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An artificial neural network approach for short-term electricity prices forecasting

J.P.S. Catalão*, S.J.P.S. Mariano*, V.M.F. Mendes† and L.A.F.M Ferreira‡

*Department of Electromechanical Engineering, University of Beira Interior, R. Fonte do Lameiro, 6201-001 Covilha, Portugal. E-mail: catalao@ubi.pt; sm@ubi.pt
†Department of Electrical Engineering and Automation, Instituto Superior de Engenharia de Lisboa, R. Conselheiro Emídio Navarro, 1950-062 Lisbon, Portugal. E-mail: vfmendes@isel.pt
‡Department of Electrical Engineering and Computers, Instituto Superior Técnico, Technical University of Lisbon, Av. Rovisco Pais, 1049-001 Lisbon, Portugal. E-mail: lmf@ist.utl.pt

This paper presents an artificial neural network approach for short-term electricity prices forecasting. In the new deregulated framework, producers and consumers require short-term price forecasting to derive their bidding strategies to the electricity market. Accurate forecasting tools are required for producers to maximize their profits and for consumers to maximize their utilities. A three-layered feedforward artificial neural network, trained by the Levenberg-Marquardt algorithm, is used for forecasting the next 168 hour electricity prices. We evaluate the accuracy of the price forecasting attained with the proposed approach, reporting the numerical results from a real-world case study based on an electricity market.

Keywords: Artificial Neural Networks; Electricity Market; Levenberg-Marquardt Algorithm; Price Forecasting

1. INTRODUCTION

The electricity industry has undergone significant transformations since the advent of electricity generation in 1882 at Pearl Street Power Station, New York. The electricity industry was organized as regulated and vertically integrated, joining generation, transmission and distribution of electricity in government owned monopolistic companies. Thus, predicting future prices involved matching regional electricity demand to regional electricity supply. The future regional demand was estimated by escalating historical data, and the regional supply was determined by stacking up existing and announced generation units in some wise order of their variable operating costs [1]. As such, electricity prices tended to reflect the government's social and industrial policy, and any price forecasting that was undertaken was really based on average costs. In this respect, it tended to be over the longer term, taking a view on fuel prices, technological innovation and generation efficiency [2]. Hence, in the regulated framework, the electricity industry's attention mainly focused on load forecasting, existing little need for tools hedging against price risk given the deterministic nature of electricity prices.

In the technical literature, several papers on load forecasting are easily found. On one hand, prediction of the short-term energy consumption could allow the utilities to improve their cash flow [3]. On the other hand, prediction of the long-term energy consumption could help utilities plan the next year's investments [4]. Researchers use assorted methodologies to develop these forecasting tools, namely statistical techniques that simulate nonlinear behavior [5].

Electricity has been turned into a traded commodity in nowadays, to be sold and bought at market prices, although with distinct characteristics since it cannot be queued and stored economically with the exception of pumped-storage hydro plants when appropriate conditions are met. Two ways of trading are usually assumed: the pool trading and bilateral contracts trading. In the pool trading, producers and consumers submit bids respectively for selling and buying electricity on established intervals, typically on an hourly basis. Finally, a market operator clears the market by accepting the appropriate selling and buying bids, giving rise to the electricity prices.

The new electricity industry deregulated framework was intended to encourage competition among companies in order to decrease the cost of electricity. However, occurrences seldom happening in the regulated framework, such as outages and blackouts, are now subject of increasing concern. Moreover, deregulation brings electricity prices uncertainty, placing higher requirements on forecasting [6]. In particular, accuracy in forecasting these electricity prices is very critical, since more accuracy in forecasting reduces the risk of under/over estimating the revenue for producers and provides better risk management [7].

Short-term electricity prices forecast has become a very helpful tool for producers and consumers. A producer needs to forecast electricity prices to derive its bidding strategy into the pool and to optimally schedule its energy resources [8]. In the regulated framework, traditional generation scheduling of energy resources was based on cost minimization [9]. In the new deregulated framework, since generation scheduling of energy resources, such as hydro resources [10], is now based on profit maximization, electricity prices forecasting has become essential for developing negotiation skills in order to achieve better profits. Consumers need short-term electricity prices forecast for the same reasons as producers.

In the technical literature, several techniques to predict electricity prices have been reported, namely hard and soft computing techniques.

The hard computing techniques include time series models [11], auto regressive — AR models [12] and auto regressive integrated moving average — ARIMA models [13]. This approach can be very accurate, but it requires a lot of information, and the computational cost is very high [14]. More recently, generalized autoregressive conditional heteroskedastic — GARCH models [15] and the Wavelet-ARIMA technique [16] have also been proposed.

The soft computing or artificial intelligence techniques include artificial neural networks [17–21], using Fourier and Hartley transforms [22], using an improved extended Kalman filter [23] or combined with fuzzy logic [14,24,25]. Artificial neural networks are simple, but powerful and flexible tools for forecasting, provided that there are enough data for training, an adequate selection of the input-output samples, an appropriate number of hidden units and enough computational resources available. Also, artificial neural networks have the well-known advantages of being able to approximate nonlinear functions and being able to solve problems where the input-output relationship is neither well defined nor easily computable, because artificial neural networks are data-driven. Three-layered feedforward artificial neural networks are specially suited for forecasting, implementing nonlinearities using sigmoid functions for the hidden layer and linear functions for the output layer.

This paper presents a successful application of using an artificial neural network approach to forecast short-term prices in the electricity market of mainland Spain. Previously reported approaches to forecast prices in the electricity market of mainland Spain were mainly based on time series models, namely the ARIMA technique. Artificial neural networks techniques are comparatively easy to implement and show good performance being less time consuming. In this paper, the Levenberg-Marquardt algorithm is used to train a three-layered feedforward artificial neural network. A case study is presented with the historical data for the artificial neural network training given by real market data at the year 2002, to evaluate the accuracy of the proposed approach.

This paper is structured as follows. Section 2 presents the artificial neural network approach. Section 3 provides the importance of price in electricity markets and the main factors that influence it, as well as the different criterions used to assess the behavior of the proposed approach. Section 4 presents the numerical results from a real-world case study based on an electricity market. Finally, Section 5 outlines the conclusions.

2. ARTIFICIAL NEURAL NETWORK APPROACH

Artificial neural networks are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task [26]. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent.

Multilayer perceptrons are the best known and most widely used kind of artificial neural network. Networks with interconnections that do not form any loops are called feedforward. Recurrent or non-feedforward networks in which there are one or more loops of interconnections are used for some kinds of applications.

The units are organized in a way that defines the network architecture. In feedforward networks, units are often arranged in layers: an input layer, one or more hidden layers and an output layer. Typically, the units in the input layer serve only for transferring the input pattern to the rest of the network, without any processing. The units in the hidden and output layers process the information.

In order to find the optimal network architecture, several combinations were evaluated. These combinations included networks with different number of hidden layers, different number of units in each layer and different types of transfer functions. We converged to a configuration consisting of a one hidden layer that uses a hyperbolic tangent sigmoid transfer function and a one unit output layer with a pure linear transfer function.

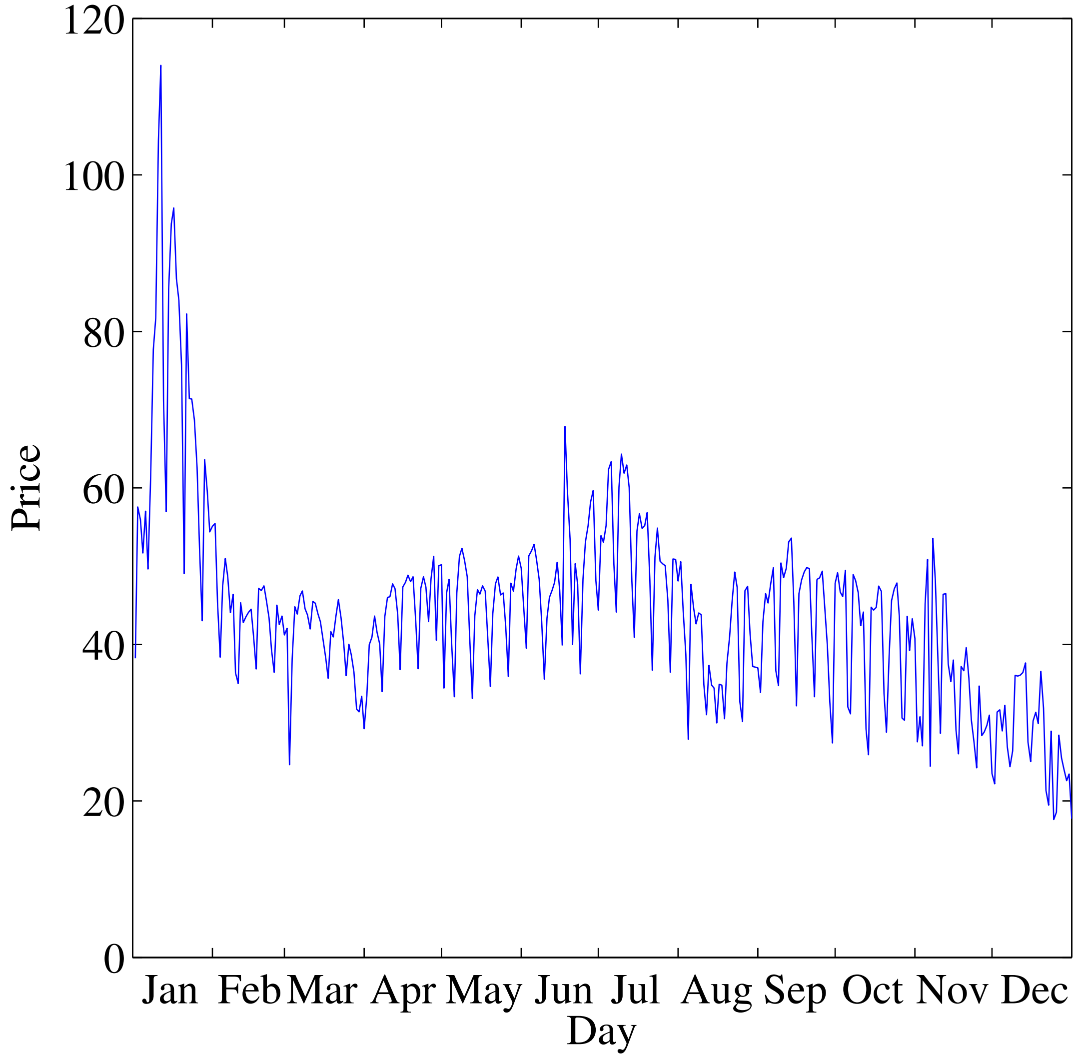

Figure 1 Daily average price in the electricity market of mainland Spain at 2002, in euro per megawatt hour.

This configuration has been proven to be a universal mapper, provided that the hidden layer has enough units [27]. On one hand, if there are too few units, the network will not be flexible enough to model the data well and, on the other hand, if there are too many units, the network may over-fit the data. Typically, the number of units in the hidden layer is chosen by trial and error, selecting a few alternatives and then running simulations to find out the one with the best results.

Forecasting with artificial neural networks involves two steps: training and learning. Training of feedforward networks is normally performed in a supervised manner. One assumes that a training set is available, given by the historical data, containing both inputs and the corresponding desired outputs, which is presented to the network. The adequate selection of inputs for artificial neural network training is highly influential to the success of training. In the learning process an artificial neural network constructs an input-output mapping, adjusting the weights and biases at each iteration based on the minimization of some error measure between the output produced and the desired output. The error minimization process is repeated until an acceptable criterion for convergence is reached.

The knowledge acquired by the artificial neural network through the learning process is tested by applying it to new data that is has never seen before, called the testing set. The network should be able to generalize and have an accurate output for this unseen data [14].

It is undesirable to over-train the artificial neural network, meaning that the network would only work well on the training set, and would not generalize well to new data outside the training set [19]. Over-training the artificial neural network can seriously deteriorate the forecasting results. Also, providing the artificial neural network with too much or wrong information can confuse the network and it can settle on weights that are unable to handle variations of larger magnitude in the input data [22].

The most common learning algorithm is the backpropagation algorithm [17,18], in which the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer. The standard backpropagation learning algorithm is a steepest descent algorithm that minimizes the sum of square errors.

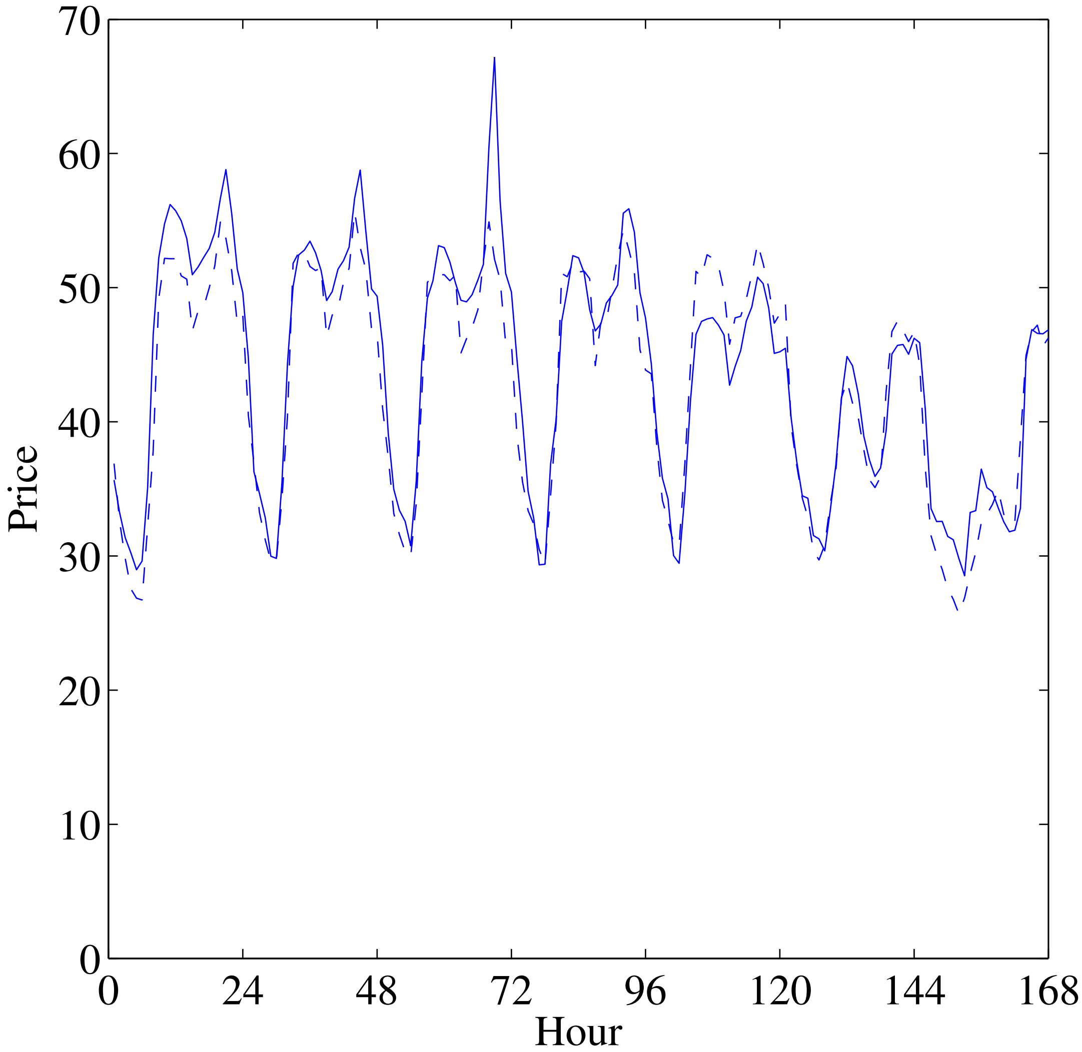

Figure 2 Winter week: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

However, the standard backpropagation learning algorithm is not efficient numerically and tends to converge slowly. In order to accelerate the learning process, two parameters of the backpropagation algorithm can be adjusted: the learning rate and the momentum. The learning rate is the proportion of error gradient by which the weights should be adjusted. Larger values can give a faster convergence to the minimum but also may produce oscillation around it. The momentum determines the proportion of the change of past weights that should be used in the calculation of the new weights [18].

An algorithm that trains an artificial neural network 10 to 100 times faster than the usual backpropagation algorithm is the Levenberg-Marquardt algorithm. While backpropagation is a steepest descent algorithm, the Levenberg-Marquardt algorithm is a variation of Newton's method [28].

A three-layered feedforward artificial neural network trained by the Levenberg-Marquardt algorithm is proposed in this paper for forecasting the next 168 hour electricity prices. The neural network toolbox of MATLAB was selected due to its flexibility and simplicity. The transfer functions used for the hidden and output layers are, respectively, MATLAB nonlinear and linear transfer functions: *tansig*, a hyperbolic tangent sigmoid transfer function with outputs between -1 and 1; *purelin*, a pure linear transfer function. The hidden layer has five units and the output layer has one unit, which was set up to output the next 168 hour electricity prices. Historical data for the year 2002 from the market, namely previous electricity prices, are the main inputs to train the artificial neural network proposed in this paper.

3. ELECTRICITY PRICES FORECASTING

The electricity price is of extreme importance in an electricity market to all the market players, and in particular for producers and consumers. A priori knowledge of the electricity price is important for risk management and may represent an advantage for a market player facing competition. For companies that trade in electricity markets, the ability to forecast prices means that the company is able to strategically set up bids for the spot market in the short-term.

Electricity price is influenced by many factors: historical prices and demand, bidding strategies, operating reserves, im-

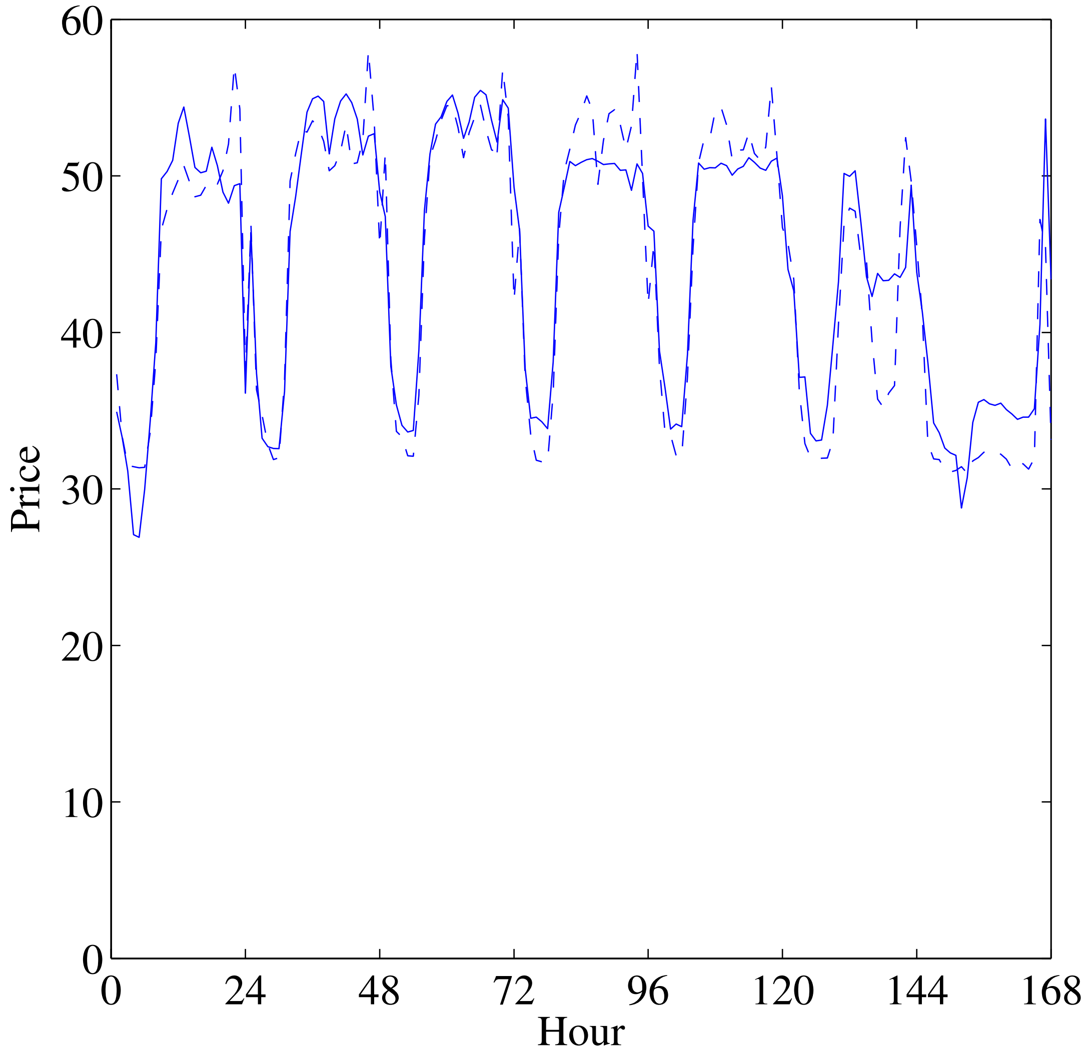

Figure 3 Spring week: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

ports, temperature effect, predicted power shortfall and generation outages.

The daily average price in the electricity market of mainland Spain at 2002 is shown in Figure 1.

If we consider all possible factors that influence the electricity price, forecasting will be very accurate, which, however, is very difficult to do in a real-world case study. Some factors are more important than others and practically we can only consider those more important. The amount of different types of reserves, power import and predicted power shortfall do not improve the forecast at all [14], the effect of the temperature can be incorporated in the demand, and unit outage information is generally proprietary thus not available to all market agents. Also, in the case of artificial neural networks and ARIMA models, historical demand data does not significantly improve predictions [8]. Extremely high prices with no assessable reasons are the consequence of bidding strategies, which are confidential. We decided to use only publicly available information, namely historical price data, to forecast the future prices. The historical prices are natural selections since history and future are correlated.

The shape of price profiles presents seasonality characteristics, usually day and week cycles. The price profile is modified from day to day and week to week, to reflect changes in the electricity market behavior. Typically, daily price profiles are classified as weekdays, from Monday to Friday, and weekend days, Saturday and Sunday, which are different. Another consideration besides weekend is public holiday, known as the calendar effect, since price profiles on non-holidays are particularly different from those on public holidays.

To evaluate the accuracy of the artificial neural network approach in forecasting electricity prices, different criterions are used. This accuracy is computed in function of the actual market prices that occurred. The mean absolute percentage error — MAPE criterion, the sum squared error — SSE criterion, and the standard deviation of error — SDE criterion, are defined as follows.

The MAPE criterion is given by:

$$\mathrm{MAPE} = \frac{100}{N} \sum_{h=1}^{N} \frac{\left| \hat{p}_h - p_h \right|}{\overline{p}} \tag{1}$$

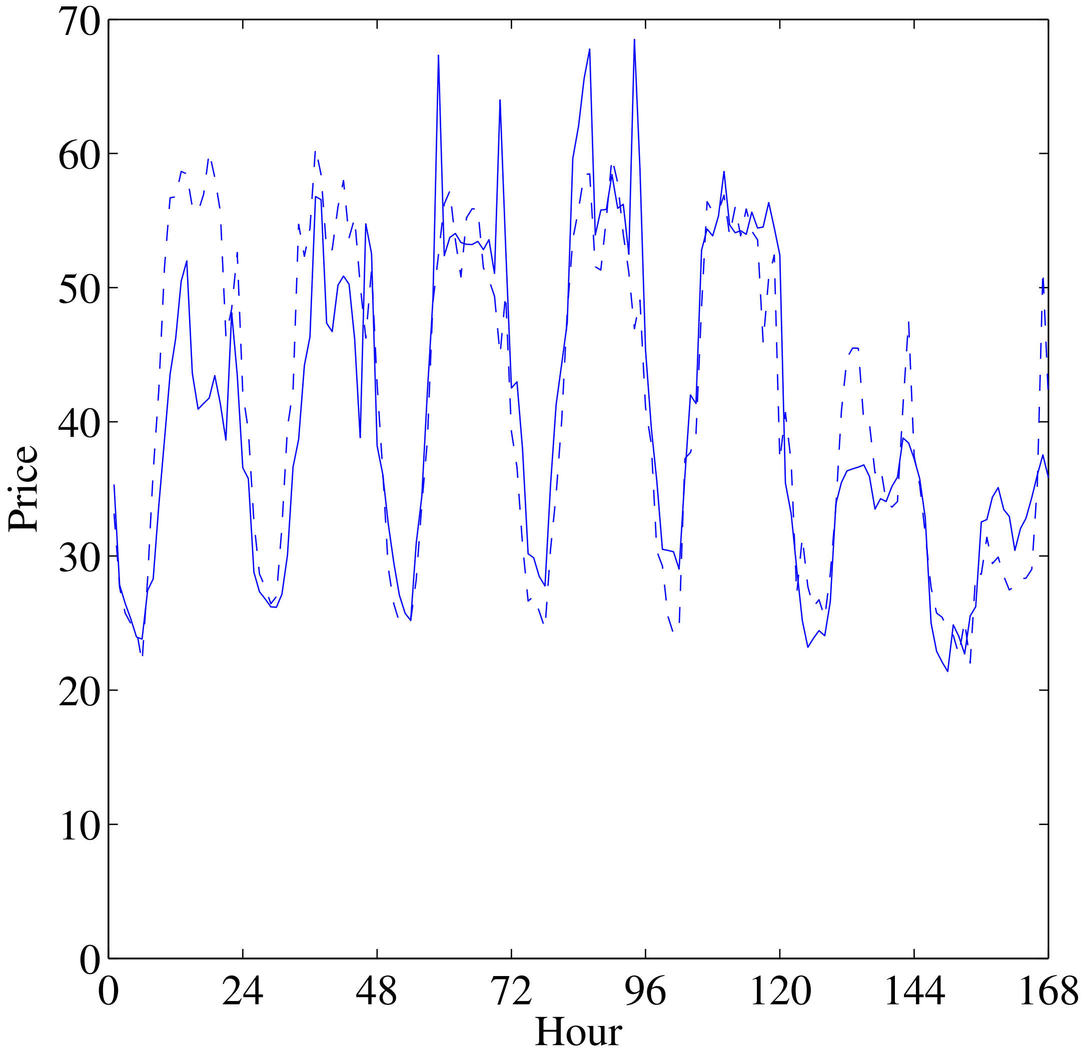

Figure 4 Summer week: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

$$\overline{p} = \frac{1}{N} \sum_{h=1}^{N} p_h \tag{2}$$

where $\hat{p}_h$ and p_h are respectively the forecasted and actual electricity prices at hour h, $\overline{p}$ is the average price of the forecasting period and N is the number of forecasted hours.

Electricity price can rise to tens or even hundreds of times of its normal value at particular hours. It may drop to zero or even to negative at other hours. Hence, the average price was used in Eq. (1) to avoid the problem caused by prices close to zero [29].

The SSE criterion is given by:

$$\mathrm{SSE} = \sum_{h=1}^{N} (\hat{p}_h - p_h)^2 \tag{3}$$

The SDE criterion is given by:

$$\mathrm{SDE} = \sqrt{\frac{1}{N} \sum_{h=1}^{N} (e_h - \overline{e})^2} \tag{4}$$

$$e_h = \hat{p}_h - p_h \tag{5}$$

$$\overline{e} = \frac{1}{N} \sum_{h=1}^{N} e_h \tag{6}$$

where e_h is the forecast error at hour h and $\overline{e}$ is the average error of the forecasting period.

4. CASE STUDY

The proposed artificial neural network approach has been applied to predict the next 168 hour prices in the electricity market of mainland Spain, in this real-world case study. Price forecasting is computed using historical data of year 2002. It should be noted that the electricity market of mainland Spain is a duopoly with a dominant player, resulting in price changes related to the strategic behavior of the dominant player, which are hard to predict [16].

The fourth weeks of February, May, August and November are selected, corresponding to the four seasons of the year 2002. Thus, we expect that representative results for the whole year are taken into account.

To build the forecasting model for each of the considered weeks, the information available includes hourly historical

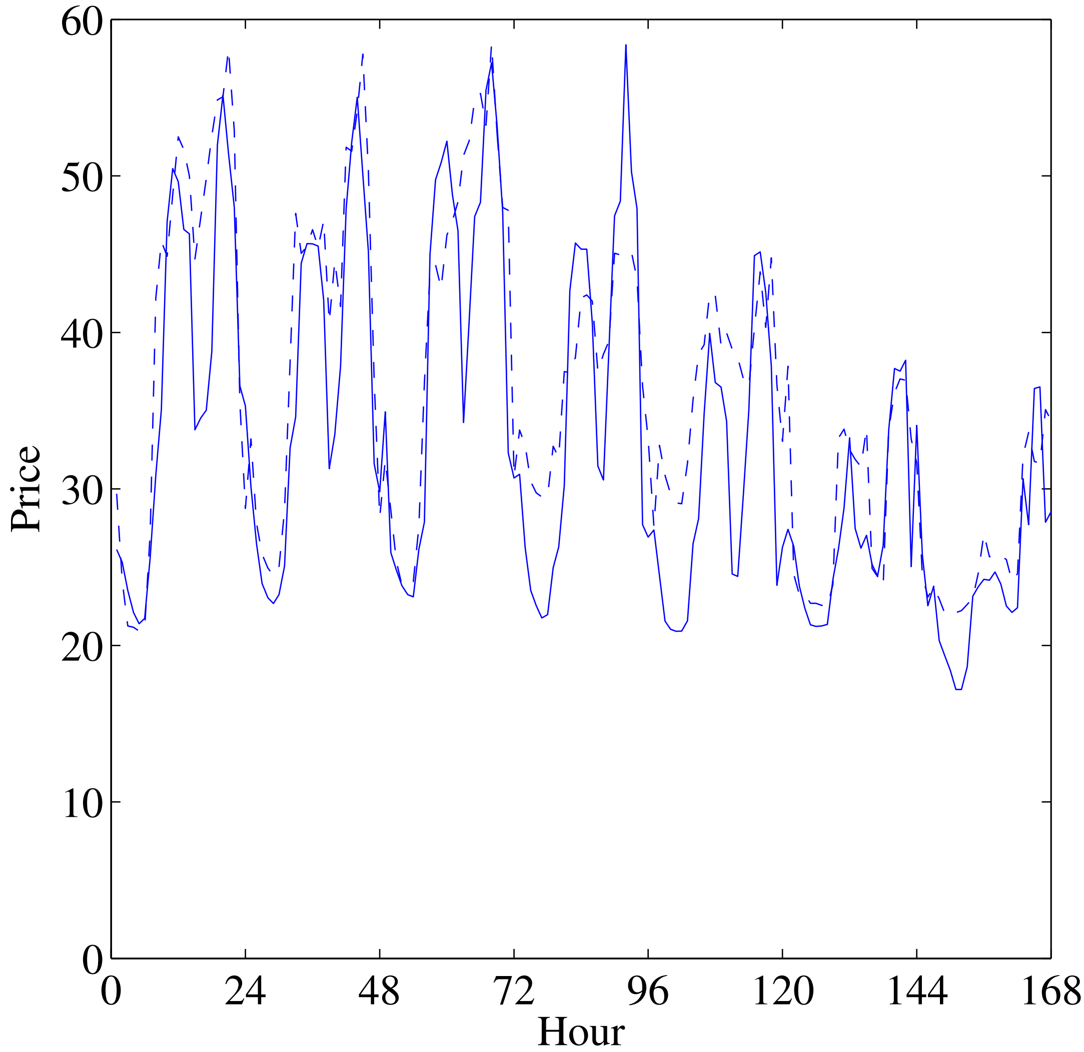

Figure 5 Fall week: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

price data of the 42 days previous to the first day of the week whose prices are to be forecasted. Large training sets should not be used to avoid over-training during the learning process.

The winter week is from February 18 to February 24, 2002; the hourly data used to forecast this winter week are from January 7 to February 17, 2002. The spring week is from May 20 to May 26, 2002; the hourly data used to forecast this spring week are from April 8 to May 19, 2002. The summer week is from August 19 to August 25, 2002; the hourly data used to forecast this summer week are from July 8 to August 18, 2002. The fall week is from November 18 to November 24, 2002; the hourly data used to forecast this fall week are from October 7 to November 17, 2002.

Numerical results with the proposed approach are shown in Figures 2–5 respectively for the winter, spring, summer and fall weeks. Each figure shows the actual prices, solid line, together with the forecasted prices, dashed line.

Table 1 presents the values for the criterions to evaluate the accuracy of the artificial neural network approach in forecasting electricity prices. The first column indicates the week, the second column presents the MAPE, the third column presents the square root of the SSE, and the fourth column presents the SDE.

Table 1 Statistical analysis of the weekly forecasting error.

Week	MAPE	$\sqrt{\text{SSE}}$	SDE
Winter	5.23%	37.92	1.82
Spring	5.36%	39.63	1.91
Summer	11.40%	81.14	4.23
Fall	13.65%	76.92	3.86

A good accuracy of the artificial neural network approach was ascertained. The MAPE has an average value of 8.91%. All the cases have been run on a PC with 512 MB of RAM and a 1.6-GHz-based processor. Running time has been under 20 seconds for each week.

Table 2 shows a comparison between the artificial neural network approach and the ARIMA technique for the MAPE criterion.

Table 2 Comparative MAPE results.

Week	Artificial Neural Networks	ARIMA
Winter	5.23%	6.32%
Spring	5.36%	6.36%
Summer	11.40%	13.39%
Fall	13.65%	13.78%

The artificial neural network approach outperforms the ARIMA technique in all considered weeks. Moreover, the artificial neural network approach is much less time consuming than the ARIMA technique, since the CPU time required by the ARIMA technique to forecast prices is about 5 minutes. Hence, the artificial neural network approach provides a powerful tool of easy implementation for forecasting electricity prices.

5. CONCLUSIONS

Artificial neural networks, which were applied with success performance for load forecasting, are now applied for electricity prices forecasting, with the well-known advantages of being able to being able to approximate nonlinear functions and being able to solve problems where the input-output relationship is neither well defined nor easily computable, because artificial neural networks are data-driven. We propose an artificial neural network approach to predict the next 168 hour prices in the electricity market of mainland Spain. The network configuration consists of three layers: the input layer, one hidden layer and the output layer. The hidden layer has five units with a hyperbolic tangent sigmoid transfer function and the output layer has only one unit with a pure linear transfer function. The Levenberg-Marquardt algorithm is used to train the network. Finally, from a real-world case study we conclude that the accuracy of the forecast ranges from 5.23% (winter week) to 13.65% (fall week). The price forecasting's can be used to support the development of bidding strategies with success, improving negotiation skills for producers to maximize their profits and for consumers to maximize their utilities. The numerical results presented in this paper confirm the considerable value of the proposed artificial neural network approach in forecasting short-term electricity prices, taking into account results previously reported in the technical literature from the ARIMA technique.

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