Forecasting Electricity Market Prices by Artificial Neural Networks

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***Abstract* – In the deregulated electrical utility industry being implemented throughout the world, electricity is traded as a commodity in an open market, and the price is determined largely by the balance of demand and supply. To survive the increased competition in the market, the estimation of electricity price is critically important. In this paper, artificial neural network is applied as an estimator of electricity market price. Moreover, to eliminate long-term trends, moving time-window scaling is applied. In the application, an hour-ahead and four hour-ahead prediction are simulated. The model is validated by Pennsylvania-New Jersey Maryland (PJM) market data.**

Keywords: Electricity market, price, neural network, moving time-window.

I. INTRODUCTION

Many countries have restructured their electrical power industry and introduced deregulation and competition by unbundling generation, transmission and distribution functions, and allowing open market access. In the deregulated environment, a market-based system of electricity transactions has been introduced [1] where electricity is traded as a commodity and the balance of supply and demand significantly influences its price. The theory of spot market pricing of electricity states that the hourly spot price can be determined by such factors as fuel and maintenance costs, the availability of generator and network, and costs to compensate for transmission losses [2].

In the modeling of spot price of electricity, one common approach is to observe the price for a long period of time and fit a statistical model based on the observed time series [3][4]. In [5] production costing model is used to represent the main variables that affect the spot price of electricity. The information on the probability distribution of prices is of particular use in managing risk and improving the decision-making. The estimated price depends on many factors such as the periodicity of demand, temperature and other meteorological influences, the loading order of generators, and so on. Artificial neural network is applied in [6] to predict electricity prices based on past price, demand, and estimated reserves. In general, traditional methods are aimed at predicting a most likely price in the future, but the other information such as extent of possible variation would be also useful to make effective decisions.

In this paper, a neural network is applied for forecasting electricity market price. Market price is fluctuating very randomly and it contains uncertainties. Therefore, it will not be efficient to forecast market price based on a linear model such as auto-regression model (AR), auto-regression moving average (ARMA) model, and so on. Therefore, an alternative way is necessary to reflect better nonlinearity and uncertainties for estimating of market price. Neural network is a candidate because it is a well-known estimator and identifier for any systems [7,8]. Moreover, moving time-window scaling is applied to eliminate longer-term trends. If there is a very huge difference in the selected data set for training and forecasting of electricity market price, that difference dominates all prediction and it produces unacceptable results. From the proposed scaling, this situation can be prevented and better estimation can be expected.

The proposed model is applied to Pennsylvania-New Jersey Maryland (PJM) market data in year 2000 [9] to predict next hour and four hour-ahead wholesale electricity using 24 hour past data, which means that a neural network has 24 data set as input. A 500 data-set are used for training of a neural network. Once a neural network is trained, the trained neural network can be applicable as an estimator and does not require retraining for other cases.

II. NEURAL NETWORK FOR MARKET PRICE

A two layer MLP neural network [8] is shown in figure 1. All activation functions in hidden layer are *tanh*(x) (described as f_j in figure 1), and the activation function in output layer is x ($F_0(\bullet) = \sum_{j=1}^{n_h}(x) + w_0$).

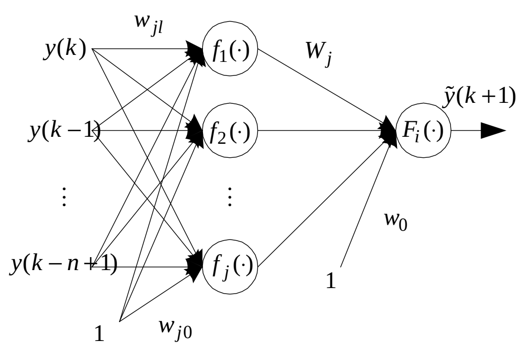

Figure 1. A fully connected two-layer feedforward network.

The output of the MLP is

$$\tilde{y}(k+1) = \sum_{j=1}^{n_h} w_j \tanh\left[\sum_{l=1}^{n} w_{jl}\varphi(l) + w_{j0}\right] + w_0 \tag{1}$$

where

$$\varphi(l) = y(k-l+1),\ \ l = 1, 2, \ldots, n$$

w_{jl} : weight which connects input and hidden layer

w_j : weight which connects output and hidden layer

n_h : number of hidden neurons

w_{j0} : weight which connects hidden layer and bias

w_0 : weight which connects output layer and bias

W^0 : vector form of w_j , $[w_1, w_2, \ldots, w_{j-1}, w_j]$

W_0 : vector form of w_{jl} , $[w_1, \ldots, w_{n_h}]$
(n_h : number of hidden neurons).

In this paper, n in figure 1 is 23. therefore, the total number of input of neural network is 24.

The scaling to remove longer-term trends is based on zero-mean unit variance (ZMUB). Before ZMUB is applied, the input data set is first normalized. The zero-mean unit variance is as following:

$$\bar{y}' = \frac{\mathrm{Y}}{X \times std} \tag{2}$$

where

$$\bar{y} = [y(1), y(2), \cdots, y(23)]^T_{(23\times 1)},$$
$$X = \text{mean value}(\bar{y}),$$
$$M = \begin{bmatrix} 1 \cdots 1 \\ \vdots \ddots \vdots \\ 1 \cdots 1 \end{bmatrix}_{(23\times 1)},$$
$$\mathrm{Y} = \bar{y} - M \cdot X,$$
$$std = \text{standard deviation}(\mathrm{Y}).$$

The above equation is applied through all procedure in training of neural network and forecasting or electricity market price.

The graphical expression of all processing can be illustrated in figure 2.

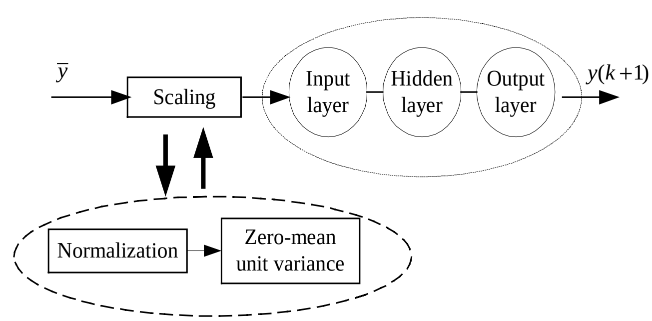

Figure 2. The overall procedure of forecasting.

III. NUMERICAL EXAMPLES

The Pennsylvania-New Jersey Maryland (PJM) market data in year 2000 [9] is applied for demonstration of the proposed model. In this example, 24 past data-set is used for the hourly and four-hour forecasting. Total sequence data used for training of neural network is 1000.

Figures 3a and 3b show the validation of neural network without and with the proposed scaling method in the case of hourly forecasting in the training mode, respectively. Market prices are scaled to make use of linear activation function.

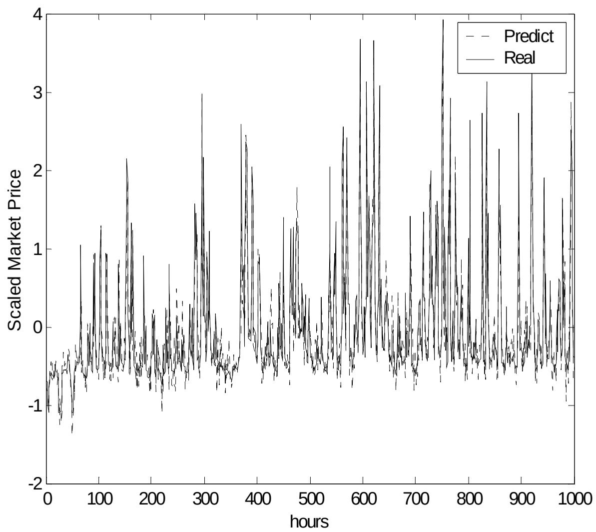

Figure 3a. The validation of hourly forecasting without the proposed scaling method in the training mode.

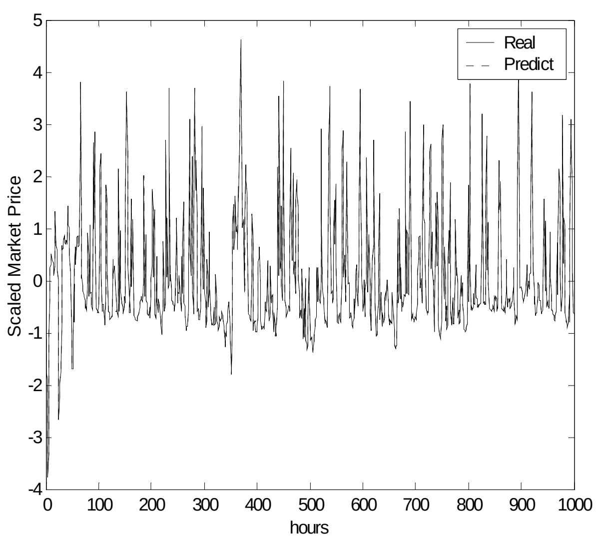

Figure 3b. The validation of hourly forecasting with the proposed scaling method in the training mode.

For the performance evaluation of the neural network model, fitness in time sequence between the predicted price $(\hat{y})$ and the scaled real market price (y) is calculated as below

$$\varepsilon = 100 \times \left(1 - \frac{norm(\hat{y} - y)}{norm(y - mean(y))} \right), \tag{3}$$

The fitness for hourly forecasting with and without the proposed scaling method in the training mode is 62.995% and 99.547%, respectively. Figures 4a and 4b show the hourly forecasting without the proposed scaling method. The total fitness is 12.83%.

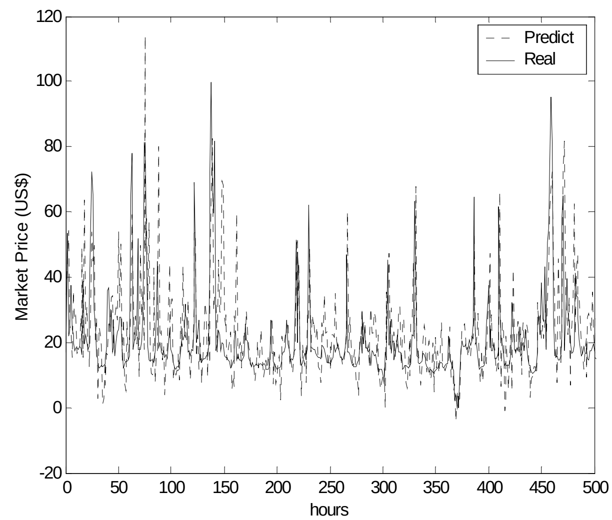

Figure 4a. The validation of hourly forecasting without the proposed scaling method (1/2).

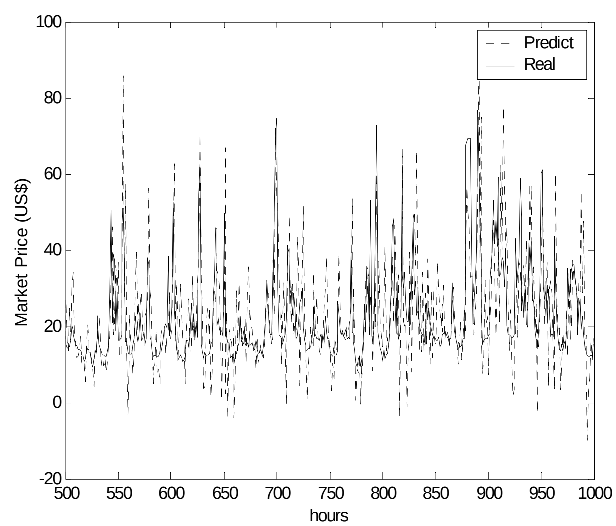

Figure 4b. The validation of hourly forecasting without the proposed scaling method (2/2).

Figures 5a and 5b shows the hourly forecasting with the proposed scaling method. The total fitness is 99.848%.

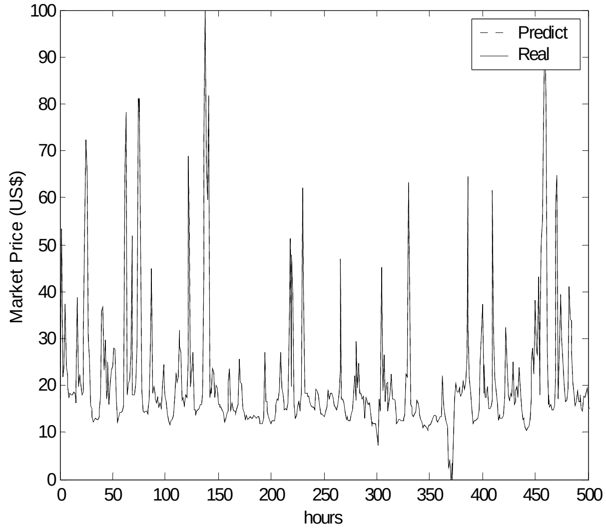

Figure 5a. The validation of hourly forecasting with the proposed scaling method (1/2).

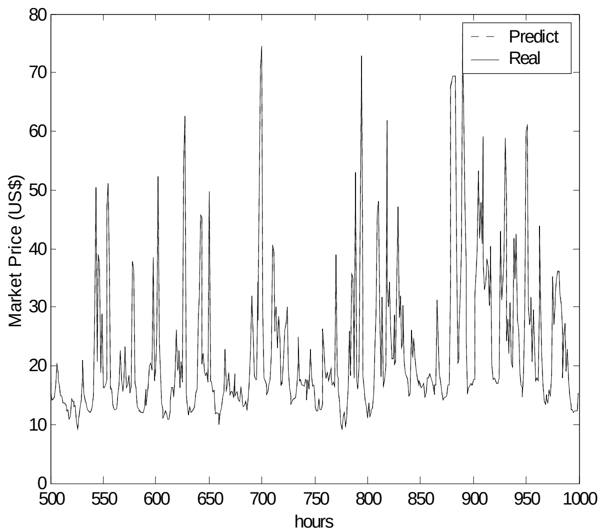

Figure 5b. The validation of hourly forecasting with the proposed scaling method (2/2).

It is very hard to distinguish between prediction price and real price. Therefore, the usefulness of the proposed scheme is demonstrated. Next, the proposed scheme is expanded for more realistic situation, which is longer term forecasting of electricity market price.

Figure 6 shows the four-hour forecasting in one and half days without the proposed scaling method. The total fitness is 17.709%.

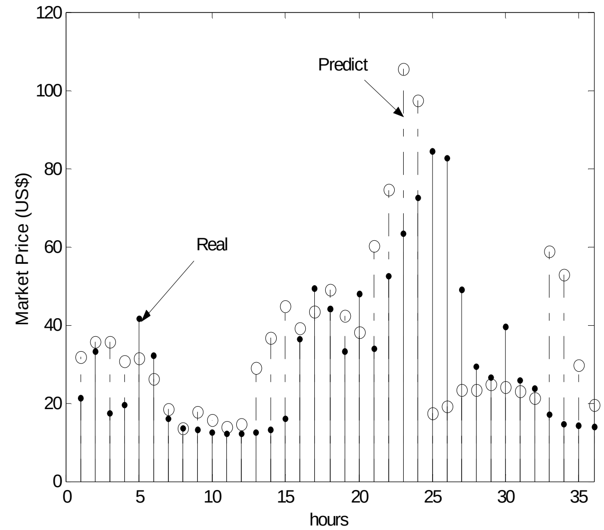

Figure 6. The validation of four-hour forecasting in one and half days without the proposed scaling method.

Figure 7 shows the four-hour forecasting in one and half days with the proposed scaling method. The total fitness is 62.105%.

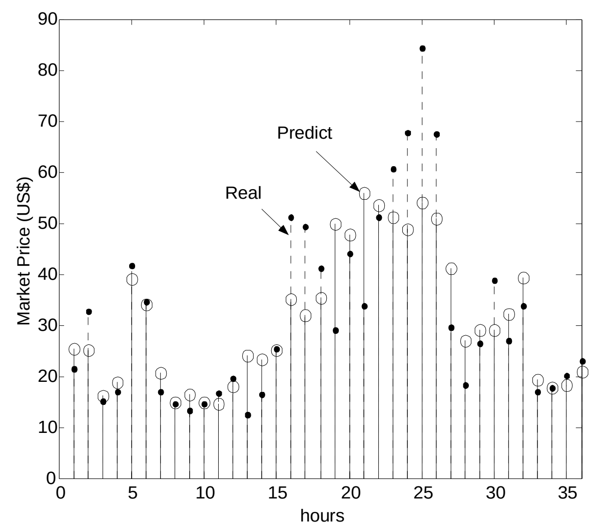

Figure 7. The validation of four-hour forecasting in one and half days with the proposed scaling method.

It is also demonstrated of the usefulness of the proposed forecasting scheme. It can be seen that the fitness is much increased when the proposed scaling scheme is applied.

The future work will be consideration of more efficient structure of neural network and much longer-term forecasting. Moreover, the proposed scheme will be expanded for fuzzy model based forecasting of electricity market prices [10].

IV. CONCLUSION

This paper presented a time series model based on neural-network estimation. A better way should be adapted to handle uncertainties and nonlinearities instead of using linear estimator such as AR, ARMA, and so on. Moreover, a scaling method should be used to reduce the effect of dominated error.

A simple and conventional neural network is adapted for uncertainties and nonlinearities. There are two steps in filtering input data set: normalization and zero-mean unit variance. The input data set is first filtered and then fine filtering procedure is done for final data-set, which is used for training and forecasting of electricity market price.

The simulation results show that the forecasting with unscaled data-set does not give reasonable result; however, based on the proposed scheme, applicable results are obtained. Therefore, it demonstrated the usefulness of the proposed method in the prediction of electricity market price.

IV. REFERENCES

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V. BIOGRAPHIES

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