Energy and Operating Reserves Procurement in Presence of Capacity Limits

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Abstract—In this paper we make use of an agent-based approach to model strategic behavior of supply units in an simultaneous clearing of spot energy and operating reserve power/energy. Generation units submit bids for energy and reserve power capacity as well as reserve energy. The test system shows the incidence of capacity limits as well as remote renewable energy penetration. The contributions of this paper are twofold: First, in contrast to the literature in agent-based electricity market simulation frameworks with discrete action sets we apply a "continuous" action set mechanism. The algorithm is derived from the common Q-learning approach. Second we show in a representative North-South model with substantial renewable energy-infeed and capacity limits the incidence of Locational Marginal Pricing on energy as well as reserve power markets in combination with strategically acting generation units.

Index Terms—Electricity Market, market design, renewable energy in-feed, multi-agent system, continuous Q-learning.

I. INTRODUCTION

Since the late 1990’s renewable energy in-feed integration is gaining more and more of attention. Large scale renewable energy in-feed in remote locations challenges grid operators as well as market participants in terms of efficient resource scheduling. In order to tackle challenges in the future market design, the interaction of all the submarkets has to be incorporated in modeling frameworks as well as in practice (see also reference [1]). A simultaneous centralized energy and reserve power scheduling mechanism may reduce the possibility of temporal arbitrage and therefore probably enhances market liquidity. Further, in terms of transmission system security and power quality, in continental Europe the Transmission System Operators (TSO) is in charge of the safe grid operation through the management of transmission capacities and the use of Congestion Management Schemes (CMS), e.g. [2]. Studies claim that a future market design will only be possible if the underlying transmission constraints are properly priced in the regular energy trade to avoid spatial arbitrage, e.g. [3].

However, the analysis of a combination of simultaneous procurement of energy and reserve power and different CMS in presence of strategically acting agents and remote renewable in-feed is the focus of this paper. This is motivated by the presumably rising demand for adequate operating reserves in times of high (remote) renewable in-feed and diminishing line capacities. The study goes also along with recent ambitions of changes in the European system operation towards nodal pricing, see also [4].

In order to model the electricity market designs and explore possible market flaws, one possibility is to use simulation models like agent-based modeling. The main advantages of agent-based modeling are twofold. First, the insight that market participants may act differently in repeated process through learning abilities. Second, there is no need of an explicit mathematical formulation of the (stochastic) environment the agent is faced with. The main research foci of electricity market models utilizing agent-based modeling are outlined by ref. [5] and [6]. Earlier large scale applications in agent-based modeling were done in e.g. ref. [7] and [8] 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 [9] points out the interaction of congestion management and energy trading, but no reserve power market was introduced. A recent large scale application done in ref. [10] investigates market power mitigation rules in the Californian electricity market. Though many learning algorithms are based on the work of ref. [11] there exists no standardized rule of choosing a special learning algorithm. One algorithm commonly used is Q-learning based on the work of ref. [12]. However, Q-learning algorithms in electricity market design suffer from the disadvantage that increasing gridding of the agent’s action space into discrete actions leads in case of more than one agent and several decision variables to an excessive rise in the computational effort. A rough fragmentation of the action space results in approximative outcomes. Therefore we apply an approach based on [13], which allows the utilization of the whole action set interval instead of discrete values.

Section II provides the proposed framework for addressing strategic bidding in the energy and reserve power market. 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 Design

The clearing platform for energy and reserve power capacity is based on the current design of markets in the US and provides the advantage of reducing the opportunity of temporal strategic behavior between different market platforms. In distinction to the common market designs in continental Europe, the function of a market operator and a Transmission System Operator are merged into one institutional framework. The incidence of significant renewable energy in-feed in the energy and the reserve power market is evaluated by a low marginal cost in-feed and a linear rising demand of the TSO.
for reserve power. We are assuming that reserves may be spinning or non-spinning but the generators are individually restricted in their provision.

The exploitation of arbitrage possibilities in the reserve power market by the generation units is assessed by assuming Locational Marginal Pricing first only in the energy market and subsequently in both market clearings (before the reserve market faces uniform prices).

Subsequently the energy/reserve capacity auction, the scheduled reserve power may be utilized following the merit order of the reserve power energy bids.

B. Agent modeling and learning

The strategically acting generators are represented by their individual cost functions. Load units are not assumed to act strategically. The cost function \( C_{ts}(P^G_{ts}) = a_{ts}P^G_{ts} + b_{ts}P^G_{ts}^2 \), \( i = 1, \ldots, NG, \) the benefit function of Load \( j \) is determined by:

\[
B_j(P^E_{js}) = c_{js}P^E_{js} + d_{js}P^E_{js}^2, \quad j = 1, \ldots, NL,
\]

where \( a_{ts} > 0, b_{ts} > 0, c_{js} > 0, d_{js} < 0 \). \( NG \) and \( NL \) are the numbers of Generators/Loads. Subscript \( s \) indicates that these variables/parameters may change with the scenario. The exploitation of arbitrage possibilities in the reserve power market by the generation units is assessed by assuming that reserves may be spinning or non-spinning but the generators are individually restricted to act strategically. The nearest neighboring action with the highest Q-values has to be evaluated. In this paper we are not assuming strategic load units. In order to reduce the dimension of the problem we assume similar to [10] a common markup for the intercept as well as the slope of the marginal cost curves.

Each agent has for every decision variable, namely the markup for the energy market, the up/down reserve capacity and the up/down reserve energy bid a separate learning sequence and respectively its own action set. We denote the different markups of agent \( j \) with \( \alpha_j, \beta_j, \gamma_j, \epsilon_j, \delta_j \) respectively. In this simulation study, the markups for down reserve capacity and energy remain zero.

\[
\text{Sender - Bid} \quad \text{Environment} \quad \text{Market clearing(s)} \quad \text{* other Agents}
\]

\[
\begin{align*}
\text{Q}_{\text{Energy}} & \quad \text{Q}_{\text{ResUpCap}} & \quad \text{Q}_{\text{ResDnCap}} & \quad \text{Q}_{\text{ResUpEn}} & \quad \text{Q}_{\text{ResDnEn}}
\end{align*}
\]

The bidding of an agent takes place 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. As exploration/exploitation strategy we choose the \( \epsilon - \text{greedy} \) strategy. The exploitation-part of the \( \epsilon - \text{greedy} \) strategy comprises that the agent chooses an action with a probability \( 1 - \epsilon \) which maximizes his expected reward. In distinction to common approaches with discrete actions set we introduce in the exploitation phase, based on [13], an algorithm which allows the utilization of the whole action-set interval instead of predefined discrete actions. The approach contributes to the issues of convergence speed and the treatment of strategically acting agents with several decision variables. In order to generate the Q-value of a bidding strategy for a decision variable we use the clearing results of the energy and reserve capacity auction and the utilization of reserve power in real-time balancing respectively (see also Figure 1).

The action set interval utilization by the algorithm operates as follows:

1) The action set values have to be ordered monotonically.
2) The maximal corresponding Q-value to each decision variable has to be evaluated.
3) The nearest upper/lower action with the corresponding highest (second-best) Q-value has to be determined. The nearest neighboring action with the highest Q-values of decision variable \( i \) and agent \( j \) (we denote them here as \( Q(a(i,j,up)) \) and \( Q(a(i,j,low)) \)) serves to calculate the correction factors \( \delta_{\text{high}}(i,j,k) \) and \( \delta_{\text{low}}(i,j,k) \):

\[
\begin{align*}
\delta_{\text{high}}(i,j,k) &= \frac{1}{2 + \frac{\left[ Q(i,j,k) - Q(a(i,j,high)) \right]^2}{Q(a(i,j,high))}}, \\
\delta_{\text{low}}(i,j,k) &= \frac{1}{2 + \frac{\left[ Q(i,j,k) - Q(a(i,j,low)) \right]^2}{Q(a(i,j,low))}},
\end{align*}
\]

with \( Q(i,j,k) \) as the currently maximum Q-value of decision variable \( i \) and agent \( j \) in learning round \( k \). \( Q(a(j,i,high/low)) \) represents the Q-value of decision variable \( i \) and agent \( j \) in the learning round \( high/low \) where the highest Q-value of the nearest neighboring action \( a(j,i,high/low) \) has been achieved. The resulting action for decision variable \( i \) of agent \( j \) in the exploitation phase of the algorithm is determined by:

\[
a_{\text{exploit}}(i,j,k) = a(i,j,\text{max}) + \delta_{\text{high}} \ast (a(i,j,\text{high}) - a(i,j,\text{max})) + \delta_{\text{low}} \ast (a(i,j,\text{low}) - a(i,j,\text{max})),
\]

whereby \( a(i,j,\text{max}) \) determines decreasing action to the currently highest Q-value. Even though the agent is continuously utilizing the action space around the currently optimal Q-value, we kept an exploration part, which chooses with a probability \( \epsilon \) a random predefined discrete action in the action set. This reduces the chance to get stuck in a local extremum.

Similar to the discrete action set Q-learning algorithm the Q-value is a mapping of the reward gained from a specific action. The rule for the update process in case of exploration is:

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

in case of exploitation, \( Q_{a_i}(k) \) is modified according to:

\[
Q_{a_i}(k) = \frac{Q_{a_i}(k) + \delta_{\text{high}} \ast Q(a(i,j,\text{high})) + \delta_{\text{low}} \ast Q(a(i,j,low))}{1 + \delta_{\text{high}} + \delta_{\text{low}}},
\]
where $a_i$ refers to the action chosen/calculated, $r_{a_i}$ to the resulting (weighted) reward and $k$ to the learning round. $\alpha$ represents the learning parameter.

C. Simultaneous Energy/Reserve Market Clearing

The aim of the trading mechanism is to maximize social welfare in accordance with cost minimization in reserve power procurement. We follow the formulation of ref. [14] and [15] and add a penalty term in the objective function to enhance sufficient utilization of online units (see also Eq. 10). The reasoning behind this is that the single period formulation, which is necessary to keep the problem of the strategic behavior analysis computationally tractable, is not incorporating an unit commitment problem. In order to overcome this drawback, we are not completely neglecting efficiency costs of partially loaded power plants and start-up/shut-down costs but using a penalty term, which approximately factors in deviations from the maximal amount of generation. The maximum generation is chosen for simplicity reasons, other "optimal" points of utilization and approximation terms are possible.

The auction is double-sided, which means that the producers as well as consumers can submit their bids. However, in this paper only the supply side may change the bidding behavior through learning.

The System Operator’s demand for reserves is symmetric and consists of two components. First, the demand due to the current load situation (known by e.g. historic data), denoted by $P_s^{load}$, is based on the ENTSOE-Formula [16].

$$P_s^{cap} = \sqrt{a \cdot \sum_{j} P_{js} + b^2 - b},$$

where $a$ and $b$ predefined parameters and $P_{js}^{en}$ is the scheduled amount of energy of Load $j$. Second, the demand due to fluctuating renewable in-feed (e.g. wind) must be considered. We assume that a percentage $p$ of the scheduled renewable in-feed are hedged by reserves:

$$P_s^{rescap} = p \cdot \sum_i P_i^{R}$$

where $P_i^{R}$ stands for all units $i$ with fluctuating in-feed behavior in scenario $s$. The percentage-factor $p$ is adjusted to the temporal allocation and may be reduced the closer the auction gets to physical delivery. Supplementary to this linear approach, further research has to be conducted about netting effects in case of distributed/concentrated fluctuating generation units. The overall reserve demand in scenario $s$ results in

$$P_s^{rescap} = P_s^{load} + P_s^{Rcap}.$$ (8)

The determination of $P_s^{en}$ for generation units 1,...,i and demand units 1,...,j on the energy market as well as $P_s^{resup}$,...,$P_s^{resdn}$ for the determination of up/down reserve capacity can be written in terms of an optimization problem as

$$\min \sum_i a_i P_i^{en} (a_i + b_i P_i^{en}) - \sum_j b_j P_j^{en} (c_j + d_j P_j^{en}) + \sum_i \beta_i P_i^{resup} (a_i + b_i P_i^{resup})$$

$$+ \sum_j \gamma_j P_j^{resdn} (a_j + b_j P_j^{resdn}) + \text{util} f_{a_i} + \text{util} f_{a_j} + \text{util} f_{quadr} + \text{util} f^2,$$

subject to

$$\sum_i P_i^{en} - \sum_j P_j^{en} = 0, (11)$$

$$P_s^{en} + P_s^{resup} - P_s^{G_{max}} \leq 0, (12)$$

$$P_s^{G_{min}} + P_s^{resdn} - P_s^{en} \leq 0, (13)$$

$$P_{js}^{en} - P_{js}^{G_{max}} \leq 0, (14)$$

$$P_{js}^{L_{min}} - P_{js}^{en} \leq 0, (15)$$

$$P_s^{resup} - \sum_i P_i^{resup} \leq 0, (16)$$

$$P_s^{resdn} - \sum_i P_i^{resdn} \leq 0, (17)$$

$$\sum_k P_{DTF}^k (P_{net}) - P_{p_{max}^{flow}} (l) \leq 0, (18)$$

$$P_{i,s}^{en,k} + P_{i,s}^{resup,k} - P_{j,s}^{en,k} = P_{n_{net}}, (19)$$

$$P_{i,s}^{G_{max}} - P_{i,s}^{en,k} = P_{p_{diff}}, (20)$$

$$0 \leq P_{i,s}^{resup,k} \leq R_{i,s}^{up_{max}}, (21)$$

$$0 \leq P_{i,s}^{resdn,k} \leq R_{i,s}^{down_{max}}, (22)$$

with $i = 1, ..., N_G$, $j = 1, ..., N_L$ and $k = 1, ..., N_k$. $N_G$ refers to the number of generators, $N_L$ to the number of loads and $N_k$ to the number of nodes. Equation (11) ensures the overall system balance. Eq. (12), (13), (14) and (15) incorporate the limits in generation and demand requirements.

Eq. (16) and (17) refer to the fulfillment of the reserve requirements. Inequality (18) states that the power flow, resulting of the generation and load at every node $k$, is not allowed to exceed a certain maximum. $P_{DTF}$ is the Power Flow Distribution Factor Matrix. The Lagrangian multiplier of eq. (11) determines $\lambda_{net}$, the market clearing price for the energy market in the case of no congestion and uniform marginal pricing. If congestion appears, equation (11) is used in combination with the dual variables of inequality (18) to obtain Locational Marginal Prices (nodal prices). The parameters $util f_{a_i}^{lin/quadr}$, $util f_{quadr}$ in Eq. (10) are penalization terms to reduce operation far from physically "optimal" (Eq. 20) in the sense that units, if scheduled for energy and/or reserve power provision, should be as much as possible utilized.

The Lagrange multipliers to (16) and (17) determine the auction clearing price for up/down reserves $\lambda_{up}^{resup}$ and $\lambda_{dn}^{resdn}$. Equations (21) and (22) state that generation units may only have limited abilities to provide reserve power ($R_{is}^{dp_{max}}$ through (14)) ramping constraints. Subsequently to the energy/reserve capacity market clearing, a clearing for the reserve power utilization takes place. As approximation of current practice we assume that reserve power is activated according to the merit order of the energy bids. The amount of reserve power utilization $P_{util}^{resup,net}$ is assumed to be the minimum of a random number $Q$ drawn from an exponential distribution and the overall scheduled
reserves \( \sum \mu_{\text{resup}, \text{resdn}} \),
\[
P_{\text{util}} = \min(\sum P_{\text{resup}, \text{resdn}}^i, Q),
\]
\[
Q - f(x)\mu_{\text{resup}, \text{resdn}} = \frac{1}{\mu_{\text{resup}, \text{resdn}}} e^{-\frac{Q}{\mu_{\text{resup}, \text{resdn}}}},
\]
with \( \mu_{\text{resup}, \text{resdn}} = \sum P_{\text{resup}, \text{resdn}}^i \). With parameter \( z \) it is possible to influence the probability of how the scheduled reserve interval is utilized. The reasoning is that we assume that small deviations (through e.g. fluctuating sources) presumably occur with higher probability than large deviations, e.g. major power plant outage. However, other types of distribution function are considerable. The clearing of the utilized reserves is as follows:
\[
\min \sum \epsilon_i P_{\text{resup}}^i (a_i + \frac{1}{2} b_i P_{\text{resup}}^i)
\]
\[+ \sum \zeta_i P_{\text{resdn}}^i (a_i + \frac{1}{2} b_i P_{\text{resdn}}^i) \]
subject to:
\[
P_{\text{resup}}^i - P_{\text{resup}}^i \leq 0,
\]
\[
P_{\text{resdn}}^i - P_{\text{resdn}}^i \leq 0,
\]
\[
P_{\text{resup}}^i - P_{\text{resup}}^i \leq 0,
\]
\[
P_{\text{resup}}^i - P_{\text{resdn}}^i \leq 0,
\]
\[
P_{\text{util}}^i - \sum P_{\text{resup}}^i \leq 0,
\]
\[
P_{\text{resdn}}^i - \sum P_{\text{resdn}}^i \leq 0.
\]
with \( i = 1, \ldots, N_G \). Equations (25) - (28) refer to the minimum and maximum amount of utilized reserve power. Eq. (29) and (30) ensure that the real-time reserve requirements are fulfilled.

D. Reward of the agents

The producer and consumer surplus based on the clearing of 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 reward for scheduled amount of reserve capacity is determined by:
\[
\text{Reward}_{\text{resup}}^i = P_{\text{resup}}^i \lambda_{\text{resup}}.
\]

For the reward for the utilized amount we follow [15]:
\[
\text{Reward}_{\text{resup}}^i =
\]
\[+ P_{\text{resup}}^i (\text{Bid}^\text{int} + \frac{1}{2} \text{Bid}^\text{slope} P_{\text{resup}}^i) \]
\[- P_{\text{resup}}^i [\text{Bid}^\text{int} - \text{Bid}^\text{int} + \frac{1}{2} \text{Bid}^\text{slope} P_{\text{resup}}^i] \]
\[- P_{\text{resup}}^i (a_i + \frac{1}{2} b_i P_{\text{resup}}^i),
\]
with \( i = 1, \ldots, N_G \). \( \text{Bid}^\text{int}, \text{Bid}^\text{slope} \) refer to the intercept/slope of the announced bids for energy, up-reserve energy and down-reserve energy in the preceding market clearing. The first term in (32) represents the reward of selling up-reserves for a given price (uniform price paid to all scheduled participants). The second term states the additional reward in the case of utilization (pay-as-bid pricing), the third term depicts the opportunity costs of providing energy for reserves instead of bidding in the energy market. The last term states the costs of utilization of scheduled reserves. Similar reasoning applies also for the reward for down-reserve except that down reserves do not face the trade off between bidding in energy and reserve market and cause additional costs in case of utilization.

III. SIMULATION FRAMEWORK AND CASE STUDIES

A. Test System

The system in Figure 2, which has strategically acting generation units at node 3, 7 and 11 which are also incorporating major parts of the available reserve power. Renewable generation units are located in nodes 1, 2, 3, 7 and 11.

The system has strategically acting generation units at node 3, 7 and 11 and load serving entities is first studied with no severe transmission line capacity constraints. With respect to the investigation of spatial arbitrage we take out the lines 2-4 and 6-11. In terms of the cost structure of the generator agents, we followed mainly the data of [2] but we removed designated generation units from the nodes 2, 5 and 11 since node 11 inherited originally 2 units. Further we reduced the original loads at nodes 1, 2 and 3 by 50%. Renewable energy in-feed is simulated in terms additional low marginal cost units and is located exclusively at nodes 1, 2 and 3. The scenarios comprise total a renewable in-feed from 0% to 42% of the total test-system load whereby the in-feed is equally distributed between the nodes 1, 2 and 3.

B. No network capacity constraints

In order to capture the results of all the scenarios, we compare them in terms of (nodal)-prices with a base case which contains no strategic behavior and no severe capacity limits. If there would be no capacity limits, the uniform price system and the nodal price system give the same results. Fig. 3 shows the scheduled quantities for energy and up-reserve capacity as well as the utilized amounts for real-time balancing. The higher in-feed leads to an overall decrease in energy supply through conventional generation and an increasing scheduling as well as utilization of reserves. With respect to this relationship it has to be noted that Fig. 3 points already to a major problem of sufficient available generation in case of high renewable in-feed. Price spikes in the reserve...
power market through scarcity considerations and line capacity limits are a possible direct consequence.

As observable in Fig. 4 and 5, in case of no lines taken out, the potential of market power exploitation and major price markups in the energy market is especially in the case of low renewable infeed recognizable. With respect to the reserve power market, scarcity in generation leaves potential for market power exploitation in all renewable in-feed scenarios. Nevertheless, as seen in Fig. 5, rising renewable in-feed leads for first to a decrease in the markup potential through additional generation.

C. Consideration of networks capacity constraints

In presence of transmission capacity limits, Fig. 6 and 7 show the results for the bus prices in different in-feed scenarios, assuming as well uniform or nodal pricing for the up-reserves. Both Figures point to a nodal price decrease for energy and reserves in case of high renewable in-feed. This indicates the incentives for investment/disinvestment in generation downstream/upstream of congested lines. In terms of the up-reserve prices, high renewable in-feed and the incorporation of congestion leads to a general revaluation of reserve prices at nodes without renewable generation units. This contradicts to attempts for local investments to balance fluctuating in-feed. Compared to the case without severe capacity limits, Fig. 7 shows further that the market power exploitation for reserve power units may take place rather in the low renewable in-feed case.

Fig. 3. Upper plot: Scheduled amount of energy from conventional generation at Node N per renewable in-feed scenario (%-of total load), Middle plot: Scheduled amount of up-reserve capacity, Lower plot: Utilized amount of reserves

Fig. 4. Nodal price markups per bus and renewable in-feed scenario (%-of total load) and in case that no lines are taken out. Upper plot: Energy price markups, Lower plot: Up-Reserves price markups with uniform pricing

Fig. 5. Nodal price markups per bus and renewable in-feed scenario (%-of total load) and in case that no lines are taken out. Upper plot: Energy price markups, Lower plot: Up-Reserves markups with nodal pricing

Fig. 6. Nodal price markups per bus and renewable in-feed scenario (%-of total load) and in case of congestion. Upper plot: Energy price markups, Lower plot: Up-Reserves markups with uniform pricing

Fig. 7. Nodal price markups per bus and renewable in-feed scenario (%-of total load) and in case of congestion. Upper plot: Energy price markups, Lower plot: Up-Reserves markups with nodal pricing
IV. CONCLUSION AND FUTURE WORK

In this simulation study we gained experiences of a Locational Marginal Pricing scheme in energy and the reserve power markets in presence of high renewable in-feed. In the reserve power market we highlighted the impact on up-reserves. In contrast to preceding studies about the incidence of LMPs as congestion management scheme in system with high renewable in-feed which focused primarily on the energy market, it has to be noted that the reserve power market faces additional special conditions: Reserve power markets are confronted with the scarcity of units with sufficient abilities to provide reserve power. Large flexible generation may be placed not locally or even only in remote locations. Both facts, the fee for scarce generation with sufficient availability and the charge of capacity limits are mapped in the LMP prices for reserve power. The incidence of scarce generation is recognizable in terms of the higher nodal price markups compared to the energy market.

Hence three major conclusions may be drawn for the ancillary service market:

First, in terms of the supply of reserve power capacity, LMPs offer incentives for investments in local balancing mechanisms like demand side management schemes in congested areas with low shares of renewable in-feed and with producers which can exercise market power. This goes along with the possibility that demand units face probably certain opportunity costs which would not be covered in the systemwide uniform price case and remote renewable generation.

The second point refers to the allocation of reserve power procurement costs. Nodal prices entail that costs for ancillary services are no more socializable over all grid participants in a uniform grid tariff, since the costs of procurement depend on the state of the grid.

Third, in terms the balancing market settlement a daily energy price component in the payment scheme is affected by the trade off between bidding on the energy spot market (and bidding on the energy spot market) and bidding for reserve power energy. Capacity limits and the utilization of market power through congestion lead to markups for deployed reserves which distort the market. The incorporation of nodal prices in a European market setup requires therefore also revisions in the whole ‘supply chain’ for ancillary services, beginning from the procurement phase to the real-time deployment.

Future work includes the advancement of the proposed agent-based algorithm to a multi-period analysis. Further, possible market deficiencies in the reserve power procurement in presence of flexible reserve power demand as well as the reserve power deployment (settlement scheme) in presence of market based and non-market based pricing instruments will be investigated.

APPENDIX A

TEST-SYSTEM DATA

Additional System Data are shown in Table I. Further data may be found in [2]. All units (except for the renewable infeed) are able to provide up to 1% of their maximal generation for up- and 2% of their maximal generation for down- reserves.

### Table I

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<tr>
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<th>G3</th>
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<td>7</td>
<td>12</td>
<td></td>
</tr>
<tr>
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<td>% of ( P_{Upmax} )</td>
<td>40</td>
<td>30</td>
<td>50</td>
</tr>
<tr>
<td>( R^{Down} )</td>
<td>% of ( P_{Downmax} )</td>
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