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An enhanced radial basis function network for short-term electricity price forecasting

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ABSTRACT

This paper proposed a price forecasting system for electric market participants to reduce the risk of price volatility. Combining the Radial Basis Function Network (RBFN) and Orthogonal Experimental Design (OED), an Enhanced Radial Basis Function Network (ERBFN) has been proposed for the solving process. The Locational Marginal Price (LMP), system load, transmission flow and temperature of the PJM system were collected and the data clusters were embedded in the Excel Database according to the year, season, workday and weekend. With the OED applied to learning rates in the ERBFN, the forecasting error can be reduced during the training process to improve both accuracy and reliability. This would mean that even the "spikes" could be tracked closely. The Back-propagation Neural Network (BPN), Probability Neural Network (PNN), other algorithms, and the proposed ERBFN were all developed and compared to check the performance. Simulation results demonstrated the effectiveness of the proposed ERBFN to provide quality information in a price volatile environment.

1. Introduction

Deregulating the power market creates competition and a trading mechanism for market players. It moves the market from a cost-based operation to a bid-based operation [1,2]. Electricity has become a commodity and the price could become volatile in an energy market where sudden "spikes" could appear. Forecasting prices accurately is an important task for producers, consumers and retailers. In accordance with a price forecast, a balancing and settlement system can be established for participants to maximize profit with lower risks [3]. Price forecasting also helps investors in better planning the Grids.

In the US, the Pennsylvania–New Jersey–Maryland (PJM) power market [4] is commonly recognized as one of the most successful market models. The PJM that operates the competitive market is coordinated by an Independent System Operator (ISO) to determine the Locational Marginal Price (LMP) according to the status of the system nodes. The LMP at each node then reflects not only the price of voluntary bids but also the overhead of delivering energy to locations. Generally, the LMP includes three components: an energy cost component, a transmission congestion component and the marginal loss component. The LMP in a pool is different for different locations while the energy cost can be identical for all the nodes. A feasible and practical method for LMP forecasting would provide better risk management for all market participants.

Many factors, including historical prices, system load, transmission flow and temperature, could impact the LMP. The loads and prices in the wholesale market are mutually intertwined activities [5]. Loads are heavily affected by weather parameters, so prices are strongly volatile with the changing weather. Another factor is use at various times of the day, week, month, season and year. Prices could rise to a hundred times the normal value in reflecting this volatility. In the PJM, the LMP is introduced at nodes. Congestion occurs when a transmission flow exceeds its limits. Line flow information becomes an important factor in price forecasting. It is complicated to perform LMP forecasting, especially when trying to find the best strategy in a world of uncertainties. Reported techniques for forecasting day-ahead prices include time series models [6], weighted nearest neighbors techniques [7], auto regressive integrated moving average models (ARIMA) [8], Mixed ARIMA models [9,10], k-factor GIGARCH process [11], and Markov models [12]. These approaches can be very accurate given sufficient information and computation time; however, no approach has shown a satisfactory performance in dealing with the spikes.

Recently, the Artificial Neural Network (ANN) has been applied to forecast prices in various markets [13–19]. The ANN is a simple, powerful and flexible tool for forecasting, providing better solutions to model complex non-linear relationships than the traditional linear models. ANNs have weaknesses in the determination of network architecture and network parameters. Running in

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a dynamic environment, especially for online applications, a traditional ANN can become a bottleneck in adaptive applications [20]. Among ANNs, the Radial Basis Function Network (RBFN) [21] can function as a classifier and forecaster, and it has the advantages of a simple construct. However, a RBFN probably causes over-learning due to large adjustable parameters. In order to improve the issue, this paper has used the Orthogonal Experimental Design (OED) to enhance the traditional RBFN.

The OED is an effective tool for robust design and engineering methodology in optimizing process conditions which are minimally sensitive to various causes of variations. The characteristics of an OED are: (1) results obtained through few experiments, (2) good recurrence of results in the same experimental environment, (3) simple construction of mathematical model with the application of an Orthogonal Array and (4) simple analytical procedure. Combining the RBFN [21] and the OED [22] into an Enhanced RBFN (ERBFN) has been proposed in this paper. The OED has been used to adjust the parameters in the RBFN training stage to improve the forecasting ability, and a good performance with a close spike tracking capability can be seen. This paper has developed day-ahead forecasts for electricity price using an ERBFN based on a similar day PJM market model. The Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) obtained from the forecasting results have demonstrated that the ERBFN can efficiently forecast the price for any day of the week.

2. Orthogonal Experimental Design

The Orthogonal experiment uses a small amount of experimental data to construct a mathematical model derived from the orthogonal experiment to calculate experiment values. The OED contains two main parts, Orthogonal Array and factor analysis. In engineering experiments, the cause that influences the result is a factor of the Orthogonal Array, while various states of the factor are called the "level number". Factor analysis is carried out after the Orthogonal Array set-up, and the "factor effects" of each factor can be obtained from the analytical results. The impact of each factor on the experiment is deduced from those effects.

An orthogonal array with F factors and Q levels can be denoted as $L_B(Q^F)$, where L denotes a Latin square, and B is the chosen number of combinations of levels. The notion of using orthogonal arrays has been associated with the Latin Square from the outset. We let $L_B(Q^F) = [e_{bf}]_{B\times F}$, where the fth factor in the bth combination has level value e_{bf} and $e_{bf} \in \{1, 2, \ldots, Q\}$. An example of an orthogonal array can be seen as:

$$L_4(2^3) = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 2 \\ 2 & 1 & 2 \\ 2 & 2 & 1 \end{bmatrix}. \tag{1}$$

Fig. 1 shows a three-factor solution space for the example. The four vertices of the cube cover presented in Eq. (1) are all facets of the problem and are representative enough to calculate the optimal solution.

Consider an experiment containing two factors, x_1 and x_2, assuming each factor has two levels. The two levels of x_1 are 2.4 and 3.6, the two levels of x_2 are 60 and 80 and the experimental output data y is obtained from the experiment. A sample of the experimental data is shown in Table 1.

Let Eq. (2) be defined as a transformation of the variable for any factor with two levels, where x is the original variable, x_U is the high level and x_L is low level. Then x_N will be a new variable with values +1 or −1, that is:

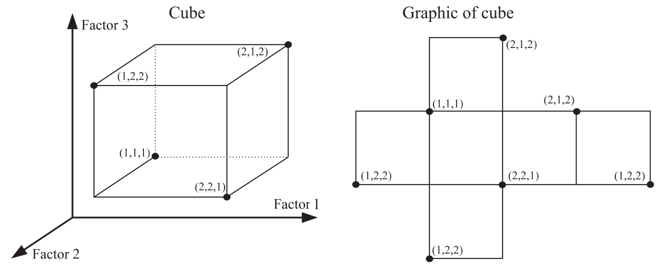

Fig. 1. Illustration of the orthogonal array $L_4(2^3)$.

Table 1
Tow factors x_1, x_2 experiments.

Experiment no.	Factors		Function value y_i
	x_1	x_2	
1	2.4	60	5.4
2	2.4	80	5.2
3	3.6	60	7.0
4	3.6	80	6.4

Table 2
Tow factors A, B experiments.

Experiment no.	Factors			Function value y_i
	A	B	$A\times B$	
1	−1	−1	1	5.4
2	−1	1	−1	5.2
3	1	−1	−1	7.0
4	1	1	1	6.4

$$x_N = \frac{x - \frac{(x_U+x_L)}{2}}{\frac{(x_U-x_L)}{2}}. \tag{2}$$

For convenience of description, a transformation of variable is made for x_1 and x_2 by:

$$A = \frac{x_1 - \frac{3.6+2.4}{2}}{\frac{3.6-2.4}{2}} = \frac{x_1 - 3.0}{0.6} \tag{3}$$

$$B = \frac{x_2 - \frac{80+60}{2}}{\frac{80-60}{2}} = \frac{x_2 - 70}{5} \tag{4}$$

A and B are used for Table 1, with another $A \times B$ added as shown in Table 2, where −1 is called "Level 1", and "+1" is Level 2. The response value $R_{f,l}$ is calculated from Eq. (5), and the effect of each factor E_f is calculated through Eq. (6). We have:

$$R_{f,l} = \text{Mean of } y_i \text{ for factor } f \text{ at Level } l \tag{5}$$

where $f = A, B$, and $l = 1, 2$, and the effect:

$$E_f = \frac{R_{f,\text{Level 2}} - R_{f,\text{Level 1}}}{2} \tag{6}$$

The related data are listed in Table 3.

With the above arrangement, the relationship [22] between function value y_i and other factors A, B, $A \times B$, $R_{f,l}$ and E_f is can be described by:

$$y_i = \text{Average} + \text{Effect}_A \times A + \text{Effect}_B \times B + \text{Effect}_{A\times B} \times A \times B \tag{7}$$

A numerical example of Experiment 1 can be seen by:

$$y_1 = 5.4 = 6 + 0.7 \times (-1) - 0.2 \times (-1) - 0.1 \times (-1) \times (-1) \tag{8}$$

Other experimental outputs can be obtained from Eq. (7) similarly. It shows that the function of an Orthogonal Array can use a