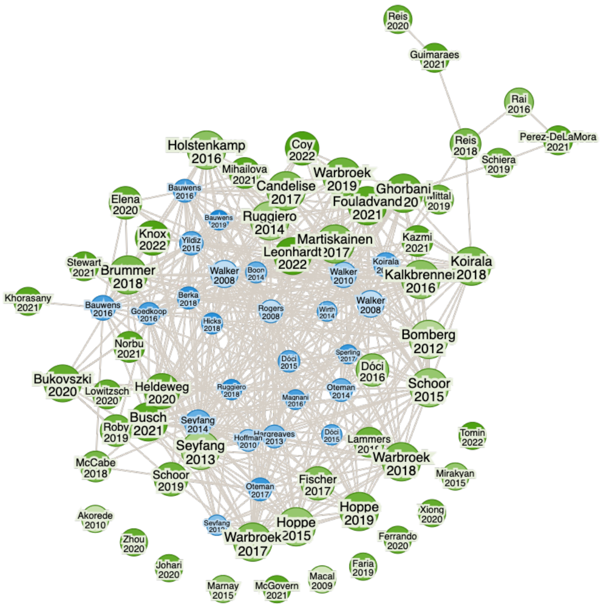

Figure 1.1: Literature Snowballing: Green bubble indicates literature included and the blue bubble indicates literature excluded from the study. The excluded papers are filtered out as per the criteria. These papers are either focused on thermal energy projects or represented through subsequent literature.

Lastly, over 60 articles/papers from different platforms/journals were initially selected and filtered using the following criteria:

- Language: Articles published in the English language were considered for this review. Because of the linguistic constraints of the author, limited Dutch articles are 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, 15 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 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.

1.2.1. 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 became bidirectional and clusters evolved as micro-grids and mini-grids (Marnay et al., 2015). However, energy clusters were formulated by the local demand or consumption patterns of an area whereas, energy communities necessarily include the energy generation profile of the area. This theoretically positions them differently but approaching these as mirror concepts provides 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 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 for electricity (IEMD). The EU (2021) provides legal rights to Households and SMEs in EU states to operate individually or form a Renewable Energy Community on a non-profit basis to consume, sell and/or store the 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 whereas Renata Leonhardt et al. (2022) provided 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 and third parties in community projects widely vary based on social and political milieu (Holstenkamp & Kahla, 2016).

1.2.2. Literature-based on community energy projects in the Netherlands

The case study conducted by (Warbroek & Hoppe, 2017) for Dutch community energy projects in Overijssel and Fryslân 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). Community energy projects require to 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. Currently, there is no regulation provision for community energy projects in the Netherlands and an experimental permit is required to operate as an energy cooperation.

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) mentions 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 peak generation and peak demand.

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 and this is evident by a reduction in feed-in-tariffs. In addition to this, the European Commission (2018) indicates 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 energy assets within the community and become self-sustaining with limited grid support (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 energy community members and their informed decision-making regarding energy transactions 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 by taking 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 do not capture all the dynamics of energy communities (particularly in the Netherlands) and therefore are not suitable for testing policies and supporting decision-making. 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 Diogo V. Guimaraes et al. (2021), Mittal et al. (2019), Schiera et al. (2019) and Tomin et al. (2022) consider only residential members for energy community. 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. Reis et al. (2020) highlights the need for including non-residential agents (i.e. SMEs, offices, and EV charging) in the energy community and evaluating their potential for self-sufficiency in energy communities. Therefore, the aforementioned models 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. Considering non-residential and EV charging stations (having complementing energy consumption profiles) can generate opportunities for demand response policies. Reis et al. (2020) explores 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) explores the demand flexibility for energy communities but the load profile 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 1.2 highlights the knowledge gaps in the recent research around energy communities. In a nutshell, these gaps include the exclusion of non-residential members in energy communities and limited exploration of demand response opportunities, for attaining self-sufficiency and reducing dependence on energy storage within the community. This research envisages bridging these knowledge gaps in the context of the Dutch socio-political and technical milieu. 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 cost for the community incurred by importing electricity from the grid for modelled 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? This is done by creating multiple scenarios for the participation of community members in the demand response program.
4. How availability of flexible demand by residential and non-residential community members affect the efficacy of demand response? Availability of flexible demand is a behavioral function of community members that signifies the extent to which a community member shifts the flexible load during demand response.

1.4. Research objective

The objective of this research is twofold. First, this research will identify key attributes of the Dutch energy communities along with the uncertainties influencing their decision-making regarding investment in generation or storage assets and responding to demand response (time-of-use tariff in this case). This information will be used for building an agent-based model to get a better understanding of the transactive behavior of Dutch energy communities. The choice of the agent-based model as a research approach is substantiated in the chapter 2. This study will also include small and 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 the literature review section 1.2.3. The scope of this model will be limited to the electricity distribution network (Low voltage) at the community level. However, this model can be extended to include heat and gas networks in future versions. Two archetypical energy community configurations inspired by real-life energy corporations are modeled with additional non-residential members to leverage the complementary electricity demand profile through demand response.

[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.

1.5. Contribution of this study

Previous studies on multi-agent based distributed energy management for smart grid applications (Radhakrishnan & Srinivasan, 2016) exploring strategies for automated energy demand management (Guo et al., 2010) using smart meters and user preference (Ramchurn et al., 2011) are focused on residential micro-grids and energy communities. This study contributes to a relatively new body of literature focused on using (multi) agent based modelling approach for exploring demand response opportunities in energy communities having residential and non-residential agents like (Reis et al., 2018) (Reis et al., 2020) (Sayfutdinov et al., 2022) (Silva et al., 2021) and (Hoffmann et al., 2020).

This model is intended to serve as a decision-aiding tool for energy planning of energy communities by facilitating virtual experimentation and act as a testing ground to evaluate demand-response policies (time-of-use tariff in this case). Through this model, energy communities can explore the demand response opportunities for reducing the dependence on storage or grid and achieve self-sustenance by including non-residential members having complimentary load profiles.

1.6. Report overview

The remaining of this report has the following structure. Chapter 2 describes research approach and methodology selected for answering the research question. Chapter 3 explains the model conceptualized for this study and the formalization of the model is discussed in Chapter 4. Model implementation along with verification and validation is described in Chapter 5. The experiments designed for using the model to answer the research question are discussed in Chapter 6. Experiment outcome and results are documented in Chapter 7. Lastly, key findings of this research are concluded, and added academic value is discussed in Chapter 8 and Chapter 9 respectively.

2
Research design and methodology

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

2.1. Research Approach

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.

2.2. Research Methodology

This methodology is designed to answer all the sub-research questions and eventually the main research question mentioned in Section 1.3. The methodology is taken from Van Dam et al. (2012) and adapted for this study. The overall research can be divided into four phases.

- Model conceptualisation,
- Model formalisation,
- Model implementation, and
- Model usage or experimentation.

The aforementioned four phases 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.

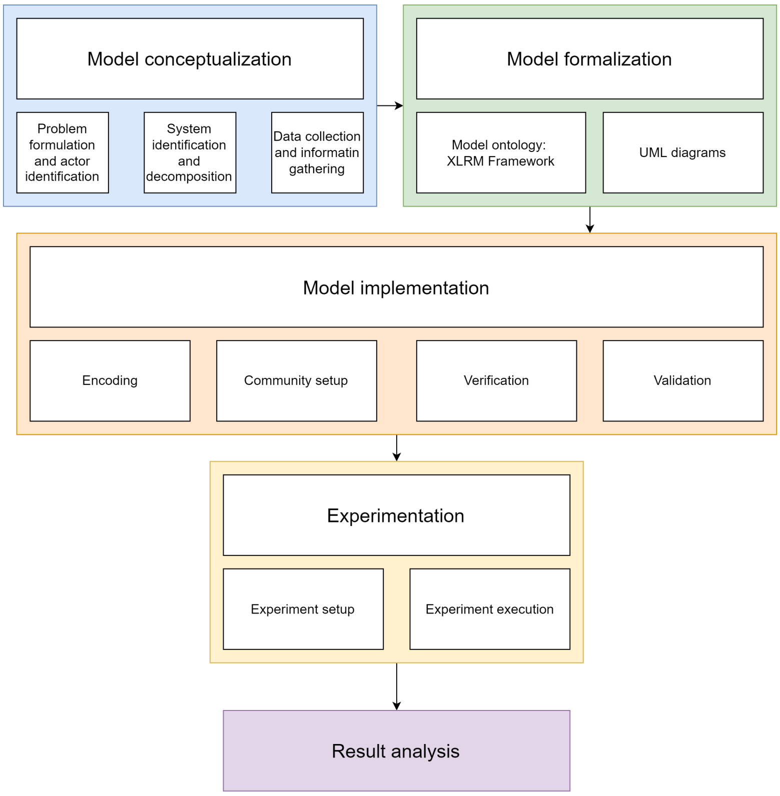

Figure 2.1: Steps for modeling energy community as a socio-technical system. These steps are adapted from Van Dam et al. (2012)

2.3. Model conceptualisation

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 involves the following steps:

1. **Problem formulation and agent identification** defines 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).
2. **System identification and decomposition** further delves into the decision arena and defines 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.
3. **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.

2.4. Model formalization

Model formalization bridges the conceptualized model to 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 can be divided into the following two steps:

1. **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.
2. **Formalised model (UML diagrams and flowcharts)** is created to capture the conceptualized model and model ontology defined in the previous step into easily understandable flowcharts and diagrams.

2.5. Model implementation

In this step, the mental and 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:

2.5.1. Model encoding

Model encoding means coding the conceptualized and formalized model into the python code. This is done while implementing verification checks to ensure that the agent interaction and behavior are following the conceptualized model. The encoded model is hosted on the GitHub repository and is available in the public domain.

2.5.2. Community setup

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.

2.5.3. 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. Verification steps used in this research are taken from Van Dam et al. (2012).

1. **Tracing the agent 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.
2. **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.
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 with a minimum number of agents required to initiate the model. First, the interaction between the coordinator and the members to get the total generation and total demand from the community members. Seconds, the interaction between members and their respective assets. This is verified by checking if captive generation is reduced from the demand schedule of an agent.
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.

2.5.4. Model validation

The objective of model validation is to evaluate its suitability to answer the research question. A simplistic energy community configuration is selected for these tests to validate the agent behavior and system relationships encoded in the model. 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.

1. **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.
2. **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.
3. **Face validation** is the validation of the model by field experts and professionals. The aforementioned validation tests and their respective results are shared with the Croonwolter&dros team and face validated by experienced energy modelers.

2.6. Model usage: 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. Experimentation can be divided into the following steps:

1. **Experiment setup** involves defining the value range for input parameters and designing the experiment setup.
2. **Experiment execution** entails simulating the model with parameters specified in the experiment setup.

The outcomes of experiments are collected at every time step to study the model and agent behavior. Lastly, the results of experiments are visualized and analyzed to derive conclusions and answer the main research question.

3 Model conceptualisation

This chapter sets the foundation for the agent-based model by identifying the "key players" to be modeled as agents. After defining the system relationships, interaction of agents and 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 its source in this chapter.

3.1. Problem formulation and actor identification

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 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 3.1. The decision arena depicted in the figure is a representation for a typical energy community project. The power perception shown in Figure 3.1 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.

3.1.1. Defenders

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.

3.1.2. Apathetic

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 the decision making.

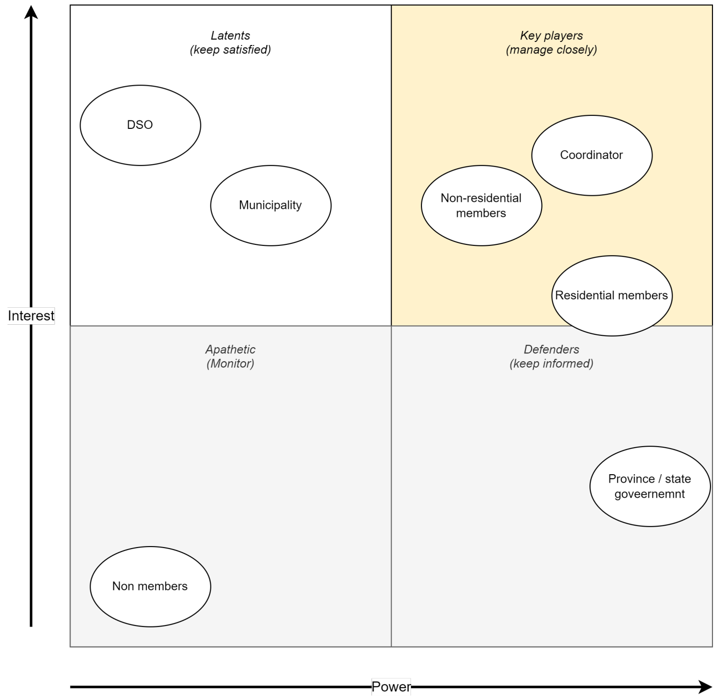

Figure 3.1: Power interest matrix of actors involved in a typical energy community

3.1.3. Latent

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 realised through community energy and demand response projects. Therefore, interests of both DSOs and local municipalities aligns with the community projects implementing demand response.

3.1.4. Key players

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.

3.2. System identification and decomposition

Figure 3.2 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 modelled 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

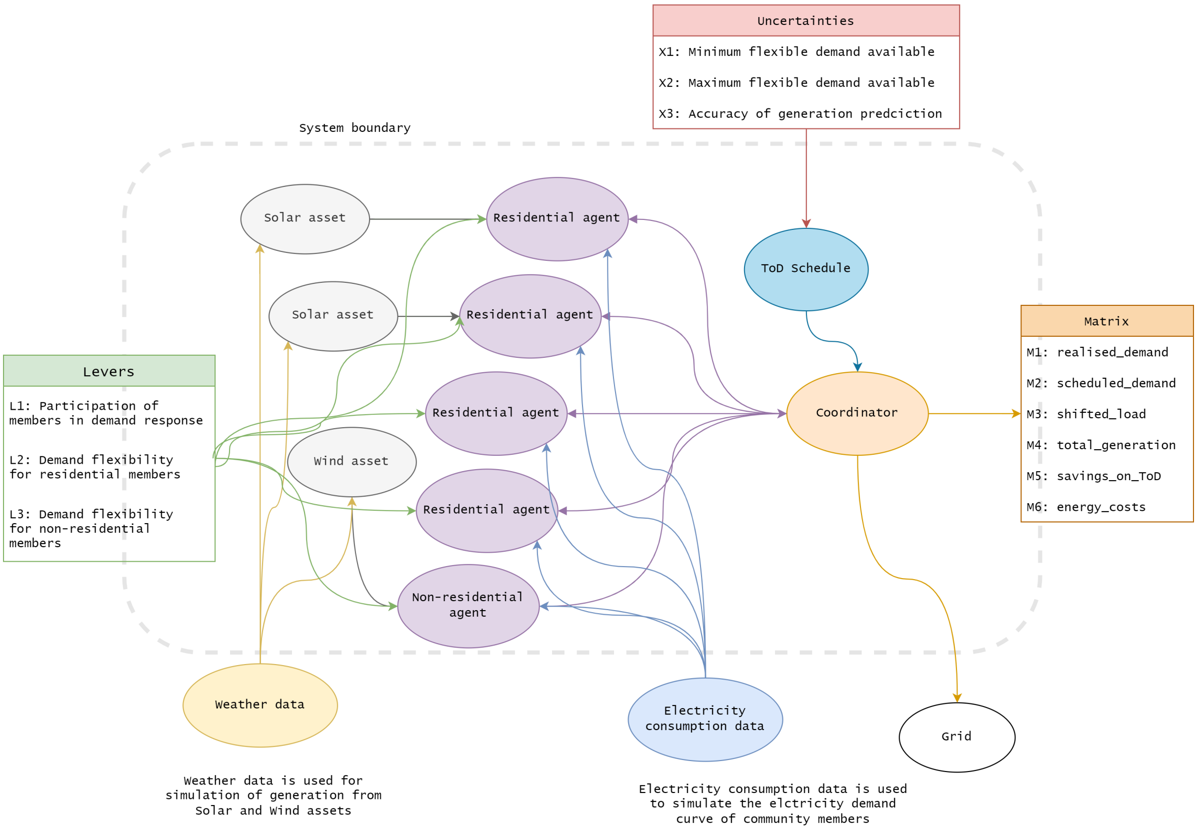

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Figure 3.2: Conceptualized model showcased as a systems diagram adapted from (Enserink et al., 2010)

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. Participation of a community member depends on two aspects. First, if the member has any flexible load which 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 as a flexible load.) Second, how much of a flexible load is available that day. For example, if a residential consumer do have a dishwasher or laundry machine which 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. Lastly, not all agents with demand flexibility would comply to demand response. This way, the system shown in the dotted box represents an energy community encoded into the agent-based model.

3.3. Data collection and information gathering

The conceptualized model shown discussed in Section 3.2 is based on qualitative data regarding the social structure of energy communities based on interviews enlisted in Table 3.1. 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 3.1.

Table 3.1: 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 Koirala et al. (2018)
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)

The 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.

4

Model formalization

This chapter formalized the conceptual model and adapted the XLRM framework for its python implementation. Further, Model and Agents ontology are discussed through UML diagrams and explanatory figures prepared to depict agents' behavior and interaction. These figures are later used as a blueprint for the python implementation of the model in the next chapter.

4.1. XLRM framework adaptation

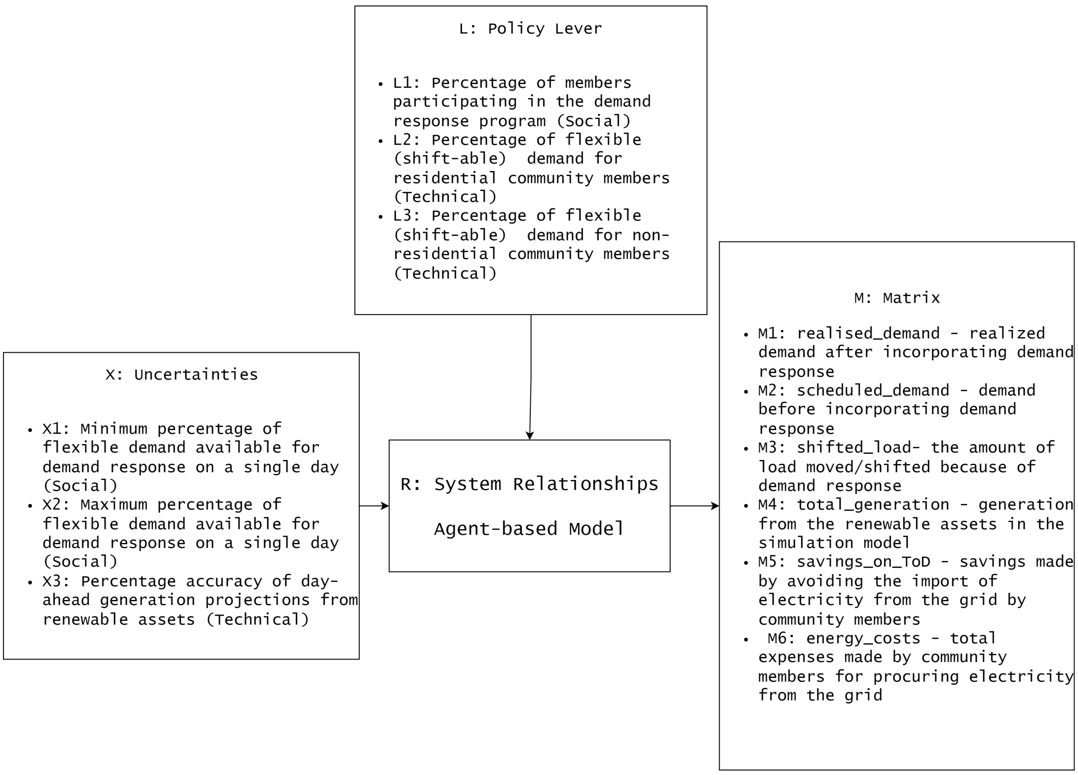

Figure 4.1: XLRM framework adapted for the model

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 4.1 showcases the XLRM framework adapted for this model. Each block of this framework is further explained below:

4.1.1. R: System relationships

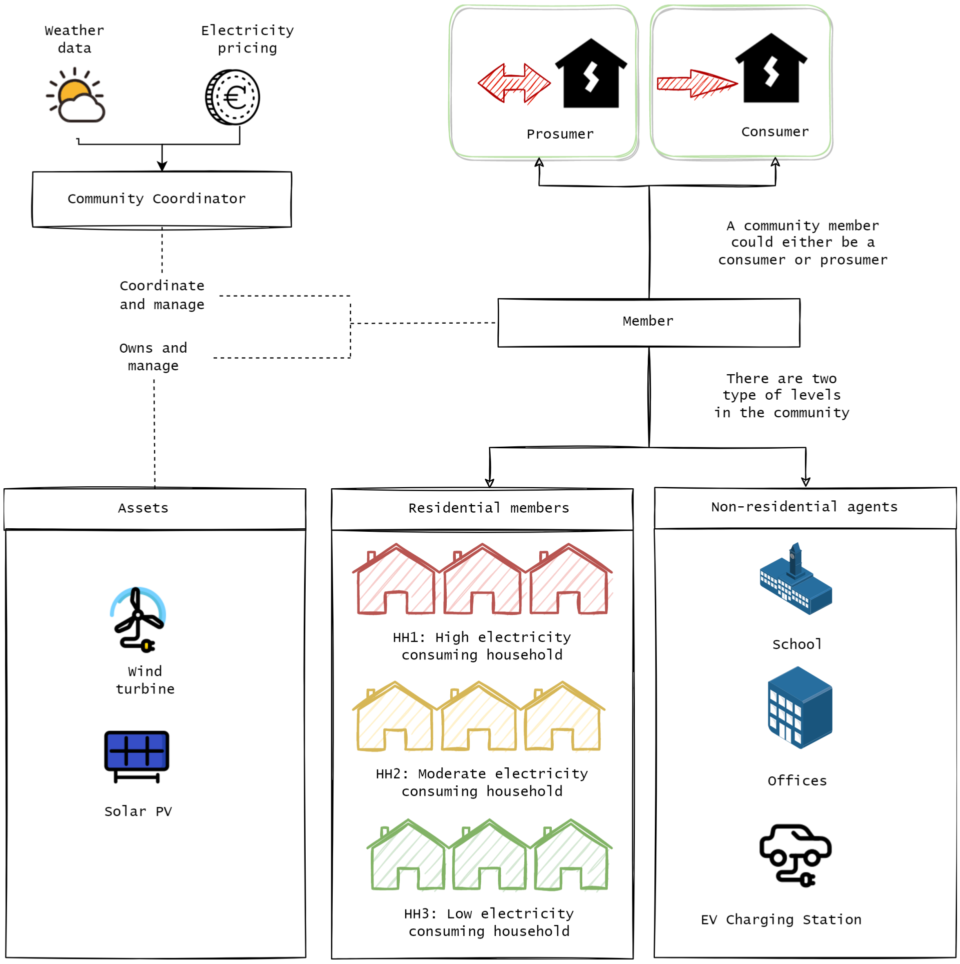

Figure 4.2: Agent relationships modeled for the research

System relationships in this context are represented by the model. The model is a scaled-down replica of system relationships in an energy community and the formalise representation of model is shown inFigure 4.2. 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 3.2.

4.1.2. L: Policy levers

The policy lever is 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.

4.1.3. X: Uncertainties

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.

4.1.4. M: Performance matrix

Lastly, the outcomes of the model simulation are captured using the performance matrix shown on the right-hand side of Figure 3.2 and Figure 4.1. This model has five performance matrices to evaluate the performance of the community to answer the research question and they are as follows:

1. *The total energy cost for the community* is the sum of the amount spent on supplying the electricity to the community members for the duration of the simulation run.
2. *The total energy cost for each agent type* is the average cost of electricity for both residential and non-residential agents.
3. *Total generation from assets* is the total electricity supplied by the community assets aggregated over agent type.
4. *Total electricity consumption by agents* is the aggregated electricity consumption for both residential and non-residential agents.
5. *Saving on energy cost because of ToD* is the amount saved on electricity purchase by demand response by community members.

4.2. Model Ontology

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 community coordinator. Different types of community members are explained in the Section 4.3.1. These agents act/react to each other based on the information available to them and decision drivers shown in Figure 4.3.

The model is run (or simulated) for the duration of a year. 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.

4.3. Agents Ontology

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 4.4, 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 4.3.3. The coordinator class represents the community coordinator that is responsible for balancing the supply and demand of electricity in the energy community. Lastly, the Member class represents the member of the energy community further explained in the Section 4.3.1.

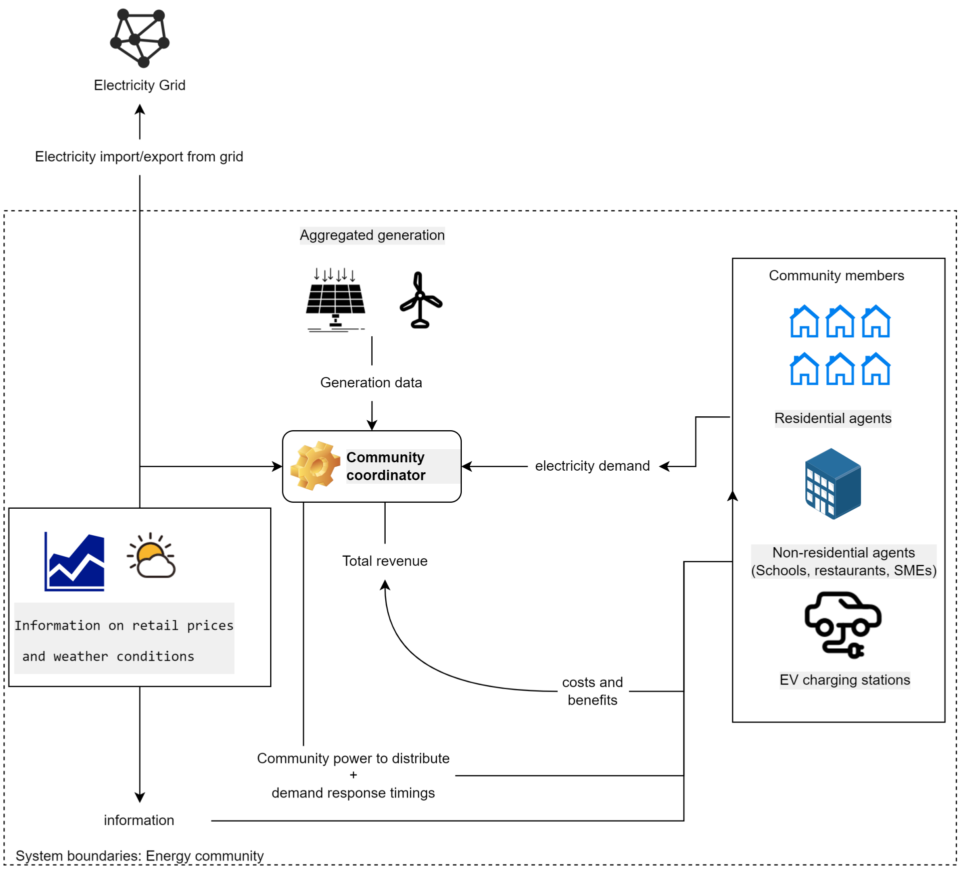

Figure 4.3: Community energy model setup

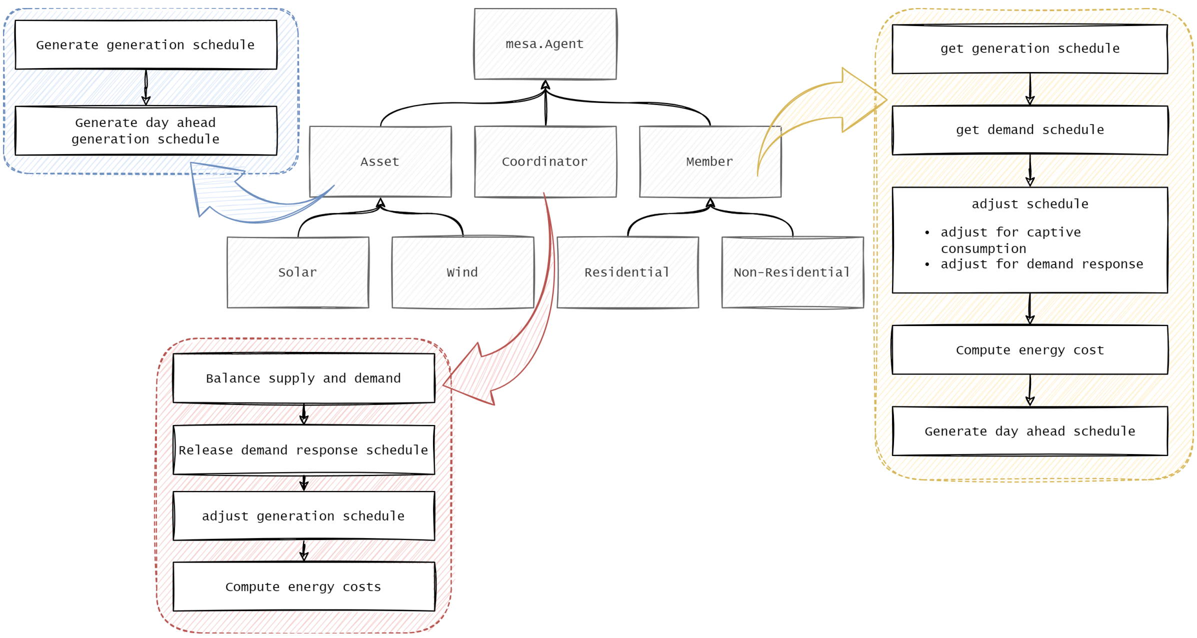

Figure 4.4: Agent ontology in the model

4.3.1. Agents: Community members

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 generation with other community members. The conceptualization of assets owned by prosumers in the community is further explained in the Section 4.3.3. The number of community members and their respective connected load and generation capacity does not change 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

This agent group represents 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 4.5 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)

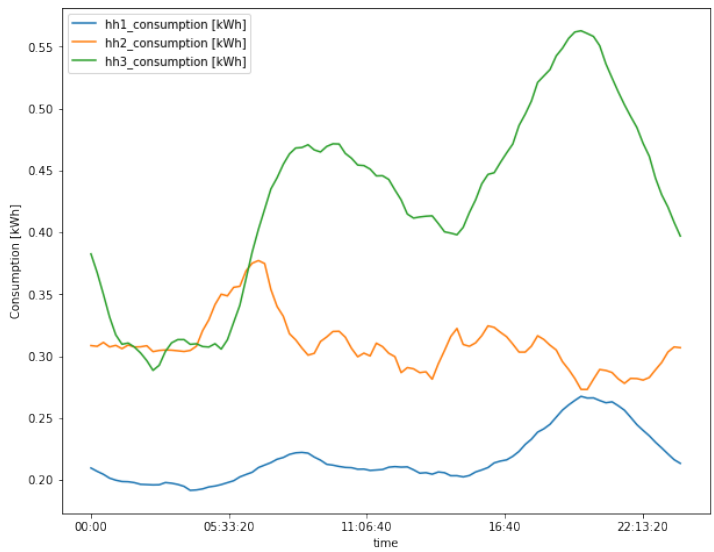

Figure 4.5: Annual average hourly load profile of residential members in the model

Non-residential community members

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 4.7 showcases the annual averaged hourly load profile of non-residential members in the model.

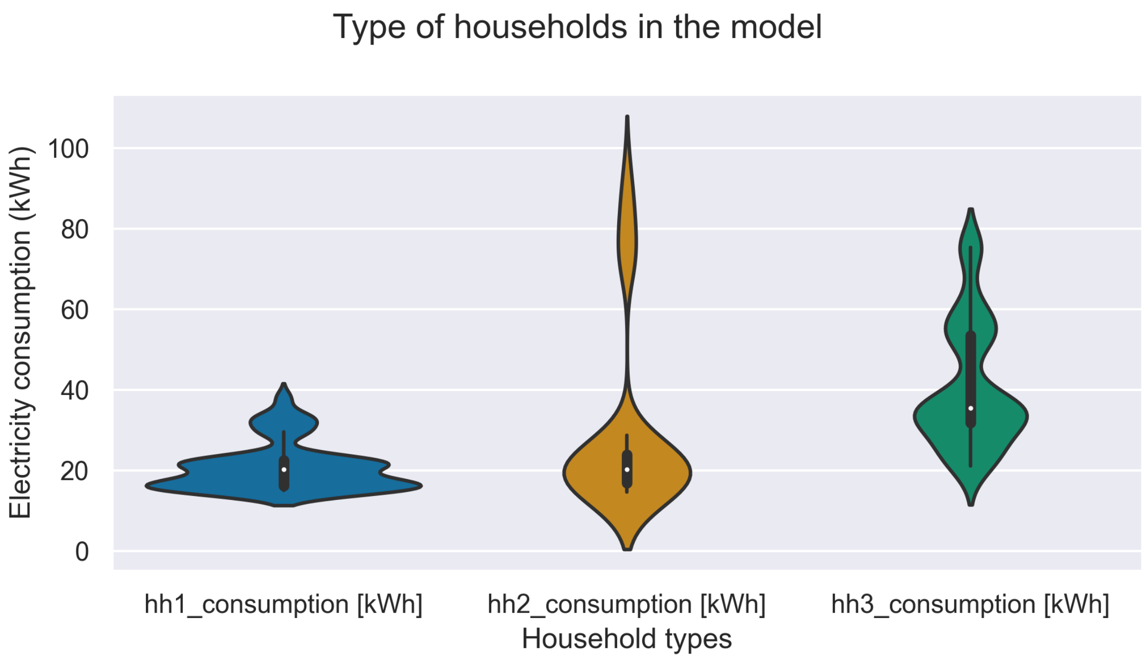

Figure 4.6: Type of households used in the model

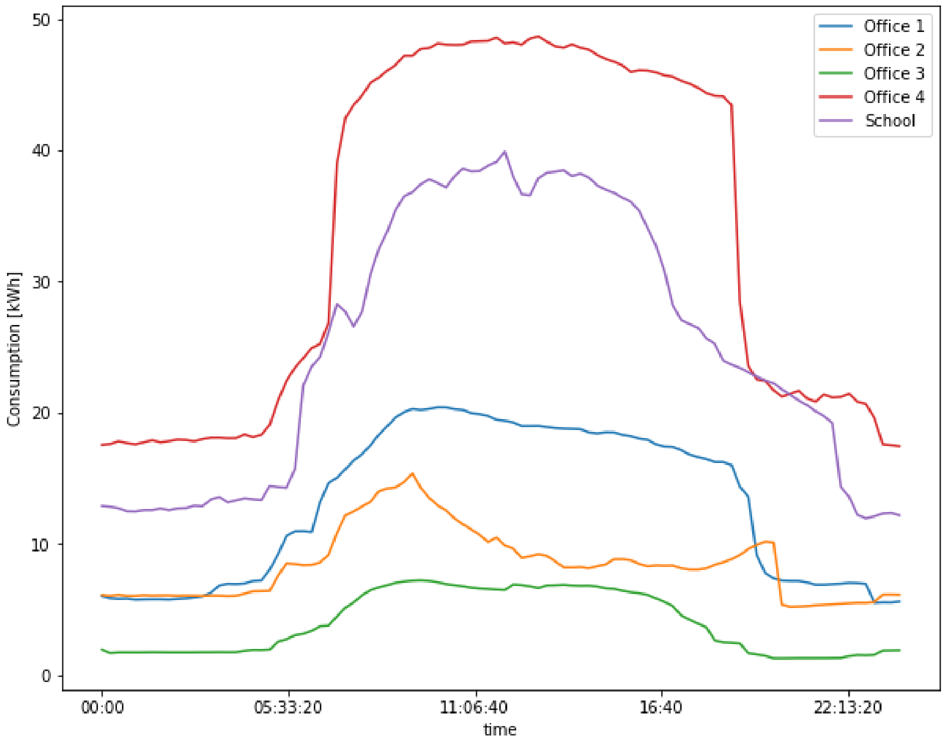

Figure 4.7: Annual average hourly load profile of non-residential members in the model

- **Office buildings**
  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 floor area. Table 4.1 contains the details of hourly consumption data sets for office buildings.
- **School**
  This represents the load profile of school buildings in the Netherlands. Further information about this building is shown in the Table 4.1.
- **EV-Charging station**
  With increased penetration of EVs in public and private transport, a provision of a 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 the charger and their ratings for future experiments.

Table 4.1: Details of non-residential profiles in the model database

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

4.3.2. Agents: Coordinator

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.

4.3.3. Agents: Assets

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 showcases the properties and methods used by 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 X capacity factor X total hours
Daily kWh from Wind turbine = $0.01328 * (rotordiameter(feet)))^2 * (averagewindspeed(mph))^3$

5
Model implementation

This chapter explains the model implementation and translation of formalized model to python using the mesa library. Apart from encoding, this chapter sheds light upon the community configuration mechanism used by the model. Lastly, the model is verified and validated for ensuring its "fit for purpose" to answer the research question.

5.1. Model encoding

The model is encoded in the python programming language using mesa, a python library designed for agent-based modeling.

In addition to this, XLRM framework by (Lempert et al., 2003) is used for setting up the experiments. This framework helps in distinguishing model parameters and outcomes as external factors (X), policy levers (L), and performance matrix (M). Further explanation on the adoption of XLRM framework is explained in the of Section 4.1 this report. 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 do their task at every time step. Energy community model uses "BaseScheduler" to activate the agent in the sequence they are initialized. This setup allows last activation of coordinator so that coordinator can compile the demand and supply for community members at the end of every time step and prepare demand response schedule for next time step (i.e. day).

5.2. Community setup

The model skeleton encoded in the 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 4.3.1 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 6.1. 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.

5.3. Verification

The methodology adopted for model verification is taken from Van Dam et al. (2012) and is explained in the Section 2.5.3. This model verification is performed to verify if the conceptual model and agent behaviors are translated to the python implementation correctly. The verification tests performed are explained below and are recorded in the validation evidence file.

5.3.1. Tracing the Agent Behaviour

Tracing the agent behavior was integrated into the encoding stage of the modeling. While model implementation, the agent behavior of each agent group was traced and checked with the conceptualization document. The tracing is done in python using tracking variables and text prompts for agent interaction. 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

5.3.2. Single-agent testing

Single-agent testing was only performed for community members and coordinators. Since assets are initialized by members, they are verified in the Section 5.3.3 and Section 5.3.4. The 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.

The Figure 5.1 showcases 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 single-agent test for the residential agent confirms the conceptualized behavior.

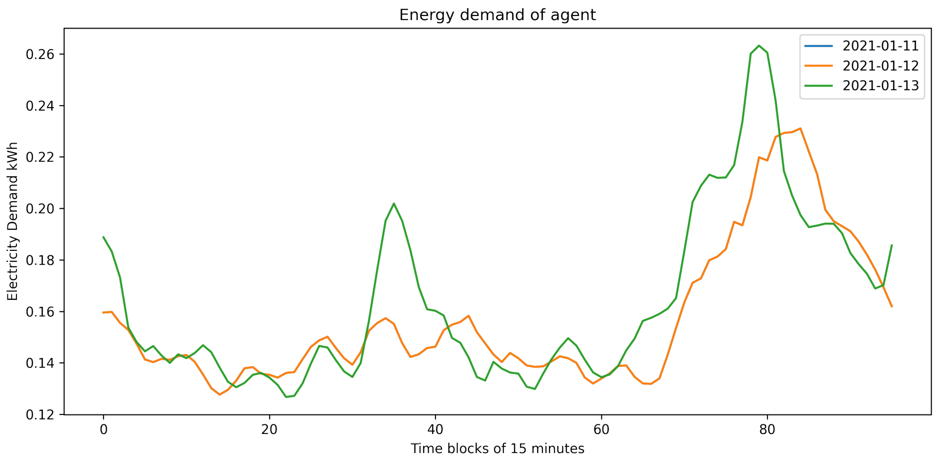

Figure 5.1: Verification check: Single-agent testing on a residential agent

Similarly, Figure 5.2 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 do not deviate significantly from each other. Therefore, it can be concluded that the single-agent testing has been conducted successfully for the model.

5.3.3. Interaction testing in a minimal model

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 5.3 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 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

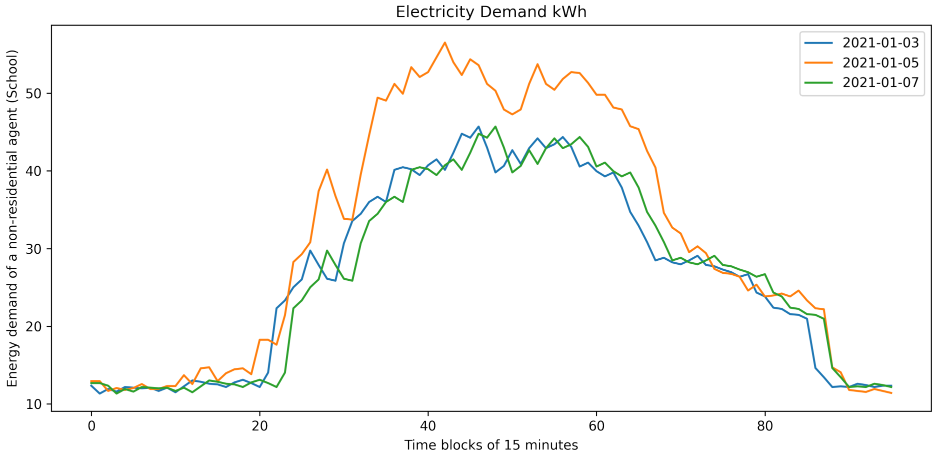

Figure 5.2: Verification check: Single-agent testing on a non-residential agent

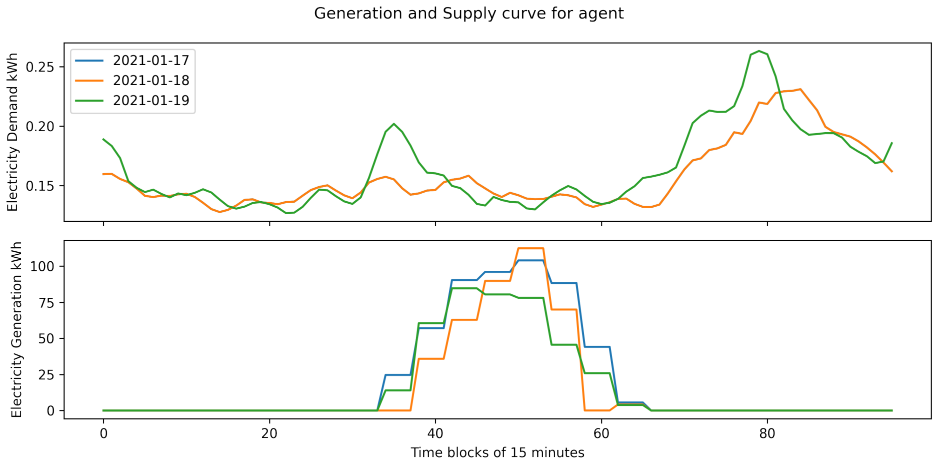

Figure 5.3: Verification check: Interaction testing

and respective asset) are interacting as per the model conceptualization. Thus, the agent interaction test is also performed successfully for the model.

5.3.4. Multi-agent testing

Lastly, 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 Figure 5.4 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.

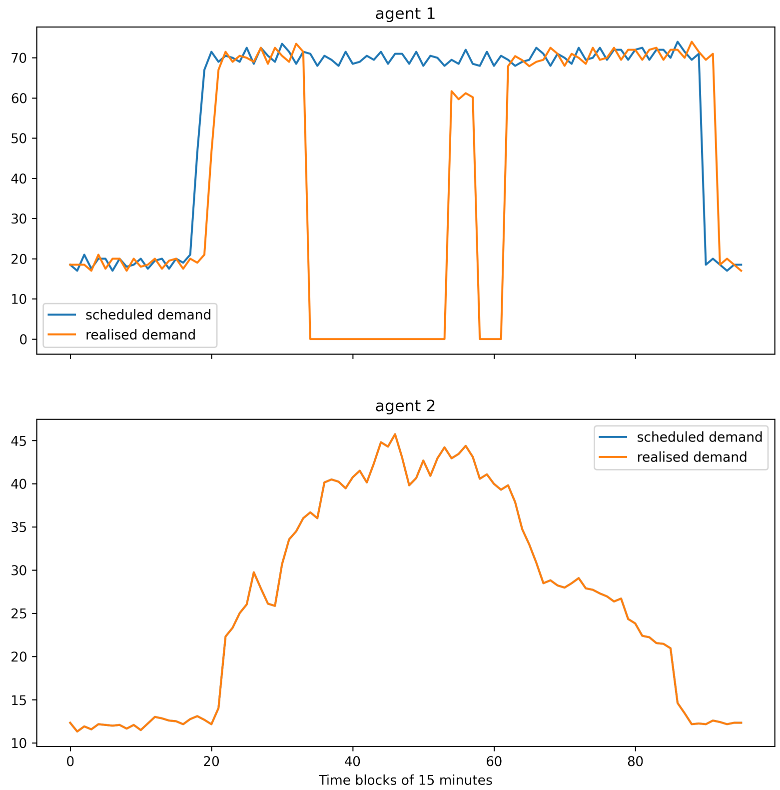

Figure 5.4: Verification check: Multi-agent testing

Extreme low	Extreme policy levers	Extreme high
0.00	L1: Percentage of members participation in demand response	1.00
0.1	L2: Percentage of total demand that can be shifted during demand response by residential community members	0.90
0.1	L3: Percentage of total demand that can be shifted during demand response by non-residential community members	0.90
Extreme low	**Extreme uncertainty values**	**Extreme high**
0.1	X1: Minimum percentage of flexible demand available for demand response on a single day	0.80
0.5	X2: Maximum percentage of flexible demand available for demand response on a single day	0.90
0.1	X3: Percentage accuracy of electricity demand forecast and day-ahead generation projections from renewable assets	0.90

Figure 5.5: Extreme policy levers and uncertainty values used for the validation tests

5.4. Validation

The model outcomes were validated after successful implementation and verification of the model. The objective of this verification step is to evaluate the extent the model is fit to answer the research question.

5.4.1. Face validation

For face validation of this model, this report along with verification and validation check results are shared with the problem owner (i.e. Croonwolter&dros team). In addition to this, these results are also shared with community managers with Mr. Willie Berentsen - cooperative Sterk op Stroom and Mr. Dominique Doedens - GridFlex Heeten energy community, and their response on the face validation is awaited.

5.4.2. Validation test setup

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.

5.4.3. 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 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

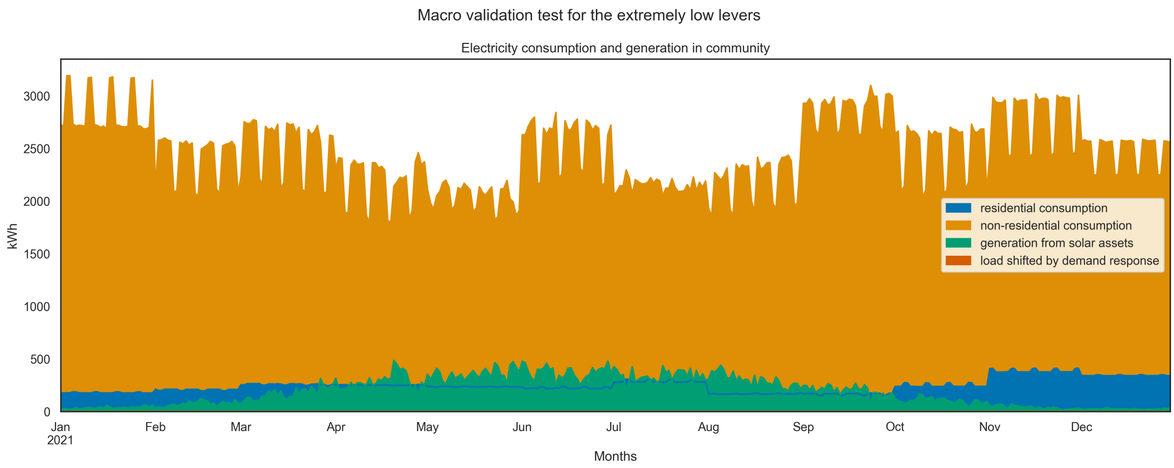

Figure 5.6: macro extreme low lever

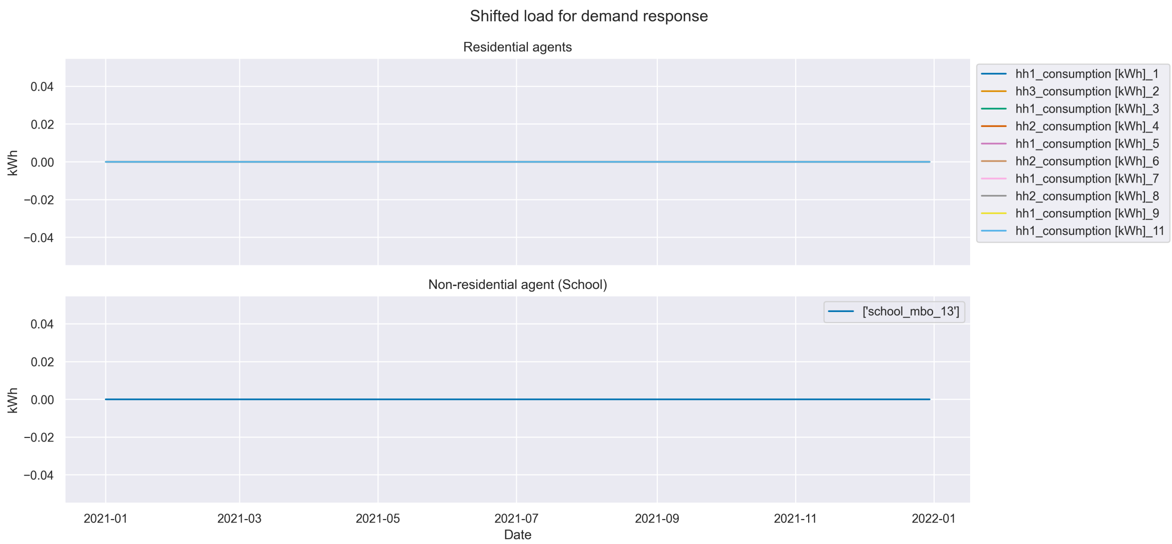

Figure 5.7: micro extreme low lever shifted load

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.

Macro validation check

The results of macro validation can be seen in the Figure 5.6. 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.

Micro validation check

Figure C.1 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 5.7. The individual agents also exhibited the expected behavior thus micro validation test for extremely low levers is conducted successfully.

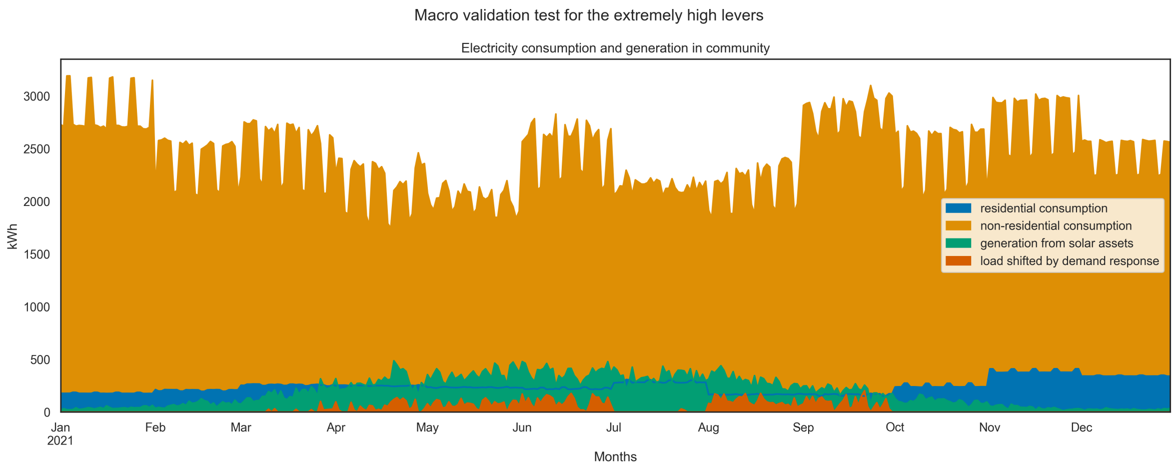

Figure 5.8: Community demand, generation, and shifted load under extremely high policy levers

5.4.4. 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.

Macro validation check

The model behavior for extremely high policy levers is captured in the Figure 5.8. The demand 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 5.8. Thus, the model exhibit expected behavior and macro validation check for extremely high policy levers conducted successfully.

Micro validation check

The individual electricity demand under extremely high policy levers is shown in the Figure C.2. Figure 5.9 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.

5.4.5. 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 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.

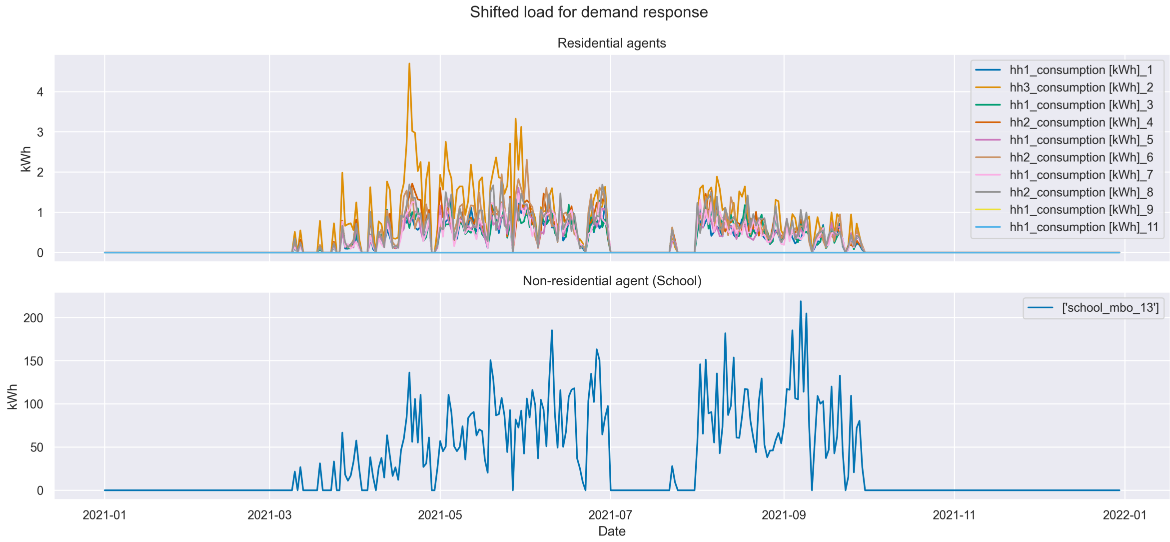

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Figure 5.9: Load shifted by community members under extremely high policy levers

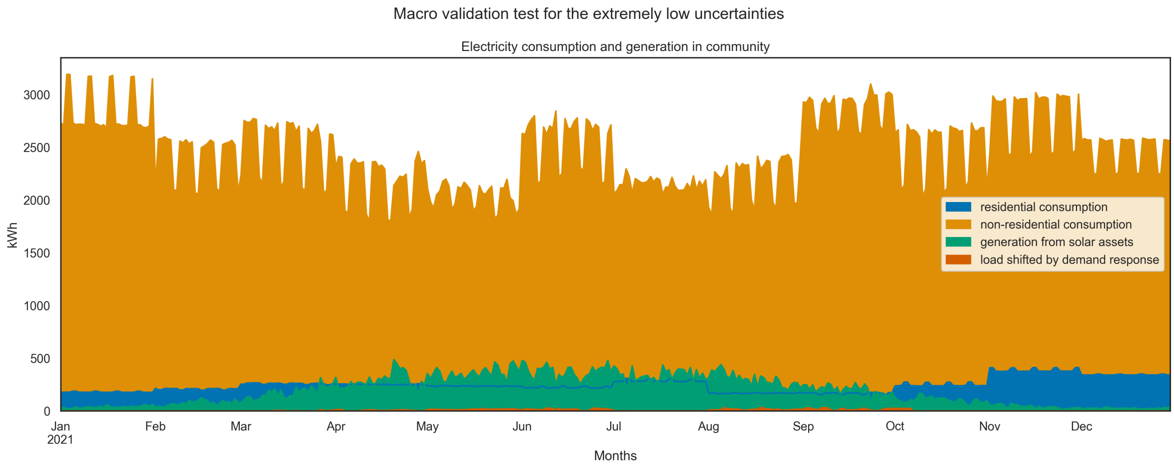

Figure 5.10: Community demand, generation, and shifted load under extremely low uncertainty

Macro validation check

Figure 5.10 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 5.8. Since the overall model behavior is explainable, a macro validation test for extremely low uncertainties was conducted successfully.

Micro validation check

The individual electricity demand of community members and generation from solar PV assets under extremely low uncertainty parameters are shown in the Figure C.3. Figure 5.11 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 5.9. 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

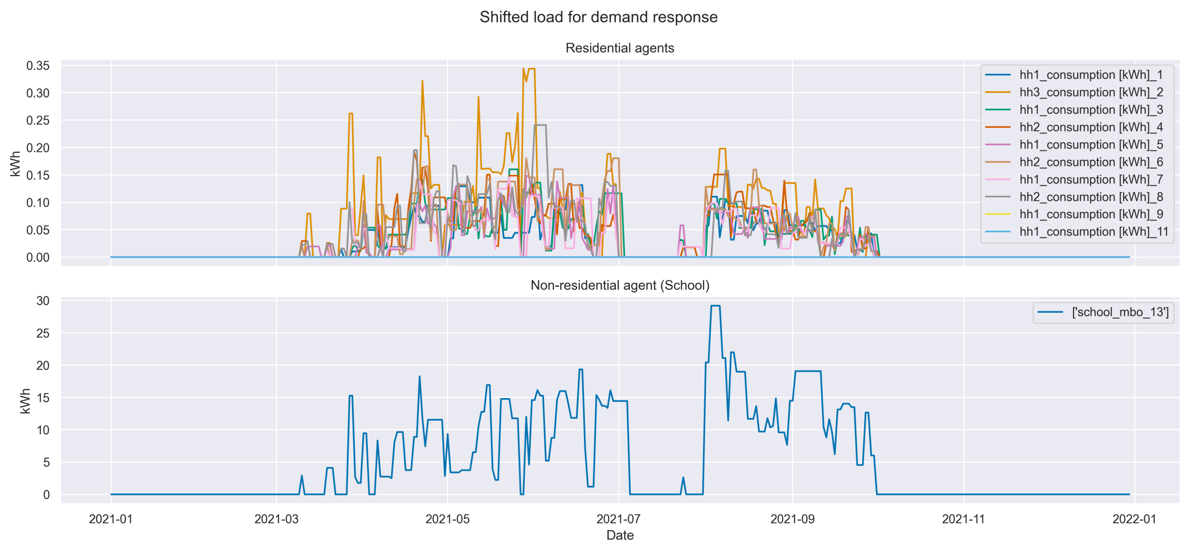

Figure 5.11: Shifted load of community members for demand response under extremely low uncertainty values

plausible behavior under extremely low uncertainty values and a micro validation test is successfully conducted.

5.4.6. 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.

Macro validation check

The overall model behavior under extremely high uncertainty parameters is shown in Figure 5.12. The increase in total load shift caused by demand response is visibly increased from the previous test shown in the Figure 5.10. Since the availability of flexible load is increased, total shifted load for the model is increased. Thus, the model has exhibited expected behavior under extremely high uncertainty parameters and a macro validation test is successfully conducted.

Micro validation check

The individual electricity demand and generation from solar PV plant is depicted in the Figure C.4. 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 5.13. Thus, agents exhibit expected behavior under extremely high uncertainty and a micro validation test is successfully conducted.

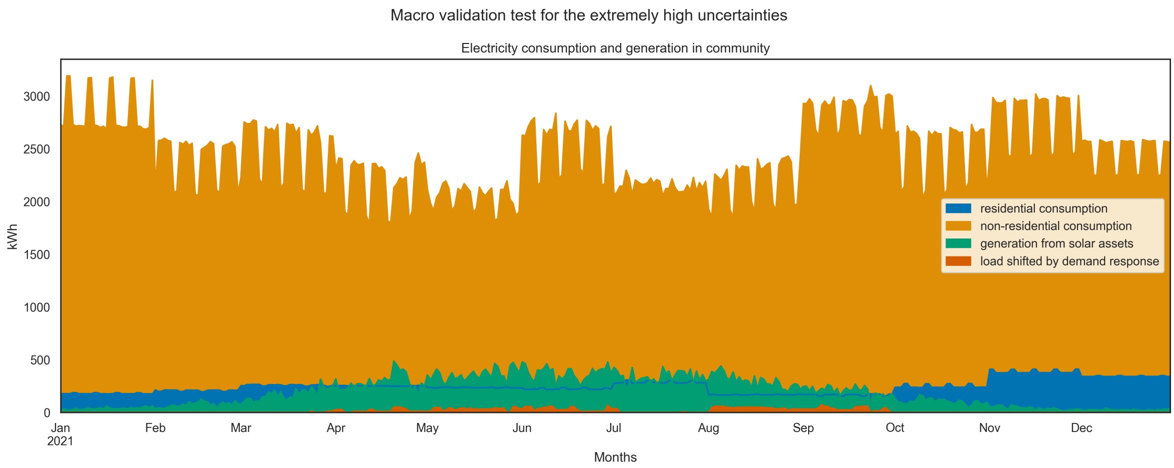

Figure 5.12: Community demand, generation, and supplied load under extremely low uncertainty

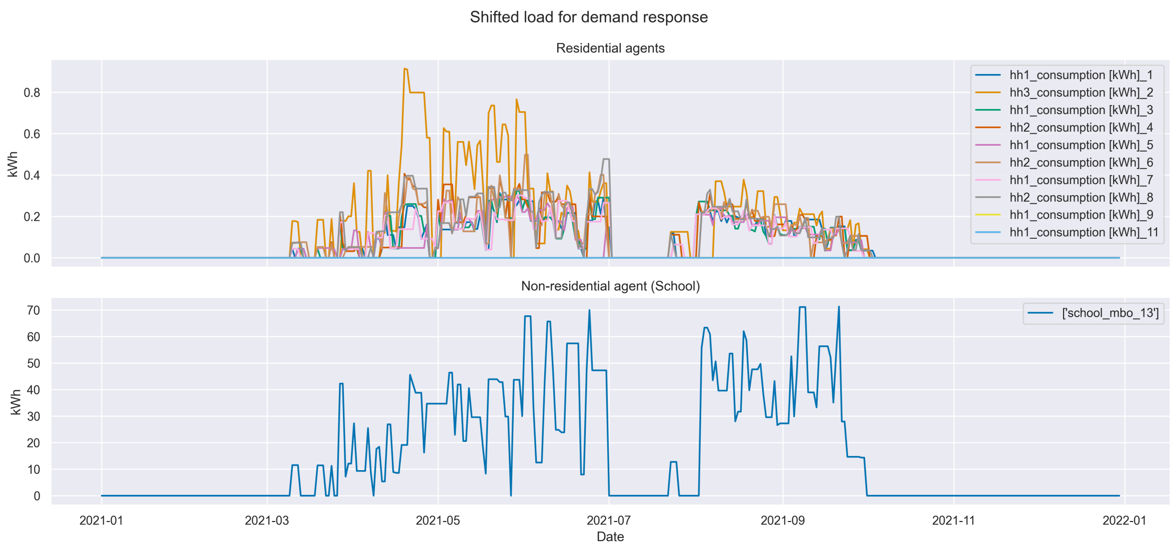

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Figure 5.13: Load shifted by agents under extreme high uncertainty values

6

Model usage: Experimentation

This chapter contains the community configuration and experiment setup used for performing the experiments to answer the research question. 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, defining the community configuration to perform experiments. The community configuration assumed for performing these experiments is explained in Section 6.1. Second, setting uncertainties and policy lever values. Section 6.3 explains the parameters range for policy levers and uncertainties used for designing the experiments. The model records a performance matrix at every step of simulation. This result collection mechanism is further explained in the Section 6.4. These experiments are facilitated by encoding an additional class to the code called the Experiments class. The ontology of this class is described in the Section 6.5. Lastly, Section 6.6 sheds light upon distributed computing and its utilization for performing these experiments.

6.1. 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:

6.1.1. Groen Mient inspired energy community setup

This 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 6.1. 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.

6.1.2. GridFlex inspired energy community setup

GridFlex is 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.

6.2. General setup

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).

6.3. Experiment design

Simulation experiments are performed by running the model for an energy community with a different set of input parameters and recording the modeling outcome for each input value. Simulating multiple iterations for a defined set of input parameters is called parameter sweep. A unique combination of input parameters is called experiment condition. As shown in Figure 4.1, model has two types of input parameters i.e. uncertainty values and policy levers. Thus, unique experiment conditions are created by combining different values for uncertainty and policy levers. Following is the parameter sweep defined for uncertainty and policy levers:

6.3.1. parameter sweep for uncertainty

Uncertainty values used by the model are discussed in Section 4.1.3. Two uncertainty scenarios are created for defining the uncertainty values for experiment design. Uncertainty scenario 1 is a "Neutral scenario" and a medium value range for each parameter is selected for this scenario. Uncertainty

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 4.5
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 4.7

Table 6.1: Configuration for groen mient inspired energy community

scenario 2 is an "Optimistic scenario" and a favorable (higher) value of uncertainty parameters is selected for this scenario. Table 6.3 showcases the parameter value defined for each uncertainty scenario.

6.3.2. parameter sweep for policy levers

Policy levers defined for the model are discussed in Section 4.1.2. Three policy scenarios are defined for designing the parameter sweep for policy levers. The first policy scenario is the "Baseline scenario" with all policy levers set to the minimum values. The second policy scenario is the "Optimistic scenario" with moderate values of policy levers that is relatively attainable. Lastly, the third policy scenario is a "Very optimistic scenario" and has policy levers set to the maximum. The value range specified for all three policy scenarios is shown in the

6.4. Results from the experimentation

All the model level and agent level performance matrices are elaborated in Section 4.1.4. All these mode 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. This result data-frame is exported as a .csv (Comma separated value: a format for storing data-frame) file and stored on the hard drive of the simulation machine. After running all the experiment setup, all the result files are read and compiled to evaluate the experiment outcomes and derive the conclusions.

6.5. Ontology of Experiment class

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 the Figure 6.1. 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. Distributed computing and its applicability for model simulation are discussed in Section 6.6.

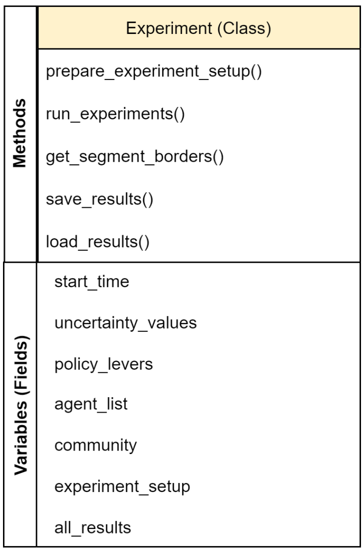

Figure 6.1: UML diagram of Experiment class

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 4.5
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 4.7

Table 6.2: Configuration for GridFlex inspired energy community

Uncertainty parameter	Neutral Scenario	Optimistic Scenario
X1: Minimum (lower cap) availability of flexible demand	0.4	0.8
X2: Maximum (upper cap) availability of flexible demand	0.5	1
X3: Accuracy of demand response schedule	0.5	0.9

Table 6.3: Parameter sweep for uncertainty values

Policy levers	Baseline scenario	Optimistic scenario	Very optimistic scenario
L1: Percentage of community members participating in demand response	0	5	7.5
L2: Flexible demand as percentage of total demand for residential members	0.1	0.5	1
L3: Flexible demand as percentage of total demand for non-residential members	0.1	0.45	0.9

Table 6.4: Parameter sweep for policy levers

6.6. Experiments run: Distributed computing

Distributed computing for simulation runs 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 are eight (i.e. 2^3) and a total number of a unique combination 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.

7 Results

This chapter will showcase the results from the experiments described in the previous chapter.

7.1. Results for Groen Mient inspired energy community setup

7.1.1. Scheduled demand vs realised demand

7.1.2. Shifted load

7.1.3. Generation from community assets

7.1.4. Energy costs and savings on electricity cost by incurring demand response

7.2. Results for GridFlex inspired energy community setup

7.2.1. Scheduled demand vs realised demand

7.2.2. Shifted load

7.2.3. Generation from community assets

7.2.4. Energy costs and savings on electricity cost by incurring demand response

8
Conclusion

A conclusion.

9
Discussions

Value added to the academic body of knowledge central to the main theme of study through this research.

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A
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.

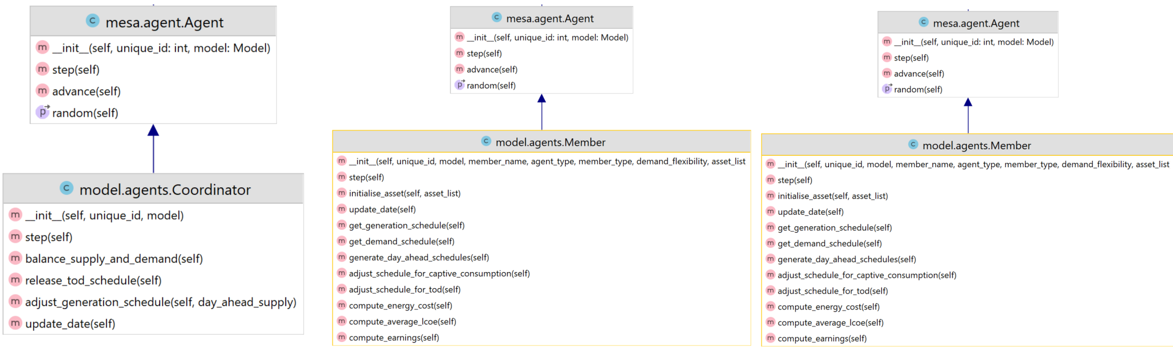

Figure B.1: UML diagram of Asset class. 'm' stands for methods in the class.

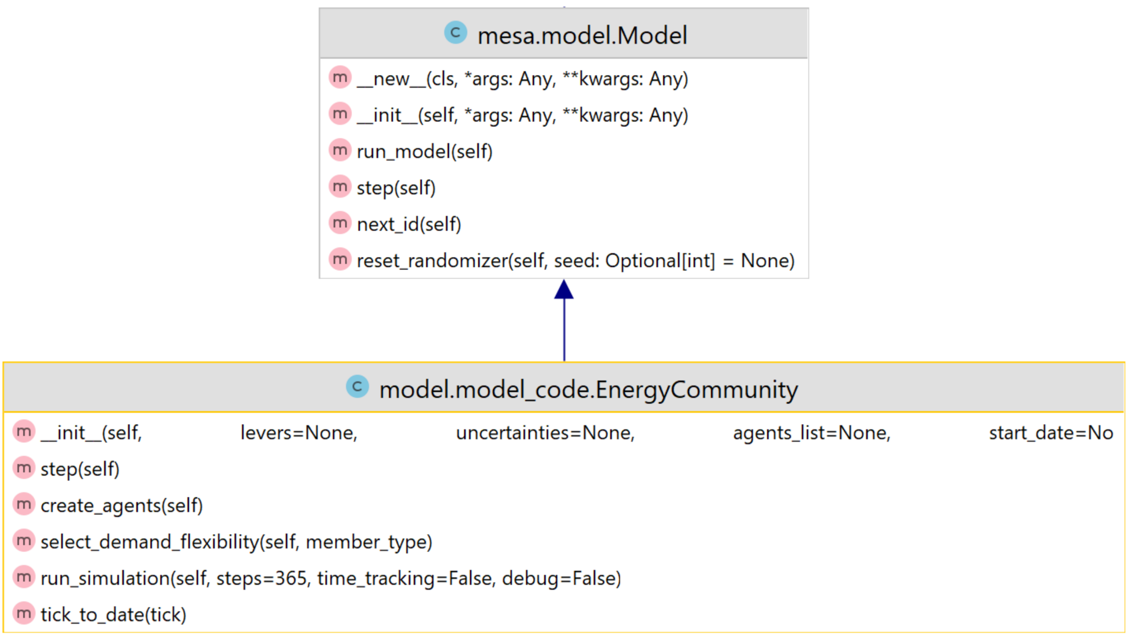

Figure B.2: UML diagram of the model setup in python. 'm' stands for methods in the class.

C
Validation plots

This appendix contains additional plots generated during model validation.

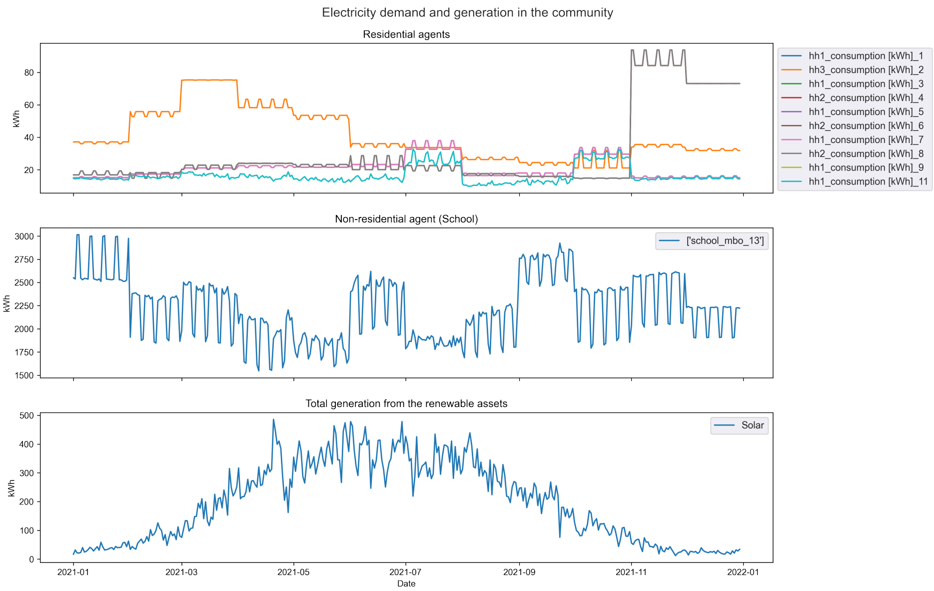

Figure C.1: Community members' demand and generation under extremely low policy levers

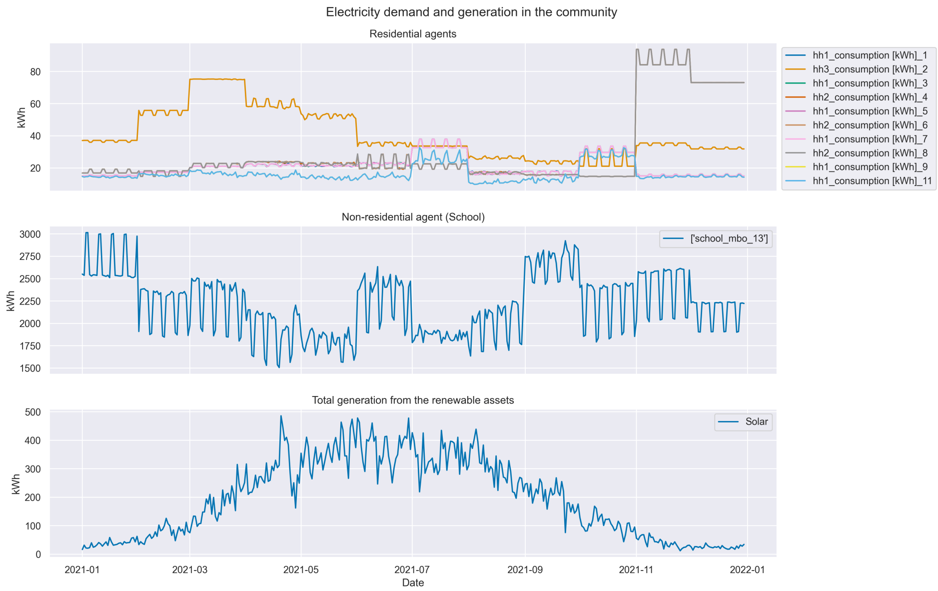

Figure C.2: Community members' demand and generation under extremely high policy levers

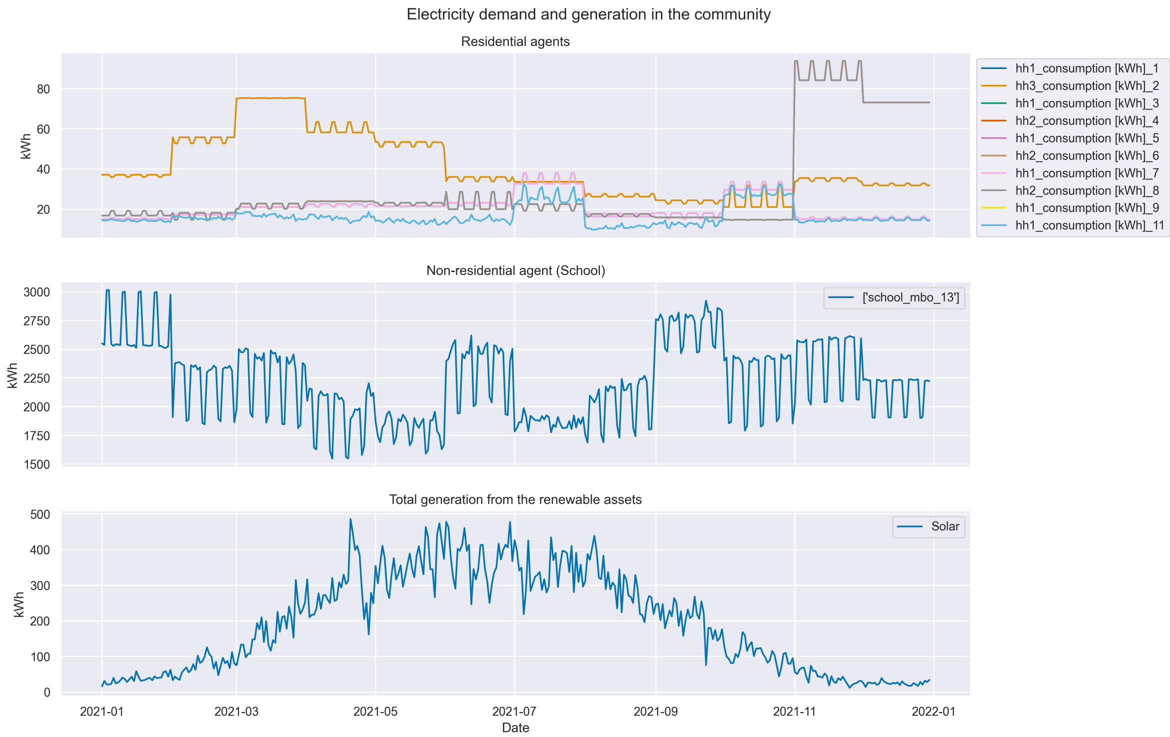

Figure C.3: Community members' demand and generation extremely low uncertainty parameters

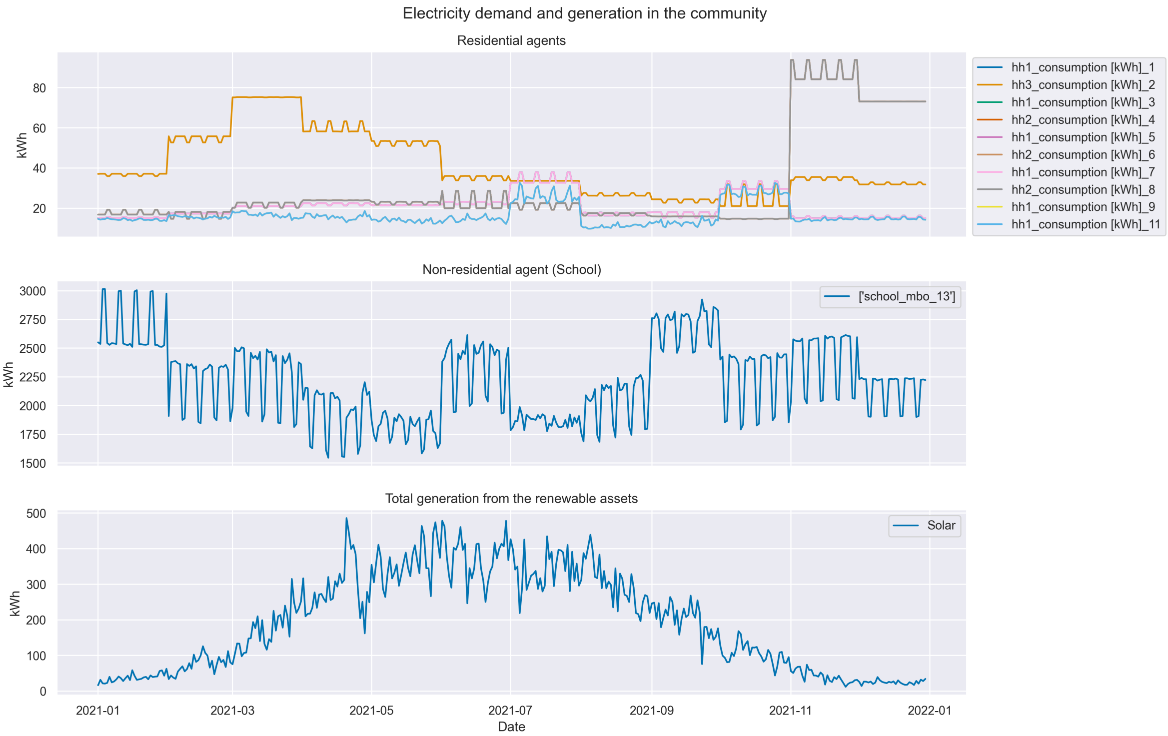

Figure C.4: Community members' demand and generation under extremely high uncertainty parameters