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The impact of intraday markets on the market value of flexibility: Decomposing effects on profile and the imbalance costs

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The impact of intraday markets on the market value of flexibility– Decomposing effects on profile and the imbalance costs

HEMF Working Paper No. 11/2017

by

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Abstract

An increasing share of variable renewable energy sources (VREs) basically affects the electricity price formation in two ways: (1) The so-called merit order effect tends to lower the base price level and challenges conventional plants to remain profitable. (2) Due to the variable nature of renewable energy infeed, the shortterm demand for flexibility increases and changes the volatility of electricity prices. The more variable prices offer opportunities for controllable electricity producers (CEPs) to provide up- and down-ramping flexibility to increase their revenues. In contrast, the VREs with high degrees of simultaneity tend to pay for this flexibility in the electricity spot market to reduce their imbalance exposure. The intraday market (IDM) for electricity has gained importance for the market value of different technologies lately and continues to expand due to the increasing efforts to balance within-day deviation from day-ahead schedules. This article presents a combination and extension of two existing models to capture the peculiarities of the intraday price formation and to analyse the impact of the IDM on the market value of VREs and CEPs. Doing so, the paper suggests an adjustment of the classical market value factor metric and to go beyond classical day-ahead market (DAM) information. The article shows that market value factors (MVF) can be stabilized if the IDM delivers 'marketbased' price signals for the costs of flexibility, that are sufficient to activate flexibilities prior to the usually more expensive imbalance mechanism (IBM). Yet, the MVFs from single VRE technologies will worsen if their market share is high enough to outweigh forecast errors from other technologies and if they become a permanent price maker in the IDM and the IBM.

Keywords : intraday markets, imbalance mechanism, market value, renewable energy

JEL-Classification : Q47, N74

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1 Introduction

The emission trading system (EU ETS) and the support of renewable energy sources (RES) are two main political instruments in Europe to fight global warming. Both instruments influence the investment behaviour and trading activities of market participants and therefore impact the electricity price volatilities and the demand for flexibility in the sector. Hereby, flexibility is understood as the up- and down-ramping from production or demand units to balance short-term (within-day) deviations from the scheduled production, e.g. due to unforeseen increase or decrease of RES production. The monetary value of this flexibility materializes in the day-ahead market (DAM) and even more in the intraday market (IDM), because the value of electricity depends on the point in time when it is produced and the IDM gate closure is significantly closer to the start of delivery compared to the DAM gate closure. Hereby, the effects from the IDM is different for variable renewable energy sources (VREs)¹ generally demanding flexibility from the system and Controllable Electricity Production (CEP) providing flexibility to the system. A commonly used metric to analyse the effects on revenues from dispatchable (controllable) and non-dispatchable (variable) technologies is the market value factor (among other see Lamont, 2008; Hirth, 2013 or Winkler et al., 2016). The measure describes the revenues earned by a production technology on the market - not including subsidy payments - relative to the base price. Typically, the market value factors (MVF) are calculated based on day-ahead prices (DAP) and include the so-called profile costs, the imbalance spread and grid related costs (see section 2). Yet, the increasing importance of flexibilities and the development of intraday trading raises the question if the DAP remains an adequate reference to quantify profile and imbalance costs in renewable-dominated energy systems. Without intraday trading, the quantity differences between the day-ahead position and the actual production will be spilled to the imbalance mechanism (IBM). By use of sufficiently liquid IDM, market participants can lower their imbalance exposure and (especially VREs) will be less obliged to rely on the IBM. The latter is important because the IBM is prone to inefficiencies resulting from market power or penalties imposed (among others see Weber, 2010 or Bueno-Lorenzo et al., 2013). Due to their dependency on uncertain weather conditions, VREs are expected to face additional (flexibility) costs in the IDM. However, by trading intraday, the VREs will more likely reduce their imbalance exposure compared to the situation without further adjustments after the DAM. In contrast, the IDM delivers revenue potentials for CEP, e.g. by allowing them to sell additional quantities or to buy back quantities after the day-ahead gate closure. In this context, this article contributes to the literature by analysing the impact from the IDM on MVFs going beyond the classical DAM and quantifying the costs of flexibility and their impact on the market value of CEP and VRE assets more rigorously. Doing so, the article suggests to adjust the market value factor metric and to consider self-curtailment during times of oversupply in the system. The methodological contribution is twofold: *First*, the article combines and further develops a parsimonious fundamental model to accurately model the price level (Kallabis et al., 2016) and an approach to account for the peculiarities of the IDM (Pape et al., 2016), i.e. notably reflecting shorter lead times and inflexibilities in the conventional power production. The combined model is extended to account for system adaptations during times of negative prices and to describe the interplay between intraday and imbalance uncertainties (forecast errors of load, wind, solar and power plant outages) and imbalance risk exposure (costs). In course of the model extension, an econometric approach is applied to quantify the shortening of the intraday supply stack based on actual intraday prices (IDPs). *Second*, the article contributes to the - as of late - scarce literature on European IDMs for electricity, by enlarging the insights

¹ RES include all Renewable sources, whereas VRE is used for the non-dispatchable RES, i.e. wind and Solar

about the IDM and about the interaction with the IBM. The modelling results shed light on the longer term impacts of the IDM on MVFs. To the best of the author's knowledge, the latter effects have not been quantified nor structurally been analysed in the literature. The remaining article is structured as follows. Section 2 explains the market value of flexibility and the relevance of forecast uncertainties. Section 3 describes the methodology applied and addresses necessary model extensions whereas section 4 describes the dataset. Section 5 presents the results from the model validation and decomposes the impacts of IDM on the MVFs. Section 6 discusses the results and section 7 summarizes the main findings.

2 The impact of intraday markets on the market value factors

The market value is defined as the market-based revenue that plant operators can earn. The value factor metric calculates the volume-weighted average revenue from a certain technology i . The resulting measure is referred to as the 'absolute' market value (MV) (Winkler et al., 2016). The 'relative' MV or MVF is expressed in percent by comparing the absolute MV to the average base price \bar{S} and is given by:

$$V_i = \frac{\bar{S}_i}{\bar{S}} \text{ where } \bar{S}_i = \frac{\sum_t S_t \cdot g_{t,i}}{\sum_t g_{t,i}}, \quad (2-1)$$

with $g_{t,i}$ the generation and S_t the market prices. Thus, the 'absolute' MV from a certain technology is compared to the average base price, which implicitly assumes a flat and non-variable production profile. Commonly in literature and in practice, the reference price to calculate the value factor V_i is the DAP (among others Hirth, 2013; Obersteiner and Saguan, 2011; Winkler et al., 2016). Traditionally, the DAP has been the reference price in electricity spot markets but the share of VRE and the relevance of the IDM are increasing (see Table 13). Hereby, the so-called imbalance spread is not included in (2-1) and would be calculated based on the difference between the DAP and the imbalance prices (IBP). As spot markets are generally defined as the markets for immediate delivery (cf. Hull, 2011), it seems logical to apply intraday instead of day-ahead information in Eq. (2-1) and calculate the imbalance spread based on intraday prices (IDP) and IBP. Though, the IDM is a subsequent market to the DAM and the DAM can be used for short term hedging, i.e. the scheduling of power plants with longer lead times. Hence, this article suggests to explicitly consider the imbalance spread in the MVF and to decompose the MVF as follows

$$V'_i = \frac{\bar{S}'_i}{\bar{S}} \text{ where } \bar{S}'_i = \frac{\sum_t (S_t^{DA} \cdot g_{t,i}^{DA} + S_t^{ID} \cdot (g_{t,i}^{ID} - g_{t,i}^{DA}) + S_t^{IB} \cdot (g_{t,i}^{IB} - g_{t,i}^{ID}))}{\sum_t g_{t,i}^{IB}}. \quad (2-2)$$

The index DA, ID and IB indicate the use of day-ahead, intraday or imbalance information. Eq. (2-2) takes the IDP to weight the forecast error or the flexibility provision ($g_{t,i}^{ID} - g_{t,i}^{DA}$). The denominator is the actual production.² As empirically observed and expected for efficient markets, the DAM and IDM market are on average free of arbitrage, such that $\bar{S}^{DA} \approx \bar{S}^{ID} \approx \bar{S}$. If DA, ID and IB information are applied in Eq. (2-2), V'_i is labelled V_i^{IB} . If the denominator in Eq. (2-2) is $\sum_t g_{t,i}^{ID}$ and $g_{t,i}^{IB} - g_{t,i}^{ID} = 0$, V'_i is called V_i^{ID} . If one neglects the deviation from the day-ahead schedule by setting $g_{t,i}^{ID} - g_{t,i}^{DA} = g_{t,i}^{IB} - g_{t,i}^{ID} = 0$ and uses $\sum_t g_{t,i}^{DA}$ as the denominator, V'_i is labelled V_i^{DA} . In this case, V_i^{DA} is equal to Eq. (2-1) based on day-ahead information.³

² IB quantities are thus not the quantities spilled into the IBM but synonymous to the actually realized production.

³ As indicated in Kallabis et al. (2016) or Beran et al. (2017) $g_{t,i}$ is a model output in the kind of fundamental model applied here. Thereby one may approximately count the number of times during which the demand falls into a certain demand interval (see section 3.13). For CEPs $V_i^{ID} \leq V_i^{IB}$ because the CEPs will probably provide the flexibility and earn additional margins. On the other hand, the IB stack is not modeled in the following and IB production for CEPs cannot be calculated.

The effects from intraday trading on MVF differ between technology types. While dispatchable assets are flexible in the sense that they may react to changes in market prices (flexibility provider) and hence may increase their revenues during the intraday trading, VREs are dependent on their respective renewable energy source (flexibility demanders), i.e. wind or solar are incentivized to maximize their electricity production if prices are not negative (see section 3.2). Figure 1 schematically summarizes the effects on the market value of VRE and CEP. Hirth (2013) points out that the market value of renewables is affected by three technology properties. First, the production of VRE depends on weather conditions. Due to the restricted potential to store electricity, this variability affects their market value. Since VRE infeed leads, other things being unchanged, to a decrease in the energy price ('merit order effect', among other see Sensfuß et al., 2008), they earn less than the base price. The effect of variability is labelled 'profile costs', 'utilization effect' or 'capture rate'. Second, due to the uncertainty of weather forecasts, the VRE production is uncertain until the delivery of electricity. Balancing these forecast errors is costly. Hence, balancing in the IBM and/or IDM reduces the MVF for VRE (first two bars on the left of the base price in Figure 1), but the trading in the IDM may increase the MVF for flexibility providing technologies (first bar on the right of the base price in Figure 1). Balancing energy costs for conventional power plants are related to outages that occur just before delivery. Third, VRE sites are usually geographically distant from load centres (e.g. due to better weather conditions or cheaper land) and their usage causes hence higher grid costs.⁴ Apart from cooling water restrictions or heat driven must-run demand, conventional power plants do not depend on weather conditions. Therefore, CEPs are not affected by profile costs and may be able to sell their flexibility in the IDM.

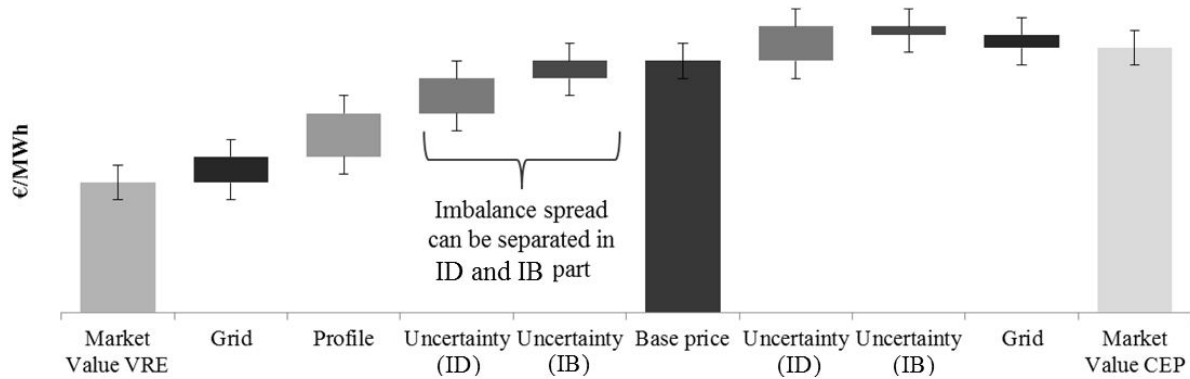


Figure 1: Different effects on the market value for VREs and CEP

Market participants with access to the IDM have the opportunity to use updated and more accurate forecasts during the intraday session to reduce their imbalance quantities or to increase revenues (among others Chaves-Ávila et al., 2013; Chaves-Ávila and Fernandes, 2015). Additionally, most electricity market designs incentivise the use of the IDM to avoid larger quantities in the IBM. In Germany, the IBM is based on a one-price system and the IBP is bounded by the average IDP depending on the grid situation at a certain point in time. This implies that deviations from the day-ahead schedule can - on average - be offset at lower costs in the IDM compared to the IBM. The smaller the time span between intraday gate closure and the IBM (delivery) is, the higher the chances to decrease the imbalance quantities. On the one hand, the forecast errors from VRE assets significantly decrease (in a non-linear form, among others Ahlstrom et al., 2013; Borggrefe and Neuhoﬀ, 2011; Holttinen et al., 2013; Kühnert, 2016; Larson et al., 2016) with time to delivery due to more accurate weather forecasts (Figure 2). On the other hand, if less time until delivery remains, the amount of assets that

⁴ This is not the case, if distributed generation at a low-voltage level reduces the net power exchange with the high-voltage network and if the grid operator pays compensations for so-called embedded benefits.

are able to up- or down-ramp their capacity decreases. Up-ramping capacity decreases due to the limitation coming from start-up or ramping times of conventional power plants. Down-ramp capabilities decrease due to down-ramping times and limited willingness to ramp down, e.g. due to (avoided) start-up costs or high minimum stable operation limits from thermal generation assets (Henriot, 2014). The IDM enables to reduce the imbalance exposure and assigns market based price signals to the flexibility needed in the system. The modelling of forecast errors and inflexibilities generation assets are subject in section 3.

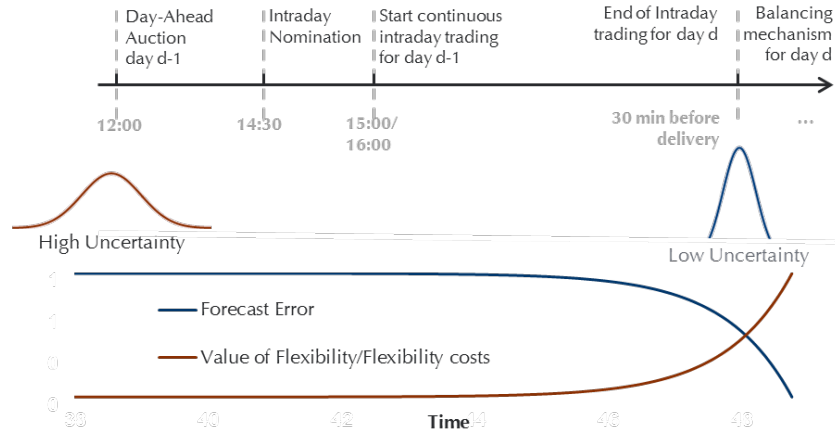


Figure 2: Intraday markets intensify system adaption prior to the IBM, cf. Bjørndal et al. (2016).

3 Methodology

The methodology aims to assess the impacts of different fundamental drivers on MVFs based on longer term simulation of DAPs and IDPs. The quantification of the impacts of the IDM on the market value of VRE furthermore requires an approximation of the imbalance exposure. Therefore, the final model combines and extends two existing models. The first part is a parsimonious modelling approach presented by Kallabis et al. (2016) which enables to model the electricity price level based on a piecewise linear bid stack. This model is extended to cover the peculiarities of the IDM as discussed by Pape et al. (2016). The major advantages of the linearized bid stack are, to quantify the shortening of the intraday merit order and to incorporate self-curtailment activities during times of oversupply. Figure 3 gives an overview about the modelling procedure.

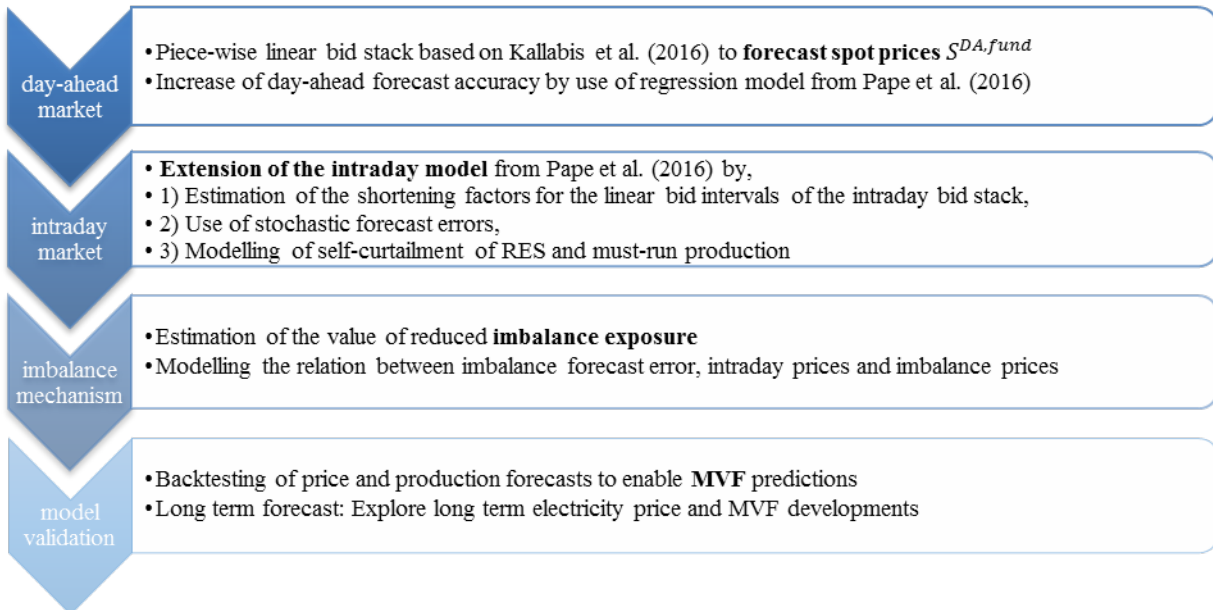


Figure 3: Overview of modelling steps and procedure

3.1 Basic Model

The modelling approach is based on a piece-wise linear approximation of the bid stack which uses a limited number of assumptions compared to so-called parameter-rich models (Weron, 2014). Instead of modelling every plant individually, $|I|$ different technology classes $i \in I$ are modelled. Thereby, differences in the efficiencies within a technology class are incorporated by assuming the heat rate (inverse efficiency) of each technology to be a linear function over the installed capacity, with $\eta_i \in [\eta_{i,\min}, \eta_{i,\max}]$. Thereby, $\eta_{i,\max}$ corresponds to the most efficient generation plant and $\eta_{i,\min}$ to the least efficient one (cf. Kallabis et al., 2016). Assuming cost-based bidding by the plant operators, the segments $b_{i,t}$ of the bid curve can be determined based on the variable costs, which include fuel and emission cost x_i derived based on the emission intensity e_i and heat rate η_i and other variable costs $c_{i,\text{other}}$. The bidding quantity equals the total available capacity $K_{i,\text{total}}$ adjusted by non-availabilities $v_{i,t}$ (e.g. maintenance). The bid curve is adjusted to account for must-run capacity from combined heat and power production $K_{i,t,\text{CHP}}$. In contrast to Kallabis et al. (2016) and Pape et al. (2016), the CHP must-run level is modelled as a linear function of the temperature (see Figure 9 in the Appendix). The bidding function describes the relation between capacities and electricity prices and thus delivers a bid quantity $b_{i,t}$ at given spot price S_t :

$$b_{i,t}(S_t) = \begin{cases} 0 & , \quad S_t < c_{i,\min} \\ K_{i,t} \cdot \frac{S_t - c_{i,\min}}{c_{i,\max} - c_{i,\min}} & , \quad c_{i,\min} < S_t < c_{i,\max}, \text{ with } K_{i,t} = K_{i,\text{total}} \cdot v_{i,t} - K_{i,t,\text{CHP}} \\ K_{i,t} & , \quad S_t > c_{i,\max} \end{cases} \quad (3-1)$$

As defined in Eq. (3-2), the demand for electricity, L_t is reduced by the variable renewable production of wind W_t and solar So_t with zero variable generation costs. Due to the modelling of the must-run generation from CHP, their capacity $K_{i,t,\text{CHP}}$ is subtracted as well. The net electricity exports are added to the domestic electricity demand. The foreign trade balance (FTB_t) is determined using a regression model (section 5.1).

$$D_t = L_t - W_t - So_t + FTB_t - \sum_I K_{i,t,\text{CHP}} \quad (3-2)$$

An increasing number of very low or negative residual demand levels due to an increasing share of RES can trigger curtailment activities from renewable technologies or from must-run assets. Therefore, the model from Kallabis et al. (2016) is extended by introducing additional intervals to $i \in I$ in Eq. (3-1) such that the adjusted bid stack covers $j \in J$ intervals. To implement potential curtailment from actively managed RES, one assumes curtailment thresholds at $c_{j,\min} < 0$ and $c_{j,\max} = 0$.⁵ The rationale is that subsidized renewable assets will not produce at prices below the negative of the subsidy payment. On the other hand, assets will drop out of the subsidy scheme in the next years and then do not have any incentive to produce at negative prices. The range for the self-curtailment of RES hence represents heterogeneity in support levels and risk aversion among market participants, e.g. windfarms operating with or without subsidy. The conventional must-run capacities have delivery obligations. Yet, negative electricity prices can provide economic incentives to reduce their production. The opportunity costs of providing heat through a heat-boiler can describe the curtailment threshold for heat driven must-run CHP. The curtailment intervals are bounded by the RES infeed and the must-run capacity, such that $K_{i,t}$ for those interval equals to W_t and $\sum_{j \in I} K_{j,t,\text{CHP}}$, respectively.

⁵ If $c_{j,\max} \geq 0$, a start of curtailment at positive prices is assumed and may reflect risk aversion due to IBP risks.

Pape et al. (2016) have shown that factors beyond pure fundamentals influence the spot price formation, in particular mark-ups during scarcity events or due to (avoided) start-up costs. Therefore, the regression model in Eq. (3-3) is applied to increase the accuracy for out-of-sample DAP predictions.

$$S_t^{DA} = c_1 + c_2 \cdot S_t^{DA,fund} + c_3 \cdot Ramp_t^{DA,Up} + c_4 \cdot Ramp_t^{DA,Down} + c_5 \cdot LSR_{low,t}^{DA} + c_6 \cdot LSR_{high,t}^{DA} + c_7 \cdot S_{t-1}^{DA,fund} + \omega_t \quad (3-3)$$

$S_t^{DA,fund}$ is the fundamental price estimate, c_n with $n = (1,...,7)$ are the regression coefficients and ω_t is an independently and identically distributed error term. The ramp-variables describe (avoided) startup-costs, the LSR variables (Load-Supply-Ratio) indicate market states with scarcities and the autoregressive component covers trading behavior. More information is found in Pape et al. (2016).

3.2 Intraday peculiarities and forecast uncertainties

The model defined in section 3.1 could be evaluated using intraday information, but the IDM is a subsequent market to the DAM and shows peculiarities. From a fundamental perspective, one expects that the bid curve in the IDM is steeper due to shorter lead times and inflexibilities and that the bid curve differs between up-ramping and down-ramping. In order to determine the up- and down-ramping potential (operating and non-operating) for the IDM, the marginal plant at the day-ahead gate closure is identified. Given the piecewise-linearized bid stack, the marginal plant is a point k_t on a linearized segment of the bidding function $b_t(S_t)$. The bidding function b_t is thereby defined as $b_t(S_t) = \sum_{j=1}^J b_{j,t}(S_t)$. The marginal plant k_t can be interpreted as an additional interval k_t with zero capacity within the range spanned by the intervals $j \in [1, ..., J]$. In the IDM, the bid stack is modified taking k_t as fix point to calculate the aggregated lower (down-ramp) part of the bid stack b_t^{down} and the upper (up-ramp) part of the bid stack b_t^{up} based on Eq. (3-4) and (3-5).

$$b_t^{down}(S_t) = D_t - \sum_{j=1}^{k_t-1} b_{j,t}(S_t) \quad (3-4)$$

$$b_t^{up}(S_t) = \sum_{j=k_t+1}^J b_{j,t}(S_t) \quad (3-5)$$

The lower part of the bid stack b_t^{down} consists of all capacities with $j < k_t$ that are online (running) before the intraday bidding to meet they day-ahead demand D_t^{DA} . The remaining capacity is offline and constitutes the upper part of the bid stack b_t^{up} . The shortening of the intraday bid stack b_t^{ID} may then be written as

$$b_t^{ID}(S_t^{ID} | S_t^{DA}) = [D_t^{DA} - b_t^{down}(S_t^{ID} | S_t^{DA}) \cdot (1 - s_{down})]^{S_t^{ID} < S_t^{DA}} + [D_t^{DA} + b_t^{up}(S_t^{ID} | S_t^{DA}) \cdot (1 - s_{up})]^{S_t^{ID} \geq S_t^{DA}} = D_t^{ID}. \quad (3-6)$$

As k_t depends on the DAP, the intraday bid stacks b_t^{down} and b_t^{up} are expressed conditional on the DAP ($\cdot | S_t^{DA}$) in Eq. (3-6). The factors s_{up} and s_{down} adjust the intraday bid stack to reflect inflexibilities of thermal power plants and other effects in the IDM. In contrast to Pape et al. (2016), the factors s_{up} and s_{down} adjust the linearized segments and not absolute capacities per power plant. By assuming that the market price contains most information about the supply and demand situation in the system, one can use observed IDPs to estimate the shortening of the intraday supply stack. Eq. (3-6) describes the functional relation of bidding capacities depending on the IDP. A modified version of this bidding stack may be used to determine the fundamentally expected intraday residual demand (produced from conventional power plants) as follows: $D_t^{ID,fund} = b_t^{ID*}(S_t^{ID})$.

Hereby, the shortening factors s_{up} and s_{down} are set to zero to determine a $D_t^{ID,fund}$ that reflects the residual demand that would correspond to the IDP without shortening, see Eq. (3-7).

$$D_t^{ID,fund} = b_t^{ID*}(S_t^{ID}) = [D_t^{DA} - b_t^{down}(S_t^{ID}|S_t^{DA})]^{S_t^{ID} < S_t^{DA}} + [D_t^{DA} + b_t^{up}(S_t^{ID}|S_t^{DA})]^{S_t^{ID} \geq S_t^{DA}} \quad (3-7)$$

$D_t^{ID,fund}$ may be determined based on the actual DAP (S_t^{DA}) or based on a DAP estimated from an application of the fundamental model to (estimated) day-ahead demand. This estimated DAP is labelled \widehat{S}_t^{DA} . For forecasts of future DAPs and IDPs, S_t^{DA} is not given and thus one uses \widehat{S}_t^{DA} for the estimation of s_{up} and s_{down} . For the estimation, one then compares the fundamentally expected residual demand to the actual residual demand. As the difference is related to the forecast error, a closer look at the intraday forecast error $FE_t^{ID,tot}$ and its possible decomposition is required.

The forecast error $FE_t^{ID,tot}$ determines whether up- or down-ramping is needed in the IDM. The smaller the time to delivery gets, the more certain the actual demand and production (see Figure 2). Thus, the highest forecast error is expected between the day-ahead position and the actual production. In absence of an IDM, the difference between the day-ahead demand D_t^{DA} and the actual (realized) demand D_t^{IB} would determine the position in the IBM ($FE_t^{DA,tot} = D_t^{IB} - D_t^{DA}$). Actually, the IDM exists and the forecast error given by $D_t^{ID} - D_t^{DA}$ can be traded intraday. Only the forecast error that occurs after the intraday gate closure will be balanced in the IBM ($FE_t^{IB,tot} = D_t^{IB} - D_t^{ID}$). The relation between the overall forecast error, the intraday forecast error $FE_t^{ID,tot}$ and the imbalance forecast error $FE_t^{IB,tot}$ may be written as follows:

$$FE_t^{tot} = FE_t^{ID,tot} + FE_t^{IB,tot} \quad (3-8)$$

The share of the forecast error that is traded in the IDM is expected to be higher if the time span between intraday gate closure and delivery gets smaller and/or if more market participants actively trade their positions intraday. From a fundamental perspective, each factor in Eq. (3-2) faces uncertainty and has its own forecast error. In practice, not all of the individual errors are observable for the system or official data is not available. In particular, the components $FE_t^{ID,tot}$ and $FE_t^{IB,tot}$ are not separable based on publicly available data. Therefore, the focus in the following is set on an analysis and decomposition of the total day-ahead forecast error in wind FE_t^W , solar FE_t^{So} , capacity FE_t^{Cap} and load FE_t^L forecast errors, see Eq. (3-9).

$$FE_t^{tot} = FE_t^{tot,obs} + FE_t^L + \epsilon_t \text{ with } FE_t^{tot,obs} = FE_t^W + FE_t^{So} + FE_t^{Cap} \quad (3-9)$$

Hereby, the forecast error is decomposed in an observable part $FE_t^{tot,obs}$, the not (well) observable load forecast error FE_t^L and a stochastic component ϵ_t which is different from Pape et al. (2016). The load forecast error FE_t^L is not (well) observable but is subject of various research. Among others Taylor and McSharpy (2007) or Hahn et al. (2009) state a RMSE for the load forecast errors around 1.9 to 2.7% of the expected load level. The observable part is further decomposed according to the sources of deviations: The forecast error of VREs (FE_t^W and FE_t^{So}) can be estimated based on historical day-ahead forecast and actual production data provided by the transmission system operators (TSOs). Prima facie the VRE errors (wind and solar) are unbiased and normally distributed $FE_t^W \sim N(0, \sigma_W^2)$ and $FE_t^{So} \sim N(0, \sigma_{So}^2)$ with variance σ_W^2 and σ_{So}^2 (possible correlation is investigated in section 5.3.1). The forecast error related to outages FE_t^{Cap} leads to additional demand in the IDM and is determined within the model based on carefully evaluated availability factors ($u_{i,t}$) for the DAM and IDM. To quantify $FE_t^{ID,Cap}$, one starts to solve the intraday model based on actual DAP and sets s_{down}

and s_{up} to zero. In this way, one compares the available intraday capacities with the expected day-ahead availabilities. $FE_t^{ID,Cap} := [D_t^{DA} - b_t^{ID}(S_t^{DA})]^+$ delivers the forecast error related to outages and uses the underlying assumption that additional supply from thermal power plants is unlikely to be activated during the intraday session if they have not been scheduled day-ahead. Strictly positive values ensure that capacity only fails if it exists. Outages after the day-ahead gate closure represent a shortening of the lower part of the bid stack b_t^{down} and are modelled explicitly (cf. section 3.1). For the upper part of the bid stack b_t^{up} availabilities can de- or increase, but increases are unlikely to happen, due to the decreasing time to delivery. After having defined $D_t^{ID,fund}$ and $FE_t^{ID,tot}$ one can continue and introduce ϕ_t as the difference between fundamental and actual residual demand in the IDM D_t^{ID} , whereby $D_t^{ID} = (D_t^{DA} + FE_t^{ID,tot})$ and then ϕ_t is given by Eq. (3-10)

$$\phi_t = D_t^{ID,fund} - D_t^{ID} = b_t^{ID*} \left(S_t^{ID} | \widehat{S}_t^{DA} \right) - \widehat{D}_t^{ID} - \gamma_t. \quad (3-10)$$

b_t^{ID*} in Eq. (3-10) describes the unadjusted intraday supply stack with $s_{up} = s_{down} = 0$ as used in Eq. (3-7) to determine $D_t^{ID,fund}$. \widehat{D}_t^{ID} is an observable proxy to the residual demand traded in the intraday market. Here the actual residual demand is taken and any difference related to $FE_t^{IB,tot}$ is included in the error term γ_t . So this equation allows to determine an observable proxy to the difference between the residual load without shortening and the actually observed residual load. Applying the definitions of Eqs. (3-6) and (3-7) one gets:

$$\phi_t = \left[-s_{down} \cdot b_t^{down} \left(S_t^{ID} | \widehat{S}_t^{DA} \right) \right]^{S_t^{ID} < \widehat{S}_t^{DA}} + \left[s_{up} \cdot b_t^{up} \left(S_t^{ID} | \widehat{S}_t^{DA} \right) \right]^{S_t^{ID} \geq \widehat{S}_t^{DA}} \quad (3-11)$$

By combining Eqs. (3-10) and (3-11) one can estimate the shortening factors based on the supply stacks b_t^{down} and b_t^{up} . If one assumes, that the error term, which is included here in Eq. (3-10) is independent of the observed respectively constructed variables, OLS delivers unbiased estimates of s_{up} and s_{down} .

Among others, Just and Weber (2015) highlight the challenge of modelling the IBM due to a possible disconnect between spot market, reserve capacity market and the IBM. Thus, a sophisticated model for imbalance prices and quantities is out of the scope of this article. However, to understand the impacts of IDM on the market value of VRE, the interaction with the IBM has to be acknowledged (Hirth, 2013; Neuhoff et al., 2013; Weber, 2010). The IBP formation is non-linear and potentially asymmetric. The main driver for the IBM outcome is the forecast error $FE_t^{IB,tot}$ as it determines if additional up- or down ramping (reserve) capacity is needed. In contrast to Just and Weber (2015), a simplified linear formulation for the IBP S_t^{IB} is used

$$S_t^{IB} - S_t^{ID,fund} = v_1 \cdot [FE_t^{IB,tot}]^+ + v_2 \cdot [FE_t^{IB,tot}]^- + \epsilon_t^{IB}. \quad (3-12)$$

Eq. (3-12) accounts for potentially asymmetric dependencies in the imbalance price formation if up- or down ramping is required.⁶ The forecast error for the individual VRE is given by Eq. (3-9) and Eq. (3-8).

⁶ In contrast to Just and Weber (2015), we do not use quarter-hourly data but model the link between the average hourly IB error and the corresponding average IBP (ReBAP: standardized price for balance energy). For hourly values no discontinuity in the IBP for decremental and incremental balancing demand is observed (cf. Figure 7 in the Appendix). Instead of Eq. (3-12), a specification similar to Just and Weber (2015) would be $S_t^{IB*} = (v_{0,1} \cdot -\mathbb{1}_{\{FE_t^{IB,tot} < 0\}} + v_1 \cdot [FE_t^{IB,tot}]^+ + v_{0,2} \cdot \mathbb{1}_{\{FE_t^{IB,tot} > 0\}} + v_2 \cdot [FE_t^{IB,tot}]^-) + S_t^{ID,fund}$. But here the coefficients for $v_{0,1}$ and $v_{0,2}$ are not significant when estimated with data from 2012 until 2015.

4 Data

The dataset for the estimation and model validation covers the years 2012 until 2015. The reference for the intraday model is the weighted average IDP during the last three hours before delivery (ID3 index as defined by the EPEX spot).⁷ The base scenario for the longer term forecast is mostly aligned on the scenario B from the 2016 grid development plan (NEP) for 2030 (50 Hertz Transmission GmbH et al., 2017). This scenario assumes a medium speed of transformation towards 100% RES and a medium intensity of innovations. Hereby, the VRE additions are based on the corridors defined in § 3 EEG 2017 (German renewable energy Act). The solar capacity additions are reduced from a level of 52 GW onwards due to the flexible cap ('atmender Förderdeckel') which equals roughly 10% of the electricity production in the base case. The main drivers for RES addition are wind onshore and offshore. EU-ETS prices are assumed to increase and are accompanied by other actions to support RES. Table 1 summarizes the data sources and the method to determine expectations. Table 2 compiles the historical values and the inputs for Base Case 2030.

The regression model for the FTB_t is slightly adjusted compared to Kallabis et al. (2016). On the one hand, the production from wind onshore and offshore sites is expected to influence the cross-border trades differently. All offshore facilities feed into the grid in the northern part of Germany whereas onshore is more dispersed across the country. On the other hand, the regressor for the available nuclear capacity is combined with the available lignite capacity due to the nuclear phase-out in Germany after 2022. Additionally, two dummies are designed to describe the typical plant behaviour. In line with Karakatsani and Bunn (2008), the intuition is that power plants ramp-up in the morning for the morning peak and tend to stay online to benefit from the evening peak. Therefore, the super peak dummy includes the hours from 9 am to 10 am and 5pm to 8pm on weekdays and the sun peak dummy covers hours from 11 am to 4 pm.⁸ The estimates for the FTB regression can be found in Table 3.

$$FTB_t = \alpha_0 + \alpha_1 L_t + \alpha_2 W_t^{Onshore} + \alpha_3 W_t^{Offshore} + \alpha_4 P_t + \alpha_5 (K_{lignite,t} + K_{nuclear,t}) + \alpha_6 Superpeak_t + \alpha_7 Sunpeak_t \quad (4-1)$$

The lower curtailment threshold for actively managed wind assets is set to -49 EUR/MWh implying an assumed average subsidy payment at 49 EUR/MWh, i.e. if the electricity price would decrease to -49.5 EUR/MWh and the subsidy payment would be at 49 EUR/MWh, subsidized assets would lose -0.5 EUR/MWh and are incentivized to curtail their production. The upper curtailment threshold is at 0 EUR/MWh. The resulting linear interval reflects heterogeneous risk aversion against negative prices of subsidy-backed and merchant wind generation.⁹ The curtailment thresholds ($c_{j,min}$ and $c_{j,max}$) for the must-run CHP are set to -50 and -100 EUR/MWh reflecting opportunity costs for the use of a heat boiler to deliver heat and/or contractual penalties if no heat is delivered to the counterparty.

⁷ Due to the continuous nature of the IDM, more than one IDP exists in Germany. The ID3 index represents the latest information before delivery and is less sensitive to outliers than last, high or low prices.

⁸ In contrast to Kallabis et al. (2016), the FTB predictions are modelled endogenously. Therefore, the exchange flows are restricted to the net transfer capacity (NTC) values reported in the NEP. Across all transmission lines, electricity exports from Germany are restricted to -32'101 MW and imports to 36'100 MW. Due to the change to flow-based market coupling in CWE, a sensitivity analysis is done for the FTB to check the robustness of the modelling approach.

⁹ To incentivize self-curtailment of subsidy-backed assets in times of negative prices in Germany, no subsidy is paid in times of six or more consecutive hours of negative prices (cf. § 51 EEG: German Renewable Energy Act). The effects on the cash flow of a wind farm without curtailment is shown in the appendix, Figure 8

Table 1: Data sources and methods used for the base case expectations

<i>Data</i>	<i>Source</i>	<i>Specification</i>	<i>Expectations</i>
Load	entsoe.eu	Hourly load values	Adjusted historical Profile
Demand	iea.org/statistics	Energy Supplied	netzentwicklungsplan.de
Electricity Price	energate.de	Phelix Futures Base	netzentwicklungsplan.de
Imbalance Price	tennetso.de	ReBAP	Regression analysis
Coal Price	ditto	API#2 (CIF ARA)	ditto or last quoted product
CO ₂	ditto	EU Allowances (EUA)	ditto
Gas price	ditto	Gas-TTF	Ditto
Wind and solar	eex-transparency.com	Ex-ante and ex-post production	Standardized Profiles from Öko Institut and ForWind GmbH (2016) calibrated to full load hours based on netzentwicklungsplan.de ¹⁰
Unavailability	ditto	Non-usability	Extrapolation (see Kallabis et al., 2016)
Cross Border Flows	transparency.entsoe.eu	Commercial Schedule	Regression analysis and NEP NTCs (cf. p. 98) as upper and lower limits
Capacities	BNetzA.de	Production capacities	netzentwicklungsplan.de
CHP production	Ditto	Electricity production	Similar to Kallabis et al. (2016)

Table 2: Historical values and input assumptions basically representing the NEP Scenario B and C for 2030 (*Mean of the ID3 index based on own calculations 2012, 2013, 2014)

<i>Information</i>		<i>Actual</i>	<i>Actual</i>	<i>Actual</i>	<i>Actual</i>	<i>Base</i>	<i>Altern.</i>				
<i>Year</i>		<i>2012</i>	<i>2013</i>	<i>2014</i>	<i>2015</i>	<i>2030</i>	<i>2030</i>	<i>Min_eta</i>	<i>Max_eta</i>	<i>c_other</i> €/MWh	<i>Emission</i>
Coal Price	€/MWh	10.5	8.8	8.1	7.3	12.0	11.6				
Gas Price	€/MWh	27.4	29.3	23.5	22.2	32.0	31.0				
EUA	€/t	7.7	4.6	6.1	7.7	22.0	28.0				
Demand	TWh	572	565	546	567	540	530				
FTB	TWh	-20.5	-34.3	-35.6	-55.5	-	-				
Wind (onshore)	TWh	50.7	51.7	57.4	88.3	82.5	68.3				
Wind (offshore)	TWh	0.5	0.7	1.1	8.0	55.0	45.5				
Solar	TWh	26.4	31.0	36.0	38.4	54.0	52.4				
Biomass	GW	5.6	6.4	6.8	6.8	7.4	7.4	-	-	-	-
Gas (CC)	GW	21.7	20.8	23.0	23.0	20.8	20.2	40%	60%	1.2	
Coal	GW	26.2	25.6	25.5	25.5	18.3	14.7	30%	46%	2.5	0.34
Lignite	GW	20.5	21.5	21.3	21.3	10.3	9.4	29%	43%	2.0	0.4
Miscellaneous	GW	4.0	4.8	4.3	4.3	3.5	3.3	-	-	-	-
Nuclear	GW	12.1	12.1	12.1	12.1	0.0	0.0	33%	36%	0.5	-
Gas (OG)	GW	9.5	9.1	10.1	10.1	9.0	8.8	25%	36%	1.2	0.2
Oil	GW	3.9	4.1	3.8	3.8	1.0	1.1	24%	44%	1.2	0.26
PSPH, RRH	GW	10.8	11.0	10.7	10.7	16.4	16.2	-	-	-	-
Base Day-ahead	€/MWh	42.6	37.8	32.8	31.6	-	-				
Base Intraday*	€/MWh	43.9	38.4	33.0	31.6	-	-				

¹⁰ Sensitivity analysis based on historical profiles from 2015 deliver no significant changes in the results.

Table 3: Estimation results for the FTB regression based on data 2015

α_0	Intercept	16'161.38***	R-squared	0.60
α_1	demand [MW]	0.04***	Adjusted R-squared	0.60
α_2	wind Onshore [MW]	-0.18***	S.D. dependent var	2742.05
α_3	wind Offshore [MW]	-0.27***	Observations (2015 only, due wind offshore data)	8753
α_4	solar [MW]	-0.23***	Durbin-Watson statistic	0.18
α_5	available base plants [%]	-0.81***	Significances are computed using standard errors obtained through the Newey-West procedure. Significances at the 0.01 level are labeled with ***, at the 0.05 level with ** and at 0.1 level with *.	
α_6	super peak	781.18***		
α_7	sun peak	-36.97***		

5 Results

In section 5.1, the results of the econometric estimation is presented. Then, the modelling equations for electricity prices and MVFs are validated using data from the period 2012 to 2015 (cf. section 5.2). Finally the results on the future development of MVFs and the main driving forces are presented in section 5.3.

5.1 Estimation

Due to better data availability and an increasing maturity of the IDM, the years 2014 and 2015 are used to determine the DAP regression results, the forecast errors and to evaluate the shortening factors of the ID model. Table 4 summarizes the estimation results for the DAP regression model which are in line with the results obtained for earlier years in Pape et al. (2016).

Table 4: Estimation results from the multiple regression model to increase the accuracy of DAP forecasts

c_0	intercept	5.236***	R-squared	0.766
c_1	fundamental price	0.868***	Adjusted R-squared	0.766
c_2	ramp up	0.346***	F-statistic	9'540.833
c_3	ramp down	-0.060**	Probability (F-statistic)	-0.000
c_4	LSR low	-8.630***	Mean dependent variable	32.195
c_5	LSR high	2.219**	S.D. dependent variable	11.142
c_6	AR	-0.006***	Observations	17514
			Durbin-Watson statistic	0.419

Significances are computed using standard errors obtained through the Newey-West procedure. Significances at the 0.01 level are labeled with ***. For the applications, the ramp-Variables in Eq. (3-3) are calculated based on $H = 4$ hours (see Pape et al., 2016)

For wind, the RMSE per unit of energy produced ranges between 17% and 19% and for solar between 16% and 20%. Recently, entsoe.eu (2017) started to publish load forecast data. The estimates based on ENTSO-E data are similar to the RMSEs reported in the literature and range between two and three percent. This percentage is significantly lower than the one for VRE since weather uncertainties have less impact on load and since the aggregate load is formed from a high number of end-users with heterogeneous error profiles. Table 5 shows the RMSEs used for the application. Low correlation coefficients and an absence of significance in the test for variance inflation for the wind and solar forecast errors support the assumption of uncorrelated error distributions.¹¹

¹¹ The variance inflation factor measures the impact of multicollinearity on an OLS regression, i.e. quantifies the increase in the variance of the regression coefficient due to collinearity (cf. e.g. Assenmacher (2002)).

Table 5: Day-ahead forecast error from load, wind and solar 2012 to 2015

RMSE in GW	load (DA)	wind (DA)	solar(DA)	balancing energy
2012	2.00	0.96	1.03	0.91
2013	1.96	1.14	1.27	0.71
2014	1.91	1.18	1.28	0.50
2015	1.98	1.75	1.23	0.45
\emptyset annual value [GW]	54.2	7.1	3.8	53.3
RMSE [% of annual average]	$\sigma_L = 2.5\text{-}3.0\%$	$\sigma_W = 17\text{-}19\%$	$\sigma_{So} = 16\text{-}20\%$	$\sigma_{IB} = 0.9\text{-}1.6\%$

The estimates for the shortening factors as described in section 3.2 are reported in Table 6. The shortening factors show the expected signs. Their magnitudes differ for the upper and lower part of the bid stack indicating that the willingness and/or ability to provide up- and down ramp flexibilities differ.

Table 6: Estimation results of the reverse-engineering based on observed intraday prices 2012-2015.

	off-peak	peak	R-squared	0.470
s_{down}	0.128***	0.120***	F-statistic	5'215
s_{up}	0.154***	0.166***	S.D. dependent variable	6'639
			Observations	17'518
			Durbin-Watson statistic	0.740

Imbalance prices and quantities in Germany are published with a two months delay in quarter hourly granularity. To estimate the parameters from Eq. (3-12), hourly average prices are used and two percent of the dataset 2012-2015 (35'062 observations) are considered as outliers to avoid an overestimation of the imbalance costs in the long term forecasting.¹² The corresponding results are reported in Table 7.

Table 7: Estimation results IBP regression based on data 2012-2015

v_1	impact negative error [MW]	0.045***	R-squared	0.486
v_2	impact positive error [MW]	0.049***	Adjusted R-squared	0.494
			S.D. dependent var	31.494

5.2 Validation

The models by Kallabis et al. (2016) and Pape et al. (2016) are validated based on futures data from 2007 to 2014 respectively are based on spot market data from 2012 until 2013. The validation period for the model developed in this article covers 2012 to 2015. Within the validation period, the DAM model explains 67.3% of the price variance. In combination with the DAP regression model, it captures almost another 4.5% reaching an overall explained variance of 71.8%. If the intraday model uses the DAP from the day-ahead model combined with the DAP-regression approach, the intraday model explains 73.5% of the IDP variance with a MAE at 5.88 EUR/MWh for 2012 until 2015. The model estimation is based on data from 2014 until 2015 (cf. section 5.1). Therefore, the in-sample results for these years indicate lower MAEs at 4.78 and 5.26 EUR/MWh based on the DAP regression approach (Eq.(3-3)). By means of the DAP as starting point for the intraday model, the explained variance is at 82.7% and the MAE decreases to 4.51 EUR/MWh for 2012 until 2015 (for 2014 and 2015 the MAEs are at 3.98 and 4.04 EUR/MWh). Figure 10 and of Figure 11 in the appendix show further performance measures evaluated on an hourly scale and the probability density function (pdf) of prices. The production amounts are verified based on monthly and yearly data from 2012 to 2015 (see appendix,

¹² Outliers are replaced by the value of the 1% (-162.98 EUR/MWh) and 99% (-151.59 EUR/MWh) quantile.

Figure 12). An extensive verification of the production quantities for the DA model is found in Beran et al. (2017). The resulting MVFs are compared to the historical observations in Figure 4 and in Table 8. Despite its parsimonious nature, the model delivers notable results with deviations measured as MAPE for the base price $< 1\%$, for the Wind MVF (WMVF) at 1.5 to 2.5% and for the Solar MFV (SMVF) between 4 and 5%.

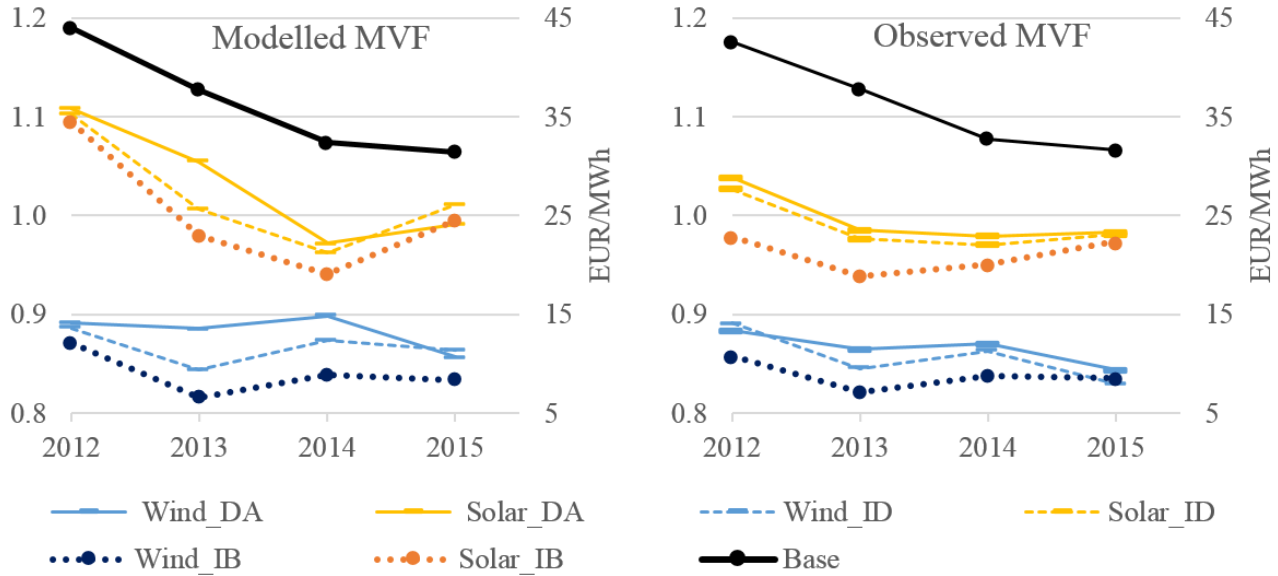


Figure 4: Comparison of observed and modelled MVF (DA: day ahead Eq. (2-1), ID: including intraday market, IB: including imbalance Eq.(2-2)) and base prices (right axis) in EUR/MWh 2012 until 2015.

Table 8: Comparison of observed and modelled MVF

	Modelled				Observed			
	2012	2013	2014	2015	2012	2013	2014	2015
V_{wind}^{DA}	0.911	0.900	0.901	0.867	0.883	0.865	0.870	0.844
V_{solar}^{DA}	1.107	1.054	1.012	1.011	1.039	0.986	0.979	0.983
V_{wind}^{ID}	0.891	0.861	0.888	0.860	0.891	0.845	0.863	0.830
V_{solar}^{ID}	1.101	1.025	0.995	0.990	1.027	0.976	0.970	0.981
V_{wind}^{IB}	0.877	0.829	0.847	0.823	0.858	0.822	0.838	0.835
V_{solar}^{IB}	1.070	0.987	0.950	0.990	0.978	0.938	0.950	0.974
Base EUR/MWh	44.5	37.4	32.4	32.0	42.6	37.8	32.8	31.6

It is assumed that 66.67% of the forecast error from each factor in Eq. (3-9) is traded intraday.¹³ The remaining 33.33% are spilled to the IBM. Table 9 shows a break-down of the WMVF and the SMWF into their components (cf. Figure 1). The profile costs for wind are around 14-16% in 2015. At the same time solar has low ($< 2\%$) profile costs. Even though a high share of the forecast error is balanced intraday (66.67% of the forecast error), the discount on the MVF for the IBM is larger than the discount due to intraday trading (ID uncertainty $<$ IB uncertainty, see Table 9). The counter-factual case in Table 9 assumes that the complete forecast error is spilled to the IBM and that no IDM exists. In this case, one neglects a potentially worsening effect on IBPs if higher errors are spilled to the IBM ($[ID \text{ uncertainty} + IB \text{ uncertainty}] < IB \text{ uncertainty}$,

¹³ The traded amount depends on various factors and varies between markets, technologies, regional deployment and behaviors of market participants. Hence, the assumption reflects an average value derived from the literature.

counter-factual). Even under such conservative assumptions, the VRE pay 0.25 to 1.40 EUR/MWh more if no IDM exists; this equals annual costs of circa 92 M EUR (76/83/91/118 M EUR in 2012/2013/2014/2015). Based on the model validation, it can be concluded that the model accurately predicts prices, quantities and MVF for the German spot market and that it provides a sound basis for longer term modelling.

Table 9: Different effects on the market value for VREs (2012 until 2015)

MVF Component (Observed MVF)	Wind				Solar			
	2012	2013	2014	2015	2012	2013	2014	2015
Profile Costs	+0.117	+0.135	+0.130	-0.039	-0.039	+0.014	+0.021	+0.017
Intraday Uncertainty ($V_i^{ID} - V_i^{DA}$)	+0.008	-0.020	-0.007	-0.014	-0.012	-0.009	-0.009	-0.002
Imbalance Uncertainty IB ($V_i^{IB} - V_i^{ID}$)	-0.033	-0.024	-0.025	+0.005	-0.049	-0.038	-0.020	-0.008
IB Uncertainty, counter-factual ($V_i^{IB} - V_i^{DA}$)	-0.042	-0.065	-0.057	-0.021	-0.092	-0.056	-0.048	-0.017

5.3 Decomposing the impact on market value factors

5.3.1 Development of variable renewable energies

The parsimonious nature of the model allows a systematic analysis of different influencing factors in a ceteris paribus a framework. The following table summarizes the results for the base case as presented in section 4. This base case serves as starting point for further analysis. Additionally, Table 10 shows the impact if different shares of the forecast error are balanced in the intraday market.

Table 10: Market value factors (MVF) per VRE technology in 2030 and for different level of IDM usage

		VRE				Prices [EUR/MWh]			
	m*	Wind	Onshore	Offshore	Solar	Base	Peak	Offpeak	Std.
Day-Ahead: V_i^{DA}		0.77	0.75	0.81	0.97	49.11	61.96	41.96	26.27
2/3 Intraday (1/3 IB)	m=2/3	0.67	0.64	0.71	0.87	48.85	61.69	41.71	27.12
$V_i^{IB} - V_i^{DA}$ with m=2/3		-0.11	-0.11	-0.10	-0.10	-0.26	-0.27	-0.25	0.85
Full Intraday (No IB)	m=1	0.74	0.74	0.74	0.93	48.70	61.48	41.60	27.97
$V_i^{IB} - V_i^{DA}$ with m=1		-0.03	-0.02	-0.07	-0.04	-0.41	-0.49	-0.36	1.70
No Intraday (Full IB)	m=0	0.04	-0.13	0.29	0.35	-	-	-	-
$V_i^{IB} - V_i^{DA}$ with m=0		-0.74	-0.88	-0.52	-0.62	-	-	-	-

*m: Share of the FE_t^{tot} that is traded intraday; $FE_t^{ID,tot} = FE_t^{tot} \cdot m$ and $FE_t^{IB,tot} = FE_t^{tot} \cdot (1 - m)$

The base price is at circa 49 EUR/MWh and the day-ahead model predicts slightly higher base prices than the ID model. At a market share of electricity production around 25% (15% onshore and 10% offshore), the WMVF is at 0.77. Onshore wind has the highest market share from the VRE in the base case and this induces a circa 6 percentage points lower V_i^{DA} for onshore compared to offshore wind.¹⁴ The SMVF is at circa 0.97 at 10% market share. Due to short lead times and the efforts of market participants to balance their forecast errors, the standard deviation of IDPs is almost 1 EUR/MWh higher than for the DAP.¹⁵ The VREs demand flexibility in the IDM and IBM and lose around 10-11 percentage points. Hereby one assumes that only two thirds of the wind and solar forecast error FE_t^{tot} (m=2/3) are traded in the IDM. If the complete forecast error is traded in

¹⁴ Another reason for higher MVF of offshore is a higher coefficient in the FTB regression, such that high offshore penetration tends to increase exports and stabilizes prices during times of high offshore supply.

¹⁵ Due to computational burden, the sampling for the intraday model was restricted to 750 paths.

the IDM ($m=1$), the MVF for the VRE is higher (WMVF 3 and SMVF 4 percentage points) compared to the situation where only 66.67% of the forecast error is traded intraday and the remaining 33.33% of the forecast error is spilled into the IBM. If we assume on the contrary that the IDM cannot be used ($m=0$) the SMVF drops to 35% and the WMVF to 4%. The onshore WMVF even gets negative, which would imply higher balancing costs than market revenues.¹⁶

For the base case, the share in electricity production is at 15% for onshore wind and at 10% for offshore wind.¹⁷ The overall base price level decreases under ceteris paribus conditions by circa 20 EUR/MWh if the wind market share increases by 30 percentage points (cf. Figure 5 and Figure 13 left). V_i^{DA} indicates profile costs for wind (offshore and onshore) around 20 to 27% for low market shares and around 61 to 66% at high market shares (Figure 5, left). With increasing market shares of the electricity production, the wind error tends to drive the IDP and IBP, which in turn increases the costs to balance their position after the DAM gate closure. With increasing share of wind production, the solar assets can stabilize their revenues in the IDM by gaining from high prices during hours in which the wind error causes IDP to move into a beneficial direction for solar based production. Solar assets also benefit from the reduced magnitude and number of negative prices due to self-curtailment of wind assets and must-run production assets. However, the leverage from additional solar capacities is limited due to the fact that solar production only impacts electricity prices during day times and due to the flexible cap at 52 GW (see Figure 5, right and Figure 13). A doubling of the 8% market share of solar production reduces the base price by 5 EUR/MWh. At high markets shares, the profile costs for solar may raise up to 35% and the imbalance and intraday costs up to another 10% compared to less than 5% at low market shares. A sensitivity analysis with respect to the correlation of forecast errors shows increasing MVFs for VRE for negative correlation and vice versa decreasing MVFs in case of positive correlation (cf. Table 11). Increasing positive or negative correlation has the highest impact on the SMVF.¹⁸

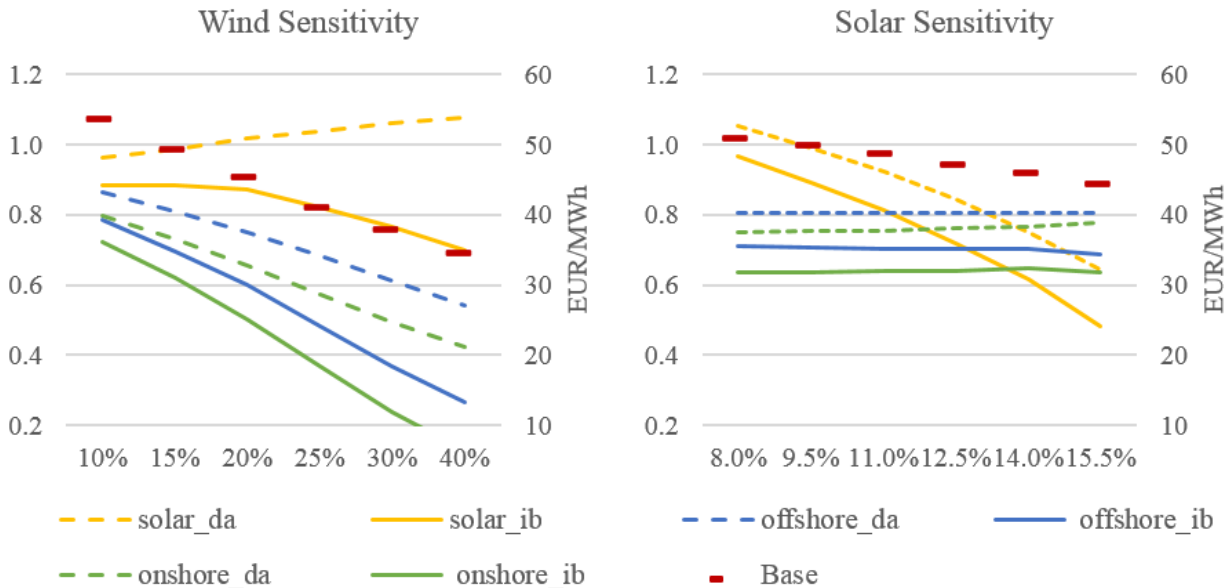


Figure 5: MVF of VEP and base prices for different level of VRE share of production (wind, left; solar, right).

¹⁶ $m=0$ and $m=1$ may overestimate the impact of no or full ID trading, because the model was calibrated based on $m=2/3$.

¹⁷ For the sensitivities, one assumes that the proportion from offshore wind increases with increasing wind production.

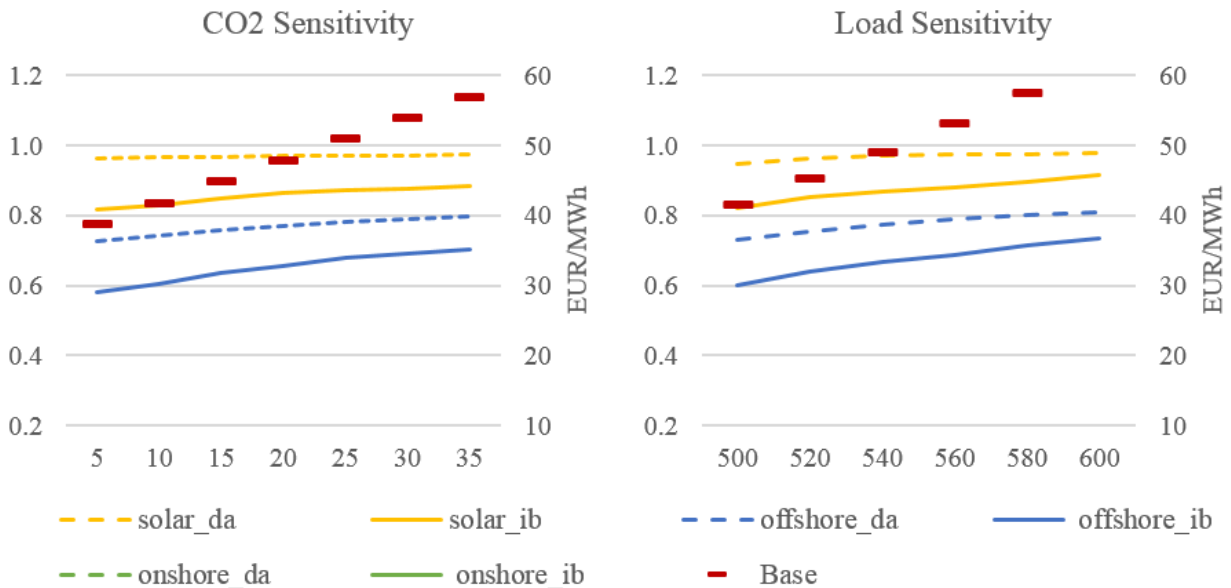
¹⁸ Figure 13 in the appendix shows the MVFs for CEPs. CEPs are able to realize additional intraday revenues at wind market shares above 20%. Although cheaper RES production shifts them to the right in the bid stack, their revenues measured relative to the base price increases due to increasing intraday scarcity. In contrast, CEPs do not profit from high market shares of solar production in the IDM because solar assets tend to produce at peak times and cannibalize return for CEPs in these hours.

Table 11: Analysis of changing correlation between forecasts error of VRE and decreasing load error

Impact on:	Unit	Base case	Correlation			
		ID	-0.5	-0.25	+0.25	+0.5
Δ onshore WMVF	/	0.64	+0.010	+0.002	-0.007	-0.007
Δ offshore WMVF	/	0.70	+0.010	+0.003	-0.006	-0.008
Δ SMVF	/	0.86	+0.024	+0.011	-0.013	-0.021
Δ base	EUR/MWh	48.85	-0.010	+0.005	+0.009	-0.152
Δ peak	EUR/MWh	61.96	-0.002	+0.070	+0.084	-0.176
Δ offpeak	EUR/MWh	41.96	-0.014	-0.031	-0.033	-0.140

5.3.2 Development of emission prices and system demand

The impacts from emission costs on the electricity prices tend to decrease in a decarbonized energy system, i.e. if less CO₂-emitting production assets set the electricity price. Yet, emission intensive technologies will persist in the European energy mix for some decades and VREs would benefit from higher emission prices. Like all infra-marginal plants, VREs earn additional carbon rents if the emission price increases and the price-setting technology is pricing in the additional costs in their bidding (Möst et al., 2016; Pahle et al., 2011; Veith et al., 2009)¹⁹. In this context, the marginal (price-setting) plant does not profit from higher emission prices but has higher costs of production. Since the base price and the absolute market value are increasing, the relative MVFs, as shown in Figure 6, only slight improve for VRE. The impact of changing emission prices is equally strong for the DAM and IDM, thus high and stable emission prices could incentivize investments in assets with low emissions or even market-based RES additions.²⁰ An analysis of changes in other input commodity prices is shown in the appendix in Figure 14. The demand in the system is a further sensitive factor impacting every hour whereas fuel and emission prices only show an effect if the respective technology is setting the price. Higher load increases the base price and has similar impact on the MVF as raising CO₂ prices.

Figure 6: MVFs and base prices for different level of CO₂ prices (left) and load (right)

¹⁹ Müsgens (2016) shows that windfall profits occur at high emission prices and stimulate investments in low emission technologies.

²⁰ On the empirical interaction effect of RES additions and emission prices see among others Rathmann (2007); Van den Bergh, K. et al. (2013); Koch et al. (2014); Kallabis et al. (2016).

6 Discussion

The modelling results underline the aforementioned need for MVF analysis to go beyond pure profile cost investigations based on day-ahead information. To accurately model the development of the market value of VREs, two aspects are relevant. On the one hand, the imbalance costs have to be reflected in the MVF to assess the profitability of VRE. On the other hand, going beyond day-ahead information means to consider intraday optimisation potentials to mitigate the imbalance risk exposure in the MVF metric (see section 2). Despite the shortening of the intraday bid stack, it is shown that the balancing of forecast errors in the IDM is preferable compared to the use of the IBM. VREs - on average - face lower risks if they balance their forecast errors in the IDM rather than relying on the IBM and this allows additional revenues for flexibility providers (CEP) even if they may face additional costs to activate their flexibility. The model validation for the years 2012 until 2015 illustrates that the development of the German IDM is one major element why imbalance energy demand did not increase, even though increasing amounts of RES have been added to the system ('German imbalance paradox', cf. Hirth and Ziegenhagen, 2015; Ocker and Ehrhart, 2017), i.e. generation assets with sufficient flexibilities are available and prices in the IDM incentivise to deliver this flexibility to the system. The longer-term development may however differ. Table 12 shows a comprehensive summary of the longer-term impacts.

Table 12: Comprehensive summary of main drivers and impacts on Base prices and MVF

Driver	Impact of an increase	Base price	MVF VRE	MVF CEP	ID specific impact	Possible action to mitigate risks
RES penetration	- Replacement of conventional capacity in the long run - Cannibalization	-	--	+	- Simultaneity effect - Market 'dominance'	- Diversification
CO₂ price	- Changing bid stack - windfall profits	+	+	-	”	- Regulation of emission quantities and/or price or consistent RES regulation
Fuel prices	- Steeper bid stack	+	+	++	- Fuel switch	/
Load	- Less oversupply - Less negative price risk	++	°/+	--	- Load shifting or load shedding	- Support of demand side management (DSM)
Flexibility (ID)²¹	Mitigate risk of higher RES penetration	°	+	+	- Stabilizing effect on MVF	- Self-curtailment - intraday market design

In line with other literature, this article shows decreasing MVFs of VREs at higher shares of installed renewable capacities due to increasing profile costs (sometimes called 'cannibalization effect'). Over and above the latest analyses in the literature, this article has shown that balancing risk can be mitigated by use of the IDM. The longer term modelling results lead to the conclusion that the imbalance paradox may disappear if the VREs breach a critical threshold for the market share and if system adaptations do not happen simultaneously. I.e. in line with Huber et al. (2014), it is expected that the situation for certain VREs worsens if they dominate the market. Market dominance means that one technology type has such a high market share that its error outweighs the forecast errors of other technologies and that the technology type becomes a permanent price-maker in the IDM. While other technologies occasionally benefit from electricity price movements in the opposite of their own forecast error position, this is not the case for the dominating VRE

²¹ The results of an analysis about changes in available flexibility is summarized in the appendix in Table 14, e.g. if no shortening of the ID bid stack is considered²¹. This would imply higher flexibility provision in the IDM. The opposite occurs if the flexibility of the windfarms is reduced in the sense that they do not down-ramp during times of negative prices.

technology. For the German electricity market, the wind technology is most prone to become the dominant VRE technology. Liquid IDM and diversification in terms of (a) technology type, (b) technological development, (c) regional deployment or (d) smart operation of RES assets may decrease the simultaneity effect of VRE and potentially mitigate the dominance of the forecast error from one technology.

(a) technology type: As highlighted by Gawel et al. (2017), many regulatory frameworks fail to internalize the costs associated with the system integration of VREs and a large part of these costs materializes in the MVFs of VREs. In this context, technology specific auctions with regulated auction budgets could ensure cost-efficiency of renewable support and diversification in terms of RES technology types (Kreiss et al., 2017).²² In case of merchant (subsidy free) RES investments, one would expect that the cheapest technology increases its market share. As seen in Europe e. g. for PV or offshore wind investments, an increasing demand for a certain technology can trigger cost reduction and accelerate this cycle (Makridis, 2013; Myhr et al., 2014). An increasing market share then bears the risk of falling MVFs in the long-run, which again underlines the requirement of technological diversification. With rational investors and market-based mechanisms, one would expect that risk aversion of investors against decreasing MVFs would lead to increased diversification.²³ *(b) technological development:* Another possibility to limit the simultaneity effect of VRE is the technological development in the sense that the production profiles differ between generations of technologies, e.g. increasing turbine capacities and hub heights impact the generation profiles due to differing power curves and wind conditions. Also, so called low-wind-speed turbines are a feasible solution (Hirth and Müller, 2016; Wichser and Klink, 2008).²⁴ However, the possible differentiation within one technology is limited compared to the choice of different technologies. *(c) regional deployment:* Profile differentiation can also be achieved by regional deployment of VRE assets. The optimal site for a wind farm should not solely be chosen based on yield maximization but also based on other possible benefits of the site, e.g. if weather fronts tend to arrive earlier. The grid however sets constraints for the regional deployment. The regulator can steer regional deployment by influencing grid extension plans.²⁵ *(d) smart operation of RES:* A smart operation of VREs assets can mitigate the MVF risk. As shown in this article, the self-curtailment of VRE production at negative prices will influence MVFs. The higher the number and magnitude of negative prices or the higher the imbalance risk exposure, the more likely it gets that VREs try to ramp down. In this context, the role of the IDM is to enable the trading of flexibilities prior to the IBM by indicating system tightness or oversupply prior to IBM. The willingness to balance open positions, in particular from VRE, induces additional revenues for actively managed CEP. Higher mark-ups for the provision of this flexibility may then intensify investments in CEP assets. Consequently, in markets with high share of VREs, a functioning IDM is important to assure system stability, to decrease the imbalance demand and to prevent investments below an optimal level ('missing money'). These findings are in line with e.g. Weber (2010) or Selasinsky (2016).

²² In technology-neutral renewable auctions, the regulatory authorities can force or intensify technological differentiation, e.g. by defining correction factors that serve as a mark-up on unfavourable technology bid prices. Technology-specific auction design may more directly support diversification. This argument only holds if the remuneration scheme leaves the MVF risk to the investors.

²³ Based on this perspective, a renewable support system that does not cover the profile cost risk seems beneficial. An exemplary design choice is a Contract for Difference (CfD) definition as implemented in the UK which sets an intermittent day-ahead index as reference. In contrast, the German regulation uses a technology specific benchmark for each RES type and includes a compensation for the profile cost development in the remuneration.

²⁴ The idea of low-wind-speed turbines is to start production earlier than other wind assets and therefore to sell electricity at times where prices are not plunging due to the merit-order effect.

²⁵ E.g. for the first German onshore auction, so-called 'grid extensions areas' were defined by the Regulatory Authority (BNetzA) to limit the maximum capacity additions in certain region with high wind penetration

7 Conclusion

This article presents a methodology to investigate MVFs going beyond classical DA-based approaches. The combination of two existing modelling approaches enables the analysis of fundamental impacts of the IDM on MVFs and enriches the MVF analysis for VREs presented in other literature (among others Green and Vasilakos, 2011; Hirth, 2013; Winkler et al., 2016). Hereby, the combined model increases the scope to quantify and mitigate the imbalance risk exposure of VRE by use of the IDM. Yet, the model is limited to a domestic view with a simplified exchange flow approximation and a simplified forecast error modelling. Therefore, the consideration of neighboring countries with direct interconnections or more sophisticated forecast error modelling (joint errors of VRE or intertemporal effects) are of interest for future research. Also, the parsimonious nature of the modelling is predestined for analysing data with higher granularity, i.e. quarter hourly contracts. As the settlement period in the German IBM covers 15 minutes, the effects, especially on the IBP regression model, may be a focus of future research.

Generally, the research on the interaction between IDM, IBM and their impact on MVFs is timely and relevant for policy makers and for investors in the energy industry. This article shows that the IDP reflects the cost for flexibility more accurately than pure DAP models and that the IDM can be used to decrease the IBM exposure. On the one hand, this has relevance for investments in assets providing flexibility (CEPs), because IDM deliver additional revenues potentials and are important for a functioning energy-only-market.²⁶ On the other hand, the price signals on the IDM are crucial for VRE investors because the IDM can be used to mitigate their IBM exposure. The biggest risk for single technologies is that one technology, e.g. wind production in the German electricity market, becomes the predominant VRE source such that its simultaneity effect diminishes ('cannibalize') DAM and IDM market revenues and that its forecast error dominates the IDM and IBM. The latter effect will cause increasing flexibility costs for this technology if it becomes a 'permanent' price maker in the balancing markets (IDM and IBM). Political guidance to intensify system flexibilization and a diversified mix of VRE generation is desirable to mitigate long-term MVF risks. The present article underlines the importance of functioning IDM for 'market-based' signals for the costs of flexibility and the activation of such flexibilities prior to the usually more expensive IBM. To support merchant²⁷ RES investments, an accompanying academic discussion of the long-term development of MVF is desired to prevent - most likely costly - political intervention at later points in time.

²⁶ If capacity mechanisms were introduced, scarcity rents would be shifted into an explicit remuneration scheme. In such a case, the base prices and especially peak prices would decrease. The market value of VRE however will fall by much less due to the fact that scarcity rents are usually concentrated during times of tightness (undersupply) in the system in which VRE production tends to be low. In a policy perspective then a capacity market design which allows the participation of VREs might be considered as beneficial. However, due to the variable nature of VRE, the participation in capacity markets would require some derating of VRE capacities compared to CEP in order to avoid distorting incentives.

²⁷ E.g. latest offshore auction results in Europe, i.e. Kriegers Flak in Denmark, Borssele 3&4 in the Netherlands and the German Offshore auction indicate that wind offshore LCOE get closer to market prices (subsidy free).

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Appendix

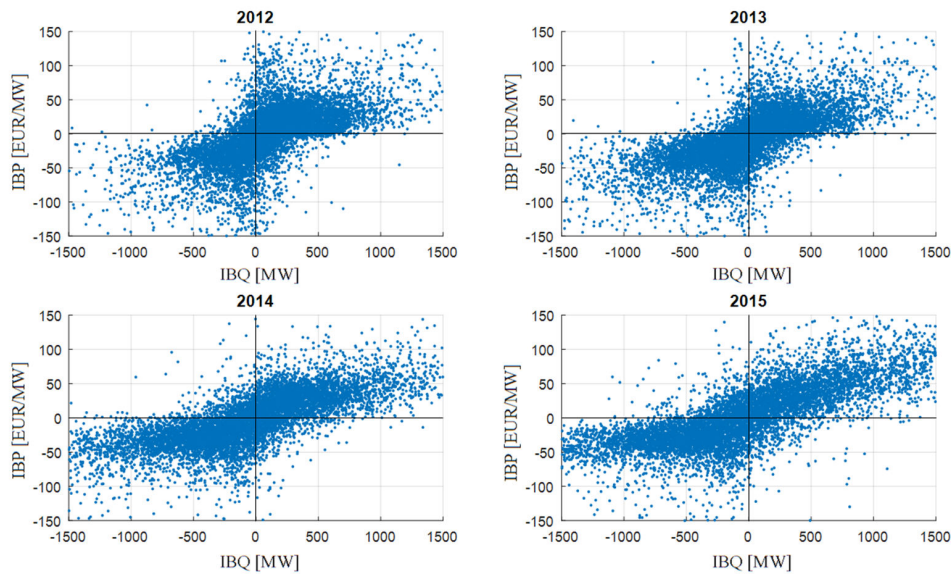


Figure 7: Scatter plot of hourly average Imbalance Quantities (IBQ, here equal to $FE_t^{IB,tot}$) and Imbalance Prices (IBP) in Germany 2012 until 2015 based on tennetso.de

Table 13: Increasing importance of intraday markets in Europe, cf. Hagemann and Weber (2015) with updates based on EPEX.com, OMEL.com, Nordpool.com etc..

Country	Gate closure [min. to delivery]	Intraday trading volume and increase in 2015 [TWh]	2014 RES* share of inst. cap. [%]	Conventional capacity [GW]
Denmark	60	0.45	~36.3	7.98
France (EPEX Spot)	30	3.29	~10.7	96.43
Germany (")	30	26.38	~39.0	99.75
UK (APX)	60	14.48	~11.6	78.30



Figure 8: Exemplary cash flow due to 6 hour rule in Germany without self-curtailment

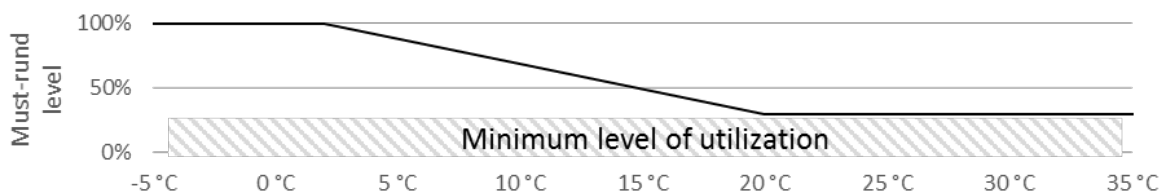


Figure 9: Must-run electricity production as a linear function of temperature

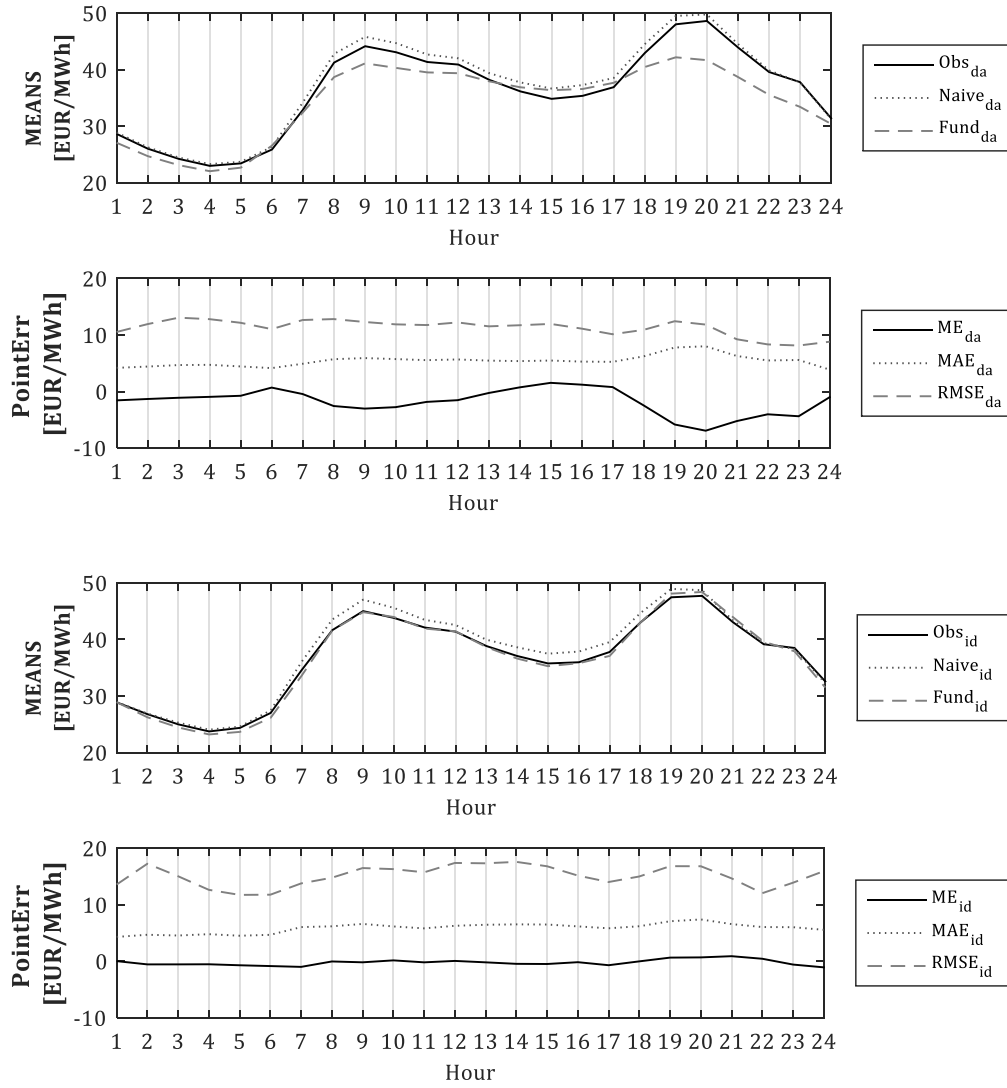


Figure 10: Hourly mean prices and point forecast errors for the day-ahead model (top) and intraday model (bottom) 2012-2015. The RMSE puts higher weight to larger deviations in single observations, thus occasionally larger errors are included in the dataset.

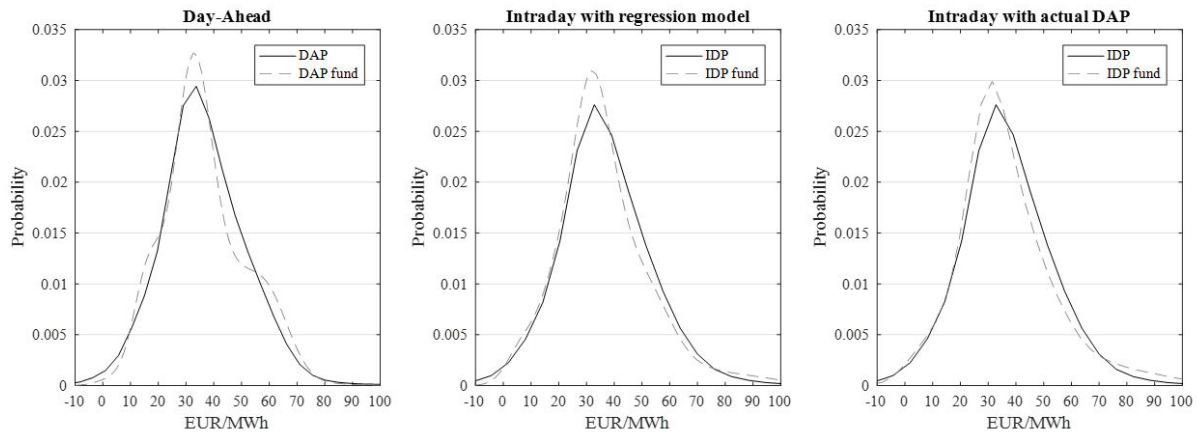


Figure 11: Distribution of actual prices and price forecasts 2014-2015 for the day-ahead model, the intraday model with use of actual DAP and the intraday model with use of the regression model. The pdf of the modelled intraday prices is closer to the pdf of actual IDP, if one uses the actual DAP to determine the separation point for the intraday supply stack. In this case, the forecast error from the day-ahead model (left of Figure 11) is not carried into the intraday model causing larger deviations between the actual and the modelled IDP.

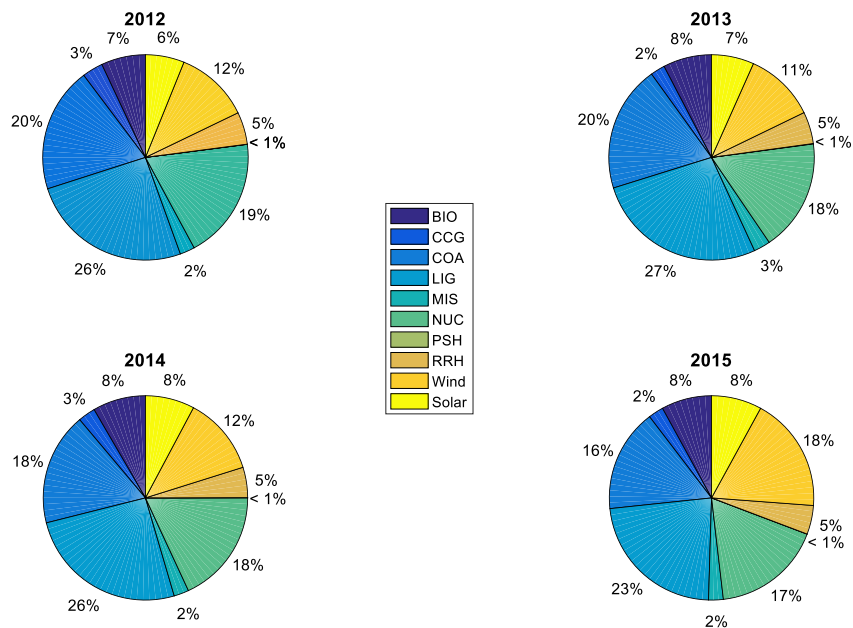


Figure 12: Shares of the overall production per fuel type 2012 to 2015

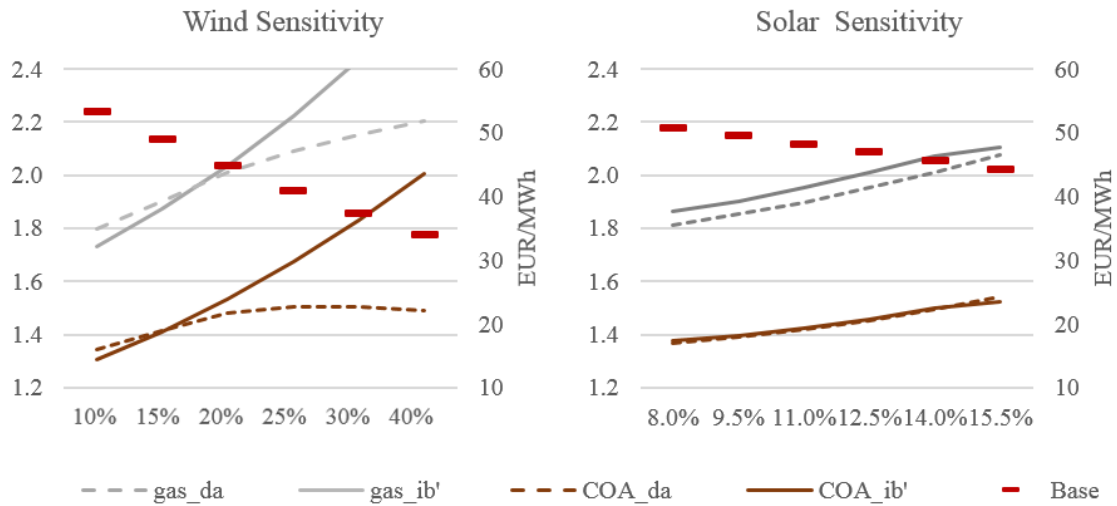


Figure 13: MVF and base prices for different level of VRE share of production (wind, left and solar, right)

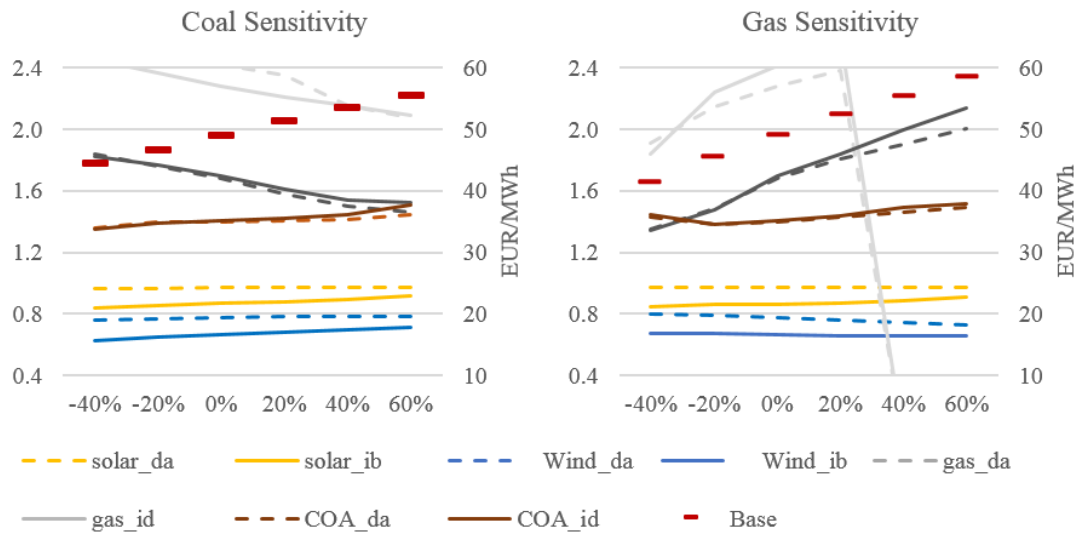


Figure 14: Coal and gas price sensitivity: The reference (0%) coal price is at 12 EUR/MWh_{th} and the reference (0%) gas price is at 32 EUR/MWh_{th}. The smaller the differences between coal and gas production costs, the flatter the slope of the intraday supply stack. This effect decreases the IDP volatility and the difference between V_i^{DA} and V_i^{IB} for VRE. At higher gas prices (>+20%) OCG production is replaced by other (formerly more expensive) technologies. The VREs neither profit nor lose from high prices in the IDM due to higher prices.

Table 14: Impact of lower capacities of base load plants (coal and lignite) or peak load plants (OCG and CCG) as well of higher ID Flexibility and no self-curtailment.

	Unit	Base case	ID Flex (no. shortening)	Self-curt. off
Δ WMVF	/	0.671	+0.01	-0.00
Δ SMVF	/	0.874	+0.03	+0.00
Δ Base	EUR/MWh	48.80	-0.01	+0.09
Δ Peak	EUR/MWh	61.65	-0.05	-0.09
Δ Sigma	EUR/MWh	27.26	-0.14	-0.01

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