A quantitative analysis of user participation in demand response in a future electricity network

An agent-based exploratory modelling study of price- and incentive-based interventions

L.N. ten Boske

March, 2021

TU Delft

Deloitte.

A quantitative analysis of user participation in demand response in a future electricity network:

An agent-based exploratory modelling study of price-and incentive-based interventions

---

Master thesis submitted to Delft University of Technology in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Engineering and Policy Analysis

by

Lisette Neline ten Boske
Student number: 4376102

To be defended publicly on March 26, 2021

Graduation Committee

First supervisor and chair:	Prof. dr. M.E. Warnier Systems Engineering
Second supervisor:	Dr. G. de Vries Organisation & Governance, Energy Transition Lab
External supervisor:	Dr. S. Broersen Deloitte Analytics & Cognitive

An electronic version of this thesis is available at
`http://repository.tudelft.nl/`

Delft University of Technology

Preface

With this thesis I conclude my Master of Science Engineering and Policy Analysis and my time at Delft University of Technology. During this period I have learned so much and have enjoyed the projects in which technology and societal challenges came together. During my specialisation in Berlin I focused on the combination of the energy transition and data science. This amazing experience has inspired me to continue working on this topic in my master thesis.

When I started my studies in Delft, I could have never expected that I would write my master thesis completely from home and only speak to my supervisors virtually. Nevertheless, they have shown that this situation did not need to stand in the way of great supervision. I want to start by thanking my supervisors for their guidance throughout the entire process. Martijn, thanks for your commitment and the numerous meetings in which you gave me advice, but always challenged me to make my own decisions. I want to thank Gerdien for introducing me to the interesting human side of the energy transition and helping me with the complex task of incorporating behavior in a quantitative model. Besides, I have really enjoyed my time as a part of the Energy Transition Lab thesis circle. I also want to thank the Deloitte A&C team and my supervisor Sjors in particular for giving me the chance to be a part of a team of smart ambitious people with a passion for data. Sjors, thanks for your feedback in which you combined your academic as well as business experience.

Even though I have unfortunately not been able to physically work together with my colleagues at Deloitte or share experiences with my fellow students at the TPM faculty, I have been anything but lonely when I was writing my thesis. For this I have to thank my friends and family. Special thanks to my parents and Ilse for being interested and supporting every choice I made. Marijn, thanks for your love and support, but especially the fun distractions and words of confidence. However most of my time was spent with my amazing roommates, who shared coffee and lunch breaks with me during 'office hours', but also distracted me from my thesis with amusing conversations and activities.

While I am writing this, my time as a student is almost officially over. I have enjoyed every part of it and have learned a lot, inside the lecture halls, but definitely outside of the faculty as well. I am very much looking forward to starting a new phase of my life and am very happy to start my professional life at Deloitte. I am curious about the new people I will meet, but will definitely never forget the people with whom I have shared my student life memories.

Enjoy reading!

Lisette ten Boske
Rotterdam, March 2021

Executive Summary

In order to reach the climate goals, many new renewable energy power plants will be constructed in the coming years. The increase of renewable energy sources is indispensable, but will present new challenges. Renewable energy sources like wind and solar energy are known for their fluctuating supply, because the generation is dependent on weather conditions. In the future, the energy supply will primarily consist of energy from renewables, which makes energy producers and grid operators fear that grid security and reliability could be threatened. On top of a more fluctuating supply, energy demand is also expected to increase in the coming years, especially if heating will be electrical when gas is phased out. Demand-side management, and more specifically demand response, could be a way to make demand match supply better and limit the foreseen energy shortages. A smart grid and smart metering technology can be implemented to overcome the hurdles of grid integration of renewables. These technologies allow for a two-way exchange of energy and information, which could improve the electricity grid reliability. Consequently, the implementation of a smart grid could potentially steer consumer electricity usage and allow for automated demand shifting.

Prior research has shown that demand response can lead to a substantive decrease of the peak demand load and overall energy reduction. However, since the shifting of demand can lead to inconveniences, consumers need an incentive to participate in demand response programs. Price-based interventions can encourage consumers to participate, which is why this study applied a real-time pricing mechanism based on real-time energy shortages. Even though many researchers have studied various price- and incentive-based demand response programs, consumer participation is understudied in current literature, because it is difficult to predict the behavior of energy consumers and incorporate this in a quantitative model. However, the effect of demand response programs strongly depends on consumer participation.

This thesis analyzes consumer participation in demand response in an electricity grid with a high share of renewables. The effect of multiple price- and incentive-based interventions are tested for different consumer populations and supply scenarios. The aim is to improve the understanding of the effect of consumer heterogeneity on the participation in demand response. An agent-based model was constructed that represents the energy system as a copper plate model and incorporates the rule-based behavior of different consumer types. This model was used to answer the main research question:

How can a simulation model be used to analyze the influence of consumer heterogeneity on the success of demand response enhancing policies in future electricity networks?

The consumer types that were included are the green, the cost-conscious, the convenience-oriented and the indifferent energy consumer. Subsequently, five personal values were identified as important moderators for consumer participation, namely the values of price, environment, comfort, safety and social norm. These values were quantified for each of these consumer types to translate real-world behavior into model variables. In the model, demand is shifted automatically by the energy producers and consumers can choose a shifting contract based on their personal values that allows for shifting of flexible demand only, shifting of semi- and flexible demand or does not allow for demand shifting at all. Additionally, consumers are part of a social network and subject to social interaction. The electricity price varied based on real-time energy shortages. Furthermore, additional interventions could be implemented to encourage consumers to switch to a different shifting contract and thereby increase the consumer participation in demand response.

All interventions interacted with one of the consumer values. The following interventions were analyzed:

- Cost comparison among consumers combined with an additional discount for consumers with a shifting contract interacts with the value of price and social norm.
- Comparison of environmentally friendly behavior based on the 'environmental score' interacts with the value of environment and social norm
- The environmental awareness campaign interacts with the value of environment
- The smart meter information campaign interacts with the value of comfort and safety
- Default shifting does not interact with a consumer value but is an opt-out policy that sets the default contract to a shifting or full shifting contract for all consumers.

These interventions and combinations of interventions were compared based on the three model KPIs energy shortage, total electricity cost and required storage. Storage was introduced as a back-up source of energy, because the analysis of different amounts of consumer participation showed that not enough demand could be shifted to solve the energy shortages completely, even if all consumers would allow for demand shifting. The consumer participation did not result in large changes in the required storage, because this depended on a specific shortage period in the winter that lasted over a day due to very low wind and solar generation. The first model conclusion therefore is that shortages cannot be solved by demand shifting if the period of shortage is too long, because demand could only be shifted for 1,5 hours to limit the consumer inconveniences.

The influence of differences in consumer population and the consumer participation were studied by comparing two cases. Base case A, where flat pricing was in place and demand was not shifted and base case B, where real-time pricing and demand shifting were added to the model. From this comparison it could be concluded that shifting can reduce energy shortages significantly if the number of consumers that allows for demand shifting is sufficient. Afterwards, the introduced interventions were added to the model to encourage consumers to switch to a shifting contract and indirectly reduce the energy shortage, but not all were able to achieve this goal. From the deep uncertainty analyses of the interventions it became clear that the amount of supply was by far the most influential variable for the energy shortage. Therefore this factor was kept constant to analyze the interaction between the interventions and the consumer population.

The cost comparison intervention could convince all cost-conscious consumers to choose for a shifting contract with an additional reduction of €15 (8.5%) per switch period and some would even choose for the full shifting contract in case of a very high reduction of €80 (45%). This financial intervention also increased the participation scores of the indifferent and convenience-oriented, but it was never enough to reach the switching threshold, because loss of convenience and aversion of control were stronger than the financial incentive. This intervention showed a clear trade-off between profits and shortage reduction for the energy producer. The effects of the environmental comparison and the environmental awareness campaign were too small to trigger consumers to switch, because the consumers that did not already have a shifting contract were not convinced by environmental arguments. The smart meter information campaign that was directed at demand response sceptics led to a higher increase of the participation score than the environmental awareness campaign, but was also not effective enough to increase consumer participation significantly. Analysis of the information campaigns showed that the strength of the effect is more important than the number of consumers it reaches, because informing more people does not improve the situation if the effect is too small to cause a change of behavior.

The comparison of the interventions and intervention combinations showed that the differences in energy shortage between the policies were limited and were mainly determined by supply. For a constant supply, the results revealed that the simultaneous implementation of all policies was most effective to reduce shortages, followed by the policy combinations that included the cost comparison with a reduction. Naturally, these combinations also resulted in lower electricity costs for the consumers. The cost comparison and reduction policy and default shifting could increase consumer participation most when used as a separate intervention.

Additionally, the social network and social interaction between consumers was analyzed. Consumers are influenced by their most influential neighbor and it was found that the network layout matters as it determines the influence of key players. The key players affect many other consumers, which can be positive or negative depending on their own personal values. Therefore the composition of the consumer population is important as it determines the probabilities of a certain consumer type to become the key player.

Some main conclusions can be drawn from the analysis of the interventions. First of all, supply was the most important influence on energy shortages. Depending on the shortage period characteristics, shortages could not always be solved completely by demand response, but a higher amount of demand shifters can improve the situation significantly. However, not all consumer types could be motivated to switch to a shifting contract, which means that the consumer population is an important influence on the effectiveness of policies.

For the generalizability of the results, it is important to know the model limitations. It is difficult to determine the model validity, because there is no existing real-world system to compare the model to. Besides, stylized data was used as model input and many assumptions and generalizations had to be made during the model conceptualization. For example, the complex real-world behavior of energy consumers needed to be quantified and only a limited amount of consumer types could be included. Therefore the numerical model output cannot be interpreted as true future values. However the relative changes and range differences in outcomes caused by input changes and interventions can be used for decision making.

Based on the gathered insights, recommendations can be made for energy producers and other interested decision makers about increasing consumer participation in demand response and lowering the energy shortages:

- Since the supply mainly determined the energy shortage, more diverse energy mixtures than only solar and wind could prevent periods of little generation and limit the required storage amount.
- To sustain a high user participation in demand response, it is important that decision-makers can permanently transform consumers from passive to active consumers that perceive reducing energy shortages as a shared responsibility. In the adoption phase, repetitive intervention is needed to sustain the effect. Additionally, it is important to choose a combination of policies that reinforce each other.
- It is important to have knowledge about your consumer population to be able to choose the most suitable intervention. Not all consumers can be convinced, so use a personalized and targeted strategy to convince the persuadable consumers. It can be a better strategy to target several consumers successfully instead of making all consumers slightly more interested in demand response.

- Financial interventions showed promise, but only under certain conditions. The electricity prices need to be adjusted in such a way that the energy producer does not lose profit, while price differences for shifting and non-shifting consumers remain large enough to encourage demand shifting.
- Try to localise the influential consumers and find out if there are possibilities to cooperate with them in the marketing of demand shifting. This can be done instead of, or in combination with, a large-scale information campaign.
- Improve the ethically debatable default shifting intervention by developing an application in which consumers can specify detailed demand shifting preferences.
- Always consider the ethical implications of the interventions. Green nudges are ethical as long as implications on the autonomy of consumers is limited, the intentions of the energy provider are transparent, consumers are not manipulated and if restrictions for consumers are proportional with the personal and societal benefits.

From this thesis it can be concluded that a simulation study is a successful way to create an inclusive model of the technical, economic and behavioral system components. The model was able to provide a system-level overview of the system dynamics and improved the understanding of interactions between interventions and consumers. Therefore this model can be used in future case studies to analyze the potential consumer participation and recommend suitable interventions to increase this. Another future research option would be to extend the model with more diversity in households and their demand, to improve the representation of reality. Finally, a cost-benefit analysis of the interventions could be done to provide more complete advice to decision-makers who want to increase consumer participation in demand response.

Contents

List of Tables

List of Figures

1
Introduction

1.1. Research Problem

In light of the energy transition, renewable forms of energy production are emerging in the Netherlands. In 2018, the share of renewable energy was 7.4 percent of the gross final energy consumption, of which a solid share came from wind and solar energy (CBS, 2019). However, considering the government's ambition to reach a share of at least 27 percent of renewables in 2030, a lot of renewable-energy power plants will need to be constructed in the near future (Minsterie van Economische Zaken en Klimaat, 2019). In many countries, similar ambitions exist. Even though a great part of the population agrees that green energy should phase out energy production from fossil fuels, protest arises quickly when wind turbines are scheduled to be constructed "in their backyard".

Just like local residents, energy producers and grid operators also see that there are clouds on the horizon, for they are the ones responsible for sufficient electricity availability and grid stability. Renewable energy sources are known for their fluctuating supply due to their dependency on natural phenomena, like wind and sunshine. This characteristic endangers the reliability of the energy supply and therefore increases the need of a more flexible electricity grid, that is capable of safeguarding energy balance, when renewable supply is low (Mureddu et al., 2015). Besides a change to more variable supply, the total energy demand will continue to grow in the coming years. Therefore, the main prospective challenges of energy management are ensuring reliability of energy supply and reducing the imbalance between energy supply and demand (Barai et al., 2015).

Notable is that in most countries, the fluctuations of the energy supply are barely reflected in the consumer electricity prices, resulting in a less than optimal balance of supply and demand. Smart meters are already enabling consumers to have better insight in their energy usage and can offer the possibility to adjust their demand relatively to varying electricity prices, allowing them to receive economical gains. A smart grid could even offer the possibility for people to sell energy back to the grid (Barai et al., 2015). For energy producers, a smart grid can offer better information exchange, which can be used to predict energy demand more accurately and match production accordingly (Yan et al., 2012). Even though these technologies could potentially steer demand to match supply better, it cannot perform well without an accompanying dynamic pricing scheme.

A field experiment in Denmark, where consumer electricity prices varied during periods of the day, has shown that a more dynamic pricing system, can indeed be a good option to incentivize more flexible energy consumption (Katz et al., 2018). While Denmark already has a relatively high share of renewables, this result shows potential for the future of other countries as well. However, real-time pricing of energy could even be a bigger stimulant for consumers to shift demand, as prices vary even more often. For example, they could do their laundry at a time when prices are low, especially if such changes are controlled automatically and do not cause inconvenience (Öhrlund et al., 2019). Even though many researches find that pricing policies can potentially optimize energy demand (Amini et al., 2019) (Dutta and Mitra, 2017), participation of consumers remains hard to predict, because consumers differ in their sensitivity to criteria as price, environmental friendliness, comfort and risks of automation and control (Batalla-Bejerano et al., 2020). Therefore, a single policy may affect some consumer groups more than others. However, in most technical studies that analyze demand response potential, this heterogeneity of energy consumers is not taking into account. On the other hand, researchers that studies the behavioral aspects of energy consumers and their decision making, fall short on inclusion of the technical and economic aspects.

1.2. Research Objective

The objective of this research is to find out how a simulation model can improve the understanding of the influence of consumer heterogeneity on the user participation in demand response. A simulation model can be used to combine the technical and behavioral aspects of the system and see the effects on future demand-supply imbalance. By using this method, some technical and behavioral details cannot be included, but the incorporation of both, results in a better understanding at a system-level.

This research with a modelling approach will be used to discover if real-time pricing strategies, could be a successful policy instrument to encourage consumers to engage in demand response and achieve a more efficient exchange of energy supply and demand. Besides, additional interventions such as electricity cost reduction, awareness campaigns, and social interaction are be analyzed as well. The model can be used to find out if these interventions can encourage all types of consumers to participate in demand response, or that the success of these interventions is susceptible to different consumer populations. Additionally, modeling under deep uncertainty can be applied to analyze the effects of changes in uncertain model inputs such as the amount of supply or the composition of the consumer population. The outcomes of this study aim to help decision makers with making a well-informed decision about demand-side management.

Although the model in this study is at a high abstraction level it can be useful for future case studies of specific cities or communities. A more certain and customized policy advise can be given if there is data available about the distribution of energy sources and their generation capacity and when a targeted survey can provide information about the values and attitudes in a certain consumer population.

1.3. Research Scope

This research focuses on the future electrical grid, where the vast majority of supply comes from renewable energy sources. In this study, solar and wind energy are incorporated, as well as a base load of fossil supply. Because this study aims to mimic real-life system behavior on a system-level, the representation of the electrical grid is simplified to energy demand and supply and includes few technical details. Likewise, the complexity of the real-life behavior of energy consumers and behavioral mechanisms that influence whether a consumer participates in demand response or not, are reduced to a more abstract quantification.

Lastly, this research focuses on demand response for residential energy demand only, where residential demand is split into fully shiftable demand such as heating, semi-shiftable demand such as a dishwasher and non-shiftable demand, such as utilisation of the internet and a computer for work.

1.4. Thesis Structure

In the next chapter relevant literature will be reviewed to explain core concepts and find out the academic knowledge gaps that leads to the main research question. Afterwards, in chapter 3 the research approach and sub-research questions will be introduced. Chapter 4 presents a consumer segmentation and important moderators for consumer decisions about participation in demand response programs. In chapter 5 the model conceptualization is discussed and in chapter 6 the XLRM framework is used to explain the experimental design and the accompanying policy interventions, uncertainties and Key Performance Indicators (KPIs). The model implementation is described in chapter 7, after which the results of the experimentation are presented and analyzed in chapters 8 and 9. Afterwards, the critical assumptions, model limitations and policy implications of the modeling results are discussed in chapter 10. In the final chapter the main question and sub-questions will be answered and the scientific and societal contribution are presented. This chapter also contains suggestions for future research.

2

Literature Review

This chapter introduces the fundamental concepts that are used in this research. Besides, former literature is discussed to discover similarities and differences and to build to the definition of the knowledge gaps. Subsequently, the research question will be introduced, based on the academic knowledge gaps.

2.1. Literature Review Process

In order to find the literature that was reviewed in this chapter, scientific databases Scopus and Web of Science have been used. Besides, a search was done in Google Scholar as well. Depending on the section of the literature review, different key terms were used to find papers. For example "(TITLE-ABS-KEY (smart AND grid) AND TITLE-ABS-KEY (smart AND metering)) AND PUBYEAR > 2009" was used to find the papers related to smart grids and smart metering in Scopus. To find out the state of the art on demand response and dynamic pricing, "TITLE-ABS-KEY (energy AND 'dynamic AND pricing') AND PUBYEAR > 2017" was used. In total, 34 papers were selected to be included in this literature review. The selection of the papers was based on the criteria of being recently published and being numerously reviewed. Besides, papers that only focused on energy storage or electric vehicles were left out. In appendix A, an overview of all exploited literature can be found in table format.

2.2. Core Concepts

This section explains some technologies and mechanisms that are important background knowledge and are core concepts underlying this research.

2.2.1. Renewable resources and electricity grid capacity

Currently energy balance is conserved by fossil-based power plants, that can generate at any time. However, an increasing share of renewables in the energy supply can endanger the network reliability, because supply will vary more. Therefore a more flexible electricity grid is needed to safeguard energy balance, even when renewable supply is low (Mureddu et al., 2015). Not only periods of energy shortage can be a future issue, but problems could also arise when renewable supply is very high. In that case, large amounts of energy would need to be transported at the same time or renewable power plants could even need to be switched off.

Several options are being mentioned in literature to deal with grid capacity issues (Poudineh and Jamasb, 2014). First of all, a solution could be to extend the physical network capacity by reinforcing the distribution grid with higher capacity transformers and thicker cables (Fürsch et al., 2013). However, Niesten argues that existent regulations are not always allowing proficient communication about investments between generators and system operators leading to lack of proper network investments (2010). Moreover, Poudineh and Jamasb disagree with the idea of network expansion. They designate distributed generation and energy storage possibilities as alternatives for network expansion, because capital could then be saved by optimizing energy efficiency within the current infrastructure (2014). A final promising solution would be implementing Smart Grid technology to balance energy supply and demand more efficiently (Lammers and Heldeweg, 2016).

2.2.2. Smart grid and smart metering

A smart grid is an electrical grid that includes regular power flow structures, but is also accompanied with a communication system (Farhangi, 2009). This communication system consists of smart appliances, such as smart meters and smart devices and collects information from points of generation as well as consumers to improve automated control (Siano, 2014). The smart grid is composed of three main systems, namely the smart infrastructure system, consisting of energy and information infrastructure, the smart protection system, consisting of security and protection mechanisms, and the smart management system that coordinates objectives such as cost reduction, demand profiling and energy efficiency (Fang et al., 2011). Smart Grid technology has the potential to overcome the hurdles of grid integration of renewable sources, because the two-way exchange of electricity and information between the utility and its costumers can make the grid more secure, efficient and reliable (Barai et al., 2015). Still, a pervasive and scalable communication infrastructure is a main criterion to guarantee a successful smart grid implementation (Yan et al., 2012).

Smart meters are designed to store and communicate data in a smart grid infrastructure. Therefore, smart meters have advanced software to ensure measuring, data storing and transmitting capabilities can be executed adequately (Barai et al., 2015). On the consumer side, this technology offers the opportunity to have better insight in personal energy consumption and the ability to lower electricity costs. On the utility side, it offers a chance to improve power supply management thanks to real-time consumption data (Yan et al., 2012). Besides, thanks to the detailed insights smart metering can grant, resilience against network disruptions can be improved (Barai et al., 2015). As smart metering requires sensitive personal data on a household level, privacy is also an important aspect to take into account (Lodder and Wisman, 2016). Regulation and a smart protection system are important tools to determine who can access the data and prevent cyber security issues as data theft or leakages (Fang et al., 2011).

Concluding, a smart grid and a large-scale rollout of smart meters can make the electricity grid more reliable and efficient. Besides, the two-sided information exchange offered by these technologies enables the potential of demand-side management such as demand response. However, this is unlikely to be achieved without a strategy to incentivize this.

2.2.3. Demand response and dynamic pricing

Demand response is a subgroup of demand-side management and can be defined as the change in the electricity consumption pattern of users or the amount of electricity used, as a response to the electricity price or other incentives such as rewards (Arias et al., 2018). From this definition, it is important to stress that the success of demand response strongly depends on consumer participation (Durillon et al., 2019).

In literature, two main types of demand response strategies can be distinguished, Incentive-based strategies (IBS) and price-based strategies (PBS) (Amini et al., 2019). In case of IBS the consumers can be influenced by certain requirements, control or transactions to change their consumption, by making the assumption that they have some sort of individual or collective commitment to changing this. In a way, IBS is very similar to PBS, because a reward is used to encourage consumers to change their behavior. However, PBS does not assume internal motivation from consumers, but aims to motivate consumption pattern changes purely by varying prices (Arias et al., 2018) (Amini et al., 2019). There are several types of pricing schemes, such as Flat Pricing, Time-of-use Pricing, Critical or variable Peak Pricing and Real-Time Pricing (Dai et al., 2017). With exception of Flat Pricing, these pricing schemes are all a kind of dynamic pricing and respond to demand in the market. Moreover, Real-Time Pricing is not only dynamic, but also real-time, which means it is not only varying over time, but also responding immediately to the market. These different pricing policies can be used to serve different objectives, such as reducing peak load or optimizing energy balance at any time (Dutta and Mitra, 2017).

Currently, weather conditions, representing renewable energy supply, are barely affecting electricity prices, leaving the price mainly determined by the marginal costs of fossil-fuel powered power plants (Mulder and Scholtens, 2013). However, PBS could be a means to make renewable supply influence the price and thus consumer electricity demand. Critics of demand response doubt the balancing effect of pricing mechanisms, because price elasticity generally is low in electricity markets. However, other environmental and demographic factors and clear communication of the benefits for consumers, can still boost demand response (Wolak, 2011). Confirming this, Arias et al. state that besides IBS and PBS, hybrid demand response strategies that combine IBS and PBS might provide an even better energy balancing solution that can benefit users, energy producers and system operators. (2018). Therefore hybrid strategies are an interesting research domain to include in this thesis.

2.2.4. Behavior and Behavior Change

Human behavior is very complex and has been the subject of many studies that have tried to comprehend and predict it. For example, behaviorism is a theory that believes that behavior can be studied by looking at observable actions and that all behaviors can be learned from the environment and conditioning (Watson, 1924). Even though behavior can be observed, understanding behavior remains difficult, because it is a combination of social, emotional, cognitive and contextual factors that influences the way humans perceive information and determine their decision-making process and behavior (Batalla-Bejerano et al., 2020). Nevertheless, the behavior of people is usually consistent with their understandings, values, beliefs, culture and upbringing. (Heimlich and Ardoin, 2008).

In order to establish a change to more environmental friendly behavior, it is important to identify the barriers and benefits that consumers experience. The barriers can be different for different consumers as well as different situations. For example, the barriers for installing a smart meter are different from the barriers associated with postponing running the dishwasher. (McKenzie-Mohr and Schultz, 2014). In a survey from Semenza et al. consumers said that the biggest barrier for behaving more environmentally friendly was not knowing how to change their behavior to be more environmentally friendly, followed by not believing their own behavior could make a difference (2008). This last statement aligns with Stern's Value-Believe-Norm theory (VBN). This theory argues that pro-environmental behavior can be achieved via values, beliefs and personal norms, where beliefs incorporate the ecological worldview, awareness of consequences and ascription of responsibility (Stern, 2000, Stern et al., 1999).

As mentioned in the previous section, behavior can be steered by interventions. However, the effect of interventions is difficult to predict and the effect can also be different for different people. Moreover, behavior is not static but can change over time, which means a change of behavior can also be temporary. Semenza et al. presented five stages of change that consumers go through, namely pre-contemplation, contemplation, preparation, action and maintenance. After these five stages the final stage of termination is reached in which a consumer prefers the new behavior over the previous behavior (Semenza et al., 2008).

Besides interventions, social interaction, social pressure and social norm can also change the behavior of individuals. Social interaction refers to any process of exchange between two or more individuals during which individuals can influence each other's behavior (Baron and Byrne, 1987). Social norms are unwritten social rules in a community, to which individuals should comply, such as looking someone in the eye during a conversation (Lapinski and Rimal, 2005). Individuals can perceive social pressure to comply to the social norm or to behave in a certain way by persuasion or pressure of other individuals (Wolske et al., 2020).

2.3. Literature Review

In this literature review, former research was compared to find out what were common outcomes, but especially what were the differences in research findings. Considering much research has been done, this literature review was useful to identify the scientific knowledge gaps that have become the focus of the current study.

2.3.1. Demand response

Quite a lot of research has already been done in the field of demand response in the energy sector. Recently, three literature reviews of the state of the art and current trends in demand response have been done, by Dutta and Mittra (2017), Arias et al. (2018) and Amini et al. (2019). General conclusions that can be drawn from those, are that most research has been done for the day-ahead market and for other pricing mechanisms than real-time pricing. A reason for this can be that it is more complex to optimize in the real-time market and for real-time pricing policies, because the behavior is more dynamic and less anticipated. Another reason that real-time pricing has been studied less, is the fact that it requires the communication possibilities of a smart grid. Due to lack of presence of large-scale implementations of a smart grid, it is more complicated to experiment with this (Khadgi and Bai, 2018). Nevertheless, considering smart grids will be implemented more often in the future, real-time market research is very relevant. Therefore, it was mentioned as a future research option multiple times (Arias et al., 2018) (Amini et al., 2019).

It has been shown that consumers can change their energy demand based on prices, for example with static on-peak and off-peak tariffs (Dutta and Mitra, 2017). Besides, dynamic pricing and real-time pricing have already been successfully implemented in other industries like online retail and travel Grewal et al. (2011). However, the true effect of the uncertainties accompanied with real-time pricing of electricity on consumer demand remains unidentified, due to lack of real-life implementations (Khadgi and Bai, 2018) (Dutta and Mitra, 2017). Nonetheless, in dynamic pricing experiments with time-of-use rates consumers were not only using energy at non-peak hours more frequently, but also less energy than before, which resulted in flatter load curves as well as a CO_2 reduction (Dutta and Mitra, 2017). These results from closely related research areas, suggest real-time pricing might have similar effects on consumer demand.

Having a closer look at some other researches displays that most of them use mathematical optimization models (Zhao and Mutale, 2018), (Durillon et al., 2019), (Wang et al., 2019) (Jordehi, 2019).

However, optimization objectives differed from reducing peak demand till optimizing the electricity price. An interesting research is the one from Campo do Prado and Qiao, where they applied a stochastic model to steer consumer energy usage to optimize the profit of the retailer (2018). In the future work section, they recommend to do a similar research from the consumer's point of view. In preceding literature, differentiation has been made in load patterns of consumers (Arias et al., 2018) and diversity between residential, commercial and industrial energy consumers has been included (Zhou et al., 2019), but the heterogeneity within residential consumers was not in the research scope. Without consideration of heterogeneity, consumer participation remains hard to predict, because individual consumers differ in their sensitivity to criteria as price, risk, privacy and the environment (Batalla-Bejerano et al., 2020). Subsequent, Dutta and Mittra as well as Arias et al. also mentioned that the further exploration of what determines consumer participation in demand response programs is an interesting future research possibility (2017), (2018).

Besides optimization, a different approach that was seen quite often as well is game theory. This approach allows for modelling strategic behavior of different players in the energy market, but assumes rationality of consumer behavior and perfect knowledge (Eksin et al., 2015) (Dai et al., 2017) (Li et al., 2014) . Both papers showed the ability of real-time pricing to optimize consumer demand. Even though the results from these papers are interesting, the assumptions of rationality and perfect knowledge are quite unrealistic. In reality, not all consumers behave rationally and it is uncertain how many consumers will respond to pricing mechanisms.

2.3.2. Consumer participation

The uncertainty in consumer participation in demand response strategies has been taken into account sometimes, but often as a single stochastic factor representing the entire group (do Prado and Qiao, 2018). However, Durillon et al. have constructed five types of residential consumers, based on sensitivity to cost, environment, and flexibility and have taken those types into account whilst optimizing for energy balance in the day ahead market (2019). They mention stakeholder objectives and behavior as an important factor in energy demand management and recommend analyzing consumer profiles in the real-time market as well as a future research option.

Researchers also emphasize that only a pro-active attitude of consumers can ensure effective demand response and underline the importance of considering the heterogeneity in the willingness of consumers to engage actively in energy management programs (Batalla-Bejerano et al., 2020) (Parrish et al., 2020) (Good, 2019). Besides socioeconomic factors such as age, culture and education, Batalla et al. found that preferences in relation to price risk, volume risk, complexity and loss of privacy also affect consumers willingness to participate in demand response (Batalla-Bejerano et al., 2020).

Parrish researched motivations and barriers for consumer engagement in residential demand response specifically and found that consumers can be discouraged by perceived risk and mistrust of the intentions of demand response facilitators. However, trust can grow with greater familiarity with demand response, based on experiences and reputation (2020). Three phases of consumer engagement can be distinguished in demand response programs: enrolment, response and persistence (Robinson et al., 2012). Parrish found that financial motivations were identified most influential in the enrolment phase, but that in the response phase, complexity and effort were weighed against expected benefits in order to decide on persistence (2020). Many researchers showed that consumers are afraid that participating in demand response programs will cause them inconvenience in their daily life (Öhrlund et al., 2019) (Sütterlin et al., 2011). De Vries et al. introduced the hassle factor that aligns with the experienced inconvenience that was mentioned by Ohrlund and the effort that was explained by Parrish. A hassle can be any annoying practical problem or a frustration or disappointment that causes stress, but not everyone experiences the same things as a hassle (De Vries et al., 2020). For example, some consumers could find checking real-time energy prices a hassle, whereas others don't mind it. Perceived hassles can be a psychological barrier for consumers to engage in demand respond.

In relation to renewables, Sangroya and Kumar Nayak found that not only on financial, but also emotional and social considerations play a role for consumers to choose for green energy (2017). Gadenne et al. confirmed this by finding a strong relationship between environmental attitudes and energy saving behavior, even without financial policies (2011). Mack et al. found that significant energy savings were made only by the households that committed fully instead of partially or not at all (Mack et al., 2019). All three results show that a positive attitude and commitment towards the environment, is a moderator for more sustainable behavior.

Summarily, prior behavioral research showed that a high price sensitivity and high value of the environment can contribute positively to consumer participation, whereas perceived risk, mistrust and inconvenience can decrease the likelihood of consumer participation in demand response.

2.3.3. Deep uncertainty

In a highly complex system, such as the future energy system, there is a lot of uncertainty on many different aspects. Besides not knowing what the physical electrical infrastructure will exactly look like, the distribution of energy sources and their realisable supply are unknown. Moreover, it is also uncertain what the attitude of the energy consumer population will be towards demand-side management at that time and how this will affect the participation in demand response. Therefore this decision making problem and associated simulation models are subject to deep uncertainty. This is the case when: "analysts do not know or can not agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes." (Lempert et al., 2003).

In prior demand response studies that examined a future situation as well, uncertainties were recognized and sometimes scenarios were defined to analyze a number of possible futures (Gyamfi and Krumdieck, 2012). However, in classical scenario analysis, only a limited amount of scenarios are included based on some prior knowledge about possible future values of the uncertain parameters. Exploratory modeling and analysis (EMA) is an approach for conducting a more extensive scenario analysis, by studying a large range of possible values for the uncertain parameters (Maier et al., 2016). Adittionally, a large number of experiments is performed to analyze the the performance of policies in all scenarios and identify vulnerabilities or strengths (Kwakkel, 2017). In this manner, exploratory modeling can perform as a tool for robust decision making under deep uncertainty (Kwakkel, 2017). This method has not yet been applied to demand response in the energy sector, even though it could be a good way to study the range of possible future scenarios and see which policies are effective under many different circumstances (Kwakkel and Pruyt, 2013).

2.4. Knowledge Gaps

Three scientific knowledge gaps were revealed by the literature review. It was discovered that real-time pricing in the real-time market, consumer participation in demand response and deep uncertainties in demand response models are understudied.

First of all, the literature review showed that most research has been done in the day-ahead market instead of the real-time energy market, because of its higher complexity and current lack of smart grid implementations to experiment in. Nevertheless, real-time market research is important to assess the potential of real-time pricing in a future where smart grid technology is implemented on a larger scale. Therefore this research will specifically look at real-time pricing in the real-time market.

Many former researches used optimization or game theory as their main methodology. In these models uncertainties such as energy supply and consumer behavior were taken into account, but only limitedly. Modeling under deep uncertainty gives the opportunity to take uncertainty ranges into account by running many experiments instead of using a limited number of scenarios. Therefore it can be a promising method to study future electricity grids, where a lot is still uncertain.

An uncertainty that has been understudied especially, is consumer participation in demand response programs. User participation was often not taken into account or intensely simplified in the predominantly technical models that were used to predict demand response potential. However, based on literature from behavioral economics and consumer psychology, the behavior of energy consumers could be taken into account more explicitly. Instead of using a single factor for user participation, different moderators of consumer participation, such as values of price, the environment, comfort, safety and social norm can be used to characterise different consumer types and include their behavior in the model. Creating a model that has a technical basis and is enriched with a behavioral component, might loose some detail in both fields, but can provide a better understanding of the promise of demand response on a system-level. This can be integrated perfectly in modelling under deep uncertainty and can contribute to current literature with a focus on the consumer side and a different modelling approach to gain new insights in the potential of demand response in future electricity grids.

2.5. Research Question

Based on the presented knowledge gaps, this research will dedicate to analyzing possible demand-side strategies to ensure future energy security in electricity grids with a high share of renewables. These strategies will incorporate smart grid and smart metering technology as well as a real-time pricing component. Price based and incentive based policies will be tested under deep uncertainty and their performance will be compared. The focus will lie on the uncertainties in renewable energy supply and consumer participation. A modelling approach will be used to be able to study the consumer participation in demand response more extensively by taking heterogeneity in residential energy consumers into account. In this thesis the following research question will be answered:

How can a simulation model be used to analyze the influence of consumer heterogeneity on the success of demand response enhancing policies in future electricity networks?

3

Research Design

This chapter presents the research objectives and research methods that have been applied to answer the main question and address the knowledge gaps that were introduced in the last chapter. The main research method is modelling and simulation, accompanied by literature review and desk research to primarily substantiate the model conceptualization. Moreover, an agent-based model is used to simulate policy implications under various scenarios, after which the modeling results can be translated to real-life implications.

First the research objective and the global research approach will be discussed. Afterwards, the research methods and tools will be explained in more detail per sub-research question.

3.1. Research Objectives

The problem context of this study is the future electricity grid and imminent energy balance issues if the uncertainty in supply increases because of renewable energy sources. The potential of demand response to reduce energy shortages has been studied often, but without including user participation in detail. However, user participation is a main influence on the success of these demand response strategies. Therefore the objective of this study is to find out how a simulation model can be used to study how policies affect user participation for different types of energy consumers. Heterogeneity of energy consumers is included and their behavior better incorporated by looking at personal values and behavioral mechanisms that influence consumers when they decide about their energy usage. Subsequently, the final objective is to find the combination of interventions, a strategy, that has the most beneficial outcomes and is robust in many scenarios of varying supply and consumer population.

Above mentioned research objectives are incorporated in the following main research question:

How can a simulation model be used to analyze the influence of consumer heterogeneity on the success of demand response enhancing policies in future electricity networks?

3.2. Research Approach

The study will explore how different policies can improve the user participation in demand response programs. A real-time dynamic pricing model based on energy availability will be considered, as well as incentive-based demand response enhancing interventions. Additionally, the influence of multiple aspects of consumer behavior will be analyzed thoroughly. A simulation modeling approach is used in this research, to test different alterations of demand response policy and visualize the impacts of these system interventions. This approach has been chosen, because it is highly suitable for testing possible future policy measures and prediction of societal impact, before truly implementing them. Besides, simulation modeling is the appropriate method to study a high-level problem and to understand the dynamics of the future electrical grid on a system-level. Limitations however are that, although modelling can provide insights in the dynamics of a system, models are always a simplification of the real-world and therefore not absolutely truthful (Sterman, 2002). For example, the representation of the energy market is simplified in this research, to keep computation times reasonable. For this research an agent based modelling approach is used to represent varying consumer behavior in the electricity market (Chappin et al., 2020). An agent-based model is a very suitable approach for this study, because of its ability to capture the long term effects of policies and human behavior changes in complex environments (Axtell, 2000). In this research the choice was made to model the system by not purely looking at the technical aspects, but to include a consumer behavioral component as well. Because of this combination, both the technical and behavioral aspect in the model are less detailed than they would be in a separate technical model or a behavioral study. Nevertheless, the model is more complete and can replicate the system behavior and assess the potential of demand response better on a system-level. A similar approach was used by Shi et al. who integrated technical models and social-behavioral factors that were determined by a survey (2019). For his thesis there was no time to conduct a survey, so the social-behavioral model module was established based on literature research. As a final step, the model behavior was tested in Python under deep uncertainty in order to find out relations between the alterations of policy and uncertainty in consumer behavior and renewable energy supply.

Dynamic electricity pricing is implemented In the model, so that electricity prices vary real-time. Time is an important aspect, because wind speed and solar irradiation vary over time and are the driving forces of the renewable energy supply (Mureddu et al., 2015). In order to see if a pricing model has significant effects, the outcomes of the model including dynamic pricing strategies are compared with the model outcomes of the base case. Therefore the system will be modelled as it is now, as well as complemented with the new dynamic pricing regulation. Additionally, the effect of non-financial policies are tested in the model by comparison as well. Ultimately, the goal is to find the design of demand response interventions and regulation, that has the most beneficial outcomes. Simultaneously, the model is used to find out how differences in consumer behavior effect the impact of these demand response strategies. Deep uncertainty scenario analysis is used to find out which policy strategies perform well in many scenarios and these results are the foundation for robust decision making.

As the main research question is at a high abstraction level, an electricity network at a level appropriate for modelling is needed to test if dynamic pricing and regulatory interventions can enhance user participation in demand response. Therefore a realistic stylized representation of an electrical network will be created in Python, involving supply, demand and agent behavior over time.

3.3. Research Methods

This study consists of different components that belong to different phases in which multiple research methods were used. The insights in the research design phase and conceptualization phase both originated mainly from literature. After the model conceptualization phase, the three components were combined in the construction of the model. The model was built incrementally, adding more complexity each iteration. Agent-based modelling (ABM) and exploratory modeling and analysis (EMA) were the main methods for running and analyzing experiments in the model use and analysis phase. All key takeaways from this research are reported in the last phase, synthesis.

The research approach steps are visualized in a research flow diagram, showing how methods, components and phases intertwine. It also shows the order in which the tasks were carried out, when research sub-questions were answered and how all components relate.

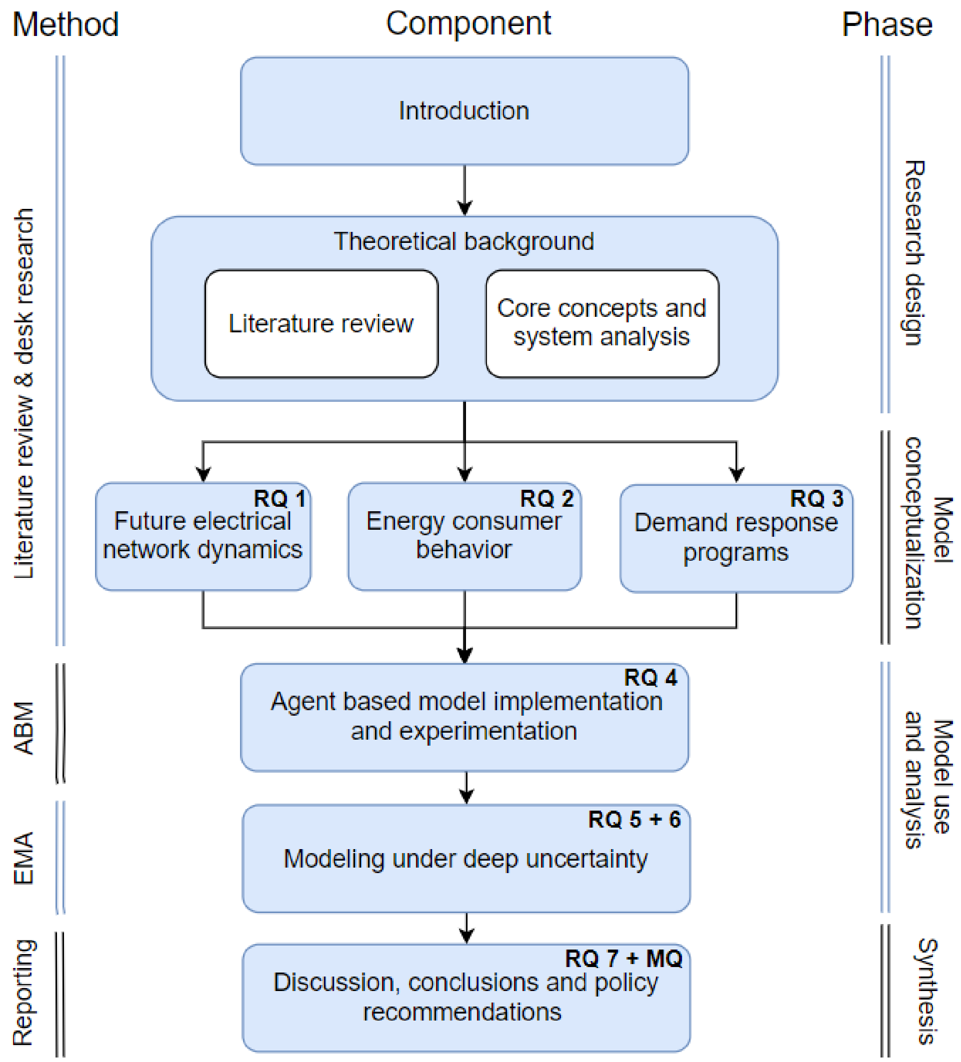


Figure 3.1: Research flow diagram

3.4. Sub-questions

As stated before, the nature of this research is exploratory, therefore using a modelling approach. In order to model a system, conceptualization of system factors and relations is key (question 1-3). After conceptualizing, the base case model was tested (question 4) and then variations of dynamic pricing regulation were employed. Subsequently, the additional price- and incentive-based interventions were tested under deep uncertainty, while looking at consumer behavior and renewable energy production as uncertainties in particular (question 5 and 6). Based on the model results, recommendations can be made to decision makers (question 7) and finally the main research question can be answered. In this section, the research methods and detailed research activities will be presented per sub-question. Also, the research tools that were used, are introduced.

3.4.1. Model conceptualization & formalization

The conceptualization of the model will be carried out according to the XLRM framework (Lempert et al., 2003). This framework helps to categorize system factors as external factors that can't be influenced by policy (X), policy strategies or levers (L), model relations between model factors (R) and model outcomes of interest or KPIs (M). The main research methods for the model conceptualization and formalization are literature reviews and desk research. The first three sub-questions are used as a guideline for the conceptualization and formalization of the model.

Sub-question 1: Which concepts can be included in the model to represent the differing energy usage decision making of energy consumers?

This first sub-question aims to give understanding of the consumer decision making about energy consumption on the current electricity market, but especially to gain insight in the response and behavioral change of consumers due to future dynamic pricing policies. Accordingly, this question partially looks at and uncertainty X in the XLRM framework as well as system relations R.

Conceptualizing energy consumption choices of consumers consists of looking at literature on present electricity pricing regulations, consumer psychology and behavioral economics. For example, green nudges, the hassle factor and social norms will be discussed in the conceptualization of consumer behavior (chapter 4). These theories can help to gather insights to be able to conceptualize user participation in future demand response programs as a range of uncertainty. To obtain this knowledge, desk research and a literature review are suitable research methods.

The model will look into one electricity consumption pattern for all consumers, but at diverse consumer characteristics and behavior. Agent-based modeling allows for studying different types of consumers, by assigning them different static and dynamic states that determine their behavior (Chappin et al., 2020). The literature review indicated that personal values in relation to price, environment, comfort and safety should be included in the model. Further desk research and possible use of social theories are applied to determine other aspects that are important as well to represent energy consumer behavior as realistically as possible.

Sub-question 2: How can the future electrical grid be modelled as an agent-based model?

The foundation of a realistic model is the conceptualization. Therefore it is very important for this research to conceptualize the electrical network properly. This research question will look at the R, M and partially X of the XLRM framework.

Important factors that are included here are types of power plants and their production capacity on the supply side and on the demand side the consumers and their consumption over time. This study uses a relatively simple model to represent the technical electricity grid, because if the model would be too complex, this would lead to very long computation times for running the model under deep uncertainty. Therefore, the base model in this study is a copper-plate model of the electrical network consisting of supply, consumers, price and their relations. To conceptualize the electrical network system dynamics in a decent way, desk research has been done using the internet as well as literature.

First of all, the energy supply in the model consists of grey and green energy production, particularly wind and solar power plants. In order to capture seasonality and hourly variation of renewable supply, a year of data was used as model input. Concerning consumer demand, the basic model will look into one main electricity consumption pattern for all consumers. Important to note is that the research focuses on residential electricity consumers only. This section also includes the specification of shiftable, semi-shiftable and non-shiftable loads.

Running the model later on will give insight in the amount of energy demand and production over time. With this information it should be easy to see if policies have reduced peak loads and energy balance issues. Key performance indicators (KPI) that are specifically of interest (M) are the total amount of energy shortage,required storage and the total energy costs for consumers.

Sub-question 3: Which price- and incentive-based interventions can be implemented as policy levers in the model?

Whereas the previous sub-questions focused on conceptualizing a real-life electricity grid to build a representative model, this sub-question fixates on designing future dynamic pricing policy options and other non-financial interventions that can increase the user participation. These policies can then be tested in the model, and give insight in the effects of implementation. This research question will conceptualise the L of the XLRM framework.

Literature review and desk research are research methods that were used for constructing dynamic pricing strategies and social interventions, based on empirical information from papers on literary databases like Scopus. Although it is important to built further on policies that seemed promising in past research, looking at other's work can be a limitation. Therefore it is important to also be innovative in the design of the dynamic pricing policies.

3.4.2. Model use

When the conceptualization and model building is finished, the model is used to find results. In the first modeling phase, implications of an increasing share of renewables on the base case are explored. In the second phase, policy and uncertainties are taken into account and the future is explored.

Sub-question 4: What is the effect of an increase in the share of renewable supply on energy balance in the electricity grid, given current infrastructure and demand?

This sub-question is the first one to be answered by analyzing modeling results. After conceptualizing the system relations, uncertainties and policies in the previous questions, the model can now be constructed. The production, consumption, price and other data have been gathered or estimated, cleaned and formatted and can be used as model input.

The constructed agent-based model is used to examine at how different shares of renewables influence the energy balance issues in a base case scenario without any policy. By doing this, the system dynamics and limits of the current grid are explored. The main insight gained here is to see what would happen to the grid stability if the share of renewable supply would increase, without implementing any policy.

As mentioned before, the research method to answer this question is modelling and simulation. More specifically, agent-based modelling will be used to represent consumer behavior and demand (Chappin et al., 2020). This modeling type is very suitable to model agent-agent interaction as well as agent-environment interaction. The agent-based model will be set up in Python, using the 'Mesa' package. The advantage of using Python is that the results can easily be handled with the 'pandas' package that will be used for analysis of the data and the results. (Elreedy et al., 2019). Even though modelling in Netlogo is more understandable thanks to clear visuals, modelling everything in Python makes it easier to connect the model to the EMA workbench for deep uncertainty analyses later on.

Sub-question 5: Which policy strategy ensures the strongest demand response under many different scenarios?

After analyzing the base case scenario, the financial and social policies are added to the model and the different results are compared. The effects of the independent interventions on the model outcomes are analyzed as well as combinations of interventions. Afterwards, scenario analysis is used to find the combination of policies that enhances demand response most effectively under deep uncertainty. Deep uncertainty refers to uncertainty about the correct probability distribution of uncertain model inputs in the future (Lempert et al., 2003). The uncertain model inputs within this model are green energy supply and the composition of the consumer population.

The research method "Exploratory Modeling and Analysis", empowered by the accompanying tool, the Python package "ema_workbench", can model under deep uncertainty. This means that it runs numerous experiments, by evaluating all selected policies over many scenarios, created by systematically varying the uncertain model inputs (Kwakkel, 2017). This can easily result in 10.000 experiments, giving insight in the system performance with policies in all type of future scenarios. The data as well as the agent-based Python model can be used here again, as Python models can be connected to the EMA_workbench package rather easily. Afterwards the results can be explored and visualized in Python as well, using different packages like seaborn and pandas.

Sub-question 6: How do different characteristics of the consumer population influence the effectiveness of policy interventions to enhance demand response?

This question is answered by the same model runs that answered the previous question, but the focus lies on the effects of the composition of the consumer population. Under deep uncertainty relations between characteristics of consumers and the success of policy strategies can be linked to see which types of consumers or aspects of behavior in energy usage decisions are most influential on achieving demand response. It also answers the question which policies perform best given a certain population of energy consumers.

Sub-question 7: How can the outcomes of this study be used to advise decision makers about stimulation of user participation in demand response?

After the entire modelling process it should be possible to advise a decision maker about at least three topics. First of all something can be said about the reductions of energy shortage that can be made for different amounts of consumers that participate for different supply scenarios. Also, the modeling results can show if certain policies can improve user participation and under which conditions. The last advice consists of aspects of consumer behavior that influence the effect of these policies most. If you know which aspects are important, you can try to incentivize a more specific group of consumers, so you can enhance demand response more effectively.

A reflection on the research approach and simulation results is also presented here. Besides, an illustration of how this model can be validated is given, to understand how the model outcomes can be generalized. Finally, policy recommendations, future research options and possible applications of this model are discussed.

3.5. Hypotheses

Based on insights from previous literature, some predictions of system dynamics and the model outcomes can be made. It is expected that a real-time pricing component and demand shifting will lead to a decrease in the energy shortage. Besides, it is expected that the required amount of storage is lower if more consumers engage in demand response programs, because the shortages will be lowered or diminished by the shifting of demand. Lastly it is presumed that participation in demand response can be encouraged for all consumer types. However, the different consumer types need to be stimulated in different ways, because they have different reasons for currently not participating. Subsequently, the following hypotheses will be tested in this study:

1. The addition of a real-time pricing component and demand shifting can reduce the energy shortage.
2. The required amount of storage capacity reduces whenever a larger share of the population allows for demand shifting
3. All consumer types can be convinced to participate in demand response, if personalized interventions are implemented

3.6. Conclusion

This chapter introduced the seven sub-research questions that will lead to the answer of the main research question. The main research method in this study is simulation and exploratory modeling. Literature review and desk research are the main methods for conceptualization of the context, agent and policy layer of the agent-based model. Agent-based modeling is used to incorporate different energy consumer types and track their behavior in a complex environment, while being exposed to different policies. Exploratory modeling is used to incorporate uncertainty of supply and consumer participation while simulating numerous experiments with varying policy interventions.

4
Conceptualization of Energy Consumer Behavior

The conceptualization of energy consumer behavior is critical to be able to understand which behavioral aspects and consumer characteristics need to be included to be able to model the consumer participation in a realistic way. In this chapter the energy consumer types are introduced and moderators for consumer participation in demand response are discussed. Even though it is impossible to grasp every aspect that defines the behavior and choices of real-life energy consumers in the model, this conceptualization tries to represent the drivers behind consumer participation as good as possible. The conceptualization is an important step in the modeling process. First, consumer participation will be explained. Then, the different types of energy consumers that are analyzed in this study are presented. Afterwards, important influential values on consumer participation in demand response are inspected. However, the main goal of this chapter is to quantify the behavior moderators of the different consumer types, based on surveys, experiments and market research from previous literature, to make it possible to incorporate human behavior in a quantitative agent-based model.

The sub-question that this chapter addresses is:

Sub-question 1: Which concepts need to be included in the model to represent the differing energy usage decision-making of energy consumers?

4.1. Consumer Participation

The consumer behavior of interest is whether consumers change their energy demand pattern. If this change occurs, depends on whether a consumer is likely to participate in demand response programs. Consecutively, this participation of consumers depends on their attitude towards different criteria, their personal values, and is also influenced by behavioral mechanisms known from behavioral sciences and consumer psychology.

Consumer participation is one of the main influences on the success of demand response programs, because if only a few consumers would participate, the effect on a macro scale would be negligible (Batalla-Bejerano et al., 2020). Therefore, utility companies need to strive to engage as many consumers as possible. This could be done by giving reduction or other benefits, but not all consumers respond in the same way to price- and incentive based interventions. Therefore, consumer participation can be predicted better, if insight is given in consumers personal interests and values. With that approach, incentives can be personalized to a consumers desires and sensitivities (Guthridge et al., 2010). So, in order to maximize consumer participation in demand response programs, it is important to understand who your consumers are and which factors drive their decisions about energy usage.

4.2. Consumer Segmentation

Every person has their own attitudes and values underlying their behavior. Likewise, energy consumers are heterogeneous, and make different choices about their energy usage. Moreover, every consumer responds differently to real-time pricing strategies and incentive-based encouragement. Therefore it is not realistic to represent the energy consumer as a single agent type in a model. However, it is also not possible to include too many different types of consumers, because the model needs to remain attainable and understandable. Consumer segmentation is a suitable way to find a balance between simplicity and reality (Frankel et al., 2013). In consumer segmentation, the consumer population is divided into multiple segments that are relatively homogeneous based on particular criteria. For example, consumers that care about the climate and the environment can be placed in the segment of the 'green' consumer. The foundation of the consumers types for the demand response model in this thesis will lie in previous literature, where surveys,experiments and regression analysis have provided valuable insights in consumer segments in the energy market and their behavioral differences.

4.2.1. Approach for the definition of the consumer types

Due to the time limitations of this research it was not possible to conduct a survey and perform consumer segmentation from the start. Therefore, the approach for the definition of consumer types started with examining consumer segmentations from preceding papers and reports (Durillon et al., 2019, Frankel et al., 2013, Guthridge et al., 2010, Sütterlin et al., 2011, Yang et al., 2015). For each of these papers, the defined energy consumer types were described and their underlying research methods and defining criteria were analyzed. Afterwards, the disparate segmentations were compared and the consumer types that will be used in this research were introduced. An extensive analysis of the consumer types in the literature that was used for the definition of the final consumer types can be found in appendix A.

4.2.2. Final consumer types

As discussed in the previous section, a clear picture of possible energy consumer segmentation has been portrayed based on former research. The consumer types of different researches showed significant overlap. Figure 4.1 gives a color-coded overview of the similar types of energy consumers, where the color range from green till red represents a high till a low likelihood of the consumer types to engage in energy saving, or demand response programs.

While comparing and looking at the overlap, four consumer types stood out, that can represent the foundation of the consumer agents in this thesis. First of all, all researches included a cost-conscious and a green environmental consumer. Therefore the green and cost-conscious consumer type will also be included in this research. Because not all researches included a idealistic proactive type of consumer and their motivations were not very measurable, this type is left out of the research scope. Although Yang et al (2015) did not include an indifferent type of consumer separately, all the others did and it is important to represent the realistic part of the population that will not engage in demand response, no matter what policies will be implemented. Therefore the indifferent consumer will be a part of the agent-based model in this thesis. The last type that will be included is the convenience-oriented energy consumer. This consumer type is a combination of all types represented in orange and is a consumer that is not very interested in energy savings at the moment, but might consider it if benefits increase and no comfort is lost or costs are made.

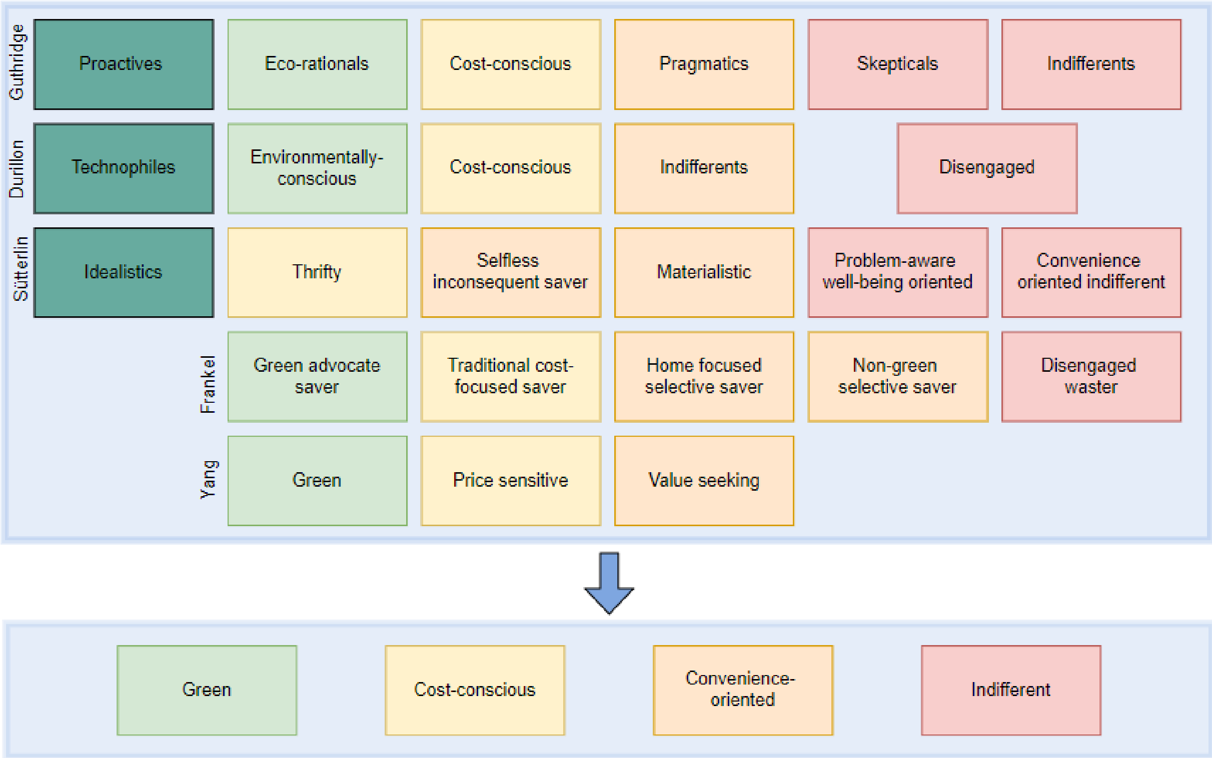


Figure 4.1: Definition of consumer types used in this study

4.3. Moderators for Consumer Participation

Based on the literature review in chapter 2 and the criteria that were used for consumer segmentation in the papers, the criteria price, environment, comfort, safety and social norm were identified as important influences on user participation in demand response programs. In the consumer conceptualization of this study, these criteria are referred to as personal values. Consumers base their choice to engage in demand response programs on their personal values, so the personal values are the moderators for consumer participation. However, each of the consumer types puts different weights on these values. Therefore, consumers have a numerical score for the value of price, value of environment, value of comfort, value of safety and value of social norm to express how much each personal value influences the decision to participate. In this section the values will be explained and the importance of these values in the decision to participate will be compared for the different consumer types.

4.3.1. Quantification and limitations

In the following paragraphs the values will be discussed and in order to take behavior into account in an agent-based model, it needs to be quantified by numeric values and formulas representing system relations. This of course has limitations, because human behavior, decision making and its underlying drivers are utterly complex and a model will always fall short in its representation of the real-world behavior. However, simplification and quantification is the only possible approach to simulate consumer behavior.

Because of time restrictions for this research, there was no opportunity to hold a survey and find numerical values for all of the personal values. Therefore, to find a quantitative realistic numeric estimate for each personal value for each consumer type, literature was consulted first to find out if a reference could be made to prior research. If there was no exact value to be found in research, an intelligent assumption was made based on literature and the relative attitudinal difference between the consumer types. If nothing useful could be said about a value, a default value was used. Thus, the numerical values that represent the personal values of each consumer type are a simplification of reality and cannot be proven to be the true values. However they are useful for explaining the differences in attitudes towards demand shifting in energy consumer populations. The personal values are computed as a score between 0 and 1, where 1 means that a value weighs heavily in the decision to participate. The values are modeled as static agent attributes, which means they stay the same during the whole simulation time.

4.3.2. Value of price

In this study, the value of price refers to how sensitive a consumer is to cost differences and price-based interventions. According to Guthridge et al.'s survey, cost savings had quite a strong bearing on energy usage decisions, with a weighting of 38 percent (2010). The literature review of Dutta et Al. also confirmed the determining effect that price has on participation in demand response (2017). In his research Lijesen compared the price elasticity of electricity in many dynamic pricing researches, but the results of these papers differed strongly (2007). However, it can be stated that the value of price can be a positive influence on the chance of participation in demand response programs, especially when financial incentives are implemented (Gyamfi et al., 2013). The more a consumer values price or costs as an important value, the more this effects the users chance of participation. If shifting demand can result in lower costs for a consumer, this tempts consumers with a higher value of price more to participate than consumers with a low value of price.

If you look at the relative values for the four defined consumer types, you find that the cost-conscious energy consumer has a high value of price and the indifferent consumers has a low value of price. Both the green and the convenience-oriented are moderately price sensitive. (Guthridge et al., 2010) (Durillon et al., 2019). The same conclusions were found when consumer scaled their financial energy saving motive (Sütterlin et al., 2011). Therefore the scores for the value of price assigned to the green, cost-conscious, convenience-oriented and indifferent consumers are respectively 0.35, 0.9, 0.35 and 0.1.

4.3.3. Value of environment

The value of environment represents environmental concern and is a measure for how sensitive a consumer is to the impact of an energy product or energy consumption on the environment. This includes how much a consumer believes that energy consumption affects the environment at all and how much he can have an impact to improve the situation by shifting demand or using more renewable energy (Guthridge et al., 2010). In energy decisions, the environmental impact weighs only 17 percent for the average consumer, because most end consumers are not aware that their energy usage has an impact on the growing amount of energy production that is needed to conform demand (Guthridge et al., 2010). Nonetheless, in general, consumers say they are willing to pay for increasing shares of renewable energy. The green group is even willing to pay 2,5 times more than the average for the increasing share of renewable energy (Yang et al., 2015). On the other hand, Frankel et al. found that messaging around environmental friendliness will resonate with green advocates but will not engage other groups Frankel et al. (2013).

When comparing the value of environment between the consumer types, the green consumer stands out with a high environmental concern (Durillon et al., 2019). They acknowledge their effect on the environment and believe their behavior can make an impact. The cost-conscious and convenience-oriented consumer do not necessarily care for the environment, but are moderately aware (Frankel et al., 2013), whereas the indifferent consumers has a very passive attitude towards the environment and does not consider it as a personal interest. Therefore the scores for the value of environment assigned to the green, cost-conscious, convenience-oriented and indifferent consumers are respectively 0.9, 0.35, 0.25 and 0.

4.3.4. Value of comfort

A principal component analysis done by Sütterlin et al. showed that besides basic convictions that underlie energy behavior, loss of convenience and comfort was another very important factor that discourages energy saving behavior (2011). In a Swedish field experiment, consumers were willing to engage in demand response if it did not cause them any inconvenience, meaning that their flexibility of other daily activities was not disturbed by demand shifting (Öhrlund et al., 2019). The value of comfort refers to the fact that consumers might not want to shift their demand, because they are afraid of inconvenience or because they think is it a hassle. Perceived hassle is a psychological barrier for consumers an a hassle can be any annoying practical problem or downside that causes stress. When there are no positive experiences or benefits, a sum of hassles can lead to not taking action (De Vries et al., 2020). This effect can be seen in energy efficiency management, where consumers do not shift their demand as a result of cumulative hassles. For example, consumers could find checking energy prices and installing a smart meter a hassle. Consumers with a higher value of comfort, are more likely to perceive hassles and be discouraged. So, the participation chance is influenced more negatively, if a consumer's value of comfort is higher. In the model, this value is again a static agent characteristic and a consumer will only shift his consumption if financial or environmental benefits outreach the comfort objection.

The value of comfort is comparable to the criterion 'self-action required' that was used in the Guthridge et al. report. What can be noticed there is that green and cost-conscious consumers are quite neutral on this front, whereas indifferents have a negative attitude towards self-action (Guthridge et al., 2010). As described by Frankel et al., the convenience-oriented type does not want to save energy if there is any inconvenience, but might be interested in set and forget actions (2013). Although the cost-conscious consumer is quite neutral to losing comfort, he does get discouraged to engage in demand response if the electricity bill gets too complex. The indifferent and convenience-oriented consumers scored relatively high on the score for loss of comfort as a criteria for energy saving behavior in the survey of Sütterlin et al. (2011).

From this it can be concluded that a green consumer does not mind to lose some comfort in order to save energy, which results in a low value of comfort, whereas the cost-conscious consumer has a moderate value of comfort, due to the fact that this consumer type might be discouraged by complexity. The convenience-oriented and the indifferent do not have a strong financial or environmental motive to save energy and prioritize their individual interest and comfort above all else. Hence the scores for the value of environment assigned to the green, cost-conscious, convenience-oriented and indifferent consumers are respectively 0.1, 0.3, 0.8 and 0.9.

4.3.5. Value of safety

The value of safety relates to the perceived risks by energy consumers linked with joining demand response programs. First of all there is the perceived risk of high price levels and less predictable pricing. Also, technologies like algorithms for optimization of energy use that may help to reduce the financial risk of varying prices over time, could be experienced as more risky, because consumers lose a sense of control (Parrish et al., 2020). Moreover, consumers mentioned in surveys that they are concerned about possible loss of control related to direct load control and automated energy systems at home (Lopes et al., 2016), (Hall et al., 2016). For example, some users firmly preferred programming their own heating system, instead of allowing for direct control. Guthridge et al.'s survey confirms that consumers are cautious to give full control to energy providers and found that in energy usage decisions, utility control weighted 37 percent (2010). However, losing control may only be a negative factor, if the trust in the companies facilitating demand response is low (Lopes et al., 2016). Parrish researched motivations and barriers for consumer engagement in residential demand response specifically and found that consumers can be discouraged by perceived risk and mistrust of the intentions of demand response facilitators. However, trust can grow with greater familiarity with demand response, based on experiences and reputation (2020). It can be stated, that trust in utility companies is a big influence on the value of safety. Another risk associated with automated demand response, that also partly determines trust in utility companies, is the handling of consumers' demand data and privacy. Even though strict guidelines should regulate utility companies, negative media presence about cyber security issues, data leakages or misuse in the past, have formed some consumers to be mistrusting about data sharing.

In the model, the value of safety is a combination of the reasons that consumers give to explain why they do not want to shift their demand. Reasons are that they perceive (privacy) risks, dislike control or mistrust demand response facilitators. The user participation score is influenced negatively, if safety is valued highly. Only when the financial or environmental benefits outreach the comfort and safety objection, a consumer will shift his consumption.

From Guthridge et al. we learn that green consumers do not like utility control, but do not perceive risks of demand response programs and the same goes for the cost-conscious to a lesser extent. Indifferents do not mind control, because they don't care about anything (Guthridge et al., 2010). However, utility control is only a part of the criterion risk that is used here. Frankel et al. concluded that green consumers as well as indifferent consumers are interested in technologies and automation that manage energy consumption (Frankel et al., 2013). Also Yang found that green consumers do not perceive risk, but they found that cost-conscious consumers are worried about risks most. Accordingly, the value of safety assigned to the green, cost-conscious, convenience-oriented and indifferent consumers in the model are respectively 0.1, 0.7, 0.5 and 0.2.

4.3.6. Value of social norm

The value of social norm represents how sensitive a consumer is to the behavior and opinion of others and how much his own behavior is influenced by this. Social norms are shared ideas within a group about desired and accepted behavior. Social norms can function as guidelines to evaluate your own and other people's behavior (Wolske et al., 2020). Normative feedback has proven to be a successful tool to motivate people to accommodate their energy consumption to others in the residential energy sector (Schultz et al., 2015). Bergquist and Nilsson also recognized the potential of using social norms in smart meter applications, but also strained the importance of an additional mechanism, the norm distance effect (Bergquist and Nilsson, 2018). This effect entails that the compliance to social norm is stronger when the desired behavior is already more similar to their own behavior and the required behavior change is smaller. In a survey among energy consumers, 60 percent of respondents declared to feel any social pressure to behave sustainably by for example recycling products, conserving water or reducing electricity consumption (Guthridge, 2010). Similarly, Sütterlin et al. found in their survey that perceived social pressure can motivate to act more environmentally friendly (Sütterlin et al., 2011). A review on existing empirical literature on energy behavior also confirmed that studies in different research disciplines showed the prominence of peers in decisions. However, it was also marked that people can influence each other both positively and negatively (Wolske et al., 2020). Many researchers found effects of peer pressure, social interaction and social norm on behavior, however a true understanding of why and how this occurs remains absent (Wolske et al., 2020). Summarily, in the conceptualization of this study, the value of social norm incorporates perceived pressure to follow social norms as well as how sensitive a consumer is to being influenced directly by the behavior of close relations.

The value of social norm is incorporated in the simulation model in a slightly different way than the other values. It does not directly affect the participation score, but the effect on the participation score is a combination of the value of social norm and the social interaction in the social network. So, a consumer's sensitivity to social pressure and social norm is incorporated in the value of social norm, whereas social interaction is based on the behavior of close relations in a consumer's social network. Section 5.2 will elaborate further on this.

Again, these insights need to be translated into scores for the defined consumer types. According to Guthridge et al.'s survey, green and cost-conscious consumers have a relatively high impact of social pressure to drive them to action compared to the other consumer types (2010). The differences however, are not very big. Sütterlin et al. also asked consumers about their perceived social pressure and again the differences were rather small. However, cost-conscious and green energy consumers felt the highest pressure and the indifferent type had a slightly higher value than the convenience-oriented (2011). Combined with the theory of the norm distance effect, the value of social norm for the green, cost-conscious, convenience-oriented and indifferent consumers in the model are respectively 0.65, 0.65, 0.35 and 0.40.

4.4. Conclusion

This chapter has defined a consumer segmentation based on surveys and experiments from prior literature. The four defined consumers that will be analyzed during the rest of this study are the green, the cost-conscious, the convenience-oriented and the indifferent energy consumer. The values of price, environment, comfort, safety and social norm were identified as moderators that affect energy consumption decision-making. Afterwards, the relative weighting of these values was studied for each consumer type and quantified for modeling purposes. However, segmentation of consumers, value selection and quantification are a simplification of the complexity of reality. With this approach, an attempt was made to conceptualize real-life behavior and to make it possible to enrich the agent-based model with a behavioral component to understand user participation in demand response better on a system-level.

5 Model Conceptualisation

This chapter establishes the model conceptualisation and model formalization of this thesis. The model consists of three main components, the representation of the electricity grid, the energy consumers and their behavior and policy interventions. This chapter will start by describing the aspects that represent the electricity grid and energy exchange. Afterwards, the formalization of the model agents and their characteristics and decision-making process is discussed. The policy interventions will be introduced in chapter 6. This model conceptualisation chapter underpins the assumptions and simplifications that were made in the creation of the agent-based model.

The sub-question that will be answered by this chapter is:

Sub-Question 2: How can the future electrical grid be modelled as an agent-based model?

And can be divided as follows:

a) *How are supply, demand and price modelled conceptually?*

b) *How can consumer heterogeneity and social interactions be incorporated in the model?*

c) *What are the underlying processes that determine user participation and demand shifting?*

The first model component is the future electrical grid, which is modeled as a copper-plate model and includes demand, supply and a pricing scheme. The second model component represents energy consumers, which are included as model agents. These agents can participate in demand shifting and determine the total demand at each time step. The third model component consists of the model interventions and interacts with the model agents.

5.1. Conceptualization of the Future Electrical Grid

The electrical grid can be modelled in a very technical way, including controllers, transmission stations and distribution extensively, but that is not the focus of this research. However, the amount of demand, availability of green and fossil supply and electricity prices over time are important for this study and are sufficient for simulation of demand response and user participation. Therefore the future electrical grid was modeled as a copper-plate model of the electricity network.

5.1.1. Context description

This study does not focus on the current electricity grid, but on a future situation. Namely, a future scenario in which strong fluctuations in supply due to a high share of renewable energy sources cause energy shortages. To be able to understand how the model outcomes can be interpreted it is very important to understand the stylized context that is represented in the model and serves as the decision context for the agents. First of all, a smart grid is implemented in the future scenario, that allows for information communication between consumers and the energy producer. With this, it is also presumed that households are connected with the smart grid and have a smart meter at home, when they are engaging in demand response programs. Not only heating and cooling can be regulated, but also smart household appliances such as a dish washer or a washing machine can be connected to the smart grid. These technologies make it possible to shift energy demand during periods of a supply deficit and the current demand cannot be satisfied. In reality, it is very unlikely that an energy shortage will really occur, because grid operators need to ensure energy safety. They can do this by importing energy from foreign countries or increasing the fossil fuel production. However these interventions are not exploited as solutions for energy balance in the future scenario in this thesis. In the model, demand response and storage are used as solution for periods of energy shortage. At those times, the energy producer can respond by shifting an amount of energy demand of the consumers that have allowed the company to do so or use energy from storage. The total storage capacity that is needed to make sure that there is energy balance, is calculated in the model. For this model conceptualisation it does not matter what kind of storage is used, because it does not influence the system-level behavior of the model. In the future this storage could be installed by utility companies or could be part of community storage programs.

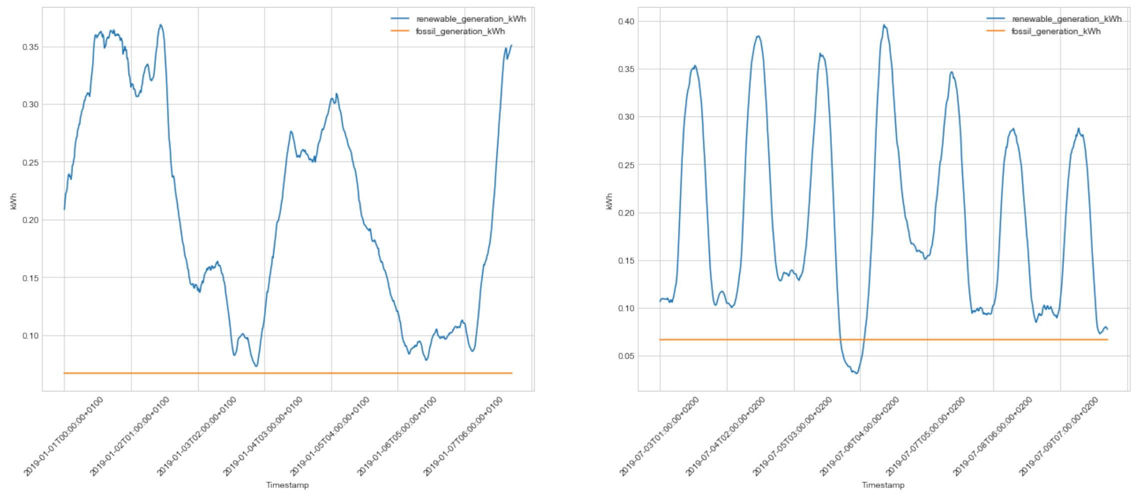
5.1.2. Energy production

The energy supply in the model consists of a fossil base load that is constant over time and fluctuating renewable supply from solar and wind power plants. These two forms of renewable generation have been chosen to be incorporated, because their generation is very volatile, because it strongly depends on weather conditions. Moreover, many future investments are planned for wind and solar energy, so they are likely to represent a large share of future energy supply.

However, the exact distribution of different types of energy sources in the future and their generation capacity is still unknown. As it was simply not possible to find future production data, assumptions had to be made about the supply. Historical production data from Germany was used as a foundation for the representation of future supply in the model. The data was retrieved from the Open Power System Data platform, that has open-source data on weather and generation of conventional and renewable power plants of most European countries (Open Power System Data, 2020). The German dataset that was used, contained the generation capacity and actual generation of solar, on-shore and off-shore wind facilities on a national level. Data was available for each 15 minute time interval in the year 2019. In that year, the total wind energy generation capacity was 48974 MW and the total solar energy generation capacity was 47480 MW, which roughly represents a 50/50 division of wind and solar in the total renewable supply. This is also the division, that was used in this simulation model, but can be adapted easily in future use cases.

A very important aspect from the data is the pattern that production followed over time. This was based on real weather conditions and is therefore really useful to adopt in the model. However, the production quantities could not be used directly, because this study focuses on residential demand only. As this was national production data, it was it was not possible to determine which share of production was allocated to residential demand from the production data. Thus, calculations were needed to scale the total production down to one household, to make it conformable with the simulation model of the future electricity grid. To accomplish this, a bottom-up approach was applied based on the yearly demand of one household to determine how much green supply would need to included in a realistic future scenario with a high share of renewables.

For the supply for one household in the model, it is assumed that the fossil base load is 30 percent of the peak demand load in a year of 0.22 kWh. Different alterations were tested, but the default for renewable supply in the model is that the yearly renewable supply represents 80 percent relatively to the 30 percent fossil supply. Afterwards, the total renewable supply was divided over the year and calculated for each 15 minute time frame, based on the generation pattern from the original German data. This results in the fact that the fossil-renewable ratio is not 80/30 at each period in the year. In figure 5.1a and 5.1b the fossil and renewable supply is shown for a winter and a summer week. Notable are that the classical solar generation curve is dominating the supply in a summer week, whereas wind is more dominant in the winter. These charts show the production for one household, but in the model total supply can easily be scaled to the amount of simulated households.



(a) Winter week production

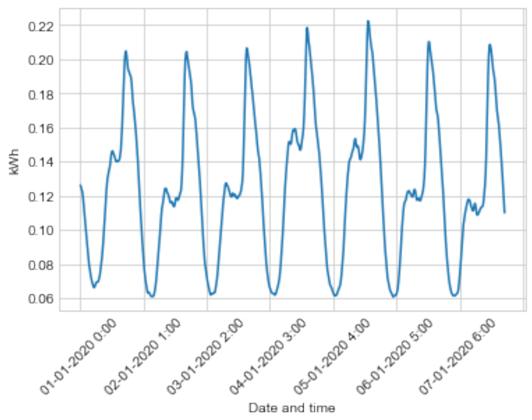
(b) Summer week production

Figure 5.1: Production for one household for a winter and a summer week

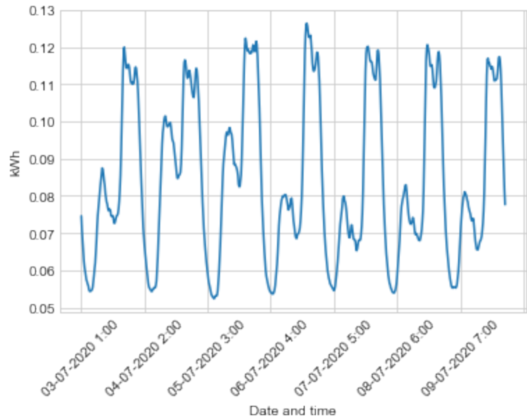
Besides energy supply, another input of the model was the predicted supply. The assumption is that companies can make predictions based on historical supply and demand data as well as current weather and generation information. This data can then be used by the energy producer to predict mismatch and anticipate demand response. In this study, the predicted production was forecasted based on a different year, 2018, to mimic the fact that utility companies in the future have prior knowledge, but not the exact data as input for their prediction models. The production was predicted with a simple machine learning regression model using the statsmodels library in Python. In the model, if there is going to be a shortage in the next 15 minutes, the energy producer decides that demand will be shifted.

5.1.3. Energy demand

As specified earlier, this research fixates on residential demand only, but residential demand can still vary a lot because of household size, housing characteristics or lifestyle. However, for this study, only one household consumption pattern is used for all households to reduce system complexity and because it does not interfere with the modeling objectives. The demand dataset originates from the Dutch association of energy data exchange (NEDU) and contains a number of demand profiles for the year 2020 (Vereniging Nederlandse EnergieDataUitwisseling, 2020). Profile E1a was used for this study and was based on smart meter data. In the dataset demand data is available at a 15 minute granularity for which it represents the fraction of the yearly demand for every period. With these fractions and the standard annual consumption of 3500 kWh per household, the demand was calculated for each 15 minute time step in the model (Vereniging Nederlandse EnergieDataUitwisseling, 2020). Figure 5.2a and 5.2b show the demand for one household for a winter and a summer week. In general it can be stated that the electricity demand is lower in the summer months than the winter months.



(a) Winter week demand



(b) Summer week demand

Figure 5.2: Demand for one household for a winter and a summer week

To allow for demand response in the model, the demand needs to be divided in non-shiftable demand, semi-shiftable demand and fully shiftable demand. The conceptualisation of the flexibility of demand was based on the PHD of Nina Voulis, who analyzed the heterogeneity in urban demand (Voulis, 2019). Then again, her division of the flexibility of demand was based on synthetic sector profiles and residential demand profiles that were measured by a Dutch DSO, Alliander. Non-shiftable demand includes demand that cannot be shifted, without a limitation of comfort, such as lighting. Semi-shiftable demand contains demand from household appliances such as a dishwasher of a laundry machine, that require some human action, such as loading the laundry. When the machines will be turned on can be controlled automatically by the energy producer, but it assumes that the machines are connected to the smart grid.

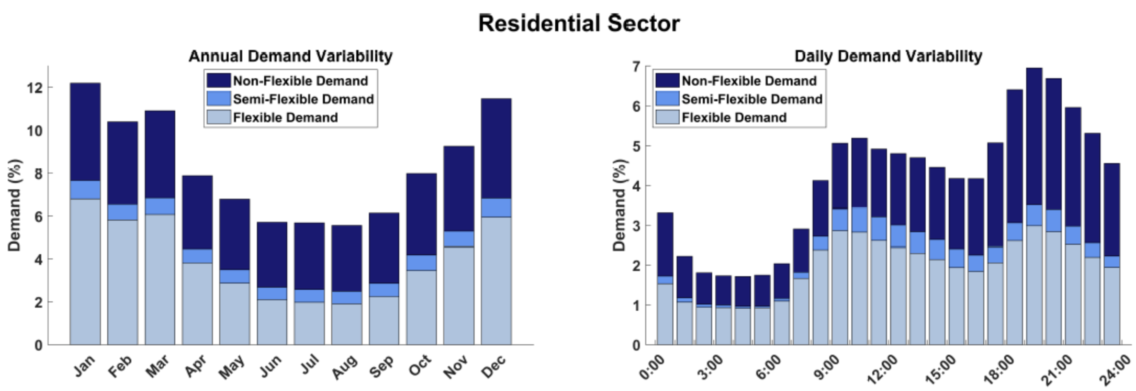


Figure 5.3: Annual and daily flexibility of demand for the residential sector as defined by (Voulis, 2019)

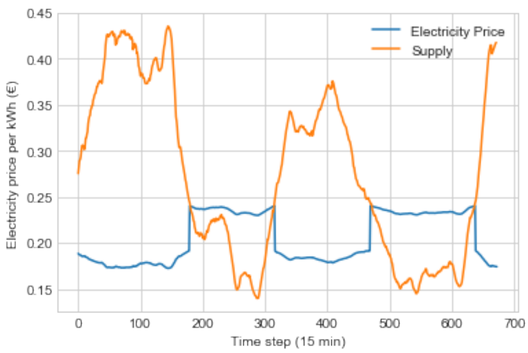
An important assumption that was made by Voulis and is made again in this thesis, is the assumption that heat pumps provide for 50 percent of heating demand. Currently, most heating demand is satisfied by heat from gas, but because of the ambition of the Dutch government to phase out gas, the future scenario in this study already includes a large share of electrical heating. Figure 5.3 shows how the shiftable shares of demand vary over the year and during a day. On average, about 40% of the yearly demand is considered flexible or semi-flexible.

5.1.4. Price

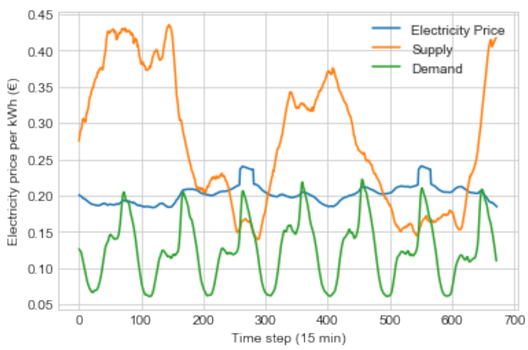
Different price settings have been added to the simulation model. In the base case, flat pricing is applied, which means that there is one electricity tariff at all times. The tariff that has been selected is € 0.216 which was the average electricity price of the countries in the European Union (EU) in 2019. Two additional real-time pricing schemes are available in the model in which prices vary around the flat price. Whenever real-time pricing is implemented, the price differs every simulation step.

The first real-time pricing scheme depends solely on supply, which means that the price rises when total supply is higher (5.1). If the supply at a certain time is higher than the mean generation of the year, the price is lower than the flat price, whereas the price is lower when the supply is lower than the mean generation. Figure 5.4a shows the resulting price graph for a winter week and it is notable that it resembles the adverse of the supply.

$$P_e(t) = P_{flat} + \pm\alpha \cdot Supply_{total}(t) \tag{5.1}$$



(a) Electricity price based on supply



(b) Electricity price based on mismatch

Figure 5.4: Electricity prices for real-time pricing schemes in a winter week

In the second scheme, the price is influenced by the mismatch between energy supply and demand (5.2. In this case, the total demand refers to the original total demand amount, if none of the households would shift demand. This way of pricing ensures high prices during periods of energy shortage. The price is calculated slightly differently for periods of mismatch, formula 5.3, than for periods of abundance, formula 5.4. In case of shortage, beta is added to the price as well, to increase the price even more during shortage and make it extra unappealing to consume energy. As can be seen in figure 5.4b, this results in two peaks in the pricing function during shortage periods in a simulated winter week.

$$Mismatch(t) = Supply_{total}(t) - Demand_{total,original}(t) \tag{5.2}$$

$$P_e(t) = P_{flat} + \gamma \cdot Mismatch(t) + beta \tag{5.3}$$

$$P_e(t) = P_{flat} - \gamma \cdot Mismatch(t) \quad (5.4)$$

In this thesis, the option to calculate the electricity price from energy mismatch was used for most simulations where real-time pricing was implemented.

5.2. Agent Attributes and Interaction

Chapter 4 has introduced the consumer types and has identified important moderators and mechanisms that influence the decision-making about energy usage and participation in demand response. This section will further elaborate on the consumer conceptualisation. Additionally, the formalization of the findings of chapter 4 and incorporation in the model agents will be described.

5.2.1. Model agents

In the model, an agent represents a household. This choice was made because electricity demand is also determined per household in reality. The number of households can be varied in the model, but in order to run the model in many different scenarios without too much computational time, the population was set to twenty households for this study. Since all agents have the same energy demand and demand pattern, there is no need to provide more detailed information about household size or demographics. However, the values of the households are interesting agent attributes that determine the decision to participate in demand response programs or not.

In the previous chapter the quantitative values for the personal values towards price, environment, comfort, safety and social norm type were specified for each consumer type. In the model, a household is one of those consumer types. However, in reality not every household can be defined as one of those types specifically, but might be somewhere in between. To cover for this heterogeneity within the consumer types, randomness is added to the model. The values from the previous chapter are the mean, but a bound of 0.1 on both sides is included for each value. For example, for a green consumer the value of environment can be somewhere in between 0.25 and 0.45.

5.2.2. Social network

As mentioned earlier, the behavior of peers can influence the behavior of a consumer (Sütterlin et al., 2011), but this influence can be positive as well as negative (Wolske et al., 2020). In order to include social interaction in the model, a social network was set up. The agents are part of the social network and have at least one connection to another agent. The network was constructed based on the Barabasi-Albert preferential attachment algorithm. This algorithm represents real social networks, where people who have a lot of connections are more likely to make new connections (Barabási and Bonabeau, 2003) (Pollner et al., 2005). Therefore, new agents wanting to join the network, have a higher probability of making a connection with a node with a high degree. Besides, people are also more likely to engage with people who have similar interests and values, which is why the Barabasi-Albert algorithm has been adapted slightly. In my model, an agent is more likely to connect with agents in the network that are of the same consumer type and have many connections already. In the final network, some agents have a lot of connections and are therefore considered more influential than others. Agents can influence the choice to allow for demand shifting of other agents, but this depends on how sensitive the other agent is for social norm and social pressure and on how influential the persuading agent is.

Each model run, a new social network is created and agents are added to the social network in a random order. When a new agent is added to the network, he selects an agent from a list of the agents that are already in the network to connect to. Agents that have multiple connections already or are of the same consumer type as the new agent, appear more often in the list and therefore have a higher chance of being chosen as the one that the new agent will connect with. An example of a constructed social network can be seen in figure 5.5.

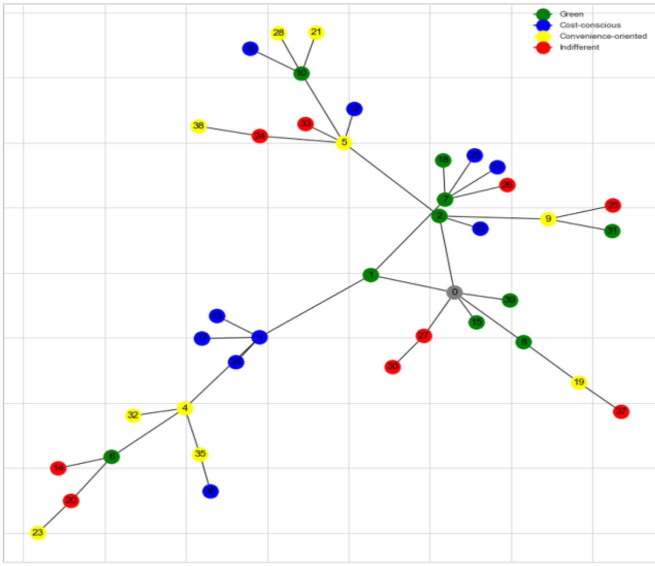


Figure 5.5: A social network of different consumer types built from the adapted barabasi-albert algorithm

5.2.3. Social interaction

Once the social network has been set up, the most influential neighbor is determined for each agent. In the model this most influential neighbor is considered to be the closest and strongest relationship of an agent and is the only one who can influence the agent in question. The most influential neighbor is the neighbor with the highest degree, but if multiple neighbors of an agent have the same degree, the one with the most similar personal values is the influencer. After this selection process, each agent has chosen a most influential neighbour, which is comparable to a best friend.

The social interaction between agents is based on how influential agents are and their value of social norm. The effect is captured in the formula below, where d is the degree and VoSN is the value of social norm. The social effect is a weight that can be used to vary the impact of the social interaction, because the strength of this effect is uncertain.

$$S = \pm \max(1, \frac{d_{influencer}}{2}) \cdot VoSN * Social_{effect} \tag{5.5}$$

In the model an agent only experiences social pressure from his connection if that agent has the same degree or higher. If an agent and his best connection have the same degree they both influence each other. If an agent is more influential than his connections, he influences others but is not influenced. The effect is positive if an agent is influenced by another agent that has a shifting option that allows for more demand response, and the effect is negative if the other agent allows less shifting or no shifting at all. If both agents have the same shifting option, there is no social effect. The social interaction between the agents is something that occurs in the model at all times and is not an external intervention, but an internal model process.

5.3. Demand Response Processes

This section describes the processes that underlie the demand response effect. The first step is the selection of a shifting contract by consumers. Then, the process of contract switching and underlying incentives are explained. Finally, the last subsection clarifies the formalization of the actual shifting of demand by the energy producer.

5.3.1. Shifting contracts

As mentioned in section 5.1.3, the demand can be divided in flexible, semi-flexible and non-flexible demand. Likewise there are three possible shifting contracts that an agent can choose from, namely 'no shifting', 'shiftable' and 'semi- and shiftable'. A shifting option states which types of energy demand, the energy consumer allows for to be shifted by the energy producer. In this model it is assumed that all agents have a contract with a certain energy producer and can choose their own shifting option. If a consumer chooses for the no shifting option, this means that the energy producer can never shift his demand and the agent will use all desired energy at his preferred time slot. If an agent chooses for the shiftable shifting contract, he states that the utility company can shift fully flexible demand that is used for heating and cooling. It is assumed that a smart meter is installed in the household when this option is chosen, if this was not the case yet. Consumers that have the last shifting option, semi- and shiftable, do not only allow for shifting heating and cooling demand, but also some household appliances, like a washing machine or dishwasher, resulting in an even bigger share of personal demand that is shiftable at times where there is an energy shortage. In a survey, householders mentioned that doing laundry and dish-washing were loads they could switch, without experiencing too much interference with their daily life (Öhrlund et al., 2019).

The initial shifting contracts can be selected in three different ways. First of all, the initial contract can be set to the shiftable contract by default, which could be a choice of the energy producer. Another option is to initialize the shifting contracts based on consumer type. This options is very useful for policy testing and comparison of model outcomes, because each consumer of a consumer type has the same contract. The last option is to initialize the shifting contracts based on the personal values of an agent. Because of the added randomness in the personal values, this can result in the fact that agents of the same consumer type, have different shifting contracts.

5.3.2. Switching between contracts

The personal values and social interaction converge in the so called participation score. The choice for a type of shifting contract relies on the participation score of an agent and the threshold values for the different contracts. A schematic overview of the participation score and how this is influenced by the personal values is provided in figure 5.6.

In the base case it is not not possible for households to switch between contracts during the year, but in the extended model version this is possible. Contract switches can take place during a switching period. For example, there could be a switching period 4 times a year, but this amount can be varied, considering the trade-off between the hassle of switching and the extra financial costs of a no shifting contract. Before each switching period, the energy producer can send out a report to each household, that includes information about their usage and costs and advises about a suitable shifting option for them. Besides, policy interventions could contribute to more people switching to contracts that allow for shifting. These policy interventions alter the participation score by interacting with different personal values. What these policies are and how they affect the agents will be explained in chapter 6. Along these lines, the option to switch between contracts is an important aspect of the model and can be used to test the effect of policies on participation in demand response for different consumer types.

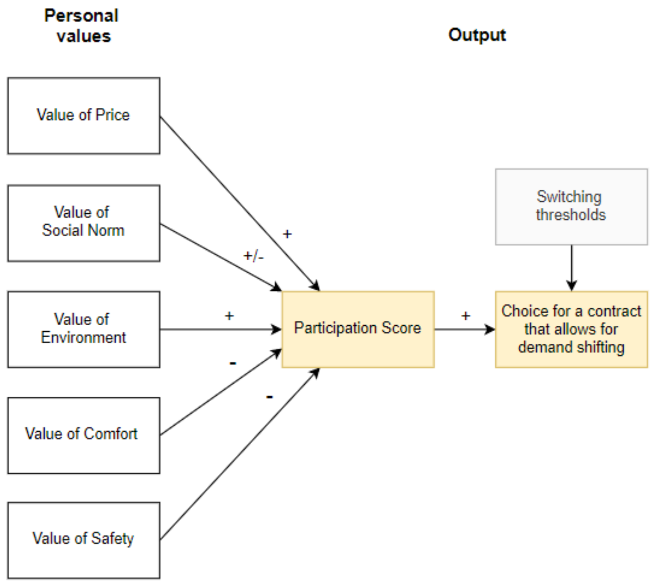


Figure 5.6: Schematic overview of the influences on the contract choice

5.3.3. Demand shifting

The actual shifting of demand is done by the energy producer and is automated thanks to the smart grid, smart meters and heat pumps. As mentioned before, heating and cooling can be steered by the energy producer without any required action from the household, but semi-flexible demand from household appliances require some human action. In the future scenario, a consumer can communicate to the energy producer that a dishwasher of laundry machine is ready to start. The energy producer can then decide, when exactly it will start within a time period of 1,5 hours, which is the maximum amount of time that demand can be shifted in this model, to make sure that the loss of convenience is acceptable and no undesirable temperature changes will take place.

At each time step in the model, the energy producer checks if there will be an energy shortage based on the predictions of supply. If an energy shortage is foreseen, demand will be shifted. The process of shifting consists of a few steps. First, it is checked if there is demand that was shifted in the past time steps that needs to or can be be used now. Then the algorithm checks how much demand could potentially be shifted from the demand of this time step, based on the number of households that allow for shifting and their shifting contracts that represent the share of demand that can be shifted at that time. After this step, the minimum and maximum amount of demand that can be used in this time step have been calculated. These amounts are compared with the supply at that time step. If the available supply is smaller than the minimum amount of demand that needs to be used now, there is still an energy shortage after shifting. If this is the case, the supply-demand gap can be filled by energy from battery storage. If the minimum amount of demand that needs to be used now is smaller than the available supply, the supply is used, because otherwise a part of demand would be shifted without the need to do that. Let's consider the case where the original demand is 100 kWh, the available supply is 80 kWh and the minimum amount of demand that needs to be used now is 70 kWh. In this case, 80 kWh will be used now, an 20 kWh will be shifted, even though 30 kWh could have theoretically been shifted. This algorithm and some other main algorithms are explained in appendix C.

When a period of energy shortage lasts longer than 1,5 hour, the shifted demand from 1,5 hours ago needs to be used again. In these situations, electricity from storage can be used if there is still an energy shortage after the demand shifting. In the model, there is a trade-off between the amount of time that demand can be shifted and the required energy storage. When there is no energy shortage anymore, the remaining demand that was shifted can be used and the battery can be charged again. The formulas for updating the state of charge (SoC) of the battery (B) are listed below.

$$B_{SoC}(t) = B_{SoC}(t-1) - (Demand_{total}(t) - Supply_{total}(t)) \tag{5.6}$$

$$B_{SoC}(t) = \min(B_{Capacity}, B_{SoC}(t-1) + Supply_{total}(t) - (Demand_{total}(t)) \tag{5.7}$$

If the total demand after shifting is still bigger than the total supply, formula 5.6 is used to calculate the battery SoC after using some of the battery storage. Formula 5.7 describes how the battery is charged again whenever supply is bigger than demand.

5.4. Assumptions

The model as described above is the context in which the agents interact. A few assumptions were already mentioned, but some remaining assumptions are also important to note, in order to understand the decision context in the model correctly.

Important assumptions were made in the conceptualisation of this model, especially on the behavioral aspect of the model. These assumptions can be debated on, but the correct values are hard to specify even for behavioral scientists, if not impossible in some cases. Also on the production and demand side, assumptions have been made about flexibility of demand and the composition of energy supply. An elaborate overview of all important model assumptions can be found in appendix B

5.5. Conclusion

The model environment represents a future scenario with a high share of renewable supply consisting of solar and wind energy. The demand pattern is the same for all households in the model and can be divided in non-shiftable, semi-shiftable and fully shiftable demand. The model agents have a consumer type, personal values and are a part of a social network. Combined, these agent attributes determine their participation score and determine the choice for a type of energy contract. Agents can switch between contracts at certain periods in the year. If an agent has a contract that allows for demand shifting, the energy producer can decide to shift a part of their demand during periods of energy shortages. If shifting all possible demand does not solve the energy shortage completely, energy from battery storage is used to restore energy balance. An overview of the algorithms and the Python code that captures the model dynamics can be found in appendix C

6
XLRM Framework

The XLRM framework as introduced by Lempert et al. is used to design the deep uncertainty analysis. This framework helps to categorize system factors as external factors that can't be influenced by policy (X), policy strategies or levers (L), model relations between model factors (R) and model outcomes of interest or KPIs (M). In the previous chapter the system was conceptualized and the model relations (R) were discussed. This chapter will start by introducing the policy levers that can be used to encourage consumers to engage in demand response. Afterwards, the uncertain factors that determine the effect of the policies are introduced. Finally the key model outcomes are discussed and an overview of all aspects is provided according to XLRM framework.

The sub-question that this chapter addresses is:

Sub-question 3: Which price- and incentive-based interventions can be implemented as policy levers in the model?

6.1. Interventions

One of the core concepts that was discussed in the literature review in chapter 2 was behavior and behavior change. One of the insights from literature was that pro-environmental behavior can be achieved via values, beliefs and personal norms and that new behavior can be learned from external intervention (Stern et al., 1999, Watson, 1924). This section introduces the policies that can be implemented, besides real-time pricing. The selected policies were partially existing interventions from field experiments and partially policies that have not been implemented yet, but are expected to encourage user participation in demand response based on behavioral research. For each policy, an explanation is given of how it functions and with which personal value or system component it interacts. Afterwards the formalization and incorporation in the quantitative model is provided.

A schematic overview of the interventions and their interaction with personal values is shown in figure 6.1. After implementation of one or multiple policies, the participation score (PS) is calculated again at each switching moment (formula 6.1). The parameters VP, VE, VC, VS and SN are a result of the interaction between the policies and the original personal values. The following subsections will further elaborate on these policies and the formalization of their effects.

$$PS = VP + VE - VC - VS \pm SN \tag{6.1}$$

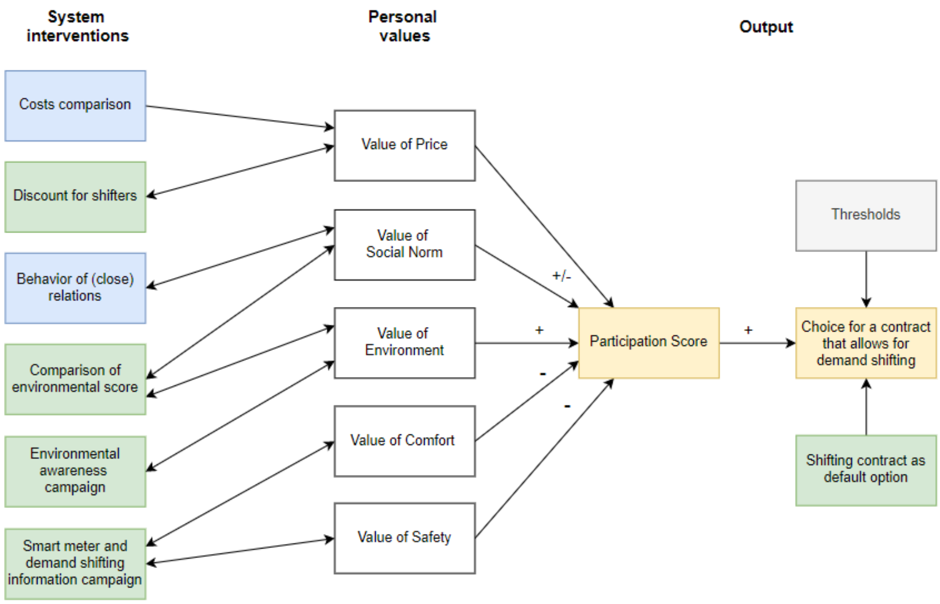


Figure 6.1: Schematic overview of interaction between interventions and personal values and shifting contract choice on an agent-level

6.1.1. Cost comparison and discount for shifters

As a result of the implementation of real-time pricing, the electricity costs over a certain time period are higher for consumers that do not allow for shifting than for consumers that had a shifting contract. If this difference is sufficiently large, this could interest non-shifting consumers to switch to a shifting contract, especially if they have a high value of price (Gyamfi et al., 2013).

The financial intervention is composed of two sub-interventions. The main component of this intervention is a cost comparison, because research showed that normative feedback can motivate people to adjust their energy consumption to others (Schultz et al., 2015). After a period of time, just before the switching period, the energy producer sends an overview of the made electricity costs to each of their clients. In this overview, the consumer does not only see his own expenditure, but also the expenses of a similar household that had the lowest costs during the previous period. As all agents in the model are exactly the same household in terms of energy usage, the lowest costs are the costs of a household that has the semi- and shiftable shifting contract. Although the costs already differ because of the real-time prices, an additional reduction can also be given by the energy producer to consumers that allow for shifting. It is assumed that energy producers are willing to do this, because demand shifting can save them costs if they don't have to buy energy elsewhere or need less battery storage. The additional reduction increases the effectiveness of the policy, because it makes the gap between the costs for shifters and non-shifters even bigger.

In the model, the costs per agent are calculated each time step as shown in 6.2. The reduction is given per switch period and is divided by the switch period, so that the total reduction has been received after the full switch period. If a household has a non-shifting contract, the reduction is 0. The cost differences are calculated on the last time step in the switch period. The effect of the policy is calculated according to formula 6.3. The formula shows that the effect of the policy is higher if the value of price (VoP) of a consumer is higher.

$$Cost_{household}(t) = P_e(t) \cdot Demand_{household}(t) - \frac{Reduction}{Switchperiod} \tag{6.2}$$

$$VP = \frac{Cost_{difference}}{\omega_{comparison}} \cdot VoP + VoP \tag{6.3}$$

6.1.2. Comparison of environmental friendly behavior

Financial interventions are not the only possible interventions in energy management policy. Another promising tool to encourage consumers to act more environmental friendly is the use of green nudges. Green nudging is the purposefully steering of people's behavior without using monetary incentives, but by changing their choice architecture (Thaler and Sunstein, 2009). For example, green nudges can be as simple as adding an eco-friendly label to a product, to attract consumers that want to sustain their 'green' self-image. Green nudges can also exploit the desire of people to behave according to social norm or stimulate social status competition through peer comparison (Schubert, 2017). An experiment of Opower found that energy consumption was reduced by two percent, if people were shown periodic home energy reports comparing them to their neighbours (Allcott and Rogers, 2014). Similar results were found by Schultz et al., who gave feedback to households about their energy usage and presented higher consumption rates as divergent and praised consumption rates below the norm (2015). Another positive effect of feedback reports is the increase of awareness of people's own energy consumption (Öhrlund et al., 2019).

Based on this literal foundation, an environmental score was added as a model intervention, which is presented in the form of periodic feedback by the energy producer to the households. As all agents have the same amount of demand, only divided differently over time, it is hard to compare CO_2 emissions. However, it can be stated that it is more environmentally friendly to use energy whenever there is a lot of renewable energy available compared to using energy in periods with a large share of fossil production or even energy shortage. Therefore, a positive or negative number is added every time step based on the supply, which results in a total environmental score each shifting period. If a consumers shifts demand from periods of shortage to times with high renewable production, his score will be higher than the score of someone who is not shifting demand. This intervention specifically encourages agents, who are not very susceptible to are financial steering, but do value the environment strongly and care about their green image.

The effect of the policy is shown in formula 6.4. The relative environment score, ES_{rel}, represents the difference between the environments score of a household and the mean environment score. If an agent has a higher score than the mean, ES_{rel} is 0, because the agent is already switching and showing environmental friendly behavior. If an agent is performing worse than the mean, his relative environment score is a weighted difference between his environmental score and the mean. This means that the effect of the policy gets stronger if an agent is performing much worse than the mean. The effect of the policy is also stronger, when a consumer's value of environment is higher.

$$VE = ES_{rel} \cdot VoE + VoE \tag{6.4}$$

6.1.3. Environmental awareness campaign

Just like the environmental score, an environmental awareness campaign can encourage consumers to behave more environmental friendly, especially if they value the social status of a green consumer. Like comparison, information to raise awareness can be a powerful tool to reduce energy usage. The results from a stated choice experiment showed that providing people with positive information about renewable generation increased the number of consumers choosing green over fossil energy (Cardella et al., 2020). A similar technique could be used by providing consumers with information about the positive effects of demand response. As long as consumers are not aware that their energy consumption is contributing to the societal problem of energy shortage and climate change, there is incentive to take action. Also, consumers are more likely to take pro-environmental actions if they believe that they can personally have an impact in decreasing the problem (Stern et al., 1999, Sütterlin et al., 2011). Although some research showed that information can reduce energy use, this also increases again slowly in longer studies. Therefore, repeated bursts of information can help to prevent this relapse (Delmas et al., 2013).

Based on these insights, the environmental awareness campaign in this thesis consists of two main messages. The campaign explains a consumer that their energy usage has a negative impact on the environment, but also emphasizes that they can have a significant positive impact by reducing their energy demand or shifting demand away from peak-periods. The agents that are affected by the campaign are randomly selected from the agents that have a non-shifting contract. Everyone has the same chance of being interested and informed, however the campaign has a bigger effect on consumers that have a higher value of environment. The number of people that is targeted each time period depends on the 'financial budget' that is spent on active marketing to persuade consumers to switch to a demand shifting contract.

The effect of informative campaigns is very difficult to review, because there are many different factors that could have played a role in observed behavioral changes. It is already quite difficult to measure the reach of an information campaign, let alone quantify the effect it has had. Besides, it is also difficult to know how long the effect lasts. Therefore different parameter values of these uncertainties will be simulated. This intervention interacts with VoE again, so if this intervention as well as an environmental score are implemented, VE is influenced positively by both. The effect of this policy on the entire agent population depends on the number of people that are informed, the strength of the effect of the campaign and the time period that the effect lasts. If an agent was informed by the awareness campaign and the effect has not yet faded, 6.5 applies to that agent.

$$VE = campaign_{effect} \cdot VoE \tag{6.5}$$

6.1.4. Smart meter information campaign

Whereas the environmental information campaign is more successful for green consumers, this smart meter information campaign is designed for consumers that are sceptical or indifferent about smart meters and demand response. Concerns about safety or loss of convenience are barriers for participation in demand response (Sütterlin et al., 2011) (Parrish et al., 2020). These barriers can be overcome by tempering these beliefs and adding features that provide consumers with a sense of control. For example, making it possible for consumers to specify time slots in an application when demand can be shifted, or sending notifications to consumers whenever demand is about to be shifted (Lopes et al., 2016) (Hall et al., 2016). Besides fear of control, fear of safety issues of the smart grid and smart meters can also be reduced by being transparent. It is important that a consumer understands that devices that are connected to the smart grid have to pass many tests and are submissive to strict regulations. Also, many rules apply to the gathering, using and storing of consumer data from smart meters (Parrish et al., 2020).

The smart meter information campaign informs consumers about two topics. First of all, the process and restrictions for demand shifting are explained, which show that the losses of convenience are not substantial, especially not when only heating and cooling demand is shifted. Furthermore, transparent information about the smart grid and regulations is provided to reduce the fears related to external control, privacy and cyber crime. Again, the agents that are affected by the campaign are randomly selected from the agents that have a non-shifting contract and the number of people that are targeted each time period depends on the 'financial budget' that is spent on active marketing to persuade consumers to switch to a demand shifting contract.

The effect of this information campaign is implemented in the model in a similar way as the environmental awareness campaign. Again, the effect of this policy on the entire agent population depends on the number of people that are informed, the strength of the effect of the campaign and the time period that the effect lasts. If an agent was informed by the awareness campaign and the effect has not yet faded, 6.6 and 6.7 apply to that agent. The effect is stronger if an agent has a high value of comfort (VoC) and a high value of safey (VoS).

$$VC = campaign_{effect} \cdot VoC \tag{6.6}$$

$$VS = campaign_{effect} \cdot VoS \tag{6.7}$$

6.1.5. Default shifting

This intervention is another kind of green nudge that deals with the fact that people are passive in making decisions (Schubert, 2017). Even if people would be interested in participating in demand response, they do not take action and switch contracts, because it is perceived as a hassle. By setting the shiftable contract as the default contract for a new consumer, a higher share of people could stick with the option after experiencing the financial benefits. This strategy is comparable with the passive-positive donor registration system that is currently applied in the Netherlands, where every citizen is an organ donor, unless you actively state otherwise (Minsterie van Volksgezondheid, Welzijn en Sport, 2020) (Chow and Lui, 2020). In Germany a local utility company implemented a similar strategy by setting the default of its consumers to using green energy (Pichert and Katsikopoulos, 2008). The upside of this policy is that it can be achieved at very low costs. However, it can be questioned that such a policy is ethical, as it intervenes with people's personal life and pushes a choice upon them. On the other hand one could argue that an intervention like this should be allowed, because it increases the societal well-being significantly. Regardless of the ethical discussion, this intervention is tested in the model, to see if such a default contract option could lead to a decrease in energy shortage that is worth the ethical discussion.

The implementation of this intervention in the model is rather simple. Instead of setting the initial shifting contracts based on personal values, all agents have the shiftable or semi- and shiftable energy contract. The only change is that consumers who would have had the no shifting contract as their initial option, now have the shiftable contract.

6.2. Uncertainties

The future electrical grid is a very uncertain environment. Yet, the effect of the selected interventions relies on this environment and can only be assessed properly if future conditions are known. However, this is not the case, because this thesis describes a general model of the future energy system and important input variables are uncertain. The two main uncertainties that affect the potential improvements of these interventions on the participation in demand response programs are energy supply and the consumer population. These uncertainties will be varied to compose many potential future scenarios. These scenarios could provide general insights about the conditions in which interventions are successful or not. Then, if the supply and population would be known in a case study, a more tailored advise could be given about the effect of interventions on the expected user participation based on this model.

Other uncertainties were not included in the deep uncertainty analysis, because the number of experiments that needs to be run would have increased to an amount that was not computationally workable considering each run has 35010 time steps. Furthermore, the causes of the changes in the model outcomes would be more difficult to interpret if a large number of uncertainties was included. However, the other uncertainties will not be neglected. A sensitivity analysis will be performed to discover the effect of changes in the demand shiftability, social interaction effect, number of switching thresholds and the number of switch periods on the model outcomes. Besides, the uncertainties in the parameters of the interventions, such as the effect of the information campaigns will be included in the deep uncertainty analysis as different variations of the policy levers.

6.2.1. Supply

As introduced before, the supply in the model consists of a fossil base load and a fluctuating renewable load. The amount of supply has been calculated based on the standard annual demand. This approach resulted in multiple periods of energy shortage during the year, especially during the evening demand peaks. This aligns with the expectations about the future, but it is uncertain how big the shortages will be. Therefore the amount of supply will be varied. In the model, the fossil supply is considered to be stable, but the renewable part of supply can be bigger or smaller. In each scenario, the renewable supply will be multiplied by the supply factor, that differs between 0.8 and 1.4.

6.2.2. Consumer population

Another important uncertainty is the consumer population. The consumer population refers to the division of the consumer types in the population. It is very useful to know the consumers in your population, because interventions can have a bigger impact on consumers with certain values. For example, if many consumers in the population have a high value of price, a financial intervention can be more successful than in a population of green consumers.

In the model, the population input parameter provides a division of consumer types, but the same division of types could result in a different division of shifting contracts. This is due to the fact that there is some randomness in the personal values of consumers, which means that a cost-conscious consumer could initially have a non-shifting contract, but also a shiftable contract. In the uncertainty analysis, the possible input values are all of the permutations of the population distribution. This means that for a consumer population of 20 households, 1771 different distributions over the consumer types are possible. However, the most interesting scenarios to compare are the ones with initially no shifters, few shifters and many shifters, which is why these options will be included in the uncertainty analysis for certain.

6.3. Key performance Indicators

The key performance indicators are the performance metrics of the model and are used to evaluate the model outcomes for the different scenarios. They can be used to asses the short and long-term effects of the interventions, but also to find out which scenarios lead to the most and least desirable model outcomes. The KPI's are listed below:

- **Energy shortage**: The energy shortage is the shortage that remains after demand has been shifted. It can be helpful to compare the total annual energy shortage between the different scenarios, but also to look at the cumulative energy shortage over time. Looking at that, can give more insights in problematic time periods that determine the energy shortage strongly.
- **Required storage**: Whenever there is an energy shortage, energy from battery storage can be used. It is important to determine the maximum amount storage that is needed to ensure that

there is no energy balance issue anymore. It is also interesting to see which period of energy shortage determines the maximum required storage.

– **Total costs**: The total energy costs depend on the electricity pricing mechanism and the times when energy is used. Total costs are the costs of all households combined, but can also be seen as the income of the energy producer.

– **Distribution of shifting contracts over time**: This performance metric consists of the shares of the three contract types over time. More specifically the change in these shares and how they are influenced by the interventions and the uncertain model inputs.

6.4. Visualization of the XLRM Framework

In the previous sections the interventions (L), uncertainties (X) and the model outcomes of interest (M) have been introduced. The framework has therefore been completed and figure 6.2 shows the graphical representation. This will be the setup for the deep uncertainty analysis that explores the effects of the interventions on the model outcomes in many different scenarios.

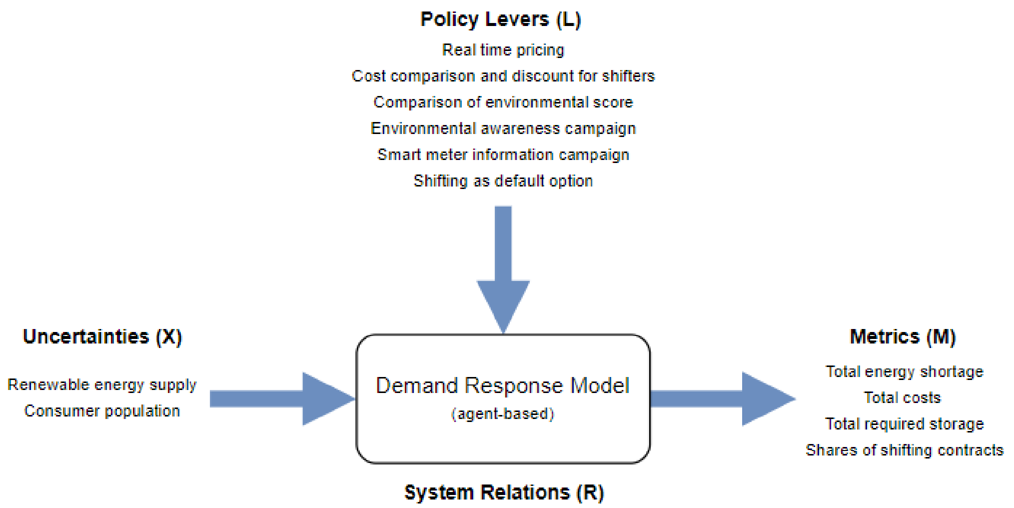


Figure 6.2: Setup for scenario analysis in conformity with the XLRM framework

6.5. Conclusion

In this chapter, the policy levers cost comparison with a discount for shifters, environmental friendliness comparison, environmental awareness campaign, smart meter information campaign and default shifting have been introduced. Subsequently, their interaction with the personal values of the consumers has been explained and formalized. Supply and the composition of the consumer population were introduced as the most important uncertainties. In the last section the XLRM framework was completed. This framework was used to create a set-up for the deep uncertainty analysis in which policy levers and uncertainties will be varied to compare the effects on the KPIs.

7

Model Implementation

In this chapter the implementation of the model is explained. The first section presents the model flow diagram and is followed by a description the modeling environment in terms of software. Afterwards the time sequence is explained. In the fourth section the parameter settings are presented. The final section explains how the model behavior was verified.

7.1. Model Flow Diagram

Figure 7.1 shows a flow diagram of the model that includes the most important decisions.

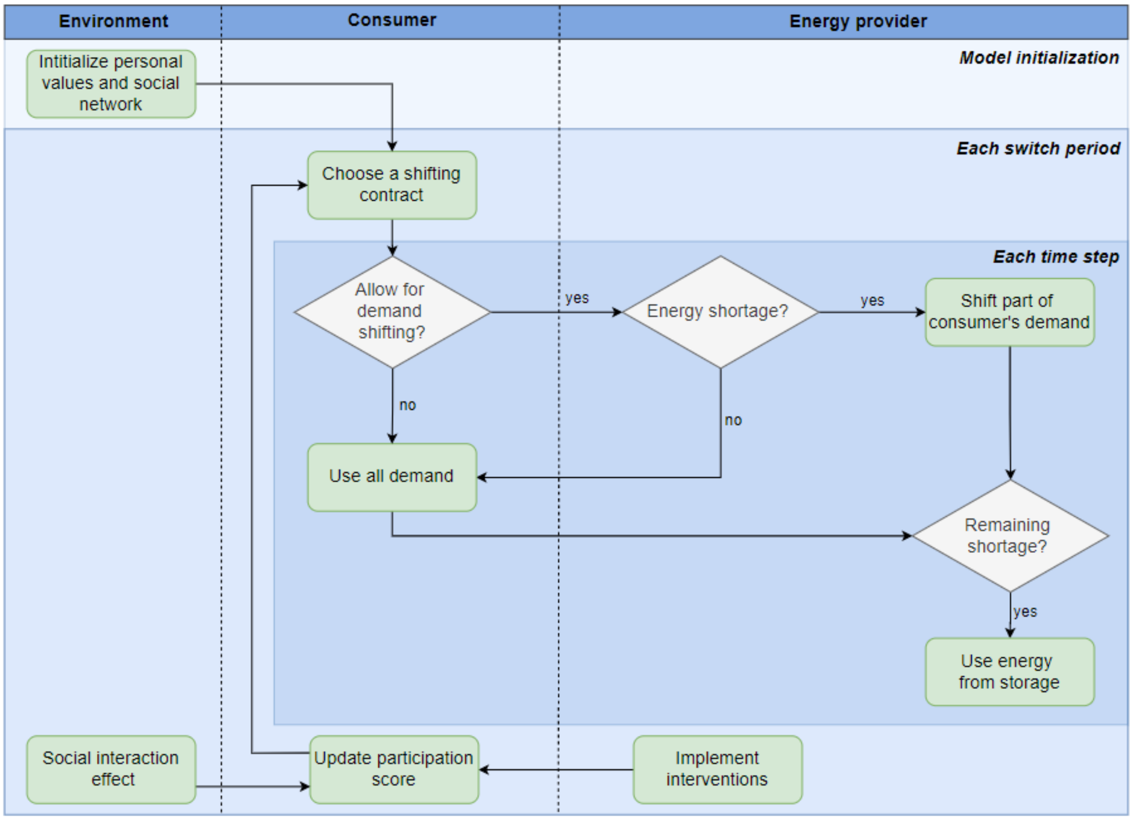


Figure 7.1: Flow diagram of the system architecture

Decisions can be made and actions can be performed by the model environment, the consumers or the energy provider, as indicated by the three lanes in the flow diagram. Additionally the actions can be performed at model initialization, at each switch period or at each time step. The flow diagram starts at the top left of the diagram with the initialization of the values and the social network. Afterwards, each consumer chooses a shifting contract. This action is repeated each switch period, based on the updated participation score. This score is influenced by the social interaction effect and the interventions that are implemented. At each time step, demand can be shifted based on the consumer's contracts and possible energy shortage. If shortage remains after the shifting of the demand, the required energy is taken from storage.

7.2. Modeling Environment

The modeling environment refers to the software infrastructure that was used to program the interaction between agents and the interaction between the agents and their environment. In this study, the agent-based model (ABM) was constructed using Mesa, which is an open-source ABM modeling framework in Python (Masad and Kazil, 2015). The mesa package uses object-oriented modeling and is easy to use, thanks to built-in core components such as a Agents class, Model class, a time scheduler and spatial grids. The tool is especially suitable if you are experienced with Python and object-oriented programming.

For this research, Mesa has been chosen over other established ABM tools as NetLogo, MASON and Repast, because it is embedded in Python. The advantage of this is that many experiments can be performed relatively fast. Besides, it is very convenient to analyze the results using existing visualization and data analysis tools in Python. Also, the model can be connected to the ema_workbench easily to conduct the deep uncertainty analysis. A disadvantage of using mesa is the fact that there are not many users yet, which means these is not a lot of documentation on energy-related projects. Moreover, mesa does not have a built-in user-interface that visualizes agent dynamics and model outcomes like NetLogo does.

7.3. Time Sequence

The model runs in discrete time steps, where each time step represents a period of 15 minutes, because this was the granularity of the supply and demand data. For a future case study, the time steps could be even smaller than 15 minutes, if data is available at that amplitude. This would be a model improvement, because a real-time pricing scheme can be implemented even more realistically. In total a period of a year is simulated, resulting in a total of 35010 time steps. This long time period was chosen for a simulation run, to make sure that not only daily variation, but also seasonal differences are incorporated. Besides, a year is also a realistic time period for a contract with an energy producer and allows for multiple contract switching moments during the year at which consumers can switch to a different shifting option. In order to be able to understand the behavior of the model over time better, time frames of weeks in different seasons are inspected.

The simulation flow of a model run is visualized in figure 7.2. After model initialization, the model loops over the time steps and over the model agents within each time step. This means that the next model step will begin after all agents have performed their actions. Due to the discrete nature of the model, the agents execute their actions sequentially. However, in reality, agents would not act sequentially, but simultaneously. Therefore, the order in which agents act, is an important aspect to consider. For example if agents would always act in the same order, this could influence the social interaction, because the participation score and contract type of agent A would always be updated before the attributes of agent B. To prevent this from happening, the order in which agents perform their actions is randomly activated at each time step (Van Dam et al., 2013).

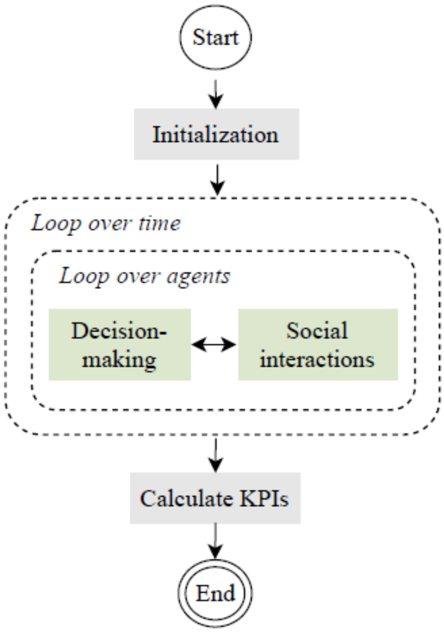


Figure 7.2: Simulation flow of the ABM (Werntges, 2020)

Not all model and agent functions are carried out at each step, but can depend on a certain time step or agent state. On a model level, only at the end of a switching period, the information campaigns select agents that receive the status of informed. Likewise, the agents only update their participation score at the end of a switching period and potentially switch contracts. The function that determines if demand should be shifted based on energy shortage predictions and the function that actually shifts the demand is carried out each time step for each agent.

7.4. Parametrisation

Parametrisation refers to the process of choosing suitable values for the model parameters. This is an important process, because the model outcomes can be sensitive to initial values (Van Dam et al., 2013). The parameter values can be selected in multiple ways. The values can be found from data, interviews with experts, from literature or could be based on an assumption.

The parametrisation in this study was particularly difficult for the variables that are a quantification of human values, social interaction or effects of non-monetary policies. These variables are very uncertain and research from behavioral science also rarely attached a numeric value to such factors. Therefore, many parameter values are based on assumptions and true values are still uncertain. To asses the impact of these parameter uncertainties on the model results, a sensitivity analysis was done. Furthermore, experiments were done with different settings of the policy effects. The results from the sensitivity analysis and the experiments are presented in chapter 8. The parametrisation of the personal values has been explained in chapter 4, but an overview of the complete parametrisation can be found in appendix D.

7.5. Model Verification

Model verification is an important step in simulation modeling and is used to confirm that the model is implemented in compliance with the model conceptualisation. This involves checking if the model components have been implemented correctly and verifying that the model behaves as expected (Sargent, 2010). The verification of the model is necessary to make sure that the model conclusions can be used to advice policy-makers.

There are multiple possible ways to verify a model, but the verification in this study was inspired by van Dam et al. and consisted of three verification methods (2013). The first method is the tracking of agent behavior and has been performed during the iterative construction of the model and the experimentation phase. The model was also verified by testing the model with a minimal number of agents and running the model under extreme conditions. The implementation of these model verification strategies and their results can be found in appendix E and show that the model implementation was consistent with the model conceptualisation.

7.6. Conclusion

This chapter has described that the model implementation was done using the Mesa library in Python as the modeling environment. One model simulation run represents a year of time and is divided into 35010 discrete time steps in which the model and agents functions are performed. Furthermore, the parametrisation section explained the difficulties of the parametrisation of model variables that represent behavioral aspects and explained the need for assumptions. The chapter ended with a successful model verification that covered multiple verification techniques.

8

Model Results

This chapter starts by explaining the design of the various experiments that have been run and will then present the most remarkable results. First, the model outcomes of base case A without any shifting, and base case B, with real-time pricing and shifting contracts are discussed. Afterwards, the model behavior under different policies and policy combinations is examined under deep uncertainty. This is done by considering it from the energy producer's perspective as well as a consumer's point of view. Finally, the sensitivity of several input parameters is tested in a sensitivity analysis.

The sub-questions that are answered in this chapter are:

- *Sub-question 4: What is the effect of an increase in the share of renewable supply on energy balance in the electricity grid, given current infrastructure and demand?*
- *Sub-question 5: Which policy strategy ensures the strongest demand response under many different scenarios?*
- *Sub-question 6: How do different characteristics of the consumer population influence the effectiveness of policy intervention to enhance demand response?*

8.1. Design of Experiments

The model is used for experimentation to gain insight in the model behavior. The experiments consist of different variations of the input parameters and implemented policies. Additionally the model behavior is analyzed under a large amount of scenarios. Latin hypercube sampling (LHS) was used to sample over the uncertainty space. The EMA workbench package in Python was used to run the experiments with the model (Kwakkel and Pruyt, 2013). The EMA workbench offers different tools for experimenting. First of all, open exploration was used to map the uncertainty, decision and outcome space by sampling over the uncertainties and decision levers. All experiments represent a scenario based on the uncertainties supply and consumers population. However, some experiments vary in scenario and policy, where a policy is a point in the decision lever space. Besides open exploration, more advanced analyses have been applied too, namely scenario discovery and feature scoring. Scenario discovery has been used to find out which value ranges of the input parameter are responsible for relatively low total energy shortages by studying specific cases of interest. Feature scoring is a tool from machine learning that was used to identify the features that influence each of the model outcomes most heavily (Kwakkel, n.d.).

Multiple sets of experiments have been run. First, experiments have been carried out to inspect the model behavior for multiple variations of the interventions cost comparison and reduction, environmental awareness campaign and smart meter information campaign. In these experiments, 500 experiments sampled over the uncertainty and the lever space. The second set of experiments sampled only over the uncertainty space for all the separate policies as well as policy combinations. These two experiment sets analyzed the difference in the high-level model outcomes energy shortage, required storage, consumers costs and contract shares. Additionally, experiments were run with the same input values, while focusing on the behavior of individual consumers in the model.

The parameter settings differed for the particular experiment sets. Table 8.1 and table 8.2 give an overview of the parameter settings for each of these experiment sets. Table 8.2 only shows which parameters are different from the standard experimentation settings, which can be found in appendix D.

8.1.1. Base model

The ultimate base model in this study, base case A, represents the situation with flat pricing and without the possibility to shift demand. This base case represents the future scenarios and problems that would occur if the electricity pricing would remain as it is. In base case B, there is a real-time pricing scheme in place and consumers choose a shifting contract that suits their personal values best. In this case real-time pricing is the only policy in place and agents do not have the ability to switch between shifting contracts. These settings make it possible to see how much demand is shifted in case of different consumer populations and supply. For both cases 200 scenarios were run, to understand the model behavior of many different combinations of supply and consumer population. The model outcomes of the experiments including implementation of one or multiple policy interventions are compared to the outcomes of these base cases, to analyze the changes that can be made by these interventions.

8.1.2. Interventions

The experimentation with the policy interventions has been conducted in two phases. In the first phase, different setups haven been tried out for the cost comparison and reduction intervention and the two information campaigns. For these interventions, samples were done over the uncertainty as well as the lever space, resulting in 500 experiments where 50 scenarios and 10 policy levers were combined. The design of the experiments can be seen in table 8.1. For the cost comparison policy, the height of the reduction and the effect of comparing costs were varied and for both of the information campaigns, the number of consumers that was reached, the effect on their behavior and the time period that the effect lasted were varied. This was done, because these parameters are uncertain in reality, so it is important to find out if a difference in these values leads to big differences in the model outcomes. For example, it is uncertain how long the effect of a campaign lasts. Therefore, the effect duration was varied between 3 months, half a year, 9 months and a full year. An effect of 1.05 in the environmental campaigns is comparable to an effect of 0.975 in the smart meter campaign, because the latter influences two values, whereas the first one only influences the value of environment. While testing for the different policy setups, the randomness of the personal values and the social interaction effect were removed, in order to be able to capture the pure effect of the different policies. The objective of these experiments was to to find one or multiple promising configurations of the policy to use in the further experimentation.

Table 8.1: Design of experiments for policy selection

Intervention	**Parameter**	**Value range**	**Scenarios / policies**
Cost comparison and reduction	cost_comparison_effect reduction	[90 - 110] [1 - 80]	50 / 10
Environmental awareness campaign	n_informed effect on value effect duration	[1 - 4] [1.05 - 20] [8751 - 35010]	50 / 10
Smart meter information campaign	n_informed effect on value effect duration	[1 - 4] [0.90 - 0.975] [8751 - 35010]	50 / 10

After the policy selection process, the second phase followed, in which each of the five interventions that can accompany real-time pricing have been tested in 200 scenarios of different supply and population conditions. Additionally, for some selected scenarios, the results have been analyzed on an individual consumer level, to increase understanding of how a policy interacts with the personal trade-offs that influence the decision for a certain energy shifting contract.

Table 8.2 gives an overview of the policies that were implemented in the model and which interventions they include. The cost comparison and reduction intervention (P2a-c) has been included with a reduction of 10,30 and 50 euro per switch period. As there are 4 switch periods, this results in an additional discount of 40, 120 and 200 euro on a yearly basis if a consumer had a shifting contract the entire year. The information campaign has been included in five different setups (P4a-e) where all campaigns reach 3 agents with a non-shifting contract at three moments in the year and the effect of the campaign on a consumer's participation score lasts for half a year. The model behavior is analyzed for both campaigns separately with the standard effect of 1.1 for the environmental awareness campaign and 0.95 for the smart meter information campaign. Additionally, the model outcomes are investigated for the case where both campaigns are implemented at the same time with the standard effect (1.1, 0.95), a weaker effect (1.05, 0.975) and a stronger effect (1.2, 0.9). The last several experiments include combinations of the interventions (P6-P13).

Table 8.2: Design of experiments

Experiment	**Parameter**	**Value / range**	**Scenarios / policies**
Base case A (P0)	price policy shifting switching	flat price off off	200 / 0
Base case B (P1)	switching	off	200 / 0
Cost comparison and reduction (P2a-c)	comparison effect reduction	100 [10, 30, 50]	200 / 0
Environmental comparison (P3)	env_score	on	200 / 0
Information campaigns (P4a-e)	environmental awareness smart meter information effect environmental effect smart meter	[off, on] [off, on] [0.90 - 0.75] [1.05 - 1.20]	200 / 0
Default shifting (P5)	initial contract	default_shift	200 / 0

Compare costs and environmental score (P6)	comparison effect reduction env_score	100 30 on	200 / 0
Full information (P7)	environmental awareness smart meter information	on on	200 / 0
Reduction and smart meter info (P8)	comparison effect reduction environmental awareness	100 30 on	200 / 0
Reduction and environmental awareness (P9)	comparison effect reduction smart meter information	100 30 on	200 / 0
Environmental comparison and awareness (P10)	env_score environmental awareness	on on	200 / 0
Flat price and high reduction (P11)	comparison effect reduction price policy	100 30 flat price	200 / 0
All policies without default shifting (P12)	comparison effect reduction env_score environmental awareness smart meter information	100 30 on on on	200 / 0
All policies (P13)	comparison effect reduction env_score environmental awareness smart meter information initial contract	100 30 on on on default_shift	200 / 0

8.2. Base Model Behavior

In this section, 200 scenarios have been run for the base case A, where no demand shifting and no contract switching is happening and base case B, where no switching occurs. For both cases 200 scenarios are analyzed to learn what the ranges of the model outcomes are in case of no policy or solely implementation of real-time pricing without additional interventions. The outcomes of the 200 scenarios will be plotted in one figure instead of the mean curve, to illustrate the diversity and distribution of the outcome possibilities.

8.2.1. Base case A

Base case A is a future representation of the current situation in which flat pricing is applied and consumers do not have the possibility to allow for demand shifting with a contract. As demand is not shifted, this base case illustrates the future energy balance issues if no policy would be implemented. Figure 8.1 displays the cumulative energy shortage of 200 scenarios for base case A. It can be noticed that the outcomes are spread rather evenly.

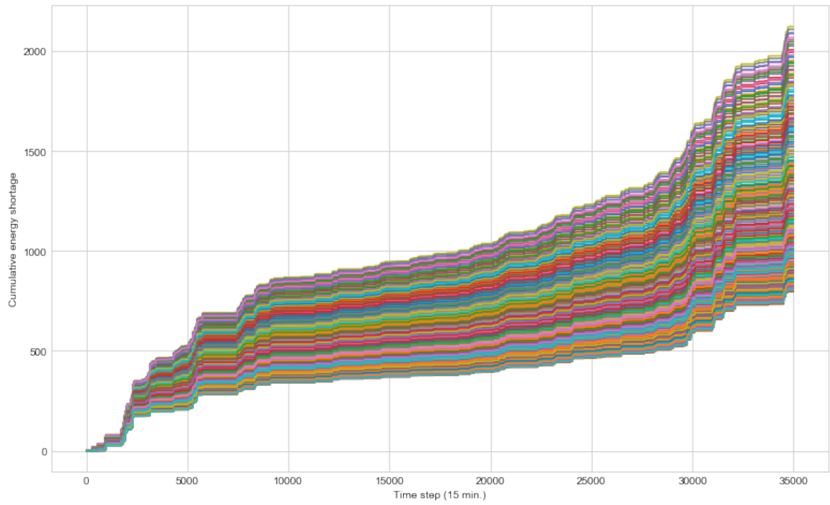


Figure 8.1: Cumulative energy shortage for base case A in 200 scenarios

The scenarios vary the consumer population composition and supply, but in this case the population composition does not influence the outcomes, only supply. The model outcome total energy shortage varies between 796.52 kWh and 2123.39 kWh and the total costs are always € 15099,53. The amount of supply was the only variable that influenced the required storage, which varied between 55.04 kWh and 98.97 kWh in the scenarios.

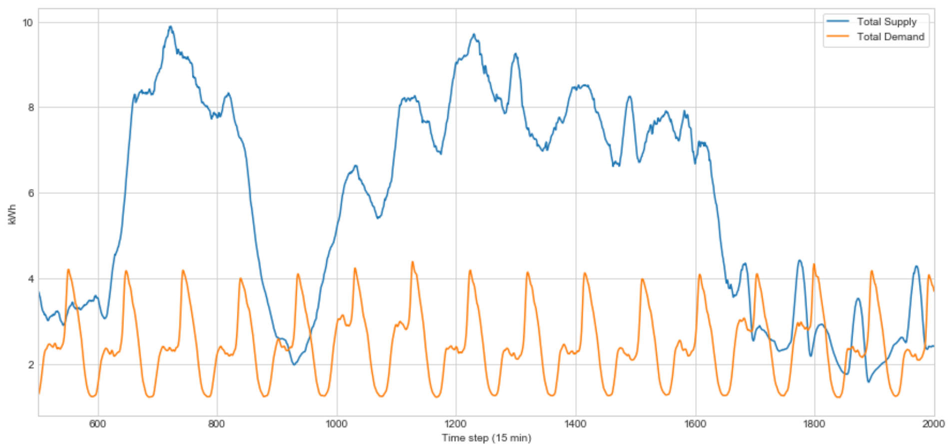


Figure 8.2: Supply and demand in two winter weeks for base case A

If we zoom in on two winter weeks where the supply factor is set to the standard value of 1, it becomes clear that energy shortage issues occur often during the evening peaks of demand. Whenever supply is considerably low, energy shortages also occur during other times of the day, which can be seen in the last 300 time steps in figure 8.2. The model outcomes for the scenarios where the supply factor is 1 are 1486.21 kWh shortage and € 15099,53 total costs for consumers. These can be seen as the base values that will be the point of comparison for the other experiments.

8.2.2. Base case B

In base case B, a real-time pricing policy and the shifting contracts are added to base case A. However it is not possible for consumers to switch between contracts yet. This model setup is used to compare the model outcomes for many scenarios that vary in supply as well as consumer types. A consumer type does not always have the same initial shifting contract, because the personal values have a little random noise. For example, a cost-conscious consumer could initially have a no shifting contract, but also a shifting contract. Therefore, the results of the base case B experiments will be analyzed by looking at the initial shares of the contracts instead of the consumer types. Figure 8.3 displays the cumulative energy shortage of 200 scenarios for base case B.

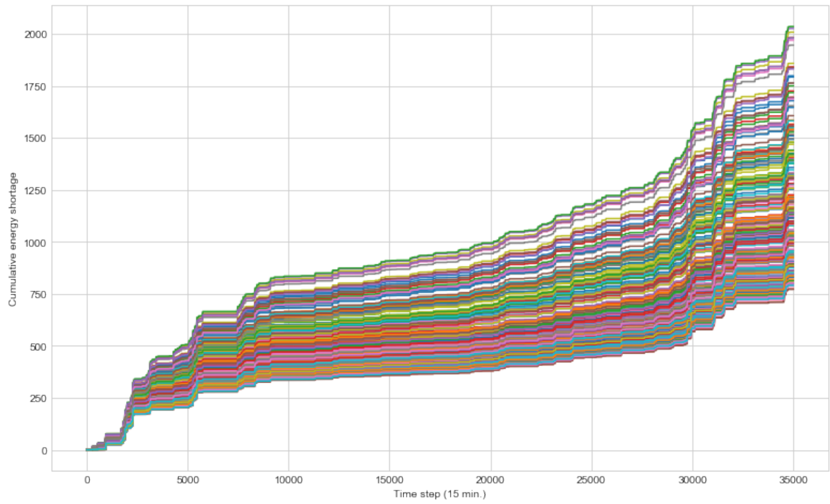


Figure 8.3: Cumulative energy shortage for base case B in 200 scenarios

If we compare this figure with the energy shortage scenarios in base case A, it can be noted that there are fewer scenarios that lead to very high energy shortages. The energy shortage in base case B varied between and 771.73 kWh and 2035.13 kWh with a mean of 1221.30 kWh. The range of energy shortage values is similar, but for base case A the mean shortage was 1324.21 kWh, which is significantly higher. The costs for base case B varied between € 13745,11 and € 14611,31. These costs are slightly lower than the costs in base case A, because the real-time pricing program entails that people with a shifting contract use a part of their energy demand in less expensive time periods. The conclusion that can be drawn from the comparison of base case A and base case B is that the addition of shifting contracts and demand response to the system reduces the total energy shortage and hence confirms hypothesis 1.

✓ Hypothesis 1: The addition of a real-time pricing component and demand shifting can reduce the energy shortage.

Figures 8.4 and 8.5 show the shifting of demand for different distributions of the shifting contracts for a few days in the winter and in the summer with the standard supply setting. First of all the difference in the supply curves for the different seasons is noticeable. In summer a daily pattern caused by solar generation can be observed, whereas the supply in winter is more random, because of the large dependence on wind energy. For the third mismatch period of the summer week, which is also the smallest shortage issue, the problem can be solved already if 25 percent of the consumers would allow for demand shifting. The second mismatch period can almost fully be shifted, if half of the population allows for demand shifting. Nevertheless it is not possible to completely solve the energy balance issues in the first mismatch period of summer and the mismatch period in the winter. By looking closely at the first energy shortage period in the summer, it becomes clear that the larger the amount of consumers that shift is, the smaller the shortage becomes in the first few time steps of the shortage period. However, in all cases, the demand curve roughly follows the original demand curve after 6 time steps. This is the consequence of the assumption that demand can only be shifted for 1,5 hours, before it needs to be used to prevent major inconveniences.

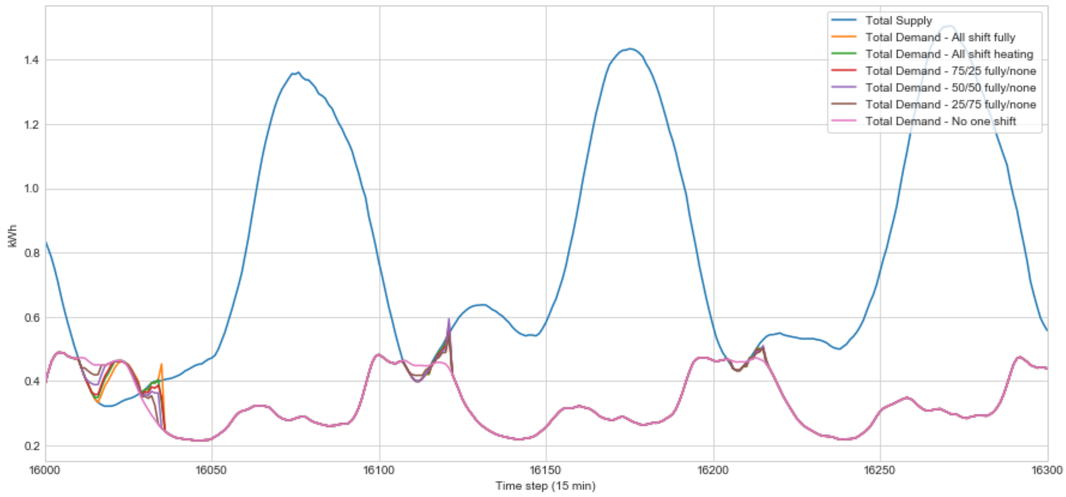


Figure 8.4: Demand and supply curve after shifting for different consumer populations for three days in summer

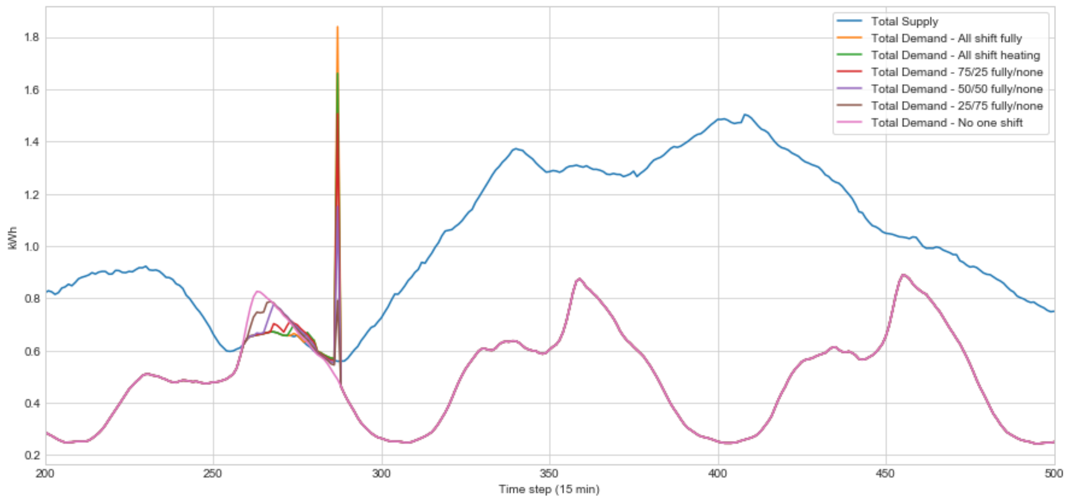


Figure 8.5: Demand and supply curve after shifting for different consumer populations for three days in winter

It is also this assumption that leads to the peaks that can be seen 6 steps after the last time step that had an energy shortage based on the supply and original demand before shifting. At this time step the residual shifted demand needs to be used. If this is not possible with the current supply, the peak arises, meaning that the residual demand amount is taken from storage. In reality, demand would be taken from storage at each time step, whenever the demand after shifting would still be larger than the supply, but due to my model formalization, this is done 6 time steps after the last shortage moment. It might seem that the area under the peak is bigger than the original shortage, but this is not the case. The surface is always smaller or the same. This was confirmed in the model verification that can be found in appendix E.

The required storage varied between 53.91 kWh and 97.63 kWh in the 200 scenarios and depended solely on the amount of supply. The share of shifting contracts, did not influence the storage for a simulation period of a year, because the required storage was caused by a winter week in which there was energy shortage for such a long time period, that demand response could only slightly improve the situation. Figure 8.6 shows this bottleneck and 8.7 shows the accompanying effect on the battery state of charge.

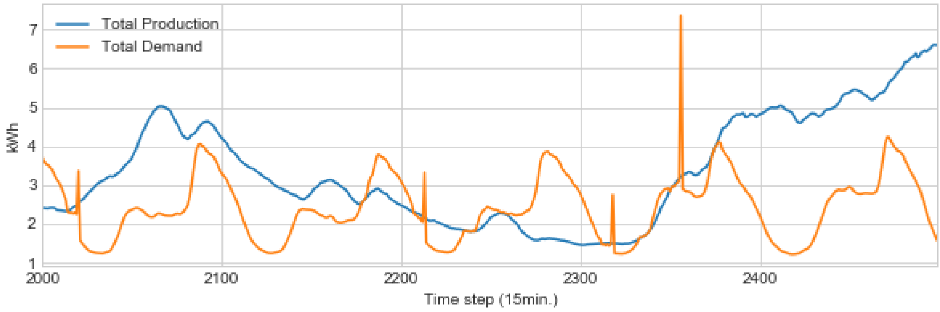


Figure 8.6: Supply and demand in the crucial winter week

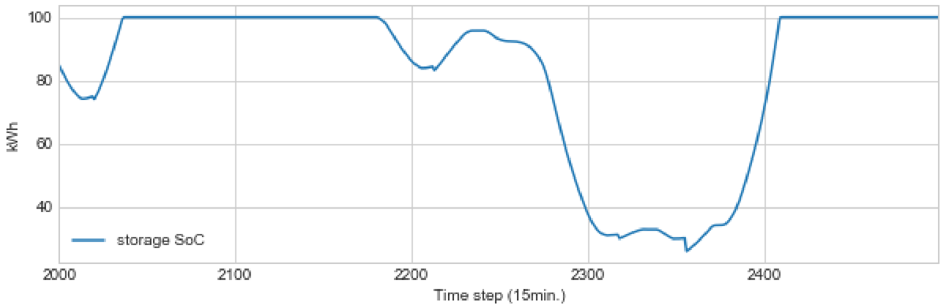


Figure 8.7: Available energy in the 100 kWh battery in the crucial winter week

The period of energy shortage in this winter week was too long to be solved by demand response and a higher share of demand shifters only resulted in a shift of the energy shortage over time instead of a reduction of the shortage. For shorter simulation times that do not include a crucial week like this, the trade-off between the amount of shifting consumers and the required storage would have become visible. For example, if only a period in summer with shortage periods that last shorter than 1.5 hours would have been studied, less storage would be needed when more consumers would allow for demand shifting. However, based on the results of the simulation of a year, the second hypothesis cannot be confirmed, because an increase in the share of consumers that engage in demand response does not always reduce the required amount of storage capacity, because this strongly depends on the available energy supply.

- ✗ Hypothesis 2: The required amount of storage capacity reduces whenever a larger share of the population allows for demand shifting

The conclusion of the analysis of the base cases is that periods of energy shortage can be solved if the shortage period is short enough and the mismatch between supply and demand is not too big. In that case, mismatches can be solved if enough consumers allow for demand shifting and the shiftable share of demand is sufficiently large. Base case B showed the potential effect of demand response with real-time pricing for different degrees of consumer participation. It also showed that a higher consumer participation can lead to less energy shortage. Therefore, the next sections will analyze if additional policies can contribute to less shortage by incentivizing consumers to switch to contracts that allow for demand shifting.

8.3. Results of Additional Interventions

This section discusses the model behavior when additional interventions are implemented besides real-time pricing. The policies that are analyzed are cost comparison with an additional reduction, comparison of environmental friendliness, an environmental awareness campaign, a smart meter information campaign and default shifting. These policies are analyzed one by one with different parameter settings and under 200 different scenarios in which supply and the composition of the consumer population are varied. The outcomes of these experiments are then compared to the results of both base cases. This section will not only look at the outcomes of interest for the energy producer, but also at the changes caused by polices on a consumer level. For each policy, it will be shown how they interact with consumers' personal values and which trade-off plays a role in the potential contract switch.

8.3.1. Cost comparison and discount for shifters

Different compositions of a cost comparison and discount intervention have been tested by varying the cost comparison weight and the reduction amount. The cost comparison weight determines how much a consumer's participation score is influenced by cost comparison. 500 Experiments were done with varying policies under different scenarios.

From the density plots that are shown in figure 8.8 it becomes clear that reductions below 30 euro do not lead to a change in the share of full shifting contracts. The figure also shows that reductions over 50 euros induce the most negative changes in the shift share of no shifting contracts, which means this share decreased strongly. Besides these takeaways it is rather hard to draw other conclusions, because the changes in the contract shares are not purely influenced by the financial intervention, but also by social interaction between the agents.

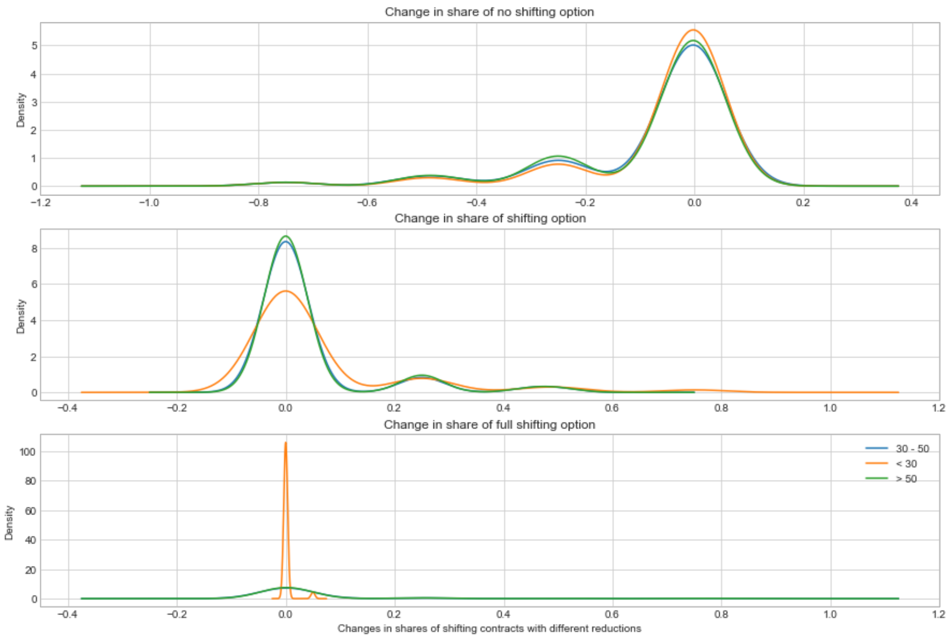
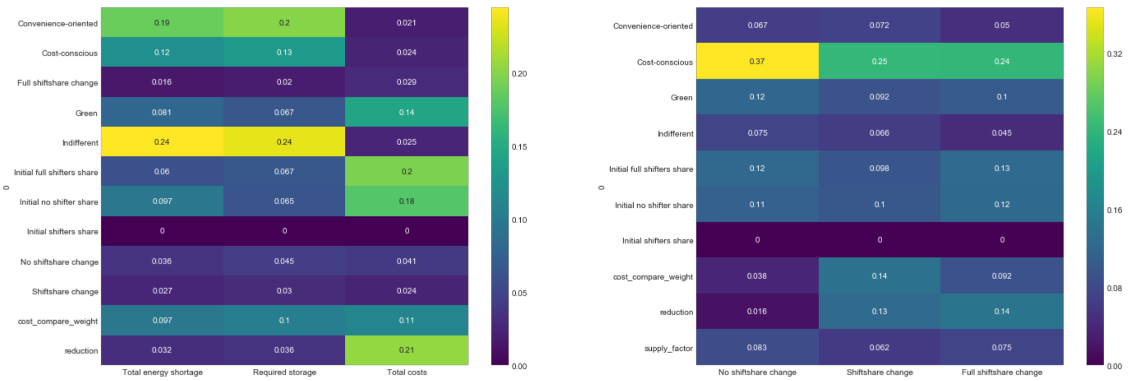


Figure 8.8: Change in shifting shares for different amounts of reduction

Feature scoring was applied to determine which variables influenced the outcomes of interest most. Figure 8.9a shows the feature scoring of the model outcomes, but all effects are not very strong. Nevertheless, the supply factor had a very strong influence. However, it was not taken account in this matrix, because it made all other factors seem unimportant. The main outcome here is that apart from supply, the amount of indifferents and convenience-orienteds in the population influence the energy shortage and required storage most. This can be explained by the fact that these consumer types always stick with the no shifting contract, regardless of the reduction or scenario. Logically, the total costs for the consumers are affected most by the reduction amount and the different contract shares, because these factors determines whether a consumer receives a reduction and how much exactly.

From figure 8.9b we learn that the amount of cost-conscious consumers in the population is most influential on the switching between contracts, with the influence of the reduction in second place.



(a) Feature scoring of model outcomes

(b) Feature scoring of changes in shares of contracts

Figure 8.9: Feature scoring for 500 experiments of cost comparison and reduction

This relation becomes clearer by zooming in on the amount of shifted demand per consumer type in figure 8.10. First of all, this plot shows that only the green and cost-conscious consumers have allowed for demand shifting and therefore reduced energy shortage. It is also striking to see that there are two tipping points for the cost-conscious consumers at which they switch to a different shifting contract. From a reduction of € 15 they switch to a shifting contract and stay committed. A reduction of 80 can even encourage them to go for the full shifting option. However a reduction of 80 euro per switch period results in a reduction of 320 euro per year, which is almost half of the total yearly costs of a consumer in this simulation. Considering the relatively small decrease in energy shortage this switch yields compared to the loss of profit for the energy producer, such a high reduction seems undesirable under the current pricing scheme. When looking at the green consumers, their amount of shifted demand slightly decreases, when the shifted demand of the cost-conscious increases. This shows the fact that a consumer needs to shift less demand individually, whenever more consumers carry the burden together. Once a certain amount of people has a shifting contract, increasing the reduction further, would therefore not improve the energy shortages significantly.

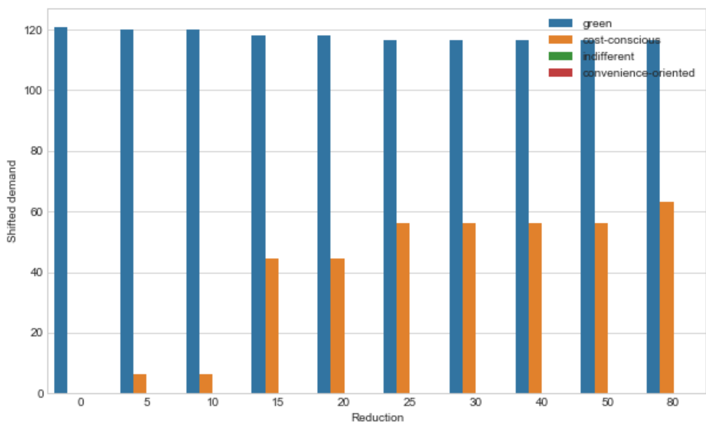
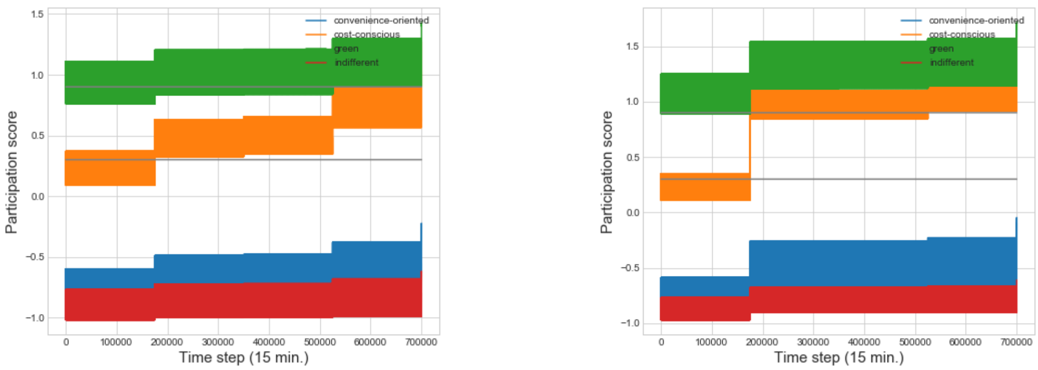


Figure 8.10: Reduction versus shifted demand

Figure 8.11 shows how the participation scores change in case of a reduction of 25 and 80 euros, where the height of the colored bars is caused by the intra-consumer type variation in the personal values. Notable is that all consumer types are affected, but the participation scores of the cost-conscious increases the most. This is caused by the fact that they have a high value of price, which makes their participation score respond more heavily to cost comparison and a reduction. The cost comparison and reduction intervention encourages cost-conscious consumers to choose for a shifting contract already with a relatively low reduction. High reductions could even make them switch to a full shifting contract. The green consumers are also influenced by higher reductions and switch to a full shifting contract as well, even though they do not value price very highly in general. The participation scores of the convenience-oriented and the indifferent consumers increase slightly as well when the reduction amount increases, but they do not reach the switching threshold, because their participation score starts at such a low point, because of their high values of comfort and safety.

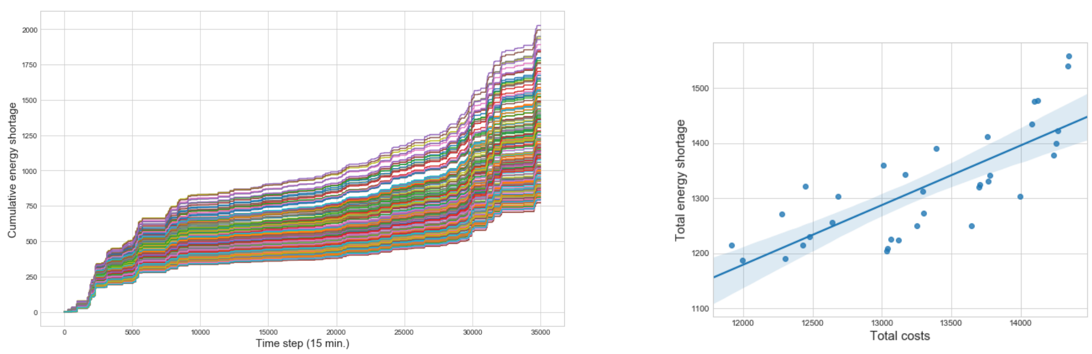


(a) Participation scores per consumer type over time with a reduction of 25 euro

(b) Participation scores per consumer type over time with a reduction of 80 euro

Figure 8.11: Participation scores for a reduction of 25 and 80 euros

Now that the effect of changes in the reduction amount has been analyzed, let's look at the specific case of a reduction of 30 euros per switch period. Figure 8.12a shows the cumulative energy shortage over time for 200 scenarios. The energy shortage varied between 771.73 and 2025.98 kWh, with a mean of 1207.99. These results are somewhat better than the results of base case B and much better than the results of base case A.



(a) Cumulative energy shortage for 200 scenarios for a reduction of 30

(b) Total costs versus total energy shortage

Figure 8.12: Outcomes of cost-comparison and a reduction of 30 euro

Figure 8.12b shows that there is trade-off for the energy producer. A desirable increase in costs for the consumers, so direct profits for the energy producer, also leads to an undesirable increase in the amount of energy shortage.

From this section it can be concluded that an intervention consisting of cost comparison with an additional discount for shifters achieves contract switches of cost-conscious consumers primarily and that an increase in the reduction amount, can convince more consumers to switch. On the other hand, convenience-oriented and indifferent consumers cannot be convinced to switch to a shifting contract by this intervention. In choosing a suitable reduction amount, the energy producer has to find the right balance between less energy shortage and less direct profits.

8.3.2. Comparison of environmentally friendly behavior

In the 200 different scenarios, this intervention did not lower the energy shortage substantially, because it did not encourage many consumers to switch to a shifting contract. As discussed in the previous section, the indifferent and convenience-oriented consumers need an unattainable lot of encouragement to switch to a shifting contract. Therefore the cost-conscious and green consumers are the ones that are persuadable to upgrade their contract. As the cost-conscious consumers generally do not have a high value of environment, they are not very sensitive to green nudges such as a comparison of environmentally friendly behavior. The green consumers already perform better than the average consumers most of the time, so they are also not really targeted by this policy.

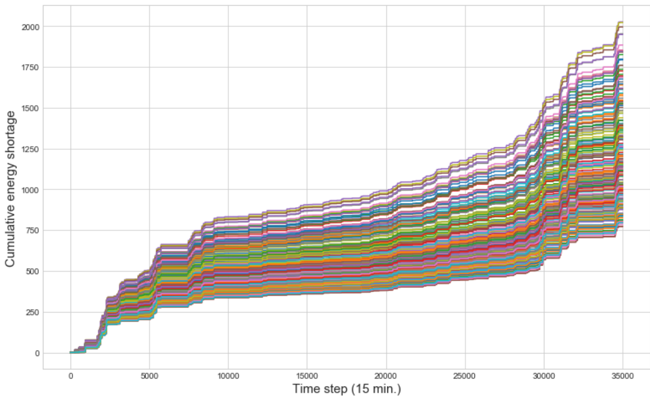


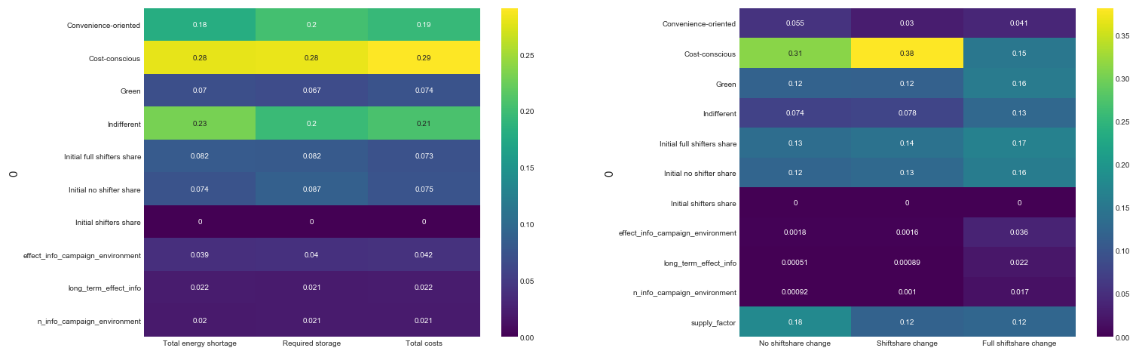
Figure 8.13: Cumulative energy shortage for comparison of environmental friendliness in 200 scenarios

Altogether this policy does not lead to a large decline of the total energy shortage. The median value of all scenarios that are shown in figure 8.13 is 1151.75 kWh, which is only slightly lower than the median of 1152.66 kWh in base case B. It can be concluded that this intervention is not very effective by itself under the current assumptions about the effect of such a social comparison.

8.3.3. Environmental awareness campaign

Different compositions of the environmental awareness campaign have been tested by varying the number of consumers that are reached by a campaign, the strength of the campaign effect and the duration of the effect. It is important to understand the effect of different values of these variables in order to know what future awareness campaigns should focus on. 500 Experiments were done with varying policies in different scenarios.

None of the 10 different setups of the awareness campaign was able to cause a significant reduction of the energy shortage and required storage. The results of the feature scoring of this intervention are presented in 8.14 and show that the model outcomes total energy shortage, required storage and costs were again dominantly determined by the supply factor. After excluding this factor from the analysis, the most important variables all represent the share of a consumer type in the population. Thus, the factors related to the awareness campaign; number of consumers that are reached by a campaign, the strength of the campaign effect and the duration of the effect, were all inferior. The feature scoring on the causes of the changes in the contract shares (fig. 8.14b) also shows that changes are not determined by the three campaign variables, but that the amount of cost-conscious consumers again has the highest influence. However, the contract changes of these consumers do not seem to be caused purely by this intervention and could also be the result of social interaction. Conclusively, higher or lower values of the intervention parameters are not reflected in the model outcomes.



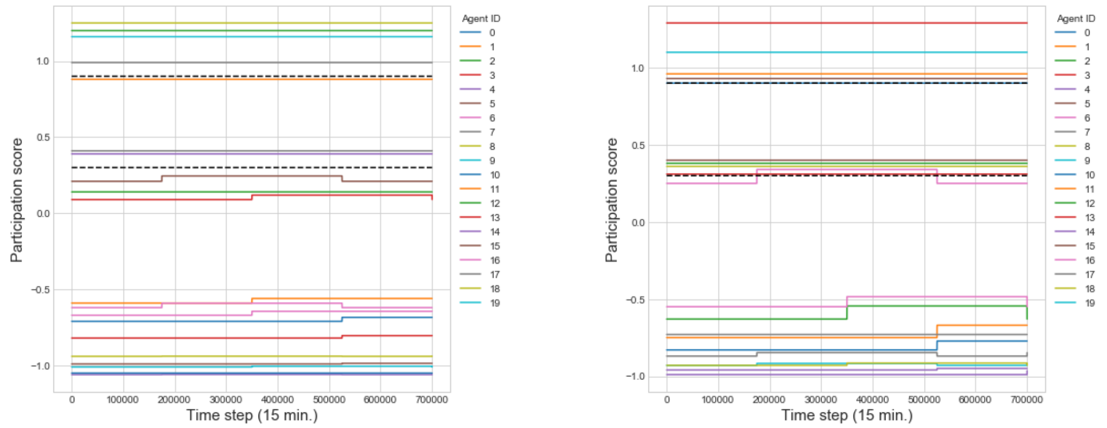
(a) Feature scoring of model outcomes (b) Feature scoring of changes in shares of contracts

Figure 8.14: Feature scoring for 500 experiments of an environmental awareness campaign

Explanations of the lack of effectiveness of this intervention can be found by reviewing the results on a consumer level. For each of the three intervention parameters, the value was increased incrementally to study the effects. An increase in the number of consumers that was affected by the campaign, resulted in more informed people and could reach all consumers with a no shifting contract within a year. However, if the effect of being informed is too small to trigger a large enough increase in the participation score to exceed a contract switching threshold, the number of informed consumers is irrelevant. The same applies to the duration of the effect once a consumer is informed. Without a significant effect, it is subordinate how long the effect lasts. However, an interaction was discovered between the number of informed people and the duration. If the number of informed consumers is high, but the duration of the effect is short, this can lead to the same outcomes as a scenario in which a low number of consumers is informed, but the effect lasts longer. Nevertheless, the strength of the effect of the information campaign can be seen as the most important condition for a successful environmental awareness campaign. Increasing this parameter led to the changes in the agents' participation scores that are shown in 8.15b.

Figure 8.15 does not only show that the increase in the participation score is rather small, but also that the participation score drops again after the duration length of the effect. In the experiments, the awareness campaign could only convince cost-conscious consumers occasionally, if they were already very close to the threshold value to switch to a shifting contract. In order to convince more cost-conscious consumers, the effect of the campaign needs to be bigger and campaigns should be repetitive as long as social norm does not lead to sufficient positive stimulation.

From the experimentation with this intervention it can be concluded that the available supply and population composition were the most influential parameters on the model outcomes. However, the environmental awareness campaign could not decrease the energy shortage significantly. In order to be able to achieve a significant change, it is important to make sure that the effect of the campaign on a consumer's personal values is sufficiently high. Informing more people does not improve the situation, as long as the effect of the campaign is not strong enough.



(a) Environmental awareness campaign with 4 informed consumers, 10% value increase for half a year

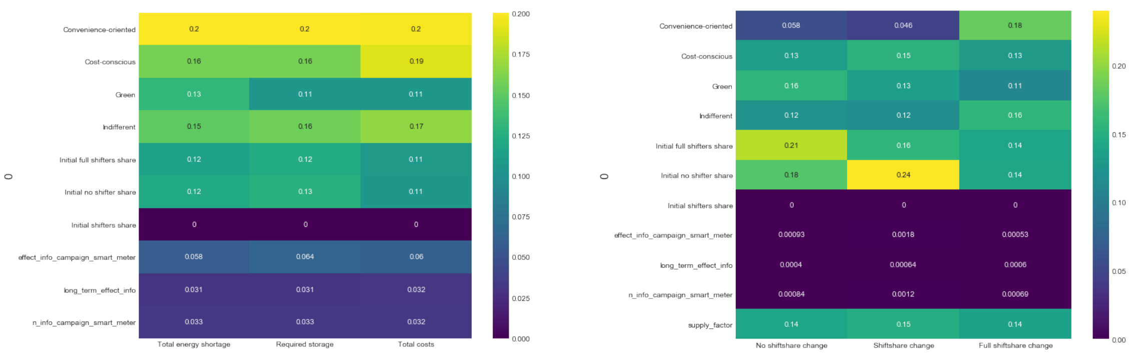
(b) Environmental awareness campaign with 3 informed consumers, 25% value increase for half a year

Figure 8.15: Participation score over time for each consumer in case of an environmental awareness campaign

8.3.4. Smart meter information campaign

Just like the environmental awareness campaign, the smart meter information campaign has been analyzed with different parameter settings. Again, 500 experiments were done with varying policies in different scenarios.

Just as the environmental awareness campaign, different setups of the smart meter information campaign barely impacted the model outcomes, which were predominantly determined by the amount of supply and the composition of the consumer population. The results of the feature scoring of this intervention are presented in 8.16. Again, the number of consumers that are reached by a campaign, the strength of the campaign effect and the duration of the effect did not have a strong influence on the model outcomes or the changes in the contract shares.



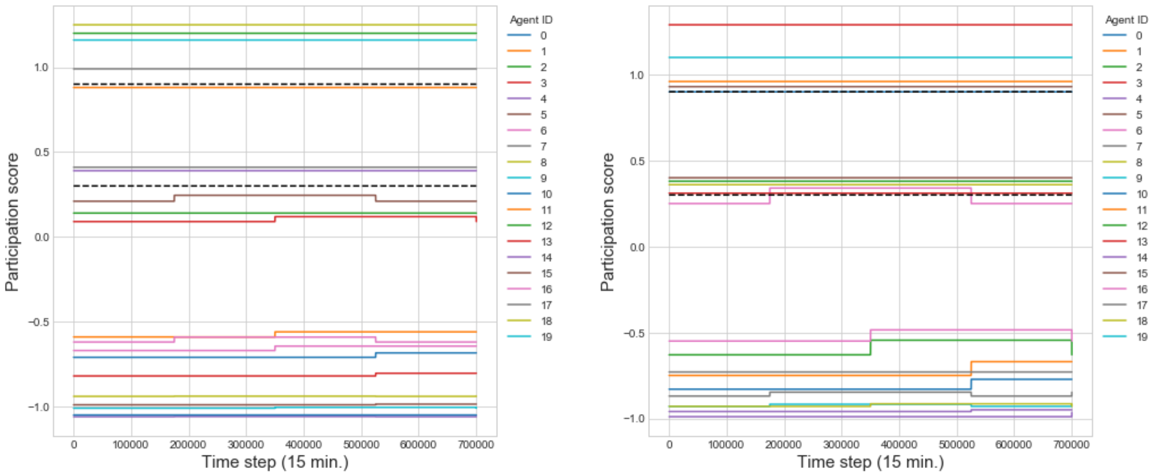
(a) Feature scoring of model outcomes

(b) Feature scoring of changes in shares of contracts

Figure 8.16: Feature scoring for 500 experiments of a smart meter information campaign

The information campaign targets consumers that did not have a shifting contract. If a consumer is impacted, the campaign interacts with two values, namely the value of comfort and value of safety. These values are relatively high for indifferent and convenience-oriented consumers, who are targeted often by this campaign. Figure 8.17 shows that the increases in the participation score are slightly smaller for cost-conscious consumers than for convenience-orienteds and indifferents, because cost-conscious consumers generally have a lower value of comfort and safety. Because this campaign aims at the values of comfort and safety, it has a larger impact on the participation score for these consumer types than the environmental campaign could have by interacting with the value of environment. However, the effect of this campaign was still not strong enough to persuade convenience-oriented and indifferent consumers to switch to a shifting contract.

In the analysis of the intervention parameters, number of informed consumers, campaign effect and duration of the effect the same conclusions were found as for the environmental awareness campaign. An increase in the number of informed consumers and a longer duration of the campaign effect could lead to more consumers to switch to a shifting contract, if the effect of the campaign is high enough. The strength of the effect of the campaign is the most influential parameter on the success of an information campaign, because it determines the increase in the participation score. However, if a contract switch is made also depends a lot on a consumer's initial participation score and how far below the thresholds it is. In order to convince more consumers to switch, the effect of the campaign needs to be bigger and the campaigns should be repetitive as the effect fades away over time.



(a) Smart meter information campaign with 4 informed consumers, 10% value decrease for half a year

(b) Smart meter information campaign with 3 informed consumers, 25% value decrease for half a year

Figure 8.17: Participation score over time for each consumer in case of a smart meter information campaign

From the experimentation with this intervention it can again be concluded that the available supply and population composition were the most influential parameters on the model outcomes and the smart meter information campaign could not decrease the energy shortage significantly by itself. In order to be able to achieve a significant change, it is most important to make sure the effect of the campaign on consumer's personal values is sufficiently high. For this intervention quality is more important than quantity, because changing the values of many consumers a little does not result in contract switches in most cases.

8.3.5. Default shifting

Figure 8.18 compares the mean and standard deviation of energy shortage for 200 scenarios for base case B and for the implementation of default shifting. The figure shows that the maximum energy shortage as well as the mean shortage are lower when default shifting is implemented. However, the best case shortage is lower for the base case, but this can be explained by the fact that there were more green consumers with a full shifting package in the base case than for the default intervention in the same scenario. This could happen due to the randomness that causes variation in personal values. The main insight is that the mean value for energy shortage is lower in case of default shifting compared to base case B, which means it can be a successful policy to decrease energy shortages.

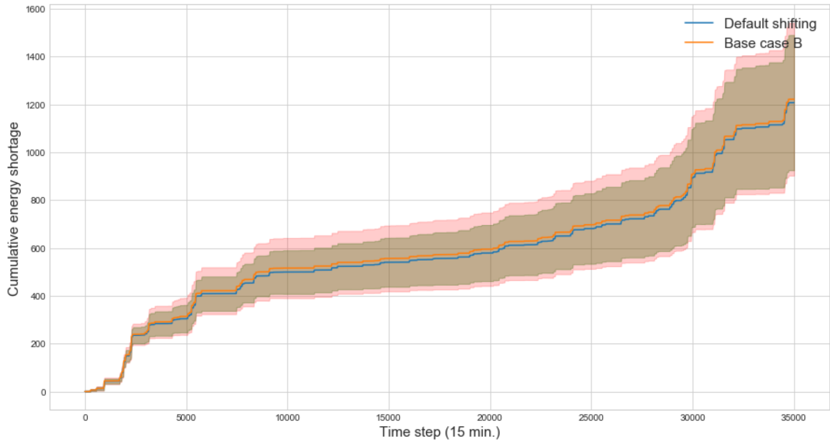


Figure 8.18: Cumulative energy shortage mean with error band for default shifting and base case B in 200 scenarios

Feature scoring again showed that the model outcomes shortage, cost and storage were again strongly influenced by the amount of supply. While looking at an experiment set where the supply was constant and only the consumer population was varied in the scenarios, feature scoring showed that for default shifting, the number of green consumers is the most influential parameter. This is conform expectation, because they are the only consumer type that does not switch to a no shifting contract directly after the first switch period and account for most of the shifted demand throughout the year.

Looking at the results on a consumer level, figure 8.19 shows that most consumers shift back after one period, because this intervention did not change their personal values. Therefore, this policy would be most effective in combination with other policies that would otherwise convince consumers to shift after one switch period. If it is combined with default shifting, these consumers would already have a shifting contract in the first period as well, which would result in lower total energy shortages.

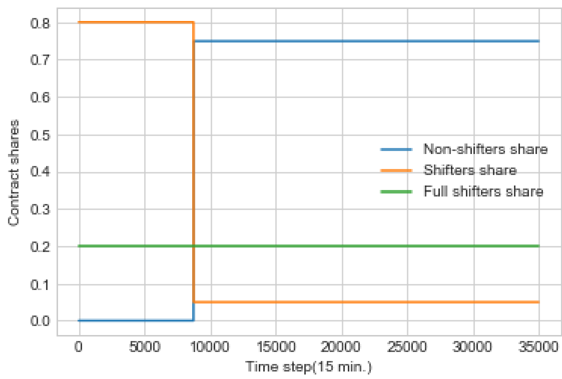


Figure 8.19: Contract shares over time with implementation of default shifting

In the first switch period when all consumers have a shifting or full shifting contract, the shifted amount per person is lower. Because of this, the comfort of the green and the cost-conscious consumers who were already planning on allowing for shifting is decreased less, because they need to shift less per person. However, this intervention has a negative impact on the convenience-oriented and the indifferent consumers, who are obliged to shift demand. Moreover, they perceive the shifting of demand even more negatively than other consumer types, because their value of comfort is higher.

8.4. Comparison of Interventions on the KPIs

In total 18 interventions and combinations of interventions have been run under 200 scenarios. This section will compare the outcomes of these experiments with the outcomes of the two base cases by comparing their output for the model outcomes energy shortage, total consumer costs and required energy storage. Additional results can be found in appendix F. While inspecting the box plots in figure 8.20, the first thing that stands out is that the energy shortage is higher in base case A than for all other experiments, which means that the implementation of a real-time pricing mechanism and introducing shifting contracts results in an improvement. This is in line with the expectations stated in hypothesis 1. However, the other box plots do not vary a lot by first inspection.

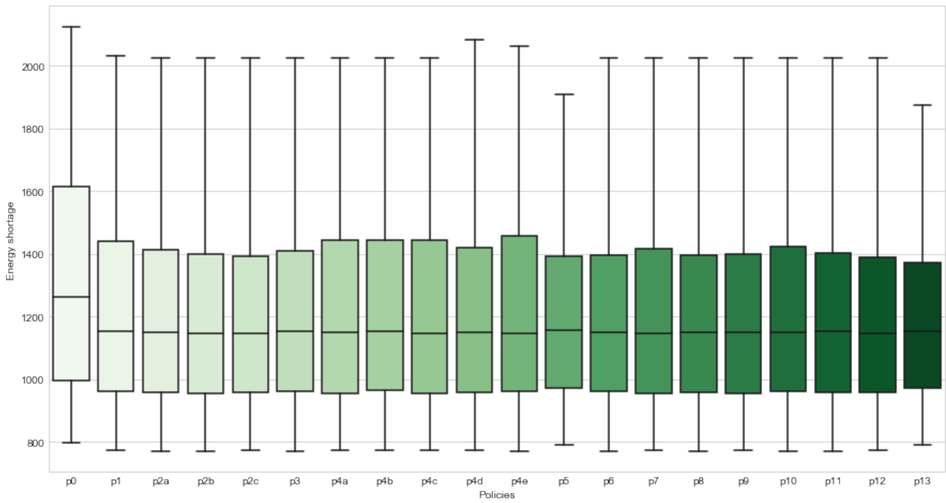


Figure 8.20: Total energy shortage per policy for 200 scenarios

The feature scoring in the previous sections showed that supply is the main influence on the total amount of energy shortage. Therefore, additional experiments have been run for all intervention strategies under 42 compositions of the consumer population with a constant supply. These experiments are shown in 8.21 and give a clearer view on the impact of consumer population on the interventions' effectiveness to reduce energy shortage.

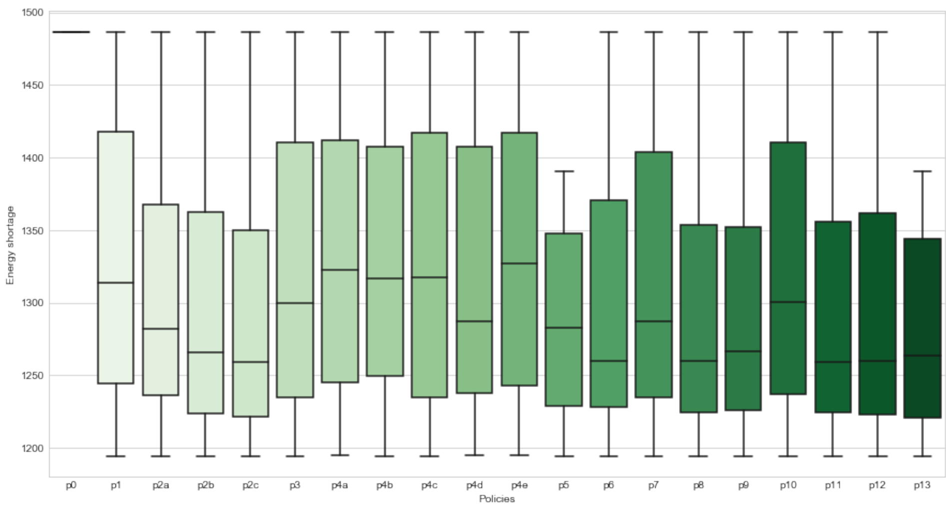


Figure 8.21: Total energy shortage per policy for 42 population compositions

P2a, P2b and P2c represent the implementation of cost comparison with an additional reduction and lower the energy shortage effectively. When a higher reduction is in place, this intervention is more effective. This conforms with the expectation that even consumers with a relatively low price sensitivity, will be tempted to engage in demand response if prices are particularly low. When a reduction was combined with an information campaign (P8, P9), the energy shortage decreased further. Nonetheless, the environmental awareness and smart meter information campaign or combinations of both (P4a-e) barely decreased the energy shortage. The best results came from intervention P4d, where both information campaigns reached 3 consumers 3 times a year and had a relatively strong campaign effect of 0.90 and 1.20. However, the result shows that even the best implementation of the information campaigns is still less effective than the cost comparison with a reduction under these modeling conditions.

The comparison of environmentally friendly behavior is not very influential on its own (P3), but is more effective in combination with both information campaigns (p7). Especially in combination with cost comparison and a reduction (P6), the median energy shortage is much lower. This intervention uses social comparison by sending an overview of the energy costs and environmentally friendliness of a certain consumer compared to the other consumers. This integrated intervention seemed promising in the model, which corresponds to findings of previous similar experiments (Allcott and Rogers, 2014) (Schubert, 2017).

Another finding is that P6 and P13, that both involve default shifting have a much lower maximum value for the energy shortage. Hence, default shifting could be seen as an effective tool. However, it is questionable if this positive impact, can justify the ethical issues of limiting consumers in their freedom to use energy whenever they want.

The two most effective unaccompanied interventions in reducing energy shortage regardless of the consumer population are cost comparison with an additional reduction and default shifting. Moreover, the shortage decreases if interventions are combined in integrated intervention strategies. More policy is less shortage, is the rule that generally applies. Even though interventions led to differences in the energy shortage, the differences were still relatively small, because of the strong influence of supply and the difficulty to engage convenience-oriented and indifferent consumer types. After analyzing all interventions and combinations of interventions, it can therefore be stated that hypotheses 3 can be rejected.

- ✗ Hypothesis 3: All consumer types can be convinced to participate in demand response, if personalized interventions are implemented

Figure 8.22 shows the cost for the energy consumers, which can also be seen as the earnings of the energy producer. It does not come as a surprise that the costs are lower whenever reductions are part of the intervention strategy. Besides, in case of flat pricing instead of real-time pricing (P0 and P11) the maximum costs are highest based on the current model price settings.

The final model outcome that is compared is the required storage and is displayed in figure 8.23. Base case A shows slightly more high values for the required energy storage than the other interventions. However, the required storage does not differ much in base case B and all the other experiment, which means real-time pricing lowered the required storage a bit, but the other additional policies did not have a lot of extra effect, except for default shifting. Default shifting was included in intervention P6 and P13 and have a lower maximum required storage than the other experiments, but the median is slightly higher. As explained earlier, the required storage primarily depends on the supply and the complementary shortage periods, which is why the values barely differ for this model outcome.

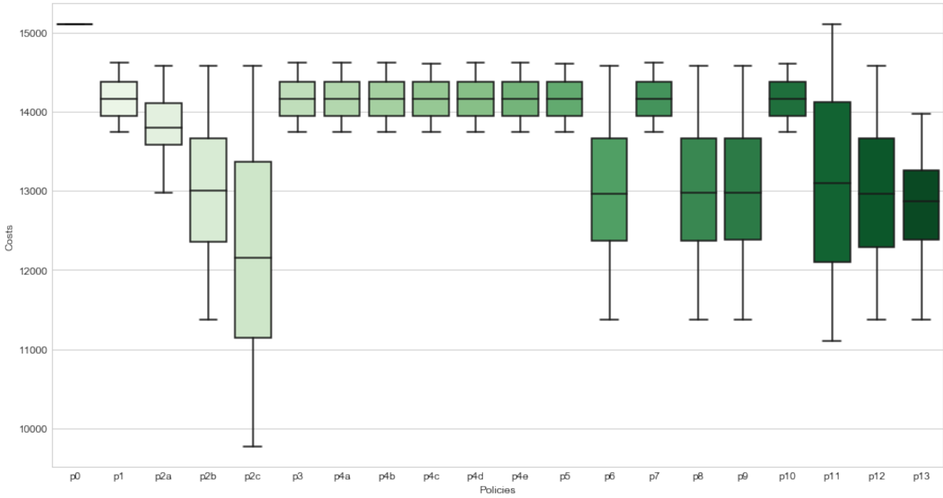


Figure 8.22: Total costs per policy for 200 scenarios

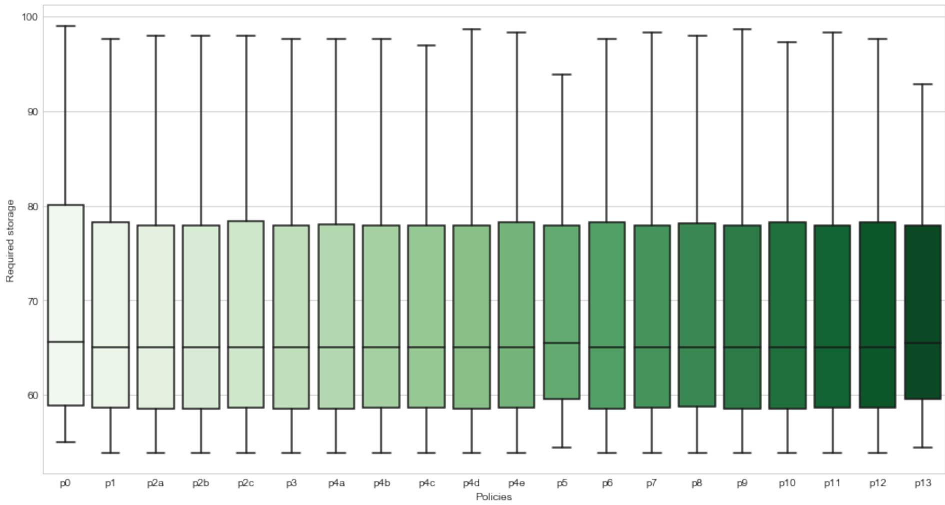


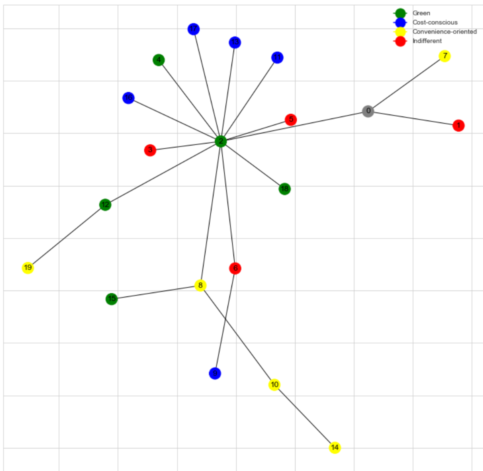
Figure 8.23: Required storage per policy for 200 scenarios

From the comparison on the different KPI's we can conclude that real-time pricing decreases the required storage and energy shortage. Besides, the required storage is not really affected by the additional interventions. On the other hand, the total energy shortage decreases with additional policy interventions, and is the lowest whenever all policies are in place or in case of a very high reduction. Reductions seem to be a very efficient tool to encourage consumers to switch to shifting contracts, but also result in lower profits for the energy producer under the current pricing scheme.

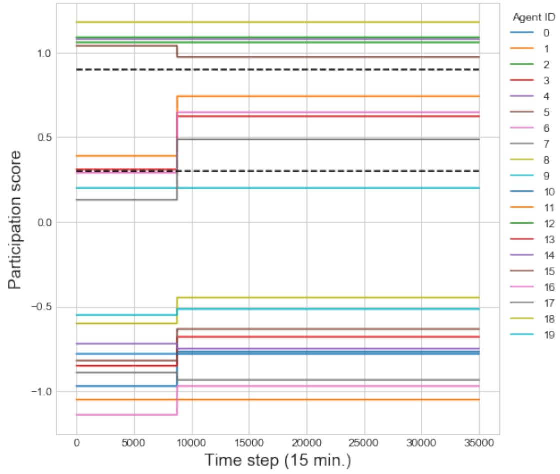
8.5. Impact of Social network and Social Interaction

To understand to what extent the social network and social interaction can support or diminish the effect of the interventions, the functioning and pure effect of the social network in the model was analyzed. The outcomes were compared by looking at the changes in the participation scores of the agents caused by social interaction. In the experiments no interventions were implemented, all other parameters were set to constant and only aspects of the grid were varied.

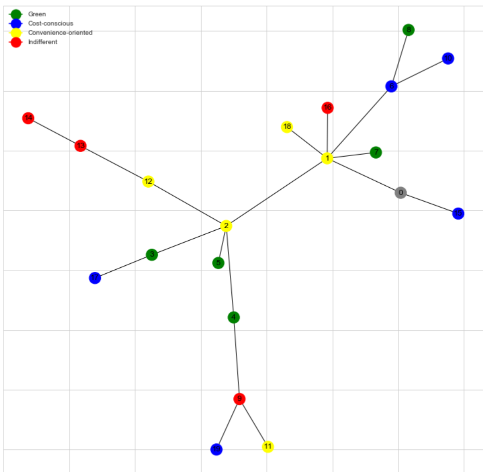
In the first set of experiments, the goal was to find out how alterations of the layout of the social grid affected the outcomes. The layout differed in the way that the nodes were connected, but also in the way that consumer types were distributed over the social network. The results are explained by means of two example networks that are shown in figure 8.24a and 8.24c. In network 1, a green consumer is at the center of the network, which results in a positive effect on the participation score of many other consumers as can be seen in 8.24d. The shifts in the participation score are also very high, because the degree of the central green agent is very high, which represents high influence. In the second network, the network is a bit more spread out, but convenience-oriented agents 1 and 2 can be considered as central, influential nodes. As can be seen in 8.24d, this results primarily in decreases in the participation scores of other consumers. However by comparison, you find that the adjustments in the scores are smaller than the adjustments in example 1.



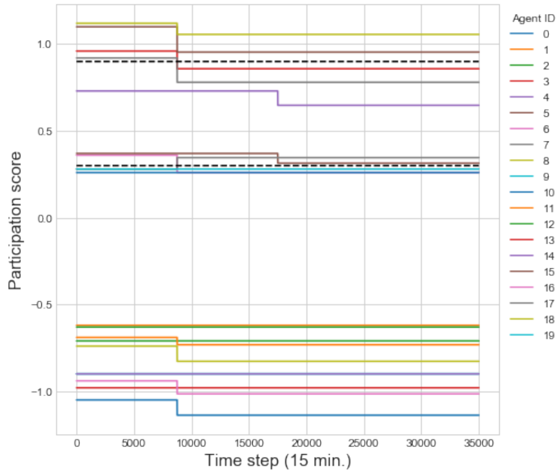
(a) Social network example 1



(b) Changes in the participation scores



(c) Social network example 2



(d) Changes in the participation scores

Figure 8.24: Two examples of social networks and the changes in the participation scores of consumers caused by interaction in the network

In the second set of experiments, the influence of the consumer population was studied. The results showed that the composition of the consumer population and thereby the initial contract shares, adjust the chance on a positive or negative social influence. For example, if 75 percent of the population had a shifting contract initially, the consumers with a no shifting contract had a higher change of being influenced positively than negatively. Moreover, the amount of cost-conscious consumers turned out to be an important factor again, as their participation score is close to the switching threshold. If a cost-conscious consumer is part of a population with a lot of green consumers, he is more likely to stay with or switch to a shifting contract. On the other hand, it is more likely that he would choose for a no shifting contract if the majority of the population is convenience-oriented or indifferent. Another situation that was studied is the one where all consumers except one are a green consumer and the other one is indifferent or convenience-oriented. In this case, the single indifferent consumer will not switch to a shifting contract, regardless of his location in the social network. This example shows that the social interaction is not determined by the complete population, but by the influential neighbor of the node. Even though in this scenario, the neighbor of the indifferent consumers is for certain a green consumer which means the participation score increases, the effect of social interaction alone is not large enough to convince a convenient-oriented or indifferent consumer to switch.

For the population it can be concluded that the composition of the consumer population and the initial shares of contracts determine whether agents are more likely to be influenced negatively or positively. On an individual consumer level, the degree and the contract type of the influential neighbor remain the most important determinants for the social influence that a consumer experiences. The layout of the grid is also an important aspect, because the consumers that have a high degree can have a strong influence on all of their neighbors. So the consumer type of the consumer in a key network position is quite influential on the social interaction in the network. On a model level, this also means that the location of consumers in the social network can have an enforcing as well as diminishing impact on the intervention effects.

8.6. Sensitivity Analysis

A sensitivity analysis has been done for the factors that are uncertain, but were not included in the deep uncertainty analysis. In this section, the sensitivity of the model results with regard to the input parameters shiftable share of demand, social interaction effect, switching thresholds and the number of switching periods was analyzed. The parameter setup for the sensitivity analyses is presented in table 8.3. All missing parameters are set to the standard parameter settings that can be found in appendix D.

Table 8.3: Setting of input parameters for sensitivity analysis

Parameter	**Value**
Demand shiftability	Varying
social interaction effect	Varying
Switching thresholds	Varying
Switch periods	Varying
Green household	5
Cost-conscious household	5
Convenience-oriented household	5
Indifferent household	5
Supply factor	1
Initial package	Value based without random noise

The analyses were conducted for a consumer population of size 20 with an equal distribution of the consumer types. The random noise of the personal values has been removed, to be able to fairly compare the different parameter settings. Whenever one of the four parameters is being analyzed, the others are set to standard conditions. The standard conditions are shiftability set to 1, social interaction effect set to 0 with a fixed social network, the switching thresholds set to 0.3 and 0.9 and the number of switch periods set to 4.

Base model B that includes demand shifting and real-time pricing was used to study the shiftable share of demand and the social interaction effect. In order to be able to conduct a sensitivity analysis for the switching thresholds and the switching periods, the base model was accompanied with some additional intervention, namely cost comparison with a reduction of 20 and a smart meter information campaign that reaches 4 consumers per switch moment and has an effect of 0.9.

8.6.1. Shiftability of demand

The shiftability of demand refers to the shiftable shares of demand, so the fully flexible demand such as heating and the semi-flexile demand such as a dish washer. In the model, this is incorporated in two lists that contain the shiftable shares at each time step of the year. Figure 8.25 shows the cumulative energy shortage for different shiftable shares. The standard setting is 1 and the shares have been multiplied with the factors 0.5, 0.75, 1.25 and 1.5 to see the effect of a decrease or increase in the share of demand that can be shifted.

The analysis of different percentages for shiftable and fully shiftable demand show the expected result that the energy shortage grows when the shiftable shares of demand are lower. Similarly, the overall energy shortage reduces if the shiftable shares rise. Compared to the default setting of 1, it is notable that lower shiftable shares have a bigger negative impact, than higher shares have a positive impact.

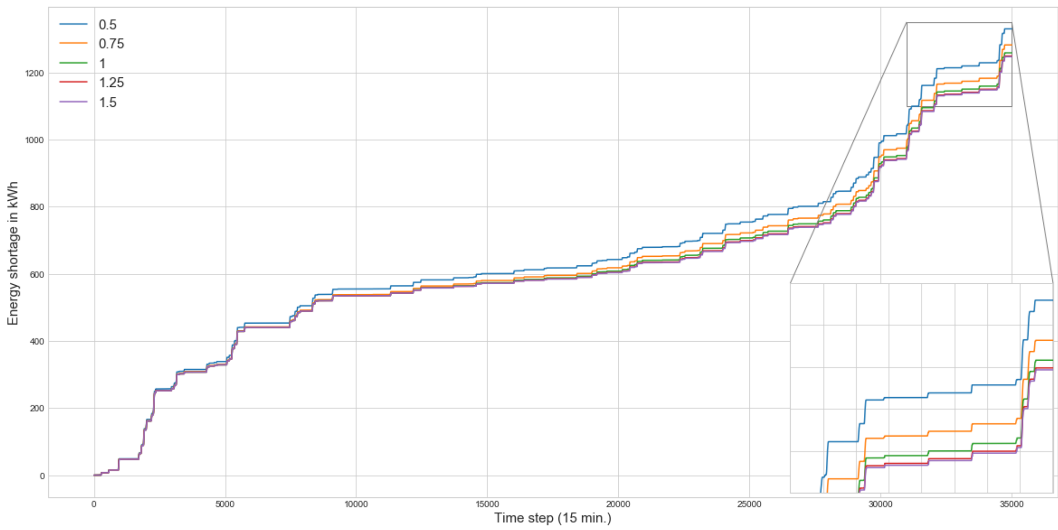


Figure 8.25: Cumulative energy shortage for different settings of the shiftable shares of demand

8.6.2. Social interaction effect

The social interaction effect is a factor in the model that determines how much a consumer is influenced by another consumer in the social network. The social interaction effect is quantified, but it is undetermined what the real value is. Again base model B was used for this sensitivity analysis with a fixed social network layout to be able to see the pure effect of social interaction effect changes. Figure 8.26 shows the energy shortage for a social interaction effect of 0, 0.01, 0.05, 0.1, 0.3 and 0.5. Without any other policy in place besides real-time pricing, nothing is changing in the energy shortage and switching, unless the social interaction effect is 0.3 or 0.5. For these two higher settings, some consumers have shifted to a different contract, in this case to the non-shifting contract, purely by the influence of social interaction. For all the other scenarios, no consumers have switched to a different contract. It seems most likely that consumers do not switch purely by social interaction, which is why 0.1 was chosen as the standard setting. Another finding is that the differences in the energy shortage are smaller for social interaction effect changes, than for changes in the shiftable shares of demand, which means that the model is more sensitive to the latter input parameter.

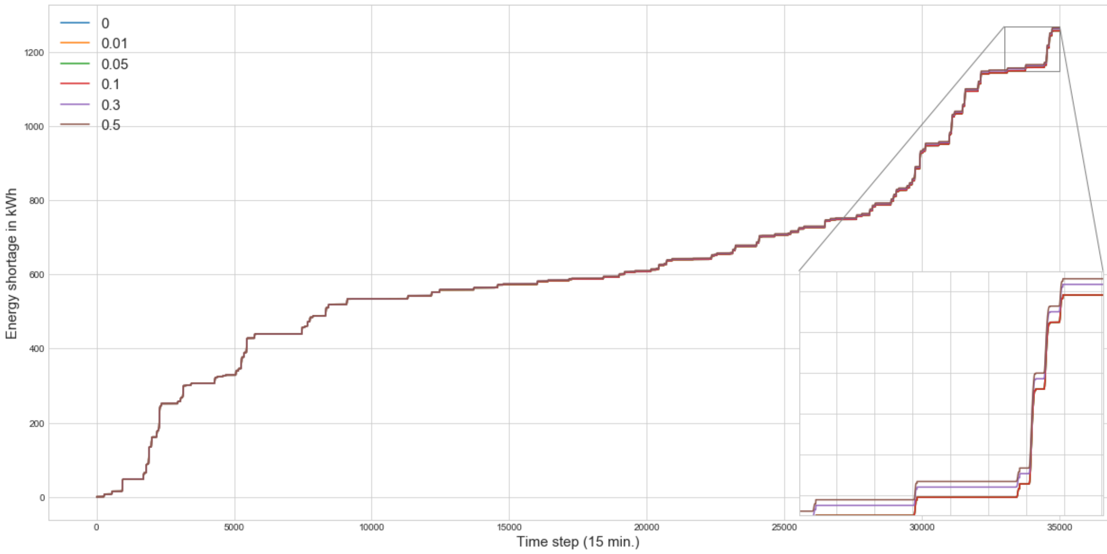


Figure 8.26: Cumulative energy shortage for different settings of the social interaction effect

8.6.3. Switching thresholds

For the sensitivity analysis of the switching thresholds the base model was accompanied with some policy interventions, because the thresholds are especially important in case of switching between contract types. Several combinations of higher and lower values for both of the thresholds have been applied, with the thresholds 0.3 and 0.9 as standard settings. TH1 represent the threshold between the no shifting and shifting contract, whereas TH2 represents the border between a shifting and a fully shifting contract.

Whenever both thresholds were very high, respectively 0.6 and 1.2, there was a lot more energy shortage. If only TH1 was increased, represented by the purple line, the shortage also increased significantly. Therefore it can be concluded that the model is quite sensitive to increases in TH1. This can be explained by the fact that the participation score of cost-conscious agents varies somewhere around 0.3. If the threshold is 0.3, the cost-conscious consumers can have either a no shifting or a shifting contract, but when the threshold is increased to 0.45 or 0.6, all cost-conscious consumers have a no shifting contract initially. The energy shortage is also sensitive to an increase in the second threshold only, represented by the brown line, but to a lesser extent. Reason for this is that this threshold is the division line between a shifting and a full shifting contract, between which the shiftable shares of demand increase less than between a no shifting and a shifting contract. Lowering the switching thresholds compared to the standard settings does not lead to significant changes in the energy shortages.

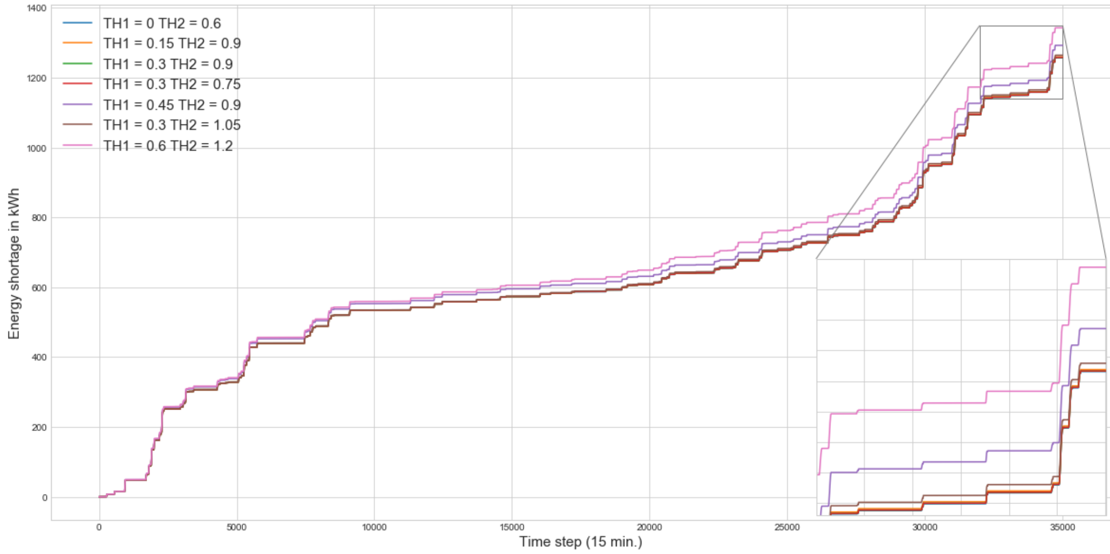


Figure 8.27: Cumulative energy shortage for different settings of the contract switching thresholds

8.6.4. Switching periods

The final input parameter that was analyzed is the number of switching periods. The parameter was also analyzed in a scenario in which a reduction and a smart meter campaign were in place, because the switching periods would not have a significant influence in the base case models. The reduction interacts with the switching period, because it is formalized as a reduction per switch period. This implies that whenever the number of switch periods increases, the total yearly reduction also increases.

The simulated year can be divided in a number of switching periods, after which each consumer can switch between contracts. So if there are 4 switching periods, the consumers can switch three times during the year and a last time at the final model step. This final switch does not influence the model outcomes anymore. The switching periods that have been analyzed represent 1,2,3,4,6 and 12 switching moments.

The results in figure 8.28 show that a decrease in the length of the switching periods, so an increase in the number of switching moments leads to lower energy shortages. This can partially be due to the increase in the yearly reduction as well. It is striking to see that 2 or 3 switching moments have a relatively small difference in shortage. Besides, even though 6 and 12 switching moments are a lot more switching moments than 4, the energy shortage does not decrease proportionally. Considering the hassle that can be perceived from switching between contracts, the best choice seems to be to include 4 switching periods, because it lowers the energy shortage compared to 1,2 or 3 switching periods, but less hassle can be perceived in comparison with 6 or 12 switching periods.

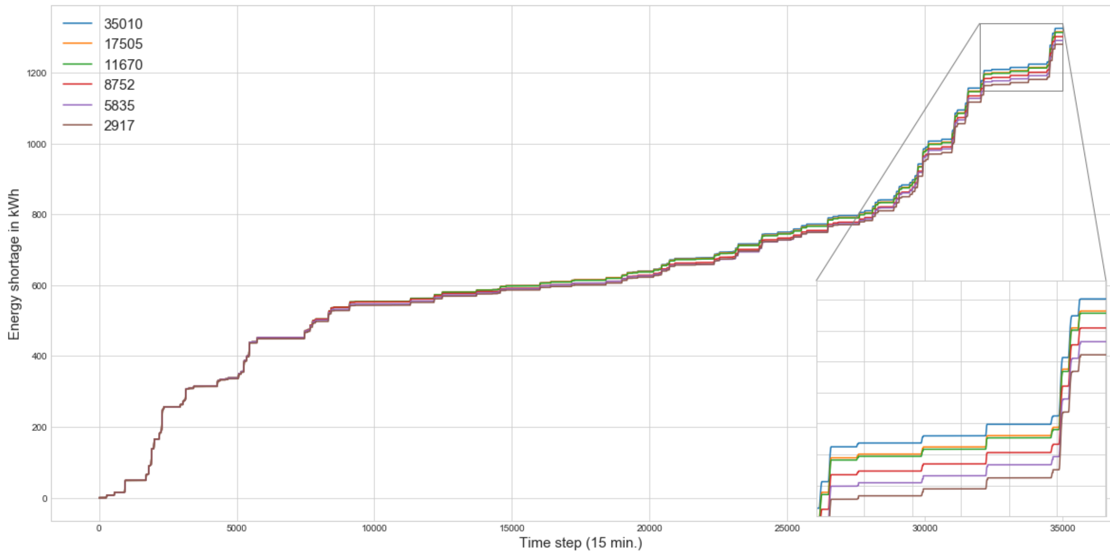


Figure 8.28: Cumulative energy shortage for different settings of the length of the switch periods in a year.

8.7. Conclusion

In this chapter the design of the experiments and the results has been presented. The effect of each of the separate policies has been analyzed and the policies and policy combinations have been compared based on the model KPIs. Real-time pricing and demand response decrease the required storage and energy shortage, but the total energy shortage decreases further with additional policy interventions, and is the lowest whenever all policies are in place. Reductions came out as the most efficient tool to encourage consumers to switch to shifting contracts, but also result in lower profits for the energy producer. In the analysis of the social network, it became clear that the consumer type of key network players determines if social interaction in the network has a positive or negative effect on other consumers' participation scores. Finally, a sensitivity analysis was performed to analyze the model sensitivity to key input parameter.

The results have confirmed one and rejected two out of the three hypotheses that were introduced in chapter 3. Firstly, the comparison of base case A and base case B confirmed that the addition of a real-time pricing component and demand shifting reduces the energy shortage. Subsequently, it was rejected that the required amount of storage capacity reduces whenever a larger share of the population allows for demand shifting, because this is only partially correct. Due to the strong influence of supply, this statement is not true when the supply is substantially low and the period of energy shortage is longer than 1.5 hours. Finally, this study could also not confirm that all consumer types can be convinced to participate in demand response, because the high values of comfort and safety of the convenience-oriented and indifferent consumers remained a barrier for engaging in demand response, even in case of interventions. In the following chapter, the model results will be analyzed more extensively.

9
Analysis

This chapter start by discussing the model validity. Subsequently the results from the experimentation will be analyzed more thoroughly. After that, the interventions will be discussed and the final section of the chapter will present the model trade-offs. Throughout the chapter, the insights of the model and this study will be translated to real-world application possibilities.

This chapter continues with answering the sub-questions:

- *Sub-question 5: Which policy strategy ensures the strongest demand response under many different scenarios?*
- *Sub-question 6: How do different characteristics of the consumer population influence the effectiveness of policy intervention to enhance demand response?*

Besides, this chapter also addresses the final sub-question:

- *Sub-question 7: How can the outcomes of this study be used to advise decision makers about stimulation of user participation in demand response?*

9.1. Model Validity

Traditional model validation refers to the process of checking whether the real-world system and system behavior are represented accurately in the model (Van Dam et al., 2013). However, there is no real-world situation to compare this model to, as the model represents a future scenario with a high share of renewables, a smart grid, real-time pricing and specific contract types for demand shifting. If a model investigates a future scenario, the model validation should focus on whether it is useful and convincing in its explanation of the system behavior. The outcome values are in this case not as important as the insights that are provided by the model (Van Dam et al., 2013). According to Sargent, each model was created with a purpose and a model should be validated according to this purpose (2010).

9.1.1. Validity with respect to the model purpose

The purpose of the model in this thesis was to gain insight in the effect of real-time pricing and additional interventions on the user participation in demand response. Particular aspects of interest were the influence of the consumer population and the amount of renewable supply. The model purpose can be validated by analyzing if the range of the results seems accurate and acceptable.

First of all the model input data is not empirical. Furthermore, many assumptions and generalizations were made in the model which led to a simplification of the real-world energy system. Because of this, the model does not accurately predict the actual values of energy shortage, costs and storage that can be generalized if a shifting and switching system would be implemented. Therefore the numerical model output cannot be interpreted straight away. However, the relative changes and range differences in the outcomes caused by interventions and input differences can be interpreted and validated. By looking at the energy shortage, it becomes clear that the energy shortage decreases by the interventions. This behavior seems valid, as it corresponds to the effects of the interventions that were mentioned in the literature that laid the foundation for the model interventions. The model results also represented the expected relation between the costs and the interventions as well as the relation between the required storage and the energy shortage. Considering the purpose of the model to gather insights in the interaction between the energy system, consumers and interventions, this model could be designated as valid.

Besides this evaluation of the operational validity, a sensitivity analysis of key input parameters and a model verification were performed to analyze whether the system behaved according to the literature-based model conceptualization (appendix E). For now the validity of the model was only discussed at a high abstraction level, but the next section suggests other validation techniques that could validate the model more comprehensively.

9.1.2. Extensive model validation approach

The costs of the model validation are often significant as validation is a very time-consuming process, especially when high model accuracy is required (Sargent, 2010). Technically, a more traditional model validation could also be applied to this project. However, in order to do this properly, this would take a lot of time, which was not available for this thesis. Nevertheless, a potential approach to validate the model is proposed here.

Even though there is no model that is directly comparable to this model, cross-validation could be done for several model components. This could for instance be applicable to the social network, the copper plate energy model and the real-time pricing component of the model. Also the financial components such as the reduction and price sensitivity could be validated with current models of energy producers. Moreover, many researchers have already analyzed the effect of various pricing policies on electricity consumers. Besides, other models outside of the energy sector that make use of a reduction as a financial incentive are available as well. The application of these other models will probably not be identical to this model, but comparison of the model behavior could be useful anyway.

Still, not a lot of models exist that also include the behavioral aspects of this model, because that aspect had not been incorporated in quantitative models often yet. For example for the effects of the policies on the user participation in demand response, validation remains difficult. Therefore the model validation would rely mainly on expert validation. Expert validation would be an appropriate method to assess if consumer values and their response to interventions are modeled realistically and how this could otherwise be improved. The expert validation is not only applicable for the consumer and intervention side of the model, but also for every assumption of the model. The assumptions could be discussed with experts that have knowledge about future trends in energy, energy policy, consumer psychology, behavioral economics and much more.

Another validation method that is seen often in modeling and simulation studies is empirical validation. Empirical validation refers to the comparison of the model behavior with historical experiments or events. Empirical validation is more difficult to perform in this case, because this study discusses a future world view. However, empirical validation of interventions might be possible on a higher level. For example empirical results of information and awareness campaigns focused on encouraging environmentally friendly energy consumption or peer comparison could be valuable to determine the validity of the results of these interventions in this model.

9.2. Analysis of the Model Results

The experimentation has provided many insights about demand shifting and contract switching and their effect on the energy shortage, the total energy consumer costs and the required storage. A main conclusion was that the addition of a real-time pricing component and the introduction of different shifting contracts, lowered the yearly energy shortage. With this, hypothesis 1 was confirmed. The results also showed that a high level of consumer participation in demand response could even completely solve shortage periods if they were shorter than 1,5 hours and the imbalance between supply and demand was not extremely large. Therefore, it can be stated that a high consumer participation should be a goal to strive for for the energy producers.

With the addition of the ability to switch between contracts a few times a year, the energy shortage could reach its minimum. However, only a small part of population turned out to be susceptible for interventions that incentivized them to switch to a shifting contract according to the model. Therefore the effect of the interventions was generally not very strong, because only green and cost-conscious consumers could be encouraged to switch to respectively a full shifting contract or a shifting contract. In line with this, the consumer population has a large influence on the success of the interventions. Not only the composition of the consumer population turned out to be influential, the supply factor was even more dominant. If the supply factor was low, longer periods of energy shortage occurred more often, which led to a large increase in the yearly energy shortage. The increase in energy shortage that was caused by very low supply, could not be compensated by the decrease of energy shortage caused by interventions that encouraged some consumers to switch to a shifting contract. However fact remains that for all supply scenarios a higher user participation leads to less energy shortage. Yet, in scenarios with more supply and shorter periods of energy shortage, a higher user participation is even more effective in reducing shortage.

It is very difficult for an energy producer to influence the distribution of consumer types in their consumer population. The supply however is something that can be influenced. Especially when it considers the future composition of supply, because the investment choices are being made now. This study showed that wind and solar are both very volatile and could lead to extreme energy shortages if generation from both sources is low. Considering the large influence of supply on the model outcomes, inclusion of more stable renewable energy sources in the future energy mix could reduce the volatility. Although supply and the consumer population were modelled as uncertainties in this study, these parameters can be certain in future case studies. For a specific case, the exact energy mix is known and consumer values and preferences can be surveyed directly. After elimination of the uncertainties, this model could be used to predict a more reliable and a narrower value range of the model outcomes.

9.2.1. Energy shortage

A main outcome of the model experiments is that the energy shortage could not be resolved entirely for the current supply and demand settings. Therefore the focus lay on reducing the energy shortage as much as possible in combination with additional energy from battery storage that could be used as a back-up. The results showed that the required amount of storage did not vary much in the different supply scenarios. This was caused by a crucial week in the winter, that can be considered as the bottleneck of the system. In this winter week, supply was particularly low, but supply was also lower than demand for a period of almost a day. Almost directly after this day, there was another period of shortage which is why there was no opportunity to recharge the battery. An energy producer should therefore be particularly cautious in the winter period, because the risks of larger shortages and longer periods of energy shortage are higher in this season. In the winter period solar generation is generally low, which makes the supply dependent on wind energy for the vast majority. This can lead to large energy shortages if wind generation is low as well. Besides lower supply, the energy demand is also higher in the winter, especially if heating is electrical. Accordingly, an energy producer should focus on worst case scenarios for a winter period, when looking at demand response potential and deciding for the required storage.

Longer periods of energy shortage are also part of the reason that the energy shortage could not completely be resolved in the model. As demand can only be shifted 1.5 hours, problems arise when the period of shortage is longer than this, because then a part of the new demand can be shifted, but an additional amount of demand that was shifted 1.5 hours ago needs to be used now. Because of this, the demand curve almost follows its original curve after 1.5 hours. Even though the 1.5 hour shifting maximum is a model assumption, this shifting problem would still occur to a lesser extent if demand could be shifted for a longer period. Even though a longer shifting period of demand would not solve the energy shortage completely, it could result in further shortage reductions. Therefore, it is something that could be considered as part of the solution.

Another way to further reduce the energy shortage is to increase the share of demand that can be shifted. However, which share of demand can really be shifted in the future, depends on many uncertain factors. For example on the heating systems consumers have in the future. Besides, other household appliances might also generate a further increase of the energy demand of households. For example, an increase in the number of electric vehicles could increase this. On the other hand, they could also serve as additional battery storage in periods of shortage.

9.2.2. Social interaction

Experimentation with the composition of the social network and the consumer population showed that the social interaction in the network depends strongly on the key players in the network. The personal values and the shifting contract of the key players determine the positive or negative influence on their neighbors, who can sometimes be quite a large share of the consumer population.

In this study, the effect of social interaction was incorporated by looking at the most influential nodes and how influential they are. However, this could have been incorporated in many different ways, because it is uncertain how social networks and interaction dynamics exactly occur. Besides, it is also very hard to tell in real life, which 'share' of a consumer's decision was influenced by the social interaction. Since personal values can be influenced by anything, it is very difficult to review if it was an internal or external factor that caused the value change. Nevertheless, for real-world decision makers the social network of their consumers is also unknown and is difficult to figure out. However a main insight from the analysis of the social network remains the importance of the key players in the network, which is useful knowledge for a decision maker. If influential key players in a network can be localized, they could potentially contribute to a positive marketing campaign of demand response. However, when an influential consumer has opposite interests, it might be very difficult to compensate for his influence on consumers that might have been persuadable to choose for a shifting contract otherwise.

9.3. Analysis of Interventions

The main finding of the analysis of the individual interventions as well as the intervention combinations is that more policy generally leads to lower energy shortages. However, currently the policies are not robust, because the uncertainties supply and consumer population influence the outcomes strongly. Therefore it is important for decision makers, to study these uncertainties closely. In this study consumer types were used for modeling purposes, but it might be difficult to fit the real-life consumers in one these four boxes. However, the results showed that the personal values are more important for the success of the interventions than the consumer types, because the interventions interact with certain values and were designed to work better for consumers with certain values. Thus, it is important for energy providers to gain insight in the values and believes of consumers when deciding on an intervention to implement.

9.3.1. Analysis of the effect of interventions

The cost comparison with a discount for shifters was the most effective separate intervention, because it targeted the cost-conscious consumer mainly, who had a high value of price. This consumer group could be engaged in demand response with a relatively small reduction, whereas other consumers would need a bigger reduction to consider switching. Reduction was a useful intervention to reduce the energy shortage, but it is important to find a reduction amount that encourages enough people to switch to a shifting contract, but not everyone. That would be undesirable, because with the current representation of the reduction, everyone with a shifting contract receives the full reduction, regardless of the amount of demand they shift. If everyone would participate in demand response, this would mean that they all receive a relatively high reduction for a smaller loss of convenience. If this is likely to happen in a real case, the reduction policy could be redesigned. For example by taking the amount that people shift into account for the reduction. Currently, price elasticity in energy is low, because of the low electricity prices that do not motivate consumers to use less energy. Adding a real-time pricing component, cost-comparison and a reduction could increase the price differences and price elasticity in energy and motivate consumers to use less energy or shift demand.

Financial interventions are quantifiable, which makes them easier to review as the effect can be measured. However, it is more difficult to review the effect of environmental comparison or awareness and information campaigns. In field experiments, peer comparison of energy usage has proven to be a successful tool to reduce energy demand. However in this study, environmental comparison was analyzed to see if it could also be a tool to encourage people to allow for demand shifting. For the consumer this is a very different intervention, because in this study, the choice that had to be made was to allow for demand shifting or not. When a consumer allowed for demand shifting, the energy producer was allowed to shift the consumer's demand if necessary and automatically which was possible thanks to the smart grid. The decision for a shifting contract might be a more difficult decision for a consumer than the decision to shift or reduce some demand by themselves without a contract. This independent demand shifting of consumers was currently not considered, but including that might increase the total amount of shifted demand. On the other hand a system without shifting contracts and automated demand response might also lead to fewer shifted demand by the consumer who would have otherwise chosen for a shifting contract. Based on this, the system of shifting contracts seems suitable for maximizing demand response, but to be sure about the best system, the different systems should be compared in a future study.

The environmental friendliness comparison and environmental awareness campaign did not lead to significant reduction of energy shortages in this model. These interventions rarely convinced a consumer to switch to a demand shifting contract by themselves. This can be explained by the fact that the environmental comparison and environmental awareness campaign both interact with a consumer's value of the environment. This value is highest for the green consumers, but they already have a switching contract, because of this value. The other consumer types are not sensitive for an environmental comparison, when their value of environment is low. However if the value of environment is increased first, by an information campaign or social interaction or another event, then an intervention that compares environmental friendliness could be more effective.

The smart meter information campaign was targeted at consumers with a no shifting contract, who were sceptic about their convenience if they would allow for demand shifting and concerned about safety issues related to the smart grid and the accompanying information communication infrastructure. This intervention was designed to target the convenience-oriented and indifferent consumers, because they have the highest value of comfort and safety. However, the effect of the campaign needed to be extremely high to convince them to switch to a shifting contract. This is because these consumers types do not only value comfort and safety high, but they also valued price and the environment low, which means that more values need to change, before they would ever be interested in a shifting contract.

With the default shifting intervention, the ability to choose a shifting contract was removed and all consumers had a shifting or full shifting contract in the first period. After this period, agents switched to a different contract that fit their values better. Even though the effect of this intervention only lasted for one switch period, the results showed clear improvements in the energy shortage. The effect did not last, because the policy did not actively change the values of the consumers. If this policy is implemented, it is important to implement additional policies that do interact with the values, to prevent people from switching back to a no shifting contract immediately. The policy was tested in this model to see if it could have positive effects, because this policy also limits people's freedom of choice and interferes with their personal life when demand is shifted. For this intervention, it is important to discuss if the energy shortages on a societal level weigh out the personal disadvantages. An intervention like this would lead to a complex ethical discussion and is therefore not likely to be implemented in real-life soon, unless it is socially accepted.

The model results showed that the user participation is more or less stable if no additional interventions are implemented to engage people in demand response. The interventions can increase the user participation, but the effect of the policies fades over time. Therefore it is important to repetitively implement policies and to choose a combination of policies that reinforce each other. The selected interventions should also be based on the consumer population. It is important to study the values and believes of the consumers to find out if they can be motivated and which values should be interacted with. In reality the consumer population does not consist of 4 types of consumers, but of persons with differing values and personal value trade-offs that determine whether they participate or not. For example there could be a consumer that cares about the environment, but is held back by safety concerns a bit. For this consumer a smart meter information campaign could be enough to engage this consumer in demand response. Therefore it is important to choose the interventions wisely. Sometimes it could be better to go for quantity and reach as many people as possible, who then all change their behavior a little. However the model results showed that choosing for quality and targeting a few consumers that are in doubt is a more successful way to induce a contract switch. In the model, this refers to the consumer group that was cost-conscious. However fact remains that it is difficult to gain insight in the values of the consumers, let alone steer people's behavior. The moderators of behavior are too complex to be captured in specific values, but this study did contribute to gaining insight in the interaction between, consumer values and interaction effectiveness.

Moreover, demand response and the shifting contracts are currently not the standard in electricity retail and consumers are used to full control of their energy usage. With a smart grid, real-time pricing and switching contracts this would change. When a new technology or system is introduced, there are only a few adopters initially. To achieve more user participation, consumers really need to be incentivized with policies. The more people experience a shifting contract and the more it becomes the social norm to participate in demand response, the less policy will be needed to retain a certain number of consumers with a shifting contract. However, the change from passive to active energy consumer needs to be stimulated. In the stimulation it is important to determine which consumers needs to be encouraged and which ones are easiest to engage. Based on that knowledge, personalized policy strategies can be implemented to address different groups of consumers.

9.3.2. Timing and long-term impact

The model results are a bit affected by the warm-up period of the model, because the interventions are implemented for the first time, right before the first switching moment. This was modeled this way, because some interventions, for example the environmental comparison and cost comparison look back on the energy usage in the previous period. In reality, interventions could be implemented immediately, because previous data is available. Considering the warm-up period, the reduction in energy shortage could have been bigger if policies were implemented from the start, especially because the first shift period is a winter period in which energy shortages are bigger.

The long-term effects of the interventions depend on whether the interaction with the values is permanent or not. In the experimentation, the influence of a policy on a value was temporal and values were 'reset' after a switch period. Because of this, a policy needs to be implemented repeatedly, to prevent oscillating behavior and make a contract switch last. Research on information campaigns has shown that the effect can fade away over time. In the model the duration of the information effect varied, but in each scenario the affect disappeared after a number of switch periods. In the model results the effect was constant for the time being and suddenly disappeared, whereas in reality the effect would fade away more gradually over time. Regardless of the duration of the effect, which is hard to review in reality, the takeaway is that interventions should be implemented repetitively to sustain the effect unless values are changed permanently.

In the experimentation the interventions were all implemented throughout the entire year or not implemented at all. However timing and the order of implementation might be important as well, but have not been analyzed in this study. Also seasonality causes that interventions, such as cost and environmental comparison have a bigger impact after periods or larger shortage, for example the winter, because the differences between non-shifters and shifters are bigger then. Therefore it might be worth considering to not compare the previous period only, but look at a longer period or the same period in the previous years. For example, the availability of data for multiple years could make it possible to compare a period with the same period in previous years.

9.4. Trade-offs

The results of the model experimentation have presented a number of trade-offs, that are important to take into account in the process of designing the best policy strategy to encourage consumers to allow for demand response. The results showed that the financial intervention consisting of cost comparison with an additional reduction could be a very effective policy instrument. However under the current implemented real-time pricing scheme, the total profits for the energy producer decreased, because of two reasons. First of all the consumers with a shifting contract paid a lower price for the electricity that was used in an off-peak period. On top of this, an additional reduction was given to consumers with a shifting contract. Since a higher reduction resulted in less energy shortage, but also less profit, this trade-off can be interpreted as a choice for the energy producer between their value of price and their value of the environment.

However, this trade-off does not have to be that black or white in reality. For example, the energy producer could reduce their profit losses by increasing the prices in periods of shortage even more or decreasing the prices less in periods of energy surplus. The price function can be tweaked in such a way, that profit losses do not need to occur. Besides, there is also the possibility of government subsidies, if they consider it a public interest to decrease the energy shortage and therefore the need of energy grid investments. In reality there is also more to the cost aspect than purely the direct profit from energy sales, that has not been taken into account in this model. The trade-off would become less strong if the costs related to solving the energy shortages by another means than demand response. Examples of these costs are grid investments, extra storage capacity, energy import or the costs of increasing the fossil production.

Although lower total profits are negative for the energy producer, lower total costs are positive for the consumers. However, these lower costs come at a cost of losing some control over your own energy consumption and can be perceived as a hassle. So, for the agents there is a trade-off between costs and loss of comfort and control. Not only the shifting of demand can cause comfort losses, also the switching between contracts can be experienced as a hassle. This applies especially to the convenience-oriented consumers, because they value comfort relatively high. Each consumer bases their choice for a contract on the weights that they attach to costs and to loss of comfort. The convenience-oriented and indifferent consumers value their comfort a lot, which leads to the fact that under the current modeling assumptions, reductions in cost cannot outweigh that. How much the perceived hassle exactly is, is uncertain. However, it is expected that people with a high value of comfort perceive things as a hassle more quickly. Therefore it could be stated that the hassle perception of contract switching is implicitly incorporated in the value of comfort.

The final trade-off is between the number of people with a shifting contract and the shiftable share of demand. If the shiftable share is bigger, less people need to shift to shift the same amount. However, on the consumer level, there is a trade-off between the number of agents that shift and the comfort loss. If more people allow for demand shifting, the consumers need to shift less demand per person and lose less comfort. However shifting more demand is not always necessary, for example if the energy shortage is only small. An additional shifter could decrease the demand by shifting full capabilities, but when enough people shift already, an extra shifting contract does not add full shifting capability. Instead all shifting people shift less, because the total amount of demand that needs to be shifted is divided over more people. Therefore if an energy producer can predict the amount of future shortage and knows how many consumers need to have a shifting contract to solve the shortage issue, this knowledge can be used to determine how many interventions are needed to achieve this. If the amount of supply is high enough, less shifting consumers are needed and the consumers that are close to switching can be targeted by interventions.

9.5. Conclusion

First, the validity of the model was discussed. Afterwards the model results were analyzed with a special focus on the model outcome energy shortage and the social interaction. The analysis showed that the model results were very dependent on the uncertainties supply and consumer population and showed the importance of key players in the social network. The analysis of the model interventions revealed that decision makers should choose interventions that target the susceptible consumers and interventions that reinforce each other. In the first phase of the demand shifting contract system, consumers need to be engaged actively by repetitive intervention implementation. The final section elaborated on the trade-offs between shortage reduction and profit, costs and loss of convenience and between the number of shifters and the shiftable share of demand.

10 Discussion

This chapter reflects on the methodology as well as the generalizability of the results. This is followed by an ethical reflection on the control of the energy provider and some of the suggested interventions. The next section contains a discussion of the critical assumptions of this study and the research limitations. The final section deliberates the implications of the findings and presents policy recommendations for decision makers.

10.1. Reflection on the Methodology

A modeling and simulation study was a very useful way to combine the technical, economic and behavioral aspects of demand response in the energy sector and create a more inclusive model than prior demand response models. Agent-based modeling was also the right modeling technique, because it enables to include consumer differences on a personal level. One could argue that specific models would provide more precise information. There may be technical models that describe the current and future energy system in more detail. There are also more suitable methods to reveal how energy consumers make choices about their energy usage and how certain interventions would contribute to this. There are also better economic models that calculate prices or assess the possibilities of demand response under different pricing mechanisms. However, this model is the only one that combines all aspects and the modeling and simulation approach that was applied in this thesis was the favorable method to gain insights in the system dynamics and the interaction between different consumers and their environment on a system-level.

Normally, the literary field of consumer psychology uses qualitative research methods mainly. However, quantification was necessary to include the behavioral aspects in a quantitative model. The participation score was used to integrate the identified drivers of user participation. Combined with numerical thresholds it was possible to represent a consumer's choice to participate in demand response. Initially the participation score is the sum of a consumer's personal values, but whenever an intervention 'interacts' with a value, the score is increased or decreased. After the first simulation time step, the participation score is no longer just the sum of the values, but the sum of the values and their interaction effect with the interventions. With regard to the formalization, the outcomes can be verified. An increase in the participation score leads to a contract switch and this aligns with the model conceptualisation and the theories that support it.

In review of the deep uncertainty analysis that was performed with the EMA workbench, the results from this analysis did not show large variations in the model outcomes for the different interventions. This aligned with the expectations, as there were no clear tipping-points expected. The value ranges of the uncertainties supply and consumer population were very large which caused the model outcomes to vary a lot as well. In a potential case study, where the ranges of these uncertainties are smaller, smaller outcome ranges are expected as well.

An aspect of the model that made it less compatible for large-scale experimentation was the fact that each model run consisted of 35010 time steps, which resulted in large output files. Because of this, only 200 scenarios were run for each experiment. Nonetheless this was sufficient to cover the uncertainty space, because only two uncertainties were considered. If more uncertainties would have been incorporated, the number of experiments and required computational power would have increased heavily. A solution for this could have been to simulate a shorter time period than a year, but that would have caused the loss of seasonality. Besides, it would also have been peculiar to have four switching periods in a total simulation period of for instance a month. The time steps could have also been increased from 15 minutes to for example 1 hour, but that would have weakened the real-time nature of the model. Therefore it can be concluded that the used approach was suitable for these circumstances, but the advice would be to use servers with more computational power in the future to be able to run more experiments and analyze larger output files.

10.2. Reflection on the Generalizability of the Model Results

The validation of the model was discussed in chapter 9 and has proven to be difficult, because there was no real-world system to compare the results to. However, considering the purpose of the model to gather insights in the interaction between the energy system, consumers and interventions, this model was considered to be valid and the relative changes in the model outcomes can be generalized.

The exact values of the model outcomes, e.g. the model costs cannot be generalized directly, because they are based on many assumptions and fabricated input data. However, the relative outcomes can be generalized. An example of a generalizable results is the finding that an energy cost reduction can engage all cost-conscious consumers, but at a certain point a higher reduction will no longer increase the number of shifting contracts, because the remaining non-shifting consumers are not sensitive enough to price changes. More in-depth knowledge about the exact tipping point could be extracted if the model was used for a case study. Besides, it would be very interesting to study a specific case with real data to see if the results are generally the same as the results of this model.

So to answer the question if the results can be generalized: the answer would be that the results cannot be generalized directly, but that the model is very useful to see how the outcomes change relatively under different circumstances. The model itself is already quite general as it was built on a high abstraction level with the intention to use it for more specific case studies later on as well. The recommendation is to perform a small-scale case study with data availability, to reduce the uncertainty in the supply. The consumer population and the effects of the interventions can then be studied again.

10.3. Ethical Reflection

An argument given by consumers that do not want to participate in demand response is that they fear that the energy producers will have too much control. A first objection is that smart meters measure personal and valuable information that will be available to the energy producers. Secondly, if the energy producer has the power to shift demand of consumers automatically, which is the case in this study, the energy producer could potentially abuse this power. These arguments raise the question if it is desirable to give that much control to an energy producer. However, there are certain ways to reduce the control of the energy producer. First of all, guidelines for the data collection and the utilisation of data would be in place. Furthermore, the power of the energy producer over a consumer's energy usage can be reduced if the shifting contract would be accompanied by an additional application in which consumers can set their preferences. For example, if they really need to do laundry at a certain time, they could block a time slot for demand shifting. Another benefit of such an application would be that the choice to allow for shifting is not so definite and more consumers might consider to choose for a shifting contract. This method resembles some characteristics of default shifting, as the energy producer can shift demand, unless the consumers states otherwise in the app.

A default, or so-called opt-out policy, refers to a situation in which people automatically participate and need to unenroll actively, instead of starting without participating and enrolling actively. An example of a successful opt-out system is the opt-out donor system that has already been implemented in a number of countries and increased the number of registered organ donors impressively (Minsterie van Volksgezondheid, Welzijn en Sport, 2020). In order to ethically evaluate a default setting, the overall goodness of the consequences needs to be weighed (Smith et al., 2013). In other words, the benefits and the non-beneficial consequences need to be scaled. If a shifting contract would be the default, a prime benefit would be the additional reduction of energy shortage. This is beneficial for the environment, if this means no extra fossil fuels need to be combusted. Besides, it can have financial benefits for the energy producer, as well as the consumers. However, the downsides, the loss of convenience and the loss of freely choosing a contract, are only experienced on the consumers side. In order to assess whether it is ethical to force a contract on consumers, the overall benefits should weigh more than the downsides for the consumers.

Besides defaults, another form of green nudging is the use of social comparison, which has been applied in the model as the environmental comparison intervention. Green nudges aim to improve social welfare, but if consumers feel limited in their freedom or deprived, it can be questioned if a green nudging policy is ethical. Evans et al. specified four criteria that should be considered in the ethical evaluation of green nudges, namely autonomy, manipulation, transparency and proportionality (2017). Schubert discussed the argument of autonomy and concluded that green nudges seldom compromise a person's autonomy, but that people can still feel manipulated or deceived by certain nudges (2017). However, the environmental comparison intervention only provides information about the energy usage of a consumer compared to other consumers. Therefore this cannot be classified as manipulation, because a consumer is not forced to do something with this information and there is no hidden information. The intervention also checks the proportionality criterion, as it serves a legitimate goal and is adequate and not restrictive. Therefore the environmental comparison policy can be considered as ethical, as long as energy producers are transparent about their intentions behind the comparison.

10.4. Limitations of this Study

In this sections some of the critical assumptions and the model limitations are discussed. An overview of all assumptions that were made in this study can be found in appendix B.

10.4.1. Critical assumptions

This study did not aim to create a model that includes every detail, but a model that can provide insights on demand response enhancing policies considering different supply and consumer population scenarios on a high abstraction level. The true values of some model parameters are uncertain, because the model represents a future energy system and behavioral aspects needed to be represented as numerical values. Therefore, many assumptions were made about the energy system, supply and demand, policy effects and consumers. Although the use of assumptions is inevitable in simulation modeling, it is very important to underpin them with literature or clear lines of reasoning. This section will discuss the most critical assumptions.

Closed energy system
The first critical assumption is that in the model, the energy system was modeled as a closed system. This means that import and export of energy were not taken into account. Besides, energy losses of transportation were neither considered. A closed system also implies that the number of consumers was constant over time, which means consumers were not able to switch to another energy producer.

Another assumption was made on the supply side. It was assumed that the energy producer could predict shortage a few time steps ahead with a reasonable accuracy and could determine the required demand response and automated shifting based on this. With this assumption it was implied that the energy producer has access to accurate machine learning models and real-time energy consumption data. The smart grid and network of smart meters are the suppliers of this data.

Shifting and switching
Another very important assumption was that demand can only be shifted, when in reality energy consumption can also be reduced. For example, field experiments of peer comparison of energy usage showed that significant energy reductions were made by some consumers (Gyamfi et al., 2013). Considering this, the effect of real-time pricing and demand response on the energy shortage is expected to be more positive than the model in this research showed.

Another assumption that also relates to contract switching and demand shifting is that the hassle of switching was assumed to be included implicitly and was otherwise negligible. For example, whenever a consumer switches to a shifting contract and experiences too much negative effects, switching back is done after a period and this switch is not postponed due to the hassle of switching. Also, the consumers that would perceive the switching as most of a hassle are the people with a high value of comfort and they are also the consumers that never reach the threshold to switch anyway. Therefore it was assumed that the hassle of switching and perceived loss of convenience of demand shifting interact in a way that the hassle of switching is included in the switching itself and the value of comfort.

Social network and interaction
Firstly, it was assumed that the social network stayed the same over the whole simulation time. This means that consumers do not make new connections and are always influenced by their most influential neighbor. Besides, there were numerous possibilities to construct the social network and model the social interaction, so choices and assumptions needed to be made. For the construction of the network it was assumed that consumers prefer to establish a connection with a consumer of the same type. Additionally, the chance that consumers that already have a lot of connections meet new people is higher, which led to the assumption that the social network was constructed based on the Barabási-Albert algorithm that was extended with preferential attachment to same type consumers. This algorithm leads to networks with a few key nodes that have a lot of connections. It was difficult to select an algorithm that resembles the social relations between consumers in a neighbourhood best and other algorithms to construct the social network could have been explored too. If another algorithm would have been applied, the key consumers might have been less powerful in the social interaction, because their degree would have been lower.

It was assumed that the influence of a consumer is determined by their degree centrality, which simply refers to the number of connections that a consumer has. Other potential measurements of a consumer's social influence that could have been used are the betweenness centrality, which counts the number of times a consumers is on the shortest path between other consumers and closeness centrality, which measures how close a consumer is to all other consumers in the network. If betweenness centrality would have been applied, the central nodes would have been more influential, even if they only have two connections and function as a connector. If closeness centrality would have been applied, the consumers in a dense part of the network would have been more influential than the consumers on the edges. This does not seem to represent the reality of social interaction, because consumers with only one connection or one 'good friend', that again has just 2 connections, would be influenced only little by this one connection. This discussion supports the choice for using the degree centrality in the model.

Another assumption was that consumers are only influenced by their most influential connection, which could be argued. However another option would be to take the average influence of all of a consumer's neighbors, but in reality a person also does not have the average opinion of all his friends. For the modeling objective it was most important that the resulting social interaction effect was reasonable and mimicked real world behavior. It was aspired to do this properly, but a formalization of social interaction cannot be perfect by definition.

10.4.2. Model limitations

By definition a simulation model is limited, because it is a simplified representation of reality and a selection has to be made of the real-world aspects that can be included. In addition to this general model limitation, specific limitations of this study are the lack of real data and uncertainty in parameter values, since it concerns a possible future scenario of the energy system. The limitations that are mentioned below are mainly consequences of the study scope and could not have been improved in all cases. Nevertheless, it is important to mention these limitations and to keep them in mind when reading the policy implications of the findings.

Data availability
Since the study focuses on a future scenario on a high abstraction level, no real case study data could be used. To solve this problem, historical data was adapted to the future expectations. The historical data that was used for demand and supply came from different countries, though with a similar climate and culture. The demand curve might look differently in the future, because there is more heating by electricity and most likely a higher total energy consumption. On the supply side, the model only took wind and solar into account as renewable sources, because they are volatile. However, if a part of the supply would consist of more stable renewable energy sources, such as hydropower or geothermal energy, the energy shortages would have been lower. In future research, the composition of the energy sources will be known, and this limitation can be solved.

Consumer conceptualization
The consumer conceptualization was mainly based on literature, instead of a survey or field experiment, because these could not be conducted due to time limitations. A survey could have presented more insights on the scores of consumer types on the selected values. However, a quantification of consumer values and behavior will always be necessary and imperfect. In the model the participation score consists of the five selected values, but in reality other values, factors or externalities can also play a role in the decision to allow for demand shifting or not. Even with more detailed research, it will remain difficult to represent the decision making of the consumers correctly, because it can be considered as a black box, where interventions and external input go in and the behavior change comes out. This study tried to capture the changes inside the black box by using the participation score and switching thresholds.

This study defined consumer types in the user segmentation section for modeling purposes, but it should be born in mind that these types are not a perfect representation of reality, as consumers are more diverse. For example, a consumer that cares about convenience, can also care about the environment. Actually, this might be one of the biggest trade-offs consumers are currently face, especially progressive energy consumers who are used to convenience, but would also want to be more environmentally friendly.

Simplification versus interpretability
The interpretation of the model results from the experiments was complicated by the randomness that was included in the consumers values and the social network. The random aspect led to the fact that the experiment setup was never exactly the same. For instance, the consumer randomness in the consumer values caused that the same amount of cost-conscious consumers could have a different distribution of initial shifting contracts, because their participation scores varied around the threshold between a no shifting and a shifting contract. On the other hand, removing the randomness of consumer values would make the consumers less truthful, because consumers are diverse in reality. For some of the experiments, certain randomness was removed from the model to look at the pure effect of a certain model parameter. Therefore a trade-off between further simplification of reality and the interpretability of the results was present due to the randomness in the model.

10.5. Implications of the Findings

The previous sections discussed the model limitations and important assumptions that need to be kept in mind while examining the model results. It was necessary to make assumptions and safeguard simplicity in the model to be able to study the desired model scope. The high-level scope of this study has made it possible to gain insight in the system dynamics of demand response in a future electricity grid. The findings of this research can be translated into policy recommendations for decision makers that want to limit the energy shortage and increase the user participation in demand response. The advice is primarily directed at energy producers, but can also be useful for decision makers in the energy transition on different governmental levels. Diverse recommendations can be made about many aspects of the system such as energy shortage, consumer participation, system interventions, but more research is sometimes needed to give more detailed and hands-on advice. This section summarizes the policy recommendations and proposes future research.

10.5.1. Policy recommendations

As the model results showed, the supply is the main determinant of the future energy shortages. Therefore it is very important for energy producers to consider a more stable future energy mix, that is still mainly renewable. Instead of only considering solar and wind, a more diverse energy mixture could prevent periods of little generation and limit the dependency on a small number of energy sources. If the energy shortage periods can be limited to short time periods, demand response could effectively reduce the shortages if the user participation is sufficiently high.

Another insight from the uncertainty analysis is that the consumer population determines the chances of increasing the user participation in demand response. Therefore it is important to have knowledge about the values of the consumers in the population to be able to choose the most suitable interventions. Not all consumers can be convinced, so it is recommended to use a personalized and targeted strategy to convince the persuadable consumers. It can be a better strategy to target several consumers successfully instead of making all consumers a bit more interested in demand response. To sustain a high user participation in demand response, it is important that decision-makers can permanently transform consumers from passive to active consumers that perceive reducing energy shortages as a shared responsibility. In the adoption phase, repetitive intervention is needed to sustain the effect. Additionally, it is important to choose a combination of policies that reinforce each other, for example an environmental awareness campaign and a comparison of environmental friendliness.

The financial interventions showed the most promise to increase the user participation. For energy producers it is recommended to use a real-time pricing function based on supply-demand mismatch to create substantial price differences between consumers that do and do not switch demand to encourage demand shifting. However, the price function should be adapted to make sure that the energy producer can provide shifters a cost reduction, without losing a lot of profit. In this study, consumers could not switch to other energy producers, but competition in the real-life energy market opposes this. Therefore, an energy producer should also assure that a no shifting contract with real-time pricing is appealing to consumers, compared to possible flat pricing options of other energy providers.

In the model, both information campaigns were targeted at all consumers that had a no shifting contract and did not lead to large increases in the user participation. However, from the analysis of the social network it became clear that a small number of key players in the social network can influence a large number of consumers. Hence, a recommendation for energy providers is to try to localise the influential consumers and find out if there are possibilities to cooperate with them in the marketing of demand shifting. This approach could be a more efficient way of informing consumers than implementing a large scale information campaign.

A final advice is to always carefully consider the ethical implications of the interventions. Green nudges are ethical as long as implications on the autonomy of consumers is limited, the intentions of the energy provider are transparent and not manipulative and if restrictions for consumers are proportional with the personal and societal benefits.

10.5.2. Recommendations that need further research

First of all, the model focused on the residential demand and did not include the energy demand from the retail sector and industry. If this would be included, the total demand curves would look differently and would have less of an evening peak. Also, shiftability of demand in these sectors might be able to compensate for the residential evening peaks as well. The interaction between these sectors could be interesting to study for the energy producers. Currently there was also no diversification of the demand curves of different consumers in the model. All consumers had the same energy demand during the year and the same demand pattern. In reality the energy demand of households varies depending on the household size, housing type and lifestyle. Therefore it is recommended to expand the model by including diversity in the household demand curves. A future study could find out if an energy producer might need to consider if some households should be prioritized in the targeting of the interventions, for example the households that use a lot more energy than average during peak demand hours.

Secondly, the consumers could choose between three contract types in the model, in which they could give the energy producer the power to switch different shares of their demand. An advantage of these contracts is that it should reduce the hassle for consumers, because demand shifting is automated. In this study, the interventions were applied to convince consumers to switch to a shifting contract. However, if these contracts were non-existent, the interventions would be aimed directly at consumers to shift demand themselves. Due to the current modeling approach it was not considered that consumers could shift some demand themselves, even if they did not have a shifting contract. On the other hand, a system without shifting contracts and automated demand response might also lead to fewer shifted demand by the consumers who would have chosen for a shifting contract in the contract system. Based on this, the system of shifting contracts seems suitable for maximizing demand response, but to be sure about the best system, it is recommended to compare demand response in a situation with and without shifting contracts in a future study.

Lastly, the results showed that the default shifting option significantly decreased the energy shortage, which makes it an interesting policy to study further. In this study it was only possible to switch to a different shifting contract after an entire switching period. However, the default shifting policy could be altered by allowing consumers to actively switch to a no shifting contract after a shorter period. Moreover, an application could be developed in which consumers can state their demand shifting preferences for certain time periods. With this application, a default shifting option would not even limit the freedom of energy usage of the consumers. It would only require the active deed to change the preferences. If this form of default shifting would be implemented by energy producers, the unethical implications would be limited and the consumer would be more aware and actively engaged in the energy shortage issue. Therefore it can be concluded that the default shifting option can be an ethically acceptable policy, if the non-beneficial consequences for the consumers are reduced. However, more research is needed to determine if a default shifting option can still reduce the energy shortage significantly with softer restrictions and an application to set preferences. More research is also needed to determine the required features for such an application for consumers.

10.6. Conclusion

This chapter has discussed the limitations of the study by reflecting on several critical assumptions and model limitations. The methodology was reviewed and it was concluded that quantification and the use of thresholds were necessary to include the behavioral and social model aspects. Since a lot of assumptions and simplifications were made, the numerical results of the model cannot be interpreted as true values. Nevertheless, the relations between changes in interventions, consumers and how they influenced the model outcomes relatively, can be generalized. The ethical reflection of the interventions and automated demand shifting concluded that there is no ethical obstruction as long as transparency and consumer autonomy are safeguarded. Many policy recommendations could be made to energy producers based on the model insights, although some require further research.

11
Conclusions and Recommendations

This final chapter concludes this study by answering the main research question. The next section revisits the sub-questions and presents a concise answer for each of them based on this research. Subsequently, the scientific and societal contribution are discussed after which the final section presents recommendations for further research.

11.1. Main Research Question

In this research an agent-based model simulation and deep uncertainty analysis have been applied to gain more insight in the effectiveness of different interventions to increase the user participation in demand response, while considering consumer diversity. The main research question will now be answered, which was the following:

How can a simulation model be used to analyze the influence of consumer heterogeneity on the success of demand response enhancing policies in future electricity networks?

A simulation study has proven to be a successful tool to perform an integrated study that includes the technical, economic and behavioral aspects of the future energy system, because it could provide a comprehensive system overview. This type of a simulation study and even this model specifically are very suitable for future case studies, especially on a local scale. The model was constructed in a very parametric way, which makes it easy to adapt parameter values and input data in future studies. The consumer population and differences in consumer values had a significant impact on the model outcomes and the number of participators in demand response, which is why it can be concluded that a behavioral component enriched the model. Therefore it is recommended to keep on including the social and behavioral component in future research to decide on a suitable approach to engage most people and better assess the potential of demand response.

The potential of demand response in the energy sector has been the topic of many research projects already, but they often focused on the technical and economic details and thereby neglected or only paid limited attention to consumer participation. Therefore, this study had a special focus on the consumer heterogeneity and the drivers of consumers to participate in demand response. An agent-based model combined with exploratory modeling was used to assess the effectiveness of interventions in increasing the user participation, while considering various consumer populations and quantities of supply.

This simulation study presented a number of trade-offs in demand response and participation for both the energy producer as well as different consumer types. The research also shed a light on the interaction between consumer values and different kinds of policy interventions, which makes it possible to present a policy strategy that is personalized and suits the consumers in the population. Besides, the results in the experimentation phase showed the large influence that supply and the composition of the consumer population have on the potential user participation of demand response. These variables were uncertain in this research, but can be included more accurately in future case studies when real-world data would be available. The results of this research showed that it is important to incorporate consumer heterogeneity in demand response research, as it can influence the effectiveness of policy interventions and strategies. Consequently, including consumer heterogeneity also enables a more realistic assessment of the consumer participation in demand response.

11.2. Sub-research Questions

After answering the main question, this section will revisit the answers to the sub-questions that led to the answer of the main question. The answers to the sub-questions are used to summarize and reflect on the research.

Sub-question 1: Which concepts can be included in the model to represent the differing energy usage decision making of energy consumers?

Four consumer types were included in the model, namely the green, cost-conscious, convenience-oriented and indifferent consumer. These consumer types were based on a review of literature and surveys. The following five values were identified as important moderators for the user participation in demand response:

– *Value of price* - The value of price refers to a consumer's sensitivity to price and cost differences.

– *Value of environment* - The value of environment represents environmental concern and is a measure for how sensitive a consumer is for the impact of an energy product or energy consumption on the environment.

– *Value of comfort* - The value of comfort refers to the fact that consumers might not want to shift their demand, because they do not want any inconvenience or because they think is it a hassle.

– *Value of safety* - The value of safety relates to the perceived risks by energy consumers linked with joining demand response programs, such as financial risks and loss of control.

– *Value of social norm* - The value of social norm represents how sensitive a consumer is to the behavior and opinion of others and how much his own behavior is influenced by this.

These values were combined in a participation score that was used to determine the initial shifting contract of a consumer. The shifting contract options were no shifting, shifting or full shifting and the contract options that allow for demand shifting were chosen if the participation score reached certain threshold values. Additionally, all agents were part of a social network that included preferential attachment, which means agents preferred to connect with consumers with a lot of connections, as well as consumers of the same consumer type. Social interaction occurred based on this network and the value of social norm of a consumer. Throughout the simulation, social interaction and interventions could interact with the personal values and change the participation score. After a switch period, it was possible for consumers to switch to a different contract type.

Sub-question 2: How can the future electrical grid be modelled as an agent-based model?

Two main features of the future grid that needed to be incorporated in the model were a high share of renewable supply and the implementation of a smart grid and smart meters. The technical electrical engineering and economic electricity market details were not included in the model, because they were not required to study the model and agent behavior on the desired study scope. For this study only a copper plate model consisting of demand and supply was used to represent the electrical grid. Additionally, the electricity price was based on demand and supply at each time step.

The energy supply in the model consisted of a constant fossil base load and a variable renewable amount of wind and solar energy. For the demand a standard demand profile was adopted from the Dutch association of energy data exchange. Each household had a total yearly energy usage of 3500 kWh of which certain amounts were shiftable. Two categories of flexible demand were included, namely fully shiftable demand such as heating and semi-shiftable demand such as a dishwasher. The supply, demand and shiftable shares of demand showed a typical daily and seasonal variability. Three different pricing schemes were incorporated in the model. First of all flat pricing, which means that the price was constant over time. Furthermore, real-time pricing was integrated in two ways, namely based on the available amount of supply and based on the current energy shortage.

In conclusion, the electrical grid could be modelled as an agent-based model by using a copper-plate model of supply, demand and price. This was the decision environment for the model agents that represent consumers. The smart grid infrastructure was implicitly incorporated by assuming that the energy producer had full information and could automatically shift demand of consumers who allowed for this in their energy contract.

Sub-question 3: Which price- and incentive-based interventions can be implemented as policy levers in the model?

The first price-based intervention that was implemented at all times besides the base case, is real-time pricing. In periods of shortage this resulted in high energy prices to discourage consumers to use energy at times of peak demand. An additional financial intervention was cost comparison with a possible supplementary reduction. This intervention led to lower costs for consumers that allow for demand shifting, because they bought less energy in expensive peak periods and received an additional reduction. To compare the costs of consumers, energy producers periodically sent their consumers a comparison of their own costs compared to other consumers.

The other interventions can all be classified as green nudges. The comparison of environmental friendly behavior intervention compared the environmental score of consumers. This score depended on whether energy was purchased in times of high renewable supply, sufficient supply or energy shortage. The energy producer could send out a similar comparison report as for the cost comparison to inform the consumers about their environmental friendliness. Two information campaigns were included in the model as well. The environmental awareness campaign focused on awareness of energy consumption and the impact on the climate, whereas the smart meter information campaign concentrated on safety and convenience concerns related to the smart grid and demand shifting. The final intervention was default shifting, that introduced an opt-out system in which all consumer started with a shifting or full shifting contract.

All of these interventions were implemented by the energy producer. However energy shortage can also be considered to be a societal problem that is of public interest. Therefore, policy makers on a governmental level might also be interested to contribute to stimulating user participation in demand response. For example, these policy makers could give subsidies to energy providers that give out reductions for shifters or launch public information and awareness campaigns.

Sub-question 4: What is the effect of an increase in the share of renewable supply on energy balance in the electricity grid, given current infrastructure and demand?

This question can be answered by looking at the results of base case A. This base case described the future scenario that would be the reality if no policies would be implemented at all and flat pricing would be the standard pricing scheme. In this scenario, consumers would not be incentivized to shift demand, which means that energy shortages would occur regularly. An increase in the share of renewables would result in a more volatile energy supply with a higher risk of energy shortages if the amount of fossil generation decreased simultaneously. However, if the fossil supply remains constant and the renewable production increases, the risk of energy shortages reduces and more energy can be stored.

The results showed clear differences in the amount of energy shortage between winter and summer weeks. In the winter weeks, periods of shortage were longer and shortages were larger, because the supply depended on wind energy mainly, as solar generation was generally low. Therefore, periods with little wind in the winter caused the biggest issues. Incorporating more stable renewable energy sources and including more storage could reduce this problem.

Sub-question 5: Which policy strategy ensures the strongest demand response under many different scenarios?

In base case B, real-time pricing and shifting contracts were implemented. Different distributions of contract shares were tested and the results showed that a high user participation in demand response could reduce or even completely resolve periods of energy shortage. However, demand response could only reduce energy shortage if the shortage period was shorter than the maximum time that demand can be shifted and if the mismatch between demand and supply was not too big. Nonetheless, a high user participation resulted in less shortage in each supply scenario, which is why interventions were implemented to encourage people to switch to a shifting contract.

These different interventions were tested in 200 scenarios which were composed of different variations of the uncertainties supply and consumer population. The two interventions that improved the user participation most independently were cost comparison with a reduction and default shifting. However, the results showed that a policy strategy could better exist of a combination of policies that reinforce each other. A policy combination that came out strong was the combination of cost comparison with a reduction and an information campaign. However, when comparing the separate interventions as well as combinations of interventions it became clear that in general, more policy led to higher user participation in demand response.

Sub-question 6: How do different characteristics of the consumer population influence the effectiveness of policy interventions to enhance demand response?

Each of the model interventions interacted with certain personal values. For example the effect of the cost comparison and reduction policy depended on the value of price. In general, the effect of an intervention was stronger if a consumer valued the targeted criterion highly.

The effectiveness of a policy intervention did not only depend on the targeted value, but also on the initial participation score of a consumer. For the green consumers, the initial score varied around the threshold between a shifting and a full shifting contract and for the cost-conscious consumers, the initial score varied around the switching threshold between a no shifting and a shifting contract. Because of this, these consumer types could be incentivized by interventions to switch to a different contract option. However, the convenience-oriented and the indifferent consumers were not encouraged enough by the interventions to pass the thresholds and switch to a shifting contract. Therefore the consumer population was an important determinant for the effectiveness of interventions. If the population consisted of a lot of cost-conscious consumers, the effectiveness of financial policies was very large. However, if the population consisted of a lot of convenience-oriented and indifferent consumer is was very difficult to make significant changes in the contract shares and increase the user participation.

The key takeaway is that it is important to understand what kind of consumers are part of the consumer population and what values they find important. Based on this knowledge, the interventions that interact best with these values should be prioritized. Based on the consumer population, it can also be concluded that the consumers might not be susceptible for the interventions and that user participation in demand response is unlikely to increase. In that case, other options than demand response need to be implemented to reduce the energy shortages. Nonetheless, if some consumers are in doubt about participating, the decision maker could better go for an intervention strategy that convinces these consumers specifically, instead of choosing an intervention that encourages all consumers a little.

Sub-question 7: How can the outcomes of this study be used to advise decision makers about stimulation of user participation in demand response?

As mentioned in the answer to the previous sub-question, the consumer population and their values determine the effectiveness of different policies, so the intervention strategy should be customized for the population and personalized for each consumer type. The deep uncertainty analysis also showed that the amount of supply mainly determined the shortage and also determined if demand response could even be useful. For example in case of very large shortages for a long period, the problem could also not be solved even if all consumers would allow for demand shifting. In scenarios with more supply, so less heavy shortages, it was beneficial to engage more consumers in demand response by using the interventions. From the analysis of the results it can be learned that it is important to choose a combination of policies that reinforce each other. Also, implementation needs to be repetitive in the adoption phase of demand response and the switching contracts in order to sustain the policy effect and prevent a fallback in the number of consumers with a shifting contract. In the long run, if participation in demand response programs has become the social standard, less interventions might be needed, because more people will be engaged if familiarity and trust have increased by experience (Parrish et al., 2020).

The exact numerical results of the experiments cannot be interpreted as true values, because of the model assumptions and stylized data. However, the relative effects of the interventions in different scenarios can be used to advice policy makers about strategies to increase user participation in demand response, as was done in the previous sub-question. Furthermore, this model could be used for small-scale case studies, to be able to advice policy makers and energy producers more explicitly.

11.3. Scientific Contribution

Quite a lot of research has already been done in the field of demand response in the energy sector. However, previous research was mainly performed for the day-ahead market and focused on the technical aspects of real-time pricing and demand response (Amini et al., 2019, Arias et al., 2018, Dutta and Mitra, 2017). Most of these studies used mathematical models to shift the demand optimally, but were limited in the incorporation of uncertainties, such as user participation (Jordehi, 2019, Wang et al., 2019, Zhao and Mutale, 2018). Demand heterogeneity was sometimes incorporated in the models, but this was not often the case for consumer heterogeneity. On the other hand, qualitative research is available from behavioral economics and consumer psychology that studied consumers and their drivers for participation in demand response. (Batalla-Bejerano et al., 2020, Parrish et al., 2020, Sütterlin et al., 2011). However, these drivers have not yet been incorporated in a quantitative demand response model.

In consideration of former research and the identified academic knowledge gaps, this thesis analyzed how interventions influence the user participation in demand response by applying exploratory modeling to an agent-based simulation model that integrates the technical, economic and behavioral aspects of the system. Thereby, scientific contributions were made to three segments of literature, namely demand response in the real-time market, user participation in demand response, and the use of simulation and exploratory modelling.

First of all, demand response in the real-time energy market was understudied, because of the current lack of the required smart grid communication infrastructure and the higher complexity of real-time predictions. However, a stylized future energy system was defined in this study to analyze demand shifting in the real-time energy market, with a real-time pricing component based on the energy mismatch at each time step. Additionally, this thesis studied an innovative demand response strategy, in which consumers do not shift demand by themselves, but the energy demand is shifted automatically by the energy producer if consumers have a contract that allows that. This research has contributed to literature about the real-time market by showing a possible contract and pricing system for automated demand shifting that could be applied in a future smart grid infrastructure.

Another knowledge gap that was discovered was the fact that user participation in demand response models was understudied, even though it is of great importance for the success of demand response. Therefore the model in this study incorporated the consumer behavior extensively by studying personal values that affect the decision to participate in demand response and by including social interaction. Firstly, a new consumer segmentation was defined based on previous literature to include consumer heterogeneity. Additionally, this research has introduced a new approach to represent consumer decision making about demand response in a quantitative manner and incorporate this in a quantitative agent-based model. The resulting simulation model was able to provide comprehensive insights about user participation in demand response on a system level, because the technical, economic and behavioral system components were combined.

The final scientific contribution relates to the exploratory modelling approach that has been applied. This study has shown that modelling under deep uncertainty can be used to systematically analyze the interventions and uncertain factors that influence the user participation in demand response. The extensive scenario analysis in this thesis showed the strong influence of supply and the consumer population on the model outcomes and once again stresses the importance of knowing your consumer population, when decisions need to be made about interventions that are supposed to increase the user participation in demand response. An intervention strategy should be custom made for the consumers and personalized to be most effective. Therefore it is definitely recommended to include a behavioral aspect in future research as well. The constructed model could be reused for future case studies to assess the user participation in demand response in specific real-life networks. Considering this, the model itself is a scientific contribution as well.

11.4. Societal Contribution

The energy transition is one of the grand challenges of our time and renewable power plants are emerging in many places already. An increase of the share of renewable energy generation decreases the reliability of energy supply, which will require policy interventions to ensure energy balance sooner or later, because energy shortages may absolutely not occur. The future energy system is susceptible to a lot of uncertainty. Therefore this simulation study of a future scenario is helpful for decision makers, because it provides a comprehensive overview of the system dynamics. Besides, the model can be used as a tool to help policy makers and energy providers decide on the best intervention strategy to increase user participation in demand response for a specific consumer population.

As this thesis studied a potential future energy grid, several lessons were learned that might influence decision making now. First of all, the results showed that the supply was a main influence on the energy shortage and that demand response could not provide significant improvements in periods of extreme shortage. These extreme shortages were caused by the volatility of solar and wind energy and were especially large in the winter. Additionally, the results showed that demand response can reduce the shortages when a substantial number of consumers allows for demand shifting, but that the shortage periods could not be solved by demand response only in most of the cases. For this reason storage was included in the model to provide energy in case of remaining shortages after demand shifting. Subsequently, the required storage amount was determined by the winter periods with the greatest shortage issues. A first conclusion that can be drawn from the above is that investing in a more stable or diverse energy mix could decrease the risk of large energy shortages during the winter. Furthermore, demand response alone cannot solve future energy shortages, but additional measures such as storage are required to serve as a back-up. This study also analyzed the effect of interventions on consumers types, but the results showed that engagement of consumers is difficult, especially in the early adoption phase of a new system with contracts for automated demand response. Therefore a final recommendation is that active stimulation is needed to engage consumers and convince them with green nudges or financial benefits. To sustain a high user participation in demand response, it is important that decision makers can transform consumers from passive to active consumers that perceive energy shortage as a shared responsibility.

11.5. Future Research Suggestions

This study developed a method to assess the potential demand response by using a model that included consumer's drivers to participate. Due to the limited time frame of this study, assumptions and simplification had to be made. These have been discussed in chapter 10. Nevertheless, the model was able to provide insights on the effectiveness of interventions to increase user participation in demand response in different scenarios of supply and consumer population. As mentioned before, the model would be suitable to use in small-scale case studies, where real data is available for the energy supply and preferably for the consumer population as well. Subsequently, the main advise for future research is too use the model for more specific case studies.

Besides this, many other suggestions for future research can be made. First of all a similar study could be done for the industrial or retail sector to find out if consumers values also play a role in participation there. Apart from this, it would also be very valuable if future research would be able to replace some of the model assumptions by empirical evidence. For example the ranges of the uncertain parameters could be defined more accurately. Likewise, when the supply and the composition of the consumer population are no longer uncertain in future case studies, the scenario analysis could be extended with other system uncertainties.

Even though the consumers were studied more in-depth in this thesis, more research can be done in this area. First of all different types of households could be included, which would result in more variety in the demand curves of the consumer population. Besides, the knowledge about consumer values for this specific system of shifting contracts could be improved by conducting a survey among energy consumers. For example, a stated choice experiment in which the future context is described clearly could be performed to gain more insight in the consumer trade-offs between loss of comfort, safety, costs and the impact on the environment. A field experiment could also be used to study consumer behavior under specific interventions. A suggestion for this would be to explore the effects of the periodical comparison of costs and the environmental score on consumer's opinion about the different shifting contracts. Additionally, future research is also suggested to gain more insights about the social network of energy consumers and the role of social interaction. Additionally, possible research options are to look at different network creation algorithms or to allow for a dynamic social network in which relations change during the model simulation.

With respect to the interventions that were studied, each of them could be studied more thoroughly to try to grasp the effect in more detail and improve the accuracy of the model. For instance, the effect of a smart meter information campaign was quantified based on literature, but future research might be able to estimate the true effect of such a campaign on different consumer types more accurately by reviewing similar campaigns or interviewing experts. It would also be interesting to not only study the best combination of policies, but also look at the best strategy over time and the order of implementation of interventions. Besides, more interventions could be considered, as this study only selected a few due to time limitations. Especially if more information is available about the consumer population that is targeted, the interventions can be accustomed to the dominant values in the population.

The only costs that were considered in this study were the electricity costs of the consumers, which were directly interpreted as profits for the energy producer. For the policies, the costs of implementation were not considered, except for the cost comparison with a reduction intervention. A financial analysis of the other interventions would make it possible to compare all of the interventions in terms of shortage reduction versus costs. Based on that, a more comprehensive advise could be given to the energy producer about the selection of interventions. Besides the costs of the interventions, the costs of demand shifting and storage should be compared to other potential technologies such as grid expansion or importing energy as well. Another recommendation for future research would thus be to perform an overall cost-benefit analysis of demand response according to the introduced contract shifting system. This would be desirable for policy makers and energy producers that need to decide if it is worth it to invest in demand response from a financial point of view.

Bibliography

Allcott, H. and Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104(10):3003–37.

Amini, M. H., Talari, S., Arasteh, H., Mahmoudi, N., Kazemi, M., Abdollahi, A., Bhattacharjee, V., Shafie-Khah, M., Siano, P., and Catalão, J. P. Demand response in future power networks: panorama and state-of-the-art. In *Sustainable interdependent networks II*, pages 167–191. Springer (2019).

Arias, L. A., Rivas, E., Santamaria, F., and Hernandez, V. (2018). A review and analysis of trends related to demand response. *Energies*, 11(7):1617.

Axtell, R. (2000), *Why agents?: on the varied motivations for agent computing in the social sciences.* Center on Social and Economic Dynamics - Brookings Institution.

Barabási, A.-L. and Bonabeau, E. (2003). Scale-free networks. *Scientific american*, 288(5):60–69.

Barai, G. R., Krishnan, S., and Venkatesh, B. (2015). Smart metering and functionalities of smart meters in smart grid-a review. *2015 IEEE Electrical Power and Energy Conference (EPEC)*, pages 138–145.

Baron, R. A. and Byrne, D. (1987), *Social psychology: Understanding human interaction.* Allyn & Bacon.

Batalla-Bejerano, J., Trujillo-Baute, E., and Villa-Arrieta, M. (2020). Smart meters and consumer behaviour: Insights from the empirical literature. *Energy Policy*, 144:111610.

Bergquist, M. and Nilsson, A. (2018). Using social norms in smart meters: the norm distance effect. *Energy Efficiency*, 11(8):2101–2109.

Cardella, E., Ewing, B. T., and Williams, R. B. (2020). Green is good–the impact of information nudges on the selection of voluntary green-power plans. *Southern Agricultural Economics Association's 2018 Annual Meeting.*

CBS (June 2019). Share of renewable energy up to 7.4 percent. Retrieved from `https://www.cbs.nl/en-gb/news/2019/22/share-of-renewable-energy-up-to-7-4-percent`. Accessed on 2010-05-02.

Chappin, É. J., Nikolic, I., and Yorke-Smith, N. (2020). Agent-based modelling of the social dynamics of energy end use. *Energy and Behaviour*, pages 321–351.

Chow, K. and Lui, S. (2020). Passive-positive organ donor registration behaviour. *Hong Kong medical journal= Xianggang yi xue za zhi*, 26(3):169–170.

Dai, Y., Gao, Y., Gao, H., Zhu, H., and Li, L. (2017). A real-time pricing scheme considering load uncertainty and price competition in smart grid market. *Journal of Industrial & Management Optimization*, 13(5):1.

De Vries, G., Rietkerk, M., and Kooger, R. (2020). The hassle factor as a psychological barrier to a green home. *Journal of Consumer Policy*, 43(2):345–352.

Delmas, M. A., Fischlein, M., and Asensio, O. I. (2013). Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. *Energy Policy*, 61: 729–739.

do Prado, J. C. and Qiao, W. (2018). A stochastic decision-making model for an electricity retailer with intermittent renewable energy and short-term demand response. *IEEE Transactions on Smart Grid*, 10(3):2581–2592.

Durillon, B., Davigny, A., Kazmierczak, S., Barry, H., Saudemont, C., and Robyns, B. Demand response methodology applied on three-axis constructed consumers profiles. In *2019 International Conference on Smart Energy Systems and Technologies (SEST)*, pages 1–6. IEEE (2019).

Dutta, G. and Mitra, K. (2017). A literature review on dynamic pricing of electricity. *Journal of the Operational Research Society*, 68(10):1131–1145.

Eksin, C., Deliç, H., and Ribeiro, A. (2015). Demand response management in smart grids with heterogeneous consumer preferences. *IEEE Transactions on Smart Grid*, 6(6):3082–3094.

Elreedy, D., Atiya, A. F., Fayed, H., and Saleh, M. (2019). A framework for an agent-based dynamic pricing for broadband wireless price rate plans. *Journal of Simulation*, 13(2):96–110.

Eurostat (2020). Electricity prices for household consumers. Retrieved from `https://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics#Electricity_prices_for_household_consumers`. Accessed on 2020-10-02.

Evans, N., Eickers, S., Geene, L., Todorovic, M., and Villmow, A. (2017). Green nudging: A discussion and preliminary evaluation of nudging as an environmental policy instrument. *Environmental Policy Research Centre FU Berlin*.

Fang, X., Misra, S., Xue, G., and Yang, D. (2011). Smart grid—the new and improved power grid: A survey. *IEEE communications surveys & tutorials*, 14(4):944–980.

Farhangi, H. (2009). The path of the smart grid. *IEEE power and energy magazine*, 8(1):18–28.

Frankel, D., Heck, S., and Tai, H. (2013). Using a consumer-segmentation approach to make energy-efficiency gains in the residential market. *McKinsey and Company*.

Fürsch, M., Hagspiel, S., Jägemann, C., Nagl, S., Lindenberger, D., and Tröster, E. (2013). The role of grid extensions in a cost-efficient transformation of the european electricity system until 2050. *Applied Energy*, 104:642–652.

Gadenne, D., Sharma, B., Kerr, D., and Smith, T. (2011). The influence of consumers' environmental beliefs and attitudes on energy saving behaviours. *Energy policy*, 39(12):7684–7694.

Good, N. (2019). Using behavioural economic theory in modelling of demand response. *Applied energy*, 239:107–116.

Grewal, D., Ailawadi, K. L., Gauri, D., Hall, K., Kopalle, P., and Robertson, J. R. (2011). Innovations in retail pricing and promotions. *Journal of Retailing*, 87:S43–S52.

Guthridge, G. S. (2010), *Understanding consumer preferences in energy efficiency: Accenture end-consumer observatory on electricity management.* Accenture, Dublin, Ireland, Tech. Rep. ACC10-0229.

Guthridge, G. S., Dary, M., Callaghan, S., Parmar, S., Manley-Casimir, N., and Bronchard, S. (2010), *Engaging the New Energy Consumer: Accenture perspective - operational imperatives for energy efficiency*. Accenture.

Gyamfi, S. and Krumdieck, S. (2012). Scenario analysis of residential demand response at network peak periods. *Electric Power Systems Research*, 93:32–38.

Gyamfi, S., Krumdieck, S., and Urmee, T. (2013). Residential peak electricity demand response—highlights of some behavioural issues. *Renewable and Sustainable Energy Reviews*, 25: 71–77.

Hall, N. L., Jeanneret, T. D., and Rai, A. (2016). Cost-reflective electricity pricing: Consumer preferences and perceptions. *Energy Policy*, 95:62–72.

Heimlich, J. E. and Ardoin, N. M. (2008). Understanding behavior to understand behavior change: A literature review. *Environmental education research*, 14(3):215–237.

Jordehi, A. R. (2019). Optimisation of demand response in electric power systems, a review. *Renewable and sustainable energy reviews*, 103:308–319.

Katz, J., Kitzing, L., Schröder, S. T., Andersen, F. M., Morthorst, P. E., and Stryg, M. (2018). Household electricity consumers' incentive to choose dynamic pricing under different taxation schemes. *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(1):e270.

Khadgi, P. and Bai, L. (2018). A simulation study for residential electricity user behavior under dynamic variable pricing with demand charge. *IISE Transactions*, 50(8):699–710.

Kwakkel, J. *EMA Workbench documentation* (n.d.). Retrieved from `https://emaworkbench.readthedocs.io/en/latest/index.html`.

Kwakkel, J. H. (2017). The exploratory modeling workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, 96:239–250.

Kwakkel, J. H. and Pruyt, E. (2013). Exploratory modeling and analysis, an approach for model-based foresight under deep uncertainty. *Technological Forecasting and Social Change*, 80(3):419–431.

Lammers, I. and Heldeweg, M. A. (2016). Smart design rules for smart grids: analysing local smart grid development through an empirico-legal institutional lens. *Energy, sustainability and society*, 6(1):36.

Lapinski, M. K. and Rimal, R. N. (2005). An explication of social norms. *Communication theory*, 15 (2):127–147.

Lempert, R. J., Popper, S. W., and Bankes, S. C. (2003), *Shaping the next one hundred years: new methods for quantitative Long-Term Policy Analysis.* RAND Santa Monica, California.

Li, S., Deng, K., and Zhou, M. (2014). Social incentive policies to engage commercial building occupants in demand response. *2014 IEEE International Conference on Automation Science and Engineering (CASE)*, pages 407–412.

Lijesen, M. G. (2007). The real-time price elasticity of electricity. *Energy economics*, 29(2):249–258.

Lodder, A. R. and Wisman, T. (2016). Artificial intelligence techniques and the smart grid: towards smart meter convenience while maintaining privacy. *Journal of Internet Law (Dec. 2015)*, 19(6): 20–27.

Lopes, M. A., Antunes, C. H., Janda, K. B., Peixoto, P., and Martins, N. (2016). The potential of energy behaviours in a smart (er) grid: Policy implications from a portuguese exploratory study. *Energy Policy*, 90:233–245.

Mack, B., Tampe-Mai, K., Kouros, J., Roth, F., Taube, O., and Diesch, E. (2019). Bridging the electricity saving intention-behavior gap: A german field experiment with a smart meter website. *Energy Research & Social Science*, 53:34–46.

Maier, H. R., Guillaume, J. H., van Delden, H., Riddell, G. A., Haasnoot, M., and Kwakkel, J. H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? *Environmental Modelling & Software*, 81:154–164.

Masad, D. and Kazil, J. (2015). Mesa: an agent-based modeling framework. *14th PYTHON in Science Conference*, pages 53–60.

McKenzie-Mohr, D. and Schultz, P. W. (2014). Choosing effective behavior change tools. *Social Marketing Quarterly*, 20(1):35–46.

Minsterie van Economische Zaken en Klimaat (November 2019). Integraal nationaal energie- en klimaatplan 2021-2030. Retrieved from`https://www.rijksoverheid.nl/documenten/rapporten/2019/11/01/integraal-nationaal-energie-en-klimaatplan`. Accessed on 2010-05-02.

Minsterie van Volksgezondheid, Welzijn en Sport (2020). Donorregister. Retrieved from `https://www.donorregister.nl/`. Accessed on 2020-01-24.

Mulder, M. and Scholtens, B. (2013). The impact of renewable energy on electricity prices in the netherlands. *Renewable energy*, 57:94–100.

Mureddu, M., Caldarelli, G., Chessa, A., Scala, A., and Damiano, A. (2015). Green power grids: How energy from renewable sources affects networks and markets. *PloS one*, 10(9).

Niesten, E. (2010). Network investments and the integration of distributed generation: Regulatory recommendations for the dutch electricity industry. *Energy Policy*, 38(8):4355–4362.

Öhrlund, I., Linné, Å., and Bartusch, C. (2019). Convenience before coins: Household responses to dual dynamic price signals and energy feedback in sweden. *Energy Research & Social Science*, 52: 236–246.

Open Power System Data. *Time series 15min single index load,wind and solar* (2020). Retrieved from `https://data.open-power-system-data.org/time_series/2020-10-06`.

Parrish, B., Heptonstall, P., Gross, R., and Sovacool, B. K. (2020). A systematic review of motivations, enablers and barriers for consumer engagement with residential demand response. *Energy Policy*, 138:111221.

Pichert, D. and Katsikopoulos, K. V. (2008). Green defaults: Information presentation and pro-environmental behaviour. *Journal of Environmental Psychology*, 28(1):63–73.

Pollner, P., Palla, G., and Vicsek, T. (2005). Preferential attachment of communities: The same principle, but a higher level. *EPL (Europhysics Letters)*, 73(3):478.

Poudineh, R. and Jamasb, T. (2014). Distributed generation, storage, demand response and energy efficiency as alternatives to grid capacity enhancement. *Energy Policy*, 67:222–231.

Robinson, J., Neenan, B., Flaim, T., and Bosivert, R. (2012). Understanding electric utility customers: What we know and what we need to know. Retrieved from `http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000000001025856`. Accessed on 2020-10-02.

Sangroya, D. and Nayak, J. K. (2017). Factors influencing buying behaviour of green energy consumer. *Journal of Cleaner Production*, 151:393–405.

Sargent, R. G. Verification and validation of simulation models. In *Proceedings of the 2010 winter simulation conference*, pages 166–183. IEEE (2010).

Schubert, C. (2017). Green nudges: Do they work? are they ethical? *Ecological Economics*, 132: 329–342.

Schultz, P. W., Estrada, M., Schmitt, J., Sokoloski, R., and Silva-Send, N. (2015). Using in-home displays to provide smart meter feedback about household electricity consumption: A randomized control trial comparing kilowatts, cost, and social norms. *Energy*, 90:351–358.

Semenza, J. C., Hall, D. E., Wilson, D. J., Bontempo, B. D., Sailor, D. J., and George, L. A. (2008). Public perception of climate change: voluntary mitigation and barriers to behavior change. *American journal of preventive medicine*, 35(5):479–487.

Shi, Q., Chen, C.-F., Mammoli, A., and Li, F. (2019). Estimating the profile of incentive-based demand response (ibdr) by integrating technical models and social-behavioral factors. *IEEE Transactions on Smart Grid*, 11(1):171–183.

Siano, P. (2014). Demand response and smart grids—a survey. *Renewable and sustainable energy reviews*, 30:461–478.

Smith, N. C., Goldstein, D. G., and Johnson, E. J. (2013). Choice without awareness: Ethical and policy implications of defaults. *Journal of Public Policy & Marketing*, 32(2):159–172.

Sterman, J. D. (2002). All models are wrong: reflections on becoming a systems scientist. *System Dynamics Review: The Journal of the System Dynamics Society*, 18(4):501–531.

Stern, P. C. (2000). New environmental theories: toward a coherent theory of environmentally significant behavior. *Journal of social issues*, 56(3):407–424.

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., and Kalof, L. (1999). A value-belief-norm theory of support for social movements: The case of environmentalism. *Human ecology review*, pages 81–97.

Sütterlin, B., Brunner, T. A., and Siegrist, M. (2011). Who puts the most energy into energy conservation? a segmentation of energy consumers based on energy-related behavioral characteristics. *Energy Policy*, 39(12):8137–8152.

Thaler, R. H. and Sunstein, C. R. (2009), *Nudge: Improving decisions about health, wealth, and happiness.* Penguin.

Van Dam, K. H., Nikolic, I., and Lukszo, Z. (2013), *Agent-based modelling of socio-technical systems*, volume 9. Springer Science & Business Media.

Vereniging Nederlandse EnergieDataUitwisseling. *Profielen Electriciteit 2020* (2020). Retrieved from `https://www.nedu.nl/documenten/verbruiksprofielen/`.

Voulis, N. (2019). Harnessing heterogeneity: Understanding urban demand to support the energy transition. (Doctoral dissertation, Delft University of technology). Retrieved from `https://doi.org/10.4233/uuid:9b121e9b-bfa0-49e6-a600-5db0fbfa904e`.

Wang, Z., Paranjape, R., Chen, Z., and Zeng, K. (2019). Multi-agent optimization for residential demand response under real-time pricing. *Energies*, 12(15):2867.

Watson, J. B. (1924), *Behaviorism.* New York, The People's Institute Publishing Co., Inc.

Werntges, A. (2020), *Diffusion of cooking practices in refugee settings.* Delft University of Technology. (MSc Thesis).

Wolak, F. A. (2011). Do residential customers respond to hourly prices? evidence from a dynamic pricing experiment. *American Economic Review*, 101(3):83–87.

Wolske, K. S., Gillingham, K. T., and Schultz, P. W. (2020). Peer influence on household energy behaviours. *Nature Energy*, pages 1–11.

Yan, Y., Qian, Y., Sharif, H., and Tipper, D. (2012). A survey on smart grid communication infrastructures: Motivations, requirements and challenges. *IEEE communications surveys & tutorials*, 15(1):5–20.

Yang, Y., Solgaard, H. S., and Haider, W. (2015). Value seeking, price sensitive, or green? analyzing preference heterogeneity among residential energy consumers in denmark. *Energy research & social science*, 6:15–28.

Zhao, Z. and Mutale, J. (2018). Improved dynamic pricing framework for demand response considering transmission limits. *2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pages 672–678.

Zhou, Y., Cheng, L., Ci, S., Yang, Y., and Ma, S. (2019). A user-oriented pricing design for demand response in smart grid. *Wireless Communications and Mobile Computing*, 2019. `https://doi.org/10.1155/2019/8694016`.

A

Review of Energy Consumer Segmentations

This appendix analyzes the consumer segmentations of a selection of papers and reports (Durillon et al., 2019, Frankel et al., 2013, Guthridge et al., 2010, Sütterlin et al., 2011, Yang et al., 2015). For each of these papers, the research method, the segmentation criteria and the defined energy consumer types are discussed and compared.

Guthridge et al.

From a survey among 9000 end consumers in 17 geographies, Guthridge et al. have identified six types of energy consumers (2010). These six types were distinguished based on demographic and behavioral variables, as well as attitudes and values, regarding the environment and perception of responsibility. The identified consumer types differ in their sensitivity to the criteria electricity bill savings, self action required, environmental impact and utility control. These criteria sensitivities that influence the decision to participate in demand response, are shown for each consumer type in figuru A.1.

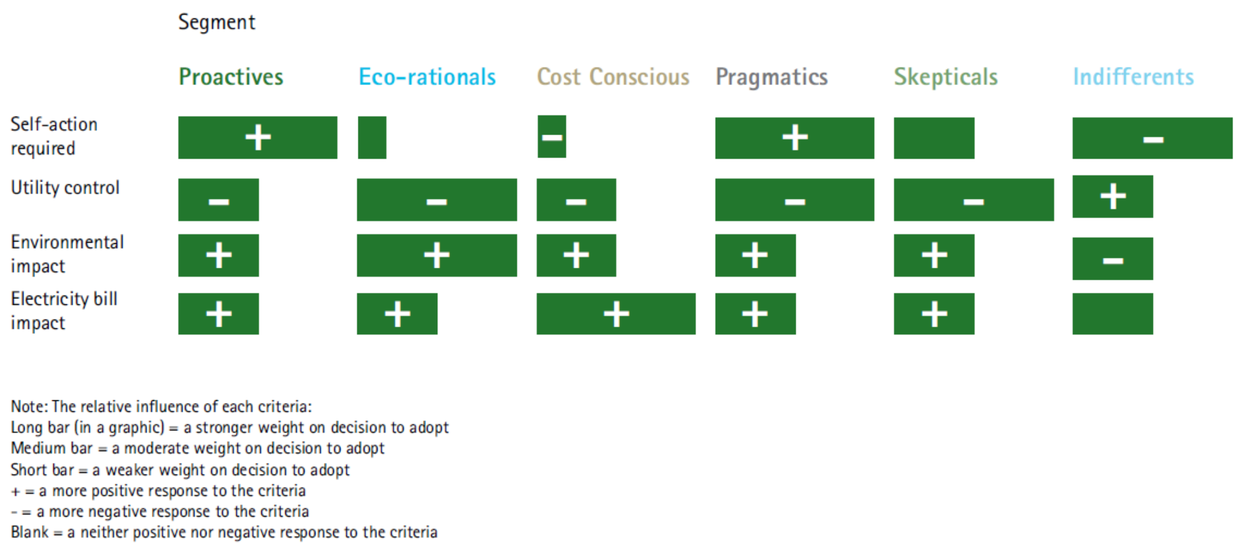


Figure A.1: Guthridge et al.'s consumer types and sensitivities to criteria (Guthridge et al., 2010)

The proactives are willing to take action to reduce their energy consumption without a clear motivation. The eco-rationals are also highly motivated to reduce their environmental impact and do not mind to give up comfort. They are also sensitive to electricity bill savings, but not as much as the cost-conscious energy consumer that is highly motivated by possible energy bill savings to change his energy consumption. Opposing these motivated consumer types, the indifferent consumer is not sensitive to bill savings or environmental concerns and are not likely to take action, unless it does not cost them any effort. They might be open to automation and accept control of utilities, but are very passive energy consumers. The pragmatics and skepticals would both definitely not accept utility control, but where the pragmatics could potentially join based on cost savings, this applies to a lesser extent for the high income skeptical energy consumer (Guthridge et al., 2010). Whereas the aforementioned criteria refer to the willingness of consumers to adapt their energy consumption, this is not the only precedent for engagement in demand response. Because, besides willing, energy consumers also need to be knowing and able to participate. According to the research of Guthridge et al., this singles out about 20 to 40 percent of the consumer population that is both able and willing (Guthridge et al., 2010).

Durillon et al.

First Durillon et al. studied the correlations between income, price, sociodemographics and household energy consumption and looked for different sensitivity groups by using French survey data and defining Engel curves. Then they combined these insights in the economic sensitivities in the population with the societal and non-economic values from the Guthridge et al. profiles, which led to five new residential energy consumer types. Each of these consumer types was then positioned along the axes representing sensitivity to environmental impact, cost and flexibility (Durillon et al., 2019). In this context, flexibility refers to the ability, capacity and acceptance of consumers to shift their energy consumption. The choice for these three criteria that influence electricity consumption behavior was based on previous literary studies (Durillon et al., 2019). The profile types and their sensitivities to the criteria are displayed in figure A.2.

Profile	Population	Cost $\alpha_{€}$	REN α_{env}	Flexibility α_{flex}
Cost-Conscious	28	90%	10%	80%
Envir-conscious	28	10%	90%	80%
Technophiles	28	50%	50%	90%
Indifferent	28	50%	50%	5%
Disengaged	28	50%	50%	-5%

Figure A.2: Durillon's consumer types and sensitivities to criteria (Durillon et al., 2019)

The cost-conscious type is similar to its namesake from Guthridge et al.'s profiles and is highly price sensitive and mainly wants to reduce his electricity bill. His flexibility varies over time, depending on price. The environmentally conscious consumer is similar to the eco-rational consumer and wants to reduce his environmental footprint while also having varying flexibility. The technophiles have a high flexbility thanks to smart appliances and are therefore highly involved in demand response, but without a very particular objective (Durillon et al., 2019). The indifferents group also lacks a clear objective and might consider shifting their consumption automatically as this causes no discomfort. This group could be compared with the pragmatics from Guthridge et al.. The final consumer type of Durillon et al is the disengaged energy consumer that has no flexibility and is not involved in energy management programs. This type could be seen as a combination of the skepticals and indifferents from Guthridge et al.. Therefore, it is very unlikely that this type of energy consumer will engage in energy demand response programs.

Sütterlin et al.
Sütterlin, Brunner and Siegrist conducted an extensive survey in which many questions were asked about energy usage, travel and other measurable behavior as well as personal norms to measure beliefs and attitudes (2011). Nonetheless, they did not include sociodemographical characteristics in the segmentation model, because prior research showed that consumer segmentation could better be founded on effective energy behavior and attitudes, than on sociodemographics (Sütterlin et al., 2011). Therefore, Sütterlin, Brunner and Siegrist, based their consumer segmentation on psychological factors, acceptance of policy and purchase and curtailment of energy like reducing room temperature, carpooling and buying seasonal food. The psychological variables embodied similar variables as Guthridge et al. and Durillon, namely financial motive, energy consciousness, perceived loss of comfort beliefs concerning response efficacy, self-efficacy, personal efficacy, awareness of consequences, ascription of responsibility, and personal norms. The segmentation was done by ward's method cluster analysis of the many variables mentioned above and resulted in six significantly different energy consumer types. Although this research did not focus on demand response specifically, but on energy-saving behavior in general, it is equally useful in pursuance of gaining insight in factors that steer consumers in their energy consumption decision making.

The consumer segments are quite different from the first two papers, but show some similar relations between sensitivities to criteria and energy saving behavior. The idealistic consumer shows most energy saving efforts and does not mind financial and convenience costs. They are very aware of the consequences of their energy usage and feel like they can induce a positive chance. They could therefore be seen as a combination of the proactives from Guthridge et al. and the environmentally conscious from Durillon. The thrifty energy consumer is also very willing to save energy as long as it does not come at high financial costs. Their motivation is mainly extrinsically, coming from regulations and policy or peer pressure. The selfless inconsequent energy savers save a substantial amount of energy, because they are very aware of the environmental consequences and belief in their ability to make a positive impact by saving energy. Even though they believe this, their actions are staying behind sometimes. The last three energy consumer types are all not very engaged. The materialistics are not very engaged, but might only change their mind for financial reasons. However they don't want to be obliged by financial policy instruments. In a sense, they are comparable with Guthridge et al.'s pragmatics. The problem-aware well-being oriented energy consumers do not really engage, because they don't feel responsible, even though they are aware of the consequences and believe they could make an impact. They are demotivated by a possible loss of convenience, but are a little sensitive for peer pressure, which could make them chance their behavior. Finally, the convenience-oriented indifferents are very unlikely to show energy saving behavior, because they dont't feel responsibility for the environment and don't see the consequences of energy usage. Besides they don't like policy and definitely don't want any inconvenience. The last two consumer types are similar to the indifferents and disengaged from the previous two papers.

Frankel et al.
Just like Sütterlin et al., Frankel et al. identified consumer types while looking at their energy-saving behavior (2013). The underlying energy consumer data came from a widespread survey in the US and segmentation was done based on consumers attitudes held and demonstrated behavior. More specifically, the criteria that were examined were concern about environmental considerations, sensitivity to energy savings, interest in new technologies or service programs and shown energy saving behavior (Frankel et al., 2013). The energy consumer types are shown in figure A.3.

The green advocate energy savers show the greatest energy saving behavior and are strongly motivated by their environmental concern. Their interest in technologies can help them improve their

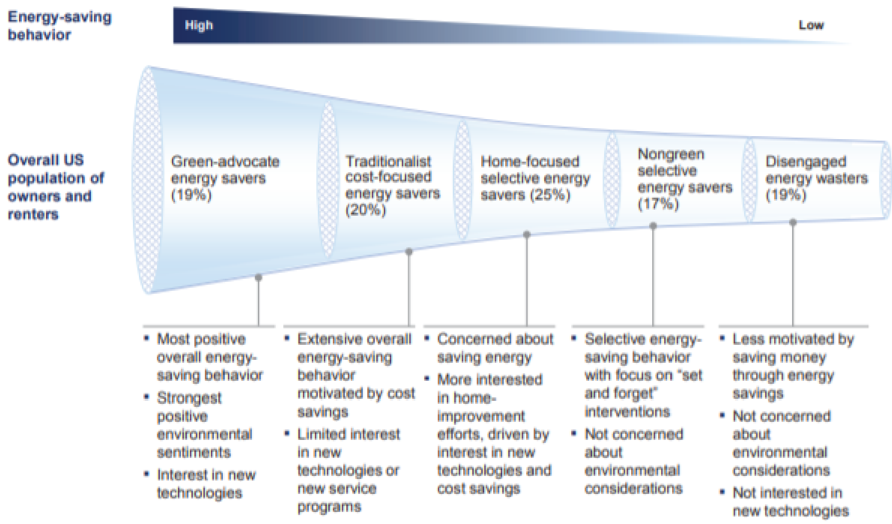


Figure A.3: Frankel et al.'s consumer types and influential characteristics (Frankel et al., 2013)

energy behavior even more. This energy consumer type is comparable to the eco-rationals, and the environmentally-conscious that were introduced earlier. The second group that also saves a substantive amount of energy are the traditionalist cost-focused energy savers, whose main motivation for energy saving is financial. They can be linked to the cost-conscious types from Guthridge et al. and Durillon. The home-focused selective energy savers are interested in saving energy, but prefer to improve their home by technologies to save energy without too much effort. The non-green selective energy savers can relate to this, because they are open to saving energy, as long as it is convenient. There are no financial or environmental motivations underlying. Therefore, these two types can be compared with Guthridge et al.'s pragmatics and Sütterlin's problem-aware well-being oriented consumer type. Lastly, the disengaged energy savers do not have any strong motivation for saving energy and therefore do not engage. They are similar to all the indifferent and disengaged consumer types that were introduced before. It is therefore striking to see, that each paper includes a disinterested type of consumer in their segmentation.

Yang et al.

Yang, Solgaar and Haider applied a slightly different approach to detect consumer preferences and attitudes (2015). They performed a stated choice experiment on choosing an electricity supplier based on the independent variables: price, percentage of renewable energy, source or renewable energy, contractual term and supplier. Afterwards they constructed a consumer type segmentation based on the choices consumers made , questions about attitudes of green electricity adoption and socioeconomic and demographic characteristics. Perceived consumer effectiveness, moral obligation and pro-environmental behavior turned out to be significant for segmenting the residential energy consumers. (Yang et al., 2015). The influences of criteria and the differences between the consumer types are shown in figure A.4.

The biggest group they identified, representing just over half of the consumers are the value seeking consumers. They show clear trade-offs in their decisions and are worried about the risks of renewable energy supply. When an electricity product is pro-environmental, they are slightly more willing to buy this. Also males are more likely to be a value seeking consumer. This consumer type is very comparable with the introduced selfless-inconsequent saver, and also has some characteristics of pragmatics. The second consumer group, the green consumers prefer a high share of re-

Influence of the adoption of green electricity factors and socio-economic demographic profile of the segments.

	Value seeking consumers	Green consumers	Price sensitive consumers
Adoption of green electricity factors			
Perceived complexity	.1028(.1456)	−.1432(.1795)	.0403(.1766)
Perceived risk	.3038(.0674)*	.3674(.0849)*	−.0636(.0792)
Social norms	−.0863(.1056)	−.8581(.1347)*	.9444(.1306)*
Perceived consumer effectiveness	.1036(.1085)	.1693(.1388)	−.2729(.1257)*
Moral obligation	−.0591(.0819)	−.3293(.1128)*	.2702(.0924)*
Pro-environmental behavior	.0681(.0399)*	.1023(.0481)*	−.0341(.0478)*
Consumer socio-demographic profiles			
Gender	.5945(.3010)*	.7740(.4443)	−.1794(.3791)*
Age	.1271(.0614)	−.1549(.0833)*	−.0278(.0739)
Household income	.0000(.0000)	.0000(.0000)	0001(.0000)**
Household with children	.1693(.1261)	.3054(.1609)*	−.4747(.1413)*

* Significance at .05 level.
** Significance at .10 level.

Figure A.4: Yang's consumer types and influential characteristics (Yang et al., 2015)

newables and are not worried about risks. They are mainly young people who want to reduce their carbon footprint and believe they can make a difference. Therefore they are very similar to the eco-rationals, environmentally conscious and the green advocate energy savers. The last consumer type is the price sensitive consumer. For this consumer, price is the main motivation for choosing an energy product. They do not feel morally obliged to reduce their energy consumption and think they cannot have a positive impact on the environment. This type is similar to earlier introduced cost-conscious consumers. It is notable that there is no explicitly disengaged group of consumers in this segmentation, which is a big difference compared to the other researches.

B

Overview of Model Assumptions

B.1. Energy Supply, Demand and Demand Shifting

- The energy mix consists of wind, solar and an unspecified kind of fossil-based energy.
- Fossil supply is stable over time and is 30 percent of peak demand load
- There are no energy losses caused by transportation and transmission.
- Only residential demand is taken into account
- The shares of flexiible and semi-flexible demand vary over time and are based on the assumption that 50 % of heating is electric (Voulis, 2019).
- Semi-flexible demand does not vary significantly over the year, so the same percentage are used every day. The percentages do differ during the day.
- Only the shifting of demand is considered. A reduction of energy demand is not included as a possibility.
- Consumers do not shift additional demand by themselves, but all demand is shifted automatically by the energy producer.
- If an agent switches from a no shifting to a shifting contract, or chooses the shifting contract initially, it is assumed that the household already had electrical heating combined with a smart meter or has installed this during the switch.
- In case of a full shifting contract, it is also implied that several household appliances are connected to the smart grid and can be controlled automatically.
- Energy producers are able to predict future energy shortages quite accurately with prediction models. Based on these predictions, it is decided whether demand should be shifted or not in the following time steps.
- The hassle of contract switching is included in the value of comfort

B.2. Households and Social Interaction

- All households are of the same composition
- All households have the same amount of yearly demand which follows the same pattern over time A consumer is one of the following consumer types: green, cost-conscious, convenience-oriented or indifferent
- An agent stays the same consumer type and cannot become another consumer type even if his values have changed
- The consumer population does not become smaller or larger, so it is assumed that consumers cannot switch to a different energy provider during the simulation
- The numerical values of the five personal values for each consumer type scores are intelligent assumptions based on surveys and research
- For each of five values there is random noise of -0.1 till + 0.1 around the average numerical values per consumer type to represent differences within groups
- The choice for a shifting contract only depends on the values of price, environment, comfort, safety and social norm
- In a social network, people are more likely to build a relation with people with similar values
- People with a lot of connections have a higher chance of making new connections, because their social network is already large.
- the relational network stays the same for the whole simulation period. Each switching period the influence of the network on personal switching is reconsidered, based on peoples packages.

B.3. Pricing Mechanisms and Additional Interventions

- The energy price that is used in flat pricing and is the base price in real-time pricing programs is the average price of the European countries in 2019.
- Consumers cannot choose between flat pricing or real time pricing, because this is determined by the energy producer.
- The reduction is provided per switch period
- The reduction amount is the same for consumers with a shifting contract and a full shifting contract.
- The energy provider can send overviews of costs and environmental friendliness to the consumers. This information is read by all consumers and all consumers are influenced by this
- The effect of the smart meter campaign and the environmental campaign is constant for half a year and disappears afterwards.
- All policies interact with one or more personal values of consumers

C

Model Logic and Pseudocode

This appendix will describe the model narrative and walk through the model logic. Afterwards, pseudocode is used to explain some of the most important algorithms from the model code. The full code for data formatting, the model and the experimentation in the EMA workbench can be found on: `https://github.com/ltenboske/thesis-abm-smart-grid-demand-response-consumer-differentiation-`.

C.1. Model Narrative

The model represents a future situation in which the electricity system is a smart grid that allows for information communication between consumers and the energy producer. In this future situation, the vast majority of the energy supply is composed of renewable generation from wind and solar energy. The volatility in the generation of these energy sources causes periods of energy shortage. In these periods of energy shortage, the energy provider can shift demand from consumers to a later time to reduce the energy shortage. Each of the consumers has a contract with the energy provider in which they state if they want to allow for demand shifting. The contract choices are no shifting, shifting of flexible demand (heating, cooling) only, and shifting of flexible demand as well as semi-flexible demand (dish-washer, laundry machine). The smart grid makes it possible for the energy provider to shift the consumer's demand, because smart meters, heating/cooling systems and household appliances are presumed to be connected with the smart grid, if a consumer has chosen a shifting contract. The contract choice of a consumers is determined by their participation score which is based on their personal values and the implemented interventions by the energy provider. If energy shortages remain even after shifting all possible demand, energy from storage is used to fulfill the current energy demand. The model calculates the required total storage capacity to make sure that energy balance is safeguarded.

C.2. Model Logic

A schematic representation of the model logic is shown in figure C.1. The model consist of processes that are either executed during the model initialization, at each model step or at each switch period. The diagram also shows if the action is performed by an agent, the energy provider or the model environment.

During the model initialization the model agents are created. Each agent sets their personal values of price, environment, comfort, safety and social norm and selects an initial shifting contract based on these values. Afterwards the social network is constructed and each agent selects his most influential neighbor. The energy provider selects the height of the model price and the pricing mechanism is chosen. The price can be determined by flat pricing or a real-time pricing function based on supply or shortage. If additional interventions are implemented in the model, these are initialized as well.

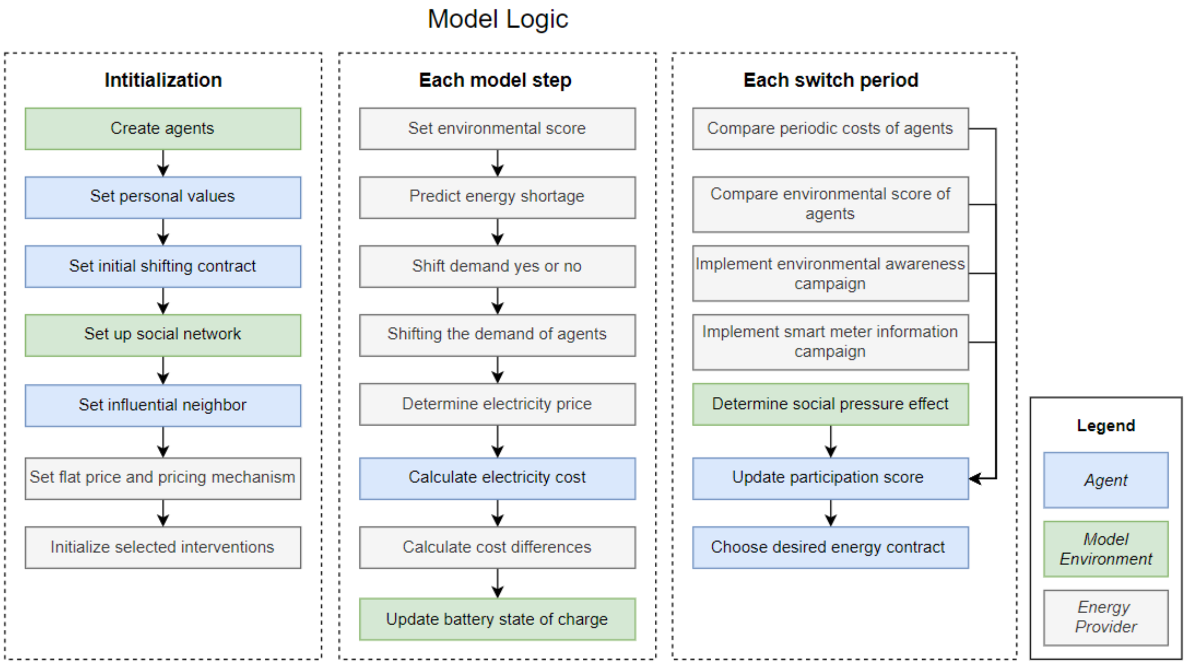


Figure C.1: Model logic showing agent, energy provider and model environment actions

At each model step, the energy provider determines the environmental score of each agent and predicts the upcoming energy shortage using machine learning models and historical demand and supply data. If a shortage was foreseen in the previous time step, the energy provider decides that demand should be shifted now. If this choice is made, the amount of demand that is shifted per agent is determined based on the shifting contracts of the consumers and the amount of energy shortage. Besides, the energy producer determines the electricity price at each time step. Based on this, the costs for each consumer and cost differences are calculated. Finally, the battery state of charge is updated depending on remaining energy shortage or supply surplus.

If a model step is the end of a switch period, additional actions are performed. First of all the energy producer compares the periodic costs and environmental scores of agents and sends out a report with this information to all individual agents. Additionally the energy producer implements the awareness and information campaign at these times that inform selected agents and interacts with their personal values. All of the actions above are only performed if these interventions were initialized. The effect of these interventions, combined with the social interaction effect result in a change in the an agent's participation score, which is updated each switch period. Finally an agent chooses the energy shifting contract that aligns with his updated participation score.

C.3. Pseudocode

This section discusses some of the most important algorithms of the model code. The algorithms that are described represent how the participation score is determined, how the demand is shifted and how the energy storage works.

The first algorithm describes how the participation score is established. Algorithm 1 shows that the participation score is a combination of the original personal values and the implemented interventions.

Algorithm 1: Determine participation score

```
Result: Updated participation score
VP = VoP                                                        // Personal values
  VE = VoE
  VC = VoC
  VS = VoS
  SN = VoSN
if cost comparison intervention == 1 then                       // Price
    VP = (cost difference / cost compare weight) * VoP + VoP
else
    VP = VoP
if environmental score comparison intervention == 1
  & environmental score < mean score then                       // Environment
    VE = ((environmental score / mean score) / environmental compare weight) * VoE + VoE
else
    VE = VoE
if agent is informed by environmental campaign then
    VE = VE * environmental campaign effect
if agent is informed by smart meter campaign then               // Comfort and safety
    VC = VoC * smart meter campaign effect
      VS = VoS * smart meter campaign effect
else
    VC = VoC
      VS = VoS
if social interaction != 0 then                                 // Social interaction
    shift contract → 'no shifting' = 0,   'shiftable' = 1,   "semi- and shiftable" = 2
      if shift contract influencer < shift contract own then
        SN = social interaction * social interaction effect
    else if shift contract influencer > shift contract own then
        SN = - social interaction * social interaction effect
    else
        SN = SN
else
    SN = 0
participation score = VP + VE + VC + VS + SN
return participation score
```

The second algorithm describes how the shifting of the demand works. Algorithm 2 consist of two parts. In the first part, the amount of demand that is used and is shifted is determined. The algorithm looks at the demand of the current time step and the demand of the previous six time steps when deciding on how much demand to shift and to use, because demand can only be shifted that long before it needs to be used. The second part of the algorithms checks if residual demand from shifting can be used.

Algorithm 2: Shifting the demand

Result: Demand divided into currently used and shifted demand per agent

```
// check how much demand should be used and shifted at each time step
if shifting contract != no shifting then
    if demand was not shifted in all of the past 6 time steps then
        if demand should not be shifted now then
            use all demand from current time step
             use previously shifted demand
        else // demand should be shifted now
            use part of current demand
             shift other part of current demand
    else // demand was shifted in all of the past 6 time steps
        if demand should be shifted now then
            use part of current demand
             shift other part of current demand
             use shifted demand from 6 time steps ago
        else // demand should not be shifted now
            use all demand from current time step
             use shifted demand from previous 6 time steps
else
    use all demand from current time step
// check if shifted demand can be used after a period of shortage
if shift residual > 0 & total demand < supply then
    use extra demand now to use all available supply
     shift residual reduces
else
    shift residual remains the same
     it needs to be used within 6 time steps and is taken from storage otherwise
return current demand, shifted demand
```

When the residual demand that was shifted cannot be used within six time steps after the end of the period of shortage, the energy is taken from energy storage. This action drains the battery, but the battery is charged again when supply is larger than demand. Algorithm 3 shows how the state of charge of the battery is updated.

Algorithm 3: Charge and discharge energy storage battery

```
Result: Battery state of charge (SoC)
if production > demand then
    SoC(t) = SoC(t-1) plus the supply surplus
      SoC remains the same if the battery capacity is reached
else
    SoC(t) = SoC(t-1) minus the energy shortage after shifting
return SoC
```

D

Parametrisation

This appendix elaborates on the parametrisation of the initial values for the model.

D.1. Model Inputs

Table D.1 gives an overview of the initial values or value ranges of variables that relate to the model, agent or policy level. it is striking to see that many input values were based on assumptions. This is the case because there are many variables that express future or behavioral aspects, that are hard to quantify with the current knowledge.

Table D.1: Parametrisation

Level	Parameter	Value / range	Source
Model	Shift_list	Varying	(Voulis, 2019)
	semi_and_shift_list	Varying	(Voulis, 2019)
	green_list	Varying	(Open Power System Data, 2020)
	green_prediction	Varying	(Open Power System Data, 2020) / Calculated
	fossil_list	Varying	(Open Power System Data, 2020)
	demand_list	Varying	(Vereniging Nederlandse EnergieDataUitwisseling, 2020)
	price_flat	€ 0.216	(Eurostat, 2020)
	Threshold_shift	0.3	Assumption
	Threshold_semi_and_shift	0.9	Assumption
	Switch periods	0 - 12	Assumption
	Storage capacity	5 * N_agents	Assumption
	Initial SoC	0 - 50 %	Assumption
	N_agents	1 - 100	Assumption
Agent	Personal values	0 - 1	Chapter 4
	Social pressure effect	0.1	Assumption

Policy	n_info_campaign	3	Assumption
	effect_smart_meter_campaign	0.1	Assumption
	effect_environment_campaign	0.05	Assumption
	long_term_effect_info	3 months	Assumption

D.2. Experimentation

D.2.1. Standard settings

Table D.2 shows the standard settings that were used for the experiments. In the design of experiments,the settings that were different from the standard settings were already presented.

The most important standard settings are that the pricing scheme set to RTP based on mismatch, but that all other policy parameters are set to 0. Besides, the initial shifting contract setting is value-based, which means that consumer choose the contract that matches their initial personal values and that different choices can be made by consumers of the same type, because of the randomness in personal values. The social pressure is set to 0.1, which means that social interaction influences the model outcomes. In some experiments this was set to 0 to be able to discover the pure effect of policies.

Table D.2: Standard settings of parameters in experimentation

Parameter	**Value**
RTP Policy	RTP Mismatch
Social pressure effect	0.1
Switching thresholds	0.3 and 0.9
Switch periods	4
Green household	5
Cost-conscious household	5
Convenience-oriented household	5
Indifferent household	5
Supply factor	1
Initial package	value_based
cost_comparison	0
reduction	0
env_score	0
effect_info_campaign_environment	1
info_campaign_env	0
effect_info_campaign_smart_meter	1
info_campaign_sm	0

D.2.2. Setups per policy

Some variables of the model input varied for the separate policies and policy combinations in the experimentation phase . Figure D.1 and D.2 present the settings for all of the experiments.

```
# Definitions of the interventions
# Base case A
p0 = {'RTP_policy':'None','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
# Base case B
p1 = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}

# Additional separate interventions
# Cost comparison and reduction
p2a = {'RTP_policy':'RTP_Mismatch', 'cost_comparison':1, 'reduction': 10, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
p2b = {'RTP_policy':'RTP_Mismatch','cost_comparison':1, 'reduction': 30, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
p2c = {'RTP_policy':'RTP_Mismatch','cost_comparison':1, 'reduction': 50, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}

# Environmental friendliness comparison
p3 = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 1,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}

# Information campaigns separate and combined
p4a = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1.1,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
p4b = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 0.95, 'info_campaign_sm': 3,'init_package':'value_based'}
p4c = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1.1,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 0.95, 'info_campaign_sm': 3,'init_package':'value_based'}
p4d = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1.2,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 0.90, 'info_campaign_sm': 3,'init_package':'value_based'}
p4e = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1.05,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 0.975, 'info_campaign_sm': 3,'init_package':'value_based'}
```

Figure D.1: Definitions of the interventions p0 - p4e

```
# Default shifting
p5 = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'default_shift'}

# Combinations of interventions
# Reduction and environmental comparison
p6 = {'RTP_policy':'RTP_Mismatch','cost_comparison':1, 'reduction': 30, 'env_score': 1,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
# Environmental comparison and information campaigns
p7 = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 1,"effect_info_campaign_environment":1.1,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 0.95, 'info_campaign_sm': 3,'init_package':'value_based'}
# Reduction + info sceptics
p8 = {'RTP_policy':'RTP_Mismatch','cost_comparison':1, 'reduction': 30, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 0.95, 'info_campaign_sm': 3,'init_package':'value_based'}
# Reduction + info green
p9 = {'RTP_policy':'RTP_Mismatch','cost_comparison':1, 'reduction': 30, 'env_score': 0,"effect_info_campaign_environment":1.1,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
# Environmental comparison + green campaign
p10 = {'RTP_policy':'RTP_Mismatch','cost_comparison':0, 'reduction': 0, 'env_score': 1,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
# Flat pricing + high reduction
p11 = {'RTP_policy':'None','cost_comparison':1, 'reduction': 50, 'env_score': 0,"effect_info_campaign_environment":1,
      'info_campaign_env': 0, "effect_info_campaign_smart_meter": 1, 'info_campaign_sm': 0,'init_package':'value_based'}
# All policies except default shifting
p12 = {'RTP_policy':'RTP_Mismatch','cost_comparison':1, 'reduction': 30, 'env_score': 1,"effect_info_campaign_environment":1.1,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 0.95, 'info_campaign_sm': 3,'init_package':'value_based'}
# All policies
p13 = {'RTP_policy':'RTP_Mismatch','cost_comparison':1, 'reduction': 30, 'env_score': 1,"effect_info_campaign_environment":1.1,
      'info_campaign_env': 3, "effect_info_campaign_smart_meter": 0.95, 'info_campaign_sm': 3,'init_package':'default_shift'}
```

Figure D.2: Definitions of the interventions p5 - p13

E
Model Verification

Model verification is applied to check if the model behavior is in line with the expected model behavior based on the model conceptualization and formalization. Van Dam et Al. have proposed multiple methods to verify the model, of which three have been used to verify the constructed model of this study (2013). The three applied methods are recording and tracking of agent behavior, interaction testing in a minimal model and extreme condition testing. A fixed seed was used, to allow for reproducability of the results.

E.1. Recording and Tracking of Agent Behavior

As the model started rather simple and was enriched with more complexity along the way, verification happened during multiple stages of the model construction process. When the final model version was ready, a structured walk-trough was applied to check if all steps were executed correctly, based on the model inputs. This was done by printing variable values during the simulation, studying short periods of simulation time and analyzing the agent and model variables over time, which was facilitated by the data-collecting functions that are built into the mesa package. For the tracking of agent behavior, a number of agents were followed throughout the simulation, to verify if the values of the agent variables were correct over time and if they had changed as expected. To do this, the different procedures and processes were tracked over time starting from the model and agent initialization.

The initialization of the agents was an important step and consisted of a number of functions already. First of all, the personal values were initialized, which could be done according to different conditions. Based on these values, an initial shifting contract was selected. It was verified that the appropriate contracts were chosen. Additionally, the social network was created and it was determined which agents were connected and how these agents influenced each other.

Other specifically interesting time steps to study were the time steps right at the end of a shifting period, because several agents actions were performed at those times. First the function *set_participation_score was* performed. In this function, the interactions between the interventions and the consumer values and the peer interactions was used to recalculate the participation score. To check if interventions had the expected effect, printing statements were used to verify this, as shown in figure E.1. Afterwards the function *package_shifting* determined which shifting contract fit the new participation score in consideration of the switching thresholds and switched the agent's shifting contract if necessary.

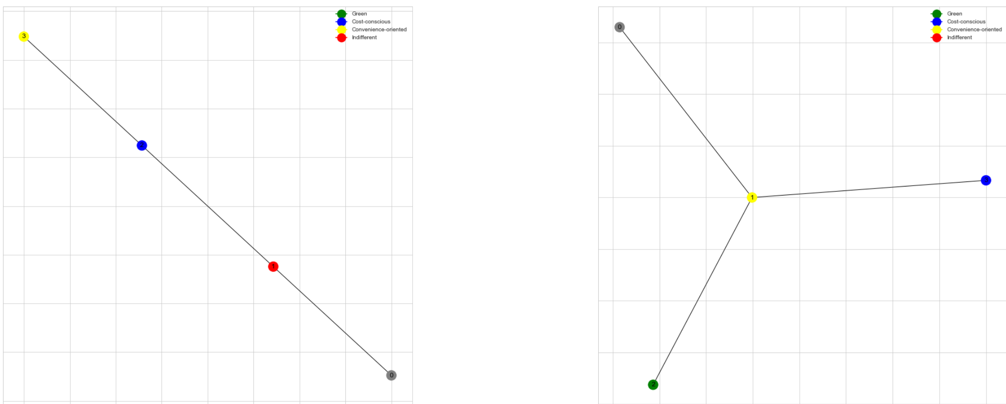
```
8752 Yes I switch ,me agent 5 had no shifting
based on the participation score -0.5746383061513283 I switched to no shifting
8752 Yes I switch ,me agent 14 had shiftable
based on the participation score 1.4604156804237887 I switched to semi- and shiftable
```

Figure E.1: Printed statements about package switching

The functions *demand_shifting_yes_or_no*, *shifting_the_demand* and *shifting_the_demand* were agent step functions that happened at each time step. These functions were rather complex and have undergone many iteration rounds of alterations and verification. Difficulties were experienced in the demand shifting procedure, because demand that was shifted was not used at a later time, but disappeared. Because of this the energy shortages were very much lower than expected in case of a high share of shifting contracts. After some model rearrangements, this error was fixed and no unexpected behavior occurred anymore.

E.2. Interaction Testing in Minimal Model

This step does not examine the values of individual agents, but is focused on interaction between agents. In order to look at a minimal model, a consumer population of only 4 consumers that were each of a different consumer type was used in this verification step. The only interaction between the agents that is considered is based on the social network. It was verified that the agents influenced each other as expected, which means that the key player in the network influenced the participation score of the other consumers in a positive or negative way. In case of only 4 consumers, the social network could only have 2 shapes, which are presented in figure E.2.



(a) Social network option one

(b) Social network option two

Figure E.2: Social network options in a minimal model of four consumers

E.3. Extreme Condition Test

The extreme condition test is used to evaluate if the model code works as expected under all conditions that could be the case during model simulation (Van Dam et al., 2013). Different extreme conditions were tested in the model, among others:

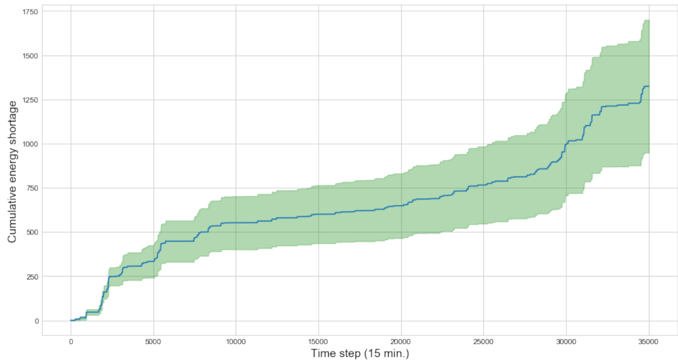
First of all extreme user participation settings were tested. The number of shifting contracts was set to all no shifting contracts, all shifting contracts and all full shifting contracts. The outcomes of these three scenarios were as expected. In the case of all no shifting contracts, energy shortage was highest, but all shifting contracts reduced the shortage a lot. All full shifting contracts could reduce the shortage a bit more.

Extreme conditions were also tested for the amount of supply. As expected, higher supply led to less and less heavy periods of energy shortage, which logically resulted in a lower total energy shortage. Other conditions that were varied till extremes were the shiftable shares of demand, the switching thresholds, the effects of policy interventions. All of which resulted in the expected behavior that fit the model conceptualisation.

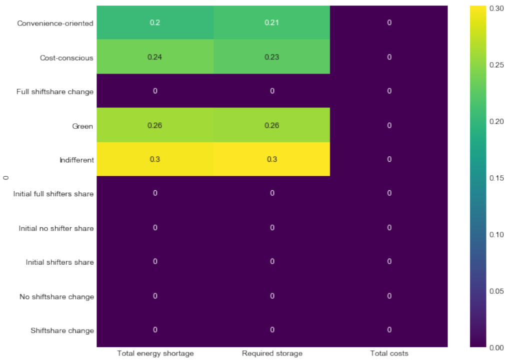
F

Model Results

Only a selection of the model results has been shown in chapter 8. This appendix will show two plots for each of the policies and policy combinations that were compared on the model KPIs. The first plot shows the mean and error band of the cumulative energy shortage over time for all scenarios. The second plot shows the feature scoring matrix for all features except the supply factor. This factor is excluded, because its strong effect eradicated the effects of all other features.

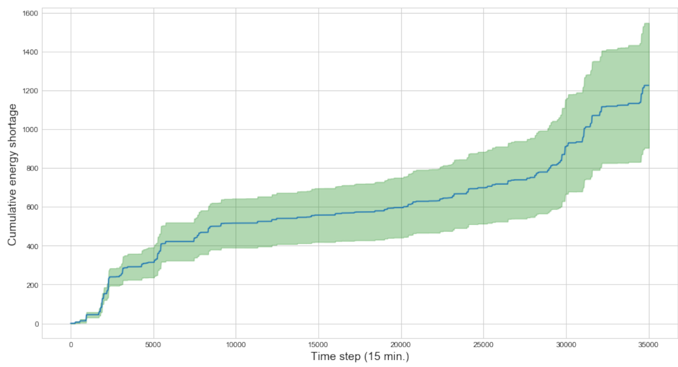


(a) Cumulative energy shortage mean with error band for 200 scenarios

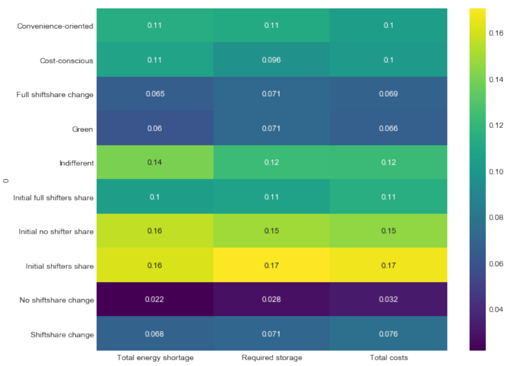


(b) Feature scoring of changes in shares of contracts

Figure F.1: Model output for P0 - Base case A

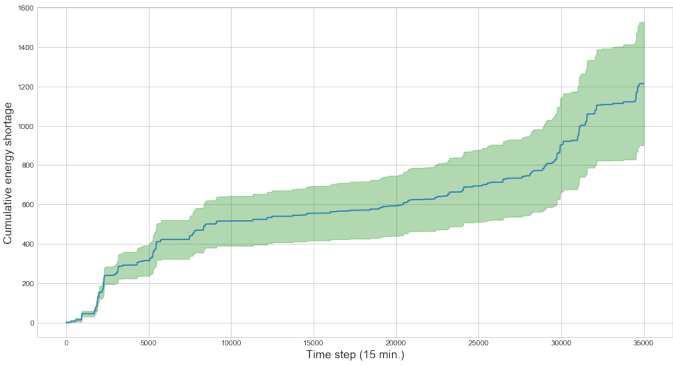


(a) Cumulative energy shortage mean with error band for 200 scenarios

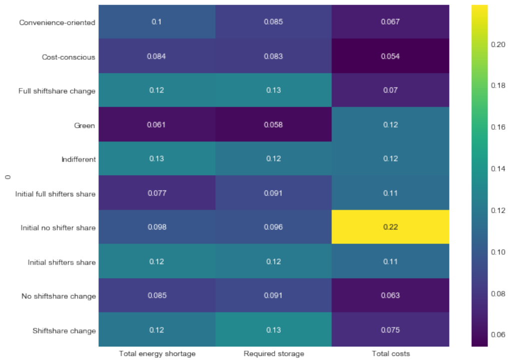


(b) Feature scoring of changes in shares of contracts

Figure F.2: Model output for P1 - Base case B

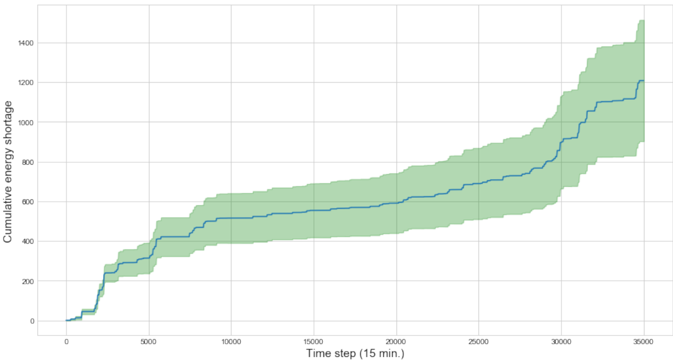


(a) Cumulative energy shortage mean with error band for 200 scenarios

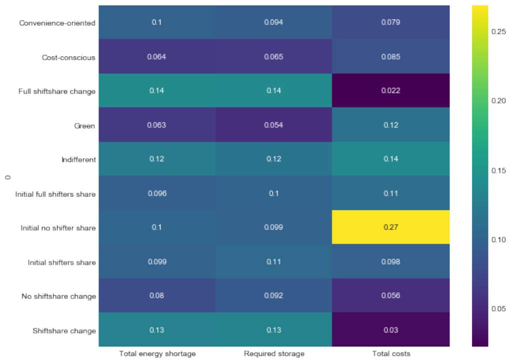


(b) Feature scoring of changes in shares of contracts

Figure F.3: Model output for P2a - Cost comparison with a reduction of €10

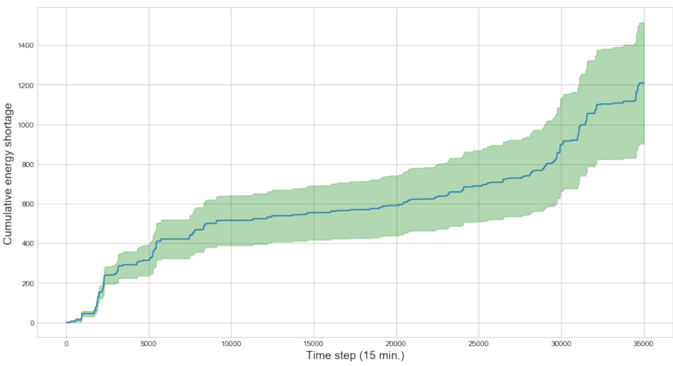


(a) Cumulative energy shortage mean with error band for 200 scenarios

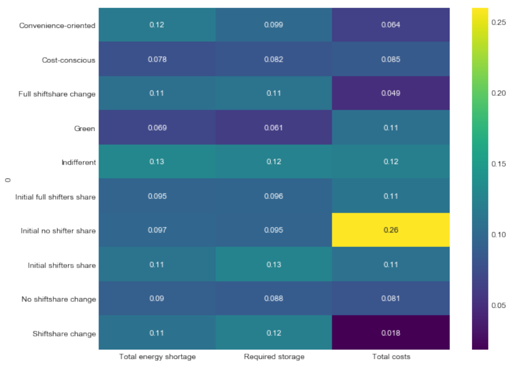


(b) Feature scoring of changes in shares of contracts

Figure F.4: Model output for P2b - Cost comparison with a reduction of €30

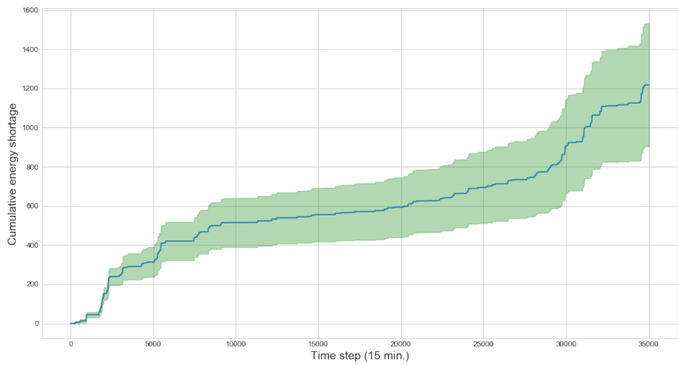


(a) Cumulative energy shortage mean with error band for 200 scenarios

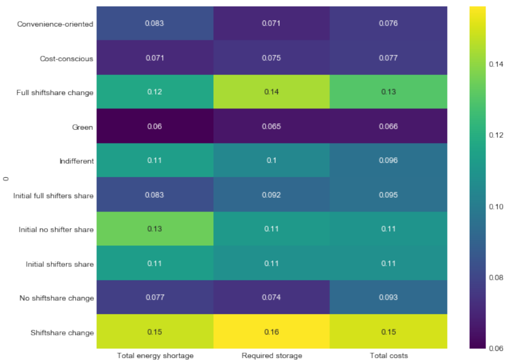


(b) Feature scoring of changes in shares of contracts

Figure F.5: Model output for P2c - Cost comparison with a reduction of €50

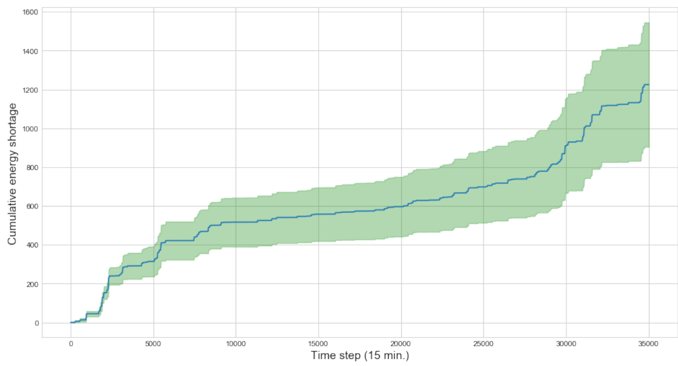


(a) Cumulative energy shortage mean with error band for 200 scenarios

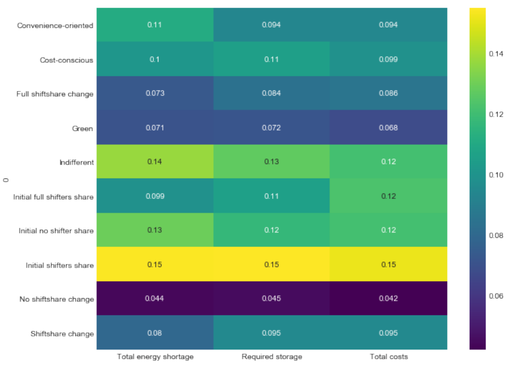


(b) Feature scoring of changes in shares of contracts

Figure F.6: Model output for P3 - Comparison of environmental friendliness

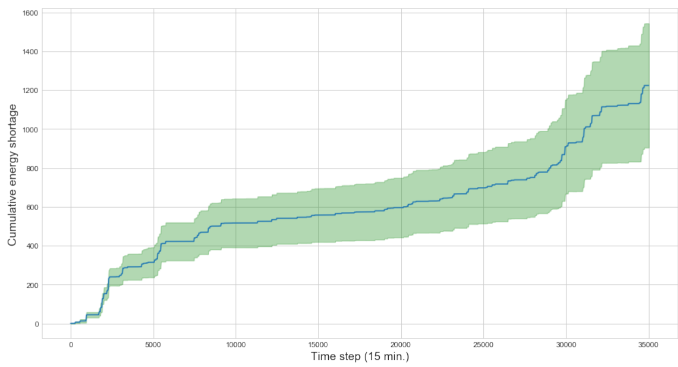


(a) Cumulative energy shortage mean with error band for 200 scenarios

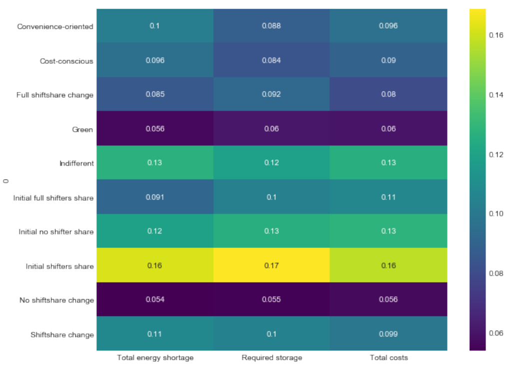


(b) Feature scoring of changes in shares of contracts

Figure F.7: Model output for P4a - Environmental awareness campaign

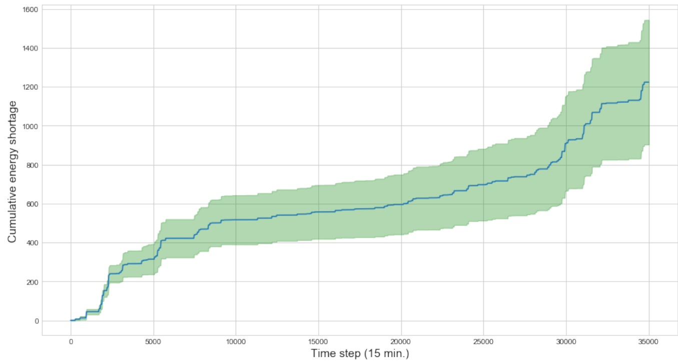


(a) Cumulative energy shortage mean with error band for 200 scenarios

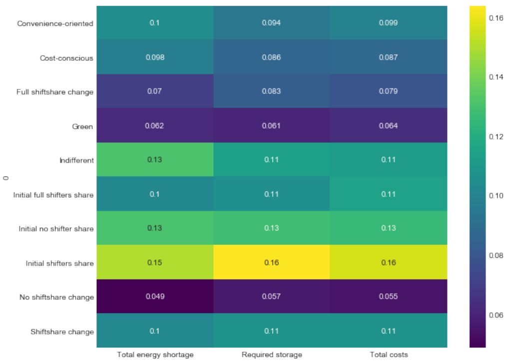


(b) Feature scoring of changes in shares of contracts

Figure F.8: Model output for P4b - Smart meter information campaign

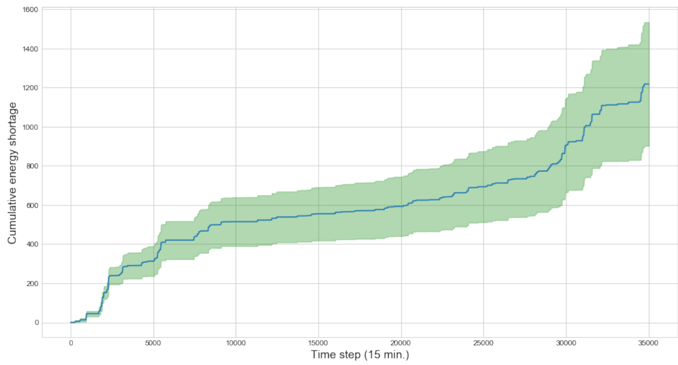


(a) Cumulative energy shortage mean with error band for 200 scenarios

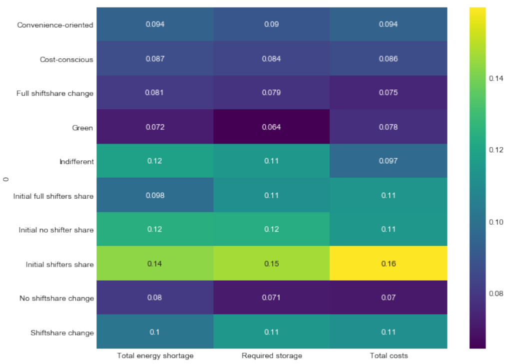


(b) Feature scoring of changes in shares of contracts

Figure F.9: Model output for P4c - Both campaigns with standard effect

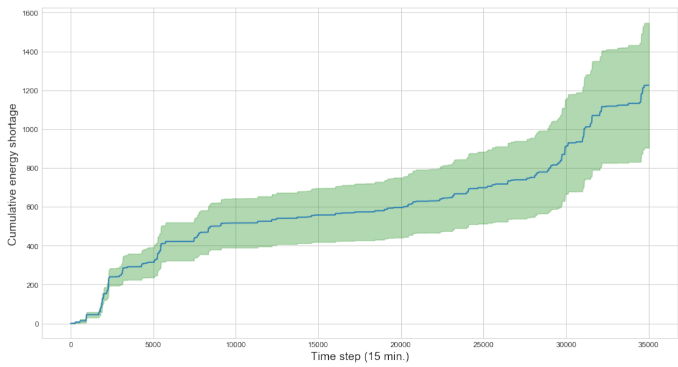


(a) Cumulative energy shortage mean with error band for 200 scenarios

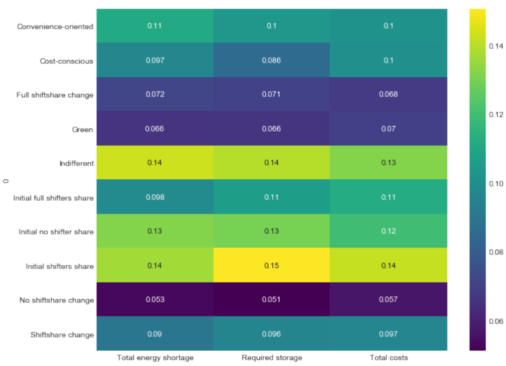


(b) Feature scoring of changes in shares of contracts

Figure F.10: Model output for P4d - Both campaigns with a stronger effect

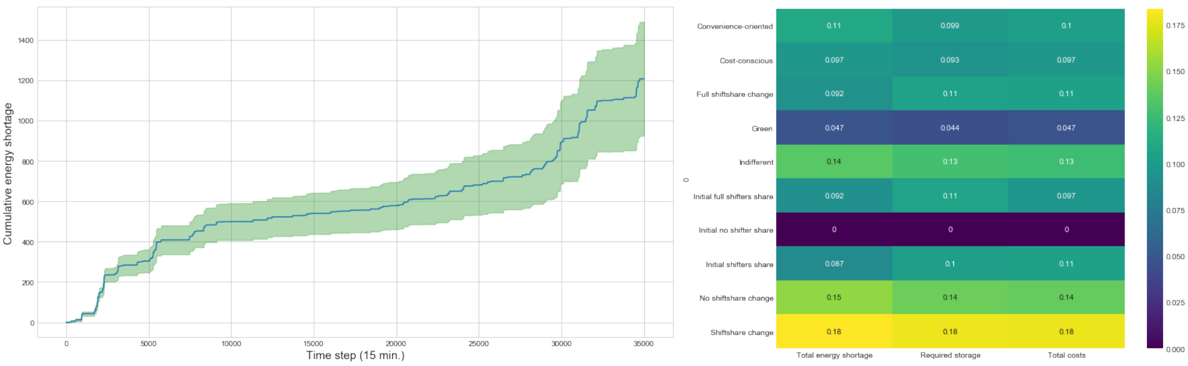


(a) Cumulative energy shortage mean with error band for 200 scenarios



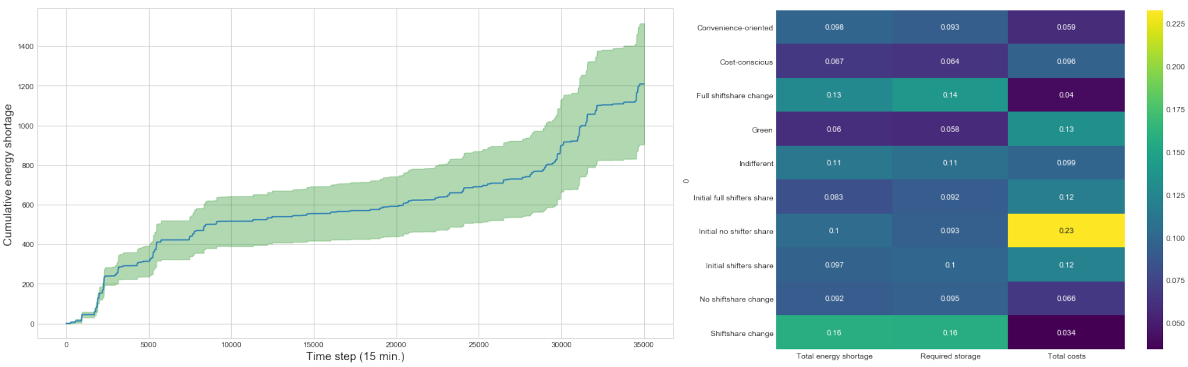
(b) Feature scoring of changes in shares of contracts

Figure F.11: Model output for P4e - Both campaigns with a weaker effect



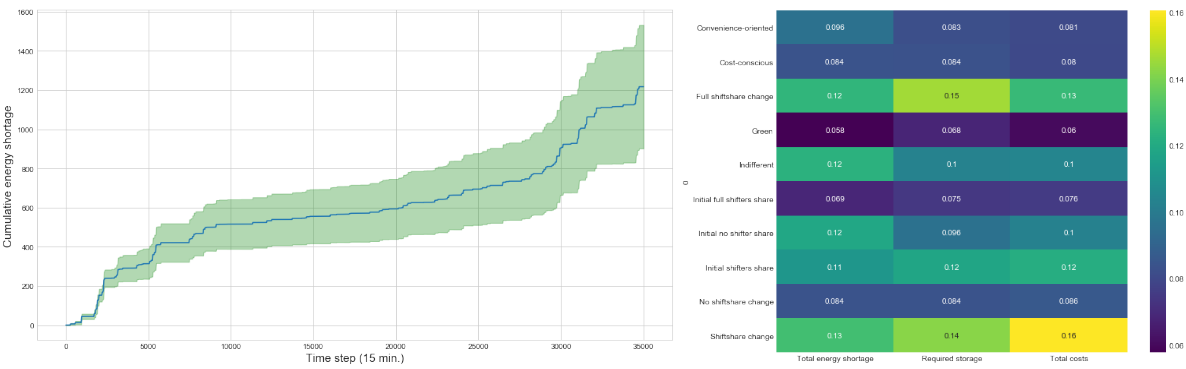
(a) Cumulative energy shortage mean with error band for 200 scenarios (b) Feature scoring of changes in shares of contracts

Figure F.12: Model output for P5 - Default shifting



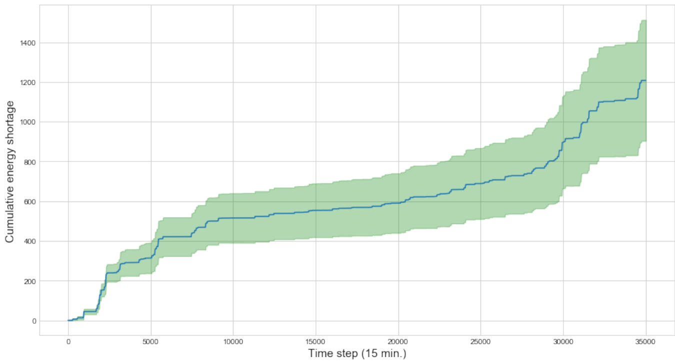
(a) Cumulative energy shortage mean with error band for 200 scenarios (b) Feature scoring of changes in shares of contracts

Figure F.13: Model output for P6 - Reduction and environmental comparison

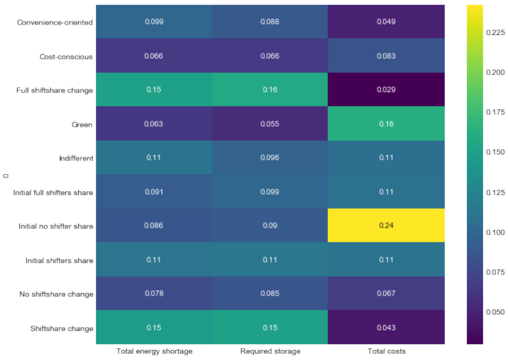


(a) Cumulative energy shortage mean with error band for 200 scenarios (b) Feature scoring of changes in shares of contracts

Figure F.14: Model output for P7 - Environmental comparison and information campaigns

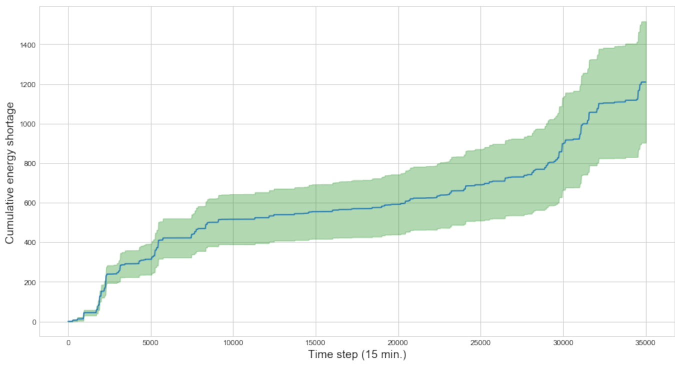


(a) Cumulative energy shortage mean with error band for 200 scenarios



(b) Feature scoring of changes in shares of contracts

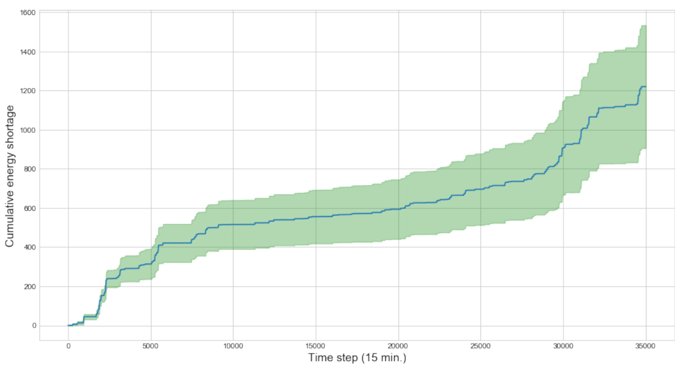
Figure F.15: Model output for P8 - Reduction and smart meter information campaign



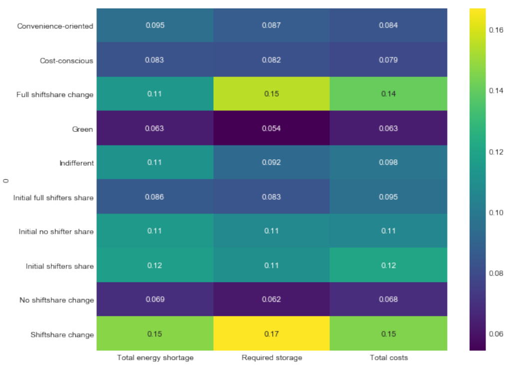
(a) Cumulative energy shortage mean with error band for 200 scenarios

(b) Feature scoring of changes in shares of contracts

Figure F.16: Model output for P9 - Reduction and environmental awareness campaign

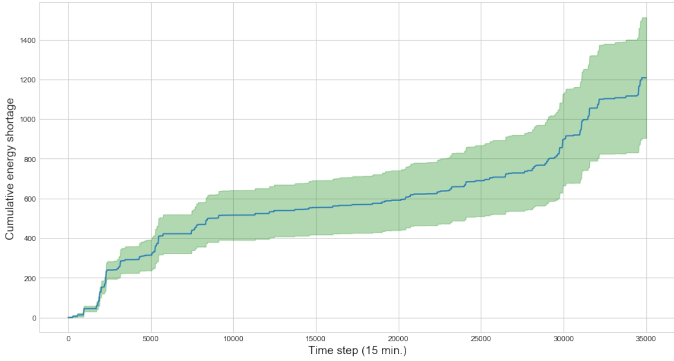


(a) Cumulative energy shortage mean with error band for 200 scenarios

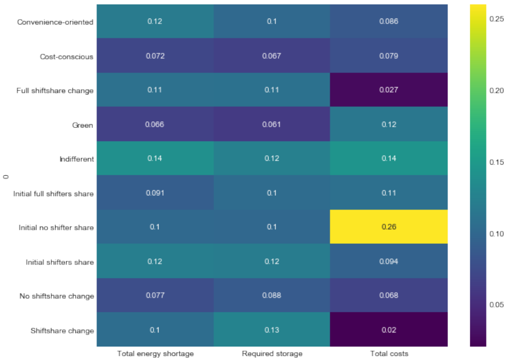


(b) Feature scoring of changes in shares of contracts

Figure F.17: Model output for P10 - Environmental comparison and environmental awareness campaign

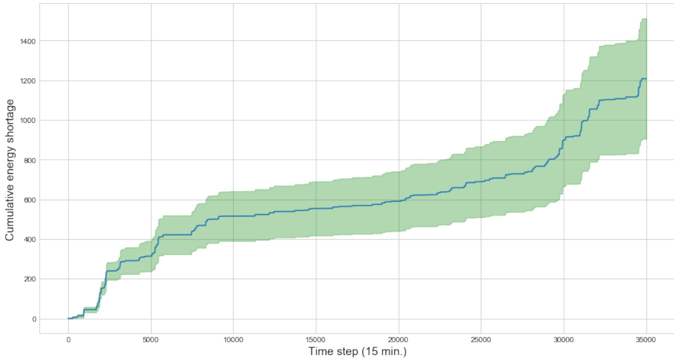


(a) Cumulative energy shortage mean with error band for 200 scenarios

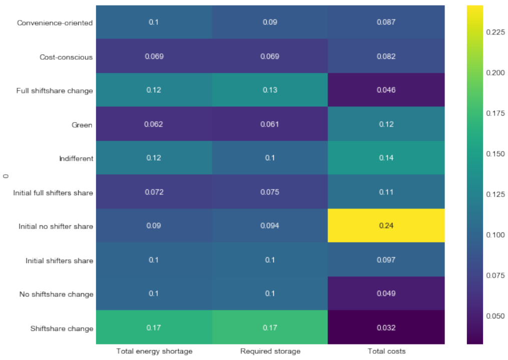


(b) Feature scoring of changes in shares of contracts

Figure F.18: Model output for P11 - Flat pricing with a high reduction

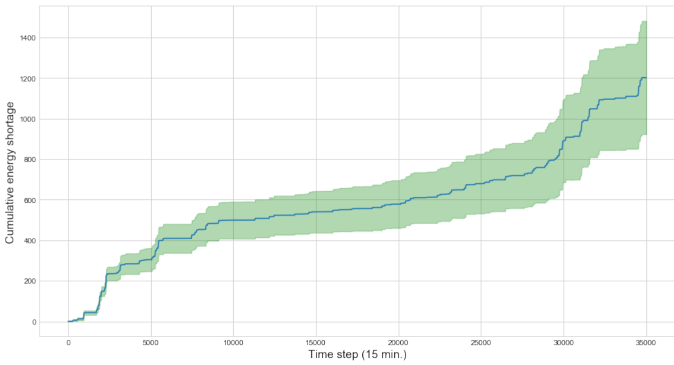


(a) Cumulative energy shortage mean with error band for 200 scenarios

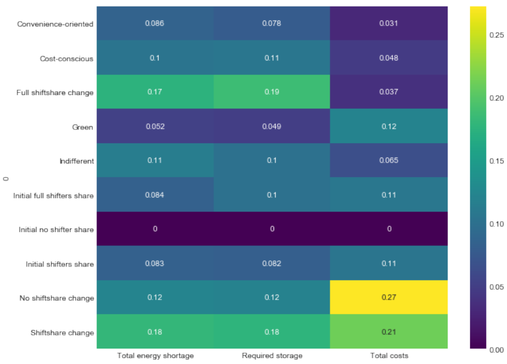


(b) Feature scoring of changes in shares of contracts

Figure F.19: Model output for P12 - All policies except default shifting



(a) Cumulative energy shortage mean with error band for 200 scenarios



(b) Feature scoring of changes in shares of contracts

Figure F.20: Model output for P13 - All policies