Supporting the adoption of smart grid appliances in city districts

A quantitative evaluation of policy options using agent-based modelling and scenario discovery

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Preface

This report is a master thesis, which has been written as part of the master programme 'Systems Engineering, Policy & Management' of the Technology, Policy and Management at the Delft University of Technology. This master programme is multidisciplinary in essence, which is strongly reflected in the content of this report. This master thesis has been written of two main audiences: policy-makers and the scientific community.

If you are a policy-maker:

- Chapter 3 will provide you with a good understanding of how households decide whether to purchase a new product and what it means for the design of policies. It is particularly important to understand how the occurrence of different consumer typologies within populations can both constrain the adoption of a product and by used to allow a step-by-step introduction of the product within a market.
- Chapter 6 will present the main directions for policy identified based on the model.
- Chapter 8 will provide a translation of directions for policy identified based on the model to real-world policies. An explanation is given about why direction for policy should be used to increase adoption of smart grid appliances on the scale of city-districts and which external factors the success of these policies is dependent.

If you are member of the scientific community:

- Chapter 3 will offer you an overview of the state of the art in modelling the diffusion of innovations. As shown in this specific chapter, a wide amount of theories has been written in order to simulate and understand how innovations diffuse. Mainly the comparison of the usage of these different theories on the final adoption curve is interesting from a scientific point of view.
- Chapter 5 will provide you an example of the application of the 'evaludation' method of Augusiak, et al. to verify and validate agent-based models. In my opinion, due to the difficulty of validating agent-based model describing human behaviours, the usage of the 'evaludation' method is highly beneficial to identify the weaknesses of the model and either find a way to deal with them or in any case be explicit about their impact on model outcomes.
- Chapter 6 will show you how the 'scenario discovery' method can help you to identify efficiently policies directly based directly on the model that was created. In my opinion, the use of the 'scenario discovery' method is strongly beneficial for the modelling of human behaviours, mainly due to the lack of data that we have about the behaviour of humans and their unreliability. By incorporating these data uncertainties into the model instead of ignoring them, we may found out whether and how these uncertainties are relevant for model outcomes. The use of the 'scenario discovery' method and the modelling of human behaviours with agent-based simulations is in my option a promising field.
- Chapter 7 is interesting to discuss the effects of adopter heterogeneity and various consumer rationalities on the adoption curve of innovations.

Acknowledgements

This report is the result of an intensive and challenging trajectory. While searching for a thesis subject, I set myself two requirements. First, I knew that I wanted to use either or both agent-based modelling and system dynamics in my research project. Based on the system modelled and the modelling requirement, I eventually decided to select agent-based modelling as modelling tool. In a way, it is amusing that one of my research outcome is that, considering the directions for policy identified, I would also have been able to select system dynamics (see 'Heterogeneity, agent-based modelling and system dynamics - a study about the effects of including adopter heterogeneity in diffusion of innovations models and the consequences on paradigm choice'). Second, I wanted to write my thesis in collaboration with a company outside the TU Delft. I am extremely grateful to Yvonne Boerakker for having given me the chance to conduct my master thesis at DNV GL. Despite her very busy schedule, Yvonne always tried her best to make herself available for comments and discussions. I felt also very lucky that Yvonne understood the challenge of conducting a research for two different publics such as policy-makers and the scientific community, which is one of the main reasons why the entire thesis process went fluently.

I would also like to thank Jan Kwakkel for his precious help during this thesis. Jan was always willing to help me in the execution of EMA experiments, PRIM analysis, and the adjustment of python code for that purpose. In addition, working with Jan was very valuable since he was always able to provide very clear feedback. Given the complexity of writing a thesis, this was essential. In addition, I would like to thanks Emile Chappin and prof. Wil Thissen for their feedback during the different meetings. The critical feedback that you provided me with helped bringing this thesis to a higher level.

I would also like to thank my parents, Jos and Ernestine, for providing me with the opportunity to study in Delft and for supporting me during the entire trajectory. Mayke and George, you also helped me greatly during my study. Finally, I would like to thank my lovely girlfriend Kirsten for her support and patience during the entire graduation project.

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Abstract

Three main goals have been assigned to Dutch electricity policy: a reliable, affordable and clean electricity sector. In order to make the electricity section cleaner by decreasing GHG emissions, the SDE+ regulation has been introduced to increase the share of renewable energies in the overall electricity production. The drawback of the introduction of renewable energies is that it also makes to the electricity grid less reliable. The main reason for this increased unreliability is the incapacity of the electricity network to cope with high electricity production fluctuations. One solution to cope with high production fluctuations is to allow electricity consumers to respond to variations of electricity prices resulting from the availability of electricity on the network over time. To allow demand response, households may purchase smart grid appliances. These appliances, for example smart washing machines or smart fridges, adapt their electricity consumption depending on the price of electricity. The benefits for households is that the purchase of smart gird appliances may lead to lower electricity costs. There is however a large uncertainty about the extent to which households will be willing to purchase smart grid appliances and provide demand response. Since demand response is important to allow a wider integration of renewable energies in the Dutch electricity sector, policy measures to support adoption of smart grid appliances might be needed. To create effective policies, more insight must be gained into the factors leading to a high share of smart grid appliance adoption.

The purpose of this work is to identify a set of directions for policy that allows a large adoption of smart grid appliances on the scale of city districts. The identification of directions for policy is done by using an agent-based model. This model allows simulating the decision-making performed by each individual households to decide whether to purchase smart grid appliances. In addition, it enables to incorporate the effects of interactions between households on the final adoption percentage of smart grid appliances. The analysis in this work has been performed by using the Diffusion of Innovations Theory of Rogers (1962). In this theory, (potential) adopters are assumed to be divided among five different categories: innovators, early adopters, early majority, late majority and laggards. Adopters of each category have different reasons to adopt and different roles in the diffusion of innovations.

The outcomes of the model shows that the adoption of smart grid appliances by innovators and early adopters, which typically represents a small size of the population, open to change and having sufficient financial resources, is not expected to be difficult. Encouraging the formation of consumer groups, for example of the scale of city streets, and the nomination of product ambassadors may largely contribute to the adoption of smart grid appliances by households belonging to these adopter categories. Underlining the benefits of adoption for the environment and for community building is expected to offer important motivation. Model outcomes however also underline the fact that convincing early majority population, late majority population and laggards, which typically represents a large size of the population, might be extremely difficult in the case of smart grid appliances. As explained by Rogers, adopters belonging to these populations are pragmatics. Important factors influencing adoption are the amount of savings that can be made through the purchase of smart grid appliances and the easiness of their utilisation. The large-scale adoption of smart grid appliances would therefore require that the plug-and-play concept is applied to smart grid appliances. According to several studies, most households request a large amount of savings per month in order to spend more on smart grid appliances. The amount of savings that can be made in comparison to these expected is low. Therefore, the expectation is that smart grid appliances will only be adopted on large scale in case their purchase costs equals the ones of traditional appliances. The adoption of smart grid appliances does however not necessarily mean that they will be used in their 'smart function'. Hence, the large-scale adoption of smart gird appliances does not necessarily mean that a city district is able to shift strongly its electricity demand when needed. The support of adoption by early majority population, late majority population and laggards on the scale of city districts is not expected to be effective, since the challenge mostly lies in the technological and commercial adjustment of smart grid appliances. Only when the characteristics of

smart grid appliances will be interesting enough for the population categories just cited, will it become effective again to support adoption on the scale of city districts. The challenge will then become to promote a new electricity consumption behaviour. This new electricity consumption behaviour is only expected to be accepted if the changes in consumption behaviour are minimal.

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List of abbreviations

Abbreviation	Full
BDI (framework)	Belief Desire Intention (framework)
EMA	Exploratory Modelling and Analysis
KDE	Kernel Density Estimation
KPI	Key Performance Indicator
ODD + D	Overview, Design Concepts and Details + Decision-making
PRIM	Patient Rule Induction Method

Illustration index

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Chapter 1 – Thesis definition

The goal of chapter 1 is to provide a clear overview of the challenge of supporting smart grid appliance adoption from a policy and scientific point of view. This is done by first introducing the benefits of smart grids to reach the policy goals of the Dutch energy sector in section 1. 1. Section 1. 2 then explains the key role of end-users in the success of smart grid deployment while section 1. 3 shows why the support of end-user participation is challenging. Finally, section 1. 4 describes the scientific work that has already been done to understand the complexity of adoption support and provides solutions for this purpose. The overview of the policy and scientific challenges created in this chapter will be used in chapter 2 to identify clear knowledge gaps. These knowledge gaps will then form the basis for the research performed in this work.

1. 1 Introduction

Similarly to many European countries, Dutch electricity policy has three main goals: a reliable, affordable and clean electricity sector (Klooster, et al., 2005). The current power system installed forms, however, an obstacle to the achievement of these goals (International Energy Agency, 2011). Traditional power systems have been designed to transport electricity from a single production location through high voltage transmission lines to progressively lower voltage networks to finally supply end-users with electricity (Jackson, 2014). There are three main shortcomings to these traditional systems. First, they provide little information to end-users about their electricity consumption and therefore offer them limited opportunity for demand response. Second, they are highly vulnerable to unanticipated fluctuation in power generation and electricity consumption. Third, they offer limited visibility about the current operating status of electricity in the network and therefore leave only little possibility for electricity flow management (International Energy Agency, 2011; Jackson, 2014). The addition of renewable energy capacity would serve the goal of making electricity supply cleaner. However, making the electricity supply cleaner this way would be at the expense of the reliability of the electricity network (Schleicher-Tappeser, 2012). Due to the shortcomings of the traditional power system, the intermittency of electricity production by renewable would not make it possible to anticipate or adapt quickly to these variations in production. The result would be the increase of power outage, thereby making the electricity system less reliable.

The incapacity of traditional power systems to allow simultaneously the increase of the reliability and the cleanness of electricity supply calls for an adjustment of the current electricity supply system. One way to do this is the installation of smart grids systems. This is done by installing tools that can provide a wide range of information about the status of the electricity grid to various stakeholders. The rollout of smart grids leads to the following benefits. First, it allows the integration of consumers as active players. Clastres (2011) explains that this integration allows the reduction of electricity consumption during demand peaks, which is a period in which the electricity production is particularly polluting. A second benefit is the possibility for wider integration of renewable energies, which makes the electricity sector more environmentally friendly (Clastres, 2011; International Energy Agency, 2011). Other benefits are the increase of robustness of the electricity grid in facing voltage fluctuations and the decrease of electricity costs for consumers (Clastres, 2011; Jackson, 2014; International Energy Agency, 2011). Smart grids, therefore, enable to increase both the reliability and the cleanness of the electricity supply system.

The definitions of smart grids are numerous and include technological, economic, social and sociological perspectives (Wolsink, 2012; Naus, et al., 2014; Clastres, 2011; Verbong & Geels, 2010). In this work, smart grids will be viewed as "electricity networks that can 'intelligently' integrate the behaviour and actions of all users connected to it (…) in order to efficiently deliver sustainable, economic and secure electricity supplies" (European Technology Platform, 2013). This definition introduces the aspect of stakeholder dependency which plays an important role in the success of smart grid systems. In order to

be able to provide financial and sustainable benefits to grid users, the participation of an important amount of different types of users (generators and consumers) is essential (Verbong, et al., 2013). Participation of energy grid users is one of the challenges that stands between the current state of smart grids and the success of this concept. Other challenges are the high sunk costs of smart grid systems, technological and regulatory immaturity and market uncertainty (Luthra, et al., 2014; Jackson, 2014). In this work, the focus is put on the desire for participation to smart grid developments of one particular type of grid users: households.

In this chapter, the problem of uncertain participation of households to the development of smart grids is defined. The next section presents a description of the problem and plausible directions for policy. This section also defines participation of households in smart grid developments. Section 1. 3 explains the various uncertainties related to the adoption of smart grid appliances by households and why understanding the drivers for household participation is complex. In section 1. 4, the state of the art of modelling the behaviour of households in smart grids and in particular the adoption of smart grid appliances is presented.

1. 2 Key role of households in the development of smart grids

In this section, the context of the challenge of participation of households in the development of smart grids issue is presented. An explanation will be given about why the participation of households will play a key role in the success of smart grids' deployment.

1. 2. 1 Households' participation to the development of smart grids

The participation of households in the development of smart grids can be seen in many ways. It can be seen as the increase of demand response by adapting domestic energy practices to decrease consumption during peak demand periods. It can be seen as the purchase of small-scale electricity generation appliances such as solar panels. It can be seen as the willingness of households to share precise information with grid operators about their daily electricity usage (Naus, et al., 2014; Wolsink, 2012).

In this work, the participation of households in the smart grid development is defined as the purchase and usage of smart grid appliances in their residences. Smart grid appliances are products that are placed and used within the parameters of a house and that are able to shift the electricity consumption to diminish operation costs. In this work, only appliances that are typically placed in-house are considered. Examples are smart washing machines, smart dish washers, smart refrigerators and smart freezers. Their main characteristics is that they allow communication with energy management systems to detect low-price periods or any other trigger signals that are contracted with the utility company: availability of local renewable energy sources or power system frequency for example (Geelen, et al., 2013).

1. 2. 2 Key role of consumer participation

There is a wide recognition that the extent to which households are willing to change their daily electricity routine and make adjustments to the type of appliances that they use, will play a key role in the development of smart grids (Verbong & Geels, 2010; International Energy Agency, 2011; Wolsink, 2012; Geelen, et al., 2013; Gangale, et al., 2013). The main benefits of smart grids were explained in section 0. Most of these benefits can be achieved through the possibility to shift the electricity consumption throughout the day. Shifting the operation of appliances to moments in time when electricity costs are low results in a lower electricity bill for users. Shifting the operation of appliances to moments in time when there is no peak consumption leads to lower GHG emissions during electricity production. Enabling to delay the operations of appliances during moments when the voltage of electricity grid is excessively high or low allows avoiding network damages.

The ability of smart grid appliances to receive and interpret information from the electricity grid plays a key role in allowing electricity consumption to be shifted (Faruqui, et al., 2010). This shifting of electricity consumption is also known as demand response. Demand response is therefore one of the methods that can allow the electricity supply system to be more reliable and cleaner. Demand response is beneficial for a wide amount of stakeholders in the electricity sector (Boisvert & Neenan, 2003). National governments, for example, will benefit from the development of smart grid systems to achieve environmental targets. The grid operator will also benefit from smart grid developments to reduce grid maintenance costs. Householders can expect cost reductions. The level of demand response needed, however, is dependent on the production fluctuations on the electricity grid and the difference between the height of high and low electricity prices. Hence in a country where the production of electricity varies strongly, e.g. because of high wind energy capacity on the grid, the level of demand response needed is higher. Regardless the percentage of households within a country that is able to adapt its electricity demand strongly if needed does not necessarily have to be equal to 100%. On the contrary, a percentage of for example 50% might offer enough demand response and decrease the overall policy costs of smart grid appliance adoption. Therefore, the goal of policy makers is not necessarily to ensure that the entire population is able to offer demand response. However, it should at least ensure that the percentage of household being able to do so is high enough considering the electricity infrastructure of the country in question.

The challenge for policy makers is that the decision to purchase and use these appliances to allow demand response does not reside in the hands of all stakeholders that could benefit from smart grid systems. This means that many actors in the electricity sector are dependent on choices made by households while having only limited possibilities to influence it. This leads to the following question: are policies needed to make sure that households are willing to purchase and use smart grid appliances to offer enough demand response and decrease GHG emissions? Moreover, if so, which are these and how should they be implemented?

1. 3 The adoption of smart grid appliances by end-users

A variety of theoretical models have been created to describe the factors influencing the adoption of innovations by households (Ajzen & Fishbein, 2005; Kim, et al., 1995; Rogers, 1962; McFarland, 1974; Engel, et al., 1995; Davis, 1989). These theories all underline the fact that the adoption of an innovation is not only the result of the properties of the product. Elements such as people's socio-demographic properties, or the social example that is being provided by other people in relation to the perception of the innovation, play a decisive role. Hence, the decision by individual households to adopt an innovation is complex.

In literature, various important aspects of smart grid appliances that are considered to play a role in their adoption by consumers are identified (Verbong, et al., 2013; Nye, et al., 2010; Anda & Temmen, 2013; Balta-Ozkan, et al., 2013; Gangale, et al., 2013; Garmendia & Stagl, 2010; Naus, et al., 2014). These aspects can be classified in four groups. First, the properties of appliances like price, the height of the return on investment, or environmental benefits, play a decisive role. Second, the risks linked to the purchase and to the use of these appliances are taken into account: risk of being non-profitable, breakdown risk and risk of losing personal data. Third, the adoption complexity that dissuade individuals to adopt is also considered: purchase complexity, installation complexity, and the complexity of operating the appliances. Fourth, the social value of the product is taken into account. Having not purchased smart grid appliances might for example be seen as a lack of smartness in case the operation of these products turns out to become highly profitable. The identification of these numerous aspects related to smart grid appliances shows the complexity of the reasoning that households make to decide about the adoption of smart grid appliances. This complexity is increased by the fact that not all households have the same interests in adoption. According to the Diffusion of Innovations Theory of Rogers (1962), some individuals are mainly interested in the financial revenues that an innovation may

provide while others essentially focus on the social recognition that they could receive. The consequence is that one innovation might not satisfy the adoption requirements of each households at the same time.

The complexity that characterises the reasons for adoption of smart grid appliances makes policy making difficult. The reason for this is the causality between the application of the policy measure and the highly uncertainty of its final result. Traditional policy measures such as subsidies for the purchase of products or wide promotion might not have the expected effect (Anda & Temmen, 2013; Balta-Ozkan, et al., 2013). Additionally households make their decisions based on external parameters that are continuously changing and that are not always in the control of policy makers: electricity price, occurrence of data leak problems and various support regimes for small-scale renewable energies. In the literature, these external parameters are clearly assumed to have an important role on the decision-making of consumers (Peattie, 1992) (Rogers, 1995).

1. 4 State of the art: analysis of the adoption of smart grid appliances by end-users

Section 1.3 reveals the complexity behind the reasons for adoption of smart grids appliances by households. This also explains the difficulty for policy makers to create effective policy measures to increase the adoption of smart grid appliances. A literature review performed during this project has shown that various studies have tried to analyse the adoption of innovations in the field of smart grids from the perspective of households (Curtius, et al., 2012; Kaufmann, et al., 2013; Kranz, et al., 2010; Mah, et al., 2012). These studies mostly use empirical analysis by means of surveys to distinguish relationships between, on one side, the characteristics of households and the perception of smart grid appliances and, on the other side, the adoption of these appliances.

From a modelling perspective, the number of studies analysing the adoption of smart grid appliances is limited. While historically, both system dynamics and agent-based modelling are used to model the adoption of innovations (Kiesling, et al., 2012; Rahmandad & Sterman, 2008), the conducted literature review shows that agent-based modelling is clearly the most preferred modelling technique to study the adoption of smart grid appliances by households. Three reasons can be distinguished. First, agent-based modelling is highly suitable to incorporate the heterogeneous properties of agents and the complexity of their behaviour resulting from their interactions and their goals (Epstein & Axtell, 1996; Miller & Page, 2007). In addition, agent-based simulation allows a better study of the dynamics of smart grid appliances diffusion instead of only focussing on the end percentage of homes with smart grid appliances (Zhang & Nuttall, 2011). Lastly, agent-based modelling is a newer tool in comparison to system dynamics. As a result, it is for many researchers more interesting to use agent-based modelling since many methodological implications of using this simulation tool are still to be discovered. The most influential work in the modelling of smart grid appliances with agent-based simulation was done by T. Zhang and W.J. Nuttall (Zhang & Nuttall, 2007; Nuttall & Zhang, 2009; Zhang & Nuttall, 2011). Their work focusses on the evaluation of government's promotion policies on the adoption of smart metering. It has since then been cited by some authors which has led to the publishing of several other papers using agent-based models on the adoption of smart grid appliances like smart meters and photovoltaic installations (Rixen, 2010; Snape, et al., 2011).

Based on the literature review performed in this project, little work has been published on agent-based modelling focusing specifically on the adoption of smart grid appliances like washing machines or dishwashers or about smart-homes. In the few modelling works published (Zhang & Nuttall, 2011; Zhang & Nuttall, 2007; Rixen, 2010), authors provide limited conclusions. Their conclusions usually only underline the predictive power of agent-based simulation in studying the adoption of smart grid appliances and mention the need for more extensive work to be able to provide solid conclusions about the effectiveness of policies in this sector. Lastly, these papers all mention the uncertainties about the

behaviour of households in their decision-making process and the evolution of the environment but do not explicitly and systematically explore these uncertainties.

Chapter 2 - Research problem

The goal of chapter 2 is to create a research structure that allows understanding the reasons why a large-scale adoption of smart grid appliances is uncertain and what could be done to support adoption. To do that, the overview of the policy and scientific challenges created in chapter 1 is used to identify knowledge gaps and formulate the problem statement in section 0. The research objectives and scope are presented in section 2. 2. Section 0 and 2. 4 form the main output of chapter 2. In section 0, a research question and sub-questions are proposed to bridge the knowledge gaps identified in section 0. These questions will determine the research performed in this work and will lastly be answered in section 9. 1. In section 2. 4, the research frameworks and the methods used to answer the research question and sub-questions are explained.

2. 1 Problem statement

Chapter 1 has shown the importance of the willingness of households to adopt smart grid appliances in order to offer enough demand response and thereby help to achieve a more reliable and cleaner electricity supply system. It has also revealed that increasing this willingness to adopt is highly complex, mainly because of the lack of understanding of the decision-making process of households, the influence of household heterogeneity and the causality between stimulation of appliances adoption and actual adoption. Lastly, it demonstrated that agent-based modelling is an effective tool to measure the effectiveness of policies to increase adoption, but that current research to build solid policy measure is lacking. For this analysis, three knowledge gaps can be identified. Considering the key properties of smart grid appliances and the various properties and behaviour of each individual household, it is unknown:

- which and to what extent various categories of policies, such as financial incentives or purchase and installation facilitation directions, may lead to a higher adoption rate of smart grid appliances by households.

Chapter 1 has shown that no ready-made simulation model is available to test policies on their ability to increase the adoption rage of smart grid appliances. Therefore, it is unknown:

- what simulation technique should be used and how the simulation model should be designed to test the performance of various policies to increase smart grid appliances adoption.

Lastly, Rogers et al. (2005) introduced the potential benefit of using agent-based modelling in combination with the Diffusion of Innovations Theory. Hence, it is interesting to see which conclusions can be drawn about the benefit of agent-based modelling in the innovation diffusion case studied in this report. Therefore, it is unknown:

- which conclusions about the use of agent-based simulation can be added to model diffusion of innovations cases.

Considering the knowledge gaps, the problem statement is the following:

- *There is a lack of knowledge about effective policies that could increase smart grid appliances adoption by households.*

In this problem, the formulation ‘increase the adoption’ is used. By using this formulation, it is shown that the focus on policies should not necessarily be on making sure that the entire city district adopts smart grid appliances. However, the directions for policy should lead to an adoption percentage that enables height peak demands to disappear while limiting financial costs of policies. As explained in section 1. 2, this percentage is dependent on the electricity production specificity of the country. In this

work, since it lies outside the scope of this project, no research is conducted on the percentage of households with smart grid appliances that is needed to offer enough demand response under various circumstances. It is however recognise that different desired percentages of households owning smart grid appliances might affect the assessment of the success of policies. Hence, a range of percentages is used and applied on the scale of a city district. Subsequent, the various directions for policy are tested under various percentages of households with smart grid appliances.

2. 2 Research objective and scope

The research objectives are twofold. The first objective is to provide directions for policy that have the potential to increase the adoption rate of smart grid appliances by end-users to a level that can offer sufficient demand response. These directions for policy will take into account the specificities of households within a certain city district, as well as the varying external parameters that could influence decision-making, as presented in section 1. 3. By mentioning 'direction for policy', we point out that this work is not about creating policy measures that are directly applicable in the real world. However, policy areas will be identified, e.g. costs of smart grid appliances, in which concrete policies are expected to become effective. In section 0, ideas about concrete policy measures within the directions for policy identified will be provided. The second objective is to contribute to the current scientific knowledge about the adoption of smart grid appliances by using agent-based modelling. First, this will be done by providing conclusions about the effectiveness of agent-based simulation to model adoption of innovations cases while taking the heterogeneity of households into account. Second, conclusions will be drawn about the benefits of exploring uncertainties in adoption of innovations cases by using the scenario discovery technique.

The scope of this study is limited by using the modelling technique agent-based modelling. The reasons for this choice are presented in section 2. 4. In addition, it uses the framework of innovation diffusion of Rogers (Rogers, 1962). The rationale for this choice is explained in section 2. 4 as well. Moreover, the scope is limited to the scale of a city district. This means that the city district is considered as an entity that contains a set of households interacting with each other. Any relevant occurrences outside of the city district influence the city district through an external variable. Last, the scope is limited to the adoption of smart grid appliances. The study of their utilisation is therefore excluded. As explained in section 1. 2, households can play a key role in the creation of demand response capacity. The creation of demand response with smart grid appliances, however, is only achieved when households both adopt smart grid appliances and use them with their 'smart' function. Due to the limited time available for this project and the strong differences in theoretical basis for the modelling of household behaviour in adoption or utilisation, the choice has been made to focus only on smart grid appliance adoption. The fact that smart grid appliance utilisation is not included in this project forms one of the limitations of this work (see section 8. 1).

2. 3 Research questions

To reach the research objectives, the questions presented in this section have to be answered.

Main research question

- Which directions for policy can stimulate the adoption of smart grid appliances to increase the capacity for demand response in city districts?

Sub research questions:

1. On which theories should a model of the adoption process of smart grid appliances in a city district be based?
2. How should this model be conceptualised and specified?
3. What are directions for policy that can increase the percentage of households owning smart grid appliances to the desired level on the scale of city-districts?

4. What lessons can be learned about the benefits of the usage of agent-based simulation and scenario discovery for adoption of innovation cases?

As explained in section 2. 2, it is assumed that households having adopted a smart grid appliance also use them in their 'smart function'. The implication of this assumption on the model and the directions for policy identified is further discussed in section 8. 1. By stimulating the adoption of smart grid appliances in city districts, it is meant an identification of directions for policy as if the only goal was to increase adoption within the city-district itself, and not necessarily outside of the city-district.

2. 4 Research methods

The research methods section first introduces the research framework of this work. The research framework will then be used to select methods to answer the research question presented in section 0.

Reading indications

The goal of this section is to identify the framework in which the adoption of smart gird appliances is studied and to support the choices for specific theoretical methods. The added value of this section is therefore mainly scientific and is not essentially relevant for any reader that is mainly interested in the policy value of this work. A summary of this section is however provided in table 1.

Table 1: Summary of the research methods section

Research framework/method	***Contribution to answer the research question***
Framework: complex adaptive system	- *A framework that allows to incorporate the complex behaviour of humans into the analysis of effective directions for policy to increase smart grid appliance adoption.*
Method: agent-based modelling	- *A simulation technique that allows to easily take the specificities of each households into account and find out whether policies directions should be designed by taking these specificities into account.*
Method: Scenario discovery	- *A technique to find out which scenarios must be taken into account to make sure that directions for policy, within the model, are effective to reach certain goal.*
Method: 'Evaludation' method	- *A profound review of the model's ability to reproduce correctly the behaviour of households in the adoption of smart grid appliances and the final impact on the adoption curve. The result is a better assessment of the validity of project conclusions based on the assumptions and uncertainties on which they rely.*
Method: ODD + D protocol	- *Helps to communicate about the structure of the model created in this project and facilitates further work to help increasing smart grid appliance adoption based on this project.*

2. 4. 1 Research framework

The theoretical framework on which this work is based is the complex adaptive system framework (Holland, 2006). In this section, the rationale for choosing the complex adaptive system framework is presented. First, it is shown that the set of entities and relevant causalities to model in this project can be viewed as a system. Second, an explanation will be given of why this system is complex. Last, the reasons why the usage of the complex adaptive system framework is effective to study the adoption of smart grid appliances as a complex system are provided.

According to Backlund (2000), a system consists of more than two interconnected elements. In order to be considered as a system, none of the elements may be independent of the rest, which means each element must influence, and be influenced, by others. Also, the set of system element must form a unified whole. In the case of the adoption of smart grid appliances, the number of households, residences and appliances is wide. Households make decisions that affect their own residences. These decisions also influence other households. The adoption of smart grid appliances in the city district can be seen as a unified whole: they are linked together by their influence on the adoption rate of smart grid appliances.

The smart grid appliances adoption system can be seen as a complex system. While Chu et al. (2003) recognise that there is a lack of general agreement on the definition of complexity, Miller & Page (2007) however offer a good discussion about what defines complexity. According to Miller & Page, a system is defined as complex when the parts of this system are able to interact which each other in multiple ways. As a result, the predictability of the influence of one or more system variables on output parameters is low. In the smart grid appliances adoption system, decreasing the costs of smart grid appliances could lead to an increase of the adoption rate of these products by households. However, due to the high installation rate of these products, households that strongly oppose this technology could start to lobby against smart grid appliances. As a result, the adoption rate of these products could still tend to decrease.

Complex adaptive systems are special cases of complex systems. Holland defines complex adaptive systems as systems "that involve many components that adapt or learn as they interact" (Holland, 2006). The interaction between these components (also called agents) is central to complex adaptive system theory. If coherent system behaviour is observed, it is the result of multiple decisions that are made by the agents in the system as a result of competition or cooperation among them (Waldrop, 1993). Different forms of coherent system behaviour can be observed (Holland, 1998). These coherent behaviours are well described by Dam, et al. (2013). One of these behaviours is emergence, which is defined as a recognisable pattern that arises from the multiple interactions between agents. Another is path dependency which is the fact that when one action is taken, the system can never return to its initial state. A last one is self-organisation; the process of creation of order and coordination as a result of the interaction of agents.

As Holland (1996) explains, the social behaviour of humans can be described in terms of complex adaptive systems. By looking at the knowledge gaps identified in the knowledge gaps section, the observation can be made that the behaviour and choices made by households will have a strong influence on the outcomes of the various solutions that will be tested in this project. Therefore, it is useful to use complex adaptive systems as the framework to view and analyse the system of interactions between households for the adoption of smart grid appliances.

2. 4. 2 Research methods

This section provides an overview of the four main research methods used in this work: agent-based simulation, scenario discovery methodology, the 'evaludation' methodology and the ODD + D protocol. The goal of this section is to explain why these research methods are necessary to identify directions for policy to increase smart grid appliance adoption.

Choice of simulation paradigm

Vangheluwe & Lara (2002) identify a wide range of simulation formalisms across the state trajectory data. Of these range for simulation formalism, three main types of modelling techniques can be distinguished: system dynamics, discrete-event simulation and agent-based simulation. In principle each of these modelling techniques are able to represent at least some parts of the smart grid appliances adoption system. However, each technique performs differently at reflecting the behaviour of some

parts of the systems. The choice for the modelling techniques must hence be based on the characteristics of the parts of the system that are expected to play a major role in explaining the system behaviour of interest (Borschev & Filipov, 2004).

Table 2 shows the main system properties that each of the three modelling techniques typically allow to reproduce. This table was created based on the paper of Borshchev & Filippov (2004). This table forms the basis for the modelling technique choice.

Table 2: Modelling technique choice, adapted from Borshchev & Filippov (2004)

Modelling technique	**Typical system properties represented**	**Type of systems typically represented**
Discrete-event simulation	- Heterogeneous entities - Passive entities	- System with operational processes
System dynamics	- Strong influence of information-feedback on the behaviour of the system - Strong influence of system delays	- Urban, social and ecological types of systems in which an aggregated view of these systems can properly reflect its behaviour
Agent-based modelling	- Heterogeneous entities - Active agents who can interact with their environment and make decisions to pursue their personal goals	- Evolutionary systems in which the choices of agents play a key role in the emergent system behaviour

In the literature, two main modelling techniques are commonly used for the simulation of dynamics of diffusions: agent-based modelling and system dynamics (Rahmandad & Sterman, 2008). Hence, both of the simulation methods could be used to simulate the dynamism of the adoption of smart grid appliances by households. According to Rahmandad & Sterman (2008), the main element to consider in the choice between both modelling techniques is the extent to which heterogeneity of agents and of their interaction must be represented in the model. The addition of heterogeneity with system dynamics is done by creating a larger set of levels, each representing one type of population. However, heterogeneity between the individuals within each level is impossible to recreate. In addition, heterogeneity of interactions between individuals is difficult to represent (Rahmandad & Sterman, 2008). The execution of simulation runs however is faster with system dynamics. Therefore, system dynamics should be chosen when the level of heterogeneity that the model should include is low and when project requirements impose a short simulation time. Agent-based modelling is more useful when a large amount of heterogeneity between agents and their interaction strongly explains the way a product is adopted. The choice between modelling techniques will be based on this distinction.

The purpose of the model is to study the adoption of smart grid appliances as a result of the process of decision-making by individual households. Heterogeneity between agents is important to explain the adoption of innovations. This was recognised by Rogers (1962) through the separation of adopters in five different categories (see section 3. 1. 3). Various authors also have recognised that the heterogeneity within these five categories have an impact on the structure of the adoption curve (Bohlmann, et al., 2010; Van den Bulde & Stremersch, 2007). Rahmandad & Sterman (2008) and Bohlmann, et al. (2010) also show that the network topology connecting households and the frequency of interactions have an impact of the adoption of an innovation. In this work, the elements mentioned in this paragraph are expected to play a role in the adoption of smart grid appliances. In addition there is in this proejct no strict requirement for limited simulation duration. Therefore agent-based modelling will be chosen to simulate the adoption of smart grid appliances.

The choice for agent-based modelling is, however, associated with the inconveniences of this modelling technique. Epstein (2011) distinguishes two limitations of agent-based modelling. The first is the difficulty to reflect the relevant properties of individuals in the model and to distinguish which property

is part of agents and which is the result of social interactions. The second is the difficulty to interpret, test and make generalisations from the outcomes of a model. On a more practical level, Castle and Crooks (2006) add the fact that, as agent-based models often describe the behaviour of complex entities, the factors inserted into the model are difficult to quantify and calibrate.

Figure 1 provides an overview of the structure of agent-based models. This figure is a relevant schematisation of Shalizi's (2006) description of agent-based modelling. According to him, it is a simulation tool where "an agent is a persistent thing which has some state we find worth representing, and which interacts with other agents, mutually modifying each other's states. The components of an agent-based model are a collection of agents and their states, the rules governing the interactions of the agents and the environment within which they live".

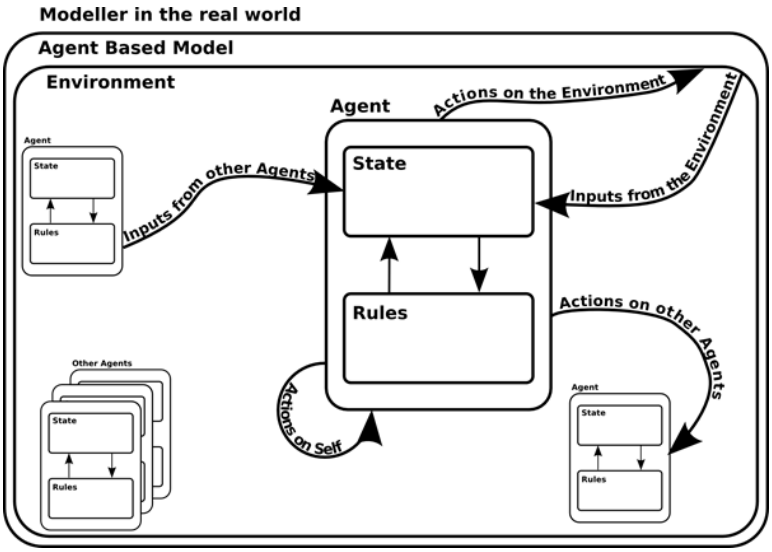


Figure 1: Structure of agent-based models (Dam, et al., 2013)

Scenario discovery

To distinguish directions for policy out a wide range of scenario's, the scenario discovery technique is used. Scenario discovery addresses problems that, among others, are characterised by a large number of uncertain factors (Kwakkel, et al., 2013). Dealing with these problems is described as decision-making under deep or severe uncertainty (Lempert, et al., 2003; Ben-Haim, 2006). To cope with the lack of knowledge or perfect understanding of the model's representation of the system, multiple and plausible alternatives are brought into the analysis of this system. In this work, these multiple alternatives will be described as uncertainties. These uncertainties will be identified and an explanation will be given of how these uncertainties will be taken into account in the analysis of best policies to increase adoption of smart grid appliances in chapter 5.

The main methodology to encompass these uncertainties is the combined usage of Exploratory Modelling and Analysis, and the Patient Rule Induction Method.

EMA (Exploratory Modelling and Analysis) is a methodology which uses computational experiments to enable the analysis of complex and uncertain systems (Bankes, 1993). EMA is based on an exploratory approach of models that strongly differs from the consolidative approach. In a consolidative approach, one searches to create a best-estimate model to increase the predictive power of this model (Hodges, 1991; Hodges & Dewar, 1992). The predictive power of these models is often low, mainly in systems that contain deep uncertainties and where the modeller has insufficient knowledge of the system in question (state and behaviour). In an exploratory approach, however, the modeller takes complete distance from the desire to predict the future. The model is seen as a plausible hypothesis about the structure of the

real system. Parametric, structural, and methodological uncertainties about the modeller's vision of a system are then included in the modelling process (Kwakkel & Pruyt, 2012). This results in the possibility to analyse the entire range of possible scenarios considering the implication of the various guesses made by the modellers. By using EMA, it is hence possible to find out under what circumstances the key performance indicators evolve to a desired/undesired level. In this project, the use of EMA will allow to create robust policies.

The Patient Rule Induction Method (PRIM) was introduced by Friedman and Fisher (1999). PRIM is a method that allows finding regions in the input parameters space that lead to a certain state of output variables (also referred as worst and best cases). Finding these regions in the input parameters spaces is done by repeating the two stages of implementation of peeling and pasting. Through these stages, some subsets of the input parameter space are removed (peeling) and added (pasting) to find a region that explains a large part of a certain outcome range (above a given threshold).

EMA and PRIM will be used together during the following four project steps:

- investigation of the variation of the first and simplest model,
- investigation of the added value of the progressive addition of model elements in the evaludation phase,
- exploration and interpretation of the final model behaviour,
- testing and adjustments of policies through worst and best case scenario analysis.

The 'evaludation' method

In their article, Augusiak, et al. (2014) underlines the existing confusion about what is meant by the term validation in the modelling of ecological models. This confusion was also noticed by Oreskes, et al. (1994) and David (2009). According to Augusiak, et al., the term validation is used rather intuitively and as a catch-all term. In the article, a wide range of articles are named and classified upon their utilisation of the term validation. Among others, validation was used to describe the processes of evaluation, testing and verification. The lack of clarity problem of the validation step is widely recognised among simulation modellers, by whom no definition has been agreed upon in the past 50 years of modelling. Augusiak, et al. mention that the confusion about the definition of model validation leads to the difficulty to find out and communicate to what extent a model is credible. Since simulation models are often used by policy makers, who are not always trained to use the model, the incorrect assessment of simulation model leads to unsuccesful policy making. In their article, Augusiak, et al. make an assessment of what is being understood by various authors under the term validation and judge that it is a mix of the evaluation and validation process. Based on these two processes, they introduce the word 'evaludation', which is a mix of the words 'evaluation' and 'validation'. The term evaludation is given the following definition: "the entire process of assessing model quality and establishing model credibility throughout all stages of model development, analysis, and application" (Augusiak, et al., 2014).

The introduction of the evaludation term is also used to propose a validation process that allows a better validation of the ecological models. The critique of Augusiak, et al. is that the traditional validation process of comparing model output with new empirical data is too limited. Three reasons are mentioned for that. First, agreements between policy maker and modeller do not always imply that the model is correct. Second, this validation is almost impossible to achieve with ecological models since relevant data often does not exist. Third, the word validation is loaded with philosophical discourses about the legitimacy of its usage. Augusiak, et al. therefore introduce a six step process of model validation. This validation process focusses on the validation of the the entire modelling process and not only on the output of the model. The use of these six steps allows the indentification of all relevant uncertainty that has been faced during the different modelling stages. Based on the uncertainties indentified, policies can be created to cope with these uncertainties.

Protocol for model description

Müller et al. (2013) argue for standardised and transparent model descriptions of agent-based models. According to them, a standardised description of models will allow better model assessment, comparison and replication of the models created. Although they do not yet succeed in creating a single model description protocol due to the diversity of model purposes, they argue for a minimum standard, which is the "provision of source code and an accessible natural language description" (Müller, et al., 2014). This minimum standard, still emergent, is called the ODD + D protocol and is strongly inspired from the ODD protocol of Grimm et al. (2006; 2010). The difference between the ODD + D and ODD protocol is that the first has been adapted for human decision-making models whereass the second was originally designed for ecological models.

In this master thesis project, a documentation of the agent-based model is made according to the ODD + D protocol of Müller, et al. (2013). This documentation can be found in Appendix D. This protocol will allow improving any communication, adjustment or further development to the model during or after the master thesis project. Figure 2 provides an overview of the seven elements of the ODD + D protocol. The reason why a standardised protocol for model description is added to this work is to facilitate further work to help increasing smart grid appliance adoption based on the project.

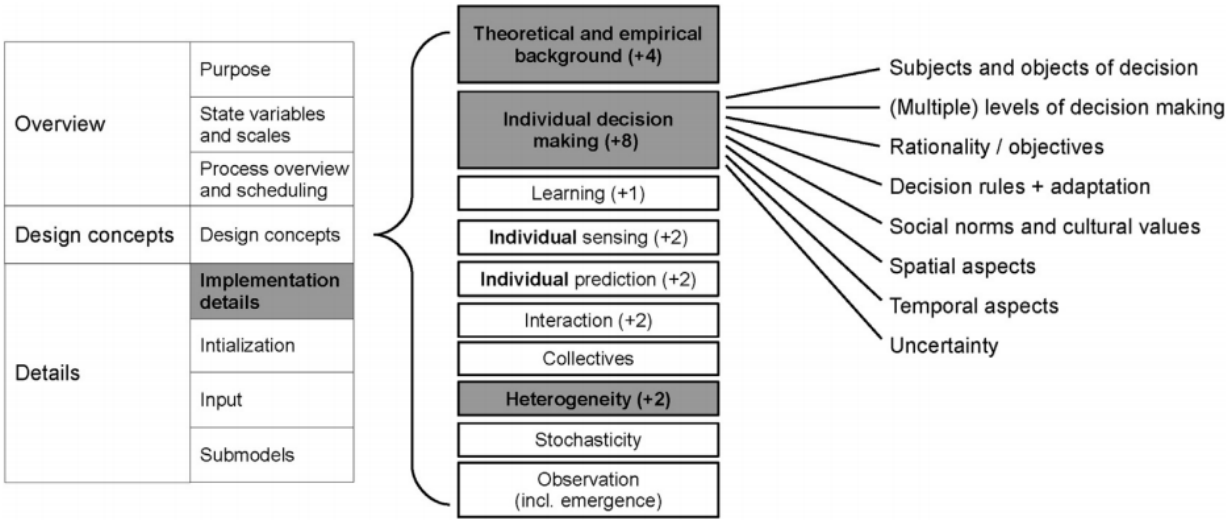


Figure 2: Structure of the ODD + D protocol of Muller et al. (2013)

Chapter 3 – Modelling the adoption of innovations

The goal of chapter 3 is to identify the theories necessary to model the adoption of smart grid appliances. This chapter will allow answering the first sub-research question of this work (see section 0). In the literature review performed in this research, a wide range of theories about the diffusion of innovations, the segmentation of adopters or the decision-making process used have been distinguished. In section 3. 1, to deal with the rich variety of literature on the topic of innovation adoption, for each relevant model aspect the most common theories used by others authors is selected. The relevant model elements are innovation diffusion theory, the segmentation of individuals and the decision-making process. Based on the research questions, objectives and scope identified in chapter 2, the most adapted theory for each model element is chosen. The theories chosen will then be used to formalise and conceptualise the model in chapter 4. In section 3. 2, the aspect of agent rationality is discussed and three different decision-making rationalities are selected. In chapter 5, each of the selected types of rationality will successively be applied in the model to validate its behaviour. In section 3. 3, the type of interactions that will be included in the model are selected. In this work, due to the time constrain of this project, only one combination of interactions is considered since it is believed that this is the closest to the real behaviour of households. The study of the impact of different types of interaction combinations on the adoption rate of smart grid appliances is however arguable. This forms one of the limitations of this project (see section 8. 1).

Reading indications

The goal of this section is to select theories that will be used to build the simulation model. The added value of this chapter is that it provides an argumentation of why some theories are better suited considering the research questions, objective and scope identified in chapter 2. For readers that are only interested in the theories that are in the end selected to build the simulation model, a summary is provided in table 3.

Table 3: Summary of the theories chosen for model construction

Theories chosen	***Contribution to answer the research question***
Segmentation of households	- *Segmentation of households in the five categories of Rogers* (1962)*: innovators, early adopters, early majority, late majority and laggards. The need for segmentation of agents as underlined by Rogers recognises the fact that not all adopters adopt innovations for the same reasons. Incorporating different types of adopters in the model will allow finding out whether it has an influence on the adoption rate of smart grid appliances and whether this should be taken into account in policy creation.*
Adoption process of households	- *The consumer decision-making process of Engel, et al.* (1995)*. This decision-making process allows distinguishing between awareness about the availability of a product and actual adoption. It also allows incorporating various aspects of adoption, and not only the financial profitability. As a result, the complex decision making process of households can be taken into account to test the effectiveness of policies.*
Relevant characteristics of innovations	- *The five innovations characteristics relevant for the adoption of individuals are incorporated: relative advantage, compatibility, complexity, triability and observability. More realistically than only the financial aspects, these relevant innovation aspects allow to take cognitive limitations, social influence and diffusion properties of innovations in the study of smart grid appliance adoption.*
Rationalities of households	- *Three different decision-making rationalities are identified in this section and the most appropriate ones will be selection in chapter 5. These*

	rationalities are neoclassical rationality (or full rationality), bounded rationality and prospect theory.
Interactions	- *Three types of interactions are selection: friend, neighbour and random interactions. All of them will be used simultaneously in the model, since this interaction structure is considered as most realistic in comparison to the actual behaviour of households.*

3. 1 Diffusion theories

In this section the two main adoption of innovation models will be presented: the Diffusion of Innovations model of Rogers (1962) and the Bass Model of diffusion (1969). Based on the characteristics of each model, a rationale will be presented of why the theory of Rogers was chosen. In the last part of this section, a more detailed explanation of the Diffusion of Innovations model of Rogers will be presented.

3. 1. 1 Diffusion of Innovations models

The Diffusion of Innovations model of Rogers (1962) is the dominant model in the field of adoption of innovations (Wilson & Dowlatabadi, 2007). Summarising, the diffusion process of an innovation is determined by four key elements: the characteristics of the innovation, the social system in which the innovation will possibly diffuse, the communication channels by which it can diffuse and time (Rogers, 2003). The specificity of the model is that it assumes a strong diversity in population characteristics that explains different adoption paths. The diffusion path is the result of a social communication process between people which is influenced by media-channels. The information transferred through these communications subsequently influences the decision-making of households. Next to the differing properties between members of a population, Rogers also recognises the need for consideration of the environment in which decision-making finds place (Faiers, et al., 2007) and the properties of the innovation itself (Wilson & Dowlatabadi, 2007).

The model of Bass was inspired by the work of Rogers. However, it uses a completely different method to describe the diffusion of innovations path. The diffusion path is described by using a differential equation that explains the speed by which non-adopters become adopters (Bass, 1969). This differential question is a linear function of the total potential adopters, the coefficient of innovation and the coefficient of imitation. Hence, the decision to adopt an innovation is either dependent on the influence of external parameters (media) or internal influence (interactions) between households. In the Bass Model, the population is viewed as homogeneous.

3. 1. 2 Rationale for choosing the Diffusion of Innovations model

There are two rationales for choosing the Diffusion of Innovations Theory over the Bass model. The first rationale is the wide possibility to test the effect on heterogeneity on the final state of innovation adoption. As explained in section 3.1.1, by not making any distinction between different types of adopters, Bass does not assume a population to be heterogeneous (Bemmaor, 1994; Van den Bulde & Stremersch, 2007). Epstein & Axtell (1996) however criticise the construction of the model from a top-down approach of modelling, especially in the case of social sciences. They explain that the specificities of individuals can have a large impact on their decision-making and hence on the final state of a system. Lutzenhiser (1993) draws similar conclusions in the case of consumer energy use. In contrast to the Bass model, the Diffusion of Innovations model of Rogers is better adapted for the inclusion of heterogeneity. The Diffusion of Innovations model divides the population into five types of adopters. The different types of adopters differ in their perception of the innovation and the ability of the product to help them reach their own goals. On the contrary, a differential equation based simulation tool would

make the modelling of a high level of heterogeneity highly time costly due to the difficulty to incorporate a wide amount of different populations in the model (Borschev & Filipov, 2004).

The second rationale for the use of the Diffusion of Innovations Theory is the large amount of existing literature about the combination of Diffusion of Innovations Theory and agent-based modelling. A wide amount of this literature is listed in the literature review made by Kiesling, et al. (2012). This existing literature is used to provide insights in the construction of the model and for model validation.

3. 1. 3 Adopter categories and adoption process

The Diffusion of Innovations Theory is built from several main components: adopter decision-making process, adopter categories and relevant innovation characteristics (Rogers, 2003). Out of these three components, two have comparable equivalents written by others authors: adopter/consumer categories and adopter decision-making process. Although the Diffusion of Innovations Theory forms the basis for the theoretical approach in this work, the choice was made to evaluate each of the relevant theories (either from Rogers of from another author) and to choose the one that is the most appropriate in this modelling work. The choice between theories was based on modelling goals, the system to model, the compatibility with other elements of the theory of Rogers and the choices made by modellers found in the literature.

In each of the sub-sections in this section, an explanation of the utility of each type of theory is given. Subsequently, comparable theories are presented and a rationale is given for the chosen theory

Segmentation of agents

Reasons for segmentation of agents

The need for segmentation of agents can be derived from the work of Epstein & Axtell (1996). Epstein & Axtell underline the effects of the heterogeneity of a population on the evolution of the system in which members of this population evolve. Hence, in the modelling of social systems, the heterogeneity of a population should be taken into consideration to reflect the differences in product preferences and behaviours related to the adoption of the innovation. On the contrary, the analysis of the customer preferences and behaviour on an aggregate level might fail to capture these differences and can therefore fail to understand under which conditions various people adopt a product (Curtius, et al., 2012).

In the field of marketing, the consideration of heterogeneity was done by segmenting the population. Like Smith (1956) explains, within a group of the population, one can find groups of people that react in a similar way to the availability of a product or service. Consumer segmentation is a method to find the right balance between fulfilling the needs of the widest amount of potential consumer and reducing the costs of product adaptation. However, the segmentation however is dependent on the product or service considered (Abratt, 1993).

Segmentation models

By conducting a literature review, two types of relevant adopter segmentations have been distinguished: theoretical based consumer segmentations and smart grid specific empirical based consumer segmentations.

Two types of theoretical adopter segmentations can be identified: the adopter segmentation as described in the Behavioural Economic Theory (DiClemente & Hantula, 2003) and the adopter segmentation as described in the Diffusion of Innovations Theory (Rogers, 1962). In the Behavioural Economic Theory, four adopter categories are identified: ‘initiators’, ‘early imitators’, ‘later imitators’ and ‘last adopters’. Each type of adopters demonstrates a specific behaviour dependent on the need that the innovation fulfils. An initiator for example uses the innovations to show social and economic achievement, while a last adopter uses it to achieve physical or social survival (having enough food or

lowering expenditures) (DiClemente & Hantula, 2003). In the Diffusion of Innovations Theory, five types of adopters are distinguished: 'innovators', 'early adopters', 'early majority', 'late majority' and 'laggards' (Rogers, 1962). Similar to the adopter categories defined in the Behavioural Economic Theory, each type of adopter has its own behaviour in relation to the adoption of innovation. Similarly, adopters are classified depending on positive attitudes towards the innovation: an 'innovator' is expected to adopt an innovation much sooner than a 'laggard'. However, The Diffusion of Innovations Theory emphasises the dependency between adopter groups. For example the 'early majority' population uses the 'early adopters' population to find out whether the investments risks are satisfying. The 'late majority' population uses the other categories to find out if the social pressure is high enough before they decide to adopt. Also, the Diffusion of Innovations Theory provides a theoretical estimation of the proportion of each population. A visualisation of the types of adopters and the proportion of each population made by Rogers can be found in figure 3.

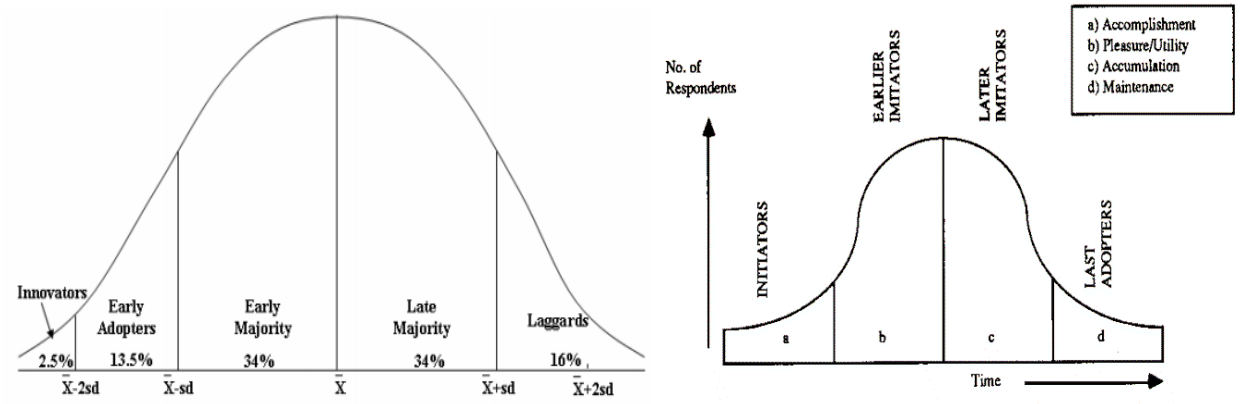


Figure 3: Adopter classes of the Behavioural Economic Theory, adapted from Foxall (1994), and adopter segmentation of Rogers (Sahin, 2006), adapted from Rogers (2003)

A wide amount of smart grid specific empirical consumer segmentations can be found in the literature. One interesting categorisation is made by Curtius et al. (2012). The segmentation created in this research is the result of an empirical cross country study carried out in four European countries. Surveys about the perception of smart grid technology by consumers has led to the identification of three segments: 'the supporters', 'the ambiguous' and 'the skeptics'. The members of each category differ in social characteristics and personal needs, which results in differing attitudes towards smart grid innovations. Another relevant characterisation has been created by the Smart Grid Consumer Collaborative (SGCC, 2011). The goal of this NGO is to conduct research in order to increase the adoption of smart grid technology by households and ensure their benefits for consumers in the USA (SGCC, 2009). Through the Consumer Pulse Research Program, a survey was conducted among households investigating their views on the rollout of smart grids and to test to what extent they were ready to participate (SGCC, 2011). Five consumer segments were identified. The distinction is made based on their perception of the utility of smart grids technology: environmental, financial and convenience. Five segments of adopters were found: 'Concerned Greens', 'Young America', 'DIY & Save', 'Easy Street' and 'Traditionals'. Similarly to the study of Curtius et al., each category differs in social characteristics, personal needs and hence in different attitudes towards smart grid technology.

Rationale for choosing the adopter segmentation of the Diffusion of Innovations Theory
In this work, the choice has been made to use the adopter segmentation of the Diffusion of Innovations Theory. First it has been preferred to choose a theoretical segmentation over an empirical approach since these two theoretical segmentations are well known and broadly recognised (Faiers, et al., 2007). Hence it is expected that the use of these theories will allow an easier communication and discussion with potential interested parties. Also, these theoretical segmentations have been used and studied widely, which offers a stronger support for their usage. Moreover, this will make the validation of the model easier since many diffusion of innovations models use the same theory. Second it has been preferred to choose the adopter segmentation of the Diffusion of Innovations Theory over the Behavioural Economic Theory because of its emphasis on the influence that different types of adopters have on each other. In the adoption of smart grid appliances, the investment risk plays a significant role due to the high costs of these products. Hence households are expected to be highly alert to the decision-making of other households to verify the extent to which the investment can be considered as risky (see section 1. 3).

Agent's adoption process

Reasons for introducing an adoption process
An adoption process is the division of the decision-making of individuals in a set of stages. The reasons why an adoption process is needed is that the adoption of an innovation cannot be considered as an instantaneous decision, as was first recognised by Ryan & Gross (1943). On the contrary, individuals go through a set of chronological stages. During each stage, actions are undertaken using information gathered during previous steps.

Main theories about adoption processes of individuals
Two main models of adoption processes of individuals can be identified: the innovation diffusion process of Rogers (1962) and the consumer adoption process of Engel et al. (1995).

Rogers identifies five stages: 'knowledge', 'persuasion', 'decision', 'implementation' and 'confirmation'. Table 4 describes the behaviour of (potential) adopters within each of these stages.

Table 4: Five stages of innovation diffusion process of the Diffusion of Innovations Theory, adapted from Rogers (1995)

Stage	Behaviour of (potential) adopters
Knowledge	- The individual is exposed to the innovation's existence and progressively understands how to use it. This is an essentially cognitive step.
Persuasion	- The individual decides whether he as a negative or positive attitude towards the innovation. The attitude is essential for the result of an affective phenomenon.
Decision	- The individual decides to adopt or reject the innovation by weighing its advantages and disadvantages.
Implementation	- The individual puts the innovation into use. In this stage, the individual faces the possible complexity of operating the innovation.
Confirmation	- The individual decides whether to continue using the innovation based on his experience and the behaviour of the group.

The consumer adoption process of Engel et al. is quite similar. The five stages identified are the following: 'problem recognition', 'information search', 'evaluation of alternatives', 'purchase decision' and 'post purchase behaviour'. Table 5 describes the behaviour of (potential) adopters within each of the stages.

Table 5: Five stages of the consumer adoption process, adapted from Engel et al. (1995)

Stage	Behaviour of (potential) adopters
Problem	- The individual becomes aware of the availability of a product and the

recognition	possibility to adopt it.
Information search	- The individual deliberately takes steps to gather information about the innovation. Information may be found through the sharing of information with other individuals or through media.
Evaluation of alternatives	- The individual judges the added value of the innovation through multiple criteria.
Purchase decision	- The individual chooses where to buy the product, and from which brand.
Purchase behaviour	- The individual forms a judgment on the extent to which the innovation has reached his expectations. Possibly he communicates about it with other (potential) adopters.

Rationale for choosing the consumer purchase decision process of Engel et al.
As explained above, the differences between the two decision processes are small. There are however two reasons why the consumer purchase decision process of Engel et al. has been preferred over the five stages identified by Rogers (1995). First, Engel et al. (1995) are more explicit about the role of interactions between households of the final decision whether to adopt an innovation. Since the role of interactions between households is expected to play a significant role in the adoption of smart grid appliances (see section 1. 3), the consumer purchase decision process of Engel et al. is preferred. Second, Rixen (2010) created an agent-based model for the adoption of smart metering appliances. In this work, he used the consumer purchase decision process of Engel et al. Hence choosing the same decision process is expected to facilitate the validation of the model.

3. 1. 4 Characteristics of innovations

Rogers (1995) underlines that it is the "receivers' perceptions of the attributes of innovations, not the attributes as classified by experts or change agents, that affect their rate of adoption". Hence, to understand the adoption of an innovation by an individual, one must not look at the attributes of an innovation, but at the perceived characteristics of this product. Using this consumer perspective of products, Rogers identifies five attributes of innovations. These attributes are presented in table 6.

Table 6: Five innovations attributes of the Diffusion of Innovations Theory, adapted from Rogers (1995)

Stage	Description of innovation attributes
Relative advantage	- Degree to which an innovation is perceived as better or more useful that others to achieve personal goals.
Compatibility	- Degree to which an innovation is compatible with the needs, way of living and values of a (potential) adopter.
Complexity	- Degree to which an innovation is perceived as difficult to understand and to use.
Triability	- Degree to which an innovation can be tried and tested by a potential adopter before potential adoption.
Observability	- Degree to which the innovation and its (potential) added values is visible to potential adopters.

3. 1. 5 Diffusion of Innovations Theory and Complex adaptive systems

As explained in section 2. 4. 1, the complex adaptive system is the framework in which the adoption of smart grid appliances is studied in this work. The combination of complex adaptive system theory and Diffusion of Innovations Theory is interesting. Historically, the assumption was often made in many innovation diffusion models that the population modelled was essentially homogeneously mixed (Stoneman, 2002; Jeuland, 1981). In other cases, they were divided in a very limited amount of groups. This is a serious limitation to the validity of the model outcomes since populations are in most systems in reality much more heterogeneous. The problem is that a strong heterogeneity of a population is

difficult to model with most simulation techniques. For example, increasing the heterogeneity of a population in a system dynamic model would impose the creation of a high number of levels in the model (Rahmandad & Sterman, 2008). As a result, the modelling duration would strongly increase and the interpretations of the results would become more difficult. The complex adaptive system theory however focuses on the heterogeneity of individuals. In complex adaptive systems, individuals are considered to make their own choice in order to reach their own goals. The combination of both theories will allow overcoming one of the shortcomings of the Diffusion of Innovations Theory.

3. 1. 6 Limitations of the Diffusion of Innovations Theory

The Diffusion of Innovations Theory has been widely used but also widely criticised. Three main critics to the Diffusion of Innovations Theory can be found in the literature. In this section, each limitation will be presented and an explanation will be given of how each limitation is coped with in this work.

The first limitation is that Rogers considers in his theory that technologies are static (Ciborra, 1996). On the contrary, there is continual innovation to convince new adopters to purchase the innovation. In this model, smart grid appliances will be considered as static since the addition of potential innovation about these products would add too much complexity in comparison to the added value that it could provide to the model. However, the model will be run for a duration of 10-15 years, which will allow limiting the effects of innovation of smart grid appliances.

The second limitation is the underlying assumption of the Diffusion of Innovations theory that individuals go through a careful cost/benefit analysis to decide upon the adoption of an innovation (Lyytinen & Damsgaard, 2001). The Diffusion of Innovations theory therefore tends to assume rational choice (Faiers, et al., 2007). Simon and Hawkins (1949) however have demonstrated that choices of individuals were constrained by cognitive and time limitations. In this work, different types of rationalities will be inserted in the model and tested on their influence of the model behaviour (see section 3. 2).

The third limitation is that Rogers assumes that the main sources of decision information are mass media and word of mouth. According to Lyytinen & Damsgaard (2001) however, numerous studies show that powerful actors (gatekeepers) are the main diffusers of innovation. These powerful actors can be governments or large industry associations. In this work, influence of powerful actors is considered not to be different from the influence of mass media. Like Rogers (1995) explains the role of mass media is crucial to share knowledge about the innovation and to increase awareness. However strong interpersonal communication between individuals is more powerful at changing the attitudes. These attitudes are essential to increase the trust of an individual that an innovation is profitable to adopt, which is something important in case of large investments.

3. 2 Rationality of households

The field of economics is divided by two schools that use completely different views of human nature (Burnham, 2013). The first school is neoclassical economics, in which individuals are assumed to behave rationally and have sufficient knowledge to maximise their profits. The second school is behavioural economics, in which individuals are seen as entities that have time and cognitive limitations and that do not only use financial parameters to decide upon alternatives. Since long, there has been a broad discussion in neoclassical economics about this assumption of rationality of agents (Sen, 1977). Although the theories of neoclassical economics have been widely criticised, these theories still form the basis of mainstream economic textbooks and teaching (Burnham, 2013). In agent-based models simulation decision-making of households, the question is also raised which rationality to apply to model the decisions of individuals (Makowsky, 2006). In this work, facing the dilemma of which rationality best suited modelling the choices in the adoption of smart grid appliances, the choice was not to use a single rationality. On the contrary, three types of rationalities are chosen and used. In the

validation phase, a selection of the most appropriate rationality will be made based on the accuracy to represent the decision-making of households.

In this section, the three types of rationalities used in this work will be presented. An explanation will also be given why these rationality types where chosen and how they will be implemented in the model.

3. 2. 1 Neoclassical rationality

Neoclassical economics is a term firstly introduced by Veblen (1900). In neoclassical economics, the state of the offer and demand of a product are explained by rational individuals maximising their profits. Central to the neoclassical economics is the assumption of rationality of individuals (Burnham, 2013). Rationality was then further defined by Simon (1969), as a contradiction to the bounded rationality theory. In this concept of rationality, it is assumed that people make choices by comparing various alternatives and choosing the one that fits best to achieve individual goals. Decision-making is hence an optimisation problem where individuals are assumed to have full information in order to take the most favourable alternative. The school of neoclassical economics also assume that any abnormalities in decision-making that do not strictly follow the rationality rules can be ignored when working on large real word problems (Burnham, 2013).

The reason why neoclassical rationality has been chosen in this model is essentially to be used as a basis in comparison with behavioural economics rationalities. The challenge is to find out, in comparison to neoclassical rational consumers, to what extent the usage of behavioural economics rationalities is able to explain part of the behaviour of households in the adoption of smart grid appliances.

In this work, neoclassical rationality of households will be introduced by using the three fundamental assumptions of neoclassical economics:

- Households have rational preferences among various alternatives,
- They have perfect knowledge about the implications of each alternative,
- They optimise their situation by maximising their profits (financial, social or emotional).

For each decision households will make, the algorithms will be modelled so that each household has full information about the alternatives. Also, households will pick the alternative that is best for them by individually making their own calculations.

3. 2. 2 Bounded rationality

Bounded rationality can be viewed as bridging the gap between neoclassical and behavioural economics (Kahneman, 2003). Bounded rationality was the first attempt to explain the non-rational behaviour of individuals in relation to economic decision-making. In contradiction to neoclassical economics, Simon (1957) started to explain the decision-making with the help of cognitive psychology (Harstad & Selten, 2003; Conlisk, 1996). The concept of bounded rationality was introduced by Simon and Hawkins (1949). The idea of bounded rationality is that individuals have limited information about the effects of the decision they are about to make. In addition, they have cognitive limitations in their mind and a limited time to make these decisions (Simon, 1955). As a result, decision-makers search for satisfactory solutions instead of optimised solutions.

In the adoption of smart grid appliances, households can be considered as making bounded rational decisions. For example, it is not expected that households make accurate calculations about the financial added value of these smart grid appliances. They are also not expected to make accurate predictions about the future development of the electricity price to see if investments are profitable. On the contrary, the information provided by other households is expected to play an important role in determining whether the investment will be profitable. Hence, the cognitive and time limitation of

households seems to be an appropriate model for their decision-making. Therefore, bounded rational decision making of households will be tested in this model.

Bounded rationality will be included in the model as follows. For each decision that households will make, the algorithms will be modelled by interpreting the assumptions of the bounded rationality theory.

- Households have limited memory about happenings of the past.
- Households prefer to follow simple forecasting heuristics in comparison to complicated processes. For example, they will prefer to use information from other households about potential savings instead of calculating the potential savings themselves.
- Households do not have all information available about the environment. Hence, they will make decisions about adoption without having all information needed.

3. 2. 3 Prospect theory rationality

Prospect theory fits within the bounded rationality framework (Kahneman, 2003). Like bounded rationality, it is a theory that tries to describe decisions made by individuals based on psychological reasons instead of economical ones. Prospect theory describes how people choose between alternatives according to the probabilities of outcomes (Kahneman & Tversky, 1979). Hence, the decision-maker makes choices based on the potential value of losses and gains and not on the alternative that might increase the decision-maker's utility most. The element of risk is important in the prospect theory. Decision-makers are risk avert in case they face decisions with sure gains. However, decision-makers are risk seeking when it involves decisions with sure losses. This effect is described by the value function presented in figure 4. To make these choices, decision-makers use a set of heuristic rules instead of optimal decisions.

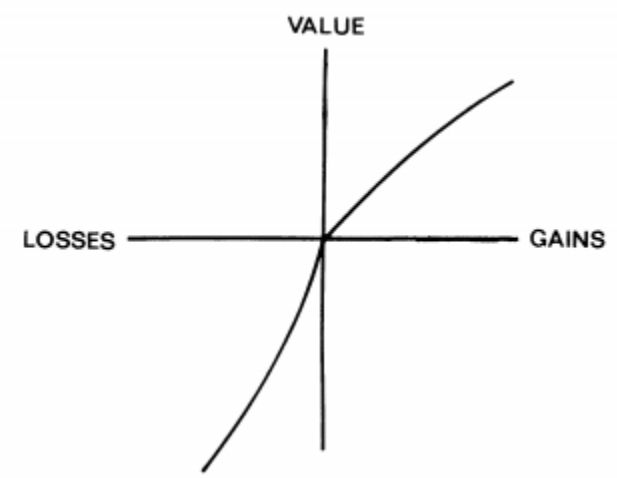


Figure 4: Prospect theory value function, adopted from Kahneman & Tversky (1979)

The reason why prospect theory is tested in this work is that it enables studying the effects of investment risks. Most of smart grid appliances are fairly expensive products on the scale of the revenue of households. The difference in price between smart and traditional products is also substantial, even though if smart appliances are expected to be cheaper when the entire life-cycle of the product is considered. However the lack of certainty that a smart appliance turns out to be cheaper, introduces the element of investment risk. The occurrence and extent of this risk can prevent households to purchase smart grid appliances.

Prospect theory will be included in the model as follows. Changes in the electricity prices will be seen as the sources of risk for households. Increasing electricity prices will increase the acceptation of risk and hence decrease the value perception of smart grid appliances. The contrary will happen for decreasing electricity prices.

3. 3 Interactions between agents: network topologies

Network topologies are recognised to play an important role in the diffusion process (Rahmandad & Sterman, 2008; Davis, 1991; Rogers, 2003; Epstein & Axtell, 1996; Valente, 1996). The case is not different for the diffusion of smart grid appliances (Nuttall, et al., 2009; Snape, et al., 2011). The effects of various types of network topologies on diffusions have also been widely studied (Gordon, 2003; Rahmandad & Sterman, 2008).

In this work, three types of interactions have been chosen. The choice was based on the work of Zhang & Nuttall (2011) in the modelling of households' adoption of smart metering. These two types of interactions are regular and random interactions. As Zhang & Nuttall explain, the advantage of their use is that they enable "the social networks in the environment to have the characteristic features of both 'smallworld' and scale-free effects". The small world network is a type of random network with many short links and a few long ones (Rahmandad & Sterman, 2008; Watts & Strogatz, 1998). Hence it is useful to study the effects of clustering. In this work, friend interactions are added to the small world network. The reason is that it is expected that this is the type of network that respresents the types of interactions that households have in a city-district best. This expectation is however not fully proven and the testing of the impact of various types of networks on the adoption curve of innovations would be a relevant additional work to this project. The fact that only one type of network is considered form one of the limitations of this project (see 8. 1).

3. 4 Conclusion

In this chapter, different relevant theories for the modelling of adoption of innovations have been presented. Based on the research question and sub-questions, objectives and scope, a selection of theories has been made to allow the modelling of smart grid appliances adoption by households. The theories selected are summarised in table 7. These theories will be used to build in the simulation model in chapter 4.

Table 7: Selection of theories for the modelling of smart grid appliances adoption

Theories chosen	Contribution to answer the research question
Diffusion of innovation model	- The Diffusion of Innovations Theory of Rogers (1962)
Segmentation of households	- The segmentation of adopters of Rogers (1962): innovators, early adopters, early majority, late majority and laggards
Adoption process of households	- The consumer decision-making process of Engel, et al. (1995): problem recognition, search for alternatives, evaluation of alternatives, purchase and post-purchase behaviour
Relevant characteristics of innovations	- The five innovations characteristics of Rogers (1962): relative advantage, compatibility, complexity, triability and observability.
Rationalities of households	- Three rationalities are chosen: neoclassical rationality, bounded rationality and prospect theory
Interactions	- Three types of interactions simultaneously used: random interactions, friend interactions and neighbour interactions

Chapter 4 – Formalisation and specification

The goal of this chapter is to build a model that will allow answering the research question and sub-questions identified in chapter 2. This chapter will allow answering the second sub-research question of this work (see section 0). This will be done by using the theories selected in chapter 3 (see table 1 for a summary of the theories selected). Before starting to create the model, the modelling objectives and key performance indicators to measure model behaviour are identified in section 4. 1. The construction of the model will be done in three steps. In the first step (section 0), the most important aspects that will have to be implemented in the model are formalised. These aspects include households, electricity prices and smart grid appliances. In the second step (section 4. 3), the model is formalised. In this case, this means that a decision-making process that households go through to decide whether to adopt a smart grid appliance is created and translated to a format that can be understood by the simulation software Netlogo (Wilensky, 1999). In the third step (section 4. 4), the model is specified. This means that relevant data from literature is selected and calibrated to be inserted into the model. The outcome of this chapter is a model that will be ready for verification and validation in chapter 5.

As explained in section 1. 2, different types of smart grid appliances exist, ranging from smart washing machines to smart freezers. From this point forward, the model is restricted to the study of the adoption of smart washing machines. The reason is that the difference between considering the adoption of each of the smart grid appliances is not expected to be large. The amount of savings that can be made by adopting may be different but households' behaviour in adoption does not differ. Therefore, conclusions about the adoption of smart washing machines will also be valid for other smart grid appliances.

4. 1 Modelling objectives and key performance indicators

The model built in this project should help answering the research question and sub-questions identified in section 0. To be able to test various policies to increase the adoption of smart washing machines, a model should be created that can simulate the response of households to these directions for policy through smart washing machine adoptions. The model should be able to generate data showing various model key performance indicators (KPIs). These KPIs are necessary to get an overview about the behaviour of the model and to investigate its response to various policies. The key performance indicators are divided into three groups: policy performance indicators, adopter specific adoption curves and indicators for adoption blockage. The full list of relevant KPIs is provided in table 8.

Policy performance indicators

Based on the research objective of this work, one simple policy objective was identified: increase of the adoption rate of smart washing machines. Therefore, the key performance indicator is a measure at each point in time of the number of households that currently have a smart washing machine at home.

Adopter specific adoption curves

The adopter specific adoption curves are not essentially relevant to assess the performance of the direction for policy since the focus of policies is to increase the total number of adoption, whoever the type of adopter is. They are however important to understand which type of adopter is not willing to adopt and to develop specific policy directions for these categories.

Indicators for adoption blockage

The third type of performance indicators shows for which reasons households refuse to adopt. These indicators are necessary to understand why adopters do not adopt and, based on that information, what the new direction for policy should focus on.

Table 8: Overview of model key performance indicators

Key performance indicators
Number of households owning smart washing machines
Percentage of innovators with smart washing machines
Percentage of early adopters with smart washing machines
Percentage of early majority population with smart washing machines
Percentage of late majority population with smart washing machines
Percentage of laggards with smart washing machines
Amount of households blocking because of a lack of savings
Amount of households blocking because adoption complexity is too high
Amount of households blocking because of a lack of adoption information
Amount of households blocking because of a lack of savings
Amount of households blocking because the investment is considered too risky

Following the research questions of section 0 and the KPIs identified here, the following modelling objective can be formulated. The modelling objective is to obtain quantitative data about the level of adoption of smart washing machines on the scale of a city district, depending on interactions between households, the properties of each individual household and the state of the environment in which they perform their decision-making. Therefore, the modelling goal is to build a model that represents the decision-making of various households as a result of interactions with other households and with their environment.

The following model requirements can be identified based on the modelling objective and goal. First, the model should be able to provide a clear overview of the KPIs indicators. This will allow to identify the performance of various directions for policy easily. Second, the model should allow different agent rationalities to be tested (see section 3. 2). This will enable to find out which type of rationality corresponds best with the actual decision-making of households. Third, the model should allow testing different scenarios. This will also be to study the performance of directions for policy depending on future possible scenarios and choose the directions that are the most robust to changes in the environment. Fourth, the model should allow the insertion and testing of various directions for policy. Preferably, the model should be built in such a way that all of the rationalities, scenarios and policies can be inserted in the model and tested quickly in order to avoid excessively long modelling time. Fifth, the model should be designed in such a way that it can used in combination with the EMA Workbench for EMA test. Concretely, this means that in the simulation software Netlogo (Wilensky, 1999), each variable to vary is defined as a global in the interface tab of the model.

4. 2 Concept formalisation

In this section, the conception formalisation of the model is presented. In this step, the relevant aspects of the system are picked up and formalised to be represented into the model. The relevant aspects chosen delineate the border of the system that will be modelled. It also provides a specification of the level of details that is considered in the model. In this section, first a basic design of the model will be presented. Then the formalisation of the following system aspects will be described: model environment, model agents and model objects.

4. 2. 1 Basic design

The basic design of the model is an area in which various households are placed. At each step, households interact with each other and exchange information about smart washing machines based on their current awareness of these products and the extent to which they have performed the entire decision-making process. Households then go through various decision-making steps (see section 4. 3). For each step, they base their decision on four elements:

- information that they just received from other households,
- information that they have in their memory,
- individual preferences, and
- environmental parameters.

The outcome of each step can either be to continue with the decision-making process or to stop it. In the last case, this means that the household did not consider the conditions for going to the next step as satisfactory. If at the outcome of the last decision-making step the household decides that the conditions for acceptation are acceptable, the smart washing machine is adopted.

Figure 5 and figure 6 present the concept formalisation used in the model. These figures show several important elements. First, they show households as entities that contain two main elements: state and rules. The state shows the collection of parameters that defines the household. The rules describe how the household translates states into actions or new states (Dam, et al., 2013). Second, the figures show which external parameters (environment) the household takes into account. Third, they show what type of interactions the household has with other households and which information is exchanged. Last, they show the relation between the household and the smart washing machine it may adopt. These two figures will be used to present the formalisation of the model environment, agents and objects.

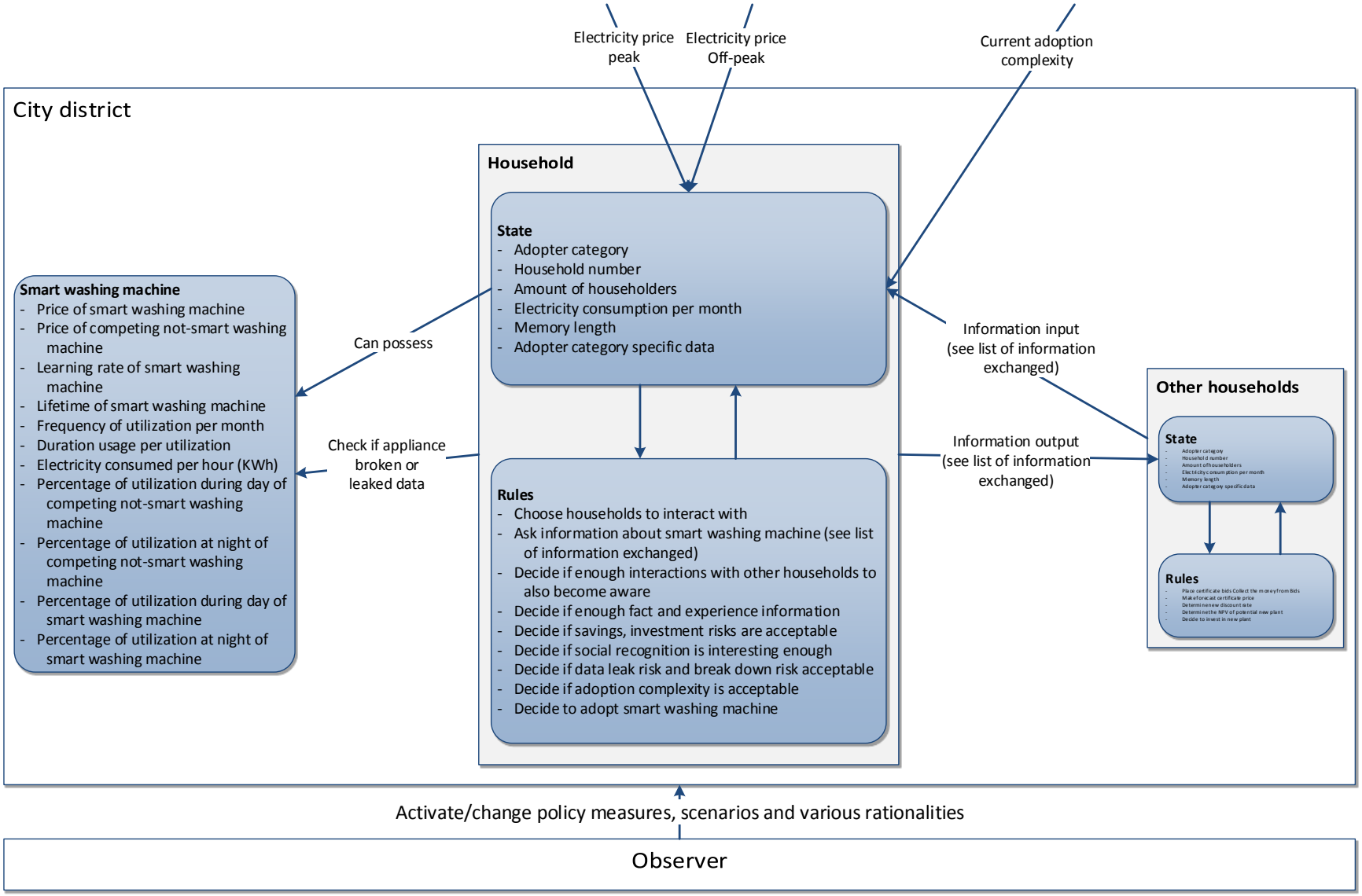


Figure 5: Relation of households with other households and their environment

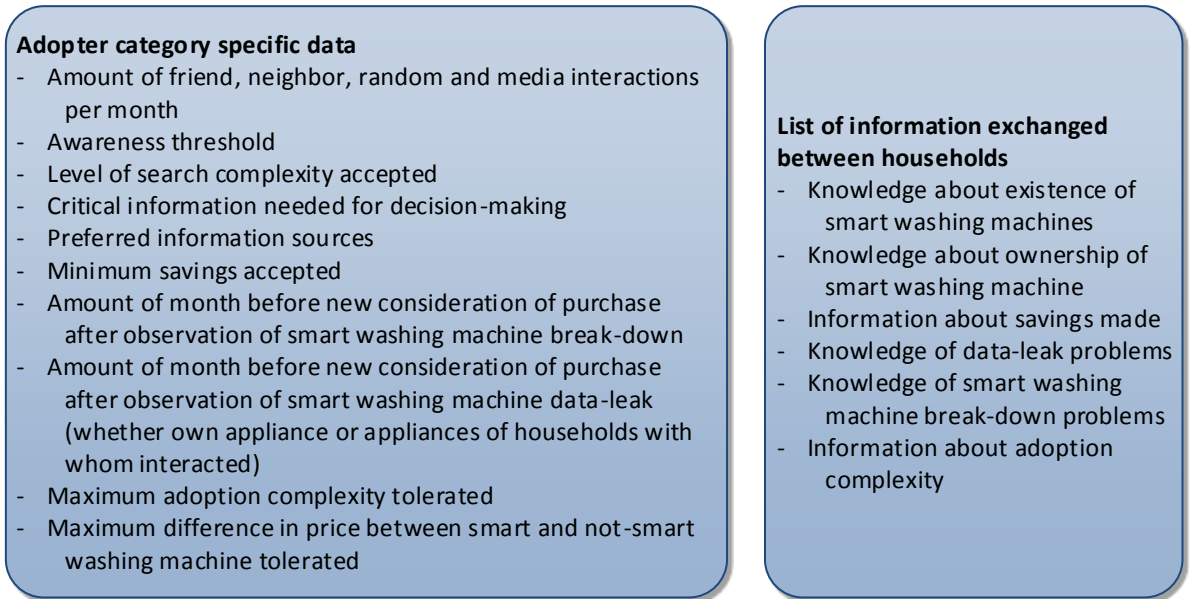


Figure 6: Adopter category specific data and list of information exchanged

4. 2. 2 Model environment

As is shown in figure 5, four variables characterise the environment. The specification of these environment variables is presented in table 9.

Table 9: overview of environment variables

Environment	
High electricity price	- Real >=0
Low electricity price	- Real >=0
Price decrease of smart washing machines	- Real >=0
Current adoption complexity	- 1, 2 or 3

Formalisation of the electricity price

Two types of electricity prices are formalised: a peak and an off-peak electricity price. In each case, the peak electricity price is assumed to be higher than the off-peak electricity price. In this model, the peak and off-peak electricity prices are kept fixed during the entire model run. The reason is that the usage of continuously fluctuating electricity prices, such as real life electricity market price, adds a lot of complexity to model behaviour while not being essential to the identification of directions for policy to support smart washing machine adoption.

In the model, the electricity price is used by household for the following three actions:

- To calculate savings that the adoption of smart washing machines could provide (prior to adoption),
- To calculate the satisfaction about savings that the adoption of the smart washing machine has brought (after the adoption),
- To calculate the amount of investment risk that households are willing to take by adopting a smart washing machine (defined by the difference between the costs of the smart and traditional appliances).

Price decrease of smart washing machines

To simulate the decrease of the smart washing price, a progress ratio is assigned. The progress ratio "derives from historical data inexperience curves (and) are used for forecasting development of many technologies as a means to model endogenous technical change in for instance climate–economy models" (Sark, 2008). This ratio is therefore an indicator of the speed of learning of a technology's utilisation and hence the speed of the decrease of its costs. This is done through a logarithmic function. Equation 1 shows how the new costs are calculated. Figure 7 shows an overview of the cost decrease with this equation.

Equation 1: Calculation of new smart washing machines costs

$$C(X_t) = C(X_0) * t^{\log(B,2)}$$

$C(X_t)$	Cost of the technology at time t
$C(X_0)$	Initial cost of the technology
t	Current time
B	Learning parameter

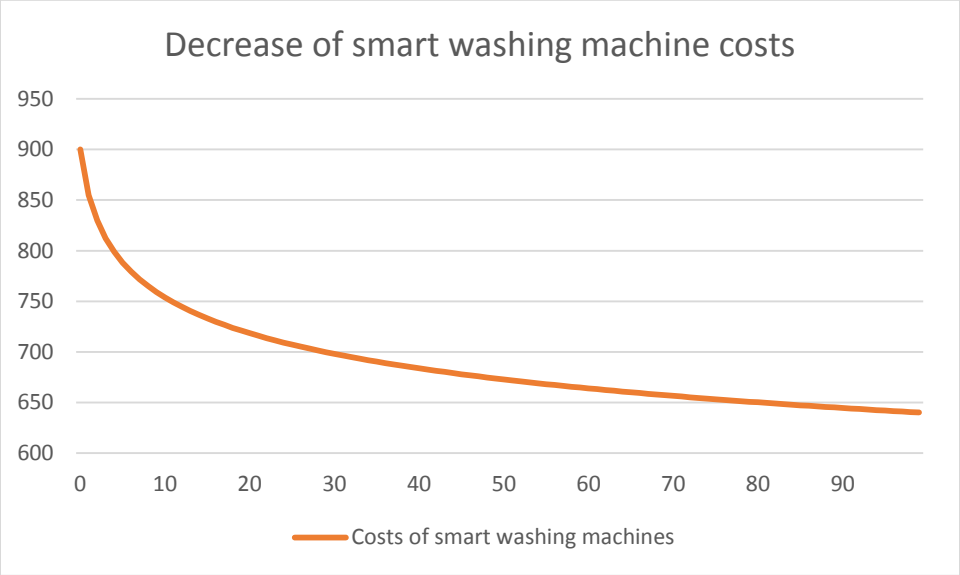


Figure 7: Decrease of the smart washing machines costs through a logarithmic function

Formalisation of complexities

Complexity forms one of the five relevant product perceptions that household use to decide whether or not to adopt an innovation (see section 3. 1. 4) (Rogers, 1995). As Rogers explains, it is not the complexity of an innovation itself that plays a role in the adoption but the perceived complexity that households have. Several types of adoption complexities can be distinguished. Examples are the complexity to purchase, to install and the complexity of the new behaviour that the operation of the technology requires.

The structure of the decrease of complexity is challenging. On one side, the decrease of adoption complexity can be seen as the result of the emergence of a limited amount of new technology design standards. The product marketing is than based on the potential that retailers see in the product as a result of the appearance of these new standards. The adoption complexity decrease would in this case be discrete. On the other side, the decrease of adoption complexity could be seen as an ever-ongoing

succession of small improvements created by a large amount of competing product designers. These improvements would then progressively decrease its utilisation complexity. Since the potential for improvements is large at the beginning of the product's development, the decrease of utilisation complexity would be stronger in the first commercialisation phases. The decrease of the adoption complexity would then be a continuous curve.

As a result of these two views of decrease of adoption complexity, two types of complexity evolution structures are designed. In case both structures are validated in the verification and validation chapter (see chapter 5), both will be used for the experiment phase in chapter 6.

Discrete decrease of the adoption curve

To conceptualise the decrease of adoption complexity, three levels of complexity are introduced. Level 3 stands for highly complex adoption. Adoption by households would in this case need self-research on internet, self-installation of the product and a large adjustment for the utilisation of the smart washing machine. An adoption complexity of 2 stands for the availability of the product in some specialist stores, the need to hire personnel to install the product and a limited need of behaviour adjustment. Level 1 stands for a commercialisation phase in which the product is available in various large-scale stores, a plug and play installation, and a no change in utilisation behaviour.

The three types of complexities are changed accordingly to the maturity of smart washing machines as a product on the market. The maturity is modelled by using the four product phases identified by Levitt (1965): market development phase, growth phase, maturity phase and decline phase. An overview of the product lifecycle is provided in figure 8.

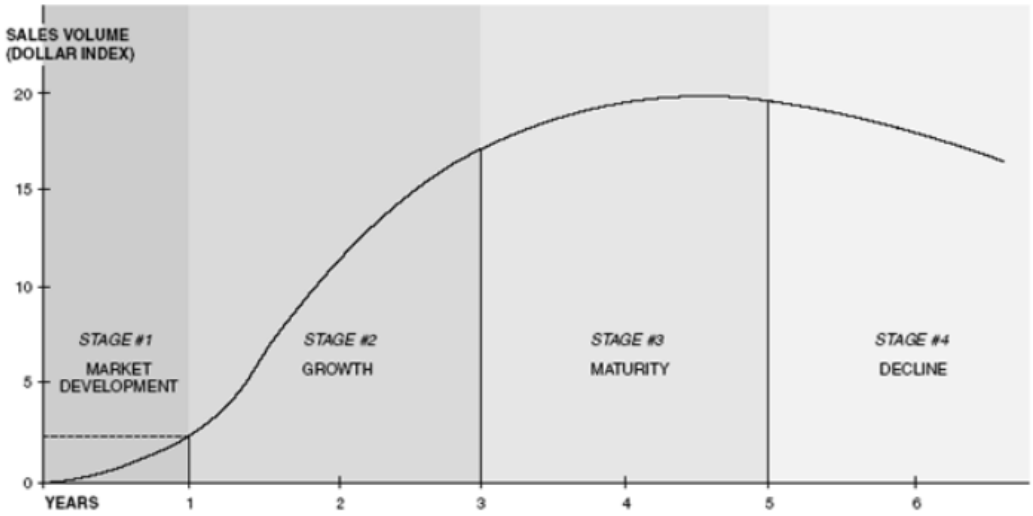


Figure 8: overview of the four product lifecycle phase, adapted from Levitt (1965)

In the market development phase, it is considered that each of the complexity is equal to 3. In the growth phase, each is equal to 2. In the maturity phase and the decline phase, each is equal to 1. In this model, only the first three-lifecycle phases are taken into account since the model length is 12.5 years and the focus is set on how to increasing adoption on a short term. A visualisation of the step decrease of adoption complexity in the model is provided in figure 9.

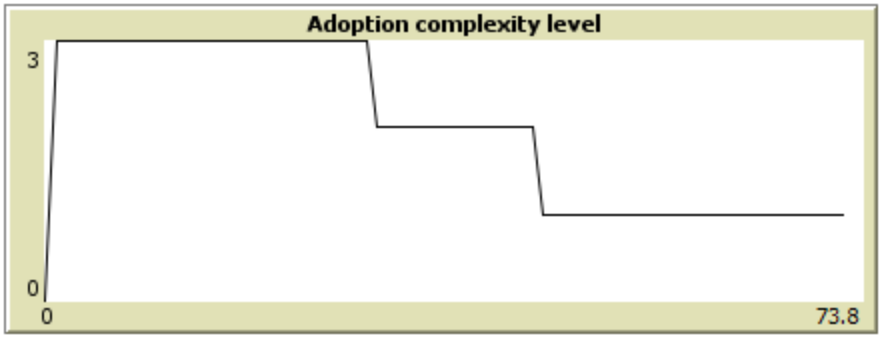


Figure 9: steps decrease of adoption complexity

Continuous decrease of the adoption curve

To model the continuous decrease of the adoption curve, the same system of three different levels of adoption complexities is used. The adoption complexity evolves however continuously between each level. The decrease of adoption complexity is modelled in the same way as the decrease of the smart washing machine costs. The use of a logarithmic function is adapted in this case since it is expected that the decrease of adoption complexity is higher in the first development phases. The typology of adoption complexity decrease is than comparable with the evolution of the logarithmic function in equation 1. A visualisation of the continuous logarithmic decrease of adoption complexity in the model is provided in figure 10.

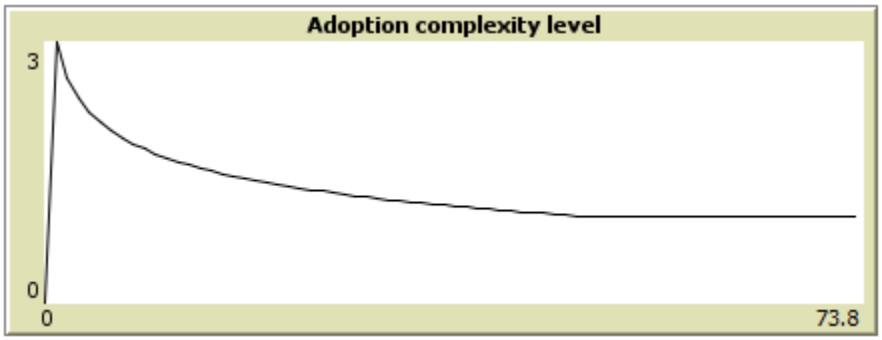


Figure 10: continuous logarithmic decrease of adoption complexity

Exchange of information between households

As Rogers (1962) explains that although mass media is the main diffuser of awareness interpersonal communication is the main mechanism of diffusion. Therefore, in this model, external sources of information (not coming from other households but from media or companies) are assumed to only influence the awareness of households. Information about the degree of complexity of adoption and the amount of savings that can be made only diffuse through face to face communication between households. In this work, the effect of social media is not taken into account. The expected effect of the adoption of smart grid appliances and the directions for policy identified in this work is discussed in section 8. 1.

4. 2. 3 Model agents

The state and rules of agents are presented in figure 5. The number of households in the model is left to the choice of the modeller.

In this section, the characteristics of agents are presented according to the BDI framework (Rao & Georgeff, 1995). The BDI framework provides an overview of the Beliefs, Desires and Intentions that motivate the behaviour of the modelled agents. An agent's beliefs represent the informational state of

the agents, hence what the agent considers as his knowledge and the knowledge of other agents. The desires of an agent stands for his motivational state, which consists of the objectives that the agent tries to achieve. The intentions of an agent represent his deliberative state. These are the set of actions that an agent chooses to use to achieve his goals. The BDI framework of households is presented in table 10. The rationality column indicates under which rationality the belief, desire or intention indicated is true.

Table 10: BDI framework of households

	Rationality	Households
Beliefs	Under all rationalities	- Knowledge of the existence of smart washing machines - Electricity consumption each month - Height of electricity bill each month - Price of smart appliances - Price of traditional appliances - Adoption complexity of smart washing machine on the market - Experienced adoption complexity as experienced by households with whom interacted - Maximum adoption complexity accepted - Knowledge of appliance breakdown cases - Knowledge of appliance data leak cases - Level of savings that can be considered interesting enough - Savings made each month with the appliance adopted - Knowledge of amount of householders encountered with and without smart washing machine - Recent increase/decrease of the electricity price - Level of investment risk that can be considered as acceptable - Type of adopters they prefer to receive information from
	Under neoclassical rationality	- Lifetime of appliances - Frequency of utilisation per month - Duration of usage per utilisation - Electricity consumed per hour - Percentage of utilisation of (smart and traditional) appliance during peak and off-peak periods - Current peak electricity price - Current off-peak electricity price
	Under bounded rationality	- Savings made by households with whom interacted
Desires	Under all rationalities	- Increase savings in relation to electricity consumption - Experience low efforts in relation to adoption of smart washing machines - Decrease operational risks (data leak and break-down cases) - Increase social recognition
	Under prospect theory	- Experience low financial risk when investing
Intentions	Under all rationalities	- Decide whether to adopt a smart washing machine - Ask other households about their experience of operational risk s (data leak and break-down cases) - Ask other households about their experience of adoption complexity. - Ask other households if they own a smart washing machine to find out about potential social recognition
	Under neoclassical rationality	- Calculate the financial benefits of adoption a smart washing machine
	Under bounded rationality	- Estimate the financial benefits of adoption a smart washing machine through information from other households

4. 2. 4 Objects

One type of object is used in this model: smart washing machines. The properties of smart washing machines that are considered in the model are presented in figure 5. Households can either own or not own a smart washing machine, How they are utilised by households is not considered in this work.

4. 3 Model formalisation

In section 0, a presentation was provided about how the relevant system concepts were formalised in the model. In the current section, the model narrative and the pseudo-code are presented. The model narrative is a story of the steps that agents and objects go through across time. More concretely, it indicates "which agent does what with whom and when" (Dam, et al., 2013). The pseudo-code is a first formalisation of the model narrative towards a code that is understandable by simulation software.

4. 3. 1 Narrative

The model narrative presented in this section shows the steps that households (may) go through for each time step of the model. Based on the consumer adoption process of Engel et al. (1995) (see section 3. 1. 3), the model narrative is divided into five main steps. Each step results in the households turning into one of the following four types of states. Households may remain unaware of the innovation, they may drop out of the decision making process because of an unsatisfactory aspect of the adoption, they may go to the next decision step or they may finally adopt the smart washing machine. The current section is divided according to these five decision-making steps. For each step, an overview of the main actions performed by households is presented. In the relevant decision-making steps, an explanation will be provided of how each of the five characteristics of innovations of Rogers (see section 3. 1. 4) are taken into account by households to realise decision-making. The detailed explanation of the content of each step is provided in Appendix B, as well as a visualisation by means of a goal tree and the equations households uses to make the necessary decisions. In Appendix A, an activity diagram showing the overall narrative of the model is presented.

Step 1: Problem recognition

The problem recognition step is the step in which households may become aware of the availability of a product and the possibility to adopt it (Engel, et al., 1995). The extent to which individuals can become aware of an appliance is dependent of the triability and observability of the innovation. These are two of the five relevant characteristics of innovations of Rogers (see section 3. 1. 4). The extent to which smart washing machines are triable and observable are included in the model through the number of interactions that households have about the appliance each month. The more triable and observable the appliance, the more interactions households have about it and the fastest households become aware of the possibility of adopting it.

An overview of the decision-making step is provided in table 11 in this section. A more detailed explanation of the actions performed by household and a visualisation of the step through a decision tree (figure 35) is provided in Appendix B.

Table 11: Overview of the problem recognition step

	Description
Goal of the step	- Decide whether to become aware of the existence of smart washing machines based on the number of households encountered that owned one.

Actions performed by households	1. Check how many interactions it is allowed to have and decide which household to interact with
	2. Check if the household already owns a smart washing machine:
	  - If yes: go to the post purchase process behaviour (see step 5)
	  - If not: continue
	3. Ask to each household whether it owns a smart washing machine
	4. Ask to each household which adopter category it belongs to
	5. For each household that owned a smart washing machine, sum up the valuation of that households according to the adopter category it belongs to. Do the same with media interactions. This is done by using equation 2

	of Appendix B. 6. Find out of the sum of the valuations is superior or equal to 1: - If yes: become aware and go to the information search step (see step 2) - If not: remain unaware and stop the decision-making process for this model step
Outcome of the step	- A list of household with whom to interaction with during this model step - A decision whether to become aware or not

Step 2: Information search

In the information search step, individuals gather information about smart washing machines. Information is found through the sharing of information between households (Engel, et al., 1995). Four types of information are exchanged between households: information about savings made, adoption complexity, breakdown problems and data-leak problems. The outcome of the step is a decision whether or not enough reliable information has been found.

An overview of the decision-making step is provided in table 12 in this section. A more detailed explanation of the action performed by household and a visualisation of the step through a decision tree (Figure 36) is provided in Appendix B.

Table 12: Overview of the information search step

	Description
Goal of the step	- Find information about adoption and decide whether enough similar information has been received to be able to consider information as reliable enough
Actions performed by households	1. Ask households in their list of households with whom interacted if they have knowledge about one of more of the following four types of information: information about break-down problems, data leak problems, adoption complexity and savings made (only for bounded rationality) - If yes: copy the information to a specific list - If no: continue with the next households in list 2. Ask each household which adopter category it belongs to 3. Find out, for each type of information, whether there is enough similar information in order to be able to consider the information as reliable. For savings and adoption complexity: this is done by using equation 3 in Appendix B. Sum up for each similar information whether the sum of the valuation of households mentioning this information is higher than 1. For break-down problems and data-leak problems: this is done by using equation 4 in Appendix B. Count the number of households that have experienced a break-down or data leak problem, or have knowledge of someone having experienced it. - If yes: proceed to the evaluation step (see step 3) - If not: stop the decision-making process and go back to the awareness step
Outcome of the step	- Information about savings made - Information about adoption complexity - Information about break-down problems - Information about data-leak problems - Decision whether enough reliable data has been found to proceed to the evaluation step

Step 3: Evaluation

In the evaluation step, the individual judges the added value of the innovation through multiple criteria (Engel, et al., 1995). Five evaluation criteria are used by households for the evaluation of smart washing machine adoption: expected savings, investment risk, expected social reward, data leak risks and breakdown risks. Information used for the calculation of expected savings (for neoclassical rationality), investment risk and expected social reward come from households' observations of the environment. Information related to expected savings (for bounded rationality), data leak and break-down risks come from communication with other households. Expected savings and expected social reward relate to the relative advantage as explained by Rogers (see section 3. 1. 4). These two variables are used by households to find out whether their financial and social status can be increased through the adoption of smart washing machines. As explained by Rogers, data leak, breakdown and investment risks relate to the compatibility aspect. Some households for example do not see the leak of their data as a major problem. Others on the contrary view this as a major factor in determining the adoption of an appliance.

An overview of the decision-making step is provided in table 13 in this section. A more detailed explanation of the action performed by households and a visualisation of the step through a decision tree (figure 37) is provided in Appendix B.

Table 13: Overview of the evaluation step

	Description
Goal of the step	- Evaluate whether the added value of adopting smart grid appliances is high enough to consider adopting according to five different criteria: o Expected savings o Investment risk o Expected social reward o Data leak risks o Breakdown risks.
Actions performed by households	1. First calculate expected savings: - In the case of neoclassical rationality: individually calculate expected savings based on information in the environment (such as smart washing machine price, peak and off-peak electricity price). Calculate whether the amount of savings is higher than a certain threshold (see equation 5 in Appendix B). o If yes: consider the level of savings as satisfactory o If no: consider the level of savings as unsatisfactory - In the case of bounded rationality: ask households with whom interacted, in case they own a smart washing machine, how much savings they are making. Calculate if the percentage of encounters with households owning a smart washing machine, that mention a level of savings that is satisfactory is higher than a certain threshold (see equation 6 in Appendix B). o If yes: consider the level of savings as satisfactory o If no: consider the level of savings as unsatisfactory 2. Calculate investment risks (only when prospect theory is taken into account) - Calculate the difference between the price of smart washing machines and the price of traditional washing machines. Adjust it by considering the recent decrease or increase of the electricity prices (see equation 7). Find out if the resulting difference in price is lower than a certain accepted threshold. o If yes: consider the level of investment risk as acceptable o If no: consider the level of investment as unacceptable

	3. Calculate social reward (only for early adopters and late majority population) - Calculate how much of the household with whom interacted already owned a smart washing machine. Find out whether this is lower/higher than a certain threshold (depending on the adopter category). o If yes: consider the level of social reward as acceptable o If no: consider the level of social reward as unacceptable 4. Find out if at least one of the households with whom interaction has experienced or if households know somebody that experienced a break-down or data-leak problem. o If yes: consider the level of break-down or data-leak risk as unacceptable o If no: consider the level of break-down or data-leak risk as acceptable 5. Control whether all of the criteria have been satisfied: - If yes: proceed to the decision-making step (see step 4) - If not: stop the decision-making process and go back to the awareness step
Outcome of the step	- A decision whether the criteria for adoption are satisfying

Step 4: Decision-making

In the decision-making step, the individual chooses where to buy the product, and from which brand (Engel, et al., 1995). The decision to adopt an appliance is however not automatic, even if the benefits of the appliance are evaluated positively (Cannière, et al., 2009). The reasons are the additional efforts of daily changing behaviours and organising the purchase and installation of the appliance. The unwillingness of some households to make these efforts constrains them to adopt an appliance that could improve their financial or social situation. This choice is irrational from a neoclassical point of view. In neoclassical theory, individuals are assumed to try to maximise their situation whenever this is possible (see section 0). Instead, this choice fits with the bounded rationality theory, in which individuals are seen as having cognitive and time limitations (see section 3. 2. 2). Hence, it is considered in this work that the consideration of complexity is only taken into account by households if they use bounded rationality. In case neoclassical rationality is used, household automatically adopt the smart washing machine when they arrive at the decision-making step.

An overview of the decision-making step is provided in table 14 in this section. A more detailed explanation of the action performed by household and a visualisation of the step through a decision tree (Figure 38) is provided in Appendix B.

Table 14: Overview of the decision-making step

	Description
Goal of the step	- Find out whether the level of adoption complexity is acceptable (only in the case of bounded rationality)
Actions performed by households	1. Ask households with whom interacted what the level of complexity is that they experienced by adopting. Calculate if the percentage of households encountered, owning a smart washing machine, and mentioning a level of complexity that is satisfactory is higher than a certain threshold (see equation 6 in Appendix B). - If yes: proceed to the post purchase behaviour step (see step 5) - If not: stop the decision-making process and go back to the awareness step

Outcome of the step	- A final decision whether to adopt a smart washing machine or not

Step 5: Post adoption behaviour

In the post adoption behaviour step, the individual forms a judgment on the extent to which the innovation has reached his expectations. Possibly he communicates with other (potential) adopters about the innovation adopted (Engel, et al., 1995). In this model, households that interact with each other are assumed to be willing to provide all information that other household request, as long as they possess the relevant information. Hence household that have completed the entire decision-making process and have adopted a smart washing machine are willing to share all information they experienced during the decision-making process and after the installation of the appliance. Households that dropped out the decision-making process in one of the steps are willing to share all information they gathered until the point where they got out of the process. A visualisation of the step through a decision tree (figure 39) is provided in Appendix B.

4. 3. 2 Pseudo-code

The pseudo-code is a first formalisation of the model narrative towards a code that can be introduced in simulation software. The pseudo-code is essentially useful for humans, since it helps them to understand the algorithms used in the model (Dam, et al., 2013). Therefore, in creating a pseudo-code, all elements that are not useful to the understanding of humans are omitted. The pseudo-code created for this model can be found in Appendix B.

4. 4 Model specification

In the model specification section, methods and data for quantification of the conceptualisation and the formalisation made in section 0 and 4. 3 is presented. As explained in section 2. 4. 2, two types of data sources are used. Data about the properties of households, electricity prices and smart washing machines originate from a data research performed on relevant websites. Data about the characteristics, preferences and behaviours per type adopter has been generated based on an interpretation of the Diffusion of Innovations Theory. The method used for data generation and the way that has been calibrated is explained in this section. The data used in the model and the assumptions used for their utilisation are presented in Appendix C.

4. 4. 1 Data generation

The literature review performed in this work did not allow to find extended information about human behaviour in relation to the adoption of smart washing machines. Therefore, the choice was made to generate data based on an interpretation of the Diffusion of Innovations Theory.

In his book about Diffusion of Innovations Theory, Rogers (1983) studies a wide range of generalisations in the form of 'earlier adopters have more/greater/higher … than later adopters'. These generalisations can also be viewed as independent variables such as age, education and social status. His finding is that most of the independent variables influencing innovation identified are "positively related to the dependent variable of innovativeness" (see figure 11). Three independent variables however do not obey to the rule. The independent variable 'opinion leadership' is positively related to the dependent variable of innovativeness apart from innovators, who are often seen as outsiders of a society. The independent variables 'dogmatism' and 'fatalism' are negatively related to the dependent variable of innovativeness.

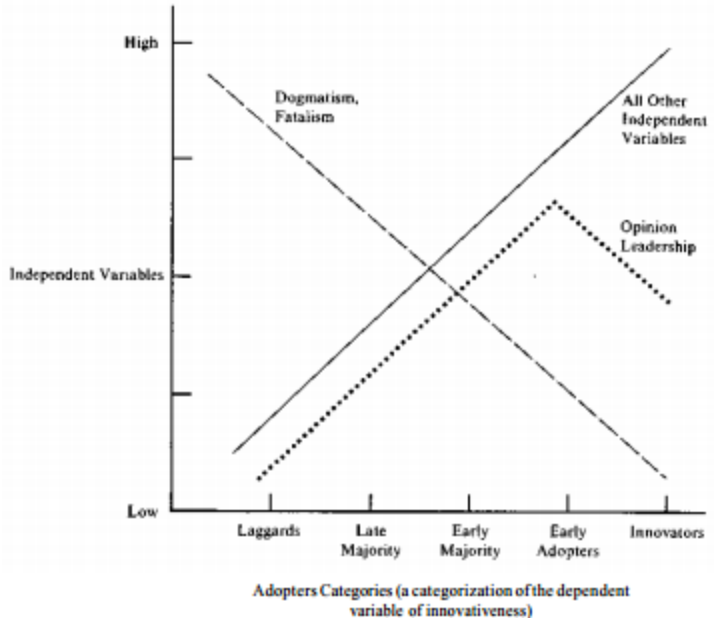


Figure 11: Relationship between independent variables and the dependent variable of innovativeness, adapted from Rogers (1983)

The data about characteristics, preferences and behaviours per type adopter has been generated based on the generalisations on a linear basis. An example of how data has been generated is provided in the text box hereunder. An overview of all the data generated and the generalisation on which they were based is provided in Appendix C.

An example of the data generation process: household interactions

In the Diffusion of Innovations book of Rogers (1983)*, the following generalisations in relation to adopter interactions are provided:*

- *"Earlier adopters have more social participation than later adopters"* (Rogers, 1983, p. 258).
- *"Earlier adopters are more highly interconnected in the social system than later adopters"* (Rogers, 1983, p. 258).
- *"Earlier adopters have more change agent contact than later adopters"* (Rogers, 1983, p. 259).

These generalisations clearly show that earlier adopters have more interactions than later adopters. We set the base number of interactions of householders per month to 6. This number is not based on any research due to the lack of data in the literature but on estimation of the behaviour of households. The correctness of this estimation and its impact on the final adoption of smart washing machines will be assessed in the verification and validation chapter (see section 5. 3). We then assumed that the amount of interaction is linearly dispatched among the five type of adopters. Therefore, the following interaction distribution among the five type of adopters is created:

Adopter category	***Number of interactions per month***
Innovators	*8*
Early adopters	*7*
Early majority	*6*
Late majority	*5*
Laggards	*4*

Households than have random, friend and neighbour interactions (see section 3. 3). The goal is to

reproduce a smart world network, in which friend interactions are also included. A small world network is characterised by a large amount of short-range interactions and a small amount of large-range interactions. We therefore divide the interactions between long interactions (random and friend) and short interactions (neighbour). The following repartition is made:

Adopter category	***Number of random interactions per month***	***Number of friend interactions per month***	***Number of neighbour interactions per month***
Innovators	*2*	*2*	*4*
Early adopters	*2*	*2*	*3*
Early majority	*2*	*1*	*3*
Late majority	*1*	*1*	*2*
Laggards	*1*	*1*	*2*

There is uncertainty, however, about the total number of interactions that households have each month and their repartition in the different types of interactions. Therefore, we use parameter ranges instead of fixed numbers. This process is further explained in section 5. 3. The resulting parameter ranges are provide hereunder. The rules applied here for creating ranges are to set the bound to +/- 1 interaction of the initial amount of interaction.

Adopter category	***Number of random interactions per month***	***Number of friend interactions per month***	***Number of neighbour interactions per month***
Innovators	*[1-3]*	*[1-3]*	*[3-5]*
Early adopters	*[1-3]*	*[1-3]*	*[3-5]*
Early majority	*[1-3]*	*[0-2]*	*[3-5]*
Late majority	*[0-2]*	*[0-2]*	*[1-3]*
Laggards	*[0-2]*	*[0-2]*	*[1-3]*

4. 4. 2 Data calibration

After the data characteristics, preferences and behaviours per type of adopter was generated, a calibration of the data was performed. The goal of the calibration is to make sure that the data generated previously fits with the system modelled. The data was calibrated to ensure that the emergent pattern of the model (the S-curve shape of adoption) was reproduced under a strict application of the Diffusion of Innovations Theory (neoclassical rationality of households for example) and product conditions that are acceptable for all types of adopters. This data calibration has been carried out in the verification and validation phase (see chapter 5) by comparing model outcomes with theories and comparable adoption curves.

Chapter 5 – Verification and validation

The goal of this chapter is to test the model built in chapter 4 on its correctness and its ability to simulate the adoption of smart washing machines by households. This will be done in several step, based on the 'evaludation' method (see section 2. 4. 2). In section 5. 1, an explanation is given of how this verification and validation step was carried out. Section 5. 2 to 5. 8 then present the outcomes of each verification and validation step, while section 5. 9 provides a conclusion about this entire section. The output of this chapter is a model that is verified and validated and hence ready to use to perform experiments in chapter 6.

Reading indications

The goal of this section is to test and increase the robustness of the model created in this work. The added value of this chapter lies essentially in exploring the suitability of the 'evaludation' method to increase the correctness and validity of diffusion of innovation models in comparison to other methods. Therefore, this chapter is essentially interesting from scientific point of view. For readers who are only interested in the implications of the work here for the next chapter, an overview of the relevant findings is provided in table 15.

Table 15: Main findings from the verification and validation chapter

Main findings	***Implication for next chapters***
High uncertainty of minimum amount of savings	- *There is a high uncertainty about the minimum amount of savings that households desire in order to be willing to consider adoption. This uncertainty will have to be considered in the identification of directions for policy and the conclusions of this report*
Two structures of decrease of adoption complexity	- *Two main structure of decrease of adoption complexity have been identified: step decrease (according to the technology life-cycle phase) and a logarithmic adoption complexity decrease (see section 4. 2. 2). Experiments will be carried out for each of the structures of adoption complexity decrease.*
Uncertainty in the distribution of households among each adopter category	- *The division of households among adopter categories has been made based on the proportions proposed by Rogers. However, this distribution is still highly uncertain. The impact of various sizes of adopters categories will not be tested in this work due to time limitation. This would however form an interesting addition to this project in future works (see section 9. 2).*
Effect of prospect theory	- *The application of prospect theory did not lead to any meaningful change in the final adoption rate of smart washing machines. As a result, prospect theory will not be applied in the model experiments part.*

Definitions

In the field of simulation, some terminologies like scenarios and experiments are recurrently used. There is however a lack of shared agreement about the exact definition of those words in the context of model simulation. In this text box, the most frequently used terminologies in model analysed are defined in order to avoid misunderstandings (see table 16).

Table 16: Main findings from the verification and validation chapter

Terms	***Definition used***
Model run	- *The 'evolution' of the model resulting from one single combination of input parameters.*

Experiment	- *An ensemble of model runs resulting from different combinations of input parameters.*
Replication	- *The re-execution of a model run with the same combination of input parameters. Each replication of one single model run uses a different seed.*
Case	- *An ensemble of model runs that have a similar (un)desired outcome. The word 'case' is here often used in the context of best and worst case. Best cases for example refer to an ensemble of model runs that all result in a certain specified model outcome.*

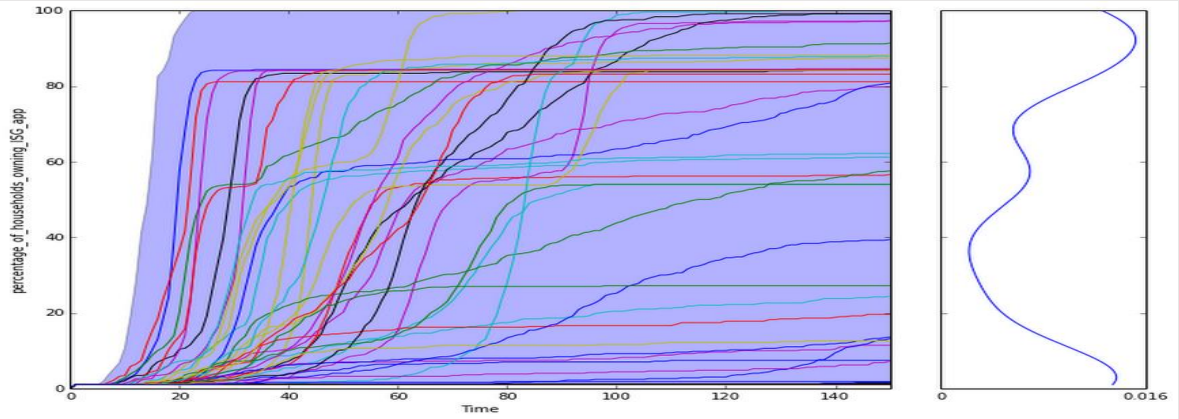
5. 1 The verification and validation process

The verification and validation process used in this work is a combination of the evaludation method of Ausgusiak, et al. (see section 2. 4. 2) and two other elements. The first element is an additional section that is added before the six evaludation steps of Augusiak, et al.. The goal of this section is to discuss the stochastic uncertainty present in the agent-based model created in this work and to explain how this stochastic uncertainty has been taken into account. Placing this section before the six steps of Augusiak, et al allows to, when proven to be useful, take stochastic uncertainty into account in the evaludation steps. The second element is the identification of uncertainties as one of the outcomes of each evaludation step. In agent-based models, four main types of uncertainties can be identified: stochastic uncertainties, parameter uncertainties, heterogeneity, and structural uncertainties (Briggs, et al., 2012). Failing to indentify and understand their impact on the model would lead to a lack of understanding of the model behaviour, since the implications resulting in various output are not all identified and understood. As a result the translation of various directions for policy (tested in the model) in real-life meaures will be less reliable because of the limited understanding of the differences between the model and real life situations. The six evaluation steps offer a good opportunity for reflection on the model creation process since it forces to reconsider each elements that was added to it and the assumption and limitations behind these elements. Hence it is a good opportunity to identify all uncertainties behind the structural, parameters, heterogeneous and stochastic elements inserted in the model or already present in the simulation software.

In section 5. 2, the stochastic uncertainty present in the model is identified. Based on this, a method is used to take this stochastic uncertainty into account in the model analysis. In section 5. 3 until 5. 8, each of the evaludation steps of Augusiak, et al. is explained and applied to the modelling process done in this work. For each, a conclusion is provided about the outcomes of the evaludation step. If any, a list of uncertainties identified is presented and an explanation is given of how these uncertainties are taken into account in the modelling process. The traditional model verification step defined as the assessment of correct translation of the conceptual model into the computational model by Ormerod & Rosewell (2009) is largely equivalent to the third evaludation step ('implemenation verification').

EMA and PRIM graphs

As from this section, EMA and PRIM graphs will be used to show the outcomes of model experiments. An example of EMA graph is provided hereunder.



These EMA graphs combine three elements. First, the large blue area shows the run envelop: the highest and lowest value of all runs combined at each point in time. Second, each line in the graph stands for the output of one model run. In the graph in this section, a limited amount of randomly chosen run are represented by a line. The line colour has no signification. Third, the element on the right is a Gaussian kernel density estimation (KDE), which provides an overview of the distribution of runs at the final run time of the model.

The figure hereunder shows the visualisation of the outcome of PRIM analysis:

box	mean	mass	coverage	density	res dim
28	0.8	0.18	0.4	0.8	13

uncertainty	box 28 min	max	qp values
Learning_rate_appliances_1	0.94 -	0.96	1.07e-11
growth_phase	6 -	26	2.37e-05
change_threshold_to_reach_for_weights_2	0.71 -	2.00	5.24e-02
memory	2 -	5	6.44e-02

In this experiment, box 28 has been identified as a segmentation of the solution space with enough mean and density (above 0.8) to explain a certain outcome (in this case a high adoption percentage of smart washing machines). Here, four variables have been identified that significantly contribute to the occurrence of high adoption rate. The quasi-p value (qp) is to be interpreted as a measure of the degree of significance of the variation of in the input parameter (Bryant & Lempert, 2010)*. In this work, we apply a minimum significance value of 0.05.*

5. 2 Stochastic uncertainty

Stochastic uncertainty describes the fact that the evolution of a certain system is determined by theories of probabilities. Table 17 decribes the different stochastic uncertainties identified in this model.

Table 17: List of stochastic uncertainties

Type of uncertainty	Method	Uncertainty
Stochastic uncertainty	Systematic usage of 5 model replications and control of possible differences	Agent iteration is randomised
		Households find other households to interact with in a random way (within the

		constrains that they were given such as the maximum radius)
		Households are placed randomly onto the map
		Uniform distributions are included in the model and determine the threshold that households use to perform a certain action

A model reproduces stochastic uncertainties based on random number generators. This random number generator always uses an equal seed number to start the creation of random numbers. Hence, if this seed number is not changed, the same sequence of random numbers will always be created. This means that if no model replications are made, only one realisation of stcochastic uncertainties will emerge, which will result in only a small range of model output possibilities being perceived (Bankes, 1993). To understand the full implication of stochastic uncertainties, simulation runs must hence be replicated with different seeds.

To incorporate stochastic uncertainty in the analysis of the model, 8 replications are made for every run. The mean of the 8 replications is then calculated and will be used to analyse the model. The number of replications chosen here is rather low. There are two reasons why the number of replications has been limited to 8. First, to execute the scenario discovery methodology, the model has to be run succesively a great amount of times. The number of runs for each experiment in chapter 6 has been set to 200. The simulation duration for 200 runs is approximately one hour with the computer used in this project. If each run is replicated 8 times, the simulation duration will be eight hours. Having in mind that several experiments have to be executed, the simulation time is quite long. The second reason is that, after several tests, it has been observed that stochastic uncertainty did not play a dominant role in explaining model outcomes. Therefore, 8 replications are expected to be enough to consider stochastic uncertainty in the model analysis.

5. 3 Step 1: Data evaluation

Augusiak, et al. (2014) define the data evaluation step as "the assessment of the quality of numerical and qualitative data used to parameterise the model, both directly and inversely via calibration, and of the observed patterns that were used to design overall model structure, whereby not only the measurement protocols need to be evaluated but conclusions drawn from the data should be challenged as well". From this definition and considering the modelling project made in this work, two concrete tasks can be identified:

1. Provide an overview of the data used for the model including sources and units. If data is guessed, explain on what grounds it was done
2. Provide an overview of the patterns used as model input

Table 55 in Appendix E provides an overview of the data evaluation of the smart grid appliance model. Table 56 in Appendix E does the same for patterns used as an input in the model. Based on this evaluation, uncertainties are identified and presented in table 18. This table also shows how these uncertainties are handled.

Table 18: uncertainties identified based on the data evaluation step

Type of uncertainty	**Method**	**Uncertainty**
Parameter uncertainty	Creation of a range around assumed number and inclusion of these uncertainties in the testing of model outcomes and directions for policy with	Price of smart washing machines
		Price of 'traditional' appliances
		Learning rate of smart washing machines
		Future duration of each life-cycle phases

	EMA. Although the model was calibrated on the basis of 1 tick = 1 month, the fact that there is a deep uncertainty about the frequency of interactions implies that no conclusions can be made by using the 1 tick = 1 month equivalence.	Adopter specific characteristics
		Parameters for prospect theory utility function
		Minimal amount of savings that households requests in order to adopt smart washing machines.
Parameter uncertainty	This observation is considered in the limitations of this work. The study of the impact of different sizes of adopter categories can form an interesting addition for future work.	Distribution of households among adopter categories
Heterogeneity	Application of a normal distribution around the parameter of adopters.	Extent of differences in adopter specific characteristics between households from some adopter categories
Structural uncertainty	Testing of several comparable structures found in the literature and comparison of their impact on the adoption of smart washing machines.	Smart washing machine price decrease
Structural uncertainty	Testing of several comparable structure to simulate the decrease of adoption complexity. Finally, two structures of adoption complexity decrease are retained: a step decrease and a logarithmic decrease of adoption complexity.	Decrease of adoption complexity

5. 4 Step 2: Conceptual model evaluation

Augusiak, et al. (2014) define the conceptual model evaluation step as "the assessment of the simplifying assumptions underlying a model's design and forming its building blocks, including an assessment of whether the structure, essential theories, concepts, assumptions, and causal relationships are reasonable to form a logically consistent model". According to Augusiak, et al., this step is difficult since there are no stecific testing strategies available. Also, erroneous conceptualisations are often only distinguished in later phases of model development, meaning that an important part of the model has to be redesigned. A rule of the thumb solution is that several conceptual models should be considered and tested during the creation of the model.

To deal with the conceptual model evaluation, two actions have been undertaken in the model creation phase. First, before the start of the model building phase, the conceptualisations used in comparable models have been studied. By comparable models is meant agent-based models about the adoption of innovations (preferably smart grid related innovations) by households. Based on this, conceptualisations that are well grounded and used in the literature have been selected and a reflection was made on their compatibility with the adoption of smart washing machines. The conceptualisation selected were the five stages of the consumer adoption process of Engel et al. (1995) and the use of the Diffusion of Innovations Theory of Rogers (1962). Second, several comparable model structures (such as types of interactions between households or types of rationality used) have been introduced in the model and can be selected by the modeller (through switches in the Netlogo model). In the model output verification phase, the right conceptualisations will be chosen based on how well the model output matches observations of comparable systems.

Table 19 summarises the uncertainties identified in the conceptual model evaluation and how they are being dealt with.

Table 19: uncertainties identified based on the concept model evaluation step

Type of uncertainty	Method	Uncertainty
Structural uncertainty	Study of literature and selection of most used conceptualisations in comparable cases. Final selection based on modelling goals and characteristics of the smart washing machine adoption system.	Overall adoption theory
		Adoption process steps of households
		Segmentations of households
Structural uncertainty	Testing of several comparable conceptualisations found in the literature and comparison of their impact on the adoption of smart washing machines. Selection of structures based on the step 4 of the evaludation process.	Type of interactions between households
		Rationality of households

5. 5 Step 3: Implementation verification

Augusiak, et al. (2014) define the implementation verification step as "the assessment of (1) whether the computerised implementation the model is correct and free of programming errors and (2) whether the implemented model performs as indicated by the model description. The aim is to ensure that the modelling formalism is accurate". In the case of agent-based modelling, it is important to verify the model both on the individual level as on the overall level (Dam, et al., 2013). The reason is that the overall behaviour of the model is not only explained by the characteristics of the agents. The overall behaviour is also explained by the interactions between agents and therefore is emergent.

To verify the implementation of the model, the four main parts for verifying agent-based models of Dam, et al. (2013) are used. The recording and tracking of agent behaviour allows to verify the various model operations through the monitoring of output variables. The single-agent verification enables finding out if any agent behaves contrary to what the modeller intended to formalise. The minimal model interaction verification allows testing the correctness of interactions between agents under a limited amount of agents present in the model. The multi-agent verification is useful to find out whether the behaviour of the entire set of agents is consistent with the expected behaviour. The application of the four steps can be found in Appendix E.

5. 6 Step 4: Model output verification

Augusiak, et al. (2014) define the model output verification step as "the assessment of (1) how well model output matches observations and (2) to what degree calibration and effects of environmental drivers were involved in obtaining good fits of model output and data. The aim is to ensure that the individuals and populations represented in the model respond to habitat features and environmental conditions in a sufficiently similar way as their real counterparts".

To go through the model output verification step, a progressive iterative model adjustment process will be created. As explained by May (2004) in a review called "Uses and abuses of mathematics in biology," modellers in mathematical model building often tend to add an extremely high amount of details into models. According to him, it makes no sense to try to build an exact mirror of reality into the model because some factors are uncertain or difficult to distinguish. Therefore, in building a simulation model, one should stick to the most important factors even though they might appear uncertain and hard to grasp. With that in mind, the model output verification step will be used to match progressively more realistic validation curves. This will be done by adjusting the model structure and progressively add heterogeneity in the characteristics of households and adopters categories.

The first version of the model is one that strictly follows the Diffusion of Innovations Theory of Rogers (1962) and the consumer decision-making process of Engel, et al. (1995). Concretely, this means that:

- adopters are divided according to the proportions of the Diffusion of Innovations Theory,
- all households within the same adopter category have exactly equal adoption preferences and conditions to adopt,
- all households having the same amount of householders have exactly the same electricity consumption per month and appliance utilisation,
- households make perfectly rational decisions (according to the neoclassical theory): they choose the alternative that maximises their financial and social positioning benefits, even if the added value of changing is very low. This means that complexity is not constraining the adoption. Also the influence of risk perception is not taken into account.

Four steps are created to realise the model output verification. The first step consists of matching the S-shape diffusion as presented by Rogers (see section 3. 1. 1). The reason why this step is chosen as the first one is that the S-shape is in a large amount of literature mentioned as being the base shape of successful innovation diffusions. Any other observed diffusion trajectories are distortions of the S-shape resulting from for example the influence of exogenous factors or the inability of the innovation to fulfil adopters' needs. The second step is to make sure that the chasm in adoption between the early adopter and early majority population is observable, as demonstrated by Moore (1999). The third step is to make sure that the model is able to recreate the patterns of failed, partial or full diffusion of innovations. This step was included since these patterns are widely observed as far as the diffusion of products is concerned. Hence, to be validated, the model must allow reproducing these patterns under different parameter settings. The last step is to validate the model by using the 'history-friendly approach' (Windrum, et al., 2007). Since smart washing machines are emerging technologies, no data about the diffusion of these appliances are available. However, the diffusion of smart washing machines can be compared to the past diffusion trajectory of similar products and under similar diffusion conditions.

The outcomes of each step can be found in Appendix E. Table 20 presents the uncertainties identified based on the model output verification step.

Table 20: uncertainties identified based on the model output verification step

Type of uncertainty	**Method**	**Uncertainty**
Structural uncertainty	Testing of the impact of the addition/removal of heterogeneity in the minimum amount of savings required by households to accept adoption. Selection of structures based in this step.	Occurrence of heterogeneity in the minimum amount of savings required by households to accept adoption
Heterogeneity	Creation a normal distribution around the minimum amount of savings required by households to accept adoption.	Extent of heterogeneity in the minimum amount of savings required by households to accept adoption

5. 7 Step 5: Model analysis

Augusiak, et al. (2014) define model analysis as "the assessment of (1) how sensitive model output is to changes in model parameters (sensitivity analysis), and (2) how well the emergence of model output has been understood. The aim is to understand the model and be able to find out why which output is being produced to avoid drawing the wrong conclusions from model output".

To perform this analysis, table 59 (see Appendix E) has been created to identify each of the model behaviours that are being observed. Through a series of tests, the reasons for the emergence of these model behaviours are found and mentioned in the same table.

5. 8 Step 6: Model output corroboration

Augusiak, et al. (2014) define the model output corroboration as "the comparison of model predictions with independent data and patterns that were not used, and preferably not even known, while the model was developed, parameterised, and verified. This step strengthens a model's credibility by proving that the model is capable of predicting/reproducing pattern and data that could not have influenced the model development".

Due to the absence of data about the smart washing machine adoption cases, this validation step will not be performed. This problem is encountered by many authors modelling the diffusion of innovations (Kiesling, et al., 2012). This evaludation step will however be interesting to perform in the future when more data will be available.

5. 9 Conclusions

The conclusions from the evaludation process, used to verify and validate the model, are the following. First, the model has been thoroughly verified and no more implementation errors are expected. Second, the research of relevant data to build the model has been challenging, mainly due to the need of data describing social behaviour and the fact that smart washing machines are new technologies. The generation of data based on the Diffusion of Innovations Theory, the creation of an iterative process of model building and the use of both EMA and PRIM however helped to calibrate data and validate the model based on observations of the adoption process of comparable innovations. Third, the evaludation process was used to identify different types of uncertainties in the model. For each of the uncertainty identified, a method was proposed to include the occurrence of these uncertainties in the analysis of the model. Of the uncertainties distinguished, the minimum amount of savings that households request to adopt smart washing machines is considered as highly uncertain and as strongly influencing the outcomes of the model. Hence, this uncertainty will have to be included in the interpretations of the outcomes of this model and the directions for policy suggested. Last, the use of prospect theory was not needed to validate the model. A series of tests have been performed to understand the impact on applying prospect theory in the decision-making of households. The impact of adding prospect theory in the model did not appear to have an influence on the behaviour of the model, nor on the structure of adoption curve or on the final percentage of adopters.

Finally, one can say that the model created in chapter 4 is fit to simulate the adoption of smart washing machines by households. There are however three elements that must be kept in mind when identifying directions for policy to support smart washing machine adoption:

- High uncertainty about the minimum level of savings that households desire to be willing to adopt smart washing machines.
- High uncertainty about the distribution of households among each adopter category. The modelling of various city districts with differing types of populations might have a large influence on the model and the directions for policy identified.
- A rationale for both a discrete and a continuous decrease of adoption complexity in the case of smart washing machine is defendable. Therefore both of them will be implemented in the identification of directions for policy (see chapter 6),

Chapter 6 – Policy identification and evaluation

In chapter 5, the model was tested to control its correctness and ability to simulate the adoption of smart washing machines by households. In this chapter, the model is used to identify directions for policy that could increase the adoption rate of smart washing machines. This chapter will allow answering the third sub-research question of this work (see section 0). In chapter 5, two relevant structures of the adoption complexity decrease have been identified. Because both of them may be applicable in the case of smart washing machine adoption, both of them will be applied in this case. In section 6. 2, the direction for policy identification process with a step decrease of the adoption curve is carried out and the outcome of each new experiment are presented. Some of the directions for policy that are identified in section 6. 2 are also expected to be effective to increase the adoption rate of smart washing machines in case of a continuous logarithmic decrease of adoption complexity. Therefore, in section 6. 3, each of the directions for directions for policy identified in section 6. 2 will be applied and a conclusion will be provided about whether they are also effective in case of a continuous logarithmic decrease of adoption complexity. If necessary, additional directions for policy will be identified. The output of chapter 6 will be a set of directions for policy that increase the adoption rate of smart washing machines in the model created in this project. A reflection about the directions for policy identified and their validity in the real world will then be provided in chapter 8.

Reading indications

The goal of this chapter is to identify directions for policy that have the potential to increase the adoption rate of smart washing machines. The added value of this chapter is twofold. First, this chapter allows understanding how scenario discovery has been used to identify directions for policy. Second, it allows understanding the reason for the necessity of these directions for policy from the perspective of the model. A summary of the directions for policy identified is provided in Table 21. The policies identified in this chapter are only based on the model. Nothing about their effectiveness at increasing adoption in real word can be said yet. A translation of these policies to the real world will be done in chapter 8.

Table 21: Summary of the theories chosen for model construction

Observations	***Directions for policy***
- *The communication of the decreased level of adoption complexity between innovators and early adopters in the transition from introduction to growth phase is a vulnerable moment. This is mainly due to the low number of innovators in an average population (as explained by Rogers* (1962)*.*	- *Involve innovators closely in new technological developments of smart washing machines. The goal is that, at some point in time, they communicate to early adopters when the smart washing machines are starting to become interesting for households from a financial and life comfort perspective.*
- *The adoption of smart washing machines by early adopters is not straightforward. Since initially smart washing machines are not expected to be highly cost-effective, targeting the social added value of adopting is a good way to increase adoption by early adopters.*	- *Promote the added value of adopting smart washing machines for society. This is aspect to allow early adopters to see the adoption of smart washing machines as a way to increase their social recognition.*
- *The amount of savings that can be made by adopting smart washing machines is very low. This constrains a large amount of households to adopt.*	- *Propose a subsidy, or other financial benefits, for the purchase of smart washing machines.*
- *According to Rogers* (1962)*, early majority population and later adopters do not adopt for the same reasons as early adopters. Early*	- *A shift of the recognised added value of smart washing machines is therefore needed. While smart washing machines were in the second*

majority population and later adopters are expected to be mostly interested in the financial benefits of adopting, if any. However, the sooner early adopters adopt, the lower their financial benefits are since the price of smart washing machines only decreases progressively. As a result, the amount of savings that early adopters make and communicate to early majority population is low, which does not make it attractive for early majority population to adopt.	*direction for policy profiled as a way to benefit society (and thereby increase individual social recognition), smart washing machines must be profiled as way to make an important amount of savings as soon as this is the case. In the literature, this shift of image or perceived added value is often described as 'product reinvention'.*
- *Reinventing smart washing machines is not enough. According to Rogers* (1962)*, early majority population and later adopters are risk avert. Therefore, they require reliable adoption information, or at least perceived as reliable by them, to be willing to adopt*	- *The direction for policy is that ways have to be found so that early majority population and later adopters experience the information they get from households having already adopted as reliable. This can for example be done by making sure they get adoption information by relatives and friends.*

6. 1 Experiment design

In section 2. 4. 2, the scenario discovery method by using EMA and PRIM is presented. The specificity of the policy identification process created in this work is that experiments to test various directions for policy are not based on various modeller's hypotheses about what could lead to more desirable model outputs. On the contrary, the identification of directions for policy comes directly from the identification of scenarios that could lead to the occurrence of certain cases. Specific scenarios are found through making an extensive sensitivity analysis with EMA and identifying the variations of input parameters that lead to best or worst cases by performing a PRIM analysis. Best cases are defined by sets of input parameters (scenarios) that lead to a satisfying improvement of model indicators. Worst cases show the sets of input parameters leading to dis-preferred cases. When variations of input parameters leading to best cases are found, new directions for policy are created to increase the occurrence of best cases. A new experiment is then created to test the effectiveness of these directions for policy by using EMA and PRIM. If new variations of input parameters that significantly improve the occurrence of best cases are identified, additional directions for policy are generated and tested with new experiments. There are always directions for policy that can increase the adoption percentage of smart washing machines, even if only slightly. Therefore, the execution of new experiments is limited to the situation where, in the model, the adoption curves of smart washing machines all increase towards a higher adoption percentage, even if this increase is slow.

As explained in this section, the word scenario refer to a certain combination of input parameters that lead to a certain outcome. The utilisation of the word scenario, however, is misleading in the simulation field, since it is used under a wide amount of definitions. In this work, the term 'model run' will be used to refer to scenarios as defined in the scenario discovery methodology.

In section 6. 2 and 6. 3, the various experiments to relevant scenarios and effective directions for policy are presented. Each experiment will systematically be presented in the same way:

- Experiment set-up: shows the main input of the experiment
- Results and interpretations

- Conclusions: concludes on the necessary type of directions for policy to reach the policy objectives

Objectives and requirements of directions for policy

Based on the research objective presented in section 0, one main performance indicator can be clearly identified: the percentage of households having adopted a smart washing machine.

One central requirement is given to the directions for policy: they should lead to a higher percentage of smart washing machines adoption, and within a reasonable amount of time. As explained in section 1. 2, a large amount of actors are dependent on the adoption of smart washing machines by households. The later the adoption of these appliances by households finds place, the later the various actors will profit from the added value of smart washing machines. Therefore, the length of a model run is set to 150 ticks, which is equal to 12.5 years.

Experimental settings

The model settings for the experiments come from the execution of the model validation phase (see section 5. 6). The most important model settings are mentioned in table 22. The entire set of initial model parameters is presented in Appendix F. The parameter setting is based on the data generated and calibrated in section 4. 4. The model settings, such as the type of rationality or the type of heterogeneity applied are based on the verification and validation of the model in chapter 5. The number of households has been set to 500, in order to represent a mid-sized city district. The initial number of innovators has been set to 5 in order to allow the diffusion to start. Since households only rely on other households to get information about adoption, there must be a minimal amount of smart washing machine owners to start the diffusion process. The number of replications has been set to 8 (see section 5. 2). The number of runs has been set to 200. After several tests, the combination of 200 runs and 8 replications has proved to be enough to allow PRIM to find parameter variations that strongly explain the occurrence of certain best and worst cases. In addition, experiments with 200 or 1000 runs did not appear to have meaningful differences in the structures of outcomes.

As identified in the verification and validation sections (see chapter 5), there is an important uncertainty about the parameters inserted in the model. To cope with that, we do not use fix parameters as model inputs but use ranges instead. The learning rate of smart washing machines for example is inserted the range [0.94-0.99]. For each new run, a parameter is picked within this range on a uniform basis. The creation of ranges is the result of model experimentations before the identification of policies. For each parameter with data uncertainty, large ranges have been created. By large ranges, it is meant that the upper and lower limits are set to values that are at the limits of being plausible. The model was then run with the ranges identified and a check has been performed to find out if some ranges led to model behaviour that could not be validated in the verification and validation phase. In these cases, the upper and lower limits of ranges were set to a value closer to their mean.

Table 22: Model settings and parameters

Model parameters	
Number of households	500
Initial number of innovators owning a smart washing machine	5
Rationality	Bounded-rationality
Prospect theory	Switched off
Peak electricity price	Fixed for entire run
Off-peak electricity price	Fixed for entire run
Networks	Households uses all three types of interaction: friend, neighbour and random
Smart washing machine included in decision-making	Smart washing machine
Heterogeneity of electricity consumption between households with same amount of householders	Is included, same value during entire run

Heterogeneity of smart washing machine consumption between households with same amount of householders	Is included, same value during entire run
Heterogeneity in minimum level of savings required between adopters of same category	Is included, new value is calculated by a random number correlated with the value of the previous time step
Height of electricity price during off-peak period	[0.15, 0.30] [€/KWh]
Height of electricity price during peak period	[0.30, 0.55] [€/KWh]
Minimum level of savings desired by households	[1,4] [€/month]
Duration of the introduction phase	[3,36] [month]
Duration of the growth phase	[3,36] [month]
Learning_rate_appliances_1	[0.94,0.99] [-]
Run length	150
Number of runs	200
Number of replications	5

6. 2 Scenario discovery and policy testing: step decrease of adoption complexity

In this section, directions for policy are identified based on the model created in chapter 4. For this range of experiments, the adoption complexity will decrease in steps (see section 4. 2. 2).

6. 2. 1 Experiment 1

Experimental set-up

In experiment 1, the type adoption complexity is a step decrease based on the product-life phases.

Table 23: Parameter settings changes for experiment 1

Model parameters	
Decrease of adoption complexity	In steps (according to product-life cycle phases)

Results and interpretations

This section provides the most relevant key performance indicators necessary for the interpretation of the model outcomes. The rest of the key performance indicators can be found in Appendix F. The main outcomes of this experiment are provided in figure 12. In this figure, one can see that only in a very limited amount of cases the smart washing machines are adopted on large scale. This is shown by the KDE graph at the right side of the figure. By looking further at the line of the figure, three types of lines can be seen clearly. The first type of lines increases quickly between t = 0 and t = 40 and then remains stable. The second type of lines increases progressively during the entire model run. The last type of lines remains very close to zero during the entire model run. The KDE of the right side of the graphs shows that these lines represent a large majority of the cases.

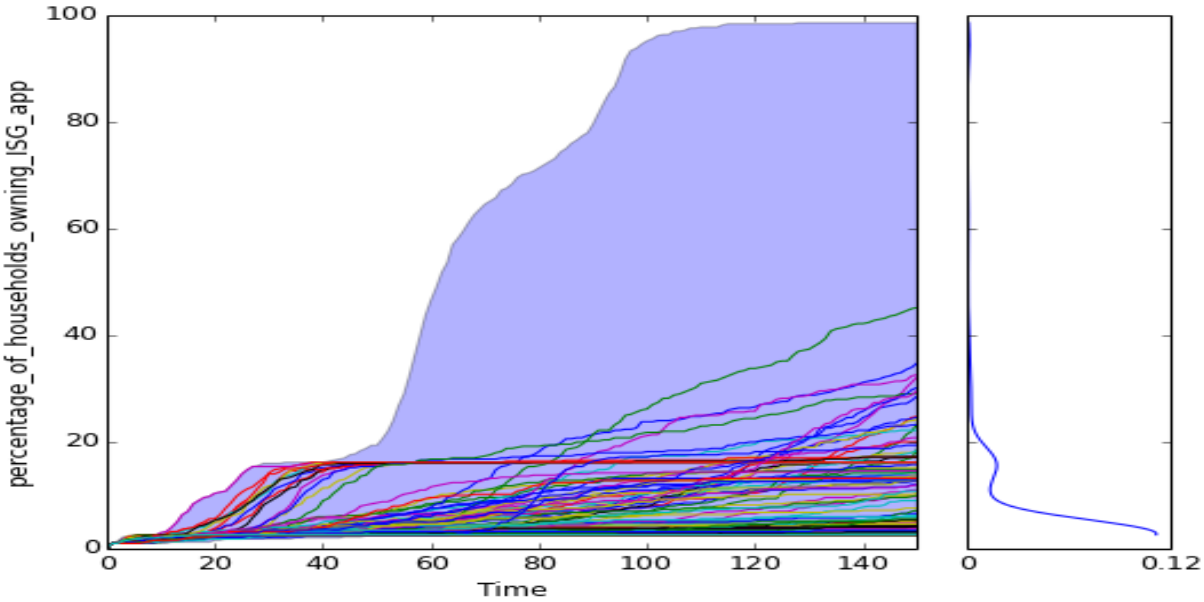


Figure 12: Experiment 1; percentage of household owning a smart washing machine

Since the types of lines that remain close to zero during the entire model run are in large majority, and because this outcome is not favourable in relation to policy goals, the analysis will focus on understanding why these cases arise. The PRIM analysis by selecting the runs that end with a percentage of households lower than 8 did not lead to the identification of variations of variables that significantly contributed to these outcomes. This is because of the very large amount of runs comply to this selection criteria. To find the relevant variables that lead to these cases, one must base the PRIM analysis on the percentage of early adopters that have adopted (see figure 13).

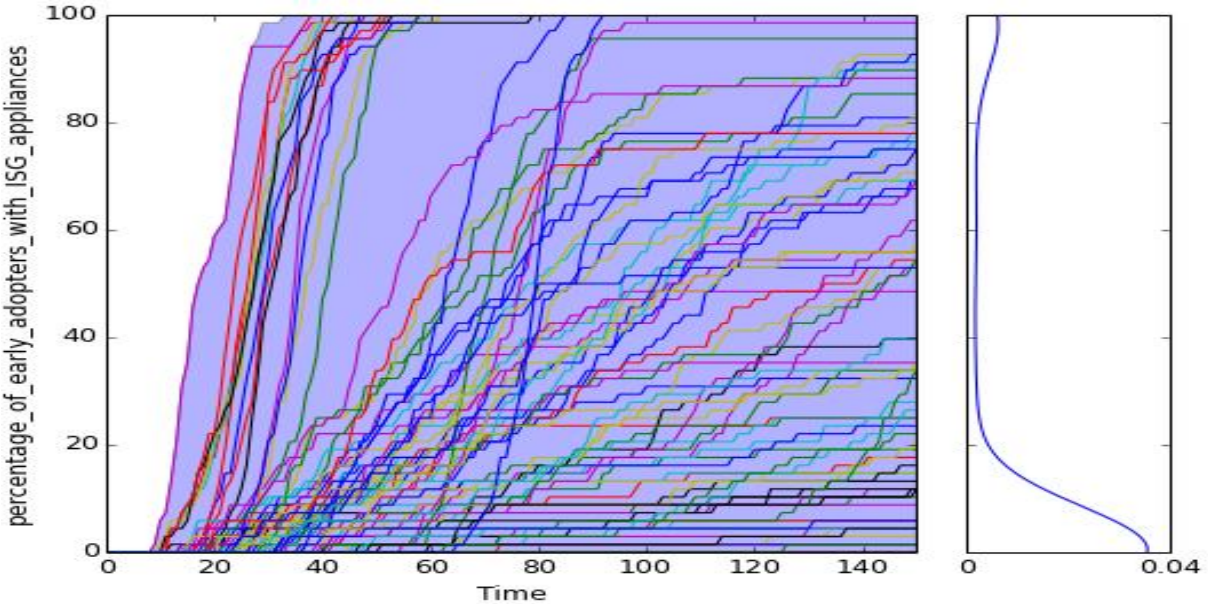


Figure 13: Experiment 1; percentage of early adopters owning a smart washing machine

A new PRIM analysis is done by selection the best cases in the adoption of early adopters (adoption percentage higher than 40%). The outcomes of the test are presented in figure 14. The pealing and pasting trajectories can be found in Appendix F.

box	mean	mass	coverage	density	res dim
25	0.83	0.18	0.83	0.83	8

uncertainty	box 25		
	min	max	qp values
introduction_phase	6 -	15	5.19e-08

Figure 14: Experiment 1; outcome of the PRIM analysis – best cases of early adopter adoption

In figure 14, we find that a low length of the introduction period clearly explains the occurrence of these best cases. If a low length of the introduction period leads to these best case, we can conclude that a high length of the introduction period leads to worst cases. By looking at the reasons why households do not adopt, we find that the high level of complexity is a main element that constrains households from adopting. This can be seen in figure 15, and in figure 66 in Appendix F.

Figure 66 shows the number of households that do not adopt, because adoption complexity is experienced as too high, for all model runs. In figure 15, we select a single model run in order to increase the visibility of what is happening in the model. The run selection is one of the run that ends with an adoption percentage lower than 8% (see figure 12). This figure shows, for the entire simulation length, the evolution of the reasons why households that have rejected smart washing machines did not want to adopt. In the run selected, we find that the main reason for not adopting is the level of adoption complexity, which is perceived as too high.

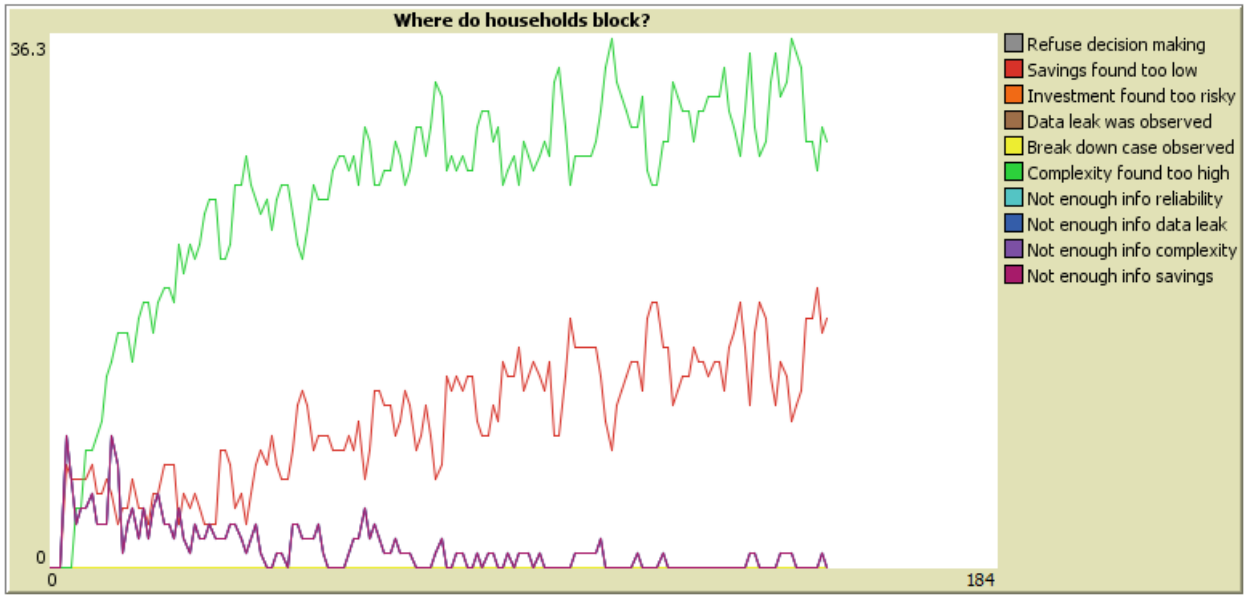


Figure 15: Experiment 1; reasons for not adopting

In this section, the change of adoption complexity is modelled by using steps that changes according to the product lifecycle phase in which the product is. The longer the introduction phase, the longer the product remains at its highest level of complexity (level 3). As explained by Rogers, innovators accept a degree of complexity that is high (level 3 in this model). Early adopters accept a lower level (level 2 in this model).

By studying this experiment in more depth, it appears that in all of these cases, all innovators have adopted smart washing machines during the introduction phase. This can be seen in figure 16. As in figure 15 only a single run has been selected. The run selected is also one that ended in an adoption percentage lower than 8%. In the upper graph of this figure, the evolution of the level of adoption complexity can be observed. The first level (adoption complexity of 3) refers to the introduction phase,

the second level (adoption complexity of 2) refers to the growth phase whereas the third level (adoption complexity of 1) is equivalent to the maturity phase. The lower graph of figure 16 shows the percentage of households that have adopted per adopter category. By looking at the two graph, one can see that the last innovators to adopt have adopted before the end of the introduction phase. By adopting in the introduction phase, households experience an adoption complexity of 3. In this model, households exclusively rely on each other to discover the degree of complexity of adoption. Therefore, when later adopters (including early adopters) will ask the level of complexity to innovators, they will get the answer that the level of complexity is equal to 3, even if the current adoption complexity has decreased since then. Since a level of adoption complexity is too high for early adopters (and later adopters), they will never adopt. However, in cases when at least one innovator has adopted after the end of the introduction phase, later adopters are given the information that the complexity is equal to 2 and early adopters start to adopt.

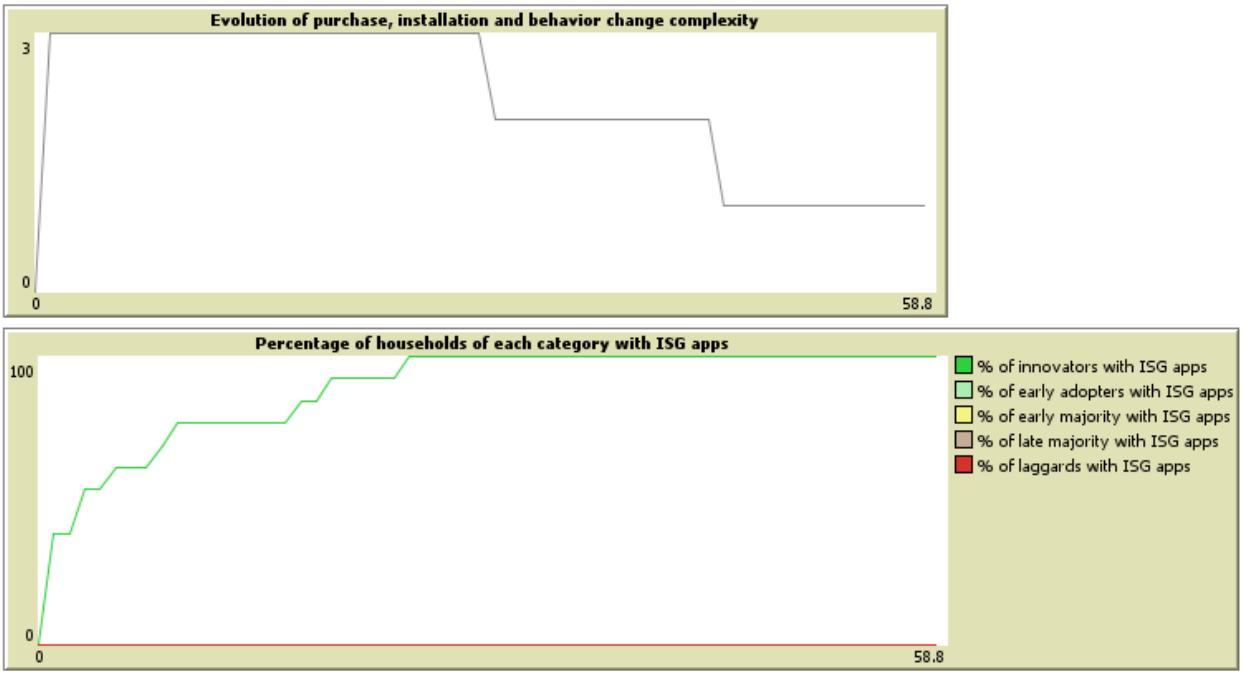


Figure 16: Experiment 1; run where all innovators adopt before the end of the introduction period

Conclusions

Experiment 1 shows that in the model, the communication of recent information between households in the first period of smart washing machine adoption is very important for the end-state of the appliance adoption. The addition of heterogeneity in the model, by allowing some early adopters to accept a level of complexity of 3, would resolve the problem of communication of lower levels of complexity, at least in the model. However, the fact still is that this is a vulnerable point in the determination of the future success of the adoption of smart washing machines. The reason for this vulnerability is that the number of innovators is low (13 out of 500 households). Therefore, assuming that already a large part of innovators have adopted in the introduction phase, the success of the entire adoption process is dependent on the few innovators (if any) that will adopt in the growth phase.

In section 6. 2. 2, a direction for policy will be created to decrease the vulnerability of the transition from introduction phase to growth phase and to support the communication of updated information about the level of adoption complexity.

6. 2. 2 Experiment 2

The conclusions of experiment 1 have shown that in the model, the communication of recent information about the level of adoption complexity plays a key role to ensure a large percentage rate of smart washing machine adoption. Since the assumption in this work is that the communication of information about smart washing machine adoption is only considered as reliable enough when the information is communicated from household to household (see section 4. 2. 2), the solution has to come from interactions between households. Therefore, the direction for policy that will be tested in the model redistribution smart washing machines to innovators whenever they are assumed to be interesting enough for early adopters. In the real world, this would mean involving innovators closely in new technological developments of smart washing machines, for example by performing technological updates on the smart washing machines or even replacing them with new ones. The costs would be limited due to the low number of innovators.

The results of the implementation of this policy in the model are presented in this section. This direction for policy has been implemented in the model by making sure that any innovators that already had a smart washing machine received a new one every two years until two years after the start of the growth phase. Hence, every innovator will end up communicating an adoption complexity of 2 to other adopters, thereby bridging the vulnerable gap between introduction phase and growth phase.

Experimental set-up

Table 24: Parameter settings changes for experiment 2

Model parameters		
Variable	**Value**	**Unit**
Duration before receiving updated smart washing machine for innovators	[24]	[month]
Duration direction for policy updated smart washing machine for innovators	[Duration of introduction phase + 24]	[month]

Results and interpretations

In figure 17, we see that a lower amount of runs has resulted in a very low adoption percentage. This can be observed with the KDE graph in this figure. Therefore, we can conclude that the direction for policy implemented in this experiment does indeed have the desired effect.

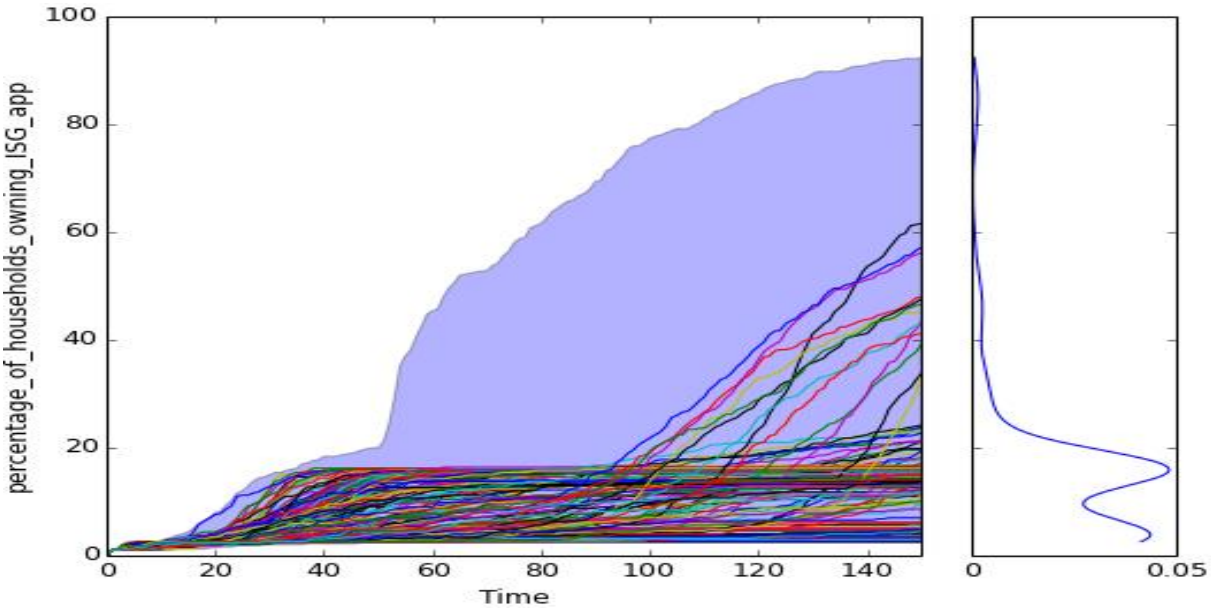


Figure 17: Experiment 2; percentage of household owning a smart washing machine

From figure 17, we can observe three types of lines. The first type of lines ends with a percentage of adoption that is lower than 10%. The second type of lines ends with a percentage of adoption that is approximately 15%. The last type of lines increases above 20% of smart washing machine adoption, but their number is very limited. This distinction between the different types of lines is visible by looking that KDE graph.

Since there is still a high number of runs that end with an adoption percentage lower than 10% and that because it is contrary to the policy objectives, we focus on these types of runs to find out the reason for their occurrence. A PRIM analysis is performed by selecting the runs ending with an adoption percentage lower than 10%. The outcomes of the analysis are presented in figure 18.

box	mean	mass	coverage	density	res dim
17	0.86	0.4	0.83	0.86	6

uncertainty	box 17		
	min	max	qp values
change_threshold_to_reach_for_weights_2	0.90 -	1.50	8.63e-08
social_value_difference_to_mean	0.40 -	0.88	1.74e-03

Figure 18: Experiment 2; outcome of the PRIM analysis – worst cases of household adoption

The PRIM analysis shows that two variables strongly explain the occurrence of these worst cases. The first variable stands for the amount of similar information that early adopters must receive in order to consider the information as reliable. The higher this threshold is, the more sources of information early adopters must have, for example about the degree of adoption complexity, to consider the information as reliable and to be able to continue the decision-making process. The second variable stands for the social recognition that early adopters and late majority population may receive by adopting (see Appendix B). As Rogers explains, these are the two categories of adopters that take the behaviour of other households (defined by whether other households have adopted or not) into account to decide whether to adopt themselves or not. In the case of early adopters, the lower this social value, the less interesting it is for them to adopt when other households have not adopted yet.

Conclusions

Experiment 2 shows that the direction for policy applied clearly has a positive effect on the adoption of smart washing machines. The experiment also shows that two variables lead to the occurence of very low adoption percentages of smart washing machines (under 10%). In section 6. 2. 3, a direction for policy will be created to assess the effect of these two parameters.

6. 2. 3 Experiment 3

The previous experiment has shown that two variables lead to the occurrence of very low adoption rates in the model. In this experiment, the threshold of information to reach for early adopters will be set to a low value, while the social value will be kept high. In the real world, this would mean that a policy would have to be applied to facilitate communication between early adopters and to show them the social value that they could receive by being one of the first households to adopt. The outcomes of this experiment are presented in figure 19.

Experimental set-up

Table 25: Parameter settings changes for experiment 3

Model parameters		
Variable	**Value**	**Unit**
Contribution of social value	[0.8 – 1] (instead of [0.4-1])	[-]
Threshold of information reliability to reach for early adopters	[0.5 – 0.8] (instead of [0.5-1.5])	[-]

Results and interpretations

In figure 19, we find that the policy has indeed led to the removal of the run that ended in a percentage of smart washing machine adoption lower than 10%. Therefore, we conclude that, in the model, the demonstration of the potential social recognition that early adopters could receive by adopting is an effective direction for policy. In addition, the facilitation of communication between early adopters also increases the level of adoption.

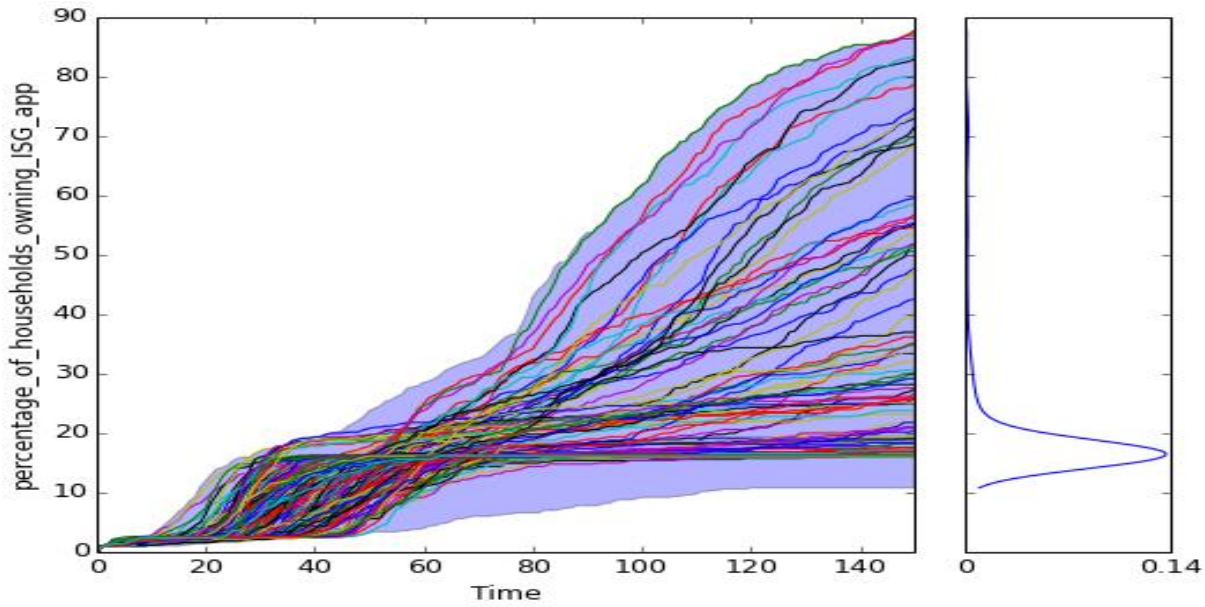


Figure 19: Experiment 3; percentage of household owning a smart washing machine

Figure 19 shows two types of lines. The first is a line that strongly increases between time = 20 and time = 40 but ends at a percentage of approximately 20%. The second is a line that increases at approximately the same time as the first line, but which then progressively continues to increase above 20%. This type of line is rare in comparison to the first type of lines, as shown by the KDE graph. The second type of line is satisfactory in relation to the goals of the directions for policy. The first type of line however is not satisfactory since the adoption rate of smart washing machines remains low. We will therefore focus on the first type of line to identify new directions for policy.

The reason why in a large amount of cases runs do not exceed approximately 20% of smart washing machine adoption is to be found in the adoption curves of early adopters (see figure 20) and early majority population (see figure 21).

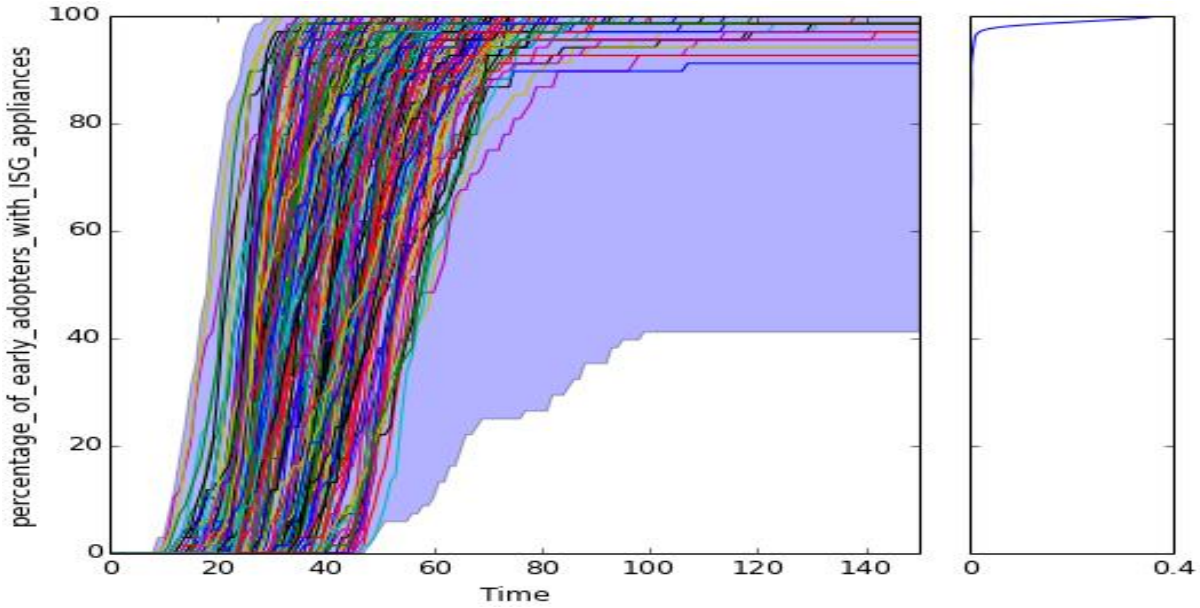


Figure 20: Experiment 3; percentage of early adopters owning a smart washing machine

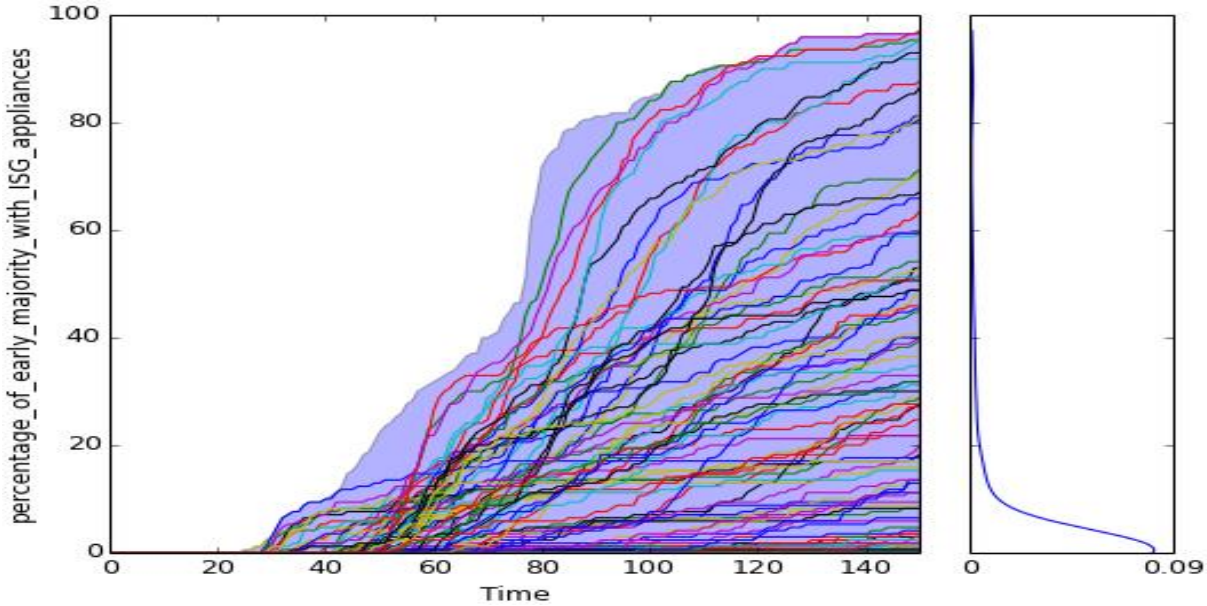


Figure 21: Experiment 3; percentage of early majority population owning a smart washing machine

In figure 20, we can see that for nearly all runs, all early adopters turn out to adopt a smart washing machine. In figure 21, we found that the amount of runs in which a rather high amount of early majority population adopts is low. In most cases, they refuse adoption. Therefore, we can say that the high number of runs ending in a percentage of adoption of approximately 20% in figure 19 is due to early adopters accepting to adopt while early majority population refuses. The challenge is now to find out why early majority population refuses to adopt. We therefore realise a PRIM analysis. To realise the PRIM analysis, we select the runs that ends in an adoption percentage of early majority population higher than 20%. The outcome of the analysis is presented in figure 22.

box	mean	mass	coverage	density	res dim
40	0.95	0.1	0.9	0.95	23

uncertainty	box 40 min	box 40 max	box 40 qp values
Learning_rate_appliances_1	0.94 -	0.97	7.63e-04

Figure 22: Experiment 3: outcome of the PRIM analysis – best cases of early adopter adoption

Figure 22 shows that one variable is mainly responsible for the occurrence of adoption percentage of early majority population higher than 20%. The learning rate of smart washing machines influences the price decrease of these appliances. The lower the learning rate, the faster the price decreases. Following, the lower the price, the higher the amount of savings that households can make by adoption is. In the PRIM analysis, a lower learning rate was identified as the variable that mainly creates the occurrence of cases where early majority population also adopt smart washing machines. Therefore, the reasons why early majority population do not adopt in the model is because of the low amount of savings that they can be make adopting.

Conclusions

Experiment 3 shows that, first, the demonstration to early adopters of potential social recognition that can be gained by adopting and, second, the facilitation of communication between early adopters leads to a higher adoption of smart washing machines in the model. The PRIM analysis performed in this section also shows that the low amount of savings that can be made by adopting is the reason why early majority population do not adopt. Therefore, we can say that a policy is needed to increase the amount of savings that households can make by adopting. This policy will be implemented in section 6. 2. 5.

6. 2. 4 Experiment 4

Experiment 3 has shown that the costs of smart washing machines and hence the amount of savings that can be made through their adoption are a highly limiting factor to their adoption on large scale. This observation strongly relies on the uncertainty identified in verification and validation phase that it is unknown what the minimum amount of savings is that households require to adopt smart washing machines (see section 5. 3). In this model, based on the calculation of savings (see equation 5 and equation 6), the amount of savings made by households mostly does not exceed 4 €/month. This is expected to be considered as a rather insignificant amount by households when compared to saving possibilities on other regular expenses. To cope with the low amount of savings made by households, a direction for policy has been created to decrease the purchase costs of smart washing machines. Still the low amount of savings made through the adoption of smart washing machines is an element that will have to be strongly considered in the conclusions of this report.

The policy applied here is a subsidy of € 200 for the purchase of each smart washing machine. The reason why € 200 has been chosen is that, based on the model and several tests, this is an amount that allows the adoption to strongly increase while still limiting the costs of the policy. The identification of this subsidy level if only based on the model. The translation of what this direction for policy in the real world is made in section 0.

Experimental set-up

Table 26: Parameter settings changes for experiment 4

Model parameters		
Variable	**Value**	**Unit**
Smart washing machine purchase subsidy	200	[€]

Results and interpretations

Figure 23 shows the effect of the directions for policy on the adoption curve. In comparison with experiment 3, we find that the amount of lines that resulted in an adoption percentage higher than 20%

has increased. This can be seen through the KDE graph on the right of the figure. Therefore, we can say that the policy implemented in this experiment was successful at increasing the percentage of smart washing machines adoption in the model.

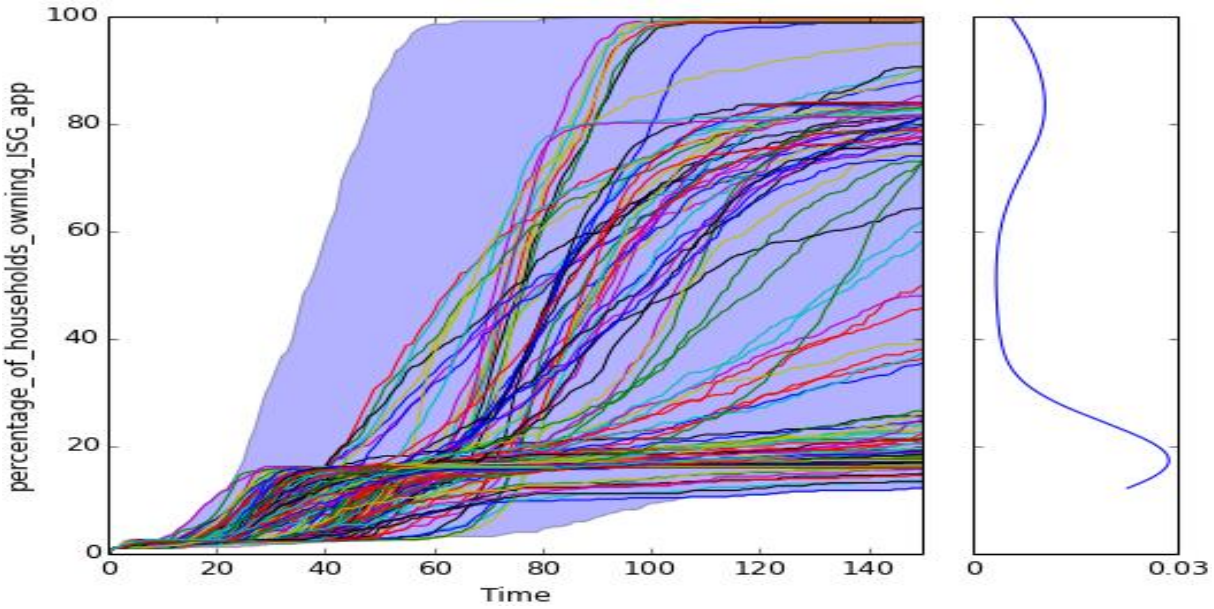


Figure 23: Experiment 4; percentage of household owning a smart washing machine

In figure 23, we still find a large amount of lines that ends with an adoption percentage of approximately 20%. In this figure, we can observe three types of lines. The first type increases progressively from t=20 to t=40 and then stabilises around a percentage of 20%. The second type increases progressively during the same period but then progressively increases to an adoption percentage of approximately 40%. The third type of lines starts its increase a bit later in comparison to the two first types of lines (between t=40 and t=60) and continues to grow above 60%. Since the third type of lines is the most contrary to the policy goals, an EMA analysis will be carried out to find out why they occur. For this analysis, we select all cases of household adoption that ended in an adoption percentage lower than 30%. The results of the PRIM analysis are presented in figure 24. The pealing and pasting trajectory can be found in figure 86 in Appendix F.

box	mean	mass	coverage	density	res dim
16	0.83	0.51	0.83	0.83	5

uncertainty	box 16		
	min	max	qp values
growth_phase	18 -	36	1.43e-08

Figure 24: Experiment 4: outcome of the PRIM analysis – worst cases of household adoption

In figure 24, we find that the duration of the growth phase is responsible for the occurrence of lines with a final adoption percentage of approximately 20%. The longer the growth phase, the higher the occurrence of these type of lines is.

Since the duration of the growth phase is not something that can be influenced by policy on the scale of a city district, the transition from the growth to the maturity phase must be targeted. The reason why households do not want to adopt is the high degree of adoption complexity that is experienced by households during the adoption process (see figure 25). In figure 25, the output of a single run ending in an adoption percentage of approximately 20% is provided. The EMA graphs showing all runs together are provided in figure 93, figure 94 and figure 95 in Appendix F.

The reason why complexity is found too high is however different from the case of the transition from introduction to growth phase. In the transition from introduction to growth phase, the vulnerability was mainly explained by the limited number of innovators. In the transition from growth to maturity phase, the number of early adopters providing information about the adoption of appliances is large enough. However, early majority population are risk avert. Therefore, in the model, they require a large percentage of households confirming to them that adopting smart washing machines is profitable. Hence, if only a few early adopters have adopted a smart washing machine after the end of the growth period, this might not be enough to convince early population that adoption complexity is indeed low.

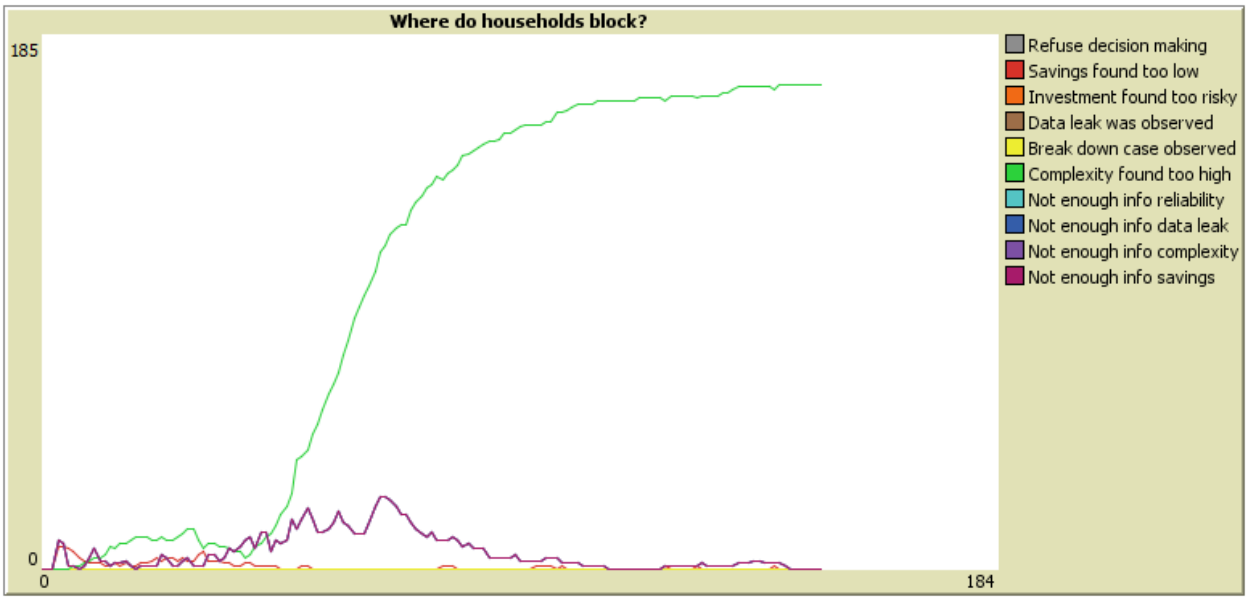


Figure 25: Experiment 4; reasons for not adopting

Conclusions

In this experiment, it appeared that a subsidy for the purchase of smart washing machines was indeed effective to increase adoption. The length of the growth life-cycle phase of smart washing machines has however been identified as the reason why a large amount of households refused to adopt. In the next experiment, a policy must be implemented to facilitate the transition from growth to majority life-cycle phase.

6. 2. 5 Experiment 5

In experiment 4, we have seen that a good transition from growth to maturity phase was key in allowing a high adoption rate of smart washing machines. The policy implemented in the model consists of, when the growth phase is over, selecting a percentage of early adopters and update their smart washing machine according to the new adoption complexity (which is then equal to one). In the real world, this would for example mean to offer some early adopters a discount on the purchase of a new smart washing machine.

Experimental set-up

Table 27: Parameter settings changes for experiment 5

Model parameters		
Variable	**Value**	**Unit**
Percentage of early adopter selected for updating their smart washing machine	25	[%]

Results and interpretations

In figure 26, we find that, in comparison to figure 23 in experiment 4, the amount of lines that has resulted in an adopter percentage higher than 20% has increased. Therefore, we can conclude that the policy implemented in this experiment indeed increases the adoption of smart washing machines in the model.

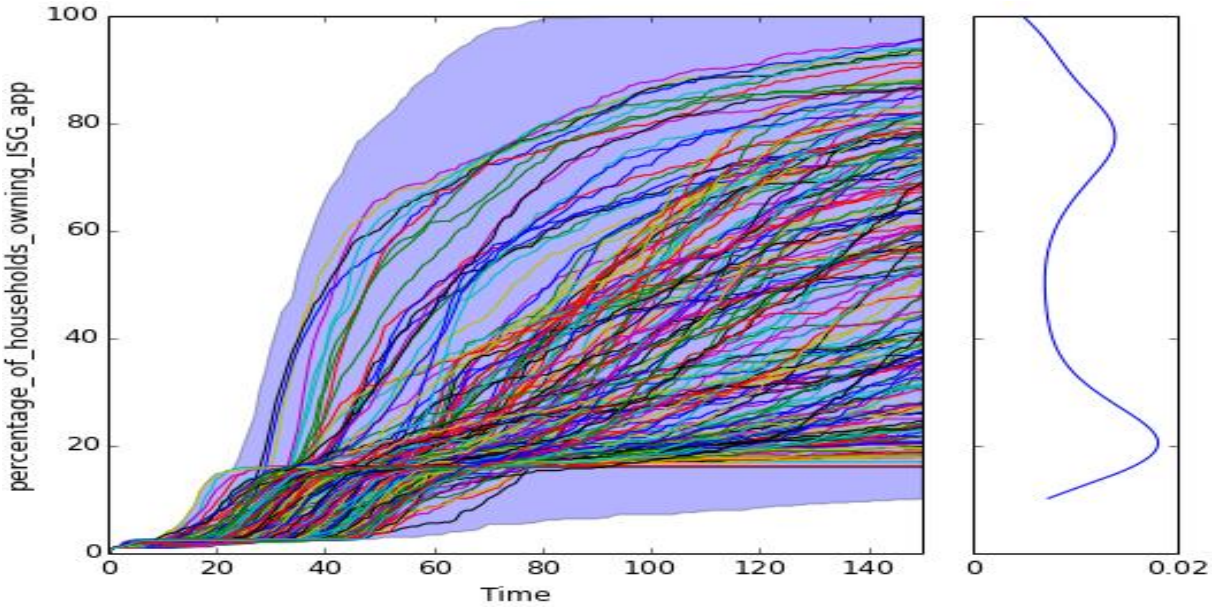


Figure 26: Experiment 5; percentage of household owning a smart washing machine

By looking at figure 26, we find that in a majority of cases, the percentage of smart washing machine adoption is progressively increasing above 20% of adoption, even if the increase is slow. In a limited amount of cases however the adoption percentage remains close to 20%. This is confirmed by figure 27 and figure 28. In figure 27, we find that in almost all cases practically all early adopters adopt smart washing machines. In figure 28, we see that, by looking at the KDE graph, there is still a large amount of cases where early majority adopters do not adopt.

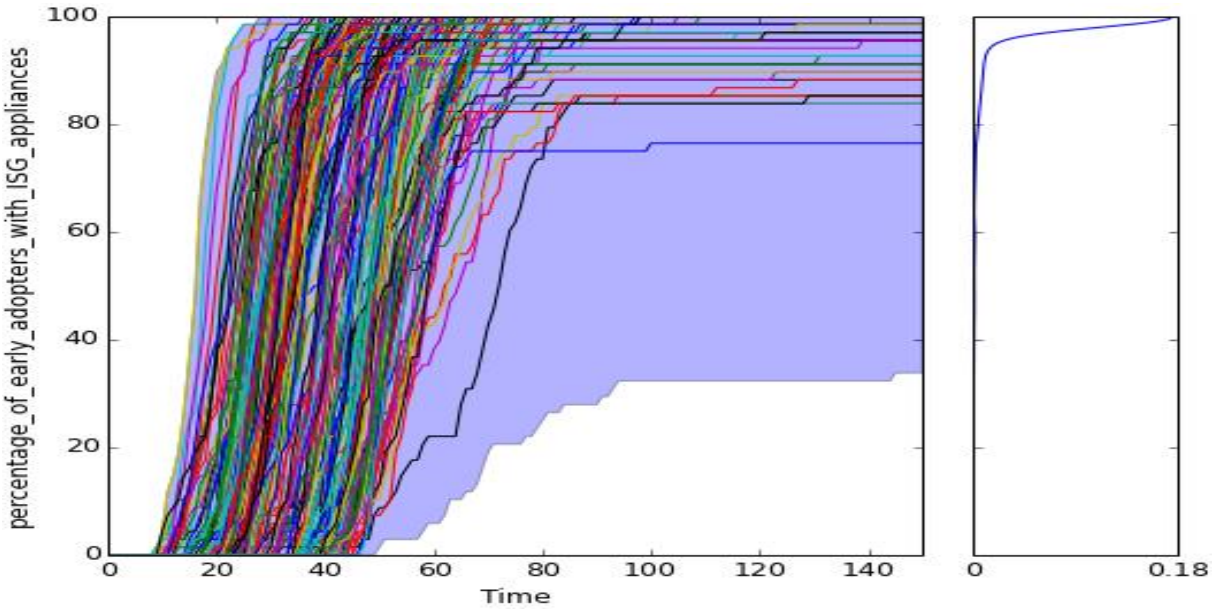


Figure 27: Experiment 5; percentage of early adopters owning a smart washing machine

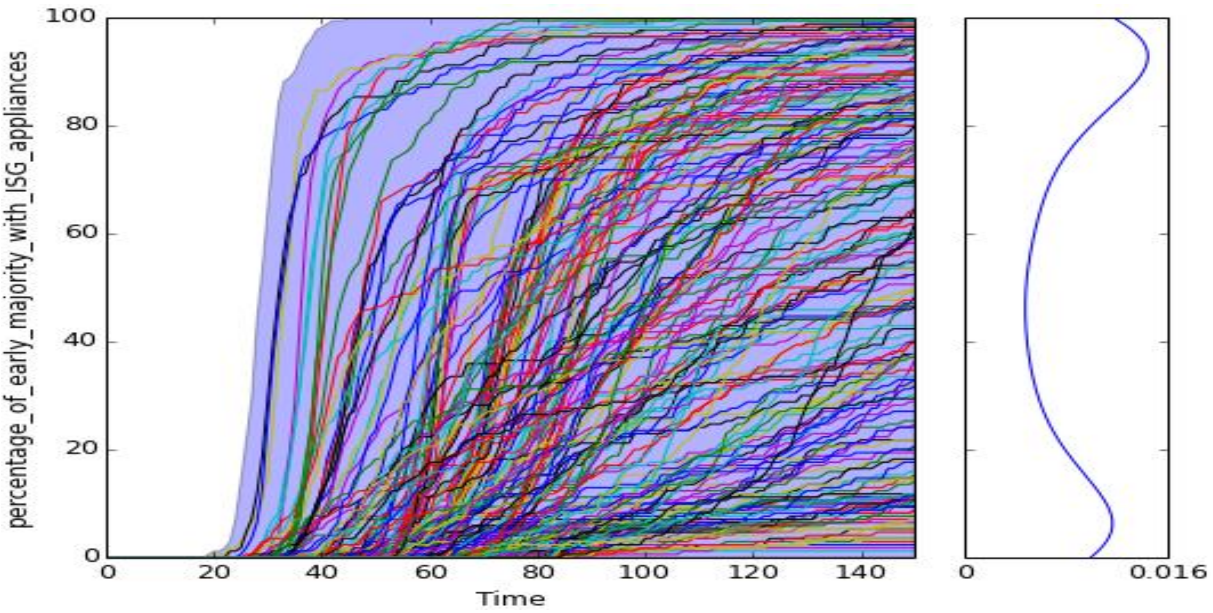


Figure 28: Experiment 5; percentage of early majority population owning a smart washing machine

To find out what leads to the occurrence of low smart washing machine adoption, we perform a PRIM analysis. For this analysis, we select all runs that ended in a household adoption percentage lower than 20%. The outcomes of the PRIM analysis are presented in figure 29. The pealing and pasting trajectory is visible in figure 96 in Appendix F.

box	mean	mass	coverage	density	res dim
34	0.81	0.13	0.81	0.81	14

uncertainty	box 34 min	box 34 max	box 34 qp values
A_S_L_preferred_information_source_early_majority_2	0.15 -	0.30	2.66e-03
change_threshold_to_reach_for_weights_3	0.79 -	1.50	7.36e-02
A_S_L_preferred_information_source_late_majority_2	0.00 -	0.08	7.36e-02

Figure 29: Experiment 5: outcome of the PRIM analysis; worst cases of household adoption

The PRIM analysis shows that three variables still explain the occurrence of worst cases. The first variable stands for the degree to which early majority population considers the information provided by early adopters as reliable. The second variable represents the amount of similar information that early majority population must receive in order to consider the information as reliable. The third variable is the degree to which late majority population considers the information provided by early adopters as reliable.

The outcomes of the PRIM analysis underline the importance of facilitating communication between early adopters and later adopter categories in the model. More specifically, the extent to which the transferred information is found reliable by households is a key to increase smart washing machine adoption. The role of early adopters is predominant in determining the success of smart washing machine adoption, which underlines the need to work with this group of adopters to create effective policies.

Conclusions

Experiment 5 shows that ensuring the renewal of smart washing machines by encouraging early adopters to adopt a new appliance indeed leads to a large adoption percentage in the model. In this experiment, we also identify three variables that still lead to a low adoption percentage. These variables

essentially relate to the extent to which information transferred from early adopters is found reliable by later adopter categories. In experiment 6, a direction for policy based on the model will be identified to allow a higher adoption rate.

6. 2. 6 Experiment 6

In experiment 5, the extent to which information is found reliable by later adopter categories has been identified as important determinant of the final adoption percentage of smart washing machines. In this experiment, the extent to which information provided by early adopters to later adopter categories is found reliable is kept high. The amount of similar information that early majority population must receive in order to consider the information as reliable is kept low.

Experimental set-up

Table 28: Parameter settings changes for experiment 6

Model parameters		
Variable	**Value**	**Unit**
Extent to which early majority population find the information provided by early adopter reliable	[0.35–0.45] (instead of [0.15-0.45])	[-]
Extent to which late majority population find the information provided by early adopter reliable	[0.35–0.45 (instead of [0-0.1])	
Threshold of information reliability to reach for early majority population	[0.5 – 0.8] (instead of [0.5-1.5])	[-]

Results and interpretations

Figure 30 shows that the number of households having adopted smart washing machines has increased due to the application of the policy. Therefore, applying a policy that increases the extent to which later adopters consider the information transferred by early adopters as reliable is effective considering the policy objectives.

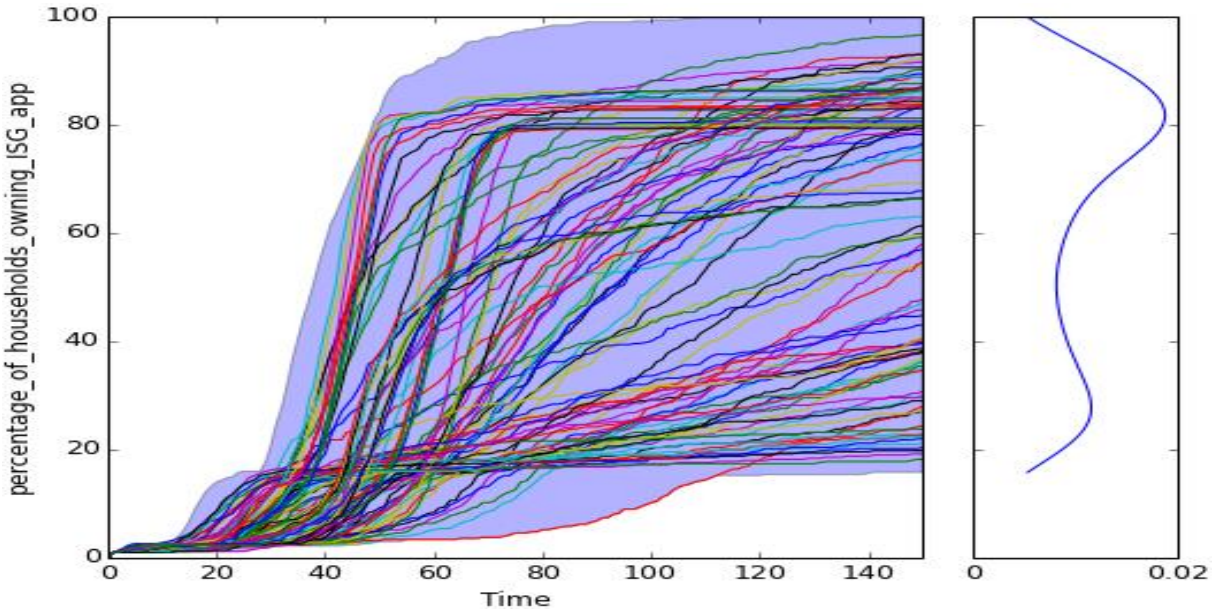


Figure 30: Experiment 6; percentage of household owning a smart washing machine

In figure 30, we find that the amount of lines that do not increase above 20% of the adoption percentage is very limited. For each model run, the adoption percentage seems to increase to a high adoption rate, even if the increase is low. This is confirmed by observing the evolution of the adoption percentage of early majority population in figure 31.

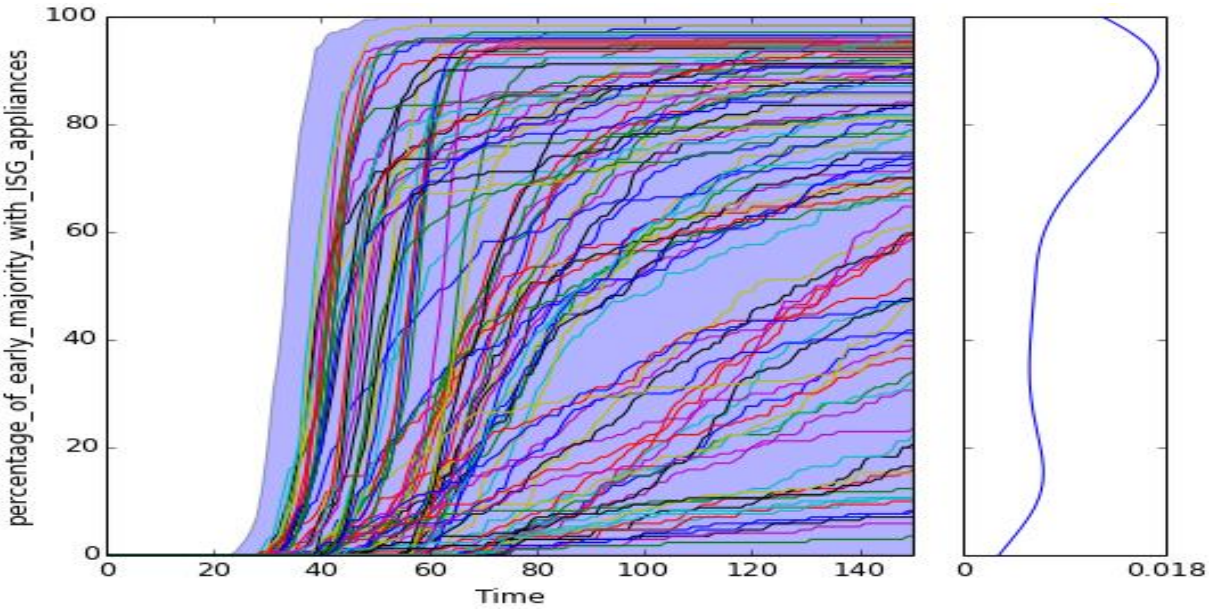


Figure 31: Experiment 6; percentage of early majority population owning a smart washing machine

Conclusions

In figure 30 and figure 31, we find that in practically no cases the adoption percentage of smart washing machines stabilises around 20%. On the contrary, a large majority of them increases progressively towards a high adoption percentage, even if this increase is low. Therefore, we can conclude that the chasm between early adopters and early majority population (see section 5. 6) has been bridged through the policies identified and applied in the model. As a result, no more experiments will be done to identify new directions for policy.

6. 2. 7 Conclusion

The experiments carried out in section 6. 2 has led to the identification of five directions for policy. The directions for policy are summarised in table 29.

Table 29: Summary of the directions for policy identified

Policy	Policy content
Direction for policy 1	Support communication between innovators and early adopters
Direction for policy 2	Promotion smart washing machines to early adopters (by focussing on their social added value)
Direction for policy 3	Purchase subsidy
Direction for policy 4	Reinvention of smart washing machines
Direction for policy 5	Ensure information communicated by early adopters is experienced as reliable

6. 3 Scenario discovery and policy testing: continuous decrease of adoption complexity

In section 6. 2, five directions for policy have been identified to increase the adoption percentage of smart washing machines. In this section, each of the policies identified will be applied sequentially and in the same order of identification in the model with continuous logarithmic decrease of adoption complexity. For each policy applied, an experiment will be carried out to find out the effect of the policy on the adoption percentage of smart washing machines. A summary of the experiment outcomes is

provided in table 31. The output of this section will be a conclusion about the effectiveness of each directions for policy identified in section 6. 2 on the model with continuous logarithmic decrease of adoption complexity. This will include a discussion about the reasons why they are or are not effective in this model setting.

Experimental set-up

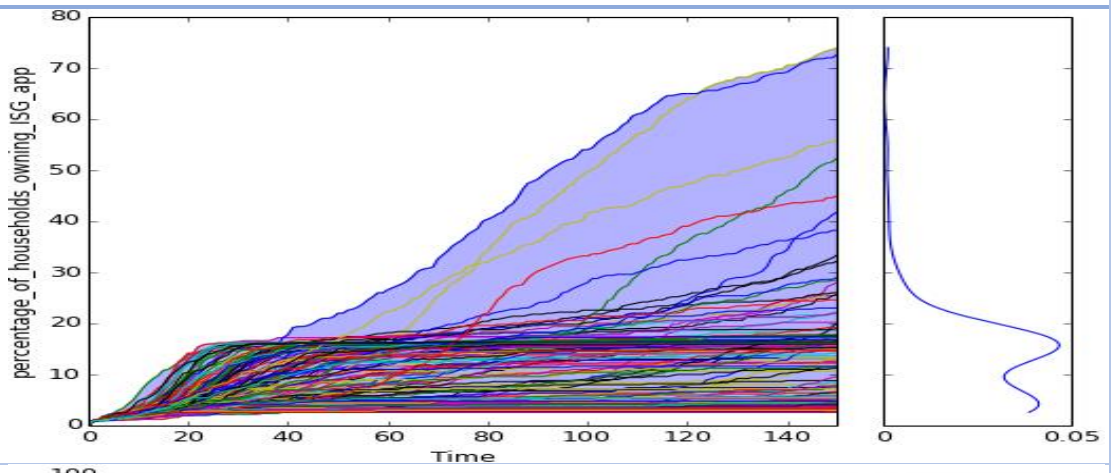
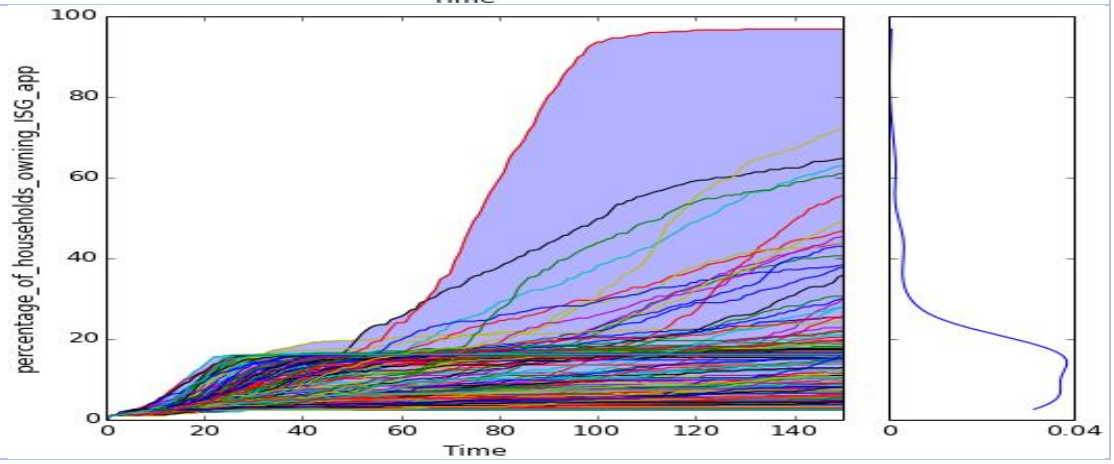
The experimental set-up is the one presented in section 6. 1 and therefore similar to the one applied in section 6. 2. The only difference is the usage of a logarithmic function to simulate the decrease of adoption complexity. The structure of this function is presented in section 4. 2. 2

Table 30: Parameter settings changes for experiments with continuous logarithmic adoption complexity decrease

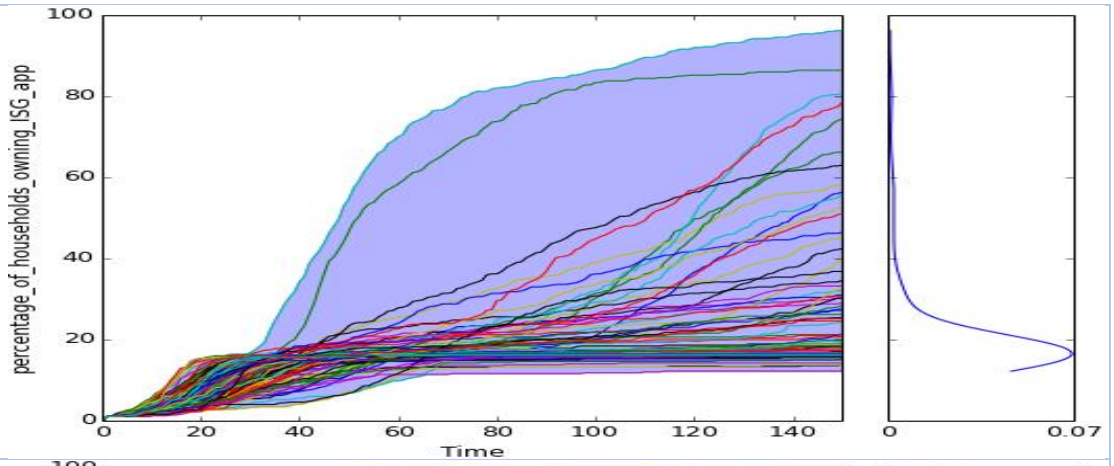
Model parameters		
Variable	**Value**	**Unit**
Learning rate of adoption complexity decrease of smart washing machine	[0.90-0.94]	[-]

Results

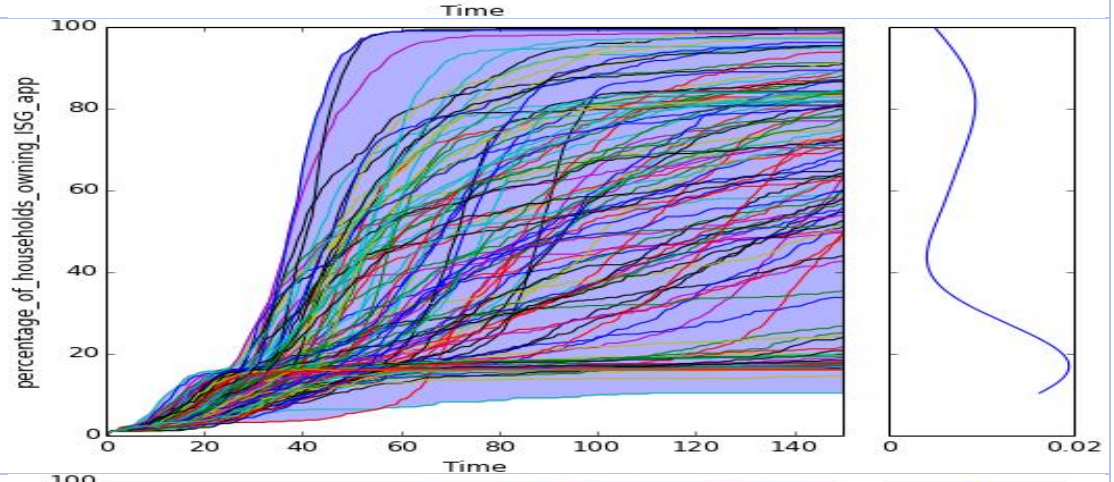
Table 31: Effect of the directions for policy identified in section 6. 2 on the model with continuous logarithmic decrease of adoption complexity

Policy applied	**Percentage of households owning a smart washing machine**
1. No policy	
2. Facilitate communication between innovators and early adopters	

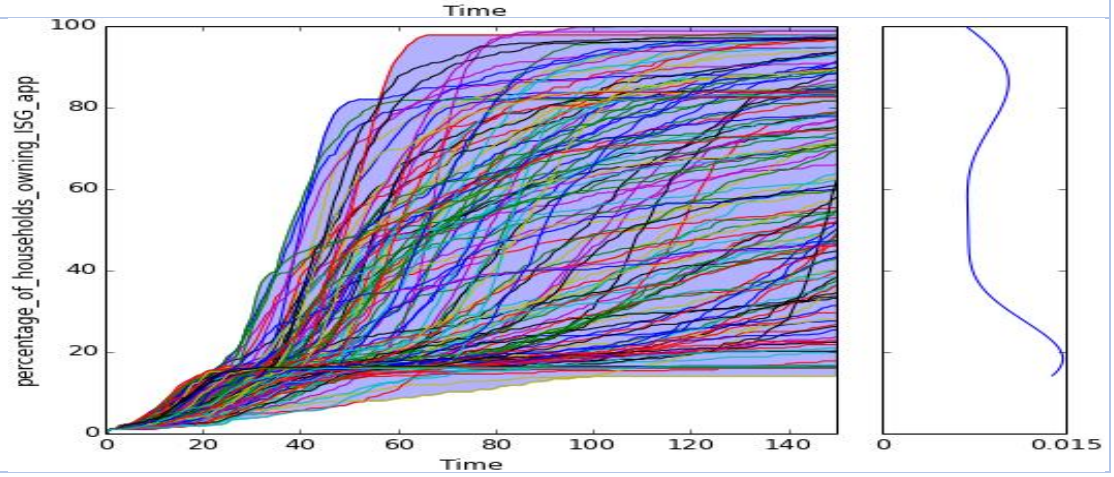
3. Promotion of smart washing machines to early adopters



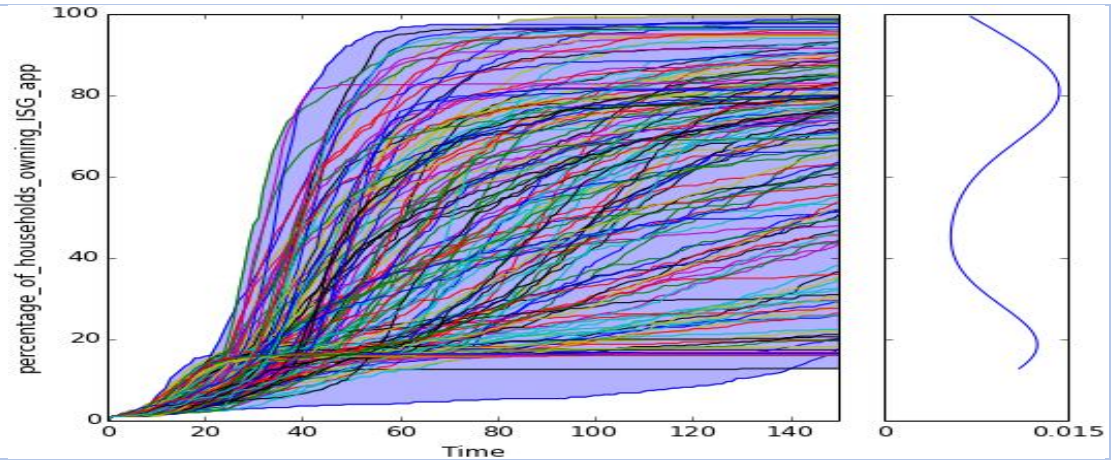
4. Subsidy



5. Reinvention of smart washing machines



6. Reliability of information between early adopters and later adopter categories



Of the five directions for policy applied, four directions seem to be effective at increasing the final percentage of smart washing machine adoption.

The facilitation of communication between innovators and early adopters does not lead to a strong increase of smart washing machine adopters. This can be seen in the KDE graph, by the amount of lines that end in an adoption percentage of approximately 4% and 18%. Either when no policy is applied or when the communication between innovators and early majority population improves, the amount of lines ending in an adoption percentage of 4% or 18% is approximately similar. The reason why this policy is not effective in this case is due to the type of adoption complexity decrease chosen in this section. In section 6. 2, the adoption complexity decreases in steps. In this section, it decreases continuously. The fact that adoption complexity is not discrete decreases the gap between two levels of complexity. Therefore, the communication of new levels of complexity is less challenging.

The direction for policy 'reinvention of smart washing machines' is also based on the assumption of a discrete decrease of adoption complexity. Surprisingly, the application of this direction for policy in the case of a continuous adoption complexity decrease still leads to a higher adoption percentage. This is due to the way the policy is build. The policy supports the renewal of smart washing machines owned by early adopters. This renewal allows the introduction of smart washing machines on the market that are more cost effective and therefore more interesting for later adopter categories. As a result, the adoption of smart washing machines increases due to this policy independently of the adoption complexity curve applied.

The application of all directions for policy still leads to a set of lines that end in an adoption percentage lower than 20%. To find the reason for the occurrence of these lines, a PRIM analysis is performed. For this analysis, all lines that ended in a household adoption percentage lower than 20% are selected. The outcome of the PRIM analysis is presented in figure 32. The pealing and pasting trajectory can be found in figure 112 in Appendix F.

box	mean	mass	coverage	density	res dim
23	0.79	0.27	0.81	0.79	12

uncertainty	box 23		
	min	max	qp values
learning_rate_adoption	0.92 -	0.94	5.31e-06

Figure 32: Experiment 1 of continuous adoption complexity decrease - outcome of the PRIM analysis; worst cases of household adoption

The PRIM analysis shows that a high learning rate of adoption complexity leads to the occurrence of these worst cases. The reason why these lines leading to an adoption percentage lower than 20% occur

in this experiment and not in section 6. 2 is hence because adoption complexity on average decreases slower here than in the case of step decrease. The slower the adoption complexity decrease, the longer the period between the adoption of early adopters and the adoption of later adopters is. As a result, the chances of an early adopter adopting in a period when the adoption complexity is equal or lower than 1 is minimal. Hence, there is no early adopter being able to communicate a level of adoption complexity low enough for early majority population. Households from the early majority category therefore never adopt. This effect can be seen in figure 33. This figure shows the output of a single run with and learning rate of adoption complexity equal to 0.94. In this figure, we see that only innovators and early adopters have adopted. The main reason for none adoption is because households initially interested in adoption considers adoption complexity to be too high.

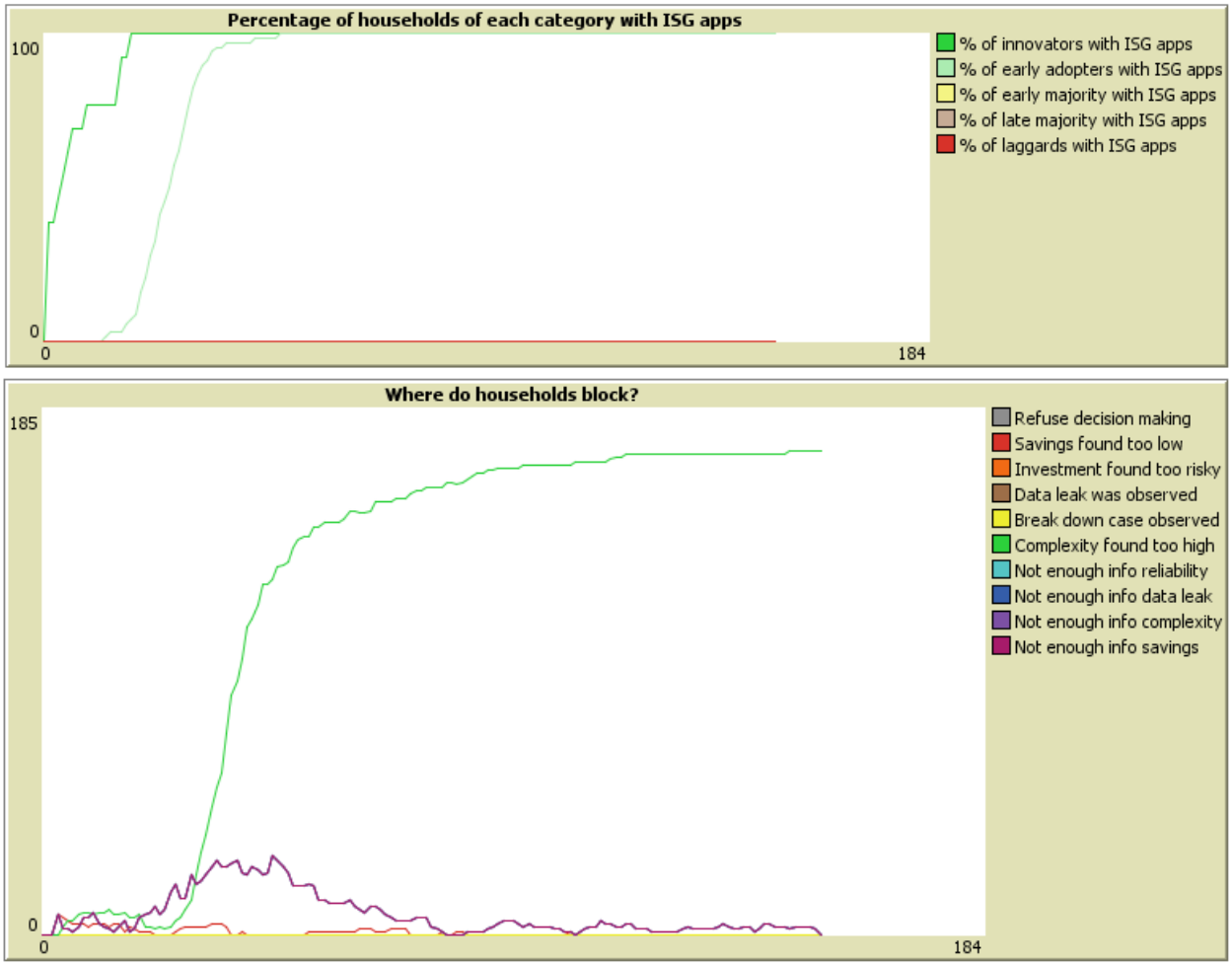


Figure 33: Experiment 1 of continuous adoption complexity decrease – reason for none adoption for early majority population and later adopter categories

Conclusions

In section 6. 3, we sequentially test five different policies that were identified based on a discrete decrease of adoption complexity. In the case of a continuous logarithmic decrease of adoption complexity, four of the five policies have been effective at increasing the adoption percentage of smart washing machines in the model. As a result, we can conclude that the application of a step or continuous decrease of adoption complexity does not strongly change the effectiveness of the directions for policy identified in the model.

6. 4 Conclusions

In chapter 6, five directions for policy have been identified based on a step decrease of the adoption complexity curve. These directions for policy have then been tested on their effectiveness to increase the adoption percentage of smart washing machines in case of a continuous decrease of adoption complexity. Of the five directions for policy initially identified, four have been effective to increase adoption in the case of continuous adoption complexity decrease. Table 32 summarises the directions for policy identified and for which type of adoption complexity decrease they are effective.

Table 32: Summary of directions for policy identified

Policy	Step decrease of adoption complexity	Continuous decrease of adoption complexity
Support communication between innovators and early adopters	Yes	No
Promotion smart washing machines to early adopters (by focussing on their social added value)	Yes	Yes
Purchase subsidy	Yes	Yes
Reinvention of smart washing machines	Yes	Yes
Ensure information communicated by early adopters is experienced as reliable	Yes	Yes

Three observations can be made about the directions for policy identified in this chapter. First, the chasms between adopter categories, due to different adoption requirements and interests in adoption are clearly the reasons that policies are needed in the model to increase adoption. Apart from the promotion of smart washing machines to early adopters, all other policies are needed to make sure new adopter categories are willing to adopt. Second, the chasm between early adopters and early majority population is clearly the most challenging. Only for this chasm, three policies are need: subsidy, reinvention and support for reliability of information between early adopters and early majority population. Third, the adoption of smart washing machines by late majority population and laggards does not seem to necessitate specific directions for policy as long as early majority population has adopted on large scale.

In chapter 6, the identification of directions for policy has been based on the model of smart washing machine adoption by households. Therefore, nothing can yet be said about their effectiveness to increase smart washing adoption in real-life. In addition, these policies were built to increase adoption in the model. Their translating to real-world policies is not straightforward. In chapter 8, a reflection will be made in order to translating these policies to real-life directions for policy. This will be done by analysing the limitations of the model in representing the actual adoption of smart washing machines by households.

Chapter 7 – Methodological experiments and reflection

In the previous chapter, two series of experiments were carried out to identify directions for policy to increase the adoption of smart washing machines. In chapter 7, the focus lies on the methodological aspects of this work. This is done by carrying out experiments and using observations made in the policy identification process of chapter 6. Chapter 7 is divided into two sections. In section 7. 1, the added value of using agent-based modelling for diffusion of innovation cases is analysed. In section 7. 2, the benefits of using scenario discovery for diffusion of innovation cases are discussed. The goal of this chapter is to answer the fourth sub-research question of this work (see section 0).

Reading indications

The goal of this section is analyse the suitability and the added value of agent-based modelling and the scenario discovery method to model the adoption of innovations. The interest of this chapter is hence mainly scientific and methodological. For readers who are not primarily interested in the methodological aspects, a summary of this chapter is presented in table 33.

Table 33: Summary of the methodological results

Methodology	***Main findings***
Agent-based modelling	- *Heterogeneity: inclusion of adopter categories allows the distinction of chasms in adoption. These chasms are widely recognised in the literature and the marketing field. The inclusion of adopter categories in the model therefore allows to identify direction for policy to bridge these chasms.* - *Heterogeneity: the inclusion of differences in household characteristics (number of householders) supports the fact that the decision-making of households is rationally bounded.*
Scenario discovery	- *Allows a convenient inclusion of parameter uncertainty in the model. Having in mind that exact data describing the behaviour of humans is rare in many cases, the combination of scenario discovery and the simulation of human decision-making with agent-based modelling is beneficial to model these systems.* - *Allows a rapid identification of directions for policy effective in the model.*

7. 1 Agent-based modelling and the adoption of innovations

In section 2. 4. 2, a rational is provided for the choice of agent-based in the modelling of the adoption of smart grid appliances. One main argument for the utilisation of agent-based modelling is easiness of including heterogeneity of agent characteristics and behaviour in the model. In this section, an analysis is provided about how the inclusion of various heterogeneities helped to model the adoption of smart washing machines by households. Agent-based models also allow a convenient testing of various form of consumer rationalities. Therefore, in this section, the impact of three different consumer rationalities on the adoption curve is discussed.

Addition of heterogeneity

Heterogeneity has been added to the model in two different ways: distinction of adopter categories and variation of household properties. To test the effect of these two types of heterogeneity, experiments are

carried out. In this section, the experimental settings are first presented. The experiments to test the effect of heterogeneity on the adoption curve are presented secondly.

Experimental settings

The model settings to perform the experiments in this chapter are based on the model validation phase made in section 5. 6. In contradiction to the experiments carried out in chapter 6, the parameters are not varied in this case. This is because the main interest is the comparison between different model settings instead of in the identification of scenarios relevant for policy construction. For each experiment carried out in this section, unless other rationality explicitly mentioned, neoclassical rationality is applied. These reason is that, in this model, the decision-making process is less complex when using neoclassical rationality. As a result, the impact of different model settings on the adoption curve is clearer.

The most important model settings are presented in table 34. The entire set of initial model parameters is presented in Appendix G. The number of households is 500, in order to represent a mid-sized city-district. The initial number of innovators owning a smart washing machine has been set to 5 in order to allow the innovation to diffuse. The number of runs is limited to 50 since it has been experienced as being enough to show the variation of outcomes between model runs. No replications are made here since parameters are not varied. The variation between each model run in the same experiment is only the result of stochastic uncertainty. Only the percentage of households owning smart washing machines is used as a key performance indicator since only effect of various model settings on the adoption curve is studied.

Table 34: Model settings and parameters

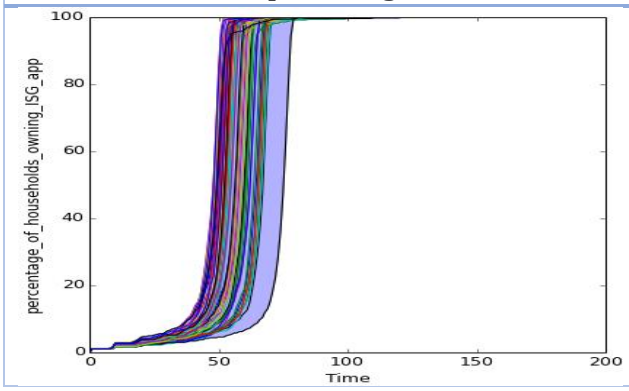
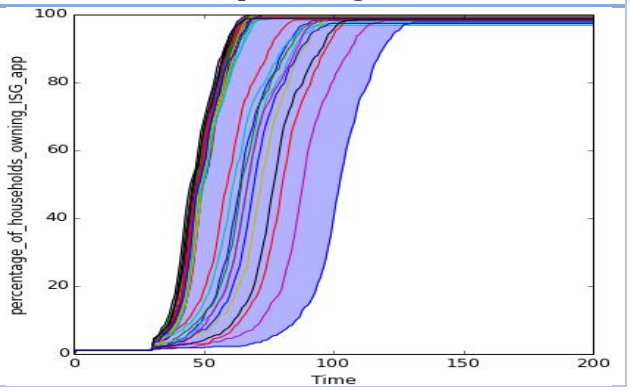
Model parameters	
Number of households	500
Initial number of innovators owning a smart washing machine	5
Rationality	Neoclassical rationality (unless other rationality explicitly mentioned)
Prospect theory	Switched off
Peak electricity price	Fixed for entire run
Off-peak electricity price	Fixed for entire run
Networks	Households uses all three types of interaction: friend, neighbour and random
Smart washing machine included in decision-making	Smart washing machine
Height of electricity price during off-peak period	0.25 [€/KWh]
Height of electricity price during peak period	0.40 [€/KWh]
Minimum level of savings desired by households	0 [€/month]
Duration of the introduction phase	24 [month]
Duration of the growth phase	24 [month]
Learning_rate_appliances_1	0.96
Run length	200
Number of runs	50
Number of replications	5

Distinction between adopter categories

The distinction between adopter categories, as suggested by Rogers (1962), allows incorporating the various expectations that adopters have from the adoption of innovations. This distinction is not taken into account in aggregated models such as the Bass model (Bass, 1969), which divides the population only in adopters and potential adopters. By not making a distinction between adopter categories, adoption is found to be quicker than in the case of adopter distinction (see table 35). The only factor that constrains adoption is the availability of information. This is the reason why a first part of an S-curve can be observed in the adoption curve. In case households are divided in adopter categories, we find that the

adoption curve increases more smoothly. There are two reasons for that. First, households from different adopter categories do not adopt under the same conditions. Later adopters for example wait until enough positive information is received in order to be able to consider the information as reliable and consider adoption. Earlier adopters, on the contrary, are risk takers according to Rogers (1962) and therefore take the risk to adopt even if information is not certain. Second, earlier adopters have more interactions then later adopters and therefore have a better access to information.

Table 35: Comparison of the adoption curve without and with adopter categories

No adopter categories	Adopter categories
	

As explained by Rahmandad & Sterman (2008) and Kiesling, et al. (2012), not making a distinction between adopter categories limits the number of adoption issues that can be explained by these models. The directions for policy identified in chapter 6 all rely on the fact that households have different characteristics and perform adoption decision-making according to different criteria. Table 36 summarises on which characteristics and decision-making differentiation the directions for policy identified in chapter 6 rely.

Table 36: Adopter differentiation on which the policies identified in chapter 6 are based

Directions for policy	Adopter differentiation on which the direction for policy is based
Support communication between innovators and early adopters	- Innovators tolerate a higher level of adoption complexity than early adopters.
Promotion smart washing machines to early adopters (by focussing on their social added value)	- Early adopters mainly see an innovation as a way to increase social status. Other adopter categories, except for late majority population, do not consider social recognition.
Purchase subsidy	- Earlier adopters are willing to take the risk of losing money by adopting. Later adopters are not.
Reinvention of smart washing machines	- Earlier adopters tolerate a higher level of adoption complexity than later adopters.
Ensure information communicated by early adopters is experienced as reliable	- Earlier adopters accept a low reliability of information whereas later adopters require a high degree of reliability

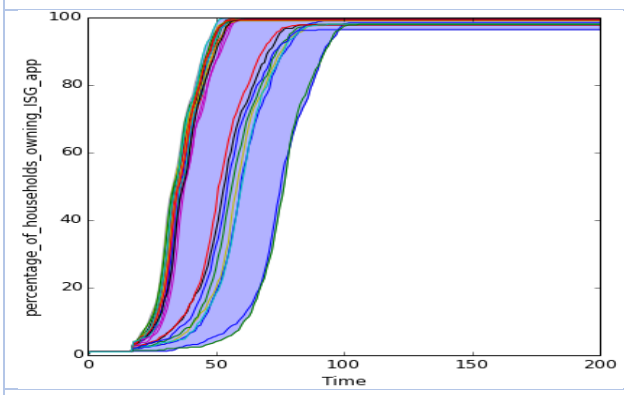
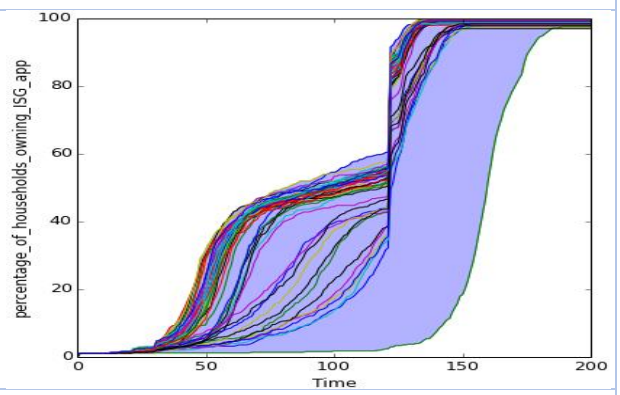
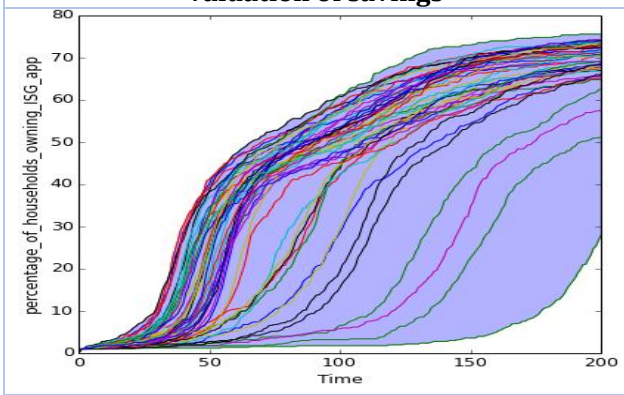
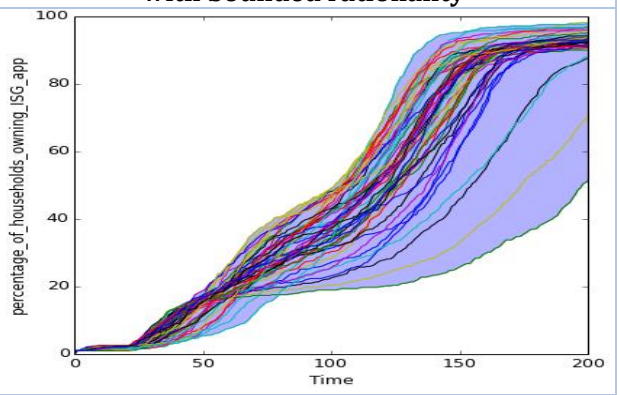
Chasms in innovation adoption are widely recognised in the literature and the marketing field (Moore, 1999). The identification of adopter categories and their inclusion in innovation diffusion models is therefore important to be able to, first, understand why these chasms arise, and second, develop directions for policy to ensure that innovation diffusion is able to bridge these chasms.

Variation of household properties

The variation between household properties has been analysed by assigning different amount of householders to households. The reason why this was done is because the amount of savings that can be made by adopting smart washing machines is strongly varying depending on the number of people per household. The amount of electricity consumed by one household is, assuming that no electricity is used for house heating, more or less proportional to the number of householders. Therefore, the amount of savings is doubled for a household with four householders than for a household with two. The purchase costs of smart washing machines however remain unchanged for each household. Assuming neoclassical rationality of decision-making, this heterogeneity has been included in the model. The result was the observation of a strong disruption in the adoption curve of smart washing machines (see table 37). Since these disruptions are not observed in any real-life adoption curve, different model changes have been made to validate the model based on observed adoption curves. Two model changes have been found to match real life observations. The first model change was the inclusion of valuation of savings heterogeneity. In this case, households do not all wait for the exact same value of saving that can be made by adoption. On the contrary, each household is assigned a different value of minimum savings required. The second model change is the application of bounded rationality. By using bounded rationality, we assume that households do not calculate the amount of savings that can be made by adopting. On the contrary, they base their judgement on opinions provided by other households. They will only find out about the real amount of savings after having purchased and used the appliance. Based on this they will communicate their satisfaction or dissatisfaction to other households. The addition of heterogeneity in household properties has therefore led to the following findings:

- The degree of heterogeneity in valuation of savings among households
- The bounded rationality character of the decision-making performed by households

Table 37: Impact of household properties heterogeneity

No heterogeneity in number of householders	Heterogeneity in number of householders
	
Heterogeneity in number of householders and valuation of savings	**Heterogeneity in number of householders with bounded rationality**
	

Testing of three different decision-making rationalities.

In this model, three types of decision-making rationalities have been tested: neoclassical rationality, bounded rationality and prospect theory rationality (see section 3. 2). There are several reasons for this. The first reason is that it was not clear which type of rationality would fit best with the decision-making that households are actually doing. The second reason is that the expectation that they will have a strong impact on the outcomes of decisions made by households and hence on the adoption curve of smart washing machines. Before describing the effect of the application of each type of rationality on the adoption curve, we must recall that the implication of applying each type of rationality can be subject to discussion, since none of these theories precisely describes what their implications mean for decision-making. An overview of how each type of rationality was implemented in this work can be found in section 3. 2.

Neoclassical rationality

By implementing neoclassical rationality, we do not find any chasm between (1) innovators and early adopters, and (2) between early adopters and early majority populations. The reason is that we assume a fully rational household to make any effort it can to improve its financial or social situation. In this case fully rational households do not take complexity into account. The result is that the adoption curve is, in any cases in which the amount of savings becomes positive at some point in time, in the form of an S-shape.

Bounded rationality

The application of bounded rationality in the model leads to one of the following adoption patterns: S-shape with fluctuation, bell curve and linear due to non-adoption. The reason why each of the patterns

can arise is the result of our interpretation of bounded rationality. In contrary to households using neoclassical rationality, we assume that bounded rational households takes the level of adoption complexity into account. Hence, households that judge the complexity as too high will not adopt the appliance, even if the financial benefits are high. Another impact of the application of bounded rationality is the lower occurrence of full appliance adoption than in the case of neoclassical rationality. In the case of neoclassical rationality, we assume that households will adopt appliances as soon as the amount of saving that can be made are positive. In the case of bounded rationality, households need a certain amount of saving above zero before they will decide to adopt.

Prospect theory

As explained in section 5. 9, the model was validated without the application of prospect theory. Some additional tests were carried out to study the effect of prospect theory, but beside a minimal delay in the adoption curve, no differences were found. The reason why no significant differences were found has to do with the way the model was set up. In the model, risk is defined by the difference in price between smart and non-smart washing machines that households are willing to pay in order to be able to save money on a later point in time. In case the difference between peak and off-peak electricity price increases, households are willing to accept a larger price difference. The contrary happens if the difference between peak and off-peak electricity prices decreases. But running the model and making sure that households use prospect theory to perform their decision making, it appears that households in some cases indeed judge the adoption risks to be too high. However, since we use a logarithmic function to describe the decrease of the smart washing machines prices, the difference between peak and off-peak electricity price will always turn out to be low enough. As a result, households will still turn out to adopt. Hence, the application of prospect theory in this model only has a delaying effect.

7. 2 Scenario discovery and the adoption of innovations

Section 2. 4. 2 explains how scenario discovery was used to analyse the model and to distinguish directions for policy. Based on this work, two main benefits of the usage of scenario discovery were observed: focus on model uncertainties and effective policy identification.

Model uncertainties

As demonstrated in chapter one, the system of the adoption of smart grid appliances is a complex system characterised by strong uncertainties. This observation can be extended to the majority of adoption of innovations cases, mainly due to the complex dynamics of social processes that influence the adoption of products (Kiesling, et al., 2012). The complexity of the system and its modelling with discrete simulations leads to four types of uncertainties that have to be distinguished to provide a good analysis of the adoption of innovations: stochastic uncertainties, parameter uncertainties, heterogeneity and structural uncertainties (Briggs, et al., 2012).

The use of scenario discovery was useful in order to take parameter uncertainty into account. On one hand, Augusiak, et al. (2014) underline the need to use data supported by reliable sources to increase the validity of the model. On the other hand, data describing the behaviour of adopters is difficult to find, which is a problem encountered by many authors modelling the diffusion of innovations (Kiesling, et al., 2012). In addition, data research for one system, for example by performing survey, cannot be transposed to another system (for example another city district) without recognising that the data might not fit the new system exactly. By using EMA, we not only recognise the uncertainty of these parameters, but we include them extensively in the analysis of the model. By using PRIM, we can find out which of the uncertain parameters really have an impact on the model behaviour and include this in the interpretation of the model outcomes. Hence, by using scenario discovery, we draw conclusions on the adoption of innovation cases of which the limitations are better defined. Hence, we believe the conclusions to be more robust.

Direction for policy identification

Using scenario discovery has been experienced as a very effective tool to generate directions for policy in this work. The use of PRIM is helpful to identify the variables that strongly affect model outcomes. As a result, policies can be created that specifically addresses these variables to increase the occurrence of a certain outcomes. By comparing this to the testing of traditional directions for policy based on common practices in the field of innovations adoptions, it is believed that the polices generated are more effective. It is then interesting to compare the policy identified in the model with traditional directions for policy used to support innovation adoption.

Chapter 8 – Implications and recommendations

In this chapter, an extensive reflection on the model outcomes, the implication for real life adoption of smart grid appliances and the use of various methodologies is presented. In section 8. 1, the limitations of the work will be presented. The identifications of limitations will then be used to reflect on the translation of model policies to real life policies in section 0. In section 8. 3 , recommendations for the use of this model in real cases will be provided.

8. 1 Limitations of this work

Based on the model created in this work, a set of directions for policy has been identified aimed at increasing the adoption of smart grid appliances. In section 0, these directions for policy, identified based on a simulation model, are discussed to discuss their validity and applicability to real world. The transition of directions for policy from simulation to real world cannot be done without a clear identification of the model's limitations. In this section, seven limitations are therefore identified, which will then be used to discuss the directions for policy identified. For each limitation, the impact of their occurrence on the directions for policy identified in chapter 6 is discussed.

Use of adopter categories

The first limitation of this work is the use of adopter categories. Although the need for the distinction between adopter categories is recognised in the adoption of innovations simulation field, we see the use of adopter categories as a large and debatable generalisation of reality on at least three points.

First, the division between adopters made by Rogers (1962) is strong. The question is whether population is in reality so strongly divided in its perception of innovations and reasons for adoption. Couldn't for example a household pay little attention to the costs of an innovation but still be unwilling to accept any adoption complexity? If this were true, it would mean that some households are early adopters in some aspects, but belong to early majority populations in other aspects. Second, Rogers assumes that, for one specific innovation, adopters never switch between adopter categories. This assumption is debatable since we could expect that households switch between adopters categories as a result of changes in their environment. For example, as a consequence of an economic crisis, we might expect that an important amount of households face a diminution of their monthly income. They would therefore pay more attention to their expenses and adopt a consumption behaviour that is closer to early majority population than to early adopters. The third question is if the adopter categorisation of Rogers is the right categorisation of households in the case of smart grid appliance adoption. As explained in section 3. 1. 3, there is a large amount of categorisations and their usage might lead to the identification of different directions for policy. The categorisation of Rogers appeared to be successful in identifying the challenges in supporting adoption recognised by sector experts and scientific authors. The use of other categorisations would however possibly lead to different directions for policy that would have been just as effective as the ones proposed in this work.

The identification of the three points of critique about the usage of the adopter categories of Rogers is crucial for the directions for policy identified in this work. Four of the directions for policy identified in this work strongly rely on the fact that there is indeed a clear division of households in adopter categories (see chapter 6). The fact that some households can belong to two adopter categories in different aspects is expected to facilitate the transition of adoption to later adopter categories. This would therefore decrease the need for policies to bridge the chasm between adopter categories. The fact that some households may in reality switch between adopter categories can decrease the effectiveness of policies due, for example, to the lower size of early adopters. The fact that other consumer categorisations could have been used would possibly have led to different but still effective policies.

The use of adopter categories also creates an implementation problem when it comes to applying policies. Rogers (1962) underlines that adopter categories are innovation dependent. For example, an adopter might be an innovator in the case of ICT products but a late adopter when it comes to energy saving products. As a result, there is no standard methodology that can be used to identify the adopter categories of individuals for all types of products. Therefore a new study would have to be carried out for each new innovation a few years later to find out whether it was indeed an appropriate consumer segmentation.

The validation of agent-based models

The second limitation is connected to the validation of agent-based models. As Epstein (2011) recognises, the validation of agent-based models is difficult. The transposition of models to the real world must therefore be done carefully. An illustration of the difficulty to validate agent-based models is the fact that, in this work, data had to be generated to represent the theoretical generalisations of Rogers (see section 4. 4. 1 and Appendix C). The need for data generation is explained by the lack of data that can be found describing the behaviour and preferences of households. To cope with the difficulty of validating agent-based models in this model, the choice was made to use the 'evaludation' method of Augusiak, et al. (2014), which is an extended verification and validation process. In addition, model uncertainties were analysed deeply and systematically through the usage of scenario discover. As a result of the utilisation of these two methods, both the impact of data scarcity and the difficulty to exactly represent the behaviour of households in the model on the directions for policy identified in the model is expected to be limited. Still, due to the typical chaotic patterns of agent-based model outcomes, the translation of model outcomes to policies applicable in real life should be carried out with care.

Households living in closed city-districts

Another limitation is the fact that households have been assumed to live in a closed city-district. This means that no interactions have been assumed between households inside and outside the city district. This has been done to facilitate the interpretation of model outcomes. We identify two types of interactions with the external world that could have had an influence on the adoption curve.

The first type is the interaction with households outside of the city district, by the same means is in the model (through direct interactions). The impact of including this type of interaction would have been a standardisation of the city district's adoption rate of smart grid appliances with the adoption rate of the external world (the country for example). The high adoption percentage in the external world would have increased the adoption rate of the city district level. A low adoption percentage in the external world, however, leads to a decrease of the adoption rate in the city district. The relevance of including interaction with households in the outside world is essentially relevant when modelling city districts in which households are not assumed to belong to earlier adopter categories. Modelling only interactions between households in this type of city district would lead to failed or partial adoption of smart grid appliances because of crucial role of earlier adopters in the diffusion process. In reality however, the adoption in these city districts could be less problematic.

The second type is the interaction through social media and internet forums. The effects of including interactions through social media and internet forums are expected to decrease the appearance of cluster of adoption and speed the adoption process through wide availability of information. A study done by A.C. Nielsen Company (1996) and published in the New York Times showed that innovations had the tendency to spread faster now than in the past, due to the ever improving access to information. However, the question is whether social media and internet forums only spread awareness about an innovation, or whether they also spread information that can be considered as reliable by households which they include in their decision-making process. This question should first be answered before including the effects of social media in this model.

Mainly the inclusion of social media and internet forums in the model is expected to influence the directions for policy identified in the model. This is particularly true for two directions for policy. The first direction for policy is the support of information communication between innovators and early adopters. This direction for policy strongly relies on the fact that households only interact directly with each other. However, the role of social media and internet forums is expected to decrease the need of this policy in reality strongly. As explained by Rogers (1962), individuals belonging to earlier adopter categories are willing to make efforts to find information about an innovation. The communication of information between innovators and early adopters would have therefore been less problematic. The fifth direction for policy identified is the support for exchange of information between early adopters and later adopter categories that are perceived as reliable. The effects of social media and internet forums is however expected to have the potential to decrease the effectiveness of this direction for policy when applied. As explained by Rogers (1962), early majority populations and later adopter categories are risk avert and therefore desire to be absolutely sure about the added value of adopting before considering to do so. The fact however that social media and internet forums favour the diffusion of rumours, even if totally untrue, may decrease the adoption speed of smart grid appliances. On the other side, from the moment when the added value (whether financial, social or user friendliness) becomes widely recognised and unquestioned, social media and internet forums are expected to strongly accelerate adoption.

Focus of the adoption of smart grid appliances and not their utilisation

In this work, the focus is put on the study of the adoption (purchase) of smart grid appliance instead of on their utilisation (see section 2. 2). Hence, a household that has adopted a smart grid appliance might possibly not use the appliance, or not use it with its 'smart' function. The effect of including the utilisation of smart grid appliances might not change the adoption curve. However, it is expected to have an influence on the answer on the research question in this research. In this work, we assume that smart grid appliances are efficiently used by a household. Therefore, the adoption of a smart grid appliance automatically increases the demand response capacity of a city district. However, the utilisation of smart grid appliances might be the result of changes in the current peak and off-peak electricity prices. In addition, typical human behaviour such as the higher motivation for product usage just after its purchase and the progressive decrease of willingness to make efforts must be taken into account. Including the utilisation of smart grid appliance would be an interesting addition to this work; this is suggested in section 9. 2. The inclusion of household utilisation of smart grid appliances is expected to be useful when integrating the effects of social media and internet forums on the adoption of these appliances. As a result, the effects of social media and internet forums on the need for two of the directions for policy identified (good communication between innovators and early adopters and reliability of information between early adopters and later adopter categories) could be researched more in-depth.

No choices between brands

In this work, we do not include the possibility for households to choose between brands because of time limitations and the complexity of including competition market mechanisms in the model. However, various other authors do take this distinction between brands into account (Zhang & Nuttall, 2007; Rixen, 2010; Schramma, et al., 2010). In this project, the addition of different smart appliances brands would probably have increased the speed of the adoption curve. The reason is that the higher the number of brands, the higher the chance is that at least one of the brands fulfils the needs of one household. In addition, it would have had an impact on the directions for policy identified. The mechanisms of product differentiation creates price diversification between appliances. As a result, smart grid appliances would have been adopted more quickly by some households. On the other side, product differentiation also creates diversification in product qualities and ease of utilisation. As a result, households that would have purchased a cheap smart grid appliance would also have faced more

breakdown and utilisation problems. The negative feedback provided by these household to the ones not having yet adopted would have decreased the overall rate of adoption. Both the positive and negative effects that product differentiation can have on the adoption rate of smart grid appliances shows that the inclusion of various brands would be an interesting addition to this work. This addition is suggested in section 9. 2.

The inclusion of product differentiation in the model due to competing brands is expected to have an influence on the fourth direction for policy identified in chapter 6. This direction for policy underlines the need for product reinvention in order to allow the adoption of smart grid appliances by early majority populations and later adopter categories. On one side, it is expected that the differentiation between products will decrease the need for reinvention. This because there is often at least one brand that focusses on the social value individuals may receive by purchasing their product, and another that focussed on the financial benefits of buying their product. One the other side, this differentiation between brands may also harm the reputation of smart grid appliances. If one brand tries to underlines the financial benefits of adopting while the actual amount of savings proves to be limited, the word could spread that the purchase of smart grid appliances is not profitable. At the end, this could strongly decrease the adoption rate of smart grid appliances.

No feedback between the adoption of smart grid appliances and the external world

The model created in this work is influenced by exogenous variables, but the elements in the model do not influence the external world in response. The reason why this is not the case is that the effect of a city district's electricity is too small to influence a national electricity market. Therefore, in this market, the feedback between, first, the adoption of smart grid appliances and their purchase price and, second, the adoption of smart grid appliances and the evolution of national peak or off-peak electricity price can be neglected.

Modelling the adoption of smart grid appliance on the scale of a country would have forced the inclusion of the feedback in the model. Including the feedback between the adoption of smart grid appliances and their price would have forced the inclusion of policies that strongly decrease the price of smart grid appliances to support adoption. In the current model, the price of smart grid appliances decreases independently from the level of adoption in the city district. As a result, the application of the third direction for policy, which underlines the need for a purchase subsidy, is mainly a way to speed up the adoption of smart grid appliances. The feedback between the adoption of smart grid appliances and their price would have made this subsidy mandatory. Including the feedback between the adoption of smart grid appliances and the peak or off-peak electricity price would have made the adoption dependent on the installation of new power capacity in the country. The higher the new installed capacity of renewables, the higher the financial interest would be for households to adopt smart grid appliances due to a higher difference between peak and off-peak prices.

Impact of various types of networks

In this model, only one type of network structure is applied: a combination of random, neighbour and friend interactions (see section 3. 3). The reason is that this type of network structure is expected to be a good representation of the actual behaviour of households in a city district. Moreover, it is close to the types of network used to simulate adoption of smart appliances found in the literature (Zhang & Nuttall, 2011). In the model, the number of interactions that households have each month is varied to include parameter uncertainty about the real number of interactions of households. From a scientific point of view, it is however arguable to support the need of including different types of networks and test their effect on the adoption curve. The application of only neighbour interactions is expected to slow down the adoption rate of smart grid appliances since it slows down the diffusion of adoption information. The application of only random interactions is on the contrary expected the speed up the adoption rate due

to the wide diffusion of information among the entire modelling space. A study of the effect of different types of networks on the adoption curve can be found in the work of Rahmandad & Sterman (2008).

The application of structurally different types of networks may affect the identification of the first direction for policy. In this direction for policy, the need for more communication between innovators and early adopters is underlined. The application of networks that are more clustered, for example around adopters that are expected to adopt quickly new available innovations, is expected to decrease the need for this direction for policy.

8. 2 Translation of policies to real world

In chapter 6, the directions for policy are identified based on the model. Therefore, nothing can yet be said about their effectiveness to increase smart grid appliance adoption in the real world. In addition, these directions for policy focus on increasing adoption specifically within the model. Their translation to policies that can be applied in the real world is not straightforward. Moreover, in this work the adoption of smart grid appliances on the scale of city districts is studied. By mentioning the support of adoption on the scale of city districts, it is meant the identification of directions for policy as if we would only want to increase the adoption of smart grid appliances within the city-district itself, and not necessarily outside of the city-district. Therefore, a distinction must be made between policies that may be applicable on this scale and those that are only applicable of national scale. In this section, a reflection on the directions for policy identified is provided. To do that, an identification of the assumptions and model limitations on which these directions for policy are based is provided. The directions for policy identified are then compared to the content of relevant scientific literature to discuss whether the need for this policy is recognised by the scientific community. Next, a reflection on the practical implementation of the policy is provided. The output of this section is a set of directions for policy, with policy measure examples, that has the potential to increase the adoption of smart grid appliances in city districts.

8. 2. 1 Support the communication between innovators and early adopters

The analysis of the model shows a chasm between innovators and early adopters. The reason for the occurrence of this chasm is the low number of innovators in populations. Due to the low number of this type of adopters, communication of recent information about the appliances is difficult. As a result, the entire diffusion process might not start at all. In section 6. 2, a direction for policy is proposed to bridge this gap. The key element of this policy is to work with innovators by updating technological elements of the smart grid appliance and help them to talk about the product.

Assumptions on which the direction for policy is based

The first assumption on which this direction for policy is based is a step decrease of adoption complexity. In the case of a continuous decrease of adoption complexity, this direction for policy does not appear to be necessary. Second, we assume a strong decrease of the purchase, installation and usage complexity form the introduction phase to the growth phase. Third, adoption conditions in the introduction phase are not considered satisfactory by early adopters. Lastly, early adopters are dependent on innovators to communicate to them that current adoption conditions are good enough for them.

Comparison with the literature

The chasm between innovators and early adopters is in the literature referred to as the ‘first crack’. According to Moore (1999), the first crack happens when “a hot technology product cannot be readily translated into a major new benefit”. Hence, the reason why the first crack happens has to do with the failure to adapt an innovation technologically and thus to increase its benefit for adopters. In this work, we find that the reason for the chasm between innovators and early adopters is indeed linked to the change of the product’s adoption properties. Contrary to Moore however, we assume that smart grid

appliances will in any case turn out to be a major benefit for households. The reason why this chasm arises in the model is due to the communication of the product's new adoption conditions.

When comparing this chasm to the agent-based diffusion of innovations literature, we find that the appearance of this chasm is typical for agent-based models, through discretisation of adopters, and through the clustering of adopters. Rahmandad & Sterman (2008) for example find that the initial geographical location of innovators clearly affects the adoption curve. In some geographical dispositions, they found that the diffusion never continues.

Reflection

The chasm between innovators and early adopters is not widely recognised as a major source of problem in the adoption of innovations, apart from the technical aspect. The reason why this chasm was discovered in this model is because the model is made on the scale of a city district, which explains why the number of innovators is very limited. This observation however should be relativized, since the distribution of households per adopter category has been identified as a large uncertainty in the verification and validation section (see chapter 5). Another reason is that we assume that early adopters only receive adoption information from other households, while in reality the role of media and promotion campaigns is also underlined (see section 8. 1). In addition, social media is expected to largely facilitate the transfer of information and therefore reduce the need for the direction for policy identified here. As a result, we conclude that this chasm is mainly interesting from a modelling point of view (see section 7. 1). We still underline that this point in the adoption trajectory of smart grid appliances remains vulnerable. Communication between households that might be strongly interested in purchasing smart grid appliances (innovators and early adopters according to Rogers) is important. On the scale of city districts, this can be done through the organisation of meetings to discuss various smart grid appliances and their utilisation. In addition, creating platforms to allow enthusiasts to discuss the utilisation of smart grid appliances, such as internet forums, is expected to contribute to an effective distribution of information to potentially interested households.

8. 2. 2 Promotion of smart grid appliances to early adopters

In the model, the promotion of smart grid appliances to early adopters is found to be essential to increase the adoption rate of smart grid appliances.

Assumptions on which the direction for policy is based

The identification of this direction for policy is based on three assumptions. First, early adopters are mainly interested in the social value of adoption and not as much in financial benefits. Second, early adopters are rich enough to take the risk of losing money by adopting. Third, at the early stage of product commercialisation, the amount of savings that can be made by adopting smart grid appliances is too little for most of the population.

Comparison with the literature

By comparing the marketing literature, we find that this direction for policy is equivalent to traditional product promotion, where the goal is mainly to increase consumers' awareness about the availability of a product. The importance of brand awareness is widely described in scientific literature (Huang & Sarigöllü, 2012).

Reflection

The direction for policy identified here is equivalent to traditional product promotion. The previous direction for policy identified (purchase subsidy) shows the smart grid appliance diffusion problem due to the lack of savings that they can provide to consumers. Therefore, product promotion should not underline the possibility of making savings. Doing so might harm the reputation of smart grid appliances and slow down diffusion. By identifying the early adopter category, Rogers underlines that there is a share of the population which is not so much interested in the financial aspect of product adoption, but

more in the social value of adopting. To allow introduction of smart grid appliances, it is therefore essential to underline the social benefits of adopting. In this project three main social added values of adoption can be identified. First, a household may adopt to help the introduction of a larger share of renewable energy in the electricity sector. Second, households may adopt to take part in a community action and feel more connected to their neighbours. Third, households may adopt to demonstrate their lifestyle to other households. The problem in this case is however that the adoption of a single smart grid appliance does not really allow a strong demarcation of its lifestyle. Concretely, it does not allow a household to strongly show off to other households how advanced their house is. The concept of smart home management systems on the contrary does allow households to do so. Therefore, the promotion of smart home management systems might be a better way to allow a larger share of smart grid appliance adoption. The profiling of smart grid appliances according to their social recognition they can provide is not expected to allow mass marketing of these appliances. This is because most households still take the financial aspect of adoption strongly into account. However, it can be seen as a good way to allow smart grid appliances to enter the market.

Controlling the image of smart gird appliances is utopic since there is a wide amount of actors, including various product brands, which might try to profile these appliances in their own way. The case of city district projects however is different. In this case, projects may be profiled on the same way that we want smart grid appliances to be profiled. Instead of underlining the cost effectiveness of participating in smart grid projects on the scale of city districts, it may be more interesting to underline the new lifestyle it promotes, community building, or the benefits of the project to the environment. An example of a policy measure that promotes smart grid appliances to early adopters is the support of the creation of consumer groups. This can for example be done on the scale of a street, by providing tools to households in order to communicate easily with each other. The goal is that households simultaneously purchase smart grid appliances and help each other during adoption. These consumer groups can be combined with the nomination of product ambassadors (Rehmet & Dinnie, 2013). Product ambassadors are people who are strongly enthusiastic about a certain product and find value in informing and convincing other people to adopt as well. Rogers would consider these ambassadors to be innovators and individuals being strongly open to adoption to be early adopters.

8. 2. 3 Purchase subsidy

One of the direction for policy proposed is a subsidy to decrease purchase costs of smart grid appliances. Based on the model, the policy proposes to decrease purchase costs of smart washing machines by 200€ through a subsidy mechanism until the price of smart appliances equals the price of traditional appliances.

Assumptions on which the direction for policy is based

This direction for policy is based on the assumption that there are two electricity prices, one for peak and one for off-peak hours. This is comparable to the current Dutch system of day and night electricity tariffs. In addition, we assume that the electricity price remains stable during the entire run in order to allow a better understanding of the impact of lower/higher peak and off-peak price difference. Testing the direction for policy with fluctuating electricity prices did not lead to different outcomes.

Comparison with the literature

The low profitability of smart grid appliances was not found in the literature. The main reason is that these appliances are at the very early stage of market entrance. Some internet documents however discuss the fact that switching to a day and night electricity monitor meter might lead to lower savings that expected for consumers (Gaslicht.com, 2013).

Reflection

One main worry about the introduction of smart grid appliances is the low level of savings that they might provide to end users. By using a fix day price of 0.235 €/kWh and a fix night price of 0.215 €/kWh (Gaslicht.com, 2013), we find that the usage of a washing machine by night instead of during day would lead to 0.23€ of savings per month for a household of two persons. The minimal amount of savings that households require in order to be willing to adopt is difficult to discover. This was identified as one of the main uncertainty in the model. As an indication however, in the case of smart meters, a survey made by Thiemann, et al. (2007) show that the average household considers adoption if at least 10€/month of savings can be made. This amount of savings is found low by other surveys, which founds the minimal amount of savings to be closer to 25€/month. This does not mean that smart grid appliances should allow this amount of savings in order to be sold on large scale. However, it shows how little insight and knowledge average households have about their energy costs.

In any case, the level of savings of 0.23€ per month for the adoption of a smart washing machine seem insignificant in comparison to the amount of savings that households require to be willing to adopt. We can expect that a different market price mechanism that is more sensible to short term variations of electricity production and consumption might slightly increase the amount of savings made per month, however this increase of savings is still expected to be minimal. Having in mind that Rogers argue that a large majority of the population (early majority population and later adopters) adopt for financial reasons, large scale adoption is difficult to imagine unless the price of smart appliances equal the one of traditional appliances. This mean that, if a subsidy is applied, it should cover the price gap between smart grid and traditional appliances. The question then is also, if the smart function of the appliance is not automated, whether they will use the smart function of the appliance (make sure that the appliance operates during off-peak hours).

The implementation of this policy on the scale of a city district is difficult since a subsidy is typically a national policy. Unless smart appliance producers are willing to lend their products as in the case of the PowerMatching City project (DNVGL, 2012), decreasing purchase costs for households on this scale is difficult from an institutional point of view. Therefore, we advise to first focus on city districts where households may adopt for other reasons than financial ones (city districts typically populated by innovators and early adopters). These reasons for adoption could be the desire to become more environmentally friendly and the desire to take part to a community action. The focus on city districts where households would typically purchase smart grid appliances for financial reasons is only advised when the price of smart grid appliances equals the price of their traditional equivalents. The goal of the project would then be to try to change consumer habits. In this case, this would mean that households would start and continue to use smart grid appliances in their smart function. Still, Rogers underlines that the willingness of most of the population to change habits is often strongly limited.

8. 2. 4 Reinvention of smart washing machines

In experiment 5 (see section 6. 2. 5 and 6. 3), a direction for policy is proposed to decrease the vulnerability of the transition from growth phase to maturity phase. The reinvention of smart washing machines is in this case defined by a change of the concept of these appliances to match the adoption requirements of early majority population and later adopter categories. To comply with the requirements of early majority population and later categories, smart grid appliances should become strongly user-friendly. Also the costs of smart grid appliances should not exceed the ones of traditional appliances. In the model, the reinvention of smart grid appliances is assumed to happen in any case. The direction for policy suggests to make sure that at least a share of early adopters adopts the reinvented smart grid appliances. The expectation is then that they communicate the outcomes of the adoption to early majority population and late adopters, who would then be convinced by the benefits of adopting.

Assumptions on which the direction for policy is based

The direction for policy relies on three main assumptions. First, the identification of this direction for policy majorly relies on the fact that there is indeed a strong distinction between lifecycle phases of smart grid appliances. More precisely, it relies on the fact that product's properties and the characteristics of its adoption all significantly decrease in complexity and at approximately the same time. The product will then enter a mass-market phase. The second assumption is that complexity in the maturity phase (mass-market phase) is low enough for early majority population and later adopters, but not in the growth phase. The third assumption is that information about adoption conditions, including the amount of savings and the degree of complexity, is only considered reliable when it is provided by other households.

Comparison with the literature

The vulnerability of the transition from product adoption by early adopters to product adoption by early majority population is widely recognised in the literature. The vulnerability is called the chasm between early adopters and early majority population. This chasm is widely discussed in the literature and has been initially suggested by Moore (1999). According to Moore, this chasm is especially visible in the case of disruptive products. Disruptive products are the products that require a change of behaviour for adopters in order to utilise them.

In this work, we find that the reason for this chasm is the difficulty of convincing early majority population of the benefits of adopting smart grid appliances, even if the current adoption satisfaction is acceptable for them. Since early majority population wants to decrease adoption risk, they communicate with early adopters to discuss how they experienced the adoption. However, since early adopters have adopted at an earlier point in time, which corresponds to moments when the adoption conditions were less beneficial, they communicate adoption conditions that are not satisfying for early majority population. As a result, the adoption is rejected by early majority population and later adopters.

According to Moore (1999), the reason for the occurrence of the chasm between early adopters and early majority population is their strongly differing reasons to adopt. Since early majority population are pragmatics, they also require aspects of adopting to be favourable. In addition, they require having a high certainty that each of these aspects, such as financial profitability and low level of complexity, is indeed favourable.

By strictly applying the adopter categories of Rogers, we indeed find the chasm that is mentioned by Moore. The occurrence of this chasm in the model was also observed in the verification and validation chapter (see section 5. 6). The reasons for the occurrence of this chasm are approximately similar; they reside in the fact that early adopters and early majority population have very different reasons to adopt innovations. The failure to adapt the products to each of the adoption requirements of early majority population leads to the rejection of the innovation. Moore however does not mention the communication between early adopters and early majority population as a necessity to ensure adoption by early majority population. Convincing them about low adoption risks can also be done through product promotion by a company.

Reflection

The chasm between early adopters is widely recognised in the literature and in the marketing field. The main reasons for the occurrence of this chasm are the different reasons for adoption between households. The problem in the case of smart grid appliance is that their purchase does not lead to a strong increase of savings. In addition, the change in behaviour that their utilisation require is still high. As underlined by Rogers, a wide share of the population is only willing to spend more money on certain appliances if they lead to a strong amount of savings. In addition, this share of population only tolerates a minimal level of additional effort to utilise the product. As a result, we expect that smart grid

appliances will only enter a mass-market phase if they equal the price of traditional appliances and if their utilisation is extremely simple.

The implementation of policy measure on the scale of city districts to support adoption by early majority population and later adopter categories is difficult. This is because the challenge of reinventing the product is essentially technical and commercial. Therefore, it is in hands of the companies developing and selling smart grid appliances. By reinventing smart grid appliances, these appliances should be profiled and designed is such a way that they are interesting for that share of the population that is mainly interested in financial profitability and which accepts very little adoption efforts. Concretely, the product should be redesigned to underline the amount of savings that are made through the adoption of the appliance. In addition, the fact that the product is user-friendly must be underlined.

Any smart grid appliances project that is willing to increase adoption by early majority population and later adopters is expected to be strongly dependent on large smart grid appliance producers and large retailers. This is because these companies are the only ones that may reinvent smart grid appliances. Any efforts made during smart grid appliance projects to support adoption by early majority population and later adopters is not expected to be effective as long as smart grid appliance reinvention did not occur according to the adoption requirement of these populations.

8. 2. 5 The importance of reliable information for early majority population and later adopter categories

In experiment 6 (see section 6. 2. 6 and 6. 3) is found that the reinvention of smart grid appliances is not enough to allow a large-scale adoption. The extent to which information from early adopters is experienced as reliable by early majority population and later adopters appears to explain the adoption rate of smart grid appliances. Therefore, a direction for policy is suggested to make sure that the perception of information reliability increases.

Assumptions on which the direction for policy is based

The main assumption on which the direction for policy is based, is that early majority population and later adopters are risk avert. Hence, they require a high level of information certainty to be willing to consider information as reliable and base their decision-making upon that. As an example, we assume that early majority population and later adopters require hearing from several other households that they trust that adopting is indeed cost-effective in order to be willing to believe so.

Comparison with the literature

The scepticism of early majority populations and later adopter categories is widely addressed in the marketing literature, but also specifically in the case of smart grid appliances (Egbue & Long, 2012). A study made by Chou & Yutami (2014) underlines that later adopters mostly require to be convinced about a product's usefulness, ease of use and financial risks.

Reflection

Smart grid appliances represent an important investment for most households. Especially for households with limited incomes, purchasing appliances that finally do not appear to fulfil expectation is a large problem. Even if, as a result of product reinvention, smart grid appliances are made financially interesting and user-friendly, the adoption by early majority population and later adopter categories is not straightforward. The main challenge is to convince these populations that smart grid appliances are indeed financially interesting and user-friendly. One important marketing concept is that individuals are more easily convinced by their relatives and friends than by external organisations (e.g. companies). This concept is actually present in the model made in this project. Companies raise awareness among households about the availability of a product, but households are in the end convinced through interactions by other households. The concept of product ambassadors is not expected to be adapted to

convince early majority population and later adopter categories. As Rogers explains, these late adopter categories typically distrust innovators since the adoption conditions (degree of complexity and amount of savings) required by both groups are too far apart from each other. A better way is to make the amount of savings that early adopters make visible to other households. This can be done by supporting the creation of electricity consumption interfaces, with a clear indication of the amount of savings that are being made, which can easily be shown to other individuals. Examples are applications for tablets or monitors that can easily be installed in a visible place at home. It is also important that a large amount of early adopters has the opportunity to show the amount of savings made. The larger the amount of early adopters showing that an important amount of savings can be made, the more convinced early majority population and later adopters are expected to be. To promote user-friendliness of smart grid appliances, the role of smart grid appliance retailers should also be taken into account. Convincing early majority population and later adopter categories about user-friendliness is expected to be only successful if smart grid appliances become plug-and-play devices.

8. 2. 6 Conclusion

The goal of this research is to identify directions for policy that can allow a large share of smart grid appliance adoption on the scale of city-districts. The five directions for policy identified in this section allow a large share of smart grid appliance adoption, but not all of these directions for policy can be typically implemented on the scale of city-districts.

The two first directions for policy are easily implementable on the scale of city-districts, for example for supporting the creation of consumer groups and by nominating product ambassadors. The case is different for purchase subsidies, which are typically implemented on by national organisations. The introduction of purchase subsidies on the scale of city-districts is hardly possible from an institutional point of view. In the case of product reinvention, the initiative lies in the hand of smart grid appliance producers and retailers. As mentioned in this section, financial aspects and ease of use of smart grid appliances are critical for the adoption by early majority population and later adopter categories. Hence, if financial aspects and ease of use are not positive enough, large scale adoption of smart grid appliances may not take place. The fact that purchase subsidy and product reinvention is needed for large-scale adoption, and that their implementation on the scale of city-districts is hardly possible, results in a large dependency on national organisations. Large-scale adoption of smart grid appliances on the scale of city-districts is not assumed to be possible, unless these policies are implemented on national scale. The fifth direction for policy is implementable on the scale of a city district, but is not effective unless the first four directions for policy are implemented successfully.

8. 3 Usage of this model

In principle, this model could be reused for some specific city districts to find out which factors would block the diffusion of smart grid appliances. Based on this, the right directions for policy could be identified. However, a strong reflection about the outcomes of the model is in any case necessary. First, each of the model limitations mentioned in section 8. 1 should be considered. Secondly, as shown in section 4. 4, the specification of agent-based models is often a source of uncertainty. This is due to the difficulty to find exact data but also to the highly complex behaviour of households. As a result, any careless quantitative interpretation of model outcomes could lead to strongly failing directions for policy. Therefore, we highly recommend interpreting model outcomes primarily in a qualitative way. Any conclusions based on the model should be subject to a strong reflection and discussion with smart grid appliances adoption experts.

Two types of inputs are needed in order to use the model: specification of smart grid appliances and specification of households. The type of data needed for smart grid appliances can be found in Appendix C. In the case of households, the necessary input is the following: electricity consumption per month, amount of householders and adopter categories. Distinguishing the adopter categories is by far the most

challenging exercise. The most reliable method to distinguish adopter categories is to carry out an enquiry among households. Using questions that will enable finding out about households' financial income, sensibility to opinions of others households and attitudes towards new technologies in general will allow dividing them into adopter categories. Another solution is to search statistics about the age, education, income and occupation distribution within a city district, by comparing them with national averages and using group means as distinguished by Mahajan, et al. (1995, p. 47). Having performed this for the case of a Dutch city district, it is found that very little variations in the group leads to strong differences in the final adopter distribution. Therefore, this method cannot be considered as fully reliable.

Chapter 9 – Conclusions and future work

In this chapter, the main conclusions of this research project are provided and directions for future research are proposed. The conclusions are answers to the research questions and sub-questions mentioned in section 0.

9. 1 Conclusions

The goal of this research was to provide an answer to the following research question: *"Which directions for policy can stimulate the adoption of smart grid appliances to increase the capacity for demand response in city districts?"*

An answer was provided by dividing the main question into four sub-questions. An answer to each sub-question is provided in this section.

1. ***On which theories should a model of the adoption process of smart grid appliances in a city district be based?***

The main theory used in this work is the Diffusion of Innovations Theory proposed by Rogers (1962). The use of this theory has proved to be very useful since it introduces five adopter categories. Through this distinction, it helps to understand why the transition from the growth to the maturity product lifecycle phase of smart grid appliances is expected to be a highly challenging step. The use of the consumer decision-making steps of Engel, et al. (1995) has proved to be useful to separate different adoption criteria and to understand which of them had an influence on the adoption or rejection of smart grid appliances. Lastly, the use of neoclassical rationality, as defined by Simon (1969) and bounded rationality (Simon & Hawkins, 1949) helped to understand why smart grid appliances were not adopted by households, even if the financial aspect was favourable.

2. ***How should this model be conceptualised and specified?***

To model the adoption of smart grid appliances, each household was modelled as an agent. At each tick, the households went through the consumer decision-making steps of Engel, et al. (1995). Decisions by households were made by asking for information from households with whom they interacted at each step, searching their memory, looking at environment parameters and making a decision based on that. If the outcome of one of the decision steps happened to be negative, the household left the decision-making step and returned to its initial state. The environment was modelled by using the four product phases of Levitt (1965) and was used to set the current adoption complexity level. The entire model was implemented in Netlogo (Wilensky, 1999).

3. ***What are directions for policy that can increase the percentage of households owning smart grid appliances to the desired level on the scale of city-districts?***

In this work, five directions for policy to support the adoption of smart grid appliances were identified. The first two directions for policy underline the need for the creation of consumer groups (for example on the scale of streets) and product ambassadors. The goal is an effective transfer of adoption information between the share of the population that is enthusiastic about smart grid appliances and the share that is willing to make efforts for that purpose. These two directions for policy are however only expected to allow the adoption of smart grid appliances by a limited share of the population (innovators and early adopters). The third direction for policy is the application of a purchase subsidy, in order to decrease the purchase costs of smart grid appliances and therefore increase the financial profitability of adopting. Because the amount of savings that can be made in comparison to consumer's expectation is low, the subsidy will have to cover the gap between the costs of smart grid and traditional appliances. In case the price of smart gird appliances is higher, early majority population and later adopter categories are not expected to adopt. The fourth direction for policy is the reinvention of the concept of smart grid

appliances. By reinvention is meant a redesign of smart grid appliances to underline the financial profitability of adopting and the easiness of use. These two elements are considered to be crucial to allow the adoption of smart grid appliances by early majority population and later adopter categories. The fifth direction for policy is the support for methods that allow households having already adopted (mainly early adopters) to show other households about the financial profitability and the easiness of use of smart grid appliances. Examples are display monitors that can be suspended on walls within houses and tablet applications.

The directions for policy differ in the extent to which they are implementable on the scale of city districts. The first two directions for policy (consumer groups and product ambassadors) can easily be implemented on this scale and are already put into practice in several smart grid projects (DNVGL, 2012; DGTV Amersfoort, 2013). The purchase subsidy and the reinvention of smart grid appliances however are not typically applicable on the scale of a city-district. The introduction of purchase subsidies or comparable financial regulations are typically determined by national policies. The introduction of financial measures on the scale of city-district is nearly impossible from an institutional point of view. The reinvention of smart grid appliances to underline financial profitability and ease of use lies in hands of smart grid appliance producers and retailers. This challenge is essentially technical and commercial. Financial profitability and ease of use are however obligatory in order to allow early majority population and later adopters. Hence, if there is no financial profitability and ease of use, no large-scale adoption of smart grid appliances can take place. Therefore projects highly depend on applied policies on national scale and on actions performed by national scale organisations. The last direction for policy may be applicable on the scale of city-districts but is only effective if the previous directions for policy have been successful.

4. ***What lessons can be learned about the benefit of the usage of agent-based simulation and scenario discovery for adoption of innovation cases?***

The usage of scenario discovery was found to be useful in the modelling of adoption of innovations cases for two main reasons. The first is the fact that scenario discovery sets the focus of modelling on the incorporation of uncertainties. This is especially useful since the behaviour of each individual household is highly uncertain, but still central in determining the adoption curve. In addition, scenario discovery allows a very effective distinction of directions for policy to increase smart grid appliance adoption. Instead of only testing traditional directions for policy, the combined use of EMA and PRIM allows to find out what variables in the model the policy should target in order to become effective.

9. 2 Directions for future research

Based on the work made in this project, we identify the following points that could be interesting for further research:

- Inclusion of different brands of the same smart grid appliance, which is believed to have a significant impact on the adoption curve,
- Inclusion of the smart grid appliance usage by households, next to its adoption, to study the demand response capacity of a city district at different points in time,
- Modelling of the diffusion of Smart Home Management Systems, which is believed to offer more financial and social benefits for households,
- Test the impact of different forms of networks on the adoption curve of smart grid appliances,
- Test the impact of a various distribution of households in adopter categories on the adoption curve of smart grid appliances and the effectiveness of policies,
- From a methodological point of view, model the adoption of smart grid appliances with a system dynamics model and compare model outcomes with the agent-based model.

Chapter 10 – Reflection

To conclude this report, a reflection is provided to provide impressions about the project realised. The goal of this chapter is to learn from and communicate about aspects of the projects, whether about the content or the process, which could be improved or done more efficiently. The added value is therefore to avoid the repetition of errors in future projects. In this chapter, a reflection is provided about the model created, the methodology used and the process that I went through.

Reflection on the model

Looking back at the model that I created in this work, I am a bit disappointed by one aspect of the model outcomes. While building the model, I expected that the model outcomes would be more essentially the result of an emergent behaviour of agents than a direct consequence of the theories and facts introduced in the model. The extent to which the directions for policy identified in this work rely on emergent behaviours of agents is low. Since agent-based models offer wide possibilities to discover emergent behaviours out of the states and interactions of agents, it seems that there is a strong added value of using agent-based models that I didn't fully take advantage of.

Even if the extent to which model outcomes rely on emergent behaviours of agents is low, this does not mean that they are untrue. In my opinion, the directions for policy identified reflect the current challenge of trying to increase network flexibility by changing the consumption behaviour of households well. While designing policies to encourage households to adapt their electricity consumption behaviour, whether by purchasing smart grid appliances or by having a stronger consumption awareness, one must not forget that a strong share of the population is not at all interested in making efforts to adapt electricity consumption. One main reason is that possibilities of making savings are very limited in comparison to other actions that may reduce monthly spending. In addition, the cognitive and physical/psychical efforts of using these appliances are perceived as high. From the perspective of the electricity sector, in the end, the central benefit of smart grid appliances is to increase network flexibility to respond to production fluctuations of renewable energies. This flexibility can also be found elsewhere: peak load production units, different network structure, specific contracts with large consumers, etc. By trying to find this flexibility at the side of small-scale consumers, one must accept the fact that consumer behaviour is complex and therefore that the extent to which households will provide this flexibility is highly uncertain.

In my opinion, the identification of directions for policy to increase adoption could be improved by including consumer's utilisation of smart grid appliances. Consumer utilisation of smart grid appliances was not included in this work since it would imply the utilisation of an entire set of theories and would strongly increase the work beyond a level that can be handled within a master thesis. The fact that households either use smart grid appliances in their 'smart function' or not is, I believe, an essential part of the communication about adoption between households. As a result, it can strongly influence the adoption of smart grid appliances in the model and effect the identified policies.

From a theoretical point of view, I think that the inclusion of the price of smart grid appliances and the electricity price within the model as endogenous factors is interesting. It would be interesting to include the feedback between the price of smart grid appliances and electricity price on one side and the adoption of smart grid appliances on the other. This integration of smart grid appliances and electricity price as endogenous was not needed in this work due to the focus on the level of city-districts and the very limited impact of adoption on this scale on these prices.

Reflection on the methodology

In this work, agent-based modelling was used to model the adoption of smart grid appliances. An outcome of the paper that has been written parallel to this report (see 'Heterogeneity, agent-based modelling and system dynamics - a study about the effects of including adopter heterogeneity in

diffusion of innovations models and the consequences on paradigm choice') is that system dynamics could also have been chosen to model the adoption of smart grid appliances. The utilisation of system dynamics would have led to similar model outcomes and hence to similar directions for policy. In this paper, we conclude by saying that in a large amount of case, both system dynamics and agent-based models can be used to model the adoption of innovations. The choice between both simulation techniques should essentially be based on modelling convenience and on the importance of low computational costs. If a large amount of various heterogeneities is expected to have a strong influence on the adoption curve, agent-based modelling should be preferred. System dynamics is more convenient in case a large amount of sensitivity tests will be performed and the project duration is short.

In my opinion it is however difficult, I, to find out to what extent various forms of heterogeneities will affect the adoption curve before having built the simulation model. Therefore, the best solutions seems to first build an agent-based model in order to easily assess the impact of heterogeneity. In case the impact of heterogeneity is low and not relevant considering the modelling goals, a system dynamics model may be built instead. Building in total two simulation models for the same purpose might seem a waste of time, but considering the fact that computational costs are sometimes ten times higher with agent-based models, a consideration might still be beneficial.

I was surprised by the extent to which scenario discovery allows to cope with one of the difficulties of modelling human behaviour with agent-based models. When building models that simulate human behaviour, the lack of data describing human behaviour is problematic. In addition, even if data is found, in my opinion the extent to which this data is reliable is often low. Instead of ignoring data uncertainty or only recognising it, scenario discovery helps to integrate data uncertainty and explore the effects on model outcomes. Further study about the benefits of combining agent-based models of human behaviour and the scenario discovery method is I believe valuable.

Reflection on the process

Surprisingly in my opinion, the process of writing my master thesis was rather fluent, although some project steps were more challenging than others. This was for example the case with scoping the project. From the beginning, it was clear that the model would be about smart grids and the behaviour of households. Whether the model would be about the purchase of smart grid appliances, their utilisation, or would have a focus on a particular city-district or not was only determined after a few weeks of reflection. Numerous discussions with my supervisors and employees of DNV GL resulted in defining a scope that was adapted for a master thesis work. Another step that I found challenging was the verification and validation of the model. Although the 'evaludation' method of Augusiak, et al (2014) allowed a profound review of the model created, I had the feeling that trying to validate a representation of behaviours that are as complex as those of humans would in any case say little about the actual performance of my model. The systematic identification of uncertainties and the use of scenario discovery however helped a lot in taking the difficulty and limitations of modelling human behaviour into account.

Overall, I am pleased with the amount of new theories, concepts and methods that I learned, such as the Diffusion of Innovations Theory. , the concept of heterogeneity in simulation models and working with Python code. I would however have liked to learn more about working with Python. Due to the limited time available to execute my master thesis, I did not succeed in learning more than what was necessary for the execution of EMA experiments and PRIM analyses.

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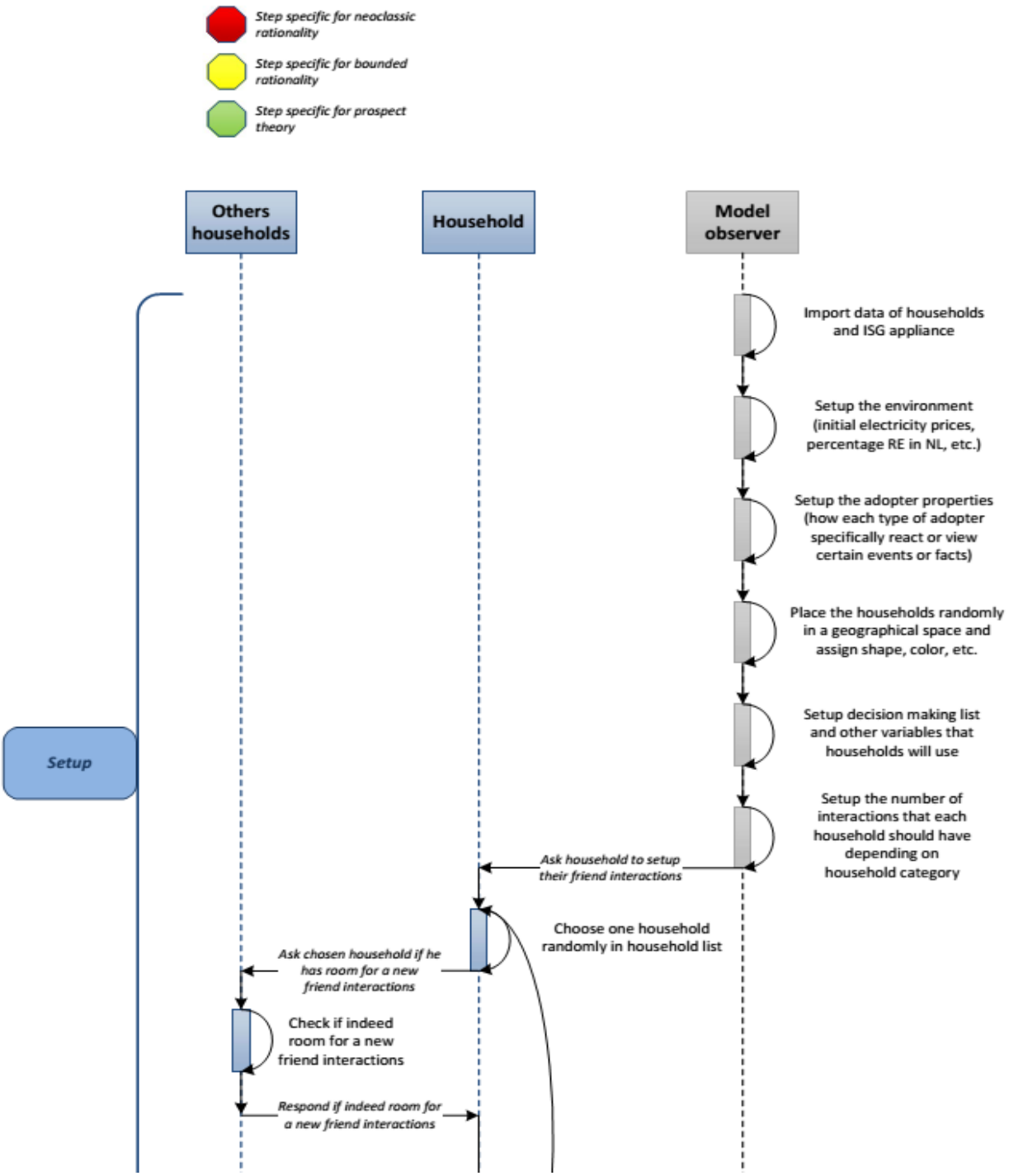
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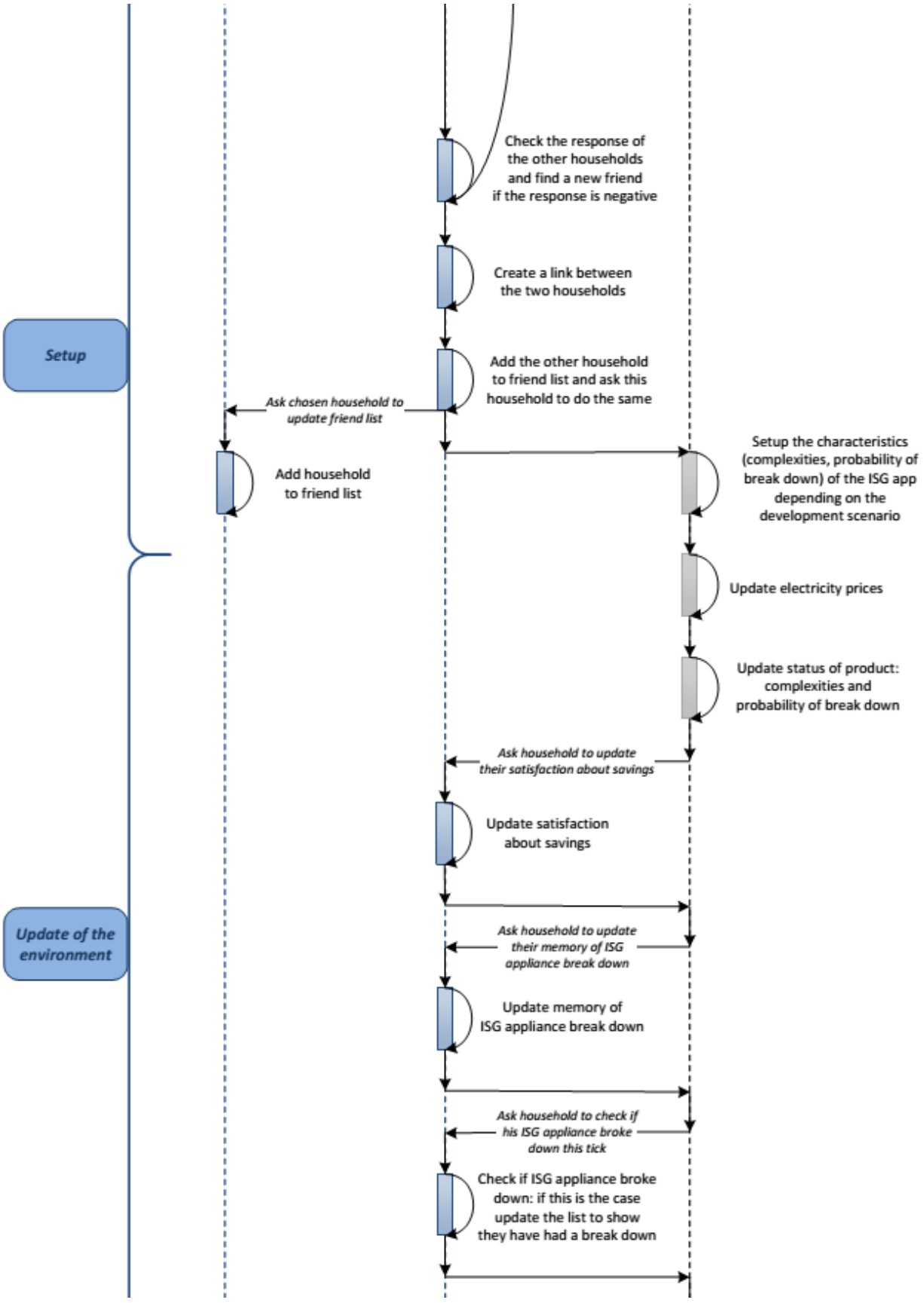
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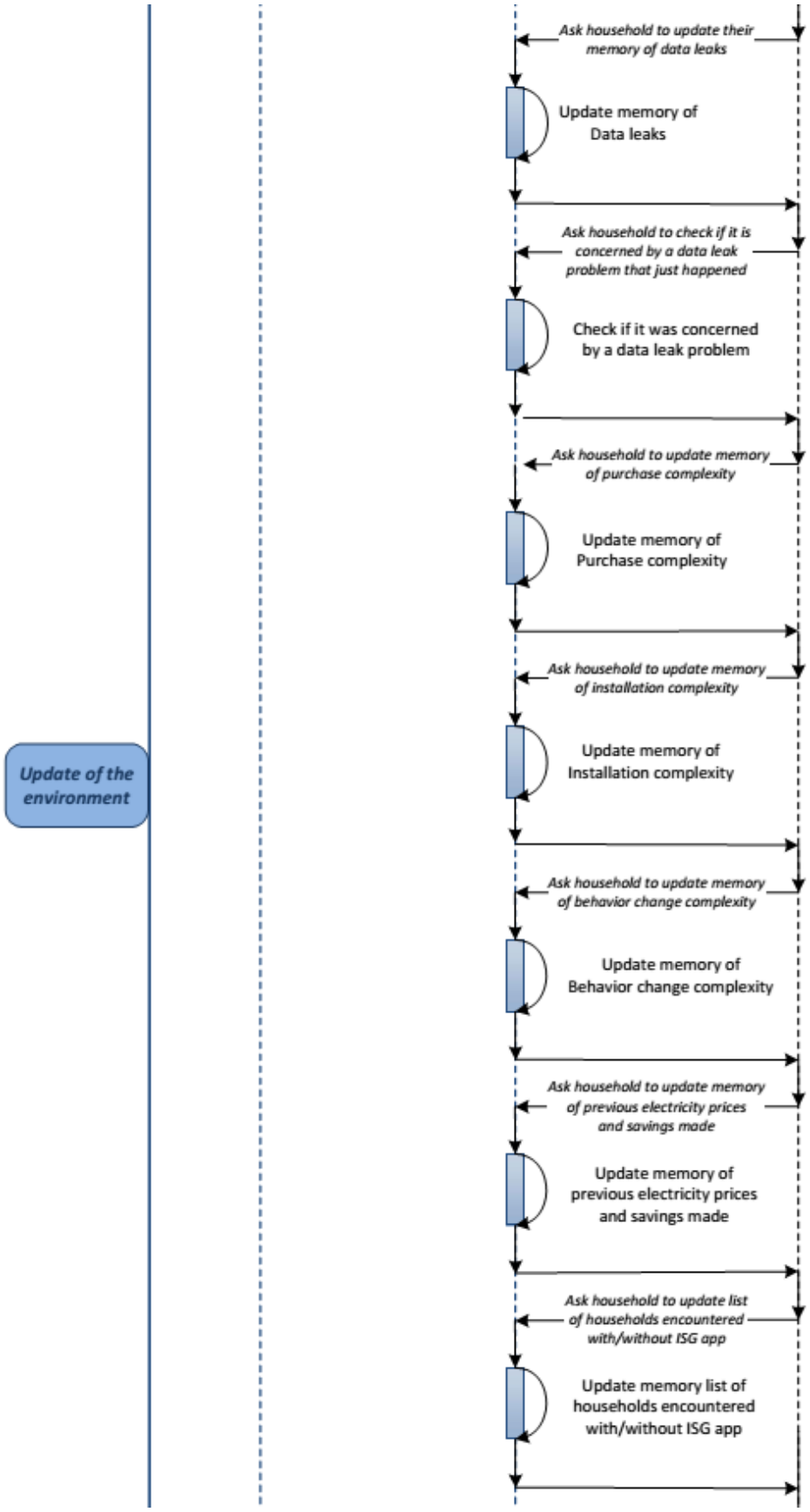
Appendix

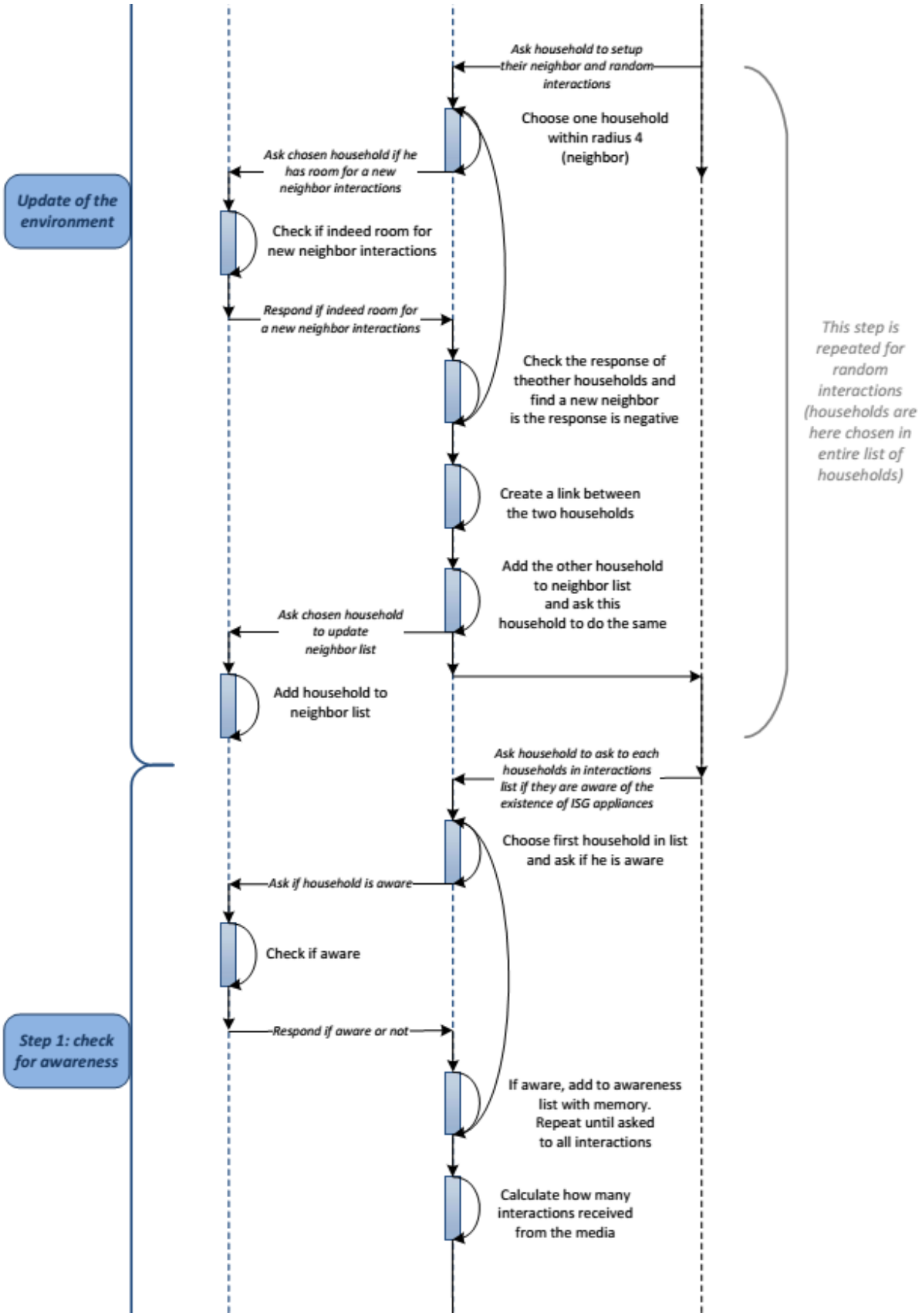
Appendix A Activity diagram

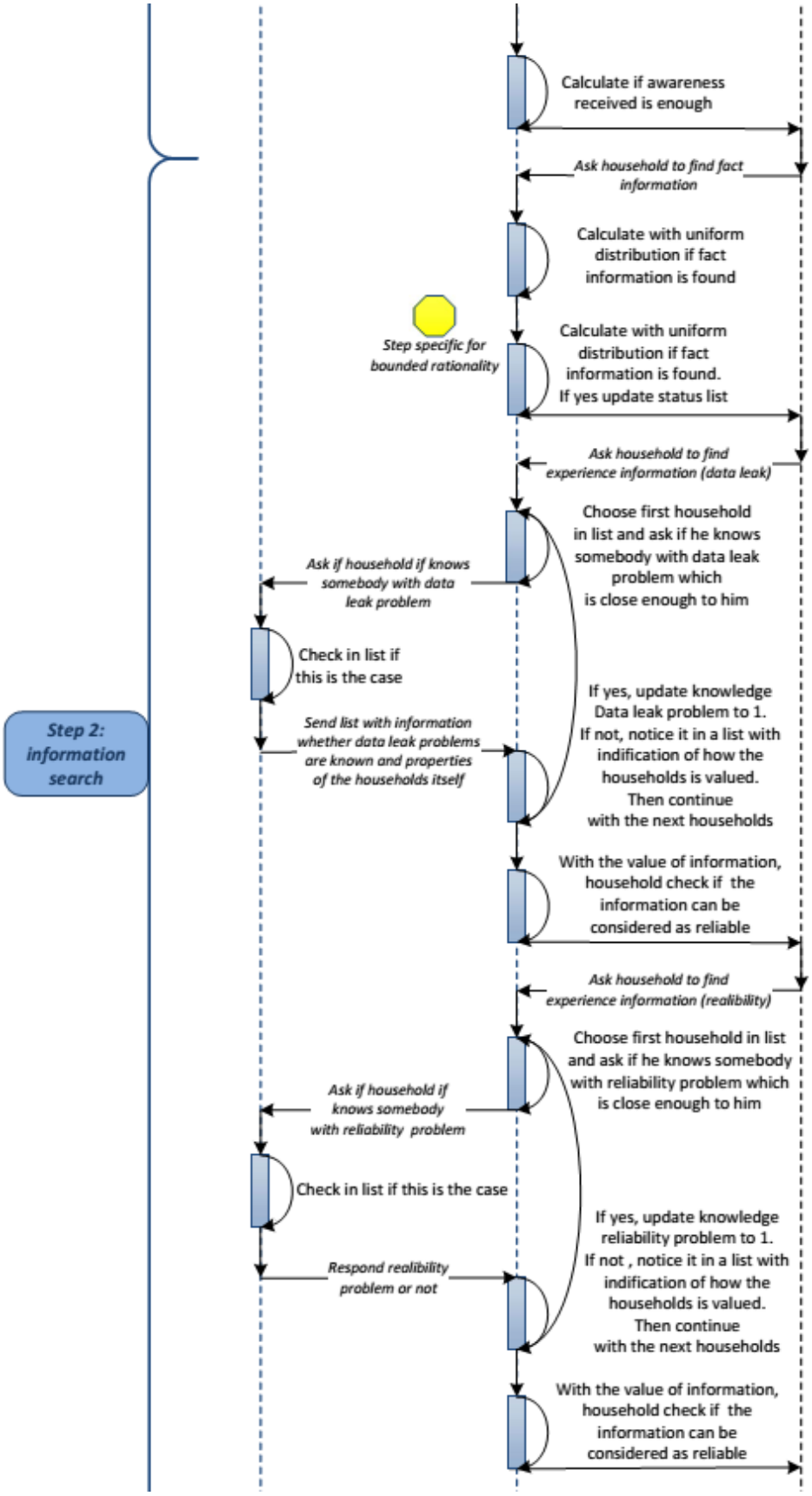
This activity diagram discribes the steps taken by one household. The interaction with others households in the same city district is also shown. In the colum on the right, the actions taken by the observer in the model are presented.

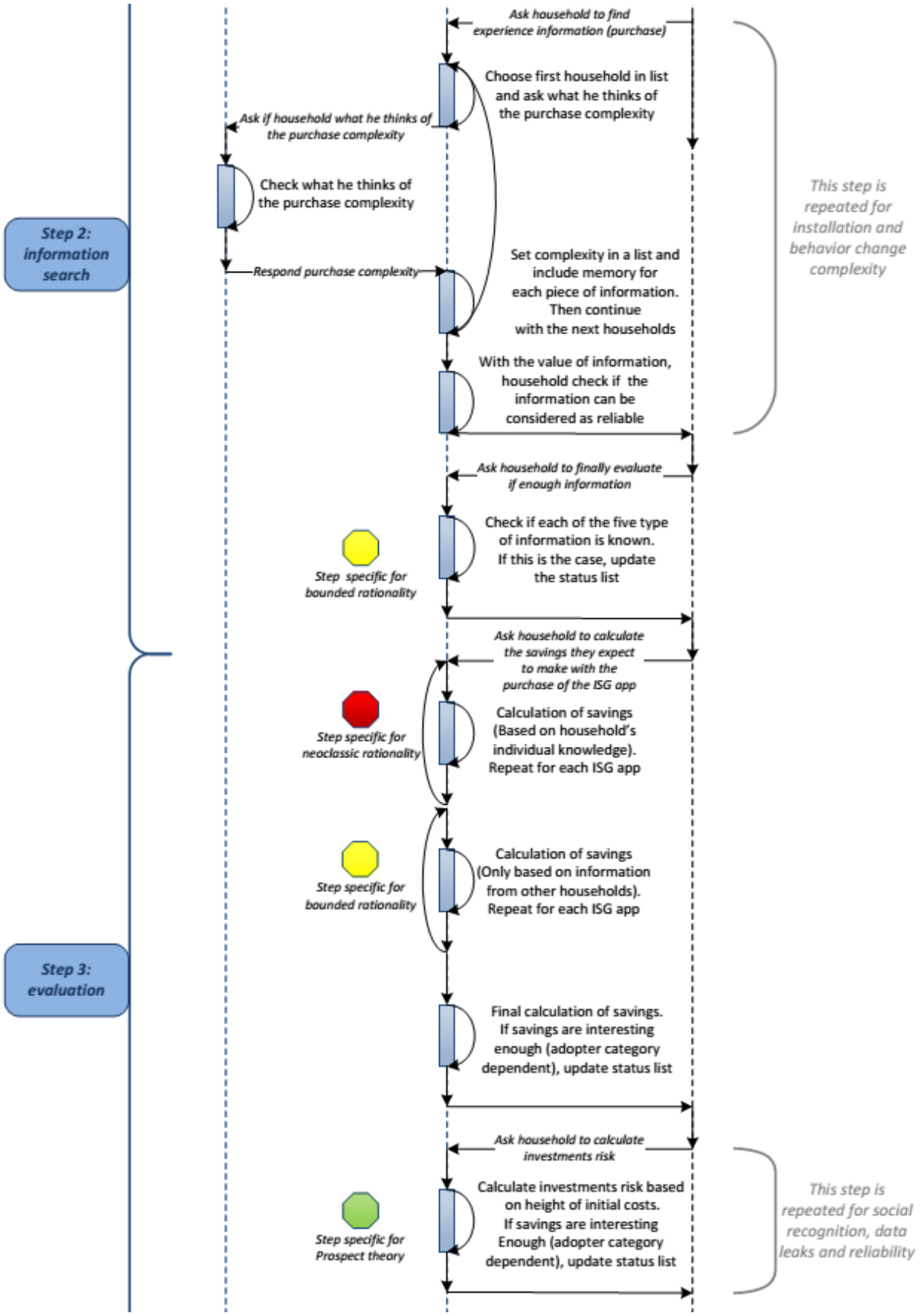


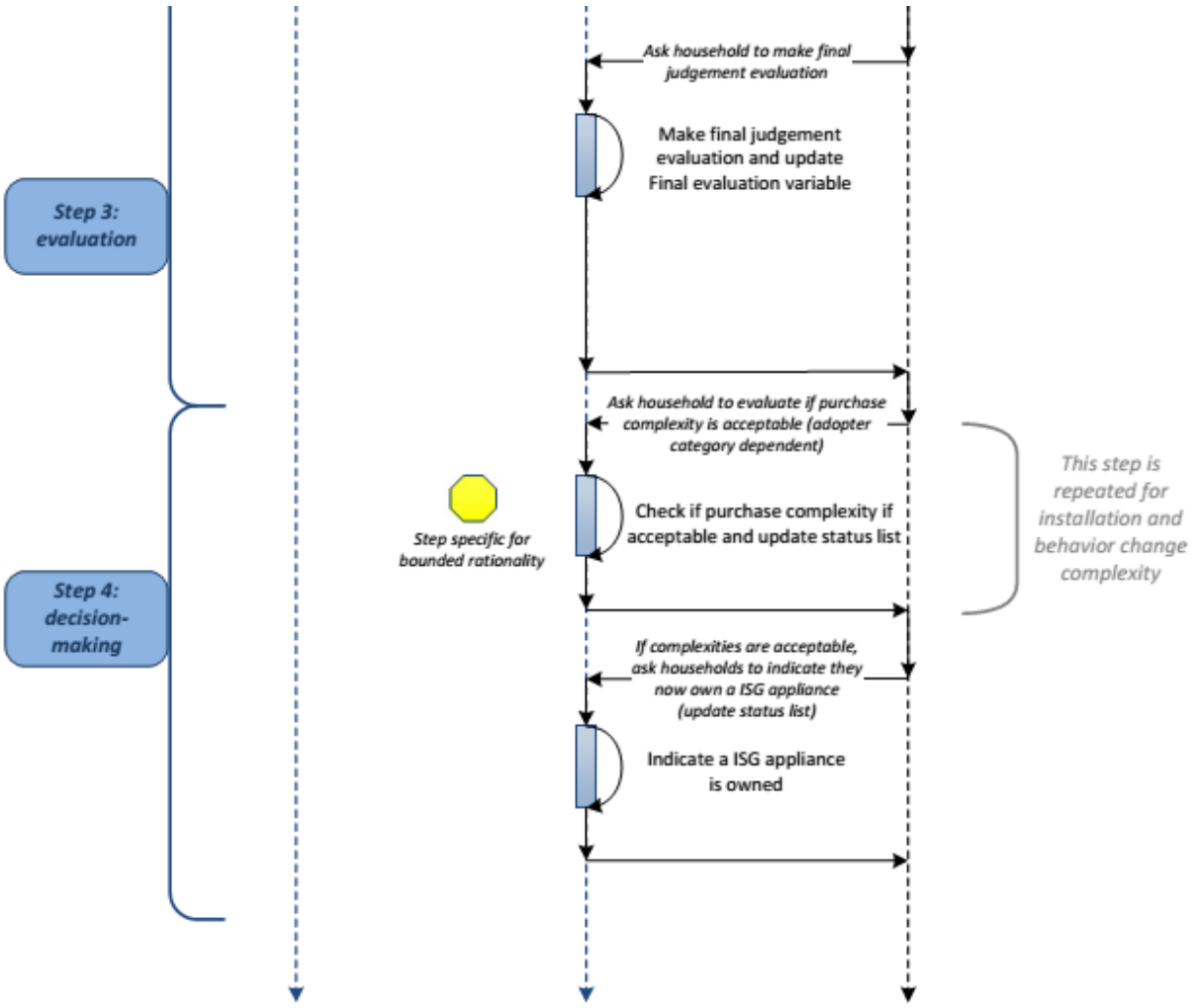

Setup
Update of the environment
Check the response of the other households and find a new friend if the response is negative
Create a link between the two households
Add the other household to friend list and ask this household to do the same
Ask chosen household to update friend list
Add household to friend list
Setup the characteristics (complexities, probability of break down) of the ISG app depending on the development scenario
Update electricity prices
Update status of product: complexities and probability of break down
Ask household to update their satisfaction about savings
Update satisfaction about savings
Ask household to update their memory of ISG appliance break down
Update memory of ISG appliance break down
Ask household to check if his ISG appliance broke down this tick
Check if ISG appliance broke down: if this is the case update the list to show they have had a break down


Update of the environment
Ask household to update their memory of data leaks
Update memory of Data leaks
Ask household to check if it is concerned by a data leak problem that just happened
Check if it was concerned by a data leak problem
Ask household to update memory of purchase complexity
Update memory of Purchase complexity
Ask household to update memory of installation complexity
Update memory of Installation complexity
Ask household to update memory of behavior change complexity
Update memory of Behavior change complexity
Ask household to update memory of previous electricity prices and savings made
Update memory of previous electricity prices and savings made
Ask household to update list of households encountered with/without ISG app
Update memory list of households encountered with/without ISG app


Update of the environment
Ask household to setup their neighbor and random interactions
Choose one household within radius 4 (neighbor)
Ask chosen household if he has room for a new neighbor interactions
Check if indeed room for new neighbor interactions
Respond if indeed room for a new neighbor interactions
Check the response of theother households and find a new neighbor is the response is negative
Create a link between the two households
Add the other household to neighbor list and ask this household to do the same
Ask chosen household to update neighbor list
Add household to neighbor list
This step is repeated for random interactions (households are here chosen in entire list of households)
Step 1: check for awareness
Ask household to ask to each households in interactions list if they are aware of the existence of ISG appliances
Choose first household in list and ask if he is aware
Ask if household is aware
Check if aware
Respond if aware or not
If aware, add to awareness list with memory. Repeat until asked to all interactions
Calculate how many interactions received from the media


Step 2: information search
Calculate if awareness received is enough
Ask household to find fact information
Calculate with uniform distribution if fact information is found
Step specific for bounded rationality
Calculate with uniform distribution if fact information is found. If yes update status list
Ask household to find experience information (data leak)
Choose first household in list and ask if he knows somebody with data leak problem which is close enough to him
Ask if household if knows somebody with data leak problem
Check in list if this is the case
Send list with information whether data leak problems are known and properties of the households itself
If yes, update knowledge Data leak problem to 1. If not, notice it in a list with indification of how the households is valued. Then continue with the next households
With the value of information, household check if the information can be considered as reliable
Ask household to find experience information (realibility)
Choose first household in list and ask if he knows somebody with reliability problem which is close enough to him
Ask if household if knows somebody with reliability problem
Check in list if this is the case
Respond realibility problem or not
If yes, update knowledge reliability problem to 1. If not , notice it in a list with indification of how the households is valued. Then continue with the next households
With the value of information, household check if the information can be considered as reliable


Step 2: information search
Step 3: evaluation
Ask household to find experience information (purchase)
Choose first household in list and ask what he thinks of the purchase complexity
Ask if household what he thinks of the purchase complexity
Check what he thinks of the purchase complexity
Respond purchase complexity
Set complexity in a list and include memory for each piece of information. Then continue with the next households
With the value of information, household check if the information can be considered as reliable
This step is repeated for installation and behavior change complexity
Ask household to finally evaluate if enough information
Check if each of the five type of information is known. If this is the case, update the status list
Step specific for bounded rationality
Ask household to calculate the savings they expect to make with the purchase of the ISG app
Calculation of savings (Based on household's individual knowledge). Repeat for each ISG app
Step specific for neoclassic rationality
Calculation of savings (Only based on information from other households). Repeat for each ISG app
Step specific for bounded rationality
Final calculation of savings. If savings are interesting enough (adopter category dependent), update status list
Ask household to calculate investments risk
Calculate investments risk based on height of initial costs. If savings are interesting Enough (adopter category dependent), update status list
Step specific for Prospect theory
This step is repeated for social recognition, data leaks and reliability


Step 3: evaluation
Step 4: decision-making
Ask household to make final judgement evaluation
Make final judgement evaluation and update Final evaluation variable
Ask household to evaluate if purchase complexity is acceptable (adopter category dependent)
Step specific for bounded rationality
Check if purchase complexity if acceptable and update status list
This step is repeated for installation and behavior change complexity
If complexities are acceptable, ask households to indicate they now own a ISG appliance (update status list)
Indicate a ISG appliance is owned

Appendix B Overview of the decision-making steps by households

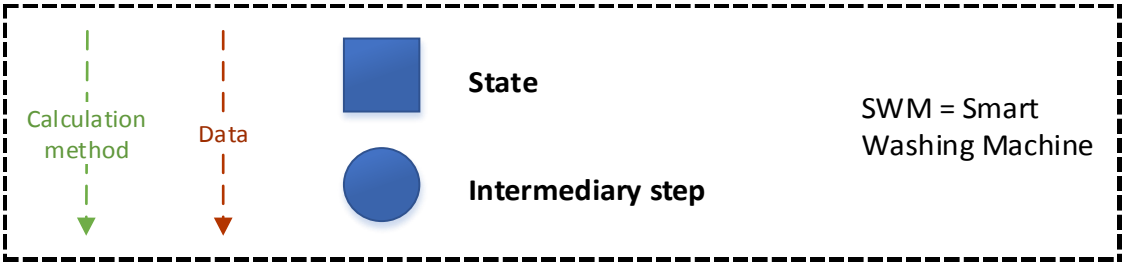


Figure 34: Legend of the five decision-making step decision trees

Step 1: Problem recognition step

The decision tree starts with performing interactions. In this step, households decide how many and which type of household to interact with according to adopter specific preferences. Each household then answers the question whether the household already has a smart washing machine or not. In case it has, the household goes to the post purchase process behaviour (see step 5). In case it hasn't, the household controls whether he is ready to go through a new decision-making process. This is done by checking how much time has passed by since the last decision-making process done and whether this duration is found long enough to accept considering the adoption once again. In case the household decides not to go through a new decision-making process, they go to the post purchase process behaviour. Otherwise, they perform a check to see how much of the households with whom interacted are aware of the existence smart washing machines. This is done by using equation 2. If the number of households owning a smart washing machine multiplied by the valuation of each individual household by the household trying to adopt exceeds 1, the household becomes aware and will proceed with the information search step. If the value is lower than 1, the household remains unaware. The valuation of households by others is an interpretation of the Diffusion of Innovations Theory and is explained in more details in Appendix C. This valuation reflects the fact that certain adopters find information emitted by certain type of adopters more reliable than others. For example, as Rogers (1983) explains, "potential adopters look to early adopters for advice and information about the innovation". However, "an innovator may not be respected by other members of a social system".

Equation 2: Calculation of awareness received

$$AR_i = \frac{\sum_{t=-n}^{0} \sum_{q=1}^{j} VA_{q,i}}{n} + \frac{\sum_{t=-n}^{0} (m * VM)}{n}$$

t	Time
AR_i	Total awareness received by household i
j	Amount of households encountered at period t
$VA_{j,i}$	Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j).
m	Amount of media interaction received (depended on the adopter category of household i)
VM	Valuation of media interaction
n	Length of the memory of household i

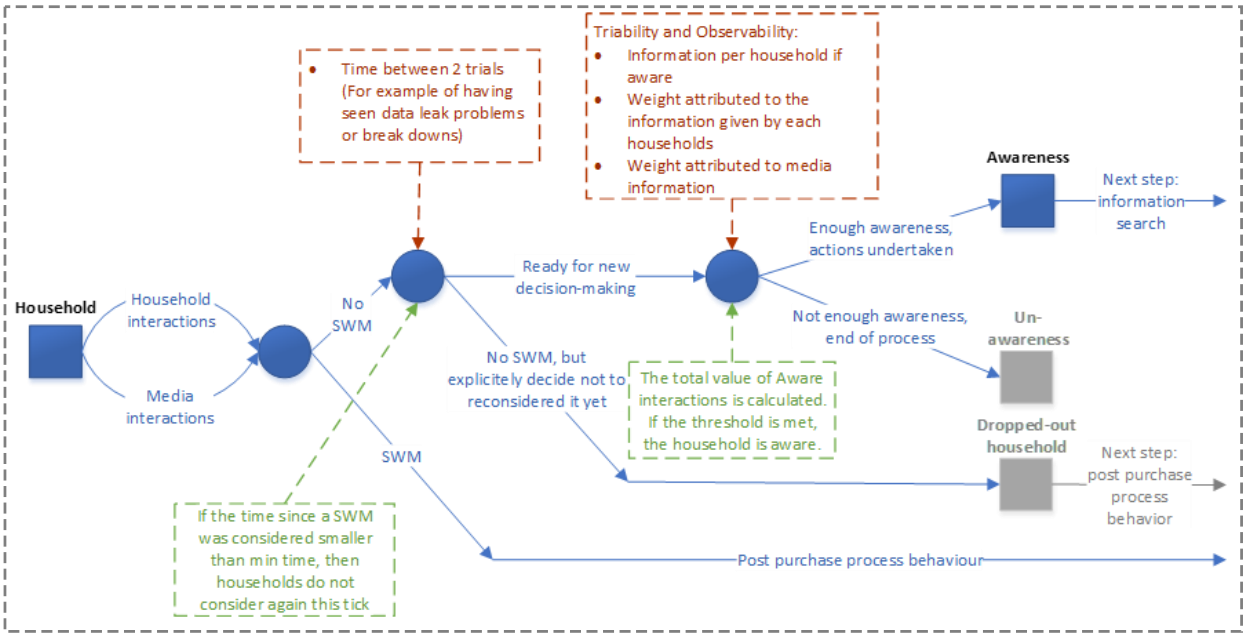


Figure 35: Decision tree of the problem recognition step

Step 2: Information search step

To find this information, households look in their list of household with whom interacted if households are found which possess relevant information.

For information related to adoption complexity, equation 3 is used. For each type of information, two cases are considered: either households have enough certainty about the information, or they have not. Equation 3 is used three times, each for one value of complexity (value 1, 2 or 3).

Equation 3: Calculation if sufficient knowledge about one type of information is received

$$IR_i = \frac{\sum_{t=-n}^{0} \sum_{q=1}^{j} VA_{q,i}}{n}$$

t	Time
IR_i	Total information received by household i
j	Amount of households encountered at period t
$VA_{j,i}$	Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j)
n	Length of the memory of household i

In case at least one of three cases (complexity of 1, 2 or 3), IR(i) is higher than 1, the household considers that it has enough information.

For information related to savings, Equation 3 is also used. No distinction between the values of the information transmitted (in this case the amount of savings made) is done. The outcome is either that households have enough information about the savings made by other households, or that they do not have enough.

In case of information about breakdown and data leak problems, three cases are considered: either they have knowledge about a breakdown or data leak problem, or they have no knowledge about it but have not enough certainty about it, or they have no knowledge and have enough certainty about it. For these

three cases, two equations are used. Equation 3 is used to find out if enough information is found about not having observed breakdown or data leak problems. Equation 4 is used to find out if information can be found about breakdown or data leak problems, whatever the valuation of the interaction.

Equation 4: Calculation of information about breakdown or data leak problems observed

$$PR_i = \frac{\sum_{t=-n}^{0} \sum_{q=1}^{j} P_q}{n}$$

t	Time
PR_i	Total information related to problems received by household i
j	Amount of households encountered at period t
P_j	Knowledge of break-down or data leak problems (either 0 or 1)
n	Length of the memory of household i

If PR(i) is equal of higher than one, households i has knowledge of a break-down or data leak problems. Information about breakdown or data leak problems is not assumed to be transferred continuously. This would otherwise mean that households having knowledge of these problems would continuously remain in the memory of agents and hence persistently constrain new households from adopting. In reality however, these types of information are progressively forgot by households. Hence, to reflect the progressive disappearance of this information, an extra number is added to the peace of information about either a breakdown or a data leak problem. When a new breakdown or data leak problems is observed by a household, this value is set to 1. When a household copies this information from the household that has knowledge of one of these problem, the value is increased by one. When this value exceeds a certain threshold, the peace of information about breakdown or data leak problems is not considered valid anymore and not taken into account.

When having gathered all types of information, households use a list showing the information they absolutely require and compare it to the list of information they actually have (and have enough certainty about their exactitude). If all information required is indeed available, households go on with the evaluation step. If not, they go to the post purchase process behaviour.

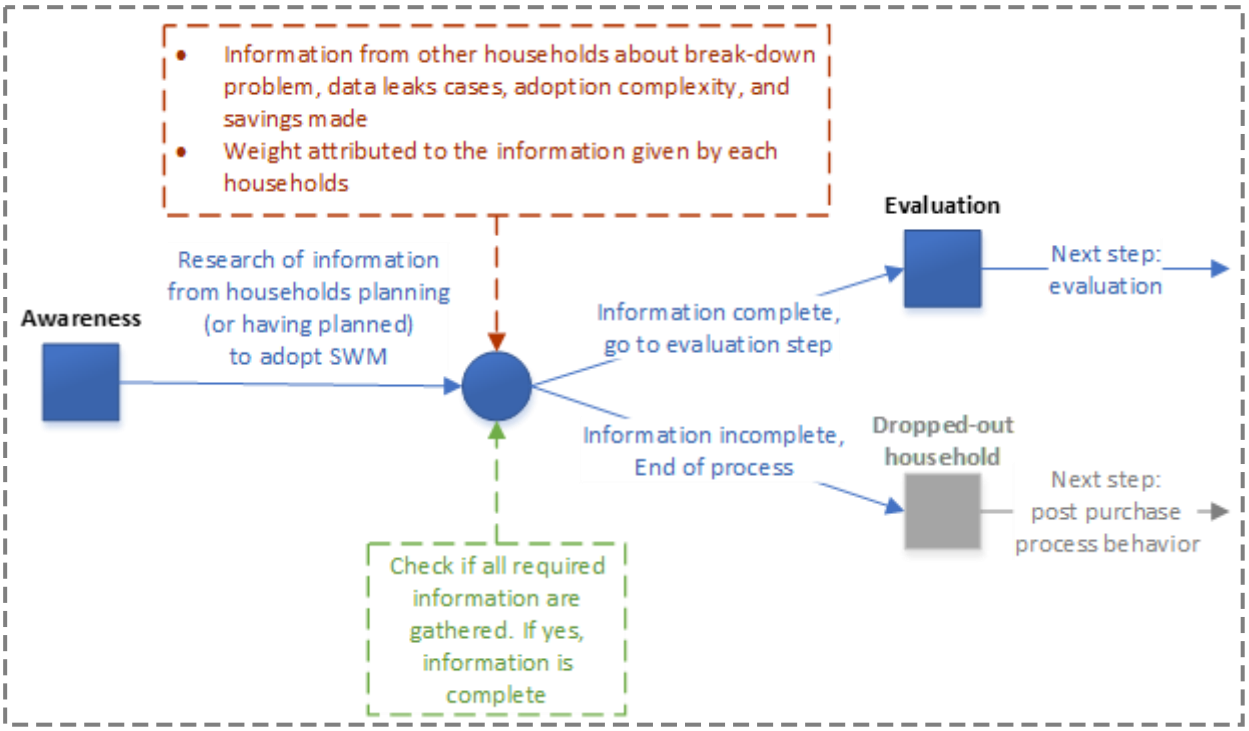


Figure 36: Decision tree of the information search step

Step 3: Evaluation step

The calculation of expected savings is not done in the same way for neoclassical or bounded rationality. In case neoclassical rationality is used, households are expected to calculate the expected savings of smart washing machines by themselves. To do that, equation 5 is used.

Equation 5: Calculation of expected savings in case of neoclassical rationality

$$Exp.Sav = C - \sum_{r=1}^{m} Q,KWh_r * \left(P_{peak} - P_{offpeak}\right) + \sum_{r=1}^{m} \frac{ICsmart_r - ICnotsmart_r}{Lifetime_r} - \sum_{s=1}^{n} Q,KWh_s * \left(P_{peak} - P_{offpeak}\right) + \sum_{s=1}^{n} \frac{ICsmart_s}{Lifetime_s}$$

C	Past average monthly electricity expenditure of one household over a period *x*
m	Smart washing machine that comes to replace an existing product (for example that replaces a traditional washing machine)
n	Smart washing machine that does not replace an existing product and are hence is a totally new product for an household
Q,KWh	Past average electricity consumption of the smart washing machine per month over a period *y*
Ppeak	Expected future average electricity price during peak period
Poffpeak	Expected future electricity price during off-peak period
ICsmart	Purchase cost of the smart washing machine
ICnotsmart	Initial cost of the appliance that the smart washing machine replaces (for example a traditional washing machine)
Lifetime	Average lifetime of the smart washing machine

Households then use a threshold (dependent on adopter category of the household and the individual characteristics of the household) to decide whether the expected savings are interesting enough. If this is the case, the evaluation of expected savings is given a one. Otherwise, it is given a 0.

In case neoclassical rationality is used, households are expected to base their expected savings on information provided by households with whom they interacted. To do that, equation 6 is used.

Equation 6: Calculation of expected savings in case of bounded rationality

$$IR_i = \frac{\sum_{t=-n}^{0} \left(\sum_{q=1}^{j} VA_{q,i} * S_q\right)}{j}$$

t	Time
IR_i	Total information received by household i
j	Amount of households encountered at period t
$VA_{j,\,i}$	Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j)
S_j	Current savings made by household j
n	Length of the memory of household i

Similarly to the calculation of expected savings in the case the neoclassical theory is used, households use a threshold to decide whether expected savings are interesting enough. If this is the case, the evaluation of expected savings is given a one. Otherwise, it is given a 0.

The expected social recognition is, according to the Diffusion of Innovations Theory mainly applicable to early adopters and late majority population. According to Rogers (1983), "the early adopter is respected by his or her peers, and is the embodiment of successful and discrete use of new ideas. And the early adopter knows that to continue to earn this esteem of colleagues and to maintain a central position in the communication structure of the system". To continue to be esteemed by his peers, early adopters try to be the first to grasp a potentially successful innovation to gain the attention of other households. Hence the lower the number of households that own smart washing machines, the more interesting it is for early adopter population to adopt them. In this model, the social value of smart washing machine adoption for early adopters is determined by the following rule. If the number of households owning a smart washing machine per month is higher than '*m*', the early adopter does not experience any social value of adopting a smart washing machine. Hence, the expected social recognition value is set to 0. In the other cases, it is set to 1.

As regards late majority population, Rogers (1983) mentions that "they can be persuaded about the utility of new ideas, but the pressure of peers is necessary to motivate adoption". Hence, the higher the number of households that own smart washing machines, the higher is their motivation to adopt one. In this model, the social value of smart washing machine adoption for late majority population is determined by the following rule. If the number of households owning a smart washing machine per month is higher than '*n*', the late majority household finds social value of adopting a smart washing machine. Hence, the expected social recognition value is set to 1. In the other cases, it is set to 0.

The investment risk is used when households use prospect theory as rationality for their decision-making. In this model, the investment risk is determined by the height of the price difference between the smart washing machine and a the traditional appliance. Each category of households has a maximum price difference that they will accept. This maximum price difference is then increased or decreased

using the prospect theory value function. This function is presented in equation 7 and originates from Kahneman & Tversky (1979).

Equation 7: Calculation of risk acceptation based on the prospect theory

$$U(x) = \begin{cases} (x - v)^{1-\beta} & for\ x - v \geq 0 \\ -\gamma * (v - x)^{1-\beta}) & for\ x - v < 0 \end{cases}$$

x	Value of gain/losses
v	Reference point
β	Risk avert coefficient
γ	Loss aversion coefficient

The risk value is calculated by comparing the past evolution of the electricity bill paid by households each month. A progressive decrease of the electricity bill for example is equal to a positive value of gain/losses and hence a lower maximum price difference accepted (*U(x)*). On the contrary, a progressive increase of the electricity bill will lead to a higher maximum price difference accepted.

The evaluation of data leak and breakdown risk is done in the same way. If in the information search step, the household observed a data leak or breakdown case, the value of the variable is set to 0. The household also sets a delay before a new decision-making process can be done equal to the one specified for the adopter category to which it belongs. If enough information has been found about each of these two types of risk in the information search phase by using equation 3 and not data leak or breakdown cases were observed the value of the data leak or breakdown risk variable is set to 1.

The final evaluation of the smart washing machine is done differently in case neoclassical or bounded rationality is used. For neoclassical rationality, households are not assumed to make decision under uncertainty. Hence, they must be certain that the smart washing machine is evaluated positively on each variable. Therefore, the value of each variable must be equal to 1. In case of bounded rationality, households are willing to accept a limited amount of variable evaluated negatively. This amount is dependent on the adopter category of the household.

The overall evaluation of the smart washing machine, the household proceeds to the decision step. Otherwise, it goes to the post purchase process behaviour.

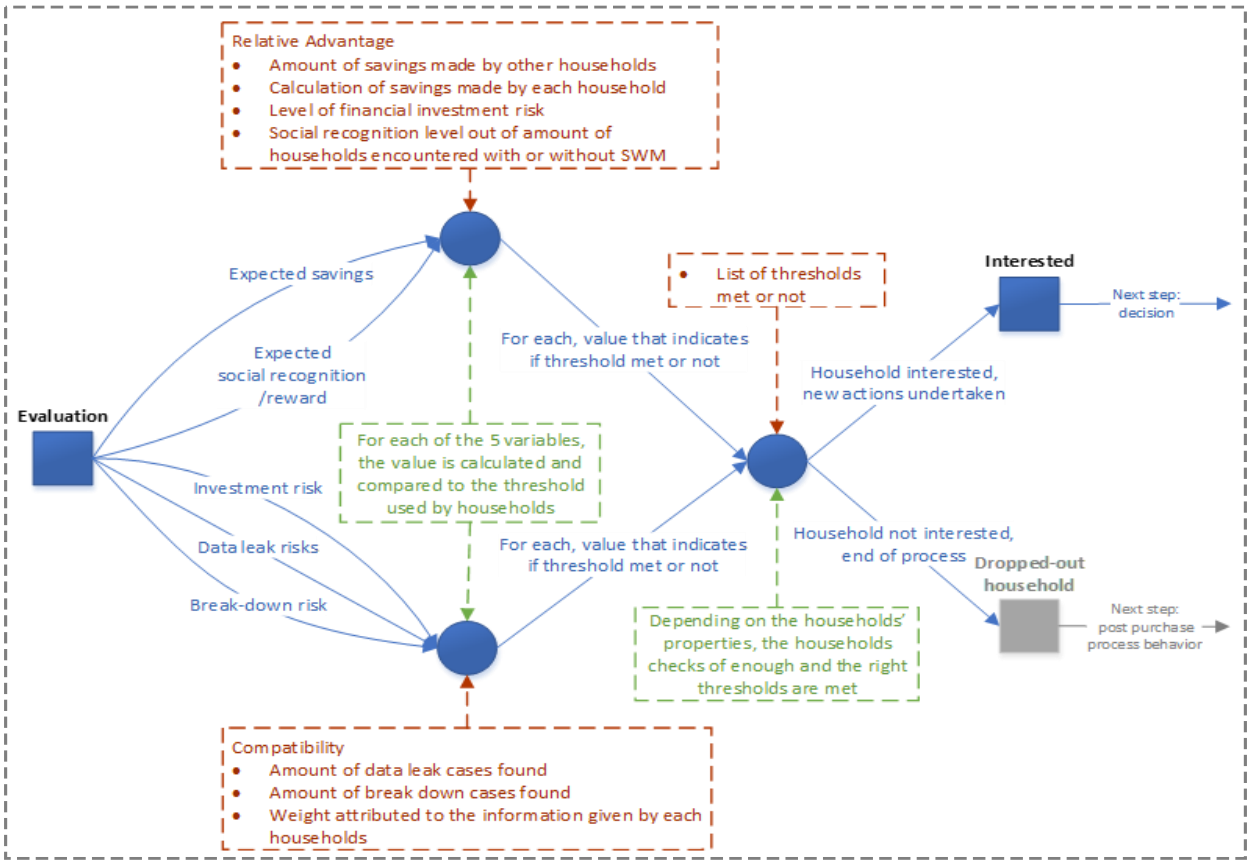


Figure 37: Decision tree of the evaluation step

Step 4: Decision-making step

To calculate adoption complexity, households use the information gathered from other households in the information search step. For each complexity and for each value of complexity, equation 3 is used. Hence to calculate adoption complexity, households individually calculate the amount of households with whom interacted saying that the complexity is equal to 3, those who say it is equal to 2 and then to 1. By using the valuation of households depending on their adopter category, households calculate which of these complexity values is the most reliable to them. If for this complexity value, the sum of the valuation of the households providing this information is equal or higher than 1, the household picks up this complexity value. The complexity value chosen is than compared to the maximum complexity level accepted by the household, and if it is lower, the level of complexity is tolerated. After having calculated the level of complexity, household controls whether each type of complexity is acceptable. If this is the case, they adopt the innovation.

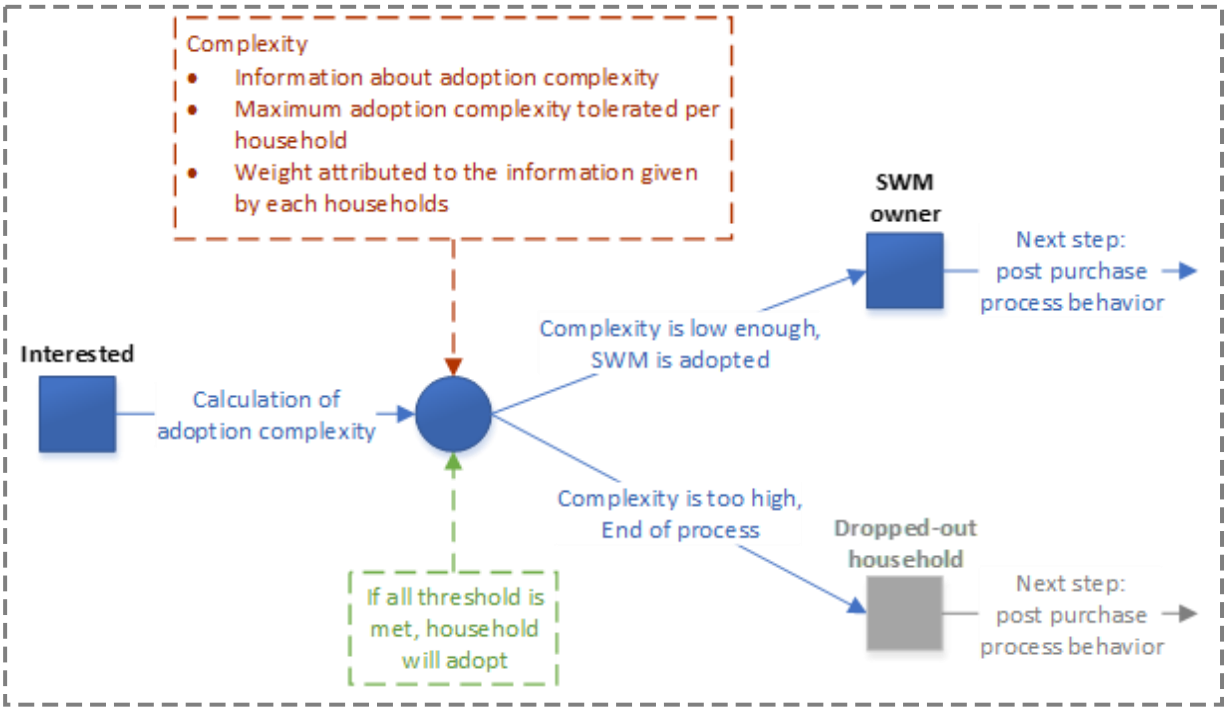


Figure 38: Decision tree of the decision-making step

Step 5: Post adoption behaviour step

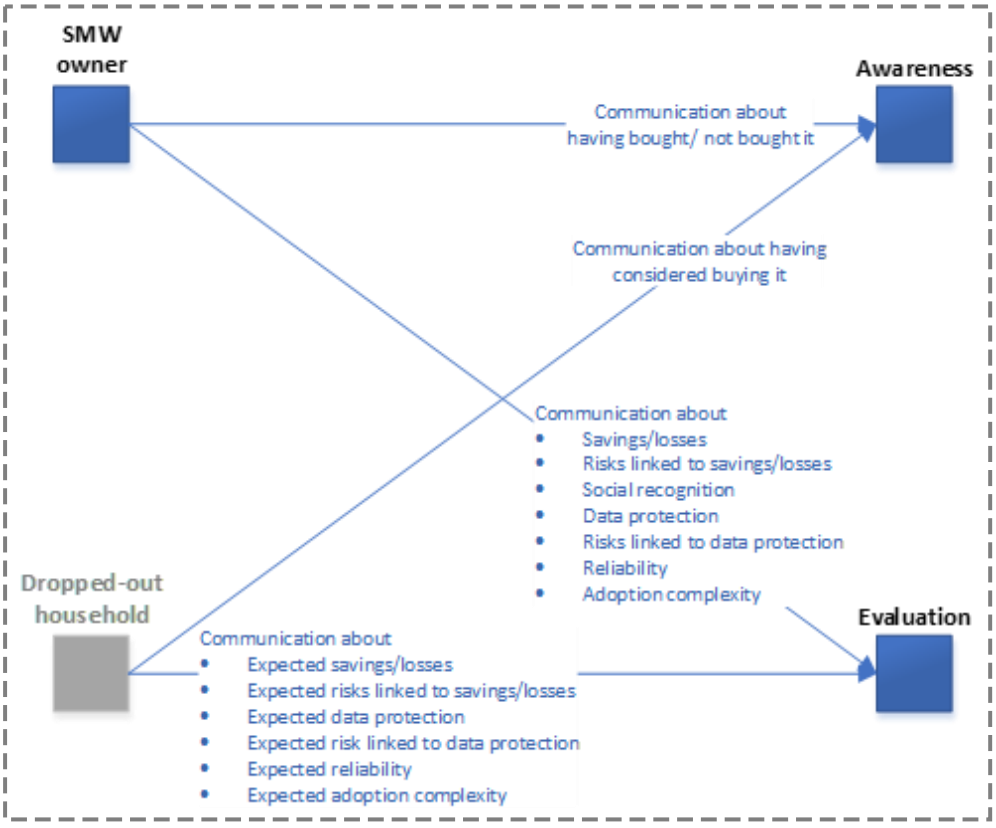


Figure 39: Decision tree of the Post adoption behaviour step

Appendix C Model data

Smart washing machines

Assumptions

- The electricity consumption of smart washing machines is the same whether smart or not
- The electricity consumed when appliances are on standby mode are not taken into account
- Except a few innovators that already have a smart washing machine set, we consider that all the other households do not have any smart washing machine yet of any kind.
- We also assume that at any time in the model, the appliances that will possibly be replaced by smart washing machines are at the end of their lifetime. Hence, there is no possibility that households refuse to purchase smart washing machines only because they have purchased a new traditional smart washing machine recently.
- We assume an average price of each type of traditional appliances and an average price of each type of smart appliances.
- When a household has purchased a smart washing machine, he will only replace this appliance by another smart washing machine after the lifetime of the first smart washing machine has finished.
- We assume no difference in the utilisation of appliances between adopter categories
- We assume the off-peak electricity tariff goes from 23.00 to 07.00 and the peak electricity tariff from 07.00 to 23.00.
- We assume that the average price of traditional appliances remain unchanged during the model run since these products are already well established on the market.
- We assume that households only have the possibility to start buying smart washing machines when smart meters are installed in their neighbourhood.
- We assume the electricity demand not to be significantly different in weekends or depending on seasons.

Data

Table 38: characteristics of smart washing machines

Specification			
Characteristics	**Specification**	**Unit**	**Source**
Initial price	900	[€]	
Development of price in the future (learning rate)	Learning rate: [.92-.98]	-	
Initial price of traditional appliance	600	[€]	
Lifetime of the appliance	14	[year]	(NAHB, 2007)
Frequency of utilisation per month (depending on size of household)	12.5	[#/month]	(Seebach, et al., 2009)
Duration of utilisation period	2	[hour]	(Seebach, et al., 2009)
Electricity consumption per hour	0.45	[KW]	(Seebach, et al., 2009)
Percentage of utilisation during peak period of traditional appliance	75.2	[%]	Adapted from (Stamminger, 2008)
Percentage of utilisation during off-peak period of traditional appliance	24.8	[%]	Adapted from (Stamminger, 2008)
Percentage of utilisation during peak period of smart appliance	20	[%]	Adapted from (Stamminger, 2008)
Percentage of utilisation during off-peak period of smart appliance	80	[%]	Adapted from (Stamminger, 2008)

Electricity prices

Table 39: data for electricity prices

Specification			
	Initial electricity	**Unit**	**Source**

	prices		
Peak tariff	0,235	[€/KWh]	(Gaslicht.com, 2013)
Off-peak tariff	0,215	[€/KWh]	(Gaslicht.com, 2013)

Electricity consumption of households

Table 40: data about electricity consumption of households

Specification		
Amount of householders per household	***Average consumption in [kWh] per year***	***[€] per month***
1	*2010*	*30*
2	*3360*	*57*
3	*4120*	*71*
4	*4580*	*80*
5	*5450*	*97*
Average per household	*5790*	*104*

Source: (NIBUD, 2014)

Product life cycle phase and complexities

Data

Table 41: data about complexities per product life cycle phase

Specification					
	Introduction	**Growth**	**Maturity**	**Decline**	**Unit**
Complexity of purchase	3	2	1	1	[1]
Complexity of installation	3	2	1	1	[1]
Change of behaviour requested	3	2	1	1	[1]
Development of the probability of failure of the smart washing machines	[2-4]	[0.5-1]	[0-0.5]	[0-0.5]	[%]

Adopter specific characteristics

Household interactions

Generalisations of Rogers

- "Earlier adopters have more social participation than later adopters" (Rogers, 1983, p. 258).
- "Earlier adopters are more highly interconnected in the social system than later adopters" (Rogers, 1983, p. 258).
- "Earlier adopters are more cosmopolite than later adopters" (so more connections with people outside their districts) (Rogers, 1983, p. 258).

Assumptions

- The usage of various rationalities is not assumed to have an impact on the amount of interactions that households have.

Data

Table 42: amount of household interactions of households per adopter category

Adopter category	**Number of random interactions**	**Number of friend interactions**	**Number of neighbour interactions**	**Unit**

Innovators	[1-3]	[1-3]	[3-5]	[Interaction/Month]
Early adopters	[1-3]	[1-3]	[3-5]	[Interaction/Month]
Early majority	[1-3]	[0-2]	[3-5]	[Interaction/Month]
Late majority	[0-2]	[0-2]	[1-3]	[Interaction/Month]
Laggards	[0-2]	[0-2]	[1-3]	[Interaction/Month]

Media interaction

Generalisations of Rogers

- "Earlier adopters have greater exposure to mass media communication channels than later adopters" (Rogers, 1983, p. 259)

Assumptions

- The usage of various rationalities is not assumed to have an impact on the amount of interactions that households have.

Data

Table 43: amount of media interactions of households per adopter category

Specification		
	Value *(in interactions per month)*	Unit
Innovators	[30-40]	[Interaction/Month]
Early adopters	[25-35]	[Interaction/Month]
Early majority	[20-30]	[Interaction/Month]
Later majority	[10-20]	[Interaction/Month]
Laggards	[5-15]	[Interaction/Month]

Threshold for enough awareness

Generalisations of Rogers

- "Earlier adopters seek information about innovations more actively than later adopters" (Rogers, 1983, p. 259).
- Innovators are "very eager to try new ideas" (Rogers, 1983, p. 249).
- Early Adopters "look to early adopters for advice and information about the innovation" (Rogers, 1983, p. 249).
- For the early Majority, "the pressure of peers is necessary to motivate adoption" (Rogers, 1983, p. 249).
- For the late Majority, "adoption may be (…) the answer to increasing network pressures" (Rogers, 1983, p. 249).

Assumptions

- We here do not assume that households start directly to search for information as soon as they hear something about smart washing machines for the first time. However, they start the process when the informational pressure to start the information search is high enough. Hence, they start the information search when a certain threshold is met. This threshold is different according to the type of adopter.

Data

Table 44: awareness threshold of households per adopter category

Specification		
	Value *(in interactions per month)*	Unit
Innovators	[4-6]	[Interaction/Month]
Early adopters	[6-8]	[Interaction/Month]
Early majority	[8-10]	[Interaction/Month]
Later majority	[10-12]	[Interaction/Month]

Laggards	[12-14]	[Interaction/Month]

Extent the list of information needs to be complete in order to start the evaluation

Generalisations of Rogers

- "Earlier adopters are more able to cope with uncertainty and risk than later adopter" (Rogers, 1983, p. 258)

Data

Table 45: required information needed by households

Specification					
	Critical info required by innovators	Critical info required by early adopters	Critical info required by early majority	Critical info required by late majority	Critical info required by laggards
Price	Yes	Yes	Yes	Yes	Yes
Lifetime of smart washing machine	Yes	Yes	Yes	Yes	Yes
Reliability		Yes	Yes	Yes	Yes
Knowledge about data leak event		Yes	Yes	Yes	Yes
Knowledge about last date failure of smart grid app					
Adoption complexity		Yes	Yes	Yes	Yes

Preferred sources of information about smart washing machines

Generalisations of Rogers

- "Communication patterns and friendships among a clique of innovators are common, even though the geographical distance between the innovators may be considerable" (Rogers, 1983, p. 248)
- "An innovator may not be respected by the other members of a social system" (Rogers, 1983, p. 248)
- "Earlier adopters have greater exposure to interpersonal communication channels than later adopters" (Rogers, 1983, p. 259)
- "Potential adopters look to early adopters for advice and information about the innovation" (Rogers, 1983, p. 259)
- "Because early adopters are not too far ahead of the average individual in innovativeness, they serve as a role model for many other members of a social system." (Rogers, 1983, p. 249)

Data

This table shows the degree to which each of the adopter segment values the information provided by others adopter segments. An innovator for example values information from another innovator with a weight of [0.3-0.5]. A laggard values information from an innovator with a weight of [0]. Hence, he does not take this information into account.

Table 46: preferred sources of information per adopter category

Specification						
	Innovators	Early adopters	Early majority	Late majority	Laggards	Unit
Innovators	[0.3-0.5]	[0]	[0]	[0]	[0]	[1]
Early adopters	[0.3-0.5]	[0.2-0.4]	[0]	[0]	[0]	[1]
Early majority	[0-0.2]	[0.4-0.6]	[0.1-0.3]	[0]	[0]	[1]
Late majority	[0-0.1]	[0.4-0.6]	[0.1-0.3]	[0.1-0.3]	[0.2-0.4]	[1]
Laggards	[0]	[0.4-0.6]	[0.1-0.3]	[0.1-0.3]	[0.1-0.3]	[1]

Evaluation about savings/losses

Assumptions

- Neoclassical rational households are expected to always choose the alternative that maximises their financial situation, even if the improvement is only very limited. The importance of costs is however very limited for innovators and early adopters (Rogers, 1983). Hence, they are considered to accept monthly losses.
- Rationally bounded households are expected to only accept the installation of smart washing machines if it significantly provides an improvement to their financial situation. In the case that the improvement is too low, they do not consider the effort to be worth it. Here also, the importance of costs is considered as very limited for innovators and early adopters (Rogers, 1983). Hence, they are considered to accept monthly losses.

Data

- Neoclassical rationality

Table 47: minimum savings required in case of neoclassical rationality per adopter category

Specification		
	Valuation of savings/losses if rational	Unit
Innovators	Min saving of [0]	[€/month]
Early adopters	Min saving of [0]	[€/month]
Early majority	Min saving of [0]	[€/month]
Late majority	Min saving of [0]	[€/month]
Laggards	Min saving of [0]	[€/month]

- Bounded rationality

Table 48: minimum savings required in case of bounded rationality per adopter category

Specification		
	Valuation of savings/losses if bounded rational	Unit
Innovators	-	[€/month]
Early adopters	-	[€/month]
Early majority	Min saving of [1,3]	[€/month]
Late majority	Min saving of [1,3]	[€/month]
Laggards	Min saving of [1,3]	[€/month]

Investment risk

Data

Table 49: maximum difference in price tolerated between smart and traditional appliance per adopter category

Specification		
	Max difference in price tolerated	Unit
Innovators	[20,60]	[%]
Early adopters	[15,35]	[%]
Early majority	[5,25]	[%]
Late majority	[0,20]	[%]

Laggards	[0,10]	[%]

Table 50: prospect theory parameters used

Specification		
	Parameters for prospect theory	Unit
Risk avert coefficient	[0.03,0.3]	[1]
Loss aversion coefficient	[1,5]	[1]

Compatibility related to protection of data

Generalisations of Rogers

- "Earlier adopters are less fatalistic than later adopters" (Rogers, 1983, p. 258)
- "Earlier adopters have greater knowledge of innovations than later adopters" (Rogers, 1983, p. 259).

Assumptions

- According to Rogers, innovators tend to have a high knowledge about innovators and their management. Hence, they feel more in control of the sharing of data about smart washing machines. As a result, we assume that the average number of month they need before having trust in these appliances again is lower than for other groups. The other categories are considered as equally affected by data leaks problems.

Data

Table 51: types of data leak events

Category of data leakage event	Type of data leakage event	Unit
1	- Scale of an individual household	[1]
2	- Scale of a city district	[1]
3	- Scale of a city and higher	[1]

Table 52: amount of month needed to recover trust per adopter category and type of data leak event

Specification				
	Month needed to recover trust for category 1	Month needed to recover trust for category 2	Month needed to recover trust for category 3	Unit
Innovators	[1-4]	[4-10]	[10-18]	[month]
Early adopters	[4-8]	[8-16]	[16-32]	[month]
Early majority	[4-8]	[8-16]	[16-32]	[month]
Late majority	[4-8]	[8-16]	[16-32]	[month]
Laggards	[4-8]	[8-16]	[16-32]	[month]

Valuation of reliability

Generalisations of Rogers

- "Earlier adopters have greater knowledge of innovations than later adopters" (Rogers, 1983, p. 259). Rogers considers that 3 of its adopter categories are pragmatics: early majority, late majority and laggards (Rogers, 1983). Hence, the acceptation of risks by households in these three categories is very low. Moore provides the following generalisations:
    - Pragmatics care about the "reliability of the service they are going to get" (Moore, 1999). Trust is hence an important element for them.

Assumptions

- Here we consider reliability as the duration for which households can prove that the smart grid app is reliable. We consider that through the monthly interactions, households are informed by other households about the duration since when these other households possess a smart

washing machine (and that the smart washing machine has not failed). If this duration is higher than the minimum duration of proof of no failure that they need, they consider the smart washing machine as being reliable. If not, they do not consider it as a proof of reliability, but neither as a proof of unreliability.

- If however a household gets from at least one interaction that the smart washing machine is not reliable, they will consider it as unreliable and stop the decision making process. It will take them a duration equal to the 'minimum duration of proof of no failure of a smart washing machine' before being able to see a smart washing machine as reliable.

Data

Table 53: minimum proof duration of no breakdown case per adopter category

Specification		
	Minimum duration of proof of no failure of a smart washing machine	Unit
Innovators	[0-2]	[month]
Early adopters	[2-6]	[month]
Early majority	[6-12]	[month]
Late majority	[6-12]	[month]
Laggards	[6-12]	[month]

Valuation of adoption complexity

Generalisations of Rogers

- "Earlier adopters have higher levels of achievement motivation than later adopters" (Rogers, 1983, p. 258)
- Since earlier adopters have higher levels of achievement motivation, we assume that they are willing to accept more purchase complexity. By purchase complexity, we mean the amount of efforts that households have to make to find and purchase the smart washing machines. Three categories of purchase complexity are distinguished in the following table.
- "Earlier adopters have higher levels of achievement motivation than later adopters" (Rogers, 1983, p. 258)
- Since earlier adopters have higher levels of achievement motivation, we assume that they are willing to accept more installation complexity. By installation complexity, we mean the amount of efforts that households have to make to install the smart washing machines. Three categories of installation complexity are distinguished in the following table.
- "Earlier adopters have a more favourable attitude toward change than later adopters." (Rogers, 1983, p. 258)
- "Earlier adopters have higher levels of achievement motivation than later adopters" (Rogers, 1983, p. 258)

Assumptions

- Since earlier adopters have a more favourable attitude toward change, we assume that they are willing to accept more change in their behaviour than other adopters. By behaviour change complexity, we mean the amount of cognitive efforts (inclusive time) that households have to make to use the smart washing machines each day.

Data

Table 54: maximum adoption complexity tolerated per adopter category

Specification		
	Max adoption complexity tolerated per adopter segment	Unit
Innovators	[3]	[1]
Early adopters	[2]	[1]
Early majority	[1]	[1]
Late majority	[1]	[1]
Laggards	[1]	[1]

Appendix D ODD + D protocol model description

<table>
<tr><td rowspan="2">Overview</td><td>Purpose</td><td>- To test various directions for policy to increase the adoption of smart grid appliances (such as smart washing machines or smart fridges) on the scale of city districts
- The model is designed for policy makers in the field of smart grid projects</td></tr>
<tr><td>State variables and scales</td><td>- The entities are households. Their attributes are :
o Number of householders
o Electricity consumption per month
o Amount of smart grid appliances in house
o Memory length
o Adopter category
- Each household belongs to an adopter category: innovators, early adopters, early majority, late majority or laggards. Households of each category differ in:
o Amount of interactions per month
o Valuation of information provided by households of each type of adopter category
o Minimum amount of savings required to be willing to adopt
o Maximum difference between price of smart and traditional grid appliance tolerated
o Percentage of similar information needed to be willing to judge the information as reliable
o Maximum degree of adoption complexity tolerated
- Space: each household is placed into a square field next to each other. The landscape is fictive. Distribution of households among the field is done randomly. Space is relevant since households may have interaction with neighbours (if switched on)
- Exogenous factors are:
o Current adoption complexity
o Electricity price (peak and off-peak)
o Smart grid appliance prices
▪ Equation for the calculation of smart grid appliance prices:
$C(X_t) = C(X_0) * t^{log(B,2)}$
$C(X_t)$ — Cost of the technology at time t
$C(X_0)$ — Initial cost of the technology
t — Current time
B — Learning parameter</td></tr>
<tr><td></td><td>Process overview and scheduling</td><td>- Each month, households in the model follow the consumer decision-making process of Engel, et al. (1995).
- If one steps does not succeed, for example because they miss information or because they find the adoption complexity to be too high, they drop of the process</td></tr>
<tr><td rowspan="2">Design concept</td><td>Theoretical and empirical background</td><td>- The main theory is the Diffusion of Innovations Theory of Rogers (1962). From this theory, two mains aspects are used:
o Division in five adopter categories, each have different behaviour properties and different reasons to adopt
o Characteristics of innovations that households use to build an opinion about a product
- Households may use neoclassical rationality or bounded rationality to perform their decision-making. In addition, the use of prospect theory can be included
- Households use the consumer decision-making process of Engel, et al. (1995) to perform decision-making
- Adoption complexity vary according to the four product lifecycle phases of Levitt (1965)
- Agent-based modelling is used as a simulation tool
- Scenario discovery (Kwakkel, et al., 2013) is used as a method to identify relevant scenario based on which policy making has to be built
- The ‘evaludation method of Augusiak et al. (2014) is used for verification and validation.</td></tr>
<tr><td>Individual decision making</td><td>- Households may adopt to reach three goals:
o Make savings
o Increase social recognition from other households
o Ensure they do not undergo social de-recognition</td></tr>
</table>

		- Which of the goals is the most important depends on the households category to which the household belong
	Learning	- Households may decide to never adopt again if they have been disappointed, whether financially or socially, by the smart grid appliance previously adopted
	Individual sensing	- Household can find out the following elements about the other household with whom they interact: o Adopter category o Owning a smart grid appliance or not o Adoption complexity level the household has experienced o Degree of satisfaction about savings after adoption o Amount of data leak cases observed o Amount of smart grid appliance breakdown cases observed
	Individual prediction	- The information that households received from others are all 'experience' information like opinions or satisfactions - Households however can also create information by observing the environment. They do this in the following two cases: o Calculation of adoption profitability o Calculation of the social recognition that can be gained by adopting or rejecting
	Interaction	- Households interact between each other at each simulation tick. They have three types of interactions: o Random interactions: households randomly choose a limited amount of other households to interact with. At each new tick, a new list of random interactions to exchange information with is made. o Neighbour interactions: similar to random interactions, but only with households within a radius of four o Friend interactions: list of households picked up randomly at the beginning of the model run, and remains unchanged until the end of the run - Households exchange: o Information about savings made through adoption o Adoption complexity they experienced o Information whether data leak cases have been observed o Information whether smart grid appliance breakdown cases have been observed o Information whether they possess a smart grid appliance
	Collectives	- Any household belongs to one of the following adopter groups: o Innovators o Early adopters o Early majority o Late majority o Laggards - Households cannot switch between adopter groups during a simulation run
	Heterogeneity	- The following heterogeneity is included: o Adopter categories which defined the following variables: ▪ Amount of interactions per month ▪ Valuation of information provided by households of each type of adopter category ▪ Minimum amount of savings required to be willing to adopt ▪ Maximum difference between price of smart and traditional grid appliance tolerated ▪ Percentage of similar information needed to be willing to judge the information as reliable ▪ Maximum degree of adoption complexity tolerated o Electricity consumption per month o Number of householders o Valuation of savings, within adopter categories
	Stochasticity	- Agent iteration is randomised - Households find others households to interact with in a random way (within the

<table>
<tr><td></td><td></td><td>constrains that they were given such as the maximum radius)
- Households are placed randomly into the map
- Uniform distributions are included in the model and determine the threshold that household use to perform or not a certain action</td></tr>
<tr><td></td><td>Observation</td><td>- The model is capable of providing the following outputs:
o Percentage of households owning a smart grid appliance
o Percentage of innovators, early adopters, early majority, late majority or laggards owning a smart grid appliance
o Amount of households having adopted a smart grid appliance during the last year
o Amount of households that refuse to adopt because of adoption complexity, savings or information lacking purposes
o Percentage of households aware of the existence of smart grid appliances</td></tr>
<tr><td>Details</td><td>Implementation details</td><td>- Model is implemented in Netlogo
- Two files belong to the model and are needed to run it:
o ‘Dataset_of_households’
o ‘Dataset_of_ISG_appliances’
- Equations used:
o Calculation of awareness received:
$AR_i = \frac{\sum_{t=-n}^{0} \sum_{q=1}^{j} VA_{q,i}}{n} + \frac{\sum_{t=-n}^{0} (m * VM)}{n}$
t — Time
AR_i — Total awareness received by household i
j — Amount of households encountered at period t
$VA_{j,i}$ — Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j).
m — Amount of media interaction received (depended on the adopter category of household i)
VM — Valuation of media interaction
n — Length of the memory of household i
o Calculation if sufficient knowledge about one type of information is received
$IR_i = \frac{\sum_{t=-n}^{0} \sum_{q=1}^{j} VA_{q,i}}{n}$
t — Time
IR_i — Total information received by household i
j — Amount of households encountered at period t
$VA_{j,i}$ — Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j)
n — Length of the memory of household i
o Calculation of information about breakdown or data leak problems observed
$PR_i = \frac{\sum_{t=-n}^{0} \sum_{q=1}^{j} P_q}{n}$
t — Time
PR_i — Total information related to problems received by household i
j — Amount of households encountered at period t
P_j — Knowledge of break-down or data leak problems (either 0 or 1)
n — Length of the memory of household i
o Calculation of expected savings in case of neoclassical rationality</td></tr>
</table>

$$Exp.Sav = C - \sum_{r=1}^{m} Q, KWh_r * (P_{peak} - P_{offpeak}) + \sum_{r=1}^{m} \frac{ICsmart_r - ICnotsmart_r}{Lifetime_r} - \sum_{s=1}^{n} Q, KWh_s * (P_{peak} - P_{offpeak}) + \sum_{s=1}^{n} \frac{ICsmart_s}{Lifetime_s}$$

C	*Past average monthly electricity expenditure of one household over a period x*
m	*Smart grid appliance that comes to replace an existing product (for example that replaces a traditional grid appliance)*
n	*Smart grid appliance that does not replace an existing product and are hence is a totally new product for an household*
Q,KWh	*Past average electricity consumption of the smart grid appliance per month over a period y*
Ppeak	*Expected future average electricity price during peak period*
Poffpeak	*Expected future electricity price during off-peak period*
ICsmart	*Purchase costs of the smart grid appliance*
ICnotsmart	*Initial costs of the appliance that the smart grid appliance replaces (for example a traditional grid appliance)*
Lifetime	*Average lifetime of the smart grid appliance*

- Calculation of expected savings in case of bounded rationality

$$IR_i = \frac{\sum_{t=-n}^{0} (\sum_{q=1}^{j} VA_{q,i} * S_q)}{j}$$

t	*Time*
IR_i	*Total information received by household i*
j	*Amount of households encountered at period t*
$VA_{j,i}$	*Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j)*
S_j	*Current savings made by household j*
n	*Length of the memory of household i*

Initialisation	- Five households already own a smart grid appliance. They are all innovators. The rest does not possess anything.

Input data	- Three types of input data can be distinguished:
	  o Input data for smart grid appliances (based on internet research)
	  o Input data for households characteristics (based on internet research and calibrated for the Dutch population)
	  o Input data for adopter categories: generated based on the Diffusion of Innovations Theory
	- An overview of the input data used can be found in Appendix C

Sub models	- No sub models

Appendix E Evaludation

Data evaluation step

Table 55: data evaluation of the smart grid appliance adoption model

Type of data	
Characteristics of smart washing machines	All are mentioned with source and unit and based on empirical findings, except for the price of price of smart and traditional appliance and the learning-rate of smart appliance. The price of smart and traditional appliance is based on an average of observations made on web-sites that sale these products. The learning-rate is guessed on observations of price decrease of similar products.
Initial electricity price	All are mentioned with source and unit and based on empirical findings.
Electricity consumption of households	All are mentioned with source and unit and based on empirical findings.
Product life cycle phase and complexities	All data are generated based on an interpretation of the product life cycle theory of Levitt (1965).
Adopter specific characteristics	All data are generated by using the Diffusion of Innovations Theory of Rogers (1962). The method for data generation is explained in section 4. 4. 1.

Table 56: data evaluation of the smart grid appliance adoption model: patterns

Type of patterns	
smart washing machine price decrease	The price is assumed to decrease with a logarithmic function as described by Sark (2008). Other price decrease structures could by tested such as a linear decrease or a step decrease.

Implementation evaluation step

Recording and tracking agent behaviour

The recording and tracking agent behaviour test is done to verify whether relevant household output variables are logical and realistic.

Relevant model outputs for each household are the following:

- Electricity consumption per month
- Total savings after purchase
- Amount of smart washing machine adopted
- Status of decision-making
- Status of knowledge gathering about user experience information
- Amount of interactions per month (neighbour, friend and random)
- List of knowledge of data leak event and failures

The recording and tracking of agent behaviour was implemented by inserting loggers in the Netlogo model. When needed, multiple loggers have been created for one single output due to differences between households.

Electricity consumption per month

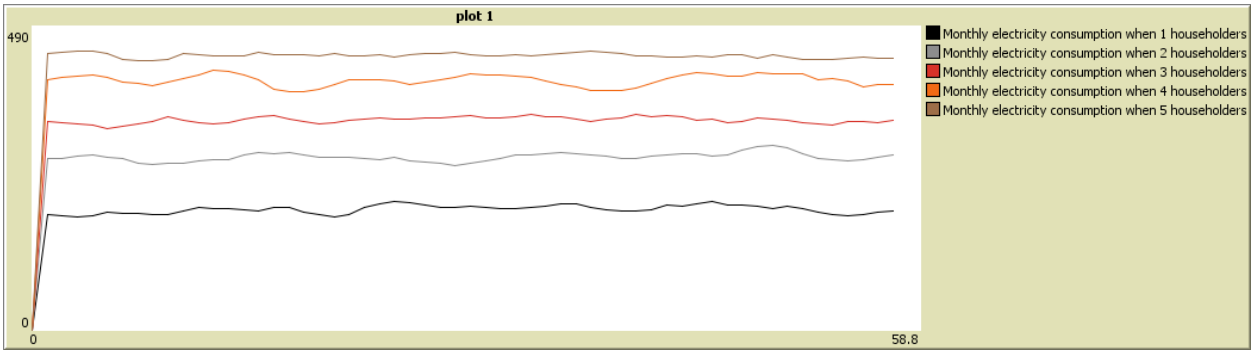


Figure 40: Evolution electricity consumption of households with 1 to 5 householders in kWh/year

Total savings after adoption

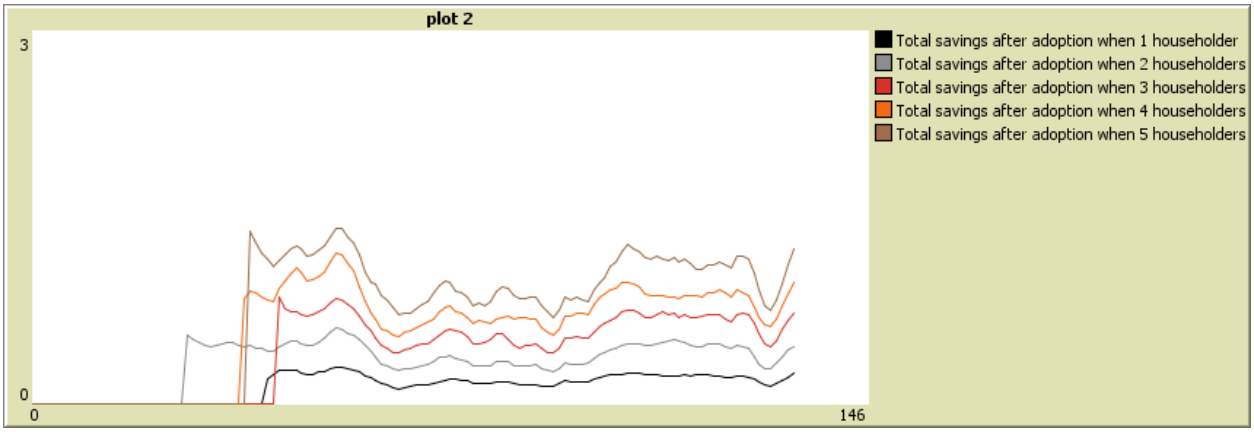


Figure 41: Evolution savings after adoption in €/month

Status of decision-making

The log of the decision-making status list, which shows the progress of the household through the decision-making process, has been observed for different types of adopters. No abnormalities were found, even in case the replacement of smart washing machines is allowed.

Status of knowledge gathering about user experience information

The knowledge gathering status list shows the progress of households in the gathering of information on which they will be able to base their decision-making. On the same basis as the verification of the decision-making status list, no abnormalities were found.

Amount of interactions per month (neighbour, friend and random)

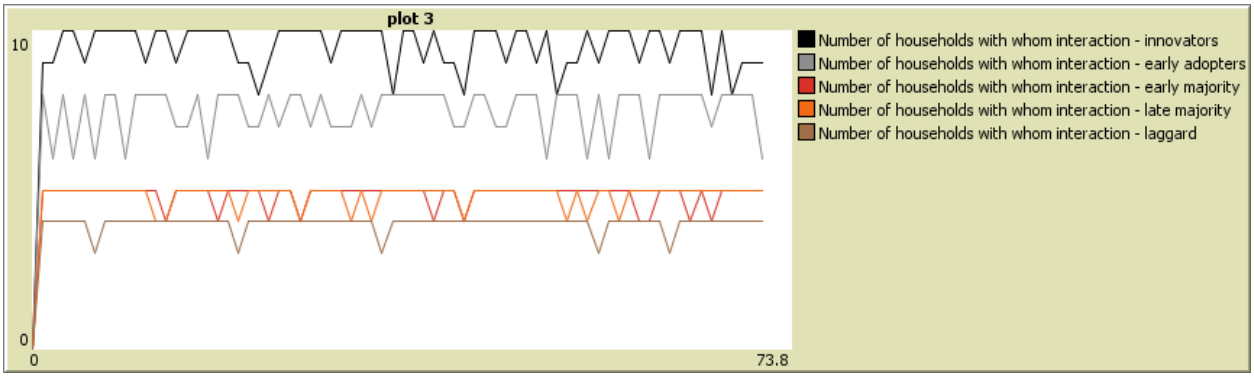


Figure 42: Amount of interactions per type of adopter in interactions/month

List of knowledge of data leak event and failures

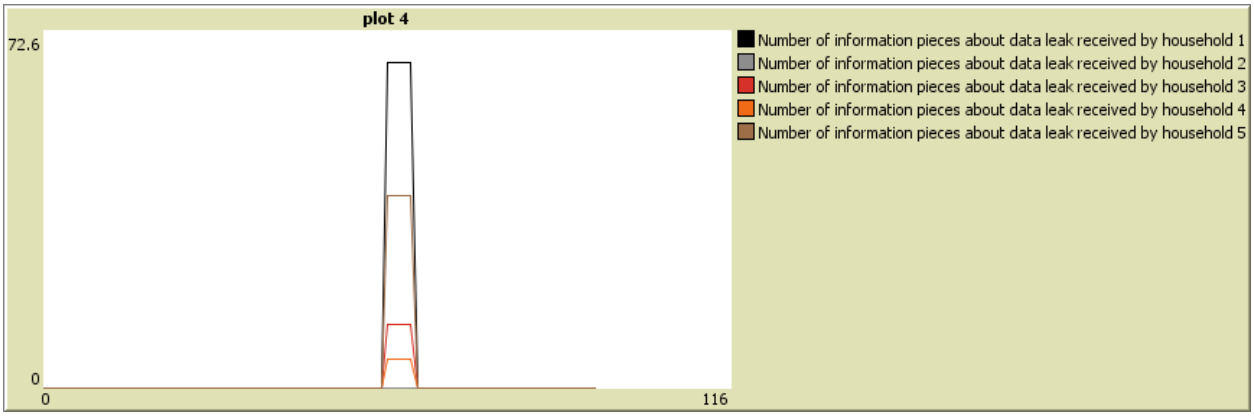


Figure 43: number of peace of information about data leak event observed for 5 different households, for a data leak event at tick =57

Single-agent testing

The goal of the single-agent testing is to find out if they are at each moment in the decision-making process the household behaves how it was intended during its formalisation.

Equations and dimension checking

Equation examination

The goal of the equation examination is to find out whether some equations unexpectedly due to variations of some inputs. Problems are mainly to be expected when variables within an equation are divided by an input that can be equal to zero (for example a variable that measures the length of a list). This step is specifically important in this project since many inputs are varied for the sake of EMA experiments.

To cope with that, all equations used in the model and presented in section 4. 3. 1 were verified based on the pseudo-code. In case lists are still empty at tick 0 but are needed for equations, some input data corresponding to the expected average were inserted into the list to simulate happenings in post model simulation time. In other cases, when no influence of the model was expected, some equations were only use at tick 1 and after.

Dimensional analysis

The goal of the dimensional analysis if to make sure that the outcome of equations can be interpreted easily by any model users. Hence, the outcome of each equation should done by using an interpretable

unit. For example in the case of Equation 2, Equation 3 and Equation 4, the unit is 'piece of information'. In case of Equation 5 and Equation 6, the unit is in €/month.

Theoretical prediction and sanity check

In the theoretical prediction and sanity check verification step, known and average inputs are provided to agents. Before verifying whether the output is correct, an expected result is formulated. In case a difference is observed between the expected result and the observed result, two possible types of errors can be expected: errors in the pseudo-code or errors in the implementation of the model in Netlogo. In this section, the theoretical prediction and sanity check performed in this work to verify the output of agents are presented.

Determine savings

Hypothesis: by using the neoclassical theory, households are expected to behave rationaly. Hence, when this type of rationality is selected, households are modelled in such a way that savings are always considered as satisfactory in case savings (including fixed costs) are higher than 0. Hence, the hypothesis is that when the product purchase costs are lower than the expected savings based on recent evolution of the peak/off-peak electricity price, the household will purchase the appliance.

Model output:

- For frequency of utilisation per month of 12.5 (for 2 householders), a duration of utilisation period of 2 hours, Electricity consumption per hour of 0.45 KW: 11.25 KWh are used per month. For a percentage of utilisation peak/off-peak of 75.2/24.8 for traditional appliances and 20/80 for smart appliances and considering the electricity price during peak of 0.31 €/KWh and 0.16 €/KWh during off-peaks, the savings excluding fixed cost is 0.90 €/month. The different in price between smart and traditional appliance divided by the lifetime of the appliance is 0.8690 €/month. Hence, in this case, savings are made.
- The household indeed adopts the appliance.
  > **Confirmed**

Determine satisfaction savings

Hypothesis: for the case of bounded rationality, households are expected to evaluate the extent to which savings can be made based on information for other household, and not from a rational calculation. The information that is communicated is whether households already having a smart washing machine are satisfied with their smart washing machine in relation to savings. Hence, the hypothesis is that, if households are not making savings above a minimum required level of savings, they will communicate the information to households that the appliance does not lead to savings.

Model output: For frequency of utilisation per month of 12.5 (for 2 householders), a duration of utilisation period of 2 hours, Electricity consumption per hour of 0.45 KW: 11.25 KWh are used per month. For a percentage of utilisation peak/off-peak of 75.2/24.8 for traditional appliances and 20/80 for smart appliances and considering the electricity price over during peak of 0.19 €/KWh and 0.15 €/KWh off-peak, the savings excluding fixed cost is 0.23 €/month. The fixed costs per month are 0.99 €/month. Hence the savings is minus 0.74€/month. The level of satisfaction is indeed 0, which means that the household is not satisfied.

- The household indeed communicates to others that he is not satisfied when it comes to savings.
  > **Confirmed**

Determine amount of interactions each month

Hypothesis: The amount of interactions for each households each months varies by using a normal distribution but is roughly similar from month to month. The hypothesis is that no large changes will be observed during the simulation run.

Model output: the focus on one household shows that the amount of random interactions is in some months abnormally high. In other month, the level is normal. An inspection of the code has showed that a variable normally used for neighbour interactions was used to calculate interactions. The adjustment of the code has solved the problem.

> **Solved and confirmed**

Determine acceptable level of complexity
Hypothesis: When heterogeneity is introduced in the model to vary the properties of adopter, the hypothesis is that households that initially have a max complexity level accepted of 2 are expected to choose equally often an acceptation of level of 1 or 3. FYI: a level 1 of is for households that accept little complexity while a level of 3 is for households that accept large complexity (see section 4. 2. 2).

Model output: the observation of outputs have shown that the complexity level of 1 was chosen much more often than 3. The testing of the code enable to find out that the pseudo-code was badly implemented because of a bad interpretation of the INTEGER function of Netlogo. The error was made that the INTEGER function would approximate to the nearest integer, which actually the lowest integer is always chosen. The adjustment of the code has solved the problem.

> **Solved and confirmed**

Determine whether reliability problem is observed
Hypothesis: When a breakdown problem happens, the household having this problem communicates this information to other households. As a result, the household getting this information and being in the middle of a decision-making process stops with the adoption process for a certain amount of time. Therefore, the hypothesis is that when information about a breakdown problem in received, the households does not adopt.

Model output: by inspecting the output, the hypothesis was confirmed. The household receiving the information indeed stopped his decision making process.

> **Confirmed**

Determine if level of positive information received is enough
Hypothesis: Some households (innovator and early majority population) just need a few positive information out of an entire range of negative information to still take a guess and decide to adopt. For example, it receives a few pieces of information about the fact that savings can be made, while also receiving many pieces of information that the appliance is not profitable, but still want to make a guess by adopting. Other households (early majority, late majority and laggards) however want to have a large amount of certainty that the adoption is worth it. Hence, the hypothesis is that the information that savings can be made by adopting communicated by others households are only considered trustful if a large amount of these households all has the same opinion.

Model output: with a high difference between peak and off-peak electricity price, the adoption of smart washing machine was made highly beneficial. Household 300 (late majority household) received 6 pieces of information. More than 80% (threshold of a late majority household) of them indicated that enough savings are possible. Therefore, household 300 decided that savings were good enough and brought this information in the next decision-making steps.

> **Confirmed**

Determine level of awareness received
Hypothesis: The hypothesis is that all households are expected to have the possibility to be aware of the existence of smart washing machines.

Model output: the observation on one laggard household however showed that it never become aware. A study of input parameters showed that the required level of awareness (amount of interactions with households having smart washing machines) was in fact too high in comparison to the amount of interactions that this household has each month. Therefore, the level awareness needed for all households was decreased.

> **Solved and confirmed**

Determine social recognition
Hypothesis: the hypothesis is that when early adopter households have encountered a high number of households already having a smart washing machine, the social recognition that they can get from the adoption is seen as lower. Hence, they will do less effort to find information in order to adopt the smart washing machine (and thereby have a lower probability to adopt).

Model output: the model output indeed show that by selecting an early adopter household that did not adopt in the early stage of diffusion of the product, this household tended to adopt at approximately the same moment as the latest adopters of the early majority group.

> **Confirmed**

Breaking the agent

In the breaking the agent step, the behaviour of the households is tested under extreme values, instead of normal values as was done in the theoretical prediction and sanity check. The goal is to define the edges of normal behaviour of households. The identification of some abnormalities does not necessarily mean that the model code has to be changed. However, it shows under which range of input space the household is capable to show a normal behaviour.

Some examples of the breaking the agent test performed in this work are presented in this section.

Test 1

Hypothesis: A household that is given zero interactions (do not interact with others households) will not succeed in any step of the decision-making process.

Model output: The household indeed remain isolated. In the case of a full diffusion of smart washing machines across all households, the household not interacting is the only one that does not adopt in the end.

Test 2

Hypothesis: there is a certain amount of interactions that households can handle. In case this amount is too high, and because of the limited amount of households in the model, the model will block and give an error.

Model output: the amount of interactions of one household was multiplied by 50. The model run speed hugely slowed down but no errors appeared.

Test 3

Hypothesis: the huge increase of the monthly electricity consumption of one household is expected not to lead to any model errors or unexpected behaviour from this household.

Model output: the monthly electricity consumption of one household was multiplied by 5000. No errors appeared. As expected, however, the average savings made by all households together was hugely increased.

Minimal model interaction verification

In the minimal model interaction verification, the lowest amount of agents is introduced in the model. The goal is to verify whether the desired interaction is seen and whether undesired interaction happen. Five different types of households are distinguished in this model, one per adopter category. Hence, to perform a minimal model interaction verification, each of the category must be represented. This experiment will be performed with 3 innovators (initially 13), 5 early adopters (initially 67), 5 early majority households (initially 170), 5 late majority households (initially 170), 5 laggards (initially 80),

Theoretical predictions and sanity checks

Emergent S-curve adoption rate

Hypothesis: The hypothesis is that the number of households in the model should not have an impact on the topology of the adoption curve. Hence, if the conditions for adoption are favourable for all households under neoclassical rationality decision making, the adoption curve should resemble to a S-shape type.

Model output: as shown in figure 44, a S-shape type of adoption curve can be observed, even though if steps can clearly be seen in the curve do to the low amount of households in the model.

> **Confirmed**

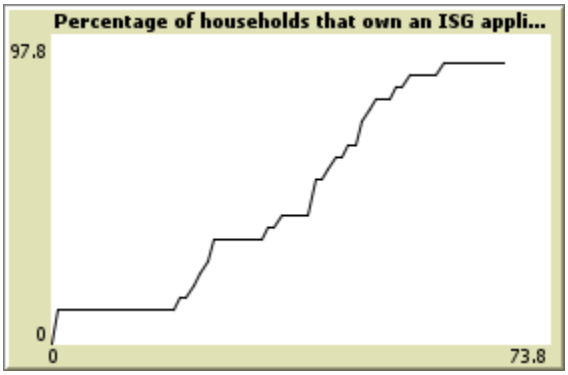


Figure 44: emergent S-shape of adoption with minimal amount of households

Exchange of information about complexity

Hypothesis: If household A has some information about the complexity of adopting and his neighbour (household B) is searching information in order to decide to adopt, then the information about complexity of household A should appear in the complexity information list (that he got from other households) of household B.

Model output: The test is confirmed. Information about complexity of household A can indeed be seen in the list of household B.

> **Confirmed**

Exchange of information about savings

Hypothesis: when using bounded rationality, households use information about savings that they received from other households instead of calculating potential savings themselves. The hypothesis is that if all households but household A have adopted are making savings, household A will only get information that savings are being made by adopting.

Model output: The test is confirmed. The savings information list of household A only contains value 1, which indicated that the others households have declared to be satisfied with the amount of savings made.

> **Confirmed**

To conclude the following questions need to be answered:

- Do the agents find each other? **YES**
- Do the agent interactions happen as defined in the narrative? **YES**
- Are the results of these interactions as expected? **YES**
- Are there any unintended interactions? **NO**

Multi-agent Testing

The multi-agent verification is useful to find out whether the behaviour of the entire set of agents is consistent with the expected behaviour. For this test, the initial setting of main parameters is presented in table 57 will be used.

Table 57: Initial parameter setting for multi-agent testing

Variable	Initial value	Unit
Electricity price off-peak	0.15	[€/KWh]
Difference between peak and off-peak price	0.15	[€/KWh]
Learning rate	0.95 (hence fast decrease of costs)	
Minimum desired savings of households	0	[€/month]
Duration introduction phase	15	[month]
Duration growth phase	15	[month]
Memory	3	[month]
Rationality	Neoclassical rationality	

Variability Testing

Since agent-based models are often chaotic due to multiple interactions between a wide number of agents, model outputs might also show comparable behaviour with only slight variation of some input. The goal of the variability test is to assess whether such behaviour arise, and if this is the case, to reflect whether behaviour is desired. This test has been performed by varying slightly the initial parameter given in table 57. The outcomes of the variability test are presented in figure 45. The figure shows that a slight variation of input parameters leads to a rather small variation of the final adoption rate of smart washing machines. In some cases still, the variation of input parameters leads to partial adoption. The outcomes of a worst cases PRIM analysis show that a high 'minimum desired savings of households' and a high 'learning rate' lead to the occurrence of these worse cases.

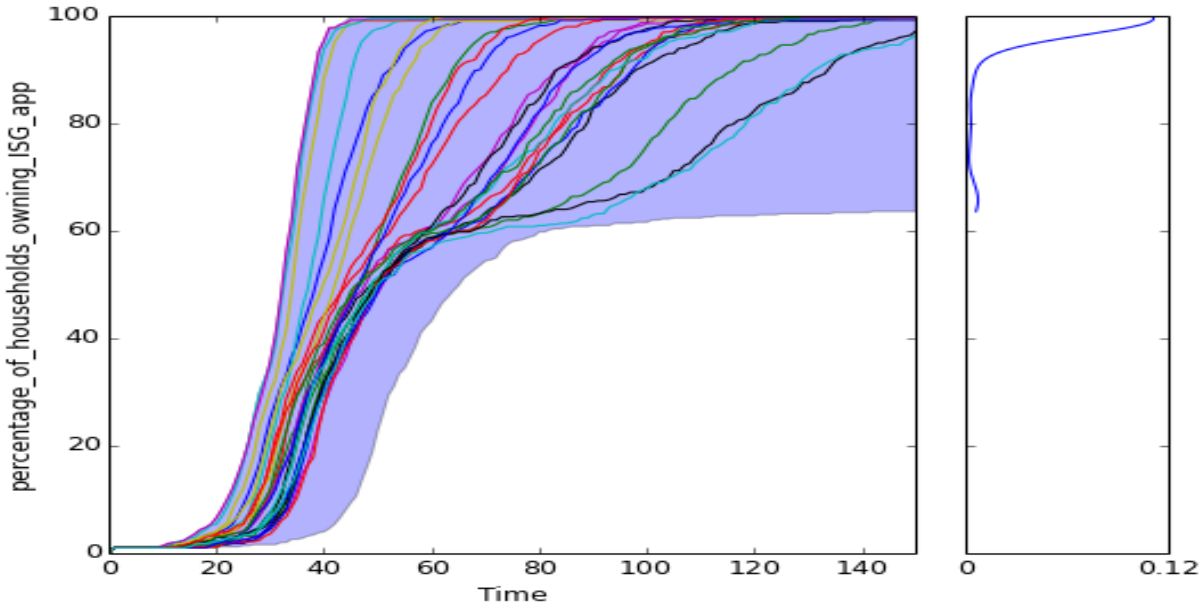


Figure 45: Percentage of households owning a smart washing machine - neoclassical rationality, no risk perception, small variation of input parameters

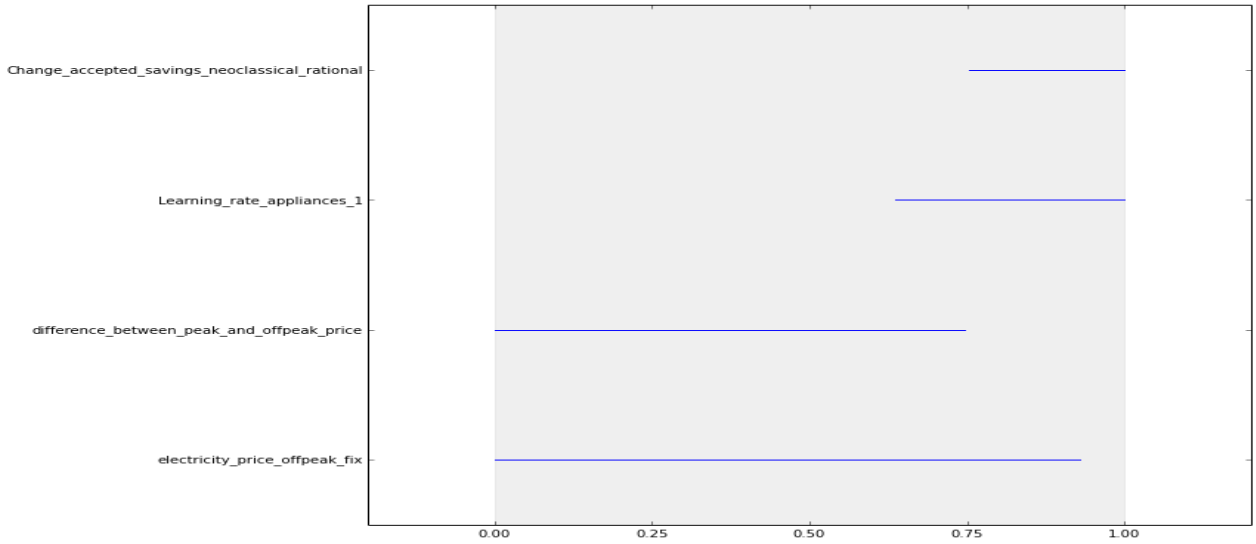


Figure 46: Outcome of the prim analysis (worst cases): percentage of households owning a smart washing machine - neoclassical rationality, no risk perception, small variation of input parameters

Timeline Sanity

The goal of the timeline sanity is to perform a list check of the model by going through the timeline of the model and observing the behaviour of households. Any output of the model that does not correspond to the model logic indicates that implementation errors might be present.

The output of the model run is shown in figure 47 and figure 48. As shown in figure 48, logically, innovators are the first to adopt smart washing machines due to their high acceptation of adoption complexity and the large amount of money they are expected to spend on these products. A S-shape type of adoption curve of innovators is however not found. As Rogers (1962) explains, innovators love to talk about the innovations they adopted to other type of adopters but do not rely on them in order to find information in order to adopt. Hence, innovators are somehow isolated from other adopters in the adoption process of innovations itself. Early adopters are then the second category to adopt. As shown

in figure 48, part of them adopt sooner that early majority adopters, but another part also later. This is due, as explained by Rogers, to the social recognition that early adopters expect from the adoption of innovations. If an early adopter has just started to consider adoption, but already sees that a large amount of households have adopted, the expected social recognition for them will be low. Hence, they will be less motivated by adoption. The early majority population quickly adoption the innovation because of the parameters setting that make the adoption highly profitable. In addition, since neoclassical rationality is used, households do not take the complexity of adoption into account. Finally, since a large amount of early majority population has adopted, late majority population quickly follows since, as Rogers explains, they do not want to be left out of the diffusion process of a successful innovation. Laggards last also quickly follows since the condition for adoption are very beneficial, and because in this parameter setting, no data leak or reliability problems are being generated.

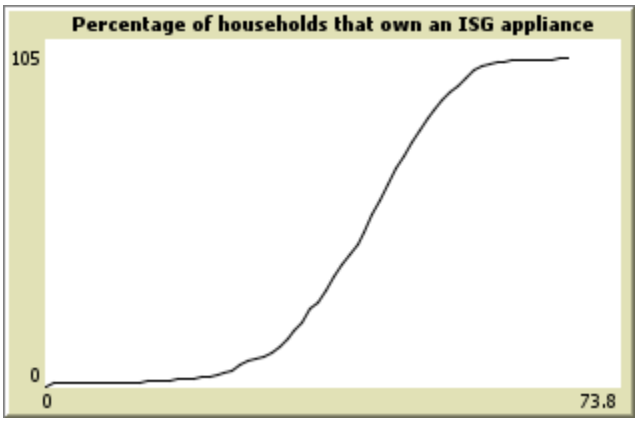


Figure 47: Evolution of the percentage of households owning a smart washing machine

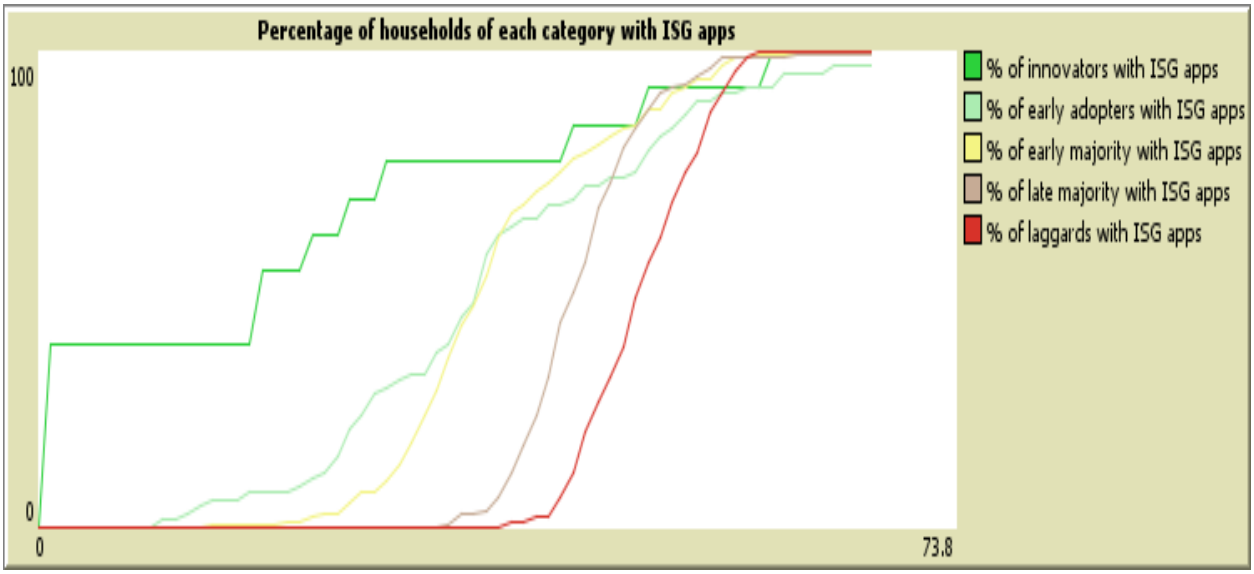


Figure 48: Evolution of the percentage of households owning a smart washing machine per adopter category

Model output verification step

Step 1: reproducing the S-shape

First, the model was run under favourable adoption conditions for households (by setting a large and fixed difference between the peak and off-peak electricity price). Figure 49 shows that indeed an S-shape type of adopt trajectory was obtained.

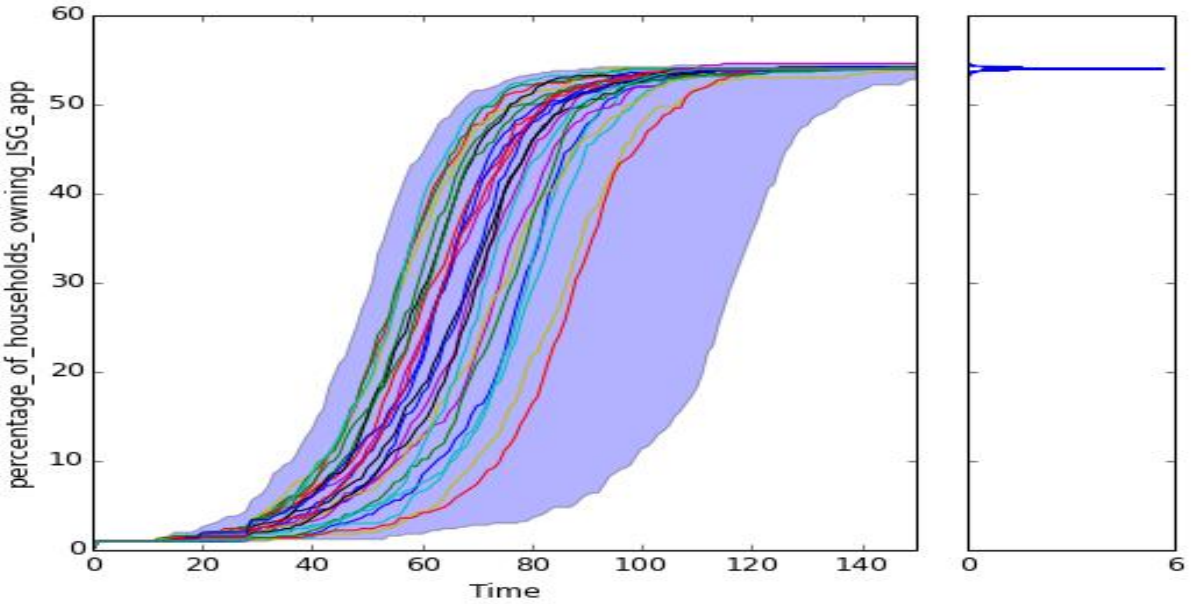


Figure 49: Percentage of households owning a smart washing machine - neoclassical rationality, no risk perception, no heterogeneity and favorable adoption conditions

Secondly, the same experiment (neoclassical rationality and no risk perception) was carried out, only the height of the peak and off-peak electricity price were varied. The evolution of the percentage of households adopting can be seen in figure 50. In this figure, the S-shape also can be observed. Some disruptions in the S-shape can in some cases however be observed (see red ellipses).

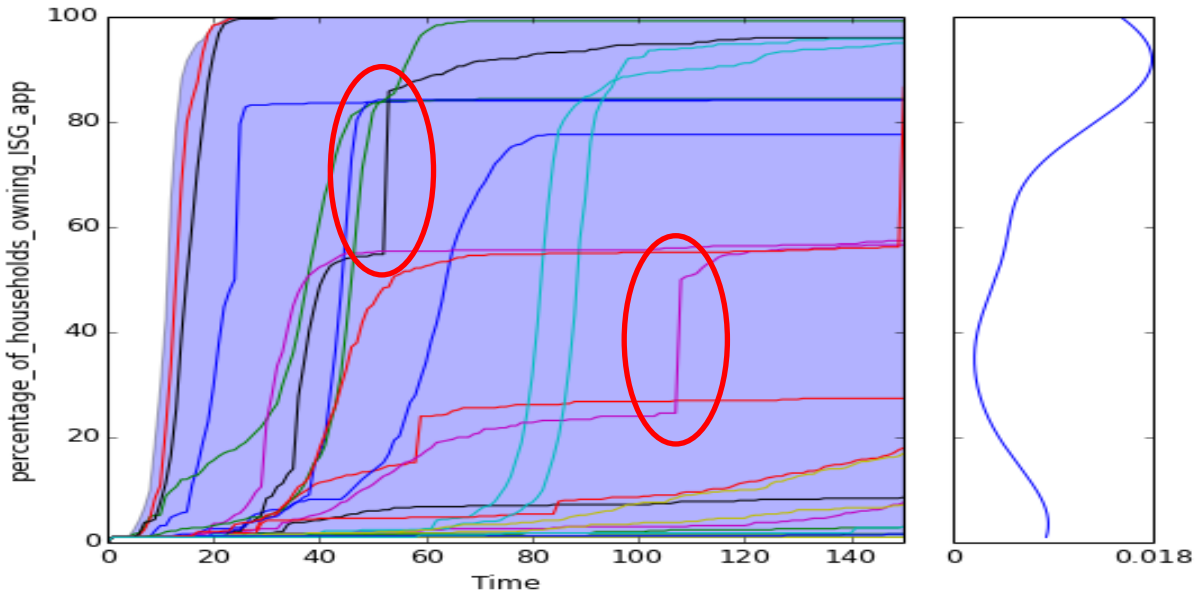


Figure 50: Percentage of households owning a smart washing machine - neoclassical rationality, no risk perception, no heterogeneity and variation of peak and off-peak electricity price

These sudden disruptions are not expected to be observed in real cases. The use of PRIM has shown that the expected savings both in best and worst case scenario strongly affected the variation of the percentage of households owning a smart washing machine (through the height of the learning rate of the appliance and the difference between peak and off-peak electricity price, see figure 51).

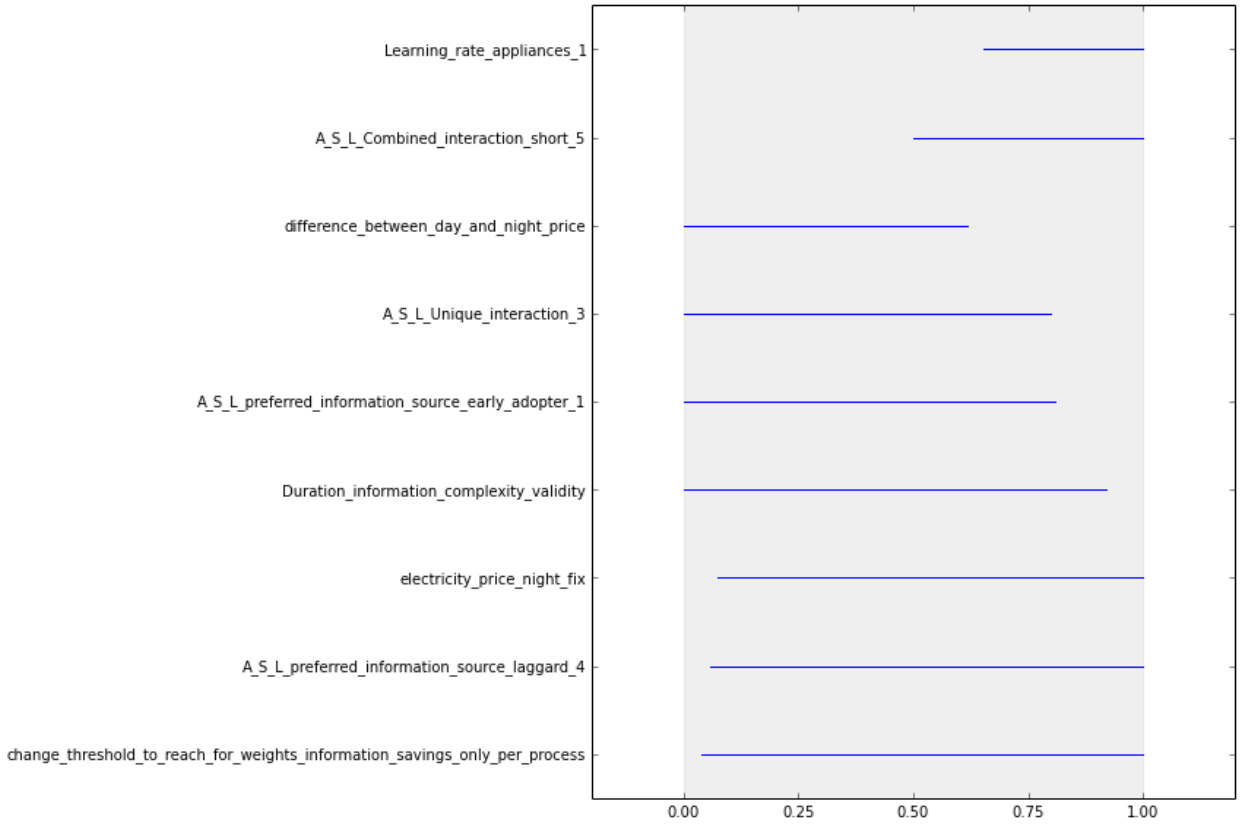


Figure 51: PRIM worst case analysis: percentage of households owning a smart washing machine - neoclassical rationality, no risk perception, no heterogeneity and variation of peak and off-peak electricity price

Based on this, it was found that the reason for these disruptions has shown that the lack of heterogeneity introduced in the model was the reason for their occurrences. More specifically, it is the fact that all households with equal amount of householders had exactly the same electricity consumption per month (and hence the exact same calculation of savings). Therefore, heterogeneity was introduced in the electricity consumption per month of households. This addition resulted in a more realistic evolution of the percentage of households owning a smart washing machine (see figure 52).

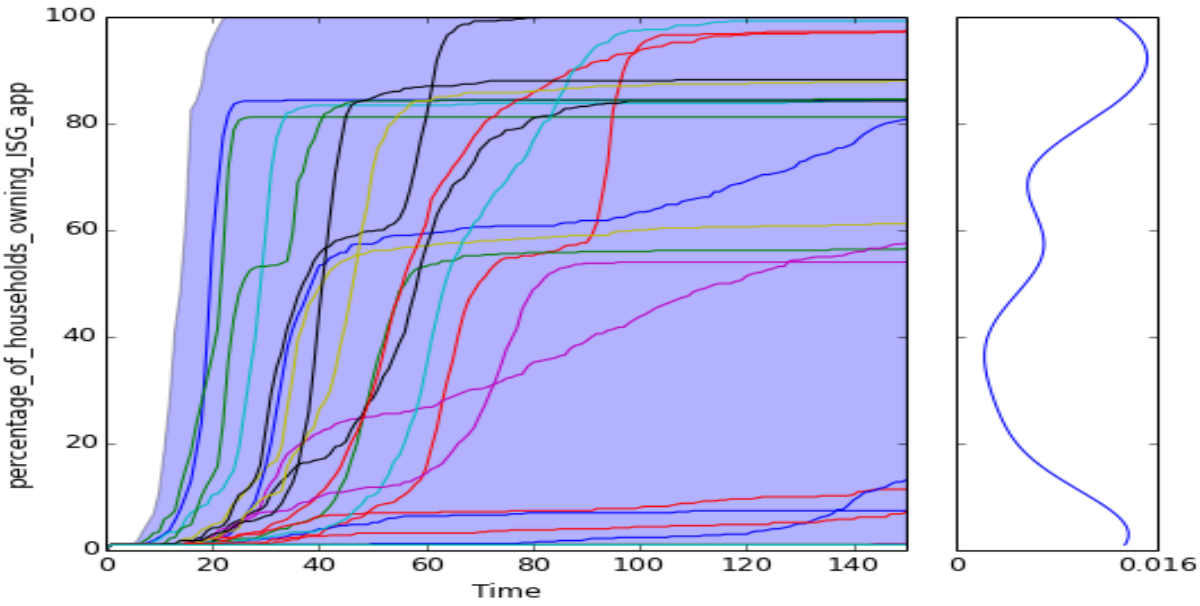


Figure 52: Percentage of households owning a smart washing machine - neoclassical rationality, no risk perception, heterogeneity electricity consumption per month and variation of peak and off-peak electricity price

Step 2: chasm in innovation adoption

Chasm between early adopters and early majority population

The chasm between early adopters and early majority is strongly supported in the literature (Moore, 1999). As explained in section 1. 3, the chasm between early adopters and early majority population appears because of the wide difference in product expectation between these two categories. While early adopters are visionaries and adopt innovations to increase their social positions, early majority population are pragmatics and look for large savings and low investment risk.

To show the emergence of the chasm in the model, the following experiment has been created. The model has been run 100 times under the same conditions as for the chasm between innovators and early adopters. The results of the experiment are shown in figure 53 to figure 55. In this experiment, mainly variables related to financial profits have been varied: peak and off-peak electricity price, and minimum of savings. Other variables varied are the delay before early adopters decide to continue using there smart washing machine and the minimum percentage of early majority population, late majority population and laggards that they have to encounter to judge the innovation as successful.

Figure 53 clearly shows the appearance of a chasm. Two main type of lines can be seen. The first type of lines increases between t=20 and t=40 and stabilises around 18% of adoption. The second type of lines continues to increase above 18% of adoption. By looking at figure 54, we see that early adopters adopt in almost all cases. By looking at figure 55, we find that early majority population adopt in a limited amount of cases. These cases corresponds to the second type of lines in figure 53. In all other cases, they do not adopt (see the KDE graph in figure 55). These cases corresponds to the first type of lines in figure 53. Hence, a chasm in smart washing machine adoption is observed between early adopters and early majority population. The reason for the appearance of this chasm in the model will be compared to the reasons mentioned by Moore (1999) in section 0.

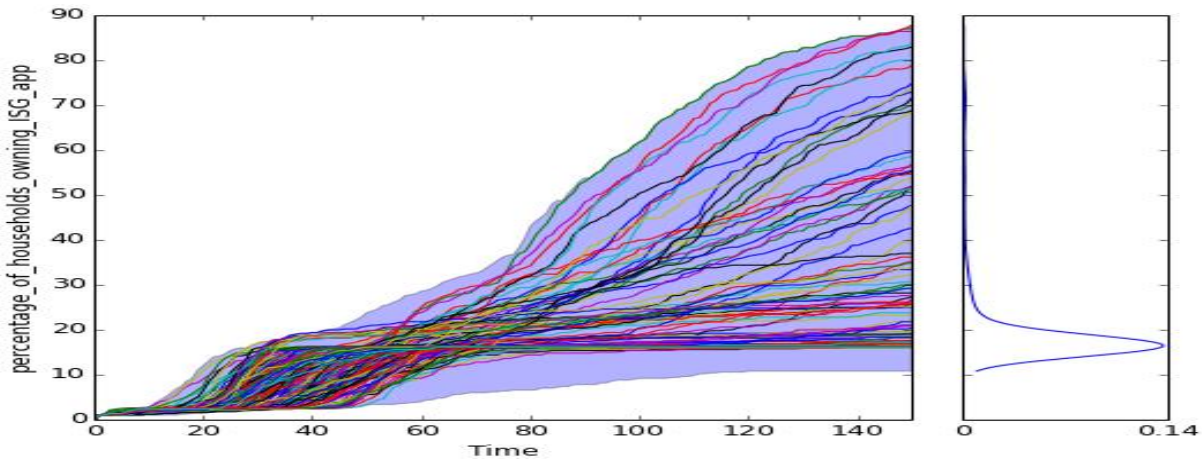


Figure 53: Percentage of households owning a smart washing machine - bounded rationality, no risk perception

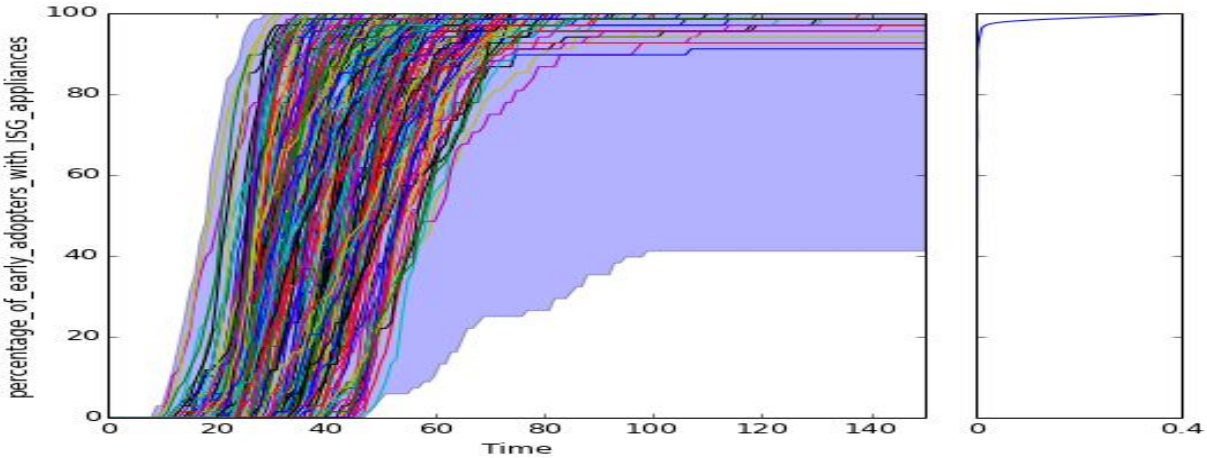


Figure 54: Percentage of early adopters owning a smart washing machine - bounded rationality, no risk perception

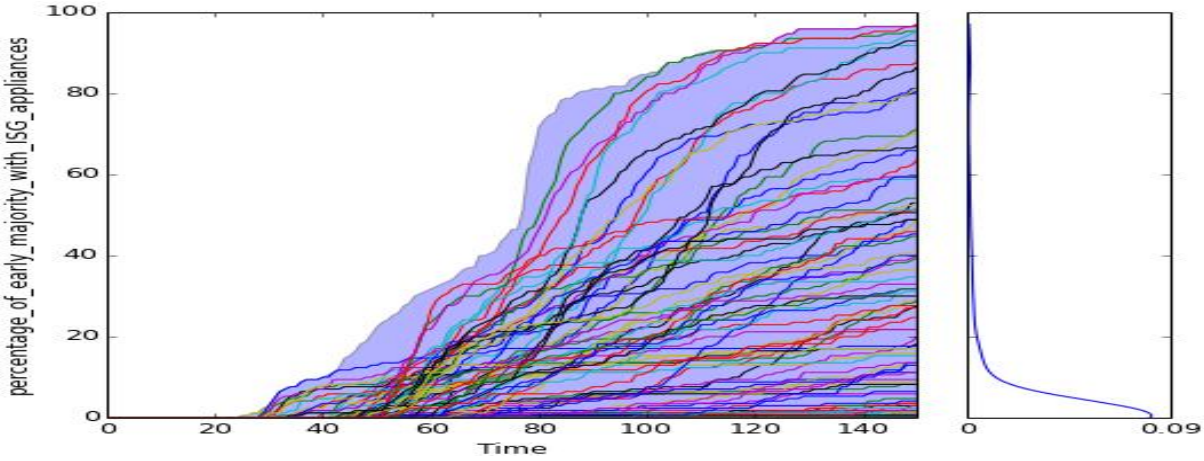


Figure 55: Percentage of early majority population owning a smart washing machine - bounded rationality

Step 3: validation by using the history-friendly approach

The validation of innovation adoption case by using simulation models is difficult is case the innovation is totally new and have not been adopted on large scale elsewhere. However, adoption curves of other innovations can be used in case a detailed comparison is made between the characteristics of the two

innovation, the type of population possibly interested in adoption and the socio-economic situation in which the innovation was/will be adopted.

To perform this validation step, the characteristics of smart washing machines must be identified. These characteristics are summarised in table 58.

Table 58: overview of smart washing machines characteristics

Characteristics of smart washing machines
- Rather expensive when compared to the average monthly salaries of households
- Long lifetime
- The type of product (for example a washing machine) is considered as 'strongly necessary' by households
- Regular usage
- Utilisation is not fundamentally new for households: usage is strongly comparable to already existing appliances
- Behaviour change required however is strong
- Added value is uncertain
- Availability of similar products with comparable properties and strong competitive position ('traditional' appliances

Based on these characteristics, a comparable innovation is colour TV. A TV is located in a comparable range of price and has a similar lifetime. It is considered as almost necessary in a house and is used regularly. A colour TV was not fundamentally new for households, since most of them already had a black and white TV. Therefor the added value of a colour TV next to a black and white TV is limited in comparison to not having a TV at all. In addition, at the time when colour TVs entered the market, black and white TVs were much more affordable.

The difference between colour TVs and smart washing machines is however that the behaviour change required is very low for colour TVs. Moreover, the benefits expected from a colour TV are comfort and social recognition while, in the case of smart washing machines, they are also financial. The adoption curves of black and white TV and colour TV are presented in figure 56.

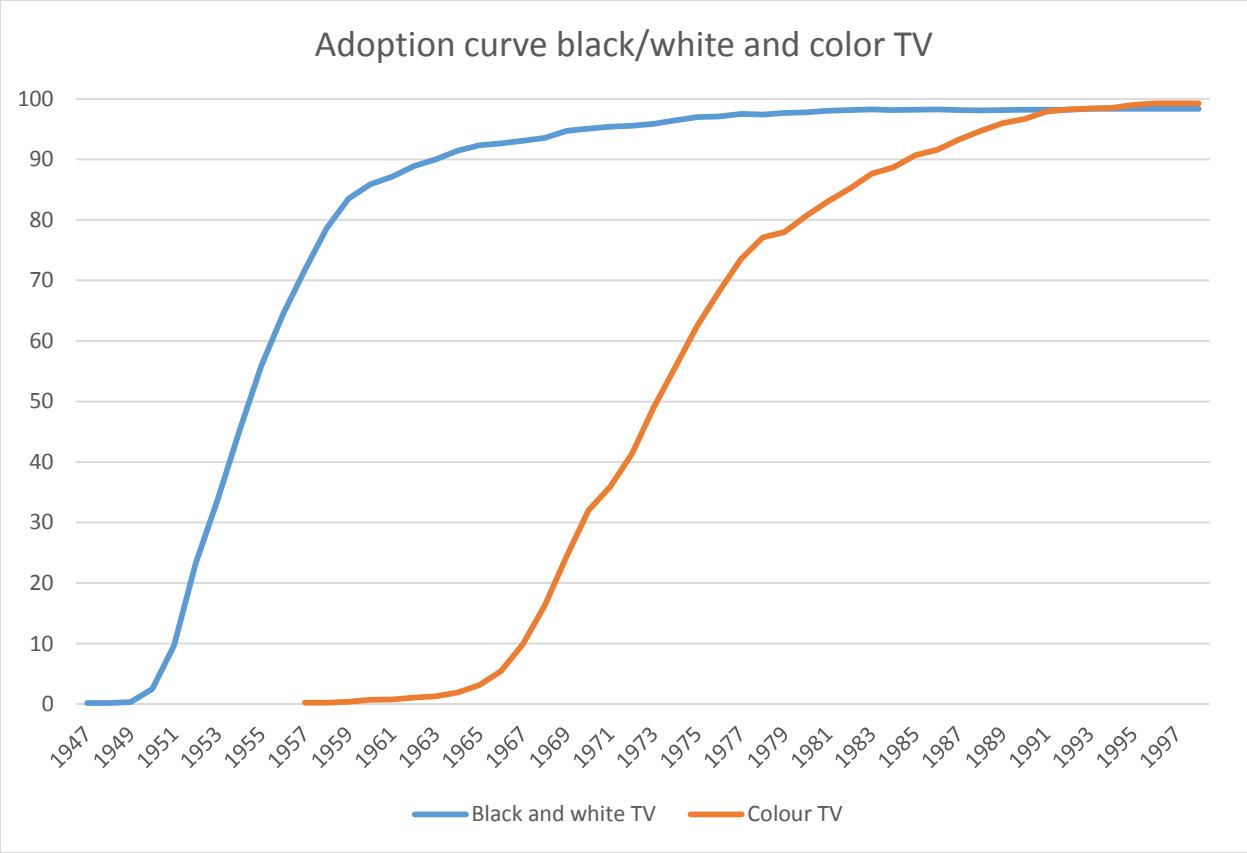


Figure 56: adoption curve of black/white and colour TVs, adopted from A.C. Nielsen Company (1996)

The characteristics of the adoption curve are the following. First, there is a rather long start period (from 1597 to 1965) where no clear increase of adoption curve is observed. Second, after 1965, the adoption curve quickly increases. Third, the second part of the S-curve (after 1973) is not increasing as strongly as in the case of black and white TV.

To validate the model made in this work based on the adoption curve of colour TV, the adoption conditions must comparable to the ones of colour TV. Since colour TV was a successful innovation, the condition for adoption of smart washing machines must be favourable. This is done by increasing the distance between peak and off-peak electricity price to increase the amount of savings that households can make.

The current adoption curve is shown in figure 57. In this figure, the first characteristics of the colour TV adoption curve can be seen: long start period. The second characteristic is also present: strong increase after the start period. The third characteristic can however not be observed. After several experiments, the addition of heterogeneity in the valuation of savings of households (the minimum amount of savings that households expect from the adoption of smart washing machines before adopting) made the second part of the S-shape increase in a more smooth way (see figure 58).

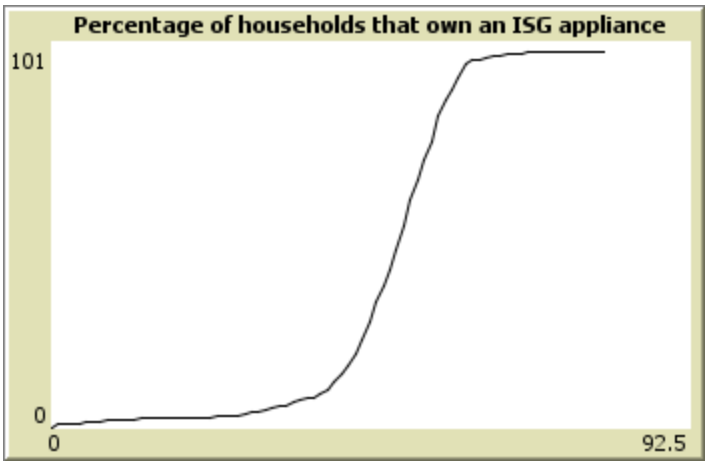


Figure 57: Percentage of households owning a smart washing machine

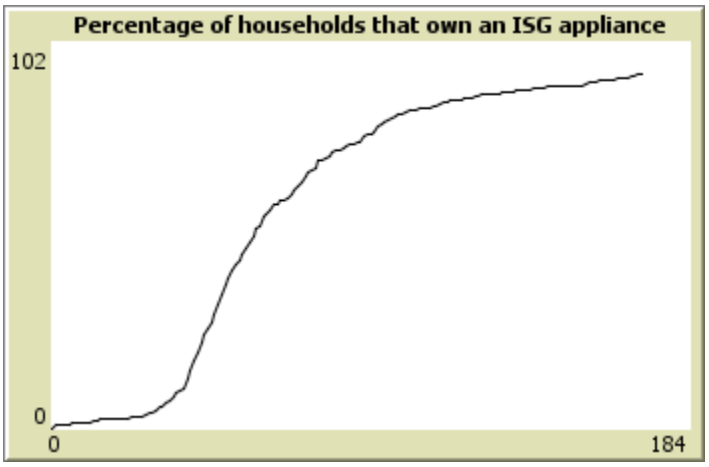


Figure 58: Percentage of households owning a smart washing machine with heterogeneity in the minimum amount of savings required by households

Conclusions of history-friendly validation by using the adoption path of comparable products is however to relativize. First, as demonstrated in this section, no products are fully comparable. In addition, adoption paths of innovations are also influenced by socio-economical events, which can greatly determine the way the adoption curve evolves. Third, the scale at which adoption curves are studied might be different. The adoption curve of colour TV is based on the entire American TV market. The model created for the adoption of smart washing machines however is on the scale of a city district. Hence, the feedback loops between the wider adoption of a product and the decrease of its price for example is not taken into account. The smoother evolution of the colour TV adoption curve in the second part of the S-shape is however not expected to be consequence of factors that might not apply to the adoption of smart washing machines. On the contrary, the changes made in this model tend to show that the diverging properties between households might affect the adoption of innovations. Still, since this model adjustment based on history-friendly validation is on certain, it should be brought as a structural uncertainty in the analysis of the model.

Model analysis step

Table 59: Identification of model behaviors and reasons for their emergence

Model behaviour	Reasons for their emergence
S-shape of adoption curve	- Flow of information necessary for the adoption of smart washing machines: to adopt, households are dependent on the information

	given by others.
Bell form of the adoption curve	- This behaviour happens when early adopters have adopted but observe after a certain time that households from later categories are not adopting. Hence, early adopters have no incentive to continue using the smart washing machine.
Smooth second part of the S-shape curve	- This behaviour happens when early majority population, late majority population and laggards also have adopted. However, they have within their adopter category diverging minimum levels of savings required to adopt.
Non adoption of early adopters	- This behaviour happens when the last innovators has adopted before the introduction life-cycle phase ended. As a result, early adopters perceived the adoption as too complex and refuse to adopt.
Partial adoption	- This behaviour happens when the learning curve of smart washing machines has stabilised. As a result, households with low amounts of householders, which have lower financial incentives to adopt, do not adopt because of the lack of savings that they expect

Appendix F Directions for policy

Experiment 1

Parameter settings

Table 60: Parameter settings of experiment 1 (all parameters)

Parameter settings			
Variable	**Value**	**Unit**	***Note***
electricity_price_offpeak_fix	[0.13, 0.17]	[€/KWh]	*Electricity price during off-peak hours*
difference_between_peak_and_offpeak_price	[0.13, 0.17]	[€/KWh]	*Difference in of electricity price between off-peak and peak hours*
division_effect_media	[6, 14]	[-]	*How many an interaction with media is valued less than an interaction with one household*
Interaction_1_multiplicator	[0.5,1.5]	[-]	*Variation of the number of interactions of innovators*
Interaction_2_multiplicator	[0.5,1.5]	[-]	*Variation of the number of interactions of early adopters*
Interaction_3_multiplicator	[0.5,1.5]	[-]	*Variation of the number of interactions of early majority*
Interaction_4_multiplicator	[0.5,1.5]	[-]	*Variation of the number of interactions of late majority*
Interaction_5_multiplicator	[0.5,1.5]	[-]	*Variation of the number of interactions of laggards*
A_S_L_preferred_information_source_innovator_1	[0.5,1]	[-]	*Innovators' valuation of an information given by an innovator*
A_S_L_preferred_information_source_innovator_2	[0]	[-]	*Innovators' valuation of an information given by an early adopter*
A_S_L_preferred_information_source_innovator_3	[0]	[-]	*Innovators' valuation of an information given by an early majority*
A_S_L_preferred_information_source_innovator_4	[0]	[-]	*Innovators' valuation of an information given by an late majority*
A_S_L_preferred_information_source_innovator_5	[0]	[-]	*Innovators' valuation of an information given by a laggard*
A_S_L_preferred_information_source_early_adopter_1	[0.25,0.55]	[-]	*Early adopter's valuation of an information given by an innovator*
A_S_L_preferred_information_source_early_adopter_2	[0.15,0.45]	[-]	*Early adopter's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_early_adopter_3	[0]	[-]	*Early adopter's valuation of an information given by an early majority*
A_S_L_preferred_information_source_early_adopter_4	[0]	[-]	*Early adopter's valuation of an information given by an late majority*

A_S_L_preferred_information_source_early_adopter_5	[0]	[-]	*Early adopter's valuation of an information given by a laggard*
A_S_L_preferred_information_source_early_majority_1	[0,0.2]	[-]	*Early majority's valuation of an information given by an innovator*
A_S_L_preferred_information_source_early_majority_2	[0.15,0.45]	[-]	*Early majority's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_early_majority_3	[0.25,0.55]	[-]	*Early majority's valuation of an information given by an early majority*
A_S_L_preferred_information_source_early_majority_4	[0]	[-]	*Early majority's valuation of an information given by an late majority*
A_S_L_preferred_information_source_early_majority_5	[0]	[-]	*Early majority's valuation of an information given by a laggard*
A_S_L_preferred_information_source_late_majority_1	[0,0.1]	[-]	*Late majority's valuation of an information given by an innovator*
A_S_L_preferred_information_source_late_majority_2	[0,0.1]	[-]	*Late majority's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_late_majority_3	[0.15,0.45]	[-]	*Late majority's valuation of an information given by an early majority*
A_S_L_preferred_information_source_late_majority_4	[0.1,0.3]	[-]	*Late majority's valuation of an information given by an late majority*
A_S_L_preferred_information_source_late_majority_5	[0]	[-]	*Late majority's valuation of an information given by a laggard*
A_S_L_preferred_information_source_laggard_1	[0]	[-]	*Laggard's valuation of an information given by an innovator*
A_S_L_preferred_information_source_laggard_2	[0]	[-]	*Laggard's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_laggard_3	[0,0.2]	[-]	*Laggard's valuation of an information given by an early majority*
A_S_L_preferred_information_source_laggard_4	[0.1,0.3]	[-]	*Laggard's valuation of an information given by an late majority*
A_S_L_preferred_information_source_laggard_5	[0.2,0.4]	[-]	*Laggard's valuation of an information given by a laggard*
Initial_minimum_amount_savings_bounded_rational	[1,4]	[€/month]	*Variation of the minimal amount of savings required by household to adopt*
minimum_percentage_for_no_rejection	[0.02,0.20]	[%]	*Minimum percentage of early majority, late majority and laggards having a smart washing machine that early innovators in order not to reject the appliance*
Number_of_month_before_decision_rejection	[12,60]	[month]	*Delay after which early adopter check whether the adoption of the appliance was successful from an social recognition point of view*
introduction_phase	[3,36]	[month]	*Number of month of the introduction phase*
growth_phase	[3,36]	[month]	*Number of month of the growth phase*
Multiplication_SD_minimum_amount_of_savings	[0.5,4]	[-]	*Variation of the standard deviation of the amount of savings required to adopt*
memory	[1,5]	[month]	*Length of the memory households have to keep information received by other households*
Degree_of_correlation_with_previous_data	[0.2,0.8]	[%]	*Degree of correlation between previous value calculated with normal distribution and current value*
variation_of_SD_normal_distribution_properties_of_households	[0.5,1.5]	[-]	*Variation of the standard deviation of the properties of households*
variation_of_SD_normal_distribution_properties_of_adopters	[0.5,1.5]	[-]	*Variation of the standard deviation of the properties of adopters*
Learning_rate_appliances_1	[0.94,0.99]	[-]	*Height of the learning rate*

Results

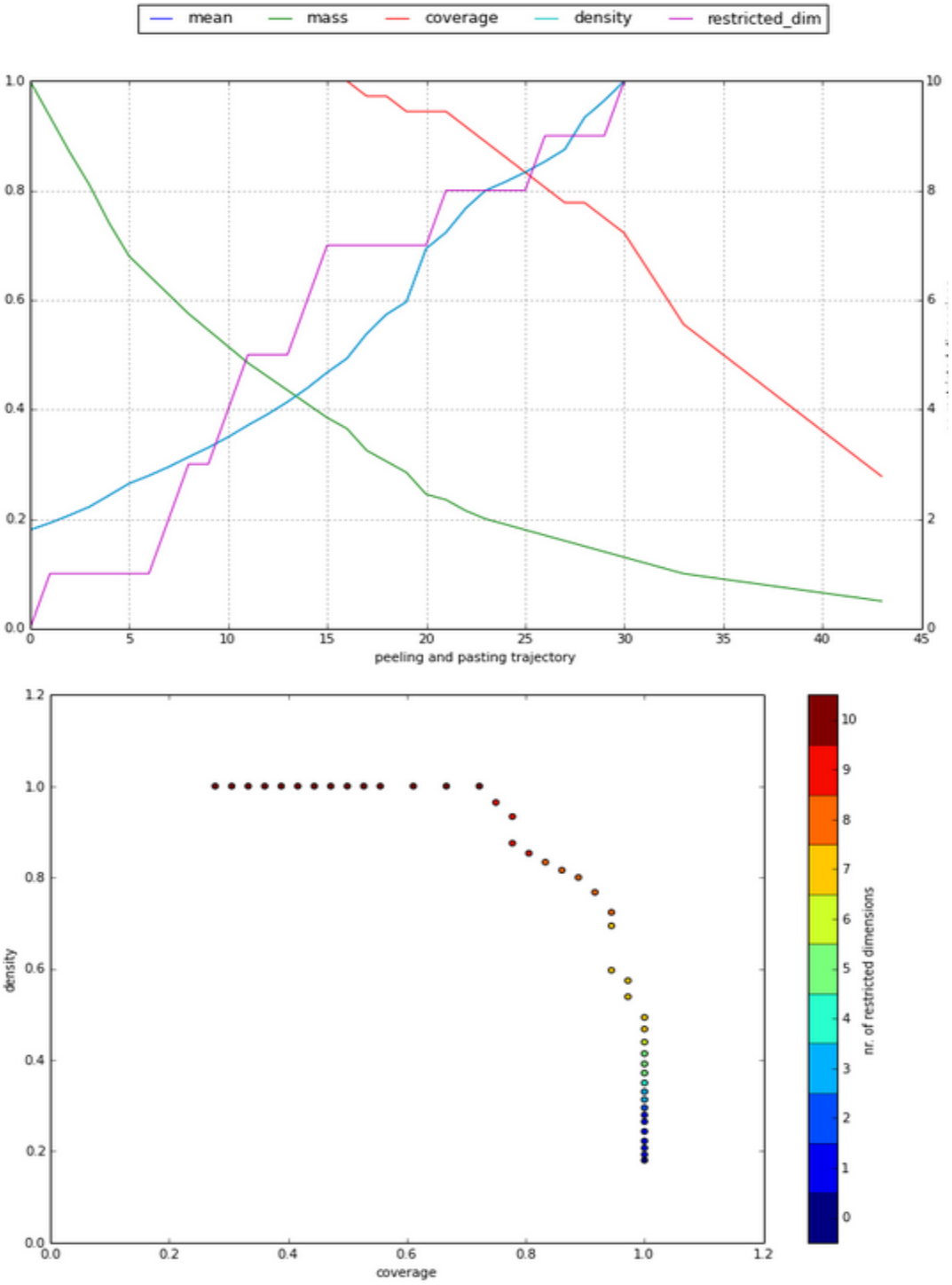


Figure 59: Experiment 1; pealing and pasting trajectories of the PRIM analysis – best cases of early adopter adoption

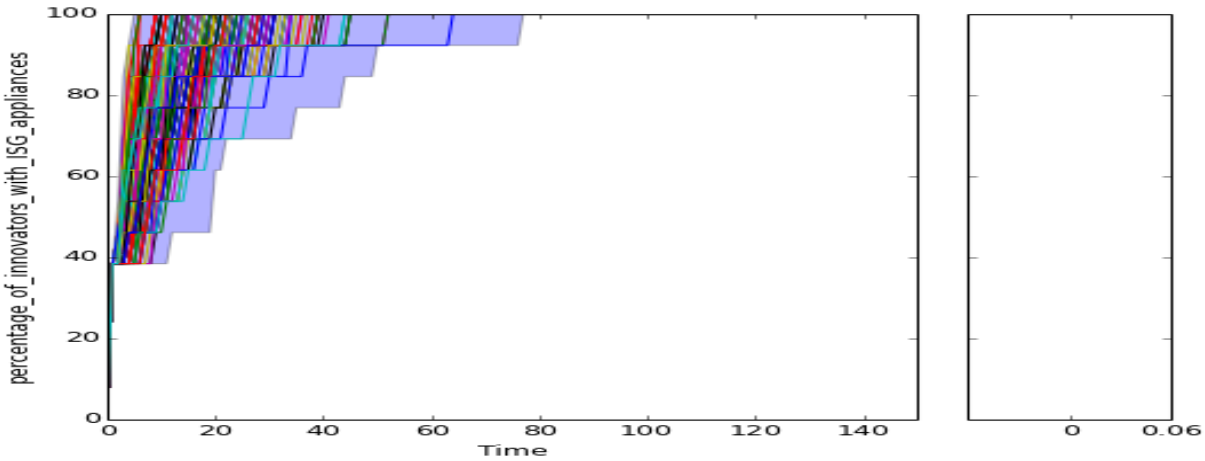


Figure 60: Experiment 1; percentage of innovators owning a smart washing machine

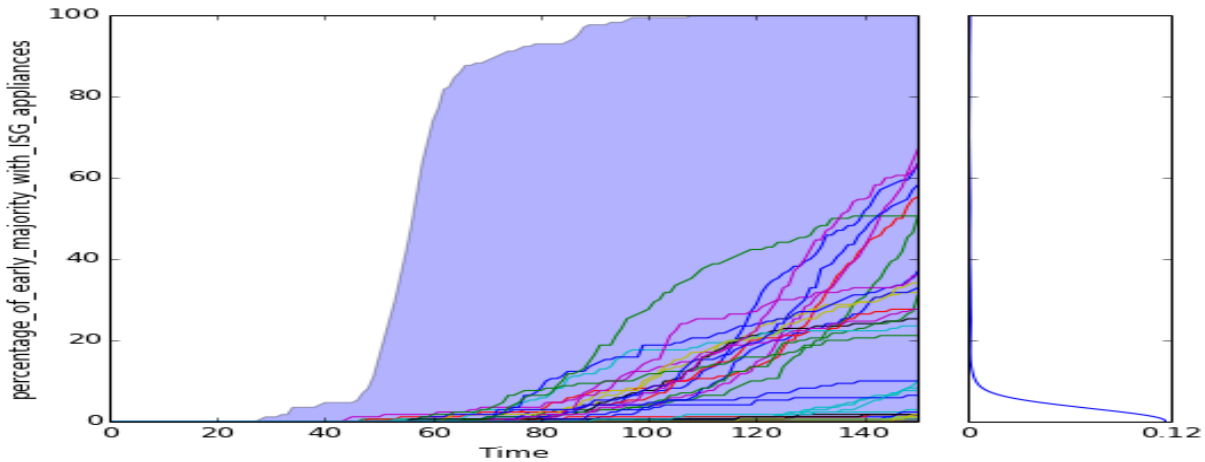


Figure 61: Experiment 1; percentage of early majority owning a smart washing machine

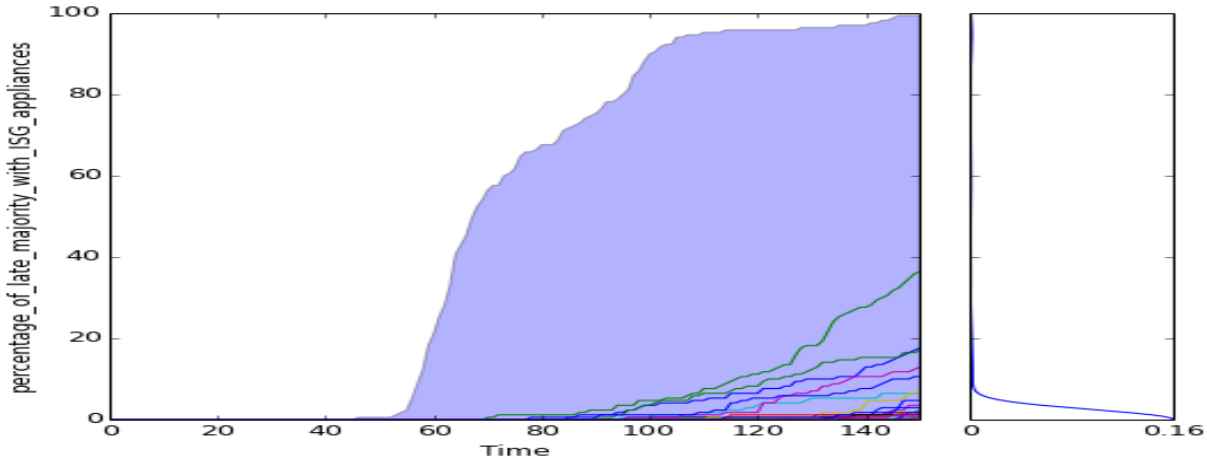


Figure 62: Experiment 1; percentage of late majority owning a smart washing machine

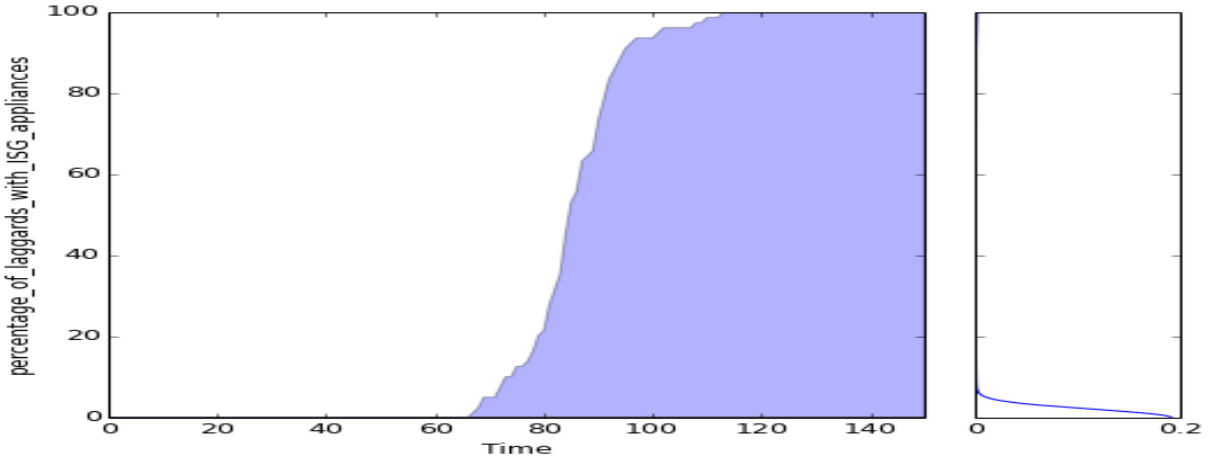


Figure 63: Experiment 1; percentage of laggards owning a smart washing machine

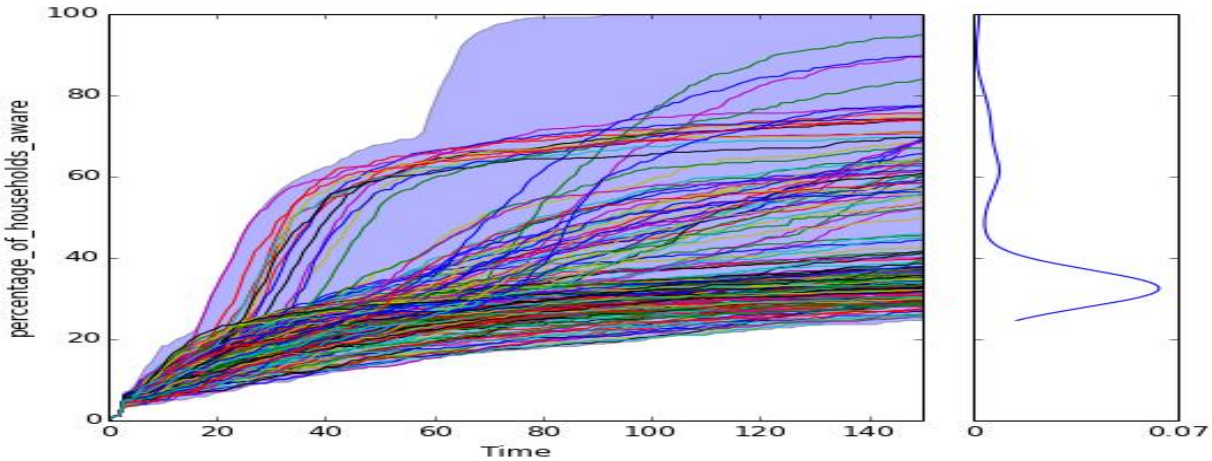


Figure 64: Experiment 1; percentage of households aware of the existence of smart washing machines

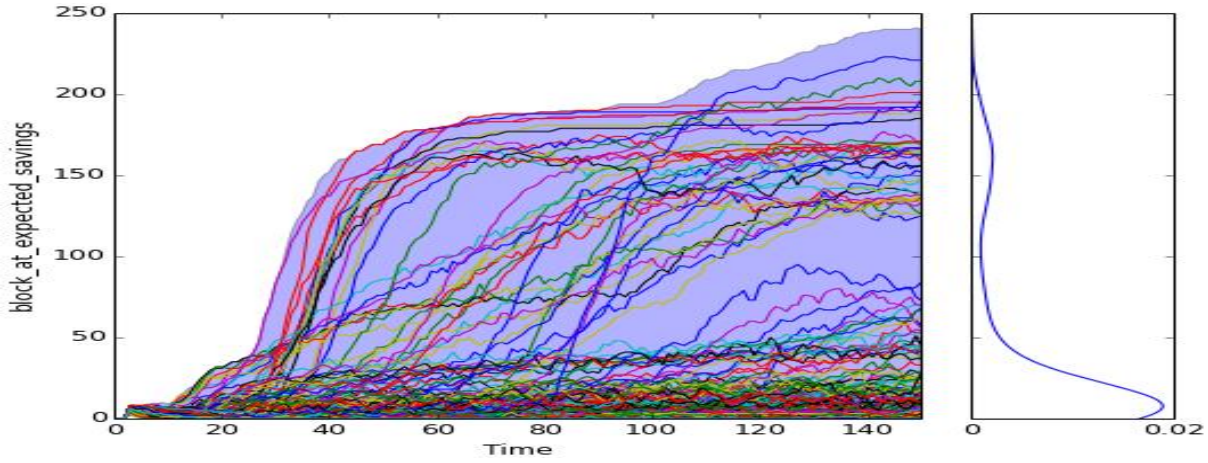


Figure 65: Experiment 1; amount of household that refuse to adopt because of the lack of savings that can be made by adopting

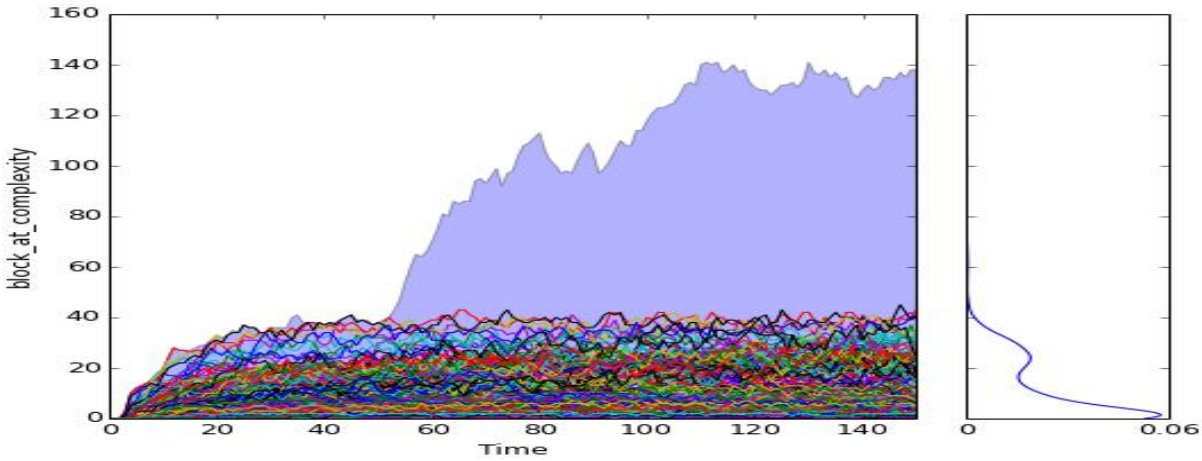


Figure 66: Experiment 1; number of households that refuse adoption because a complexity that is too high

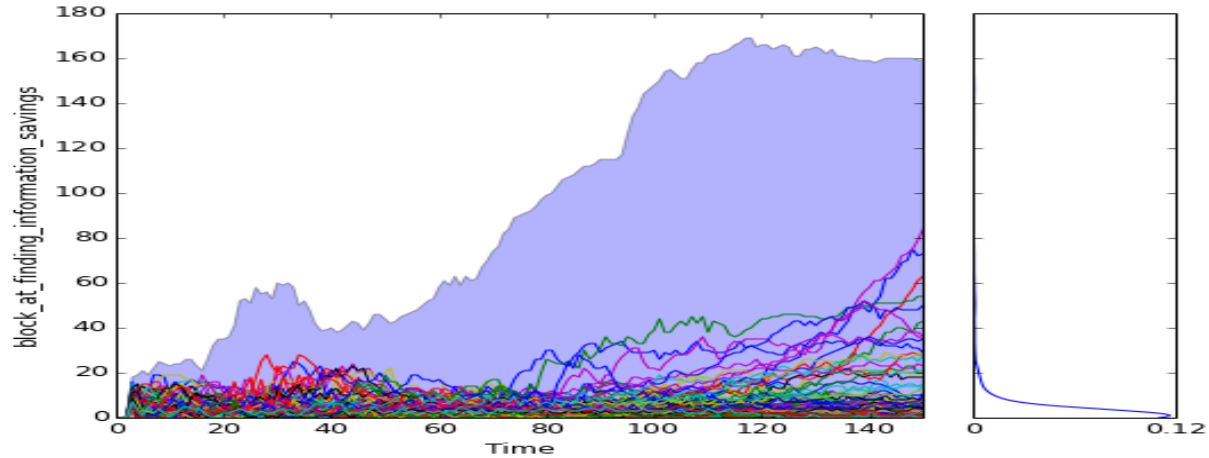


Figure 67: Experiment 1; number of households that refuse adoption because of lack of information

Experiment 2

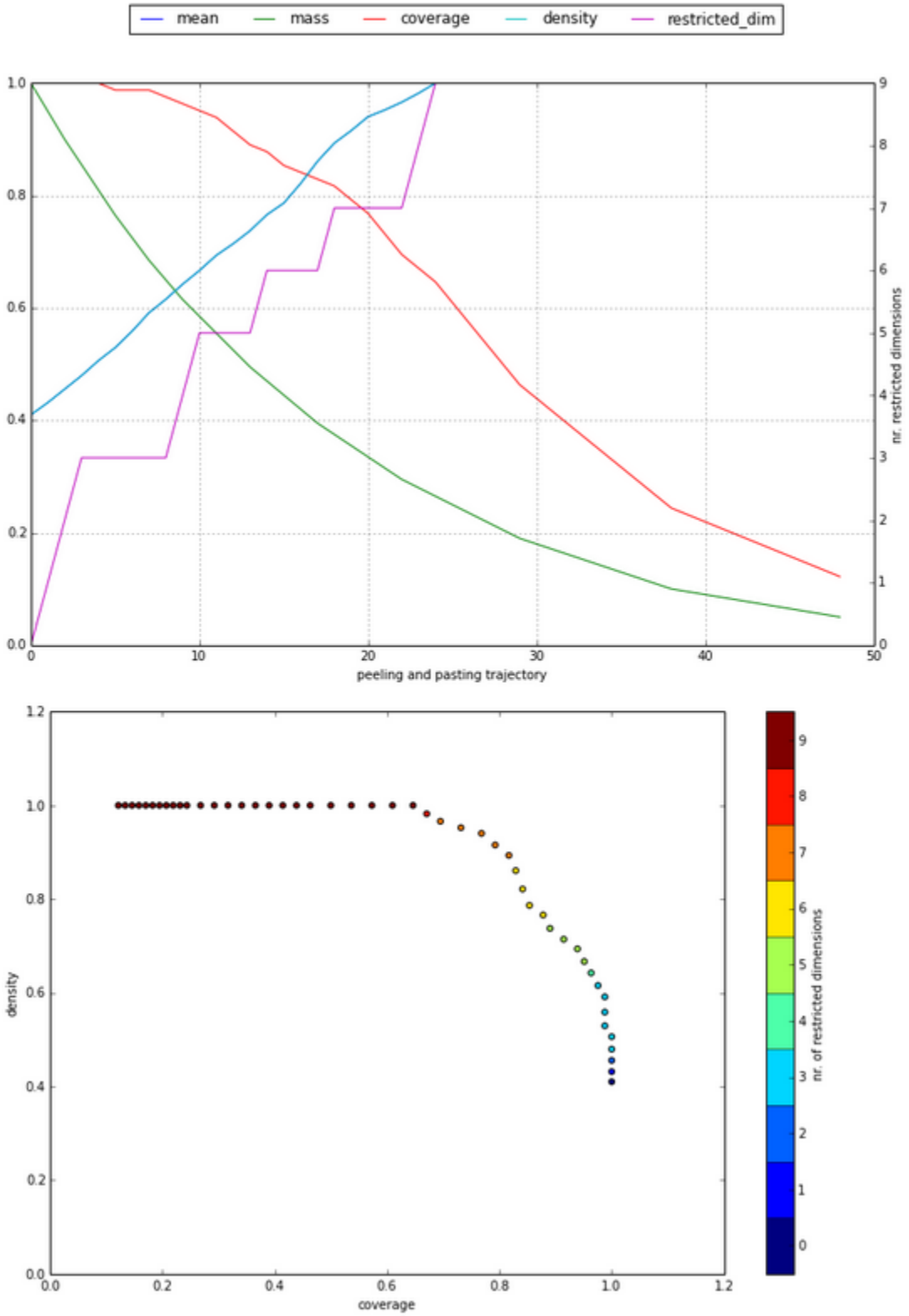


Figure 68: Experiment 2; pealing and pasting trajectories of the PRIM analysis – worst cases of household adoption

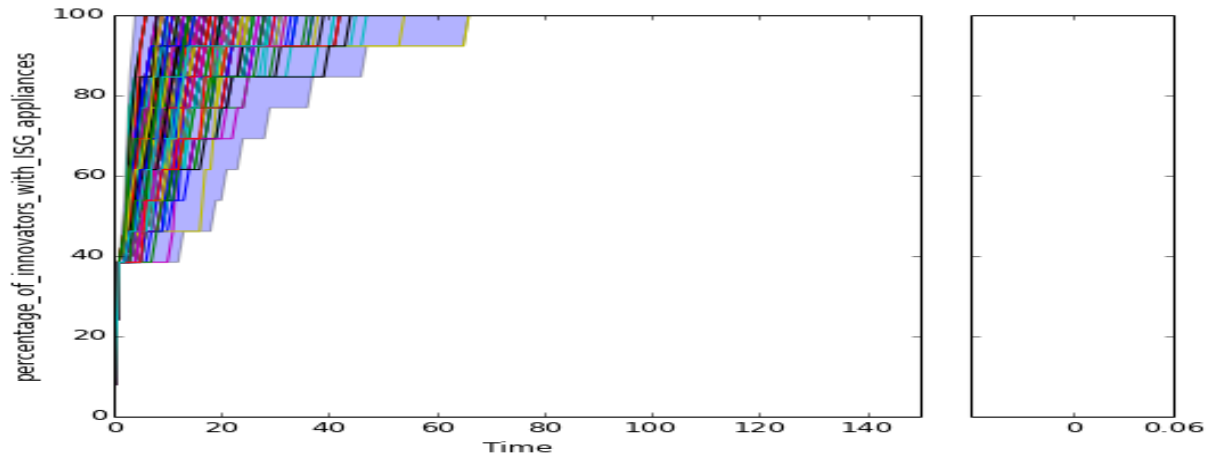


Figure 69: Experiment 2; percentage of innovators owning a smart washing machine

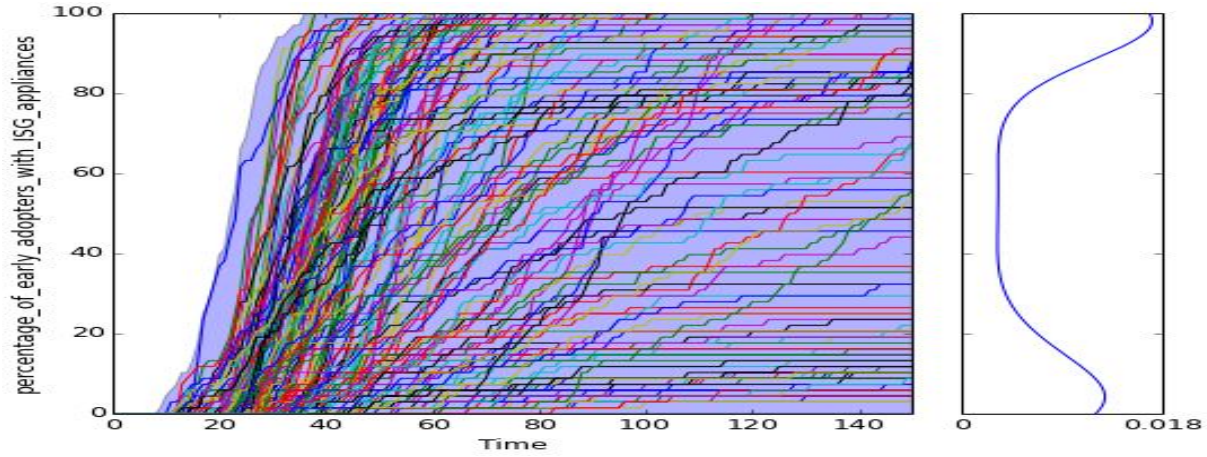


Figure 70: Experiment 2; percentage of early adopters owning a smart washing machine

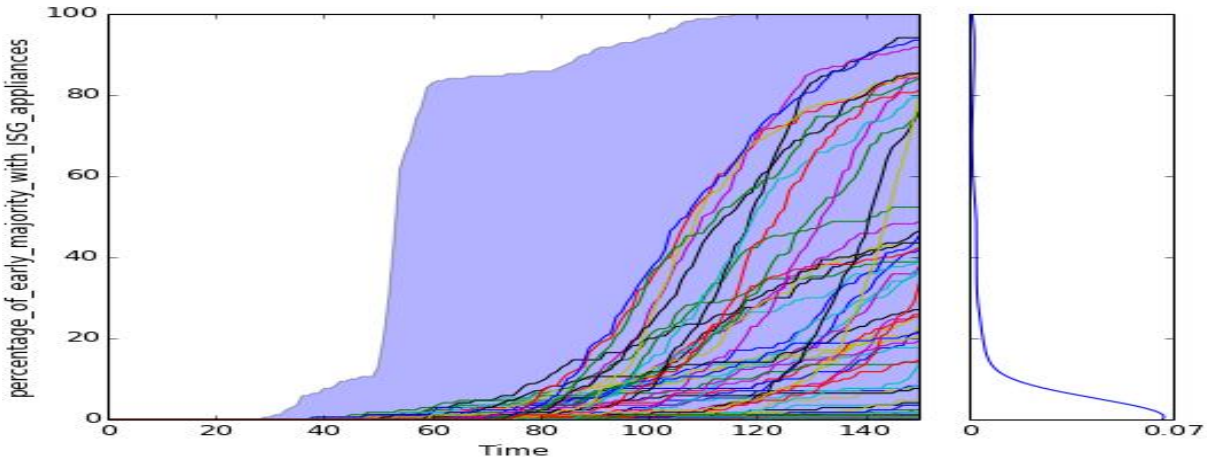


Figure 71: Experiment 2; percentage of early majority owning a smart washing machine

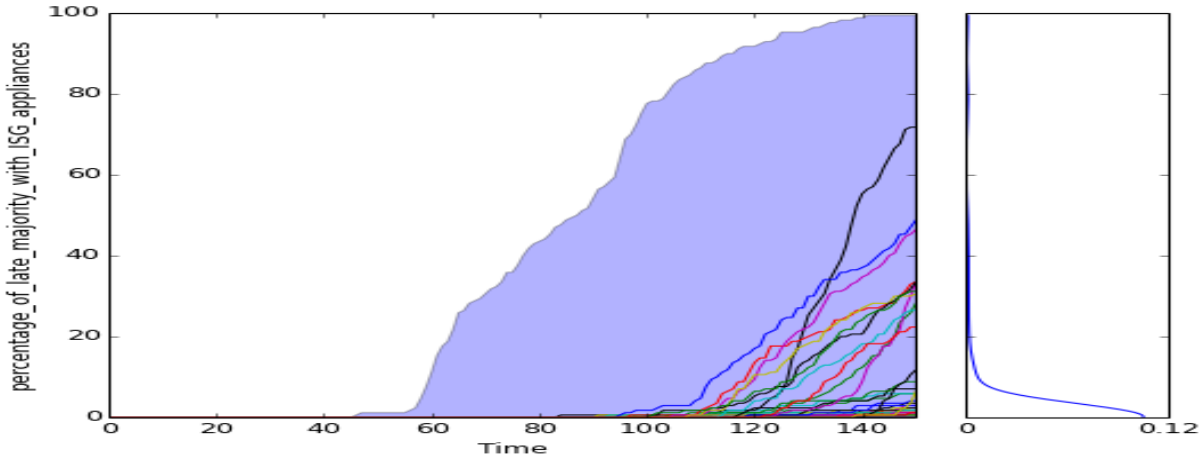


Figure 72: Experiment 2; percentage of late majority owning a smart washing machine

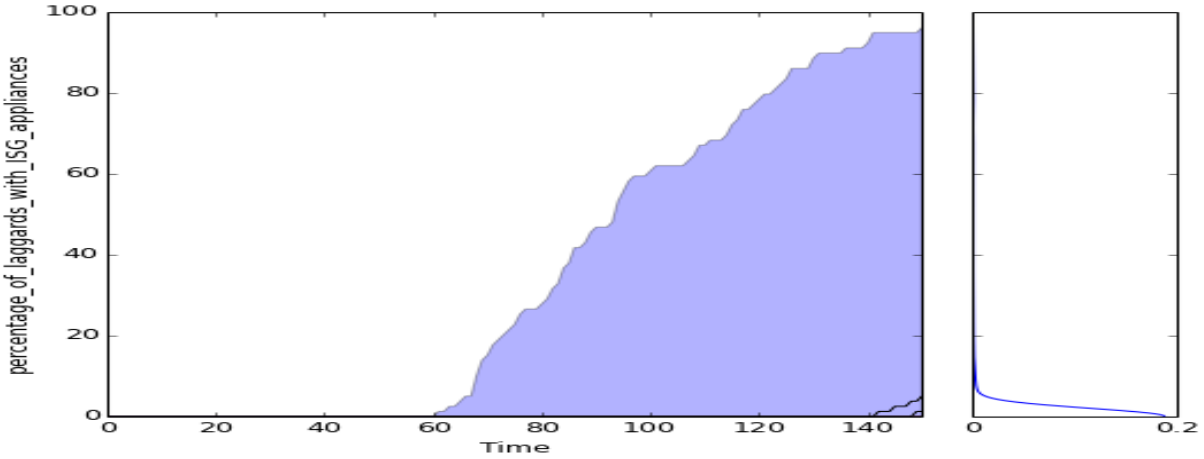


Figure 73: Experiment 2; percentage of laggards owning a smart washing machine

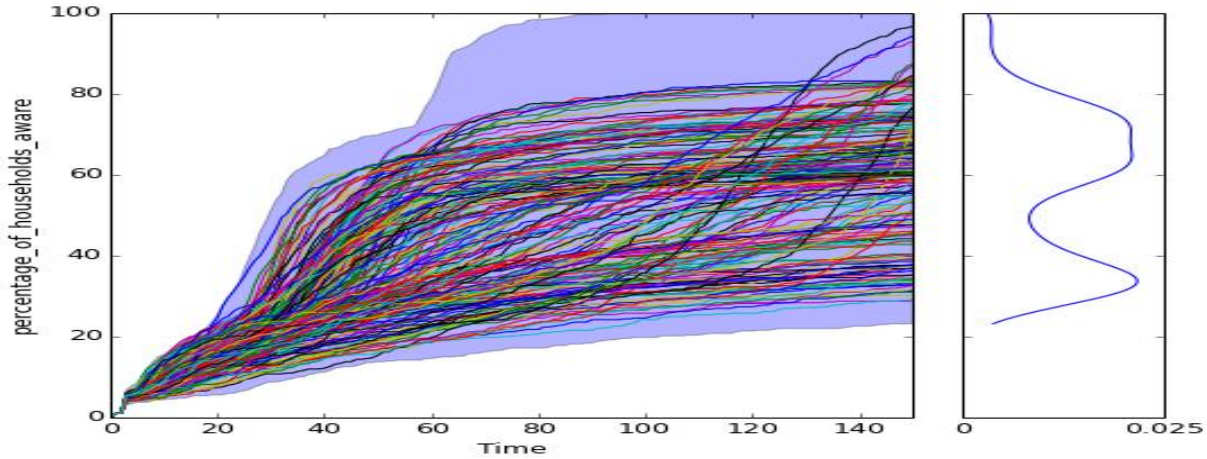


Figure 74: Experiment 2; percentage of households aware of the existence of smart washing machines

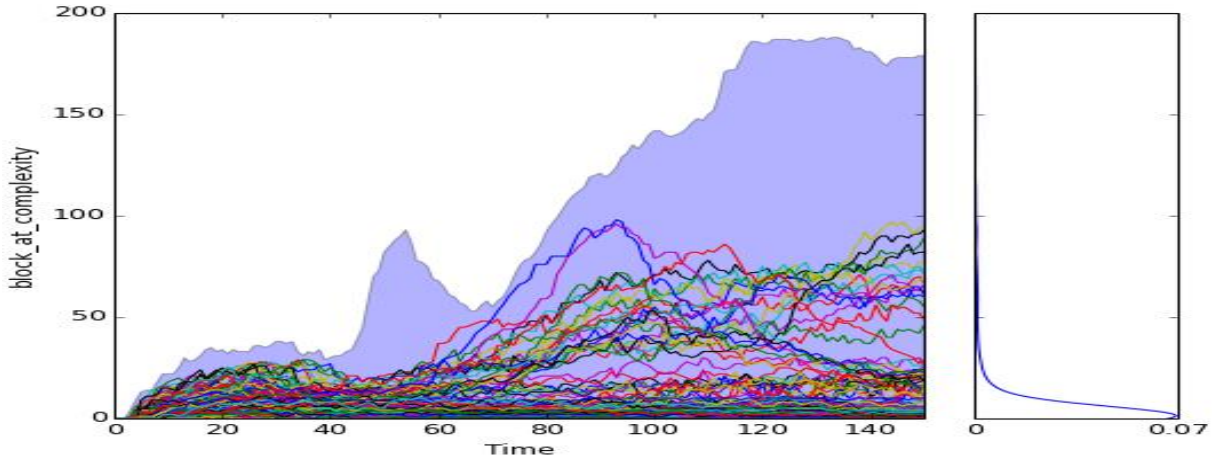


Figure 75: Experiment 2; number of households that refuse adoption because a complexity that is too high

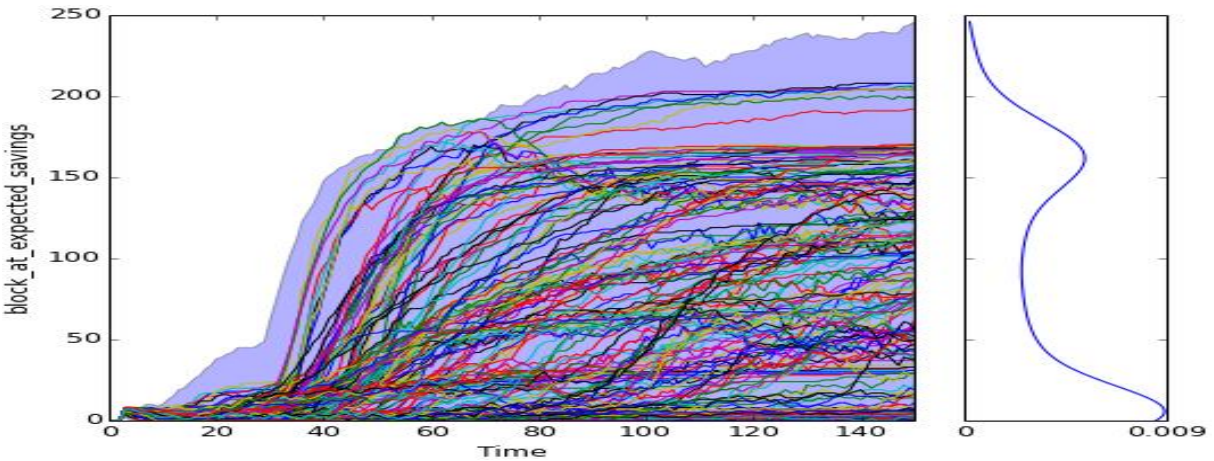


Figure 76: Experiment 2; amount of household that refuse to adopt because of the lack of savings that can be made by adopting

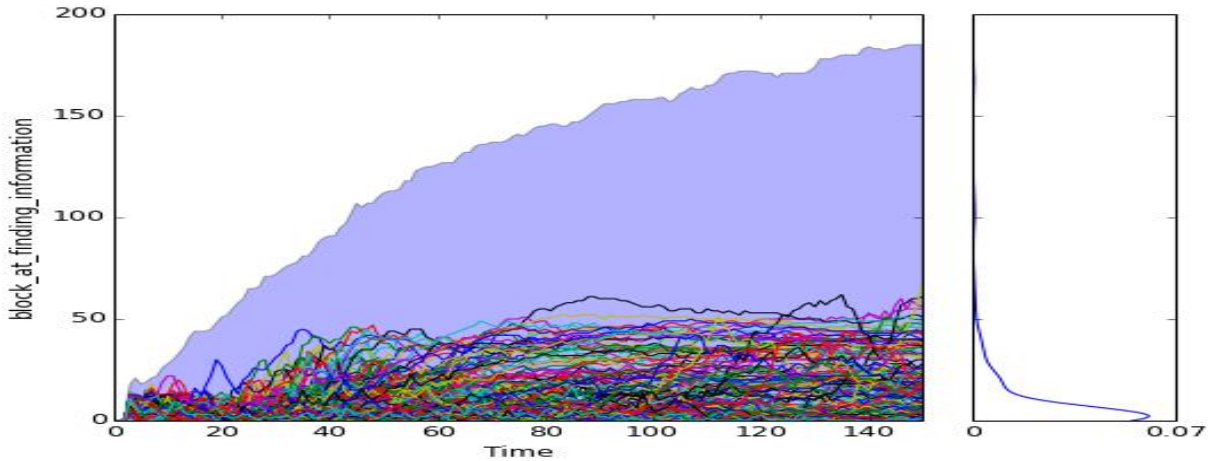


Figure 77: Experiment 2; number of households that refuse adoption because of lack of information

Experiment 3

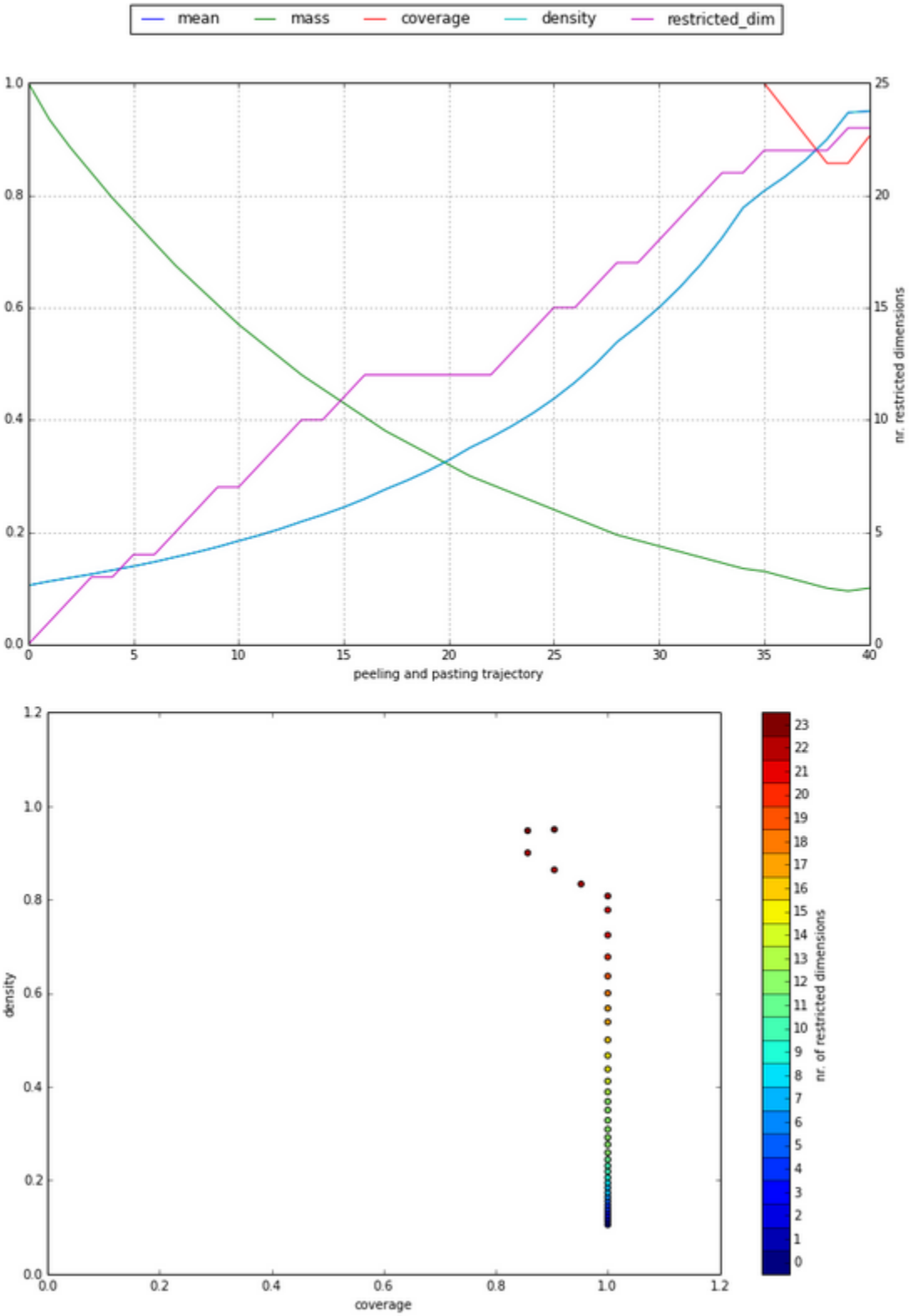


Figure 78: Experiment 3; pealing and pasting trajectories of the PRIM analysis – best cases of early majority population adoption

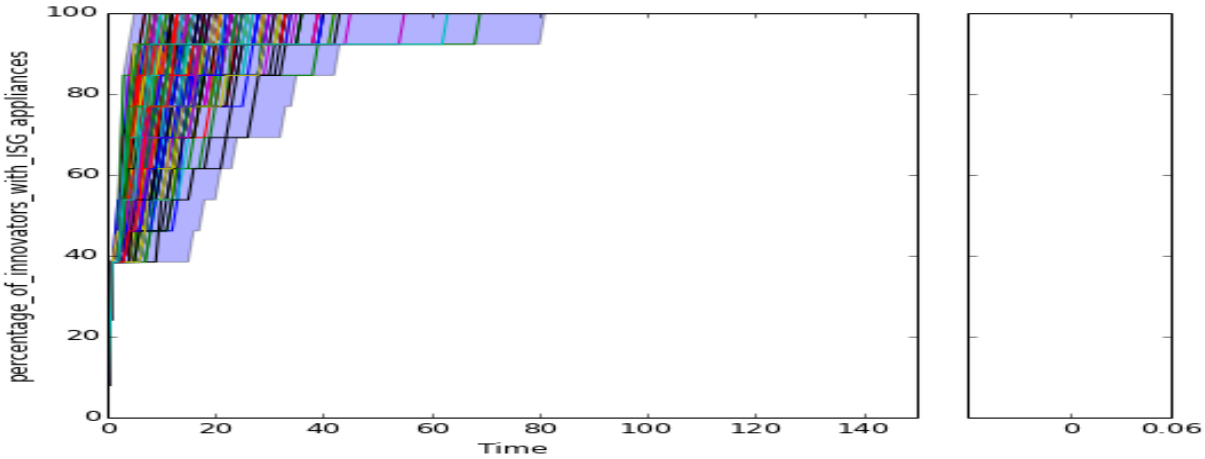


Figure 79: Experiment 3; percentage of innovators owning a smart washing machine

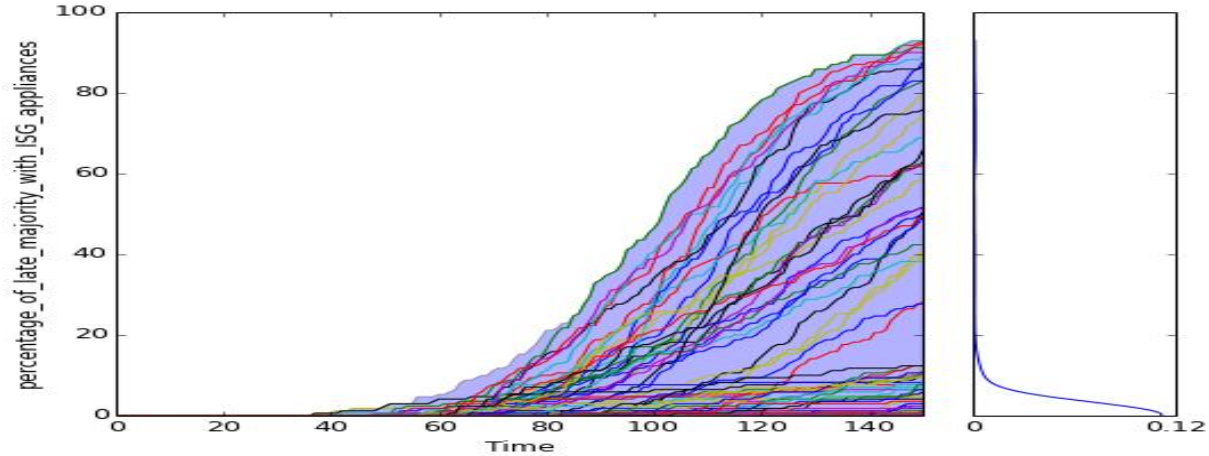


Figure 80: Experiment 3; percentage of late majority owning a smart washing machine

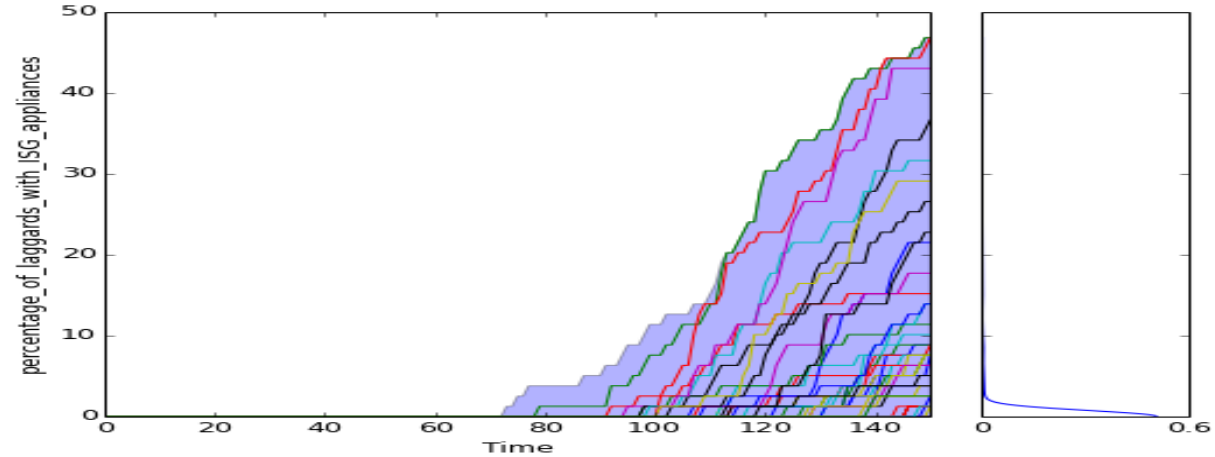


Figure 81: Experiment 3; percentage of laggards owning a smart washing machine

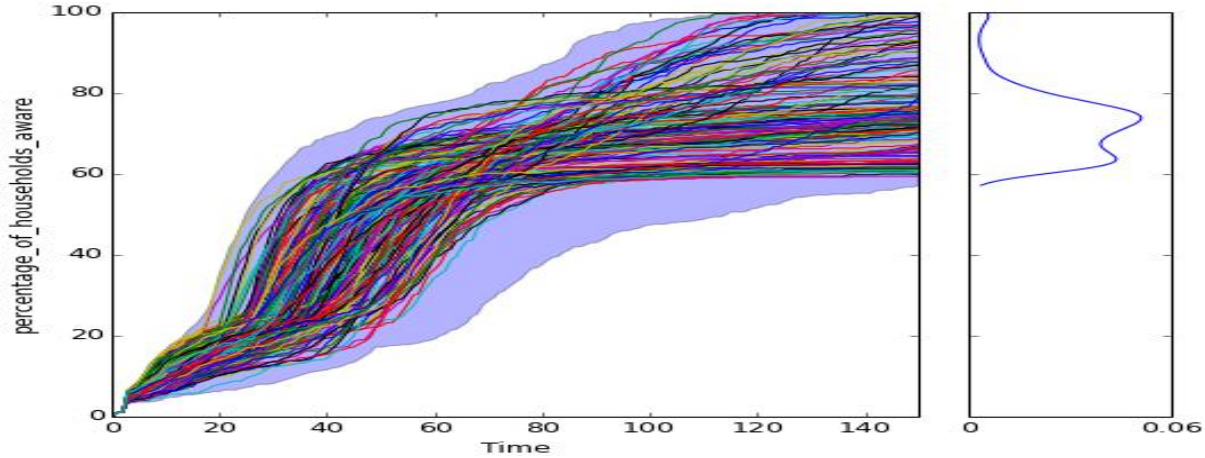


Figure 82: Experiment 3; percentage of households aware of the existence of smart washing machines

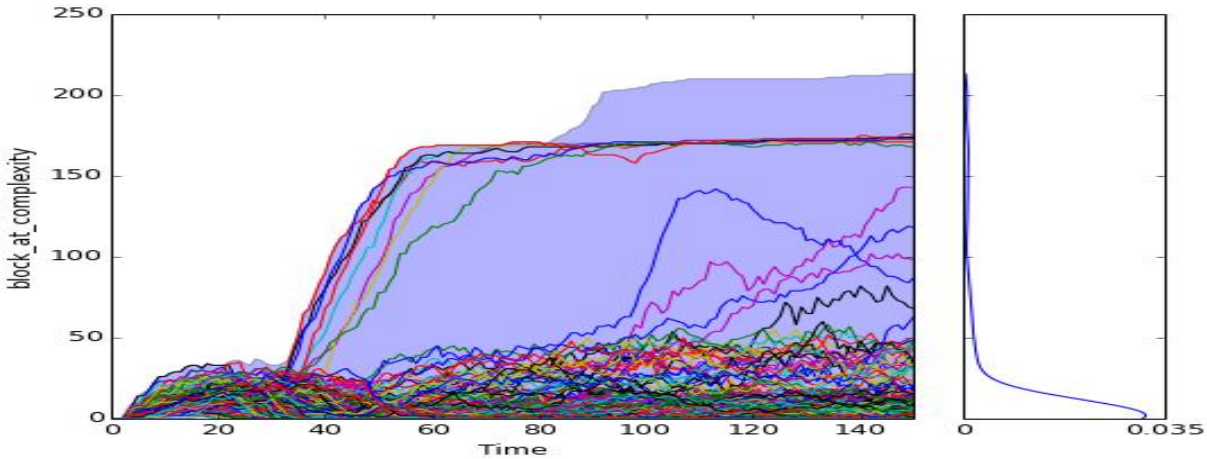


Figure 83: Experiment 3; number of households that refuse adoption because a complexity that is too high

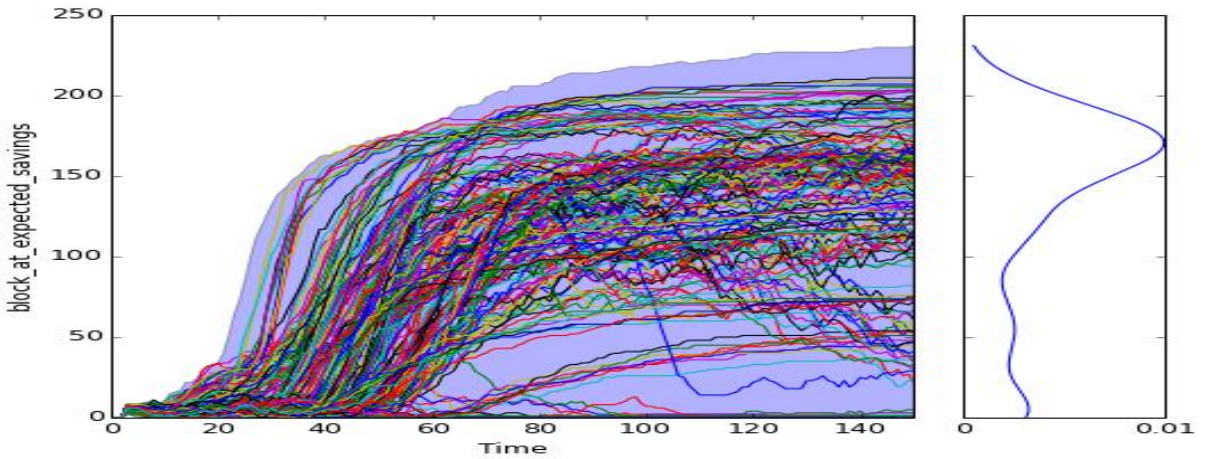


Figure 84: Experiment 3; amount of household that refuse to adopt because of the lack of savings that can be made by adopting

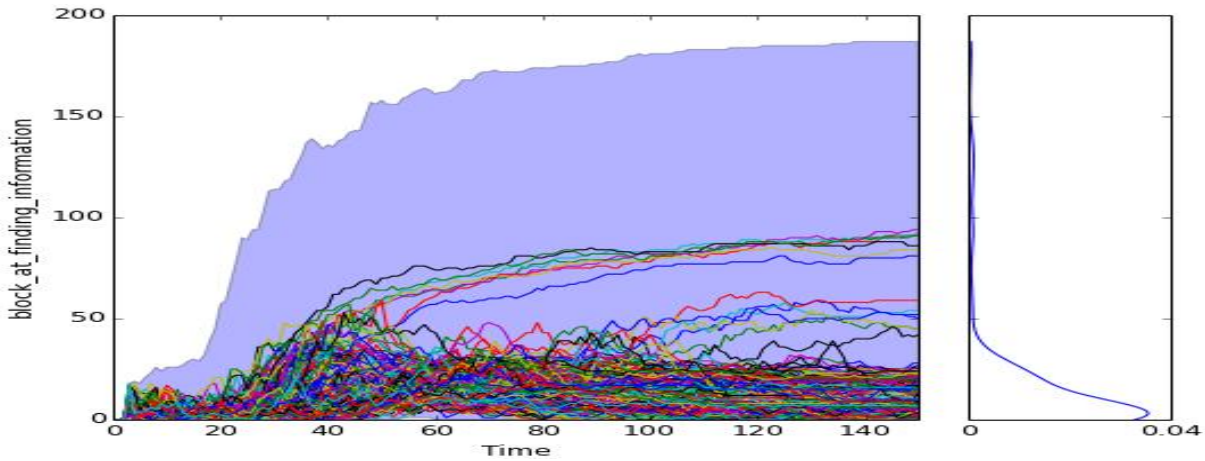


Figure 85: Experiment 3; number of households that refuse adoption because of lack of information

Experiment 4

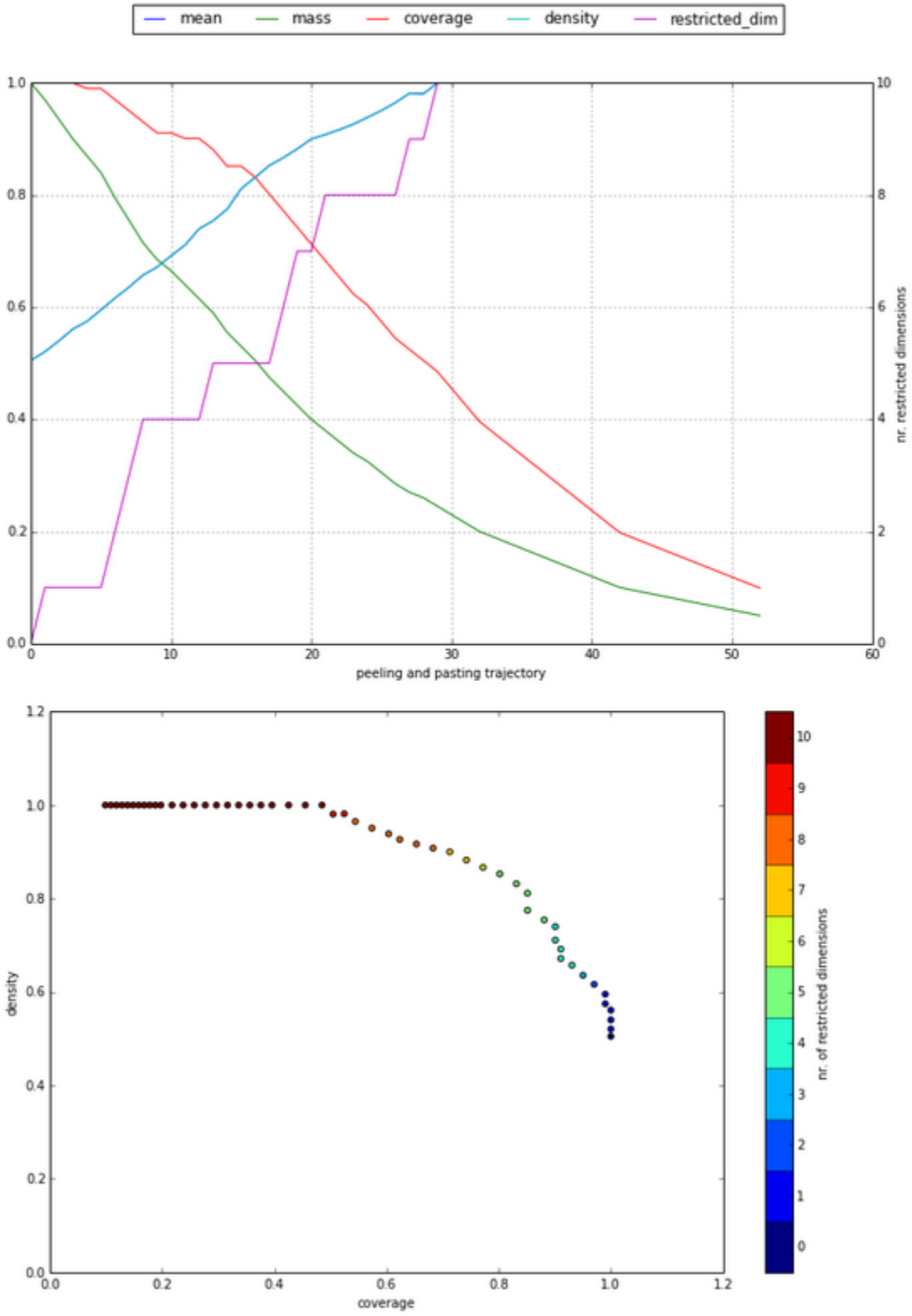


Figure 86: Experiment 4; pealing and pasting trajectories of the PRIM analysis – worst cases of household adoption n

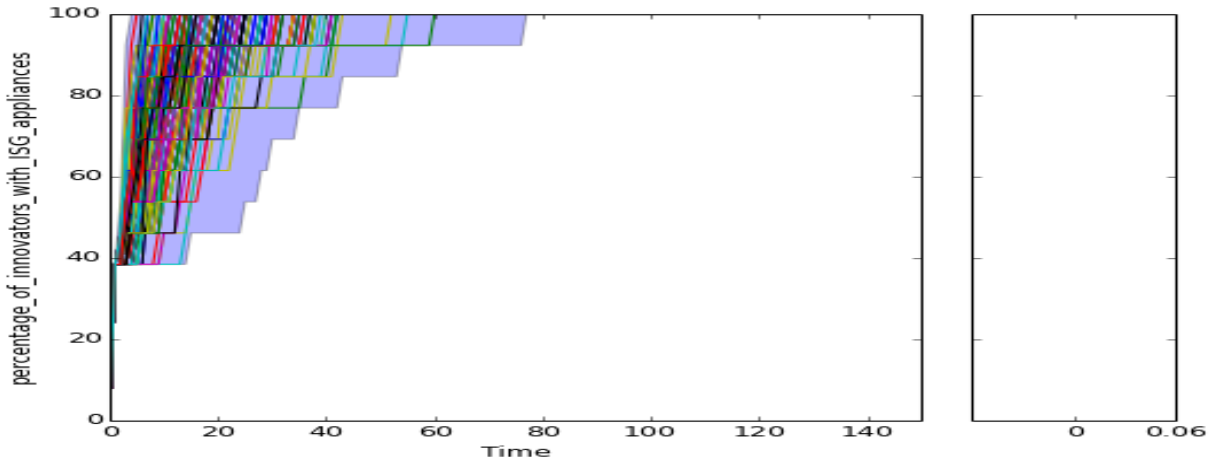


Figure 87: Experiment 4; percentage of innovators owning a smart washing machine

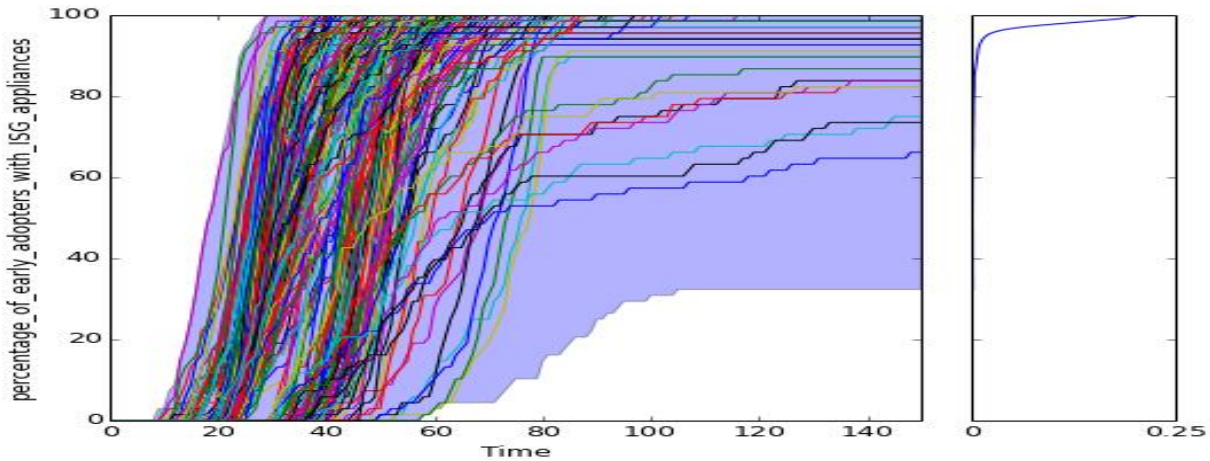


Figure 88: Experiment 4; percentage of early adopters owning a smart washing machine

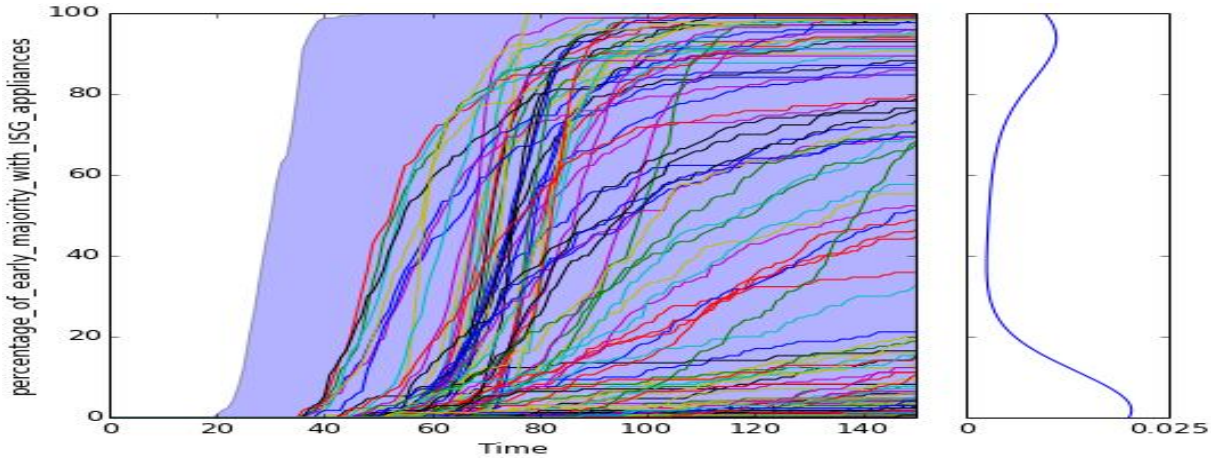


Figure 89: Experiment 4; percentage of early majority owning a smart washing machine

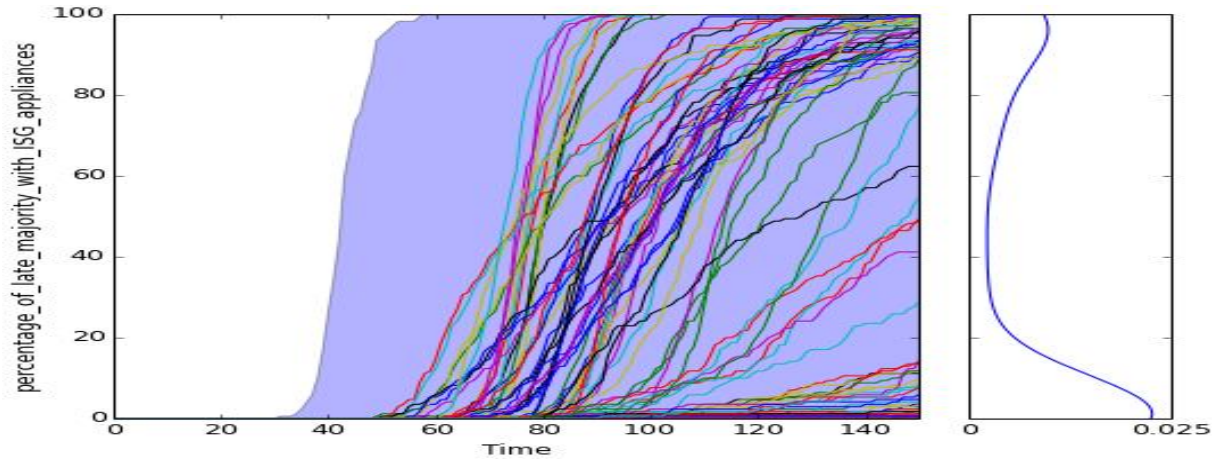


Figure 90: Experiment 4; percentage of late majority owning a smart washing machine

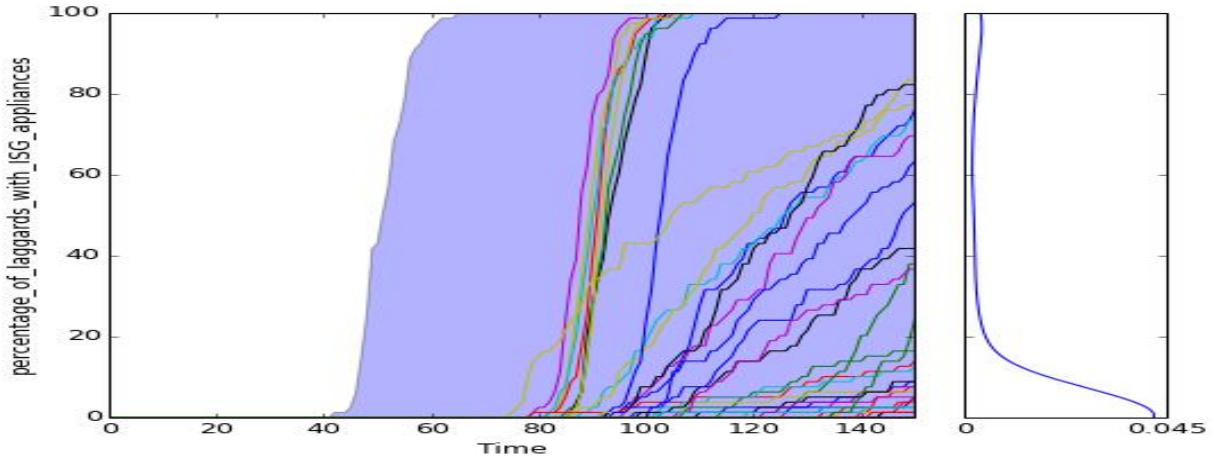


Figure 91: Experiment 4; percentage of laggards owning a smart washing machine

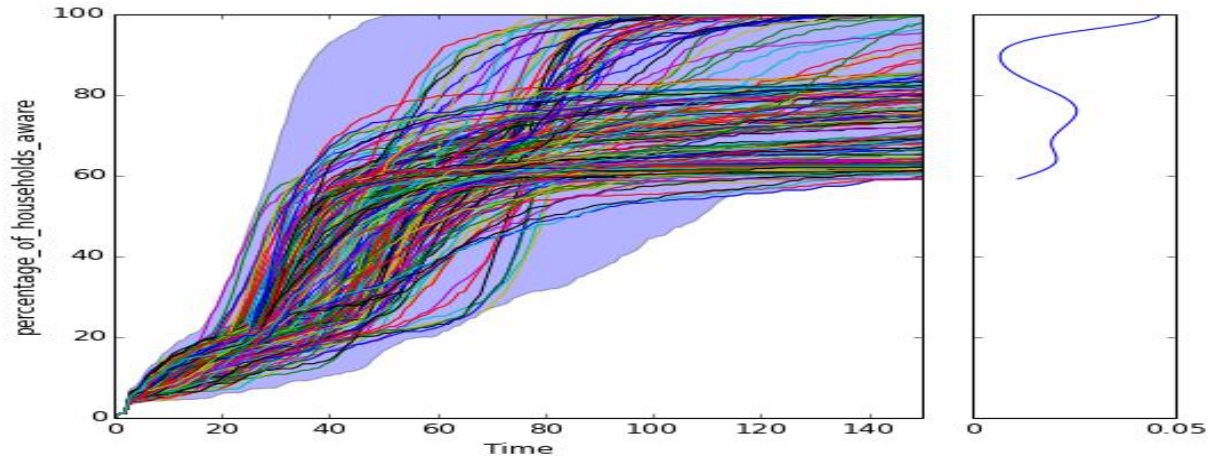


Figure 92: Experiment 4; percentage of households aware of the existence of smart washing machines

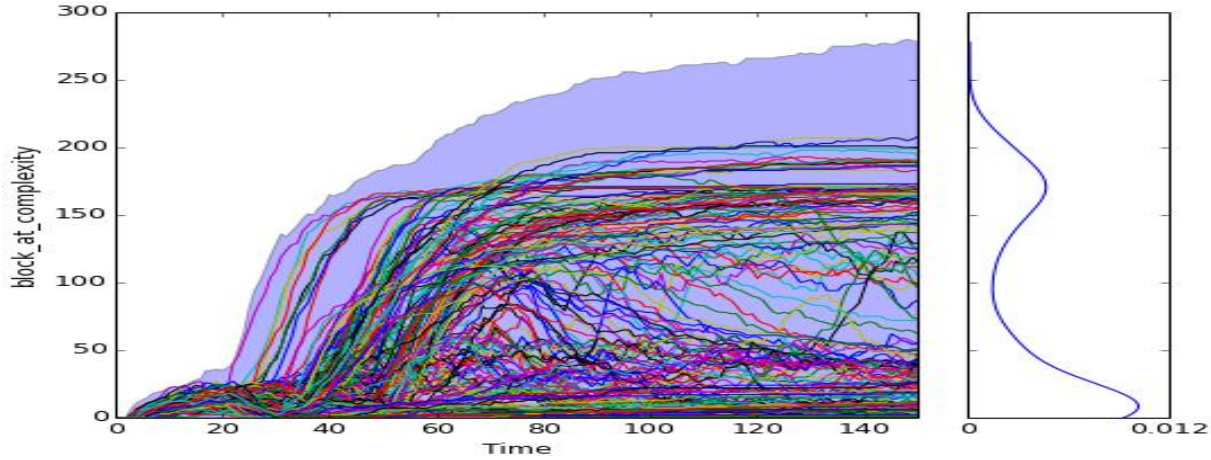


Figure 93: Experiment 4; number of households that refuse adoption because a complexity that is too high

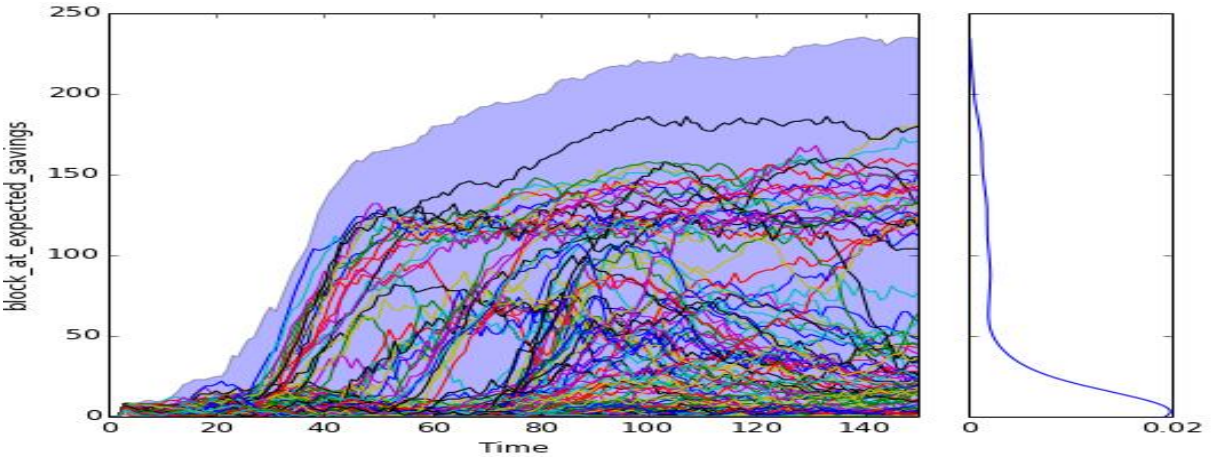


Figure 94: Experiment 4; amount of household that refuse to adopt because of the lack of savings that can be made by adopting

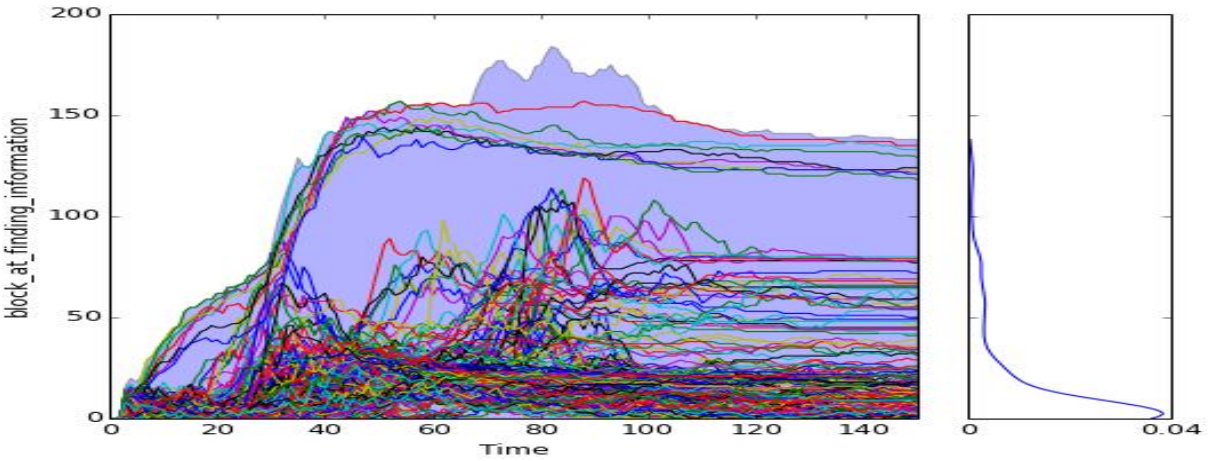


Figure 95: Experiment 4; number of households that refuse adoption because of lack of information

Experiment 5

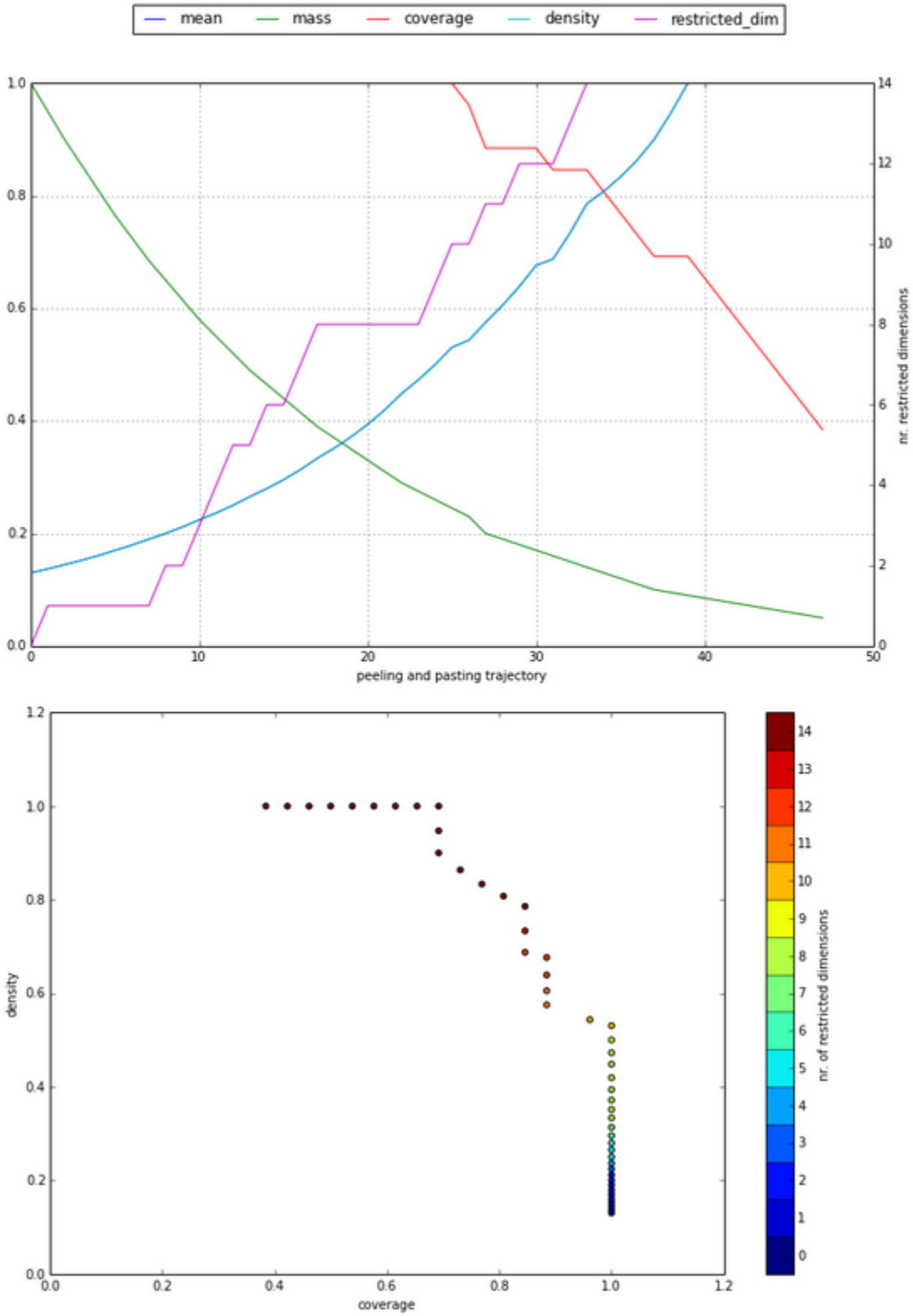


Figure 96: Experiment 5; pealing and pasting trajectories of the PRIM analysis – best cases of early majority population adoption

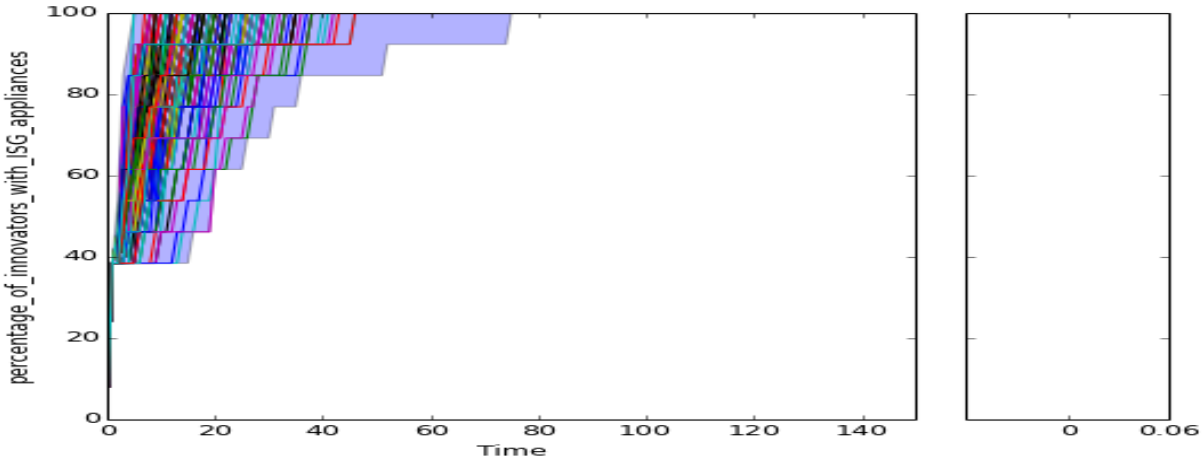


Figure 97: Experiment 5; percentage of innovators owning a smart washing machine

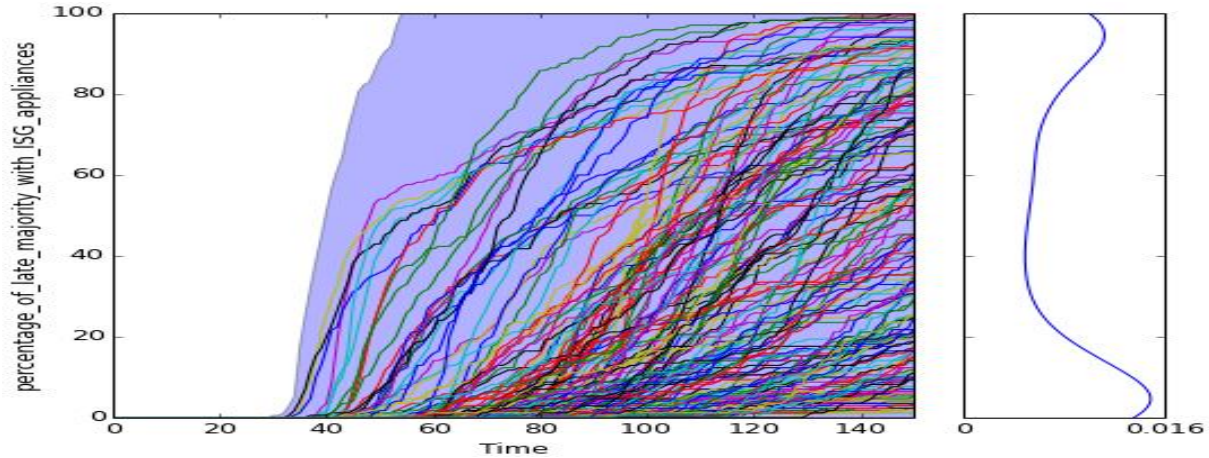


Figure 98: Experiment 5; percentage of late majority owning a smart washing machine

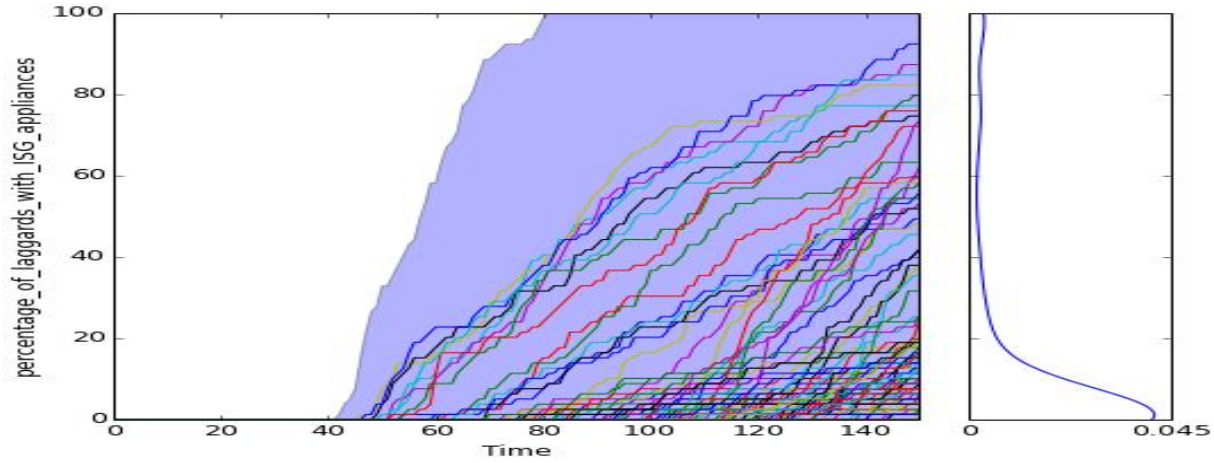


Figure 99: Experiment 5; percentage of laggards owning a smart washing machine

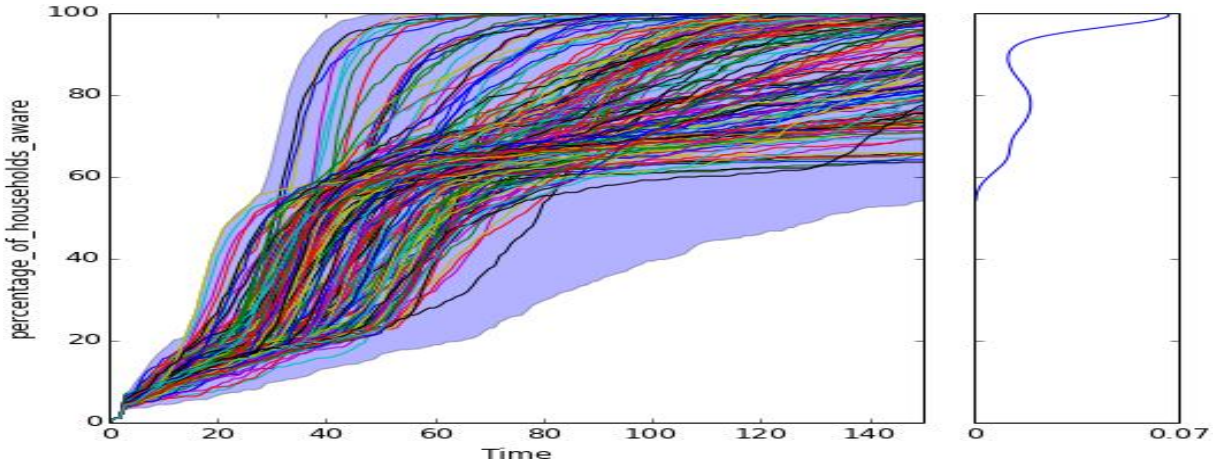


Figure 100: Experiment 5; percentage of households aware of the existence of smart washing machines

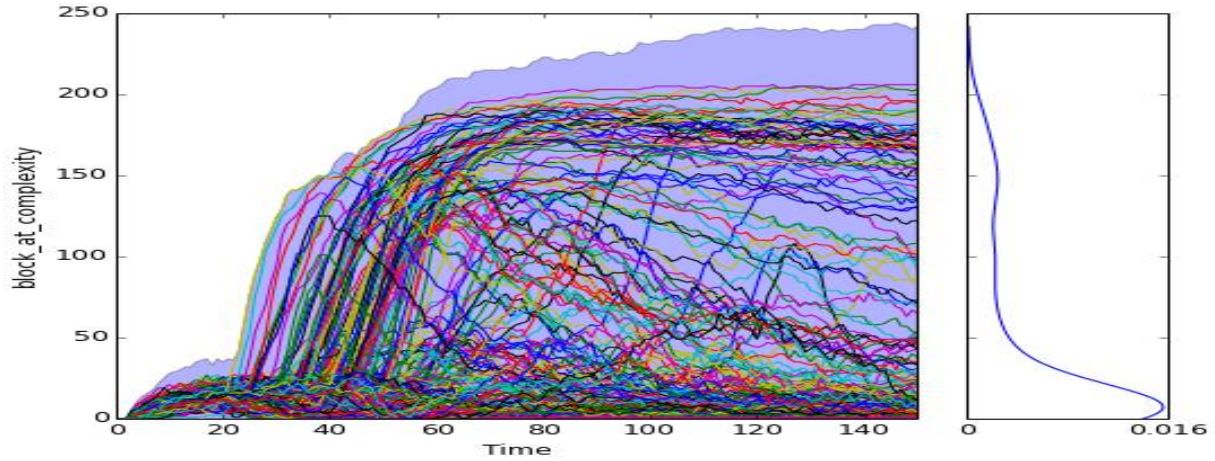


Figure 101: Experiment 5; number of households that refuse adoption because a complexity that is too high

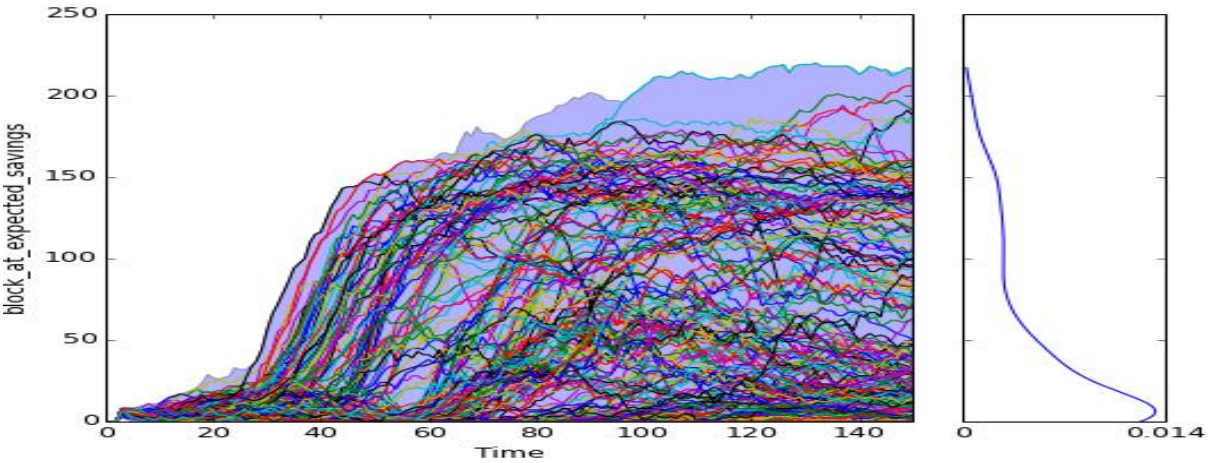


Figure 102: Experiment 5; amount of household that refuse to adopt because of the lack of savings that can be made by adopting

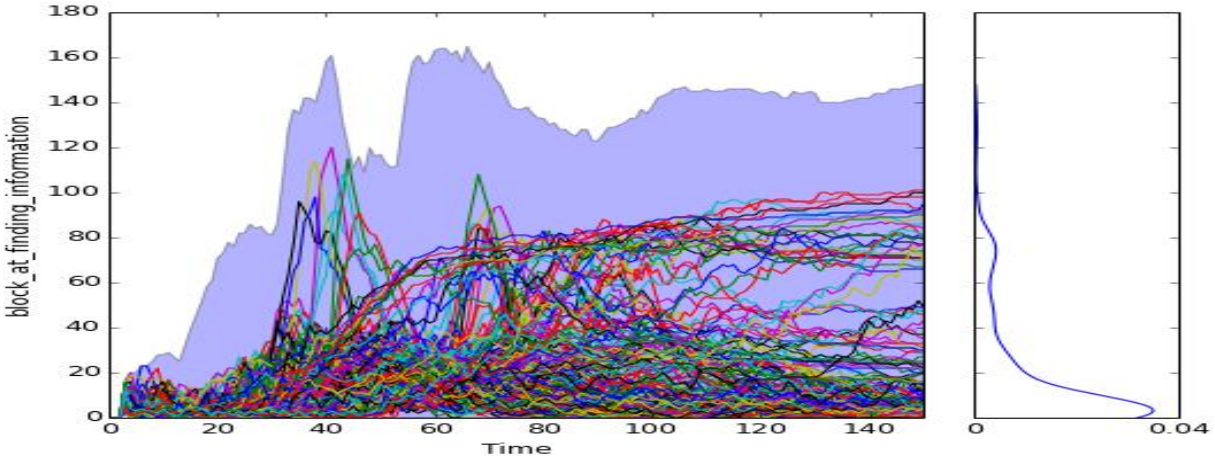


Figure 103: Experiment 5; number of households that refuse adoption because of lack of information

Experiment 6

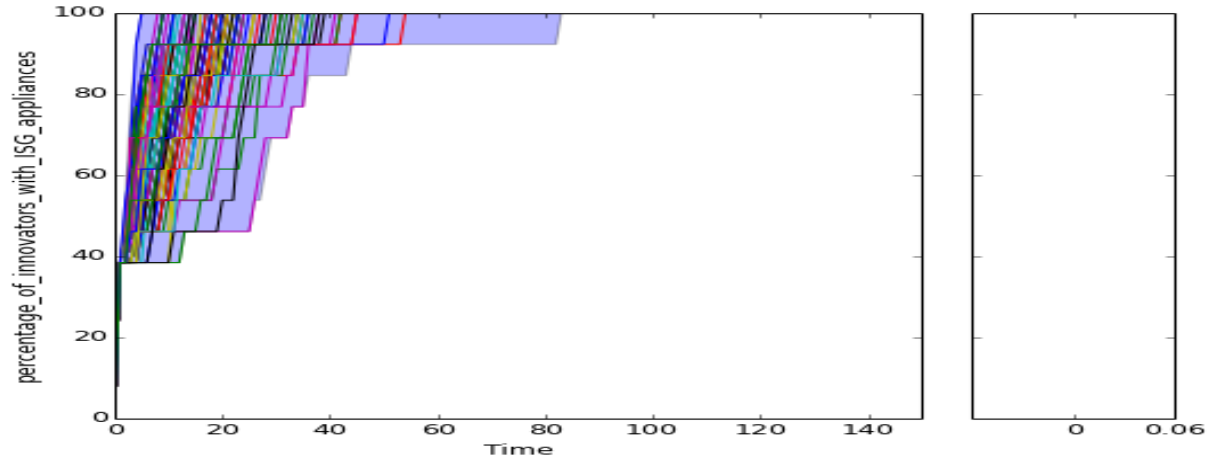


Figure 104: Experiment 6; percentage of innovators owning a smart washing machine

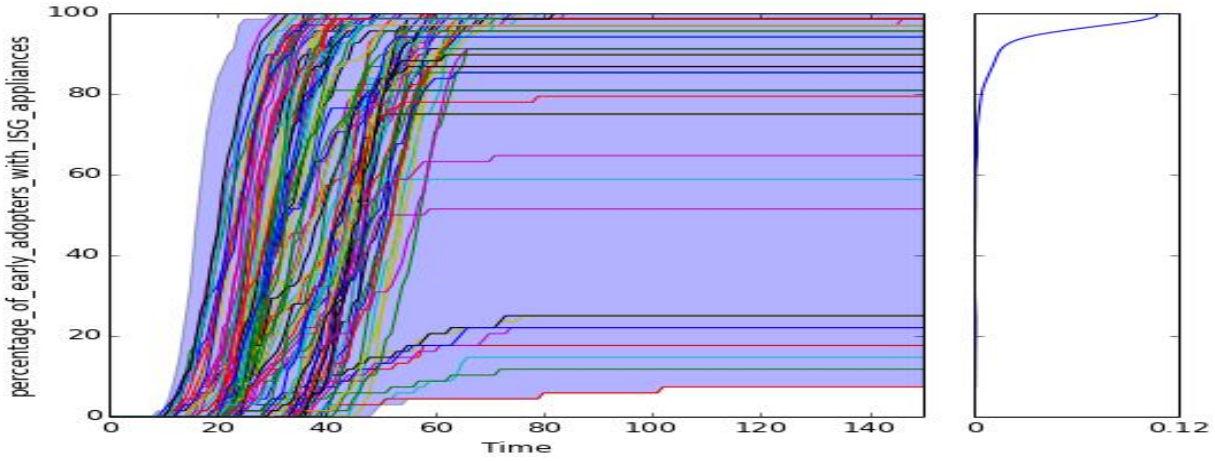


Figure 105: Experiment 6; percentage of early adopters owning a smart washing machine

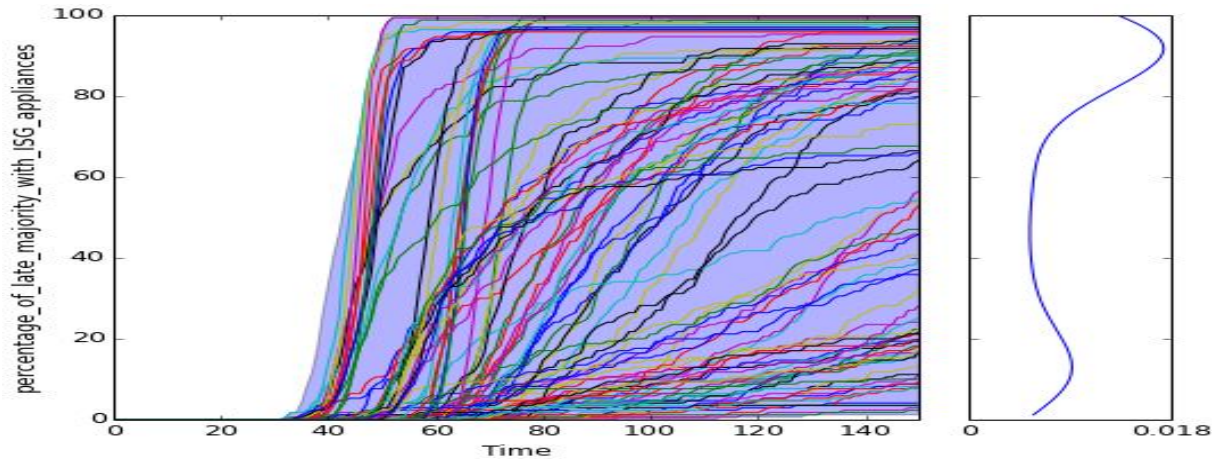


Figure 106: Experiment 6; percentage of late majority owning a smart washing machine

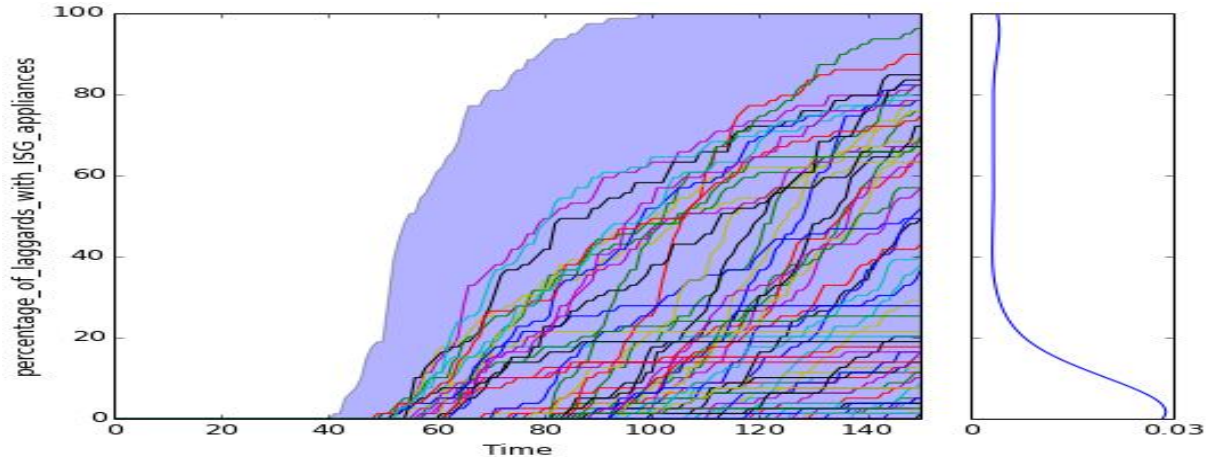


Figure 107: Experiment 6; percentage of laggards owning a smart washing machine

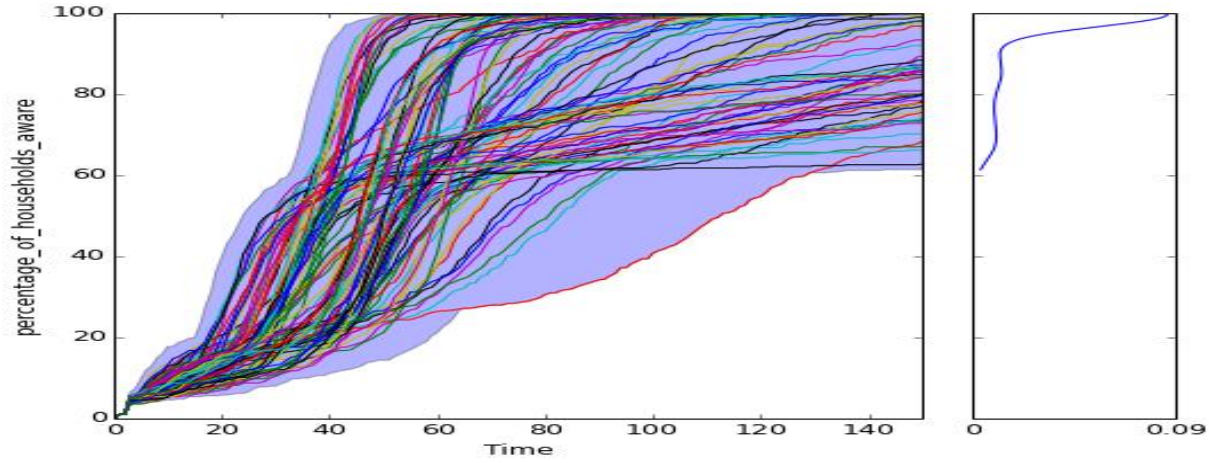


Figure 108: Experiment 6; percentage of households aware of the existence of smart washing machines

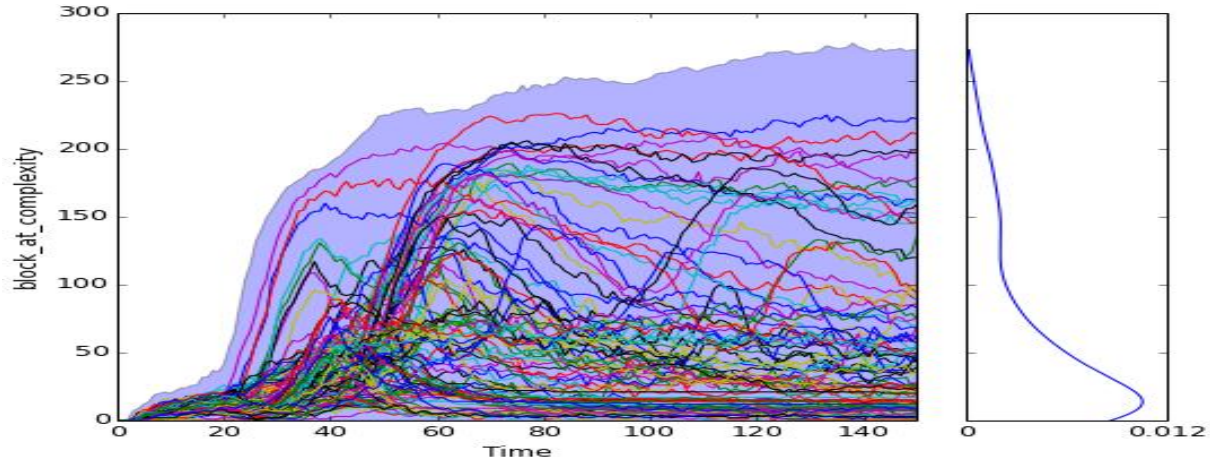


Figure 109: Experiment 6; number of households that refuse adoption because a complexity that is too high

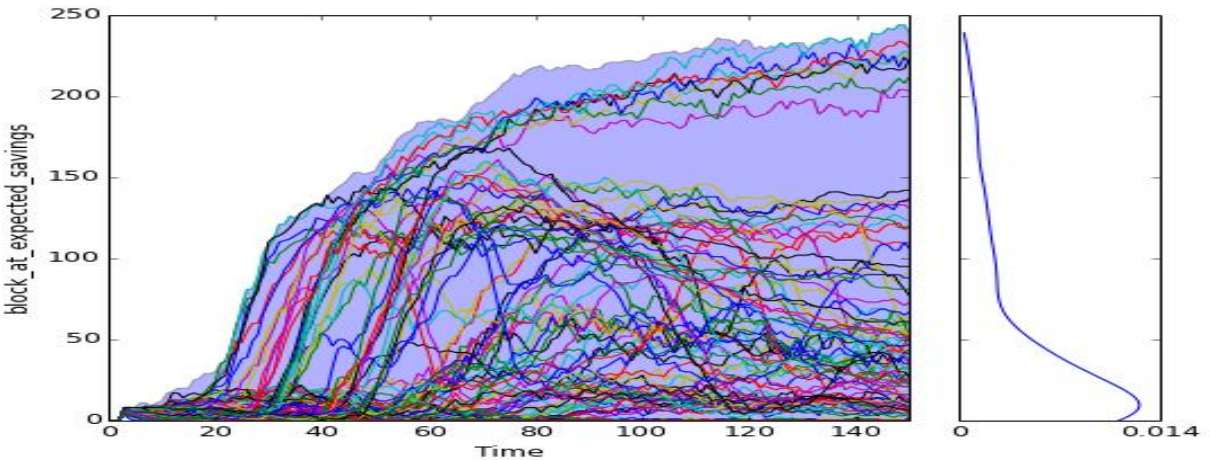


Figure 110: Experiment 6; amount of household that refuse to adopt because of the lack of savings that can be made by adopting

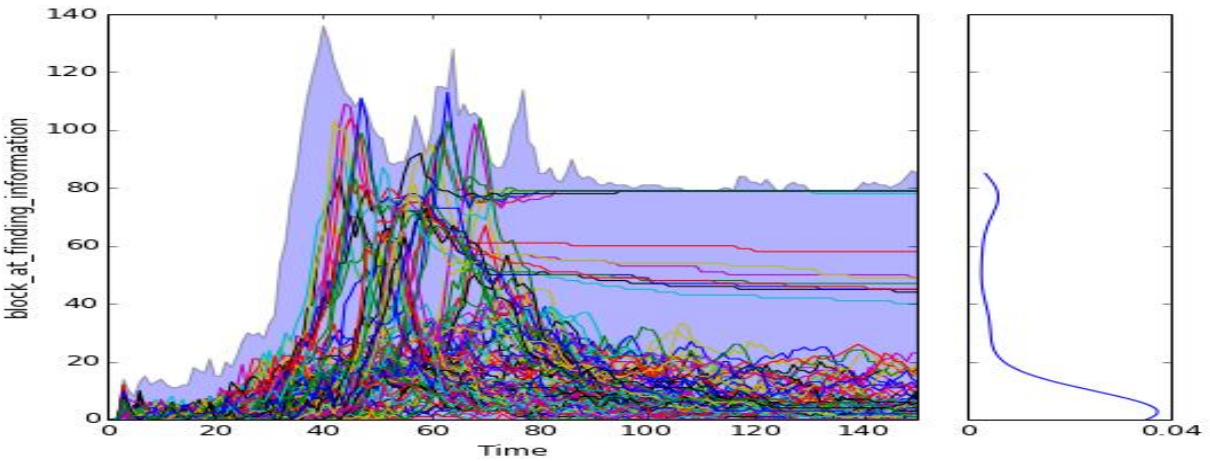


Figure 111: Experiment 6; number of households that refuse adoption because of lack of information

Experiment 1 of continuous adoption complexity decrease

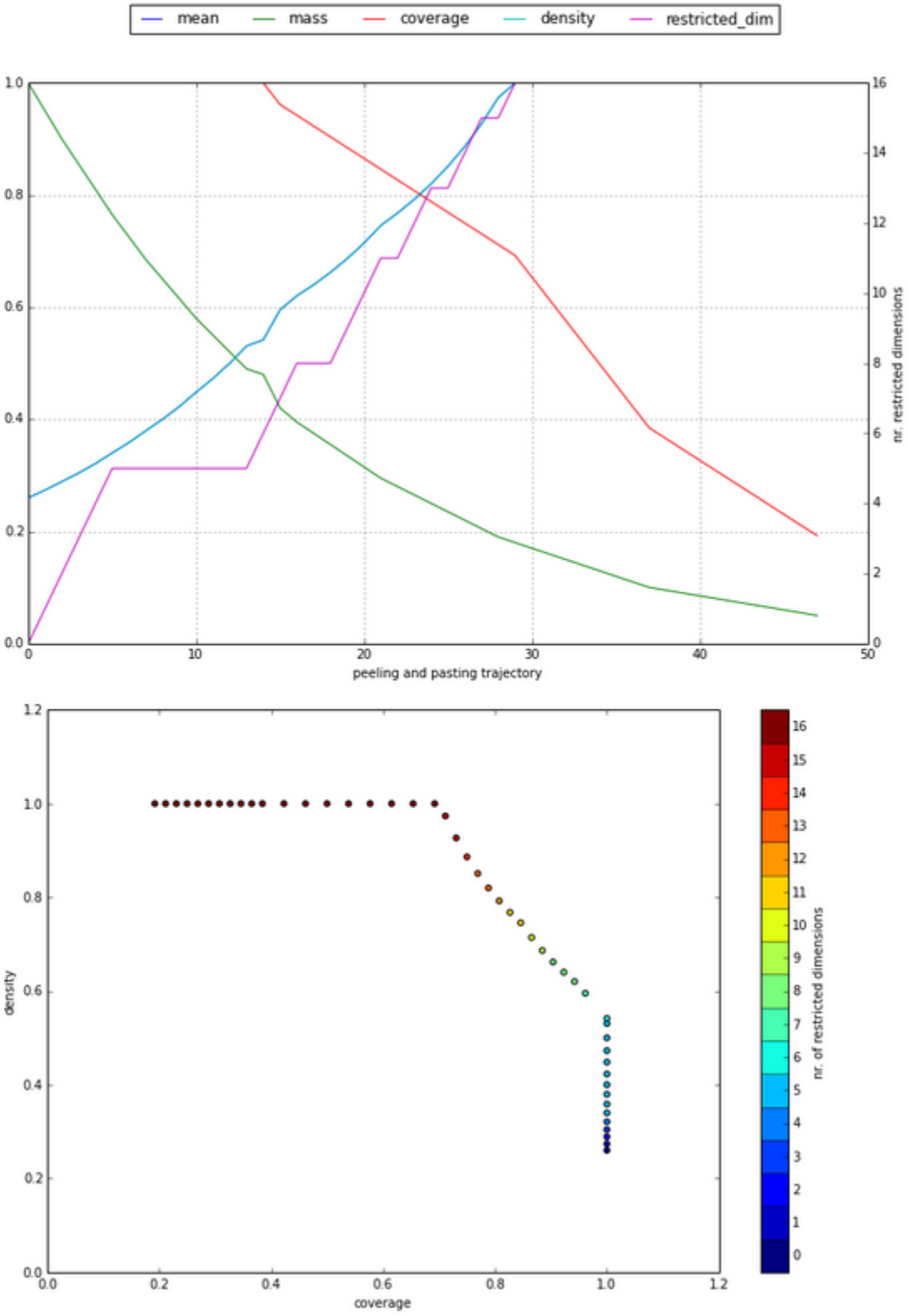


Figure 112: Experiment 1 of continuous adoption complexity decrease - pealing and pasting trajectories of the PRIM analysis; worst cases of household adoption

Appendix G Methodological analysis

Parameter settings

Table 61: Parameter settings of methodological analysis (all parameters)

Parameter settings			
Variable	**Value**	**Unit**	***Note***
electricity_price_offpeak_fix	0.25	[€/KWh]	*Electricity price during off-peak hours*
difference_between_peak_and_offpeak_price	0.40	[€/KWh]	*Difference in of electricity price between off-peak and peak hours*
division_effect_media	10	[-]	*How many an interaction with media is valued less than an interaction with one household*
A_S_L_preferred_information_source_innovator_1	0.75	[-]	*Innovators' valuation of an information given by an innovator*
A_S_L_preferred_information_source_innovator_2	0	[-]	*Innovators' valuation of an information given by an early adopter*
A_S_L_preferred_information_source_innovator_3	0	[-]	*Innovators' valuation of an information given by an early majority*
A_S_L_preferred_information_source_innovator_4	0	[-]	*Innovators' valuation of an information given by an late majority*
A_S_L_preferred_information_source_innovator_5	0	[-]	*Innovators' valuation of an information given by a laggard*
A_S_L_preferred_information_source_early_adopter_1	0.40	[-]	*Early adopter's valuation of an information given by an innovator*
A_S_L_preferred_information_source_early_adopter_2	0.30	[-]	*Early adopter's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_early_adopter_3	0	[-]	*Early adopter's valuation of an information given by an early majority*
A_S_L_preferred_information_source_early_adopter_4	0	[-]	*Early adopter's valuation of an information given by an late majority*
A_S_L_preferred_information_source_early_adopter_5	0	[-]	*Early adopter's valuation of an information given by a laggard*
A_S_L_preferred_information_source_early_majority_1	0.1	[-]	*Early majority's valuation of an information given by an innovator*
A_S_L_preferred_information_source_early_majority_2	0.30	[-]	*Early majority's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_early_majority_3	0.40	[-]	*Early majority's valuation of an information given by an early majority*
A_S_L_preferred_information_source_early_majority_4	0	[-]	*Early majority's valuation of an information given by an late majority*
A_S_L_preferred_information_source_early_majority_5	0	[-]	*Early majority's valuation of an information given by a laggard*
A_S_L_preferred_information_source_late_majority_1	0.05	[-]	*Late majority's valuation of an information given by an innovator*
A_S_L_preferred_information_source_late_majority_2	0.05	[-]	*Late majority's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_late_majority_3	0.30	[-]	*Late majority's valuation of an information given by an early majority*
A_S_L_preferred_information_source_late_majority_4	0.2	[-]	*Late majority's valuation of an information given by an late majority*
A_S_L_preferred_information_source_late_majority_5	0	[-]	*Late majority's valuation of an information given by a laggard*
A_S_L_preferred_information_source_laggard_1	0	[-]	*Laggard's valuation of an information given by an innovator*
A_S_L_preferred_information_source_laggard_2	0	[-]	*Laggard's valuation of an information given by an early adopter*
A_S_L_preferred_information_source_laggard_3	0.1	[-]	*Laggard's valuation of an information given by an early majority*

A_S_L_preferred_information_source_laggard_4	0.2	[-]	*Laggard's valuation of an information given by an late majority*
A_S_L_preferred_information_source_laggard_5	0.3	[-]	*Laggard's valuation of an information given by a laggard*
Initial_minimum_amount_savings	0	[€/month]	*Minimal amount of savings required by household to adopt*
minimum_percentage_for_no_rejection	0.10	[%]	*Minimum percentage of early majority, late majority and laggards having a smart washing machine that early innovators in order not to reject the appliance*
Number_of_month_before_decision_rejection	36	[month]	*Delay after which early adopter check whether the adoption of the appliance was successful from an social recognition point of view*
introduction_phase	24	[month]	*Number of month of the introduction phase*
growth_phase	24	[month]	*Number of month of the growth phase*
memory	3	[month]	*Length of the memory households have to keep information received by other households*
Degree_of_correlation_with_previous_data	0.5	[%]	*Degree of correlation between previous value calculated with normal distribution and current value*
Learning_rate_appliances_1	0.96	[-]	*Height of the learning rate*