Consumer Participation in Demand Response Programs: Development of a Consumat-based Toy Model

Judith Schwarzer[1] and Dominik Engel[1]

[1] Centre for Secure Energy Informatics, Salzburg University of Applied Sciences, Urstein Sued 1, A–5412 Puch/Salzburg, Austria

judith.schwarzer@en-trust.at

Abstract. Modeling of the smart grid architecture and its subsystems is a basic requirement for the success of these new technologies to address climate change effects. For a comprehensive research especially on effects of demand response systems, the integration of consumers' decisions and interactions is essential. To model consumer participation in demand response programs this paper introduces an agent-based approach using the Consumat framework. The implementation in NetLogo provides high scalability and flexibility concerning input parameters and can easily interact with other simulation frameworks. It also forms a possible basis for an overall demand response consumer model. As a so-called toy model, simple correlations in this socio-technical scenario can already be explored.

Keywords: consumat, demand response, toy model, agent.

1 Introduction

The establishment of demand response systems as a key application of smart grid architectures represents one of the most important measures to address climate change effects. The corresponding technologies have to be enabled in the residential sector to meet the European targets for a reduction of greenhouse gas emissions by 2030 (40% compared to 1990) and a greater share of renewable energy of at least 27% [1]. Demand response in this context refers to "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [2]. Based on data from the US energy market (2014) demand response in the residential sector contributes 20% of the total peak demand savings and 61% of the overall energy savings [3].

As shown in, e.g., [4] and [5], the success of a demand response program essentially depends on the end consumers' participation and their behavior when configuring and using a DR system. Based on an own comprehensive structural analysis of the corresponding complex socio-technical system [6] Fig. 1 gives an overview on relevant consumer decisions in this context.

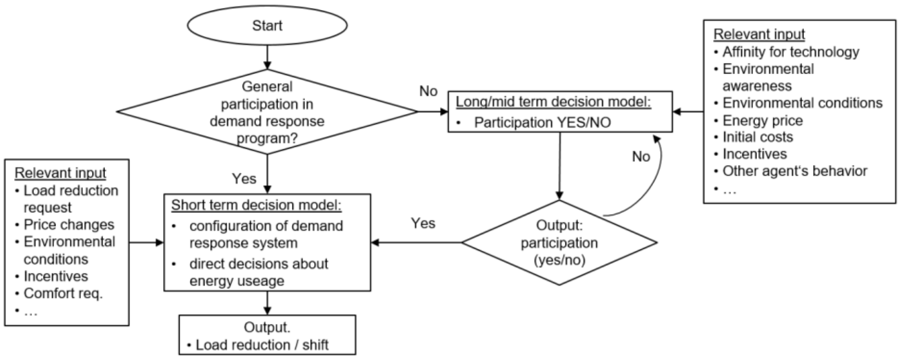

Fig. 1. Consumer decisions in the context of demand response

A simulation model that integrates all these aspects would be very helpful to support the deployment of a new energy infrastructure. Analyzing such socio-technical systems is a major research field in social sciences and agent-based models can be considered as a preferred simulation tool (see, e.g., [7]–[9]). A general concept to model the consumers' behavior was developed by our group and presented in [10] focusing on the long/mid-term decision concerning general participation in a demand response program (see Fig. 1). This work is based on the Consumat framework of Jager and Janssen first published in [11]. Several other publications already exist which use this approach to model sustainable behaviors but also other types of decision making like farmer crop choices (see, e.g., [12], [13]). Based on [14] also the perspective of innovation diffusion and transition theories (e.g., Rogers theory on innovation diffusion, as cited in [14]) can be considered with Consumat. The aim of this work is to extend and refine the existing approach and to implement it in a simulation environment. As a so-called toy model, it may support the finding of simple correlations in the complex socio-technical demand response system and provides the basis for further implementation in an overall socio-technical demand response consumer model.

The following Section 2 first introduces relevant demand response knowledge especially concerning the role of consumers. After a brief general overview on human decisions in agent-based models, in Section 2.2 the Consumat framework is shortly described and some outcomes of relevant existing implementations are presented. The ODD+D based model description and results of the implementation can be found in the following two main sections 3 and 4. A summary and an outlook on future work is given in the final Section 5.

2 Related work

The section on the theoretical background of this work is divided in two parts: (1) a short review on demand response models with focus on the role of consumers and (2) an introduction to the Consumat framework including some background knowledge on human decision making in agent-based models.

2.1 The role of consumers in demand response models

There exists a huge amount of publications about demand response systems and corresponding models to simulate their efficiency and their role in future energy systems. An overview is, e.g., given in [15]. The authors classify demand response programs into different categories based on classifiers like control mechanism and motivations offered to consumers. The latter one includes different pricing schemes (price-based or incentive-based) as strategies to motivate consumers to the desired behavior related to demand response. Potential actions are reduction or time shifting of electricity usage, known as direct load control and reducing the peak to average ratio, respectively. Load management can be performed either in a multi-user scenario, where the schedules of energy consumption will be optimized for a group of users (see, e.g., [16]) or in a single-user scenarios (see, e.g., [17]). Considering the large number of contributions on demand response, the following algorithm classes are frequently employed: game theory, linear programming, particle swarm optimization, arrival processes and multi-agent based models. In our meta-analysis evaluating the data communication requirements of common demand response models a more detailed overview can be found [18]. Demand response decisions are not made by the consumers in a case-to-case-manner but usually an algorithm implemented in a technical demand response system optimizes the performed actions. Nevertheless, corresponding modeling and simulation approaches in most cases require presumptions concerning consumers' decisions and behavior. There are some proposals, which explicitly integrate this perspective. As one of the relevant aspects, the preferences of optimal appliance scheduling are one focus of the approaches presented, e.g., in [19] and [20].

In most of the considered studies related to consumers in demand response scenarios the main focus is on dynamic short-term behavior concerning load management itself. Regarding the relevance of the mid/long-term decision to even participate in such a program Miller et al. [5] show the high impact of humans' decision to participate in a direct load control program. This finding could be confirmed by our own simulations where the role of user interaction and acceptance for a cloud-based DR model has been investigated [4]. It was found that the number of participating users has a strong effect on cost cutting for a certain load reduction. Within this setup the user acceptance did not increase with more configuration options and higher amount of possible user interactions. In order to avoid complex configuration of a demand response system with autonomous appliance scheduling, as, e.g., proposed in [21], there is no need of user interaction. In this model, time of use probabilities of the appliances will be learned automatically from energy consumption patterns under varying weather conditions, day of week, etc. The method proposed in [22] also uses such a forecasting approach.

2.2 The Consumat approach

Human decisions in agent-based models. Agent-based models address a wide range of simulation challenges in very different research areas. They are used both for social simulations and for models focusing on technical aspects. This is possible due to the generic characteristic of multi-agent systems: they are particularly suited for situations characterized by autonomous entities whose actions and interactions determine the overall system [23]. For simulating human systems with agent-based modeling, Bonabeau states the following three benefits in [8]: (1) it captures emergent phenomena, (2) provides a natural description of the system and (3) is flexible. In general, agent-based modeling has been considered as a promising methodology for social science research in the last two decades (see, e.g., [24]). Different frameworks exist to integrate the process of human decision making in agent-based models. They differ in aspects like level of complexity, research questions that may be answered with their help and psychological background. In [25] five main dimensions are distinguished to classify human agent architectures:

- Cognitive level (reactive, deliberative…)
- Affective level (representation of emotions)
- Social level (representation of complex social concepts, status…)
- Norm consideration (agents' ability to reason about social and formal norms)
- Support of learning

Using these description categories, the Consumat approach, which is used in this project, simulates reactive/deliberative agents, who are able to consider values and morality on the affective level. Their social focus is on success comparison with others. Consumat agents are able to learn and norms may be represented as model input parameters.

Background to Consumat and related implementations. Consumat is a socio-psychological framework which allows the agent-based simulation of human decision making in situations related to consumption of goods or opportunities such as doing a specific activity, deciding where to live, and others. Details of the model and its updates as well as the underlying theoretical background can be found in [11], [26]–[28]. In [12] different applications of the Consumat approach are discussed. Some results related to consumer behavior are briefly described below:

Household lighting. Based on a Consumat model the purchase decision concerning lighting technology were simulated in order to explore different policies for an increased market share of LED lamps. The observed behavior show that the pure appearance of a new product on the market does not strongly influence the consumers' decision but additional incentives do.

Diffusion of electric car. Similar simulations were made to investigate the diffusion of electric cars using policies, such as taxing fuel cars and subsidising electric cars. The results generally show the slowness of that process and indicate the high relevance of an optimal mixture and timing of different policies.

The developers of the Consumat framework used their approach to model the diffusion of green products with low environmental impacts simulating the behavior of both, consumers and firms [14]. The results represent the high relevance of social interactions and also reproduce empirical data. Also in [29] scenarios of green consumption are modeled with Consumat. The authors mainly explored effects of increasing prices for non-green products and an increasing environmental awareness of the consumers. Studies like [13] and [30] confirm the suitability of the Consumat framework to analyse and optimize policies and other measures to improve the market share of green products and services. In [10] the general concept of modeling demand response consumers as 'consumats' is already presented. Relevant details of the framework related to its application in this socio-technical environment will be considered within the model description (see Section 3.2).

3 Demand response consumers as 'consumats': model description

In this section, the application of the Consumat model to simulate the decision of consumers concerning participation in a demand response program is presented. The model description is based on ODD+D which extends the original Overview, Design Concepts and Detail (ODD) protocol with human decision-making aspects [31].

3.1 Overview

Purpose. This model aims to represent the decision-making of consumers to generally participate in demand response programs. Depending on the selected decision strategy other agents' behavior may be integrated into the corresponding cognitive process. The model was created to prove the suitability of the Consumat framework within this context and to identify relevant dependencies of the variables for further research.

Entities, state variables and scales. The model includes agents representing demand response consumers and the human and natural environment. Agents can decide to generally participate in demand response programs or not. They are characterized by individual levels of need satisfaction concerning their financial, personal and social state. The discrete time steps of the model are called ticks. Typical time scales for one tick can be daily to weekly.

Process overview and scheduling. With each tick, agents make their decision concerning participation and all attributes and parameters will be updated.

3.2 Design Concepts

Theoretical and empirical background. The agents' decision-making is based on the Consumat approach due to its ability to simulate consumers' behavior in different domains including social aspects (see Section 2.2). The simulated consumers have existential, social and personal needs and they are equipped with abilities and opportunities to satisfy these needs with a certain behavior.
The corresponding decision strategies are:

- Optimization: maximize the level of need satisfaction (LNS) based on own calculations
- Inquiring: check behavior of peers, compare possible imitation of their decision with own calculations to decide for maximum LNS
- Repetition: repeat decision of last tick
- Imitation: copy last behavior of peers (peers: agents with similar attributes)

The Consumat approach also integrates uncertainty of an agent as a relevant factor for decision making which leads to the following key rules for the engagement in a specific cognitive process [28]:

- with decreasing satisfaction, an agent accepts more effort to find the optimal behavioral option
- with increasing uncertainty, the behavior of other agents becomes more relevant

Fig. 2 illustrates the adaption of the underlying Consumat model (see [26], [28]) on the decision behavior of a demand response consumer. Based on own results published in [4], [10], [32], [33], the following driving forces on the micro level were identified and implemented:

- Needs: financial state, personal state (comfort and environment), social state
- Opportunities and abilities: participation in demand response program
- Uncertainty

More detailed descriptions of individual decision making will follow in the subsection below.

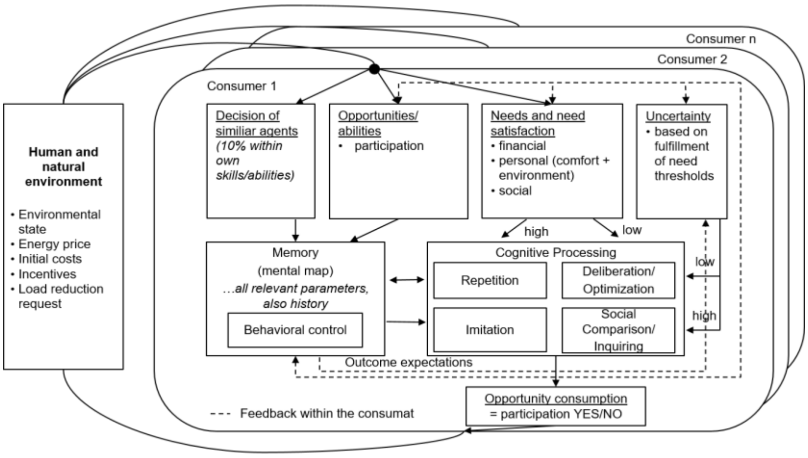

Fig. 2. Conceptual demand response consumer model based on Consumat

Interactions and individual decision-making, sensing and prediction. In the original model the engagement in one of the four decision rules depends on current uncertainty of the agent and its level of need satisfaction (LNS). In [26] uncertainty is described as the difference between expectations and the real outcome of an action. The updated version of the Consumat framework [28] directly couples uncertainty to the existence and social needs. With Consumat II different uncertainties concerning the several needs may have different weights within the overall uncertainty. However, the authors of [13] state that householders rather consider inconsistencies between needs and its satisfaction level than perform a statistical evaluation of uncertainty. Due to the similarity of the research domain (residential energy efficiency), we transfer this criteria-based approach and define the following rules to select the suitable decision mode within the model:

- For each of the three needs (financial, social, personal) a threshold of the LNS is defined as a criterion which is met or not
- The overall satisfaction and uncertainty of an agent depend on the fulfillment of these criteria
- The selection of a decision strategy is based on satisfaction and uncertainty following the assumptions of the original Consumat approach (see also Fig. 2)

This leads to the following logic (see Table 1):

Table 1. Criteria-based agent's decision logic

no. of fulfilled criteria	0	1	2	3
level of satisfaction	unsatisfied	unsatisfied	satisfied	satisfied
level of uncertainty	certain	uncertain	uncertain	certain
decision strategy	optimization	inquiry	imitation	repetition

Heterogeneity, stochasticity and observations. For most of the agent's own parameters, both a global and an individual randomized configuration is possible. For details on the different performed simulation runs and the output data analysis, see Section 4.

3.3 Details

Implementation, initialisation and data input. The model is implemented in NetLogo version 6.0.4. The presented code is roughly based on an existing Consumat implementation [34] and available at https://www.en-trust.at/downloads/. An initial setup procedure activates all parameters. If heterogeneity/variability is activated, it calculates the individual variables within configurable ranges. Although the current version of the model does not integrate import of data from external files this option could be easily included.

Submodels. Within this section model parameters and submodels are described.

Model parameters. Table 2 gives an overview on the relevant parameters used in the model.

Table 2. Model parameters.

Variable	Scope	Range/Condition	Explanation
number of agents	global	Natural number	
initial participants	global	percent of number of agents	configurable during setup
DR_{income}	global	0…1	profit of participation
initial participation	individual	0 or 1	
γ_{need}	individual	0…1, with $\gamma_{comfort} + \gamma_{environ} = 1$ $\gamma_{similar} + \gamma_{superior} = 1$	weight of a certain need, randomly assigned during setup

Needs. At each tick an agent calculates its overall level of need satisfaction (LNS) as a sum of the existential (financial), personal and social need:

$$LNS = LNS_{fin} + LNS_{pers} + LNS_{soc} \tag{1}$$

with

$$LNS_{fin} = participation * DR_{income} \tag{2}$$

$$\mathrm{LNS}_{pers} = \mathrm{LNS}_{environment} + \mathrm{LNS}_{comfort} = \begin{cases} \gamma_{comfort}, & participation = 0 \\ \gamma_{environ}, & participation = 1 \end{cases} \tag{3}$$

$$LNS_{soc} = \gamma_{similar} * need_{similar} + \gamma_{superior} * need_{superior} \tag{4}$$

The level of social need satisfaction is composed of the agent's need of being similar respectively superior compared to its peers/other agents balanced by individual weighting factors $\gamma_{similar}$ and $\gamma_{superior}$:

$$need_{similar} = 1 - abs(participation_{own} - mean(participation_{peers}) \tag{5}$$

$$need_{superior} = abs(participation_{own} - mean(participation_{all}) \tag{6}$$

Agent's behavior. In order to improve its individual level of need satisfaction, an agent evaluates its participation decision at each tick. The underlying strategy for the new decision is based on the fulfillment of three criteria concerning thresholds for the financial, personal and social need satisfaction (see Table 1). Each of these LNS values is always between 0 and 1. Due to the fact that individual preferences are already represented by the weighting factors the criteria are defined as fulfilled when the LNS value of the need is above or equal 0.5. Nevertheless, the model is also suitable for individual and variable threshold settings.

4 Results

To check the general suitability and logical correctness of the model, two main aspects were investigated: (1) variation of the agents' general behavior in time and (2) influence of varying input parameters on participation decision.

4.1 Variation in time

Fig. 3 exemplarily shows the participation behavior of 500 consumers over 30 time steps as provided by the NetLogo interface tab. The DR incentive was set to DR_{income} = 0.2, during initialization 25% of agents were configured with participation = YES and the individual weights of the needs were randomly distributed (0…1). With this parameter setup, the percentage of agent participation and the related decision strategies are already stable after five ticks of the simulation run. Other parameter configurations also show this short warm up period.

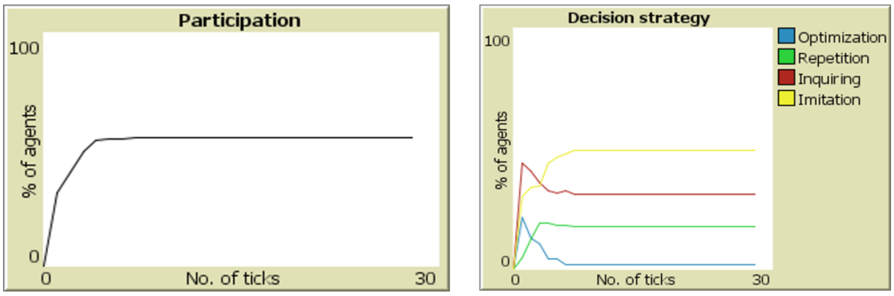

Fig. 3. Variation of behavior in time

4.2 Varying input parameters

The NetLogo tool “BehaviorSpace” allows to run a model systematically with varying parameter settings and to report selected variables after each run. Using this tool, a broad range of value combinations were simulated and analyzed. Fig. 4 exemplarily shows the percentage of agent participation depending on the DR income under several conditions (varying weights of the needs and different initial participation distributions). Each simulation run was performed five times with identical settings and the measured value reported after 30 ticks (see warm up period in Fig. 3). The graphs visualize logical effects of increasing income (higher participation rates) but also the importance of different weights of the agent’s needs. In the example a high importance of comfort needs (compared to environmental needs) has a high influence on participation, especially when the initial participation is low (see the two lower graphs: no participation when income and/or initial participation is low). All graphs show a broad distribution of the results for an initial participation of 50%. Additional simulation runs in this parameter range confirmed a very high sensitivity of the final participation for the randomized initial settings.

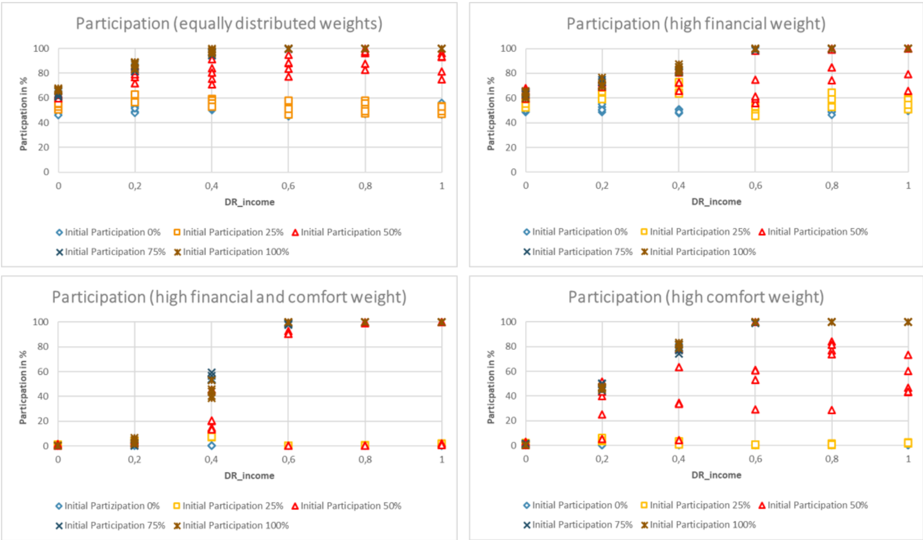

Fig. 4. Participation of 500 agents depending on DR_{income}, initial participation and weights

5 Conclusion

This work presents the development and implementation of an agent-based model of consumer participation in demand response programs based on the Consumat approach. At the current state of the project, the model provides first reproduceable results for a large variety of parameter settings. As a so-called toy model, it can be already used to find relevant correlations. Due to the simple and scalable parameter definitions, the model can easily be calibrated and validated based on empirical data. Additionally, considering the general participation in DR programs as a diffusion process offers the application of corresponding innovation and transition theories (for an overview see e.g., [35]). The model itself is scalable and can be extended by an additional logic considering the short-term aspects of consumers' interactions in the context of demand response (see Fig. 1). The underlying NetLogo tool allows interaction with other simulation frameworks like, e.g., mosaik. Future work will focus on two aspects: (1) improve, refine and validate the Consumat approach to model consumer participation in demand response programs and (2) integrate it in an overall model of consumer decisions in the demand response context. In a final state the model should provide quantifiable results for the optimal adjustment of incentives both for general participations and short-term energy price adaptions.

References

[1] European Commission, “COM(2014) 15 final: A policy framework for climate and energy in the period from 2020 to 2030,” no. 2014, pp. 1–18, 2012.

[2] Federal Energy Regulatory Commission, "Assessment of Demand Response & Advanced Metering," 2006.

[3] Owen Comstock, "Demand response saves electricity during times of high demand," 2016. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=24872. [Accessed: 10-Jun-2020].

[4] J. Schwarzer, A. Kiefel, and D. Engel, "The role of user interaction and acceptance in a cloud-based demand response model," in *IECON Proceedings (Industrial Electronics Conference)*, 2013.

[5] M. Z. Miller, K. Griendling, and D. N. Mavris, "Exploring human factors effects in the Smart Grid system of systems Demand Response," in *2012 7th International Conference on System of Systems Engineering (SoSE)*, 2012, pp. 1–6.

[6] J. Schwarzer, D. Engel, and S. Lehnhoff, "Conceptual Design of an Agent-based Socio-technical Demand Response Consumer Model," in *International Conference on Industrial Informatics*, 2018, pp. 680–685.

[7] M. Moglia, S. Cook, and J. McGregor, "A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency," *Sustain. Cities Soc.*, vol. 31, pp. 173–182, 2017.

[8] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," vol. 99, pp. 7280–7287, 2002.

[9] C. Le Page, D. Bazile, N. Becu, and P. Bommel, "Agent-Based Modelling and Simulation Applied to Environmental Management," in *Simulating Social Complexity*, no. November, B. Edmonds and R. Meyer, Eds. Springer, 2013.

[10] J. Schwarzer and D. Engel, "Agent-based Modeling of Consumer Participation in Demand Response Programs with the Consumat Framework," in *Abstracts from the 9th DACH+ Conference on Energy Informatics*, 2020, vol. 3, no. 27, pp. 13–15.

[11] W. Jager, M. A. Janssen, and C. A. J. Vlek, *Consumats in a commons dilemma: Testing the behavioural rules of simulated consumers*. 1999.

[12] S. Schaat, W. Jager, and S. Dickert, "Psychologically Plausible Models in Agent-Based Simulations of Sustainable Behavior," in *Agent-Based Modeling of Sustainable Behaviors*, A. Alonso-Betanzos, N. Sánchez-Maroño, O. Fontenla-Romero, J. G. Polhill, T. Craig, J. Bajo, and J. M. Corchado, Eds. Cham: Springer International Publishing, 2017, pp. 1–25.

[13] M. Moglia, A. Podkalicka, and J. Mcgregor, "An Agent-Based Model of Residential Energy Efficiency Adoption," *J. ofArtificial Soc. Soc. Simul.*, vol. 21, no. 3, p. 26, 2018.

[14] M. A. Janssen and W. Jager, "Stimulating diffusion of green products - Co-evolution between firms and consumers," *J. Evol. Econ.*, vol. 12, no. 3, pp. 283–306, 2002.

[15] J. S. Vardakas, N. Zorba, and C. V. Verikoukis, "A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms," *IEEE Commun. Surv. Tutorials*, vol. 17, no. 1, pp. 152–178, 2015.

[16] H. Kim, Y. J. Kim, K. Yang, and M. Thottan, "Cloud-based demand response for smart grid: Architecture and distributed algorithms," *2011 IEEE Int. Conf. Smart Grid Commun. SmartGridComm 2011*, pp. 398–403, 2011.

[17] A. Barbato, A. Capone, G. Carello, M. Delfanti, M. Merlo, and A. Zaminga, "House energy demand optimization in single and multi-user scenarios," *2011 IEEE Int. Conf. Smart Grid Commun. SmartGridComm 2011*, pp. 345–350, 2011.

[18] J. Schwarzer and D. Engel, “Evaluation of data communication requirements for common demand response models,” in *Proceedings of IEEE International Conference on Industrial Technology (ICIT) 2015*, 2015, pp. 1311–1316.

[19] N. Li, L. Chen, and S. H. Low, “Optimal demand response based on utility maximization in power networks,” *IEEE Power Energy Soc. Gen. Meet.*, 2011.

[20] D. Seetharam, T. Bapat, N. Sengupta, S. K. Ghai, Y. B. Shrinivasan, and V. Arya, “User-sensitive scheduling of home appliances,” no. August, p. 43, 2011.

[21] C. W. L. Adika, “Autonomous Appliance Scheduling for Household Energy Management,” *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 673–682, 2014.

[22] A. Barbato, A. Capone, M. Rodolfi, and D. Tagliaferri, “Forecasting the usage of household appliances through power meter sensors for demand management in the smart grid,” *2011 IEEE Int. Conf. Smart Grid Commun. SmartGridComm 2011*, pp. 404–409, 2011.

[23] S. Bandini, S. Manzoni, and G. Vizzari, “Agent Based Modeling and Simulation: An Informatics Perspective,” *J. Artif. Soc. Soc. Simul.*, vol. 12, no. 4, p. 4, 2009.

[24] M. Janssen and E. Ostrom, “Empirically based, agent-based models,” *Ecol. Soc.*, vol. 11, no. 2, 2006.

[25] T. Balke and N. Gilbert, “How Do Agents Make Decisions ? A Survey Introduction : Purpose & Goals Dimensions of Comparison Production Rule Systems,” vol. 17, no. 2014, pp. 1–30, 2014.

[26] W. Jager, *Modelling consumer behaviour*. 2000.

[27] W. Jager, M. A. Janssen, H. J. M. De Vries, J. De Greef, and C. A. J. Vlek, “Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model,” *Ecol. Econ.*, vol. 35, no. 3, pp. 357–379, 2000.

[28] W. Jager and M. Janssen, “An updated conceptual framework for integrated modeling of human decision making: The Consumat II,” *Eccs 2012*, p. 10, 2012.

[29] G. Bravo, E. Vallino, A. K. Cerutti, and M. B. Pairotti, “Alternative scenarios of green consumption in Italy: An empirically grounded model,” *Environ. Model. Softw.*, vol. 47, no. 256, pp. 225–234, 2013.

[30] D. Natalini and G. Bravo, “Encouraging sustainable transport choices in american households: Results from an empirically grounded agent-based model,” *Sustain.*, vol. 6, no. 1, pp. 50–69, 2014.

[31] B. Müller *et al.*, “Describing human decisions in agent-based models - ODD+D, an extension of the ODD protocol,” *Environ. Model. Softw.*, vol. 48, pp. 37–48, 2013.

[32] J. Schwarzer, D. Engel, and S. Lehnhoff, “Conceptual Design of an Agent-Based Socio-Technical Demand Response Consumer Model,” in *Proceedings - IEEE 16th International Conference on Industrial Informatics, INDIN 2018*, 2018.

[33] F. Fredersdorf, J. Schwarzer, and D. Engel, “Die Sicht der Endanwender im Smart Meter Datenschutz,” *Datenschutz und Datensicherheit - DuD*, vol. 39, no. 10, pp. 682–686, 2015.

[34] M. Janssen and W. Jager, “Lakeland 2,” 2017. [Online]. Available: https://www.comses.net/codebases/5793/releases/1.0.0/%0A.

[35] N. Bergman, A. Haxeltine, L. Whitmarsh, J. Köhler, M. Schilperoord, and J. Rotmans, “Modelling Socio-Technical Transition Patterns and Pathways,” *J. Artif. Soc. Soc. Simul.*, vol. 11, no. 3, p. 7, 2008.