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Abstract

With the ongoing deployment of smart grids, price-responsive demand is playing an increasingly important role in the paradigm shifting of electricity markets. Taking a multi-agent system modeling approach, this paper presents a conceptual platform for discovering dynamic pricing solutions that reflect the varying cost of electricity in the wholesale market as well as the level of demand participation, especially regarding household customers and small and medium sized businesses. At first, an agent-based meta-model representing various concepts, relations, and structure of agents is constructed. Then a domain model can be instantiated based upon the meta-model. Finally, a simulation experiment is developed for use case demonstration and model validation. The simulation is for the supplier to obtain the profit-maximizing demand curve which has such a shape that it follows the spot price curve in inverse ratio. The result suggests that this multi-agent-based construct could contribute to 1) estimating the impacts of various time-varying tariff options on peak-period energy use through simulation, before any experimental pilots can be carried out; 2) modeling the electricity retail market evolving interactions in a systematic manner; 3) inducing innovative simulation configurations.

Keywords: Agent-based Modeling, Computational Intelligence, Demand Response, Electricity Markets, Meta-model, Multi-agent Systems, Real-time Pricing, Smart Grids.

1. Introduction

The deployment of Advanced Metering Infrastructure (AMI) in many countries allows bi-directional communications between electricity consumers and suppliers. It is creating a platform for demand-responsive load control within the smart grids, which will shift the paradigm of electricity markets in many ways. Foreseeably, consumers will be able to manage and adjust their electricity consumption in response to real-time information and changing price signals. Accordingly, electric utilities will be capable of altering the timing, level of instantaneous demand, or the total electricity consumption at times of high wholesale market prices or when electric system reliability is jeopardized [1]. Such a price-responsive interaction between demand and supply (a.k.a. Demand Response) will in turn impact the spot market prices directly as well as over time [2], eventually, improve the link between wholesale and retail power markets which to a great extent are disconnected currently. The potential benefits of full participation by demand include flattening daily load patterns, optimizing the production portfolio by mitigating the variability of generation from renewable sources, and reducing the investment in reserve capacity needed to maintain resource adequacy and system reliability [3], thus improving overall market efficiency.

However, in order for the above mentioned demand responsive paradigm to be realized, the understanding of the ever-evolving interaction between the demand and the supply sides in the electricity retail market is crucial. As the competitive electricity retail markets are relatively new and the demand response electricity markets are acknowledged as one of the most complex adaptive systems, there is an increasing need for advanced modeling approaches that simulate the emergent behavior (demand responsiveness) among market participants (e.g., consumers, suppliers, producers, prosumers, etc.). Agent-based modeling (ABM), compared to traditional system-modeling techniques, is one appealing approach for studying how the market participants might act and react to the complex economic, financial, regulatory, and environmental circumstances embedded in the electricity sector.

Agent-based modeling has been extensively studied for the simulation of electricity markets in recent decades, alongside with the electricity industry restructuring and the generation, transmission, distribution, and supply business entities unbundling. The large majority of ABM research related to the electricity markets simulation is centered around the analysis of market power and market mechanisms in the wholesale electricity trading. Very often the demand side is represented as a fixed and price-insensitive load [4]. Only a handful of research has touched upon modeling the price-responsive electricity consumer behavior at the retail level [28]-[31]. In this paper, we will introduce a multi-agent-based meta-model (MAMM) for systematically modeling the price-responsive emergent behavior in the context of demand response electricity retail market. The proposed MAMM is to present a conceptual platform for discovering dynamic pricing solutions that reflect the varying cost of electricity in the wholesale market as well as the level of demand participation (e.g., demand responsiveness vs.

various rate designs), especially regarding household customers and small and medium sized businesses.

One of the unknowns in implementing dynamic pricing is whether and by how much customers would reduce peak loads in response to changing price signals [5]. Therefore, it would be necessary to estimate the impacts of various time-varying tariff options on peak-period energy use, before any experimental pilots can be carried out (Quite often, it is complicated, costly, and time-consuming to organize this kind of pricing pilot programs). Hence, the research objective of the agent-based demand modeling is to help address this estimation issue through simulation experiments. To be close to real conditions the simulation experiments ought to capture a large variety of aspects and side conditions influencing the energy consumption. Therefore, we introduce at first a MAMM that defines the concepts, relations, and structure of *utility-based agents* on abstraction level being independent of any concrete domain. Secondly, instantiating the MAMM with domain specific notions, e.g. with those needed for electricity market modeling, provides a uniform abstract interpretation of all domain models that conform to the MAMM. Thirdly, given a MAMM, it supports systematic construction of models that articulate different static, dynamic, and/or interactive aspects relevant to specific simulation experiment. Thus, our research goal in this paper is to demonstrate how the MAMM guided domain model construction can be exploited to address the impacts analysis problems of various time-varying tariff options by means of agent model simulation experiments.

The paper is organized as follows: the next section will present the research method and related research. The conceptual construct will be introduced in Section 3&4. In Section 5, a use case is used to demonstrate the simulation, in the meantime, to validate the conceptual model. In the final part of this paper, the conclusion will be drawn and future research will be addressed.

2. Methodology and Related Works

Agent-based modeling for electricity markets simulation has experienced increasing popularity in the past decades. For instance, within the research paradigm of Agent-Based Computational Economics (ACE), agent-based simulation offers methods to understand electricity market dynamics and to derive advice for the design of appropriate regulatory frameworks [4]. Compared to other electricity market modeling approaches, such as optimization models or equilibrium models, agent-based modeling as a bottom-up approach has the advantage of integrating a high level of detail and players' interactions, which are necessary to analyze short-term development in the electricity markets [6]. Agent-based models not only offered the possibility of realistically describing relationships in complex systems, but growing them in an artificial environment [7], thus the evolving behavior can be observed step by step [8].

A great deal of research in the field of agent-based simulation of electricity markets has concentrated on the analysis of market power and market design in wholesale electricity trading. Bower and Bunn (2000) present an agent-based simulation for analyzing trading arrangements in the England and Wales electricity market, in order to compare different market mechanisms. Consequently, various wholesale electricity market simulation models were developed by Bower et al. (2001) for German electricity sector, Cau and Anderson (2002) for the Australian National Electricity Market, and by the research group at Iowa State University for the Wholesale Power Market Platform proposed by the U.S. Federal Energy Regulatory Commission [12]-[14]. In addition, different computational algorithms were examined for the agent-based electricity market modeling. For instance, Visudhiphan and Ilić (1999, 2001, and 2002) modeled electricity trading strategies in the wholesale market by comparing different adaptation algorithms. On the other hand, some power market models applied genetic algorithms for representing the agents' bidding behavior [18], [19], [21], whereas some AB models simulated the power market by applying Erev-Roth reinforcement learning algorithm [12]- [14], [20], [22]. Other simulation methods include learning Classifier Systems which are rule-based learning mechanisms combining reinforcement learning and genetic algorithms [23]-[27]. Very often, among the majority of agent-based electricity wholesale market studies, the demand side is simplified to a fixed and price inelastic aggregate daily curve. To certain extent, this reflects the disconnection of the wholesale and retail power markets, which will be the obstacle of improving the overall market efficiency as will be enabled by the smart grids functionality.

In the meantime, only a few agent-based research modeled electricity consumer behavior at the retail level. Ehlen et al. (2007) presented a simulation based on N-ABLETM, in which they studied the effects of residential real-time pricing contracts on demand aggregators' load, pricing, and profitability. Müller et al. (2007) investigated the interdependencies between the customer's engagement and the suppliers' pricing strategies in the German retail market by modeling the suppliers as rationally bounded agents and by quantifying the households' decision making (i.e., switching the supplier by agreeing on a new standard contract) with surveyed data. In addition, two agent-based studies focused on the Time of Use (TOU) pricing for residential customers under different context. Roop and Fathelrahman (2003) simulated the changes in contracts in the context of a distribution grid model, by modeling the distribution grid based on the IEEE 13-bus test case and using a modified Roth-Erev algorithm for contract choice modeling. Hämäläinen et al. (2000) examined the consumption strategies of individual electricity consumers with electric space heating within a coalition. Based on the experiment conducted in Helsinki during the winter of 1996, they constructed different groups of consumer behavior to simulate this coalition.

The heterogeneity of agent-based electricity market research, as discussed above, has led to that the models are rarely comparable, and sometimes cannot be described in all necessary detail, especially in terms of electricity retail market simulation. Therefore, it is necessary and relevant to take an integral and systematic approach in this matter. Since price-responsive demand will play an important role in linking the electricity wholesale and retail markets driven by the smart grids functionality, we will propose a

multi-agent-based conceptual model for demand response retail market modeling in the following section.

The multi-agent-based conceptual model is constructed with the deregulated European electricity market structure in mind, in which the electricity generation, transmission, distribution, and supply business are legally unbundled, with the generation and supply sectors open for free competition while the transmission and distribution business are subject to regulation due to their monopolistic nature. Any producers can deliver electricity to their respective common electricity wholesale market -- for example, the producers in Nordic area can deliver electricity to Nord Pool exchange. The electricity wholesale market consists of power producers, power suppliers, retailers, industry and other large undertakings. The electricity retail market includes all end-users equipped with hourly measured smart meters, for instance, industries, public/commercial buildings, households, small businesses, and so on. These are the prerequisites for the demand response under study.

3. The Conceptual Platform

Meta-modeling is used in Artificial Intelligence (AI) and knowledge engineering for the analysis, construction and development of generic concepts, rules, constraints, components, frames, and models applicable and useful to certain predefined problem domain. As a domain model (DM) is an abstraction of phenomena in the real world, a meta-model is the abstraction and specification of the properties of domain models. In other words, a domain model can be considered always as an instantiation of certain abstract meta-model. In the context of deregulated electricity markets, the function of the meta-model under study is to set up a conceptual platform for modeling the demand responsiveness against various dynamic pricing solutions. Since the agents of given domain are reflective to their environment changes (caused by other agents), they chose their reactive actions based on their own goals and try to follow certain utility function on that, we propose a customized version of utility-based agents meta-model introduced in [32].

Our MAMM contains abstract concepts interrelated via abstract relations. Each domain model that refines MAMM is considered as an instantiation of MAMM. Since the domain model includes usually multiple notions all being instances of meta-notions of MAMM, the concrete selection of the domain concepts depends on the specific analysis problem the domain model has to be constructed for. To give some intuition about the notions of MAMM we describe them informally by showing their relationships in the form a semantic network depicted in Fig. 1.

An agent has one or more roles; each of these roles determines one or more goals. The way how an agent reacts to the environment (to other agents) with different actions depends on its mode and the goal of given mode. A mode includes a set of agent's states and related to given mode goal. Generally, we assume that our DMs are stationary

meaning that the agents' roles and their goals do not change during a simulation experiment. To fulfill its role an agent performs actions that are triggered by some event. The actions, in turn, can generate new events when terminating (atomic actions) or in the course of execution (non-atomic actions). Event is a notion related to both - time and state. Event reflects the instant of time when some change of state occurs (is observable/has some influence to other agents). Agent has a state that is defined as a valuation of agent attributes. Agent attributes which are used to define local state are usually called internals. Whereas, some of attributes can be shared (common) by many agents and define the global state, we call them externals. State is changed by actions. Action may have non-zero extent in time. Since each action describes only a subset of state changes, the action is enabled only in certain states (generally it does not exclude enabledness of some actions in all states). The agent's actions are grouped into modes to define the subspaces of the state space and are related to enabling conditions and events in modular way. The actions (except the mode changing actions) of a mode depend only on the states of the mode subspace.

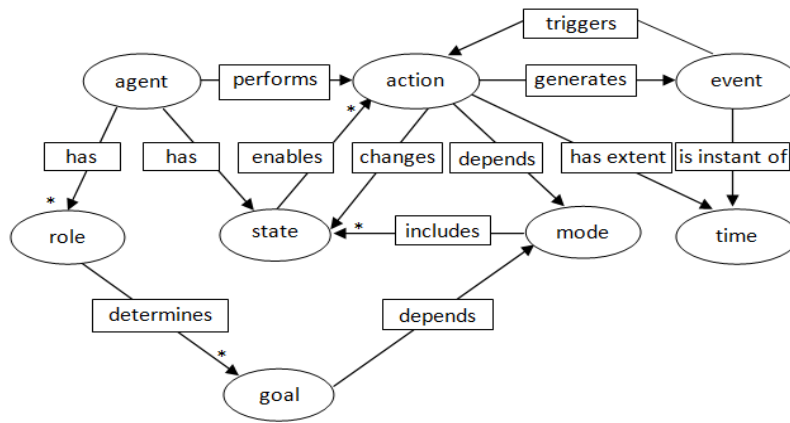


Figure 1. Semantic network of the meta-model.

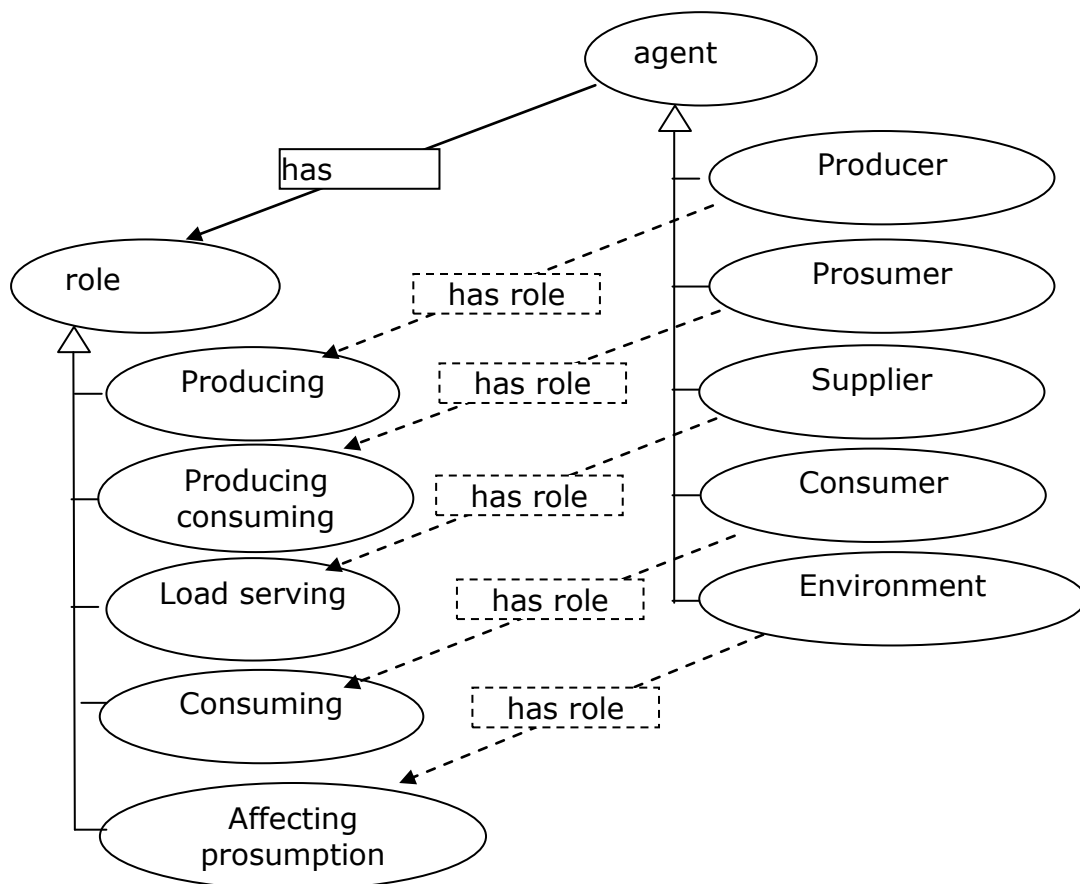
For the clarity of further presentation we introduce some meta-notions that refine MAMM but are still domain independent. We call a set of actions to *interaction* if two or more agent's actions on shared externals are respectively in the *changes* and *depends* relations. An interaction is *joint action* if the actions of different agents share also a common start event.

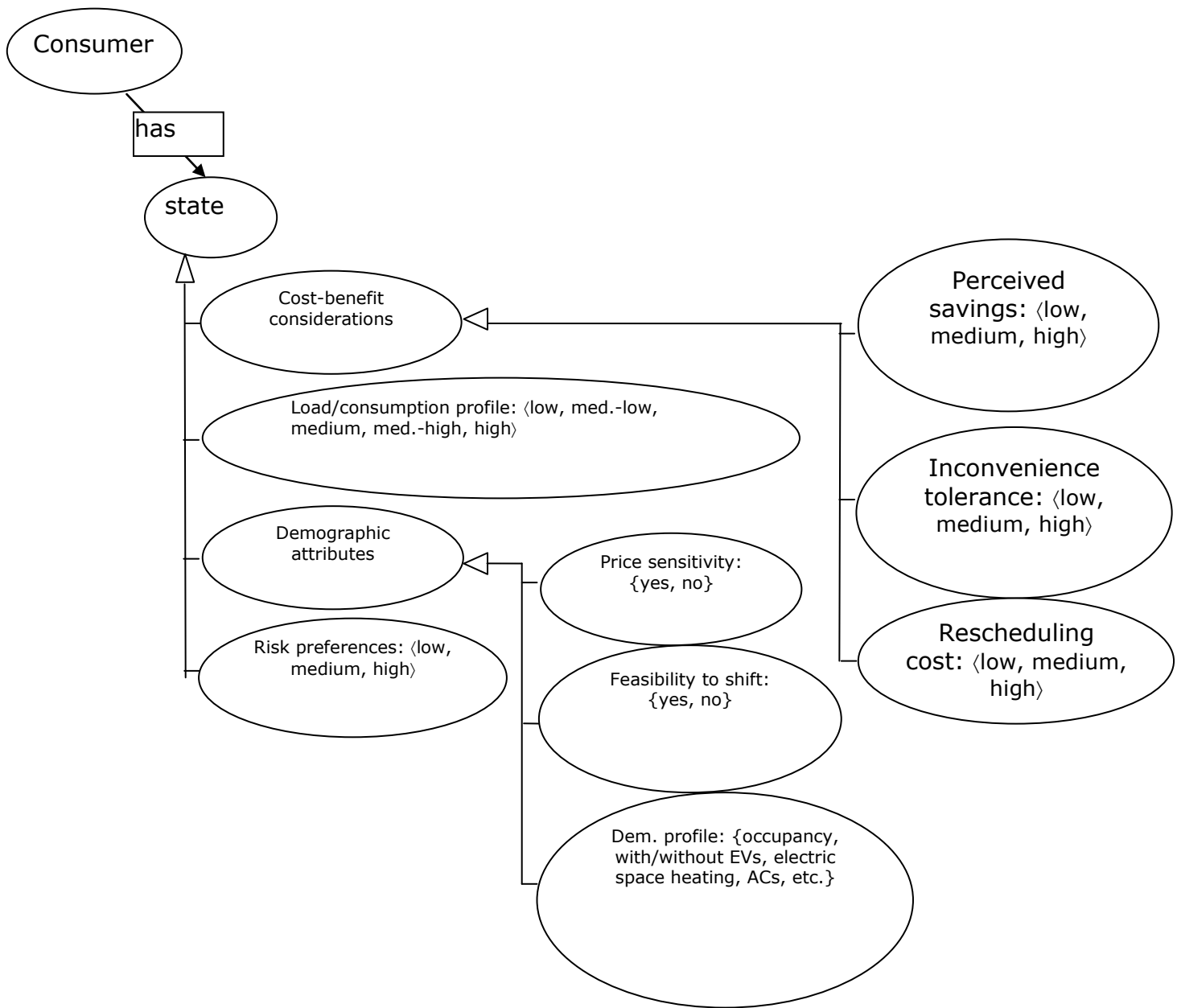
Before delving into MAMM based construction of DM we summarize the key properties of agents that constitute our further space of discourse: autonomy (capable of operating and making decision on its own), sociability (capable of interacting with other agents), reactivity (capable of responding to a perceived change of environment), proactivity (capable of acting on its own initiative in order to achieve certain goals/utilities), and adaptivity (with sophisticated learning capabilities) [33], [29].

4. Domain Model for Price-Responsive Demand Analysis

The agent is to represent the market actors in the real world and act on behalf of them. In the context of electricity markets, it includes producers, transmission and distribution operators, suppliers, consumers, prosumers, and other load servicing entities (e.g., demand aggregators). Even though the environment is external and largely uncontrollable, it is necessary to be simulated also as an agent to make explicit the way how it will affect production and consumption activities of the market actors.

For price-responsive demand modeling, a domain instantiation can be characterized as in Fig. 2. Since the consumer and the supplier are the focal market players in this context, the focus of the DM is on the respective actions of the supplier and the consumer and on their interactions.





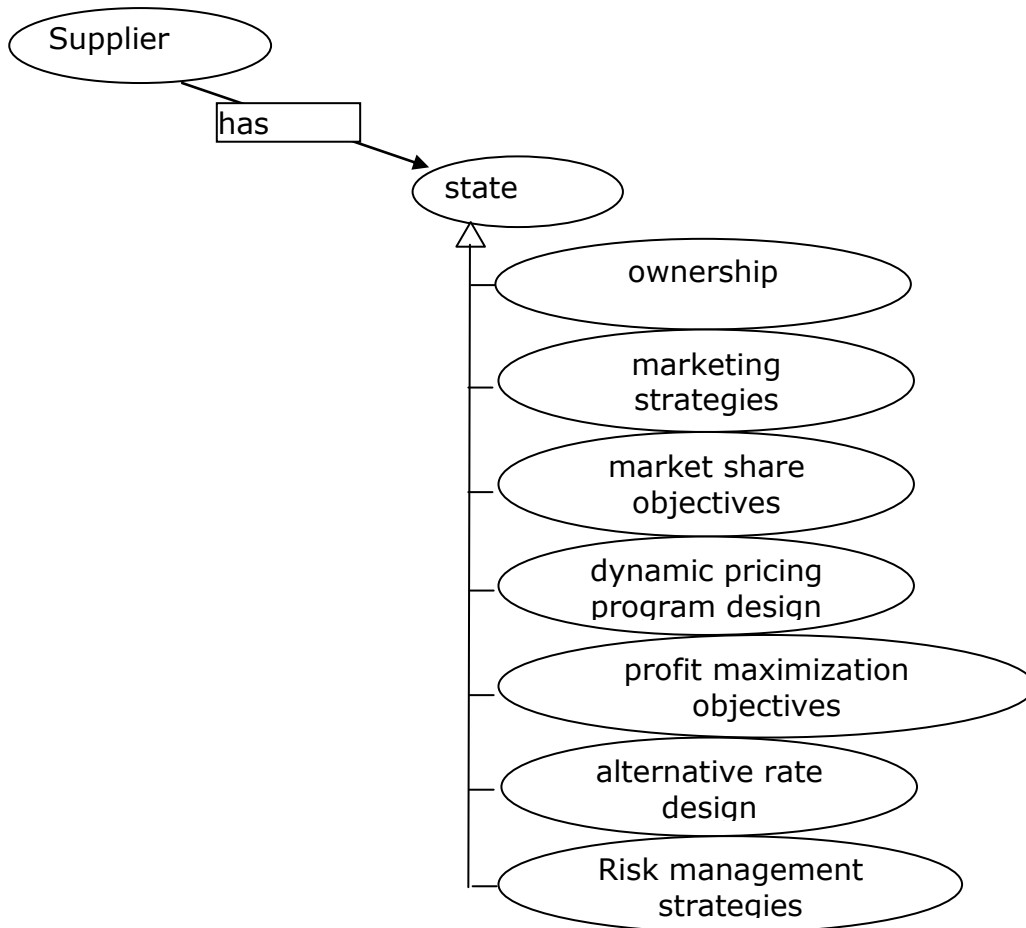


Figure 2. Instantiation of MAMM with domain specific concepts.

5. Use Case

Based on the domain model described above, simulation experiments can be carried out. In this section, we will demonstrate a use case, in order to validate the conceptual construct. The simulation model is formalized and run on the UPPAAL environment, which is an academic-free modeling, simulation and model-checking tool.

The simulation setup. As mentioned earlier, one of the potential benefits of demand response is to flatten daily load patterns. Therefore, the example scenario is for the supplier to obtain the ideal demand curve which has such a shape that it follows the spot price curve in inverse ratio. We introduce the model representing the Supplier-Consumer interaction with spot price and hourly consumption both being the interaction observables. Thus, the main actors in the simulation model are Consumer and Supplier. The third actor - Environment serves to demonstrate the flexibility and scalability of the model for different time scales and contexts. It allows us to take into account the dynamics of long term factors - outdoors temperature, hours of daylight etc. that all have impact on the consumption.

Simulation consists of 1 supplier and N consumers. The consumers belong to high consumption cluster (HCC), which makes steering their demand according to the spot price a priority in relation to the supplier's goal of profit maximization. The spot price is based on the Nord Pool Spot published system price for Estonia during the 2nd week of January, 2013 (see Table 1).

Table 1. Elspot prices [EE] in [EUR/MWh] (7.01-13.01, 2013)

Time	Mon	Tue	Wed	Thu	Fri	Sat	Sun
00 - 01	40,08	37,94	33,32	34,16	33,3	32,88	34,96
01 - 02	38,36	37,52	32,99	33,91	33,05	32,52	33,7
02 - 03	37,9	36,9	32,85	32,97	32,96	32,29	33,12
03 - 04	36,81	36,98	32,91	34,08	33	32,2	33,26
04 - 05	36,87	36,86	35,71	35,75	33,89	34,27	34,18
05 - 06	37,35	37,24	40	37,08	34,5	36,35	35,88
06 - 07	37,29	37,9	44,62	38,82	40,22	39,39	40,6
07 - 08	37,68	38,62	54,84	42,19	44,08	38,61	48,04
08 - 09	37,82	39,27	54,93	45,59	48,02	40,09	44,03
09 - 10	38,46	40,51	48,59	43,61	44,07	40,73	44,02
10 - 11	44,04	41,22	46,8	42,49	44,06	41,73	44,02
11 - 12	44,05	41,5	44,94	42,32	44,05	41,48	43,51
12 - 13	40,11	41,23	44,77	42,44	44,07	44,02	44,02
13 - 14	39,94	40,95	44,03	43,31	44,06	44	44,02
14 - 15	40,97	40,95	45,15	44,46	44,02	44,01	44,02
15 - 16	39,5	43,17	53,27	45,78	44,07	44,01	44,02
16 - 17	40,39	46,98	52,68	51,64	44,06	44,02	44,01
17 - 18	44,38	53,45	54,03	52,03	44,09	44	42,71
18 - 19	47,73	49,16	45,29	44,08	42,24	40,18	41,28
19 - 20	43,08	42,67	43,64	41,95	40,14	37,9	39,14
20 - 21	40,63	40,11	40,47	40,51	39,03	32,97	38,05
21 - 22	39,64	39,98	39,91	37,04	37,95	31,19	37,45
22 - 23	39,66	40,13	36,39	33,78	35,04	15,09	36,49
23 - 00	38,02	40,18	37,08	33,27	34,2	28,04	34,49

The pricing algorithm. When designing the pricing function for hourly price we aim at getting the driving effects that smoothen sharp fluctuations in consumption without alternating HCC's total consumption and possibly increasing supplier's profit. Also we set an upper limit Δ^{TL} to hourly price change Δ to avoid overshoots and instability of consumption.

The basis of next day hourly price $P'(T)$ at hour T is the spot price $P(T)$ of the previous day at T . Let $Q(T)$ be the consumption at T on previous day. Then the next day hourly price $P'(T)$ at hour T is calculated in our simulation by formula (1).

$$P'(T) = P(T) (1 + \Delta(T)/100), \text{ where} \quad (1)$$

$$\Delta(T) = \begin{cases} \frac{\nu \cdot [P(T) \cdot Q(T) - \text{avg}(P(T) \cdot Q(T))]}{\text{avg}(P(T) \cdot Q(T))} \cdot \frac{\Delta^{\pi}}{P(T)}, & \text{if } \frac{\Delta(T)}{P(T)} < \Delta^{\pi} \\ \text{sign}(\Delta(T)) \cdot \Delta^{\pi} \cdot \frac{P(T)}{100}, & \text{otherwise} \end{cases} \quad (2)$$

where

ν is parameter to amplify or suppress the effect of calculated price correction;

Δ^{π} is acceptable price change (%);

$\text{sign}(\Delta(T))$ is the sign function with co-domain $\{-1, 1\}$ showing if the price correction is positive or negative comparing to previous day spot price.

The hourly price calculated by (1) is proportional to the difference $P(T) \cdot Q(T) - \text{avg}(P(T) \cdot Q(T))$, where $\text{avg}(P(T) \cdot Q(T))$ is arithmetic mean of $P(T) \cdot Q(T)$ over 24 hours. The formula (2) guarantees that the calculated change of hourly price never exceeds the limit set by Δ^{π} . That is needed for keeping the stability of price response.

Consumer's behaviour. All consumers of HCC are modeled with the same model template. The template is parameterized with cluster specific attributes that allow modeling variations in cluster consumption patterns.

The consumption pattern includes consumption activities, e.g. ironing, room heating, water heating, etc. Each activity is characterized by following attributes: enabling condition and consumption interval or function. When consumption dependency is well-defined it is specified by means of explicit function. When non-determinism is presented in the consumption pattern the consumption interval is specified instead so that random value from that interval is generated for variable $Q'(T)$ update.

Since our simulations are approximating we abstract away from exact prices and use price intervals called Price Sensitivity Zones (PSZs) instead. PSZs approximate the price intervals acceptable for a customer for his/her consumption activities. PSZs may be different for different consumer clusters. For instance, PSZs of HCC are following: $Z_1 = [\perp, 34]$, $Z_2 = [35, 39]$, $Z_3 = [40, 44]$, $Z_4 = [45, 49]$, $Z_5 = [50, \top]$ (EUR/MWh). The zones define the factor space of hourly price, where \perp and \top denote respectively the bottom and top element of the price domain.

Table 2: Consumption patterns.

Action (high consumer)	Action enabling condition(s)			Consumption interval/func. (W/h)
	Time interval	Tolerable price	Outdoors temp.	
Laundry, dish washing	00 - 24	$P \in Z_1$	-	$[C_1, C_2]$
Ironing	19 - 22	$P \in Z_1 \cup Z_2$	-	$[C_3, C_4]$
Water heating	06 - 23	$P \in Z_1 \cup Z_2$	-	$[C_4, C_5]$
Cooking	07 - 08; 18 - 19	$P \in \cup_{i=1,5} Z_i$	-	$[C_6, C_7]$
Lighting	07 - 09; 18 - 24	$P \in \cup_{i=1,5} Z_i$	-	$[C_8, C_9]$
Heating	00 - 24	$P \in \cup_{i=1,3} Z_i$	$T < T_{crit}$	$(T_{crit} - T) * E$

Note:

T_{crit} -- The highest outdoors temperature when to start the house heating (e.g., $T_{crit} = 16$);

E - amount of heating energy needed to compensate the decrease of outdoors temperature by one degree (e.g., $E=50W$).

Model constructs. Now we can specify the formal models of agents Consumer, Supplier, and Environment that constitute our simulation use case.

Consumer template. The template modeling Consumer is depicted in Fig. 3. To avoid the overloading of model templates with technical details we model time counting and energy metering functions in separate templates that have joint actions synchronized via channels 'evolve', 'sum_up', and 'spot_price' with the templates Consumer, Supplier, and Environment.

Supplier template. As in Fig. 4, it has two actions 'Collect_consumption_data' and 'Planning'. The later is joint action with implicit template Meter. Supplier waits until the metering of daily consumption is completed which triggers the action 'Planning' that calculates the next day hourly prices by function 'NewHourlyPrice' (following formula (1) and (2)). Recall that the consumer's choice of consumption actions depends on that hourly price.

Environment template. To keep the simulation model tractable for given use case we model the dynamics of only one observable state component - 'OutdoorTemperature' as in Fig. 5. Changing fuel prices and macro-economic factors are assumed to be constants. Modeling the temperature changes allows to simulate the consumers' responses in broader variety of contexts, e.g., at very low winter temperatures, at sharp changes of day and night temperatures, etc. In our simulations, the actual outdoor temperatures in the period of 09 -10. 01, 2013 did not change considerably and have actually minor effect.

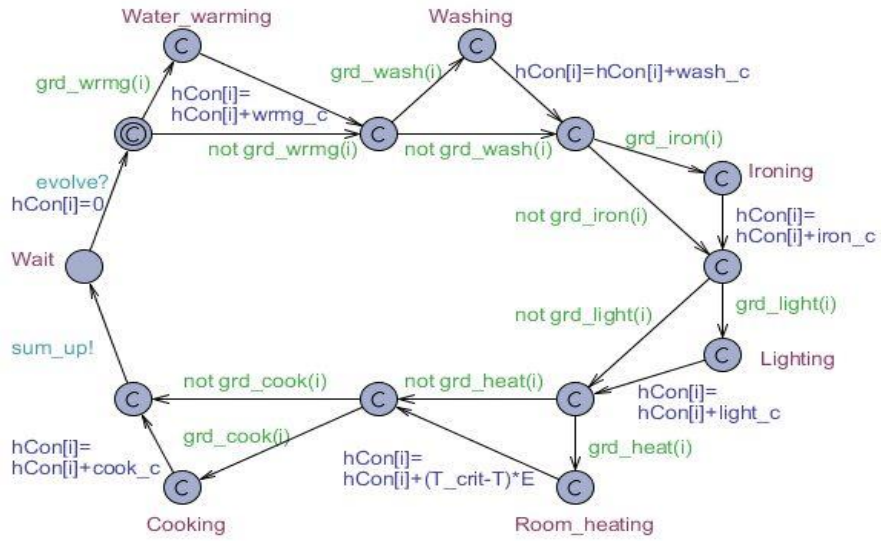


Figure 3. Consumer template.

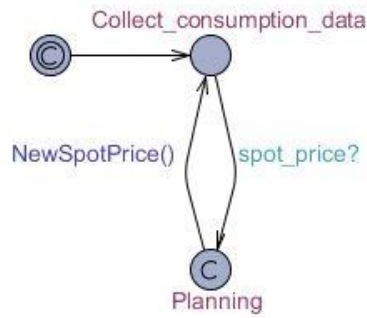


Figure 4. Supplier template.

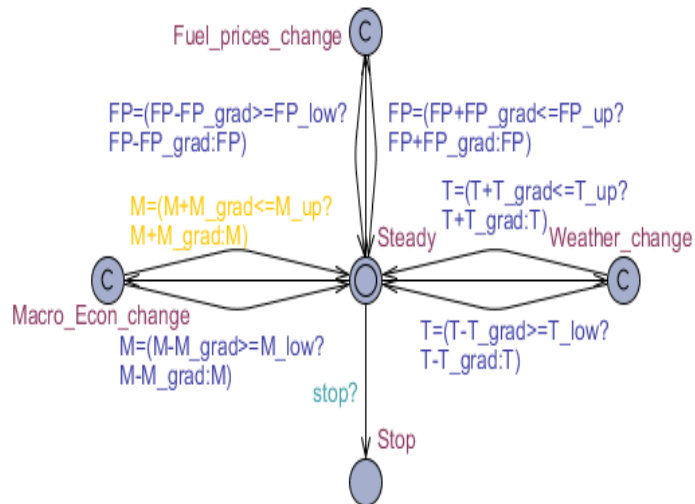


Figure 5. Environment template.

Simulation results. Fig. 6 shows the dynamics of hourly spot prices: P - curve of real spot price of the first day (09.01.2013), P' - real spot price of the next day, P'_{model} - spot price generated by the model as described in formula (1) and (2). As shown from the chart the model calculated price curve P'_{model} is more conservative than real one P' . Fig. 7 indicates that sharp peaks in P' comparing to P do not have considerable effect to the consumption. The consecutive days are chosen intentionally in the middle of week to reduce the effect of the weekend.

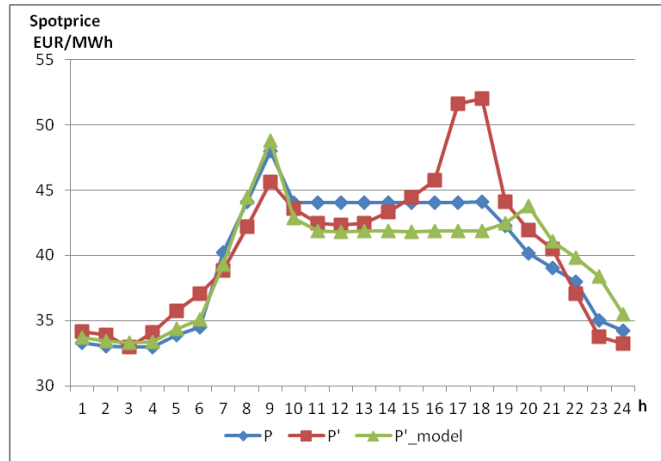


Figure 6. Comparison of real and simulated spot price.

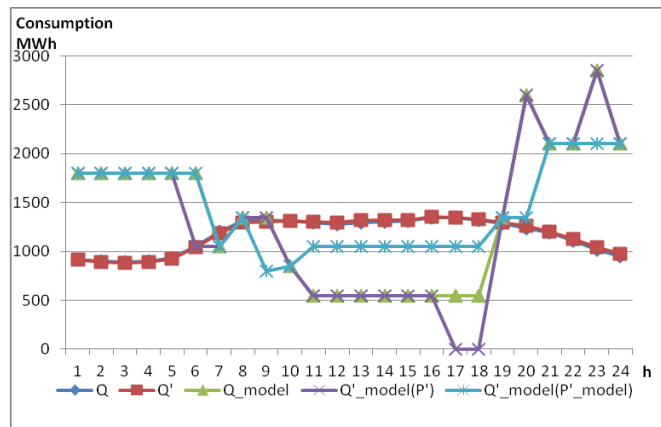


Figure 7. Consumption depending on different price signals

In Fig. 7 Q and Q' presents real aggregated consumption of all consumer clusters including industry on the same days of week (9.01.2013 and 10.01.2013) as reference to aggregated consumption pattern. According to our model assumptions the high (private) consumer's consumption patterns Q_{model} and Q'_{model} differ considerably from Q and Q' although the spot prices are same. Real price correction even introduces severe fluctuations in simulated high consumer behavior (see $Q'_{model}(P)$). The pricing strategy specified in our Supplier model instead provides considerably better stabilizing effect (standard deviation decreases about 57%).

It is important to note that the simulation is based on a theoretical scenario. It does not take into account the impact of other market actor's activities such as the producer's actions and the environmental factors such as weather condition (except outdoors temperature) caused spot price change and demand adjustment. In addition, the agent capacity of learning and adaptation is not considered in the simulation.

6. Conclusion

Electricity markets are deemed as complex adaptive system. It will be even more so with the deployment of smart grids functionality. From a system analysis point of view, in this paper, we present a conceptual platform for modeling the price-responsive demand, in order to discover the dynamic pricing solutions that reflect the varying cost of electricity in the wholesale market as well as the level of demand participation. We took a bottom-up approach, i.e., multi-agent-based modeling approach, in the attempt to capture and observe the emergent behavior in the electricity demand and supply interactions. We hope that the proposed construct will contribute to both the real-world practice and the agent-based research community by allowing 1) to estimate the impacts of various time-varying tariff options on peak-period energy use through simulation, before any experimental pilots can be carried out; 2) to model the electricity retail market evolving interactions in a systematic manner; 3) to induce innovative simulation configurations. Going without saying, the applicability and scalability of this construct need to be further examined in future research.

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