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Enhancing load, wind and solar generation for day-ahead forecasting of electricity prices

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ABSTRACT

In recent years, a rapid development of renewable energy sources (RES) has been observed across the world. Intermittent energy sources, which depend strongly on weather conditions, induce additional uncertainty to the system and impact the level and variability of electricity prices. Predictions of RES, together with the level of demand, have been recognized as one of the most important determinants of future electricity prices. In this research, it is shown that forecasts of these fundamental variables, which are published by Transmission System Operators (TSO), are biased and could be improved with simple regression models. Enhanced predictions are next used for forecasting of spot and intraday prices in Germany. The results indicate that improving the forecasts of fundamentals leads to more accurate predictions of both, the spot and the intraday prices. Finally, it is demonstrated that utilization of enhanced forecasts is helpful in a day-ahead choice of a market (spot or intraday), and results in a substantial increase of revenues.

1. Introduction

In the recent decades, electricity markets across the world have undergone reforms, which have resulted in a deep market deregulation. Electricity power exchanges have been created, such as Nord Pool or EEX in Europe, PJM in the USA and NEM in Australia, which allow for a competitive electricity trade. Nowadays, a large share of the transactions is done in the day-ahead markets, where offers are placed around noon on the day preceding the delivery. The day-ahead prices, which clear the markets, are often called 'spot prices'. In order to allow for an adoption of trading positions to unplanned events, spot markets have been complemented by intraday and balancing markets. The intraday markets, typically organized by power exchanges, take the form of auctions (e.g., in Spain) or continuous trading (e.g., in Germany), and allow to trade the electricity throughout the whole day, up to a few minutes before the physical delivery. The final balancing of the demand and the supply is achieved via the balancing markets, which are controlled by the Transmission System Operators (TSO) and aim at securing the system stability. A more detailed explanations of the European electricity markets can be found in Gianfreda et al. (2016) and Koch and Hirth (2019). It is worth noting that trading in the day-ahead or intraday markets is usually not mandatory, neither for generators nor for consumption units.

The market participants are now facing new trade opportunities and can, to some extent, choose between different markets and contract types. In particular, RES utilities do not know their exact generation and therefore, are encouraged to self-balance their position in the intraday market (Pape et al., 2016; Kiesel and Paraschiv, 2017; Gianfreda et al., 2016). As the result, managers can offer the majority of their predicted generation in the day-ahead market and leave a part for flexible trade in order to manage the risk and revenue. Finally, it should be underlined here, that the core business of RES utilities is electricity generation and therefore, it focuses on a real trade rather than speculation.

The literature indicates that the choice of the trading strategy could result in a profit increase (Maciejowska et al., 2019) or risk reduction (Kath and Ziel, 2018). In order to support the decision process, accurate day-ahead predictions of spot and intraday prices are needed. The literature is rich in publications focusing on modelling and forecasting of spot prices (see Weron, 2014; Nowotarski and Weron, 2018, for a comprehensive review). Many papers indicate that the predicted RES generation and electricity demand are one of the main drivers of the day-ahead prices (Paraschiv et al., 2014; Woo et al., 2016; Gürtler and Paulsen, 2018; Pape et al., 2016) and hence should be included in the modelling scheme (Uniejewski and Weron, 2018; Ziel and Steinert, 2018; Gianfreda et al., 2020).

At the same time, not much attention has been placed on modelling intraday markets. There are a few articles which analyze the intraday markets in Europe (Kath and Ziel, 2018; Kiesel and Paraschiv, 2017; Monteiro et al., 2016) and the US (Woo et al., 2016). Most of them focus on a very short term – a few hours ahead – forecast, as in

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Uniejewski et al. (2019b) and hence, assume the knowledge of spot prices. This type of models could not be directly used by utilities when making operational decisions, such as a choice between the spot and intraday market (see Maciejowska et al., 2019). In such case, new models of intraday prices, which only use the information available at the time of the decision, need to be developed.

This article extends the literature in various directions. First, it shows that the TSO forecasts of total load, wind and solar generations, which are crucial for electricity markets, may be systematically biased and could be improved with autoregressive types of models. Although the literature considers TSO predictions as the most efficient ones, practitioners seek more accurate ways of forecasting the demand and the generation structure. This article follows this idea and corrects the TSO predictions with information available day-ahead, ensuring that the outcomes could be used by utilities while placing final orders in the spot market.

Second, it is investigated if the corrected forecasts could enhance the predictions of the spot and intraday prices. Here, a novel approach for forecasting of intraday electricity prices is adopted, which explores the difference between the enhanced and TSO predictions. One could see this model as a day-ahead counterpart of an approach used by Kiesel and Paraschiv (2017). The results indicate that predictions of both day-ahead and intraday prices could be significantly improved with the use of enhanced fundamental variables forecasts.

Finally, the possibility of price spread forecast is examined. While a related topic of forecasting load imbalance volumes has gained some interest from researchers (Lisi and Edoli, 2018; Bunn et al., 2018), this issue, although of a great practical importance, has not been studied much in the literature. The results confirm previous findings of Maciejowska et al. (2019) and show that the forecasted sign of the difference between intraday and spot prices could be used in the decision process and may lead to an increase of utility revenue. Moreover, usage of the enhanced predictions of fundamentals in a decision process substantially raises the additional revenues.

The article is structured as follows. First, in Section 2, we present and discuss the data. Then, in Section 3, we introduce and describe the models. Next, in Section 4, we show the results and finally, in Section 5, we conclude the study.

2. Data

This article analyzes the German electricity market, which is known for its high RES penetration. In the first two quarters of the year 2019, the RES share in the total electricity production exceeded 47% (see https://www.energy-charts.de). The data used in this research is hourly and spans the period from 1 October 2015 to 30 September 2019. The sample is divided into four years. The first year, 1 October 2015–30 September 2016, is utilized for calibrating models used for forecasting fundamental variables. In the second one, 1 October 2016–30 September 2017, the predictions of the fundamentals are collected, evaluated and next used as an input to price models. Finally, in the last two years, 1 October 2017–30 September 2019, the performance of price forecasts is assessed and financial gains from the proposed approach are computed. The notation and sample division are summarized in Table 1.

Table 1
Sample division and notation.

Notation	Start date	End date
2015	1 October 2015	30 September 2016
2016	1 October 2016	30 September 2017
2017	1 October 2017	30 September 2018
2018	1 October 2018	30 September 2019

The data set comprises day-ahead ($DA_{h,t}$) and intraday ($ID_{h,t}$) market prices for corresponding bidding zones: Austria + Germany + Luxembourg before 1 October 2018, Germany + Luxembourg after 1 October 2018. The intraday prices used in this research are ID3 indexes (volume weighted prices from the last 3 hours of trade). They are complemented by actual levels and system forecasts of fundamental variables: the total load ($L_{h,t}$), which can be treated as a proxy for the demand, and the RES (wind – $W_{h,t}$ and solar – $S_{h,t}$) generation. Fundamental variables are collected for Germany. They are supplemented by the forecasted temperatures for two German cities: Hamburg and Munich ($FT_{h,t}$). In the remaining part of the paper, the index h stands for an hour and t for a day number. Data sources, units and notation are summarized in Table 2.

The time paths of the day-ahead and intraday prices are presented in Fig. 1. For illustrative purposes two hours, $h = 4, 18$, have been chosen, representing the peak and the off-peak periods of a day. It can be noticed that peak prices are higher than off-peak ones, both for the day-ahead and intraday markets. Their variability changes in time and exhibits a tendency for clustering. Finally, prices in different markets co-move together. The occurrence of positive and negative spikes is synchronized in both markets, but their magnitude is more pronounced for the intraday prices.

When the fundamental variables are considered, it could be observed that load, wind and solar generations have different statistical properties. Daily averages of the variables together with their TSO forecast errors are presented in Fig. 2. The plots indicate that load depends strongly on a day of the week and follows a yearly seasonality. In Germany, the electricity consumption is the highest during the winter, when the energy is used for heating, and falls when the temperature increases. Additionally, one could observe a slight increase in the demand during summer months, when air-conditioning is used. Unlike the load, the RES generation does not exhibit a weekly pattern because it does not depend on the electricity consumption. The wind generation rises in the winter and drops slightly in the summer. Moreover, wind shows a lot of variation and can change drastically within a few days. At the same time, solar generation has an opposite yearly pattern with a peak in summertime. It falls almost to zero during winter, when days are short and the sunlight is insufficient.

In Fig. 2, fundamental variables are accompanied by their forecast errors, computed as the difference between their actual values and corresponding TSO predictions. Unlike fundamentals, forecast errors follow neither weekly nor yearly seasonality. Only solar errors seem to be larger in spring, when the PV (photovoltaic) generation increases. The basic statistical properties of TSO forecast errors are presented in Table 3, which includes information on their means and mean standard deviations across peak (9–20) and off-peak (1–8, 21–24) hours. It is clearly visible that there is a substantial bias in the TSO forecasts for all three fundamental variables. The biggest bias is observed for load,

Table 2
Data sources and units.

Data	Notation	Units	Source
Day-ahead prices	*DA*	EUR/MWh	EPEX SPOT, http://www.epexspot.com
Intraday prices	*ID*	EUR/MWh	EPEX SPOT, http://www.epexspot.com
Load	*L*	GWh	https://transparency.entsoe.eu
Wind generation	*W*	GWh	https://transparency.entsoe.eu
PV generation	*S*	GWh	https://transparency.entsoe.eu
Forecasted load	*FL*	GWh	https://transparency.entsoe.eu
Forecasted wind generation	*FW*	GWh	https://transparency.entsoe.eu
Forecasted PV generation	*FS*	GWh	https://transparency.entsoe.eu
Forecasted temperature	*FT*	°C	https://api.meteo.pl

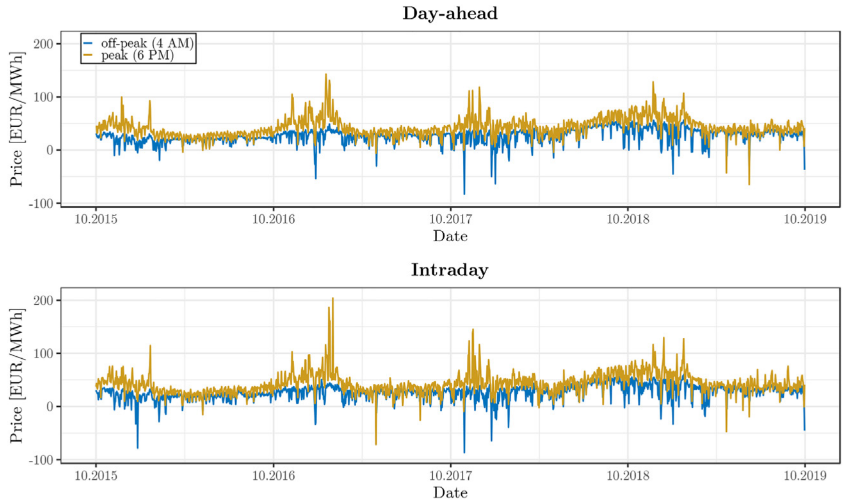

Fig. 1. Time plots of the day-ahead and intraday prices for two illustrative hours (4 a.m. and 6 p.m.).

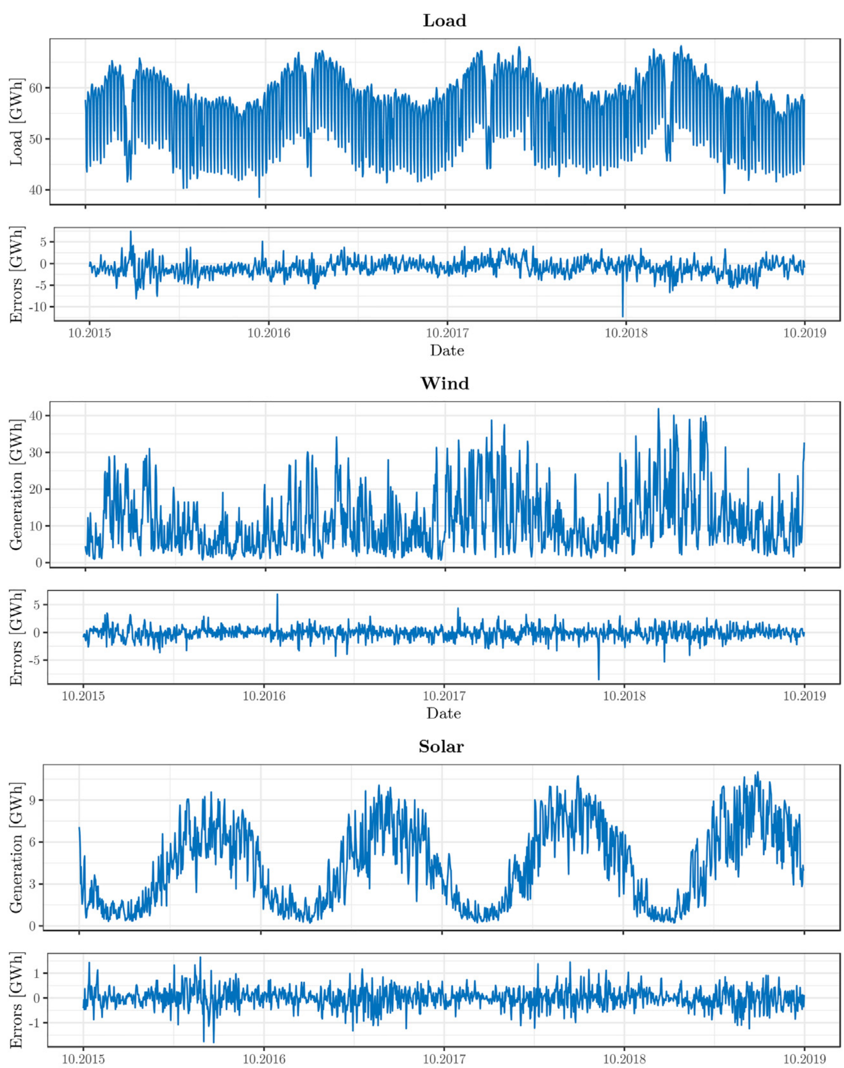

Fig. 2. Time plots of daily averages of fundamental variables and the TSO forecasts errors.

Table 3
Descriptive statistics of TSO forecast errors.

Statistics	Peak			Off-peak		
	Load	Wind	Solar	Load	Wind	Solar
Mean	−1.022	−0.041	0.009	−0.915	−0.139	0.002
	(0.017)	(0.012)	(0.008)	(0.014)	(0.012)	(0.001)
LB test	12	11	12	12	12	5

Note: standard deviations of the mean estimators are stated in brackets; Ljung-Box (LB) test reports a number of hours from the twelve-hour-long peak/off-peak blocks, where the null is rejected at 5% significance level.

which, with mean error of −1.022 GWh during peak hours and −0.915 GWh in off-peak hours, is systematically underestimated. The standard deviations of the mean of load, wind and solar generation are presented in brackets. They indicate that biases are significantly different from zero for both peak and off-peak hours, and all the fundamental variables. Next, the autocorrelation of residuals is verified with the Ljung-Box (LB) test statistic, for each hour separately. The last row of Table 3 shows the number of hours from the twelve-hour-long peak/off-peak blocks, where the LB test rejects the null hypothesis at 5% significance level. The results indicate a strong autocorrelation of forecast errors. It can be observed that only for seven hours of solar generation and one hour of wind generation the null hypothesis cannot be rejected. Most of these hours coincide with times of very low or no photovoltaic generation. To sum up, the initial analysis suggests that TSO forecasts are not only systematically underestimated but also could be improved with autoregressive type of models, which explore the autocorrelation structure of TSO forecast errors.

3. Methods

3.1. Problem setup

This research consists of three major parts: (i) a calibration of ARX-type models of load, wind and solar generation, and a calculation of their day-ahead forecasts, (ii) an assessment of prediction accuracy of fundamental variables, (iii) an evaluation of financial gains resulting from enhancement of fundamental forecasts. The gains are measured in two ways. First, it is verified whether more accurate predictions of load, wind and solar improve electricity price forecasts. Second, additional revenues from the price-driven choice of the trading strategy are calculated and compared with those based on TSO information only.

Like the majority of energy studies, we consider a rolling window scheme with a limited memory and model separately each hour of a day. The algorithm consists of three steps. First, the model parameters are estimated using the data from a calibration window of a fixed length. Next, one day ahead forecasts of fundamental variables or electricity prices are calculated. Finally, the window is moved one step ahead. All the steps are repeated until the forecasts of the last observation in the evaluation window are computed.

Two forecasting methods are used, conditional on the modeled variable. In case of fundamentals, we follow recent papers of Hubicka et al. (2019) and Marcjasz et al. (2018), which show that averaging across different calibration windows yields better results than selecting ex-ante a single window length. Here, we combine forecasts based on three short and three long estimation windows. A similar choice of window lengths was previously used by Marcjasz et al. (2018) and Serafin et al. (2019). When we consider the electricity prices, the models are calibrated with one year of observations. We restrict the analysis to a single window length in order to capture the direct impact of enhanced fundamental forecasts on the price predictions.

Finally, it should be emphasised here that the article focuses on day-ahead forecasts because the market participants need to place their orders in the morning of the day preceding the delivery. Moreover, the forecasts are calculated before the decisions are made, which is assumed to happen at 11 am. As a consequence, any new information arriving after 10 am, for example an actual level of generation and its structure or the level of intraday prices, are excluded from the information set and not used for fundamental variables or price predictions.

3.2. Forecasting fundamentals

In order to forecast fundamental variables, ARX type of models are adopted, which utilize both the information on system forecasts and actual past realizations of these variables. In this research, three different model specifications are adopted. First, the total load is modeled as follows

$$\begin{aligned} L_{t,h} = {} & \alpha_h^L D_t^L + \underbrace{\theta_{h,1}^L L_{t-1,h}^* + \sum_{p\in\{2,7\}} \theta_{h,p}^L L_{t-p,h}}_{\text{AR component}} + \underbrace{\beta_{h,1}^L FL_{t,h} + \beta_{h,2}^L FW_{t,h} + \beta_{h,3}^L FS_{t,h}}_{\text{Forecasts off undamentals}} \\ & + \underbrace{\beta_{h,4}^L FL_{t,ave} + \beta_{h,5}^L FL_{t,max} + \beta_{h,6}^L FL_{t,min}}_{\text{Daily statistics}} + \underbrace{\beta_{h,7}^L FT_{t,h}}_{\text{Weather forecasts}} + \varepsilon_{t,h}^L, \end{aligned} \tag{1}$$

where D_t^L is a (4×1) vector of deterministic variables consisting of a constant and three dummy variables for Mondays, Saturdays and Sundays/Holidays. $FL_{t,h}$, $FW_{t,h}$ and $FS_{t,h}$ are the TSO forecasts of all three fundamental variables for the current day and hour, as defined in Table 2. $FL_{t,ave}$, $FL_{t,max}$ and $FL_{t,min}$ are daily statistics computed as the mean, maximum and minimum of the TSO load forecast for the day t over 24 hours. The weather forecast vector, $FT_{t,h}$, includes predicted temperature for two cities: Hamburg and Munich). In the AR part, lags $p \in \{1,2,7\}$ are chosen, which corresponds to lags used in price forecasting studies (see Nowotarski et al., 2014; Uniejewski et al., 2016, 2019a; Ziel, 2016 among others). This lag structure captures both the short run dependence and the weekly seasonality. It should be mentioned here that for some hours, $h > 10$, there is no information on the actual generation available at the time of forecasts. Therefore we define a variable:

$$L_{t,h}^* = \begin{cases} L_{t,h} & \text{if } h \le 10, \\ FL_{t,h} & \text{if } h > 10, \end{cases} \tag{2}$$

which replaces the missing observations with their TSO forecasts.

The model for wind generation is simpler than (1) and is given by

$$\begin{aligned} W_{t,h} = {} & \alpha_h^W D_t^W + \theta_h^W W_{t-1,h}^* + \beta_{h,1}^W FW_{t,h} + \beta_{h,2}^W FW_{t,h-1} + \beta_{h,3}^W FW_{t,h+1} \\ & + \varepsilon_{t,h}^W. \end{aligned} \tag{3}$$

The deterministic variable, D_t^W, includes only a constant because wind does not follow a weekly seasonality. The variable $W_{t-1,h}^*$ controls for missing information and is defined as (2). Finally, Eq. (3) includes also information on predicted wind generation in two neighbouring hours: $h-1$ and $h+1$ (when such information is available). It is assumed that wind generation does not depend on the other fundamental variables: load or solar, and its AR structure consists of only one lag.

A similar model is adopted for solar generation. It is described by the following equation

$$S_{t,h} = \alpha_h^S D_t^S + \theta_h^S S_{t-1,h}^* + \beta_{h,1}^S FS_{t,h} + \beta_{h,2}^W FS_{t,h-1} + \beta_{h,3}^W FS_{t,h+1} + \varepsilon_{t,h}^S, \tag{4}$$

where D_t^S consists of an intercept and the number of sun hours within a day, which approximates the yearly seasonality. Analogously to (3), we use a simple autoregressive structure with one lag.

The models (1), (3) and (4) are estimated for different lengths, τ, of calibration windows. Following Marcjasz et al. (2018); Serafin et al. (2019), we choose three short windows with $\tau \in \{56,84,112\}$, which correspond to 8, 12 and 16 weeks of observations, and three long windows with $\tau \in \{351,358,365\}$, which balance the short term effect. The predictions are next computed as a simple average over individual forecasts.

It should be noticed here that the model (4) can be estimated only for hours in which at least some TSO forecasts are different from zero for each of the calibration windows. The proportion of nonzero TSO solar predictions ($FS_{t,h}$) in consecutive calibration windows (56-day long) are presented in Fig. 3, Appendix. The plots indicate that only hours 8–17 satisfy the nonzero condition and therefore the prediction of solar generation and its usage in the analysis is limited to hours 8–17.

3.3. Forecasting electricity prices

In order to compute the day-ahead forecasts of electricity prices, we use autoregressive models with exogenous variables. The $DA_{t,h}$ price of the day t and hour h is given by

$$\begin{aligned} DA_{t,h} = \alpha_h D_t + & \underbrace{\sum_{p \in \{1,2,7\}} \theta_{h,p} DA_{t-p,h}}_{\text{AR component}} \\ & + \underbrace{\beta_{h,4} DA_{t-1,ave} + \beta_{h,4} DA_{t-1,min} + \beta_{h,5} DA_{t-1,max}}_{\text{Daily quantities}} \\ & + \underbrace{\beta_{h,6} DA_{t-1,24}}_{\text{Last known price}} + \underbrace{\theta_h \widehat{X}_{t,h}}_{\text{Fundamentals}} + \varepsilon_{t,h}, \end{aligned} \tag{5}$$

where $DA_{t-1,ave}$, $DA_{t-1,min}$ and $DA_{t-1,max}$ are the average, the minimum and the maximum of prices from the preceding day, $DA_{t-1,24}$ is the last known price and D_t is a (4×1) vector of deterministic variables: a constant and dummies for Mondays, Saturdays and Sundays/Holidays. Finally, $\widehat{X}_{t,h} = \left(\widehat{L}_{t,h}, \widehat{W}_{t,h}, \widehat{S}_{t,h}\right)'$ is a vector of forecasts of fundamental variables, which are based either on TSO predictions (then $\widehat{X}_{t,h} = (FL_{t,h}, FW_{t,h}, FS_{t,h})'$) or results from models described in the previous section. Note that the predictions of solar generation are included in the model only for hours $8-17$, when the solar radiation is substantial.

In this research, two different models of intraday prices are considered. The first model is based on the approach adopted for forecasting of day-ahead prices and takes the following form:

$$\begin{aligned} ID_{t,h} = \alpha_h D_t + \theta_{h,1} ID^*_{t-1,h} + & \underbrace{\sum_{p \in \{2,7\}} \theta_{h,p} ID_{t-p,h}}_{\text{AR component}} \\ & + \underbrace{\beta_{h,4} DA_{t-1,ave} + \beta_{h,4} DA_{t-1,min} + \beta_{h,5} DA_{t-1,max}}_{\text{Daily day-ahead quantities}} \\ & + \underbrace{\beta_{h,6} DA_{t-1,24}}_{\text{Last known price}} + \underbrace{\theta_h \widehat{X}_{t,h}}_{\text{Fundamentals}} + \varepsilon_{t,h}. \end{aligned} \tag{6}$$

It should be noticed that for hours $h > 10$, the intraday prices – $ID_{t,h}$ – are not known. In such case, they are replaced by their day-ahead counterparts. Hence

$$ID^*_{t,h} = \begin{cases} ID_{t,h} & \text{if } h \le 10, \\ DA_{t,h} & \text{if } h > 10. \end{cases} \tag{7}$$

Moreover, due to the lack of sufficient information, we can use neither average, minimum, maximum nor last intraday price from the day $t-1$. Therefore the model (6) uses the corresponding quantities from the day-ahead market.

The second model is similar to the approach proposed by Kiesel and Paraschiv (2017), in which the intraday prices are conditioned on the day-ahead prices and fundamental forecast errors. In this research, the model includes additionally lagged prices and the current predictions of fundamentals. Since the forecast errors of fundamentals are not known, they are approximated by the difference between the model based and TSO forecasts. The final form of the model is given by the following equation

$$\begin{aligned} ID_{t,h} = \alpha_h D_t + \beta_{h,1} \widehat{DA}_{t,h} + \beta_{h,2} ID^*_{t-1,h} + \theta_{h,1} \widehat{X}_{t,h} \\ + \underbrace{\theta_{h,2}\left(\widehat{X}_{t,h} - FX_{t,h}\right) + \theta_{h,3}\left(X^*_{t-1,h} - FX_{t-1,h}\right)}_{\text{forecast errors of fundamentals}} + \varepsilon_{t,h}, \end{aligned} \tag{8}$$

where $FX_{t,h} = (FL_{t,h}, FW_{t,h}, FS_{t,h})'$ is a (3×1) vector of summarizing TSO forecasts and the difference $\left(\widehat{X}_{t,h} - FX_{t,h}\right)$ approximates the forecast error of fundamental variables. The variable $X^*_{t,h}$ is defined similar to (2), with $X^*_{t,h} = \widehat{X}_{t,h}$ for $h > 10$. Notice that when the model (8) is estimated using only the information provided by TSO, then the forecast error, $\left(\widehat{X}_{t,h} - FX_{t,h}\right)$, equals to zero and hence it needs to be removed from the equation. Finally, while calculating $ID_{t,h}$, there is no information on $DA_{t,h}$ available. Therefore, instead of actual level of day-ahead prices, the model utilizes their forecasts, $\widehat{DA}_{t,h}$, obtained with model (5).

3.4. Forecasting the sign of the price spread

When modelling the market choice, we follow the methodology established in Maciejowska et al. (2019). A binary decision variable $Y_{t,h}$ is defined, which equals to one when the generator decides to sell the electricity produced for day t hour h in the intraday market, and zero otherwise. Following Maciejowska et al. (2019), a benchmark, called a naïve day-ahead strategy is considered. It assumes that all generated electricity is sold in the day-ahead market and hence $Y_{t,h} = 0$ for all t and h. This benchmark strategy is compared with a data-driven approach, which links the decision to the relationship between the day-ahead and the intraday price:

$$Y_{t,h} = \begin{cases} 1 & \text{if } ID_{t,h} - DA_{t,h} > 0, \\ 0 & \text{if } ID_{t,h} - DA_{t,h} \le 0. \end{cases} \tag{9}$$

As the utility has to make its decision before the actual price difference $\Delta P_{t,h} = ID_{t,h} - DA_{t,h}$ is known, it has to be based on the forecasted spread $\Delta\widehat{P}_{t,h} = \widehat{ID}_{t,h} - \widehat{DA}_{t,h}$. Hence, the generator sells electricity in the intraday market, if the predicted spread is positive and in the day-ahead market otherwise.

4. Results

In this research, three types of results are analyzed. First, the possibility of an improvement of fundamental predictions over their TSO forecasts is considered. The outcomes are compared using MAE and RMSE forecast accuracy measures. Second, gains from enhancement of fundamentals predictions in forecasting of electricity price is analyzed. Finally, improved price forecasts are used in a decision process. The resulting revenues are calculated and compared with the TSO based strategies.

4.1. Enhancing the forecasts of fundamentals

The forecasts computed with models (1), (3) and (4) are compared with those published by TSO using the data from the last three years: 2016–2018. The results are presented in Table 4, which shows MAE and RMSE for the three considered fundamentals and three analyzed years. The significance of the forecast accuracy change is statistically verified with the Diebold-Mariano (DM) test (Diebold and Mariano, 1995). In order to compare the model performance across all 24 hours, we follow a vectorized DM approach described by Ziel and

Table 4
Forecast accuracy of fundamental variables.

Variable	Load			Wind			Solar		
Year	2016	2017	2018	2016	2017	2018	2016	2017	2018
MAE									
TSO	1.529	1.538	1.940	0.999	1.180	1.160	0.740	0.679	0.718
Enhanced	1.045	1.125	1.204	1.013	1.166	1.147	0.740	0.677	0.707
(p-val)	(0.000)	(0.000)	(0.000)	(0.017)	(0.795)	(0.249)	(0.383)	(0.352)	(0.832)
RMSE									
TSO	1.961	2.024	2.475	1.538	1.765	1.580	1.077	1.003	1.014
Enhanced	1.496	1.631	1.624	1.537	1.746	1.549	1.076	0.999	1.008
(p-val)	(0.000)	(0.000)	(0.000)	(0.960)	(0.978)	(0.929)	(0.789)	(0.292)	(0.852)

Note: the difference of the forecast accuracy is tested with Diebold-Mariano test with autocorrelation of order 7 and 2 for load and RES variables, respectively; *p*-values of the DM test are presented in brackets.

Weron (2018). We apply the DM test to the multivariate loss differential series between compared models *X*, *Y* defined as

$$\Delta_{X,Y,d} = \|\widehat{\varepsilon}_{X,d}\| - \|\widehat{\varepsilon}_{Y,d}\|, \tag{10}$$

where $\widehat{\varepsilon}_{X,d}$ and $\widehat{\varepsilon}_{Y,d}$ are the 24-dimensional vectors of out-of-sample errors for models *X* and *Y* respectively. The norm utilized for calculation of the loss differential depends on the forecast accuracy measure. We use Euclidean, $\|.\|_2$, norm for RMSE and $\|.\|_1$ for MAE. Since not all market information is available when calculating the predictions, we allow for the autocorrelation of forecast errors while computing DM test statistics.

The outcomes indicate that load and wind forecasts could be significantly improved with ARX types of models. The results show that MAE of load is reduced by 31.6%, 26.8% and 37.9% in years 2016 to 2018, respectively. Also RMSE measure decreases considerably and falls by more than 20% in all years. This indicates that TSO load forecasts are strongly biased and could be substantially improved by the employment of statistical models. When wind forecast is considered, it should be noticed that gains from prediction enhancement are much lower than in load case. The MAE of wind forecast rises slightly in 2016 and falls by 1.1% in years 2017 and 2018. Similar, RMSE decreases by less than 2%. The changes of wind forecast accuracy in years 2017 and 2018 are not statistically significant.

The solar predictions seem to be the most difficult to improve. The proposed models are not able to significantly reduce the MAE and RMSE. We believe that the proposed linear model is not sufficient enough to capture the dynamic structure of solar generation.

Table 5
MAE and RMSE of price forecasts (DA and ID), in years 2017–2018.

Variable	Model	Measure	Fundamentals			
			TSO	None	Enhanced	Real
DA	(5)	MAE	6.004	7.195	5.920	5.912
		(p-val)		(0.000)	(0.033)	(0.229)
		RMSE	8.526	10.885	8.434	8.621
		(p-val)		(0.000)	(0.037)	(0.370)
ID	(6)	MAE	7.701	8.638	7.621	7.176
		(p-val)		(0.000)	(0.014)	(0.000)
		RMSE	11.183	12.994	11.066	10.523
		(p-val)		(0.000)	(0.002)	(0.000)
	(8)	MAE	7.899	8.935	7.719	7.058
		(p-val)		(0.005)	(0.001)	(0.000)
		RMSE	11.315	13.470	11.117	10.363
		(p-val)		(0.920)	(0.094)	(0.000)

Note: the difference of the forecast accuracy is tested with Diebold-Mariano test with autocorrelation of order 7; p-values of the DM test are presented in brackets.

4.2. Price forecasts

The enhanced predictions of load, wind and solar generation are next used for electricity price forecasting. In order to evaluate the impact of fundamentals on price predictions, four model setups are considered. In the first one, later called a benchmark, the TSO forecasts are included in models (5), (6) and (8). The benchmarks are compared with models, in which fundamentals are excluded from mentioned regressions. It should be noticed that in such case, the model (8) is simplified substantially and includes only the predicted level of day-ahead prices and lagged intraday prices. Next, we assess the performance of models utilizing the predictions obtained with models (1), (3) and (4). Finally, we consider a case, in which perfect forecasts of fundamental variables are available for researchers. This means that the real values of load, wind and solar generations are known before the price forecasts are calculated.

Two measures of price forecast accuracy, MAE and RMSE, are presented in Table 5 jointly for years 2017–2018. They are complemented by DM tests, which compare the forecast performance of a particular model with a benchmark (TSO) model. Since we propose two different model specifications for intraday prices, their outcomes are evaluated separately.

The results indicate that fundamental variables contain information, which can significantly improve price forecast accuracy. MAE of models, which do not include fundamentals, is larger by 19.8%, 12.2% and 13.1% respectively than MAE of benchmark models.

When day-ahead prices are considered the results are mixed. MAE measure indicates that improving the fundamental forecasts (Enhanced and Real columns) results in more accurate price forecasts. On the other hand, when RMSE is analyzed, forecasts utilizing real generation structure are not significantly different from predictions computed with the benchmark model. Hence, the exact knowledge of future levels of load, wind and solar generation does not help in predicting the day-ahead prices.

The results for intraday prices depend on the model specification. It could be noticed that in the case of perfect forecasts of fundamentals, model (8) gives more accurate predictions than the other (6). This implies that day-ahead prices are main driver of intraday prices, which

Table 6
Share of correct market classifications and additional revenues, in years 2017–2018.

Models		Correct classifications, p (%)			Revenues, π (EUR)		
DA	ID	TSO	Enhanced	Real	TSO	Enhanced	Real
(5)	(6)	52.0%	52.1%	52.9%	5705	5908	7577
(5)	(8)	49.6%	50.8%	58.9%	4075	4627	16,333

confirms previous findings of Kiesel and Paraschiv (2017) and Ziel (2017). Secondly, the outcomes indicate that models using the enhanced forecasts of fundamentals are significantly better than the TSO based predictions. The differences between models are more pronounced for model (8), when the MAE falls from 7.899 to 7.719. At the same time, using the real observations of load, wind and solar generation decreases MAE by 10.6% to 7058. This shows the range of potential gains from the enhancement of forecasts of fundamentals.

4.3. Market choice

In this research, the market choice in based on the sign of the price spread. The decision variable, $Y_{t,h} \in \{0,1\}$, is defined by (9). It takes value 1, when the intraday price is higher than the day-ahead price, $ID_{t,h} > DA_{t,h}$, and zero otherwise. Since the actual prices are not known, the sign of the spread is predicted using the day-ahead price forecasts. In such case, $\widehat{Y}_{t,h} = 1$ when $\widehat{ID}_{t,h} > \widehat{DA}_{t,h}$ and $\widehat{Y}_{t,h} = 0$, when $\widehat{ID}_{t,h} \le \widehat{DA}_{t,h}$. Similar to Maciejowska et al. (2019), the accuracy of forecasts, $\widehat{Y}_{t,h}$, is evaluated using two measures: a ratio of correct predictions (p) and an additional revenues (π). The ratio of correct predictions is computed as follows

$$p = \frac{\#\left(Y_{t,h} = \widehat{Y}_{t,h}\right)}{\#Y_{t,h}}, \tag{11}$$

where $\#\left(Y_{t,h} = \widehat{Y}_{t,h}\right)$ is the number of correctly predicted spread signs and $\#Y_{t,h}$ is the size of the evaluation sample.

The additional revenues are calculated as income from selling 1 MWh according to the predicted decision variable, $\widehat{Y}_{t,h}$, over the day-ahead benchmark. This implies that the total additional daily revenue, π_t, becomes

$$\pi_t = \sum_{h=1}^{24} \left(\widehat{Y}_{t,h} ID_{t,h} + \left(1 - \widehat{Y}_{t,h}\right) DA_{t,h} - DA_{t,h}\right) = \sum_{h=1}^{24} \widehat{Y}_{t,h} \Delta P_{t,h}. \tag{12}$$

The two-year additional revenue, π, is computed as a sum of daily revenues from 1 October 2017 to 30 September 2019. As shown by the literature (Kath and Ziel, 2018; Gianfreda et al., 2018; Maciejowska et al., 2019), financial measures are of particular importance in evaluation of forecast accuracy and does not necessary coincide with classical statistical measures, for example p.

The results are presented in Table 6. First, the ratio of correct market classification is evaluated. The TSO based models are able to predict correctly, which market offers a higher price, in 49.6%–52.0% of cases. The ratios for models using the enhanced forecasts range from 50.8% to 52.1% and reach the higher level with the intraday model (6). At the same time, an access to perfect forecasts of fundamentals enables to choose the market correctly in 52.9%–58.9% of cases. In this case utilizing the intraday model (8) is favorable, showing that this model (8) has more potential, should the forecast be improved further.

Next, additional revenues from the price driven market choice are compared. It can be noticed that the additional revenues will reach more than 16,000 EUR from 1 October 2017 to 30 September 2019, if the true values of fundamentals are known at the time of the decision. It approximates the upper bound of the presented methodology. At the same time, revenues from the choice utilizing the TSO predictions vary between 4075 and 5705 EUR, which is about 30% of the perfect information result. Finally, decision based on enhanced fundamentals leads to an increase of the revenue by 4627–5908.

Finally, when the results of specifications using enhanced fundamental forecasts are analyzed, one could observe gains over the TSO based approaches in both cases. When the model (8) is adopted for forecasting intraday prices, the revenues reach 4627 EUR, which is 552 EUR more than the benchmark. Although the additional revenues increase slightly, the full information case shows that there is a plenty of room for the further improvement, and that the main idea itself is reasonable.

5. Conclusions

This article analyzes the German electricity market and evaluates the system forecasts of the fundamental variables: load, wind and solar generation. The research consists of three parts: calibration of time series models of fundamentals and assessment of their prediction accuracy, utilization of the enhanced predictions in day-ahead forecasting of the day-ahead and intraday electricity prices and finally, an employment of the calculated forecasts in the utility decision process.

First, ARX types of models are employed for forecasting fundamental variables. Since we do not know the optimal length of a calibration window, we follow an approach proposed by Hubicka et al. (2019) and combine forecasts computed from a few short and a few long window sizes. The obtained results show that the load forecast can be significantly improved over the TSO benchmark. This indicates that the system operator does not utilize all the information available in the market at the time of the forecast publication. On the other hand, the ARX types of models are able to improve the TSO wind and solar predictions only slightly. Hence, these two turn out to be more demanding variables, which need a particular modelling approach (nonlinear or/and including additional exogenous variables).

Second, the enhanced predictions of fundamentals are used for forecasting day-ahead and intraday prices. Both variables are predicted day-ahead, as they are later used for choosing an optimal market for selling the energy. Two types of intraday models are analyzed: one using the ARX specification similar to the day-ahead market and second, exploring the dependence on the day-ahead prices and fundamentals forecasts errors. The results reveal that the knowledge of real levels of generation and its structure does not help to forecast day-ahead prices. On the other hand, enhanced fundamental forecasts reduce both MAE and RMSE of day-ahead prices, as compared to the TSO benchmark. This indicates that market participants use the information available at the time of taking decision to place their offers. When the intraday prices are considered, the results clearly demonstrate that any improvement of accuracy of fundamental predictions leads to better price forecasts, both in terms of MAE and RMSE measures.

Finally, the improved forecasts of fundamentals and electricity prices are utilized in the decision process. In this article, a utility needs to choose where to sell 1 MWh of electricity: in the day-ahead or in the intraday market. The decision is data driven and is compared with a benchmark (selling 1 MWh in the day-ahead market). The gains from prediction enhancement are measured by an additional yearly revenue. It turns out that the correction of fundamental forecasts results in a significant income increase. The extra revenue coming from the market choice rises by 13.5% from 4075 EUR to 4627 EUR a year per 1 MWh. Moreover, the results show that if the actual values of fundamentals are known, the revenue could reach 16,333 EUR, which encourages further research in the field.

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Appendix A

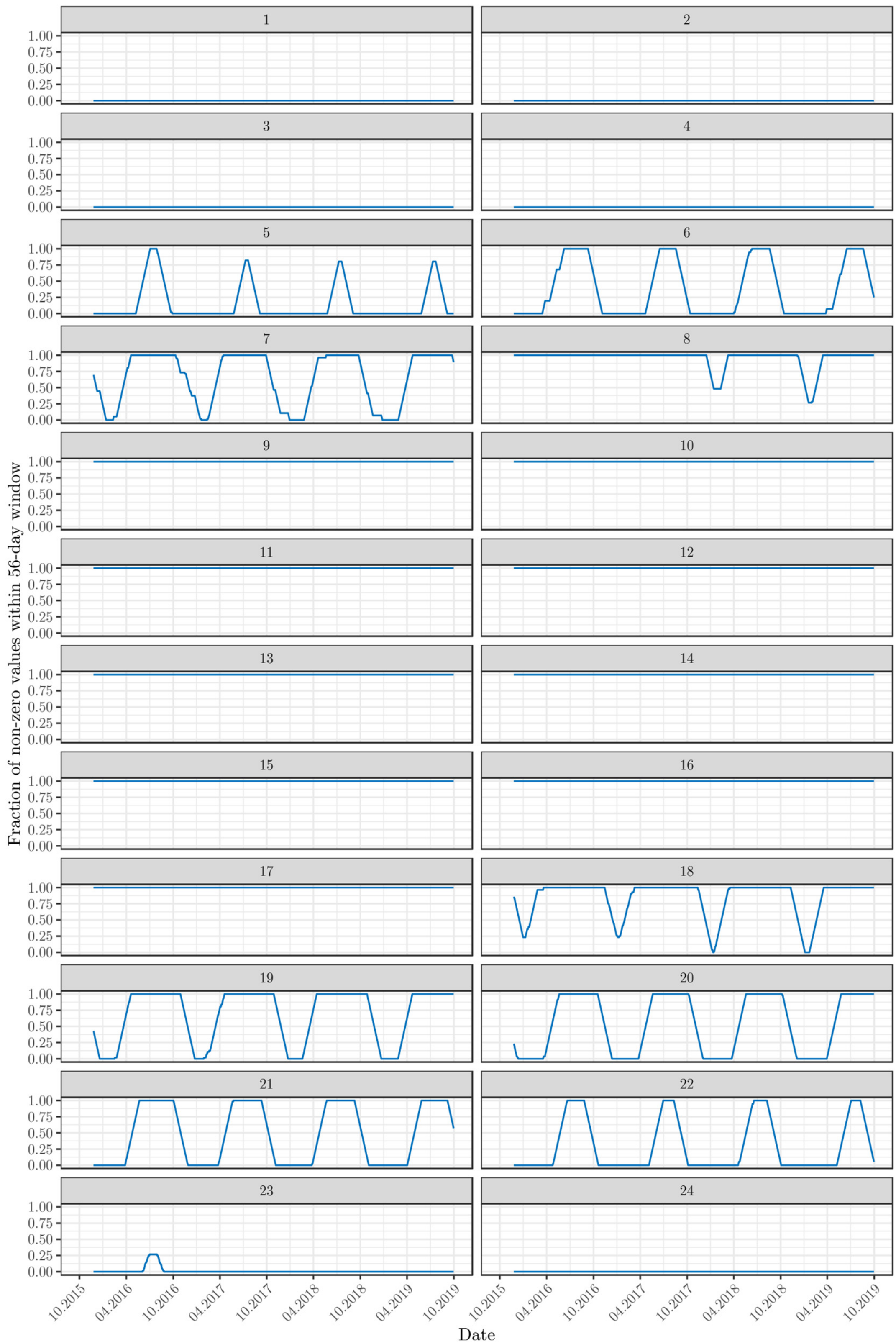

Fig. 3. Fraction of days within a 56-day rolling window with forecasted solar energy values greater than 0 MWh for every hour of the day.

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