# POWER TO ENGAGE

TU Delft

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# A Community Perspective on Smart Grid Projects

Preselecting community-oriented smart grid projects sites within Dutch neighborhoods for end-user flexible behavior potential

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in partial fulfilment of the requirements for the degree of

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Faculty of Technology, Policy and Management

by

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## Preface

*Silent gratitude isn't much use to anyone - G.B. Stern*

This thesis is submitted to the degree of Master of Science at the Delft University of Technology. It is written at the faculty of Technology, Policy and Management and the Utilities department at Accenture. Its story has an explorative character and was written for an audience that wishes to gain insights into several dimensions of the consumer perspective of smart grid solutions. Conducting this research had been impossible without the numerous computations done, yet in order to make the thesis a bit more pleasant to read, a large number of them have been moved to the back. Those interested in equations and statistics behind this report can find them there.

This research is the finalization of a total of 457-ETCS-long and interesting study curriculum. 96 ECTS of them were collected at this faculty. During that study time, theories concerning the future electricity markets and quantitative modeling have been especially drawn my interests. This research project combines elements from both of these, even though the modeling type in particular has eventually been one I learned in a non-study environment and the main system engineering concept has been one I predominantly studied in an external course.

Nevertheless, this research allowed me to combine two favorite activities: building and applying quantitative models and articulating findings in the shortest possible, readable manner. Although most final thesis works are considered to be a student's 'opus magnus', I even regard the study of Japanese grammar and characters during my exchange period as a less flawed process than answering this research question. In that sense, I regard it to be a good experience to discover some pitfalls to watch out for in the future.

The findings presented in this thesis would never have been drawn without the help of the graduation committee. Therefore, I would like to give a special thanks Martijn Warnier to pull me through this process. His great intelligence allows to cut through complex matter and the obstacles I encountered. I very appreciated his flexibility in responding to my nocturnal e-mails. I also want to especially thank Mark Ruiter for all his patience and attempts to follow my progress. Also many thanks for Emile Chappin for pointing out important findings I usually did not consider. Furthermore, I would like to thank Paulien Herder for her correct criticism during the meetings and to Sofie Hees for her linguistic advice. Then a special thanks to those within the faculty, company and in my life in general who supported with me by answering my questions and or by simply being there.

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## List of abbreviations

| | |
|---|---|
| avg | average |
| CBSM | Community Based Social Marketing |
| DER | Decentralized Energy Resources |
| DSM | Demand Side Management |
| DSO | Distribution System Operator |
| DR | Demand Response |
| EV | Electric Vehicle |
| HEMS | Home Energy Management Systems |
| HV | High Voltage |
| LV | Low Voltage |
| MV | Medium Voltage |
| NIMBY | not in my backyard |
| SoC | Sense of Community |
| PV | Photovoltaic |
| PLM | Peak load mitigation |
| TPB | Theory of Planned Behavior |
| TSO | Transport System Operator |
| VBN | Value Belief Norm |
| Vba | Visual Basic for Applications |

## Executive summary

**Situation** Within several testing grounds in The Netherlands, Decentralized System Operators (DSOs) test a variety of smart grid solutions in order to anticipate on expected peak load increase; Most future energy system scenarios point out issues related to the functioning of the grid. Examples are blackout risks and large voltage fluctuations, which occur due to peak load as a result of rising electricity peak demand (for example because of electric vehicles) as well as decentralized electricity generation. The classic solution for the DSO to handle peak load are grid reinforcements which are costly and do not support the uptake of sustainable energy technology. In effect, the DSOs assess the suitability of alternative, possibly cheaper and more sustainable solutions for the future energy system. One measure is to mitigate peak load by incentivizing time-flexible electricity consumption. Through stimuli triggering a behavioral reaction, the DSO wishes to make residents adaptive end-users. Within previous pilot projects, DSOs predominantly assessed the effectiveness of stimuli related to electricity pricing schemes and real-time consumption information on end-user flexibility behavior.

**Complication** Unfortunately, completed pilot projects resulted in a rather small end-user flexibility size. Up to now, the measures tested for did not have a considerable impact on electricity consumption behavior. A reason for the limited response is the lack of end-user motivation due to price-inelasticity of electricity. Another reason is the fact that psychological barriers inhibit people to act according to their intentions. Additionally, a general incomprehension of the energy system does not contribute in engaging the end-user in the behavior change projects.

**Possible solution** Incentives from a social approach, however, are known for targeting people's long term engagement. Social interventions can trigger behavior to a greater extent for a longer time period. For these reasons, a consensus grows that social interventions are required to shape energy behavior and therefore are necessary in experimental energy systems. Specifically for end-user flexible behavior, community-oriented interventions can enlarge a common responsibility to use energy more efficiently. Moreover, its personal touch anticipates on household-specific and cognitive barriers. This research defines community-oriented interventions as a general framework of measures to stimulate the social diffusion of efficient energy use on a neighborhood or street level. This involves increasing peer-to-peer interactions on subjects related to electricity consumption. Despite initial indications of success, the effectiveness of a community-oriented approach is situation-dependent and consequently, it leads to a dispersion of results; This means that only a part of the neighborhoods in The Netherlands are suitable for social interventions concerning flexible electricity behavior. The main issue is that it is unknown which neighborhoods are likely to show end-user flexible load within a community-oriented smart grid project.

**Objective** All things considered, pilot projects with a community-oriented approach support in gaining knowledge on how to keep the residential electricity grid functional in the future energy system. Due to the expected dispersion of project outcomes, Decentralized System Operators wish to know why and which Dutch neighborhoods are most suitable for projects of this behavior-driven approach. Up to now, no systematic method exists on how to make this site preselection. Given these points, the purpose of this research is to compare Dutch residential areas for the likely response to community-oriented smart grids targeting flexible electricity consumption behavior.

**Approach** Through the use of Key Performance Indicators (KPI), neighborhood-specific behavior impact on grid functioning is benchmarked and evaluated. KPIs formulated in this research address issues relevant to the DSOs: the problem scope, the damaging effect of overload or reverse load, energy savings and efficient use of the grid assets. The KPIs are assessed by means of a quantitative modeling study. The model computes two neighborhood-specific outputs: likely flexible behavior and daily load profile forecasts. The neighborhood-specific behavior is a percentage indicating likely peak load mitigation. The percentages allow to quickly compare neighborhoods for behavior differences. They are a compound of separate behavior dimensions using the input of neighborhood-specific socio-demographic characteristics. Load profile forecasts are a scaled compound of neighborhood-specific data such as yearly energy use, EV and PV penetration and generic load profile scenarios. The output is two aggregated load profiles: with and without the likely flexible behavior. It shows peak shaving between the evening peak of 17.40 and 21.10 and valley filling behavior outside these peak (day and night) hours. The load profile forecasts allow for the evaluation of the formulated KPIs. KPIs as relative values are comparable among neighborhoods, contrary to absolute ones which are only used within the sensitivity analysis. The model incorporates two types of input data. The first type is generic scenario data such as PV electricity production and load profile forecasts. The second type is demographic neighborhood-specific data, such as electricity use, urbanity level, age groups and household compositions.

Concerning model computations for creating the flexible behavior estimation output, three behavior dimensions are considered. Individual scores per behavior dimension are computed of which mostly linear functions serve as a basis. These functions summarize likely relations between neighborhood characteristics and a behavior dimension. The relations between neighborhood characteristics and behavior dimensions are assumed due to a variety of related findings collected within a literature study. The relations included in the model are the following. Firstly, the realizable flexible load is related to neighborhood household size proportions. Secondly, demand side management (DSM) acceptance is related to a handful of energy consumption perspectives. Lastly, affinity to community participation which is classified as group similarity to relevant energy communities, is related to a number of psychologic and demographic neighborhood characteristics: The data analysis is an investigation of traits of suchlike groups: The over- or underrepresentation of relevant neighborhood characteristics is derived by comparing group characteristics between a handful of community groups and average groups.

**Results** This research shows that community-oriented interventions help to diminish congestion risk within a selection of neighborhoods and scenarios: Out of a total of 1013 neighborhoods within a sample of 20 municipalities, the first ones on an alphabetical list, a relatively small number of neighborhoods (38) is likely to show a large flexibility behavior in effect to community-oriented interventions. Most of them are situated in the municipalities Aa en Hunze, Apeldoorn and Assen. This selection has a likely aggregated evening load shift of between 3%-4% as a share of peak demand. Of the remaining share, 875 neighborhoods have a likely moderate behavior response (1%-3%) while 100 are likely to not respond at all (0%-1%). The high response group shows significantly different aggregated load consumption within diverse seasonal and PV-penetration scenarios. In summer scenarios, the seasonal demand drop and a sizable PV electricity generation far outweighs the impact of the behavior change. Hence, the intervention is more relevant in winter scenarios which results in a drop in maximum as well as average peak load. The flexible behavior leads to diminishing congestion risk, which means that the consumption change decreases the risk for outages and damaging of grid and electric device assets and increases the grid utility. The behavior estimations have been computed using available neighborhood-specific characteristics, which are only demographic data. The precision of this outcome would increase if other relevant non-demographic neighborhood characteristics are also available.

**Recommendations** The above selection of neighborhoods is the most suitable starting point for an in-depth area evaluation and further development of a DR pilot project incorporating end-user behavior. A more in-depth evaluation should verify this likely flexible consumption behavior size. Means to do so are in-depth interviews as well as surveys with local residents. The general aim of new pilot projects is to increase the social diffusion of flexible energy practices. More specific community-oriented strategies which may support end-user engagement and acceptance of smart grid services are peer-to-peer oriented commitment and messaging. Moreover, targeting governance boundaries, rules and agreements, monitoring, conflict resolution and self-organization ability institutionally embeds the smart grid solutions within the neighborhood.

**Further research** The following extensions of the model may lead to more powerful estimations of situation-dependent end-user flexible behavior. Because this research functions as a preliminary scan of the solution space, research on the inclusion of more valid and reliable data sources on the relation between demographic of psychological neighborhood characteristics and flexible behavior and other behavior related to demand side management would make the assumptions within this model more valid. Furthermore, the inclusion of other relevant behavioral aspects such as social norms and the effects of peer pressure would allow to create more extensive behavior estimations. In addition, incorporating financial cost-benefit analyses would allow for a greater model's involvement into grid planning processes of DSOs.

# PART I

## Chapter 1: Introduction

*'For, usually and fitly, the presence of an introduction is held to imply that there is something of consequence and importance to be introduced'* – *Arthur Machen*

### 1.1 Situation: Testing ground DSM experiments

During the past years, Distribution System Operators (DSOs) experiment together with other parties on a mix of smart grid solutions within various testing grounds in the Netherlands, the so-called 'proeftuinen'. One of the solutions tested for is Demand Side Management (DSM) which means the modification of end-user electricity consumption. One type of DSM is tested in particular: Demand Response (DR) covers all possible flexibility (supply as well as demand) at the end-user side. For the DSO, this DR flexibility has a large potential future value: It may limit a variety of issues with regard to the electricity distribution grid such as increasing congestion risk, energy losses and local voltage increase. It may contribute to assets' lifetime by offsetting costly grid reinforcements (Blanc et al., 2014) while supporting sustainable energy generation developments. For this reason, the DSO investigates whether end-user flexibility is feasible. Pilot studies play a major part in this field for they allow DSOs to experiment with these aspects. For a long time, technological feasibility seemed to be the focus of the future residential grid due to the often usage of smart grid technologies, called passive load steering (Elzinga, 2015). Aspects which require more research are new products and services, changes in regulation and new tariff structures for the flexible energy supply (RVO n.d.). As a result, various researches explored the possibilities of energy storage and micro grid technologies (Guerrero et al., 2013). So far, these technological solutions indeed seem feasible, for example within the first experiments, called INZET in Zeewolde. Then, an economic value of flexibility seems to be the new research focus. That is to say, the DSO explores possibilities to make end-user flexibility a business case. To realize this, it should be valuable for all stakeholders within this matter, such as end-users, energy producers and new energy service companies. Within these testing grounds, a variety of interventions such as monetary incentives, technological solutions and innovative business cases should reveal the size and value of this consumption flexibility to estimate its impact on the future residential grid system. Within an increasing number of experiments, flexibility seems to have an economic value. For example, the testing ground PMC2 in 2010 using the Powermatcher® software technology and

USEF market framework, did show a positive value of flexibility for consumers and a new market party: the aggregator (of approximately 3,5 billion euros) (Morshed, 2016).

## 1.2 Complication: The size and value of flexibility

Still, the test outcomes seem to be insufficient for the DSO to defer the planned grid reinforcements for longer than two years, as proved from the PMC2 test (Morshed, 2015) not to mention the fact that people respond to prices in a limited, complex manner (McKenna, 2013). The low response is related to the fact that energy has a doubtful price-elasticity (Van den Bergh, 2008) and many psychological and cognitive barriers towards the complex product of electricity exist. New testing grounds are being set up to further pursue a possibly larger (and more consistent) size of demand-side flexibility (Geijp, 2017). They test another combination of new solutions such as blockchain technology, smart appliances and "Internet of Things" (IoT) (Mihaylov et al, 2014), (Kobus et al., 2015), (Zanellla et al, 2014).

This way, the smart grid is regarded as a predominant technical-system, while in fact, consumers actually want to stay in control of their energy usage (Spencer et al. 2015) which makes this complex problem rather socio-technical. Unpredictable and inert energy end-user behavior is often neglected within research on smart and micro grids whereas DR research lacks a technological approach, (Appendix I), (Hull, 2015); Testing grounds resemble a more technology-push, rather than consumer-oriented smart grid systems despite the fact that energy systems research is located at the interdisciplinary boundaries of social science and technology fields (Adil & Ko, 2016). Summarized, smart grids have mainly been defined in technological or economic terms. Accordingly, Verbong et al. (2008) also mention a lack of attention to the social embeddedness of new technologies.

This has implications for the smart grid functioning; RVO (2015) has revealed that households often stick within the role of the consumer. Be that as it may, the authors also point out that an attitude change is required in order to trigger energy-oriented behavior. Overlooking this aspect limits the uptake of smart grid solutions, letting demand-side flexibility size remain low. There is a knowledge gap with regard to the consumers' attitude towards smart grids and how they are going to integrate these options in their daily life.' (Verbong et al., 2013)

## 1.3 Solution: A customized, community approach

Ecofys (2016) concludes that grid reinforcements cannot be avoided, yet DR flexibility may still have a value for the DSO: It possibly postpones grid reinforcements in *specific* areas for a significant amount of time, saving investment costs. To realize this, Sintov & Schultz (2015) find that an integrated systems approach including technological, economic and institutional aspects explains and supports acceptance, adoption and use of smart grid technologies. Considering the steering of consumer behavior is one step of the process: For this reason, behavioral DSM R&D spending is expected to increase considerably on a global scale for the coming decades (figure below). Social practices go in hand with behavior. According to Beaulieu et al. (2016), a focus on social practices will help to get away from this technology push approach whereas Strengers (2012) points out that social practice theory provides an alternative framing to redefine this issue and potential responses. Several testing grounds have already experimented with a social intervention. Social interventions, consider consumer decisions to be tightly interdependent with its social context (Scepanovic et al., in press) and correspondingly Milovanovic et al. (2014) points out the correlation between social norms and the adoption of smart energy technology. It targets people's long term engagement which is often lacking at individual approaches. It is for these reasons why incorporating a social approach may increase the functioning of the smart grid more than individual, predominantly financial incentives and technological solutions alone. This research field, however, is rather new and it is yet uncertain how this approach should be designed and analyzed. Specifically, social activity is a powerful means to increase engagement and participation of contemporary and future changes to the energy system (Bird & Barnes, 2014). It may play a significant role within the future energy system and should be supported by greater experimentation: Community-oriented energy planning allows for participative energy generation where utilities can engage with prosumer groups rather than passive individuals (Adil & Ko, 2016). For this, a likely successful design scope is at neighborhood level; Incorporating social behavior into the system asks for a more local approach.

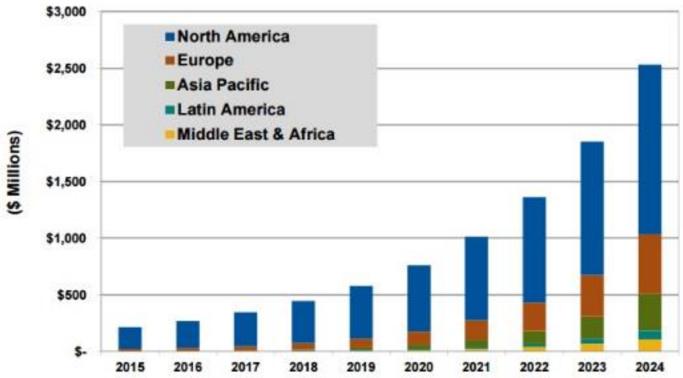


*Figure 1. The increase of behavioral and analytical DSM spending per region is foreseen to increase considerably. Source: Walton (2015)*

Accordingly, EEA (2013) point out that engagement through a community can be effective, yet will not necessarily work in all areas. (RVO, 2015) also remark the importance of interventions responding to the specific area, local needs and developments and so, this solution does most probably not fit all; Its effectiveness varies greatly depending on the situation the intervention is taking place (Scepanovic et al., in press) and hence, it requires a feasibility analysis area by area: a customized approach. RVO (2015) remarks that a standard approach is not effective for changing energy behavior. Studies report diverging peak mitigation sizes which may be explained by different non-influenceable factors, such as household characteristics (Kobus et al, 2015). Verbong et al. (2013) mention that to maximize the effectiveness of behavior programs, corresponding community culture should be carefully fostered. With regard to strategy, Hine et al., (2013) remark the segmentation of audiences and targeting tailored messages to specific segments. Which neighborhood aspects should be taken into account for this is yet unknown. Future work should investigate outcomes beyond energy savings and explore underlying processes of behavior change (Sintov & Schulz, 2015). Taking into account the socio-demographic and psychological profiles of the target population, as well as relevant contextual factors and experiences (social, cultural economic, political, environmental) that may influence this population leads to better estimations of the outcome of smart grid solutions (Frederiks et al. 2015). Change in a specific population of interest is most likely to sustain when profiles of consumers are understood, since policymakers will be able to identify and target profile-specific opportunities. Up to now it is hard to draw general conclusions from current data, since differences in scope makes comparing studies hard. Electricity consumption behavior and change depends on countless factors. Therefore, this research is an attempt to reveal a part of these factors to better estimate an end-user flexibility potential size of a neighborhood resulting from a local community-oriented behavioral intervention. For this, Chapter 2 draws a general problem context to point out unknowns necessary to ask a suitable main research question. This question leads to a handful of sub questions, which function as a starting point to design a research method.

## 1.4 The storyline

This thesis is a modelling study which estimates aggregated flexible energy behavior within a community-oriented smart grid project scope. Roughly, the thesis contains four parts: (I) Research definition, (II) Literature study, (III) Model and (IV) Conclusions and recommendations. The first part (I) defines the research problem and provides the method framework to solve it. This current Chapter 1 'Introduction' introduces the research subject and research direction, whereas Chapter 2 'Research definition' defines the research motivation, scope and method for the data collection and analyses. The first part ends with Chapter 3 'Assessing impact' which formulates the problem owner's (the DSO's) needs and provides a framework to evaluate the research outcomes. Then, Part II formulates relevant assumptions following from a data collection. These assumptions concern aspects of energy behavior and are formulated from a variety of findings within scientific literature and some cases in particular. The assumptions are summarized using an energy behavior framework and serve as input for the model architectural design.

Not only is the chapter content the line of reasoning for the formulation of the assumptions, the assumptions are also tested for their quality. Part II is concluded by presenting all relevant assumptions and their limitations. These assumptions are used within Part III (Chapter 5 'Model architecture design') as a design input. The purpose of the third research part is to make an evaluation tool to estimate and benchmark residential areas for flexible behavior using neighborhood-specific predictors and scenarios. The chapter explains subsequently the model output, input and functions. The chapter is concluded with a model validation by showing the model's possibilities and drawbacks. Using the validated model, Chapter 6 'Model results' is a summary of the model outcomes. Firstly, it shows results for neighborhood-specific flexible behavior and analyses the meaning of the behaviors. Secondly, the chapter provides more extensive behavior results for one promising neighborhood in the shape of neighborhood-specific load profiles. To address the impact and dependency of the behavior on functioning of the residential grid, several scenarios as well as sensitivity analyses are presented. Part IV, Chapter 8 'Conclusions and recommendations', summarizes all findings with regard to the systematic approach used and its results. Firstly, a discussion section provides the significance of the research results and shows its underlying meaning by referring it to related (scientific) knowledge. Secondly, the conclusion answers the main research question by showing the answer to the three sub questions. It shows the manner which flexible behavior impact can be evaluated, the method for attaining the assumptions relevant for the model and summarizes the model design. Thirdly, policy recommendations are formulated for the problem owner (the DSO) using the model results. Lastly, the limitations of the model, the assumptions and the research scope are summarized in the very last part of the thesis and suggests future research topics.

## Chapter 2: Research definition

*If you define the problem correctly, you almost have the solution – Steve Jobs*

The previous chapter introduced the topic on end-user flexibility and pilot studies. It introduced a new research direction: A community-oriented approach may support the increase end-user flexibility within a selection of residential areas. This chapter sets up a framework allowing to investigate this research direction further. It is a description of the problem, the solution space and the research method to solve the problem. The problem definition is a description of relevant knowledge gaps which allow to translate them into research questions. These research questions the required step between firstly plan and secondly to design a research method to answer them.

### 2.1 Problem context: Individual and situational variables relate to energy behavior

**Scope** This research assesses flexible electricity behavior of and among Dutch residential end-users. Specifically, the focus is on the increase of flexible behavior using a local, social approach which is formulated as a community-oriented smart grid project. Due to the fact that a social approach and the research problem involves a cluster of households, the research scope is on neighborhood level, rather than household level. In the light of the viability of flexible behavior, business cases and corresponding cost savings are due to time restrictions out of scope of this research.

**Framework** As previously argued, the situation where interventions for increasing flexible electricity behavior are taken place, plays a larger role than firstly assumed; According to Frederiks et al. (2015), greater knowledge and understanding of how to intervene and with whom, where and when, may make a valuable contribution towards the cost-effective design and delivery of consumer-focused behavioral interventions: By firstly identifying potential *causal* and *explanatory* variables for the impact on the nature, intensity, frequency and duration of behavior across time and contexts facilitates the design of successful energy behavioral interventions. This holds especially for social incentives which are assumed to be fairly situation-sensitive. The variables relevant for energy behavior exist on various levels as suggested by Frederiks et al.; A common assumption exists that energy behavior arises from an ongoing interaction of multiple factors varying from small and individual to large and situational. Therefore, they mentioned that over the years, researchers within the field of energy behavior predictions increasingly favor integrated impact assessment approaches. Frederiks et al. concludes that within the total behavior system, individual predictors can be generally categorized within two main groups: Socio-demographic as well as psychological variables explain a variability of household energy consumption and conservation. The socio-demographic variables are measurable characteristics such as age, gender, level of education and literacy, employment and socio-economic status, dwelling characteristic and geographical location. The psychological variables include a person's knowledge, value and beliefs, motives and goals, personal and social norms, responsibility and attitudes and many other variables such as cognitive processes which hard-to-pinpoint to a single characteristic. Socio-demographic factors are usually easy accessible pieces of data. If this predictor type is relevant, then this opens up possibilities to forecast energy behavior based on this available data. Then again, behavior is a result from not only from small, individual 'hard' factors, but also from 'soft' ones, not to mention larger, situational factors. These include laws and policies, technology available, pricing, built environment such as infrastructure, neighborhood factors, public norms and community expectations, traditions and customs and other factors which are not influenced by an individual system. An overview of this system is given in the following figure.

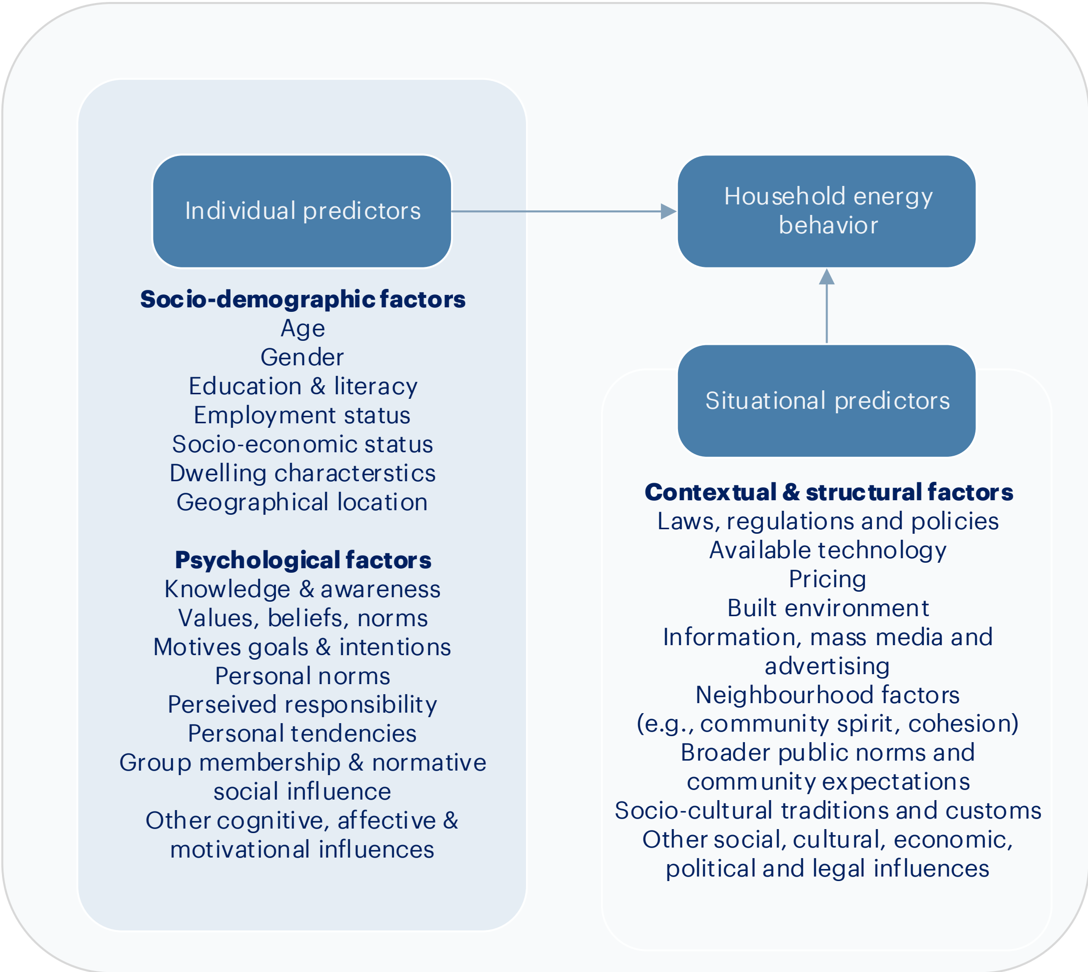


*Figure 2. Integrative conceptualization of the various individual and situational variables that may influence household energy consumption and conservation. Based on source: Frederiks et al. (2015)*

**Interpretation** To change energy behavior, this framework explains the necessity for taking not only situational factors into account, but that individual factors ask for increasing attention. In the past, most interventions targeted flexible behavior with predominantly general measures, such as smart technology and electricity pricing, while numerous individual as well as situational variables largely affect the intervention's response. Contrary to the growing interest in price-based demand response instruments, experiments with them show mixed results (Gyamfi et al., 2013); A demand response appears to be mostly on the aggregate level, while a more detailed analysis shows a surprisingly high household share which does not respond to the electricity price at all. One reason is the rather small financial benefit, not to mention a possibility to crowd out its effect (Delmas et al. 2013). Furthermore, Van den Bergh (2008) argued that numerous factors account for a limited predictability for the accuracy of electricity price elasticity due to variables such as individual preferences and substitutes for electric goods and non-linearity. Also other, energy curtailment experiments show that the effectiveness of monetary incentives very depends on the type of household. A dispersion of project outcomes will most probably hold even more for incentives from a social perspective, which is the scope of this research; The framework above shows that social behavior is included in both situational as well as contextual variables which relate to energy behavior: The social behavior of the individual is dependent on other individuals' (social) behavior and vice-versa. More dependencies exists amongst other variables: The social influence approach as well as the target group affects the behavior outcome (Abrahamse & Steg, 2013). Although it is hence hard to make conclusions on social incentives on energy behavior, this also shows the necessity of social embeddedness of energy behavior incentives. As Lopes et al. (2015) have remarked, interventions should consider end-users' profiles plus their personal and social context and target specific behaviors instead of focusing on the potential instruments of change per se. As an example, Van Melle et al. (2016) point out that a neighborhood with 61% EV penetration would either cause or avoid a large impact on the grid when they combine EVs usage with different (smart or dumb) charging behaviors which depends on more than only charging interventions. Although many more of these examples can be given, a complete overview of all the numerous variables relevant for end-user flexible behavior is lacking.

Drawing conclusions on these relevant predictors is hard. Frederiks et al. (2015) strongly recommend that researchers and practitioners exercise due caution when drawing inferences regarding the effects of individual variables, without taking careful account of the complex interplay among the various factors. Associations are not always substantial, straightforward or consistent. Moreover, not only predictors, but also mediators and moderators are factors which result in energy behavior. They write that a few studies suggest curvilinear effects on energy consumption for certain socio-demographic factors: age, income, stage of family life cycle. However, this does not hold for every study; Most research has observed a simple linear association among the variables and behavior, such as the one from Sardianou (n.d.) on energy conservation.

This research aims to use neighborhood predictors to estimate end-user flexible behavior of and among Dutch residential areas. For this, the following knowledge gaps exist. Firstly, although knowledge on energy behavior practices is affluent, specifically, it is unknown which individual and situational factors are required to react on social interventions targeting flexible behavior. Secondly, this behavior framework is a general framework to predict energy behavior based on partially individual household characteristics. This thesis, however, is aimed to assess behavior on a neighborhood level, in order to target suitable neighborhoods for community-oriented smart grid projects. It is unknown how this framework is applicable for an assessment on neighborhood-level. In the latter case, not individual factors, but neighborhood characteristics should be predictors of neighborhood aggregated energy behavior. In essence, it is unknown how transform this information on individual and contextual factors into a framework to evaluate and select suitable neighborhoods.

## 2.2 Research purpose: Selecting smart grid project sites based on local predictors

Considering the knowledge gaps proposed within the previous paragraph, the following research purpose is formulated. Community-oriented smart grid projects support in gaining knowledge on how to keep the residential electricity grid functional in the future energy system. Due to the expected dispersion of project outcomes, which depend on situational and individual neighborhood factors, not all areas are suitable for this social, behavior-driven approach. DSOs wish to know why and which Dutch neighborhood preselection is most suitable. Given these points, the purpose of this research is to compare Dutch residential areas for their suitability for community-oriented smart grid projects targeting flexible electricity consumption behavior in order to provide a preselection on smart grid sites. The research objectives and deliverables are the following:

- Conceptualize community-oriented smart grid projects
- Formulate requirements for neighborhood suitability for community-oriented smart grid projects
- Show relevant neighborhood predictors for flexible behavior
- Provide a framework allowing to estimate and benchmark neighborhood-specific aggregated flexibility
    - Translate residential characteristics into aggregated consumer electricity profiles
    - Estimate a potential flexible aggregated load profile based on the benchmark
- Validate the framework suitability
- Collect neighborhood-specific data for the model
- Finalize the construction of the evaluation tool in such manner that it can be adjusted and used for different household scenarios and purposes.

## 2.3 Research questions

As a result from the analysis in the previous section, the main research question is the following:

*How can Dutch residential areas be compared regarding flexible electricity consumption in the context of community-oriented smart grid projects?*

The question is hereby two-fold: What are relevant predictors for flexible behavior and how can the predictors be used to evaluate and compare residential areas? As pointed out in the problem context, several aspects make this research question a complex issue. Delineating individual elements with the use of the following **sub questions**, enables to solve it. These are the following.

1. How can the impact of a community-oriented smart grid project be evaluated?
    a. What is a community-oriented smart grid project?
    b. What is the possible impact of a smart grid project?
    c. Which KPIs are relevant for a smart grid project?
2. How can assumptions concerning relevant predictors for the neighborhood suitability to a community-oriented smart grid project be formulated?
3. How do the predictors contribute to the evaluation and comparison of the impact of flexible behavior among residential areas?
    a. How do predictors indicate flexible behavior of and among residential areas?
    b. How can the indicated flexible behavior of and among residential areas be translated to the KPIs?

## 2.4 Societal and scientific relevance: Systematic approach to pre-select areas

**Scientific relevance** is an essential aspect of conducting research: Further building on state-of-the-art knowledge keeps expanding a universities' and general scientific world's knowledge base. To contribute in this, the research' scientific relevance is the creation of a systematic method to create a site preselection for the suitability for smart grid projects involving community-oriented incentives. Despite the vast amount of research on energy behavior, integrative models on this aspect has had limited development. This research contributes in developing a model which allows to relate a number of relevant individual as well as contextual predictors to flexible energy behavior in order to benchmark neighborhoods on their impact within community-oriented smart grid projects.

**Societal relevance** Equally important, universities also have a societal purpose which is to be a facilitator of knowledge, information and ideas within the global system. The societal contribution of this research is the following: Smart grid projects targeting peak load mitigation (PLM) can keep the energy grid affordable and reliable within the Dutch energy system, as it limits future grid load and thus planned future grid reinforcement costs for the DSO's. However, due to the expected dispersion of project outcomes, Decentralized System Operators are interested in a systematic approach in order to know why and which Dutch neighborhoods are likely suitable for interventions of a social, behavior-driven approach. The contribution of this research is to show this approach with the corresponding neighborhood preselection which has positive behavior outcomes. This way, the project is the first step in order to show possibilities to saving asset's lifetime, diminishing grid losses and supporting in times of grid outage risk. Furthermore, by shifting consumer time-of-use, smart grid solutions could make PV systems more useful.

## 2.5 Hypothesis

Several hypotheses are formulated before the start of the research. Firstly, I estimate that a large part of communities are unsuitable for community-oriented smart grid projects. I assume this because of Hofman & High-Rippert (2010) indicates that not all or even a majority of residents are motivated by the personal appeal of communities. For this reason, I estimate that many neighborhood characteristics can be related to community-oriented incentives and energy behavior change. As for energy flexibility, I regard a neighborhood with an overall high education level as a predictor for flexible electricity behavior; The residential energy system is becoming increasingly complex and in my opinion, having an educational degree indicates whether people have a basic understanding of the purpose and necessity of flexible behavior. Secondly, because tenants usually do not have any insights into energy use data, I think that neighborhoods with a large amount of tenants' lack the engagement and possibilities to change their own energy behavior. Lastly, may be some barriers present in the neighborhood which limits the uptake of flexible behavior incentives. One is a large household size: Because people are sharing household appliances their usage is dependent on others, which this literally leads to a limited flexibility. Another is a person's high age which indicates inflexible lifestyles. Therefore, I regard a neighborhood with a lot of elderly people as well as a lot of large families not suitable for incentives for flexible energy behavior. Also, the amount of PV in this neighborhood affects the consumer willingness to change its consumption pattern due to cognitive factors such as producing your 'own' electricity. As for social behavior, I regard to be important whether there is a pre-existing relationship with the participants, whether the participants share pro-environmental views and whether there exists a kind of role model.

## 2.6 Research method

### 2.6.1 Overview

Within this research, a variety of methods have been allocated as follows. Next to quantitative modeling, the research requires a variety of additional research methods. A total overview is shown in the table below.

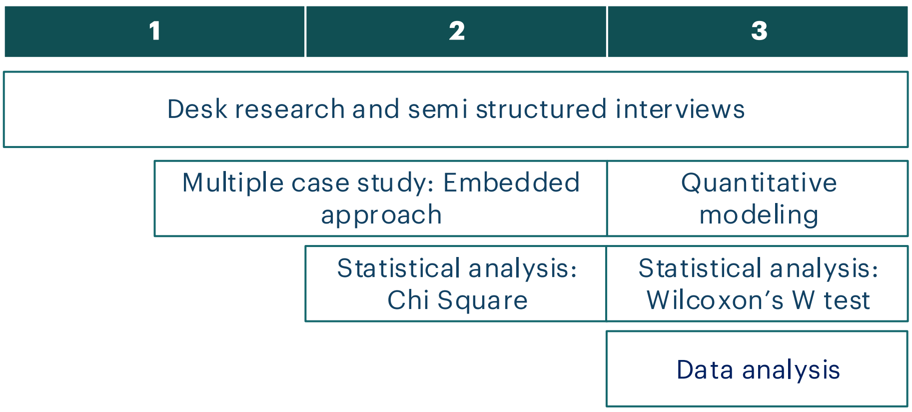


*Figure 3. Overview of research method per research question*

### 2.6.2 Main research method

Part III of the research covers the main research method: quantitative modeling involving coding, theme developing, interrelating and interpreting data (Creswell, 2009). The model is a spreadsheet incorporating Visual Basic for Applications (vba) macro's. The choice for this model was based on the speed and ease of use for a larger public, the compatibility with input data and the possibility for future adaptions. Concerning speed, models with a top-down approach are amongst the fastest; A top-down model does not distinguish between the energy consumption of individual end-users but they determine the effect on energy consumption caused by ongoing long-term changes or transitions. For example, previous models used variables such as macro-economic indicators, climate data and housing construction rates and balances historical energy consumption with estimations due to input variables. Bottom-up models on the other hand, "calculate the energy consumption of individual or groups of houses and then extrapolate these results to represent the region or nation" (Swan & Ugursal p.1822). They use a variety of input data from a lower hierarchical level than the top-down model's. Because the purpose of the thesis is to estimate aggregated energy consumption change using data on a neighborhood-level disregarding the individual household, the bottom-up approach provides the results in a faster and easier manner. Moreover, the model's interface is one of the most common programs existing, which makes it easy for the problem owner and the wider public to adapt and work with.

### 2.6.3 Additional research methods

#### 2.6.2.1 Desk research and literature study

Desk research and semi-structured interviews are being used throughout all research questions. They provide the research questions a context and pointed out and filled in relevant knowledge gaps. Scientific literature provided the main theory topics: (1) theory on social behavior, (2) energy behavior and (3) theory on integrated energy systems. Unlike technical and economic approaches, social science concentrates on exploring personal and contextual factors activating energy behavior. Behavioral economics recognizes that during this decision process individuals may have information processing limitations and use heuristics and other information simplification processes. Moreover, behavior decisions are influenced by their environment: 'Psychology focuses on the individual perspective, identifying personal determinants (e.g., intentions, attitudes, norms, beliefs, values) or contextual influences to explain or predict energy behaviors. In turn, sociology and other social studies see energy behaviors as the result of the social context and not a consequence of individual decisions. In these disciplines, energy behaviors are considered to be a result of the social organization in which individuals live such as social rules, lifestyles, standards or practices.' (Lopes et al., 2015). For obtaining scientific literature, three platforms, Web of Science, Scopus and Google Scholar, served as primary sources. A variety of key terms obtained topics within the research field. Then, a brief article analysis created the subtopics which allowed for the specification of a new set of key terms. The data collection was extensive until no new recent (up to a maximum of 10 years old) articles concerning the subtopics appeared.

In order to present the knowledge which is most recent and relevant, scientific literature is insufficient. Websites published by community initiatives, printed material and grey literature as well as mapping meetings are reviewed. Perceptions of experts and opinion leaders in the field of electricity markets, retail and community energy provided additional information. To cope with the variety of the interviews as well as being able to provide some guidance while doing, unstructured interviews are best suitable (Verschuren & Doorewaard, 2010). Using these ones, experts will have most room available for providing information whereas the interviewer can ask for relevant information based on the previous answers.

#### 2.6.2.2 Literature study

Sub-question 2 of the research involves an explorative literature study. The goal of the study is to formulate and generalize assumptions on flexible behavior from relevant findings within scientific literature. These assumptions are evaluated relations between neighborhood characteristics and a range of energy behaviors and intentions. They are used as an input for the model's architectural design. The study is conducted with as many relevant resources as possible. For this reason, qualitative as well as quantitative data are included and integrated using a mixed-method embedded approach in line with Cresswell's (2003) theory, presented in the following figure. Due to the fact that quantitative data are most suitable for the research model, the choice for the mixed-method strategy is a sequential, embedded approach. While quantitative data are prioritized and emphasized within this study, qualitative data are used as a support for the line of reasoning; To formulate qualitative assumptions for the model, some cases and other resources on behavior aspects are studied more specifically while other literature sources support or limit the findings. Less suitable findings from literature, which for example describe the subject too generally, are used to verify assumptions and to show directions for further research.

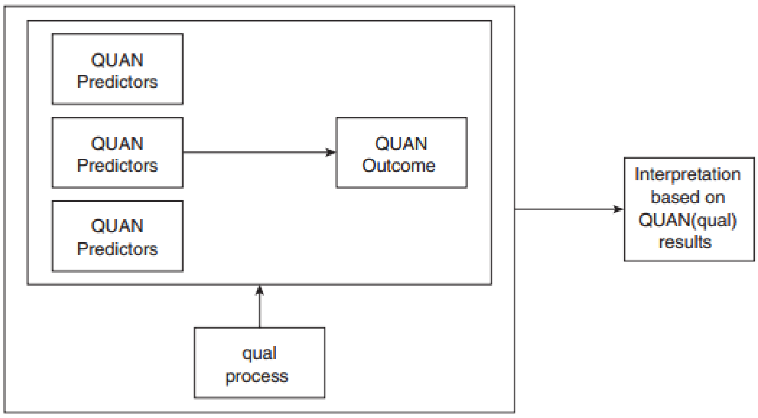


*Figure 3. The embedded research design used within multiple case study. Source: Creswell (2003)*

Although a multiple case study is suitable to provide a general overview about a subject, as required for this research, it also shows some limitations. The number of resources addressing the research question is rather low. Mostly data addressing topics *around* the knowledge gaps are available, affecting the quality of the formulated assumptions. For this reason, validity and reliability is a point of attention within the research. Setting up a psychological research using a survey or a controlled experiment would overcome the limitations by a multiple fold, yet however, due to the length and scope, this will not be conducted within this research. Moreover, the benefit of a literature study, the possibility to collect a large and diverse amount of data outweighs the benefits of a more valid and narrow experiment, for this research is aimed at making a basic, preliminary comparison of neighborhoods, not to assess a single neighborhood in exact behavior estimations.

In order to incorporate the data limitations into the research outcome, the resources used as the basis for the assumptions are evaluated and coded for validity and reliability. External validity concerns the generalization of the research for a broader scope, that is defined in this case: applicable for the model. Internal reliability describes the extent to which the finding follows the principle of cause and effect, that is the extent to which the phenomenon has not occurred by chance or due to something else. Reliability concerns the findings accuracy. Information on these three data quality criteria allows to show the model limitations and opportunities to improve the model.

#### 2.6.2.3 Statistical analyses

Several statistical tests are used to indicate a significant difference between data groups. Firstly, the Wilcoxon's W-test checks the significance of load profile differences within the model output to show whether the flexible behavior is meaningful or whether the changes in load profiles may also happen by chance. Secondly, a Chi Square test or a Fishers Exact tests supports the analysis to address neighborhood characteristics as predictors. It assesses whether a group characteristic is significantly different within a case or whether the an abnormal representivity could happen by chance. If there are multiple group characteristics from one case, then the test will be only assess the characteristic with the smallest difference. If this test shows significance, then significance is also assumed for the other characteristics.

#### 2.6.2.4 Data analysis

A quantitative data analysis shows the meaning of the model output. This involves plotting relevant load profile characteristics. Moreover, it also involves multiple sensitivity analyses to show the responsiveness of the model outcome to three input factors (scenarios as well predictors).

## 2.7 Research process

The research development phases are based on the V-model of the system engineering framework (Sidsoft, 2014) which is shown in the figure below. It involves iterating stages ranging from conceptual to detailed engineering activities. The framework's left-side stages define the research features whereas the right-side stages test and integrate them. The right-side stages are related to a corresponding level at the left-side through verification, evaluation and validation activities. For the purpose of readability and due to the scope of the research, the conceptual engineering stages are included within the research core text whereas the detailed engineering stages are moved to the Appendix (V). The actual model is free to download from the link goo.gl/1wz9UP and works when its macros are enabled.

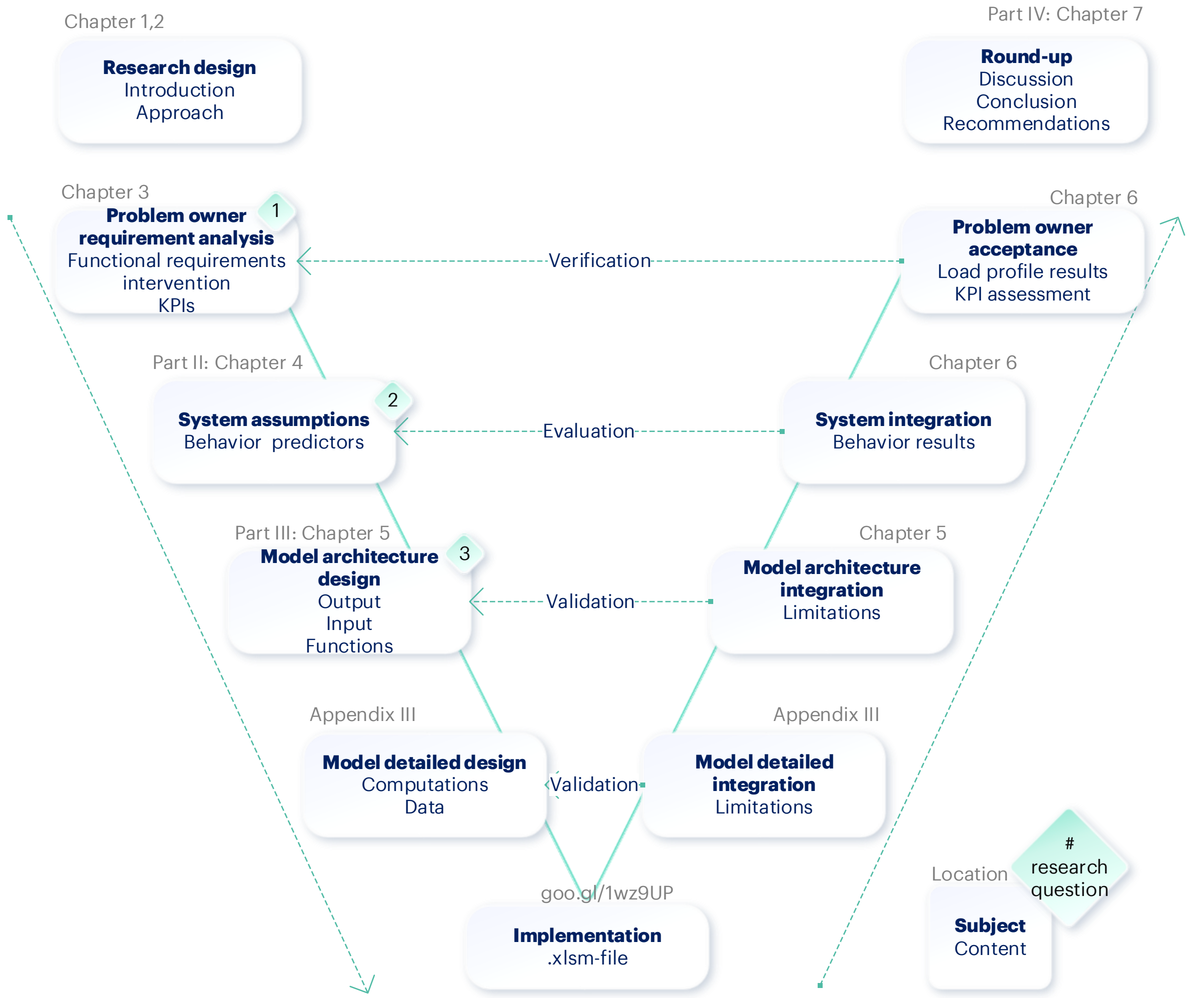


*Figure 4. Research design. Based on systems engineering V-model from source: Sidsoft (2014)*

# Chapter 3: Assessing impact

*If you cannot measure it, you cannot improve it – Lord Kelvin*

This chapter addresses the first research question by setting up a framework to evaluate the impact of smart grid projects. It is written in the following manner. Firstly, the chapter explains the impact of the solution scope: a smart grid project involving a community-oriented incentive scheme. Then, it proposes a set of requirements for the impact of the solution scope; Starting with the end in mind by aligning the design outcome to the requirements, which are expressed as KPIs, is a way to ensure the design's benefits for the problem owner.

## 3.1 Solution scope: Smart grids projects incentivizing flexible behavior

### 3.1.2 Arguments for social incentives as an addition to monetary incentives

As shown above, end-user flexibility reduces grid issues load by changing electricity peak demand (Moslehi & Kumar, 2010). Flexible behavior is not imminently aimed at saving energy in general, but saving it temporally at specific times. This behavior called load shifting, shifts the time of electricity consumption to times with preferably less congestion and so it directly reduces congestion risks by diminishing peak loads (Moslehi & Kumar). Flexible behavior is categorized in two types: once-off actions to save energy e.g. investing in home improvements (Frederiks et al. 2015), new device procurement or changing settings and ongoing day-to-day actions by unplugging devices, lowering heated temperatures such as water and rooms and avoiding device usage (Scepanovic et al., 2013). Both behavior types lead in peak load mitigation. As previously mentioned, DSO have earlier experimented with options to trigger these flexible behavior. In the first place, monetary incentives have been implemented. Indeed, electricity price appeared to be a major and very likely necessary, driver for flexible demand; A peak load mitigation between 12%-20% may be feasible if it is combined with critical peak pricing tariffs (Moslehi & Kumar, 2010). Electricity tariffs support DR and smart automation by increasing program enrollment and participation in events (Sintov & Schultz, 2015). Also Frederiks et al. (2015) suggests that behavioral change is often affected by economic instruments such as pricing, taxation and other, instrumental incentives. They argue that, despite positive attitude towards changing energy consumption, still considerable additional efforts – such as price incentives - are required to trigger people to act. Despite the fact that electricity price is an effective initiator for DR, additional factors may enhance the price signal's effectiveness. This is a phenomenon very similar to all other consumer goods. For these reasons, DR program designers should use a hybrid approach employing knowledge from social psychology and economic behavior models; Therefore, McKenna & Thompson (2014) suggest a range of behavior signals for the end-user to have room to act. Behavioral interventions together with information strategies can be important complements to price-based policies (Ansensio & Delmas, 2016). They mention framing, informational strategies which trigger normative, intrinsic or social motivation.

As previously mentioned, not only Ansensio & Delmas, (2016), but an considerable number of other researchers mention the relevance of a social approach for a functioning energy system; A considerable amount of research attention on the social aspects of energy systems, behavior and demand response, as shown in the table. The table shows some compelling points regarding perspectives on demand response, energy behavior or integrated energy systems in general. One point is the need for more scientific research on social aspects. Although mentioning a future research direction is a compulsory aspect within scientific literature, the number of researchers mentioning a required direction towards a social system is striking. Then on the other hand, a remarkable small amount of researchers has transformed these presumptions into steps for incorporating this into actual solutions of the energy system. Despite the evident benefits of social motivators, relatively few projects have incorporated these noneconomic levers (also see Appendix I). An even smaller amount has elaborated on substantial experiments. The second point is an apparent consensus on an evident impact of norms and peers: These are powerful tools to shape energy behavior. With regard to norms, they motivate human behavior in the interests of the long-term benefits of the social group rather than the short term, self-interested behavior of one person (Ansensio & Delmas, 2015). Scepanovic et al., (in press) and Milovanovic et al. (2014) point out a correlation between social norms and the adoption of smart energy technology. Several norms are distinguished: Social norms are external norms imposed by the surroundings whereas personal norms are individual ones, which are the persons own beliefs in what is 'right'. Likewise, also social comparisons are powerful for shaping behavior. In some cases, their effect even outperforms monetary incentives. By all means, both behavior tools are starting points for shaping an effective social framework around flexibility behavior, yet knowledge on an actual plan is lacking.

| **Integrated energy systems** | **Behavior change** | **Peak demand** |
|---|---|---|
| 'neighborhood comparisons additionally encourage communication among utility customers regarding methods of energy conservation' Iyer et al.' (2006) | 'Social norms and community engagement [as part of a wider program] result in long term behavior.' (Ozaki, 2011) | 'The effect of peers has been found to be more effective than incentives such as saving money, conserving resources, or being socially conscious' Vine et al. (2013) |
| 'Normative strategies can motivate interests of the long-term benefits of the social group rather than the short term, self-interested behavior of one person' (McKenzie-Mohr, 2000) | 'While the potential mechanisms linking social influence approaches to pro-environmental behaviour change have been developed in theoretical models, more empirical field research is needed on how social influence affects behaviour change in real-life settings.' (Abrahamse *& Steg, 2011) | 'A variety of social, cultural, economic, and regulatory factors would likely play a role in the success of demand response in individual countries.' Krishnamurti et al. (2012) |
| 'Integrative modeling of energy behaviors had limited development' (Geels et al., 2016) | 'In terms of psychological predictors of energy usage, our review identified several factors that seem to play an important role, with normative social influence being especially powerful.' (Frederiks et al. 2015) | 'From this perspective, the problem of peak demand can be usefully viewed as a symptom of changing expectations and conventions associated with everyday household practices, such as cooling, heating and entertaining' (Strengers, 2012) |
| 'social aspects play a decisive role when an energy system is substantially modified' (Bush & McCormick, 2014) | 'the use of both descriptive and injunctive norms is important in shaping household energy behaviors' (Schulz, et al. 2008) | |
| | 'Comparing the consumption of one household to that of others is said to elicit social pressure to understand why consumption levels differ and to stimulate competition and ambition' (Vine et al., 2013) | |
| | 'although people may not believe that the behavior of others should motivate them to conserve energy, their behavior was powerfully influenced by it nonetheless' (Nolan et al., 2008) | |

| | |
|---|---|
| | 'social norms can result in household energy savings of 5.7–10%' (Nolan et al., 2008, Schultz et al., 2007) |

*Table 1. Overview literature on several social aspects of energy*

### 3.1.2 Community incentives

In essence, there is still a large solution space in which the incorporation of social incentives, such as norms and peers is considered to support the uptake smart grid systems. One option to enhance the social motivation within a smart grid system is to create the project on a local scale, such as a community project. This also allows to incentivize energy autonomy, which is a more direct and appealing motivator for energy behavior rather than ambiguous, distant benefits, such as carbon footprint savings. Additional benefits of community projects are possibilities to potentially solve social dilemmas, social conventions, shared infrastructures and a psychological feeling of individual helplessness towards energy issues (Heiskanen et al. 2010). For example, offering electricity prices variable with their own PV output fosters community goodwill (McKenna et al. 2014). In the past, energy communities have played a large role in the purchase and adoption of sustainable energy technology, such as PVs, EVs, heat pumps, biogas and heat networks and many others (Schwenke, 2015). Energy communities increase end-user engagement while they decrease cognitive barriers, ensure energy self-provision and contribute to the functioning of the larger future energy system (Kiolara et al., 2015). The number of communities in The Netherlands is growing (Schwenke) and a report from OVO Energy (2014) points out that community energy may take a leading role towards the distributed energy system. According to Wolsink (2012), decentralized socio-technical networks such as communities support the electricity consumption of end-user groups who are increasingly becoming energy autonomous. The benefits with regard to behavior change are solid reasons that communities are worthwhile testing for their future role within the end-user flexibility solution space.

As previously mentioned, a limited amount of researchers has specified community-oriented designs for the purpose of end-user flexibility. One particular example is community energy management. It concerns a bi-directional distributed network where all agents are able to communicate and coordinate and control their consumption and generation amongst themselves. Negotiation is used as a control mechanism, different from price signals or external device control (Verschae et al. 2016). Verbong et al. (2015) dive into the theory of an autonomous community a bit further and mention social and technical interactions that affect performance and needs to strive for macro-control of self-interested, interacting micro-players. The emerging smart grid can open a new vision, a brand-new approach for the operation of power systems, by making it possible to have a self-organized community of prosumers. In both cases, (local) energy autonomy is a recurring factor.

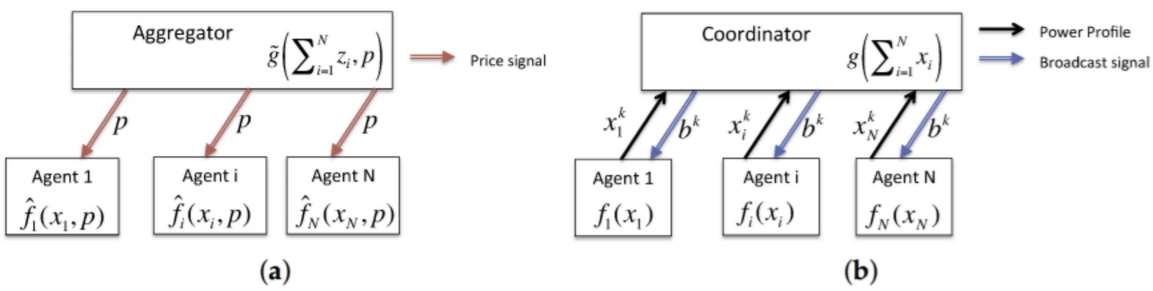


*Figure 5. Illustration of aggregated electricity management and community energy management. Source: Verschae et al. (2016)*

Due to lack of more related data on this type of community energy management, the scope of the community-oriented smart grid project is a general framework of measures to stimulate the social diffusion of efficient energy use on a neighborhood or street level. Framing and marketing plays a role; According to Hine et al. (2014), there is a growing interest in applying social marketing principles, including audience segmentation. For this reason, a part of the Theory of Community Based Social Marketing (CBSM) is considered to enhance community energy practices. Of the total CBSM framework, the following four incentive strategies are relevant as community-oriented incentives. The structural strategy concerns removing external barriers, such as 'hassle' and costs. Obviously, this can be done by providing smart devices embedded within an easy-to-use smart grid ICT framework. When people regard end-user flexibility behaviors as worthwhile practices, the commitment strategy decreases a cognitive gap between behavior and behavior intention. Peer pressure is created by binding an individual to a certain opinion which will be shared throughout the public (Abrahamse & Steg, 2013). Messaging would be a suitable means for people who do not yet believe the action is worthwhile, by shaping social norms around them. This involves creating a culture of responsibility rather than a push for maximum uptake of technology (Bergman, 2009). This maintains the link between individual, routine behavior and energy use and climate change. Social diffusion can be enhanced by increasing a variety of social interactions such as face-to-face but also digital interactions. Examples include forums, discussion groups, shared repositories and meetings. According to Abrahamse & Steg (2015), face to face interactions (such as block leaders and public commitments) combined with existing social groups tend to be the most effective way of stimulating energy savings. The measures are summarized in the table below.

| **CBSM strategy** | **Manner** | **When** |
|---|---|---|
| Structural | Smart grid technologies | Remove external barriers |
| Commitment | Anchor behavior intention | When people believe the action is **worthwhile** |
| Social norms + prompts | Messaging | When people believe the action is **not worthwhile** |
| Social diffusion | Increase of social interactions | *(not mentioned)* |

*Table 2. Smart grid-relevant CBSM strategies. Based on source: McKenzie-Mohr (2000)*

## 3.2 Requirement analysis: Developing KPIs

As previously mentioned, smart grid projects have been set up to anticipate on a variety of future issues with regard to the functioning of the electricity distribution grid, which are the result of changing load profiles at the residential level. Not anticipating on these developments would lead to very costly grid reinforcements: Blokhuis et al., (2011) shows an estimated investment of 305- 375 million Euros only for the city of Eindhoven. From this amount 80% is needed at the MV and 20% at the LV level (Blokhuis et al.). Melle et al, (2016) points out the additional congestion costs per households are between 139 and 406 euro per year. Haque et al. (2014) claims that upgrading capital intensive grid assets will not serve as a cost-effective solution in modern grids since the electricity network congestions are temporary. Furthermore, reinforcement costs will eventually be transferred to residents through the increase of fees on the electricity bill. Because the socialization of the reinforcement costs, means to avoid this peak development would be beneficial for the resident. Not only is flexibility possibly a more (cost) effective solution compared to grid reinforcements, in addition, it may also be a more sustainable solution. According to Pina et al. (2012), DSM strategies may lead to a significant delay in the investment on new, renewable generation capacity and improve the operation of the existing installed capacity. Thus, flexibility allows the DSO to support the sustainable energy transition and therefore the DSO is looking for options to order to keep the grid reliable and robust while avoiding large grid reinforcement investment costs. However, due to the fact that activities around flexible load are not directly linked to the distribution of transport, the DSO is restricted to set up the same (price-based) incentives and other services such as providing storage options like commercial retail companies can: although a considerable contributor to flexibility is the access to storage technology such as batteries, EVs, CPHs etc., according to Alam et al. (2013), energy storage is up to now far from feasible and not allowed for the DSO to implement. This aspect seems to be a point of discussion within regulating parties, since eventually all these costs are being socialized. Despite reasons to keep the unbundling of energy generation and distribution as it is right now, this system may put more costs on society and especially electricity consumers than is necessary. A new, future role of the DSO involves the facilitation and coordination of commercial activities of third parties by supporting the monitoring ability and controllability of the electricity flow (Geode; 2014) while safeguarding the interest of the electricity customers. In contrast to other parties acting regionally, the

DSO can be use his local know-how to engage consumers in local partnerships and to initialize public commitment. Social interventions are examples for a DSO to roll out in a smart grid project.

For these reasons, this research is aimed at assessing the impact of (permitted) smart grid projects for flexible consumption. The first step of the impact assessment a specification of impact requirements; In order to call the project successful, it should align with the needs of the problem owner. The impact requirements are expressed as Key Performance Indicators (KPIs) which are variables generally used to analyze organizational performance and to evaluate an organizations achievement of its goals. In this case they will verify the design to the problem owner's interest. KPI's are usually defined within the SMART principle: Specific, Measurable, Acceptable, Realistic and Time bounded (Marketing Abacus, 2014).

The KPIs should indicate the possibility to limit the following developments. Firstly, the project should limit the development of evening peak load; Scenarios for the upcoming decades show an increased frequency of a higher and longer peak. Consumption load, technological (such as electrification and increasing electric vehicle (EV) usage) and social developments (such as growing population) may result in a higher household base load (Van Melle, 2016) and even higher peak electricity demand during the evening hours. This scenario does not, however, seem to include the increase of 1 million one-person households by 2050 (CBS, 2009). This fact may counteract the foreseen developments. According to Kiolara et al. (2015 p 4)., world energy average demand is expected to increase by 2,2% between 2010 and 2035 whereas its share of electricity will double by 2050. Within The Netherlands, a worst-case scenario study in the city of Eindhoven foresees a total consumer peak demand growing from 198 MVA to in 2009 to 591-633 MVA in 2040 (Blokhuis et al., 2011). Based on various 2030 EV adoption scenarios from Movares (2013), average peak load going from the MV feed varying increases from approximately 25% to 50%. Moreover, a set of 2050 scenarios for additional peak load due to EV adoption created by Dekker (2015) shows an additional load varying between 33% - 200% depending on a 35%, 70% or 95% penetration rate of EV in 2050 (figure below).

When the generation peak demand exceeds the transfer capabilities, grid congestion occurs which may lead to asset degradation and blackouts (Morshed, 2016). Based on different future EV penetration scenarios, Movares (2013) predicts that 10%- 30% of the total number of cables are bound to overload. Looking back to the Eindhoven case, the authors generally assume that the current energy distribution networks, both medium voltage (MV) and low voltage (LV) connecting systems will be not suitable for transporting this peak load (Blokhuis et al., 2011). Veldman et al. (2013) concludes the same for 87% of the (high-cost) LV/MV transformers.

Due to the many issues peak load creates, the DSO requires a smart grid project to mitigate it. The following set of KPIs should allow to assess the grid impact of peak load mitigation. Firstly, if the limit of the capacity is surpassed, the size and duration of the overload indicate the possible damage: short yet high congestion triggers safety, leading to a black out affecting the consumers, whereas a small but longer lasting congestion event leads to asset damage such as transformers (Lerner, 2014) and the lifespan of electrical devices. Therefore, the absolute maximum peak load KPI (5) addresses the scope and black-out risk of the problem, whereas KPI (1) addresses the height of average peak load over a certain time span, called average peak load. Together with KPI (3) addressing the length of the average peak load, this indicates the possible asset damaging impact. For this average peak load is regarded as the highest 10% of the load while average peak time is the time span where the load is at least as high as the average load. Due to time restrictions of this research, the KPIs cannot assess the actual damaging effect, yet the KPIs do provide an indication and a starting point for expanding the model for this matter.

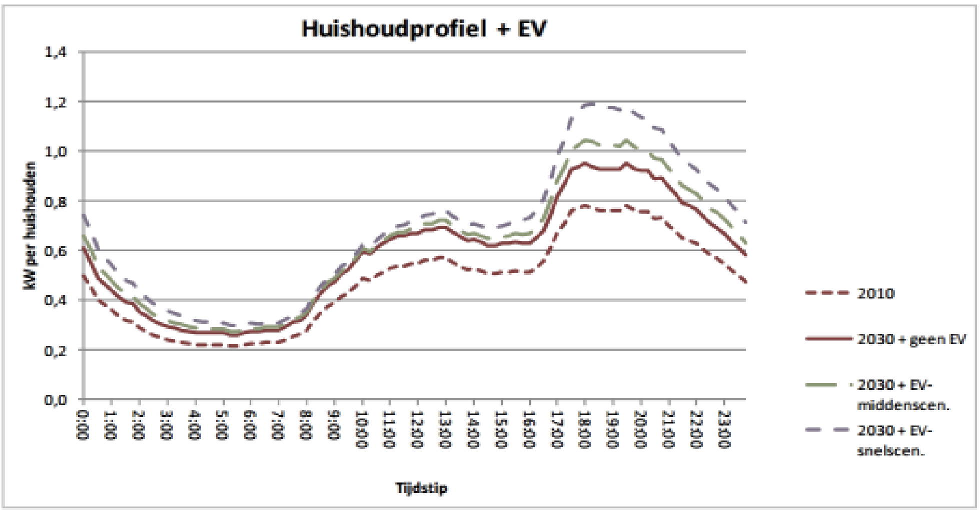


*Figure 4. Base profile households 2030 scenario. Source: Movares (2013)*

Then, the trend with regard to peak load is two-fold; The day generation peak is forecasted to increase due to the rising penetration of - time-sensitive - renewable energy sources, of which the uptake of residential photovoltaic (PV) generation systems in particular. A high penetration of PV systems in a clustered low voltage distribution network also has an impact on the quality and reliability of the grid (Ali et al., 2012). According to PV scenario's (Bernards, et al. 2014), decentral generated electricity will flow more frequently into the LV feed, which is originally created for only one-way distribution. The reverse power flow results risks concerning LV system voltage rises. Larger voltage deviations put the customers' appliances at risk and diminish the grid quality (Strauss, 2013); If the voltage deviation is more than 10%, the performance of many household' appliances is affected considerably while extended overvoltage decreases the lifetime of most devices (Passey et al, 2011). Likewise, the lifespan of the LV/MV transformer will be affected (Manito et al, 2016). Curtailing the PV generation should be an easy means to solve this problem, yet this would lead to resistance of the PV owners due to loss of production yield and revenue (Tonkoski & Lopes, 2011). For these reasons, the DSO also requires a smart grid project which mitigates day peak load. Therefore, the corresponding set of KPIs the following: KPI (2) addresses the average minimum peak load, KPI (4) addresses the average minimum peak time and KPI (6) addresses the absolute minimum peak load. KPI (9) indicates how much PV is used within the community to show locally used solar electricity and a decrease of reversed power flow. This KPI would be an incentive for the residents.

Furthermore, a set of additional KPIs are the following. Because smart grid projects may go along with energy conservation, KPI (7) addresses average load. When average load (KPI 7) is divided by peak load (KPI 5), grid utility is computed, which is a measure for efficient use of the grid assets. This KPI (8). All KPIs are summarized in the following table.

| # | KPI | Metric | Reason |
|---|---|---|---|
| **1+2** | Average peak load | Mean 10th (20th) percentile aggregated load, Ampère | Indicates the **damaging impact** on electrical devices and the grid system. |
| **3+4** | Average peak time | Mean time of 10th (20th) percentile aggregated load , s/m/h | Indicates system **flexibility**: What is the problem timespan? How predictable/robust is the peak load? Indication of the change potential. |

| | | | |
|---|---|---|---|
| **5+6** | Peak load | Ampère | Indicates the **scope** of the problem: Evening/daytime peak. Critical moments: outages. |
| **7** | Average load | Ampère | Indicates energy saving **effect** due to change energy behavior |
| **8** | Grid utilization factor | % (1/EDSN flatness) | Indicates **grid usage**, (return on) investment potential |

*Table 3. KPIs for assessing flexibility behavior under a variety of scenarios*

Important to realize that, within this issue, an *aggregated* daily electricity profile in particular is the most relevant system to derive KPIs from; Not an individual household, but the sum of a neighborhood's electricity demand is the phenomenon predominantly causing the LV/MV grid issues. While most congestion problems are not present at the individual household level, in addition, individual household electricity profiles are far more unpredictable. Generally speaking, demonstrating changes in aggregated electricity profiles pinpoints the solution impact in a simple and effective manner.

## 3.3 Concluding remarks

This chapter answered the following research sub-question: 'How can the impact of community-oriented smart grid project be evaluated?' The research argued for conducting a smart grid project with an incorporation of community-oriented interventions. This research defines community-oriented interventions as a general framework of measures to stimulate the social diffusion of efficient energy use on a neighborhood or street level. This involves increasing peer-to-peer interactions on subjects related to electricity consumption. The impact of a smart grid project can be evaluated using DSO requirements expressed as KPIs. Because the DSO is mostly interested in the aggregated consumption of a residential area due to the fact that the sum of household consumption and generation contributes to LV/MV grid issues, end-user flexibility is to be measured using a variety of KPIs expressing aggregated grid load changes. These KPIs address aspects with regard to problem scope, the damaging effect of overload or reverse load, energy savings and efficient use of the grid assets. These KPIs guide the design of a suitable impact assessment which assess alignment of the project outcome to the needs of the DSO.

# PART II

## Chapter 4: Behavior predictors

*Past behavior is the most reliable predictor of future behavior – Gordon Livingston*

The previous chapter showed the design space of a community-oriented smart grid project. Then, it presented the problem owners' needs and a corresponding requirement framework to evaluate the impact of the project outcome. This chapter answers the second sub-question by showing the formulation of assumptions on predictors related to the outcome of the smart grid project. This information allows for an architectural design of the model, which will be the following design step in Chapter 5. As mentioned previously in Section 2.6.2.2, exploring the relation between predictors and flexible behavior happens by means of a literature study. The literature study provided insights into the relations between predictors (individual and contextual) and energy behavior dimensions. Together with the theory of Frederiks et al. (2, 2015) within the Problem Context in Section 2.1, the study led to a flexible behavior framework conceptualization. Then, a detailed framework, which is used for the model's architecture design within the next chapter, is specified using a selection of cases.

### 4.1 Conceptual behavior framework

The chapter's outcome is a sum of conclusions on relevant (individual and contextual) predictors for flexible behavior. The conclusions are a combination of a variety of findings retrieved from relevant literature resources. The quality of the findings depends greatly on several aspects such as their generalizability, accuracy and causality. For this reason, a data assessment evaluates this: Appendix II shows all individual cases' assessments and their detailed analyses. The chapter conclusions are summarized within a behavior framework. It is a combination of flexible behavior dimensions and their relevant individual and psychological predictors. The two behavior dimensions are flexible load and behavior motivation. Important predictors are individual socio-demographic and psychological variables as well as social context. The main elements which are included in the framework are described in the following section.

**Realizable flexible load** A relevant behavior dimension is the amount of shiftable peak load. It is a theoretical value, an upper limit; A person's resources, specifically the means to shift consumption, relate to flexible behavior (Berenschot, 2015). One example of such means is the presence of automatic Home Energy Management Systems (HEMS) where algorithms control smart appliances to (unburden and to) support energy decisions (Orehouning et al., 2015). This involves devices operating (semi-) autonomous. Accordingly, Frederiks et al. (1, 2015) mentions the introduction of these appliances as a promising means for flexible load. However, an actual flexible load greatly differs from the theoretical load. Assessing the size of realizable flexible load involves not only an estimation of available smart appliances, but also an estimation of to what extent the appliances are used; One example is the Electric Vehicle (EV) technology penetration within a neighborhood (Van Melle et al., 2016). EV has a high flexible load, yet exploiting this potential to its full extent is highly unlikely; The realizable flexibility is limited by the usability and affordability of the technology by the users. A flexible behavior framework therefore should include a realizable flexible load as a result of the theoretical flexible load as well as predictors specifying flexible appliance usage. Funke & Speckman (2010) pointed out that household size indicates the number of appliance usages. Accordingly, household size is a predictor for realizable flexible load. The specification of the predictor within the framework is elaborated in Section 4.2.

**Motivation** Nevertheless, flexible load does not automatically lead to flexible behavior, but merely the maximum possibility. According to Kobus et al. (2015), not only a lot of uncertainly about households' flexible means exits, but also their willingness to shift time of consumption. Despite a technological solution space, motivation is also a major driver for flexible behavior (Berenschot, 2015), (Hoffman & High-Pippert 2010). Also within the Theory of Planned Behavior (TPB), the assumption holds that behavior intention precedes behavior (Awuni et al., 2016). Concerning motivation towards smart grid solutions, psychological elements such as attitude, engagement and acceptance towards end-user technological flexibility play some role. Lopes et al. (2015) mentions that personal, psychological determinants (internal drives e.g., intentions, attitudes, norms, beliefs, values) generally explain or predict energy behaviors. Although this may true, Frederiks et al. (2, 2015) also points out that this correspondence between psychological factors, such as values, beliefs and attitudes, and actual energy use, seems to be a relatively poor. Nevertheless, Abrahamse & Steg (2011) do mention that 'psychological variables are able to explain some proportion of the variance in the outcome behavior in question — which seems to suggest that such an approach is useful'. Indeed, Spence et al. (2015) showed some general perspectives on energy consumption as considerable predictors for (monetary incentivized) DSM acceptance. The specification of these predictors within the framework is elaborated in Section 4.3. Given the previous points, individual, psychological elements do predict an intention to accept flexible consumption. However, also a large discrepancy between intention or (willingness to) accept certain behavior and actual behavior exists; Numerous other psychological factors of unknown sizes and directions which ask for additional research hold as well as the assumption that internal factors merely account for behavior up to a limited extent.

**Social context** Not only psychological predictors exist; Wang et al. (2010) indicate the relevance of external, behavioral incentives to accept flexible appliance (semi-) automation. For example, communities indirectly shape flexible behavior motivation by changing people's internal drivers; Many previous community programs in The Netherlands, have targeted energy reduction and incentivized to think more about energy consumption: Schwenke (2015) showed that 70% of all energy communities within the Netherlands aimed for energy use reduction even though this finding does not even include many off-the-radar communities which mostly aim for increasing energy efficiency, too. Aspects such as social diffusion and norms (indirectly) change consumer attitudes which are predictors for DSM acceptance. Although community-oriented incentives affect energy behavior, their effect is for some groups more than for others; Community participation is mostly drawn by specific groups. Significantly different characteristics of these groups, which are socio-demographic and psychological, are elaborated within Section 4.2.4 whereas Appendix II provides a detailed description and analysis.

The figure below presents a summary of the framework conclusions and findings from resources supporting them. Although it covers major behavior components, the design is far from extensive. The remaining of this chapter further specifies this behavior framework. Some additional cases pointed out other relevant framework components which are shown in the extended framework design in Appendix II: Literature study.

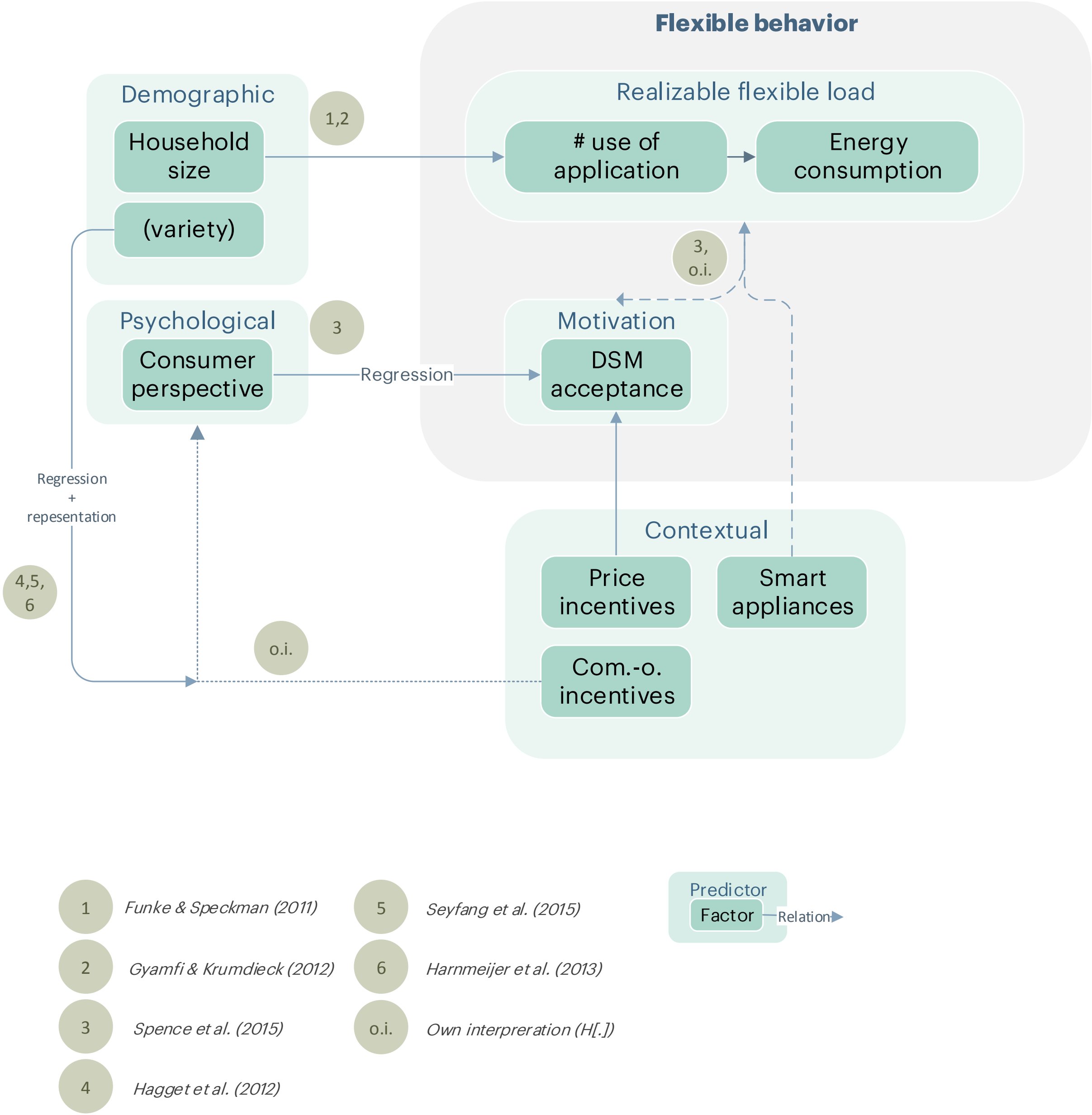


*Figure 6. Summary of predictors for flexible behavior. Framework based on: Frederiks et al. (2, 2015)*

## 4.2 Detailed behavior framework

### 4.2.1 Assumptions on flexible load

As previously mentioned, flexible behavior depends on the presence of flexible load. Although the means for flexible load are in reality more wide-ranging, this research delimits flexible load as load used by the following smart appliances. Firstly, wet appliances involve washing machines, dryers and dishwashers and are considered devices most easy for shifting usage time. It involves semi-automation and so people can adjust washing time settings based on their preferences. This asks for manual actions as well. These devices are particularly effective at load shifting, for there is a large time space allowed to shift the usage of these type of appliances to. Secondly, cold appliances concern refrigerators and freezers which can deliver flexibility by temporarily shutting off cooling functions automatically within acceptable temperature boundaries. This type of flexibility is rather short term compared to the washing machine, yet only requires the consumer merely to 'set and forget': no further actions are required. The flexibility depends on the acceptable temperature boundaries. This is a large research topic currently. To provide a general impression of flexible load size, the usage of a smart thermostat may account for 18,8% peak load shift according to Perez et al. (2016), while other appliance account for 5,1%. Its combination would be a total shift of 25,5% of peak load. The appliance with the most potential for DR is air conditioning (Nationalgrid, 2009; Perez et al. 2016), yet for the case of The Netherlands, due to the cold climate its potential is limited. Similarly, flexible thermostat is considered out of scope, since indoor heating is mostly fueled by gas (or waste heat) within the Netherlands. Then, despite the uprise of heat pumps within the Netherlands, due to the length of this research these appliances are not taken into the solution (and problem) scope. Specifically, the behavior framework incorporates flexible load concerning wet and cold appliances which is assessed using the following two cases.

**Case 1** Within case 1, Funke & Speckman (2010) calculated a current and future flexibility potential for the district of Harz in Germany taking the development of energy efficient appliances, distribution of heat pumps and EVs and other technologies into account. They presented a flexible load potential for a set of applications. Amongst them, washing machines, tumble dryers, dish washers, refrigerators and freezers are regarded relevant for this research. Other - energy storing - applications are not included within the research due to uncommon usage within Dutch residential areas. To asses theoretical flexible load, the authors assessed the prevalence of the applications within the research district. As mentioned within Section 4.1, realizable potential is a also the result of appliance usage. Accordingly, the authors estimated appliance usage as a function of household size: The more people share a household, the more frequent or intense appliances are used. However on the other hand, shared households have increasing options to coordinate appliance usage, due to the fact that energy consumption is less dependent on one occupant's presence. The factors somewhat counteract each other. For this reason, Funke & Speckman's research outcome shows flexible load as a result of household size which is a non-linear relation when the flexible load is expressed as a percentage of total consumption. The following table shows their results, which is the DSM potential of a variety of household sizes within a 20-year amount (GWh) time frame.

| *Household size (persons)/ appliance demand (GWh/20years):* | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **Washing machine** | 2,3 | 4,1 | 2,6 | 1,4 | 0,4 |
| **Tumble dryer** | 1,7 | 6,2 | 4,8 | 2,8 | 0,9 |
| **Dish washer** | 1,5 | 4,6 | 3 | 1,7 | 0,5 |
| **Refrigerator** | 15,2 | 15,7 | 6,9 | 2,9 | 0,7 |
| **Freezer** | 3,3 | 7,8 | 4 | 2 | 0,6 |
| **Absolute** | 24 | 38,4 | 21,3 | 10,8 | 3,1 |
| **Total** | 460 | 680 | 820 | 920 | 1060 |

*Table 4. Flexible behavior per appliance per household size (GWh per 20 years). Source: Funke & Speckman (2011)*

**Case 2** also indicates a realizable potential by conducting a voluntary evening flexibility experiment in Halswell, a suburb in New Zealand (Gyamfi and Krumdieck, 2011). The research results show a flexibility percentage per appliance which are wet and cold appliances, heaters and kitchen appliances specifically. Only the wet appliances - washing machines and clothes dryers - are within this research scope and taken into account in the behavior framework, which are presented in the following table.

| | **Washing machine** | **Clothes dryer** |
|---|---|---|
| **Evening average** | 3,2 | 2,1 |
| **% Evening peak** | **1,9** | 0,1 |

*Table 5. Flexibility per appliance, evening peak and average. Source: Gyamfi & Krumdieck (2012)*

Due to the fact that this research seeks for generalizable relations, a combination of the results from both cases are used for the detailed framework design. The flexible load data are integrated using relative values: percentages of peak demand. The first case's percentages show a maximum estimated flexibility range of 0,3%-5,6% depending on household size (1 to 5 persons per household, table below). The table clearly shows a non-linear relationship of household size and flexible load.

| ***Household size/appliance:*** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **Wet appliances** | 1,8% | 2,9% | 1,6% | 0,8% | 0,2% |
| **Cold appliances** | 4,0% | 3,5% | 1,3% | 0,5% | 0,1% |
| **% of the total** | **5,2%** | **5,6%** | **2,6%** | **1,2%** | **0,3%** |

*Table 6. End-user flexibility potential per people per household. Source: Funke & Speckman (2011)*

A comparison of the data shows a large discrepancy of washing machines and clothes dryer appliance flexibility. Case 2 date far exceeds the respective 0,6% and 0,9% flexibility in case 1. In order to estimate a flexible load size which is more reliable and generalizable for a large number of neighborhoods the flexibility sizes are averaged. To create an average value, case 1 is used as the lower bound whereas a composition of case 1 and 2 is set as the upper bound: the (larger) flexibility for wet appliance load from case 2 (1,9% instead of 0,5%) for a 2-person household is combined with the cold appliance load flexibility of case 1. This results in an upper bound flexibility potential range of 0,4%-7%. The average of these bounds is assumed to be a reasonable estimate: a flexibility potential range of 0,3% - 6,3% depending on the household size, shown in the table below). As a result, the percentage range 0,3%-6,3% of the total electricity demand is the wet and cold appliance realizable flexible load which is used within the behavior framework. A complete analysis for this conclusion shown in Appendix III.

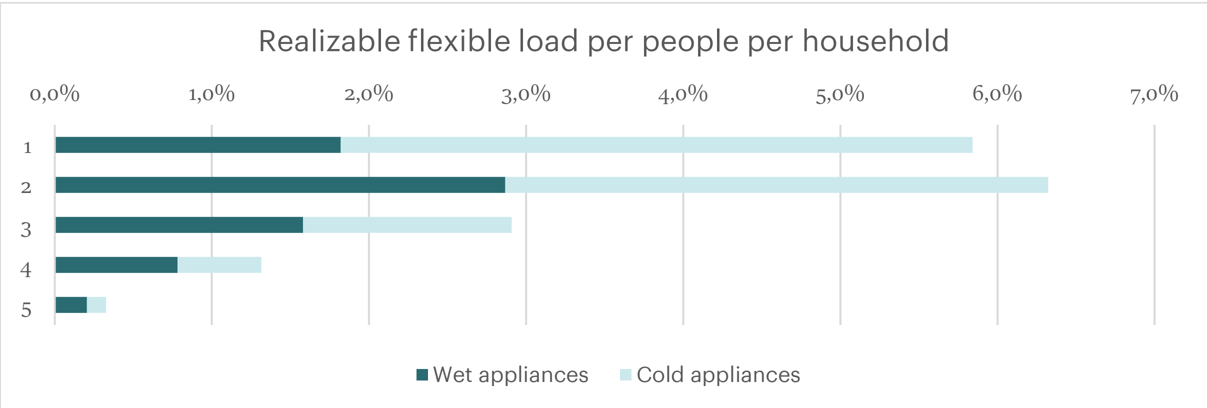


*Figure 7. Flexibility (% of total peak demand) for the following devices: washing machine, tumble dryer, dish washer, refrigerator and freezer categorized per household size. Analysis based on sources Funcke & Speckmann (2010) & Gyamfi & Krumdieck, (2012)*

**Assumptions applicability** Following from the literature of which the two cases in particular, two assumptions are formulated. The first assumption is that smart appliances such as cold and wet appliances can lead to flexible behavior. Although this conclusions is quite generalizable for Dutch neighborhoods, the flexibility size has a limited reliability, since the two cases differed considerably. The inclusion of more cases may provide a more solid and more consistent conclusion on likely flexible load. Moreover, a limitation of this analysis is its small scope: This analysis merely shows the flexibility of a limited part of the total energy usage. There is a large part not investigated yet e.g. flexibility from other appliances such as standby devices, EVs and heat pumps. Future research may investigate this further. In the light of future prospects, Funke & Speckman (2011) show that this flexibility potential will decline within the future due to the increase of energy efficiency (figure 29 in table 15 in Appendix II-a). This seems like the problem would be solved another way. Yet in reality, the point is that this energy efficiency would not outweigh the growing energy demand due to the increasing number of devices used within the residential sector; The flexibility potential from individual smart appliances will become actually more insignificant in future electricity systems. A rising number of flexible appliances need to compensate for the growing electrification if energy storage will not be part of the solution scope. Secondly, household size is related to flexible load. Although this assumption is very general and applicable for Dutch neighborhoods, its reliability is limited due to the lack of a reference source and limited proof of the causality.

### 4.2.2 Assumption on psychological predictors

Despite a technological solutions space, it is only one side of flexible behavior. Motivation towards the participation in smart grid projects and corresponding consumption change is also a major predictor for flexible behavior (Berenschot, 2015), (Hoffman & High-Pippert 2010). As argued within Section 2.1, behavior motivation is partially led by internal, psychological drivers, such as intention and attitude. This makes a smart grid project outcome less straightforward to estimate, contrary to predominantly hard factors as for the technical potential. Not only internal drivers, but also, the type of appliance indicates a level of DSM acceptance: For example, the acceptance of standby device control is a great deal larger than external control of the freezer or water heating: nearly 80% versus 30%, shown in the following figure. Most UK electricity consumers want to be better in charge of their electricity usage *themselves* while the largest share of consumers does not want to transfer this control to *external parties* (50%) or seem to be neutral about that point (20%) (Spence et al., 2015).

**Case 3** Regarding the behavior framework design, the Case 3 by Spence et al (2015) shows that the average (monetary incentive based) DSM acceptance level for wet and cold appliances was 50% and 30% respectively. People are more willing to change their washing and drying patterns, than to let the refrigerator be externally controlled. The underlying reasons have not been explained, yet it likely comes from a desire to stay in control of their own electricity consumption.

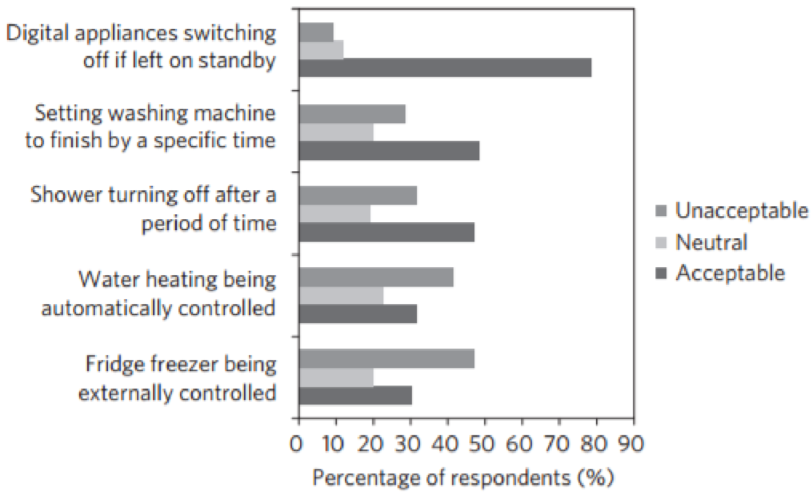


*Figure 8. DSM acceptance levels per application. Source: Spence et al. (2015)*

Case 3 shows that not only appliance type, but also psychological variables are related to DSM acceptance; Consumption perspectives have been related to DSM acceptance within a regression analysis. Spence et al. (2015) shows that a general DSM acceptance level can be predicted by some perspectives about household energy use and broader societal concerns. The perspectives ‘preparedness to reduce energy use’ and to ‘think about energy’, showed an effect size (unstandardized beta coefficient) of 21,7% and 18,7% respectively. Additionally, the following attitudes also showed significant predictive power: ‘energy security issues’ (effect size of 3%), ‘willingness to share energy data’ (effect size of 39,3%) and ‘interest in energy data’ (effect size of 34,5%). Surprisingly, the factor ‘affordability concern’ predicts the overall DSM acceptance negatively: it showed an effect size of -10,3%. An overview of the regression variables is presented in the graph below.

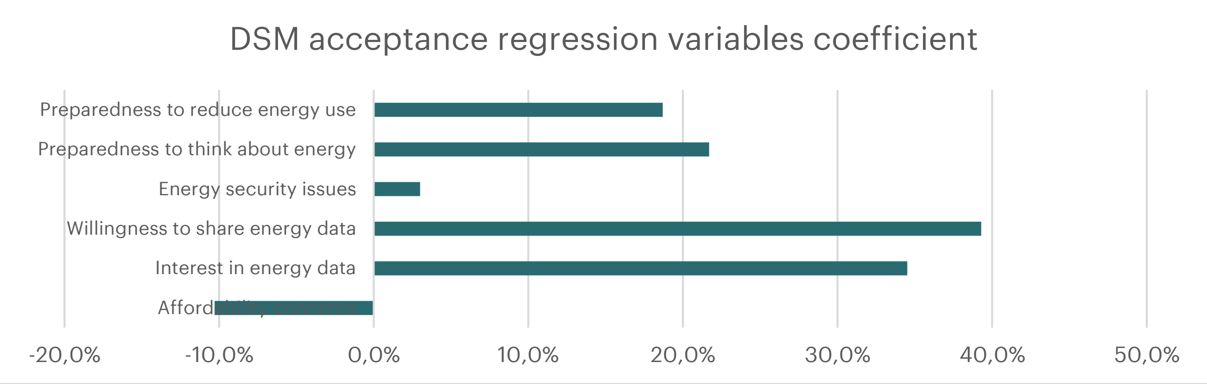


*Figure 9. Visual of regression analysis from source: Spence et al. (2015)*

The case findings relate to wet and cold flexible load and so they allow to estimate a resulting flexible behavior. The line of reasoning for this is the following. Spencer et al. (2015) revealed that the average positive acceptance level of cold and wet appliances is 30% and 50%. If this implies to be a percentage of people willing to fully accept the smart technology, then logically, it would suggest that an indication of aggregated flexibility behavior within an area is this acceptance percentage times the maximum flexibility technological potential. For example, an residential area with an average acceptance level, would theoretically show flexible behavior of 0,1%-2,6%, depending on the proportion of household sizes. Analyzing the regression coefficients of energy consumption perspectives, it seems that when all attitudes would hold for every person within an area (the ones shown in the figure above), then the maximum DSM acceptance level specific for the technology scope is 1,5 times the average. Following from this analysis, it seems that the total of four attitudes has a considerable effect on DSM acceptance. This average and maximum estimation considering the two dimensions is shown in the figure below. It shows from the graph that the maximum acceptance range attributable to attitude is somewhat between 0% and 64%, while other, more general cases also show attitude to affect behavior intention of somewhat 35%: Awuni et al. (2016) show that attitude towards environmental concern has a 28% correlation to the intention to purchase green products. A positive attitude towards and the intention to use solar heaters, EVs and support policy show a correlation value of 32% (Ajzen, 2011).

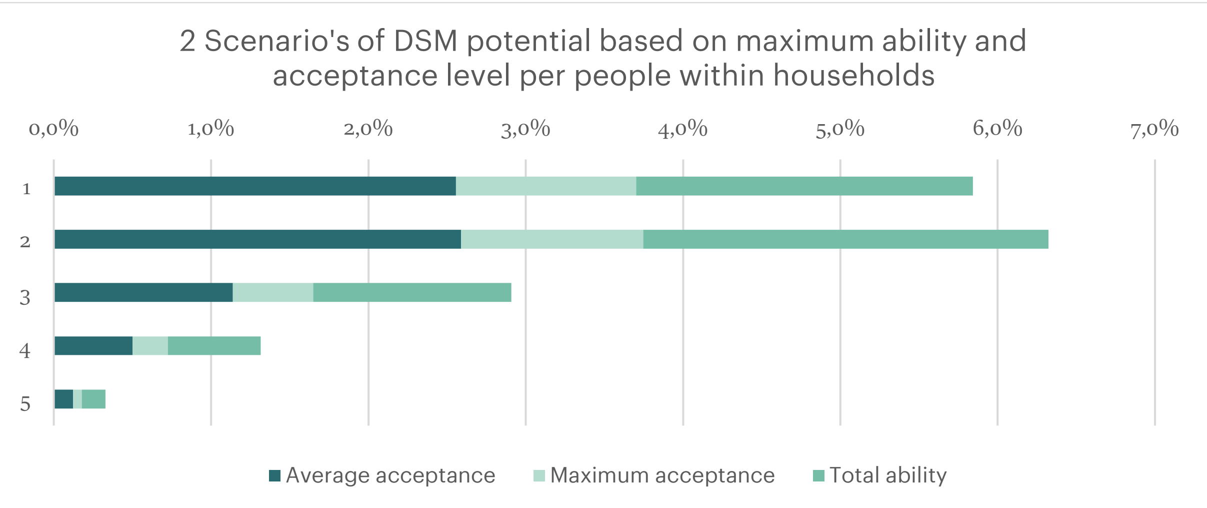


*Figure 10. Two estimations for acceptance flexibility wet and cold appliances. Based on sources from Chapter 4 and 5*

**Assumption quality** From the available literature, two assumptions are formulated. Firstly, motivation (acceptance) precedes flexible behavior. Although this might sound a bit obvious, also a large number of cognitive barriers and other psychological variables creates an intention-behavior gap. Behavior intention is certainly not the same as behavior (Berenschot, 2015). Awuni et al. (2016) showed that behavior intention is moderately related to green purchasing behavior. Also Da Silva et al. (2012) and Owens & Driffil (2008) have pointed out a substantial discrepancy among energy motivations and actual energy behavior; It seems that although electricity consumers are willing to modify their behavior for sustainable purposes, pro-environmental attitudes do not necessarily reflect in significant behavioral changes. Consumers' energy behavior is led by irrational aspects (Frederiks et al., (1) 2015), not to mention the complex physical, economic and institutional smart grid system characteristics in which consumer energy decisions ask a lot from the consumer in terms of decision making effort, money and time. For example, environmental benefits but also external factors such as saving money play a role with energy saving behavior (Wüstenhagen et al. 2007). Yet in order to make a basic estimation of psychological predictors affecting flexible behavior, the assumption that motivation is related to flexibility will do. Secondly, consumer attitude is related to DSM acceptance, and while the results are regarded as reliable due to the scope of the relevant case, also numerous other psychological (Appendix II- c) and contextual predictors (e.g. monetary incentives within the case) are related to DSM acceptance. As previously argued by Frederiks et al., the relations drawn between consumer perspectives and DSM acceptance is not at all an absolute judgement on people's motivation, rather a simplified indication. It does not take into account a possible correlation of the predictors as well as other psychological drivers and barriers such as the endowment effect and human rational limits (Appendix II-c).

### 4.2.3 Assumptions on contextual predictors

Concerning behavioral effects of the social context, energy communities indirectly lead to a larger acceptance of DSM technology if they are successful at triggering the relevant energy consumption attitudes. If community-based incentives trigger the perspectives shown below, the DSM acceptance level can increase with 18,7% to 39,4%.

1. Preparedness to think about energy use (79% average)
2. Preparedness to reduce energy use (56% average)
3. Interest in energy data (56% average)
4. Willingness to share energy data (56% average)

The way a community context triggers these perspectives are assumed to be the following. Firstly, it can be assumed that participation within energy communities obviously indicates people being prepared to think about energy use (point 1). The level of this perspective is then 100% instead of an average of 79%. It may also be likely that communities excite the interest in actual energy data (point 3), yet estimating an actual number would be too much of a guess. Secondly, the preparedness to reduce energy use (point 2) has within energy communities an average of at least 70% (Schwenke, 2015) compared to 56%. Thirdly, the social community possibly allows for an increase of willingness to share energy data (point 4), yet similarly for the third point, data about that is lacking. Future (physiological) research may fill in these knowledge gaps. If 100% of consumers would share all four perspectives, DSM acceptance increases by to a maximum of 62% (based on Case 3 data).

### 4.2.4 Assumptions on affinity to community participation

Communities are effective triggers for DR purposes if other powerful influences such as personal situation do not counter its effects. For instance, [community] projects like these draw people mostly by personal appeal (Hofman & High-Rippert, 2010), yet that does not indicate that all or even a majority of residents are motivated by them. According to Van der Schoor & Scholtens (2015), communities struggle for continuity and also, they depend on community core members (Appendix II-c). Because Frederiks et al. (2, 2015) addressed the relevance of individual predictors for the behavior response to a social context, the following analysis is conducted. The study checks for neighborhood characteristics which have predominantly been present or absent in relevant energy communities to generalize them as predictors; An assumption holds that the representation of a neighborhood characteristic in previous communities indicates future community affinity. An under- or overrepresenation of a characteristic is addressed by the comparison of group characteristics within a community group and another (average) group. For this, three cases are included: descriptive statistics from several energy community development stages (Hull, 2015), group characteristics from grass root initiatives (Seyfang & Haxeltine, 2012) and characteristics from energy communities in general (Hine et al., 2013). The community traits are compared to an average or another group using the method described in Appendix [II].

**Case 4,5,6** The two figures below summarize the main assumptions for community affinity predictors. Age groups, self- and part time employment, degree (in a small manner), collective agency, in other words: years of community activity, community primary objectives, urban level seem are significantly different within community groups than other groups and are therefore related to community affinity. Specifically, the case data implies that the elderly age group has a negative representation and the middle-aged group a positive representation within grass root initiatives compared to the average population. Surprisingly, this is also shown within the research of Taló's et al. (2014). Then, self-employed people seem to be exceedingly represented (225% compared the total population) within grass root initiatives, as well as part time employed ones (62,9%). This result extremity may be explained by the specificity of the community type: grass root initiatives. Then, another case shows that Scottish energy communities which have energy autonomy and self- government or environment as a primary goal are likely to progress to operational phase whereas communities which aspire income generation are not. Collective agency seems to be related to community progress as well. This may result from the fact that social contact increases the likelihood to build relationships and other aspects such as social norms. Lastly, the second figure shows the representation of urbanity levels within Scottish energy communities. It implies that a rural and distant character of the area is strongly related to community affinity. All characteristics are shown to be significantly different compared to a benchmark group (Appendix II).

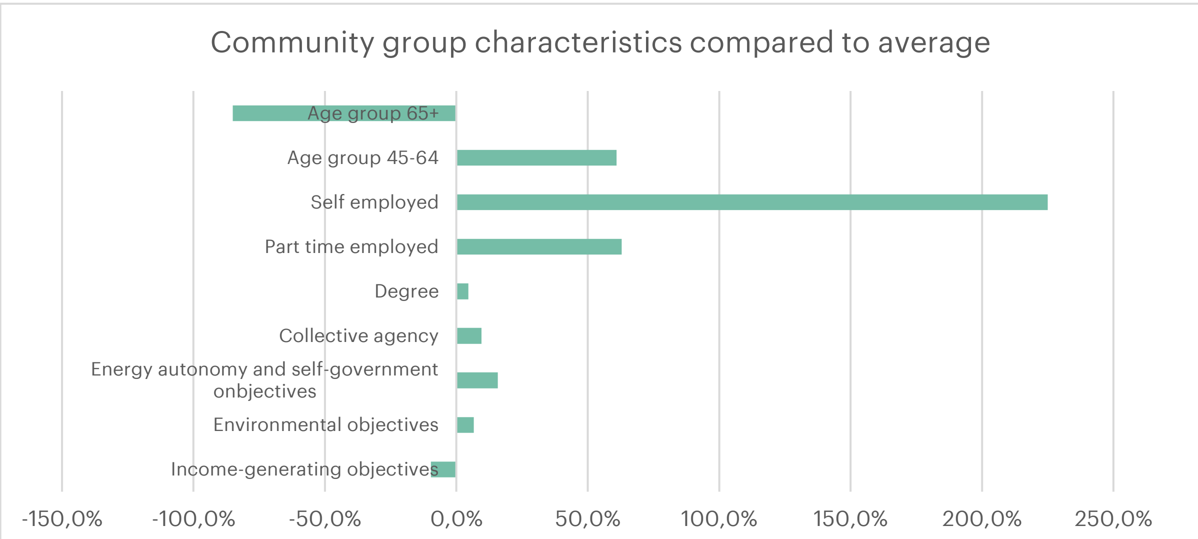


*Figure 11. Relative represented features within energy communities. Analysis based on sources of Section 4.*

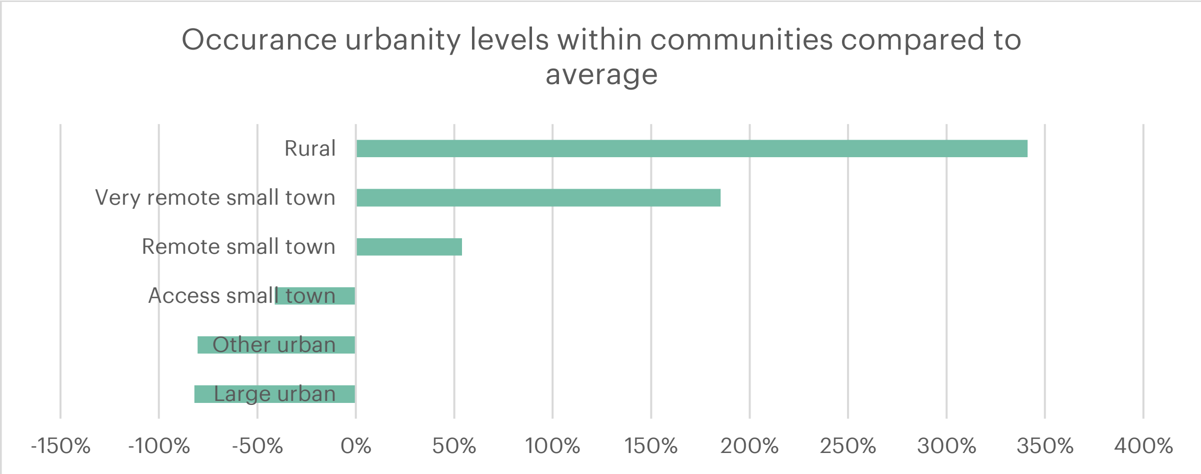


*Figure 12. Relative represented urbanity levels within energy communities. Analysis based on sources of Section 4.*

**Assumption quality** The previous section led to the formulation of the two last assumptions for the behavior framework: An energy community context can shape people's psychology, e.g. consumer energy attitudes. However this only holds when the person is sensitive to these social contexts. Several socio-demographic and community-related psychological neighborhood characteristics are related to this sensitivity which is defined as community affinity. Because a further data quality assessment is lacking, arguments for the generalizability of the found characteristics of energy communities to the community affinity are the following. A rural neighborhood encourages social behavior on a local (= community) scale and for the case of Scotland it also encourages to be energy autonomous. The reliability however, is rather limited; This case concerns rural Scotland which has spacial differences with The 'rural' Netherlands. An elderly age group would have an adverse effect by low understanding of ICT and the lack of social behavior due to limited mobility, inert behavior. A middle-aged group would have a beneficial effect on community functioning due to engagement in local developments (compared to younger groups) and often owing means to invest into sustainable technology. The self-employment of a neighborhood has a limited generality for this case since these community-interventions would be incentivized by external parties, yet Appendix II does show that core community members are essential for community functioning. Self-employment has a reasonable predictability for community affinity due to the fact that this group has the most realizable flexible load and is more engaged with the home surroundings. Degree ownership is a sound predictor, since it would correlate to the understanding of the functioning of a smart grid project, which is for that reason also one of the hypotheses. Collective agency would indeed be a sound predictor of community functioning: social activities in the past are likely indicators for social behavior in the future. The generalizability of having 'energy autonomy' as a community primary goal would be a very likely predictor whereas 'income generation' as a primary goal is a doubtful indicator. A primary goal of 'environmental purposes' would possibly even have an opposite effect for this case, since these communities would rather increase their day peak by buying more solar energy. However, it would also indicate more response to energy behavior incentives to use more solar energy, yet research on this is limited. Considering all arguments, most of the typical energy community characteristics are reasonable predictors of community functioning and generalizable for community-oriented incentives for this kind. However, the internal validity assessment involves only a statistical analysis to prove this finding and not a regression or anything similar. More research on the causality of energy community characteristics would improve the internal validity of the framework.

Moreover, although the findings on communities and flexible behavior are a step towards the understanding of community-oriented smart grid project outcomes, still many aspects are yet to discover. The effectiveness of monetary incentives remains a big discussion point. The case is vague about the height of the promised monetary benefits of DSM. Also, the behavior framework could be largely improved if some more ideas around the integration of monetary and social incentives would be added, e.g. electricity prices which are depended on local solar production (Appendix II-c). Moreover, the behavior model excludes other, highly relevant external behavior triggers such as existence of solar energy sources combined with the endowment effect (Appendix II). Numbers are lacking to include this into the framework. Lastly, incorporating social norms and peer pressure effects would increase the estimations on community behavior effects considerably. These are all compelling points for further research.

## 4.3 Concluding remarks

This chapter showed the formulation of assumptions on relations between flexible behavior and individual and contextual predictors and structured them within a behavior framework. The framework incorporates two main elements of flexible behavior, namely realizable flexible load and DSM acceptance. These behavior dimensions are related to a variety of socio-demographic, psychological and contextual variables. Although Frederiks et al. (1, 2015) pointed out that psychological variables have limited predictive power within a total behavior framework, yet information from Case 3 and Abrahamse & Steg (2011) showed otherwise. Nonetheless, consumer acceptance also depends strongly on contextual factors such as social norms and peer pressure, monetary incentives and realistic flexible load, limiting individual psychological influence, yet no research assessed a result of all factors together. Also, despite the fact that there are sound arguments for the fact that the socio-demographic and psychological characteristics of a 'typical' energy community are an indication for the social diffusion of energy-related practices, this does not mean that it is ultimately so. Considering the findings as an extensive consumer's psyche description would be an utterly bold assumption. Therefore, some caution with the integration of this framework within a model would be appropriate. Nevertheless, this framework can be used as a model architectural design input in the following chapter, for it is suitable to make a basic comparison of flexible behavior based on several plausible neighborhood predictors. The table below summarizes al 6 behavior assumptions including the evaluations on assumption quality aspects such as generalizability, reliability and causality.

| **Assumption** | **Source** (case) | **Generalizability** | **Reliability** | **Causality** | **Remarks** |
|---|---|---|---|---|---|
| Household size → realizable flexible load | 1 | + | +- | - | No explicit internal validity assessment<br><br>Based on a single research |
| Smart appliances → flexible load | 1,2 | + | +- | + | Limited future potential and limited scope (only wet and cold smart appliances)<br><br>Case outcome size differs |
| DSM acceptance >< flexible behavior | 3, o.i. | + | +- | +- | Behavior intention ≠ behavior: Cognitive barriers and other variables apply (Appendix II- c) |
| Consumer attitude → DSM acceptance | 3 | + | + | + | Numerous other psychological (Appendix II- c) and contextual predictors (monetary incentives) are related |
| Community context → consumer attitude | o.i. Frederiks et al. (2, 2015) | - | +- | +- | Whether a community affects psychological characteristics of people depends on a person's sensitivity to social context (see next conclusion)<br>Peer pressure + norms are excluded (Chapter 2) |
| Community characteristics → response to community-oriented incentives | 4,5,6 | + | - | +- | Depends on psychological (SoC) and other contextual predictors (block leaders, core members) (Appendix II -c)<br><br>Internal validity assessment and reliability questionable |

*Table 7. Summarizing table for the applicability of findings for the behavior framework.*

# PART III

## Chapter 5: Model architecture design

*Why have computers? Politicians are far more calculating – Andre Brie*

The previous chapter explained the method to create a list of behavior predictors and showed the results. This chapter answers the last research question on how these behavior predictors contribute to the evaluation and comparison of the impact of flexible behavior among residential areas. The predictors from Chapter 4 as well as the KPIs from Chapter 3 allow for a quantitative model architectural design which is explained within the following sections. The design of its components, categorized into the sections *input*, *computations* and *output* is presented. The end of the chapter presents the model limitations and validates the model usage.

### 5.1 The model functional design

#### 5.1.1 Model overview

A model architecture is defined as a concept which supports the reasoning for the model structure behavior. The first research question (Part I) contributed to the design of the model's output, whereas the second research question (Part I) contributed to the design of the model's functions and input options. A model conceptual design overview shown in the figure below. In brief, the output of the model is converting relevant neighborhood predictors and scenarios into neighborhood-specific load profile changes using an estimation on neighborhood-specific flexible behavior. By providing neighborhood-specific output, it can be used as a tool to benchmark residential areas for likely flexible behavior and therefore favorability for community-oriented smart grid projects.

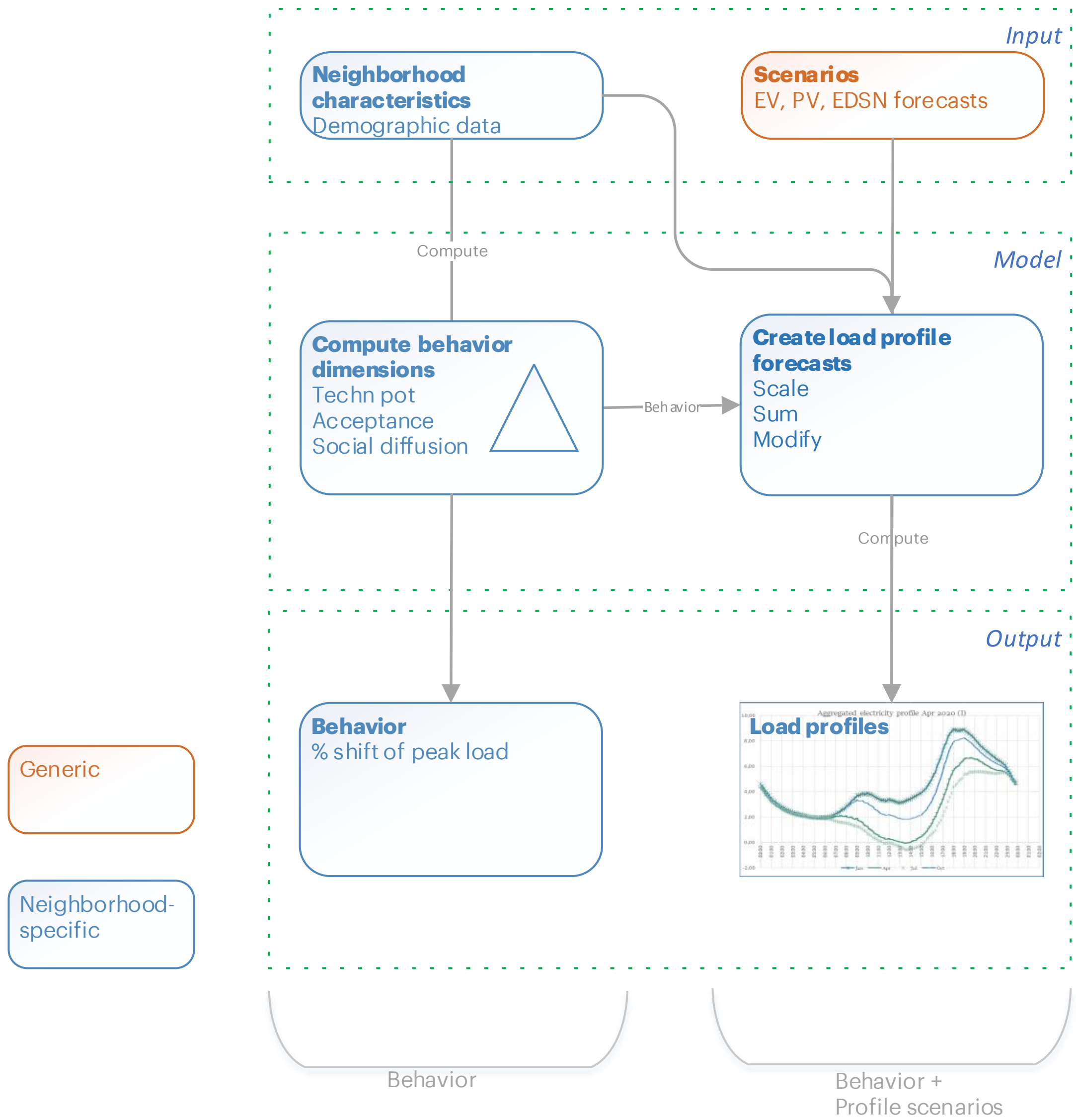


*Figure 13. Research model architectural design*

### 5.1.2 Model output

#### 5.1.2.1 Behavior

The model computes two neighborhood-specific outputs: likely flexible behavior and day load profile forecasts. The estimation on flexible behavior is a percentage indicating evening peak load mitigation. The likely maximum evening peak load shift is computed as:

$$likely\ shift\ =\ peak\ load\ *\ (1 - estimated\ behavior)$$

The output allows to benchmark neighborhoods based on their correspondence with relevant behavior predictors for flexible behavior differences due to the fact that the behavior is described as a percentage score. This benchmark supports in making a preselection of favorable sites for community-oriented smart grid areas by showing the most responsive neighborhoods.

#### 5.1.2.2 Load profiles

Then, to assess the impact of the energy behavior estimations for the functioning of the electricity grid, their power to change aggregated load profiles is estimated. To show load profile change, two aggregated profile estimations are computed: one with and one without the likely flexible behavior. The corresponding load shift takes place between the peak time of 17:10 and 21:20, because a, pragmatic, assumption holds that the intervention is set up for this time frame. This tool does on only allow to benchmark neighborhoods on flexible behavior response, but also for the intervention correspondence to KPIs, thus on the problem owner's requirements. The electricity demand change within a time frame is based on the electricity demand and the likely load shift, due to the assumption that load shift is a proportion (a percentage) also frequently assumed within other research such as (Kobus, 2015). Therefore the assumption holds that DR with rebound is the most likely flexible behavior in this case (figure below).

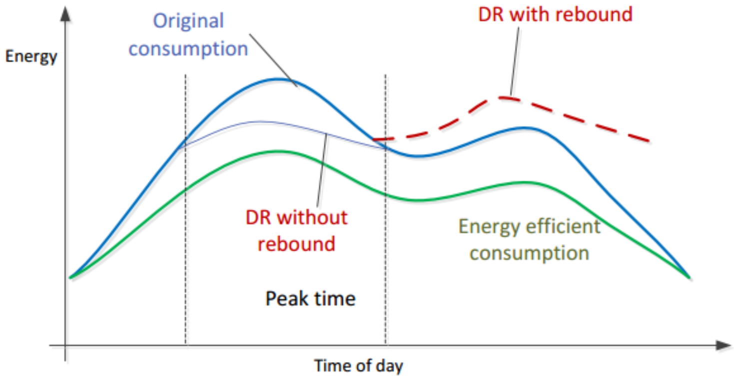


*Figure 14. Flexible behavior types. Source: (Ramanathan, 2014)*

## 5.1.3 Data input

### 5.1.2.1 Neighborhood characteristics

In order to compute the outputs, the model uses the following input data. Firstly, in order to compare neighborhoods, the model incorporates neighborhood-specific input data. It uses available relevant flexible behavior predictors which is a total of socio-demographic, social and psychological characteristics. Moreover, the model also uses the neighborhood's electricity consumption (in yearly KWh) to create neighborhood-specific load profiles. The socio- demographic neighborhood statistics such as electricity use, urbanity level, age groups and household compositions are retrieved from the Dutch National database (CBS, 2015) which is an open-source database. Because this particular model is only created to demonstrate its functioning as well as a larger sample decreases model speed, it only includes neighborhoods from actual Dutch municipalities starting with an 'A' (a total of 20 Dutch existing municipalities). Relevant social and psychological neighborhood characteristics cannot be attained by open source databases and need to be retrieved elsewise. Within the scope of this research, neighborhood-specific psychological and social data are therefore disregarded, allocated the same or - within the sensitivity analysis - handled as a variable parameter in order to test the functioning of the model and to create variable neighborhood scenario's. Other variable parameters are which are used are PV and EV penetration levels (which is 'PV installed in MW' and 'number of EV cars' within the neighborhood).

### 5.1.2.2 Scenario's

Secondly, the model also incorporates generic input data: It uses load profile data such as PV electricity production and base load profile forecasts in order to create the neighborhood's load profile estimations. The generic input data are forecasts for aggregated base load (EDSN) and scenario's for EV and PV profiles within the neighborhood. The base load profile is a retrieved aggregated base load forecast for the year 2020. The EV profile is a standard consumption profile. The PV profile is a historic Belgian nation-wide PV output. A detailed description of all input data is shown in Appendix III-a.

## 5.1.4 Model functions

### 5.1.4.1 Behavior computations

The model transforms the input data into the model output. Two separate functions exist: (1) estimating the flexible behavior and (2) computing the neighborhood-specific aggregated load profiles. The first function has several steps, described in the figure below. Three computations are switched on subsequently because the output is a composite of the previous. Firstly, the neighborhood-specific realizable flexible load - which is a percentage indicating maximum peak load mitigation - is combined with the DSM acceptance score - which is a percentage of people in the neighborhood which would accept the smart grid project. Because the scope of the research is about aggregated load, flexible behavior score is the results of the DSM acceptance score and the realizable flexible behavior score. Secondly, the community affinity score adjusts the flexible behavior score. A positive community affinity score increases the flexibility whereas a negative score decreases the flexibility. In this research, the highest acceptance is 62%, because that is maximum acceptance as a result of consumer attitudes (Figure 10). The other acceptance scores are four discrete downward steps, which are 0,5 * (62% - DSM acceptance score). In the case of an average DSM acceptance, this would be 9,5%, so the DSM acceptance range depending on community affinity is 24%-62%. The acceptance is never 0% due to the assumption that at least a small amount of people are engaged in money-earning projects. As already mentioned, the behavior output is the likely flexible load in percentages, based on flexible load and flexibility acceptance.

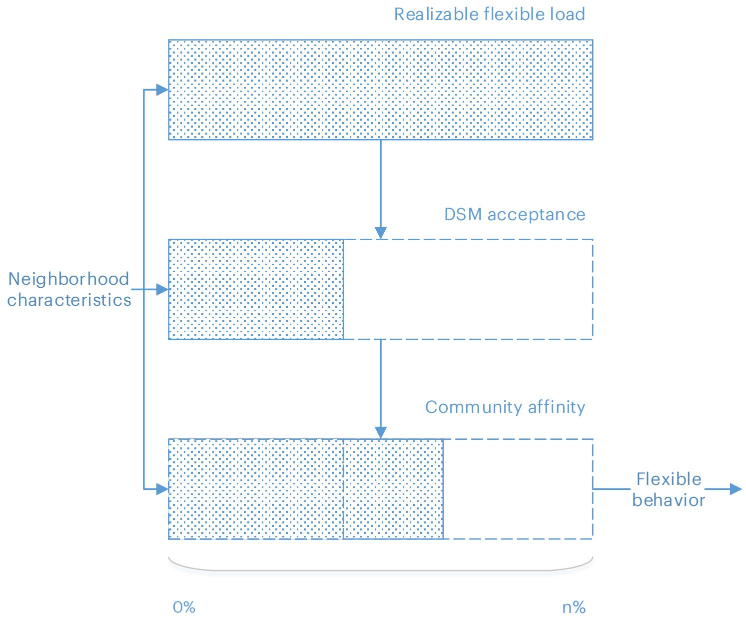


*Figure 15. Flexible behavior estimation (% as part of the evening peak consumption)*

Previous to the flexible behavior estimation function above, the three neighborhood-specific behavior dimensions are computed using relevant neighborhood characteristics as predictors. The assumptions for the calculations are based on arguments and findings of Chapter 4. Firstly, for a realizable flexible load, the number of people sharing a household matters: Two-person households have the largest realizable flexible load while the load deceases quickly as the number of persons within a household increases, while the difference between one- and two– person households is rather small. For this reason, the realizable flexible load is based on three household sizes: one-person, two-person and multi-person households. This results in a score between 0,4% and 7%. Secondly, for DSM acceptance, how much people within an area are prepared to reduce and to think about energy and have a certain interest and are willing to share energy data matters. Surprisingly, the number of people with affordability concerns affect the DSM motivation in a negative manner, contrary to the possibility for the consumer to earn money by DSM practices. Thirdly, a number of psychologic and demographic aspects of a group are predictors for community affinity. It seems to matter how old people are, whether they have a flexible occupation and have a degree and share certain objectives for the community. Elderly people seem not be prone to join an energy community whereas entrepreneurs very much do. Furthermore, the more rural an area is, the larger the likeliness to create a community (as interpreted from in these cases). The assumption holds that these over- and underrepresented characteristics can be used as predictors to show community affinity. The detailed functions to relate the predictors to behavior dimensions are are predominantly linear functions and are presented in Appendix III.

#### 5.1.4.2 Load profiles

**Load profile functions: Scale and sum** The second function computes neighborhood-specific aggregated load profiles which are a sum of scaled PV, EV and EDSN scenarios (figure below). The scaling of these scenarios is based on neighborhood characteristics such as electricity demand and PV installed. The computed electricity profiles results are month- and day- specific; They are either averages or a random (historical) day of the months January, April, July or October. The detailed design for the scaling and composing functions of these scenario's is described in Appendix III.

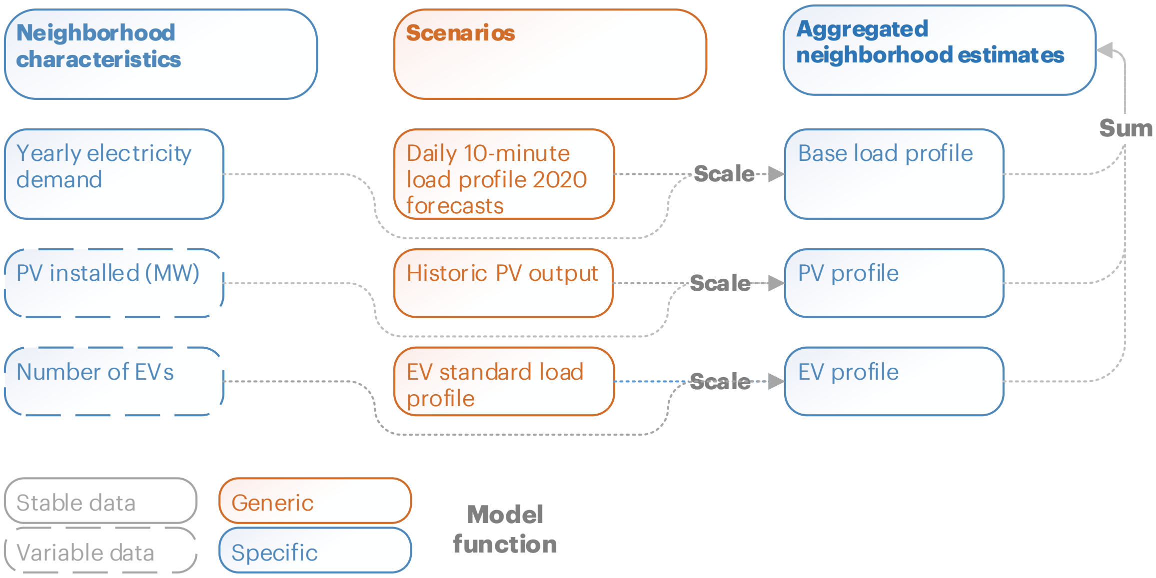


*Figure 16. Model function description*

These base case neighborhood-specific aggregated electricity profiles represent the neighborhood's profile without any behavior-related interventions. Examples of aggregated profiles along four seasons are presented in the figure below. Here, the January profile show a large evening (upward) peak, April and July profiles a large afternoon (downward) peak and October profiles show a combination of both peak types. The shape of the profile depends on many factors: number of EVs, PV installed, electricity demand and weekend and week days.

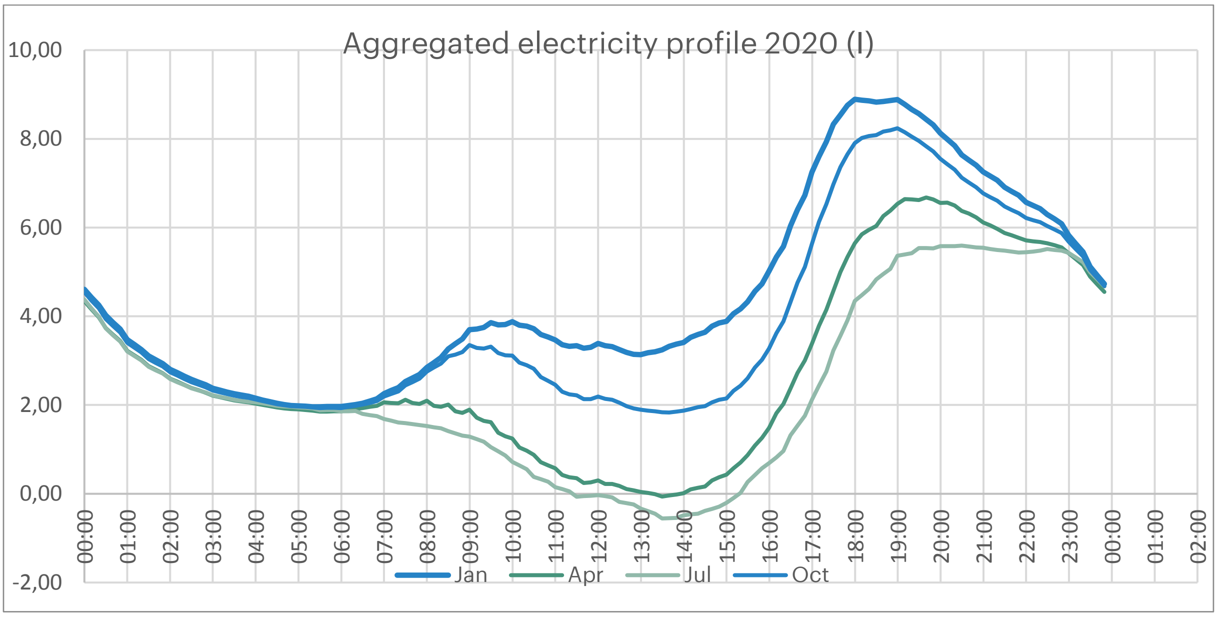


*Figure 17. Load profiles over the day as mean average month values*

**Estimate profile change: Modify.** The last part of the model's second function is computing a likely load profile change combining the estimation on the neighborhood's flexible behavior and the aggregated load profiles. Because the case studies used within the model predominantly show possibilities for diminishing *evening* peak, this model scope is a load shift of evening demand onto night and day hours equally. The assumption holds that some people rather shift demand to the day hours while some shift to the night, partly measured in (Kobus).The model computes peak shaving behavior between the times 17.40 and 21.10 and valley filling behavior outside these peak (day and night) hours. Likely energy savings are not taken into the model's functions and therefore the total energy curtailment is equal to the increase of electricity demand outside peak hours: The sum the electricity reduction within the intervention time frame is equally distributed outside the peak hours. Equations in Appendix III calculate the energy reduction at each time point within the time frame.

## 5.2 The model's limitations

### 5.2.1 Output limitations

A point which must be remembered, is that the outcome of this research indicates a likelihood based on available data, and does not show an explicit outcome taking every relevant predictor into consideration. In the light of model usability, the outcomes are much more powerful to compare household groups to present a neighborhood preselection based on available data and relevant criteria rather than showing an accurate outcome for one particular group, for the first option smooths out wrongly taken general. The fact that behavior output is shown in only one dimension limits the possibilities to interpret peak load mitigation in terms of time space. While this research regards that load is shifted equally through the day, in reality, flexible behavior mostly involves increasing energy behavior during the nights and late evenings while day demand largely depends on residents' occupancies. Not only the behavior output, the load profile estimations are also a basic sketch of the real situation. Each neighborhood is considered to have the same base case load profile, while in reality, this depends considerably on the households' occupancy and lifestyle. Moreover, the model's scope is rather limited: it only assesses flexible behavior from two application types whereas the issues around residential grids are heat pumps and EVs are far larger than these appliances can buffer. Although the model provides opportunities to assess grid impact, the model does not translate the impact to cost savings not to mention to a business case weighing them against the likely high smart grid project costs.

### 5.2.2 Input limitations

Although the data shows explicit behavior outcomes, drawing hard conclusions on merely socio-demographic predictors would be rather far-fetched. The lack of non-demographic data limits to calculate more accurate flexible behavior estimations; A large share of the preconditions concerns psychological predictors which are - within the scope of this research - unavailable as data input . The (accuracy of the) estimation changes if the psychological key factors are added. On the other hand, Frederiks et al. (2, 2015) did mention that socio-demographic factors have a large predictive power so the model has sufficient predictive power in order to make a basic neighborhood preselection.

### 5.2.3 Functions limitations

#### 5.2.3.1 Type of causality

Frederiks et al. (2, 2015) quote some limitations on drawing relations between individual factors and energy usage: 'This is not simply a matter of household energy use being shaped—in a direct and linear fashion—by just a few principal individual-level factors. Rather, there are a multitude of variables (predictors, mediators and moderators) that together influence the nature, intensity and duration of behavior around energy consumption and conservation. This complexity and inconsistency pose some challenges for drawing firm conclusions about specific effects (e.g., the size and direction of a particular variable's impact on household energy use), and especially for generalizing findings more broadly.'

Hence, the models conclusions are a basic version of the entire complex energy behavior system. Confirming Frederiks et al (2, 2015), the literature study did show some curvilinear relations such as age and employment. To compromise, some clusters are taken as a predictor clusters e.g. middle-aged and elderly groups. Yet, most relations are regarded linear as it was the only possible option with the available data. It does certainly not mean that all relations in fact are.

#### 5.2.3.2 Generalization and accuracy

A large limitation of the research is the assumption that individual predictors are the same as neighborhood predictors, while this is not always be the case: Social interactions may change the total behavior. One other limitation  is the questionable large weight which has some socio-demographic factors. Moreover, Moreover, because the link between socio-demographic predictors, community affinity and DSM acceptance is fairly weak, the outcome reliability is limited. In order to draw more reliable relations of neighborhood characteristics and flexibility behavior, more similar cases, such as Dutch testing grounds may be added. On the other hand, due to the lack of scientifically proven data on this new, particular field, the limited assessment methods such as interviews will decrease the overall data reliability, since biases from one person put a sizable weight on the outcome. Then another alternative for attaining more model input is to conduct valid and reliable surveys and to draw regression analyses from them or by using the increasingly popular machine learning techniques.

#### 5.2.3.2 Simplicity of behavior estimations

The model estimates a fairly basic electricity behavior change. It only incorporates consumption shifts which is set by two time points. The load shift is a simple mechanism in which is assumed that load shift is equally distributed to night and day hours. The model assumes that peak consumption can be shifted to any other time point during the day, while in reality, this is limited. Whereas wet appliances could be easily shifted to a variety of time points, cold appliances can only be shifted to a little earlier and later time point in the evening. In reality, the shift could cause a morning peak or may extend the evening peak towards the late evening hours. Then, the model is set up with the assumption that realizable flexible load, DSM acceptance and community affinity can be studied separately, yet in reality DSM acceptance and realizable flexibility are correlated. Furthermore, the model only incorporates flexible behavior. Whereas community-oriented interventions would most probably target both energy savings as well as efficient energy use, only the latter behavior type is incorporated into the model.

## 5.3 Concluding remarks

This section answered the very last research sub-question on how the predictors contribute to the evaluation and comparison of the impact of flexible behavior among residential areas. The predictors allow to set up a model to evaluate neighborhood-specific KPIs for impact on grid functioning. Relative KPIs allow for the evaluation *and* the comparison of grid impact within different scenarios. In order to assess the KPIs, the model computes two types of neighborhoods-specific output: load profile forecasts and flexible behavior estimations. The load profile forecasts are a sum of separate generic base and PV generation load scenarios scaled per neighborhood using neighborhood-specific yearly energy use and a PV penetration variable. The output is two aggregated load profiles: one with and one without the flexible behavior estimation which it shows peak shaving behavior between the evening peak of 17.40 and 21.10 and valley filling behavior outside these peak (day and night) hours.

The flexible behavior estimation which allows to produce the peak mitigation load profile and additionally allows to compare neighborhoods for behavior intervention response, is computed using three neighborhood-specific behavior dimension scores: realizable flexible load, DSM acceptance and community affinity. A behavior dimension score is computed using relevant neighborhood characteristics which serve as a predictor. The base of these score computations is mostly a linear function. For this, the quantitative model relates relevant socio-demographic and psychologic neighborhood characteristics to a behavior dimension. The quantitative model can compute these steps fast enough to compare a large amount of neighborhoods and analyze specific neighborhoods more in-depth to show significance, smart grid project favorability and KPIs (sensitivity) for a variety of seasonal and demand fluctuation scenarios.

**Limitations** The model results need to be taken carefully in consideration due to the following model limitations. Firstly, the outcomes are much more powerful to compare household groups rather than showing an accurate outcome for one particular group due to the fact that the model is better at making a basic preselection than providing accurate forecasts. The behavior estimations are merely one-dimensional while cost savings and opportunities for flexible behavior from other (technological) means are disregarded. Behavior is a complex subject and additional research such as local interviews are required to check the reliability of the model results. Secondly, the model results within this thesis are based on nothing but demographic data, to say nothing of the fact that highly relevant other psychological and contextual factors such as social norms and behavioral control could not be taken into account. Therefore, the estimations are not at all a total picture of neighborhood behavior. The behavior estimation would change when these are considered, yet nevertheless Frederiks et al. (2, 2015) shows that socio-demographic predictors are powerful. Thirdly, the model estimates behavior using mostly usually linear functions, while in reality the relations of predictors and behavior are more complex and involve interferences. However, some characteristics showed to be a strong predictor in a large research population. Also, the linear functions have a limited reliability because non-fully applicable cases serve as a basis. Lastly, the model also does not include the interference of other behavior such as energy savings and behavior barriers not to mention that the model uses one energy load profile which are merely scaled for each neighborhood.

# Chapter 6: Model results

*In life, we either have reasons or results – Peter McWilliams*

The previous chapter showed the conceptual design of the model together and showed its possibilities and limitations. The following chapter presents the model results. Firstly, the neighborhoods are compared for flexible behavior. Secondly load profiles of one neighborhood in particular are presented. Lastly, some data analyses transform the outcomes into meaningful data such as KPIs.

## 6.1 Results on behavior estimations

### 6.1.1 Output on realizable flexible load

All model results are based on the input data from Appendix III. Table 10 shows a brief summary the realizable flexible load of all neighborhoods included (a sample of 1017 over a total of the first 20 municipalities on an alphabetical list) whereas the next graph displays a selection of the most compelling municipalities. It shows that despite a technical potential of 7% would be possible in theory, only 179 out of 1017 (= 17%) show a technical potential larger than 5%. An explanation for this, is the large share of families with children throughout all municipalities the Netherlands. The only exception seems to be the municipality of Amsterdam, which shows an average household size of 1,8, most probably due to the high costs of housing. Therefore, Figure 18 shows that the municipality of Amsterdam predominantly shows the two most flexible categories. Within the municipality of Aa en Hunze, on the other hand, neighborhoods have mostly medium-sized realizable flexible load while within the municipality of Aalburg, large families seem to dominate within the neighborhoods, showing a very small realizable flexible load.

| Aggregated realizable flexible load | # Of neighborhoods |
|---|---|
| **>5%** | 179 |
| **4-5%** | 551 |
| **3-4%** | 255 |
| **2-3%** | 29 |
| **1-2%** | 2 |

*Table 8. Summary of the municipalities categorized by realizable flexible load*

| Community affinity | # Of neighborhoods |
|---|---|
| **<1** | 265 |
| **0-1** | 126 |
| **-1-0** | 616 |
| **-2- -1** | 10 |

*Table 9. Summary of the municipalities categorized by community affinity*

| Flexible behavior | # Of neighborhoods |
|---|---|
| **3-4%** | 38 |
| **2-3%** | 302 |
| **1-2%** | 573 |
| **0-1%** | 100 |

*Table 13. Summary of the municipalities categorized by a flexibility behavior estimation*

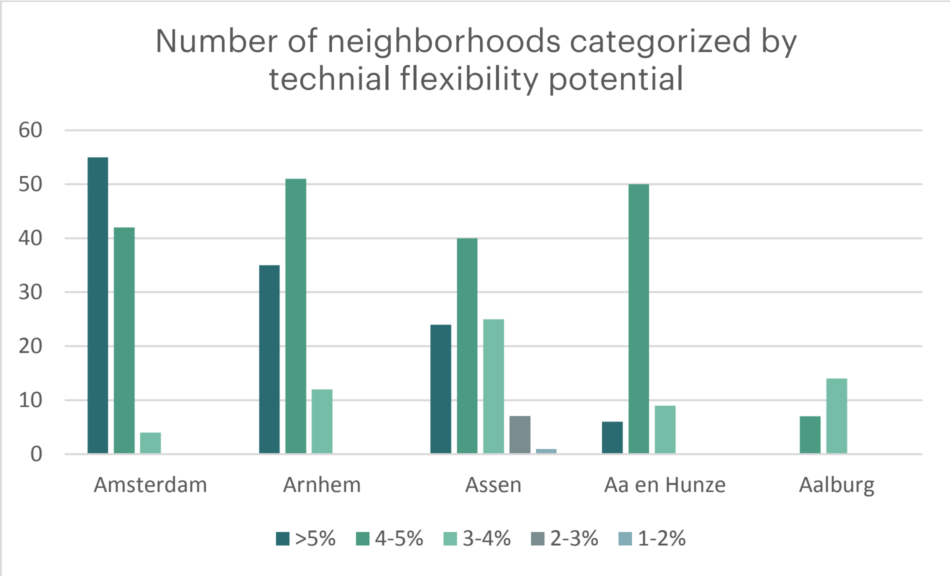


*Figure 18. Histograms for technical flexibility of the 5 most compelling neighborhoods categorized by municipality*

Mapping the top flexible neighborhoods within the sample of 20 municipalities results in the following image. The map shows that indeed, neighborhoods with the most realizable flexible load are within the municipalities of Amsterdam, Arnhem and Assen. This is contrary to the municipalities of Aalten, Asten and Aalburg which do not have a single of these municipalities.

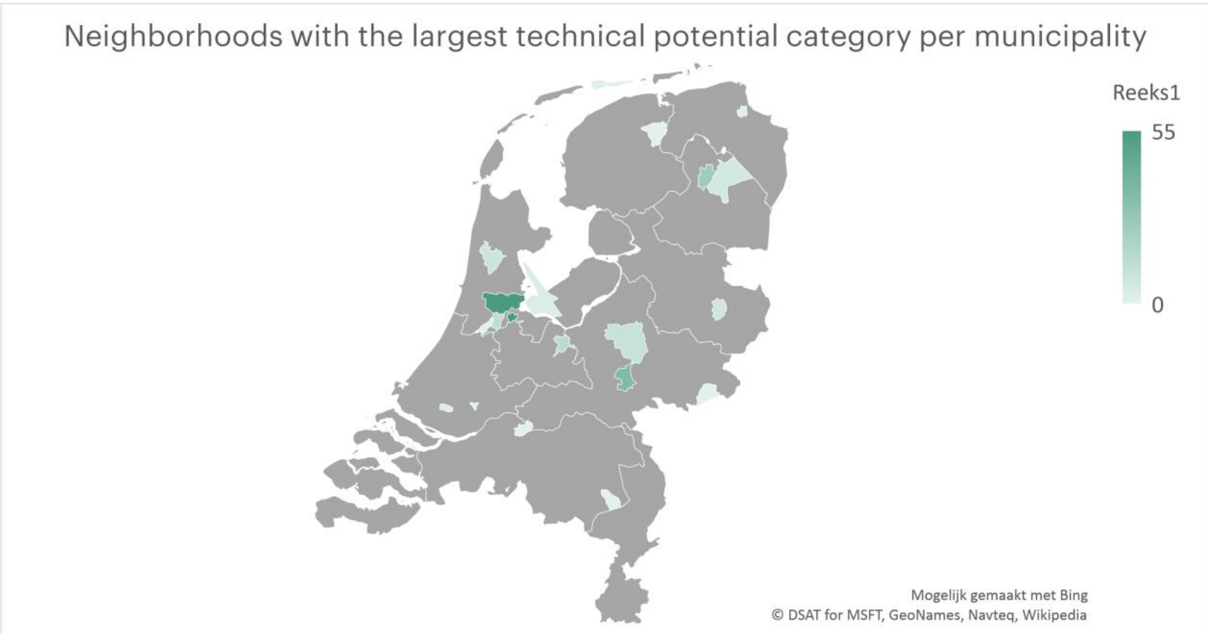


*Figure 19. Computations based on modeling output. Calculated with: Bing software*

### 6.1.2 Community affinity output

The model output in Table 11 is similar to the previous table but these are the results on community potential (based on only demographic data: age group proportion and urbanity level). It shows that most neighborhoods of the data sample have a small community affinity (a total of 626 relatively low affinity versus 391 relatively high affinity). Surprisingly, it shows that neighborhoods either have very high or fairly

low affinity. This is explained by a very large weight of the urbanity factor in this matter through a large linear coefficient and the lack of relevant soft factors.
The next graph shows an overview of these community categories per municipality. This graph also points out that most neighborhoods (in pink) not have community affinity. It also shows that plenty municipalities such as Achtkarspelen, Aalten, Aalburg and Aa en Hunze have neighborhoods (in dark blue) which have very high community affinity. However, the previous paragraph showed that most of the neighborhoods in Aalten do not have a large realizable flexible load. It would be very possible so, that these features would cancel each other out. The next paragraph will check this for the case of Aalten and the other municipalities.

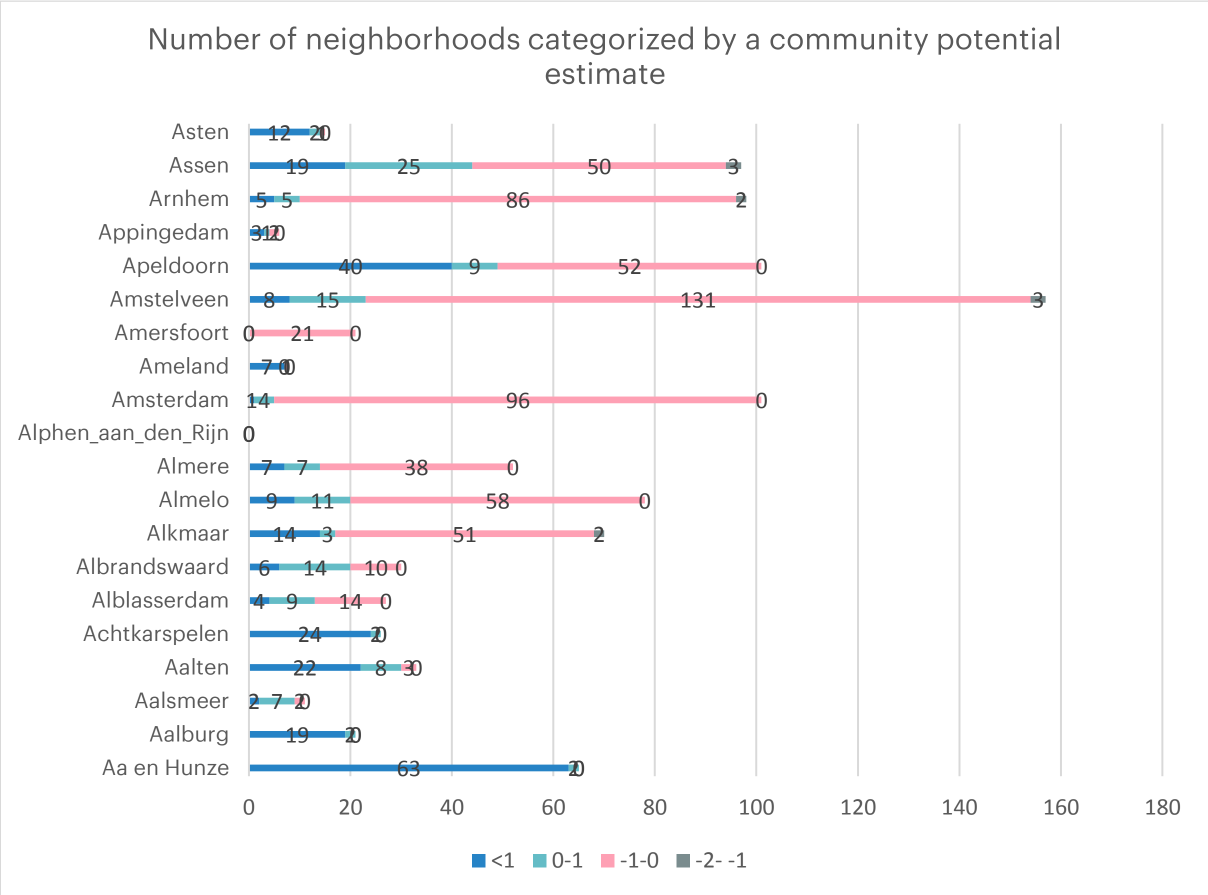


*Table 10. Histograms for community affinity estimations of the neighborhoods categorized by municipality (the larger the number the higher the affinity)*

### 6.1.3 Likely flexible behavior output

Figure 12 depicts the likely flexible behavior. Due to lack of data, it the model assumed that all neighborhoods initially have an average DSM acceptance, which is 43% (based on assumptions in Appendix III. In order to experiment with community- oriented smart grid projects, the advice would be to choose one of the 38 neighborhoods from the total sample which have the largest likely flexible behavior (between 3%-4%). These are displayed in the following figure and map. The graphs present the clusters of suitable neighborhoods. This does not necessarily mean that Aa en Hunze or Apeldoorn are the best areas to start such interventions. The single one high scoring neighborhood in Arnhem for example, would also be perfectly suitable, just like the other, more dispersed neighborhoods.

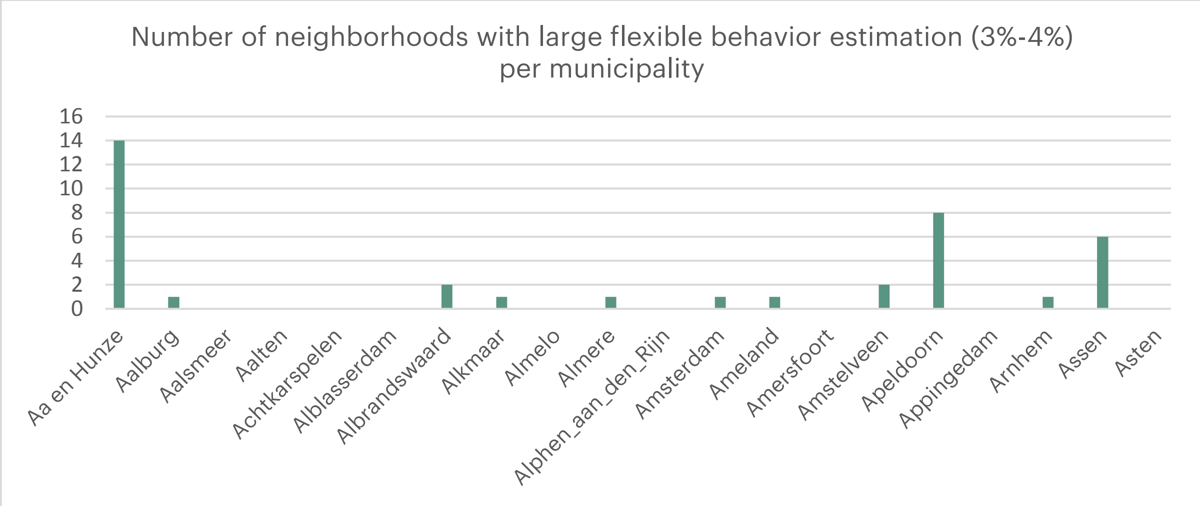


*Figure 20. Summary of neighborhoods with the largest end-user flexibility behavior size estimation*

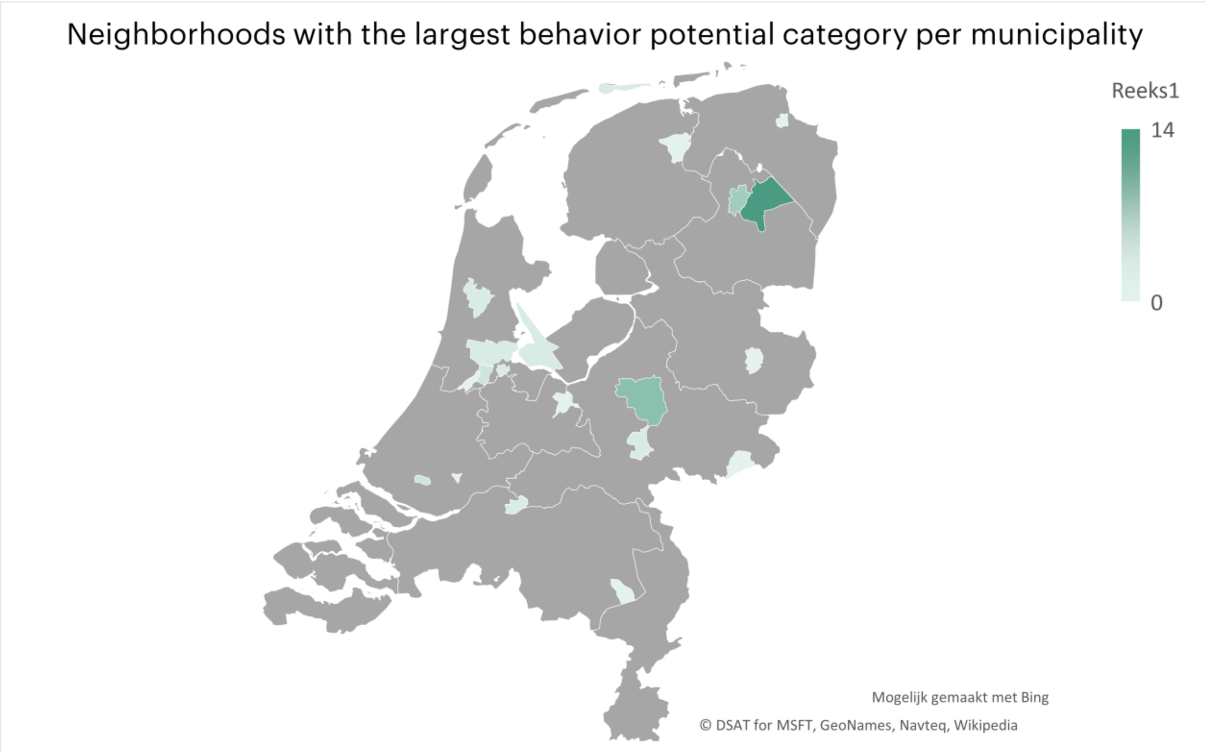


*Figure 21. Computations based on modeling output. Calculated with: Bing software*

As an illustration, the sample of 20 neighborhoods is graphically spread out by their average score on community affinity and their score on realizable flexible load, shown in the figure below. The bubble size indicates the area favorability as likely flexible behavior. Although the realizable flexible load scores can evenly vary between approximately 3,5%-5%, the community affinity scores resemble a more discrete distribution. Three clusters exist: negative to neutral affinity, somewhat positive and very positive scores showing a gap between the latter two clusters. Specifically, the neighborhoods in the municipalities in the middle and at the right cluster mostly have an urban factor of 4 and 5 respectively. The municipalities at the left side have a predomination of the urban factors 1,2,3. Because the urban factor 4 and 5 have been given a large weight, other factors matter less than for the urban factors 1,2,3 which results in the demarcated community affinity score. From the bubble size the figure shows that only communities with urban factors 4 and 5 are favorable for community-oriented smart grid projects. The results show indeed that mostly the urbanity factor and the proportion of elderly people within the area are decisive within this model, whereas in reality, many other factors which are now excluded would provide a different model outcome.

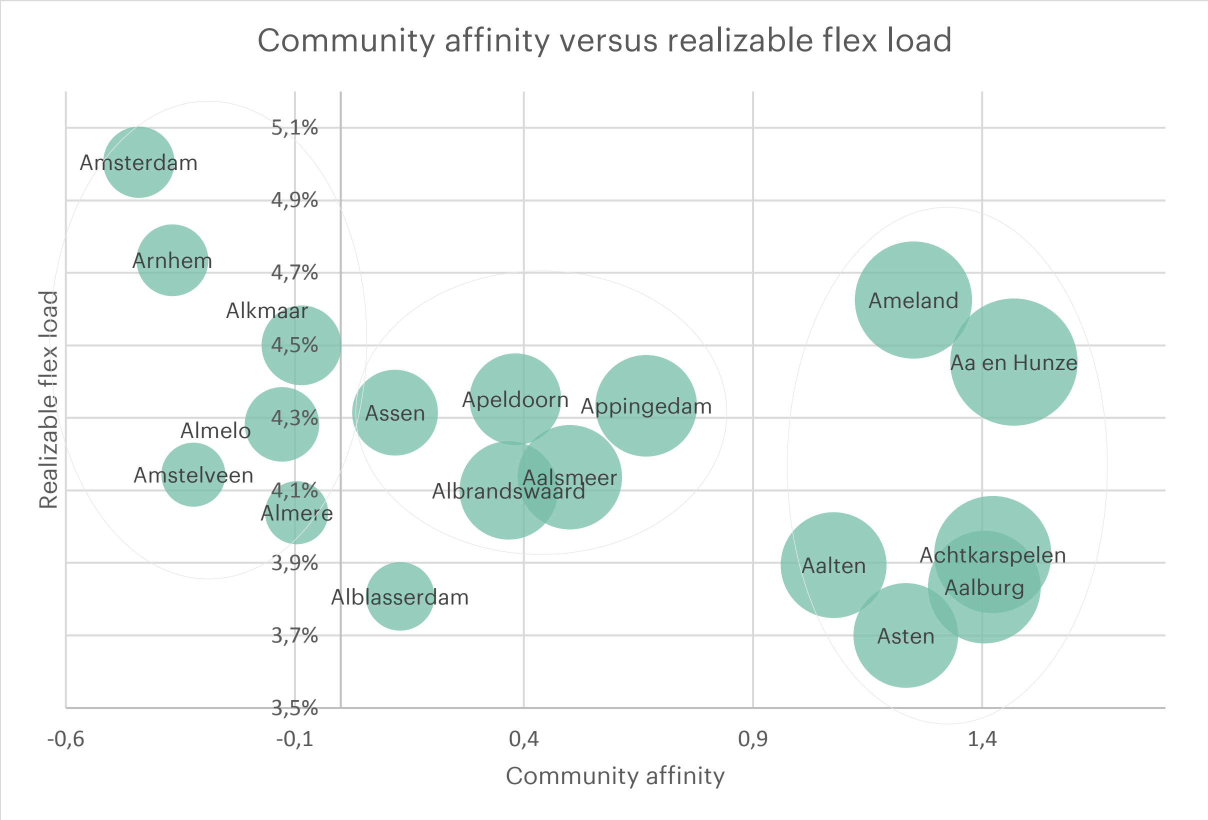


*Figure 22. Community score versus realizable flexible load of municipalities. Bubble size is the score on likely flexible load (favorable for community-oriented smart grid projects).*

The scores on realizable flexible load and community affinity result on the following outcomes. The next figure plots the likely flexible behavior per municipality. As shown, the most favorable selection – the areas with the most likely flexible load – is not the group which shows the largest realizable flexible load such as Amsterdam. This can be explained by the fact that large household sizes have a higher occurrence in rural areas. Nevertheless, some areas also have a score on both factors which makes them slightly more preferable to start a community-oriented smart grid project. Also for neighborhoods specifically, often, the computed behavior scores cancel each other out: Most neighborhoods have a moderate flexible behavior estimation, while a small share of the neighborhoods have either a very large or very small behavior change estimation, which is partly explained by the large weight on the urban factor (figure below).

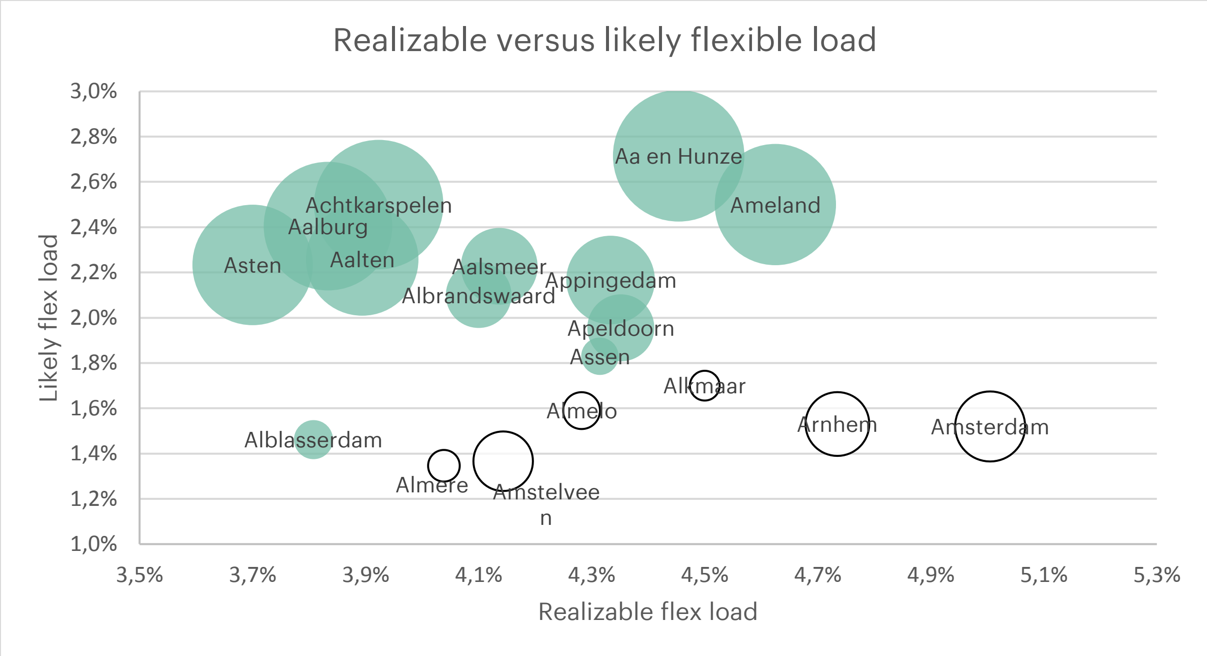


*Figure 23. Flexible load versus likely flexible load due to community incentives of municipalities. Bubble size indicates the likeliness to accept community incentives (empty bubbles have a negative score)*

## 6.2 Load profile output

The following section presents the model output on neighborhood-specific load profile. The neighborhood which is used as a case is West van Schaarsbergen in Arnhem. The CBS statistics reveal West van Schaarsbergen as a rural area, with many middle-aged residents, a low elderly rate and low average household size. It is for this reason that West van Schaarsbergen has been rated a 5,1% for realizable flexible load and a 2,0 for community affinity. This results in an estimated 'high' flexibility behavior of 3,2% of the total electricity demand. The neighborhood shows a fairly large yearly electricity usage of 4260 KWh. The next two figures show scenarios of different seasons (January or July) and PV technology installed (a large amount or totally absent). Whereas within the second scenario, where peak demand mitigation in the summer month in a neighborhood with much PV installed seems unnecessary and also less possible, both profiles within the graphs are in fact statistically significant with a p-value < 0,0001 (Appendix IV). Figure 24 shows a winter peak load shift. It seems like curtailment, yet the graph represents a kind of 'valley filling' behavior which is hard to see due to the aggregated shift size which is a neighborhood average: As previously told washing machines have a large alternative time space. Here it is shown that minimum peak load does increase by 2,8% for January and between 1,7%-2,6% for other seasons.

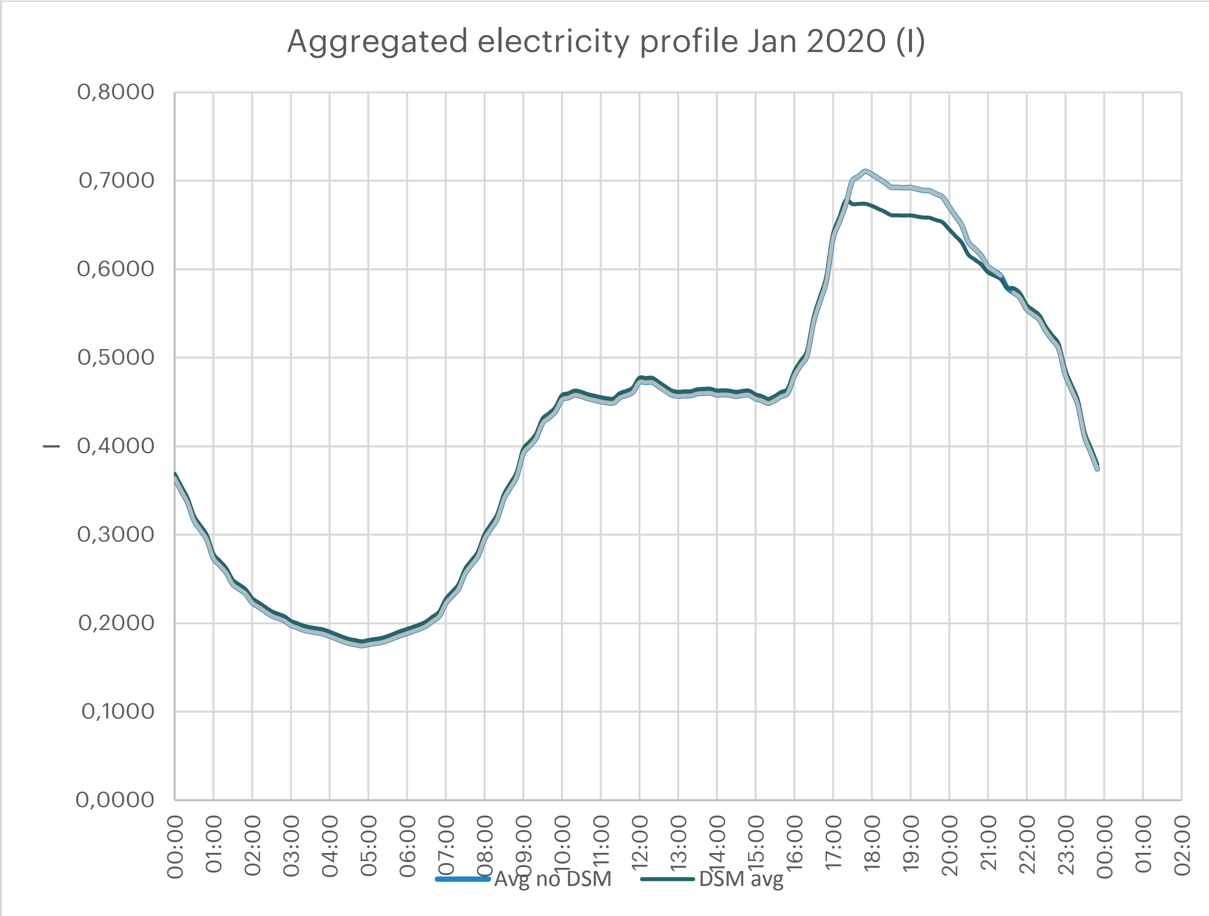


*Figure 24. Electricity behavior estimation of an average January day based on a combination of cold and wet appliance smart technology, price incentives and community-oriented incentives without EV and PV for the West van Schaarsbergen neighborhood*

The added value of extending the model through the addition of several scenario's is apparent from the following figures. It shows the same neighborhood's summer scenario with a maximum PV penetration which is strikingly different from the other scenario. It shows a much lower and actually a much less needful evening peak shift: the summer demand drop greatly outweighs the intervention demand shift. The scenario also shows the need for peak shift to the day: the average daily day peak seems negative. Although this model does not consider day peak shift, other research from Kobus et al. (2015) shows that this would be (partially) realizable. Concluding, the addition of scenario shows how useful the behavior change would be throughout the year. Further an examination and comparison of specific monthly outliers would be also possible with the current model. These may be laid down within, however these two scenario's provide the reader the most relevant information on energy behavior throughout the year.

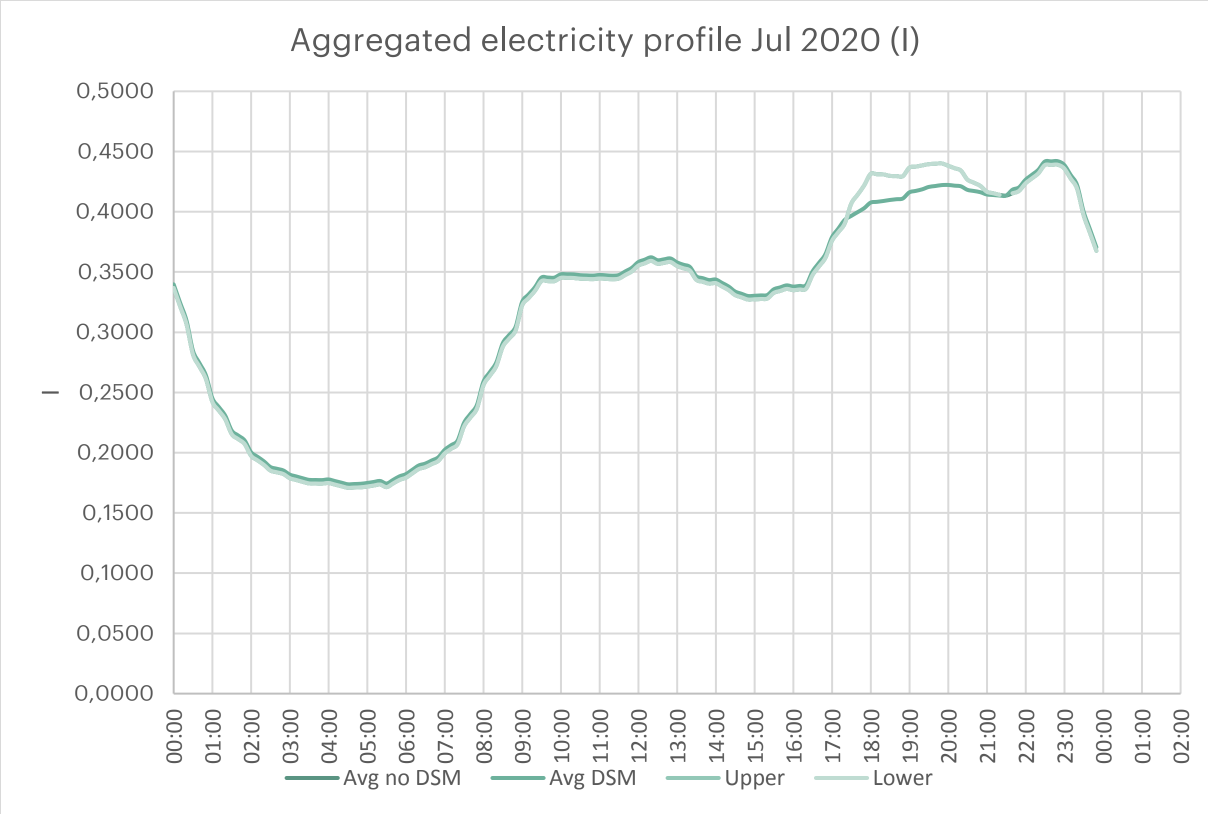


*Figure 25. Electricity behavior estimation of an average July day based on a combination of cold and wet appliance smart technology, price incentives and community-oriented incentives without EV and 0,8 MW installed PV for the West van Schaarsbergen neighborhood*

## 6.3 Data analysis

**KPIs** From the available load profiles, the behavior intervention can be assessed through the use of KPIs, which will happen in the current section. Absolute KPIs are hard to compare, since they are neighborhood-specific and its values do not point out behavior *change*. For this reason, the model's measured output are relative values comparing the base case and changed load profiles. Hence, the following KPIs are shown as relative values, rather than absolute ones. The KPIs also show that due to peak flattening, the average peak (10% highest load) time increases considerably. If the average peak load still remains a risk, this might even more damage grid assets. On the other hand, the decrease of maximum load does limit outage risk. It is up to the DSO to weigh up the effects. This would depend on the state of the grid assets. Either way, the grid utilization factor increases slightly leading to a somewhat better usage of the assets. Concerning average load, nothing changes, because contingent energy savings are not incorporated in the model. In reality, flexibility behavior would party result into spillover such as energy curtailment. This is a point to further extend the model.

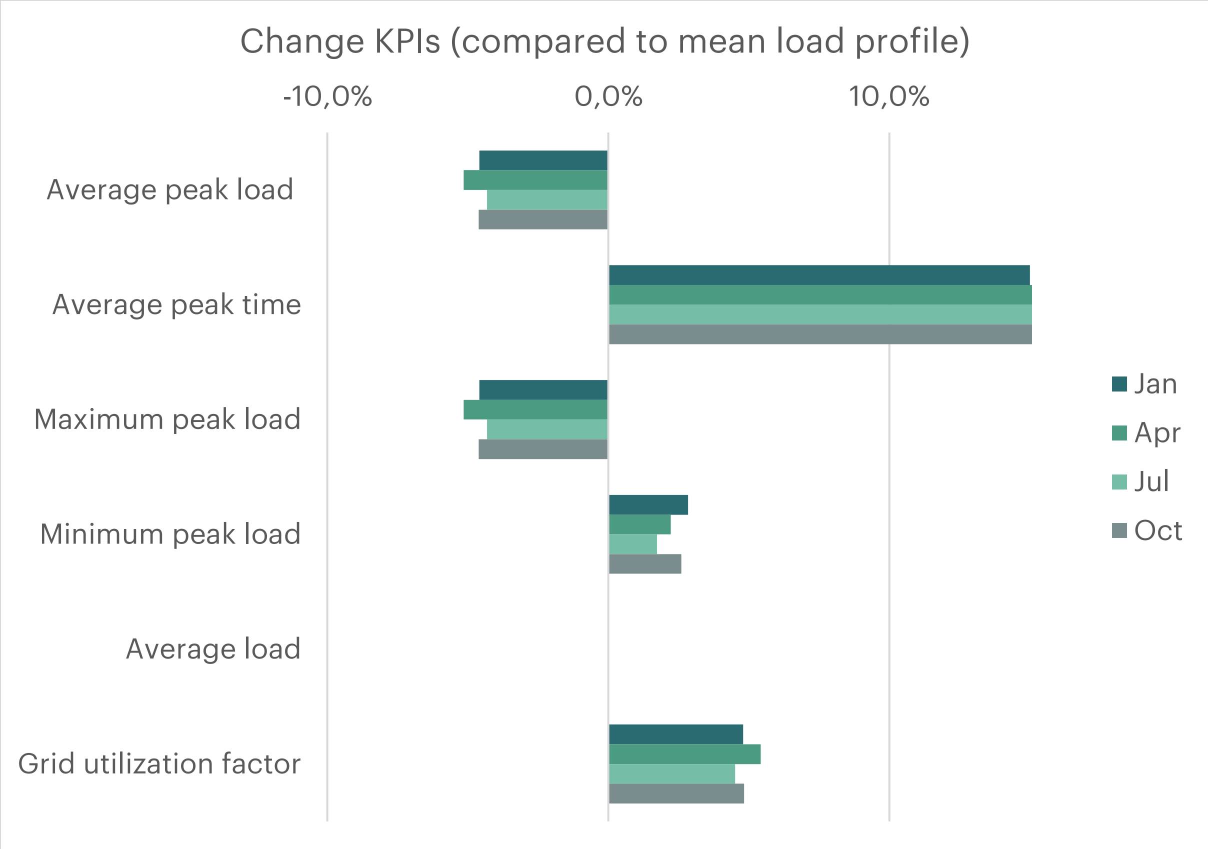


*Figure 26. KPIs West van Schaarsbergen. Winter scenario without PV installed*

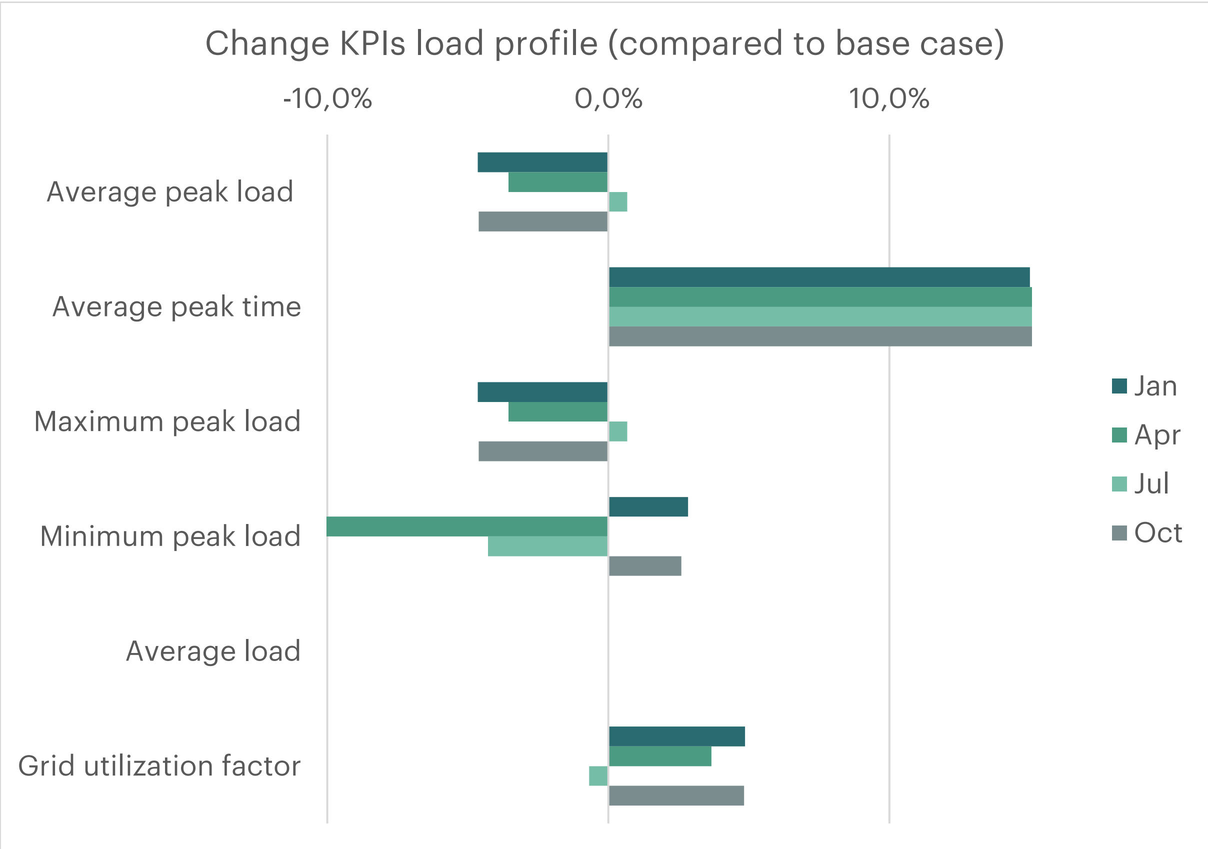


*Figure 27. KPIs West van Schaarsbergen. Summer scenario with 0,8MW PV installed*

**KPI sensitivity** While the KPIs in the above two figures show a likely smart grid outcome with regard to relative changes in grid aspects, the DSO also wishes to put the KPIs in a broader perspective to see a clearer relation of KPIs and seasonal and demand fluctuations. For this reason, sensitivity analyses are performed. The two figures below show the analysis summary based on the Figures 42-45 in Appendix IV. The analysis involves the sorting of 30 load profiles where one parameter is a fixed, average variable while the other parameter varies. The varying parameter is the historical 30-day PV generation and base load fluctuation load profile fluctuation, scaled for the neighborhood specifically and sorted from low to high peaks. The figures below show the some KPI outputs (maximum and minimum) peak load using all 30 scenarios from either January or July. The left figure shows that the maximum load does not very depend on PV production for either summer or winter while the minimum peak load very depends on the PV generation in summer: This PV penetration scenario shows that the minimum peak load will vary between 100% and 50% of the total production. The right figure illustrates that the maximum peak load is slightly sensitive to demand fluctuations (around 5%). Both figures also show the peak loads as a result from the flexible behavior. A remarkable point is for this is that for the case of West van Schaarsbergen, the KPIs for maximum and minimum load are in general more sensitive to PV generation and month-specific demand fluctuations than for the flexible behavior. In that sense, the significance of the flexible behavior from wet and cold appliances on grid impact is rather limited. Nevertheless, if the DSO is interested in testing grid impact through a broader perspective of measures, such as EV storage and heat pumps, this case of West van Schaarsbergen would lead to a significant grid impact through most seasonal and demand fluctuation scenarios.

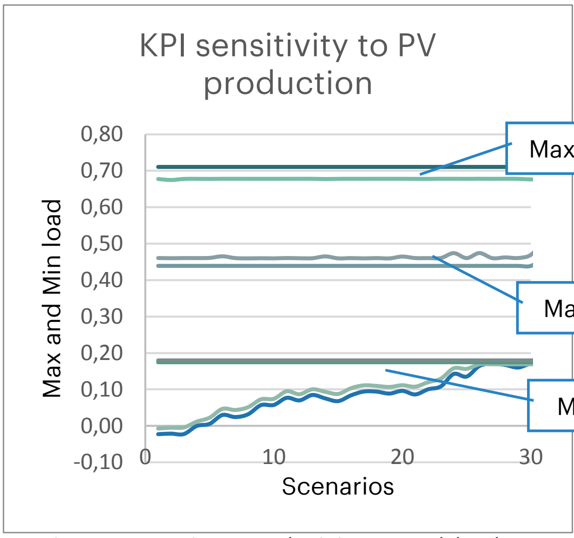


*Figure 28. Maximum and minimum peak load as a result of 30 historically-based solar production (summer and winter) scenarios (sorted by size)*

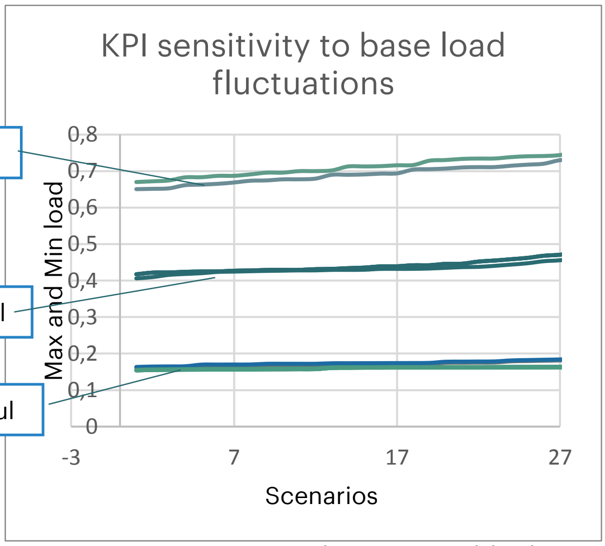


*Figure 29. Maximum and minimum peak load as a result of 30 historically-based base load scenarios (summer and winter, sorted by size)*

## 6.4 Concluding remarks

This chapter was an overview of the model results and analysis. The model output shows that most neighborhoods have a realizable flexible load of only half of the 7% upper limit while only a fifth of the neighborhoods have a higher score of more than 5%. These neighborhoods are mostly in Amsterdam, Arnhem and Assen, where apparently, the household size is small. Furthermore, most neighborhoods show either a very large community affinity or a rather small community affinity. This has to do with the fact that the urban factor puts a very large weight on the behavior dimension score not to mention the absence of relevant psychological neighborhood-specific characteristics. These numbers result in only 38 neighborhoods out of 1017 which comply to both realizable flexible load and community affinity. Often, these the effect from both behavior dimensions cancel themselves out, which leaves a large number of neighborhoods with a medium/low-sized flexibility estimate. As for the neighborhoods with the largest behavior estimate, their change in load profiles is significant in most scenario's regarding PV penetration and demand fluctuations. Obviously the KPIs show a decrease in peak load, but also a very large increase in peak time and a reasonable increase in grid utility. As seen from a comparison from two scenario's, the usefulness of behavior change on the most relevant KPIs depends greatly on the time of year and the PV penetration; the KPIs are more sensitive to the scenario fluctuations than for the behavior intervention. The model results show that indeed the quantitative model is a suitable means to compare and evaluate neighborhoods for favorability for community-oriented smart grid projects by providing a systematic tool to make a neighborhood preselection.

# PART IV

## Chapter 7: Discussion and conclusion

The following section provides the research discussion and conclusion and the research limitations. Firstly, the discussion shows a critical analysis of the research subject by presenting the meaning and significance of its findings. It also confirms the research hypotheses. It also shows recommendations for the problem owner. Secondly, the conclusion provides a summary of the key research findings by answering the research questions. Lastly, the limitations present the research deficiencies and their importance for the conclusions, reflect on the nature of the limitations and justifies the research choices and suggests how the limitations should be overcome in future research.

### 7.1 Research discussion

**Result interpretation** The research showed that incentivizing flexible behavior asks for a wide approach of monetary, social and technological smart grid incentives. The diffusion of energy practices within a local setting contributes indirectly to a consumers' willingness to be flexible end-users. Then again, consumer behavior depends on numerous variables other than only the smart grid contextual settings such as individual characteristics and (social) institutions within the area. Especially, the response to social incentives which target flexible energy behavior is not so straightforward at all. For this reason, there are indeed considerable differences among neighborhoods on likely outcome of smart grid projects, as posed in the hypothesis in Section 2.5. Then again, a large part of the neighborhoods in The Netherlands is - based on the available data analysis – moderately suitable for social flexibility interventions, because they meet the requirements of at least a few behavior aspects to make them preferable. A few of these requirements were indeed mentioned in the hypothesis; Education level, households size and high age did prove themselves as neighborhood predictors for the functioning of a community-oriented smart grid project due to the fact that the older and larger a household is, the harder it is to change their behavior. Contrary to the hypothesis however, the research did show that slightly younger neighborhoods (mostly middle-aged people) have a large affinity for community participation. The tiny fraction of the neighborhoods with the largest estimation, would therefore be rural neighborhoods with already grown-up families. On the other hand, despite large differences among neighborhoods, in any case, the research showed low flexible behavior in terms of a flexible load percentage. Although this research is a considerable step towards the creation of energy systems containing a flexible demand side, not only the end-users' intentions and responsiveness, but also the current means for peak load mitigation are considerable inhibitors for this.

**Significance of findings to existing knowledge** Although earlier research has analyzed criteria for demand response such as the framework of Frederiks et al. (2, 2015), the study of a large variety of individual cases and other resources in order to use generalizable assumptions for the evaluation of a large scale preselection is limited. Ultimately, this modeling approach integrating various aspects of local and social complexities contributes to the analysis of flexible behavior disparities and dependencies. This research is a first step with many open questions and opportunities for extensions, but it also suggests that this type of analysis is feasible.

**Generalization: New problem understanding** This research is a contribution towards creating systematic evaluations of sites for customized smart grid project suitability, towards enhancing the outcome accuracy on pilot project activities for the DSO and other interested parties who are willing to upscale and design a feasible system for energy flexibility. The insights on the social context of smart grids can be used as a support to upscale and make DR pilot projects more mature by showing areas which most likely allows for a social and institutional embedding. Also the research is a step towards taking relevant individual circumstances into account during the smart grid project development phase. Although now new knowledge exists on individual and situational predictors of energy behavior, the research also shows mutual dependencies of situation-specific variables not to mention the lack of access to numerous relevant ones. The model design is therefore useful to assess likely flexible behavior, yet it computes results which are far from extensive. The complex system of dependencies within smart grid projects pose various further questions.

## 7.2 Research conclusion

The central question within this research was how Dutch residential areas can be compared regarding flexible electricity consumption in the context of community-oriented smart grid projects. The answer is a result of answers to three research sub-questions.

The first sub-question asked how the impact of a community-oriented smart grid project can be evaluated, which resulted in the following method. Because the DSO is mostly interested in an aggregated consumption of an area due to the solution scope, but also due to the consumptions' effect on the MV/LV system of the grid, end-user flexibility should be measured using a variety of KPIs for aggregated grid load. These KPIs address aspects with regard to problem scope, the damaging effect of overload or reverse load, energy savings and efficient use of the grid assets. A community-oriented smart grid project is a general framework of measures to stimulate the social diffusion of efficient energy use on a neighborhood or street level.

The second sub-question asked in what manner relevant assumptions on predictors for the response to a community-oriented smart grid project are formulated, which are the following. The assumptions can be based on findings from a variety of resources if the findings available are (externally and internally) valid and reliable. With the data available, a literature study incorporating a handful of cases allowed for the conceptualization of a flexible behavior framework. The framework incorporated a handful of individual (socio-demographic and psychological) predictors as well as several contextual (social, financial, technological) predictors related to either flexible load or acceptance of flexible consumption.

The last research question asked how the predictors contribute to the evaluation and comparison of the impact of flexible behavior among residential areas which is through the use of a quantitative model. It allows to benchmark residential areas on likely flexible load where findings from the conceptual flexible behavior framework are an input for its design. To compare neighborhoods, the model produces two neighborhood-specific output types: flexible load (as a percentage of peak load) and load profiles based on a variety of scenarios. The model incorporates two types of input data. The first type is generic scenario data such as PV electricity production and load profile forecasts. The second type is demographic neighborhood-specific data such as available neighborhood characteristics marked as behavior predictors. The model's functions are twofold. Firstly, it computes an estimation of neighborhood-specific flexible load using linear functions and available neighborhood data. This allows for a basic estimation of flexible behavior within a neighborhood. Secondly, the model computes neighborhood-specific load profiles using several (seasonal demand and PV generation) scenarios and neighborhood characteristics (historical electricity demand and variable PV and EV penetration values) and estimates a change in load profile using the estimated neighborhood-specific flexible load. To assess the impact of the behavior change for the DSO, a data analysis transforms these load profile changes into KPIs.

## 7.3 Recommendations for the problem owner

The central question for the problem owner was which means will lead to peak demand mitigation in the residential grid. The research outcome shows that a community-oriented smart grid project which incentivizes the social diffusion of energy practices on a neighborhood/street level, incorporating flexible technologies (making wet and cold appliances flexible) and using monetary incentives results in an evening peak shift between 0% and 4%. Approximately half of that percentage in a diminishing day peak where 1%-3% is the most likely scenario based on the available data while a very small number of neighborhoods show a higher estimation. The areas which are most likely to succeed with experiments on community-oriented flexibility incentives are a number of neighborhoods in Aa en Hunze, Apeldoorn and Assen, yet other, more dispersed neighborhoods throughout the country are equally suitable as well.

This research collected a large and diverse amount of data to provide a preliminary overview of research possibilities for the problem owner. Therefore, conclusions from the research outcomes should be carefully drawn, because they function merely as a preliminary rough scan of the environment. Now, more valid and narrow psychological experiments have a starting point to verify the findings of this research to further analyze a potential pilot site.

## 7.4 Research limitations

Although the results of this research are valuable for the problem owner as well as for scientific purposes, all findings need to be taken in consideration with a certain caution. Limitations are unavoidable while doing research. It is part of the research and therefore part of the research reflection. The following aspects are the biggest limitations of this research.

**Model limitations** In the first place, the largest limitation of this research is that neighborhood predictor relations are unfairly assumed to be linear, while in reality various other variables such as mediators as well as moderators transform the linear relation into diverse effect types. With the knowledge available, the model design assesses only a simple version of the neighborhoods' complex behavior interactions and does not show an ultimate outcome of flexible and social behavior based on the data and model extensions should include possible correlations. Not only are various complexities not taken into account for the model design, a lot of relevant predictors and interactions are entirely disregarded, for reasons of either lack of understanding as well as limitations to relevant data assess. A large deficiency is the neglecting of the impact of social norms and peer pressure coming from community-oriented incentives (Nolan et al., 2008). Furthermore, a large gap is the lack of neighborhood-specific input data on psychological predictors such as consumer attitudes related to DSM acceptance. Only socio-demographic predictors are taking into account which describe the behavior system for a large part, yet not ultimately. The model estimations are not complete, for psychological predictors did show a considerable effect on flexible behavior. However, the models accuracy increases when by the use of site-specific surveys, more psychological data can be included in the model.

Lastly, the numerous predictors of neighborhoods which have been included in the model, lead to a one-dimensional model result, while in reality, the behavior outcome would at least be two-dimensional. Not only is a DSO interested in a neighborhood's likely flexible load size, but also a flexible time space to where the load can be shifted to. Contrary, this model assumes that the flexible time space is all hours outside the peak hours, which in reality is questionable. The load shift would most probably take place more at night and the late evening hours than during the day in further model developments should take the time dimension into account. Furthermore, the model computes very simple load profiles based on generic data while in reality, not only would the base load profile be more diverse in terms of evening end morning peaks due to different occupancies and lifestyles, the PV profiles would in reality also more volatile and dependent on neighborhood-specific circumstances such as amount of shade, roof position and different types of technology. All in all, the model results are a basic version of the whole, complex energy behavior system which asks for further developments by means of a using variety of consumer profiles. Therefore, results from the model should be used carefully, because they function merely as a preliminary basic scan of the environment. Now, more valid and narrow psychological experiments have a starting point to verify the findings of this research to further analyze a potential smart grid pilot site.

**Assumption limitations** For the model design, this research formulated a set of assumptions in order to show a preliminary overview of neighborhood criteria. Due to the fact that the assumptions are based on a large and diverse amount of (scientific) literature which are mostly not entirely applicable for this situation, the assumptions which serve as the model's basis do show limitations which are the following. Firstly, the assumptions' reliability have many flaws; Due to lack of findings which describe the phenomenon for the case of The Netherlands more accurately, predictors which are taken into account might have been given a too large weight on its effect. Secondly, in some cases, the internal validity of the assumptions is questionable. Not all assumptions are based on solid findings on the causal effect of a predictor on the behavior outcome because merely a small research area has tested for causal relationships between predictors and behavior using an appropriate scientific methodology such as controlled trials which limitedly allowed to formulate assumptions for causal effects. Although some assumptions are formulated using additional internal validity analyses such as statistical tests and inductive reasoning, these findings do not give a guarantee that the causation ultimately exists. Furthermore, internal and external validity is to a certain extern inversely related; While for a specific situation multiple reasons exists for a occurrence of a phenomenon while for most situations in general, this is not the case. The aim of the literature study was to formulate assumptions which are at least generalizable for a community-oriented smart grid project situation in The Netherlands. Although the data presented findings which in mostly were, some assumptions did still lack external validity to some extent: most sources date from the first years of '10 for example and due to the fast developments of the smart grid, data from the year of 2010 might be less valid than assumed. Also, lack of data from Dutch cases lowers the generalizability of this research as well. The inclusion of more cases from different scopes and areas may provide more valid, reliable assumptions estimation. Yet, the use of a literature study to formulate the assumptions will always show minor limitations in validity and reliability. In the future, other research types would show more generalizable and reliable causal effects such as surveys, interviews and experiments.

**Scope limitations** Fourthly, the analysis does not include some future trends which will affect flexible load in a later stage. These are two things: the increase of energy efficiency, as pointed out by the writers (Funke & Speckmann, 2015) and the increase of one-person households (CBS, 2009). The trends both have an opposite effect and so, making a quick estimation on the trend as a whole is not that easy. This might go in both directions as well, for technology acceptance has often increased in the past before, yet maybe not in this case. Although it is included in the model, the largest system regarding peak load - the EV - has not been tested specifically. Especially smart EVs are expected to fulfill a considerable role in demand flexibility due to Vehicle to Grid (VtG) technology. It may play a key role in DR as it can smooth out the consumption profiles by connecting day time charging and evening time discharging. The narrow model's scope can be expanded by the inclusion of more smart grid solutions: Flexibility from other appliances such as standby devices, EVs and heat pumps would improve the models function to estimate project sites for a whole range of smart grid solutions. This may concern other types of end-user flexibility, but also other behavior such as energy efficiency and energy curtailment.

Lastly, another drawback is the lack of a business case; Incorporating financial cost-benefit analyses would allow for a greater model's involvement into grid planning processes of DSOs. Both before and after the implementation of any behavior change intervention, cost-effectiveness and return-on-investment which are not only compared to operational activities (not implement the intervention at all), but equally important, compared to other interventions that can result in similar outcomes but in a far more or less costly manner (Frederiks et al., 2, 2015). Concerning community incentives, they may show themselves effective, but also ask for a higher initial investment. At the same time, it is also imperative to consider the socio-demographic and psychological profiles of individual consumers and households, to ensure behavioral strategies are appropriately tailored and customized to the target population of interest. In studies on energy savings, social interactions have proven themselves to be the least cost effective option (Abrahamse & Steg, 2013). Further research should evaluate these findings for the situation of flexible behavior.

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## Appendixes

### Appendix I: Research topic scopes

A visual, shown below indicates the relative research attention of research topics relevant for this research. It shows what other topics researchers mostly related to either smart grids, micro grids, demand response and local energy communities. The figures are based on the quantity of search results of a topic combination as a share of the total number of topic search results within the Web of Knowledge (WoK) database for scientific literature. It shows that research on smart and micro grids has a mainly technological scope whereas research on DR and local energy communities have a rather social and behavioral scope. Another finding is the large emphasis of electricity storage technology within the topics smart and micro grid; Also, the lack of research of local energy communities within research on smart and micro grids and demand response (indicated in red) is noteworthy. Up to now, technical, behavioral and social research scopes on residential energy have been barely integrated, contrary to many opinions on its importance to a functioning energy system (table 1).

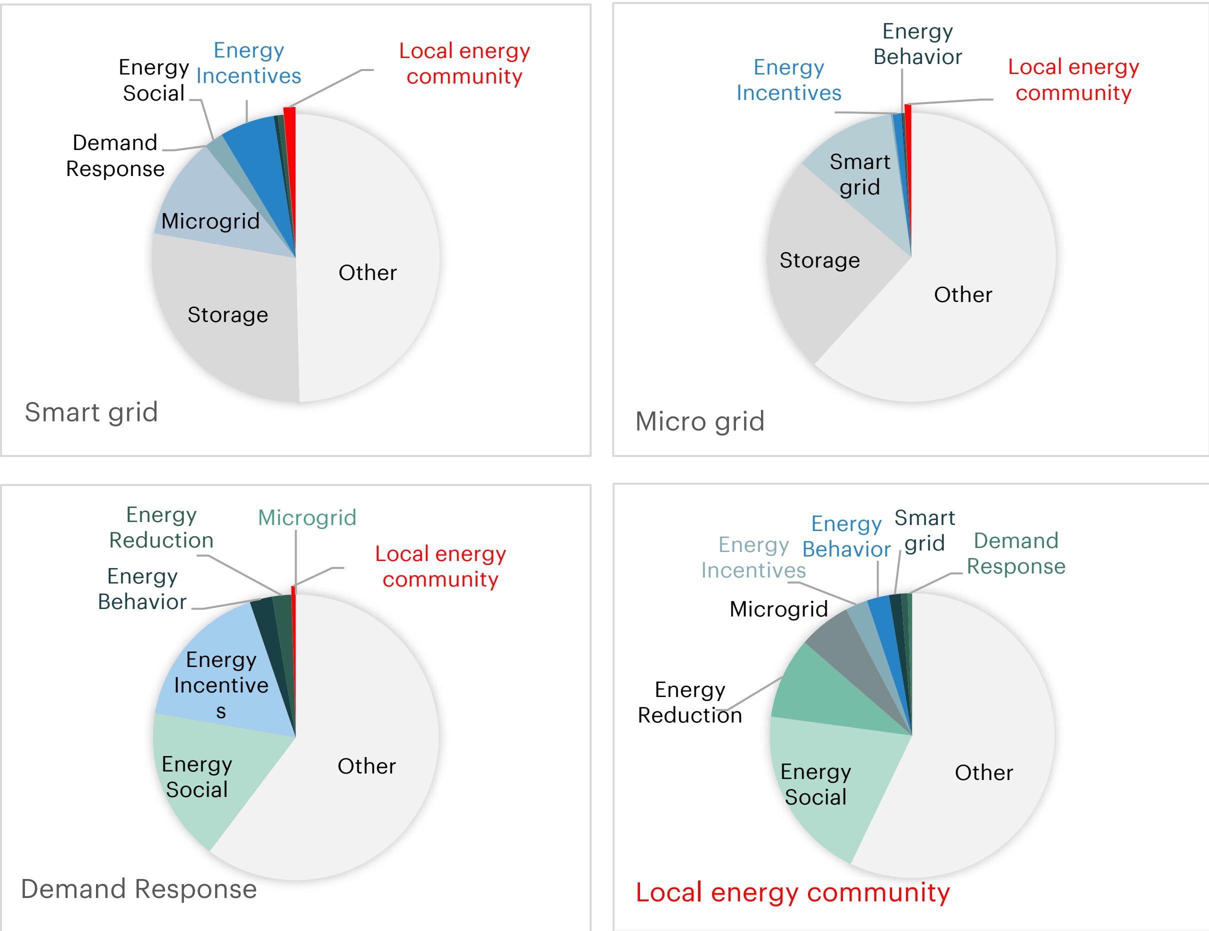


*Figure 30.* Research scope of smart and micro grids, demand response and local energy communities based on Web of Knowledge database topic combinations

## Appendix II: Literature study

### a. Literature study data quality assessment

As indicated in Section 4.1, each finding on a relation between predictors flexible behavior is assessed for the following three criteria. Firstly, a finding is externally valid when it is generalizable for a broader scope (Explorable, 2017). It addresses the applicability of the finding, in this case for flexible behavior in Dutch neighborhoods in particular. A finding is regarded externally valid if the context of the data based on the finding are similar to this research context. For example, the conclusions drawn from energy savings behavior within an area in Japan measured just after a nuclear energy crisis would have less generalizability for energy flexible behavior in Dutch neighborhoods nowadays than for example a German smart grid experiment. For this reason, two criteria apply to assess the external validity of a case: (1) the case shows a relation between a predictor and a flexible behavior aspect or the relation between them and (2) the research group is representative for a Dutch residential group. This representability depends on the number of differences in time, geographical situation and many others. Secondly, a finding is reliable when it describes a phenomenon accurately e.g. whether the occurrence of a certain variable can accurately predict if flexible behavior will not only increases, but also by how much in particular. Therefore, the reliability of the data tested by evaluating whether the research would give the same outcome when it is replicated. The factors increasing reliability are (1) research size and (2) number of cases. A numerical ranking between 1 and 4 for the categories external validity and reliability (the lowest and highest score respectively) conclude the inclusion assessment. Moreover, the reliability increases with the addition of case data, because the assumption holds that aggregated conclusion from multiple studies has a larger statistical power and is more robust than the original studies individually; A model based on a large number of reliable cases evaluates community-oriented incentives more accurately consistent. Therefore, when more cases on one phenomenon are available, a combination (an average) of their effect size is used for the model.

Thirdly, the internal validity of a finding describes the extent to which the finding follows the principle of cause and effect (Explorable, 2017), that is to say whether the findings have not occurred by chance. An example is the extent to which the psychology of a person actually causes a behavior versus whether the other way around, a person's psychology is affected by his actions. Within this research, a case is regarded internally valid if its conclusion is statistically significant and if no other arguments and reasons are to be found for explaining the phenomenon. The internal validity test depends on the type of relations presented within the case. This is further explained in the following paragraph.

A significance assessment checks for the internal validity of the findings which is the following. The case can contain one of the three following relations. The relations may either be <u>regression</u> analyses (I). That is to say, neighborhood characteristics and behavior are described as respectively independent and dependent variables using a regression coefficient. Also, the data may contain <u>correlation</u> analyses of group characteristics and behavior (II). The difference between the first and the second group is that within the latter group the direction of the effect is not explicated: the variables could be both independent and dependent. Therefore, this group is only taken into consideration and further treated the same as the first group if the direction of the correlation is obvious, such as the evidently independent variable 'age'. Moreover, the data may define a <u>representation of a group characteristic</u> for certain situations, an over- or underrepresentation of characteristics within communities (III). For this data type, the relative difference of the characteristic between the test group and the control (or average population) group is used:

$$representation = \frac{characteristic\ group}{avg\ characteristic}.$$

Where:

Underrepresentation = representation < 100%

Overrepresentation = representation > 100%

For the first two data types (regression (I) and correlation (II) analyses), significance levels are given in the case. Then, the research result and the significance are retrieved directly from the case. Regarding the last group (III) (group characteristic proportions), the significance level may be obtained in two ways. If possible, significance may be directly retrieved from the available data. If not, it may be retrieved from a Chi-square or a Fishers Exact statistical test. Special attention went to the control group; In order to derive meaningful effects, characteristics of specific (behavior) groups need to be compared to an average group. For this reason, a necessary criterion is the presence of the total/average population characteristic. The data quality assessment is summarized in the following figure.

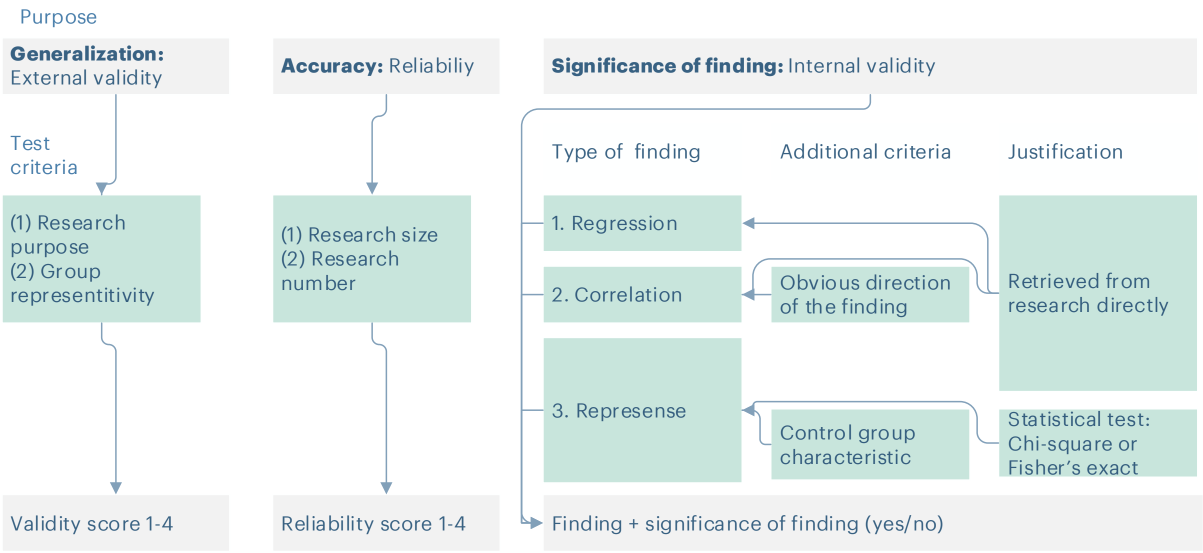


*Figure 31. Case data quality assessment*

## b. Case assessments

The following table summarizes the case assessments. It shows that most cases are valid (internally and externally), but that not all cases are reliable; When the research would be repeated then the outcome would differ with some cases.

| Case | External validity | Reliability | Internal validity |
|---|---|---|---|
| **1** | 4 | 4 | - |
| **2** | 4 | 3 | (Obvious) |
| **3** | 4 | 4 | Yes |
| **4** | 4 | 2 | Yes |
| **5** | 3 | 4 | Yes |
| **6** | 3 | 2 | Yes |

*Table 11. Summary of the cases' quality*

### Flexible load

| | |
|---|---|
| **Case 1** | Technical and Future Potential of Demand Response |
| **External validity** | (1) Relates household size and smart appliances to realizable flexible load<br>(2) The German and Dutch population has cultural similarities and weather conditions are similar. This case (Harz) is a rural area, yet the appliances used are fairly the same within regions. Slightly dated research. |

→ All criteria met, so external validity is a score of 4
.

**Reliability**

Survey of 28.000 participants is a large research size.

→ Due to the large scope and size, the reliability is a score of 4.

**Internal validity**

No explicit internal validity assessment

→ External validity lacking

**Analysis and findings**

The case shows a detailed analysis of flexibility potential within a 20-year amount (GWh) time frame per household size for the following applications: Electrical storage heaters, washing machines, tumble dryers, dish washers, storage water heater, refrigerator and freezer. Of all these appliances, washing machines, tumble dryers, dish washers, refrigerators and freezers are included within this research. The total flexibility is taken as a share of total energy use per household size.

| **Appliance/ Household size** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **Washing machine** | 2,3 | 4,1 | 2,6 | 1,4 | 0,4 |
| **Tumble dryer** | 1,7 | 6,2 | 4,8 | 2,8 | 0,9 |
| **Dish washer** | 1,5 | 4,6 | 3 | 1,7 | 0,5 |
| **Refrigerato r** | 15,2 | 15,7 | 6,9 | 2,9 | 0,7 |
| **Freezer** | 3,3 | 7,8 | 4 | 2 | 0,6 |
| **Absolute** | 24 | 38,4 | 21,3 | 10,8 | 3,1 |
| **Total use (GWh/20ye ars)** | 460 | 680 | 820 | 920 | 1060 |
| **Relative** | 62,5% | 100,0% | 55,5% | 28,1% | 8,1% |
| **Total (%)** | **5,2%** | **5,6%** | **2,6%** | **1,2%** | **0,3%** |

*Table 12. Flexibility potential per household size 1 to 5 in percentage of total peak demand*

Residents have a DSM potential (realizable flexible load of cold and wet appliances) of 5,6% to 0,3% depending on the amount of people in households. This might decrease to 38% in the future due to the increase of energy efficiency (time frame is not defined) and might increase due to the addition of storage appliances.

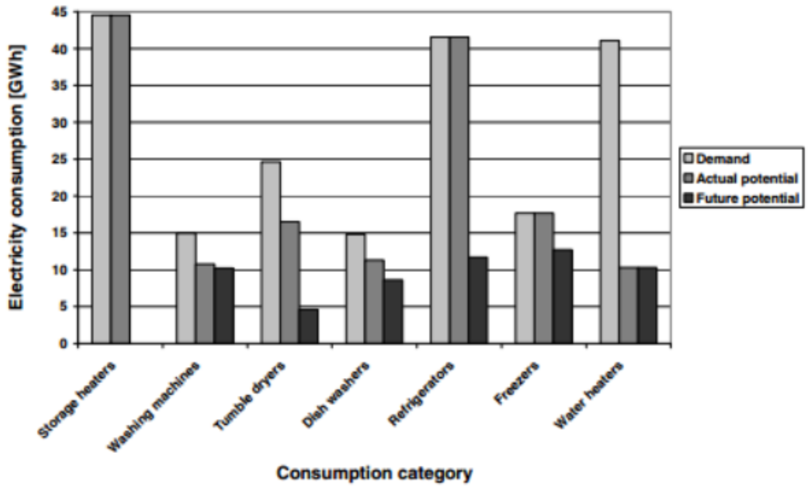


*Figure 32. Actual electricity demand and actual DSM potential as well as future DSM potential of all households*

*Table 13. Case assessment based on source: Funke & Speckman (2010)*

| **Case 2** | **Price, environment and security: Exploring multi-modal motivation in voluntary residential peak demand response** |
|---|---|
| **External validity** | (1) Relates (smart) appliances to flexible load<br>(2) The New Zealand's and Dutch population has cultural similarities and weather conditions are similar. This is a suburban area which may represent a large part of the Netherlands., yet the appliances used are fairly the same within regions. Up-to-date article<br>→ All criteria met, so validity is a score of 4. |
| **Reliability** | (1) Survey of 400 participants is a medium-sized research size.<br>→ Due to the medium-sized scope and size, the reliability is a score of 3. |
| **Internal validity** | (Obvious causation) |

**Findings**

The case shows a maximum evening (voluntary) flexibility of 7,3%. This includes: washing machines (1,9%), clothes dryer (0,1%), range (0,3%), microwave (0,5%), electric heater (1,9%) and heat pump (2%). This differs slightly with the first case, which shows a DSM potential for washing machines of 0,6-0% and the clothes dryer of 0,9-0%).

| Peak time | Washing machine | Clothes dryer | Range | Micro-wave | Electric heater | Heat pump | All |
|---|---|---|---|---|---|---|---|
| **7:00–8:00** | 39.5 | 1.1 | 3.7 | 5.6 | 55.4 | 49.7 | 155.0 |
| **8:00–9:00** | 30.2 | 2.9 | 5.8 | 8.8 | 44.6 | 40.4 | 132.7 |
| **Morning average** | 34.9 | 2.0 | 4.7 | 7.2 | 50.0 | 45.0 | 143.8 |
| **% Morning peak** | **2.4** | **0.1** | **0.3** | **0.5** | **3.4** | **3.1** | **9.9** |
| **18:00–19:00** | 32.6 | 2.4 | 28.6 | 6.4 | 36.8 | 38.7 | 145.6 |
| **19:00–20:00** | 32.6 | 1.8 | 8.6 | 4.7 | 28.1 | 27.5 | 103.3 |
| **Evening average** | 32.6 | 2.1 | 18.6 | 5.5 | 32.5 | 33.1 | 124.5 |
| **% Evening peak** | **1.9** | **0.1** | **1.1** | **0.3** | **1.9** | **2.0** | **7.4** |

*Table 14. Evening peak per appliance. Source: Gyamfi & Krumdieck (2012)*

*Table 15. Case assessment based on source: Gyamfi & Krumdieck (2012)*

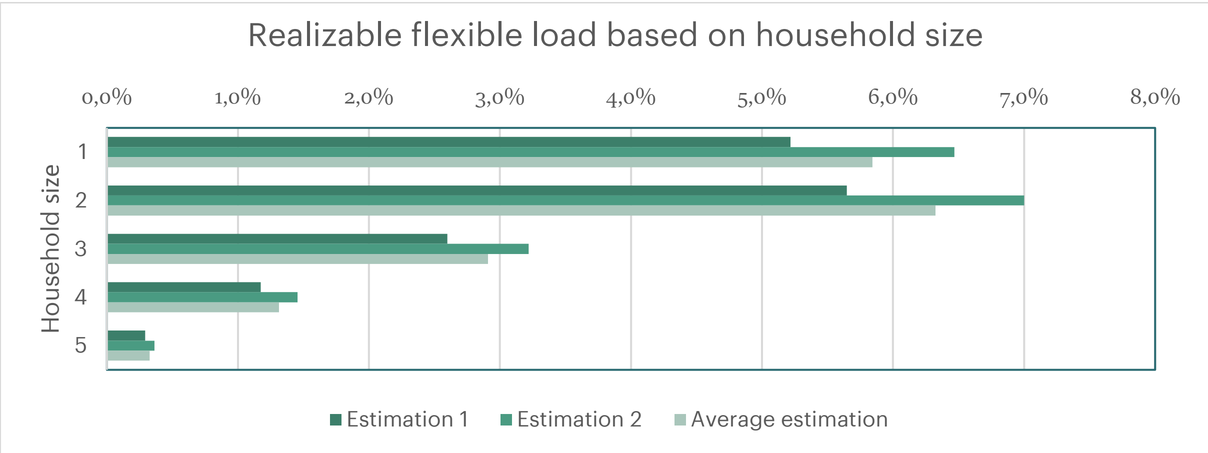


*Figure 33. Flexibility analysis result per household size in percentage of total peak demand. Estimation 1 based on case 1, estimation 2 based on case 1+2.*

| **Case 3** | **Public perceptions of demand-side management and a smarter energy future** |
|---|---|
| **External validity** | (1) Relates consumer psychological attitudes to DSM acceptance<br>(2) The UK and Dutch population has cultural similarities and weather conditions are similar. The survey is taken under a demographic representative group. Recent article.<br><br>→ Two criteria met, so validity is a score of 4. |
| **Reliability** | (1) Survey of 2441 participants is a large research size.<br><br>→ Due to the representative scope and size, the reliability is a score of 4. |
| **Internal validity** | Only significant findings (shown with *) are taken into account. |
| **Findings** | The regression analysis within the research is the following (table below). It shows significant independent variables for: 'preparedness to reduce energy use', 'time willing to spend thinking about electricity', 'interest in energy information', 'willingness to share energy data', 'concern about climate change' and 'affordability concerns' with the dependent variable 'DSM acceptance'. |

**Table 2 | Predicting DSM acceptance from perceptions about household energy use, and broader societal concerns.**

| | *r* | *B* (SE) | *t* | *B* (SE) | *t* |
|---|---|---|---|---|---|
| Preparedness to reduce energy use | 0.28** | 0.16 (0.02) | 7.49** | 0.13 (0.02) | 5.99** |
| Time willing to spend thinking about electricity | 0.24** | 0.22 (0.04) | 5.33** | 0.17 (0.04) | 3.99** |
| Interest in energy information | 0.24** | 0.38 (0.06) | 6.11** | 0.35 (0.06) | 5.63** |
| Willingness to share energy information | 0.35** | 0.39 (0.03) | 12.73** | 0.37 (0.03) | 12.10** |
| Concern about climate change | 0.26** | | | 0.17 (0.03) | 6.68** |
| Concern about energy security | 0.05* | | | 0.03 (0.04) | 0.66 |
| Affordability concerns | −0.02 | | | −0.10 (0.03) | −2.92* |
| Adjusted $R^2$ | | | 0.19 | | 0.21 |
| *F* change | | | 129.93** | | 15.82** |

* = $p < 0.05$, ** = $p < 0.01$. *B* = unstandardized beta coefficients, SE = standard error. $N$ = 2,211, with pairwise deletion for missing data. Variables were coded so that higher values indicated higher levels of that factor, for example, higher values of concern indicate greater concern. Collinearity tests yielded acceptable variance inflation factor (VIF) levels[30]. (Here *t* is a test of statistical significance; *r* refers to Pearson's correlation coefficient.)

*Table 16. UK representative survey regression analysis with DSM acceptance as dependent and energy consumption perspectives as dependent variables. Source: Spence et al. (2015)*

*Table 17. Case 3 analysis: DSM acceptance based on energy consumption perspectives. Based on source: Spence et al. (2015)*

| Case 4 | From command and control to local democracy? |
|---|---|
| **External validity** | (1a) Relates urbanity level to community affinity<br>(1b) Relates collective agency to community project completion<br>(2) Scottish communities represent the Dutch total energy community population in cultural similarities. The weather conditions are somehow similar.<br><br>→ Criteria met, external validity score of 4. |
| **Reliability** | (1) A nation-wide research sample of 301 energy communities is a representative research size.<br>(2) Scottish and Dutch communities differ due to other standards for definition and proximity: spatial differences. The British author concludes: "A UK analysis would be necessary to substantiate the findings." (p.2)<br><br>→ Due to the large scope and size differences, the reliability of the data is 2. |
| **Internal validity** | Table 22 output has a Fisher's exact test: $p < 0{,}001$ for the smallest difference (accessible rural).<br><br>a: The data for 'collective agency' is significant.<br>b: The data for urbanity is significant.<br><br>2: The difference between the total population and the community group is significant. Therefore, urbanity indicates community presence and continuity. |
| **Additional criteria** | Retrieved data from the UK government shows the average urbanity level. |

**Findings**

a) The number of years of community oriented activity have a 9,6% positive effect on renewable energy project completion (significant regression value).
b) The relative difference of urbanity level for communities and the total population is presented in the following table. Urban areas and accessible small towns are significantly underrepresented within communities and whereas remote and rural areas are significantly overrepresented. The tables 22 show the SPSS output for the smallest difference (accessible rural). Whereas the Chi Square test is invalid, the Fisher's exact test shows a p<<0,05.

| Urbanity level | Scotland-wide % | Energy Communities % | Relative difference |
|---|---|---|---|
| **Large urban** | 38,9 | 7 | **-82%** |
| **Other urban** | 30,6 | 6 | **-80%** |
| **Accessible small towns** | 8,5 | 5 | **-41%** |
| **Remote small towns** | 2,6 | 4 | **54%** |
| **Very remote small towns** | 1,2 | 6 | **400%** |
| **Access rural** | 11,6 | 15 | **29%** |
| **Remote rural** | 3,4 | 15 | **341%** |
| **Very remote rural** | 3,1 | 42 | **1255%** |
| | **100** | **100** | |

*Table 18. Relative proportion of urbanity level for the average and community group*

**Average * Communities Crosstabulation**

Count

| | | Communities: Acces | Communities: Other | Total |
|---|---|---|---|---|
| Average | Acces | 34 | 0 | 34 |
| | Other | 11 | 256 | 267 |
| Total | | 45 | 256 | 301 |

**Chi-Square Tests**

| | Value | df | Asymptotic Significance (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 218,053[a] | 1 | ,000 | | |
| Continuity Correction[b] | 210,577 | 1 | ,000 | | |
| Likelihood Ratio | 162,244 | 1 | ,000 | | |
| Fisher's Exact Test | | | | ,000 | ,000 |
| N of Valid Cases | 301 | | | | |

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 5,08.

b. Computed only for a 2x2 table

*Table 19. Spss output urban level difference*

*Table 20. Case 4 analysis: Urbanity level represented within communities. Based on source: Hagget et al. (2012) and Scottish government (2014)*

| **Case 5** | **Community Energy in Scotland: the Social Factors for Success** |
|---|---|

**External validity**

(1) Relating community primary goals to communities reaching developmental stage operational development stage
Reaching a far development stage as a group indicates community success potential
(2) Scottish communities represent the Dutch energy community population in cultural similarities. The weather conditions are somehow similar.

→ The fourth criteria is slightly not met, so external validity is scored 3.

**Reliability**

(1) 360 Energy communities is a large research size. A national-wide research is a representative research scope.

→ Due to the large scope and size, the reliability is scored 4.

**Internal validity**

Table 23 output has a Fisher's exact test: p < 0,001 for the smallest difference (environmental objectives)

1: The data for 'primary motivation' is significant.

**Additional criteria**

The community primary motivation is shown for both the total population and the group in operational phase and so, the data is suitable for analysis.

**Findings**

The relative difference among communities with primary motivation is shown in the following table. Economic motivations have had a negative effect on taking the community into the operation phase whereas environmental and motivations for control/autonomy have had a positive effect (of which the latter twice as much). The 'other' category will not be taken into consideration, since these motivations may be a summary of exceptional cases and therefore any drawn conclusions are risky. The smallest difference – environmental objectives – is significant: The SPSS-output from Table 23 shows a Chi Square p<<0,05.

| | Total communities | Operational communities | Relative difference |
|---|---|---|---|
| **Economic** | 62 | 56 | **-9,7%** |
| **Environmental** | 15 | 16 | **6,7%** |
| **Control/autonomy** | 19 | 22 | **15,8%** |
| **Other** | 7 | 6 | **-14,3%** |

*Table 21. Number of communities based on primary motivations. Source: Hagget et al. (2012)*

**Energy_communities * Population_total Crosstabulation**

Count

| | | Population_total | | |
|---|---|---|---|---|
| | | Environm | Other | Total |
| Energy_communities | Environm | 54 | 3 | 57 |
| | Other | 0 | 303 | 303 |
| Total | | 54 | 306 | 360 |

**Chi-Square Tests**

| | Value | df | Asymptotic Significance (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 337,709[a] | 1 | ,000 | | |
| Continuity Correction[b] | 330,320 | 1 | ,000 | | |
| Likelihood Ratio | 280,845 | 1 | ,000 | | |
| Fisher's Exact Test | | | | ,000 | ,000 |
| N of Valid Cases | 360 | | | | |

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 8,55.

b. Computed only for a 2x2 table

*Table 22. SPSS output primary motivation*

*Table 23. Case 5 analysis. Representation of community objectives in total and progressed communities. Analysis based on: Hagget et al. (2012)*

| **Case 6** | **Growing Grassroots Innovations: Exploring the Role of Community-Based Initiatives in Governing Sustainable Energy Transitions** |
|---|---|
| **External validity** | (1) Relating socio-demographic variables to grassroot communities (Transition Towns). This innovative type of energy community differs from the research scope<br>(2) Research is UK based which represent the Dutch energy community population in cultural similarities. The weather conditions are somehow similar. Slightly dated (2009).<br><br>→ Criteria not entirely met, so external validity is scored 3. |
| **Reliability** | (1) The findings are based on a UK-wide survey to 200 involved persons of grassroot communities with a reasonable response rate of 59 (27%). 'The respondents are broadly representative of the sample population' as indicated by 'ethnographic observation'.<br><br>→ Due to the small scope and size, the reliability is scored 2. |
| **Internal validity** | Spss output has a Fisher's exact test: $p < 0{,}001$ for the smallest difference |
| **Findings** | (see table below) |

| | **Total population** | **Grassroot communities** | **Relative difference** |
|---|---|---|---|
| **Economic activity** | 78% | 82% | **+4,9%** |
| **Part-time employed** | 16% | 24% | **+225%** |
| **Self employed** | 8% | 26% | **+62,9%** |
| **Age group: 45-64** | 37% | 50% | **+61%** |
| **Age group: 65+** | 20% | 3% | **-85%** |

The grassroot community population represents 15% of the total UK population. The smallest difference – economic activity – is significant: Whereas the Chi Square test is invalid, the SPSS-output from Table 24 shows a Fisher's test of $p << 0{,}05$.

**Tot_population * Grassroot_comm Crosstabulation**

Count

| | | Grassroot_comm | | Total |
|---|---|---|---|---|
| | | Econ_act | Econ_n_a | |
| Tot_population | Econ_act | 46 | 0 | 46 |
| | Econ_n_a | 2 | 11 | 13 |
| Total | | 48 | 11 | 59 |

**Chi-Square Tests**

| | Value | df | Asymptotic Significance (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---|---|---|---|---|---|
| Pearson Chi-Square | 47,843[a] | 1 | ,000 | | |
| Continuity Correction[b] | 42,427 | 1 | ,000 | | |
| Likelihood Ratio | 45,598 | 1 | ,000 | | |
| Fisher's Exact Test | | | | ,000 | ,000 |
| N of Valid Cases | 59 | | | | |

a. 1 cells (25,0%) have expected count less than 5. The minimum expected count is 2,42.

b. Computed only for a 2x2 table

*Table 24. Spss output on economic activity*

*Table 25. Case 6 analysis. Representation of socio-demographic variables in UK grassroot communities. Analysis from: Seyfang & Haxeltine (2011)*

c. Additional cases

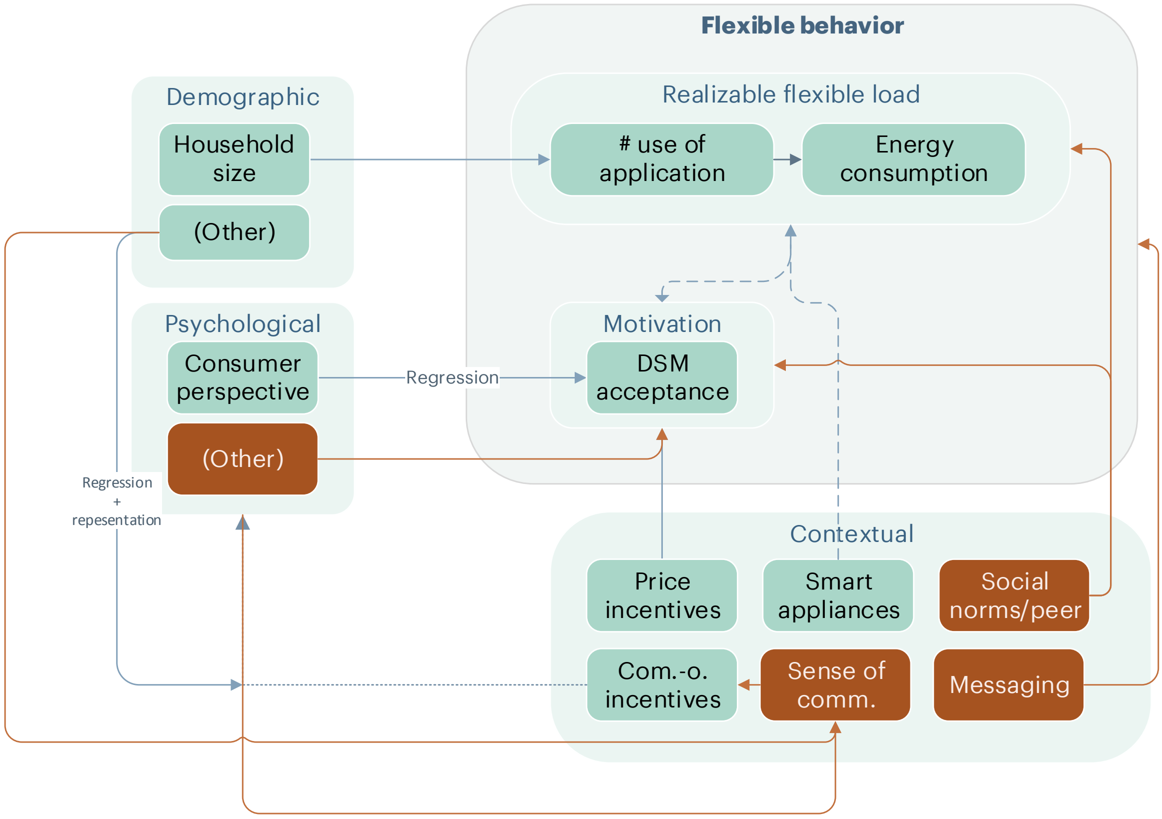


*Figure 34. Extended behavior framework. Based assumptions and limitations from Table 8*

**Endowment effect** An endowment effect can affect the behavior of PV technology owners; As a response to psychological loss-aversion, a good's value increases when the individual owns the good. Within classic behavior science experiments the endowment resulted in a duplication of a good's value whereas within a smart grid project it resulted in the increase of people's own solar energy usage. A considerable motivation of people exist to use their own solar energy: The participants owing PV panels in her research have enjoyed the concept of producing and consuming their own electricity, *even* without financial benefit in doing so. This concept explains partially small-scale energy project enthusiasm, because it shows a special engagement incentive for PV-owners. Moreover, the concept of *free* electricity seems particularly interesting for the consumer: consumers respond to free electricity prices noticeably more than to near-zero prices (McKenna & Thompson, 2014).

**Barriers** A few psychological barriers are the following. Firstly, Wüstenhagen et al. (2007) remark the Not In My Backyard (NIMBY) effect: peoples' positive attitude towards a thing only holds when they are not actually confronted with the matter themselves. Secondly, according to McKenna (2013), the largest barrier to behavior change is the 'hassle' it goes along with. Surprisingly, he also reveals that even though most people do not like this hassle, in fact, some find putting this effort in to DR enjoyable. Lastly, according to McKenna (2013), examples of cognitive barriers for energy behavior decisions are inattention, anchoring and menu-effects. These aspects explain the limited rationality of the energy consumer: Inattention refers to overlooking relevant aspects for the decision making. By the same token, anchoring refers to judgements based on irrelevant or arbitrary factors. Menu-effects refers to the simplification of options, reducing it to merely items standing out. The more complex consumer decisions are, the larger these factors play a role. Unintended effects from social norms also exist: The 'boomerang effect' shows that people with a low resource usage tend to increase their usage due to positive feedback rather than decrease more. On the other hand, this can be neutralized by the use of specific psychological labels (Clee and Wicklund, 1980).

All in all, previous research points out that psychological factors either enhance or limit energy friendly and also DR-related behavior motivation. Investigating the whole of their exact effect sizes and modeling them all into a resulting behavior estimation would be due to time restrictions and data limitations impossible: Unfortunately, no numbers yet exist on the size of endowment effect for locally produced electricity (McKenna & Thompson, 2014) as well as for most of the psychological barriers.

**Motivators to join energy communities** EEA (2013) mention that reasons for members to join a community are protection of the environment, financial benefits due to economies of scale, opportunities to get to know their neighbors. Newcomers in the area see opportunities to be accepted. A social hierarchy exists. Hoffmann & High-Pippert (2010) argue that civic participation is not a pure rational choice approach and results from a mix of social gratification plus civic gratification. Contrary to other research, participation in the case's community did not result from financial gratification. Docí & Vasileiadou (2015) have investigated the reasons for communities to participate (table below). There are three main goals for people to participate. Gain concerns one's motivation to increase or protect resources. In practice this concerns cutting energy cost and gaining energy in(ter-)depenende. Normative concerns the moral and/or social obligation of people to act appropriately. Hedonic means that people regard participating in an community as enjoyable: social connections and doing projects together are regarded as fun. The authors proclaim that different goals ask for different incentivizing strategies. Gain-dominant communities are open to all kinds of opportunities and incentives as long as it promises some benefit. Normative-dominant communities are more likely to act accordingly, yet on the other hand only if the costs do not increase and the act is not too complicated and time consuming. Then, hedonic reasons can be enhanced through its emphasis by local organizations. They conclude within their research that gain is the dominant reason for participation, followed by the normative one. Hedonic considerations seemed less important yet still present in only a part of the communities. It can therefore be concluded that communities *mostly* are open to various interventions as long as they are provided with a certain benefit. Moreover, a strategy to increase normative goal while unburdening the consumer is worthwhile. As a support some hedonic strategies can be applied. However, this might be slightly out of scope of the problem owner. For the problem owner it would be more suitable to create the right institutional, technological and process conditions. Concerning the institutional ones, Ostrom (1990) identified features of traditional communities which have successfully shared resources and argues that such features are notably lacking in today's world of energy use and carbon emissions. These include governance boundaries, rules and agreements, monitoring, conflict resolution and self-organization ability.

| Goal | Shown importance | Explanation | Strategy |
|---|---|---|---|
| **Gain (*focus*)** | High | Cutting energy costs<br>Independence (rural areas)<br>Interdependence (urban area) | Any strategy which promises benefit |
| **Normative (*focus*)** | Medium | Protection of the environment | Unburden |
| **Hedonic** | Low | Social goals<br>Get to know each other<br>Friendships | Can be emphasized by local organizations and connecting networks |

*Table 26. Motivations for participating in energy communities. The first two are the most cost effective to trigger. Based on source: (Dóci & Vasileiadou, 2015)*

**Predictors for behavior from community incentives** Concerning less qualitative cases, Taló et al. (2014) assesses factors important for Sense of Community (SoC). These are summarized below:

- The psychological dimension of being part of a territorial community: Feelings of membership, interpersonal sharing and emotional connection, show a significant relation with active community participation
- High civic engagement (activism for example) is also related to SoC
- Age; SoC increases as individuals reach the central and late stages of their life cycles. The adolescents, young adults and elderly show weaker forms of SoC.

**Importance of key community members** KTH et al., (2014) point out that some members are central to community dynamics while others are less engaging and acting at the boundary of the community. These different participation levels contribute to community functioning. Online social networks seem to contain a large, strongly connected core of high-degree nodes, surrounded by many small clusters of low-degree nodes. The network is held together by about 10% of the nodes with the highest communication degree (Hyang et al, 2013). According to Hoffman & High-Pipert (2010) the commitment of the 'few' transform the minimally engaged citizens into effective community programs. Networks can be destabilized by removing the key persons in it (Carley et al., 2001). Concluding, community' functioning depends on the existence of 'core' members.

## Appendix III: Detailed model design, assumptions and limitations

### a. Model detailed input

#### Neighborhood data

The following neighborhoods-specific socio-demographic data is used for the model.

- **Household size** Statline (2017) provides information on household size. It provides the following data: one-person households, households without children, households without children and average household size. Although in reality this is not always the case, the assumption holds that households with children are 2 person-households whereas households with children are >2-person households. The data allows to calculate the relative proportion of household size whereas the proportions combined with the average household size allows to calculate the average third household size which represents the average family size.
- **Age groups** Statline (2017) provides the total number of people categorized per age group: 0-15, 15-25, 25-45, 45-65 and 65+. The absolute numbers allow to calculate relative age group proportions within the neighborhood.
- **Urban level** Statline (2017) provides the urban level of an area show in a score where 1 is most the urban and 5 is most rural score. This number is based on the proximity of facilities and other households.
- **Electricity use** Statline (2017) provides an area-specific yearly electricity usage which is given as the average KWh usage per resident.

#### Base load profiles

NEDU (2017) provides open source electricity base load profile prognoses for 2020 as fractions of electricity current. The sum of these fractions shows a yearly electricity profile sample (365 days within 10-minute intervals). The following figure shows prognoses of the daily electricity demand for the months January, April, July and October (in normalized values where 1 is the average demand). It points out the difference of electricity demand for winter and summer months: The electricity demand in January and October is above average whereas July and April is below average. The electricity demand between summer and winter scenarios differ considerably. Moreover, the monthly electricity demand also depends on the day of the month: The average electricity demand differs between 4% within the July scenario and 7% within the January scenario.

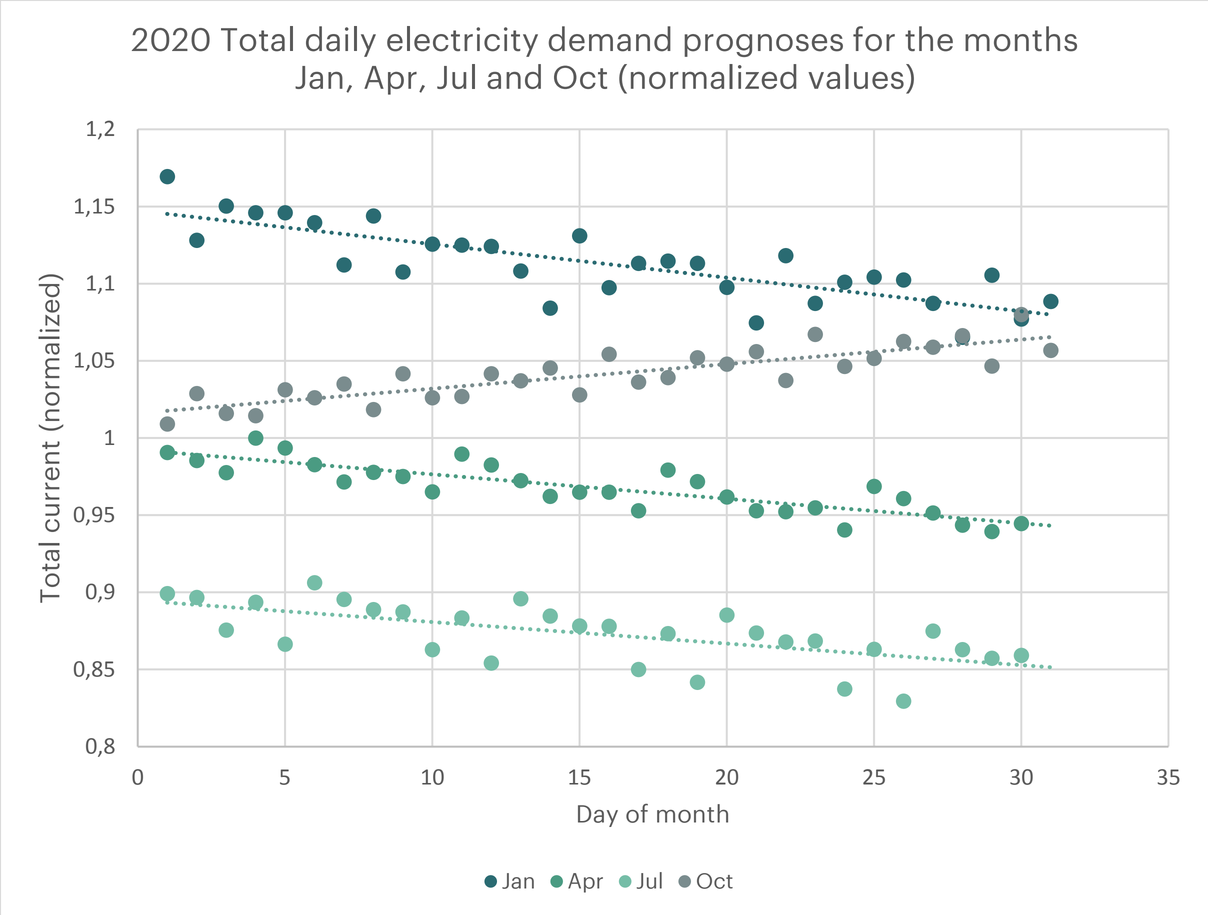


*Figure 35. Daily load profile size categorized per month (normalized). Based on database: NEDU (2017)*

The seasonal differences in peak demand are even larger than the total day electricity demand. The figure below shows that the total day (normalized) demand yearly varies approximately between 60% and 100% while peak demand yearly varies between 55% and 100%. The January total demand specifically varies between 90%-100% while the corresponding peak demand varies between 85%-100%. The July scenario on the other hand shows a smaller variation, yet peak demand also differs more than the total demand (55%-65% versus 70%-77%).

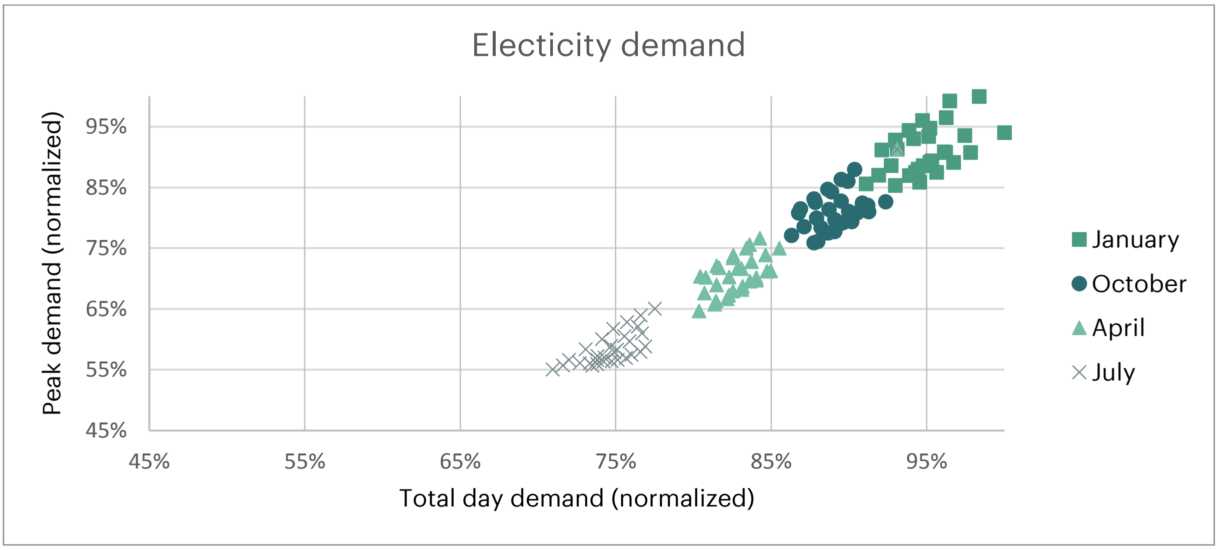


*Figure 36. Plot of total demand and peak demand of base load profiles (30 forecasted days in 2020). Based on source: NEDU (2017)*

The following calculation normalized the data. It was done by means of a division of all data points by the total sum of data points:

$$y\text{ (norm)}= \frac{y\,(o)}{factor1}$$

Where,

y(0) = previous electricity demand on time point t

factor1 = average sum of y(0): $\sum_{t=1}^{144} y\,(o)$, assuming the time frame are 144 10-minute intervals (= 24 hours * 6 data points per hour)

The average daily household electricity demand (P) from CBS transforms the normalized day profiles into neighborhood-specific day profiles (I) in the following way,

$$\text{average neighborhood daily demand} = \frac{P(household)*households}{230*365}$$

Where,

I= $\frac{P}{U}$ , assuming U is a constant (230V)

The neighborhood-specific load profile is then computed as y (t) = y (norm) * average neighborhood daily demand of which an example is given in the following figure. Although the data is rather generic to describe neighborhood-specific electricity demand per time-of-day, due to the lack of more specific data, this will do. The future model can be improved by scaling not only generic load profiles, but also using load profile categories based on e.g. lifestyles where day, evening and night demand differs more realistically.

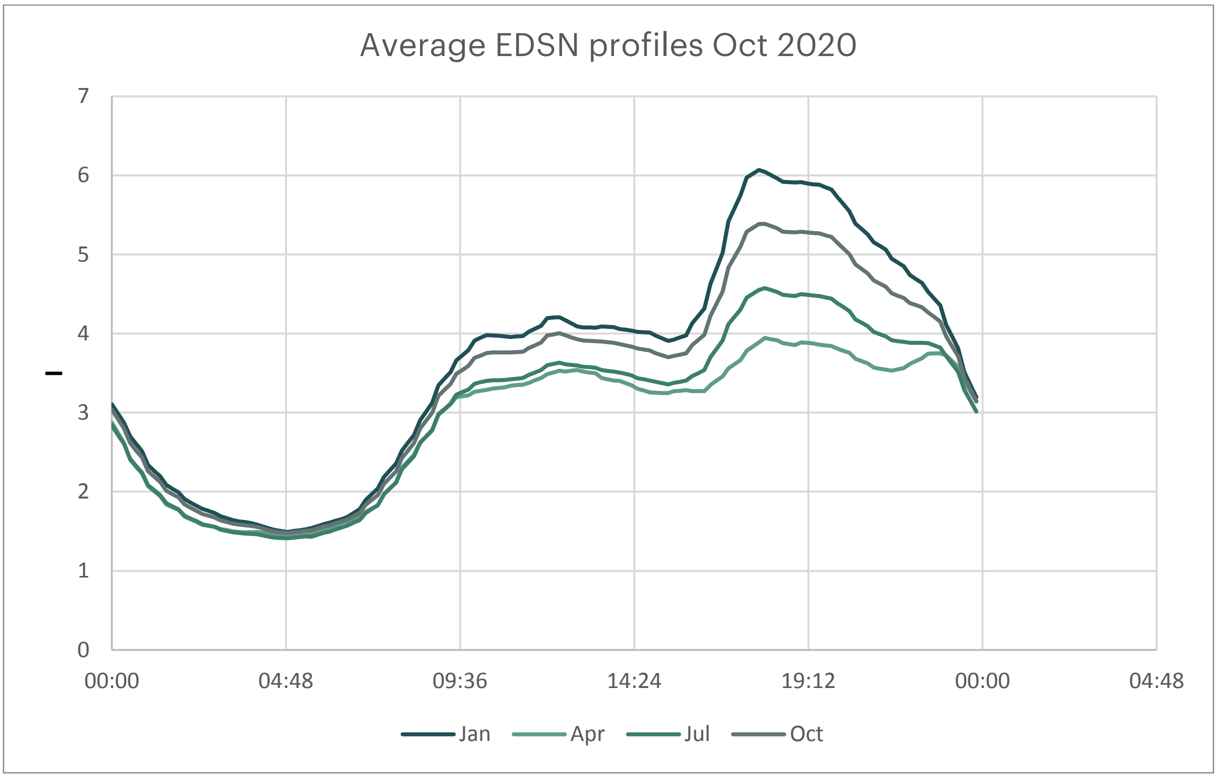


*Figure 37. Analysis of an average load profile categorized per month. Based on data source: NEDU (2017)*

### PV profiles

Elia (2017) provides open source Belgium-wide PV production data. This load profile data is assumed to be similar to the Dutch profiles, since both countries are small and fairly similar with regard to weather conditions (clouds, rain, coastlines). In reality, the weather is slightly different, the number of sun hours differ less during seasons in the southern country and a small community is subjective to more intermittency from isolation. Further sophistication of the model could include a small correction factor for these slight weather, scope and orientation differences. The retrieved data shows a yearly solar electricity production profile of 15-minute intervals. To make the data comparable to the 10-minute intervals of EDSN and EV profiles, the 4 hourly data points are transformed to 6 hourly data points by adding averages of the data between the first and second and third and fourth data point. This method does not transform the data optimally, yet for the purpose of this research, this rough transformation will do. Similarly to the EDSN data, these profiles will be normalized by dividing each data point by the sum of all data points. Then, monthly day profiles are adjusted for specific neighborhood.

$$y\ (x) = y\ (norm) * factor$$

*Where,*

$$factor = \frac{installed\ PV\ in\ ampere}{highest\ value\ y\ (norm)}$$

highest value y(norm) = PV output with maximum sun in June

The following figure shows the daily PV production for the months January, April, July and October (in normalized values where 1 is the maximum PV production). It points out the difference of PV production for winter and summer months: The production in July and April is fairly high whereas July and April is very low. Surprisingly, a maximum production is very rare. Moreover, the monthly production also depends on the day of the month: The average production differs between 8% within the July scenario and 5% within the January scenario.

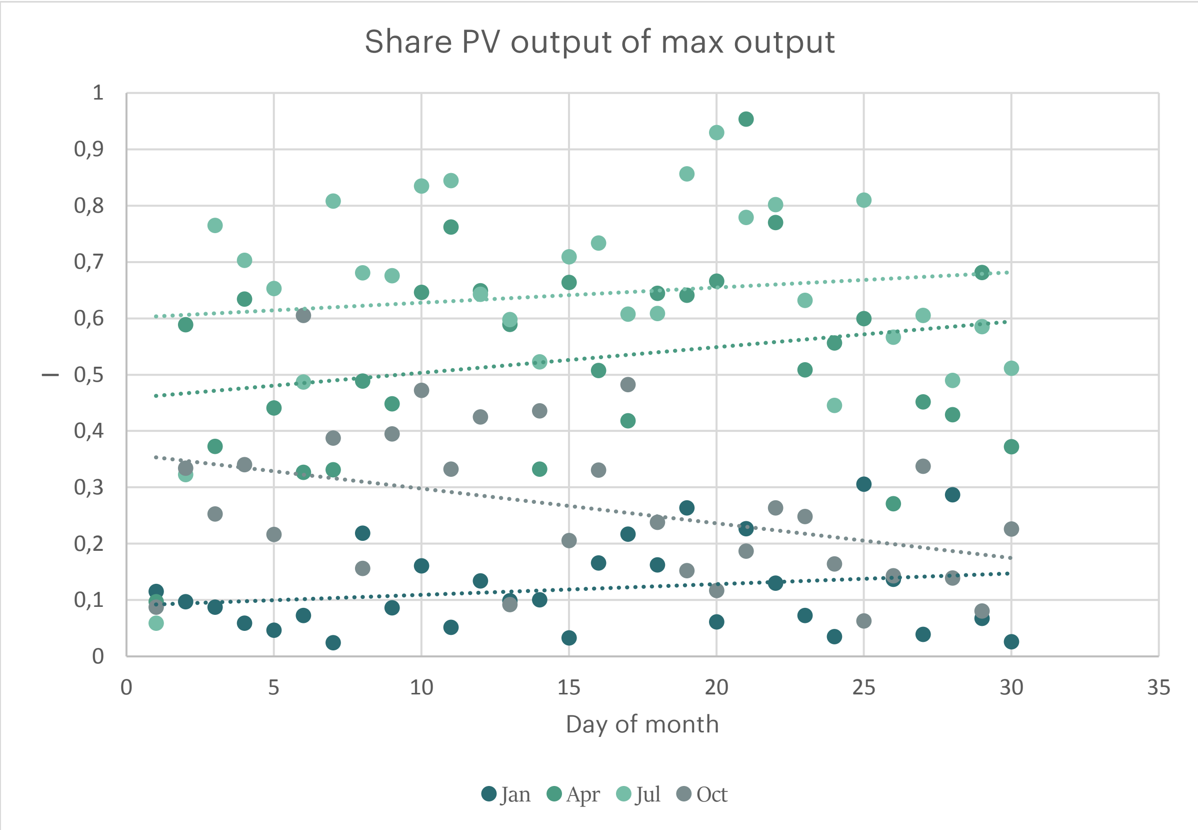


*Figure 38. Daily PV production categorized per month (as a share of maximum output). Based on database: NEDU (2017)*

Not only the total production differs, also the production time and peak production differ greatly. The following figure shows that the total production during winter is between 7 and 9 hours whereas the total production in summer is between 13 and 16 hours. The peak production differs between 5%-60% (winter) and 30%-100% (summer). The historical load profile input data for this are shown in Figure 38. Following from the data, winter peak generation load would not likely cause grid issues whereas the PV technology can cause not only a high but also a very long peak generation in summer. Nevertheless, a large PV installation in summer also means that solar energy is produced during peak hours, diminishing (an already low) peak demand.

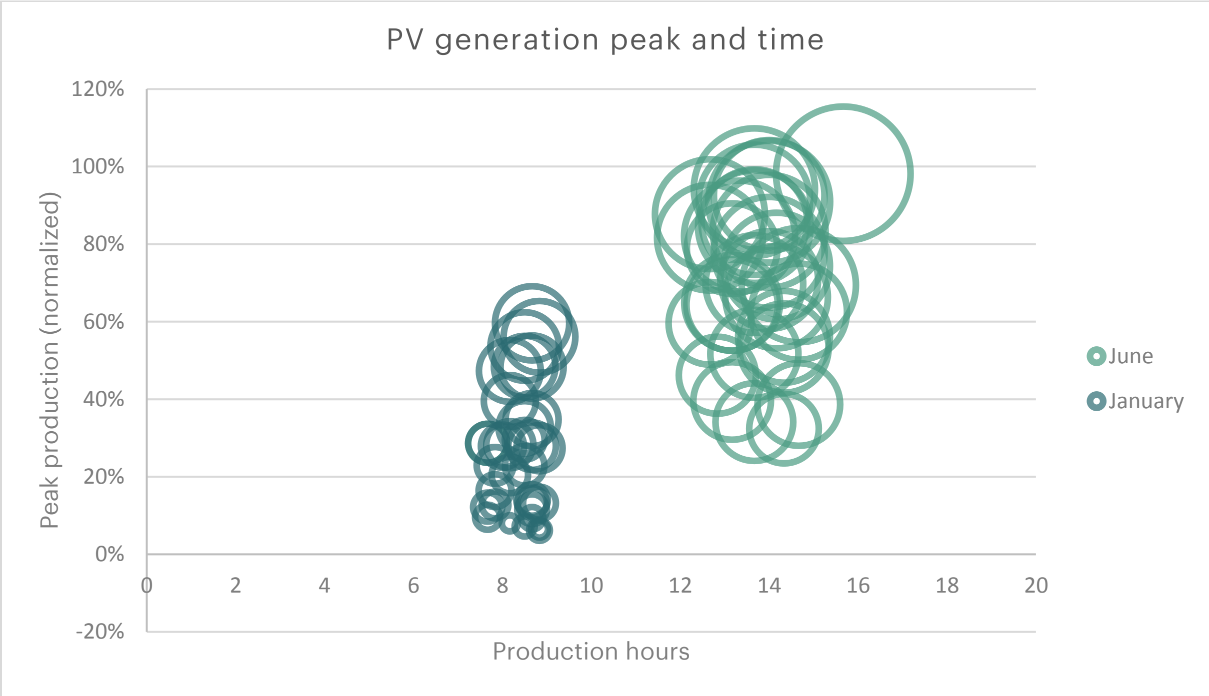


*Table 27. Bubble plot of production houses and peak production PV production profiles (30 historical days in 2016). Bubble size is the relative day production*

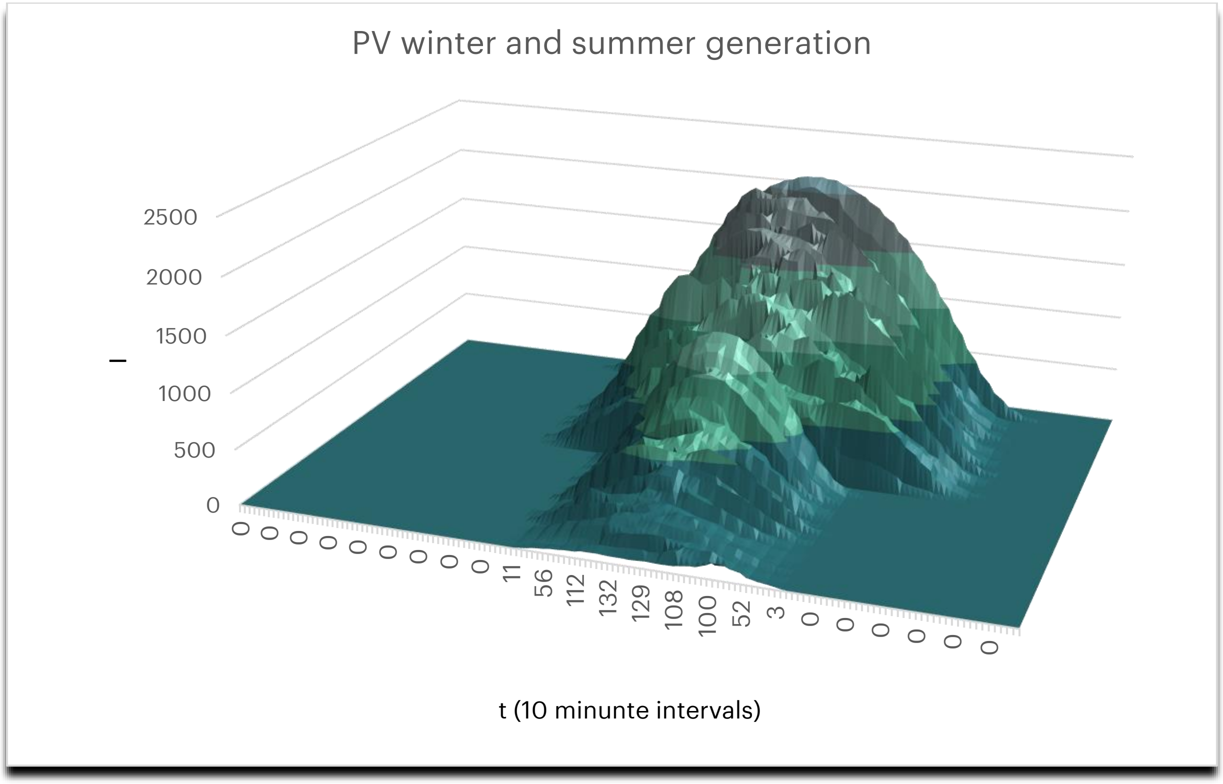


*Figure 39. PV generation in winter and summer 2016. Source: Elia.be*

## b. Model detailed functions

### Model relations

The following model computations precede the model function which estimates flexible behavior, which is described in Section 5.1.4. It calculates the individual neighborhood-specific behavior dimensions where relevant neighborhood-specific characteristics serve as predictors. The detailed behavior framework from Chapter 3 served as an input for the design of these computations. As previously told, three behavior dimensions (realizable flexible load, DSM acceptance and community affinity) are calculated separately. Due to lack of neighborhood-specific non-demographic data, only the black parts of the equation are used whereas the grey parts can be used in future research when the non-demographic data would be available.

**Realizable flexible load** Wet and cold appliances allow to realize end-user flexible load. The load size is depended on household size. Because the input data only involves 3 types of household size (1-person, 2-person and larger families, the following computation is included within the model.

$$flexibility = 5{,}8\%,* \ (1hh\%) + \ 6{,}3\% * (2hh\%) + 0{,}61\% \ (nhh\%)^2 - 4{,}99\% \ (nhh\%) + 0{,}1065$$

Where:

flexibility = the realizable flexible load for wet and cold appliances within a residential area (as a percentage of total peak demand)

((n)hh%)= the proportion of n people households within a residential area (one-, two- and n-person households)

n = average size of the third group (families)

The function simply adds the aggregated realizable flexible load of three household sizes, because the assumption holds that it only depends on appliance usage. 1 and 2-person household load are computed using the estimated coefficients. Because the large n-person household is mostly not a round number yet an average for all family houses (Appendix III-a, neighborhood input), the load is computed using a polynomic function (n=2), which is a derived from Figure 37's trendline (following figure). The assumptions for the trendline are the following. If one-person households are considered as an outlier, the flexible load data points below feature an polynomic function. The following equation: x= 2-5: y = $0{,}0061x^2 - 0{,}0499x + 0{,}1065$ (x= family household size), which only holds for household sizes 2 to 5.

The function is a sum of the flexibility potential of individual households in the neighborhood in which a possible correlation (e.g. of the household size or social behavior) is disregarded. The exponential function may also be used to compute the flexibility potential of a neighborhood for household sizes 2-5, yet that function is devious to get the same result. Because the function is non-linear, the best outcome results from summing the individual outcomes. Using average household sizes leads to a less accurate outcome. Nevertheless, computing it is still useful when it merely a small share of the neighborhood is taken as an average e.g. when in this case, more specific data on large families is lacking; The difference flexible load between large household sizes is smaller anyway, so the accuracy decrease is limited.

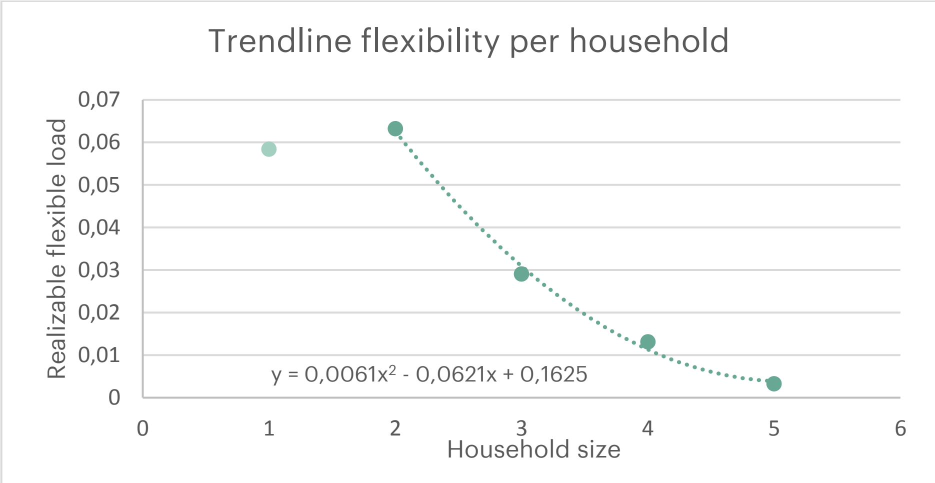


*Figure 40. Polynomic (n=2) Trendline computation for the estimation* of Figure 30 for *households 2 to 5 in order to estimate flexibility potential of an average household.*

**Behavior motivation** The following equation is included to calculate DSM acceptance from consumer attitudes. 6 separate behavior estimations are summed to one.

$$motivation = 21{,}8\% * (reduce\%) + 18{,}7\% * (think\%) + 3\% * (security\%) + 39{,}9\% * (share\%) + 34{,}5\% * (interest\%) - 34{,}5\% * (affordability\%)$$

Where:

motivation = A general acceptance for technical smart grid solutions within the neighborhood (as a factor)

(reduce%) = Proportion of people prepared to reduce energy use

(think%) = Proportion of people prepared to think about energy use

(security%) = Proportion of people having energy security issues

(share%) = Proportion of people prepared to share energy data

(interest%) = Proportion of people interested in energy

(affordability%) =

Proportion of people having affordability concerns with regard to DSM

**Likeliness community-oriented incentive response** The following equation is included to calculate community affinity from a various kind of predictors. Individual effects are added to one total estimation. The function is computes the relative community potential within a residential area based on this data is the following. Relative, in this case, refers to a comparison to an average likelihood of community affinity. In that sense, the factor refers to a better or worse community affinity than average.

$$community = 61{,}0\% * \ (age45 - 64\%) - 85\% \ * (age65 + \%) + (urban\ factor) + \ 225\% * (self\%) + \ 62{,}9\% * (partt\%) + \ 4{,}6\% * (degree\%) - \ 9{,}6\% * (collective) + 6{,}7\ (environment\%) + 15{,}8\%\ (autonomy\%) - 9{,}7\%\ (income\ )$$

Where:

(self%) = Proportion of self-employed people

(partt%) = Proportion of part time employed people

(degree%) = Proportion of people with a degree (any)

(collective) = Years of community activity

(environment%)=Proportion of people with primarily environmental objectives

(autonomy%)= Proportion of people with primarily objectives for energy autonomy

(income%)= Proportion of people with income generating objectives

community = Relative likelihood of community functioning and stability (as a factor)

(age45-64%) = Proportion of age group 45-64 years old, directly retrieved from Statline (2017)

(age65+%) = Proportion of people age group +65 years old, directly retrieved from Statline (2017)

(urbanfactor)= Factor allocated to one of the relevant urban categories. The following figure holds. It is based on literature data (Figure 12) where the Dutch urbanity factor (1-5) is related to a Scottish urbanity level and a corresponding factor. Because the distances in Scotland are larger than in the Netherlands, very remote settlements are disregarded while the 'Accessible rural' and 'remote rural' are taken as an average (coupled to urban factor 5). The following table sums the factors per urbanity level. Settlements of urban factor 4 and 5 are regarded as advantageous for community affinity, whereas the other factors are regarded as disadvantageous.

| Urban factor | Size |
|---|---|
| **1** | -82% |
| **2** | -80% |
| **3** | -41% |
| **4** | 54% |
| **5** | 1,85% |

Table 29. Urban factor impact estimation used within the model.

### Assumptions DSM acceptance

Within this research, the average DSM acceptance is regarded 43,8%. This is calculated by assuming a DSM acceptance of wet and cold appliances of 30% and 50% respectively (Spence et al. 2015) proportionate to their flexibility share of (cold and wet appliances contribute to 31% and 69% flexible load respectively, (Gyamfi & Krumdieck, 2012)).

### Peak mitigation equation

The following equation computes the load profile change due to flexible behavior. It reduces the peak load during peak times and increases the load outside peak times.

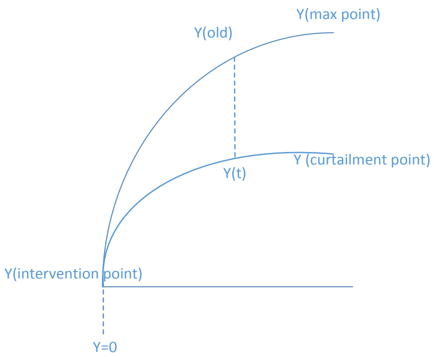


*Figure 14. Assumption for peak load mitigation. Based on source: Kobus (2015)*

$$y(t) = \frac{y^{curtailment\ point} - y^{intervention\ point}}{y^{max\ point} - y^{intervention\ point}} * \left(y^{old} - y^{intervention\ point}\right) + y^{intervention\ point}$$

Where:

$y(t)$= new electricity demand on time point t

$y^{old}$ = previous electricity demand on time point t

$y^{curtailment\ point}$ = new electricity demand at the maximum peak load point (≥ lowest $y^{intervention\ point}$)

$y^{intervention\ point}$ = energy demand on the intervention starting or ending time point (17:20 or 21:10)

$y^{max\ point}$ = peak electricity demand

The equation draws the new electricity demand between the intervention starting or ending time point (17:20 or 21:10) to the peak point (demand on a time point between 17:20 and 21.00 where the load is maximum) considering its previous shape.

If t = [one of the intervention time points], the equation left side equals zero (because $y^{curtailment\ point}$ = $y^{intervention\ point}$) leaving the equation as $y(t)$ = $y^{intervention\ point}$, which leaves the electricity demand at the intervention time unchanged.

If t = [time at the peak point] , $y^{max\ point} - y^{intervention\ point}$ equals $y^{old} - y^{intervention\ point}$, leaving the total equation as $y^{curtailment\ point} + y^{intervention\ point} - y^{intervention\ point} = y^{curtailment\ point}$.

## Appendix IV: Data analysis

### a. Statistical analyses

The Wilcoxon signed rank test tests whether two related samples come from the same distribution (SciPy.Org, n.d.). The data set meets these criteria since it resembles two load sizes per 10-minute time point leading to an n=144. The following tables are the SPSS-test output for the load profiles in the Figures 24 and 25 to test if the load profile changes from to the behavior interventions are significantly different. Following from the SPSS-output, both load profile changes are indeed significantly different.

**Hypothesis Test Summary**

| | Null Hypothesis | Test | Sig. | Decision |
|---|---|---|---|---|
| 1 | The median of differences between Vlasakkers_Base and Vlasakkers_Intervention equals 0. | Related-Samples Wilcoxon Signed Rank Test | ,001 | Reject the null hypothesis. |

Asymptotic significances are displayed. The significance level is ,05.

**Hypothesis Test Summary**

| | Null Hypothesis | Test | Sig. | Decision |
|---|---|---|---|---|
| 1 | The median of differences between Base_profile and Intervention_profile equals 0. | Related-Samples Wilcoxon Signed Rank Test | ,000 | Reject the null hypothesis. |

Asymptotic significances are displayed. The significance level is ,05.

*Table 28. Wilcoxon ranked test for base case and likely load profile with behavior change. SPSS Statistics 23 output for West van Schaarsbergen, Arnhem*

### b. Sensitivity analyses

**DSM acceptance sensitivity** A sensitivity analysis is conducted using the case of West of Schaarsbergen in Arnhem to address the relevance of one not-available predictor - primary community motivation – on community affinity. The next figure below shows how much the community affinity score would be affected when the primary motivation moves from 100% of the community proportion aiming for energy autonomy to 100% of the community proportion aiming for income generation. Since income generation is assumed to have a negative effect (-9,7%) on community functioning and energy autonomy is assumed to have a positive effect (15,8%) on community functioning, it seems that the community score decreases by the proportion of people in the area which are striving for energy autonomy, yet the difference in this case is rather small. This would have to do with a large weight of other factors such as urbanity level.

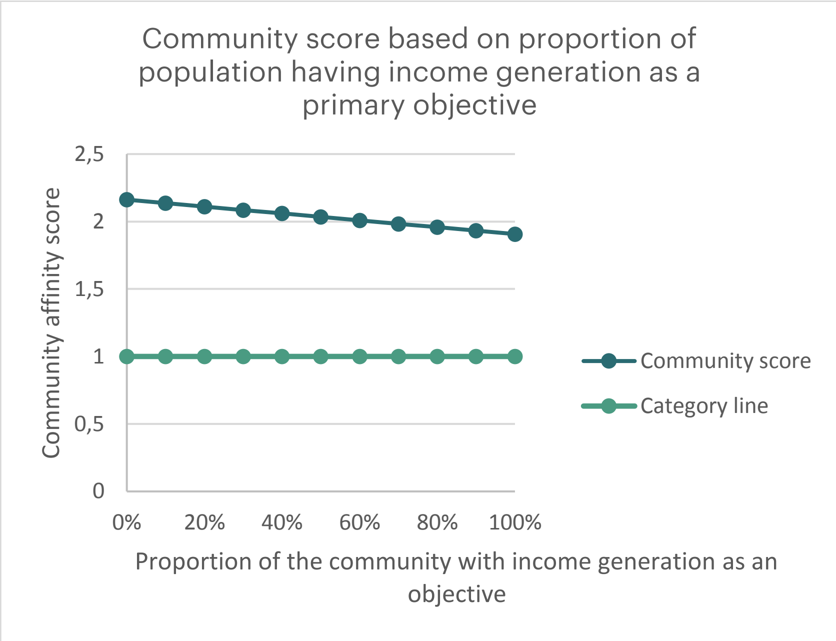


*Figure 41. Sensitivity of the community score based on the addition of community primary motivations 'income generation' and 'energy autonomy' for the case of West of Schaarsbergen*

**Solar sensitivity** The following two figures are solar sensitivity analyses for the neighborhood West van Schaarsbergen in Arnhem. They resemble an average flexible winter and summer load profile including 30 historically-based PV production scenarios from 0,5MW installed PV technology, which are sorted by production peak size.

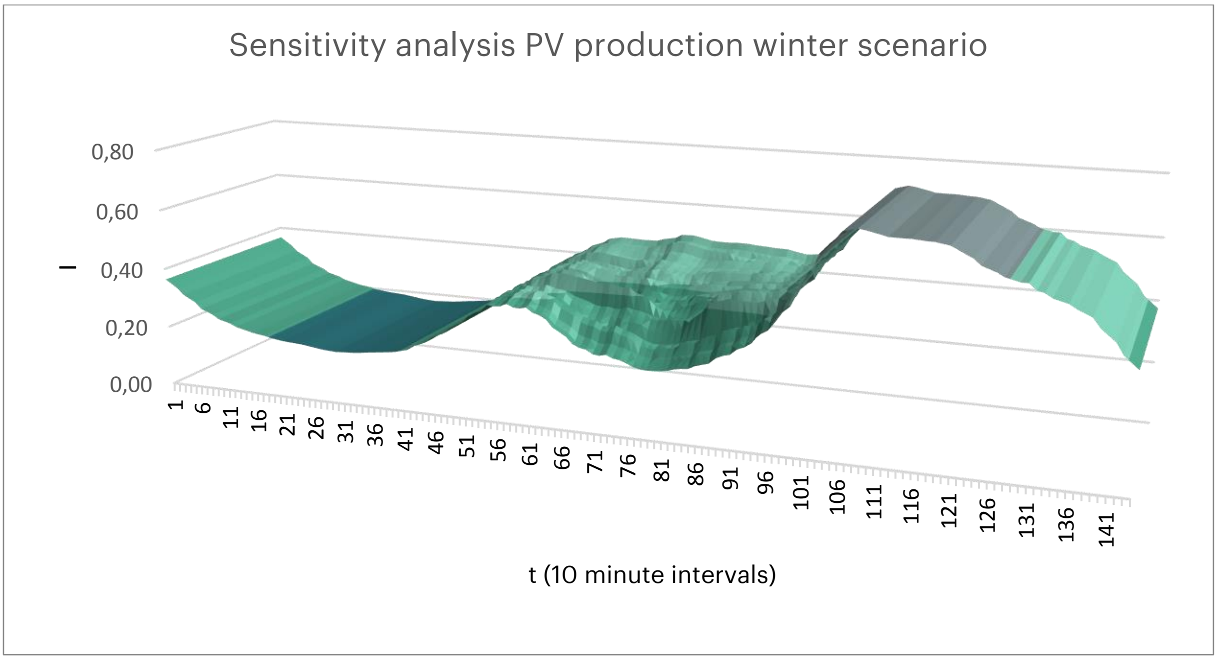


*Figure 42. Sensitivity analysis for PV production in January (30 scaled historical PV production days)*

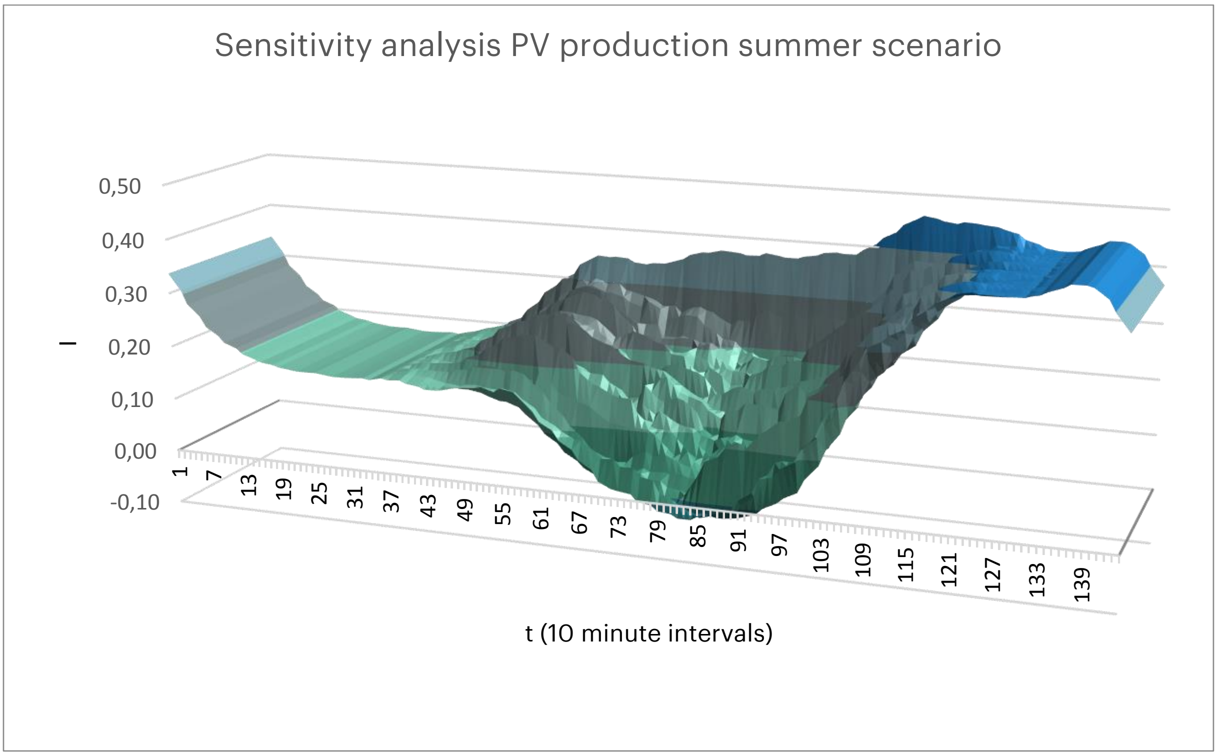


*Figure 43. Sensitivity analysis for PV production in January (30 scaled historical PV production days)*

**Demand sensitivity** The following two figures are energy demand sensitivity analyses for the neighborhood West van Schaarsbergen in Arnhem. They resemble an average flexible winter and summer load profile including 30 historically-based load profile scenarios (including weekends), which are sorted by peak demand.

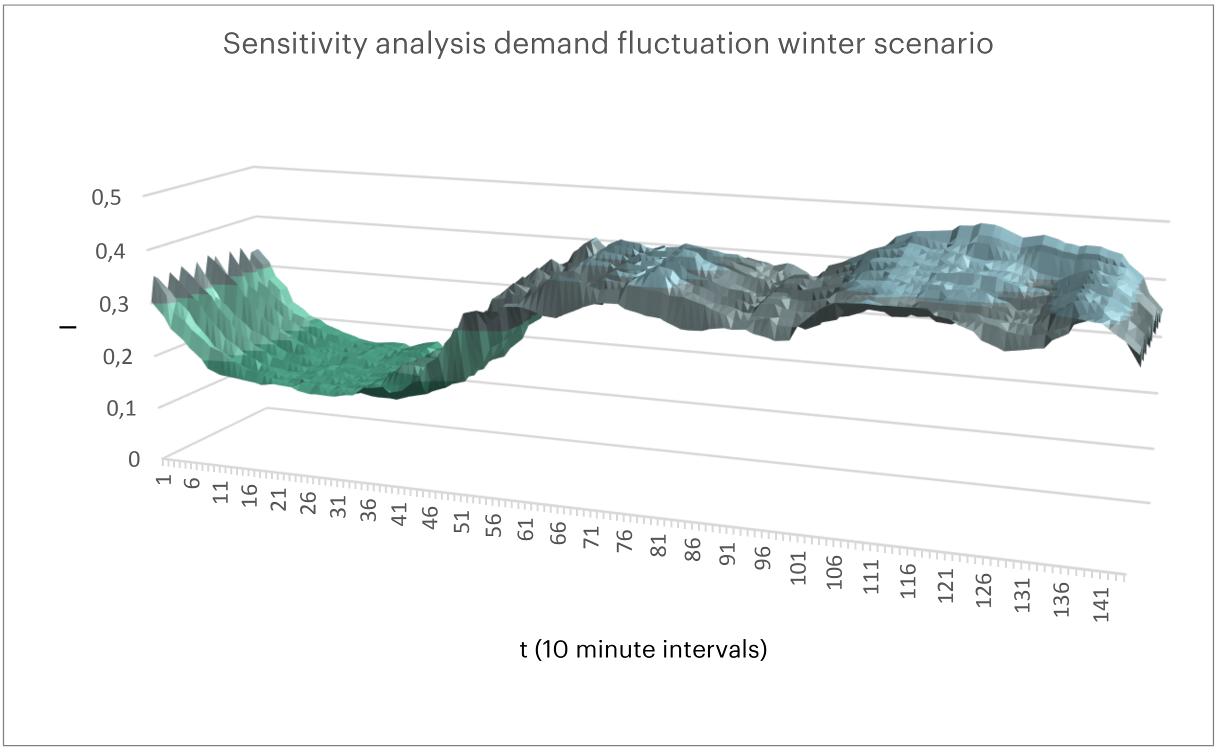


*Figure 44. Sensitivity analysis for demand fluctuation in January (30 scaled forecasted base load days)*

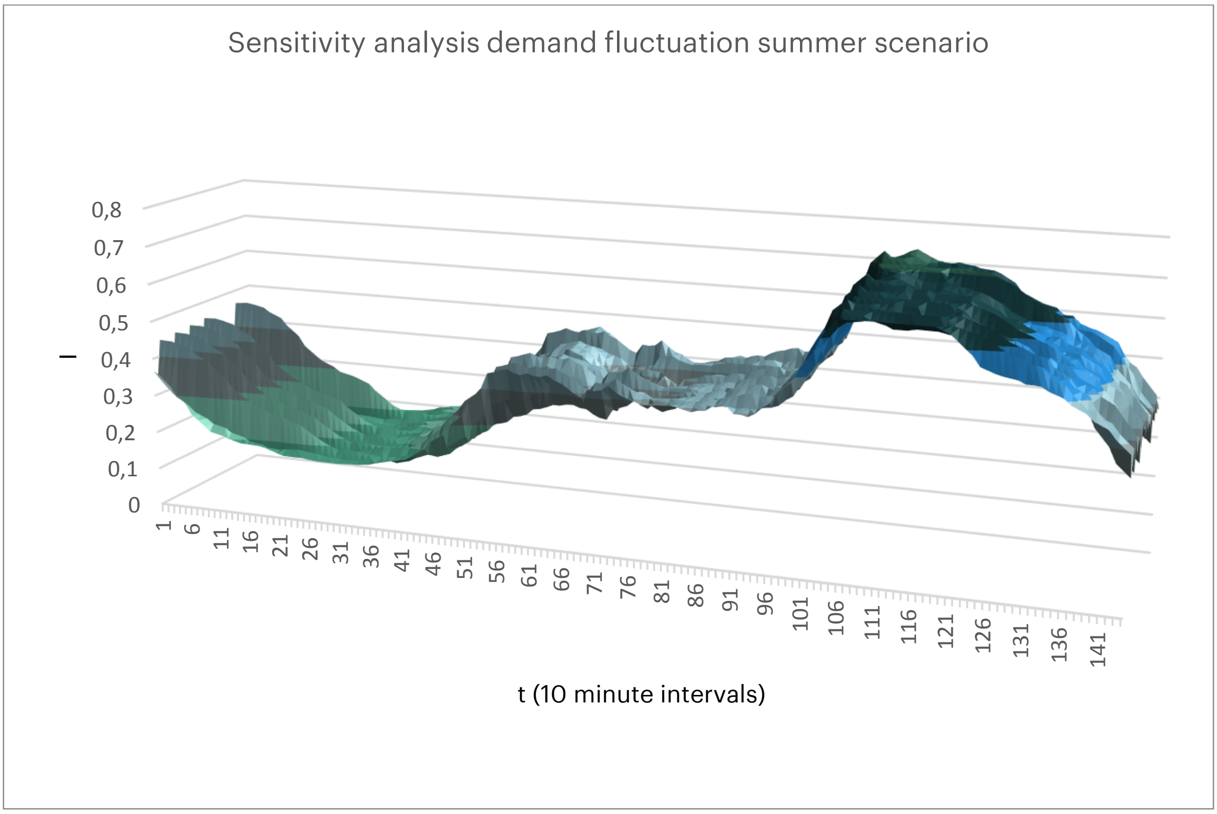


*Figure 45. Sensitivity analysis for demand fluctuation in July (30 scaled forecasted base load days)*