Residential Demand Response

Exploring household reliability

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Katherina Konst

Delft University of Technology

TU Delft

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by

Katherina Konst

Student Name	Student Number
Katherina Konst	4568044

Chair:	Emile Chappin
First supervisor:	Özge Okur
Project Duration:	February, 2024 - August, 2026
Faculty:	Faculty of Technology, Policy and Management, Delft

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Preface

This thesis was written as the final part of my graduation from the master EPA. I learned a lot while writing this thesis. It only took me two and a half years to finish it. I wish I had found more time during that time to improve this work. I both feel like time has stood still during these past years and that a lot has happened. Anyways.
I would like to express my deepest gratitude to my first supervisor Özge Okur. She has been incredibly supportive and patient during the process of writing and finishing this thesis. I genuinely do not see how I could have finished this thesis without her.
Another bound of gratitude goes to my chair, Emile Chappin who has been very accommodating to my sporadic progress.

Katherina Konst
Delft, August 2026

Summary

The balancing of demand and supply is an important part of energy systems. Traditionally the supply would alter its production to ensure this balance. However, rising need in flexible resources has increased the interest in the demand side as a potential source of flexibility. The demand side could offer flexibility through demand response. This involves consumers altering their energy consumption based on external factors. One sector that is seen as having great potential for demand response is the residential sector. This potential is often discussed in context of an aggregator who pools their resources, as it is difficult for individual households to participate in electricity markets. Thus the topic of this thesis is aggregator provided Residential Demand Response (RDR).

This would create a situation were the energy system partly relies on aggregators who rely on households to offer a source of flexibility. Households energy behaviour tends to be uncertain however. This could make it difficult for aggregators to deliver on offered flexibility. Thus it is important for the evaluation of RDR to explore the reliability of households in their engagement with aggregator provided residential demand response.

The lack of experience with Residential Demand Response (RDR) means simulation and forecasting models are needed to evaluate its potential value. However, these models tend to not portray household behaviour in a way meaningful way. This limits the insights these models can provide. Especially since the uncertain energy behaviour of households is a large issue with RDR. Thus a model that does include household behaviour in a meaningful way, will be able to evaluate RDR in a different way.
This lack of experience also means it is difficult to evaluate longer term engagement with RDR. Pilots and behavioural studies tend to focus on how to improve household participation and initial engagement. Furthermore, habitual energy behaviour, behaviour that forms after longer term engagement, is different from initial (one-shot) behaviour. Thus RDR evaluation would benefit from a longer-term perspective.

The objective of this thesis is to explore the reliability of households altering their energy demand under an aggregator with a model that represents household behaviour in a meaningful way. This exploration will furthermore be performed through the lens of long-term engagement. To this end an agent-based model was designed and implemented.

The model focusses on the interaction between households and aggregators, and household energy behaviour. Aggregator interaction with electricity markets does influence how they interact with households. Since it was not the focus of this research, its influence was included through external factors. Households and the aggregator interact through the RDR program. RDR can exist in many different forms. A specific configuration was chosen that best suits the purposes of this study. The included RDR program consists of aggregators scheduling the semi-flexible appliance uses of households. The shifting of appliance use away from their normal time is how aggregators gain flexibility. Aggregators design their schedule day-ahead based on household provided appliance need and expected availability. Household behaviour has been conceptualized as the combination of routine and a decision-function. Routines inform expected availability, actual availability and appliance type specific preferred times of use. The decision-function determines whether the motivations for compliance with the RDR program outweigh daily inconveniences.

The model results show that households are unreliable in their use of semi-flexible appliances under an aggregator provided RDR program. Aggregators would have to manage uncertainty in both capacity and program compliance in their daily operations. This also implies that the potential value of RDR to energy systems would be small. Large variations in offered capacity and uncertainty in the delivery of said capacity would make it difficult for system operators to plan and secure system balance. This is compounded by the question whether the potential small quantity of loads offered would be worth the complexities of implementing an unreliable source.

Contents

1 Introduction

1.1. Problem formulation

The balancing of demand and supply is an integral part of energy systems (Okur et al., 2021). Traditionally, the supply tries to meet the inelastic demand by producing energy when the demand needs it (Paterakis et al., 2017). This paradigm has been gradually shifting as energy efficiency (O′Connell et al., 2014), renewable energy source generation (Okur et al., 2021) and active demand side participation (Paterakis et al., 2017) have become important considerations in energy systems. This has complicated the balancing of energy grids and thus increased the need for flexibility. A number of solutions are explored in the literature to improve grid flexibility. Flexible generation resources can offer flexibility by ramping their production fast up and down. Interconnection can smooth fluctuations in power output through funnelling energy to other regions. Energy storage can help balance the grid during over-or under supply. Lastly, the demand side can offer flexibility through demand response (Okur et al., 2021).

Demand response (DR) entails consumers altering their energy consumption in response to external factors (Okur et al., 2021). In DR programs, providers try to influence participant's energy consumption through incentives or prices. These programs can consist of participants reducing a specific load over a given time period, or participants providing load reductions in response to economic signals (Paterakis et al., 2017). The timing of the program signals may also vary per program from daily to a couple of times a year (Parrish et al., 2020). The flexibility demand response can offer is especially suited for the uncertain and fluctuating generation of renewable sources (O′Connell et al., 2014).

The main sectors of interest for demand response are industrial, commercial and residential (Okur et al., 2021). The industrial sector has many big energy users. Temporary interruptions in their processes can result in significant load reductions. However, industrial users have complicated processes with different levels of criticality and production targets to uphold. This means they may not be able to reduce their consumption whenever the system needs their flexibility critically. This unlike commercial and residential consumers whose main concern with interrupting energy usage is comfort. Commercial consumers are suited for thermal-based DR, as larger rooms keep their temperature longer. This means interruptions in temperature-based appliances can be longer without causing discomfort. Residential consumers are suited for direct load control and price-based programs (Paterakis et al., 2017).

The focus of DR has been on industrial and large commercial consumers (Muratori & Rizzoni, 2016), but interest in residential demand response (RDR) has been growing. Residential energy consumption is responsible for about 30% of total energy usage (Qazi & Flynn, 2016; Wang et al., 2018). Also, unlike industrial consumers, the consumption of residential and commercial consumers is growing (Okur et al., 2021). It is expected that residential consumption will continue to grow with continued economic development (Qazi & Flynn, 2016; Wang et al., 2018), technical advancements and urbanization (Khan et al., 2021). Residential energy consumption is also a large contributor to the peaks and troughs in the system load profile (Gyamfi et al., 2013; Qazi & Flynn, 2016). Thus this sector has great potential for demand peak reduction (O′Connell et al., 2014). The potential for residential flexibility can also be seen in the availability of their loads. Their loads are conceptually available all year around and 24h a day for load management (Sajjad et al., 2014).

However, it is difficult to impossible for households to participate in electricity markets as the individual loads of households participating in RDR are small (Okur et al., 2021). This is why a common proposal for RDR is through the use of an aggregator (O'Connell et al., 2014). An aggregator is an actor who can participate in electricity markets and bid by pooling household's assets (Okur et al., 2021).

Another complication of RDR is that households tend towards economically irrational behaviour when it comes to their energy consumption (O'Connell et al., 2014). Studies have shown households tend to be unresponsive to energy prices (Gyamfi et al., 2013). This is an issue as the main incentives for RDR are financially based. Furthermore, there is high variability in residential energy consumption (Khan et al., 2021) and the external factors influencing it (O'Connell et al., 2014). This makes household energy behaviour difficult to predict and thereby uncertain. This in turn makes it difficult for aggregators to offer flexibility in energy markets as they base their bids on the expected behaviour of households.

1.2. Literature review

In this section, the literature on household energy behaviour in demand response will be discussed to reach the objective of this thesis. The structure is as follows. Firstly, a summary will be provided of the qualitative literature on RDR-related household behaviour. Followed by a synthesis on RDR model-based research. Lastly, the objective of this thesis will be formulated.

1.2.1. Qualitative research on household behaviour

One of the biggest challenges for adopting demand response is effectively controlling the demand (O'Connell et al., 2014). Thus, it is important for evaluating the potential of demand response to understand the energy consumption behaviour of households. This is why this part of the literature review will look into how households behave under RDR. To this end, there will be looked at general household energy behaviour and RDR related household energy behaviour.

General household energy behaviour

It is difficult to understand and predict household energy behaviour in general. One of the reasons for this is the variability of their energy usage. The variability is significantly different between households. Trends in variations can be attributed to, among others, economic factors and household characteristics. However, large variations in energy usage of households can still be noted when these factors are controlled for (Gyamfi et al., 2013). As mentioned households do not show economically rational behaviour in their energy consumption. This means a number of things about their behaviour. Firstly, households are motivated by other factors than price (Darby, 2020) and are influenced by external factors as well (O'Connell et al., 2014). They also have different priorities next to their energy consumption thus may not be concerned with minimizing their electric costs (O'Connell et al., 2014). Secondly, households do not act to maximize their utility as economic theories assume. They cannot make the consistent rational decisions that maximizing their utility would entail (Gyamfi et al., 2013).

RDR-related household energy behaviour

In energy behaviour, a distinction can be made between habitual and one-shot behaviour. Habitual behaviour relates to household routines and the energy usage associated with that. Examples of habitual behaviour are cooking or washing. One-shot behaviour relates to changing these routines. Examples of one-shot behaviour are acquiring a new appliance or participating in an energy efficiency program (Ellabban & Abu-Rub, 2016). In the initial 'activation' phase of one-shot behaviour, households need to make conscious decisions to adapt their routines. Once these routines have been adapted, energy habits are formed in the 'continuation' phase (Valkering et al., 2014). The decision to participate in RDR would thus be considered one-shot behaviour. Habitual behaviour could be formed through continued engagement with the program. This distinction can also be found in the qualitative literature.

Studies analysing RDR experiences have identified motivators and indicators for both initial participation and continuing engagement with RDR programs. Siitonen et al. (2023) provides a thematic synthesis of 12 RDR pilots. They wanted to understand household participation and engagement with RDR. The motivational factors influencing participation were identified as financial incentives, environmental issues and novelty. For improving engagement based on interaction between the RDR provider and customer, they found that community focus, face-to-face interaction, text-based communication and mobile communication were important factors. For improving engagement through feedback information, they found that type of information, monitoring systems and, data security and privacy were influential factors. Parrish et al. (2020) did a review of RDR trials, programs and surveys. They found that the main motivator for initial participation in a RDR program was financial. For continued engagement, however they found that participants were continuing to weigh the potential savings against the effort, time, convenience and comfort participation entailed. Barsanti et al.(2020) found that financial incentives had limited success in engaging households. They also recommend automation in RDR for reducing high-dropout rates. However, Darby (2020) found that even with automation, demand to be situated and social. They reviewed a RDR thermal storage demonstration for their research. They found five themes that contributed to a good customer experience in their review of the demonstration. These are comfort, cost, connectivity, control and care. They do not think it realistic to see implementation of RDR as a self-regulating, wholly automated, fit-and-forget process. This is supported by O′Connell et al. (2014) who state that automation will still need to include some household interaction. This is because household interaction does not only concern economic decisions, but physical availability of their demand as well.

Conclusion

The described qualitative literature provides insights into household energy behaviour. These are listed below:

- Variations in household energy demand can be partially explained by economic factors and household characteristics
- Households do not optimise their utility or make continuous rational decisions in their energy behaviour
- Households do not only consider price when making energy related decisions
- Even with automated control, household energy behaviour is dependent on their interaction with the program

Furthermore, household energy behaviour can be characterised in one-shot and habitual behaviour. The insights from the RDR experience studies show how households can be motivated into the one-shot behaviour of deciding to participate in RDR programs. These studies also provide insight into what influences the transition from one-shot to habitual behaviour through analysing household RDR engagement.

1.2.2. Model-based research on RDR

There is a lack of experience with demand response. Because of this simulation and forecasting models are needed to evaluate the value demand response can provide to energy systems. These models can provide insights into the long-term benefits and impacts of demand response (O′Connell et al., 2014). Household behaviour is an important factor to consider when modelling as their actions directly influence demand response. In this section, the model-based literature related to RDR will be analysed on whether the behaviour of households has been included in a meaningful way. For this analysis, the purpose of the paper needs to be taken into account when appraising the sufficiency of the captured household behaviour. To this end the model-based literature has been grouped based on the purpose of the paper. These groups are: estimating consumption behaviour, evaluating system implications of RDR and evaluating specific RDR programs.

Estimating household energy consumption

In this paragraph an analysis will be provided on whether the models used for estimating household energy consumption captured household behaviour sufficiently.
Household behaviour is relevant for the purpose of Shao et al. (2013)'s paper in the way that it is needed as input for the designed appliance models. The models account for this input but focus more on the physical factors. Household behaviour is thus mostly out of the scope of this paper. Zhang et al. (2023) and Khan et al. (2021) use machine-learning methods trained on consumption data to predict energy consumption. The accuracy of these types of models is dependent on the amount and quality

of available consumption data. There is not a lot of data available for demand response as this is a new initiative. However, since these models are not used in the pursuit of DR evaluation, this does not reflect on the sufficiency of captured household behaviour.

Evaluating RDR programs

In the following paragraph, the papers focused on evaluating specific RDR programs will be analysed on the sufficiency of captured behaviour. Ul Hassan et al. (2015), Mehta et al. (2017), Muratori and Rizzoni (2016) and Goudarzi et al. (2021) all evaluate programs were algorithms optimize individual household's energy consumption. These algorithms do include household specific characteristics, but function to minimize energy costs within the constraints provided by these parameters. In Ul Hassan et al. (2015) and Mehta et al. (2017) these algorithms replace the interaction of households with the RDR program by deciding how households should consume energy. As mentioned, households would still influence their consumption behaviour even with the support of automated control. Thus these models do not include household behaviour. In Muratori and Rizzoni (2016) and Goudarzi et al. (2021) the behaviour of households is represented by these optimizing algorithms that only consider financial factors. Since these papers try to evaluate RDR programs, it is important that household behaviour is captured sufficiently. As mentioned in 1.2.1, households do not optimize their behaviour and consider more factors than financial ones when engaging with RDR. Interestingly, Goudarzi et al. (2021) do include a representation of households deciding to participate in the RDR program in their utility function. Thomas et al. (2019) use stochastically modelled changes in energy consumption-states to represent household behaviour. Since the probabilities of state-changes are extracted from data of the respective RDR program, the strength of the captured behaviour is dependent on the data. This is an important consideration as part of the purpose of the paper is to evaluate the RDR program. Thus the sufficiency of captured household behaviour is questionable here as this new program did not have much data.

Evaluating system implications of RDR

In the next paragraph, analysis on the sufficiency of captured household behaviour will be provided for papers whose purpose concerned evaluating the system implications of RDR.
Taherian et al. (2022), Kiguchi et al. (2021), Shao et al. (2010) and Sajjad et al. (2014) all use consumption data as the basis for their analysis. Taherian et al. (2022) and Kiguchi et al. (2021) use this data to train machine-learning models for predicting household response to time-of-use prices. As mentioned before, the amount of available data is important for the accuracy of machine-learning models and there is very little data on demand response. However, unlike mentioned before, this does bring the sufficiency of captured household behaviour into question here as the purpose of these models is to evaluate the impact of DR programs on the energy system. Shao et al. (2010) apply a simple assumption on households reacting to changes in prices to study DR implications. As mentioned in 1.2.1, household behaviour is complex and economically irrational which this simple assumption does not capture. Sajjad et al. (2014) want to support aggregators and policymakers in designing RDR programs by studying current variations in residential load patterns. To this end, current data on consumption is sufficient to capture household behaviour. Qazi and Flynn (2016) attempt to draw system-wide implications on the implementation of a RDR program focused on fridges and freezers as representation for all temperature-controlled appliances. As the only interaction between households and fridges and freezers is through opening these appliances, stochastically modelling this based on survey data seems sufficient for capturing household behaviour. Especially as behaviour on fridge-and freezer-openings is not likely to change under demand response.

Conclusion

The captured behaviour of households is questionable in the papers that attempt to evaluate RDR programs or their system implications. As there is a lack of RDR experience, there is not a large amount of data that data-based models can use to capture household behaviour. The other models either negate inclusion of household behaviour by evaluating the fully assumed usage of an automated algorithm, or represent household behaviour through financially-based optimizing algorithms. Only one of the models included a direct interaction of households with a RDR program by having them decide to participate in the program inside their utility function.

1.2.3. Thesis objective

Residential demand response is an initiative that can support energy systems by offering flexibility. Aggregators could offer this flexibility through pooling households' assets. Their main challenge lies in dealing with the uncertain and economically irrational behaviour of households. Thus it is important for understanding the potential of RDR to consider the reliability of household energy behaviour.
Models are an important way to evaluate the potential of RDR. They can contribute especially to the understanding of the long-term implications of RDR because of a lack of RDR experience. However, the current models used to evaluate RDR do not capture household behaviour sufficiently. This puts limitations on what these models can bring to the understanding of the potential of RDR.
The qualitative literature offers insights into the RDR related energy behaviour of households. These insights provide understanding of the factors and motivators influencing their initial participation and continuing engagement with RDR. However, they do not provide insights into the impact of their long-term engagement with RDR on the energy system. Thus it would be beneficial for the understanding of RDR to gain insights into the long-term reliability of household RDR behaviour.
This leads to the following thesis objective:

"To explore the reliability of households altering their energy demand under an aggregator with a model that represents household behaviour in a meaningful way."

1.3. Research questions and approach

In this section, the research questions will be presented and the approach will be described.

1.3.1. Research questions

For the design of future energy systems, it is important to understand the system implications of energy initiatives. To understand the implications of RDR, the reliability of households altering their energy demand under an aggregator will be explored in this thesis. Thus the main research question of this thesis is:

"How reliable are households in altering their energy demand under an aggregator providing residential demand response?"

As described in 1.1, aggregator provided RDR can take different forms. To explore the reliability, it is important to have an overview of the different ways aggregators can gain flexibility from households. This is why the first sub-question is:

1. *"What are the different forms of aggregator provided RDR?"*

This question will be answered through a literature review. The answer to this question will help designing the model by giving shape to the aggregator and RDR program parts. It will also provide context in which the conclusions are to be made.
In 1.2 was described why it is important to include meaningful household behaviour when evaluating RDR. Thus the second sub-question focusses on this.

2. *"How to include meaningful household behaviour when exploring the reliability of aggregator provided RDR?"*

This question has two parts: 1) understanding household energy behaviour and 2) understanding what meaningful household behaviour involves in context of this research. The first part has been answered in the literature review. Then the system boundaries will inform what will make household behaviour meaningful in context of the thesis objective and the model. The outcome of this question will provide how household behaviour is to be included and implemented in the model.
Finally to answer the main research question, the explored reliability needs to be analysed. The third sub-question will thus be:

3. *"What factors influence the reliability of aggregator provided RDR?"*

This question will be answered through analysing the model results. The answer to this question will provide insights to reach the conclusions of this thesis.

1.3.2. Approach

In pursuit of answering the main research-question, an ABM simulation-model will be built and analysed. This model will represent an aggregator provided RDR program and include meaningful household behaviour. Simulation models can explore the performance of systems under a specific set of inputs. They are especially well-suited for gauging the performance of systems that are variable, complex and interconnected (Robinson, 2004). To include household behaviour meaningfully, the model needs to be able to represent differences in household behaviour based on characteristics and behavioural factors. To this extend the model needs to be able to include varying household characteristics, household interactions with their environment and household interaction with the aggregator. ABM is well-suited to accomplish this as it can model individual active agents and their interactions with the environment and other agents.

Agent-Based Modelling is a simulation-modelling approach where the combination of individual agent behaviour results in the overall system behaviour. The behaviour of agents is based on varying behavioural rules and interactions with their environment and other agents (Borshchev & Filippov, 2004). During the building process, a simulation model goes through different iterative phases. In the first stage, a problem in a real-system is identified and analysed. In the second stage, the model is designed and a description of is provided through a conceptual model. In the third stage the conceptual model is programmed and results in a computer model. In the last stage, insights from the model are mapped back to the real-system (Robinson, 2004). This thesis is structured on these modelling phases.

1.4. Relevance

In this section, the societal and scientific relevance of this thesis will be provided.

1.4.1. Societal relevance

The societal relevance of this contribution is twofold. 1) As societies depend on energy, changes in energy systems will bring societal change with it (Ellabban & Abu-Rub, 2016). RDR especially would entail societal adaption as it shifts a long existing energy paradigm of supply meeting demand to the option of demand meeting supply. The insights of this thesis will contribute to the understanding of RDR caused societal change.; potential effect on society 2) RDR can aid in the energy transition through its potential for offering flexibility and aiding the integration of renewable energy sources (Siitonen et al., 2023). Because of this, RDR may be able to play an integral part in climate action (Torriti et al., 2010). The insights form this thesis may support the design of RDR programs and with that support the energy transition.

1.4.2. Scientific relevance

This thesis will contribute to the existing literature by addressing two novelties. 1) The first novelty this thesis will address is the inclusion of meaningful household behaviour in a RDR model. This inclusion will contribute to the literature body through providing insights into how to include meaningful household behaviour. Furthermore, through this inclusion of meaningful behaviour the model will be able to provide insights into the reliability of aggregator provided RDR. There has been little focus in the model-backed literature on testing the potential of RDR through a focus on the reliability on households. The insights form this thesis will thus contribute to the existing literature by providing this focus. 2) The second novelty concerns the long-term implications of aggregator provided RDR. There has been little focus in the existing literature on long-term engagement were households have had the change to form habitual energy behaviour. Thus this thesis will contribute to the existing literature by offering implications of a different RDR perspective.

1.5. Structure

The structure of this thesis is depicted in figure 1.1. Chapter 2 will provide the theoretical background. This chapter provides the knowledge and context necessary to understand the rest of the thesis. This chapter will also answer the first sub-research question concerning aggregator provided RDR. Chapters

3, 4 and 5 are the modelling chapters. Chapter 3 explains how modelling assumptions and decisions have resulted in the conceptual model. This chapter will answer the second sub-research question on the inclusion of meaningful household behaviour. The conceptual model will be translated into the computer model in chapter 4. This chapter also describes how the computer model will be used to run experiments. Chapter 5 presents the results from the experiments. The third sub-research question on the influences on RDR reliability will be answered in this chapter. Chapter 6 will discuss the limitations of this research and its influence on the conclusion. In chapter 6 the final conclusions will be provided and the research-question will be answered.

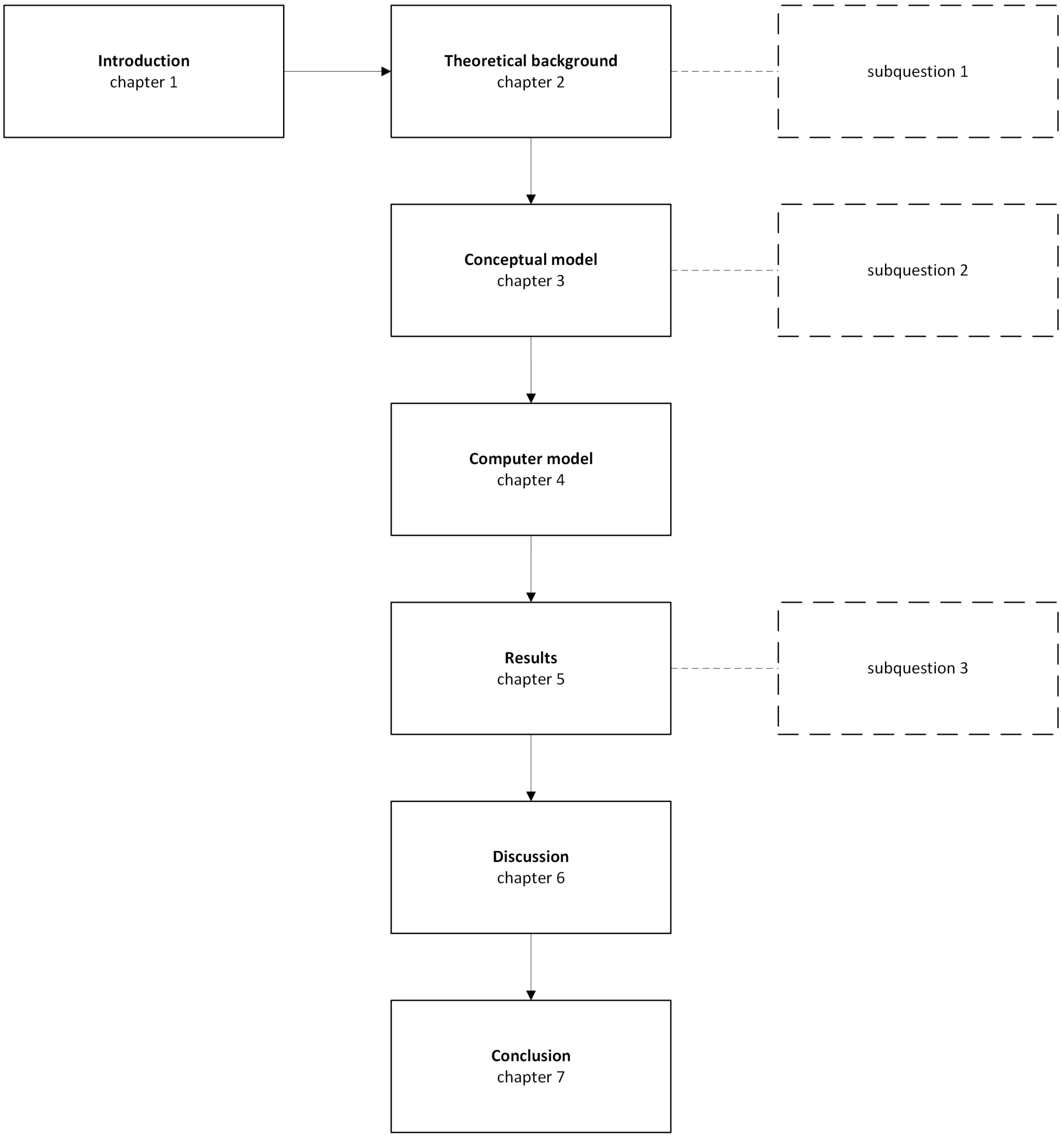

Figure 1.1: Research flow-chart

2 Theoretical background

The goal of this chapter is to provide theoretical knowledge that will aid in understanding the rest of the thesis. The first section will provide a more detailed understanding of aggregator provided RDR. This will include the aggregator concept, RDR programs and system implications. The last section will extend on the agent-based modelling method. This will be done by explaining the theory and the modelling steps.

2.1. Aggregator provided residential demand response

In 1.1 demand response and aggregators were discussed in a concise way. This section will extend on these concepts. The concept of an aggregator will be explained in context of energy systems. Then the different ways in which RDR programs can be designed will be provided. This section will end with a summary of the different implications that aggregator provided residential demand response can have in energy systems.

2.1.1. Aggregator concept

To explain the concept of aggregators, it is first important to have a general understanding of energy systems. Energy is generated by electricity producers who sell their energy on wholesale markets to the consumers. Big consumers and retailers tend to buy their electricity directly from these markets, while small consumers buy from the retailers. Electricity travels from the producers to the consumers through transmission and distribution networks. Transmission system operators (TSO) and Distribution system operators (DSO) are responsible for balancing and managing their respective networks (de Vries et al., 2019).

Balancing markets are market-based mechanisms or arrangements employed to ensure balance between electricity generation and consumption. Balance Responsible Parties (BRP's) are assigned a consumer and producer portfolio for whom they have the responsibility of ensuring energy program compliancy. Balancing services are offered on balancing markets to restore balance through a balancing resource (generation or load). There is a distinction in balancing services between balancing energy and reserve capacity. Balancing energy concerns real-time adjustment of a balancing resource to restore real-time imbalances. Reserve capacity concerns contracting the availability of a balancing resource for system balancing during a specific time-period (de Vries et al., 2019).

With this general understanding of energy systems, the concept of aggregators can be delved into. Aggregation in energy systems involves the grouping of distinct agents who act as a single entity. These agents can be consumers, producers, prosumers or a mix. An aggregator acts as this single entity. They can be seen as an intermediary between consumers, producers and other energy system participants (Burger et al., 2017).

There are different ways in which the aggregator role can appear in an energy system. Existing market actors can take up the role or an aggregator can function independently. Retailers may take up an aggregator function where they trade the flexibility of households while delivering their daily energy consumption (Lu et al., 2020). BRP's and DSO's could also take up an aggregator function . An independent aggregator would only trade flexibility. Depending on the specifics of the energy system, they could be obliged to form contracts with other market participants before being allowed to trade (Okur, 2021).

Aggregators could partake in different energy markets to trade flexibility. If prosumers are included in their portfolio, they could participate in the wholesale market. However as their main trade is flexibility, the balancing markets are best suited to them. They could also sell their flexibility directly to the TSO or DSO to facilitate congestion management (Barbero et al., 2020).

2.1.2. Residential demand response programs

Aggregators can offer flexibility through load shifts and curtailments to the energy system. They gain this flexibility through households participating in their programs. There are different ways aggregators can design their RDR programs. In this section the different types of program and the different loads for shifting and curtailment are presented.

Types of program

Paterakis et al. (2017) identifies two types of demand response programs. These are incentive-based and price-based programs. In incentive-based programs, customers are offered financial compensation for reducing a specific amount of load usage over a provided time period. In price-based programs customers reduce their loads based on economic signals. For specifically residential customers, direct load control and price-based programs are most suited.

Price-based programs

Time-of-use (TOU) pricing are the main sort of price-based demand response program. Instead of the common flat-rate prices, time-of-use tariffs depict the varying cost of electricity production. TOU pricing is a stepped rate structure that typically includes a peak rate, off-peak rate and a shoulder-peak rate. The prices reflect the electricity prices under average market conditions on different times of the day and season. The pricing is decided based on long-term costs of the electricity system. Critical peak pricing does attempt to depict the short-term costs of the electricity system. Specifically the periods that are considered critical. Critical peak pricing entails are adding a tariff to the existing electricity price whenever a system criteria is triggered. Examples of criteria are the unavailability of reserves and extreme weather conditions. Real time pricing involves directly exposing customers to the variability of electricity production costs. In this pricing scheme energy prices are updated on short notice, typically hourly (Paterakis et al., 2017).

Direct load control

In these types of programs, aggregators could directly control specific types of appliances in households. Because the aggregator directly manages the appliances, the household may not be notified of an interruption. Furthermore, the aggregator may decide to interrupt appliances by economic or reliability events. Often these programs involve boundaries on the duration and number of interruptions. The household is compensated through financial means (Paterakis et al., 2017). However, there will still be a degree of uncertainty in household behaviour. This is not linked to economical behaviour but to the physical availability of the appliances. Appliances need to be turned on and need to demand a specific electricity output (O'Connell et al., 2014).

Comparison

Aggregators are trying to gain a certain response from the households that are part of their demand response programs. Through price-based programs, they expect households to alter their energy consumption in reaction to varying electricity prices. The aggregator has to estimate the reaction of households to these varying prices with limited information on the amount of demand (O'Connell et al., 2014). In direct load control programs, aggregators can directly alter the electricity consumption of specific household appliances. They would need direct communication with individual appliances and detailed information on the appliance usage to achieve this. When this works, aggregators are able to deliver a more precise response compared to the price-based programs. Direct load control also has the advantage of being able to response faster (Okur et al., 2021). Because direct load control offers more certainty and a faster response than price-based programs, it is preferable for delivering ancillary services to ensure the stability of the system (O′Connell et al., 2014).

Load types

The aggregated demand of households consists out of different appliances with different operating characteristics and constraints. Thus the amount of demand available and its ability to respond to signals may vary in time (O′Connell et al., 2014). This influences the capacity and ramping ability that aggregators have to plan with. Okur et al. (2021) identifies three categories for separating household appliances based on their flexibility.

- Non-flexible: these appliances cannot be shifted or curtailed without bringing significant inconvenience, examples are computers and lighting.
- Semi-flexible: these appliances can be shifted or curtailed without bringing significant inconvenience provided that their altered consumption is notified in advance, examples are washing machines and dishwashers.
- Flexible: these appliances can be shifted or curtailed on short notice without bringing significant inconvenience, examples are refrigerators and AC's.

2.1.3. System implications

With the flexibility aggregators gain through the load shifting and curtailment of households, aggregators can offer system services. In this section these potential services and their benefits are discussed. Lastly, a brief overview of concerns related to aggregator provided RDR is provided.

System services

The problem formulation in chapter 1 mentioned how RDR could support energy systems through offering flexibility. This section will elaborate on this point through summarizing the potential benefits of RDR.

Peak reduction

One of the anticipated effects of RDR is the flattening of the system load profile. This entails electricity demand shifting away from peak hours (peak shaving) and moving to off-peak hours (valley filling) (Paterakis et al., 2017). Demand response has already been proven effective at shifting electricity loads away from peak hours (Muratori & Rizzoni, 2016). Peak reduction would aid in reducing the marginal costs of generation, cost of system balancing and grid reinforcement investment (O′Connell et al., 2014). Thus overall improving the efficiency of the energy system.

Generation capacity requirements

The security of supply is a major concern in energy systems. To ensure security of supply, the totality of generation capacity must be larger than the maximum demand of energy. This must be guaranteed given severe demand variations and unsuspected events. RDR may contribute to lower capacity requirements through lowering overall electricity consumption and peak shaving (Paterakis et al., 2017).

Balancing services and congestion management

The balancing of energy systems is traditionally accomplished by the supply-side. The generators alter their production to balance the demand. However, interest has risen in enabling the demand-side to participate in system balancing as well (Paterakis et al., 2017). Demand response could offer balancing services to support system balancing on different time scales. These services could consist out of providing reserves, both capacity (Paterakis et al., 2017) and standing (O′Connell et al., 2014). Furthermore, DR could help with congestion management (Okur et al., 2021) through utilizing locally distributed grits (Bignucolo et al., 2019). DR may even be able to offer these services more reliably than generators. This is because the aggregated response of a large number of loads is more reliable than the response of a small number of generators (Paterakis et al., 2017) (Ma et al., 2013). Furthermore, demand response may be capable of adjusting energy consumption almost instantaneously depending on load type. This could results in demand response producing larger effective ramping rates compared to large generators (O′Connell et al., 2014).

Integrating RES

The increased integration of renewable energy sources (RES) in energy systems brings uncertainty for system operators. They need to serve both varying loads and high amounts of variable generation. To combat this they will need more capacity and ramping reserves. However, conventional generators will have increased rates of emission and high operating and maintenance costs to meet the RES uncertainty. The demand side could offer reserves and ancillary services to combat the uncertainty (Paterakis et al., 2017). There are indications that improved system flexibility can aid the integration of renewable energy sources, with residential consumers offering a potential large source (Parrish et al., 2020).

Concerns

The first concern with RDR comprises the objective of this thesis. Namely the reliability on household energy behaviour for aggregator provided RDR. If RDR cannot provide the flexibility it offers reliably, it may well be disregarded for more reliable resources (O′Connell et al., 2014). This is specifically relevant for RDR's potential in providing critical services.

The second concern of RDR arises from the influence of RDR on flexible and peaking generators. RDR will impact the potential for flexible generators to recover their investment. This could lead to the decommissioning of these generators. This in turn may cause difficulties if the system operator is still in need of them. Their capacity may still be needed if RDR's reduction of capacity requirements through flexibility is not always available (eg seasonal variability). Furthermore, conventional generators also offer services that RDR is not able to provide (eg inertial and voltage support) (O′Connell et al., 2014).

Another concern relates to the availability of demand. RDR can only provide limited value to the system if it is not flexible when critical balancing services are required. For example, demand needs a high correlation with wind generation if it wants to balance its fluctuations (O′Connell et al., 2014).

The last concern is potential equity issues. Households could be exploited once they have become active energy system participants through RDR. This could be done by exposing them to high or fluctuating prices. This way they could be unwillingly used to provide system services. This would place a large burden on them to provide these services, even though this was originally the responsibility of the system operator (O′Connell et al., 2014).

2.2. Agent-based modelling

In this section the simulation modelling method of ABM will be delved into. The method itself will be discussed through the lenses of modelling, global method description, model anatomy and method fundamentals.

2.2.1. Method

Modelling: Modelling as a research method consists of mapping a problem from real-life to a model through abstraction. This model is then analysed and mapped back to real-life (Borshchev & Filippov, 2004). The inferences drawn from the model may improve understanding of the real-life system (Rosen, 2012). The modelling method can be categorized into analytical and simulation models. Analytical models are equation based and functionally depend on the input for the model results. Simulation models have a set of rules that decide how the system may change over time (Borshchev & Filippov, 2004).

Global: Agent-based modelling (ABM) is a simulation modelling method. The fundamental feature of this method is a bottom-up approach. The global model behaviour is formed by the combined actions of individual agents. Agents have their own behaviour rules, interactions with each other and interactions with the environment (Borshchev & Filippov, 2004). This is possible because agents possess the properties of being encapsulated, autonomous and goal-oriented. Encapsulated means that agents are clearly identifiable as a single unit through boundaries and interfaces. Autonomous means agents have total control over their internal state and actions. Goal-oriented in the context of a model means the agents are designed to meet an objective (Van Dam et al., 2012).

Anatomy: ABM models have an anatomy consisting of agents, environment and time. Agents are the entities whose individual behaviour amounts to the model behaviour. Their behaviour is the sum of their state changes, rules and actions. The agent's state consists of all the parameters that define an agent. Their state exists and belongs to the agents individually. Agent rules describes how states map to actions or new states. Actions are activities agents perform based on rules. The environment describes the space the agents 'live' in. It contains all external information and provides structure or space for agent interaction. Depending on the environment rules, agents can affect the environment and be affected by it. The time-steps a ABM model runs through are called ticks. The time unit a tick entails depends on the purpose of the model. The main difference in time compared to reality is parallelism. In reality individuals act at the same time, but in ABM agents take turns acting during each time-step (Van Dam et al., 2012).

Fundamentals: ABM is a method that combines the scientific perspectives of induction and deduction. Induction involves analyzing empirical data to discover patterns. Deduction involves setting explicit assumptions and proving their consequences. Like deduction ABM also starts with setting assumptions, but for the purpose of generating data instead of proving a theorem. Furthermore, ABM also includes the analysis of data, but this data is generated by ABM instead of measured from the real world. Traditionally, the purpose of ABM is to aid intuition through offering a way of doing thought experiments (Axelrod, 1997).

3 Conceptual model

The conceptual model will be presented in this chapter. First, the model boundaries will be made which will set the base for the conceptual model. Then the model anatomy will be described. This will provide a high-level narrative of model behaviour. Following this will be the explanations of two agent-classes and their main methods. Lastly, the model outcomes will be provided.

3.1. Model boundaries

A model cannot include everything of a real system, thus boundaries need to be included. Model boundaries describe explicitly what parts of the real system will be inside the model and what parts will not. Part of setting model boundaries is the simplification of structures and concepts. These boundaries should reflect the objective of the model to ensure the model can provide the needed insights (Van Dam et al., 2012).

The system description provided in 2.1 will be held next to the objective to decide the scope of the model. A brief description of such as system with aggregator as the focus point would be: households have a demand for different types of energy load. This demand has different levels of flexibility. They may be willing to offer (part) of their demand flexibility to an aggregator through participation in a RDR program. The aggregator is able to acquire flexibility through this program. Aggregators can use the acquired flexibility to interact with other energy system participants. This interaction is likely to happen through a balancing market.

The objective of this thesis is to explore how reliable households are in their RDR program participation. This means that household behaving under a RDR program is integral to the objective. Therefore household behaviour, an RDR program and household interaction with an RDR program will be included in the model. RDR programs are formed by the aggregator in charge of them. This means an aggregator will also be included in the model. An aggregator wants to offer the flexibility gained from their RDR program on a balancing market. This connection influences how aggregators interact with their RDR program and thereby influences household RDR participation. However, there are many different ways aggregator can participate in balancing markets (see 2.1.1). Thus to include this in a way that explores reliability, different configurations and their influence on an RDR program will be used as model input.

As mentioned in chapter 1, part of the objective of this thesis is to explore the reliability of aggregator provided RDR accounting for two different perspectives. The first perspective concerns long-term aggregator provided RDR and the second perspective concerns meaningful household behaviour. These perspectives also inform the model boundaries. This will be discussed in the next sections.

3.1.1. Long-term aggregator provided residential demand response

This perspective concerns itself with the lack of understanding of long-term consumer engagement with demand response. The model needs to represent long-term household engagement with RDR for it to provide insight into this lack of understanding. Households will have formed habitual energy behaviour when they have engaged in the RDR program for a while. This leads to the model assumption that households are already signed-up to the RDR program and thereby motivated to participate in the program.

The model will need to include a RDR program that can offer the best insights into the reliability of aggregator provided RDR. As discussed in 2.1.2, RDR programs are made up of different aspects. The first aspect is who will be operating the appliances. There are a couple of reasons as to why households have been chosen to operate the appliances for the model. Firstly, household interaction with the program and thereby their appliances is detrimental to reliability. Secondly, the other option of direct load control does not fit within the thesis objective. This is because direct load control is more a problem of technical capabilities. It would also take away from household interaction with the appliances.

The second aspect is on the question of the type of appliance involved. Non-flexible appliances are not suited for RDR programs and are thereby excluded from consideration. The main difference between the other appliance types lies in semi-flexible appliances requiring a more advanced notification compared to flexible appliances. This advanced notification requires more involvement from the households. Semi-flexible appliances are also less suited for direct load control. The higher degree of household involvement and incompatibility with direct load control, make semi-flexible appliances more relevant for reliability.

The third aspect is the question of how the appliances are operated. Semi-flexible appliances cannot be interrupted or curtailed. Thus for an aggregator to gain flexibility from them they would need to be shifted. Because aggregators are offering this flexibility and have insight into when flexibility is required, they need to influence at what time these appliances are used. For the model this means that aggregators will be responsible for setting the time of the appliance usage. However, aggregators need to account for household availability when scheduling appliance use as they are the ones operating the appliances. This adds another aspect where households need to provide aggregators with their expected availability.

The last aspect concerns itself with the question of whether households will comply with the appliance use schedule made by the aggregator. The objective of this thesis is to explore how reliable they are in this compliancy. Thus it is important that households are able to both comply and not comply with the scheduled appliance uses.

In summary, the RDR program will take the following form:

- Households operate appliances
- Semi-flexible appliances (dryer, washing machine and dishwasher)
- Aggregator schedules, based on household expected availability
- Households will comply with scheduled use or will not comply

3.1.2. Meaningful household behaviour

Household energy behaviour will need to be included in a way where it can provide insight into the objective. This is complicated by the fact that households, unlike other energy system participants, function largely outside of the energy system. Thus incorporating household behaviour in a meaningful way provides a challenge.

The established RDR program mentioned in the section above provides a starting point for describing household behaviour. Aggregators will provide an appliance schedule based on household expected availability. Thus firstly, households will need a description of their expected availability. The daily goings-on, habits and thereby their time at home are part of their routine. This means that routines are an important factor for their behaviour. Furthermore for households to comply with the scheduled appliance uses, they will need to perform multiple actions during the day to accomplish this. This can also be included in their routine.

Another point mentioned in the established RDR program, is the ability of households to decide to use or to not use the scheduled appliance uses. Thus decisions on scheduled appliance uses will be part of household behaviour. This will be done through a decision-function.

Chapter 1 presented a list describing household energy behaviour. This list was compared to the objective of model studies to test for meaningful household behaviour. The objective of this model study is to explore the reliability of aggregator provided RDR. Thus the list should be applicable to household behaviour produced by the thesis model, where possible. The list from chapter 1 describing household energy behaviour was as follows:

1. Variations in household energy demand can be partially explained by economic factors and household characteristics
2. Households do not optimise their utility or make continuous rational decisions in their energy behaviour
3. Households do not only consider price when making energy related decisions
4. Even with automated control, household energy behaviour is dependent on their interaction with the program

Points 1, 2 and 3 should be included in the household behaviour of this thesis. Point 4 covers household behaviour under direct load control. This is out of the thesis scope and therefore the model does not have to represent point 4. To facilitate the points, it should be possible to model households individually. This way variations in household characteristics, factors influencing their decisions and program interactions can be modelled. This means that the model needs a bottom-up approach. The points also inform how household behaviour in the RDR program should be included. Point 1 refers to household energy demand and thus informs the appliance needs household provide to the aggregator. To include this point, household appliances need should be partially dependent on economic factors and household characteristics. Point 2 and 3 both relate to energy decisions and thus informs the decision-making function of households concerning appliance use compliance. The inclusion of point 2 requires another approach to household decision-making outside of optimizing utility and continuous rational decisions. The inclusion of point 3 entails ensuring that price is not the only factor households include in the decision-function.

3.2. Model anatomy

The anatomy of ABM models, as discussed in 2.2, consists of agents, environment and time. In this section, the different agent classes and their interactions with each other and the environment will be explained. But first, a high-level overview of the model will be provided.

3.2.1. High-level overview

The currency of the model are the appliance uses which flow through the model from the aggregator to the household. Figure 3.1 depicts the main dynamics of the model. The dotted box represents the boundaries of the model. Inside the boundaries are the aggregator and the households.

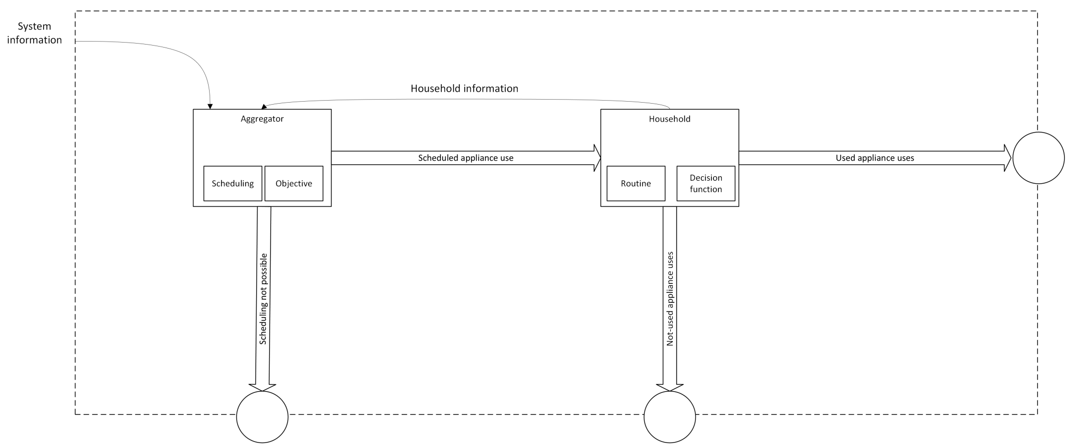

Figure 3.1: High-level conceptual diagram

The aggregator's behaviour is formed by their scheduling algorithm and the objective with which they operate. In the model, the aggregator tries to schedule the appliance uses of the households based on their objective, household information and system information. The aggregator creates an appliance use when it tries to schedule. When the aggregator is unable to schedule the appliance use, it is labelled 'scheduling not possible' and leaves the model. Scheduled appliance uses are labelled 'scheduled' and passed on to the household it was scheduled for. Household behaviour is formed by their routine and a decision function. Their routine determines when they are available for appliance interaction. The decision-function determines whether the household wants to comply with that specific scheduled appliance use. Both the routine and decision-function may cause the scheduled appliance use to be not-used. This appliance use gains the additional label of 'not-used' and leaves the model. Scheduled appliance uses can gain this label up until its moment of scheduled use. If the appliance use is used as scheduled, it gains the label 'used' and leaves the system.

The use of scheduled appliance uses is determined by the aggregators ability to schedule, the household's ability to interact with the appliances and their decisions regarding the scheduled appliance uses.

3.2.2. Environment

The environment of ABM-models describes all external information and provides the space for interaction. It can be viewed as everything not influenced by the agents that does affect them (Van Dam et al., 2012). In 3.1 was explained why different configurations of aggregator interaction with balancing markets would be used for model input. This will be further extended on in this section as this will be part of the environment.

The interest with this interaction is on how it influences the RDR program. With an established RDR program, these influences are easier to see. In essence, the RDR program entails the aggregator scheduling household semi-flexible appliances. For the system load profile this means that demand can be shifted towards a different time. Thus the service offered is taking generation of the grid when balancing markets are asking for it. This could aid in e.g. valley-filling and RES integration.

On the other hand, the aggregators have their own goal in shifting demand while offering this service. They could be non-profit seeking with their only objective being balancing support. They could put an emphasis on continued household engagement with a goal of lessening their participation burden. They could be fully profit driven and try to make as much money as possible. They could also have a combination of these goals. Either way, their objective influences how the RDR program will work.

In conclusion, there are two aspects to how aggregator could interact with balancing markets that can influence the RDR program. These are 1) demand shifting to when balancing markets want it and 2) aggregator objective. In the model this means the following external factors will be included in the environment:

- Hours available for scheduling
- Scheduling objective

3.2.3. Agents

Following the boundaries set in 3.1, the model will include two agent classes: households and aggregators. The individual appliances of households were also considered for an agent class. This is because the appliances have state changes through their (un)loading and activation. However, to avoid confusion with the model outcomes (see section 3.4), the appliances will be included as household attributes instead. But for the purpose of explaining agent interactions, they will be depicted as a separate entities instead of falling households.

Agents interact with each other and the environment. Figure 3.2 shows the interactions. Most interactions are formed by the information exchanges needed for appliance scheduling. The aggregator needs information from the environment and households to make the appliance use schedule. From households, aggregators need to know when they plan to use what appliance. Furthermore, since households are not available full day, aggregators need to know when households expect to be available for appliance use. From the environment, aggregators receive hours available for scheduling and their scheduling objective. The aggregator in turn sends the schedule they made back to the households. Next to these information exchanges, households need to interact with the appliances themselves. This includes loading, unloading and starting the appliance.

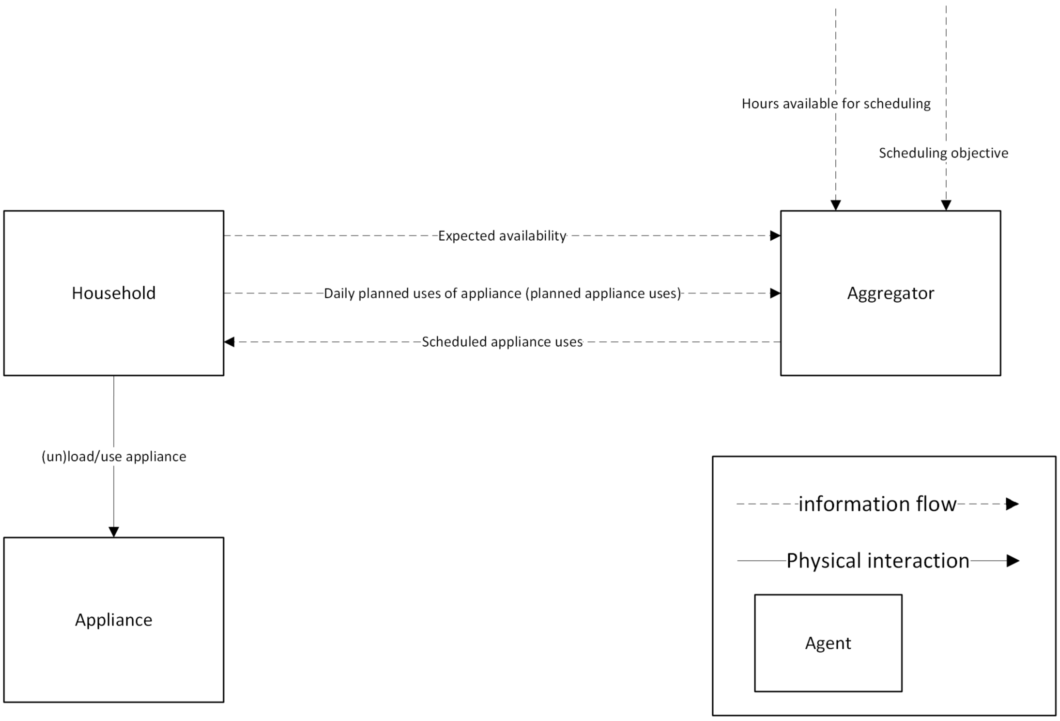

Figure 3.2: Agent interaction chart

3.3. Main methods

With this clear definition of model anatomy, the main methods included in the model will be provided. These methods will form the basis of the model behaviour. The methods will be discussed per agent-class. Firstly, the scheduling-method of the aggregator class will be explained. Then the methods describing household behaviour will be discussed.

3.3.1. Aggregator scheduling

The aggregators role in the model will be to make the schedule day-ahead for household appliance use. The scheduling algorithm will work as follows: aggregators schedule appliances for the next day, thus they receive an overview of the needed information from households day ahead. This overview includes:

- What appliance(s) the household plans to use the following day (eg dishwasher)
- The duration of said appliance (eg 1 hour)
- Hourly intervals of when they expect to be able to use the appliance. (eg from 10am to 3pm, or 7pm to 11pm)

As explained, the aggregator interaction with balancing markets has been simplified to two variables which will be included in the scheduling algorithm. These are: hours available for scheduling and scheduling objective.

Figure 3.3 provides an example for understanding how the scheduling-algorithm works. The first row ‘hours available for scheduling’ are the hours when flexibility is needed. The second row ‘expected household availability’ are the hours a specific household is expecting to be available for appliance use. The four shows the hour the aggregator would like to schedule the appliance according to the ’scheduling objective’. The first step the aggregator takes is seeing if the hours where flexibility is needed overlaps with the hours where households expect to be available for appliance use. In the figure, this is shown through the red lines. If the overlap is at least as big as the duration of the appliance use, the aggregator is able to schedule the appliance of that specific household. The aggregator will try to schedule the appliance close to its objective hour. Thus it looks at the options it has for scheduling. In the figure these are the blue boxes on the third row. Then the aggregator picks the option closest to its objective. In the figure, this is shown with the arrows measuring how close the options on the third row are to the objective orange box on the fourth row. The dark blue box is closest to the orange box thus the aggregator schedules the appliance for 10am.

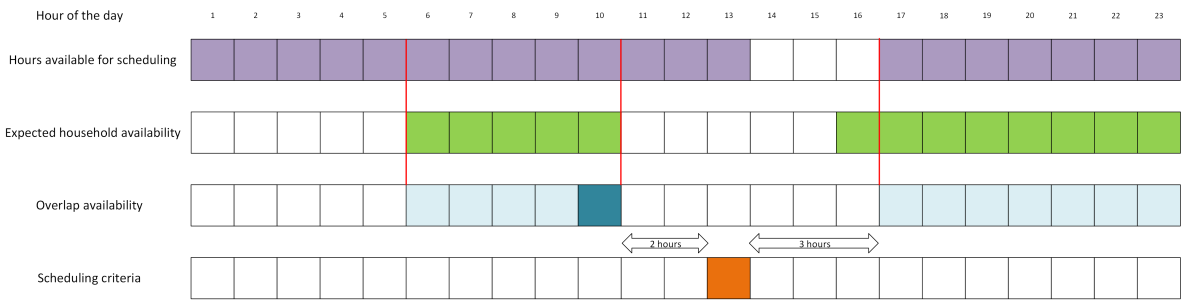

Figure 3.3: Example aggregator scheduling

The scheduling-algorithm will try to schedule the dryer together with the washing machine. The dryer will always be scheduled after the washing machine has finished. However, the overlap in expected availability and hours available for scheduling may not be enough to cover the duration of both the washing machine and the dryer. In this case the aggregator will not schedule the dryer.

3.3.2. Household behaviour

One of the perspectives this thesis adheres to is the assumption of 'long-term engagement with the RDR program'. This means that households have settled on habitual behaviour around the RDR program and thus that a learning curve and wavering motivation are not present. However, this does not mean that households will consistently deliver the flexibility that the aggregator expects from them.

Firstly, there is an extent to which routines allow households to be flexible (Parrish et al., 2020). This is considered in the scheduling algorithm through including household expected availability. However, households may deviate from this expected availability. This means they may not be home to start the appliance or they may not have the time to prepare for a scheduled appliance use. Secondly, households may choose to not use the appliance at the scheduled time. It is assumed that households are motivated to participate. However, this motivation will not always weigh up to the daily inconveniences caused by the scheduled appliance. These daily factors influence household willingness to comply with the scheduled use of appliances. All in all, household behaviour in the model will have two facets: household routines and a decision-function.

These two facets will influence each other. The decisions of households to use the scheduled appliance use or not will be partially dependent on their routine. On the other hand, the outcome of the decision will influence household routine as it may lead to a deviation in their daily planning.

Routines

The way routines are conceptualized for the model is a daily overview which includes a slot for every hour of the day. Households can perform actions within any of these slots. The slots are filled with actions through two methods: daily initialization and actions economy. The daily initialization resets the overview of a household every day and places the predetermined actions in the overview. The action economy may add actions to this overview on an hourly basis.

Daily initialization

In the model, households will have to provide the aggregator with their expected availability the day before appliance scheduling. In the daily initialization, this expected availability is turned into the actual availability. Thus firstly the establishment of the expected availability will be explained. Households are considered available for RDR engagement when someone is home. Thus expected availability will consist of intervals describing the hours of the day households are expecting to be home. This availability will depend on the type of weekday and on the household type. The three types of day considered are: work from home, work at location and weekend. When households work at location, they expect to be available from the time they get up to when they leave for work, and from the time they get back to the time they go to sleep. When households work from home and on the weekends, they expect to be available a little after they get up until they go to bed. The difference being in the time they get up, which is assumed to be later in the weekend. Single households have less working from home days compared to couples and couples with kids. Seniors only have weekend days. Couples with kids have stricter intervals because they need to take their children to school and pick them up. They also have more limited flexibility because they will only say they are available for scheduled appliance use after their children have gone to bed.

The expected availability provides the blueprint for the actual availability. Households may expect to be available at certain times but in actuality there are a lot of things that may cause a household to deviate from this. To account for this a random factor will be added to each hour household availability changes. This number is pulled from a normal distribution with average 0 and standard deviation 0.5. For instance, a household expects to be home at 3pm. The random factor is 1. This means they will be home an hour later than expected. Since the random distribution does average on 0, indicating no change in availability, the difference between expected availability and actual availability will be small.

Next to the availability, scheduled appliance uses and actions carried over from the prior day are added to the daily initialization. These actions will be discussed in the next section as well.

Action economy In the model, households will be able to perform 3 types of action. These are:

- Decisions
- Appliance interactions
- Availability changes

Decisions: This is the first type of action households will be able to perform. Every day households have scheduled appliances they decide to use or decide to not use. They make this decision through the use of a decision function. The decision function itself will be explained later. This section will focus on when decisions happen. Whenever this decision function is called upon, households perform a decision-action. Firstly, there is a difference in decisions made before the final decision moment (push-decisions) and decisions made on or after the final decision moment (final-decisions). When a push-decision is accepted, a new decision-action is planned. A final-decision is the last decision that can be made for a scheduled appliance use thus no further decision-actions are planned afterwards. Whenever either of the two decision types leads to a decision to not use, the scheduled appliance use is removed from its time-slot and no further decisions on this specific use are made.

Secondly, decision-actions are planned once in the daily initialization, then added to the daily overview depending on its outcome. It is assumed that households will look at their scheduled appliance uses for that day when they get up. Thus each scheduled appliance use has a decision made about them in the morning. For most scheduled appliance uses, this is also their first decision. The exception to this is when this first decision is also a final-decision. For example the following situation: a household gets up at 7am, their dishwasher is scheduled at 9am and the final decision moment for this dishwasher use is at 6am. In cases like this, the first decision is made the evening before. Thus making the morning decision the second decision.

For all possible decision moments counts that a decision-action is only planned at its hour if the prior push-decision was accepted. Next to the morning and evening decisions, there are three more possible decision moments. The first one is an inbetween decision. This is on the hour right between the morning decision and the scheduled hour of use. The second one is a gethome decision. This decision moment can only happen if the scheduled appliance use is after households have left their home and come back. In that case, the hour they come home is a decision moment. The last decision moment is on the final decision moment. Not all of these decision moment exist for every scheduled appliance uses. But the later on the day an appliance is scheduled to be used, the more decision moments are possible. Looking at the prior example, the gethome and inbetween decision moments are not possible. This is because the morning decision is the final-decision. Gethome and inbetween decisions would be present in the following example: a household gets up at 7am, their dishwasher is scheduled at 9pm, they come home from work at 6pm and the final decision moment for this dishwasher use is at 8pm. There is a possible morning decision at 7am, an inbetween decision at 2pm, a gethome decision at 6pm and a final decision at 8pm.

Appliance interactions: This is the second type of action households will be able to perform. Households need to interact with the appliances to ensure a successful use at the scheduled time. For this, the prior appliance use needs to be unloaded, the appliance needs to be loaded for the new use and the appliance needs to be started. Households will unload an appliance whenever it receives the status 'finished'. This can be in the same hour as the appliance is finished. Households will try to load the appliance for a new use if the scheduled use is within a set number of hours or the evening before if the appliance is scheduled early. The households will start the appliance within the given hour slot if it is loaded.

Availability changes This is the last type of action households will be able to perform. Households need to be home to perform the described actions. Whether households are home or not, will depend on the availability set in the daily initialization. This change in households presence at home is noted with an action in the decided hour.

Many conditions need to be included to make sure all the actions are executed correctly. The circle of the appliance being unloaded, loaded, started and finished needs conditions to ensure the correct steps follow each other up. Furthermore, a household is assumed to have a maximum number of RDR related actions it can take. For instance, it is not realistic for a household to unload, load and start an appliance on the hour where the aggregator calculated the start to be at the beginning of that hour.

Decision function

Once habitual behaviour with the RDR program has formed, households may continue to weigh the potential savings against the effort of responding (Parrish et al., 2020). This will be interpreted as households weighing the motivations for RDR participation against daily efforts when deciding to follow the appliance schedule. The motivations for compliance to the RDR program are based on expected benefits that are yet to come. While the motivations against compliance are inconveniences felt in that moment of decision. This shows a difference in the timing of motivations. Thus long-term and short-term motivations will be included in the decision function.

The long-term motivations are concerned with RDR participation. Both Parrish et al. (2020) and Siitonen et al. (2023) found financial and environmental motivations to be the most common for enrolment.

The short-term motivations are concerned with daily inconveniences. Active participation in RDR is partly hindered by the disruption it causes to household routines (Siitonen et al., 2023). This deviation from routine causes household discomfort (Naeem et al., 2015) and provides the short-term motivation of comfort. Households may be more inclined to accept this disruption however if their appliance need is high. This provides the short-term motivation of urgency.

Another factor considered is the uncertainty households deal with on a daily basis. In the morning, they may feel uncertain over their availability in the afternoon. Thus an uncertainty factor will also be taken into the decision-function. The uncertainty factor may either add to the willingness or take from it. Before the final-decision moment, uncertainty adds to the willingness as there is no pressure yet to make a decision. Thus the households do not feel pressure as they can push the decision to a later moment (push decision). On the other hand, the households do feel pressure at the final-decision moment where uncertainty works against them (final decision).

This leads to the following equation for a push decision:

$$(financial + environmental) - (urgency + comfort) + uncertainty = \begin{cases} Accepted, & \text{if } > 0 \\ Overruled, & \text{else} \end{cases} \tag{3.1}$$

The following equation describes a final decision:

$$(financial + environmental) - (urgency + comfort) - uncertainty = \begin{cases} Accepted, & \text{if} > 0 \\ Overruled, & \text{else} \end{cases} \quad (3.2)$$

The variables in these equations have been quantified so the decision-function can be executed. The motivations will be represented through scores. These scores should be of similar scale as they should be able to cancel each other out. To this end these scores will be calculated on scale from 1 to 5. However because the assumption is that households are motivated to participate, the long-term motivations should generally be equal to short-term motivations. Thus the long-term motivations together should always be equal to or higher than 3. Now the different variable quantifications will be explained.

Financial: this variable will vary dependent on the income-level of the household. Low income households will have the highest financial-scores and high income households the lowest.

Environmental: this variable will vary dependent on household type. Younger households tend to be more responsive to environmental motivations (Annala et al., 2012). To represent this, single and young couple households will have higher environmental scores compared to couples with children and seniors.

Comfort: this variable will be calculated based on the difference between the scheduled time and the household specific preferred time of use. The comfort-score will be assigned based on this difference. Seniors are more sensitive to comfort and thus will have lower comfort-scores compared to the other household types (Naeem et al., 2015).

Urgency: urgency is felt when the appliance need is high. Thus when urgency is high, households will be inclined to use the scheduled appliance. As the decision-function subtracts the short-term motivations from the long-term motivations, the urgency score needs to be low when the sense of urgency is high. The urgency score is decided based on a flowchart. This flowchart sets the urgency-score based on planned appliances, the last time the appliance was used and the time until the appliance is next used.

Uncertainty: this variable has been quantified through two components. The first one is the difference between the time of decision and the time of scheduled use (htill). It is difficult to know something for certain when it is in the future. The second one is how close the scheduled time is to when a household expects to arrive or leave home (intToU). This is based around the uncertainty of being home or having to leave home on time. Figure 3.4 explains these components through an example.

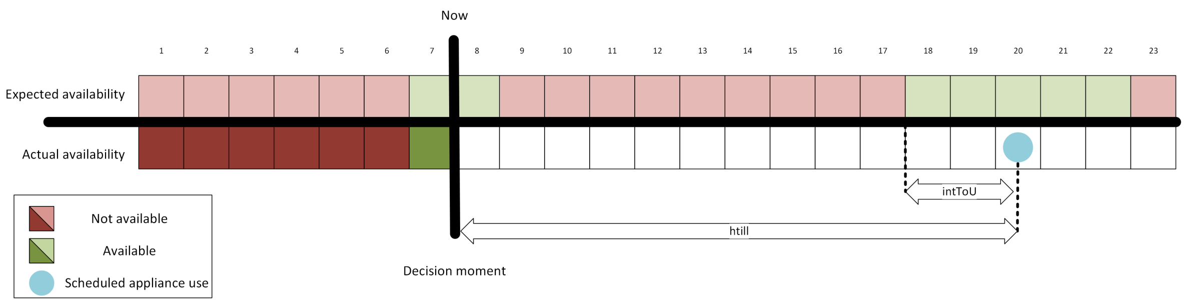

Figure 3.4: Example uncertainty components

3.3.3. Household characteristics

The sections above have spoken about the different ways household characteristics interact with different variables of the model. These have been summarised in table 3.1.

In this table, an x represents the case were the characteristic does not influence the model variable. The values given are also a simplified way of describing the influence. Financial-scores are decided based on income-level. Low income households either have financial-scores of either 4 or 5. Middle income have financial scores of 3 or 4 and high income have scores of 2 or 3. The environmental-score is decided through a triangular random distribution. Single and young couple households have scores ranging from 2 to 5 with an average of 3. Couples with children and seniors have scores ranging from 1 to 5 with an average of 5. The calculation of comfort-score of seniors includes an added weight whenever the scheduled time is not the preferred time of use. The urgency-score is based on appliance need. Part of household appliance need depends on how often they ask the aggregator to schedule their appliances. Higher income households are assumed to ask more often for appliance uses compared to lower income households. They ask for more uses than they actually need. Lastly, the number of days a household works from home is based on their household type. It is assumed that more people in a household means more days someone works from home. Seniors are retired thus this variable does not apply to them.

Household characteristic		**Financial -score**	**Environment -score**	**Comfort -score**	**Urgency -score** (planned : need)	**Home work days**
Household type	Single	x	+2	0	x	2
	Young couple	x	+2	0	x	3
	Couple w/ children	x	0	0	x	3
	Seniors	x	0	+1	x	other
Income-level	low	+2	x	x	0	x
	middle	+1	x	x	+1	x
	high	0	x	x	+2	x

Table 3.1: Differences model variables based on household characteristics

Aggregators will schedule the use of semi-flexible appliances for households. The three appliance types included in the model are dishwasher, washing machine and dryer. The model will include different weekly needs and appliance durations for the appliance types. Appliance need will depend on appliance type and household type. Dishwashers have a higher weekly need than washing machines and dryers. Households with more occupants also have higher appliance needs compared to households with less occupants. It is assumed that a washing machine is always planned to be used with a dryer and they are thus always scheduled together.

3.4. Model outcomes

Model insights are derived from its outcomes. Model outcomes are selected from the model variables that are measured during a model run. Thus thinking about the outcomes of the model is integral to model development. Since the objective is exploring reliability, the model should be able to measure the reliability of households in some way. In this case reliability means that households use the appliances at the times the aggregator has scheduled. Thus the model should keep track of the appliance uses the aggregator schedules and whether or not they are used at the scheduled time or not. To understand variations in reliability, the model should keep track of scheduled appliance use together with the reason why the appliances were (not) used and the household characteristics. To summarise, the model should be able to provide and measure appliance uses as its outcome.

The model needs to be able to keep track of appliance use while also saving information on why a scheduled appliance uses was overruled and what kind of household. Preferably, the model should keep track of both types of data in a structured way. Thus to keep track of the appliance uses, a new agent type will be created whose instances will be able to store the required information: appliance use. An appliance use will be an instance of whenever the household wants to use an appliance. It can be considered a possibility of an appliance being used. Planned appliance uses are instances of households informing the aggregator of the appliances they plan to use the following day. For example, a household tells the aggregator they want to use the dishwasher the following day, than an ‘appliance use’ instance with the property ‘planned’ is made. Not-planned appliance uses are instances of households using an appliance outside of the program. For example: if a household had to overrule a scheduled use, they may decide to use the appliance outside of the program. Now an instance of 'appliance use' is made with property 'not-planned'. Furthermore, if the aggregator was not able to schedule a planned appliance use, an instant of 'appliance use' is made with properties 'planned' and 'scheduling not possible'. Appliance uses with the property 'scheduled', can either be used at the scheduled time, or not. If they are not used as scheduled, they were either overruled (before final-decision moment) or failed (after final-decision moment). Appliance uses with the properties 'accepted', 'overruled' and 'failed' thus also have the properties of 'planned' and 'scheduled'. Figure 3.5 shows the relation of these properties.

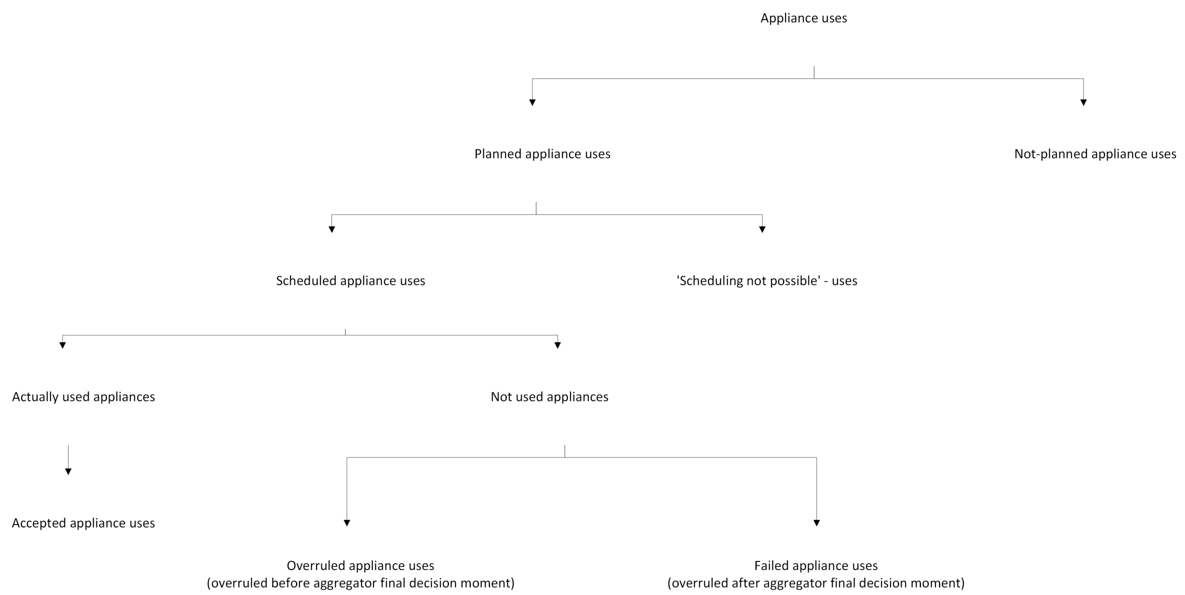

Figure 3.5: Appliance use class tree

The appliance use-class will record a number of different attributes which will provide inside in the appliance uses. They will record the following:

- appliance use: according to the appliance use tree in figure 3.5
- the characteristics of the household they belong to
- their usage type, so whether they were accepted, overruled or failed
- decision-function: they will store all the components and information resulting in the decision made about their use
- temporal information: eg hour, day, week of use
- reason for not use

The reasons for not-use are summarized in table 3.2. The main-difference in reasons for not-use is in their connection to household routines and decision-function. Routines may lead to a not-used appliance because of the time-constraints it led to. The decision-function on the other hand entails households deciding over appliance uses.

Basis	Reason	Explanation
Time-constraint	not (un)loaded	Scheduled use not possible because prior load was not unloaded or current load was not loaded in appliance
	nobody home	Household was not home at time of scheduled start
	max activities	Household was not able to perform all appliance-use related activities thus had to drop scheduled appliance use
Decision-function	push-decision	Household decided to not-use scheduled appliance through push-decision
	final-decision	Household decided to not-use scheduled appliance through final-decision
Other	washingmachine not-used	Dryer was not-used because the washing machine was not used

Table 3.2: Reasons for not-use of scheduled appliances

4

Computer model

In this chapter the computer model will be provided. This will start with how the conceptual model was implemented to make the computer model. Then model verification and validation will be discussed. Finally, the experimental design will be discussed and implemented in the computer model.

4.1. Implementation

The conceptual model needs to be transformed into an implemented model. To this end, the data needed for the model will be discussed. Then the encoding of the conceptual model will be explained.

4.1.1. Data

Since the aim of this thesis is to explore a possible RDR program in a long-term scenario, the usefulness of data is limited. However, to place the behaviour of household in a somewhat realistic scenario, two types of data have been found and implemented.

The Centraal Bureau voor Statistiek (CBS) is a Dutch government agency responsible for collecting and publishing statistical information. In 2022, CBS published data on the water consumption of households in the Netherlands (Bakker et al., 2022). Their estimations are based on a questionnaire send to randomly selected households. The published data includes sections on the average daily water consumption of different appliance types. For example, there is a separate section for the shower and for the faucet. The data includes the average number of times a day the appliance is used per person. This data is presented for different household characteristics. For example, different age-groups and different levels of urbanization. In this thesis, this data was used to define the weekly need households have of their semi-flexible appliances. Specifically, the average number of times a day the washing machine and dishwasher are used per household size. The characteristic of household size was chosen because it relates to the variable household type. Figure 4.1 shows the data used to set the weekly household need for dishwashers and washing machines.

Household size	Dishwasher	Washing machine
One person	0.51	0.52
Two persons	0.35	0.34
Three persons	0.28	0.31
Four persons	0.24	0.31
Five or more persons	0.22	0.28

Table 4.1: Average times a day appliances are used per person (Bakker et al., 2022)

The weekly need was calculated by multiplying the averages by 7 (for weekdays) and multiplying again by number of occupants (as the averages are per person).

Torriti (2017) published a paper on the relation between energy demand and the social practices of households. To this end they analysed the 2005 time of use survey data from the UK Office for National

Statistics. They looked at how time dependent different social practices are overall, and its variations over different weekdays and seasons. The findings from this paper were used to set the preferred time of use per appliance type for households in the model. Firstly, dishwasher usage was considered part of the social practise: preparing food and washing the dishes. Figure 4.1 shows the time dependency of this social practice.

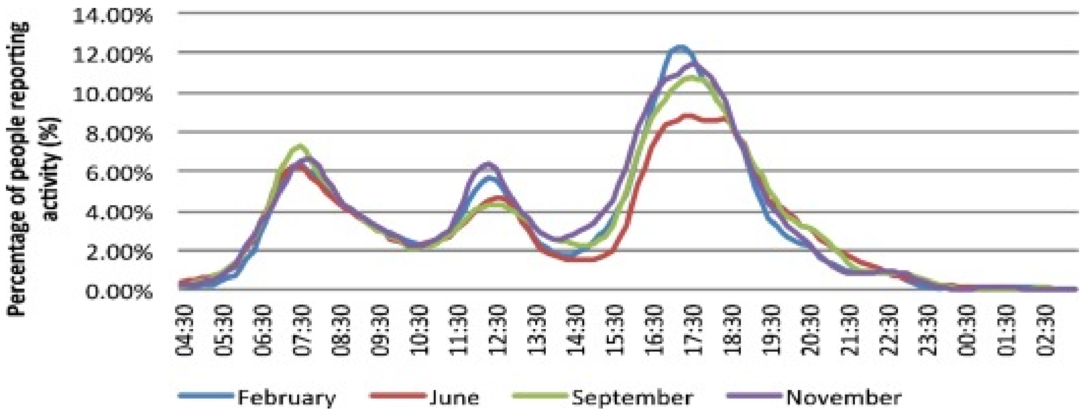

Figure 4.1: Centred average percentage of preparing food throughout the day in February, June, September and November (Torriti, 2017)

For the thesis, the peaks of the figure were used as the hours households tend to prefer to use their dishwasher. These are: 8 am, 1 pm, 6 pm.

This same logic was used to set the preferred time of use of the washing machines. Figure 4.2 shows the time dependency of washing clothes. The hours used for preferred time of use are: 10 am, 3 pm and 8 pm.

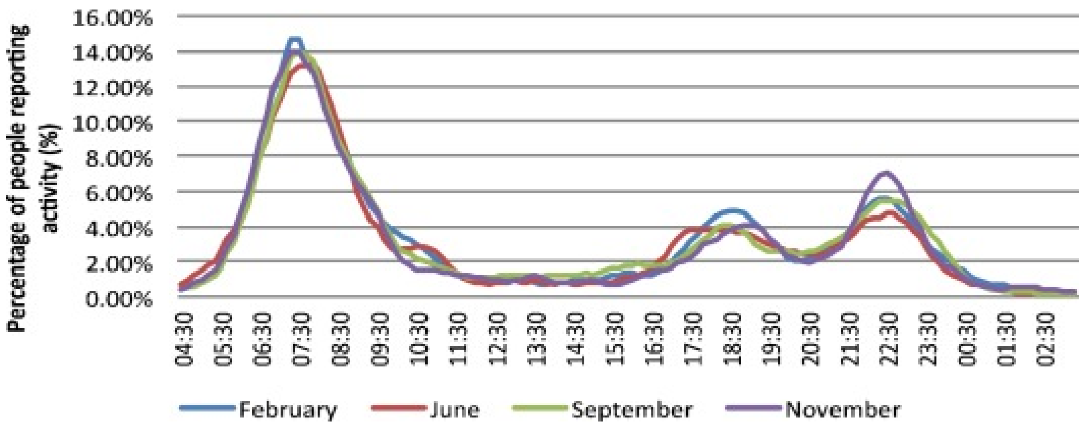

Figure 4.2: Centred average percentage of washing clothes throughout the day in February, June, September and November (Torriti, 2017)

4.1.2. Encoding

The conceptualized model is translated into the encoded model in this step. The model is implemented in an appropriate modelling language. This language needs to provide the software infrastructure to facilitate the programming of agents, their interactions and the environment (Van Dam et al., 2012). For this purpose the python library Mesa was used (ter Hoeven et al., 2025). This library was designed for the development of agent-based models and thus includes the necessary elements for encoding an agent-based model and for running experiments with an agent-based model.

4.1.3. Basic run description

To demonstrate the functionality of the model, an appliance use will be followed in a basic model run from creation to leaving the model.

The model day is Wednesday and the hour is 12. The aggregator starts scheduling appliance uses for the next day. On Thursday, household 55 has planned to use their dishwasher which has a duration of an hour. The aggregator knows this and thus is trying to schedule this use of their dishwasher. They know the household is available from 7 to 9 and 17 to 22. Based on the system information the options for scheduling are 8, 19, 20, 21, 22. The aggregator chooses to schedule the appliance at 22 because it is closest to their objective hour of 23. Thus the scheduled use of the dishwasher is model day Thursday hour 22. The scheduled appliance use is transferred to the scheduled$_appliancesholdinglistofhousehold55.$

For the scheduled appliance use time steps continue on hourly until the household does something relevant for this scheduled use at Wednesday hour 18 when it unloads the prior use of the dishwasher. Time steps continue hourly until model day Thursday hour 0. This is when the day is planned for household 55. The scheduled use of the dishwasher is transferred from the scheduled$_applianceholdinglisttoitsstartinghourintheho$

Time steps continue on hourly until model day Thursday hour 7, when the availability of household 55 switches on. They make their first decision. Household 55 is a low income single household. Their long term motivations are 4 for financial and 4 for environmental. Household 55 prefers to use their dishwasher at hour 8. This means the scheduled use of the dishwasher at hour 22 has a comfort-score of 4. The last time household 55 used their dishwasher was 4 days ago and the next day is 2 days from now. This leads to an urgency score of 2. The uncertainty of commitment has a score of 1. Thus the decision leads to 8 - 6 +1 = 3. The scheduled appliance use stays in the hourly overview dictionary. Another decision for this scheduled appliance use is added to the hourly overview dictionary of household 55 at hour 15. Time steps continue on hourly as household 55 continues its daily actions.

At hour 15 household 55 makes its next decision on the scheduled appliance use of the dishwasher. The financial, environmental, comfort and urgency scores are the same as the decision of hour 7. The uncertain commitment now has a score of 0.25. This leads to the decision: 8 - 6 + 0.25 = 2.25. Again, the scheduled appliance use stays in the hourly overview dictionary and the next decision is added to the hourly overview dictionary at hour 17. This decision is the same as the decision at hour 15 and thus the same happens only the next decision is planned at 21. At hour 17 the household also starts planning for the appliance use at 22 and loads the dishwasher.

At hour 21 the last decision is made on the scheduled appliance use. Again the scores are the same for the last decisions except for the uncertain commitment. At this hour it has a score of 0. Now the decision is 8 - 6 - 0 = 2. Thus the household has decided to use the dishwasher as the aggregator had scheduled.

At hour 22 the dishwasher is scheduled to be used. It first checks if its conditions are met. Whether the household is home and the dishwasher has been loaded with dirty dishes. These conditions are met and thus the dishwasher is used as scheduled. The appliance use leaves the hourly overview dictionary and goes to the model data collection.

household would like to use dishwasher

4.2. Model verification and validation

4.2.1. Verification

Model verification is the process of ensuring that the conceptual model has been translated accurately into the finished model (Robinson, 2004). One of the methods used for verification is tracking agent behaviour. This method verifies the translation from conceptual model to implemented model through logging agent processes. Through logging agent states, input and output, their behaviour can be viewed from the outside (Van Dam et al., 2012). For this thesis, the tracking test was continuously performed during the modelling process and continued passively in the experiments through error codes.

The model was built up slowly. It started with a simple version where actions were taken and added to a households day. This required assumed functions and inputs for the parts that would be added later. With the simple version and after every added model part, extensive print functions were used to ensure the methods and states were functioning in accordance with the conceptual model. The assumed functions and inputs would also be varied at each stage to limit the change of the model breaking later. This was necessary because it becomes more difficult to find the origin of unwanted behaviour with increased model complexity.

In addition, error codes were added to finished model functions. If a function does not bring the result it should, the model will print an error code with information of said function. The error codes were mainly used to test for continuity, method functionality and conditionality. The continuity errors test whether household actions happen in the right order and at the right time. For example, that unloading of the dryer happens before loading, or if the appliances scheduled are actually for that day. The method-functionality test whether method output make sense. For example, if the scheduled appliance time is actually in the household estimated availability. Lastly, the conditionality errors test whether methods and actions meet the right conditions for execution. For example, that the washing machine is loaded with the right load before being started.

4.2.2. Validation

Model validation is the process of ensuring the model is sufficiently accurate to fit its purpose (Robinson, 2004). The clearest way to do this is through comparing the model to its real-life equivalent. However, this is difficult if the model represents a possible future system, instead of a current real-life one. Validation with this type of model tends to focus on whether the model is useful and convincing in the knowledge gained from its outcomes (Van Dam et al., 2012). In other words, creating confidence in the model so its results may be accepted (Robinson, 2004). This too, provides a challenge for this thesis as demand response does not have a unilateral reaction from residential users nor unanimity in its theoretical research. This is also complicated by the many different forms a RDR program can take. One objective for the model was the inclusion of meaningful behaviour. To this end a list was compiled to give direction on how to include household behaviour meaningfully. The model may be validated by ensuring the model behaviour represents the relevant points of this list. From this list, the following points could be formed by modelling behaviour:

1. Variations in household energy demand can be partially explained by economic factors and household characteristics: this point is validated by the fact that the number of planned appliance uses varies across households with regard to their income level and household type.
2. Households do not optimise their utility or make continuous rational decisions: this point is validated by the simple fact that households decide to not-use their scheduled appliance uses. If households did optimize, the only reason for not-use would be linked to time limitations.
3. Households do not only consider price when making energy related decisions: this point is validated by the fact that urgency and comfort influenced household decision-making over the different scenarios.

4.3. Experimental design

4.3.1. Key Performance Indicators

In 3.4 was explained how the model outcomes will be measured through use of the appliance use-class. This will be extended on in this section by identifying model outcomes that can provide insight into the reliability of households. These Key Performance Indicators (KPI's) will be analysed in the result chapter. There are different ways in which reliability can be understood in an RDR program. To be able to deliver flexibility, and thereby a possible important system service, the aggregator needs reliability on different levels (see 3.5). Aggregators want to reliably offer flexibility to the energy system. For this they need load capacity and certainty that they will deliver their offered capacity. So firstly, they need to be able to reliably schedule appliance uses to gain capacity. In the model the aggregator can only schedule if household expected availability overlaps with their hours available for scheduling. They need to be able to reliably schedule otherwise they have no flexibility to offer. The scheduled appliance uses than need to be reliable used by the households. Thus the second level describes the not-used scheduled appliance uses.

In summary, the model will measure the following KPI's:

- Not-scheduled appliance uses
- Not-used scheduled appliance uses

4.3.2. Scenario space

The modelling objective is to gather insights through exploring household behaviour under an aggregator provided RDR program. The model provides the space in which the exploration takes place. The variables in this scenario space consist out of:

- External factors
- Internal parameters

The external factors will be used to design the scenario's. The external factors are variables whose values are determined outside of the modelled system. The internal parameters are set within the modelled system. Their values have varying influences on the system but will stay consistent across scenario's.

The household characteristics of appliance type, household type and income level explained in 3.3.3 will be considered the household characteristics. The values per characteristic influence the model parameters and variables in different ways. Thereby they influence the KPI's differently. They can offer inside into the KPI's through analysing them over the scenario's.

External factors

The external factors will be considered the aggregator operations in terms of their objective and the specific system need they try to meet. These are translated into the model as the aggregator policies and consist out of the factors 'scheduling objective' and 'scheduling availability' respectively. Aggregators can also set the final-decision moment.

The factor 'scheduling availability' represent the hours when the market would like the demand side to use energy. For the scenario space, off-peak hours and RES production will serve as the determinant for variety in value. The off-peak hours will be represented with two values for the scenarios. This is because demand and thus peak hours are dependent on seasonality. Thus winter and summer have different off-peak hours. Furthermore, RES generation is uncertain and thus will be represented through a more sporadic input. To represent this uncertain nature, the scheduling availability 'sporadic' will be different from day to day. The hours available for scheduling per value for 'scheduling availability' is shown in figure 4.3.

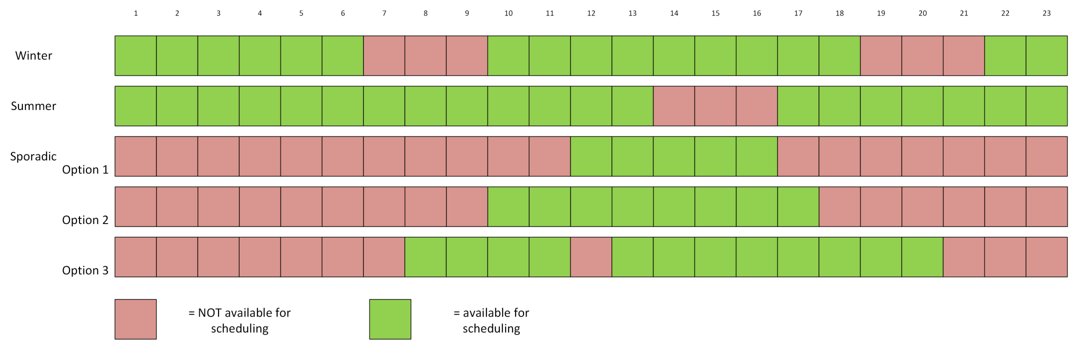

Figure 4.3: Hours available for scheduling per scenario value

Winter and summer availability will have the same hours available for scheduling every day. Sporadic availability will have available hours depended on a random draw from the options presented in the figure.

The factor 'scheduling objective' represents the objective the aggregator is trying to reach within the hours available for scheduling. This factor will also have three values for the scenarios. Table 4.2 explains what each objective means.

Value	Meaning
Peak scheduling	Aggregator schedules as close to the height of hours available for scheduling (valley-filling) as they can. Note: If there are multiple intervals in the hours available for scheduling, aggregator will schedule within the interval that is closest to household preferred time of use.
Nice scheduling	Aggregator schedules as close to household preferred time of use as they can.
Random scheduling	Scheduling hour is randomly selected. Aggregators may have multiple objectives and is likely to spread its schedule out over the available hours. This scheduling objective tries to resemble this through its randomness.

Table 4.2: Model input for scenario variable 'scheduling objective'

The factor 'final-decision moment' represents the last moment a household can overrule an appliance. This time is set by the aggregator. For the scenarios, a difference was made between a set hour of the day and a set number of hours before scheduled use as the final-decision moment. The option of not having a final-decision moment was also included. In effect this option means that the final-decision moment is the moment of scheduled use. Table 5.1 shows the values that will be included for final-decision moment:

Type	Value	Meaning
Number of hours before	-1	One hour before scheduled use
	-4	Four hours before scheduled use
No final decision	0	At hour of scheduled use
Set daily hour	11	Every day at 11am
	15	Every day at 3pm

Table 4.3: Final-decision moment

An overview of the different scenario variables with their values and model meaning is presented in table 4.4.

Scenario variable	Value		Meaning
Scheduling availability	Winter hours		Hours available for scheduling according to winter peak hours
	Summer hours		Hours available for scheduling according to summer peak hours
	Sporadic hours		Hours available for scheduling representing the sporadic nature of RES generation
Scheduling objective	Peak scheduling		Scheduling to approximate height of valley hours
	Nice scheduling		Scheduling to approximate household preferred time of use
	Random scheduling		Scheduling randomly
Final-decision moment	Number of hours before	-1	One hour before scheduled use
		-4	Four hours before scheduled use
	No final-decision moment	0	At moment of scheduled use
	Set daily hour	11	Every day at 11am
		15	Every day at 3pm

Table 4.4: Scenario space summary

4.3.3. Experimental setup and execution

This section concerns itself with the practical settings for the experiments. For starters, a full factorial experiment was chosen were all variable combinations are run. Thus 3 options for scheduling availability times 3 options for scheduling objective times 5 options for final-decision moment. This means 45 different scenarios. Each scenario will have 10 repetitions thus in total 450 model runs will form the base for experiment analysis.

The experiment was run through initialisation of the batchrunner class. This is a Mesa specific class that allows for the factorial execution of Mesa-model experiments (ter Hoeven et al., 2025). Parallel execution through multiprocessing was not computationally feasible because of the work-memory required. Thus the model was run per scenario. Because of this computational limit, the batchrunner had to be looped over a variable. The variable ‘scheduling objective’ was used for this. This meant the experiment results were spread over three datasets. Data was collected at the last step of the model.

5 Results

In this chapter the results from the experiments will be presented. Per KPI, the influence of aggregator policies and household characteristics will be discussed. Then each section will end with a conclusion.

The aggregator policies used for scenario's were:

- Scheduling objective
- Scheduling availability
- Final-decision moment

The household characteristics that stayed consistent across scenario's were:

- Appliance type: dishwasher, washing machine, dryer
- Household type: single, young couple, couple with children, seniors
- Income level: low, middle, high

5.1. Not-scheduled appliance uses

The overlap of hours available for scheduling and household estimated availability determines whether or not aggregators can schedule planned appliance uses. The aggregator has direct influence on this KPI through their policy of scheduling availability. The appliance type and household type interact with this policy in their influence on percentage of appliance uses that were not possible to schedule. This section will first look at the influence of scheduling availability. Then the interactions with appliance type and household type will be explained and described. Finally, conclusions will be drawn in the last section. Figures of the other policy and characteristic showing they are not influencing this KPI can be found in appendix A.

5.1.1. Scheduling availability

The aggregator has direct influence on the percentage of non-scheduled appliances through the hours they want to offer flexibility to the system. Figure 5.1 shows the percentages of appliance-uses that the aggregator was unable to schedule for the different scheduling availabilities. The figure shows a clear distinction in percentages per scheduling availability thus this scenario variable greatly influence the percentage of not-scheduled appliance uses. The aggregator was able to schedule all appliance uses in summer. For winter hours, they were able to schedule around 3% of planned appliances uses. For sporadic hours this was around 9%.

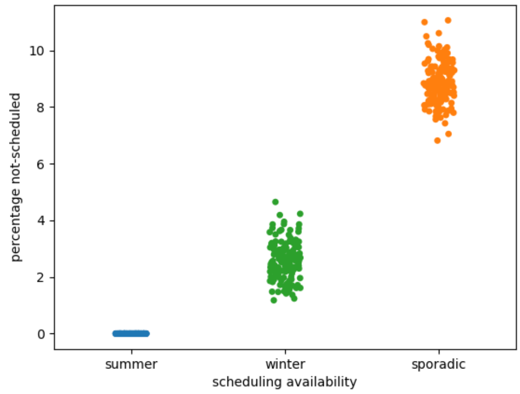

Figure 5.1: Percentage of not-scheduled appliance uses per scheduling availability

The differences in percentages are caused by the different hours the different scheduling availabilities offer. Summer hours cover the largest numbers of hours spread out over the day. Winter-hours covers hours in the mornings and evenings. Sporadic-hours covers the least number of hours with varying tendencies towards times of the day.

5.1.2. Interactions household characteristics

Scheduling availability interacts with appliance type and household type on the percentage of not-scheduled appliance uses. These characteristics interact because they are linked with the expected availability of households.

Appliance type

Figure 5.2 shows the percentage of appliances uses the aggregator was unable to schedule per appliance type with scheduling availability. It shows noticeable differences both between appliance types and per appliance type between scheduling availabilities. The figure shows dishwasher with the highest percentages overall and strong scheduling availability dependency. It has clear separate percentages per scheduling availability. Dryer has high percentages for sporadic-hours but similar hours to washing machine for winter-hours. Washing machine has the lowest percentages and does not interact with scheduling availability.

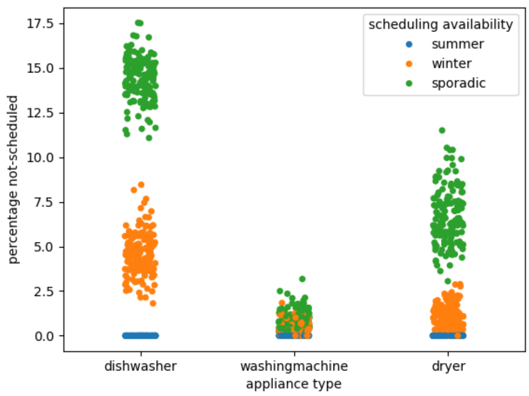

Figure 5.2: Percentage of not-scheduled appliance uses per appliance-type with scheduling availability

Dishwasher is most sensitive to scheduling availability. This is linked to their higher need compared to the other appliance types. The model prefers to plan appliance uses on days when households have higher availabilities (weekend and work-from-home days). Appliance-uses will only be planned on days with lower availability (work-at-location days) if there are no high availability days left. Thus appliances with higher needs are more likely to be planned on days with lower availability. Dishwashers have a higher need compared to washing machines and dryers. Dryer interacts with sporadic-hours. This can be explained by their scheduling being linked to the washing machine. Dryers need to be scheduled after the washing machine. If there is not enough time available to schedule both in-sequence, the dryer will not be scheduled. Sporadic-hours has the lowest number of hours available for scheduling and thus the likelihood that the dryer cannot be scheduled is higher.

Household type

As figure 5.3 shows, the household-type influences whether an appliance can be scheduled or not. There are differences between household types and per household type between the different scheduling availabilities. For sporadic-hours, singles and couples with children have the highest and similar percentages. Young-couples have slightly lower percentages and seniors have the lowest percentages. For winter hours, couples with kids have the highest percentages. Singles and young couples have lower percentages and seniors average a percentage of 0. Overall the order of percentage of appliance-uses the aggregator was unable to follow from highest to lowest is: couples with children, singles, young couples and seniors.

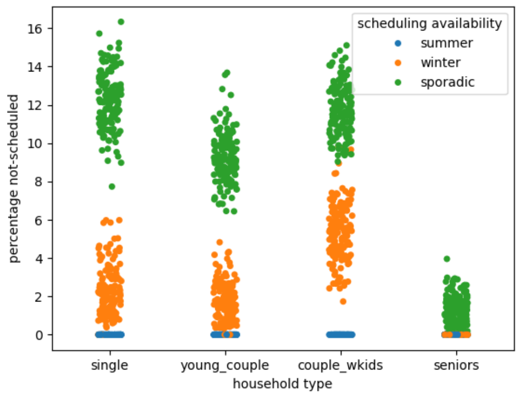

Figure 5.3: Percentage of not-scheduled appliance uses per household-type with scheduling availability

The interesting thing to note is that the differences between household-types are not-consistent over scheduling availability. In winter hours, couples with kids have higher percentages compared to singles and young couples. However in sporadic hours, singles and couples with kids have higher percentages compared to young couples. This means that the household types interact with the scheduling availability differently. These different interactions can be explained by the differences in routines between the household-types which informs their expected availability. Singles and young-couples have the same daily routines while couples with kids and young-couples have the same number of days they work from home. Thus in winter hours the routines are more important, while in sporadic hours the number of days they work form home are.

5.1.3. Conclusion

The rates of not-scheduled appliances is mostly determined by the scheduling availability which interacts with the household characteristics of appliance type and household type. The aggregator benefits from scheduling more appliances as this increases the capacity they can offer. The scheduling availability of summer-hours had the lowest rates of not-scheduled appliances. This indicates that the aggregator is able to schedule more appliance uses when the scheduling hours are in-line with off-peak hours during summer. The highest rates occurred during sporadic-hours. Since these hours represent RES generation, this indicates that the aggregator will have difficulty scheduling appliance uses during periods of RES generation.

High need appliances will need to be scheduled by the aggregator more often. This means high need appliances can offer higher capacity compared to lower need appliances. However, they also have higher rates of not-scheduled. This is because they are likely to be scheduled on a day when households have less availability. Thus aggregators have a higher certainty in the potential to schedule lower need appliances while higher need appliances can offer a potential higher capacity with lower certainty. This may lead to a situation were aggregators have to consider a trade-off between lower but certain capacity and higher but uncertain capacity.

The differences in not-scheduled appliance rates between household types are caused by their differences in expected availability. The results indicate that during winter hours, higher daily available hours is linked to lower rates of not-scheduled. They also show that in sporadic hours higher number of days households work form home is linked to lower-rates of not-scheduled. The main difference between winter hours and sporadic hours is that winter hours cover the same hours available for scheduling every day while sporadic hours has variations in the hours available for scheduling. Thus this all indicates that the number of days a household works from home is more important when the scheduling availability is uncertain, while the hours themselves are more important when the scheduling availability is certain.

5.2. Not-used scheduled appliances

There are a number of reasons modelled for why households do not use a scheduled appliance use. There are three different bases for why an appliance was not-used. These are: the decision-function, washing machine not-used and time-based. Time-based reasons have four more specified reasons for not-use. A more elaborate explanation of these reasons can be found in 3.4. The reasons for not-use have been listed below to provide a simple overview:

- Decision-function
- Washing machine not-used
- Time-based
  - Nobody home
  - Max actions
  - Appliance not loaded
  - Appliance not UNloaded

In this section, there will be figures showing the counted reasons for not-use over different variables. It should be noted that the counted number should not be compared across values on themselves because the counted number has not been corrected for the number of scheduled appliance uses.

Most policies and characteristics influence the percentage of not-used appliance uses either by design or as a result of emergent behaviour. This section will discuss and explain these differences per policy and characteristic. Figures of the other policy and characteristic showing they are not influencing this KPI can be found in appendix A.

5.2.1. Dshour

The variable Dshour is the combination of the aggregator policies 'scheduling objective' and 'scheduling availability'. Together these policies determine the starting hour of scheduled appliance uses (determinant staring hour). The influence these policies have on the percentages of not-used appliance uses is through the starting hour. This is why their combination offers the best insight in the percentages of scheduled appliances that were not-used. Table 5.1 provides an overview of Dshour values.

Figure 5.4 shows the percentage of appliances-not used per Dshour. The figure shows that Dshour influences the tendency of the percentage of appliances not-used. The main trend is related to the scheduling objective. The spread of percentages are close together when they have the same objective. Dshour (1, 2, 3) for peak, (4, 5, 6) for nice and (7, 8, 9) for random. Overall nice-scheduling has the lowest percentages, followed by peak-scheduling, and random-scheduling with the highest percentages. Thus the best results are yielded when the aggregator tries to schedule close to the individual households preferred time-of-use. Within the scheduling objectives are differences in the per-

Dshour	Scheduling hours	Scheduling objective
1	summer hours	peak-scheduling
2	winter hours	peak-scheduling
3	sporadic hours	peak-scheduling
4	summer hours	nice-scheduling
5	winter hours	nice-scheduling
6	sporadic hours	nice-scheduling
7	summer hours	random-scheduling
8	winter hours	random-scheduling
9	sporadic hours	random-scheduling

Table 5.1: Final-decision moment

centage of not-used in combination with the scheduling availabilities. For peak-scheduling the mean of percentages from high to low is summer (Dshour 1), sporadic (Dshour 3), winter (Dshour 2). For nice-scheduling it is sporadic (Dshour 6), summer (Dshour 4) and winter (Dshour 5). For random-scheduling it is summer (Dshour 7) and, winter and sporadic (Dshour 8 and 9).

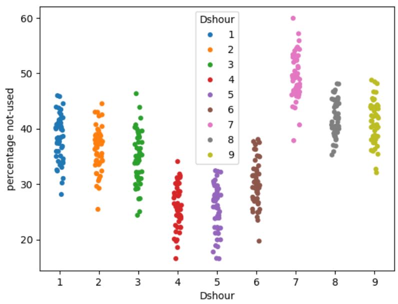

Figure 5.4: Percentage of appliances not-used per Dshour

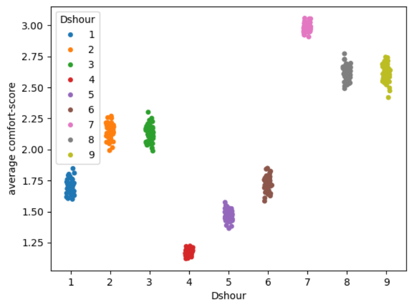

Figure 5.5: Average comfort-score per Dshour

Comfort-scores are determined based on discomfort. Discomfort is the difference between scheduled start and household preferred time of use. Thus trends in scheduled start lead to trends in discomfort which in turn leads to trends in comfort-score. Comparing the percentages of not-used in figure 5.4 to the average comfort-score in figure 5.5, shows a clear link. Most of the noted trends in rates of not-use follow the average comfort-score per Dshour. The averages cluster per scheduling objective with differences per scheduling availability. There are two exceptions to this. Based on comfort-scores, both peak-scheduling and nice-scheduling should have their lowest percentages with summer hours (Dshour 1 and 4). But peak-scheduling has the highest percentages of not-used with summer hours (Dshour 1) while nice-scheduling has similar low percentages with summer hours and winter hours (Dshour 4 & 5).

Figures 5.6 and 5.7 provide insight into this. These figures show the counted reasons for not-use per Dshour. Because these counted numbers are not compensating for the number of scheduled appliance uses, they cannot be directly compared to the percentages of not-used appliances. However, they can provide insight into what contributed to these percentages. Overall, figure 5.6 shows that the decision-function is the main contributor to households not-using their scheduled appliances. The counted numbers of dryers not-used because the washing machine scheduled before them was not-used comes second. The time-based reasons for not-use are overall the smallest counted reason for not-use. However, their counted numbers are noticeably higher in Dshour 1 and 4. These are the two Dshours with deviating percentages of not-used from the comfort-scores. Looking at figure 5.7, Dshour 1 and 4 also have visually high numbers of 'nobody home' reason for not-use. Thus Dshour 1 and 4 have higher percentages of not-used compared to what is expected because households are more often not home at the starting hour of appliance uses.

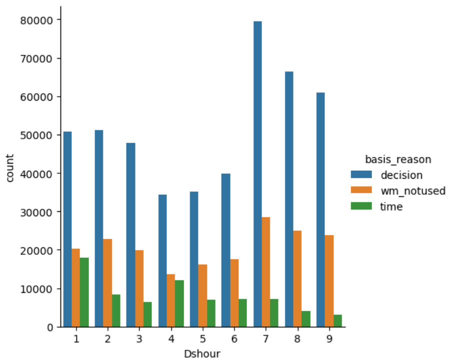

Figure 5.6: Counted basis reasons for not-use

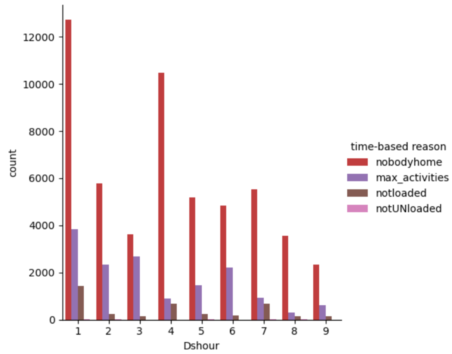

Figure 5.7: Counted time-based reasons for not-use

5.2.2. Household characteristics

There are differences in percentages of not-used scheduled appliance uses within the household characteristics. All characteristics show strong links to the decision-function in their percentages of not-use. All the characteristics influence the decision-function through in their design. Thus the differences in percentages are mostly caused by attributes inherent to the implementation of the characteristic.

In this section the differences in percentages will be explained briefly by noting the differences within a characteristic. Trends that cannot be explained by the inherent differences between types will be explained in more detail.

Appliance types

Figure 5.8 shows the percentages of not-used scheduled appliances per appliance type. It shows differences with dishwasher having the lowest percentages of not-use and dryer having the highest percentages. Figure 5.9 shows the basis reasons for why the scheduled appliances were not-used. Only dryer does not have the decision-function as main basis reason. However, its main reason is that the washing machine it was scheduled in combination with was not-used. Thus indirectly the main reason for dryer not-use is the decision-function as well.

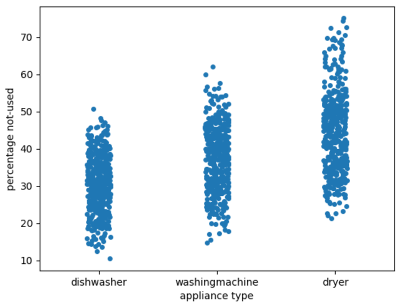

Figure 5.8: Percentages of appliances not-used per appliance type

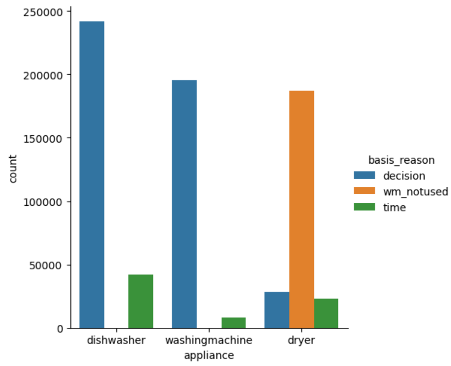

Figure 5.9: Counted basis reasons for not-use per appliance type

The appliance type influences the decision-function through their weekly need. The appliances types have a different number for how many times a week they are needed. The dishwasher has a higher need compared to the other appliances. Higher need equals higher sense of urgency and thereby lower urgency-scores. Thus dishwashers are less likely to be overruled by the decision-function.

Household type

Figure 5.10 shows the percentages of not-used scheduled appliances per household type. There are differences with seniors having the highest percentages of not-use, then couples with children who also have the smallest spread, singles and young couples have the lowest percentages. Figure 5.11

shows the basis reasons for why the scheduled appliances were not-used. Again, overall the main basis reason for not-use is the decision-function. Other differences of note are the ratio's of decision-function to washing machine not-used, and couples with children having a noticeably higher count for time-based reasons for not-use.

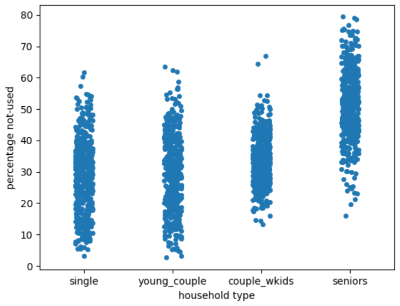

Figure 5.10: Percentages of appliances not-used per household type

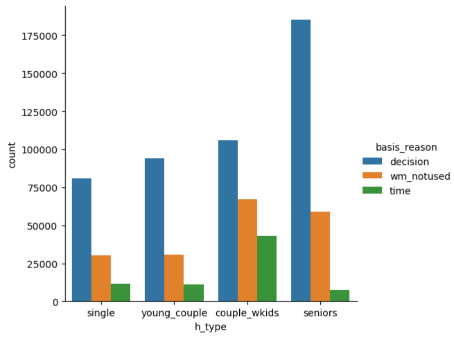

Figure 5.11: Counted basis reasons for not-use per household type

The household type influences the decision-function in different ways. For long-term motivations, single households and young couples have higher environmental scores compared to couples with children and seniors. Appliance need is also tied in with the household type and based on number of occupants. This means that households with children have a higher need for especially the washing machine compared to the other household types. Higher need leads to higher sense of urgency and thus lower urgency-scores. Lastly, seniors prioritize comfort more than the other household types and have thus higher comfort-scores. Thus singles and young couples have similar influence on the decision-function with higher environmental motivation leading to higher decision scores. Couples with children have lower environmental motivation which is slightly compensated for with higher feeling of urgency and thus lower urgency-scores. Seniors have both lower environmental motivation and higher comfort priority. This leads to lower-decision scores.

Income level

Figure 5.12 shows the percentages of not-used scheduled appliance uses for the different income levels. It shows that overall low-income households have the lowest percentages of not-used, followed by middle-income and lastly high-income households with the highest percentages of not-used. Figure 5.13 shows the basis reason for why appliances were not-used per income level. Both middle- and high-income households have the decision-function as their main reason for not-use. Low-income households have time-based reasons as their main reason for not-use.

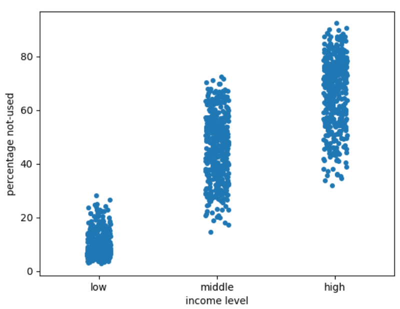

Figure 5.12: Percentages of appliances not-used per income level

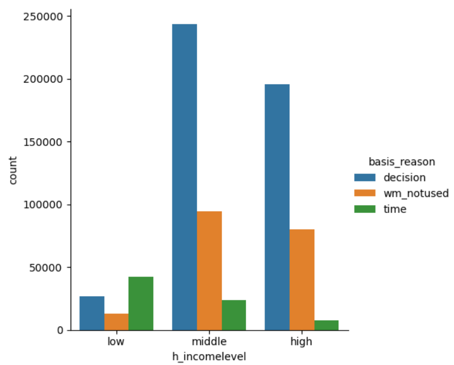

Figure 5.13: Counted basis reasons for not-use per income level

Household income-level has two influences on the decision-function causing these differences. Firstly, financial motivation is tied to income level. Low-income households have the highest financial motivation, followed by middle-income and high-income. Secondly, there are differences in the over-planning of appliance uses that influences the urgency-score. Both middle- and high-income households request more appliance uses than they need. This means they do not feel the same sense of urgency to use the scheduled appliance uses compared to low-income households.

These differences in influence on the decision-function also explain why low-income households have higher time-based reasons for not-use. Because they are unlikely to chose to overrule their scheduled appliance uses, there is more space for time to cause the not-use.

5.2.3. Conclusion

Unlike with not-scheduled appliances, the rates of not-use are not linked strongly to a singular variable. The results show that all aggregator policies and household characteristics included in the model influence the rates of not-use. Most of these variables have noticeable differences between values but also show large spreads. This indicates that although the variables influence the rates of not-use, their influence is not strong.

To perform their operations well, the aggregator wants their actual response to be close to or equal to their planned response. This means they want households to comply with the scheduled appliance uses. The aggregator has two policies included in the model that influence the rates of not-use through their combined effect on the scheduled start of appliance uses. The trends in rates of not-use follow the scheduling objective stronger than scheduling availability. This indicates that how aggregators are choosing to schedule the appliance uses is more influential than the hours where they need to schedule the appliances. The rates of not-use were lowest when the preferred time of use was considered in the scheduling objective and thus when household discomfort was lower. This all indicates that the aggregator is more likely to have better household compliance when they include their preferred time of use in their scheduling of household appliances.

6
Discussion

This chapter will reflect on the performed analysis and research of this thesis. First the key implications that can be drawn from this research will be summarized. Then the limitations will be underlined.

6.1. Research implications

6.1.1. Aggregator implications

Household availability needs to correspond with the flexibility objective of the aggregator. Otherwise the aggregator will have no capacity to offer. The model includes variations in household availability through the number of days a household has somebody working from home and the actual daily hours a household is at home and available for RDR. The number of days a household works from home can also be seen as days when households are more flexible and stray from availabilities tied to the standard work day. The model results show that flexible days become especially influential on the aggregators ability to schedule appliances when the flexibility they try to meet is uncertain. This implies that households with more flexible days are better suited to meet RES generation and highly variable balancing markets. On the other hand, when the aggregator offers a flexible service that describes a set number of daily hours, the daily hours of routine days is more influential.

Aggregator value to the energy system aligns with the size and timing of the capacity they can offer. The results show that this capacity is variable when looking at the overlap of household availability and system need. It shows the lowest rates of not-scheduled appliance uses for summer and thereby the most opportunity for scheduling. The highest rates of not-scheduled appliance uses were during varying hours of system need. These hours were specifically chosen to represent RES generation. This indicates that aggregators may find scheduling appliances especially difficult in periods of uncertain system need. The system need for flexibility is less dire during summer compared to the winter or for RES generation. Furthermore, the potential value of residential demand response to the energy system is often mentioned in context of RES generation. This indicates that aggregators may have more difficulty scheduling appliances and delivering flexible capacity when the system is in higher need of it. This puts their potential value to the energy system in question.

Aggregator capacity both in terms of being able to schedule and compliance with that schedule are influenced by multiple household specific variables. Thus a way for aggregators to be more certain of their ability to offer flexibility, is to select the households that can participate in their program. However, this also bring a multitude of challenges. Firstly, this requires very specific and detailed information on household routines and their potential motivations for participation. These types of information are not readily available nor are households likely to want to part with this type of sensitive information. Selecting while households are participating will at the very least damage household willingness participate. Secondly, selecting households will also influence the capacity the aggregator is able to offer. For example, if they only select households who are highly available and very likely to comply, they will have a small pool of resources.

Earlier was described how there are large variations within the rates of not-use even under the combined policies determining the starting hour. There are also overall large spreads of not-use between the values of the household characteristics. This confirms the large variations in household compliance with the scheduled use of semi-flexible appliances. For the aggregator these large variations mean high uncertainty in household compliance. Non-compliance on itself makes aggregator functioning difficult because they have less capacity to offer overall. However, aggregators could plan around this if the non-compliance was predictable. Predictable non-compliance would enable the aggregators to better gage the capacity they can offer and thus what flexibility bids they can assure. They could do this by incorporating the expected non-compliance in their bids and balancing their portfolio. But the findings show the opposite. Uncertain non-compliance will make it more difficult for the aggregator to keep to their offered capacity. This in turn can become a system-wide issue when the system relies on the aggregator to provide a balancing service.

6.1.2. System implications

The model results have implications for RDR's potential role as a flexible source. Firstly, for the type of service it could offer. Semi-flexible appliances can only be shifted to another time and cannot be curtailed. This means altering their demand requires notice far in advance. Thus the aggregator can only use semi-flexible appliances to offer services with longer time frames. Flexible appliances may not have this limitation, but are still susceptible to limitations caused by household availability. Some flexible appliances, like lighting and heating, are only used around the times when households are home and have thereby limitations on when they can be curtailed. This means that the aggregator may be able to curtail appliances at shorter notice with flexible appliances, but they will not be able to offer this at every moment of the day. Furthermore, the model results indicate that the aggregator will have difficulty acquiring capacity when the flexible service they offer is uncertain and varying in time. This means RDR may be better suited to flattening of the system profile and peak-reduction over meeting RES generation and competing in highly variable balancing markets.

The insights on household compliance with scheduled semi-flexible appliances also has implications for RDR's potential role as a flexible source. The results show large variations in compliance influenced by many different factors. Although the rates of non-compliance were overall high, aggregators may be able to mitigate this somewhat by including household preferences and selecting participating households. However, even low rates of non-compliance will cause issues for the aggregator as it makes the capacity they offer uncertain. Uncertainty on their delivery of bid capacity will make it difficult for aggregators to compete in balancing markets.

The insights of this thesis have implications for the value of RDR to energy systems. This is firstly in the uncertainty it may bring to the system balance and the system operators who need to regulate it. Capacity requirements will be made more complicated by RDR. Because RDR's capacity will be time-varying, regardless of the type of service offered or appliance type involved, the capacity of flexible sources outside of RDR required for system balance and security will be more uncertain as well. This will increase the difficulty of ensuring enough energy generation, especially during seasonally dependent peak moments. RDR's involvement in energy balancing will also influence the operations of other flexible sources. It could create a situatuion were RDR can compete with these sources, but only during specific time periods both seasonally as weekly. Some of the other flexible sources who may be crucial during other time periods, may not be able to recover there costs and thus become unavailable for functioning as a flexible resource.

6.2. Research limitations

In this thesis, the reliability of household response was explored through a model. This goal of exploration means that the model results should not be interpreted at face-value. The model does not predict a potential future. The model variables, and specifically the percentages, are not real-life indicators of reliability. The value of the model is in the analysis on how and what influences changes in variables and output. The limitations have been structured as follows: thesis objective, implemented RDR program and conceptualization of household routines.

6.2.1. Thesis focus

The focus of this thesis was RDR reliability with the two perspectives of meaningful household behaviour and long-term RDR program engagement. This focus has guided all steps taken and decisions made in the research process. However, this progress of narrowing down the scope also limits what the research can contribute to the understanding of the topic.

A first point of note is the contradiction between including meaningful household behaviour and long-term RDR program engagement. Including behaviour meaningfully depends mostly on the objective of the research, but knowledge and understanding of household behaviour is still fundamental to this end. Thus behaviour can be better included meaningfully when there is a well of knowledge. A body of qualitative research focussed on household behaviour in RDR programs does exist. However, there has not been a lot of long-term RDR engagement. This means there is not a lot of knowledge and understanding on specifically long-term household behaviour. Thus this limits how this type of behaviour can be included meaningfully.

Secondly, the thesis focus of reliability means that the KPI's measuring model performance also focus on reliability. Other factors that could provide insight into RDR's value and feasibility to energy systems were not included in the KPI's. For example, aggregator potential financial gains were not measured because of the simplified way energy market dynamics were incorporated.

6.2.2. Implemented program

The model needed to include a specified RDR program to explore the reliability. This specification was necessary to model household response to RDR but limits what the model is able to say about reliability.

Firstly, the selected program only included the use of semi-flexible appliances. This appliance type was selected because of the level of household interaction it requires. Both through needing to load and unload the appliances and through the need to be present to start the appliance. This means households have to put in effort that is not present in most other RDR program configurations and existing ones. Furthermore, semi-flexible appliances have different load profiles compared to other appliance types. Semi-flexible appliances have a set duration time and load demand during their run. A dishwasher cannot lower its energy demand during its run unless its fully stopped. They are thereby only able to provide flexibility by shifting its use to specific times. Flexible appliances, like lighting and heating, do not have these constraints and can be curtailed. Furthermore, the time frame in which these appliances types can be operated for RDR is different. Because semi-flexible appliances need household interaction and preparation, their demand cannot be altered on short notice. This unlike flexible appliances whose demand can in theory be altered in seconds.

Secondly, the scheduled starting time is set day-ahead. After this moment the starting hour will not change. This puts a strain on the aggregators ability to balance their own portfolio. Thus aggregators not requesting different starting hours after this moment is not likely to be seen in real-life implementations of RDR programs. This means the model cannot provide insight into potential reactions from households to aggregator schedule alterations closer in time to the scheduled start.

Thirdly, the aggregator in the program has taken up the role of an independent aggregator and thereby solely focusses on shifting the semi-flexible appliances to a different time. The aggregator schedules semi-flexible appliance based on the number of times households have requested their usage. However, the household is still able to use these appliances outside of the program. Their attitude towards the program would be different if all uses of their semi-flexible appliances would have to be through the RDR program. This would influence the inconvenience they experience and the urgency for compliance. This would in turn influence how they would interact with and behave under the RDR program.

6.2.3. Routines

Another aspect that influences the insights that can be gained from the model is the conceptualisation of the household routines. Firstly, a big assumption in the model is that households will ask the aggregator to prioritize scheduling their appliance on days were their availability is high. These are weekend days and days were a member of the household works from home. However, especially in the case of weekends, households may want to avoid these days for scheduling as it impacts their ability to plan activities in their free time.

The model also does not account for variations in availability week to week. This is not necessarily an issue as the modelled behaviour still represents households providing their expected availability day-ahead to the aggregator. It does mean that the model paints a rosy picture on household availability as social and weekend-plans are not included in their expected availability. These plans would reduce their availability and thereby influence the reliability.

The influence of days households work from home should also be noted as an important factor. The way the model includes households with members who work from home is not representable of real-life. First off, there are many jobs were working from home is impossible. Then there are jobs that can fully be done at home. There are also members of households who do not work. All these variations influence household availability which the model does not account for.

Another way in which the model limits the representation of household routines are the deviations from expected availability. In the model, the deviations between expected availability and actual availability on the day itself is the same across all household types for all days. However, there are differences in how strict households adhere to their routines. For example, couples with children tend to follow stricter routines to handle the chaos of living with children and are thus not likely to deviate from their expected availability.

7
Conclusion

The objective of this thesis was to explore the reliability of aggregator provided residential demand response. This exploration occurred through the lenses of long-term engagement and modelling meaningful household behaviour. To this end, an agent-based model was designed and implemented. A specific RDR program was included in the model. This program entails the aggregator scheduling semi-flexible appliances of the households in their portfolio. The process of the research was given form through research questions. These questions will be addressed in this chapter. Based on the insights gained from the key-findings and research-questions, recommendations will be formulated. Lastly, this chapter will finish with identified areas of research the topic could benefit from.

7.1. Addressing the research questions

7.1.1. Sub-questions

Question 1: "What are the different forms of aggregator provided RDR?"

The first sub-question aims to gain oversight of the many different ways aggregator provided RDR programs can take shape. Aggregator programs can use the shifting of household energy consumption to a different time and the curtailment of active household energy consumption to gain flexibility.

The first aspect of aggregator provided RDR programs is the means the aggregator uses to incite changes in household energy consumption. These can broadly be divided into two. Firstly, households alter their consumption in response to changes of energy prices. The aggregator would take a more passive role in this case. Secondly, aggregators would be actively involved in energy consumption. This is likely to be through Direct Load Control.

The second aspect of aggregator provided RDR programs is the type of appliances that are part of the program. Three main categories can be distinguished. Firstly, non-flexible appliances. These are appliances whose shifting or curtailment would lead to severe inconvenience to households. Secondly, semi-flexible appliances. The shifting or curtailment of these appliances would not lead to sever inconvenience as long as their desired altered consumption is notified in advance. Lastly, flexible appliances. The consumption of these appliances can be altered on short notice without bringing severe inconvenience to households.

The third aspect of aggregator provided RDR programs is the type of flexibility the program offers. Again, three main categories can be distinguished. Firstly, the program could aim to reduce peak-consumption. By curtailing energy consumption of appliances or by shifting their usage to a different time, energy consumption at peak-hours could be reduced. Secondly, balancing services and congestion management. The program could attempt to increase or decrease household energy consumption to offer balancing and congestion services. These types of services are needed on shorter notice compared to peak-reduction. This is because peak-reduction has known hours while balancing services can be requested hours to minutes before the flexibility is needed. Lastly, the program could solely focus on renewable energy sources. The aggregator would aim to shift household energy demand to those moments when RES are producing energy. These sources tend to be uncertain and unpredictable. This uncertain nature also means that changes may need to be made on short-notice.

Question 2: "How to include meaningful household behaviour when exploring the reliability of aggregator provided RDR?"
The second sub-question focusses on how to include meaningful household behaviour in the model. This forms a challenge as household behaviour is observed to be uncertain and non-price responsive within demand response. However, household behaviour can still be meaningfully included depending on the purpose of the model. In this thesis, the purpose was to explore the reliability of aggregator provided RDR. Thus household behaviour is directly linked with the output of the model. For the output to be meaningful, the model should represent households interacting with an aggregator provided RDR program well. The objective of exploration makes behaviour as the cumulation of factors interacting more important than accurate output numbers. This translates into the need to understand the factors influencing household behaviour under an RDR program. Through analysing qualitative research, a list was formed summarizing this.

The list on insights into household behaviour under an RDR program gained from qualitative research is as follows:

- Variations in household energy demand can be partially explained by economic factors and household characteristics
- Households do not optimise their utility or make continuous rational decisions in their energy behaviour
- Households do not only consider price when making energy related decisions
- Even with automated control, household energy behaviour is dependent on their interaction with the program

Variations in household energy demand can be partially explained by economic factors and household characteristics: This point was incorporated in the model by inclusion of household income-levels. This factor influences financial motivation and urgency.

Households do not optimise their utility or make continuous rational decisions in their energy behaviour: This point was incorporated through a decision-function that trades off long-term motivations against short-term motivations.

Households do not only consider price when making energy related decisions: this point was incorporated through the decision-function consisting out of several motivations. These are: financial, environmental, comfort and urgency.

Even with automated control, household energy behaviour is dependent on their interaction with the program: this point was not relevant as the model does not include automated control.

Question 3: “What factors influence the reliability of aggregator provided RDR?”
This sub-question aims to understand the influences on reliability from the model. The model experimentation focussed on two KPI’s representing reliability. Thus this sub-question will be answered in two parts.

The first KPI focuses on whether aggregators can gain flexibility from households through measuring appliance uses that they were not able to schedule. The factors influencing this KPI were:

- *Scheduling availability:* This factor represents the hours when the system needs flexibility. Higher numbers of available hours lead to lower rates of appliance uses that cannot be scheduled.
- *Appliance type:* Higher need appliances had higher rates of not being able to be scheduled overall. Appliances that needed to be scheduled in-sequence had high rates when the scheduling availability did not cover many hours.
- *Household type:* Households with higher appliance need had overall higher rates of not being able to be scheduled. The number of days a household works from home influences the rates stronger when the scheduling availability is uncertain and variable. The daily availability varying per type of day influences the rates stronger when the scheduling availability is set.

The second KPI focuses on whether households comply with the appliance uses scheduled by the aggregator through measuring the scheduled appliances that were not-used. The factors influencing this KPI were:

- *Dshour:* This factor is the combination of scheduling objective and scheduling availability and determines the starting hour of scheduled appliance uses. The difference between starting hour and household preferred time of use determines household comfort-scores. High differences mean high discomfort and thus higher rates of not-use.
- *Appliance type:* This factor influences the urgency-scores through appliance need. Higher need appliances cause households to experience higher feelings of urgency which leads to lower rates of not-used scheduled appliances.
- *Household type:* This factor determines the long-term environmental motivation. Higher long-term motivations lead to lower rates of not-used scheduled appliances. This factor also influences the urgency-scores through appliance need that partly depends on the household type. Households with higher appliance needs have lower urgency-scores which leads to lower rates of not-used. Lastly, this factor determines sensitivity to comfort. Households who are more sensitive to deviations in the scheduled appliance time of use, have higher rates of not-use.
- *Income level:* This factor determines the long-term financial motivation. Higher long-term motivations lead to lower rates of not-used scheduled appliance uses. This factor also determines the extent to which household over plan their appliance uses. The number of times appliances are scheduled over their need influences the urgency-scores. With more appliances scheduled than needed, the household experiences less urgency. This leads to higher urgency-scores and thereby to higher rates of not-used scheduled appliance uses.

7.1.2. Main question

"How reliable are households in altering their energy demand under an aggregator providing residential demand response?"

This research question was formulated to examine the problem around the uncertainty of households functioning under an aggregator. Reliability in this context refers to the aggregators ability to reliably deliver flexibility through households. An agent-based model was developed and experiments were run and analysed to answer this research question. The model describes a situation where households are participating in a residential demand response program were the aggregator schedules their use of semi-flexible appliances day-ahead. The aggregator gains flexibility through shifting appliance uses to another time. The model runs hourly and simulates both aggregator scheduling and households behaving and interacting with the program. The model also includes two different groups of variables: aggregator policies and household characteristics. The aggregator policies represent different RDR situations through the variables aggregator objective and scheduling availability. The household characteristics offer insight into how reliable different households can be. The characteristic included are household type, income level and appliance type.

The main intent of the model design was to measure household compliance with the scheduled appliance uses. Household compliance informs the extent to which the aggregator can deliver flexibility. Differences between what an aggregator thinks it can deliver and what it actual delivers informs how reliable they can operate. In the model this compliance is influenced by households trading off their motivations for participation and daily inconveniences, and disruptions to their routines. However, the model also provides insight into the effects of household availability on the aggregator's ability to schedule appliance uses. This informs aggregator capacity and can thus provide insight into how reliable aggregators can be in delivering flexibility when their capacity is time-varying. Overall, the model offers two metrics for insights into household reliability: compliance and the aggregators ability to schedule appliances.

The rates of non-compliance are overall high and have large variations. The rates are most influenced by the discomfort household experience from deviations to their preferred times of use. Discomfort is in the model directly influenced by the objective with which the aggregator schedules. The lowest rates of non-compliance are seen when the aggregator's objective is to schedule appliance uses as close to the household preferred time of use as the scheduling availability allows. The scheduling availability interacts with this somewhat as the scheduling hours available provide the time-frame in which the aggregator schedules. Another factor the model indicates as influential is appliance need. The household characteristics appliance type and household type determine appliance need. The model assumes that high need of an appliance means that households experience a higher urgency to use the appliance as scheduled. Thus larger households and appliances that are used more often lead to lower rates of non-compliance. Lastly, income level is a strong determinant for compliance rates also. These households have a stronger financial incentive for participating and are thereby more likely to decide to comply.

The aggregator can only schedule appliance uses when household availability and the system's need for flexibility overlap. The rates of not-scheduled appliance are thus strongly linked with the type of flexibility the aggregator tries to provide and when households are home. The model shows that the scheduling availability has the most influence on the rates of not-scheduled appliance uses. Scheduling availabilities that cover a higher number of hours, especially in the morning and evening, yield low rates of not-scheduled appliance uses. The model further indicates that high rates of not-scheduled are linked with appliance need. This is because appliances that are used more often are more likely to be planned on days when households have less availability.

The issues with household reliability would create a very complex and uncertain situation for aggregators. Firstly, the load capacity they are offering is uncertain. They would have to plan their operations with an overall uncertain capacity caused by variations in households appliance need, their expected availability and their routines. Furthermore, they have to manage changes in their offered capacity close to time of use caused by households non-compliance. They may be able to mitigate some of this last uncertainty through their scheduling algorithms. But these algorithms would need to be complex and customized to individual household preferences to be effective. Thus overall, aggregators would have to account for a lot in their objective of delivering flexibility.

Aggregators may also want to consider selecting the households they want to be part of their RDR portfolio. For starters, aggregators should consider household availability in conjunction with the flexibility they want to provide. If the availability is not compatible with the flexibility, the aggregator may consider excluding those households from participation. It would also be recommended to look at when on a day a household prefers to use their semi-flexible appliances. Aggregator can directly influence household comfort through the starting hour of appliances. Deviation from their preferences may cause households to overrule the scheduled appliance uses. This means 1) aggregators may consider excluding those households from their program whose preferences are too far out of the flexibility need, and 2) aggregator should consider including household preferences for time of use in their scheduling algorithm.

The results further indicate that the inclusion of aggregator provided RDR with semi-flexible appliances in energy systems will not be appealing to system operators. Firstly, RDR needs to have a decent capacity to be a valuable source of flexibility. The capacity that semi-flexible appliance offer already is small. On top of this, the results showed issues with household availability at times of system need limiting the capacity further. Furthermore, RDR will have large variations in its capacity caused by differences in appliance need across household characteristics and in time. These large variations will make it difficult for system operators to plan with RDR as a flexibility source as their capacity would be different all the time. Lastly, the system operator needs insurance that the offered flexibility is delivered. The unreliable households will make this difficult for the aggregator. This forms a risk to system security that system operators may not be willing to take. Especially when their value as a flexibility source is limited.

7.1.3. Further research

The limitations and implications of this research point towards areas were knowledge lacks. Further research into these areas could benefit understanding of RDR programs and its role in energy systems.

Firstly, the variability of semi-flexible appliances in RDR programs. As discussed, this research indicates the potential of using semi-flexible appliances in RDR. However, further research into these appliances is necessary to better grasp their potential. As the need of these appliances is hourly and daily dependent, the total daily flexibility they offer could be limited. This could also lead to unwelcome uncertainty for system operators and balancing parties. Thus the overall understanding of the hourly and daily variations in context of an RDR program would aid the understanding of the value of RDR. Also to see if increasing the number of households would average out this uncertainty.

Secondly, research is needed on different compositions of aggregator portfolios. As mentioned, it could be beneficial for aggregators to make selections on who can participate in their programs. Depending on different flexibility objectives, different households could offer the flexibility the aggregator needs. Further research could offer more insight into this topic. It might be interesting to see if aggregators could have different household groups that aid in providing flexibility for different objectives or time-periods. For example, a pool of highly flexible households to provide flexibility for more uncertain hours or a pool of strict routine households whose availabilities overlap with valley-hours.

Thirdly, the effect of semi-flexible appliances that can be started remotely could be beneficial. This removes some of the difficulty with household availability overlapping with flexibility need. This would still eliminate household discomfort with the loss caused by direct load control. It would add potential discomfort with wet goods and night sounds.

Lastly, within the focus of long-term RDR participation, it would be interesting to see how other configurations of RDR programs compare on reliability.

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A

Results

[intro]

A.1. Scheduling not possible

A.1.1. Scheduling objective

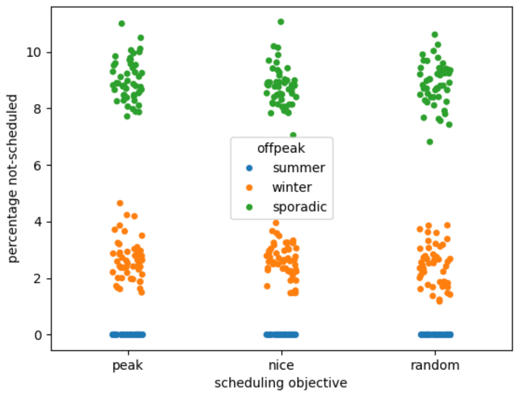

Figure A.1: Percentage of not-scheduled appliance uses per scheduling objective with scheduling availability

A.1.2. Final-decision moment

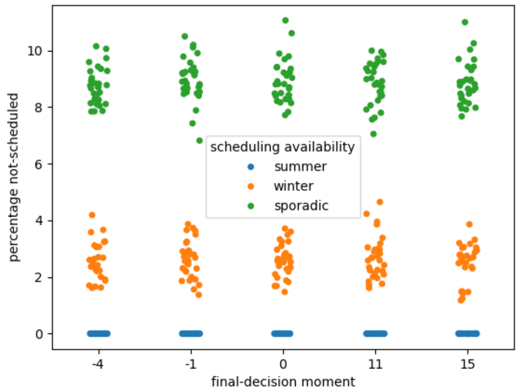

Figure A.2: Percentage of not-scheduled appliance uses per final-decision moment with scheduling availability

A.1.3. Household characteristic

Income level

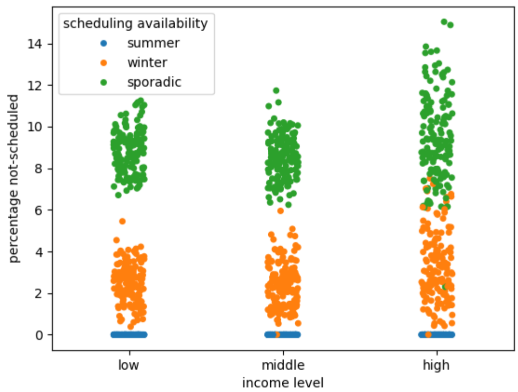

Figure A.3: Percentage of not-scheduled appliance uses per household income level with scheduling availability

A.2. Not-used scheduled appliances

A.2.1. Final-decision moment

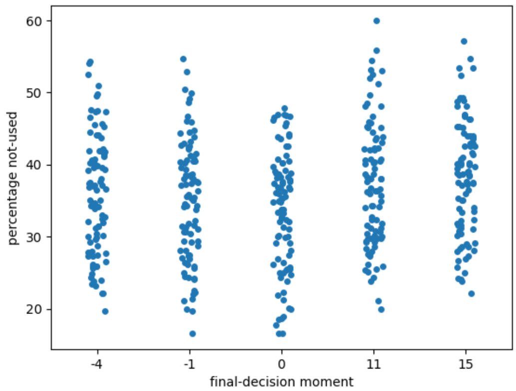

Figure A.4: Percentage of appliances not-used per final-decision moment