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Short-term electricity prices forecasting in a competitive market: A neural network approach

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Abstract

This paper proposes a neural network approach for forecasting short-term electricity prices. Almost until the end of last century, electricity supply was considered a public service and any price forecasting which was undertaken tended to be over the longer term, concerning future fuel prices and technical improvements. Nowadays, short-term forecasts have become increasingly important since the rise of the competitive electricity markets. In this new competitive framework, short-term price forecasting is required by producers and consumers to derive their bidding strategies to the electricity market. Accurate forecasting tools are essential for producers to maximize their profits, avowing profit losses over the misjudgement of future price movements, and for consumers to maximize their utilities. A three-layered feedforward neural network, trained by the Levenberg-Marquardt algorithm, is used for forecasting next-week electricity prices. We evaluate the accuracy of the price forecasting attained with the proposed neural network approach, reporting the results from the electricity markets of mainland Spain and California.

Keywords: Price forecasting; Competitive market; Neural network; Levenberg-Marquardt algorithm

1. Introduction

All over the world, the electricity industry is converging toward a competitive framework and a market environment is replacing the traditional monopolistic scenery for the electricity industry. In 1982, Chile was a pioneer country to introduce new market-oriented approaches in the electricity industry sector, later spreading to countries such as England and Wales, Norway, Argentina, Australia, Spain, and various regions of the United States.

In the regulated framework, electricity supply was considered a public service with the electric energy industry 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 which 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 electric energy industry's attention mainly focused on load forecasting, existing little need for tools hedging against price risk given the deterministic nature of electricity prices.

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

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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 competitive framework, coming from the deregulation of the electricity markets, was intended to encourage competition among companies in order to decrease the cost of electricity. Unfortunately, occurrences seldom happening in the regulated framework, such as outages, blackouts and price peaks are now subject of increasing concern. Moreover, deregulation brings electricity prices uncertainty, placing higher requirements on forecasting. 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 from the generators for the power companies and provides better risk management [3]. Forecast errors have significant implications for profits, market shares and ultimately shareholder value [4].

An accurate forecast of electricity prices has become a very important tool for producers and consumers. In the short-term, a producer needs to forecast electricity prices to derive its bidding strategy in the pool and to optimally schedule its electric energy resources [5]. In a regulated environment, traditional generation scheduling of energy resources was based on cost minimization, satisfying the electricity demand and all operating constraints [6]. Therefore, the key issue was how to accurately forecast electricity demand. In a deregulated environment, since generation scheduling of energy resources, such as hydro [7] and thermal resources [8], is now based on profit maximization [9], it is an accurate price forecasting that embodies crucial information for any decision making. Consumers need short-term price forecasts for the same reasons as producers.

It should be noted that price series exhibit greater complexity than demand series, given specific characteristics existing in price series. In most competitive electricity markets the series of prices presents the following features: high frequency, nonconstant mean and variance, daily and weekly seasonality, calendar effect on weekend and public holidays, high volatility and high percentage of unusual prices [10].

Price forecasting has become in recent years an important research area in electrical engineering, and several techniques have been tried out in this task. In general, hard and soft computing techniques [11] could be used to predict electricity prices.

The hard computing techniques, where an exact model of the system is built and the solution is found using algorithms that consider the physical phenomena that govern the process, include time series models [10], auto regressive — AR models [9] and auto regressive integrated moving average — ARIMA models [12]. This approach can be very accurate, but it requires a lot of information, and the computational cost is very high [13]. More recently, generalized autoregressive conditional heteroskedastic — GARCH models [14] and the Wavelet-ARIMA technique [15] have also been proposed.

The soft computing techniques, namely artificial intelligence techniques, do not model the system; instead, they find an appropriate mapping between the several inputs and the electricity price, usually learned from historical examples, thus being computationally more efficient. In particular, neural networks approaches, that have been widely used for load forecasting with successful performance [16,17], are now used to predict electricity prices [18–24], using Fourier and Hartley transforms as filters to the price data [25], using extended Kalman filter [26] or combined with fuzzy logic in a hybrid approach [13,27,28].

Neural networks and ARIMA models are often compared with mixed conclusions in terms of forecasting capacity. A comparison of neural networks and ARIMA models to forecast commodity prices showed that neural network forecasts were more accurate than ARIMA forecasts. Moreover, the success of ARIMA models is conditional upon the underlying data generating process being linear, while neural networks can account for nonlinear relationships [29]. Hybrid methodologies, that combine neural networks and ARIMA models, have been also proposed [30] to take advantage of the unique strength of each model in linear and nonlinear modeling.

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, neural networks have the well-known advantages of being able to approximate any nonlinear function and being able to solve problems where the input–output relationship is neither well defined nor easily computable, because neural networks are data-driven. Three-layered feedforward 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 proposes a neural network approach to forecast next-week prices in the electricity market of mainland Spain. The Levenberg-Marquardt algorithm is used to train a three-layered feedforward neural network. Previously reported approaches to forecast prices in the electricity market of mainland Spain were mainly based on time series models, namely the ARIMA technique. Neural networks approaches are comparatively easy to implement and show good performance being less time consuming. The proposed neural network approach is also applied to forecast next-week prices in the California electricity market, to further assess the validity of the approach.

This paper is structured as follows. Section 2 presents the 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 validity of the proposed approach. Section 4 presents the case studies, based on real-world electricity markets, to evaluate the accuracy of the neural network approach in forecasting short-term electricity prices. Section 5 outlines the conclusions.

2. Neural network approach

Neural networks are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task [31]. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term

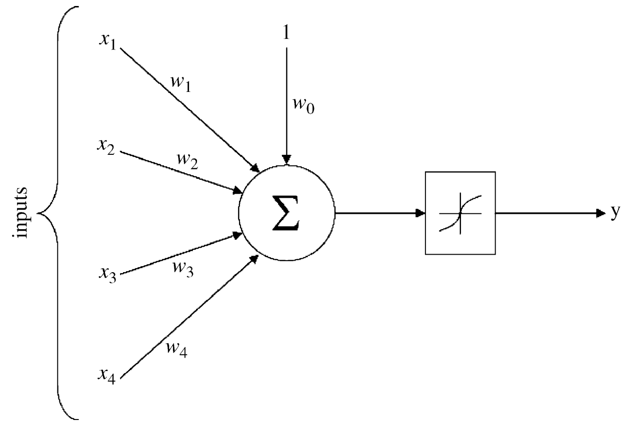

Fig. 1. Internal structure of a neuron.

called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent. Fig. 1 shows the internal structure of a neuron.

Multilayer perceptrons are the best known and most widely used kind of 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 [32].

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. The units in each layer may share the same inputs, but are not connected to each other. Typically, the units in the input layer serve only for transferring the input pattern to the rest of the network, without any processing. The information is processed by the units in the hidden and output layers. Fig. 2 shows the architecture of a generic three-layered feedforward neural network model. The neural network considered is fully connected in the sense that every unit belonging to each layer is connected to every unit belonging to the adjacent layer.

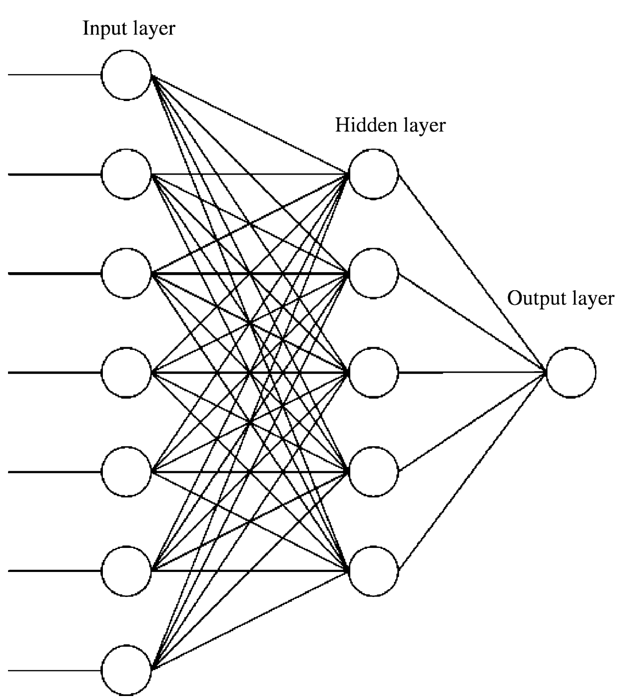

Fig. 2. Example of a three-layered feedforward neural network model with a single output unit.

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, defined as:

$$f(s) = \frac{1 - e^{-s}}{1 + e^{-s}} \tag{1}$$

where s is the weighted input of the hidden layer, and $f(s)$ is the output of the hidden layer. The output layer has only one unit with a pure linear transfer function.

This configuration has been proven to be a universal mapper, provided that the hidden layer has enough units [33]. On the 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 overfit 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 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 neural network training is highly influential to the success of training. In the learning process a 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. Thus, learning entails an optimization process. The error minimization process is repeated until an acceptable criterion for convergence is reached.

The knowledge acquired by the neural network through the learning process is tested by applying new data that it has never seen before, called the testing set. The network should be able to generalize and have an accurate output for this unseen data [13]. It is undesirable to overtrain the 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 [20]. Overtraining the neural network can seriously deteriorate the forecasting results. Also, providing the 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 [25].

The most common learning algorithm is the backpropagation algorithm [18,19], 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.

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 the minimum. The momentum determines the proportion of the change of past weights that should be used in the calculation of the new weights [19].

An algorithm that trains a neural network 10–100 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 [34].

Newton's update for minimizing a function $V(\boldsymbol{x})$ with respect to the vector $\boldsymbol{x}$ is given by:

$$\Delta \boldsymbol{x} = -[\nabla^2 V(\boldsymbol{x})]^{-1} \nabla V(\boldsymbol{x}) \tag{2}$$

where $\nabla^2 V(\boldsymbol{x})$ is the Hessian matrix and $\nabla V(\boldsymbol{x})$ is the gradient vector. Assuming that $V(\boldsymbol{x})$ is the sum of square errors, given by:

$$V(\boldsymbol{x}) = \sum_{h=1}^{N} e_h^2(\boldsymbol{x}) \tag{3}$$

then:

$$\nabla V(\boldsymbol{x}) = 2\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{e}(\boldsymbol{x}) \tag{4}$$

$$\nabla^2 V(\boldsymbol{x}) = 2\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{J}(\boldsymbol{x}) + 2\boldsymbol{S}(\boldsymbol{x}) \tag{5}$$

where $\boldsymbol{e}(\boldsymbol{x})$ is the error vector, $\boldsymbol{J}(\boldsymbol{x})$ is the Jacobian matrix given by:

$$\boldsymbol{J}(\boldsymbol{x}) = \begin{bmatrix} \dfrac{\partial e_1(\boldsymbol{x})}{\partial x_1} & \dfrac{\partial e_1(\boldsymbol{x})}{\partial x_2} & \cdots & \dfrac{\partial e_1(\boldsymbol{x})}{\partial x_n} \\ \dfrac{\partial e_2(\boldsymbol{x})}{\partial x_1} & \dfrac{\partial e_2(\boldsymbol{x})}{\partial x_2} & \cdots & \dfrac{\partial e_2(\boldsymbol{x})}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{\partial e_N(\boldsymbol{x})}{\partial x_1} & \dfrac{\partial e_N(\boldsymbol{x})}{\partial x_2} & \cdots & \dfrac{\partial e_N(\boldsymbol{x})}{\partial x_n} \end{bmatrix} \tag{6}$$

and where $\boldsymbol{S}(\boldsymbol{x})$ is given by:

$$\boldsymbol{S}(\boldsymbol{x}) = \sum_{h=1}^{N} e_h(\boldsymbol{x}) \nabla^2 e_h(\boldsymbol{x}) \tag{7}$$

Neglecting the second-order derivatives of the error vector, i.e., assuming that $\boldsymbol{S}(\boldsymbol{x}) \approx 0$, the Hessian matrix is given by:

$$\nabla^2 V(\boldsymbol{x}) = 2\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{J}(\boldsymbol{x}) \tag{8}$$

and substituting Eqs. (8) and (4) into Eq. (2) we obtain the Gauss–Newton update, given by:

$$\Delta \boldsymbol{x} = -[\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{J}(\boldsymbol{x})]^{-1} \boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{e}(\boldsymbol{x}) \tag{9}$$

The advantage of Gauss–Newton over the standard Newton's method is that it does not require calculation of second-order derivatives. Nevertheless, the matrix $\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\ \boldsymbol{J}(\boldsymbol{x})$ may not be invertible. This is overcome with the Levenberg-Marquardt algorithm, which consists in finding the update given by:

$$\Delta \boldsymbol{x} = -[\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{J}(\boldsymbol{x}) + \mu \boldsymbol{I}]^{-1} \boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{e}(\boldsymbol{x}) \tag{10}$$

where parameter μ is conveniently modified during the algorithm iterations.

When μ is very small or null the Levenberg-Marquardt algorithm becomes Gauss-Newton, which should provide faster convergence, while for higher μ values, when the first term within square brackets of Eq. (10) is negligible with respect to the second term within square brackets, the algorithm becomes steepest descent. Hence, the Levenberg-Marquardt algorithm provides a nice compromise between the speed of Gauss-Newton and the guaranteed convergence of steepest descent [35].

A three-layered feedforward neural network trained by the Levenberg-Marquardt algorithm is proposed in this paper for forecasting next-week electricity prices. The neural network toolbox of MATLAB was selected due to its flexibility and simplicity [36]. 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. At the training stage, various numbers of units in the hidden layer were tested. The best results were produced with five hidden units. The output layer has one unit, which was set up to output the next-week electricity prices. Historical data from the markets, namely previous electricity prices, are the main inputs to train the neural network proposed in this paper.

3. Electricity prices forecasting

The electricity price is of extreme importance in a competitive 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.

A good price forecasting tool in deregulated markets should be able to capture the uncertainty associated with those prices. Some of the key uncertainties are fuel prices, future additions of generation and transmission capacity, regulatory structure and rules, future demand growth, plant operations and climate changes [1].

Electricity price is influenced by many factors: historical prices and demand, bidding strategies, operating reserves, imports, temperature effect, predicted power shortfall and generation outages. The daily average price in the electricity market of mainland Spain at 2002 is shown in Fig. 3.

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 [13], the effect of the temperature and other weather related variables can be incorporated in the demand, and unit outage information is generally

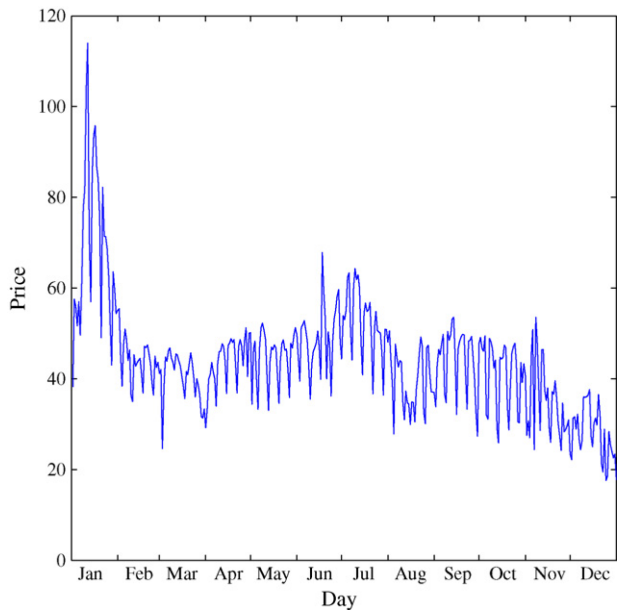

Fig. 3. Daily average price in the electricity market of mainland Spain at 2002, in euro per megawatt hour.

proprietary thus not available to all market agents. Also, in the case of neural networks and ARIMA models, historical demand data does not significantly improve predictions [5]. Extremely high prices with no assessable reasons are the consequence of bidding strategies, which are confidential. We decided to use only historical price data to forecast the future prices, not only because this selection enables a fair comparison between the ARIMA models in [12,15] and our neural network approach, but also because it reveals a good compromise between accuracy and time consumption.

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 behaviour. 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 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:

$$\mathrm{MAPE} = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{11}$$

$$\bar{p} = \frac{1}{N}\sum_{h=1}^{N} p_h \tag{12}$$

where $\hat{p}_h$ and p_h are respectively the forecasted and actual electricity prices at hour h, $\bar{p}$ 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. (11) to avoid the problem caused by prices close to zero [37].

The SSE criterion is given by:

$$\mathrm{SSE} = \sum_{h=1}^{N}(\hat{p}_h - p_h)^2 \tag{13}$$

The SDE criterion is given by:

$$\mathrm{SDE} = \sqrt{\frac{1}{N}\sum_{h=1}^{N}(e_h - \bar{e})^2} \tag{14}$$

$$e_h = \hat{p}_h - p_h \tag{15}$$

$$\bar{e} = \frac{1}{N}\sum_{h=1}^{N} e_h \tag{16}$$

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

4. Case studies

The proposed neural network approach is applied to forecast next-week prices in the electricity market of mainland Spain [38] and the California electricity market [39].

Price forecasting is computed using historical data of year 2002 for the Spanish market. It should be noted that the Spanish market is a duopoly with a dominant player, resulting in price changes related to the strategic behaviour of the dominant player, which are hard to predict. For the sake of a fair comparison, the fourth week of February, May, August, and November are selected, i.e., weeks with particularly good price behaviour are deliberately not chosen. This results in an uneven accuracy distribution throughout the year that reflects reality [15]. For the Californian market, one week of year 2000 has been selected to further assess the validity of the proposed approach.

To build the forecasting model for each of the considered weeks, the information available includes hourly historical price data of the 42 days previous to the day of the week whose prices are to be forecasted. Very large training sets should not be used to avoid overtraining during the learning process.

For the Spanish market, 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.

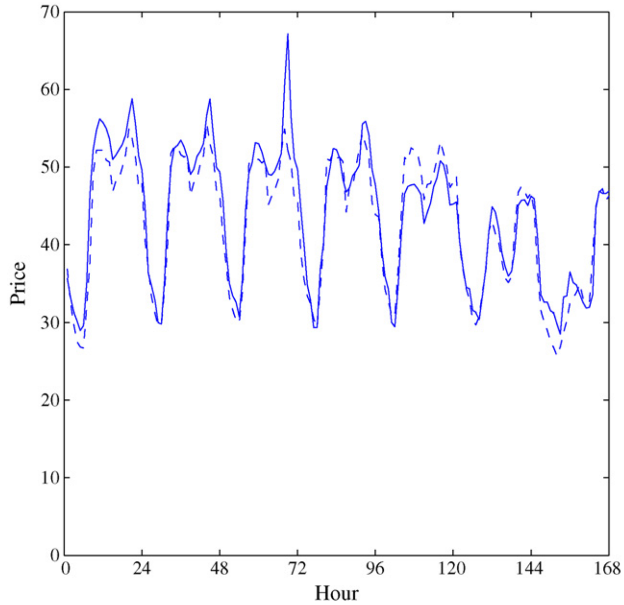

Fig. 4. Winter week for the Spanish market: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

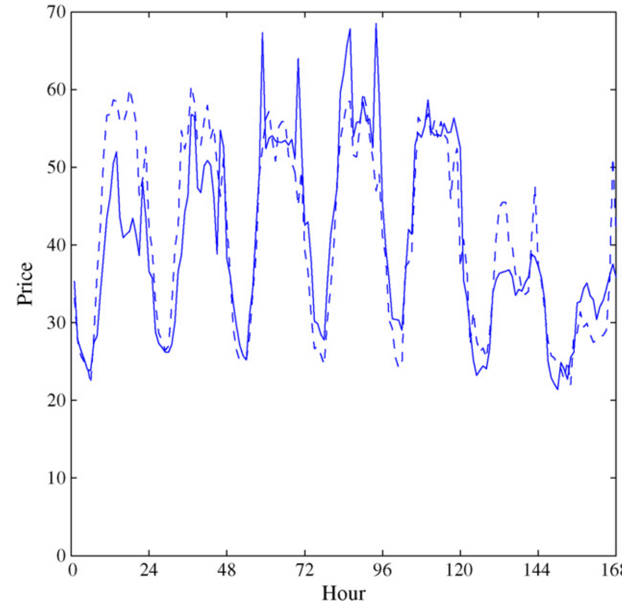

Fig. 6. Summer week for the Spanish market: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

For the Californian market, the spring week is from April 3 to April 9, 2000. This week is prior in time to the beginning of the dramatic price volatility period that took place afterwards [12]. The hourly data used to forecast this spring week are from February 21 to April 2, 2000.

Figs. 4–8 show the numerical results with the proposed approach for the five weeks studied—four weeks for the Spanish market and one week for the Californian market. Each figure shows the forecasted prices, dashed line, together with the actual prices, solid line.

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

The MAPE for the Spanish market has an average value of 8.91% and for the Californian market has an average value of 3.09%. All the cases have been run on a PC with 512 MB of RAM and a 1.6-GHz-based processor. Running time is less than 20 s for each week.

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

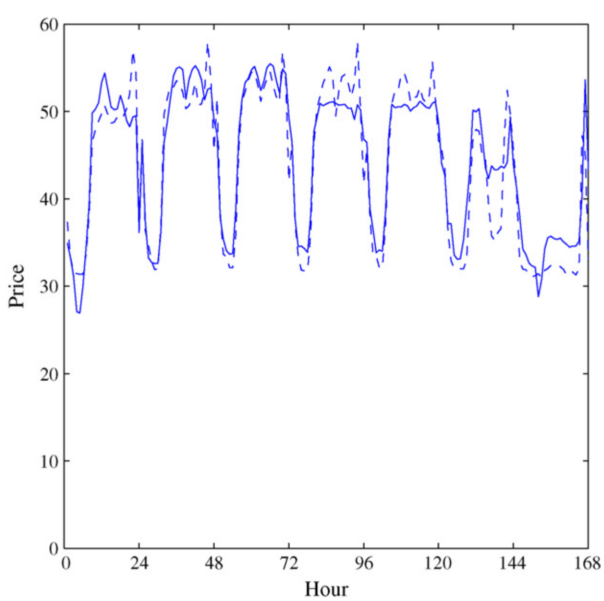

Fig. 5. Spring week for the Spanish market: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

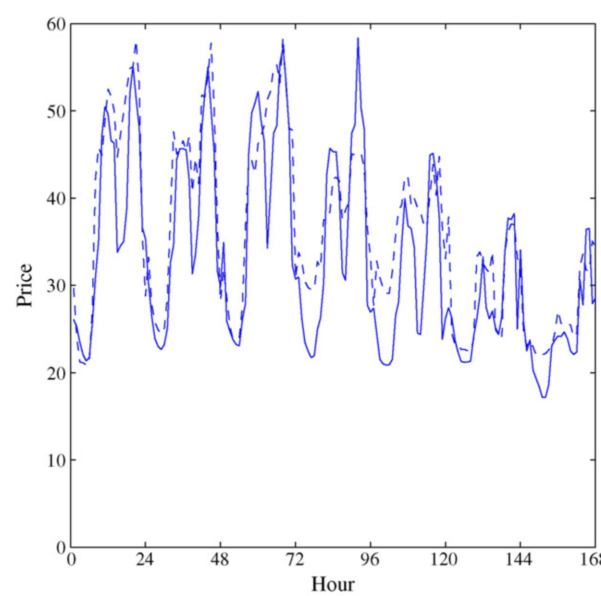

Fig. 7. Fall week for the Spanish market: actual prices, solid line, together with the forecasted prices, dashed line, in euro per megawatt hour.

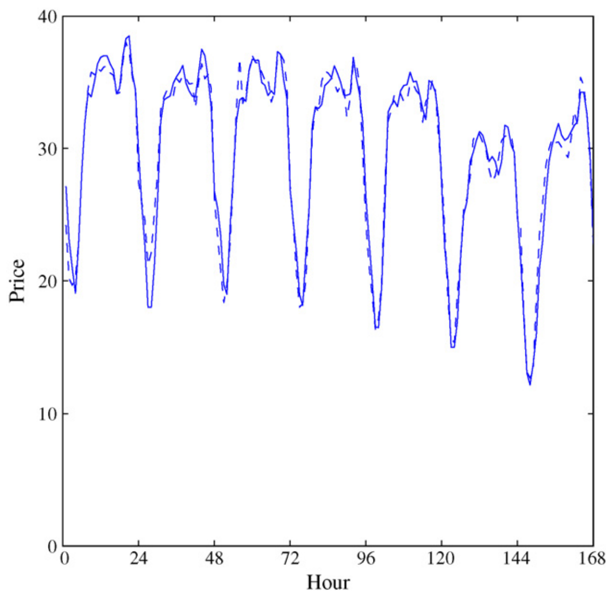

Fig. 8. Spring week for the Californian market: actual prices, solid line, together with the forecasted prices, dashed line, in euros per megawatt hour.

Table 1
Statistical analysis of the weekly forecasting error attained with the neural network approach for the five weeks analyzed

Market	Week	MAPE	$\sqrt{\text{SSE}}$	SDE
Spanish	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
Californian	Spring	3.09%	15.93	0.81

Also, the MAPE criterion for a naïve procedure is presented. The naïve procedure establishes just that the prices forecasted for a given week are the actual prices of the previous week, therefore, using a no-change criterion.

The neural network approach outperforms the ARIMA technique and the naïve procedure in all considered weeks. Moreover, the 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 min. Hence, the neural network approach provides a very powerful tool of easy implementation for forecasting electricity prices.

Table 2
Comparative MAPE results between the neural network approach, the ARIMA technique and the naïve procedure

Market	Week	Neural networks	ARIMA	Naïve
Spanish	Winter	5.23%	6.32%	7.68%
	Spring	5.36%	6.36%	7.27%
	Summer	11.40%	13.39%	27.30%
	Fall	13.65%	13.78%	19.98%
Californian	Spring	3.09%	5.01%	6.98%

5. Conclusion

This paper proposes a neural network approach to forecast next-week prices in the electricity markets of mainland Spain and California. The Levenberg-Marquardt algorithm is used to train the network.

Average errors in the Spanish market are around 9% for the weeks under study, and around 3% in the stable period of the Californian market. The results presented confirm the considerable value of the proposed 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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