MASTER

Business models for fuel-shift technology in heat and electricity smart grids

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Business models for fuel-shift technology in heat and electricity smart grids

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Abstract

Fuel-shift technologies have the capability of shifting between fuel sources, so that they always use the most beneficial source at a given time. Fuel-shift appliances can be applied in households that are connected to a smart multi-energy grid. This means that appliances can make fuel decisions based on time-based dynamic prices, or that they can be centrally controlled by utility companies to create the most beneficial energy consumption mix. This is a form of demand response, with the consumption shifting between energy sources instead of shifting in time. Fuel-shift technologies are investigated as part of EnergyLab Nordhavn, a large scale integrated energy research project in Nordhavn, Copenhagen.

Business model theory describes how proposed value is created and captured. By extending traditional business models to including societal costs and benefits, they can be used to propagate diffusion of sustainable technologies, as good technology is by itself no guarantee for success. There are two ways in which a business model can contribute to sustainable development: commercialization of a sustainable technology or creation of a sustainable industry recipe. Literature shows the potential benefits of smart grids, but most current smart grid projects do not manage to capture their created value. The potential value of fuel-shift was therefore framed in this thesis in such a way as to enable the construction of a business model around them.

The value propositions of fuel-shift that are investigated here are their ability to reduce household energy bills, reduce peak loads, and reduce energy carbon emissions. In order to gain insight in how value is captured across the system, a model was made to simulate energy consumption with fuel-shift appliances is 50 Danish households. Individual consumption patterns were created using a bottom-up modeling technique, using data from a variety of Danish and international sources.

Multiple sets of fuel-shift decision algorithms were formulated, optimizing for household energy bills, total carbon emissions, and peak loads. These algorithms either reflected price based demand response, where the fuel-shift technologies use the cheapest fuel under a variety of pricing conditions, or based on an incentive based demand response. In that case, central control of fuel-shift applications was assumed, optimizing for the overall best solution regarding peak load or carbon emissions.

It could be concluded that gains for a washing machine were very low, while gains for a dishwasher and dryer might warrant investing in fuel-shift technology. However, since these appliance would shift to fuel-shift most of the time, making them grid-connected without the electric heating option might be an even better option, while losing the ability to fuel-shift.

Shifting to the cheapest fuel turned out to lower carbon emissions and peak loads in most cases as well, so private ownership of fuel-shift appliances with households as target customer appears to be able to lead to a more sustainable system through commercialization of the technology.

Space heating and domestic hot water did gave some possibilities to create value regarding peak reduction, but almost exclusively with a heat pump as electric heat supplier. The potential monetary savings were not large enough to warrant buying a heat pump, but it does make a good business model when a household is already connected to a heat pump as well as the district heating system. In this case, the business model would have to take the form of an energy service company (ESCo), that is in a position to capture value from many revenue streams and target customers like grid operators and households. A new ownership model for fuel-shift technologies and appliances needs to be defined, indicating that a successful business model here would contribute to sustainability by defining a new industry recipe for utility services.

Preface

I spent the bulk of the time doing this research away from the known realms of the TU/e campus, on the campus of DTU in Lyngby, just a few kilometers north of Copenhagen. I wanted to get to know Scandinavia to see if it really is the Valhalla of social welfare, education, and general happiness it is always made out to be and I must say that Copenhagen for a large part confirmed that premise for me. Besides spending an excellent long, warm and dry summer swimming in the canals of this amazing city, I also got to learn a lot about district heating systems, a technology the Danes have decades of experience with.

In Denmark I was not only welcomed and supported by two very engaged supervisors, Brian and Torben, but I also felt very welcome in the large community of international students that flocked to the university for their exchange programs. Meanwhile, my supervisors Bert and Jan provided excellent help from back in Eindhoven, not letting the 750 km distance get into the way of their engagement in my project.

Special thanks go out to my friends Bruno and Jesper, always willing to brainstorm if I got stuck with my research, and to my parents and sister for hopping to Denmark every now and then to check whether I was still doing fine (although I expect they actually just wanted to go on holidays).

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Chapter 1

Introduction

Fuel-shift technologies have the option to switch between multiple types of heat sources, depending on which one is most beneficial at the moment. Usually heat is generated either using electricity, by burning gas, or heat is received from a district heating system. Fuel-shift applications have connections to more than one fuel source, allowing them to decide the best source to use, based on a set of criteria.

Commercial fuel-shift applications do not exist yet, and investigating their possible utility is the goal of this research. A first fuel-shift prototype hot tap water heater has been constructed as part of Energylab Nordhavn, and is currently being tested (Cai, You, Wang, Bindner, & Klyapovskiy, 2018). In this report, other applications of fuel-shift are explored and their possible benefits are investigated. The goal is to find out in which cases fuel-shift technology can be most beneficial, and how large these benefits are.

The City of Copenhagen aims to have a CO_2 neutral energy supply by 2025, and the long-term vision for Denmark is to be completely powered by renewable energy in 2050 (Vad, Lund, Connolly, Ridjan, & Nielsen, 2015). Reaching these goals requires a systemic change to energy infrastructures, combined with the introduction of technologies that enable interaction between the demand sides and supply sides of energy systems.

The City of Copenhagen has designated Nordhavn as a trial ground for the development of a sustainable city, finding new ways to reduce resource and energy use and to shift from car transportation to walking, cycling, and public transport. Nordhavn is a former harbor area in Copenhagen that is being redeveloped into a residential neighborhood in order to accommodate the expected growth in population of the city. The district should eventually provide housing for 40 000 inhabitants and provide about as many jobs (By&Havn, 2012). EnergyLab Nordhavn is a large-scale integrated energy demonstration and research smart grid project in the Nordhavn district, executed by a consortium of 11 public and private parties. The aim of EnergyLab Nordhavn is to support the transformation of the current energy system into a reliable, cost-effective, and sustainable energy system, based on integrated urban energy infrastructures (Greisen, Honore, & Foteinaki, 2016). One of the challenges that is addressed in EnergyLab Nordhavn is the reduction of district heat grid capacity with declining temperatures as a result of sustainable heat sources replacing conventional boilers and power plants.

Figure 1.1: The location of Nordhavn in Copenhagen (By&Havn, 2012)

An integrated energy infrastructure such as proposed in Nordhavn is a form of smart grid. Smart grids are characterized by the introduction of information and communication technologies in energy infrastructures (Verbong, Beemsterboer, & Sengers, 2013). They are part of a shift from a engineering dominated energy sector, to a more market based system, and now towards a more users-focused energy system. Although the focus of smart grids has mainly been on integrating these new sources on the supply side, attention is increasingly turning to the demand side and the integration of new kinds of loads (Verbong et al., 2013). The term 'smart grid' is usually reserved for electricity systems, but with increased attention for decentralized heat generation (Blaauwbroek, 2014), and the increased coupling of power and heat technologies (Bloess, Schill, & Zerrahn, 2018), the smart grid concept naturally expands beyond electricity grids to encompass all kinds of energy infrastructures.

1.1 The Danish energy system

1.1.1 Electricity

Denmark has a liberalized electricity market. Consumers can choose to buy their electricity from a large number of suppliers (Elpris.dk, 2018). These suppliers sometimes own production facilities of their own, in other cases they have to buy electricity on the wholesale market, Nord Pool, where electricity is traded between the Scandinavian and Baltic countries (Nord Pool, 2018). The electricity that is generated in power plants, wind farms, and other sources of production, is transported over the high-voltage transmission networks to the distribution networks (Energinet, n.d.). The national transmission network is owned by Energinet, a state-owned independent public enterprise (Energinet, n.d.). The medium and low-voltage distribution grid that covers Nordhavn is operated by Radius, a subsidiary of Ørsted (Radius, n.d.-b). The costs for transmission and distribution of electricity are calculated into the consumer electricity price (Radius, n.d.-a).

1.1.2 District heating

The district heating networks works differently, as they are regarded as a natural monopoly (Dansk Fjernvarme, 2017). Roughly one third of Danish households is provided with heat from a district heating network (Dansk Fjernvarme, 2017), in the Greater Copenhagen area, 500 000 end-users are connected (Varmelast.dk, n.d.) Households buy their heat from their local district heating company, which also acts as distribution system operator. These companies are often owned by the local municipality, or by cooperatives of users (Dansk Fjernvarme, 2017). In the Greater Copenhagen area, the local grids are supplied by one of three transmission systems, owned by Hofor, Veks, and CTR respectively. These grids are integrated and operated by Varmelast.dk (Varmelast.dk, n.d.).

The heat in the Copenhagen area is supplied by three combined heat and power (CHP) plants, three waste incineration plants, an experimental geothermal plant, four large reserver boilers, and approximately thirty peak load boilers (Varmelast.dk, n.d.). The geothermal installation and the waste incineration plants are politically prioritized, meaning they are always free to generate the amount of heat they desire. The three CHP plants can put in bids to produce heat, based on the 24 hour heat plan provided by Varmelast.dk, who will then plan the heat production for the day based on the lowest costs.

1.2 Relevance

The work for this thesis will be part of the EnergyLab Nordhavn project, it will contribute to the development of a catalog of fuel-shift technologies for residential buildings, which is part of work package 4. In an integrated energy infrastructure different flows of energy like (green)gas, electricity, district heating, district cooling, and vehicle charging and fueling are highly integrated and may even be offered by a single energy service provider. Fuel-shift technologies may potentially provide added value in this combination of flows

Being valuable on itself is not necessarily a guarantee that these technologies will be implemented. For this, a business model should be formulated, stating how consumers can be enticed to pay for value that is provided (Teece, 2017). Niesten and Alkemade (2016) state that the lack of new business models for smart grid applications stands in the way of their wide scale implementation. They define business models as "ways in which companies create value for consumers and capture value for themselves."

EnergyLab Nordhavn has as aim to develop a system that may function as a blueprint for future sustainable urban energy systems. This means that apart from providing technical data about the technologies being developed and tested in the EnergyLab, insights into business models that can capture the created value are necessary. Niesten and Alkemade (2016) show that in general for these kind of pilot projects, working with demand response and integration of renewable energies, the focus remains on value creation for costumers and system operators, without formulating innovative business models that can capture this value.

This report provides an overview of business model theory and its application in smart grid services, as well as testing those business models in a household energy demand simulation. Existing methods of modeling household energy consumption usually focus either on heat consumption (Elmegaard, Ommen, Markussen, & Iversen, 2016; Emmi, Zarrella, & De Carli, 2017) or on electricity consumption (Fischer, Härtl, & Wille-Haussmann, 2015; Gottwalt, Ketter, Block, Collins, & Weinhardt, 2011; Kohlmann, Vossen, Knigge, Kobus, & Slootweg, 2011) In order to be able to analyze the effects of demand response in integrated energy infrastructures, existing knowledge on modeling demand response in electricity infrastructures needs to be expanded to include all energy flows.

The energy consumption of households is highly diverse and dependent on occupant behavior, even in identical dwellings (Andersen, 2012). Household consumption profiles are usually made for specific purposes, and only validated on the basis of individual cases (Gottwalt et al., 2011; Song, Alvehag, Widén, & Parisio, 2014). The model that is presented in this report is applicable for simulating energy consumption for Danish households in the context of Nordhavn.

1.3 Research questions

The goal of this thesis work is to determine whether fuel-shift technologies could create value as part of an integrated energy structure, for example in terms of carbon emission reduction, cost reduction, and capacity benefits. This is formulated in the main research question:

What are the the main value propositions of fuel-shift technologies and how can this value be created and captured using business models in the context of newly built residences in Denmark?

This work aims to provide some insight in how business model theory can be applied in the creation and capture of value by fuel-shift technologies. Especially how internalizing values using dynamic pricing can distribute value among stakeholders in the integrated energy system. This leads to the first sub-question that will need to be answered before the main research question can be answered:

What concepts of business model theory can be applied to formulate value proposition, and value creation and capture methods for fuel-shift technologies?

After the business models of fuel-shift are formulated, they are tested using a simulation model. In this simulation, a set of households is modeled equipped with a range of fuel-shift appliances. In modeling the applications of fuel-shift technologies, decision algorithms will try to optimize the energy consumption mix, based on the used business model. The second sub-question considers this relationship between business models and decisions algorithms:

How can multi-fuel household energy consumption with fuel-shift technologies be modeled in *order to investigate the value propositions from fuel-shift?*

These sub-questions can again be broken down, as there are several things that need to be understood before they can be modeled:

> *How can business model theory contribute to sustainable value creation using new technologies?*
>
> *How can concepts from business model theory by applied to create quantifiable business scenarios that can be simulated and compared?*
>
> *How can household energy consumption be modeled in order to investigate the effects of fuel-shift technologies?*

1.4 Outline

The rest of the chapters show the steps that were taken in order to answer these research questions. Although concepts from both Sustainable Energy Technology (SET) and Innovation Sciences (IS) are integrated throughout this report, some chapters have a stronger relation with one of these master's programs. The next chapters provide an overview of business model theory from an IS perspective (chapter 2) and how it can be applied to formulate business models for fuel-shift (chapter 3). Chapter 4 starts with a short overview of how demand response is handled in literature, from a SET perspective. Next, the methods of the model creation and scenario analysis are described. Chapter 5 shows the results of the simulation (SET emphasis) with some remarks about the sensitivity of these results. Chapter 6 shows how value is distributed among actors in the different business models (IS emphasis). In chapter 7 the results are discussed and the conclusions can be found in chapter 8.

Chapter 2

Business model theory

Business enterprises always, explicitly or implicitly, deploy a business model that describes how value is created and delivered, and how part of that value is captured (Teece, 2010). Teece (2010) states that a well-developed business model is necessary for innovators to deliver and capture value from their innovations.

This chapter provides an overview of what business models are, what their role is in generating value from innovative technologies, and how they can be applied in smart grids in general. After that, the application of business models for fuel-shift technologies is investigated. This chapter builds mostly on the papers “Business models, business strategy and innovation” by Teece (2010) and “Clarifying business models: origins, present, and future of the concept by Osterwalder, Pigneur, and Tucci (2005), as their work is often cited in papers investigating business models in relation to smart grids For the section on sustainability transitions grateful use was made of the master thesis “Sharing is caring: A road towards a green, global and connected Sydney? A case study about the roles of business models in sustainability transitions” by Meijer (2016).

2.1 What are business models

The most cited definition of a business model in literature according to Andreini and Bettinelli (2017) is the one from Amit and Zott (2001): “the content, structure, and governance of transactions designed so as to create value through the exploitation of business opportunities.” This definition has been expanded upon and more refined over the years, but the core idea that remains that business models revolve around value.

Osterwalder et al. (2005) say that business models serve as a building plan for designing and realizing business structure and systems. They say that the concept is generally understood as a view of the firm’s logic for creating and commercializing value. Business models implementation contains its translation into concrete things, such as structure and processes of a business, and infrastructure and systems.

Teece (2010) describes a business model as defining “how the enterprise creates and delivers value to customers, and then converts payments received to profits”. Business models fill in

Table 2.1: Nine building blocks of a business model (Osterwalder et al., 2005)

1. Target customer	Segments of customers to which a company wants to offer value
2. Value proposition	A company's bundle of products and services
3. Distribution channel	Means a company uses to contact its customer
4. Relationship	Links between a company and different customer segments
5. Revenue model	How a company generates revenue with a business model
6. Value configuration	Arrangement of activities and resources of the company
7. Core competency	Competencies necessary to execute a business model
8. Partner network	Network of cooperative agreements with other companies necessary to offer value
9. Cost structure	Monetary consequences of means used in a business model

a gap left by textbook economics, where theoretical constructs often assume fully developed markets, strong property rights, perfect arbitrage, and no innovation. They articulate the logic, the data, and other evidence that support the value proposition for the customer, and a viable structure of revenues and costs for the enterprise delivering that value. In essence, a business model crystallizes customer needs and ability to pay, they define the manner by which value is delivered to customers and entices customers to pay for value.

2.1.1 Value and business models

Building on the work of Teece (2010) and Osterwalder et al. (2005), business models are now usually defined as the way a firm creates and delivers value for customers, and how it captures value for itself (Giordano & Fulli, 2012; Niesten & Alkemade, 2016). This definition focuses on 'value' as a core part of the business model. For Osterwalder and Pigneur (2009) and Teece (2017), value is delivered by customers embedded in products or services that are created by the company. In return, a revenue stream is established from the customers to the firm.

Based on their definition of a business model, Osterwalder et al. (2005) propose nine building blocks, displayed in table 2.1. These building blocks can be used to trace different kinds of value throughout a business model, and how a model captures and delivers this value. Four of these buildings blocks are especially relevant to business models in smart grids, so these are described in more detail here.

In the first building block of a business model as shown in table 2.1 the target customer is defined. According to Osterwalder and Pigneur (2009), this should be the answer to the question "for whom are we creating value?" Once this target customer or customer groups are defined, a value proposition can be made.

The second building block, value proposition, solves a customer problem or satisfies a customer need. Osterwalder and Pigneur (2009) describe it as a bundle of benefits that a company offers customers. Value may be found, among other places, in satisfying a new set of needs, increase performance of a product or service, tailoring products or services to the specific needs of individual customers, or offering similar value for a lower price.

The fifth building block deals with converting value into revenue streams, it seeks answers to the question "For what values are customers really willing to pay?" Then, a pricing system can be formulated around this, such as list pricing, real-time-markets, and auctions. The ninth building block is 'cost structure', and deals with the costs that are involved in deploying resources and activities. Business models can be cost-driven, when minimizing costs is the focus of the business, or value-driven, when costs are of a lesser concern to the customer than other values, like quality or availability.

By filling in these building blocks for a business model, the flows of value and money become apparent. This way insights are gained in where value is created, delivered to customers, and captured by firms. Filling in the building blocks for a variety of business models allows for comparison between them.

2.1.2 Business models and social value

The city of Copenhagen has formulated the goal to become CO_2 neutral by 2025. Such a shift towards sustainable development can only be achieved by systemic change to current production and consumption patterns (Bidmon & Knab, 2017). Societal transitions, according to Bidmon and Knab (2017), are large-scale and long-term changes of systems fulfill societal functions such as transport, energy provision, or housing. These systemic shifts will not be achieved by technology alone. In order to understand the possible role of fuel-shift in contributing towards Copenhagen's climate goals, its position in this societal transition should be better understood.

A key element of business model design is figuring out how to capture value from innovation, as technological innovation alone is far from a guarantee for economic success (Teece, 2010). The traditional revenue model to capture value from innovation, according to Teece (2010), is embedding the innovation in products, and sell those. The business model can support stabilization of an emerging technology (Meijer, 2016). It can help to unlock the latent value of technological innovation, as a technology on itself has no value, but gains its value through system interaction (Geels, 2002; Meijer, 2016).

Business models have been described as having potential to disrupt industries, and are therefor important in achieving systemic change (Bidmon & Knab, 2017). Bidmon and Knab (2017) categorizes three functions that business models fulfill in the context of societal transitions. In their first function, business models function as industry recipes, reflecting firms' hypotheses on how to fulfill customers' needs. When such a hypothesis survives for a long time, it may converge towards a common industry logic, establishing how organizations in the same industry work. According to Meijer (2016) this describes the way new innovations become part of the common industry logic, while at the same time describing how path dependencies arise surrounding the currently dominant industry logic that may form barriers to innovation.

The second business model function is as device to commercialize technology, when it connects a technology's potential with the realization of economic value. Osterwalder et al. (2005) describe the ability of business models to form a conceptual bridge to align business strategy and technology, acting as a mediator between technology and economic value. This way, business models support the commercialization of innovative processes and services. In its third function, a business model is subject to innovation itself, as novel business models have been ascribed potential to disrupt industries. This third function is outside the scope of this thesis work.

Table 2.2: The two building blocks that are added to Osterwalder et al. (2005)'s list by Meijer (2016)

10. Societal costs	Non-monetary consequences of means used in a business model
11. Social benefits	How a company generates positive ecological and social impacts

Sustainability

The section above showed the applicability of business models in sustainable development. However, the fact that sustainability should be incorporated in the business model is only implied. Wells (2013) provides six major principles that underpin business models for sustainability, two of which are resource efficiency and social relevance. Resource efficiency is relevant for business models, as businesses are the main form of social organization through which materials are extracted from the environment. The social relevance of business models, is found in the idea that any product or service should contribute to the health and happiness of humanity. Boons and Lüdeke-Freund (2013) state that the value proposition offers room for ecological and/or social value, next to economic value. They also say that the revenue model and cost structure should reflect an appropriate distribution of costs and benefits among actors involved, as well as account for the firm's ecological and social impacts.

Based on Wells (2013) and Boons and Lüdeke-Freund (2013), Meijer (2016) adds two more building blocks to Osterwalder et al. (2005)'s list, as shown in table 2.2. This way, both value for the customers and businesses, as well as for society are explicitly covered in a business model.

Chapter 3

Business models for fuel-shift: conceptual model

3.1 Smart grid business models

As established in chapter 1, fuel-shift operates in the context of a smart grid. A smart grid encompasses a set of technologies, including smart meters, ICT infrastructure, and the fuel-shift technologies themselves. The section on the application of business model theory in smart grids mainly uses "How is value created and captured in smart grids? A review of the literature and an analysis of pilot projects" by Niesten and Alkemade (2016) and "Business model innovation in electricity supply markets: The role of complex value in the United Kingdom" by Hall and Roelich (2016).

According to Niesten and Alkemade (2016), these technologies can be considered enabling technologies, as they enable firms to offer smart grid services to consumers. In addition to these technologies, companies need to develop smart grid business models to create and capture value, and deliver value to customers. Niesten and Alkemade (2016) find that there is a lot of attention given to value creation for grid operators and customers in pilot projects, but that focus on value capturing business models for smart grid companies is lacking.

Hall and Roelich (2016) describe how current energy utility models cannot reasonably pursue a transformation of the energy system, as it undermines their core value proposition. According to Hall and Roelich (2016), major difficulty with new energy business models is that their value propositions often lie outside the current energy system. They call this 'complex value', defined as "the production of financial, developmental, social and environmental benefits which accrue to different parties, across multiple spaces and times, and through several systems." Business models with complex value propositions must be effective at capturing value streams across a variety of systems in order to remain viable.

Table 3.1 shows an overview of value propositions regarding demand response services, which according to Niesten and Alkemade (2016) is one of the three most often discussed types of smart grid service. As the table shows, both consumers and system operators, as well as society, can gain both monetary and non-monetary value from smart grid services. Moreover,

Table 3.1: Value for actors for demand response services based on pilot projects Niesten and Alkemade (2016)

Value for consumer	Value for system operator	Value for society
- Reduced energy use - Reduced energy bills - Enhanced control over energy consumption - Consumer comfort	- Reduced peak demand - Optimized grid operation - Improved access to regulation power - Improved system reliability & stability - Reduced system losses & costs - Improved power quality & security of supply	- Environmental benefits

'system operators' is a collective term that can encompass distribution system operators for both heat and electricity, utility companies, and energy suppliers. This means that business models for smart grid services could potentially describe a multitude of values and revenue streams, making it complicated for a firm to define the best place to capture value.

Hall and Roelich (2016) describes nine business archetypes that articulate how business models turn value propositions into value capture methods. The fuel-shift business models formulated here are set in the context of one of two archetypes: the corporate utility or the ESCo archetype.

The current energy system model is the corporate supplier archetype, as displayed in figure 3.1. Consumers pay the energy supplier for the amount of energy they use and when they use it. The supplier in turn pays producers of energy (if they do not own production facilities themselves) for the amount of energy needed, as well as distribution system operators and transmission system operators for the use of the energy grids. Consumers may create value by reducing their own energy consumption, by shifting to another fuel, or by shifting their demand to time when energy is cheaper. The utility company may incentivize consumers to change their consumption patterns by setting flexible tariffs on consumption, allowing them to supply energy they bought at a more favorable price.

With an energy service companies (ESCo), displayed in figure 3.1 consumers no longer pay for energy per kWh, but for a service agreement that provides them with heat, light, etc. This way, the choice of the most beneficial energy source is put with the ESCo, and no longer with the consumer. The ESCo is in a position to buy and deliver services from and to all other actors on the market. An ESCo can provide peak load reduction services to a DSO by shifting load when necessary, it can fuel-shift to a fuel that is more favorable for the generators. ESCos, especially when government owned, can priority more environmental friendly fuels, or shift consumer demand towards these fuels. Consumers can vary the degree to which they allow the ESCo to control their load, in exchange for lower energy bills. More control over consumer loads gives the ESCo more opportunities to create valuable services for the other actors.

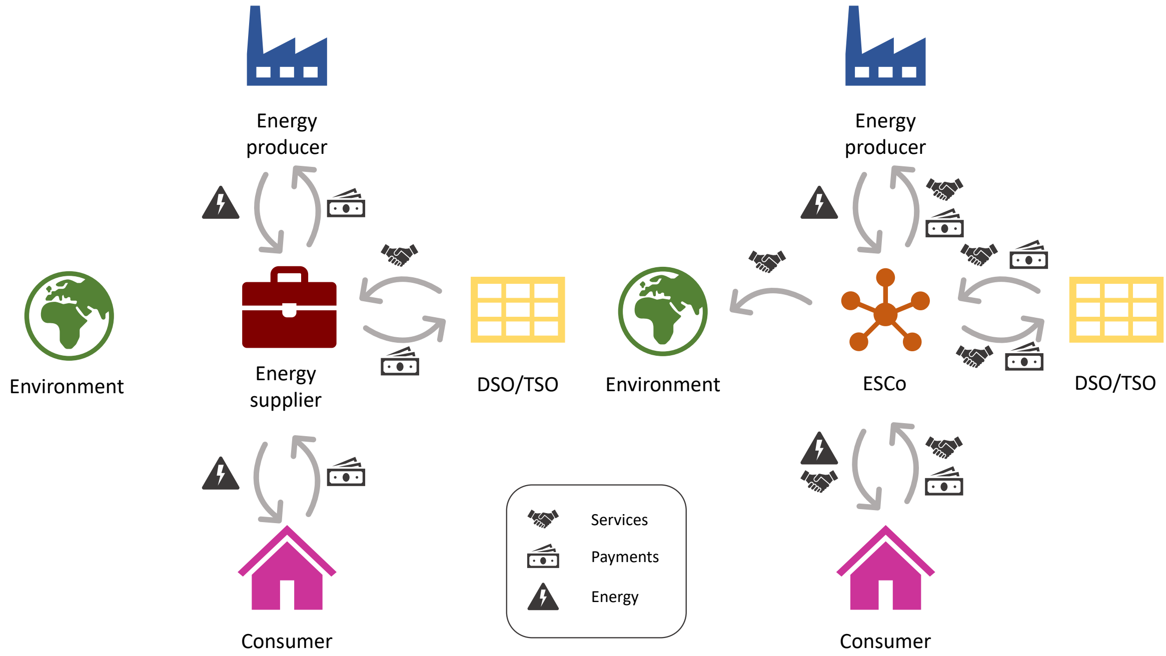


Figure 3.1: Value streams in the corporate supplier (left) and ESCo archetypes

3.1.1 Demand response

Demand response is a form of demand side management (DSM), which is using smart grid technology to allow demand to follow supply (Verbong et al., 2013). It is a method for creating value that is widely used in smart grids (Niesten & Alkemade, 2016). Demand response is defined by Albadi and El-Saadany (2008) as "the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time."

Fuel-shift is a form of demand response, except that instead of shifting to a different moment in time, the shift is between fuel sources. To the best knowledge of the author, no research has been published on demand response using fuel-shift on a consumer level. As a result, this report often draws on studies on DR time-shift for methodology and benchmarks.

Niesten and Alkemade (2016) define two types of demand response services: price-based and incentive-based responses. For price-based responses, consumers adjust their consumption as a direct response to dynamic energy retail prices. These can take the form of time-of-use pricing (TOU), critical-peak pricing (CPP), and real-time pricing (RTP). For time-of-use pricing, the tariffs are dependent on the time of day, mostly having lower tariffs during off-peak hours and higher during peak hours. This is already standard practice in some countries, where electricity is often cheaper during the night and in the weekends. Critical-peak pricing is an option where prices can raise significantly when the grid is close to maximum capacity. Real-time pricing provides consumers with prices one day ahead, depending on the expected demand and supply patterns for that day.

In incentive based response programs, the monetary incentives to consumers are separated from electricity retail prices. In this case, consumers receive payments or discounts on their energy bills for allowing companies direct and remote control over their loads. The size of the payment can be dependent on the amount of control the consumer is willing to hand over.

On a consumer level, DR with real-time pricing or critical-peak pricing is currently still mostly limited to pilot projects (e.g. Kobus, Klaassen, Mugge, & Schoormans, 2015; Kohlmann et al., 2011). In these projects, consumers are usually provided with an in-home display showing their current consumption and production of electricity, and the current electricity tariff. Most modern dishwashers, washing machines, and tumble dryers are equipped with a programmable time delay, allowing users to set the cycle to a time with more beneficial tariffs, within the user's convenience. In the case of Kobus et al. (2015), households were provided with washing machines on which they could select a desired ultimate end time, after which the machine itself decides the best time to run the cycle, based on price information.

3.2 Business models for fuel-shift

The business model theory in chapter 2 showed that a business model should define a target customer, a value proposition for that customer, and a cost and a revenue structure (Osterwalder & Pigneur, 2009). Meijer (2016) added societal costs and social benefits to this list, so a business model can make its sustainability explicit. Business models can contribute to sustainable development by changing an industry recipe or by commercializing sustainable technology (Bidmon & Knab, 2017). This chapter has so far showed that with regard to smart grids, Niesten and Alkemade (2016) showed that value can be created for consumers, system operators, and for society. Hall and Roelich (2016) described a set of archetypes that can work as a context for smart grid business models. In the case of demand response, there are two general ways to generate the desired behavior: price-based and incentive based (Niesten & Alkemade, 2016).

What follows in this section, are some conceptual business models that are formulated taking into account the characteristics mentioned above. The aim of the simulations that are described in the next chapter is to test expectations regarding these business models.

When households are defined as target customer, value creation according to table 3.1 revolves around reduced energy use and bills, as well as enhanced comfort. In the case of fuel-shift, total energy use is expected to be the same and there should be no change in comfort, as there should be no noticeable difference when using different fuels. Enhanced control is also mentioned as a value for consumers. Since it is assumed here that consumers will always choose the cheapest fuel, this value is measured as reduced energy bills as well. Calculated per kWh, heat from the district heating network is a lot cheaper than when using electricity to generate heat with resistance or infrared. The average Danish consumer electricity price in 2016 was 2.30 DKK/kWh (0.31 €/kWh) (Danish Energy Agency, 2016), while the consumer district heating price in 2018 in Copenhagen is 0.68 DKK/kWh (0.09 €/kWh) (HOFOR, 2018). This would make it beneficial for consumers to shift away from electric heating as much as possible. As a business model, it is assumed that the households own fuel-shift appliances in the context of a corporate supplier archetype, so that the only exchange of information between the households and the energy supplier is the energy price.

Hypothesis 1: When households own and control fuel-shift appliance, it will lead to lower household energy bills.

This business model may create value for households, but reduce value for system operators and society as their needs and wishes are not taken into account. According to table 3.1 there are a number of value propositions for system operators, but this thesis focuses on 'reduced peak demand'. Capacity in both the heat and the electricity grid is limited. Fuel-shift technologies may shift away from a fuel when its grid is at maximum capacity. If it is known beforehand that a neighborhood is going to have fuel-shift technology implemented that can respond to capacity restraints, utility companies can build infrastructure with a lower peak capacity, or hold off grid investments. By including price-based demand response, this value proposition for system operators may be included. The price-based conditions can be created by making the transmission and distribution price per kWh variable.

Hypothesis 2: When provided with appropriate price-based demand response, fuel-shift technology will lead to lower peak demand.

For the purpose of this thesis, societal value is measured purely as the amount of greenhouse gas that is emitted when generating heat or electricity. CO_2 emissions per kWh differ throughout the day and the year for both district heating heat generation and electricity generation. The emissions are a result of the mix of energy sources that are dispatched at a given time. In Denmark, renewable sources like wind and solar energy are usually given priority in the electricity grid [1]. Similarly, geothermal heat and heat from waste incineration are prioritized in the district heating grid (Harrestrup & Svendsen, 2012). This mix changes continuously, and since different sources of energy have differing carbon emissions, the carbon emissions of electricity and heat change continuously as well. By making the energy price depended on the CO_2 emissions, price-based demand response might include societal value as well. This condition can be created when the government makes the energy tax variable, as the government is considered to hold agency to act in society's best interest.

Hypothesis 3: When provided with appropriate price-based demand response, fuel-shift technology will lead to lower CO_2 emissions.

An alternative way of reducing peak demand or CO_2 emissions is in an ESCo archetype context, using incentive-based demand response. In this case, the households no longer necessarily own the fuel-shift devices, as they become part of the energy service agreement offered by the ESCo. They also no longer control the fuel-shift devices, as fuel-shifting is deployed by the ESCo to create value for any stakeholder in the network, as depicted in figure 3.1. As an ESCo would always have perfect control and perfect information, it would be more effective in reaching its goals then when indirect control via prices is applied.

Hypothesis 4: When fuel-shift technologies are controlled by a central operator, it will lead to more effective peak load reduction than when using price-based demand response.

[1] § 27c par. 5 Act on Electricity Supply

Hypothesis 5: When fuel-shift technologies are controlled by a central operator, it will lead to even lower CO_2 emissions than when using price-based demand response.

Chapter 4

Methods

With the business models defined, the next step is to analyze them using a household energy demand simulation. The aim of the simulation was to show the possibilities of fuel-shift technologies in households. In order to analyze this, 50 Danish houses were modeled with their general occupancy, electricity demand and heating demand. The model was made using Matlab (The Mathworks Inc., n.d.).

The intention throughout was to find the fit-for-purpose model, where a balance is struck between model complexity and model uncertainty. Gaetani, Hoes, and Hensen (2016) present this framework to select the appropriate complexity when modeling occupancy for building performance simulation. Simple models introduce approximation errors, while complex models introduce uncertainty due to estimation. An optimum needs to be found that minimizes the potential error in performance prediction, as displayed in figure 4.1. The optimum complexity is case specific, and a fit-for-purpose model is defined plainly as “something good enough to do the job it was designed to do.” Fit-for purpose modeling was interpreted here in such a way that complexity was added to the model up to the point were more complexity was not believed to give more reliable results.

This chapter first covers the theoretical discussion on household demand response simulation, and the energy demand of individual appliances in section 4.1. Section 4.2 gives the general assumptions and boundaries of the model. In section 4.3 it is described how appliance usage is modeled based on Gottwalt et al. (2011), and extended to include space heating and domestic hot water usage. These variables are included using real data from Liander (2014) and Ahmed, Pylsy, and Kurnitski (2016), respectively, adapted to the Danish situation using data from Danish Energy Agency (2016). To characterize the interaction between appliance usage and supply, section 4.4 describes how the energy supply is modeled. This is done based on supply data taken for the Danish wholesale energy markets from Energi Data Service (2018). Section 4.5 covers the formulation of the scenarios, based on the hypotheses formulated in chapter 3, as well as the pricing schemes that are tested for price-based demand response.

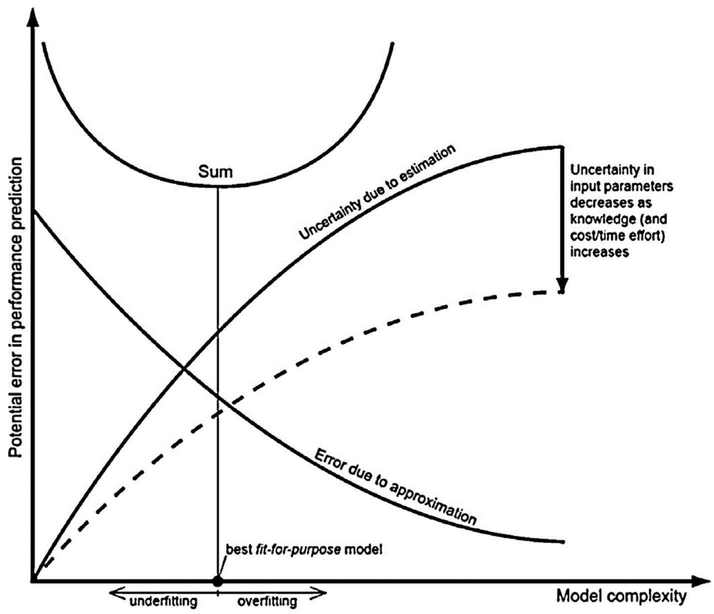


Figure 4.1: The fit-for-purpose framework (Gaetani et al., 2016; Trčka & Hensen, 2010)

4.1 Demand response modeling theory

Many examples of smart grid simulations can be found in literature, as models are often written to investigate a specific aspect of the smart grid. Since this paper focuses on demand response, it draws upon earlier work in demand response modeling, particularly on models that address the main three value propositions for fuel-shift defined in chapter 3: energy bill reduction for households, peak load reduction for system operators, carbon emission reduction for the environment.

Gottwalt et al. (2011) and Song et al. (2014) used models to analyze household energy consumption change under different incentives. They both investigated the effect on household energy bills, while Gottwalt et al. (2011) also focused on the effects on peak demand and Song et al. (2014) on the effects on carbon emissions. Kobus et al. (2015) developed a dynamic pricing solution which they used in a real-life demand response experiment, which was formulated from a system operator perspective.

Gottwalt et al. (2011) defined two kinds of modeling approaches: top-down and bottom up. Top-down approaches model total residential sector electricity consumption to trace consumption back to characteristics of the housing sector, while bottom-up approaches create household level load profiles which are extrapolated and projected to present a region. Using a bottom-up approach, household profiles can be based on statistical data or generated and then validated using reference data. Here, a mixed method was chosen, with appliance usage and domestic hot water demand generated using statistical input and then validated, and space heating and base load electricity based on national consumption averages.

Gottwalt et al. (2011) created a model that consists of a generator to create the load profiles, and a scheduler that then assigns appliances to optimized time slots. A similar approach is used here, with the model first generating demand profiles with a certain part of their demand available for fuel-shift. The decision algorithm will then choose the optimum fuel for each appliance cycle and time step, based on conditions set on the energy supply side. The energy supply side is defined using historical data for energy generation costs and emissions in Denmark.

Both Gottwalt et al. (2011) and Song et al. (2014) use occupancy profiles to decide when an appliance load cycle starts. Gottwalt et al. (2011) used a method where occupants can be at home or away, depending on the day being a weekday, weekend day, or holiday. For Gottwalt et al. (2011) cycle may start whenever a person is at home, while for Song et al. (2014) occupancy profile was based on a Markov-chain load model, in which the probability of an occupant starting an appliance is not only dependent on them not being away, but also on their current state, which was based on data from a time use study. Here, it was chosen to make appliance use dependent on the state of the occupants, also using time use data. Contrary to Gottwalt et al. (2011), it was chosen not to make distinctions between different days of the year, and contrary to Song et al. (2014), the state was not dependent on the previous state, but only on the time of day.

Pricing conditions are either based on the current Danish energy price, or an artificially generated price scheme, depending on the scenario that is being investigated. Kobus et al. (2015) provided a variable tariff structure that is used for this artificial generation, as described in section 4.5.2. They create a tariff structure that is dependent on the expected grid load, based on historical data. This tariff structure has been applied here in a slightly modified form, where the base case simulation data is used instead of historical data.

4.2 General assumptions

The household dwellings were modeled starting from the assumptions made by Cai et al. (2018). Houses were thus assumed to have a heated floor area of 140 m^2 with 3 occupants. Assuming they were built according to the most recent Danish Building Regulations 2015, total annual energy demand for heating and domestic hot water (DHW) was 5.2 MWh on average. The model covered a year of demand on a 15-minute time step basis, as also done by Gottwalt et al. (2011).

The sources of demand that were deemed available for fuel-shift were modeled individually, and then aggregated with a base load to form demand profiles. Each demand source was modeled with stochastic elements, so that individual households differ in the size and timing of their energy consumption. It was assumed that there were five types of household demand that could be fuel-shifted when beneficial: space heating, domestic hot water, washing machine, clothes dryer, and dishwasher. These applications were assumed to be able to shift their heat demand between district heating and electricity. Cooking was simulated as well, but without fuel-shift capabilities.

Space heating and district heating appliances were already widely available using either district heat or electricity, but as far as the author was aware not for multiple sources at the same time. As part of EnergyLab Nordhavn, a prototype of a domestic hot water boiler has been built that runs on both district heating and electricity (Cai et al., 2018). Washing machines and dishwashers currently only run on electricity, supplying their heat from the district heat network would not require major modifications to the design of the appliances, but the dwellings would need to be designed in such a way that the appliances have access to the district heat grid. A dryer can run on gas or electricity. District heat may theoretically be used as a heat source for the dryer's heat exchanger. This would require major modifications to the appliance, the design of which are outside the scope of this master thesis. Here it is assumed that the dryer has district heat as a heat source available and is free to draw heat from the district heat grid or the electricity grid without consequence to its operation or total energy usage.

In order to analyze the value of fuel-shift, it was important to introduce high degrees of variability in the models. Andersen (2012) showed that high variability in total demand occurs even in identical dwellings, so it is deemed likely that variability would also occur in timing of demand. This is introduced into the model with probabilistic elements to

4.3 Demand

4.3.1 Appliances

Based on the time use survey data, a probability was calculated of a household member doing a cooking or washing activity. Figure 4.2 shows the probability for an occupant to be engaged in an activity during the day. Washing activities include running the washing machine and the dryer, cooking activities include cooking and running the dishwasher. For every time step, an activity was appointed to each of the residents of each dwelling based on this probability. Three residents were assumed per household, so an appliance cycle could begin if any of the three occupants were currently engaged in the appropriate activity. The chance that an appliance's cycle will start, was calculated based on the expected share of the appliance's electricity consumption in the total expected electricity consumption of the household, displayed in equation 4.1 (Gottwalt et al., 2011):

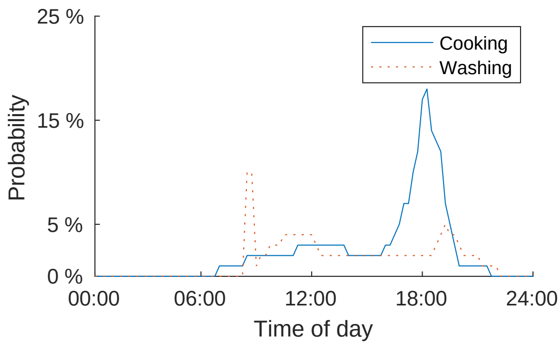


Figure 4.2: Probability of an occupant doing cooking or washing related activities for during the day

Table 4.1: Characteristics of the appliances used in the model: the model type, the length of a cycle, the energy consumption per cycle, and the share of electricity in the total electricity consumption

Appliance	Type	Length	Consumption [kWh]	Share of total
Washing machine	LG WM2016CW	01:00	0.0991	1 %
Dryer	GE WSM2420D3WW	01:00	1.4390	13 %
Dishwasher	Kenmore 665.13242K900	01:45	0.7167	3.7 %

$$M_i = \frac{h_k \cdot c_i}{d_i \cdot p_i} \tag{4.1}$$

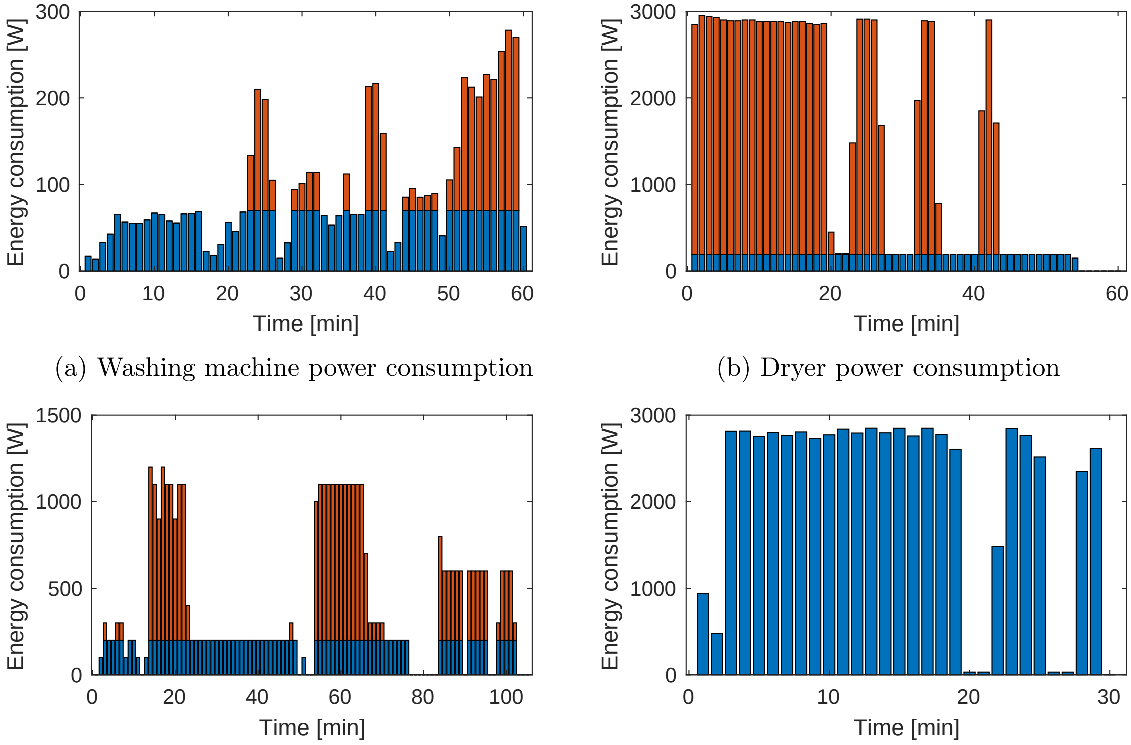
In this equation, M_i is the number of cycles appliance i runs per year, h_k is the total household consumption of household k, c_i is the share of appliance i of the total household consumption, as shown in table 4.1, d_i is the length of the cycle and p_i is the average power consumption of appliance i. The expected number of cycles is then divided by the total amount of time slots that are allocated to the appropriate activity for the household. This results in a chance for the cycle to start, each time the household occupancy profile shows that the activity is being deployed.

Appliance energy consumption was taken from Pipattanasomporn, Kuzlu, Rahman, and Teklu (2014). They analyzed the consumption of a range of appliances in two homes in the United States. The exact type and characteristics of these appliances can be found in table 4.1. It is assumed that all dwellings in the simulation own these same models.

Cooking is hard to model reliably, as a result of the wide ranges of energy consumption between kinds of meals (Carlsson-kanyama & Boström-Carlsson, 2001; Fischer et al., 2015), choice of cooking methods (Carlsson-kanyama & Boström-Carlsson, 2001), and even whether the person cooking is in a hurry or not (Hager & Morawicki, 2013). The method that was chosen here, was to take the oven electricity consumption presented by Pipattanasomporn et al. (2014), and consider that to be the net energy requirement for cooking.

Figure 4.3 shows the consumption profiles of the four appliances in minute resolution. These had been converted to 15-minute time step resolutions, as can be found in figure A.1. For these figures, the orange parts were assumed to be fully available for fuel-shift, while the blue parts always had te be powered by electricity. This is because only the appliances' heat demand can be shifted, and power for pumps and motors is always necessary. As mentioned above, cooking is not available for fuel-shifting, but it was included because of it's high power demand and the effect this had on peak loads.

The washing machine and cooking were leading activities, as a dryer cycle or dishwasher cycle always had to follow a washing or cooking cycle. Since there were fewer dishwasher cycles than cooking cycles, and fewer dryer cycles than washing cycles, theses following activities are triggered with a certain probability after the leading activity. A dishwasher, when triggered, started randomly 0-2 hours after the end of the cooking cycle, the drying cycle 0-3 hours after the end of the washing cycle.



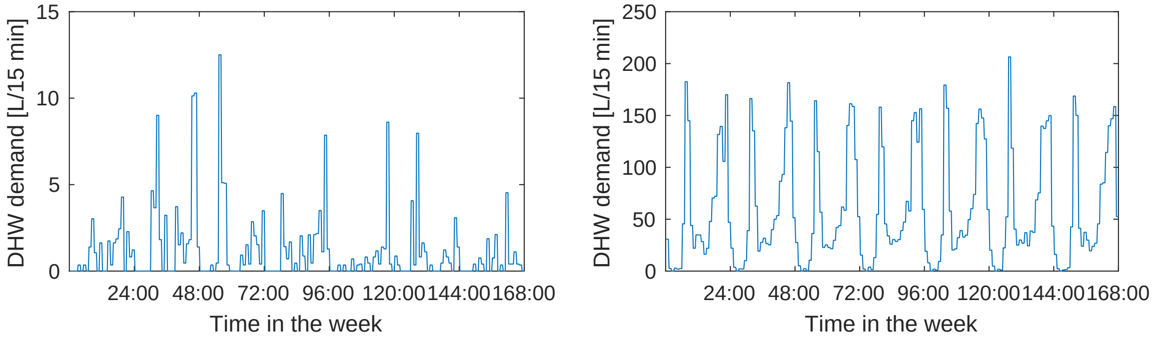
(a) Washing machine power consumption

(b) Dryer power consumption

(c) Dishwasher power consumption

(d) Cooking power consumption

Figure 4.3: Power consumption of the three appliances and cooking, based on Pipattanasomporn et al. (2014). Orange parts were assumed to be the heat part of the demand. Blue parts are always electricity.



(a) Single household, sum of three occupants

(b) Total demand of all 50 households

Figure 4.4: Domestic hot water demand profiles for a single week

4.3.2 Domestic hot water

Domestic hot water (DHW) demand was generated based on the data provided by Ahmed et al. (2016). They took the water consumption data of 86 Finnish apartments with 191 occupants to create frequency tables for hot tap water demand. These frequency tables were used as input for the hot water demand profile, each frequency depicting the likelihood of a profile having tap water demand at that time of the day, in that month. This makes domestic hot water consumption independent of occupancy. The total demand was scaled so that each occupant uses 33 L of hot water per day, so assuming that Danish households consume hot tap water with the same frequencies as Finnish households, but with a different total consumption.

Figure 4.4a shows a single week of demand for one of the households, given in liters per 15-minute time slot. The total demand of all 50 households is shown in figure 4.4b. This figure shows two peaks per day, one in the morning and one in the evening, as was expected from the frequency tables given by Ahmed et al. (2016),.

It is assumed that each dwelling has a buffer tank for domestic hot water of 92 L (Cai et al., 2018). Following Cai et al. (2018), tap water is assumed to be 42 °C, the tank is assumed to be completely at this temperature at the beginning of the simulation. For the energy calculations, it is assumed that the tank is perfectly stratified with a layer of 10 °C and a layer of 42 °C. The tank can be charged at 3.5 kW using electricity, or 5.2 kW using district heating, depending on what is applicable, and a charging cycle is started when there is enough 10 °C water in the tank that a charging cycle will never raise the average tank temperature over 42 °C. It can be discharged at any required power. Ambient heat loss is calculated assuming the tank has an outside area of 1.13 m^2 and heat transfer coefficient of 0.314 W/m^2K, and is perfectly mixed. When charging or discharging the tank, the energy is assumed to be directly converted to heat up 10 °C water to 42 °C, or to replace 42 °C water with 10 °C water.

4.3.3 Space heating

Space heating data was simulating using average gas consumption data for apartments from a gas distribution system operator in the Netherlands (Liander, 2014). This gas consumption

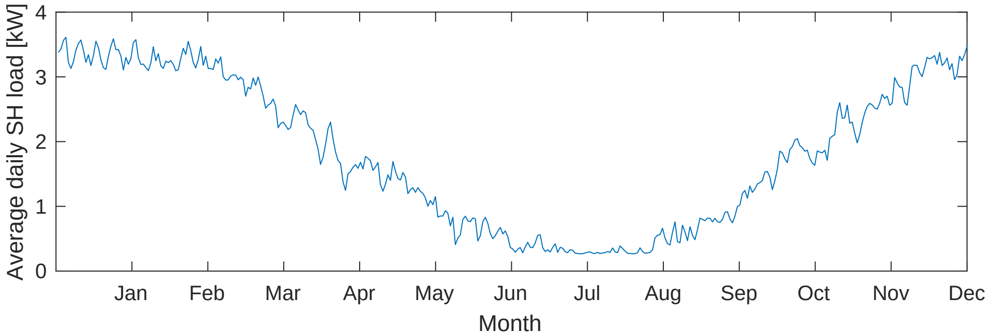


Figure 4.5: Average daily household space heating demand during the year

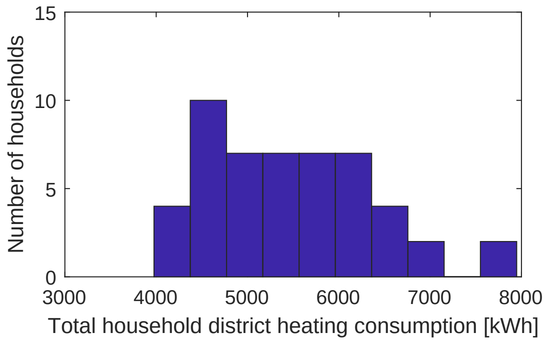


Figure 4.6: Distribution of total household space heating and domestic hot water energy consumption

data was corrected to account for gas usage for cooking and hot tap water, and then scaled, so that the total average yearly consumption of space heating and DHW together was 5200 kWh, which was the average heating consumption in Nordhavn according to Cai et al. (2018). With average DHW consumption being 1350 kWh per household, this leaves 3850 kWh per household per year for space heating consumption, on average. These profiles were then shifted in time with a normal distribution and a standard deviation of $\sigma = 2$ hours, as suggested by Cai et al., as well as scaled in size with a scaling factor $\mu = 1$, $\sigma = 0.5$ to include the variation in consumption seen by Andersen (2012). The resulting total summed space heating demand for the neighborhood can be seen in figure 4.5. Figure 4.6 shows the distribution of the total household energy consumption for district heating and domestic hot water consumption combined.

4.3.4 Electricity

The base electricity load was taken as the average Danish load, from Elforbrugspanel.dk (2012). This was assumed to cover the electricity consumption of all appliances that will not be fuel-shifted, like televisions, lights, and refrigerators. This profile was then scaled to fit a total household electricity consumption of $\mu = 3440$ kWh, $\sigma = \frac{\mu}{3}$, to get the average Danish electricity consumption per household (Danish Energy Agency, 2016). The washing

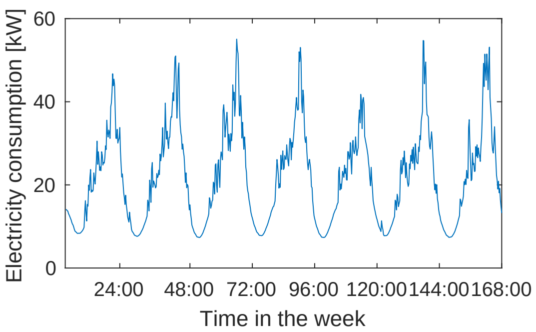


Figure 4.7: Total neighborhood electricity consumption

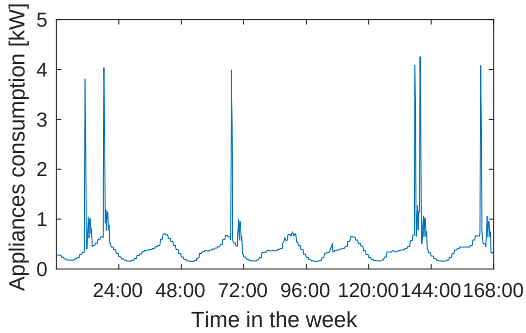


Figure 4.8: A single household's electricity consumption

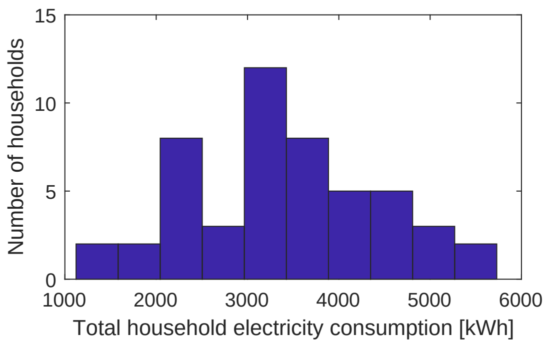


Figure 4.9: Distribution of total household electricity consumption

machine, dishwasher, dryer, and cooking base consumption profiles were then added to create profiles that differ between households. Figure 4.7 shows the total neighbourhood electricity consumption, assuming the fuel-shift appliances run completely on electricity, figure 4.8 a week of consumption for a single household, figure 4.9 shows the distribution of total household electricity consumption in that case.

4.4 Fuel properties

There were two types of fuel taken as input to the model; electricity and district heating. Both of these have a certain price, that may vary per minute, hour, or a different timescale, depending on the fuel. They also all have varying CO_2 emissions and peak loads.

4.4.1 CO_2 emissions

CO_2 emissions are taken as an independent variable during the simulation. The average carbon emissions of electricity production in the eastern side of Denmark (DK2) are tracked with 5-minute intervals and this data is provided by Energi Data Service (2018). CO_2 emissions from district heating are not made public. Instead, the CO_2 emissions for district heat were calculated using data on the Danish energy mix and a set of assumptions.

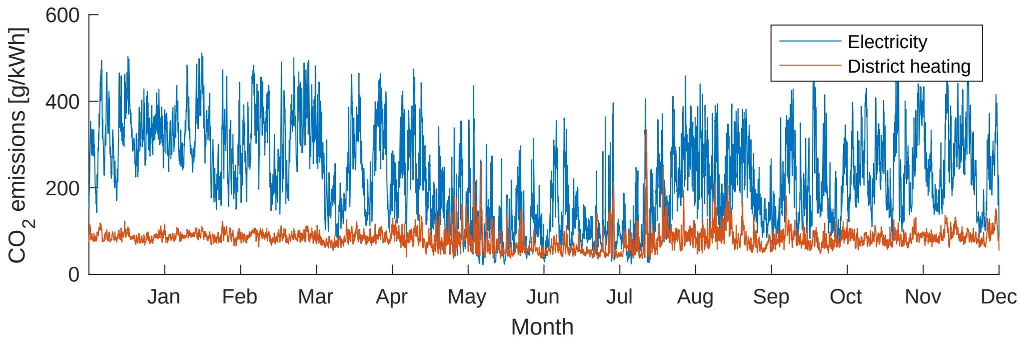


Figure 4.10: Estimation of CO_2 emissions for electricity and district heat throughout the year

Almost all electricity in Denmark is either generated by wind power, or in CHP plants. Since wind power has no (marginal) CO_2 emissions, all emissions that are published by Energi Data Service (2018) are assumed to have come from the CHP plans. Energi Data Service also tracks the share of wind energy of the total electricity production on a 5-minute basis. This way, it can be found out how much emission per kWh electricity is produced by CHP plants.

Heat is produced in Denmark using CHP plants firing fossil fuels (66.5%), plants firing waste or biomass (14.4%), or natural gas-fired boilers (11.5%)[1] (Danish Energy Agency, 2016). For natural gas, a fixed emission of 204 gCO_2/kWh is assumed, while for biomass and waste, no extra carbon emissions are emitted. Assuming these fuel ratios are fixed during the year, and the ratio of electricity production/heat production of the CHP plants is fixed as well, it was possible to make an estimate of the amount of CO_2 emitted per kWh of heat production in the Danish district heating system. The CO_2 throughout the year that were thus calculated, can be seen in figure 4.10.

4.4.2 Consumer costs

For the business-as-usual base case the price of district heat is constant throughout the year, while the electricity price is dependent on time-of-use (TOU) pricing set by DSO Radius. This sets the electricity price at 229.575 øre/kWh (0.31 €/kWh) during most of the year, and 333.95 (0.45 €/kWh) between 17:00 and 20:00 in the winter months (Energitilsynet, 2018) and the district heat price 67.505 øre/kWh (HOFOR, 2018). The development of this price throughout the year is given in figure 4.11.

4.4.3 Heat pump

All scenarios were tested with and without a heat pump to supply space heating and/or domestic hot water. The heat pump that was simulated was the Mitsubishi Electric SUHZ-SW45VA (Mitsubishi Electric, 2017). It was assumed that the water outlet temperature was constant at 45 °C and that the pump always operated at a nominal level.

The data from the data sheet, as shown in table A.1, were extrapolated to find the capacity and

[1]Percentages do not add up to 100 % as a result of rounding errors in the underlying data.

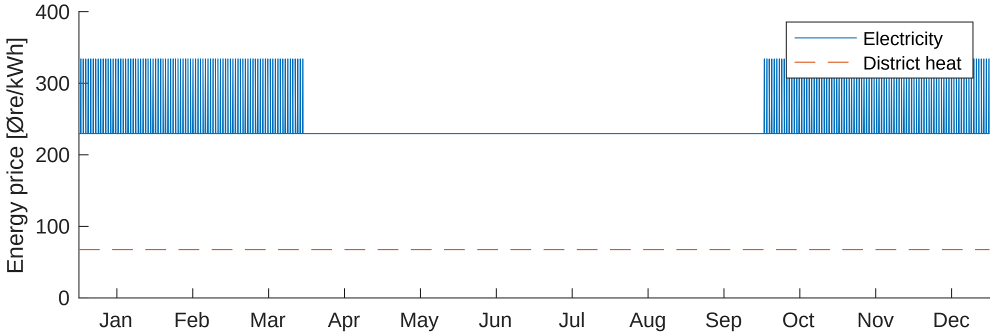
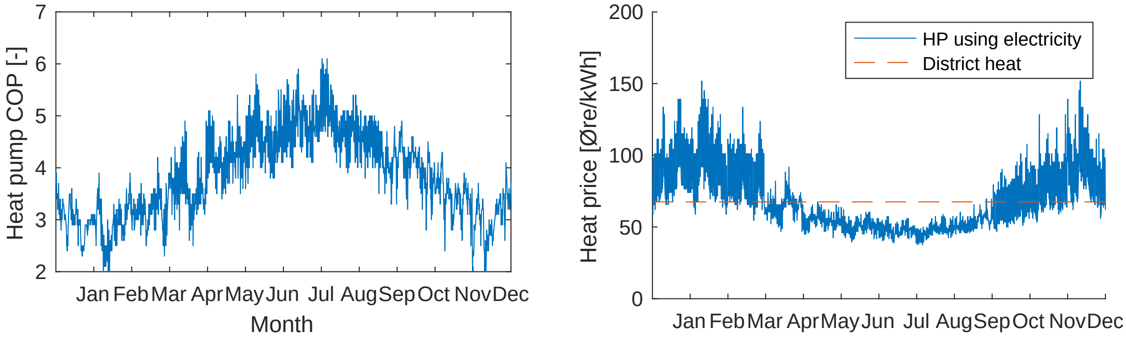


Figure 4.11: Business-as-usual consumer prices



(a) COP

(b) Cost of heat generation

Figure 4.12: Heat pump COP and cost per kWh of heat produced under business-as-usual electricity tariffs

coefficient of performance (COP) for the whole temperature range. The heat pump capacity and COP for the whole year were then found using wet bulb outside temperature data for the Copenhagen area from ASHRAE (2001). The capacity of the heat pump at nominal level was found to be enough in all cases to supply the dwellings with heat. Figure 4.12a shows how the COP of the heat pump changes throughout the year, based on the outside temperature. Figure 4.12b shows the real price of heat using electricity for a heat pump, compared to when using district heating.

4.5 Scenarios

The business models can be divided in two categories: the price-based models and the incentive-based models. The price-based scenarios leave the decision to the households, which are assumed to always make rational decisions regarding their energy bill, possibly using smart appliances. The incentive-based scenarios give full control over fuel-shift to a third party, which then chooses the most beneficial fuel.

The full overview of all scenarios can be found in table 4.2. The six scenarios are all tested under three conditions: No heat pump available (*No HP*), heat pump available for space

Price based	Business as usual
	Time of use district heat prices
	Real time peak load electricity prices
Incentive based	Peak load controlled space heating
	Peak load controlled domestic hot water
	Emission controlled

Table 4.2: The scenarios that are simulated

heating(*HP SH*), and heat pump available for space heating and domestic hot water (*Full HP*). For the *No HP* condition, the choice of fuel-shift is between district heat and electric resistive heating for all appliances. In the *HP SH* condition, heat from the air-to-water heat pump is available for space heating, while all other appliances, including domestic hot water production, use resistive heat when electricity is the chosen fuel. The *Full HP* condition allows for domestic hot water production to use the remaining available capacity of the heat pump, after space heating production.

Fuel-shift decisions were always made for a full cycle. In the cases of SH and DHW, the cycle length was considered to be one time step. This means that for each time step, the algorithm checked what fuel source was the most beneficial to use. For the appliances, the fuel was chosen for the whole cycle. This implies that all prices and tariffs for the whole cycle are known at the beginning of each cycle.

4.5.1 Base cases

Base cases were used to benchmark the outcomes of other scenarios. The goal of the base cases was to formulate a situation without fuel-shift that could conceivably found in the Danish context. A base case was formulated for each of the three heat pump cases. Code for the base case without heat pump can be found in appendix C.1.

In the base case *No HP*, it was assumed that non of the households have any fuel-shift appliances. Domestic hot water and space heating were operating fully on district heating. The dishwasher, washing machine and dryer ran completely on electricity.

In the *HP SH* condition, it was chosen to assume there is no district heating connection for the house. Space heating is provided by a heat pump, while domestic hot water is provided with an electric resistive heating. Appliances are connected to electricity only.

The *Full HP* condition assumes the same situation as the *HP SH* condition, except that the domestic hot water is also provided by the heat pump. Whenever the hot water tank needs charging, the surplus capacity of the heat pump after space heating demand is fulfilled is used.

4.5.2 Price based demand response

The first set of scenarios applies price-based demand response. At the beginning of each cycle, the algorithm checks the costs of running the cycle in either of the fuel types. It will then commit to the cheapest fuel type, and run the whole cycle in that fuel. This is the basis for all the price-based scenarios, which will use the same decision algorithm, but under differing pricing conditions. The code for the price based demand response can be found in appendix C.2.

The households made their fuel-shift decisions based on the cheapest fuel for the cycle. Equation 4.2 shows how this fuel is chosen, with P_{f_i} the prices for fuel i for each time step t during the cycle and $\mathbf{c}$ the consumption per time step during this cycle. Only when this total cycle cost for a fuel is lower than the total fuel cost of another fuel, will the algorithm decide to take this fuel. For domestic hot water and space heating, a cycle is a single 15-minute time step. The cycle length for each appliance can be found in table 4.1.

$$\text{Fuel}_{t \to t+t_{cycle}} = \begin{cases} \text{Fuel 1 if } P_{f1} \cdot \mathbf{c} < P_{f2} \cdot \mathbf{c} \\ \text{Fuel 2 if } P_{f2} \cdot \mathbf{c} < P_{f1} \cdot \mathbf{c} \end{cases} \tag{4.2}$$

With:

$$P_{fi} = \begin{bmatrix} p_{fi,t} & .. & p_{fi,t+t_{cycle}} \end{bmatrix}, \mathbf{c} = \begin{bmatrix} c_t \\ .. \\ c_{t+t_{cycle}} \end{bmatrix} \tag{4.3}$$

Business-as-usual prices

The first scenario uses the business-as-usual prices as shown in figure 4.11. The goal of the scenario was to test the effect of households owning fuel-shift appliances with everything else remaining the same. It was expected that fuel-shift allowed households to reduce their energy bill.

Time-of-use prices

The second price based scenario was formulated using a pricing method that is under possible consideration for the Nordhavn neighborhood, In this TOU pricing case, the tariffs for district heat are higher during the winter season, low during summer, and in between during spring and fall. Figure 4.13 shows a proposal for a TOU scheme that will be applied here. This scheme uses a price of 25 øre/kWh as the low rate, 50 øre/kWh for the medium rate, and 90 øre/kWh for the high rate. This way the average district heating bill for a household that is not using fuel-shift is the same in both the BAU and the TOU tariff schemes. The goal of using TOU district heating prices was to facilitate consumption during times of high availability and discourage demand during times of low availability, thus reducing high peak loads.

Peak load prices

The peak load prices scenario used a flexible electricity price, based on the expected district heat grid load. This scenario works with two tariffs, P_{high} and P_{normal}, for both the district heating and the electricity usage. What tariff was applied at a given time, was decided using equation 4.4, based on Kobus et al. (2015).

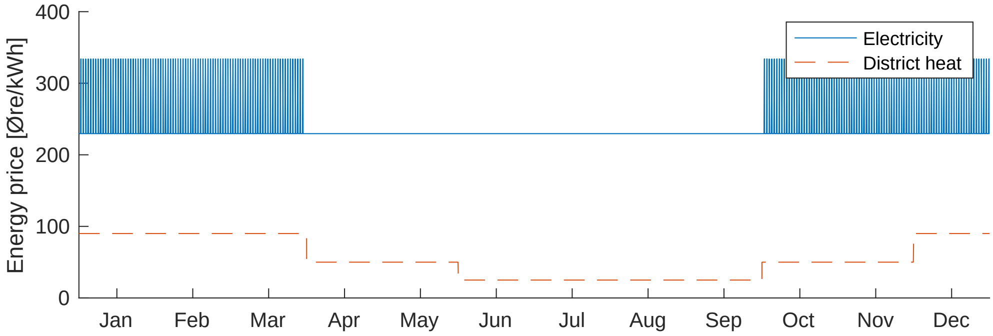


Figure 4.13: Consumer prices with TOU DH tariff

$$\text{Tariff}_N(t) = \begin{cases} P_{high} \text{ if } L(t) > c \cdot L_{max} \\ P_{normal} \text{ if } L(t) < c \cdot L_{max} \end{cases} \tag{4.4}$$

In equation 4.4, $\text{Tariff}_N(t)$ is the tariff at time slot t in network N (electricity or district heating) L_{max} is the maximum predicted load in the network in the year, $L(t)$ is the normalized predicted load during that time slot, based on the base case predictions. c is the turning points between tariffs. So for each time slot, it was tested whether the expected load based on the base case load would be higher than the maximum predicted load time the turning point. If this was the case, the high tariff would be applied, otherwise the low tariff was kept. This scenario simulated with values for c varying between 5 %-95 %. In order to maintain price neutrality, the high tariff would be increased or decreased when necessary, until the average total energy cost for the base case *No HP* demand was the same using the generated price scheme and business-as-usual prices. The normal tariff was set at 60 øre/kWh for cases without heat pump and 120 øre/kWh for cases with a heat pump, so that electricity would be supplied at a cheaper rate than district heat, which was kept at the BAU rate of 67.505 øre/kWh.

Emission based prices

In the original hypotheses it was proposed to also test emission based prices. However, after preliminary analysis of the results of the "private economics" scenario, it was chosen not to pursue this. It appeared to be the case that the cheapest fuel was also the fuel with the lowest emissions for most of the year. This is discussed in more detail in chapter 5.

4.5.3 Direct control

In the direct control scenarios, the algorithm checked the most beneficial fuel for each individual household at the beginning of each cycle. For each time step, the algorithm started by checking whether a fuel was more beneficial than another. It would then assign households with a fuel demand to this fuel for as long as it was available.

Peak load controlled

The goal of the peak load controlled cases was to find out how much the maximum peak district heat demand could be reduced, and what the effect of this would be on the peak electricity demand. This was done by defining the peak district heat demand as a percentage of the peak demand in the *No HP* base case. This percentage was lowered with 2 per cent point at a time, to find out at which point the peak demand could no longer be reduced. The algorithm checked per time step and per household whether maximum peak demand was reached. If it was not, then the demand of the next household could be filled with district heat. If maximum peak demand was reached, the remaining households were shifted to electricity. The order in which the households were checked was randomized for each time step. This can be found in the code in appendix C.3. Four cases were run like this: shifting space heating with and without heat pump, and shifting domestic hot water demand with and without heat pump.

Emission controlled

The emission controlled scenario always chose the fuel with the lowest expected CO_2 emissions for the duration of the load cycle. Since fuel carbon emissions were considered independent of consumption, there was no capacity constraint when shifting households towards the most beneficial fuel. This scenario was analyzed for the *No HP*, *HP SH*, and the *Full HP* cases.

4.6 Sensitivity

In order to be able to make statements about the generalizibility of the simulation results, a sensitivity analysis was conducted on some parameters and outputs were checked for validity. The sensitivity analysis was conducted by testing the base case scenario for a range of different values for several parameters at the same time. Validity was checked by comparing outcomes to expected outcomes based on literature.

Sensitivity was tested for five sets of parameters, an overview of the sets and all tested variabled can be found in table 4.3. Each of these sets contained the variables that had some influence on the results within this category. A lot of these variables did not have a noticable effect on the outcome. Especially the standard deviation of demand had little effect, as the results were always expressed in averages. Some variables that had clear effects are presented in appendix A.4.

Except for cooking, non of the parameters appeared to have disproportionate effects on simulation outputs. As established in chapter 4, it is very hard to reliably simulate cooking, as its consumption patterns are highly dependent on behavior. As fuel-shift showed little opportunity to reduce peak electricity load in the scenarios tested here, the high impact of variability in cooking is not considered a problem for the result analysis in this case. It does show that for future work, it is important to be aware of the impact of cooking on electricity consumption and peak loads, and adapt the model accordingly.

Table 4.3: Variable sets for sensitivity analysis

Set number	Variables	Original value	Tested range
01	Electricity consumption mean [kWh/yr]	3440	1000 - 5500
	Electricity consumption standard deviation [kWh/yr]	$\mu/3$	$\mu/1$ - $\mu/13$
02	Space heating consumption mean scale factor [-]	1	0.5 - 2.5
	Space heating consumption standard deviation [-]	0.25	0.1 - 0.9
	Domestic hot water consumption mean scale factor[-]	1.5	0.5 - 2.5
	Domestic hot water standard deviation [-]	0.25	0.1 - 0.9
03	Dryer saturation [-]	0.42	0 - 1
	Dryer share of total consumption [-]	0.13	0.05 - 0.2
	Dishwasher share of total consumption [-]	0.037	0.005 - 0.15
	Washing machine share of total consumption [-]	0.01	0.005 - 0.015
	Cooking share of total consumption [-]	0.09	0.05 - 0.15
04	Ambiant temperature deviation [K]	0	-5 - 3
	Heat pump capacity scaling [-]	1	0.5 - 2
	Heat pump COP scaling [-]	1	0.5 - 2
05	DHW charge power electric [W]	3500	1000 - 4000
	DHW charge power distric heat [W]	5200	2000 - 8000

Chapter 5

Results

In this chapter the results of the simulations are reported. The order in which these are presented are the same as in chapter 4, starting with the base case, then the price based scenarios, followed by the incentive base scenarios. The division of costs and benefits that allow the viability of the business cases to be analyzed, are described in chapter 6.

5.1 Base cases

The total actual average base case consumption can be seen in figure 5.1. It shows that the average electricity consumption was slightly lower than the Danish average (3405 kWh vs. 3440 kWh), and the district heat consumption was slightly higher than specified by the build code (5480 kWh vs. 5200 kWh). This was considered well within acceptable margins of error. It also becomes clear that the consumption of the shiftable appliances is very low compared to the total electricity consumption, and the space heating and hot water consumption. This was especially the case, considering that this is the total electricity consumption and only part of this consumption is considered shiftable.

Figure 5.2 shows the total electricity consumption of the three base cases in a winter week. As expected, electricity consumption was higher for the *HP SH* and *Full HP* cases, as these did not use any district heating at all. At the same time, the total energy demand for *HP SH* and *Full HP* were lower than the total demand for the *No HP* case, as the use of a heat pump reduced the total demand. The differences between *HP SH* and *Full HP* were completely due to the domestic hot water demand.

The total emissions, consumption and costs for the base cases can be found in table 5.1. This shows that implementing a heat pump led to slightly higher costs and slightly lower

Table 5.1: The average household consumption values for all three base cases

Scenario	Case	Electricity [MWh]	DH [MWh]	Cost [DKK]	Emissions [tCO_2]	Heat pump COP [-]
Base case	No HP	3.40	5.48	12 178	1.28	-
	HP SH	6.10	-	14 793	1.47	3.31
	Full HP	5.02	-	12 224	1.23	3.36

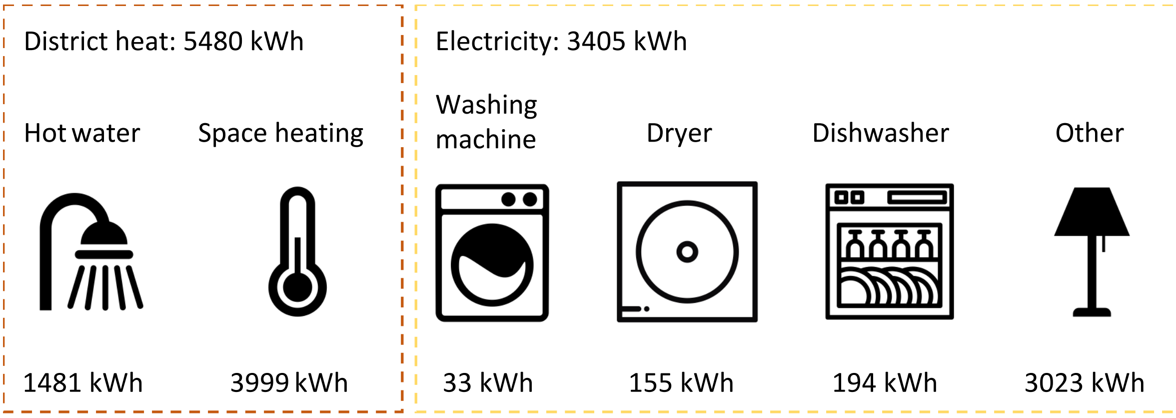


Figure 5.1: Actual average yearly household energy consumption in the base case

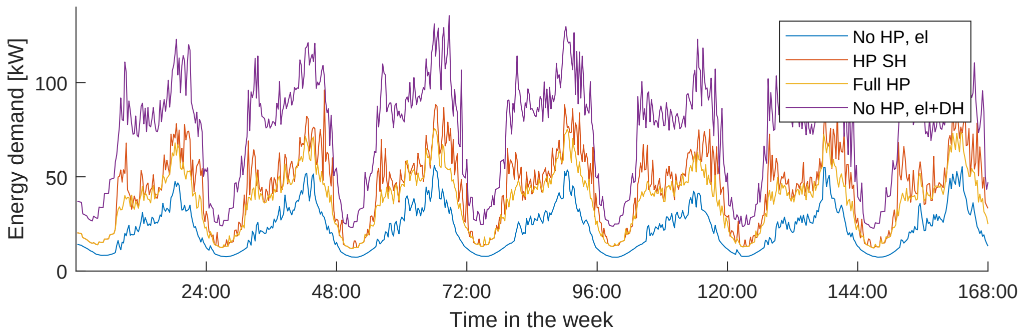


Figure 5.2: Total energy demand of the three base cases in a winter week

emissions, but only when used for domestic hot water as well as space heating. An overview of the consumption distributions of all base cases can be found in appendix A.2.

Adding a heat pump for space heating led to higher yearly energy costs, while adding it for domestic hot water led to a slight decrease. This was expected, as figure 4.12b showed that heat from the heat pump was only cheaper than district heat during the summer half of the year. Space heating demand was low during this period, while domestic hot water demand was more consistent throughout the year. As a result, space heating would almost only use the heat pump during periods that it was more expensive than district heat, while for domestic hot water demand those higher wintertime energy costs were balanced out with cheaper summertime energy costs.

5.2 Price based demand response

5.2.1 Business-as-usual prices

The first scenario that was tested, used the business-as-usual price scheme. Figure 5.3 shows the fuel-shift of district heat in the *No HP* case. The blue lines show the energy prices, the orange line the percentage of district heat shifted, compared to the base case with -100 % meaning all DH demand is shifted to electricity. Since electricity per kWh was consistently more expensive than district heat, the only fuel-shift that was observed, was the shift towards DH by the dishwasher, clothes washer and dryer. This shift was relatively larger in summer, when these appliances made up a larger part of total consumption due to low space heating demand. 30 % of consumption from the appliances was shifted towards district heat, which is equal to their complete heat consumption, with the other 70 % demand being electricity for pumps etc.

In figure 5.4 the fuel-shift is displayed for the *HP SH* case. Now, a third blue line is added, showing the cost of generating heat using the heat pump, defined as the price of electricity divided by the heat pump COP. This time, a fuel-shift from district heat to electricity was observed during the summer months, when the high heat pump COP made electricity the cheapest fuel per kWh. In the middle of July, space heating demand is almost zero, leading to a fuel-shift of almost zero. Between October and April heat from district heat is almost

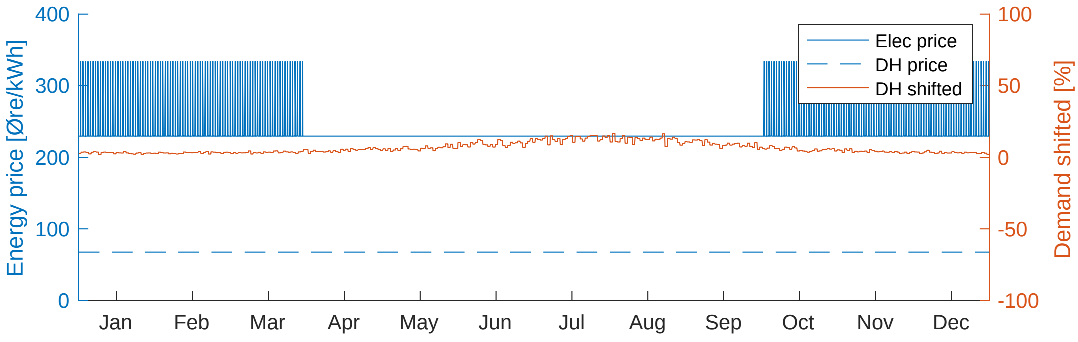


Figure 5.3: The price development and the fuel shift with BAU prices *No HP*

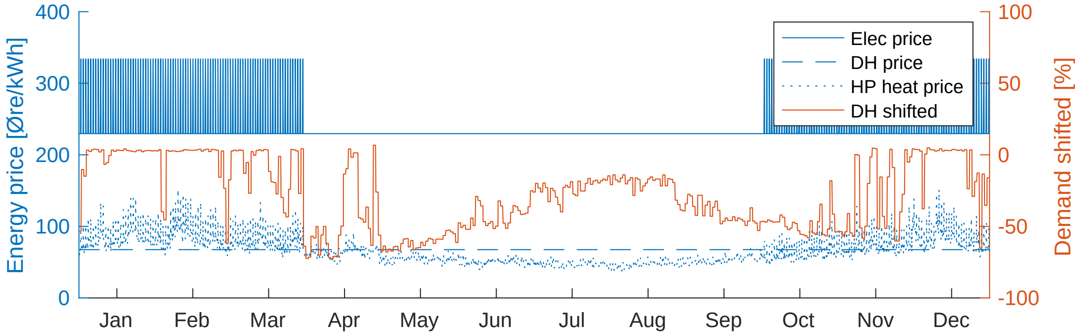


Figure 5.4: The price development and the fuel shift with BAU prices *HP SH*

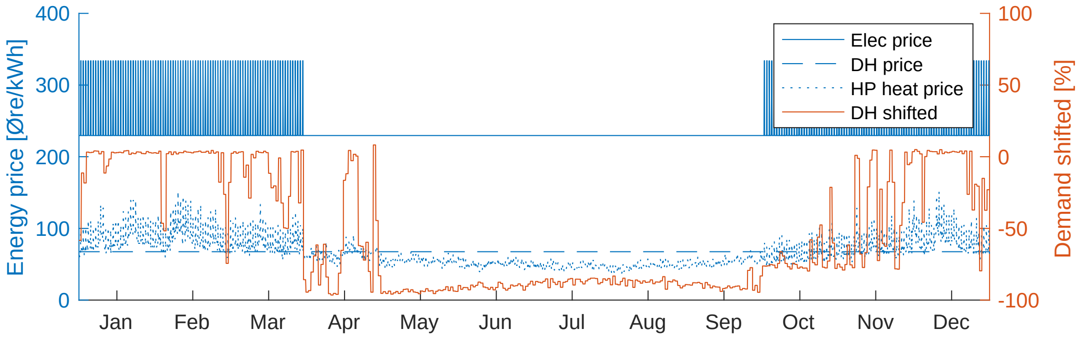


Figure 5.5: The price development and the fuel shift with BAU prices *Full HP*

always cheaper than using a heat pump. Most fuel shifting occurs in the spring and fall months, when there is still space heating demand and the heat pump can supply heat cheaper than the district heating system. However, since heat demand was low during these months, the total amount shifted was only 13 % of total space heating demand.

The same effect can be seen in the *Full HP* case in figure 5.5. In this case, the full domestic hot water and space heating demand shifted to the heat pump, while the appliances shift to district heat. Eventually 23 % of domestic hot water demand was met using the heat pump in this case. This meant that almost the full district heat demand was shifted to heat pump electricity during April-September, leaving only the appliances' heat demand to be covered with district heat, as they still shifted from electricity to district heat.

5.2.2 Time-of-use district heat prices

In the TOU price scenario district heat costs were reduced in during summer and increased during wintertime. In the *No HP* case, there was no difference in fuel shifted between the TOU pricing and the business-as-usual pricing, as can be seen in figure 5.6. District heat was still consistently cheaper than electricity, so all heat demand, which was 30 % of appliance and 100 % of space heating and hot water demand, was taken from district heat.

Figures 5.7 and 5.8 do show a difference in fuel-shift behavior compared to the BAU scenario.

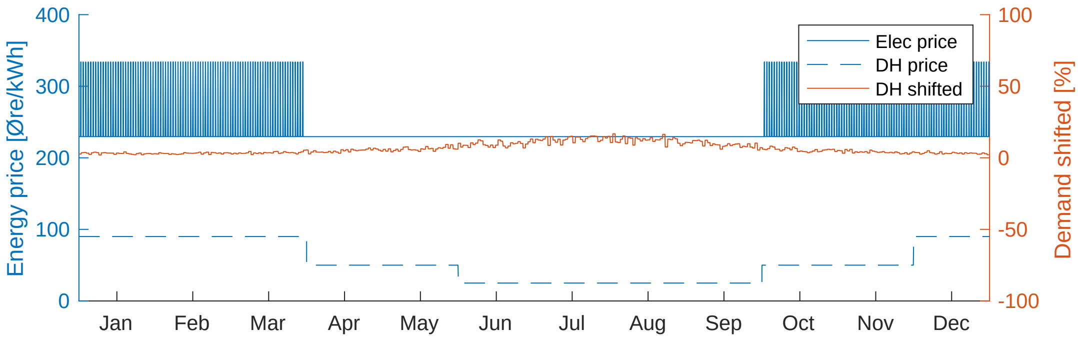


Figure 5.6: The price development and the fuel shift with TOU prices *No HP*

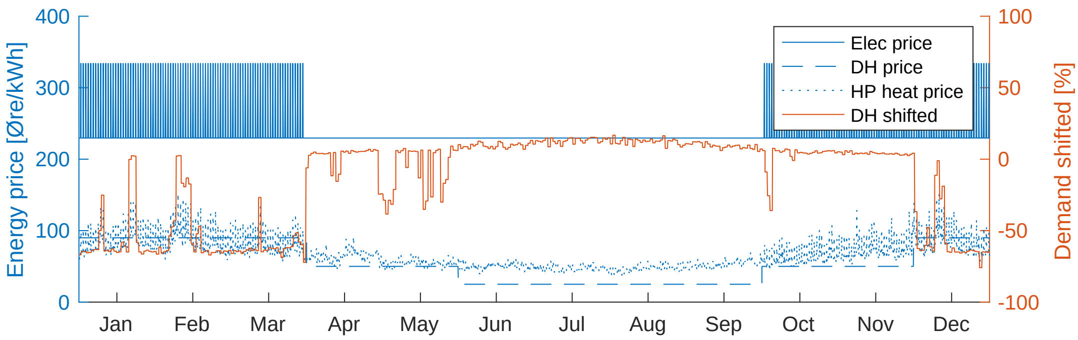


Figure 5.7: The price development and the fuel shift with TOU prices *HP SH*

The winter DH prices were high enough to trigger fuel shift towards electricity during winter months, when a heat pump was applied. Meanwhile, the summer district heat prices were low enough to out-compete the heat pump, meaning that most heat in the period from March to November was supplied using district heat. This is almost the opposite behavior when comparing to the business-as-usual price scheme. 20 % of space heating demand and 9 % of domestic hot water demand was supplied using electricity, when a heat pump was applied.

5.2.3 Emission prices

Originally it was planned to create a price scheme that coupled price to CO_2 emissions. However, after looking at the base case results, it became clear that less than 3 % of the total base load occurred during time slots in which carbon emissions from the cheapest fuel were higher than from the most expensive fuel. Also the incentive based emissions reduction scenario as presented in section 5.3.2 showed that it was hardly possible to get emissions lower than in the price based scenario with business-as-usual prices. It was therefore chosen not to pursue a price based scenario with the aim to reduce emissions.

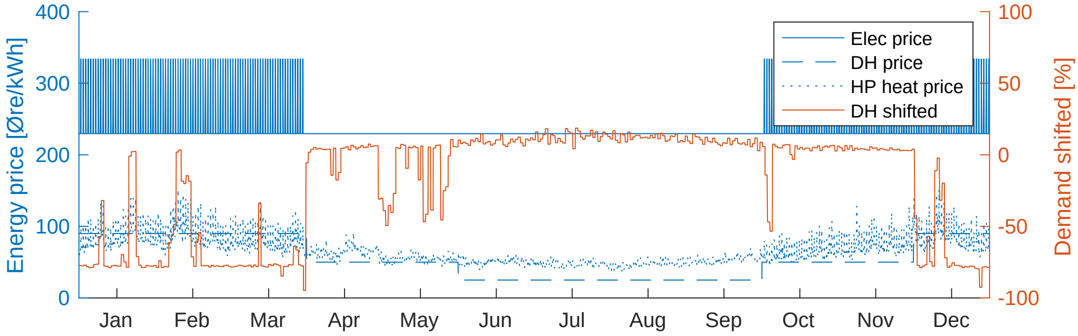
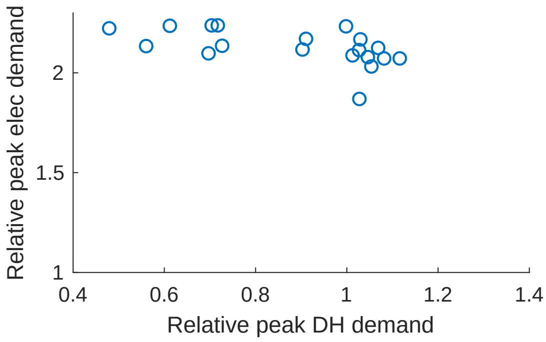


Figure 5.8: The price development and the fuel shift with TOU prices *Full HP*

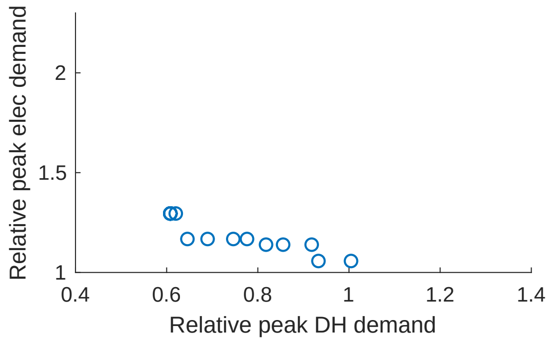
5.2.4 Peak load prices

With peak load prices scenario, the electricity price was made variable with the goal of reducing the district heat peak load. The graphs in figure 5.9 show the increase and decrease in maximum yearly peak load for electricity and district heat relative to the base case *No HP*, using peak load-based real-time pricing (RTP). The graphs show that while it was possible to reduce the maximum yearly DH peak using RTP, it had a negative effect on the yearly maximum electricity peak. Figure 5.10 clearly shows why this was the case, as the decrease of the electricity price to a level below the district heat price led to a complete shift to electricity of all available loads, behavior that was also observed by Gottwalt et al. (2011) and which they called " avalanche effects". This means that peak load pricing was only effective to reduce district heat peaks when there was no constraint for electricity peaks.

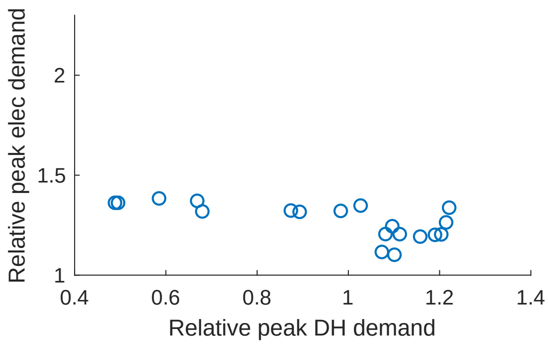
The scenario formulated for each case a cutoff point as a percentage of the peak district heat load in the base case. When the expected load for a time step, based on the base case demand profile, would not surpass this cutoff point, the high electricity tariff would apply. This high electricity tariff was set in such a way that the total energy bill for an average household would not be different than in the base case, if they would not posses fuel-shift technologies. This way, the high electricity tariff would compensate for the moments when the low tariff was applied to encourage shifting away from district heat. Figure 5.11 shows the peak electricity tariff that was generated with the resulting relative peak district heat load. These electricity prices became extremely high, up to 15 times higher than the BAU normal price, leading to a 6,000 % price increase between normal and peak electricity prices in the most extreme case. When keeping the high electricity price beneath 400 øre/kWh, a peak district heat load reduction of 27 % was possible without a heat pump, and 13 % with a heat pump, given a normal electricity tariff of 60 øre/kWh and 120 øre/kWh, respectively.



(a) Relative peak effects, *No HP*



(b) Relative peak effects, *HP SH*



(c) Relative peak effects, *Full HP*

Figure 5.9: Relative peak load effects of peak load pricing scenario

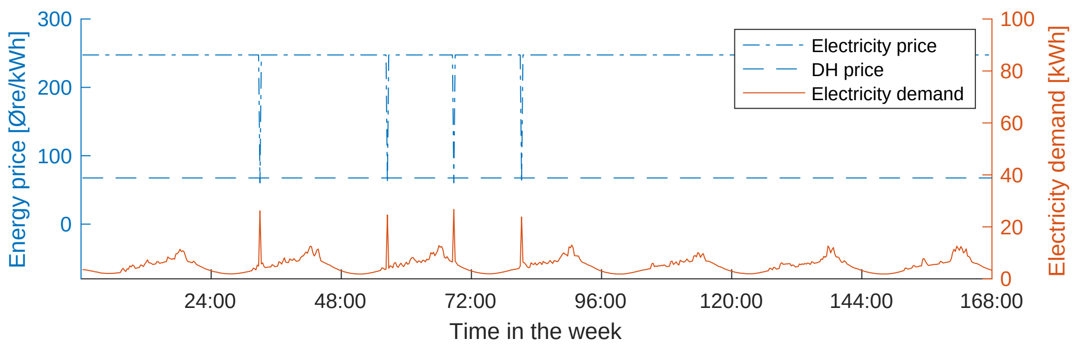


Figure 5.10: A week of electricity consumption using real-time peak load pricing

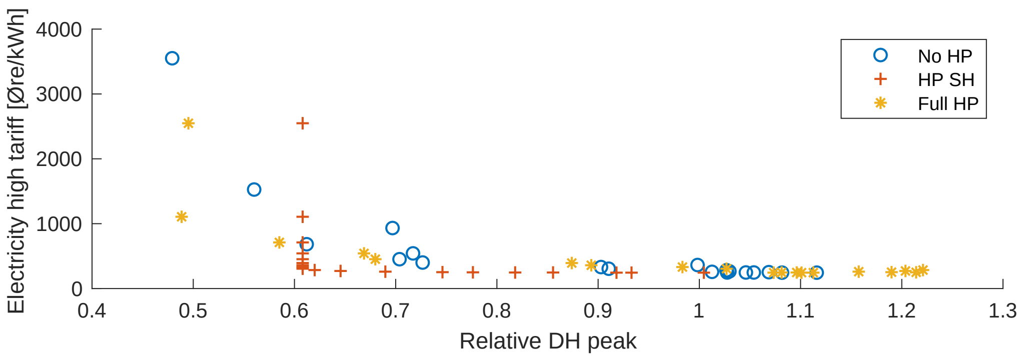


Figure 5.11: The high price tariff and the relative district heat peak load

5.3 Incentive based scenarios

5.3.1 Peak load controlled

The peak load controlled scenarios shifted devices to the most beneficial fuel on a household-by-household basis. Avalanche effects were avoided this way, as only the optimum total load was shifted to a fuel, keeping the maximum allowed peak load for that fuel in mind. Similar to the peak load prices scenario, the goal was each time to reduce the total yearly district heat peak demand based on the base case simulation.

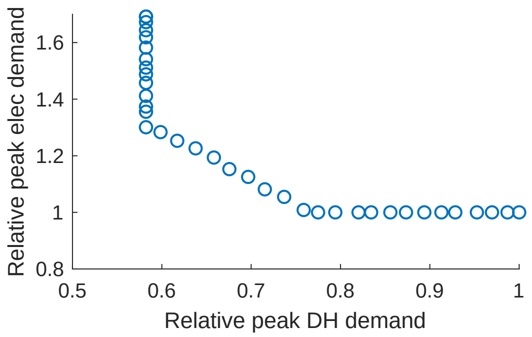
Space heating and domestic hot water

In the case of peak load control, either DHW demand or space heating demand was fuel-shifted with the objective of bringing the maximum district heat peak demand down. The results of these simulations are displayed in figure 5.12 and table 5.2.

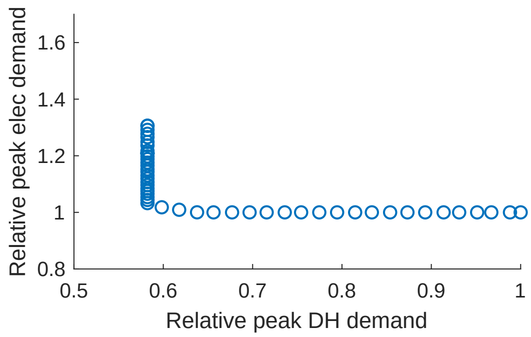
The graphs in figure 5.12 show the relative peak demand for electricity and district heat. ‘Relative peak’ means in this case the maximum peak of the year in a case, relative to the maximum yearly peak demand in the base case. Fuel-shift away from district heat was enforced at a certain percentage of the base case maximum peak demand. This percentage was lowered between cases in 2 %-point increments. The graphs show that there was a point at which it was not possible to reduce the maximum district heat demand peak anymore by shifting away only space heating demand or domestic hot water demand.

Case	Lowest district heat peak	Electricity peak	Lowest district heat peak without higher electricity peak
Space heating	58 %	130 %	77 %
Space heating HP	58 %	103 %	64 %
Domestic hot water	58 %	142 %	73 %
Domestic hot water HP	58 %	104 %	59 %

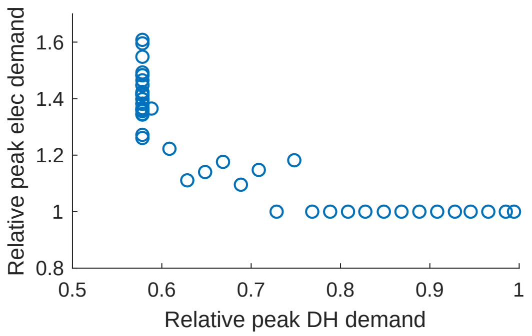
Table 5.2: Peak demand reduction with direct control fuel-shift



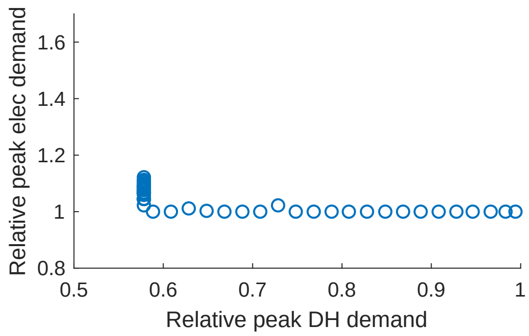
(a) Peak demand reduction when shifting space heating



(b) Peak demand reduction when shifting space heating with a heat pump



(c) Peak demand reduction when shifting domestic hot water



(d) Peak demand reduction when shifting domestic hot water with a heat pump

Figure 5.12: Peak demand reduction with direct control fuel-shift

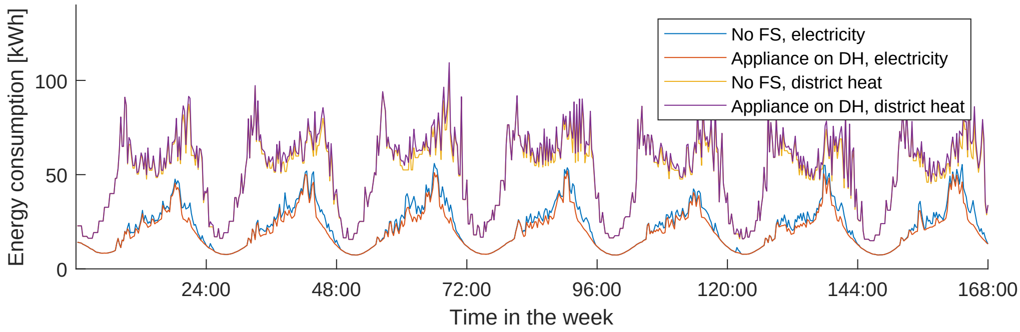


Figure 5.13: Effect of fuel-shifting all appliances

Table 5.2 shows that the lowest possible peak demand in all cases was 58 % of the maximum peak in the base case. This means that there was a moment in the year when domestic hot water or space heating consumption alone would require 58 % of base case peak demand. After this point, the highest electricity peak demand would increase, without decreasing the district heat peak demand.

Using a heat pump, peak district heating demand could be reduced a lot further without requiring extra peak demand from the electricity network than when a heat pump was not used. The third column of table 5.2 shows the minimum size of the highest electricity peak demand in cases the district heating peak demand has been reduced to 58 %. For the cases with heat pumps, these peaks were only a few per cent higher, while this increased significantly more when a heat pump was not applied.

Appliances on district heating

Another option might have been to shift the appliances away from electricity to reduce electricity peak demand. Figure 5.13 shows a week of demand for the base case and for a situation where all appliance had their fuel heating load on district heat. The relative effect of shifting appliances on the total demand was very low. The total peak demand could not be lowered in any meaningful way by shifting away the dishwasher, washing machine, and dryer. This was largely the result of the cooking peak being the dominant electricity demand peak. It was therefore chosen not to create a scenario with the aim to reduce maximum yearly electricity peak load using fuel-shift.

5.3.2 Emission controlled

In the emission controlled incentive based scenario the fuel with the lowest expected emissions was selected. Table 5.3 shows the results for these three cases, as well as the base case: *No HP* for comparison. Without a heat pump present, the emission control scenario shifted almost all consumption towards district heat. When a heat pump was introduced, electricity consumption went up at the cost of district heat consumption.

Figures 5.14 5.15, and 5.16 show the district heat consumption shift in comparison to the *No*

Case	Electricity [MWh]	DH [MWh]	Cost [DKK]	Emissions [tCO_2]
Base case No HP	3.40	5.48	12 178	1.28
Emission No HP	3.25	5.63	11 719	1.22
Emission HP SH	3.81	3.45	11 581	1.16
Emission Full HP	4.01	2.47	11 412	1.13

Table 5.3: The consumption values for the direct control: emission cases

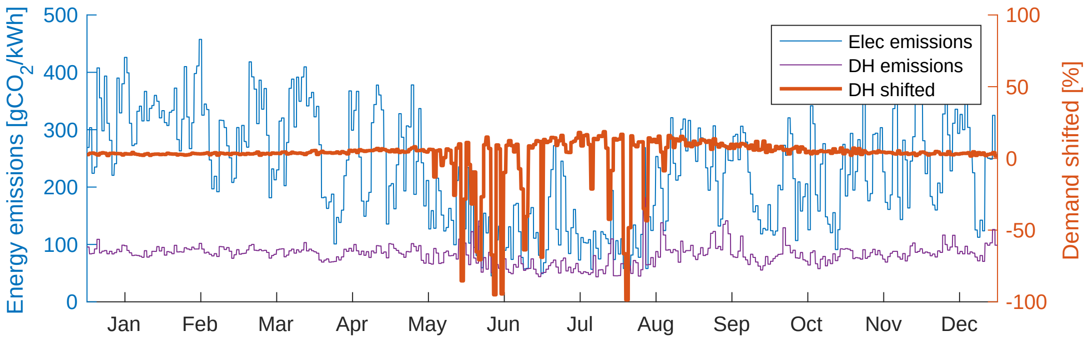


Figure 5.14: District heat shifted in the emission scenario, *No HP* case. Daily averages.

HP base case for the *No HP*, *HP SH*, and *Full HP* cases respectively. The three blue lines show the carbon emissions of electricity, district heat, and heat generated using a heat pump respectively. The orange line shows the shift of district heat compared to the base case. -100 % means that all the district heat consumption was shifted to electricity or heat pump sourced heat. Figure 5.14 shows that without a heat pump, district heat consumption throughout the year was slightly higher than in the base case, as the appliances were shifted towards district heat. Only during the summer months, when carbon emissions from electricity were lower than carbon emissions from district heat during some time slots, would a full fuel-shift towards district heat happen. This turned out to be 3 % of domestic hot water consumption and 1 % of space heating consumption, for a 5 % decrease in total emissions.

In figures 5.15 and 5.16, fuel shift is more apparent. The heat pump created a situation where heat from electricity had lower carbon emissions than district heat for a larger part of the year, especially during the warmer months when heat pump COP was higher and the emissions from electricity were lower. Eventually, 26 % of space heating and 36 % of domestic hot water demand were shifted to electricity when using a heat pump. The maximum total emission reduction thus achieved was 12 %.

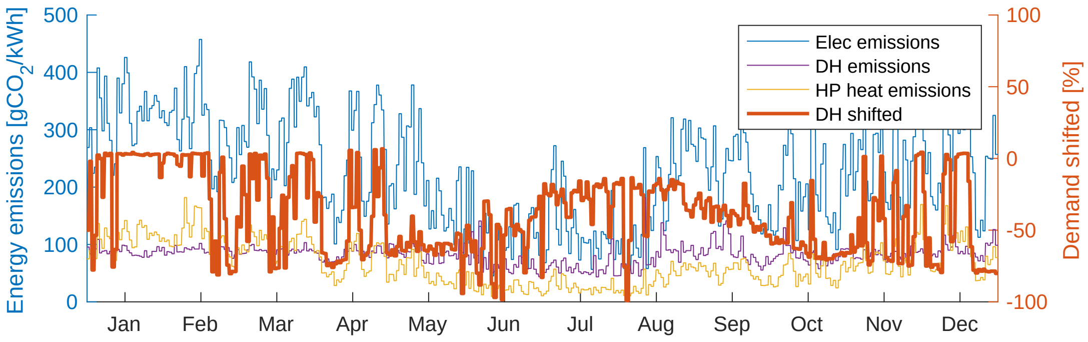


Figure 5.15: District heat shifted in the emission scenario, *HP SH* case. Daily averages.

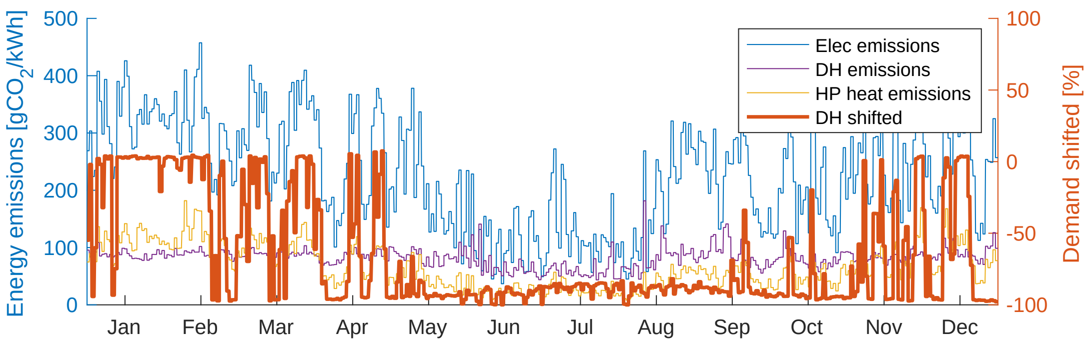


Figure 5.16: District heat shifted in the emission scenario, *Full HP* case. Daily averages.

5.4 Overall fuel-shifted

The total average yearly energy consumption per fuel per application for all relevant scenarios and cases can be found in table 5.4. Table 5.5 shows the ratio of electric and district heat fuel sources that were demanded in each scenario and for each case.

Table 5.4: Yearly average electricity and district heat fuel consumption of all five fuel-shift application in kWh

		Dishwasher		Washing machine		Dryer		Space heating		Domestic hot water	
		Electricity	DH	Electricity	DH	Electricity	DH	Electricity	DH	Electricity	DH
Base case	No HP	194	0	33	0	155	0	0	3999	0	1481
	HP SH	194	0	33	0	155	0	1207	0	410	0
	Full HP	194	0	33	0	155	0	1207	0	1488	0
BAU prices	No HP	76	118	19	14	19	140	0	3999	0	1481
	HP SH	76	118	19	14	19	140	373	2491	0	1481
	Full HP	76	118	19	14	19	140	373	2491	196	638
TOU prices	No HP	76	118	19	14	19	140	0	3999	0	1481
	HP SH	76	118	19	14	19	140	551	2258	0	1481
	Full HP	76	118	19	14	19	140	551	2258	110	1129
Emissions	No HP	81	113	20	13	24	134	57	3942	49	1432
	HP SH	81	113	20	13	24	134	611	1755	49	1432
	Full HP	81	113	20	13	24	134	611	1755	255	456
Peak load control	Appliances DH	76	118	19	14	19	136	0	3999	0	1481
Peak load control	Space heating	270	0	33	0	155	0	133	3866	0	1481
Maximum reduction	Space heating, HP	270	0	33	0	155	0	44	3867	0	1481
	DWH	270	0	33	0	155	0	0	3999	86	1343
	DHW, HP	270	0	33	0	155	0	0	3999	29	1341
Peak load control	Space heating	270	0	33	0	155	0	7	3992	0	1481
No elec load increase	Space heating, HP	270	0	33	0	155	0	21	3937	0	1481
	DWH	270	0	33	0	155	0	0	3999	8	1419
	DHW, HP	270	0	33	0	155	0	0	3999	22	1362

Table 5.5: Percentages of fuel shifted in each scenario

		Space heating		Domestic hot water		Appliances	
Scenario	Case	DH	Electricity	DH	Electricity	DH	Electricity
Base case	No HP	100	0	100	0	0	100
	HP SH	0	100	0	100	0	100
	Full HP	0	100	0	100	0	100
BAU prices	No HP	100	0	100	0	70	30
	HP SH	87	13	100	0	70	30
	Full HP	87	13	77	23	70	30
TOU prices	No HP	100	0	100	0	70	30
	HP SH	80	20	100	0	70	30
	Full HP	80	20	91	9	70	30
Emission control	No HP	99	1	97	3	67	33
	HP SH	74	26	97	3	67	33
	Full HP	74	26	64	36	67	33
Peak load control	Appliances DH	100	0	100	0	70	30
Peak load control	Space heating	97	3	100	0	0	100
Maximum reduction	Space heating, HP	99	1	100	0	0	100
	DHW	100	0	94	6	0	100
	DHW, HP	100	0	98	2	0	100
Peak load control	Space heating	100	0	100	0	0	100
No elec load increase	Space heating, HP	99	1	100	0	0	100
	DHW	100	0	99	1	0	100
	DHW, HP	100	0	98	2	0	100

Chapter 6

Value capture

6.1 Price based demand response

6.1.1 Business-as-usual prices

The most simple business model was for a company to sell the appliances to households. The value proposition for the households was to have a reduced energy bill, part of this saved money could be spent on more expensive appliances that are fuel-shift enabled. The full overview of fuel-shift benefits by application is given in table 6.1.

The dishwasher consumed for DKK 473 (€64) worth of energy per year in the base case for an average household. With fuel-shift and business-as-usual prices, this became DKK 265 (€36), a decrease of 44 %. Not discounting costs and assuming energy prices do not change, this means that over a 10 year write-off period for an appliance, fuel-shift dishwashers can be around DKK 2080 (€280) more expensive than their conventional counterparts for the households to break even. Reductions for the washing machine (30 %) and the dryer (62 %) can be calculated in a similar way to save DKK 240 (€32) and DKK 2350 (€316) over this 10 year period, respectively. Especially for the dishwasher it seems that the savings are high enough for an appliance upgrade to fuel-shift to be feasible, as only minor modifications to the appliance design would be necessary.

For fuel-shift to have effect on the energy bill for space heating and domestic hot water, implementation of a heat pump is necessary. Implementing a heat pump without fuel-shift will only increase the energy bill for space heating by DKK 246 per year for an average household. A fuel-shift heat pump will decrease the bill with DKK 162 per year compared to the case without fuel-shift and without heat pump, a decrease of 5 %. The domestic hot water bill is slightly reduced (1 %) when a heat pump is used and even more with a heat pump with fuel-shift (15 %). The savings on the energy bill for these two applications do not seem to be able to cover increased investment costs, but it can be said that when a heat pump is considered anyway, it might be feasible to implement fuel-shift as well.

Table 6.1: Energy costs for each appliance in the private economics scenarios and the base case in DKK per household per year

Scenario	Case	Dishwasher	Clothes washer	Dryer	SH	DHW
Base case	No HP	473	80	371	2 700	1 000
	HP SH	473	80	371	2 946	3 554
	Full HP	473	80	371	2 946	986
BAU prices	No HP	265	56	139	2 700	1 000
	HP SH	265	56	139	2 538	1 000
	Full HP	265	56	139	2 538	850
TOU prices	No HP	250	54	122	2 823	802
	HP SH	250	54	122	2 555	802
	Full HP	250	54	122	2 555	751

6.1.2 Time-of-use prices

Time-of-use pricing did not change the value proposition of fuel-shift compared to business-as-usual prices much, as can also be seen in table 6.1. Almost all applications have even lower energy bills than in the BAU prices scenario, which is a result of the district heat cost being lower than in the base case for more months than it was higher. Without a heat pump, this price difference was covered by an increased space heating bill of DKK 123 (€17) per year, but with a heat pump, space heating costs also reduced to almost BAU prices levels. The goal of time-of-use prices was to reduce peak district heat demand, which it did not manage to do with the price scheme and configuration proposed here.

6.1.3 CO_2 emissions

As mentioned before, fuel-shift already had a positive effect on carbon emissions from energy production, without having to formulate a specific price scheme. Implementing fuel-shift with BAU or TOU prices reduces CO_2 emissions by 60 kg per household per year on average. While a heat pump in base case conditions will decrease carbon emissions by 100 kg per year compared to the base case with heat pump, and 150 kg compared to the base case *No HP*.

6.1.4 Peak load pricing

As described in section 5.2.4, peak load pricing was effective in reducing district heat peak price. Due to the price-neutral way in which the electricity tariffs were defined, there were no large effects on the household energy bill. As can be seen in figure 6.1, for cases without a heat pump the CO_2 emissions went up with a decrease in district heat peak load. This was a result of more electricity being consumed during winter time, when average carbon emissions per kWh of electricity are higher. In cases with a heat pump, this effect was compensated as the heat pump led to lower total energy consumption.

The exact energy costs for households differs depending on the chosen cutoff point and peak tariff, but in general households are still able to safe on the energy bills of appliances with

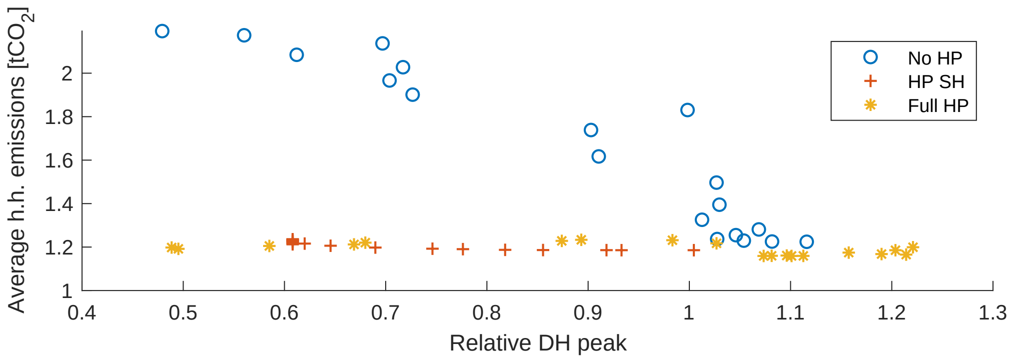


Figure 6.1: Average household CO_2 emissions and relative peak district heat load in the price based scenario

this price scheme in place.

6.2 Incentive based scenarios

6.2.1 Peak load controlled

The peak load controlled scenario aimed to lower district heat peak loads, while avoiding avalanche effects that are usually found in price based demand response. As already described in 5.3.1, peak district heat load could be reduced up to 42 %, and up to 40 % without increasing electricity load. Table 6.2 shows the space heating and domestic hot water energy bills for the four cases of maximum DH peak load reduction and the four cases of maximum reduction without increasing electricity peak load. The table shows an increase in space heating costs when peak load based shifting is applied, but a decrease in domestic hot water costs when compared to base case.

CO_2 emissions rise with the reduction in peak DH load, but less so than in the price based scenario. All cases start out at base case emission levels, as appliances were fuel by electricity and space heating and domestic hot water by district heat. Emissions rose as peak load was reduced by shifting space heating or domestic hot water to electricity. As emissions are dependent on total consumption and not load size, and only a small portion of total demand is actually shifted, emissions rise only slightly with decrease in peak load. Once a relative peak load of 58 % of base case peak load is reached, carbon emissions keep rising without decreasing the district heat peak load further, in the cases without heat pumps. This is illustrated in figure 6.2. In the cases with heat pumps, there were no large correlations between carbon emissions and peak load reduction found.

6.2.2 Emission controlled

To get a bit more insight into the relation between household cost and emission reduction, a Pareto front was constructed. Details on how this was done can be found in appendix B. Figure 6.3 shows the three fronts that were created for the three cases. The figure displays the fronts on which the solutions lay at which emission could not be reduced further without increasing costs and vice versa. It shows that the availability of a heat pump had a much larger effect on the emissions than the distinction between cheap and low emission solutions.

Table 6.2: Energy costs for space heating and domestic hot water in several peak load controlled cases, in DKK per household per year

Scenario	Case	SH	DHW
Peak load controlled	SH 58 %	2946	1000
	SH HP 58 %	2 723	1 000
	DWH 58 %	2 700	1 123
	DWH HP 58 %	2 700	980
	SH 78 %	2 711	1 000
	SH HP 68 %	2 748	1 000
	DHW 74 %	2 700	977
	DHW HP 60 %	2 700	976

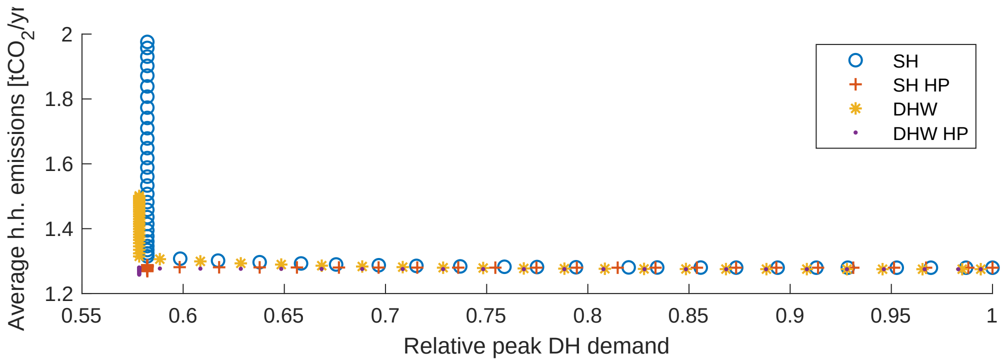


Figure 6.2: Average household CO_2 emissions and relative peak district heat load in the incentive based scenario

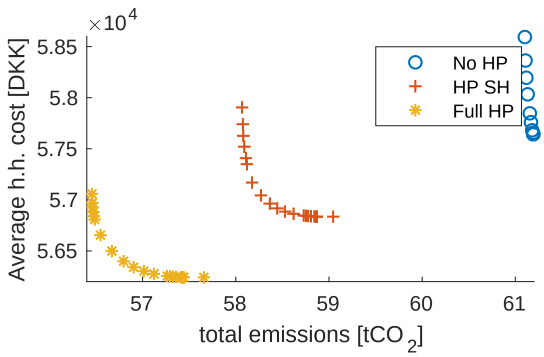


Figure 6.3: Pareto fronts between costs and emissions for the three cases

This is a result of the low emission fuel being at the same time the low cost fuel in most time slots, leaving only a few time slots in which a meaningful choice can be made between costs and emissions.

Chapter 7

Discussion

This thesis is part of a preliminary investigation into the possibilities of fuel-shift technologies. It was therefore necessary to limit the scope of the study. This chapter describes some limitations of the presented model, and opens some doors towards future work that can be done regarding fuel-shift technologies.

7.1 Assumptions and limitations

As this was the first attempt to investigate the possibilities of fuel-shift technologies in household dwellings, the model results could not be validated using any kind of practical situation. As described before, a domestic hot water fuel-shift prototype has been developed in the context of EnergyLab Nordhavn, and has been made ready for experimental implementation. Once the results of those experiments are known, they can be used to validate the model presented here. Similar validations should be made for the appliances modeled here, as well as space heating in combination with a heat pump.

Although care was taken to create variety in consumption profiles, the study still only focused on 140 m^2 newly built houses. A large part of the building stock in Copenhagen, as in any European city, consist of existing houses. These could be renovated to integrate the newest energy technologies, but the results presented in this study cannot immediately be extended to included scenarios with renovated houses. More work should be done to find out whether these fuel-shift results hold for different types of households, in different compositions and in different kinds of dwellings.

Niesten and Alkemade (2016) and Hall and Roelich (2016) provided a wide range of value propositions for fuel-shift technologies, like enhanced grid control, integration of electric vehicle charging infrastructure, and integration of renewable energy sources. While fuel-shift may provided value on these points as well, it was not taken into consideration for this model, meaning that there is still room to extend the investigation of business models for fuel-shift.

Throughout the report a distinction was made between time-shift demand response and fuel-shift demand response. While the focus of this research was fuel-shift demand response, there is no reason why the two forms of demand response could not be applied together. Especially in the case of price-based demand response, households might choose to shift their demand in time at moments when both district heat and electricity prices are high. Since both forms of demand response require real time price and load information to be exchanged between appliances and system operators, it would require little technical change to operate fuel-shift and time-shift in parallel. In such a case, a planning algorithm would not only plan the most beneficial fuel, but also the most beneficial moment in the day at which this fuel should be consumed.

The results presented in this report are valid for current energy prices and fuel mixes only. Because of the large number of uncertainties, making a forecast of price and fuel mix development was deemed outside the scope of this thesis. However, some developments may affect the business cases of fuel-shift technologies in the long term, and therefore warrant closer investigation when further researching fuel-shift technologies.

7.2 Implications for business models

The hypotheses that were formulated in chapter 3 implicitly assumed a trade-off between costs, emissions, and peak loads. However, throughout the simulations it became clear that, especially between costs and emissions, no real trade-off existed. This led to some scenarios being discarded before they could be investigated, as their intended outcomes were already realized in other scenarios.

Hypothesis 1: When households own and control fuel-shift appliance, it will lead to lower household energy bills.

Hypothesis 2: When provided with appropriate price-based demand response, fuel-shift technology will lead to lower peak demand.

Hypothesis 3: When provided with appropriate price-based demand response, fuel-shift technology will lead to lower CO_2 emissions.

Hypothesis 4: When fuel-shift technologies are controlled by a central operator, it will lead to more effective peak load reduction than when using price-based demand response.

Hypothesis 5: When fuel-shift technologies are controlled by a central operator, it will lead to even lower CO_2 emissions than when using price-based demand response.

Hypothesis 1 was confirmed, as there are a range of moments throughout the year when an appliance does not run on the cheapest possible fuel. Especially with a heat pump, the option to shift between district heat and heat from the heat pump proved valuable. This hypothesis held under all of the tested pricing schemes, as household energy bills always decreased when fuel-shift technologies were available and were allowed shift to the most competitive fuel, compared to situations without fuel-shift. In the case of appliances, the necessity of fuel-shifting may be brought into question. The appliances shifted to district heat almost all the time in any scenario, so developing appliances the get their heat solely from district heat, without the option of using electric heating, might be just as beneficial and cheaper than building smart fuel-shift appliances.

Hypothesis 2 was also confirmed, but with the side note that price based demand response does lead to avalanche effects. This meant that, while fuel-shift was seen to be able to reduce district heat peak loads, it lead to large increases in electricity peak loads, as the full energy demand would shift to electricity then. Gottwalt et al. (2011) propose giving different consumer groups different tariffs to negate this effect.

Both price based and incentive based demand response turned out to be ineffective for electricity peak load reductions using fuel shift. This could largely be attributed to electric cooking requiring a high load, which could not be fuel-shifted. Time-shift demand response might be more effective here, but as established before, cooking energy and power consumption are highly variable and dependent on behavior.

Hypothesis 3 was not tested, as business-as-usual prices were already seen to reduce CO_2 emissions by almost as much as in the emission controlled scenario. It was therefor deemed plausible that appropriate prices would be able to reduce carbon emissions even further.

Hypotheses 4 and 5 were tested in scenarios with incentive based demand response. The nature of the incentive given to households to allow a system operator to fuel-shift their load was not made explicit, rather it was assumed that some reason was given to households to comply with the required fuel-shift. With hypothesis 4 the expectation was formulated that centrally controlled fuel-shift would lead to even lower peak loads than price based scenarios would. In a centrally controlled fuel-shift situation a controller could reduce the consumption of district heat to 0 for the whole neighborhood for the whole year, but this was not considered to be a useful case to test. What was shown in the simulation, was that central control effectively got rid of avalanche effects, making it possible to reduce district heat peak loads, without increasing electricity peak loads. Whether incentive based or price based demand response is most beneficial thus depends the required size of the peak load reduction and the acceptable size of the increase of peak load for the other fuel.

Emission controlled fuel-shift indeed was the most effective way of reducing carbon emissions, as stated in hypothesis 5. However, the total available CO_2 emission reduction was only 12 % of base case emissions, while a 10 % emission reduction could already be realized by just applying fuel-shift technologies under current prices. Without heat pump, emission controlled fuel-shift did not lead to lower emissions than price based fuel-shift with business as usual prices. It appears that using incentive based fuel-shift in order to reduce CO_2 emissions would thus be unnecessarily complicated.

7.2.1 User involvement

This thesis present two business model archetypes as a context for fuel-shift technologies: the traditional model in which households own the fuel-shift technologies, and an ESCo model in which fuel-shift is centrally controlled and the technologies may be owned by an ESCo. Although the exact way in which users can be persuaded to invest in fuel-shift technologies, or convinced to become client of an ESCo, depends on the exact details of the business model, literature can provide some insights.

In the case of market failure, consumer cooperatives are presented as a possible way of introducing an technology (Sadowski, 2017b). They may emerge when risk and uncertainty associated with private financing are too high. According to Sadowski (2017b) consumer cooperatives emerge as a response to specific types of risks: high fixed costs and switching costs. Additionally, there are two types of benefits that motivate consumers to join a network: deriving from an increasing number of users and indirect effects rising from managing infrastructure.

Another way of diffusion of advanced technologies, proposed by Sadowski (2017a), is through advanced users. These users have high technical skills and willingness to experiment and test advanced services. In the cases investigated by Sadowski (2017a), services are hardly self sustaining after subsidy stopped, even with advanced user involvement. Both advanced users and consumer cooperative insights come from ICT and broadband network contexts, but parallels may be drawn with smart grid service implementation, especially if user cooperatives take the form of ESCos. This could be a topic for further research.

Chapter 8

Conclusion

The goal of this thesis was the find the main value propositions of fuel-shift technology that shift between district heat and electricity. In order to do this, a model was developed to simulate fuel-shifting in five applications: space heating, domestic hot water production, clothes washing, clothes drying, and dish washing. These were tested under price-based and incentive-based scenarios, investigating the effects of fuel-shift on household electricity bills, CO_2 emissions and district heat peak loads. This was done for 50 newly built medium-size residences in the context of the Nordhavn neighborhood in Copenhagen, Denmark.

Of the five fuel-shift applications that were tested, the three appliances, dryer, washing machine and dishwasher, clearly perform better on district heat than on electricity. Their value proposition mainly consisted of district heat usually being a lower emission and cheaper fuel than electricity, leading to a full fuel-shift to district heat almost 100 % of the time. This indicates that it might be a good idea to develop these appliances in such a way that they only run on district heat, rather than have the ability the shift between district heat and electricity. This is further affirmed by the fact that the appliances did not show potential to contribute to peak load reduction, which was found to be a major source of fuel-shifting value for the other two applications. Connecting appliances to district heat would require dwellings to have the necessary connections, and in the case of the washing machine the added monetary value was very low.

Space heating and domestic hot water production show more added value for fuel-shift, not only in reducing energy bills and CO_2 emissions, but also in reducing district heat peak loads. Rather than a trade-off, simulation results show that these values can work in a complementary way, both in cases of price-based demand response and incentive-based demand response with direct control over the applications. However, this is only the case when the electric heat is supplied by a heat pump, as this brings the emissions and costs per kWh of heat down to similar levels as district heat. At the same time, the monetary benefits might not be high enough to justify the installation of an air-to-water heat pump. This leaves the scenarios with the largest potential fuel-shift value to only apply to the rather limited number of situations were houses are built with both a heat pump and a district heat connection. Future cost reductions of air-to-water heat pumps, especially in combinations with more district heat grid congestions and thus higher attributed value to demand response services that can bring peak loads down may expand the business cases for fuel-shift technology.

To summarize, a price based demand response business model with households as target customer has positive impacts on household energy bills and heating carbon emissions. A business model would contribute to sustainable development by simply commercializing this technology. An incentive based demand response model with a central ESCo controlling appliances to capture value by offering fuel-shift services as a method to reduce peak loads can be effective in certain cases, especially when households have a heat pump and a district heat connection. Whether the business model can be profitable is dependent on the exact situation, but fuel shift likely reduces household energy bills and carbon emissions. This path of fuel-shift contributing to sustainable development takes the form of a new industry recipe, in which ownership of appliances and grid operations would shift to new actors.

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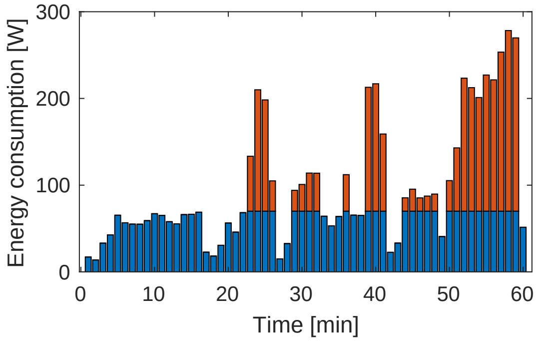
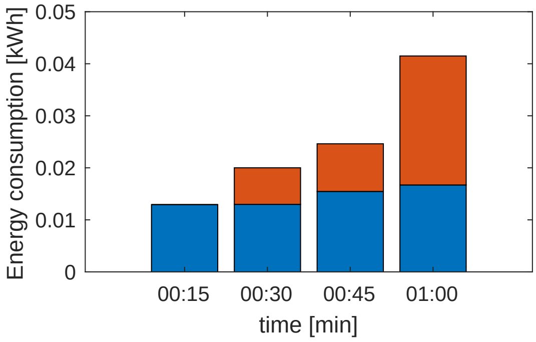
Appendix A

Data

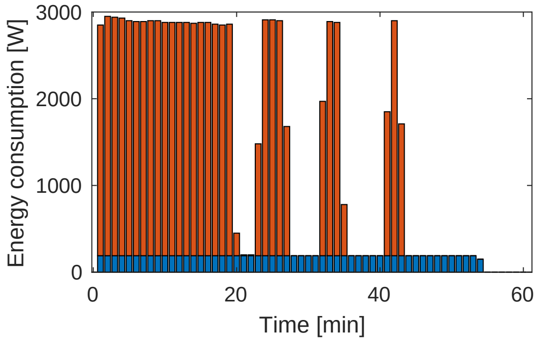
A.1 Appliances



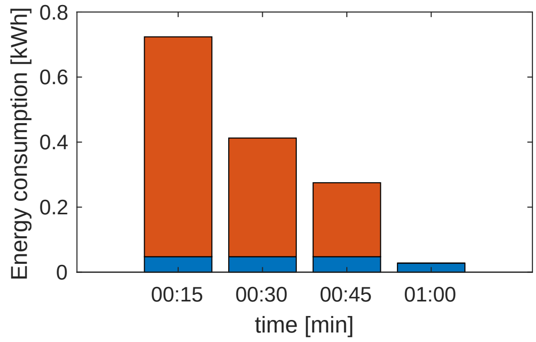
(a) Clothes washer power consumption



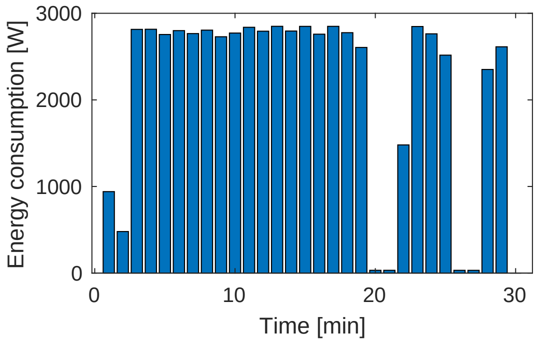
(b) Clothes washer energy consumption



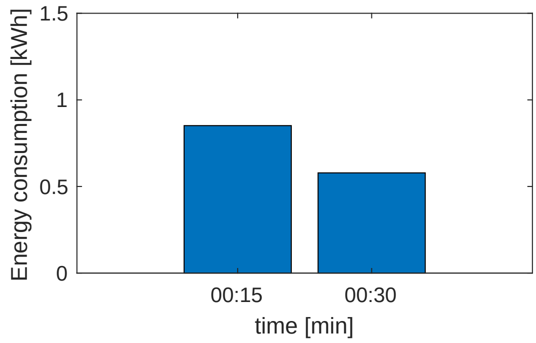
(c) Dryer power consumption



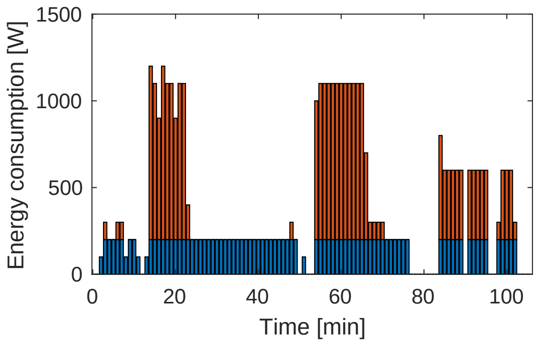
(d) Dryer energy consumption



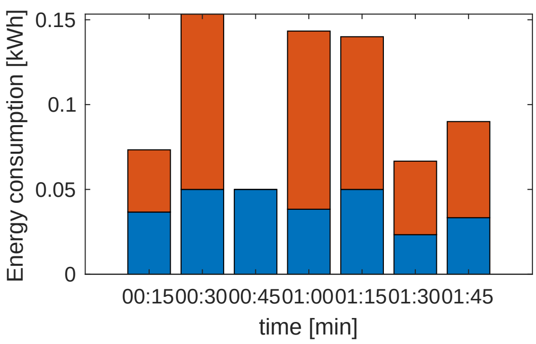
(e) Cooking power consumption



(f) Cooking energy consumption



(g) Dishwasher power consumption

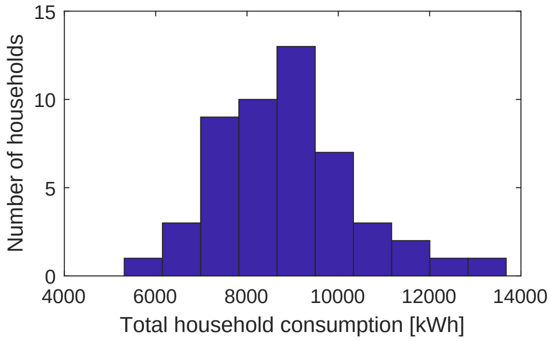


(h) Dishwasher energy consumption

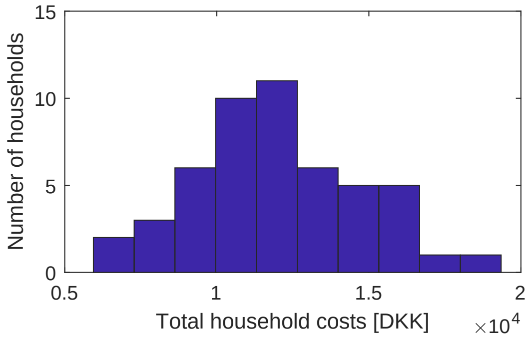
Figure A.1: Power and energy consumption profiles. On the left side are the minute profiles provided by Pipattanasomporn et al. (2014). On the right the 15-minute consumption profiles that were based on it and that were used in the model.

A.2 Base cases

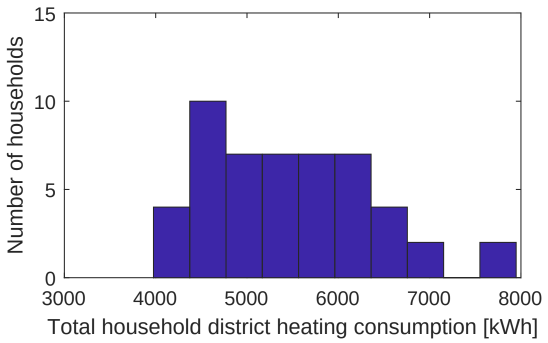
A.2.1 No fuel-shift



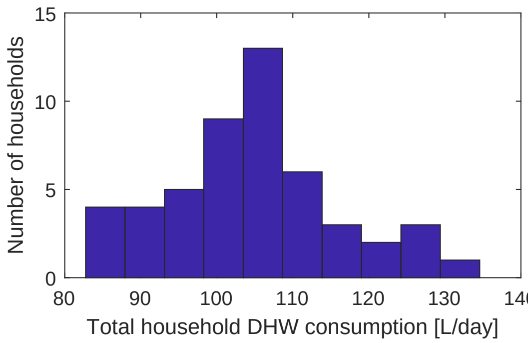
(a) Distribution of total household consumption



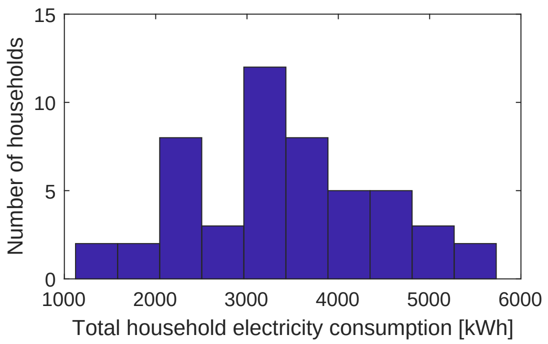
(b) Distribution of total household cost



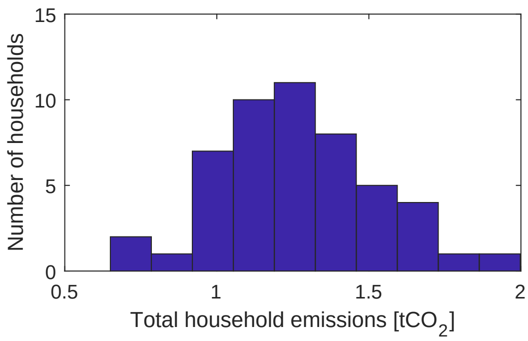
(c) Distribution of total household DH consumption



(d) Distribution of total household DHW consumption

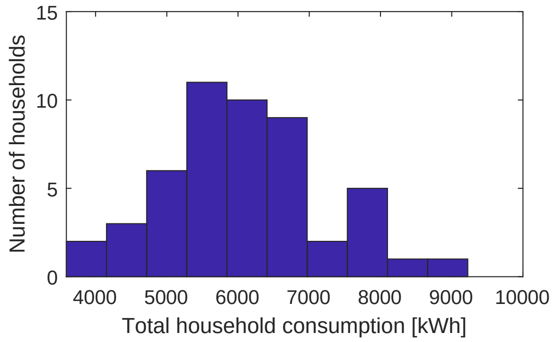


(e) Distribution of total household elec consumption

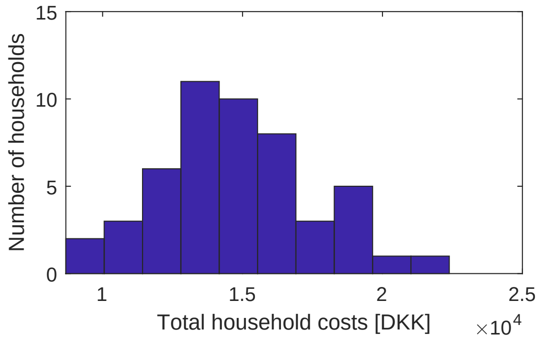


(f) Distribution of total household emissions

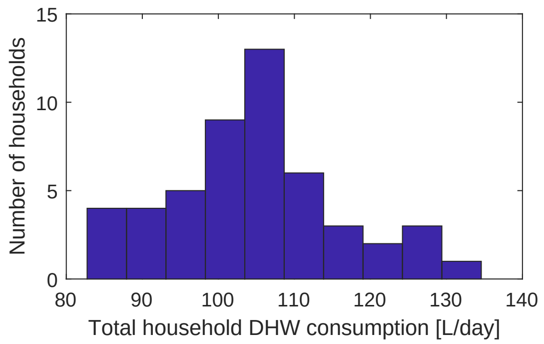
A.2.2 Heat pump for space heating



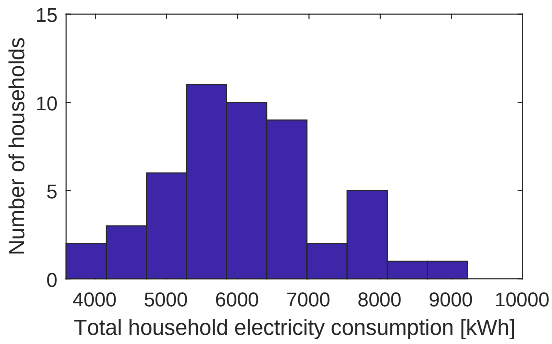
(a) Distribution of total household consumption



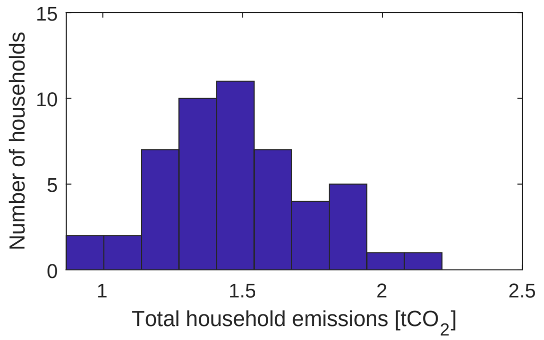
(b) Distribution of total household cost



(c) Distribution of total household DHW consumption

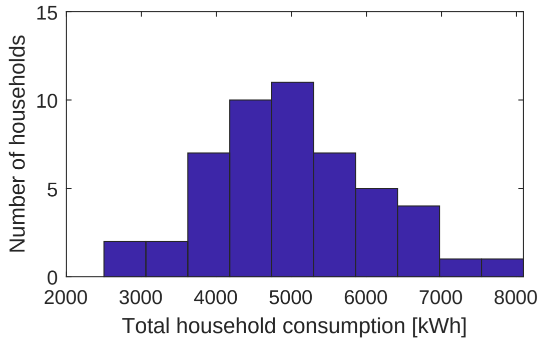


(d) Distribution of total household elec consumption

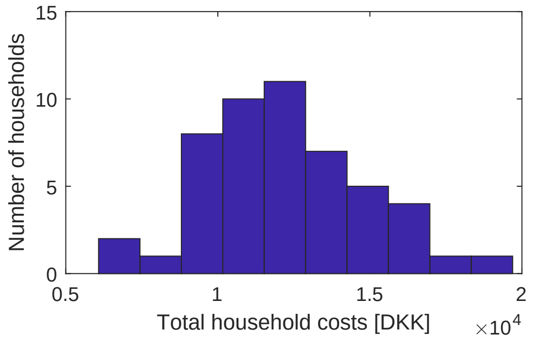


(e) Distribution of total household emissions

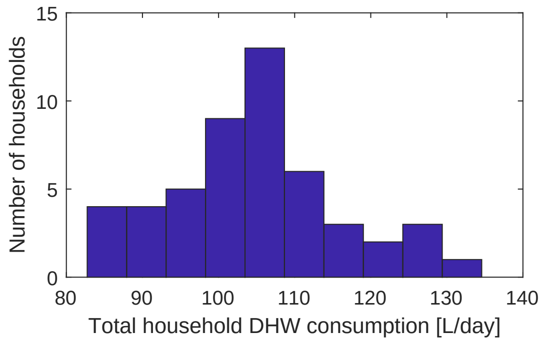
A.2.3 Full heat pump



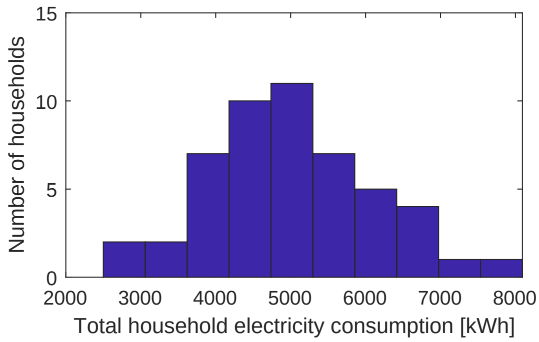
(a) Distribution of total household consumption



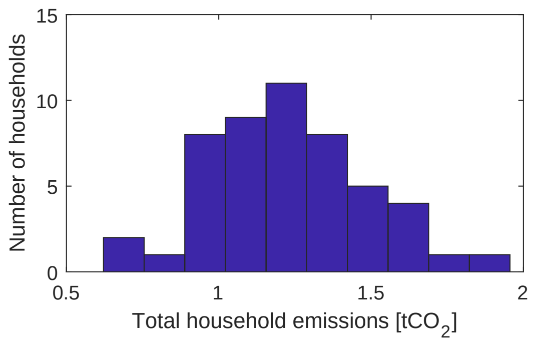
(b) Distribution of total household cost



(c) Distribution of total household DHW consumption

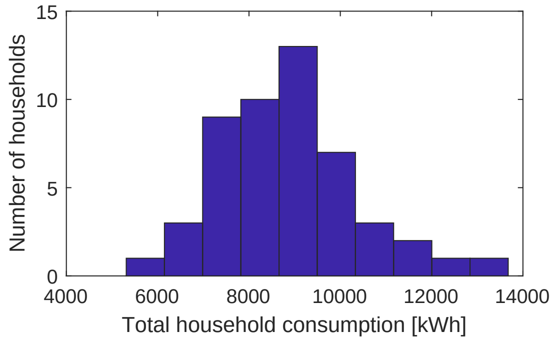


(d) Distribution of total household elec consumption

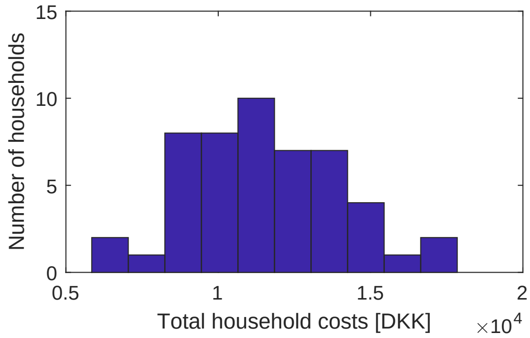


(e) Distribution of total household emissions

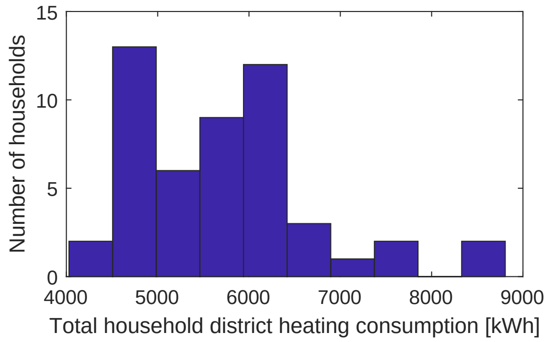
A.2.4 Appliances on district heat



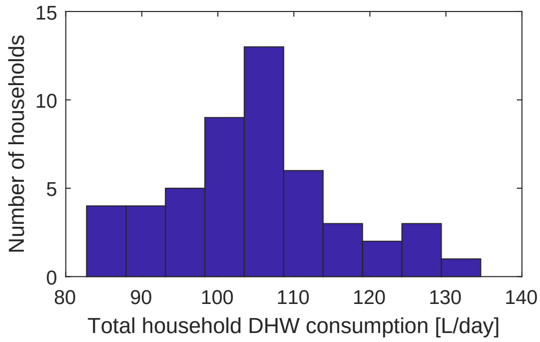
(a) Distribution of total household consumption



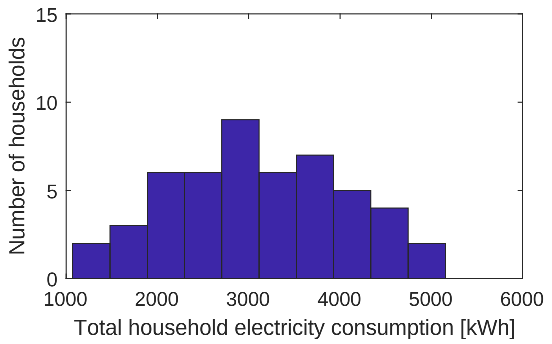
(b) Distribution of total household cost



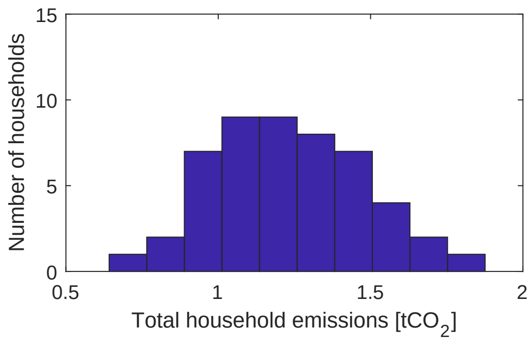
(c) Distribution of total household DH consumption



(d) Distribution of total household DHW consumption



(e) Distribution of total household elec consumption



(f) Distribution of total household emissions

A.3 Heat pump

Table A.1: Heat pump capacity and COP according to the data sheet (Mitsubishi Electric, 2017)

Ambient temperature [°C]	Capacity [kW]	COP [-]
-20	-	-
-15	2.8	1.48
-10	3.4	1.86
-7	3.8	2.08
2	3.5	2.80
7	4.5	3.70
12	5.1	4.22
15	5.4	4.54
20	6.0	5.06

A.4 Sensitivity

Figure A.6 shows the average total household consumption as function of the mean total electricity consumption. As expected, there appears to be linear correlation between the two, with higher electricity consumption leading to higher total consumption. The same goes for the electricity peak load (figure A.7), although a doubling of the mean consumption does not directly lead to a doubling of the peak load, there appears to be a correlation between the two. In both cases, as the mean consumption gets higher, the standard deviation starts to have a larger effect, as this is formulated as a percentage of the mean. Scaling the mean domestic hot water demand (figure A.8) or space heating demand (figure A.9) also led to a linear increase in costs. Of the appliances, only the cooking had a large effect on the total electric consumption (figure A.10), as well as on the electricity peak load (figure A.11).

Both the outside temperature and the heat pump COP had a decreasing effect on the household energy consumption (figures A.12 and A.13). The electric charge power for domestic hot water had no visible effect on electric or district heat peak load, but the DHW charge power when using district heat did have an effect on the district heat peak load, as can be seen in figure A.14.

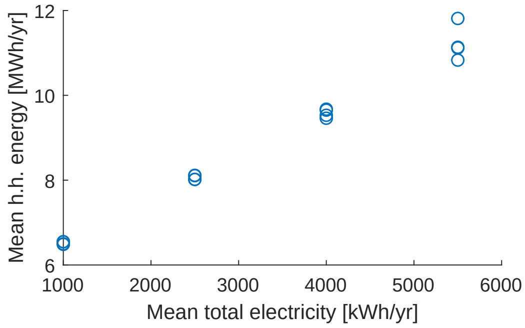


Figure A.6: Mean household consumption as function of mean electricity consumption

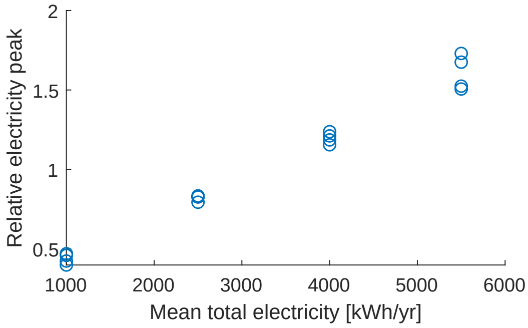


Figure A.7: Relative electricity peak load as function of mean electricity consumption

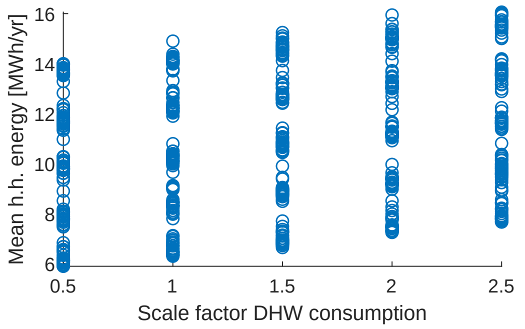


Figure A.8: Mean household total consumption as function of mean DHW consumption

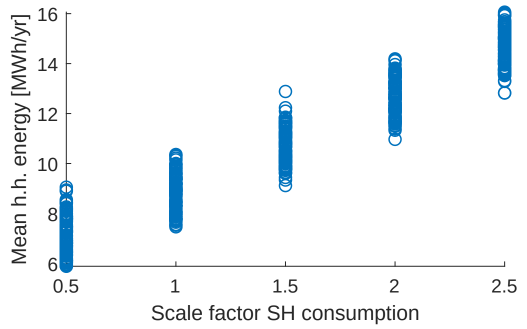


Figure A.9: Average household cost as function of mean space heating consumption

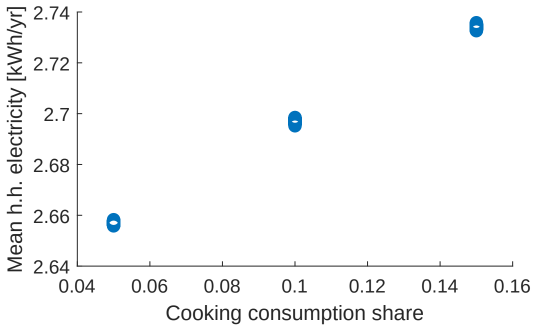


Figure A.10: Average household electricity consumption as function of share of cooking in total consumption

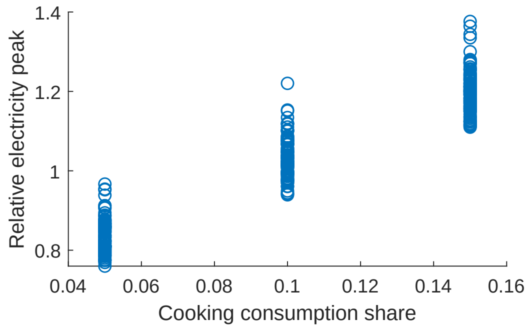


Figure A.11: Relative electricity peak load as function of share of cooking in total consumption

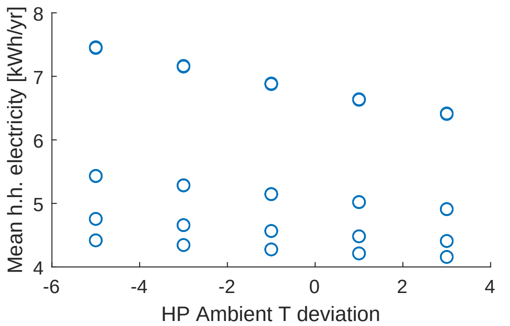


Figure A.12: Ambient temperature deviation and household electricity consumption

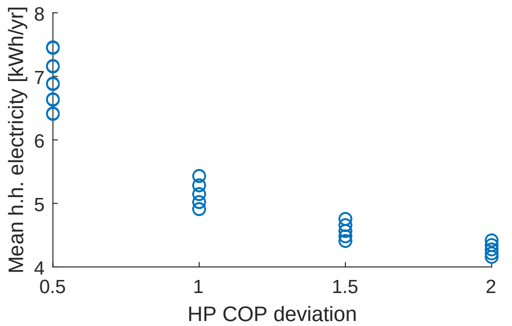


Figure A.13: Heat pump COP and average household electricity consumption

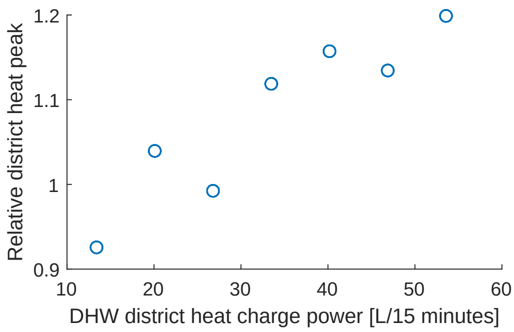


Figure A.14: Charge power for domestic hot water using district heat and relative DH peak load

Appendix B

Results

Pareto front

To get a bit more insight into the relation between private cost and emission reduction, a Pareto front was constructed. To formulate what could be considered “most beneficial”, a decision formula adapted from Song et al. (2014) was used, displayed in equation B.1.

$$\sum_{t=1}^{m}\sum_{o=1}^{r}((1-\lambda)C^{t,o}+\lambda E^{t,o})(\sum_{i=1}^{N}\sum_{j=1}^{n_j}p_{ij}^{t}), \lambda \in [0,1] \tag{B.1}$$

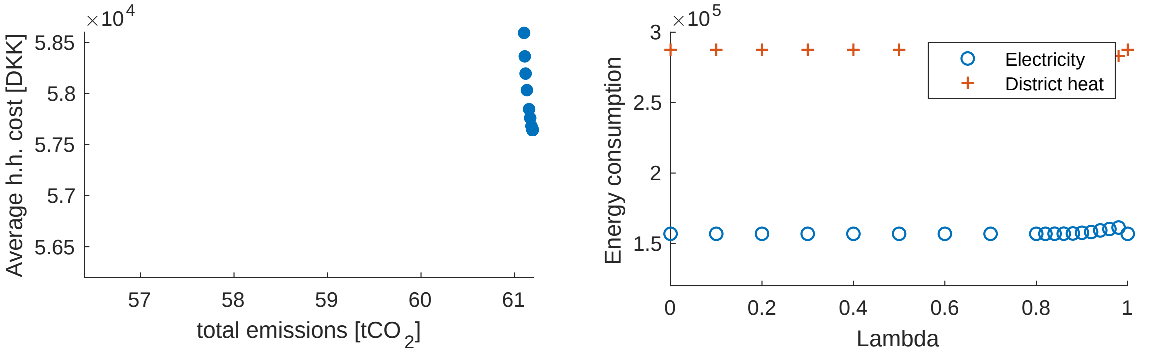
In B.1, $C^{t,o}$ and $E^{t,o}$ are the normalized costs and emissions for fuel source o in time slot t, with m being the total number of time slots in the simulation, as depicted in equations B.2 and B.3.

$$C^{t,o} = \frac{c^{t,o}}{\text{Max}(c^{1,1}, c^{1,2}, ..., c^{o,m}, c^{2,1}, c^{2,2}, ..., c^{o,m})} \tag{B.2}$$

$$E^{t,o} = \frac{e^{t,o}}{\text{Max}(e^{1,1}, e^{1,2}, ..., e^{o,m}, e^{2,1}, e^{2,2}, ..., e^{o,m})} \tag{B.3}$$

Each appliance i was considered to have a cycle length of n_j, with at each time step in its cycle energy consumption p_{ij}^{t}. By varying the λ between 0 and 1, and plotting these points in a graph, a Pareto front could be created, that showed the solutions in which emissions could not be reduced, without increasing costs and vice versa.

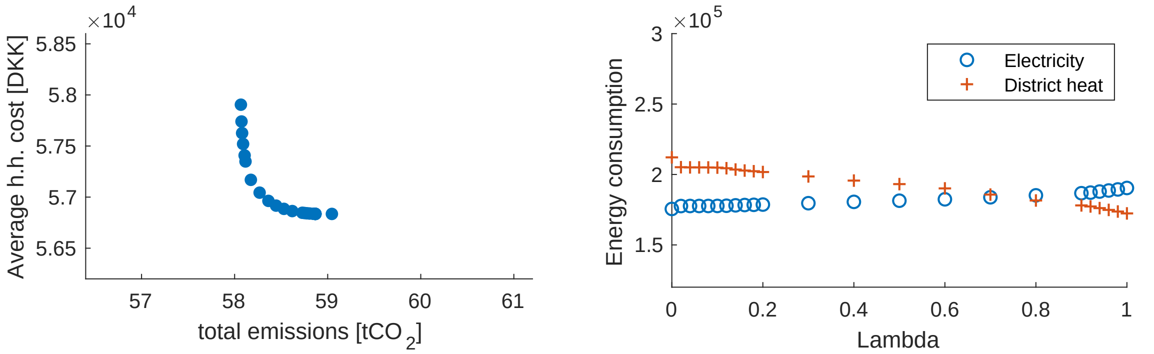
Figure B.1a shows this front for the *No HP* case. The shape of the front was as expected, with increasing costs for decreasing emissions. The front shows that increasing the emphasis on emission reduction would hardly reduce emissions, and increase costs only very slightly. Figure B.1b displays the DH and electricity consumption with a shifting lambda, showing again that the actual shift in fuel between λs was very small. This is a result of the fact that district heat had both lower cost and lower emissions per kWh than electricity for most of the year.



(a) Pareto frontier between cost and emission (b) Consumption shift with changing lambda

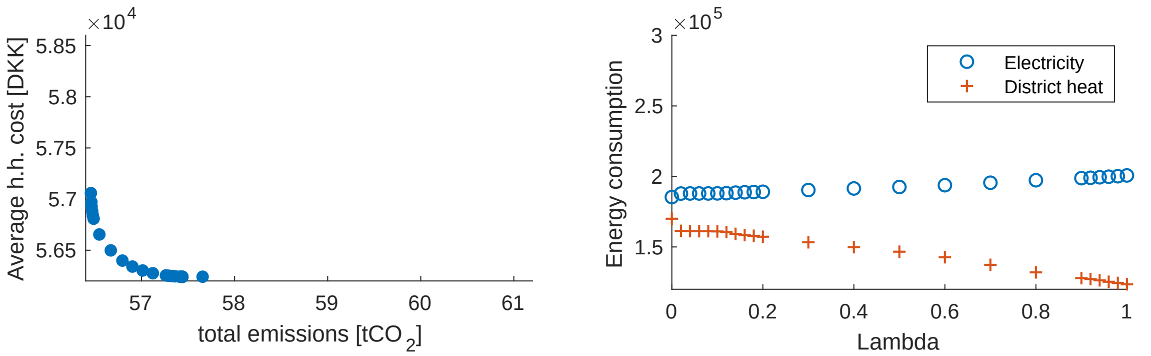
Figure B.1: The pareto front and consumption shift *No HP*

When a heat pump is introduced for space heating, a shift in fuels can be observed (figures B.2a and B.2b). Again, the gains in emission reduction were comparatively low, as were the changes in the total household costs. Introducing a heat pump had by itself a much larger effect than any fuel-shift choice had.



(a) Pareto frontier between cost and emission (b) Consumption shift with changing lambda

Figure B.2: The pareto front and consumption shift *HP SH*



(a) Pareto frontier between cost and emission

(b) Consumption shift with changing lambda

Figure B.3: The pareto front and consumption shift *Full HP*

Appendix C

Matlab code

C.1 Base case

```
% loop runs for 50 households
for ii = 1:50
    % preallocation
    basecase.(profileNames{ii}).consumption = table;
    basecase.(profileNames{ii}).dishwasher = table;
    basecase.(profileNames{ii}).clotheswasher = table;
    basecase.(profileNames{ii}).dryer = table;
    basecase.(profileNames{ii}).cooking = table;

    basecase.(profileNames{ii}).DHW = table;
    basecase.(profileNames{ii}).SH = table;
    basecase.(profileNames{ii}).cost = table;
    basecase.(profileNames{ii}).emissions = table;

    basecase.(profileNames{ii}).dishwasher.elec = profiles.(
       profileNames{ii}).dishwasher.elec + profiles.(profileNames
       {ii}).dishwasher.heat;
    basecase.(profileNames{ii}).dishwasher.DH = zeros(year,1);
    basecase.(profileNames{ii}).clotheswasher.elec = profiles.(
       profileNames{ii}).clotheswasher.elec + profiles.(
       profileNames{ii}).clotheswasher.heat;
    basecase.(profileNames{ii}).clotheswasher.DH = zeros(year,1);
    basecase.(profileNames{ii}).dryer.elec = profiles.(
       profileNames{ii}).dryer.elec + profiles.(profileNames{ii})
       .dryer.heat;
    basecase.(profileNames{ii}).dryer.DH = zeros(year,1);
    basecase.(profileNames{ii}).cooking.elec = profiles.(
       profileNames{ii}).cooking.elec;
```

```
        basecase.(profileNames{ii}).DHW.tank = zeros(year,1);
        basecase.(profileNames{ii}).DHW.loss = zeros(year,1);
    basecase.(profileNames{ii}).DHW.charge_elec = zeros(year,1);
    basecase.(profileNames{ii}).DHW.charge_DH = zeros(year,1);
    basecase.(profileNames{ii}).DHW.tank(1) = V_tank;

    % charging of the DHW tank. Charging cycle starts when the
       tank has
    % dropped below the point where a 15 minute cycle will top it
        up again
    for i = 2:year
        if basecase.(profileNames{ii}).DHW.tank(i-1) < V_tank -
           P_charge_DH
            basecase.(profileNames{ii}).DHW.charge_DH(i) =
               P_charge_DH;
        end
        % heat loss to ambient
        basecase.(profileNames{ii}).DHW.loss(i) = (15*60*U*Ar*((
           basecase.(profileNames{ii}).DHW.tank(i-1)*T_hot+(
           V_tank-basecase.(profileNames{ii}).DHW.tank(i-1))*
           T_cold)/V_tank -T_amb))*(1/(c_w *(T_hot-T_cold)));
        basecase.(profileNames{ii}).DHW.tank(i) = basecase.(
           profileNames{ii}).DHW.tank(i-1) + basecase.(
           profileNames{ii}).DHW.charge_elec(i) + basecase.(
           profileNames{ii}).DHW.charge_DH(i) - profiles.(
           profileNames{ii}).DHW.liters(i) - basecase.(
           profileNames{ii}).DHW.loss(i);
    end

    % charging was calculated in liters of hot water, here it is
       converted
    % to energy used
    basecase.(profileNames{ii}).DHW.elec = basecase.(profileNames
       {ii}).DHW.charge_elec * (rho_w/1000) * c_w *(T_hot-T_cold)
        / (15*60) * (1/hour) * (1/1000);
    basecase.(profileNames{ii}).DHW.DH = basecase.(profileNames{
       ii}).DHW.charge_DH * (rho_w/1000) * c_w *(T_hot-T_cold) /
       (15*60) * (1/hour) * (1/1000);

    % base case assumptions: space heating is done with DH, the
       rest fully
    % electric
    basecase.(profileNames{ii}).SH.elec = zeros(year,1);
    basecase.(profileNames{ii}).SH.DH = profiles.(profileNames{ii
       }).SpaceHeating.kwh;

    basecase.(profileNames{ii}).consumption.elec = profiles.(
```

```
        profileNames{ii}).ElecBase/4000 + basecase.(profileNames{
        ii}).cooking.elec + basecase.(profileNames{ii}).dishwasher
        .elec  + basecase.(profileNames{ii}).clotheswasher.elec +
        basecase.(profileNames{ii}).dryer.elec + basecase.(
        profileNames{ii}).DHW.elec + basecase.(profileNames{ii}).
        SH.elec;
    basecase.(profileNames{ii}).consumption.DH = basecase.(
        profileNames{ii}).dishwasher.DH  + basecase.(profileNames{
        ii}).clotheswasher.DH + basecase.(profileNames{ii}).dryer.
        DH + basecase.(profileNames{ii}).DHW.DH + basecase.(
        profileNames{ii}).SH.DH;

    basecase.(profileNames{ii}).DH_cap = max(basecase.(
        profileNames{ii}).consumption.DH*hour) * DH_captariff;
    basecase.(profileNames{ii}).cost.elec = supply.elec_price.
        total.*basecase.(profileNames{ii}).consumption.elec;
    basecase.(profileNames{ii}).cost.DH = supply.DH_price.total
        .* basecase.(profileNames{ii}).consumption.DH;
    basecase.(profileNames{ii}).cost.total = basecase.(
        profileNames{ii}).cost.elec + basecase.(profileNames{ii}).
        cost.DH;
    basecase.(profileNames{ii}).cost.cumulative = cumsum(basecase
        .(profileNames{ii}).cost.total);

    basecase.(profileNames{ii}).emissions.DH = basecase.(
        profileNames{ii}).consumption.DH .* DH_CO2;
    basecase.(profileNames{ii}).emissions.elec = elec_CO2 .*
        basecase.(profileNames{ii}).consumption.elec;
    basecase.(profileNames{ii}).emissions.total = basecase.(
        profileNames{ii}).emissions.elec + basecase.(profileNames{
        ii}).emissions.DH;
    basecase.(profileNames{ii}).emissions.cumulative = cumsum(
        basecase.(profileNames{ii}).emissions.total);
end

clearvars i
```

C.2 Price-based fuel shift

```
%% decision algorithm
private = struct;

% again, 50 times
for ii = 1:50
    %% Base load
    private.(profileNames{ii}).consumption = table;
```

```
    private.(profileNames{ii}).consumption.elec = profiles.(
       profileNames{ii}).ElecBase/4000 + profiles.(profileNames{
       ii}).clotheswasher.elec + profiles.(profileNames{ii}).
       dishwasher.elec + profiles.(profileNames{ii}).dryer.elec;
    private.(profileNames{ii}).consumption.DH = zeros(year,1);


    %% Dishwasher

    elec_dish = zeros(year,1);
    DH_dish = zeros(year,1);
    private.(profileNames{ii}).dishwasher = table;

    for i = 1:year-dishwasher.length+1

        % check whether there is a dishwasher starting moment,
           calculated
        % earlier based on occupation
        if profiles.(profileNames{ii}).dishwasher.starttime(i)
%               calculate cost for a cycle on electricity and
   distric heat
            cost_elec = sum(dishwasher.heat.*supply.elec_price.
               total(i:i-1+dishwasher.length));
            cost_DH = sum(dishwasher.heat.*supply.DH_price.total(
               i:i-1+dishwasher.length));
            % choose the cheapest fuel
            if cost_elec < cost_DH
                elec_dish(i:i-1+dishwasher.length) = dishwasher.
                   heat;
            else
                DH_dish(i:i-1+dishwasher.length) = dishwasher.
                   heat;
            end
        end
    end

    % fill in the results in the household profile
    private.(profileNames{ii}).consumption.elec = private.(
       profileNames{ii}).consumption.elec + elec_dish;
    private.(profileNames{ii}).dishwasher.elec = elec_dish +
       profiles.(profileNames{ii}).dishwasher.elec;
    private.(profileNames{ii}).consumption.DH = private.(
       profileNames{ii}).consumption.DH + DH_dish;
    private.(profileNames{ii}).dishwasher.DH = DH_dish;

    clearvars cost_elec cost_DH
```

```
%% Clothes washer

elec_wash = zeros(year,1);
DH_wash = zeros(year,1);

private.(profileNames{ii}).clotheswasher = table;

for i = 1:year-(-1+clotheswasher.length)

    if profiles.(profileNames{ii}).clotheswasher.starttime(i)
        cost_elec = sum(clotheswasher.heat.*supply.elec_price
           .total(i:i-1+clotheswasher.length));
        cost_DH = sum(clotheswasher.heat.*supply.DH_price.
           total(i:i-1+clotheswasher.length));
        if cost_elec<cost_DH
            elec_wash(i:i-1+clotheswasher.length) =
               clotheswasher.heat;
        else
            DH_wash(i:i-1+clotheswasher.length) =
               clotheswasher.heat;
        end
    end
end


private.(profileNames{ii}).consumption.elec = private.(
   profileNames{ii}).consumption.elec + elec_wash;
private.(profileNames{ii}).clotheswasher.elec = elec_wash +
   profiles.(profileNames{ii}).clotheswasher.elec;
private.(profileNames{ii}).consumption.DH = private.(
   profileNames{ii}).consumption.DH + DH_wash;
private.(profileNames{ii}).clotheswasher.DH = DH_wash;

%% Dryer

elec_dry = zeros(year,1);
DH_dry = zeros(year,1);
    private.(profileNames{ii}).dryer = table;

for i = 1:year

    if profiles.(profileNames{ii}).dryer.starttime(i)
        cost_elec = sum(dryer.heat .* supply.elec_price.total
           (i:i-1+dryer.length));
        cost_DH = sum(dryer.heat .* supply.DH_price.total(i:i
           -1+dryer.length));
        if cost_elec<cost_DH
```

```
                elec_dry(i:i-1+dryer.length) = dryer.heat;
            else
                DH_dry(i:i-1+dryer.length) = dryer.heat;

            end
        end
    end

    private.(profileNames{ii}).consumption.elec = private.(
       profileNames{ii}).consumption.elec + elec_dry;
    private.(profileNames{ii}).dryer.elec = elec_dry + profiles.(
       profileNames{ii}).dryer.elec;
    private.(profileNames{ii}).consumption.DH = private.(
       profileNames{ii}).consumption.DH + DH_dry;
    private.(profileNames{ii}).dryer.DH = DH_dry;


    %% Cooking
    private.(profileNames{ii}).cooking = table;

    % cooking was calculated earlier, based on occupation
    elec_cook = profiles.(profileNames{ii}).cooking.elec;


    private.(profileNames{ii}).consumption.elec = private.(
       profileNames{ii}).consumption.elec + elec_cook;
    private.(profileNames{ii}).cooking.elec = elec_cook;


    %% DHW

    private.(profileNames{ii}).DHW = table;
    private.(profileNames{ii}).DHW.tank = zeros(year,1);
    private.(profileNames{ii}).DHW.loss = zeros(year,1);
    private.(profileNames{ii}).DHW.charge_elec = zeros(year,1);
    private.(profileNames{ii}).DHW.charge_DH = zeros(year,1);
    % tank starts fully charged
    private.(profileNames{ii}).DHW.tank(1) = V_tank;

    for i = 2:year
        % charge cycle starts when a charge cycle will top it up,
            depending
        % on whether a DH or elec charge cycle provides more
           energy
        if private.(profileNames{ii}).DHW.tank(i-1) < V_tank -
           max(P_charge_elec,P_charge_DH)
            % test which one is cheaper
```

```
            if supply.elec_price.total(i) < supply.DH_price.total
               (i)
                private.(profileNames{ii}).DHW.charge_elec(i) =
                   P_charge_elec;
            else
                private.(profileNames{ii}).DHW.charge_DH(i) =
                   P_charge_DH;
            end
        end
        % convert liters of hot water to kWh
        private.(profileNames{ii}).DHW.loss(i) = (15*60*U*Ar*((
           private.(profileNames{ii}).DHW.tank(i-1)*T_hot+(V_tank
           -private.(profileNames{ii}).DHW.tank(i-1))*T_cold)/
           V_tank -T_amb))*(1/(c_w *(T_hot-T_cold)));
        private.(profileNames{ii}).DHW.tank(i) = private.(
           profileNames{ii}).DHW.tank(i-1) + private.(
           profileNames{ii}).DHW.charge_elec(i) + private.(
           profileNames{ii}).DHW.charge_DH(i) - profiles.(
           profileNames{ii}).DHW.liters(i) - private.(
           profileNames{ii}).DHW.loss(i);
    end

    private.(profileNames{ii}).DHW.elec = private.(profileNames{
       ii}).DHW.charge_elec * (rho_w/1000) * c_w *(T_hot-T_cold)
       / (15*60) * (1/hour) * (1/1000);
    private.(profileNames{ii}).DHW.DH = private.(profileNames{ii
       }).DHW.charge_DH * (rho_w/1000) * c_w *(T_hot-T_cold) /
       (15*60) * (1/hour) * (1/1000);

    private.(profileNames{ii}).consumption.elec = private.(
       profileNames{ii}).consumption.elec + private.(profileNames
       {ii}).DHW.elec;
    private.(profileNames{ii}).consumption.DH = private.(
       profileNames{ii}).consumption.DH + private.(profileNames{
       ii}).DHW.DH;


    %% Space heating
    private.(profileNames{ii}).SH = table;
    elec_SH = zeros(year,1);
    DH_SH = zeros(year,1);

    for i = 1:year
        % whenever there is space heating demand, start a cycle
        if any(profiles.(profileNames{ii}).SpaceHeating.kwh(i))
            % check what's cheapest
            if supply.elec_price.total(i)  < supply.DH_price.
```

```
                total(i)
                 elec_SH(i) = profiles.(profileNames{ii}).
                    SpaceHeating.kwh(i);
            else
                 DH_SH(i) = profiles.(profileNames{ii}).
                    SpaceHeating.kwh(i);
            end
        end
    end

    private.(profileNames{ii}).consumption.elec = private.(
       profileNames{ii}).consumption.elec + elec_SH;
    private.(profileNames{ii}).SH.elec = elec_SH;
    private.(profileNames{ii}).consumption.DH = private.(
       profileNames{ii}).consumption.DH + DH_SH;
    private.(profileNames{ii}).SH.DH = DH_SH;

    %% Costs and emissions

    % calculate costs and emissions and fill it in the household
       profile
    private.(profileNames{ii}).cost = table;
    private.(profileNames{ii}).emissions = table;

    private.(profileNames{ii}).cost.elec = supply.elec_price.
       total.*private.(profileNames{ii}).consumption.elec;
    private.(profileNames{ii}).cost.DH = supply.DH_price.total .*
        private.(profileNames{ii}).consumption.DH;

    private.(profileNames{ii}).cost.total = private.(profileNames
       {ii}).cost.elec + private.(profileNames{ii}).cost.DH;
    private.(profileNames{ii}).cost.cumulative = cumsum(private.(
       profileNames{ii}).cost.total);

    private.(profileNames{ii}).emissions.DH = private.(
       profileNames{ii}).consumption.DH .* supply.DH_CO2;
    private.(profileNames{ii}).emissions.elec = supply.elec_CO2
       .* private.(profileNames{ii}).consumption.elec;

    private.(profileNames{ii}).emissions.total = private.(
       profileNames{ii}).emissions.elec + private.(profileNames{
       ii}).emissions.DH;
    private.(profileNames{ii}).emissions.cumulative = cumsum(
       private.(profileNames{ii}).emissions.total);


end
```

```
%% clear variables

clearvars elec_cook DH_cook gas_cook elec_dry DH_dry gas_dry
   elec_wash DH_wash elec_dish DH_dish elec_DHW DH_DHW gas_DHW
   elec_SH gas_SH DH_SH cost_DH cost_gas cost_elec ii i
```

C.3 Incentive-based fuel-shift

```
L_max = max(gridload.DH);
cap_DH = struct;
saved = profileNames;

%% Base load
for ii = 1:50
    cap_DH.(profileNames{ii}).consumption = table;
    cap_DH.(profileNames{ii}).dishwasher = basecase.(profileNames
       {ii}).dishwasher;
    cap_DH.(profileNames{ii}).clotheswasher = basecase.(
       profileNames{ii}).clotheswasher;
    cap_DH.(profileNames{ii}).dryer = basecase.(profileNames{ii})
       .dryer;
    cap_DH.(profileNames{ii}).cooking = basecase.(profileNames{ii
       }).cooking;

    cap_DH.(profileNames{ii}).DHW = basecase.(profileNames{ii}).
       DHW;
    cap_DH.(profileNames{ii}).SH = table;

    cap_DH.(profileNames{ii}).cost = table;
    cap_DH.(profileNames{ii}).emissions = table;

    cap_DH.(profileNames{ii}).consumption.elec = basecase.(
       profileNames{ii}).consumption.elec;
    cap_DH.(profileNames{ii}).consumption.DH = basecase.(
       profileNames{ii}).DHW.DH;


    cap_DH.(profileNames{ii}).SH.DH = zeros(year,1);
    cap_DH.(profileNames{ii}).SH.elec = zeros(year,1);
end


%% capacity restriction

% see for which time steps in the base case the grid load is too
   high
```

```
idx = false(year,1);
L_max = max(gridload.DH); % Lmax is the maximum yearly total DH
   grid load in the base case
for i = 1:year
    if gridload.DH(i)/L_max > cutoff % this creates a binary
       which is "true" at the time steps when the total load is
       larger than a set maximum
        idx(i) = true;
    end
end

load_now = zeros(year,1);
load_ = zeros(50,1);

for i = 1:year
    if idx(i) % this part only runs when the grid load is too
       high
        for ii = 1:50
            load_(ii) = cap_DH.(profileNames{ii}).consumption.DH(
               i);
        end
        load_now(i) = sum(load_); % This is the minimum size of
           the DH load at this time step, because of hot water

        ii = 1;
        profileNames=profileNames(randperm(length(profileNames)))
           ;
        while load_now(i) < L_max * cutoff && ii < 51 % While
           this load is smaller than the maximum
            cap_DH.(profileNames{ii}).SH.DH(i) = profiles.(
               profileNames{ii}).SpaceHeating.kwh(i); % Household
                "ii" is heated with district heat
            load_now(i) = load_now(i) + cap_DH.(profileNames{ii})
               .SH.DH(i); % Calculate the new actual load
            ii = ii + 1;
        end

        % when capacity is reached, fill in the rest with
           electricity
        for iii = ii:50
            cap_DH.(profileNames{iii}).SH.elec(i) = profiles.(
               profileNames{iii}).SpaceHeating.kwh(i);
        end
        profileNames = saved;

        % if there is no capacity problem, just do everything
           with DH
```

```
    else
        for ii = 1:50
            cap_DH.(profileNames{ii}).SH.DH(i) = profiles.(
               profileNames{ii}).SpaceHeating.kwh(i);
        end
    end
end

for ii = 1:50
    cap_DH.(profileNames{ii}).consumption.elec = cap_DH.(
       profileNames{ii}).consumption.elec + cap_DH.(profileNames{
       ii}).SH.elec;
    cap_DH.(profileNames{ii}).consumption.DH = cap_DH.(
       profileNames{ii}).consumption.DH + cap_DH.(profileNames{ii
       }).SH.DH;
end

for i = 1:50
    cap_DH.(profileNames{i}).cost.elec = supply.elec_price.total
       .*cap_DH.(profileNames{i}).consumption.elec;
    cap_DH.(profileNames{i}).cost.DH = supply.DH_price.total .*
       cap_DH.(profileNames{i}).consumption.DH;
    cap_DH.(profileNames{i}).cost.total = cap_DH.(profileNames{i
       }).cost.elec + cap_DH.(profileNames{i}).cost.DH;
    cap_DH.(profileNames{i}).cost.cumulative = cumsum(cap_DH.(
       profileNames{i}).cost.total);

    cap_DH.(profileNames{i}).emissions.DH = cap_DH.(profileNames{
       i}).consumption.DH .* DH_CO2;
    cap_DH.(profileNames{i}).emissions.elec = elec_CO2 .* cap_DH
       .(profileNames{i}).consumption.elec;
    cap_DH.(profileNames{i}).emissions.total = cap_DH.(
       profileNames{i}).emissions.elec + cap_DH.(profileNames{i})
       .emissions.DH;
    cap_DH.(profileNames{i}).emissions.cumulative = cumsum(cap_DH
       .(profileNames{i}).emissions.total);
end
```

Appendix D

Declaration code of scientific conduct

TU/e Technische Universiteit Eindhoven University of Technology

End Master Thesis Project HTI - IS

TU/e Technische Universiteit **Eindhoven** University of Technology

Declaration concerning the TU/e Code of Scientific Conduct for the Master's/PDEng/PhD thesis

I have read the TU/e Code of Scientific Conduct[1].
I hereby declare that my Master's/PDEng/PhD-thesis has been carried out in accordance with the rules of the TU/e Code of Scientific Conduct

Date
12-09-2018

Name
Stef Boesten

ID-nr
0846815

Signature
....

[1] See: http://www.tue.nl/en/university/about-the-university/integrity/scientific-integrity/
The Netherlands Code of Conduct for Academic Practice of the VSNU can be found here also. More information about scientific integrity is published on the websites of TU/e and VSNU.

Education Administration Form – End Master Thesis Project, document versionSeptember 2015