International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

September 2017 | Issue 32 | Volume 9 | Number 3 | Pages 30-34

EFFICIENT ELECTRIC PRICE FORECASTING USING NEURAL NETWORKS

R. Esmaeilzadeh A. Roshan Milani

Azarbaijan Regional Electric Company, Tabriz, Iran, rasoul_zadeh@yahoo.com, r_milani2003@yahoo.com

Abstract- The prediction of electricity prices is one of the most important issues that has been addressed by many market operators and researchers in the field since the start of the restructuring of the electricity industry. One of the most important applications of this forecast is to formulate appropriate strategies for bidding on energy markets. Considering the importance of this issue, this article, while reviewing the work done so far, will provide short-term forecasts for electricity prices. The method used in the prediction process is based on artificial neural networks and in order to improve the accuracy of the predictions, a series of measures for the pre-processing of input data has been used. These measures include extracting possible correlation coefficients between input data to select the most effective data as neural network inputs.

Keywords: Electricity Price Forecast, Restructuring, Electricity Market, Artificial Neural Networks.

I. INTRODUCTION

The results of the forecast of electricity prices can have a significant impact on the energy market. For example, market-based manufacturers use the price forecast results to formulate an appropriate bid strategy to maximize their profits, while consumers, by the same token, set their purchases from each of the energy markets to the lowest possible cost to purchase energy. Consumers with scattered sources of production are also able to plan their products for peak hours of electricity prices and according to market outlook predictions, overcome them the high prices of instantaneous markets [2]. Therefore, any improvement in the short-term forecast of electricity prices can lead to major changes in the way in which the electricity market is traded and to the benefit of the participants [1].

On the other hand, the proper precision in the mid-term forecast of electricity prices will allow successful negotiations on bilateral contracts. In fact, this type of prediction, which is related to the horizon of six months to one year, is used to determine and regulate the monthly planning of contracts. In fact, power generators use the results of this prediction to decide how much to allocate their content for sale through bilateral contracts and for the amount sold for sale in the energy market [2].

The important use of long-term forecasting is also in some cases, such as the decision to develop transmission lines, increased production, the construction of distribution systems and inter-district networks [1]. The main purpose of this research is to provide a short-term forecast price for electricity through artificial neural networks.

II. PRINCIPLE OF ELECTRICITY PRICE

In an electricity market, electricity prices are the most important signal for all market participants and the market clearing price (MCP) is the most basic concept of pricing. Often, when the density of the transmission lines is present, the zonal market clearing price (ZMCP) or the local market price (LMP) can be used. The ZMCP value may vary from region to region but is the same for the same area, and the LMP may also vary for different busses.

MCP calculation: After receiving price offers, ISO (Independent System Operation) will raise all the price proposals for production as a curve and collect all the price offer for consumption as a demand curve.

ZMCP calculation: If, in a given time period, the ISO encounters a congestion path, it will modify the relevant zonal schedules to eliminate the density at both ends of the route. Therefore, the MCP of two regions can be different, which is titled as the ZMCP. Using ZMCP, the cost of computing is calculated for each density path.

III. PROBLEM WITH THE WAY TO FORECAST ELECTRICITY PRICES

One of the most important problems with the signal of the price of electrical energy is instability. There is the same instability that has made the price prediction difficult. The main reason for such instabilities is the choice of selective pricing strategies by market players as well as a huge amount of effective uncertainties.

In general, the main characteristics of prices in competitive electricity markets can be as follows:
- High Frequency
- The mean and variance variability
- Impact of seasonal factors
- a lot of instability

IV. ARTIFICIAL INTELLIGENCE METHOD

The set of intelligent methods used in various articles about price prediction is categorized into three categories of artificial neural networks (ANN), fuzzy logic, and the combination of these two methods, the Neuro-Fuzzy method.

One of the most common types of artificial neural networks used in the process of price prediction is the neural network having Multi-Layer Perceptron [1] and Recurrent Neural Networks [3, 4]. In addition to the various types of artificial neural networks used in the prediction process, actions such as preprocessing input data, the prevention of over training, the classification of input data and the elimination of very high mutations also have been used to reduce the amount of forecast error [3-5]. However, there is a very important question about the application of neural networks, whether these methods are accurate to estimate data outside the field of training [4].

In [6] and [7], the combination of a group of neural networks with various decorations has helped to predict the price. In [7], writers believed that the use of a neural network to map a number of input data with similar outputs was not appropriate therefore recommended the use of several networks. The most difficult part in the implementation process is how to combine the outputs of these networks to get the final results. Therefore, this reference provides a new method for combining present predictions from different networks. The use of this method to predict MCP of the New England market suggests improvement in results rather than the use of a single neural network.

In [8], a detailed review of price prediction models, due to the impact of bid strategy approaches, has oscillatory and non-alternating nature. Therefore, the use of a series of dynamic models linked to each other by the Markov chain is considered to be inappropriate. In this paper, a special type of Hidden Markov model called IOHMM (Input-Output Hidden Markov model) is used to analyze and forecast the price of electricity. This method, which consists of two methods of artificial neural network, is able to enable accurate prediction of prices to allow some dynamic information, such as the behavioral status of the market and its effect on futures prices. This method has been implemented on the Spain electricity market. According to the results, it is seen that the prediction error rate is higher with this method than other methods. Therefore, the only advantage of this method is its ability to model time series dynamics.

Along with the various applications that come from neural networks, there are some other intelligent ways. For example, in [9], a neuro-fuzzy system or ANFIS (Adaptive Neuro-Fuzzy Inference System) is used. In this reference, the method used to predict the price of electricity is based on the combination of artificial neural networks and fuzzy logic which is used to predict the MCP of Ontario power market. The data used in this method includes past market MCPs data, hourly system time, under operating system storages, and transmission constraints.

Neural network training has been used for data from 2 to 4 weeks ago and its learning algorithm is titled Levenberg Marquardt algorithm. The latest available electricity pricing forecast has provided a new way to anticipate short-term electricity prices in Spain market. This new fuzzy-neural method has an aesthetic structure that has been achieved by combining fuzzy logic and a specific training algorithm, a suitable model for Non-static behaviors, and also the sudden jump in electricity prices. The results of the proposed prediction indicate that this method is superior to previous methods, such as ARIMA, multi-layer perceptron neural networks and RBF (Radial Bias Function) neural networks.

V. LEVENBERG-MARQURADT ALGORITHM

The algorithm used in this project is Levenberg-Marquardt's algorithm. In the Leven berg algorithm, it is stated that if we want to minimize the cost function $V(x)$ by changing x, the x-correction is as follows:

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

which the function $V(x)$ is the error squared:

$$V(x) = \sum_{i=1}^{N} e_i^2(x) \quad (2)$$

then:

$$\nabla^2 V(x) = J^T(x) J(x) + S(x) \quad (3)$$

In this case, J is the Jacobin matrix.

$$J(x) = \begin{bmatrix} \frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \cdots & \frac{\partial e_1(x)}{\partial x_n} \\ . & & & \\ . & & & \\ . & & & \\ \frac{\partial e_N(x)}{\partial x_1} & \frac{\partial e_N(x)}{\partial x_2} & \cdots & \frac{\partial e_N(x)}{\partial x_n} \end{bmatrix} \quad (4)$$

$$S(x) = \sum_{i=1}^{n} e_i(x) \nabla^2 e_i(x) \quad (5)$$

Supposing s=0, the X modification is done as follows:

$$\Delta x = [J^T(x) J(x)]^{-1} J^T(x) e(x) \quad (6)$$

The parameter μ is a multiplication factor multiplied by I matrix, to reverse the matrix inside the bracket. In practice, since μ used in the weight correction equation then its function is opposite of the learning coefficient in the ordinary error in propagation algorithm. Meanwhile, μ is lengthening the steps, resulting in faster learning, but the accuracy of the final error is less and with increasing the length of the steps is shorter and the learning time is increased, but it ensures greater convergence. Hence, in Levenberg Marquardt algorithm, in addition to μ, another parameter is defined as β, which is a real integer greater than one. The function of this parameter is that if the weight correction results in an error reduction, μ is divided in order to increase the learning speed, and if the correction of the recent weight results in an increase in error, then μ is multiplied.

With regard to what has been said so far, for the structure of the neural network with a hidden layer, with the nonlinear function of the sigmoid tangent in the middle layer and the linear function in the output layer neurons, the network learning algorithm can be summarized in the following relationships:

$$\left.\begin{aligned}\Delta W &= [J^T J+\mu I]^{-1} J^T e\\ J &= \frac{\partial e}{\partial W} = -y\end{aligned}\right\} \Rightarrow \Delta W = [y^T y+\mu I] y^T (d-z) \quad (7)$$

$$\left.\begin{aligned}\Delta V &= [J^T J+\mu I]^{-1} J^T e W^T\\ J &= x^T(1-y^2)\end{aligned}\right\} \Rightarrow$$

$$\Delta V = \left[\left(x^T(1-y^2)\right)\left(x^T(1-y^2)\right)^T+\mu I\right]^{-1}\left(x^T(1-y^2)\right)\left(d-z\right)W^T \quad (8)$$

where, V is the weights between the neurons and the hidden layer and W is the weights between the hidden neurons and the output neurons:

The x is vector of the input neurons, y is the median neuron, and z is the output of the output neurons. Vector d is optimal output (target), e and μ and I are error friction quantity and unit matrix, respectively.

VI. DESIGN MAIN STRUCTURE OF NEURAL NETWORK TO PREDICT THE PRICE

As noted above, this involves performing a prediction without considering any kind of category, and only the prices and charges of the system being studied will be used in the prediction process.

A. Neural Network Structure

The neural network used is non-linear multi-layer perceptron, with an input layer, a hidden layer, and an output layer. The number of neurons in the input layer of the neural networks is 18, of which 15 neurons are the prices of the previous hours, and the rest of the neurons are the previous values of the load and its predicted value that The selection of these inputs are based on the results of the sensitivity analysis for the predicted value of the load, results of the prediction of the price-sensitive load, as presented in the previous section, have been used.

The number of neurons in the hidden layer of the network is 18, and the network output is a neuron. Therefore, it is clear that the price forecast is done on an hourly basis and 24-hour prediction of price is performed 24 hours a day. The function of selective performance of the intermediate layer neurons is sigmoid tangent function and function of output layer network is linear.

B. Neural Network Training

As previously stated, the characteristics of the neural network are the ability to learn the connection between the input and output of a system, which establishes this internal relationship by finding the values of the weights of the successive layers of the neurons in the training process. This step is done by showing several examples of past inputs and outputs to the neural network.

During the training process, weighing vectors and neural network biases change to minimize the target function of the network. The objective function used in most networks is the mean squared error (between the output of the neural network and the target output).

In this research, the preferred method for learning the network is the method of error propagation. Conventional error propagation techniques are usually not sufficiently fast for practical applications. In order to increase the training speed, the Levenberg-Marquardt method, which is a particular type of error propagation method, is used. This method can be ten to one hundred times faster than conventional methods.

In the process of training the network, the amount of training coefficient is 0.1 and the magnitude of the coefficient of Momentum is 0.005, which is obtained experimentally and with trial and error.

Since the functions of the network neurons are sigmoid tangent types and the outputs of this function are in [-1, 1], the amount of all training data (including price and load data) is out of this range, therefore To converge the training algorithm, all data must first be scaled up with a linear or nonlinear transformation function within the range [-1, 1].

Using the maximum and minimum scaling method, all data is depicted in an unsaturated domain of the sigmoid tangent function, that is, with this conversion, the input and output values of all neurons are always within the range [-1, 1], and during the training process never compares two very large and very small signals, which leads to instability and non-convergence of the error propagation algorithm. A function that can do this is as follows:

$$P_{normalized} = 2\left(\frac{P_{actual}-P_{\min}}{P_{\max}-P_{\min}}\right)-1 \quad (9)$$

where, $P_{\max}$, $P_{\min}$ are maximum and minimum amount, P_{actual} is unscaled true value, and $P_{normalized}$ is scaled value.

In the training process of the neural network, fist the input and output vectors are assigned to each hour of the day (for a day or night, there are 24 input vector and 24 output vectors) and for each day and night, the minimum and maximum vector inputs and outputs are computed (Maximum and minimum vectors are obtained by following the maximum and minimum values of each corresponding element of the input and output vectors of a one-night-time), which is used to scale up all incoming and outgoing vectors for a day or night. This method of scaling, used in both training and in forecasting is achieved with trial and error and has been used as the best way to improve the performance of the neural network. The number of days used in training takes 48 days, we have 1152 vectors as inputs.

C. Price Forecasting

After obtaining the weight and bias values in the training step, it is time to predict the future values. The prediction is infecting similar to the neural network constructor using the results of the training course. The prediction can be done for an hour to a week.

The forecast is done in hours per hour method, so that at first the price of the first hour is calculated and used to predict the next hours. Also, because there is only one input vector per clock hour, in order to scale this input, as well as to convert the prediction values from the scaled state to real state, we need to have a minimum and maximum in accordance with Equations (3) to (5). Therefore, the minimum and maximum input and output vectors are obtained by the values of the last 14 days (two weeks before). In the past 14 days, the input and output vectors of the corresponding network are generated, and then the minimum and maximum input and output vectors are computed.

VII. CONCLUSION

The methodology for the 2002 PJM market data has been tested and the results have been extracted and summarized in Table 1. In this test data from 48 days prior to the prediction period for the neural network test is used and the weekly prices are expected. This work has been done for two two-month periods and the results have been presented. The courses cover two distinct seasons, the winter (January and February) and the summer (July and August), to examine the effect of the load pattern on prediction accuracy. In Figures 1 to 3, the examples of the price prediction results, along with the bar graph of the predicted error values, are shown. The results show the efficiency of neural network in precise price forecasting.

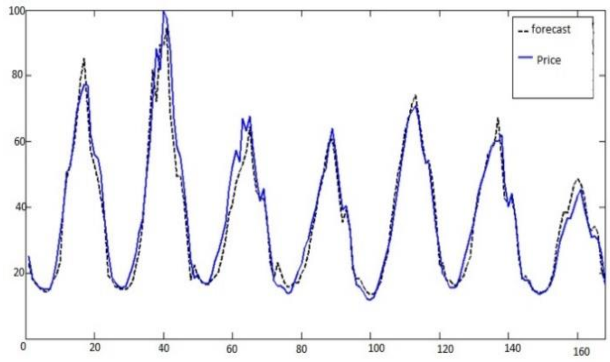

Figure 1. A Sample of price forecasting results (*Mape*=8.966%)

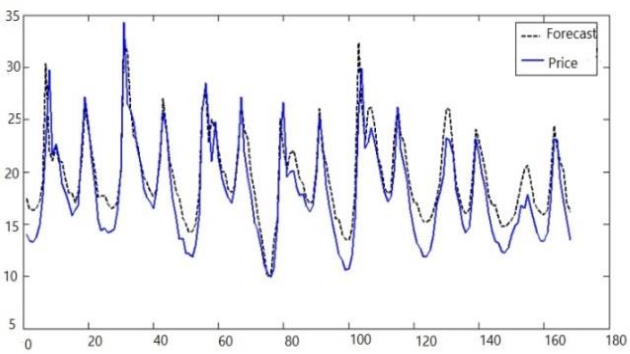

Figure 2. A Sample of price forecasting results (*Mape*=9.595%)

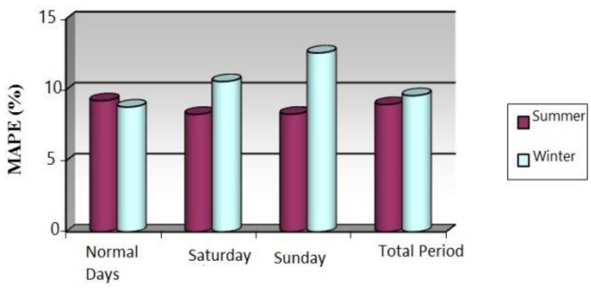

Figure 3. comparison of *Mape* of price forecasting in different days

Table 1. Result of price forecast in different months

	Hours type / Error amount	Normal days	Saturdays	Sundays	Total period
Summer	Average absolute error (S/MWh)	3.452	2.365	3.223	3.264
	Average absolute error percent (%)	9.238	8.281	8.290	8.966
Winter	Average absolute error (S/MWh)	1.762	2.015	2.238	1.866
	Average absolute error percent (%)	8.795	10.589	12.602	9.595

REFERENCES

[1] B.R. Szkuta, L.A. Sanavria, T.S. Dillon, "Electricity Price Short Term Forecasting Using Artificial Neural Networks", IEEE Transaction on Power Systems, Vol. 14, No. 3, pp. 851-857, August 1999.

[2] F.J. Nogales, J. Contreras, A.J. Conejo, R. Espinola, "Forecasting Next-Day Electricity Prices by Time Series Models", IEEE Trans. on Power Systems, Vol. 17, No. 2, pp. 342-348, May 2002.

[3] Y.Y. Hong, C.Y. Hsiao, "Locational Marginal Price Forecasting in Deregulated Electric Markets Using a Recurrent Neural Network", IEE Proceeding on Generation, Transmission and Distribution, Vol. 149, No. 5, September 2002.

[4] Y.Y. Hong, C.Y. Hsiao, "Locational Marginal Price Forecasting in Deregulated Electric Markets Using Artificial Intelligence", IEEE Conference, 2001.

[5] F. Gao, X. Guan, X. Cao, A. Papalexopoulos, "Forecasting Power Market Clearing Price and Quantity Using a Neural Network Method", Power Engineering Summer Meeting, Seattle, WA, pp. 2183-2188, July 2000.

[6] L. Zhang, P.B. Luh, K. Kasiviswanathan, "Energy Clearing Price Prediction and Confidence Interval Estimation with Cascaded Neural Networks", IEEE Transactions on Power Systems, Vol. 18, No. 1, pp. 99-105, February 2003.

[7] J.J. Guo, P.B. Luh, "Improving Market Clearing Price Prediction by Using a Committee Machine of Neural Networks", IEEE Transactions on Power Systems, Vol. 19, No. 4, pp. 1867-1876, November 2004.

[8] A.M. Gonzalez, A.M.S. Roque, J. Garcia Gonzalez, "Modeling and Forecasting Electricity Prices with Input-Output Hidden Markov Models", IEEE Trans. on Power Systems, Vol. 20, No. 1, pp. 13-24, February 2005.

[9] C.P. Rodriguez, G.J. Anders, "Energy Price Forecasting in the Ontario Competitive Power System Market", IEEE Transactions on Power Systems, Vol. 19, No. 1, pp. 366-374, February 2004.

BIOGRAPHIES

Rasoul Esmaeilzadeh was born in Tabriz, Iran. He received the B.Sc. and M.Sc. degrees in Electric Power Engineering. Currently he is a Ph.D. student in Electric Power Engineering at Azarbaijan Shahid Madani University (Tabriz, Iran). He has published papers in power systems. Currently he is Manger of Office of Research and Quality Control Equipment in Azarbaijan Regional Electric Company (Tabriz, Iran). His interest topics include power system operation, FACTS, power quality and power system protection.

Afshin Roshan Milani was born in Tabriz, Iran, 1963. He received the B.Sc. and M.Sc. degrees in Electric Power Engineering from University of Tabriz (Tabriz, Iran), in 1985 and 1990, respectively and his Ph.D. degree in Power Quality from the same university in 2013. He has published more than 40 papers in power system and power electronics related topics. Currently, he is CEO of Azarbaijan Regional Electric Company (Tabriz, Iran). His interest topics include power system operation, FACTS, power quality and power system protection.