MASTER

Shifting domestic electricity demand
facilitating domestic electricity demand shift with demand side management technologies

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"It is not the strongest of the species that survive, nor the most intelligent, but the one most responsive to change." – **Charles Darwin**

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Preface

This thesis encloses my graduation project for the master degree of Innovation Management at the faculty of industrial engineering and innovation sciences belonging to the Eindhoven University of Technology. The results in this thesis are ultimately based on the experimental apparatus and data of the Jouw Energie Moment experimental project, the subject of a collaboration between Enexis, Green Choice, SWz, Dong Energy, FlexiControl, CGI and the Technical University of Eindhoven. The questionnaire design was done primarily done by Charlotte Kobus. All data analysis is original work done by myself.

As an intern at Enexis, it has been an astonishing journey towards a better understanding of what is happening behind the electric wall socket. Never again would I take electricity for credit just as easy as flipping the switch. The amount of complexity surrounding the reliable, sustainable and economical transportation of electricity has unleashed an interest upon which I am determined to develop my future career. I am very grateful for the opportunity that has been given to me and the way Enexis enabled me to participate in this world. I would like to thank all people involved for their, inspiration and support. That is the motivating and great team of innovation of Enexis, my encouraging supervisors from the TU/e who formed a balanced team between socio-technical and statistical advisors, the inspiring participants of the pilot and of course my ever interested friends and family. Further I want to thank Charlotte Kobus, my supervisor at Enexis, from which I received all the required freedom to fulfil this project in a self-developing manner and who gave me insights and direction at times needed.

I hope this thesis will contribute to the debate, discussions and insights about the future domestic role in the energy transition. Furthermore, I hope it will contribute in strengthening the Smart Grid strategies of Enexis, and possibly also to that of other grid operators, in order to meet the current and future energy demand of consumers in an optimal way.

Nick Hubbers

Executive Summary

Abstract

79 Households in a pilot district in Zwolle have been provided with a smart meter, a Home Energy Management System, a smart white good appliance, solar panels and a dynamic electricity price in order to induce electricity demand shift. The results show that people avoid the peak hours with their smart white good appliances, however do not shift other appliances which serve a more ad hoc electricity need. Although there is a high level of environmental motivation found with the households, having control on the electricity bill seems to be the most important incentive to shift electricity demand. The households who are more present at home are also better able to use electricity during off-peak hours. The overall impact of the shifted electricity on the peak usage behaviour is still low as no significant difference has been found with a reference group without the provided technologies.

Introduction

The current pace in which energy developments are being realized is unprecedented. The increasing introduction of decentralised energy sources (Dril & Boelhouwer, 2012, Energieraad, 2009, Schwencke, 2012) and new energy loads such as electric vehicles (Appels, 2012, EL & I, 2011), are expected to pose great challenges to the balancing of supply and demand in the electricity grids in the Netherlands.

Enriching the electricity network with information communication technology facilitates two way traffic of energy and information between supplier and consumer, which is commonly referred to as 'making the grid smarter'. This smarter grid is necessary in the light of future developments.

Today there is considerable focus on the technological aspects of delivering a smarter grid. However, little is understood about to what extent domestic end users are willing to embrace these new technologies and initiatives that enable them to manage their use of electricity. If domestic end users do not adopt new approaches in the way that they consume electricity, Smart Grids may not be able to achieve full potential. The involvement and understanding of these end users is thus of substantial importance to the further development and deployment of the Smart Grid.

Research methodology

The participants in this study are 79 Households who live in an new constructed residential area called the Muziekwijk, northwest from the centre of Zwolle, the Netherlands. The homes, that can either be rented or owned, are provided with a Smart Meter, a Home Energy Management System (HEMS), a Smart white good appliance and 6 Solar Panels. A dynamic electricity price is introduced in order to induce the shift of electricity usage towards off-peak moments. Peak moments are defined using a relative value based on the dynamic electricity price.

The interaction with the introduced technologies and the amount of electricity that is used by the household is monitored between the period of 01-01-2013 and 01-07-2013. Further, two surveys are used to determine the characteristics of the households and the reported intention and performance of the shift in use of electrical appliances.

A reference group with 26 non-participating households who live in the same new constructed area, is used to determine the effect of the introduction of smart grid technologies to electricity usage.

Results

The peak usage of electricity takes place between 4pm and 6pm and reaches between 130Wh and 160Wh based on a confidence interval of 95%. On average, a participating household consumed between 91,24Wh and 93.39Wh per quarter of an hour. This results in an annual usage between 3197 kWh and 3272 kWh which is slightly below normal usage (3312kWh in 2012). On average 71.73% of this electricity is used during off-peak hours, with individual scores ranging from 63% up to 79%. The amount of electricity used during off-peak moments by a reference group is 71.75%. The probability of a difference between these groups is 49.79%, suggesting that it is not possible to state that the participants group is performing better or worse than the reference group on electricity usage on off peak hours.
The results show that for households that shift their usage of white good appliances use more electricity during off-peak hours ($r=.34$, $p<.05$). The reported demand shift of other appliances did not prove to have a significant effect on the amount of electricity usage during off-peak moments.
Out of the 1265 washes, 1060 (16%) are planned by the HEMS. No relation is found between the amount of auto planned washes and the electricity usage during off-peak hours. However the starting times of most washes are between 8am and 1pm which deviates from earlier findings showing a second peak between 5pm and 10pm. The absence of the second peak suggests an avoidance of washing on peak hours. Furthermore no relations are found between the type of feedback (financial or ecological) or the the amount of interaction with the and the shifted use of white good appliances.
Households who do shift white good appliances have a higher behavioural intention to shift the white good appliances. This relation is mediated by the goal that is set on the HEMS. Households with higher intention set higher goals (.42, $p=<.01$) and households who set higher goals are reporting more shifted usage of white good appliances (.33, $p=<.01$). The behavioural intention is partially caused by the perceived usefulness (.47, $p<.01$), which in turn cannot be further predicted using the amount of ecological, control or social motivation of the household to shift usage or the households characteristics. The results further show that only the motivation to control the electricity usage is found to be positively influencing the reported demand shift (.32 $p<.01$). Within this control, an important component is the control of the electricity bill, suggesting that financial incentives does play a role in the shift of electricity to other moments. None of the household characteristics in this study predict the control motivation of the household. Last, the presence of the household is a predictor for the reported shift in white good usage (.20, $p<.05$).

Conclusion

Overall, based on these findings, it is possible to conclude that households who shift the usage of white good appliances, achieve a peak demand reduction. Households who are better able to perform this demand shift have a *high motivation to control the electricity usage* and are *more present at home*. Further they have a *high goal set* which is the results of a *higher behavioural intention to use technologies* for using electricity during off-peak hours. The amount of *perceived usefulness* plays an important effect in

predicting this behavioural intention but it remains unclear which households possess this higher perceived usefulness.
Households who are higher educated see the HEMS as more easy to use which lead to a higher interaction with the HEMS. Although the HEMS is becoming part of a households routine and interaction with the HEMS display is high, the automatic planning function of the HEMS is not being used much. This is generally caused by the perception of lack in control when using the automatic planning function. The feedback of the HEMS which is preferred is financial by nature and is typically chosen because the financial benefits outweigh the ecological benefits. Direct interaction and usage of the automatic planning capabilities of the HEMS are not found to be influencing the reported demand shift. This said, households are able to shift the usage of white good appliances without having frequent interaction with the HEMS.

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1. Context: The need for a smarter grid

The current pace in which energy developments are being realized is unprecedented. The increasing introduction of decentralised energy sources (Dril & Boelhouwer, 2012, Energieraad, 2009, Schwencke, 2012) and new energy loads such as electric vehicles (Appels, 2012, EL & I, 2011), are expected to pose great challenges to the electricity grids in the Netherlands (G. P. Verbong, Beemsterboer, & Sengers, 2012). The most obvious and perhaps simplest solution to these challenges would be to expand the current grid to meet the future demand. Nevertheless, with the large scale introduction of local renewable energy sources to the electricity grid, the balancing of energy demand and supply will be increasing challenging. This eventually leads to an energy system which needs to be flexible and able to switch between different energy sources (and suppliers). Demand should respond to supply conditions in order to facilitate efficient use of renewable energy while minimizing network infrastructure costs and reserve capacity costs. This is basically the essence of a Smart Grid, which enriches the electricity network with information communication technology in order to facilitate two way traffic of energy and information between supplier and consumer. It is generally accepted that making the grids smart is necessary in the light of future developments (Veldman, Geldtmeijer, Knigge, & Slootweg, 2010).

The Smart Grid and its promises have sparked worldwide research and demonstration projects, some of which focus on how to empower its users with better tools, to monitor, understand and manage their energy behaviour (Silva, Karnouskos, & Ilic, 2012). It is often seen, however, that the providers of these tools are largely driven by a technology push instead and therefore make assumptions that could fall short in consumer expectations. The lack of real world experiences may lead to a discontinuation of innovative approaches.

Matters of what the future smart grid will contain and how residential consumers will benefit from this grid and its associating services, are hot topics. New, flexible, autonomous technologies are emerging in the domestic applications market. Smart meters and intelligent sensors and actuators will provide the basis for the information that the stakeholders will have access to. On top of this information layer, Smart Appliances such as a washing machine which starts washing when the sun is providing energy to the Photo voltaic installation. This way it is expected that in the future Smart Grid as much as 10% of the normal domestic electricity use for household appliances can be shifted to other times in the day (Veldman, Gibescu, Slootweg, & Kling, 2013). This highly interactive infrastructure will enable residential consumers to play a more active role in the system and change how they utilize electrical power in the near future (Silva et al., 2012). Although the Smart Grid may seem great on paper, there is no guarantee that applications will be used, or even accepted, by the residential users. In order to make the Smart Grid a reality, a paradigm shift is needed which presents a major challenge that goes beyond technological innovation in various aspects (Veldman et al., 2010). In order to get Smart Grid innovations adopted by user in the future, it is important to gain insight in the willingness of consumers to accept different kinds of measures when it comes to smart metering and smart appliances in their daily life. This research is therefore concerned with the issue of how consumer behaviour and attitudes affects the mobilizing of flexible demand through smart appliances. It aims at mapping consumers' motives for interaction with Smart Appliances and the effect this has on demand side management.

1.1 Research Scope: Involving domestic end users in the Netherlands

Today there is considerable focus on the technological aspects of delivering these Smart Grids. However, little is understood about the extent to which domestic end users are willing to embrace these new technologies and initiatives that enable them to manage their use of electricity. If domestic end users do not adopt new approaches in the way that they consume electricity, Smart Grids may not be able to achieve full potential. The involvement and understanding of these end users is thus of substantial importance to the further development and deployment of the Smart Grid. In this research we will therefore focus on the understanding of domestic end-users in relation to Smart Grid technologies. More precise, this study covers the interaction with Smart Grid technology by a group of 79 domestic end users in the Netherlands.

1.2 Problem statement: Are they willing and able?

In order to prepare the electricity grid to make it smart, it is important to understand how the needs of the consumer can be aligned with the needs of other stakeholders. Because consumer characteristics vary from one place to the next, we can expect the implementation of smart grid capabilities to be geographically different. Efforts to construct a Smart Grid infrastructure that is uniform and standardised will face huge acceptance problems (Wolsink, 2011), but on the other hand could lead to an acceleration in the Smart Grid innovation adoption due to financial advantages. In order to effectively roll out smart technologies in the future a balance is needed between tailor made solutions and standardised innovations. This research covers part of the understanding of consumers in relation to Smart Grid technologies. It tries to find if consumers use technologies that enable the Smart Grid and if this will lead to flexibility in electricity demand. This leads to the central research question:

To what extent are domestic consumers willing and able to use electricity during off-peak hours by using demand side management enabling technologies?

1.3 Research questions

Elaborating on the problem statement, this research aims to investigate how early adopters of Smart appliances interact and react to Smart Grid technology. Preparatory to the answering of the central research question, several preliminary questions need to be answered.

- First we need to know *if* domestic consumers interact with Smart Grid technology?
- Second, *if* interaction with the Smart Appliances has led to electricity usage during off-peak hours?
- Third *what* differences in interaction and off-peak usage can be measured over the different households?
- And last, *if* certain groups can be identified based on these differences?

1.4 The added value of this research

This research deals with the understanding of consumer energy usage routines and their interaction with flexible interactive systems which try to influence their electricity related behaviours. It adds to scientific knowledge as current literature has a considerable focus on the technological aspects of Smart Grids. Furthermore this study provides new insights in user interaction and acceptation of technological innovations towards the socio-technical issue of sustainable energy technology adoption. Current theoretical findings on the benefits and the effects of Smart Grid technologies for the consumer can be further substantiated and tested. Furthermore this knowledge has practical relevance because the introduction of new electricity loads such as electrical transportation and heat pumps raises the need of realignment of electricity consumption. If the current electricity system can be transformed into one in which the electricity consumption is being adapted to the availability of electricity, this could lead to more efficient usage of the current electricity grid.

2. Theoretical background and Research model

"Unus pro omnibus, omnes pro uno" *- One for all, all for one*

The Dutch energy sector is changing. For over a decade the production and distribution of energy is built upon a centralized, predictable and reliable system. However, recent developments led to rethinking of this system. From the top-down side, developments like environmental goals, regulation and resource scarcity play a significant role in rethinking of the system. From the bottom-up side, these developments include decentralized energy production and increasing peak demand of electricity. Because of these developments a considerable level of unpredictability and inefficient usage of the system might be introduced.
In regard of this project, the following relevant fields of Smart Grid related literature are studied:
First the developments in the in the electricity consumption of domestic users. Second the part of the Smart Grid which is directly connected to the domestic users and last the attitudes and perception of domestic users towards these smart grid solutions. The literature on developments in electricity consumption in the domestic sector is interesting as it provides insights in the necessity for a Smarter Grid and provides a direction on what is being expected from the demand side. Literature on the definition and methods concerning the consumer side of this smarter grid, helps us to understand in what ways end users are involved in the Smart Grid and what position they could take in the future. Last the literature on Consumer Interaction with Smart Grid technologies provides us with a theoretical assumptions on how Consumers Interact with Smart Grid technology, which could serve as hypothesis for further field analysis in this research.

2.1 Introduction: Reengaging the disengaged consumers.

Back in 1880, electricity began to make its entrance in the energy sector then dominated by gas. It started with small scale generation with installations which were privately owned. But to make this electricity commercially available for the whole country, a nationally integrated electricity system was needed. Consequently the evolution of the electricity industry over the last century centred upon extending the grid and scaling up centralized generation (Verbong, van der Vleuten &Scheepers, 2002) Reasons why this approach has proven to be working successful are found in theory on standardization and economies of scale. Moreover the resources used for energy production were highly concentrated and not as easy distributed as the electricity form created from those resource and thus best processed centrally.
Years of investment in the distribution network has resulted in great success of this approach: Affordable and reliable electricity with the allowance of end-users to be completely disengaged from the system (Hamilton, Thomas, Park, & Choi, 2011, 2013, F. Sioshansi, 2011, F. P. Sioshansi, 2011, 2011). Obtaining energy had become as simple as flipping a switch for almost all citizens in developed parts of the word, resulting in a perception of an endless supply which will honour just about every demand of energy. Because the non-existence of controlling methods the way small end users choose to consume electricity (F. P. Sioshansi, 2011)) , the focus of suppliers became meeting future demand through the augmentation of supply. This said the energy scarcity as generally presented and is in fact not as such experienced by the end user. Instead, energy is experienced as a rather cheap indefinite source.
The oil crisis in 1973 formed an external landscape shock which led to the governments publication of its first energy white paper (Geert Verbong & Geels, 2007). This white paper was dealing with new the

issues surfacing in the energy systems like dependency, reliability, affordability and environmental problems. Rethinking the energy system led to the identification of four important principles which needed to be provided: (1) cheap energy for large consumers, (2) reliability of supply, (3) decrease of dependency and (4) increase efficiency to address the environmental impact (Verbong & Geels, 2006). These principles were later translated to the more generally known principles of energy to be: (1) Reliable, (2) Affordable, (3) Environmental responsible (de Vries, Correljé, & Knops, 2009). In practice there is a trade-off needed between these goals. Reliability for example comes at a cost, which raises the question how much society is willing to pay for a certain level of reliability? With this in mind the energy sector underwent a large scale restructure towards liberalization of the market in the last two decades. In essence competition was introduced where possible, under the assumption that the pressure from competitors will force the market parties to become more efficient and innovative as well as improved customer service and choice (F. P. Sioshansi, 2011). Changes in the institutional framework resulted in a shift from a system dominated by engineers to a market based system ruled by managers and despite an increasing interest in renewable energy technologies; the transition towards a competitive market has mixed outcomes and did not (yet) contribute to a large scale introduction of renewables in the Netherlands (GPJ Verbong & Geels, 2010).

Nowadays, arguably more pressing drivers have emerged in forms of endless demand growth, climate change and increasing energy prices due to resource scarcity or geo-political reasons. The Netherlands is falling behind in the production of renewable energy and still far away from its own goal of a fourteen percent share of renewables in 2020. However, there is a promising range of existing and emerging technologies which are capable of helping to address these challenges. Some of them fit in the current centralized supply system but most of them centre upon distributed energy options including energy efficiency and demand management arrangements (F. P. Sioshansi, 2011). Utilizing the potential of these kind of options will require a very different relation between the historical established electricity industry and the end-user. This recent development towards end user engagement in the energy sector is quite controversial to the developments towards end user disengagement taken place earlier. According to Rotmans (2013) this marks the beginning of a period of decentralization and bottom-up approach. To shift from the centralized existing energy system towards a more decentralized structure requires a market and regulatory environment which is in favour of the effective exercise of consumer sovereignty. This again implies the necessity of a better understanding of the consumer and the position they will take in the future energy grid.

2.2 Developments and trends in domestic electricity consumption

The electricity consumption of the domestic sector in the Netherlands mostly increased during the last two decades.

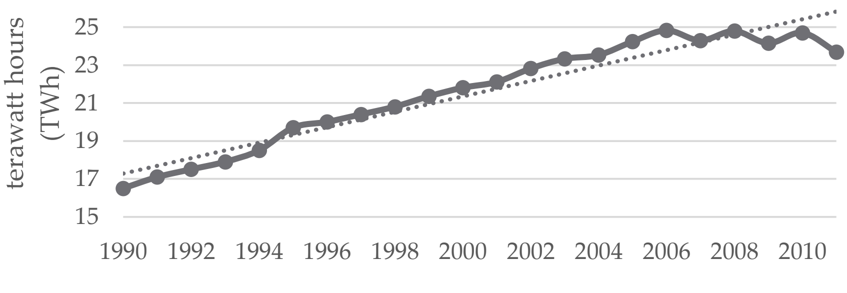

Figure 1: Electricity consumption of households in the Netherlands (source: Eurostat)

As seen in Figure 1, the electricity consumed by the Dutch households steadily increased up until approx. 2005. After then the electricity consumption stabilized around 25 Terawatt-hour. This electricity consumption together with an decrease in gas consumption (Dril & Boelhouwer, 2012)("Energie in Nederland 2011," 2011)(de Vries et al., 2009), increases the share of electricity in the total energy consumption of the domestic sector. This is also referred to as the electrification of society.

This section will deal with how and when this electricity is being consumed and by who. We first explore how the Dutch domestic sector is composed and what future trends in this composition induce change in future electricity consumption. Second the energy usage by households is analysed. This section ends with an analysis of the time when this consumption is taking place and what the aggregated demand on specific times means for the electricity net.

2.2.1 Domestic electricity usage

The entire domestic market is currently responsible for 24 percent of the Dutch electricity consumption ("Energie in Nederland 2011," 2011). Since 1988, the average electricity consumption per household has steadily increased, reaching a maximum of 3,558 kWh in 2008 ("Energie in Nederland 2011," 2011). After 2008, the amount of electricity consumed has been stable with a slight decrease towards 3,312 kWh in 2012). Factors that are thought to have played a role in the stabilization of the average consumption per household is the levelling of the market penetration of appliances that typically use a large amount of electricity (refrigerators, washing machines, dryers, etc.) in combination with an increase of more energy efficient appliances available (Dril & Boelhouwer, 2012). Noteworthy is that there is a wide dispersion in electricity usage per household. This spread indicates the variety found in electricity usage of Dutch households. Variables explaining this dispersion are: household composition, dwelling size, appliances owned, degree of insulation and usage of appliances (Dril & Boelhouwer, 2012). Literature further indicates that the largest part of electricity is consumed on the activities: cleaning, refrigeration, lighting and heating (: Energie in Nederland 2011). The appliances that are responsible for the greatest consumption of electricity are the refrigerator (10%) Washing machine + Tumble dryer (11%) and Hot water appliances (9%) (see Figure 2).

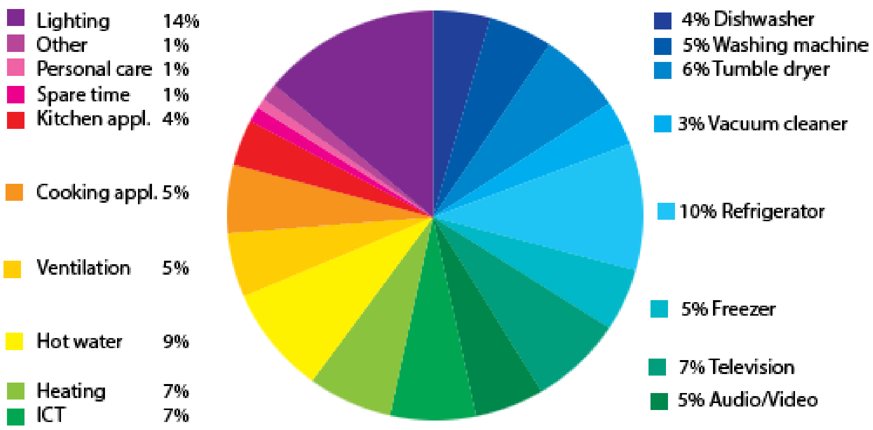

Figure 2: Average electricity consumption per appliance (source: (Dril & Boelhouwer, 2012)

2.2.2 Increase in domestic peak electricity demand

When consumers simultaneously use electrical appliances there is more electricity needed to cover that aggregated demand leading to an increase in electricity production and transportation, hence the term peak demand. Although there is little consensus on the exact definition of peak demand in essence it describes a period in which electricity is expected to be provided for a sustained period at a significantly higher than average supply level. Peak demand occurs at certain predictable times during the day as there is a likelihood that consumers use appliances only during some part of the day (Gyamfi & Krumdieck, 2012). As seen in Figure 3, the electricity demand of an average household in the Netherlands peaks between 17:00 and 20:00.

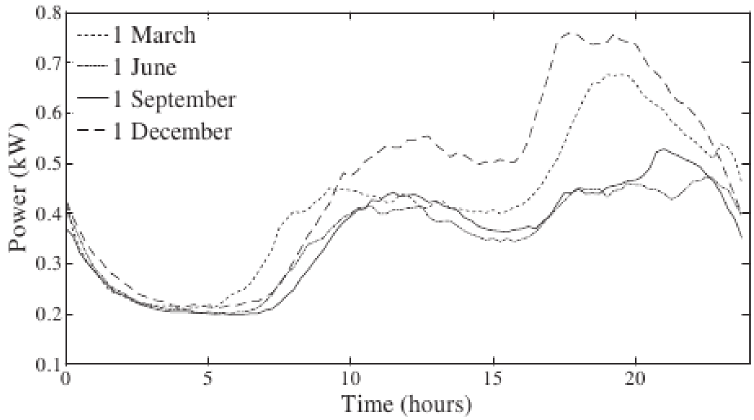

Figure 3: Daily load profiles of normal residential electricity use in the Netherlands (source: (Veldman et al., 2013)

The electricity distribution grids today are designed to handle peak demands. This is inevitable due to the fact that storage for the application for energy management in distribution grids has been technically and economically infeasible (Veldman et al., 2013). Producers of electricity supply a constant minimum of energy needed through large coal fired plants that were un-easy to adjust but provide low cost electricity. The flexible demand throughout the day is provided by plants capable of adjusting generation through controllability. These plants are often gas or oil fired, and are designed for quicker reactions to electricity fluctuations against the cost of more expensive production of electricity.

Current developments amplify peak demand. The most important developments as identified by (Energieraad, 2009) are the penetration of air conditionings, heat pumps and even more important, the introduction of electrical vehicles.

2.2.3 Trends that further increase peak demand.

Several trends are expected to further increase the domestic peak demand. We will elaborate on the introduction of electric vehicles and heat pumps.

Despite the approx. amount of 1,400 electrical vehicles in the Netherlands on January 2012 (Appels, 2012) and the absence of a wide variety of electrical vehicle models in the Netherlands, the Dutch government has the ambition to stimulate and facilitate the adoption of 20,000 electrical vehicles in 2015 (EL & I, 2011). After 2015 the Dutch government expects an increasing growth following an S-curve resulting in 200.000 electrical vehicles in 2020 and 1 million EV's in 2025 (Ministeries van I&M en EL&I, 2009). In the case where charging is not restricted by anything other than the driver's usage, the single most important factor in charge timing is when people arrive home after the last trip of the day.(Weiller, 2011). For 1 million cars this creates an increase in load at the current evening peak hours after people get home from work around 5-6 (Weiller, 2011). Then again, the electric vehicle could also be charged at more locations than merely at home or at different speeds (Rotering and Ilic, 2009) and there could be a time delay incorporated in the charging profile to minimize electricity costs (Parks et al., 2007). This brings certain complications in predicting charging patterns. Weiller, (2011) made a prediction of the average load profile of an individual electrical vehicle at home for the US. In this prediction he incorporated the assumption that the electric vehicle is only charged, excluding the possibility to drain the cars battery for load shifting purpose. Results are based on a US 3.88 kW circuit which is slightly different than the common used 3.5 kW (230 V / 16 A) circuit in the Netherlands. Nevertheless, the results give an indication of the impact of an electrical vehicle on the net.

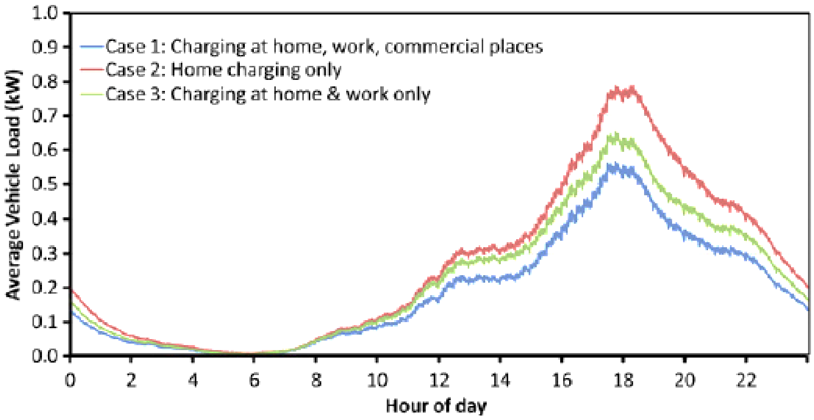

Figure 4: Added load at home as result of electrical vehicle charging under different scenarios (Source: Weiller, 2011)

As shown in Figure 4, the electricity load at home during peak hours in increased with 0.5-0.8 kW depending on the locations where the car is charged elsewhere than at home. In the most likely case 1 where the vehicle is charged at as many locations as possible, the existing load during peak hours is almost doubled. To upscale this increased load to one million cars one can imagine this has a massive impact on the electricity net.

Another important component influencing peak demand at households is the large scale introduction of heat pumps. Just like electric vehicles these electric appliances are expected to reduce the overall energy usage due to efficiency increase, but will lead to substantial additional demand for electricity. In the Dutch domestic sector, increasing heat pump installation (Peter Oostendorp, 2012) is concentrated on new building construction (Kleefkens, 2008). By the end of 2010 about 120,000 heat pumps were in operation in The Netherlands in the domestic and utility sector. However, the rate of new construction of single/two-family houses at the moment is momentarily equivalent to only 0.6 % of the existing housing stock of 7.2 million (43,200 new houses were built in 2010)(Peter Oostendorp, 2012). To meet the European 2020 objectives, pressure increases to see the existing housing stock as a very relevant market for heat pumps. In order to do so, the Dutch Heat Pump Association (to which most manufacturers and suppliers of domestic heat pumps belong) prepared a 500,000 heat pump plan in which the focus is put on existing housing. It is however not clear what impact the large scale introduction of heat pumps has on domestic load profiles. For different households the total heat demand can differ substantially, depending on the type of house, insulation and individual preferences and number of the residents. However, the load profile of the heat pump is not susceptible to customer behaviour, because the settings of the heat pump are fixed with limited degrees of freedom (Veldman, Gibescu, Slootweg, & Kling, 2011). Veldman et al (2011), also found that in reality the peak demand of the heat pump is randomly spread out over the day and electricity consumption during those peaks vary between 0.61 and 1.02 kW. Compared to the 0.45 – 0.78 kW peak demand as shown in Figure 3, this results in a substantial increase in electricity demand per household.

2.2.4 Increase in domestic electricity production

In the energy sector which was traditionally led by governments and large commercial market parties, there is an upcoming self-organising citizen driven power towards decentralised energy autonomy (Schwencke, 2012). Households are slowly starting to generate part of their own energy(Leenheer, De Nooij, & Sheikh, 2011). Technologies that help them to (partly) generate their own electricity are increasingly available. These technologies change the use of the grid; households who generate their own power will supply electricity to the grid if they produce more than they need and use electricity from the grid if they produce less than they use. In the Netherlands there is a growth in local energy production. An increase in initiatives (Rotmans, 2013) in forms of combined local energy production, knowledge sharing, combined PV purchase etc. Because of the decentralized and independent nature of these initiatives it is hard to pinpoint the exact number of initiatives nonetheless numbers vary between one- and three hundred in 2012 (Schwencke, 2012) which is growing day by day. The national knowledge platform *HIER opgewekt* tries to get more insight in magnitude of these initiatives and helps to amplify the local energy production movement by connecting existing initiatives for knowledge sharing purposes. They registered over 160 initiatives spreading all over the country and claims to have spotted over three hundred initiatives.

What are motivations for this large group of local citizens to combine powers to facilitate self-produced energy? From a top-down view we see market opportunities for new service providers in a liberated energy market (Schwencke, 2012). More interesting is the intrinsic motivation of the bottom up, local citizens to participate in such initiatives. Empirical data from more than 2000 Dutch households reveal that environmental concerns are the most important driver of households' intention to generate its own electricity (Leenheer et al., 2011). Second, affinity with energy and to lesser extent affinity with technology drive the intentions to generate own power. Leenheer et al (2011), expects that affinity with energy and technology is to high extent stable over time and therefore this characteristic is probably better able to explain differences between households than to play a role in developments over time. Third, reputation of energy companies are a motive to generate own power. This implies that households value social corporate responsible behaviour of energy companies. What is most remarkable is that financial motives do not seem to play a role as a motive according to the research of Leenheer et al (2011). Studies on adoption behaviour have found that economic considerations do play a role ((Farhar, 1999, Scarpa & Willis, 2010), therefore monetary incentives are believed to play a strong moderating role between intention and behaviour. That is, households may have a high intention to produce own energy but are limited due to financial constraints.

2.2.5 Impact on future electricity demand

What the developments discussed in the previous section mean for the average electricity demand of an household throughout the day in 2040 is predicted by Veldman et al (2013) based on area density and according to 3 different scenarios incorporating the trends in both energy production as well as electricity demand:

A. **Little change.** *Demand side*: no demand growth of normal domestic electricity use, low penetration of electric vehicles (40%) and low penetration of heat pumps in new and existing areas of resp. 40% and 4.5%. *Supply side*: Mainly centralised generation, level of distributed generation same as 2011: low penetration of solar panels (0.34 GW) and μ-CHP's (50,000 per year in existing houses)

B. **Global economy.** *Demand side*: 1.5% demand growth of normal domestic electricity use per year, high penetration of electric vehicles (75%) and high penetration degree of heat pumps in new and existing areas of resp. 68% and 67%. *Supply side*: Growth on generation on all levels. Gas fires generation grows, but share of centralised generation grows even more. Share of Solar panels and μ-CHP's is limited as in the case of scenario A.

C. **Energy policies.** *Demand side*: 1.0% decrease in normal domestic electricity use per year, high penetration of electric vehicles (75%) and high penetration degree of heat pumps in new areas of 66% and low penetration of heat pumps in existing areas (34%). ***Supply side:*** large increase in distributed generation. The amount of Solar panels and μ-CHP's grows substantial. Solar panels on domestic buildings have a capacity of 10 GW and another 10 GW is produced at local centralised initiatives.

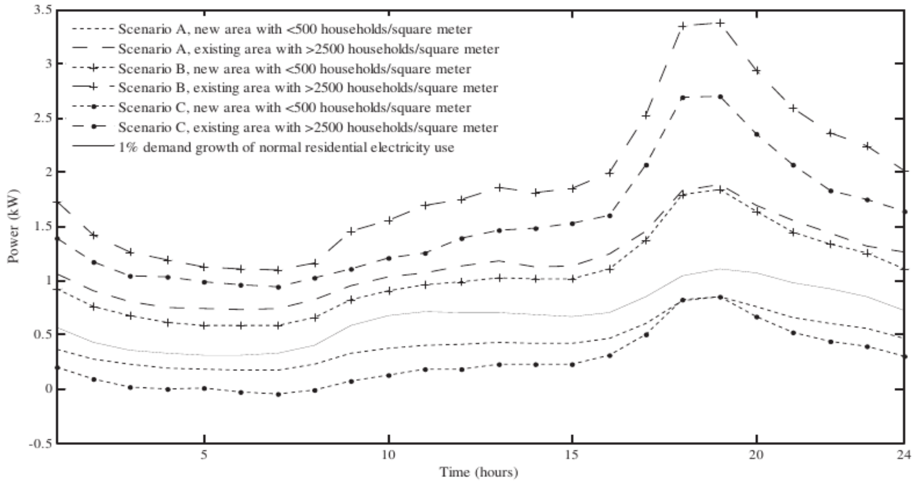

Figure 5: Predicted residential net load profiles in 2040

As seen in Figure 5, the load of a household in a dense area in 2040 has a substantial increase in peak demand in all scenarios compared to the current peak load as seen in Figure 3, which is around 0.8 kW when accounted for an annual demand growth of 1%. In worst case scenario (Scenario B in a dense area) the peak load of a household reaches 3.5 kW, almost four times the peak of a household nowadays (see Figure 3).

2.3 The solution: A Smarter Grid

The developments above ask for a different way we balance our energy demand and supply. The increase in difficulty to balance this supply and demand ask for intelligence in the electricity grid. This is basically the essence of a Smart Grid, which enriches the electricity network with information communication technology in order to facilitate two way traffic of energy and information between Supplier and Consumer. A Smart Grid can be described as a socio-technical network characterized by the active management of both information and energy flows, in order to control practices of distributed generation, storage, consumption and flexible demand (Wolsink, 2011). As seen in Figure 6, the Smart Grid consist of many actors that each play a significant role in the Smart Grid. In this research we focus on the Houses area in figure 13 also known as the domestic sector. Two important enablers of the Smart Grid in the domestic sector are demand management and smart appliances. Therefore those two subjects in the perspective of the consumer, will be the focus in describing the relevant parts of the Smart Grid in this section.

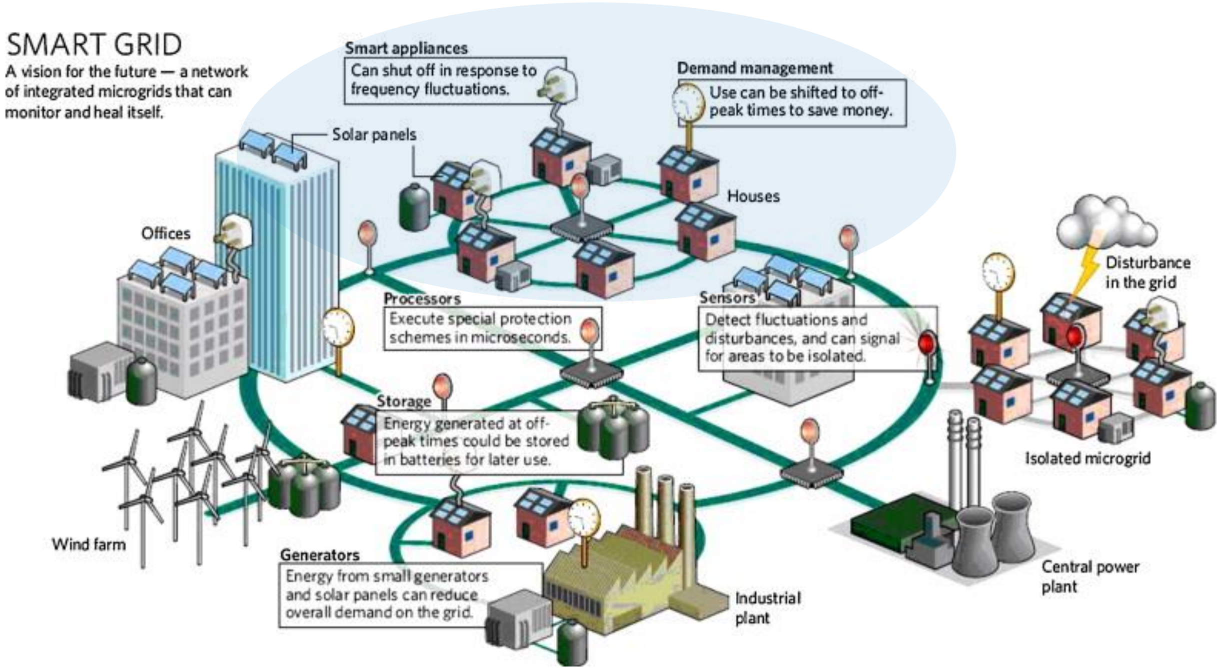

Figure 6: Illustration of a smart grid (Marris, 2008)

2.3.1 Demand side management

One important element of the Smart Grid is the creation of flexibility through the management of energy consumption at the consumer side or Demand Side Management (DSM). DSM includes all programs and activities (planning, implementation and monitoring) designed to influence the customer's energy use and thereby reallocating demand to times of less load and/or increased electricity generation from renewable energy sources (Finn, Fitzpatrick, & Connolly, 2012) (Gottwalt, Ketter, Block, Collins, & Weinhardt, 2011). It is expected that in the future smart grid 10% of the normal domestic electricity use for household appliances can be shifted to other times in day through demand side management (Veldman et al., 2013). This percentage is based on an extensive European research on the potential of load shifting by domestic appliances (Stamminger, 2009).This is done by focusing on changing the shape of the electricity load curve and thereby helping to optimize the whole power system from generation to delivery, to end use (Arteconi, Hewitt, & Polonara, 2012) (Kreith & Goswami, 2007). There are six generic load shape objectives that can be considered during DSM planning, namely peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape (Kreith & Goswami, 2007). This is achieved through dynamic load shifting which can be done by indirect load shifting methods such as different electricity tariffs, discounts, bonus payments and advertising etc. which aims to constrain consumption at peak demand times and make customers shift their normal consumption pattern to off-peak times (Zehir & Bagriyanik, 2012) (Aazami, Aflaki, & Haghifam, 2011). Other methods are using direct load shifting which basically relies on 'smart technology to shift loads over time in order to better match demand with supply (Gottwalt et al., 2011). In both indirect as direct load shifting the end user is playing a substantial role. In indirect load shifting actions of the end use consumer are directly mobilized resulting in a change in load. In case of the direct load control, the consumer himself does not play a direct role in the shift load but nevertheless need to accept the level of automation for scribed by the technology.

Other than conventional energy storage methods, DSM does not suffer from the inefficiencies inherited from mechanical or chemical properties and has the potential to be 100% efficient as it does not require any conversion of energy into an intermediary form (Finn et al., 2012). This makes DSM an interesting choice of creating flexibility in the net, allowing better integration of variable generation capacities such as those from renewable energy sources.

Demand side management can involve both reducing demand and shifting it through time (Darby & McKenna, 2012); (Di Giorgio & Pimpinella, 2012). The relationship between these is not straightforward and has been discussed by a number of authors (e.g., York and Kushler, 2005; Boshell and Veloza, 2008; Alexander, 2010). Although the focus of this study is more on the shift of demand through time, load-shifting and demand reduction can reinforce each other (Darby & McKenna, 2012). For example, lower overall demand is likely to involve some reduction at peak, while shifting peak demand reduces distribution losses and hence overall demand (Shaw et al., 2009); energy- efficient housing not only reduces overall demand for heating but makes it possible to shift load from heat pumps over longer periods of time (Hong et al., 2011).

2.3.2 Smart Household Appliances

As discussed in the previous chapters the increasing number of electric appliances causes a growing demand for energy and peak load in households. Other than indirect load shifting aiming at behavioural change of the consumer, direct load control could help to reduce energy demand and peak load. Key in this context could be the so called smart appliances. As seen in Figure 2, refrigerators, freezers, washing machines, tumble dryers and dishwashers are amongst the most energy consuming appliances used in households and together accountable for approx. 25% of the electricity demand of a household. By adding ICT to these appliances they could enable demand response on the consumer side.

Hence the term "smart appliance" means a product that uses electricity for its main power source which has the capability to receive, interpret and act on a signal received from a utility, third party energy service provider or home energy management device, and automatically adjust its operation depending on both the signal's contents and settings from the consumer. (Sastry, Pratt, Srivastava, & Li, 2010) These signals include (but are not limited to) appliance delay load, time-based pricing and notifications for load-shedding to meet spinning reserve requirements. Any appliance operation settings or modes shall be easy for an average, non-technical consumer to activate or implement. Additionally, a smart appliance may have the capability to provide alerts and information to consumers via either visual or audible means. An example of the application of smart technology is the possibility to partly or completely switch off an appliance during its runtime without any noticeable consequences for the consumer. More generally, in all appliances that need energy, but are flexible in terms of the moment at which this energy is delivered, this kind of technology can be integrated (Sastry et al., 2010, Stragier, Hauttekeete, & De Marez, 2010). While some appliances may benefit more than other, it must be said that it is their collective contribution to the richness of the information that enables value in active domestic energy management (Sastry et al., 2010).

However, the question arises to what extent the consumer will allow interference of those machines into their life? While these applications of smart technology might be important to reduce household energy consumption in a substantial way, it is important to keep the consumer's attitudes and opinions in mind, especially in terms of their control over these, in a certain way, self-regulating devices (Stragier et al., 2010). A key success factor to achieve peak load reduction in the domestic sector is to understand customer behaviour and the willingness to accept demand response programs(Gyamfi & Krumdieck, 2012) and smart appliances (G. P. Verbong et al., 2012, Wolsink, 2011). In the following section, current findings in this willingness are discussed.

2.4 Households' perception and attitudes towards the Smart Grid

In order to diffuse the innovation called the Smart Grid, the end users needs to accept the designed technologies and understand the idea behind the innovation . There is a growing body of smart grid studies trying to grasp the current consumer opinion and attitude towards the Smart Grid. Most of them found in the context of energy efficiency. This section uses the current developed literature on energy related behaviour in order to identify factors influencing the adoption and diffusion of Smart Grid technology. First the consumers perceptions and expectations of the Smart Grid found in current studies are described. This section is categorized in the two enablers for the Smart Grid on the residential side: demand side management and smart appliances; although it could be discussed that smart appliances are instruments to facilitate demand side management.

2.4.1 Households' perception and attitude towards demand side management

Poortinga, Spence, Demski, & Pidgeon (2012) showed the applicability of the Value Belief Norm model for measuring acceptability of demand side measures in the private sphere. They found that *environmental identity*, *climate change concern*, and *personal norms* are all significantly associated with the acceptability of demand-side measures (see Figure 7). While personal norms were also important, their associations were mediated by more specific factors. Although the study of Poortinga et al. (2012) primarily focussed on the acceptability of demand side measures in order to reduce carbon dioxide, the study is a useful framework for studying the individual-motivational factors in environmentally significant behaviours. One of its key findings is the central role environmental identity is playing in influencing concerns about climate change, energy security and the development of personal norms to do something about climate change. Making environmental identity among the most important individual motivational factors in explaining environmentally significant intentions. Therefore in order to predict the degree of shift in electricity demand over time it is expected that a higher degree of Environmental identify leads to a higher degree of demand shift. Therefore:

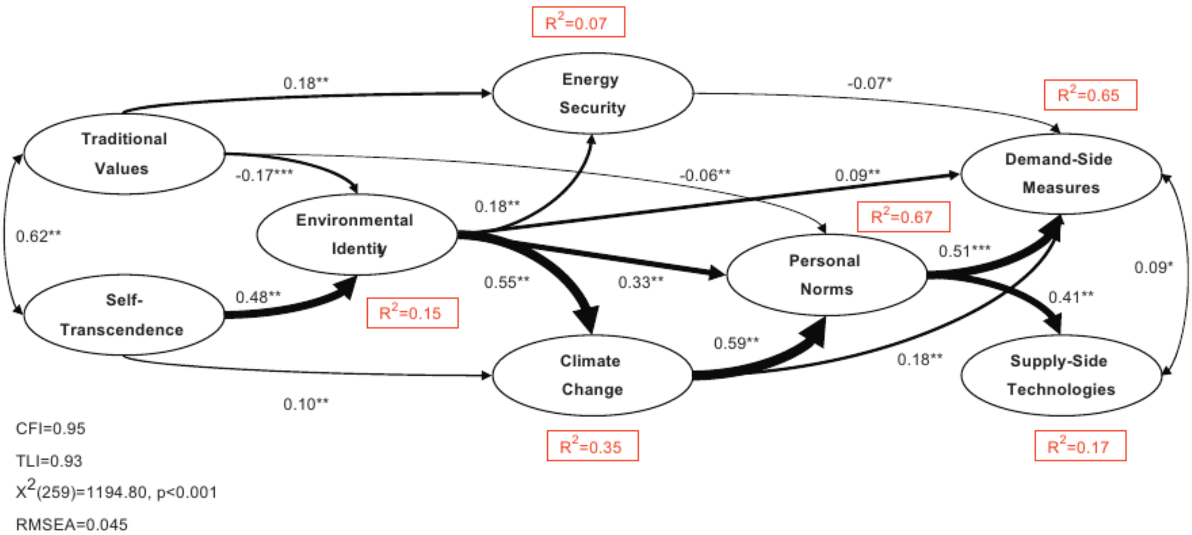

Figure 7: model of the acceptability of demand-side measures and supply-side technologies to reduce carbon emissions. The width of the arrows reflects the strength of association (source: W. Poortinga et al., 2012)

Furthermore they found that energy security appears to be submerged into a more traditional worldview (sample of British population with n=1822), having little effect on the acceptability of Demand Side Measures. Climate change on the contrary are more developed by Environmental identity and find their roots in more altruistic self-transcending world view. Personal norms to do something about climate change are only developed by those who have an environmental identity and a concern for climate change.

2.4.2 Households' perception and attitude towards smart household appliances

Stragier et al. (2010) showed the applicability of the Technology Acceptance model (Davis, 1989) for measuring the perception, attitude and intention to use smart household appliances (see Figure 8) . The Technology Acceptance Model has become the most prevalent model for studying user acceptance in the field of information technology (Mayer, Volland, Thiesse, & Fleisch, 2011). It includes two major predictors of the dependent variable Behavioural Intention, which is assumed to be closely linked to actual behaviour: Perceived Ease of Use and Perceived Usefulness. Stragier et al. (2010) found that Perceived ease of use have a strong influence on Perceived usefulness, which implies:
Both Perceived usefulness and Perceived ease of use have a significant effect on Attitude, with Perceived usefulness as most influencing. This means that people need to have a good perception of how useful smart appliances can be in order to have a positive attitude about using them. The same goes for perceived ease of use. If the perception of a smart appliance is that it is easy to use or at least as difficult as regular household appliances, this will contribute positive to the attitude towards smart appliances. Through the mediating factor Attitude this usefulness and ease of use form an important predictor for the intention to use Smart Appliances. There was no direct effect found between usefulness and intention to use. This could be explained by poor knowledge about the usefulness of smart appliances in terms of energy efficiency and financial profits for households, but also in terms of environmental impact and energy production efficiency (Stragier et al., 2010).

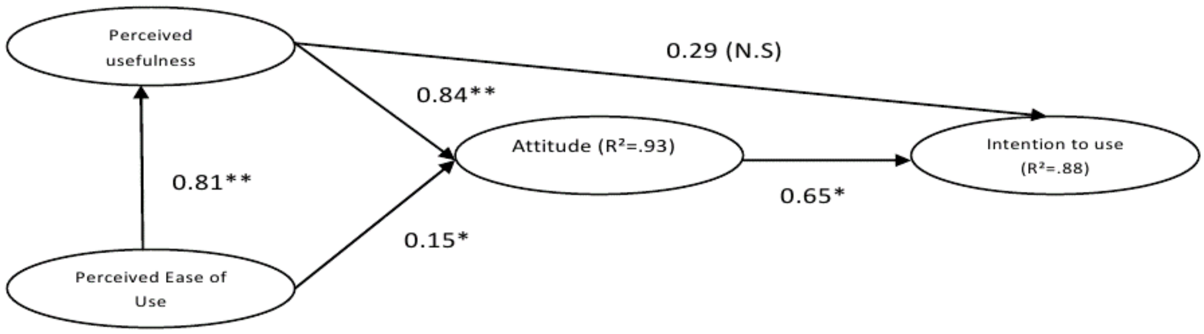

Figure 8: Applied Technology Acceptance Model in Households perception of Smart Appliances (source: J. Stragier, 2010)

An important feature of Smart Appliances is the provisioning of feedback on energy related behaviour. Silva et al. (2012) found that depending on the information they acquire, the overwhelming majority of people respond to be willing to modify their own energy related behaviour. Over 90% of the asked consumers wishes a better information overview of electricity consumption, and would like to have a better understanding on the impact of individual devices on their energy bill and behaviour. This service could be fulfilled by Smart Appliances. With concern to this, numerous studies ((Fischer, 2008), ACEEE 2010) have shown that consumer feedback on their energy consumption habits can result in modified energy related behaviour. Similar results have been observed in utility field studies reviewed by Faruqui (2009). The studies reviewed still leave many details to be resolved, however a relative sound body of evidence indicates that consumers will change their energy consumption behaviour in response to feedback. The studies show that feedback tends to be most effective when it:

- is based on actual usage data
- is provided on a frequent basis (daily is better than weekly, etc.)
- involves interaction and goal setting
- is given over a longer period (year or more)
- involves specific behavioural recommendations regarding appliances
- involves normative or historical comparisons.
- Is presented in an understandable and appealing way

This is partly in line with findings of Abrahamse, Steg, Vlek, & Rothengatter (2005), who found that feedback appears to be an effective strategy for reducing household energy use in most studies examined. The more frequent the feedback is given the more effective it is. And giving feedback about the price differences in on- off- peak hours result in shift in consumption to off-peak hours. Combining feedback with goal setting resulted in reductions in energy consumption (McCalley & Midden, 2002), especially when combined with a difficult goal (Becker, 1978). It is not clear whether it makes a difference to give feedback in terms of monetary rather than environmental costs, since studies investigating this difference did not find any (Abrahamse et al., 2005). For that reason, in this study we try to verify whether feedback in terms of monetary or environmental costs will have a predilection with households. By giving households a choice in selecting either monetary or environmental feedback we expect to find a higher performance on demand shift due to a better reflection of the households' need.

2.5 Research model and Hypothesis

The previous sections provided an overview of existing knowledge on consumers attitudes towards- and perceptions of the Smart Grid. However, two major gaps in existing knowledge remain. First, the literature on the interactions between consumers and demand-side management has remained relatively limited (Mah, van der Vleuten, Hills, & Tao, 2012) Second, public opinion surveys on smart grid-related issues have been growing but few are able to assesses their perception and behaviour, and how they would respond to the possible deployment of smart grids in the future (Mah et al., 2012). What is missing in current literature is the combination of the two gaps in forms of practical evidence if the provision and usage of smart grid technologies will lead to the effect wanted: shifting energy usage towards off-peak hours on the demand side. One thing that is often assumed is that only people who have a high environmental identity are willing to shift electricity demand because people are not willing to give in on comfort without being rewarded. This is also due to the absence of an financial incentive such as a dynamic pricing structure. Including motives like financial as well as environmental should therefore be incorporated in research to electricity demand shift. Furthermore it is not certain if people are willing to accept and use technologies which would help them shift electricity demand. Insights on characteristics of households who are able to use electricity during off-peak hours and to what extent the usage of Smart Grid technologies offers them help in doing so, gives direction in future Smart Grid development.

The Technology Acceptance Model

The most obvious choice regarding the basis of the theoretical framework for a study like these seems to be the classical TAM as tested by Stragier, 2010 (Figure 9). The TAM focuses on the attitude explanations of intention to use a specific technology or service and has become a widely applied model for user acceptance and usage. There are a number of meta-analyses on the TAM that have demonstrated that it is a valid, robust and powerful model for predicting user acceptance (Bertrand and Bouchard, 2008).

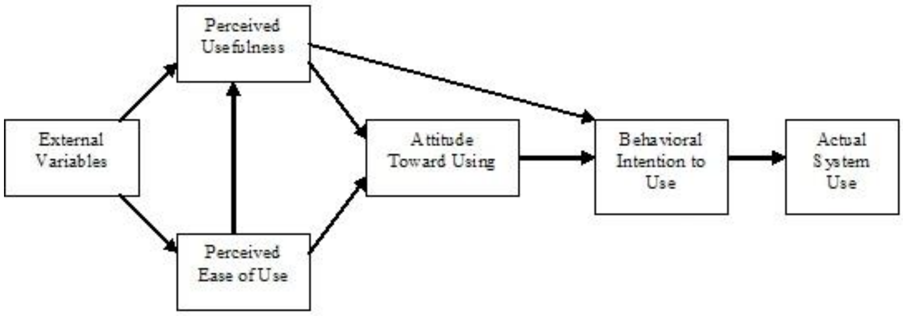

Figure 9: Classical Technology Acceptance Model

The extension of the Technology Acceptance Model

For the present study however, the TAM alone may have only limited ability to explain smart electricity products acceptance because it neglects the social context in which an environmental technology is being adopted as stressed by Poortinga, 2012. For this reason, it is decided to extent the original TAM model by using motivational factors as external variables inspired by the adapted Value Norm Belief Model as proposed by Poortinga, 2012 in order to find what motivations are driving households to use the technologies. As seen in Figure 10, the motivational factors which are included are environmental, financial and social. These motivational factors are expected to influence the perceived usefulness of the system as suggested by Stragier, 2010.

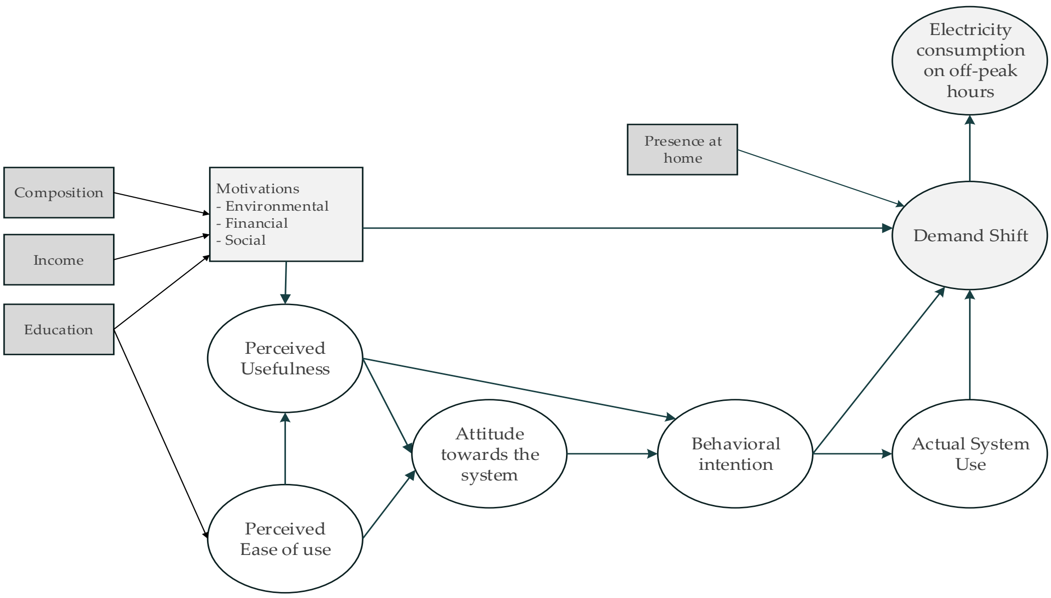

Figure 10: Conceptual model electricity demand shift by using Smart technologies

Furthermore the end goal that is reached by using the technology is included. But then again what is this ultimate end goal? For the utility company it is reducing the electricity consumption during the peak moments resulting in a more stable electricity consumption throughout the day which benefits the balancing of electricity supply and demand. For the residential end user of the system, who has other motives lying behind the reduction of peak demand, the usage of the system will ultimately help them in shifting their electricity demand to moments which serve their motivational incentives. This said, both end goals are included. The reduction of electricity usage during peak hours as end goal which is the result of the shifted demand. The motivations for this demand shift are drivers for the user and therefore included as a predictor for demand shift.

Last, the households' demographics are included to find specific segments who are higher motivated to perform demand shift with smart technologies and to find which households are better able to shift electricity demand. These demographics consist out of the composition and number of persons in the household, the daily presence time at home, the households' income and education.

Hypothesis

As explained in the previous paragraph it is expected that ultimately a reduction of electricity usage during peak moments is achieved by the shift of electricity demand. From this follows:

H1: Demand shift of electrical appliances will lead to a reduction of electricity use during peak moments.

Second, we expect that the usage of the smart technologies will assist in the achievement of the electricity demand shift. From this follows:

H2: Usage of the system will lead to an increase in demand shift of electrical appliances.

However, it is also expected that there are other ways to shift electricity demand which are not directly explained by the usage of the system and smart appliances. Households are able to shift the usage of appliances not directly linked to the system based on their behaviour, from this follows:

H3: Households with a higher behavioural intention to shift demand will be better able to achieve this demand shift.

Then the motivational factors environmental, financial and social are added as explaining predictors for the shifted electricity demand. It is expected that households who are highly motivated to shift demand will be better able to shift demand.

H4: Households who are highly motivated will be better able to shift electricity demand.

- *a) Households with a high environmental motivation will be better able to shift electricity demand*
- *b) Households with a high financial motivation will be better able to shift electricity demand*
- *c) Households with a high social motivation will be better able to shift electricity demand*

The five main constructs of the technology acceptance model are Perceived Ease of Use (PEoU), Perceived Usefulness (PU), Attitude towards using the technology (AT), Behavioural Intention (BI) and the Actual System Use (ASU). The baseline of the model is that Perceived Ease of Use and Perceived Usefulness can be used to predict the intention to use. Though TAM is mostly used for information technology, the ideas that are behind the model are also applicable in the context of innovative technologies with regard to energy efficiency(Stragier et al., 2010). The hypotheses of the Technology Acceptance Model can be stated as follows:

H5 PEoU has a significant positive influence on PU

H6 PU has a significant positive influence on BI

H7 AT has a significant positive influence on BI

H8 PU has a significant positive influence on Attitude towards using

H9 PEoU has a significant positive influence on Attitude towards using

H10: BI has a positive influence on the ASU.

The three motivational factors are also used as external variables of the TAM models' perceived usefulness as suggested by Stragier, 2010. This lead to the following added hypothesis of the Technology Acceptance Model:

H11: Households who are highly motivated will have a higher perceived usefulness of the technology.

a) Households with a high environmental motivation will have a higher perceived usefulness

b) Households with a high financial motivation will have a higher perceived usefulness

c) Households with a high social motivation will have a higher perceived usefulness

Finally we use the households' characteristics to find specific target groups who are highly motivated to shift demand, perceive the technology as easy to use and are better able to perform demand shift. For this segmentation the following propositions are made:

H12 Households with a higher income have a lower financial motivation

H13a Households with a larger family composition will have a higher environmental motivation

H13b Households with a larger family composition will have a higher social motivation

H14 Households with a higher education will have a higher environmental motivation

H15 Households with a higher education will see the technology as more easy to use

H16 Households who are more present at home will be better able to shift electricity demand

3. Research methodology

This chapter outlines the research methodology of this study. One of the features of this study is the combination between reported data from households and observed data from Smart Appliances. In order to obtain both sorts of data a small scale residential area has been supplied with Smart Appliances and monitored during 5 months. Furthermore a survey is conducted to classify the households occupying the households.

3.1 Appropriateness of the Research Design

This research aims to find whether or not certain segments of households are able to shift electricity demand by making use of Smart Appliances. This said, the study needed for this aim is of an *descriptive* nature. It goal is to provide a valid representation of the current state and to test hypotheses. However some elements of an *exploratory study* are also present as the results will likely raise new research questions. The method of data collection contains *monitoring* since we want to measure interactions with the system as well as *communicative* methods since we want to know more about the households attitudes and characteristics. An *ex-post facto* design is used since we do not want to control variables during the study, and only report what is happening under actual residential environment conditions (*field conditions)*. The study is *longitudinal* since we measure usage over an extensive period and participants know that they are studied during this time.

3.2 The participating households

This study is taking place in an new constructed residential area called Muziekwijk, northwest from the centre of Zwolle, the Netherlands. This new residential area is a mixture of both apartments as well as land based houses. An overview of the different types of houses can be found in the Appendix. The houses can either be rented (47) or owned (38) totalling to 85 homes included in the study. All these homes are built with the latest energy efficiency requirements.

Figure 11: study setting in the Muziekwijk Zwolle

Furthermore the homes are provided with a:

- A Smart Meter
- A Home Energy Management System (HEMS)
- A Smart white good appliance
    - 75% of the participants received a smart washing machine
    - 25% of the participants received a smart tumble dryer
- 6 Solar Panels

The Smart Meter is a digital metering instrument which measures electricity and gas usage. The Smart Meter enables a more precise and detailed registration of the actual usage. The HEMS (Figure 12) is custom built for this pilot study and allows to send information to and from the households.

Figure 12: The Home Energy Management System

The HEMS further assists households in understanding their electricity usage and generation in an intuitive manner. For an extensive overview of the functionalities of the HEMS please refer to the Appendix. The Smart White good appliance is planned by the HEMS according to an algorithm which determines the most favourable moment. This most favourable moment is depending on the preference of the household which could be either Eco- or Cost oriented. With an Eco profile enabled, the Smart White good appliance will be planned when most electricity is produced locally. With a cost profile, the Smart White good appliance will be planned when the electricity price is at its lowest. These favourable moments are translated into graphical figures on the HEMS in forms of leaves for favourable Eco moments and Coins for favourable Cost moments. The user is always able to override the planning algorithm as they wish. Solar panels are installed in order to stimulate using energy while PV production is high.

3.2.1 Dynamic Pricing

In order to provide the households with a financial incentive to shift demand, the electricity price is made dynamic. This price consists out of three elements: (1) a fixed Energy tax, (2) a dynamic Energy delivery tariff by the energy supplier and (3) a dynamic Network operator Tariff. All tariffs are calculated per quarter of an hour (€/kWh) and are calculated without VAT of 21 percent. The *Energy tax* is a constant price of € 0,114 per kWh (2012), determined by the Dutch government. The *Delivery tariff* is the price that the electricity company askes of the consumer and has been made variable based on differences in the APX (power spot exchange) price and squared in order to amplify the difference. The algorithm to calculate the *delivery tariff* is found in Appendix IV. The *Network tariff* is the price grid operators add to the electricity price, based on yearly transport costs. This yearly transport costs is mostly determined by peak demand and therefore made dynamic according to the peak usage. The algorithm to calculate the *Network tariff* is found in Appendix IV. Combined the Dynamic Tariff is determined as:

$$Tariff_{total}(t) = (Tariff_{Network}(t) + Tariff_{delivery}(t) + Tariff_{E-tax}(t)) \cdot (1 + VAT)$$

Based on predictions of standard load and PV production this leads to the electricity price during the day as seen in Figure 13.

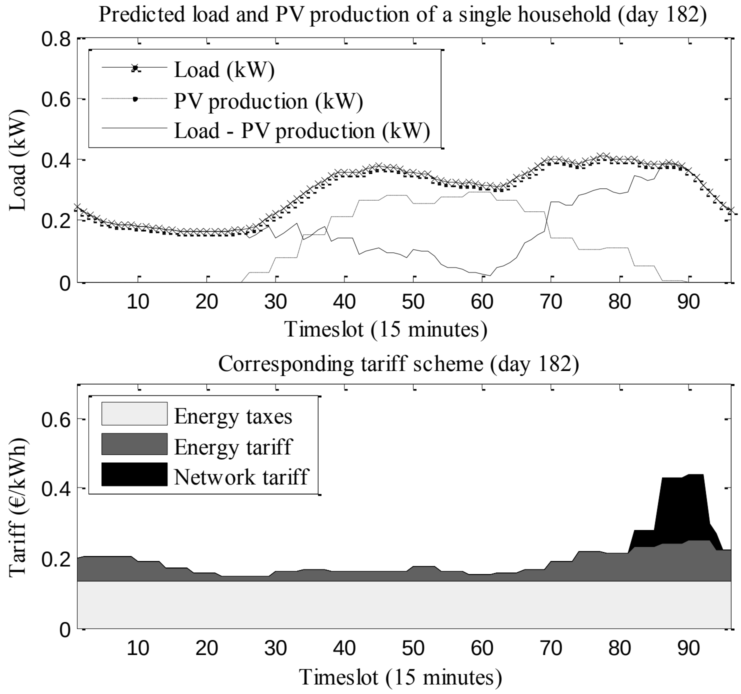

Figure 13: Example of Dynamic Pricing during the day (source: Enexis 2012)

As seen in figure 14 the electricity peak price is primarily caused due to the differences in Network tariff.

3.2.2 Goals

The households are able to set goals on the HEMS. Households who have selected an Eco oriented profile are able to achieve certain goals if they use relatively more electricity when there is high PV production throughout the day.. Households who have selected a Cost oriented profile are able to achieve certain goals if they use relatively more electricity when the electricity price is low. The Households will receive virtual stars on their HEMS display if they achieve their set goals.

3.2.3 Participation

Every household could subscribe for pilot participation. The homes are provided with the technology as described above without any extra costs for the household. In exchange participants agreed to be monitored and to fill in several questionnaires during the research phase of two years. On November the 30th 2012, the project officially launched.

3.2.4 Reference Group

For the reference group 26 non-participating households in the pilot study are used. These households live in similar houses. The reference group has not been provided with Smart Appliances nor solar panels. They also receive electricity bill based on the regular electricity prices instead of the dynamic prices. Data on quarterly aggregated usage is obtained through transformer measurements. Further information on the reference group data is found in Appendix XIII.

3.3 Data collection methods

This section explains the methods used to extract data from the pilot setting. In this study multiple methods are used in order to combine reported behaviour with real usage. First the data collected through monitoring is described. Second the collection of data through surveys is described and last the method of semi-structured interviews is described.

3.3.1 Data extraction from the HEMS

Households are monitored by the HEMS from within the homes. This analysis is done to find *if* the provided Smart Appliances has led to the effect wanted (which is peak reduction) and *if* households interact with the Smart Appliances.

The HEMS logs all activities and information coming to and from it with updates every quarter of an hour. This includes:

- Usage of the HEMS by logging the touchscreen
- Set Goals
- Planned wash cycles
- Consumption and production of Electricity

For all participants, this information is stored in a central SQL database. The individual information is grouped by an (anonym) Home_Id. For this study we use the HEMS data in order to determine: (1) the level of usage of the Smart Appliances, (2) what profile the household prefers and what goals are set and (3) how well the household is performing demand shift. Data is collected every quarter of an hour for the period 01-02-2013 until 01-07-2013. This results in 122 days or 11712 measurement flows per household.

3.3.2 Data from questionnaires

Second, data obtained through questionnaires is used for inferential analyses. This analysis is done in order to check for the behavioural intention a households has to shift electricity demand. Furthermore this analysis is done to identify target groups for further roll out of Smart Grid when found to be an success. In order to test the hypotheses data will be gathered regarding the different constructs from the research model, by means of an online survey. The choice for an online survey was made on the bases of several arguments. a) because it is cheaper and easier for both participant and researcher. b) Because the online availability of data prevents mistakes made by entering the data into SPSS. Furthermore problems with the representation of an internet-user sample to the larger sample (Hewson, 2003), is not an issue in our analysis because having an internet connection was one of the preconditions in participating in the pilot. This is due to the fact that the sample population is created by people who bought or rented a home in the Muziekwijk. Since this population agreed to fill in the questionnaires prior to the study, high response levels are expected making bias in representation less likely. Two surveys were conducted, the first prior to the launch of the project and the second follow up survey

after a period of 6 months. The first survey gives an impression of how the households expect the system to work, the second gives an impression on how they find it works based on experience.
For the sake of validity, the survey is mainly based on existing measures and questions developed by other researchers. Some of these measurements are in English. The choice for these measurements is based on two arguments: a) "a common international interpretation and analysis of the results is only possible if the data come from the same instrument" and b) all new data acquired about an instrument contribute to the validation and reputation of the instrument (especially relevant in the context of much-used instruments) (Harkness & Schoua-Glusberg, 1998). Thus, the use of these measurements grant the validity of the measurement of the constructs. However, since our population is Dutch oriented, the measures are translated into Dutch. The intended meaning of an item will be documented.
When matching data from the HEMS to the data from the survey, privacy is of great importance. Multiple studies stress the importance of the privacy concerns regarding Smart Appliances (Hamilton et al., 2011, Mayer et al., 2011, G. P. Verbong et al., 2012, Wimberly, 2011). In order to cope with these privacy concerns the data from the HEMS is combined with data from the survey and anonymized, making it untraceable back to a home address or specific person. The data will be treated with confidentiality and can only be accessed by the student, the supervisor from Enexis and the mentors of the University of Technology Eindhoven.

3.4 Measures

This section concerns the item scales used to measure all the variables of our conceptual framework.
We will first discuss the measures as proposed by the TAM model. Second we will discuss the measures needed to determine the electricity usage during off-peak hours.

Measures of the TAM model

Perceived Usefulness- Perceived Usefulness is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance, in this case, shifting electricity demand (Venkatesh et al., 2003). It uses items found in the constructs of perceived usefulness (Davis, 1989), extrinsic motivation (davis et al. 1992), Job-fit (Thomson et al. 1981), relative advantage (Moore and Benbasat, 1991) and Outcome expectations (Compeau et al. 1999). As Vankatesh, 2003 showed the similarities within these constructs. Respondents could answer using a 5-point scale from ''strongly agree'' to ''strongly disagree'', with ''neither agree nor disagree'' in the middle.
Perceived Ease of Use - Perceived Ease of Use is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). Three constructs from existing models capture the concept of perceived Ease of Use : perceived ease of use, complexity, and ease of use . Venkatesh et al. (2003) shows that there is substantial similarity among the construct definitions and measurement scales. Items from across these constructs are used in the Perceived Ease of Use on working with the Smart Appliances. Respondents could answer using a 5-point scale from ''strongly agree'' to ''strongly disagree'', with ''neither agree nor disagree'' in the middle.
Behavioural intention to shift demand - For measuring the behavioural intention to shift electricity demand by using the system, the respondents are asked to indicate whether they intend to shift the usage of

electrical appliances in home. Respondents could answer for each specific electrical appliance or appliance group whether they expected to shift usage during the day by participating in the study. Respondents could answer using a 5-point scale from ‘’almost never” to ‘’almost always’’, with ‘’sometimes’’ in the middle. middle.

HEMS usage behaviour - For the usage of the Smart Appliances the information provided by the HEMS is used. Data obtained from the HEMS includes interaction frequency with the HEMS and the number of washes who are automatically planned by the HEMS. Further the respondents are asked if they use the automatic scheduling function on the white good appliance and if the HEMS usage has become part of their routine.

Moderating variables - The questionnaire included some general questions for measuring age, gender, education and the number of persons in the household. Further the respondent is asked to indicate how often he or she and his/her partner is present at home on a five-point scale. These items will be used as control variables in our correlation matrix and regression analyses in order to check for any moderating effects. Experience is measured as time in the pilot study from 01-01-2013 to 01-07-2013.

Motivations

Environmental- An environmental motivation scale is constructed by expanding the scale items from the acceptability of demand side measures theory by Poortinga et al. (2012). These items include the feeling for responsibility for the climate change and the extinction of fossil fuels. Furthermore items are added concerning the importance of environmental related issues in participating in this project. Respondents could answer using a 5-point scale from ‘’strongly agree’’ to ‘’strongly disagree’’, with ‘’neither agree nor disagree’’ in the middle.

Financial-

Social-

Demand shift

For measuring the amount of electricity shifted as reported by the participant, the respondents are asked to indicate whether they shifted the usage of electrical appliances in home. Respondents could answer for each specific electrical appliance or appliance group whether they expected to shift usage during the day by participating in the study. Respondents could answer using a 5-point scale from ‘’almost never” to ‘’almost always’’, with ‘’sometimes’’ in the middle. middle.

Measures of the electricity usage during off-peak hours

Electricity consumption - The amount of individual electricity consumption is logged by the HEMS in periods of 15 minutes and found in Appendix IV.

Electricity price - The electricity price is logged by the HEMS in periods of 15 minutes and is determined by the price algorithm as found in Appendix IV.

Relative value - By using the electricity price a relative value is calculated. This relative value represents how bad or good it is at a certain time to use electricity relatively to the other periods. Three relative values are available ranging from 0 (peak hour moments) to 1 (good moments) and used to advise the participants on when to use electricity. The relative values are determined by using a configurable absolute boundary value. To determine the relative value the price plan day is divided in timeslots of 2 hours. For each timeslot an average total price is calculated and this average is matched against the relative boundary values according to the formula:

$$Relative\ value(t) = \begin{cases} 1 & if \quad Average\ Total\ Price_{timeslot} < Boundary_{low} \\ 0{,}5 & if \quad Boundary_{low} > Average\ Total\ Price_{timeslot} < Boundary_{medium} \\ 0 & if \quad Average\ Total\ Price_{timeslot} > Boundary_{medium} \end{cases}$$

Electricity usage during off-peak moments - Since we are interested in how well the participants are avoiding the bad times to use electricity, the total amount of used electricity on good times is compared to the total amount of electricity used per day. If only the absolute good moments are of interest, than the electricity used on times with relative value is 1 is divided by the total amount of electricity used.

It is also possible to use a weighted method in which we not only compare the good moments, but also take into account the moments which are bad but are not defined as peak hours. These bad moments give only half the score compared to good moments. This done by multiplying by the electricity usage to the relative values as stated above. This multiplication brings us the total amount of electricity used on good and bad moments excluding the peak hour moments. Electricity used on good moments count as normal, electricity used on bad moments count half and electricity used on worse moments (peak hours) count as nothing. Dividing the total amount by the total amount of electricity used per day, results in a score which is a percentage of electricity used on good moments. The higher this percentage, the more electricity is used on good moments and therefore resembles the performance to shift electricity usage towards off-peak hours.

$$Offpeakusage_{weighted}\ (\%) = \frac{\sum_{i=96}^{t} \overline{U_{n(t)}} * \overline{RelativeValue\ (t)}}{\sum_{i=96}^{t} \overline{U_n(t)}}$$

In which: $U_n(t)$ = The electricity consumption in period t for household n (15 minutes)

3.5 Reliability and validity analysis

All items from the survey can be found in Appendix V. The underlying basics of these scales were developed and tested by other researchers. These researchers assured the quality of their scales by means of a reliability and validity check. However, for the purpose of this study, we translated some of the scales into Dutch and made the questions more appropriate for our research setting. For this reason we have to check on the reliability and validity of the measures again.

Resulting from confirmatory factor analysis and reliability tests found in Appendix V several constructs were divided. The construct for measuring Perceived Ease of Use is split into four items (factor loadings >0.77) measuring the PEoU of the Project itself called PEoU_JEM (Cronbach's α = 0.84) and three items (factor loadings >0.93) for measuring the PEoU of the home energy management system called PEoU_HEMS (Cronbach's α = 0.95). The construct for measuring Behavioral Intention is split into three items (factor loadings >0.46) measuring the Behavioural intention to shift White Goods (Cronbach's α = 0.84) and Intention to shift other appliances (Cronbach's α = 0.88). Four items from environmental motivation were deleted resulting in an six item scale (factor loadings > 0.75) with high reliability (Cronbach's α=0.90). Perceived usefulness remained the original five items (factor loadings >0.69) with high reliability (Cronbach's α =0.79). Attitude remained the original seven items (factor loadings >0.63) with high reliability (Cronbach's α =0.83).

3.6 Data Analysis

First a t-test is used to determine whether the means of price paid per kWh of our two groups (participants and non-participants) are statistically different from each other. This is done in order to find if the pilot participants are shifting electricity usage compared to the reference group.
Then, a path analysis using STATA will be used to examine the direct and indirect effects between the variables who could explain in between differences for participants as proposed in the previous section and in order to find segments who perform better in the usage of electricity during off-peak hours.

4. Results

In this section we will describe the results of the analysis as stated in section 3.6. First the *descriptive statistics* of the population and the data will be given. Second the results of the *interaction* with the Smart Grid technologies are discussed. Third, the results of the analysis on *electricity usage* are being described. Fourth, we will elaborate on the *differences* in interaction and electricity usage between the households, and last the results of the *TAM model* will be discussed.

4.1 Descriptive statistics

Data was collected from 79 households. Of all 79 households, 71 responses where collected resulting in a response rate of 90%. In the follow up survey 5 households did not respond again resulting in a reduction of the respond rate to 84%. Furthermore there were 6 households who did not respond in the first survey, but did respond to the follow up survey making the total response rate of survey 2 72. In total there are 66 complete responses over the first and second survey and 77 responses to either survey 1 or survey 2. This very high response rate is likely to be the result of the commitment of participation in the survey in the preliminary stage of the enrolment in the project.

Demographics

The results from the first survey with n=71, showed that the division between man and women is about equal with respectively 52 to 48 percent. The age of the respondents range between 22 and 63 with an average of 32 years old. 66% Of the respondents has a bachelor degree or higher (see Appendix VI). The income of the households is more spread with an average yearly income between 30500-36500 per household (see Appendix VI). Most households exist out of 2 persons (see) who live in a house which size ranges between 30m2 and 170m2 with an average of 100m2. The family composition of most households are cohabiting or married partners without children (see Figure 14). The respondents are on average sometimes (2,3 on a scale of 1 being never to 5 meaning always) at home between 9am and 17pm and those with a partner, state that their partner is home more often (2,8).

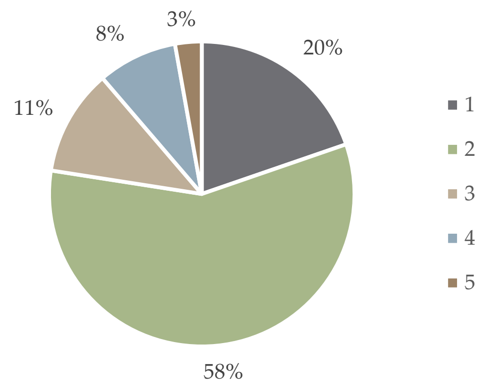

Figure 15: Number of persons in the participating households

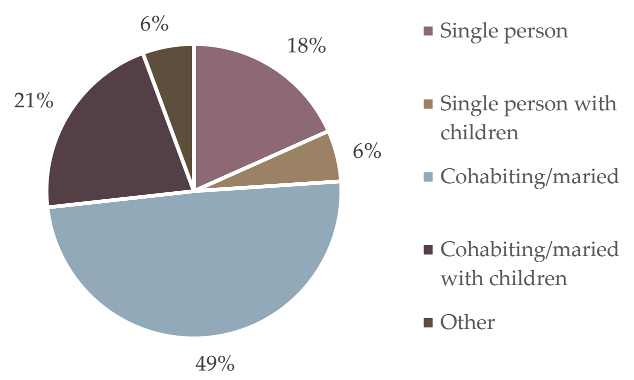

Figure 14: Household composition of the participating households

HEMS recordings

Overall, the quality of the raw data obtained from the Home Energy Management System (HEMS) varies over the different measurements. The theoretical stated population of 79 household is not found in the HEMS usage. There were no HEMS recordings found at 2 out of 79 households. 12 out of the remaining 77 households do not have complete daily recordings over the period 01-01-2013 to 01-07-2013. In total the HEMS of the 77 households have an online ratio of 94,35%. Furthermore, 91% of the HEMS systems send information on Smart Appliance usage.

4.2 Smart Grid technology interaction

In order to answer the research question whether domestic consumers interact with demand side management technologies, several measures on HEMS usage are taken. First we will discuss the interaction frequency with the HEMS display as the system records the touches by the household. Second we will discuss the usage of the smart functionality of the white good appliances.

HEMS interaction

HEMS touches where recorded during the period 01-01-2013 and 01-07-2013 (n=76). The results in Figure 16 show that on average the HEMS systems are daily touched 400 times by the participating group. The amount of touches per household per day varies between 0 and 44 with a mean of 5 touches per day. There is a small decreasing trend in the number of HEMS touches by the participants. Starting with an average of approximately 450 touches per day, the number of HEMS slowly decreases towards approximately 350 touches per day. During the measured period, the HEMS systems are touched 67801 times in total. More detailed information on HEMS touches is found in 0.

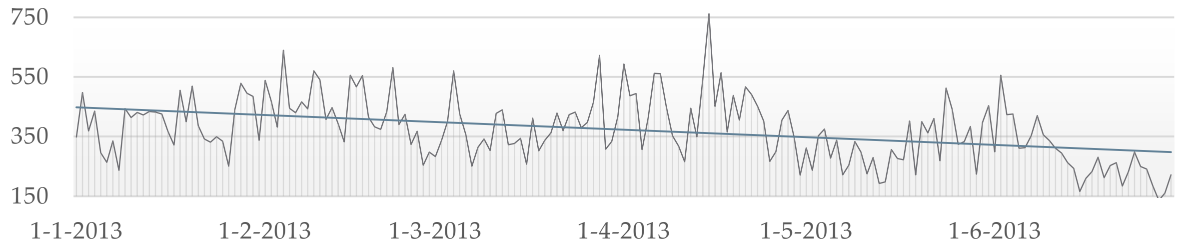

Figure 16: Number of HEMS touches during period 01-01-2013 until 01-07-2013 (n=79)

Smart Washing

Results from the survey show that the usage of the automatic scheduling function of the white good (smart) appliances, scores on average 2,36 on a 5 point scale which resembles the score between 'infrequently' and 'sometimes'. In addition, the HEMS recordings has been used to determine the amount of automatically planned washes between the period 18-04-2013 and 01-07-2013. In total 1265 washes are done within this period and analysed. Out of the 1265 washes, 1060 (84%) are done manual. Out of 70 households, 35 households (50%) has approved at least once to let the HEMS automatically schedule the start time.

The start times of 1624 washes are registered between the (longer) period 01-01-2013 and 01-07-2013. Most of the washes are done between 8am and 1pm. Figure 18 shows the energy consumption of those

1624 washes divided over the hours on a day. A maximum is reached around 10am where approximately 150 washes have taken place (see Appendix X), consuming a total of 200 kWh during the measured period.

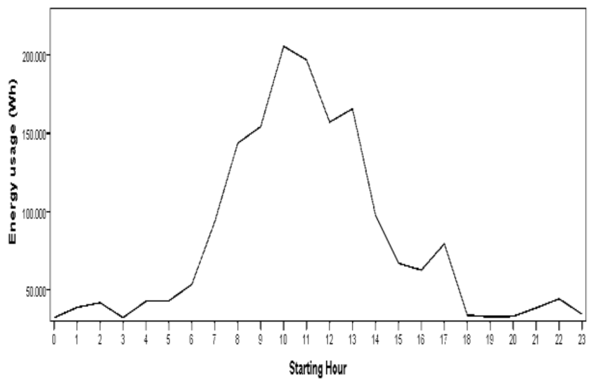

Figure 18: Average energy consumption of the washing machines (n=70)

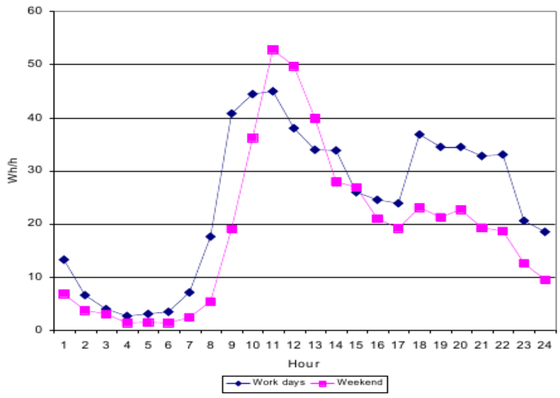

Figure 17: Average energy consumption of the Washing Machine per household (n=1300) (source: de Almeida et al., 2006)

The shape of the energy consumption of the 70 white good appliances deviates from the curve that was expected (see Figure 17), based on the findings by (de Almeida, Fonseca, Schlomann, Feilberg, & Ferreira, 2006). This study showed the average electricity usage of white good appliance throughout the day by monitoring 1300 households in the EU. As seen in Figure , this energy consumption has a peak similar to our findings, but show a second peak between 5pm and 10pm which is not found in the energy usage of the white good appliances by the participants. The absence of the second peak suggests an avoidance of washing on peak hours, which was intended with this pilot study. Nevertheless, explanations are not directly found in HEMS usage.

Feedback profile selection

The selection of the energy profile (either Price or Eco) is daily monitored during the period 01-01-2013 until 01-07-2013. A total of 79 different participating households where monitored during this period. In this period, 153 days where successfully measured upon 73 of the 79 households. The remaining 7 households had 87 successful measures out of 178 days. The results show that out of the 79 households only 12 had made a choice for using the Eco profile for at least one day. Further these 12 households choose on average to keep the Eco profile for 21% of the time.

The total number of simultaneous activated Eco profiles does never exceed 5 as. The period in which the most Eco profiles are enabled is during the early stage of the experiment of the experiment between the 9th and 13th of January. Starting in the last week of January the number of Eco profiles stabilized on 2 out of 73 households. After 2,5 months the total number of Eco profiles drops to 1. It recovers during the period 28th of march until the 16th of April after which the number of eco profiles stabilizes on one again.

4.3 Electricity usage during off-peak hours

In order to give answer to the research question whether the interaction with demand side management technologies has led to peak load reduction, several measures on electricity usage are taken. First we will discuss how the average daily electricity consumption of a participating household looks like. Second we will discuss what the off-peak times where during the pilot. Last we will discuss how many electricity the participating households consumed during those hours and if this deviates from a reference group.

Electricity consumption

Appendix XI shows the analysis on electricity consumption and the results of the dynamic pricing algorithm. The aggregation of the load profiles leads to the graph as seen in Figure 19. The peak usage of electricity takes place between 4pm and 6pm and reaches between 130Wh and 160Wh based on a confidence interval of 95%.

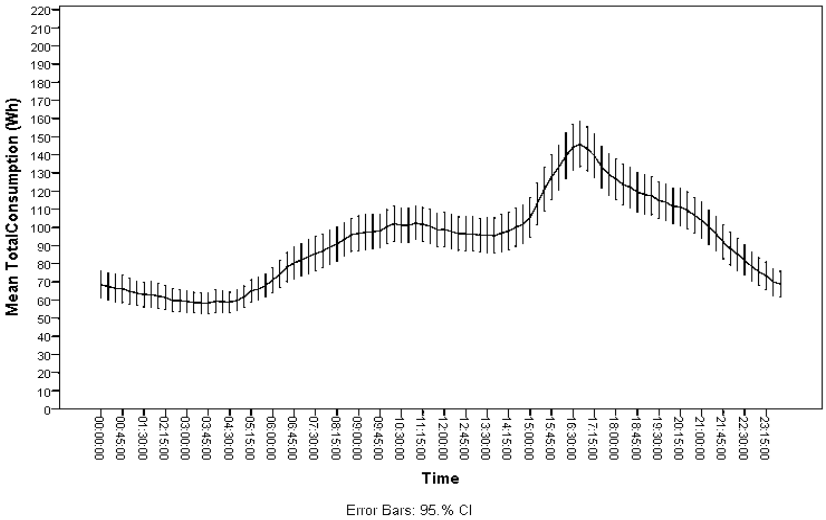

Figure 19: Average load profile for a participating household

On average, a participating household consumed between 91,24Wh and 93.39Wh of electricity per quarter of an hour (based on a 95% confidence interval). This results in an annual usage between 3197 kWh and 3272 kWh which is slightly below normal usage according to the average electricity consumption measure of a Dutch household (3312kWh in 2012). However one must take notice that only the first half of the year is measured therefore seasonal influences could be present. Furthermore the participants do not have a gas connection, making electricity their only source of energy.

Definition of 'off-peak hours'

Based on the results of the dynamic price found in Appendix XII, the relative value algorithm produced the values throughout the day as seen in Figure 20. In this the value 1 is a good moment to use electricity, 0,5 a bad moment and 0 the worst moment to use electricity.

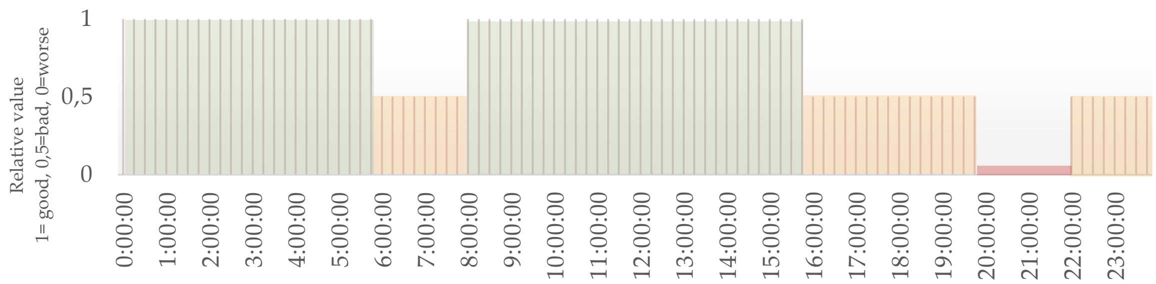

Figure 20: Average relative value over period 01-01-2013 to 01-07-2013

Electricity consumpton during off-peak hours

As Table 1 shows, 74 participants used on average 52.93% of their electricity on good moments only (green in Figure 20) with individual scores between 40% and 63%. Using the weighted score (1= good, 0,5=bad & 0=worse) the households on average used 71.73% of their electricity during off-peak hours, with individual scores ranging from 63% up to 79%.

Table 1: Results of demand shift performance

	N	Min	Max	Mean	Std. Deviation	Var
Usage on good moments	74	,40	,63	,5293	,04099	,002
Usage on off peak hours	74	,63	,79	,7173	,02844	,001

Using $\mu_{\bar{x}} = \overline{X} \pm Z\frac{\sigma}{\sqrt{n}}$ where:

μ= Population mean,

σ= Population standard deviation

n= number of samples (number of test records used); and

Z= the normal distribution's critical value for a probability of $\alpha/2$ in each tail.

It is possible to determine the confidence interval on the predicted mean of usage during off-peak hours. For the participating groups holds:

99% confidence interval: $0.70869 \leq x \leq 0.72591$

95% confidence interval: $0.71081 \leq x \leq 0.72379$

90% confidence interval: $0.71188 \leq x \leq 0.72272$

For the reference group, 28,070 successful measurements are taken from 26 non-participating households who live in similar houses during the period from 01-01-2013 until 01-07-2013. The amount of electricity used during off-peak moments by this reference group is 71.75%. This suggest that the reference group is performing 0.02% better in using electricity demand during off-peak hours. By using this difference in performance, it is now possible to calculate the probability that one group is actually performing better than the other using the formula:

$0.02 = Z\frac{0.02844}{\sqrt{74}}$ from which follows that Z=-0.0052, which corresponds with an probability of 49.79% which is about one in 2. This said it is *not possible* to state that the participants group is performing better or worse than the reference group on electricity usage on off peak hours.

4.4 Differences in interaction and electricity usage between the households

In order to answer the research question whether there are differences in between the households on interaction with the HEMS and electricity usage during off-peak hours, the households are individually analysed. First we will discuss the differences in HEMS usage. Second we will discuss the differences in electricity consumption during off-peak hours.

Differences in levels of autonomy in white good planning

As seen in Appendix X , there is a large proportion of variance between the households who have decided to let the HEMS automatically plan the wash cycle. Percentages of auto washes compared to the total washes done range per household from 3 up to 100 percent. 17 out of 35 households only have let the HEMS plan the wash cycle for less than 20 percent, 10 out of 35 households have let the HEMS plan between 20 and 60 percent. 8 out of 35 households have let the HEMS decide very often, ranging between 60-100 percent. Results from the survey shown that most important motives to use the auto scheduling function are:

- Financial reason (mentioned 10 times)
- Ecological reasons (mentioned 2 times)
- Easy to use (mentioned 1 time)

On the contrary, the most important reasons to not use the automatic scheduling function are:

- Household wants to keep control (mentioned 8 times)
- Times suggested are not pleasant (mentioned 7 times)
- Technical difficulties (mentioned 6 times)
- Wash will stay too long in the machine (mentioned 4 times)
- Do not know how it works (mentioned 4times)

Differences in Feedback profile selection

Out of the 73 successfully monitored households, there are 12 household who have chosen for the Eco profile for at least 1 day. There is a large variation in between the duration of the eco profiles between the 12 households. Fig shows the IDs of 12 households who used the Eco profile and the percentage of the time the HEMS was set on Eco profile. The results show that 6 out of 12 households did not use the Eco profile for more than 10% of the time.

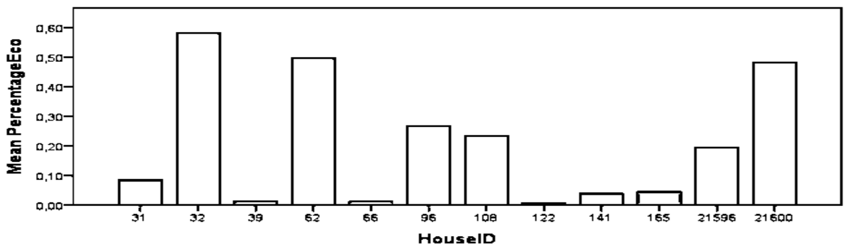

Figure 21: Percentage of time with Eco profile enabled per household

Results from the survey shown that most important motives for the choice of the feedback profile are:

- Prefer financial benefits above ecological (mentioned 32 times)
- Too little sun hours in period (mentioned 5 times)
- Default setting not changed (mentioned 4 times)

- Not a considered choice (mentioned 4 times)
- Easier interpretation (mentioned 4 times)

Differences in electricity usage during off-peak hours

Individually the 74 successfully measured households score between 63% and up to 79% on electricity consumption during off-peak hours. The individual scores follow a distribution that shows similarity to a slightly skewed normal distribution (see Figure 22).

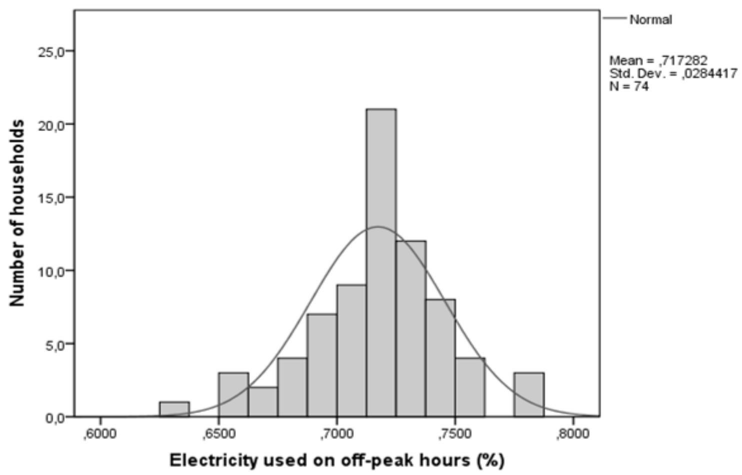

Figure 22: Distribution of electricity usage on off-peak hours

4.5 Descriptive results of the TAM measures

In order to find explanations for the differences in electricity demand shift through demand side management technologies, the technology acceptance model is used. The measures from the TAM model we discuss are: Perceived usefulness, perceived ease of use, attitude, behavioural intention and actual behaviour. last the added motivation variables are discussed.

All variables are measured on a 5 point Likert scale ranging from 1 (low) to 5 (high). Overall the respondents scored above average on most measures (see Appendix VII). The respondents are well able to identify the usefulness of the pilot and its purpose (4.3). The respondents find the HEMS easy to use (4.1) and do not expect that participating itself would require a lot of effort (3.7). Their attitude towards the system is positive (4.1) which is partly expected because of the voluntary enrolment nature of the participation. Furthermore the respondents are intending to shift their white goods with an average score of 3.75 resembling a value between sometimes and frequently. Respondents are willing to shift other goods to a much lower extend, resulting in a score of 2.39 which resembles a value between infrequently and sometimes. Results from the follow up survey show that the actual demand shift with demand side management technologies is actually lower than originally intended. For white goods this results in a score of 3.40 resembling a value between sometimes and frequently and for other goods 1,57 which resembles a value between 'never' and 'infrequently'.

Results from the survey shown that the most important individual motive to shift demand is the control of the electricity usage and the electricity bill (4.19 out of 5). Participants reported that the least important motivation is the social aspect (2.94 out of 5) containing elements as 'saving energy together' and 'performing better than others'. The other motivation Environmental 3.70 out of 5.

4.6 Path analysis of the TAM model

In order to find predictors for the electricity demand shift through demand side management technology usage, the complete model as first presented in section 2.5 is tested using the structural equation modelling technique in STATA. We will first discuss the results of the basic TAM model. Second we will discuss the extension of the model with the introduction of the reported demand shift and the achieved peak demand reduction. Third we will discuss the extension of the model with the introduction of the motivations of the household to shift electricity demand. Last we will discuss the extension of the model by introducing the household characteristics.

4.6.1 Basic TAM Model

The results in Figure 23 show that Perceived usefulness does indeed predict the attitude towards the system (.37, p=<.05). Perceived usefulness also predict the behavioural intention, however this only applies to the (smart) white good appliances (.47, p<.01). The perceived ease use (or effort expectancy) of the system does indeed predict the attitude towards the system, however this only applies for the expected effort of participating in the project as a whole (.36, p<.05) and not for the effort expected to understand the HEMS. Attitude is not found to be a significant predictor for the behavioural intention. This confirms earlier findings of Venkatesh et al. (2003), who found that observed relationships between attitude towards a technology and behavioural intention to use the technology are spurious and resulting from the omission of the other key variables performance and effort expectancies. Furthermore the perceived ease of use does not have a significant effect on the perceived usefulness.

In the final model, the system usage is reduced to the HEMS display touches and the goal set on the HEMS. This is done for the reason that the usage of the automatic scheduling function and the time the eco profile is used, do not prove to be significantly correlated to either the behavioural intention nor the demand shift. Unexpectedly, the behavioural intention to shift white good appliances is found to be a negative predictor for the amount of HEMS touches. Further the perceived ease of use of the HEMS does predict the HEMS usage (.34 p<.05).The behavioural intention to shift white goods predicts the goal which is set on the HEMS (.42, p=<.01). The behavioural intention to shift other appliances does not significantly predict any of the system usage variables.

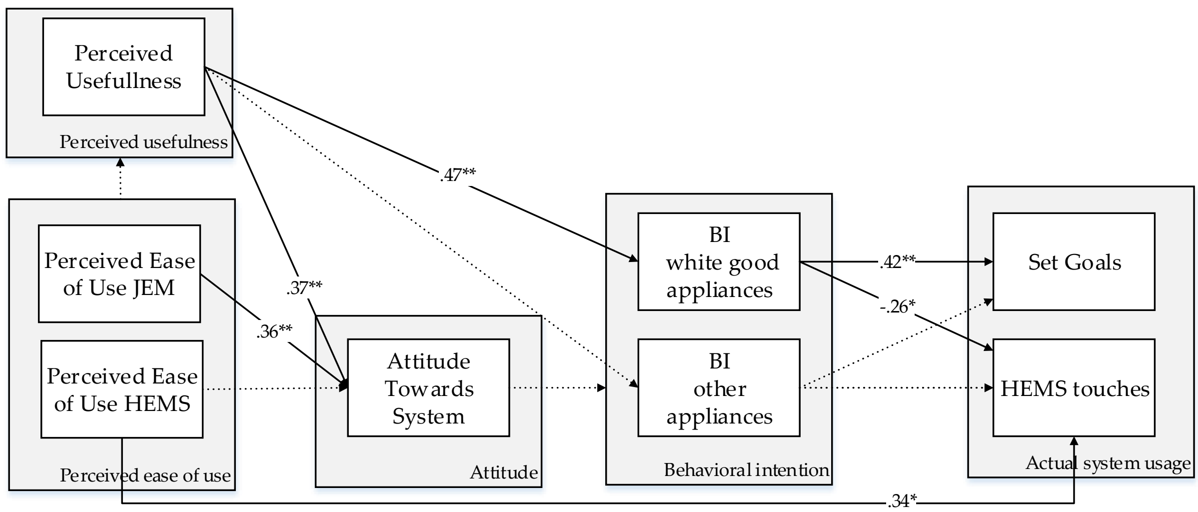

Figure 23: Results from the basic TAM model

4.6.2 Extended model: demand shift and electricity usage during off-peak moments.

In the extended model, the demand shift and the percentage of electricity that is used during off-peak moments are incorporated in the model. The results in Figure 24 show that the demand shift of white good appliances indeed found to be significantly influencing the percentage of electricity used during off-peak hours (r=.34, p<.05). The reported demand shift of other appliances did not prove to have a significant effect on the amount of electricity usage during off-peak moments.

The demand shift of the other appliances was not significantly influenced by the usage of the system. For the demand shift of white goods, the set goal on the HEMS did significantly influence the reported demand shift of the white good appliances (r=.37, p<.01). The number of daily touches on the HEMS screen did not influence the demand shift of white good appliances.

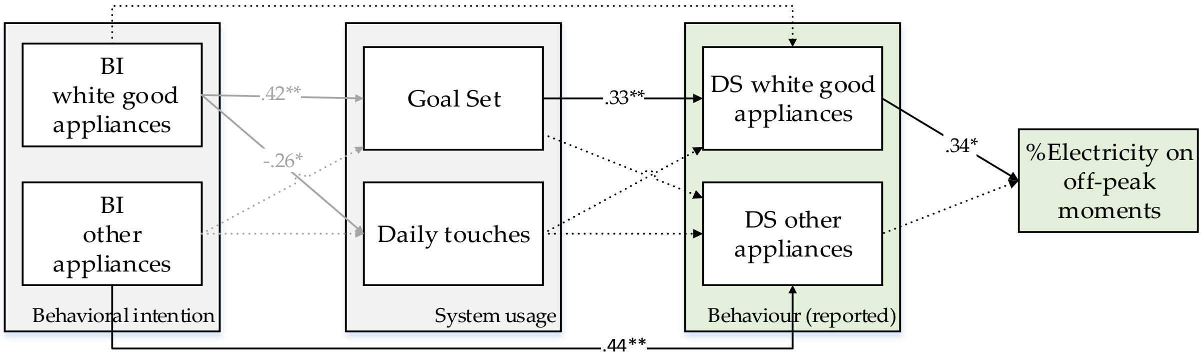

Figure 24: Extended TAM model introducing demand shift and peak electricity usage

The behavioural intention to shift appliances by using the technologies does indeed predict the actual reported demand shift. For other appliances this effect is .44 (p<.01). The set goal on the HEMS mediates the effect of the behavioural intention to shift white good appliances on the reported shift of white good appliances (Figure 25). All three variables are significantly correlated (p<.01), however only the set goal is found to be a significant predictor for the self-reported demand-shift (β=.0.65, p<.01). This indicates that the households difference on the reported demand shift, is explained by the fact that they also differ on the set goal. Which suggest that the mechanism by which behaviour intention effects reported demand shift is contained within the goal variable.

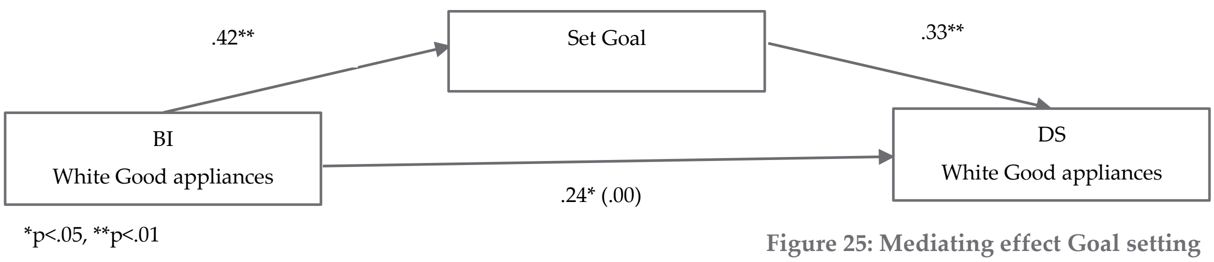

Figure 25: Mediating effect Goal setting

4.6.3 Extended model: Motivations to shift demand using the technologies

In the extended model, the households' motivations for shifting electricity demand are incorporated. These motivations are categorized in environmental motivations, motivations to control the electricity usage and social motivations. The results in Figure 26 show that only the motivation to control the electricity usage is found to be positively influencing the reported demand shift (.32 p<.01). Within this control, an important component is the control of the electricity bill, suggesting that financial incentives does play a role in the shift of electricity to other moments. There is a border line significant effect found between the Households who have a higher motivation to control the electricity expenses and the perceived usefulness of the technology (.24 p<.07).

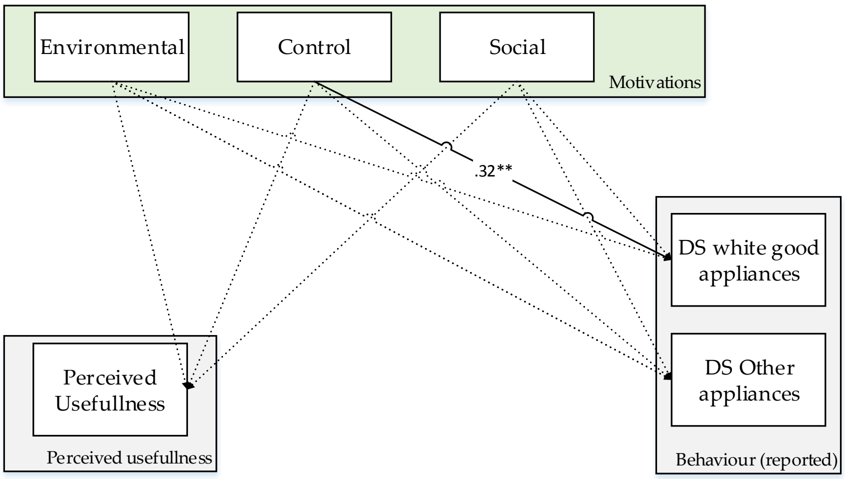

Figure 26: Extended TAM model introducing households' motivations

Surprisingly, households with a higher motivation to shift electricity based on environmental or social incentives do not see the technologies as more useful and are not reporting a higher demand shift.

4.6.4 Extended model: segmentation based on household characteristics

In the extended model, we use household characteristics to find segmentations which are more likely to engage in using DSM technologies to shift electricity demand. The results in Figure 27 Results show that there is no evidence found for the households' income or the family composition to influence the motivation to shift electricity demand. The level of education in the household does have an influence in the perceived ease of use of the HEMS device (.20, p<.05). Furthermore the time that the household is present in the home does influence the ability to shift electricity demand of the White Good appliances.

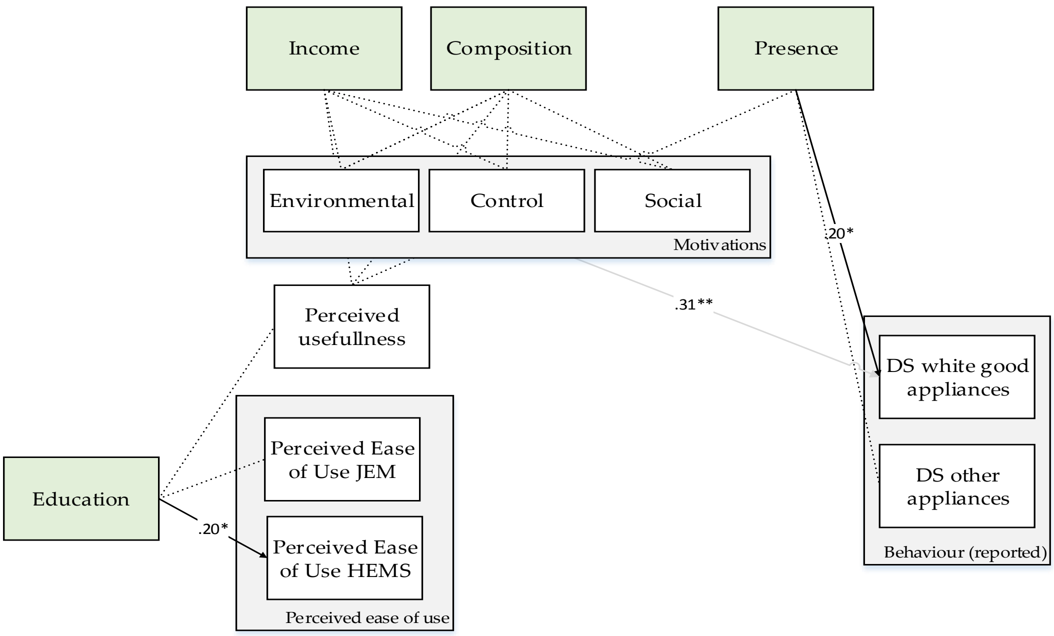

Figure 27: Extended TAM model introducing households' characteristics

4.6.5 Complete model

An overview of the complete model can be found in Appendix XIV.

5. Conclusions

This final chapter will draw the conclusions that can be derived from this study. First, general conclusions will be given, outlining the main findings and conclusions of this Master thesis, in which also the specific contributions of this research are outlined. Second, an overall conclusion is given. Third, we will discuss the limitations of this research. To end, discussions along with further research are presented.

5.1 General conclusions and contributions

No evidence for peak demand reduction of the participating group as a whole found

This study set out to determine if households are able and willing to shift electricity demand by using demand side management (DSM) technologies. The results show that the electricity usage during non-peak hours by the complete group of participating households who are provided with DSM technologies is 71.73%. This is not significantly differing from a reference group which means that based on our findings, it is not possible to state if the large scale provisioning and usage of DSM technologies will eventually lead to peak demand reduction in a real world setting.

Evidence found for a relation between white good appliance shift and peak demand reduction

However, within the participating group, there is evidence found for a positive relationship between the demand shift of white good appliances and the amount of electricity that is used during non-peak moments. Households reported that they shifted their white good appliances somewhere between 'sometimes' and 'often' (3.4 out of 5). Other appliances were shifted between 'almost never' and 'infrequently' (1.6 out of 5). This result suggest that indeed the shift of smart electrical appliances leads to peak reduction thus supporting hypothesis 1.

No evidence found that HEMS usage is responsible for demand shift

Surprisingly, no evidence is found that the usage of the demand side management technologies is significantly effecting this shifted demand. Therefore hypothesis 2 is not supported. This usage is tested by the amount of interaction with a Home Energy Management System (HEMS), the level of routine in the HEMS usage, the amount of usage of the automatic scheduling function and the selection of either an ecological or economical feedback profile. This does not imply that the technology is not being used, on the contrary, the amount of HEMS touches per household per day varies between 0 and 44 times with a mean of 4.8 touches per day. The interaction amount is decreasing during the period of 6 months with a 20% decline at the end of the period compared to the start. Further the HEMS recorded that 16% of the washes was automatically scheduled by the HEMS.

Households make only limited use of the automation function of the HEMS

Results from the survey showed that the households on average use the automatic scheduling function of the white good (smart) appliances 'sometimes' (2.36 out of 5). The most important reasons to use the auto scheduling function are financial of nature. The most important reasons to not use the automatic scheduling function are that the household wants to keep control or the times as suggested by the HEMS are not pleasant.

Household prefer a financial based feedback profile

The option to choose a financial based feedback profile has a profound predilection above an ecological based profile, as on average only 3.21% of the time an ecological feedback profile is activated. Results show that far-out the most important reasons for the financial feedback profile is that households prefer financial benefits above ecological.

Evidence found for an influence of Intention to shift with DSM on demand shift.

A predictor for the amount of demand shift is the behavioural intention to shift demand through smart appliances which supports hypothesis 3. The relationship between the behavioural intention and the reported demand shift of the smart white good appliances is mediated by the height of the goal set by the household on the HEMS. This suggest that in the view of the household, the HEMS is a device which helps them to manage their smart (white good) appliances. The shift of other appliances are less controlled by the HEMS as there is no direct link between those appliances and the HEMS.

Control on electricity expenditures most important motivation for demand shift

The results also show a relationship between the motivation of a household to control the electricity expenditures and the reported demand shift of the (smart) white good appliances thus partially supporting hypothesis 4b. This implies that household who intent to shift demand with DSM technologies are better able to realize this demand shift with a more profound motivation on controlling the electricity expenditures.

The other motivations Social and Environmental were not found to be significantly influencing the Demand shift of either the White good appliances or the Other appliances thus not supporting hypothesis 4a and 4c.

The results show no evidence to support any of the relations between the household characteristics income, education and composition to the type of motivation to shift electricity, thus not support hypothesis 12,13 and 14. Also no segmentation could be made for the type of household that has a higher motivation for control on electricity expenditures.

Type of motivation does not impact the perceived usefulness of the technology

The results did not find evidence for a relation between a higher motivational factor on either environment, control on electricity or social is influencing the perceived usefulness of using the technologies to shift the electricity demand thereby not supporting hypothesis 11 a,b and c.

Evidence found that the presence of the household influences the amount of shifted demand

Results show a positive relationship between the time a household spends at home and the amount of white good appliance demand that is shifted. This suggest that households who are more present at home, are better able to shift electricity demand which supports hypothesis 16.

Basic TAM model has only limited explanatory value in acceptance of the DSM technology

The Technology Acceptance Model has only limited explanatory value for the deeper rooted motivations of the households acceptability of the presented DSM technologies for inducing demand shift. The effort expected to shift demand with DSM technologies is not found to be significantly predicting the perceived usefulness therefore hypothesis 5 is not supported. The amount of effort that is expected for understanding the HEMS will be less when the household has had a higher education, therefore supporting hypothesis 15.

Perceived usefulness is significantly contributing to the behavioural intention to shift electricity demand with DSM technologies, however this only applies to the intention to shift white good appliances which only partially supports hypothesis 6. This implies that although households see the shift of electronic appliances as useful, they are only willing to do so with the smart appliances who can be postponed to other times. This is a logic conclusion since only the white good appliances are connected to the system. The perceived usefulness and the effort expected to shift demand with DSM technologies do significantly contribute to the attitude towards the system thus supporting hypothesis 8 and 9. However, a more positive attitude towards the system is not found to be contributing to an increase in behavioural intention to shift electricity demand with DSM technologies, therefore hypothesis 7 is not supported.

Last the relationship between behavioural intention to shift electricity demand with DSM technologies and the actual system use, is not clear. The Behavioural intention to use the system to shift white good appliances demand does positively influence the goal that is being set on the HEMS. Furthermore there is a significant relationship found between the behavioural intention to shift white good appliances and the amount of interaction with the HEMS display, being it a negative relationship which rejects hypothesis 10. This last peculiar finding suggest that the households who have a higher intention to shift white good appliances, use the HEMS display less.

5.2 Overall conclusion

Overall, based on these findings, it is possible to conclude that households who shift the usage of white good appliances, achieve a peak demand reduction. Households who are better able to perform this demand shift have a *high motivation to control the electricity usage* and are *more present at home*. Further they have a *high goal set* which is the results of a *higher behavioural intention to use technologies* for using electricity during off-peak hours. The amount of *perceived usefulness* plays an important effect in predicting this behavioural intention but it remains unclear which households possess this higher perceived usefulness.

Households who are higher educated see the HEMS as more easy to use which lead to a higher interaction with the HEMS. Although the HEMS is becoming part of a households routine and interaction with the HEMS display is high, the automatic planning function of the HEMS is not being used much. This is generally caused by the perception of lack in control when using the automatic planning function. The feedback of the HEMS which is preferred is financial by nature and is typically chosen because the financial benefits outweigh the ecological benefits. Direct interaction and usage of the automatic planning capabilities of the HEMS are not found to be influencing the reported demand shift. This said, households are able to shift the usage of white good appliances without having frequent interaction with the HEMS.

5.3 Limitations

In this section some of the limitations of this study will be discussed. First, the households that have subscribed for participating in this pilot knew the 'energy saving' nature of the pilot before participation. Also the participants are rather highly educated. This makes our participating group slightly in-representable for the Dutch population and therefore results less generalizable. Moreover, the participants already accepted the technology before taking part of the first survey in which some parts of the Technology Acceptance Model are tested.

Second, this study included only limited smart appliances. Somewhere around 75% of the participants were provided with a smart washing machine, the other 25% were provided with a smart tumble dryer. As Figure 2 shows, these appliances only account for respectively 5% and 6% of the total households' electricity consumption. Therefore the impact of the shift of smart appliances that could be achieved is relatively low. Also it is questionable if these technologies are representable for the diverse set of Smart technologies that are in development for the upcoming years? Since Smart grid technologies still are being developed, it is not clear what the definite form will look like, if there will be a definite form at all. In the iterating process towards a smarter grid and the involvement of end-user, we try to learn what is important to which end-user.

Third, because most of the technologies used in the HEMS are new and being custom developed, data quality issues occur. In most of the cases these issues will eventually average out. For some variables however this resulted in less observations than the available 6 months, for example the amount of washes. For regression analysis the unavailability of either a HEMS measure or measure one of two the Survey leads to a list wise exclusion of the case in the analysis.

Fourth, because these houses were all newly build, we lack a baseline measurement before the household had the access to DSM technologies. The difference in baseline measurement and the actual accomplishment after DSM technology implementation could identify the households who are sensitive for these technologies and is better able to provide information on the amount of shift that can be induced using certain segments in the population.

Last the usage of different feedback profiles did not provide with the amount of variation needed for proper analysis.

5.4 Discussion and future research

As a logical consequence of the conclusions and limitations, some discussions and suggestions for further research can be outlined. The major point of discussion out of the results is why HEMS system usage is not being responsible for demand shift of neither the white good appliances nor the other

appliances? A possible explanation for this surprising result can be found in the habit formation of the participants. As seen in Appendix XII, the dynamic price is high almost always at the same moments. This said, households could easily learn when to do the washes based on former experience. This makes the interaction with the HEMS superfluous for realizing the wanted demand shift behaviour.
Another point of discussion is obviously the surprisingly low usage of the smart function in the white good appliances (2,36 out of 5), giving the promotion that smart appliances deliver only advantages to consumers. Results from the follow up survey indicate that there is still a great deal of resistance towards giving away of control to Smart Appliances.
Corresponding to the ratio of financial and ecological reasons to use the automatic scheduling function, the absence of any effects of the selected feedback profile and the demand shift could by caused due to the low usage of the ecological feedback profile. This is inconsequent with the overall higher environmental motivation of the participants (3.8 out of 5). Results from the follow up survey indicate that financial benefits are found important in type of feedback a HEMS is giving even when there is a high environmental motivation present. It could be, however, that the ecological profile as proposed is not satisfying the needs of the consumer. Other than a choice, it could well be that some elements of both profiles lead to the optimal amount of feedback.
Overall the Technology Acceptance Model seem to have limited explanatory value in predicting and the usage of the DSM technologies. As often being mentioned as criticism on the TAM (Bagozzi 2007), cause of this miss-fit could be found in the ignorance of the essentially social processes of the adoption of innovative environmental technologies in the TAM. Also the intention-actual behaviour linkage in the model, has only limited power in our results (intention explaining between 20% and 25% of the variance in actual behaviour). Reasons could be found in the issue that the TAM model treats the actual usage as a means itself failing to take account the ultimate goal that is wanted by the actual usage which can be traced back into the intention to use certain technologies. For example, a participant in our pilot could intent to adopt DSM technologies because they want to achieve the higher goal which is shifting demand for fulfilling their motivation. By the focus of the TAM on usage of the system, the benefits of the usage are not being taken account for. Also, the TAM model does not take account for misjudged expectations of the technology that is adopted. As seen in the reasons why certain choices are made against using the DSM technologies, there could be complications in the DSM usage can arise making the decision making for DSM technology usage a dynamic process. These incompetence's of the TAM is often referred to as the 'intention-behaviour gap'.

Future research

The major avenue for further research will be the establishment of a more powerful explanatory model what drives people to shift electricity demand and in what ways DSM technologies could help them. This model should incorporate the goal that is being pursued , and strived for by the participants. Further, theoretical and empirical support is needed for the explanations why HEMS usage as proposed in this study is not responsible for the found demand shift in smart appliances. The formation of habitual behaviour could be an important direction in this explanation. Also the functionality and effectiveness of the HEMS and the smart appliances as proposed in this study could be further extended as their impact is still low. Further, in order to improve smart appliance usage, future research should focus on how to improve the sense of control since this is found to be an important reason not to use the smart functions of the appliances. Last, when more smart appliances are introduced on the market, future research could measure the differences in effect of more appliances on demand shift and the percentage of electricity used during off-peak hours this demand shift provides.

6. List of figures and tables

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Appendix I. Theory search strategy

As a start, various social and environmental journals and books were consulted using the Science Direct Database. Using the following strings to search the Abstract, Title and Keywords resulted in 614 studies found with the search criteria:

Table 2: Search method

STRING			Results	Title's Selected	Excluded	Ratio
SMART GRID	AND	BEHAVIOR	36	13	23	36%
SMART GRID	AND	CONSUMER	66	19	47	29%
DEMAND SIDE MANAGEMENT	AND	CONSUMER	84	10	74	12%
SMART GRID	AND	DEMAND SHIFT	10	9	1	90%
SMART GRID	AND	INTERACTION	21	8	13	38%
SMART GRID	AND	USERS	42	16	26	38%
ENERGY	AND	DEMAND SHIFT	355	10	345	3%
TOTAL			**614**	**85**	**529**	**14%**

By examining the studies titles on relevance to this study, led to the exclusion of 529 studies resulting in 85 studies included. As seen in the table above the String SMART GRID AND CONSUMER is best describing the type of studies searched for with a ninety percent inclusion. Then again the string SMART GRID AND CONSUMER resulted in the most studies included. Using the term ENERGY in the string ENERGY AND DEMAND SHIFT seems to be too broad for this literature review leading in results with only 3 % inclusion. The term SMART GRID combined with CONSUMER delivered most articles but again was a string with a poor efficiency of only 29%. The term SMART GRID combined with DEMAND SHIFT was the most efficient string providing 9 relevant articles of the total 10, thus 90% hit rate. Furthermore publicized studies of direct colleagues who do research on the project are also included which led to the inclusion of 8 studies.

Worth noticing is that this is a rather recent topic studied as seen in Figure 28. The selected studies mostly manifest in the late 2000's with the more than 80% of the total selected studies released in the recent five years.

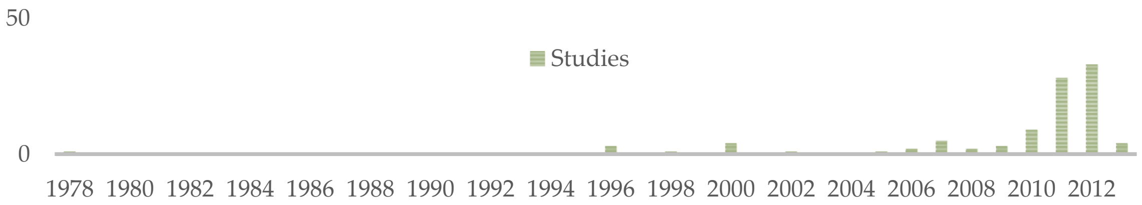


Figure 28: Search results

Then, studies selected for the Eindhoven University of Technology course 0C903 – Energy and Consumer are included due to relevance with the intervention topic. This led to the inclusion of 16 more studies. Checking for duplicates leads to the exclusion of 12 studies resulting in a total selection of 97 studies by title and direct relevance. After reading the abstract a total number of 25 studies were excluded primarily due to an excessively focus on the technical aspect, lacking relevance to the consumer side of Smart Grids. The selection of relevant studies was then further read and used to find recent developments and trends. Among this process, several studies were added through snowballing in order to obtain a broad perspective on the topic. The developed knowledge of recent developments was then used to search for connections with studies who are not directly related to the topic to use as explanatory basis. Studies selected for the Eindhoven University of Technology 1ZM05 - Innovation Management course involving innovation adoption, lead user development and social innovation are introduced in this process to explain the developments and trends found in the literature.

Appendix II. Types of residents.

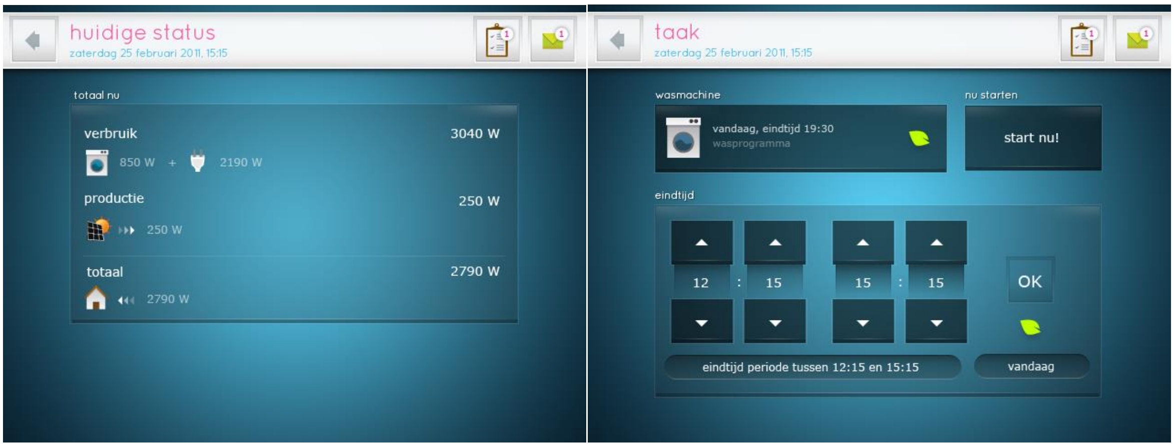
Impression of a porch house type resident in the Muziekwijk Zwolle.

Impression of a apartment type resident in the Muziekwijk Zwolle.

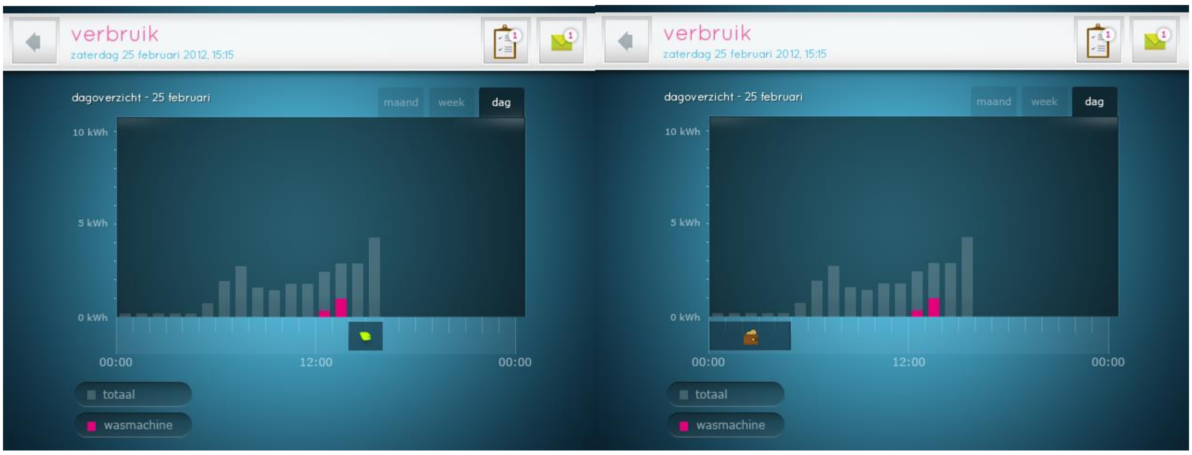
Impression of a garden type resident in the Muziekwijk Zwolle.

Appendix III. Functionalities of the HEMS

Left: Homescreen showing the current electricity consumption, production, totals of today and prediction of beneficial electricity usage moments. Right: 2nd Home screen with total costs of usage, total benefits from production, the current weather forecast, settings and reached goals.



Left: Status screen with specified usage and specified production. Right: Scheduling screen for the white good appliance.



Left: Usage screen with specified daily usage for an Economical profile. Right: Usage screen with specified daily usage for an Financial profile.

Left: Usage screen with specified weekly usage. Right: Usage screen with specified monthly usage.

Left: Production screen with weekly production and forecast. Right: Financial overview showing weekly consumption costs and production benefits.

Left: Prediction screen for financial beneficial electricity consumption moments. Right: Prediction screen for economical beneficial electricity consumption moments.

Left: Goal screen where the participant can set his or her preferred goal. Right: Progress screen which shows the participants wheter or not he or she reached his or her goal.

Appendix IV. Calculation of the Dynamic Price

Costs per kWh

The tariff in €/kWh on a given quarter is defined as:

$$Tariff_{totall}(t) = (Tarief_{gridoperator}(t) + Tarief_{delivery}(t) + Tarief_{E-tax}(t)) \cdot (1 + VAT)$$

Costs of Net usage

The algorithm to calculate the costs of Net usage or the *Grid Operator tariff* is defined as:

$$Tariff_{go}(t) = \begin{cases} Tariff_{high} & if \quad Load(t) > \beta \cdot Load_{max} \\ Tariff_{medium} & if \quad \gamma \cdot Load_{max} < Load(t) < \beta \cdot Load_{max} \\ Tariff_{low} & if \quad Load(t) < \gamma \cdot Load_{max} \end{cases}$$

$$Load(t) = demandprofile(t) - PV_{generation}(t)$$

$$PV_{generation}(t) = predicted\ sun(t) \cdot kWp_{in\ the\ area}$$

$$demandprofile(t) = E1a(t) \cdot \#households \cdot yearly\ consumption$$

In which:

- **Demandprofile (t):** demand at neigborhood level [kW]
- **$PV_{generation}$(t):** predicted PV generation at neighborhood level [kW]
- **$Load_{max}$(t):** maximum load over the day [kW]
- **$Tarief_{high}$:** 0.16 [€/kWh], excl. BTW
- **$Tarief_{medium}$:** 0.042 [€/kWh], excl. BTW
- **$Tarief_{low}$:** 0 [€/kWh], excl. BTW
- $\boldsymbol{\gamma}$: 0.7 [-]
- $\boldsymbol{\beta}$: 0.83 [-]

The multipliers are set in a way the households price will never exceed the standard profile price which is E1A, 3000kWh. .

Costs of electricity delivery

The algorithm to calculate the *delivery price* is defined as:

$$Tariff_{delivery}(t) = \begin{cases} \left(\frac{APX(t)}{APX_{avg}} - Sun\right)^{\delta} \cdot \alpha & if \quad 0 < \left(\frac{APX(t)}{APX_{avg}} - Sun(t)\right)^{\delta} \cdot \alpha < 0{,}50 \\ 0 & if \quad \left(\frac{APX(t)}{APX_{avg}} - Sun\ (t)\right) < 0 \\ 0{,}50 & if \quad \left(\frac{APX(t)}{APX_{avg}} - Sun\ (t)\right)^{\delta} \cdot \alpha > 0{,}50 \end{cases}$$

In which:

- **Tarifdelivery(t):** The energy Tariff per quarter of an hour excl. VAT [€/kWh]
- **APX_{avg}:** avarage APX price of the day [€/MWh]
- **APX(t):** APX price per hour [€/MWh]
- $\boldsymbol{\delta}$ **= 2:**, this het verschil tussen min en max groter is (meer tariefschommelingen) [-]
- **Sun(t):** predicted solar generation kWp (0-1) [%]
- $\boldsymbol{\alpha}$**= 0.05785 (excl. VAT):** multiplier in order to let the costs not exceed the normal tariff for not-participants based on a constant energy price and a yearly consumtion of 3000 kWh.

Energy tax

The *Energy tax* is a constant price of € 0,114 per kWh (2012), determined by the Dutch government.

VAT

The *VAT* is a constant percentage of 21 percent (2012), determined by the Dutch government.

Appendix V. List of items and verification

Constructs

Construct	Items
Environmental motivation	Kun je per stelling aangeven in hoeverre je het er mee eens bent? • Ik vind innovaties op het gebied van energie interessant Ik ben op de hoogte van recente ontwikkelingen op het gebied van energie • Ik voel me mede verantwoordelijk voor het opraken van de fossiele brandstoffen • Ik voel me mede verantwoordelijk voor het broeikaseffect • Ik maak verantwoord gebruik van energie • Ik probeer zoveel mogelijk energie te besparen Kun je aangeven hoe belangrijk de volgende redenen zijn voor jou voor deelname: • Minder milieuvervuiling • Het opraken van energiebronnen • De toekomst verzekeren voor volgende generaties • Het nemen van maatschappelijke verantwoordelijkheid
Perceived Usefulness	Met JEM verwacht ik… • energie te besparen • geld te besparen • mijn energie te gaan verbruiken op een manier die beter is voor het milieu. • meer controle te krijgen op mijn energieverbruik. • zonne-energie direct te gaan benutten.
Perceived Ease of Use	• Ik denk dat deelname aan JEM weinig tijd gaat kosten • Ik denk dat deelname aan JEM weinig moeite zal kosten • Ik denk dat de techniek van JEM naar tevredenheid gaat werken • Er kan weinig mis gaan wanneer ik gebruik ga maken van de producten van JEM Kun je aangeven in hoeverre je het eens bent met de volgende stellingen over de energiecomputer? • Het gebruik van de energiecomputer was voor mij gemakkelijk om te leren • De energiecomputer is gemakkelijk te gebruiken • Het gebruik van de energiecomputer is begrijpelijk • Ik kan in een oogopslag de belangrijkste informatie zien • Ik ken alle mogelijkheden van de energiecomputer
Attitude	Jouw Energie Moment.. • is leuk • is aantrekkelijk • is positief • is interessant • is waardevol • is voor mij belangrijk • gaat voordelen brengen

Demand Shift Behavioural Intention / Behaviour	BI: Hoe vaak verwacht je het gebruik van de volgende apparatuur te verschuiven? B: Hoe vaak verschuif je je het gebruik van de volgende apparatuur? • Droger • Wasmachine • Vaatwasser • Overige keukenapparatuur (oven, waterkoker, etc.) • Overige huishoudelijke apparatuur (strijken, stofzuigen, etc.) • Entertainment (TV, spelcomputer, etc.) • Werkgerelateerde apparatuur (computer, printer, etc.) • Opladen van apparatuur
Motivations	Kun je aangeven hoe belangrijk de volgende redenen zijn voor jou om je verbruik aan te passen? • Minder geld uitgeven aan energie • Controle over mijn energieverbruik • Minder milieuvervuiling • Het opraken van energiebronnen • De toekomst verzekeren voor volgende generaties • Het uitproberen van een nieuwe techniek • Het is een uitdaging • Het is leuk • Het nemen van maatschappelijke verantwoordelijkheid • Het geeft een goed gevoel • Mijn eigen opgewekte energie efficiënt benutten • Me onafhankelijker voelen • Uit nieuwsgierigheid • Het beter doen dan andere deelnemers • Het samen doen in de wijk

Factor analysis and reliability tests

Environmental motivation

A principal component analysis (PCA) was conducted on the 10 items. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .718 ('good' according to Field, 2009). All the individual KMO values are above the bare minimum of 0.5 (Field, 2009) except for 'ik probeer zo veel mogelijk energie te besparen' This indicates this could be a problematic item.

Bartlett's test of sphericity χ^2 (45) = 348,985, p < .000, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each component in the data. Three components had eigenvalues over Kaiser's criterion of 1 and in combination explained 73.38% of the variance. The scree plot was slightly ambiguous and showed inflexions that would justify retaining both components 2 and 4. Table shows the factor loadings. The items that cluster on the same components suggest that component 1 represents an environmental motivation, component 2 energy savings and component 3 an Environmental interest. For this reason we exclude four items for our measure resulting in 6 items which are used for testing environmental motivation. This Environmental motivation scale has a high reliability since Cronbach's $\alpha = 0.90$.

Component Matrix[a]

	Component		
	1	2	3
Kun je per stelling aangeven in hoeverre je het er mee eens bent? - Ik vind innovaties op het gebied van energie interessant			,841
- Ik ben op de hoogte van recente ontwikkelingen op het gebied van energie			,793
- Ik voel me mede verantwoordelijk voor het opraken van de fossiele brandstoffen	,809		
- Ik voel me mede verantwoordelijk voor het broeikaseffect	,850		
- Ik maak verantwoord gebruik van energie		,842	
- Ik probeer zoveel mogelijk energie te besparen		,857	
Kun je aangeven hoe belangrijk de volgende redenen zijn voor jou voor deelname? - Minder milieuvervuiling	,752		
- Het opraken van energiebronnen	,840		
- De toekomst verzekeren voor volgende generaties	,793		
- Het nemen van maatschappelijke verantwoordelijkheid	,753		

Extraction Method: Principal Component Analysis.
a. 3 components extracted.

Perceived Usefulness

A principal component analysis (PCA) was conducted on the 5 items. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .73 ('good' according to Field, 2009). Also, all the individual KMO values are above 0.652 which exceeds the bare minimum of 0.5 (Field, 2009. Bartlett's test of sphericity χ^2 (10) = 120,220, p < .000, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each component in the data. One component had an eigenvalue over Kaiser's criterion of 1 and explained 55.16% of the variance. The scree plot was slightly ambiguous and showed inflexions that would justify retaining 2 components. Table shows the factor loadings. This Perceived Usefulness scale has a high reliability since Cronbach's $\alpha = 0.79$

Component Matrix[a]

	Component
	1
Kun je per stelling aangeven in hoeverre je het er mee eens bent? Ik verwacht energie te besparen	,748
geld te besparen	,823
energie te gaan verbruiken op een manier die beter is voor het milieu.	,649
meer controle te krijgen op mijn energieverbruik.	,791
zonne-energie direct te gaan benutten.	,688

Extraction Method: Principal Component Analysis.
a. 1 components extracted.

Perceived Ease of Use

A principal component analysis (PCA) was conducted on the 8 items with orthogonal rotation (varimax).. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .679 ('mediocre' according to Field, 2009). Also, all the individual KMO values are above 0.586 which exceeds the bare minimum of 0.5 (Field, 2009).

Bartlett's test of sphericity χ^2 (28) = 281,563 p < .000, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each component in the data. Two components had eigenvalues over Kaiser's criterion of 1 and in combination explained 70.367% of the variance. The scree plot showed inflexions that would justify retaining 3 components.

Table shows the factor loadings. The items that cluster on the same components suggest that component 1 represents an Perceived Ease of Use for the JEM project in general, component 2 Perceived Ease of Use of the HEMS. The item 'ik kan in een oogopslag de belangrijkste informatie zien' has only limited factor loading (0.511). Stevens (2002, pg. 395) stated that a factor is reliable if it has 3 or more variables with loadings of 0.8 and any *n,* also with an sample size between 50 and 100 factor loadings should be between respectively 0.722 and 0.512. This said we exclude this item for further analysis of this factor. Both the two factors have a high reliability since Cronbach's for PEoU JEM $\alpha = 0.84$ and PEoU HEMS $\alpha = 0.95$

Rotated Component Matrix[a]

	Component	
	1	2
Kun je per stelling aangeven in hoeverre je het er mee eens bent? Ik denk dat deelname aan Jouw Energie Moment weinig tijd gaat kosten		,852
Ik denk dat deelname aan Jouw Energie Moment weinig moeite zal kosten		,875
Ik denk dat de techniek van Jouw Energie Moment naar tevredenheid gaat werken		,776
Er kan weinig mis gaan wanneer ik gebruik ga maken van de producten van JEM		,770
Het gebruik van de energiecomputer was voor mij gemakkelijk om te leren	,928	
De energiecomputer is gemakkelijk te gebruiken	,921	
Het gebruik van de energiecomputer is begrijpelijk	,946	
Ik kan in een oogopslag de belangrijkste informatie zien	,511	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Behavioural intention to shift demand

A principal component analysis (PCA) was conducted on the 8 items. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .737 ('good' according to Field, 2009). Not all the individual KMO values are above the bare minimum of 0.5 (Field, 2009). The intention to shift demand of the Dryer and Dishwasher score respectively 0.398 and 0.423. This indicates that these variables could be problematic. A possible explanation for this could be that not all the households have a dryer and/or dishwasher. We have to take account for this when computing the Behavioural Intention variable. The intention to shift the white good appliance has a KMO value of 0.509 which is just above the bare minimum. This should also be noticed in further analysis.

Bartlett's test of sphericity χ^2 (28) = 234.789, $p < .000$, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each component in the data. Three components had eigenvalues over Kaiser's criterion of 1 and in combination explained 72.75% of the variance. The scree plot showed an inflexion that would justify retaining 2 components. Table shows the factor loadings. The items that cluster on the same components suggest that component 2 represents white goods appliances and component 1 as other appliances. As seen, the white good appliance has only a low factor loading on component 2 and is also been identified as a third component. A possible explanation could be that households could either get a Smart Washing machine or Smart Dryer. In most cases the households got a Smart Washing machine. This could provoke a perception of 3rd type of appliance which represent the Smart Appliances. Nevertheless we made only two components. Both components have a high reliability since Intention to shift White Goods has a reliability with Cronbach's $\alpha = 0.835$ and Intention to shift other appliances has a reliability with Cronbach's $\alpha = 0.879$.

Component Matrix[a]

	Component		
	1	2	3
Met JEM, kun je energieverbruik verschuiven naar gunstige momenten. Hoe vaak verwacht je het gebruik van de volgende apparatuur te ver –			
Droger		,696	
Wasmachine		,461	,765
Vaatwasser		,706	
Overige keukenapparatuur (oven, waterkoker, etc.)	,898		
Overige huishoudelijke apparatuur (strijken, stofzuigen, etc.)	,792		
Entertainment (TV, spelcomputer, etc.)	,871		
Werkgerelateerde apparatuur (computer, printer, etc.)	,848		
Opladen van apparatuur	,631		

Extraction Method: Principal Component Analysis. a. 3 components extracted.

Demand Shift

Besides the measurement of the shift in electricity usage, participants were asked how many shift in electricity consumption they experienced. A principal component analysis (PCA) with varimax rotation was conducted on the 8 items. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .682 ('mediocre' according to Field, 2009). All the individual KMO values are above the bare minimum of 0.5 (Field, 2009). Bartlett's test of sphericity χ^2 (28) = 104.089, p < .000, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each component in the data. Two components had eigenvalues over Kaiser's criterion of 1 and in combination explained 75.20% of the variance. The scree plot showed an inflexion that would justify retaining 2 components. Table shows the factor loadings. Again, the items that cluster on the same components suggest that component 2 represents white goods appliances and component 1 as other appliances. Both components have a high reliability since Intention to shift White Goods has a reliability with Cronbach's α = 0.855 and Intention to shift other appliances has a reliability with Cronbach's α = 0.799.

Rotated Component Matrix[a]	Component	
	1	2
Droger		,902
Wasmachine		,848
Vaatwasser		,761
Overige keukenapparatuur (oven, waterkoker, etc.)	,755	,505
Overige huishoudelijke apparatuur (strijken, stofzuigen, etc.)	,707	,490
Entertainment (TV, spelcomputer, etc.)	,956	
Werkgerelateerde apparatuur (computer, printer, etc.)	,962	
Opladen van apparatuur	,566	

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 3 iterations.

Motivation

Respondents were asked what their motivation is to shift electricity demand with smart appliances. A principal component analysis (PCA) with oblimin rotation was conducted on the 8 items, allowing for correlation between variables. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .813 ('great' according to Field, 2009). All the individual KMO values are above the bare minimum of 0.5 (Field, 2009). Bartlett's test of sphericity χ^2 (28) = 574.022, p < .000, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each component in the data. Five components had eigenvalues over Kaiser's criterion of 1 and in combination explained 77.47% of the variance. The scree plot showed an inflexion that would justify retaining 3 components. Table shows the factor loadings. Items loading on factor one suggest that component one suggest an *emotional satisfaction* as motivation to participate (MO_Emo). The items with loadings on factor two suggest for a motivation that is *environmentally* related (MO_Env). Items loading on factor 3 does not clearly identify a financial incentive but suggest a sense of *control on energy usage* as a motivation (MO_Con) which includes the ability to pay less for energy based on this control. Loadings on factor 4 suggest a component that represents a *social* motivation (MO_Soc). Items with loadings on factor 5 suggest a motivation that represents some *fun with new technology* (MO_Fun).

The components that are included in the research are environmental, social and financial motications. . MO_Env has a reliability with Cronbach's $\alpha = 0.895$, but is increased to 0.928 as item 'Het nemen van maatschappelijke verantwoordelijkheid' is deleted. MO_Con has a reliability with Cronbach's $\alpha = 0.687$. MO_Soc has a reliability with Cronbach's $\alpha = 0.721$.

Structure Matrix

	Component				
	1	2	3	4	5
Minder geld uitgeven aan energie			,866		
Controle over mijn energieverbruik			,785		
Minder milieuvervuiling		,912			
Het opraken van energiebronnen		,925			
De toekomst verzekeren voor volgende generaties		,929			
Het uitproberen van een nieuwe techniek					-,808
Het is een uitdaging					-,884
Het is leuk					-,896
Het nemen van maatschappelijke verantwoordelijkheid		,688			
Het geeft een goed gevoel	,713				
Mijn eigen opgewekte energie efficiënt benutten			,602		-,626
Me onafhankelijker voelen	,807				
Uit nieuwsgierigheid	,814				
Het beter doen dan andere deelnemers				,866	
Het samen doen in de wijk				,841	

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Hems Usage

Respondents were asked if the HEMS usage has become part of their routine using four items. A principal component analysis (PCA) was conducted on the 4 items. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = .72 ('good' according to Field, 2009). Bartlett's test of sphericity χ^2 (6) = 114.829, p < .000, indicated that correlations between items were sufficiently large for PCA. One component had eigenvalues larger than one, which explains 64% of the variance. One item barely exceeds the bare minimum of 0.5 (Field, 2009), which is left out in the final construct. The other items three items had a reliability with Cronbach's $\alpha = 0.866$ and are used as an average in the measure.

Component Matrix[a]

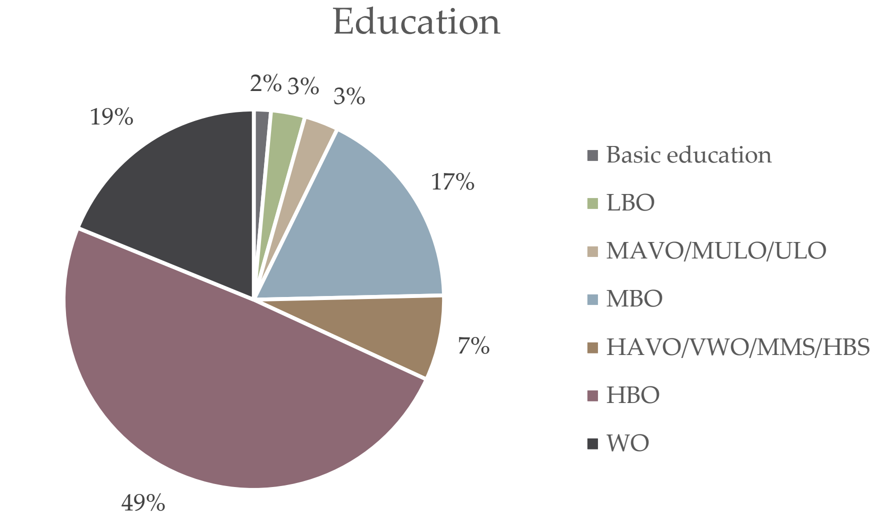
	Component
	1
Op de energiecomputer kijken is een automatisme	,922
Ik kijk vaak op de energiecomputer zonder er heel bewust mee bezig te zijn	,520
Het kijken op de energiecomputer past bij mijn routine	,870
Ik ben nu volledig gewend aan het werken met de energiecomputer	,820

Extraction Method: Principal Component Analysis.

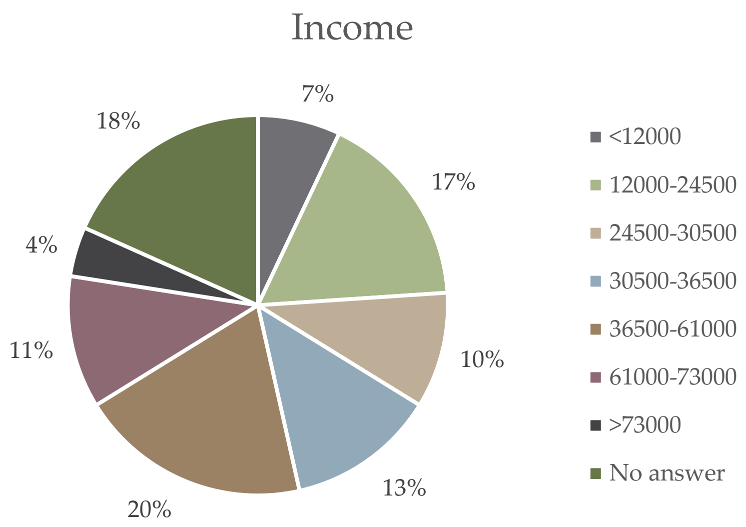
a. 1 components extracted.

Appendix VI. descriptive statistics of the households

Descriptive Statistics households in pilot Jouw Energie Moment					
	N	Minimum	Maximum	Mean	Std. Deviation
Male	71	0	1	,52	,503
Female	71	0	1	,48	,503
Residents	71	1	5	2,17	,9409
Age	71	22	63	32,38	9,0827
Presence	71	1	5	2,31	1,3158
PresencePartner	50	1	5	2,80	1,3248
MeanPresence	71	1	5	2,48	1,1724
HouseSize	67	30	170	100,76	31,60
BasicEducation	71	0	1	,01	,12
LBO	71	0	1	,03	,167
MAVO	71	0	1	,03	,167
MBO	71	0	1	,17	,377
HBO	71	0	1	,48	,503
WO	71	0	1	,18	,390
SinglePerson	71	0	1	,18	,390
SinglePersonwithKids	71	0	1	,06	,232
Cohabiting_Married_withoutKids	71	0	1	,49	,504
Cohabiting_Married_withKids	71	0	1	,21	,411
12000-24500	71	0	1	,17	,37743
24500-30500	71	0	1	,10	,30023
30500-36500	71	0	1	,13	,33507
36500-61000	71	0	1	,20	,40070
61000-73000	71	0	1	,11	,31845
>73000	71	0	1	,04	,20260
Income	71	0	7	3,17	2,17772
Valid N (listwise)	46				



As seen in the graph above, the participant are rather highly educated, with 68% having a bachelor degree or higher.

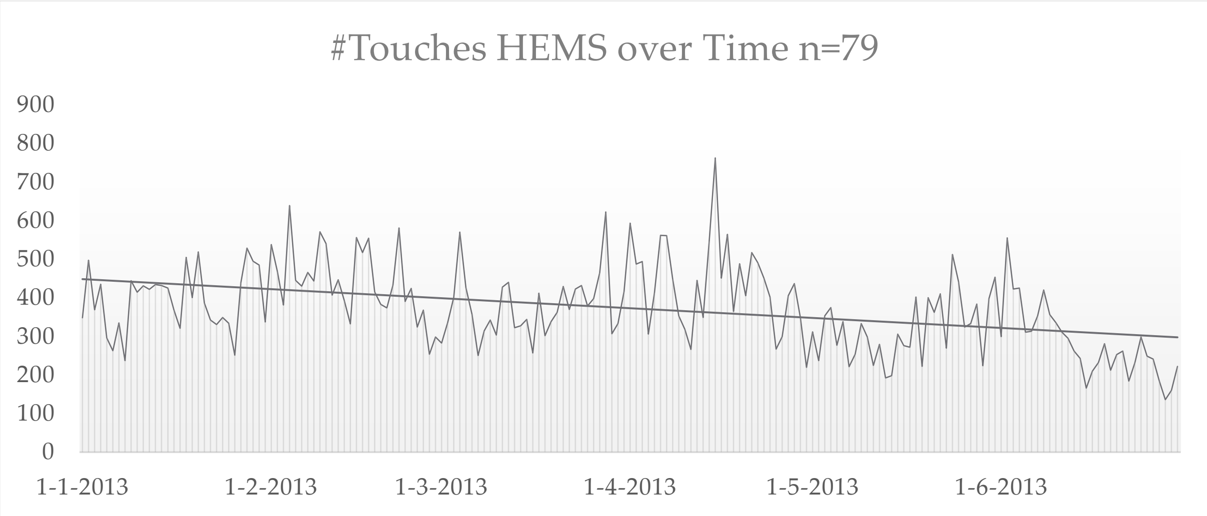


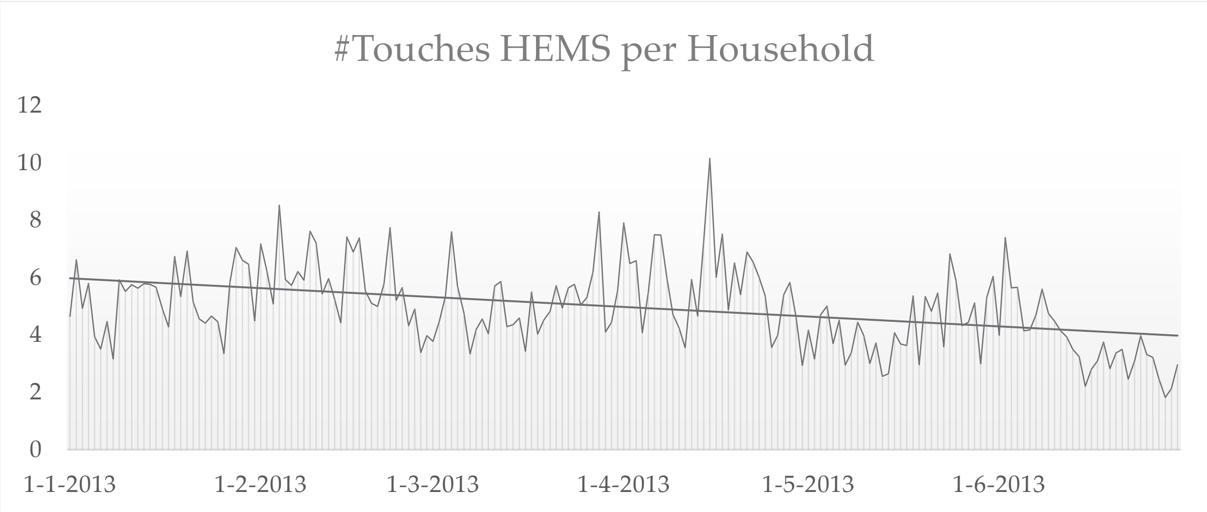
The income of the families is rather equally divided with most households earning between 36500 and 61000 per year.

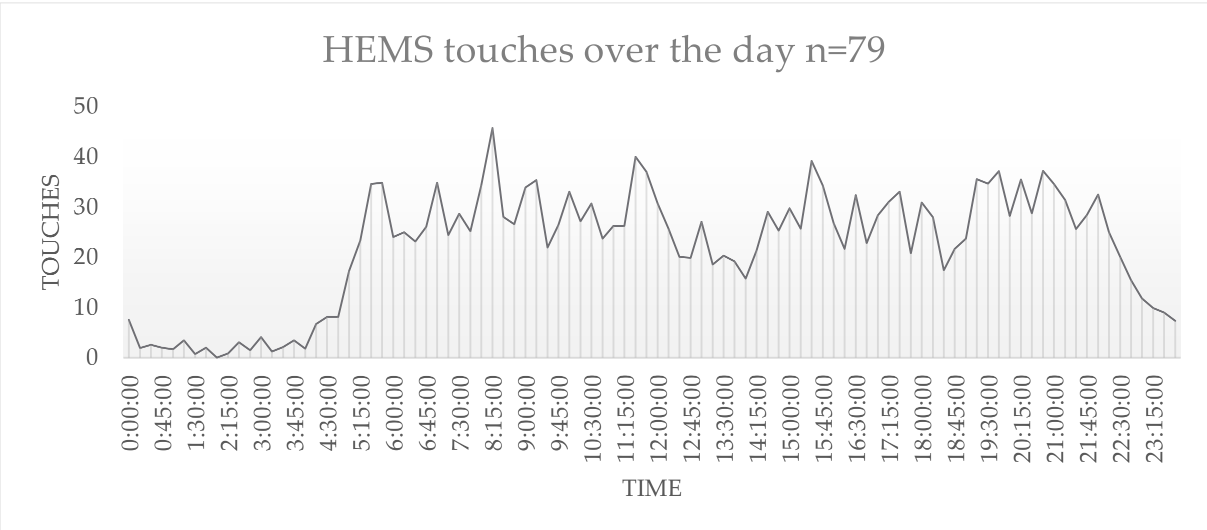
Appendix VII. Descriptive statistics of the measures

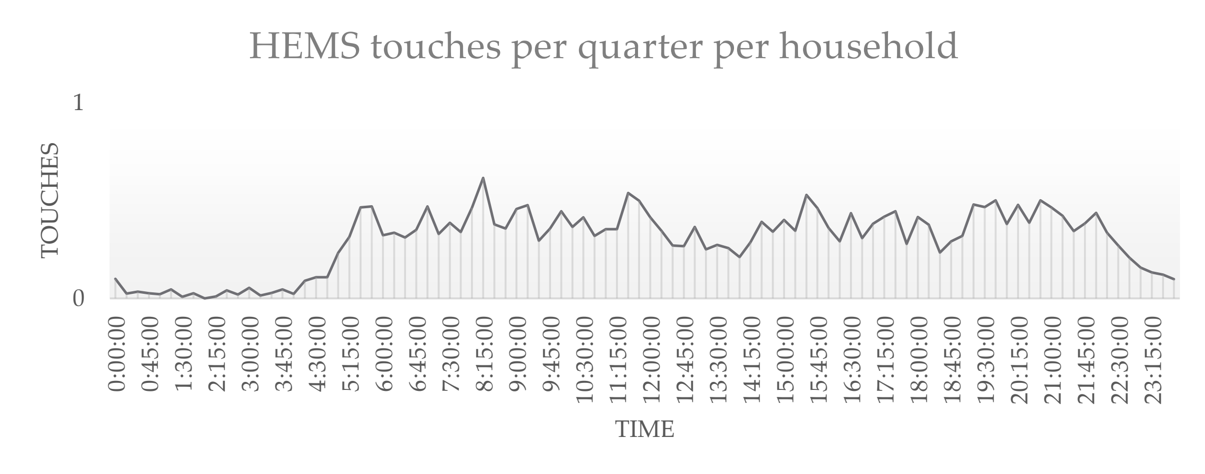
	N	Minimum	Maximum	Mean	Std. Deviation
EI	70	1,67	5,00	3,8220	,63998
BI_WG	70	1,50	5,00	3,7476	,86661
BI_OG	70	1,00	5,00	2,3869	,86661
PU	70	3,60	5,00	4,3457	,42518
PeOU_JEM	70	2,50	5,00	3,6857	,48843
PeOU_HEMS	70	2,00	5,00	4,1333	,69853
AT	70	3,29	5,00	4,1126	,42314
DS_WG	68	1,00	5,00	3,4019	1,20206
DS_OG	65	1,00	4,00	1,5731	,75024
HEMS_Routine	69	1,00	5,00	3,46	,931
SA_Usage	69	1,00	5,00	2,36	1,294
MO_Emotional	69	1,00	5,00	3,6232	,74954
MO_Environmental	69	1,00	5,00	3,6957	,75134
MO_Control	69	3,00	5,00	4,1884	,53161
MO_Social	69	1,00	5,00	2,9420	,86830
MO_Fun	69	2,00	5,00	3,8454	,70845

Appendix VIII. Descriptive of HEMS usage









House-DimensionID	Mean-Dailytouches	**House-DimensionID**	Mean-Dailytouches	**House-DimensionID**	Mean-Dailytouches
3	2	43	1	**111**	1
4	-	**44**	13	**120**	12
5	1	**47**	3	**121**	11
7	3	**48**	1	**122**	44
8	2	**50**	5	**128**	9
11	0	**52**	-	**132**	1
12	1	**53**	7	**141**	3
13	1	**59**	5	**146**	4
14	5	**60**	12	**165**	1
15	3	**62**	7	**21585**	3
17	2	**64**	0	**21586**	0
19	16	**66**	4	**21587**	2
21	1	**68**	1	**21589**	8
22	8	**75**	6	**21590**	7
23	6	**77**	6	**21591**	5
24	4	**78**	2	**21592**	2
27	19	**79**	2	**21594**	4
28	10	**80**	23	**21595**	0
29	2	**82**	6	**21596**	3
31	7	**83**	5	**21597**	1
32	4	**86**	5	**21598**	2
33	3	**94**	1	**21599**	3
34	3	**96**	3	**21600**	-
36	1	**97**	10	**21601**	1
39	5	**100**	0	**21602**	9
40	1	**103**	2		
42	1	**108**	5		

	N	Minimum	Maximum	Mean	Std. Deviation
DailyTouches	76	0	44	4,84	6,273

Top 10 most used screens

The top 10 touched screens of the 27 available screens are responsible for 60231 touches or 89% of the total. The two Homescreens are responsible for the largest proportion of the touches (53%). The three most pressed screens after the Homescreens are the detailed descriptions on consumption (6%), usage (5%) and production (5%).

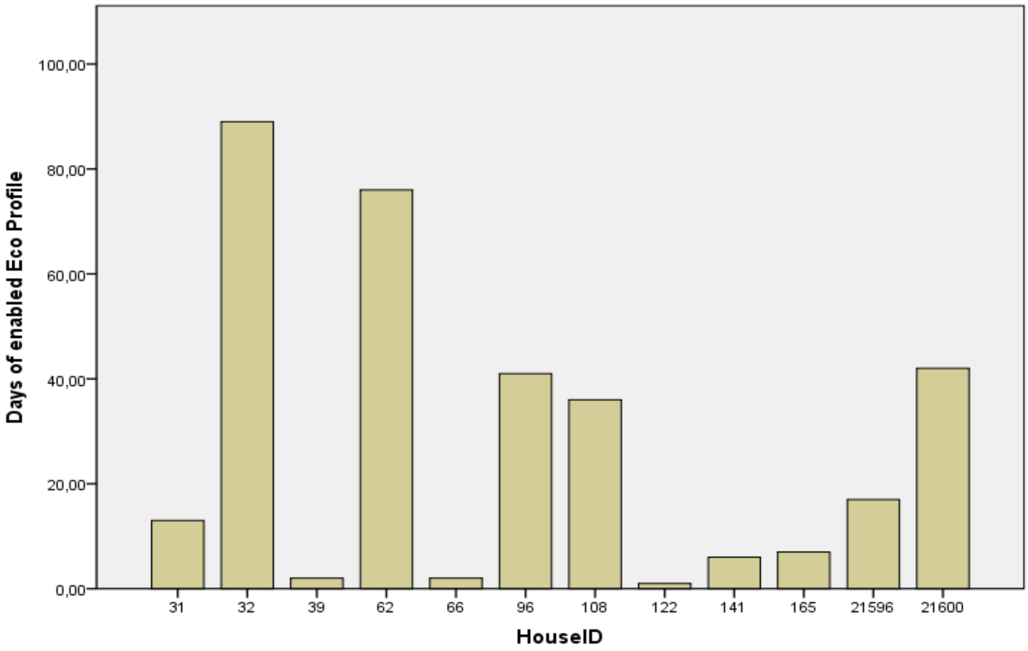
Then comes the overview of planned smart appliances jobs (5%) and the weather forecast (5%). The advice on when it is best to use electricity is consulted 2744 times (4%). The settings screen and the progress on the set goal are the least used in this top 10 (3%).

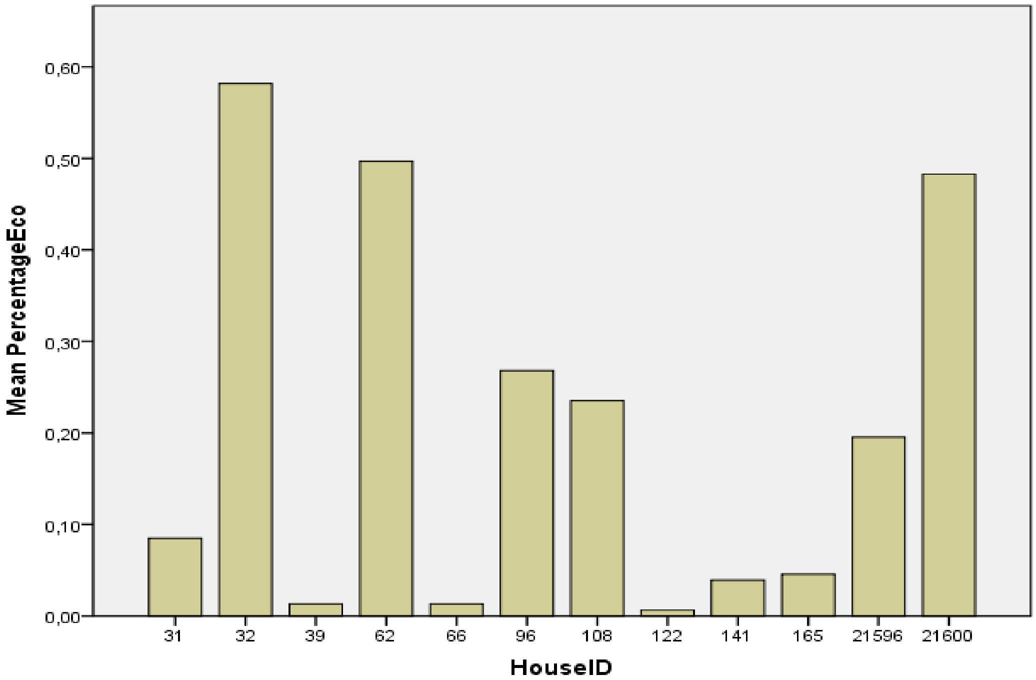
Nr	Screen	Times touched	Avarage per day	Percentage	Cumulative Percentage
1	Homescreen	19510	256,7105	29%	29%
2	Homescreen2	16366	215,3421	24%	53%
3	Comsumption	4116	54,15789	6%	59%
4	Netusage	3539	46,56579	5%	64%
5	Production	3503	46,09211	5%	69%
6	Jobs	3494	45,97368	5%	75%
7	Weather	3114	40,97368	5%	79%
8	Moments	2744	36,10526	4%	83%
9	Settings	2133	28,06579	3%	86%
10	Progressgoals	1712	22,52632	3%	89%
11	MessageOverview	1451	19,09211	2%	91%
12	Job	1047	13,77632	2%	93%
13	JobSelected	1037	13,64474	2%	94%
14	CurrentStatus	970	12,76316	1%	95%
15	Status	756	9,947368	1%	97%
16	Message	626	8,236842	1%	98%
17	Goal	412	5,421053	1%	98%
18	Profile	274	3,605263	0%	99%
19	Saver	256	3,368421	0%	99%
20	ApplianceMaintanaince	254	3,342105	0%	99%
21	Maintenance	218	2,868421	0%	100%
22	Appliance	168	2,210526	0%	100%
23	Appliance	168	2,210526	0%	100%
24	EcoMoments	66	0,868421	0%	100%
25	Dryer	64	0,842105	0%	100%
26	Tunnel	27	0,355263	0%	100%
27	Backup	10	0,131579	0%	100%

Appendix IX. Profile Selection

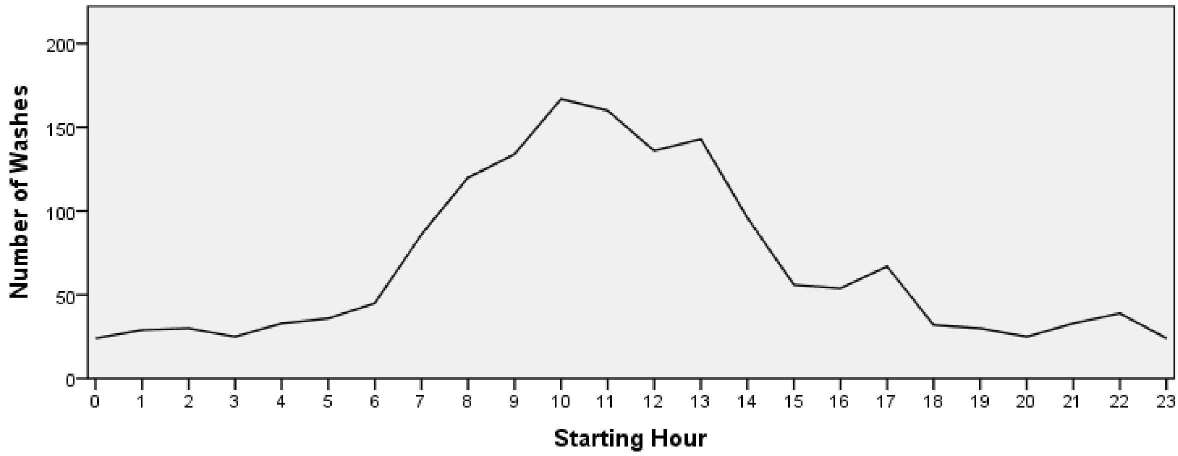
Descriptive Statistics

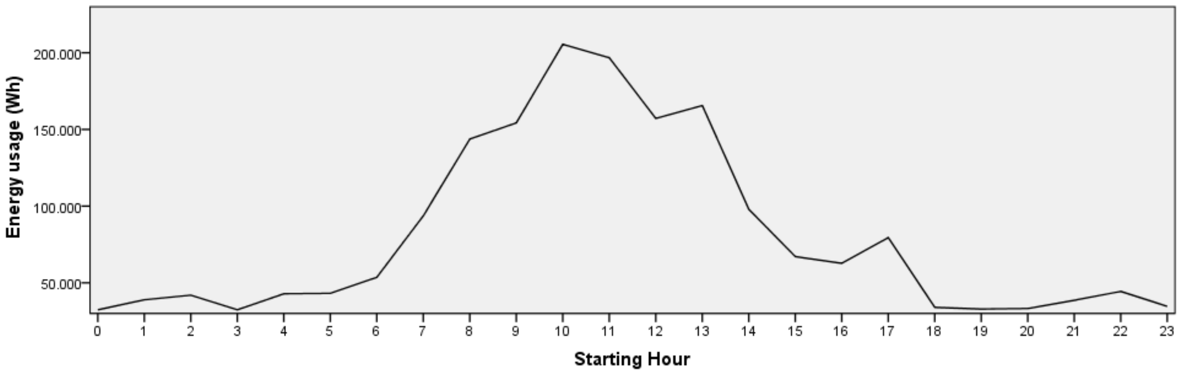
	N	Minimum	Maximum	Mean	Std. Deviation
HouseID	80	3	21602	4635,24	8864,851
PercentageEco	12	,01	,58	,2052	,21094
Valid N (listwise)	12				

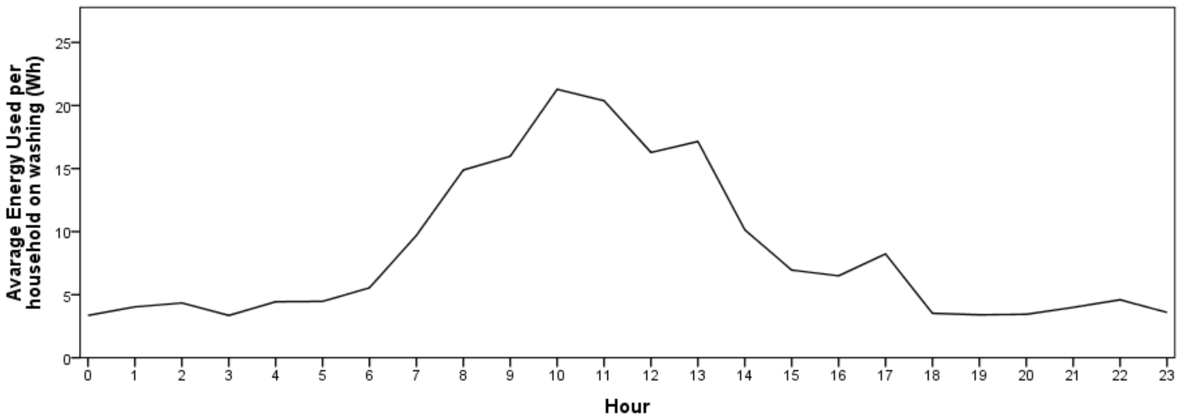


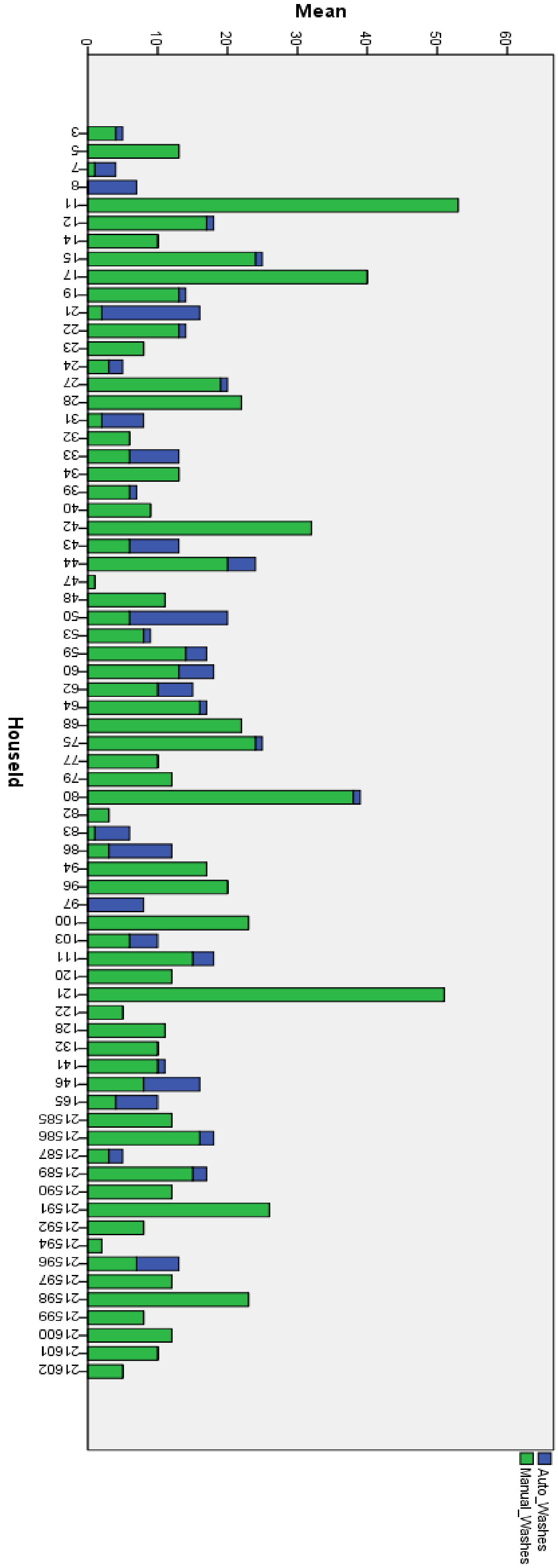


Appendix X. Smart Washing








Mean
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21600
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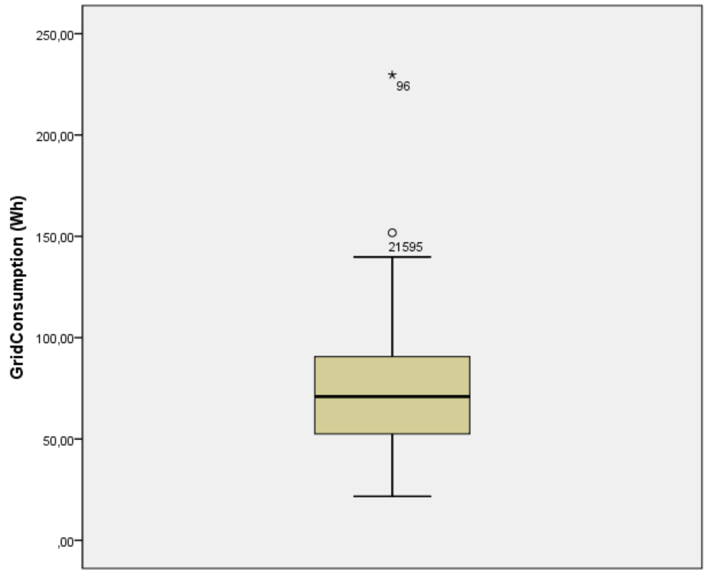
21602
Auto_Washes
Manual_Washes

Appendix XI. Analysis electricity consumption

Outliers

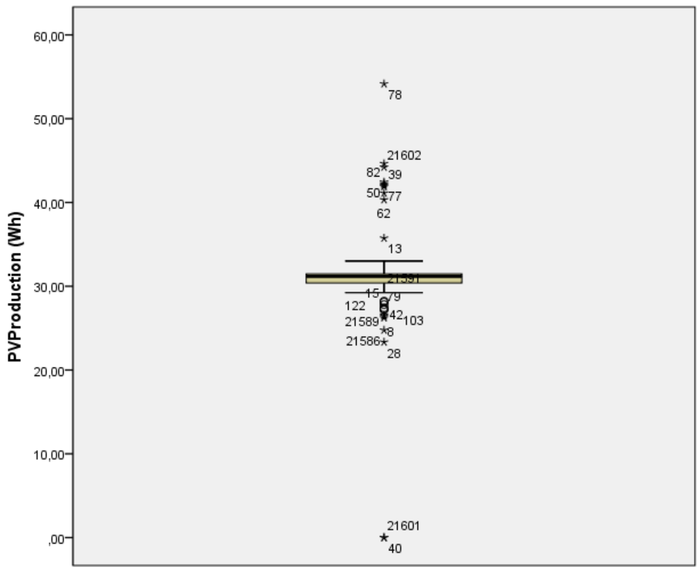
Electricity consumption

The Household with identity 96 is identified as an outlier in electricity consumption. Consumption normally ranges between 40 and 180 Wh per 15 minutes. The consumption of HomeID 96 is 262Wh per 15 minutes. It is not clear why this household is consuming such amount of electricity. Even though this consumption is extraordinary high, we are particularly interested in the moments Household 96 is consuming this electricity. For this reason it is not excluded from the analysis.



Electricity production

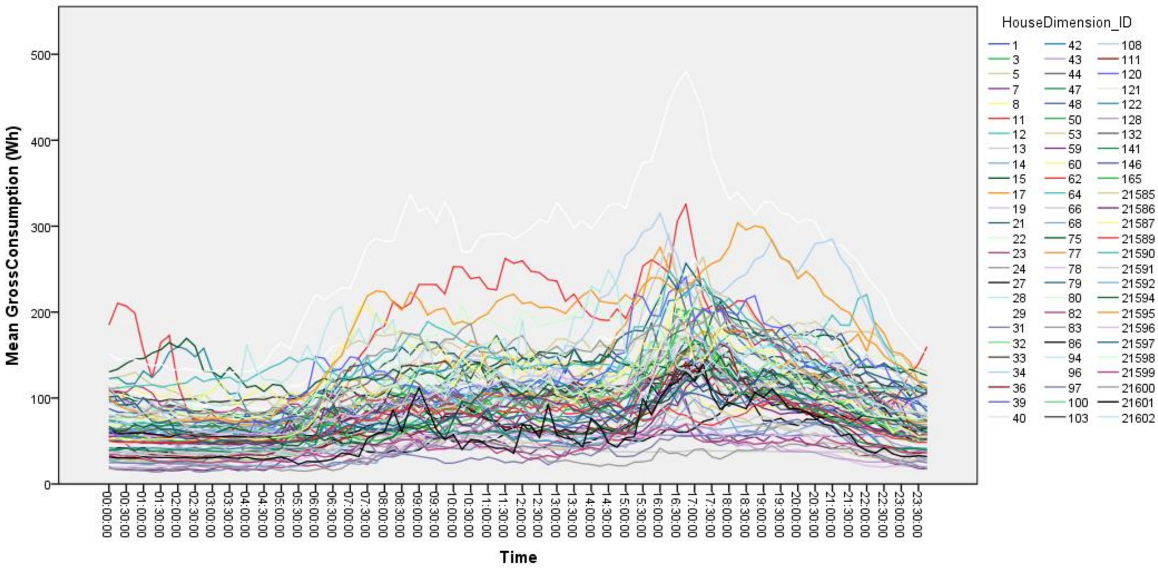
Electricity production by PV is registered by the HEMS. All the participating household have Solar panels and therefore should produce some amount of electricity. This said, the households with HomeID 21601 and HomeID 40 are not producing electricity, meaning there is something wrong in the registration of the PV electricity production. Because of this the gross consumption is incorrectly calculated due to the lacking of information on how much electricity is used which is produced by the PV. These households are excluded for further analysis.



Additionally the household with HomeID 78 is producing more electricity than the other households. This is caused due the installation of extra Solar panels. Instead of the usual 6 solar panels installed at the participating homes, this household has 10. This extra production of electricity through PV is not disrupting the measurements of this household. It is believed that extra electricity production on off-peak hours strengthens the incentive to use electricity at these moments. Due to the reason HomeID 78 is the only home with extra solar panels, we will not be able to draw conclusions out of any significant differences found in the electricity shift to off peak hours compared to the rest of the group.

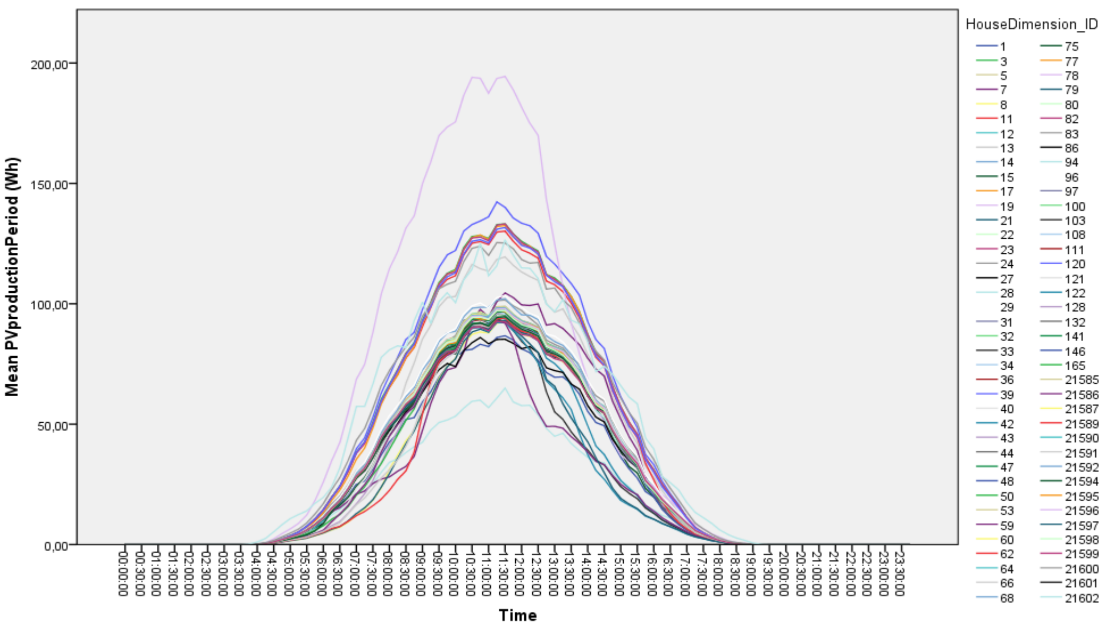
Electricity consumption

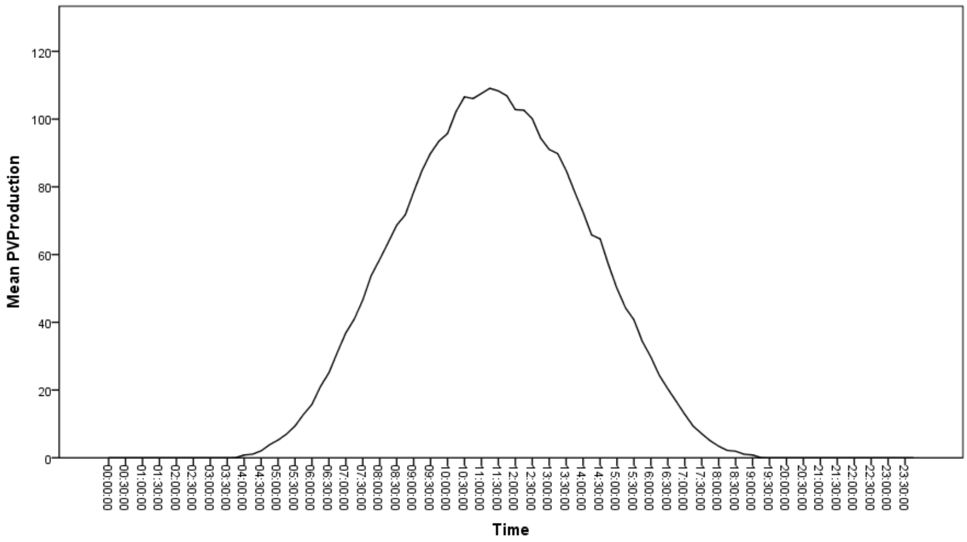
As seen below, the usage of electricity is subject to various unpredictable factors. Therefore the individual usage lines are rather spikey instead of smooth lines even though we use average values for over 150 days. Furthermore the graph illustrates that most households use maximum electricity during the peak hours, however there is a lot of variance in electricity use during the day.



Electricity production

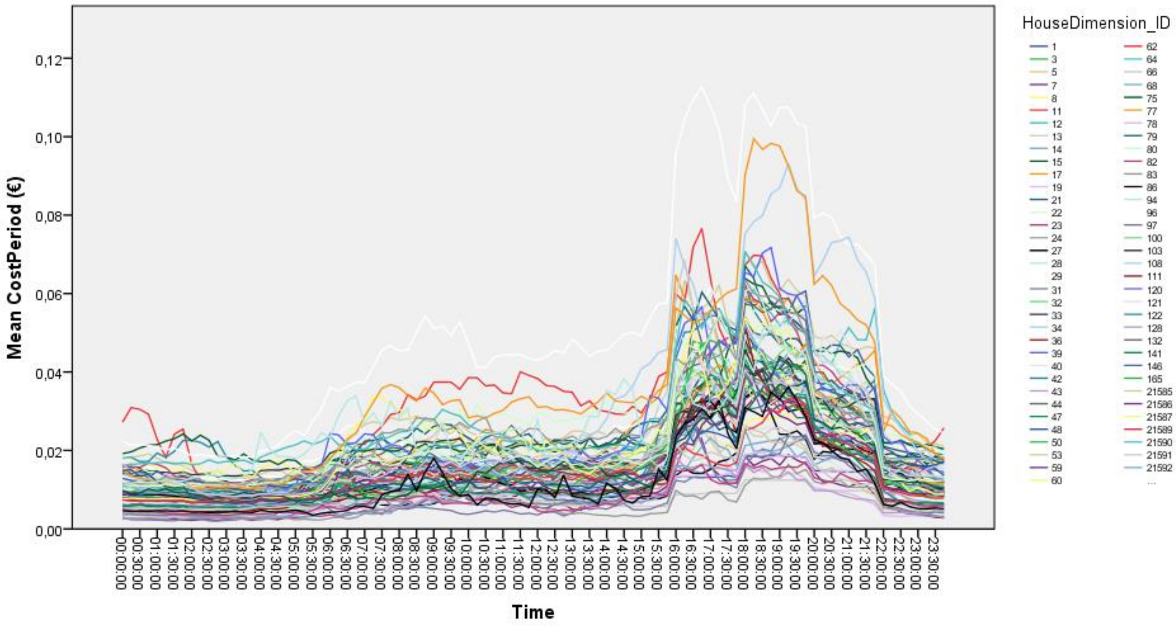
In the graph below, the PV production of the participants is depicted.





Electricity price

Multiplying the dynamic price with the electricity consumption results in the graph below. This graph shows that during peak hours, in extreme cases households pay as much as €0.10 per quarter (or €0.40 per hour) to cover their electricity need during peak hours.



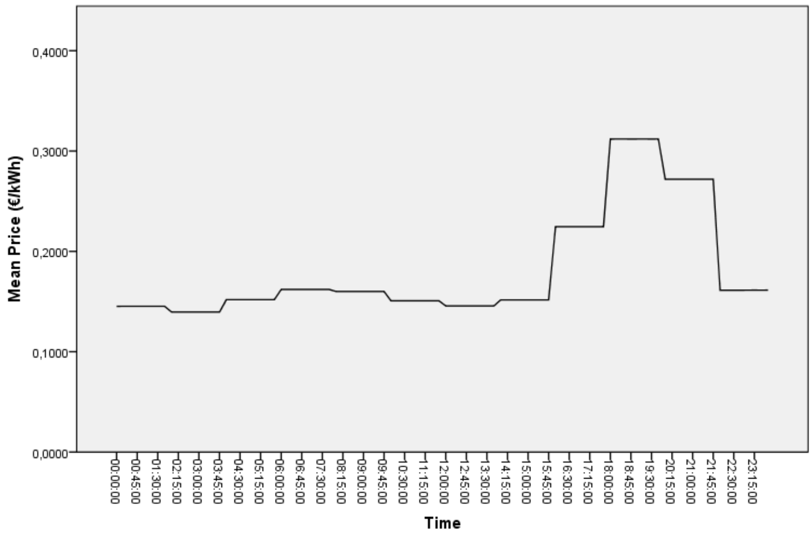


Figure 29: Average price paid over time

Figure 29 shows the aggregated daily prices paid per kWh during the experiment. This graph clearly shows the fluctuations in the price, resulting in a small peak price during 6am until 8am (€ 0,1621 pkWh) and from 6pm until 9 pm (€ 0,3120 pkWh). The small peak price in the morning is almost neglatable compared to the increase in price during the evening. Although the price is determined per quarter of an hour we see large steps in the dynamic price during the period 3 pm until 9pm. This is caused by the different time intervals used in the algorithm. In an ideal situation we want this price to be more curved to better represent the increase in price during the day.

Electricity Costs

The average electricity costs of a participant is calculated by multiplying the daily individual electricity profiles to the average price during the day as result of the pricing algorithm.

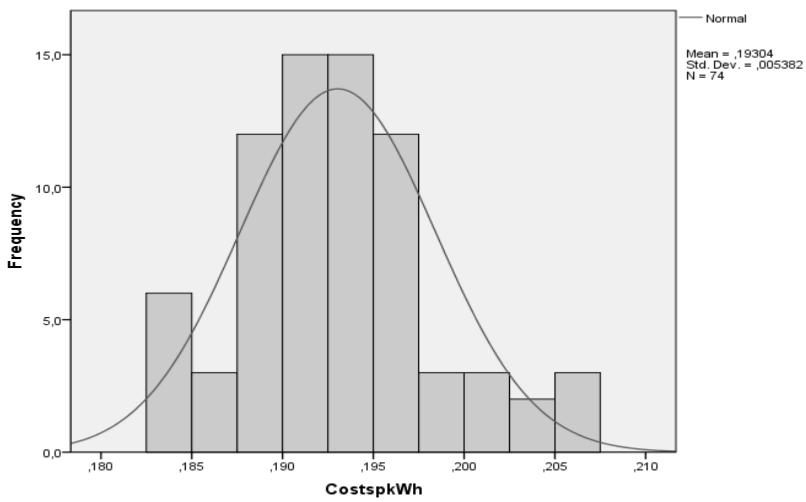
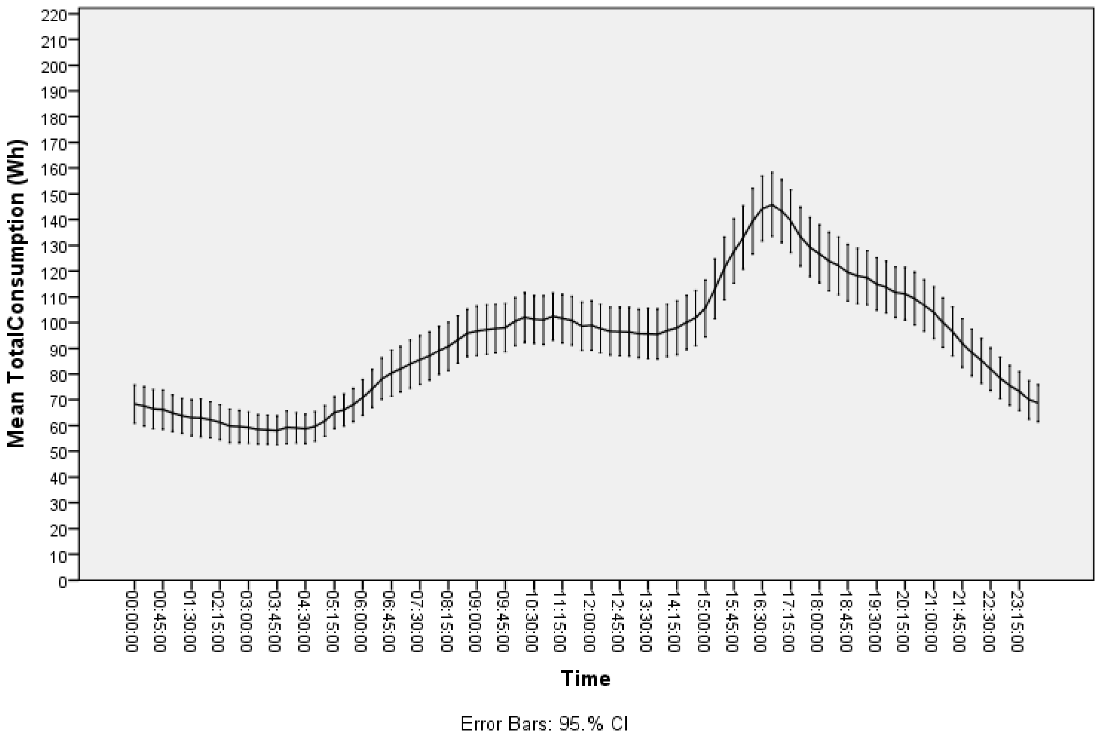


Figure 30: Average price paid per kWh

Average Load profile of the participating households

The aggregation of the load profiles leads to the graph as seen below. The peak usage of electricity takes place between 4pm and 6pm and reaches between 130Wh and 160Wh based on a confidence interval of 95%.



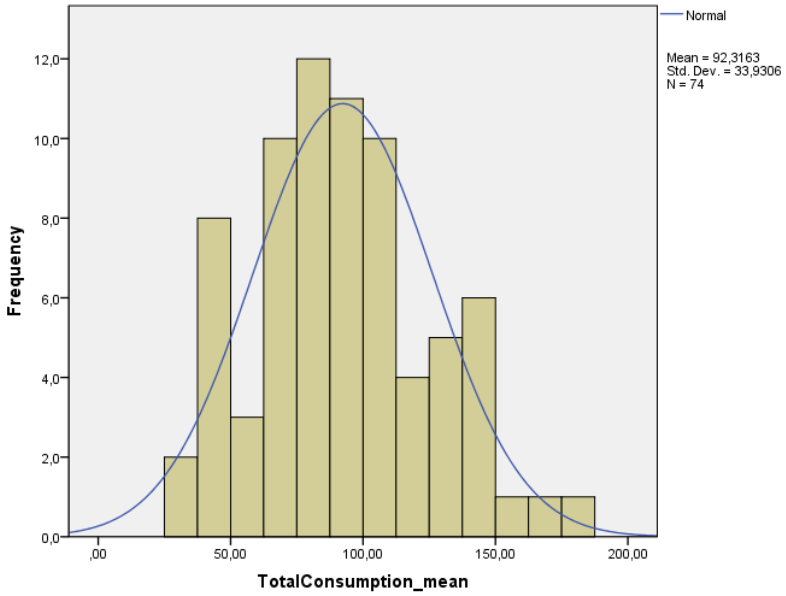
On average, a participating family consumes between 91,24Wh and 93.39Wh of electricity per quarter of an hour (based on a 95% confidence interval). This results in an annual usage between 3197kWh and 3272 kWh which is slightly below normal usage according to the average electricity consumption measure of a Dutch household (3312kWh in 2012). However one must take notice that only the first half of the year is measured therefore seasonal influences could be present. Furthermore this participants do not have a gas connection, making electricity their only source of energy.

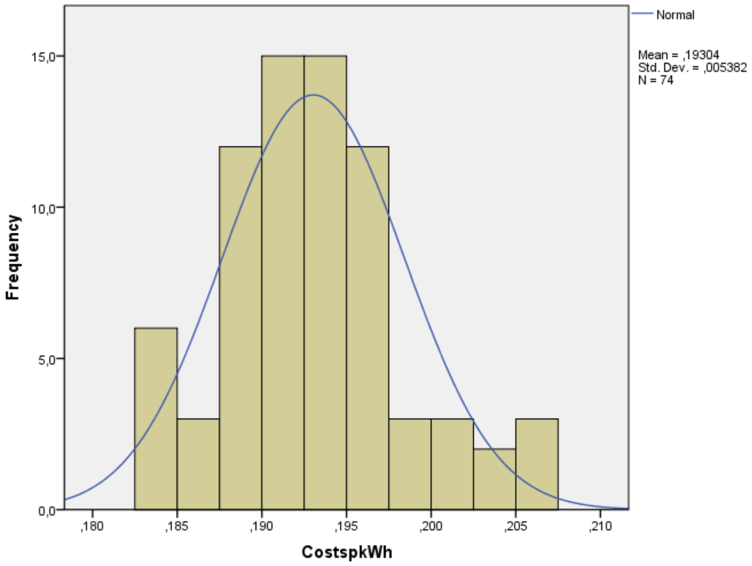
Descriptives

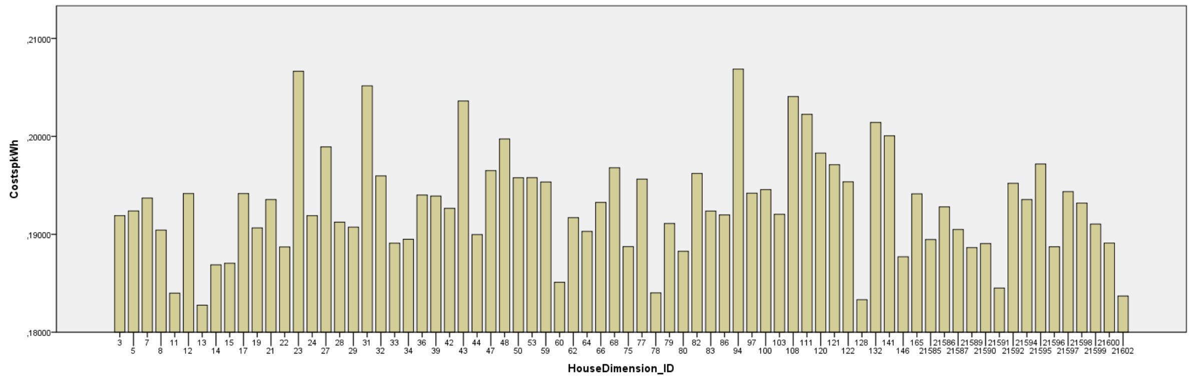
			Statistic	Std. Error
TotalConsumption	Mean		92,32	,548
	95% Confidence Interval for Mean	Lower Bound	91,24	
		Upper Bound	93,39	
	5% Trimmed Mean		89,53	
	Median		86,00	
	Variance		2131,004	
	Std. Deviation		46,163	
	Minimum		15	
	Maximum		309	
	Range		294	
	Interquartile Range		61	
	Skewness		,927	,029
	Kurtosis		1,052	,058

Differences in electricity consumption between participants

The graph below shows the average amount of electricity consumed by the participating households.

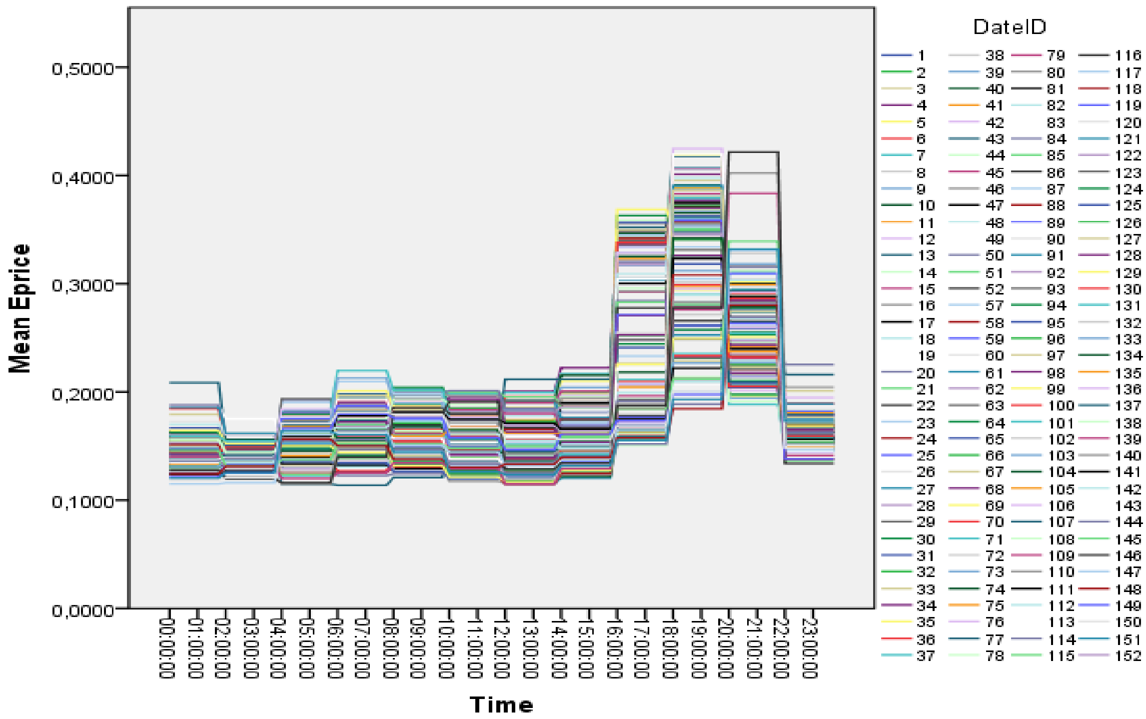




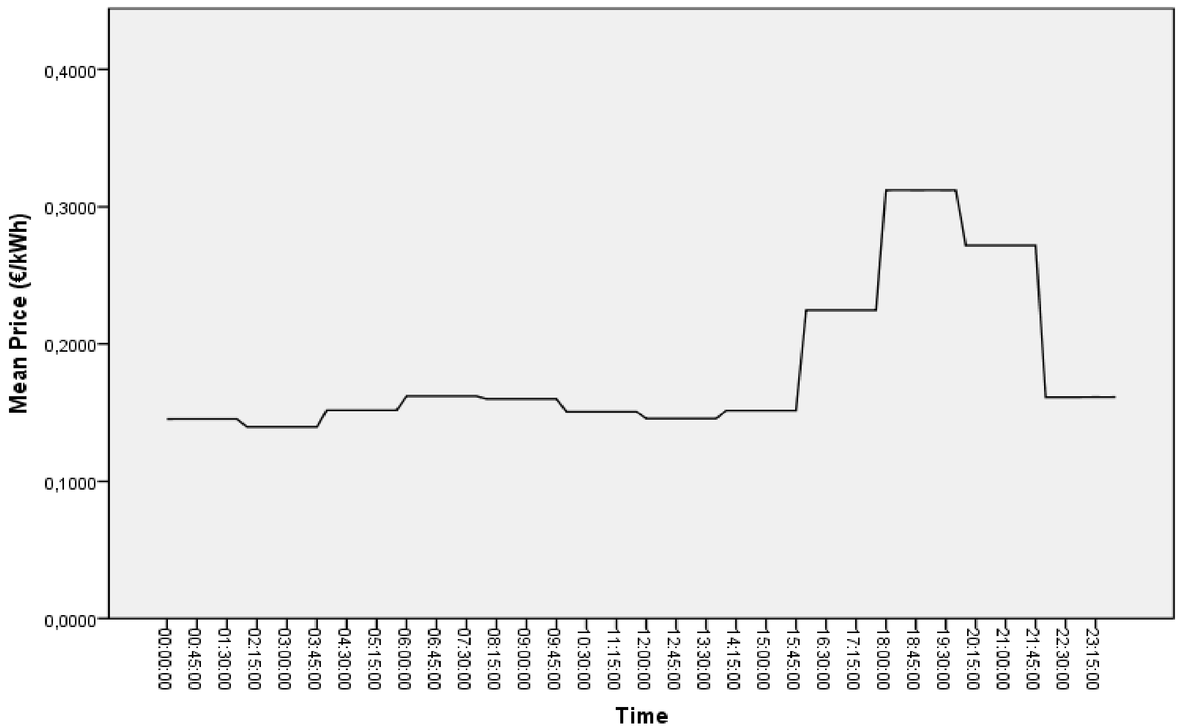


Appendix XII. Analysis dynamic pricing

As a result of the dynamic pricing algorithm as discussed in section Appendix IV, daily



This graph shows the daily price graphs, as a result of the dynamic pricing. As seen the price fluctuates during the experiment. However a peak in the price is noticeable from 4pm until 9pm.



This graph shows the aggregated daily prices paid per kWh during the experiment. This graph clearly shows the fluctuations in the price, resulting in a small peak price during 6am until 8am (€ 0,1621 pkWh) and from 6pm until 9 pm (€ 0,3120 pkWh). The small peak price in the morning is almost neglatable compared to the increase in price during the evening. Although the price is determined per quarter of an hour we see large steps in the dynamic price during the period 3 pm until 9pm. This is caused by the different time intervals used in the algorithm. In an ideal situation we want this price to be more curved to better represent the increase in price during the day.

Period	Avg Price in Period	Period	Avg Price in Period	Period	Avg Price in Period
0:00-0:15	€ 0,1452	**8:15-8:30**	€ 0,1600	**16:30-16:45**	€ 0,2246
0:15-0:30	€ 0,1453	**8:30-8:45**	€ 0,1600	**16:45-17:00**	€ 0,2246
0:30-0:45	€ 0,1453	**8:45-9:00**	€ 0,1600	**17:00-17:15**	€ 0,2246
0:45-1:00	€ 0,1453	**9:00-9:15**	€ 0,1600	**17:15-17:30**	€ 0,2246
1:00-1:15	€ 0,1453	**9:15-9:30**	€ 0,1600	**17:30-17:45**	€ 0,2246
1:15-1:30	€ 0,1453	**9:30-9:45**	€ 0,1600	**17:45-18:00**	€ 0,2246
1:30-1:45	€ 0,1453	**9:45-10:00**	€ 0,1600	**18:00-18:15**	€ 0,3120
1:45-2:00	€ 0,1453	**10:00-10:15**	€ 0,1508	**18:15-18:30**	€ 0,3120
2:00-2:15	€ 0,1396	**10:15-10:30**	€ 0,1508	**18:30-18:45**	€ 0,3120
2:15-2:30	€ 0,1396	**10:30-10:45**	€ 0,1508	**18:45-19:00**	€ 0,3119
2:30-2:45	€ 0,1396	**10:45-11:00**	€ 0,1508	**19:00-19:15**	€ 0,3120
2:45-3:00	€ 0,1396	**11:00-11:15**	€ 0,1508	**19:15-19:30**	€ 0,3120
3:00-3:15	€ 0,1396	**11:15-11:30**	€ 0,1508	**19:30-19:45**	€ 0,3120
3:15-3:30	€ 0,1396	**11:30-11:45**	€ 0,1508	**19:45-20:00**	€ 0,3120
3:30-3:45	€ 0,1396	**11:45-12:00**	€ 0,1508	**20:00-20:15**	€ 0,2719
3:45-4:00	€ 0,1396	**12:00-12:15**	€ 0,1456	**20:15-20:30**	€ 0,2719
4:00-4:15	€ 0,1519	**12:15-12:30**	€ 0,1456	**20:30-20:45**	€ 0,2719
4:15-4:30	€ 0,1519	**12:30-12:45**	€ 0,1456	**20:45-21:00**	€ 0,2719
4:30-4:45	€ 0,1519	**12:45-13:00**	€ 0,1456	**21:00-21:15**	€ 0,2719
4:45-5:00	€ 0,1519	**13:00-13:15**	€ 0,1456	**21:15-21:30**	€ 0,2719
5:00-5:15	€ 0,1519	**13:15-13:30**	€ 0,1456	**21:30-21:45**	€ 0,2719
5:15-5:30	€ 0,1519	**13:30-13:45**	€ 0,1456	**21:45-22:00**	€ 0,2719
5:30-5:45	€ 0,1519	**13:45-14:00**	€ 0,1456	**22:00-22:15**	€ 0,1612
5:45-6:00	€ 0,1519	**14:00-14:15**	€ 0,1516	**22:15-22:30**	€ 0,1613
6:00-6:15	€ 0,1621	**14:15-14:30**	€ 0,1516	**22:30-22:45**	€ 0,1613
6:15-6:30	€ 0,1621	**14:30-14:45**	€ 0,1516	**22:45-23:00**	€ 0,1613
6:30-6:45	€ 0,1621	**14:45-15:00**	€ 0,1516	**23:00-23:15**	€ 0,1613
6:45-7:00	€ 0,1621	**15:00-15:15**	€ 0,1516	**23:15-23:30**	€ 0,1613
7:00-7:15	€ 0,1621	**15:15-15:30**	€ 0,1516	**23:30-23:45**	€ 0,1613
7:15-7:30	€ 0,1621	**15:30-15:45**	€ 0,1516	**23:45-24:00**	€ 0,1613
7:30-7:45	€ 0,1621	**15:45-16:00**	€ 0,1516		
7:45-8:00	€ 0,1621	**16:00-16:15**	€ 0,2246		
8:00-8:15	€ 0,1600	**16:15-16:30**	€ 0,2246		

Appendix XIII. Load participants vs. reference group

In this analyses the avarage electricty usage during a day in the experiment is determined.

Reference group

For the reference group, similar houses with non-participating household are being used. The reference group is divided over two power lines with line ID 2 and Line ID 9. On line with ID 2, there are 21 households connected, on line with ID 9 there are 5 households connected. During the period from 01-01-2013 until 01-07-2013 there are 28,070 successful measurements taken from both lines, containing the electricity meter reading per quarter of an hour. In order to calculate the consumption, the meter reading from moment i is subtracted from moment i-1. To prevent erroneous values the consumption is only calculated if the quarter value from moment i is the follow up quarter value from moment i-1 (so no quarter values may be skipped). Furthermore all values smaller than the starting value on 01-01-2013 or larger than the ending value on 01-07-2013 are deleted.

The graph shows the average daily electricity consumption during the period between 01-01-2013 and 01-07-2013. The two lines resemble the two reference group which is provided by the two electricity lines. As seen the relatively smaller reference group has a more spiked curve compared to the participants group. This resembles the uncertainty accompanied with an individual's electricity usage. The larger the group, the more fluctuant the average consumption is. The electricity consumption of both groups peak between 4pm and 5 pm.

The amount of electricity used on off-peak moments by households on cable 2 amounts **71.88%.** The amount of electricity used on off-peak moments by households on cable 9 amounts **71.61%.** Together this results in a electricity use on off peak hours of **71.75%.** The participating group reached an electricity usage of **71.73**%.

Using $\mu_{\bar{x}} = \overline{X} \pm Z \frac{\sigma}{\sqrt{n}}$ where:

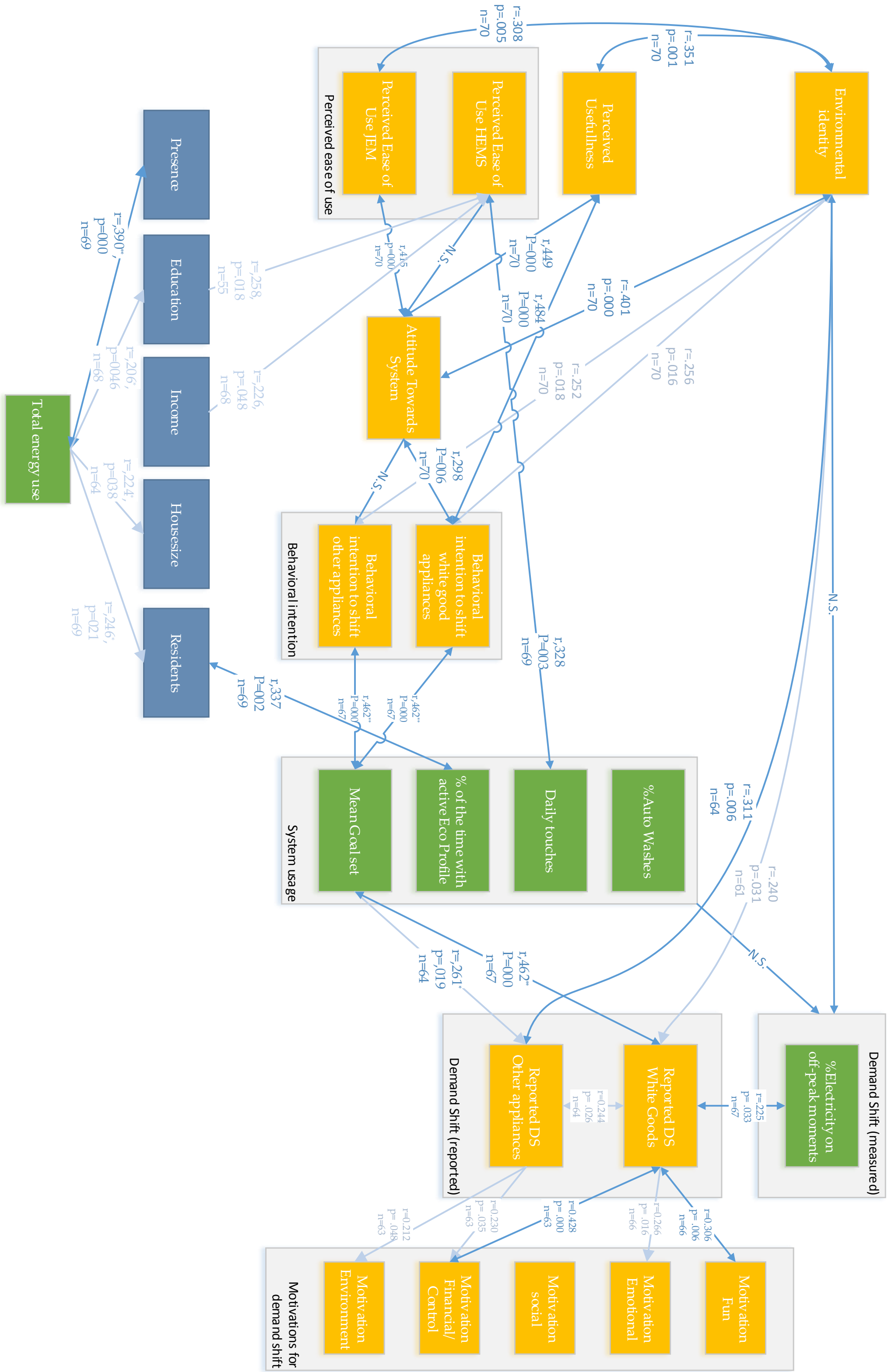
μ= Population Mean,
σ= Population standard deviation
n= number of samples (number of test records used); and
Z= the normal distribution's critical value for a probability of $\alpha/2$ in each tail.
We can now calculate that the probability that the participating group is actually performing better than the reference group (together) is:

$0.02 = Z \frac{0.02844}{\sqrt{74}}$ from which follows that Z=-0.0052 which corresponds with an probability of 0.4979 which is about one in 2. This said it is not possible to state that the participants group is performing better than the reference group on electricity usage on off peak hours.
For the participating groups holds:

99% confidence interval:	$0.70869 \le x \le 0.72591$
95% confidence interval:	$0.71081 \le x \le 0.72379$
90% confidence interval:	$0.71188 \le x \le 0.72272$

Appendix XIV. results from TAM model testing

Correlations

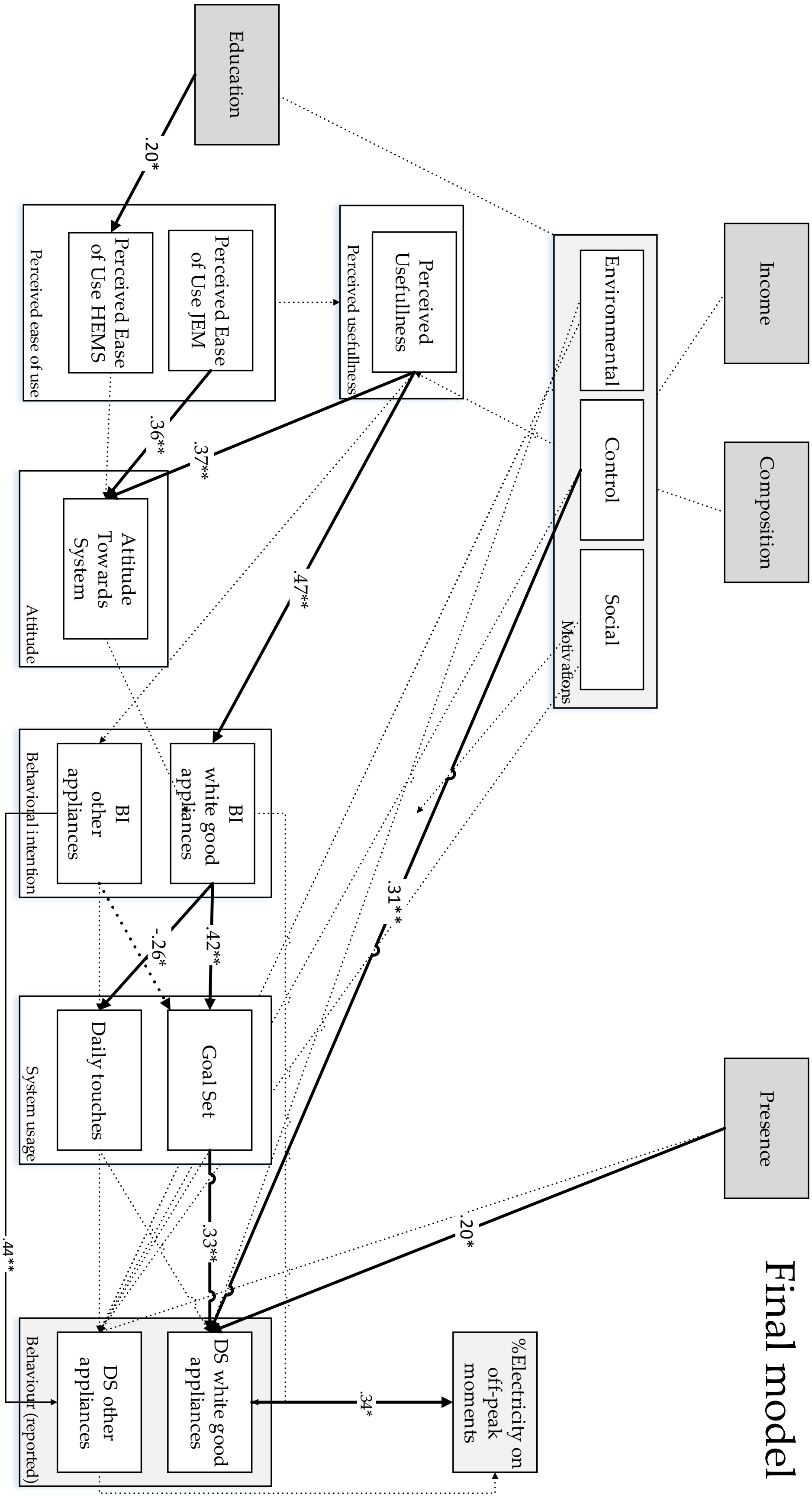


```
Structural equation model                       Number of obs      =        58
Estimation method  = ml
Log likelihood     =  -1692.201
```

	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf.	Interval]
Structural						
ZPU <-						
ZPeOU_HEMS	-.1879541	.1593704	-1.18	0.238	-.5003143	.1244061
ZPeOU_JEM	.0728389	.1339713	0.54	0.587	-.1897399	.3354178
ZMO_Soc	.1630599	.1270531	1.28	0.199	-.0859595	.4120794
ZMO_Con	.2733757	.133369	2.05	0.040	.0119772	.5347742
ZMO_Env	.1636029	.120813	1.35	0.176	-.0731862	.400392
_cons	.0968183	.1250514	0.77	0.439	-.148278	.3419146
ZAT <-						
ZPU	.3763624	.1100002	3.42	0.001	.160766	.5919588
ZPeOU_HEMS	.0986258	.1325891	0.74	0.457	-.161244	.3584956
ZPeOU_JEM	.3716756	.1122234	3.31	0.001	.1517218	.5916293
_cons	.0414064	.1126931	0.37	0.713	-.1794679	.2622808
ZBI_WG <-						
ZPU	.493829	.1182542	4.18	0.000	.2620551	.725603
ZAT	.1003691	.1177202	0.85	0.394	-.1303582	.3310964
_cons	-.0734759	.1078168	-0.68	0.496	-.284793	.1378412
ZBI_OG <-						
ZPU	.0895896	.1140498	0.79	0.432	-.1339439	.3131232
ZAT	.1016306	.1135348	0.90	0.371	-.1208935	.3241548
_cons	-.23341	.1039836	-2.24	0.025	-.4372141	-.0296059
ZPeOU_HEMS <-						
Education	.195281	.082938	2.35	0.019	.0327256	.3578364
_cons	-.8864726	.4677755	-1.90	0.058	-1.803296	.0303506
ZDailyTouches <-						
ZBI_WG	-.256086	.1327708	-1.93	0.054	-.516312	.0041401
ZBI_OG	.1535075	.1623157	0.95	0.344	-.1646255	.4716405
ZPeOU_HEMS	.3939576	.1526633	2.58	0.010	.094743	.6931721
_cons	-.020557	.1313973	-0.16	0.876	-.2780909	.2369768
ZPeOU_JEM <-						
Education	-.0452461	.1053576	-0.43	0.668	-.2517432	.1612509
_cons	.2039726	.5942236	0.34	0.731	-.9606841	1.368629
ZDS_WG <-						
ZBI_WG	.0507173	.1185031	0.43	0.669	-.1815444	.2829791
ZDailyTouches	.122627	.1037024	1.18	0.237	-.0806259	.3258799
ZGoalMean	.2907	.110403	2.63	0.008	.0743141	.5070859
ZMO_Soc	-.0651725	.1034635	-0.63	0.529	-.2679572	.1376122
ZMO_Con	.3078961	.1022512	3.01	0.003	.1074874	.5083049
ZMO_Env	.1193359	.0952163	1.25	0.210	-.0672846	.3059564
RMeanPresence	.2040441	.0964464	2.12	0.034	.0150127	.3930755
_cons	-.6557483	.3628411	-1.81	0.071	-1.366904	.055407
ZGoalMean <-						
ZBI_WG	.4231143	.1236844	3.42	0.001	.1806973	.6655312
ZBI_OG	.0653296	.1520359	0.43	0.667	-.2326553	.3633146
_cons	-.009589	.1210769	-0.08	0.937	-.2468953	.2277173

ZDS_OG <-						
ZBI_OG	.4530535	.1359931	3.33	0.001	.186512	.7195951
ZDailyTouches	.150359	.1033981	1.45	0.146	-.0522975	.3530155
ZGoalMean	.1429487	.1061633	1.35	0.178	-.0651274	.3510249
ZMO_Soc	-.0255866	.1093827	-0.23	0.815	-.2399729	.1887996
ZMO_Con	.1071656	.1113721	0.96	0.336	-.1111197	.325451
ZMO_Env	.1245854	.1001157	1.24	0.213	-.0716377	.3208086
RMeanPresence	.0660109	.1004988	0.66	0.511	-.1309631	.262985
_cons	-.1845043	.3762734	-0.49	0.624	-.9219866	.5529779
ZConsumption_OffpeakMoments <-						
ZDS_WG	.3403757	.1474745	2.31	0.021	.051331	.6294204
ZDS_OG	-.1342128	.1484376	-0.90	0.366	-.425145	.1567195
_cons	-.0966925	.1329828	-0.73	0.467	-.357334	.163949
ZMO_Soc <-						
Education	.0836272	.1070209	0.78	0.435	-.1261298	.2933842
Income	-.0036896	.0038675	-0.95	0.340	-.0112697	.0038906
SinglePerson	.1505857	.3227889	0.47	0.641	-.4820689	.7832402
SinglePersonwithKids	.2350619	.4247905	0.55	0.580	-.5975122	1.067636
Cohabiting_Married_withKids	-.1210839	.2947797	-0.41	0.681	-.6988416	.4566737
_cons	-.4509393	.6163991	-0.73	0.464	-1.659059	.7571808
ZMO_Con <-						
Education	.1094242	.1020126	1.07	0.283	-.0905168	.3093653
Income	-.001873	.0037244	-0.50	0.615	-.0091727	.0054267
SinglePerson	.3973819	.308345	1.29	0.197	-.2069633	1.001727
SinglePersonwithKids	.5110518	.5041835	1.01	0.311	-.4771298	1.499233
Cohabiting_Married_withoutKids	-.4148023	.2451301	-1.69	0.091	-.8952486	.0656439
Cohabiting_Married_withKids	-.240988	.2882109	-0.84	0.403	-.8058711	.3238951
_cons	-.3842939	.5854767	-0.66	0.512	-1.531807	.7632194
ZMO_Env <-						
Education	.1690281	.1032598	1.64	0.102	-.0333573	.3714136
Income	-.001633	.0037699	-0.43	0.665	-.009022	.0057559
SinglePerson	.0802296	.3121148	0.26	0.797	-.5315041	.6919633
SinglePersonwithKids	.153956	.5103475	0.30	0.763	-.8463068	1.154219
Cohabiting_Married_withoutKids	-.1798723	.248127	-0.72	0.469	-.6661923	.3064477
Cohabiting_Married_withKids	.2389098	.2917345	0.82	0.413	-.3328793	.810699
_cons	-.8597659	.5926346	-1.45	0.147	-2.021308	.3017765
Variance						
e.ZPU	.8551228	.1587923			.5942434	1.230531
e.ZAT	.6952769	.1291097			.483163	1.000511
e.ZBI_WG	.6705473	.1245175			.4659778	.964925
e.ZBI_OG	.6237144	.1158209			.4334326	.8975319
e.ZPeOU_HEMS	.6225227	.1155996			.4326045	.8958171
e.ZDailyTouches	.8945182	.1661079			.6216201	1.287222
e.ZPeOU_JEM	1.004569	.1865438			.698097	1.445587
e.ZDS_WG	.5317567	.0987447			.3695292	.7652038
e.ZGoalMean	.7890232	.1465179			.5483093	1.135413
e.ZDS_OG	.5924176	.1100092			.4116838	.8524955
e.ZConsumption_OffpeakMoments	1.012118	.1879455			.7033425	1.456449
e.ZMO_Soc	1.030699	.1913961			.7162553	1.483188
e.ZMO_Con	.920086	.1708557			.6393877	1.324014
e.ZMO_Env	.9427209	.1750589			.6551172	1.356586

LR test of model vs. saturated: chi2(137) = 172.14, Prob > chi2 = 0.0225


Final model
Education
Income
Composition
Presence
Environmental
Control
Social
Motivations
Perceived Usefulness
Perceived usefulness
Perceived Ease of Use JEM
Perceived Ease of Use HEMS
Perceived ease of use
Attitude Towards System
Attitude
BI white good appliances
BI other appliances
Behavioral intention
Goal Set
Daily touches
System usage
DS white good appliances
DS other appliances
Behaviour (reported)
%Electricity on off-peak moments
.20*
.36**
.37**
.47**
.31**
.42**
-.26*
.33**
.44**
.20*
.34*

Appendix XV. Query's used in SQL database

Electricity prices as result of the algorithm

```
SELECT [EnergyPrice]
         ,[DateDimension_ID]
      ,[PeriodDimension_Id]
  FROM [dbo].[BillingFacts]
  where ([DateTime] between '2013-01-01' and '2013-06-01')
  group by DateDimension_ID, PeriodDimension_Id, [EnergyPrice]
  order by PeriodDimension_Id

GO
```

Average electricity Price per period for lookupTable

```
SELECT Avg([EnergyPrice])
      ,[PeriodDimension_Id]
  FROM [dbo].[BillingFacts]
  where ([DateTime] between '2013-01-01' and '2013-06-01')
  group by PeriodDimension_Id
  order by PeriodDimension_Id
GO
```

Period Times for LookupTable

```
SELECT [Id]
      ,[PeriodCode]
      ,[PeriodName]
  FROM [dbo].[Periods]
  order by Id
GO
```

Average electricity Usage, Production and Return per quarter per Household

```
SELECT   efacts.[HouseDimension_Id]
        ,efacts.[PeriodDimension_Id]
           ,avg(cast(efacts.[NetUsage] AS float)) as ConsumptionPeriod
              ,avg(cast(efacts.[PvProduced] AS float)) as PVProductionPeriod
              ,avg(cast(efacts.[NetSupply] AS float)) as NetreturnPeriod
  FROM [dbo].EnergyMeterFacts as efacts
  where (efacts.[DateTime] between '2013-01-01' and '2013-06-01')
   and (efacts.[NetSupply]<= efacts.[PvProduced])
   and (efacts.[NetUsage]> (0-efacts.[PvProduced]))
  Group by efacts.[HouseDimension_Id], efacts.[PeriodDimension_Id]
  order by efacts.[HouseDimension_Id], efacts.[PeriodDimension_Id]
GO
```

To exclude impossible values the following statements are made in the query above:

- Electricity return can never exceed PV production
  `(efacts.[NetSupply]<= efacts.[PvProduced])`
- Electricity consumption can never be less than the full return of PV production
  `(efacts.[NetUsage]> (0-efacts.[PvProduced])`

When one of these statements is violated, the value will not be included in the average. The results are 9984 average values.

V2

```
SELECT   [HouseDimension_Id]
        ,[PeriodDimension_Id]
              ,avg([ConsumeHigh]) as GridConsumptionHigh
              ,avg([ConsumeLow]) as GridConsumptionLow
              ,avg([ProduceHigh]) as GridReturnHigh
              ,avg([ProduceLow]) as  GridReturnLow
              ,avg(cast([PvProduced] AS float)) as PVProduction
           ,avg(cast([NetUsage] AS float)) as TotalConsumption
  FROM [dbo].EnergyMeterFacts
  where ([DateTime] between '2013-01-01' and '2013-07-01')
   and ([NetSupply]<= [PvProduced])
   and ([NetUsage]> (0))
  Group by [HouseDimension_Id], [PeriodDimension_Id]
  order by [HouseDimension_Id], [PeriodDimension_Id]
GO
```

Goals set by the Household

```
SELECT [HouseDimension_Id], AVG(cast([GoalPosition] AS FLOAT))
       FROM [dbo].[PerformanceStarAchievedFacts]
          where [datetime] between '2013-03-01' and '2013-07-01'
          Group By [HouseDimension_Id]
          order by [HouseDimension_Id]
GO
```

Washes done by the households

```
SELECT [HouseDimension_Id],
             Count ([HouseDimension_Id]) as TotalWashes
      ,sum (case when [ScheduleID] > '0' then 1 else 0 END) as WashesAuto
  FROM [dbo].[WashCycleFacts]
  where ([DateTime] between '2013-01-01' and '2013-06-01') and [Status] = 'Finished'
  Group by [HouseDimension_Id]
  order by [Housedimension_Id]
GO
```

Washes over time

```
SELECT cast(([ScheduledStart]) As Date) as ScheduledStartDate
          ,cast(([ScheduledStart]) As Time(7)) as ScheduledStartTime
       ,cast(([ActualStart]) As Date) as ActualStartDate
          ,cast(([ActualStart]) As Time) as ActualStartTime
          ,cast(([CommitTime]) As Date) as CommitDate
          ,cast(([CommitTime]) As Time) as CommitTime
          ,cast(([FinishTime]) As Date) as FinishDate
          ,cast(([FinishTime]) As Time) as FinishTime
       ,[DateDimension_Id]
       ,[HouseDimension_Id]
  FROM [dbo].[WashCycleFacts]
  where ([DateTime] between '2013-01-01' and '2013-07-01') and [Status] = 'Finished'
GO
```

```
Recode in hours
DATASET ACTIVATE DataSet1.
RECODE VAR00001 (0 thru 3600=0) (3601 thru 7200=1) (7201 thru 10800=2) (10801 thru
14400=3) (14401
```

```
    thru 18000=4) (18001 thru 21600=5) (21601 thru 25200=6) (25201 thru 28800=7)
(28801 thru 32400=8)
    (32401 thru 36000=9) (36001 thru 39600=10) (39601 thru 43200=11) (43201 thru
46800=12) (46801 thru
    50400=13) (50401 thru 54000=14) (54001 thru 57600=15) (57601 thru 61200=16) (61201
thru 64800=17)
    (64801 thru 68400=18) (68401 thru 72000=19) (72001 thru 75600=20) (75601 thru
79200=21) (79201 thru
    82800=22) (82801 thru 86400=23) INTO ActualStartHour.
EXECUTE.
```

HEMS usage

HEMS usage over time:

```
SELECT [DateDimension_Id],
              [HouseDimension_Id],
              Sum (case when [EventCode] = '1' then 1 else 0 END) as TouchHEMS
FROM [dbo].[DisplayUsageFacts]
where ([DateTime] between '2013-01-01' and '2013-07-01')
Group by [DateDimension_Id], [HouseDimension_Id]
Order by [DateDimension_Id], [HouseDimension_Id]
GO

V2
USE [CemsResearch]
GO

SELECT Count([EventCode]) as touches
      ,[HouseDimension_Id]
      ,[DateDimension_Id]
  FROM [dbo].[DisplayUsageFacts]
  where [EventCode]='1' and (datetime between '2013-01-01' and '2013-07-01')
  group by  [HouseDimension_Id], [DateDimension_Id]
  order by Housedimension_ID
GO
```

HEMS daily usage:

```
SELECT [PeriodDimension_Id],
              [HouseDimension_Id],
              Sum (case when [EventCode] = '1' then 1 else 0 END) as TouchHEMS
FROM [dbo].[DisplayUsageFacts]
where ([DateTime] between '2013-04-18' and '2013-07-01')
Group by [PeriodDimension_Id], [HouseDimension_Id]
Order by [PeriodDimension_Id], [HouseDimension_Id]
GO
```

From 18 april, HEMS usage is recorded on quarterly basis, therefor this is used as start date.

HEMS usage screens:

```
SELECT [HouseDimension_Id],
              sum (case when [EventCode] = '1' then 1 else 0 END) as TouchHEMS,
              Sum (case when [EventValue] = 'Selected screen: 0' then 1 else 0 END) as
TouchHomescreen,
```

```
              Sum (case when [EventValue] = 'Selected screen: 1' then 1 else 0 END) as
TouchHomescreen2,
              Sum (case when [EventValue] = 'Selected screen: 9' then 1 else 0 END) as
TouchMoments,
              Sum (case when ([EventValue] = 'Selected screen: 9' and [AdditionalValue]
= 'financiële momenten')  then 1 else 0 END) as TouchFinancialMoments,
              Sum (case when ([EventValue] = 'Selected screen: 9' and [AdditionalValue]
= 'Duurzame momenten')    then 1 else 0 END) as TouchEcoMoments,
              Sum (case when [EventValue] = 'Selected screen: 4' then 1 else 0 END) as
TouchComsumption,
              Sum (case when [EventValue] = 'Selected screen: 5' then 1 else 0 END) as
TouchProduction,
              Sum (case when [EventValue] = 'Selected screen: 11' then 1 else 0 END) as
TouchProgressgoals,
              Sum (case when [EventValue] = 'Selected screen: 12' then 1 else 0 END) as
TouchWeather,
              Sum (case when [EventValue] = 'Selected screen: 13' then 1 else 0 END) as
TouchNetusage,
              Sum (case when [EventValue] = 'Selected screen: 6' then 1 else 0 END) as
TouchJobs,
              Sum (case when [EventValue] = 'Selected screen: 20' then 1 else 0 END) as
TouchMessageOverview,
              Sum (case when [EventValue] = 'Selected screen: 3' then 1 else 0 END) as
TouchSettings,
              Sum (case when [EventValue] = 'Selected screen: 7' then 1 else 0 END) as
TouchJob,
              Sum (case when [EventValue] = 'Selected screen: 2' then 1 else 0 END) as
TouchCurrentStatus,
              Sum (case when [EventValue] = 'Selected screen: 17' then 1 else 0 END) as
TouchAppliance,
              Sum (case when [EventValue] = 'Selected screen: 15' then 1 else 0 END) as
TouchMaintenance,
              Sum (case when [EventValue] = 'Selected screen: 16' then 1 else 0 END) as
TouchApplianceMaintanaince,
              Sum (case when [EventValue] = 'Selected screen: 8' then 1 else 0 END) as
TouchProfile,
              Sum (case when [EventValue] = 'Selected screen: 21' then 1 else 0 END) as
TouchMessage,
              Sum (case when [EventValue] = 'Selected screen: 10' then 1 else 0 END) as
TouchGoal,
              Sum (case when [EventValue] = 'Selected screen: 17' then 1 else 0 END) as
TouchAppliance,
              Sum (case when [EventValue] = 'Selected screen: 14' then 1 else 0 END) as
TouchStatus,
              Sum (case when [EventValue] = 'Selected screen: 18' then 1 else 0 END) as
TouchBackup,
              Sum (case when [EventValue] = 'Selected screen: 19' then 1 else 0 END) as
TouchSaver,
              Sum (case when [EventValue] = 'Selected screen: 22' then 1 else 0 END) as
TouchTunnel,
              Sum (case when [EventValue] = 'Selected screen: 23' then 1 else 0 END) as
TouchDryer,
              Sum (case when [EventValue] = 'Job Selected' then 1 else 0 END) as
TouchJobSelected
  FROM [dbo].[DisplayUsageFacts]
  where ([DateTime] between '2013-03-01' and '2013-07-01') and [EventCode] = '1'
  Group by [HouseDimension_Id]
  order by [Housedimension_Id]
GO
```

HEMS profile Selection

```
SELECT [SelectedEnergyProfile]
      ,[HouseDimension_Id]
      ,cast ([DateTime] as Date)
      ,[DateDimension_Id]
      ,[SelectedEnergyProfileName]
  FROM [dbo].[ResidentProfileFacts]
  where ([DateTime] between '2013-01-01' and '2013-07-01')
GO
```

Relative Value

```
SELECT avg ([RelativeValue])
      ,[PeriodDimension_Id]
  FROM [dbo].[PricePlanFacts]
  where ([datetime] between '2013-01-01'and '2013-07-01')
  group by [PeriodDimension_Id]
GO
```

Reference Group analysis

Cable 2

```
USE [CemsResearch]
GO

SELECT [PowerApparentTotal]
      ,[CableData_Id]
      ,[DateDimension_Id]
      ,[PeriodDimension_Id]
      ,[DateTime]
  FROM [dbo].[CableFacts]
  where ([datetime] between '2013-01-01' and '2013-07-01') and ([cabledata_id] = 2)
and ([PowerApparentTotal] between 25495305 and 65675549)
  GO


Cable 9
USE [CemsResearch]
GO

SELECT [PowerApparentTotal]
      ,[CableData_Id]
      ,[DateDimension_Id]
      ,[PeriodDimension_Id]
      ,[DateTime]
  FROM [dbo].[CableFacts]
  where ([datetime] between '2013-01-01' and '2013-07-01') and ([cabledata_id] = 9)
and ([PowerApparentTotal] between 6180000 and 15780000)
  GO
```