Technische Universiteit Delft

The Financial Feasibility of Flexibility Expansion

An Emperical Analysis on the Financial Feasibility of Demand Side Management for the Aggregator

M.Sc. Thesis - Engineering and Policy Analysis

Steven Jongerden

TU Delft essent

The Financial Feasibility of Flexibility Expansion

An Empirical Analysis on the Financial Feasibility of Demand Side Management for the Aggregator

By

Steven Jongerden

A Research Thesis Submitted to the Department of Engineering Systems and Services in Partial Fulfilment for the degree of

Master in Science
in Engineering and Policy Analysis

at the Faculty Technology, Policy and Management
Delft University of Technology

to be defended publicly on Monday August 8th, 2016 at 16:00

Student number:	4389409	
	s.jongerden@student.tudelft.nl	
Date:	08-08-2016	
Chair:	Prof. Dr. K. Blok	Delft University of Technology
1st Supervisor:	Dr. Ir. P.W. Heijnen	Delft University of Technology
2nd Supervisor:	Dr. D.J. Scholten	Delft University of Technology
Company supervisor:	Ir. E. Woittiez	Essent

TU Delft


TU Delft

Acknowledgement

The moment I write this sentence I spend 600 hours writing this document, conveying my message through the 55219 words. It has been a long journey, coming from the lowest level this education system has to offer, working my way up to the highest education level that same education level can offer. It is sometimes hard to imagine, that I might achieve something that was always believed to be out of reach. I can only thank my family and my close friends that have always believed in me, and pushed me to pursue beyond my current achievements. My mother who always supported my ambition to pursue higher levels of education and assisted me throughout the years, and Rob van Gameren, who always challenged my thinking and ideas, and stimulated me to pursue my Masters. Last, my grandfather, who's soul shall rest in peace, who always convinced me to never give up, as he would say '*Wat een ander kan, dat kan jij ook*'.

In order to have made it this far within my Master's at the Delft University of Technology, I would first like to thank Essent, and especially Eric Woittiez and Rudolph Harmsen, for the project assignment and their supervision during the project. From my graduation committee I would like to extend my gratitude to Prof. Dr. K. Blok for chairing my thesis and Dr. D.J. Scholten as my second supervisor. Especially I would like to thank Dr. Ir. P.W. Heijnen for bringing me in contact with Essent, and second for her comments and feedback on my work.

Last and most, I would like to thank my partner for her endless support during my Masters. Without her I would not have been able to work as hard as I did and been able to reach this point today. Her love and care allowed me to go beyond my own abilities, and become the person I am today.

Steven Jongerden

Executive Summary

Introduction

High oil prices and the desire to reduce the overall CO_2 output is creating a shift in electricity generation. Originally, electricity was produced by centralized power plants, where nowadays more and more electricity is produced decentralized, by for example solar panels that are installed on households roofs. Due to the use of these solar panels, which production is very dependent on the sun, a mismatch between the supply and demand of electricity emerged. As a result of this mismatch, the electricity grid is confronted with network congestion and balancing problems. In order to resolve such balancing problems and threats of network congestion, direct load control Demand Side Management (DSM) was introduced as a possible solution. This control mechanism (DSM) allows a third party (the Aggregator) to control appliances within the households in order to regulate the load of these households on the electricity network. By controlling these household appliances, the Aggregator provides an electricity flexibility service to the Balance Responsible Party (BRP) (such as Essent, Eneco and Vattenfall) and the Distribution System Operator (DSO) (such as Alliander, Stedin and Enixis). The BRP is interested in procuring electricity flexibility from the Aggregator to maintain the balance between electricity demand and supply, and the DSO in order to reduce grid congestion and prevent system overload (in order to prevent electricity system blackouts). However, as the effect of such a control mechanism on the electricity grid is uncertain (for example due to the available electricity flexibility, the participation of the DSO, etc.), Essent (a BRP and energy supplier) and Alliander (a DSO) are currently performing a field trial in Heerhugowaard. Within this field trial, 201 households are equipped with solar panels, heat pumps, fuel cells and electric boilers, and directly controlled by the Aggregator. Nevertheless, before such a control mechanism can be employed on a large scale, uncertainties with regards to the financial feasibility of the Aggregator must be alleviated. The theoretical body of knowledge on the financial outcome of DSM for the Aggregator is inconclusive, due to the uncertain:

1. Cost of control technology for direct load control DSM
2. The availability of electricity flexibility
3. The influence of additional electricity flexibility on the spot market price
4. The non-extendibility of the results from other foreign large scale DSM feasibility studies to the Netherlands.

Consequently, the research performed within this thesis focussed on the financial feasibility of the expansion of direct load control DSM projects for the Aggregator within the Netherlands, by means of the following research question:

How does the electricity flexibility availability and trading, provided by direct load control Demand Side Management, influence the financial feasibility for the Aggregator, based on the Heerhugowaard field trial?

Methodology

In order to answer this research question, this thesis first examined direct load control DSM and the financial feasibility for the Aggregator by means of a literature review of for example Gellings (1981) and Strbac (2005) in chapter 2. Afterwards, in order to determine the financial feasibility of DSM for the Aggregator, a simulation model was constructed that replicates the electricity flexibility trade process between the Aggregator, DSO and BRP. In order to construct this simulation model, literature research was performed to determine factors that influence the output of the controllable household appliances in chapter 3. Thereafter, based on these insights, prediction models were constructed based on the data collected from the Heerhugowaard field trial, as a sufficient large data set was available for all the household appliances. These prediction models were constructed through various statistical techniques (panel data regression, logistics regression and simulation) for the Photovoltaic panels, Heat Pumps, and Electric Boilers in chapter 5. No prediction model was constructed for the Fuel Cell, as the outcome of the Fuel Cell is not influenced by outside factors. Last, the predictions models were combined with a set of household electricity load curves in an excel spreadsheet in order to replicate the electricity flexibility trade process. Based on this simulation model a volume optimization analysis was performed (chapter 6) in order to determine the preferred smart appliances for an Aggregator, and a financial analysis in order to determine the financial outcome of direct load control DSM for the Aggregator (in chapter 7).

Conclusions Volume Optimization

Conclusions Financial Feasibility for the Aggregator

Table of Content

1 **Introduction** ... 1
1.1 The Research Problem ... 1
1.2 Research Questions ... 3
1.3 The Scientific and Social Justification ... 3
1.3.1 Scientific Relevance ... 3
1.3.2 Social Relevance ... 4
1.4 Proposed Research Design ... 4
1.5 Thesis Outline ... 4

2 **Demand Side Management** ... 7
2.1 The Development of Demand Side Management ... 7
2.1.1 Indirect Load Control ... 9
2.1.2 Direct Load Control ... 10
2.2 The Introduction of the Role of the Aggregator ... 10
2.3 A Review of the Financial Feasibility of the Aggregator ... 11
2.4 A Practical Application of Demand Side Management ... 11
2.4.1 The Heerhugowaard Field Trial ... 12
2.4.2 Electricity Flexibility Trading with the BRP and DSO through USEF ... 12
2.4.3 The Compensation Scheme for the Aggregator ... 14

3 **Electricity Flexibility** ... 19
3.1 Electricity Flexibility from Smart Appliances ... 19
3.2 Potential Factors that Influence the Available Electricity Flexibility ... 21
3.2.1 The Available Electricity Flexibility from the Photovoltaic Panels ... 21
3.2.2 The Available Electricity Flexibility from the Electric Boilers ... 21
3.2.3 The Available Electricity Flexibility from the Heat Pumps ... 22
3.2.4 The Available Electricity Flexibility from the Fuel Cells ... 23
3.3 Hypothesized Causal Model for the Available Electricity Flexibility ... 24

4 **Methodology** ... 27
4.1 Research Design ... 27
4.1.1 Qualitative Research ... 27
4.1.2 Quantitative Research ... 28
4.2 The Sampling Frame ... 30
4.3 The Sampling Technique ... 30
4.4 Population ... 31
4.4.1 The Heerhugowaard Field Trial Sample Population ... 31
4.4.2 The Demographics of the Target Population ... 31
4.5 The Generalizability of the Results ... 32
4.5.1 The Representativeness of the Sample ... 32
4.5.2 The Effect from the Sample Size on the Confidence Levels ... 35
4.6 The Data Collection Procedure ... 36
4.7 Data Processing ... 36
4.7.1 Data Sources ... 36
4.7.2 Data Preparation ... 37
4.7.3 Outlier removal and Missing Values ... 37
4.7.4 Time verification with external sources ... 37
4.7.5 Software ... 38

5 Predicting the Available Electricity Flexibility ... 41
5.1 An Introduction to Panel Data Regression ... 41
5.1.1 Fixed Effects and Random Effects ... 42
5.1.2 The Assumptions for Fixed and Random Effects ... 43
5.2 Bivariate Analysis ... 45
5.2.1 Bivariate Analysis for Photovoltaic Output ... 45
5.2.2 Bivariate Analysis for Warm Water Consumption ... 46
5.2.3 Bivariate Analysis for Heat Pump Load ... 46
5.3 Smart Appliance Electricity Flexibility ... 47
5.3.1 Predicting the Available Electricity Flexibility from Photovoltaic Panels ... 47
5.3.2 Predicting the Available Electricity Flexibility from the Electric Boiler ... 50
5.3.3 Predicting the Available Electricity Flexibility from the Heat Pump ... 54
5.4 The Smart Appliance Electricity Flexibility Prediction Models ... 58
6 Electricity Flexibility Trade Optimization ... 61
6.1 The Influence of the Appliance Mix ... 61
6.2 A Theoretical Electricity Distribution Grid ... 62
6.2.1 Dutch Household Load Curves ... 62
6.2.2 Low Voltage Congestion Limits ... 62
6.3 Optimization of the Appliance Mix ... 62
6.3.1 An Introduction to Numeric Optimization ... 62
6.3.2 Assumption for the Non-Linear Optimization ... 63
6.3.3 Optimization for the DSO ... 63
6.3.4 Optimization for the BRP ... 65
6.3.5 Optimization for the BRP and DSO ... 66
6.4 Optimization Results ... 68
7 The Financial Outcome and Uncertainty of Electricity Flexibility Expansion for the Aggregator ... 71
7.1 The Financial Outcome of DSM for the Aggregator ... 71
7.1.1 An Introduction to the Stroomversnellings Project ... 71
7.1.2 A Financial Analysis Simulation Model ... 72
7.1.3 The Financial Outcome of Flexibility Trading for a Stroomversnellings Project ... 73
7.1.4 The Financial Outcome of Flexibility Trading with the Optimized Configuration Mix ... 78
7.2 The Uncertainties of Flexibility Expansion ... 80
7.2.1 Future Trends Influencing the Financial Outcome of Demand Side Management for the Aggregator 80
7.2.2 Scenario Analysis ... 83
7.3 The Financial Prospect of Electricity Flexibility for the Aggregator ... 86
7.4 A Reflection on the use of Field Trial Data ... 87
8 Conclusions and Recommendations ... 89
8.1 Conclusion ... 89
8.1.1 The Availability of Electricity Flexibility ... 89
8.1.2 The Smart Appliance Configuration ... 90
8.1.3 The Financial Feasibility of Demand Side Management ... 90
8.2 Limitations ... 91
8.3 Reflection on the Scientific Body of Knowledge ... 92
8.4 Recommendation for Further Research ... 93
9 References ... 95
10 Appendix List ... 100

Table of Figures

Figure 1: DMS Concepts: Peak clipping, Valley filling and Load shifting 8
Figure 2: DSM Concepts: Strategic conservation, Strategic load growth and Flexible load shape........ 9
Figure 3: Hierarchical Load Control........ 10
Figure 4: The USEF Electricity Flexibility Supply Chain........ 12
Figure 5: The USEF Market-Based Coordination Mechanism (USEF Foundation, 2014)........ 13
Figure 6: Different types of Electricity Flexibility........ 20
Figure 7: Hypothesized Causal model for the Available Electricity Flexibility........ 24
Figure 8: The Research Flowchart 29
Figure 9: Age Distribution........ 33
Figure 10: Number of Individuals per Household 33
Figure 11: Education Distribution........ 33
Figure 12: Energy Class Distribution........ 34
Figure 13: Household Type........ 34
Figure 14: The Population Size for various Confidence Intervals 35
Figure 15: UML Overview of the SESP – Prosumers Interface (based on Koenders (2014))........ 36
Figure 16: Actual versus Predict Photovoltaic Power Output per Hour........ 50
Figure 17: Liter Hot Water Consumption from a random household at a random period of time........ 50
Figure 18: Daily Average Hot Water Consumption Per Capita (from 100 random samples)........ 52
Figure 19: Daily Cumulative Hot Water Consumption Frequency Comparison........ 53
Figure 20: The Available Electricity Flexibility of the Electric Boiler........ 53
Figure 21: The Percentage of Heat Pump Load Observed........ 54
Figure 22: The Relationship between ρ^2 and R^2 55
Figure 23: The Probability of Heat Pump Load for Air Heating over the year 56
Figure 24: The Heat Pump Load (Wh) over a year........ 57
Figure 25: The Average Electricity Flexibility Up from the EB and PV over a day 61
Figure 26: The Average Electricity Flexibility Down from the FC and HP over a day........ 61
Figure 27: The Effect of the Photovoltaic System Capacity on the required number of Controllable Photovoltaic Systems 65
Figure 28: A Boxplot of the APX price (€/MWh) of the year 2015 over a day........ 65
Figure 29: The Aggregator Profit per Household per Year, sorted from least to most for the Stroomversnellings project........ 74
Figure 30: The Sensitivity of the Profits per Household per year to changes in the Photovoltaic system capacity..... 75
Figure 31: The Sensitivity of the Profits per year to changes in the Photovoltaic system capacity........ 75
Figure 32: The Sensitivity of the Profits per Household per year to changes in the Congestion Limit 76
Figure 33: The Sensitivity of the Profits per year to changes in the Congestion Limit 76
Figure 34: The Sensitivity of the Profits per Household per year to changes in the Aggregator Margin 76
Figure 35: The Sensitivity of the Profits per year to changes in the Aggregator Margin 76
Figure 36: The Sensitivity of the Profits per Household per year to changes in the Variable Cost........ 77
Figure 37: The Sensitivity of the Profits per year to changes in the Variable Cost........ 77
Figure 38: The Aggregator Profit per Household per Year, sorted from least to most for two case studies........ 78
Figure 39: The Yearly Electricity Flexibility Traded........ 79
Figure 40: The Transition of the Profits per Household per Year for DSM with DSO Ordering - Stroomversnelling 84
Figure 41: The Transition of the Profits per Household per Year for DSM without DSO Ordering – Stroomversnelling........ 84
Figure 42: The Transition of the Profits per Household per Year for DSM with DSO Ordering – Optimized Configuration........ 85
Figure 43: The Transition of the Profits per Household per Year for DSM without DSO Ordering – Optimized Configuration........ 85

Figure 44: The Causal Map Diagram for the Available Electricity Flexibility 101
Figure 45: The sampling locations 102
Figure 46: The Bivariate Relation between *PV-Power* and *SunAzimuthFrom180* 103
Figure 47: The Bivariate Relation between *PV-Power* and *PV-CapacityIrradianceState* 103
Figure 48: The Bivariate Relation between *PV-Power* and *Irradiance* 104
Figure 49: The Bivariate Relation between *PV-Power* and *PV-Capacity* 104
Figure 50: The Bivariate Relation between *PV-Power* and *Humidity* 105
Figure 51: The Bivariate Relation between *PV-Power* and *ElevationAboveHorizon* 105
Figure 52: The Bivariate Relation between *PV-Power* and *Temperature* 106
Figure 53: The Bivariate Relation between *PV-Power* and *SunAzimuthFrom180* Corrected 106
Figure 54: The Bivariate Relation between *PV-Power* and *PV-CapacityIrradianceState* Corrected 107
Figure 55: The Bivariate Relation between *PV-Power* and *Irradiance* Corrected 107
Figure 56: The Bivariate Relation between *PV-Power* and *Humidity* Corrected 108
Figure 57: The Bivariate Relation between *PV-Power* and *ElevationAboveHorizon* Corrected 108
Figure 58: The Normality Plot for the Residuals from the Photovoltaic Linear Prediction 111
Figure 59: The Bivariate Relation between *Hot Water Consumption* and *Temperature* 112
Figure 60: The Bivariate Relation between *Heat Pump Load* and *Temperature* 113
Figure 61: The Bivariate Relation between *Heat Pump Load* and *Irradiance* 113
Figure 62: The Bivariate Relation between *Heat Pump Load* and *StateSESP* 114
Figure 63: The Bivariate Relation between *Heat Pump Load* and *Windspeed* 114
Figure 64: A Boxplot of the Imbalance price (€/MWh) of the year 2015 over a day 116
Figure 65: Traded Electricity Flexibility Up 117
Figure 66: Traded Electricity Flexibility Down 117
Figure 67: Flex Order from the BRP 121
Figure 68: Flex Orders from the DSO 121
Figure 69: The Sensitivity of the Profits per Household per year to changes in the Congestion Limit 123
Figure 70: The Sensitivity of the Profits per Year to changes in the Congestion Limit 123
Figure 71: The Sensitivity of the Profits per Household per year to changes in the Aggregator Margin 123
Figure 72: The Sensitivity of the Profits per Year to changes in the Aggregator Margin 123
Figure 73: The Sensitivity of the Profits per Household per year to changes in the Variable Cost 124
Figure 74: The Sensitivity of the Profits per Year to changes in the Prosumer Margin 124
Figure 75: The Sensitivity of the Profits per Year to changes in the Variable Cost 124
Figure 76: The Sensitivity of the Profits per Household per year to changes in the Prosumer Margin 124
Figure 77: The Confidence Interval for various Population sizes dependent on the Sample size 125

Table of Tables

Table 1: Smart Appliances in the Field Trial (Energiekoplopers, 2015; Inventum, 2015) 12
Table 2: The Electricity Flexibility Prices (€/kWh) for the BRP and DSO 15
Table 3: Electricity Flexibility in the Energy System 19
Table 4: The Sampling Locations in Heerhugowaard (Energiekoplopers, 2015) 30
Table 5: The Level of Measurement for Demographic Comparison 31
Table 6: Goodness of Fit Test Demographics 33
Table 7: Rejected Households 37
Table 8: Photovoltaic Hypothesized Exploratory Variable Transformation 46
Table 9: Pearson's Correlation Coefficients for the Hypothesized Photovoltaic Relations 46
Table 10: Heat Pump Hypothesized Exploratory Variable Transformation 47
Table 11: Pearson's Correlation Coefficients for the Hypothesized Heat Pump Relations 47
Table 12: Random Effects Regression for PV-Output (α 0.05) 48
Table 13: Zero Conditional Mean for u_i and a_i for PV-Output 48
Table 14: VIF Analysis for PV-Output 48
Table 15: Driscoll and Kraay correction for PV-Output 49
Table 16: Characteristics of the Electric Boiler 53
Table 17: Logit Panel Regression Estimation 55
Table 18: Standardized Beta Coefficients 58
Table 19: Assumptions for the Optimization Analysis 63
Table 20: Optimization for the DSO 64
Table 21: Optimization for the BRP and DSO for 100 households 67
Table 22: Optimization for the BRP and DSO for 500 Households 67
Table 23: Optimization for the BRP and DSO for 100 Households with 0% Fuel Cell 67
Table 24: Optimization for the BRP and DSO for 500 Households with 0% Fuel Cell 67
Table 25: Optimization for the BRP and DSO for 100 Households with 0% Fuel Cell and 50% Photovoltaic systems 68
Table 26: Optimization for the BRP and DSO for 500 Households with 0% Fuel Cell and 50% Photovoltaic systems 68
Table 27: Assumption for the Financial Simulation Model 72
Table 28: The Breakeven Configuration for the Aggregator 74
Table 29: The Sensitivity of the Financial Outcome of the Stroomversnelling configuration to changes in the Control Variables from the Initial Situation 77
Table 30: The Sensitivity of the Financial Outcome of the Optimized Configuration to Changes in the Control Variables from the Initial Situation 79
Table 31: Contextual Factors influencing the Financial Outcome of DSM for the Aggregator (Schoots & Hammingh, 2015) 81
Table 32: Classification of Contextual Factors 82
Table 33: The Percentual Change in the APX, Electricity and Gas Price 83
Table 34: Possible Scenarios for the Scenario Analysis of the Financial Outcome of DSM for the Aggregator 83
Table 35: Independent Variable Units 115
Table 36: Statistical Results from the PV, EB Flex Trade Comparison 117
Table 37: The Profits per Household per Year under Different Sized Household Groups 119
Table 38: The Profits per Year under Different Sized Household Groups 119

1

1 Introduction

Countries have become highly dependent on oil as 70% of the world's energy is produced by means of fossil fuel (Warren, 2014). Power plants that use fossil fuel are large contributors (37.5%) to worldwide carbon emissions (Sims, Rogner, & Gregory, 2003). As a result of the agreements made during the Kyoto summit in 1997 and during the Sustainable Innovations Forum in 2015, EU countries have invested significantly in expanding their share of renewable energy generation (Menegaki, 2011). Therefore, shifting to renewable energy generation has moved to the forefront of the Dutch political agenda (Sociaal Economische Raad, 2013). In the Energy Agreement for Durable Development, parties have agreed to increase the generation of renewable energy from the current 4%, to 14% in 2020, and further to 16% in 2023 (Sociaal Economische Raad, 2013). However, these renewable energy sources do not provide a stable and predictable output as conventional power plants do, because their level of output is highly dependent on for example sun irradiance. This increase in local renewable energy generation and the fluctuating output from these energy sources, aggravated the existing mismatch between electricity supply and demand. As a result of this mismatch, electricity grids are confronted with network congestion and balancing problems, where these problems are currently resolved by an increase of power plants reserve capacity. Consequently, higher levels of reserve capacity led to lower utilization of power plants and through higher marginal cost of generation to higher prices of electricity (Strbac, 2008). Since the objective of the Energy Agreement for Durable Development was not only the reduction of emission but also to provide electricity affordability and consequently electricity security, the Dutch government is challenged to find additional measures to this problem (Sociaal Economische Raad, 2013).

A possible solution for this mismatch and for the higher electricity prices, was already mentioned in the Energy Agreement for Durable Development (Sociaal Economische Raad, 2013) and discussed years ago, when the Electric Power Research Institute in 1984 introduced Demand Side Management (DSM). Gellings (1996) described DSM as "*…designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape…*" (p. 285). Projections indicate that DSM would allow better synchronization between electricity demand and supply and thereby provide a partial solution to these higher levels of power plant reserve capacity and network congestion (Negnevitsky, Nguyen, & de Groot, 2010; Babar, Taj, Ahamed, & Al-Ammar, 2013). However, there is currently little proof on what the effects from DSM applications might be on the electricity grid. Therefore, the Dutch government would like to see experiments, in collaboration with the electricity sector, that provide insight into DSM and if DSM should be applied on a larger scale (Sociaal Economische Raad, 2013).

Consequently, this chapter will first elaborate on one of the uncertainties related to the application of DSM innovations within the Netherlands in section 1.1. Based on this research problem the chapter will introduce the research question and further divide the described problem in sub-research questions in section 1.2. Then, the chapter indicates the relevance of the study in section 1.3. Based on these sub-research question a research design is proposed, and last the chapter proposes an outline for the thesis in section 1.4.

1.1 The Research Problem

DSM was initially developed for two reasons: to optimize the supply demand interface (balancing activities) and to introduce a new marketing utility (an incentive based marketing model to offset the peak demand). As DSM started to receive more attention, more DSM alternatives, such as load management, strategic conservation and consumer generation, evolved (Strbac, 2008). This development enabled the control of consumer electricity demand and the possibility to shift the demand for electricity from high peaks to low peaks of demand (Gellings, 1996; Negnevitsky, Nguyen, & de Groot, 2010). This balancing mechanism is referred to as Demand Response (DR), which provides electricity 'flexibility' (Eurelectric. , 2015), that is described as: "*the ability to vary the performance characteristics or resources to maintain a balanced and efficient power system*" (Mohler & Sowder, 2014, p. 285). To create electricity flexibility within DSM, two control mechanism, referred to as direct and indirect load control, are used.

In-direct load control is a medium to long term approach to change the consumer's electricity **consumption** by means of financial incentives. This is achieved by means of electricity price negotiation on the electricity trading market, and by reimbursing consumers in the form of electricity rate discounts or direct payments (Strbac, 2008). However, Torriti, Hassan and Leach (2010) argue that there has been an observation that "*customer[s] lack means and [that only a] limited number of incentives are in place to respond to change[s] in prices*" (p. 1581). Additionally, there is still a great deal of uncertainty on the relation between the responses to changes in electricity prices and actual electricity demand. This uncertainty makes it hard to determine if in-direct load control is really as effective as governments tend to believe (Gillingham, Rapson, & Wagner, 2014).

Within direct load control, smart appliances such as (but not limited to) solar panels, heat pumps, natural gas electricity generators and electric boilers, are installed within households. Through the control of these smart appliances, the system operator is able to dynamically control loads (heat pump, boiler) and energy sources (solar panels and natural gas electricity generators) permitting flexible **demand and local supply adjustments**, resulting in lower demand for reserve capacity, and consequently, lower electricity prices and network congestion (Warren, 2014; Behrangrad, 2015).

As a consequence of the application of direct load control, a transition occurred from only electricity demand to electricity demand and electricity supply, resulting in the transformation from consumers to prosumers, a combination of consumers and producers. The creation of this new party and the establishment of a bi-directional electricity grid, required a new approach to optimally integrate new electricity and electricity flexibility into the electricity system (USEF Foundation, 2014). Therefore, the USEF Foundation (2014) developed the Universal Smart Energy Framework (USEF) to support the integration of flexibility into the electricity market.

One of the accompaniments of direct load control is the introduction of the Aggregator within the electricity system, a party that is responsible for maximizing the value of electricity flexibility generated by the prosumers. The Aggregator performs the maximization of the value of flexibility by taking into consideration prosumers' needs, economic optimization and the electricity grids' capacity. Thereby, the Aggregator directly represents the prosumers on the electricity market and trades electricity flexibility, for example, with the Balance Responsible Party (BRP) and the Distribution System Operator (DSO) (USEF Foundation, 2014). Within this trade, the BRP is interested in procuring flexibility to "*maintain a continuous balance between their clients' electricity demand and the electricity produced*" (USEF, 2014, p. 9), while the DSO is interest in procuring flexibility to reduce grid congestion and prevent system overload (USEF, 2014). Consequently, the contribution of the Aggregator solves the complexity of contracts in the balancing mechanism and the ambiguity on how to involve consumers into the capacity market (Warren, 2014). Additionally, if the flexibility would be offered by independent households to the wholesale electricity market, these households would have little transaction freedom. The addition of the Aggregator allows prosumers to pool available flexibility and gain additional bargaining power on this electricity market (Alizadeh, Li, Wang, Scaglione, & Melton, 2012). Consequently, the Aggregator ensures that, within the particular context of direct load control, flexibility can be traded between the prosumers and the BRP and DSO, and enables demand and local supply adjustments. However, it remains unclear if there is a financial benefit for the Aggregator when the Aggregator takes the role of energy aggregation and trading. Therefore, the Dutch government is financing multiple experiments through the *Innovatieprogramma Intelligente Netten* subsidy, where Essent (a BRP and energy supplier) and Alliander (a DSO) are currently performing such an experiment in Heerhugowaard, and are trying to determine the effect of direct load control DSM on the electricity grid. Within this experiment 201 households are equipped with smart appliances such as Photovoltaic panels, Heat Pumps, Fuel Cells and Electric Boilers, and directly controlled by the Aggregator (USEF, 2014).

Throughout the years, due to innovations in technology and electrification, the role of the Aggregator is urgently becoming more important. Consequently, research has been performed on the cost and benefits of DSM implementations. Initially, in the late 1990, a CBA by Byrne et al. (1996) on five different DSM applications within different parts of the USA, and a CBA by Reddy and Parikh (1997) on twelve DSM applications within India, indicated that the cost of DSM at that point would exceed the benefits. However, recent CBA by Sheen (2005), Weigt (2009), Liu, Xu and Wang (2015) on DSM applications in Taiwan, Germany and China respectively, indicate that DSM has become financially feasible. Furthermore, research from Hull (2001) and Lambert (2012) indicate that not only DSM has become financially feasible but also the role of the Aggregator. However, the financial feasibility of the Aggregator is uncertain due to the cost of direct control technology, the availability of electricity flexibility and the influence of additional electricity flexibility on the spot market price.

Even when a number of case studies and research indicates that the role of the Aggregator might be financially feasible, Torriti, Hassan and Leach (2010) mention that it is not possible to extend such results to other countries, and that only insights can be gained through a real application of DSM (Lambert, 2012). Therefore, due to the non-extendibility of the financial feasibility of the Aggregator in large scale direct load control DSM applications, organizations that are investigating the roll of the Aggregator are unaware of the financial feasibility of DSM and subsequently hesitant to implement DSM on a larger scale in the Netherlands. Therefore, taking into consideration the importance of the role of the Aggregator in the success of DSM and the further integration of renewable electricity sources into the electricity network, research should be performed on the financial feasibility for the Aggregator, in order to eliminate possible uncertainties of DSM before direct load control can be fully implemented on a larger scale and be integrated in the electricity grid.

1.2 Research Questions

To support the further integration of renewable energy sources into the electricity grid and consequently prevent congestion and supply and demand mismatches, DSM might be expanded to constitute larger groups of households. However, due to the uncertain cost of control technology, the availability of electricity flexibility, the influence of additional electricity flexibility on the spot market price, and the non-extendibility of the results from other large scale feasibility studies to the Netherlands, the financial feasibility of the Aggregator within the Netherlands remains uncertain. Therefore, this thesis proposes the following research question with the aim to determine the financial feasibility of direct load control DSM for the Aggregator within the Netherlands:

Main research question:

How does the electricity flexibility availability and trading, provided by direct load control Demand Side Management, influence the financial feasibility for the Aggregator, based on the Heerhugowaard field trial?

Sub questions:

1. What is Demand Side Management and how is Demand Side Management applied in the Heerhugowaard field trial?
2. What is the role of the Aggregator in Demand Side Management and how is this role applied in the Heerhugowaard field trial?
3. What is electricity flexibility and how is electricity flexibility traded in the Heerhugowaard field trial?
4. What are potential factors (weather, people per household etc.) that influence the available electricity flexibility within Demand Side Management applications?
5. To what extent are the results from the Heerhugowaard field trial generalizable for the expansion of Demand Side Management to more households in the Netherlands?
6. What type of model can predict the available electricity flexibility when Demand Side Management is expanded to more households within the Netherlands?
7. What is the relationship between the potential factors that predict the available electricity flexibility and the measured available electricity flexibility?
8. Which configuration of smart appliances, used in the Heerhugowaard field trial, results in the maximization of electricity flexibility trading for the Aggregator?
9. What is the financial outcome and uncertainty of Demand Side Management expansion within the Netherlands for the Aggregator, taking into consideration the appliances used in the Heerhugowaard field trial?

1.3 The Scientific and Social Justification

The relevance of performing research on the financial feasibility for the Aggregator when DSM is expanded to more households can be divided into: Scientific and Social relevance, and will be elaborated on further respectively:

1.3.1 Scientific Relevance

Literature (Byrne, Letendre, Govindarajaly, Wang, & Nigro, 1996; Reddy & Parikh, 1997; Sheen, 2005; Weigt, 2009; Liu, Xu, & Wang, 2015; Hull, 2001; Lambert, 2012) indicate that research has been performed on the costs and benefits of DSM and the financial feasibility of the Aggregator. However, due to the uncertain cost of control technology, the availability of electricity flexibility, the influence of additional electricity flexibility on the spot market price, and the non-extendibility of the results from other large scale feasibility studies to the Netherlands, the financial feasibility of large scale direct load control DSM applications within the Netherlands remains uncertain for the Aggregator (Torriti, Hassan, & Leach, 2010). Accordingly, research on the financial feasibility of DSM for the Aggregator in the Netherlands will lead to an extension of knowledge on the role of the Aggregator within the application of DSM. Possible insights gained from this analysis adds to the scientific body of knowledge and might assist in further substantiating the financial certainty with respect to the possibility for organizations to pursue a role as an Aggregator, and consequently, allow for the further integration of renewable energy sources into the electricity grid.

1.3.2 Social Relevance

The addition of the Aggregator to DSM ensures that flexibility can be traded between the prosumers (and possibly industry) and the BRP and DSO (and possibly the TSO), enabling demand and local supply adjustments, and providing a possible solution to demand and supply mismatches and grid congestion (Alizadeh, Li, Wang, Scaglione, & Melton, 2012). Therefore, the role of the Aggregator is essential to the application of DSM and an enabler for the further integration of renewable energy into the electricity network. However, due to the various reasons mentioned earlier, parties that are investigating the roll of the Aggregator, are unaware of the financial feasibility of DSM applications and subsequently hesitant to implement DSM on a larger scale. Therefore, to enable further application of DSM and enable further growth of renewable electricity sources in the electricity system without electricity network congestion and supply and demand mismatches, research should be performed on the financial feasibility for the Aggregator. Additionally, when the role of the Aggregator can be integrated within the electricity system, the trade of electricity flexibility may result in financial benefits for Prosumers, as prosumers are financially remunerated for the participations within the electricity flexibility service. Consequently, a second social relevance is that the application of DSM might results in a financial saving for Prosumers within the electricity system under control of an Aggregator.

1.4 Proposed Research Design

In order to provide answers to the stated main research question in section 1.2, a research design will be followed in order to provide answers to the sub-research questions as unambiguously as possible. To answer the first three sub-research questions, literature research will be employed as the current scientific body of knowledge provides sufficient insights on the use of DSM, as for example Gellings (1981) and Strbac (2008). For sub-research question 4, literature research will be performed for the appliances applied in the Heerhugowaard field trial, in order to uncover exogenous factors that might influence the functioning of these devices. Sub-research question 5 then moves to determine the effect from the sample size on the extendibility of the results, which can be addressed through statistical analysis and scientific literature, as for example Kruskal and Mosteller (1979). Sub-research question 6 and 7 then touch upon a more quantitative nature, where the relation between the exogenous variables and the output of the four smart appliances is determined. Through literature, as for example Wooldridge (2010; 2015), possible techniques are investigated, and employed on the data collected from the Heerhugowaard field trial. The techniques that will be employed are random effect panel data regression, logistics regression and statistical simulation through density distribution functions. Based on the prediction models estimated through the earlier mention techniques, electricity flexibility volume optimization is performed to determine if there is a preference for certain smart appliances within the context of USEF, which will be performed through experimental optimization as addressed by FrontlineSolver (2016). Last, in order to answer sub-research question 8, a simulation model will be constructed in order to determine the financial outcome of electricity flexibility trading for the Aggregator.

1.5 Thesis Outline

In order to present the analysis and outcome of the sub-research questions, leading to answering the main research question, in a structured manner, the outline proposed by Sekaran and Bougie (2012) is used within this thesis. Consequently, Chapter 2 will first present a literature review of DSM, the role of the Aggregator within DSM, and how DSM is currently employed within the Heerhugowaard field trial. Based on this review, Chapter 3 elaborates on electricity flexibility, as a result of direct load control DSM, and presents the potential factors that might have an influence on the available electricity flexibility. However, before analysis can be performed to determine if such potential factors statistically have a relation with the available electricity flexibility, analysis is performed on the generalizability of the data from the Heerhugowaard field trial. This analysis, in addition to the methodology is presented in Chapter 4. After that, in order to proof if these potential factors might have a relationship with the available electricity flexibility, Chapter 5 first discusses the selection of the statistical approach and secondly presents a multitude of statistical models that predict the electricity flexibility for the smart appliances. Based on these statistical models it is possible to determine the electricity flexibility over an entire year. With such an opportunity, one can question if the smart appliances used in the Heerhugowaard field trial configuration is optimal in contrast to the electricity demand and supply. Therefore, with the aim of addressing the alignment of the smart appliances with the demand and supply for electricity, Chapter 6 addresses the smart appliance configuration optimization. With this insight, and the available electricity flexibility prediction models, it is possible to analyse the financial outcome and uncertainty of electricity flexibility trading for the Aggregator within a multitude of scenarios. Subsequently, Chapter 7 addresses the financial outcome and uncertainty of DSM expansion, based on the analysis and outcomes of the previous chapters. In conclusion, chapter 8 present the conclusion of the analysis on the financial feasibility for DSM expansion for the Aggregator. In addition, Chapter 9 and 10 present the references and Appendix list of this thesis.


2

2 Demand Side Management

The term 'Demand Side Management' is a commonly used term in the energy domain but has been described differently over time. The most cited papers that address DSM refer to it as following: "*Demand Side Management commonly refers to programs implemented by utility companies to control the energy consumption at the costumer side of the meter*" (Mohsenian-Rad, Wong, Jatskevich, Schober, & Leon-Garcia, 2010, p. 320) or "*Demand Side Management includes everything that is done on the demand side of an energy system, ranging from exchanging old incandescent light bulbs to compact fluorescent lights, up to installing a sophisticated dynamic load management system*" (Palensky & Dietrich, 2011, p. 381). The differences in descriptions are not surprising as Nilsson (1994) already mentioned that DSM is confusing because of the different appearances DSM can take. To clarify the concept of DSM, section 2.1 first presents the development and the two approaches that enable DSM. The introduction of one of the concepts of DSM resulted in the establishment of supervisory control, which later in literature (Jose, Muller, & Royletman, 2010; Lazaros, Koutsopoulos, & Salonidis, 2013; Siano, 2014) is described as the role of Aggregator. Throughout time, this party has taken an important role in the execution of DSM and is consequently discussed in section 2.2. Even though the Aggregator takes such an important role in the DSM concept - direct load control - , limited research has been performed on the financial feasibility for this party. Therefore, section 2.3 investigates these sources in order to gain insights into earlier attempts to determine the financial feasibility of the role as an Aggregator. To further examine this role, among other research, two Dutch organizations (Essent and Alliander), are currently performing a DSM - direct load control - field experiment in Heerhugowaard. This field experiment might assist in shedding light on the financial feasibility of the Aggregator and is therefore introduced in section 2.4.

2.1 The Development of Demand Side Management

To supply electricity during peak loads, gas and oil power plants are presented into service, whereas nuclear and coal power plants provide the base load because these are considered to be more economical. Due to the significant increase in oil and gas prices over the last decades, the cost for peak demand has risen tremendously. To alleviate these higher costs, additional base load capacity might be constructed; however, the mere suggestion to construct a new coal or nuclear power plant draws vociferous discontentment. As a possible solution to these issues, Gellings (1981) coined the term 'Demand Side Management' which portrayed the shift from energy utilities into the, once forbidden, customer side of the meter (Gellings, 1996). The most accepted definition of DSM is as following:

> *"Demand-side management is the planning, implementation, and monitoring of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load share, i.e., changes in the time pattern and magnitude of a utility's load" (Gellings & Parmenter, 1988, p. 290).*

In order to fully capture the benefits that DSM might have to offer, DSM was integrated in electric utility planning and operation (Gellings & Smith, 1989). The connection between utility planning and DSM was also recognized by Gellings as he, in 1982, referred to DSM as 'demand-side planning' (Gellings & Parmenter, 1988). As part of energy planning, components that embrace the following aspects might be considered to be DSM (Gellings & Parmenter, 1988):

1. ***Demand side management will influence customer use***
   Programs that are considered to influence the customer's use of energy are considered DSM.
2. ***Demand side management must achieve selected objectives***
   DSM was proposed as a solution to the increase in peak prices. The changes in the load shape, due to DSM, must consequently, also result in a reduction in energy rates, elevated customer satisfaction and higher levels of reliability, etc.
3. ***Demand side management will be evaluated against non-demand side management alternatives***
   DSM should be considered as an alternative to, for example, the construction of additional capacity. It is only then when DSM becomes an integrate part of energy planning.
4. ***Demand side management will identify how customers will respond***
   DSM is considered to be pragmatic, it constitutes 'if then else' relations. Therefore, DSM identifies how customers *will* respond.

5. ***Demand side management value is influenced by the load shape***
The value of DSM is determined by the capability of altering the load shape and accordingly influencing the cost and benefits throughout the day.

From these components it is possible to distil that DSM only includes activities that result in deliberate interventions, from the utility provider in the marketplace, to change the load shape (consumer demand)(Gellings, 1985). Regardless of this definition, literature on DSM provides examples for DSM that should not be considered as such. For example, Boshell and Veloza (2008) mention that replacing light bulbs with more efficient bulbs is an example of energy efficiency, as part of DSM concepts, while Gellings (1985) states that: "*… customer purchases of energy-efficient appliances as a reaction to the perceived need for conservation would not be classified as DSM*" (p. 1468). This follows from the statements that DSM determines how customers *will* respond, not how they *might* respond.

The utility programs and concepts that do fall under DSM are described by Gellings (1985) and consists of the following: Peak clipping, Valley filling, Load shifting, Strategic Conservation, Strategic load growth and Flexible load shape.

1. ***Peak Clipping***
Peak clipping (Figure 1) is the reduction of the peak load during, for example, solar peaks or evening peaks. This concept is applied either through a time based rate or incentive-based strategy, with or without enabling technology (Gellings & Parmenter, 1988). Although that most utilities only consider this concept applicable to prevent congestion, the concept of peak clipping can also be applied to reduce costs. If the peak load can be prevented, utilities would not have to shift to less economical means of energy production and thus lower production cost (Gellings, 1985).

2. ***Valley Filling***
Valley filling (Figure 1) is the increase of loads during periods of low energy consumption. Valley filling is desired as it can make the energy production and transmission more efficient. This concept is achieved by adding thermal energy storages which can be charged in off-peak periods. Thermal energy storage units are for example electric boilers or space heating/cooling (for example for a house or industrial freezing cell) (Gellings, 1985; Gellings & Parmenter, 1988).

3. ***Load Shifting***
Load shifting (Figure 1) is a concept where loads are shifted from peak to off peak periods. Possible techniques to accomplish such a shift is through energy storage units, as for example, water heaters and space heating (Gellings & Parmenter, 1988). The water inside the water heater or the air within the house can be heated in off peaks because both the house and the water heater are capable to retain their temperature over a longer period of time (Gellings, 1985).

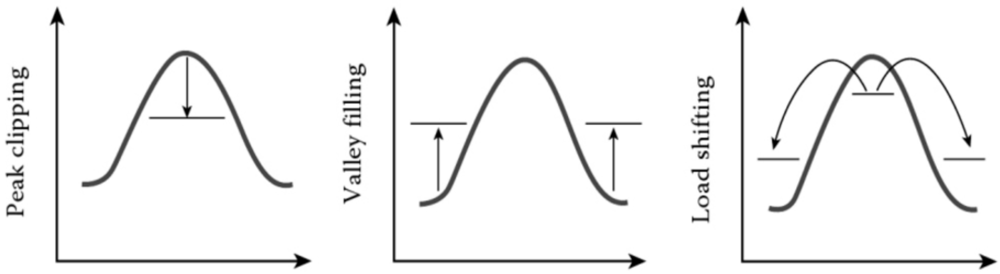

Figure 1: DMS Concepts: Peak clipping, Valley filling and Load shifting
From: Gellings & Parmenter, Demand-side management, 1988

4. ***Strategic Conservation***
   Strategic conservation (Figure 2) is the change in the load shape as the result from utility stimulated programs directed to reduce end use electricity consumption. In most cases strategic conservation occurs due to the efficiency increase of appliances or weatherization, where weatherization is the practice of protecting the household from the outside elements as wind, sun and participation, in order to reduce energy consumption (Gellings, 1985).

5. ***Strategic Load Growth***
   Strategic load growth (Figure 2) is the primary result of either an increase in sales due to an increase in market share or due to electrification, where electrification is a term used to refer to new emerging technologies as for example electric vehicles (Gellings & Parmenter, 1988). Strategic load growth might be considered illusive to be part of DSM as it concerns a load increase; however, DSM is defined as 'changes in the utility's load', not mentioning if this change is conservative or growth.

6. ***Flexible Load Shape***
   In the concept of a flexible load shape (Figure 2), the load shape is considered to be controllable through the use of curtail-able loads or individual customer load control appliances. This concept is strongly related to the reliability of the grid where a forecast, over a certain planning horizon, indicates if curtailment is requirement to ensure that the load remains within the desired limits (Gellings, 1985).

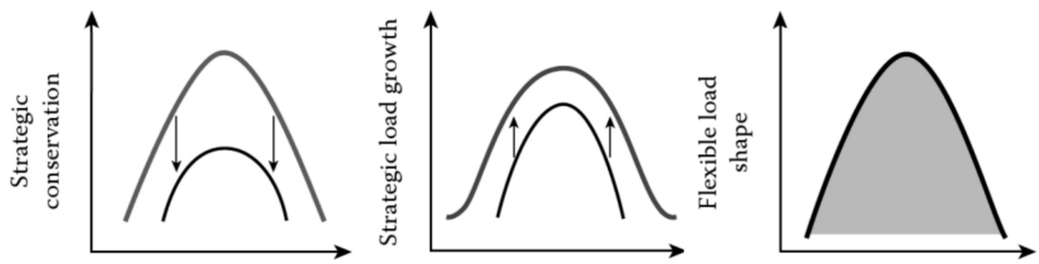

Figure 2: DSM Concepts: Strategic conservation, Strategic load growth and Flexible load shape
From: Gellings & Parmenter, Demand-side management, 1988

To enable these load shifts, two DSM approaches are used, which are pricing incentives, or indirect load control, and direct load control. Both these means use different approaches in enabling a customer to change his or her electricity consumption willingly, and consequently, these approaches are presented in section 2.1.1 and 2.1.2.

2.1.1 Indirect Load Control

Indirect load control is a control mechanisms where the direct relation between the control response and outcome is broken. Therefore, the control mechanism is only an incentive to direct consumers into a desired direction, where the outcome is often unobservable and loathed with time delays (Heussen, You, Hansen, & Andersen, 2012). Within indirect load control, the incentive to alter the consumer's behaviour is time of use rates, where the time of use is related to the price of electricity. By elevating the price of electricity in the peak hours, the generator expects that the consumer will be incentivised to shift the consumption to other, cheaper off peak periods. Other approaches are for example interruptible rates, off-peak rates, seasonal rates, conservation rates, promotional rates and variable reliability pricing. Although, these approaches do not differ much from time to use, only the relation to time is regulated differently.

One of the weaknesses of indirect load control is that the consumers must first be aware of the desire to shift the load, second, be able to respond to this desire of the generator and last, be willing to respond (Torriti, Hassan & Leach, 2010; Mohsenian-Rad, 2012). Furthermore, Heassen, You and Andersen (2012) mention that due to the non-responses to the desire to shift the load, indirect load control may not be able to achieve a consistent response level and might result in highly volatile pricing signals, that might even exceed the value of the desired response.

2.1.2 Direct Load Control

Direct load control, in contrast to indirect load control, is a closed loop control system where the outcome of the control signal is directly observed (Heussen, You, Hansen, & Andersen, 2012). Direct load control is realized through the control of appliances within the household by means of a communication interface. Having direct control over the appliances in the household resolves the problem of unreliable response from the consumers to the incentive and makes the form of DSM more reliable. Approaches that fall under direct load control are for example: load shedding, thermal energy storage, appliance control cycling and cogeneration.

However, the disadvantage of direct load control is that controlling the appliances within the household might result in declining levels of comfort for the inhabitants. Therefore, a payback structure is an inherent nature of direct load control, where the consumer should not only remunerated for the losses in energy production (from for example photovoltaic panels) but also for possible losses in comfort (Shafiu & Watts, 2007).

2.2 The Introduction of the Role of the Aggregator

As introduced in section 2.1, DSM consists of two distinct concepts: indirect load control and direct load control, where Gellings (1981) mentions that direct load control is the most effective tool for load management because of the ability to control consumers' appliances. However, when direct load control is applied on a larger scale, and considered as supervisory control, the utility provider might retain most of the benefits for itself, as each individual household only provides a small portion of the total demand/supply and consequently, only has limited negotiation power (Lazaros, Koutsopoulos, & Salonidis, 2013). Conversely, the application of direct load control on a larger scale would provide a higher probability that adjustable loads are available when there is a need to control the load curve (Seung-Jun & Giannakis, 2013) and therefore, increasing the amount of flexibility that is traded, where electricity flexibility is defined as "*the extent to which a power system can modify electricity production or consumption in response to variability…*" (Energy Agency, 2011, p. 37). Nevertheless, the utility provider does not contain the required knowledge on how to design and apply direct load control on a larger scale and would consequently, result in scalability issues (Lazaros, Koutsopoulos, & Salonidis, 2013; Karfopoulos, et al., 2015).

The projected challenges of providing direct load control on a larger scale, motivated the introduction of the aggregator into the energy system. Within this context, the aggregator provides two different functions; to provide load adjustment services to operators of the electricity grid, and to represent the consumers on the electricity capacity market. By representing the consumers, the Aggregator provided the solution to the complexity of contracts in the balancing mechanism and the ambiguity on how to involve consumers into the capacity market (Warren, 2014). Additionally, since the Aggregator can dynamically shape the load curve through the consumer's appliances, the Aggregator is considered equivalent to a generation resource, and can consequently, participate in the wholesale energy market. In this hierarchical load control approach (Figure 3) by means of multiple Aggregators, an Aggregator has the jurisdiction over a group of households (load group) and provides a bridge between the households and the energy system operators. The Aggregator defines the availability of load actions and uses this information to describe the responsiveness of the entire group. Since the Aggregator is considered to be equivalent to a generation resource, the same commands (to raise or lower the load) are used as for individual generators. The Aggregator then uses these commands in order to control the consumers' equipment accordingly and change the load respectively (Callawar & Hiskens, 2011). This allows independent households (through the Aggregator) to offer load adjustments to the wholesale electricity market and gain additional transaction freedom (Bessa & Matos, 2010).

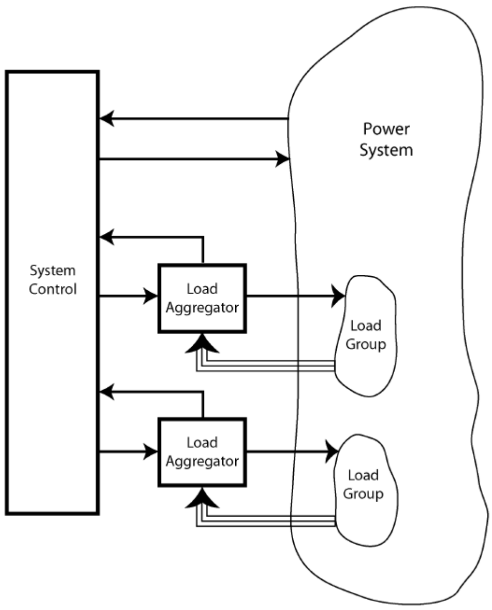

Figure 3: Hierarchical Load Control

From: Callaway, D. S., & Hiskens, I. A. (2011). Achieving controllability of electric loads. Proceedings of the IEEE, 99(1), 184-199.

2.3 A Review of the Financial Feasibility of the Aggregator

The role of the Aggregator is essential in the execution of direct load control DSM. Without the aggregator the households are not represented on the wholesale electricity market and the utility provider is tempted to retain all benefits. However, before any party will attempt to take the role of the Aggregator, it must be clear that such a party can at least break-even. The following cases provide some initial insights:

1. A theoretical analysis of Lambert (2012) on the financial sustainability of the role of the Aggregator indicates that, due to the high investment cost and the low variations in the electricity market, such a role would hardly be economically feasible over a longer period of time. Especially when a DSO will decide to invest in the electricity grid and would no longer require the services of an Aggregator.
2. A case study on the use of dynamic response of residential heating load in France indicates different conclusions. The analysis indicates that there is a a potential for the Aggregator to have a profitable business case; however, due to the energy legislation applied in France, the Aggregator is required to compensate the utility provider for the losses of revenue, which has a significant impact on the financial feasibility. Consequently, the business case of the Aggregator is inevitably not financially feasible (Hull, 2001).
3. For a different case study on dynamic control of electric heaters in Finland, based on the assumption that only an investment is required for control, monitoring and communication technology, the Aggregator is capable of breaking even in 20 years while selling demand response for £69/MWh to the BRP. Accordingly, this case study indicates that the role of the Aggregators might become feasible. However, no research in the case study has been performed if the Aggregator is able to retail the electricity flexibility for that price, and consequently, the financial feasibility remains uncertain (Hull, 2001).
4. A fourth case of direct load control of commercial air-condition units in the United Kingdom has indicated a positive financial feasibility for the Aggregator. Based on the analysis of the load of the air-conditioning units and the minimum usage of 10% days per year, the Aggregator is able to break even within 10 years with a benefit of £65/customer/year. With fluctuating demand and usage the benefits tend to shift between €15 till €240 per customer per year (Hull, 2001).

Hull (2001) concludes on an analysis of a multitude of case studies that the financial feasibility of direct load control for the Aggregator is shrouded in uncertainty due to the use of historical information, the uncertainty of the cost of control, monitoring and communication technology and the possible influence from electricity flexibility on the spot market price. Additionally, Lambert (2012) adds that the involvement of the end users in such a new energy framework is hard to predict, resulting in an uncertain financial sustainability for the Aggregator.

Although that these case studies indicate varying uncertain economic results for the role of the Aggregator, Torriti, Hassan and Leach (2010) mention that it is not possible to extend such results to other countries. This extension is not feasible due to the divergent penetration level of DSM technologies, the amount of manageable power, and the household load curves. Lambert (2012) adds that only a real application of DSM could help to provide more insights in the interconnection between the Aggregator and market actors.

2.4 A Practical Application of Demand Side Management

The energy transition, where consumers are starting to generate their own electricity, has resulted in a number of necessary measures to prepare the electricity network for the future. These measures are for example the development of electricity storage capacity or research on the use of hydrogen, but also the introduction of smart grids and DSM (Sociaal Economische Raad, 2013). In order to gain more insights into the effect of DSM on the electricity infrastructure, the Smart Energy Collective (SEC) performs research and demonstrates the smart energy networks in practice (Energiekaart, 2016). These experiments are performed in five experimental projects, which are: the Proeftuin Heerhugowaard, the Proeftuin Goese, the Proeftuin Gorichem, the Proeftuin Haarlemmermeer, and Smart Offices. As was already introduced earlier, this thesis focuses on the Heerhugowaard field trial, which will consequently be shortly introduced in section 2.4.1. Additionally, the experiment in Heerhugowaard assists in the development of the Universal Smart Energy Framework (USEF) as a market standard for the exchange and trade of electricity flexibility from consumer household to the wholesale electricity market (Energiekaart, 2016). Accordingly, USEF will be introduced in section 2.4.2. Based on USEF, the Aggregator trades the electricity flexibility with the BRP and DSO, and receives payment for this exchanges. In order to shed more light on these transactions, as the core of the financial business model for the Aggregator, section 2.4.3 introduces the remuneration scheme for the Aggregator, applicable in the Heerhugowaard field trial.

2.4.1 The Heerhugowaard Field Trial

The Heerhugowaard field trial is an experiment where 201 households are equipped with direct load control appliances, in order to investigate if direct load control could postpone grid investment for the DSO, and if direct load control might contribute to sourcing and balancing strategies for the BRP. Direct load control is achieved by the interaction of electricity consumption and gas consumption, where the reserve capacity of one network could be used to absorb the overload of the other network (Energiekaart, 2016). In other words, when there is a peak load in the electricity network, an electric device (Heat Pump) is switched off and a gas consuming unit takes over. Additionally, direct load control on Photovoltaic panels is used to absorb the peak of the solar peak. The four appliances used in the field trial have the specifications presented in Table 1, where each controlled household has one controllable smart appliance installed.

Table 1: Smart Appliances in the Field Trial (Energiekoplopers, 2015; Inventum, 2015)

Device Type	*Households*	*Base State*	*Flex*	*Max Capacity per unit (W)*
Photovoltaic Panel	89	On	Flex Up	380 - 6000
Heat Pump[1]	50	On	Flex Down	620
Electric Boiler	44	Off	Flex Up	1000 / 1500 / 2500
Fuel Cell	18	Off	Flex Down	1500

2.4.2 Electricity Flexibility Trading with the BRP and DSO through USEF

The electricity flexibility that is created through the use of smart appliances (indicated as ADS in Figure 4) from the prosumers, as for example by means of Photovoltaic panels or Heat Pumps, is aggregated by the Aggregator in an electricity flexibility portfolio. Such a portfolio creates the opportunity to provide flexibility services to different markets, serving different players. The Universal Smart Energy Framework provides a scalable and standardized market solution, and allows the Aggregator to provide flexibility services to the BRP, DSO and TSO. These parties are interested in using such a service for the following reasons (USEF Foundation, 2014):

1. The BRP is interested in procuring electricity flexibility in order to reduce the costs of sourcing and balancing, and to avoid imbalance charges.
2. The DSO is interested in procuring electricity flexibility to prevent congestion on the electricity grid, retain the voltage levels within constraints, increase controlled islanding and further increase redundancy.
3. The TSO is interested in procuring electricity flexibility through the BRP in order to perform *Primary Control*, or frequency containment, *Secondary Control* in order to reduce imbalances on the imbalance market and *Tertiary Control*, which resembles secondary control, but on a longer time period.

These parties purchase electricity flexibility from the Aggregator by means of the USEF flexibility supply chain (
Figure 4). In this supply chain the Aggregator maximizes the value of the electricity flexibility in the portfolio by selling it to the party with the most urgent need, and consequently the party that is willing to pay the highest price.

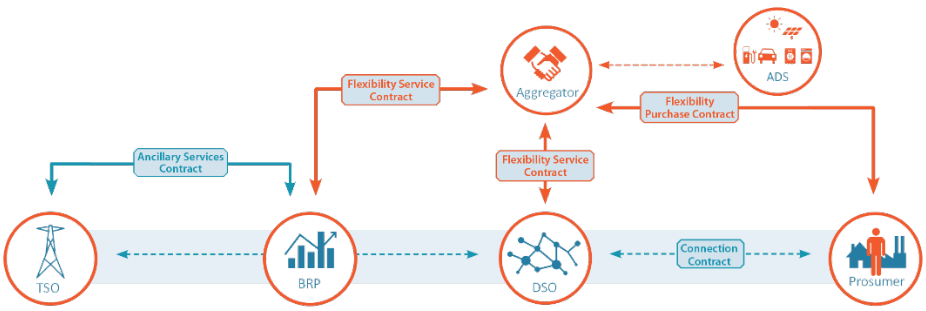

Figure 4: The USEF Electricity Flexibility Supply Chain (USEF Foundation, 2014)

[1] The Heat Pump is only designed to keep the house on temperature, therefore the heat pump has only a low capacity.

In order to provide the parties with equal access to the electricity flexibility services, USEF introduced a market-based coordination mechanism. This market-based coordination mechanism consists of five different phases with different actions and requirements for the involved parties. These five phases are: Contract, Plan, Validate, Operate and Settle[2] (USEF Foundation, 2014).

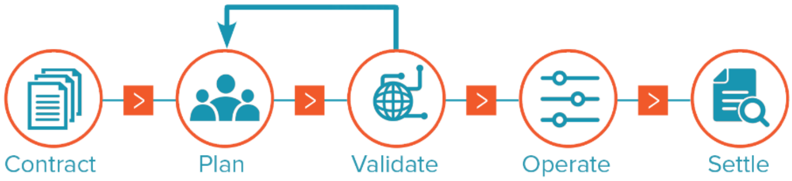

Figure 5: The USEF Market-Based Coordination Mechanism (USEF Foundation, 2014)

1. ***Contract Phase***
   In order for USEF to function accordingly, contractual relationships between the Aggregator, Prosumers, BRP and DSO need to be established. In this phase the TSO is not involved as the TSO already has an ancillary service contract with the BRP.

2. ***Plan Phase***
   In the plan phase the aim is to determine an economically optimal program that meets the electricity demands of the BRP and Aggregator portfolio. The results of this plan are reflected in the A-plan. The following steps in the respective order are undertaken in the plan phase:
   - Agg: Collect forecast information and create forecast for the entire portfolio
   - Agg: Optimize the internal portfolio
   - Agg: Generate A-plan and communicate to BRP (electricity flexibility offered)
   - BRP: Receive A-plan and optimize internal portfolio
   - BRP: Request electricity flexibility from the Aggregator (electricity flexibility ordered)
   - Agg: Trade electricity flexibility with the BRP

3. ***Validate Phase***
   The Validate phase is related to ensuring that the electricity load remains within the network congestion limits. The Aggregator performs a D-prognoses in order to forecast the load for the controlled households, after which the DSO combines this forecast with the forecast of the DSO controlled households in order to determine if network congestion might occur. The following steps are taken in the validate phase:
   - Agg: Creates D-prognoses and communicate with DSO
   - DSO: Receive D-prognoses and perform grid safety analysis
   - DSO: Request electricity flexibility from the Aggregator
   - Agg: Trade electricity flexibility with the DSO
   - Agg: Adjusts the A-plan iteratively through the Plan Phase (the arrow in Figure 5 from validate to plan)

4. ***Operate Phase***
   In the operate phase the Aggregator controls the smart appliances in the households of the prosumers in order to deliver the sold flex to the BRP and DSO. However, deviation in the D-prognoses may occur due to, for example, forecast errors, hardware/IT errors, and human interaction. In order to ensure that the DSO is able to prevent additional network congestion, the DSO can order additional electricity flexibility in the operate phase.
   - DSO: If needed the DSO orders additional electricity flexibility in order to preserve network reliability
   - Execute the A-plan and D-prognoses by scheduling active control of the smart appliances

[2] The presented description and overview of steps are associated with the Heerhugowaard Field Trial. USEF originally constitutes of an additional number of steps which are not performed in the field trial and consequently not discussed.

5. ***Settle Phase***
   In the settle phase the Aggregator calculates the amount of electricity flexibility sold to the BRP and DSO and settles the offered flexibility. The BRP and DSO will consequently remunerate the Aggregator for the provided services, as the Aggregator remunerates the Prosumers for the provided electricity flexibility.

As one might expect, the Contract phase is only performed ones or periodically. The Plan and Validate phases may take place both day-ahead and intraday, where day-ahead concerns the coming 24 hours (from 00:00 till 23:59) and intraday the next coming 4 hours (a day is split in 6 blocks of 4 hours). In contrast, the Operate phase is executed every 15 min time period, in order for the DSO to correct the D-prognoses in regards to the observed network congestion (USEF Foundation, 2014). An additional difference is that the BRP uses the APX market for day-ahead and the Imbalance market for intraday electricity flexibility trading.

2.4.3 The Compensation Scheme for the Aggregator

2.4.3.1 Electricity Flexibility Pricing

2.4.3.2 The Decision Making Process of the BRP

The BRP orders electricity flexibility in order to reduce the cost of electricity purchasing, which implies that the cost of electricity flexibility, in combination with the APX, Imbalance market and retail price are primary drivers for the purchasing behaviour of the BRP. Based on these influential factors the decision making process of the BRP can be captured in two equations, with the difference that in one the BRP orders electricity flexibility up and in the other orders electricity flexibility down:

The BRP orders electricity flexibility up if:

$$\textit{APX Price} + \textit{Electricity Flexibility Price} < \textit{Electricity Supply Tariff}$$
$$\textit{Unbalance Price} + \textit{Electricity Flexibility Price} < \textit{Electricity Supply Tariff}$$

The BRP orders electricity flexibility down if:

$$\textit{APX Price} - \textit{Electricity Flexibility Price} > \textit{Electricity Supply Tariff}$$
$$\textit{Unbalance Price} - \textit{Electricity Flexibility Price} > \textit{Electricity Supply Tariff}$$

2.4.3.3 The Variable Cost for the Aggregator


3

3 Electricity Flexibility

The financial business case of the Aggregator pivots on the trade of electricity flexibility with the BRP, DSO and TSO. In order to determine the financial outcome for the Aggregator when DSM is expanded, it is essential to know how much electricity flexibility can be sold per time unit per smart device. With the aim of predicting electricity flexibility, section 3.1 first addresses the types of electricity flexibility to provide a clear understanding of the different aspects of electricity flexibility. Furthermore, since electricity flexibility is procured from different appliances, the factors that influence the available electricity flexibility of these appliances are device specific. Hence, section 3.2 describes the potential factors that might have a relation with the available electricity flexibility per smart device. Last, section 3.3 provides an overview of the hypothesized causal relations between the potential factors that could influence the available electricity flexibility and the available electricity flexibility by means of a causal diagram.

3.1 Electricity Flexibility from Smart Appliances

Electricity flexibility, in the context of electricity systems, is defined by the International Energy Agency (2011) as: "*the extent to which a power system can modify electricity production or consumption in response to variability…*" (p. 37). In this setting, electricity flexibility is employed to maintain a reliable supply of electricity while faced with large and rapid imbalances. Because the deployment of electricity flexibility prevents such imbalances, one might believe that electricity flexibility is a balancing activity. However, Tripple (2014) mentions that balancing activities and electricity flexibility are not the same, as balancing activities only have a short time span, from seconds to an hour, whereas electricity flexibility includes daily, weekly and seasonal variations. From this perspective, electricity flexibility includes balancing activities, but balancing activities are not explicitly achieved through the use of electricity flexibility.

Electricity flexibility provides means to 'regulate up' or 'regulate down', where up regulation ensures an increase in the energy output from power plants, and down regulation reduces the energy output from power plants. Although that traditionally these services were only associated with dispatch-able generators, other resources as DSM are now also considered (Tripple, 2014). In the context of DSM, up regulation is provided by reducing the load of controllable appliances and down regulation by increasing the load of controllable appliances (Ecofys, 2014). Additionally, in the context of the Heerhugowaard field trial, electricity flexibility provides 'flex up' or 'flex down', where flex down reduces the load from appliances or increases the output from appliances, and flex up increases the load from appliances or reduces the output from appliances. An overview of these control actions is presented in Table 3.

Table 3: Electricity Flexibility in the Energy System

Type of control	*Control action*	*Control result*	*Energy system result*
Power plant	Regulate up	Increases the power plant output	Increase in energy available
	Regulate down	Decreases the power plant output	Decrease in energy available
Demand Side Management	Regulate up	Reduces the load of the device	Increase in energy available
	Regulate down	Increases the load of the device	Decrease in energy available
	Flex up	Increases the load of the device	Decrease in energy available
		Reduces the output of a device	Decrease re energy available
	Flex down	Reduces the load of a device	Increase in energy available
		Increases the output of a device	Increase in energy available

Although that the control actions and results between regulate up and regulate down and flex up and down seem illogical, it helps to realize that the results of DSM for regulate up and regulate down are comparable to when a control action is taken for the power plant. In other words, regulate up for DSM has the same effect on the total available energy as regulate up for the power plant. Additionally, if a comparison is made for the effect on the load curve, regulate down would elevate the load curve as the load of a device is increased, while regulate down for the power plant would decrease the load curve as a smaller amount of energy is available. The same effect is realized with flex up, where the term 'up' refers to the change in the load curve. Therefore, the changes in the load curve or in the power plant output level are comparable.

When electricity flexibility is procured from a device, a particular device's load is disconnected from, or connected to the electricity system, which results that the electricity flexibility of that device is equal to the load (where the load of a solar panel and fuel cell are negative) of the device at time *t*. This implies that the amount of electricity flexibility is limited by the amount of appliances and their respective load on the electricity system (or supply to the electricity system), since when a device is switched off to create flex, this device cannot be switched off again, and vice versa. Accordingly, the current measure of electricity flexibility is unable to capture these differences. Consequently, other measures are introduced to define electricity flexibility more closely in all stages of operation. Throughout this thesis the following three measures are used:

1. ***Available Electricity Flexibility***
   The available electricity flexibility is the total flexibility that is available at time *t* from each smart appliance. For example, Figure 6 displays the energy output of 4 houses with controllable Photovoltaic panels, where the sum of these outputs represents the total available flexibility, and the independent output the available electricity flexibility per device. This implies that the total, and independent, available flexibility changes over the day, dependent on, for example, the irradiance at that particular point in time.

2. ***Controlled Electricity Flexibility***
   The moment, for example, flex up is requested by a BRP or DSO, the Aggregator may decide to switch off one of a Photovoltaic panels. Figure 6 presents this transition where Photovoltaic panel 4 is switched off, and causes a reduction in the produced Photovoltaic electricity. This reduction is the controlled electricity flexibility. Due to this 'control' the overall available electricity flexibility does not change, as indicated by the dashed line. This is because at any point in time, the Aggregator can switch the Photovoltaic panel back on, restoring the original situation.

3. ***Remaining Electricity Flexibility***
   When a Photovoltaic panel is controlled, other Photovoltaic panels might still be producing electricity. These remaining sources of electricity flexibility are still available for the Aggregator to provide electric flexibility service for the BRP and DSO. Therefore, the electricity flexibility that can still be requested (available electricity flexibility - controlled electricity flexibility) is referred to as the remaining electricity flexibility.

   From these three measures of electricity flexibility it is possible to conclude that:

$$Available\ Electricity\ Flexibility = Controlled\ Electricity\ Flexibility + Remaining\ Electricity\ Flexibility$$

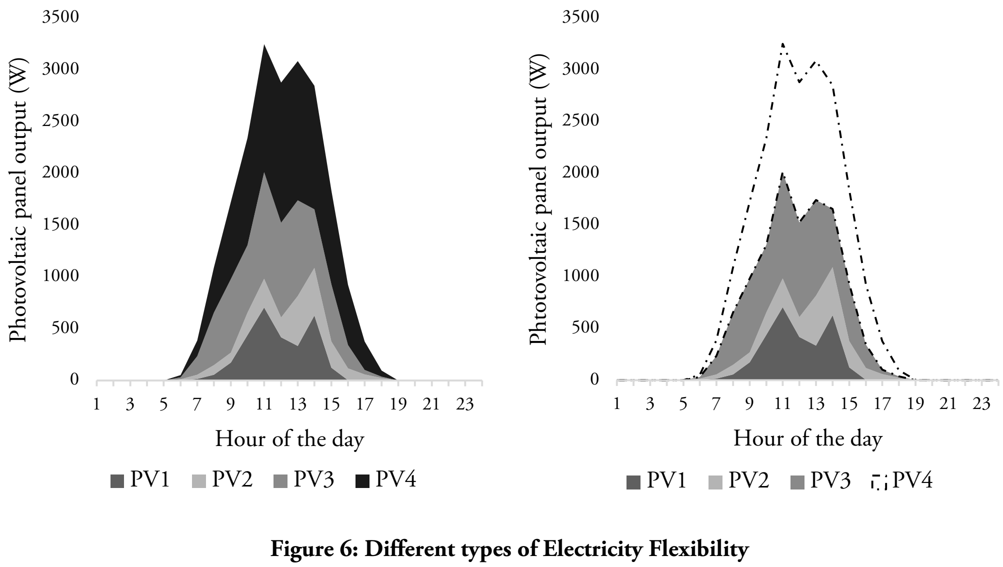

Figure 6: Different types of Electricity Flexibility

As was already presented in Table 3, electricity flexibility can be procured from different types of appliances, where these appliances can be categorized as; Energy Storage, Demand, Supply and Network (Ecofys, 2014). In the Heerhugowaard field trial only the Demand and Supply category are present, where the Photovoltaic panels and the Fuel Cells both belong to the supply category and the Electric Boilers and the Heat Pumps to the Demand category (Ecofys, 2014). As these appliances are different, the factors that influence the available electricity flexibility from these appliances also varies. Therefore, in order to predict the available electricity flexibility from the appliances in the Heerhugowaard field trial, the potential factors that influence the available electricity flexibility are investigated per device.

3.2 Potential Factors that Influence the Available Electricity Flexibility

The electricity flexibility from the four appliances, even when the appliances are from the same electricity flexibility category, are the result from a varying set of household exogenous and endogenous factors. In order to predict the available electricity flexibility of these appliances, the household exogenous and endogenous factors that might have an influence on these appliances are investigated and discussed in section 3.2.1 through 3.2.4 for the Photovoltaic panels, the Electric boiler, the Heat Pump and the Fuel cell respectively.

3.2.1 The Available Electricity Flexibility from the Photovoltaic Panels

Electricity from photovoltaic panels is created through the principle of conservation of momentum and energy and the photovoltaic effect which converts the energy from incident photons into electrical energy (Mekhilef, Saidur, & Kamalisarvestani, 2012). The available electricity flexibility from a photovoltaic panel is equal to the production of electrical energy from the photovoltaic panel at time *t,* as this amount of load on the electricity network can be increased by switching the energy provision from the photovoltaic panels to off. Therefore, to determine what influences the available electricity flexibility from a photovoltaic panel, the potential factors that influence the photovoltaic output are investigated. The output from photovoltaic panels can be approached through the following state equation (Ashouri, 2014):

$$\dot{\boldsymbol{E}}^{\boldsymbol{d}}_{\boldsymbol{PVS,out}}(\boldsymbol{i}) = A^{d}_{PVS} \cdot \eta_{PVS}(i) \cdot I_{PVS}(i) \; i = 1, 2, \dots, t.$$

where $E^{d}_{PVS,\,out}$ is the electrical power output of the photovoltaic panel, $A^{d}_{PVS,}$ the area of the photovoltaic panel (cq. the photovoltaic capacity), η_{PVS} the photovoltaic energy transition efficiency and I_{PVS} the vector of total solar incidents on the photovoltaic panel. The vector of the total solar incidents, which provides the relative intensity of the irradiance, is further dependent on the solar elevation angle, the solar zenith angle and the local irradiance (Tao, Shanxu, & Changsong, 2010). Furthermore, the efficiency of the photovoltaic panel, η_{PVS}, is negatively dependent on the outside air temperature as it influences the panel temperature and reduces the energy conversion efficiency (Dubey, Sarvaiya, & Seshadri, 2013). Additionally, humidity also negatively influences the output of the photovoltaic panel as water in the atmosphere causes the light to refract, reflect or diffract, which causes a decreases in the reception levels for photovoltaic panels (Mekhilef, Saidur, & Kamalisarvestani, 2012).

Next to the hypothesized exogenous variables the Aggregator also has control over the photovoltaic panels and may decide, based on the demand for electricity flexibility, to switch off the photovoltaic panel. This action significantly influences the output of the photovoltaic panel even in the presence of irradiance. Therefore, due to the presence of this control, the effect of irradiance and the capacity of the photovoltaic panel differ over time. When such an effect is present, terms are interacting with each other and might be combined in an 'interaction term'. Consequently the term *PV-Capacity*Irradiance*State* refers to the interaction between Irradiance, the photovoltaic state and photovoltaic capacity of the panel.

Based on this analysis the following factors can be stated to be potential factors that might influence the available electricity flexibility from Photovoltaic Panels: *Solar Irradiance*, *PV-CapacityIrradianceState, Solar Elevation Angle, Solar Azimuth Angle, Outside Air Temperature, Outside Air Humidity, Photovoltaic Energy Transition Efficiency,* and the *PV-Capacity.*

3.2.2 The Available Electricity Flexibility from the Electric Boilers

The electric boiler can be considered to be a Thermal Energy Storage (TES) unit as it is able to store energy in the form of warm water for a longer period of time. Electricity demand from the electric boiler is created when the electric boiler is switched on by the Aggregator and when the boiler charge level is lower than 100%. This implies that the electric boiler will not heat the stored water when there is demand from the household for hot water, in the absence of a control signal from the Aggregator. The electricity flexibility, which can be created per *t* from the electric boiler, is equal to the load from the boiler and varies per household from 1 kW to 2.5 kW. However, in contrast to the other smart appliances, the duration the electric boiler can create electricity flexibility is not only dependent on household exogenous factors, like for example the irradiance for the photovoltaic panels, but also household endogenous factors. The system state equation for a thermal energy storage system substantiates this distinction (Ashouri, 2014):

$$\boldsymbol{Q_{TES}(i)} = (1 - \sigma_{TES}) \cdot Q_{TES}(i-1) + t_s \cdot \left(Q^d_{TES,in}(i-1) - Q^d_{TES,out}(i-1)\right), i = 2,3, \dots, t$$
$$0 \leq Q_{TES}(i) \leq C^d_{TES}$$

where Q_{TES} indicates the current energy in the electric boiler, σ_{TES} the self-discharge of the electric boiler and $Q^d_{TES,\,in}$ and $Q^d_{TES,\,out}$, the energy charge and energy discharge respectively, in which both $Q^d_{TES,\,in}$ and $Q^d_{TES,\,out}$, are constrained to the capacity (C^d_{TES}) of the electric boiler. The system state equation identifies that the electric load, resulting in $Q^d_{TES,\,in}$, can only occur when $Q_{TES} \leq C^d_{TES}$. Implying that the total available electricity flexibility from the electric boiler is limited by the capacity of the electric boiler, and the remaining electricity flexibility at time t is limited to the charge level at time t. Concluding that when an electric boiler is fully charged, electricity flexibility can no longer be requested from that electric boiler.

The household endogenous influence is also identified in the electric boiler state equation as $Q^d_{TES,\,out}$. $Q^d_{TES,\,out}$ identifies the withdrawal of energy from the electric boiler, outside of the thermal losses, and is a direct result of hot water consumption by the household. Because charging the electric boiler results in a decrease in the remaining available electricity flexibility, the consumption of hot water, results in an increase of the remaining available electricity flexibility from the electric boiler. Subsequently, the remaining electricity flexibility (C^d_{TES} - Q_{TES}) at time t depends on $Q^d_{TES,\,in}$ and $Q^d_{TES,\,out}$. Since $Q^d_{TES,\,in}$ fully depends on the exogenous control signal from the Aggregator, and is therefore in direct control by the Aggregator, it is possible to conclude that only the $Q^d_{TES,\,out}$ is uncertain. Implying that, hot water consumption should be investigated in order to predict the available electricity flexibility from the electric boiler.

Analysis on water consumption in households in the Netherlands have been performed in the past by for example TNS NIPO (2013) and Blokker (2010). However, these analysis did not specifically analyse 'hot' water consumption. An analysis from Defra (2008) did focus especially on hot water consumption and found, by analysing the hot water consumption from 120 households in the United Kingdom, that only the time of the day and the number of inhabitants significantly influence the hot water consumption. Furthermore, research from Kalogirou and Tripanagnostopoulos (2006) indicates that higher outside air temperatures reduce the demand for hot water from households.

Based on this analysis the following factors can be stated to be potential factors that might influence the hot water consumption and indirectly, in combination with the control from the Aggregator, the available electricity flexibility from the Electric Boiler: *Hour of the Day, Number of Inhabitants per Household* and the *Outside Air Temperature.*

3.2.3 The Available Electricity Flexibility from the Heat Pumps

The heat pump is a device that requires electrical energy to initiate a reverse vapour compression refrigeration cycle where outside thermal energy is used to warm indoor air or tap water. Electric demand from the heat pump is created by two different heat demands. These demand for heating can either come from the electric boiler installed in the heat pump, or from the household thermostat. The available electricity flexibility from the heat pump consequently depends on the electric load generated by supply of thermal energy either to the household air or to the water boiler. This relation is substantiated by the following heat pump state equation (Ashouri, 2014):

$$E^d_{AHP,in} = \left(\frac{Q^d_{AHP \to TES} \cdot f_{TES}}{COP_{AHP \to TES}}\right) + \left(\frac{Q^d_{AHP \to BDG} \cdot f_{BDG}}{COP_{AHP \to BDG}}\right)$$

$$Q^{min}_{AHP} \leq Q^d_{AHP} \leq Q^{max}_{AHP}$$

where $E^d_{AHP,in}$ indicates the load of the heat pump, depended on the energy required per ^oC to charge the boiler and to heat the household, indicated by $Q^d_{AHP\text{->}TES}$ and $Q^d_{AHP\text{->}BDG}$ respectively. The amount of energy that is required for the boiler and the household further depends on the difference between the current temperature and the desired temperature, indicated by f_{TES} and f_{BDG}, and the Coefficient of Performance (COP) of the heat pump for both processes.

The heat pump combines the operation of a normal household heat installation and the electric boiler, as described in 3.2.2. The household exogenous factors that influence the household heating function are possibly the *Outside Air Temperature* (T_{amb}), the *Size of the House*, the *Type of the House* and the *Energy Class of the House* (Verhallen

& van Raaij, 1981; Ashouri, 2014). These four factors might play a role in the transfer of heat from the household to the environment, following the law of Fourier (Thermopedia, 2015):

$$\frac{J_x}{S} = -\lambda \frac{dT}{dx}$$

where J_x is the heat flux in direction x (W), S is the surface area under which the heat transfer takes place (m^2), λ is the negative temperature coefficient (W m^{-1} K^{-1}) and dT/dx is the temperature gradient (K/m). The type of the house and the size of the house might have an influence as they have a relation with the surface area under which the heat transfer can take place, in other words, a larger house has a larger surface area contacting the outside air, which might influencing the heat transfer, and consequently the heat pump load. Additionally, the temperature coefficient might have a relation with the energy class of the house, as the energy classification 2, 3 and 4 specifically take into consideration household isolation (Milieu Centraal, 2016). Furthermore, the temperature difference between the inside and the outside of the household might also have a positive influence on the heat transfer, as directly indicated by the law of Fourier, and therefore also influences the heat pump load (the lower the outside air temperature the higher the heat pump load).

Additional to the direct relation to the Fourier equation, other factors might also influence the heat transfer. For example the irradiance during the day heats the house, which consequently postpones the heating activity of the heat pump. Additionally, the wind speed during the day increases the subtraction of energy from the house and thus ensures that the house cools down faster. Therefore the heat pump load might also have relations with the solar irradiance and wind speed (Badescu & Sicre, 2003).

Next to the natural order, the heat pump might also influenced by household endogenous factors. Two of these possible factors are the number of inhabitants in the household and the hour of the day (Defra, 2008). Because the heat pump pre-heats water for hot water consumption, the load of the heat pump might be related to the number of household inhabitants (as was indicated in section 3.2.2). Furthermore, the operation of the heat pump is scheduled, following a daily pattern and in some cases even a night clock, or even a summer/winter schedule (Inventum, 2015). Therefore, this schedule could play an important role in predicting the load of the heat pump. A third factors is that the heat pump is also controlled through the Aggregator, which results in the inactivity of the heat pump, and consequently results in a direct relation between the SESP state (the state of the Heat Pump, 1 being off and 2 being on) and the heat pump load.

Based on this analysis the following factors can be stated to be potential factors that might influence the available electricity flexibility from the Heat Pump: *Outside Air Temperature, Solar Irradiance, Wind speed, Hour of the Day, House Size, House Type, The Energy Class, Number of Inhabitants and the SESP State.*

3.2.4 The Available Electricity Flexibility from the Fuel Cells

The Fuel Cell produces electricity due to the chemical reaction between positively charged hydrogen ions and an oxidizing agent (oxygen) (also referred to as a redox reaction). The conversion process from chemical energy (from gas) into electrical energy is of a continuous nature. In other words, in order to produce electrical energy, the Fuel Cell, requires a continuous supply of chemical energy. The moment the supply of chemical energy is halted, the output of electrical energy, coming from the Fuel Cell, returns to zero.

Based on this simplified description of the Fuel Cell, it is possible to defer that the Fuel Cell's output is primarily influenced by the supply of chemical energy. This implies that the available electricity flexibility is primarily influenced by the supply of chemical energy to the Fuel Cell. The supply of gas to the Fuel Cell is directly regulated by the Power Matcher and consequently in control by the Aggregator. The output and the available electricity flexibility for the Fuel Cell are thus fully predictable for the Aggregator, where the Aggregator can control the Fuel Cell between 500 and 1500 W. Based on this analysis only the *SESP State* is identified as a potential factor that might influence the available electricity flexibility from the Fuel Cell.

3.3 Hypothesized Causal Model for the Available Electricity Flexibility

In the previous sections, relations between the available electricity flexibility and household endogenous and exogenous influences, are hypothesized. In order to provide a clear overview of these relations a causal relations diagram can be presented. However, a causal relations diagram is a model that expresses more than correlation (Judea, 2000), as correlation does not imply causation. In order to indicate causation, outside the field of philosophy, it is understood that the cause and effect relation must be in accordance with the known laws of nature (Beebee, Hitchcock, & Menzies, 2009). Consequently, it is possible to construct a causal map as the proposed relations are based on the state equations presented by Ashouri (2014) and the law of Fourier.

A causal map may be constructed using the ordered tripled $\langle Y, X, E \rangle$ where Y is the independent variable, X is the dependent variable and E is the set of structural equations. In a causal map the relationship is identified by means of an arrow, indicating the direction of the causal relationship. Figure 7 illustrates a graphical representation of the causal map, where the scientific representation of the causal map can be found in Appendix I.

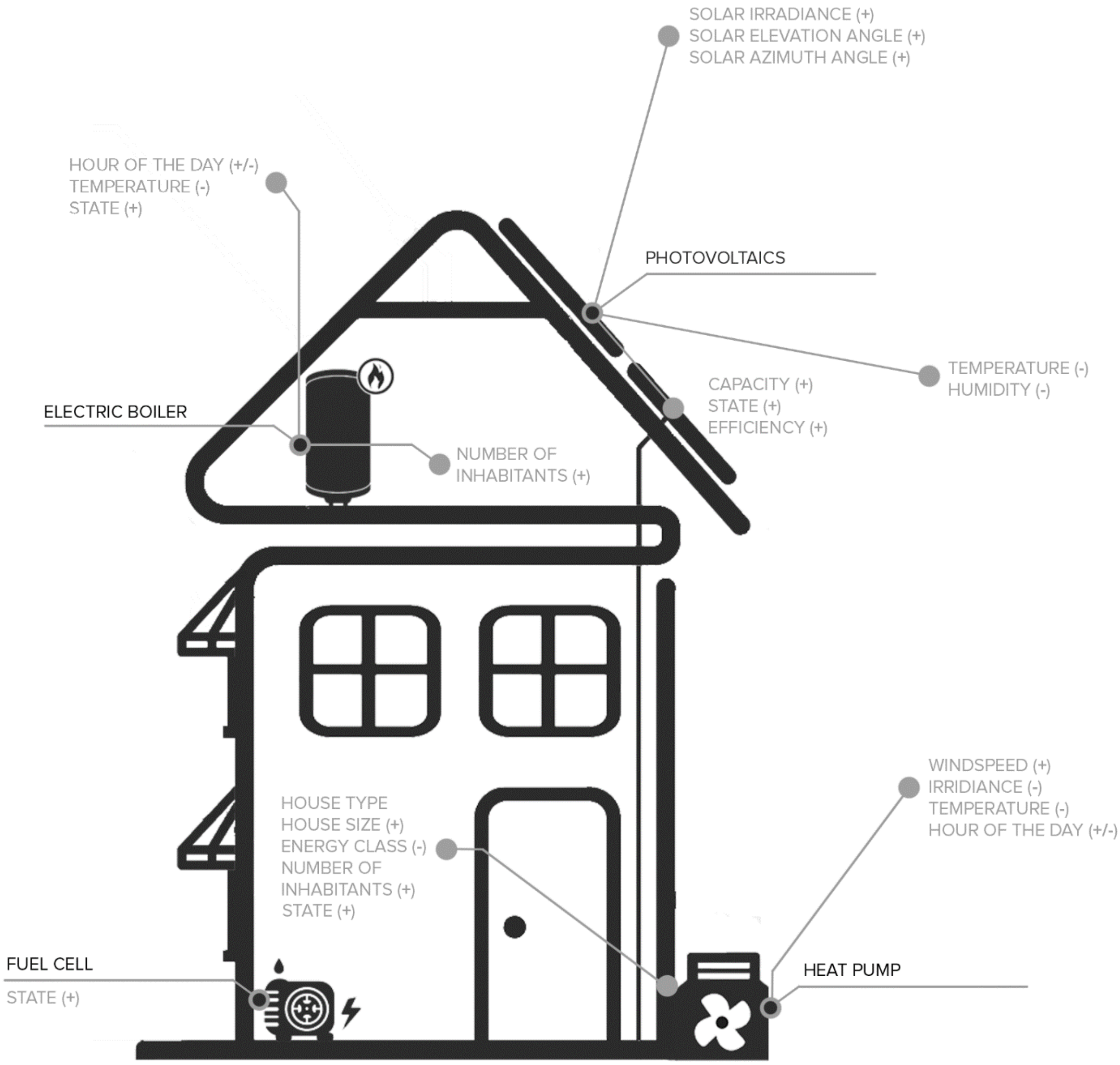

Figure 7: Hypothesized Causal model for the Available Electricity Flexibility

4

4 Methodology

The methodology describes the justification of the used techniques and procedures to identify, select and analyse the information required to establish an answer to the proposed research problem, in order to allow the reader to critically assess the validity and reliability of the study (Kallet, 2004). In order to provide the reader with the required information, to assess the validity and reliability, the chapter will first introduce the research design in section 4.1. Second, the chapter provides an overview on how the sampled households were selected, how representative these households are to the Dutch population, and to what extend the sample size has an influence on the confidence interval in section 4.2 through 4.5. Furthermore, section 4.6 provides a description on how the data, which was used in the analysis, was collected from the individual households, and last, section 4.7 indicates how the data was processed and by means of which software the data was analysed.

4.1 Research Design

The research design aims to assist the researcher in obtaining answers to the initially stated sub-research questions as unambiguously as possible. In other words, "*given this research question (or theory), what type of evidence is needed to answer the question (or test the theory) in a convincing way?*" (De Vaus, 2001, p. 9). Therefore, this section provides the types of evidence required to answer the sub-research questions and provides a rigor methodology through which this evidence can be found. The sub-research questions will be grouped in Qualitative research (4.1.1) and Quantitative research (4.1.2).

4.1.1 Qualitative Research

Qualitative research questions are primarily exploratory in nature and are used to gain understanding of underlying reasons and provides further insights into the problem. The most popular methodology for exploratory research is the analysis of secondary data, also referred to as literature search (Onwuegbuzie, Leech, & Collins, 2012). These sources are reviewed to discover what is already known about the subject. Furthermore, exploratory research assists in discovering causal relations which later can be proven by causal research (De Vaus, 2001). The following research questions belong within the qualitative research category:

1. What is Demand Side Management and how is Demand Side Management applied in the Heerhugowaard field trial?
2. What is the role of the Aggregator in Demand Side Management and how is this role applied in the Heerhugowaard field trial?
3. What is electricity flexibility and how is electricity flexibility traded?
4. What are potential factors (weather, people per household etc.) that influence the available flexibility within DSM applications?
5. What type of model can predict the available flexibility when Demand Side Management is expanded to more households within the Netherlands?

Sub-research question 1 – 3 focused on what is known regarding DSM, the role of the Aggregator in DSM and the concept of Electricity Flexibility. As these concepts are not new, and DSM has been around since the beginning of the 1980's, the current scientific body of knowledge should be an appropriate source of information, as for example Gellings (1981, 1985 and 1996). For this reason, the analysis of secondary data was chosen to provide an answer to these questions.

Sub-research question 4 aimed at providing evidence for the relation between potential factors, as for example the weather and socio demographics, and the electricity flexibility within DSM applications. This analysis was not performed to prove the actual existence of the relationship but merely to indicate that a theoretical relation exists. The electricity flexibility within DSM systems is present because of the use of four types of appliances which have been addressed in 2.4.1. These appliances have been in use for a longer period of time, although not necessarily for DSM. Therefore, literature should provide sufficient information on the possible relation between potential exogenous and endogenous factors and the functioning of these appliances. Consequently, a literature review in combination with a qualitative comparative analysis was performed (Onwuegbuzie, Leech, & Collins, 2012).

Sub-research question 5 addressed the question which methodology can be employed to predict the available electricity flexibility for a larger set of households. Therefore, this question required an analysis and comparison of methods applied for prediction. The initial information for such an analysis was found by means of a literature review in combination with a qualitative comparative analysis, as sufficient literature is available regarding these methods.

4.1.2 Quantitative Research

Quantitative research is referred to as "*techniques that seek to understand behaviour by using complex mathematical and statistical modelling, measurements and research*" (Investopedia , 2015). Quantitative research uses deductive reasoning to derive a set of outcomes from observations following a certain theory (De Vaus, 2001). The following research questions belong within the quantitative research category:

6. To what extent are the results from the Heerhugowaard field trial generalizable for the expansion of Demand Side Management to more households in the Netherlands?
7. What is the relationship between the potential factors that predict the available electricity flexibility and the measured available electricity flexibility?
8. Which configuration of smart appliances, used in the Heerhugowaard field trial, results in the maximization of flexibility trading for the Aggregator?
9. What is the financial outcome and uncertainty of Demand Side Management expansion for the Aggregator within the Netherlands, taking into consideration the appliances used in the Heerhugowaard field trial?

Sub-research question 6 investigated if the sample, which is taken from a longitudinal continuous panel in a field experiment, is statistically representative with respect to the Dutch households. This analysis was performed with goodness of fit tests as Tomlin (2014) mentioned the usefulness of such test for sample representative testing. The goodness of fits tests that were employed are the Pearson statistics, the one sample t-test and the independent sample student t-tests because of the differing levels of measurement. Through these statistical tests, the difference between the sample and the population were proven with a certain level of significance.

Sub-research question 7 investigated the relationship between the potential factors that predict the available electricity flexibility and the measured available electricity flexibility from the Heerhugowaard field trial. As the question placed substantial focus on the 'relation', regression was used in the context of longitudinal data (Tso & Yau, 2007; Wooldridge, 2015). Therefore, to predict the available electricity flexibility from the Photovoltaic panels, random effect regression was used. For the prediction of the available electricity flexibility of the Electric Boiler linear regression was also inapplicable due to the absence of a useful dataset. Therefore, a simulation study was performed, as introduced by Blokker (2010), in order to approximate the Dutch household hot water consumption pattern. Additionally, for the prediction of the Heat Pump load, normal panel data regression could also not be employed because the data from the Heat Pump was considered to be binary choice data. Consequently, logistics panel regression was performed in order to capture the high numbers of zero correctly (Wooldridge, 2015).

Sub-research question 8 focussed on the optimization of electricity flexibility trading, where electricity flexibility is traded when there is a demand for electricity flexibility and electricity flexibility is available. As this question focused on the optimum configuration mix, linear and non-linear optimization was initially attempted (Jorge & Wright, 2006). However, due to the nature of the optimization problem, the solution space was non-linear, non-smooth and assumed to be non-convex. These implications resulted in a shift from non-linear optimization to Evolutionary optimization because with a non-smooth solution space, derivative or gradients generally cannot be used within the optimization process (FrontlineSolvers, 2016).

The last sub-research question, question 8, focussed on the financial outcome and uncertainty of this outcome for the Aggregator. As no experiment of large scale DSM projects were available, the only financially feasible alternative was selected, which is a simulation model. This simulation model was constructed in Excel through the prediction models estimated in earlier analysis and combined with an automated Visual Basis executive runtime simulation model. Through, verification and validation methods presented by Sargent (2012) the model was validated for operational use, and through the work from Schoots and Hammingh (2015), the uncertainty of the outcome was analysed through scenario analysis.

Based on the presented qualitative and quantitative research methods, the following research flowchart can be drawn:

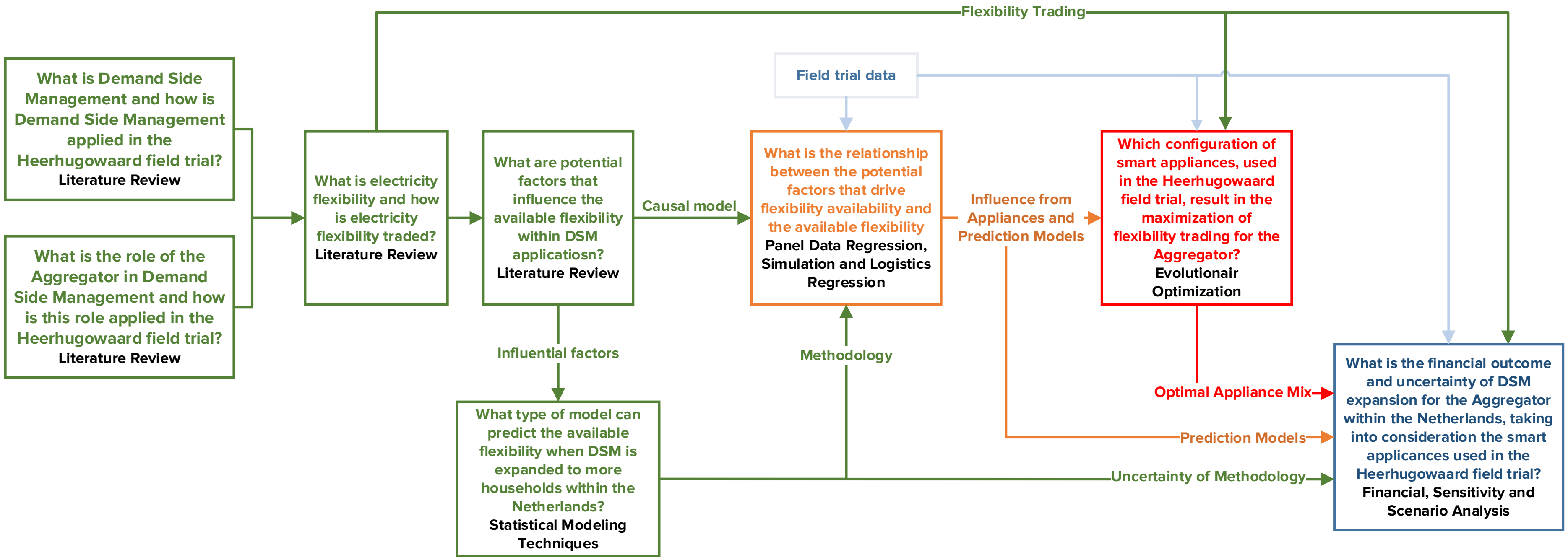

Figure 8: The Research Flowchart

4.2 The Sampling Frame

The sampling frame, or just the frame, is the 'device' used to obtain observational access to the population of interest. The device assists in identifying and selecting a sample from the finite population in a manner that respects the probability sampling design (Särndal, Swensson, & Wretman, 2003). The sample frame with respect to the research of DSM in households, requires a particular type of households. Only households that are connected to a rigid energy grid with overcapacity might be eligible for selection. The overcapacity of the energy grid is essential in order to simulate congestion without endangering the reliability of the energy provision to the households that are participating (Energiekoplopers, 2015). Without the simulation of congestion, tests with respect to DSM and flexibility trading cannot be performed. Consequently, the sample frame might be formulated as following:

"Households that are connected to a rigid energy grid that allows for simulated congestion without endangering the reliability of the energy provision to the households"

Because the city of Heerhugowaard, or more precisely the district, the 'city of the sun', was constructed with the viewpoint of energy neutral living, a high number of photovoltaic panels are installed on the households. This resulted in the installation of an energy grid with a higher capacity in comparison to other energy grids in the Netherlands (Energiekoplopers, 2015). Additionally, the presence of the photovoltaic panels relaxes one of the barriers for the application of DSM as Gellings and Parmenter (1988) mention that the implementer should obtain the customer's trust to install smart appliances in the households. Consequently, the presence of the photovoltaic panels and the high capacity energy grid resulted in the selection of the city of Heerhugowaard. Therefore, the sampling frame can be adjusted to the following:

"Households in Heerhugowaard that are connected to the rigid energy grid that allows for simulated congestion without endangering the reliability of the energy provision to the households"

The sampling technique that was used in order to draw a sample through means of the presented sampling frame is discussed in the next section.

4.3 The Sampling Technique

In all research, analysing the complete population is desired; however, often too time consuming and expensive. Therefore, a sample of the population is selected in attempt to approximate the total population on a smaller scale. However, research on the topic of DSM, simply due to the limitations of the sampling frame, automatically results in a convenient (non-random) sample (Heerhugowaard was chosen because the convenient high capacity electricity systems and the installed photovoltaic panels).

With the stratum selected, participants were nest-sampled randomly from the district of the sun in the city of Heerhugowaard. Alliander/SEC (2013) describes that employees randomly addressed pedestrians on the street (*Location column in Table 4*) and visited random households (*Type of household's column in Table 4*) on the locations presented in Table 4 and Appendix II.

Table 4: The Sampling Locations in Heerhugowaard (Energiekoplopers, 2015)

	Location		*Type of households*
1	Primary School 'Reflector'	A	Free standing
1	Child day care 'de Komeet'	B	Apartment
2	Shopping mal	C	Apartment
3	Restaurant 'de Mediaan'	D	Maisonette
4	Bus stop	E	Town House
5	Pharmacy	F	Two under one roof
6	Playground	G	Town House + Free standing
7	Basketball court	H	Town House
8	Playground	I	Town House
9	Playground		
10	Primary School 'de Cocon'		
11	Playground		

4.4 Population

The population of interest to this analysis is twofold. Initially, only the population of the city of Heerhugowaard, and especially the district: 'the city of the sun', is of interest, and will consequently be addressed in 4.4.1. However, for extendibility of the results to other section of the Netherlands, the target population must also be defined, and will subsequently be presented in 4.4.2.

4.4.1 The Heerhugowaard Field Trial Sample Population

From the 201 participating households, demographic information is available for 185 households. The demographic data from these households is collected by Essent in the initial stages of the field trial and on a **categorical level of measurement**. One of the limitations of the collected data is that the information is limited to one person. For example, for a household with multiple inhabitants, only one age and one level of education is available which limits the precision of the representability analysis. The information that is available from the households are: the amount of inhabitants per household, the income level, the education level, the age of the inhabitants, the size of the house, the type of the house, the energy class of the house and the year of construction of the house. Additionally, information on electricity and gas consumption is available on a 15 min basis as recorded in the SESP database.

4.4.2 The Demographics of the Target Population

The Aggregator is interested in expanding DSM to possible areas within the Netherlands, which due to the penetration level of smart appliances, are in need of electricity flexibility. Therefore, in order to allow for a wide comparison, that takes such potential areas into consideration, a comparison to the Dutch household population is performed.

In order to compare the demographics from the sample of Heerhugowaard with the Dutch household population, demographic data from the Central Bureau of Statistics (CBS) is used. However, not all demographic data collected by the CSB is available on a categorical level of measurement, as is the data from Essent. Therefore, Table 5 provides an overview of which demographics are available, and consequently can only be compared on which level of measurement.

Table 5: The Level of Measurement for Demographic Comparison

	Level of measurement
The age of inhabitants	Categorical
The number of inhabitants per household	Categorical
Level of education	Categorical
Energy consumption	Ratio
Gas consumption	Ratio
The year of household construction	Ratio
The household energy label	Categorical
The household size	Ratio
The household type	Categorical

4.5 The Generalizability of the Results

The generalizability of results, or external validity, is commonly referred to by the degree to which the sample is similar in essential characteristics to its parent population. Furthermore, a sample should not only be similar on a global scale, but also on a local scale for each consecutive part. A sample that is representative on a global scale but not on a local scale can still deviates significantly from the probability distribution function (Kahneman & Tversky, 1972). However, to what extend should a sample represent the population and on which and how many characteristics? Because of this particular question, Kruskal and Mosteller (1979) (taken from pp. 31-32 of Stephan, Frederick F., and McCarthy, Philip J., Sampling Opinions: An Analysis of Survey Procedure, New York: Wiley, 1958) define a representative sample as:

> *"A representative sample is a sample which, for a specified set of variables, resembles the population … [in that] certain specified analyses … (computation of means, standard deviations, etc.…) will yield results … within acceptable limits set about the corresponding population values, except that … [rarely] the results will fall outside the limits …" (p. 251).*

A second notion with respect to a representative sample is that the sample should be taken randomly from the population. This implies that each unit of the population has an equal probability of being selected for the sample and that no selective forces have been present (Kruskal & Mosteller, 1979). However, Yule, Udney and Kendall (1950) state that:

> *"It may be claimed, with some plausibility, that [a] purposive method is more likely to give us a sample which is typical or representative of the population than a random method ... [but] as the sample becomes larger the random sample becomes more and more representative of the parent, whereas owing to bias, the purposive sample in general does not." (p. 382).*

In the analysis presented in this thesis, the initial sample was sampled conveniently, as described in section 4.3. This non-random sampling technique limits representativeness of that specific sample. However, taking regards of the notion presented from Yule, Udney and Kendall (1950), such a sample could still present a representable sample with regards to the selected population variables within acceptable statistical limits. Teddlie and Yu (2007) substantiate this statement as they mention that such as sample may seeks the form of generalizability and consequently could be considered to have the characteristics of transferability.

To indicate if the sample in the current form is representative to the population, even though the non-random sampling approach, a representative analysis will be performed in section 4.5.1. Furthermore, the effect of the sample size will be investigated in order to determine with what level of confidence the results can be transferred to a larger population in section 4.5.2.

4.5.1 The Representativeness of the Sample

In order to investigate if the sample taken from Heerhugowaard is representative to Dutch household, a representative analysis is performed. In order to test the representativeness of a sample Tomlin (2014) mentions the use of goodness of fit tests, where possible goodness of fit tests are for example the Pearson Statistic (also known as the χ^2 test) and the Kolmogorov Smirnov test (Olivares & Garcia-Forero, 2010). The selection of either test initially depends on the level of measurement, the number of intervals and the sample size. If the sample size is large enough (>100) the Kolmogorov Smirnov test performs equal or better than the Pearson Statistic. Additionally, as the number of intervals increase the type 1 error of the Pearson Statistic increases, making the Kolmogorov Smirnov test preferable (Wang, 2009; Olivares & Garcia-Forero, 2010). Therefore, when the level of measurement is numerical and the sample size >100, the Kolmogorov Smirnov test is preferred. Conversely, when the data is of categorical level of measurement and no more than 20% of all expected counts is smaller than 5, the Pearson Statistic is used. However, in some cases no numeric or categorical information is available for both groups. In that case the data can only be compared by means of a one sample student t-test, if the data is parametric, or the Wilcoxen signed rank test if the data is non-parametric.

The goodness of fit tests are performed for the available demographics from the Heerhugowaard field trial with the *H0* hypotheses that there is no significant difference between the samples, and a significance level of 95%. Based on these settings, Table 6 presents the outcome of the goodness of fits tests. As the type of demographics can be separated in three distinct groups; Household characteristics, House characteristics and Consumption characteristics, the sections 4.5.1.1, 4.5.1.2 and 4.5.1.3 will discuss the results respectively.

Table 6: Goodness of Fit Test Demographics

	Test	*Chi Square value*	*T-test value*	*Degrees of freedom*	*95% Rejection value*	*Hypotheses*	*Sig.*
Age	χ^2	104.623		15	26.3	Rejected	0.000
Education	χ^2	214.7585		5	11.07	Rejected	0.000
Number of people per household	χ^2	97.984		4	9.49	Rejected	0.000
Average Construction year house	t-test		31.169	184	1.96	Rejected	0.000
Energy Class	χ^2	328.364		2	5.99	Rejected	0.000
Size of the house	t-test		2.2294	184	1.96	Rejected	0.027
Type of house	χ^2	20.075		4	9.49	Rejected	0.000
Average Energy Consumption	t-test		6.324	2835794	1.96	Rejected	0.000
Average Gas Consumption	t-test		-23.832	1196140	1.96	Rejected	0.000

4.5.1.1 Household Characteristics

The outcome of the goodness of fit tests, performed through the Pearson Statistic, indicate that the Heerhugowaard field trial sample significantly deviates from the Dutch households on Age, Education and the Amount of people per household. This outcome was expected, as the Central Planning Bureau (2015) indicates that newly constructed districts are expected to have a higher number of young families. Although that the Pearson Statistic cannot significantly proof that the sample is significantly younger, the mean of the sample of Heerhugowaard indicates an average age of 45 in comparison to the average age of 50 for Dutch households (Figure 9). Additionally, the higher number of families was also observed in the higher average of number of people per household, as the sample indicates an average of 2.84 in comparison to the average of 2.15 people per household for Dutch households (CBS, 2015).

Additional to the Age and Number of people per households, the Education level of the sample is also significantly different from the Dutch population (CBS, 2015). From the comparison of the two distributions, Figure 11, it appears that the level of education is higher for the sample of Heerhugowaard in comparison to the Dutch population. This is especially observable in the higher frequency for HBO educated and the lower frequency for VMBO educated in the Heerhugowaard sample. This difference was to be expected as the Ministry of Welfare of the Netherlands (2014) indicates that nowadays younger people have a higher education than older people. This might be contradictory as education is positively correlated with age; however, due to the increase of people following a secondary or tertiary level of education in the last years, this shift has occurred. Therefore, in contrast with the higher number of young people in the sample, a higher level of education is justified.

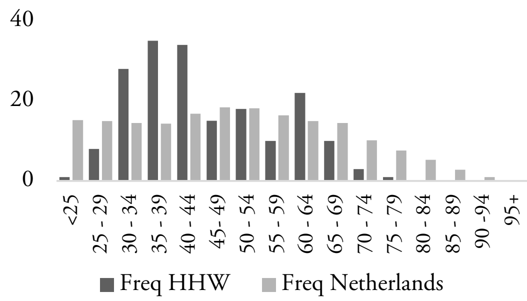

Figure 9: Age Distribution

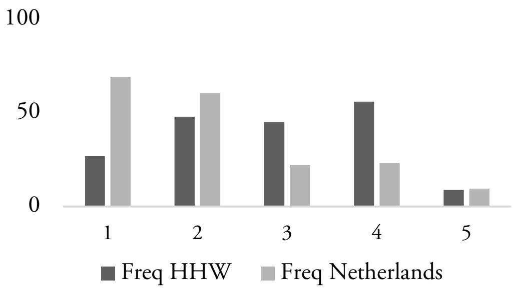

Figure 10: Number of Individuals per Household

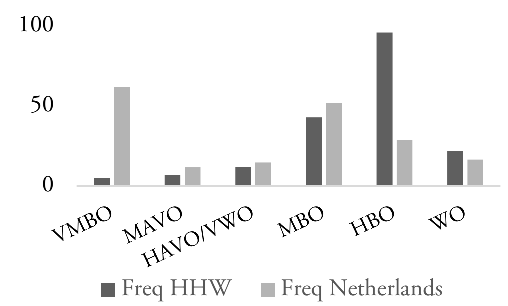

Figure 11: Education Distribution

4.5.1.2 House Characteristics

The goodness of fit analysis for the house characteristics, in comparison to the Dutch average houses, indicates that the Heerhugowaard sample is significantly different on all categories. The average construction year of the houses in the sample of Heerhugowaard is 1997 in contrast to the average construction year of 1959 for average Dutch houses (CBS, 2015). This deviation in the construction year of the house is in line with the energy class of the house, as newer houses tend to have a higher energy class (Figure 12) (Bosch, 2011). Furthermore, the district in Heerhugowaard, from which the sample was taken, consists of a small set of different house types, and one might therefore expect that the sample would significantly deviate from the house types in the Netherlands, which through the Pearson Statistic is substantiated. Last, the size of the house only differs slightly from the average of the Netherlands, 128 m^2 compared to 123 m^2 respectively (CBS, 2015). However, this difference is still significant and the houses in the sample cannot be considered to be the same as the average houses of the Netherlands.

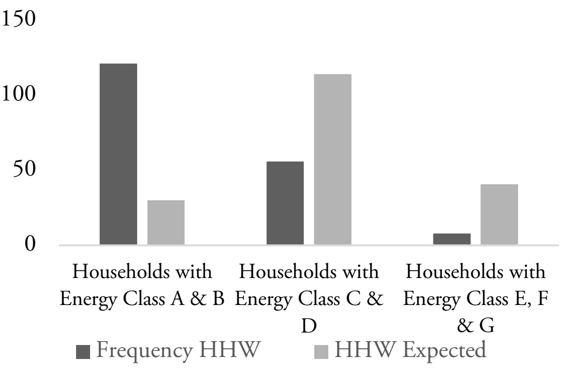

Figure 12: Energy Class Distribution

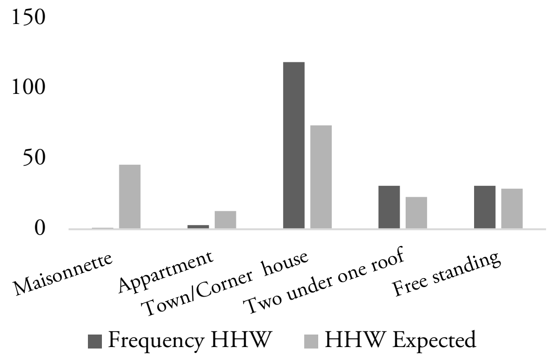

Figure 13: Household Type

4.5.1.3 Consumption Characteristics

For the comparison of the energy consumption and the gas consumption of the households, measured data is used. The availability of measured data of these households provides the advantage that these households can be compared within the sample, as one might expect a difference in the consumption patterns due to different appliances per households. In other words, one might expect a higher level of gas consumption for a household with a Fuel Cell, and a lower gas consumption for a household with a Heat Pump, and vice versa for electricity. This expectation is substantiated by the outcome of an Analysis of Variance that indicates that there is a significant (F value: 123.49, sig. 0.000 for α: 0.05) difference between the households gas consumption, with the groups categorized per type of device. Therefore, the addition of a gas consuming or reducing device significantly changes the gas consumption pattern. In order to take this difference into account, the gas consumption of the households with controllable photovoltaic panels (and thus no Heat Pump, Boiler or Fuel Cell) is compared to the Dutch average household gas consumption. This comparison shows, through a one sample t test, that the gas consumption is significantly (t value -23.823, sig. 0.000 for α: 0.05) lower than the Dutch average household gas consumption. In contrast, the Heerhugowaard sample household yearly gas consumption is 1121 m^3 compared to the 1430 m^3 for average Dutch households (NIBUD, 2015).

For electricity consumption the household load must be corrected, as all smart appliances influence the total energy consumption differently. This statement is substantiated by the significant (F value: 1270.93, sig. 0.000 for α: 0.05) results from an Analysis of Variance on household energy consumption. Consequently, the household load is corrected by subtracting the generated load or supply of electricity from the smart appliances. Based on the one sample t-test the corrected average household electricity consumption of 3773 kW per year is significantly (t value 6.324, sig. 0.000 for α: 0.05) higher than the Dutch average of 2970 kW per year (NIBUD, 2015).

Based on the results presented from the representativeness analysis, it is possible to conclude that the sample of the Heerhugowaard field trial is not representable to the Dutch population. However, this does not necessarily imply that the data from the sample cannot be used. The bias that is present due to the non-random sample may not be of influence on the estimators of the prediction models, as the prediction models might not have independent variables that are related to these demographics. Therefore, to validate that the proposed estimators are correct, the influence from the demographics must be investigated, and if significant, the estimators corrected.

4.5.2 The Effect from the Sample Size on the Confidence Levels

The size of the sample together with the desired confidence interval, confidence level and the population size, determine to what extend the results from the analysis may become statically accurate. These variables are related in the following two equations:

$$n_0 = \frac{z^2 pq}{e^2} \quad n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

where n_0 is the infinite population sample size, z is the abscissa of the normal curve that cuts off an area α at the tails, e is the desired level of precision, p is the estimated proportion of an attribute that is present in the population, and q is 1-p (Israel, 1992). Furthermore, the calculated sample size must be corrected for the finite population, which is accomplished with the second equations where n is the required sample size and N the population size.

With regards to the field experiment performed in Heerhugowaard, a sample of 201 households was used, that at this point in in time cannot be altered, and consequently implies that the results may only be extended to N number of households with a confidence interval of e. Furthermore, because the prediction of the available electricity flexibility is based on the types of appliances, the sample size is reduced further to 89 for the Photovoltaic panels, 18 for the Fuel Cell, 44 for the Electric Boiler and 50 for the Heat Pump. Based on these sample sizes (n), a confidence level of 95% (z = 1.96) and p and q fixed to 0.5 as mentioned by Dusick (2016) for sample size estimation, the following equation can be used to determine the population size, based on the confidence interval e (which is incorporated in n_0).

$$N = \frac{n(n_0 - 1)}{n_0 - n}$$

The outcomes of this equation indicates (Figure 14) that for the extendibility of the results, from the prediction models to a larger set of households, the minimum confidence interval is strictly related to the sample size (because higher sample sizes give a smaller confidence interval). Furthermore, Figure 14 also indicates that beyond a certain population size the relation asymptotically approaches a certain confidence interval, which can be determined by analysing the domain of the function.

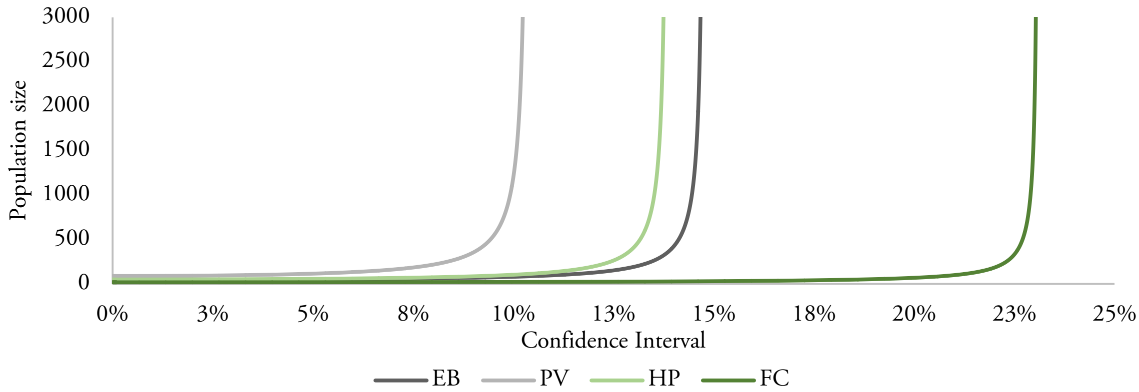

Figure 14: The Population Size for various Confidence Intervals

By transforming the equation for $N \rightarrow n_0$, and substituting it into the equation for e, the domain can be obtained as N goes to infinity.

$$N = \frac{n(n_0 - 1)}{n_0 - n} \rightarrow n_0 = \frac{Nn - n}{N - n} \rightarrow \lim_{N \to \infty} e = \sqrt{\frac{z^2 pq}{\left(\frac{Nn - n}{N - n}\right)}}$$

Based on this transformation, the confidence interval is 10.38% for the Photovoltaic Panels prediction, 13.86% for the Heat Pump prediction, 23.10% for the Fuel Cell prediction and 14.77% for the Electric Boiler prediction.

4.6 The Data Collection Procedure

The data on the smart appliances and household consumption, which is used in the data analysis, is collected through the SESP interface with the Prosumer household (Koenders, 2014). The interface is primary used by the Aggregator in order to control the smart appliances, and by the User Portal to present electricity consumption and generation to the inhabitants of the household. Next to these primary functions, the interface is also used to collect data on the smart appliances such as the electricity consumption, generation, state and charge levels. The data is collected on a 15 minute interval through the SESP home gateway and the SESP back-office. After the collection of the data, the data is stored in a SQL database that can be accessed through an ODBC with Microsoft Access. Figure 15 presents an overview, in the UML format, of the interface between the SESP SQL database, the Prosumer interface, and its associated units.

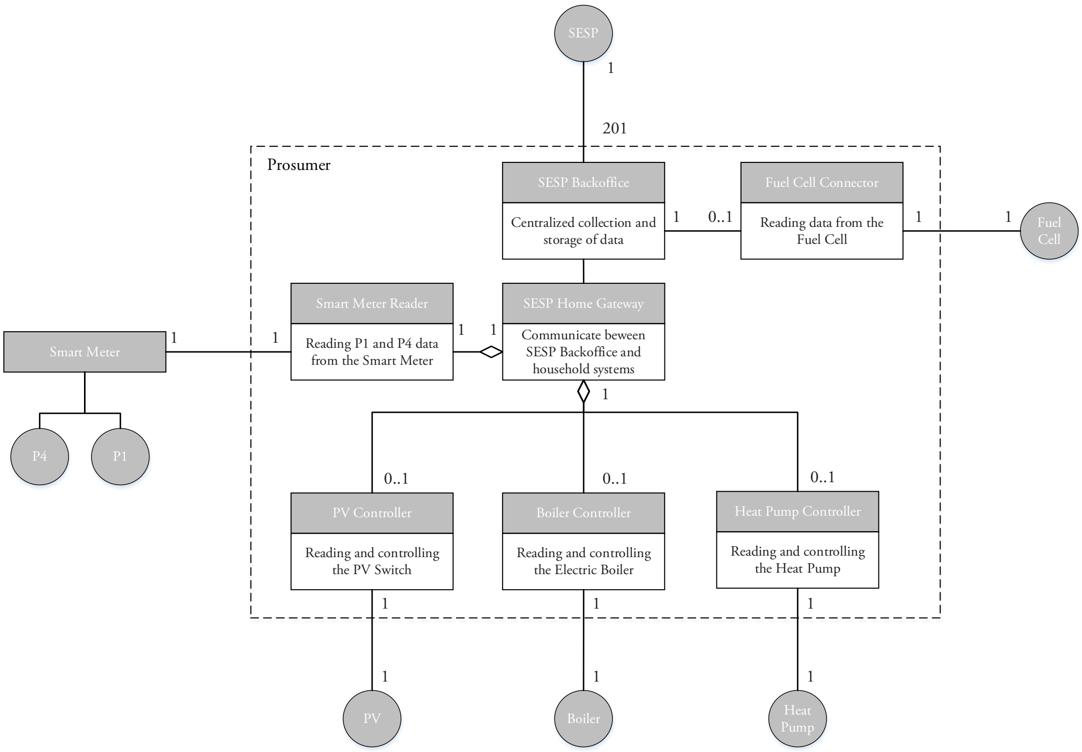

Figure 15: UML Overview of the SESP – Prosumers Interface (based on Koenders, 2014).

From the SESP database information was available from the 4th of August to the 29th of February starting from hour 00:00 and ending on hour 00:00. This resulted in 4095 15 min intervals for 201 household on 4 different appliances.

4.7 Data Processing

The data gathered for the analysis of available electricity flexibility of the smart appliance could not be directly used in data analyses. In order to prepare the data for analysis, the steps presented in section 4.7.1through 4.7.5 were performed.

4.7.1 Data Sources

Next to the SESP data collected from the field trial, two other data sources are used. For weather data, information is collected from the Koninklijk Nederlands Meterologisch Instituut. Because of the absence of a weather station in Heerhugowaard, weather information from the closest weather station, Berkhout, is used.

The second data source provides information on the elevation and azimuth angle of the sun. This information originates from the Earth System Research Laboratory and may be calculated for any time interval required. Additionally, the data is calculated based on the longitudinal and latitudinal (52°40'N, 04°51'E for Heerhugowaard) values and consequently corrects the results to match with the geographical location.

4.7.2 Data Preparation

The available data from the SESP database consisted of approximately 30000 individual files of 70 kb, with the following format:

20150718000000;EEXPLOW;ea1.2015-03.nl.energiekoplopers:Huishouden088;191.288;0.000;;;;

In order to analyse the data efficiently, these files were combined by means of the following DOS subroutine:

```
for %f in (*.txt) do type "%f" >> output.txt
```

The output of the presented DOS subroutine resulted in an output.txt file of 3.08 GB containing 2,939,813 rows of information on 36 variables. Furthermore, household level data was extracted from the complete dataset to compile household specific datasets as analysis could not be performed in Excel due to the 1,048,576 row limit. This resulted in four different datasets, each containing the households related to one smart appliance.

4.7.3 Outlier removal and Missing Values

Outlier are data points that fall within a specific rejection zone, where numerous techniques, such as the Grubbs' technique or the modified Thompson τ test, can be performed to detect such data point. However, outlier removal is biased in philosophical sense as Dieck (2007) mentions that: "*Outlier removal is used to make the data 'look' better and is therefore the preconceived notion of the analyst, toward making the data set better to prove the thesis*" (p. 168). Therefore, removing outlier, if even attempted, should be done with great caution as it elevates the risk to type one errors. Consequently, the rejection zone outlier technique was no used for detection and removal of data points.

Next to the rejection zone, it is also possible to determine outliers through common sense, by for example evaluating the measurement in contrast to the expected value. For example, a Heat Pump theoretically cannot consume more than 620 Wh (Inventum, 2015); therefore, finding a consumption of 2000 Wh is simply not possible and should be accounted as a measurement error. Comparably, finding a Photovoltaic output that is higher than the Photovoltaic panel capacity. Analysis of the data for outliers resulted in 1002 values out of 281751 being market as outlier for the Photovoltaic dataset, and 6635 values out of 143321 for the Heat Pump. Outlier analysis for the Electric Boiler and Fuel Cell was not performed as these datasets were not used for relation analysis.

With the removal of the outlier the number of missing data point in the dataset increased, in comparison to the initially missing data points. Missing panel data results in an unbalanced longitudinal dataset and has consequences for the random and fixed effect estimators. However, due to the implementation of the Swamy – Arora method in the fixed and random effect estimators, this consequence only starts to play a role when the sample size of the unbalanced panel is 200 or less (STATA, 2014). Therefore, when panels have a sample size smaller than 200 data points, these panels (or households) are not taken into consideration for the data analysis. Based on this criteria, the households presented in Table 7 were rejected for analysis, where the light grey coloured household numbers are reserve numbers, and initially did not contain any information. In total, the remaining household panels for the Photovoltaic panels contained 21188 (7.52%) missing data points, and for the Heat Pump 45450 (31.71%) missing data points.

Table 7: Rejected Households

Photovoltaic Panel	*Heat Pump*	
5	2	558
68	44	636
722	55	672
769	100	682
807	107	713
809	116	754
811	167	781
830	178	783
832	188	788
819	229	792
956	340	804
992	351	891
	391	909
	420	914
	467	934
	505	947
	536	991
	555	998

4.7.4 Time verification with external sources

The data collected from the households in Heerhugowaard is collected on a 15 min interval, or 96 times per day. On the other hand, the weather data from the KNMI is recorded on an hourly basis, 24 times per day. In order to manage this inconsistency the household data is averaged over 4, 15 minute time intervals, transforming the data into hourly data.

Additional inconsistencies arise due to the missing values in the data set, because the missing data is not recorded as empty values. This inconsistencies results in synchronization errors between the household data and the weather data. For example, due to a few hours missing, the solar irradiance becomes positive during the night and zero during the day. To prevent this error a Lookup function was used in Excel, which matches the dates of both data sets and transposes the corresponding household data.

4.7.5 Software

The software packages used in the data analysis are:

- STATA v. 14 Parallel Edition Single-user 8-core
- IBM SPSS Statistics v. 22 64-bit
- Microsoft Excel 2013 v. 15.0.4649.1000 64-bit


5

5 Predicting the Available Electricity Flexibility

In order to predict the available electricity flexibility one must investigate the relationship between the potential factors that predict the available electricity flexibility and the measured available electricity flexibility. The term 'relationship' identifies that this question aims at finding the cause and effect association between two elements and is consequently of causal nature. However, one is never able to observe cause, one can only observe correlation (De Vaus, 2001). Therefore, in order to provide evidence of the relationship, a method must be employed that can proof the existence of correlation. The data that is available from the field experiment is taken from a longitudinal continuous panel and can therefore be considered as panel data. Panel data from a longitudinal continuous panel consists of a time series for each cross-section household in the data set. Using data from **households** and predicting for **households** allows the possibility to include the household demographics that might have a significant influence on the available electricity flexibility, which allows further adjustment when such prediction models are used for different cities in the Netherlands. Additionally, observing the same household over time has an advantage makes it possible to distinguish between the prediction error and the household related errors, which are caused, for example, by the changing demographics of the household (Wooldridge, 2015). To determine correlation between a dependent variable (the available electricity flexibility) and independent variables for panel data, one could use panel data regression (Wooldridge, 2015). However, as the answer to this question is inevitably used to predict the available electricity flexibility, one should also assess prediction techniques.

A common used technique in prediction, next to regression, is a neural network and explained as (Tso & Yau, 2007). Even though that neural networks have proven to be better in prediction than regression analysis (Tso & Yau, 2007), neural networks are 'black boxes'. The term 'black box' implies that the neural network does not provide any insights into the form of the function the neural network uses to predict. Therefore, from a statistical viewpoint, the neural network is a non-identifiable model. Consequently, neural networks are not able to assist in answering the research question with respects to the relationship between the potential factors that predict the available electricity flexibility and the measured available electricity flexibility and consequently regression is used.

In order to use regression for panel data, or longitudinal data, the concepts of panel data regression will first be introduced in section 5.1. To then employ regression, the bivariate relationships between the dependent and independent variables are investigated in section 5.2. On the basis of possible significant bivariate relationships, an attempt is made to construct models that predict the available flexibility of the smart appliances in section 5.3. Last, the chapter concludes by presenting an overview of the models that predict the available electricity flexibility for the smart appliances in section 5.4.

5.1 An Introduction to Panel Data Regression

As was already mentioned in the introduction of this chapter, panel data is longitudinal data and consists of a cross-section, which is represented by the households, and a time series, which is represented by the passing of time. To collect such data, the same individuals must be sampled over multiple, subsequent moments in time. This provides a significant benefit for the researcher as it is possible to isolate specific effects and policies, but prevents that individuals are independently distributed over time. Furthermore, panel data provides the researcher with a larger number of observations, increases the degrees of freedom, and reduces the change of collinear explanatory variables, and consequently improves the estimates (Hurlin, 2010). Additionally, panel data makes it possible to obtain a more accurate representation of an individual's behaviour by supplementing observation of the individual with observations from other individuals (Cheng, 2003). But maybe the most important reason to collect panel data is that it allows for the control of omitted variables, where these omitted variables can either be unobserved or miss-measured (Wooldridge, 2015).

The omitted variable problem occurs when one attempts to estimate coefficients for the population when not all correlating explanatory variables are taken into consideration. Since it is always possible to find additional explanatory variables that are correlated with the independent and dependent variable, this will lead to the violation of the $E\ (u_{it} \mid \boldsymbol{X}_i,\ a_i) = 0$ Gauss–Markov assumption. Even with the assumption that u_{it} (the idiosyncratic error) is uncorrelated with x_{it}, the OLS estimators are biased and inconsistent (heterogeneity bias). By means of panel data it is possible to control for some types of omitted variables and therefore should provide more consistent and less biased estimators (Wooldridge, 2015).

In econometrics there are two possible approaches to take heterogeneity bias into consideration. One approach is first differencing to remove a_i (the unobserved effect[3], or fixed effect), or assuming that a_i is negligible when one has good control variables in the regression equation (random effects). In the case of electricity flexibility prediction for the Heat Pump and Electric Boiler one can assume that something within the household might impact or bias the estimator, as flexibility is a direct response from energy consumption and individual behaviour, and therefore there is a need to correct for this. By estimating a_i, it is possible to take into consideration the time invariant characteristics and predict the net effect of the estimators on the dependent variable. To take a_i into consideration during panel data regression, a fixed effects regression model is required (Torres-Reyna, 2007). However, as one assumes that a_i is uncorrelated with each explanatory variable, like for example with the production of electricity flexibility from the Photovoltaic panels, then using such an estimation would result in inefficient estimators. In that case one should not use fixed effects regression but random effects regression (Wooldridge, 2015).

5.1.1 Fixed Effects and Random Effects

Next to using first differencing, the fixed effect regression is a method of dealing with the a_i. Because fixed effects assumes that a_i is constant over time, the a_i will not be taken into consideration within the estimation of the estimators. This fixed effect transformation is mathematically represented as:

$$Y_{it} = \beta_1 X_1 + \alpha_i + u_{it}$$

The estimators found by means of OLS, based on the within transformation, are referred to within estimators or fixed effect estimators. In within estimation, OLS uses the time variation in y and x within each cross sectional observation. Under the strict exogeneity, homoscedasticity and no serial correlation assumptions the explanatory variables from the fixed effect estimation are unbiased (Wooldridge, 2015).

When there is the assumption that a_i is uncorrelated with x_{it} one should use random effects. However, if this holds true, then why should one even endeavour to use random effects as the correlation of a_i to x_{it} was the reason to shift to fixed effects? The main reason to use random effects when a_i and x_{it} are uncorrelated is that OLS will result in incorrect standard errors due to positive serial correlation in the composite error, v_{it} ($a_i + u_{it}$) (Wooldridge, 2015). Therefore, instead of using fixed effects, random effects should be used, where random effects is mathematically represented as:

$$Y_{it} = \beta X_{it} + \alpha + u_{it} + \varepsilon_{it}$$

Due to the non-observability of the $a_{i,}$ the selection of a regression method might become arbitrary without further statistical direction or substantiation, as it would always remain uncertain which approach is deemed to be best, or provide unbiased and consistent estimators (Hausman, 1978). In order to make this decision three tests are available:

1. ***The Fixed Effect F-Test***

   The *H0* hypotheses of the F-test assumes that the regression function will have the following structure

   $$y_{it} = X'_{it}\beta + u_i + \varepsilon_{it}$$

   where the observed and unobserved u_i are equal to zero. The *H1* hypotheses assumes that the u_i are not equal to zero, and would imply that OLS and random effects will be biased. However, this conclusion only hold if the $Cov(X_{it}, u_i) \neq 0$, which can be tested through the Durbin–Wu–Hausman test (Park, 2011).

2. ***Breusch and Pagan Lagrange- Multiplier Test for Random Effects***

   The Breusch and Pagan Lagrange- multiplier test, or LM test, hypothesizes that the variance of u_i is equal to zero ($Var(u_{it}) = 0$). Rejecting this *H0* implies that OLS would result in biased estimators and that random effects should be preferred (Breusch & Pagan, 1980).

[3] The unobserved effect or time invariant characteristics are for example gender, religion, culture, race, etc.

3. Durbin–Wu–Hausman Test

The Durbin-Wu-Hausman test, also referred to as the Hausman specification tests evaluates that consistence of estimators in comparison to less efficient estimators. Under the *H0* the Hausman specification tests assumes that the random effect estimators are consistent and efficient, while under the *H1* that the fixed effect estimators are consistent and efficient. Therefore, if *H0* is rejected, fixed effect is preferred over random effects (Hausman, 1978).

A combination of these test should be employed to determine which regression approach leads to consistent and efficient estimators. In most cases the Fixed Effects F-Test and LM test are performed and later contrasted through means of the Hausman specification test.

5.1.2 The Assumptions for Fixed and Random Effects

In order to find the Best Linear Unbiased Estimators (BLUE), where best implies the lowest variance, for Fixed Effects regression the following assumptions must be proven and hold (Wooldridge, 2015):

1. Linearity

According to Wooldridge (2015) a *population model*, or the *true model*, is considered to be a model with the following structure for fixed and random effects.

$$y_{it} = \beta_1 x_{it1} + \ldots + \beta_k x_{itk} + a_i + u_{it},\ t = 1,\ldots,\mathrm{T}$$

This implies that the model is linear in the estimator's $\beta_0, \beta_1, \ldots, \beta_k$. This further implies that the relation between the independent and the dependent variable must be of linear nature. Any violation of this assumption might lead to heteroscedasticity, non-normal residuals and consequently biased and non-consistent estimators. Berry and Feldman (1985) describe three methods to verify the linearity of the relation: theory analysis on the relation, analysis of the standardized residuals or detecting curve-linearity. However, if a relation is assumed to be linear, this does not imply that the data used for the regression analysis is also linear. Therefore, to assess the linearity of each relation the standardized residuals will be examined as a function of the standardized predicted values. If this relation does not proof to be linear, the dependent or independent variable will be transformed by means of the required curvilinear component.

2. Random Sample

The second assumption for fixed effects is that the cross-section is sampled randomly. If this is not the case the estimators might be biased for extension to the population, which was discussed partly in 4.5. For this analysis, due to the sampling technique applied, a non-random sample is available, and therefore the estimators are equally biased as the sample is biased from the population ($E(\hat{\beta}|x_i) \neq \beta^p$) (Wooldridge, 2015).

3. Zero Conditional Mean

The zero conditional mean error assumption assumes that $\mathrm{E}(u_{it} | \boldsymbol{X}_i, a_i) = 0$ and implies that the expectation of the error, given any independent variable has to be equal to zero. If this assumption is violated the estimators of the regression model are biased ($E(\hat{\beta}|x_i) \neq \beta^p$). A possible method to verify if $\mathrm{E}(u_{it} | \boldsymbol{X}_i, a_i) = 0$ is to investigate if the $Cov(u_i | \boldsymbol{X}_i, a_i) = 0$. In the absence of AR terms, this assumption holds for all t and is referred to as the strict exogeneity assumption. If AR terms are present, there is a transition from strict to weak exogeneity where $Cov(u_i | \boldsymbol{X}_i, a_i) = 0$ only has to be valid for t.

4. No Perfect Collinearity

Perfect collinearity, or multicollinearity, may not exist between independent variables and each variables has to change over time. Multicollinearity can be investigated by determining the variance inflation factor (VIF), where a VIF of 5 or more would indicate multicollinearity (O'Brien, 2007). The existence of multicollinearity can be corrected by removing independent variables that indicate a high VIF value.

5. Homoscedasticity

Homoscedasticity assumes that the variance of u_{it}, conditional to the independent variable is constant ($Var(u_{it} | \boldsymbol{X}_i, a_i) = Var(u_{it}) = \sigma^2_u$, for all $t = 1, \ldots, \mathrm{T}$). Therefore, this assumption fails when the variance of the residuals changes across different segments of the population. The violation of this assumption implies that the standard errors are incorrect and that the estimators are inefficient, as when heteroscedasticity is present, more efficient estimation is possible (Wooldridge, 2010).

To test if the homoscedasticity assumption is violated in a fixed effect model the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity. The Breusch-Pagan / Cook-Weisberg test determines homoscedasticity by regressing the residuals based on the independent variables and investigating if the independent variables are responsible for the residuals. To determine the significance of homoscedasticity the Breusch-Pagan / Cook-Weisberg test calculates the F value for *H0*: homoscedastic variance and *H1*: heteroscedastic variance. However the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity assumes that u_{it} should not be serial correlated. Therefore, the assumption of serial correlation should be tested first before any attempt should be made to test or correct for heteroscedasticity (Wooldridge, 2015). However, as heteroscedasticity does not result in biased and inefficient estimators a robust fixed effect estimation can be performed.

6. ***No Serial Correlated Errors***
Serial correlation occurs when there is a relation between u_t and u_{t-1}. Serial correlation of residuals can be tested by means of the Wooldridge test for autocorrelation which tests the *H0* that the residual are not serial correlated and *H1* that the residual are serial correlated. The Wooldridge test for autocorrelation is considered to be robust and can therefore be applied to panels that are conditionally heteroscedastic (Drukker, 2003).

Just like heteroscedasticity, serial correlation does not influence the estimators of the fixed effects regression and can thus considered to be efficient and unbiased. However, the standard error and confidence intervals are affected and thus biased. To correct for serial correlation and heteroscedasticity it is possible to use a variety of robust alternatives depending on the type of disturbances. The most popular robust estimators are based on White, Huber and Eicker; however these approaches do not take into consideration the cross sectional correlation. In the situation where one assumes that cross sectional dependence is present, caused by for example spatial dependence, and one wants to retain the fixed and random effects estimators, the Driscoll and Kraay correction can be used (Drukker, 2003; De Hoyos & Sarafidis, 2006). The Driscoll and Kraay correction ensures that the standard errors are corrected for heteroscedasticity and serial correlated residuals, while retaining the cross sectional dependence.

7. ***Normally Distributed Residuals***
The last assumption of fixed effects is not related to the unbiasedness of the estimators but to the interference of the t distribution and the F-statistic. This assumption requires that the u_{it} are normally distributed with a mean of zero. This assumption can be tested by performing a Shapiro Wilk test on the residuals after fixed or random effects regression. Shapiro Wilk, tests through the *H0,* if the sample comes from a normally distributed population. However, with increasing sample size, the normality test also increases in power and will reject the *H0* hypotheses almost instantly.

From a different perspective, Wooldridge (2015) states that the assumption of normally distributed residuals is equivalent to saying that the distribution of y, given $x_1, x_2, \ldots, x_k$ is normal. This in relation to the large sample size, one can conclude through the central limit theorem, that y, even if y is not normally distributed, comes from a normal distribution and therefore one can also conclude that u_{it} is normally distributed. However, for this condition to hold, it is very important that the residuals are homoscedastic and that there is a zero conditional mean. Without these condition, the t statistic and the related confidence intervals are invalid regardless of the size of the sample. However, as heteroscedasticity can be treated through means of the Driscoll and Kraay correction, the confidence intervals for the estimators are considered to be valid (Wooldridge, 2015). For additional substantiation a normally plot will be estimated and evaluated for each regression model.

In addition to the fixed effects assumption the following assumptions have to be added for random effects:

1. ***Zero Conditional Mean a_i***
The expected value of a_i, given all explanatory variables is zero: $E(a_i \mid \boldsymbol{X}_i) = 0$.

2. ***Homoscedastic a_i***
The variance of a_i given all explanatory variables is constant: $Var(a_i \mid \boldsymbol{X}_{i,}) = \sigma^2_a$.

5.2 Bivariate Analysis

In section 3.2 causal relations were presented in order to determine the influence of hypothesized exogenous factors on the available flexibility from the smart appliances. In order to determine if such relations exist, a literature study was performed. However, literature cannot be considered a fool proof technique to determine if such a relation actually exists (Berry & Feldman, 1985). In order to proof that a relation exists, a bivariate analysis may be performed. This analysis will be done by means of the Pearson correlation coefficient as it is possible to assume, through the central limit theorem, that the arithmetic mean of the independent and dependent variables approximate a normal distribution as a very large sample size is available (Mordkoff, 2011). Next to the assumption of an interval or ratio level of measurement, a third assumption is that the relationship between the two variables must be linear in order for the Pearson coefficient to be consistent through the law of large numbers.

The linearity of the relationship is presented and substantiated through literature in section 3.2; however, the same reasoning holds that a theoretical indication of linearity does not proof linearity. Linearity of the relation can be observed by the Augmented Partial Residuals (APR) plot (Mallows, 1986). The APR plot has proven to be very effective in detecting significant outliers and non-linear relationships (Fernandez, 2003). However, due to the sheer size of the dataset, it was not possible to compute these ARP plots. Therefore, non-linearity will be observed through scatter plots. If non-linearity is observed, the variables can be transformed by means of mathematical transformations. In this transformation, the dependent and independent variable may be transformed; however, the dependent variable may only be transformed in the presence of heteroscedasticity (Hair et. al, 2009).

By transforming the independent and dependent variable, the aim is to reduce the Mean Square Error for that particular relation. However, as multiple independent variables have a relation with the same dependent variable, the transformation of the dependent variable will influence the relations with the untransformed independent variables. To find the most suitable transformation which takes into account all relations, the following non-linear optimization approach is proposed:

$$max \sum_{i=1}^{n} \frac{c\hat{o}v(X_i^{x_{ti}}, Y^{y_t})}{s_{X_i} s_Y}$$

where X_i are the independent variables, Y is the dependent variable, and x_{ti} and y_t are the transformation and decision variables respectively. The limitation of this approach is that this optimization methodology can only transform convex and concave functions to linear. Therefore, if other transformation are required these will be performed manual. If only the Y dependent variable is transformed with a different transformation the same approach can be used to optimize the linear relation for the independent variable X. The presented methods shall be implemented in the following order for each set of relationships belonging to each smart device:

1. Observe the scatter plot in order to determine if a transformation is required;
2. Test for heteroscedasticity in each relationship to determine if the dependent variable should be transformed;
3. Transform the variables by means of the proposed non-linear optimization approach;
4. Perform Pearson correlation to determine if a significant relation is present between the dependent and independent variable.

5.2.1 Bivariate Analysis for Photovoltaic Output

The bivariate analysis of the hypothesized explanatory variables by means of a scatter plot (Appendix III.a) indicates that the relations between the dependent variable *PV-Output* and independent variables *SunAzimuthFrom180, PV-CapacityIrradianceState, Irradiance, PV-Capacity, ElevationAboveHorizon, Temperature,* and *Humidity* are non-linear. An analysis of the *Photovoltaic Energy Transition Efficiency* cannot be performed due to an absence of data. Furthermore, the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity indicates that the relations between the independent variable and the dependent variable are all heteroscedastic (significance 0.000) and that consequently, the dependent variable *PV-Output* should also be transformed. With the proposed optimization approach, the dependent and independent variables are transformed to maximize the summed R^2. This approach resulted in the transformations indicated in Table 8. The transformation of the independent variables and the dependent variables for the prediction of *PV-Output* was also indicated by Moghram and Rahman (1989) and by Soares (2014).

Table 8: Photovoltaic Hypothesized Exploratory Variable Transformation

	PV-Output	*SunAzim*	*Interaction*	*Irradiance*	*PV-Capacity*	*Elevation*	*Temperature*	*Humidity*
Transformation	0.353	0.481	0.474	0.463	0	0.587	0	-0.098
Parsimony Transformation	0.33	0.5	0.5	0.5	0	0.5	0	0

After this transformation was performed, the Pearson correlation coefficient was calculated for each relation to test the proposed hypotheses in 3.3. From this analysis Table 9 presents the correlation coefficients where all except the *Temperature* and *Humidity, PV-Output* relations tested significant with a α of 0.05.

Table 9: Pearson's Correlation Coefficients for the Hypothesized Photovoltaic Relations

	SunAzim	*Interaction*	*Irradiance*	*PV-Capacity*	*Elevation*	*Temperature*	*Humidity*
Original dependent and independent variables	-0.329	0.794	0.644	0.147	0.521	0.304	-0.456
Transformed dependent and independent variables	-0.515	0.831	0.737	0.058	0.657	0.326	0.475
H0 hypotheses	Rejected	Rejected	Rejected	Rejected	Rejected	Cannot reject	Cannot reject

From these results it is possible to conclude that for the *SunAzimuthFrom180, PV-CapacityIrradianceState, Irradiance, PV-Capacity* and *ElevationAboveHorizon* the *H0* hypotheses are rejected and that the hypothesized relation exists between these independent variables and the *PV-Output*. However, although the correlation coefficients for *Temperature* and *Humidity* are significant, the *H0* cannot be rejected because an inverse relation is found. This inverse relation might be the cause of multicollinearity between *Humidity*, *Temperature* and *Irradiance* (0.626 and 0.477, respectively). The existence of this relation was also indicated by the work of Chang and Root (1974) as they performed an analysis on the relationship between irradiance and air temperature. Consequently, *SunAzimuthFrom180, PV-CapacityIrradianceState, Irradiance, PV-Capacity* and *ElevationAboveHorizon* will be used for the Panel Data Regression in order to predict the *PV-Output.*

5.2.2 Bivariate Analysis for Warm Water Consumption

In section 3.2.2 the independent variables that influence water consumption were introduced. From these independent variables only the *Temperature* can be analysed in a bivariate analysis as the number of inhabitants per household is not known and the hour of the day is a categorical variable that does not portray linear behaviour due to the distinct double peak pattern over the day (morning and evening peak).

The scatter plot (Appendix IV) for the relation between the *Hot Water Consumption* and the *Temperature* indicate that the relation can be considered to be linear. Therefore, further transformation of the independent variable is not required. The Pearson correlation coefficient for this relation further indicates a significant (significance 0.000) negative relation of -0.0649. Consequently it is possible to reject the *H0* hypotheses and conclude that an increase of the outside air *Temperature* has an inverse relation with *Hot Water Consumption*. Subsequently, the influence from *Temperature* will be taken into consideration to predict the *Hot Water Consumption.*

5.2.3 Bivariate Analysis for Heat Pump Load

In section 3.2.3 a large number of relations were hypothesized based on the Heat Pump state equation and the law of Fourier. However, due to the absence of household specific information not all of these relations can be empirically tested. Therefore, for the hypothesized relationships with the independent variables *House size, House type, Energy class and Household Inhabitants* no bivariate analysis can be performed[4], and these variables can consequently not be used in the regression analysis. The data on the remaining independent variables: *Temperature, Irradiance, Wind speed* and the *StateSESP* are available and of interval level of measurement, resulting that the relations can be investigated by means of Pearson's correlation.

[4] Because of legal concerns (confidentiality agreements) it was not possible to connect the household demographic data to the measure data from the household. Consequently, the demographics could not be tested in relation to the hot water consumption.

The scatter plots of the four relations with the Heat Pump Load indicate (Appendix V) an approximation to a linear relationship. Additionally, optimization as proposed in 5.2, indicates corrections (Table 10) for the dependent and the independent variables that indicate that the relationships can be considered to be linear. The proposed transformation for *Irradiance* is not taken into consideration as the difference in the R^2 is only 0.8% and would not result in a parsimony regression model. Therefore, the Pearson correlation coefficient is calculated for the untransformed dependent and independent variables as proposed in the hypotheses in section 3.2.3.

Table 10: Heat Pump Hypothesized Exploratory Variable Transformation

	Heat Pump Load	*Temperature*	*Irradiance*	*Wind speed*	*StateSESP*
Transformation	1.00	1.00	1.55	1.00	1.00
Parsimony Transformation	1.00	1.00	1.50	1.00	1.00

Table 11: Pearson's Correlation Coefficients for the Hypothesized Heat Pump Relations

	Temperature	*Irradiance*	*Wind speed*	*StateSESP*
Heat Pump Load	-0.297	-0.070	0.136	0.480
H0 hypotheses	Rejected	Rejected	Rejected	Rejected

Based on these significant results (all 0.000 for $\alpha = 0.05$) it is possible to conclude that all *H0* hypotheses can be rejected and that there is a relationship between the *Temperature, Irradiance, Wind speed* and *StateSESP* and the *Heat Pump Load*. Additionally the analysis of the *Irradiance* indicated that the relation between the 8 hour lagged *Irradiance* and the Heat Pump load was stronger (-0.07 for *Irradiance* and -0.20 for *Irradiance lagged 8*). This lag is substantiated by the Low Energy Architecture Research Unit (2016) whom mentions that the thermal capacity of the building causes a delay in the heat transfer to the interior of the building. Therefore, the lagged independent *Irradiance*, in combination with the other presented independent variables, are used for further regression analysis.

5.3 Smart Appliance Electricity Flexibility

The bivariate analysis performed in the previous section indicates multiple significant relations between dependent and independent variables. Based on these relations it is feasible to predict the available electricity flexibility from the smart appliances. Consequently, section 5.3.1 through 5.3.3 present prediction models for the Photovoltaic Panels, the Electric Boilers and the Heat Pumps respectively. A prediction model for the Fuel Cell is not required as was already discussed in 3.2.4 and will therefore not be addressed.

5.3.1 Predicting the Available Electricity Flexibility from Photovoltaic Panels

Controllable photovoltaic panels are installed on 89 of the houses in the Heerhugowaard field trial with varying levels of capacity. The output of these photovoltaic panels is unaffected by any interference from unobservable errors, as discussed in 5.1. This is because it is assumed that the household characteristics do not influence the output of the photovoltaic panel in any manner. The only two differences that exist between households are the difference in the panel capacity and the geographical location of the households in Heerhugowaard. However, the panel capacity is available per household and therefore controllable in the regression model, and the geographical difference between households are considered to be negligible as all the households are in the city of Heerhugowaard and exogenous influence should not differ significantly. Therefore, to predict the output of these photovoltaic panels one can assume that a_i is uncorrelated with any x_i and random effects regression can be employed. The random effects model is estimated by the dependent variable *PV-Output* and independent variables *ElevationAboveHorizon and SunAzimuthFrom180*, and the interaction terms *PV-CapacityIrradianceState*, which were introduced and discussed in 3.2.1. Furthermore, to correctly apply the interaction term, *Irradiance, State* and *PV-Capacity* are also included.

The estimated random effects model (Table 12) tests all independent variables significant with an overall R^2 of 0.7084. Furthermore, the Hausman tests, which compares the estimators from the fixed effects model with the random effects model, concludes (significance of 0.9623) that the random effects model has more consistent estimators. Furthermore the Breusch and Pagan Lagrange- multiplier test for random effects rejects (significance 0.000) the *H0* hypotheses that OLS is more consistent than random effects resulting in that random effects has efficient estimators. Concluding, that the random effects model should be estimated and will be used throughout the prediction of the *PV-Output*. A complete overview of all tests can be found in Appendix III.c.

Table 12: Random Effects Regression for PV-Output (α 0.05)

PvOutput	*Coef.*	*Std. Err.*	*z*	*P>z*	*[95% Conf. Interval]*	
ElevationAboveHorizon	.1423402	.0023054	61.74	0.000	.1378217	.1468586
SunAzimuthFrom180	-.0387559	.0019197	-20.19	0.000	-.0425185	-.0349933
PV-CapacityIrradianceState	.0200485	.0000587	341.70	0.000	.0199335	.0201635
Irradiance	.013744	.0025794	5.33	0.000	.0086885	.0187996
PVCapacity	-.0002322	.000093	-2.50	0.013	-.0004145	-.00005
State	.2369979	.0144818	16.37	0.000	.2086141	.2653816
Constant	1.045971	.2167404	4.83	0.000	.6211673	1.470774

To determine if the estimators presented by the fixed effects regression estimation are BLUE, the assumptions discussed in 5.1.2 will be evaluated accordingly.

1. ***Zero Conditional Mean***

The zero conditional mean assumes for random effects E (u_{it} | $\boldsymbol{X}_i$, a_i) = 0 and E (a_i | $\boldsymbol{X}_i$) = 0 which result in unbiased and efficient estimators. The *Cov* (u_{it}| $\boldsymbol{X}_i$, a_i) matrix (Table 13) indicates that the idiosyncratic (u_{it}) error is indeed uncorrelated with X_i for *t*. However, not for all *t*, as with $u_{i,\ t-1}$ the *Cov* (u_{it}| $\boldsymbol{X}_i$, a_i) matrix indicates that correlation are present. The presence of correlated u_i with X_i might be the cause of the AR term which is present in the *PV-output.* In other words, *PV-output* is auto correlated with AR_{t-1} which implies that the errors will also be correlated with *PV-output*$_{-1}$. For that reason a transition is made from strict exogeneity to weak exogeneity and one can state that the condition for *Cov* (u_{it}| $\boldsymbol{X}_i$, a_i) is valid (Wooldridge, 2015). Furthermore, the *Cov* (u_{it}| $\boldsymbol{X}_i$, a_i) matrix (Table 13) indicates that there is only a very weak correlation between u_i and a_i, and results in a substantiation of a zero conditional mean in regards to the assumption of weak exogeneity.

The second assumption, related to random effects, indicates that E (a_i | $\boldsymbol{X}_i$) = 0 is violated due to the correlation of the a_i and the independent variable *PV-CapacityIrradianceState* and *State.* This violation can be explained by the fact that there is a geographical difference between the households, which might results in different irradiance levels per time. Due to the absence of additional independent variables concerning the irradiance per household or additional instrumental variables for IV panel regression, it is not possible to correct for this exogeneity, which implies that the estimators are not BLUE. However, the level of violation is minimal and will therefore not have a large impact on the estimators.

Table 13: Zero Conditional Mean for u_i and a_i for PV-Output

	SunAzim	*PV-Power*	*Irradiance*	*PV-Capacity*	*Elevation*	*State*	a_i
u_{it}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
$u_{i,\ t-1}$	0.0191	-0.0039	-0.0516	0.0000	-0.0176	0.0756	
u_i							0.0005
a_i	-0.0001	-0,0106	-0.0003	-0.0007	-0.0001	-0.0435	

2. ***No Perfect Collinearity***

Both the assumptions for fixed effects and random effects assume that the independent variables are not collinear. A VIF analysis (Table 14) indicates that irradiance and elevation shows high levels of multicollinearity, but is not perfectly collinear. This high level of VIF can be explained by the presence of the irradiance in the interaction term *PV-CapacityIrradianceState.* However, removing this independent variable would result in the improper use of the interaction term. Therefore, the current independent variables will be maintained as they do not violate the perfect collinearity assumption.

Table 14: VIF Analysis for PV-Output

	SunAzim	*PV-Power*	*Irradiance*	*PV-Capacity*	*Elevation*	*State*
VIF	2.40	3.90	3.72	1.11	4.24	1.38
VIF - Irradiance	2.27	2.45		1.07	3.56	1.22

3. *Homoscedasticity and Serial Correlation*

Homoscedasticity for *PV-Output* was investigated through the The Breusch-Pagan / Cook-Weisberg test which rejects the *H0* hypotheses (significance 0.000) and indicates that the variance of the residuals significantly deviates from zero. Furthermore, the Wooldridge test for autocorrelation also indicates that the *H0* hypotheses is rejected (significance 0.000) and that the residuals are serial correlated. Both these violations result in that the standard errors and confidence intervals are biased and inefficient. To take serial correlated residuals and heteroscedasticity into account the Driscoll and Kraay correction will be applied as the Friendman test indicates (significance 0.000) that the panel is cross sectional correlated. The application of the Driscoll and Kraay correction resulted in loss of *Irradiance* and *State* due to insignificance. The results of the Driscoll and Kraay correction are presented in Table 15.

Table 15: Driscoll and Kraay correction for PV-Output

PvOutput	*Coef.*	*Std. Err.*	*z*	*P>z*	*[95% Conf. Interval]*	
ElevationAboveHorizon	.1405118	.0150301	9.35	0.000	.1110447	.169979
SunAzimuthFrom180	-.0410736	.0135	-3.04	0.002	-.0675409	-.0146063
PV-CapacityIrradianceState	.0204076	.0002816	72.48	0.000	.0198556	.0209597
PVCapacity	-.0002381	9.07e-06	-26.25	0.000	-.0002559	-.0002203
Constant	1.300594	.1280255	10.16	0.000	1.049594	1.551594

The model estimated to predict the *PV-Output* has an R^2 of 0.7085 with a constant and four independent variables. According to the random effects regression model, the interclass correlation, or the variance caused by the differences across the panels, is 19.92%. This implies that additional information on the differences between the households would allow the model to explain 19.92% more variance. The regression model for *PV-Output* with the Driscoll and Kraay correction, taking into account the data transformations, has the following form:

$$\widehat{PVOutput}\,(W) = \left(\widehat{1.3} - \widehat{0.000238} * PVcapacity + \widehat{0.0204} * \sqrt[2]{PVCapacity * Irradiance * State} - \widehat{0.0411} * \sqrt[2]{SunAzimuthFrom180} + \widehat{0.141} * \sqrt[2]{ElevationAboveHorizon}\right)^{2.75}$$

With the following upper and lower 95% confidence intervals respectively:

$$Lower\ 95\%\ conf.\widehat{PVOutput} = \left(\widehat{1.05} - \widehat{0.000256} * PVcapacity + \widehat{0.0196} * \sqrt[2]{PVCapacity * Irradiance * State} - \widehat{0.0675} * \sqrt[2]{SunAzimuthFrom180} + \widehat{0.111} * \sqrt[2]{ElevationAboveHorizon}\right)^{2.75}$$

$$Upper\ 95\%\ conf.\widehat{PVOutput} = \left(\widehat{1.55} - \widehat{0.00022} * PVcapacity + \widehat{0.0210} * \sqrt[2]{PVCapacity * Irradiance * State} - \widehat{0.0146} * \sqrt[2]{SunAzimuthFrom180} + \widehat{0.170} * \sqrt[2]{ElevationAboveHorizon}\right)^{2.75}$$

The presented regression model is validated by means of data from a household that was not taken into consideration during the model estimation (Household 757), where such a technique is referred to as predictive validation (Sargent, 2005). Figure 16 presents the measured photovoltaic output of a 2750 Watt panel (from a random point in time) in comparison to the predicted output. From this fit it is possible to conclude that the regression model is capable of closely following the overall trend in the photovoltaic output. However, some over- and underestimation do occur, which can be explained by the fact that the used weather data is not exactly in line with the city of Heerhugowaard. Based on these observations it is possible to conclude that the regression model is capable of predicting the photovoltaic output on a household level. Furthermore, it is also possible to conclude that these results are generalizable to other sections of the Netherlands as no demographic or household specific aspects are included in the regression function and consequently the model is applicable to all regions of the Netherlands.

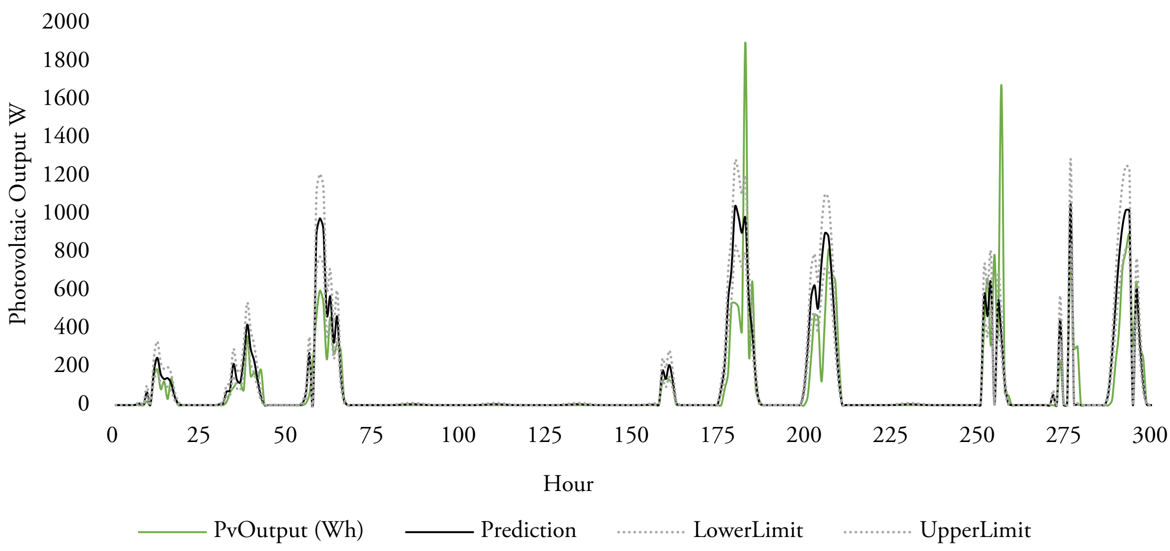

Figure 16: Actual versus Predict Photovoltaic Power Output per Hour

5.3.2 Predicting the Available Electricity Flexibility from the Electric Boiler

Electric boilers are installed in 45 houses in the Heerhugowaard field trial with different load characteristics. In contrast to the photovoltaic panels, the electric boiler load fully depends on the control of the Power Matcher and the water consumption of the household, as discussed in 3.2.2. This implies that, as water consumption is clearly endogenous to the household, a fixed effect approach should be considered as one could assume that a_i is associated with the particular household. However, attempts to construct a regression model with fixed effects and the independent variables *Hour of the Day, Temperature* and *Number of Inhabitants* (which had to be estimated based on the household load) provided an R^2 of 0.01, which is clearly unacceptable. If the pattern of water consumption is observed on a daily level for a random household, the discrete nature becomes apparent (Figure 17).

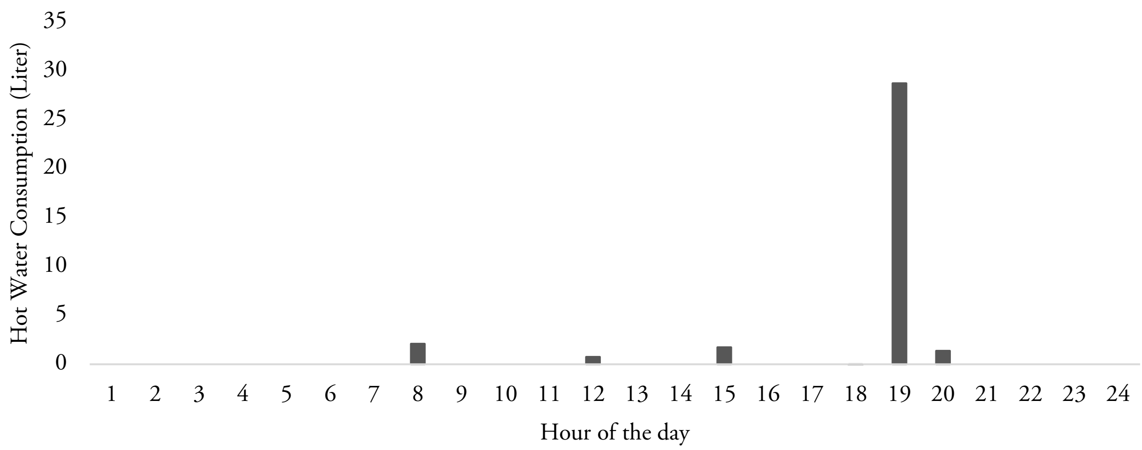

Figure 17: Liter Hot Water Consumption from a random household at a random period of time

If the water consumption over the complete dataset is observed, it becomes clear that the data can be classified as Zero-Inflated Negative Binomial data as 127,238 out of the 171,989 (73.98%) hot water observations are zero. This data can be identified by the excessive number of zeros, which are generated by two independent process. In the case of hot water consumptions for the households, the measures used for hot water consumption is related to the charge level of the electric boiler. If the electric boiler is uncharged, hot water consumption cannot be observed. Therefore, water consumption can take the value of zero because the household is not consuming hot water or hot water consumption could not be observed because the electric boiler is uncharged and a gas generated heater generates the hot water provision. To estimate the influences of these processes, Zero-Inflated Negative Binomial regression could be attempted. However, the independent variables that hypothetically explain water consumption are either not available (the number of inhabitants) or are not on a categorical scale. Consequently, regression cannot be employed to determine the *Hot Water Consumption* per household. The limitations presented by the discrete and zero inflated nature of water consumption ask for a different approach than regression. Studies from for example Jordan and Vajen (2001) and Blokker (2010) consider a simulation approach to predict daily household water consumption. Consequently, a simulation model is presented for *Hot Water Consumption*.

According to Jordan and Vajen (2001), Defra (2008) and Blokker (2010) water consumption patterns depend on three independent aspects: Frequency of occurrence, Duration and Intensity. Furthermore Jordan and Vajen (2001) classify four distinct categories for hot water consumption: short loads (for example washing and shaving), medium loads (for example washing the dishes), showering and taking a bath. Consequently the consumption patterns for these categories are investigated in order to construct a simulation model.

1. ***Short Hot Water Consumption***

   Hot water consumption for washing and shaving per household occurs on average 4.1 times per day and follows a Binomial Distribution (Blokker, 2010) and are assumed to take place between 05:00 and 23:00 (Jordan & Vajen, 2001). The duration of this occurrence is further estimated to follow a Normal distribution with a mean of 40 seconds and a standard deviation of 15 seconds (Blokker, 2010). The consumption of water is estimated to be 0.042 liter per second; however, this is an estimation for 'water consumption' and not hot water consumption. Research from De Oreo and Mayer (2000) on the water consumption in 10 households in Seattle[5] indicates that 72.7% of the small loads water consumption is hot water. Therefore, the hot water consumption is estimated to be 0.0305 liter per second. Consequently small load hot water consumption can be simulated with the following equation:

   $$Short\ Hot\ Water\ Consumption = B(1{,}0.309) \cdot N(40{,}15) \cdot 0.0305\ for\ 05{:}00 \leq t \leq 23{:}00$$

2. ***Medium Hot Water Consumption***

   Hot water consumption for medium loads as doing the dishes is assumed to occur 0.39 times per day, following a Binominal distribution (TNS NIPO, 2013). This probability is not equal to 1 due to the presence of dishwashers (66%) in Dutch households. Furthermore, this medium hot water consumption load is estimated to occur between 05:00 and 23:00, following the same pattern as the small consumptions of hot water consumption (Jordan & Vajen, 2001). Per occurrence 3.6 liter of water is consumed, which does not have to be transformed as 100% of this water is hot water (De Oreo & Mayer, 2000). Concluding that medium hot water consumption can be simulated by means of the following equation:

   $$Medium\ Hot\ Water\ Consumption = B(1{,}0.39) \cdot 3.6\ for\ 05{:}00 \leq t \leq 23{:}00$$

3. ***Showering Hot Water Consumption***

   Showering for the Dutch population is estimated to occur 0.72 times per day per person (TNS NIPO, 2013), and occurs around 7:00 in the morning or around 19:00 in the evening following a Normal distribution with a standard deviation of 2 hours (Jordan & Vajen, 2001). Furthermore, showering is assumed to occur 2 hours later on average during weekends as people tend to sleep longer on weekends. Additionally, showering can either occur in the morning and the evening, where the evening has a probability of 0.5 following a Binomial distribution (Jordan & Vajen, 2001). The showering duration is then estimated to follow a LogNormal distribution with a mean of 2 and a standard deviation 0.5 (Blokker, 2010). Per second a shower would then consume 0.142 liter per second, which can be translated to 6.228 liter of hot water per minute (De Oreo & Mayer, 2000). These estimations enable that hot water consumption from showering can be simulated with the following equations:

   $$Shower\ Hot\ Water\ Consumption = B(1{,}0.72) \cdot\ LN(2{,}0.5) \cdot 6.228$$

[5] The water consumption in Seattle is 95 liter per capita per day (De Oreo & Mayer, 2000). In comparison, the water consumption in the Netherlands is 118 liter per day per capita (TNS NIPO, 2013). Although this difference, it can be assumed that the overall percentage of hot water consumption would not change.

4. ***Bath Hot Water Consumption***

Bathing consumes the most water but is also the least common activity. Bathing occurs approximately 0.27 times per week (0.04 times per day), following a Binomial distribution. However, this only applies to households that own a bathtub as only 36% of the households do (TNS NIPO, 2013). If the bathtub is used, per bath on average 89.5 liter of hot water is used. Just like showering does bathing also occur around 19:00 in the evening, but does not occur in the morning (Jordan & Vajen, 2001). The consumption of hot water of the bathtub can then be summarized as:

$$Bathtub\ Hot\ Water\ Consumptuon = B(1{,}0.04) \cdot 89.5$$

The simulation model presented through these four equations represent the discrete behaviour of *Hot Water Consumption* per hour, but do not include the influence from the *Number of Inhabitants* and the influence from *Temperature.* To include the *Number of Inhabitants* it is possible to look at the research performed by Defra (2008) on hot water consumption in households. The outcome of the research from Defra is comparable to the average hot water consumption in the Netherlands, as Defra estimated an average of 46 liters per capita per day in comparison to the average hot water consumption, according to TNS NIPO (2013), of 46.7 liter per capita per day (46.7 = 118*0.396 (TNS NIPO, 2013; De Oreo & Mayer, 2000)). In this research the influence from the *Number of Inhabitants* is estimated to be an increase of 22 liter per person per day, which will be associated to the shower hot water consumption. To take this increase into consideration, the *Number of Inhabitants* per household must be included. Therefore, the *Number of Inhabitants* per household was simulated based on the Dutch population demographics according to the CBS, to follow the distribution of 1 = 0.3741, 2 = 0.3277, 3 = 0.1205, 4 = 0.1254 and 5 = 0.0523.

To take into consideration the influence from *Temperature* it is possible to determine the influence on *Hot Water Consumption* through a simple OLS regression. Although this model will not explain *Hot Water Consumption,* it is possible to explain the variance caused by the change in *Temperature*, and then through the coefficient determine the influence from *Temperature* on the *Hot Water Consumption*. The OLS regression indicates that with a one degree increasing temperature, the consumption of water decreases with 0.0213782 liter. However, this only applies to the consumption of hot water in showering (Kalogirou & Tripanagnostopoulos, 2006).

When the presented simulation equations are combined, the average hot water distribution presented in Figure 18 arises from 100 simulations of one year for a one capita household.

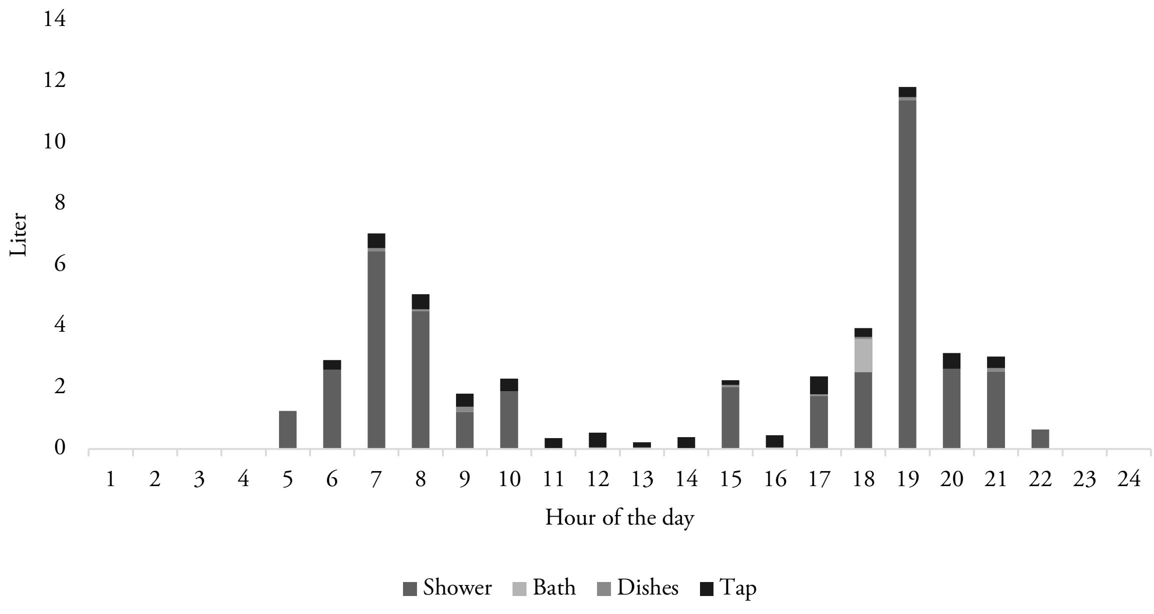

Figure 18: Daily Average Hot Water Consumption Per Capita (from 100 random samples)

On average the average hot water consumption from the simulation is estimated to be 42.73 liter with a standard deviation of 2.30 (estimated on 100 simulation for a year for one capita). Although this average is significantly (0.000) different from the average hot water consumption per day per capita (46 liter), the difference is only very small. Furthermore, by comparing the percentage cumulative average hot water consumption over a day with the percentage cumulative hot water consumption from the field trial in Heerhugowaard (Figure 19), the Mann-Whitney Test cannot reject (sig. 0.443) the *H0* hypotheses that the distributions are significantly different. From these comparisons and the use of average Dutch household hot water consumption values, one can conclude that the presented simulation model is capable of approximating the *Hot Water Consumption* of households in the Netherlands and can consequently be used for further analysis of the available electricity flexibility of the electric boiler.

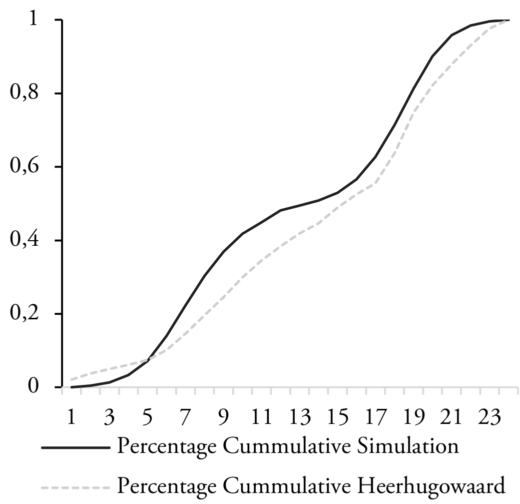

Figure 19: Daily Cumulative Hot Water Consumption Frequency Comparison

In order to use the *Hot Water Consumption* from the regression model to predict the available electricity flexibility from the electric boilers, a conversion must be made, taking into consideration the characteristics of the boiler. The electric boilers that are used in the Heerhugowaard field trial have either 80 or 120 liter capacity with varying levels of electrical load as represented in Table 16.

Table 16: Characteristics of the Electric Boiler

Capacity (liter)	*Wattage*	*Charge time from empty (hr)*	*Stored Energy (W)*	*Required energy per liter (W/liter)*	*Charging speed (liter/hour)*
80	1000	7:35	7583.3	94.79	10.55
80	1500				
80	2500	3:00	7500	93.75	26.67

Taking into consideration these limitations of the electric boiler, the following example (Figure 20) explains how the electricity flexibility is calculated. Assume that the electric boiler on t = 0 is fully charged and that at time t = 6, 50 liter of hot water is consumed for showering. Due to the showering activity, the hot water in the electric boiler is consumed and respectively the remaining flexibility of the electric boiler increases. At t = 10, electric flexibility is procured by the Aggregator to, for example, compensate for the solar peak, and consequently the electric boiler heats the water with 1000 Watt per hour. The result of this activity is that the amount of hot water in the electric boiler increases and the remaining flexibility decreases.

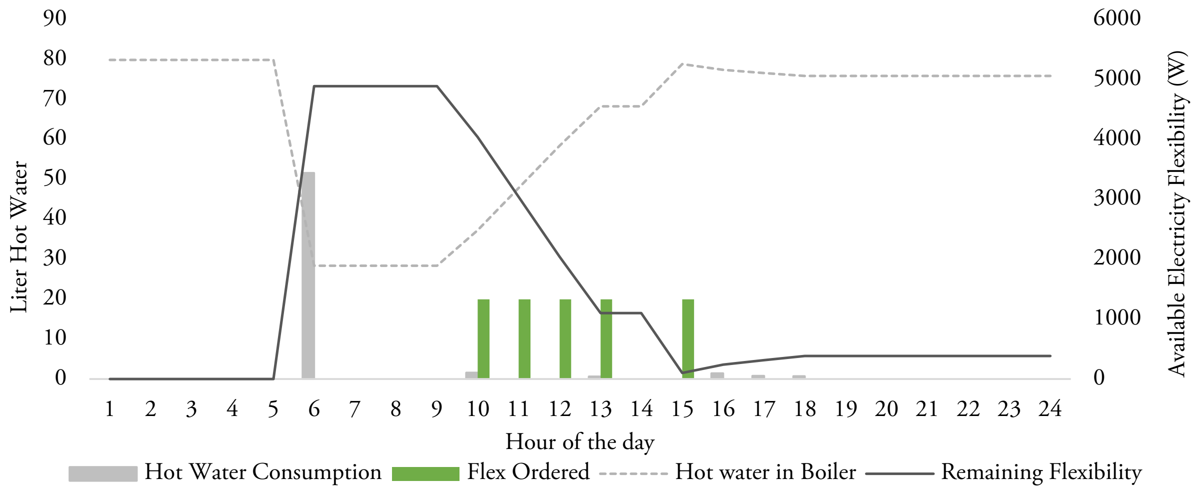

Figure 20: The Available Electricity Flexibility of the Electric Boiler

5.3.3 Predicting the Available Electricity Flexibility from the Heat Pump

The available electricity flexibility from the heat pump is influenced by household endogenous and exogenous effects. The household endogenous effects are for example the hour of the day, as the heat pump has a timed operation, the energy class of the household, the size of the house or the influence of the activities in the household. Therefore, due to the household endogenous influences, one can assume that a_i is correlated with x_i and consequently that there is a need for fixed effects regression. However, computation of the fixed effects regression results in a numerical overflow, and prevents that fixed effects can be computed. Consequently, in order to predict the electricity flexibility from the heat pump, random effects must be assumed. This implies that the assumption is made that a_i is negligible.

To determine the estimators of random effects regression for the heat pump load it is not efficient to use normal linear regression. This is because the load from the heat pump approaches a binary choice model (varying between zero and a constant). This can be implied because the load of the heat pump is zero 85% of the time. In the remaining 15% of the values, the heat pump load fluctuates between 1 and 500Wh, with a clear spike around 300Wh (Figure 21).

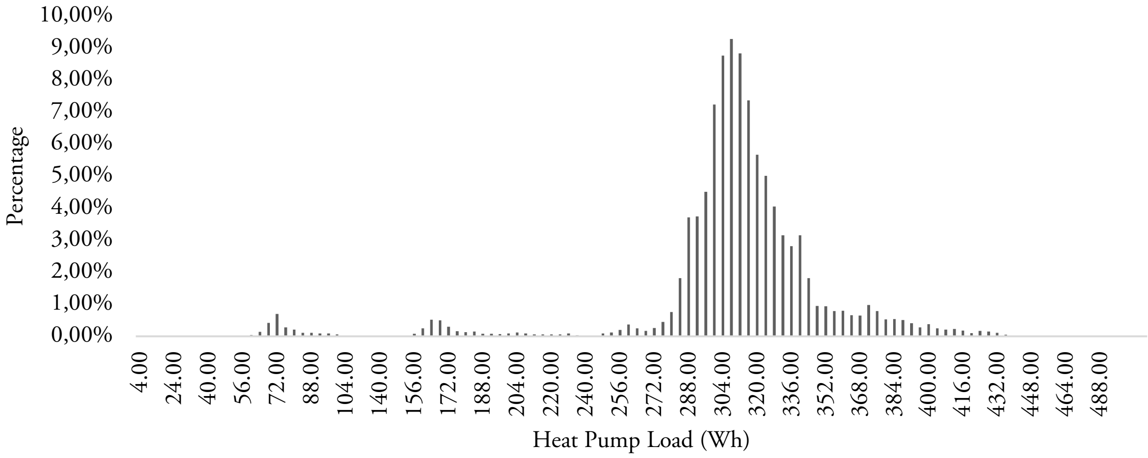

Figure 21: The Percentage of Heat Pump Load Observed

If OLS would be used to estimate the coefficients for the heat pump load for air heating, which clearly fluctuates between zero and 500, OLS will estimate predictions that fall outside this interval. This occurs because OLS cannot take the operational limits into consideration during estimator fit. Predictions outside the operational interval would make the results questionable and ambiguous. Additionally, when there is such a clear binary process, OLS estimation will result in heteroscedastic residuals. Even though that heteroscedasticity can be corrected through robust estimations, it should clearly be prevented by selecting an appropriate regression technique. Last, due to the heteroscedastic errors, the residuals are also non-normally distributed, resulting in inconsistent results from F and t tests (Söderbom, 2009).

An alternative approach, that takes into account the operational interval and approaches the system as a binary choice model, is Logit regression. A Logit binary response model is described as:

$$Pr(y = 1|x) = G(\beta_1 + \beta_2 X_2 + \cdots + \beta_K x_K)$$

where G is a function that strictly predicts between zero and one, for all real number. Using Logit regression would result in binary state outcomes of zero and one, where one would depict a constant heat pump load. Logit regression also applies for panel data, and assists in estimating the unobserved individual effects. Therefore, a Logit regression model for the presence of a Heat pump load is estimated for the longitudinal data set with the independent variables *Temperature, IrradianceL8, SESPState, Wind speed* and the categorical variable *Hour.*

Table 17: Logit Panel Regression Estimation

HeatPumpON	*Coef.*	*Std. Err.*	*z*	*P>z*	*[95% Conf. Interval]*	
StateSESP	3.104897	0.0295318	105.14	0.000	3.047015	3.162778
Temperature	-0.0151885	0.0002596	-58.51	0.000	-0.0156972	-0.0146797
IrradianceL8	-0.0047467	0.0005676	-8.36	0.000	-0.0058591	-0.0036343
Wind speed	0.0091514	0.0003538	25.87	0.000	0.008458	0.0098449
Constant	-5.838895	0.2960106	-19.73	0.000	-6.419065	-5.258724
Hour						
3	0.1293005	0.0659842	1.96	0.050	-0.0000261	0.2586272
4	0.188673	0.0658466	2.87	0.004	0.059616	0.31773
5	0.2413404	0.0660866	3.65	0.000	0.111813	0.3708678
6	0.3536307	0.0661084	5.35	0.000	0.2240607	0.4832007
7	0.2000092	0.0668524	2.99	0.003	0.068981	0.3310375
8	-0.2299082	0.067783	-3.39	0.001	-0.3627604	-0.097056
11	0.4118793	0.0681407	6.04	0.000	0.278326	0.5454325
12	0.5963495	0.0674498	8.84	0.000	0.4641503	0.7285487
13	0.587542	0.0674075	8.72	0.000	0.4554256	0.7196583
14	0.4968283	0.0676691	7.34	0.000	0.3641994	0.6294573
15	0.5504221	0.0678904	8.11	0.000	0.4173594	0.6834849
16	0.5094269	0.0687051	7.41	0.000	0.3747674	0.6440864
17	-0.8478335	0.076955	-11.02	0.000	-0.9986626	-0.6970044
18	-1.905886	0.1140652	-16.71	0.000	-2.129449	-1.682322
19	-1.133251	0.1137157	-9.97	0.000	-1.356129	-0.9103718
20	-0.8620521	0.1053132	-8.19	0.000	-1.068462	-0.655642
21	-0.2454671	0.0868452	-2.83	0.005	-0.4156806	-0.0752536
24	0.2993223	0.0687389	4.35	0.000	0.1645966	0.434048

The outcome of the Logit regression for random effects (Table 17) indicates a Log Likelihood of -29582, in comparison to the Log Likelihood of -45936 for the constant only model. A possible approach to determine the increase in goodness of fit due to the addition of the independent variables was described by Mac Fadden (1974). Mac Fadden mentioned that the Log Likelihood may be transformed into an "*index analogous to the multiple correlation coefficient*" (p. 123) and could serve as an index for goodness of fit. This transformation is performed through the following equation:

$$\rho^2 = 1 - L(\hat{\beta})/L(\bar{\beta})$$

where $\hat{\beta}$ represents the Log Likelihood of the estimated model, and $\hat{\beta}$ represents the Log Likelihood of the constant model. The ρ^2 for the heat pump load then computes to 0.356, or 35.6%.

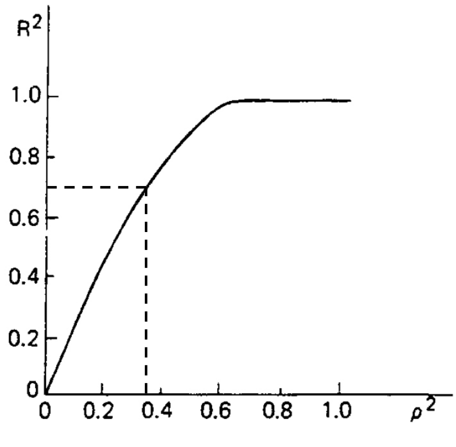

Figure 22: The Relationship between ρ^2 and R^2 From Mac Fadden (1974)

In most cases, the ρ^2 introduced by Mac Fadden, is referred to as the Pseudo R^2, and is consequently believed to be interpretable in the same manner as an OLS R^2. However, this is not the case as Mac Fadden mentions that the ρ^2 and R^2 vary in the unit interval. In order to make these two indexes comparable, Mac Fadden provided a graph (Figure 22) that provides the relative stable empirical relationship between these two indexes. The dashed line in Figure 22 indicates that a ρ^2 of 0.356 corresponds with an R^2 of approximately 0.7, or 70%, which indicates a strong fit. Additionally, the panel level variance, or the variance caused by the differences across the panels, is 4.04%, which implies that with more independent household variables 4.04% more variance can be explained.

The regression model for presence of a heat pump load, based on Logit regression, has the following form[6,7]:

$$\widehat{HeatPump\ Probability} = \widehat{0.371} - \widehat{0.0152} \cdot Temperature - \widehat{0.0048} \cdot L^8 Radiation_t + \widehat{0.0092} \cdot Windspeed +/- HourDummy$$

With the following upper and lower 95% confidence intervals respectively:

$$Lower\ 95\%\ conf.\widehat{HeatPump\ Probability} = -\widehat{0.325} - \widehat{0.0157} \cdot Temperature - \widehat{0.0059} \cdot L^8 Radiation_t + \widehat{0.0085} \cdot Windspeed +/- HourDummy$$

$$Upper\ 95\%\ conf.\widehat{HeatPump\ Probability} = \widehat{1.066} - \widehat{0{,}0147} \cdot Temperature - \widehat{0.0036} \cdot L^8 Radiation_t + \widehat{0.0099} \cdot Windspeed +/- HourDummy$$

The linear prediction of the Logit regression is not interpretable in the same manner as the OLS estimators. Firstly, Logit regression estimates coefficients that indicate the odds ratio, or the probability of an event occurring, where an event implies the heat pump load is non-zero. Secondly, the estimators need to be transformed in order to predict the probability correctly (Torres-Reyna, 2007). This transformation can be performed with the following function:

$$\frac{1}{1 + \left(\frac{1}{e^{(\beta_1 + \beta_2 X_2 + \cdots + \beta_K x_K)}}\right)}$$

After this transformation, the linear prediction provides the probability of the heat pump load to be non-zero, varying between zero and one. As Logit regression is based on the Bernoulli distribution, the probability also follows a Bernoulli distribution. The state of the heat pump load can then be found by using the Binomial distribution for 1 trial with the following equation (Yoshimoto, 2008):

$$P(X = k) = \binom{n}{k} p^k q^{(n-k)}$$

The probability to find a Heat Pump load provides the distribution over a year as presented in Figure 23. Figure 23 figure also clearly indicates the influence from the weather on the household heat requirement, as the probability for heat pump air heating lowers during warm periods and raises during cold periods. Furthermore, it is to be expected that the Heat Pump load does not decline to zero probability due to the operation of the boiler.

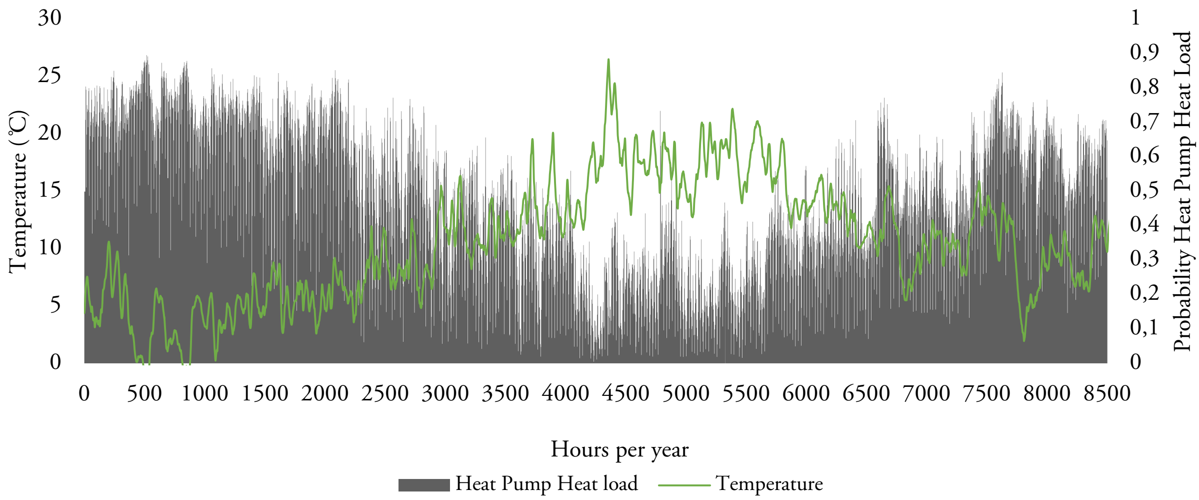

Figure 23: The Probability of Heat Pump Load for Air Heating over the year

---

[6] In the regression function, the constant and the *StateSESP* term are combined as for prediction the device is default in operation and the value of the *StateSESP* is then be equal to 1.

[7] $L^8 Irradiance_t$ is a lag operator where the term *Irradiance* is lagged by 8 hours.

The presented Logit regression model predicts the probability of a Heat Pump load but not the actual load. Figure 21 indicates that it would be incorrect to assume that when the Heat Pump is on, only one load may be expected. Therefore, a second stage model should predict the load for the Heat Pump when the Heat Pump is estimated to be operational. To determine if the Heat Pump load is influenced by any of the independent variables used in the Logit regression, normal OLS regression is performed. The outcome of the regression model with the dependent variable *Heat Pump Load* and independent variables *Temperature, Irradiance* and *Wind speed* indicates a R^2 of 0.0034, or 0.34%. Furthermore the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity indicates a χ^2 value of 8.97, which significantly indicates heteroscedasticity, but not to a large extend (especially when the large sample size is taken into consideration). Therefore, it is possible to conclude that the load of the Heat Pump is uncorrelated with the independent variables and has (almost) equal variance over the predictors. Consequently, the assumption is made that the Heat Pump load can be approached through a distribution with a mean and standard deviation.

Estimating the data with multiple distributions indicated that the Normal distribution has the closest fit with a mean of 311.41 and standard deviation of 26.48. The average of 311.41 Wh closely represents the average consumption of 300 Wh stated by the manufacturer of the device (Inventum, 2015).

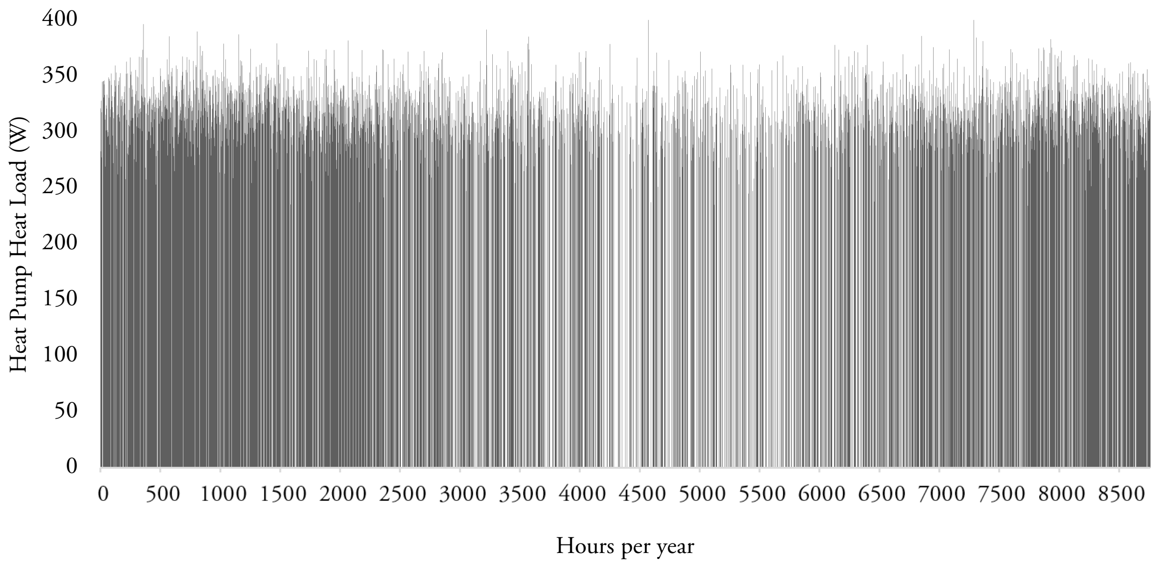

Figure 24: The Heat Pump Load (W) over a year

Based on the probability and average Heat Pump load, it is possible to predict the Heat Pump load all over a year for one household (Figure 24). Figure 24 presents the probability as the density of lines, and the Heat Pump load as the height of the line.

In order to validate these results, a comparison is performed between the predicted Heat Pump load and the measured Heat Pump load. For this comparison, only the households that have less than 1000 values missing are selected to prevent underestimation of the consumption level. If the cut-off value would be reduced further, the sample size would become too small (less than 10) to estimate an accurate household consumption level. Based on this setting, the observed Heat Pump Load from the period of 04-08-2015 till 29-01-2016 is 414.74 kW in comparison to the predicted Heat Pump Load for the same period of 524.28 kW, which, through an independent student t-test indicates to be significantly (t value 2.9816, sig. 0.0023 for α: 0.05) higher than the observed consumption.

Although that the prediction model overestimates the Heat Pump load for the households in Heerhugowaard by a factor of 1.265, it approximates the average Dutch households closely. On average the Dutch gas consumption is (1430 m^3/1121 m^3) 1.27 times higher than the gas consumption from the households in the Heerhugowaard sample (as discussed in 4.5.1.3). In line with this thought, the Heat Pump load from the households in Heerhugowaard might be corrected to approximate the Heat Pump load from Dutch households. However, the corrected average does not significantly deviate from the uncorrected sample (t value -1.2429, sig. 0.2235 for α: 0.05) and correction would thus result in no significant change. Consequently, the presented prediction model can be used to approximate the Dutch household Heat Pump Load.

5.4 The Smart Appliance Electricity Flexibility Prediction Models

In attempt to predict the available electricity flexibility from the smart appliances, the relationships between the potential factors that explain the available electricity flexibility and the measured available electricity flexibility were investigated. Based on a set of independent variables, these relationships were combined in the form of a linear function, a simulation model and a probability model for the Photovoltaic panels, Electric boiler and Heat Pump respectively. Additionally, these models have taken into consideration the non-generalizability of the sample as presented in 4.5.1 by correcting the model where necessary. Based on the analysis presented in the previous sections the following three models might be used to predict (with the precision and confidence intervals mentioned in the associated sub-sections) the available electricity flexibility for Dutch households:

Photovoltaic Panel Available Electricity Flexibility (Watt):

$$\left(\widehat{1.3} - 0.\widehat{000238} \cdot PVcapacity + 0.\widehat{0204} \cdot \sqrt[2]{PVCapacity * Irradiance * State} - 0.\widehat{0411} \cdot \sqrt[2]{SunAzimuthFrom180} + 0.\widehat{141} \cdot \sqrt[2]{ElevationAboveHorizon}\right)^{2.75}$$

Hot Water Consumption:

$$Short\ Hot\ Water\ Consumption = B(1{,}0.309) \cdot N(40{,}15) \cdot 0.0305\ for\ 05{:}00 < t < 23{:}00$$

$$Medium\ Hot\ Water\ Consumption = B(1{,}0.39) \cdot 3.6\ for\ 05{:}00 < t < 23{:}00$$

$$Shower\ Hot\ Water\ Consumption = B(1{,}0.72) \cdot LN(2{,}0.5) \cdot 6.228$$

$$Bathtub\ Hot\ Water\ Consumptuon = B(1{,}0.04) \cdot 89.5$$

Heat Pump Available Electricity Flexibility (Watt)

$$\left(1 + \left(e^{(0.\widehat{371} - 0.\widehat{0152} \cdot Temperature - 0.\widehat{0048} \cdot L^8 Radiation_t + 0.\widehat{0092} \cdot Windspeed +/- HourDummy)}\right)^{-1}\right)^{-1} \cdot N(311.41, 26.48)$$

In order to provide the correct input for the presented regression models Appendix VI presents an overview of the format of the input variables.

The models presented in their current form indicate the unstandardized population estimators ($\hat{\beta}$) which cannot be directly interpreted to determine the contribution to the prediction of *y,* due to the difference in the units and degrees of variability of the *x* variables. In order to determine which coefficients provide the highest relative contribution to the regression plane, the standardized coefficients must be investigated. The larger the magnitude of the standardized $\widehat{\beta_i}$, the more x_i adds to the prediction of *y.*
The standardized coefficients can further be interpreted as the standard deviation change in the dependent variable when the independent variable is changed by one standard deviation, holding all other variables constant (*ceteris paribus*) (Bring, 1994). This holds also true for the negative standardized beta coefficients, only changing the negative change of the standard deviation in *y.* The standardized coefficients for the Photovoltaic and Heat Pump regression models are presented in Table 18. Based on these results it is possible to conclude that the Interaction term and the Sun elevation above the horizon have the largest influence on the *PV-Output,* and the Temperature and the SESP State the largest influence on the Heat Pump, which are both clearly in line with what one might expect for such appliances.

Table 18: Standardized Beta Coefficients

Model	*Independent Variable*	*Beta*
Photovoltaic Panel	PV Capacity	-0.075
	PVCapacityIrradianceState	0.746
	SunAzimuthFrom180	-0.030
	ElevationAboveHorizon	0.119
Heat Pump	Temperature	-0.225
	Irradiance	0.033
	Wind speed	0.0851
	State SESP	0.409

6

6 Electricity Flexibility Trade Optimization

6.1 The Influence of the Appliance Mix

6.2 A Theoretical Electricity Distribution Grid

6.2.1 Dutch Household Load Curves

6.2.2 Low Voltage Congestion Limits

6.3 Optimization of the Appliance Mix

6.3.1 An Introduction to Numeric Optimization

6.3.2 Assumption for the Non-Linear Optimization

6.3.3 Optimization for the DSO

6.3.4 Optimization for the BRP

6.3.5 Optimization for the BRP and DSO

6.4 Optimization Results

7 The Financial Outcome and Uncertainty of Electricity Flexibility Expansion for the Aggregator

7.1 The Financial Outcome of DSM for the Aggregator

7.1.1 An Introduction to the Stroomversnellings Project

7.1.2 A Financial Analysis Simulation Model

7.1.3 The Financial Outcome of Flexibility Trading for a Stroomversnellings Project

7.1.3.1 The Breakeven Configuration for the Aggregator

7.1.3.2 The Sensitivity of the Financial Outcome for the Aggregator

7.1.4 The Financial Outcome of Flexibility Trading with the Optimized Configuration Mix

7.2 The Uncertainties of Flexibility Expansion

7.2.1 Future Trends Influencing the Financial Outcome of Demand Side Management for the Aggregator

7.2.1.1 Exogenous Factors Influencing the Financial Outcome of DSM for the Aggregator

7.2.1.2 The Uncertainty and Significance of Exogenous Factors Influencing the Financial Outcome of DSM for the Aggregator

7.2.1.3 Scenario Generation

7.2.2 Scenario Analysis

7.2.2.1 Scenario Analysis Stroomversnelling

7.2.2.2 Scenario Analysis Optimized Configuration Mix

7.3 The Financial Prospect of Electricity Flexibility for the Aggregator

7.4 A Reflection on the use of Field Trial Data

8

8 Conclusions and Recommendations

8.1 Conclusion

8.1.1 The Availability of Electricity Flexibility

8.1.2 The Smart Appliance Configuration

8.1.3 The Financial Feasibility of Demand Side Management

8.2 Limitations

8.3 Reflection on the Scientific Body of Knowledge

8.4

9 References

Abi Morshed, F. (2016). *The Prospects of Flexibility on Congestion Mitigation against Network Reinforcement.* Delft: TU Delft.

Alizadeh, M., Li, X., Wang, Z., Scaglione, A., & Melton, R. (2012). Demand-side management in the smart gird: Information processing for the power switch. *Signal Processing Magazine, IEEE, 29(5)*, 55-67.

Alliander/SEC-team. (2013). *Klantensafari Stad van de Zon.* Hilversum: Beautiful Lives.

ANP. (2016, 06 06). *Nu.nl.* Retrieved from Nu.nl: http://www.nu.nl/economie/3576910/binnenkort-nog-meer-goedkope-duitse-stroom.html

Ashouri, A. (2014). *Simultaneous Design and Control of Energy Systems.* Zürich: Diss., Eidgenössische Technische Hochschule ETH.

Attila Boer, C., & Verbraeck, A. (2003). DISTRIBUTED SIMULATION WITH COTS SIMULATION PACKAGES. *Proceedings of the 2003 Winter Simulation Conference*, (pp. 597 - 605).

Babar, M., Taj, T., Ahamed, T., & Al-Ammar, E. (2013). The conception of the aggregator in demand side management for domestic consumers. *International Journal of Smart Grid and Clean Energy*, 371.

Bach, S., & Wevers, H. (2014). Resultaten deelnamebereidheidsonderzoek.

Badescu, V., & Sicre, B. (2003). Renewable energy for passive house heating. *Energy and Building*, 1085 - 1096.

Beebee, H., Hitchcock, C., & Menzies, P. (2009). *The Oxford Handbook of Causation.* Oxford: Oxford University Press.

Behrangrad, M. (2015). A review of demand side management business models in the electricty market. *Renewable and Sustainable Energy Reviews*, 177-185.

Belastingdienst. (2016). *Tabellen tarieven milieubelasting*. Retrieved from Belastingdienst: http://www.belastingdienst.nl/wps/wcm/connect/bldcontentnl/belastingdienst/zakelijk/overige_belastingen/belastingen_op_milieugrondslag/tarieven_milieubelastingen/tabellen_tarieven_milieubelastingen?projectid=6750bae7-383b-4c97-bc7a-802790bd1110

Berry, W. D., & Feldman, S. (1985). *Multiple regression in practice.* Newbury Park: Sage.

Bessa, R. J., & Matos, M. A. (2010). THe role of an aggregator agent for EV in the electricy market. *Power Generation, Transmission, Distribution and Energy Conversion 7th Mediterranean Conference and Exhibition* (pp. 1 -9). MedPower .

Blokker, E. J. (2010). Stochastic water demand modelling for a better understanding of hydraulics in water distribution networks. Delft: TU Delft, Delft University of Technology.

Bosch, M. (2011). *Werkelijk v Theoretisch Energieverbruik.* Saxion Hogescholen.

Boshell, F., & Veloza, O. P. (2008). Review of developed demand side management programs including different concepts and their results. *Transmission and distribution conference and exposition* (pp. 1- 7). Latin America: IEEE.

Bradley, S., Hax, A., & Magnanti, T. (1977). *Applied Mathematical Programming.*

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *Review of Economic Studies*, 239 - 253.

Bring, J. (1994). How to Standardize Regression Coefficients. *The American Statistician*, 209 - 213.

Byrne, J., Letendre, S., Govindarajaly, C., Wang, Y., & Nigro, R. (1996). Evaluating the economics of photovoltaics in a demand-side management role. *Energy Policy*, 177-185.

Callawar, D. S., & Hiskens, I. A. (2011). Achieving controllability of electric loads. *Proceedings of the IEEE*, 184 - 199.

CBS. (2015, 09 04). *Gediplomeerden en afgestudeerden; onderwijssoort, vanaf 1900*. Retrieved from CBS Statline: http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=80384NED&D1=0-5,8,19,22,49,56,70,110,119,141&D2=0&D3=l&VW=T

CBS. (2015, 12 08). *Huishoudens; grootte, samenstelling, positie in het huishouden, 1 januari*. Retrieved from CBS Statline: http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=82905NED&D1=24,26-29&D2=l&HDR=T&STB=G1&VW=T

CBS. (2015, 04 15). *Voorraad woningen; woningtype, bouwjaar, oppervlakte, regio*. Retrieved from CBS Statline: http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=82550NED&D1=0&D2=1-20&D3=0&D4=l&HDR=T,G3&STB=G2,G1&VW=T

Chang, J. H., & Root, B. (1974). On the Relationship between Mean Monthly Global Radiation and Air Temperature. *Archiv für Meteorologie, Geophysik und Bioklimatologie*, 13 - 30.

Cheng, H. (2003). *Analysis of Panel Data.* Cambridge: Cambridge University Press.

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *Stata Journal*, 482.

De Oreo, W., & Mayer, P. W. (2000). The end use of hot water in single family homes from flow trace analysis. *Water Engineering and Management*, 1 - 11.

De Vaus, D. A. (2001). *Research design in social research.* London: Sage.

Defra. (2008). *Measurement of Domestic Hot Water Consumption in Dwellings.* Energy Monitoring Company.

Dieck, R. H. (2007). *Measurement Uncertainty: Methods and Applications ISA.*

DNV-GL. (2014). *Scenario ontwikkeling energievoorziening 2030.* Delft: Netbeheer Nederland.

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *Stata Journal*, 168 - 177.

Dubey, S., Sarvaiya, J. N., & Seshadri, B. (2013). Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world–a review. *Energy Procedia*, 311 - 321.

Dusick, D. M. (2016, 04 10). *Sample Size Calculator*. Retrieved from BOLD Educational Software: http://bold-ed.com/barrc/calculator.htm

Ecofys. (2014). *Flexibility options in electricity systems.* Petersdorff: Ecofys.

Electric Power Research Institute. (1992). *TAG TM Technical Assessment Guide Vol 2 Electricity End Use, Part 2: Commercial Electricity Use.* Palo Alto: EPRI.

Energiekaart. (2016, 04 16). *Heerhugowaard: Stad van de zon*. Retrieved from https://www.energiekaart.net/initiatieven/heerhugowaard-stad-van-de-zon/

Energiekaart. (2016, 04 16). *SEC Forecasting, planning & stability of Smart Energy Markets*. Retrieved from http://www.energiekaart.net/initiatieven/sec-forecasting-planning-stability-of-smart-energy-markets/

Energiekoplopers. (2015, 3 21). *Energiekoplopers*. Retrieved from Energiekoplopers samen gemakkelijk duurzaam: https://www.energiekoplopers.nl/vragen/

Energievergelijken. (2015). *Energievergelijken.nl.* Retrieved from ODE: https://www.energievergelijken.nl/nl/energierekening/ode

Erbrink, J. (2015). *Stroomversnellingswijk Heerhugowaard.* Alkmaar: Alliander.

Eurelectric. . (2015). *Demand Response.*

Fernandez, G. C. (2003). Regression Diagnostic Plots. Reno, NV.

FrontlineSolvers. (2016, 05 08). *OPTIMIZATION PROBLEM TYPES - NONSMOOTH OPTIMIZATION.* Retrieved from FrontlineSolvers: http://www.solver.com/nonsmooth-optimization

Gamage, K. A., & Gelazanskas, L. (2014). Demand side management in smart grid: a review and proposals for future direction. *Sustainable Cities and Society*, 22-30.

Gelazanskas,, L., & Gamage, , K. A. (2014). emand side management in smart grid: a review and proposals for future direction. *Sustainable Cities and Society*, 22-30.

Gellings, C. W. (1981). Demand Side Load Management. *Spectrum IEEE*, 49 - 52.

Gellings, C. W. (1985). The concept of demand-side management for electric utilities. 1468 - 1470.

Gellings, C. W. (1996). Then and now: The perspective of the man who coined the term 'DSM'. *Energy Policy*, 285 - 288.

Gellings, C. W., & Parmenter, K. E. (1988). Demand-side management. In D. Y. Goswami, & F. Kreith, *Energy Efficiency and Renewable Energy* (pp. 289 - 310). Boca Raton: CRC Press.

Gellings, C. W., & Smith, W. M. (1989). Integrating demand-side managemente into utility planning. *Proceedings of IEEE*, 908 - 918.

Gillingham, K., Rapson, D., & Wagner, G. (2014, November). The rebound effect and energy efficiency policy. Waschington: Resources.

Hausman, J. (1978). Specification tests in econometrics. *Ecnometrica*, 1251 - 1271.

Heussen, K., You, S., Hansen, L. H., & Andersen, K. B. (2012). In-direct control for demand side. *Innovative Smart Grid Technologies* (pp. 1-8). Berlin: IEEE.

Himmelweit, S., Simonetti, R., & Trigg, A. (2001). *Microeconomics. Neoclassical and Institutionalis Perspectives on Econmic Behaviour.* Cengage.

Hull, L. (2001). *Evaluating the Business Case for Micro Demand Response and Energy Saving.* London: International Energy Agency Demand-Side Management Programme.

Hurlin, C. (2010, Jan). Panel Data Econometrics. Orléans.

International Energy Agency. (2011). *Harnessing Variable Renewables.* Paris: OECD/IEA.

Inventum. (2015). *Ecolution ventilatiewarmtepomp.*

Investopedia. (2015). *Quantitative Analysis*. Retrieved from Investopedia: http://www.investopedia.com/terms/q/quantitativeanalysis.asp

Israel, G. D. (1992). *Determining sample size.* University of Florida Cooperative Extension Service, Institute of Food and Agriculture Sciences, EDIS.

Jordan, U., & Vajen, K. (2001). *Realistic domestic hot-water profiles in different time scales.* IEA-SHC.

Jorge, N., & Wright, S. (2006). *Numerical Optimization.* Springer Science & Business Media.

Jose, M., Muller, N., & Royletman, I. (2010). Demand response and distribution grid operation: Opportunities and challenges. *Smart Grid IEEE Transactions*, 193 - 198.

Judea, P. (2000). *Causality: Models, Reasoning, and Interference.* Cambridge University Press.

Kahneman, D., & Tversky, A. (1972). Subjective proability: A judgement of representativeness. *Cognitive psychology*, 430 - 454.

Kallet, R. H. (2004). How to Write the Method Section of a Research Paper. *Respiratory Care*, 1229 - 1232.

Kalogirou, S. A., & Tripanagnostopoulos, Y. (2006). Hybrid PV/T solar systems for domestic hot water and electricity production. *Energy Conversion and Management*, 3368 - 3382.

Karfopoulos, E., Tena, L., Torres, A., Salas, P., Jorda, J., Dimeas, A., & Hatziargyriou, N. (2015). A multi-agent system providing demand response services from residential consumers. *Electric Power Systems Research*, 163 - 176.

Koenders, I. (2014). *Concept Architectuur Heerhugowaard.* Den Bosch: Essent.

Kosow, H., & GaBner, R. (2008). *Methods of Future and Scenario Analysis.* Born: German Developement Institute.

Kruskal, W., & Mosteller, F. (1979). Representative Sampling, III: The Current Statistical Literature. *International Statistical Review*, 245 - 265.

KUUB. (2015). *Wijkanalyse NOM.*

Lambert, Q. (2012). *Business Models for an Aggregator.*

Lazaros, G., Koutsopoulos, I., & Salonidis, T. (2013). The role of aggregators in smart grid demand response markets. *IEEE*, 1247 - 1257.

Levine, M. D., & Sonnenblick, R. (1994). On the assessment of utility demand-side management pro-grams. *Energy Policy*, 848-856.

Liu, Q. H., Xu, K., & Wang, H. M. (2015). Study of Nanjing Demand Side Management Based on Cost-Benefit Analysis-Take Green Lighting as an Example. *Applied Mechanics and Materials*, 260 - 268.

Low Energy Architecture Research Unit. (2016, 04 04). *Heavy vs. Light Thermal Mass*. Retrieved from CLEAR (Comfort and Low Energy ARchitecture): http://www.new-learn.info/packages/clear/thermal/buildings/building_fabric/properties/thermal_mass.html

Lukszo, Z. (2016). Engineering optimization in energy and industry. Delft.

Lumley, T., Diehr, P., Emerson, S., & Chen, L. (2002). The Importance of the Normality Assumption in Large Public Health Data Sets. *Annual Review of Public Health*, 151 - 169.

Mac Fadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Bahavior. 105 - 142.

Mallows, C. L. (1986). Augmented partial residuals. *Technometrics*, 313 - 319.

Mekhilef, S., Saidur, R., & Kamalisarvestani, M. (2012). Effect of dust, humidity and air velocity on efficiency of photovoltaic cells. *Renewable and Sustainable Energy Reviews*, 2920-2925.

Menegaki, A. N. (2011). Growth and renewable energy in Europe: A random effect model with evidence for neutrality hypothesis. *Energy Economics*, 257 - 263.

Milieu Centraal. (2016, 04 01). *Energielabel*. Retrieved from https://www.energielabel.nl/woningen

Ministry of Welfare of the Netherlands. (2014). *Sociaaleconomische status: Wat is de huidige situatie? In: Volksgezondheid Toekomst Verkenning, Nationaal Kompas Volksgezondheid.* Bilthoven: Ministry of Welfare of the Netherlands.

Moghram, I., & Rahman, S. (1989). ANALYSIS AND EVALUATION OF FIVE SHORT-TERM LOAD FORECASTING TECHNIQUES. *IEEE Transactions on Power Systems*, 1484 - 1491.

Mohler, D., & Sowder, D. (2014). Energy Flexibility and the Need for Flexibility on the Grid. *Renewable Energy Integration*, 285 - 292.

Mohsenian-Rad, A. H., Wong, V. W., Jatskevich, J., Schober, R., & Leon-Garcia, A. (2010). Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid. *Smart Grids*, 320 = 331.

Mohsenian-Rad, H. (2012). Demand Response. Texas.

Mordkoff, J. T. (2011). The Assumption(s) of Normality.

Negnevitsky, M., Nguyen, T. D., & de Groot, M. (2010). Novel business models for demand response exchange. *Power and Energy Society General Meeting,* 1 - 7.

NIBUD. (2015). *Energie en water*. Retrieved from NIBUD: https://www.nibud.nl/consumenten/energie-en-water/

Nilsson, H. (1994). The many faces of demand-side management. *Power Engineering Journal,* 207 - 210.

NutsConnect. (2015). Overzicht stroom en gas tarieven Essent.

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflaction factors. *Quality & Quantity*, 673.

Olivares, M. A., & Garcia-Forero, C. (2010). Goodness of fit testing. *International Encyclopedia of Education*, 190 - 196.

Onwuegbuzie, A. J., Leech, N. L., & Collins, K. M. (2012). Qualitative analysis techniques for the review of the literature. *The qualitative report*, 17 - 28.

Palensky, P., & Dietrich, D. (2011). Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. *Transactions on Industrial Informatics*, 381 - 388.

Papagiannis, G., Dagoumas, A., Lettas, N., & Dokopoulos, P. (2008). Economic and environmental im-pacts from the implementation of an intelligent demand side management system at the European level. *Energy Policy*, 163 - 180.

Park, H. M. (2011). *Practical Guides to Panel Data Modeling.* Japan: International University of Japan.

Planbureau voor de Leefomgeving. (2015, 3 21). *Regionale bevolkingsprognose*. Retrieved from Planbureau voor de Leefomgeving: http://www.pbl.nl/themasites/regionale-bevolkingsprognose/prognoses-in-beeld/bevolking

Reddy, B. S., & Parikh, J. K. (1997). Economic and environmental impacts of demand side management programmes. *Energy Policy*, 349 - 356.

Rijksdienst voor Ondernemen Nederland. (2015). *Nul op de Meter.* Utrecht: Rijksdienst voor Ondernemend Nederland.

Sargent, R. G. (2005). Verification and validation of simulation models. *Proceedings of the 37th conference on winter simulation. Winter simulation conference*, (pp. 130 - 145).

Särndal, C. E., Swensson, B., & Wretman, J. (2003). *Model assisted survey sampling.*

Schoots, K., & Hammingh, P. (2015). *Nationale Energieverkenning 2015.* Petten: Energieonderzoek Centrum Nederland.

Sekaran, U., & Bougie, R. (2012). *Research Methods for Business.* John Wiley and Sons Ltd.

Semykina, A., & Wooldridge, J. M. (2010). Estimating panel data models in the presence of endogeneity and selection. *Journal of Econometrics*, 375 - 380.

Seung-Jun, K., & Giannakis, G. (2013). Scalable and robust demand response with mixed-integer constraints. *Smart Grids*, 2089 - 2099.

Shafiu, A., & Watts, M. (2007). *A Working Document on Communication and Control Requirements.*

Shannon, R. E. (1998). Introduction to the art and science of simulation. (pp. 7 - 14). Proceedings of the 1998 Winter Simulation Conference.

Sheen, J. N. (2005). Economic profitability analysis of demand side management program. *Energy conversion and management*, 2919 - 3935.

Siano, P. (2014). Demand response and smart grids - a survey. *Renewable and Sustainable Energy Reviews*, 461 - 478.

Siares, T. D. (2014). Analysing productivity in Photovoltaic systems under different atmospheric conditions.

Sims, R. E., Rogner, H. H., & Gregory, K. (2003). Carbon emission and mitigation cost comparisons between fossil fuel, nuclear and renewable energy resources for electricity generation. *Energy policy*, 1315 - 1326.

Sociaal Economische Raad. (2013). *Energieakkoord voor duurzame groei.* Den Haag.

Söderbom, M. (2009). *ERSA Training Workshop Lecture 5: Estimation of Binary Choice Models with Panel Data.*

STATA. (2014). *Xtreg.* Retrieved from http://www.stata.com/manuals13/xtxtreg.pdf#xtxtregMethodsandformulasxtreg%2Cre

Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy policy*, 4419 - 4426.

Sunday. (2015, 3 21). *Top 5 BIPV-gebouwen en (BI) PV-woonwijken in woord en beeld*. Retrieved from Sunday: http://www.sundaynl.nl/nieuws/i47/top-5-bipv-gebouwen-en-bi-pv-woonwijken-in-woord-en-beeld

Tao, C., Shanxu, D., & Changsong, C. (2010). Forecasting power output for grid-connected photovoltaic power system without using solar radiation measurement. *Power Electronics for Distributed Generation Systems,* 773 - 777.

Teddlie, C., & Yu, F. (2007). Mixed Methods Sampling: A typology with examples. *Journal of Mixed methods research*, 77 - 100.

Thermopedia. (2015, 04 01). *Fourier's law*. Retrieved from Thermopedia: http://www.thermopedia.com/content/781/

TNS NIPO. (2013). *Watergebruik Thuis 2013.* Vewin.

Tomlin, R. S. (2014). *Basic Word Order: Functional Principles.* Routledge.

Torres-Reyna, O. (2007). *Getting started in Logit and Ordered Logit regression.* Princeton.

Torres-Reyna, O. (2007, Dec). Panel Data Analysis Fixed and Random Effects. Princeton, NY, USA.

Torriti, J., Hassan, M. G., & Leach, M. (2010). Demand response experience in Europe: Policies, programmes and implementation. *Energy*, 1575 - 1583.

Tripple. (2014). *The Balance of Power – Flexibility Options for the Dutch Electricity Market.* Rotterdam.

Tso, G. K., & Yau, K. K. (2007). Predicting electrcity energy consumption: A comparasion of regression analysis, decision tree and neural networks. *Energy*, 1761 - 1768.

USEF Foundation. (2014). *USEF summary of the introduction of the USEF model.* USEF Fondation.

Verbeek, M., & Nijman, T. (1992). Testing for selectivity bias in panel data models. *International Economic Review*, 681 - 703.

Verhallen, T. M., & van Raaij, W. F. (1981). Household Behavior and the Use of Natural Gas for Home Heating. *Journal of Consumer Research*, 253 - 257.

Wang, H. M. (2009). Comparison of the Goodness-of-Fit Tests: the Pearson Chi-square and Kolmogorov-Smirnov Tests. *量管理期刊*, 57 - 64.

Warren, P. (2014). A review of demand-side management policy in the UK. *Renewable and Sustainable Energy Reviews*, 941 - 951.

Weigt, H. (2009). Germany's wind energy: the potential for fossil capacity replacement and cost saving. *Applied Energy*, 1857 - 1863.

Whitner, R. B., & Balci, O. (1989). *Guidelines for selecting and using simulation model verification techniques.* Virginia: Department of Computer Science Virginia Polytechnic Institute and State University.

Woittiez, E., & Stomphorst, Y. (2015). *Pricing of flexibility.* Den Bosch: Essent.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

Wooldridge, J. M. (2015). *Introductory Econometrics: a modern approach.* Nelson Education.

Yoshimoto, H. (2008). Binary Choice (Probit and Logit) Models. *ECON 203C: System Models*, 1 - 18.

Yule, G., Udney, & Kendall, M. G. (1950). *An introduction to the theory of statistics.* New York: Hafner.

10 Appendix List

Appendix I. Causal Map Diagram ... 101
Appendix II. Sample location ... 102
Appendix III. Photovoltaic Electricity Flexibility ... 103
a. Bivariate Relationships Uncorrected ... 103
b. Bivariate Relationships Corrected ... 106
c. Regression Estimation Tests ... 109
Appendix IV. Bivariate Relationship Electric Boiler ... 112
Appendix V. Bivariate Relationship Heat Pump ... 113
Appendix VI. Input Variables ... 115
Appendix VII. Unbalance Trading ... 116
Appendix VIII. Smart Appliance Comparison ... 117
Appendix IX. The Financial Outcome Under Different Sized Household Groups ... 119
Appendix X. Financial Simulation Model ... 120
a. Verification of the Financial Analysis Simulation Model ... 120
b. Validation of the Financial Analysis Simulation Model ... 121
Appendix XI. Sensitivity Analysis Optimized Mix ... 123
Appendix XII. Confidence Interval ... 125

Appendix I. Causal Map Diagram

The causal map diagram, as presented in Figure 44, indicates the hypothesized causal relations between the household endogenous and exogenous factors that might influence the available electricity flexibility from the four appliances. The arrows not only indicate the relation, but also the direction of the causal relation, in other words the cause and effect relation. A positive sign on the arrow indicates that the independent household endogenous or exogenous factor positively influences the available electricity flexibility from the device. Consequently, a negative sign on the arrow indicates that the independent household endogenous or exogenous factor negatively influences the available electricity flexibility from the device.

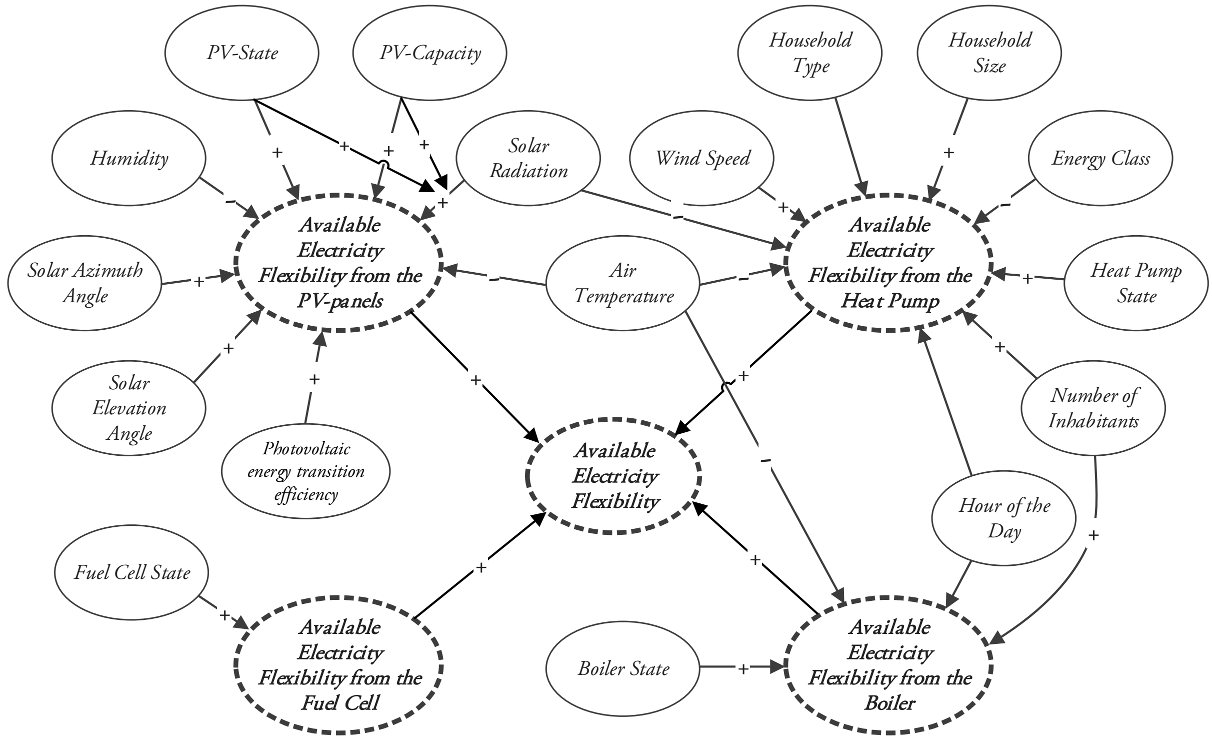

Figure 44: The Causal Map Diagram for the Available Electricity Flexibility

Appendix II. Sample location

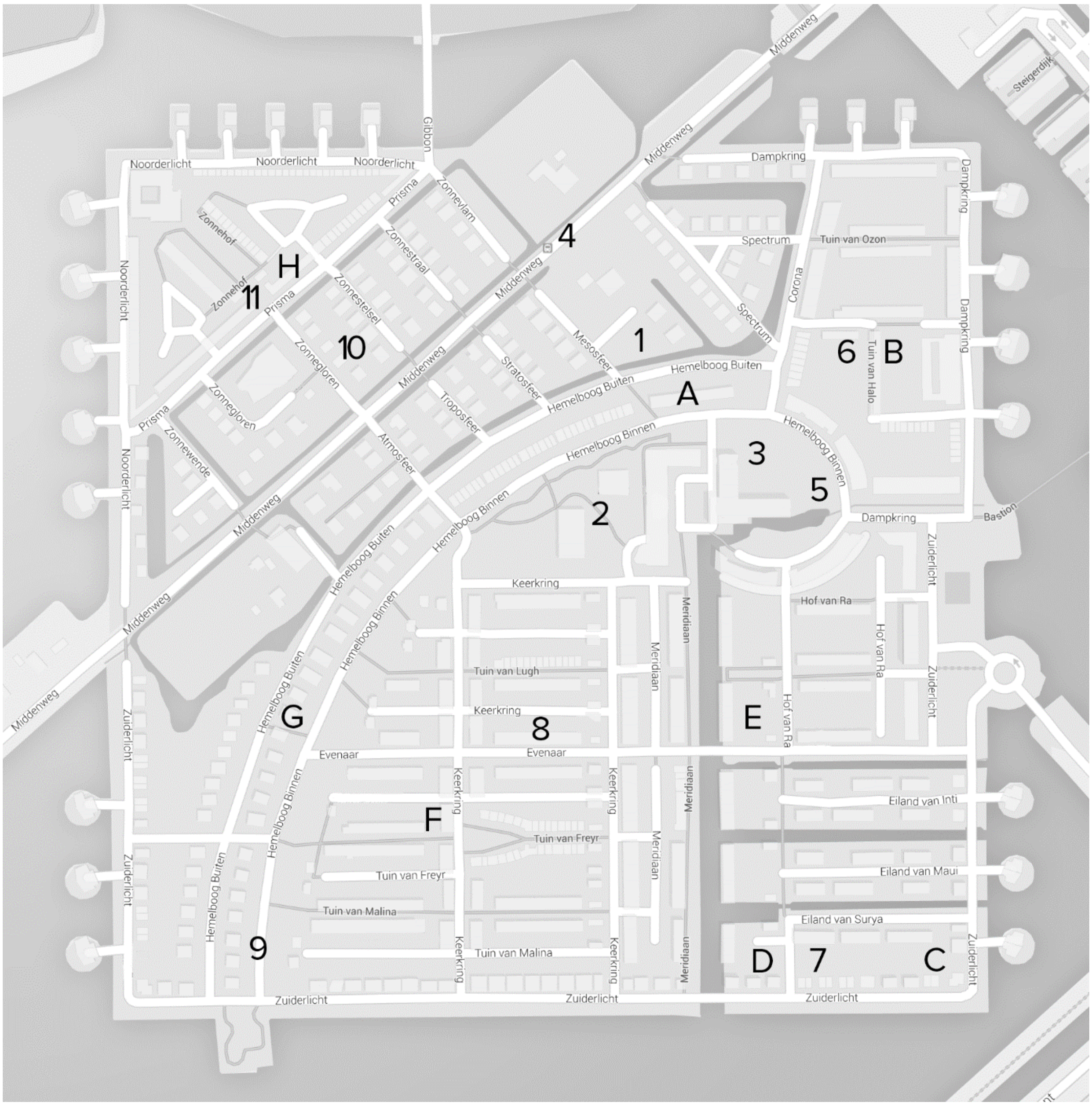

Figure 45: The sampling locations

Appendix III. Photovoltaic Electricity Flexibility

The regression analysis performed in 5.3 requires bivariate analysis and linearity proof. This appendix provides an overview of the scatter plots, corrected and uncorrected, for the bivariate relations between the hypothetical factors that might influence the Photovoltaic Electricity Flexibility. Furthermore, this appendix also provides an overview of all the statistical tests that have been performed to fit a regression model.

a. Bivariate Relationships Uncorrected

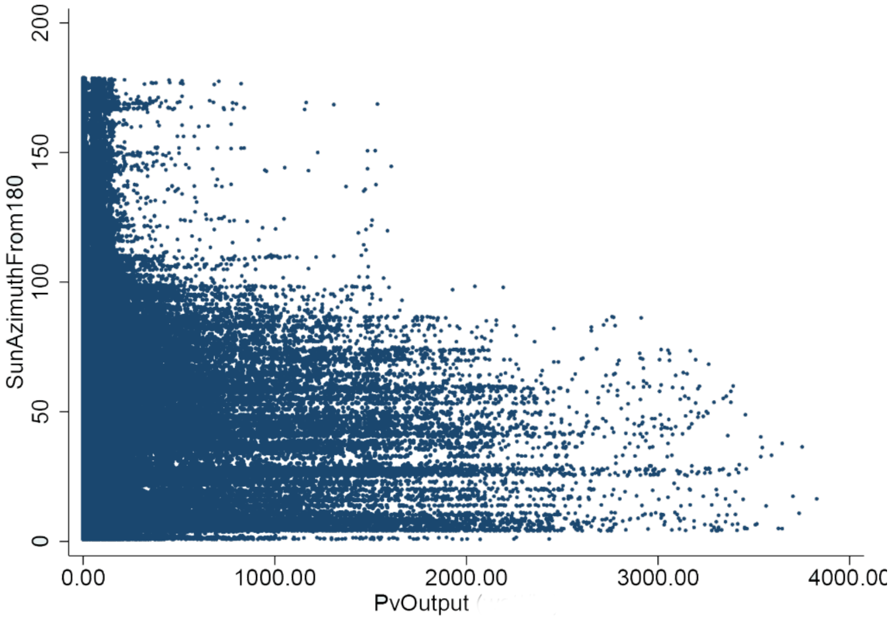

Figure 46: The Bivariate Relation between *PV-Power* and *SunAzimuthFrom180*

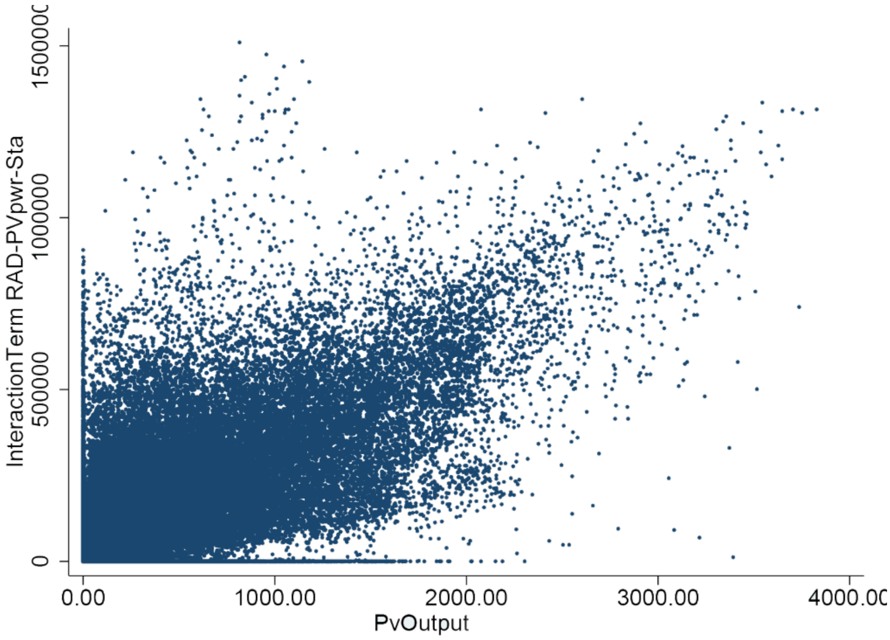

Figure 47: The Bivariate Relation between *PV-Power* and *PV-CapacityIrradianceState*

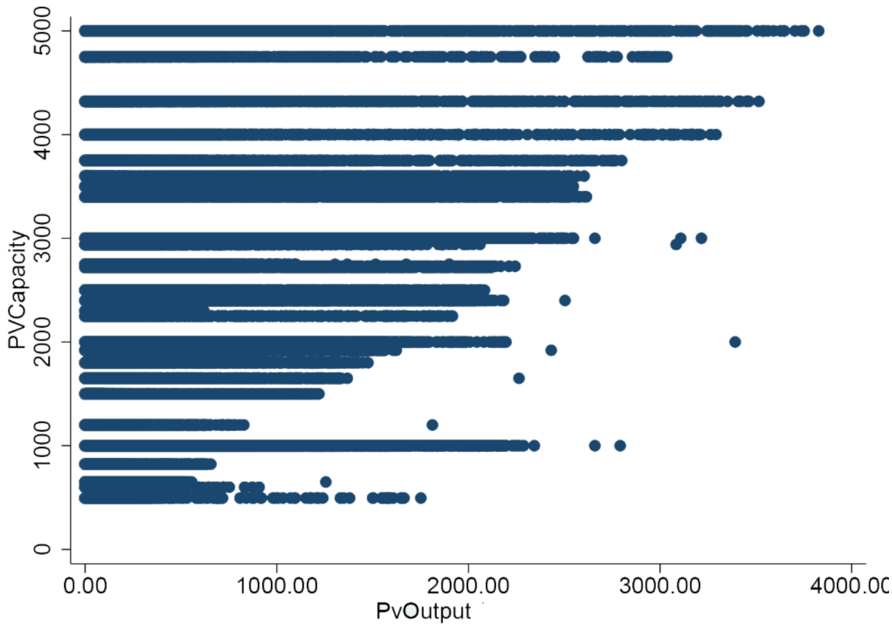

Figure 49: The Bivariate Relation between *PV-Power* and *PV-Capacity*

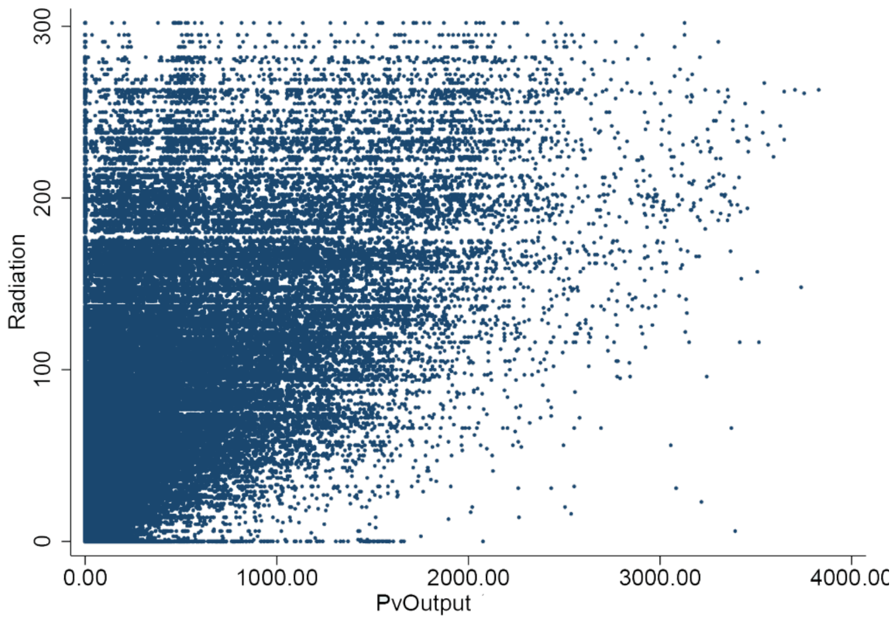

Figure 48: The Bivariate Relation between *PV-Power* and *Irradiance*

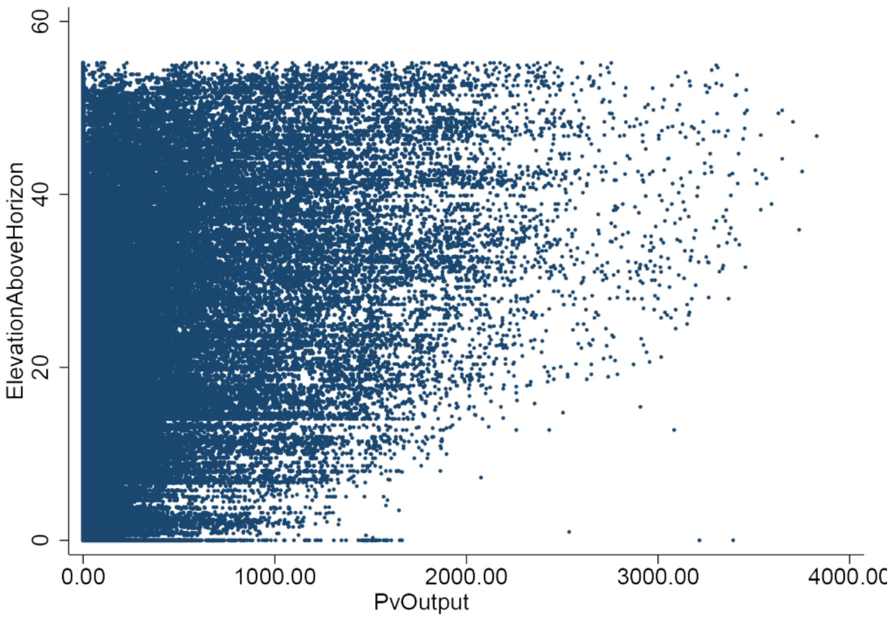

Figure 51: The Bivariate Relation between *PV-Power* and *ElevationAboveHorizon*

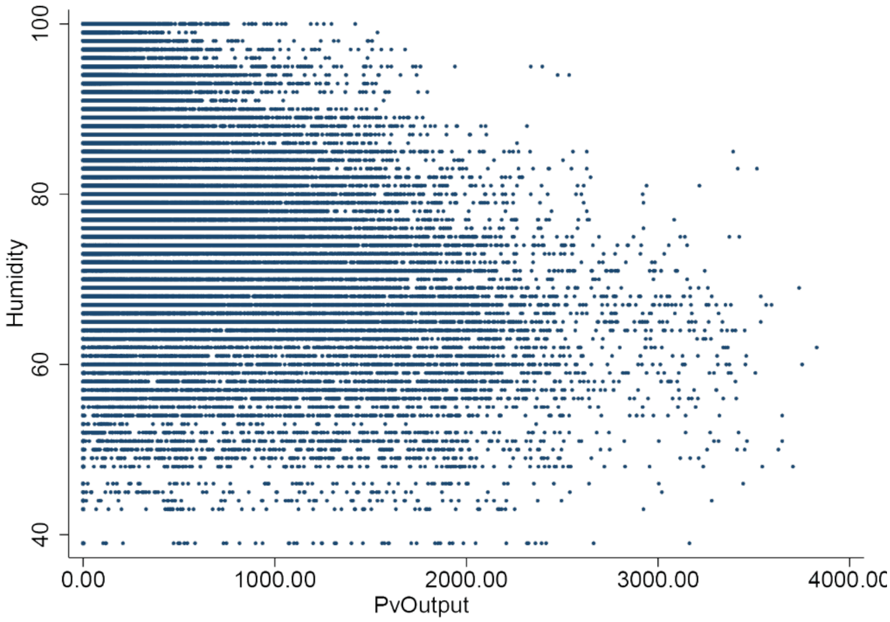

Figure 50: The Bivariate Relation between *PV-Power* and *Humidity*

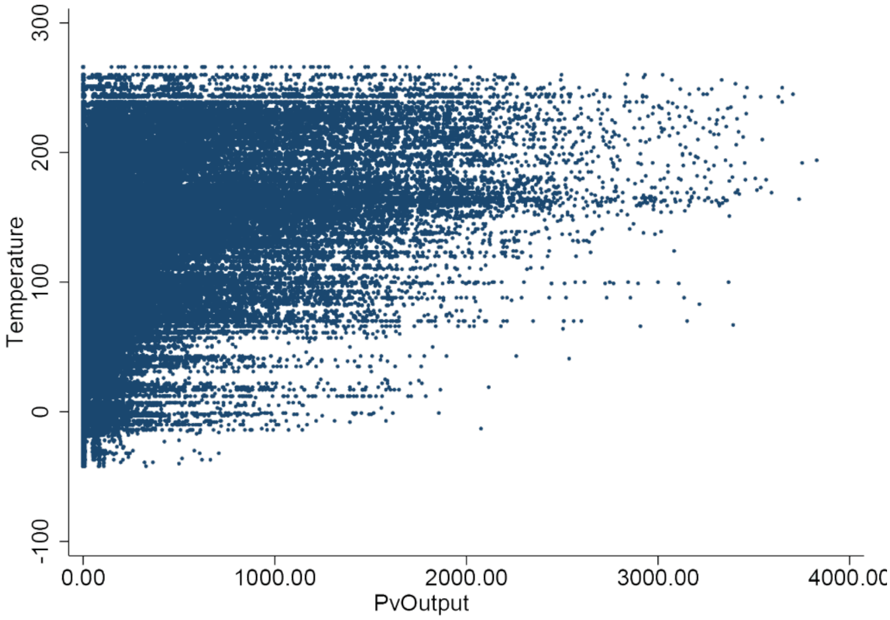

Figure 52: The Bivariate Relation between *PV-Power* and *Temperature*

b. Bivariate Relationships Corrected

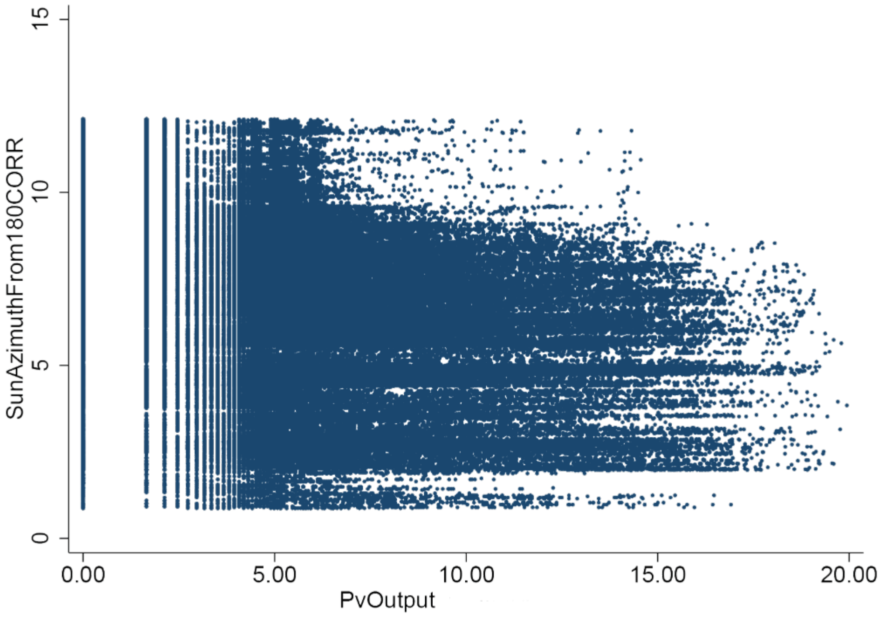

Figure 53: The Bivariate Relation between *PV-Power* and *SunAzimuthFrom180* Corrected

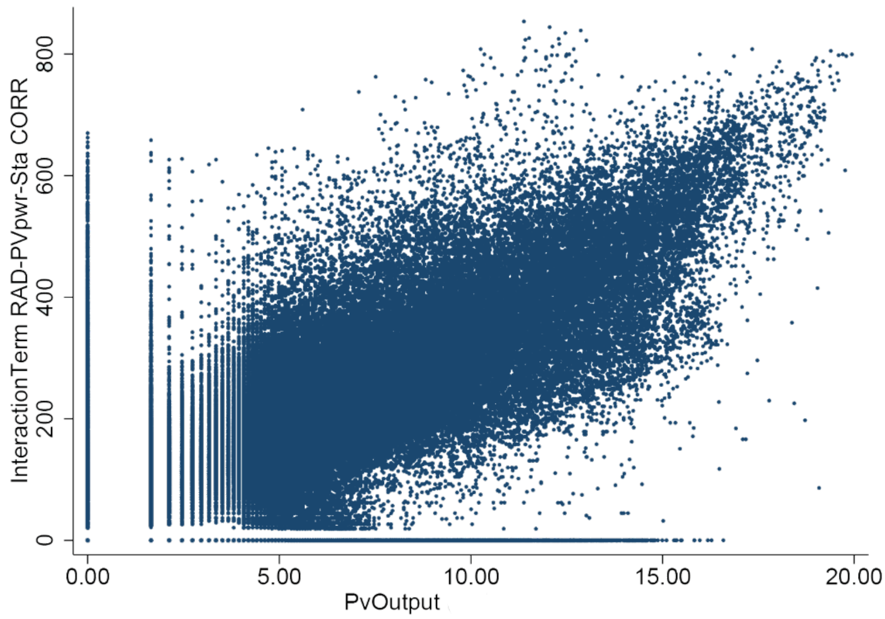

Figure 54: The Bivariate Relation between *PV-Power* and *PV-CapacityIrradianceState* Corrected

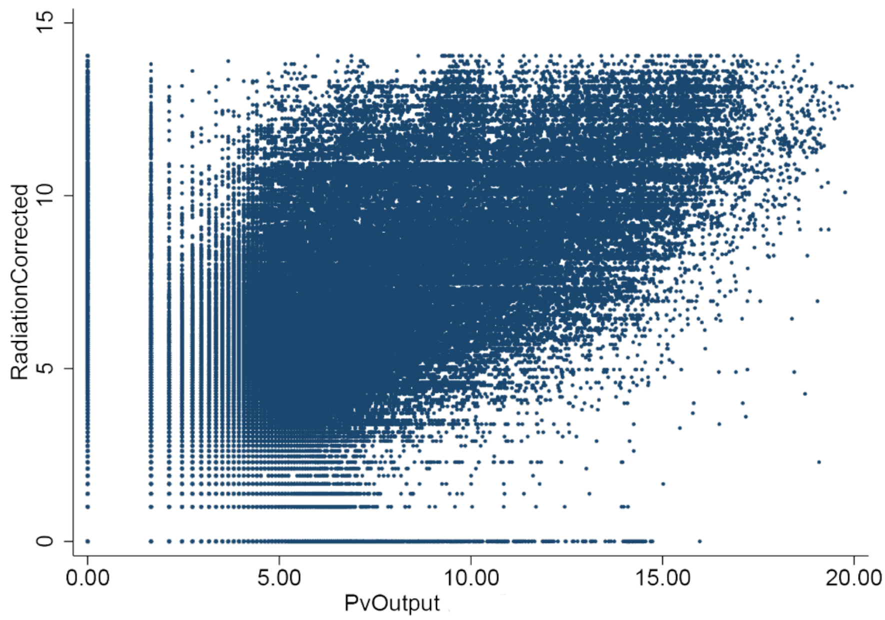

Figure 55: The Bivariate Relation between *PV-Power* and *Irradiance* Corrected

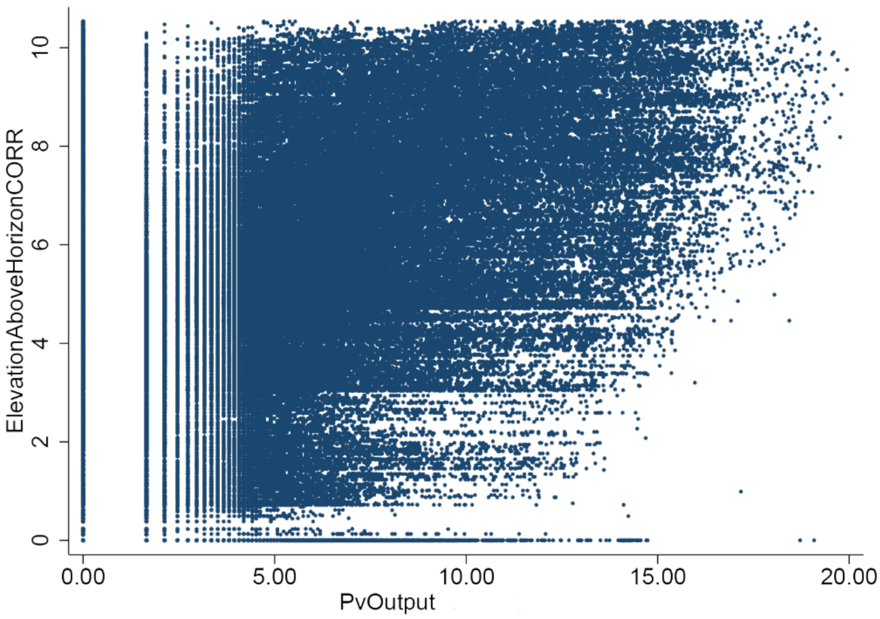

Figure 57: The Bivariate Relation between *PV-Power* and *ElevationAboveHorizon* Corrected

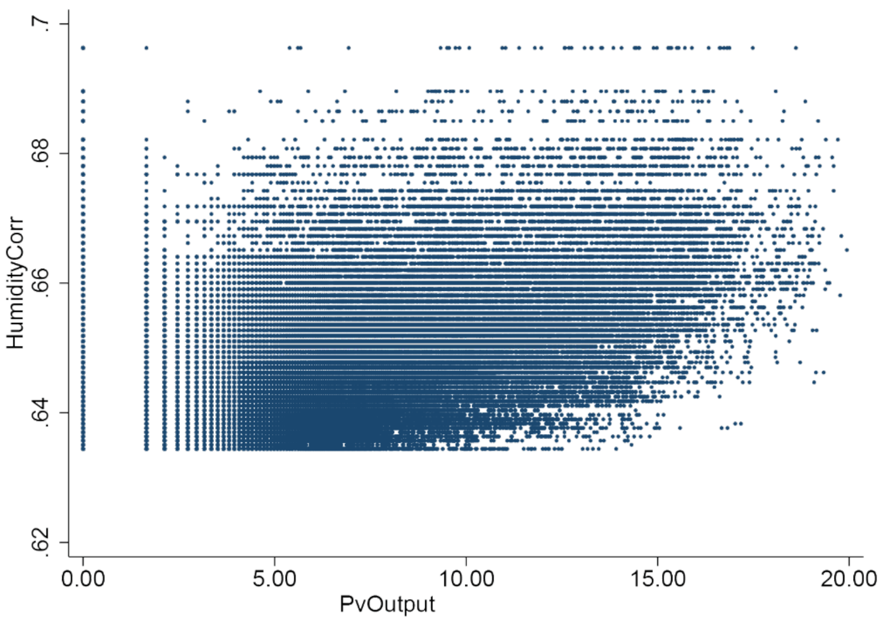

Figure 56: The Bivariate Relation between *PV-Power* and *Humidity* Corrected

c. Regression Estimation Tests

In order to perform estimate a model that is capable of predicting the Photovoltaic panel output per household, multiple statistical test are performed. The following outcomes are the results from these statistical analysis in STATA.

Random Effects Regression

```
Random-effects GLS regression                   Number of obs     =    281,751
Group variable: HouseHold                       Number of groups  =         69

R-sq:                                           Obs per group:
     within  = 0.7489                                         min =      3,291
     between = 0.1062                                         avg =    4,083.3
     overall = 0.7084                                         max =      4,095

                                                Wald chi2(6)      =  840245.18
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

PvOutputwatthrCORR	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ElevationAboveHorizonCORR	.1423402	.0023054	61.74	0.000	.1378217	.1468586
SunAzimuthFrom180CORR	-.0387559	.0019197	-20.19	0.000	-.0425185	-.0349933
InteractionTermRADPVpwrStaCO	.0200485	.0000587	341.70	0.000	.0199335	.0201635
RadiationCorrected	.013744	.0025794	5.33	0.000	.0086885	.0187996
PVCapacity	-.0002322	.000093	-2.50	0.013	-.0004145	-.00005
State	.2369979	.0144818	16.37	0.000	.2086141	.2653816
_cons	1.045971	.2167404	4.83	0.000	.6211673	1.470774
sigma_u	.88366279					
sigma_e	1.7605195					
rho	.20123758	(fraction of variance due to u_i)				

Fixed Effects Regression

```
Fixed-effects (within) regression               Number of obs     =    281,751
Group variable: HouseHold                       Number of groups  =         69

R-sq:                                           Obs per group:
     within  = 0.7489                                         min =      3,291
     between = 0.1038                                         avg =    4,083.3
     overall = 0.7032                                         max =      4,095

                                                F(5,281677)       =  168046.46
corr(u_i, Xb)  = -0.0553                        Prob > F          =     0.0000
```

PvOutputwatthrCORR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ElevationAboveHorizonCORR	.1423419	.0023054	61.74	0.000	.1378235	.1468603
SunAzimuthFrom180CORR	-.0387541	.0019198	-20.19	0.000	-.0425168	-.0349915
InteractionTermRADPVpwrStaCO	.0200484	.0000587	341.69	0.000	.0199334	.0201634
RadiationCorrected	.0137492	.0025794	5.33	0.000	.0086936	.0188048
PVCapacity	0	(omitted)				
State	.2371552	.0144826	16.38	0.000	.2087696	.2655407
_cons	.578239	.0236855	24.41	0.000	.5318161	.624662
sigma_u	.90543039					
sigma_e	1.7605195					
rho	.20917464	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(68, 281677) = 1069.21             Prob > F = 0.0000
```

Hausman Specification Test (Fixed vs. Random Effects)

The outcome of the Hausman Specification test which cannot reject the *H0* hypotheses and thereby concludes that the random effect estimators are efficient.

```
                     ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
ElevationA~R |    .1423419     .1423402        1.75e-06        6.26e-06
SunAzimuth~R |   -.0387541    -.0387559        1.78e-06        5.33e-06
Interactio~O |    .0200484     .0200485       -1.22e-07        2.91e-07
RadiationC~d |    .0137492      .013744        5.17e-06        .0000109
       State |    .2371552     .2369979        .0001573        .0001583
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        1.00
                Prob>chi2 =      0.9623
```

The Breusch-Pagan / Cook-Weisberg test for Homoscedasticity

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of PvOutputwatthrCORR

         chi2(1)      = 56329.44
         Prob > chi2  =   0.0000
```

Wooldridge test for Autocorrelation

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      68) =    337.512
           Prob > F =      0.0000
```

The Driscoll and Kraay correction for serial correlation and heteroscedasticity

```
Regression with Driscoll-Kraay standard errors   Number of obs     =    281751
Method: Pooled OLS                               Number of groups  =        69
Group variable (i): HouseHold                    F(  4,  4094)     =   4980.44
maximum lag: 9                                   Prob > F          =    0.0000
                                                 R-squared         =    0.7085
                                                 Root MSE          =    1.9588

------------------------------------------------------------------------------------------
                             |             Drisc/Kraay
          PvOutputwatthrCORR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------------------+------------------------------------------------------------
   ElevationAboveHorizonCORR |   .1405118   .0150301     9.35   0.000     .1110447     .169979
       SunAzimuthFrom180CORR |  -.0410736      .0135    -3.04   0.002    -.0675409   -.0146063
InteractionTermRADPVpwrStaCO |   .0204076   .0002816    72.48   0.000     .0198556    .0209597
                  PVCapacity |  -.0002381   9.07e-06   -26.25   0.000    -.0002559   -.0002203
                       _cons |   1.300594   .1280255    10.16   0.000     1.049594    1.551594
------------------------------------------------------------------------------------------
```

Residual Normality Plot

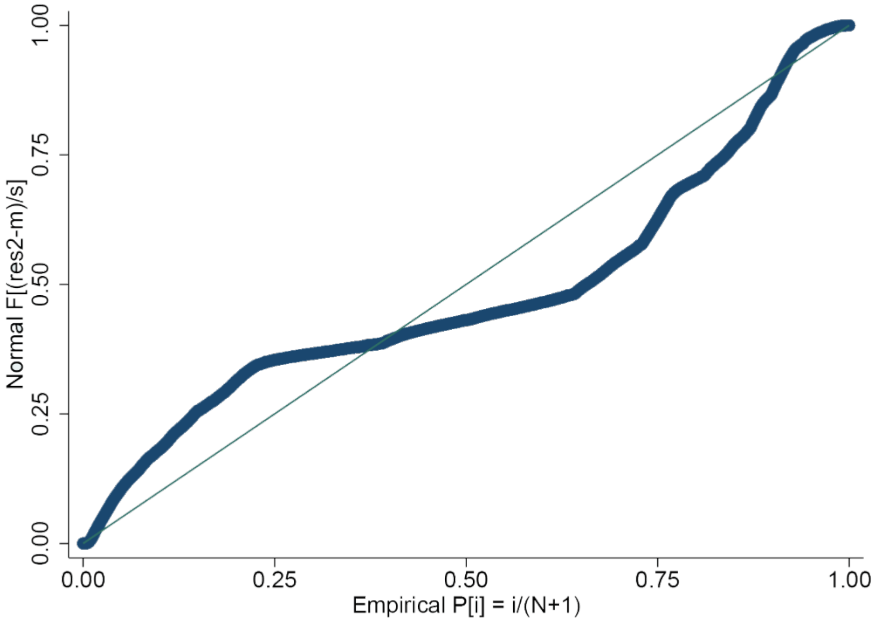

Figure 58: The Normality Plot for the Residuals from the Photovoltaic Linear Prediction

Appendix IV. Bivariate Relationship Electric Boiler

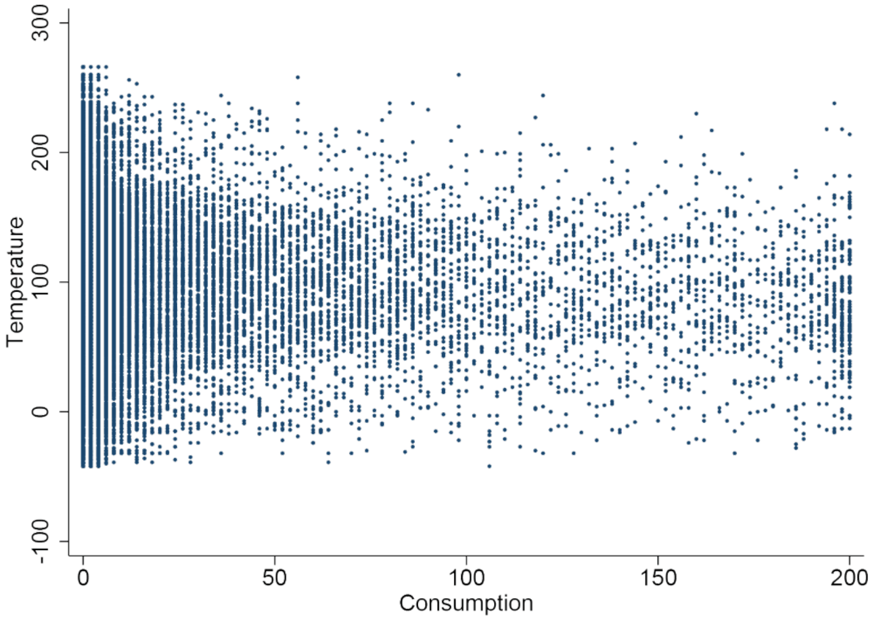

Figure 59: The Bivariate Relation between *Hot Water Consumption* and *Temperature*

Appendix V. Bivariate Relationship Heat Pump

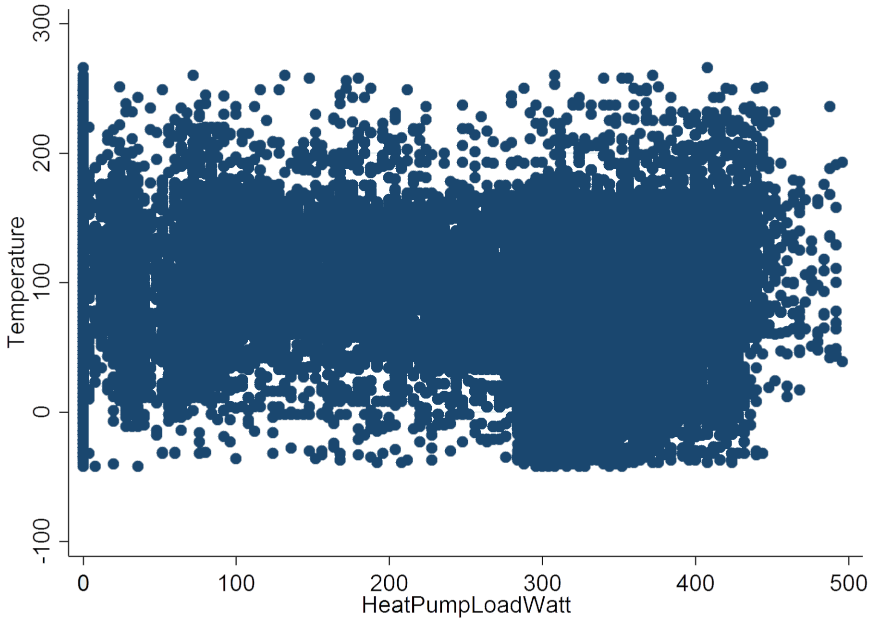

Figure 60: The Bivariate Relation between *Heat Pump Load* and *Temperature*

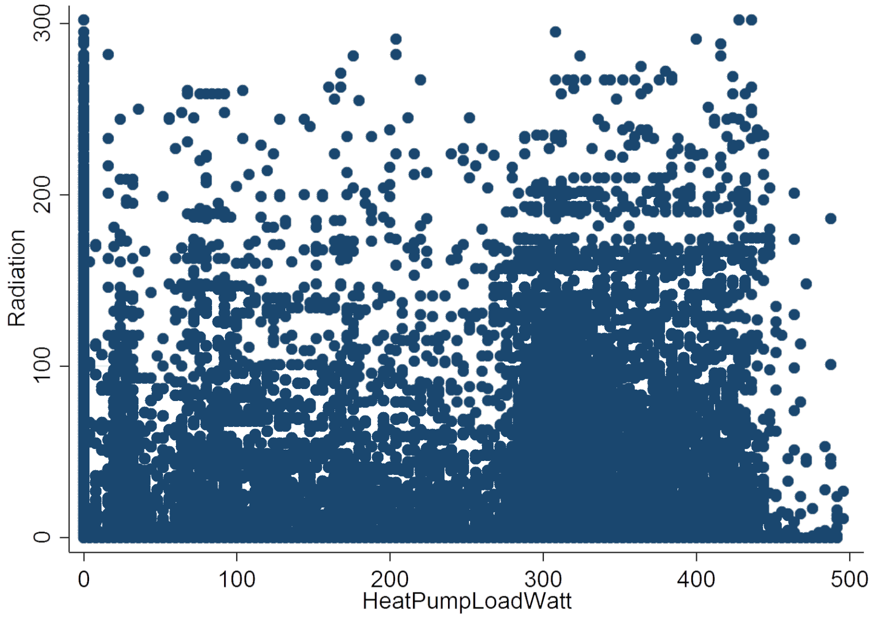

Figure 61: The Bivariate Relation between *Heat Pump Load* and *Irradiance*

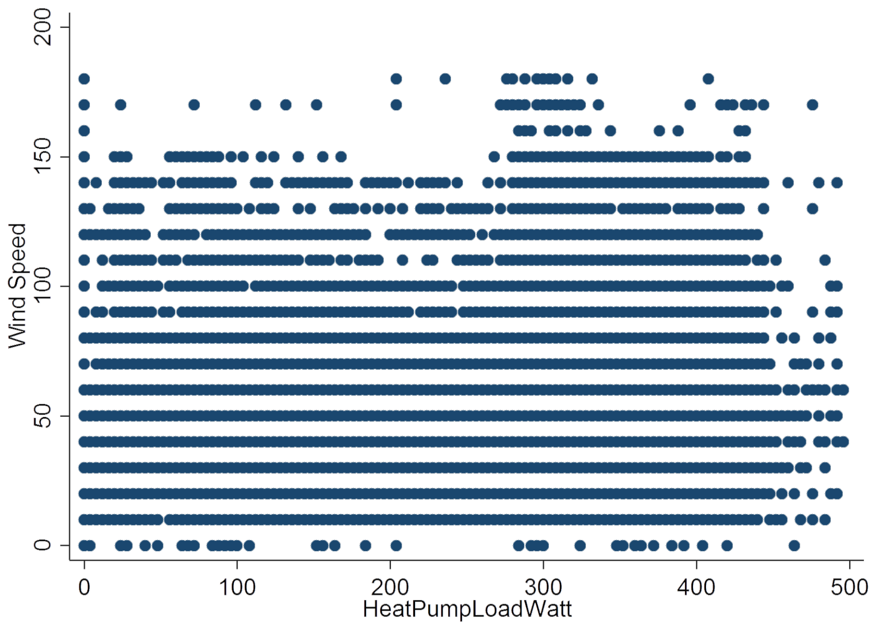

Figure 63: The Bivariate Relation between *Heat Pump Load* and *Windspeed*

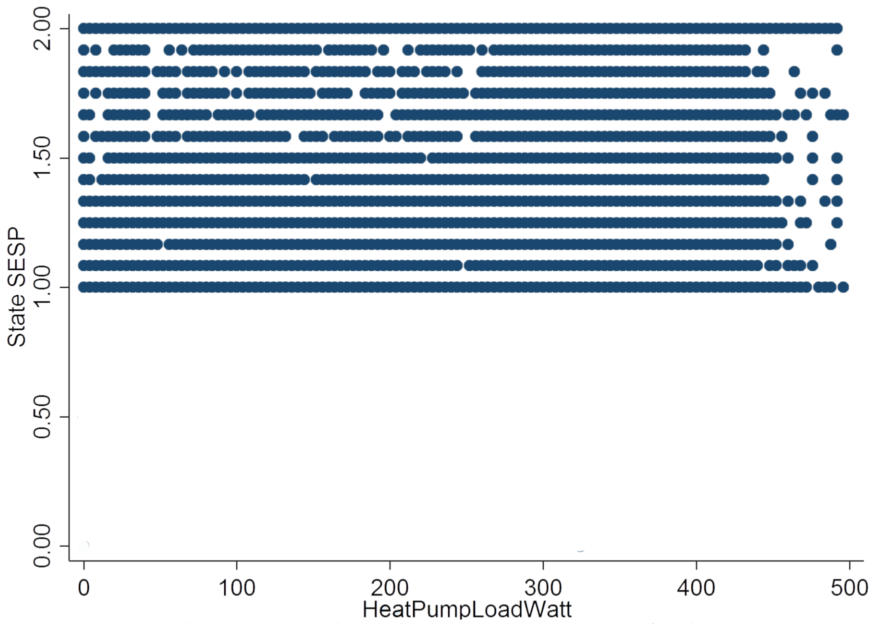

Figure 62: The Bivariate Relation between *Heat Pump Load* and *StateSESP*

Appendix VI. Input Variables

Table 35: Independent Variable Units

Model	*Independent Variable*	*Unit*	*Calculation*
Photovoltaic Panel	PV Capacity	W	
	PVCapacityIrradianceState	(J/cm2)*W	Irradiance * PVCapacity * State
	SunAzimuthFrom180	°	| 180 - Solar Azimuth Angle (deg from N) |
	ElevationAboveHorizon	°	IF(ElevationAngle >0; ElevationAngle; 0)
Heat Pump	Temperature	°C	The data from the KNMI is Temperature*10
	Irradiance	J/cm^2	
	Wind speed	m/s	

Appendix VII. Unbalance Trading

Figure 64 presents an overview of the Imbalance prices and the electricity flexibility prices of the Heat Pump, Fuel Cell, Electric Boiler and Photovoltaic Systems respectively from the upper red horizontal line to the lowest horizontal green line. As with the APX price, the Imbalance price is mostly too low for the Heat Pump to become attractive as an alternative to other energy sources. The same holds for the Electric Boiler and Photovoltaic systems. However, as with the APX prices, the Fuel Cell is highly desired due to its low electricity flexibility price.

Figure 64: A Boxplot of the Imbalance price (€/MWh) of the year 2015 over a day

Appendix VIII. Smart Appliance Comparison

Appendix IX. The Financial Outcome Under Different Sized Household Groups

Appendix X. Financial Simulation Model

Simulations are considered the closest approach next to observing reality, as the methodology allows the researcher to study the system in a situation where it is too expensive or difficult to experiment in reality. Additionally, simulation studies allow the researcher to perform 'what if' analysis and allows the researcher to control time, as it is possible to observe the system over multiple years (Shannon, 1998). Within the domain of simulation, simulation is defined as: "*the process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behavior of the system or evaluating various strategies…*" (Shannon, 1998, p. 7), where Shannon uses the term 'model' as a representation of a group of ideas in some form, different from the real world object (Shannon, 1998; Attila Boer & Verbraeck, 2003). In order to construct such a simulation model, Rosen (2012) presented four steps that describe the modeling relation between two systems (the real observed system and the simulation model). These four steps are *Causality, Encoding, Simulation* and *Decoding*, where *Causality* was performed in the analysis of section 3.2, *Encoding* was partly performed in section 5.3, and finalized in the creation of the financial analysis simulation model based on the guidelines of USEF. Furthermore, the *Simulation* step is syntactic and does not require a semantic approach as this process is fully automated through means of a Visual Basic Interface in Microsoft Excel. The only remaining phase is *Validation*, and will be divided into two distinct steps referred to as Implementation verification and Operational Validation (Sargent, 2005). Consequently, these two steps are addressed in section a and b respectively.

a. Verification of the Financial Analysis Simulation Model

Sargent (2005) defines the verification process, and specifically the Implementation Verification as "*assuring that the simulation model has been implemented according to the simulation model specification*" (p. 40). This implies that the model is programmed according to the USEF electricity flexibility trade processes between the BRP and the DSO, and that the decision making processes from both the BRP and DSO are correct. Whitner and Balci (1989) describe a multitude of verification techniques as informal analysis, dynamic analysis, constraint analysis and formal analysis. However, due to the simplistic nature of the programming language, which is nothing more than general purpose programming langue (Shannon, 1998), only informal analysis is performed. Informal analysis verification can be performed by investigating the input-output relations of the model and evaluating if the presented outcome is correct (Whitner & Balci, 1989; Sargent, 2005).

In order to investigate the input-output relationships, the response of the simulation models is evaluated on the DSO and BRP decision making processes. This implies that for the BRP the decision making process as described in section 2.4.3.2 is used. However, for the DSO the electricity flexibility decision making process does not directly depend on the electricity prices on the APX and Imbalance market but simply on the situation of network congestion. A DSO will order electricity flexibility when the load exceeds the network capacity limitation in order to resolve this exceedance, with the cheapest form of electricity flexibility. The results from this investigation are presented in Figure 67and Figure 68

Figure 67 presents a comparison between the actual observed ordered flex (observed from Heerhugowaard) and simulated ordered flex for the BRP over a period from the 16th December till the 31st of December 2015. This specific period was chosen as in this period all the smart appliances were available and provide electricity flexibility to the BRP and DSO. Based on this analysis, one can conclude that the simulated ordering process of the BRP complies with specification outlined in USEF and is comparable to the ordering process performed in Heerhugowaard.

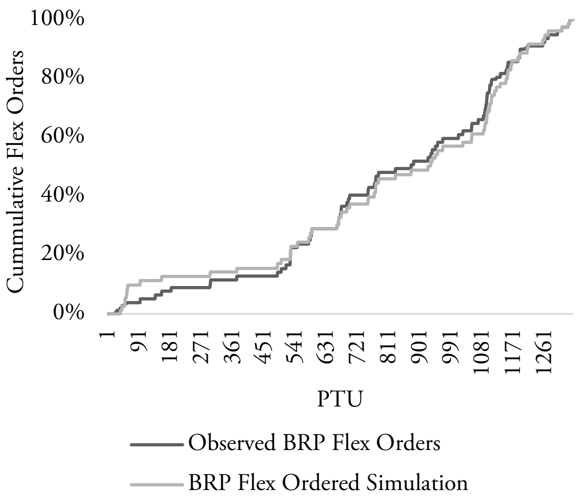

Figure 67: Flex Order from the BRP

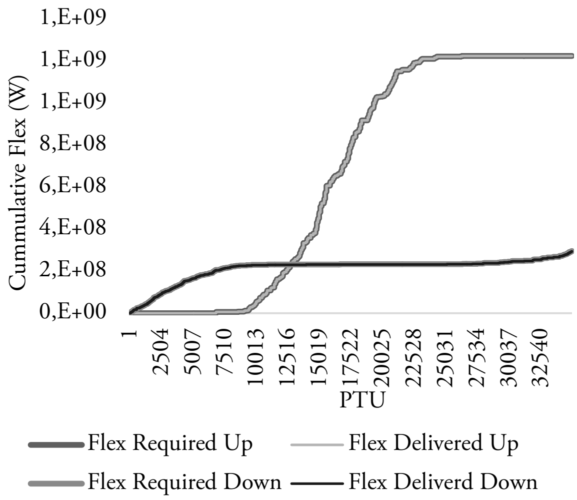

Figure 68: Flex Orders from the DSO

Figure 68 presents a comparison between the electricity flexibility required by the DSO and the electricity flexibility delivered to the DSO. As one might infer from this figure, is that there is no difference between the required and delivered quantity of electricity flexibility. Consequently, one can conclude that also the DSO ordering process complies with USEF and can be assessed as correct.

b. Validation of the Financial Analysis Simulation Model

Implementation verification allows a research to perform experimentation with the simulation model and interpret simulation model results. However, before such results can be used in order to draw conclusion regarding the financial outcome for the Aggregator, Operational validation must be performed. According to Sargent (2005) Operational validation is defined as: "*determining that the model's output behaviour has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability*" (p. 40), where Sargent further describes that Extreme Condition tests, and Degenerate tests are often used for validation of simulation models.

Extreme Condition Tests

The extreme condition test verifies if the model produces plausible outputs under extreme conditions. For example, no electricity flexibility can be traded when there are no controllable smart appliances. The following Extreme condition tests are performed and result in the following outcomes:

1. Congestion Limits of 10 kVA per household results in no congestion and no electricity flexibility traded with the DSO.
2.
3. Zero controllable smart appliances results in zero electricity flexibility traded
4. Zero households results in no load curve and no electricity flexibility traded
5.

Degeneracy Tests

The degeneracy tests validates if the response from the simulation model is in line with expectations from the system. For example, when the number of smart appliances is increased, more electricity flexibility is traded, which is in line with the expectancy from the real system, as more flexibility becomes available and the BRP will order more electricity flexibility. The following degeneracy test are performed and result in the following outcomes:

1. When the number of controllable smart appliances is increased the traded electricity flexibility increases
2. When the electricity flexibility price is increased (BRP) the traded electricity flexibility decreases[15]
3. When the electricity flexibility price is increased (DSO) the traded electricity flexibility is constant[16]
4. When the margin for the Aggregator is increased the profits for the Aggregator increases

[15] When the price of electricity flexibility increases, the probability that the BRP will order electricity flexibility instead of electricity from the APX market decreases, and consequently, less electricity flexibility is ordered from the Aggregator.

[16] Within the current USEF model it is assumed that the DSO orders electricity flexibility whatever the electricity flexibility price

5. When the congestion limit is reduced the traded electricity flexibility increases
6. When the Aggregator cost per household increase, the profits for the Aggregator decrease

Based on the performed tests and the outcome of these tests, in combination with the verification results, one can conclude that the simulation model constructed for the analysis of the financial feasibility of direct load control DSM is verified and validated for operational use.

Appendix XI. Sensitivity Analysis Optimized Mix

Appendix XII. Confidence Interval

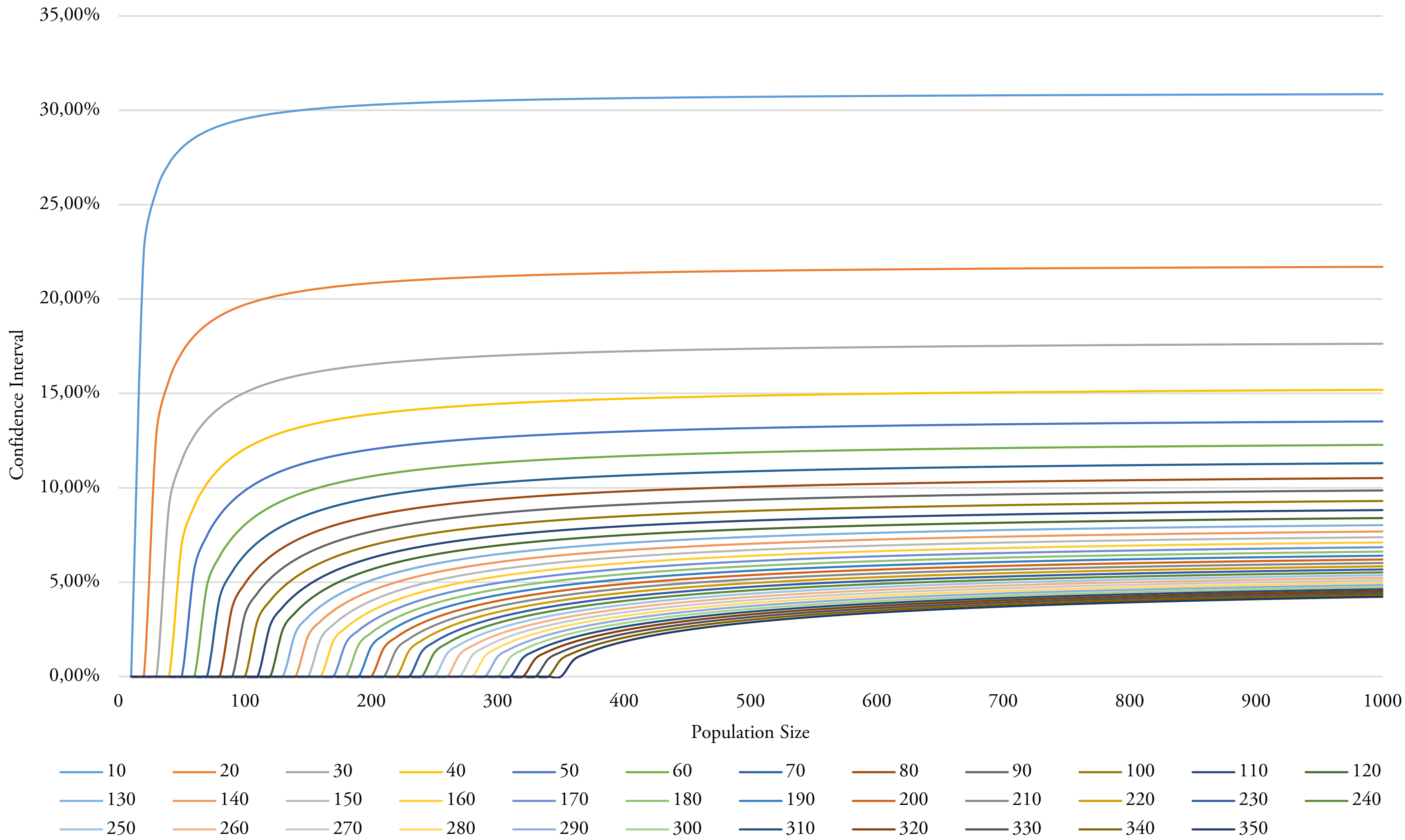

Figure 77: The Confidence Interval for various Population sizes dependent on the Sample size

The Financial Feasibility of Flexibility Expansion

A reasearch performed on the Financial Feasbility of Demand Side Management expansion for the Aggregator, in order to support the further integration of renewable electricity sources in the electricty grid

A Research Thesis Submitted to the Department of Engineering Systems and Services in Partial Fullfilment for the degree of Master in Science in Engineering and Policy Analysis at the Delft University of Technology