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SUPPORTING TSO IN EFFICIENT INTEGRATION OF RENEWABLE ENERGY INTO ELECTRICITY MARKET

Valeriia Algeier, Dirk Westermann

Power Systems Department
Institute of Electric Power and Control Technologies
Faculty of Electrical Engineering and Information Technology
University of Technology Ilmenau

ABSTRACT

According to the EU objectives there are national plans to increase the share of electricity produced by renewable energy sources (RES) significantly. The German Renewable Energy Sources Act ("Erneuerbare-Energien-Gesetz" – EEG) claims for priority purchase and transmission of, and payment for electricity from RES by the transmission system operators (TSO). The allocation of purchased and paid RES electricity is regulated by means of a nation-wide equalization scheme. According to this scheme TSOs are obliged to deliver the fluctuating electricity infeeds from RES to the utilities serving the final customers in the form of monthly constant bands. In order to compensate the stochastic RES-infeeds fluctuations, the TSO needs to purchase or dispose RES-electricity on the market. This paper is a research continuation of the authors' previous paper [1], and describes a decision support tool (DST) developed to assist the TSO in its obligation of "sublimation" (compensation) of the fluctuating RES-electricity infeeds. With help of its different modules it provides the possibility to "learn" an optimal strategy for an efficient appearance on the electricity market.

Index Terms - wind power trading, TSO, German nation-wide equalization scheme, agent-based modeling, Q-Learning

1. INTRODUCTION: RENEWABLE ENERGY AND ITS ROLE IN SUSTAINABLE ENERGY SUPPLY

Electric utilities in Europe – and the most of the world – are structured around large, central power stations, connected to transmission systems which deliver electricity to final customers on distribution networks. The output from these power stations is controlled, so that the stations are "dispatched" (i.e. are able to produce) in order of increasing cost (short-run marginal costs) as the demand rises. Such centralized and integrated power systems, with the power generated and delivered by monopoly operators, became the dominate pattern of electricity system development around the world.

However, in the past twenty years, this pattern has begun to break down. Altering of demand, input costs, technology developments and environmental pressure have led to changes on regulatory structures allowing new entrants and new decision-makers acting on the electricity market. The whole context for decision-making concerning power systems is changing, in ways that have profound implications for renewable energy.

The renewable sources of "primary electricity" – those such as wind, solar, hydro, wave and tidal energy that produce electricity directly from mechanical or photoelectric conversion – differ from most conventional power sources in several important ways. Their output is "variable": it follows the fluctuations of the natural cycles. They are usually available on much smaller scales; as such they can be installed in relatively short time and would usually connect to distribution networks rather than feed directly into the high-voltage transmission system (except of large on-shore and especially off-shore wind parks). Finally, they are cheap to operate once constructed; the main cost lies in the construction.

Additionally renewable sources of electricity build the basis for substantial climate protection. Renewable energy and energy efficiency technologies are now of prime importance for creating a clean energy future for not only the nation, but the world. It increases diversity of energy supplies and its use can significantly reduce greenhouse gases and other pollutants.

2. GERMAN NATION-WIDE EQUALIZATION SCHEME OF RES-ELECTRICITY

The deployment of renewable energy requires appropriate economic, market and regulatory instruments. The so-called "20-20-20" climate change proposal of the European Commission is one of numerous measures undertaken in Europe to promote renewable energy. In its second Strategic Energy Review [2] the European Commission strives for sustainability, competitiveness and security of energy supply, by reducing greenhouse gas emissions by

20%, increasing the share of renewables in the energy consumption to 20% and improving energy efficiency by 20%, all of it by 2020.

National economics following the European instructions go even further in their ambition to reduce the dependence on imported primary energy carriers. In particular, in Germany, motivated by goals of climate and environment protection, a law was passed, that aims to increase the share of renewable energy sources (RES) in electricity supply to 30% by 2020. This law, called The German Renewable Energy Sources Act (RESA, "Erneuerbare-Energie-Gesetz" – EEG), renewed for 2009 [3], regulates:

- "priority connections to the grid systems for general electricity supply of plants generating electricity from RES and from mine gas within the territory of the Federal Republic of Germany
- the priority purchase and transmission of, and payment for, such electricity by the grid system operators and
- the nation-wide equalization scheme for the quantity of electricity purchased and paid for"
- purchase of RES-electricity by utility companies which deliver electricity to final customers in accordance with a profile made available in due time and approximated to the actually purchased quantity of electricity.

Through this intensive governmental assistance the share of electricity generated from RES has almost quintupled in Germany in the last 17 years [4]. The major engine of this growth is the wind energy. Its share amounts to 45,2% of the total amount of electricity generated from RES [5].

With growing rate of renewables in energy-mix in Germany obligations of transmission system operators (TSO) are changing. Primarily responsible for operation of national energy grid, particularly with regard of guarantee the nominal grid frequency of 50 hertz, they assume now a new responsibility of coordination of a RES balancing group (EEG-Bilanzkreis).

In general a balancing group consists of any number of feeding and/or withdrawal points (nodes) within a TSO control area. In the balancing group the equilibrium between the infeeds from the assigned feeding points and deliveries from other balancing groups on the one hand (procurement) and the withdrawals of the assigned nodes together with deliveries to other balancing groups on the other hand (delivery) must be secured at any time [6].

In the RES balancing group exclusively acquisitions and deliveries of renewable energy are summarized. That distinguishes RES balancing group from the general definition. The responsibility of TSO as coordinator of RES balancing group is best explained with the following scheme (Figure 1).

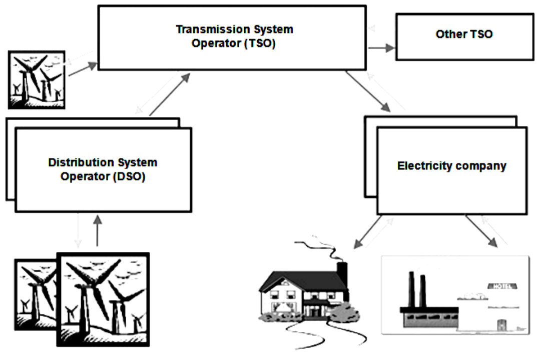

Figure 1 The German nation-wide equalization scheme

RESA and other legislative acts prescribe this process as follows. According to Article 8 of RESA the grid system operators (GSOs) are obliged to prior *purchasing, transferring and distribution* of the whole electricity from RES power plants. These RES-electricity infeeds, purchased by the appropriate GSOs, must be instantly transmitted to the preceding TSOs.

TSOs are responsible for regulation and coordination of RES-infeeds in their control area. In accordance with Article 36(1) of RESA, they must register, "the different volumes of and periods of generation of energy…, and "provisionally equalize such differences amongst themselves without undue delay". This process is called *horizontal equalization* between the TSOs. The volumes of energy that are equalized between TSOs correspond to the relation of the final energy consumption in the control area of individual TSO to the total amount of final energy consumption in Germany, which is agreed to begin of the equalization process.

Consequently every TSO must consider only the amount of electricity generated from RES in its balancing group, which corresponds to its share in the whole final energy consumption in Germany. Hence the expenses of system integration of renewables are "equally" distributed among all TSOs.

After being equalized among individual control areas electricity is transferred to utility companies, which deliver it to final customers. This process is called vertical equalization. The utility companies have to purchase and pay for that share of electricity, which corresponds to an approximated profile of actually quantity of electricity, purchased by final consumers of utility companies. The interim profile (RES-Quote) is evaluated from monthly forecasted data of infeeds from RES and the electricity purchased by final customers. It is used for determination of TSO's delivery commitments towards utility companies.

At the end of the year, when all feeding and consumption data is available, a final RES-Quote for the particular year is defined.

The profile that corresponds to the RES-Quote is a constant supply band. The related quote is updated monthly. The difference in character of fluctuating

RES-infeeds and constant deliveries must be smoothed out. This process is called *sublimation* (Figure 2).

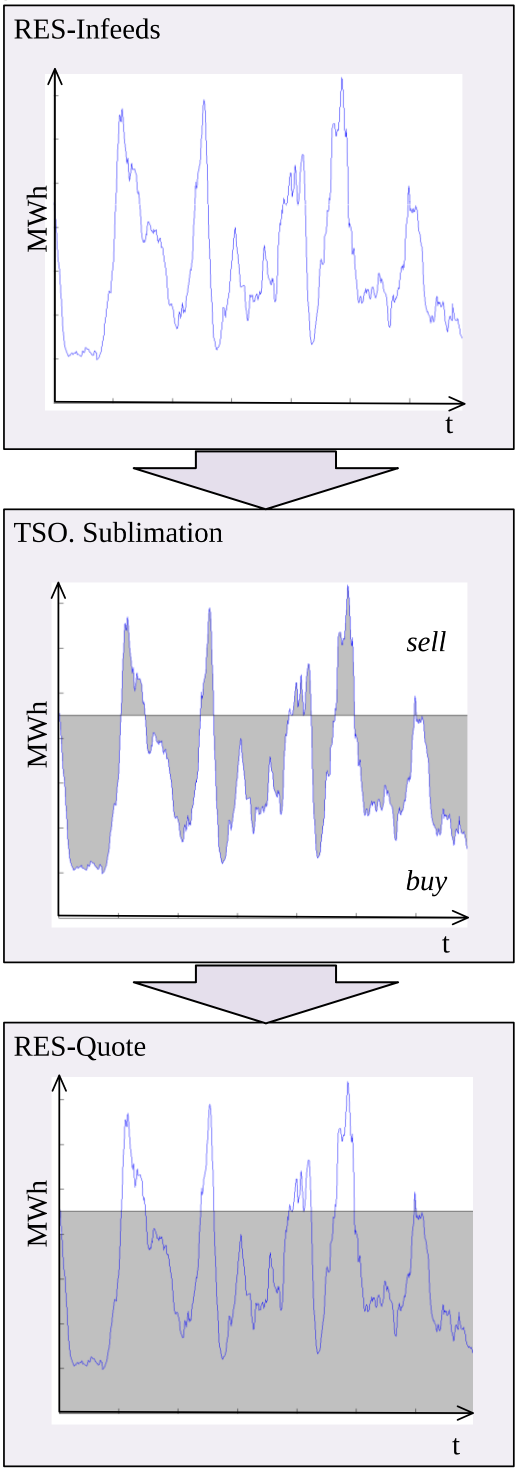

Figure 2 Sublimation process of TSO

Within this process the lacking or superfluous (with respect to delivery commitment) quantities of electricity must be sublimated, i.e. compensated. Both actions can be fulfilled within an electricity market. This includes in Germany the following forms: central energy exchange (European Energy Exchange, EEX) and over-the-counter (OTC) market.

OTC market activities are usually used to perform long-term planning, as there year, quarter, month, week schedules can be obtained. This kind of electricity market can also be used in a very short-term, e.g. to obtain 15-minutes-profile, as soon as the counterpart could be found. In contrast to this the smallest time resolution for an energy contract by the energy exchange is one hour. Since OTC market suffers from a lack of transparency, whereas TSOs' expenses are subject to government oversight and regulation, it can not be used for TSO's sublimation process. But the energy exchange.

Based on the hourly forecast, provided day-ahead of the delivery deadline, there is a possibility to use the spot market of energy exchange EEX for smoothing of RES-infeeds. The contracts conducted today (at the *day-ahead market*) will be accomplished on the following day.

After the negotiations for the following day closed, the forecasts for the RES-infeeds for the current day are obtained. This morning forecast will be of higher quality than that of the previous day. To respond to these new changes occurred, there is a possibility to alter the delivery schedules for the current day.

Within *intraday trading* contracts for deliveries on current and on following day can be conducted. In this way very short-term deviations of forecasts are considered and schedule discrepancies can be avoided. According to the historical data available to TSO the prices on the intraday market are usually much more unfavorable (for the purchase – much more expensive, for the selling – much cheaper) than on the day-ahead market. Therefore it is better to accomplish the sublimation of possible deviations on the day-ahead market.

In order to support the TSO in its role of coordinator of RES balancing group and to provide its efficient performance on the day-ahead energy market a decision support tool is developed. The methods applied and the experiments conducted are described in the sections below.

3. DECISION SUPPORT TOOL: METHODS, EXPERIMENTS, RESULTS

The biggest difficulty for efficient integration of RES-energy into electricity market is the consideration of its strong fluctuating character in planning of energy deliveries. As mentioned before especially wind energy infeeds can change within a few minutes and hence can add significant changes to planned delivery schedules.

As already outlined procurement of very short-term energy demand can be exposed to much more unfavorable trade terms as on the longer-term energy market such as day ahead-market. Imbalances between available RES-energy and delivery commitments that remain after market deals or the use of own resources are forced to be covered through the means of balancing power.

The decision support tool, described here, was developed to support a TSO in its everyday decision, in particular, how much RES-energy has to be procured from or offered to the day-ahead electricity market, in order to avoid unnecessary expenses due to participation on intraday electricity market because of possible forecast inaccuracies. Its main goal is to suggest the TSO, at each forecasted wind infeeds value, the amount of additional energy it must obtain today in order to reduce or eliminate the necessity of participation on unfavorable intraday market tomorrow.

Every day the TSO receives a forecast about wind energy infeeds for the following day. Possessing this information, it can calculate excess on or lack of energy amounts with regard to delivery commitments it has (called sublimation values). The most important questions the TSO have now are:

- whether these values are still the same the next day?
- if they change, how dramatically will these changes be?
- can these changes be predicted?
- if so, how good can these predictions be?

In order to answer these questions, several procurement strategies were investigated within the decision support tool for the TSO presented here.

To analyse the TSO's behaviour within RES-sublimation process methods of agent-based modeling (ABM) were used.

3.1. Methods used: Agent-based modeling and Q-Learning

Since the electricity market can be described as a complex adaptive system, i.e. a system where complexity arises because of the way a large number of agents are interacting, it becomes in vain, or at least very cumbersome, to study this system using deductive analysis. Rather than deductive analysis ABM researchers synthesize, i.e. they try to understand economic processes by synthetically creating them. The synthetic approach to model building is a bottom-up approach, where a model is build up by simple components that are assembled into a working system and simulated using computers (synthesis by simulation) [7].

ABM is a relatively new and important approach to representing and exploring phenomena of heterogeneous agents interacting. Taking a disaggregate perspective to the various agents of which such human systems are composed, and utilizing the power of modern object-oriented programming languages, AB models have the potential to be more sophisticated, subtle and faithful to the complexity of such phenomena than do more traditional modeling approaches such as econometrics or game theory or indeed older approaches to simulation such as system dynamics [8].

Special attention in the simulation is devoted to learning mechanism of the agent. The main goal of simulation is to help the TSO to predict the real values of energy quantities it has to deliver on the certain day in order to secure the according volumes in advance. Therefore the learning module of decision support tool assists the TSO by developing its optimal (with respect to the main goal) offering/bidding strategy for participating in a daily repeated electricity auction market (called game). Since other market participants of the energy market (i.e. opponents) are invisible for the TSO, participating in an energy auction becomes a game with an unknown counterpart.

Q-learning algorithm is used to define quantity offers/bids for TSO-agents for the day-ahead electricity market. Q-learning is a recent form of reinforcement learning algorithm throughout one can learn directly from raw experience without a model of the environment's dynamics [9]. Therefore, it is very suited for repeated games against an unknown opponent. Q-learning algorithm works by estimating the values of state-action pairs. The value $Q(s_t, a_t)$ is defined to be the expected discounted sum of future payoffs obtained by taking action a_t from state s_t and following an optimal policy thereafter. Once these values have been learned, the optimal action from any state is the one with the highest Q-value. After being initialized to arbitrary numbers, Q-values are estimated on the basis of experience as follows:

1) From the current state s_t, select an action a_t. This will cause a receipt of an immediate payoff r_t, and arrival at a next state s_{t+1}.
2) Update $Q(s_t, a_t)$ based upon this experience as follows:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha_t(s_t, a_t) * \\ * [r_t + \gamma max_a Q(s_{t+1}, a_t) - Q(s_t, a_t)] \quad (1)$$

where r_t is an observed real reward at time t, $\alpha_t(s, a)$ are the learning rates such that $0 \leq \alpha_t(s, a) \leq 1$, and γ is the discount factor such that $0 \leq \gamma < 1$.

3) Go to 1).

This algorithm is guaranteed to converge to the correct Q-values with the probability one if the environment is stationary and depends on the current state and the action taken in it; a lookup table is used to store the Q-values, every state-action pair continues to be visited, and the learning rate is decreased appropriately over time.

3.2. Experiments

In order to identify the best procurement strategy for the TSO several possibilities were investigated.

The simulation data consisted of information about infeeds of wind energy in four control areas of the TSOs. This was acquired from corresponding statistics published by German TSOs on their Internet pages [10].

The information about wind energy infeeds was used to calculate the energy amounts to be exchanged between TSOs (as it is required by horizontal equalization). After that the forecasted amounts of wind energy in each of control areas of four TSOs were determined within the horizontal equalization module of decision support tool. Afterwards sublimation values for each TSO were figured out. They build the basis of the TSO's bidding strategy for each hour of the day-ahead electricity market.

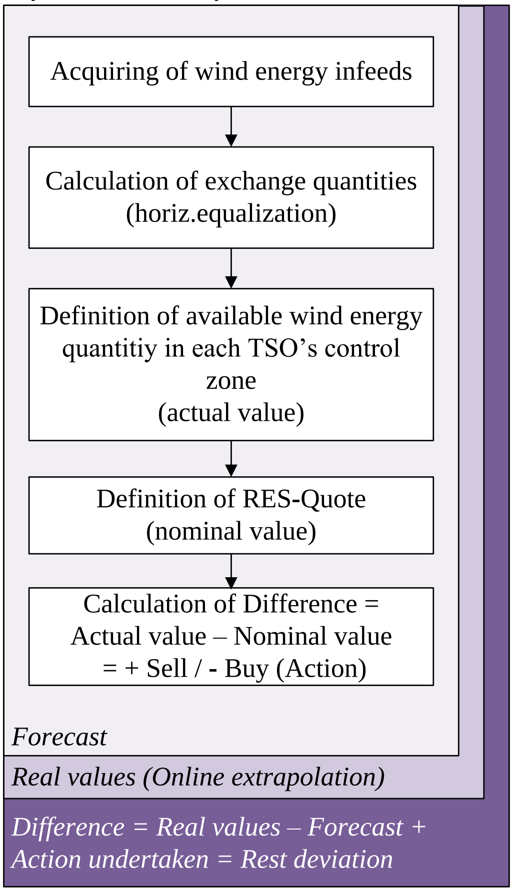

Figure 3 Decision support tool components

This algorithm (Figure 3) is applied for both forecasted wind infeeds values and their real rates (online extrapolation). In case of calculation for the forecasted data, energy amounts to be sold or bought on the electricity market are defined. Applying this algorithm to real values allows user to calculate the rest deviation, i.e. the energy amount that must be procured by means of intraday trading. This index is used here as rate of effectiveness of procurement strategies for the day-ahead market, analyzed in this paper. The less is this rate, the better is the performance of an appropriate strategy.

There were several procurement strategies which were investigated on their effectiveness for the implementation on the day-ahead electricity market.

One of the possible strategies explored was the strategy of confidence in forecasted values. In other words, the TSO, having received its day-ahead forecast of wind energy infeeds, trusts them and procures from or offers to the day-ahead electricity market exactly the same quantities that are in the forecast.

Since the TSO receives the information with nearly exact values of wind energy infeeds (due to online extrapolation) on the following day, it knows at least now, if its predictions on the day before were correct or false. It can use this updated information to adjust its day-ahead behavior in the future.

Therefore the second possibility explored within the scope of this paper is that the mean error (ME) of 24 hours from day-ahead prediction is used as deviation, the TSO assumes to occur on the next day. This factor is added to the forecasted sublimation value to procure today. In this way the sublimation values are adjusted to possible deviations of the next day.

It is calculated as follows:

$$ME_x = \frac{1}{N}\sum_{i=1}^{N} \Delta_{i_{x-1}} \quad (2)$$

where N is the number of observed hours (in this case 24), Δ_i is the difference between real and forecasted sublimation values of TSO i on the day before $(x - 1)$.

The third possibility to foresee potential deviations on the day of delivery is the Q-Learning algorithm. This method allows the TSO to "learn" the possible deviations for the certain number of defined states, i.e. day-ahead forecasted values. As a result, the TSO, having acquired the day-ahead forecast, can predict the changes to these values that are most likely to occur on the next day.

The first experiments based on the implementation of described strategies were conducted in [1]. The parameters for Q-Learning algorithm were defined as follows further.

It was assumed, that a learning agent (TSO) interacts with its environment at each of a sequence of discrete time steps, $t = 0,1,2,\ldots$. Time steps are represented by hours of each day of the year. Possible states of environment are defined through the possible values of forecasted energy amounts, the TSO need to sublimate in order to meet its delivery. It is the finite set, denoted as $S = \{s_1, s_2, s_3, \ldots, s_n\}$. The finite set of admissible actions, the agent can take, $A = \{a_1, a_2, a_3, \ldots, a_n\}$, are the possible deviations to forecasted values, the agent consider to appear on the day of delivery. In the model, there are $n = 20$ states and actions. These are intervals that are equally distributed between their minimum and maximum values, as it is shown in Figure 4.

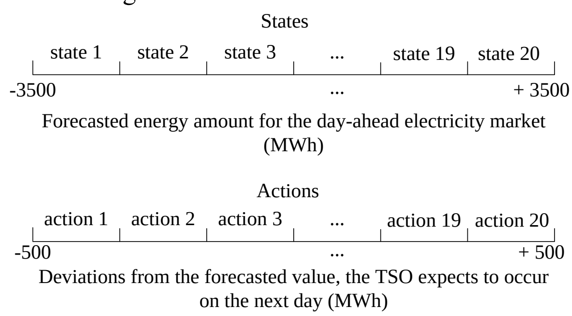

Figure 4 States and agent's actions

The main goal of each TSO is to find an optimal policy for each state, i.e. to "predict" the real quantity of wind energy it will receive the next day. Q-Learning algorithm provides an approach to determine the optimal policy by estimating the optimal Q-values $\mathrm{Q(s, a)}$ for pairs of states and admissible actions. It is implemented according to the following order:

1) *State identification*. At each step *t*, i.e. in every hour, the agent receives its forecast of sublimation values and gets to its current state $\mathrm{s_t = s \in S}$ of its environment. In this way energy quantity is given, the TSO has to consider on its day-ahead trading.
2) *Action selection*. After having obtained its state, each TSO inquires the Q-value look up tables to select the optimal action $a_t^* = a \in A$., i.e. the deviation of the forecasted sublimation value, it wants to buy or sell additionally. Thereby it selects an action with maximum $Q(s,a)$ in the state *s* (optimal policy).
3) *Q-value update.* As a result of its action, the agent receives an immediate reward $\pi_{i,t}(s,a)$, and updates the Q-values based on available rewards according to the following equations:

$$Q_{t+1}(s,a) = \begin{cases} Q_t(s,a) + \alpha\Delta Q_t(s,a), & \\ & if\ s = s_t\ and\ a = a_t \\ Q_t(s,a), & otherwise \end{cases} \quad (3)$$

where α is the learning rate and

$$\Delta Q_t(s,a) = \{\pi_{i,t}(s,a) + \gamma max_{a^*} Q(s_{t+1}, a_t^*) - Q(s_t, a_t)\} \quad (4)$$

Learning rate α is the degree to which estimated Q-values are altered by new data. For $\alpha = 1$, the estimated Q-value by choosing action a is equal to the reward the agent obtained the last time it played this strategy. For $\alpha = 0$, there is no learning and the Q-function stays unchanged. γ is the amount to discount future rewards.

The reward $\pi_{i,t}(s,a)$ considers the information about the real sublimation values the TSO receives the next day after its decision on the day-ahead market. The better the TSO could "predict" the deviation of forecasted values from real ones by choosing its action, the higher is the value of its reward and the corresponding Q-value. If the Q-value for each admissible state-action pair *(s,a)* is visited infinitely often, and the learning rate α decreases over the time step *t* in a suitable way, then as $t \to \infty$, $Q_t(s,a)$ converges with probability one to optimal policy for all admissible pairs *(s,a)* [9].

Q-values for each state-action pair of each TSO calculated in accordance with (3) and (4) are then stored in four lookup tables for four TSOs.

In order to emphasize the importance of guessing the right deviation, a penalty function is developed. It reduces the reward, the agent attains for its action, if the deviation it has chosen, did not meet the real value. Two variants of penalty function were tested: linear and exponential. They are calculated for each of the four TSO, as follows:

$$\pi_{i,t}(s,a)_{lin} = r_t - ratio \quad (5)$$

$$\pi_{i,t}(s,a)_{exp} = r_t * m * e^{-\frac{m*ratio}{r_t}} \quad (6)$$

where i is TSO's index, $\mathrm{r_t}$ is maximum profit the TSO can get for its action, ratio is modulated difference between real sublimation values and forecasted sublimation values together with the chosen deviation (action), m is a parameter of exponential function.

To obtain the initial Q-values of each agent, the simulation process is designed to run first for 180 learning days. The discount factor γ is set to 0,1 for all agents. The learning rate α is designed to be state-action dependent varying with time. That is, the learning rate in the initial learning phase of simulation is inversely proportional to the visited number $\beta_t(s,a)$ of state-action pairs (s,a) up to the present trading day, as follows:

$$\alpha_t(s,a) = \frac{1}{\beta_t(s,a)} \quad (7)$$

During the initial learning phase no optimal action selection is introduced and each agent is assumed to just randomly select an action in each state.

After evaluation of all initial learning data Q-values achieve the certain levels, which are further used to meet the optimal decision concerning how much additional energy must be procured today in order to reduce intraday acting or involvement of balancing energy. During the next following prediction learning phase each of TSOs uses its Q-value table to choose an optimal action according to sublimation values it receives for every hour. Applying the same update rule as in initial learning TSOs develop their Q-values further.

In [1] implementation of the Q-Learning brought the best results of prediction of possible deviations in comparison with other possible strategies of TSOs and hence could reduce the volume of additional intraday trading up to 26% (maximal value).

It was claimed that for the further improvement of the Q-Learning performance additional learning data must be acquired. This was executed in this paper.

To the real-world data about forecasted and real occurred wind energy infeeds from the year 2007 appropriate values from the year 2006 were added.

3.3. Results

The intention was to increase the number of learning data in order to improve Q-values for the further prediction phase.

But the results achieved showed that the performance of Q-Learning algorithm became worse. For comparison, on Figure 5, the results from [1] are shown with following parameters: 180 days for initial learning, and 185 days for prediction learning (2007) and the outcomes from recent experiments with parameters: 360 days for initial learning phase and 366 days of prediction (2006-2007). All other factors remained constant. On the y-axis the rest deviation is placed, which remains even after the correction of forecasted sublimation value with predicted change. These amounts must be procured within intraday trading or by means of own resources (if available).

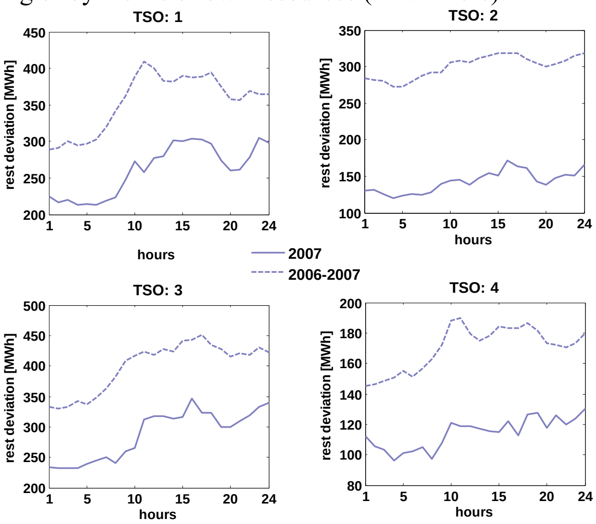

Figure 5Results of including of additional learning data

Degradation of results is explained by several reasons. Firstly, the simple adding of data does not bring any improvement, but more stochastic and, therefore, more unstable data to consider. Secondly, different weather conditions in these two years provide different forecast values. It means in particular, that the data that was learned during the year 2006 may not be valid anymore for the year 2007.

Several conclusions can be drawn from these results for further simulations with Q-Learning algorithm:

1) It is not really an issue, how much data is provided for simulation. Certainly this must be plenty enough to achieve feasible results. But once the sophisticated number of data is achieved, further increasing of this number may not contribute to improvement of simulation results.
2) Wind generation data shows such stochastic characteristics as non-standard distributions, instationarity, complex chronological persistence, intermittency and interdependence phenomena [11], [12]. That's why a method must be found, which could learn this unstable behavior and consider it for further predictions.
3) For proper forecasting of deviations of sublimation quantities with the Q-Learning method some special time frames (number of learning and prediction days) must be found, for which it provides the best results. During learning in these time frames stochastic characteristics of wind generation data (and since data of sublimation quantities) must present a certain stable development and since bring feasible results. It is obvious for now, that these feasible predictions can be only achieved for some short period of time.

Within this paper the special attention is dedicated to the last mentioned conclusion. The authors tried to find certain time frames for which the Q-Learning algorithm yields its best outcomes. Different combinations of learning/prediction days were simulated and compared on basis of day mean deviation. Since the achieved results are rather similar for all four TSOs and differs almost only in a value of rest deviation, just one of four graphics is shown on Figure 6, the one of TSO 4.

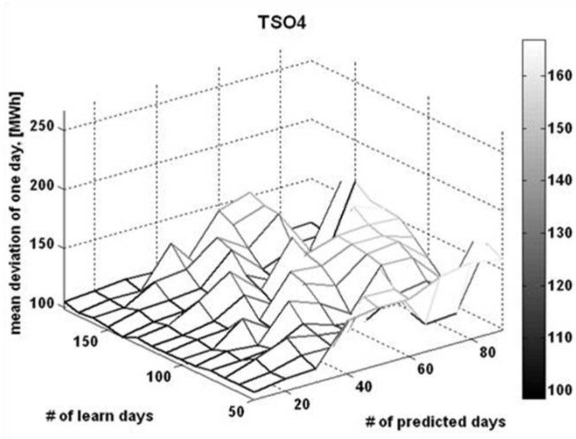

Figure 6 Comparison of different combinations of learning/prediction days for the Q-Learning algorithm

Obviously, the best results the Q-Learning algorithm are achieved for low levels of prediction days' quantity. Through increasing of the number of prediction days results become unstable.

The divergence of rest deviations between various levels of learning days is minimal for small number of prediction days (e.g. 10-20). It changes with the growth of the number of predictions days.

Through these simulations best combinations of learning/prediction days for each of four TSOs was found. These are as follows:

TSO 1	TSO 2	TSO 3	TSO 4
80/10	110/10	90/10	140/10

It means in particular, that values of lookup Q-tables, gained by initial learning phase are valid for the next 10 days (predictions days); afterwards another Q-values table must be formulated. Maximal values stored in Q-tables provide for each level of forecasted sublimation values the additional quantity of energy that must be procured on the day-ahead electricity market. In this way forecast errors can be eliminated even before they arise.

Number of learning days varies from TSO to TSO. It testifies to the fact, that wind infeeds data of each TSO has its individual stochastic characteristic. Consequently it takes from 80 till 140 days to learn these special features.

Compared with other two strategies, described before, implementation of the Q-Learning algorithm provides the best results and can improve the performance of TSO in average on 15% in one day.

4. CONCLUSIONS

In this research continuation of the authors' previous paper [1], a decision support tool (DST) is described. It was developed to assist the TSO in its obligation of "sublimation" (compensation) of the fluctuating RES-electricity infeeds. For simulation agent-based modeling was implemented with Q-Learning algorithm for agents' adaptive behavior.

By simulations it is transpired that the quantity of simulated data plays only a mediated role for the Q-Learning's performance. Much more important is to find certain time frames, during which the best results of implementation of Q-Learning algorithm can be achieved. These time frames were found for four TSOs that were explored.

Additionally the simulation results has shown that wind generation data is subjected to such stochastic characteristics as non-standard distributions, instationarity, complex chronological persistence, intermittency and interdependence phenomena. These characteristics can distort the performance of Q-Learning method. Other methods consider this volatility as defective observations and (together with known mathematical structure of time series) predict the current state of a dynamic system. One of the methods that can be used for described task is Kalman filter [13].

5. REFERENCES

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