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Price forecasting and validation in the Spanish electricity market using forecasts as input data

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ABSTRACT

The electricity sector has been subjected to major changes in the last few years. Previously, there existed a regulated system where electric companies could know beforehand the amount of energy each generator would produce, hence basing their largely operational strategy on cost minimization in order to increase their profits. In Spain, from 1988 till 1997, electricity prices were established by the 'Marco Legal Estable' – *Stable Legal Framework* –, where the Ministry of Industry and Energy acknowledged the existence of certain generation costs related to each type of technology. It was an industrial sector with no actual competition and therefore, with very few controllable risks. In the aftermath of the electricity market liberalization competition and uncertainty arose. Electricity spot prices became highly volatile due to the specific characteristics of electricity as a commodity. Long-term contracts allowed for hedge funds to act against price fluctuation in the electricity market. As a consequence, developing an accurate electricity price forecasting model is an extremely difficult task for electricity market agents. This work aims to propose a methodology to improve the limitations of those methodologies just using historical data to forecast electricity prices. In this manner, and in order to gain access to more recent data, instead of using natural gas prices and electricity load historical data, a regression model to forecast the evolution of natural gas prices, and a model based on artificial neural networks (ANN) to forecast electricity loads, are proposed. The results of these models are used as input for an electricity price forecast model. Finally, and to demonstrate the effectiveness of the proposed methodology, several study cases applied to the Spanish market, using real price data, are presented.

Introduction

Electricity is of great importance to society and essential for economic and industrial development. The main difference between electricity and other commodities is that it cannot be stored in large quantities and, thus, a constant balance between supply and demand is necessary, leading to highly volatile market prices.

The electricity sector has undergone important changes since the beginning of the deregulation process brought about by Spanish Electric Power Act 54/1997 of November 27. Since then, consumers have been facing high levels of uncertainty due to price volatility.

The peculiarities of electricity as a commodity make for an extremely difficult price evolution forecast. Therefore, it is necessary to develop more accurate and robust methods to support long term contract decisions.

Marketers, producers, and end users are subject to the risk of buying or selling a fixed amount of electricity at a fixed price, without knowing the ultimate price of this asset. Therefore, this is a sector in which monetary costs resulting from an ineffective price forecast can be rather high. A procedure to increase the accuracy of electricity price forecasts can actually maximize the benefits for all market players. In this manner, there is an essential need for an efficient and robust forecasting method for these different players participating in the electricity market to maximize their profits and improve in terms of risk management.

For this reason, price forecasting has become a basic decision-making issue for power companies worldwide, though the special

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characteristics of electricity represent a challenge to achieve this task [1].

Several factors affect the price formation of electricity and determining them is of the most importance. To that end, factors included in the model, according by Gianfreda and Grossi [9] such as technology, market concentration, congestions and volumes, are relevant to forecast the final Single National Price.

There are many efforts by researchers to solve this problem. Many techniques have been employed in electricity price forecasts such as, for instance, artificial neural networks (ANNs) [10,17,14], fuzzy inference systems (FIS) [18], and support vector machines (SVMs) [6,22].

Other researchers used time series models like ARIMA [7,5] and GARCH [8] and also proved to be effective for electricity price forecast. A summary of the different methods used to predict the price of electricity is presented in Jain et al. [13] and Lawarree et al. [15].

Forecasting the hourly market-clearing price (MCP) on electricity spot markets is an essential basic task for decision-making in order to maximize benefits [19]. Many efforts have been made to accurately forecast electricity market spot prices [16]. But, in long-term planning, it makes more sense to obtain a monthly average price than just the hourly price. The goal according by Torbaghan [20] is to forecast the monthly electricity average price for Ontario and Nord Pool electricity markets, for the following 12 months.

The successful negotiation of a contract price for the participants in these markets is driven by an accurate forecast of the price of electricity, which is why developing methodologies to solve this problem is so necessary [3,4,2].

An artificial neural network (ANN) model has been used in this research. Before applying the electricity price forecasting model (MBF), it is necessary to get the input variables which can be obtained with two others models: a regression model, used to calculate the gas price (MBF-GP), and another artificial neural network to obtain the electricity load (MBF-LD). By means of those models, the monthly average price for the Spanish electricity market can be forecasted throughout different years.

Model based on forecasted data – MBF

This work presents a model based on one-year forecast data (MBF). In order to use the most recent data possibly available, it is necessary to include data forecasted with other used models.

This new model uses forecast input variables, so it is necessary to previously prepare a forecast for load and natural gas prices during the same time period. Therefore, monthly average forecast values for the year ahead are obtained (load and natural gas prices). Results which are then used as input in the electricity price forecast model. A description of the model is shown in Fig. 1.

The first step is to forecast the load and the gas price for the corresponding period. For that reason, it is necessary to develop a load forecasting model (MBF-LD) and a gas price forecasting model (MBF-GP). The results obtained are used as input data in the electricity price forecasting model (MBF).

MBF-LD

The proposed load forecasting method is a model based on artificial neural networks (ANN).

ANNs are a good learning and automatic data processing example based on how a nervous system works – a network of interconnected neurons trying to learn from the information received to later produce an output stimulus. Connections between neurons, defined as synaptic weights (w), are optimized by the learning algorithm.

The ANN has a distributed calculus structure that allows for a quick resolution of time-consuming problems when using classical computers. It also has the ability to learn tasks based on training or initial experience [11,12].

First, it is necessary to divide historical data into groups. These groups are then classified according to month, since a monthly seasonality is observed.

A set of vectors is then created in order to train and validate the neural network. The input vector for training and testing the network is shown in Eq. (1).

$$I_{i,j} = [C_{i-1,j}, C_{i,j-1}, C_{i,j-2}] \tag{1}$$

where $C_{i-1,j}$ is the load value for month $(i-1)$ and year (j), $C_{i,j-1}$ is the load value for month (i) and year $(j-1)$, and $C_{i,j-2}$ is the load value for month (i) and year $(j-2)$.

The target vector used for network training and validation is presented in Eq. (2).

$$T_{i,j} = [C_{i,j}] \tag{2}$$

The training method used is known as a Bayesian regulation backpropagation. This function updates weight and bias values according to the Levenberg–Marquardt optimization algorithm. This method follows a Bayesian regulatory process which determines the right combination, once the squared errors and the weights necessary to produce a correct network have been minimized.

Before training the network, the inputs and outputs must be scaled in a $[-1,1]$ range. Two 16-neuron hidden layers were used – a tan-sigmoid transfer function for hidden layers and a linear transfer function for the output layer – for the network to take on a [3-16-16-1] configuration. The method output is the monthly average load for one year period.

Monthly energy historical data were used and collected from OMI (Iberian Energy Market Operator) between January 2004 and December 2011. Fig. 2 presents the data within this period.

Fig. 3 shows the load distribution broken down by month, with January and December as the coldest months and June, July and August as the hottest ones. Energy demand will be consequently higher in these months, than in the temperate ones, such as April, May and September.

MBF-GP

The proposed method for the gas price forecast is based on a regression model. This regression model is a mathematical method which correlates a dependent variable Y_t, – that is, the variable to be explained – to other independent X_i variables – which are the factors influencing the formation of the variable Y –, and a random ε term representing the error term. This general model is expressed in Eq. (3).

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon_t \tag{3}$$

where $\beta_0, \ldots, \beta_n$ are regression parameters and $X_1, X_2, \ldots, X_n$ are independent parameters.

Regression parameters $(\beta_0, \ldots, \beta_n)$ are determined by several optimization algorithms; in this case, genetic algorithms. These algorithms evolve to a population of individuals subjected to random actions imitating biological evolution. The solution is based on the survival of the strongest ones according to certain optimization criteria.

This methodology aims to figure out those regression parameters minimizing the absolute error.

Gas prices are not as highly volatile as electricity prices. Fig. 4 shows the monthly historical average gas price from January 2003 to December 2011. It can be observed that the curve has a positive trend. There are certain peaks to be found in said figure but monthly price variations do not experience dramatic changes.

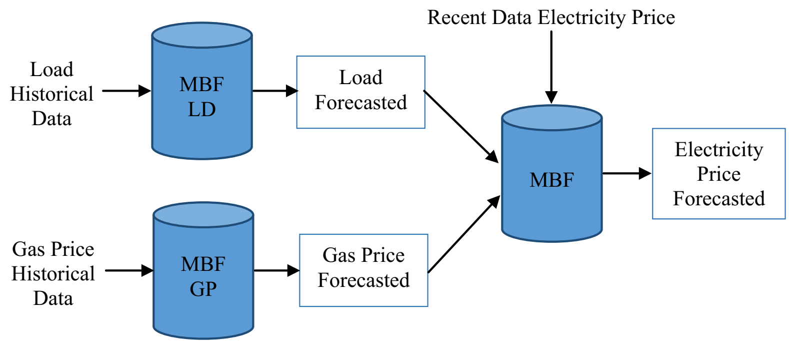

Fig. 1. Electricity price forecast model block diagram.

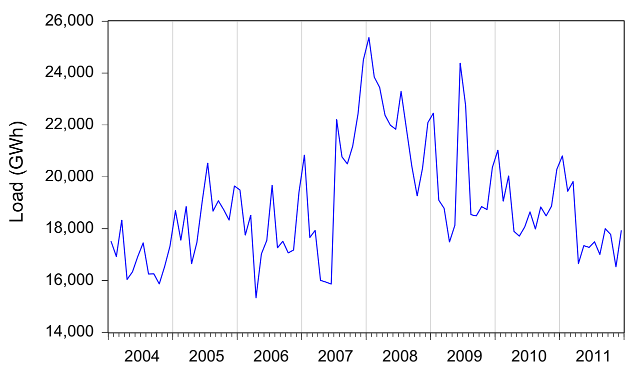

Fig. 2. Monthly historical data from OMI between 2004 and 2011.

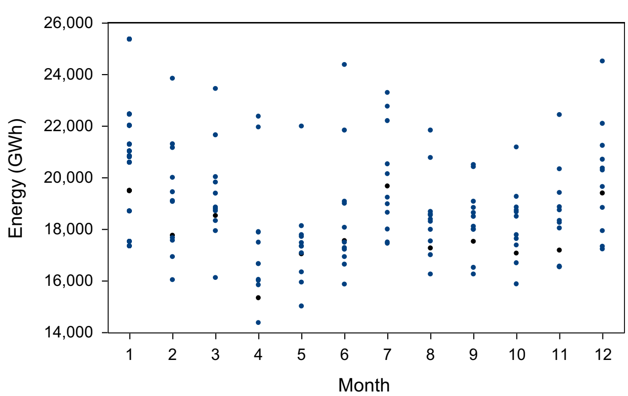

Fig. 3. Monthly load distribution.

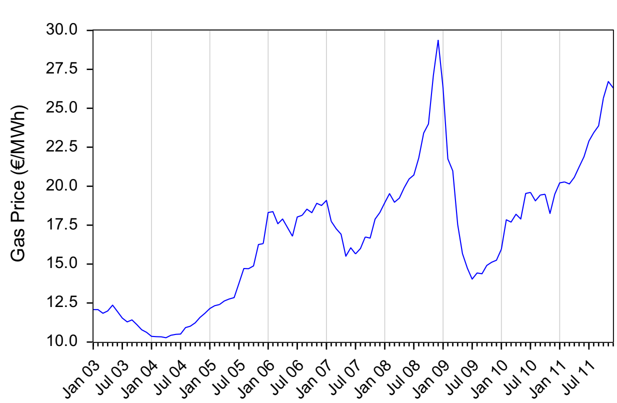

Fig. 4. Gas price historical data.

The biggest change is observed between December 2008 and July 2009. There's considerable seven month period drop with values decreasing from 29,366 €/MW h to 14,033 €/MW h. Nevertheless, it is possible to find electricity price values dramatically rising from 18 €/MW h to 43 €/MW h, from one month to another, which speaks of a greater variability.

The model uses historical data gathered throughout an 8 year-span. The function aims to minimize the difference between the actual value and the forecast value, as shown in Eq. (4).

$$\mathrm{Min}\sum_{i=1}^{12}\sum_{j=1}^{N}|G_{i,j}-\hat{G}_{i,j}| \tag{4}$$

$G_{i,j}$ being the gas price for month (i), year (j), and $\hat{G}_{i,j}$ the average gas price forecast for month (i) and year (j). Eq. (5) is then applied to find the monthly average gas price forecast.

$$\hat{G}_i = \beta_0 G_{i-1} + \beta_1 G_{i-2} + \beta_2 G_{i-3} \tag{5}$$

where G_{i-1} is the average gas price for month $(i-1)$, G_{i-2} is the average gas price for month $(i-2)$, and G_{i-3} is the average gas price for month $(i-3)$.

The meta-heuristic Genetic algorithm is used to find regression parameters.

Historical data of average gas prices collected from CNE (National Energy Commission) reports, between January 2003 and December 2011, have been used in this study.

Regression parameters which minimize the absolute error are shown in Table 1.

MBF

Results obtained from MBF-LD and MBF-GP are introduced into MBF. The MBF model uses artificial neural networks. The input vector of the artificial neural network based model MBF is shown in Eq. (6).

$$I_{i,j} = \left[\hat{C}_{i,j}, \hat{G}_{i,j}, P^{med}_{i-1,j}, P^{med}_{i,j-1}\right] \tag{6}$$

where $\hat{C}_{i,j}$ is the load forecast for month (i) and year (j), $\hat{G}_{i,j}$ is the gas price forecast for month (i) and year (j), $P^{med}_{i-1,j}$ is the electricity average price for the month $(i-1)$ and year (j) and $P^{med}_{i,j-1}$ is the electricity average price for the month (i) and year $(j-1)$.

Before training, the network inputs must be scaled in a $[-1,1]$ range. Two 10-neuron and 9-neuron hidden layers were used – a tan-sigmoid transfer function for hidden layers and a linear transfer function for the output layer – for the network to take on a [8-10-9-3] configuration. The outputs of this method are the maximum, average, and minimum monthly electricity prices. The network is trained with historical data from the last 5 years.

Table 1
Regression coefficient.

Coefficient	Value
β_0	0.7929
β_1	0.1499
β_2	0.0670

Result analysis

In this study we have used a new method, explained in Section 'Model based on forecasted data – MBF', – that is, MBF –, to forecast the monthly electricity average price, using an ANN structure for year 2011 and year 2012.

The monthly electricity price forecast for year 2011, showing great accuracy, is presented in Fig. 5a. The trend is soundly forecasted since the resulting prices are lower in March, April or May than in August or September.

Fig. 5b shows electricity price forecasting data compared to the actual data for year 2012. Accuracy is very high and shows a well-forecasted trend.

Differences between the two years have been noted, which led to a highly difficult forecast. This methodology is very accurate due to data precision.

In order to assess the forecasting performance the most common measure used is the MAPE (Mean Absolute Percentage Error) [21], given by Eq. (7).

$$\mathrm{MAPE} = \frac{1}{12}\sum_{i=1}^{12}\left|\frac{P_i - \hat{P}_i}{P_i}\right| \tag{7}$$

MAPE sometimes does not work well if values are low which could lead to bad results, particularly when electricity prices drop towards zero. For this reason, other measures have been found in literature [21], specifically MME (Mean Month Error, given by Eq. (8)), getting better results.

$$\mathrm{MME} = \frac{1}{12}\sum_{i=1}^{12}\left|\frac{P_i - \hat{P}_i}{\bar{P}_{12}}\right| \tag{8}$$

where P_i is the electricity price for month (i) and $\bar{P}_i$ is the electricity mean price in a year.

However, the median being more robust to outliers or spikes than the mean, MeME (Median Month Error, given by Eq. (9)) will improve the results.

$$\mathrm{MeME} = \frac{1}{12}\sum_{i=1}^{12}\left|\frac{P_i - \hat{P}_i}{\tilde{P}_{12}}\right| \tag{9}$$

where P_i is the electricity price for month (i) and $\tilde{P}_i$ is the electricity median price in a year.

Table 2 shows those errors arising from the MBF model. Figures show that forecasting models using recent data offer better results. In addition, this methodology is more comprehensive because it offers both electricity load and a gas price forecasting results. Hence, market players have access to more information which could be significant to the decision-making process.

In addition and as previously mentioned, once the error measures have been explained, MeME obtains the best results followed by MME, MAPE being the one obtaining the worst results.

This new methodology proposes breaking down the problem into forecast blocks. The methodology does not use a lot of variables, which clearly evinces that having more information does not necessarily lead to better results. It is important to correctly choose the useful information to be entered into the electricity price forecast. Time horizon is also highly important when it comes to input variable selection. Proper variable selection is essential for success with the monthly electricity price forecast model.

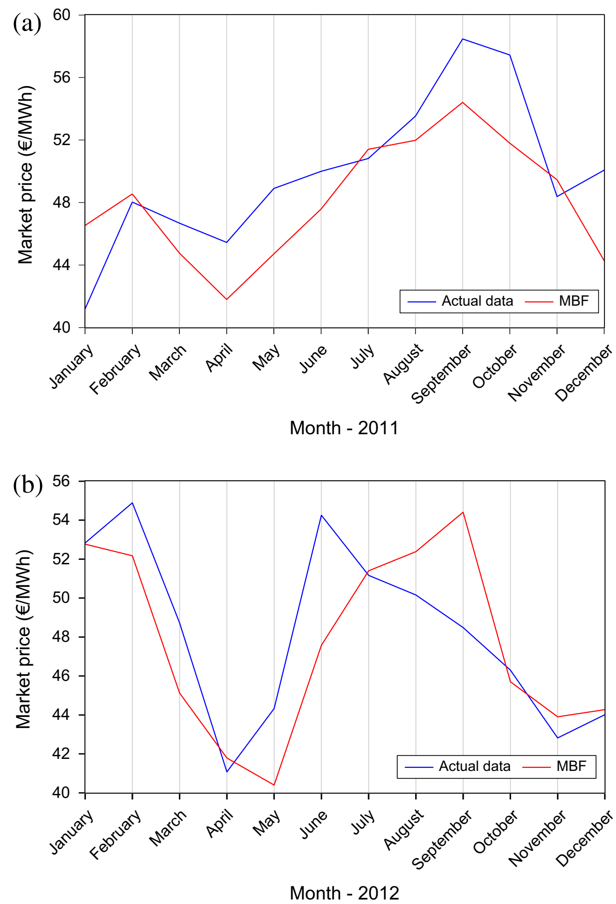

Fig. 5. Electricity price forecast results.

Table 2
Error measures for electricity price results.

Year	MAPE	MME	MeME
2011	8.35	8.06	8.14
2012	4.74	4.84	4.80

Conclusions

This paper presents a forecast method MBF applied to electricity prices in the Spanish market. The presented methodology uses artificial neural networks in MBF and MBF-LD and a regression model in MBF-GP. One of the advantages of the method here presented is the fact that it uses recent data instead of just historical data. It was necessary to develop three different models: an electricity load forecasting model (MBF-LD), using an artificial neural network; a gas price forecasting model (MBF-GP), using a regression model; and an electricity price forecasting model (MBF), using an artificial neural network.

A number of input variables have also been included, indicating that an increase in information does not lead to better results. It is important to make a correct selection of the relevant information to be entered into the forecasting model, adding forecast time horizons into the equation. A successful outcome will be due to the proper selection of the most adequate input variables.

The method here explained can be used to forecast electricity market prices for several periods ahead. The results offer a lot of information significant for decision-making, when market players have to settle their contracts on a long-term basis.

This methodology aims to develop better forecasting algorithms. It also reduces uncertainty in the electricity market, improves forecasts, and leads to satisfactory agreements between the different actors involved in the market.

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