Conceptual Design of an Agent-based Socio-technical Demand Response Consumer Model

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***Abstract*— Demand response (DR) management is one of the key applications of today's and future energy systems. The success of the DR programs strongly depends on several consumer-specific parameters, as, e.g., willingness to participate, comfort requirements, technical affinity etc., which are often neglected in corresponding simulation models. In this paper, a conceptual design of an agent-based socio-technical DR consumer model is proposed. It is based on a structural agent analysis mapped to a framework for a multi-agent simulation model.**

***Keywords*— demand response, user model, structural agent analysis, agent based simulation**

I. Introduction

Achieving optimal generation, distribution, storage and consumption of electric energy – while preserving natural resources – is one of the main goals of todays and future electricity grids. As one of the essential smart grid technologies, demand response (DR) has to be enabled in the residential sector. DR 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" [1]. According to [2], DR programs provide the capability to achieve 25-50% of the EUs 2020 targets concerning energy savings and CO2 emission reductions. As shown in [3] and [4] the success of a DR program essentially depends on the end consumers' participation and their behavior when configuring and using a DR system.

Due to the critical infrastructure, the integration of new smart grid technologies requires extensive tests and simulations before any large-scale deployment. Several tools and frameworks exist, which offer solutions for complex smart grid simulation challenges (see e.g. [5]). Concerning DR systems and algorithms, most of the proposals include a simulation part; some of them also consider certain aspects of consumers' behavior (see Section II.B). However, to our knowledge an adequate representation of all relevant user interactions and decisions is missing in these approaches.

Analyzing such socio-technical systems is a major research field in social sciences. A review on literature in this area has shown that agent-based models might be considered as a preferred simulation tool (see Section II.C). In these approaches, agents are human individuals or organizations of them. Based on a more generic agency definition (see Section II.D), also technical subsystems may be considered as agents and corresponding models are applied in fields such as biological sciences, ecology, economy and others [6]. In [7] and [8] reviews on multi-agents concepts used for grid energy management are provided.

Multi-agent systems are increasingly used in the quantitative social sciences as a promising method [9], [10], [11]. Nevertheless, especially when it comes to decision models in socio-technical systems, it is repeatedly stated that these models have weaknesses when it comes to applying them to real-world problems [12], [13]. To our knowledge, no model exists that combines social simulation of an energy consumers' behavior with realistic simulation models of the energy grid. Therefore, the aim of this work is to design a concept for an agent-based socio-technical user model, which can be integrated in more comprehensive smart grid simulations.

The rest of this paper is structured as follows: In Section II an overview of related work in the field of demand response and the corresponding consumer behavior is provided. In addition, literature on general user models from the field of social sciences is reviewed along with relevant aspects of agent-based simulation models. As the system model is based on this specific approach, Section III describes the framework of a structural agent analysis (SAA) proposed by Binder [14] and the rules to map this into an agent-based simulation model. Results of applying these steps to designing an agent-based consumer model in the context of demand response systems will be shown and discussed in Section IV; we conclude in Section V with a summary and an outlook on future work.

II. Related Work

The section on the theoretical background of this work is divided in four main parts: (1) a short review on DR models, (2) an overview of research work dealing with consumers' behavior in the context of demand response, (3) an introduction to general user models, which are assessed to be relevant for the research question and (4) a subsection dealing with relevant basics of agent-based simulation models.

A. Demand Response Models

Based on the common DR definition given in Section I, Albadi et al. give a more detailed definition: “DR includes all intentional modifications to consumption patterns of electricity of end-use customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption” [15]. Customers’ potential actions are reduction or time shifting of electricity usage, known as direct load control (DLC) and reducing the peak to average ratio (PAR), respectively. As a third option in [15] the usage of onsite generation and storage capacities is mentioned. Different pricing schemes (price based or incentive based) are employed as strategies to motivate consumers to choose any of these options, e.g., real time pricing (RTP). In case of incentive-based DR, customers get incentives, e.g., for switching off an appliance as a response to a certain load reduction request or they are rewarded for allowing direct load control (DLC). DLC is a specific DR model enabling the utility to directly control customers’ equipment, as, e.g., proposed in [16]. This approach reduces peaks by temporarily inhibiting the turn-on of certain high power appliances without disturbing already in-use appliances. Also in [17], a DLC model is used to centrally schedule and control power demand tasks at the customer side. In [18], a cloud-based DR scheme is proposed, where the optimal incentive price to achieve a certain load reduction is determined based on a publish-subscribe communication scheme. Different from DLC, here the control of appliances is realized at the customer premises, not at the utility side. Additionally, the model used in [18] optimizes the schedules of energy consumption for a group of users (multi-user scenario), also in [19], a coordinated load management of several flexible electricity consumers is presented. In a single-user scenarios the optimization is performed per household [20]. Demand response decisions are not made by the consumers in a case-to-case-manner but usually an algorithm implemented in a technical DR system (also referred to as energy management system) optimizes the performed actions. Considering the large number of contributions on DR, the following algorithms 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 DR models a more detailed overview can be found [21].

B. Consumer behaviour in the context of demand response

As the previous overview on demand response programs has shown, corresponding modeling and simulation approaches in most cases require presumptions concerning consumers’ decisions and behavior. There are some DR 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 [22] and [23]. Since these approaches require complex fine-grained appliance-level information, Chandan et al. [24] present an inclusive DR planning system (*iDR*) using only smart meter data to determine utility functions. In [25] a model is proposed that differentiates a long-term steady and a short-term dynamic consumer behavior: The steady component represents the typical usage pattern of appliances and the dynamic one responds to variations of the electricity price. A more general methodology for modeling the behavior of electricity prosumers is provided in [26]. To present the possibilities of that framework, a case study is shown that models the car drivers’ behavior and the corresponding impact of the electric vehicle charging on the electricity grid. In a sensitivity analysis, Miller et al. [4] 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 [3]. 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 DR system with autonomous appliance scheduling, as, e.g., proposed in [27], 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 [28] also uses such a forecasting approach.

C. User Models of consumer behavior

Independent of the specific demand response context, general models and theoretical background concerning consumers’ behavior will be considered in the following. The focus of this review is set on models of human behavior that specifically impacts an ecosystem and a combined analysis of material and social flows. According to [29], the term *material* stands for both, substances and goods, whereas goods are considered as mixtures of substances that have economic values assigned by markets. This terminology only includes material goods, immaterial goods such as energy, services, or information and their analysis might be coupled with corresponding *material flow analyses* (MFA). In [30] a generalized framework for materials and energy flow analysis is presented which does not explicitly distinguish between them. The authors of [31] compare ten frameworks established in the research area of socio-ecological models, the approaches are categorized and a general guideline for selecting the adequate framework for a given research issue is provided. With respect to the aim of the project presented here, the Human Environment Systems (HES) approach [32] will be further considered. In their HES framework, Scholz and Binder define the following six basic principles: (1) human and environmental system are different but interrelated, with actions and reactions being part of both systems, (2) human and environmental systems should be considered hierarchically, (3) a model of the environmental system and its dynamics needs to be constructed, (4) goals and strategies are basic components of behavior (decision theory), (5) environmental awareness has to be conceptualized concerning the strategies found in (4), and (6) post-decisional evaluation of environmental reactions (also delayed and dislocated) has to be performed. In [33], Binder gives an overview on social sciences modeling approaches, which are coupled to MFA based on the hierarchical level they are used for, ranging from the society (national level) down to an individual (household). The general idea of these models is to provide additional information not only to analyze, but also to manage material flows with respect to social interactions. In her review Binder identifies some shortcomings of these approaches and proposes in [14] a heuristic that combines a *structural agent analysis* (SAA) with MFA. Since this approach provides the basic principles for the conceptual model design within the here presented project details will be described in Section III.A.

D. Agent-based Simulation Models

As already mentioned in Section I, 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 [34]. For simulating human systems with agent-based modeling (ABM), Bonabeau states the following three benefits in [35]: (1) ABM captures emergent phenomena, (2) provides a natural description of the system and (3) is flexible. In general, ABM has been considered as a promising methodology for social science research in the last two decades (see, e.g., [36], [37]). Due to the multiple and heterogeneous application areas and disciplines of agent-based modeling, many differing definitions of agency exist. However, they all share the following concepts: notion of an agent, its environment and autonomy [8]. Wooldridge [38] considers agents as intelligent with flexible autonomy having the three characteristics reactivity, proactiveness and social ability. Based on [29] “everything associated with an agent is either an agent attribute” (static or dynamic) or a method (as, e.g., behavior and behavior rules). These rules lead to certain decisions and further interactions with the environment or other agents. To model the process of human decision making in agent-based models the belief-desire-intention (BDI) framework is widely used, see, e.g., [39], [40], [41], [42]. BDI is a specific agent architecture deviated from the theory of practical reasoning [43]. It is based on three components: belief (agent’s knowledge about environment and own state), desire (objectives, goals), and intention (plans, course of action). Several frameworks have been already proposed that implement the BDI architecture’s agents in already existing agent-based modeling and simulation platforms, as, e.g., Netlogo [42].

III. System Model

The approach presented here to design a consumer model in the context of demand response systems is based on the aforementioned heuristic technique proposed by Binder [14]. The author combines material *flow analysis* with *structural agent analysis* (SAA) and thus provides strategies dealing with challenges arising from material flow management. In order to apply the combined MFA-SAA heuristic to design a consumer model in the context of demand response, energy flows are interpreted as material flows within the here presented approach. It might be used to analyze the impact of social structures on agents’ actions but also the feedback from these actions on social structures and the corresponding material consequences.

The identified agents and their structural factors will be further implemented in a general framework of an agent-based simulation model. These types of models are increasingly used both in corresponding social sciences approaches and in smart grid models and thus represent a promising method to figure out aspects of interactions between them.

A. Structural agent analysis

The structural agent analysis proposed in [14] is based on Giddens structuration theory [44] which provides a general framework for studying the systems of social interactions. The SAA consists of seven steps which will be shortly described below.

1) Identification of relevant agents

Based on MFA, agents affecting relevant variables are identified in this step. Two types of agents exist: directly interacting ones and agents, which indirectly affect the system. Note that *agent* in this context means persons and organizations that might be asked for their interactions and other influencing factors.

2) Analysis of structural factors (SF)

Agents’ decisions influencing MFA variables depend on several structural factors. The second step of the SAA which might be performed together with step 1 aims to analyze these factors for each agent based on Giddens key categories (see also [45]): signification rules, legitimation rules, allocative resources and authoritative resources. Beside determination of the structural factors, the interactions between them have to be analyzed in this phase. A matrix may be a helpful tool to visualize the impact of one factor on the others, e.g., in an ordinal scale from 0 to 2 (0 = no, 1 = weak and 2 = strong influence). Note that the values in this matrix might differ depending on the agent’s perspective.

3) Weigthing the relevance of SF

In the third step, Binder recommends in her approach to rank the structural factors concerning their weighted impact on agents’ actions. The results will be closely related to the cross-impact matrix developed within step 2.

4) Step 4: Agent –structure diagram

To finalize the steps 1-3 an agent-structure diagram will help to visualize their results. Arrows of different thickness also allow representing the weight of the structural factors.

5) Step 5: Agents‘ options, constraints and facilitators

Starting from an understanding view of agents, their interactions and structural factors provided by the steps 1-4, options to manage and change the MFA system have to be identified in step 5. Options are ways of acting that affect the material flows. Structural factors might constrain or facilitate them. This overall analysis results in a list of options and their supporting or constraining structural factors for each agent.

6) Interferences among agents

Agents, their options and the corresponding facilitators and constraints might interfere with each other and thus affecting also the consequences on material flow management. In this step, therefore, the outcome of the steps 1-5 has to be further analyzed to determine these interferences.

7) Effects of agents' action on structure

Finally, the expected long-term effects of agents' action on structure have to be estimated, e.g., impact of certain actions on consumers' affinity on technology (signification).

Binder recommends several research methods in order to perform the required analyses for each step, such as literature reviews, surveys, expert interviews and MFA methods. The selection of the combined MFA-SAA technique as framework for developing the conceptual design of a socio-technical DR consumer model is based on two crucial factors. First, as already stated energy flows might be interpreted as material flows. Second, the agent-based approach of the model offers all advantages of this technique to represent human individuals or organizations as well as technical systems as agents.

B. *From SAA to a Multi-agent Simulation Model*

In order to perform a combined modeling and simulation of consumers' behavior and their technical environment the results from the SAA shall be implemented in a computational agent-based simulation model. This step requires the transformation of the agent-structure diagram (Fig. 2) into an agent-based modeling framework with its typical characteristics, rules and terminology (see Section II.D). Based on the literature review for SAA and multi-agent simulation models the mapping shown in TABLE I. will be applied.

TABLE I. FROM SAA TO A MULTI-AGENT SIMULATION MODEL

Structural Agent Analysis	Multi-agent Simulation Model
agent	agent
structural factor	attributes
changes of structural factors	perception
options of agents	interaction
interaction among structural factors	reasoning / decision making
influence of structural factors on options	reasoning / decision making

IV. RESULTS

The focus of the design presented here is set on a scenario mainly considering consumers using a demand response system to manage their energy loads and storages. The results present a stepwise development of a structural agent diagram based on a combined MFA and SAA which is further implemented in a MAS modeling framework.

A. *High level MFA and SAA for a DR scenario*

From the energy perspective, the goal of a demand response system is to shift or curtail residential loads in order to assist the energy system's reliability. Visualizing the results of a high level MFA and SAA, Fig. 1 shows the main agents involved in the general energy supply chain and the corresponding energy flow (steps 1-4, simplified). Note that distributed energy resources are not included in this scenario.

The integration of the DR system as an agent is based on the general agency definition (see Section II.D) and extends the natural SAA model, which focuses only on individuals or organizations. This adaption allows the integrated analysis of interactions between consumers and their DR system, which is described in detail in the following section.

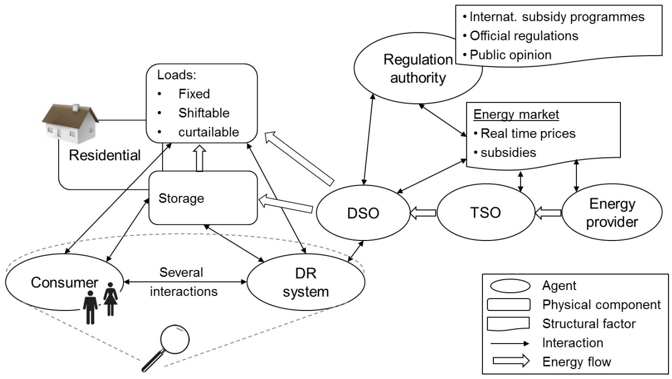

Fig. 1. High Lever MFA and SAA for a smart grid scenario with DRM

B. *SAA for consumers in a DR scenario*

Based on the general overview on energy flow and participating agents in an overall DR scenario given in section A, a more detailed analysis of structural factors and interactions between consumers and demand response systems is provided here. Applying steps 1-4 of the proposed model on this specific constellation identifies agents, structural factors and relevant interactions shown in Fig. 2. The findings are based on a comprehensive research in DR literature (see section II.A) and own projects [3], [46].

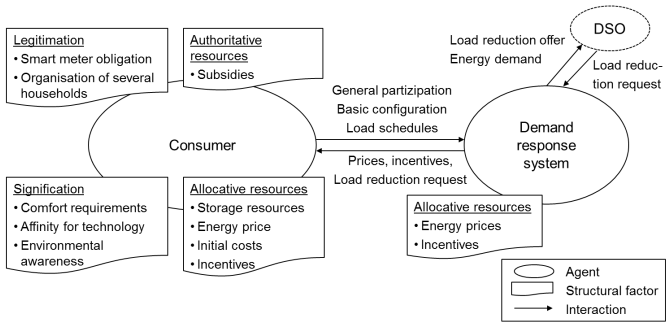

Fig. 2. Agent-structure diagram for consumer and DR system

As already stated in the system model description (see Section III.A.2), not only agents but also structural factors may interact with each other. A corresponding analysis of these impacts between structural factors is part of step 2. First, two categories have been identified: non-interacting and interacting structural factors. As non-interacting factors the legitimation rules (smart meter obligation, organization of several households) and authoritative resources (subsides) can be considered. For some of the remaining structural factors, the matrix shown in TABLE II. exemplarily represents the impact these factors have on each other. The estimated strength of the impact is given as no impact (0), weak direct relation (1) and strong direct relation (2). The value expresses the potential of one factor to influence/change the other factor. A general dependency/ relationship as, e.g., persons with a high affinity for technology would accept higher initial costs than persons without, is not illustrated here, since the person's technological affinity has no impact on the initial costs.

TABLE II. IMPACT AMONG SFs (0 = NO, 1 = WEAK AND 2 = STRONG)

from\to	price/ incentive	initial costs	comfort req.	techn. affinity	environ. awaren.
price/ incentive	-	0	2	0	0
initial costs	0	-	1	1	0
comfort req.	0	0	-	1	0
techn. affinity	0	0	1	-	0
environ. awaren.	0	0	2	1	-

Performing step 5 of the SAA, TABLE III. shows exemplarily the options/possible interactions of the consumer-agent and their corresponding constraints and facilitators.

TABLE III. Options of consumers influenced by structural factors

options of consumers	influencing structural factor
participation in DR program	initial costs
	affinity for technology
	smart meter obligation
basic configuration of DR system	affinity for technology
	comfort requirements
load schedule	energy price
	comfort requirements
allowed shut down	energy price, incentive
	comfort requirements
consumer association	initial costs
	energy price, incentive
…	…

C. MAS modeling framework

Using the mapping rules proposed in TABLE I. an approach that follows the formal description of multi agent simulation models (see section II.D) is shown in Fig. 3. Structural factors identified within the SAA are represented as agents' attributes, their interactions and also their influence on options/actions will be part of the reasoning and decision-making process which is out of scope of this work.

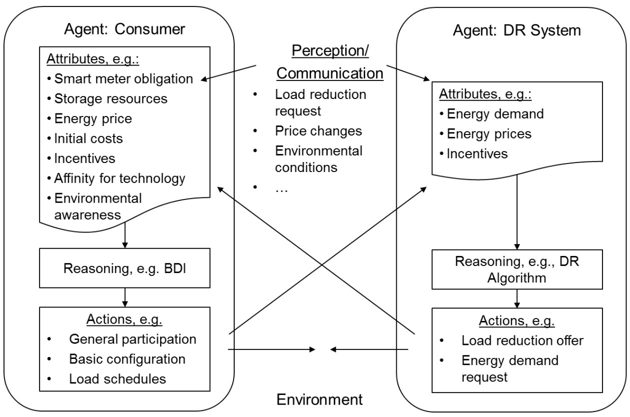

Fig. 3. Consumer and DR system: MAS modeling framework

D. Discussion

Whereas the results presented here do not provide a complete socio-technical DR user model, the developed design gives valuable input for further refinement of a corresponding agent-based simulation. The impact among structural factors and their influence on agents‘ options (actions) is only analyzed within the SAA approach, but especially the results shown in TABLE II. and TABLE III. will aid to precise the decision-making framework of the consumer agent. In a corresponding BDI approach the findings can be used to formalize the choice of plans based on the evaluation of certain criteria [42].

V. Conclusion

The agent structure-diagram shown in Fig. 2 and the corresponding agent-based simulation framework (Fig. 3) provide a detailed insight in a DR scenario mainly considering consumers' options to behave and interact in its environment. The process of reasoning and decision-making is not integrated yet in detail, but the SAA already provides valuable input for this upcoming step. The target framework shall be used for further simulation of more comprehensive MAS-based smart grid models.

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