BIDDING IN INTERRELATED DAY-AHEAD ELECTRICITY MARKETS: INSIGHTS FROM AN AGENT-BASED SIMULATION MODEL

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Abstract
In this paper we present results from an agent-based simulation model of two sequentially cleared electricity markets. Agents can bid on both a day-ahead market for physical delivery contracts and a day-ahead balancing power market and learn from their achieved results. Different scenarios of the order of market clearing and pricing rules are tested and their results are compared. We show that prices are lower in both markets when the day-ahead market is cleared first. We also show that pay-as-bid leads to lower resulting prices than a uniform price mechanism.

Key words: agent-based simulation, agent-based computational economics (ACE), electricity market modelling, sequential market clearing

1. Introduction
During the last decades, electricity markets have been restructured in many regions worldwide. One effort in this ongoing change in the regulatory framework is to separate transmission system operations from other parts of the electricity system, such as generation and retail services. When transmission and generation are separated, the transmission system operator (TSO) needs to procure balancing power from the market. This leads to the emergence of markets for primary and secondary reserve, as well as for minute reserve. In this environment, a generator that disposes of fast controllable generation units faces the problem of deciding whether to bid in a day-ahead market or to commit his units for balancing purposes. This increasing complexity of electricity trading and bidding decisions raises the necessity for methods and tools that allow modelling a variety of aspects.

One important issue in electricity market modelling is strategic behaviour. In competitive equilibrium models of electricity markets it is assumed that no agent tries to game the market and all market participants are price takers. In equilibrium, all agents bid their marginal generating costs and the (uniform) market clearing price is equal to the marginal unit bid. In real electricity markets, however, the market structure is oligopolistic and each agent can potentially influence market prices. As one example, Cramton [2004] shows how agents rationally bid in oligopolistic electricity markets and argues that bidding above marginal cost is a rational behaviour and must not be considered as anti-competitive. Realistic electricity market modelling must therefore account for profit-seeking agent behaviour that involves bidding above marginal costs.

A second important aspect that a realistic electricity market model should account for is the factor of daily repetition in trading. Rothkopf [1999] argues that the repetitive nature of electricity trading is a crucial factor in market design. He argues that the choice of an efficient market mechanism may differ when moving from one-shot auctions to repeated auctions.

A third aspect that should be addressed by electricity models is market interrelationships. Electricity is traded on different time scales, e.g. day-ahead, real-time, and also in form of different products, e.g. physical delivery, reserved (balance) capacity. The outcome of one market may influence an
agent’s bidding strategy on another market. Realistic electricity market modelling should thus account for interrelations between different markets.

Agent-based simulation has the potential to meet the aforementioned requirements and is a very promising approach for realistic electricity market modelling. It allows representing bidders as profit-maximising adaptive agents that can learn from their trading results in daily repeated auctions. It is also possible to simulate learning agents trading on different markets. The markets are then linked together through the agents’ trading decisions, which allows for studying market interrelationship aspects.

Several studies have demonstrated the usefulness of agent-based simulation for the analysis of energy systems, e.g. [Koesrindartoto et al. 2005], [Bunn, Oliveira 2003], or [Bagnall 2004]. Agent-based models considering market interrelationships include [Rupérez Micola, Estañol, Bunn 2006], who studies vertical integration in a multi-tier energy market including gas shippers, electricity generators and retailers; [Veit et al. 2006] study the interplay between a forward market and a spot market for electricity contracts and its effect on price stability.

In the following, we report results from an agent-based simulation that comprises a day-ahead market for physical delivery contracts and a day-ahead balancing power market. Agents are endowed with learning capabilities and develop strategies that maximise their profits. The remainder of this paper is structured as follows: section two introduces the simulation model and the agents’ trading problem. Section three summarises the characteristics of the simulation scenarios and section four reports and discusses the results from these simulations. Section five finally concludes and gives an outlook on future research.

2. The model

In our model we simulate sequenced trading in both a day-ahead market for physical delivery with uniform price clearing, or “pay system marginal price”, and a balancing power market where agents bid their capacity to a transmission system operator as minute reserve. On the latter market, both pay-as-bid and uniform pricing schemes have been implemented for different scenarios. The simulation model has been implemented with Java using Repast\(^1\), a toolkit for agent-based modelling.

2.1. The day-ahead market

A bid on the day-ahead market consists of different price volume pairs. A supply bid by generator \(i\) takes the following form:

\[
b_{i,h}^{\text{dayAhead}} = \left\{ (p_{i,h,1}, q_{i,h,1}), ..., (p_{i,h,s}, q_{i,h,s}) \right\}
\]

where \(p\) is the bid price and \(q\) is the quantity that the agent is willing to sell/buy at this bid price. The index \(h\) denotes the hour for which the bid is valid and \(s\) is an index for the different price volume pairs\(^2\). In our simulations we assume that an agent submits the same bid for every hour, so the index \(h\) can be omitted in the following presentation. In further extensions of the model, however, it is envisaged to let agents optimise their bids individually for each hour.

The day-ahead market operator collects all supply and demand bids and orders them into 24 hourly bid collections. Market clearing is done once per trading day and separately for each hour; physical delivery of the sold electricity is effected on the following day. The day-ahead market is designed as a sealed-bid double auction. However, in the current model active demand bidding doesn’t occur. Instead, generators submit supply bids for satisfying a fixed inelastic demand.

\(^1\) Information about this tool can be found on http://repast.sourceforge.net.

\(^2\) The bid format is designed in the style of the spot market concept used at the [European Energy Exchange 2005].
In order to determine the market outcome, the market operator sums up all supply and demand bids. Supply bids are ordered from the lowest to the highest bid price and from highest to lowest bid volume in the case of equal bid prices. The market clearing price and volume are determined by the intersection of the supply and demand curves. If necessary, the marginal bid is only partially fulfilled. If many market equilibria exist, i.e. when the intersection between the supply and demand curves is not a single point but a vertical line segment, the midpoint between the lower and the upper limit of the intersecting line segment is taken as the market clearing price. Figure 1 shows an example of the summed supply and demand bids in a day-ahead electricity auction.

Figure 1: Summed supply and demand bids in a day-ahead market

At the end of each trading round, every agent receives information about the resulting market clearing price and the individual volume that it has been able to sell or buy in the auction. Agents use this information in order to calculate their profits and reinforce their chosen strategies.

2.2. The balancing power market

In the balancing power market an agent bids a capacity price \((\text{cap})\) at which it is willing to provide its capacity as positive minute reserve to a transmission system operator. If the TSO actually needs electric work for stabilising the transmission system, he bases the decision on which capacity to deploy on the basis of the bid work price among all accepted bids. A bid on the balancing power market thus consists of a capacity price and a work price, together with the bid quantity for each bidding bloc \(b\):

\[
b_{i,b}^{\text{balance}} = \{p_{i,b}^{\text{cap}}, p_{i,b}^{\text{work}}, q_{i,b}\}
\]

The market clearing of the procurement auction for minute reserve is effected in two stages. In the first stage, which takes place one day ahead of physical delivery, the TSO selects the power plants that are held in reserve. For simplicity, we assume that there is only one bidding bloc covering all 24 hours of one day. Hence, the index \(b\) can be omitted in the following. Among several different options for choosing the best bids, the algorithm applied in our simulations is solely based on the capacity bid prices. This reflects the fact that in real-world balancing power markets for minute reserve, the actual minute reserve deployment is only in few cases greater than zero\(^3\) and thus work prices play a minor role in the optimal bid allocation. Bids are ordered from the lowest to the highest capacity bid price and from highest to lowest bid volume in the case of equal bid prices. Bids are accepted up to the demand volume as put to tender by the TSO.

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In the second stage, all accepted bids are sorted according to their bid work prices (merit order). If on the following day the TSO is in need of electric work from minute reserve, he determines the capacity to be started-up on the basis of the work price merit order. In the case of uniform price clearing, all successful generators are paid the uniform capacity price, which corresponds to the capacity bid price of the last unit needed to satisfy the demand. Those generation units that actually delivered electric work will be remunerated the uniform work price, which is again determined by the last successful bid. In the pay-as-bid case, all successful generators receive their individual bid prices for their committed capacity and, if applicable, their bid work prices for delivered electric work.

2.3. Agent learning

Agents choose their bids according to a probability distribution developed within a reinforcement learning algorithm. The learning representation applied in our simulation takes the form of a Modified Erev-Roth reinforcement learning algorithm as presented in [Nicolaisen, Petrov, Tesfatsion 2001]. It is a three parameter algorithm developed on the basis of the findings in [Erev and Roth 1998] and is described in the following.

For each situation in which learning is applied, an agent can choose from a set of possible actions \( M \). If generator \( i \) chooses his \( k \)th action at time \( t \) and receives a reinforcement of \( R(x) \), it updates its individual propensities to choose action \( j = (1, \ldots, M) \) according to the following function:

\[
s_{ij}(t + 1) = (1 - f) \cdot s_{ij}(t) + \begin{cases} R(x) \cdot (1 - e) & j = k \\ s_{ij}(t) \cdot \frac{e}{(M - 1)} & \text{otherwise} \end{cases}
\]

Here, \( s_{ij} \) is the propensity to choose a specific action in the next round, \( f \) is the “recency” parameter and \( e \) the “experimentation” parameter. The recency parameter reflects the agents’ tendency to forget past experience over time, and the experimentation parameter defines the extent to which agents engage in information exploration through trying strategies that don’t have the highest propensity. It has the effect that agents do not lock into one choice at a too early stage. The third parameter specifying the presented reinforcement learning algorithm is the scaling parameter \( s(0) \). It defines the initial propensities for all actions. Agents choose an action \( k \) according to the following probability:

\[
p_{ik}(t + 1) = \frac{s_{ik}(t + 1)}{\sum_{j=1}^{M} s_{ij}(t + 1)}
\]

They thus reinforce actions which have resulted in a high payoff and choose these again with a higher probability in the future. Accordingly, less successful actions are weakened and chosen again with a lower probability.

As probabilities should not be negative, it must be ensured that the propensities always have a positive value. If agents bid a price below their marginal generation costs, they face the risk to be called into operation at a price at which they make losses. For ensuring positive propensities we follow the proposition of Erev and Roth [1998], who subtract the smallest possible payoff \( x_{\text{min}} \) from all payoffs:

\[
R(x) = x - x_{\text{min}}
\]

In order for the algorithm to represent agent learning in a realistic manner, the parameters specifying the algorithm have to be set carefully. Erev and Roth [1998] state that a combination of \( f = 0.1 \) and \( e = 0.2 \) leads to the best prediction of the empirical outcome for their studied matrix games. The order of magnitude of the scaling parameter \( s(0) \) depends on the magnitude of the
possible reinforcements. In an effort “standardise” this parameter we restrict the reinforcement to be in the interval [0,1] by dividing each reinforcement by the highest possible reinforcement. In other simulations that we have carried out, we find that the value for the scaling factor doesn’t influence the results significantly\(^4\). We also found that the parameter combination stated by Erev and Roth as the best for predicting the results of their studied human experiments actually leads to a low variability of simulation outcomes over a series of 100 simulations, which means that the choice of a random number seed influences the results less than most other tested combinations\(^5\). These findings led us to the following choice of a parameter combination for every Modified Erev-Roth reinforcement learning algorithm: \(f = 0.1; e = 0.2; s(0) = 1.0\).

2.4. The agents’ action domains

On the day-ahead market, we model an agent as trying to optimise both its bid prices and quantities in order to maximise its individual profit. Thus, an agent can engage in withholding strategies if it finds these profitable. The possible bid prices for an agent on the day-ahead market range from the minimum to the maximum admissible price, where \(p_{\text{dayAhead}}^{\text{min}} = 0\) and \(p_{\text{dayAhead}}^{\text{max}} = 50\). A generator chooses the bid quantity as a fraction of his available capacity. The intervals \([a,b]\) of possible prices and capacity fractions are stratified into 21 discrete values for the bidding price and six values for the bidding quantity. The action domain for an agent bidding on the day-ahead market thus comprises \(M = 126\) possible actions and summarises to the following form:

\[
M^{\text{balance}} = \begin{bmatrix} p_{\text{dayAhead}}, q_{\text{dayAhead}} \end{bmatrix} = \begin{bmatrix} \{0,0\}, \{0,0.2\}, \ldots, \{0,1\}, \{5,0\}, \{5,0.2\}, \ldots, \{100,1\} \end{bmatrix}
\]

On the balancing power market, an agent always chooses its bid quantity as equal to the net installed capacity, reduced, if applicable, by the amount of capacity it has already committed on the day-ahead market. Thus, an agent only “learns” to choose its bid prices, and employs a fixed strategy for the bid volume. As a bid on the balancing power market comprises a capacity price and a work price, this again leads to a two-dimensional action domain. Admissible prices range from \(p_{\text{balance, cap}}^{\text{min}} = 0\) to \(p_{\text{balance, cap}}^{\text{max}} = 500\) and \(p_{\text{balance, work}}^{\text{min}} = 0\) to \(p_{\text{balance, work}}^{\text{max}} = 100\), stratified into 21 possible capacity prices and five work prices, which results into the following action domain:

\[
M^{\text{balance}} = \begin{bmatrix} p_{\text{balance, cap}}, p_{\text{balance, work}} \end{bmatrix} = \begin{bmatrix} \{0,0\}, \{0,0.25\}, \ldots, \{0,1\}, \{25,0\}, \{25,0.25\}, \ldots, \{500,100\} \end{bmatrix}
\]

2.5. The agents’ strategy

The problem facing the agent can be divided into the strategy to choose for the day-ahead market and the strategy for the balancing power market. The learning task for each agent is consequently separated into two individual learning problems. On the level of implementation, this results in each agent employing two instances of the learning algorithm, with the same parameter values but different action domains for both instances.

In our simulation scenario, each agent \(i\) owns one generation unit \(u\) which is characterised by a linear variable generation cost function, i.e. constant marginal generation costs \(MC_{i,u}\). Each power plant has a net installed capacity \(Q_{i,u}^{\text{inst}}\) and no-load costs \(NLC_{i,u}\). Ramping costs or other commitment constraints are abandoned in this simulation for simplification reasons.

As some capacity \(q_{i,u,t}^{\text{comm}}\) of a generation unit may have been committed in one electricity market for a period of time \(t\), the available capacity for this unit \(q_{i,u,t}^{\text{avail}}\) is defined as

\(^{4}\) The tested scaling parameters range from \(s(0) = 0.5\) to \(s(0) = 1.0\).

\(^{5}\) The tested parameter values range from \(f = 0.0\) to \(f = 0.5\) and \(e = 0.1\) to \(e = 0.5\).
\[ q_{\text{avail}}^{i,u,t} = Q_{\text{inst}}^{i,u} - q_{\text{comm}}^{i,u,t} \]

for this specific period. Other reasons for reduced power plant availability, such as maintenance periods or unplanned outages, are not included in the current simulation implementation. We assume that an agent bids one price volume pair for every generation unit it owns; agents cannot bid more than their available capacity into the market:

\[ q_{\text{dayAhead}}^{i,u,h} \leq q_{\text{avail}}^{i,u,h}, \quad q_{\text{balance}}^{i,u,b} \leq q_{\text{avail}}^{i,u,b} \]

An agent tries to maximise profits on both markets. It does so by favouring actions that have yielded higher profits in the past trading round through reinforcement learning. The reinforcement of each chosen action comprises the profit achieved on the market, and also includes opportunity costs to a certain extent. On the day-ahead market, the agent’s profit is defined as follows:

\[ \pi_{\text{dayAhead}}^{i,u} = q_{\text{dayAhead}}^{i,u} \left( p_{\text{dayAhead}}^{i,u} - MC_{i,u} (q_{\text{dayAhead}}^{i,u}) \right) \]

Here, \( p_{i,u} \) is the profit that agent \( i \) achieves for its generating unit \( u \), \( p_{\text{dayAhead}}^{i,u} \) is the resulting uniform price on the day-ahead market and \( q_{\text{dayAhead}}^{i,u} \) is the quantity of unit \( u \) that agent \( i \) was able to sell on the day-ahead market. The opportunity cost \( oc_{\text{dayAhead}}^{i,u} \) for agent \( i \) on the day-ahead market is the profit it could have achieved if it had bid its capacity on the balancing power market. It is defined as:

\[ oc_{\text{dayAhead}}^{i,u} = q_{\text{dayAhead}}^{i,u} \left( p_{\text{balance}}^{i,u} - NLC_{i,u} \right) \]

The profit an agent achieves on the balancing power market is defined as follows:

\[ \pi_{\text{balance}}^{i,u} = q_{\text{balance}}^{i,u} \left( p_{\text{balance},\text{cap}}^{i,u} - NLC_{i,u} \right) + q_{\text{balance,work}}^{i,u} \left( p_{\text{balance,work}}^{i,u} - MC(q_{\text{balance,work}}^{i,u}) \right) \]

Here, the subscript \((i,u)\) indicates that the capacity and work price can either be a single uniform price or an individual bid price for each agent/unit, depending on the pricing rule employed. As the produced electric work is remunerated separately, the cost that an agent \( i \) faces for providing minute reserve capacity is only limited to the no-load costs of its unit. However, an agent faces high opportunity costs, because it could also use its unit for producing electricity that it can sell on the day-ahead market. This opportunity cost is calculated as:

\[ oc_{\text{balance}}^{i,u} = q_{\text{balance,\text{cap}}^{i,u}} \left( p_{\text{dayAhead}}^{i,u} - MC(q_{\text{balance,\text{cap}}^{i,u}}) \right) \]

In both markets, the opportunity costs are subtracted from the profit that an agent receives. In order to prevent unintended effects, we restrict the opportunity costs to be positive through applying a \( \min() \) function. In addition, we ensure that the inclusion of opportunity costs doesn’t lead to negative reinforcements.

### 3. Simulation scenarios

Because of the probabilistic nature of the applied reinforcement learning algorithm, the outcome from our agent-based simulations partly depends on the random number seed with which learning instances are initialised. We derive individual random number seeds for each instance of the learning module, so as to avoid unintended similarity among agents which would occur if all learners had the same seed. Every simulation setting is run 100 times with different random number seeds at each run. All seeds employed in one set of 100 runs are stored and used again for different simulation scenarios. By doing so, we can best exploit the advantages of agent-based simulation: different settings, e.g. different market mechanisms can be tested under exactly the same conditions. By ensuring that all agents in principal learn exactly in the same way in one setting as in another, we can derive qualitative conclusions about market efficiency through comparing the resulting outcome of both settings.
In this paper, we explore four different scenarios which differ in the order of market execution and the pricing mechanism on the balancing power market:

- DayAheadBalance_uniform
- DayAheadBalance_payAsBid
- BalanceDayAhead_uniform
- BalanceDayAhead_payAsBid

DayAheadBalance refers to a scenario where the day-ahead market is cleared first, and then results from this market are published before the balancing power market clears. BalanceDayAhead switches the order of market execution. The endings _uniform and _payAsBid correspond to a uniform price and a pay-as-bid pricing rule on the balancing power market. On the day-ahead market, uniform pricing is employed in all cases.

The participating agents and their generation unit characteristics are summarised in Table 1.

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Generator1</td>
<td>300</td>
<td>5.00</td>
<td>75.00</td>
</tr>
<tr>
<td>Generator2</td>
<td>300</td>
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<td>300</td>
<td>15.00</td>
<td>75.00</td>
</tr>
<tr>
<td>Generator4</td>
<td>300</td>
<td>20.00</td>
<td>75.00</td>
</tr>
<tr>
<td>Generator5</td>
<td>300</td>
<td>30.00</td>
<td>75.00</td>
</tr>
<tr>
<td>Generator6</td>
<td>300</td>
<td>5.00</td>
<td>150.00</td>
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<tr>
<td>Generator7</td>
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<tr>
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<tr>
<td>Generator9</td>
<td>300</td>
<td>20.00</td>
<td>150.00</td>
</tr>
<tr>
<td>Generator10</td>
<td>300</td>
<td>30.00</td>
<td>150.00</td>
</tr>
</tbody>
</table>

Table 1: Characteristics of the agent’s generating units

The static demand throughout the simulation is $D_{\text{dayAhead}}^{\text{dayAhead}} = 1500$ MW and $D_{\text{balance, cap}}^{\text{balance, cap}} = 800$ MW, both constantly for every hour. The demand for electric work from minute reserve is $D_{\text{balance, work}}^{\text{balance, work}} = 160$ MW, which occurs in one hour per day.

4. Simulation outcome

Each run within one simulation scenario has been simulated over at most 2,000 trading days. In many runs, however, all agents locked into some preferred action earlier, because the propensities of all other actions were so low that they were hardly chosen. A simulation run was stopped if the resulting market price did not change over a period of 200 trading days. In all cases, the mean bid/market prices and bid/resulting volumes over the last 200 trading days was recorded as a result for each run. In the following, the simulation results for each scenario are reported. They comprise the average, minimum and maximum resulting values over 100 runs with different random number seeds, as well as the standard deviations (SD).

Resulting prices on the day-ahead market are depicted in Table 2. Prices attain a higher level if the day-ahead market is cleared after the balancing power market. The intuition behind this result is that competition is lower on the supply side in these cases, as some generators have already committed a part of their capacity on the balancing power market. When fewer agents compete on the day-ahead market, they can more successfully bid above marginal cost and thus achieve higher prices.
### Table 2: Simulated market clearing prices on the day-ahead market

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Average $p_{\text{dayAhead}}$</th>
<th>Minimum $p_{\text{dayAhead}}$</th>
<th>Maximum $p_{\text{dayAhead}}$</th>
<th>SD $p_{\text{dayAhead}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>DayAheadBalance_uniform</td>
<td>40.65</td>
<td>30.00</td>
<td>60.00</td>
<td>6.45</td>
</tr>
<tr>
<td>DayAheadBalance_payAsBid</td>
<td>37.01</td>
<td>20.00</td>
<td>65.00</td>
<td>7.32</td>
</tr>
<tr>
<td>BalanceDayAhead_uniform</td>
<td>66.14</td>
<td>35.00</td>
<td>100.00</td>
<td>15.56</td>
</tr>
<tr>
<td>BalanceDayAhead_payAsBid</td>
<td>64.03</td>
<td>35.00</td>
<td>100.00</td>
<td>16.28</td>
</tr>
</tbody>
</table>

### Table 3: Simulated capacity/work prices on the balancing power market

Table 3 represents the resulting capacity and work prices on the balancing power market. Here, we observe the opposite structure as on the day-ahead market, i.e. prices tend to be lower when the market is cleared second. This outcome cannot be explained by the supply concentration; another aspect influences the outcome in a stronger manner in this case. Whereas price information on the second market plays only a minor role for bidding strategies on the day-ahead market, on the balancing power market agents mainly base their bid decision on their opportunity costs. High prices on the day-ahead market mean high foregone profits for an agent that commits his capacity for minute reserve purposes. So, when prices are high on the day-ahead market, agents tend to bid higher on the balancing power market as well.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Average $p_{\text{balance,cap}} / p_{\text{balance,work}}$</th>
<th>Minimum $p_{\text{balance,cap}} / p_{\text{balance,work}}$</th>
<th>Maximum $p_{\text{balance,cap}} / p_{\text{balance,work}}$</th>
<th>SD $p_{\text{balance,cap}} / p_{\text{balance,work}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>DayAheadBalance_uniform</td>
<td>358.82 / 19.10</td>
<td>158.00 / 0.00</td>
<td>500.00 / 75.00</td>
<td>65.70 / 21.52</td>
</tr>
<tr>
<td>DayAheadBalance_payAsBid</td>
<td>273.80 / 17.54</td>
<td>60.23 / 0.00</td>
<td>431.25 / 75.00</td>
<td>75.00 / 20.26</td>
</tr>
<tr>
<td>BalanceDayAhead_uniform</td>
<td>393.79 / 17.51</td>
<td>225.00 / 0.00</td>
<td>475.00 / 99.75</td>
<td>51.00 / 20.53</td>
</tr>
<tr>
<td>BalanceDayAhead_payAsBid</td>
<td>354.29 / 17.21</td>
<td>206.25 / 0.00</td>
<td>457.88 / 75.00</td>
<td>55.04 / 21.24</td>
</tr>
</tbody>
</table>

### Table 4: Individual agents’ bid prices and volumes on the day-ahead market (simulation scenario: DayAheadBalance_uniform)

The single agents’ bidding decisions on the day-ahead market are summarised in Table 4. It can be shown that agents with low marginal costs realise their strategic advantage through bidding at lower prices on average. This ensures that their bids are accepted with a higher probability, so they are able to sell more electricity. It can also be shown that agents with high marginal costs tend to bid less capacity into the market. This can be interpreted as a withholding strategy, which is applied in order to raise the market price. According to the observed bidding strategies, it can be stated that no-load costs don’t play a significant role in the bidding decision on the day-ahead market; agents

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6 SD = standard deviation
whose generation unit characteristics only differ in no-load costs tend to apply very similar bidding strategies.

Table 5 shows the individual bidding decisions on the balancing power market. Only capacity bid prices are displayed. It can be seen that on average, most agents bid higher prices in a market with pay-as-bid pricing as compared to a uniform-price market. However, this rise in bid prices does not lead to higher market clearing prices in a pay-as-bid setting (see results for the balancing power market in Table 3). The average gain agents attain from receiving their – higher – bid prices under pay-as-bid does not outweigh the gain that infra-marginal bidders have from receiving the uniform price, which corresponds to the highest accepted bid. It is also interesting to note that generators with lower marginal cost tend to bid higher prices in the balancing power market; this, too, is due to the strong influence of opportunity costs on the bidding decision.

<table>
<thead>
<tr>
<th>Agent</th>
<th>( p_{\text{balance}}^{\text{cap}} ), BalancingDayAhead_uniform</th>
<th>( p_{\text{balance}}^{\text{cap}} ), BalancingDayAhead_payAsBid</th>
</tr>
</thead>
<tbody>
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<td>Average</td>
<td>Min</td>
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<td>Gen1</td>
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<tr>
<td>Gen2</td>
<td>434.21</td>
<td>275.00</td>
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</tr>
<tr>
<td>Gen9</td>
<td>397.46</td>
<td>100.00</td>
</tr>
<tr>
<td>Gen10</td>
<td>388.59</td>
<td>75.00</td>
</tr>
</tbody>
</table>

Table 5: Individual agents' bid prices and volumes on the balancing power market (simulation scenario: BalanceDayAhead_uniform and BalanceDayAhead_payAsBid)

The question whether pay-as-bid or uniform price leads to lower market prices is controversially discussed in the literature (e.g. [Kahn et al. 2001], [Rassenti, Smith, Wilson 2003], [Bower, Bunn 2001], [Xiong, Okuma, Fujita 2004]). Some researchers argue that pay-as-bid leads agents to bid at higher prices, resulting in higher average market prices. Others, in contrast, argue that it leads to lower overall prices, because infra-marginal agents reach lower prices as they would under uniform-pricing. Our simulation results suggest that pay-as-bid does in fact result in higher bid prices, but the bid price increase is not high enough to result in higher overall prices.

5. Conclusions and outlook

In this paper we modelled different scenarios with sequentially cleared electricity markets and two different pricing mechanisms. We apply agent-based simulation for evaluating market outcomes for the different tested scenario and for analysing market interrelationships. Generators are modelled as adaptive agents that apply a reinforcement learning algorithm which allows them to iteratively approximate their profit maximizing strategy. Within the tested scenarios, we differentiate between bidding strategies in a day-ahead market with physical settlement, and strategies in a day-ahead balancing power market. We shift the order of market execution and vary the pricing mechanism from pay-as-bid to uniform price. Simulations for each setting are repeated over 100 runs in order to level out the influence of the random number seeds taken for each learning instance.

We find that prices on the day-ahead market are higher if this market is cleared after the balancing power market. We argue that this is due to the fact that competition is weaker in this case, as some agents have already committed (part of) their capacity on the balancing power market. The reduced supplier concentration enables agents to successfully bid higher mark-ups to their marginal costs. Results on the balancing power market give a different picture: prices are lower if this market is
cleared second. Here, the effect of agents integrating their opportunity costs into their result evaluation leads to higher prices when day-ahead prices are high, and lower prices when day-ahead prices are low. As for the pricing rule on the balancing power market, we find the following result: average prices are higher under uniform price than under pay-as-bid although agents bid at higher prices under pay-as-bid. The increase in bid prices is outweighed by the effect of all infra-marginal bidders receiving the marginal, i.e. highest accepted bid under uniform pricing.

The findings presented in this paper leave us confident that agent-based simulation can reproduce realistic market outcomes. It is therefore a suitable tool for market design questions, because different market mechanisms can be tested under exactly the same condition of agent learning. In order to make agent-based simulation a useful market design tool, we will include more realistic data characterising the electricity system into our model. Our simulation model is implemented in a flexible way, so that is also easily extensible to other forms of generation or demand representation. For example, marginal costs can also take a linear form instead of being constant, or agents can own several generation units and engage in combined trading strategies for all their capacity. Hourly contracts and smaller bid blocs for the minute reserve can also be modelled with the current implementation. Using these features for analysing more settings is subject to our future research.

**References**


