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Economic Implications of Forecasting Electricity Generation from Variable Renewable Energy Sources

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Abstract

Short-term forecasting of electricity generation from variable renewable energy sources is not an end in itself but should provide some net benefit to its user. In the case of electricity trading, which is in the focus of this paper, the benefit can be quantified in terms of an improved economic outcome. Although some effort has been made to evaluate and to improve the profitability of electricity forecasts, the understanding of the underlying effects has remained incomplete so far. In this paper, we develop a more comprehensive theoretical framework of the connection between the statistical and the economic properties of day-ahead electricity forecasts. We find that, apart from the accuracy and the bias, which have already been extensively researched, the correlation between the forecast errors and the market price spread determines the economic implications - a phenomenon which we refer to as 'correlation effect'. Our analysis is completed by a case study on solar electricity forecasting in Germany which illustrates the relevance and the limits of both our theoretical framework and the correlation effect.

Keywords: Forecasting evaluation; renewable energy; electricity markets; balancing costs; artificial neural network; clear sky model; Germany.

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1 Introduction

The combination of governmental incentives and falling investment costs has led to a rapidly growing share of electricity generation from variable renewable energy sources (VRE), such as wind and solar energy. In Germany, for example, these sources temporarily met around 80% of the electricity demand in 2019[1] (Hein, Peter, & Graichen, 2020). Consequently, wind and solar energy become more and more important to the electricity system, including the challenge of handling their variability. One part of the solution to this challenge are good short-term electricity generation forecasts (Sinsel, Riemke, & Hoffmann, 2020).

Several recent studies present forecasting models for solar and wind electricity generation using fundamental equations, statistical methods, artificial intelligence techniques, or a combination of these. The assessment of those forecasting models has a strong focus on accuracy, which becomes manifest most clearly in electricity forecasting competitions (e.g. Hong, Pinson, & Fan, 2014; Hong et al., 2016), reviews (e.g. Foley, Leahy, Marvuglia, & McKeogh, 2012; Voyant et al., 2017), and benchmarking studies (e.g. Lorenz et al., 2009). Unfortunately, the relative performance ranking of methods varies with the accuracy measure (Crone, Hibon, & Nikolopoulos, 2011). In order to remedy this shortcoming with regard to choosing the optimal forecast, some studies are specifically dedicated to discuss the pros and cons of different error measures (e.g. Madsen, Pinson, Kariniotakis, Nielsen, & Nielsen, 2005). In this context, Bessa, Miranda, Botterud, and Wang (2011) argue that the goodness of a forecast depends on the specific forecasting application, notably electricity trading or system operation.

With regard to electricity trading, few existing studies extend the focus on forecast accuracy by including the assessment of economic implications, i.e. the related trading revenues and costs. Across different renewable energy sources and market conditions, these studies attribute economic benefits to forecasting, i.e. the net revenues of forecast-based trading are better than the net revenues in a reference scenario, such as trading on the basis of naïve habit persistence or no forecast-based trading at all (e.g. Kraas, Schroedter-Homscheidt, & Madlener, 2013; Parkes, Wasey, Tindal, & Munoz, 2006). The relative economic performance of different forecasts, however, is strongly dependent on the prevailing market conditions.

[1]This happened on April 22, 2019. Including non-variable sources, such as biomass and hydro, renewable energies contributed even as much as 92% of the electricity demand.

In this context, some studies focus on what we will refer to as "asymmetry effect" (Bessa et al., 2011; Botterud et al., 2012; Pinson, Chevallier, & Kariniotakis, 2007). This effect occurs under asymmetric market conditions, i.e. if the magnitude of the (expected) economic implications per unit of forecast error differs with regard to the sign of the forecast error (underestimation or overestimation). Under such market conditions, it is economically advantageous to follow a trading strategy which is biased towards underestimation or overestimation, depending on which one is economically preferable. A more general discussion of decision-making under asymmetric conditions is provided by Granger and Pesaran (2000). Biased electricity trading strategies can be derived from probabilistic density forecasts, as demonstrated by Pinson et al. (2007) for the Netherlands as well as by Botterud et al. (2012) for the United States. Biased trading strategies can also follow biased point forecasts as shown by Bessa et al. (2011).

So far, it has been consensus that, in the absence of the asymmetry effect, the conditional mean point forecast is economically efficient (Granger & Pesaran, 2000). As a result, a more accurate point forecast should go hand in hand with better economic performance. In the energy domain, this idea is supported, e.g., in a sensitivity analysis of simulated electricity forecasts of different predefined error levels carried out by Barthelmie, Murray, and Pryor (2008) for the United Kingdom.

In this paper, we introduce the "correlation effect", which refutes this consensus. This effect occurs whenever the economic implications of forecast errors are time-dependent and correlated with the forecast errors. As we show in the following - theoretically and, for the case of solar photovoltaics (PV) in Germany, empirically -, this correlation affects the economic performance of forecasts and should thus be taken into account during forecast development and selection.

With our analysis, we aim to contribute to a better and more complete understanding of the connection between the errors and the economic implications of electricity generation forecasts. In the case study, we intentionally use well-known forecasting models with different accuracy, which provides useful for our analysis and the exposition of our insights gained. Besides two minor methodological refinements of the statistical clear sky approach that has been applied, major mathematical advances in forecasting methods are beyond the scope of our paper. However, our new insights about the correlation effect can be used in the future for developing better forecasts with enhanced economic implications.

In fact, we strive for filling a conceptual gap in the existing forecasting literature: even though it is widely acknowledged that the electricity from VRE has an influence on market prices (e.g. Sensfuß, Ragwitz, & Genoese, 2008), the resulting correlation has been neglected so far. Instead, existing studies explicitly assume that forecast errors and market prices (which determine the economic implications of forecast errors) are statistically independent (Botterud et al., 2012; Pinson et al., 2007).

In the first part of this paper, we develop a theoretical framework that explains both the asymmetry effect and the correlation effect (section 2). Initially, we give a short introduction to electricity trading and set up a framework for the evaluation of its economic implications (subsections 2.1 and 2.2). Thereupon, we analytically derive formulas for the two economic dimensions "expected value" and "risk" of the forecast implications which give insights into both effects, and reveal under which market conditions either effect may or may not occur (subsection 2.3). In addition, we discuss the fundamental background of the correlation effect (subsection 2.4).

In the second part of this paper, we carry out a case study to validate the theoretical framework behind the correlation effect and to quantify its magnitude. The setup of the case study is described in section 3. As our case study is for a specific country (Germany), we give an introduction to the prevailing market conditions which we interpret in the context of the previously developed framework (subsection 3.1). Subsequently, we briefly characterize the portfolio of PV systems and the numerical weather predictions that are used for our modeling (subsection 3.2). The following subsection 3.3 outlines the forecasting models implemented: a clear sky model (CSM) which has been combined with a linear model (LM), an autoregressive model (ARX), and an artificial neural network (ANN). Finally, we provide some information about the evaluation approach adopted (subsection 3.4). The results of the case study are presented in section 4, and discussed in section 5 which also concludes.

2 Theoretical Framework

2.1 Forecast-Based Electricity Trading

In order to strike a balance with demand and residual generation, the electricity from VRE is normally traded in successive spot markets, namely the day-ahead and the intra-day electricity market. In the day-ahead auction, bids for each delivery hour of the next day are submitted based on day-ahead point or density forecasts. After the gate closure, these bids are ranked for each hour in ascending order of price. Hourly market clearing prices and corresponding delivery schedules are derived from the intersection of the aggregated bid curves of demand and supply. Intra-day trading is possible from a given time after the day-ahead market gate closure until a given time before delivery. It allows market participants to take corrective actions on their schedules based on intra-day forecasts. In other words, expected undesirable deviations between day-ahead bids and actual delivery can be balanced. Deviations that occur after intra-day gate closure, i.e. deviations between the corrected intra-day schedule and delivery, are balanced in the imbalance market. However, as we consider day-ahead forecasts only, this is beyond the scope of our study.

2.2 The Concept of Balancing Costs

Economic implications of trading the electricity from VRE can be quantified in terms of balancing costs (BC_t), i.e. the time-varying costs arising from the settlement of deviations between the initial bids in the day-ahead market and the actual delivery. They are normally calculated by comparing the revenues from bidding according to a given forecast with the revenues from bidding according to the perfect point forecast (which is equal to the actual delivery). This concept leads to the following equation

$$BC_t = E_t P_t^{DA} - [E_t^{DA} P_t^{DA} + (E_t^{ID} - E_t^{DA}) P_t^{ID} + (E_t - E_t^{ID}) P_t^{B}], \qquad (1)$$

where E_t is the actual electricity generation, E_t^{DA} and E_t^{ID} are the day-ahead and intra-day electricity schedules, P_t^{DA} and P_t^{ID} are electricity prices at the day-ahead and intra-day markets, and P_t^B is the imbalance price. $BC_t > 0$ is related to costs and $BC_t < 0$ is related to revenues through balancing efforts.

This study focuses on day-ahead electricity forecasts. For this reason, balancing costs can be rewritten as

$$BC_t = (E_t^{DA} - E_t)(P_t^{ID} - P_t^{DA}) + (E_t^{ID} - E_t)(P_t^{B} - P_t^{ID}), \qquad (2)$$

where the first part of the equation is dependent on the deviations of the day-ahead bids, and the second part is dependent on the deviations of the intra-day bids. In the following, we consider the day-ahead part only, which is equivalent to assuming the intra-day bids to match actual delivery:

$$BC_t = (E_t^{DA} - E_t)(P_t^{ID} - P_t^{DA}) = \Delta E_t \; \Delta P_t. \tag{3}$$

Thus, at any given point in time, the economic implications of inaccuracies of the day-ahead bids and the underlying forecast depend on the magnitude and sign of the deviations from actual delivery (ΔE_t), as well as on the price spread between the day-ahead and the intra-day market (ΔP_t). If the price spread is positive, upward deviations will be costly while downward deviations are beneficial and vice versa. This setting does not consider individual penalties for upward and downward deviations, which are present in some (balancing) market environments (e.g. Kraas et al., 2013). For a detailed discussion of the economic implications of penalties, the reader might refer to Botterud et al. (2012).

It seems intuitive to interpret balancing costs as the loss function of electricity forecasts. However, such an interpretation is not in line with the requirements that Granger (1999) defines for loss functions: balancing costs are in general not minimal when the forecast error is zero, and they decrease as the forecast error moves away from zero in the same direction as the one that is favorable according to the price spread. Thus, the economic implications of forecasting in terms of balancing costs merit a special investigation, which is provided by this study.

2.3 The Connection Between Economic Implications and Bid Properties

According to the main principle of decision theory, we consider the expected value as well as the risk that is associated with the balancing costs of bidding on the basis of a given forecast. In this subsection, we analytically derive formulas that link these two economic dimensions to the statistical properties of the considered bids and eventually to the properties of the underlying forecast.

2.3.1 Expected Value

From the definition of covariance, it can be derived that

$$\mathbb{E}(BC_t) = \mathbb{E}(\Delta E_t \; \Delta P_t) = \mathbb{E}(\Delta E_t) \; \mathbb{E}(\Delta P_t) + cov(\Delta E_t, \Delta P_t), \tag{4}$$

where $\mathbb{E}$ and cov denote the expected value and the covariance, respectively. Replacing the covariance by the Pearson product-moment correlation coefficient (denoted by cor) leads to

$$\mathbb{E}(BC_t) = \mathbb{E}(\Delta E_t)\ \mathbb{E}(\Delta P_t) + cor(\Delta E_t, \Delta P_t)\ \sqrt{var(\Delta E_t) var(\Delta P_t)}, \tag{5}$$

where var is the variance. This fundamental formula provides information on how the properties of electricity bids and the underlying forecast as well as the characteristics of a given market interact and determine the resulting expected balancing costs. The first part of the formula represents what we call the asymmetry effect. If the expected price spread between the day-ahead and the intraday market $\mathbb{E}(\Delta P_t)$ is unequal to zero, one will profit from a bidding strategy which is biased such that the expected deviation $\mathbb{E}(\Delta E_t)$ has the opposite sign of the expected price spread. The second part of the formula represents the correlation effect which is in the focus of this paper. The sign of the correlation effect is determined by the correlation between deviations and the price spread $cor(\Delta E_t, \Delta P_t)$ such that positive (negative) correlation leads to increasing (decreasing) expected balancing costs. The magnitude of the effect depends on the strength of the correlation as well as on the variance of the bids' deviations, $var(\Delta E_t)$, and on the variance of the price spread, $var(\Delta P_t)$.[2]

In the case of bidding on the basis of an unbiased point forecast, the estimated variance of the bids' deviations is directly related to forecast accuracy:

$$\widehat{var}(\Delta E_T) = \frac{1}{T-1}\sum_{t=1}^{T}(\Delta E_t - \overline{\Delta E_T}) \approx \frac{1}{T}\sum_{t=1}^{T}\Delta E_t = RMSE^2, \tag{6}$$

where the mean forecast error $\overline{\Delta E_T}$ is approximately zero (for a large sample) and $RMSE$ denotes the root mean squared forecast error. Thus, the expected value of the economic implications of such a forecast depends on both its accuracy and its correlation with the price spread.

2.3.2 Risk

In order to derive some fundamental insight on the risk dimension, we make two simplifying assumptions which we will contrast with the empirical findings from

[2] Note that the variance of the bids' deviations has previously been referred to as forecast efficiency (Mincer & Zarnowitz, 1969).

our case study afterwards. First, we suppose that the probability distributions of different forecasts are similar in terms of their tail extremity. In that case, state-of-the-art risk measures such as the conditional value-at-risk (CVaR) are proportional to the standard deviation, which allows us to focus on the latter or, equivalently, on the variance. Second, we assume that the bids' deviations ΔE_t and the price spread ΔP_t are normally distributed.

According to Appendix A, the variance of the balancing costs can be calculated as follows:

$$\begin{aligned} var(BC_t) &= var(\Delta E_t \Delta P_t) \\ &= \mathbb{E}(\Delta E_t)^2 var(\Delta P_t) + \mathbb{E}(\Delta P_t)^2 var(\Delta E_t) \\ &+ 2\mathbb{E}(\Delta E_t)\mathbb{E}(\Delta P_t)\sqrt{var(\Delta E_t) var(\Delta P_t)}\, cor(\Delta E_t, \Delta P_t) \\ &+ var(\Delta E_t) var(\Delta P_t)(1 + cor(\Delta E_t, \Delta P_t)^2). \end{aligned} \tag{7}$$

From eq. (7), we can draw conclusions regarding the connection between bid properties and the related economic risk. First, if we only consider the asymmetry effect and assume $cor(\Delta E_t, \Delta P_t) = 0$, we can see that the risk increases with the magnitude of the forecast bias $\mathbb{E}(\Delta E_t)$ (first part of eq. (7)). Thus, in an asymmetric market environment, there is a trade-off between the expected value and the economic risk. This finding is in line with Botterud et al. (2012), where optimal bids are derived for different risk preferences. Second, if we isolate the correlation effect ($\mathbb{E}(\Delta E_t) = \mathbb{E}(\Delta P_t) = 0$), we see that the risk decreases if the absolute value of the correlation coefficient $cor(\Delta E_t, \Delta P_t)$ decreases (last part of eq. (7)). Hence, to lower the (positive) correlation between bid deviations and the price spread can be expected to be a promising way of economic forecast optimization, as it seems to improve both the expected value and the economic risk at the same time. In both cases (pure asymmetry effect and pure correlation effect), the variance of the balancing costs increases with the variance of the bids's deviations which can be related to the forecast accuracy (eq. (6)).

2.4 The Relevance of the Correlation Effect

So far, we have shown that correlation between forecast errors and the price spread co-determines the economic performance of forecasts. But under which conditions can we fundamentally expect a significant (positive) correlation between these? The answer is related to the merit order effect, which explains the influence that the electricity generation from VRE has on the wholesale market price. In contrast to other studies that usually examine the influence on day-ahead prices (e.g. Sensfuß et al., 2008), we are mainly interested in the influence on the price spread between the day-ahead and the intra-day market. This price spread can generally be explained by the total deviation between the day-ahead bids and the updated intra-day forecasts. If the market is short of energy, the intra-day price will rise above the day-ahead price up to the point where a sufficient number of additional power plants has been ramped up. The other way around, if there is excess electricity surplus in the market, the intra-day price will fall down to the point where enough power plants have exited the market. Of course, the deviations of several individual market participants can cancel each other out such that they do not have an impact on the market. However, if the share of electricity from VRE is high and the deviations from single VRE are positively correlated with each other, they can be expected to considerably affect the market balance such that the deviations of single market participants will be correlated with the price spread. The deviations of single VRE generators will be correlated with each other, for instance, if they are of the same kind and located close to each other or if all market participants use similar forecasting models and input data.

3 Setup of the Case Study

3.1 German Market Conditions

In our case study, the economic impacts of different electricity generation forecasts are analyzed in the context of German electricity markets, more precisely in the context of the day-ahead and the intra-day market. According to common market practice, we assume that solar electricity is sold in the day-ahead market. Further, in order to isolate the economic implications of the day-ahead forecast, we assume that all deviations are settled in the intra-day market (eq. (3)).

In addition to forecast-based trading (cf. subsection 2.1), the German day-ahead and intra-day market are open for financial trading, i.e. it is allowed to speculate on the price spread between the day-ahead and the intra-day market. As a result, due to the no-arbitrage condition, the price spread is expected to be close to zero. As we will show in subsection 4.1, the statistical evaluation of price data from the year 2014 supports this proposition. Thus, we assume that the German market conditions are symmetrical, in contrast to, for instance, the case of the Netherlands (Botterud et al., 2012) and the United States (Pinson et al., 2007).

The assumption on symmetrical market conditions has two major consequences for our case study. First, any economic implications that occur must be due to the correlation effect which allows us to analyze this effect in detail and in isolation from the asymmetry effect. Second, as argued in the introduction, it is not advantageous to follow biased trading strategies in a symmetrical market environment. Hence, in the following, it is appropriate to focus on different conditional mean point forecasts, of which the accuracy can be appropriately evaluated by the RMSE, and bid deviations are equivalent to forecast errors.

Note that the German intra-day market is continuous so that prices are highly time-dependent, and intra-day balancing costs can be optimized through strategic timing of the deviation settlement (Garnier & Madlener, 2015). To exclude such influences from our analysis, the intra-day reference price is used, which is the volume-weighted average price of all deals that are related to a given quarter-hour and that were realized during the last 15 minutes before the respective intra-day gate closure. Thus, we assume that deviations are balanced (at the last-15-minutes average price) right before gate closure, which is in line with the reality of the German intra-day market.

3.2 Data Used

Our analysis is based on a portfolio of ten large-scale PV systems installed all over Germany, with a total capacity of 156.7 MW[3]. Electricity generation time series from 2014 are available for those systems in a quarter-hourly resolution. Time series for 2013 are additionally available for PV systems nos. 6 and 10. For each quarter-hour of the year, there is a value indicating how much electricity has been fed into the grid.

Our forecasting models use numerical weather predictions for the parameters "solar irradiance" and "clear sky irradiance" as inputs. For testing, two historical prediction runs of the global atmospheric re-analysis model *ERA-Interim* from ECMWF[4] are available per day, starting from the initial points 00:00 h UTC and 12:00 h UTC. For the purpose of day-ahead electricity forecasting, NWPs from 00:00 h UTC of the previous day are of interest as 12:00 h UTC is after

[3]The installed peak capacity of the individual PV systems ranges from 0.8 MW to 82 MW.

[4]European Centre for Medium-Range Weather Forecasts, an independent intergovernmental organization supported by 34 states and based in Reading, UK.

gate closure of the day-ahead electricity market which is at 11:00 h (10:00 h) UTC for winter (summer) time. Operating at the global scale, the ERA-Interim model generates data at relatively low spatial (about 28 x 17 km) and temporal (6 h) resolution. Hence, we apply interpolation to generate site-specific time series with a quarter-hourly resolution. More detailed information about the ERA-Interim re-analysis model of ECMWF can be found in Berrisford et al. (2009).

3.3 Forecasting Models

The electricity output of a solar PV system is a function of (1) deterministic factors, such as the position of the sun and the orientation of the collector (tilt and azimuth), and (2) stochastic weather impacts, such as cloud cover, aerosols, fog, snow, and temperature. In this study, deterministic and stochastic factors are modeled separately by means of a clear sky approach. To this end, the actual (forecasted) solar irradiance $I_t^{(DA)}$ is defined as

$$I_t^{(DA)} = f_t^{CSI} I_t^{CS}, \tag{8}$$

where f_t^{CSI} is the (stochastic and unitless) clear sky irradiance factor and I_t^{CS} is the (deterministic) irradiance under clear sky conditions. Similarly, the actual (forecasted) electricity generation can be written as

$$E_t^{(DA)} = f_t^{CSE} E_t^{CS}, \tag{9}$$

where f_t^{CSE} is the clear sky electricity factor and E_t^{CS} is the clear sky electricity generation. Using these definitions, both clear sky factors are high (low) for clear (overcast) days[5]. Note that even under clear sky conditions, the electricity generation is weather-dependent due to temperature effects on the PV system's efficiency. However, this effect is rather small[6] and thus can be safely neglected when calculating E_t^{CS}.

The next subsection describes how the electricity generation under clear sky conditions is calculated. Thereafter, three different forecasting models for the

[5] Ideally, the clear sky factors should take values between zero and one. In our case, however, they can also be slightly above unity due to the statistical approach that has been applied (subsection 3.3.1).

[6] According to Marion et al. (2005), the so-called power correction factor amounts to -0.45%/K.

clear sky electricity factor are introduced (the LM, the ARX, and the ANN).

3.3.1 Clear Sky Model

Calculation of the clear sky electricity generation can follow either the fundamental or a statistical approach. In this study, an advanced statistical CSM based on Bacher, Madsen, and Nielsen (2009) is implemented. Calculations use the actual generation time series E_t as presented in subsection 2.1. This time series can be rearranged such that

$$E_t = E(x_t, y_t), \tag{10}$$

where $x = 1, \ldots, 365$ is the day of the year and $y = 1, \ldots, 96$ is the quarter-hour of the day. The clear sky electricity generation time series can be seen as the upper surface of the resulting point cloud and can be estimated by statistical methods. In this study, we apply weighted quantile regression as described in Bacher et al. (2009), except for two refinements that we developed with the aim of rectifying two shortcomings of the original approach. Firstly, the "day of the year" distance function is modified in order to address scarcity of clear sky winter days. Secondly, a simple correction tool deals with systematic overestimation of the clear sky electricity generation around the start and the end of the daily generation. Both refinements are described in detail in the Appendices B and C, respectively. To illustrate the performance of the (enhanced) clear sky model, the rearranged time series of actual and clear sky electricity generation are shown for one of the ten PV plants in the two three-dimensional plots depicted in Fig. 1.

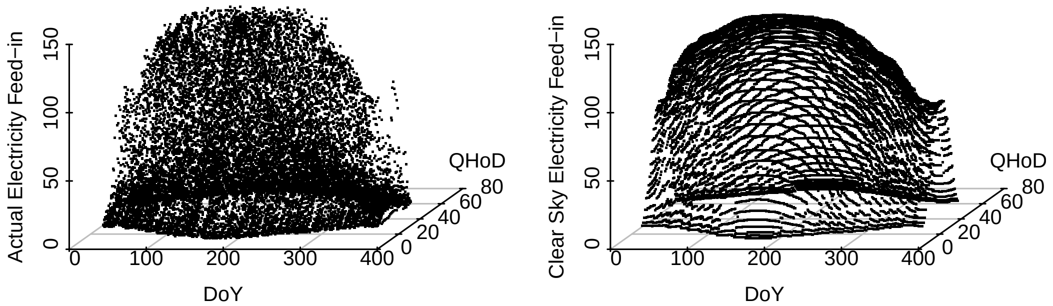

Figure 1: Actual (left) and clear sky (right) electricity generation from PV system no. 10 for the year 2014. The values are given in kWh/quarter-hour and were rearranged by the day of the year (DoY) and the quarter-hour of the day (QHoD).

Bacher et al. (2009) use one and the same time series of actual values as input to both the clear sky estimation and the model evaluation. This seems unsatisfactorily with regard to the forecasting application considered here. The estimated clear sky values might be affected by yearly particularities in the actual electricity generation data and thus enhance the forecasting performance compared to a true out-of-sample forecast. We investigate this hypothesis using the example of the PV systems nos. 6 and 10 where generation time series are available for 2013 and 2014. The analysis of the resulting clear sky electricity time series reveals significant inter-yearly differences[7]. However, very similar forecast accuracies can be achieved with both time series. Apparently, the integrated model architecture is able to balance inter-yearly differences[8]. In the following, given these results, we use actual values for 2014 as an input to the clear sky estimation (as those values are available for all PV systems) and assume that the same forecast accuracy can be achieved if using actual values for 2013 (which seems feasible in practice).

3.3.2 Linear Model

The LM can be described as

$$f_t^{CSE} = \beta_0 + \beta_1 f_t^{CSI} + \epsilon_t, \tag{11}$$

where f_t^{CSI} is obtained from NWP, β_0 and β_1 are regression coefficients, and ϵ_t is the residual term, which is assumed to be normally distributed. For each forecasting day, coefficients are estimated by ordinary least squares regression based on quarter-hours from a fixed number of preceding days (30), where the actual electricity generation exceeded a given threshold (0.2% of installed-capacity-equivalent generation)[9]. Thus, the model features seasonality, and very unproductive quarter-hours are excluded from the regression, because both f_t^{CSE} and f_t^{CSI} do not take reasonable values in that case.

[7]Those differences can be explained by weather influences. In case there are many (few) clear sky days in the environment of an estimation point, this will increase (decrease) the estimation result of the quantile regression. For example, comparatively low clear sky values in spring 2013 can be explained by a long-lasting period of snow cover in that year.

[8]If the CSM is combined with a linear model, for example, regression coefficients during winter can be observed to be significantly higher when using (low winter) clear sky values from 2013.

[9]The values chosen show the best results in our sensitivity analyses.

3.3.3 Autoregressive Model with Exogenous Input

The ARX forecasting model can be characterized by

$$f_t^{CSE} = \beta_0 + \beta_1 f_t^{CSI} + \beta_2 f_{(t-d)}^{CSE} + \epsilon_t, \tag{12}$$

where $f_{(t-d)}^{CSE}$ is the most recent observation of the clear sky electricity factor at the same time of the day which is available for forecasting. Regression coefficients are computed based on weighted least squares with exponential forgetting (forgetting factor 0.999) as proposed in Bacher et al. (2009). This technique accounts for seasonality by reducing the effect of past observations on the coefficients as their time lag increases. Again, a threshold is applied in connection with actual generation (same value as for the LM).

3.3.4 Artificial Neural Network

The ANN used in our study is of the Multilayer Perceptron (MLP) type. It consists of one input neuron (clear sky irradiance factor), one output neuron (clear sky electricity factor), and one layer of hidden neurons featuring sigmoid activation functions. Connection weights and biases of the MLP are determined with the help of a back-propagation training algorithm. The structure of MLPs and of the back-propagation concept in the context of PV electricity forecasts is described in detail in Mellit and Kalogirou (2008).

In order to avoid over-fitting of the MLP, a cross-validation algorithm has been developed to select the optimal number of hidden neurons, the initial weights, and the number of iterations for back-propagation. The algorithm randomly assigns input and output values from the 30 most recent days to two disjunct data sets, one for the training (70% of the data) and one for the cross-validation (30% of the data). Several MLPs are trained on the training data set with different parameters and initial weights. When the training is finished after a predefined number of iterations, the network error is calculated for the cross-validation set. The MLP with the lowest cross-validation error is chosen for the forecasting.

For every period of ten days, 2160 new MLPs are trained and the best one is selected by cross-validation[10]. As results might be dependent on the composition

[10] 12 cross-validation loops x 4 different numbers of hidden neurons x 20 random sets of initial weights = 2160 MLPs in total.

of training and cross-validation data, the random creation of data sets is repeated several times, a procedure which we refer to as "cross-validation loop". Table 1 summarizes cross-validation and back-propagation parameters that, according to our sensitivity analyses, generated good and robust results.

3.4 Evaluation

We quantify the forecast accuracy in terms of RMSE following eq. (6). The expected values of forecast errors (bias) and prices are estimated by the sample mean, and the variance of the price spread is estimated by the formula for the sample variance. The correlation between forecast errors and the price spread is calculated using the Pearson product-moment correlation coefficient, and the CVaR is computed for a probability of 1%. Note that, for all calculations, values when there was no sunshine have been removed from the time series.

4 Results of the Case Study

4.1 Statistical Analysis

In order to characterize the empirical distribution of the price spread and the portfolio errors of the different forecasting models, some statistical parameters are summarized in Table 2. Additionally, Fig. 2 shows the density functions of the price spread and of the portfolio forecast errors from the ARX compared to normal distributions with equivalent means and variances.

Apparently, the mean price spread is not exactly zero, and the price spread's distribution features positive skewness, which means that the expected economic implications are not perfectly symmetrical. However, notice that the significance of these statistics is partly offset by the comparatively high standard deviation and kurtosis of the price spread, which indicate that the economic implications are generally hardly predictable. Thus, and with regard to the no-arbitrage condition (subsection 3.1), we argue that it is appropriate to assume that economic implications are symmetrical.

The errors from the three forecasting models all follow similar distributions with low bias and skewness as well as high kurtosis. As a result, the distribution's peak is taller and its tails are fatter than the mean-variance equivalent normal distribution. Note that this does not contradict the normality assumptions regarding the clear sky electricity factor (subsections 2.3.2 and 2.3.3) but can be explained by the diurnal pattern of clear sky electricity generation which co-determines the forecast errors (eq. (9)).

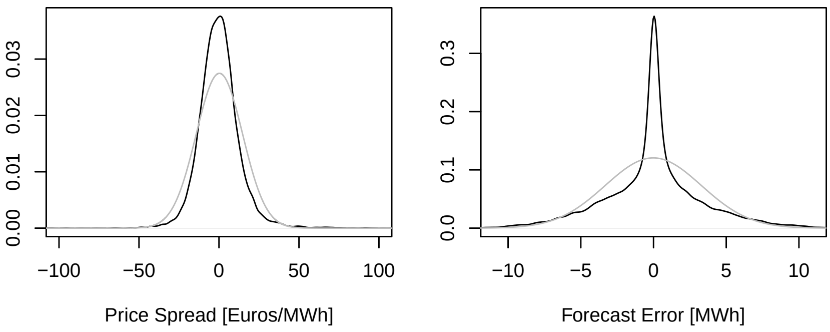

Figure 2: Empirical densities of the price spread (left plot, black curve) and of the portfolio forecast error from the ARX (right plot, black curve) compared to normal distributions with equivalent means and variances (gray curves).

4.2 Expected Value

The left plot in Fig. 3 successfully validates the fundamental formula for the expected value of balancing costs (eq. (5)) on the basis of our case study. As argued in subsection 2.3.1 for a symmetrical market environment, the right-hand side of eq. (5) reduces to its second part, and the variance of the deviations can be replaced by the RMSE according to eq. (6). The right plot in Fig. 3 decomposes the expected balancing costs into its forecast-specific determinants, the RMSE and the correlation between the forecast errors and the price spread. Due to the multiplicative connection (eq. (5), part 2), the expected balancing costs are proportional to both determinants and curves of constant expected balancing costs follow a hyperbolic function in the plot (gray curves). Apparently, the correlation varies substantially and has indeed a large impact on the expected balancing costs which, in turn, demonstrates the relevance of the correlation effect. The majority of this variation occurs across various PV systems (displayed with different colors) which can be traced back to their diverse locations.[11]

Further variation of the correlation occurs across various forecasting models and is in the same range as the variation of the RMSE for one specific system. As

[11]There is no significant relationship between the system size and the correlation, and all other technical parameters are very similar across different systems.

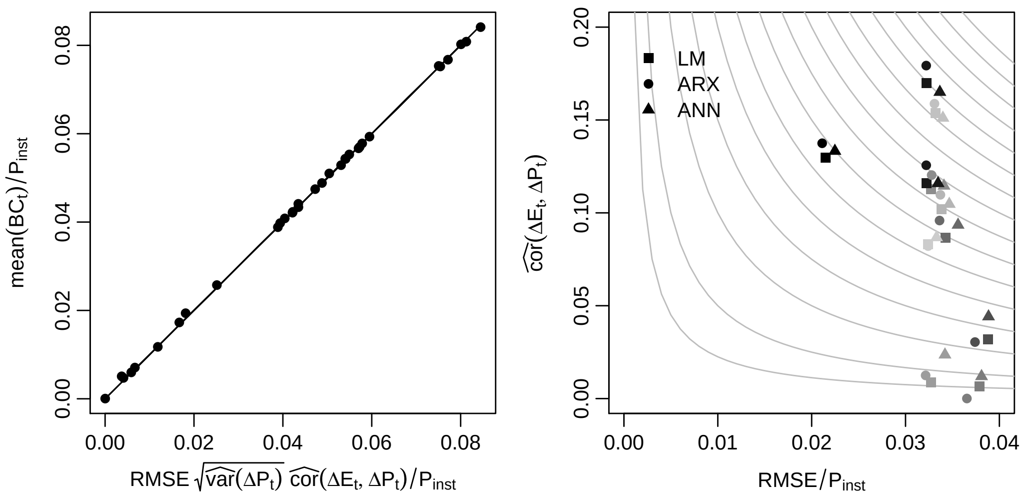

Figure 3: Left plot: Normalized mean balancing costs as calculated according to the second part of eq. (5) on the x-axis and as observed in the sample on the y-axis; the black line indicates equivalence. Right plot: Combinations of normalized RMSE and the correlation between deviations and the price spread; the grey curves indicate constant expected balancing costs as calculated according to the second part of eq. (5). Various PV systems and forecasting models are displayed in different colors and shapes, respectively. The left-most points refer to the portfolio.

a result, an optimization of the expected balancing costs should account for both accuracy and correlation. For example, we consider the results on the portfolio level which are displayed by the left-most points in the plot. Apparently, the LM outperforms the other models due to low correlation, even though it has a slightly higher RMSE. Note that the RMSE of the portfolio is lower than for single systems due to the so-called smoothing effect, i.e. due to the partial leveling of forecast errors from different systems. The mean balancing costs of the portfolio, however, are the weighted average of the mean balancing costs of single systems (portfolio theory; cf. Markowitz, 1952).

4.3 Risk

The left plot in Fig. 4 tests the assumption made in subsection 2.3.2 about the equivalence of the CVaR and the standard deviation of balancing costs. Apparently, the correlation between both parameters is high but the relationship is not perfect, which can be explained by differing tail characteristics of the underlying density functions (cf. subsection 4.1). Hence, the risk might be roughly approximated by the standard deviation in a first step, but it subsequently merits investigation by more appropriate risk measures.

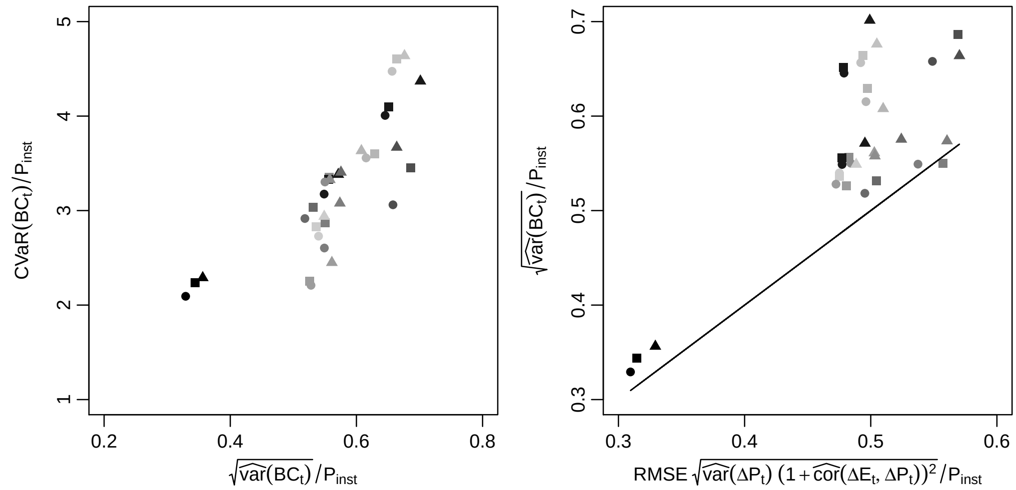

Figure 4: Left plot: Comparison between the empirical standard deviation of balancing costs and the CVaR. Right plot: Standard deviation of balancing costs as calculated according to the last part of eq. (7) on the x-axis and as observed in the sample on the y-axis; the black line indicates equivalence. Various PV systems and forecasting models are displayed in different colors and shapes, respectively. The left-most points refer to the portfolio.

The right plot in Fig. 4 examines if the analytically derived term for the variance of balancing costs (eq. (7)) holds true for our case study. Again, we account for the market's symmetry by reducing the right-hand side of the formula to its last addend and by applying eq. (6). The result shows that, instead of being a good approximation, our formula is rather a lower bound for the variance (or standard deviation) of the balancing costs. Once more, the reason lies in an inappropriate assumption which became obvious in subsection 4.1: instead of being normally distributed, the density functions of the deviations and the price spread feature fatter tails, which has an amplifying effect on the risk. In both plots, we can observe the portfolio effect, i.e. the sum of all PV systems implies lower risk than each single system. In addition, the validity of both theoretical connections ($CVaR \sim \sqrt{\widehat{var}}$ and eq. (7)) seems to improve substantially on the portfolio level which could be attributed to the leveling of extremes.

5 Discussion and Conclusion

In this paper, we elaborated on the determinants of the economic implications of electricity forecasts. We developed a theoretical framework that reveals two fundamental effects behind the economic forecast performance: the asymmetry effect and the correlation effect. Subsequently, we substantiated our analytical results by means of a case study with PV systems in Germany, a market environment which we find to be approximately symmetrical and thus suitable for an in-depth examination of the correlation effect.

Both the theoretical and the empirical investigation lead to the conclusion that, apart from accuracy and asymmetry, correlation matters for the economic implications of a forecast. More precisely, it is the correlation between the forecast errors (or the deviations of the consequential bids) and the price spread between the day-ahead and the intra-day market that co-determines the expected value of the economic implications. With regard to the forecast-related risk, however, it was not possible to derive general results due to non-normally distributed forecast errors and price spreads. Thus, the risk of a certain combination of a forecast and a market always merits an individual evaluation.

The insights from our analysis are useful for both forecast development and practice. On the one hand, instead of focusing on accuracy only, forecast development should systematically search for models which at the same time feature high accuracy and low correlation. For example, including the correlation in learning criteria of artificial intelligence techniques might be a promising approach. On the other hand, our study provides further evidence that unidimensional accuracy-based forecast assessment, as it is still widely used by forecast practitioners, remains incomplete and thus suboptimal from an economic perspective. Instead, the expected value and the risk of a forecast should be considered. In contrast to existing studies that already apply decision-theoretic approaches (e.g. Botterud et al., 2012), the assumption of statistical independence between electricity forecasts and prices should be reviewed in order to take the correlation effect adequately into account.

This study evaluates the economic implications of electricity forecasts from the private perspective of a generator or portfolio owner. However, if markets work well, the price spread between the day-ahead and the intra-day markets will reflect the cost of balancing forecast errors. Hence, if private agents take the correlation with market prices into account when developing and choosing forecasts, this will also optimize (social) system costs. In fact, a forecast that is less correlated with market prices can be expected to be less correlated with the forecasts of other market participants. As a result, the error of the aggregated forecast would reduce. This rationale is in line with Mc Garrigle and Leahy (2015), finding reduced system costs for reduced system-level forecast errors.

Our analysis considers day-ahead forecasts in the context of day-ahead and intra-day markets. The fundamental effects discussed might also occur in the context of intra-day forecasts and imbalance markets, which is at least as important and thus promising for further research. Moreover, our case study focuses on the specific field of PV electricity forecasting in the German market context. The results, however, are limited neither to photovoltaics nor to Germany. In fact, the correlation effect will be always applicable if the forecast errors of a given application are correlated with each other and can altogether have an impact on market prices. This is notably the case not only for solar but also for wind generation and (partly) for electricity demand forecasts in many market environments. The correlation effect is expected to be even stronger for wind energy due to higher market penetration, and its relevance is likely to increase further as the shares of VRE increase.

A Variance of the Product of Two Correlated Variables

The aim is to derive a formula for $var(XY)$ where $X \sim N(\mu_X, \sigma_X^2)$, $Y \sim N(\mu_Y, \sigma_Y^2)$ and $cor(X,Y) = \rho$. For this purpose, let $X = \mu_X + \sigma_X U$ and $Y = \mu_Y + \sigma_Y(\rho U + \sqrt{1-\rho^2}V)$ with $U, V \overset{iid}{\sim} N(0,1)$. Then

$$\begin{aligned} var(XY) &= var\Big((\mu_X + \sigma_X U)(\mu_Y + \sigma_Y(\rho U + \sqrt{1-\rho^2}V))\Big) \\ &= var\Big(\mu_X\mu_Y + (\mu_X\sigma_Y\rho + \mu_Y\sigma_X)U + \mu_X\sigma_Y\sqrt{1-\rho^2}V \\ &+ \sigma_X\sigma_Y\rho U^2 + \sigma_X\sigma_Y\sqrt{1-\rho^2}UV\Big). \end{aligned} \tag{13}$$

By definition, U and V are uncorrelated. Furthermore, $cov(U,U^2) = E(U^3) - E(U)E(U^2) = 0$ and $cov(U,UV) = E(U^2V) - E(U)E(UV) = 0$, such that

$$\begin{aligned} var(XY) = &(\mu_X^2\sigma_Y^2\rho^2 + 2\mu_X\mu_Y\sigma_X\sigma_Y\rho + \mu_Y^2\sigma_X^2)\ var(U) \\ &+ \mu_X^2\sigma_Y^2(1-\rho^2)\ var(V) + \sigma_X^2\sigma_Y^2\rho^2\ var(U^2) \\ &+ \sigma_X^2\sigma_Y^2(1-\rho^2)\ var(UV). \end{aligned} \tag{14}$$

We know that $var(U) = var(V) = 1$ and $var(U^2) = 2$, because $U^2 \sim \chi_1^2$. For the product of U and V, we consider

$$var(UV) = \mathbb{E}(U^2V^2) - \mathbb{E}(UV)^2. \tag{15}$$

The second part of this equation is zero. Using the definition of the covariance, the first part can be rewritten as

$$\mathbb{E}(U^2V^2) = cov(U^2, V^2) + \mathbb{E}(U^2)\mathbb{E}(V^2), \tag{16}$$

where $cov(U^2, V^2) = 0$, because U and V are independent, and $\mathbb{E}(U^2) = \mathbb{E}(V^2) = 1$, because $U^2, V^2 \sim \chi^2(1)$. As a result, $var(UV) = 1$ and

$$var(XY) = \mu_X^2\sigma_Y^2 + 2\mu_X\mu_Y\sigma_X\sigma_Y\rho + \mu_Y^2\sigma_X^2 + \sigma_X^2\sigma_Y^2(1+\rho^2). \tag{17}$$

B Clear Sky Model Weight Assignment

In order to estimate clear sky electricity generation, local weights are assigned by means of a two-dimensional smoothing kernel function in such a way that the influence of the observation at (x_i, y_i) is decreasing with increasing distance from the estimation point (x_t, y_t). The local weighting function for observations is defined as

$$k(x_t, y_t, x_i, y_i) = \frac{w(x_t, x_i, h_x) * w(y_t, y_i, h_y)}{\sum_i w(x_t, x_i, h_x) * w(y_t, y_i, h_y)}, \tag{18}$$

where

$$w(x_t, x_i, h_x) = f_{std}(dist(x_t, x_i)/h_x) \tag{19}$$

and

$$w(y_t, y_i, h_y) = f_{std}(dist(y_t, y_i)/h_y) \tag{20}$$

are Gaussian kernel functions of each dimension, h_x and h_y determine the width of the weighting kernel, and f_{std} is the standard normal probability density function. The distance functions are specified as

$$dist(x_t, x_i) = min\{|x_t - x_i|, ||x_t - x_i| - 365|\} \tag{21}$$

and

$$dist(y_t, y_i) = |y_t - y_i| \tag{22}$$

for the two dimensions “day of year” and “quarter-hour of day”, respectively.

Compared to Bacher et al. (2009), the “day of year” distance function has been refined. With the new distance function, the first day of the year is defined to succeed the last day of the year. Thus higher weights are assigned to end-of-year actual values when calculating start-of-year clear sky values, and vice versa. This procedure arises from fundamental similarities between the end-of-year and start-of-year values and is supposed to generate more robust results for this season as more actual values are taken into account for the clear sky calculation. The resulting smoothing kernel is shown in Fig. 5 for $h_x = 35$ and $h_y = 0.8$, which has been identified in Bacher et al. (2009) as the optimal parametrization.

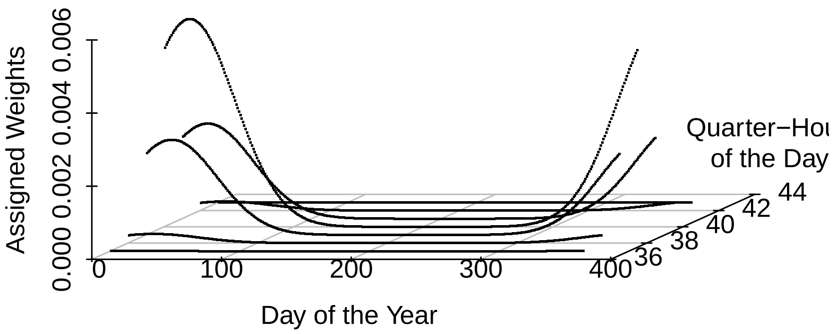

Figure 5: Smoothing kernel with refined day of year distance function for parameters $h_x = 35$ and $h_y = 0.8$ at the position $x_t = 20$ and $y_t = 40$.

C Correction Procedure for the Start and the End of the Daily Electricity Generation

The CSM as presented in Bacher et al. (2009) systematically overestimates the clear sky electricity generation around the start and the end of the daily generation. This appendix presents a simple correction procedure for this bias. In a first step, the quarter-hour of the (actual) start of the daily generation is defined as

$$s_x = min\{y|E(x,y) > 0\} \qquad \forall x = 1, \ldots, 365 \tag{23}$$

whereas the quarter-hour of the (actual) end of the daily generation is defined as

$$e_x = max\{(y|E(x,y) > 0\} \qquad \forall x = 1, \ldots, 365 \tag{24}$$

for each day of the year x. The results are shown in Fig. 6 (gray points). On this basis, the following estimation algorithm computes the estimated start of the daily generation, $\hat{s}_x$, from the recent start of the daily generation observations, s_x:

1. Initial estimation at winter solstice (around December 21), i.e. at $x = 355$:

$$\hat{s}_{355} = min\{s_{344}, s_{345}, \ldots, s_{354}\} \tag{25}$$

2. Estimation from after winter solstice until summer solstice (around June 21), i.e. at $x = 356, \ldots, 365, 1, \ldots, 172$:

$$\hat{s}_x = min\{\hat{s}_{x-1}, s_{x-1}\} \tag{26}$$

   with $\hat{s}_0 = \hat{s}_{365}$ and $s_0 = s_{365}$.

3. Estimation after summer solstice until winter solstice, i.e. at $x = 173, \ldots, 354$:

$$\hat{s}_x = \begin{cases} \hat{s}_{x-1} + 1 & \text{if } s_i > \hat{s}_{x-1} \qquad \forall i = x-5, \ldots, x-1 \\ \hat{s}_{x-1} & \text{else.} \end{cases} \tag{27}$$

Note that this algorithm estimates the lower bounds of s_x. Assuming clear sky days to feature an early start of the daily generation, $\hat{s}_x$ can be interpreted as the clear sky start of the daily generation. Thus a correction tool for the clear sky series based on $\hat{s}_x$ seems reasonable. Estimation of the end of the daily generation, $\hat{e}_x$, follows the same procedure, with inverse signs. The estimation results are again shown in Fig. 6 (solid lines). This figure also presents the estimates of the start (end) of the generation $\hat{s}_x^{CS}$ ($\hat{e}_x^{CS}$) which originally result from the presented CSM (dashed lines). It can be seen that the new estimates $\hat{s}_x$ and $\hat{e}_x$ are much more accurate and thus more satisfactory.

The gap between both estimates is defined as $\delta_{s,x} = \hat{s}_x - \hat{s}_x^{CS}$ for the start of the daily generation and $\delta_{e,x} = \hat{e}_x^{CS} - \hat{e}_x$ for the end of the daily generation, respectively. Based on these considerations, the time series of the clear sky electricity generation is corrected as follows: Clear sky estimates within the correction gap are set to zero and a linear interpolation is performed on those quarter-hours that follow (precede) the corrected start (end) of the generation. The calculation rule for the corrected clear sky estimates for morning quarter-

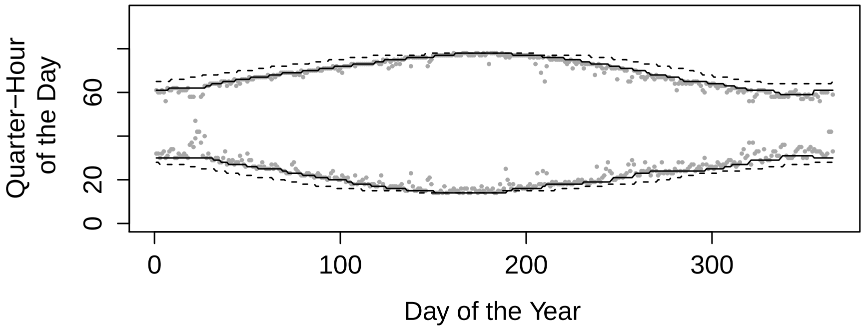

Figure 6: Actual start and end of the electricity generation (gray points) and the corresponding estimates by the CSM (dashed lines) and the estimation algorithm (solid lines).

hours can be written as

$$E_t^{CS,C} = \begin{cases} 0 & \text{if } y < \hat{s}_x \\ \frac{y-\hat{s}_x+1}{c\ \delta_{s,x}+1} & \text{if } \hat{s}_x < y < \hat{s}_x + c\ \delta_{s,x} \\ E_t^{CS} & \text{else,} \end{cases} \tag{28}$$

for each day $x = 1, \dots, 356$, where c is the correction procedure parameter. Evening quarter-hours are corrected accordingly. Sensitivity analysis shows that optimal results are obtained at $c = 2$. When choosing this value, in combination with the LM, our correction leads to an accuracy improvement of around 2% in terms of the MAE.

Fig. 7 compares uncorrected and corrected clear sky estimates along with actual values for a sample of five days that actually feature clear sky conditions. As stated at the beginning of this appendix, the original CSM systematically overestimates electricity generation around the start and the end of the daily generation. The presented correction algorithm significantly reduces this bias.

Note that the bias around the start and the end of the daily generation is an intrinsic result of the clear sky calculation method. Due to the two-dimensional smoothing kernel, actual electricity generation of neighboring quarter-hours is taken into account when estimating the clear sky electricity generation at a given point. At a point right before (after) the start (end) of the daily generation, this neighborhood is fundamentally asymmetric: Subsequent (precedent) quarter-hours feature positive values whereas the lower limit of the remaining values is zero. As quantile regression does not account for these fundamental

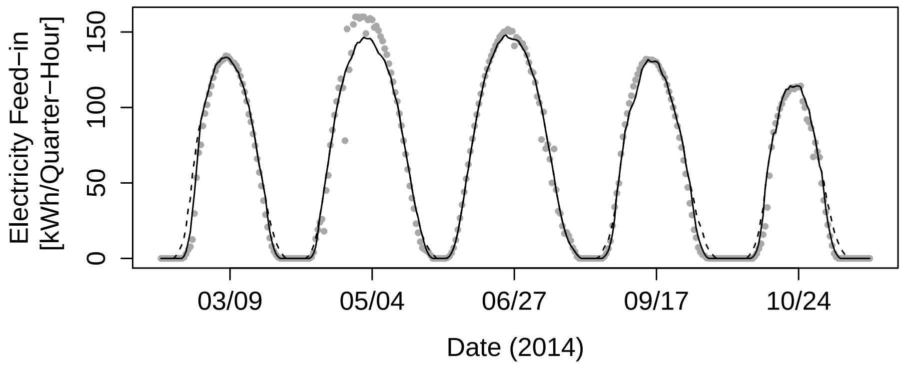

Figure 7: Clear sky estimates (dashed line), corrected clear sky estimates (solid line) and actual values (gray points) of electricity generation for a sample of five clear sky days in 2014.

properties of the environment, quantile regression overestimates clear sky electricity generation at these points.

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Table 1: Cross-validation parameters.

Parameter	Value(s)
Number of cross-validation loops	12
Number of hidden neurons	{1, 3, 6, 10}
Number of random sets of initial weights	20
Number of training iterations	{10, 30, 60, 100}
Learning rate	0.01

Table 2: Parameters of the empirical distributions of the price spread and the portfolio forecast errors from different models. SD denotes standard deviation.

Parameter	Mean	SD	Skewness	Kurtosis
Price spread [Euros/MWh]	0.27	14.52	2.25	31.15
LM [MWh]	0.56	3.32	0.41	4.68
ARX [MWh]	-0.02	3.31	0.07	4.67
ANN [MWh]	-0.07	3.52	-0.22	5.46

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2015

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