Evaluating Market Designs in Power Systems with High Wind Penetration

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Abstract—In this paper we assess the incidence of strategic behavior of demand and supply units in market set ups which should enable the efficient in-feed of renewable energy sources. Therefore, a sequence of energy and reserve power auctions is modeled in an agent-based framework in order to approximately come up with the drawbacks of the different market designs. The main focus lies on the reserve power market. The generation companies as well as representative consumers are facilitated with Q-learning in order to exploit market flaws. The representative network includes a renewable in-feed, which is characterized by low marginal generation costs. In terms of congestion management, we assume in a first step uniform marginal pricing, in a second step nodal pricing for the energy power auction.

Index Terms—Electricity Market, market design, renewable energy in-feed, demand side participation, multi-agent system.

I. INTRODUCTION

A. Needs of future electricity market design

Since the late 1990’s the focus of electricity market design has shifted. The first phase of electricity market design literature dealt mainly with issues brought up through the liberalization of power markets. Reference [1] summarizes the current setup of major electricity market-designs in Europe. The common property of the spot market designs is the clear separation between day-ahead, intraday and balancing markets. Auction protocols and pricing mechanisms which facilitate trade (see e.g. in [2]) have been discussed in the literature. The major threat in terms of short-term market operation is the issue of sufficient market liquidity for intraday markets (see also [3]). Ancillary service markets in general (ancillary services are in this paper reduced to frequency control) may be divided into the reserve power determination and procurement by the Transmission System Operator (TSO) and the deployment in real-time balancing. The reserve power determination process will not be further discussed in this paper. The proper design of the procurement auction has been analyzed (e.g. in [4]), whereby again sufficient liquidity is one of the key issues.

However, the requirements in electricity market design have changed. Renewable energy generation, characterized by a low marginal cost structure and often prioritized feed-in, calls for progressions in terms of day-ahead and intraday markets, reserve power procurement and real-time balancing [5]. Further, the role of demand side participation and sufficient power system flexibility in general (see also [6]) will increase. Reference [7] points out that in order to tackle all the challenges above in the future market design, the interaction of all the submarkets has to be considered. To study the interconnection of energy spot markets (day ahead and intraday markets) and reserve power procurement is the subject of the first part of this simulation study.

Further, studies claim that a future market design will only be possible if the underlying transmission constraints are also properly priced in the regular energy trade to avoid spatial arbitrage (e.g. [8]), this aspect is also studied in this paper. The modeling of electricity markets is feasible by different approaches. Reference [9] points out the still ongoing trend of using optimization, equilibrium and simulation models. Optimization problems offer the advantage of stochastic modeling. Reference [10] also takes the offering of rival producers by bilevel optimization techniques into account. Equilibrium models explicitly try to take multi-agent behavior in a mathematical framework into account. Common approaches are Cournot and supply function equilibria models (e.g. [11], [12] and [13]). Simulation models try to address problems without a formal definition of an equilibrium by using for example sequential rules, which require of course theoretical justification. The virtue of a simulation model like an agent-based model lies in the intuitive insight that bidding experience and the interaction of several market participants in repeated auctions may result in outcomes different from a single-shot analysis.

References [14] and [15] outline the broad research focuses in electricity market modeling via agent-based modeling, such as market power and market design analysis, long- and short term decision making and the design of proper agent decision rules. Earlier large scale applications in agent-based modeling were done in e.g. [16] and [17] with a bilateral forward market, a balancing mechanism and imbalance settlement. Start up costs were indirectly incorporated via limits in the on/off cycles per time period. Reference [18] points out the interaction of congestion management and energy trading. A recent large scale application done in [19] investigates market power mitigation rules in the Californian electricity market. Though many learning algorithms are based on the work of [20] there exists no standardized rule of choosing a special learning algorithm.

B. Objective and problem statement

The main objective of this simulation study is primarily the assessment of the incidence of significant renewable energy in-feed and demand side participation in the energy and the
reserve power market, represented by low marginal cost units and strategically acting consumer units. The exploitation of arbitrage possibilities due to economic withholding of all market participants on the day-ahead/ the intraday and on the reserve power market are investigated. In order to capture variations in the arbitrage possibilities we assume three different market designs as denoted in the following Section.

In contrast to the considerations about temporal arbitrage, not taking bottlenecks (and therefore no spatial arbitrage opportunities) in the grid into account, we did a supplementary design analysis with capacity limits subject to Locational Marginal Pricing.

Section II provides the proposed framework for addressing the energy and reserve power market clearing. Section III includes the simulation framework and the numerical results based on the problem statements. Section IV provides concluding remarks and directions of future works.

II. MARKET MODELING

A. Proposed Market Designs

The considered markets designs are denoted with Market A,B and C. In the first one (Fig. 1(a)), a day-ahead market for energy procurement (e.g. Power Exchange Platform (PX)) and a day-ahead reserve power acquisition by the TSO take place. The need for reserves is determined separately. Finally, an intraday auction gives the opportunity to adjust the day-ahead scheduling. This market approximately comes up with some current market designs in Europe.

With the second design proposal (Fig. 1(b)), the effect of a temporal shift of the reserve power auction to an intraday basis is investigated.

Finally, in contrast to Market B we assume that on an intraday basis the energy and reserve power auction are merged together in one step (Fig. 1(c)). The process of a simultaneous centralized auction may further reduce problems of temporal arbitrage and liquidity and is following anglophone market approaches.

Fig. 1. Considered market designs in terms of temporal auction allocation

B. Agent modeling and learning

The strategically acting market participants are represented by their individual cost (Generation) or benefit (Load) functions. The cost function $C_{G_i}$ of Generator $i$ equals:

$$C_{G_i}(P_{G_i}^t) = a_{G_i} + b_{G_i}P_{G_i}^t, \quad i = 1, ..., N_G,$$

the benefit function of Load $j$ is determined by:

$$B_{L_j}(P_{L_j}^t) = c_{L_j} + d_{L_j}P_{L_j}^t, \quad j = 1, ..., N_L,$$

where $a_{G_i} > 0$, $b_{G_i} > 0$, $c_{L_j} > 0$, $d_{L_j} < 0$, $N_G$ and $N_L$ are the numbers of Generators/Loads. Subscript $s$ indicates that these variables/parameters may change with the scenario. The derivation of the marginal cost and benefit curves gives linear functions in dependence of the supplied/consumed amount of energy, whereby the agents are able to modify the intercept and the slope of these functions. Further in order to simulate demand-side participation in the reserve power markets we assume in case of the loads also a cost-function for reserve power provision similar to the ones for generation.

Each agent has a finite discrete set of actions available to adapt the intercept and/or slope of the cost/benefit function: $A^G = \{a^G, b^G, c^G, d^G, \alpha^G, \beta^G, \gamma^G, \delta^G, \epsilon^G, \zeta^G\}$ and $A^L = \{a^L, b^L, c^L, d^L, \alpha^L, \beta^L, \gamma^L, \delta^L, \epsilon^L, \zeta^L\}$ and $\alpha^G, \beta^G, \gamma^G, \delta^G, \epsilon^G, \zeta^G$ and $\alpha^L, \beta^L, \gamma^L, \delta^L, \epsilon^L, \zeta^L$ are vectors and represent the markups for the day-ahead power exchange bids, the intraday power exchange bids, the capacity bids for up/down reserves and the energy bids for up/dn reserves respectively. In order to reduce the dimension of the problem we assume similar to [19] a common markup for the intercept as well as the slope of the marginal benefit and marginal cost curves as shown in Fig. 2. Note that the goal of the agents is the maximization of their individual surplus.

![Fig. 2. Illustrative bidding of generators (G) and load serving entities (LSE) on the day-ahead market. The shaded areas refer to the consumer surplus (CS,green) and producer surplus (PS,red) at the equilibrium point (P*,Q*)](image)

The learning process of the agents takes place through Q-learning. The Q-learning algorithm is a mapping of the reward gained from a specific action and is used in a proper exploration/exploitation strategy to maximize the reward in a learning process. The rule for the update process of the Q-value is,

$$Q_{a_i}(k + 1) = Q_{a_i}(k) + \alpha(r_{a_i}(k + 1) - Q_{a_i}(k)),$$

where $a_i$ refers to the action choosen, $r_{a_i}$ to the resulting reward and $k$ to the learning round. $\alpha$ represents the learning parameter. As exploration/exploitation strategy we choose the $\epsilon - greedy$ strategy. The exploitation-part of the $\epsilon - greedy$ strategy comprises that the agent chooses an action with a probability $1 - \epsilon$ which maximizes his expected reward. The exploration part choses with a probability $\epsilon$ a random action, which reduces the chance to get stuck in a local extremum.
The bidding of an agent happens in terms of a pure strategy (joint bidding), meaning that at the beginning of every learning round their strategy for all kinds of bids is fixed.

C. Day-ahead Energy Market

The aim of the trading mechanism is to maximize social welfare and to facilitate trade. The auction is double-sided, which means that the producers as well as consumers can submit their bids, as explained in the following section. The determination of \( (P^G, \ldots, P^L, P^{L}_{s}, \ldots, P^{L}_{j}) \) can be written in terms of an optimization problem as

$$\max \sum \frac{1}{2} \alpha_{sj} P^L_{sj} (c_{ij} + \frac{1}{2} d_{sj} P^L_{sj}) - \sum \frac{1}{2} \alpha_i P_t (a_{ij} + \frac{1}{2} b_i P_c),$$

subject to

$$\sum P^G_{is} - \sum P^L_{js} = 0, \quad (5)$$
$$P^G_{ij} - P^G_{ij, \max} \leq 0, \quad (6)$$
$$P^G_{ij, \min} - P^G_{ij} \leq 0, \quad (7)$$
$$|| P^{DF} P^L_k (P^G_{is} - P^L_{js}) || - P_{\max, flow} (l) \leq 0, \quad (8)$$

with \( i = 1, \ldots, N_G, \ j = 1, \ldots, N_L \) and \( k = 1, \ldots, N_k \). \( N_G \) refers to the number of generators, \( N_L \) to the number of loads and \( N_k \) to the number of nodes. Equation (5) ensures the overall system balance. Eq. (6) and (7) incorporate the limits in generation and demand requirements. Inequality (8) states that the power flow, resulting of the generation and load at every node \( k \), is not allowed to exceed a certain maximum. \( P^{DF} \) corresponds to the Power Flow Distribution Factor Matrix. The Lagrangian multiplier of eq. (5) determines \( \lambda_{\text{DF}} \), the market clearing price for the energy market in the case of no congestion and uniform marginal pricing. If congestion appears, equation (5) is used in combination with the dual variables of inequality (8) to obtain Locational Marginal Prices.

D. Reserve power auction

After the bidding process on the Power Exchange, the agents may bid in a reserve power auction. The auction mechanism aims to minimize the procurement costs of reserve power. The auction is single sided, which means that generators as well as consumers may submit bids (for capacity and energy) to provide reserve power, but the TSO is the only buyer of reserve power. The auction mechanism does neither include a symmetric bidding nor a distinction in spinning or non-spinning reserves.

The TSO demand for reserves is based on two components. First the demand due to the current load situation, denoted by \( P^{L}_{res, s} \), is based on the ENTSO-Formular [21]. Second, the demand due to fluctuating renewable in-feed (e.g. wind). We assume that a percentage \( p \) of the scheduled renewable in-feed are hedged by reserves:

$$P^{R}_{res, s} = p \cdot \sum P^R_i$$

where \( P^R_i \) stands for all units \( i \) with fluctuating in-feed behavior in scenario \( s \). The percentage-factor \( p \) is adjusted to the temporal allocation and is reduced the closer the auction gets to physical delivery. The overall reserve demand in scenario \( s \) results in

$$P^{R}_{res, s} = P^{L}_{res, s} + P^{R}_{res, s}, \quad (10)$$

The cost minimization problem is formulated as in [22]. The provision of reserve power by the load and generator units is restricted to their scenario-dependent minimum and maximum power consumption and the result of possible previous auctions. The contribution for up/down reserves by the supply and demand side, \( (P^{resup}, P^{resup}, P^{resdn}, P^{resdn}, P^{resup}, P^{resup}, P^{resdn}, P^{resdn}) \), can be written as

$$\min (\gamma_i a_i + F_{\text{weight}, c_i} a_i) P^{resup} + \frac{1}{2} (\gamma_i b_i + F_{\text{weight}, c_i} b_i) (P^{resup})^2 + \frac{1}{2} (\gamma_i c_i + F_{\text{weight}, c_i} c_i) (P^{resup})^2 + \frac{1}{2} (\gamma_i d_i + F_{\text{weight}, c_i} d_i) (P^{resup})^2$$

subject to:

$$P^G_{is} + P^{resup}_{is} - P^{resdn}_{is} \leq 0, \quad (12)$$
$$P^L_{js} + P^{resup}_{js} - P^{resdn}_{js} \leq 0, \quad (13)$$
$$P^{G\min} + P^{resdn}_{is} - P^{Gmax} \leq 0, \quad (14)$$
$$P^{L\min} + P^{resup}_{js} - P^{L\max} \leq 0, \quad (15)$$

with \( i = 1, \ldots, N_G, j = 1, \ldots, N_L, k = 1, \ldots, N_k \). The factor \( F_{\text{weight}, c} \) considers how the TSO weights the energy bids besides the capacity bids in the auction process. We show in the simulation studies only the cases where no weighting of the energy bids takes place. Nevertheless, the possibility to do so offers interesting research issues.

The Lagrange multipliers to (16) and (17) determine the auction clearing price for up/down reserves \( \lambda^{resup}_{PDA, s} \) and \( \lambda^{resdn}_{PDA, s} \).

E. Intra-day Market

The structure of the intra-day market matches mostly the day-ahead energy auction. The goal is to determine
(P_i^GID, \ldots, P_j^GID, P_i^{LID}, \ldots, P_j^{LID}) \) which means in terms of an optimization problem

\[
\begin{align*}
\max & \sum_j \beta_j P_j^{GID}(c_j + \frac{1}{2} d_j, P_j^{GID}) \\
& - \sum_i \beta_i^G P_i^{GID}(a_i + \frac{1}{2} b_i, P_i^{GID}),
\end{align*}
\]  

(21)

subject to

\[
\begin{align*}
\sum_i P_i^{GID} - \sum_j P_j^{GID} & = 0, \\
\sum_i P_i^{GID} - P_i^{G,L\text{max}ID} & \leq 0, \\
\sum_i P_i^{G,L\text{min}ID} - P_i^{G,LID} & \leq 0,
\end{align*}
\]

(22)

\[
\sum_k P_DTF_k^G(P_{net}) \leq (P_{\text{max}}^\text{flow,}(l) - P_D^\text{flow,}(l)) \leq 0,
\]

(25)

with \( i = 1, \ldots, N_G, j = 1, \ldots, N_L, k = 1, \ldots, N_k \), and

\[
P_j^{GID} = P_j^{LID}\max P_j^{LID}, \\
P_j^{LID}\min = P_j^{LID}\max P_j^{LID}.
\]

\]

(26)

(27)

(28)

\( P_{\text{LID}\max} \) and \( P_{\text{LID}\min} \) are external factors, determining the amount of ID - Load. For all proposed designs we assumed the same percentage of load adjustment requirements. \( P_{i,j}^{GID} \) and \( P_{i,j}^{LID}\) are adapted with respect to the auction result(s) before. We assume only positive adjustment values in our simulations. Equation (22) determines the market clearing price for the intra-day market \( \lambda^{\text{energyDA},i} \), if, as explained in the day-ahead case, there is no congestion assumed. In the case of a combined auction with an intraday energy and reserve procurement, the features of the latter two optimization problem are combined in one framework. From a market design point of view it supports the joint bid assumption we have done and obviously prevents from temporal arbitrage. From a institutional point of view it assumes implicitly a central market operation units.

\[ P_i^{GID,k} - P_j^{GID,k} - P_{net} = 0, \]

F. Reward of the agents

The producer and consumer surplus based on the clearing results on the energy markets are determined by using the clearing prices, the individual amounts of energy produced and consumed and the marginal cost/benefit functions. The reserve power market reward is determined by the weighting factors of the energy bids, which results from the trade off of providing reserves instead of bidding into the energy market and the costs of the utilization of the reserves:

\[
\begin{align*}
\text{Reward}_{G\text{resup}} & = P_{resup}^G \lambda_{resup,DA}, \\
& + F_{util, j} P_{resup} [\text{Bid}_{G\text{resup}} - \frac{1}{2} \text{Bid}_{G\text{resup}}^\text{flow,}] P_{resup}, \\
& - F_{\text{weight}, j} P_{resup} [\text{Bid}_{G\text{energy}} - \text{Bid}_{G\text{resup}}], \\
& + \frac{1}{2} P_{resup} [\text{Bid}_{G\text{resup}}^\text{flow,}] P_{resup}, \\
& - F_{util, i} (M_{i} P_{resup}^G + \frac{1}{2} M_{i} P_{resup}^G),
\end{align*}
\]

(29)

with \( i = 1, \ldots, N_G \). The first term in (29) represents the reward of selling up-reserves for a given price. The second term states the additional reward in the case of utilization, the third term depicts the opportunity costs of providing energy for reserves instead of bidding on the Power Exchange, and the last term states the costs of utilization of reserves. Clearly, the reward in providing down reserves does not include the possibility of bidding into the energy or reserve market:

\[
\begin{align*}
\text{Reward}_{G\text{resdn}} & = P_{resdn}^G \lambda_{resdn,DA}, \\
& + F_{util, j} P_{resdn} [\text{Bid}_{G\text{resdn}} - \frac{1}{2} \text{Bid}_{G\text{resdn}}^\text{flow,}] P_{resdn}, \\
& - F_{\text{weight}, j} P_{resdn} [\text{Bid}_{G\text{energy}} - \text{Bid}_{G\text{resdn}}], \\
& + \frac{1}{2} P_{resdn} [\text{Bid}_{G\text{resdn}}^\text{flow,}] P_{resdn}.
\end{align*}
\]

(30)

with \( i = 1, \ldots, N_G \). The demand units do not share this reward structure entirely, since they are not directly affected by the possibility of bidding into the reserve market and the energy market (reserve market participation adds to the consumer surplus):

\[
\begin{align*}
\text{Reward}_{P\text{resup}} & = P_{resup} \lambda_{resup,DA}, \\
& + F_{util, j} P_{resup} [\text{Bid}_{G\text{resup}} - \frac{1}{2} \text{Bid}_{G\text{resup}}^\text{flow,}] P_{resup}, \\
& - F_{util, i} (M_{i} P_{resup}^G + \frac{1}{2} M_{i} P_{resup}^G),
\end{align*}
\]

(31)

with \( j = 1, \ldots, N_L \) and

\[
\begin{align*}
\text{Reward}_{P\text{resdn}} & = P_{resdn} \lambda_{resdn,DA}, \\
& + F_{util, j} P_{resdn} [\text{Bid}_{G\text{resdn}} - \frac{1}{2} \text{Bid}_{G\text{resdn}}^\text{flow,}] P_{resdn}, \\
& - F_{util, i} (M_{i} P_{resup}^G + \frac{1}{2} M_{i} P_{resup}^G).
\end{align*}
\]

(32)

with \( j = 1, \ldots, N_L \). The strategic element for down-reserves lies in the trade off between loss of Consumer Surplus in the energy market clearing through reduced stated demand and the gained increase in welfare through rewards on the reserve market.

III. SIMULATION FRAMEWORK AND CASE STUDIES

A. Test System

![Test system with strategic agents](Fig. 3)
investigation of spatial arbitrage we introduced a capacity limit of 100 MW for the lines 3-4 and 2-5 (the results from the PDTF - Matrix see Appendix A). In terms of the cost structure of the generator agents, we assumed very low marginal costs for the unit G5, representing renewable in-feed. Generators G1 and G3 represent medium cost units, whereas G2 and G5 represent a base and peak power plant, respectively (detailed data see Appendix B).

B. Temporal order of auctions

We denote different cases of market order, following the same notation as in Fig. 1:

- In Market Design A we assume that 20% of the scheduled renewable in-feed is hedged by reserves.
- In Market Design B and C all the simulations have been carried out with additional reserves for 5% of the scheduled non-conventional generation. The demand side bid into the reserve market with a cost structure similar to a medium cost generation unit.

The simulation scenarios are recognizable by the load situation (Base, Mid, Peak) and the amount of wind power infeed (0%, 50% and 100% of the maximum capacity). We build up our analysis by a comparison with a base case: Market Design A with no congestion and no strategic behavior (we also concentrate on the scenarios with wind-infeed). The prices resulting from the clearing procedures on the day-ahead, reserve power and intraday market based on the setup of Market A are shown in Figure 4.

![Fig. 4. Prices resulting from energy and reserve power market clearing in the competitive case of Design A.](image)

With regard to prices of every market design in case Demand Side Participation (DSP) we identify possibilities

- No DSP on the energy and reserve power market (noDSP).
- DSP on the energy market but not in the reserve power auction. The reason may be restrictive regulations in terms of concession (EnDSP).
- DSP in the energy and reserve power auction (EnResDSP).

In order to evaluate the influence in terms of market power we use as proposed in [23] the Herfindahl-Hirschman Index (HHI) which enables us to provide a fast comparison between the case studies. The HHI is defined as,

$$HHI = \sum_{i=1}^{N} \left( \frac{x_i}{\sum_{j=1}^{N} x_j} \right)^2,$$

whereas $x_i$ equals the share of supplier’s $i$ production and $N$ equals the number of generation units.

As expected, in the case of strategic behavior in Market A, day-ahead as well as intraday prices rise. Moreover, Fig. 6 and 7 show that also the prices for reserves rise though the market concentration decreased in the case of demand side participation in the reserve power market. This is related to the fact that through rising wind-infeed the demand for reserve rises and due to the efforts of demand units to maximize their reward in the reserve power auction in addition to the consumer surplus in the energy market actions.

Market Design B is not assuming a common determination of energy and reserve power. This leaves the opportunity for arbitrage. Figs. 8(a) and 9(a) show, that though our assumption of joint bidding, we get similar but not identical results as in Design C (Figs. 8(b) and 9(b)) for the changes in prices as
well as the HHI for reserve power.
In comparison to the results in the base case and even though the amount of scheduled reserves is clearly reduced, there is only a slight tendency of cheaper reserves in both market setups if there exists DSP in the reserve markets. This attributable to the increasing scarcity of generation in case of intraday reserves and the cost structure of additional reserves provided by demand units. Further, in case of no DSP, the reserve power market in design B shows a higher concentration in the supply (see Fig. 9(a)), which is an indicator of insufficient liquidity. This concentration increases with higher day-ahead wind power scheduling, which is reasonable since additional capacity is needed to hedge uncertainties and decreases if DSP in the reserve market is allowed.

In Market Design C we recognize as well a positive impact in terms of the market concentration (see Fig. 9(b)). As a first conclusion for Markets B and C, DSP does not lead to a general significant decrease in the price levels, which of course relies on the assumed system settings, nor does a shift of the reserve power auction closer to real time. In the case of DSP in the reserve power action an improvement in terms of market concentration for up-reserves and therefore liquidity is observable.
However, though not shown in the figures, in all so far assumed market designs DSP did in general not contribute to an improvement of prices or HHI of down reserves. This stems from the strategic environment and the interconnection of markets. Demand units were not able to absorb losses in the consumer surplus in the energy market trough rewards in down-reserves provision.

**C. Consideration of networks capacity constraints**

As noted in the introduction, the comparison between the market design in consideration of transmission constraints
gives rise to a second possibility of arbitrage. We refer to the base market scenario A and assume capacity limits in the transmission grid. LMPs implicitly take care of transmission constraints since by definition "penalties" for congestion are included. With respect to a remote renewable in-feed we observed a decrease of the nodal prices through the generation component but with increasing in-feed this descent is increasingly compensated by the congestion rent. In the case of strategic behavior and DSP in the energy as well as the reserve market the prices seem to decrease. The Nodes IV and V gain most from the possibility of DSP. Table I. Figure 10 again shows the positive influence of DSP on the market concentration index, this time also in the case of down reserves. The capacity limits influenced prices sufficiently enough to give demand units incentives to provide down reserves.

IV. EVALUATION, CONCLUSION AND FUTURE WORK

With this simulation study we gained insights into the incidence of strategic behavior of demand and supply units in connected markets in the presence of renewable in-feed. Temporal as well as spatial related results were observed: The shift of the market clearing for reserves did not contribute to significant decreases in the prices level and market concentration. Market concentration rose with higher wind power penetration which implies possible liquidity problems. The reasons may be found in the scarcity of suitable generation units and the presence of strategic behavior. Significant improvements through merging energy and reserve power auction on an intraday-basis were not found in this study.

Further, the simulation results show that even with the assumed flexibility of the power system, DSP in the reserve market offers gains in the uncongested as well as the congested case in terms of reduction of market concentration. In consideration of limited generation flexibility in real power systems, DSP seems to be most fruitful if it is allowed also in the reserve power auction. In the case of down-reserves, demand units were not able to bring the expected gain through the connection with the energy market clearing. The incentives for reserve power provision must outweigh the loss of consumer surplus in the energy market clearing. Clearly, in presence
of highly inelastic demand the potential gets more limited. A general reduction in prices for up-reserves is only to be expected if demand units, though acting strategically, are able to bid in at lower costs than the participating generation units. Note that the cost functions of the demand units in the reserve power provision are, if treated carefully, again a function of the energy market demand elasticity. 

As shown in the study with nodal prices, proper locational prices signals in a congested network provide sufficient incentives to shift demand for up/down reserve purposes. Nodes with higher generation costs gained relatively most from an increased DSP.

With respect to future work the goals are twofold: In terms of application of agent-based modeling in power market analysis we want to improve the action set by making it continuous and introduce decision making procedures for multiple time steps instead of joint bidding. In terms of market power analysis we plan to improve the agent decision processes by introducing time constrained bidding behavior.

**APPENDIX A**

**PDFT - MATRIX AND SYSTEM DATA**

**TABLE II**

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**TABLE III**

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<td>Pmax MW</td>
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<td>MWT MW</td>
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<tr>
<td>max. MW</td>
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<td>min. MW</td>
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**REFERENCES**


