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A COMPREHENSIVE ELECTRICITY MARKET MODEL USING SIMULATION AND OPTIMIZATION TECHNIQUES

David Steber
Jakob Hübler
Marco Pruckner

Computer Science 7
Friedrich-Alexander University Erlangen-Nürnberg (FAU)
Martensstr. 3, 91058 Erlangen, GERMANY

ABSTRACT

Worldwide Electrical Power Systems (EPSs) are faced with tremendous challenges because of the reduction of greenhouse gas emissions and the increasing number of renewables. EPS analysis can help to show future developments in an uncertain environment and is an important task for the assessment of greenhouse gas emissions. In order to perform such a complex analysis of future EPSs, a huge number of input parameters is needed. Moreover, technical and also economical processes have to be considered. Thereby, one major task is the modeling of electricity markets. In this paper, we present an approach for the modeling of the German EPS including electricity markets using hybrid simulation and mathematical optimization. We contribute an object-oriented electricity market model which can be utilized to study different exchange mechanisms and behavior patterns of generation unit operators. Simulation results show market results for different generation unit operators and realistic market prices.

1 INTRODUCTION

All over the world EPSs are faced with greenhouse gas emission reduction policies and the integration of electricity generated by renewables. According to the Renewable Energy Policy Network for the 21st Century (2017), the global renewable power capacity reached 2,017 GW at the end of 2016. Renewable energy sources are sustainable and very useful to reduce the dependency on crude oil but often they are very volatile and hard to predict.

In Germany, electricity generated by renewables had a share of 29 % in 2016. Until 2025, the German government aims to have a 40-45 % share of renewables in electricity generation. Hence, the German EPS is faced with tremendous challenges in the next years. For instance, the residual load, which is defined as the difference of electricity demand and the feed-in of renewables, will still decrease in the next years. A declining residual load means less service times for conventional generation units (e.g. lignite, hardcoal, or gas).

In order to understand the complexity of the EPS and to evaluate its future development under uncertain conditions, EPS analysis is an important task. In our interdisciplinary research project KOSiNeK (Combined Optimization, Simulation and Grid Analysis of the German EPS in an European Context) three groups of Friedrich-Alexander University Erlangen-Nürnberg (FAU) perform an interdisciplinary, comprehensive, and holistic analysis of the German EPS. Within the subproject *Simulation* our group combines discrete event simulation and System Dynamics in one framework in order to model different components like renewables, electrical loads, thermal generation units, storage systems, and the control of the interaction of these components (Pruckner and German 2013; Pruckner 2016). Due to the expansion of the spatial and temporal resolution and the aim of modeling the electricity market in more details by using mathematical optimization for solving the unit commitment problem, the complexity of our simulation model is still increasing until the end of the research project KOSiNeK in 09/2019.

To present the current state of our simulation model, this paper contribute an approach for modeling the German electricity market. For the development of our object-oriented electricity market model, we couple hybrid simulation techniques and mathematical optimization in one framework. Thus it is possible to study different exchange mechanisms and behavior patterns of operators and fleet managers (aggregators) of generation units. For the simulation model we utilize the multimethod modeling environment AnyLogic (The AnyLogic Company 2018) and developed different classes of software agents for the modeling of different market roles and various electricity trading platforms (e.g., day-ahead markets, intraday markets). For solving the mixed integer linear optimization program (MILP) within the market model we use Gurobi (Gurobi Optimization 2018).

The paper is structured as follows: Section 2 discusses related work. A general description of our model is provided in Section 3, which also presents the local simulation of the residual load that is necessary for the optimal dispatch of fossil fired generation units. In Section 4 we describe the object-oriented electricity market model based on a MILP. Section 5 shows first simulation results, as we just present an intermediate state of our model here. Section 6 concludes the paper and gives an outlook on future work.

2 RELATED WORK

There are several publications in the field of the combination of simulation and mathematical optimization in the energy domain. Brenna et al. (2017) used simulation and optimization for the integration of renewables and storage systems for remote communities electrification. Simulation is used for the electricity demand and the grid injection of different renewables. Optimization is applied for finding the optimal size of PV-generators or battery capacities and the number of wind power plants within the microgrid. The authors found out that the implementation of on-site microgrids for rural or remote locations plays an important role to reduce the main drawbacks in the socio-economic developments. Lee et al. (2015) investigated the energy efficient operation of heating, ventilation and air conditioning (HVAC) as demand response service with decentralized renewable generation units. Therefore, they simulated different HVAC control strategies and used the generated data for analysis and modeling. The simulation results stated that different control strategies have an impact on energy consumption and energy costs. Solving a MILP optimization model based on the simulation results can identify energy saving opportunities.

In both publications the interaction of simulation and optimization is utilized on low voltage levels of the EPS. Nevertheless, they give an interesting idea of combining different methodologies in one framework in order to solve complex decision problems within the energy domain.

Now we concentrate on the simulation and optimization of electricity markets which takes place on upper system levels. For instance, Sarica et al. (2012) developed an hourly day-ahead electricity market model based on an integrated simulation/optimization approach. The simulation model describes the interaction between different market participants (e.g., system operators, power transmitter, power generators) by a multi-agent simulation approach. The integrated optimization model controls the electricity flows and dispatches the generation units. Results showed insights into structural aspects of a decentralized electricity market for small regions with up to ten generators.

The benefits of introducing financial transmission rights in electricity markets in order to allocate congested capacity are examined by Zambrano et al. (2014). Therefore, the authors combined agent-based simulation with optimization including the physical features of the interconnected system and the economic features. As a result they showed that financial transmission rights can help to manage transmission congestion, although it increases the complexity of the market rules.

Ringler et al. (2017) investigated the effect of different design aspects of electricity markets to the welfare and generation adequacy in Europe. Therefore, *PowerACE* was utilized, which is an agent-based bottom-up model for wholesale electricity markets. In *PowerACE* relevant market participants are modeled as software entities and the market clearing is implemented as linear maximization program.

Sarica et al. (2012) and Zambrano et al. (2014) give interesting insights into combining agent-based simulation and mathematical optimization for modeling electricity markets. As they consider only a limited number of generators, their findings are only viable for decentralized electricity markets of smaller regions. Additionally, they do not take new market players such as aggregators of renewables sufficiently into account.

The idea of the work presented within this paper is to contribute a detailed integrated object-oriented electricity market model by combining hybrid simulation techniques and mathematical optimization. Therefore, we take the electricity trading platforms of the EPEX spot-market (day-ahead and intra-day market) into account. We use different software agents in AnyLogic for different market roles and manage a closer linkage between simulation and optimization. For the solution of the thermal unit commitment problem we take technical and economical constraints of thermal generation units into account. The general formulation of the unit commitment optimization problem is based on Arroyo and Conejo (2000), Carrion and Arroyo (2006), Morales-Espaa et al. (2013), Rajan and Takriti (2005). Moreover, our contributed electricity market model will be integrated in a comprehensive hybrid simulation model of the German EPS (Steber et al. 2017). Earlier versions of our EPS model are described in (Pruckner and German 2013) and (Pruckner 2016). They were strongly focused on the EPS of the German federal state of Bavaria and did not consider neighboring countries of Germany excluding Austria. Additionally, we substantially increase the regional granularity meaning the grid injection of German PV-generators and wind energy plants is now modeled on the counties level (401 German counties). Another improvement is the modeling of the power plant operation. So far we have used a simple merit order approach which is now replaced by the electricity market model contributed in this paper.

3 GENERAL MODEL DESCRIPTION

Figure 1 shows the interaction of simulation (dark gray boxes) and optimization (light gray boxes) in the implemented model of the German EPS plus its general day-ahead and intra-day iteration sequence. The structure of the model is described in the second half of this Section.

The day-ahead market sequence (see Sect. 4) takes place once every day at noon in order to determine the dispatch of generation units for the upcoming day. Therefore, each aggregator creates an individual supply curve which are put together to an aggregated supply curve at the electricity exchange. There, the market-clearing takes place. It merges supply and demand for each hour. Thus, the optimized dispatch of generation units to the residual load is determined. The market clearing price results from the intersection of the aggregated supply and demand curve.

Each hour in the simulation model the current load and renewable generation are simulated on the county level first. The residual load emerges on the aggregated level. It has to be covered by conventional generation units and differs to the load predicted for generating the day-ahead supply curves. Then the aggregators place buy (in case of underproduction) and sell (in case of overproduction) orders at the intra-day

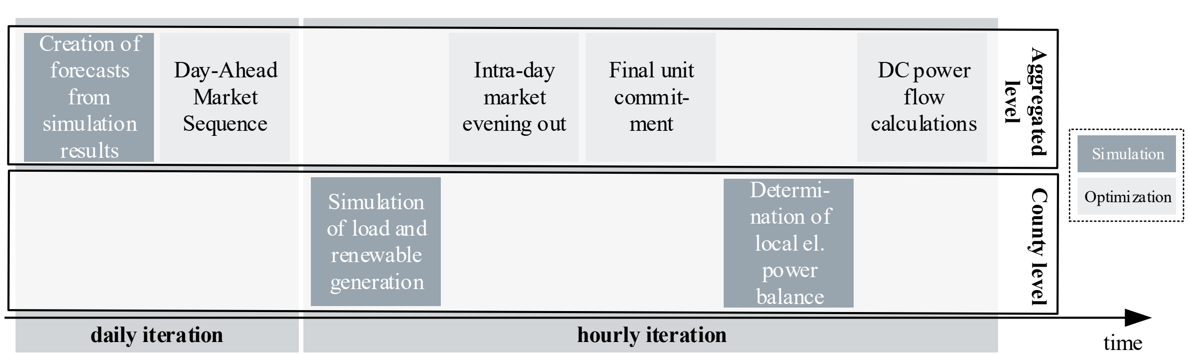


Figure 1: Sequence of the combined simulation and optimization model of the German EPS.

market to maximize their yield and to even out the deviations from timetables determined by the day-ahead auction to the real residual load. After this intra-day sequence, the aggregators re-optimize themselves internally to maximize their profit of generating electricity. Finally, the local power balance in each county can be determined by taking together the market based generation per unit, the renewable generation, and the load. The emerging power balance on the aggregated level of grid groups is then used for DC power flow calculations in order to assess situations overstraining the EPS. Evaluations and validations are also done on aggregated levels for reasons of real data availability. DC power flow calculations (Zelmer 2010) contain again an optimization but are not considered here.

In this paper, we mainly focus on the market sequences described in detail in Section 4. Before, a brief introduction into the structure of the model and the simulation of the local electrical load plus the renewable generation on county level is given. Therefore, Figure 2 sketches the basic structure of the simulation and optimization model of the German EPS.

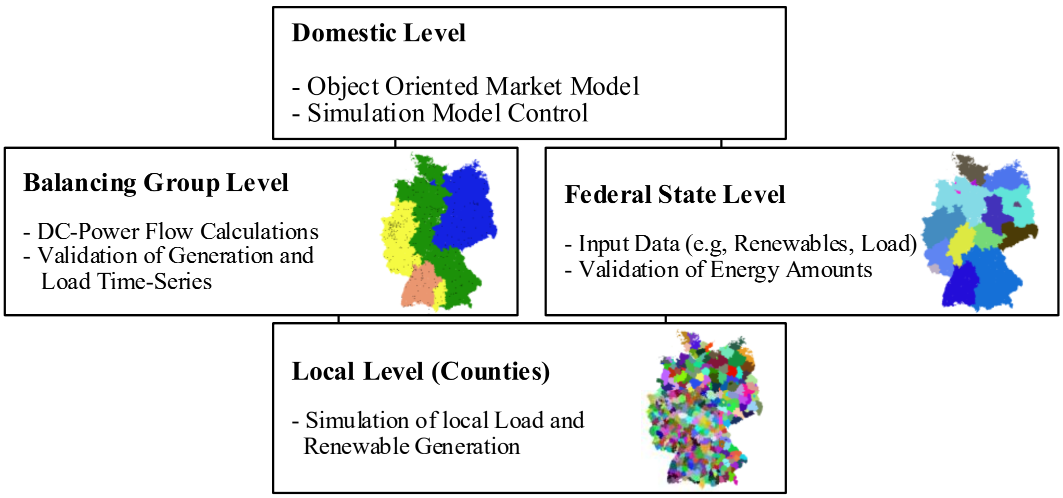


Figure 2: Levels of the simulation model (map: ©GeoBasis-DE / BKG 2017, http://www.bkg.bund.de).

The locally resolved model level is build by 401 German counties, which can for instance be aggregated to balancing groups or federal states. In order to determine the optimal dispatch of generation units (see Sect. 4) on the domestic level, the residual electrical load must be calculated first. It serves as an input for the electricity market optimization model, as it must be covered by the generation units dispatched by the market results.

To deduce the residual electrical load on domestic level, we first simulate the renewable generation and the electrical load on county level and then aggregate it on the respective model layers. As mentioned above, a county represents the smallest entity of model levels. It composes of separate models for simulating the fluctuating renewable generation (wind and solar), the seasonal renewable generation (geothermal and hydro), the constant renewable generation (biomass and renewable gases), and the load of all final energy consumption sectors (residential, trade and commerce, traffic (railways, buses), and industry).

We calculate the residential load based on standardized load profiles (VDI 2008) in addition with weather data having a high spatial resolution (COSMO-REA6 2017) and census data (Destatis 2017). The electrical load of the trade and commerce sector is determined by scaling standardized load profiles (VDEW 2002) with specific energy consumption data of each economic sector (Destatis 2017) and numbers of employees (BA 2017). The electrical load of the traffic sector (e.g., railways or electrical buses) is determined by taking into account the overall annual consumption scaled with the inhabitants per county as a base for a constant yearly load. As no standardized load of the industrial sector is available, we summed up the derived demand curves of the other sectors and subtracted it from the real load curve (ENTSO-E 2018), normalized the resulting profile and scaled it with specific energy consumption data of each economic sector (Destatis 2017) and numbers of employees (BA 2017) to the county level.

This regional model has already been described in detail in (Steber et al. 2018b), where the comparison of simulated and real time series shows coefficients of determination (R^2) greater than 90 %. Thus, the determination of the local load and renewable generation is not dealt with further here.

In addition to the described model functionality, we need a forecast of load and renewable generation on the domestic level, as the day-ahead market clearing takes place around noon on the day before delivery. Therefore, we use a persistence forecast for solar generation and the load. The wind generation forecast is realized by applying a RMSE profile to the wind data within the model. Thus, it is possible to gain a forecast of the residual load as an input of the market model.

4 OBJECT ORIENTED GERMAN ELECTRICITY MARKET MODEL

For the simulation of the German electricity market, different individual market roles have to be modeled using single software agents in AnyLogic (e.g., electricity exchange, generation unit (fleet) operators, or generation units).

The focus here is on the modeling of market relevant decisions of the individual aggregators of fossil fired and pumped-hydro-storage generation units. These aggregators are companies, which are active in the electricity market and operate a fleet composed of different kind of generation units and thus represent the suppliers of electricity. In addition, the electricity market model includes the spot-market as a platform for electricity trading. Due to increasing renewable capacities and their poor long-term predictability, the spot market is the primary sales market for renewable generation. With regard to the still increasing renewable capacities plus the phase out of different generation units and model complexity, we neglect over the counter (OTC) trades here. Thus, the whole generation for covering the residual load is contracted at the spot (day-ahead plus intra-day) market at the current model status. In perspective, also some renewable capacity should be integrated into the market by aggregators.

Within the simulation and optimization model the spot market (day-ahead and intra-day) enables supply and demand to be synchronized. Forecasts are integrated by forecasting service providers during run-time where these services are based on past simulation model results (e.g., market prices, renewable generation, load). The aggregators need these forecasts in order to optimize their bids at the day-ahead market and thus to maximize their profits.

According to Figure 1, first market actions concerning one day take place once at the day-ahead market and afterwards trades are made at the intra-day market over the whole day. So, Subsection 4.1 introduces the implemented day-ahead market model, Subsection 4.2 explains the day-ahead market clearing, Subsection 4.3 describes the implemented intra-day market model and finally Subsection 4.4 represents the optimal unit commitment of aggregators.

4.1 Day-Ahead Market Supply Curve Creation of Aggregators

As a first step in the entire sequence (see Figure 1), aggregators determine their bids for the day-ahead market clearing based on available forecasts of aggregated bid curves, renewable generation and load. This bid creation takes place every day before noon, where electricity is traded for delivery at the following day in 24 hour intervals (EPEX SPOT 2018). A bid must be submitted in the form of an supply curve with a minimum price increment of 0.1 €/MWh and a minimum volume increment of 0.1 MW. An hourly specified supply curve may contain up to 256 price [€]/volume [MWh] combinations, where the allowed interval is from −500 €/MWh up to 3000 €/MWh (EPEX SPOT 2018). These price/volume combinations must be linked to a piecewise linear function (supply curve), where each determined price/volume combination represents a sampling point. In general, the supply curve should guarantee the optimal dispatch of generation units maximizing the yield as best as possible from the point of view of the aggregator at the time of bid creation.

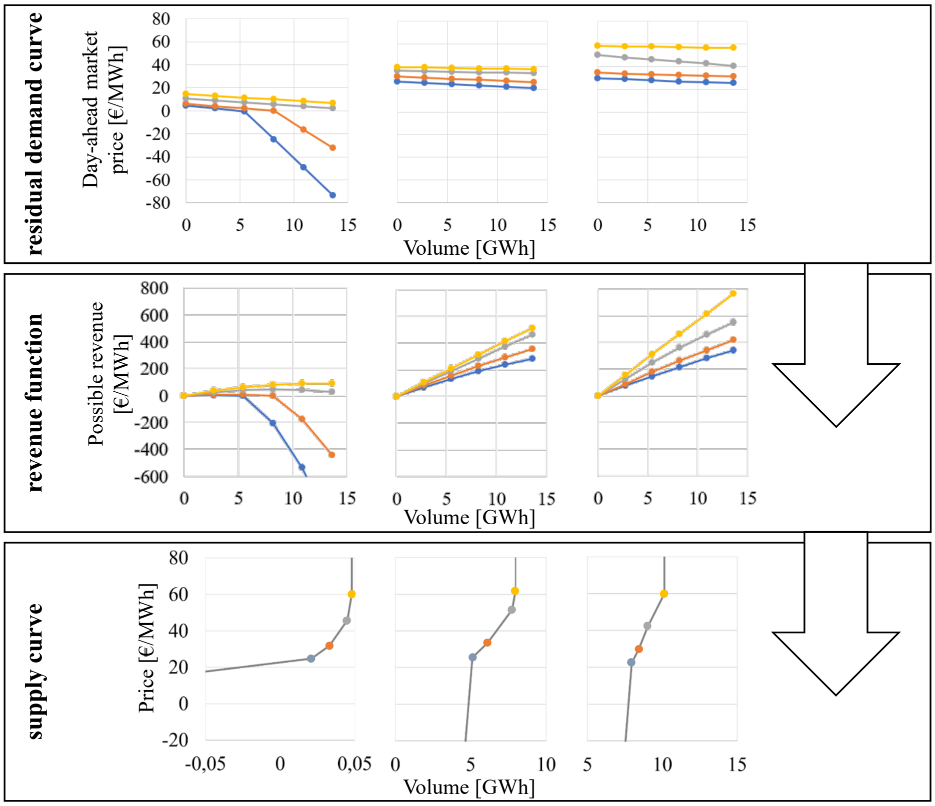


Figure 3: Exemplary residual demand curves (top) and derived revenue curves (bottom) of an aggregator per forecast scenario with low (left), average (middle) and high demand (right).

To achieve this, the creation of day-ahead supply curves proceeds in each aggregator as follows (see Figure 3). As there are forecast uncertainties, different scenarios of load and renewable generation are taken into account, represented by the different colors in Figure 3. The number of forecast scenarios is generally variable but too much scenarios overextend the run-time of the simulation model, whereas too less scenarios lead to an inaccurate supply curve (see also 5.1). For determining the supply curve first the revenue curve of the aggregator must be deduced based on the residual demand curve method (Varian 2016), which enables to map the influence of the aggregator on the market. Thus, the model takes also market power (price makers and price takers) into account. In general, the residual demand curve indicates the amount of a good depending on the price that is not covered by competing suppliers. Here, it represents the marketable amount of energy per a fixed price from the point of view of an aggregator. According to Eq. (1) the residual demand curve (rdc_t^{Agg}) results from subtracting the aggregated supply curve of the concurrent aggregators ($sc_t^{\sum comp}$) from the aggregated supply curve of all aggregators ($sc_t^{\sum agg}$). The supply curve of the competitors results from the aggregated supply curve of all aggregators minus the supply curve of the one of the bid creating aggregator.

$$rdc_t^{Agg} = sc_t^{\sum agg} - sc_t^{\sum comp} \tag{1}$$

The provision of the past and forecasted aggregated supply curves is a forecast service within the simulation model. To simplify matters, the forecasts are based on the statistics derived from relevant real data time series (e.g., load, renewable generation) for the following day, which are present in the model and falsified by a random forecast error based on real data evaluations.

The revenue curve can easily be derived from the residual demand curve by multiplying the market clearing price with the corresponding volume. The revenue curve is used for the final creation of the supply curve within the MILP optimization model. Therefore, it has to be linearized.

The creation of realistic supply curves for the day-ahead spot market is challenging. In order to obtain a maximum yield price/volume combination per scenario from the point of view of the aggregators, the existing MILP optimization model for determining the unit commitment (Steber et al. 2018a) must be extended

Therefore, first the optimization target function has to be adapted according to Eq. (2) to maximize the revenue achievable at the day-ahead market $\left(rev_t^{DA}\right)$, also considering the generation cost $c_t^{operation}$.

$$\max \sum_{t=0}^{T=24} \left(rev_t^{DA} - c_t^{operation}\right) = \sum_{t=0}^{T=24} \left(rdc_t^{Agg} - c_t^{operation}\right) \tag{2}$$

An optimization run is done per each scenario resulting in a price-volume combination per forecast scenario. It represents the optimal operation point of the generation unit fleet (volume) on the revenue curve (price per volume) with regard to uncertainties.

4.2 Day-Ahead Market-Clearing

Once the day-ahead supply curves have been created, submitted by the aggregators, and aggregated by the market agent, he calculates its intersection with an artificially generated aggregated demand curve. Thus, he determines the market-clearing price per hour (valid for all market participants – *uniform pricing*) and the delivery obligations of the individual aggregators, which is feed back to them. The delivery obligation of an aggregator per hour of the following day result from the intersection of the market clearing price with its submitted respective supply curve.

4.3 Intraday-Market Actions

The next step in the simulation model (see Figure 1) is to evening out the delivery obligations of the aggregators resulting from the day-ahead market and the forecast uncertainties by means of trading on the intra-day market. Therefore, the aggregators have to submit sell and buy orders to the market.

The possibility to purchase or sell volumes is supported by the adaption of the unit commitment optimization by two variables, as stated in Eq. (3), which maximizes the achievable revenue at the intra-day market. In principle, these variables can be considered as dummy generation units, which buy (c_t^{ID}) or sell (rev_t^{ID}) electricity at a specified price (intra-day price; p_t^{ID}). However, this happens with the difference that the respective volume is determined by a competitive generation unit outside the fleet of the corresponding aggregator.

$$\max \left(rev_t^{ID} - c_t^{ID} - c_t^{operation}\right) \quad \forall\, t \,\in\, T \tag{3}$$

The hourly day-ahead market trading results (market-clearing price (p_t^{DA}) and the delivery obligation of the individual aggregators) are the starting point of the intra-day market. To achieve a coupling of both markets, the intra-day price assumed for the determination of buy and sell orders results from the product of an iteratively changed factor (f^{ID} = 0.75 to 1.25) multiplied with the market-clearing price of the day-ahead market ($\mathrm{p}_t^{ID} = \mathrm{p}_t^{DA} \cdot f^{ID}$). The merging of orders at the intra-day market is handled by the market agent.

Existing European intra-day markets are characterized by a low market liquidity, which is in general the ability to trade a certain amount of an asset quickly without a single transaction having a significant impact on the market price (Weber 2010). In the model presented here, a non-liquid market is prevailing due to the small number of players. In order to adequately reflect this lack of liquidity, the modeling approach described in (Scharff and Amelin 2013) is used. Therefore, a function is implemented in the market agent that controls the intra-day trading between the individual aggregators. Here, the temporal resolution of the

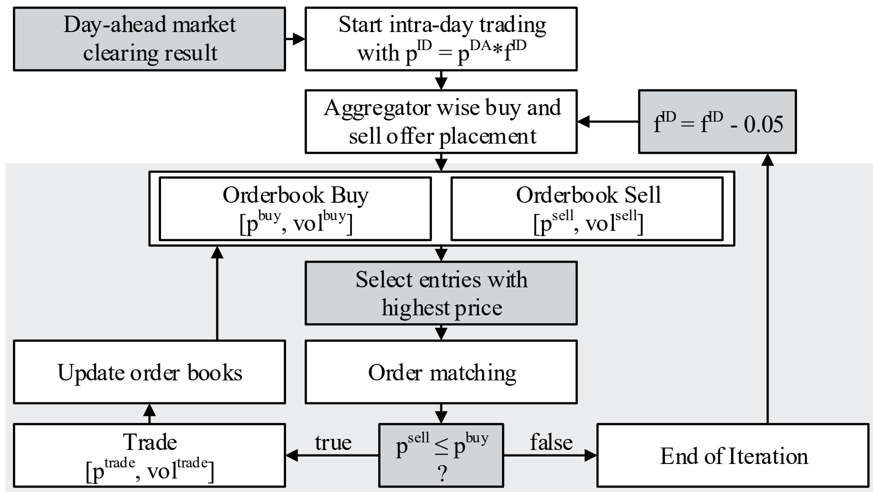


Figure 4: Sequence of the intra-day market within the simulation model.

intra-day market is increased from 15 min to 1 h compared to the real intra-day market in order to ensure the resource efficiency of the simulation model. The procedure follows a fixed iterative scheme, which is shown in Figure 4 and described as follows: Buy and sell offers are entered in an open, electronic order book with details of volume and price limit. All offers are sorted and compared according to price ($p^{buy/sell}$) and volume ($vol^{buy/sell}$). Buy offers are sorted in descending order, sell offers in ascending order of the price. If several buy or sell orders have the same price, they are sorted in descending order of the volume. The special feature of this procedure implemented here is that all buy and sell orders of an iteration have the same price due to assuming the price as the day-ahead market price multiplied with f^{ID}. Sorting the orders by volume at the same price as on the real stock exchanges would therefore put smaller providers at a disadvantage. Therefore, all buy and sell orders are selected and merged at random.

A trade is executed, if the first entries in the buy and sell order books match, e.g., the selling price is less than or equal to the buy price (Genoese 2010). The price of the transaction is determined by the price limit of the buy order. This pricing procedure is referred to as the pay-as-bid (Tierney et al. 2008). The transaction volume is the minimum of both, the buy and the sell order. If an order has been successfully executed, it is removed from both order books. Otherwise its order volume is adjusted accordingly. Thus, it may happen that an order is merged several times with other orders, if in each case only part of the order volume is served by a transaction (Eurex Exchange 2018). This process is repeated as long as there are no matching orders anymore. Every successful trade is then published in the transaction order book. Thus, the market activity is made transparent (Konstantin 2013).

4.4 Optimal Unit Commitment of Aggregators

Having determined the prices and volumes traded on the spot market, the aggregators know their final delivery obligations and selling prices. Thus, they re-optimize their generation unit fleet by a final unit commitment in order to maximize their profit under given conditions.

5 RESULTS

For the results presented in this Section, we first introduce the model setting. For our investigations, we focused on the optimization parts of the model (see Figure 1).

For a block-wise consideration of generation units and their assignment to aggregators we took public available lists of generation units installed in Germany into account (UBA 2017, BNetzA 2017). Concerning the amount and installed capacity of the aggregators of generation units, a large part of the generation unit capacity is accounted for by a few large suppliers. Only six aggregators account for a respective installed generation capacity greater then 2 GW and around 70 % of the overall installed generation capacity. In contrast there are 122 aggregators with less then 0.1 GW installed generation capacity which account for 4 % of the overall installed generation capacity. For the parameterization of the generation units we used (DIW 2013).

5.1 Run-time

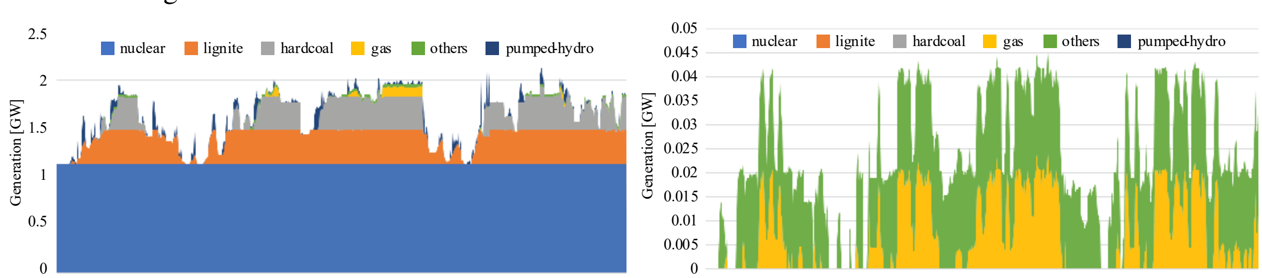
For optimal utilization of several cores, the optimization steps were implemented in such a way that the calculations of the individual aggregators can be processed in parallel (*multi-threading*). First investigations showed, that 76 % of the whole run-time are spent on creating the day-ahead supply curves. Additional 13 % are spent on the intra-day market mechanism and further 8 % on the final unit commitment.

The following parameters related to the optimization were identified, influencing the run-time of the model: Gurobi MIPGap-Parameter (accepted maximum relative distance from optimum (standard: 0.005)), the amount of sampling points of the aggregator's revenue function (standard: 6), and the amount of scenarios for day-ahead supply curve creation (standard: 8). We found, that varying the amount of sampling points of the aggregator's revenue function has no significant effect on the run-time here. In contrast, setting the MIPGap parameter to 0.01 reduces the run-time around 10 % and cutting in half amount of scenarios for day-ahead supply curve creation brings a run-time reduction of circa 35 % by guaranteeing only small deviations of traded volumes and market prices.

5.2 Resulting Dispatch of Generation Units

Figure 5 shows exemplary the resulting generation dispatch for a big aggregator (Figure 5a) and a small aggregator (Figure 5b) for the same time-span of the whole February 2016. Concerning the big aggregator, we observe the following behavior: Due to the low variable costs, the nuclear fired generation units run under full load throughout. In the second half of the month, a drop in demand can be observed down to nuclear power plant capacity. The use of each type of generation unit is also clearly visible, depending on the total generation volume. As expected, pumped-hydro storages (blue) are mainly used during peak times. Concerning the small aggregator, we observe the following behavior: He is mainly active during times of high generation of the big aggregator. As his portfolio contains generation units with high variable costs, his behavior to act mainly during times of high load (resulting mostly also in high prices) is plausible.

Concerning the utilization of generation units we gained the following results (compared to (AEE 2013)): nuclear fired generation units 99 % (cf. 99 %), lignite fired generation units 93 % (cf. ca. 70 %), hardcoal fired generation units 56 % (cf. ca. 43 %), and gas fired generation units 27 % (cf. ca. 39 %). These deviations mainly result from fixed fuel prices over the whole year and inaccurate generation unit parameters as we used only public available data (DIW 2013) which do not map all existing technologies detailed enough.



(a) Fleet generation of a big aggregator (b) Fleet generation of a small aggregator

Figure 5: Resulting exemplary generation dispatch for February 2016.

5.3 Market Prices

According to (Destatis 2017) the mean electricity price at the EPEX spot market was 34.2 €/MWh in 2016. The evaluation of a one year simulation run for 2016 shows that around 80 % of all resulting hourly electricity market prices were in the interval of 25 €/MWh to 40 €/MWh, with a maximum incidence around 30 €/MWh, which is in line with the real mean electricity market price of 2016.

5.4 Model Behavior at Times of Negative Residual Load

If the renewable generation exceeds the load, this results in a negative residual load. However, this only occurs for ten hours in the entire simulation year. The aggregators react clearly to this extreme situation and submit extremely low offers for this period. Thus, the market clearing price falls also to a level around (and below) 0 €/MWh, which represents a real behavior.

6 CONCLUSION

To perform a complex analysis of future EPS, we set up a hybrid simulation model of the German EPS, which also includes optimization mainly for considering the market mechanisms. In this paper, we contributed an object-oriented electricity market model which can be utilized to study different exchange mechanisms and behavior patterns of generation units. Therefore, we introduced our general model and the derivation of the residual load. Moreover, we explained the implementation of an object-oriented electricity market model including the day-ahead market supply curve creation and the intra-day market actions in detail. Simulations results showed that the run-time of the model can be influenced by the amount of sampling points of the revenue function of the aggregator. In order to reduce the run-time the optimization steps were implemented in parallel. Additionally, our simulation results gave interesting insights in the model behavior at times of negative residual load and demonstrated realistic generation dispatch of generation units for different aggregators.

The following steps within the research project KOSiNeK include mainly the integration of aggregators of renewables and running through future development scenarios (e.g., resulting from the grid development plants of different entities) taking also the phase-out of coal-fired generation units into account.

ACKNOWLEDGMENTS

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AUTHOR BIOGRAPHIES

DAVID STEBER is a research assistant and doctoral candidate at the group of Computer Science 7 at the Friedrich-Alexander University Erlangen-Nürnberg (FAU). He received his M.Sc. degree in Business Administration and Engineering with a specialization in Electrical Power Engineering from RWTH Aachen University in 2014. At FAU he works in the field of the simulation of electrical power systems on different system levels. His e-mail address is david.steber@fau.de.

JAKOB HÜBLER was a student of FAU, where he received his M.Sc. degree in International Production Engineering and Management in 2018. His e-mail address is jakob.huebler@fau.de.

MARCO PRUCKNER is an Assistant Professor at the Department of Computer Science at the Friedrich-Alexander University Erlangen-Nürnberg (FAU). He received his Ph.D. degree in engineering (Dr.-Ing.) and his M.Sc. degree in mathematics (Dipl. Math. Univ.) from the FAU in 2015 and 2011, respectively. He is especially interested in the analysis of future electrical power systems with a high share of renewable energy resources based on hybrid simulation techniques. His further research interests include modeling and simulation of electro mobility issues and future mobility solutions within smart cities. His e-mail address is marco.pruckner@fau.de.