An Agent-based Modeling for Price-responsive Demand Simulation

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

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.

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 (Albadi and El-Saadany, 2007). 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 (CEER, 2011), 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 (Schuler, 2012), 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. Agent-based modeling (ABM), compared to traditional system-modeling techniques, is one appealing approach for studying how the market participants (e.g., consumers, suppliers, producers, prosumers, etc.) 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 unbundling. Very often the demand side is represented as a fixed and price-

Liu H. and Vain J..
An Agent-based Modeling for Price-responsive Demand Simulation.
DOI: 10.5220/0004417504360443
In *Proceedings of the 15th International Conference on Enterprise Information Systems* (ICEIS-2013), pages 436-443
ISBN: 978-989-8565-59-4

insensitive load (Weidlich and Veit, 2008). 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.

Firstly, we introduce 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 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 objective 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 recent 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 (Weidlich and Veit, 2008). 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 (Sensfuß et al., 2007). Agent-based models not only offered the possibility of realistically describing relationships in complex systems, but growing them in an artificial environment (Epstein and Axtell, 1996), thus the evolving behavior can be observed step by step (Holland and Miller, 1991).

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. Various wholesale electricity market simulation models were developed, for instance, by Bower and Bunn (2000) in England and Wales electricity market, 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 (Koesrindartoto et al., 2005); (Sun and Tesfatsion, 2007). In addition, different computational algorithms were examined for the agent-based electricity market modelling, including genetic algorithms for representing the agents' bidding behavior (Nicolaisen et al., 2000); (Richter and Sheblé, 1998), Erev-Roth reinforcement learning algorithm (Nicolaisen et al., 2001; Petrov and Sheblé, 2001), and rule-based learning mechanisms combining reinforcement learning and genetic algorithms (Bagnall and Smith, 2005). In the meantime, an alternative body of agent-based research modeled electricity consumer behavior at the retail level. Zhou et al. (2011) studied the consumption behavior of commercial buildings with different levels of demand response penetration in different market structures. 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. In addition, some agent-based studies focused on the Time of Use (TOU) pricing for residential customers under different context (Roop and Fathelrahman, 2003) and (Hämäläinen et al., 2000).

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 regard.

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 transmission and distribution operators, suppliers, 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 FRAMEWORK

We propose a customized version of *utility-based agents meta-model* introduced by Russell and Norvig (2003). Our MAMM contains abstract concepts interrelated via abstract relations. Each domain model that refines MAMM is considered as its instantiation. 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 Figure 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 the mode and its goal. A *mode* includes a set of agent's states. To fulfil 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. A state is defined as a valuation of agent attributes. 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.

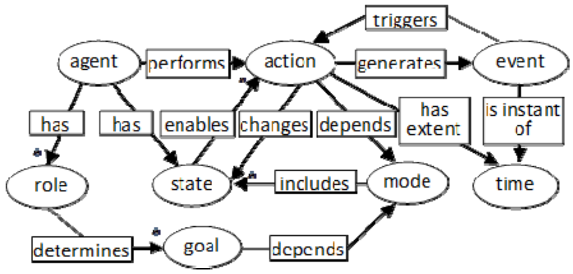

Figure 1: Semantic network of the meta-model.

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 the agents' actions on shared states are in the *changes* and *depends* relations.

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 change of environment), proactivity (capable of acting on its own initiative in order to achieve certain goals/utilities), and adaptivity (with sophisticated learning capabilities) (Müller et al., 2007); (Wooldridge and Jennings, 1995).

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 Figure 2. Since the consumer and the supplier are the focal market players in this context, the focus of the DM is on their roles, actions and interactions.

The supplier's major business activities include (1) pricing in the retail market (i.e., offering various retail electricity rates to different consumer groups) according to the supplier's market share and profit maximization objectives; (2) bidding in the

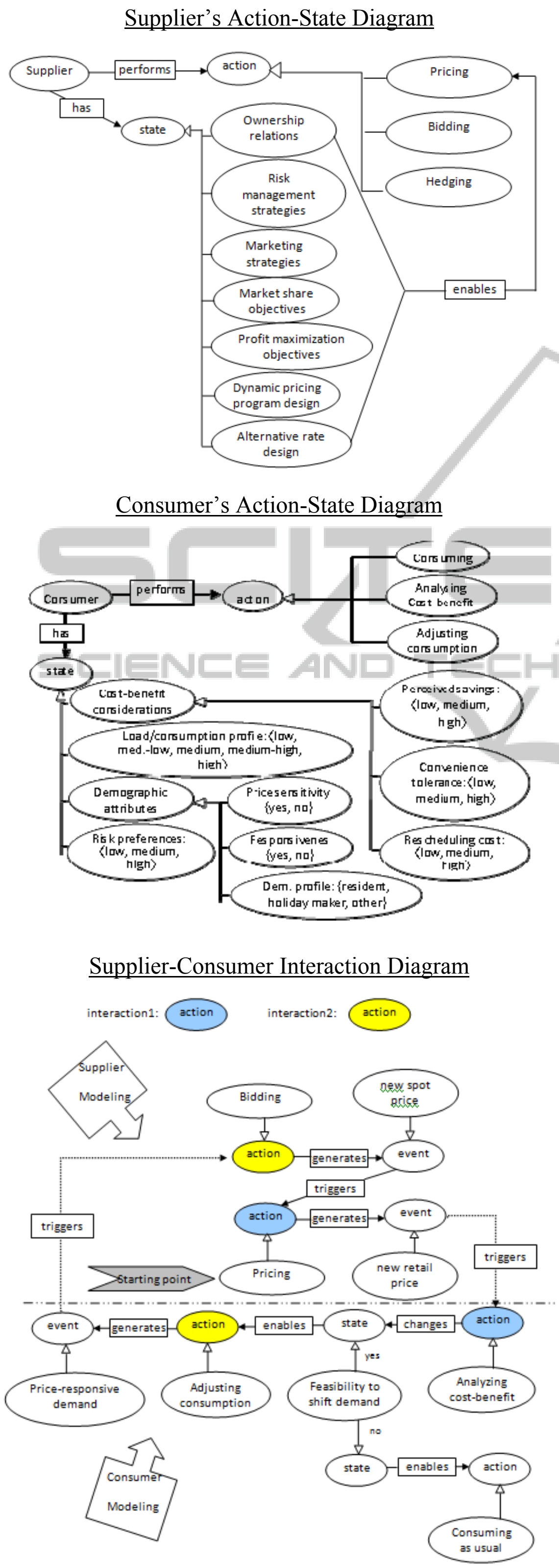

Figure 2: Instantiation of MAMM with domain specific concepts.

wholesale market, which will generate the following day's hourly spot price; and (3) hedging in the financial market in order to avoid the risk caused by energy price volatility.

The consumer's activities in relation to electricity consumption include (1) consuming electricity according to their business nature and living needs; (2) analyzing the possible saving from choosing the demand response tariff, and the feasibility and the cost/the inconvenience of rescheduling electricity consuming activities in order to respond to changing price signals (i.e., cost-benefit analyzing when facing time-varying price or demand response tariff); (3) adjusting timing and level of consumption based on the real-time information and price signals.

The supplier's initial pricing action is determined by their state. Various ownership relations, different marketing and risk management strategies, the supplier's market share and profit maximization objectives, and the supplier's rate portfolio and dynamic pricing program design have decided the supplier's state. The varying state, in turn, will have influence on the supplier's pricing practice.

Similarly, the consumer's state will determine the consumer's actions in terms of electricity consuming and the possibility to respond to dynamic pricing. The varying demographic attributes (e.g., price sensitivity, risk preferences, and the composition of electric appliances), the feasibility to shift certain electricity usage to off-peak time, the perceived saving, the rescheduling cost, the tolerance towards inconvenience, and so on will all affect the consumer's price responsiveness when the consumer is facing new pricing offer.

The adjusted electricity consumption is the consumer's price-responsive demand, which will have impact on the supplier's bidding activities in the next day. Accordingly, the new spot price resulted from the current interaction will trigger the next round interaction between the supplier's pricing activity and the consumer's cost-benefit analyzing and electricity usage adjusting (if possible) activities.

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 (Bengtsson and Yi, 2004), which is an academic-free modeling, simulation, and model-checking tool.

As mentioned earlier, one of the potential benefits of demand response is to flatten daily load patterns. Therefore, the specific theoretical simulation 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 (Belonogova et al., 2011).

5.1 Simulation Design

The simulation setup 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 (www.nordpoolspot.com). The consumption pattern of HCC depends on the day of the week and also on external factors, e.g. outdoor temperature. To be able to compare the simulation results of different days we take two consecutive days in the middle of the week Wednesday and Thursday being closest in their energy consumption, and calculate the hourly price of Thursday based on the spot price on Wednesday and show how the hourly price influences the consumption. We assume that the difference between contextual factors on Wednesday and Thursday is insignificant.

5.2 Simulation Assumptions and Constraints

We introduce the simulation model representing the Supplier-Consumer interaction where the only interaction observables are hourly price and hourly consumption by HCC. Thus, the main agents in the simulation model are *Consumer* and *Supplier*. The third agent - *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 - outdoor temperature, hours of daylight, etc. - that all have impact on the consumption.

The pricing algorithm. When designing the pricing function for hourly price we aim at getting the driving effect that smoothens 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).

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

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

where

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

Δ^{TL} is acceptable price change (%);

$sign(\Delta(T))$ 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 $P(T)\cdot Q(T) - avg(P(T)\cdot Q(T))$, where $avg(P(T)\cdot Q(T))$ 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^{TL}. 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 1: Descriptive attributes of HCC's consumption.

Action	Enabling condition(s)			Consumption interval/ func. (W/h)
	Time interval	Price zone	Outdoor 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	$P \in \cup_{i=1,5} Z_i$	-	$[C_8,C_9]$
Space heating	00 - 24	$P \in \cup_{i=1,3} Z_i$	$T < T_{crit}^{a}$	$E^{b}\,(T_{crit}-T)$

Note:
a. T_{crit} is the highest outdoor temperature when the space heating is activated (e.g., $T_{crit} = 16$ °C);
b. E is the amount of energy needed for space heating in order to compensate the decrease of outdoor temperature by one degree (e.g., $E = 50$ W/° C).

5.3 Formalization Preliminaries

Model constructs. We formalize the agent as a template of UPPAAL timed automaton (UPTA).

An atomic action is represented in UPTA as a model fragment consisting of pre-location, post-location and body-location connected via edges (see Figure 3). Pre- and post- locations are for composing aggregate actions from the atomic ones.

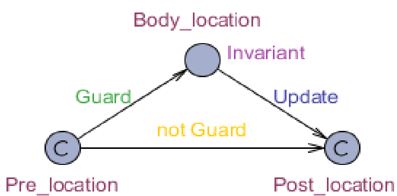

Figure 3: The model fragment of an atomic action.

Having two actions a_i and a_j with post- and pre-locations $Post(a_i)$ and $Pre(a_j)$, their *sequential composition* $a_i\,;\,a_j$ is constructed by merging $Post(a_i)$ and $Pre(a_j)$ into one location. The pre- and post-locations are of type "committed", meaning that their execution is instantaneous.

Consumer template. The template modeling Consumer is depicted in Figure 4. The guards and updates of each action are defined in Table 1 and implemented by using the function programming language of UPPAAL.

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 Figure 5, 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.

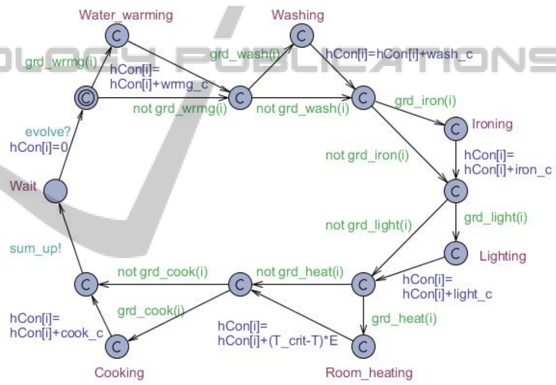

Figure 4: Consumer template.

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 Figure 6. 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 during 09-10 Jan., 2013 did not change considerably and have minor effect.

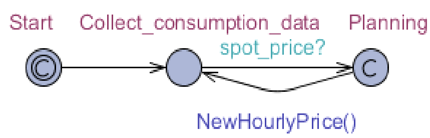

Figure 5: Supplier template.

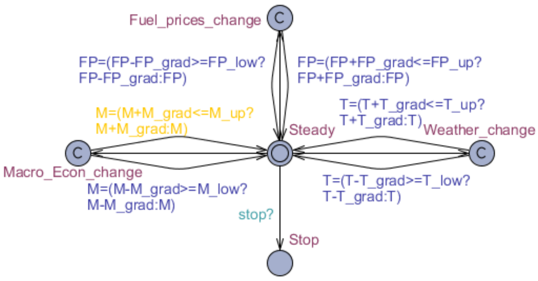

Figure 6: Environment template.

5.4 Simulation Results

The simulation results show that in the presence of HCC consumption patterns the implemented pricing strategy allows to smoothen the demand peak in relation to the spot price.

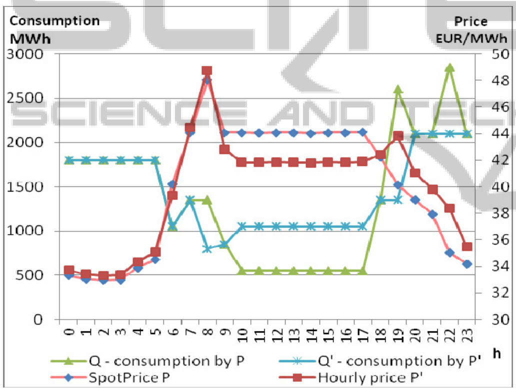

Figure 7: Price-responsive demand.

Figure 7 shows the dynamics of pricing-demand interplay: *P* is the curve of spot price of Jan. 09, 2013, and *P*' represents the hourly price curve generated by the model as described in formula (1). If the price is lowered from 44 to 42 EUR/MWh at off-peak time period (11-17hrs), it will encourage considerable demand shifting to this period (from 500 to 1000 MWh). On the contrary, if the price is increased during the spikes of *Q* from 40 to 44 EUR/MWh at 19hrs and from 34 to 38 EUR/MWh at 22hrs, it will cut down the demand to *Q*' (from 2600 and 2800 to 2200 MWh).

The pricing strategy specified in Supplier model demonstrates the effect of flattening the daily load. The standard deviation of the demand *Q*' decreases about 57 % in comparison to demand *Q*.

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 actors' activities such as the producer's actions and other environmental factors except the outdoor temperature caused spot price change and demand adjustment. In addition, the agent capacity of learning and adaptation is not considered in the simulation due to short time range.

5.5 Discussion

Based on the domain model and its formalized representation described above, also other simulation experiments can be developed. In this section, we show that the DM is rich enough in order to validate the conceptual construct and these constructs provide a set of model patterns that are easy to handle when formalizing the domain model. We have chosen UPPAAL timed automata to formalize the domain model and UPPAAL tool to run the simulation experiments, but we do not limit the approach with UPPAAL tool only. Large simulations presume highly scalable modeling environments, hence we consider NetLogo as likely environment for our future work.

6 CONCLUDING REMARKS

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 an 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. Additionally, the agent capacity of learning and adaptation needs to be included in future research.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the financial support by the Fortum Foundation, the Academy of Finland (Grant No. 127592), ELIKO and European

Social Fund's Doctoral Studies and Internationalization Programme DoRa.

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