Novel Price Prediction by Using Neural Network Under Large Volatility in Electric Power Exchange

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Abstract: - This paper proposes a novel and practical approach to forecast electricity prices with large volatility based on neural networks. Under the situation in which deregulation and liberalization of power industries are put forward in many countries, an electricity market has been commenced since April 2005 also in Japan. So, it becomes difficult to forecast electricity prices precisely, because a large number of customers became eligible. Therefore in this paper, firstly, the maximum power demand of the next day is predicted using neural networks with data observed for appropriate periods in the past. Secondly, based on the obtained power demand, a forecasting method of electric power prices at peak time over 24 hours of the next day is presented. Finally, the proposed forecasting methods are applied to an actual power market in Japan and are verified to be effective to predict volatility of electricity prices.

Key-Words: - Deregulation, Forecast, JEPX, Price volatility, Power demand, Neural network

1 Introduction

Up to the present, electric industries have been deregulated and restructured worldwide [1]. The competition in electricity prices among new market participants and existing companies is enacted by the easing of conventional regulations on entry to the market and electricity rate for electric utilities. Various new services, reduction of electricity rate level, diversification of electricity rate scheme and promotion of innovation in techniques are expected to be realized through the relaxation [2].

In Japan, restrictions to enter into the wholesale power business were abolished by The Electricity Enterprises Act revised in 1995. Furthermore, so called “partial retail liberalization” has been practiced since March 21, 2000 and the range of customer eligibility has extended gradually. Under these situations, The Japan Electric Power Exchange (JEPX) where electric power companies, power producers and suppliers (PPS) and independent power producers (IPP) deal with the electric power was started on April 1 2005 [3]. As a result, electric power trading on a nationwide scale is expected to be activated, and the competition between companies is also anticipated to be promoted furthermore. Therefore, power exchanges are indispensable because companies are able to secure power supply by procurement through JEPX in addition to their own power supply. Since market prices influence prices of bilateral contracts, the market price of JEPX is very critical for participants. The electricity market in Japan has adopted the single price auction scheme where a specific price is determined at the equilibrium point of biddings of buyers and sellers in the market.

This price is decided at the cross point of demands 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 [4]-[7]. However, electric power prices which are decided by such a single price auction are actually different from settlement prices that had been decided before deregulation. Moreover the price volatility is anticipated to be more complicated since elasticity of demands is not clear in the new competitive market and electricity differs from commodities due to the necessity for social lifelines and industrial activities.

In the proposed method, firstly, neural networks are applied to forecast total maximum power demand on the next day of the mainland in Japan. Secondly, electricity price at peak time on the next day is predicted based on the previously forecasted demand. Moreover, various kinds of nonlinear data relating to electricity price are shown, and electricity price is predicted with real data of JEPX. In this paper, by using strong correlation of power demands and electricity prices, we improve the accuracy of electricity price prediction.

2 The effects of the regulation in Japan

In Japan, partial retail liberalization is carried out since 2000 and the range of customer eligibility has extended gradually. As a result, the total capacity of generations supplied by PPSs is slowly-increasing compared with that in 2000, as shown in Fig.1. Moreover, in 2005, the electric industry low was revised to expand the eligibility to all customers connecting to high voltage transmission networks, so the number of PPSs who participate into electric power markets is expected to increase abruptly. The Japan Electric Power Exchange has started since April 2005 in Japan. Electricity prices in the JEPX can be an index that enables electricity related companies to make decisions and to evaluate risk management for developments of electric generation resources, and companies are able to secure the supply power by procurement through the market in case of the mismatch between demand and supply of power. As a result, we carry on an electricity transaction with fairness and highly transparency. In the future, it is observed that an electricity transaction will be more active and the market will be more competitive.

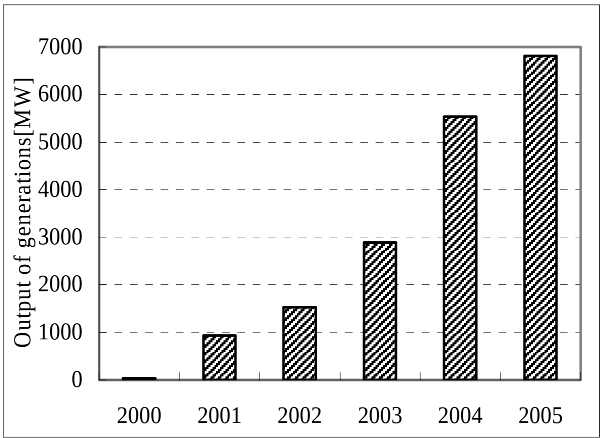

Fig.1 The Output of PPSs' Generations

3 Neural Network

3.1 Forecasting of electric power price and neural network

In this paper, power demand of a day to forecast is unknown, so firstly neural networks are applied to forecast the maximum power demand on the next day. The electric power supply system is indispensable for lifeline systems and industrial activities. However, electric power is not storable, so it is necessary for system operators to keep adequacy of electric power against continuously varying power demands, and at the same time, it is necessary to forecast daily power demands accurately for stable and efficient power system operations.

Forecasting of power demands is classified into two categories; one is the long term for a year and the other is the short term for a week, a day and an hour depending on the purpose and the targeted period of prediction. In this paper, we focus on the prediction of demand for the next day, because it is fundamental data to work out daily generation planning.

Fig.2 shows change of the maximum electric demands from April to December 2005. The large fluctuations are seasonal change, and especially electric demands in summer and winter are very large. Compared with them, electric demands in spring and autumn are relatively small. The small fluctuations are weekly change. The electric demands on weekdays are larger than those on weekends and holidays.

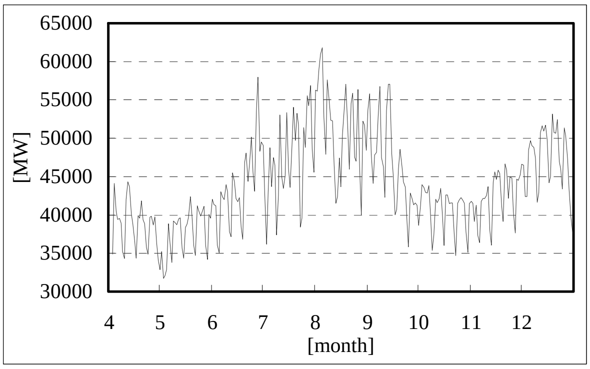

Fig.2 The maximum electric demand in Tokyo area in 2005

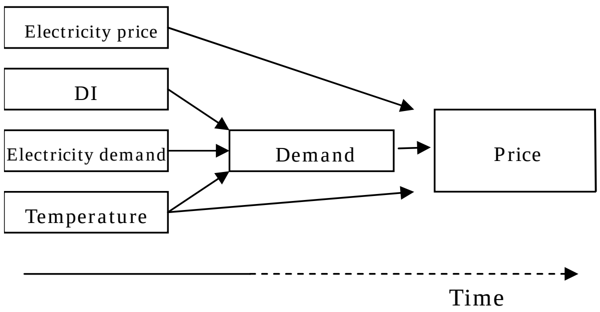

Fig.3 The concept of forecasting of electricity price

In this way, electric power demands are influenced by various kinds of nonlinear data. Moreover, electric power prices are also influenced by various kinds of nonlinear data such as the type of power supply and the price of the fuel, and so on. Therefore, for predicting electricity prices, we applied neural networks which hold high performances to extract dynamic features, to learn unstudied data and to represent nonlinear correlations. Fig.3 shows the concept of the method for forecasting the electric power price.

3.2 Time Series Estimation

The multilayer perceptron (MLP) neural network is applied to determine parameters for an autoregressive (AR) model considering n discrete time periods as below.

$$\hat{y}(k+1) = a_1 y(k) + a_2 y(k-1) + \cdots + a_n y(k-n+1) \quad (1)$$

where *y(k)* is a time series datum observed.

A three layer MLP neural network, as shown in Fig.4, is introduced to obtain the AR model. All activation functions in hidden layer are tanh(x) (described as f_j in Fig.4), and the activation function in the output layer is $x(F_0(\Sigma) = \sum_{j=1}^{n_h}(x) + w_0)$.

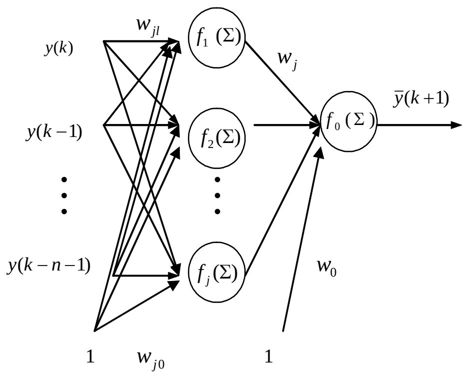

Fig.4 A fully connected three-layer feedforward network

The output of the MLP is

$$\tilde{y}(k+1) = \sum_{j=1}^{n_h} w_j \tanh\left[\sum_{l=1}^{n} w_{jl}\varphi(l) + w_{j0}\right] + w_0 \quad (2)$$

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 , $[w_1, w_2, \ldots, w_{n_h}]$
W_l^I : Vector form of w_{jl} , $[w_{1l}, w_{2l}, \ldots, w_{n_h l}]^T$

The derivative of the output with respect to the input φ_l is

$$\frac{\partial \tilde{y}(k+1)}{\partial \varphi(l)} = \sum_{j=1}^{n_h} w_j w_{jl}\left(1 - \tanh^2\left[\sum_{l=1}^{n} w_{jl}\cdot\varphi(l) + w_{j0}\right]\right) \quad (3)$$

Now, to make the model much simpler, linear activation function for f_j and F_o is applied to the MLP in Fig.4, and the linear output can be represented as follows:

$$\hat{y}(k+1) = \sum_{j=1}^{n_h} w_j \left[\sum_{l=1}^{n} w_{jl}\cdot\varphi(l) + w_{j0}\right] + w_0 \quad (4)$$

and the derivative of the output with respect to the input $\varphi(l)$ is

$$\frac{\partial \hat{y}(k+1)}{\partial \varphi(l)} = \sum_{j=1}^{n_h} w_j w_{jl} = W^0 W_l^I \quad (5)$$

From Taylor series expansion, parameter a_1 is obtained by

$$a_1 = \frac{\partial \hat{y}(k+1)}{\partial y(k)} = \frac{\partial \hat{y}(k+1)}{\partial \varphi(1)} = W^0 W_1^I \quad (6)$$

In general, the parameters of the AR model (1) can be obtained as follows:

$$\left[a_1, a_2, \ldots, a_n\right] = \left[W^0 W_1^I, W^0 W_2^I, \ldots, W^0 W_n^I\right] \quad (7)$$

From (1) and (7), the vector of the most likely demand (crisp value) can be obtained.

For the linear activation function in the neural network the inputs are scaled between 0.1 and 0.9 by the maximum and minimum inputs of the time window considered as below

$$y'(k-l+1) = s \cdot y(k-l+1) + b \quad (8)$$

where

$$s = \frac{0.8}{y^{\max} - y^{\min}}$$

and

$$b = \frac{0.1y^{\max} - 0.9y^{\min}}{y^{\max} - y^{\min}}$$

Here

$$y^{\max} = \underset{l}{Max}[y(k-l+1)]$$

$$y^{\min} = \underset{l}{Min}[y(k-l+1)]$$

and

$$l = 1, 2, \ldots, n$$

Because the time window for the training moves step by step, $y^{\max}$ and $y^{\min}$ are subsequently updated for a correct scaling. Outside of this window there is no need of assuming normal distribution of errors, which can give rise to the difficulty of stationary in regular regression-based time series modeling. This scaling is also consistent with the fuzzy model introduced below which observes the possible data ranges within an interval determined by the past data.

3.3 The relation between electricity price and nonlinear data

In this paper, maximum electric demand, weather factor and electricity price are used as input variables of the neural network for forecasting of the electric price. These variables have the strong correlation with electricity price [Fig.5]. Coefficients of the correlation are in the range from -1 to +1. Here, +1 shows the increase of coefficients as demands increase, and -1 shows the decrease of coefficients as demands increase. Also, 0 shows coefficients do not affect. As the results, it shows that there is the strong correlation between electric power prices and power demand [Fig. 6].

Coefficients of the correlation show that electricity prices have the time series characteristic. From this analysis, it has shown that the maximum electricity prices have three characteristics;

- Electricity prices are influenced by the power demand.
- Electricity prices have the time series characteristic.
- Features of electricity prices differ on weekdays, weekend and holidays.

Then, we describe when electric power prices at peak time of the next day are predicted and what kind of data it can be used then.

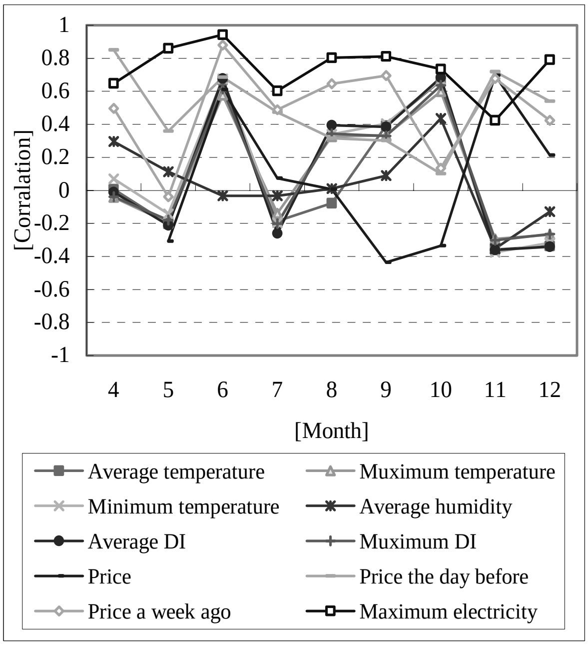

Fig.5 The correlation between electricity price and nonlinear data in 2005

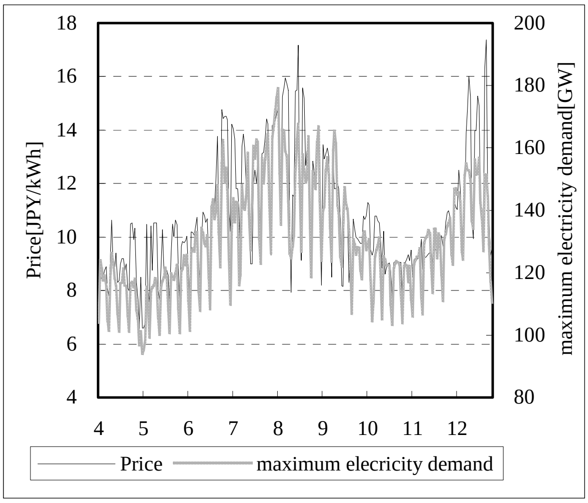

Fig.6 The relation between electricity price and day demand in 2005

We define that a day to predict electricity prices is called a day for prediction, and a day to predict electricity prices of it is called a day for prediction of the day. A day for prediction of the day is the day before of a day for prediction, so the usable data for a prediction are data before a day for prediction of the day (weather, power demand and price data and so on) and weather forecast data of a day for prediction. Electricity prices are influenced by the power demand of a day for prediction, but the usable data of that day is not actual data of that day but forecasting data of power demands. Therefore the next characteristic adds.

- Forecasting error of power demands includes that of the electricity price

We conducted simulations on three cases in order to show the effectiveness and practicability of forecasting of the electricity price, which utilize the correlation.

case1: Forecasting method not to use the power demand.

case2: Forecasting method to use forecasting of power demands.

case3: Forecasting method to use the power demand.

The correlations between electricity prices and power demands are proved by these 3 cases.

3.4 The model for forecasting of the electricity demand based on neural network

In this paper, three-layer neural networks have been used to forecast the power demand, and the number of input neurons is four and that of output neurons is one. As the input parameters, the maximum temperature, the maximum DI, and the maximum electric energy a week before and a day before are selected out of the factors of the correlation analysis. Previous one month demand data are used for learning of the three-layer neural networks to forecast demands of the next month. Fig.7 shows the neural network model for the proposed forecasting.

The total data of whole mainland are needed for electricity demand data to forecast the electricity price. The Japanese electric power system is like Fig.8 and is divided into the nine regions from Hokkaido to Kyushu in Japan. In this paper, neural networks for forecasting the maximum electricity demands are individually prepared for the nine regions. The power demand for whole mainland of the next day is calculated by forecasting the total maximum demand and the total demand of whole mainland is a sum of forecasted total maximum demand at each region as shown in equation (9).

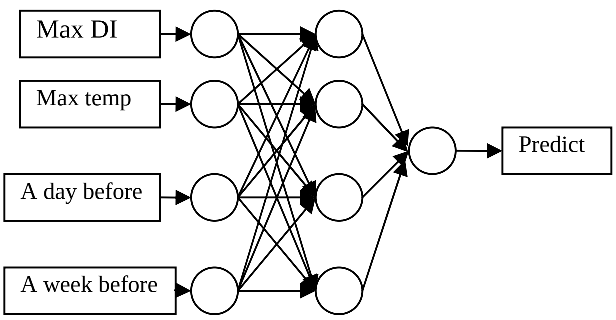

Fig.7 Neural network model for forecasting

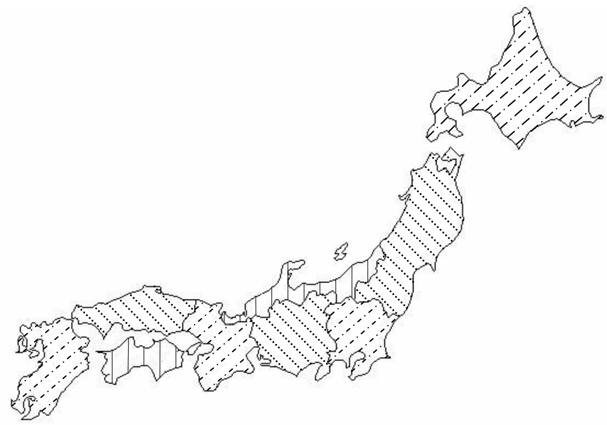

Fig.8 Nine areas in Japan

$$D_{whole} = D_1 + D_2 + \ldots + D_9 \quad (9)$$

D_{whole}: Forecasted total maximum power demand of whole mainland.

D_n : Forecasted total maximum power demand at each region.

3.5 The model for forecasting of the electricity price based on neural network

A weighted sum of temperature at each region is used as an input datum to neural networks and weight coefficients are determined by demand ratios in different regions as shown in equation (10).

$$T_{ave} = w_1 T_1 + w_2 T_2 + \cdots + w_9 T_9 \quad (10)$$

$$W_n = \frac{D_n}{D_{whole}}$$

T_{ave} : Normal temperature at all parts of the country.

T_n : Normal temperature at each region.

w_n : Wight of various places in demand.

4. The results of the forecasting of the electricity demand and price

Fig.9 and 10 shows the result by using neural networks. Fig.9 shows the result of forecasting maximum electricity demand of the next day. Fig.10 shows the result of the forecasted electricity prices at peak time.

Fig.10 shows that case3 has the higher accuracy than case1. The correlations between electricity prices and power demands were proved.

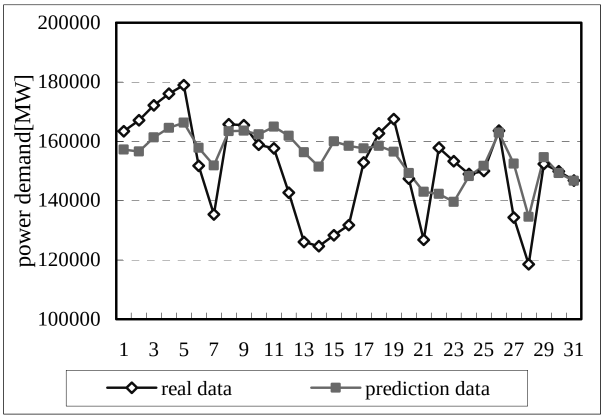

Fig.9 Result of next day maximum demand forecast on August 2005

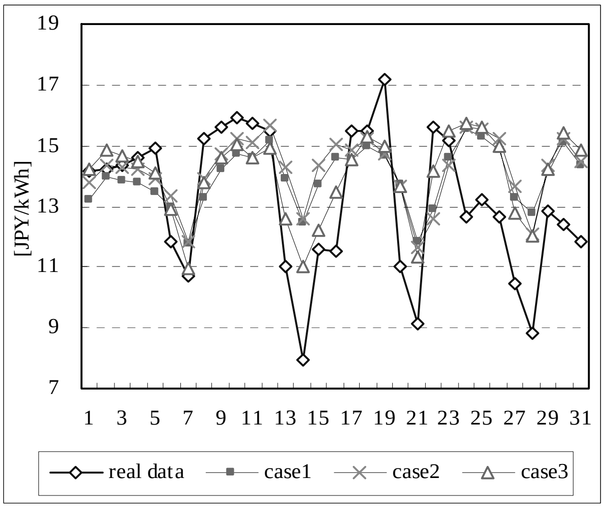

Fig.10 Result of next day electricity price forecast on August 2005

5 Conclusions

In this paper, a method for forecasting electric power prices was proposed by using the neural network and applied to Japan Electric Power Exchange that had began in April, 2005 where the change of the electric power price would give the important effect on both demand and supply sides. In the proposed method, electricity demands are selected as input variables to the neural network as well as the past electricity demands, because demands have strong influence on electricity prices. Forecasting electricity demands on the next day from May to December, 2005 was carried out by the neural network to confirm the validity of the proposal method. In addition, the forecasting electricity price on the next day at peak time was conducted by using the forecasted values of electricity demands.

As a result, it has been shown that the amount of the electricity demands is closely related to the electricity price from case1 and case2 and moreover the proposed method can follow the price fluctuation which changes on Saturday and Sunday and Monday when the volatility of price from a day ahead is large. By those applications, it is verified that the method is able to cope with the large price fluctuation in such as in the electric power exchange in Japan.

Case2 had the points which had lower accuracy than case1, since the forecasting error of power demands produces the forecasting error of electricity price. However, improvement of power demands forecasting will bring high accuracy such as case3.

In the application this time, data after May in 2005 is intentionally used because number of contracts is small and the price is not stable in the Japanese electric power exchange that have just started their dealing from April, 2005. It expected that more accurate forecast of the system becomes possible when the amount of the electric power dealings will increase in the future and the electric power price become stable.

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