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Forecasting of Electricity Price and Demand Using Autoregressive Neural Networks

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Abstract: This paper proposes a forecasting technique of electricity demand and price with volatility based on neural networks. Recent deregulation and liberalization are worldwide currents in the electric industry. The price competition was introduced in a spot market, and the price volatility is concerned because the demand side is non-elastic, and electricity differs from other general commodities. The authors firstly predict an uncertain electric power demand by using the auto-regressive model of the neural networks. The neural network is a popular feed-forward three-layer model, and the input variables of the neural networks include the historical demand, temperature, weather-related discomfort index, and the day of the week. Secondly, by using the demand forecasted and the past prices, we apply the technique for forecasting the electricity price of the next day. The utility of the proposed technique was verified by using real data of the electric power wholesale spot market.

1. INTRODUCTION

Electric industries have been deregulated and restructured worldwide for reducing electricity prices and extending customer services (Shahidehpour, et al., 2002). Due to the deregulation, various new services, reduction of electricity rates and the diversification of electricity rate scheme are expected to be realized through the introduction and promotion of the market competition. On the other hand, it may incur the risk of electricity prices rising/falling excessively when demand increases/decreases. Thus, forecasting of electricity demand and prices with high accuracy is required for the financial risk management (Bunn, 2000).

The electricity market in Japan has adopted a single price auction scheme where a specific price is determined at the equilibrium point of bids and offers in the market (Hoki, 2005). This price is decided at the cross point of demand and supply in the market. The single price auction has been used in many markets in the world because there is an advantage in transparency as a price index (Yokoyama, 2001). However, electricity prices decided in such a single price auction can be drastically different from settlement prices that had been negotiated before deregulation. Moreover, price volatility in the market is anticipated to be rampant since the elasticity of demand is not much expected in the new competitive market.

In this paper, firstly, the authors analyze the correlation of various nonlinear factors that influence the prices, then neural networks are designed to forecast the maximum power demand on the next day; Then, electricity price at peak time on the next day is predicted based on the forecasted demand. In this paper, by using strong correlation of power demand and electricity prices, we improve the accuracy of electricity price prediction. The proposed forecasting methods are applied to the actual power market data in Japan.

2. STRUCTURE AND DATA OF NEURAL NETWORKS

2.1 *The relation between electricity prices and other nonlinear data.*

The Japan Electric Power Exchange (JEPX) commenced trading in April 2005, and its volume of daily transaction set a record at 9GWh in 2006. The daily electricity transaction is increasing steadily and it is expected that the number of transactions will increase furthermore in the near future for maintaining social, economic, and industrial activities in Japan. In this chapter, daily transition of electricity prices is compared with other data for improving the accuracy of electricity prediction.

Fig. 1 shows the change of the electricity price in the spot market and the peak electric demand from April 2005 to March 2006. The large fluctuations are seasonal change, and especially electric demand in summer and winter are very large. Compared with them, electric demand in spring and autumn are relatively small. The small fluctuations are weekly changes. The electric demand on weekdays are larger than those on weekends and holidays.

It can be said that the electric power demand is influenced by various kinds of nonlinear data. Electricity price is also influenced by various kinds of nonlinear data such as the type of power supply and the price of the fuel, and so on (Amajady and Hemmati, 2006). Therefore, for predicting electricity price, we applied neural networks that exhibit high performance to extract dynamic features, to learn unstudied data, and to represent nonlinear correlations. Fig. 2 shows the concept of the relation of factors for forecasting the electricity price.

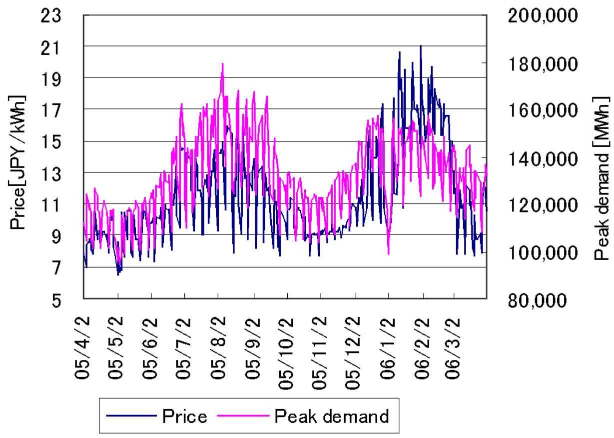

Fig. 1. The electricity price and the peak demand from April 2005 to March 2006 in Japan.

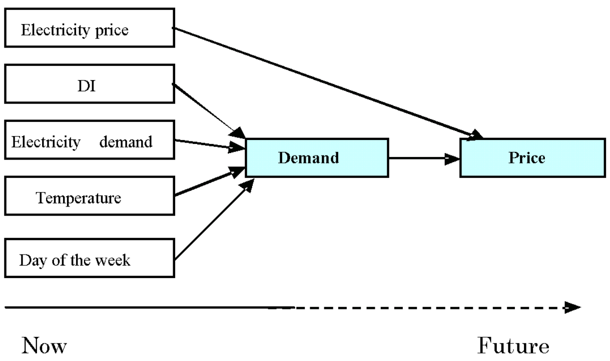

Fig. 2. Concept and input variables for forecasting electricity prices.

Because it is important to select the input variables for forecasting electricity spot price, the correlation between the electricity price and various nonlinear data is analyzed. Fig. 3 shows the correlation between electricity price and nonlinear data from July 2005 to June 2006. Correlation coefficients are in the range from -1 to +1. Here, positive coefficients show the increase of electricity price as demand or other data increase, and the negative coefficients show the decrease of price as demand or other data increase. In addition, coefficient being 0 means that changes in demand or other parameters do not influence the price. Analysis of the historical data shows that there is the strong correlation between electricity price and power demand.

From the correlation analysis, it has been shown that the peak electricity price has three characteristics:

- Electricity price is strongly influenced by the power demand.

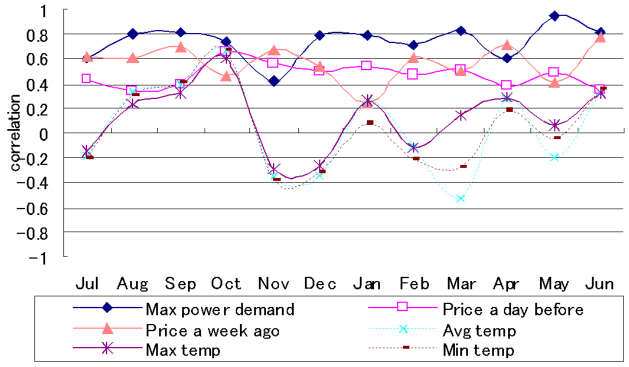

Fig. 3. The correlation between electricity price and nonlinear data.

- Electricity price has the time series characteristic.
- Features of electricity price differ on weekdays, weekend and holidays.

Moreover, it can be said that the correlation of the power demand of the day is stronger than the power demand of a day ahead, and by utilizing the power demand of the day the spot price can be forecasted with more accuracy. Therefore, this proposed method forecasts the peak power demand of the day firstly, and then the electricity price is forecasted by using the forecasted peak demand and the electricity price of a day ahead.

Next, the data set is selected to forecast the electricity demand by using the correlation. Fig. 4 shows the correlation between peak demand and nonlinear data. From this analysis, it has shown that the peak power demand has the following characteristics:

- Peak power demand is influenced by the weather factor.
- Peak power demand has the time series characteristic.
- Peak power demand differs on weekdays, weekend and holidays.
- Peak power demand differs in each season.

From Fig. 4, it can be seen that the maximum temperature and the maximum discomfort index* (DI) have the strongest correlation with the peak power demand. After the deregulation, not only in the demand but also in electricity prices, the difference of values between weekdays and holidays has become larger, and it is needed to use data related to the day of the week as one of the input vectors to forecast power demand and electricity prices accurately under large volatility.

*Discomfort index is calculated by temperature (T) and humidity (H) such that

$$DI = 1.8\,T - 0.55\,(1\text{-}H/100)(1.8T - 26) + 32.$$

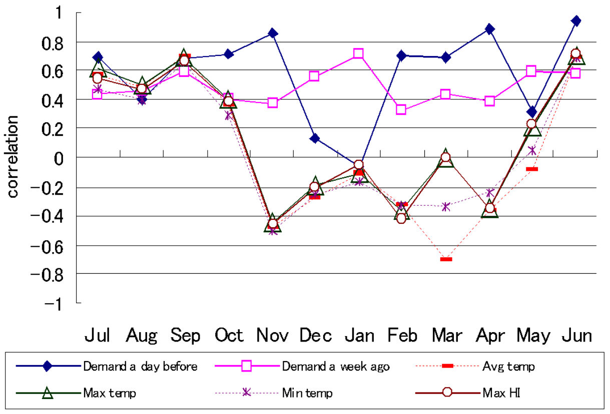

Fig. 4. Correlation between peak demand and nonlinear data.

2.2 The model for forecasting of the electricity price based on neural networks.

In this paper, three-layer neural networks (Haykin, 1999) have been used to forecast the power demand. As the input variables, the maximum temperature, the maximum DI (discomfort index), and the day ahead peak electric demand are selected out of the factors of the correlation analysis from Fig. 4. The previous month demand data are used for the learning process of the three-layer neural networks to forecast the peak demand of the next month.

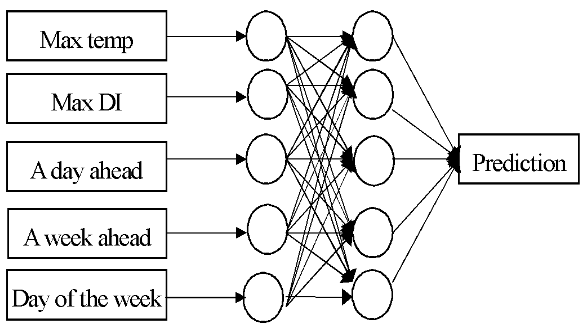

Fig. 5. Neural network model for demand forecasting.

In this paper, one three-layer neural network is implemented to forecast the power demand. Another neural network of the same three-layer structure as the one used for demand forecasting is utilized to forecast the electricity price. The input variables include: the previous day electricity price and the forecasted peak demand of the day. As shown in Fig. 4, these variables have a very high correlation factor with the electricity price.

The three-layer perceptron network consists of L-dimensional input-layer, M-dimensional single hidden-layer, and N-dimensional output-layer.

With the input $x = (x_1, \ldots x_L)^T$ the output $z = (z_1, \ldots z_N)^T$ is obtained (^{T} represents the vector transposed.).

The relation between the input and the output is represented by the following equation:

$$z_n = g\{\sum_{m=1}^{M} w_{nm} f(\sum_{l=1}^{L} v_{ml} x_l + \theta_m)\} \tag{1}$$

where

$$g(s) = f(s) = \frac{1}{1 + \exp(-cs)} \tag{2}$$

and

v_{ml}: Weighting coefficients on connections between the input and the hidden-layer;

w_{nm}: Weighting coefficients on connections between the output and the hidden-layer;

θ_m: Weighting coefficients on connections between the hidden-layer and bias.

The neural network is trained by adjusting its weighting coefficients on connections using a set of observed input-output data. It is formulated as a problem to minimize the absolute error of output from a desired output.

It is assumed that P desired output vector $d^1, \ldots, d^P$ which corresponds to P input vector is known. The error of current output for an input data set p is measured by

$$e_n(V, W, \theta; x^p) = \left| d_n^p - g\{\sum_{m=1}^{M} w_{nm} f(\sum_{l=1}^{L} v_{ml} x_l^p + \theta_m)\} \right| \tag{3}$$

where $p = 1, \ldots, P$.

We applied the Newton's method to solve the training problem. Practically, in the minimization algorithm, the maximum permissible error ε is assumed such as

$$\left| d_n^P - g\{\sum_{m=1}^{M} w_{nm} f(\sum_{l=1}^{L} v_{ml} x_l^P + \theta_m)\} \right| < \varepsilon_n^p \tag{4}$$

3. THE RESULTS OF FORECASTING OF ELECTRICITY DEMAND AND PRICES

The proposed forecasting method was applied to the JEPX market data by using data from July 2005 to June 2006 period to examine its effectiveness. Firstly, the maximum power demand in a day was forecasted, and then the electricity prices are predicted based on the obtained maximum demand. The data of April and May 2005 are ignored intentionally because JEPX just began its trading and the market was unstable around these periods.

To evaluate the influence of the peak demand on the spot price, prices are forecasted in three different cases, and the forecasted prices are compared with real market prices which are published by JEPX.

In the first case, we ignored data for the peak demand and the day of the week, and therefore we forecasted prices by using only electricity prices of the previous day. In the second case, we introduced the forecasted peak demand and the day of the week as input.

In the third case we forecasted the electricity price using the real power demand. For practical forecasting purposes it is not possible to know in advance the real power demand of the next day. Even so, we show this case with the intent to confirm our assumption of correlation between price and peak demand.

Fig. 6 shows the result of forecasting the peak demand of the next day. It is evident that the neural network performs accurately in the prediction of the demand fluctuation. Table 1 shows the average error ratio in different periods.

Fig. 7 shows the results of the forecasted electricity prices at peak time. Table 2 shows the comparison of the average error ratio of each case.

From Fig. 7 and Table 2, it can be understood that case 3 has the highest accuracy. It can be said that the correlation between price and demand is very high and reproducible by the neural network.

As a result, it has been shown that the amount of the electricity demand is closely related to the electricity price and that the proposed method can follow the price fluctuation even when the volatility of price from a day ahead is large.

By these application tests, it is verified that the method is able to cope with the large price fluctuation in the electric power market. Because the number of transaction is still small and the price is not stable in the Japanese electric power exchange that have just started its operation from April 2005, it is expected that more accurate forecast of the market becomes possible when the amount of the electric power transactions increases in the future and the electric power price will become stable.

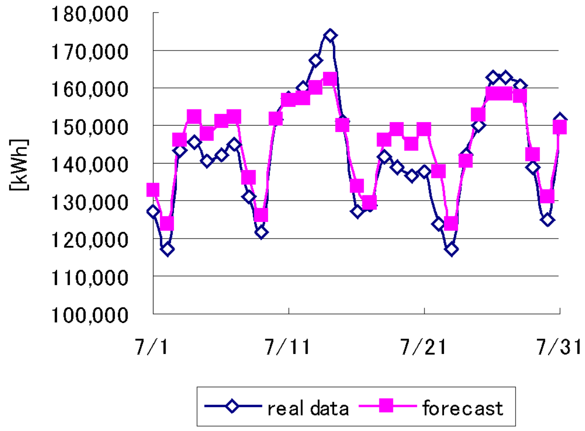

Fig. 6. Result of next day maximum demand forecast.

Table 1 Average error of demand forecast

Period	Average error [%]
July	2.69
August	2.91
September	4.17
October	2.86
November	4.41
December	3.45
January	5.31
February	5.86
March	4.21
April	2.31
May	4.07
June	4.00
Total average	3.85

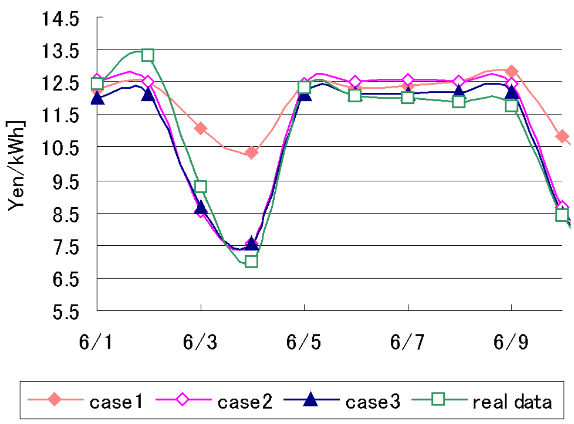

Fig. 7. Result of next day electricity price forecast.

Table 2 Comparison of average errors of each case

Cases	Case 1	Case2	Case3
Average error [%]	13.06	7.05	5.94

4. CONCLUSIONS

In this paper, a practical method for forecasting electric power prices has been proposed by using neural networks under the condition in which the change of electricity prices would give the important effects on both sides of demand and supply in the market. In the proposed method, electricity demand is selected as one of the input variables to the neural network, because demand have strong influence on electricity prices.

Forecasting electricity demand on the next day using the data from the Japan Electric Power Exchange from July 2005 to June 2006 was carried out by the neural networks to confirm the validity of the proposed method. In addition, the forecasting of electricity price on the next day at the peak time was conducted by using the forecasted values of electricity demand.

The paper demonstrates how the two-step forecasting process can improve the price forecast accuracy compared to methods that consider only the electricity price historical data.

To improve the accuracy of the proposed method furthermore, authors are now working toward taking the influence of fuel price on the electricity price into consideration (Shahidehpour, et al., 2005). Also, it would be more practical to combine the neural networks with fuzzy auto-regressive models for forecasting price intervals (Zhang and Luh, 2005).

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