The Prospects of Flexibility on Congestion Mitigation against Network Reinforcement

An Empirical Study based on the Heerhugowaard Field Experiment

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An Empirical Study based on Heerhugowaard Field Experiment

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Executive Summary

Introduction

Traditionally, the transmission network transported electricity over extended distances from local large scale electricity generation plants to distribution networks that transported electricity to end consumers (Ekanayake, 2012). In order to ensure that such a system remains operational, a Distribution System Operator (DSO) maintains, operates and invests in the grid at the distributional level. One of the reasons grid investment is performed is to prevent grid congestion that occurs when the electricity load exceeds the grid capacity. Investing in reinforcing the distribution grid components (cables, transformers, fuses, etc.) increases the capacity of the electricity grid, which, in turn, prevents grid congestion.

However, with the advent of renewable energy sources, decentralized generation units and electrical appliances (electric vehicles, heat pumps, electric boilers etc.), there is an increasing pressure on modern electricity networks because of overproduction at the local level that leads to reverse transfer of power, increase in grid losses, and voltage and current fluctuations. This increasing pressure on the electricity grid could be reduced by grid reinforcement; however, it is argued that grid reinforcement and investments cannot keep up with the growth of intermittent renewable energy sources, which may result in interim and short term congestion. Moreover, Haque et al. (2014) claimed that upgrading grid assets, which is considered capital intensive, will not serve as a cost-effective solution in modern grids, as the electricity network congestions are temporary.

Although the integration of renewable and distributed resources increases the complexity of operation and preservation of the reliability of the grid, it also provides opportunities to manage the load on the network. These opportunities surface and evolve from the flexibility that results from Demand Response (DR), also referred to as Demand-Side Flexibility. Flexibility, provided by DR, is created by controlling the distributed energy resources and electrical appliances (heat pumps, electric boilers etc.) on the distribution network, which may potentially reduce peak loads or shift loads to off peak periods of time. With flexibility from such decentralized electricity sources and appliances, it is possible to manage the electricity load variability in a more cost effective manner, which may result in postponing capital intensive grid reinforcement (Ecofys, 2015). A third party, called the aggregator, is responsible to aggregate the flexibility from controlled devices and sources. Therefore, the DSO engages in short/long term contracts with the aggregator to procure the flexibility to resolve congestion.

Although demand-side flexibility holds potential in preserving network reliability by mitigating congestion, and thus postponing grid investment, the impact of demand-side flexibility provided by Demand Response on congestion mitigation, from a technical perspective, is blurred and indeterminate (Moslehi & Kumar, 2010). Moreover, the prospects of financial savings for the DSO are not guaranteed (Torriti et al., 2010). Therefore, to bridge this knowledge gap, the thesis explored the following main research question:

"To what extent can the DSO mitigate grid congestion by means of Demand-Side Flexibility to defer grid reinforcement?"

Methodology

An integrated technical and financial approach was adopted to investigate the potential of demand-side flexibility on mitigating congestion and therefore postponing grid reinforcement. The first exploratory phase of the research investigated the problem of electricity grid congestion at the distribution level, and studied the conventional and alternative solutions to congestion (the conventional technique entails load forecast and long term grid investment versus the new alternative demand-side flexibility provided by DR).

To empirically investigate the impact of demand-side flexibility, provided by DR, on grid congestion at the distribution level, **three methodologies** were employed. In the **first methodology**, data analysis was performed on real-time measured data collected from the Heerhugowaard's low-voltage grid field experiments. These two-month field experiments were performed in Heerhugowaard city, in the Netherlands, to investigate smart energy systems via the participation of 201 households. The DSO procured flexibility from the following four smart devices installed in the houses (one device in each house): Photovoltaic System (PV), Electric Boiler (EB), Heat Pump (HP), and Fuel Cell (FC).
However, since the sample collected from Heerhugowaard is not representative to the Dutch population, and performing field experiments to test whether flexibility can resolve congestion is expensive and time consuming, a second methodology

was adopted. In the **second approach**, a simulation model was constructed in order to mimic the impact of flexibility on grid congestion, which requires predicting the yearly flexibility from the four smart devices. To construct device-specific flexibility prediction models, flexibility from each of the four devices was predicted by using Time Series Regression and Count Data modelling on the data collected from the Heerhugowaard field trial. Thereafter, a **third analysis** was performed, where the simulation model was used together with scenario analysis to study, technically and financially, **the impact of flexibility on the grid congestion** and **the potential of grid investment postponement** on four other grids in the Netherlands.

Conclusions

Analysis of the measured data from the Heerhugowaard field experiments indicate that the influence of demand-side flexibility on the load volatility, which directly affects grid congestion, is limited. ***Generally, it can be concluded from the conducted analysis that the application of demand-side flexibility from the PV, HP, EB, and FC, can reduce the volatility of the electricity load between 4% and 12%.***

Based on the same analysis, it can be deduced that the impact of demand-side flexibility on congestion mitigation is limited and consequently, insufficient to resolve all electricity network congestion. This is partly caused by the fact that flexibility from the employed PVs and HPs is volatile and sensitive to seasonality. Additionally, flexibility from the Electric Boiler depends on hot water consumption, which is very much affected by human consumption/behaviour. However, it is important to note that flexibility from the FCs is constant and thus has a significant higher impact on congestion mitigation.

Overall, it can be concluded that the incapability of flexibility to resolve all network congestion could be caused by the lack of reliability of the flexibility delivery, as the reliability of the delivered flexibility is limited due to the flexibility forecast errors (which are influenced by the weather and human behaviour) for the different devices, load forecast error, and other exogenous factors such as IT error.

In the second analysis, which was performed by means of a simulation model that evaluated the impact of flexibility on grid congestion at the distribution level, it can be realized that flexibility significantly reduces both the duration (minutes) and magnitude (Watts) of congestion and might eliminate blackouts. ***Generally, it is possible to conclude that flexibility steering can reduce the magnitude of congestion (in Watts) between 55% and 67%. Additionally, flexibility steering reduces the duration of congestion in the PV and FC experiments between 34% and 67%; however, it reduces the duration of congestion in the HP experiment with only 2.5%.***

In the third analysis, a set of four case studies (two streets and two cities: one urban & one rural) in the Netherlands were investigated by means of scenario analysis and a simulation model in order to study the extent to which demand-side flexibility can postpone grid investment in different low voltage networks. Scenario analysis was employed on a wide range of electricity load projections, smart appliance penetration level changes, different electric vehicle penetration levels and discount rate changes. **The analysis of these four case studies indicates that grid investment postponement by means of demand-side flexibility is technically feasible in some cases and scenarios.** ***Generally, it can be concluded for the considered period (2015-2050), that flexibility steering can on average reduce blackouts between 10% and 74%, and can on average postpone grid investment by 2 years.***

Nevertheless, even when analysis on some cases and scenarios indicate that grid investment postponement by means of demand-side flexibility is technically feasible, this does not imply that it is also advisable from a financial perspective. Analysis indicate that the financial outcome in these four case studies present mixed results (negative savings for the two urban streets, zero savings for the urban city, and positive significant results for the rural city). **The financial savings were calculated as the difference between the savings gained due to postponing network reinforcement and the costs incurred due to flexibility ordering.** Based on these outcomes it is possible to draw the following general conclusions:

1. The financial savings of grid investment postponement by means of demand-side flexibility is highly sensitive to the grid investment cost per kVA per household. Thus, financial savings from grid investments might be more significant in rural areas (high grid investment cost per kVA per household) in comparison to urban areas (lower grid investment cost per kVA per household).
2. The financial savings of grid investment postponement for the DSO are more significant in large districts/cities in comparison to small streets because in the former more investments are needed to upgrade the city grid.
3. The significance of any positive financial savings are strongly dependent on the grid investment cost per kVA per household, on the price of flexibility, load growth projections, and the grid congestion limits.

These findings indicate that grid investment postponement by means of demand-side flexibility might be technically feasible in some cases and scenarios, as flexibility can be deployed to reduce the duration and magnitude of congestions, and consequently prevent blackouts. However, as the postponement of grid investment by means of flexibility might not provide significant financial savings for the DSO, and the questionable impact of flexibility on congestion mitigation, due to flexibility forecast error and load forecast error and IT errors, it can be concluded that demand-side flexibility might not yet be a good alternative for grid investment.

Recommendations

Although the derived conclusions based on results obtained from the Heerhugowaard field experiment, the simulation model, and scenario analysis, give generic insights on the extent demand-side flexibility can mitigate grid congestion and postpone grid investment, results from the conducted analysis are limited to: the assumptions taken in the simulation model and the scenario analysis, the un-generalizable Heerhugowaard sample characteristics, the assumptions used in blackouts calculation, the configuration of the used smart appliances, and the market coordination energy mechanism that coordinates flexibility trading. Based on those limitations and findings, it is recommended that:

I. The DSO deploys demand-side flexibility, provided by DR, in large cities/ regions rather than in small streets, since positive significant savings are more probable in large cities because more investments are needed to upgrade the city grid and its components.

II. Within large cities/regions, the DSO deploys demands-side flexibility in rural areas rather than in urban areas, since more financial savings can be reaped.

III. The DSO deploys Demand Response tools, source of flexibility, in areas where congestion is occasional and temporary, and not in areas where congestion is persistent and acute. This is because in the latter case, high flexibility ordering leads to high cost incurred that will probably outweigh savings gained from grid investment postponement.

IV. The DSO invests in flexibility forecasting and load forecasting to enhance the reliability of flexibility availability and trading, prior to full employment of demand response tools as means to mitigate congestion, in order to prevent jeopardizing the electricity system reliability.

V. With the current imprecise forecast of flexibility from smart devices, the load forecast error, and IT errors, it is recommended that the DSO orders extra flexibility, as a safety margin, beyond the flexibility needed to mitigate congestion; however, this may shrink the financial savings.

VI. The aggregator achieves a profitable business from aggregating and selling flexibility to ensure that he can stay in the business and hence the DSO can trust a continuous existing market of flexibility trading.

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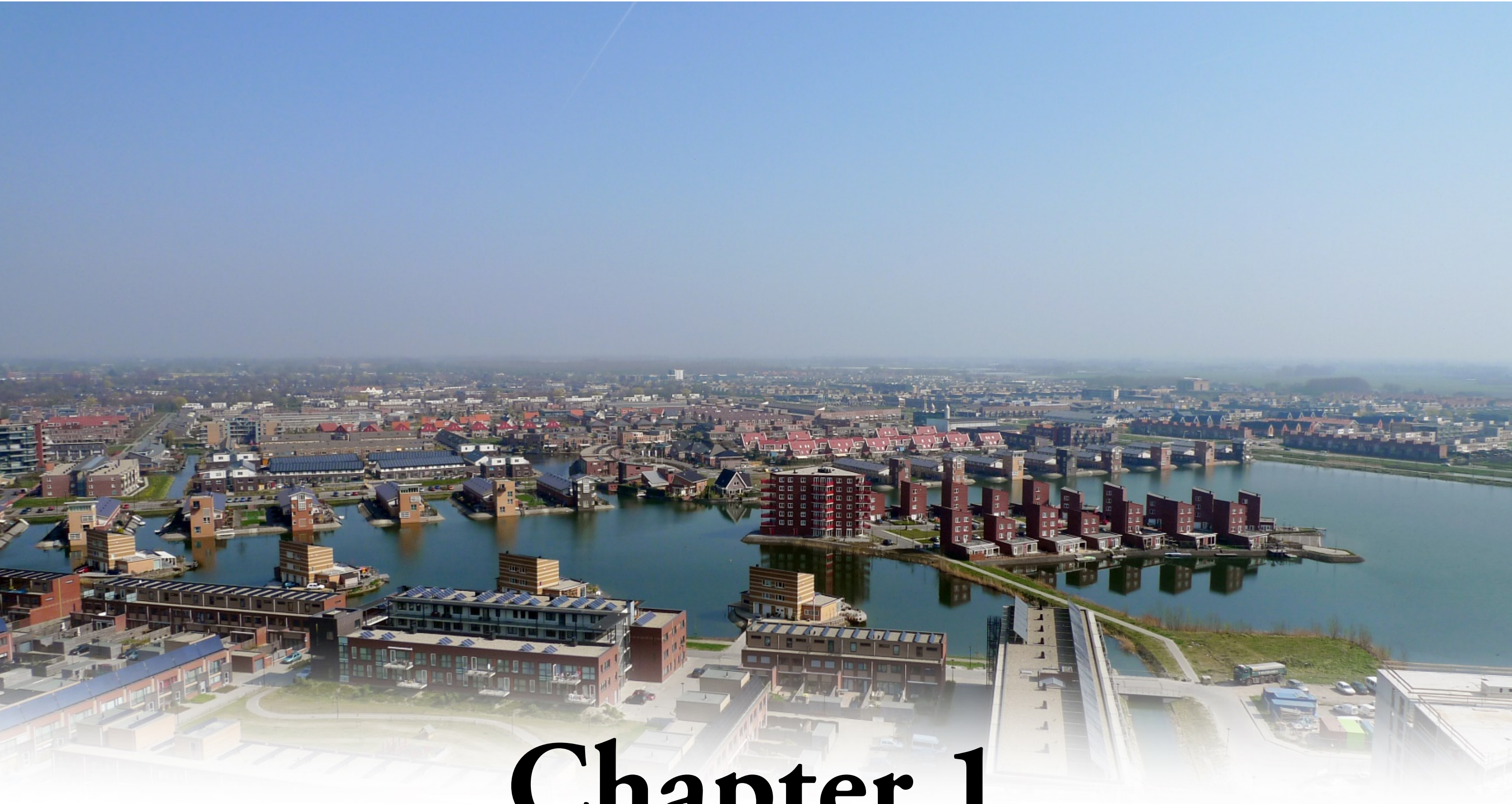
List of Acronyms

Acronym	Meaning
DSO	Distribution System Operator
BRP	Balancing Responsible Party
DSM	Demand-Side Management
DR	Demand Response
PV	Photovoltaic Cells
EB	Electric Boilers
HP	Heat Pumps
FC	Fuel Cells
EV	Electric Vehicle
Flex	Demand-Side Flexibility
USEF	Universal Smart Energy Framework
PTU	Power Time Unit (15 minutes)
EDSN	Energy Data Services Netherlands
CV	Gas Central Heating
OLS	Ordinary Least Squared
AMPDs	Almanac of Minutely Power Dataset
KNMI	The Royal Netherlands Meteorological Institute
MA	Moving Average
AR	Autoregressive Model
FDL	Finite Distributed Lagged Models
AC	Autocorrelation
PAC	Partial Autocorrelation
GLS	Generalized Least Squares
Cpk	Process Capability Potential Index
CBS	Central Bureau of Statistics
df	Degrees of Freedom
CAPEX	Capital Costs
OPEX	Operational Costs
LV	Low Voltage
K-S test	Kolmogorov Simonov



Chapter 1

1 Introduction

The current century is witnessing an increase in oil price volatility, an aging infrastructure that requires upgrading, an increase in energy consumption that is necessitating grid reinforcement, and air pollution that is posing an increasing risk on global warming (Saker et al., 2012). However, meeting the increase in demand, while the electricity grid is utilized to its full capacity, necessitates grid reinforcement and an increase in reserve capacity. This investment in grid and reserve capacity allows more energy consumption which makes it even more difficult to limit emissions. Furthermore, electricity supply chains are extensive and complex and any planned investment should involve generation, transmission and distribution. The latter drives research and development (R&D) to shift from a focus on investments in supply and alternatively looks at ways of managing electricity demand more efficiently. Concurrently, there is a vast development in renewable energy technologies and a shift in paradigm from a large centralized system to a more local distributed approach that better incorporates renewable energy generation at a local scale. The shift from supply investments to demand control and from centralized systems to decentralized local generation units require methods to level demand with supply to defer investments at the supply side (Aghaei & Alizadeh, 2013).

Conversely, renewable energy sources such as electricity generated by PVs (photovoltaic systems) and windmills, is intermittent in nature due to its dependence on the weather which makes it hard to ensure a stable supply of electricity (Logenthiran, Srinivasan, & Shun, 2012). Moreover, the electricity system is inherently characterized by a need to balance supply and demand, the minimal capability to store power, a fluctuating electricity demand due to unpredicted consumer behavior, and volatile generation costs. The aftermath of these inherent and intermittent characteristics in energy generation and networks, is a shift to deregulated and restructured market policies that allow a transition from old philosophies that support supplying the requested demand to new approaches that advocate a leveling of demand and minimization of load fluctuation (Albadi & El-Saadany, 2008). While smart grids can help in integrating renewable energy in the electricity network, Lund et al. (2012) adds that:

> "the typical core of defining a smart grid consists of a bi-directional power flow, i.e. the consumers are also producing to the grid, which differs from the traditional grid in which there is a clear separation between producers on the one side and consumers on the other side resulting in a uni-directional power flow." (p. 97)

For 'smart grids' to see the light and be successful in supporting a bi-directional power flow, managing electricity demand, and meeting environmental targets, a proper and intelligent application of the new philosophies is a must (Ipakchi & Albuyeh, 2009). In order to overcome those hurdles of intermittent energy generation, and inherent complications of the

electricity network, a need arises to control the system intelligently using mechanisms such as Demand Side Management (DSM) (Aghaei & Alizadeh, 2013).
DSM works on the demand side rather than the supply side and comprises Energy Efficiency and Demand Response (DR). Energy efficiency is achieving an overall reduction in energy consumption and Demand Response, which provides flexibility to the electricity system by controlling smart appliances, is the physical control of demand to achieve load shifting (Davito, Tai, & Uhlaner, 2010). Flexibility, from DR, is defined by Eurelectric (2014, p. 12) as the:

> "modification of generation injection and/or consumption patterns, on an individual or aggregated level, in reaction to an external signal (price signal/network tariff/activation) in order to provide a service within the energy system. The parameters used to characterise flexibility include: the amount of power modulation, the duration, the rate of change, the response time, the location etc."

The demand-side flexibility in controlling demand allows taming peak loads, less probability of blackouts, and better adoption of renewable energy. Although the success of smart grids depends on DSM, DSM is still not widely adopted and there is a wide gap between its perceived substantial benefits and its actual implementation in the electricity industry (Strbac, 2008; Walawalkar et al., 2010).

Having said that, many European countries want to achieve an overall change in the traditional electricity networks, shift towards a smart gird, and engage in DSM programs, but many challenges impede the implementation of DSM within smart grids (SER, 2013). One of those impediments, which the paper attempt to study, is the lack of empirical proof on the contribution of demand-side flexibility to network congestion management and ultimately network reliability. For instance, in the Netherlands, the Dutch government together with local energy parties are performing field experiments to gain better insights into the effects of smarts grids and DSM programs on the energy infrastructure (SER, 2013).
In section 1.1, this chapters presents the research problem based on the identified knowledge gap. In section 1.2, the social and scientific relevance of the research is explained. In section 1.3, a brief description of the field experiment performed in the Netherlands is presented. In section 1.4, a concise research design is presented and to be expanded and elaborated in chapter 3.

1.1 Problem Statement

A major concern in electricity infrastructure networks, which opts for a solution via smart grids, is the risk of transmission and distribution congestion during peak demand periods. According to Albaijat, Aflaki, and Mukherjee (2012), congestion is defined as: "a state in which the flow of electricity across the transmission line has exceeded the maximum capacity of that line" (p. 2). Currently, the electricity grid requires reinforcement to handle peak loads and preserve grid reliability. This reinforcement can take two forms: either upgrading the existing distribution assets to handle increasing demand or reinvesting in the assets by the end of their life cycle, where both alternatives are considered expensive (Koliou et al., 2014). The required reinforcement of the grid depends on the level of demand and the distributed production increase over the years. Nevertheless, it is argued that upgrading the grid components and reinforcing the grid may not be able to follow-up with the pace of renewable energy sources growth and distributed energy generation, which could result in interim and short term congestion. Moreover, it is argued that upgrading the grid assets will not serve as a cost-effective solution since such congestions are momentary and occasional (Haque et al., 2014).

To solve the risk of congestion, smart grids, by means of DSM, adapt the demand for electricity to the local production of electricity, in an attempt to lower demand peaks and level the network load. According to Pachauri, Ürge-Vorsatz, and LaBelle (2012), one of the primary reasons for load levelling is to reduce the risk of an electricity outage that can occur due to an emergency situation, an error in transmission or distribution, or a high peak load that exceeds the capacity of the grid. Mitigating congestion in the electricity network by load levelling contributes to network reliability (Bradley, Leach, & Torriti, 2013). Reliability can be achieved by flattening the load curve, to reduce the risk of congestion, after shaving the peak via load shifting (Moslehi & Kumar, 2010).

If the capacity limit is surpassed, the damage of overload (congestion) is dependent on the magnitude and duration of the overload: short but high congestion will trigger the safety fuse, causing a black out that impacts the consumers, whereas longer lasting but slight congestion leads to damage in assets (e.g. transformers) (Lerner, 2014). Thus, there is a dire need to keep the load within the grid capacity.

Conversely, successfully reducing peak demand by the implementation of DR, a source of demand-side flexibility, can result in a decrease of energy losses in distribution and transmission, regulate voltage and current problems, contribute to assets' lifetime, and can defer grid reinforcement. Although DSM holds substantial potential in preserving network reliability and thus postponing the investment in the grid capacity, the impact of demand-side flexibility provided by DR on congestion mitigation and thus preserving network reliability, to defer grid reinforcement, is blurred and indeterminate, due to the reasons explained in the following paragraph (Moslehi & Kumar, 2010). Moreover, the prospects of financial savings are not guaranteed (Torriti et al., 2010).

In modern energy networks, the smart system facilitates a two-way flow of energy from the generator to the consumer and from the prosumer (consumer that produces energy) to the grid. As argued by Moslehi and Kumar (2010), system reliability is considered critical for modern energy networks since many variables can impact the gird reliability differently:

- Overproduction by sub local generation may cause **network reliability** concerns which the smart system aims to control and integrate;
- Renewable energy can aggravate the network reliability because of their intermittent nature;
- Forecasting renewable energy, such as solar and wind energy, entails a lot of errors depending on the forecast horizon and methods used, which disturbs network reliability;
- The decentralization of energy sources is obscuring the difference between transmission and distribution and stressing the network complexity.

Grid reliability concerns play an important role in realizing smart grids and DSM and therefore, the following will explain the scientific and social relevance of the research.

1.2 Research Relevance

From a **scientific** point of view, measuring and quantifying the impact of demand-side flexibility on network congestion mitigation, prior to shifting to smart grids and DSM implementation to defer grid reinforcement, is fundamental. Thus, the research attempts to bridge the knowledge gap by investigating empirically the impact of demand-side flexibility on grid congestion management and subsequently study the potential of postponing grid reinforcement via demand-side flexibility. The party that is responsible to maintain, operate and invest in the grid if needed, is the Distribution System Operator (DSO). The DSO is the market facilitator who supplies the demanded energy to the end-user and ensures quality of service (Eurelectric, 2014). In contemporary electricity grids, ensuring good quality may require managing congestion points via procuring flexibility in order to preserve the network reliability. Ultimately, flexibility can benefit the DSO and society as a whole (**societal** relevance), from a distribution perspective, by managing congestion points and voltage and power control, as follows (Triple E Consulting, 2015):

- Defer network reinforcement/investment
- Reduce peak loads on the distribution grid and the risk of blackouts, which is dependent on the magnitude and duration of the overload.
- Optimize the capacity of distribution networks

Safeguarding **the reliability of the network** is critical for the DSO since he is responsible to balance between the costs entailed because of procured **flexibility** and the level of network reliability to avoid being fined because of blackouts. Therefore, the question that remains: **should the DSO continue investing in the grid (grid reinforcement) or go for DSM within smart grids?** In order to investigate the demand-side flexibility and its influence of congestion mitigation and ultimately network reliability, a field experiment is being performed in Heerhugowaard, in the Netherlands.

1.3 Field Experiment Description

Currently, in the Netherlands, in Heerhugowaard, a field experiment is being performed to investigate a smart energy system via the participation of 201 households. The following smart devices are installed in the houses: Photovoltaic Panel, Electric Boiler, Heat Pump, and Fuel Cell. Each household has only one of these smart devices. Some of the houses connected to Heerhugowaard low-voltage grid have smart devices but they are uncontrolled, as shown in Table 1.

Table 1: Number of smart devices controlled and uncontrolled

Smart Devices	Number of smart devices controlled	Number of smart devices uncontrolled
PV (photovoltaic panels)	89	60
EB (Electric Boilers)	44	105
FC (Fuel Cells)	18	34
HP (Heat Pumps)	50	25
Total	201	224

In the Heerhugowaard field experiment, the smart devices are controlled (turned on or off) by an intelligent unit (the Power Matcher) based on the market spot electricity prices, energy demand, energy supply, risk of congestion and the distribution grid capacity. The value of demand-side flexibility and the access to flexibility among different stakeholders is determined using the USEF market model. USEF is a Universal Smart Energy Framework that provides the basic structure of guidelines, designs and specifications that enables stakeholders to develop smart energy services and solutions and deploy them at a large scale. Using USEF, in Heerhugowaard field experiment, the DSO (Alliander) procures flexibility from the aggregator (Essent). The aggregator (Essent) is the party responsible to aggregate the flexibility from the controlled smart devises. Alliander procures flexibility from Essent at potential congestion points to manage congestion and ensure the load stays within the predefined grid capacity limitations. **By means of this case study, Alliander is investigating whether managing congestion via procuring flexibility can defer grid reinforcement** (USEF, 2014). This paves the way to the following research design that introduces the main research question and a brief overview of the methodology that will be followed to answer the main research question.

1.4 Research Design

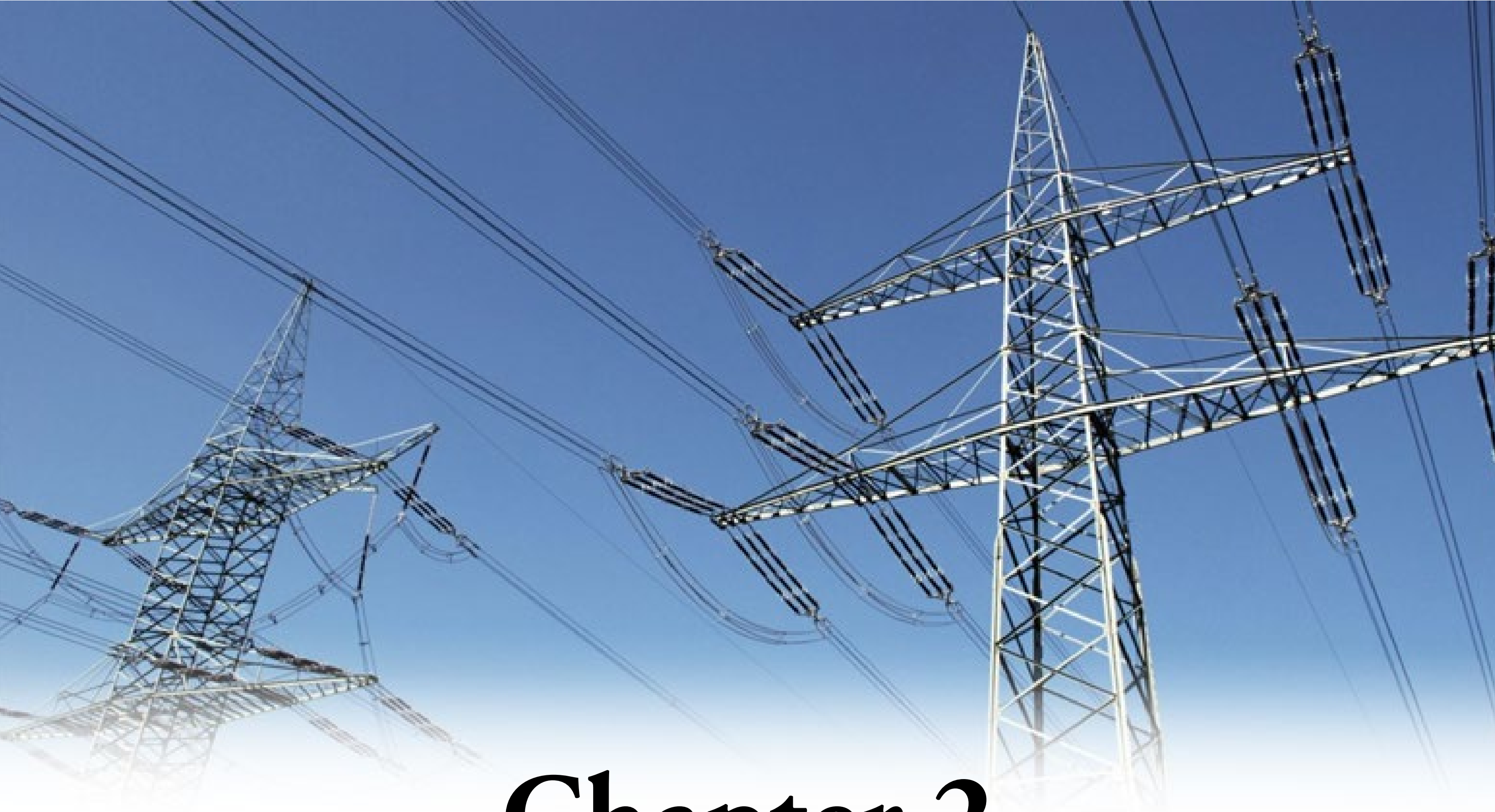
By means of the Heerhugowaard field experiment, the impact of demand-side flexibility, provided by DR, on grid congestion is investigated. Thereafter, the potential postponement of grid investment via flexibility will be explored to answer the following main research question:

"To what extent can the DSO mitigate grid congestion by means of demand-side flexibility to defer grid reinforcement?"

Therefore, it can be derived that the main research question is two-fold: one if demand-side flexibility can mitigate grid congestion and if yes, can it be used to defer grid reinforcement? Hence, an integrated two-sided approach will be adopted to research the main question: from a **technical** and **financial** perspective. To investigate the impact of flexibility on grid congestion mitigation, from a **technical** perspective, real-time measured data collected from two-month experiments from the Heerhugowaard field experiment will be analysed.

However, since conclusions based on two-month experiments renders the analysis un-generalizable, and since performing field experiments to test whether flexibility can resolve congestion is expensive and time consuming, a second methodology will be adopted. In the **second approach**, a simulation model will be constructed to mimic the impact of flexibility on grid congestion by first predicting the yearly flexibility where the DSO procures this flexibility to mitigate potential congestion. Thereafter, the simulation model will be used together with scenario analysis to study, **technically**, **the impact of flexibility on the grid congestion** and, **financially**, **the potential grid investment postponement** on four other grids in the Netherlands. **Chapter 3** will introduce the sub-research questions, how the research will be performed, and what reasoning lies behind the chosen techniques.

Prior to that, the coming chapter, **Chapter 2** will explore the current threats to the electricity network reliability in general and the need for congestion management to improve/preserve network reliability, based on literature review. Moreover, it will describe the traditional and contemporary methods for congestion mitigation. The literature will introduce Demand Side Management (DSM), in smart grids, as a potential solution for grid congestion while integrating distributed and intermittent renewable energy sources.



Chapter 2

2 The Reliability of the Electricity Network

A prominent and practical definition of reliability presented by NERC (1996) is that reliability constitutes two concepts: "security" and "adequacy". While "adequacy" is more long term oriented and that ensures sufficient generation, transmission, and distribution resources are existing to supply sufficient energy at any point in time with the desired quality, "security" is more short term oriented and is concerned with the ability of the system to withstand abrupt disturbances especially in case of outages or equipment breakdown. Addressing reliability concerns requires satisfying both security and adequacy concerns, short term system operational stability and long term system durability, respectively. Consequently, this chapter first presents an overview of the current threats to the reliability of the electricity network in section 2.1. Because of these threats to the reliability of the electricity distribution network, a need arises for a means to alleviate such threats and consequently, section 2.2 introduces the need for congestion management within electricity distribution networks. Section 2.3 addresses means to measure the reliability of the electricity network through means of official network reliability indices and operationalize the impact of congestion on grid reliability. Finally, in order to mitigate congestion within electricity distribution networks, a multitude of options are available, where section 2.4 presents an overview of some of these techniques.

2.1 Threats to the Electricity Network Reliability

The electricity supply chain from generation, transmission, and distribution is considered to be reliable and secure up to this moment in time; however, Crane and Frank (1992) argues that it can be more effectual and economical. Especially, with the advent of renewable energy resources and decentralized generation units, there is an increasing pressure on the electricity network and its changing requirements. Because of de-carbonization and the search for cheaper energy sources, renewable energy and decentralized generation sources, away from the conventional power plants, started to emerge. In parallel to the changes in the energy production sources, the market failed to invest in developing the transmission grids, and the upgrading of aging assets has been lagging behind (Crane & Frank, 1992).

The greatest worry for the electricity system is the integration of those decentralized and renewable energy sources into the electricity grid. Distributed renewable energy sources are mainly attached to the low-medium voltage networks or close to end users, which poses a problem because of the intermittent nature of these renewable energy sources (e.g. solar and wind) which necessitates ramping up and down power plants to accommodate the alternating production of energy. Moreover, conventionally, central power plants are connected to high voltage transmission networks, which results in unidirectional flow of energy from high voltage to low voltage; however, with distributed energy sources the flow of energy became bidirectional. Consequently, renewable energy integration increases the complexity of the distribution grid which affect the reliability of the system and necessitates further development of the electricity network (Ecofys, 2015).

The electricity infrastructure is composed of the transmission and the distribution systems. The transmission system is the connection between the central generation units and the adjacent load hubs. The transmission grid is usually automated and operated between 110 kV and 380 kV. On the other hand, the distribution grid connects the load hubs with the end user and is operated between 25 kV and 120 kV (Tennet, 2009). Connecting solar and wind energy to the electricity network requires a dynamic power support to ensure the applicable voltage level is sustained. For example, an induction generator is required to ensure that with the production of wind energy the electricity frequency is constant regardless of the wind speed. In contrast, photovoltaic panels require an inverter that transforms the direct current to alternating current to ensure connect-ability to the electricity network.

Unlike traditional networks planning that is based solely on the load projections based on past data, in the current grids, planning is complex due to the decentralized renewable energy sources (with diverse geographical and temporal features), which requires a backup of storage units in order to adopt renewable energy sources without affecting the reliability of the grid. However, investment and innovation in storage units still has a long way to go. Similarly, a fundamental concern that affects the reliability of the electricity network was introduced by Osborn and Kawann (2001), as they stated that the increasing demand coupled with the reduction in the reserve capacity available, at both the distribution and transmission levels, is also at the heart of network reliability concerns. Furthermore, they argued that the decrease in the reserve capacity is due to the decrease in investments in the electricity infrastructure. Therefore, aside from the demand increase and reserve capacity decrease, the increase in the spatially distributed and intermittent energy sources result in an increase in the technical complexity and poses a spatial and temporal risk that needs to be predicted and managed (Johansson & Nakićenović, 2012).

Additionally, Johansson and Nakićenović (2012) discuss the increase in the level of interconnectedness in modern networks, within the renewable energy integration development, that may result in "cascading failure". A "cascading failure" is when a small failure cause an extensive widespread failure. Such a threat can be connected to the network vulnerability. For instance, the load volatility caused by intermittent renewable energy sources cause an increase in the network vulnerability that may result in "cascading failures" (Wang, Scaglione, & Thomas, 2012). Holmgren (2007) defines vulnerability of the infrastructure as "the collection of properties of an infrastructure system that might weaken or limit its ability to maintain its intended function, or provide its intended services, when exposed to threats and hazards that originate both within and outside of the boundaries of the system". Therefore, the increase in the network's interconnectedness and load volatility, coupled with a grid running at its critical capacity, may result in an increase of the electricity network vulnerability.

Based on this literature review a number of threats to grid reliability are introduced. Such threats are the integration of renewable energy, bidirectional power flows, distributed energy sources, a decrease in reserve capacity, and the interconnectedness and risk of cascading failures. As such threats may cause an increase in the electricity network vulnerability, a need arises for means to counter such threats, and consequently, the next section addresses the need for congestion management in order to preserve or improve network reliability.

2.2 The Need for Congestion Management to Improve / Preserve Network Reliability

Traditionally, the electricity distribution system was considered very passive in nature, its operation very limited, and the flow of energy unidirectional. Through a "top-down" designed system, the transmission network transported energy over extended distances from the local large scale production plants to distribution networks that transported energy to end users (Ekanayake et al., 2012). Based on the forecasted change in energy demand or network congestion, where Haque et al. (2014) defines congestion as "a situation when the demand or generation at a certain point in the distribution network exceeds the transfer capabilities" (p. 26), the network reliability was estimated, and if required, the electricity network reinforced. The margin of error in predicting the energy demand has been minimal. Throughout the years, energy demand has followed the economic growth and human behaviour (consumption) and has been merely time dependent (Veldman, 2013). Therefore, based on the long term load prediction and reliability measurements, gird reinforcement and investment followed. Moreover, since demand was inflexible while energy production was fully controlled and predicted, energy supply followed energy demand (Veldman, 2013). However, current changes in the electricity systems make congestion management more required and technically complex than ever before. Consequently, the following sections will shed light on the rising congestion problems at the distribution level:

1. Earlier, congestion was managed at the transmission level; however, with the integration of distribution energy sources, congestion problems are arising at the distribution level. For instance, the overproduction at a local level may cause a reverse transfer of power to the higher grid levels, causing voltage and current problems and fluctuations. The reverse power flow requires a distribution network design that can handle peak demand and peak production and a different operating mechanism by the distribution operator in order to protect the grid assets and regulate the power flow.

2. Congestion at the transmission level was dealt with by re-dispatching, in other words re-scheduling the energy production from the central power plants. However, in modern grids with high penetration levels of renewable energy and electrification (EVs, HP, EB etc.), congestion is more frequent at the distribution level, where earlier, congestion at the distribution level was dealt with by upgrading the distribution grid assets (cables, fuses, transformers etc.). Nevertheless, upgrading the grid components cannot follow up with the pace of renewable energy sources growth, which results in interim and short term congestion. Moreover, it is argued that upgrading the grid assets will not serve as a cost-effective solution since such congestions are temporary (Haque et al., 2014).

3. Conventionally, customers located near the production units receive voltages with higher magnitude than those in rural areas, and thus to stabilize the difference in voltage, a voltage regulator is installed within the electricity network. Currently, with the increase in the distributed energy sources, and in cases where demand is less than the generated local energy, the voltage may exceed the operational voltage limit. Such voltage problems put the customers' appliances at risk and threaten the power quality, which necessitates dynamic voltage control as part of congestion management. However, dynamic voltage control is still not prominent at the low-voltage level.

4. Depending on the amount of energy produced by the distributed energy sources and its distance from demand, grid losses may increase or decrease. In cases where the distributed energy source is close to the demand, the electricity network witnesses a decrease in losses in comparison to the grid without distributed energy sources. However, if the generation source is distant, or electricity is produced at night while the demand is low at night, the grid losses increase. Solving this problem requires additional reactive power control as part of congestion management.

Thus, from these four problems at the distribution level it can be inferred that congestion challenges are arising due to the challenges faced in integrating renewable and distributed energy sources in the electricity network. Finally, striking a balance between a high level of network reliability, a high utilization rate of the grid, the lowest rate of blackouts, and the highest integration rate of renewable energies is a challenging pursuit that requires a smart distribution network. Congestion mitigation require a dynamic voltage control, reactive power to enhance the transferring capacity of the grid, and balancing demand and production (Sansawatt, Ochoa, & Harrison, 2010). Thus, the following section presents the operationalization of network reliability and the operationalization of congestion management on network reliability.

2.3 Measuring the Influence of Congestion on Grid Reliability

Vulnerability is related to the **resilience** and **robustness** of the network. If the degree of resilience increases, the threats defined as potential harms, will probably decrease. On the other hand, the load volatility in combination with the percentage capacity used of the network are related to the robustness of the network. The higher the volatility of the load and the percentage network capacity used, especially at peak hours, the less is the robustness of the network and the higher is its vulnerability. According to Holmgren (2007), robustness and resilience can be defined as follows:

> "**Robustness** signifies that the system will retain its system structure (function) intact (remains unchanged or nearly unchanged) when exposed to perturbations, and **resilience** implicates that the system can adapt to regain a new stable position (recover or return to, or close to, it's original state) after perturbations" (p. 33)

In official terms, vulnerability is related to the probability a disturbance occurs that could pose a negative impact on the electricity network (Holmgren, 2007). For instance, if the energy produced by the renewable generation sources far exceeds demand and exceeds the capacity of the electricity network responsible to transport this energy, there is a probability that the load exceeds the capacity of the cables, fuses, or/and transformers, and thus depending on the duration and magnitude of overload, a blackout may be triggered (Čepin, 2011). Villemeur (1992) defines reliability as follows: "Reliability of a system is the ability of the system to perform its required function for a specified time period when operating under stated environmental conditions" (p. 296).In order to determine when congestion causes negative impacts on the electricity network, and thereby directly influence the reliability of the electricity network, one must first have understanding of the causes behind blackouts and why electricity network assets degrade. Based on these insights, it is possible to determine the maximum capacity of the assets (fuse and transformer) and how congestion may have different consequences (asset degradation or blackout) depending on the magnitude and duration of exceedance. Consequently, section 2.3.1 first presents how the assets respond to congestion and when does asset degradation occur, and second, section 2.3.2 presents a set of official indices that assist in the quantification of network reliability and allows for comparative analysis when solutions are proposed to improve the electricity network reliability.

2.3.1 Blackouts and Degradation of Assets

The current electricity network is operating close to the maximum capacity, due to for example the use of additional electric devices, electric vehicles and the use of renewable energy. Even though that this increase in electricity load is causing network congestion, this does not imply that this also leads to degradation of the assets or blackout, where a blackout is defined as: "a zero voltage condition that last for more than two cycles" (Curtis, 2011, p. 206), and a cycle is defined as 1/30 of a second. Thus, for both the blackouts and the degradation of the network assets, not only the amplitude of the overload plays a role, but also the duration of the overload. In order to determine how the duration and level of overload results in either a blackout, or the degradation of the assets, an analysis of the circuit breakers and transformers is performed in section 2.3.1.1 and section 2.3.1.2 respectively.

2.3.1.1 Circuit Breakers

Blackouts are often caused by the tripping of circuit breakers, where circuit breakers trip because of a possible overloaded circuit, a short circuit or a ground fault. With regards to the overload of the circuit breaker, both the magnitude of the overload and duration play an important role in determining when a circuit breaker might trip. Based on an analysis of the gG400V Weber fuse (Table 2), which can be found in Oil-Immersed Power Transformers, the maximum tolerated overload rate decreases when the overload duration increases (Weber, 2004). The values presented in Table 2 were derived from **Figure 66 presented in appendix C.9.**

Table 2: The Relation between the Duration and Maximum Level of the Overload for a gG400V Weber Circuit Breaker (Weber, 2004)

Time (min)	**15**	**30**	**45**	**60**	**75**	**90**	**105**	**120**	**135**	**150**	**165**	**180**	**195**	**210**	**225**	**240**
Overload (%)	224	200	190	180	172	168	164	160	156	152	147	144	142	140	138	136

However, even though that the circuit breaker is installed to protect the transformer, the transformer also has a maximum tolerated loading capacity that limit its operation, and might cause degradation of the transformer without an occurrence of a blackout. Consequently, the maximum tolerated loading capacity of the transformer are also taken into consideration.

2.3.1.2 Power Transformers

The distribution transformer is a transformer that converts the transmission voltage to the distribution voltage, which is the same voltage used by consumers households (220 – 230 Volt, 50 Hz). The life expectancy of the transformer is based on the operational ambient temperature and the operational circumstances, where three modes of operational circumstances are defined with their respective durations and overload limitations (Table 3) (Nederlands Elektrotechnisch Comité, 2008). Even when the overload is kept within the duration limitations, this does not imply that asset degradation is prevented. For example, the Nederlands Elektrotechnisch Comité (2008) mentions that with long time emergency loading, degradation already starts due to an increase of the temperature and subsequently might results in situations where the transformer has an increased risk of failure.

Table 3: The Oil Immersed Power Transformer limitations based on Nederlands Elektrotechnisch Comité (2008) and Watson (1991).

Mode of Operation	**Load Limitation**	**Duration Limitation**
Normal Cyclic Loading	150%	None
Long Time Emergency Loading	180%	1 to 1.5 hours based on the winding hot spot temperature in order to prevent serious degradation of the transformer (Watson, 1991).
Short-Time Emergency Loading	200%	Less than 30 minutes

Based on these results, one can infer that in order to prevent blackouts (maximum tolerated capacity of a circuit breaker) and degradation of transformer (maximum tolerated capacity of a transformer), both the magnitude of the overload and the duration of the overload must be taken into consideration. Consequently, the operational range of the overload in combination with the duration of the overload is determined as the minimum between the maximum tolerated capacity of the circuit breaker and the transformer. Both the duration and the number of blackouts are essential in the determination of network reliability through a set of official indices. Consequently, the next section will introduce these indices based on the quantified duration, the number of customers affected, and the frequency of blackouts within the electricity network.

2.3.2 Indices of Network Reliability

Throughout history, power supply planners' concern is to balance between the investment needed to cope with the predicted load and the opted network reliability (Allan & da Silva, 1995). Electricity network reliability encompass the quality of the system along with the appropriate voltage and frequency. To evaluate the reliability of the distribution grids quantitatively, many indices have emerged based on the IEEE guide for electric power that evaluate network reliability by its average performance. Having introduced blackouts/interruptions in section 2.3.1, the most prominent distribution reliability indices are (Čepin, 2011):

1. **System Average Interruption Duration Index (SAIDI):**
   SAIDI measures the total interruption duration by multiplying the "duration of the interruption until it is restored (r_i)" by the "number of customers who suffered from an interruption (N_i)" and then divided by "the total number of utility customers (N_T)". If the duration of interruption was measured in minutes, the SAIDI index will take the unit "minutes". The following is the SAIDI index represented mathematically:

$$SAIDI = \frac{\sum N_i * r_i}{N_T}$$

2. **Customer Average Interruption Duration Index (CAIDI):**
   CAIDI is very similar to SAIDI index, the only difference is that the total minutes-customers is divided by the customers who suffered from an interruption and not all the utility customers. Thus, formulated mathematically as follows:

$$CAIDI = \frac{\sum (r_i * N_i)}{\sum N_i}$$

3. **System Average Interruption Frequency Index (SAIFI):**
   SAIFI is the number of customers who suffered interruption under the period of study divided by the number of utility served customers. Such an index is unit-less and it indicates the probability a customer may suffer from an outage during the period of study.

$$SAIFI = \frac{\sum N_i}{N_T}$$

The three indices give a good indication of the network reliability. All three indicators imply the average reliability of the electricity network and thus do not indicate the duration or frequency of outages experienced by each served customer. A decrease in the SAIDI and SAIFI indices indicate an improvement of the reliability of the network because both duration and frequency of interruptions are critical performance indicators. However, if SAIFI and SAIDI witnessed a decrease, CAIDI will witness an increase, but still it serves as a good indicator, although not helpful for comparisons (Čepin, 2011). Having introduced network reliability measurement, the means to evaluate the reliability of the distribution grids quantitatively, and the influence of congestion on network reliability, the question remains what are the means to mitigate congestion to improve/preserve network reliability, which will be discussed in section 2.4.

2.4 Means to Mitigate Congestion at the Distribution Level

Grids that possess substantial capacity may not suffer from potential congestion in the short or medium run. However, mitigating congestion is a necessity in grids that are being used to their full capacity. Allowing the load to exceed the congestion limit comes at the expense of the lifetime of assets and the rise of outages. To avoid outages and asset degradation, the DSO may resort to the conventional option to mitigate network congestion caused by an increase in demand or overproduction. Such an option entails predicting demand and local production, and long term planning to invest in upgrading the grid to handle the estimated growth in energy production and consumption. However, other means and tools have been emerging to mitigate congestion in the short term and long term while avoiding expensive investments. For instance, Demand Response tools are a source of flexibility within smart grids and may potentially reduce peak loads or shift loads to off peak periods of time. The DSO may engage in short or long term contracts with aggregators in order to procure Demand-Side Flexibility to resolve congestion in the upcoming hours/days or upcoming months, respectively. Additionally, the DSO may invest in batteries and storage units as a form of flexibility that can serve the shifting of load from peak to off-peak hours. Thus, the following section attempts to answer the following sub-research question "*How is grid congestion mitigated?*" and section 2.4.1 will put emphasis on the conventional alternative, grid investment, and section 2.4.2 will introduce Demand-Side Flexibility.

2.4.1 Grid Investment

Traditionally, congestion has been mitigated by the government and the distribution system operator (DSO) by investing large sums of money to strengthen the gird and ensure coping with the increase in demand. Investment is considered capital intensive due to the need to invest in upgrading the grid assets (putting new cables, transformers, or breakers). In other cases, there is a need to modify the grid topology to ease the operation of the grid and predict the energy flow and the points of potential congestion. Modifying the grid topology requires adding breakers and cables to operate it radially (NEAS Energy & Ea Energy Analyses, 2012).

Two types of network investment exist: upgrading the gird and reinvesting in the grid. Upgrading the gird occurs when there is a need to improve the performance of the grid and expand its capacity. Reinvesting in the grid happens by the end of the lifetime of assets and grid components which necessitate replacement. However, both investment can be intertwined because of the long lifetime of assets. In most of the cases, when the assets are nearing the end of their period, they are replaced and upgraded to cope with predicted potential increase in demand.

Based on an analysis done by the Dutch Association of Energy Network Operators in the Netherlands, the average transmission and distribution grid investment by the network operators is roughly around 467 million euros per year (EURELECTRIC, 2014). The average yearly investment of all the Dutch distribution electricity grids is 297 million euros (Netbeheer Nederland, 2011). This proves that the electricity network investments are substantial and intensive.

Upgrading the grid was mainly driven by the increase in energy demand that is mainly driven by population growth, climate changes, and domestic economic growth. For instance, as shown in Figure 1, the electricity demand per capita per day in the Netherlands has been soaring since year 1960 as published in the Central Bureau of Statistics (2014). According to Osborn and Kawann (2001), if energy demand growth is not faced by an increase in supply capacity and network capacity, it may pose a risk on network reliability that can compromise the system stability.

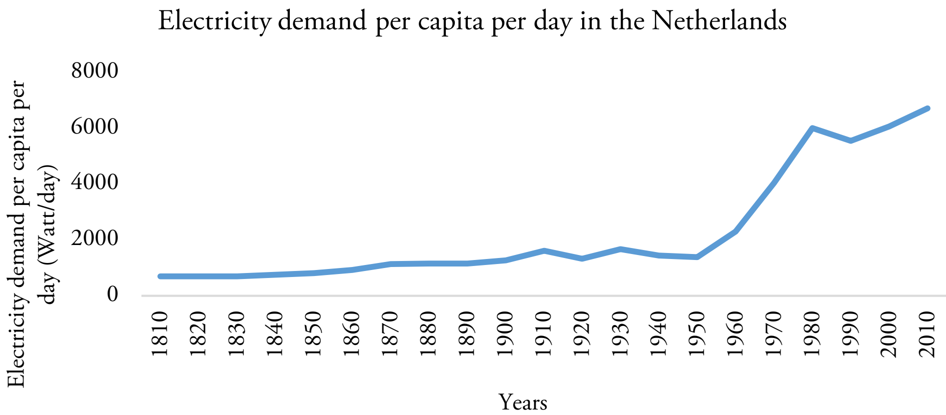


Figure 1: Electricity demand per capita per day

To understand the costs incurred by the DSO to preserve network stability, it is important to dig deeper into the different types of costs. Costs of the DSO are divided into (1) capital costs-CAPEX and (2) operational costs-OPEX. Capital costs are the investments in grid upgrades or reinvestment due to depreciation of assets. The operation costs are split into uncontrolled and controlled. Uncontrolled are mainly due to taxes, authorization fees, and fees for connecting to the transmission grids. For the meantime, controlled operational costs are dependent on the costs of operating a grid efficiently which affects the maintenance costs, grid losses, and outage planning costs (Koliou et al., 2014; SEDC, 2016). Nevertheless, the capital and controlled operational costs and investments at the distribution level are expected to increase due to the following reasons:

- With the increase in the number of PV and windmills, extension investment is needed to ensure the integration of renewable energies into the grid.
- Continuous investment in the aging infrastructure is a necessity to replace depreciating assets on one hand and to expand the network and extend its capacity on the other hand.
- The widespread expansion of the distributed generation and the increase in electrification such as EVs require to keep a close eye on the reliability of the network and the supply of energy.
- Moreover, within the modern grid scope, the DSO is expected to supply smart metering to enable the two-way communication between the central system and the local meters and to measure at an hourly basis the energy consumption and communicate this information to the system for billing.

Meanwhile, although those changes in the electricity grid increase the complexity of operating the grid and preserving network reliability, they also provide room to optimize the system. Distributed energy generation and decentralized renewable energy sources can provide flexibility opportunities to manage the load demand variability in a more cost effective manner (Ecofys, 2015). Consequently, section 1.3.2, will investigate demand-side flexibility as a means for congestion management as a result of demand load volatility and the intricate changes in the modern grid.

2.4.2 Demand-Side Flexibility as a Means to Mitigate Congestion

Traditionally, with the increase in energy demand at the distribution level, the DSO resorted to investing in the grid to handle the increase in demand. However, this solution is not any more cost-effective with the increase in load volatility because of distributed energy sources, renewable local energy production, and electrification (HP, EB, EV etc.), as argued by SEDC (2016). The complexity that arises from integrating renewable and distributed resources can provide opportunities to optimize the system and postpone the capital intensive grid reinforcement. These opportunities surface and evolve from the flexibility that results from demand-side management. According to SEDC (2016, p. 19), "Demand-side flexibility can provide a reliable way to relieve peaks in demand, compensate for large in-feeds from renewables and generally help to balance the system and stabilize the grid". Demand-Side Flexibility is dependent on the timing and degree to which energy demand and production can be controlled or changed.

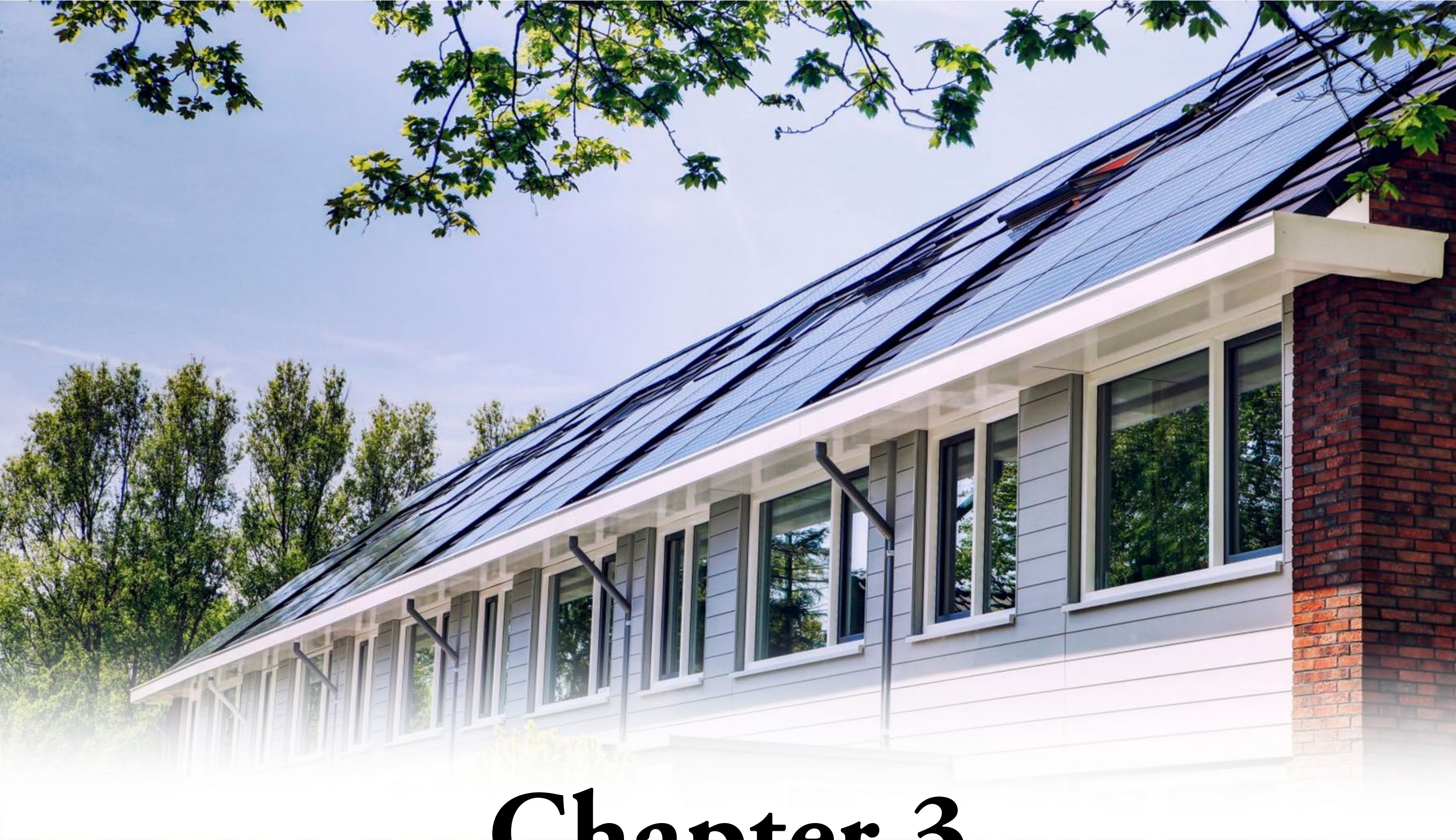
Via demand-side flexibility, the DSO can level the load by shaving peak loads and thus postpones the need for grid reinforcement (CAPEX). Moreover, by controlling the renewable sources and smart devices, the DSO can reduce operational costs (OPEX) by dealing with outages differently and decrease grid losses. For instance, the location of the source of flexibility can play a role in resolving the problem of voltage and congestion and thus decrease grid losses (Ecofys, 2015).

Conversely, the extent demand-side flexibility can resolve grid congestion is primarily grid specific because it depends on the age of the grid, the percentage capacity available of the grid, the penetration level of renewable energy, the forecasted growth in demand etc. Furthermore, the paradigm shift from top-down and unidirectional energy system to a decentralized and bidirectional energy system entails incentivizing consumers to offer their flexibility from smart devices and renewable sources in return for a financial benefit. However, different incentivizing programs should be enacted since different consumers/prosumers have heterogeneous behaviour and perception (SEDC, 2016).

The success of demand-side flexibility is dependent on other factors, other than the customers' willingness to participate. For instance, the DSO is liable to install smart metering to collect data impartially from prosumers and put it into perspective while protecting the data and the customer privacy. Data collected will inform the consumer on his consumption patterns against price signals and will give the DSO valuable information on the grid remaining capacity and potential congestion. This flexibility from residential, industrial, and commercial consumers/prosumers should be aggregated into pools and utilized to reveal its full prospective, for example procured by the DSO to mitigate congestion. Thus, it requires a grid operator or an independent party, called the aggregator, to aggregate the flexibility. Finally, the aggregated flexibility should have a well-defined purpose, since in some moments of time, flexibility will be needed due to excessive consumption (e.g. very cold days) and in some other time flexibility is needed due to excessive production (e.g. high wind and solar energy production) (Koliou et al., 2014).

In theory, several studies indicated that demand-side flexibility is more cost-effective in congestion mitigation in contrast to the conventional capital intensive alternative. However, the value of demand-side flexibility remains specific to the grid characteristics. It is such theoretical findings that drive actual field experimentations that investigate the impact of flexibility on congestion management against grid reinforcement.

Moreover, although DSM holds substantial potential in preserving network reliability and thus postponing the investment in the grid capacity, the impact of demand-side flexibility provided by DR on congestion mitigation and thus network reliability, to defer grid reinforcement, is blurred and indeterminate (Moslehi & Kumar, 2010). Therefore, the following chapter will establish the research design and methodology that will be used to investigate the impact of demand-side flexibility on grid congestion in Heerhugowaard field trial (as a case study) and generalize the models and estimations thereafter to other low voltage grids.



Chapter 3

3 Research Design and Methodology

The purpose of a design methodology is to establish the research questions, to explain how the research will be performed, what reasoning lies behind the chosen techniques, and the means to be used to process the data in order to assist a researcher or reader in judging the credibility of the conducted analysis and derived results. Therefore, the design methodology is presented as follows: section 3.1 presents the research objective and research questions, section 3.2 gives reasons behind the quantitative and qualitative methods undertaken to reach an answer to the main research question. Last, section 3.3 presents a flowchart of the workflow and provides an overview of the thesis outline.

3.1 Research Objectives and Research Questions

Since the impact of demand-side flexibility on congestion management/mitigation, to defer grid reinforcement, is blurred and indeterminate, research is conducted on the Heerhugowaard field experiment, as a case study, to bridge this knowledge gap. Additionally, the results attained and the models constructed from such an investigation will be used for generalizing the results to other case studies (low-voltage grids). Therefore, Table 4 presents the **objectives** and **expected deliverable(s)** of the research:

Table 4: Research Objectives and Deliverables

	Research Objectives and Deliverables
1.	Provide insight on the variables that predict flexibility from four smart appliances in Heerhugowaard field trial.
2.	Build multiple regression models in an attempt to predict flexibility availability from the four smart devices.
3.	Provide insights on congestion management in a LV-grid and the role of flexibility in mitigating congestion.
4.	Quantify the contribution of flexibility on load shifting and thus congestion mitigation.
5.	Finalize the construction of a simulation model in such a manner that it can be adjusted and used for different scenarios and LV-grids.
6.	Generalize the constructed model to other LV-grids.
7.	Perform initial financial analysis on grid congestion mitigation by means of electricity flexibility versus grid reinforcement.

To meet the objectives of this research and investigate congestion mitigation by means of flexibility, provided by DR, to postpone grid reinforcement, an empirical analysis will be performed on the data from the conducted field experiment in Heerhugowaard, in the Netherlands, to answer the following main research question and sub-research questions.

Main research question:

"To what extent can the DSO mitigate grid congestion by means of demand-side flexibility to defer grid reinforcement?"

Sub research questions:

1. How is Demand Response employed as a potential solution for electricity network congestion in the Heerhugowaard field experiment?
    a. What are the benefits of demand response in general?
    b. How is demand-side flexibility, provided by Demand Response, traded based on USEF in Heerhugowaard field experiment?
2. What are the key hypothetical determinants of demand-side flexibility from the four smart devices at the Heerhugowaard field trial?
3. How do the hypothetical determinants of demand-side flexibility influence the flexibility prediction?
4. What is the impact of demand-side flexibility on grid congestion at a distribution level in Heerhugowaard?
    a. What is the reliability of the delivered flexibility of each controllable device?
    b. In the case that the load was successfully kept within the limits, how much of this effect was the result of demand-side flexibility, as opposed to weather, participant behaviour or other exogenous factors?
    c. How does the amount of delivered flexibility influence the probability of grid congestion?
    d. How does the probability of grid congestion for the load with and without flex, based on Heerhugowaard field trial, translate to the entire year and vary over the different seasons?
5. How do the results of the Heerhugowaard field experiment translate to other low-voltage networks within the Netherlands?
6. To what extent can distribution grid reinforcements/investments be deferred by means of flexibility?

The main research question was split into sub-research questions to ease tackling the problem step wise. Section 3.2 presents the strategies that will be adopted in order to answer each sub-research question and how these questions interweave to add precision and consistency to the research.

3.2 Research Design

To answer the sub-research questions and ultimately the main research question, the following methods shall be undertaken. Table 5 shows the respective research method for each of the 6 sub-research questions along with the different phases in the research process (Whittemore & Melkus, 2008). Qualitative research will be performed to answer the first two sub-research questions, while quantitative research will conducted to answer the last four sub-research questions.

Table 5: Methods to be implemented to answer the sub-research questions

	Sub-research questions	*Method*	*Phase*
Qualitative Research	*1*	Literature review and Case Study Description	Conceptual /Theoretical phase
	2	Literature review	Conceptual /Theoretical phase
Quantitative Research	*3*	Data analysis Statistical modelling (bivariate and multivariate regression analysis) and Time Series Analysis;	Empirical phase and Design phase
	4	Data analysis and Model estimation	Empirical phase, Design phase, and Analytical phase
	5	Model generalization	Empirical phase and Analytical phase
	6	Scenario analysis	Analytical phase and Dissemination phase

The following sub-sections (3.2.1) will explain the reasoning behind the chosen qualitative research methods. On the other hand, the quantitate sub-section (3.2.2) will explain the reasoning behind the chosen numerical techniques as a means to answer the empirical sub-research questions.

3.2.1 Qualitative Research Design

Several qualitative research methods can be performed to gain further insights into the problem, the potential solutions and relevant contextual factors. The following sub-research questions will be explored qualitatively:

Table 6: Sub-research questions to be explored qualitatively

1.		**How is Demand Response employed as a potential solution for electricity network congestion in the Heerhugowaard field experiment?**
	a.	What are the benefits of demand response in general?
	b.	How is demand-side flexibility, provided by Demand Response, traded based on USEF in Heerhugowaard field experiment?
2.		**What are the key hypothetical determinants of demand-side flexibility from the four smart devices at the Heerhugowaard field trial?**

Literature review on smart energy networks and DSM will be performed to answer sub-research question 1, where state of the art scientific articles shall be identified and via the snowballing technique other references and conference papers will be pinpointed. However, other ways to gain information on DSM, its benefits, and its value to different stakeholders are interviews and surveys. However, those methods are considered time consuming and the validity of the collected information from these methods is often questioned because it might be subjective and un-generalizable. Therefore, the articles for Aghaei and Alizadeh (2013), and Strbac (2008) will be used as the stepping stones for conducting the literature review due to their novel analytical approaches and methodologies in smart energy grids, which were used by the industry and regulatory agents for actual implementation.

Moreover, to answer the sub-sub-research question 2b, concerning the demand-side flexibility trading, company literature and relevant publications on the USEF management mechanism will be used to gain information about USEF and its implementation in the Heerhugowaard field experiment. To be specific, the exploration and description of USEF will be based on the two published specification documents of USEF: The Framework Explained (2015) and The Framework Specification (2015).

With respect to sub-research question 2, since the success of DSM depends on the availability of flexibility from the different smart devices and its prediction, an extensive literature review will be conducted to explore the meteorological and socio-demographic variables that may influence demand-side flexibility. Thus, hypothetical relations between the variables and electricity flexibility from the 4 smart devices will be derived. To statistically prove if the hypothesized relationships are significant between those variables and flexibility, and to predict flexibility accordingly, quantitative research will be conducted. The quantitative research methods to be used will be presented in the coming section.

3.2.2 Quantitative Research Design

The purpose of quantitative research is to investigate a phenomena empirically by employing numerical and statistical tools in an objective manner in an attempt to generalize the results to the population. The following sub-research questions will be explored quantitatively:

Table 7: Sub-research questions to be explored quantitatively

3.		**How do the hypothetical determinants of demand-side flexibility influence the flexibility prediction?**
4.		**What is the impact of demand-side flexibility on grid congestion at a distribution level in Heerhugowaard?**
	a.	What is the reliability of the delivered flexibility of each controllable device?
	b.	In the case that the load was successfully kept within the limits, how much of this effect was the result of demand-side flexibility, as opposed to weather, participant behavior or other exogenous factors?
	c.	How does the amount of delivered flexibility influence the probability of grid congestion?
	d.	How does the probability of grid congestion for the load with and without flex, based on Heerhugowaard field trial, translate to the entire year and vary over the different seasons?
5.		**How do the results of the Heerhugowaard field experiment translate to other low-voltage networks within the Netherlands?**
6.		**To what extent can distribution grid reinforcements/investments be deferred by means of flexibility?**

The aim of sub-research question 3 is to predict the demand-side flexibility from the different smart devices. To answer sub-research question 3, hypotheses testing will be conducted based on the collected data from the Heerhugowaard experiment and based on the derived hypotheses from literature. There is an array of techniques to predict demand-side flexibility, as illustrated in Table 8 (Gellings, 1992):

Table 8: Different prediction techniques advantages and disadvantages

Prediction Techniques	Description	Advantages	Disadvantages
Trend Method	The demand-side flexibility from specific devices is merely predicted as a function of time by projecting past data into the future without taking other socio-demographic, weather, economic etc. variables into account.	It is considered to be: +Simplistic when it comes to implementation. +Suitable for short term prediction. +Gives preliminary indication.	-It does not take into account other variables other than time, thus it cannot internalize other factors that may affect the trend into the future.
End-Use Method	This model focuses on the end service which a sector serves. For instance, the energy demand or energy production from a device is limited to the multiplication of the following parameters: the number of customers who have the device, the number of devices per household, the number of hours the device is on, the average energy produced/consumed by the device.	+It is beneficial when no time data from the device is available. +The level of detail it requires is low, which renders the method simplistic.	-It may result in mechanical calculations and predictions. - It does not take into account the socio-demographic and weather factors that can influence the energy produced or consumed.
Regression Modelling	Is a statistical techniques that uses explanatory variables to predict the variable under study (the dependent variables), for instance the demand-side flexibility. The dependent variable is predicted as a function of independent variables that are proved to be significantly related to the dependent variable.	+ Accurate and reliable indication of the strength and direction of the relationship between the explanatory variables and the variable undergoing prediction. +Accurate predictions	- A growth rate cannot be applied to the independent variables while predicting. - The method cannot account for any shocks in the system that may affect the dependent variable under prediction.
Time Series Modelling	It differs from the regression model in that the explanatory variables used to predict the variable under study are lagged (previous) versions or measurements of itself. Thus, this technique relies on past data points to project into the future.	+The technique generates the predictions internally based on the trends of its past value. +Shocks can be incorporated and accounted for in the process of prediction	-The method requires a minimum number of past data points to produce reliable results.
Count Data Modelling (Poisson or Negative Binomial)	When the variable under study is discrete in nature and not continuous, and has a large number of zeros, count data regression modelling is applied to account for such a data set by fitting it to Poisson or Negative Binomial distributions. It regresses the ln(dependent variable) as linear function of the explanatory variables.	+ allows skewed distributions +does not predict negative values which do not have any practical meaning.	-it is applicable to non-negative integers. Thus, rounding up/down non-integers is mandatory prior to modelling the variable under study

Based on the techniques presented in Table 8, **Time Series Regression** will be performed, as a hybrid method of **Time Series Modelling** and **Regression Modelling**, due to the temporal measurement of the data sets collected at different congestion block levels in the Heerhugowaard field experiment (especially from the Heat Pumps and the Photovoltaic systems) and the huge number of data points collected at a 15 minutes interval. Furthermore, in **Time Series Regression**, the lagged values of the time series of independent variables are assumed to influence the present value of the time series of the dependent variable (Wooldridge, 2015). On other hand, flexibility from the Electric Boiler (one of the smart devices experimented) is dependent on hot water consumption, which can be considered discrete and non-negative in nature, and thus **Count Data Modelling** will be used to predict flexibility from the electric boiler.

However, the time series regression models and count data models to be estimated, require validation. Validation is an integral part of the models' construction and requires "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Schlesinger et al., 1979). Different techniques are prevalent for model validation: (1) Comparison to Other Models, (2) Event Validity, (3) Extreme Conditions, (4) Historical Data Validation, (5) Prediction Validation (Sargent, 2005). The estimated models will be validated by using the estimated models for different cases and statistically comparing the **predicted** results with the **observed/measured** results, which is considered **Prediction Validation**. Since access to other models was limited, **Comparisons to Other Models** will not be used. **Event Validity** requires actual occurrence of events (e.g. blackouts), which was not observed in this field experiment. **Historical Data Validation** method requires splitting the data and thus it reduces the size of the data set to be used for the actual modelling.

To answer sub-research 4, the impact of flexibility on electricity network congestion will be analysed quantitatively using the data collected from the experiments performed in the Heerhugowaard field trial. Non-parametric tests, such as the Dunn test, will be used to answer sub-sub-research question 4a. Additionally, to answer sub-sub-research 4c that aims at calculating the probability of grid congestion (load exceeding the congestion limit), the measured load with flexibility and without flexibility will be fitted to the best theoretical distribution based on **Kolmogorov Simonov test (K-S)** at all congestion block levels. Tests other than Kolmogorov Simonov test (e.g. Anderson Darling and Chi squared) can be used but K-S test has advantage over others: (1) it accounts for each data point separately without categorizing it (thus no data is lost), (2) probability can be calculated for one-tailed and two-tailed hypotheses (Wall & Jenkins, 2012).

To answer sub-sub-research question 4d, which aims to predict the probability of grid congestion for a year, a Simulation Excel Model will be constructed that predicts the flexibility available at each congestion block level based on the penetration level of smart devices, the number of controlled devices, the congestion limit, the predicted household load, and the predicted flex. The regression models for flexibility prediction for the 4 devices will also be imbedded in the excel model. A random error generator of flexibility delivered will be derived from the results of sub-research question 4a, will also be imbedded in the excel simulation model. The excel simulation model aims to estimate the extent to which demand-side flexibility from Demand Response can mitigate congestion. The **Prediction Validation** and the **Extreme Conditions** methods will be used for simulation model validation. **It is important to note, that USEF market based coordination mechanism, that defines how flexibility is traded among the different actors and the number of iterations designed to procure flex, is a critical influencing factor but will be disregarded in the final simulation model because of the intricate interactions with flexibility availability yielding ambiguity in the congestion mitigation outcome. Since, the purpose of the final model is not to design the best market coordination mechanism for demand-side flexibility but to convey the extent to which a DSO can resolve congestion and defer grid reinforcement by means of flexibility. Thus, the model will be constructed in a relatively simplistic manner and not restricted to a specific market mechanism to enable its usage by any DSO for any targeted grid.**

To answer sub-research 5 and 6, the simulation model will be used to investigate the impact of demand-side flexibility on congestion mitigation in different low-voltage grids in the Netherlands. To quantify financially the estimated investment needed to reinforce the grid versus the cost incurred for ordering flexibility, **Projective Scenario Analysis** will be conducted on the different low voltage grids in the Netherlands. Such a technique allows to draw different conceptual pictures of the future with best and worst case scenarios based on policy drivers while projecting them into the future. Projective Scenario Analysis has advantages over other techniques (e.g. Prognoses) because unlike Prognoses it does not rely on past data in order to project into the future. Other techniques like Delphi techniques rely on experts' opinion to draw future scenarios but such a technique may result in the prediction of wrong or biased scenarios.

3.3 Research Plan and Thesis Outline

To summarize and visualize how the research plan and workflow will take place chronologically in the thesis, the following diagram shows the chapters as boxes and the interrelations as connecting arrows (Figure 2).

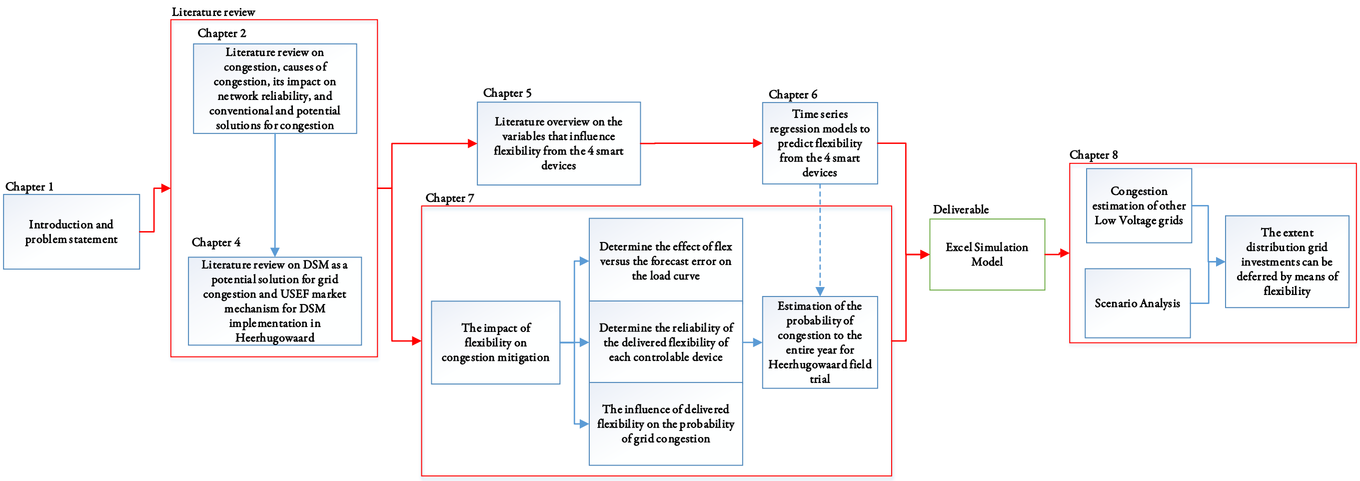


Figure 2: Flowchart of the process/workflow and the thesis chapters

The thesis outline follows the Harvard University Thesis Guide (2012). After the introductory chapter, secondly in Chapter 2, the thesis discussed the problem of congestion at the distribution level. In **Chapter 4**, the thesis will present a literature review on DSM, a source of demand-side flexibility, as a potential solution for congestion. Further, it will describe the Heerhugowaard field trail, in which demand-side flexibility is traded, and it describes the market management mechanism used at the field trail for trading flexibility. In **Chapter 5**, the key hypothetical determinants of demand-side flexibility from the four smart devices at the Heerhugowaard field trial will be presented. In **Chapter 6**, the flexibility from the 4 devices is predicted by performing empirical analysis using the hypothetical determinants as an input. In **Chapter 7**, the thesis will present the quantitative analysis of the impact of flexibility on grid congestion at a distribution level in Heerhugowaard field trial. In **Chapter 8**, the thesis will investigate the impact of flexibility on the grid congestion on four other grids in the Netherlands and concludes with the extent to which the DSO can mitigate congestion by flexibility to postpone grid investment. **Chapter 9** will present the conclusions, recommendations, and limitations. An overview of the thesis's chapters is outlined as follows:

Chapter 4 will present an overview on the key benefits of DSM in smart energy grids and the value of DR for the different stakeholders, and the distribution system operator (DSO) in specific. It will describe Heerhugowaard field trial and will introduce the USEF management mechanism for flexibility trading, which is implemented in Heerhugowaard field experiment. The chapter will answer the sub-research question: *How is Demand Response employed as a potential solution for electricity network congestion in the Heerhugowaard field experiment?*

Chapter 5 will explore the meteorological and socio-demographic variables that may influence flexibility from the four smart devices in Heerhugowaard field trail. Thus, hypothetical relations between the variables and electricity flexibility from the 4 smart devices will be derived. The chapter will answer the sub-research question: *What are the key hypothetical determinants of demand-side flexibility from the four smart devices at the Heerhugowaard field trial?*

Chapter 6 will study statistically the influence of the key hypothetical determinants of electricity flexibility on electricity flexibility prediction. Using the explanatory hypothesized variables from chapter 5, the chapter performs Time Series Regression and Count Data modelling on the data collected from Heerhugowaard field trial. The chapter will answer the sub-research question: *How do the hypothetical determinants of demand-side flexibility influence the flexibility prediction?*

Chapter 7 will investigate quantitatively the impact of flexibility from the four devices on grid congestion using the data collected from the experiments performed in Heerhugowaard field trial. It will calculate the probability of grid congestion for the load with flexibility and without flexibility. It translates the results of the experiment for an entire year post constructing a simulation model. The chapter will answer the sub-research question: *What is the impact of demand-side flexibility on grid congestion at a distribution level in Heerhugowaard?*

Chapter 8 will study the impact of flexibility on the grid congestion on four other grids in the Netherlands using the constructed simulation model. Different scenarios will be drawn to investigate the impact of flexibility on congestion mitigation and the extent grid investment can be deferred. The chapter will answer the sub-research questions: *How do the results of the Heerhugowaard field experiment translate to other low voltage networks within the Netherlands? and To what extent can distribution grid reinforcements/investments be deferred by means of flexibility?*

Chapter 4

4 The Value of Demand Response in the Electricity System

In the current electricity market, the system witness a shift from a top-down structure where generation follows demand to a system where demand and supply are optimized within the capacity of the network. This shift is advisable to cope with the increase in decentralized and distributed generation, intermittent and non-dispatchable renewable energy sources, and the increase in EVs (Ruester et al., 2014). Following this shift requires greater flexibility at the distribution network level to cope with potential congestion at the distribution level due the integration of renewable energy and distributed energy sources, as explained in chapter 2. One major source of flexibility is residential dynamic demand response which is not yet tapped and can be incentivized either indirectly by price-based mechanism or directly by incentive-based mechanism.

It is expected that the prevalence of DR within smart grids will not only serve the environment by integrating renewable energies, but can also ensure a secure supply of energy by mitigating congestion while postponing grid investment. In other words, DR may hold potentially many cost saving opportunities for different stakeholders in the electricity market (Koliou et al., 2015). Hence, this chapter attempts to answer the following sub-research question:

How is Demand Response employed as a potential solution for electricity network congestion in the Heerhugowaard field experiment?

by first shedding light on the benefits of Demand Response in general, and then describing how demand-side flexibility, provided by Demand Response, is traded based on USEF in Heerhugowaard field experiment.

Therefore, section 4.1 of this chapter introduces smart grids and demand response benefits in general. Section 4.2 describes the value of demand-side flexibility, provided by DR, for the different stakeholders. Section 4.3 describes the application of demand-side flexibility within the experiment performed in Heerhugowaard, in the Netherlands, and the Universal Smart Energy Framework (USEF), which serves as the management mechanism for flexibility trading.

4.1 The Introduction of Smart Grids and Demand Response

Many drivers are behind smart grids emergence such as **Environmental**, **Operational**, and **System Reliability** as shown in Figure 3. **Environmental drivers** comprise renewable energy sources (e.g. solar and wind energy) and Demand Response Programs that targets a **more efficient operation of the network** by managing distributed resources and variable generation within the network capacity, serving the **System Reliability**. Moreover, **operational drivers** opt for increasing customer choices and improving the interaction between transmission (at a wholesale market level) and distribution (at a retail market level) (Rahimi & Ipakchi, 2010). With regard to the scope of this project, the term "smart grid" is limited to operational excellence (operational efficiency), system reliability (variable generation, distributed resources, and capacity limitations), and the environment (demand response and renewable resources).

Figure 3: Drivers of Smart Grids (taken from: Rahimi & Ipakchi, 2010)

Smart energy grids can enhance/preserve network reliability because it attempts to control excess demand to protect against outages (balance supply and demand), allow hosting smart applications like DR, and estimate imbalances in real time (Leeds, 2009). Three layers constitute smart grids:

- The physical layer for transmission and distribution
- The data transport and control layer that allows two-way communication between stakeholders
- The application layer that enables DR, electric vehicles charging, and energy trading

Consequently, it is fair to say that smart energy grids possess many advantages: it allows consumer involvement, a cost effective use of assets, the possibility of storing energy, and EV (Electrical Vehicles) charging.

The question remains what are the differences between conventional grids and smart grids that necessitate demand response as a key element in preserving network reliability. While conventional grids allow a unidirectional power flow from the centralized power plants to the areas of demand, and an information flow from low voltage areas to the higher functioning centers, smart grids differ in many aspects. Table 9 presents the characteristics and prospects of the smart grids (Ipakchi & Albuyeh, 2009; Rahimi & Ipakchi, 2010):

Table 9: Smart grids Characteristics

	Smart Grids
Power Flow	➢ Power flows in both directions (bidirectional) from the prosumers (consumers that produce energy) to higher order production sources (wind farms, solar farms, and power plants)
Power flow calculation	➢ To account for the distribution generation, a need arise to shift from deterministic power flow calculations of the diesel engines and power plants to probabilistic calculations and advanced algorithms of, for instance, the solar and wind energy generation.
Information Flow	➢ Informational flow is bidirectional and this tailored communication allows a better satisfaction of the consumer's preferences by altering their consumption pattern (variable tariff based, or incentive based) (Moslehi & Kumar, 2010). ➢ The onset of smart sensors and IT systems allow a secure communication between different stakeholders in the electricity chain
Renewable Energy & Distributed generation	➢ While conventional grids cannot cope with the distributed generation volatility that affects the distribution network reliability because of affected planning and scheduling of resources, and lack of real-time monitoring, smart grids try to elevate the utilization of distributed generation by shifting from (Zhou et al., 2013): (1) unidirectional to bidirectional power flow and (2) from passive grid

	management to active grid management, and (3) by hosting DSM to counter the variability of renewable energies and distributed generation. Conventionally, power compensation was achieved by controlling generation, fine-tuning a transformer, or switching on/off the reactive compensation equipment. However, the addition of distribution generation makes power compensation difficult because of the volatility of voltage, load fluctuations, and because of intermittent generation (Zhou et al., 2013; Zhang & Xia, 2009).

Beyond the technical contrast between smart grids and conventional grids, it is important to note that in conventional grids, distribution system operators (DSOs) are regulated monopolies in a market that does not allow the participation of the public. This is due to the underlying convictions that comprise: (1) economies of scales, (2) risk of loss of efficiency in a free competition, (3) huge sunk costs, and (4) the public property provision (Joskow, 2005). Conversely, in smart grids, the roles of the different stakeholders are evolving as the DSO's duty is to equally integrate the distributed generation and renewable energies and to secure the quality of service and reliability of energy.

As perceived from the Table 9, smart grid is the product of four initiatives: (1) renewable energy, (2) system reliability, (3) demand response, and (4) energy storage units. Those initiatives are considered to be mutually dependent: integrating renewable energy can jeopardize the system reliability because of its intermittent and volatile nature which subsequently aggravates peak loads and thus a need for demand response (DR) arises to integrate renewable energies and energy storage units while levelling peak loads and managing energy volatility. Consequently, the following section (**section 4.1.1**), explores DR and its benefits overall. However, DR also provides actor specific benefits that are introduced in **section 4.1.2**.

4.1.1 Demand Response and its Benefits

The success of smart grids depend on DSM, which constitutes demand response (DR), which is achieving flexibility in demand and peak shaving through direct or indirect control (Gelazanskas & Gamage, 2014). Peak load is defined by Jones and Zoppo (2014, p. 61) as: "the maximum total demand on the system during a given period of time. Peak demand fluctuations may occur on daily, monthly, seasonal, and yearly cycles". Load management can be achieved either **directly** by assigning a system operator to control the load by controlling smart appliances (such as heat pumps, solar panels, air conditioning, boilers etc.) or **indirectly** by incentivizing the consumers to shift demand/production by themselves. Furthermore, according to Kathan et al. (2008), energy demand can be controlled in two ways, either by paying the consumer to shift consumption of energy to off peak periods (price induced), or by pricing energy differently at different times of the day, higher prices at peak demand (incentive based). Load management can be of many types (Saker et al., 2012), as explained in Table 10 and shown in Figure 4.

Table 10: The different types of load management

Mode	Description
Peak clipping	To achieve peak clipping, variable electricity pricing for peak and off peak hours can be exercised or a direct control over demand. The result will be a reduction of congestion in the network and a decrease in the need for costly peak generation.
Valley filling	Valley filling can be achieved by direct control over demand.
Load shifting	Load shifting is the most popular form of load management; it is the shift of the load from peak to off peak time.
Strategic conservation	Strategic conservation targets a reduction in the overall demand in an attempt to optimize the load shape.
Strategic load growth	With load growth beyond what valley filling can handle, strategic load growth is applied which requires infrastructure reinforcement.
Flexible load shape	Flexible load shape is the result of customers who have flexible demand and willing to be under control in return for incentives.

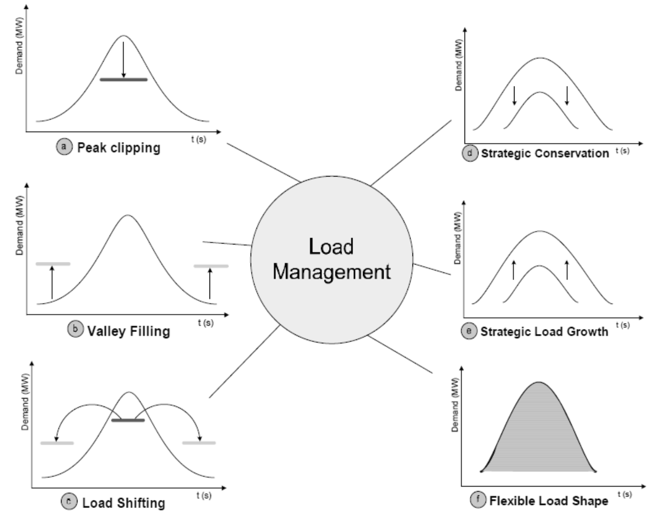


Figure 4: The different types of load management (Taken from: Saker et al., 2012)

Demand Response, which is intended to shift or reduce peak load is denoted as load management. DR has been the focus in many energy policies (Aghaei & Alizadeh, 2013) due to its economic benefits, network related benefits, and market benefits:

1. Economic and pricing benefits:

Via DR, economic benefits can be gained in the long and the short run. In the long run, Strbac (2008) underlines that through DR, a decline in wholesale prices can be achieved due to the efficient use of infrastructure, as a result of reduction or management of demand that allows a reduction in the number of required units for generation and a decrease in the need for network reinforcement. On the other hand, in the short run, customers can benefit by shifting their demand from peak to off peak periods and be rebated for consuming less than the average consumption in peak hours (Aghaei & Alizadeh, 2013). Therefore, DR enables a decrease in price volatility due to this shift in peak load as shown in Figure 5. As proven in the graph, a shift in demand to off-peak times where the quantity of electricity is low, the price of electricity is between Plow and Paverage, while in peak period the price will be between Paverage and B' (above the Ppeak). If peaks are reduced on a regular basis then this will reduce generation, distribution and transmission needed capacity which contributes to economic gains in the short and long term (Bradley, Leach, & Torriti, 2013).

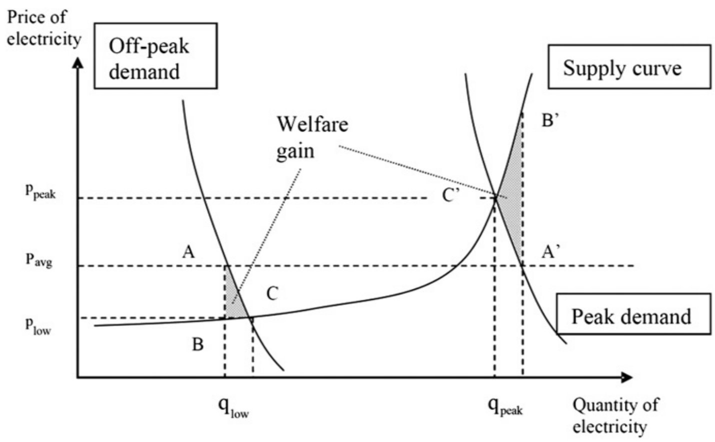


Figure 5: Price volatility with demand response – peak demand versus off-peak demand (Taken from: Aghaei & Alizadeh, 2013)

2. Network reliability and grid capacity benefits:

A major concern in energy infrastructure networks, which opts for a solution via smart grids, is the risk of grid congestion during peak demand periods. To solve the risk of congestion, smart grids, by means of DR, adapt the demand for energy to the production of energy, in an attempt to lower demand peaks and level the network load. Reducing congestion in the network by load levelling contributes to network reliability; this action is considered a **corrective action** (Bradley, Leach, & Torriti, 2013). Conversely, network reliability is conventionally secured by **preventive actions** and not corrective ones; in other words, in order to reduce the risk of any outage, power plants run 24 hours for 365 days on the expense of system efficiency, operational costs, and network utility (Strbac, 2008). Likewise, Triplett (2013) states that, conventionally, meeting peak demand is dependent on creating reserve capacity which is more capital intensive in comparison to incorporating DR in the system. Furthermore, by shaving peak demand, more capacity is available in wires and transformers, and thus extra connection to the grid can be made. As a result, peak shaving provides additional capacity for renewable energy integration (Aghaei & Alizadeh, 2013).

3. **Market performance benefit:**

According to Albadi and El-Saadany (2008), a reduction in price volatility in spot markets, prevents big actors from exercising monopolistic behaviour in the market. This is due to the fact that when energy generation is near maximum, the cost of generation increases exponentially. Thus, any slight reduction in energy demand, can reduce the costs of generation which results in a reduction of the average electricity market price. This behaviour is presented in Figure 6, where a shift from the demand curve without DR (the red curve) to the demand curve with DR (the green curve) lead to a decrease in price from P_0 to P_1.

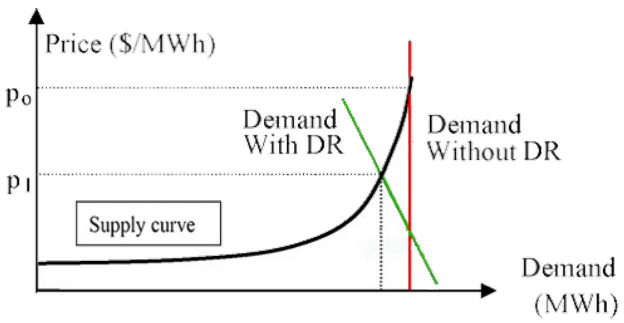


Figure 6: The effect of demand response on the market price of electricity (Adapted from: Albadi, & El-Saadany, 2008)

Finally, it should be realized that those benefits pertain to more than one actor and the gains should be distributed in balance among the different stakeholders.

4.2 The Value of Demand Response for the Different Actors in Heerhugowaard Field Experiment

With the increase of renewable energy shares and their integration at the distribution network level, there is an increasing need to manage load peaks via demand-side flexibility, provided by DR. Demand-side flexibility is viable by modifying energy production and consumption by controlling smart devices and distributed energy sources. In the Netherlands, in Heerhugowaard, a field trial is conducted where smart devices and distributed energy source (Heat Pump, Fuel Cell, Electric Boiler, and Photovoltaic panel) are installed and flexibility from those sources is traded based on the universal smart energy framework (USEF). In this setup, the prosumers will provide the load management, demand response, via the smart devices installed at their houses. However, to aggregate those small sources of flexibility, a party, the aggregator, is responsible to aggregate those sources to realize the potential of demand-side flexibility. This section focuses on the parties engaged in Heerhugowaard field experiment and are interested in trading and procuring flexibility for numerous reasons. Within Heerhugowaard field experiment, the aggregator is collecting flexibility from 201 households and selling it to the Distribution System Operator (DSO) and the Balancing Responsible Party (BRP), as depicted in Figure 7.

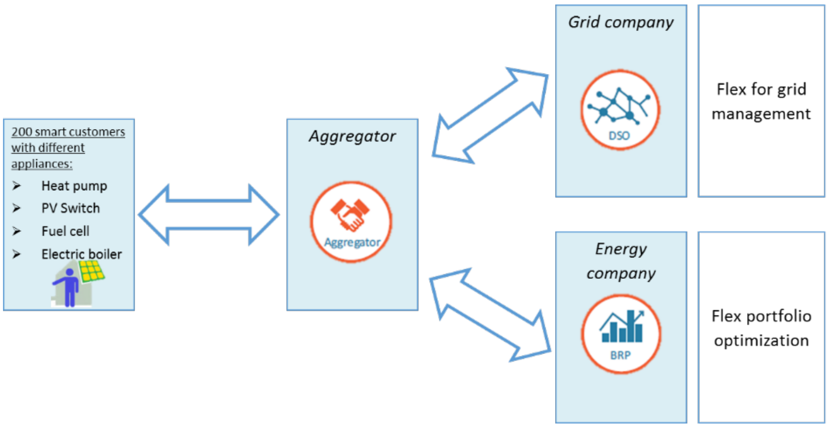


Figure 7: The transaction process among stakeholders based on USEF (Taken from: USEF - The Framework Explained, 2015)

Flexibility from end users' smart devices is an asset that needs to be utilized for the advantage of many stakeholders. Therefore, the value of demand-side flexibility for the parties engaged in Heerhugowaard field experiment (the aggregator, DSO, BRP, and prosumers) is presented in the following sub-sections.

4.2.1 Value of Demand-Side Flexibility for the Aggregator

The aggregator, is an actor that can play the role of aggregating this energy at a domestic level to be used for managing the intermittent distributed energy, shave peak loads, prevent inefficient investment in generation units, reduce the customs' bills, and balance energy supply with demand. The aggregator aggregates the flexibility at the domestic level and utilizes it to adapt the household consumption to energy production (e.g. turning electric boilers on during solar peaks or heating the house during the day and turning off the heat pump during the evening peak). The aggregator uses the flexibility short-term to compensate for changes due to the unpredicted renewable energies. The aggregator is positioned in the middle of the transaction process among stakeholders. First, he is responsible to collect flexibility from the prosumer, and build offers to other market parties that serve their interests, such as the DSO and the BRP. The DSO procures flexibility in an attempt to manage grid congestion, while the BRP procures flexibility to minimize imbalance charges. The aggregator gets remunerated for the procured flexibility and reimburse the prosumers accordingly as an incentive to shift their demand and indirectly their load.

4.2.2 Value of Demand-Side Flexibility for the Distribution System Operator

Distribution system operators are responsible to ensure the continuous flow of energy from the supplier to the customers and ensure that the grid has the capacity to transport the energy reliably. Traditionally, the DSO had to rely on the only resort, grid reinforcement, to ensure a safe energy flow and avoid congestion that either harm the assets or lead to a blackout. Those investments and grid reinforcements are usually huge and long term oriented, thus they are planned carefully in advance. Moreover, in order to make the investment socially acceptable, the life expectancy of the grid is usually 30 to 50 years (USEF, 2014).

Demand-side Flexibility from smart demand response appliances may reduce peak loads and avoid expensive reinforcement of the grid. First, the DSO can reduce the overheating of components by mitigating peak load. Second, due to the increase in PV output, the system may suffer from a voltage push up that may exceed the limit. Procuring flex up, by increasing the load or turning off PVs to limit generation, can mitigate the voltage exceedance problem. Third, decreasing peak loads can play a role in saving assets' lifetime and diminishing the grid losses. Fourth, in cases of a high risk of outage, flexibility can help in shedding load or serve as a backup in periods of grid/component maintenance.

4.2.3 Value of Demand-Side Flexibility for the Balancing Responsible Party

The Balancing Responsible Party (BRP) is the party responsible to balance the consumption of energy to its generation and to account for any imbalances that arise. The BRP opts to reduce the purchase costs of energy to minimize imbalance charges. Thus, flexibility procuring may serve in reducing the BRP's cost by for instance shifting consumption from peak hours (high price intervals) to off-peak hours (low price intervals) and thus reduce his total energy purchase expenses. Moreover, the BRP tries to optimize the costs incurred by the production units. Production units take time to ramp up and down and consume fuel meanwhile, thus attempting to reduce the ramping up and down by procuring flexibility may also contribute to cost reduction.

4.2.4 Value of Demand-Side Flexibility for the Prosumers

Consumers are becoming more inclined towards green and sustainable energy and ready to invest in PVs or collectively seek ownership of windmills. In addition, they are striving to reduce their bills by increasing the energy grade of their houses (e.g. applying house insulation), or installing more efficient appliances like heat pumps and electric boilers. This transforms consumers from being passive to being active parties in the energy market. However, to successfully reduce their bills they need to be capable of tracking and recording their consumption patterns. Moreover, to actively get the energy they need to charge their EVs and the network ready to handle the energy produced by the PVs and wind sources, there is a need to redefine the energy market.

On the other hand, aggregated flexibility may serve as a solution, since the integration of demand-side flexibility reduces the risk of depending on one individual household and allows active households to sell their flex without having to bare the risk of entering the market on their own. Moreover, flexibility can be of value for the prosumer by: (1) the energy consumption for each household can be optimized by shifting from high priced intervals to low priced intervals especially if the energy tariffs are pronounced day-ahead, (2) it allows households to self-balance between the price of energy produced, energy bought, and energy sold, and (3) if storage units are introduced domestically, flexibility can increase the availability of the network and reduce the risk of outages and increase energy reliability (USEF: The Framework Explained, 2015). In the Heerhugowaard experiment, the aggregator is controlling the smart devices (photovoltaic panels, electric boilers, heat pumps, and fuel cell) of 201 households based on the flex orders and remunerating the households per kWh when controlling their smart devices.

To successfully ensure that the costs, risks, and benefits of Demand-Side Flexibility are well distributed among stakeholders, a framework is needed to specify the roles and responsibilities and to provide the basic structure of guidelines, designs and specifications. Therefore, the following section will describe the market coordination framework employed in Heerhugowaard field experiment.

4.3 Application of Demand-Side Flexibility as a Control Mechanism outlined in USEF in Heerhugowaard Field Experiment

In the current setting, the active demand and supply system at the domestic individual level may contain a lot of untapped energy if used only for the individual domestic needs and thus there is a need to aggregate it within a fully functional energy market and governing specifications as per a universal smart energy framework (USEF). The USEF flexibility value chain specifies the access to flexibility among different stakeholders and the rules and specifications that govern the interaction between involved stakeholders according to the energy market. Furthermore, while USEF value chain aligns the trade of flexibility to the energy markets' needs, it also provides a levelled playing field to all stakeholders by specifying the roles and responsibilities.

One of the corner stones of USEF is flexibility coming from smart appliances like heat pumps, electric boilers, fuel cells, HVAC systems, renewable energy sources like photovoltaic panels and wind mills, and storage systems like batteries and EVs. Moreover, USEF considers that reducing the load or shifting it is equivalent to increasing the generation capacity. Sections 4.3.1 and 4.3.2 provide an overview of how USEF is implemented and operated in Heerhugowaard field experiment with an emphasis on the relation between the aggregator and the DSO.

4.3.1 USEF Management Mechanism

USEF mechanism is designed to allow flexibility trading among all stakeholders, equally under same conditions, in one market. To do so, the USEF scheme is split into four phases: (1) Plan, (2) Validate, (3) Operate, and (4) Settle, as presented in Figure 8.

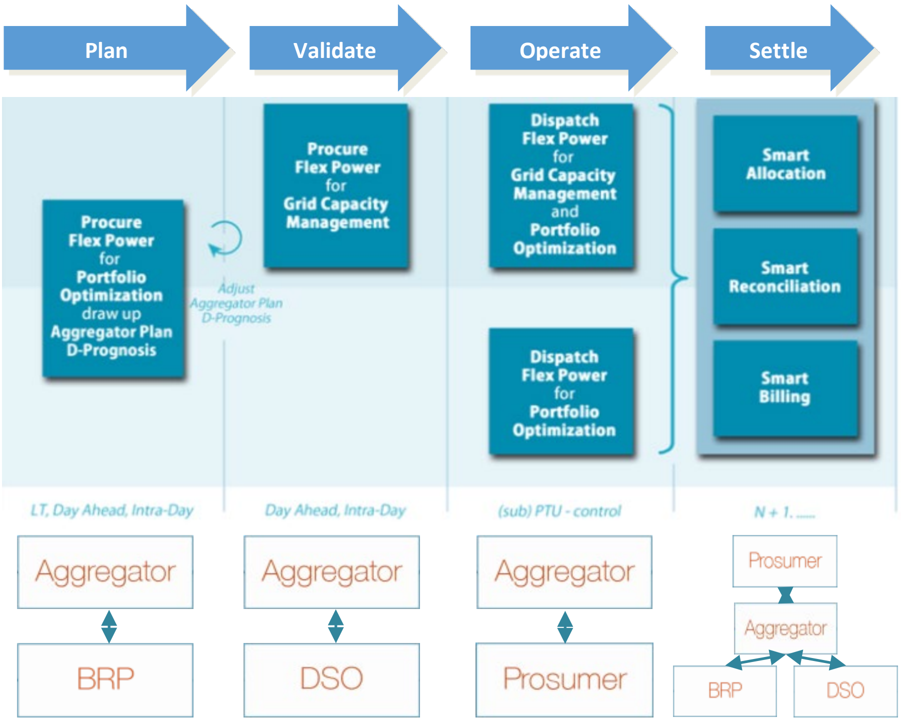


Figure 8: USEF Operation Scheme (Taken from: USEF - The framework specifications, 2015)

In the plan phase, the aggregator and the BRP agree on plan-A optimization, where the BRP procures flex from the aggregator for the coming day (day-ahead) or upcoming period (intra-day). In this phase, the DSO specifies the potential congestion points, where a congestion point is a group of feeders and connectors where grid capacity exceedance may occur (a key point is that a congestion point is not a point where congestion happens but may potentially happen). Furthermore, plan-A is subject to change since the aggregator may optimize the distribution of flex or receive a new weather update that requires updating plan-A and consequently informing the BRP for validation (USEF: The framework specifications, 2015).

In the second phase, the D-plan is planned between the aggregator and the DSO where the DSO validates that the exchanged demand and supply of energy fits within the congestion limits. If not, the DSO orders flex in order to shave peak loads and ensure the load stays within the grid capacity. It is important to note that an iterative process can occur between Plan and Validate phases to ensure optimal economic benefits and safe distribution of load within the grid constraints. When the D-prognosis is obtained, the DSO performs a final check by adding the load forecasts to cross-check the safety of the grid and ensure the load stays within the congestion limits.

During the operate phase, the aggregator should abide by the D-plan and the A-plan and dispatch the ordered flex accordingly. However, as it was implemented in Heerhugowaard field experiment, the DSO can still order flex in the operate phase in order to resolve unanticipated congestion. Finally, in the Settle phase, the ordered flex by the DSO and the BRP is settled and the remaining flex is reconciled afterwards (USEF: The framework specifications, 2015).

The trading of flexibility happens at different time frames, it can be done for a year (long term contracts), month, or day ahead, or even for the upcoming hours (intraday) or the same or upcoming PTU (operate phase). PTU stands for Power Time Unit, which is equivalent to 15 minutes, and there exist 96 PTUs in a day. This eases and advocates the optimization of flex trading at the "forward market, day-ahead spot market, and intra-day spot market" (USEF: The framework specifications, 2015, p. 11). In Heerhugowaard field experiment, flex trading happens at 7 moments in time (excluding the operate phase): once day-ahead and 6 times intra-day as depicted in Figure 9.

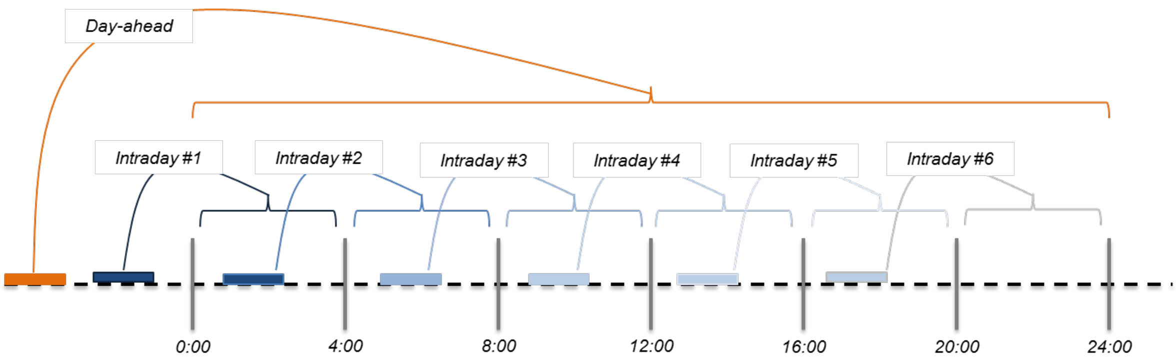


Figure 9: Flex Trading during day-ahead and intra-day (Retrieved from: (EnergieKoplopers, 2015))

Before the day-ahead closure time, the A-plan and the D-plan can be updated while iteratively going back and forth to the Plan and Validate phase. However, those plans are definitive after the closer time and used as input for the intra-day period. During the intra-day period, the same applies, trading can be updated and deemed to change as long as it didn't cross the closure time. Nevertheless, changes in the forecasted available flex and the forecasted load is doomed to happen due to the intermittent nature of renewable energies and incapability to fully predict the human behaviour and weather, which will in return affect the A-plan (create imbalances for the BRP) and the D-plan (create congestion for the DSO). Hence, as mentioned earlier, there is a need for the operate phase, that allows the DSO and the BRP to order flex real time for the current PTU or the upcoming one to compensate for deviances in the plans. In the Heerhugowaard experiment, only the DSO can procure flex in the operate phase (EnergieKoplopers, 2015). Finally, the DSO is procuring per PTU (small timeslots) because at longer timeslots the load will be averaged out and thus affect the need for flex and the chances of mitigating congestion.

4.3.2 USEF rules that govern flexibility trading between the DSO and the Aggregator

In the Heerhugowaard field experiment, four experiments were performed during the period November 18, 2015 and March 8, 2016. In two of those experiments, the DSO procured flex at the **congestion block level**. In the other two experiments, the BRP and the DSO procured flex at the **mixture level**. Figure 10 depicts the **mixture level** that encompass the **block levels**: the Electric Boiler block level that consolidates 4 feeders, the Heat Pump block level collects 2 feeders, and Fuel Cell and PV block levels with no feeders. At the congestion block level, congestion may arise due to overproduction or overconsumption and thus at each congestion level, the D-plan should include the consumption and generation as a result of adding all the load from the controlled and uncontrolled households connected to that congestion point.

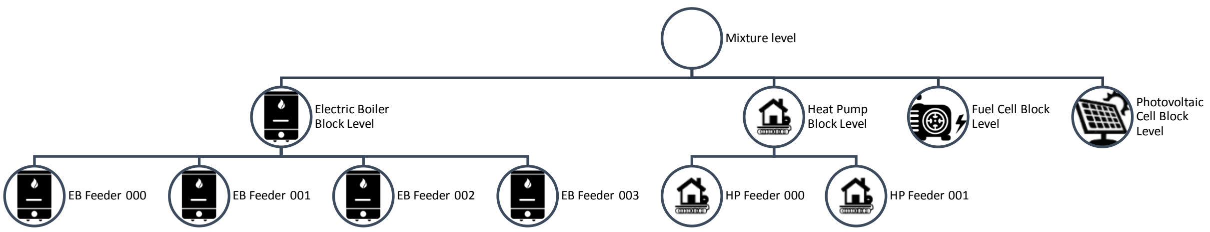


Figure 10: Various Congestion Levels (Feeder level, Block level, and Mixture level)

The DSO is given the liberty to choose between ordering day ahead to secure the availability of flex or procuring as late as possible (operate phase) in order to guarantee the need for flex (USEF: The framework specifications, 2015). Weighing those two options can be hectic. In Heerhugowaard experiment, the DSO ordered flex day ahead, intra-day and operate to strike a balance between the two options.

Other rules that govern the procurement of flex by the DSO, according to USEF, are as follows (USEF: The framework specifications, 2015):

1. The flexibility offer is always valid unless a new offer is presented or the old offer expires or retracted.
2. Once an offer is agreed upon between the two parties, it is binding and cannot be derailed.

3. The DSO has the full freedom to choose whatever offer presented by the aggregators and not necessarily the offer with the least price. In Heerhugowaard field experiment, there is only one aggregator (Essent).
4. Since the DSO ensures that congestion does not arise at a congestion point, orders are made at a congestion point level and thus making each congestion level a local market on its own.
5. The DSO is allowed to place an order for flex if his analysis showed that the load may exceed the congestion limit.
6. The aggregator collects the volume of flex settled and flex price after having received from the DSO the following: the settled volumes of flex, the agreed upon D-plan, the deviation from the D-plan, and the accumulated settled flex price over the PTUs.

In conclusion, the value of demand side-flexibility for the different stakeholders was explained along with the application of flexibility within USEF. However, the success of demand-side flexibility application is contingent upon predicting flexibility from the different smart devices installed in the controlled houses in Heerhugowaard field experiment. Thus, the following chapter (Chapter 5) studies the key determinants that may influence hypothetically the prediction of flexibility from the four smart devices installed in Heerhugowaard.

Chapter 5

5 The Key Determinants of Demand-Side Flexibility

Mitigating congestion and thus preserving network reliability is conditional upon the availability of flex that is ready to be procured by the DSO from the responsible aggregator. Moreover, since different smart appliances are in place to provide this flexibility, predicting flexibility per device type is a pre-requisite for all involved parties for the following reasons: (1) flex offered by the aggregator is provisional upon the prediction of flex, (2) the DSO and PRP orders are dependent on flex offered by the aggregator and their benefits are dependent on the reliability of this flexibility. On the other hand, mitigating congestion and shaving peaks over the year depends on flex available during the different months and seasons of the year, thus specifying the variables that may influence the availability of flex for each smart device is vital. Consequently, this section attempts to answer the following sub-research question:

What are the key hypothetical determinants of demand-side flexibility from the four smart devices at the Heerhugowaard field trial?

Hence, this chapter is split into 4 parts, to cover variables that may influence flexibility and the casual map of predictors for the Photovoltaic system (section 5.1), electric boiler (section 5.2), heat pump (section 5.3), and fuel cell (section 5.4).

5.1 Determinants of flexibility from a Photovoltaic System

In the Heerhugowaard field experiment, most 201 households have PV systems installed. However, only 89 of those households have PV systems that can be freely controlled by the aggregator upon flex ordering. The default/initial state of the panels is always on and thus PV output (Watt) is continuous unless those panels were ordered to go off due to a flex order, either by the DSO due to a risk of congestion or by the BRP because of price difference offered at the market. Therefore, turning off the PV systems lead to a direct increase or an upward shift in the load curve, which is named interchangeably "**flex up**", as specified in USEF, as applied in Heerhugowaard field experiment. Available **flex up** at the **PV Congestion Block Level** is equivalent to the total output (Watt) from the controllable PV systems. The PV output from each panel corresponds to the standardized labelled capacity of the panel. The available flex up at each PTU is influenced by the total PV capacity which is the total standardized capacity of the PVs.

However, other **exogenous factors** might as well dictate the output from a PV panel. Those factors are for example metrological factors such as radiation, humidity, wind speed, and the ambient air temperature. According to Gordo et al. (2015), the thermodynamics and conduction efficiency of the panel is affected by the panel temperature, which subsequently is affected by the outside air temperature, wind speed, precipitation, and humidity. On the other hand, the dirt particles and humidity directly affect the conduction efficiency of the photovoltaic panel. Furthermore, the increase in radiation intensity has a positive linear influence on the PV output, while the cloud cover has a negative influence on the radiation intensity (Gordo et al., 2015). However, as the PV panel temperature increase beyond a threshold limit the energy conversion effectiveness of the PV cell decrease and thus affect the PV output negatively. To ensure the PV panel efficiency is not affected, the panel temperature should be kept within a standardized limit, and possible dust and dirt particles should be removed regularly (Mekhilef, Saidur, & Kamalisarvestani, 2012). However, if the PV panel temperature is within the limit, the efficiency of the PV output can be considered to be stable.

On the other hand, humidity can impact the PV Output in two scenarios: (1) water vapour particles can affect the absorption of sunlight, or (2) the water vapour particles can enter the PV cell enclosure. In both cases, humidity will reduce the thermodynamics and conduction efficiency of the PV cells (Mekhilef, Saidur, & Kamalisarvestani, 2012). In addition, the intensity of the radiation is affected by the position of the sun to the earth. The latitude or elevation angle changes over the day based on the position of the sun. Thus, the sun's elevation angle is considered a key variable that influences the output of the PV system. Consequently, the PV output might also be affected by the position and tilt angle of the panels. The maximum output of PV system is achieved when the sun is perpendicular to the panel and thus the position and the tilt angle of the panels are usually configured in a manner to optimize the output.

In addition, since the number of "panels on" influences how much radiation might be absorbed by the PV systems and consequently influences the PV output, an interaction term is hypothesized, encompassing the radiation and the total PV capacity (radiation * total PV capacity). Furthermore, because one might expect that there is a significant difference between the PV outputs during day and night, due to the absence of radiation, an additional dummy variable is hypothesized. The dummy variable takes the value of 1 if it is daylight and a value of zero if it is not daylight (night). Thus, it can be expected that the relation between the dummy variable day-night and the PV output is positive.

In conclusion, Figure 11 depicts the key hypothetical factors that may affect PV output (Watt) with the hypothesized direction of influence.

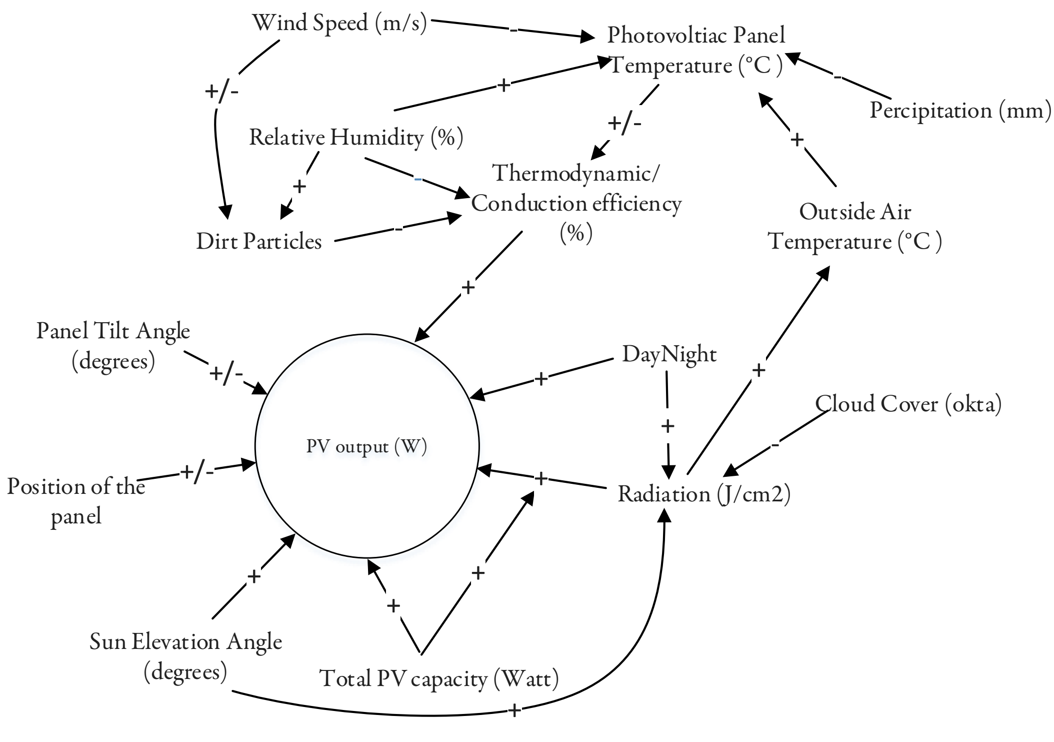


Figure 11: Causal Diagram of PV output (Watt)

5.2 Determinants of flexibility from an Electric Boiler

Within the Heerhugowaard field experiment, 44 of the households have electric boilers installed. Those households have electric boilers that can be freely controlled by the aggregator upon flex ordering. The default/initial state of the boilers is always off and thus the boiler does not heat the water unless those boilers were ordered to go on due to a flex order, either by the DSO due to a risk of congestion (too much generation of energy) or by the BRP because of price difference offered at the market. Therefore, turning on the electric boiler (EB) leads to a direct increase or an upward shift in the load curve, which is named interchangeably "**flex up**", as specified in USEF framework, as applied in the Heerhugowaard field experiment. Available **flex up** at the EB congestion block level is equivalent to the total energy that is consumed by the EBs, when ordered to be on. The 44 boilers are however different, the hot water tank size varies between 80 liters and 120 liters. The energy consumed by each boiler at a PTU is equivalent to the water (liters) that has been heated by the boiler. In other words, the electric boiler is fully charged if there is no consumption of hot water. The decrease in the charge level of an EB is directly equivalent to the amount of hot water consumed. Thus, if hot water was not consumed, even if the EB was turned on, it will not consume energy (no flex available) because the EB is fully charged. However, if for instance, all the hot water was consumed (80 liters), and the boiler uses 2500 W and requires 3 hours in total to charge the 80 liters, thus there is 7500 Wh available flex from the EB for the coming 3 hours. Consequently, it can be derived that if the electric boiler was 80% charged and was ordered to turn on in the morning to offer flex, it may become fully charged (100%) and thus no remaining flex can be offered by the EB at later PTUs unless hot water was consumed. Thus, the charge level of the EB dictates the amount of flex that is available from each EB. The total flex from the 44 EBs at a PTU is equivalent to the total remaining charge for all EBs, depending on the boiler tank size and it's Wattage.

Exogenous factors that may affect hot water consumption fall under two categories: (1) demographic characteristics, and (2) weather parameters. Weather data such as outdoor air temperature might indirectly affect the hot water consumption by influencing primarily the frequency and duration of activities that involve hot water consumption (bathing, showering, laundry, washing, cleaning etc.). Humidity is another factor that may affect hot water consumption (Fredric, 1994). It is argued that with the increase in temperature and humidity, e.g. in summer and spring, the household's activity may increase (bathing, showering, laundry washing etc.), which may result in the increase in hot water consumption but conversely, hot water consumption may decrease because hot water is less desired (Kalogirou & Tripanagnostopoulos, 2006). Thus, the hypotheses for the outside air temperature and humidity will be considered two-tailed (affecting hot water consumption positively or negatively). Additionally, demographic characteristics (the number of occupants, families' habitual patterns, and household income) may influence the frequency and duration of activities that require hot water consumption (Fredric, 1994). Moreover, the household load (watt) is added as a hypothetical parameter that may influence hot water consumption, based on the assumption that the household load may resemble the domestic habitual pattern of the household. For instance, if the household load increases, it is an indication that there is activity at home and thus may capture human behaviour and patterns. Finally, since categorical variables like the hour of the day may capture partly the variance in hot water consumption, an "hour of the day" factor is developed (Defra, 2008).

In conclusion, Figure 12 shows the final variables that may hypothetically influence Hot water consumption (liters) with the hypothesized direction of influence.

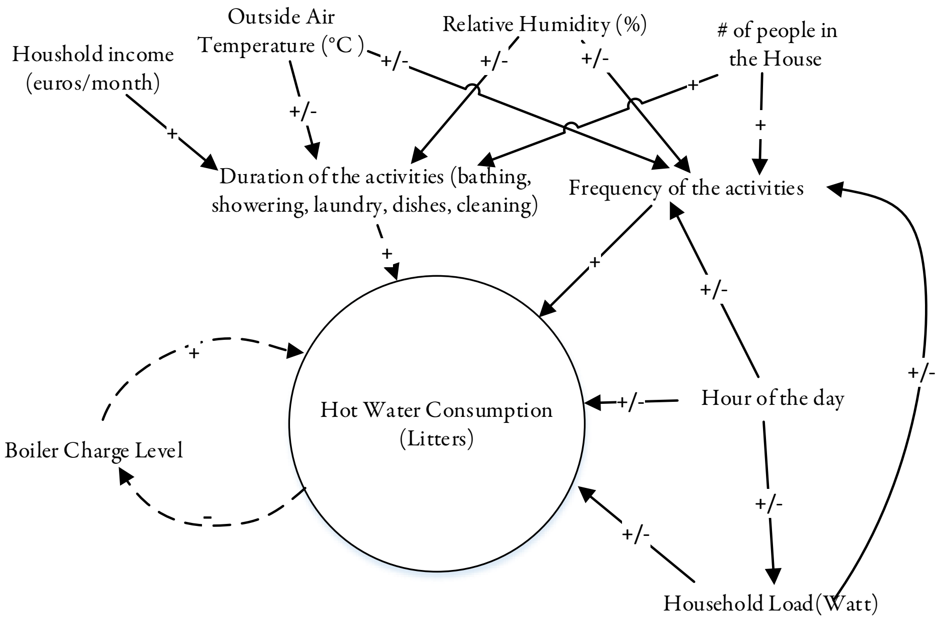


Figure 12: Causal Diagram of Hot Water Consumption (Liters)

5.3 Determinants of flexibility from a Heat Pump

Heat Pumps in the Heerhugowaard households have a combined system, where the heat pump can be used to heat the tap water and for preserving the air temperature within the home. This type of system is considered efficient because it keeps the house heated at the desired temperature. However, a hybrid system of kettle (CV) and a heat pump is needed to heat the house, especially in cold weather. During other seasons, the heat pump can keep the house at the desired temp and provide the primary heating. According to the heat pump manufacturer Inventum, it is more efficient if the heat pump heats continuously for the entire day rather than in the morning and the evening only (Inventum, 2015). However, the user has the liberty to schedule this differently. Furthermore, the heat pump has a boiler barrel of 50 liters and a heat exchanger to heat the tap water. It does not provide primary heating to the tap water but functions as a pre-heater; it heats the water up to 50 degrees Celsius. Afterwards the kettle (CV) heats the water to 60 or 65 degrees (additional 15 degrees). According to the manufacturer, the heat pump gives priority to this process and first heat the tap water before heating the house.

At the Heerhugowaard field experiment, 50 of the households have Heat Pumps (HP) installed. Those households have heat pumps that can be controlled by the aggregator upon flex ordering. The default/initial state of the heat pump is always on and thus the heat pumps is always heating the tap water and the house, dependent on the indoor temperature, unless those heat pumps were ordered to go off due to a flex order, either by the DSO due to a risk of congestion or by the BRP because of price difference offered at the market. Therefore, turning off the heat pumps lead to a direct decrease or a downward shift in the load curve, which is named interchangeably "**flex down**", as specified in USEF and applied in the Heerhugowaard field experiment. Available **flex down** at the **HP Congestion Block Level** is equivalent to the total energy that is consumed by the HPs. The energy consumed by each heat pump at a PTU is equivalent to the hot tap water (litters) that has been heated by the heat pump and the indoor heating undergone by the HP. Similar to the EB, the decrease in the charge level of the HP barrel is directly equivalent to the amount of hot tap water consumed. Thus, if hot water was not consumed, even if the HP was turned off, it will not provide flex because it was not consuming energy at the first place since it is fully charged, unless there was a requirement for indoor heating. Thus, the charge level of the tap water of the HP and the need for indoor heating dictates the amount of flex that is available from each HP. The total flex from the 50 HPs at a PTU is equivalent to the requirement for heating and total remaining charge of the hot tap water for all HPs.

Since the heat pump has two functions, heating the air and the tap water, the heat pump function is split into two.To predict the energy consumed due to heating the indoor air, the temperature plays a critical role. Temperature indoor is affected indirectly by the temperature outdoor because of the house characteristics that affect the temperature indoor and the need for heating such as: the house size, the walls' insulation, the energy grade of the house, the window's insulation, the households' income etc. (Newman & Day, 1975).

Furthermore, other predictors may affect the indoor temperature and the need for heating: the relative humidity level, radiation, and the wind speed. As the humidity increase, it is expected that the need for indoor heating decreases because of the indoor air temperature decreasing/stable. While, as the wind speed increase, the house outer structure cools down, and thus the indoor temperature drops down. Unlike the wind speed, the more the radiation sheds on the house, the more the indoor air temperature is expected to increase and thus the requirement for heating decreases (Cummings & Withers, 2011). However, it is crucial to note that the influence of the radiation on the indoor temperature and hence on the need for heating is lagged due to the thickness of the building material used, the heat transfer based on the thermodynamics law, and the absorption rate of the exterior structure (Zhu et al., 2009). An experiment done Figueira et al. (2003), concluded that the irradiance requires on average 4 to 5 hours to transfer the heat through the wall. Finally, to predict the heat pump load from heating the tap water, the same theoretical variables that predicted the hot water consumption for the EB are used. Such variables are: socio-demographic variables that may hypothetically influence the frequency and duration of the activities that require hot water consumption, weather data, and variables to capture the habitual pattern (e.g. hours of the day and household load). Figure 13 depicts the causal diagram of the variables that may hypothetically be correlated to the heat pump load for heating the indoor air and the tap water.

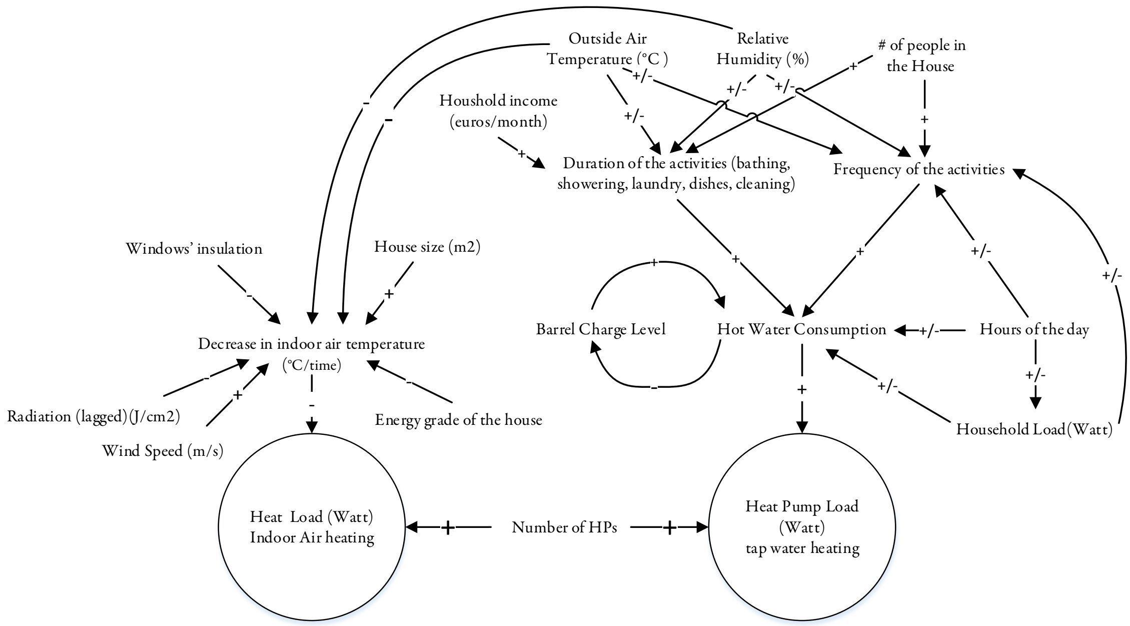


Figure 13: Causal Diagram of the Heat Pump Load (Watt)

5.4 Determinants of flexibility from a Fuel Cell

At the Heerhugowaard field experiment, 18 of the households have Fuel Cells installed. Those households have Fuel Cells (FC) that can be controlled by the aggregator upon flex ordering. The default/initial state of the FC is always on, producing a minimum of 500 Watt, and thus the FC energy production can be ramped up to produce 1500 Watt upon a flex order, either by the DSO due to a risk of congestion or by the BRP because of price difference offered at the market. Therefore, ramping up the FC production leads to a direct decrease or a downward shift in the load curve, which is named interchangeably "**flex down**". Available **flex down** at the FC Congestion Block Level is equivalent to the total energy that is generated by the FCs, when ordered to produce more energy. Thus, each of those FCs can generate a maximum of 1000 Watt flexibility. Thus, if the 18 FCs are ramped up at a PTU (from 500 watt to 1500 watt), the electricity flexibility generated is 18000 Watt.

In the fuel cell, the process of generating energy is based on an electrochemical reaction. In the case of the Heerhugowaard Field Experiment, the fuel cell takes gas as its fuel and the energy in the gaseous molecules, like oxygen, to undergo a chemical reaction to produce electricity and heat (Barbir, 2012). This reaction is simplistic because it is the reverse of electrolysis: when current is applied to water to produce oxygen, hydrogen, and water. This electrochemical reaction is based on a continuous source of fuel, gas in this case. No other exogenous factors impact the electricity generation of the fuel cell. The FC depends on fuel for the electrochemical reaction and not the combustion of fuel like in combustion engines. Thus, the energy production of a fuel cell is not affected by exogenous factors (not user or weather dependent), and therefore no prediction model will be estimated.

In conclusion, the key hypothetical determinants of flexibility for the four smart devices were explored and depicted in casual diagrams with the hypothesized direction of influence. Consequently, the following chapter (Chapter 6), will be analysing data collected on the hypothesized key determinants in order to estimate statistical models to predict flexibility from the four smart devices installed in Heerhugowaard field experiment.

Chapter 6

6 Predicting Flexibility from Each Controllable Device per Congestion Point: A Quantitative Analysis

The electrification, renewable energy, and the overall increase of electricity demand is pushing the load on the grid close to the maximum capacity. In order to investigate if demand side management might be considered a remedial measure to congestion and could defer the need for grid reinforcement into the future, predicting flexibility is a pre-requisite. Flexibility must be available at the right time and in the right amount to shave peak demand and thus mitigate congestion. Therefore, this chapter attempts to answer the following sub-research question:

How do the hypothetical determinants of demand-side flexibility influence the flexibility prediction?

To answer this research question, empirical analysis will be performed on the data collected from Heerhugowaard. The data that is available from the Heerhugowaard field trial is time series data, because the information is collected at a congestion point level per device type, for an interval of time. Therefore, in order to investigate the impact of flexibility on network congestion, time series regression will be employed to predict flexibility availability from different devices at congestion block levels. However, prior to applying Time Series Regression, the data should be gathered, processed and cleaned. Thus, **Section 6.1** will illustrate on data collection, processing and cleaning. Consequently, **Section 6.2** will introduce time series because of the temporal aspects within time series analysis that can have a significant influence on the modelling process, as time series that are 'non-stationary' might cause spurious regression, which implies that independent variables are tested significant but in reality are not. Based on the time series theory presented, the smart appliances that are present in the Heerhugowaard field trial are investigated and the flexibility from those devices is modelled accordingly in **section 6.3** through **section 6.6**. However, in **section 6.3** additional emphasis is given to the regression conditions that are applicable within Ordinary Least Square (OLS) and will be applied and justified profoundly for the PV-Output model. Furthermore, **section 6.4** shall use Count Data Modeling to estimate the Electric Boiler prediction model, due to the discrete nature of the data. Since the heat pump has two functions: preserving the air temperature within the home and heating the tap water, two regression models will be constructed (one to predict the heat load for indoor heating (**section 6.5**)), and the other to predict the total heat pump load for both functions (**section 6.6**). Finally **section 6.7** will presents an overview of the flexibility prediction models.

6.1 Data Collection, Processing, and Cleaning

In order to build regression models to estimate demand-side flexibility from the 4 smart devices, data from the Heerhugowaard field trial is required. Due to the nature of the project, with respect to energy consumption, a fully automated approach to data collection was used, which will be addressed in **section 6.1.1**. This approach resulted in a large amount of data, which consequently had to be processed before analysis could be performed. Data processing is subsequently addressed in **section 6.1.2**. Even though that the data was collected automatically, preventing missing data due to human errors, the data set still contains invalid measurements due to, for example IT errors. Thus, **section 6.1.3** addresses data cleaning to prepare it for analysis.

6.1.1 Data Gathering

The collection of data from the 201 sampled households in Heerhugowaard is centralized at the SESP back office. The SESP back office interface receives the smart meter recordings and the update on the devices' statuses. The SESP interface is also responsible to configure the devices when needed. However, it is the Smart Meter Reader that reads the installed smart meters and communicate this information to the SESP back office for storage purposes. For communication purposes between the SESP back office and the households, the SESP Home Gateway permits this interaction. The SESP data set was used to estimate the PV output model and the Heat Pump model. However, the data for the electric boiler like the charge level which indicated hot water consumption contained a lot of missing data and showed high levels of noise and disturbances. Therefore, for the estimation of the Electric Boiler prediction model, a household data set was acquired from the Almanac of Minutely Power Dataset (AMPds). The dataset contains minutely measurement for hot water consumption for one household in Canada.

Aside from the SESP and the AMPds data sets, two other weather data sources were used. For the estimation of the Electric Boiler model, the hourly weather data was acquired from the "Environment Canada's YVR weather station" (Makonin et al., 2013). For the estimation models of the PV and the HP based on the SESP files, the weather data was retrieved from the KNMI website (The Royal Netherlands Meteorological Institute).

6.1.2 Data Processing

The text files collected from SESP from the period August 2015 till February 2016 were roughly 32,000 text files. The data was compiled to one text file and imported to SPSS because excel is incapable of handling the 2.9 million rows. The SESP text files had 36 parameters recorded (e.g. Household number, PTU, Year, Month, Day, Hours, Minutes, Minute Interval, Total Counter, Minute Counter, State, Meter ID… etc.) for every PTU (15 minute interval). Since data will be analysed at a congestion block level, and not at household level, the data for the pertaining households for each congestion block level were aggregated, which resulted in compiled datasets for the different 4 devices at the 4 congestion block levels. Moreover, since SESP data is recorded every 15 minutes while the weather data is recorded every hour, the SESP data had to be transformed by summing the 15minute data to get the hourly values like in the case of hot water consumption.

For processing the data from SESP and AMPds, different software's were used. For demand-side flexibility prediction on a distribution level, SPSS (IBM version 23), STATA (version 14), and R (version 3.3.0) were used for data processing and analysis.

6.1.3 Outlier Detection and Cleaning

The data gathering and processing procedure discussed in the previous section should deal with a clean and unbiased dataset. Thus, data points that significantly deviate from the majority of the sample should be studied in order to determine if these data point should be kept or discarded. Such data points are referred to in literature as outliers and defined as: "An outlier is an observation that lies an abnormal distance from other values in a random sample from a population" (Rose, 2015, p. 287). Outliers can be the result of many irregular causes such a smart device malfunction, an error in recording, or in transmission or a skewness in the data.

One of the techniques to perform such an assessment is logical error detection of individual single data points (Gong and Mu, 2000). For example it would be logical to detect PV-Output during the day, but not during the night. Consequently, data points that indicate PV-Output during the night were considered as a logical error and removed from the data set. Another witnessed measurement outlier is when the state of the heat pump was off but the load of the heat pump was recorded positive. Such outliers were discarded from the data set.

6.2 A Primer on Time Series Regression

Within the concept of time series, it is important to realize that past data might affect future data in a temporal manner. When variables are indexed by time sequentially, they are considered a time series sequence/process. Detecting such process might be done in a wide variety of manners which vary from easy, to very complex. The former techniques require the decomposition of the time series to investigate the presence of **trends**, **seasonality**, and other "**irregular fluctuations**" (Kendall & Stuart, 1966).

1. A trend is when the mean changes over time and thus exhibits a tendency either upward or downward.
2. Seasonality is observed when variations occur over equal intervals of time (hourly, monthly, seasonally, annually etc.).
3. Irregular fluctuations might be the result of an error term (the residuals) that are not random but correlated with the independent variable(s) which in some cases can be modelled probabilistically by moving averages (MA) or autoregressive models (AR) (to be explained later in this chapter) (Chatfield, 2013).

Thus, it is important to first understand the different properties of time series that might affect the prediction model before attempting to model flexibility. In order to provide this understanding, section 6.2.1 introduces the elements of time series and the concept of stationarity. In most time series analysis the researchers must prove the existence of un-stationarity in order to apply the required corrections to ensure unbiased estimators. Therefore, section 6.2.2 introduces a set of approaches that can be used in order to determine if a time series is stationary or not. In order to elaborate on these theoretical approaches, these approaches will be applied to the PV model in section 6.2.2.

6.2.1 Stationary and Non-Stationary Time Series

Stationary time series are a series of variables whose mean and variance does not change over time, in other words the probability distribution is independent of time and does not exhibit a trend or a form of a periodic behaviour. The first step to detect if a series is stationary is by plotting the records over time. Transformation of the data might be required to change a non-stationary time series in order to stabilize the variance or the seasonal effects in case the variance changes with the mean or seasonality is proportional to the mean over time (Chatfield, 2013). Series that do not require transformation are those where Y_t (the observations), m_t (the average indexed to time), s_t (the seasonal effect), the ε_t (the error term) are stable, and have non-multiplicative seasonality, and non-multiplicative error terms such as:

$$Y_t = m_t + s_t + \varepsilon_t$$

Unlike in the following model, where there is multiplicative seasonality and error terms:

$$Y_t = m_t * s_t * \varepsilon_t$$

In order to describe such time series, the auto-correlated coefficient is important. In order to construct these stationary models, the following different stochastic models can be used:

1- **The Moving Average MA(p) model:** is when the series is a function of a finite number of lags of the forecast error term such as:

$$Y_t = e_t + \alpha_1 e_{t-1} + \alpha_2 e_{t-2} + \cdots + \alpha_p e_{t-p}$$

2- **The Autoregressive AR(r) model:** is when the series is a function of a finite number of lags of its self, just like a multiple regression model but not of independent X variables rather with autoregressive lags:

$$Y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + \cdots + \rho_r y_{t-r} + e_t$$

3- **ARMA (r, p) mixed models:** is when a series is a function of auto-regressed lags of its self and the forecast error term, as follows:

$$Y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + \cdots + \rho_r y_{t-r} + e_t + \alpha_1 e_{t-1} + \alpha_2 e_{t-2} + \cdots + \alpha_p e_{t-p}$$

4- **Finite-Distributed lagged models (FDL):** are models where lagged variables affect the dependent variable Y, can be justified as a lagged response, as follows:

$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 X_{t-1} + \beta_3 X_{t-2} + u_t \qquad for\ t = 1,2,3 \ldots, n$$

Understanding these types of non-stationarity and the different forms of non-stationarity is vital in order perform the correct transformation. For non-stationary series, either the variance or the mean can change over time, and can be taken into consideration in different ways:

1- **Random Walk:**
A random walk occurs when the value of Y_t is equal to Y_{t-1} plus a stochastic error term, which is also referred to as white noise (ε_t). The random walk model is characterized either with a unit root (to be explained later in the chapter) or with a stochastic trends, where the variance changes over time.

2- **Random walk with drift:**
A random walk with a drift is characterized by Y_t being equal to Y_{t-1} plus a drift (α) and a white noise error (ε_t). In such a model the variance is dependent on time, as is applicable with the random walk models without a drift.
$$Y_t = \alpha + \rho y_{t-1} + \varepsilon_t \quad for\ t = 1,2 \ldots, n$$

3- **Deterministic trend:**
Deterministic trend models are time series where Y_t is not regressed on its past value but on a time trend (β_t) and where the mean grows with a constant trend. Deterministic trend models can be modelled as:
$$Y_t = \alpha + \beta t + \varepsilon_t \quad for\ t = 1,2 \ldots, n$$

4- **Random walk with Drift and Trend:**
A random walk with a drift and a trend is a non-stationary model that comprises a random walk with a drift and a deterministic trend, and can be modelled as follows:
$$Y_t = \alpha + \rho y_{t-1} + \beta t + \varepsilon_t$$

Non-stationarity can cause spurious regression that may show a significant relation while in reality this significance is only caused by the trend. Transforming such a non-stationary process by correcting for trends or by taking the first difference of the time series, if the time series is a Random Walk with/without a trend, is vital in order to avoid misleading results. Additionally, de-trending can be used in order to correct for deterministic trends or to correct for the change in the variance. Non-stationarity can also cause inconsistent regression as a result of regressing a non-stationary dependent variable (time changing mean) on a stationary independent variable which will results in a changing coefficient (β) over time. Consequently, in order to prevent spurious and inconsistent regression, it is important to test for stationarity and exercise the right transformation in case of non-stationarity prior to modelling.

6.2.2 Testing for Stationarity in Time Series

As mentioned earlier, stationary time series are characterized with a constant mean ($E(X_t)$), constant variance $Var(X_t)$, and a time independent covariance/correlation. Testing if the time series is stationary or non-stationary can be performed with different approaches. The tests used to investigate if the series is stationary or non-stationary are explained and practiced on the PV-Output data set.

1. **Correlogram:**
A technique to investigate stationarity is by considering the correlogram, which illustrates the autocorrelation (AC) between the variable and its past values, and the partial autocorrelation (PAC). Using STATA, the correlogram for PV output is presented in Table 11.

Table 11: Correlogram for PV Output

LAG	AC	PAC	Q	Prob>Q
1	0.8650	0.8650	3066.3	0.0000
2	0.7177	-0.1213	5177.7	0.0000
3	0.5405	-0.2045	6375.2	0.0000
4	0.3532	-0.1513	6887	0.0000
5	0.1776	-0.0788	7016.3	0.0000
6	0.0383	0.0128	7022.3	0.0000
7	-0.0698	-0.0139	7042.3	0.0000
8	-0.1411	-0.0035	7124	0.0000
9	-0.1851	-0.0295	7264.6	0.0000
10	-0.2070	-0.0326	7440.7	0.0000
11	-0.2139	-0.0321	7628.6	0.0000
12	-0.2121	-0.0364	7813.4	0.0000
13	-0.2046	-0.0283	7985.5	0.0000
14	-0.1896	-0.0073	8133.3	0.0000
15	-0.1618	0.0290	8240.9	0.0000
16	-0.1150	0.0674	8295.3	0.0000
17	-0.0419	0.1112	8302.5	0.0000
18	0.0566	0.1307	8315.7	0.0000
19	0.1789	0.1560	8447.4	0.0000
20	0.3171	0.1743	8861.3	0.0000

-1 0 1 [Autocorrelation] -1 0 1 [Partial Autocor]

The autocorrelation (AC) column in Table 11 shows that the correlation between (PV output) 3 hours ago and its current value is 0.5405, which resembles the MA(p) in stationary time series. The PAC indicates that the correlation of PV output 3 hours lagged with its current value is -0.2045 without the effect of the first and the second lag, which defines AR(r) in stationary series. Furthermore, column 5 in Table 11 indicates if these correlations are significant according to the following hypothesis:

H0: All lags are not correlated (correlations = 0)
H1: All lags are correlated

Thus according to the Prob>Q, all the probability are less than 0.05 (assuming a 95% confidence interval), and consequently the lags are significantly correlated. If the autocorrelation graph in column 6 of Table 11 shows a sharp decay in the trend it suggests that the series is stationary; however, a slow decay suggests a non-stationary time series. In this particular case, the graph does not provide decisive results due to the cyclical behavior of the autocorrelation of the hours. The partial autocorrelation graph in column 7 of Table 11 indicates a major spike at the first lag and thus one might infer that the other lags are mirrors of the first lag. Consequently, based on the correlogram, one can conclude that the time series of PV output requires an AR1 term.

2. **Augmented Dickey-Fuller test**
   The Dickey-Fuller test tests if the time series has a unit root (stationary) or non-stationary (further explanation can be found in **Appendix A.1**). If there is a risk that the variable is plagued with serial correlation especially with ARMA(r,p) models and one wants to verify if the series is stationary, the Augmented Dickey-Fuller test can be performed. The tests assumes for the null hypothesis that the model is non-stationary (has a unit root either random walk, or random walk with a drift, or deterministic trend or random walk with Drift and Trend). From the PV output correlogram (Table 11), it is not statistically clear whether the series is stationary or not, thus the augmented Dickey-Fuller test is performed.
   In the PV output data set no apparent trend is observed and consequently tests are performed to detect random walks without drifts and trends. **Table 71 in Appendix A.1** presents the outcome of the Augmented Dickey Fuller test for the PV output and reports a p-value of 0.000 which implies that the null hypothesis can be rejected, and thus the series is stationary. Consequently it is possible to conclude, based on the aforementioned tests, that an AR(1) model can be followed.

Based on this analysis, as presented through the use of the augmented Dickey-Fuller tests, one can conclude that the time series is stationary and that an AR1 term must be included in the prediction model of the PV output. With this knowledge, additional steps in estimating a prediction model are taken in the next section.

6.3 Econometric considerations and Modelling of the Photovoltaic Panel Output

In order to predict the output from PV-panels for an entire year or in other low voltage grids other than Heerhugowaard, a prediction model is estimated. This model is estimated based on the hypothetical determinants and relations presented in **section 5.1** but should also include the AR1 term presented in the previous sections. Therefore, the hypothetical regressors that are added to the model based on **section 5.1, Figure 11**, for predicting the PV output (Watt) as the dependent variable are: the one hour lagged PV out (Watt), Radiation*Total PV capacity (J*Watt/cm^2), Radiation (J/cm^2), total PV capacity (Watt), temperature (°C), relative humidity (%), sun elevation angle measured from the horizon (degrees), and a day-night dummy. However, not all hypothetical relations can be included as no information is available on the cloud cover, the dirt particles, the panel temperature, and the panel efficiency.

Moreover, since the threshold temperature is not available for the installed PVs, as is the case within the Heerhugowaard Field Experiment, it is hard to determine whether the outside air temperature will influence the PV cell efficiency positively or negatively depending on whether it is below or beyond the threshold (Meral & Dinçer, 2011). Accordingly, statistically speaking, the correlation between temperature and PV output is hypothesized to be two-tailed.
Additionally, the position of the panels and the angle of inclination are not recorded for the Heerhugowaard field experiment; however, the position of the panel systems can be roughly estimated from the time of the day the output is maximum (explained and documented in **Appendix A.2**).

In order to estimate the PV-output model, OLS regression is employed in combination with time series independent terms. In order to ensure that such a model is efficient and unbiased a set of conditions must be met (Noh & Lee, 2013; Wooldridge, 2015). Consequently, **section 6.3.1** addresses the conditions for time series OLS regression. After the estimation and verification of the conditions for regression, **section 6.3.2** provides an overview of the output of the regression model. However, before the model can be used, **section 6.3.3** addresses the validation of the PV output model, in order to verify that the model predicts accurately, resulting in a validated PV output prediction model.

6.3.1 Time series conditions and verification

In order for time series regression to provide consistent and unbiased estimators a set of conditions must be met (Noh & Lee, 2013; Wooldridge, 2015). Consequently, these conditions are introduced next and applied to the time series model for the PV output in order to provide an explanatory and practical example on how such conditions are tested and if violated, how are they mitigated. The conditions that must be met are:

1. Linearity in parameters
2. No perfect collinearity
3. Strict Exogeneity
4. Homoscedasticity
5. No Serial Correlation
6. Normally distributed errors

6.3.1.1 TS1: Linearity in parameters:

One of the conditions that must be satisfied before Ordinary Least Square (OLS) estimation can be performed, is that the relations between the independent and the dependent variables are linear. Linearity in parameters defines that the dependent variable Y is a linear function of the parameters (β_1, β_2, β_3) and is defined as:

$$y_t = \beta_0 + \beta_1 X_{t1} + \beta_2 X_{t2} + \beta_3 X_{t3} + ut$$

A graphical representation (scatter plot) is a good measure to determine if such a relation approaches linearity. For the case of the PV, Figure 14 presents the linear relation (colored in yellow) between the PV output and the lagged PV output$_{t-1}$. The plot indicates that the linear relation captures the variance in the PV output and implies that the relation between the dependent and independent variable can be assumed to be linear. Additionally, the **augmented component plus residual plot** can be used to identify the linear observed pattern (as shown in the red line) in Figure 14, which indicates that the actual linear relationship (as shown in the yellow line) and the linear observed pattern are very similar. However, if such a nice fit is not the case, the linearity assumption is violated and requires correction. In order to correct for such violations it is possible to transform the data through means of curvilinear relationships. This implies that the independent variable is multiplied, divided or transformed through a log of LN transformation, resulting in a change in the relationship between the dependent and independent variable. For this particular case (the PV output case), the independent variable Temperature was transformed by means of a cubed transformation, resulting in an increase of the R^2 of 9.57% as can be seen in Table 12.

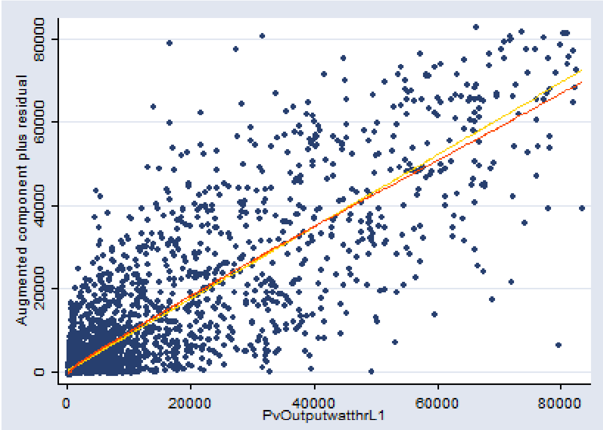


Figure 14: The Scatter Plot and the Augmented Component Plus Residual Plot for the PV output

Before additional steps are taken through means of OLS regression, it is crucial to perform a bivariate analysis in order to determine if the relationships between the dependent and the independent variables are not only present and linear, but also significant and consequently allows one to draw a conclusion with respect to the direction of the relationship. In order to determine which statistical test might be employed to statistically prove if the relation is significantly linear, the level of measurement is investigated. For the particular case of the photovoltaic panel, the dependent variable (PV output) and the independent variables, except the Day-Night dummy, are interval/ratio level of measurement and thus the Pearson's correlation coefficient test (parametric test) is performed. **Table 12 presents the bivariate relations** along with the direction of the relationships and their respective significance.

Table 12: Bivariate relationships and its transformation and significance

	Curvilinear relationship	Possible Transformation of the independent variables	Adjusted R^2 before Transformation	Adjusted R^2 after Transformation	Significance	Direction of relationship
PVoutputLag1	N.A	N.A	N.A	74.83%	0.0000	Positive
Interaction term	N.A	N.A	N.A	85.45%	0.0000	Positive
Temperature	Positive convex	X^3	18.24%	27.81%	0.0000	Positive
Humidity	N.A	N.A	N.A	42.06%	0.0000	Negative
Total PV Capacity	N.A	N.A	N.A	2.78%	0.0000	Negative
Sun Elevation Angle	N.A	N.A	N.A	54.92%	0.0000	Positive
Radiation	N.A	N.A	N.A	83.96%	0.0000	Positive

Based on these results one can conclude that the bivariate relationship between all the identified variables and dependent variable (PV output) are significant. The R^2, is an indication of the quality of the bivariate relationship, and defined as the percentage of variance of the dependent variable that is explained by the independent variable. The R^2 is calculated by correlating the estimated values to the observed values. The adjusted R^2 is then estimated to correct for the representativeness of the R^2 for the population, especially when the sample size is small, the higher the R^2, the less representative this value is.

As shown in Table 12, the sign of the relationship for the Total PV capacity with the PV output is not consistent with theoretical inference (the more the Total PV capacity, the more is the PV output). Thus, the total PV capacity is excluded from the prediction model. The interaction term constitutes of the radiation and total PV capacity. Thus, the analysis results into the following accepted alternative hypotheses:

- The more the (Radiation*TotalPVcapacity), the more the (PV output)
- There is a significant relation between Cubed temperature and (PV output), the relation is considered two-tailed as explained in section 6.3 and 5.1.
- The more the humidity, the less the (PV output)
- The more the sun elevation angle, the more the (PV output)
- The more the radiation, the more the (PV output)

6.3.1.2 TS2: No perfect collinearity:

To predict the PV output, based on the identified independent variables, a multi-regression analysis is performed. Variables are kept in the model based on their level of contribution and significance to the variance of the PV output. For this analysis, it is important to construct a parsimony model, which implies the construction of a model with the highest level of explained variance and the lowest number of regressors. In an attempt to maximize the predicted variance of the dependent variable more independent variables are added, with the risk of adding independent variables that are collinear (that do not explain any unique variance, variance that is already explained by the existing independent variables). Perfect collinearity occurs when a variable is a multiple of another, and thus has zero tolerance (the inverse of VIF). Due to the "Enter" method employed in STATA, there is a risk of perfect collinear independent variables, and consequently, collinearity is investigated.

In order to perform such an analysis, first a multivariate time series regression model must be estimated. The **multivariate time series regression model, in Table 13**, includes all the independent variables that turned out to be significant. However, it is important to note that the sign of the correlation coefficient for the regressor "Elevation Angle", "Radiation" and "DayNight" dummy are inversed which might be caused by multicollinearity. Also, "Elevation Angle" variable turned out to be insignificant (0.068>0.05). Thus, the Elevation Angle, Radiation and DayNight are dropped from the regression model.

Table 13: First Regression output for the PV-Output prediction

	Coef.	Std. Err.	t	Sig.	95% Confidence interval	
PvOutputL1	0.35000	0.00965	36.29	0.000	0.33100	0.36900
Interaction Term	0.00155	0.00000	22.92	0.000	0.00141	0.00168
Temperature cubed	-0.00042	0.00040	-10.52	0.000	-0.00050	-0.00034
Humidity	-44.32400	10.55149	-4.20	0.000	-65.01075	-23.63741
DayNight	-1292.00400	208.60210	-6.19	0.000	-1700.97800	-883.03070
Elevation Angle	-21.88481	11.99096	-1.83	0.068	-45.39362	1.62400
Radiation	-28.65285	8.26211	3.47	0.001	-44.85108	-12.45461
Constant	4994.80300	973.16190	5.13	0.000	3086.87600	6902.73100

Therefore, the second regression model regresses the dependent variable (PV output) on the lagged dependent (PVoutputL1), the Interaction Term (TotalPvCapacity*Radiation), cubed temperature (Temperture^3) and Humidity, as shown in Table 14.

Table 14: Second Regression model for PV-Output prediction

	Coef.	Std. Err.	t	Sig.	95% Confidence interval	
PvOutputwatthrL1	0.34090	0.00871	39.16	0.000	0.32383	0.35797
Interaction Term	0.00171	0.00002	73.60	0.000	0.00166	0.00175
Temperature cubed	-0.00041	0.00004	-11.13	0.000	-0.00049	-0.00034
Humidity	-51.07351	10.55838	-4.84	0.000	-71.77368	-30.37334
Constant	5145.09000	974.02780	5.28	0.000	3235.46500	7054.71500

The second multivariate regression model proves that the R^2, which is the coefficient of determination and a statistical estimation of how fitted the data is to the regression model, is 0.9. Thus, with the current 4 regressors, the model explains roughly 90% of the variance, and concludes that the model became increasingly parsimony (Table 14).

For the perfect collinearity check, Table 15 proves that the tolerance, defined as 1/VIF, of the 4 regressors is adequate and unique variance can be explained by each of the regressors. None of the 4 regressors show very low tolerance and thus one can conclude no perfect collinearity.

Table 15: regression model (collinearity check)

	VIF	1/VIF (tolerance)
PvOutput L1	3.37	0.296736
Interaction Term	3.08	0.324675
Temperature cubed	1.93	0.518135
Humidity	1.64	0.609756

6.3.1.3 TS3: Strict exogeneity (zero conditional mean):

To satisfy the strict exogeneity condition the error term should be independent and uncorrelated with the independent variables at all periods of time (the current, lagged values, and future values of the regressors). To be expressed as follows:

$$E(u_t / X_{t1}, X_{t2}, X_{t3}, \dots X_{t-1}, X_{t-2}, X_{t-3} \dots .) = 0$$

However, with AR (1) models, the condition of **strict exogeneity** is breached because the error term u_t is regressed with the lagged dependent (y_{t-1}). Thus, there is a shift from strict exogeneity to **weak exogeneity**, which states that the error term should not be related to the independent variables at **the current moment in time only** (Gourieroux, Monfort, & Gallo, 1997). Thus, this excludes the relation between the error term and the independent variables in past or future moments/periods of time. To test for correlation $[(u_t / X_t) \neq 0]$, the $Cov(y_t / u_t)$ is calculated, as follows in Table 16. The results prove that the correlation coefficient is zero between the residuals (the error term) and the independent variables, **as marked in red in Table 16**. Consequently, this implies that the weak exogeneity assumption is met, and based on this assumption, the estimators should be unbiased and efficient (Wooldridge, 2015).

Table 16: Correlation between the error term and the independent regressors

	Residuals (error term)	PvOutput L1	Interaction Term	Temperature cubed	Humidity
Residuals	1.0000				
PvOutputL1	0.0000	1.0000			
Interaction Term	0.0000	0.8052	1.0000		
Temperature cubed	0.0000	0.5279	0.5982	1.0000	
Humidity	0.0000	-0.6427	-0.6427	-0.5191	1.0000

6.3.1.4 TS4: Homoscedasticity

The core definition of homoscedasticity is that the dispersion of the dependent variable, the variance in other words, is **constant over the fitting line** $(\beta_0 + \beta_1 X_{t1} + \beta_2 X_{t2} + \beta_3 X_{t3})$ and thus **independent of the regressors across all time** periods (X_{t1}, X_{t2}, X_{t3} ....). Due to the heteroscedasticity error, the coefficients of determination and the covariance will be biased and inconsistent and thus testing for heteroscedasticity before presenting the regression results is a must. In order to test for heteroscedasticity it is possible to analyze the residuals plotted across the fitted line of the dependent variable or across all the explanatory independent variables (as shown in **Figure 52** in **Appendix A.3.**). When the residuals do not portray a distinct cloud shape this provides an initial indication that the data might be heteroscedastic. To statistically proof the existence of heteroscedasticity it is vital to undergo formal testing. To formally test for heteroscedasticity the Lagrange Multiplier, or Breusch-Pagan test for heteroscedasticity can be performed.

The Lagrange Multiplier test or Breusch-Pagan test for heteroscedasticity checks whether the variance of the error term $(\sigma_t^2 = \sum \varepsilon_t^2 / n)$ is volatile or related to the explanatory variables. First a normal OLS model is computed and the error term is calculated. Then the variance of the error term is regressed against the independent variables as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 X_{t1} + \alpha_2 X_{t2} + \alpha_3 X_{t3}$$

Where the null hypothesis defined as: H0: $\alpha_0, \alpha_1, \alpha_2 \dots = 0$

Applying the Breusch-Pagan test for heteroscedasticity to the PV model indicates a χ^2 value of 5694, and a significance of 0.000, resulting in a rejection of the H0 hypotheses, and indicating that the residuals are heteroscedastic, which implies that one can conclude that the variance is not constant over time and is dependent on the explanatory variables.

A possible remedial measure for heteroscedasticity is Generalized least squares (GLS) estimation; however, in order to use GLS the estimator that is causing heteroscedasticity should be known beforehand, in order to divide all independent variables by that estimator (independent variable). If the suggested cause behind heteroscedasticity was correct, the White Test can be performed to test if the residuals become homoscedastic. However, in most cases, the estimator that is causing heteroscedasticity is not known. Thus, implementing OLS with heteroscedasticity would result in unbiased and inefficient estimators. Otherwise, when the cause of heteroscedasticity is not known, heteroscedasticity can be corrected through White Robust Standard error (Table 17), which provides consistent estimates under heteroscedasticity. This estimation technique was later extended and become known as Newey-West standard errors (1987). The Newey-West standard errors estimate consistent estimators when the residuals are heteroscedastic and serially correlated. Therefore, by using Newey-West standard errors it is possible to estimate unbiased and efficient estimators in the presence of heteroscedasticity, and adjustment of the data or model do not have to be performed.

Table 17: Newey West Standard Errors Regression

	Coef.	Newey-West Std. Err.	t	Sig.	95% Confidence interval	
PvOutput L1	0.34090	0.01836	18.57	0.000	0.30491	0.37689
Interaction Term	0.00171	0.00004	36.42	0.000	0.00161	0.00180
Temperature cubed	-0.00041	0.00005	-7.70	0.000	-0.00052	-0.00031
Humidity	-51.07351	11.51985	-4.43	0.000	-73.65869	-28.48833
Constant	5145.09000	1076.11800	4.78	0.000	3035.31400	7254.86600

6.3.1.5 TS5: Serial Correlation:

No Serial correlation in the error terms (u_t) means that there is no relation between the error terms at different time periods. The null hypothesis involves no correlation between the error and its lagged variable and to be written as follows:

$$corr(u_t, u_{t-s}) = 0, \text{ where s is the lagged period of time s=1,2,3..p}$$

In order to test for serial correlation either the Durbin Watson test or the Breusch-Godfrey Lagrange multiplier test might be employed. When the Durbin Watson test is employed this test is rendered invalid if there is autoregressive dependent variable (y), in other words a lagged variable of the dependent (y_{t-1}) is one of the independent regressors in the regression model, just like in the case of the PV output. Moreover, the Durbin Watson test tests only for the first order correlation between u_t and u_{t-1} as follows: $u_t = \rho u_{t-1} + \varepsilon$. More explanation of **Durbin Watson test** and **Durbin's alternative test** can be found in **Appendix A.4.**

In case of more than one order of correlation in the error term, until p order of correlation, the Breusch-Godfrey Lagrange multiplier test can be performed. If the error term is not dependent on the lagged variable of the error term, then the disturbance (residual) is considered to be white noise. White noise is considered to be the normal error term with zero mean, variance=σ2, and zero correlation between the error term and its lagged variables. Thus the zero hypothesis of the test is that the error term is white noise.
Based on the Durbin Watson Alternative test the null hypothesis can be rejected (χ^2 value of 23.197, and a significance of 0.000, as documented in **appendix A.4 in Table 72**) and thus there exist a significant first order of correlation: $u_t = \rho u_{t-1} + \varepsilon$, where $\rho \neq 0$. Additionally, based on the **Breusch-Godfrey Lagrange multiplier test** the zero hypothesis can be rejected and thus the error terms are serially correlated for more than the first order (**appendix A.4 in Table 73**).

Remedial measures for serial correlation:

Having serial correlation between the errors terms can lead to spurious errors, therefore the following techniques can correct for such a deviation:

1. **First Differencing** the dependent variable at time t and t-1. However, because of the lagged dependent variable AR (1) for the PV model, this remedial measure is not possible.
2. **Cochrane-Orcutt (CORC) Iterative Procedure (Prais Winsten test), which** repeats the CORC iterative procedure until no correlation shows between the error term and its past variables. Nevertheless, **(CORC)/Prais Winsten** are also not adequate for models with lagged dependent variable as an explanatory variable. More elaboration on the two techniques (**First Differencing and (CORC)/Prais Winsten**) can be found in **Appendix A.5**.
3. **Hildreth-Lu test:** The procedure for the Hilreth-Lu test is very iterative similar to that of the CORC test, where ρ is allowed to hover between -1 and 1. By implementing OLS in the following equation, for an incremental

increase in ρ, the test selects the best equation which has the lowest Sum of Squared Residuals (SSR) (Watson & Teelucksingh, 2002). This method is considered to be computer intensive and tedious because once an indication is inferred about the value of ρ that minimizes the SSR, more iterations are performed until a decisive conclusion is reached.

$$y_t - \rho y_{t-1} = \beta_1(1-\rho) + \beta_2(X_t - \rho X_{t-1}) + \cdots + (u_t - \rho u_{t-1})$$

The test can be performed on models where the lagged dependent variable is an explanatory variable. Hence, the results of the Hildreth-Lu test for the PV model is presented in Table 18, which presents the regression model with an adjusted R^2 of roughly 90%.

Table 18: The PV regression model having undergone Hildreth-Lu test

	Coef.	Std. Err.	t	Sig.	95% Confidence interval	
PvOutput L1	0.34023	0.00872	39.03	0.000	0.32314	0.35732
Interaction Term	0.00171	0.00002	73.54	0.000	0.00166	0.00175
Temperature cubed	-0.00041	0.00004	-11.11	0.000	-0.00048	-0.00034
Humidity	-51.41816	10.58070	-4.86	0.000	-72.16209	-30.67423
Constant	5177.12000	976.08630	5.30	0.000	3263.46000	7090.78000

Based on the outcome of the Hildreth-Lu test and the corresponding regression estimators it is possible to conclude that the estimators are unbiased and efficient with respect to the serial correlated residuals.

6.3.1.6 TS6: Normal distributed errors

Errors should be independent of the explanatory variables and normally distributed with a zero mean Normal(0, σ^2). Typically a residual plot of the error term can indicate normality. Moreover, the Shapiro Wilk test can be used to test for normality of the error term, where the null hypothesis is: the error terms are normally distributed; and the alternative hypothesis is: the error term is not normally distributed. However, the Shapiro-Wilk tends to have high statistical power in the presence of very large number of observations, and thus can instantly reject the null hypothesis although the residuals do appear to be normally distributed, graphically. Reasons behind non normal residuals are that the independent variables are not linearly related to the dependent variable. Transformation of the independent variable and the dependent variable can serve as a solution to the non-normal errors, which was already executed in the linearity condition check (TS1). However, it is important to note that the condition: the error term is normally distributed is equivalent to the assumption that the distribution of the dependent variable is normal given the independent variables (X1, X2, X3 etc.). Often, it is easier to carry on with the assumption that the distribution of the dependent variable is normal than with that of the unobserved error term (u). Following that line of thought, it is reasonable to conclude that the average of the dependent variable follows a normal distribution based on the central limit theorem, since the sample size is larger enough (Bollerslev, Engle, & Wooldridge, 1988).

Having checked all the time series regression conditions and have applied a mitigation if needed for the PV output regression model, from section 6.3.1.1 to section 6.3.1.6, it is safe to proceed with presenting the PV output regression model results.

6.3.2 PV Output Regression Model Results

The **Newey-West standard errors** and **the Hildreth Lu test**, both estimated the same correlation coefficients for the four regressors. Therefore, the regression model, after having satisfied all the six time series conditions, is presented in Table 19 with an adjusted R^2 of 90%. This implies that with the applicable regressors, 90% of the variance of PV output is explained, which indicates that the model can be considered as of good quality.

Table 19: Final PV regression model after undergoing Hildreth-Lu test

PVoutput	Coef.	Std. Err.	t	P>t	95% Conf. Interval	
(PVoutputLag1)	0.340	0.008717	39.03	0.00	0.32314	0.3573
Interaction Term	0.001707	0.0000232	73.54	0.00	0.0016618	0.001752
Temperature^3	-0.0004148	0.0000373	-11.11	0.00	-0.0004879	-0.0003416
Humidity	-51.418	10.5807	-4.86	0.00	-72.162	-30.67
Constant	5177.12	976	5.30	0.00	3263.46	7090.78

The regression model for the PV output can be written as follows:

$$\widehat{\boldsymbol{PV\ output}} = 5\widehat{177.12} + \widehat{0.34} * (\text{PVoutput})\text{L1} + 0.0\widehat{01707} * (\text{TotalPVcapacity} * \text{Radiation}) - 4.1\widehat{48 * 10}^{-4} * \text{Temperature}^3 - 5\widehat{177.12} * \text{Humidity}$$

The following graphs (**Figure 15 and Figure 16**) present the predicted PV output (W) using the above described regression model, and the actual/observed PVoutput (W). The representation of the model indicates that in some moments in time, the PVoutput is underestimated in comparison to the actual, and in some other time it is overestimating (Figure 16). Reasons behind this imperfect prediction is that (1) the model is explaining/predicting 90%, (2) the weather station from which the data (radiation, humidity, temperature) were extracted belongs to the city Berkhout, which is nearby Heerhugowaard but not in the city of Heerhugowaard, (3) the root mean squared error (the standard deviation of the unexplained variance), (4) the cloud shade data which is not available and thus could not be included in the model, (5) other exogenous factors that could explain the PV output but were not added to the model could be the tilt angle of the panels on the roofs , the position of the panel with respect to the sun (the azimuth angle which is the compass direction of the sun which changes over the day and over the year).

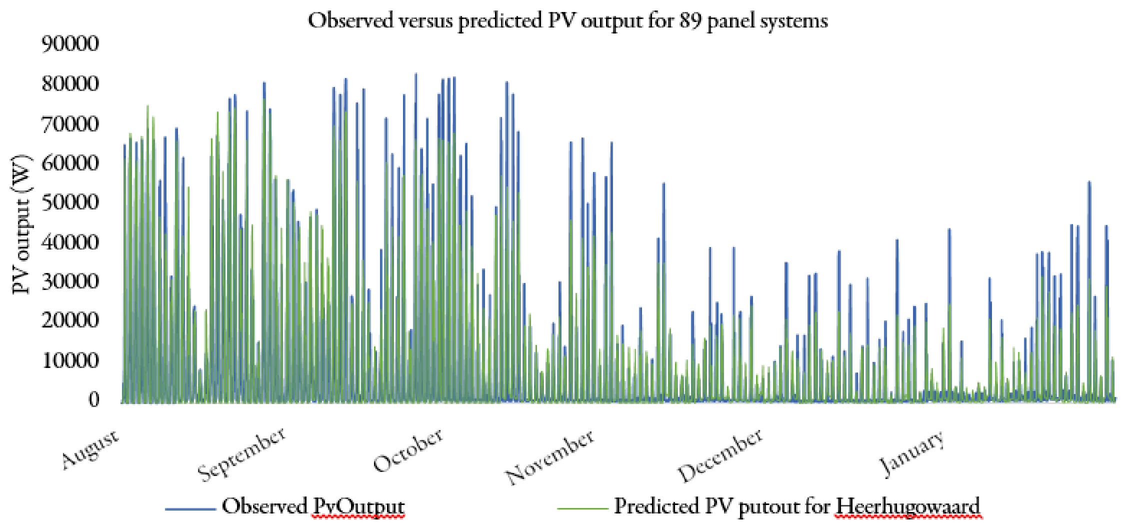


Figure 15: Actual PV output versus Predicted PV output from Aug 2015 till Jan 2016

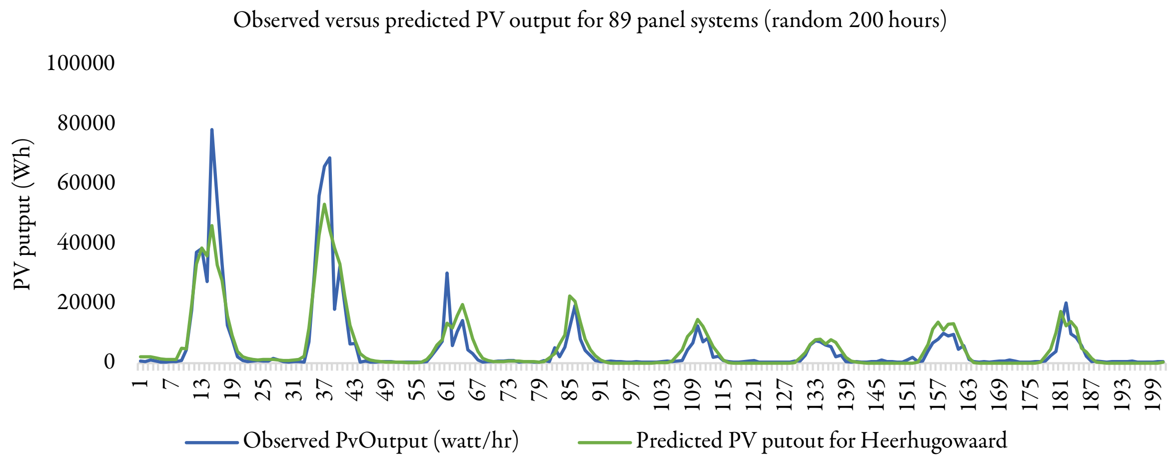


Figure 16: Actual PV output versus Predicted PV output

However, even though that the regression model performs well for predicting the PV-Output on which the regression model was built, that does not imply that the model will also predict accurately for other PV-systems. In order to validate the PV-Output model, a validation procedure is performed in the next section.

6.3.3 PV Output Regression Model Validation

The validation process allows a researcher to verify if the prediction model does not only behave according to expectation but also if the predicted values are comparable to the observed values in other PV systems. In order to validate the prediction model for the PV output, the model is used to predict the PV output for a different PV system where afterwards these results are statically compared to the measured output.

The PV system selected for the validation process is a PV system containing 440 solar panels with a capacity of 240 watt each, installed in the city of Harmelen (PV Output free data set). Due to the lack of weather data from the city Harmelen, weather data from city De Bilt, which is the nearest to Harmelen with available weather data, were extracted from the KNMI data server for year 2015. Thus, using the regression model for the PV output, the data from De Bilt city were used for Humidity, Temperature, and Radiation, while the TotalPVcapacity was substituted with (440*240Watts). Finally, the predicted data computed from the regression model for Harmelen city over the year 2015 was compared to the measured data for validation, as shown in Figure 17. Graphically, both curves look similar and overlapping.

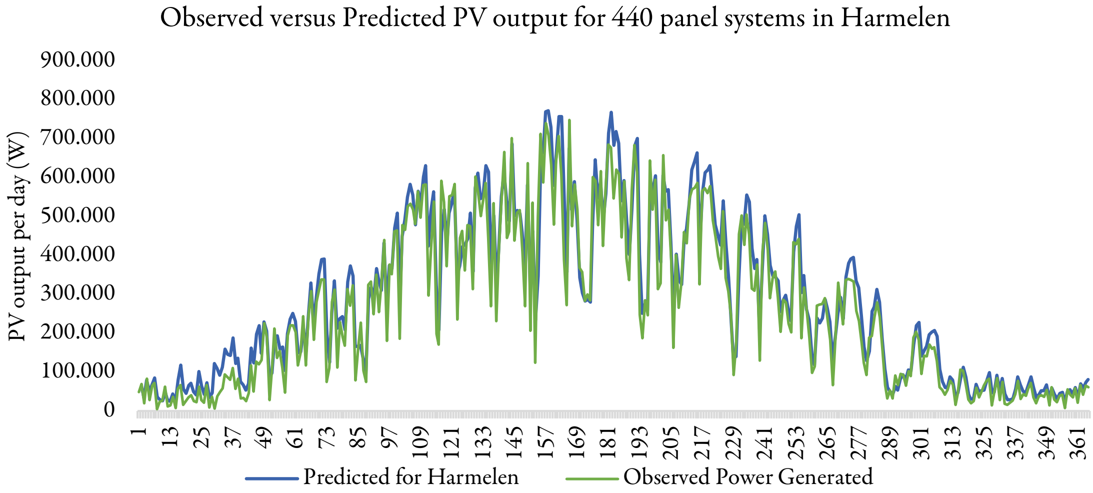


Figure 17: Observed versus predicted PV output per day for a year for Harmelen city for 440 panels

However, statistical testing is needed to draw a statistical conclusion with respect to the predicted versus observed data, a Two-sample Kolmogorov-Smirnov test for equality of distribution is computed with the following hypothesis:

H0: the two curves come from a common distribution
H1: the two curves do not come from a common distribution

The test is a non-parametric test which is considered powerful and sensitive to the difference between the curves without having to specify the common distribution assumed (Hazewinkel, 2001). From analyzing the exact P-value (significance 0.06) from the combined K-S, it can be derived that that the null hypothesis cannot be rejected and thus the two curves come from a common distribution.

However, it is important to note that Figure 17 shows some differences between the two curves which can be justified as follows:

1. The PV regression model was built for 89 panel systems scattered over the roofs of residential households, while the data that was measured from Harmelen is for 440 panels located side by side in one area. Thus, the cloud shadow that may affect few panels of households, it may entirely cover the 440 panels which are located in one area. Thus, the constructed model can overestimate the PV production if applied to panels located in one area, as proven in Figure 17.
2. The model was used to predict for a population of 440 panels which thus affect the margin of error and the confidence interval.

Based on the analysis performed in chapter 5, combined with the validation results, it is possible to conclude that the PV-Output model is not only valid but can be also used for other low voltage grids in the Netherlands. This is because neither the socio-demographics, nor the household energy consumption have any influence on the prediction model.

6.4 Econometric considerations and Modelling of the Electric Boiler

The electric boiler provides flexibility through the heating of the water, which is consumed by the household. As was introduced in chapter 5, it is not the electric boiler load that is uncertain, but the hot water consumption from the households. Consequently, the purpose of predicting hot water consumption is to estimate the Electric Boiler load. However, initial analysis of the data on hot water consumption, taken from the sample of Heerhugowaard, indicates a high level of noise and disturbances due to the following reasons:

1. The Electric Boiler default status is always off and it is turned on for charging when flex is ordered
2. The electric boiler is not the main apparatus for heating the water (the gas-heated "CV-kettle" is the main source for heating)
3. Data from the CV-kettle is not available
4. When the EB is charging it is not possible to observe hot water consumption
5. When the EB is ordered to charge for few PTUs, the EB may not have charged fully.

Thus, in order to ensure an appropriate prediction of the household hot water consumption, another data sample was acquired from the Almanac of Minutely Power Dataset (AMPds). This dataset contains minutely measured information on hot water consumption for one household in Canada and does not contain any missing data points. Furthermore, the household uses an instant hot water unit that uses natural gas, and consequently does not influence any other measurements in the households, as for example electricity consumption, as would be the case in the Heerhugowaard field experiment. However, the consequences of using data from outside the Netherlands results in different hot water consumption patterns, different household habits, and different weather influences (Makonin et al., 2013). As this deviation is known beforehand, the model will be adjusted in order to correct for disparities between the two countries and to ensure the model can be used reliably for the Netherlands.

In order to estimate a prediction model for the hot water consumption and subsequently for the load of the electric boiler, the hypothetical determinants described in section 5.2 will be included. However, since not all demographical variables are present, the household load (watt) is used as a proxy, alongside the weather data (relative humidity and temperature). The purpose of adding weather variables and the household load (Watt) to the prediction model is to capture any deviation from a typical hot water consumption pattern and the household behavior, respectively. Moreover, in order to capture the hot water consumption habits of the household and their lifestyle, hourly dummies were used as explanatory variables, as was also indicated by Granger et al. (1979), who performed research on the residential load curves and used hourly dummies to capture the household lifestyle requirements. Additionally, the first hour of the day was omitted to act as a benchmark for other hours to be compared to a base period of reference.

In the previous section (6.3), time series data was used in combination with OLS regression to estimate efficient and unbiased estimators for the Photovoltaic system output; however, for the prediction of the hot water consumption, because the data is considered count data, such an approach is insufficient. Consequently, **section 6.4.1** introduces an alternative approach that allows the estimation of unbiased and efficient estimators on count data. After the introduction and estimation of hot water consumption estimators, **section 6.4.2** presents the final hot water consumption regression model. In addition, as with the PV prediction model, the model must be validated before used within practice to predict the hot water consumption. Consequently, this will be addressed last in **section 6.4.3**.

6.4.1 Count Data Regression Models

Initial analysis of the hot water consumption distribution indicates that instead of a normal distribution, the hot water consumption portrays the histogram presented in Figure 18, where most of the observations fall within the 0 till 50 liter range with only a small amount of observations beyond that. Due to this high number of zeros, and the limited amount of other possible values, linear regression cannot be employed as this technique would fail to capture these zeros accurately. Consequently, hot water consumption is considered as count data. One of the properties of count data is non-negative integers and having a sample that is concentrated on small discrete values. Hence, this transformation to discrete numbers is required in order to perform count data modelling by means of Poisson or Negative

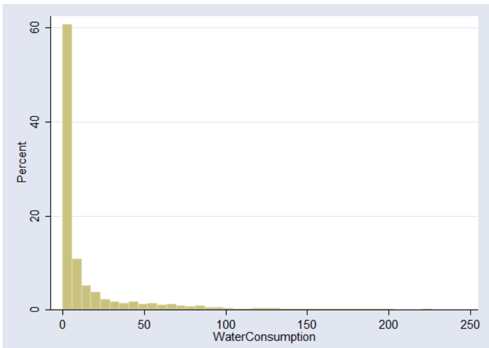


Figure 18: A Histogram of the Hot Water Consumption

Binominal Regression, otherwise such technique cannot be employed (Faraway, 2005).

In order to model count data, Poisson regression is often used, as Poisson models are capable of predicting the number of occurrences of an event and estimates the maximum likelihood of occurrence. The probability equation of the Poisson is:

$P(x\backslash\mu) = \frac{e^{-\mu} * \mu^{x}}{x!}$, where μ is the mean of the distribution and x is the number of occurrences.

One of the requirements to use Poisson regression is that the mean is equal to the variance of the data distribution:

$$E(y|x) = var(y|x) = u$$

Usually this condition does not hold in practice as mostly the variance is bigger than the mean. This violation is also present within the analysis of the Hot Water Consumption as the mean equals 15.501 and the variance equals 843.66. Consequently, there is a need for a more flexible approach in order to deal with this dispersion in the data. Such an approach is available and referred to as the **Negative Binomial Model**. Moreover, in the case of hot water consumption, there is an over dispersion of zeros, which implies that there are more zeros than a Poisson model usually predicts. The over dispersion may lead to over-confidence in the results and more type one errors (Cameron & Trivedi, 1998). Thus, it is required to use Negative Binomial models to correct for this issue.
One of the more flexible and less restrictive properties of the **Negative Binomial Models**, in comparison to Poisson, is that the variance can exceed the mean:

$$var(y|x) = \mu + \varepsilon, \text{ where } \varepsilon = \alpha\mu^2$$

$$\mu = e^{(\sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_i)}$$

While the Poisson distribution is fully characterized by the mean μ, the negative binomial is characterized by two parameters: the mean, μ, and the parameter α. Thus, when estimating the negative binomial model, over dispersion can be investigated by studying the parameter α. To test whether α is significantly different from zero, the following null and alternative hypotheses are used:

H0: when α=0, then Poisson model
H1: when α>0, then over-dispersion, when α<0, then under-dispersion

Table 20 shows that the standard deviation of the dependent variable hot water consumption is higher than the mean, then the variance will surely be more than the double of the mean and thus it suggests an indication of over dispersion, which Poisson distribution may not be able to compensate (Cameron & Trivedi, 1998).

Table 20: Summary statistics of the dependent and independent variables

	Observations	Mean	Std. Dev	Min	Max
Hot water consumption (liter)	8760	15.62	29.07	0.00	227.00
Temperature	8760	10.46	5.73	-5.10	27.60
Relative Humidity	8760	75.78	12.85	28.00	99.00
Household load	8760	1131.83	697.76	403.17	5784.42

Although, Poisson distribution may not be the correct regression approach, a Poisson model is estimated (Table 74**, in Appendix A.6.**).

It is important to note that during the estimation the constant was suppressed in the Hot Water Consumption regression model. Regression through the origin was imposed because when X_i=0, it is expected that the y is zero. Two types of zeros exist, zero because there is no hot water consumption and zero because the heating unit is off. Hot water consumption activity is restricted to showering, bathing, washing dishes, cooking, cleaning, teeth brushing, and laundry washing which requires the presence of inhabitants at home. Thus, it is rational to assume a zero intercept, which means no hot water consumption without the presence of inhabitants. **Since, the duration and frequency of the activities that require hot water are not recorded, the variables used to run a Poisson Regression for Hot Water Consumption are: Outside air temperature, relative humidity, household load, and the hourly dummies.**

To assess the fitness of the observations of the Poisson model, Table 21 presents the results from the chi-square goodness-of-fit test which was performed and assumes the following null and alternative hypothesis:

H0: The data are consistent with the assumed distribution.
H1: The data are not consistent with the assumed distribution.

The large and significant value of the goodness of fit tests in show that the Poisson distribution is not the right model, since the ($P < 0.05$) and thus the null hypothesis can be rejected.

Table 21: Goodness-of-fit chi-square test

Deviance goodness-of-fit =	3175816
Prob > chi2(136802)	0.000
Pearson goodness-of-fit=	4668963
Prob > chi2(136802)	0.000

To test for over-dispersion, where the variance exceeds the mean, and whether **negative binomial distribution** is a good fit, a negative binomial model is estimated. One of the disparities between Poisson and Negative Binomial is that, if the distribution is over dispersed, the confidence interval for the coefficients is narrower for the Negative Binomial model in comparison to the Poisson model. The results tabulated below (Table 22) prove that the confidence interval is narrower. Furthermore, the maximum likelihood of (α) is calculated and the Chi-Square test proves that alpha (α) is significant (last row in Table 22) and thus the **Negative Binomial model is more appropriate than the Poisson regression model.**

Table 22: Negative Binomial Count Data Regression for Hot Water Consumption

Rounded Hot Water Consumption		Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Temperature		0.028747	0.000356	80.85	0	0.0280505	0.0294443
Relative Humidity		0.027287	0.000102	267.68	0	0.0270869	0.0274865
Household Load Watt		0.000122	3.40E-06	35.76	0	0.000115	0.0001283
Hour	**2**	1.16472	0.014729	79.08	0	1.135853	1.193587
	3	1.259349	0.014234	88.47	0	1.23145	1.287248
	4	1.220698	0.01344	90.82	0	1.194355	1.24704
	5	1.276064	0.012465	102.37	0	1.251634	1.300495
	6	1.431146	0.011114	128.77	0	1.409363	1.452928
	7	1.632217	0.010431	156.48	0	1.611773	1.652661
	8	1.888777	0.009662	195.49	0	1.86984	1.907714
	9	2.034842	0.00949	214.42	0	2.016242	2.053442
	10	2.101659	0.00944	222.63	0	2.083156	2.120161
	11	1.883125	0.010682	176.3	0	1.862189	1.90406
	12	1.711635	0.012992	131.74	0	1.68617	1.7371
	13	1.428188	0.017921	79.69	0	1.393063	1.463313
	14	0.407053	0.046301	8.79	0	0.316305	0.4978011
	15	-0.34725	0.113692	-3.05	0.002	-0.5700825	-0.124417
	16	-0.4491	0.151564	-2.96	0.003	-0.7461605	-0.1520426
	17	0.515454	0.074513	6.92	0	0.3694113	0.6614971
	18	0.546609	0.045832	11.93	0	0.45678	0.6364379
	19	0.760457	0.02005	37.93	0	0.7211589	0.7997545
	20	0.689127	0.016896	40.79	0	0.6560123	0.7222414
	21	0.8091	0.013821	58.54	0	0.7820121	0.836188
	22	0.939232	0.014052	66.84	0	0.9116915	0.966773
	23	1.148867	0.014048	81.78	0	1.121335	1.1764
	24	0.767806	0.015629	49.13	0	0.7371743	0.7984384
/lnalpha		**-0.7545**	**0.003811**			**-0.7619653**	**-0.747028**
alpha		**0.470247**	**0.001792**			**0.4667482**	**0.4737725**
Likelihood-ratio test of alpha=0: $\chi^2 = 2.6e+06$ Prob>=chibar2 = 0.000							

Based on the analysis performed, the Negative Binominal model was estimated to be more appropriate than the Poisson regression model. Consequently the results from this analysis and the estimated model are presented in the next section.

6.4.2 Hot Water Consumption Regression Model Results

Through means of Negative Binominal regression, regression coefficients were estimated in order to predict the hot water consumption based on the Temperature, Humidity, Household load and Hourly dummies. Based on these estimators and the correction required for Negative Binomial Regression, the hot water consumption prediction model can be formulated as:

$$\widehat{Hot\ Water\ Consumption}\ (liters) = exp(0.\widehat{028}747 * Temp + 0.\widehat{027}287 * Humidity + 0.\widehat{000}122 * HouseholdLoad + \widehat{B}_i\ HourlyDummies)$$

Where the coefficients can be interpreted in the same way as in Poisson Regression Modelling. Thus, a one degree increase in temperature leads to a 2.88% increase in hot water consumption (liters) (Table 22).

For the sake of comparison, the predicted ŷ is summarized in Table 23. The summary in Table 23 shows that the average of the predicted versus the measured is roughly the same; however, what's important is the individual prediction of each observation. Moreover, the results in Table 23 show that the regression model cannot fully capture the maximum and minimum values.

Table 23: Summary of the predicted versus the observed Hot Water Consumption

Variable	Observations	Mean	Std. Dev.	Min	Max
Predicted ŷ (liters)	8,759	15.89526	18.34058	3.16	125.6099
Hot Water Consumption measured (liters)	8,760	15.61975	29.07199	0	227

In order to investigate the individual prediction, Figure 19 presents the Hot Water consumption (liters) and the measured/observed Hot Water consumption (Liters) using the estimated Negative Binomial model. The model (Figure 19) shows that in some moments in time, the Hot Water consumption is underestimated in comparison to the actual, and in some other time it is overestimating. Reasons behind this imperfect prediction could be the socio-demographic variables that were not added to the model, due to lack of data.

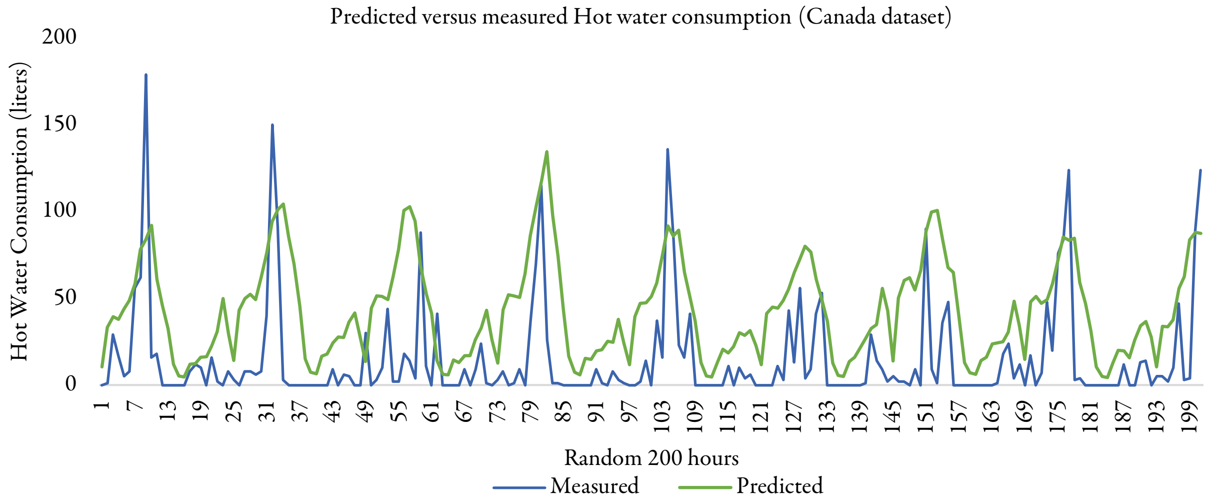


Figure 19: Predicted versus measured Hot water consumption (liters)

The presented hot water prediction model is based on one household in Canada and thus, before attempting to validate the model, the model is corrected to approach the water consumption for the Netherlands. Because the prediction model is incapable of capturing the zeros as the minimum is 3.16 liters, 3.16 liters shall be subtracted from the predicted ŷ. Additionally, to correct for the disparities between the average hot water consumption for this household in comparison to the average Hot water consumption in USA/Canada, and consequently that in the Netherlands, the following steps are executed:

1. The average predicted hot water consumption per day from the one year predicted data, acquired from the AMPds dataset, was calculated and turned out to be 1000.2 liters. Unfortunately, no information is available regarding the number of occupants in the household, and thus it cannot be inferred this average predicted hot water consumption per day is for how many occupants.

2. Referring to the average estimation of hot water use in North America's households presented at 2015 ASHRAE conference, the average household hot water use is 193 liters per day. This average is associated with 2.8 occupants per household (Parker & Fairey, 2015).
3. To compute the correction factor of the average hot water user per day for the household, the 1000.2 predicted average (liters) is divided by 193 (liters) to give 5.18.
4. The average hot water use per day in the Netherlands is roughly 85.6 litters for an average of 2.8 occupants (TNS NIPO, 2014). Thus, to compute the correction factor of the average hot water usage per day for the household, the 193 (USA average) (liters) is divided by the 85.6 (Netherlands average) to give 2.25.
5. The average number of occupants in the Netherlands is 2.1 and the hot water use per day is roughly 70 litters (Defra, 2008). Thus, to compute the correction factor of the average hot water usage per day for the household, the 85.6 (Netherlands average for 2.8 occupants) is divided by the 70 (Netherlands average of 2.1 occupants) to give 1.23.
6. Finally the correction factor that should be applied to the model in order to make it applicable for the Netherlands is: $5.18 * 2.25 * 1.23 = 14.33$

Thus, the new regression model to be written as follows:

$$Hot\ Wat\widehat{er\ Consumpt}\imath on\ (liters) = \frac{\left(exp\left(0.0\widehat{28}747 * Temp + 0.0\widehat{27}287 * Humidity + 0.0\widehat{001}22 * HouseholdLoad + \widehat{B_\imath}\ HourlyDummies\right)\right) - 3.16}{14.33}$$

Even though that this model has been corrected for the Netherlands household water consumption, this does not imply that such a model is also valid for use. In order to determine the validity of the prediction model, validation is performed in the next section.

6.4.3 Hot Water Consumption Regression Model Validation

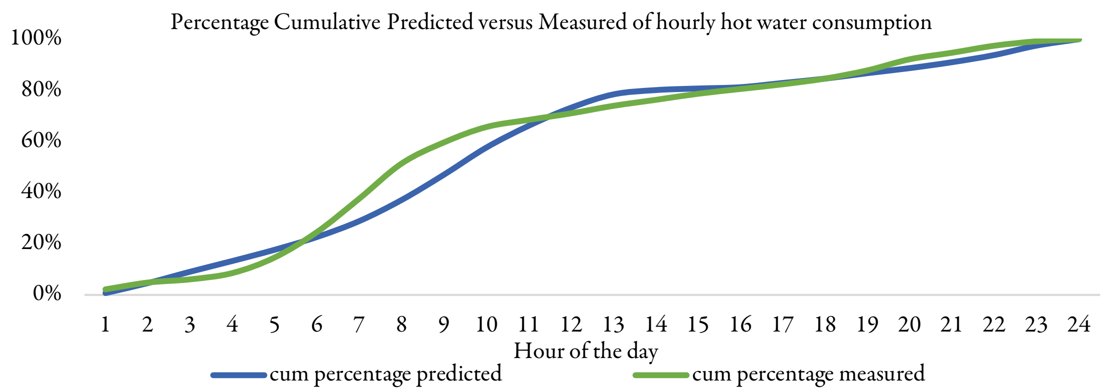
After the prediction model for the hot water consumption underwent correction in order to represent the average Dutch household, validation must be performed in order to verify if the regression model is representative to the Netherlands' average household hot water consumption pattern and weather. Accordingly, the following steps are undertaken:

1. The 44 households with EBs from the Heerhugowaard field experiment were considered for validation. The measured household loads of the 44 households, from August 15/2015 till Jan 29/2016, were averaged to get an average hourly household load for that period.
2. The average hourly household load (W) was substituted in the computed regression model. Weather data (Humidity and temperature) for Berkhout city, the nearest city to Heerhugowaard with available weather data, was substituted in the regression model.
3. Percentage hourly water use for a single family in the Netherlands was retrieved from a paper published by Blokker et al. (2009) where domestic water demand was simulated through means of a stochastic model. The extracted data is present in **appendix A.7, Table 75**.
4. The hourly prediction was averaged and compared to the percentage hourly measured for a single family in the Netherlands. The following graph (Figure 20) shows the percentage cumulative predicted hot water usage versus the measured. The predicted data does not fully overlap the measured data; however, statistical testing is needed to confirm/negate any observations inferred from the graph.
5. The Wilcoxon rank-sum test (Mann-Whitney) was performed to test for the following null and alternative hypothesis

H0: data from both samples come from a common distribution
H1: data from both samples do not come from a common distribution

The tests results in a z score of 0.072, which indicates that the null hypotheses cannot be rejected at a 5% significance level (the test results are presented in **Appendix A.7. Table 76**).

Figure 20: Percentage Cumulative Predicted versus Measured of hourly hot water consumption



Based on the analysis performed in chapter 5, combined with the validation results, it is possible to conclude that the Electic Boiler model is not only valid but can be also used for other low voltage grids in the Netherlands.

6.5 Econometric considerations and Modelling the Heat Load

To predict the flexibility that is available from the heat pumps at the congestion level, it is vital to capture the heat pump's two functions: (1) preserving the home temperature and (2) heating the tap water. In order to estimate a regression model that can predict the heat load for preserving the home temperature, the independent variables introduced in section 5.3 will be taken into consideration. However, as with the earlier presented regression models, it is not possible to take all hypothesized relations into account. For example, the energy grade, household insulation, house size, and indoor temperature are not available.

To capture flexibility available when the heat pump is preserving the home temperature (but not the tap water), a time series regression model is estimated using the following explanatory variables (as explained in section 5.3):

- radiation lagged 6 hours (J/cm^2)
- relative humidity (%)
- wind speed (m/sec)
- number of heat pumps
- heating required (°C)
- an interaction term (the number of heat pumps on * heating required)
- outdoor temperature (°C)

The "heating required" is the difference between the measured temperature and a threshold of 18 degrees Celsius (calculated as follows, by using the if-then-else script: if$(18 - temp > 0, 18 - temp)$, and if$(18 - temp < 0, 0)$. According to Hart and de Dear (2004), the average daily temperature is considered the most appropriate base heating requirement. Hence, the heating required (18 °C – temp), is considered as one of the predictors of the heat load. Therefore, the "heating required" predictor is: 18 °C – temp-outdoor. As the difference between the threshold temp (18 °C) and the outdoor temperature increase, the heat load (Watt) is expected to increase. Moreover, the heat load (W) interacts directly with the number of Heat pumps on. Hence, an interaction term is added that constitutes "the number of heat pumps on" and "the heating required". Furthermore, the 6 hour lagged radiation independent variable is inferred from a cross-correlation of a bivariate time series between radiation and the dependent variable (HeatLoad). The cross correlation, via STATA (Table 24), shows that at lag 6, a stronger negative correlation persists between lagged radiation and HeatLoad. As mentioned earlier in section 5.3, and published by Figueira et al. (2003), the irradiance takes 4 to 5 hours to transfer the heat through the walls. Since, the energy class of the houses in Heerhugowaard are overall higher than the average energy class in the Netherlands, the 6 hour lag can be justified.

Table 24: Cross-Correlation between Radiation and Heat Load

LAG	-6	-5	-4	-3	-2	-1	0
[Cross-correlation]	-0.1883	-0.1862	-0.1847	-0.1741	-0.1699	-0.1633	-0.1504

With the proposed set of independent variables, estimation can be performed in order to construct a Heat Load prediction model for predicting the load for indoor heating. Accordingly, section 6.5.1 first addresses the conditions for time series regression and applies the required transformations and corrections to achieve an unbiased and efficient estimated model. Last, section 6.5.2 presents the outcome of the regression analysis and presents how the model might be used to predict the heat load.

6.5.1 Time series conditions and verification for the Heat Load

As one of the conditions for time series analysis it is essential to determine if the data has a constant mean and variance over time (stationary), as discussed in section 6.2.1. Consequently, before any time series conditions are investigated the Augmented Dicky fuller test is performed (Table 25).

Table 25: Augmented Dickey-Fuller test for unit root for Heat Load

Augmented Dickey-Fuller test for unit root			**Number of obs. =**	**4094**
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-21.069	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000				

According to the p-value, the zero hypothesis (the time series has a unit root – non-stationary) is rejected and thus it can be concluded that the series is stationary.

As the Augmented Dickey Fuller test has proven that the data is stationary it is possible to move to the verification of the time series regression for the Heat Load prediction model. As already introduced in section 6.3.1, the time series model is investigated for (1) Linearity in parameters, (2) No perfect collinearity, (3) Strict Exogeneity, (4)Homoscedasticity, (5) No Serial Correlation and (6) Normally distributed errors, which will be addressed in **section 6.5.1.1** through **section 6.5.1.6**.

6.5.1.1 TS1: Linearity in parameters:

To check whether the dependent variable is a linear function of the explanatory variables, a graphical representation (scatter plot) and (augmented component plus residual plots) were analyzed for all independent variables. Consequently, a bivariate analysis is performed to determine if the relationships between the dependent and the independent variables are not only present but also significant and consequently allows one to draw a conclusion with respect to the direction of the relationship. Since the dependent variable (heat load) and the independent variables are interval/ratio level of measurement, the Pearson's correlation coefficient test (parametric test) is performed. Table 26 shows the bivariate correlation between the heat load and the independent variables.

Table 26: Bivariate Correlation between the Heat Load (dependent variable) and the independent variables

HeatLoad (Watt)	Adjusted R^2	Significance	Direction of relationship
Interaction Term (# of heatpumps on* heating required)	51.12	0	Positive
Humidity	15	0.007	Negative
Radiation Lagged 6	4.3	0	Negative
Wind Speed	3.96	0	Positive
Number of heatpumps ON	56.11	0	Positive
Heating required (180-measured temp)	21.24	0	Positive
Temperature	22.27	0	Negative

It can be concluded that all the identified variables are significant. Thus, the bivariate correlation analysis results in the following accepted alternative hypothesis:

- The more the interaction term (# of heatpumps on* heating required), the more the Heat Load
- The more the humidity, the less the heat load
- The more the radiation lagged 6, the less the heatload
- The more wind speed, the more the heatload
- The more the heat pumps on, the more the heat load
- The more the difference between the measured temp and the 18 degrees threshold, the more the heatload
- The more the temperature, the less the heat load

Thus, the latter are the independent variables to be used in the multivariate regression model in order to predict Heat Load.

6.5.1.2 TS2: No perfect collinearity:

Perfect collinearity occurs when a variable is a multiple of another, and thus has zero tolerance (the inverse of VIF). Due to the "Enter" method employed in STATA, there is a risk of perfect collinear independent variables, and consequently, collinearity is investigated. To test whether any of the variables are collinear with the other variables, a multivariate regression analysis is performed in STATA (Table 27), and the results showed a flipped sign for the variable Heating required (180-measured temp), which may be caused by collinearity, and insignificant coefficients for temperature and number of heat pumps on. The results of the multivariate regression model with the significant regressors are tabulated below, using the "Enter" method employed in STATA.

Table 27: Multivariate Regression Analysis for the Heat Load

HeatLoad	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Interaction Term (# of heatpumps on* heating required)	1.111824	0.0177907	62.49	0.0000	1.0769	1.146704
Radiation L6	-1.715799	0.4402286	-3.90	0.0000	-2.578887	-.8527112
Humidity	-7.890768	0.6067972	-13.00	0.0000	-9.0804	-6.701115
WindSpeed	10.70296	0.7082357	15.11	0.0000	9.3144	12.09148

It is important to note that the constant was suppressed in the Heat Load regression model. Regression through the origin was imposed because when Xi=0, it is expected that the y is zero. Heat load is restricted to having the heat pumps on. Thus, it is rational to assume a zero intercept. The R^2, a statistical estimation of how fitted the data is to the regression model, turned out to be 70.52%.

To check for perfect collinearity, the VIF values and the tolerance (1/VIF) values are calculated. Table 28 shows that all the regressors have high tolerance (no perfect collinearity) and thus each explains unique variance of the dependent variable.

Table 28: Collinearity check

Variable	VIF	1/VIF
Humidity	1.23	0.810570
Interaction Term	1.15	0.872047
Wind Speed	1.13	0.883756
Radiation L6	1.22	0.820409

6.5.1.3 TS3: Strict Exogeneity (zero conditional mean):

To satisfy the conditions of weak exogeneity, where the error term should be independent and uncorrelated with the independent variables at the current moment in time, the correlation between u_t and X_t is tested as showed in Table 29.

Table 29: Correlation between the error term and the independent regressors for the Heat Load Model

	Residuals	Interaction term	Humidity	Radiation L6	Wind Speed
Interaction term	0.0000	1			
Humidity	0.0000	0.2338	1		
RadiationL6	0.0000	-0.3166	-0.2794	1	
Wind Speed	0.0000	0.0643	-0.2507	-0.1415	1

The results proves that the correlation coefficient is zero between the residuals (the error term) and the independent variables, as marked in red. The weak exogeneity condition is satisfied; however, strict exogeneity, where the error term should be independent and uncorrelated with the independent variables at all periods of time, does not need to be satisfied since time series data correlations between the dependent variable and lagged versions of itself may exist, whether tested as significant or non-significant.

6.5.1.4 TS4: Homoscedasticity

To test whether the variance of the dependent variable (Heat Load), is constant over the fitting line and independent of the regressors across all time periods, the Breusch-Pagan test for heteroscedasticity is performed (as explained in the PV regression model in section 6.3.1. The Breusch-Pagen test indicates with a χ^2 of 466.56 that the residuals are significantly heteroscedastic. Hence, since the Breusch-Pagan test for heteroscedasticity rejects the null hypothesis, and thus one can conclude that the variance is not constant over time and is dependent on the explanatory variables. Since the cause behind heteroscedasticity is not known and implementing multivariate regression with heteroscedasticity gives unbiased but inefficient results, correcting for heteroscedasticity by performing **Newey-West standard errors** is a must. The results for **Newey-West standard errors test** are tabulated below (Table 30):

Table 30: Newey West Standard Error Regression

HeatLoad	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Interaction Term	1.111824	.0175113	63.49	0.000	1.077492	1.146156
Humidity	-7.890768	.5251348	-15.03	0.000	-8.92031	-6.861217
Radiation L6	-1.715799	.2948812	-5.82	0.000	-2.2939	-1.137671
WindSpeed	10.70296	.7738113	13.83	0.000	9.18586	12.22005

Thus, it can be trusted, after performing the Newey-West standard errors, that the estimated coefficients are unbiased and efficient estimators.

6.5.1.5 TS5: Serial Correlation:

To test whether the error term is independent of the lagged variables of the error term, in other words white noise, the Breusch-Godfrey Lagrange multiplier test is performed. The test results show that the zero hypothesis can be rejected and thus the error terms are serially correlated for more than the first order (results are presented in **Appendix A.8 in Table 77**). Having serial correlation between the error terms can lead to spurious results, thus Prais Winsten test is performed as a remedial measure for serial correlation. The results are tabulated as follows (Table 31):

Table 31: Prais Winsten Regression

HeatLoad	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Interaction Term	0.996958	0.030317	32.89	0.0000	0.937522	1.056395
Humidity	-5.56193	1.04572	-5.32	0.0000	-7.61211	-3.511744
RadiationL6	-2.18674	0.698734	-3.13	0.0020	-3.55664	-0.8168389
WindSpeed	10.22549	1.196821	8.54	0.0000	7.879073	12.57191

6.5.1.6 TS6: Normal distributed errors

To test whether the residuals are normally distributed, the following residual plot of the error term is presented. The residuals of the Heat Load model looks normally distributed by examining Figure 21, which shows a little of deviance at the tails of the distribution. However, overall it can be concluded that the residuals are normally distributed.

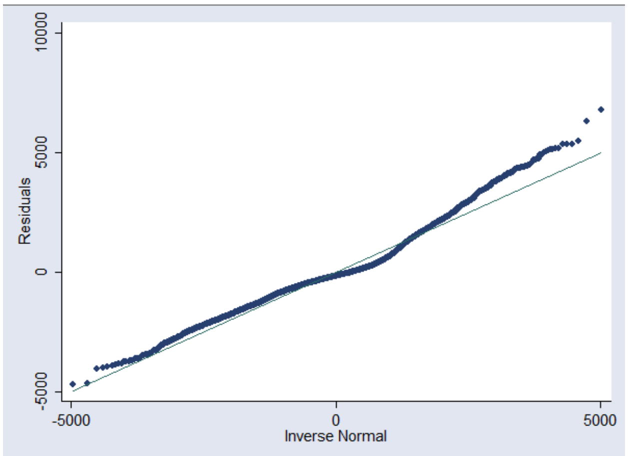


Figure 21: Normal Probability residual plot

Having checked all the time series regression conditions and have applied a mitigation if needed for the Heat Load regression model, from section 6.5.1.1 to section 6.5.1.6, it is safe to proceed with presenting the Heat Load regression model.

6.5.2 HeatLoad Regression Model Results

Having satisfied all six time series conditions, the final regression model for the Heat Load has a coefficient of determination of roughly 70%, this means that with the following independent variables, 70% of the variance of Heat load is predicted. The regression model for the heat load can be written as:

$$\widehat{\boldsymbol{HeatLoad}} = 0.\widehat{996958} * (\text{Number of HP on}) * (\text{heating required}) - \widehat{5.56193} * (\text{Humidity}) - 2.\widehat{18674} * (\text{Radiation } \mathrm{L}^6) + 10.\widehat{22549} * (\text{Wind Speed})$$

Figure 22 presents the predicted Heat Load for 50 Heat Pumps, using the above regression model, and the observed Heat Load. The figure indicates that in some moments in time, the Heat load is underestimated in comparison to the actual measured heat load, and in different points in time is overestimating. Reasons behind this imperfect prediction are: (1) the model is predicting 70%, (2) linear regression undesirable property is that it predicts within the interval of Max and Min but cannot capture the extremes especially when the data is very discrete, (3) weather station where the data (Windspeed, humidity, radiation, temperature) was retrieved from belongs to the city (Berkhout) which is nearby Heerhugowaard but not in the city of Heerhugowaard, (4) the root mean squared error (the standard deviation of the unexplained variance), (5) other exogenous factors that could not be captured such as the human behavior and liberty to schedule their heat pump and adjust the threshold temp, (6) the Heat Pump is affected by flex ordering (for instance, the Heat pump is turned off during evening peaks), while this endogeneity was captured by the state variable "number of HPs on" for each hour, it was not fully captured per PTU.

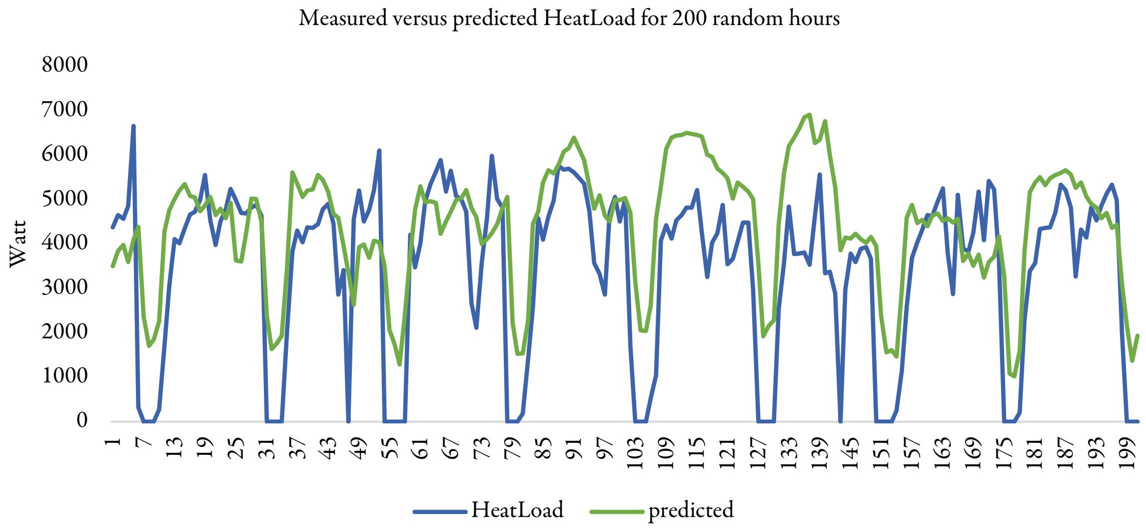


Figure 22: Measured versus Predicted Heat Load

6.6 Econometric considerations and Modelling of the Heat Pump

To capture flexibility available when the heat pump is both, preserving the home temperature and pre-heating the tap water, a time series regression model is estimated using the following explanatory variables (as explained in section 5.3), radiation lagged, humidity, household load PV corrected (watt), number of heat pumps, and an interaction term that is constituted of the number of heat pumps on, and the heating required. The "heating required" is the difference between the measured temperature and a threshold of 18 degrees Celsius, as explained in section 6.5. The household load (watt), may capture hypothetically the domestic habitual pattern of the household. The increase in household load is thus used as a proxy for the household activity, where household activity is often related to the use of hot water. The 12 hour lagged radiation is inferred from a cross-correlation of a bivariate time series between radiation and the dependent variable (heat pump load) (combined functions) (Table 32). The following tabulated cross correlation shows that at lag 12, a stronger negative correlation persists between the lagged radiation and Heat Pump Load.

Table 32: Cross-Correlagram between Radiation and Heat Pump Load

LAG	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0
[Cross-correlation]	-0.214	-0.207	-0.204	-0.203	-0.200	-0.196	-0.188	-0.179	-0.173	-0.163	-0.155	-0.139	-0.120

To test whether the heat pump load (combined) is stationary, with a constant mean and variance, and whether the covariance is independent over time, the augmented Dicky fuller test is performed (Table 33).

Table 33: Augmented Dickey-Fuller test for unit root for the Heat Pump Load

		Augmented Dickey-Fuller test for unit root		Number of obs. = 4094
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-26.831	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000				

According to the p-value, the zero hypothesis (the time series has a unit root – non-stationary) is rejected and thus it can be concluded that the series is stationary.

Analogous to heat load, having satisfied all six time series conditions, the final regression model has a coefficient of determination of roughly 75%, this means that with the following independent variables, 75% of the variance of Heat Pump load is predicted. The regression model for the heat pump load, with combined activities, can be written as:

$$\boldsymbol{Heat\ \widehat{Pump}\ Load\ (combined\ functions)} = 0.7\widehat{0685}04 * (\text{Number of HP}) * (\text{heating required}) - 1\widehat{6.78}634 * (\text{Humidity}) - 2.5\widehat{809}91 * (\text{Radiation L}^{12}) + 58.\widehat{43}59 * (\text{Household Load PV corrected}) + 12\widehat{9.93}42 * (\text{Number of Heat Pumps})$$

Figure 23 shows the predicted Heat Pump Load, using the above regression model, and the observed Heat Pump Load. The graph shows that in some moments in time, the predicted heat pump load is underestimated in comparison to the actual, and in some other time it is overestimating. Reasons behind this imperfect prediction are similar to that of the heat load, in section 6.5.2.

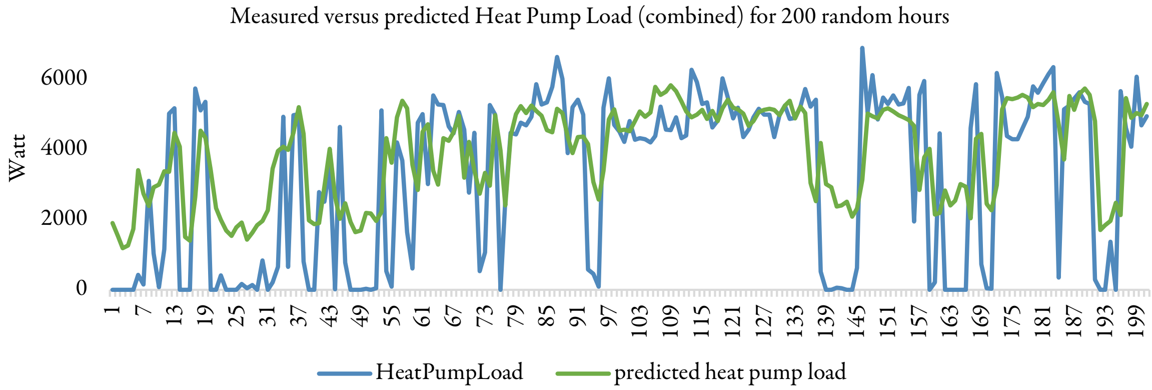


Figure 23: Measured versus Predicted Heat Pump Load (combined)

In order to validate the results from the Heat Pump prediction model, Predictive Validation is performed (Sargent, 2015). Within predictive validation, the results from the prediction model are compared to other data sources, than the data sources which were used for the regression analysis. Based on Energiekoplopers (2015), Energiesite (2016), Energieconsultant (2016) and HVP Duurzaamheid (2016), the average load of a Heat Pump is calculated to be 152 Wh in comparison to the predicted 147.44 Wh, which are very comparable. However, due to the large same size of the predicted data (8760), and consequently, the narrow confidence interval, the difference is tested to be statistically significant. Even though that this difference is statistically significant, it cannot be considered practically significant, where practical significance is defined as: "the concern whether the result is useful in the real world" (Kirk, 1996). Consequently, based on these finding, one can conclude that the prediction model is validated, and can be used for heat pump load prediction.

6.7 Flexibility Prediction Models: An Overview

In the previous sections 6.2 through 6.6 time series regression models were presented for the flex prediction of the 3 smart appliances. These models were constructed based on a set of significant independent variables, and consequently tested based on the applicable statistical requirements.

From the quantitative statistical analysis, prediction models were constructed to predict flexibility from four smart devices employed in the Heerhugowaard field trial. Generally, it can be concluded that the PV output and the Heat Pump load are time-based, have a temporal dimension, and are continuous in nature and thus **Time Series Regression** modelling is a good technique to predict PV output and the Heat Pump load. In contrast, the Electric Boiler load, which is dependent on hot water consumption, is discrete in nature and its data points are concentrated on small discrete and non-negative values with a high number of zeros, and thus **Count Data Regression** is a good technique to predict the Electric Boiler load. The energy production of a Fuel Cell is not affected by exogenous factors (not user or weather dependent), and therefore no prediction model is needed.

In order to predict the flexibility for the entire year for the congestion block levels in the Heerhugowaard field trial or for other low-voltage grids within the Netherlands, the following four regression models can be used, where Table 34, indicates the regression estimators for the PV-Output and the prediction model, Table 35 the regression estimators for the Hot Water Consumption and the prediction model, Table 36 the regression estimators for the Heat Load of the Heat-Pump and the prediction model, and last, Table 37 with the regression estimators for the Heat-Pump Load (combined functions) and the prediction model.

Table 34: The Regression Estimations for the PV-Output Regression Model

PVoutput	Coef.
(PVoutputLag1)	0.340
Interaction Term (Total PV capacity*Radiation)	0.001707
Temperature^3	-0.0004148
Humidity	-51.418
Constant	5177.12

$$\boldsymbol{PV\ \widehat{output}} = \widehat{5177.12} + \widehat{0.34} * (\text{PVoutput})\text{L1} + \widehat{0.001707} * (\text{TotalPVcapacity} * \text{Radiation}) - \widehat{4.148 * 10^{-4}} * \text{Temperature}^3 - \widehat{5177.12} * \text{Humidity}$$

Table 35: The Estimators for the Hot Water Consumption for the Electric Boiler

Hot Water Consumption	Coef.
Temperature	0.028747
Relative Humidity	0.027287
Household Load Watt	0.000122
Hourly Dummies	β_i

$$\boldsymbol{Hot\ Water\ \widehat{Consumption}\ (liters)} = \frac{\left(exp\left(\widehat{0.028747} * Temp + \widehat{0.027287} * Humidity + \widehat{0.000122} * HouseholdLoad + \widehat{B_i}\ HourlyDummies\right)\right) - 3.16}{14.33}$$

Table 36: The Estimators for the Heat Load of the Heat-Pump

HeatLoad	Coef.
Number HP on * Heating Required	0.996958
Humidity	-5.56193
RadiationL6	-2.18674
WindSpeed	10.22549

$$\boldsymbol{\widehat{HeatLoad}} = \widehat{0.996958} * (\text{Number of HP on}) * (\text{heating required}) - \widehat{5.56193} * (\text{Humidity}) - \widehat{2.18674} * (\text{Radiation L}^6) + \widehat{10.22549} * (\text{Wind Speed})$$

Table 37: The Estimators for the Heat-Pump Load (combined functions)

Heat-Pump Load	Coef.
Number of Heat Pumps * Heating Required	0.706850
Humidity	-16.78634
RadiationL12	-2.580991
Household load PV corrected	58.4359
Number of Heat Pumps	129.9342

$$\boldsymbol{Heat\ \widehat{Pump}\ Load}\ (\boldsymbol{combined\ functions}) = 0.7\widehat{068}504\ *(\text{Number of HP}) * (\text{heating required}) - 1\widehat{6.78}634 * (\text{Humidity}) - 2.\widehat{580}991 * (\text{Radiation L}^{12}) + 58.\widehat{435}9\ * (\text{Household Load PV corrected}) + 12\widehat{9.93}42 * (\text{Number of Heat Pumps})$$

Chapter 7

7 The Influence of Flexibility on Congestion Management

When studying the influence of demand-side flexibility on congestion management, a detailed step by step analysis on collected data from a low voltage grid is a perquisite prior to generalizing the impact of demand-side flexibility on congestion mitigation. Thus, the purpose of this chapter is to answer the following sub-research question, based on the **collected data** from Heerhugowaard field experiment:

What is the impact of demand-side flexibility on grid congestion at a distribution level in Heerhugowaard?

The detailed analysis entails an investigation of the goodness of prediction or, in other words, the impact of false predictions and forecast errors on flex ordered by the DSO and flex offered by the aggregator. **While a wrong forecast of weather data, or a false prediction of human behaviour can lead to an underestimation or overestimation of flexibility offered, an incorrect load forecast can lead to false flexibility ordering.** Together, error in flex ordering and flex offering, will most likely affect flex delivered, where the latter is defined as "the reliability of flex ordered versus delivered". Therefore, this requires investigating the influence of the reliability of flexibility (ordered versus delivered) and the goodness of prediction (forecast error in load prediction) on the load curve and its capability of staying within the congestion limits. The following experiments were performed in Heerhugowaard field trial in the following time periods (Table 38):

Table 38: Heerhugowaard experiments and their respective time interval

Heerhugowaard Experiments	Period
DSO ordering flex at congestion Block levels (PV, EB, HP, FC)	Nov 18, 2015 - Dec 15, 2015
DSO and BRP ordering flex at Mixture level	Dec 16, 2015 - Jan 12, 2016
DSO ordering flex at congestion Block levels (PV, EB, HP, FC)	Jan 13, 2016 - Feb 9, 2016
DSO and BRP ordering flex at Mixture level	Feb 10, 2016 - March 8, 2016

Since two of the four experiments are performed at the different congestion block levels (HP, PV, EB, & FC), as presented in Table 38, this chapter will investigate the reliability of flexibility from different device types and its effect on the load curve and the reduction in the probability of congestion based on the measured data of the loads with and without flex.

Furthermore, beyond analysing the load curve, operationalizing congestion occurrence, or in other words, the risk of the load exceeding the congestion limits, is fundamental to study the influence of flexibility steering on the probability of congestion.

Nevertheless, investigating the influence of flexibility on grid congestion at the **mixture point level** is imperative because unlike at block congestion levels, where the DSO is solely procuring, at a mixture point level both the BRP and DSO are procuring according to the USEF framework (day ahead, intraday, and operate phase). Accordingly, the reliability of flex and its impact on the grid congestion at a mixture point level will be analyzed and the risk of congestion occurrence for the load with flex steered and the load without flex is compared, based on the measured data.

Since the Heerhugowaard field experiment is performed on a **period of 4 month (2 experiments at a congestion block level and 2 at a mixture block level)**, it is fundamental to predict the probability of congestion for the load with and without flexibility steering for the entire year for the Heerhugowaard low-voltage grid and derive the probability of congestion for the different seasons at the different congestion block levels.

Therefore, the chapter is divided as follows: **Section 7.1** will study the "reliability of flex ordered versus delivered" at the congestion block levels (FC, PV, EB, & HP) based on the measured data during the two experiments' periods: Nov 18, 2015 till Dec 15, 2015 and Jan 13, 2016 till Feb 9, 2016. In **section 7.2**, the contribution of the flex steered on the load curve at the 4 different congestion block levels is calculated and analysed, based on the two aforementioned experiments. **Section 7.3** will compare the load with flex to the load without flex and the capability of keeping the load within the congestion limit. **Section 7.4,** will investigate the influence of flex steering on congestion probability and the correlation of the reliability of flex ordered versus delivered on the load exceedance from the congestion limit, based on the measured data in the two experiments. **Section 7.5**, will investigate the influence of flex steering on the probability of congestion at a mixture level point where both the DSO and BRP are procuring concurrently. In **section 7.6,** the yearly probability of congestion is predicted for the Heerhugowaard low voltage grid at the four congestion block levels based on an estimated simulation model, which has built-in device specific Regression Models created and validated in chapter 6 to predict flexibility from the smart devices for a complete year.

7.1 The Reliability of the Flexibility Ordered versus Delivered

Flexibility from different appliances are affected by different factors and the variance of demand-side flexibility from different appliances is predicted by different explanatory variables. For instance, as regression was performed earlier to predict flexibility from different devices, the PV output is affected by weather factors while the electric boiler energy consumption is affected by weather factors and human behaviour. Thus, the reliability of the flexibility delivered from the different smart devices may vary. Consequently, this section attempts to answer the following sub-sub-research question, based on measured data:

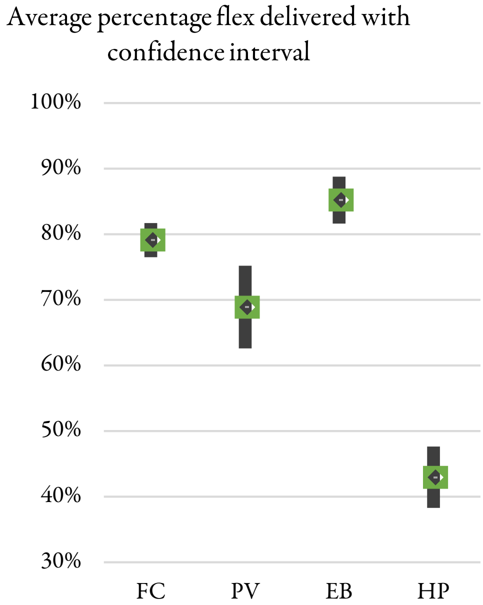
What is the reliability of the delivered flexibility of each controllable device?

To answer the sub-research question, measured data from the two experiments performed during the periods, Nov 18, 2015 till Dec 15, 2015 and Jan 13, 2016 till Feb 9, 2016, where the DSO procured flex at the four congestion block levels according to the load congestion prediction and congestion limit, are analysed and the percentage flexibility delivered is calculated as follows:

$$percentage\ delivered\ (\%) = \frac{delieverd\ flex(Watt)}{ordered\ flex\ (Watt)}$$

Figure 24 presents the average percentage flex delivered at the 4 congestion blocks for the two experiments, graphically portrayed with the average 95% upper and lower confidence interval. **Table 78, in appendix B.1** presents the detailed average percentage flex delivered for both experiments at the 4 congestion bock levels.

The graphical representation of the estimated averages indicates (Figure 24) that the average percentage flex delivered at the HP congestion level is the least among other congestion block levels, while that at the EB congestion level and the FC congestion level seems to be comparably the highest. To prove this graphical interpretation statistically, a non-parametric test is performed. A non-parametric test is chosen as not all the conditions of ANOVA, a parametric test, are satisfied since the variance of all groups is not the same, and the samples are not totally independent. The Kruskal-Wallis test is performed to check whether the groups are significantly different from each other. The Kruskal-Wallis test proved that the averages of the percentage flex delivered at the different congestion blocks are significantly different and the zero hypothesis (equal averages) is rejected. A post-hoc test, which does not assume equal variance, is the Dunn test and determines which of the sample groups are significantly different (Dunn, 1964). The Pairwise comparison presented in Table 39 indicates the Dunn test results, where the p-values proves that the groups' averages are significantly different except the average percentage flex delivered for the FC and the EB block, where the p-value is bigger than 0.05 and consequently, it is not possible to reject the zero hypothesis (averages are the same).



	FC	PV	EB	HP
Total Number of orders from both experiments	1106	300	267	534

Figure 24: Average percentage flex delivered with the 95% confidence interval for the 4 congestion block levels

Table 39: Dunn-test – nonparametric test

		FC	PV	EB
PV	Z-test	3.358107		
	P-value	0.0012		
EB	Z-test	-0.71242	-3.17468	
	P-value	0.2381	0.0015	
HP	Z-test	18.0588	10.17408	13.34428
	P-value	0.0000	0.0000	0.0000

It can be reasoned that the high average percentage of flex delivered for the FC block, relative to other block levels, is due to the fact that predicting the flex from the FC is straight forward since it is not affected by other exogenous factors such as weather and human behaviour. Furthermore, one can also reason that the comparable high average percentage flex delivered for the EB block is due to the fact that the EB is always off by default and it delivers flex once it is ordered to go on. Additionally, it can be argued that flex from an EB is affected by temperature and hot water consumption household pattern, but since it is always off and goes on according to flex ordering, it is more likely that flex ordered which is ordered is also to be delivered. One may expect that the percentage flex delivered from the PV is higher because the PV is affected by weather and not by human behaviour, but most likely since both experiments are performed in the winter, the PV output is low in comparison to the output in spring and summer. For instance, during winter, in some days the lack of sun radiation may result in zero PV production, while hot water consumption (EB flex) will most likely occur every day. **However, the number of times flex was ordered at the EB and the PV congestion level is low in comparison to that of the FC and HP congestion level and thus does not allow for a fair comparison of percentage flex delivered among different block levels (as shown in the last row of Figure 24). Finally, since the experiments are restricted to two months in winter, it is not possible to draw conclusions with respect to the yearly difference in average percentage flex delivered at different congestion block levels (PV, EB, HP, and FC) over a year.**

In conclusion, the takeaway message from the analysis of the reliability of flex ordered versus delivered is that flex ordered is only partly delivered due to the error in forecasting flexibility for the different devices, and possibly from other exogenous factors such as IT error. Certainly, forecasting flex is a continuous learning process that may result in higher percentages of flex delivered into the future.

7.2 The Influence of Flexibility versus the Forecast Error on the Load Curve

This section will look into the influence of flex on the aggregated load curve versus the influence of the forecast error (error in weather forecasting, the error in energy load forecasting and forecasting human behaviour, and other exogenous factors). During the two periods, Nov 18, 2015 till Dec 15, 2015 and Jan 13, 2016 till Feb 9, 2016, two experiments were performed, where the DSO procured flex at four congestion block levels according to the load forecast and the congestion limits. The following steps are undertaken to answer the following sub-research question:

In the case that the load was successfully kept within the limits, how much of this effect was the result of demand-side flexibility, as opposed to weather, participant behaviour or other exogenous factors (forecast error)?

To check whether the change in the load curve after flex steering was the result of flex delivered, as opposed to weather, participant behaviour or other exogenous factors, the following steps were undertaken:

- The load at the PTUs where flex is ordered is analysed.
- The load forecasted without flex is subtracted from the load measured with flex, the difference gives the forecast error and the flex delivered, as follows:

$$forecast\ error + flex\ delivered = forecasted\ load\ without\ flex - actual\ load\ with\ flex$$

- The forecast error is equal to the forecasted load without flex subtracted from the actual load without flex.

$$forecast\ error = |forecasted\ load\ without\ flex - actual\ load\ without\ flex|$$

- The percentage forecast error contribution to the change in load is the division of the forecast error with the total of forecast error and flex applied.

$$\%\ forecast\ error\ contribution = \frac{forecast\ error}{forecast\ error + flex\ delivered}$$

- The contribution of the flex to the change in load is equal to flex steered divided with the total of forecast error and flex applied.

$$\%\ flex\ contribution = \frac{flex\ delivered}{forecast\ error + flex\ applied}$$

- **Forecast error** stands for weather forecast error, demand forecast error, consumption pattern prediction error, reliability of flex ordered, or IT bugs when ordering and delivering flex etc.

As an example, Figure 25 illustrates this calculation by graphically presenting the contribution of the forecast error in comparison to the flex, to the change in the load.

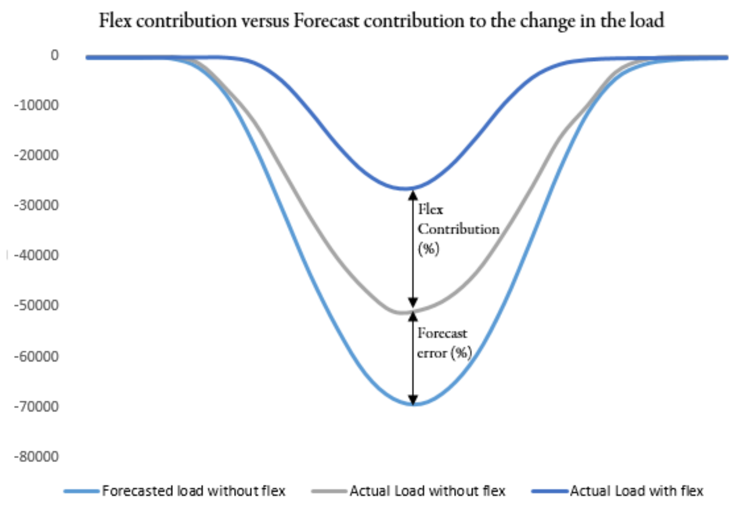


Figure 25: Flex contribution versus forecast error contribution to the change in the load curve

By analysing Figure 26, it can be witnessed that the contribution of the flex versus the forecast error for the Fuel Cell block, is roughly 50%/50% while for the HP block it is 36% flex contribution versus 64% caused by forecast error. Furthermore, for the EB and the PV block, 24% caused by flex and 76% by forecast error.

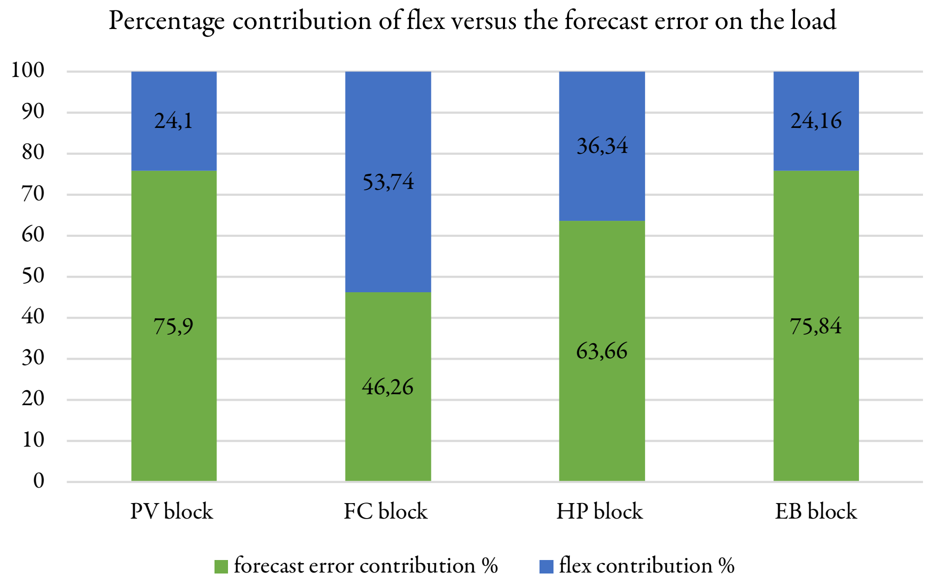


Figure 26: Percentage contribution of flex versus the forecast error on the load for the 4 congestion block levels

The results indicate that the Fuel Cell flexibility is more reliable because it is not affected by human behaviour nor weather forecast error, in contrast to the HP and EB where human behaviour plays a big role in the forecast and the weather conditions that plays a big role in PV output. Additionally, the high percentage of forecast error is probably due to the error in energy load forecast.

From these results, it is possible to conclude that based on the two experiments, the change in the load curve is primarily caused by the forecast error, while flex provides a smaller contribution at the congestion block level. Note, this conclusion cannot be generalized, knowing that predicting flexibility and energy load may improve, following some learning curve.

7.3 The Load With and Without Flexibility Steering

To determine the influence of the delivered flexibility on the load curve, a comparison of the actual load curve without flex and the measured load curve with flex is analysed for all PTUs (not only in the PTUs where flex is ordered). Figure 27 presents the average load with and without flex for all congestion block levels with the percentage reduction in the standard deviation of the load. Since the purpose of flex steering is to mitigate congestion by shaving peaks, it is expected that the load curve after flex steering will be less volatile and thus will witness a reduction in the standard deviation.

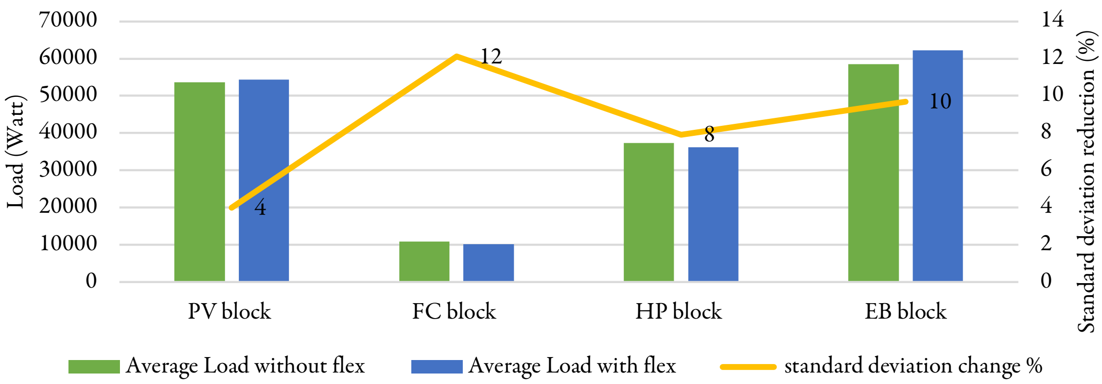


Figure 27: Average load with/without flex for the 4 congestion block levels with the percent reduction in the standard deviation of the load

The low percentage change in the average load and the standard deviation (4% reduction) of the curve with and without flex at the PV congestion level, is perhaps related to the fact that the PV flex, by turning off PVs, might be successful in resolving solar peaks but may not directly solve evening peaks. Thus, the load in the evening may not be affected by flex. However, the experiment with the Fuel Cell has witnessed the highest reduction in the standard deviation of the load curve (12%) and this proves again that the Fuel cell impact is the most significant in comparison to other smart appliances. While, one would expect that the reduction in the standard deviation for the load curve for the HP and the EB experiment to be prominent during the winter due to higher availability of flex (due to the need for heating and hot water consumption), the standard deviation witnessed an 8% and 10% reduction, respectively, which is less than that of the fuel cell. **In conclusion, the average percentage decrease in the load standard deviation for all the four devices, which is an indication of the load volatility decrease, is between 4% and 12%. Nevertheless, it is important to note that these conclusions are based on a two month experiment from Nov 18 till Dec 15 and from Jan 13, 2016 till Feb 9, 2016 and therefore results might change if additional months, including different seasons, were experimented in the field trial.**

Analogous to process capability in an industrial setting, quantitative measurement is desirable to test how the load curve compares to the specified limits or "congestion limits". Thus, it is insightful to study the performance of the load and its ability to stay within the specified limits. The process is considered to be ***incapable***, if the natural limit spread (which is the 6σ) is wider than that of the specification limits (the congestion limit). To test for this conformance, a quantitative measurement is performed, **the process capability potential index:**

$$C_p = \frac{USL - LSL}{6\sigma}$$

This index represents the tolerance spread (the congestion limits) over the natural spread (the 6σ). The 6σ will encompass 99.7% of the observations, almost all observations, if the spread is a nice bell curve. If $C_P>1$, then the tolerance spread exceeds that of the natural spread. Since the congestion limit is constant, thus the more the C_P the less is the natural spread, which indicates the better is the curve performance within the congestion limits. The C_P index assumes that the curve follows a normal distribution and that the average is centered in the middle between the two congestion limits. Since one of the shortcoming of the C_p index is that it does not take into account if the load curve is not centered in the middle of the two congestion limits, which is the case in the 4 conducted experiments, it is more relevant to examine the **C_{pk} index which accounts for the curve centering,** which is calculated as follows:

$$C_{pk} = \min\left\{\frac{u - LSL}{3\sigma}, \frac{USL - u}{3\sigma}\right\}, where\ u\ is\ the\ average$$

The C_{pk} index is tabulated below for all 4 experiments (Table 40):

Table 40: C_{pk} index for the load with/without flex at the four congestion block levels

	PV block	FC block	HP block	EB block
C_{pk} index for load without flex	0.57	1.33	0.44	0.55
C_{pk} index for load with flex	0.58	1.59	0.52	0.58

Thus, it can be concluded that only the load curve with/without flex for the FC block experiment is *capable* of performing within the congestion limits, since the C_{pk} >1. Although, the C_{pk} index increased for all load curves without flex to load curves with flex, the C_{pk} is still below 1 and thus the load curve is *incapable* of performing within the congestion limit for the PV, HP, and EB experiments. However, one drawback of this approach is that the load is assumed to follow a normal distribution, and consequently might provide inaccurate results when such an assumption cannot be made. Therefore, the following section will tackle this shortcoming by fitting the data to the best fitting theoretical distribution.

7.4 The Influence of Flexibility on the Probability of Congestion at a Block level

The comparison of the actual load curve without flex and the actual load curve with flex served as an initial indicator of the volatility of the load before and after flex steering, by calculating the change in the standard deviation, and the capability of the load of staying within the congestion limit, by studying the process capability potential index. However, to draw more insights with respect to the influence of flexibility on grid congestion, and to operationalize the risk of congestion happening, the following steps are undertaken to answer the following sub-research question, based on collected data:

How does the amount of delivered flexibility influence the probability of grid congestion?

1. The two experiments done from Nov 18, 2015 till Dec 15, 2015 and from Jan 13, 2016 till Feb 9, 2016, are analysed. During those two experiments, the DSO procured from the aggregator at the 4 congestion block levels.
2. The measured data of the load without flex and the load with flex for the 4 congestion block levels is fitted against a theoretical distribution using EasyFit software.
3. To assess which probability distribution is the best, the Kolmogorov Simonov test was chosen to rank the distributions from best to worst. The test is used as a goodness of fit test, which compares the sample to a hypothesized continuous distribution. The zero and alternative hypothesis are:

H0: the sample follows the specified distribution
H1: the sample does not follow the specified distribution

4. Table 41 shows the best probability plot that fits the data, according to Kolmogorov and Simonov test. The measured data fitted against the best fitted theoretical distribution is graphically presented in **Figure 52, Figure 53, and Figure 54 in appendix B.2.**

Table 41: The best fitting theoretical distribution of the load with/without at the 4 congestion block levels

	EB Block & PV Block	HP Block	FC Block
Prob. Distribution	The 3-parameter Weibull (3P)	Gumbel max	Logistic
Prob. Density Function	$f(t) = \left(\frac{\beta}{\eta}\right)\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{1-\gamma}{\eta}\right)^{\beta}}$	$f(t) = \left(\frac{1}{\sigma}\right) e^{z-e^{z}}$ Where: Z=(t-μ)/σ	$f(t) = \frac{e^{z}}{\sigma(1+e^{z})^{2}}$ Where: Z=(t-μ)/σ
Parameters	α= scale parameter β= shape parameter γ= location parameter	μ= location parameter σ=scale parameter	μ= location parameter σ=scale parameter

The probability of exceeding the congestion limit set at the congestion block levels is calculated based on the probability distributions for the load without flex and the load with flex delivered. **The probability of exceedance is simply the number of PTUs the load exceeds the congestion limit versus all the studied PTUs. As expected and depicted in the graph (Figure 28) the load at all congestion block levels witnessed a decrease in probability of exceedance of the congestion limit as flex was delivered, but the percentage reduction of the probability of exceedance differs among different congestion block levels.**

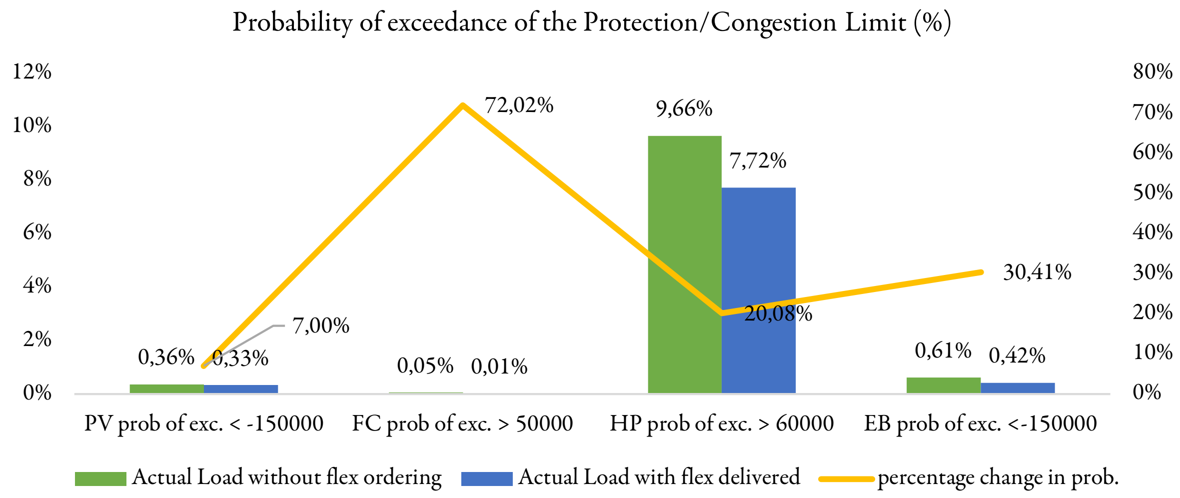


Figure 28: Probability of exceedance of the Protection Limit (%) and the percentage change in the probability

For instance, at the FC congestion block level, ramping up the FCs to deliver flex is meant to protect the load from surpassing the upper congestion limit (50,000 Watt). The probability of exceeding the load without flex was equal to 0.045%, which is equivalent to 1 congestion exceedance in 2220 PTUs, in comparison to a probability of 0.013% for the load with flex delivered, which is equivalent to 1 congestion exceedance in 7692 PTUs. However, it is important to note the following:

1. The initial characteristics of the load and the set congestion limit affects the probability of congestion at the different congestion block levels.
2. The percentage change in the probability of exceedance of the congestion limit is more informative and indicative in contrast to comparing the percentages among the congestion blocks. For instance, the percentage change in the probability of exceedance of the congestion limit is 72% for the FC block level, while only 20% for the HP congestion block.
3. The percentage change in the probability of exceedance of the congestion limit for the 4 congestion blocks is comparable to the load standard deviation percentage change calculated earlier (Figure 27). For instance, the load at the FC block has witnessed the highest percentage change in standard deviation and the highest percentage change in probability of exceedance. The percentage change in the load standard deviation with and without flex is tabulated below along with the percentage change in probability of exceedance of the load with and without flex for the different congestion block levels (Table 42).

Table 42: The % change in the load standard deviation with/without flex along with the % change in probability of exceedance of the load with/without flex

	Percentage change in the load standard deviation	Percentage change in probability of exceedance
PV	4%	14%
FC	12%	72%
HP	8%	20%
EB	10%	30%

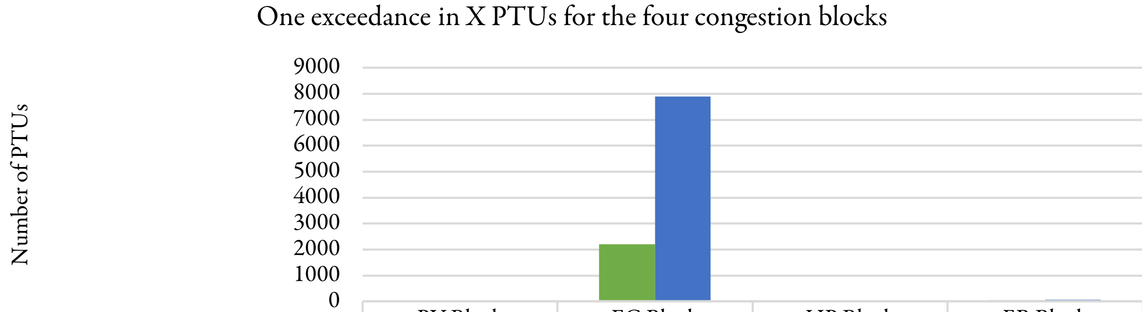
Thus, it can be concluded that the influence of flex on the load at the FC congestion block level is more pronounced than at other congestion block levels, which is consistent with the earlier results that have proven that the percentage flex delivered is the highest at the FC block level and the percentage of flex contribution versus forecast error is also the highest at the FC congestion block level. While the influence of flex on the percentage reduction in the congestion probability at the PV congestion level is most subtle (14%), this is most likely caused by the fact that the PV may not resolve congestion in the evening peaks because of the limited flex to offer during the evening. However, the highest probability of exceedance of the congestion limit is at the HP block level, which is roughly in consistence with earlier results since the percentage flex delivered turned out to be the lowest at the HP block level in comparison to others and flex has a low level of contribution to the load versus forecast error contribution at the HP congestion level.

The total probability of exceedance from the upper and lower congestion limits are calculated for the load without flex and the load with delivered flex and the probability that the load stays within the congestion limits, for the 4 congestion blocks, as presented in Table 43. **Again, the load with flex delivered at the FC congestion block is doing the best in terms of probability of staying within the congestion limits while the load with flex delivered at the HP congestion block has the least probability of staying within the congestion limits.**

Table 43: The probability that the load stays within the congestion limit for the load with/without flex for all congestion block levels

Congestion Block	Congestion Limit	*Load without flex ordering*	*Load with flex delivered*
EB Block - Weibull (3P)	Total prob of exceedance (%)	1.83%	1.47%
	-150000<X<150000	98.17%	98.53%
HP Block - Gumbel Max	Total prob of exceedance (%)	9.66%	7.72%
	-60000<X<60000	90.34%	92.28%
FC Block - Logistic	Total prob of exceedance (%)	0.05%	0.01%
	-50000<X< 50000	99.95%	99.99%
PV Block - Weibull (3P)	Total prob of exceedance (%)	2.833%	2.6683%
	-150000<X<150000	97.167%	97.3320%

To translate the probability of exceedance to the number of exceedances, or one exceedance in how many PTUs, 1 is divided by the probability of exceedance, and the results presented in **Figure 29**. For example, the load without flex for the FC will witness one exceedance every 2,208 PTUs (equivalent to 23 days), while the load with flex delivered is probable to witness one exceedance every 7893 PTUs (equivalent to 82 days). **The advantage of fitting the load to a theoretical distribution, is for instance that the load with flex at the FC congestion block level witnessed zero exceedance in the two month experiments; however, according to the probability derived from the theoretical distribution, there is chance of one exceedance every 82 days (2.7 months), which simply due to the short time length of the experiment this exceedance was not observed.**



	PV Block	FC Block	HP Block	EB Block
Actual Load without flex ordering	35	2208	10	55
Actual Load with flex delivered	37	7893	13	68

Figure 29: One exceedance in X PTUs for the four congestion blocks

It is needless to say that even a perfect fitting theoretical distribution, can never be a duplicate of the actual data, there will always be some discrepancies. Thus, in order to verify whether the results from the theoretical distribution are approximately in conformity with the average percentage exceedance calculated from the actual data (load curves) is important. Therefore, the average number of PTUs until one exceedance occurs for the load curve with flex at the 4 congestion block levels was calculated and presented as follows (Table 44):

Table 44: A check whether the results from the theoretical distribution are in conformity with the results calculated from the actual data

	One exceedance in average X PTUs (calculated from the theoretical distribution for the load curve with flex)	One exceedance in average X PTUs (calculated from the actual load curves with flex)
PV congestion block	37	43
FC congestion block	7893 (equivalent to 2.7 months)	>5760 (no exceedances in the 2 month experiments)
HP congestion block	13	9.2
EB congestion block	68	50

It can be proven from the results presented in Table 44 that the estimated probabilities from the theoretical distributions are roughly in consistency with the probability of exceedance from the actual data. However, at the PV congestion block level, it is important to note that at the PV congestion block level only half of the dataset was used (around one month data) because for the other half of the dataset the congestion limit was set differently. In that one month only 40 exceedances occurred and thus the average number of PTUs for one exceedance to occur was limited to 40 data points. This small dataset at the PV congestion block level in comparison to other block levels will reduce the trustworthiness of the comparison for the PV block level.

Finally, it can be reasoned that the congestion (exceedance) at different block levels (Watt) is correlated with **flex shortage in Watts (calculated as the absolute of |ordered – delivered|).** Thus, a statistical correlation is investigated between flex shortage and the exceedance from the congestion limit (Watt), where the exceedance (Watt) is regressed against the independent variable (flex shortage). Hypothetically, as the flex shortage increase, it is expected that the exceedance in contrast to the congestion limit will increase (positively correlated). The bivariate regression models, tabulated in **Appendix B.3.**, prove a significant positive correlation coefficient with an adjusted R^2 of 7.68%, 10.7%, 25%, and 31.3% respectively for PV, FC, HP, and EB congestion block, for the two month experiments combined (Nov 18, 2015 till Dec

15, 2015 and from Jan 13, 2016 till Feb 9, 2016). This means that, for instance, at the EB block level, 31% of the variance of the dependent variable (exceedance) is explained by the flex shortage. The fact that the flex shortage explains less than 30% of variance of the dependent variable (exceedance of the congestion limit) for all block levels, indicates that other regressors could explain the remaining variance. **However, the purpose of proving a significant relation is to prove that the percentage of flex ordered may not be all delivered and thus this flex shortage does affect congestion (exceedance in Watt).** The remaining unexplained variance of the dependent variable, can perhaps be explained by the forecast error (weather forecast error, demand forecast error, energy load prediction error etc.).

7.5 The Influence of Flexibility on the Probability of Congestion at a Mixture Congestion Level

The two experiments performed from Dec 16, 2015 till Jan 12, 2016 and from Feb 10, 2016 till March 8, 2016, are analysed, where during those two experiments, the DSO together with the BRP procured flex from the aggregator at the mixture congestion level. **Table 79 in the appendix B.4**. presents the percentage decrease in the total probability of exceedance for the load curve with flex for both experiments at the congestion Block Level. The statistical correlation between the forecast error and congestion limit exceedance turned out to be significantly positively correlated, as would have been hypothesized, with an adjusted R^2 of 20% (as presented and illustrated in **Table 80 and Figure 57 in appendix B.4**). **Further analysis and elaboration is presented in Appendix B.4.**

Hypothetically, it can be assumed that the ordered flex up (Watt) by the BRP may be positively correlated to the load exceedance (Watt). Thus, load exceedance was regressed on the ordered flex by the BRP to test the assumed correlation but the strength of the relationship showed less than 5%. Another hypothetical correlation would be that the more the ordered **flex up** by the BRP will result in more **flex down** orders by the DSO. However, bivariate regression resulted in a non-significant correlation. Furthermore, a hypothetical correlation between flex ordered by the BRP and the percentage of flex delivered to the DSO was tested statistically, assuming that the high flex ordered by the BRP may be correlated negatively by the percentage flex delivered to the DSO. However, again bivariate regression resulted in a non-significant correlation.

Roughly, it can be concluded that the price of flex may influence the amount of flex ordered by the BRP but it does not seem to influence the percentage flex delivered to the DSO; however, it may have influenced the percentage flex offered to the DSO (the more the BRP orders the less flex available), which could explain the high probability of congestion at the mixture congestion level since offered flex may not have been enough to resolve congestion. However, those results are derived from 2 month experiments and if performed for a longer period of time, results may have changed.

Section 7.1 till 7.5 analysed the influence of demand-side flexibility on grid congestion based on the collected data from the two month experiments at the congestion block levels and the mixture levels from Heerhugowaard field trial. Thus, the derived results cannot be generalized for the entire year. Therefore, **section 7.6** will predict and investigate the influence of demand-side flexibility on grid congestion block levels for the entire year in Heerhugowaard.

7.6 The Predicted Yearly Probability of Grid Congestion at Block levels for Heerhugowaard

Analysis on the measured data, in section 7.1 to 7.5, on the two experiments performed in Heerhugowaard, provides insights on the reliability of flex delivered. Moreover, the probability of congestion of the load with and without flex calculated at the congestion block levels gave an indication on the potential reduction in congestion by flex. **Conversely, these conclusions are based on two month experiments only, which renders the analysis un-generalizable.** Therefore, with the aim of providing a more generalized conclusion with respect to the mitigation of congestion via flexibility for Heerhugowaard, this section attempts to answer the following sub-sub-research question:

How does the probability of grid congestion for the load with and without flex, based on Heerhugowaard field trial, ***translate to the entire year*** *and* ***vary over the different seasons****?*

Before such an analysis can be performed, the available flexibility must first be predicted for an entire year and over the different seasons. Such a translation can easily be performed, using the regression models presented in Chapter 6. Consequently, section 7.6.1 first presents the prediction of flexibility for the 3 smart devices (Photovoltaic system, Electric

Boiler, Heat Pump) for an entire year, by means of the regression models. It also presents the difference in flexibility availability over the different seasons from the 3 smart devices. Note, the Heat Pump load is predicted assuming both functions: preserving indoor heating and pre-heating of the tap water. The flexibility prediction for the Heat Pump having only one function (preserving indoor heating) can be found in **appendix B.5**. Section 7.6.2 configures and validates a **simulation model** that estimates the probability of congestion and blackouts for the load without flex and with flex at congestion block levels.

7.6.1 Translation of Demand-Side Flexibility to an entire year and over different seasons

In order to calculate the probability of congestion to an entire year for Heerhugowaard low-voltage grid for the load with and without flex, demand-side flexibility must be predicted for each moment in time for an entire year. As chapter 6 focussed on determining regression models for predicting flexibility, these models will be used to estimate the flex for the entire year. **As four such regression models were estimated in chapter 6, section 7.6.1.1 through 7.6.1.4 present the yearly predicted flexibility for the PV, EB, and HP, respectively, and the difference in the flexibility available over the different seasons from each smart device.**

7.6.1.1 Flexibility prediction for the entire year based on the PV output regression model

In order to predict the flexibility from the photovoltaic panels, the regression model as estimated in section 6.3 is used. Therefore, to predict the PV output from the 89 controlled households in Heerhugowaard, the total PV capacity of the 89 households is substituted in the model (171,852Watts). Furthermore, the weather data on the Humidity, Temperature and Radiation is used from year 2015 for the city Berkhout, the nearest city to Heerhugowaard. The predicted PV output, with all the PVs assumed on, per day for one year based on these inputs is presented in Figure 30.

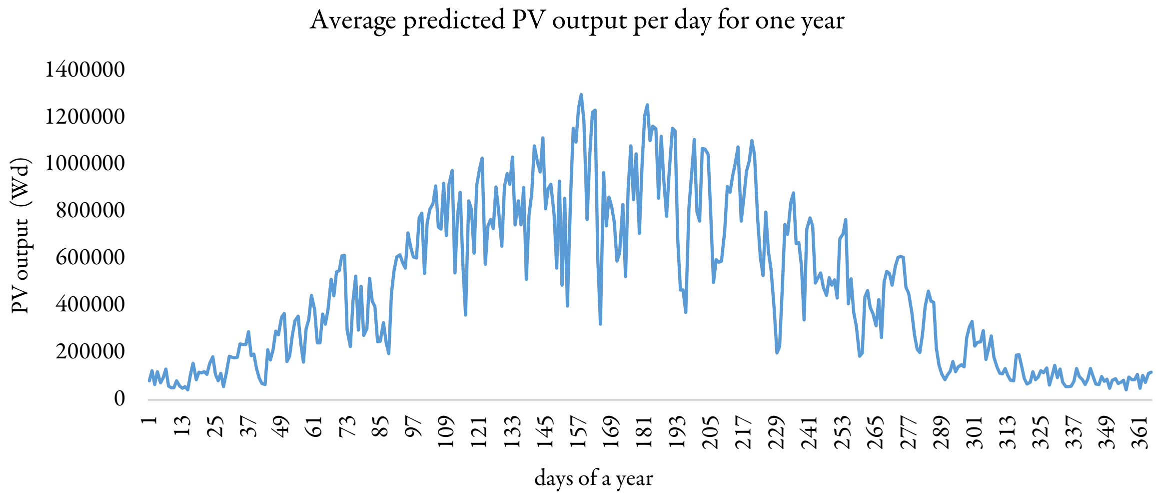


Figure 30: PV Prediction over a year

To gain more insight in the differences between the average PV outputs per hour over the different seasons in Heerhugowaard, the regression model was used to predict the PV output per hour for the 89 PV systems (171,852Watts) for year 2015. Weather data from year 2015 was extracted from the KNMI for the city Berkhout, the nearest city to Heerhugowaard. It is assumed that the 89 PV systems are on all day long. Consequently, the average PV output per hour for Spring, Summer, Fall, and Winter is calculated.

The following graph, Figure 31, shows the average PV output per hour of the day. While the average PV output in the summer or spring tends to reach roughly around 80,000 Watt for 89 PV systems at the mid of the day, the average PV output in the Fall or Winter tends to reach roughly around 30,000 Watt at the mid of the day. Another realization, is that during Spring and Summer, PV generation commences at 5:00am at dawn while in the Fall and Winter, it commences later in time, around 7:00am. Similarly, at dusk, the PV generation lingers till 21:00pm in Spring and Summer while it stops at 19:00pm during the Fall and Winter. Furthermore, Figure 32, shows the maximum PV output per hour for the 89 panels, which is insightful for the DSO, who either wants to reinforce the grid to handle the maximum load or procure flex, as this peak drives the maximum required network capacity. **It can be inferred that the PV output in Summer and Spring is at least as twice as that in Fall and Winter. Additionally, the PV output commences at 5 am and lingers**

till 7 pm in Summer and Spring (14 hours of varying PV output); however, PV output commences at 7 am and lingers till 5 pm in Fall and Winter (10 hours of varying PV output).

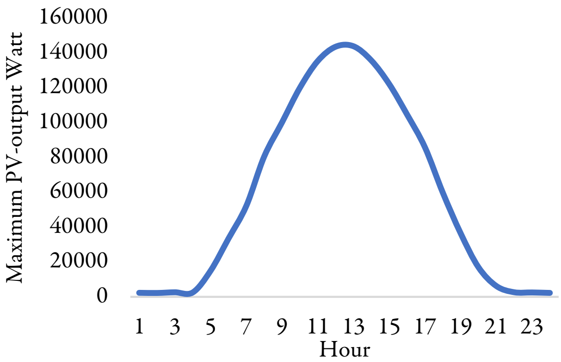


Figure 32: Max PV-Output per hour over a day

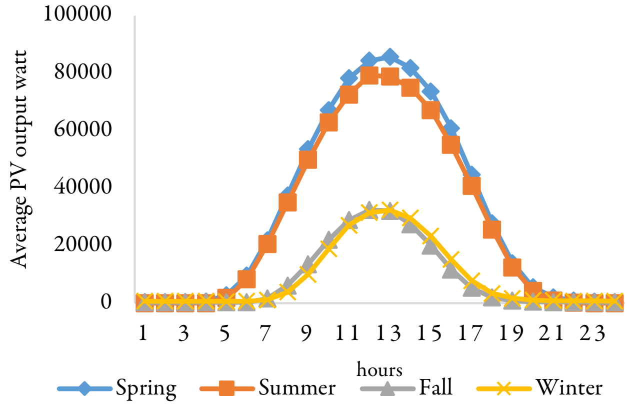


Figure 31: Average PV output per hour for the four seasons

To get more insights over how the PV output varies per hour over the seasons, the following boxplots, in Figure 33, show the 25 percentile, 50 percentile, and 75 percentile of the PV output per hour over a day for the four seasons. The boxplots of Spring and Summer in comparison to Fall and Winter are comparatively taller and this suggests that PV output varies more in the former two seasons than in the latter two seasons. Furthermore, the median, the middle line, which is usually close to the average, varies roughly between 0 W and 80,000W in the Spring and Summer; however, in the Fall and Winter it varies roughly between 0 W and 30,000 W. Moreover, by examining the 4 sections of the box plots, one can suggest that for the Spring and Summer, the most positive quartile is smaller than that of the least positive quartile (the whiskers) and thus the PV output varies more in the latter (lower 25% PV output) in comparison to the former (highest 25% of the PV output). While in Fall and Winter, the PV output varies more in the most positive quartile in comparison to the least positive quartile. Finally, no data points happen to exist beyond the upper whisker (95% percentile) during the Summer and Spring; however, the boxplots suggest that several data points beyond the upper whisker exist in the Fall and Winter.

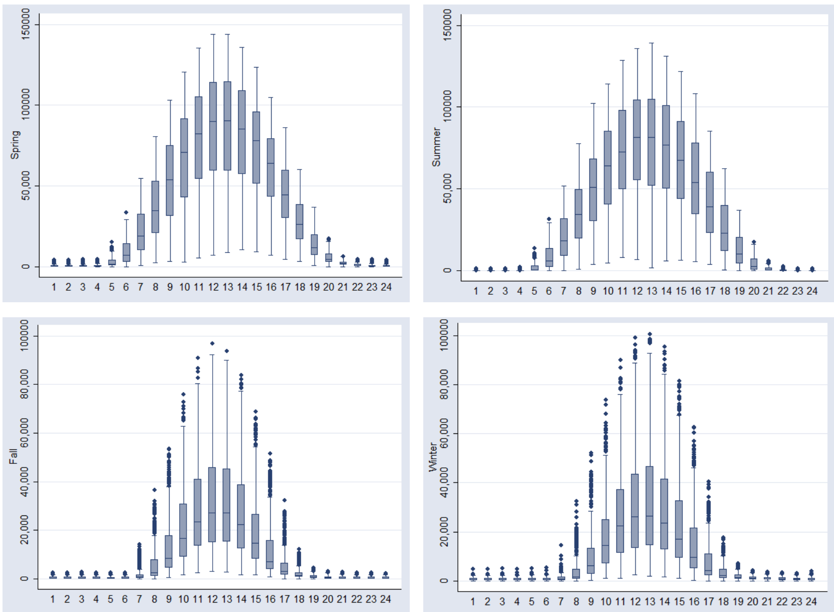


Figure 33: BoxPlot of the average Predicted PV output per hour for Spring, Summer, Fall, and Winter

7.6.1.2 Flexibility prediction for the entire year based on the EB regression model

To predict the Electric Boiler energy consumption from the 44 controlled households in Heerhugowaard, which will be equivalent to the flexibility available from Electric boilers, the following steps are undertaken. First, weather data for year 2015 for Humidity, and Temperature are substituted in the regression model. Second, load for one household is substituted in the regression model (Household 359 was chosen randomly). Third, the regression model predicts the hot water consumption per hour for one household in the Heerhugowaard. Since 44 households have controlled EBs, the output from the regression model was multiplied by 44 to get the hot water consumption (liters) for the 44 households. Fourth, to convert the output from liters to Watts, the conversion, as presented in Table 45, was used. The 44 electric boilers are a mixture of 1500 watts and 2500 watts and 80 liters and 120 liters. Different boilers require a different charge time, and energy (watts) to be fully charged. Thus, on average 94.7 Wh are needed per liter. Therefore, the output from the regression model is multiplied by 94.7 to convert it from liters to Wh. In such a case, the flex available from the electric boilers is equivalent to the energy needed to recharge the amount of hot water consumed.

Table 45: Electric Boilers volume, wattage, and charge time

EB Litter	Amount of Boilers (44 boilers)	Wattage	Charge time from zero	Charging energy to full (Wh)	Wh per liter
80.00	15	2500	3:00	7500	93.75
120.00	14	1500	7:35	11375	94.79
120.00	15	2500	4:35	11458.33	95.49
				average	94.68

Consequently, the predicted average energy (Wh) to be used by the electric boiler per day is calculated by adding all the energy consumed per hour for a day. The following graph, Figure 34, presents the energy usage by the electric boiler for a day over a year.

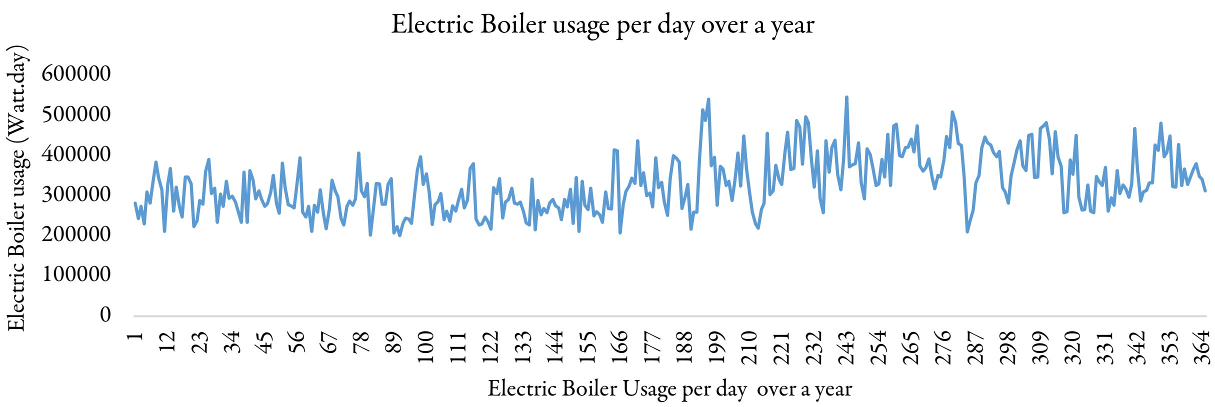


Figure 34: The EB usage per day over a year

The average electric boiler usage does not seem to vary significantly among the different seasons, as it seems to hover between 300,000 and 400,000 watt.day over the year, which is equivalent to roughly 12 and 16 kWh.

7.6.1.3 Flexibility prediction for the entire year based on the Heat Pump Regression model

The Heat Pump Load (for both functions: indoor heating and pre-heating of the tap water) is predicted for the entire year, using the regression model, for the Heerhugowaard area assuming the 50 Heat pumps are on. Weather data for year 2015 from Berkhout city is substituted in the regression equation (radiation, humidity and temperature) and the household loads (PV corrected). **The estimated Heat Pump load for the 50 households per hour for the year are presented in Figure 35.** The graph shows an apparent decrease in the heat pump load during June, July, August and September, and apparent increase beyond September. However, more insights can be gained with respect to the difference in the average heat pump load among the seasons.

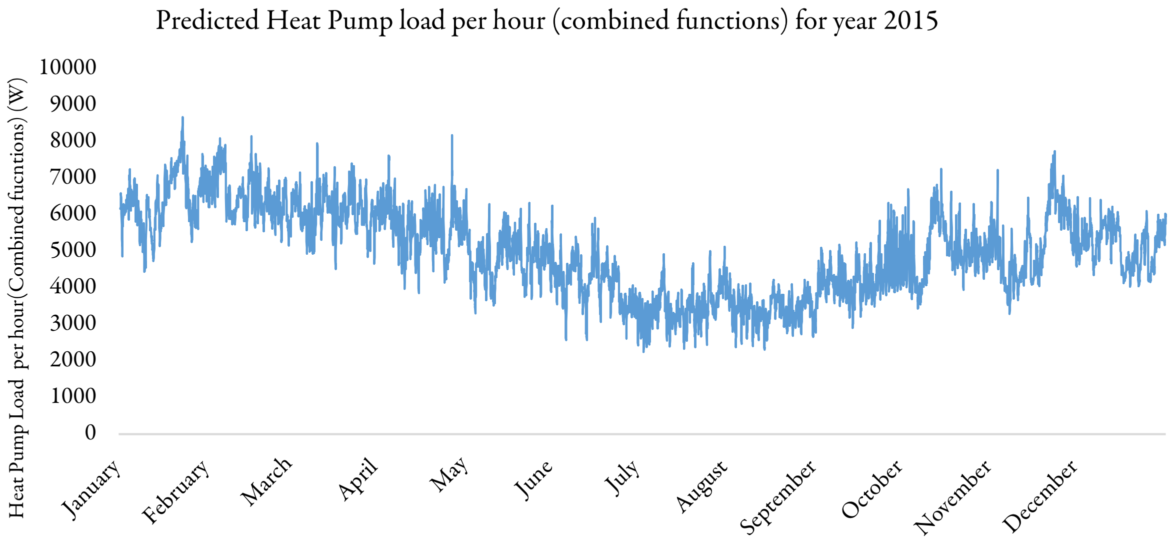


Figure 35: Predicted Heat Pump load predicted (combined functions) for year 2015

To gain more insight on the differences between the average Heat pump load per hour for the 4 different seasons in Heerhugowaard, the regression model was used to predict Heat pump load per hour for the 50 Heat pumps. Consequently, the average heat pump load per hour over a day for Spring, Summer, Fall, and Winter was calculated.
The following graph, Figure 36, shows the mean heat load per hour of the day. While the average heat pump load in the Fall or Spring tends to hover roughly around 5000 W for 50 heat pumps, the average heat pump load in the Winter tends to hover roughly between 6000 and 6500 W. While that in the Summer hovers roughly around 3500 W. Another realization, is that during Spring and Fall, the heat pump load tends to roughly start subsiding at 6:00am at dawn with sun rise while in the Winter, it subsides later in time, around 7:00am with the sun rise. During Summer, it looks stable, and the reason behind it could be that during the summer, the heat pump is pre-heating the tap water but doing very little to heat the air. Similarly, at dusk, the heat pump load starts to increase again at 18:00 in Spring and Fall while it starts increasing at 16:00pm during the Winter. Generally, **it can be concluded that the Heat Pump load in Winter is roughly twice the Heat Pump load in Summer and roughly one third more than the Heat Pump load in Spring and Fall. Additionally, the heat pump load is high in the Winter starting at 4 pm in the afternoon till 7am in the morning (15hrs); however, the heat pump load is high in the Spring and Fall starting at 6 pm in the evening till 6am in the morning (12 hrs). The heat pump load in the summer is constant (low) throughout the day.**

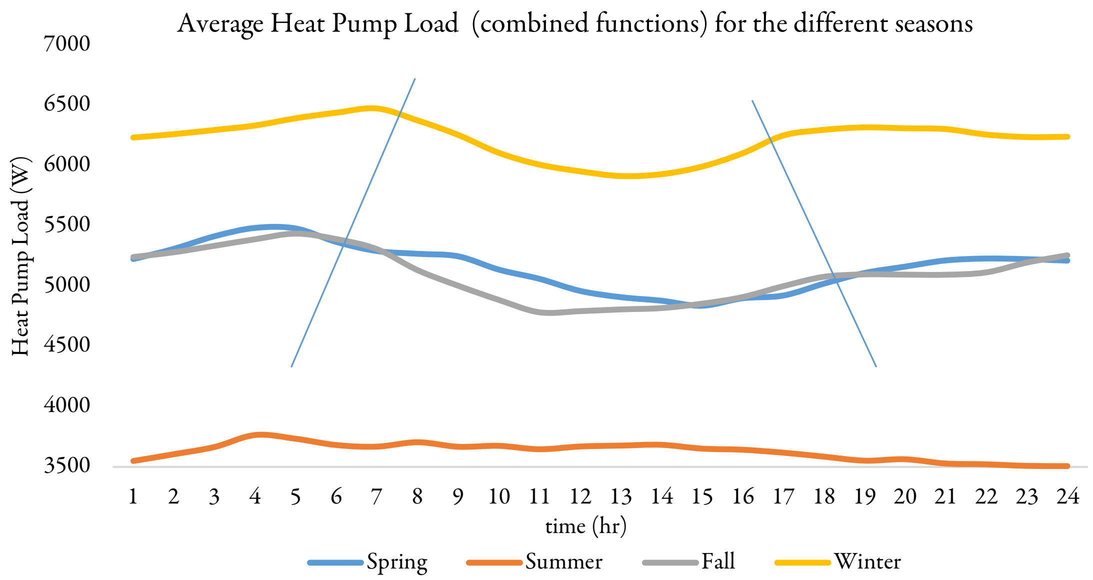


Figure 36: Average Heat Pumps Load per hour (combined functions) (W) for the different seasons

To test if the different seasonal averages over the day differ significantly from each other, the ANOVA test is performed but since the group' variance is not the same for all groups, based on the Levene's test for homogeneity of variance, ANOVA could not be used. Instead, the non-parametric Kruskal-Wallis test is performed, where the Kruskal-Wallis test tests whether the average of the different seasons are the same. The results showed that the averages are significantly different. Dunn's Pairwise test proves that the average heat pump load is significantly different between all seasons except between Spring and Fall (the p value is bigger than 5% and thus we cannot reject the zero hypothesis). This results is in line with the graphical representation of the average heat pump load over a day for the 4 seasons, Figure 36, where Spring and Fall seem to overlap.

7.6.1.4 Flexibility Prediction Overview of the smart devices over the four seasons

In order to give an overview of the average available flexibility per hour per device, a comparative analysis is performed. This analysis is performed by comparing the average flex levels per hour over the four seasons for the different devices: PV, EB, Heat Load (indoor air heating function), and Heat Pump Load (both functions: tap water heating and indoor air heating). The results from this analysis are presented in Figure 37.

From these results it is possible to observe that the largest average amount of flex per hour is provided by the PV systems (89 PV systems), but also that the PV flexibility (Watt) is highly sensitive to seasonality. In contrast, the Electric Boilers' flex (44 EB) is not as high as that of the PV systems, but shows a higher level of stability in the flex provision over the seasons. Furthermore, both the Heat Load flex (indoor air heating) and Heat Pump Load flex (tap water heating and indoor air heating) from the 50 HPs indicate roughly the same pattern of seasonal behaviour, as the summer produces a lower amount of flex (Watt) than other seasons, as to be expected, and the colder winter months, a higher amount of flex.

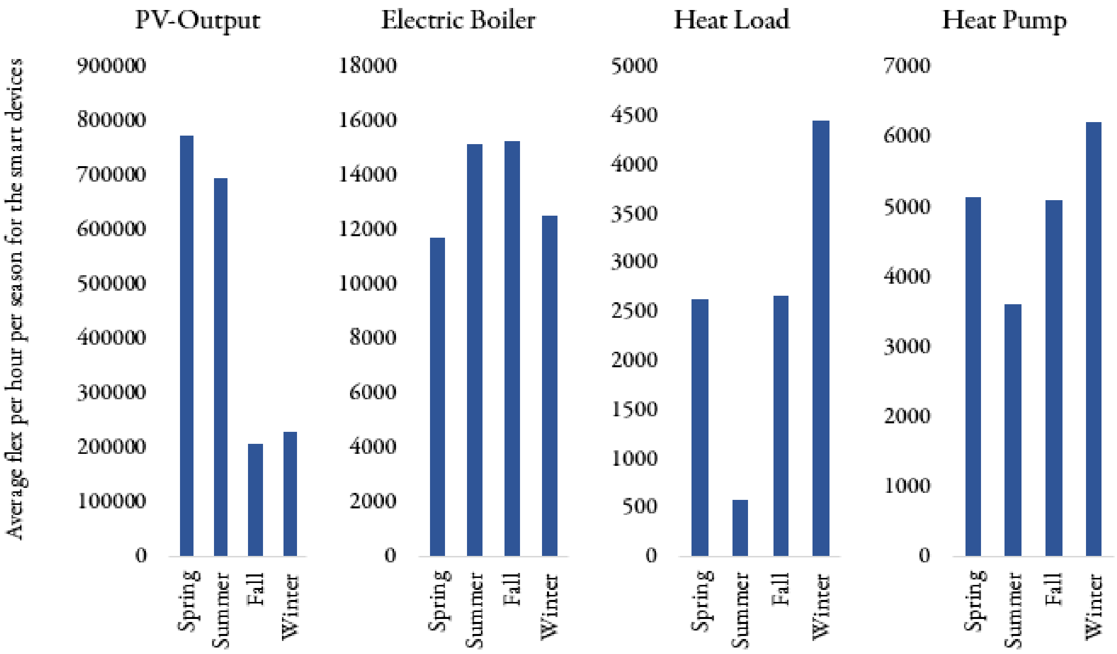


Figure 37: Average flex per hour (Watt) over the different seasons from the devices

Based on these yearly flexibility predictions per hour from the smart devices (89 PV systems, 44 EBs, and 50 HPs), it is possible to provide insights into the grid congestion over an entire year for Heerhugowaard, by building a simulation model that estimates the probability of congestion for the load without flex and with flex steering at the different congestion block levels. Thus, section 7.6.2 will present the model, its configuration, and validation prior to using the model for predicting the percentage of congestion for the load with flex and without flex for the entire year at all congestion block levels.

7.6.2 The Simulation Model for Congestion Mitigation via Demand-Side Flexibility

Since the DSO procured flex in two-month experiments only at the 4 congestion block levels to mitigate congestion, a simulation model is calculated in order to predict the probability of congestion at the 4 congestion block levels for the entire year for the load with and without flex based on the flex predicted per hour for the entire year in section 7.1 to 7.5. Having set the purpose of the simulation model, the second step in simulation is collecting data. The hypothetical parameters and data collection were performed in chapter 5 (the Key Determinants for Demand-Side Flexibility) and in chapter 6. In the third step in simulation, the model is built, which was partially constructed in chapter 6 (the estimated regression model for flex prediction) and to be completed in 7.6.2.1. In step 4 in simulation, the model should be validated to assess whether it is behaving as expected in order to trust the simulation results, which will be validated in section 7.6.2.2. Collecting and analysing results are steps 5 and 6 in simulation, which will be addressed in section 7.6.2.3.

7.6.2.1 Simulation Model Configuration

In this model, the USEF market based coordination mechanism, that defines how flexibility is traded among the different actors and the number of iterations designed to procure flex, was disregarded because the purpose of this analysis is to calculate the extent to which the DSO can resolve congestion by means of electricity flexibility at each congestion block level over the seasons regardless of the market coordination mechanism. Especially, because of the intricate interactions of the market based coordination mechanism with flexibility availability which may yield to ambiguity in the congestion mitigation outcome. The reason behind disregarding the USEF market mechanism in the simulation model are:

- The USEF market mechanism is not necessarily required to investigate technically the influence of demand-side flexibility on congestion management.
- If USEF market coordination mechanism was included, the results will be restricted to this mechanism and might be invalid for generalization purposes. And being not restricted to a specific market mechanism, enables its usage by any DSO for any targeted grid.
- The different USEF procurement rounds (day-ahead, intra-day, and in operate phase) are there because of the error in load prediction which is not captured in this model since the predicted load is assumed to be the load.
- The downside of not including the BRP is that the pool of available flex might have been affected if the BRP was procuring flex along with the DSO, but simulating and predicting when the BRP orders flex based on the APX market and the imbalance market, is beyond the scope of this analysis.
- the purpose of the final model is not to design the best market coordination mechanism for demand-side flexibility but to convey the extent to which a DSO can resolve congestion and defer grid reinforcement by means of flexibility.

Thus, it is assumed that (1) only the DSO is ordering flexibility, and (2) the DSO orders flexibility day ahead only. However, the default state of the devices, was considered the same as decided upon in the Heerhugowaard field experiment, which my pose a limitation on the generalization of this model. However, the lack of access to data collected from devices having different default states, and since the constructed regression models in chapter 6 are based on collected data from the devices employed in Heerhugowaard, this restricts the ability to overcome this limitation. As a recap, the devices default state is as follows (Table 46):

Table 46: Device default state and its respective flex order

	Device default state	Flex Order
PV	Always On	To be turned off – flex up
EB	Always Off	To be turned on – flex up
HP	Always On	To be turned off – flex down
FC	Always On (at its minimum 500 Watt)	To be ramped up – flex down

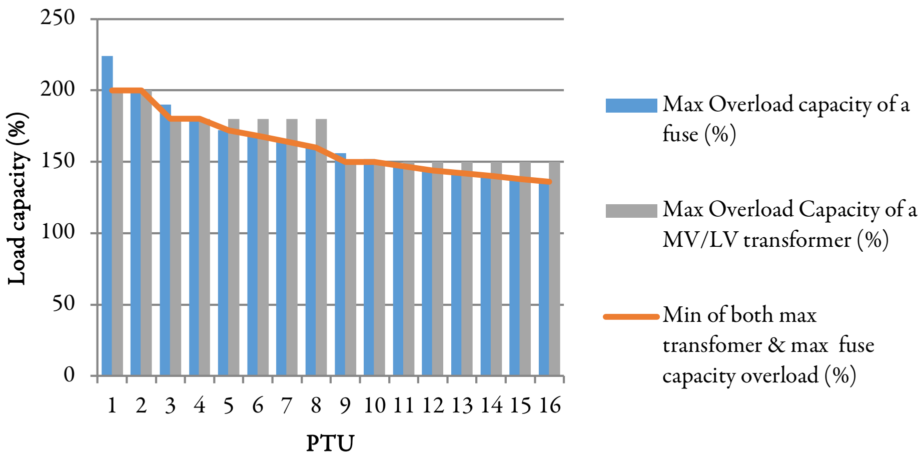
Using the regression models which are built-in the simulation model, flexibility is predicted per hour per device, which is then translated to flexibility prediction per PTU. This translation is performed by assuming that the load for PV, HP, and FC is constant over the hour. While, the predicted hot water consumption per hour from the EB was divided by four to calculate the hot water consumption per PTU. Thus, the model is built in a manner that the DSO orders flex per PTU, where there is predicted congestion, to shave the peak load with the congestion limit. If the flex predicted/available is more than is needed, the DSO orders flex equivalent to the congestion (Watt). On the other hand, if the flex needed to shave the peak load is more than the available flex, he can only order everything predicted as available. Since not everything ordered will be delivered due to forecast error in flex prediction and IT error, as proven in section 7.1, a random error distribution generator was built in the model (device specific) that randomly draws the percentage delivered and multiplies it with the flex ordered to compute the flex delivered. The random error distribution generator was calculated by fitting the percentage delivered at each congestion block level in the executed field experiments to the best fitting theoretical distribution. Table 47 shows the best fitting theoretical distributions with the respective parameters:

Table 47: Best fitting theoretical distributions with their respective parameters of the percentage flex delivered at each congestion block level

	FC	HP	EB	PV
Theoretical Distribution	Beta	Beta	Gamma	Gamma
Probability density function	$f(x) = \frac{1}{B(\alpha_1, \alpha_2)} \frac{(x-a)^{\alpha_1 - 1}(b-x)^{\alpha_2 - 1}}{(b-a)^{\alpha_1+\alpha_2-1}}$	$f(x) = \frac{1}{B(\alpha_1, \alpha_2)} \frac{(x-a)^{\alpha_1 - 1}(b-x)^{\alpha_2 - 1}}{(b-a)^{\alpha_1+\alpha_2-1}}$	$f(x) = \frac{x^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} \exp(-x/\beta)$	$f(x) = \frac{x^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} \exp(-x/\beta)$
Parameters	BetaPdf(alpha1;alpha2;a;b) = BetaPdf (0.5; 0.07; 0; 1)	BetaPdf(alpha1;alpha2;a;b) = BetaPdf (0.8,0.2,0,1)	GammaPdf(alpha,beta) = GammaPdf(11, 0.08)	GammaPdf(alpha,beta) = GammaPdf(6, 0.15)

As presented in Table 47, the best fitting theoretical distribution for the flexibility delivered at the FC and HP congestion blocks is Beta, whereas the best fitting theoretical distribution for the flexibility delivered at the EB and PV congestion blocks is Gamma, and are built in the simulation model accordingly. This error in flex delivery poses a limitation to the simulation model because the error in flex delivery is derived from two-months field experiments, which might be subject to improvement in the future.

Furthermore, it can be argued that when the load exceeds the congestion limit in consecutive PTUs (successively), that such an exceedance should be considered as one congestion and depending on the duration and magnitude of the congestion, it may result in a blackout or affect the lifetime of the assets due to overheating, as explained in **section 2.3**. Therefore, the model was constructed in such a manner to count the number of successive exceedances as one exceedance, and to determine the duration (in PTUs) of the exceedance. Depending on the duration of the congestion (number of PTUs) and the level of overload of the assets (the fuse or transformer limits) based on the maximum load within the duration of congestion, a blackout may happen due to a breakdown of the asset or overheating of assets might occur (Erbrink, 2015). As depicted in the Figure 38, as the duration increase, the allowable overload of the fuse and transformer decrease. Beyond the allowable overload capacity, the fuse and transformer will burn out. The portrayed data in Figure 38 is derived from the maximum tolerated capacity a fuse and transformer can hold for a specific duration of time, as per IEC 60076-7 specification document (Nederlands Elektrotechnisch Comité, 2008), as presented in **Table 2 and Table 3 in section 2.3.1.**



PTUs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Min of both max transfomer & max fuse capacity overload (%)	200	200	180	180	172	168	164	160	150	150	147	144	142	140	138	136

Figure 38: Maximum overload capacity of a transformer and a fuse (%)

Consequently, based on the minimum of both the maximum overload capacity of the transformer and the maximum overload capacity of the fuse, per duration of overload, the number of potential blackouts with and without flexibility steering is calculated per congestion block level. This calculation assumes that the congestion limit set at each congestion

block level is equivalent to the 100% capacity of the transformers and fuses installed at each congestion block level. Thus, in the simulation mode, first, the duration of exceedance is counted (min), second the maximum overload is recorded (%) within the spotted exceedance, and third the values are compared to the values in Figure 38. If the values are larger than the specified values in Figure 38, the exceedance is counted as a blackout. Asset overheating that leads to the depreciation of the lifetime of the assets is not accounted for in the model, as this goes beyond the purpose of this model.
Having configured the model and presented its assumptions, the following section will present the model validation.

7.6.2.2 Model Validation

Prior using the model for predicting the congestion and blackouts for the load without flex and with flex steering at congestion block levels for an entire year, model validation is mandatory, in order to validate that the models' outcome is in compliance with the anticipated purpose (Sargent, 2005).

The **Predictive Validation** is done in this case, which is conducted as follows: "The model is used to predict (forecast) the system's behavior, and then comparisons are made between the system's behavior and the model's forecast to determine if they are the same" (Sargent, 2005, p. 129). Thus, the measured load without flexibility for the period Jan 13/2016 till Feb 9/2016 was inputted into the model and the model was executed in order to simulate flex ordering according to congestion estimation. The estimated number of exceedances (PTUs), after the model was executed and flex was steered, was compared to the observed (real) number of exceedances (PTUs) after flex steering that happened during that period, as shown in Table 48. To test whether the estimated counts are significantly different from the observed counts, the Chi-Squared test is conducted. The null and alternative hypotheses are:

H0: There is no difference between the estimated counts (model) and the observed counts (real)
H1: There is a difference between the estimated counts (model) and the observed counts (real)

Based on the chi-squared density function, the upper critical value for α=5% for degrees of freedom of 1, is 3.84. Since the chi-squared values at all congestion block levels are less than 3.84, as shown in Table 48, the null hypothesis cannot be rejected and thus it can be concluded that there is no difference between the groups at all congestion block levels.

Table 48: Chi-squared test results for the observed versus the "model" number of exceedances at congestion block levels

	Congestion Block Levels			
Period (Jan 13/2016 till Feb 9/2016)	PV	EB	HP	FC
Congestion limit (Watt) (+/-)	150000	150000	60000	40000
Real Number of Exceedances after flex steering	38	38	211	258
Model Number of Exceedances after flex steering	50	52	230	232
Chi-Square Value	2.88	3.769	1.569	2.913
Conclusion (reject/accept the null hypothesis)	Accept	Accept	Accept	Accept

Other **structural validation** is performed by testing **extreme values**. For instance, the number of controlled devices was set to zero and thus, the model showed no flexibility is ordered from the DSO. The congestion limit was set to 0 and thus all flexibility is ordered by the DSO, according to the model. The maximum overload capacity of the transformer and the fuse were given very high values, and thus the model estimated no blackouts, as would have been expected. This concludes that the model outcome can be trusted to meet its intended purpose.

7.6.2.3 Model Results on the Yearly Probability of Grid Congestion at each Block Level

Using the simulation model which was configured and validated, the flexibility at each congestion block level is calculated based on the number of devices controlled, the weather data from year 2015 for the city Berkhout (the nearest city to Heerhugowaard), and a standardized average yearly load curve. A standardized average yearly load curve is used because there no collected data on the load curve for an entire year for Heerhugowaard. To estimate the aggregate load at each congestion block level, the energy consumed or produced from the smart devices in the controlled and uncontrolled households are added to the standardized average yearly load curve per household which is multiplied by the number of houses at each congestion block level. This standardized average yearly load curve per household was a result of measured curves from a large number of households in the Netherlands (EDSN curve, Energy Data Services Netherlands). The standardized average yearly load curve per household was used, since load data collected from Heerhugowaard does not stretch over a year. The number of controlled and uncontrolled households and the congestion limit at each congestion block level is depicted in Table 49 . Some of the uncontrolled households have PV systems installed (more details can be found in **appendix B.6. in Table 86**).

Table 49: Number of controlled and uncontrolled households at different congestion block levels

Congestion Block Levels	PV	HP	EB	FC
Number of Uncontrolled households	60	25	105	34
Number of Controlled households	89	50	44	18
Congestion Limit + (Watt)	150000	60000	150000	40000
Congestion Limit - (Watt)	-150000	-60000	-150000	-40000

Graphically the predicted load without flex and with flex for the entire year at the PV congestion block level looks as per Figure 39. As apparent in the figure, the load with flex is not always shaved with the congestion limit (-150,000 Watt) because of the percentage error in flex delivered.

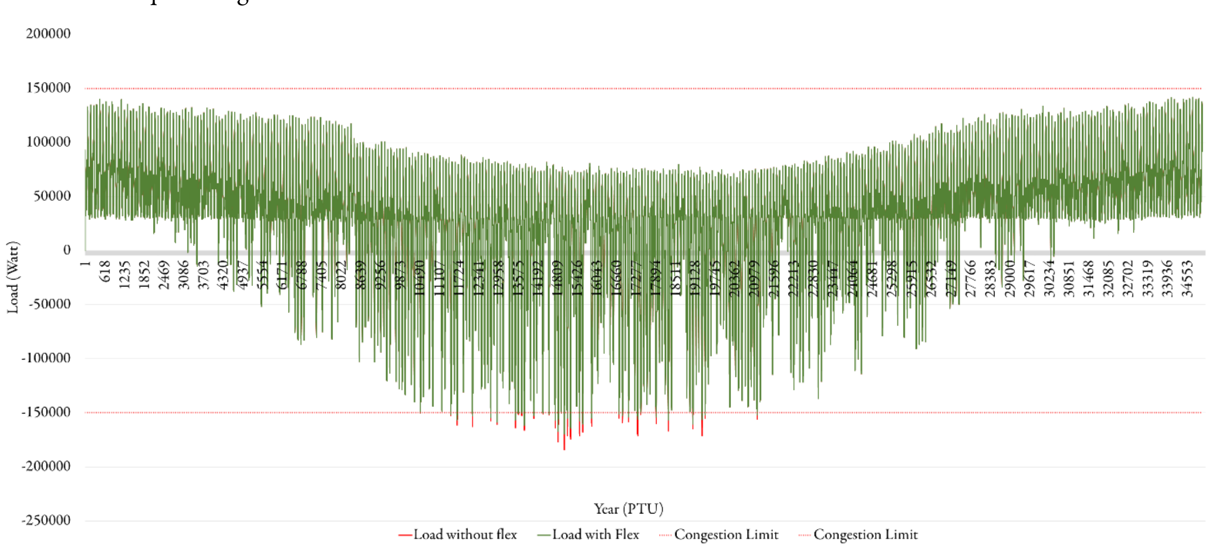


Figure 39: Load with flex and without flex at the PV congestion block level

To know in which season the congestion is concentrated, Figure 40 presents the results of the probability of exceedance (percentage of PTUs where the load exceeded the congestion limit) for the load with flex and without flex at the PV congestion block level for the different seasons for the city Heerhugowaard. In compliance with Figure 39, and as expected, the congestion at the PV congestion block level is concentrated at the Spring and Summer because of the solar peak and high radiation intensity. Similar graphs for the HP, EB, and FC congestion block levels, can be found in (**appendix B.7 in Figure 60, Figure 61, and Figure 62).**

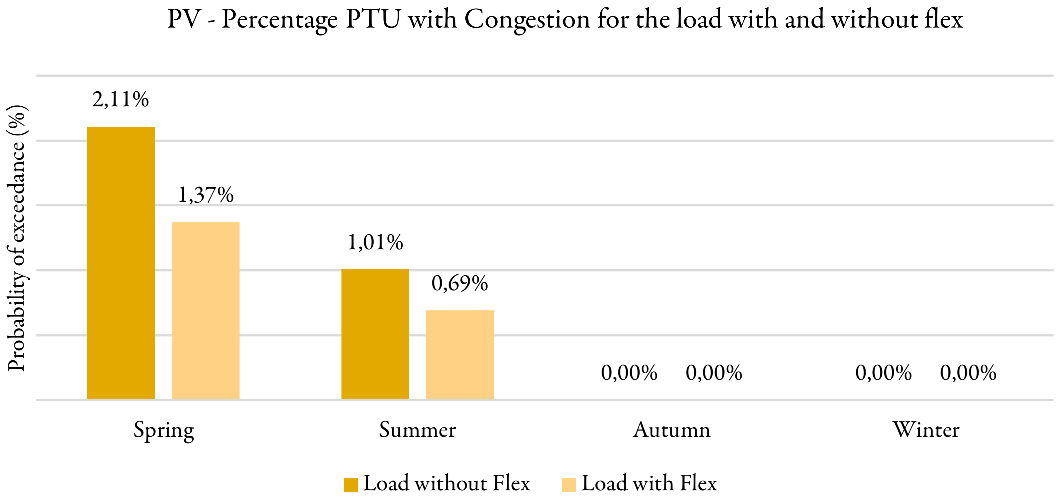


Figure 40: Probability of exceedance of the Congestion Limit (%) for the PV congestion block level at Heerhugowaard

The number of exceedances at the different congestion block levels for the 4 seasons is tabulated in Table 50. The number of exceedances is simply the number of PTUs where the load exceeds the upper or lower congestion limit. The large number of exceedances at the HP congestion block level in Fall and Winter is not mitigated due to the little flexibility available from the controlled HPs (as depicted in Figure 37 in section 7.6.1.4) and because of the simulated error in delivery. However, the congestion at the HP congestion block level during the Spring and Summer is due to over production because of the uncontrolled PVs installed at the houses, which cannot be solved by the HPs, because the HPs can only offer flex down (by turning the HPs off).

Similarly, at the FC congestion block level, during the Spring and Summer, congestion is due to over production because of uncontrolled PVs, and thus the FC cannot resolve any congestion during Spring and Summer (since FCs provide flex down by ramping them up). **Thus, it can be concluded that those results of the exceedance are affected by the large number of uncontrolled devices and the fact that at every congestion block level only one type of controlled device is present.**

Table 50: Number of exceedances per season per congestion block level

	Congestion Block Levels							
	PV		**EB**		**HP**		**FC**	
Number of exceedances per season (PTUs)	Without flex	With Flex	Without flex	With Flex	Without flex	With Flex	Without flex	With Flex
Spring	186	124	0	0	168	168	661	661
Summer	89	61	0	0	12	12	424	424
Fall	0	0	0	0	1368	1367	0	0
Winter	0	0	0	0	1798	1797	10	5

However, even though the number of exceedances (number of PTUs where load exceeded the congestion limit per season) do not seem to have been reduced a lot, what matters for blackouts estimation is the duration and magnitude of the congestion, whether they have decreased due to flexibility steering. As explained earlier, when the load exceeds the congestion limit in consecutive PTUs (successively), such an exceedance should be considered as one congestion and depending on the duration and magnitude of the congestion, it may result in a blackout. The following table, Table 51, shows that the average duration of congestion (in PTUs) and the average magnitude of congestion (in Watt) has decreased at all congestion block levels. **The average percentage decrease in the magnitude of congestion (Watts) is between 55% and 67% at all congestion block levels. However, the average percentage decrease in the duration of congestion ranges between 34% and 67% at the FC and PV congestion block level, while the percentage decrease in the duration of congestion at the HP congestion block level is 2.5% only.**

Table 51: Average duration and magnitude of congestion at the four congestion block levels

	Congestion Block Levels									
	PV			**EB**		**HP**			**FC**		
	Load without Flex	Load with flex	% decrease	Load without flex	Load with flex	Load without flex	Load with flex	% decrease	Load without flex	Load with flex	% decrease
Average Duration of Congestion (PTUs)	7.05	2.28	67%	0.00	0.00	17.28	16.83	2.5%	2.75	1.80	34%
Average Magnitude of Congestion (Watt)	-6817	-3037	55%	0.00	0.00	8066	2695	66%	136	45	67%

Therefore, not all those congestions translate into blackouts, because it is dependent on the duration and magnitude of the congestion, as depicted in Figure 38 in section 7.6.2.1. Accordingly, the number of potential blackouts for Heerhugowaard city are estimated for the load with flex and without flex for the four congestion block levels as simulated in the simulation model, as shown in Table 52.

Table 52: Number of blackouts for load with and without flex for the 4 congestion block levels

	Number of Blackouts			
Congestion Block Levels	**PV**	**EB**	**HP**	**FC**
Load without Flex	1	0	1	0
Load with flex	0	0	0	0

It can be concluded from this section that the number of estimated blackouts after flex steering in the Heerhugowaard grid is nil. Those numbers are dependent upon the penetration level of smart devices, the percentage controlled smart devices, the percentage uncontrolled smart devices, the default state of the devices, the random error applied in flex delivery, the number of households connected at each congestion block level, and the congestion limit at each congestion block level. The random error applied on flex delivered is derived from the two month experiments performed at each congestion block level, and thus it is assumed that the forecast error that affects flex delivery stays constant (not improved) over the year. Those grid characteristics and input variables can be changed in the final simulation excel model accompanied with this report (except for the default state of the devices), in order to examine the impact of changes in grid characteristics and available flexibility on the reduction of blackouts. Snapshots of the excel simulation model can be found in **Appendix B.8 (Table 87, Table 88, Table 89, Table 90, Table 91, Figure 63).**

7.7 Conclusion on the Influence of Demand-Side Flexibility on Congestion Management

This chapter investigated the impact of flexibility on grid congestion at the distribution level in Heerhugowaard. In order to perform this analysis, two types of methodologies were employed. The analysis presented from section 7.1 till section 7.5 was performed on real measured data from Heerhugowaard, which implies that the derived conclusions mimic reality. However, the conclusions derived from section 7.6 are based on predictions and estimations from the simulation model, where this simulations model partly portrays a perfect world, which implies that these results are only limitedly generalizable to reality.

In the first half of the chapter (section 7.1 till 7.5), the analysis performed on the collected data from the Heerhugowaard field experiments, indicated the following insights for the influence of demand-side flexibility on congestion mitigation:

1. The analysis of the reliability of flexibility orders indicates that only part of the flex orders are delivered due to forecast errors and other exogenous factors such as IT errors. Furthermore, the analysis indicates that the Fuel Cell flexibility is the most reliable, in contrast to the HP, PV and EB, as is not affected by human behaviour nor weather forecast error.
2. Based on the Heerhugowaard field experiments data from two experiments, it is possible to conclude that changes in the load curve, in contrast to the forecasted load, are primarily caused by forecast errors and only limitedly changed by the delivery of flexibility. However, this conclusion cannot be generalized, knowing that the prediction of the electricity load curve and flexibility prediction might improve in the future.
3. Based on the analysis performed on the Heerhugowaard field experiments data it is **possible to conclude that the application of demand-side flexibility from the PV, HP, EB, and FC, can reduce the volatility of the electricity load between 4% and 12%.**
4. The analysis of the electricity load, in contrast to the congestion limits, indicates that the electricity load remains more within the congestion limits when flexibility is steered. However, the analysis of the systems capability (C_{pk} index) indicates that the electricity load curve with flexibility is still *incapable* of remaining within the congestion limits for the PV, HP, and EB experiments. Only in the FC experiment, the electricity load was capable of staying within the congestion limits. Thus, it can be concluded, that the influence of flexibility from the FC is more pronounced than at other congestion block levels.
5. **The analysis of the effectiveness of electricity flexibility in mitigating grid congestion indicates that flexibility is insufficient to resolve all congestion.** While the probability of network congestion went down with flex steering, it was not fully eliminated by using flexibility because of the following reasons:
   a. Within the Heerhugowaard congestion block levels, only one type of device is investigated and thus, for instance, if congestion occurred at the evening peak due to an increase in consumption, the PV cannot resolve this congestion at the PV congestion block level.
   b. The initial default state of the devices influences the offered flex (flex up or flex down), and consequently, not both types of flexibility can be provided at one congestion block level.
   c. The number of the uncontrolled devices that directly affects the potential mitigation of congestion.
   d. The flexibility prediction error affects the reliability of the flex delivered.
   e. The electricity load prediction error affects the flexibility ordered by the DSO and limits the potential of flexibility to mitigate electricity network congestion.
   f. The employed USEF market coordination mechanism, that defines how flexibility is traded among the different actors and the number of iterations designed to procure flex, limits the available flexibility and thus the offered flexibility to the DSO.
   g. The congestion limit directly affects the amount of flexibility required to resolve congestion.

In the second half of the chapter (section 7.6), where the Yearly Probability of Grid Congestion at Block levels for the Heerhugowaard field experiment was predicted and estimated based on a simulation model, slightly different conclusions were derived in contrast to the conclusions found in section 7.1 to 7.5 based on real measured data. The difference between these conclusions is the result from a transition from measured data that mimics reality with all its imperfections, to simulated data, which partly assumes a perfect world, because it could never duplicate reality.

It can be concluded from predicting flexibility from each device over a year that the PV output and the Heat Pump load are sensitive to seasonality, while that of Electric Boiler load and the Fuel cell is not sensitive to seasonality. However, the electric boiler load is dependent on hot water consumption, and thus affected by human behaviour/consumption. Specific conclusions that can be generalized with respect to the flexibility from the 4 devices are:

1. **It can be concluded that the PV output in Summer and Spring is at least as twice as that in Fall and Winter.**
2. **PV output commences at 5 am and lingers till 7 pm in Summer and Spring (14 hours of varying PV output); however, PV output commences at 7 am and lingers till 5 pm in Fall and Winter (10 hours of varying PV output).**
3. **It can be concluded that the Heat Pump load in Winter is roughly twice the Heat Pump load in Summer and roughly one third more than the Heat Pump load in Spring and Fall.**
4. **The heat pump load is high in the Winter starting at 4 pm in the afternoon till 7am in the morning (15hrs); however, the heat pump load is high in the Spring and Fall starting at 6 pm in the evening till 6am in the morning (12 hrs).The heat pump load in the summer is constant (low) throughout the day.**
5. **The Fuel cell energy production is constant over the day and the seasons.**

The results from the simulation study indicate that, similarly, as concluded from the real data, collected from the 2-month experiment in Heerhugowaard, that congestion at all congestion block levels from all devices cannot be fully resolved. However, as congestion does not result into blackouts, as in the field experiment **abstract/ theoretical congestion limits** were set, a translation based on the magnitude and duration of the congestion was made, in order to determine if the predicted congestion would result in blackouts. **From this analysis it can be derived that flexibility significantly reduces both the duration (min) and magnitude (Watts) of congestion and might eliminate blackouts. It is possible to conclude that flex steering can reduce the magnitude of congestion (in Watts) between 55% and 67%. Additionally, flexibility steering reduces the duration of congestion for the PV and FC experiments between 34% and 67%; however, flexibility steering reduces the duration of congestion for the HP experiment with only 2.5%.** However, this conclusion is limited to the following model assumptions:

1. Only the DSO is ordering flexibility
2. The DSO only orders flexibility day ahead
3. The error in the delivery of flexibility for all devices was incorporated in the model but the error in load prediction was not, since data on the load predicted versus measured over a year was not available to derive an error in load prediction.
4. The error in the delivery of flexibility for all devices was derived from two-month experiments. If experimented for longer with an assumed learning curve, the derived error in flex delivery could change over time. Thus, the error in the delivery of flexibility for all devices was set constant over the year, no improvements were enacted.
5. The theoretical congestion limit set was considered to be the maximum capacity of the grid components (transformers, cables, and fuses).

Finally, since performing field experiments to test whether flexibility can resolve congestion at the distribution level is expensive and time consuming, the simulation model will be used to predict the probability of congestion for different low voltage grids in the Netherlands for the load before and after applying flex, in the coming chapter, Chapter 8. Additionally, the financial viability of congestion mitigation via demand-side flexibility will be investigated versus capital intensive grid reinforcement using scenario analysis.

Chapter 8

8 The Extent Distribution Network Investment can be postponed by Means of Flexibility

The extent flexibility can mitigate distribution network congestion is considered network specific, as it is affected by the age of the network and assets, the remaining capacity of the network, the penetration level of smart devices and distributed generation sources, the percentage controlled of the devices, the growth rate of electrification (HP, EB, EV) etc. Conventionally, congestion was resolved by long term capital intensive reinforcement of the gird. However, with the increase in renewable energy sources decentralized production units and electrification of vehicles and heating, network investment is expected to rise in order to cope with this paradigm shift from unidirectional to bi-directional energy flow. Based on the Heerhugowaard field trial analysis in chapter 7, demand-side flexibility has indicated some potential to resolve congestion and minimize the number of blackouts, which is contingent on the prediction of the load and the flexibility available and delivered. Therefore, this chapter attempts to answer the following sub-research questions:

> *How do the results of the Heerhugowaard field experiment translate to other low voltage networks within the Netherlands and to what extent can distribution grid reinforcements/investments be deferred by means of flexibility?*

To study the extent demand-side flexibility can mitigate congestion in different low voltage networks, a case study analysis is performed on other low voltage networks within the Netherlands. A generalization and representability of the Heerhugowaard sample to the population is determined in section 8.1, prior to generalizing the flexibility prediction models and the Simulation model to other low-voltage networks. Subsequently, section 8.2, describes four other networks within the Netherlands and performs scenario analysis on those networks, which is conducted in section 8.5. Prior to that, the drivers behind the future scenarios are presented in section 8.3 and the modelling assumptions are stated in section 8.4. Last, section 8.7 concludes by presenting the prospects of demand-side flexibility in postponing network investment.

8.1 Generalization of the Flexibility Prediction Models to other Low Voltage Networks

To study the extent of which demand-side flexibility can mitigate network congestion and defer network reinforcement in a low voltage network, the results derived from the Heerhugowaard field experiment are first extended to other low voltage networks in the Netherlands. However, since the impact of flexibility on network congestion will be calculated for each network using an Excel simulation model, it is the flexibility prediction models estimated from the Heerhugowaard sample that should be representable to the population. Prior to using the prediction models in other low voltage networks, in other words generalizing the results, the representation of the households in the city of Heerhugowaard to the households in the Netherland should be examined and verified statistically.
The targeted parent population, in this project, are the households of the Netherlands. However, since Heerhugowaard is considered a modern green district with unique characteristics in terms of the population it attracts and the penetration level of renewable decentralized energy units, it is more appropriate to compare Heerhugowaard to similar districts with high renewable energy units' penetration levels that may possibly undergo a demand response implementation. Therefore, the sample from the Heerhugowaard low voltage network will be compared to the population of comparable low voltage electricity networks in the Netherlands with relatively considerable penetration levels of renewable energies and smart devices.

According to Sunday (2015), "The Largest Dutch Solar conference", the largest districts in the Netherlands with buildings equipped with photovoltaic panels are: Nieuwland (Amersfoort), Columbuskwartier (Almere), Vogeltjesbuurt (Tilburg), and Woudhuis (Apeldoorn), with the following generation capacities in kilo watt peak (kWp), respectively: 1351 kWp, 550 kWp, 450 kWp, and 218 kWp. Those districts were chosen because they might be applicable for demand response implementation due to the high penetration level of PVs. Therefore, the Heerhugowaard sample will be compared to those districts and if the statistical analysis between the sample and the targeted population resulted in that they are indifferent then it can be concluded that the Heerhogowaard sample is representable. Additionally, it is also argued that the representation of the sample to the population is also contingent upon having a randomly drawn sample (Kruskal & Mosteller, 1980), which will be addressed in section 8.1.1.1. Consequently, sub-section 8.1.1.2 will discuss the sample representation to the population by comparing socio-demographic parameters and sub-section 8.1.1.3 will discuss the sample representation to the population by comparing the energy consumption (kW/year).

8.1.1.1 Sampling

It is logistically impossible to sample the whole population, and thus a keen choice of the sample is necessary to ensure that such a sample is representable to the population. Statistical sampling is testing whether the sample is representative to the population before attempting to generalize the results. According to Lewis et al. (2007, p. 204), "sampling techniques provide a range of methods that enable you to reduce the amount of data you need to collect by considering only data from a subgroup rather than all possible cases or elements full set of cases from which a sample is taken is called the population".

In order to experiment with demand-side flexibility in a field trial, without jeopardizing the network reliability, convenient sampling was implemented. Convenient sampling is a non-probability sampling technique in which participants are selected due to the ease of reaching a pool of participants or due the convenience of the location (Henry, 1990). For instance, according to EnergieKoplopers (2015), the city Heerhugowaard was chosen because the electricity network's capacity is high enough to handle the high penetration level of PVs. Thus, actual network congestion and risk of blackouts in the Heerhugowaard electricity network shall not occur as a result of the demand response experiment. For the sake of this experiment, and to simulate congestion, an assumed 1 kVA congestion limit per household is activated. This renders the sample as non-randomly selected because the electricity network is pre-selected. Although, that the families in Heerhugowaard were asked randomly to participate in this field trial, this does not change the fact that the sample was conveniently selected.

8.1.1.2 Socio-demographic characteristics

The representation of the sample to the population is investigated by comparing certain features of the sample (201 households in Heerhugowaard) to the populations of the 4 districts. Demographic data from the 4 identified districts are acquired from the Central Bureau of Statistics (CBS). The parameters that were subject to a statistical comparison are: the average number of individuals per household, the average house construction year, the average house size, and the age distribution recorded as categories. Although, those parameters are not input parameters of the regression models, those socio-demographic characteristics define the sample on which the regression models were built upon. The analysis done on those variables depend on the level of measurement of the variables. The level of measurement of all categories are ratio level except for the age which is recorded by CBS as categories. Levels of measurement of the parameters and the corresponding suitable statistical tests are tabulated in Table 53.

Table 53: Level of measurement

Variable	Level of measurement	Statistical test
the average number of individuals per household	Ratio	One-sample student t test
the average house construction year	Ratio	One-sample student t test
the average house size	Ratio	One-sample student t test
the age distribution	Categorical (Ordinal)	Chi-squared test (χ^2)

Since, (1) the sample and population average values of the first 3 parameters are known, (2) the sample statistics and the population are normally distributed (central limit theorem), and (3) the parameters are of ratio scale of measurement, the One-Sample Student t test will be conducted with the following null and alternative hypothesis (Moore, 2007):

H0: The population mean is equal to the sample mean
H1: The population mean is different from the sample mean (two tailed)

When the "t" value is calculated, as shown in Table 54, the corresponding p-value is derived from the Student t-distributions. The threshold that was chosen to check for statistical significant is 0.05, thus when the derived p-value is smaller than the pre-defined threshold, the null hypothesis is rejected.

Table 54: The One Sample Student t test between the sample and the populations

Variable	Population		Heerhugowaard Sample		One sample t test results		Conclusion (reject/accept the null hypothesis)
		Mean	Mean	Std. Dev.	t value	P value	
Average Number of individuals per Household	Almere	2.17	2.848	1.15	8.02	0.0000	Rejected
	Amersfoort	2.71	2.848	1.15	1.62	0.1030	Accept
	Tilburg	1.74	2.848	1.15	13.1	0.0000	Rejected
	Apeldoorn	2.71	2.848	1.15	1.64	0.103	Accept
		Mean	Mean	Std. Dev.	t value	P value	
Average house construction year	Almere	1993.7	1997.07	13.49	3.39	0.0008	Rejected
	Amersfoort	1970.4	1997.07	13.49	26.79	0.0000	Rejected
	Tilburg	1970.43	1997.07	13.49	26.84	0.0000	Rejected
	Apeldoorn	1969.65	1997.07	13.49	27.63	0.0000	Rejected
		Mean	Mean	Std. Dev.	t value	P value	
Average house size (m^2)	Almere	116.75	128.97	30.47	5.45	0.0000	Rejected
	Amersfoort	125.59	128.97	30.47	1.51	0.1331	Accept
	Tilburg	118.36	128.97	30.47	4.73	0.0000	Rejected
	Apeldoorn	120.94	128.97	30.47	3.58	0.0004	Rejected

Therefore, based on the tabulated results of the student t test, all the averages are significantly different between the sample and the population of the 4 districts except the average number individuals per households for the Heerhugowaard turned out to be significantly indifferent from Amersfoort and Apeldoorn and the average house size for the Heerhugowaard turned out to be significantly indifferent from Amersfoort (as highlighted in green). Hence, it can be concluded that overall Heerhugowaard sample is significantly different from the population on the three socio-demographic parameters. Regarding the 4th parameter (age), as portrayed from Figure 41, not much can be said on whether the sample is significantly different from the 4 populations. Thus, to check whether the sample and the population of the 4 districts are significantly different or equal on the age distribution, the Chi-squared test (χ^2) is conducted based on the foundation that the sample and the populations are independent, all counts are larger than zero, and less than 20% of the counts are less than 5. One important limitation to note, is that one age per household was recorded in Heerhugowaard sample although multiple individuals per household might be present. In addition, since the sample size is 201 and the population size of the 4 districts are larger, the populations' size were proportionally adjusted to the Heerhugowaard sample to allow a fair comparison between the sample and the 4 populations.

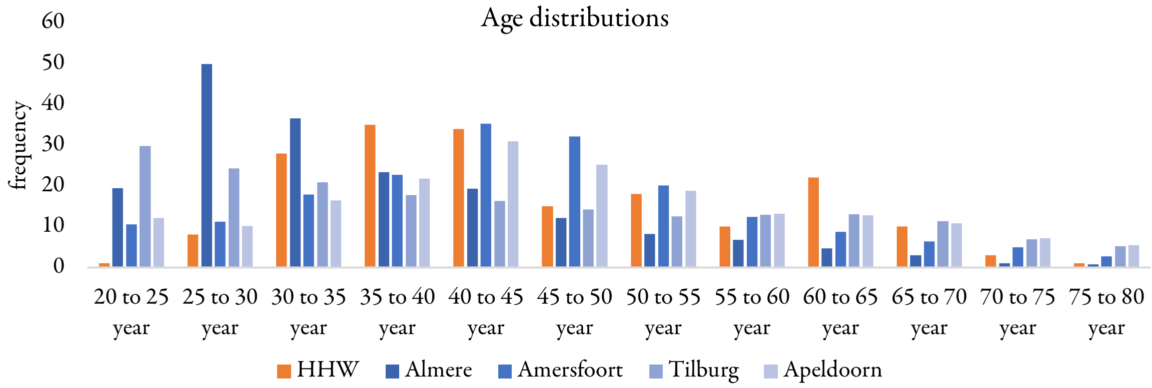


Figure 41: Age Distributions for the Heerhugowaard sample and 4 other populations

The Chi-squared test is considered to be a "goodness of fit" test where the sample distribution is compared to the populations' distributions, after having neutralized the difference between the sample size and the population sizes. The following null and alternative hypotheses are formulated:

H0: there is no difference between the sample and the population, $\chi^2=0$
H1: there is a difference between the sample the population, $\chi^2>0$

If the sample is a perfect reflection of the population, then the difference is nil, and the zero hypothesis cannot be rejected. However, the bigger is the difference between the sample and the population, the higher is the χ^2 value. The following table (Table 55) shows the χ^2 values of Heerhugowaard with the 4 other populations for the age distribution.

Table 55: Chi-Square Test for the Age Distributions

	Chi Square value (χ^2)	95% Rejection value	Hypotheses	Sig.
Heerhugowaard - Almere	170.66	19.68	Rejected	0.000
Heerhugowaard - Amersfoort	56.071	19.68	Rejected	0.000
Heerhugowaard - Tilburg	91.903	19.68	Rejected	0.000
Heerhugowaard - Apeldoorn	44.797	19.68	Rejected	0.000

According to the χ^2 density function, the upper critical value is 19.68, for $\alpha=0.05$ and 11 degrees of freedom. The degrees of freedom (df) is calculated as follows: df=(r-1) in which r is the number of categories (12 age categories). All the χ^2 values are bigger than the upper critical threshold (19.68) and thus the zero hypothesis is rejected. The Heerhugowaard sample is significantly different from the 4 other population districts. The highest χ^2 value is found between the Heerhugowaard sample and the Almere population and the smallest χ^2 value found was between the Heerhugowaard sample and the Apeldoorn population, which indicates that the Almere population is the most different from the Heerhugowaard sample and the Apeldoorn population is the least different from the Heerhugowaard sample, relative to others. However, overall it can be concluded that the Heerhugowaard sample is significantly different than the populations on the four socio-demographic parameters and thus not representable. The following sub-section will discuss the sample representation to the population by comparing the energy consumption (kWh).

8.1.1.3 Energy consumption

The average independent household energy consumption of the Heerhugowaard field trial is 3773 kWh per year (based on the field trial data). This average consumption is determined by correcting the household load for all the smart appliances and linearly interpolating the value for an entire year. The Heerhugowaard average household loads are compared by means of an independent student t-test to 78 selected households' loads from the Netherlands, excluding Heerhugowaard. The 78 selected households' loads were acquired from Alliander's database. To test whether the energy consumption of the sample of Heerhugowaard is significantly different from the 78 households' loads from the Netherlands, the Independent Student t-test is conducted based on the foundation that: (1) the dependent variable (energy consumption) is measured at a continuous scale, (2) the two groups are independent, and (3) the average of the dependent variable (energy consumption) is approximately normally distributed based on the central limit theorem. The null and alternative hypotheses are formulated as follows:

H0: the averages of the two groups are not different
H1: the averages of the two groups are different

One additional condition to verify before the test can be performed is whether the two groups have equal variance. Since the Levene's test indicates that the variance of both groups are not significantly different (sig =0.284 >0.05), equal variance can be assumed and the Student t-test in the first row of Table 56 is analyzed. The Independent Student t-test indicates that the two tailed probability is 15.1% and thus there is no significant differences between the two groups' averages, as shown in Table 56. Additionally, the 78 selected Dutch households show no significant difference in the energy consumption in comparison to the average Dutch energy consumption of 3050 kWh, acquired from CBA, using One Sample t test (the results are documented in **Table 92 in appendix C.1.**). Therefore, it can be concluded that the Heerhugowaard sample is representable to the population based on the energy consumption parameter.

Table 56: The Independent Student T-Test comparing the Energy consumption of Heerhugowaard with 78 Dutch Households

	Levene's Test for Equal Variance		Independent Student T-Test		
	F	Sig.	t	df	Sig. (2-tailed)
Equal Variance assumed	1.153	.284	1.441	279	.151
Equal Variance not assumed			1.416	134.93	.159

Never the less, Heerhugowaard is significantly different on the 4 socio-demographic parameters, as proven in section 8.1.1.2, and thus not representable and not generalizable to the population. Moreover, the representation of the sample to the population is contingent upon having a randomly drawn sample, which was proven in section 8.1.1.1 to be conveniently and non-randomly sampled. This implies, that the non-representability, non-generalizability, and non-randomness of the sample to the population will limit the conclusions drawn from the analysis. However, according to Visser, Krosnick, and Lavrakas (2000): "even data collected from samples that are decidedly unrepresentative of the general population can be used to draw inferences about that population" (p. 223). **Thus, although the prediction models were based on Heerhugowaard sample, which is not representable and not generalizable to the population, implications about other low voltage electricity networks can be drawn using the prediction models, but it is important to keep in mind the limitations of the conclusions since they are not generalizable to the population.** Therefore, section 8.2 will introduce other low voltage networks in the Netherlands, and will perform a quantitate analysis on the influence of demand-side flexibility on mitigating congestion and the prospects on postposing networks investments.

8.2 Other Low Voltage Networks within the Netherlands – Case Study

The use of demand-side flexibility to mitigate congestion and postpone distribution network investment might have different outcomes under different electricity network characteristics. In order to determine the influence of flexibility in that matter, a multitude of different electricity networks are investigated, which were chosen because of the availability of data. These electricity distribution networks vary from small single street network, as introduced in section 8.2.1 and 8.2.2, to larger distribution networks for cities and rural areas within the Netherlands, as introduced in section 8.2.3 and 8.2.4, respectively.

8.2.1 Case Study: The Bosboomstraat in Heerhugowaard City

In the Bosboomstraat in Heerhugowaard, 138 households are renovated in accordance with the Stroomversnelling initiative. This initiative proposes to renovate social renting households, by enhancing the insulation of the houses and installing smart appliances, in order to create energy neutral households. The energy neutral house implies that the household produces its own electricity. However as zero electricity is unequal to zero power, the household still requires to be connected to the electricity grid. In order to achieve household independent electricity generation, the houses are equipped with 7.8 kWp photovoltaic panels, and a heat pump. Consequently, due to the installation of a large amount of PV capacity, the current electricity distribution network in the Bosboomstraat is threatened, as the current distribution network is not designed to take into account such levels of electricity generation. For example, with the current 2.28 kVA congestion limit per household, the PV capacity on its own already exceeds this limit with more than 3 times. Consequently, in such a situation where low congestion limits are combined with high electricity production, there is a high risk of congestion and blackouts.

Table 57: The Characteristics of the Bosboomstraat in accordance with Stroomversnellings initiative

Nr. Households	Congestion limit per household (W)	Nr. PV	PV Capacity (W)	Nr. EB	Nr. HP	Nr. FC
138	2.28	138	7,800	0	138	0

8.2.2 Case Study: The Kleynstraat in Den Helder City

The Kleynstraat is a street in the city of Den Helder which consists of 334 social renting households. These households are connected to a low voltage electricity network with a congestion limit of 943 VA per household (Korver, 2015). This network is investigated because the installation of Photovoltaic panels might pose a threat to the existing distribution network, and could results in future blackouts. Within this low voltage electricity network, a total peak Photovoltaic capacity of 209 kWp is planned to be installed over the 334 households. However, since no further information on the distribution of these Photovoltaic panels is available, the assumption is made that every household has a Photovoltaic capacity of 625 Wp (209kWp/334 househols). An overview of these characteristics is presented in Table 58.

Table 58: The Characteristics of the Kleynstraat in Den Helder

Nr. Households	Congestion limit per household (W)	Nr. PV	PV Capacity (W)	Nr. EB	Nr. HP	Nr. FC
334	943	334	625	0	0	0

8.2.3 Case Study: The City of Steenwijk

The city of Steenwijk is an urban district that contains 4701 households, varying from townhouses to two under one roof houses. The electricity network employed in this district is very common in the Netherlands and approximately applied 600 times in other cities, in terms of topology and grid assets characteristics (Ecofys, 2014). Furthermore, Liandon states that in this electricity network a maximum load of 1 kVA per household can be expected (Ecofys, 2014). Consequently, the congestion limits is set to 1000 W per household for all the households in Steenwijk. However, no information is available regarding the number of smart appliances installed within these households. Therefore, scenarios will be sketched (section 8.3) to take into account, for instance, the growth of renewable electricity sources and smart appliances based on realistic drivers of future scenarios. An overview of the network characteristics is presented in Table 59.

Table 59: The Characteristics of the city Steenwijk

Nr. Households	Congestion limit per household (W)	Nr. PV	PV Capacity (W)	Nr. EB	Nr. HP	Nr. FC
4,701	1,000	unknown	unknown	unknown	unknown	unknown

8.2.4 Case Study: The City of Drechterland

In contrast to the city of Steenwijk, the city of Drechterland is a rural area and contains 3459 free standing households, which are either located in city centers or linearly spaced next to main roads. According to Liandon, the electricity network in Drechterland can sustain a maximum load of 1 kVA per household (Ecofys, 2014). The electricity network that is applied in this city has also been applied in approximately 1500 other cities in the Netherlands and can therefore be considered a common distribution network (Ecofys, 2015). However, as with the case of Steenwijk, no information is available with regards to penetration level of smart appliances and renewable electricity sources. An overview of the characteristics of this electricity network is presented in Table 60.

Table 60: The Characteristics of the city Drechterland

Nr. Households	Congestion limit per household (W)	Nr. PV	PV Capacity (W)	Nr. EB	Nr. HP	Nr. FC
3,459	1,000	unknown	unknown	unknown	unknown	unknown

Based on these four different case studies, the extent to which demand-side flexibility can postpone network investment is investigated. However, future scenarios may look different from the status quo and have a different influence on the current grid and the need for reinforcement, such as: the projected penetration level of smart devices, the energy demand growth rate, the number of EVs etc. Consequently, the drivers of future scenarios that might influence the need for network reinforcement are investigated first.

8.3 Future Scenarios Influencing the need for Network Reinforcement

As discussed in the chapter 4, smart networks with the new communication and information systems, enable the DSO to exercise flexibility in controlling the domestic loads and shaving peak loads. Without smartly managing the load profile, Blockhuis et al. (2011) estimate that network investments will potentially increase significantly. The reduction of peak load via flexibility, may contribute to reducing the required capacity of cables and transformers needed and could possibly lead to a decrease in investments. Thus, to realize future investment savings for the DSO, the potential required grid capacity (e.g. cables, transformers, fuses) should be determined. This estimation is contingent upon determining the long run load curve and flexibility availability, which are both inherently hard to predict and are subsequently, uncertain in nature. Consequently, the need for a method arises that allows one to take into account the impact and uncertainty of possible future scenarios. Such a method is Scenario Analysis and consist of the following steps (Enserink et al., 2010): (1) Identify Exogenous factors, (2) Identify the uncertainty and significance of the exogenous factors, (3) create a scenario logic and (4) perform scenario analysis. Consequently, these steps are addressed in section 8.3.1 through 8.3.3 However, the fourth step, 'performing scenario analyses', is performed as part of the network investment postponement analysis in section 8.5.

8.3.1 Exogenous Factors Influencing the need for Network Reinforcement

Exogenous factors are factors that influence the system, but are factors the DSO is unable to control. In order to determine such factors, Enserink et al. (2010) mentions techniques as brainstorming and causal maps. Through such causal maps, which are based on for example Veldman et al. (2013) and Ecofys (2015), the following exogenous factors are identified.

1. Electricity demand
2. Capacity of Photovoltaic systems
3. Number of Electric Vehicles
4. Number of Heat Pumps
5. Battery storage technology
6. Electricity flexibility price
7. Interest rate
8. Multiple Aggregators

However, not all exogenous factors are relevant for scenario analysis, as some factors have, for example, a very low impact on the potential of network investment postponement through demand-side flexibility, or the development of such exogenous factors is certain. Consequently, the next section performs an analysis on the **impact** and **uncertainty** of the identified exogenous factors.

8.3.2 The Uncertainty and Impact of Exogenous Factors

In order to determine which of the exogenous variables could have a large influence on the potential of network investment postponement, the impact and uncertainty of each exogenous factor is analysed. Consequently, in order to present the decision making process, in which these exogenous factors are ordered in high/low **impact** and **uncertainty** categories, each exogenous factor is discussed individually.

Electricity Demand

As mentioned in the introduction of this chapter, the electricity load plays a large role on the risk of blackouts and consequently, on the possibility to postpone grid investment. Veldman et al. (2013) draws three possible future scenarios for changes in the electricity load, where these scenarios are based on the Dutch Environmental Assessment Agency, which studied the current energy market and climate policies and their long term impact.

1. The first scenario assumes a low economic growth and an effective climate policy, which results in a decrease in electricity demand of approximately 1% per year.
2. In the second scenario, it was assumed that the economy is booming but the climate policy in place is not that effective. It is assumed that in such scenario the demand for energy will increase with approximately 1.5% per year due to the increase in electricity demand.
3. In the third scenario, the economy is stable and the climate policy is effective resulting in an increase in investment in renewable energies and a restrained growth of approximately 0.35% per year in demand for electricity.

Capacity of Photovoltaic systems
Analysis of the capacity of the PV panels installed on Dutch households is based on a study from the Planbureau voor Leefomgeving (2014), which indicates a strong increase in the use of PV panels on households. This strong increase of PV systems, has a strong influence on the load and the available flexibility, and consequently, on the possibility to postpone network investment. A realistic expected capacity for the PV capacity per household is estimated to be 0.05 kWp in 2015, 0.3 kWp in 2020, 1.6 kWp in 2030 and 2.5 kWp in 2050 (Ecofys, 2015).

Number of Electric Vehicles
Next to the increase in PV capacity, Movares (2013) indicates a strong increase in the EV penetration level. The increase in EV activity will have a strong impact on the evening network peak load, as most EVs are connected to the network when people come home from work (around 18:00). Ecofys (2015) present an EDSN curve for the hourly EV load on the network, which is presented in **Figure 64 in Appendix C.2** of this thesis, and clearly presents this evening peak. Even though that the Netherlands is a frontrunner in the use of EVs, this does not mean that the future of EV development is certain, as the development is strongly dependent on the fuel prices, regulatory environment and infrastructure policies (McKinsey, 2014). At this point in time, Movares (2013) estimates the penetration level of EVs to be 5% in 2020, 35% in 2030 and 65% in 2050.

Number of Heat Pumps and Fuel Cells
The penetration level of the HP and Fc is expected to be 5% in 2020, 10% in 2030, and 35% in 2050 (CE Delft, 2014). This is because, for example, a large amount of HP will be installed within Stroomversnellings projects. Kuub (2015) has indicated that the Netherlands has large potential for such Stroomversnellings projects, but the development is uncertain. Although 110,000 household are eligible, no strict planning for renovation has be established. Consequently, the development of the penetration level of HP and FC is somewhat uncertain. Furthermore, the HP does not only lead to additional load to the electricity network, but can also be used as a source for flexibility. Therefore, the addition of HPs and FCs on the electricity network has a large impact on the load, but also on the potential to postpone network investment.

Battery storage technology
Battery technology has been an increasing market since the further integration of PV systems on households. For example, MIT (2015) mentions that battery storage systems would enable homeowners to have more control over how and when power is obtained within the households. Additionally, it would allow homeowners to provide support for utilities in "shifting demand to off-peak hours and smoothing out the load on the system" (MIT, 2015). Consequently, battery technology supports resolving congestion and postponing network investment without having to purchase flexibility from an Aggregator. Although that battery technology seems promising, its current state of technology does not allow homeowners to store sufficient energy to capture large solar peaks. Additionally, the current developed battery packs are not available on the market, and not expected to be available soon (MIT, 2015).

Electricity flexibility price
Based on research from DNV-GL (2014), the electricity price is expected to increase, which has direct implications on the electricity flexibility price. However, as the electricity price only increases very slightly, it is expected that the flexibility price will also increase very slightly, while excluding other overhead variable costs and non-delivery penalties that my affect the price of flex. Thus, it can be assumed that the insignificant increase in flexibility prices, based on electricity prices, will have very little influence on the potential to postpone network investment.

Discount rate
Electricity generation projects, due to their high project specific risk, which is also mostly unsystematic, makes past project discount rates unsuitable (where the discount rate implies the hurdle rate). Consequently, Oxera (2011) performed research on the required discount rates within low carbon generation technologies deployed in 2011. This analysis is essential as the discount rates are uncertain due to changes in the wholesale electricity prices, governmental policies, the overall risk perception of the technology and the maturity of the technology. Consequently, the discount rates are estimated to be 3.5%, 5% or 10%. The uncertainty of the discount rate in the future is reflected in the wide range of the discount rates (3.5%, 5% or 10%).

Multiple Aggregators
At this point in time the DSO is ordering flexibility from one Aggregator. However, in time, additional Aggregators might enter the market. Due to the existence of additional Aggregators in the market, the price of flex should decrease to the

marginal cost and provide a lower cost for the DSO, while excluding any potential increase in the price of flex due to overhead costs. However, according to Stomphort and Woittiez (2015), the estimated profits of the Aggregator is very low (€0.01), and thus the influence additional Aggregators might have on the flex price is expected to be very low.

Based on the descriptions and analysis of the **impact** and **uncertainty** of the presented exogenous factors, Table 61 is constructed. For scenario analysis, only the exogenous factors that have a high impact and high uncertainty are investigated (Enserink et al., 2010). This implies that a scenario logic is established for: Electricity demand, Capacity of Photovoltaic systems, Number of Electric Vehicles, Number of Heat Pumps and the Discount rate.

Table 61: The Uncertainty / Impact Matrix for Exogenous Factors

		Uncertainty	
		High	**Low**
Impact	**High**	Electricity demand Capacity of Photovoltaic systems Number of Electric Vehicles Number of Heat Pumps Discount rate	Battery storage technology Electricity flexibility price
	Low	Multiple Aggregators	None

8.3.3 Scenario Logic

The exogenous factors that are identified as **high impact-high uncertainty,** form the basis for the axis of the scenario logic. The scenario logic then forms the scenario space in which possible scenarios can be found. For the Electricity demand, three possible scenarios are identified based on Veldman et al. (2013), and presented in **Table 93 in Appendix C.3**. Furthermore, two possible scenarios are identified for each PV, EB and EV penetration level into the future (high and low penetration), and are presented in **Table 94 in Appendix C.3.** Last, for the discount rate, three possible scenarios are identified based on Oxera (2011). Based on these scenarios, a total of 72 scenarios can be tested. However, in some case studies, some scenarios are not applicable, due to for example the initial presence of PV capacity or HP pre-defined penetration level, as within the Stroomversnellings case study. Consequently, the number of scenarios investigated for these case studies (Bosboomstraat and Kleynstraat) is limited.

Based on the presented growth scenarios of the electricity load, the penetration level of the HP and EV and the estimated growth in PV capacity, and the case studies introduced in section 8.2, scenario analysis can be performed. However, before this analysis is performed, the next section introduces the modelling assumptions used within the analysis.

8.4 Modelling Assumptions

In order to analyse to what extent network investment can be postponed by means of demand-side flexibility in the different cases and scenarios, a set of modelling assumptions is made. The description of these assumptions is paramount as it enables other researchers to verify the research outcome and conclusion. The assumptions made within the analyses are presented in Table 62.

Table 62: Modelling Assumptions for the Quantitative Analysis of Network Investment Postponement

Modelling aspect	Assumptions	Sources
Timescale	2015 - 2050	N/A
Flexibility trading scheme	Only DSO trading, no BRP present	N/A
	Flexibility was ordered to resolve congestion	N/A
	No flexibility assumed from the EVs, since no prediction model was built for the EV	N/A
	All available smart appliances can be controlled	N/A
Flexibility delivery error	Error in flex delivery apply (section 7.6.2.1)	N/A
Network investment cost per kVA per household in Bosboomstraat in Heerhugowaard	€250 per kVA per household	Erbrink (2015)
Network investment cost per kVA per household in Kleynstraat in Den Helder	€250 per kVA per household	Erbrink (2015)
Network investment cost Steenwijk (urban city)	€250 per kVA per household (urban area)	Ecofys (2015)

Network investment cost Drechterland (rural city)	€740 per kVA per household (rural area)	Ecofys (2015)
Network investment calculation	|maximum load without flex-congestion limit|* (cost/kVA/ household)	N/A
Electricity load increase scenarios	+0.35% per year, +1.5% per year or -1% per year	Veldman et al. (2013)
High PV penetration	0.05 kWp in 2015, 0.3 kWp in 2020, 1.6 kWp in 2030, and 2.5 kWp in 2050	Ecofys (2015)
Low PV penetration	0.025 kWp in 2015, 0.15 kWp in 2020, 0.8 kWp in 2030, and 1.25 kWp in 2050	
High EV penetration	5% in 2020, 35% in 2030 and 65% in 2050.	Movares (2013)
Low EV penetration	2.5% in 2020, 17.5% in 2030 and 32.5% in 2050.	
High HP and FC penetration	5% in 2020, 10% in 2030, and 35% in 2050	CE Delft (2014)
Low HP and FC penetration	2.5% in 2020, 5% in 2030, and 17.5% in 2050	
Discount rate	3.5%, 5% and 10%	Oxera (2011)
Electricity flexibility price for the PV		Stomphort and Woittiez (2015) Alliander and Essent pricings
Electricity flexibility price for the HP		
Electricity flexibility price for the FC		
Heat Pumps	The HP that are used within Heerhugowaard are also applied to the experimental case studies	
Base state of the devices	Same as applied in the Heerhugowaard field trial	

8.5 A Quantitative Analysis of the Influence of Flexibility on Postponing Network Reinforcement – Case Study

As introduced in section 8.2, four different low voltage networks throughout the Netherlands are used to investigate the influence of flexibility on postponing network reinforcement. Consequently, section 8.5.1 through 8.5.4 present the analysis of these four case studies and provides insights into the cost-effectiveness of flexibility in resolving congestion and postponing network reinforcement.

8.5.1 Case Study Analysis: The Bosboomstraat in Heerhugowaard

The Bosboomstraat in the city of Heerhugowaard is a street in which households will be renovated based on the Stroomversnellings concept. Consequently, these households are equipped with 138 PVs (7800 W) and 138 HPs (the same HP functions and characteristics as that in Heerhugowaard field trial) in order to reduce the load of the household to zero and reduce the dependency on the gas network. The number of EVs is expected to grow from 5% to 65% from year 2020 till 2050. However, the electricity network in this street has a low capacity limit per household and subsequently, requires either demand-side management or network investment in order to prevent blackouts (Figure 42).

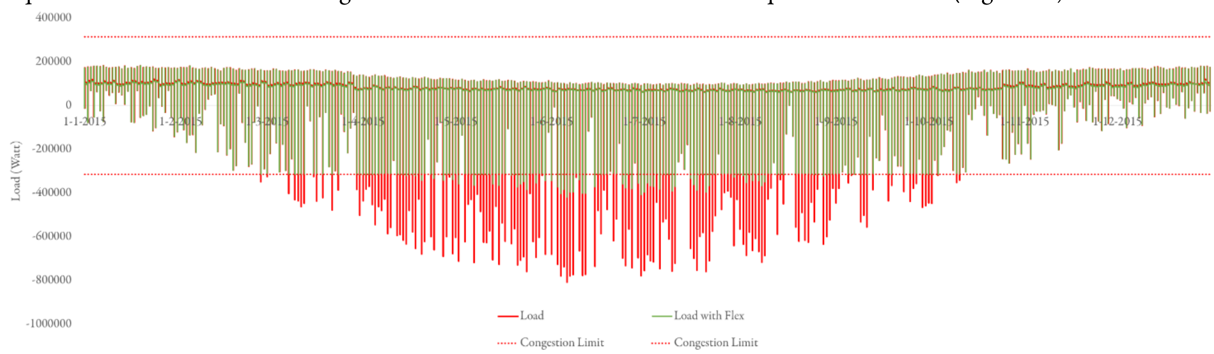


Figure 42: Bosboomstraat congestion limit and load with and without PV flex for the year 2015 for 0.35% load increase scenario

Analysis of the possibility to use demand-side flexibility as a means to postpone network investment for multiple load scenarios (Table 63), indicates that network investment in all cases can be postponed with 35 years. However, postponing the network investment can only be done when sufficient PV flex is purchased from the Aggregator, as shown in Figure 42, and these costs are higher than the savings realized by postponing the network investment. Thus, **the savings are calculated as the difference between the savings gained due to postponing network reinforcement and the costs incurred due to flex ordering** (for further information on the calculations, **refer to appendix C.4**). Flex ordered in this case is from the PVs, since the congestion is happening with the lower congestion block level (Figure 42). **The average number of blackouts that were resolved by flexibility steering for all scenarios is 121. However, it is possible to** conclude that, even though network investment can be postponed via flexibility, postponing investments does not provide any savings for the DSO. On the contrary, as shown in Table 63, the savings are negative, thus it is more expensive to order flex than invest in the grid. This conclusion is reached because the amount of flex required to resolve congestion within this electricity network is very high due to the high capacity of PVs installed. Even in the scenarios where the load of the households is increasing over time, and the increase in EVs penetration, the load is not sufficiently high to reduce the need for flex.

Table 63: Different load scenarios to postpone network investment in the Bosboomstraat Heerhugowaard with High EV integration

Load Scenarios	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment Required (with flex steering)	Network Investment (with flex steering)	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	35	2015	Further than 2050	€ 0	-€ 473,896	-€ 360,617	-€ 157,909
1.5% Load Increase	35	2015	Further than 2050	€ 0	-€ 441,923	-€ 339,555	-€ 154,334
-1% Load Decrease	35	2015	Further than 2050	€ 0	-€ 507,265	-€ 383,856	-€ 164,572

Within a different future scenario, than the scenarios presented by Movares (2013), one could expect that the EVs penetration level is lower than estimated (half the percentage estimated by Movares (2013)). Therefore, the prospect of flexibility to network investment postponement is also investigated for this alternative scenario, where the results are presented in Table 95 in **appendix C.5. As was the case with the high EV penetration level, the cost savings from network investment postponement do not outweigh the cost for flex, and no positive savings are created for the DSO, making the postponement of network investment undesired.**

8.5.2 Case Study Analysis: The Kleynstraat in Den Helder

The Kleynstraat in Den Helder city where Photovoltaic panels are initially installed in year 2015 and an increasing number of HPs (controlled) and EVs over multiple years can be expected according to the drawn scenarios, is analysed (as addressed in section 8.3 and Table 58). The analysis provides multiple outcomes with respect to the possibility to postpone network investment (as presented in Table 64). The results with the two scenarios of a load increase of 0.35% and 1.5% per year, indicate that network investment should take place in year 2028 and 2024 respectively. Before year 2028 and 2024, there is no need to order flex. However, demand-side flexibility from controlled HPs as a means to postpone network investment are incapable of resolving all congestion beyond those two years (blackouts were reduced by 20.19% and 11.33% respectively, but they were not eliminated). This can be portrayed in Figure 43.

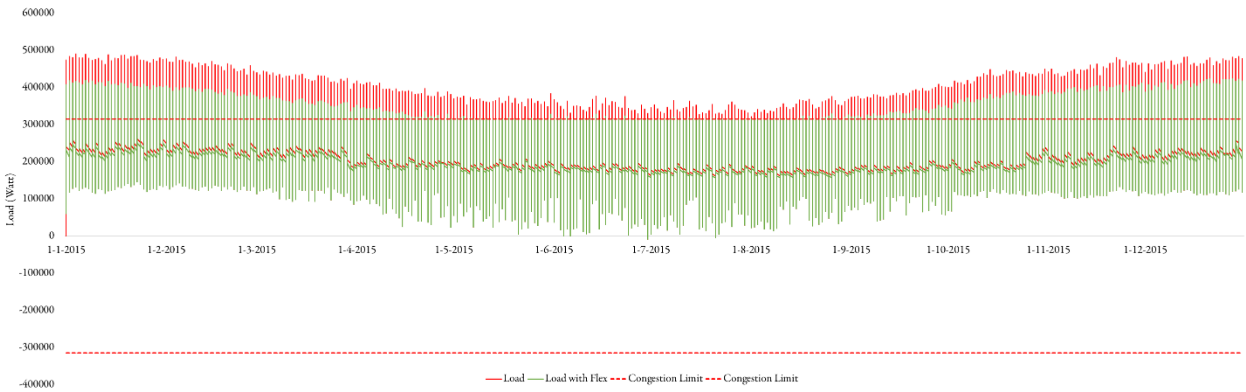


Figure 43: Kleynstraat congestion limit and load with and without HP flex for the year 2029 for 0.35% load increase scenario

However, in the third scenario, where the electricity load on the network is expected to decrease with 1% per year, results show that congestion start occurring in year 2044. Therefore, in year 2044 flex from the controlled HPs can be purchased and results indicate that it is possible to postpone network investment with a maximum of 7 years, by year 2050. However, postponing the network investment with 7 years is only financially feasible with a 10% discount rate (as presented in Table 64), and creates savings of €511 for the DSO, which is considered roughly negligible. However, savings for the DSO can be slightly improved to €1271, if network investment is planned in 2047 (after 3 years) instead of beyond 2050 (after 7 years). The reason behind it, is because over the years with the increase in EVs, more flexibility is needed to resolve congestion and eliminate blackouts which means the cost incurred due to flexibility ordering outweighed the saving gained due to network investments. This implies that network investment for this scenario (1% load decrease) can be postponed with maximum 7 years but are most financially attractive with 3 years, where a future value of €1271 savings can be realised at the10% discount rate. The value of savings is calculated by subtracting the savings gained due to network investment postponement with the present value of the cost of flexibility ordered over the specified years. **So overall the savings are less than 3% of the total network investment needed, which renders these financial savings negligible, especially if the flex prices increased, or the discount rate was set at low rates, or flexibility availability was affected due to the engagement of many DSOs or BRP…etc.**

Table 64: Different load scenarios to postpone network investment in the Kleynestraat Den Helder with high HP and high EV

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	0	Flex not helpful	2028	€ 67,729	€ -	€ -	€ -
1.5% Load Increase	0	Flex not helpful	2024	€ 112,174	€ -	€ -	€ -
-1% Load Decrease	7	2044	Further than 2050 (with flex)	€ 33,684	€ -13,095	€ -9,390	€ 511

As the future is uncertain, it is possible that both the HP and EV might not grow in number as fast as indicated by Ecofys (2015). Consequently, supplementary scenarios are investigated with respect to the same network configuration, but with different penetration levels of HPs and EVs. This investigation results in three additional scenarios, where **either** the EV, or HP penetration level increase half as fast as predicted, which are discussed in section 8.5.2.1 and **appendix C.6** respectively, and a scenario where **both** the HP and EV penetration level increase half as fast as predicted, which is presented in **appendix C.6**, Table 97. Additionally, although unlikely, the FC might be deployed as a flexibility providing appliance in replacement of the HP, as the HP is not always capable of resolving congestion successfully due to the limited flex it can offer. Consequently, additional research is performed on the effect of the flexibility gained from FCs on network investment postponement in the Kleynstraat in Den Helder in section 8.5.2.2 and **appendix C.6**.

8.5.2.1 Network investment postponement for the Kleynstraat with Low EV penetration

By considering a decrease in the penetration level of EVs, the load of the households will witness a slow increase, in comparison to the high increase of EVs, and results in a lower risk of blackouts. Consequently, it can be expected that network investment is required at a later point in time, in comparison to the high EV growth speed. Results of this analysis, as presented in Table 65, substantiate this assumption as flex is required in year 2048 and 2031, for the 0.35% and 1.5% load increase scenarios, respectively. As for the 1% load decrease scenario, network investment is even not required at all, within the time interval analysed (2015-2050). Additionally, results indicate that by means of flex from HPs, network investment can be postponed by 3 and 1 year for both the cases with a 0.35% and 1.5% load increase per year, correspondingly. Furthermore, these network investment postponements also provide the DSO with financial savings varying from €711 till €6651, dependent on the discount rate, **which is again not enough to conclude that demand-side flexibility can result in significant cost savings in comparison to network investments.** Similar results are presented in **appendix C.6** for the scenario with low HP penetration and high EV penetration (Table 96) and for the scenario with low EV and low HP penetration (Table 97).

Table 65: Different load scenarios to postpone network investment in the Kleynstraat in Den Helder with High HP and Low EV growth

	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment Required (with flex)	Network investment	Discount Rate		
					3.50%	5%	10%
0.35% Load Increase	3	2048	Beyond 2050	€ 31,389	€ 711	€ 1,975	€ 5,712
1.5% Load Increase	1	2031	2032	€ 76,007	€ 2,295	€ 3,348	€ 6,651
-1% Load Decrease	0	Flex not required	Beyond 2050	€ -	€ -	€ -	€ -

From the outcomes presented in Table 64, Table 65, and (Table 96 & Table 97 in appendix C.6), for the different scenarios, it can be concluded that network investment can be postponed, but only when sufficient flex is available from the HP, to resolve congestion and eliminate blackouts. **The average percentage decrease in blackouts for all scenarios for Kleynstraat is roughly 10%.** In other situations, where these conditions are not met, network investment is simply not required, or network investment cannot be postponed by flex, and consequently, the network needs to be reinforced.

When network investment can be postponed and flex is applied, the positive financial savings created from this postponement vary. **According to the One Sample Wilcoxon Signed Rank Test, the financial savings do not significantly deviate from €0 (Sig. 0.173). Consequently, it can be concluded that the savings gained, which is calculated as the difference between savings from network postponement and the costs incurred due to flex ordering, are negligible.** Additionally, it is important to note the uncertainty of possible future scenarios, discount rate fluctuations, price of flex changes, the reliability of flexibility available, and the presence of different DSOs or BRP ordering, which may affect the potential savings.

8.5.2.2 Network investment postponement for the Kleynstraat with FC

One could argue that the postponement of network investment might be different when the HPs are replaced by FCs (the FC will follow the same penetration growth as the HP, as presented in Table 62). Consequently, in order to provide additional insights into the possibility to postpone network investment, additional analysis is performed for the Kleynstraat in Den Helder, where the HPs are replaced with FCs. In order to provide a fair comparison, the same scenarios are analysed as with the deployment of the HP, and the results are presented in Table 66, and Table 98, Table 99, Table 100 in **appendix C.6.**

Table 66: Different load scenarios to postpone network investment in the Kleynestraat Den Helder with high FC and high EV integration

	Network Investment				Savings		
	Postponement	Year of Flex Required	Year Network Investment Required	Network investment	Discount Rate		
					3.50%	5%	10%
0.35% Load	20	2031	Further than 2050	€ 46,915.33	€ 18,508	€ 25,115	€ 37,368
1.5% Load Increase	2	2026	2028	€ 90,913.52	€ 5,730	€ 8,144	€ 15,491
-1% Load Decrease	0	Flex not required	Further than 2050	€ 13,119.76	€ -	€ -	€ -

Results from the application of the FC, in replacement of the HP, indicate (Table 66, and Table 98, Table 99, Table 100 in **appendix C.6**) that the FC is very capable of resolving blackouts and postponing the need for network investment with a maximum of 20 years, this is because flex available from the FC is more than the HP and is not dependent on weather and human behaviour. Although that the results of network investment postponement fluctuate with different scenarios, as was the case with the use of the HP, the cost savings through postponing network investment are now on average €13,400. The savings from the flexibility from the FC are significantly different from that of the HP due to the difference in flex prices (€X per kWh of FC flex and €Y per kWh of HP flex). Based on the One Sample Wilcoxon Signed Rank Test (significant 0.000), the presented average cost savings is significantly different than zero. Consequently, it can be concluded that in this case, and with these scenarios and smart appliances, the use of flex in network investment postponement provides significant cost savings for the DSO within a multitude of different possible future scenarios.

Based on these results it can be concluded that network investment postponement for the Kleynstraat in Den Helder with the use of HP is feasible, but based on the financial aspect included in this analysis, not financially better than postponing network investment. Furthermore, based on the analysis of the FC, it can be concluded that network investment postponement is feasible, and financial savings are possible and significantly different from zero. However, it must be noted that these results are only valid for the configuration of the used smart appliances, and the constructed scenarios and assumptions.

8.5.3 Case Study Analysis: The City of Steenwijk

In order to extend the analysis from small scale street level network investment projects, to large scale city wide distribution networks investment, a case study of the city Steenwijk is performed. The city of Steenwijk, with the distribution network specification as addressed in section 8.2.3, is analysed under a wide set of scenarios, as presented in section 8.3. These scenarios include increasing loads, increasing PV capacity, an increasing HP penetration level and an increasing EV penetration level. Additionally, with the uncertainty of the future, the growth for these scenarios is fluctuated, as also addressed in section 8.3. Thus, it results in 8 possible future scenarios for the city of Steenwijk (Table 67), where per scenario, the changes in the electricity load and changes in the discount rate are also taken into consideration. Consequently, section 8.5.3.1 will present and discuss the outcome of these scenarios, and last, section 8.5.3.2 will conclude if network investment postponement is feasible and financially desired for the city of Steenwijk.

Table 67: Possible Scenarios for the Analysis for the Distribution Network in the City Steenwijk

	PV	HP	EV
Scenario 1	High	High	High
Scenario 2	High	High	Low
Scenario 3	High	Low	High
Scenario 4	High	Low	Low
Scenario 5	Low	High	High
Scenario 6	Low	High	Low
Scenario 7	Low	Low	High
Scenario 8	Low	Low	Low

8.5.3.1 Steenwijk Scenario 1:

Following the projections from Movares (2013), the Planbureau voor Leefomgeving (2014) and Ecofys (2015) on the development of the PV capacity, HPs and EVs, results of the network analysis indicate, that with an increase in the electricity load, a network investment is required in year 2030 for the 0.35% Load Increase scenario and year 2026 for the 1.5% Load Increase scenario Table 68). This network investment is required as both the upper and lower congestion limits are exceeded, as presented in Figure 44. However, network investment can be postponed by means of flexibility ordered from the PV and HP through the Aggregator, to solve congestion from the lower and upper congestion limit, respectively. With flexibility, network investment can be postponed to 2033 and 2027 for the 0.35% and 1.5% load increase scenarios, respectively (as shown in Table 68). However, for the 0.35% load increase scenario, only the postponement with a 10% discount rate provides positive savings for the DSO. In contrast, with the 1.5% load increase, all possible network investment postponements provide financial savings for the DSO; **however, the postponement is possible for one year only which can be considered negligible. From these results it is possible to conclude that network investment postponement is partly feasible; however, the savings depend on the applicable discount factor and electricity load projection into the future.**

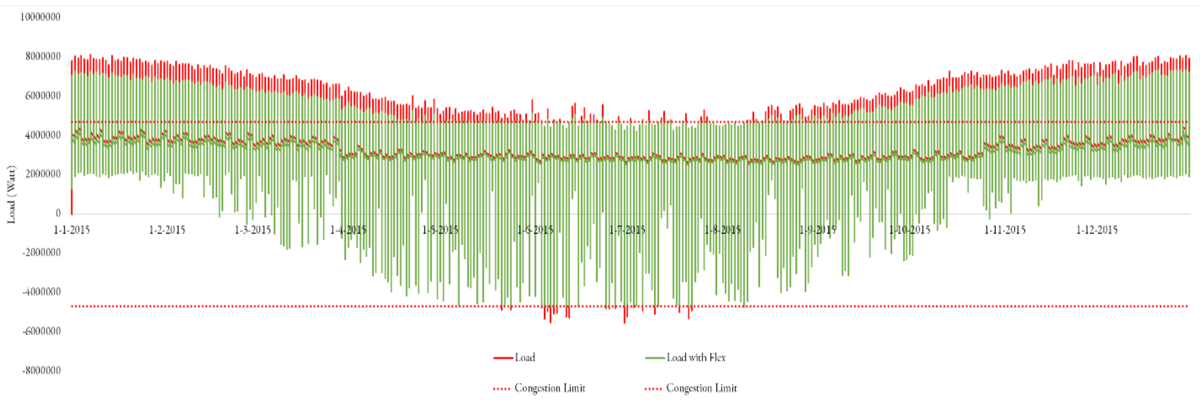


Figure 44: The Yearly load of Steenwijk for the year 2035 for the 0.35% load increase

Table 68: Different load scenarios to postpone network investment for the city Steenwijk with high PV, HP and EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required (with flex)	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	3	2030	2033	€ 1,040,271	-€ 44,017	-€ 77	€ 129,912
1.5% Load Increase	1	2026	2027	€ 1,674,804	€ 18,928	€ 42,584	€ 116,776
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

In the case that the EV development is slower than estimated (**scenario 2**), the network investments postponement financial results are comparable to that in scenario 1. Analysis and results of **scenario 2** are presented in **appendix C.7,** Table 101**.** In **scenario 3**, for the load increase of 0.35%, flexibility can postpone network investment with 2 years and provides financial savings for the DSO. Full presentation of the analysis and results are documented in **appendix C.7,** Table 102**. In scenario 4,** with low HP, low EV, and high PV, network investment postponement is possible, although for a shorter period of time, resulting in the case of the 0.35% load increase in no financial savings, and for the 1.5% load increase savings ranging from €15,000 to €84,000, for various discount rates. Results are documented in **appendix C.7**, Table 103. The results from **scenario 5** with low PV capacities are similar to scenario 1 in terms of network investment and network investments postponement. Analysis and results of **scenario 5** are also documented in **appendix C.7,** Table 104. Similarly, the scenarios with low PV capacity (**scenario 6, 7 and 8**) are also very comparable to scenario 2, 3 and 4 with high PV capacity. Consequently, no additional analysis is performed on these analysis, and only the results are presented to substantiate the claim that these scenarios are comparable (Table 105, Table 106, and Table 107 in **appendix C.7**).

8.5.3.2 Overview of the results of the 8 scenarios for the City Steenwijk

Based on the results presented from the different scenarios for the city Steenwijk, it can be concluded that the postponement of network investment is possible, although varying in the number of years, dependent on the level of penetration in HP, PV or EV. The average percentage decrease in blackouts is roughly around 74% for all scenarios for Steenwijk. Furthermore, because of these different penetration levels, the overall savings from network investment postponement fluctuate from positive to negative. The average financial savings from all scenarios were calculated and based on the One Sample Wilcoxon Signed Rank Test it can be concluded that the savings for the DSO are not significantly (sig. 0.712) different from zero. Consequently, network postponement does not provide significant financial savings for the DSO. However, it is possible to conclude that network investment postponements with a short postponement duration, provide more savings than long network investment postponement. Moreover, it can be concluded that financial savings are more significant in large districts in comparison to small streets.

8.5.4 Case Study Analysis: The City of Drechterland

The city of Drechterland is located in a rural area, in contrast to the city of Steenwijk, which is a more densely populated area of the Netherlands. The difference in density population influences the cost entailed for network reinforcement, as Ecofys (2015) mentions that the investment cost per kVA per household for rural area is €740 in comparison to €250 investment cost per kVA per household for an urban area. **This difference in investment cost will probably result in different savings for the DSO, as the overall investment for network reinforcement are higher, and consequently also the savings from postponing network reinforcement. Results from this analysis** (Table 69, **and Appendix C.8) indicate that postponing network investment in the city of Drechterland can be considered feasible and financially attractive for a DSO, as an average savings of €265,000 is significant (sig. 0.000) according to One Sample Wilcoxon Signed Rank Test for an average network investment postponement of 2.25 years. Moreover, the average percentage decrease in blackouts is roughly around 49% for all scenarios for Drechterland.**

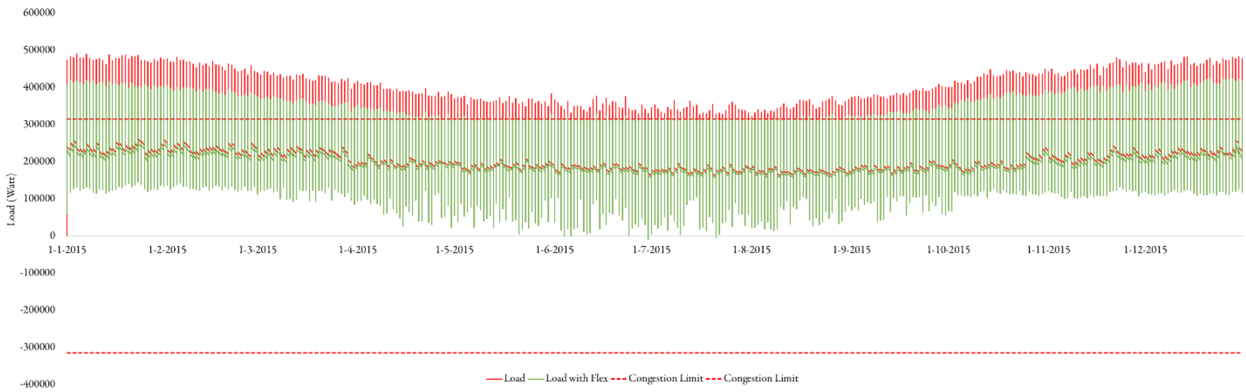


Figure 45: Drechterland congestion limit and load with and without flex from HP in the year 2040 for the 0.35% load scenario

Table 69: Different load scenarios to postpone network investment for the city of Drechterland with high PV, HP and EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	4	2035	2039	€ 3,241,112	€ 192,596	€ 358,748	€ 835,616
1.5% Load Increase	1	2028	2029	€ 5,101,363	€ 140,375	€ 211,246	€ 433,524
-1% Load Decrease	0	Flex not helpful	Further than 2050	€ 0	€ 0	€ 0	€ 0

On the basis of this outcome, it is possible to infer that the savings realized by network investment postponement are sensitive to the grid investment costs.

8.6 Conclusion on the Prospects of Flexibility in Postponing Network Reinforcement

This chapter investigated the extent to which demand-side flexibility can postpone grid investment in different low-voltage networks by means of a set of case studies. Additionally, in order to investigate multiple possible futures, scenario analysis was employed on a wide range of electricity load changes, smart appliance penetration level changes, electric vehicle penetration level changes and discount rate changes. **However, before any conclusions are drawn, it is imperative to mention that all the results presented in this conclusion and chapter are highly dependent on the assumptions drawn earlier in this chapter and might result in different outcomes if different assumptions are drawn.**

Results from this analysis indicate that the potential of grid investment postponement varies over different cases, due to different levels of required grid investment and electricity grid characteristics. However, it is possible to conclude from these outcomes that grid investment postponement by means of demand-side flexibility in some cases is technically feasible. For instance, Figure 47, **shows in a form of boxplots the number of years of postponement for all scenarios for each case. The average number of years of postponement for all cases, except Bosboomstraat is 2 years. The average number of postponement for Bosboomstraat is 34 years, and that is because all the high capacity PVs that are causing the congestion can be shut off as part of Demand Response experiment, as proven in** Figure 42, **and** Table 63. **Besides, it can concluded for the considered period (2015-2050), that flexibility steering can on average cause a percentage reduction of blackouts between 10% and 74% and postpone the grid investment by 2 years.**

Even when analysis indicates that grid investment postponement by means of demand-side flexibility is technically feasible in some cases and scenarios, this does not imply that it is also advisable from a financial perspective. The results from the various scenarios indicate (Figure 46) that for the Bosboomstraat and Kleynstraat case studies, the grid investment postponement by means of demand-side flexibility is not financially feasible, as the savings are negative, or not significantly different than zero. Figure 46 portrays in the form of a box-plot the financial savings (euros) of all scenarios for each case. For instance, financial savings for Bosbomstraat case, are negative and vary between -517,000 euros and -154,000 euros for all scenarios, and that explains the high number of years of postponement. However, in the Kleynstraat case study, when the FC is deployed as a replacement for the HP, the financial perspective inverses to significant positive average savings of €13,400, as depicted in Figure 46. Although such results provide a positive financial perspective of grid investment postponement by means of demand-side flexibility, one should question the viability of this outcome as the presented penetration levels for the FC are very unlikely.

The analysis of the city of Steenwijk reconfirms these findings, as grid investment postponement is possible in some scenarios and might be possible to postpone the investment, but not financially advisable as the savings are not significantly different from zero. On the other hand, the results from the city of Drechterland indicate a positive financial saving of grid investment postponement by means of demand-side flexibility. Within the city of Drechterland, a significant average saving of €265,000 can be realized when grid investment is postponed with approximately 2.25 years. **This result indicates that the financial savings of grid investment postponement by means of demand-side flexibility is highly sensitive to the grid investment cost per kVA per household**, as the grid investment cost are almost three times as high in Drechterland, a rural city, than in the city Steenwijk, an urban city. **Consequently, it is possible to conclude that grid investment postponement by means of demand-side flexibility might not provide financial savings for the DSO; however, if it provides positive financial savings like in the case of Drechterland city, the significance of these savings are strongly dependent on the grid investment cost per kVA per household, on the price of flexibility, load increase projections, and the congestion limit.**

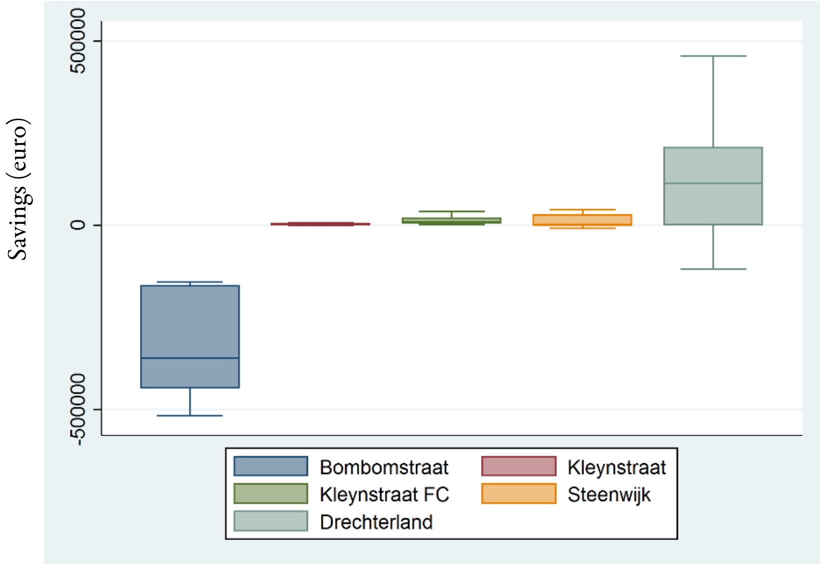


Figure 46: The average savings (€) for the DSO of grid investment postponement from all scenarios

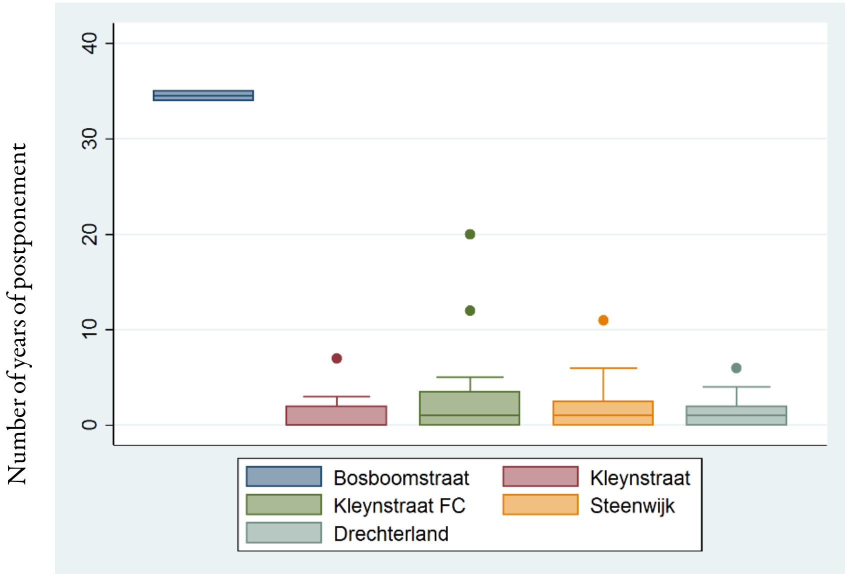
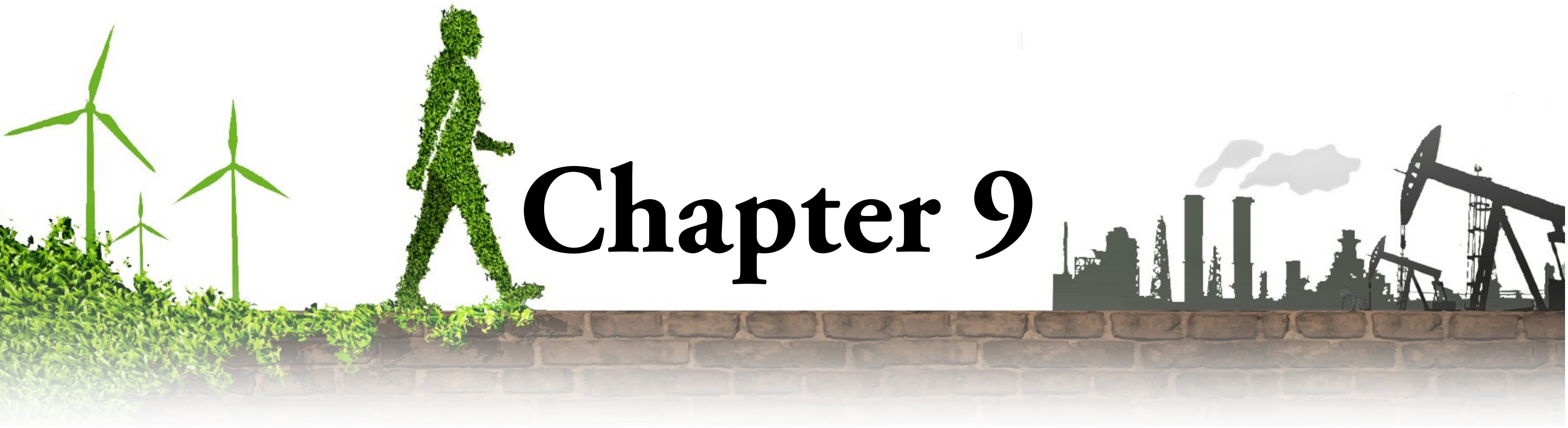


Figure 47: Number of years of postponement for all scenarios for all cases



Chapter 9

9 Conclusions, Recommendations, Limitations & Reflection

This chapter answers the main research question formulated in chapter 3, by providing the final conclusions in section 9.1, recommendations in section 9.2, discussion and reflection on the scientific relevance in section 9.3, limitations of the research from a scope and methodological perspective in section 9.4, and the future research in section 9.5.

9.1 Conclusions

In modern electricity grids, that have high penetration levels of intermittent renewable energy sources, distributed energy generation, and electrical appliances (electrical vehicles, heat pumps, electric boilers etc.), electricity grid congestion has become more frequent. Earlier, electricity grid congestion at the distribution level was dealt with by reinforcing the distribution grid assets (cables, transformers etc.). Nevertheless, it is argued that grid investment cannot keep up with the growth of renewable energy sources and electric appliances, which results in interim and short term congestion. Moreover, Haque et al. (2014) claims that upgrading grid assets will not serve as a cost-effective solution as the electricity network congestions are temporary.

Meanwhile, although those changes (intermittent renewable energy sources, electrical appliances etc.) in the electricity grid increase the complexity of operating the grid and preserving network reliability, they also provide room to optimize the electricity network system. Distributed energy sources and electrical appliances can provide flexibility opportunities to manage the load demand variability in a more cost effective manner (Ecofys, 2015). Demand Response tools are a source of flexibility within smart grids and may potentially reduce peak loads or shift loads to off peak periods of time. The Distribution System Operator (DSO) may engage in short or long term contracts in order to procure Demand-Side Flexibility, provided by Demand Response, to resolve congestion. Although demand-side flexibility holds potential in mitigating grid congestion, and thus postponing the investment in the grid capacity, the impact of demand-side flexibility on congestion mitigation, is blurred and indeterminate from a technical perspective (Moslehi & Kumar, 2010). Moreover, the prospects of financial savings for the DSO are not guaranteed (Torriti et al., 2010). Therefore, to bridge this knowledge gap, the thesis explored the following main research question:

"To what extent can the DSO mitigate grid congestion by means of Demand-Side Flexibility to defer grid reinforcement?"

To investigate the potential of demand-side flexibility on postponing grid reinforcement, the first exploratory phase of the research investigated the problem of electricity grid congestion at the distribution level, arising mainly due to the increase in intermittent renewable energy sources, electrical appliances, and distributed energy sources. Research commenced by investigating demand-side flexibility as a potential solution to grid congestion via a caste study (a field experiment conducted in the city of Heerhugowaard in the Netherlands). Thereafter, empirical models were estimated to predict demand-side flexibility over a year from four smart devices (photovoltaic systems, electric boilers, heat pumps, fuel cells).

Based on the empirical analysis, conclusions with respect to the technical feasibility of demand-side flexibility on mitigating congestion within the Heerhugowaard's low voltage distribution grid, were derived.
Furthermore, analysis proceeded via the construction of a simulation model, which allowed the investigation of the impact of demand-side flexibility on mitigating congestion on different low voltage grids within the Netherlands, from a technical perspective. Based on this analysis, scenario analysis was performed to study the financial feasibility of demand-side management to mitigate grid congestion in contrast to grid reinforcement. Such an empirical and experimental analysis, from a technical and financial perspective, led to the answer with respect to the extent the DSO can mitigate grid congestion by means of Demand-Side Flexibility in order to defer grid reinforcement.

9.1.1 Conclusions on the prediction techniques used for predicting Demand-Side Flexibility

To predict flexibility from Photovoltaic PV systems and Heat Pump Loads, **Time Series Regression** was performed due to the temporal measurement of the data for a one-dimensional panel data set. It can be concluded that when the data set is **one dimensional** and has a **temporal dimension**, like in the PV systems and HPs where the data is collected at a congestion point level for a continuous interval of time using identical spacing between successive points in time, that Time Series Regression can be a good modelling technique. Using autoregressive lags of the dependent variable (PV output) together with other explanatory variable (total PV capacity, radiation, temperature, and humidity), a time series regression model can predict up to 90% of the variance of the PV output (flexibility). The PV output and Heat Pump load are **time-based** and **continuous** and thus, **time series regression modelling** is a good technique to predict PV output and the Heat Pump load.

For predicting hot water consumption for the Electric Boiler, negative binomial **Count Data Regression modelling** was used. When data falls within a **small range** with a **high number of zeros**, and a limited amount of other possible values, linear regression cannot be employed as this technique would fail to capture these zeros accurately. Consequently, it can be concluded, that when the data is concentrated on **small discrete, non-negative values**, Count Data Regression is a good technique to predict the variable under study.

9.1.2 Conclusions on Demand-Side Flexibility from four Smart Devices

Prediction models were constructed to predict flexibility from the four smart devices employed in the Heerhugowaard field trial. Prior to investigating the influence of demand-side flexibility on grid congestion mitigation, a quantitative comparative analysis on the available predicted flexibility was performed over the **different seasons** (**Figure 48**) and **over the hours of the day (Figure 49** and **Figure 50).**

From the conducted analysis on **the available flexibility over the different seasons (Figure 48**) it is possible to conclude that the largest average amount of flexibility per hour is provided by the PV systems (89 PV systems), but also that the PV flexibility (Watt) is highly sensitive to seasonality. In contrast, the available flexibility from Electric Boilers (44 EB) is not as high as that of the PV systems, but shows more stability in the flex provision over the seasons. Furthermore, the available flexibility from the Heat Pumps (50 HPs) is the least among the other three smart devices and is also sensitive to seasonality. The flexibility provided by the Fuel Cells (18 FCs) per hour turned out to be higher than that of the EBs and HPs and the most stable among the other smart devices.

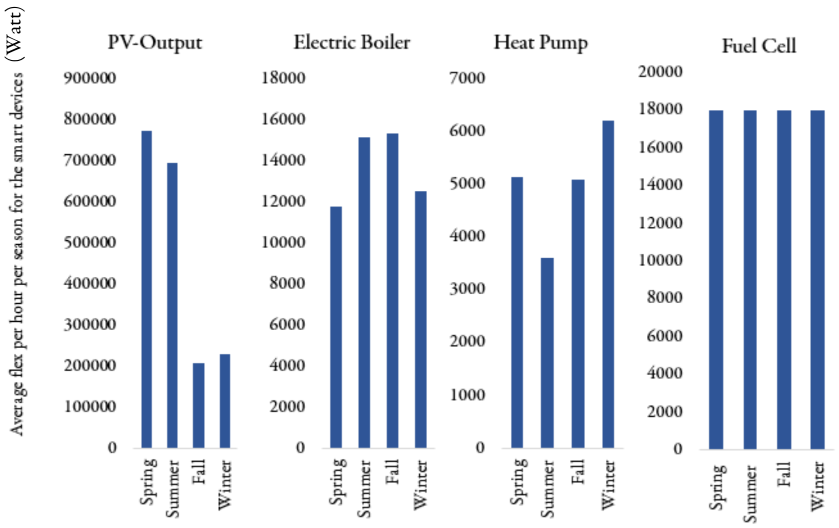


Figure 48: Average flexibility per hour of the smart devices over the seasons

From the conducted analysis on **the available flexibility over the hours of the day (Figure 49** and **Figure 50)**, it can be concluded that the PV output in Summer and Spring is at least as twice as that in Fall and Winter. Additionally, PV output commences at 5 am and lingers till 7 pm in Summer and Spring (14 hours of varying PV output); however, PV output commences at 7 am and lingers till 5 pm in Fall and Winter (10 hours of varying PV output). Regarding the heat pump, it can be concluded that the Heat Pump load in Winter is roughly twice the Heat Pump load in Summer and roughly one third more than the Heat Pump load in Spring and Fall. The heat pump load is high in the Winter starting at 4 pm in the afternoon till 7am in the morning (15hrs); however, the heat pump load is high in the Spring and Fall starting at 6 pm in the evening till 5am in the morning (11 hrs).The heat pump load in the summer is constant (low) throughout the day. The Fuel cell energy production is constant over the day and the seasons.

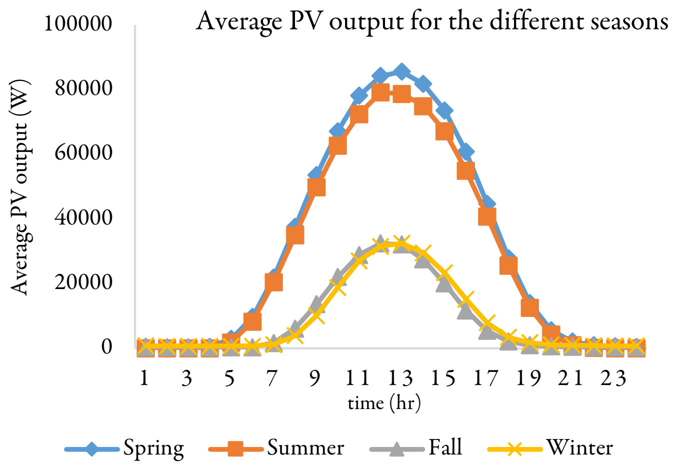


Figure 49: Average PV output per hour over the four seasons

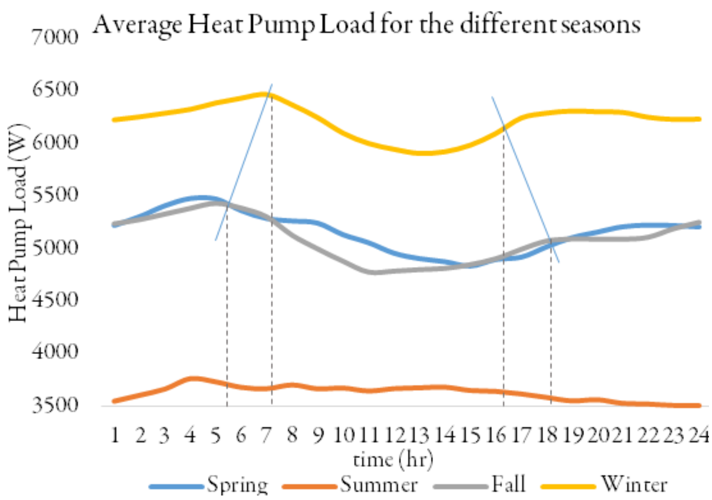


Figure 50: Average HP load per hour over the four seasons

The take away message from such a conclusion about flexibility availability is that: for stable and unchanging flexibility over the day and the four seasons, the Fuel Cell is recommended. To put the expectations in place for the DSO, in the case of flexibility from the PV systems, higher and more lasting (14 hrs) flexibility over the day is present in Spring and Summer in comparison to Fall and Winter (10 hrs). In case of flexibility from the Heat Pump, higher and more lasting flexibility over the day is present in Winter (15 hrs) in comparison to Spring and Fall (11 hrs). Flexibility from the Electric Boiler is not that sensitive to seasonality but it is sporadic over the day, since it is dependent on hot water consumption.

9.1.3 Conclusions on the Influence of Demand-Side Flexibility on Congestion Mitigation in Heerhugowaard City

In order to investigate the impact of flexibility on grid congestion at the distribution level in Heerhugowaard, two types of methodologies were employed. The primary analysis was performed on measured data from the experiments accomplished in Heerhugowaard (2-months experiments), which implies that the derived conclusions mimic reality. However, the conclusions derived from the second analysis, which are based on predictions and estimations from a simulation model, where this simulations model partly portrays a perfect world, implies that these results are only limitedly generalizable to reality.

Analysis of the measured data from the Heerhugowaard field experiments indicates that the influence of demand-side flexibility on congestion mitigation is only limited and consequently, insufficient to resolve all electricity network congestion. **Based on the performed analysis, it is possible to conclude that the application of demand-side flexibility from the PV, HP, EB, and FC, can reduce the volatility of the electricity load only limitedly, between 4% and 12%.** Additionally, flexibility is capable of reducing the level of congestion, as indicated by for example the process capability analysis; however, the electricity load with flexibility steering is still occasionally *incapable* of remaining within the congestion limits for the PV, HP, and EB experiments. Only for the FC experiment, the electricity load was capable of remaining within the congestion limits.
The incapability of flexibility to resolve all network congestion could be caused by the reliability of the flexibility delivery, as the reliability of the delivered flexibility is limited due to the flexibility forecast errors (which are influenced by the weather and human behaviour) for the different devices, from the load forecast errors, and from other exogenous factors such as IT error.

In the second analysis, which was performed by means of a simulation model that evaluated the impact of flexibility on grid congestion at the distribution level in Heerhugowaard for an entire year, similar results were found. Consequently, based on the simulation study it also possible to conclude that congestion at all congestion block levels from all devices cannot be fully resolved by means of demand-side flexibility. However, as congestion does not necessarily result into blackouts, as theoretical congestion limits were set in the field experiment, a translation based on the magnitude and duration of the congestion was made, in order to determine if the predicted congestion would result in blackouts.
From this analysis, it can be concluded that flexibility significantly reduces both the duration (min) and magnitude (Watts) of congestion and might eliminate blackouts. Generally, it can be concluded that flex steering can reduce the magnitude of congestion (Watts) between 55% and 67%. Additionally, flexibility steering reduces the duration of congestion in the PV and FC experiments between 34% and 67%; however, flexibility steering reduces the duration of congestion in the HP experiment with only 2.5%.

Overall, it is possible to conclude that demand side flexibility is capable of reducing the duration and severity of congestion, and consequently might be capable of reducing possible electricity network blackouts; however, due to the unreliable delivery of flexibility and load forecast error, demand-side flexibility cannot be used to resolve all congestion at all congestion block levels.

9.1.4 Conclusions on the Prospects of Demand-Side Flexibility in Mitigating Congestion and Postponing Network Reinforcement in other Low-Voltage Grids in the Netherlands

A set of four case studies (two streets and two cities: one urban & one rural) were investigated to study the extent to which demand-side flexibility can postpone grid investment in different low voltage networks. Additionally, in order to investigate multiple possible futures, scenario analysis was employed on a wide range of electricity load projections, smart appliance penetration level changes, different electric vehicle penetration levels and discount rate changes. The financial savings were calculated as the difference between the savings gained due to postponing network reinforcement and the costs incurred due to flexibility ordering.

The analysis of these four case studies indicates that grid investment postponement by means of demand-side flexibility is technically feasible in some cases and scenarios. **It can concluded for the considered period (2015-2050), that flexibility steering can on average cause a percentage reduction of blackouts between 10% and 74% and postpone the grid investment by 2 years.**

However, even when analysis indicates that grid investment postponement by means of demand-side flexibility is technically feasible, in some cases and scenarios, this does not imply that it is also advisable from a financial perspective. Analysis indicates that the financial outcome in these four case studies present mixed results, where for the two urban streets the savings are negative. The results from an urban city do not provide significant savings, and the results from a rural city provide significant savings. Based on these outcomes it is possible to generalize the following conclusions:

1. The financial savings of grid investment postponement by means of demand-side flexibility is highly sensitive to the grid investment cost per kVA per household. Thus, savings from grid investments might be more significant in rural areas (high grid investment cost per kVA per household) in comparison to urban areas (lower grid investment cost per kVA per household).
2. The financial savings of grid investment postponement for the DSO are more significant in large districts in comparison to small streets because in the former, more investments are needed to upgrade the city grid and its components.
3. Financial savings are more significant in areas where congestion is occasional and temporary, in comparison to areas where congestion is persistent and severe, because in the latter high flexibility ordering leads to high cost incurred that will probably outweigh savings gained from grid investment postponement.

Based on these findings, it is possible to conclude that grid investment postponement by means of demand-side flexibility might not provide financial savings for the DSO; however, the significance of these savings are strongly dependent on the grid investment cost per kVA per household, on the price of flexibility, load growth projections, and the grid congestion limits.

9.1.5 Conclusion on the Postponement of Grid Investment by means of Demand-side Flexibility

Based on the findings presented in this thesis, insights were gained on the potential that demand-side flexibility hold in postponing grid investment. These findings indicate that grid investment postponement by means of demand-side flexibility might be technically feasible in some cases and scenarios, as flexibility can be deployed to reduce the duration and magnitude of congestions, and consequently prevent blackouts. Consequently, in some cases and scenarios, grid reliability at the distribution level can be preserved. However, as the postponement of grid investment by means of flexibility might not provide financial savings for the DSO, and the questionable impact of flexibility on congestion mitigation, due to flexibility forecast error and load forecast error and IT errors, it can be concluded that demand side flexibility might not yet be a good alternative for grid investment.

9.2 Recommendations

Based on the conclusions derived from demand-side flexibility prediction provided by Demand Response, its impact on congestion mitigation, and eventually its prospects on grid investment postponement, it is possible to recommend that:

VII. The DSO deploys demand-side flexibility, provided by DR, in large cities/ regions rather than in small streets, since positive significant savings are more probable in large cities because higher investments are needed to upgrade the city grid and its components.

VIII. Within large cities/regions, the DSO deploys demands-side flexibility in rural areas rather than in urban areas, since more financial savings can be reaped because of the high cost per kVA per household that can be saved.

IX. The DSO deploys Demand Response tools, source of flexibility, in areas where congestion is occasional and temporary, and not in areas where congestion is persistent and severe, because in the latter high flexibility ordering leads to high cost incurred that will probably outweigh savings gained from grid investment postponement.

X. The DSO invests in flexibility forecasting and load forecasting to enhance the reliability of flexibility availability and trading, prior to full employment of demand response tools as means to mitigate congestion, in order to prevent jeopardizing the electricity system reliability.

XI. With the current imprecise forecast of flexibility from smart devices, the load forecast error, and IT errors, it is recommended that the DSO orders extra flexibility, as a safety margin, beyond the flexibility needed to mitigate congestion; however, this may reduce the financial savings.

XII. The aggregator achieves a profitable business from aggregating and selling flexibility to ensure that he can stay in the business and hence the DSO can trust a continuous existing market of flexibility trading.

XIII. The market coordination energy system that coordinates flexibility trading among stakeholders provides room to revise orders done by other stakeholders (e.g. Balancing Responsible Party) if this may jeopardize congestion on the grid and offer a real-time scheme with good redundancy and backup.

9.3 Discussion and Reflection on the conceptual-scientific relevance

The findings and conclusions drawn from the analysis performed within this thesis, nest themselves within the existing theoretical body of knowledge. This implies that the research performed in this thesis might have contributed, substantiated or contradicted statements and conclusions from earlier work. In order to provide an overview of these implications, the findings of this thesis are reflected on research that has been performed on demand-side flexibility and the postponement of grid investment.

The research performed within this thesis aimed at identifying the extent to which the DSO, by means of demand-side flexibility, can mitigate grid congestion and defer grid reinforcement. Earlier research from SEDC (2016) describes demand response in the context of grid reinforcement deferral as a "reliable way to relieve peaks in demand, compensate for large in-feeds from renewables and generally help to balance the system and stabilize the grid" (p. 5). However, findings in this thesis indicate that that the influence of demand-side flexibility on congestion mitigation is only limited and consequently, insufficient to resolve all electricity network congestion. It was concluded that the application of demand-side flexibility from the PV, HP, EB, and FC, can reduce the volatility of the electricity load only limitedly, between 4% and 12%. Therefore, the findings in this thesis are not fully in line with the optimistic findings from SEDC (2016). However, the findings of this thesis overlap with the conclusion from Ecofys (2016), which concludes that the available flexibility, provided from demand response, might not be sufficient to completely resolve all network congestion. Nevertheless, the findings in this thesis do substantiate some findings from SEDC (2016) with regards to the extent demand-side flexibility may postpone grid postponement from a technical perspective, as both SEDC and this analysis indicate that the extent grid investment may be postponed is dependent on the network characteristics, the increase in renewable electricity sources, and electrical appliances.

A possible reason why demand response is incapable of resolving all congestion was already identified by Moslehi and Kumar (2010), who indicate that the intermittent nature of decentralized electricity sources and the unreliability of renewable energy forecasting, might aggravate the network reliability. As such sources are hard to predict, due to their intermittent and volatile nature, it affects the reliability of demand-side flexibility and its prospects on deferring grid reinforcement. This judgement is substantiated by the analysis performed in this thesis, as it was possible to conclude that the incapability of flexibility to resolve network congestion could be caused by the reliability of the flexibility delivery, as the reliability of the delivered flexibility is limited due to the flexibility forecast errors (which are influenced by the weather and human behavior) and the insufficient flexibility from the devices installed in the field experiment. In addition to that, it can be concluded that the load forecast error and other exogenous factors such as IT error contribute to the incapability of flexibility to resolve all network congestion. Thus, it can be recommended, if subjected to further research, that near real-time flexibility trading with good redundancy and backup might alleviate part of the flexibility reliability issues.

More methodological inferences, based on the conducted analysis in this thesis, can be added to those findings, with respect to device specific flexibility and its prediction, which could assist the coming researcher or scholar. As argued by Wan et al. (2015), predicting and forecasting demand-side flexibility is critical for an economic operation of grids. Among the experimented techniques, Wan et al. (2015) developed time series regression models to predict PV output. This substantiates what has been concluded in this thesis, that for one-dimensional panel data that is time-based and continuous in nature, Time Series Regression modelling is a good technique, like in the case of PV output prediction and the heat pump load prediction. Conversely, for data sets that fall within a small range and its data points are concentrated on small discrete, non-negative values, Count Data Regression modelling is a good technique, like in the case of the electric boiler load prediction (which is dependent on hot water consumption prediction). The estimated device specific prediction models, constructed in this thesis, predict flexibility per hour for the entire year, which could enhance the expectations of the DSO on the reliability of flexibility, its impact on congestion management in different seasons, and its capability of postponing grid investment.

Veldam et al. (2013) performed a scenario analysis based on simulated flexibility loads and projected energy loads to explore the potential of flexible demand in optimizing the grid and mitigating congestion in the low-medium voltage grids in Netherlands. The article concluded that controlling flexible demand can realize a 21% to 40% decrease in the capacity needed of grid assets (cables and transformers) and most likely the gained savings offset the costs incurred from controlling flexible demand. However, those conclusions are limited to standardized simulated load curves and flexibility curves that do not capture the volatility of energy demand and consumption. Moreover, costs of flexibility were not accounted for in their analysis. The conclusions derived from this thesis coincide partly with the findings of Veldman et al. (2013) since it was concluded in this thesis that flexibility significantly reduces both the duration (min) and magnitude (Watts) of congestion and can reduce blackouts. Generally, it was concluded, in this thesis, that flex steering can reduce the magnitude of congestion (Watts) between 55% and 67%. Additionally, flexibility steering reduces the duration of congestion in the PV and FC experiments between 34% and 67%. Hence, because the analysis was performed on real measured data collected from a field experiment and constructed regression models that predict device specific flexibility per hour, it is possible to indicate that the unreliable availability and delivery of flexibility and load forecast error, demand-side flexibility cannot be used to resolve all congestion and the calculated grid capacity gained by Veldman and the other co-authors is not guaranteed. Moreover, due to the same reasons, it can be concluded in this thesis for the considered period (2015-2050), that flexibility steering can cause on average a percentage reduction of blackouts between 10% and 74% and postpone the grid investment by only 2 years. This estimated wide interval of percentage reduction of blackouts proves the unreliability of flexibility in mitigating all congestion and postponing grid investments for long.

In cases where demand side flexibility is capable of postponing grid reinforcement, SEDC (2010) indicates that such a postponement might generate high value. This statement is substantiated by this thesis, which identified that postponing grid investment solely results in high value for the DSO; however, this value quickly diminishes due to the purchase of flexibility in order to resolve congestion. Furthermore, this thesis substantiates research from Ecofys (2016), which concluded that grid investment cannot be substituted by means of demand response, but can only be postponed in some cases in low-voltage grids, and if postponement is feasible, that such postponement might result in financial savings for the DSO.

Additionally, both Torriti et al., (2010) and Ecofys (2016) indicate that the postponement of grid investments, and consequently the financial savings for the DSO, strongly depend on the network characteristics, the projection of renewable electricity sources, and electrical appliances. This conclusion was also found within this thesis as it could be concluded that: the significance of any positive financial savings are strongly dependent on the grid investment cost per kVA per household, on the price of flexibility, load growth projections, and the grid congestion limits.

The analysis in this thesis has added the following conclusions with respect to the grid characteristics and specificities where demand-side flexibility can be technically and financially feasible. (1) The financial savings of grid investment postponement for the DSO are more significant in large districts in comparison to small streets because in the former more investments are needed to upgrade the city grid and its components. (2) Within large districts, savings from grid investments are more significant in rural areas (high grid investment cost per kVA per household) in comparison to urban areas (lower grid investment cost per kVA per household). (3) Financial savings are more significant in areas where congestion is occasional and temporary, in comparison to areas where congestion is persistent and severe, because in the latter, high flexibility ordering leads to high cost incurred that will probably outweigh savings gained from grid investment postponement.

Based on this discussion and reflection within the current body of literature, it is possible to state that this research provides additional insights into demand-side flexibility availability and delivery reliability concerns, the prospects of demand-side flexibility in mitigating congestion, preventing blackouts, and grid investment postponement.

9.4 Limitations

Answering the main research question entailed scoping the research problem, and exploring its solution from specific aspects by conducting techniques and methodologies with built-in assumptions. Therefore, the following section gives an overview of the limitations of the research scope and the conducted research methodology.

Limitations of the Research Scope

1. When investigating the influence of demand-side flexibility on congestion mitigation, it is imperative to study the demand response projection into the future, not only in terms of the penetration level of smart devices but also the potential number of residential and non-residential customers who are ready to participate in demand response programs. Nevertheless, this would entail studying from a social perspective the heterogeneous behaviour of consumers/prosumers and the different incentivizing programs that can promote consumers' willingness to participate. However, this thesis focused on the technical and financial impact of demand response on congestion management and not on the social aspect that drives demand response, which could be important when choosing the most probable future scenario.
2. The investigation performed on demand-side flexibility on congestion mitigation is limited to the devices employed in the experiment and the default state of the devices which limits the type of flex offered by such devices (flex up/ flex down). The consequence of such a limitation is that it can affect the flex available, its reliability, flex procured, and the flex prices as well. For instance, the flexibility from the projected number of EVs was not predicted because of the lack of data collected on EVs within the field experiment. Such a limitation affects the generalizability of the results since if flexibility from EVs were accounted for in the analysis, it could have affected the results on the prospects of flexibility on congestion mitigation.
3. The data analysis was performed on a sample of 201 households from the Netherlands that is not randomly sampled nor representable to the population. Thus, this renders the results/conclusions from such analysis to be non-generalizable beyond Heerhugowaard city. Therefore, while those results can give an indication on the impact of demand-side flexibility on congestion mitigation in general, its extendibility should be assessed cautiously.
4. The implicit influence of the market coordination mechanism (USEF) on the available, offered, and procured flexibility from the DSO and BRP in the Heerhugowaard field experiment was not quantitatively/ qualitatively analysed in order to investigate if such a mechanism has direct effect on the extent flexibility can resolve congestion. Such an analysis was beyond the project scope, since it would have entailed comparing and contrasting different market coordination mechanisms and the lack of a coordination mechanism on the impact of flex on congestion mitigation. The consequence of such a limitation is the generalizability of the results since the deployment of a different market coordination mechanism in Heerhugowaard could have resulted in different findings.

Limitations of the Research Methodology

As mentioned and explained earlier, the simulation model has built-in assumptions with respect to flex procurement conditions that govern the DSO orders: the day-ahead procurement of flex by the DSO, the error in flex delivery by each device, the capacity and charging time of the EB and the capacity of the HP and its combined functions. Although, the derived conclusions based on results computed from this model give generic insights on the extent demand-side flexibility can mitigate grid congestion and eliminate blackouts, results from this model are limited to the assumptions made and bold conclusions must be made with caution. The reason behind this statement, is that flex procurement will most probably happen in a dynamic trading environment due to error in flex delivery and error in load forecast that in reality may pose a threat on grid reliability if not dealt with by real time flex ordering.

Additionally, the standardized assumed load (EDSN curve (Energy Data Services Netherlands) over a year per PTU) could have been replaced with a more sophisticated forecast/prediction of the load, especially if past data was collected on the investigated grid (cities or neighbourhoods). On the other hand, the regression prediction models that are built-in the simulation model are limited to the type of devices, characteristics and efficiency of the devices, and assumed default state of such devices, since the estimated regression models were calculated from the data collected from such devices.

Furthermore, the estimated prediction regression models are limited because those models for the PV, EB, and HP were limited to the available data on the hypothetical explanatory variables. Other factors might have significantly contributed to the prediction of flexibility from the 3 devices. For instance, the lack of data on the tilt angle of the solar panels, the position of the solar panels, the efficiency of the panels, the temperature recording of the panel, the roof inclinations of the panels etc. all together affect the quality of the PV prediction model.

The model can be taken to a new level and complemented by an optimized trading mechanism that takes the BRP's interest into account [BRP's flex ordering based on the APX and imbalance market] and real time orders and re-orders of the flex from the DSO to resolve congestion. The trading framework might be simulated in a dynamic manner that puts in some cases the interest of the DSO in priority if grid reliability is jeopardized, and in other "un-risky" cases it follows a standardized order of flex trading among different stakeholders. However, predicting flexibility is device specific and building generalized regression models that represent devices with different characteristics and efficiencies will be always a challenge especially when it comes to devices which are related to human behaviour and weather projections that vary among cities and regions.

Finally, with respect to the conducted scenario analysis, and the monetarization of the investment needed to reinforce the grid, an average cost per kVa per household was assumed. However, performing a more thorough and precise analysis requires a detailed analysis at the level of the cables, their capacity, transformers' age, and fuses in order to get a thorough estimation of the capital and operational costs entailed in such an investment.

Although such limitations limit the generalizability of the results and in some cases give a broad indication and not a precise one, that does not imply that with the absence of such limitations, totally different results can be expected. The reasoning behind such a judgement is that even if different smart appliances were installed, they are still affected by exogenous meteorological or behavioural factors and thus flexibility prediction and reliability will still be an issue. Additionally, if data on the load was collected on the grid under study, more accurate results could have been derived but it won't give totally contradicting results since smoothened standardized curves (EDSN) are a good resemblance of actual curves. Similarly, if the simulation model was constructed in a more complex manner to mimic reality more closely, the impact of flex on congestion mitigation might be more pronounced especially if flex ordering happened real-time (operate phase) but the financial feasibility findings are not expected to change a lot.

9.5 Future Research

Based on the research findings, research scope limitations, and methodology limitations, it is possible to recommend the following future research:

I. Not only Residential but also Industrial and Commercial Programs

This research investigated the impact of demand-side flexibility from residential customers on the grid congestion mitigation and the extent it can defer grid reinforcement. However, to study the influence of DSM on congestion mitigation in a more comprehensive manner, it is imperative to include demand-side flexibility from commercial and industrial customers/prosumers. This is vital for the generalization of the conclusions with respect to the technical and cost-effectiveness of DSM on preserving grid reliability. Thus, it is recommended to conduct a field experiment that takes into account flexibility from commercial and industrial customers who play a big role in the net energy consumption (lighting of green houses, chemical or mechanical production factories etc.)

II. DSM Social Benefits' Monetarization

The social relevance of this research was limited to the distribution grid optimization, reduction in risk of blackouts, and the potential postponement of grid investment. However, the social relevance of DSM can be extended to encompass the reduction in carbon emissions and dependency on fossil fuels. Since, high prices of carbon quota and electricity prices can make the financial savings more attractive and thus DSM more desirable. Thus, it is recommended to extend the social relevance of such a research to include the potential gains from reduced fossil fuels and carbon footprint.

III. DSM from the perspective of different stakeholders

The current analysis focused on the DSO and the benefit gained from mitigating congestion via demand-side flexibility versus grid reinforcement. However, this analysis did not tackle the impact of DSM on the Balancing Responsible Party or the prosumers, in terms of profit maximization, nor did it tackle the impact of DSM on society in terms of gained societal and environmental benefits. Such a comprehensive analysis can position DSM in a different intended purpose.

IV. Variable Time Tariff – Indirect Load Control

The success of DSM depends on the pool of demand-side flexibility, aggregated by the aggregator, to be procured by the DSO to mitigate grid congestion. The current DSM experiment in Heerhugowaard was motivated by direct load control of smart devices in controlled households who are remunerated in return for giving the aggregator the liberty to control the devices. Such a remuneration adds to the overhead cost of flexibility and directly affects the price of flex. Therefore, it is recommended to experiment as well with indirect load control where residential and non-residential customers are stimulated to change their energy consumption and production behaviour based on variable electricity tariffs. This might have a positive direct influence on the cost of flexibility aggregated and thus may witness a reduction of the price of flexibility procured, which may affect the results regarding the extent DSM can resolve congestion and defer grid reinforcement.

V. Different Time Flexible Devices

This research was based on a field trial experimenting with demand-side flexibility from four smart devices (Photovoltaic Panel, Electric Boiler, Heat Pump, and Fuel Cell). Thus, results derived with respect to the extent demand-side flexibility can resolve congestion and defer grid reinforcement was limited to the flexibility output of such devices and its reliability. It is recommended, in order to seek a better understanding of flexibility and its impact on grid congestion, to experiment with different popular time flexible devices, such as: air conditioning, electric vehicles, storage heaters, refrigerators, lightning, or a programmable thermostat for residential, commercial, and industrial customers. Depending on the availability and reliability of flexibility from those devices, the impact of flex on resolving congestion might become more or less pronounced.

VI. Different Market Regulatory Framework

USEF (Universal Smart Energy Framework) is used in the investigated experiment as the market regulatory framework that defines the value of demand-side flexibility, the access to flexibility among different stakeholders, and provide the basic structure of guidelines that govern the trading. However, a regulatory market framework acts as a facilitator but in many cases can act as a barrier to the technology (DSM) within smart grids. Thus, experimenting with different regulatory market mechanisms and frameworks is crucial to ensure a free trade of energy, a levelled playing field for all sizes of households, and a reliable integration of all the local distributed generation units to optimize the benefits from this new technology. That does not necessarily mean that the results will change drastically when a different market regulatory framework is deployed but optimizing the benefits from such a technology necessitate experimenting with different frameworks.

VII. Congestion Limit Sensitivity Analysis

In this analysis a strict grid congestion limit was assumed and flexibility was procured based on the load exceeding the congestion limit. However, it can be argued that the DSO might allow a little of congestion and thus flexibility is not procured to shave the load strictly with the congestion limit. This act will lead to less costs incurred due to less flexibility ordered; however, on the other hand it might degrade the life time of the assets. Therefore, it is recommended to perform sensitivity analysis on the congestion limit to gain insights on its impact on the costs incurred due to flexibility procurement and the savings gained. That will not necessarily lead to different results but may explore different scenarios and grid characteristics where demand-side flexibility is technically and financially more desirable.

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11 Appendices

Appendices A

A.1. Dickey-Fuller test

Graphical representations are not enough to draw a conclusion in regards to the stationarity of the series, accordingly a unit root test is performed. One of the practiced tests is the Dickey-Fuller test (Dickey, Hasza, & Fuller, 1984). Such a test involves testing for the presence of a unit root in an autoregressive model through the following hypotheses:

H0 = the time series has a unit root (non-stationary)
H1= the time series does not have a unit root (stationary)

The unit root stands for the one-on-one impact of the lagged variable on its current value. For instance, the correlogram for the PV output indicates a time series characterized by AR(1). Thus, taking the random walk as for example: $Y_t = \rho y_{t-1} + \varepsilon_t$, if ρ=1 would indicate that the time series has a unit root (non-stationary). Performing the Dickey-Fuller for the PV flex indicates the following results as shown in Table 70.

Table 70: Dickey-Fuller test for unit root for (PV output)

Dickey-Fuller test for unit root Number of obs = 4094

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-17.208	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

With a p-value less than 0.05 (95% confidence interval), the zero hypothesis is rejected and one can conclude that the series does not have a unit root. However, one of the conditions of Dickey-Fuller test is that the errors are independent (not serially correlated) and the variance is constant. With a serially correlated error term (the errors are correlated in different periods of time), the Augmented Dickey-Fuller test must be performed to test for stationarity. The following table, Table 71, shows the Augmented Dickey-Fuller test for the unit root for PV output.

Table 71: Augmented Dickey-Fuller test for unit root for PV output

Augmented Dickey-Fuller test for unit root Number of obs = 4093

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-18.768	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

D. PvOutputwatthr	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
PvOutputwatthr						
L1.	-.1513345	.0080633	-18.77	0.000	-.1671431	-.135526
LD.	.1213328	.0155208	7.82	0.000	.0909035	.151762
_cons	1184.613	135.6807	8.73	0.000	918.605	1450.621

A.2. Rough Estimation of the Panels' position for the 89 panels systems in Heerhugoward

According to the EIA (2008), the maximum average energy production for a panel tilted south or flat (not tilted) is around 12 noon, while the maximum average energy production for a panel tilted west is between 1 and 2 afternoon and for a panel tilted east is around 11 am. The position of the 89 panel systems in Heerhugowaard is estimated, and the percentage of panels that are positioned south, west, and east is depicted in the Figure 51.

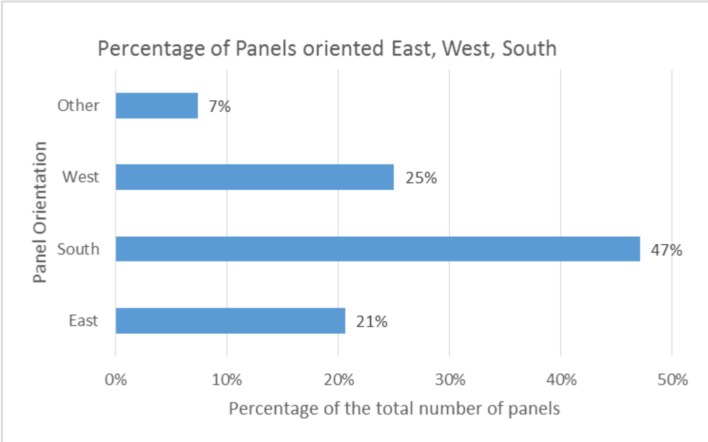


Figure 51: PV Panels' Orientation

A.3. Testing for Heteroscedasticity (residual plot)

When the residuals do not portray a distinct cloud shape this provides an initial indication that the data might be heteroscedastic, and further formal testing is required.

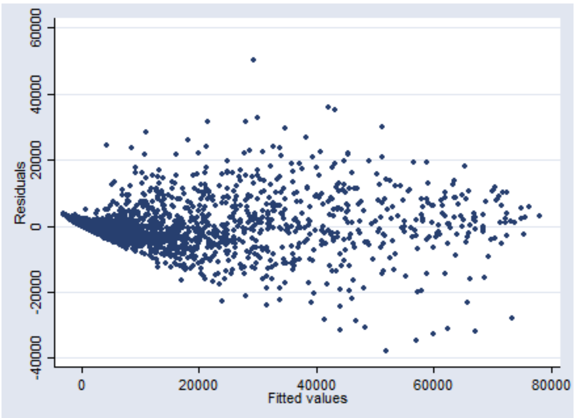


Figure 52: Heteroscedasticity plot

A.4. Serial Correlation – Durbin Watson Test and Durbin's alternative test

1. Durbin Watson Test

Firstly, testing for serial correlation involves performing the Durbin Watson Test, which is considered the oldest among other tests. To test for the serial correlation in the residual (the error term), the following test calculates d, where e_t is the error term and T is the number of observations (Montgomery et al., 2015):

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2},$$

"e_t" is the difference between the observed and the predicted (yi and ŷi, respectively). Let "ρ" be the autocorrelation coefficient between the e_t and e_{t-1}. Based on the number of observation and the number of regressors, the d_{Lower} and d_{Upper} are tabulated, where the null hypothesis and the alternative hypothesis are defined as follows:

If d < dL reject H0 : ρ = 0 (the error terms are serially independent)
If d > dU do not reject H0 : ρ = 0
If dL < d < dU test is inconclusive

For a visual representation, the following figure (Figure 53) explains the autocorrelation and intervals of serial correlation (positive or negative) based on d_{Lower} and d_{Upper}.

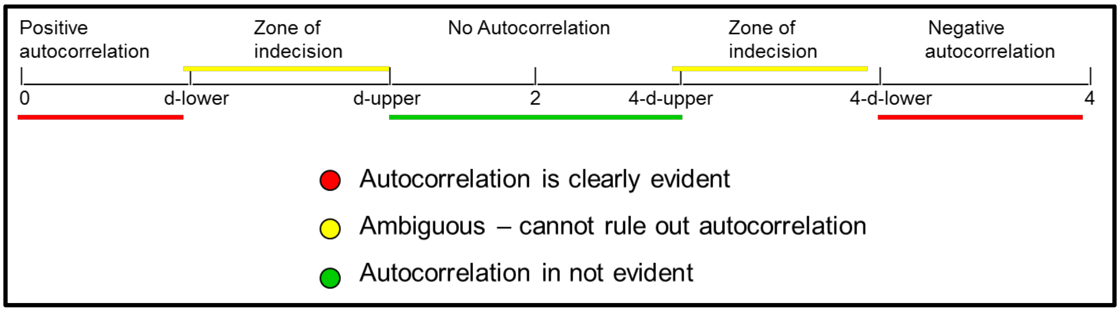


Figure 53: Serial correlation intervals to accept/reject null hypothesis

However, this test is rendered invalid if there is autoregressive dependent variable (y), in other words a lagged variable of the dependent (y_{t-1}) is one of the independent repressors in the regression model. Moreover, the Durbin Watson test tests only for the first order correlation between u_t and u_{t-1} as follows: $u_t = \rho u_{t-1} + \varepsilon$

However, **Durbin's alternative test for serial correlation** does not require that the error term is strictly exogenous from the explanatory variables. Thus, the results of the test **Durbin's alternative test,** which tests for the **first order serial correlation** is as follows in Table 72.

Table 72: Durbin's alternative test for first order serial correlation

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	23.197	1	0.0000

H0: no serial correlation

The test results shows that the null hypothesis can be rejected and thus there exist a significant first order of correlation, $u_t = \rho u_{t-1} + \varepsilon$, where ρ≠0.

2. Breusch-Godfrey Lagrange multiplier test

In case of more than one order of correlation in the error term, until p order of correlation, the Breusch-Godfrey Lagrange multiplier test can be performed. If the error term is not dependent on the lagged variable of the error term, then the disturbance (residual) is considered to be white noise. White noise is considered to be the normal error term with zero mean, variance=σ^2, and zero correlation between the error term and its lagged variable. Thus the zero hypothesis of the test is that the error term is white noise. The regression for Breusch-Godfrey Lagrange multiplier test is as follows:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \cdots \rho_p u_{t-p} + \beta X_t + \varepsilon$$

Where β is the vector of coefficients between the independent variables and the dependent and Xt is the vector of independent variables. The BC(p)= n*R^2, to be distributed as χ^2 (p) where n is the number of observations. If the coefficient of determination is near zero then, there is no serial correlation and the disturbance is white noise (cannot reject the zero hypothesis).

The following test results show that the zero hypothesis can be rejected and thus the error terms are serially correlated for more than the first order, as presented Table 73.

Table 73: Breusch–Godfrey test for higher-order serial correlation

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	23.100	1	0.0000
2	33.530	2	0.0000
3	38.461	3	0.0000

H0: no serial correlation

A.5. Remedial Measures for Serial Correlation

- **First Differences:** one of the ways to solve for serial correlation is by first differencing the dependent variable at time t and t-1, and to be written as follows:

$$y_t - \rho y_{t-1} = \beta_1(X_t - \rho X_{t-1}) + (u_t - \rho u_{t-1})$$

However, this remedial measure is contingent upon having strictly exogenous regressors and first order serial correlation, which is not the case in the PV model because of the lagged dependent variable AR(1).

- **Cochrane-Orcutt (CORC) Iterative Procedure (Prais Winsten test):** if first differencing did not eliminate the problem of serial correlation, Cochrane-Orcutt (CORC) can be performed by applying quasi or generalized differencing transformation. To carry out CORC, the orderly least squared model is performed (OLS) and the error term ε_t (residuals) are computed. The first correlation between the ε_t and ε_{t-1} is performed as follows to compute ρ:

$$\varepsilon_t = \rho\varepsilon_{t-1} + u_t$$

Then the independent and dependent variables are transformed as follows:

$$y_t *= y_t - \rho\, y_{t-1} \text{ and } x_{t1} *= x_{t1} - \rho x_{t-1,1}$$

Where the Y_t^* is regressed with X_{t1}^*, and X_{t2}^*... etc. in order to get the new coefficient of estimation $\beta_j^*$for j=1, 2, 3..etc.

Use the new β_j^*into the original regression model, and compute again the revised error term ε_t and repeat the CORC iterative procedure until no correlation shows between the error term and its past variables. However, it is important to note that **Cochrane-Orcutt (CORC)/Prais Winsten** are not adequate for models with lagged dependent variable as an explanatory variable (Keele & Kelly, 2006).

A.6. Poisson Count Data Regression for Hot Water Consumption

Within this Poisson model the coefficients can be interpreted as follows: for instance a one degree increase in temperature leads to a 0.38% increase in hot water consumption.

Table 74: Poisson Regression for Hot Water Consumption

Rounded Hot Water Consumption	Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Outside air temperature (°C)	0.003841	0.000542	7.09	0.000	0.0027794	0.0049025
Relative Humidity (%)	0.012983	0.000221	58.63	0.000	0.0125493	0.0134174
Household Load (Watt)	0.000128	4.69E-06	27.25	0.000	0.0001187	0.0001371
Hour **2**	1.055033	0.02639	39.98	0.000	1.00331	1.106755
3	1.108259	0.026076	42.5	0.000	1.057151	1.159368
4	1.278959	0.025251	50.65	0.000	1.229468	1.32845
5	1.558365	0.024093	64.68	0.000	1.511143	1.605586
6	1.954029	0.022903	85.32	0.000	1.909141	1.998918
7	2.223213	0.022284	99.77	0.000	2.179537	2.26689
8	2.632288	0.021639	121.65	0.000	2.589877	2.674699
9	2.973735	0.02127	139.81	0.000	2.932046	3.015424
10	2.839835	0.021098	134.6	0.000	2.798484	2.881186
11	2.119747	0.022199	95.49	0.000	2.076237	2.163257
12	1.394688	0.024548	56.81	0.000	1.346575	1.442802
13	0.519483	0.030176	17.22	0.000	0.4603385	0.5786268
14	-1.46252	0.065331	-22.39	0.000	-1.590565	-1.33447
15	-3.12513	0.145617	-21.46	0.000	-3.410537	-2.839729
16	-3.6345	0.186698	-19.47	0.000	-4.000422	-3.26858
17	-2.44726	0.102898	-23.78	0.000	-2.648935	-2.245583
18	-1.49721	0.064525	-23.2	0.000	-1.623678	-1.370745
19	0.286377	0.032064	8.93	0.000	0.2235316	0.3492217
20	0.684	0.028731	23.81	0.000	0.6276897	0.740311
21	1.214694	0.025639	47.38	0.000	1.164442	1.264946
22	1.095195	0.02625	41.72	0.000	1.043746	1.146643
23	1.082002	0.02634	41.08	0.000	1.030376	1.133627
24	0.85303	0.027491	31.03	0.000	0.7991498	0.906911

A.7. Percentage water consumption of a Dutch family

Percentage hourly water use for a single family in the Netherlands was retrieved from a paper published by Blokker et al. (2009) where domestic water demand was simulated through means of a stochastic model. The extracted data is presented in Table 75.

Table 75: Percentage water consumption for a single Dutch family

Hour	Single-family: % of Total Daily Water Use
1	2.12%
2	2.66%
3	1.25%
4	2.47%
5	6.11%
6	9.97%
7	13.09%
8	13.73%
9	8.25%
10	6.00%
11	2.79%
12	2.56%
13	2.94%
14	2.34%
15	2.38%
16	1.87%
17	1.84%
18	2.24%
19	3.21%
20	4.34%
21	2.56%
22	2.75%
23	1.72%
24	0.83%

Wilcoxon rank-sum test (Mann-Whitney) for Validation Purposes:

The Wilcoxon rank-sum test (Mann-Whitney) was performed to test whether the predicted versus the measured percentage cumulative of hot water consumption come from a common distribution.

Table 76: Wilcoxon rank-sum test (Mann-Whitney) to compare the predicted versus measured percentage cumulative hot water consumption

```
Two-sample Wilcoxon rank-sum (Mann-Whitney) test

KolmogrovS~v |      obs    rank sum    expected
-------------+---------------------------------
           1 |       24       584.5         588
           2 |       24       591.5         588
-------------+---------------------------------
    combined |       48        1176        1176

unadjusted variance     2352.00
adjustment for ties       -0.13
                     ----------
adjusted variance       2351.87

Ho: cumper~d(Kolmog~v==1) = cumper~d(Kolmog~v==2)
             z =  -0.072
    Prob > |z| =   0.9425
```

A.8. Breusch-Godfrey Lagrange multiplier test for autocorrelation in the error (Heat Load Model)

In case of more than one order of correlation in the error term, until p order of correlation, the Breusch-Godfrey Lagrange multiplier test is performed. If the error term is not dependent on the lagged variable of the error term, then the disturbance (residual) is considered to be white noise. However, Table 77 shows that there is a significant correlation between the error term and the lagged variables of the error term.

Table 77: Breusch-Godfrey LM test for autocorrelation in the error (The Heat Load model)

Breusch-Godfrey LM test for autocorrelation in the error (The Heat Load model)			
lags(p)	**chi2**	**df**	**Prob > chi2**
1	1333.853	1	0.000
2	1392.765	2	0.000
3	1397.327	3	0.000
H0: no serial correlation			

Appendices B

B.1. Reliability of flex delivered versus ordered

Table 78 presents the detailed average percentage flex delivered for both experiments at the 4 congestion block levels for the two experiments.

Table 78: Average percentage flex delivered at the 4 congestion blocks

	Percentage delivered at FC block	Percentage delivered at PV block	Percentage delivered at EB block	Percentage delivered at HP block
Nov 18-Dec 15	76.23%	65.16%	93.25%	36.39%
Jan 13- Feb 9	81.97%	72.56%	77.15%	49.46%
Average of the two experiments	79.08%	68.86%	85.21%	42.93%
Average Upper confidence interval	81.72%	75.18%	88.76%	47.59%
Average Lower confidence interval	76.50%	62.54%	81.64%	38.28%
Total Number of orders from both experiments	1106	300	267	534

B.2. Probability Distribution Function for the load at different Distribution Blocks

The best fitting theoretical distribution of the load with/without at the 4 congestion block levels. The best fitting distribution for the HP load with and without flex is Gumbel Max, as depicted in Figure 54. The best fitting distribution for the FC load with and without flex is Logistic, as depicted in Figure 53. The best fitting distribution for the EB and PV load with and without flex is Weibull (3P), as depicted in Figure 54.

Probability Density Function at the HP BLOCK:

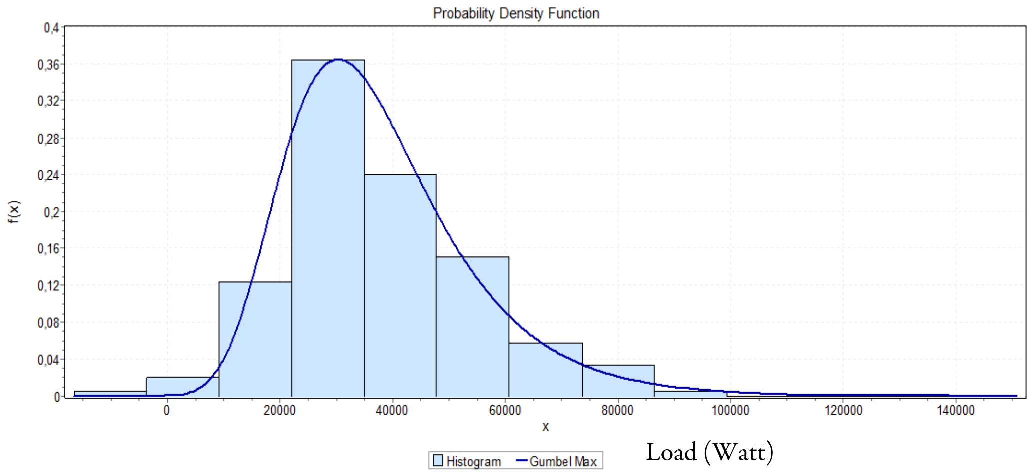


Figure 54: HP block level - PDF is Gumbel Max

Probability Density Function at the FC BLOCK:

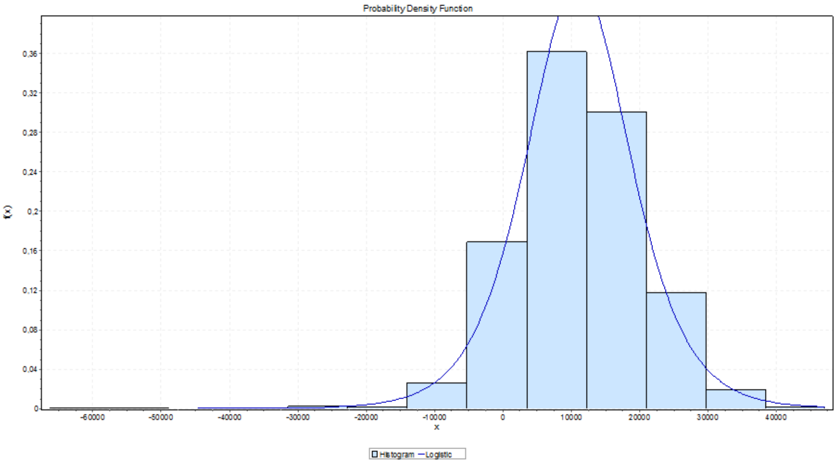


Figure 55: FC block level - PDF is Logistic

Probability Density Function at the EB BLOCK:

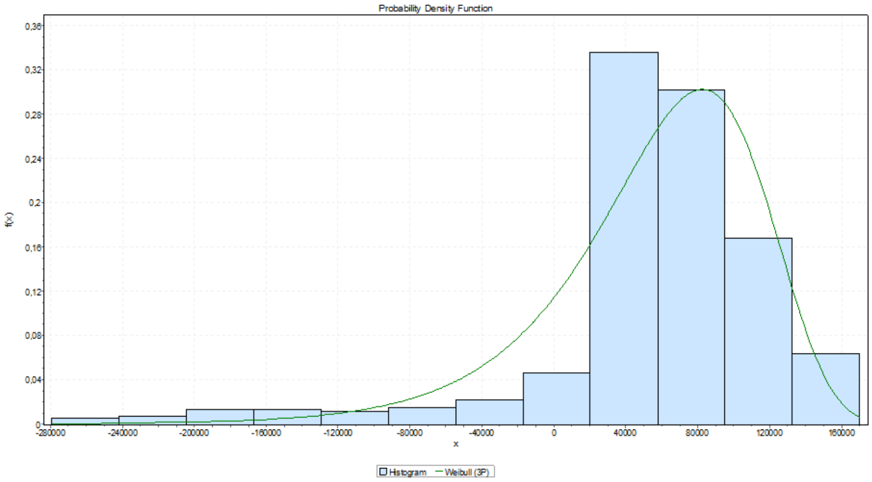


Figure 56: EB block level - PDF is Weibull (3P)

B.3. Correlation between Exceedance and Flex Shortage at the 4 Congestion Block Levels

The bivariate regression models, tabulated in the following tables, prove a significant positive correlation coefficient with an adjusted R^2 of 7.68%, 10.7%, 25%, and 31.3% respectively for PV, FC, HP, and EB congestion block, for the two month experiments combined (Nov 18, 2015 till Dec 15, 2015 and from Jan 13, 2016 till Feb 9, 2016).

Exceedance at the PV congestion block (watt)	*coef.*	*std. err.*	*t*	*p>t*	*[95% conf. interval]*	
Flex shortage at PV congestion block (watt)	0.425056	0.023667	17.96	0.000	0.378649	0.471463
Constant	119.9569	58.68022	2.04	0.041	4.893927	235.0199

Exceedance at the FC congestion block (watt)	*coef.*	*std. err.*	*t*	*p>t*	*[95% conf. interval]*	
Flex shortage at FC congestion block (watt)	0.257339	0.017055	15.09	0.000	0.223897	0.29078
Constant	274.5999	29.17549	9.41	0.000	217.3912	331.8086

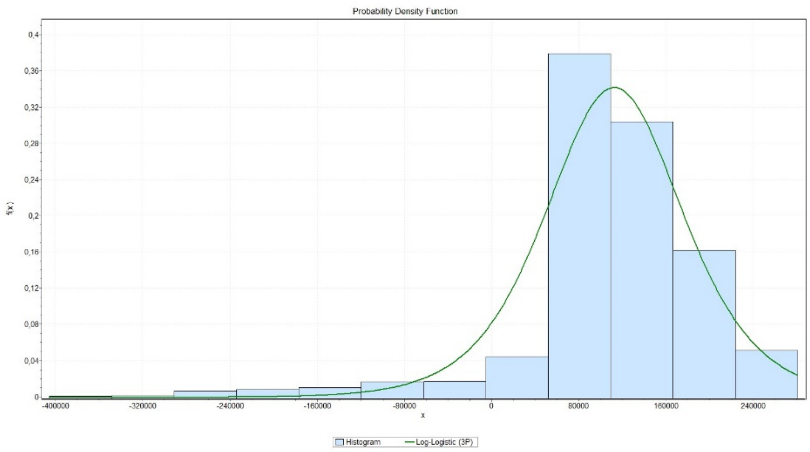
Exceedance at the HP congestion block (watt)	*coef.*	*std. err.*	*t*	*p>t*	*[95% conf. interval]*	
Flex shortage at HP congestion block (watt)	0.391048	0.011169	35.01	0.000	0.369147	0.412949
Constant	385.4924	51.06727	7.55	0.000	285.3573	485.6276

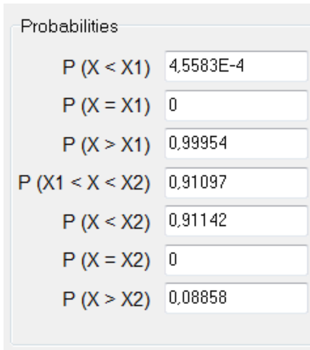
Exceedance at the EB congestion block (watt)	coef.	std. err.	t	p>t	[95% conf. interval]	
Flex shortage at EB congestion block (watt)	0.445033	0.014854	29.96	0.000	0.415906	0.47416
Constant	175.2231	88.3066	1.98	0.047	2.067342	348.3789

B.4. The Influence of Flexibility on the Probability of Congestion at a Mixture Congestion Level for the Two Experiments

Mixture Congestion Block (experiment Dec 16 - Jan 12)

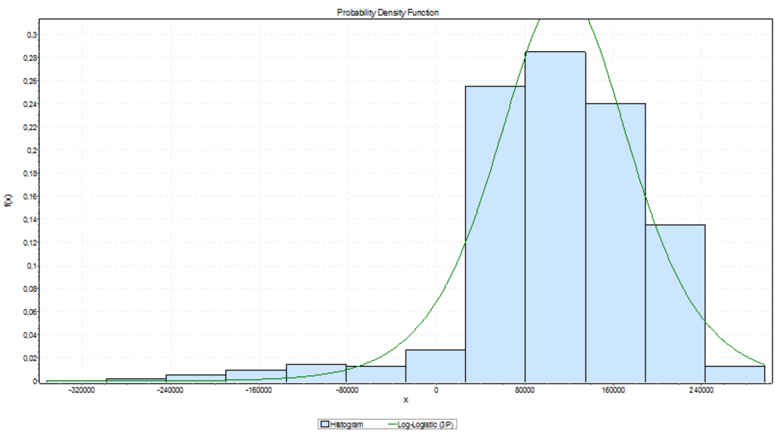
Load without flex ordering

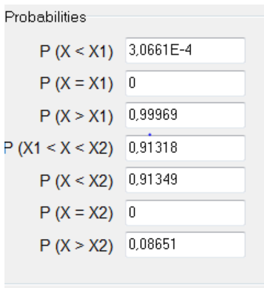




Probabilities	
P (X < X1)	4,5583E-4
P (X = X1)	0
P (X > X1)	0,99954
P (X1 < X < X2)	0,91097
P (X < X2)	0,91142
P (X = X2)	0
P (X > X2)	0,08858

Load with flex ordering

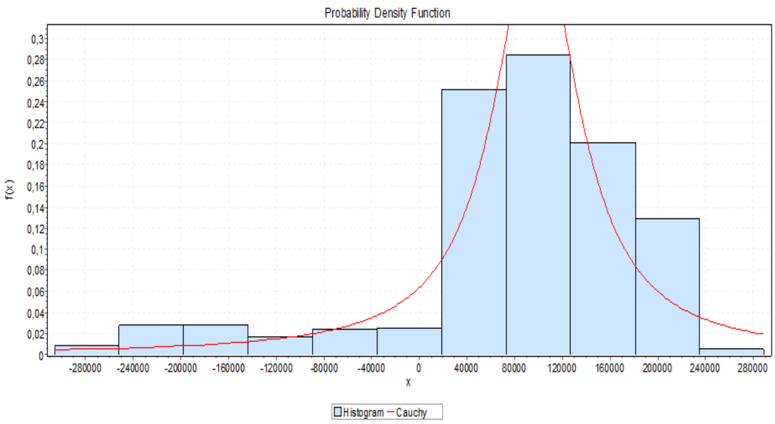


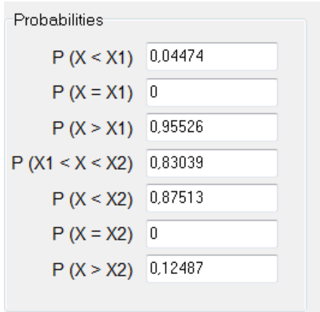


Probabilities	
P (X < X1)	3,0661E-4
P (X = X1)	0
P (X > X1)	0,99969
P (X1 < X < X2)	0,91318
P (X < X2)	0,91349
P (X = X2)	0
P (X > X2)	0,08651

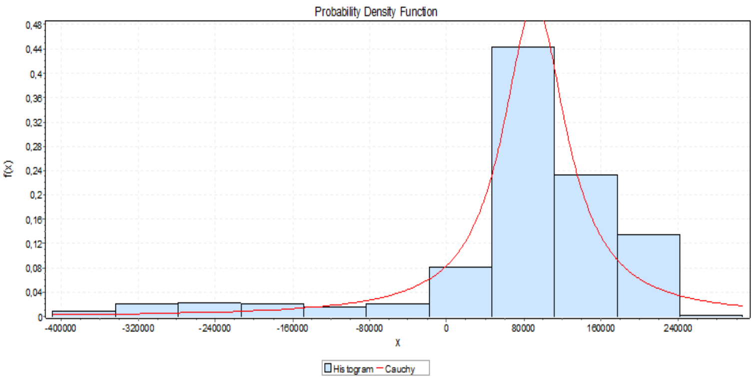
Mixture Congestion Block (experiment Feb 10 - March 8)

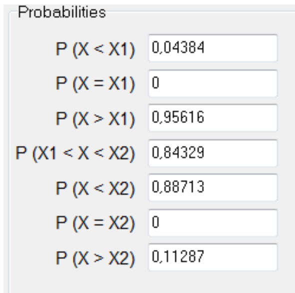
Load without flex ordering





Load with flex delivered





The two experiments performed from Dec 16, 2015 till Jan 12, 2016 and from Feb 10, 2016 till March 8, 2016, are analysed, where during those two experiments, the DSO together with the BRP procured flex from the aggregator at the mixture congestion level. To calculate the probability of congestion for the load without flex and with flex, the measured data of the load without flex and the load with flex is fitted against a theoretical distribution using EasyFit software. To assess which probability distribution is the best, the Kolmogorov Simonov test was chosen to rank the distributions from best to worst. Probability of congestion was calculated from the log-logistic (3-parameter Weibull) theoretical distribution model and the Cauchy theoretical distribution model for the two experiments, respectively. Table 79 presents the percentage decrease in the total probability of exceedance for the load curve for both experiments.

Table 79: Probability of exceedance for the load with/without flex for the Mixture congestion block level

Congestion Block	Congestion Limit	Load without flex ordering	Load with flex delivered
Mixture Congestion Block (Dec 16 - Jan 12) Log-logistic (3P) pdf	Total prob of exceedance (%)	8.9%	8.7%
	-210000<X<210000	91.1%	91.3%
	1 exceedance in X PTUs	11.2	11.5
Mixture Congestion Block (Feb 10 - March 8) Cauchy pdf	Total prob of exceedance (%)	17.0%	15.7%
	-200000<X<200000	83.0%	84.3%
	1 exceedance in X PTUs	5.9	6.4

Values tabulated above show that the total probability of exceedance did not decrease significantly and the probability of an exceedance is on average every 8 PTUs for both experiments. Thus, to prove whether the forecast error ((forecast load without flex - actual load without flex) (Watts)), which stands for weather forecast error, demand forecast error, or consumption pattern prediction error, is significantly affecting the load with flex exceedance from the congestion limit

(Watt), a bivariate regression analysis is performed. The exceedance of the load with flex is regressed on the absolute value of (forecast load without flex - actual load without flex)(Table 80).The statistical correlation between the forecast error and congestion limit exceedance turned out to be significantly positively correlated, as would have been hypothesized, with an adjusted R^2 of 20%. The results are tabulated in Table 80 and a graphical representation of the correlation is presented in Figure 57.

Table 80: A bivariate regression between the forecast error and load with flex exceedance to the congestion limit

Exceedance at the mixture congestion level (watt)	Coef.	Std. err.	t	p>t	[95% conf. interval]	
Flex shortage at the mixture congestion level (watt)	.2571524	.0218244	11.78	0.000	.2142886	.3000162
Constant	22881.24	2564.924	8.92	0.000	17843.66	27918.82

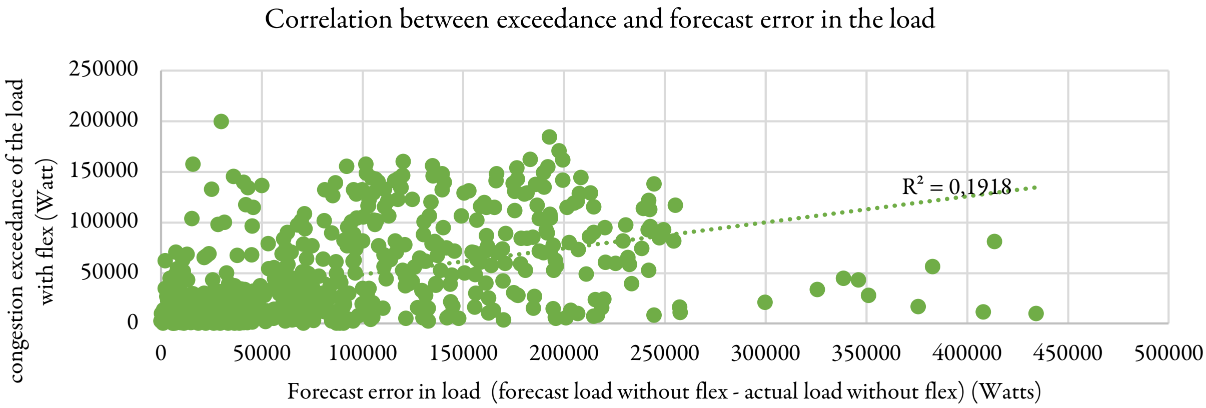


Figure 57: Correlation between the forecast error and load with flex exceedance to the congestion limit

In the two month experiment, in the first two weeks of both experiments, the prices of flex were set realistically and the BRP was ordering accordingly; however in the second 2 weeks of both experiments, the flex was sold for 1 cent for every kWh flex sold of the electric boiler and the fuel cell for the BRP. Table 81 presents the different prices per time and type of device:

Table 81: The different prices per time and type of device

Price of flex – device specific	Dec 16 - Dec 29		Dec 30 - Jan 12	
EB price of flex (cent/kWh)	11.14	11.14	1.0	1.0
PV price of flex (cent/kWh)	15.21	15.21	15.2	15.2
FC price of flex (cent/kWh)	37.0	37.0	1.0	1.0
HP price of flex (cent/kWh)	25.39	25.39	25.39	25.39

Thus, it would have been expected that the BRP will order more day ahead in the second 2 weeks since the price of flex was less than that at the APX market. According to USEF, the BRP procures day ahead before the DSO, and thus may affect the amount of flex offered to the DSO, and again the reliability of the flex to be delivered. Reciprocally, this will likely affect the DSO's utility of keeping the load within the congestion limit. For instance, if the BRP orders flex up by shutting down the PVs this may create congestion on the network where the DSO has to deal with. On the other hand, if the BRP orders all the flex up coming from an electric boiler during the morning, the electric boilers may be fully charged and thus affects the DSO's orders from an electric boiler at a different moment in time. A comparison table of the average flex ordered, average flex delivered, and average percentage delivered day ahead, intraday, and operation, for the BRP versus DSO was calculated for the first two weeks (realistic flex prices offered to the BRP) and the second two weeks (cheap prices of the EB and FC) and presented in Table 83 and Table 84.

First two weeks (Dec 16 – Dec 29)

Table 82: the average flex ordered, average flex delivered, and average percentage delivered day ahead, intraday, and operation, for the BRP versus DSO for the first two weeks (realistic flex prices offered to the BRP)

DSO/BRP experiment	BRP		DSO	
Day Ahead	Flex up +	Flex down -	Flex up +	Flex down -
Average Ordered (Watt)	1359	225	1232	530
Average Delivered (Watt)	1100	87	1035	338
Average percentage delivered	80.94%	38.67%	84.01%	63.77%

DSO/BRP experiment	BRP		DSO	
Intra Day	Flex up +	Flex down -	Flex up +	Flex down -
Average Ordered (Watt)	4317	3	64	314
Average Delivered (Watt)	2250	0	22	266
Average percentage delivered	52.12%	0.00%	34.38%	84.71%

DSO/BRP experiment	DSO	
Operate Phase	Flex up +	Flex down -
Average Ordered (Watt)	127	1981
Average Delivered (Watt)	105	1277
Average percentage delivered	82.68%	64.46%

Last two weeks (Dec 29– Jan 12)

Table 83: the average flex ordered, average flex delivered, and average percentage delivered day ahead, intraday, and operation, for the BRP versus DSO for the first two weeks (cheap prices of the EB and FC)

DSO/BRP experiment	BRP		DSO	
Day Ahead	Flex up +	Flex down -	Flex up +	Flex down -
Average Ordered (Watt)	34701	5437	1672	1206
Average Delivered (Watt)	11289	1446	1367	1141
Average percentage delivered	32.53%	26.60%	81.76%	94.61%

DSO/BRP experiment	BRP		DSO	
Intra Day	Flex up +	Flex down -	Flex up +	Flex down -
Average Ordered (Watt)	16328	2842	2157	1222
Average Delivered (Watt)	7616	1813	1648	1023
Average percentage delivered	46.64%	63.79%	76.40%	83.72%

DSO/BRP experiment	DSO	
Operate Phase	Flex up +	Flex down -
Average Ordered (Watt)	308	2294
Average Delivered (Watt)	106	1079
Average percentage delivered	34.42%	47.04%

It can be inferred from analysing the first and last two weeks that the BRP is ordering flex in the last 2 weeks significantly more, when prices offered are low, than in the first 2 weeks. Hypothetically, it can be assumed that the ordered flex up (Watt) by the BRP may be positively correlated to the load exceedance (Watt). Thus, load exceedance was regressed on the ordered flex by the BRP to test the assumed correlation but the strength of the relationship showed less than 5%. Another hypothetical correlation would be that the more the ordered flex up by the BRP will result in more flex down orders by the DSO. However, bivariate regression resulted in a non-significant correlation. Furthermore, a hypothetical correlation between flex ordered by the BRP in the second 2 weeks and the percentage of flex delivered to the DSO was tested statistically, assuming that the high flex ordered by the BRP may be correlated negatively by the percentage flex delivered to the DSO. However, again bivariate regression resulted in a non-significant correlation.

Roughly, it can be concluded that the price of flex may influence the amount of flex ordered by the BRP but it does not seem to influence the percentage flex delivered to the DSO; however, it may have influenced the percentage flex offered to the DSO (the more the BRP orders the less flex available), which could explain the high probability of congestion since offered flex may not have been enough to resolve congestion.

B.5. The Predicted Heat Load (preserving indoor heating) for all Seasons

In an attempt to predict the heat load (for indoor heating only) for the entire year for the Heerhugowaard area, the 34 Heat pumps are assumed on. Weather data for year 2015 from Berkhout city is substituted in the regression equation (radiation, humidity, wind speed, and temperature). Consequently, the Heat load is estimated using the regression model for the 34 households for the year, and is presented in Figure 58. The graph shows an apparent decrease in the heat load during June, July, August and September, and apparent increase beyond September. However, more insights can be gained with respect to the difference between the seasons.

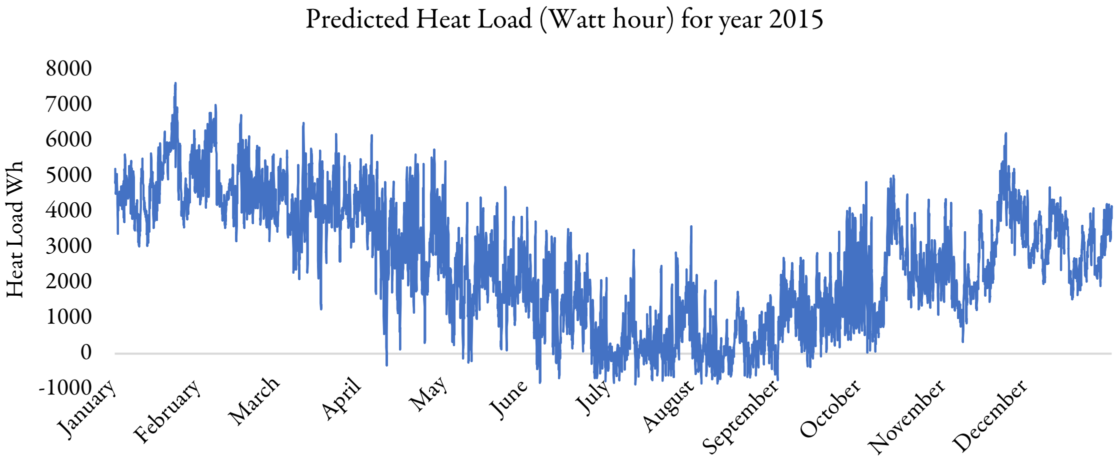


Figure 58: Predicted Heat Load for year 2015

To gain more insight on the differences between the average Heat load per hour for the 4 different seasons in Heerhugowaard, the regression model was used to predict Heat load per hour for the 34 Heat pumps. Consequently, the average heat load (Wh) per hour over a day for Spring, Summer, Fall, and Winter was calculated. The following graph, Figure 59 shows the mean heat load per hour of the day. While the average heat load in the Fall or Spring tends to hover roughly between 2000 and 3500 Wh for 34 heat pumps, the average heat load in the Winter tends to hover roughly between 4000 and 5000 Wh. While that in the Summer hover roughly between 0 and 1000 Wh. Another realization, is that during Spring and Summer, the heat load tends to roughly start subsiding at 4:00am at dawn with sun rise while in the Fall and Winter, it subsides later in time, around 7:00am with the sun rise. Similarly, at dusk, the heat load starts to increase again at 18:00 in Spring and Summer while it starts increasing at 16:00pm during the Fall and Winter.

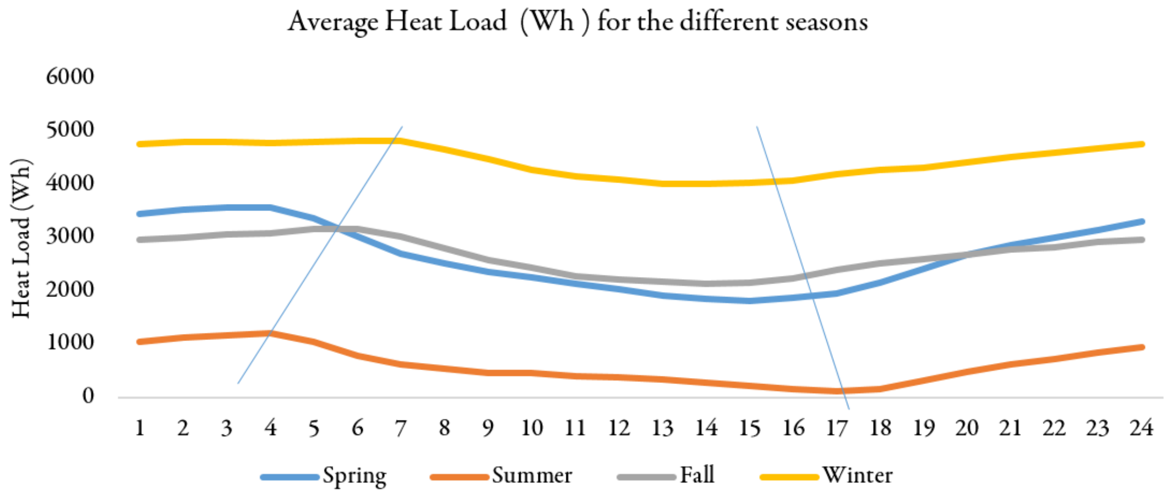


Figure 59: Average heat load per hour for the different seasons

To test if the different seasonal averages over the day differ significantly from each other, ANOVA, analysis of variance test, is performed. Prior to performing ANOVA, ANOVA conditions are cross-checked: (1) samples are independent and random, (2) population is normally distributed (central limit theorem), (3) the variance is the same in all groups. ANOVA null and alternative hypothesis are as follows:

H0: All group averages are the same, i.e. F = 1.
H1: Not all group averages are the same, i.e. F > 1.

To test whether the variance is the same for all groups, Levene's test for homogeneity of variance is performed with the following zero and alternative hypothesis:

H0: All group variances are the same, i.e. $.\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_k^2$
H1: Not all group variances are the same

The Leven's test demonstrates that the probability is smaller than 5%, and thus the zero hypothesis is rejected. Not all the group variances are the same. Thus, ANOVA test cannot be used. Instead, the non-parametric Kruskal-Wallis test is performed, where the Kruskal-Wallis test tests whether the averages of the heat load for the different seasons are the same. The test results in Table 84 show that the zero hypothesis can be rejected and thus, the averages are different.

Table 84: Kruskal Wallis Test

Test Statistics	
Chi-Square	80.192
df	3
Asymp. Sig.	0.000

To test which averages are different, the non-parametric, Dunn's Pairwise Comparison test is performed, which proves that the average heat load is significantly different between all seasons except between Spring and Fall (the p value is bigger than 5% and thus we cannot reject the zero hypothesis), as shown in Table 85. These results are in line with the graphical representation of the average heat load over a day for the 4 seasons, as portrayed in Figure 59, where Spring and Fall seem overlapping.

Table 85: Dunn's Pairwise Test

	Spring	Summer	Fall
Summer	4.393841		
	0.0000		
Fall	-0.16581	-4.55965	
	0.4342	0.0000	
Winter	-4.55965	-8.95349	-4.39384
	0.0000	0.0000	0.0000

B.6. Controlled and uncontrolled houses with PVs systems and their capacity

Table 86: Controlled and Uncontrolled houses PVs systems capacity

average capacity per PV (Watt)	Congestion Block levels	Total PVs Capacity (controlled & uncontrolled)	Controlled houses with PVs Installed	Controlled houses (total PVs capacity Installed) (Watt)	Uncontrolled houses with PVs Installed	Uncontrolled houses (total PVs capacity Installed) (Watt)
1700	**HP**	127500	50	85000	25	42500
1700	**EB**	253300	44	74800	105	178500
1700	**FC**	88400	18	30600	34	57800
2000	**PV**	298000	89	178000	60	120000

B.7. Percentage PTUs with Congestion at each Season for all congestion Block Levels

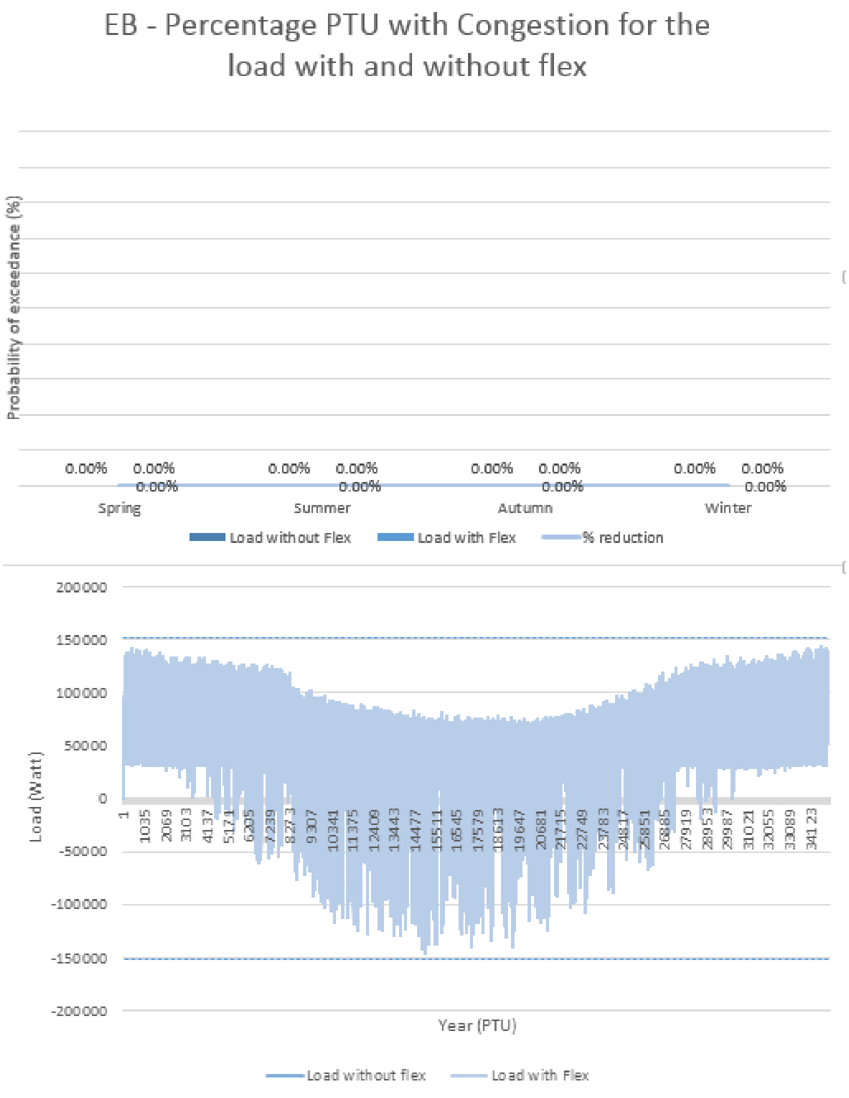


Figure 60: Percentage PTUs with congestion at the EB congestion block level

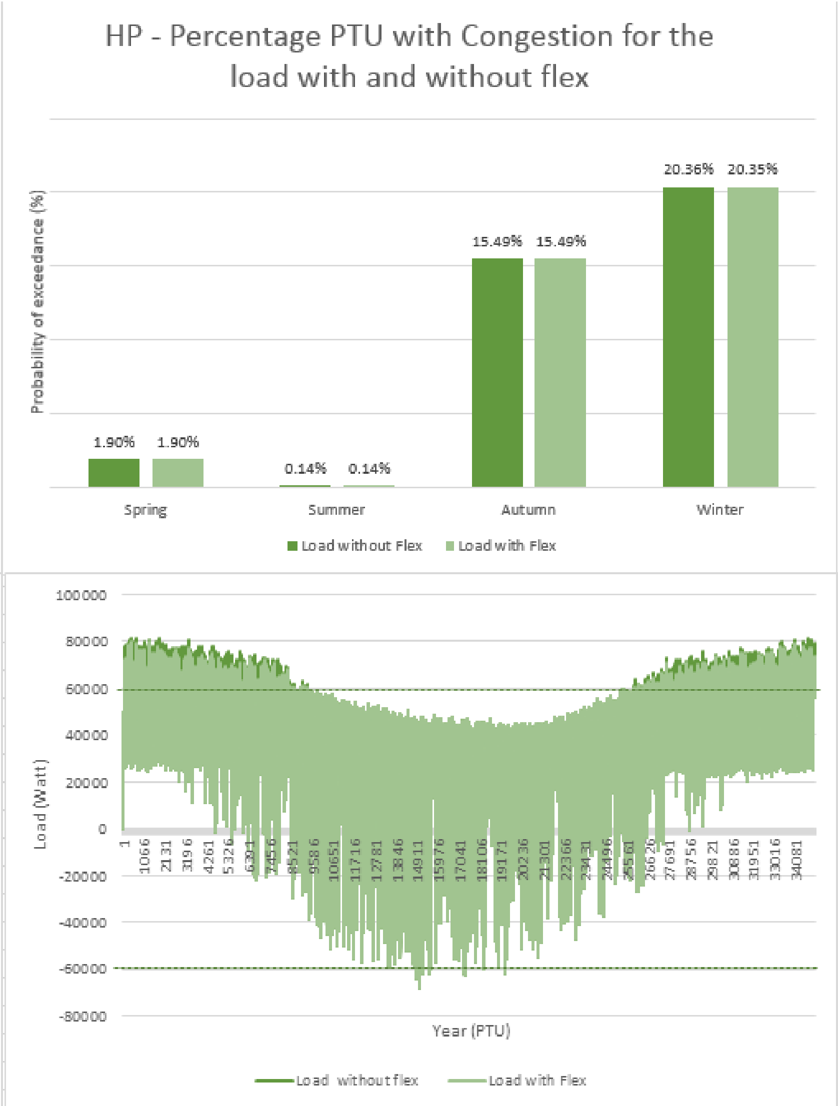


Figure 61: Percentage PTUs with congestion at the HP congestion block level

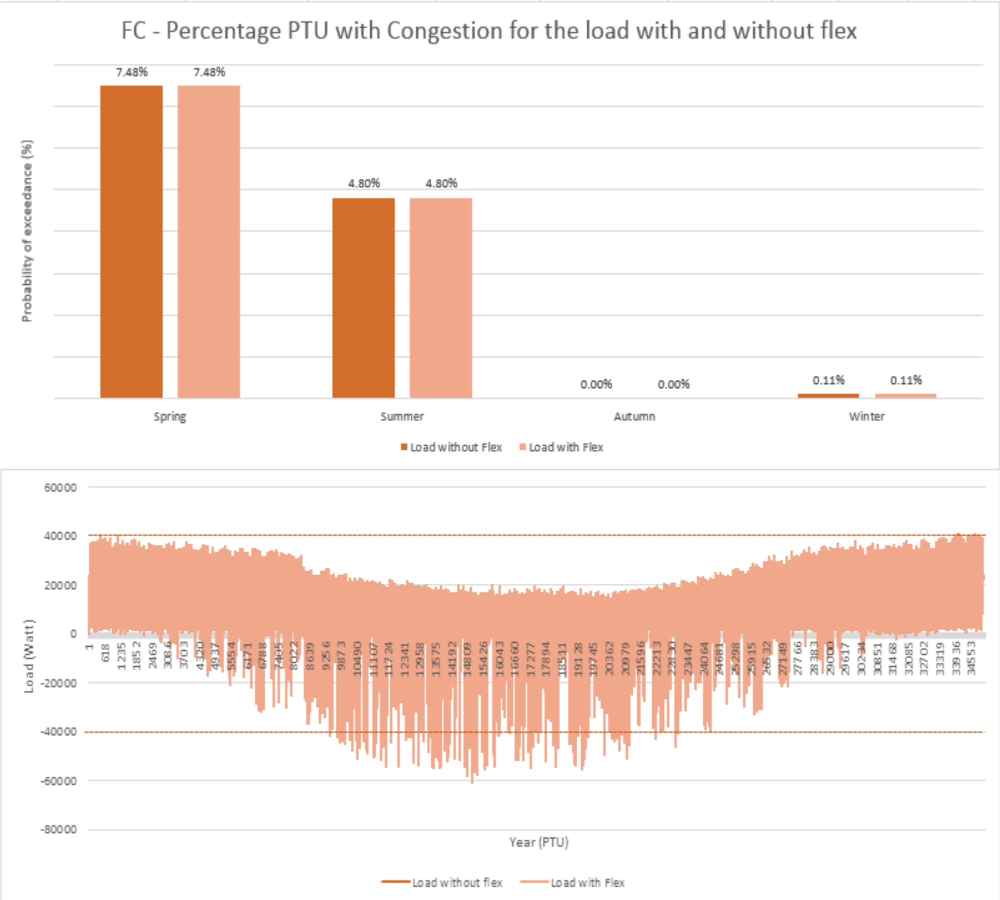
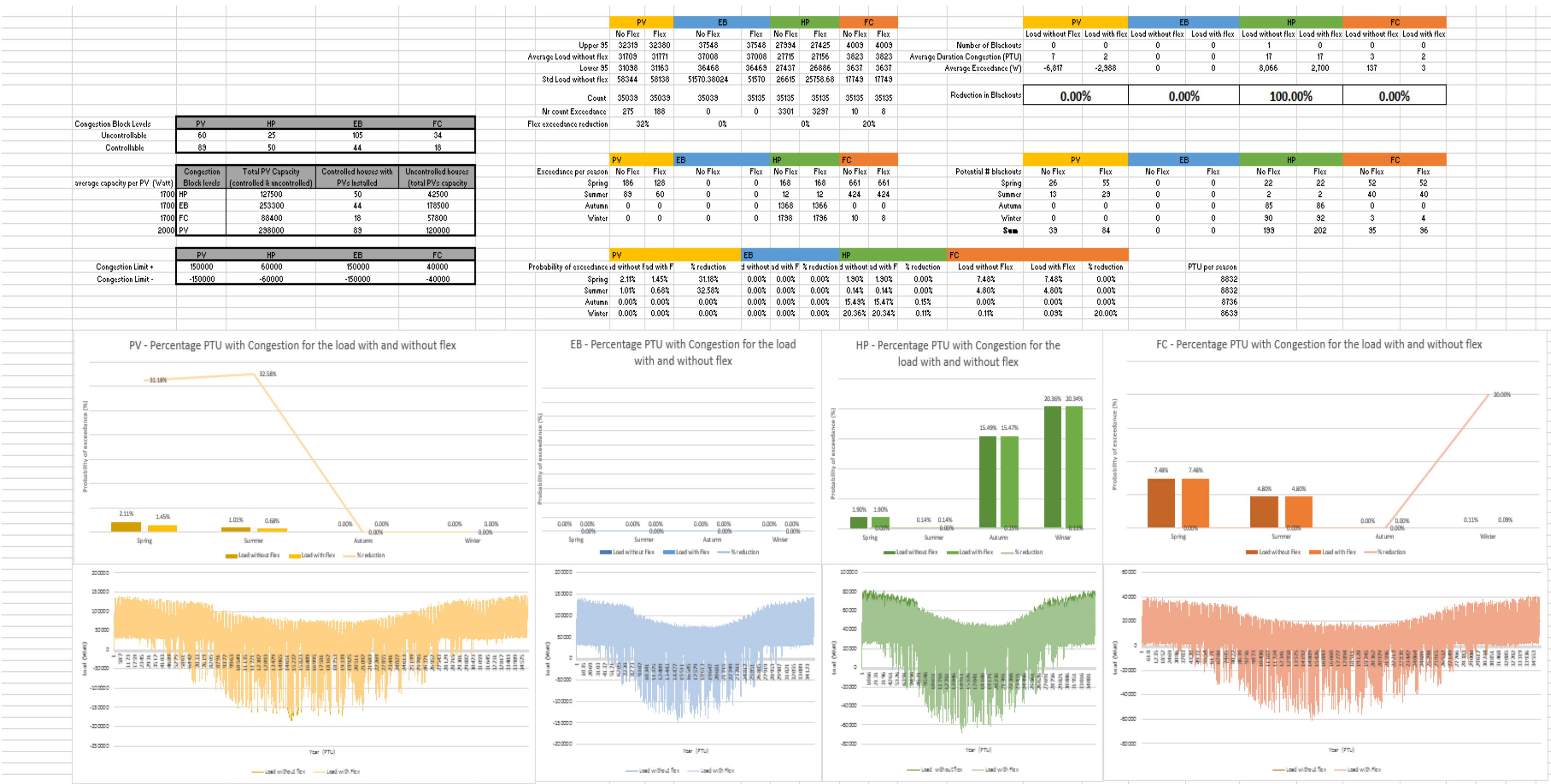


Figure 62: Percentage PTUs with congestion at the FC congestion block level

B.8. Snapshots of the Excel Simulation Model

Table 87: Probability of congestion at all congestion block levels and for all seasons

	PV			EB			HP			FC		
Probability of exceedance	Load without Flex	Load with Flex	% reduction	Load without Flex	Load with Flex	% reduction	Load without Flex	Load with Flex	% reduction	Load without Flex	Load with Flex	% reduction
Spring	21.68%	18.13%	16.40%	22.63%	22.02%	2.70%	1.73%	1.73%	0.00%	1.42%	1.42%	0.00%
Summer	19.55%	16.72%	14.48%	20.97%	20.20%	3.67%	0.00%	0.00%	0.00%	0.37%	0.37%	0.00%
Autumn	1.56%	0.94%	39.86%	2.00%	1.81%	9.60%	15.59%	15.59%	0.00%	0.00%	0.00%	0.00%
Winter	1.49%	1.03%	31.06%	1.68%	1.60%	4.73%	20.53%	20.50%	0.11%	0.11%	0.10%	10.00%



Congestion Block Levels	PV	HP	EB	FC
Uncontrollable	60	25	105	34
Controllable	89	50	44	18

average capacity per PV (Watt)	Congestion Block levels	Total PV Capacity (controlled & uncontrolled)	Controlled houses with PVs Installed	Uncontrolled houses (total PVs capacity
1700	HP	127500	50	42500
1700	EB	253300	44	178500
1700	FC	88400	18	57800
2000	PV	298000	89	120000

	PV	HP	EB	FC
Congestion Limit +	150000	60000	150000	40000
Congestion Limit -	-150000	-60000	-150000	-40000

	PV		EB		HP		FC	
	No Flex	Flex	No Flex	Flex	No Flex	Flex	No Flex	Flex
Upper 95	32319	32380	37548	37548	27994	27425	4009	4009
Average Load without flex	31709	31771	37008	37008	27715	27156	3823	3823
Lower 95	31098	31163	36468	36469	27437	26886	3637	3637
Std Load without flex	58344	58138	51570.38024	51570	26615	25758.68	17749	17749
Count	35039	35039	35039	35135	35135	35135	35135	35135
Nr count Exceedance	275	188	0	0	3301	3297	10	8
Flex exceedance reduction	32%		0%		0%		20%	

	PV		EB		HP		FC	
	Load without Flex	Load with flex	Load without flex	Load with flex	Load without flex	Load with flex	Load without flex	Load with flex
Number of Blackouts	0	0	0	0	1	0	0	0
Average Duration Congestion (PTU)	7	2	0	0	17	17	3	2
Average Exceedance (W)	-6,817	-2,988	0	0	8,066	2,700	137	3
Reduction in Blackouts	0.00%		0.00%		100.00%		0.00%	

	PV		EB		HP		FC	
Exceedance per season	No Flex	Flex	No Flex	Flex	No Flex	Flex	No Flex	Flex
Spring	186	128	0	0	168	168	661	661
Summer	89	60	0	0	12	12	424	424
Autumn	0	0	0	0	1368	1366	0	0
Winter	0	0	0	0	1798	1796	10	8

	PV		EB		HP		FC	
Potential # blackouts	No Flex	Flex	No Flex	Flex	No Flex	Flex	No Flex	Flex
Spring	26	55	0	0	22	22	52	52
Summer	13	29	0	0	2	2	40	40
Autumn	0	0	0	0	85	86	0	0
Winter	0	0	0	0	90	92	3	4
Sum	39	84	0	0	199	202	95	96

	PV			EB			HP			FC			
Probability of exceedance	d without F	ad with F	% reduction	d without	ad with F	% reduction	d without	ad with F	% reduction	Load without Flex	Load with Flex	% reduction	PTU per season
Spring	2.11%	1.45%	31.18%	0.00%	0.00%	0.00%	1.90%	1.90%	0.00%	7.48%	7.48%	0.00%	8832
Summer	1.01%	0.68%	32.58%	0.00%	0.00%	0.00%	0.14%	0.14%	0.00%	4.80%	4.80%	0.00%	8832
Autumn	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	15.49%	15.47%	0.15%	0.00%	0.00%	0.00%	8736
Winter	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	20.36%	20.34%	0.11%	0.11%	0.09%	20.00%	8639

Figure 63: The Excel Simulation Model Dashboard

Table 88: The Excel Simulation Model input variables

Congestion Block Levels	PV	HP	EB	FC
Uncontrollable	60	25	105	34
Controllable	89	50	44	18

average capacity per PV (Watt)	Congestion Block levels	Total PV Capacity (controlled & uncontrolled)	Controlled houses with PVs Installed	Uncontrolled houses (total PVs capacity)
1700	HP	127500	50	42500
1700	EB	253300	44	178500
1700	FC	88400	18	57800
2000	PV	298000	89	120000

	PV	HP	EB	FC
Congestion Limit +	150000	60000	150000	40000
Congestion Limit -	-150000	-60000	-150000	-40000

Table 89: The Excel Simulation Model output variables (the number of predicted blackouts, the congestion magnitude and congestion duration)

	PV		EB		HP		FC	
	Load without Flex	Load with flex	Load without flex	Load with flex	Load without flex	Load with flex	Load without flex	Load with flex
Number of Blackouts	0	0	0	0	1	0	0	0
Average Duration Congestion (PTU)	7	3	0	0	17	17	3	3
Average Magnitude Congestion (W)	-6,817	-2,920	0	0	8,066	2,704	137	6
Reduction in Blackouts	0.00%		0.00%		100.00%		0.00%	

Table 90: The Excel Simulation Model input variable (the blackout limit in terms of percentage overload and duration)

PTU	Blackoutlimit
1	200.00%
2	200.00%
3	180.00%
4	180.00%
5	172.00%
6	168.00%
7	164.00%
8	160.00%
9	150.00%
10	150.00%
11	147.00%
12	144.00%
13	142.00%
14	140.00%
15	138.00%
16	136.00%

Table 91: The Excel Simulation Model output (the number of PTUs where load exceeds the congestion limit for each month of the year)

	PV	PV	EB	EB	HP	HP	FC	FC
Exceedance per month	No Flex	Flex	No Flex	Flex	No Flex	Flex	No Flex	Flex
Jan	0	0	0	0	693	693	0	0
Feb	0	0	0	0	541	539	0	0
Mrt	0	0	0	0	417	416	0	0
Apr	9	7	0	0	18	18	163	163
Mei	71	43	0	0	0	0	258	258
Jun	134	95	0	0	41	41	338	338
Jul	53	40	0	0	4	4	213	213
Aug	8	7	0	0	0	0	113	113
Sep	0	0	0	0	19	19	0	0
Okt	0	0	0	0	371	371	0	0
Nov	0	0	0	0	550	549	0	0
Dec	0	0	0	0	692	692	10	9

Appendices C

C.1. Energy consumption One-Sample T-Test

Table 92: The One Sample T-Test comparing the Energy consumption of 78 Dutch Households to the Dutch average energy consumption

One-sample t test						
Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
78 Household Energy	78	3415.718	216.8963	1915.576	2983.822	3847.606
mean = mean(var1)						t = 1.6861
Ho: mean = 3050						degrees of freedom = 77
Ha: mean < 3050			Ha: mean != 3050			Ha: mean > 3050
Pr(T < t) = 0.9521			Pr(|T| > |t|) = 0.0958			Pr(T > t) = 0.0479

C.2. EDSN curve for the EV over a day

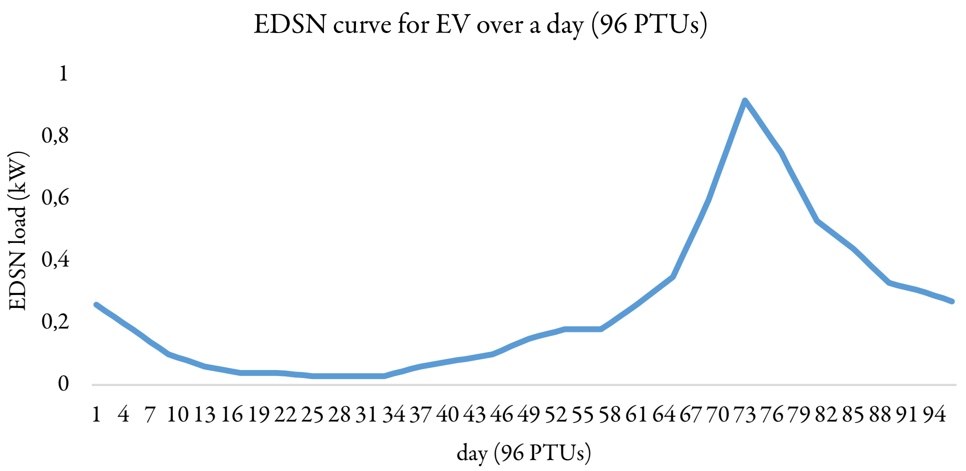


Figure 64: EDSN curve for the EV over a day (Ecofys, 2015)

C.3. Future Load Curves and Penetration Levels of smart devices

Table 93: Load curve changes from 2015 till 2050

	+0.35%	+1.5%	-1%
2015	0.00%	0.00%	0.00%
2016	0.35%	1.50%	-1.00%
2017	0.70%	3.02%	-1.99%
2018	1.05%	4.57%	-2.97%
2019	1.41%	6.14%	-3.94%
2020	1.76%	7.73%	-4.90%
2021	2.12%	9.34%	-5.85%
2022	2.48%	10.98%	-6.79%
2023	2.83%	12.65%	-7.73%
2024	3.19%	14.34%	-8.65%
2025	3.56%	16.05%	-9.56%
2026	3.92%	17.79%	-10.47%
2027	4.28%	19.56%	-11.36%
2028	4.65%	21.36%	-12.25%
2029	5.01%	23.18%	-13.13%
2030	5.38%	25.02%	-13.99%
2031	5.75%	26.90%	-14.85%
2032	6.12%	28.80%	-15.71%
2033	6.49%	30.73%	-16.55%
2034	6.86%	32.70%	-17.38%
2035	7.24%	34.69%	-18.21%
2036	7.61%	36.71%	-19.03%
2037	7.99%	38.76%	-19.84%
2038	8.37%	40.84%	-20.64%
2039	8.75%	42.95%	-21.43%
2040	9.13%	45.09%	-22.22%
2041	9.51%	47.27%	-23.00%
2042	9.89%	49.48%	-23.77%
2043	10.28%	51.72%	-24.53%
2044	10.66%	54.00%	-25.28%
2045	11.05%	56.31%	-26.03%
2046	11.44%	58.65%	-26.77%
2047	11.83%	61.03%	-27.50%
2048	12.22%	63.45%	-28.23%
2049	12.61%	65.90%	-28.94%
2050	13.01%	68.39%	-29.66%

Table 94: Future scenario penetration levels for EV, HP and PV Capacity from 2015 till 2050

	High EV	Low EV	High HP	Low HP	High PV capacity (Watt)	Low PV capacity (Watt)
2015	0.00%	0.00%	0.00%	0.00%	50	25
2016	1.45%	0.72%	2.89%	1.45%	100	50
2017	2.17%	1.08%	5.06%	2.53%	150	75
2018	2.89%	1.45%	7.25%	3.64%	200	100
2019	4.34%	2.17%	9.42%	4.72%	250	125
2020	5.06%	2.53%	12.32%	6.17%	300	150
2021	7.98%	4.00%	13.76%	6.89%	430	215
2022	10.87%	5.45%	15.21%	7.62%	560	280
2023	13.76%	6.89%	15.93%	7.98%	690	345
2024	17.40%	8.70%	17.40%	8.70%	820	410
2025	20.29%	10.15%	18.85%	9.42%	950	475
2026	23.19%	11.59%	20.29%	10.15%	1080	540
2027	26.08%	13.04%	21.74%	10.87%	1210	605
2028	28.99%	14.51%	22.46%	11.23%	1340	670
2029	31.89%	15.95%	23.91%	11.95%	1470	735
2030	34.78%	17.40%	25.36%	12.68%	1600	800
2031	36.23%	18.12%	28.27%	14.15%	1645	823
2032	37.67%	18.85%	31.16%	15.59%	1690	845
2033	39.86%	19.93%	34.06%	17.04%	1735	868
2034	41.31%	20.66%	36.95%	18.49%	1780	890
2035	42.76%	21.38%	39.86%	19.93%	1825	913
2036	44.20%	22.10%	42.76%	21.38%	1870	935
2037	45.65%	22.82%	45.65%	22.82%	1915	958
2038	47.10%	23.55%	48.54%	24.27%	1960	980
2039	48.54%	24.27%	51.46%	25.74%	2005	1003
2040	50.01%	25.02%	55.07%	27.55%	2050	1025
2041	51.46%	25.74%	57.97%	28.99%	2095	1048
2042	52.90%	26.46%	60.86%	30.44%	2140	1070
2043	54.35%	27.19%	63.77%	31.89%	2185	1093
2044	55.80%	27.91%	66.67%	33.33%	2230	1115
2045	57.24%	28.63%	69.56%	34.78%	2275	1138
2046	58.69%	29.36%	72.47%	36.25%	2320	1160
2047	60.14%	30.08%	75.37%	37.69%	2365	1183
2048	62.33%	31.16%	78.26%	39.14%	2410	1205
2049	63.77%	31.89%	81.15%	40.59%	2455	1228
2050	65.22%	32.61%	84.79%	42.40%	2500	1250

C.4. Calculating the savings from grid investment postponement and flex procurement

In order to calculate the savings realized by the DSO due to postponement of grid investment, through demand-side flexibility, both the grid investment, required flexibility and savings are calculated. The following steps are performed for each savings calculation:

Initial simulation

1. Simulation is performed with a set of growth scenarios for the PV, EV, HP, and Electricity growth
2. The blackouts for the upper and lower congestion limit are calculated with and without flexibility based on the simulation results.
3. The absolute maximum load over the entire year with and without flex are calculated.
4. The flexibility ordered from all smart appliances is calculated for each year

Required additional grid capacity and investment cost

5. The grid reinforcement is calculated by deducting the congestion limit from absolute maximum load. Based on the largest 'exceedance' of the grid congestion limit, the **required additional grid capacity** is determined (Figure 65).

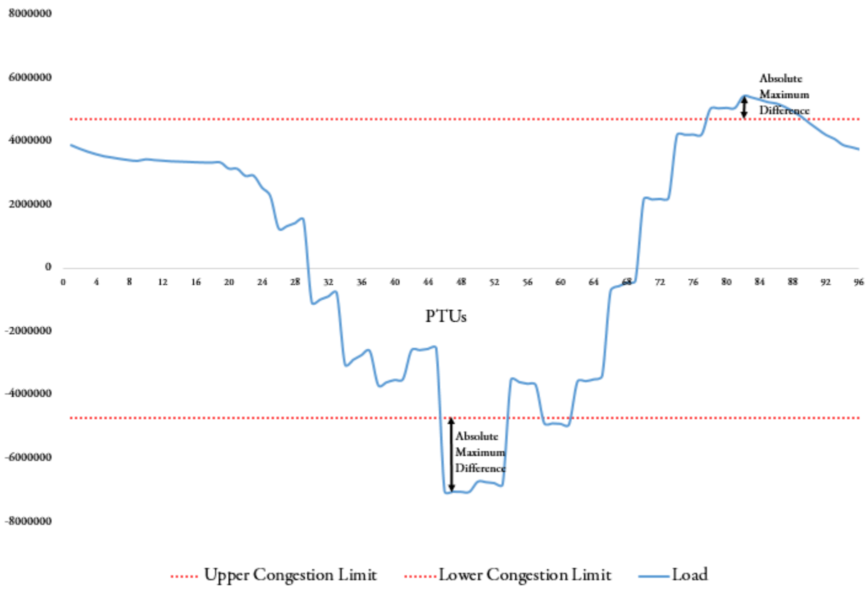


Figure 65: Required additional grid capacity (Watt)

6. The investment cost is then calculated by multiplying the investment cost per kVA per household with the required additional capacity.

Grid investment required and savings of grid investment postponement

7. The year in which grid investment is required is calculated based on the first year where flexibility is incapable of resolving congestion and eliminating blackouts.
8. The grid investment postponement via flex is then determined based on the first year where flex is ordered and no blackouts occur with flex, till the first year where grid investment is required.
9. The savings gained because of grid investment postponement are then determined by deducting the discounted grid investment cost from the initial investment cost (C_0).

   Savings gained from grid investment postponement = $C_0 - \frac{C_0}{(1+r)^t}$ where "r" is the discounted rate and "t" is the number of years of postponement.

Cost for flexibility

10. The cost for flexibility is then determined based on the amount of flexibility ordered in each year multiplied with the cost for that type of flexibility, to be named as C_f. These costs are then discounted to the year where grid investment postponement starts.
11. The cost of the flex for each year are added, because for each year of postponement flexibility should be purchased.

    Present Value of the Total flex cost = $PV = \frac{C_{f1}}{(1+r)^1} + \frac{C_{f2}}{(1+r)^2} + \frac{C_{f3}}{(1+r)^3} + \cdots$

Savings for the DSO

12. Last, in the year where grid investment is required, the **Present Value of the total cost of flex** is deducted from the **Savings gained from grid investment postponement**.

C.5. Calculating the grid investment postponement savings for Bosboomstraat

When the EVs penetration level increases slowly, in contrast to the high integration speed, one can expect that the load increase is also slower and consequently, more PV flexibility is needed to resolve congestion, since the congestion is happening due to high PV production.

Table 95: Different load scenarios to postpone network investment in the Bosboomstraat Heerhugowaard with Low EV integration

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	36	2016	Further than 2050	€ 0	-€ 481,632	-€ 365,815	-€ 158,963
1.5% Load Increase	36	2016	Further than 2050	€ 0	-€ 448,927	-€ 344,233	-€ 155,202
-1% Load Decrease	36	2016	Further than 2050	€ 0	-€ 517,038	-€ 391,080	-€ 167,564

This assumption is substantiated by the results, as the negative savings are higher in Table 95 than Table 63 (high EV scenario), which indicates that more flexibility is required. **As was the case with the high EV penetration level, the cost savings from network investment postponement do not outweigh the cost for flex, and no positive savings are created for the DSO, making the postponement of network investment undesired.**

C.6. Calculating the grid investment postponement savings for Kleynstraat with HP

Network investment postponement for the Kleynstraat with both low HP and high EV penetration

When the HP penetration level is lower than expected, the flexibility that can be ordered to resolve blackouts is also reduced significantly. Consequently, in such situations, it can be expected that the network investment postponement, by means of flex ordering, cannot be as extended for too long, in contrast to the high HP penetration level. This hypotheses is substantiated by the results presented in Table 96, where the possibility to postpone network investment has been reduced from 7 years to 2 years, for a -1% load decrease scenario. The network investment in this scenario is lower than that of the high HP penetration level, as HPs consume electricity and consequently, results in an increase in the electricity load. With the possibility to postpone network investment, this postponement is capable of providing the DSO with a cost saving of €2,325, if the discount rate is estimated to be equal to 10%. In the other discount rate scenarios, or load increases scenarios the use of flexibility is not helpful and the network must be reinforced when congestion is predicted, as presented in Table 96.

Table 96: Different load scenarios to postpone network investment in the Kleynstraat Den Helder with Low HP and High EV integration

	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment is Required	Network investment	Discount Rate		
					3.50%	5%	10%
0.35% Load Increase	0	Flex not helpful	2029	€ 64,459	€ -	€ -	€ -
1.5% Load Increase	0	Flex not helpful	2025	€ 108,707	€ -	€ -	€ -
-1% Load Decrease	2	2049	Further than 2050 (with flex)	€ 30,376	€ -1,210	€ -337	€ 2,325

Network investment postponement for the Kleynstraat with both low EV and low HP penetration

In the possible scenario where both the HP and EV penetration rate increase slowly, one might expect that the load will also witness a slow increase in comparison to the normal integration of EV and HP. This expectation is also substantiated by the results presented in Table 97, where the network investment is considerably lower in comparison to the initial case. In this scenario, network investment can only be postponed by 2 years for the case where the load will increase with 0.35% per year, and results in some positive financial savings for the DSO. For the 1.5% load increase, the current number of HPs are insufficient to resolve congestion, and consequently, leads to the conclusion that flexibility is not helpful in postponing network investment. Last, for the load decrease of 1%, flex is not required in order to postpone network investment beyond 2050.

Table 97: Different load scenarios to postpone network investment in the Kleynestraat Den Helder with only low HP and low EV integration

	Network Investment				Savings		
	Postpone ment (years)	Year when Flex is Required	Year Network Investment Required (with flex)	Network investment	Discount Rate		
					3.50%	5%	10%
0.35% Load	2	2040	2042	€ 39,619.13	€ 102	€ 1,206	€ 4,566
1.5% Load Increase	0	Flex not helpful	2028	€ 83,867.90	€ -	€ -	€ -
-1% Load Decrease	0	Flex not required	Beyond 2050	€ -	€ -	€ -	€ -

Calculating the grid investment postponement savings for Kleynstraat with FC instead of HP

Table 98: Different load scenarios to postpone network investment in the Kleynestraat Den Helder with high FC and low EV integration

	Network Investment				Savings		
	Postpone ment	Year of Flex Required	Year Network Investment Required	Network investment	Discount Rate		
					3.50%	5%	10%
0.35% Load	0	Flex not required	Further than 2050	€ 22,075.33	€ -	€ -	€ -
1.5% Load Increase	12	2030	2042	€ 66,073.52	€ 18,904	€ 26,175	€ 42,759
-1% Load Decrease	0	Flex not required	Further than 2050	€ 1,277.99	€ -	€ -	€ -

Table 99: Different load scenarios to postpone network investment in the Kleynestraat Den Helder with low FC and high EV integration

	Network Investment				Savings		
	Postpone ment	Year of Flex Required	Year Network Investment Required	Network investment	Discount Rate		
					3.50%	5%	10%
0.35% Load	5	2030	2035	€ 54,165.33	€ 7,977	€ 11,168	€ 20,050
1.5% Load Increase	1	2026	2027	€ 98,163.52	€ 3,233	€ 4,589	€ 8,842
-1% Load Decrease	0	Flex not required	Further than 2050	€ 20,331.25	€ -	€ -	€ -

Table 100: Different load scenarios to postpone network investment in the Kleynestraat Den Helder with low FC and low EV integration

	Network Investment				Savings due to Investment postponement		
	Postpone ment (year)	Year when Flex Required	Year Network Investment is Required	Network investment	Discount Rate		
					3.50%	5%	10%
0.35% Load	1	2050	Further than 2050	€ 29,325.33	€ 770	€ 1,178	€ 2,458
1.5% Load Increase	2	2029	2031	€ 73,323.52	€ 4,661	€ 6,608	€ 12,531
-1% Load Decrease	0	Flex not required	Further than 2050	€ 1,536.34	€ -	€ -	€ -

C.7. Calculating the grid investment postponement savings for Steenwijk (Scenario 2, 3, 5, 6,7, 8)

Steenwijk Scenario 2:

In contrast to scenario 1, the future might develop differently than initially predicted. In the case that the EV development is slower than estimated, the network investments postponement possibilities change. Results from this analysis (Table 101) indicate that for the 0.35% and 1.5% load increase scenarios, network investment can be postponed further than with a normal EV penetration level, to 11 and 2 years respectively, as the load increases slower due to lower number of EVs. However, due to the longer duration of postponement, a larger amount of flexibility is required, which automatically results in higher cost for the DSO. Additionally, due to the increase in the load, more flexibility per year is required in contrast to the year before; consequently, the cost for flex rises exponentially. These results are clearly visible when the savings are compared to the previous scenario. Therefore, it can be concluded that network investment postponement over a longer period of time has increasing cost and consequently, lower savings. In this particular case, only the 2 year network investment postponement for the 1.5% load increase with a 5 or 10% discount rate provide positive financial savings for the DSO. The increase in savings in the 5% and 10% interest rate scenarios is due to the fact that with increasing interest rate, the savings gained due to investment postponement will increase and the present value of the costs incurred due to flex ordering will decrease, thus the overall savings will increase.

Table 101: Different load scenarios to postpone network investment for the city Steenwijk with high PV, high HP and low EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required (with flex)	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	11	2038	2049	€ 687,681	-€ 940,727	-€ 769,346	-€ 346,119
1.5% Load Increase	2	2029	2031	€ 1,322,214	-€ 7,558	€ 29,529	€ 142,446
-1% Load Decrease	0	Flex not helpful	Further than 2050	€ 0	€ 0	€ 0	€ 0

Steenwijk Scenario 3:

In the third scenario, it is assumed that the HP penetration level is lower than normal, resulting in a lower increase of the load, but also less access to flexibility from these appliances. This decrease in available flexibility is reflected in the fact that for an electricity load increase of 1.5%, flexibility is no longer helpful in order to resolve blackouts in the electricity network (Table 102). Additionally, for the load increase of 0.35%, flexibility can only postpone network investment with 2 years. Still, even with lower number of HP, and consequently less flexibility, the postponement of network investment with 2 years for the 0.35% load increase is feasible and provides financial savings for the DSO.

Table 102: Different load scenarios to postpone network investment for the city Steenwijk with high PV, low HP and high EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required (with flex)	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	2	2031	2033	€ 907,007	€ 10,619	€ 35,717	€ 112,121
1.5% Load Increase	0	Flex not helpful	2027	€ 1,530,052	€ 0	€ 0	€ 0
-1% Load Decrease	0	Flex not helpful	Further than 2050	€ 0	€ 0	€ 0	€ 0

Steenwijk Scenario 4:

In this scenario, for both the HP and EV, the assumption is made that the penetration level declines in contrast to the prediction of Movares (2013), and Ecofys (2015), which results in lower electricity loads and lower available flexibility from the HP. The reduced load increase results in an increase of the postponement for the 0.35% load increase, in contrast to the previous scenario, where a normal EVs integration rate is assumed, from 2 years to 6 years. However, network investment could not be postponed for too long, in comparison to scenario 2, because the number of HP is reduced, which results in less available flexibility (Table 103). Consequently, network investment postponement is possible, although for a shorter period of time, resulting in the case of the 0.35% load increase in no financial savings, and for the 1.5% load increase savings ranging from €15,000 to €84,000, for various discount rates. However, for the 1.5% load increase, the postponement is possible for 1 year, which is roughly negligible.

Table 103: Different load scenarios to postpone network investment for the city Steenwijk with high PV, low HP and low EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	6	2043	2049	€ 554,417	-€ 282,849	-€ 225,322	-€ 67,448
1.5% Load Increase	1	2030	2031	€ 1,177,462	€ 15,376	€ 31,977	€ 84,044
-1% Load Decrease	0	Flex not helpful	Further than 2050	€ 0	€ 0	€ 0	€ 0

Steenwijk Scenario 5:

In comparison to the earlier scenarios, in this particular scenario the HP and EV penetration is high, but the PV capacity increase is low. A decrease in the PV capacity results in higher loads and consequently, more risk in blackouts at the upper congestion limit. Although, the results, presented in Table 104, do present a slight decrease in the network investment required, this decrease is only very small. Consequently, the savings and network investments postponement are not much different from scenario 1.

Table 104: Different load scenarios to postpone network investment for the city Steenwijk with low PV, high HP and high EV penetration levels

Load Scenarios	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	3	2030	2033	€ 1,041,991	-€ 47,267	-€ 3,157	€ 127,338
1.5% Load Increase	1	2026	2027	€ 1,676,525	€ 18,500	€ 42,186	€ 116,474
-1% Load Decrease	0	0	Further than 2050	€ 0	€ 0	€ 0	€ 0

Steenwijk Scenario 6,7,8:

The results from scenario 5 with low PV capacities are similar to scenario 1 in terms of network investment and network investments postponement. Similarly, the scenarios with low PV capacity (scenario 6, 7 and 8) are also very comparable to scenario 2, 3 and 4 with high PV capacity. Consequently, no additional analysis is performed on these analysis, and only the results are presented to substantiate the claim that these scenarios are comparable (Table 105, Table 106, and Table 107).

Table 105: Different load scenarios to postpone network investment for the city Steenwijk with low PV, high HP and low EV penetration levels

Load Scenarios	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	11	2038	2049	€ 689,401	-€ 972,073	-€ 797,483	-€ 366,163
1.5% Load Increase	2	2029	2031	€ 1,323,935	-€ 8,940	€ 28,226	€ 141,384
-1% Load Decrease	0	Flex not helpful	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 106: Different load scenarios to postpone network investment for the city Steenwijk with low PV, low HP and high EV penetration levels

Load Scenarios	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	2	2031	2033	€ 908,727	€ 9,618	€ 34,786	€ 111,405
1.5% Load Increase	0	Flex not helpful	2027	€ 1,531,772	€ 0	€ 0	€ 0
-1% Load Decrease	0	Flex not helpful	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 107: Different load scenarios to postpone network investment for the city Steenwijk with low PV, low HP and low EV penetration levels

Load Scenarios	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	Discount Rate		
					3.5%	5%	10%
0.35% Load Increase	6	2043	2049	€ 556,137	-€ 263,072	-€ 207,139	-€ 53,587
1.5% Load Increase	1	2030	2031	€ 1,179,182	€ 15,055	€ 31,685	€ 83,844
-1% Load Decrease	0	Flex not helpful	Further than 2050	€ 0	€ 0	€ 0	€ 0

C.8. Calculating the grid investment postponement savings for Drechterland

Table 108: Different load scenarios to postpone network investment for the city of Drechterland with High PV, High HP and High EV penetration levels

Load Scenarios	Network Investment				Savings		
	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	4	2035	2039	€ 3,241,112	€ 192,596	€ 358,748	€ 835,616
1.5% Load Increase	1	2028	2029	€ 5,101,363	€ 140,375	€ 211,246	€ 433,524
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 109: Different load scenarios to postpone network investment for the city of Drechterland High PV, High HP and Low EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	6	2045	Further than 2050	€ 2,473,169	-€ 108,815	€ 86,347	€ 617,337
1.5% Load Increase	2	2031	2033	€ 4,333,420	€ 200,297	€ 316,967	€ 672,050
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 110: Different load scenarios to postpone network investment for the city of Drechterland High PV, Low HP and High EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	2	2037	2039	€ 2,953,731	€ 137,199	€ 216,693	€ 458,635
1.5% Load Increase	1	2028	2029	€ 4,802,551	€ 147,048	€ 213,555	€ 422,146
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 111: Different load scenarios to postpone network investment for the city of Drechterland High PV, Low HP and Low EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	1	2050	Further than 2050	€ 2,185,789	€ 20,621	€ 51,552	€ 148,563
1.5% Load Increase	1	2032	2033	€ 4,034,609	€ 113,564	€ 169,579	€ 345,262
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 112: Different load scenarios to postpone network investment for the city of Drechterland Low PV, High HP and High EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	4	2035	2039	€ 3,244,858	€ 188,569	€ 355,074	€ 832,967
1.5% Load Increase	1	2028	2029	€ 5,105,109	€ 140,106	€ 211,035	€ 433,493
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 113: Different load scenarios to postpone network investment for the city of Drechterland Low PV, High HP and Low EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	6	2045	Further than 2050	€ 2,476,916	-€ 119,637	€ 76,378	€ 609,746
1.5% Load Increase	2	2031	2033	€ 4,337,167	€ 199,425	€ 316,219	€ 671,680
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 114: Different load scenarios to postpone network investment for the city of Drechterland Low PV, Low HP and High EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	2	2037	2039	€ 2,957,158	€ 136,266	€ 215,877	€ 458,173
1.5% Load Increase	1	2028	2029	€ 4,806,885	€ 147,026	€ 213,595	€ 422,381
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

Table 115: Different load scenarios to postpone network investment for the city of Drechterland Low PV, Low HP and Low EV penetration levels

	Network Investment				Savings		
Load Scenarios	Postponement (years)	Year when Flex is Required	Year Network Investment Required	Network Investment	3.5%	5%	10%
0.35% Load Increase	1	2050	Further than 2050	€ 2,189,215	€ 19,760	€ 50,752	€ 147,955
1.5% Load Increase	1	2032	2033	€ 4,038,942	€ 113,432	€ 169,511	€ 345,394
-1% Load Decrease	0	Flex not required	Further than 2050	€ 0	€ 0	€ 0	€ 0

C.9. Time/Current diagram for the gG400V circuit breaker

WEBER

gG 400 V

tijd/stroom

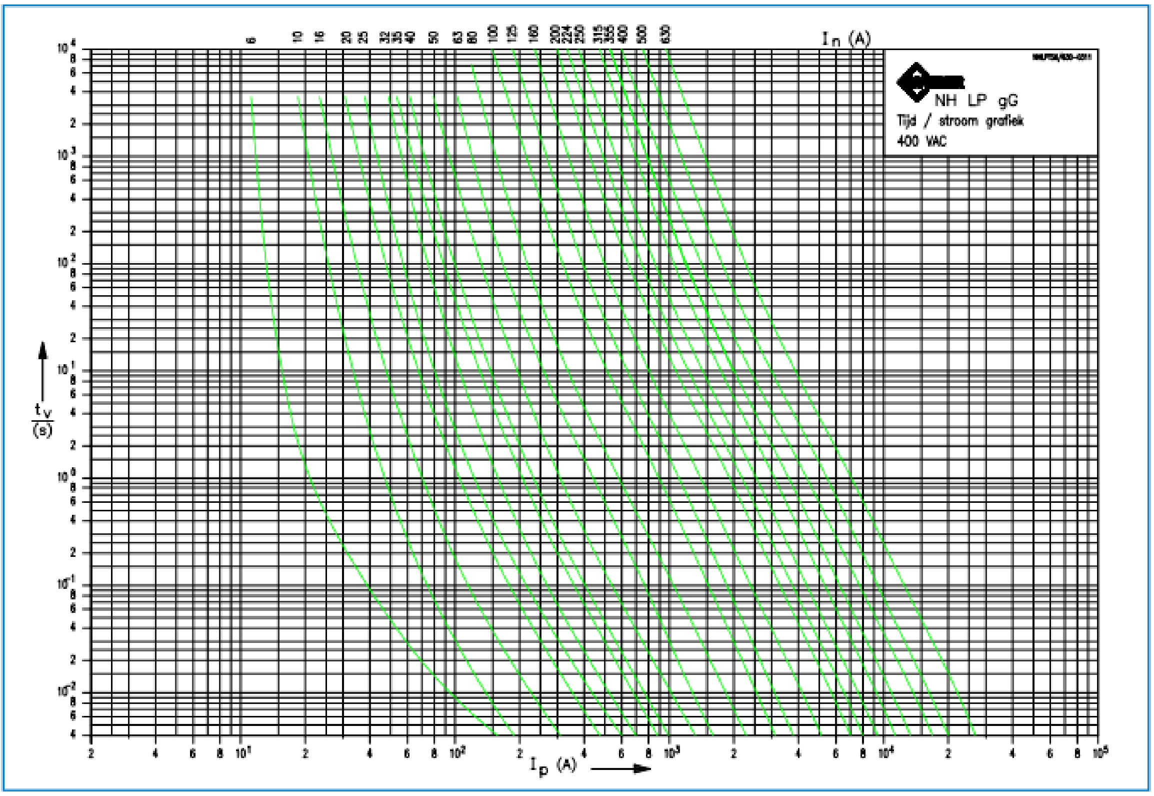


Figure 66: Time/Current diagram for the gG400V circuit breaker (Weber, 2004)

The Prospects of Flexibility on Congestion Mitigation Against Network Reinforcement

A Thesis submitted in fulfilment of the requirements for the degree of Masters in Science in Engineering and Policy Analysis