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# Simplified dispatching method for unlocking energy flexibilities of decentralized energy systems for the day-ahead and balancing power market

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**Abstract:**

The expansion of renewable energies in the power supply and the shutdown of conventional power plants can only succeed with an advancing flexibilization of the energy system. Decentralized energy systems, such as the energy supply system of a chemical site, can contribute to this, by unlocking the still unused potential for flexibilization. In order to lower the barriers to market participation, user-friendly and simple methods for the economic evaluation of flexibility with regard to the day-ahead and balancing power market are necessary.
Accordingly, in this work a simplified dispatching method considering the day-ahead and the balancing power market in Germany for the mentioned distributed energy systems is developed using mixed-integer linear programming. Linear constraints commonly used in dispatching problems, such as energy balances, conversion efficiencies, and technical constraints, are coupled with new constraints representing the participation in the day-ahead and balancing power market. For the balancing power market the reserve of capacity and the balancing of energy with the uncertainty of calls are taken into account. As a result, the method can be used for day-ahead dispatching by considering the day-ahead energy market and the balancing power market simultaneously.
Because the developed simplified method has low computation times compared to stochastic optimization, for example, it can additionally be applied for hourly resolved annual input data. These evaluations can support strategic planning by determining the economic value of flexibility in the event of market participation. Thus, the results form a starting point for further decisions to unlock unused flexibility.

**Keywords:**

Electricity markets, Balancing power market, Decentralized energy systems, Energy system optimization.

## 1. Introduction

### 1.1 Multi market participation

The expansion of renewable energies in the power supply and the shutdown of conventional power plants can only succeed with an advancing flexibilization of the energy system. Decentralized, small energy systems, such as the energy supply system of a chemical site, can contribute to this, by identifying the existing flexibilities in a first step and offering them on the market in a second step. However, marketing these distributed energy systems goes along with challenges because the systems are complex and the different demands on the site can only be supplied through an integrated operation. In practice, the dispatching is realized in simple systems based on heuristic rules, such as the definition of a switch-on sequence, or in more complex systems based on experienced methods, such as mathematical optimization. Typically, the unit commitment of the decentralized energy systems, such as hybrid renewable systems [1] or combined cooling, heat, and power generation systems [2] is optimized for the participation on the day-ahead market. In most cases, due to the availability of robust and efficient solving methods, mixed-integer linear programming (MILP) formulations are used to minimize economic parameters, such as total operating cost [1–4]. The models, which are mainly based on energy balances, conversion efficiencies, and technical conditions, such as part load behaviour, can be applied to a wide range of large, real world optimization problems. Following this, dispatching can be managed for the day-ahead market of distributed energy systems with several technologies, including renewable energy systems, cogeneration systems, energy storages, or conventional generation [5–7].

The expansion of fluctuating renewable energy sources increases supply uncertainty in the power grid. As a result more short-term system balancing is needed [8,9]. Thus, the demand of flexibility on the short-term markets will also increase in the future. In this changing market environment, it may be economically worthwhile

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for the decentralized energy systems to identify their flexible capacity and monetize it on either the balancing-power market or the continuous intraday market in addition to the aforementioned participation on the day-ahead market. However, simultaneous participation in different energy markets is a complex problem that leads to a sequential decision-making process. In Germany and similarly in other European power markets, for example, the balancing reserve capacity auction starts in the morning on the day before delivery. Shortly thereafter, trading on the day-ahead market closes, and the continuous trading on the intraday market starts finally. In this marketing procedure, flexibility that has been already traded on one market can no longer be offered on another market. The optimal behavior with coordinated bidding in the mentioned multiple markets is usually computed by multi-stage stochastic optimization problems [10–12]. In these approaches, uncertainties, such as the request of control energy or the acceptance of a bid in the balancing power market, can be handled. The literature of multi market participation can be classified based on the model complexity of the market on the one hand and on the nature of the portfolio of assets in form of the complexity of the energy system on the other hand. On the market side, the work from [13] considers the day-ahead and balancing power market using averaged prices of capacity and energy without optimizing price bids. Other works optimize only the bids of the capacity price [14] or only the bids of the energy price [15] for balancing power. An even more detailed modeling of the balancing power market taking into account the relevant market rules for capacity and work can be found in [16]. In addition to the aforementioned works with the coupled marketing on the day-ahead and balancing power market, there are more complex models with the additional consideration of the intraday market [12,17,18]. On the energy system side, the developed methods are applied on hydro power plants [19,20], a virtual power plant [21,22], a portfolio with biogas power plants and photovoltaic systems [17], combined heat and power plants [13,23], a cement mill [16], energy storages [24], or a distributed multi-energy system [12].

### 1.2 Contribution of this work

The presented multi market participation of a decentralized energy system is a cross-sectional topic from the field of energy system engineering with the unit commitment problem and the field of operations research with the optimal trading problem for multiple markets. The combination of these areas leads to the multi-stage stochastic optimization problems that are formulated for the energy system to participate in the multi-market setting. The detailed modeling of the day-ahead, intraday and balancing power market leads to a complex problem with a large scenario tree that is additionally linked to an often no less complicated energy system model. Thus, in case studies, the complexity is usually reduced to keep the problems manageable [17, 24]. However, the methods mentioned remain complicated to handle, for example, due to the modeling of scenario trees, discretization of bid prices or the use of possible reduction methods.

Accordingly, this paper presents an alternative deterministic method that simplifies the described complexity on the market side, taking into account the day-ahead and the balancing power market in Germany, resulting in the following advantages:

1) As complexity on the market side is reduced, complexity on the energy system side can be maintained, and common unit commitment models with constraints for start costs, load changes, or piecewise linear characteristics can be used. Thus, an easy integration into possibly existing dispatching procedures using existing MILP-models is possible.
2) Due to the low computation times, the developed method can be used not only for dispatching but also for strategic planning by using hourly resolved annual input data. In comparison, the temporal resolution of the mentioned case studies is, for example, a quarter-hourly resolution of 18 typical days [18] or an hourly resolution for four typical weeks [13]. However, based on such results, the economic value of the different flexibilities or units in the energy system in case of a market participation can be quickly determined. These evaluations are of interest to companies planning to enter a specific market. They form a starting point for further decisions to unlock the unused flexibility.

Another aspect that is relevant in the energy transition is the changing actor structure. As more and more small players, who do not have the capacity to apply multilevel stochastic programming methods, enter the market, the demand on user-friendly, simplified methods increases. For the small market players, such as the operators of decentralized energy systems, the market entry is accompanied by technical and economic risks, which are caused by the additional personnel and administrative effort on the one hand and by the changed operation modes of the units, which are adapted to the market, on the other hand. Based on the developed method, some of the risks can be minimized, because the behavior of the energy system during market participation is calculated while the economic value of the flexible capacities can be estimated.

## 2. Simplified dispatching method for the day-ahead and balancing power market

The proposed method allocates the flexible capacity of a distributed energy system to the balancing power and the day-ahead market. In a first chapter 2.1, the constraints for the German short term electricity and balancing power market are presented. In order to investigate the mechanisms of the balancing power market, historical data is analysed in a subchapter. Based on this, subchapter 2.2 presents the developed methods with their respective modelling equations.

## 2.1 Short term electricity and balancing power market in Germany

Germany's electricity market design is similar to the EU's overall electricity market design, but with some specific characteristics and features. The design of the balancing power market in Germany has undergone some adjustments in recent years. To ensure consistent market constraints, we focus on the rules for the period 08/01/2019 to 07/31/2020 in this work.

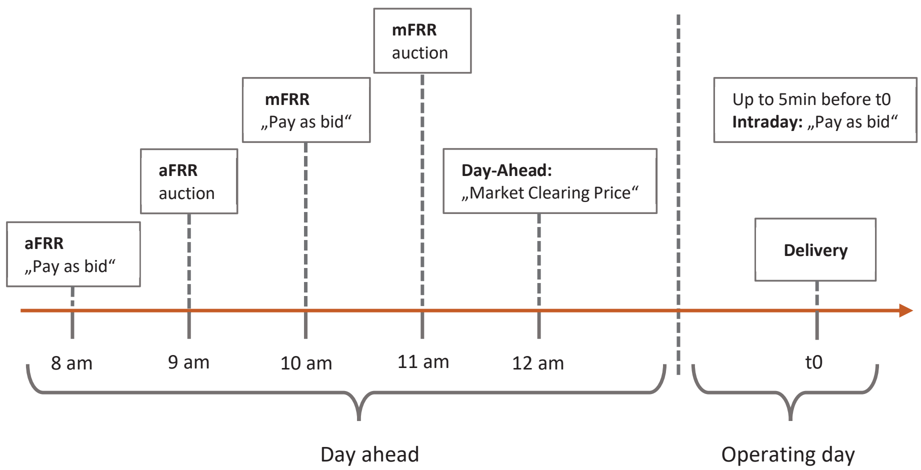


**Figure 1:** Germany's electricity market design with trading deadlines for the secondary (aFRR) and tertiary (mFRR) reserve of the balancing power market, followed by the day-ahead auction and the continuous intraday trading.

day-ahead market. In the balancing power market, balancing power is traded in the form of automatic frequency restoration reserve (aFRR) and frequency restoration reserve with manual activation (mFRR) in pay-as-bid procedures. For both products, suppliers can submit bids for 4-hour time slices for positive or negative control energy. In addition to the capacity quantity, the participants offer a price for the reserve of the capacity and an energy price for the actual request of balancing power. The tenders have to be submitted for aFRR by 9 a.m. The auction results are published at 10 a.m. This is followed by an equivalent procedure for the mFRR with the results being published at 11 a.m. The transmission system operator (TSO) realizes in a two-stage procedure the procurement of aFRR and mFRR. In the first stage, a merit order is used to select which suppliers are accepted. The decision is based on the capacity price bids and the total balancing power demand, which is determined by the TSO. In the second stage, a merit order for the operating day is formed from all the suppliers accepted in the first stage. The merit order is based on the energy price bids. If balancing power is needed, the suppliers with the lowest energy prices are called up first. In this paper, we focus on the aFRR market, which is the most important balancing power market in Germany with the highest demands [25].

On the day-ahead market, electricity is traded in hourly contracts for the following day. The market closes at 12 p.m., and results are published at 1 p.m. Trading on this market is subject to the market-clearing principle, where the last accepted bid sets the price for all transactions.

### 2.1.1 Historical data of the balancing power market

This Section analyzes the historical data of the balancing power market for the mentioned one-year period 08/01/2019 to 07/31/2020. The evaluations are based on raw data with a resolution of four seconds from the platform regelleistung.net [26]. In a first step, the request probabilities for positive and negative aFRR are calculated as a function of the energy price bids for the respective 4 h time slices of a day, as illustrated in Figure 2. Following the work of [27], the request probability results from the number of all 4-second blocks with request of aFRR for the respective energy price, divided by the total number of 4-second blocks. The results show a decrease of the request probability with increasing energy prices for positive and negative aFRR. For positive aFRR, the most frequent calls were made in the range below 40 EUR/MWh with a probability of about 50 %. In the energy price range from 40 EUR/MWh to 100 EUR/MWh, there is a large gradient where the number of requests strongly depends on the energy prices offered.

For the negative aFRR, electricity is supplied from the grid during the request, leading to profitable negative energy prices, as seen in Figure 2 (right). The request probabilities for negative aFRR are highest at energy prices below minus 20 EUR/MWh with 50%.

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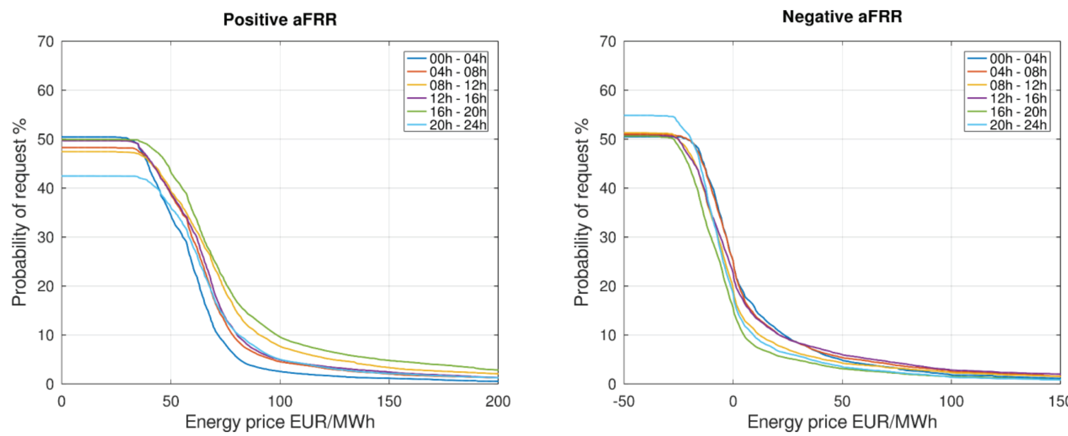


**Figure 2:** Probabilities of request as a function of energy price bids for positive aFRR (left) and negative aFRR (right) for the period 08/01/2019 to 07/31/2020.

Following the work of [27], the theoretical potential of the profits regarding the balancing power requests can be determined on the basis of the historical data, as shown in Figure 3 (left) for positive aFRR. This potential of profit can be calculated for different flexible capacities in form of different marginal costs. The marginal costs were assumed to be constant costs that are incurred when the balancing power is requested. These results give an insight into the relationship between the energy price bid, the energy system with the respective marginal costs, and the possible profits regarding the balancing requests. The balancing providers have to manage the trade-off between the bids for energy prices and the corresponding request probabilities: Low energy prices lead to high requests with low revenues per request, and high energy prices lead to low requests but with high revenues per request on the other side. As seen in Figure 3 (left), in theory there are optimal electricity bids that resolve the mentioned trade-off with maximum potential of profit. This maximum potential of profit decreases rapidly with increasing marginal costs, as illustrated in Figure 3 (right).

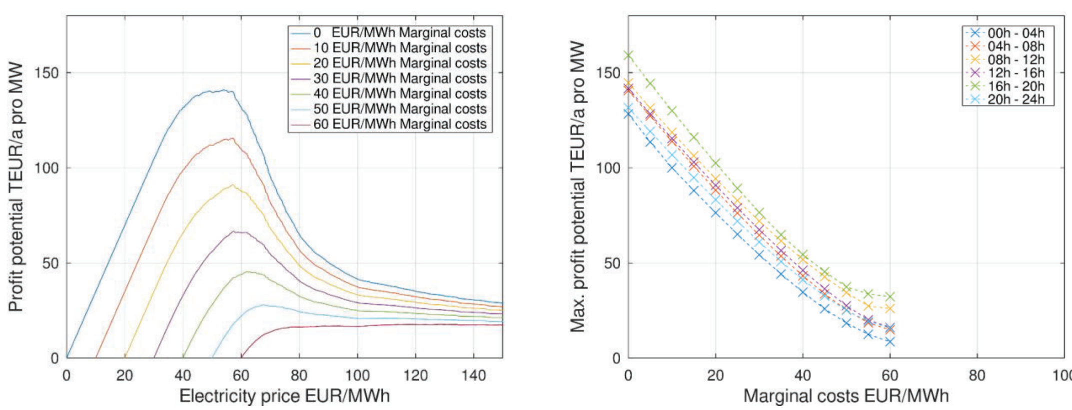


**Figure 3:** Potential of profit from positive aFRR requests for different marginal costs of electricity generation as a function of energy price bids (left) and the maximum potential of profit as a function of the marginal costs (right) the period 08/01/2019 to 07/31/2020.

## 2.2 Formulation of the developed dispatching methods

The developed methods optimize the participation of a distributed energy system in the balancing power and day-ahead market for the next day (*d-1*), as seen in Figure 1. In this paper, we focus on the market of aFRR, which is the most important balancing power market in Germany [25]. The coupled multi-market optimization can resolve the trade-off faced by flexibility providers in deciding which of the two markets to operate in. The methods are based on a mixed-integer linear programming (MILP) model of the energy system. This approach is commonly used for unit commitment by minimizing the operating costs of the system under linear constraints such as energy balances, efficiencies, and technical constraints for the day-ahead market [3,4].

In the following Section, the two developed methods *Perfect forecast* and *Virtual capacity price* are presented. The method *Perfect forecast* calculates an upper limit of the possible profits for a first estimation of the market potential. The method *Virtual capacity price* uses a 2-stage modeling approach that represents the balancing power market in more detail. In the presentation of the methods, we focus on the formulation of the market constraints because modeling the energy system is implemented according to the aforementioned common formulations. Note that all MILP variables are formatted in bold style while normal font style is used for all coefficients.

**One-stage algorithm: Perfect forecast**

The basis of the *Perfect forecast* method is the assumption that the exact request of balancing power on the day of marketing *d-1* is known. The power reserve is modeled using integer variables for positive $\boldsymbol{BP_t^+}$ and negative $\boldsymbol{BP_t^-}$ balancing power for each time step $t \in T$. Each integer variable represents the acquisition in discrete 1 [MW] steps. The variables are coupled to represent the respective 4 h time slices of the aFRR product, as illustrated in Figure 4.

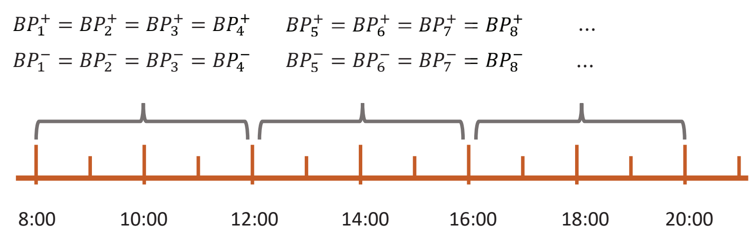


**Figure 4:** Modelling of positive and negative balancing power for the respective 4h time slices using integer variables, representing the acquisition in discrete 1 [MW] steps.

Based on the mentioned variables, a technical constraint with the blocking of the respective unit capacity for the balancing power market is modeled, using the electrical power $\boldsymbol{\dot{P}_{el,t}}$ with the associated minimum partial load $\dot{P}_{min}$ and nominal load $\dot{P}_{max}$ of the unit. The blocking is reduced to allow the request of balancing power with $\boldsymbol{\dot{P}_{req,t}}$.

$$\dot{P}_{min} + \boldsymbol{BP_t^-} \geq \boldsymbol{\dot{P}_{el,t}} + \boldsymbol{\dot{P}_{req,t}} \geq \dot{P}_{max} - \boldsymbol{BP_t^+}, \qquad \forall\, t \in T \tag{1}$$

Note that, in this formulation, it is assumed that the unit is not capable of fast start-ups and can offer balancing power only in the range between the minimum part load and the nominal load. The request of balancing power is calculated with the factors $f_t^-$ and $f_t^+$. The factors represent a specific time series of requested balancing power for a given energy price $pe$ and were created from historical data:

$$\boldsymbol{\dot{P}_{req,t}} = -\boldsymbol{BP_t^-} \cdot f_t^- + \boldsymbol{BP_t^+} \cdot f_t^+, \qquad \forall\, t \in T \tag{2}$$

The revenues on the balancing power market for the capacity reserve is formulated with the average, historical capacity prices for positive and negative $pc_t^-$ balance of the pay-as-bid procedure. By using the average prices, it is assumed that with these average price bids, the surcharge for the balancing power offered in the pay-as-bid procedure is always accepted. The revenues acquired from requests are calculated using the energy prices $pe^-$ and $pe^t$. Both revenues are added to the common target function of the operational cost *OPEX* of the energy system model.

$$\boldsymbol{OPEX_{BP,t}} = -\boldsymbol{BP_t^-}(f_t^- \cdot pe^- + pc_t^-) - \boldsymbol{BP_t^+}(f_t^+ \cdot pe^+ + pc_t^+), \qquad \forall\, t \in T \tag{3}$$

In summary, this formulation means that when deciding whether participation in the balancing power market is worthwhile, the optimization simultaneously takes into account the request of balancing power with the respective remuneration via the energy price. In this respect, the model can perfectly predict during optimization on *d-1* at which exact points in time balancing power will be requested.

The revenues from the day-ahead market participation equals the electricity fed into the grid $\boldsymbol{\dot{P}_{el,t}^{DA,fed-in}}$ and purchased from the grid $\boldsymbol{\dot{P}_{el,t}^{DA,pur}}$ multiplied with the day-ahead market price for selling $pe_t^{DA,sell}$ and buying $pe_t^{DA,buy}$.

$$\boldsymbol{OPEX_{DA,t}} = -\boldsymbol{\dot{P}_{el,t}^{DA,fed-in}} \cdot pe_t^{DA,sell} + \boldsymbol{\dot{P}_{el,t}^{DA,pur}} \cdot pe_t^{DA,buy}, \qquad \forall\, t \in T \tag{4}$$

Because the prices of the day-ahead market are well predictable on *d-1*, the method uses the exact historical data of the market clearing price.


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**Two-stage algorithm: Virtual capacity pricing**

Compared to the *Perfect forecast* method, the *Virtual capacity pricing* algorithm takes uncertainties of the balancing power market into account. For this purpose, an averaged statement about the balancing power requests on the following day is made on *d-1*, based on historical request probabilities. In detail, the procedure is as follows:

**Stage 1:** In addition to the average capacity price $pc_t^+$ and $pc_t^-$, a virtual capacity price $pc_{\mathrm{virtual,t}}$ is integrated into the model.

$$\boldsymbol{OPEX_{BP,t}} = -\boldsymbol{BP_t^-}(f_t^- \cdot pe^- + pc_t^- + pc_{virtual,t}^-) - \boldsymbol{BP_t^+}(f_t^+ \cdot pe^+ + pc_t^+ + pc_{virtual,t}^+), \qquad \forall\, t \in T \tag{5}$$

This virtual price is calculated with historical data and reflects the averaged revenues from a possible balancing power call on the operating day. Specific balancing power requests are not considered in this stage by setting the request factors· $f_t^-$ and $f_t^+$ to zero in equation (2). In this stage, the optimization model can calculate the trade-off between the participation on the balancing power market with the possible reserve of power and the day-ahead market based on the resulting capacity price.

**Stage 2:** In this stage, the market participation from stage 1 is fixed. The virtual capacity price is removed and the historical requests are imposed with a fixed energy price. This stage calculates in detail how the power system behaves after the optimal marketing on *d-1* from stage 1 on the operating day while responding to the specific balancing power requests.

The challenge of the methodology is the calculation of the virtual capacity price, which has a large impact on the optimization results. Exact details of these difficulties are presented in the case study. All equations not mentioned in this method are formulated equal to the *Perfect forcast* method.

# 3. Case study for market participation of an ideal-typical utility infrastructure of a chemical site

## 3.1 Input parameters and solving method

The methods proposed are applied to an ideal-typical utility infrastructure (iCV) of a chemical site from [28]. The utility infrastructure supplies electricity and heat for the local chemical companies. The layout of the supply structure is shown in Figure 5. The heat demand consists of a medium-pressure (31 bar) and a low-pressure (6 bar) steam demand. The primary process unit is a gas turbine with 114 MW electrical power followed by a heat recovery steam generator with 150 MW thermal power. In addition to the heat recovery steam generator, two separate gas-fired steam generators and an electrode boiler can provide steam. The high-pressure steam can be expanded to 31 bar and 6 bar via a turbine system, generating additional electricity. The supply structure is generally operated on a heat-led basis to cover the 31 bar and 6 bar steam demand. Differences between electricity generation and electricity demand are balanced by the purchase of electricity from the grid.

**Table 1:** Data sources for the case study of the iCV model.

| Parameter | Data source | Parameter | Data source |
|---|---|---|---|
| Electricity demand | Bauer et al. [28] | Capacity price balancing power market | Regelleistung.net [26] |
| Steam demand 31bar | | Energy price balancing power market | |
| Steam demand 6bar | | | |
| Gas price | EPEX SPOT [29] | Day-ahead market price | Bundesnetzagentur SMARD.de [30] |

The overall iCV energy system participates in the day-ahead market (DA) and the gas turbine additionally participates in the balancing power market (BP) for aFRR. The gas turbine in the iCV model generates electricity and steam and this coupled generation is tightly integrated in the overall energy system. Therefore, the entire iCV energy system must be considered to analyze the multi-market participation of the gas turbine.

Historical data from the period August 2019 to July 2020 are used to ensure consistent market constraints for the balancing power market. An overview of the data sources for the relevant input parameters is shown in Table 1. All optimization problems are calculated with Gurobi 9.5.0 on an Intel Core i5-8250U processor with 8GB RAM with hourly resolved annual input data. All solving parameters are set to default values with a relative gap of 1e-3. To handle the time-coupled constraints such as the coupling of time steps for the 4 h time slices of the balancing power market, a rolling horizon approach with a time horizon of 24 h was applied in all optimization runs [31].

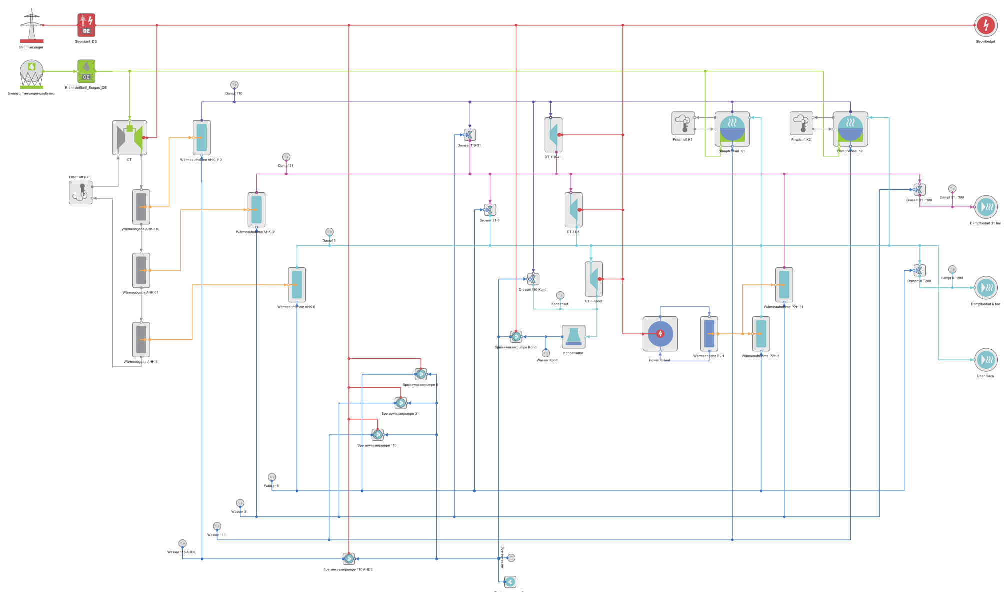

**Figure 5:** Layout of the ideal-typical utility infrastructure of a chemical site by [28] in the software TOP-Energy. A gas turbine with heat recovery steam generator, two gas-fired steam generators and a power-to-heat unit can produce steam, which is expanded to 31 bar and 6 bar by a turbine system to cover the heat demands.

## 3.2 Perfect forecast method

The operation of the gas turbine for the case of marketing on the day-ahead market is shown in Figure 6, as a function of the ratio of electricity price to clean gas price R. For low ratios of R with low electricity prices, electricity generation on site using the gas turbine is not worthwhile. For values of approximately R≥1.2, own generation is profitable with the operation at full load with 114 MW electrical power.

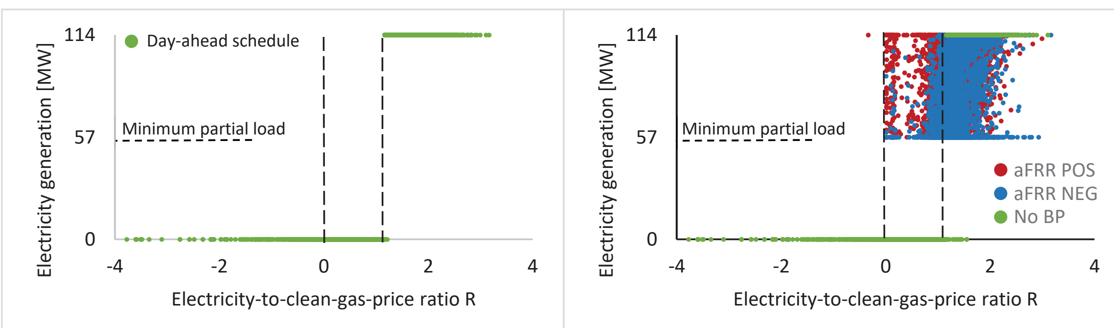


**Figure 6:** Electricity generation of the gas turbine for the case of marketing on the day-ahead market (left) and marketing on the day-ahead and balancing power market for aFRR using the *Perfect forecast* method (right) as a function of the electricity-to-clean-gas-price ratio R.

Compared to the pure day-ahead marketing, Figure 6 (right) shows the result of the coupled marketing on the day-ahead and balancing power market. The gas turbine is not capable of fast start-ups and can offer balancing power only in the range between the minimum part load and the nominal load with a maximum flexibility of 57 MW. In a range around the turnover point with R=1.2, the marketing of positive and negative aFRR is worthwhile. During the respective marketing of balancing power, the gas turbine operates flexible in the range above the minimum part load to control the balancing requests.


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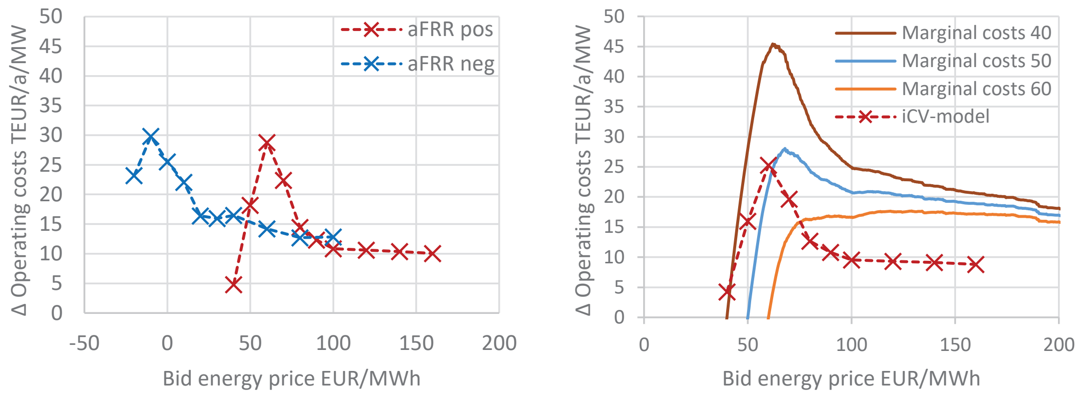


**Figure 7:** Delta of operational costs (DA – DA and BP marketing) per MW of gas turbine flexibility as function of the energy price bid for positive and negative aFRR (left) and the comparison to the theoretical potential of profit for positive aFRR for different marginal costs in EUR/MWh, as originally presented in Figure 3 (right).

The influence of revenues from the marketing of positive and negative aFRR on energy price bids is presented in Figure 7 (left). The revenues are illustrated as difference of operating costs between the scenario with day-ahead marketing and the scenario with day-ahead and balancing power marketing. Both curves show an optimum with maximum revenues at 60 EUR/MWh for positive aFRR and –10 EUR/MWh for negative aFRR. However, the optimal energy price bid depends on the marginal costs of the unit, as analyzed in Section 2.1.1. A comparison of the discussed theoretical profit to the results of the iCV-model for positive aFRR is shown in Figure 7 (left) for different marginal costs. The average marginal costs of the gas turbine can be estimated at 40 EUR/MWh for the iCV-model, taking into account the coupled generation of electricity and steam. The curve of the iCV-model corresponds qualitavely to the theoretical evaluation when the same marginal costs are assumed, with the same energy price bid at the optimum. This result shows that a reasonable energy price bid can be estimated using historical data and marginal costs of the unit participating in the market. Quantitatively, the revenues of the iCV-model are lower, because the model takes into account the entire energy system with more precise technical constraints, such as partial load behavior.

### 3.3 Virtual capacity pricing

In the 2-stage algorithm *Virtual capacity pricing*, a constant virtual price is added to the original capacity price time series in the first stage. The results of the algorithm depend on the level of this virtual price accordingly, as shown in Figure 8.

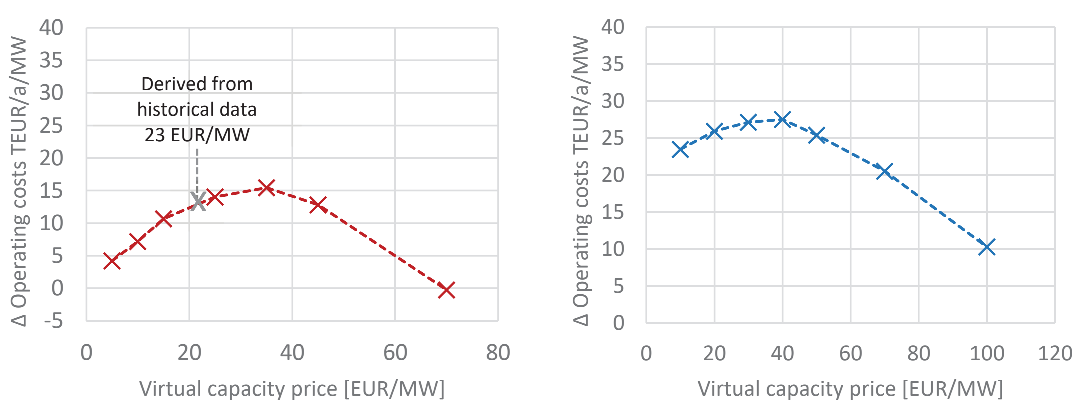


**Figure 8:** Delta of operational costs (DA – DA and BP marketing) per MW of gas turbine flexibility as function of the virtual capacity price for positive (left) and negative aFRR (right).

For both positive and negative aFRR, the revenues on the balancing power market are underestimated if a too small virtual capacity price is chosen. In these cases, only a few time slices are purchased on the balancing power market in the first stage of the algorithm, resulting in low total revenues in the second stage of the optimization. The choice of a too large virtual capacity price causes a possibly too strong marketing of balancing power in the model. This also leads to a non-optimal operation in the second stage with lower total revenues. At the highest virtual power capacity for positive aFRR, economic losses even occur compared to the pure day-ahead marketing. The best results are achieved for positive aFRR at a virtual capacity price of 35 EUR/MW and for negative aFRR at a virtual capacity price of 40 EUR/MW.

The challenge of the methodology is to determine a suitable virtual capacity price without performing a parameter study as illustrated in Figure 8. For this purpose, a price can be calculated in advance from the theoretical profit potential of the balancing power market using historic data, as demonstrated in Figure 3. However, the marginal costs of the unit participating in the market must be estimated for this purpose. In the case study, the approximate marginal costs of the gas turbine are 40 EUR/MWh. In theory, such a unit can generate about 50 TEUR/MW per year with balancing requests following the evaluations in Figure 3. From this, an average virtual capacity price of 23 EUR/MW can be calculated. Although this value does not meet the optimum of 35 EUR/MW, it still provides a good estimation for setting a reasonable virtual capacity price.

## 3.4 Evaluation and comparison with simple trading strategies

A comparison of the developed methods *Perfect forecast* and *Virtual capacity price* is shown in Figure 9. In both methods, the total revenues on the balancing power market consist of a small share of revenues from the capacity reserve and a main share of revenues from balancing power requests. When deciding whether participation in the balancing power market is worthwhile or not, the *Perfect forecast* method can simultaneously take into account the balancing requests with the respective revenues. In doing so, the model can preferentially select profitable time slices with many request calls. Accordingly, the results for this methodology in Figure 9 show high revenues from balancing power requests compared to the *Virtual capacity price* method. The total number of purchased time slices on the balancing power market is similar for both methods. However, more negative time slices are marketed in the *Virtual capacity price* method compared to the *Perfect forecast* method, resulting in increased use of the gas turbine with higher fuel costs and lower electricity costs due to the higher on site electricity generation.

In summary, the results of the presented *Perfect forecast* method with the total revenues of 55 TEUR/MW provide a theoretical profit potential of the market. A more realistic view, in which no exact requests are predicted on *d-1*, is calculated by the *Virtual power price* method leading to lower total revenues of 33 TEUR/MW.

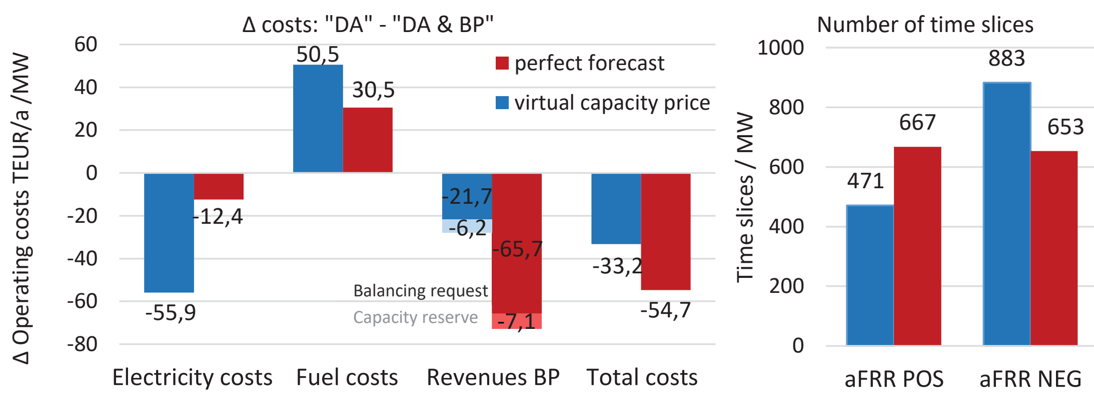


**Figure 9:** Delta of cost components (DA – DA and BP marketing) for electricity, fuel and balancing power (aFRR) per MW of gas turbine flexibility (left) and the number of aFRR time slices acquired (right).

In summary, the results of the presented *Perfect forecast* method with the total revenues of 55 TEUR/MW provide a theoretical profit potential of the market. A more realistic view, in which no exact requests are predicted on *d-1*, is calculated by the *Virtual power price* method leading to lower total revenues of 33 TEUR/MW.

The presented results are compared with different simple bidding strategies for the balancing power market in the following Section. These simple bidding strategies are based on the optimal gas turbine commitment for the scenario where the energy system participates only on the day-ahead market, as illustrated in Figure 6 (left). Accordingly, the following presented strategies 1a), 1b), 2a) and 2b) are derived from the optimal gas turbine schedule, as also shown in Figure 10.

**1a)** The day-ahead schedule is not adjusted and negative balancing power is marketed at the times when the gas turbine is running at full load. In this strategy, a maximum capacity price and a maximum energy price are bid. It is assumed that by bidding the high energy price, no balancing power is requested.

**1b)** As in 1a) but a bidding strategy with a medium capacity price and a medium energy price with consideration of balancing requests.


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**2a)** The day-ahead schedule is adjusted. At the times when the gas turbine is off, the turbine is ramped up to market positive balancing power. At times when the gas turbine is on, negative balancing power is marketed. For positive and negative balancing power, an average capacity price and an average energy price are used, taking into account balancing power requests.

**2b)** The day-ahead schedule is adjusted. At the times when the gas turbine is on, the gas turbine is shut down to minimum partial load in order to offer positive balancing power. For the positive balancing power, an average capacity price and an average energy price are used, taking into account balancing power requests.

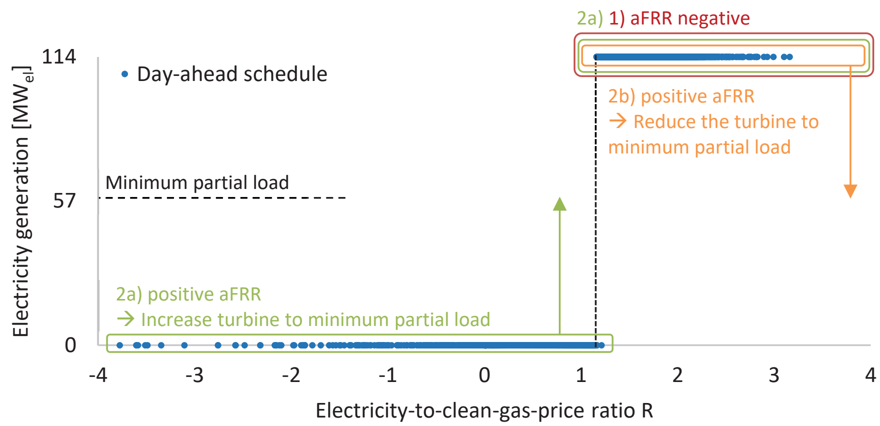


**Figure 10:** Simple bidding strategies 1), 2a) and 2b) for the balancing power market based on the optimal day-ahead schedule (without BP) of the gas turbine.

The overall results are shown in Figure 11 for the presented four bidding strategies (schedule adjusted) and the developed methods *Perfect forecast* and *Virtual capacity price* (Coupled optimization). The first three bidding strategies 1a), 1b) and 2a) show small revenues between 2.2 TEUR/MW to 5.5 TEUR/MW. In strategy 1a) the high energy price bid leads to the avoidance of balancing power requests. However, we have shown that balancing power requests are relevant for the generation of profits and, accordingly, higher revenues are found in strategy 1b), which considers requests. In bidding strategies 2a) and 2b) the day-ahead schedule is adjusted leading to strongly different revenues. In strategy 2a) very low revenues are generated, whereas strategy 2b) leads to significant profits with 18 TEUR/MW per year.

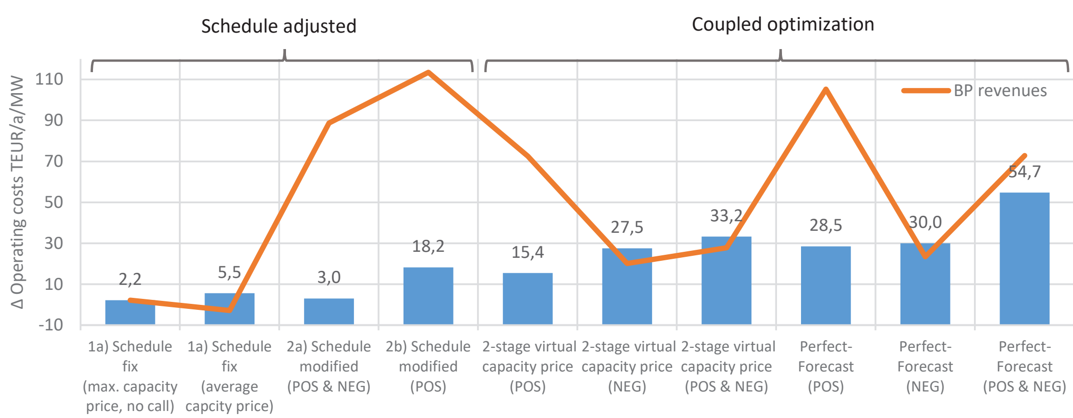


**Figure 11:** Delta of operational costs (DA – DA and BP marketing) per MW of gas turbine flexibility for the presented four simple bidding strategies (schedule adjusted) and the developed methods *Perfect forecast* and *Virtual power price* (Coupled optimization).

Basically, the simple bidding strategies for the balancing power market based on the day-ahead schedule can generate profits. However, this scheduling "by hand" is not ideal and the revenues are fluctuating and difficult to estimate. In comparison, marketing with the presented simplified optimization methods can generate higher revenues. The one-stage *Perfect forecast* method provides a theoretical potential of profit based on historical data, resulting in the maximum revenues in Figure 11. The *Virtual capacity price* method takes into account the uncertainties of the requests in a simple way, providing a more realistic market potential with lower revenues.

## 4. Conclusion

The results of the case study demonstrate that the developed methods manage the coupled marketing of a distributed energy system on the day-ahead and balancing power market in a simplified way. For the methods, historical data can be used to determine reasonable values for energy price bids and virtual capacity prices by considering the marginal cost of the corresponding unit.

The disadvantages of the simplified methods are caused by the complexity reduction of the market side. In reality, market participation leads to a sequential decision-making process that is not modeled in detail. Accordingly, it is not possible to compute optimal bidding strategies taking into account uncertainties, as is the case by using common multi-level stochastic programming approaches.

However, the main advantage of the methods is the low complexity, compared to e.g. stochastic optimization, leading to a high user-friendliness with an easy integration into possibly existing dispatching procedures. The methods can additionally be used for strategic planning to quickly estimate the economic value for different flexibel capcities in the energy system in case of a market participation, as seen in the case study. These evaluations are of interest to companies planning to enter a specific market. In particular, as more and more small players enter the market in the context of the energy transition who do not have the capacity to apply multi-level stochastic programming methods, the demand for user-friendly, simplified methods is increasing. However, the developed methods must be extended in the future for the complete short-term electricity market. For this purpose, the opportunity of intraday trading must be taken into account at *d-1*.

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