Modelling uncertainty of household decision-making process in smart grid appliances adoption

Including household behavioural uncertainty in the identification of policies to support smart grid appliances adoption by using agent-based modelling and the scenario discovery technique

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ABSTRACT

The rollout of smart grids is beneficial for allowing the entire electricity infrastructure to cope with the important production fluctuations that can be occasioned by renewable energy sources. The extent to which smart grid infrastructures are able to cope with production fluctuations is largely dependent on the extent to which households are willing to purchase smart grid appliances and install them in their homes. Creating policies to support smart grid appliances is difficult since the reasons for adoption by households are not well understood and are expected to change constantly through time. In this paper, we show how the combined usage of agent-based modelling and the scenario-discovery methodology allows, through a simulation model, to incorporate in a systematic way the uncertainties about the decision-making process of households in the identification process of policies, instead of rejecting them. The usage of agent-based modelling and scenario-discovery is mainly useful in building policies that are more robust to various scenarios, even in case various stakeholders disagree about the exact representation of households' decision-making process in the adoption of smart grid appliances.

Introduction

The incapacity of traditional grids to cope with large production fluctuation of various renewable energy sources calls for the installation of smart grid systems. One essential part of smart grids is constituted of smart grid appliances that are installed in people’s houses (Faruqui, Sergici, & Sharif, 2010). The rollout of smart grids is beneficial for a large amount of stakeholders in the electricity sector: national governments, grids operators and electricity producers (Boisvert & Neenan, 2003). However the decision to adopt and use smart grid appliances in their ‘smart function’ lies in the hands of households. Hence, there is a large dependency of various electricity sector stakeholders on the actions taken by households. The installation of smart grid appliances in people’s houses can hardly be made mandatory and must be the result of households’ willingness to adopt these appliances. The extent to which they will be willing to do so is highly uncertain. This is mainly because the reasons and requirements for smart grid appliance adoption by households are hardly comprehended. Therefore, it is also difficult to find out which policies to support adoption might be effective. Traditional policies such as subsidies for the purchase of appliances might not be as successful as expected (Anda & Temmen, 2013; Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013).

The difficulty to understand how households decide to adopt smart grid appliances is due to large uncertainties in the adoption process of these appliances. Uncertainty is in this work defined as an aberration from utter certainty (Walker, et al., 2003). The omission of uncertainties in the design of policies in complex issues is often the reason why these policies fail (Walker, Marchau, & Swanson, 2010). One policy, for example, which was proven to be effective at a particular point in time, will appear to be unsuccessful at a later moment (Hamarat, Kwakkel, & Pruyt, 2013). Hence, the reason why these policies fail is because they are not made robust to any other changes of the environments in which they were designed.

There are at least two sources of uncertainties that should be distinguished in designing policies. First, there are uncertainties about the future. In the case of smart grid appliances, policies to support adoption might only be successful in case of economic growth and increase of household salaries, but might fail in a moment of economic crisis. Second, there are uncertainties about the understanding of the decision-making process made by households. For example, it is unclear according to which criteria households decide whether to adopt smart grid appliances. A policy based on the assumption that households essentially search to make savings might fail because of the influence of other factors such as purchase or usage complexity. Also, it is unclear how and to what extent interactions between households play a role in the transfer of information about smart grid appliances and the decision to adopt.

Instead of ignoring the occurrence of uncertainties in the adoption of smart grid appliances, or only partially including them in the assessment of policies, we use a technique that allows a systematic inclusion and exploration of uncertainties to evaluate the effectiveness of various policies to support smart grid appliances adoption. The scenario discovery technique will be explained in more detail in section four of this paper. The aim of this paper is to show how the inclusion of uncertainties about the future and about our understanding of the adoption process of smart grid appliances by households, allows the creation of more robust and effective policies to support adoption. In this paper, we exclusively focus on the identification of policies by using simulation models.

The paper is structured as follows. First, an introduction is provided about the simulation model used to simulate the adoption of smart grid appliances by households. In section three, four forms of uncertainties about the modelling of smart grid appliances adoption are identified. This section is followed by an explanation of how these uncertainties were included in the simulation model and the modelling process of smart grid appliances adoption. In section five, the added-values of using the scenario discovery technique to identify policies to support adoption are identified. The paper ends with some limitations associated with the use of simulation models and scenario discovery for policy makers and some conclusions about the work presented in this paper.

A model of the adoption of smart grid appliances

To illustrate how uncertainty can be included in the identification of policies, an agent-based model about the adoption of smart grid appliances by households is used. The model was created to answer the following question: Which directions for policy can stimulate the adoption of smart grid appliances to increase the capacity for demand response in city districts? With smart grid appliances, we refer to products used regularly by households to support daily activities, which are placed within the parameter of their houses. Examples are smart washing machines, smart freezers and smart fridges.

The model has been created based on the Diffusion of Innovations Theory of Rogers (1962). In the model, 500 households are divided among the five adopter categories of Rogers, and distributed among the proportions suggested by this same author. The five adopter categories are the following: innovators, early adopters, early majority, late majority and laggards. The reason why households are divided among various categories in this model is that it is not expected that each household has the same expectations and requirements in the purchase of new products. Various consumer segmentations can be found in the literature, whether based on theoretical (Rogers, 1962; Foxall, 1994), or empirical division (Curtius, Künzel, & Loock, 2012; SGCC, 2011) specifically made for the case of smart grid appliances. The fact that individuals have different expectations and requirements in the purchase of innovation leads to the appearances of chasms in the adoption curve of a product (Moore, 1999). These chasms, mainly the one between early adopters and early majority, majorly explain the difficulty to make sure that an innovation is adopted on large scale. In the model, households belonging to each category differ in the extent to which they are interested in the financial or social added-value of adopting smart grid appliances. Households of each category also differ in the degree to which they accept investment risks. Finally, households vary in the amount of householders they have, and hence in the amount of electricity they consume each month.

To perform decisions, households use the decision-making structure of Engel, et al. (1995). The five steps of the decision-making structure are the following: problem recognition, information search, evaluation of alternatives, purchase decision and post-purchase behaviour. A main advantage of using this decision-making structure is that it underlines the distinction between being aware of the existence of a product and the actual action of adopting it. Also, it incorporates a post-purchase behaviour, that is, the feedback that individuals provide to other households after having adopted an innovation.

In the model, households judge the added-value of adopting smart grid appliances upon the five perceived attributes of innovations as described by Rogers (1962): relative advantage, compatibility, complexity, triability, and observability. The reason why five different innovation attributes are taken into account is that expecting that households only decide to adopt based on financial profits is expected to be unreal and strongly limits the understanding of the adoption process. On the contrary, households may decide not to purchase an appliance because the purchase process is perceived as being too difficult, although the adoption of the appliance might improve the financial situation of the household.

The model simulates the adoption of smart grid appliances on the scale of city districts. Therefore, no link is assumed between, on one side, the purchase (and utilisation) of smart grid appliances within the city district and, on the other side, the prices of electricity and the prices of smart grid appliances. The reason why no links are assumed is that the effect of the purchase of smart grid appliances on the scale of a city district in comparison to national of international ones is expected to be negligible. The prices of smart grid appliances and of electricity are hence modelled as exogenous parameters. The price of smart grid appliances decreases based on a logarithmic function. Two electricity prices are modelled: peak and off-peak electricity prices. The usage of smart grid appliances in the model allows shifting electricity consumption to moments in time when electricity prices are off-peak. The savings made by households are hence defined as the difference in electricity consumption in peak and off-peak periods before and after the adoption of smart grid appliances.

The main model output is the percentage of adopters having adopted smart grid appliances. An important limitation of the model is that it only studies the adoption of smart grid appliances and not their utilisation by households. While households may adopt smart grid appliances, they may decide not to use them in their ‘smart function’, for example due to the limited amount of savings they make or the inconveniency of adjusting their daily life. Their electricity consumption would in this case not be different than if they would only own traditional appliances. To study the extent to which households will shift their electricity consumption, the utilisation of the smart grid appliances should hence be added in the model.

A more detailed overview of the model is presented in the appendix. The model description has been created according to the ODD + D protocol. This protocol, developed by Müller, et al. (2013), allows a standardised and more transparent description of agent-based models in order to facilitate communication and usage of the model by other authors.

Uncertainties in the modelling of household decision-making process

In the first section of this paper, the relevancy of including uncertainty about the households represented in simulation models to identify effective policies is introduced. In the modelling of decision-making by individuals, Briggs, et al, (2012) identify four forms of uncertainties: stochastic uncertainty, parameter uncertainty, structural uncertainty and heterogeneity. Of these four forms of uncertainties, one comes from the usage of a discrete simulation tool. Stochastic uncertainty arises from the fact that, for example in agent-based models, the order of the execution of actions by the individuals modelled is sequential and randomised. Hence, by running a model two times with the exact same input parameters, the models outcomes might not be similar. The three other forms of uncertainty arise from the representation of the system modelled, which is in this case the decision-making process of households in the adoption of smart grids appliances.

Parameter uncertainty is defined by the incertitude of parameters describing the decision-making process performed by individuals. One example is the amount of interactions that innovators each month have with others households in which smart grid appliances are discussed. Parameter uncertainty can also be seen as the incertitude about the exact value and future development of exogenous variables such as electricity prices.

Structural uncertainty is the incertitude about how to represent a certain system, in this case the decision-making process of households, in a simulation model. This structural uncertainty can be about which theory to use to represent certain elements of the decision-making process of households. In the model introduced in section two, the decision-making steps of Engel, et al. (1995) were chosen. Rogers (1962), however, also proposed five decision-making steps which are not exactly the same as the ones of Engel, et al. If the use of the decision-making steps of Rogers also appears to be arguable to model the adoption process of smart grid appliances by households, it might be necessary to include both decision-making structures in the simulation model. Including both decision-making processes in one single simulation model is hence a way to deal with one form of structural uncertainty. Another form of structural uncertainty has to do with which variables actually do or do not play a role in the adoption of smart grid appliances. For example, as demonstrated in section two, Rogers (1962) identified five relevant innovation characteristics in the adoption of innovations. The five innovation characteristics were however identified for innovations in general. In the case of smart grid appliances, some of them could appear to be irrelevant or unnecessary to explore the adoption of appliances by households.

Heterogeneity is defined by the incertitude about the degree to which individuals differ in characteristics and preferences. For example, households might have different minimal saving requirements in order to be willing to adopt smart grid appliances. Households also might have differing number of interactions per month. This difference might also occur for households belonging to the same adopter category.

The reason why these four types of uncertainties are identified and should be included in a simulation model is because it is expected that they will have an influence on the model's adoption curve of smart grid appliances and hence on the policy identified based on the simulation model. In the next section, the combination of agent-based models and the scenario discovery technique is presented in order to show how these four types of uncertainties can be incorporated in the analysis of a simulation model.

Including uncertainty: agent-based modelling and the scenario discovery technique

In the previous section, four forms of uncertainties in the modelling of the adoption of smart grid appliances by households are identified. In this section, we show how these uncertainties are included in the modelling process, both through the usage of agent-based models and with the scenario discovery technique.

Agent-based modelling

In the field of innovation diffusion modelling, two different types of simulation methods are majorly chosen: system dynamics and agent-based modelling (Rahmandad & Sterman, 2008; Kiesling, Günther, Stummer, & Wakolbinger, 2012). There are no absolute rules to decide whether to choose system dynamics or agent-based modelling. According to Rahmandad & Sterman (2008), agent-based modelling, however, is more convenient when a large amount of heterogeneity has to be included in the characteristics of individuals, and when different types of interaction networks between individuals have to be tested. System dynamics is more convenient when computational costs need to be reduced. In the model introduced in section two, agent-based modelling was chosen in order to easily test the effects of heterogeneity between households on the adoption of smart grid appliances (e.g. adopter categories, number of inhabitants per households).

Agent-based modelling is a simulation tool that focusses on the actions and interactions of numerous individuals (agents) to study their impact on the development of the entire system regrouping the individuals (Epstein & Axtell, 1996; Miller & Page, 2007). In the case of smart grid appliances, one studies how the actions and interactions of each household (the individuals) influence the adoption rate of the city district (the system regrouping the individuals). An agent is characterised by two elements: a state, which stands for the set of characteristics that describes the agent, and rules, that describe the entire set of actions that the agent may perform (Dam, Nikolic, & Lukszo, 2013). Agent-based modelling is a discrete simulation tool. This means that agents can only perform actions at a specific moment in time. Concretely, when the model is at time 0, an order of action determined randomly is provided to each agent in the model. Based on the order of action, each agent sequentially executes the actions it is asked to perform. When the last agent in line has performed its actions, the time is advanced to time 1, a new order of action is randomly determined and all agents execute their actions once again. This discrete process is continued until the modeller decides to stop the simulation run.

In relation to the uncertainties identified in section three, agent-based modelling mainly allows to easily include different forms of heterogeneity, as explained earlier in this section. Heterogeneity can be introduced by applying different types of probabilistic distributions to the characteristics of each household.

Scenario discovery

Scenario discovery is a technique that is essentially useful to model problems that are characterised by a large number of uncertain factors (Kwakkel, Auping, & Pruyt, 2013). Making decisions in relation to these kinds of problems is described as decision-making under deep or severe uncertainty (Lempert, Popper, & Bankes, 2003; Ben-Haim, 2006). The essence of the scenario discovery technique is the recognition that one might have a limited knowledge and understanding of the system that has to be analysed. Instead of ignoring this lack of knowledge and understanding of the system, one could include them in the analysis of the system and the identification of policies.

The scenario discovery technique is performed by combining the usage of Exploratory Modelling and Analysis (EMA) and the Patient Rule Induction Method (PRIM).

The EMA methodology uses computational experiments to analyse complex and uncertain system (Bankes, 1993). As indicated in its name, the methodology takes distance from the predictive ambition of using simulation models and focuses on an exploratory approach. Instead of trying to create a best-estimate model to try to predict the future, one sees the model as one of the multiple plausible hypotheses about the structure of a real system (Hodges, 1991; Hodges & Dewar, 1992). As explained by Kwakkel & Pruyt (2012), EMA allows to include parameter and structural uncertainty in the model, which are two of the uncertainties mentioned in section three. Including parameter uncertainty with EMA is done by setting ranges as input parameters in the model instead of fixed numbers. The number of interactions of households per month is for example set to a range of integers between 3 and 7, instead of considering it to be fixed at 5 interactions per month. The creation of ranges is done for any input parameters of which the value can be considered as uncertain.

The simulation model is then run successively for a large amount of times. For each run, one value within the range of each input parameter is chosen. The result of the EMA experiment is a dataset with the simulation output of a large amount of simulation runs. The inclusion of parameter uncertainty can also be combined with the inclusion of structural uncertainty. For that, some structures will be switched on for some runs while others will be switched off. For example, the complexity criteria of smart grid appliances, which is one of the five innovation characteristics identified by Rogers (1962) (see section two), might be switched on for some model runs while being switched off for others. The addition of various structural uncertainties, however, strongly increases the number of runs in the EMA experiments. Carrying out EMA experiments could then turn out to be too time consuming considering the time available for the simulation project. Therefore, different structural uncertainties should only be included in the model if they could not be rejected in the model validation process.

The last type of uncertainty identified in section three is stochastic uncertainty, which results from the use of a discrete simulation tool such as agent-based models. To take this stochastic uncertainty into account, several model runs are made with an exact same combination of input parameters and model structures. The mean of model outputs based on the various model runs with the exact same combination of input parameters and model structures is used for model analysis.

The dataset created through the EMA experiment, which was based on various parameters and structural uncertainties can be seen as an ensemble of plausible scenarios of the representation of a certain system, in this case the decision-making process of households to adopt smart grid appliances, and its development in the future. Each model run is thus equal to one plausible scenario. The challenge then is to find out, from the multiple ensemble of scenario, which of them is relevant for a particular preferred or dis-preferred value of a model outcome. Concretely, this means that in the case of the model about the adoption of smart grid appliances, one wants to know which range of input parameters or which model structure leads to a high or a low adoption percentage of smart grid appliances. Examples could be that mainly a low number of interactions of early adopters per month leads to an adoption percentage lower than 20 percent in 2050. To find out which sets of scenarios are relevant for a certain outcome, one uses the second method of which the scenario discovery technique is composed. PRIM was first introduced by Friedman and Fisher (1999). As explained before, PRIM allows finding out which combination of ranges of input parameters and model structures leads to a certain outcome, as specified by the author. This is done by repeating the two stages of peeling and pasting. To find which subset of input parameters and model structure leads to a certain outcome range (above or under a given threshold), subsets of the input parameters are progressively removed (peeling) and added (pasting).

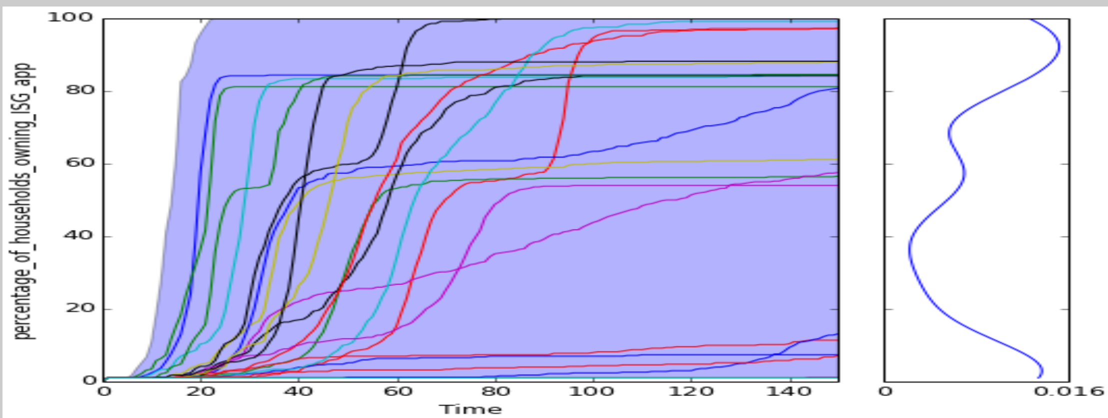
Concluding, in this section, it is shown that the four types of uncertainties identified in section three can be included in the analysis of a model through some adjustments to the agent-based model created and through the use of the scenario discovery technique. In the next chapter, an analysis is provided of how the inclusion of uncertainty into the process of modelling changes allows the creation of more robust policies.

Added-value of using the scenario discovery technique to deal with uncertainties

Three main advantages of using the scenario discovery methodology with the combination of agent-based modelling to identify policies can be identified. The first is to find out the extent to which policies are robust to different scenarios and hence to various modelling uncertainties. The second is to build a set of policies that are robust to the occurrence of various scenarios. The third is the possibility to include different world views within a single model.

EMA graphs

To present the outcomes of experiments, EMA graphs are used. An example is provided hereunder.



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, lines represent limited amounts of randomly chosen runs. The line colour has no signification. Third, the element on the right is a Gaussian kernel density estimation (KDE). This shows the distribution of runs at the final run time of the model.

To illustrate the first advantage, experiments are carried out with the model presented in section two. In the first experiment, the simulation model is run without any policies to support smart grid appliance adoption by households. The model is run for a duration of 150 time steps. This will be the case for each experiment presented in this section. The results of the experiment are presented in **figure 1**. The figure shows the evolution of the percentage of households adopting a smart grid appliance. In this figure, we can see that, at the end of the simulation run, the percentage of households having adopted lies around 6-7%. Therefore, we can conclude that smart grid appliances are not adopted on large scale, and that policies may be needed to support adoption.

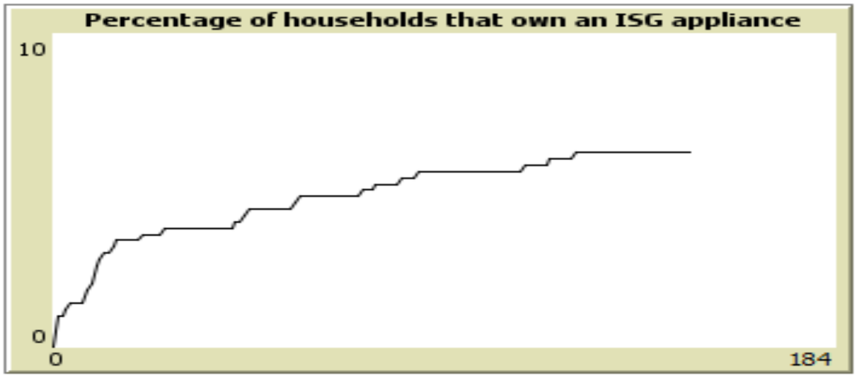


Figure 1: percentage of households owning a smart grid appliance; single simulation run and no policies

A second experiment is carried out with the inclusion of a purchase subsidy of 200€ per smart grid appliance during the entire duration of the simulation run. The experiment results are presented in **figure 2**. In this figure, one can see that the percentage of households having adopted smart grid appliances is close to 100% at the end of the simulation run. Therefore, based on the two experiments just carried out, one could conclude that in the model created in this work, the only policy needed to strongly increase the adoption of smart grid appliances is a purchase subsidy.

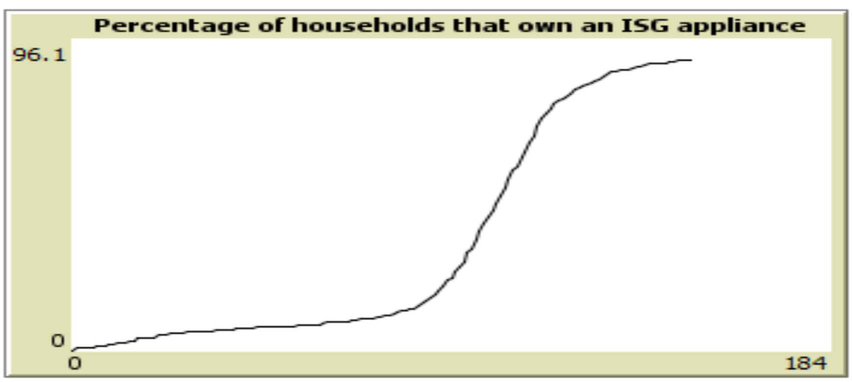


Figure 2: percentage of households owning a smart grid appliance; single simulation run and purchase subsidy

In this paper, we point out that this policy is not robust. To illustrate that, a third experiment is carried out. This experiment will be done with the EMA methodology. Hence, 200 simulation runs will be made instead of one. Instead of using fixed numbers as model inputs, ranges will be included. Hence parameter uncertainty will be included in the model. In this experiment, the purchase subsidy as a policy to support smart grid appliance adoption is applied. The experiment outcomes are presented in **figure 3**.

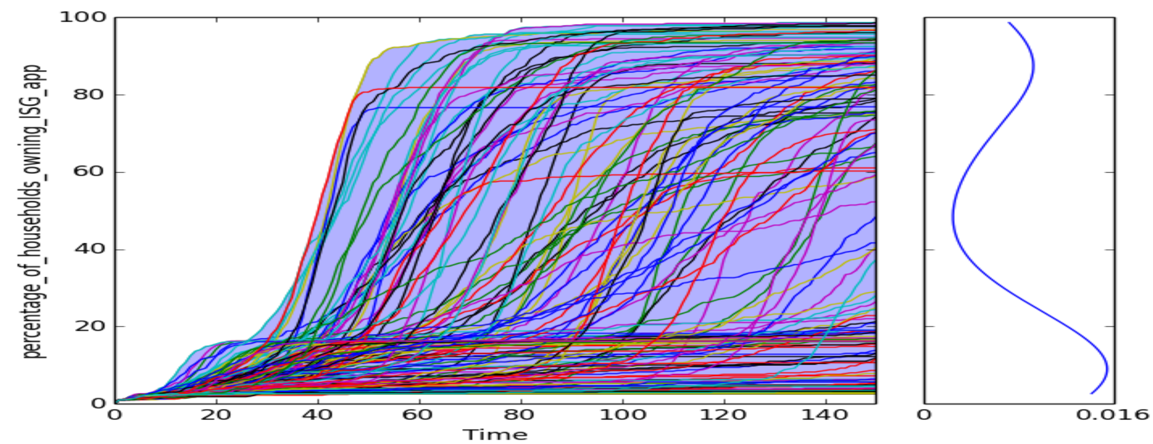


Figure 3: percentage of households owning a smart grid appliance; use of EMA with 200 simulation runs and purchase subsidy

The third experiment shows that, indeed, a purchase subsidy may lead to a large adoption of smart grid appliances. This can be seen by looking in the distribution of outcomes in the KDE graph. The KDE graph, however, also shows that in a large amount of cases, smart grid appliances are not adopted on large scale. In many cases, the adoption percentage at time 150 ends at 18% or even around 5%. Therefore, one can conclude that in the simulation model created to simulate the adoption of smart grid appliances by households, a purchase subsidy is not robust to various scenarios to support adoption. It is at this point important to underline that we cannot yet conclude that a purchase subsidy as a policy to support adoption is not robust in real-world. The outcomes presented in the figures in this section only say something about the model created. A translation of conclusions from model to real-world is in any case essential.

As explained in the first part of this section, the second advantage of using the scenario discovery methodology is to build policies that are robust to various scenarios. This is done by using PRIM. PRIM also allows to find out why to which scenarios a certain policy is not robust. By performing a PRIM analysis on the third experiment performed in this section, seven different scenarios are found to lead to a low adoption percentage of smart grid appliances, even though a purchase subsidy is applied. The scenarios are listed in **table 1**. Concretely, this means that in the model, if at least one of the input parameter corresponds to a scenario described in **table 1**, the percentage of households owning a smart grid appliance will remain low. For example, a growth duration value superior to the average of the range introduced in the model will lead to a low adoption of smart grid appliances by households.

Table 1: list of scenarios leading to a low adoption percentage of smart grid appliances

1.	Low social value experienced by early adopters in smart grid appliance adoption
2.	High degree of suspiciousness experienced by early adopters towards the reliability of information transferred between households
3.	High degree of suspiciousness experienced by early majority population towards the reliability of information transferred between households

4.	Slow decrease of smart grid appliance prices
5.	Long growth phase (duration before the complexity of purchasing and using smart grid appliances is acceptable for all type of households)
6.	Low amount of interactions between early majority population and early adopters
7.	Low amount of interactions between late majority population and early adopters

A last experiment is carried out to show the effect of policies that assess precisely the scenarios identified in **table 1**. These policies are called directions for policy in this case, since they come directly from the model and only show what real policies should target to support smart grid appliance adoption. The directions for policy are listed in **table 2**.

Table 2: directions for policy to support smart grid appliance adoption

Directions for policy	**Policy examples**
Encourage communication between innovators and early adopters	Nomination of product ambassadors, creation of consumer groups
Promotion of smart grid appliances to early adopters	Nomination of product ambassadors, creation of consumer groups
Decrease adoption costs	Purchase subsidy
When smart grid appliances may become interesting for early majority population and later adopters, reinvent the product	Redesign the product to underline ease of use, savings that can be made to change product perception
Make product usage and the added value of owning it visible to others	Redesign the product to make it visible to others

The implementation of the directions for policy listed in **table 2** leads to the experiment outcomes presented in **figure 4**. In this figure, one can see that in major cases, smart grid appliances are adopted on large scale. In some cases, smart grid appliance adoption is low but still increases progressively towards a high adoption percentage.

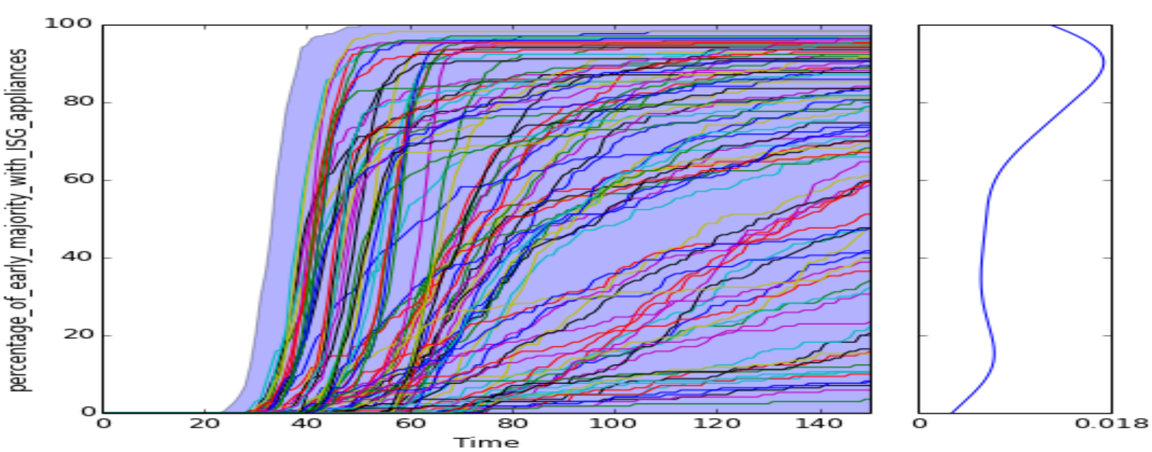


Figure 4: percentage of households owning a smart grid appliance; use of EMA with 200 simulation runs and all directions for policy applied

The third advantage of using scenario discovery is the possibility to include various world views in one single simulation model (Kwakkel & Pruyt, 2012). As various stakeholders have different world views about how a system works – in this case about how households decide to adopt smart grid appliances, the possibility of including structural uncertainty in a simulation model with EMA is interesting. As explained by Kwakkel & Pruyt, the need of making various models, each based on a particular world view, disappears. Hence, one can find out which policies are effective for all world views included in the model.

Reflections and limitations to the usage of the identification process

The previous section shows that the usage of scenario discovery and agent-based modelling to model the decision-making process of households may provide some interesting benefits to create more effective policies. They are still some limitations to the use of scenario discovery and agent-based models for the identification of policies.

First, the policies identified are based on a simulation model and not on reality. Therefore, a robust policy in the simulation model may not be robust in real world. The same is valid for non-robust policies. After having identified policies, an important work of reflection and translation of policies to real world has to be carried out. This can be done by, on one side, making a clear overview of the limitations of the model created, and on the other side, discussing the policies identified with several sector experts.

The second limitation is related to the use of agent-based models for the diffusion of innovations. As explained in section four, agent-based modelling was chosen over system dynamics because this simulation methods is more convenient to test various forms of heterogeneity. Using system dynamics, however, strongly reduces the computational costs of modelling and therefore may be an interesting choice if heterogeneity in the model is limited and if one prefers to spend a large amount of time on model analyses. System dynamics is also compliable with scenario discovery and is often used to model the diffusion of innovations (Rahmandad & Sterman, 2008; Kiesling, Günther, Stummer, & Wakolbinger, 2012).

The last limitation is the fact that a large amount of uncertainties included in the model strongly increases the computation costs of analysing the model. Although a large amount of world views may be included in one model, these should only be added when they are validated in the verification and validation phase of the model.

Conclusions

In this article, the added-value of using the scenario-discovery methodology and agent-based modelling to identify policies to support smart grid appliance adoption is provided. Globally, the usage of agent-based modelling allows to easily include uncertainties about the heterogeneity between individuals. The scenario-discovery technique is useful to include parameter, structural and stochastic uncertainties.

In the case of the identification of policies to support smart grid appliance adoption, the combination of agent-based modelling and the scenario-discovery technique is, firstly, beneficial to test the robustness of policies to various scenarios, whether linked to uncertainties about the future or about the extent to which the decision-making process of households is correctly modelled. This combined usage allows for example to show why a purchase subsidy cannot be considered as a robust policy to increase smart grid appliance adoption. Secondly, this combined usage is beneficial to build new policies that are robust to the occurrence of these various scenarios. Thirdly, the usage of agent-based modelling and scenario-discovery allows to identify effective policies, even though there are disagreements about the exact representation of households' decision-making process to adopt smart grid appliances within the simulation model.

The model presented in section two is part of a thesis work on the adoption of smart grid appliances, written in collaboration between DNV GL and the Delft University of Technology. The entire thesis can be consulted by using the following link: http://repository.tudelft.nl/view/ir/uuid%3A07b27819-1e34-4a36-848b-29858f5139be

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Appendix

ODD + D model description

Overview	Purpose	- 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
	State variables and scales	- 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

<table>
<tr><td rowspan="2"></td><td></td><td>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:
<table><tr><td colspan="2"></td></tr><tr><td>$C(X_t)$</td><td>Cost of the technology at time t</td></tr><tr><td>$C(X_0)$</td><td>Initial cost of the technology</td></tr><tr><td>t</td><td>Current time</td></tr><tr><td></td><td>Learning parameter</td></tr></table></td></tr>
<tr><td>Process overview and scheduling</td><td>- Each month, households in the model follow the consumer decision-making structure of Engel, et al. (Consumer behavior, 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="4">Design concept</td><td>Theoretical and empirical background</td><td>- The main theory is the Diffusion of Innovations Theory of Rogers (Diffusion of Innovations, 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 structure of Engel, et al. (Consumer behavior, 1995) to perform decision-making
- Adoption complexity vary according to the four product lifecycle phases of Levitt (Exploit the Product Life Cycle, 1965)
- Agent-based modelling is used as a simulation tool
- Scenario discovery (Kwakkel, Auping, & Pruyt, 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. (Merging validation and evaluation of ecological models to ‘evaludation’: A review of terminology and a practical approach, 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
- Which of the goals is the most important depends on the households category to which the household belong</td></tr>
<tr><td>Learning</td><td>- Households may decide to never adopt again if they have been disappointed, whether financially or socially, by the smart grid appliance previously adopted</td></tr>
<tr><td>Individual sensing</td><td>- 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</td></tr>
</table>

	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 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
	Observation	- 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

- Percentage of households aware of the existence of smart grid appliances

Details

Implementation details

- Model is implemented in Netlogo
- Two files belong to the model and are needed to run it:
  - 'Dataset_of_households'
  - 'Dataset_of_ISG_appliances'
- Equations used:
  - Calculation of awareness received:

t	*Time*
AR_i	*Total awareness received by household i*
j	*Amount of households encountered at period t*
	Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j).
	Amount of media interaction received (depended on the adopter category of household i)
	Valuation of media interaction
n	*Length of the memory of household i*

  - Calculation if sufficient knowledge about one type of information is received

t	Time
IR_i	Total information received by household i
j	Amount of households encountered at period t
	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

  - Calculation of information about breakdown or data leak problems observed

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

  - Calculation of expected savings in case of neoclassical rationality

C	*Past average monthly electricity expenditure of one household over a period x*

<table>
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<tr><td>m</td><td>Smart grid appliance that comes to replace an existing product (for example that replaces a traditional grid appliance)</td></tr>
<tr><td>n</td><td>Smart grid appliance that does not replace an existing product and are hence is a totally new product for an household</td></tr>
<tr><td>Vh</td><td>Past average electricity consumption of the smart grid appliance per month over a period y</td></tr>
<tr><td>Ppeak</td><td>Expected future average electricity price during peak period</td></tr>
<tr><td>Poffpeak</td><td>Expected future electricity price during off-peak period</td></tr>
<tr><td>ICsmart</td><td>Purchase costs of the smart grid appliance</td></tr>
<tr><td>ICnotsmart</td><td>Initial costs of the appliance that the smart grid appliance replaces (for example a traditional grid appliance)</td></tr>
<tr><td>Lifetime</td><td>Average lifetime of the smart grid appliance</td></tr>
</table>
Calculation of expected savings in case of bounded rationality
<table>
<tr><td colspan="2"></td></tr>
<tr><td>t</td><td>Time</td></tr>
<tr><td>IR_i</td><td>Total information received by household i</td></tr>
<tr><td>j</td><td>Amount of households encountered at period t</td></tr>
<tr><td></td><td>Valuation of household j encountered by household i (depended on the adopter category of household i and adopter category household j)</td></tr>
<tr><td></td><td>Current savings made by household j</td></tr>
<tr><td>n</td><td>Length of the memory of household i</td></tr>
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</td></tr>
<tr><td></td><td>Initialisation</td><td>- Five households already own a smart grid appliance. They are all innovators. The rest does not possess anything.</td></tr>
<tr><td></td><td>Input data</td><td>- 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</td></tr>
<tr><td></td><td>Sub models</td><td>- No sub models</td></tr>
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