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Forecasting day-ahead electricity prices in Europe: The importance of considering market integration

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HIGHLIGHTS

- Models to include market integration in electricity price forecasting are proposed.
- The forecasters lead to accuracy improvements that are statistically significant.
- Deep neural networks are used as based models of the larger modeling framework.
- A forecasters that predicts prices in various markets leads to the best results.
- A novel feature selection algorithm based on functional ANOVA is proposed.

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ABSTRACT

Motivated by the increasing integration among electricity markets, in this paper we propose two different methods to incorporate market integration in electricity price forecasting and to improve the predictive performance. First, we propose a deep neural network that considers features from connected markets to improve the predictive accuracy in a local market. To measure the importance of these features, we propose a novel feature selection algorithm that, by using Bayesian optimization and functional analysis of variance, evaluates the effect of the features on the algorithm performance. In addition, using market integration, we propose a second model that, by simultaneously predicting prices from two markets, improves the forecasting accuracy even further. As a case study, we consider the electricity market in Belgium and the improvements in forecasting accuracy when using various French electricity features. We show that the two proposed models lead to improvements that are statistically significant. Particularly, due to market integration, the predictive accuracy is improved from 15.7% to 12.5% sMAPE (symmetric mean absolute percentage error). In addition, we show that the proposed feature selection algorithm is able to perform a correct assessment, i.e. to discard the irrelevant features.

1. Introduction

As a result of the liberalization and deregulation of the electricity markets in the last two decades, the dynamics of electricity trade have been completely reshaped. In particular, electricity has become a commodity that displays a set of characteristics that are uncommon to other markets: a constant balance between production and consumption, load and generation that are influenced by external weather conditions, and dependence of the consumption on the hour of the day, day of the week, and time of the year [1]. Due to these facts, the dynamics of electricity prices exhibit behavior unseen in other markets, e.g. sudden and unexpected price peaks or seasonality of prices at three different levels (daily, weekly, and yearly) [1].

As a result of this unique behavior, electricity markets have become a central point of research in the energy sector and accurate electricity price forecasting has emerged as one of the biggest challenges faced by the different market entities. The usual motivation behind these efforts is a purely economic one: as forecasting accuracy increases, the negative economic effects of price uncertainty are mitigated and the market players make an economic profit. In addition, another important fact to consider is that electricity markets are established to keep the grid stable. In particular, as prices become more volatile, the balance of the grid is compromised, strategic reserves may have to be used, and the risk of a blackout increases. Therefore, by accurately forecasting

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electricity prices, not only economic profits can be made, but also the system stability is improved.

Due to the above motivations, electricity price forecasting has been continuously developed and improved for the last decades, and as a result, the literature comprises a large variety of distinctive approaches, e.g. see the literature review [1]. Nevertheless, to the best of our knowledge, a topic that has been not yet addressed is the influence of neighboring and connected markets, i.e. market integration, on the forecast accuracy. In particular, as different areas in the world, e.g. the European Union [2], are enforcing a larger level of integration across national electricity markets, it is sensible to assume that neighboring markets might play a role in the forecasting efficiency. To address this scientific gap, this paper proposes a modeling framework that is able to improve predictive accuracy by exploiting the relations across electricity markets. In particular, by modeling market integration in two different ways, the proposed framework is shown to obtain statistically significant improvements.

The paper is organized as follows: Section 2 starts by presenting the literature review, motivation, and contributions. Next, Sections 3 and 4 respectively describe the methods and data that are used in the research. Then, Section 5 defines the proposed modeling framework. Next, Section 6 derives a novel approach for feature selection and uses it to select the optimal features in the case study. Finally, Section 7 evaluates the proposed modeling framework by means of predictive accuracy, and Section 8 summarizes and concludes the paper.

2. Literature survey and contributions

In this section, we present the literature review of three topics that are relevant for the research: electricity price forecasting, market integration, and feature selection. Based on that, we motivate our work and explain our contributions.

2.1. Electricity price forecasting

The price forecasting literature is typically divided into five areas: (1) multi-agent or game theory models simulating the operation of market agents, (2) fundamental methods employing physical and economic factors, (3) reduced-form models using statistical properties of electricity trade for risk and derivatives evaluation, (4) statistical models comprising time series and econometric models, and (5) artificial intelligence methods [1]. For forecasting day-ahead prices, or in general any other type of electricity spot prices, statistical and artificial intelligence methods have showed to yield the best results [1]. As a result, they are the main focus of this review.

Typical statistical methods are: AR and ARX models [3], ARIMA models [4,5], dynamic regression [6], transfer functions [6], double seasonal Holtz-Winter model [7], TARX model [8], semi/non-parametric models [3], or GARCH-based models [9]. In addition, within the same class of methods, different hybrid models have been also applied, e.g. wavelet-based models [5,10,11].

Statistical models are usually linear forecasters, and as such, they are successful in the areas where the frequency of the data is low, e.g. for weekly patterns. However, for hourly values, the nonlinear behavior of the data might be too complicated to predict [12]. As a result, motivated by the need for forecasters that are able to predict the nonlinear behavior of hourly prices, several artificial intelligence methods have been proposed. Among these methods, artificial neural networks [13–16], support vector regressors [17], radial basis function networks [18], and fuzzy networks [19] are among the most commonly used. A recent study [20] showed that *Deep Neural Networks (DNNs)* can also be a successful alternative.

The results comparing the accuracy of the mentioned models have however produced unclear conclusions [14]. In general, the effectiveness of each model seems to depend on the market under study and on the period considered.

2.2. Market integration

In the last decades, the EU has passed several laws trying to achieve a single and integrated European electricity market [2,21]. At the moment, while a single market is far from existing, there is evidence suggesting that the level of integration across the different regional markets has been increasing over time [22]. In particular, evidence suggests that in the case of Belgium and France, the spot prices share strong common dynamics [23].

While some researchers have evaluated the level of integration of the European markets [22–24], and others have proposed statistical models to evaluate the probability of spike transmissions across EU markets [25], the literature regarding market integration to improve forecasting accuracy is rather scarce. To the best of our knowledge, only two other works have taken into account some sort of market integration, namely [26,27].

In particular, [26] analyzes the effect of using the day-ahead prices of the *Energy Exchange Austria (EXAA)* on a given day to forecast the prices of other European markets on the same day. Using the fact that for the EXAA market the clearing prices are released before the closure of other European markets, [26] models the price dynamics of several European markets and considers the EXAA prices of the same day as part of these models. It is shown that, for certain European markets, using the available prices from the EXAA improves the forecasting accuracy in a statistically significant manner.

Similarly, [27] considers external price forecasts from other European markets as exogenous inputs of an artificial neural network to predict Italian day-ahead prices. [27] shows that using the given forecasts the accuracy of their network can be improved from 19.08% to 18.40% *mean absolute percentage error (MAPE)*.

2.3. Feature selection

Feature selection is defined as the process to select, for a given model, the subset of important and relevant input variables, i.e. features. Typically, three families of methods to perform feature selection exist: *filter*, *wrapper*, and *embedded methods* [28]. Filter methods apply some statistical measure to assess the importance of features [29]. Their main disadvantage is that, as the specific model performance is not evaluated and the relations between features are not considered, they may select redundant information or avoid selecting some important features. Their main advantage is that, as a model does not have to be estimated, they are very fast. By contrast, wrapper methods perform a search across several feature sets, evaluating the performance of a given set by first estimating the prediction model and then using the predictive accuracy of the model as the performance measure of the set [29]. Their main advantage is that they consider a more realistic evaluation of the performance and interrelations of the features; their drawback is a long computation time. Finally, embedded methods, e.g. regularization [30, Chapter 7], learn the feature selection at the same time the model is estimated. Their advantage is that, while being less computationally expensive than wrapper methods, they still consider the underlying model. However, as a drawback, they are specific to a learning algorithm, and thus, they cannot always be applied.

Approaches for feature selection in the electricity price forecasting literature vary according to the prediction model used. For time series methods using only prices, e.g. ARIMA, autocorrelation plots [10] or the Akaike information criterion [31] have been commonly used. In the case of forecasters with explanatory variables, e.g. neural networks, most researchers have used trial and error or filter methods based on linear analysis techniques: statistical sensitivity analysis [7,13], correlation analysis [32], or principal component analysis [33]. Since prices display nonlinear dynamics, the mentioned techniques might be limited [34]; to address this, nonlinear filter methods such as the relief algorithm [35] or techniques based on mutual information [34,36,37] have been proposed. More recently, a hybrid nonlinear filter-wrapper