Proceedings of the 6th WSEAS Int. Conf. on NEURAL NETWORKS, Lisbon, Portugal, June 16-18, 2005 (pp80-83)

An Artificial Neural Network Approach for Day-Ahead Electricity Prices Forecasting

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Abstract: - This paper is about the use of artificial neural networks on day-ahead electricity prices forecasting. In nowadays competitive electricity markets, good forecasting tools hedging against daily price volatility are becoming increasingly important. The accuracy and performance of the proposed approach, making use of a three-layered artificial neural network with backpropagation, is evaluated. Results from a real-world case study based on an electricity market are presented.

Key-Words: - Prices forecasting, electricity markets, artificial neural networks

1 Introduction

Since the advent of electricity generation in 1882 at Pearl Street Power Station, New York, the electricity industry has undergone significant transformations. The industry was organized as regulated, vertically integrated joining generation, transmission and distribution of electricity in state-owned monopolistic companies.

All over the world, the electricity industry is moving toward a competitive framework and a market environment is replacing the traditional monopolistic scenery for the electricity. Chile was a pioneer country, in 1982, to introduce new market-oriented approaches in the electricity sector. Electricity sector deregulation brought competition through biding to win the best profit in the electricity market. Also, environmental protection and sustainable development are main politic concerns nowadays. The world encounters at Rio de Janeiro in Brazil, 1992, and at Kyoto in Japan, 1997, are evidence of international concern about the global warming brought about by the enhanced greenhouse effect, due to human activity. Hence, constraining greenhouse gas emissions, due to power plants burning fossil fuels to convert into electric energy, is an emerging issue [1-2].

In a day-ahead electricity market based on a pool, generating and consumer companies submit bids for selling and buying electricity for the next 24 hours. The bids submitted to the market derive the profit of the generating company, supporting those bids is usually a guess for the anticipated electricity prices.

The deregulation of the electricity markets brings uncertainty to electricity prices. A good forecasting tool provides a risk hedging mechanism for generating companies against daily price volatility. In addition, a generating company can develop an appropriate bidding strategy to maximize its own profit with an accurate next-day price forecast, which represents an advantage facing competition.

There are several techniques applied for electricity prices forecasting in the literature. Traditional time series models in [3], Auto Regressive Integrated Moving Average (ARIMA) models in [4] and simpler Auto Regressive (AR) models in [5] have been used for price forecasting. Artificial Neural Networks (ANN) techniques in [6-11], combined with fuzzy logic in [12-13], which have been mainly used for load forecasting are now used to predict electricity prices.

A comparison of neural network and ARIMA models to forecast commodity prices in [14] showed the neural network forecasts were considerably more accurate than those of the traditional ARIMA models.

Moreover, the success of ARIMA models is conditional upon the underlying data generating process being linear, while ANN can approximate any nonlinear function.

In particular, feedforward backpropagation neural networks are specially suited for electricity prices forecasting because they can process nonlinearities using sigmoid functions for the inputs and linear functions for the outputs.

This paper focuses in the day-ahead electricity prices forecast using ANN. We propose a three-layered feedforward ANN with backpropagation, showing the results for an electricity market. Historical data for this market at the year 2001 is used to train the ANN.

2 Price Forecasting Using ANN

ANN are highly interconnected simple processing units inspired in the human brain and its actual learning process. Interconnections between units have weights that multiply the values which go through them. Also, units normally have a fixed input called bias. Each of these units forms a weighted sum of its inputs, to which the bias is added. This sum is then passed through a transfer function.

Multilayer perceptrons are the most commonly used kind of ANN. They are composed of an input layer, one or more hidden layers and an output layer. Networks with interconnections that do not form any loops are called feedforward. Fig. 1 shows the architecture of a generic three-layered feedforward ANN model.

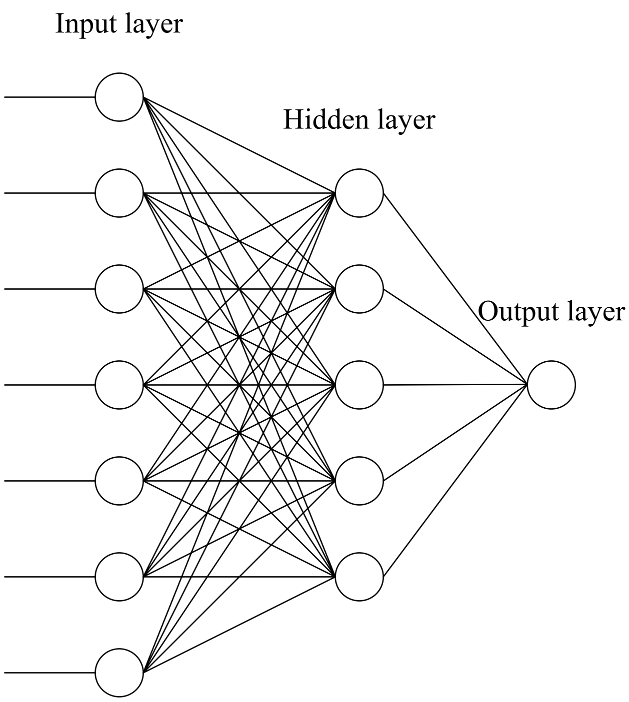

Fig. 1 Generic example of a three-layered feedforward ANN model.

A one hidden layer sigmoid/linear network is chosen. The transfer function of the hidden layer is a sigmoid function. The transfer function for the output layer is a pure linear function. Feedforward networks are a class of ANN which uses supervised learning. Forecasting with ANN involves two steps: training and learning. At the training stage, using historical data, both inputs and the corresponding desired outputs are presented to the network. Through learning algorithms the network tries to minimize the error between the output produced and the desired output, adjusting the weights and biases. The error minimization process is repeated until the error converges to a predefined small value.

Backpropagation networks employ the gradient descent algorithm for adjusting the weights and biases. The magnitude of the adjustments depends on two parameters: 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 gradient 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. The adequate selection of inputs for ANN training is highly influential to the success of training as well as verification. The pool price is major influenced by the following factors: historical prices, electricity demand and bidding behaviors. The influence of historical data results from the daily cycle characteristics of the price curves. In a week span, each day’s pattern would also be different especially between a weekday and weekend. Consequently, week cycle characteristics of the price curves have to be considered. Another consideration is public holiday, since price pattern of public holidays are entirely different from that of the weekdays. The trend of electricity demand influences the trend of price curves. The demand at a weekend is usually much lower than at a weekday. Therefore, it is desirable to have different models for weekdays and weekends.

In this paper, we propose a three-layered feedforward ANN, trained by error backpropagated algorithm, for forecasting the next 24 hour electricity prices. The electricity prices forecasting is of major importance to support management decisions, guiding business performance on the electricity market.

The neural network toolbox of MATLAB was selected due to its flexibility and simplicity. The investigation of the influence of bidding behaviors, normally, handled using game theory will be reported in another paper. Historical data for the year 2001 from the market, which includes day-ahead electricity prices as well as forecasted load, are the main inputs to train the ANN in the numerical results presented in this paper.

3 Numerical Results

The proposed ANN forecasting model has been applied to predict the electricity prices of the electricity market. Two days have been selected to forecast and validate the performance of the proposed model. The first one corresponds to a typically low demand day, in the last week of August 2001. The second one corresponds to a typically high demand day, in the final week of November 2001. The hourly data used to forecast the summer day are from July 1, 2001 to August 27, 2001. The hourly data used to forecast the winter day are from October 1, 2001 to November 27, 2001.

To evaluate the forecast capacity of the ANN model, different criterions are used. This capacity can be checked afterwards, given the actual market prices that occurred. The Mean Absolute Percentage Error (MAPE) and the Standard Deviation of Error (SDE) were computed, along with the Sum Squared Error (SSE). The MAPE criterion is given by:

$$\mathrm{MAPE} = \frac{1}{24}\sum_{i=1}^{24}\left|\frac{\hat{f}_i - f_i}{\bar{f}}\right| \times 100\% \qquad (1)$$

$$\bar{f} = \frac{1}{24}\sum_{i=1}^{24} f_i \qquad (2)$$

where $\hat{f}_i$ and f_i are the forecasted and actual electricity prices at hour i, respectively. The SSE criterion is the sum of the 24 square differences between the forecasted prices and the actual ones. SSE, which measures the overall performance of a model, is given by:

$$\mathrm{SSE} = \sum_{i=1}^{24}(\hat{f}_i - f_i)^2 \qquad (3)$$

The transfer functions used for the hidden and output layers, respectively, are nonlinear (‘logsig’) and linear (‘purelin’). In MATLAB, ‘logsig’ is the log-sigmoid transfer function with outputs between -1 and 1 while ‘purelin’ is the linear transfer function. Numerical results with the proposed model are presented in Fig. 2 and Fig. 3, showing the forecast prices, dashed line, together with the actual ones, solid line, respectively for a summer and a winter day.

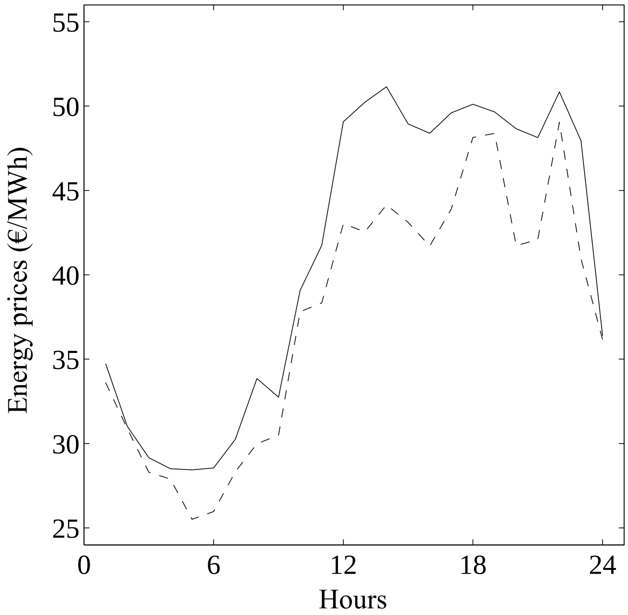

Fig. 2 Forecasted electricity price for a summer day.

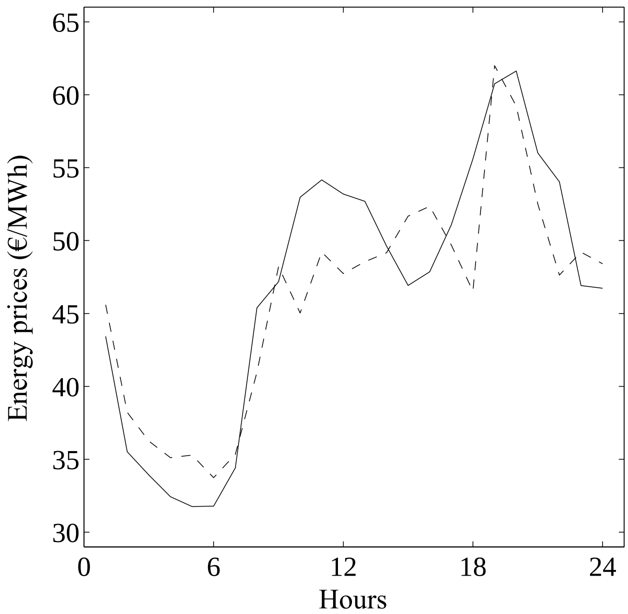

Fig. 3 Forecasted electricity price for a winter day.

Table 1 summarizes the results. First column indicates the day, second column shows the MAPE, the third column presents the SDE, and the fourth column shows the square root of the SSE.

	MAPE	SDE	$\sqrt{\mathrm{SSE}}$
summer day	8.63%	2.56	21.27
winter day	7.28%	2.22	19.82

Table 1 Statistical analysis of the ANN errors.

A good performance of the ANN model can be attested. The mean errors are around 8%. All the studies have been run on a PC with 512 MB of RAM and a 1.6-GHz-based processor. Running time has been under one minute for each case.

4 Conclusion

This paper proposes an artificial neural network approach to predict hourly prices in an electricity market.

Mean errors in the market ranges from 7.28% (Winter) to 8.63% (Summer), representing reasonable errors taking into account results previously reported in the technical literature. Price forecasting's obtained are accurate enough to be used by generating companies to develop appropriate bidding strategies in the competitive electricity market with tangible financial benefits.

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