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Management Decision Support using Long-Term Market Simulation

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Abstract In recent years Agent-based Computational Economics (ACE) has become an increasingly important method in market simulation. After liberalization of many former governmental owned or controlled industries the used operations research models are not longer sufficient to simulate market behavior due to individual action and increasing competition. Agent-based simulation appears to be an alternative approach considering also individual behavior and competition. Some short-term simulation approaches have shown promising results for the simulation in the domain of electricity markets. Picking up the desire for a long-term oriented simulation, this paper presents a basic agent-based model considering the investment decision within long-term planning of electricity markets. Additionally, regulatory agents are introduced as a third side in the market simulation to represent governmental decisions. This results in the definition of three types of agents representing electricity generating companies, consumers and governmental instances.

1 Introduction

The deregulation of former governmental controlled markets and the economic integration of national markets leads to an increasing competition.

Individual market participants need to assess the market to learn advantageous behavior. Managers benefit from basic information about markets and market behavior to estimate the influence of their decisions on the development of the market. Consumers on the other side can use their knowledge about market behavior to improve their buying decisions. Governments set rules, enact laws and raise taxes to affect market behavior in a desired way. Small changes in regulations might have a large impact on the market. Therefore, tools for market simulation help to understand the development of the market, help to assess the impact of individual actions, and consequently help to improve market participants' decisions.

Agents representing individual behavior within an agent-based market simulation show promising results in studying markets as evolving systems. Electricity markets have gained tremendous interest in agent-based simulation. The existing models focus on a short-term view, especially on the price movements. Changes in production technologies and environmental restrictions are ignored. This paper overcomes these limitations by introducing regulatory agents representing governmental decisions and additionally enhancing the suppliers' decision making framework to a longer-term view by considering the investment decision on specific production techniques. We adapt the described model for the use in electricity market simulation as one domain of application for an agent-based market simulation model. Therefore, in the following we describe characteristics of electricity. Electricity is not an ordinary commodity. On the one hand it has specific characteristics in production, distribution and consumption. This is because of very short temporal differences between production and consumption. Storage is hardly limited and linked with high loss of energy, so that production is tried to be adjusted to consumption at any time. Consumption however depends on many temporally varying parameters and is not easy to anticipate. On the other hand electricity is a basic and major resource for industrial countries, which has to be available at any time. Even short interruptions might disturb economic production. Consequently, a reliable anticipation and analysis of future electricity consumption is necessary for effective planning.

Decentralized approaches as *Multi Agent Systems (MAS)* promise potential to reproduce individual behavior and characteristics of different market participants.

Section 2 introduces software agents and gives a brief overview to Multi Agent-based Simulation (MABS). Several multi agent-based models for electricity market simulation have been proposed and will be summarized in Section 3. These models have in common to simulate short-term price development in electricity markets without considering long-term decisions as for example investment planning. We suggest mechanisms to integrate long-term planning into an agent-based approach for electricity market simulation. Section 4 describes the model in more detail. The concluding Section 5 summarizes the proposed model and discusses its compatibility to existing models.

2 Multi Agent-based Simulation

Weiss (1999, p.1) characterizes intelligent software agents as "computational entity [..] that can be viewed as perceiving and acting upon its environment and that is autonomous in that its behavior at least partially depends on its own experience." Jennings and Wooldridge (1998) point out that the capability of *flexible autonomous acting* in different environments constitutes the intelligence of software agents. Many characteristics of intelligent agents are described in literature mentioning *reactivity* and *proactivity* (Wooldridge and Ciancarini, 2001) and *rationality* (Rosenschein and Genesereth, 1985) as other main features. *Adaptive behavior* comprehends the ability of learning within the agents environment (Brenner et al., 1998). Two or more intelligent agents acting in one system constitute a MAS and necessitate communication and interaction amongst the agents (Huhns and Stephens, 1999). To ensure reasonable interaction and communication in a MAS agents need to consider not only their own actions but also need to anticipate future actions of other agents to coordinate their actions (Jennings, 1996).
Multi Agent-Based Simulation (MABS) is an intensive field of research for example in computer science, social science, mathematics or economics. The study of economic systems with MABS have become known as *Agent-based Computational Economics (ACE)*. Economies are modelled as independent evolving systems of autonomous interacting intelligent agents. Mizuta and Yamagata (2001) enhanced the gold-food-market model of Steiglitz et al. (1996) to simulate the Kyoto-protocol green house emission trading. Goal of market simulations is to asses the market behavior and its development over time. Therefore, autonomous agents represent market participants, but cannot copy the behavior of real market participants in all detail. Agents applied in simulations normally use simple decision rules, learning algorithms, or statistical analysis to adapt their strategies. Tesfatsion (2002) provides a detailed overview on ACE research and describes studies of market simulations in electricity and financial markets.
In the following section existing agent-based models for the simulation of electricity markets are summarized.

3 Simulation of electricity markets

Since the two oil crises in the seventies, a growing number of models of energy systems have been developed and used to analyze the energy sector. The conceptual structure of energy models can be found in Hafkamp (1984) and in Lev (1983) different energy models are presented. In the Eighties, some energy models were extended by environmental modules in order to address environmental problems related to energy conversion, such as acidification and eutrophication. Since the early Nineties, energy system models have also been used for the elaboration of greenhouse gas emission reduction strategies in the context of the global warming discussion. In the context of energy planning the investment and production planning of electric utilities in particular has received considerable attention and many formulations of the problem have been proposed over the last decades (see e.g. (Anderson, 1972; Caramanis, 1983; International Atomic Energy Agency, 1995)). Therefore, the use of mathematical programming in the context of electricity market simulation is a well-known field of research (Gately, 1970), that is still of great interest (see e.g. (Gonzalez-Monroy and Cordoba, 2002; Song, 1999)) due to the new situation in liberalized energy markets. However, the existing electricity models, which are based on Operations Research methods, can hardly be used to reproduce individual behavior and characteristics of different market participants in a liberalized market.

Consequently, to better represent the individual behavior of market participants MABS became more important for simulation of electricity markets. ACE studies markets as evolving systems. Much work has been done in the short-term simulation of electricity markets especially of the electricity markets of England and Wales. In the following we discuss some of these approaches.

Bower and Bunn (2000) studied the impact of the Revised Electricity Trading Arrangements of England and Wales (RETA) on pricing and strategy. Each agent of the Multi Agent System represents an electricity generating company and has the goal to increase overall profitability and to reach a target utilization rate on its plant portfolio. A simple reinforcement-learning algorithm enables the agents to learn the best bidding strategy. The agents on the demand side are implemented as price takers and have no ability to influence the market through strategic behavior. The application of four different combinations of auction mechanisms allows a comparison of the market development and a valuation of RETA. Quantitative results are not obtained from this model, but it is applicable to anticipate market trends.

Bower et al. (2001) developed a model for the simulation of the German electricity market based on the model of Bower and Bunn (2000) to understand the strategic consolidation of the German electricity market. Agents represent the main electricity companies on the German market, whereas smaller companies are aggregated in one agent. Customers have no strategic influence on the market behavior, their demand is implemented as an aggregated demand curve. Agents knowledge is just linked to their internal state and the agents do not posses information about the environment or other agents behavior. The authors use auction mechanisms for the simulation and each agent submits 24 bids per day for each plant. Simulations under different starting conditions are realized to study market development after merger of two or more companies. Due to many assumptions the model is not suited for quantitative conclusions but it helps understanding the market development under different initial strategies.

For the simulation of the New Electricity Trading Arrangements of England and Wales (NETA) Bunn and Oliveira (2002) suggest an agent-based approach and use it for evolutionary computation. In contrast to Bower and Bunn (2000) who simplified the market by means of a discriminatory double auction, Bunn and Oliveira (2002) present a new model containing two markets, the *bilateral market* and a so called *balancing mechanism.* Demand side is implemented actively by merchants. Demand and supply agents trade energy for every hour of the following day. By closing time every agent knows exactly how much energy it traded itself and submits this information to the systems operator, who compares forecasted and effectively traded amount of electricity to balance the system through direct trade with suppliers and customers. Agents optimize their behavior using a reinforcement learning algorithm. A reinforcement learning algorithm uses feedback to assess the value of the action performed (Sen and Weiss, 1999). The results indicate a higher risk for the demand side because customers depend on forecast accuracy of the industry.

Nicolaisen et al. (2001) study market power effects of electricity markets. To distinguish between the influence of market structure and buyer and seller learning on market power they use an agent-based electricity market framework. They conduct experiments under different starting conditions. The MAS consists of two different types of agents, which represent demand and supply side. Trading is realized by a discriminatory double auction. A reinforcement learning algorithm is used for learning new prices of the following auction round. Experiments could not bring empirical evidence about the influence of market structure and buyer and seller learning. A comparison of the learning algorithm used to the results of a genetic algorithm produces no differences. Market efficiency of the tested agent-based framework appears to perform very close to efficiency of perfect competition.

The described approaches for agent-based simulation of electricity markets have in common to simulate price development in a short term. The simulations base on the assumption that the plant capacity of each Supply Agent is fix from the start. In the following section we present a model for the long term simulation of electricity markets, considering capacity planning and investment decisions.

4 Agent-based market simulation model

This section describes the concept of a market model for a MAS simulating long-term development in the domain of a liberalized electricity market. Following the approaches of short-term simulation discussed in Section 2 the described model provides additionally long-term decision making. The development of price and sales volume has an important impact on the market participants' behavior. Adaption to changes in demand as well as changes of political basic conditions affect long-term decisions, and therefore, the study of the long-term market behavior is extraordinary important. Even small environmental changes can have an important impact on market participants' decisions. For that reason, it appears useful to enhance short-term market simulation by long term decisions.

Basically a market consists of three different groups of market participants: suppliers, customers and a neutral regulatory authority. Each of the three types of market participants is interested in different aspects of a long-term market simulation. Suppliers for example want to increase the overall profit and therefore need efficient production technology. Customers mainly focus on the price of electricity, whereas governmental organizations are interested in the influence of political decisions not only on the price development, but also on long-term market development. Hence, three types of agents are built, Electricity Supply Agents (ESA), Electricity Consuming Agents (ECA), and Regulatory Agents (RA). Each agent participating in the market is an instance of one of these agent types differing in the initial values of characterizing parameters.

In each period t ESA and ECA negotiate prices for certain amounts of electricity. To reproduce the oscillating electricity demand, which depends both on seasonal effects and on daily characteristics, electricity demand of a working day of the actual period t is reproduced exemplarily for each hour of this day. One period represents a week. Based on the results of this negotiation agents plan their further actions and make long-term decisions. The environment is dynamic due to competing goals of the individual agents, which complicates the forecast of the market development. For simplification reasons the transmission grid is not considered in this model, although it is an important component on real electricity markets.

The following sections describe the model and the agents in more detail, starting with overall coordination and communication mechanisms in Section 4.1. In Section 4.2 we describe the agent model types and their characteristic mechanisms.

4.1 Coordination and Communication

Coordination of the market can be achieved by different market mechanisms. Auctions are often used in liberalized electricity markets to coordinate daily electricity trade. Consumers in general conclude bilateral contracts with electricity generating companies or electricity traders. In our model ECA represent aggregated groups of consumers which take part in a centralized discriminatory double auction. Discriminatory double auctions are characterized by setting individual prices for each matched pair of offer and bid.

The coordination of the auction in the model is accomplished by a central auctioneer-agent who receives bids from both ECA and ESA. Agent communication has been formalized. Table 1 describes the structure and possible types of messages.

Communication converges in case of central coordination by auction at the auctioneer-agent which might produce a bottleneck for the communication process. The sequence of the communication process is shown in Figure 1 in more detail.

At the beginning of each period the ESA computes electricity prices exemplarily for a working day of the period on basis of the result of the preceding periods, governmental rules (e.g. tax on harmful substances), seasonal characteristics and disposable capacity. The agents submit bids for each hour of

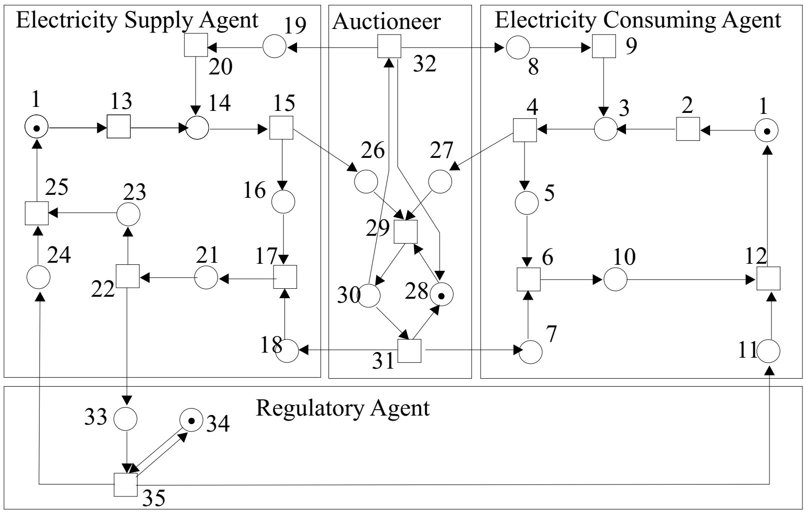
Type	**Description**	**Content**
bid	consumer amount-/price ask	$\{amount/price\}_{period;hour}$
offer	generators amount-/price offer	$\{amount/price\}_{period;hour}$
agreement	confirmation of agreement	$\{amount/price\}_{period;hour}$
refusal	refusal of a bid/offer	$\{amount/price\}_{period;hour}$ counter proposal
information	information (e.g. to regulatory authority)	*Identifier* of the kind of information (price, amount, harmful substance, etc.), *information*
command	compelling message of the regulatory agent	*Identifier* (e.g. change of tax for harmful substances, etc.) *information*

Table 1 Description of possible message types

a working day specifying amount and price. Regional and individual factors are described by intrinsic strategies of each agent.
At the same time all ECA compute the amount of electricity needed for each hour of a normal working day in the following period. The 24 bids are submitted to the auctioneer-agent including amount of electricity and the price the agent is willing to pay.
The auctioneer-agent determines market equilibrium for each hour by accomplishing a discriminatory double auction. The auctioneer-agent examines whether total demand is matched. If total demand is not matched, the auctioneer-agent informs suppliers and all consumers who have not been matched about the negative result (refusal) and about the price of the counter-offer. Additional auctions are accomplished until total demand is satisfied. When total demand is matched all participants will be informed about their achieved results. Based on these results all ESA compute the actual power plant deployment and submit the achieved price and information about produced harmful substances to the regulatory agent. The regulatory agent examines the contracts on compliance with the defined general framework and decides on sanctions and about taxation for harmful substances. Any decision will be communicated to the ESA.
In the following section we discuss the agent types in more detail.

4.2 Basic agent model and learning method

In this section, a description of the three agent types, Electricity Supply Agent (ESA), Electricity Consuming Agent (ECA) and Regulatory Agent (RA) is given. We first introduce the general agent platform as a basis for all agent types. Different agent strategies and the long-term decision mechanism are presented in each subsection of the agent types.
All agent types consist of different layers for communication and for strate-



1 start period
2 compute demand (CD); choose strategy
3 CD for each hour finished
4 submit CD
5 wait for result
6 analyse result
7 results received
8 CD not met
9 choose new strategy
10 wait for following period
11 signal f. following period; Change of parameters
12 start following period
13 compute supply; choose strategy
14 supply computation for each hour finished
15 submit supply
16 wait for results
17 compute plant utilization and profit
18 results received
19 market demand not met
20 compute supply new
21 profit and plant utilization results ready
22 submit plant utilization to regulatory agent
23 wait for signal of regulatory agent
24 final signal of RA and information or penalties
25 start next period
26 supply received
27 CD received
28 ready for auction
29 conduct auction
30 auction result
31 auction successful; submit results
32 auction unsuccessf.; reset auction (inform about reasons)
33 plant utilization (incl. Harmfull substances)
34 ready for computation
35 choose strategy (penalties)

Fig. 1 Communication process

gic planning. Figure 2 shows the general architecture of the agents. In the following we describe the process of strategy planning and the layers for short-term and long-term strategy in more detail.
Erev and Roth (1998) developed a reinforcement learning algorithm to reproduce human behavior. The basis of their learning algorithm are two psychological principals, the *law of effect (LOE)* and the *power law of practice (LOP)*. Actions are reinforced or weakened (LOE) depending on the quality of the produced results. It is assumed that learning curves are ini-

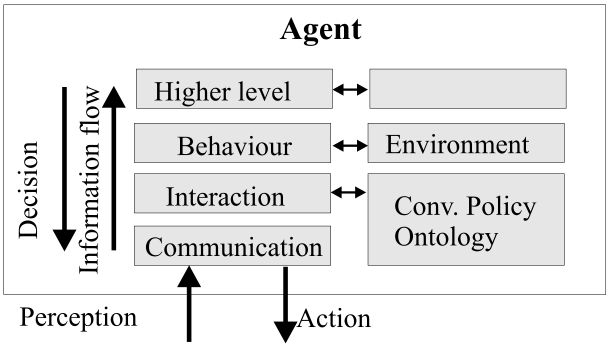


Fig. 2 General agent architecture

tially steep and then flatten out (LOP). We adapt this learning algorithm to our model. Each agent can choose out of K actions $a_1, ..., a_K$. The environment and its changes are described by N perceptions $(w_1, ..., w_N)$, e.g. $w_1 = \{\text{electricity-price rises}\}$. The agents can choose any action $a_1, ..., a_K$ in any perceived situation w_n. The goal is to decide on an appropriate action in a particular situation. Consequently, the propensity parameter $g_{nk}(t)$ assigns a propensity to perform action k in situation n in period t. The feedback for the chosen action k determines the new value of the propensity parameter $g_{nk}(t)$. The likelihood for choosing action a_k in situation w_n in period t is

$$h_{nk}(t) = \frac{g_{nk}(t)}{\sum_{j=1}^{K} g_{nj}(t)} \tag{1}$$

The basic setting of the propensity parameter determines an agent's individual strategy. By introducing the experimentation parameter ε and the recency parameter ϕ an extension of the basic model is possible. The experimentation parameter ε considers not only successful actions but also similar actions. The recency parameter causes exponential smoothing of the collected knowledge in order that recently collected knowledge is emphasized more in comparison to past experience (Erev and Roth, 1998). The reinforcement function $R(x)$ computes the enhancement of a propensity at a received result x on the performed action a_k:

$$g_{nj}(t+1) = (1-\phi)g_{nj}(t) + \begin{cases} R(x)(1-\varepsilon) & \text{if } j = k \\ R(x)\frac{(1-\varepsilon)}{K-1} & \text{otherwise} \end{cases} \tag{2}$$

This learning algorithm is applied to our model. In the following we describe the architecture of the agent types and the mechanisms used in order to illustrate how the Erev and Roth (1998) learning algorithm can be integrated in this model.

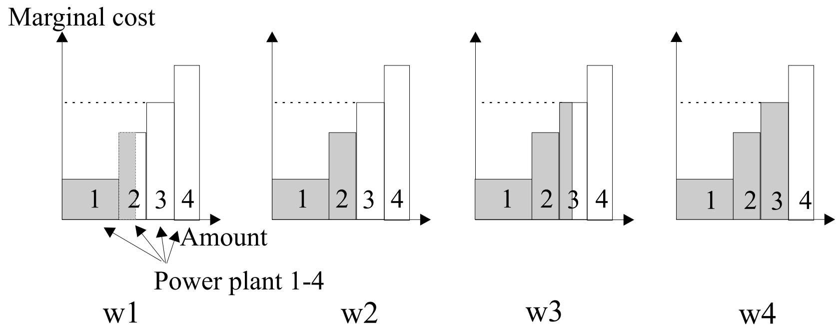


Fig. 3 Possible perceptions of Electricity Supply Agents

4.3 Electricity Supply Agents

ESA have to decide about an efficient plant utilization in consideration of environmental regulations, investments and profit. The decision problem can be divided into the subproblems plant utilization and plant investment planning. Hence two separate layers are introduced into the agent model. One layer for the short-term planning and an other layer for long-term planning. In the following possible strategies are determined and the mechanisms for decision making in the particular layer will be described.

4.3.1 Strategies of ESA The environment is specified by a non-deterministic set S of environmental states. The agent perceives these environmental states by a set W of possible perceptions and chooses an action a_i out of the set of possible actions A. The function $action : W \rightarrow A$ describes the coherence between perception and possible action and therefore characterizes the set of possible strategies. The overall goal of the agents decisions is profit maximization. In short-term the agents plan how much electricity to offer and at which minimum price. At a given amount of electricity generated the minimum price at which a supplier earns profits equals the marginal running costs of the marginal unit (Green, 2000). The agent can choose either the minimum price $p_{th}^{min}(Q_{th}^{calc})$ or a higher price $p_{th}^{+}(Q_{th}^{calc})$. Q_{th}^{calc} is the calculated amount of electricity to offer in period t in hour h provided by the long term planning layer. The achieved results provide feedback to the agent for the last performed action. This feedback creates a particular perception $w_j \in W$. Possible perceptions are shown in Figure 3. Independent from a particular perception each agent can increase, decrease or maintain the amount of electricity offered within its capacity restrictions. In combination with the normal and the higher price there exist six possible actions:

- a_1: increase the offered amount of electricity and price $p_{th}^{min}(Q_{th}^{calc})$
- a_2: increase the offered amount of electricity and price $p_{th}^{+}(Q_{th}^{calc})$

- a_3: maintain the offered amount of electricity and price $p_{th}^{min}(Q_{th}^{calc})$
- a_4: maintain the offered amount of electricity and price $p_{th}^{+}(Q_{th}^{calc})$
- a_5: decrease the offered amount of electricity and price $p_{th}^{min}(Q_{th}^{calc})$
- a_6: decrease the offered amount of electricity and price $p_{th}^{+}(Q_{th}^{calc})$

Perception w_1 is shown in Figure 3. The amount of electricity offered was too high: less electricity than calculated was sold due to the expensive price. One possible action is a reduction of the amount of electricity and a resulting lower price (action a_5 or a_6). On the other hand maintaining the amount of electricity, but changing the price is an other possible strategy (action a_3 or a_4).
Perception w_2 shows the marginal case with a calculated sales volume including capacity of plant 3 which in fact has not been utilized. This points out that the salable amount of electricity is at least as much as capacity of plant 1 and plant 2. The capacity of the competitors might have been exhausted so that consumers had to buy electricity at relative high price of this agent. If competitors expand their cheap capacities whereas the own capacity remains constant, it appears reasonable to decrease the amount of electricity offered and therefore lower the price (action a_5 or a_6). Assuming that competitors maintain their capacities and the demand for electricity increases, the supply of electricity can be maintained and the price can be varied (action a_3 or a_4).
Perception w_3 is almost similar to perception w_2 because plant 3 has been considered in supply planning, but the capacity of plant 3 has not been fully used. One reason might be the lower price of a competitor, another possible reason is the absence of adequate demand at this stage. One possible action is to maintain the offer and keep the higher price (action a_4) or to lower the price (action a_3) to increase sales volume. Assuming increasing demand it is even possible to increase the offer and vary the price (action a_1 or a_2).
The fourth chart of Figure 3 shows perception w_4. The calculated sales volume was sold completely. Therefore, it is reasonable either to maintain the sold amount of electricity and to keep (action a_4) or to vary the price (action a_3), or to increase the amount of electricity provided and to bid the minimum price (action a_1) or to bid the maximum price (action a_2).
Based on these considerations the mapping $action : W \rightarrow A$ is possible; $W = \{w_1, w_2, w_3, w_4\}$ and $A = \{a_1, a_2, a_3, a_4, a_5, a_6\}$:

$$w_1 \rightarrow \{a_3, a_4, a_5, a_6\}$$

$$w_2 \rightarrow \{a_3, a_4, a_5, a_6\}$$

$$w_3 \rightarrow \{a_1, a_2, a_3, a_4\}$$

$$w_4 \rightarrow \{a_1, a_2, a_3, a_4\}$$

To realize these actions appropriate prices and production plans have to be determined. The short-term planning layer and the long-term planning layer fulfil this task. Below we describe these layers at length.

4.3.2 Planning layer For the planning of production and investments some considerations have to be taken. To simplify the planning process, we introduce two planning layers, one for the short-term and one for the long-term planning. Due to the fact, that the production planning is a complex task, we describe our consideration in detail.

1. The short term planning layer
   The short-term planning layer serves for calculation of an efficient plant utilization at a particular sales volume and determines an appropriate bid price. Consequently, the goal of this layer is to determine which plant to use at which time and to decide on the sales price. Bower et al. (2001) solve the problem of plant utilization in such a way that all plants offer the maximum capacity. The suppliers decide on the price per plant per hour and therefore the decision is left to the market. Thus the short-term planning layer just decides on the price and not on plant utilization.
   In our approach we suggest to shift the plant utilization decision back to the agent itself. The plant utilization is a cost minimization problem for each hour h in period t. This results in the following model:

$$\min_{q_{ith}} \sum_i (c_i \beta_i + (b_i + \sum_j S_{ij} C_j^S) q_{ith}) \tag{3}$$

subject to (s.t.):

$$\sum_i q_{ith} = Q_{th}^{calc} \qquad \forall h \tag{4}$$

$$0 \leq q_{ith} \leq c_i \qquad \forall i \tag{5}$$

b_i: running costs per unit of generated electricity
β_i: fixed costs per capacity of plant type i
c_i: usable capacity of plant type i in period t
C_j^S: tax per generated unit of harmful substance j
q_{ith}: calculated amount of electricity for plant i in hour h of period t
Q_{th}^{calc}: calculated sales volume in hour h of period t
S_{ij}: amount of harmful substance j per generated unit of electricity of plant i

The minimum bidding price p_{th}^{min} for the calculated sales volume Q_{th}^{calc} is the maximum marginal cost of all utilized plants:

$$p_{th}^{min}(Q_{th}^{calc}) = max_i(b_i + \sum_{j=1}^{J} S_{ij} C_j^S) v_i) \tag{6}$$

$$\text{and: } v_i = f(q_{ith}) = \begin{cases} 1 & , \quad q_{ith} > 0 \\ 0 & , \quad \text{otherwise} \end{cases} \tag{7}$$

The higher price $p^{+}_{th}(Q^{calc}_{th})$ can be computed on basis of the minimum price and a premium $\pi > 0$, which is defined at the beginning of the simulation for each agent: $p^{+}_{th}(Q^{calc}_{th}) = p^{min}_{th} + \pi$. As reinforcement learning function $R(x)$ we suggest to use the achieved profit. The benefit of an action is as much greater as the profit could be increased. Hence we suggest:

$$R(x) = \frac{\text{achieved profit - minimum profit}}{\text{minimum profit}} \tag{8}$$

The short-term planning layer decides on the price and on optimal plant utilization at a given target sales level, which is determined in the long-term planning layer. This will be described in more detail below.

2. The long-term planning layer

The long-term planning layer lies above the short-term planning layer and has to handle problems, which are not solvable in the short-term layer. Investment decisions for power plants are accomplished. The performance of the strategy used so far is being evaluated and compared to the defined goals and the side conditions. A very important side condition is the liquidity of the company. Each company has a budget B_t per period t:

$$B_{t+1} = B_t + G_t - I^{ges}_t \tag{9}$$

and

$$G_t = \sum_h \sum_i (((P^{RA}_{th} - (b_i + \sum_j S_{ij} C^S_j))q^m_{ith} - \beta_i c_i) \tag{10}$$

$$I^{ges}_t = \sum_i Z^{inv}_i c^{inv}_i I_{i0} \tag{11}$$

c^{inv}_i:	capacity unit of type i
G_t:	profit/loss in period t
I_{i0}:	initial investment for one capacity unit c_i of plant type i
I^{ges}_t:	total investment in period t of this agent
P^{RA}_{th}:	achieved market price in hour h of period t communicated by the Regulatory Agent
q^m_{ith}:	produced amount of electricity of plant i in hour h of period t (sales volume)
Z^{inv}_i:	number of capacity units of type i invested in period t

Total investment I^{ges}_t is the sum of investments per plant type, whereas c^{inv}_i is one capacity unit of the plant type i (e.g. capacity of a generator) and Z^{inv}_i is the number of capacity units built.
The accounting income is computed at the end of each period and used

for determination of the budget of the following period. The profit development influences the choice of particular strategies. Investment decisions are substantial decisions which have to be based on a long-term forecast of electricity consumption and on an estimation for the development of the tax for harmful substances. In this model we suggest a simple time series analysis for this forecast. For estimation of the tax development we use an average means analysis of the tax in recent periods:

$$C_{it}^{Sprog} = C_{i(t-1)}^{S} \frac{1}{t-1} \sum_{j=1}^{t-1} \left(\frac{C_{ij}^{S}}{C_{i(j-1)}^{S}} \right) \tag{12}$$

C_{it}^{Sprog}: forecast of tax for production of harmful substances in period t
C_{it}^{S}: tax for production of harmful substances in period t

The demand of electricity is subject to seasonal effects and therefore demand forecast is revised by a seasonal factor. We assume that the development of the average electricity consumption is a linear function with gradient γ (trend coefficient). We further assume that seasonal demand deviates from average demand with factor $sais_t$. Therefore forecast of total market demand in periods $t+j$ (with $j = 0, ..., T$) is defined:

$$Q_{h(t+j)}^{tot(prog)} = \left\{ \frac{Q_{h(t-1)}^{tot}}{sais_{t-1}} + (j+1)\hat{E}(\gamma_{t-1}) \right\} sais_{t+j} \tag{13}$$

where:

$$\hat{E}(\gamma_{t-1}) = 0,1(Q_{h(t-1)}^{tot} - Q_{h(t-2)}^{tot}) + 0,9\hat{E}(\gamma_{t-2}) \tag{14}$$

$\hat{E}(\gamma_{t-1})$: estimation of the trend coefficient
Q_{ht}^{tot}: total market demand at hour h in period t
$Q_{ht}^{tot(prog)}$: forecast of total market demand at hour h in period t

For the estimation of the trend coefficient we use exponential smoothing as defined above. The forecast is based on data of all periods in the past including period $t-1$. Starting with that forecast of the total market demand each agent computes possible sales volume with consideration of the individual market share for the periods t to $t+T$. The anticipated sales volume is used in the planning layers and can be varied by increasing, decreasing or retaining the forecasted value. To retain the sales volume value means to achieve the same market share[1] $S_t = \frac{Q_{th}^R}{Q_{th}^{tot}}$ as in the previous period: $Q_{th}^{prog} = Q_{th}^{tot(prog)} S_t$. This sales volume can be varied by adding or subtracting the factor $\delta > 0$. For this reason the volume used in further calculation is defined:

$$Q_{th}^{calc} = \begin{cases} Q_{th}^{prog} - \delta & \text{decrease} \\ Q_{th}^{prog} & \text{constant} \\ Q_{th}^{prog} + \delta & \text{increase} \end{cases} \tag{15}$$

[1] Q_{th}^R is the actual achieved sales volume in hour h of period t.

For all further calculations the agents use Q_{th}^{calc}. After determination of the calculation quantity investment decisions have to be carried out. There are different reasons for investments: (1) Replacement investment, if a plant has to be closed for example due to technical problems. Zäpfel (1989) adduces two other reasons for investment: (2) product differentiation and (3) price leadership. Other potential reasons can be expressed as a combination of these basic reasons. We assume in the following that product differentiation in the electricity market is not possible, although electricity can be differentiated by the generating technique as for example nuclear power versus water power. This assumption holds due to the fact that the majority of electricity is consumed by industry. The most important fact for industry is the price and the permanent availability, but not the production technology. We further assume that there exists no possibility of debts. In this case, an investment is reasonable, if the discounted cash flow is positive during the operating time until period T. Consequently the investment decision can be described as linear optimization problem acting on the maxim of profit maximization:

$$\max \sum_{i=1}^{N} \{-I_{i0} c_i^{inv} Z_i^{inv} + \sum_{t=1}^{T} r^{-t} R_{it} + c_i^{inv} Z_i^{inv} L_{iT} r^{-T}\} \tag{16}$$

and:

$$R_{it} = \sum_{h=0}^{23} \{(p_h - b_{ih} - \sum_{j=1}^{J} S_{ijt} C_j^{Sprog})(q_{ith} + q_{ith}^{inv}) - \beta_i (c_i + Z_i^{inv} c_i^{inv})\} \tag{17}$$

s.t.

$$q_{ith}^{inv} \leq Z_i^{inv} c_i^{inv} \qquad \forall i \tag{18}$$

$$0 \leq q_{ith} \leq c_i \qquad \forall i \tag{19}$$

$$\sum_{i=1}^{N} q_{ith} + q_{ith}^{inv} = Q_{th}^{calc} \qquad \forall t, h \tag{20}$$

$$\sum_{i=1}^{N} I_{i0} c_i^{inv} Z_i^{inv} \leq B_0 \tag{21}$$

c_i^{inv}: newly built capacity in actual period
I_{i0}: expenditure in actual period for investment of capacity c_i^{inv}
L_{iT}: residual value of plant type i in period T
p_h: calculation price is equal to the achieved price in hour h of the previous period
q_{ith}^{inv}: amount of electricity produced with the newly build plant
r: internal interest rate
Z_i^{inv}: whole-numbered decision variable to assure only discrete values of invested capacities

Prices are not anticipated. In this model the prices of the previous period are used. The residual values of different plant types are defined at the beginning of the simulation. The capacity restrictions ensure that no more electricity can be produced than capacity is provided. Furthermore, the constraints guarantee that the estimated sales volume can be satisfied and that the budget constraints are fulfilled. To consider the remaining life time of other plants within the model, further constraints have to be introduced.

The long-term planning layer determines the target sales volume and makes investment decisions. The value of the target production volume is transferred to the short-term planning layer where the necessary computations are conducted. The short-term planning layer transfers the results to the subordinate interaction layer. The communication layer submits the information to the Regulatory Agent. The proposed model includes increased responsibility and more capabilities for the agent. In the following section we describe the architecture and functionality of ECA.

4.4 Electricity Consuming Agents

Consumers' behavior varies depending on their preferences of electricity consumption, e.g. there exist companies with and without electricity generating possibilities or private customers who need just a fractional amount of electricity compared to large energy intensive industrial companies. For the simulation of electricity consumption it is either possible to implement consumers as price takers or to use agents for consumer representation. An agent-based approach for the demand side promises a more flexible and therefore dynamic reaction. Consumer agents represent different characteristic consumer types, react dynamically on changed circumstances, and are therefore more realistic. In the following we discuss a possible approach for the design of ECA.
ECA use the communication and coordination layers of the general layer architecture. The planning layer decides about the strategy and determines the bids. Generally consumers maximize their utility. Electricity consumption leads to a higher utility level. Consumers try to reach a particular utility level by consuming electricity at acceptable prices. The acceptance for a specific price varies among the consumers. Hence we identify three general options to achieve a special utility level. Consumer Agents either bid the same price (a_1) as they achieved in the previous period or they bid a higher (a_2) or lower price (a_3).

4.4.1 Strategies of ECA The individual electricity demand of each ECA is determined at the beginning of the simulation. During the simulation the agents have to buy electricity to satisfy their individual needs. Prices of previous periods are basis for further steps. The agents have three perceptions of environmental change: increasing (w_1), stable (w_2) or falling prices (w_3). Depending on the perception w_i agents have to decide on the bid price for the actual period. In case of increasing prices it appears reasonable to bid the same (a_1) or a higher price (a_2) as in the previous period. Perceiving stable prices all actions are possible. If prices were falling in recent periods, it is useful to bid lower prices (a_3), but it may also be useful maintain the previous price (a_1). Therefore the following allocation results:

$$w_1 \rightarrow \{a_1, a_2\}$$

$$w_2 \rightarrow \{a_1, a_2, a_3\}$$

$$w_3 \rightarrow \{a_1, a_3\}$$

4.4.2 The planning layer The planning layer decides on the bid price. The demand of electricity is determined manually at the beginning of the simulation and the ECA just decides on the bid price. The prices can be altered by the value π, which was defined at the beginning of the simulation. The effectiveness of the chosen strategy can be determined by the deviation of the bid price and the achieved price:

$$R(x) = \frac{\text{bid price - achieved price}}{\text{bid price}} \tag{22}$$

The learning algorithm as described above is used for within the architecture of the ECA for the decision making process.

4.5 Regulatory Agent

The regulatory authority defines market rules and other directives. On the one hand, this includes the evaluation of external effects resulting for example from emission of harmful substances during the electricity generating process. On the other hand, regulatory authorities have to ensure fair competition. In the following we discuss a model for a regulatory agent which is also based on the general layer architecture.
Goal of the RA is to maximize utility of the national economy. In the present problem this implies reducing the emission of harmful substances and prevent increasing electricity prices. To contain emission of harmful substances the government can either define limits or tax these substances per unit. Taxation has the advantage of monetary valuation of the emission of harmful substances and therefore is used in the model. An augmentation of taxation implies an increase of electricity costs as long as the company does not switch to other technologies. The regulatory agent therefore must find an appropriate balance between emission reduction and price augmentation.

Perception	**Emission**	**price developm.**	**Action**
w_1	constant	constant	a_1, a_2, a_3
w_2	constant	increasing	a_2, a_3
w_3	constant	falling	a_1, a_2
w_4	increasing	constant	a_1, a_2
w_5	increasing	falling	a_1
w_6	increasing	increasing	a_2
w_7	falling	constant	a_2
w_8	falling	falling	a_2
w_9	falling	increasing	a_2, a_3

Table 2 possible perceptions of a regulatory agent

4.5.1 Strategies of RA Basically three actions are possible to choose:

- increasing tax on emission (a_1)
- maintain stable tax (a_2)
- reduce tax on harmful substances (a_3)

The agent perceives the electricity price development and the development of harmful substances production. Hence results the perception and possible actions as illustrated in Table 2.

4.5.2 Planning layer RA uses the common layers for communication and coordination. The planning layer assesses the reduction of harmful substance emission $d_i = \frac{S_i^{t-1} - S_i^t}{S_i^{t-1}}$, whereas S_i^t specifies the amount of harmful substance emission in period t. Higher prices due to tax augmentation can not be averted, so that we interpret price augmentation ($u_h = \frac{P_{th} - P_{(t-1)h}}{P_{(t-1)h}}$) within a specific bandwidth as constant prices.
At the beginning of the simulation target values for emission reduction are defined, which the RA has to achieve within a defined period of time. An evaluation of emission of harmful substances is necessary to facilitate a utility comparison of the reduction of different types of substances. A detailed evaluation of harmful substances is not possible within the work for this paper, hence we use general parameters for harmful substances in order to include them within the model. The present proposition for the integration of regulatory instances into a general market model requires further intense studies.

5 Conclusion

This paper describes an agent-based model for long-term simulation of electricity markets. Firstly, we described some approaches to electricity market

simulation with MABS. These models all treat short-term simulation of electricity markets, which especially concerns price development. The results of the simulations were used to analyze the impact of changes in the regulatory mechanisms of the electricity markets of England and Wales as well as to study the strategic consolidation of the German electricity market.
Due to the significant results of the discussed simulation models, our goal is to enhance these short-term planning models for long-term simulation. Consequently, we present mechanisms to enable electricity generating agents for both short-term and long-term decisions. Another idea included into our approach is to represent a governmental or regulatory unit as an autonomous agent. Consumers have not been modelled as autonomous agents in the presented short-term simulation models. Hence, we introduce electricity consumer agents which try to achieve acceptable prices depending on their preferences. The actuating variables for both ESA and ECA are the price per unit electricity and the amount of electricity. The influence of governmental instances is included in the model by regulatory agents affecting taxes on the emission of harmful substances and monitoring prices. The decision of regulatory organizations is limited to favor or to hamper certain generating methods including the prohibition. Prohibition is realized within the model by infinite hight costs on the emission of harmful substances.
In the years of national controlled electricity markets, operations research (OR) methods were successfully used for plant utilization and investment decisions. In the present paper we combine these traditional mechanisms with the decentralized approaches such as agent-based simulation. Electricity Supply Agents use these mechanisms for individual optimization of the plant utilization as well as for investment planning. Consequently, individual decision rules are based on rational behavior applying traditional OR algorithms.
We discussed a framework for coordination and communication using a discriminatory double auction. Suppliers optimize their plant utilization and determine the amount and price of electricity to offer at each hour of a day. The bids including price and volume are matched with the bids of the customers. Suppliers inform the regulatory agent about the plants used and the regulatory agents decide on taxes for the emission of harmful substances. All agents use a common layered architecture with differences in the individual planning layers. Adaptivity is accomplished by a reinforcement learning algorithm developed by Erev and Roth (1998). Linear programming is used for the long-term planning of supply agents assuming profit maximization.
The present model presents a further step towards the development of ACE in electricity markets. We kept the model as simple as possible, because the goal is not to represent real market participants behavior in all detail, but to build a model which represents the overall market behavior with simple mechanisms. This approach appears promising, because first models of short-term agent-based simulation have shown useful results. Operation Research methods has been successfully used for long-term planning. Consequently, the combination of both approaches appears useful. A first

computation will show if the assumptions are valid. As a next step the calibration of the basic model is necessary before adding more complexity as e.g. integrating the transmission grid and transmission restrictions to study geographical characteristics. The consideration of preferences for the production technology (e.g. electricity produced by regenerative energy utilities) will show a more precise picture of consumers' behavior and therefore will draw a more detailed market picture.

A central problem in agent-based models is the representation of individual behavior. Knowledge about competitors and consumers plays an important role in decision making of suppliers or consumers. A detailed evaluation of possible strategies and development of a decision making framework allow the computational representation of individual behavior. The present model presents the first steps on the way to a comprehensive market simulation for management decision support.

The next necessary steps are to implement the proposed model and to validate its behavior. Shortcomings have to be identified and fixed. A calibration of the model using historic data is essential before further evaluation. The results will certainly contribute to the development of a comprehensive market simulation and to ACE as a whole.

However, the present model and further developments contribute to the understanding of the market development and therefore will help to provide decision making support not only for electricity companies but also for governmental organizations or consumers. ACE appear to generate promising results, so that future scientific research and development by economist and computer scientists will enhance market simulation and understanding of market systems.

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