Study of Factors Affecting the Long-term Spanish Electricity Price Formation and Corresponding Validation Using a Long-term Neural Network Forecast Model

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Abstract—**The deregulation of electricity markets has resulted on a competitive sector. The impossibility to store energy in large scale together with the constant balance between supply and demand is at the origin of high volatility of market clearing prices. The electricity market players use long-term contracts to practice the hedge against the price risk. The success of those contracts is directly related on the accuracy of long-term price forecast. This paper presents a study of the factors that affects long-term Spanish electricity price formation makes use of a neural network model applied to long-term forecast to validate that study. The use of correct input variables is essential for a forecast accurate. It is presented a case study with real data and the results are compared and discussed in detail.**

***Index Terms*—Electricity Markets, Long-term Price Forecast, Artificial Neural Networks, Electricity Price Formation, Artificial Intelligence.**

I. INTRODUCTION

Electricity has a great importance in modern societies. It is impossible to understand any activity without electricity. That is why it has become an essential asset for economic and industrial development. The main difference of electricity related to other commodities is that it cannot be stored in large scale and, as a result, it is necessary to maintain a constant balance between supply and demand causing volatility in the market price.

Before the deregulation, in Spain, the authorities fixed the electricity prices based in the production cost, this way the risk was inexistent. But in 1998 began the deregulation process with Law 54/1997 of November 27, of the Electricity Sector. Later, it was created the Iberian Electricity Market (MIBEL*)* that involves Spain and Portugal. Since then, consumers face prices that present a high short and long-term volatility. This makes difficult the long-term investment decisions.

This characteristic had important repercussions in the last years, and there are many studies were made, which show the efforts of the researchers in trying to forecast electricity prices with the best accuracy. Research works are based in past experiences for the selection of the input variables of their forecast model. The variable which is most used as an input in forecast models is the historical data of the price of electricity [1]-[10]. The load curve is another factor which some researchers have been using when it comes to compute the electricity prices forecast [1]-[4], [11]. Due to the existing relation between load and temperature, certain authors have used this factor as an input [12]-[14]. The fuel price is another factor in the forecast model in [13]-[15].

In addition, there are some uncontrollable and difficult factors that have highly impact in volatility of the electricity prices and in the appearance of spikes. Those factors are climatic changes, generation facilities availability, fuel prices volatility; electricity markets strategies, unexpected events and congestion of the transmission lines [1].

Therefore, long term electricity price forecasting is difficult due to high number of factors that have influence on it. The succeed contracts is given by an accurate forecast of electricity price, which is why it is necessary to develop methodologies that solve this problem [1]-[4]. For the forecasting model, finding the correct input variables that affect to the electricity prices is essential.

In the references we can find different methods to solve the problem of electricity short-term (hours) and medium-term (days/weeks) price forecasting [7]-[9], [16]-[18]. The time series methodology is highly used [19]. Especially using ARIMA models [10],[20], due to the accuracy of short-term forecast.

But, in order to explain the behavior of a given variable through other independent variables, the regression models [2] are one of the techniques used, with a high degree of success.

Due to the fast response other methodologies used for electricity price in the short-term forecasting are Artificial Neural Networks [21]-[27].

In this work, it is presented an artificial neural network model to forecasting electricity price on long-term. This model makes use of input variables. To decide which are the most appropriate variables to use it is essential to make an analysis of them and study their impact in price formation.

This paper is organized as follows: Section 3 presents the analysis of different variables and the selection of the best ones. Section 3 presents a long-term price forecasting method. Section 4 presents the application of the method to a case study. Finally, Section 5 draws the relevant conclusions

II. Input Variables

Electricity price forecast is a hard task. For that, a correct selection of the input variables is essential for an accurate forecast. The variables are different and are dependent of the period that we want to make the forecast, this means that if the forecast is on short term (hours), the inputs variables are not the same than the ones used long-term (months) forecasting. In this paper it is addressed the problem of long-term electricity market forecast. So it is important to make an analysis of the variables/factors and study their impact in long-term price formation and use the most important input variables/factors in the predictive model.

A. *Analysis of the variables*

It is fundamental to understand the effect of each variable in the long-term electricity price formation. For that, the analysis of the distinct variables, which affect the electricity price, is a key task.

There are more than 40 variables, which affect the formation of the price [9], [28]. Researcher based their studies in past experience to select their input variables. According with that, it is selected the following:

- Temperature (T)
- Previous Month Electricity Market Price (PMEMP)
- Brent Price (BP)
- Gas Price (GP)
- Load (L)
- Thermal Production (TP)
- Wind Production (WP)

For the study of the above variables it was collected data from January 2007 to December 2011.

Brent and Gas prices evolution for the mentioned period are presented on Fig. 1 and Fig. 2, respectively. In the year 2008 prices rises to the onset of the economic crisis (Subprime Mortgage Crisis). This is a clear example of how unexpected events are difficult to predict. Fig. 3 shows the historical data for electricity market average monthly prices. With these figures we can analyse the importance fossil fuels in the Spanish electricity sector.

Figure 1. Historical data for Brent pices

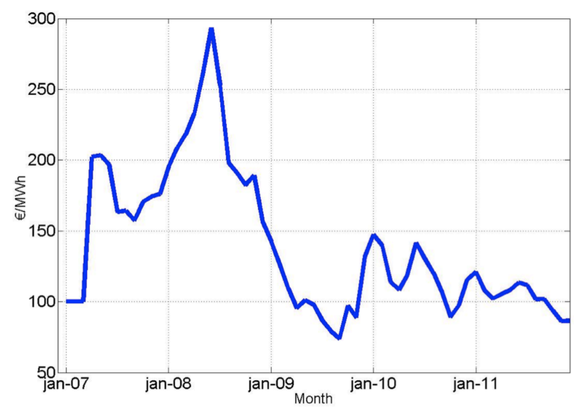

Figure 2. Historical data for Gas pices

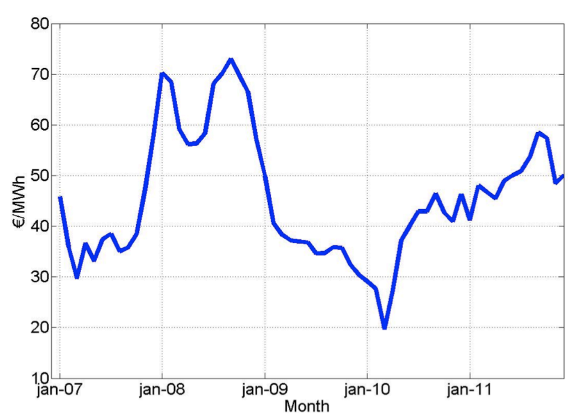

Figure 3. Historical data for electricity prices

To discard the least significant variables in the formation of prices on long term, it has been developed a correlation matrix between the monthly electricity average prices to each of the variables identified in Table I. The choice of using the correlation coefficient as a measure is that it is dimensionless. This is an advantage because it compares the relationship among different pairs of variables measured in different units.

After the development of the matrix, the results are shown in Table I. This matrix gives two types of information. The first one is related to the sign of each term of the matrix (positive or negative). If the correlation is negative it means that the corresponding variable has an inverse effect. Values close to 1 or -1 indicate a strong correlation, however if the values are close to 0, the correlation between the values is weak. When assessing the results, it is assumed that from 0.1 to 0.3 the ratio is low, from 0.31 to 0.6 is normal and from 0.61 to 0.9 is high.

TABLE I. CORRELATION BETWEEN ELECTRICITY PRICES AND VARIABLES

Variables	***Correlation (r)***
Previous Month Electricity Market PriceAverage	0.91
Thermal Production	0.77
Gas Price	0.64
Brent Price	0.43
Load	0.43
Wind prodution	-0.22
Temperature	0.06

B. *Selection of the input variables*

Once the analysis of variables is done, the most influence variables in long-term electricity price formation were chosen.

From Table I we conclude that the previous month average price has a strong relationship with the price of the next month (0.91). This variable is used on a lot of researches works and, with this analysis; it can be shown that this variable will be a key variable to introduce in the predictive model.

As it is said above, Spain is very depending of fossil fuel. So those variables will be important to use in the long-term forecast model. The correlation values show that when fossil fuel prices rise, electricity price does it too, due to their strong dependence. The correlation is very strong, gas (0.64) and Brent oil (0.43). This implies that the formation of the electricity prices depends on these values. In addition, increased thermal production causes an increase of the electricity prices. This is due to the use of gas on electricity production, so if the thermal process needs gas and the gas prices increase, the electricity prices increase too. The correlation between electricity prices and thermal production is the second most important (0.77), which means that thermal production, it is clearly important in the formation of long-term electricity prices.

The load curve is another important factor, because it has a 0.43 correlation value, which means a high dependence. In fact, the correlation is positive meaning that if the demand increases the electricity price increase too.

It is also concluded from the results that the increase of wind power plants production implies a reduction in thermal production and vice-versa. However, the correlation is very weak (-0.22), indicating that they are not so important factors to be introduced into the long-term forecast model. Finally, the last variable studied is the temperature. The correlation is very weak (0.06), making unnecessary this variable as input to the long-term electricity price forecast model.

As a conclusion it can be said that the variables that have a strong correlation with the price of electricity are provide by previous month price of electricity (0.91), thermal production (0.77), the price of Brent (0.43), natural gas prices (0.64) and load (0.43).

Thus, the following variables are the input variables to introduce into the long-term electricity price forecast model:

- Electricity Market Price (EMP)
- Brent Price (BP)
- Gas Price (GP)
- Load (L)
- Thermal Production (TP)

III. ARTIFICIAL NEURAL NETWORK

The artificial neural networks (ANN) are an example of learning and automatic processing based on the nervous system operation. A network of interconnected neurons tries to learn from the provided data to produce an output stimulus. Connections between neurons are termed synaptic weights (w), which are optimized by the learning algorithm. The general structure of an artificial neural network is shown in Fig. 4.

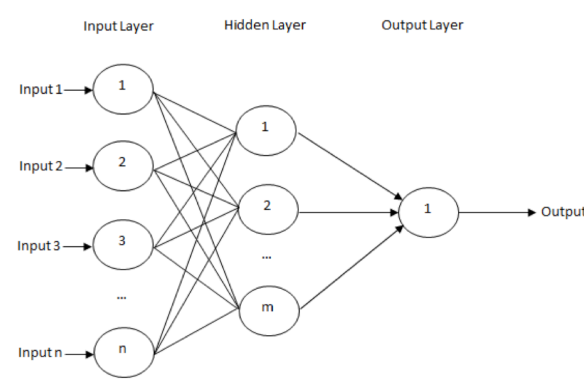

Figure 4. Artificial Neural Network

The input layer is composed of independent variables selected for prediction. Each input has an associated weight ω.

In this model, the input vector to train and validate the network is shown in (1). This vector contains 7 inputs:

thermal production, the Brent oil price, gas price, load curve, the minimum, and the average and maximum monthly electricity price.

$$I_{i,j} = [TP_{i,j-1},\ BP_{i,j-1},\ GP_{i,j-1},\ L_{i,j-1},\ EMP^{max}{}_{i-1,j},\ EMP^{med}{}_{i-1,j},\ EMP^{min}{}_{i-1,j}] \quad (1)$$

The propagation is performed so that each neuron makes a combination of signals from neurons in the previous layer.

Finally, the transformed data reaches the output layer where the results are obtained. In this case the target vector has the form shown in (2).

$$T_{i,j} = [EMP^{max}{}_{i,j},\ EMP^{med}{}_{i,j},\ EMP^{min}{}_{i,j}] \quad (2)$$

ANN has a distributed calculus structure that allows quick resolution of problems which require large amount of time in classical computers. It also has the ability to learn how tasks based on training or initial experience [29]-[30].

However, this model also has some limitations. Due to its complexity, once trained a neural network, it is difficult to explain its operation; it is even difficult to guarantee a level of accuracy in cases never seen before.

IV. CASE STUDY

For this case study it is used the historical data of monthly electricity price average for the Spanish market between January 2007 and December 2011, presented in Fig. 5.

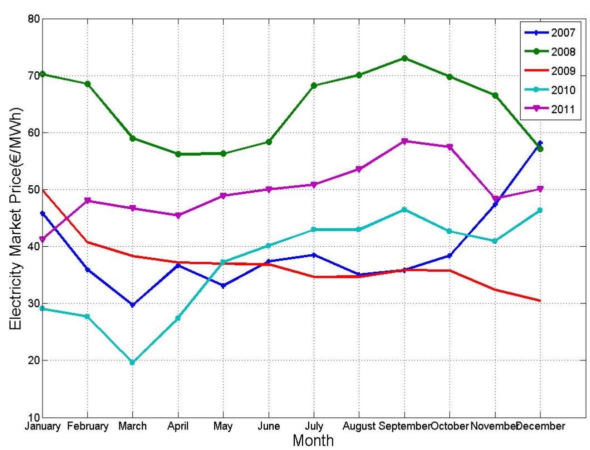

Figure 5. Monthly electricity price average for Spanih market

Artificial Neural Network uses a neural network for each month for this calculus. The training method used is 'Bayesian backpropagation regulation. It is a function that updates the weights values and bias values according to the Levenberg-Marquardt optimization algorithm. This method follows a Bayesian regulatory process that determines the right combination once been minimized squared errors and weights to produce a network that generalizes correctly.

Before training the network, the inputs and outputs in the range [-1, 1] have to be scaled. There have been used two hidden layers of 16 neurons for each one (tan-sigmoid transfer function for hidden layers and linear transfer function for the output layer), so that the network has the form [7-16-16-3]. The outputs of this method are the maximum, the average and the minimum monthly electricity price with a confidence level α=95.

Fig. 6 shows the result of the forecast by the neural network. In addition, it is shows the real values for 2012. Analyzing this figure, it can be verified that the forecast is quite accurate. The learning time is very low (1 minute) which is an advantage of this model.

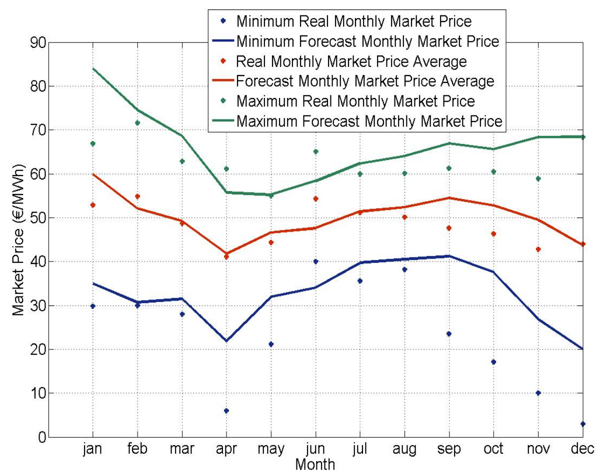

Figure 6. Artificial Neural Network Forecast for 2012

V. CONCLUSIONS

This paper presents a new method for long-term electricity price forecasting, based on artificial neural networks. Before making the forecast is necessary to choose the correct input variables. Therefore, an analysis was made of the variables that influence price formation. The correlation matrix has carried this out.

One of the advantages of the long-term price forecast model here presented is the fact that it does not make any statistical assumption about the probability distribution of the historical data. This method has used historical data to training and validate. In addition, the learning time is very short which is another advantage of this method.

The method here presented can be used to forecast the electricity market price range for several programming periods ahead. For this, Artificial Neural Network method needs to update constantly historical data. The result reveals high accuracy for one year forecast.

The most difficult task is to forecast a good minimum value due to large price variations. Therefore, is not only important to get an exact price, but also a good interpretation of the results.

The model presented in this work has as main goal to help the different players involved in the Spanish electricity market to take decisions helping them to manage the price risk and make contracts that maximize their profits.

GLOSSARY

$TP_{i,j-1}$	thermal production in month i, year j-1(MWh)
$BP_{i,j-1}$	brent price in month i, year j-1(€/Bbl)
$GP_{i,j-1}$	gas price in month i, year j-1(€/MWh)
$L_{i,j-1}$	load in month i, year j-1(MWh)
$EMP^{max}_{i-1,j}$	maximum monthly market price in month i-1, year j(€/MWh)
$EMP^{med}_{i-1,j}$	average monthly market price in month i-1, year j(€/MWh)
$EMP^{min}_{i-1,j}$	minimum monthly market price in month i-1, year j(€/MWh)

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