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Demand and Price Forecasting by Artificial Neural Networks (ANNs) in a Deregulated Power Market

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Abstract: In a deregulated electricity market, where the electricity is trading among power suppliers and retailers in the pool market. The demand and price forecasting become important and play an important role for the market participants. Accurate forecasting tools are essential for producers to maximize their profits, avowing profit losses over the misjudgment of future price movements and for consumers to maximize their utilities. This study proposes two step forecast model by the Artificial Neural Networks (ANNs) to forecast one hour ahead demand and price of electricity. A three-layer BP (Back-Propagation) model was designed to train the historical data, then it was tested to predict both demand and price of electricity. In this study, the data from Queensland electricity market of Australia is used and promising results were obtained.

Key words: Electricity power market, price forecasting, demand forecasting, Artificial Neural networks (ANNs), demand

INTRODUCTION

Before the electric power deregulation, the power system belonged the country and the electricity price variations were minimal and heavily controlled by the regulator. So that time, the electricity price evolution was closely dependent on the government. Since 1990s, with some countries deregulated the electricity markets, the electricity has been turned into a commodity be traded in the electricity market, the suppliers and buyers compete between themselves to sell and buy the electricity at the market. In a deregulated power market, the Market Clearing Price (MCP) shows important information, which is helpful to the market participants in developing their bidding strategies. But the electricity has itself characteristic that it do not like ordinarily commodity that can be stored economically, the supply and the demand must balance simultaneously. The price will be changed with the change for supply and demand, both supply and demand sides need the price information to adjust their price submission to gain more profit or hedge the bidding risk. The electricity market price forecasting is a crucial information for the producers' production arrangement and bidding strategies and the regulators need to analyze the market behavior and monitor the market evolution with the price forecast tool.

So the price forecasting is important for the market participants including generation companies, retail companies, transmission network providers and market manager (Shahidehpour and Alomoush, 2001). Many techniques have been used to forecast the price and demand in electricity market. Contreras *et al.* (2003), the ARIMA models were used to predict next-day electricity prices. The wavelet transform and ARIMA models were used to forecast Day-ahead electricity price in Conejo *et al.* (2005). Niimura and Ko (2002), they used fuzzy-neural autoregressive to forecast the price, other attempts in this field include time series analysis (Nogales *et al.*, 2002; Cuaresma *et al.*, 2004). These existing methods have shown a good ability to forecast the electricity market price. Recently, the artificial neural networks was used to forecast the price by trained historical price data (Szkuta *et al.*, 1999; Guo and Luh, 2003; Xu *et al.*, 2004), these methods has been applied in electricity market price forecasting and has achieved satisfactory results. However, these methods just focus on forecast the market price, do not consider the relation between the electricity demand and the market price. But through analyze the relation of the demand and the price, we can know the demand is an important factor to effect the accurate of the price forecasting.

In this study, based on consider the affect of demand, the demand forecasting as an input factor be used to forecast the price. This study proposes an Artificial Neural Networks approach to forecast one hour-ahead demand and one-hour ahead price and test the model by the data from the electricity market of Queensland of Australia. The Back-Propagation algorithm was used to train a three-layer feed forward neural network. A tangent sigmoid function is chosen as the transfer function.

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MATERIALS AND METHODS

Artificial neural networks: Artificial neural networks are powerful and flexible tools for forecasting if provide enough data for training. It is highly interconnected simple processing units that called neurons, to model how the human brain performs a particulate task. Theses neurons forms a weighted sum of its inputs, this sum is then passed through a transfer function. Commonly the transfer function has three types: sigmoid, linear or hyperbolic tangent. In this study, a tangent sigmoid function w chosen as the transfer function as shown in Eq. 1:

$$f(u) = \frac{1}{1+e^{-u}} \tag{1}$$

Where:

u = The net input to the neurons

f(u) = The output of that neuron

Different learning algorithm of ANN(s) have been applied to price forecasting, such as Radial Basis Function Networks (RBFNs), Recurrent Neural Network (RNN) and Back Propagation (BP). In the BP learning algorithm, the input is passed layer through layer until output is calculated and compared to the actual output to calculate the error. The error is then propagated back to the input adjusting the weights and biases in each layer. In this study, a three-layer Back-Propagation (BP) model is used to forecast the demand and the price. The BP consists have three layers: input layer, hidden layer and output layer. The nodes within each layer are fully connected to the previous layer. The Fig. 1 is an example of a three-layered feed forward neural network model with a single output unit, an adequate selection of the input-output samples, an appropriate number of hidden layer and enough computational resources available. In order to accelerate the learning process, two parameters of the back-propagation algorithm can be adjusted: the learning rate and the momentum. The learning rate is the proportion of error gradient by which the weights should be adjusted. The momentum determines the proportion of the change of past weights that should be used in the calculation of the new weights. In the BP algorithm learning based, the initial weights of connections are randomly chosen. Suppose we have N learning examples with each example having n inputs and l outputs, the input vector can be described as $X_j = (X1_j, \ldots, Xn_j)$ and the output vector as $A_j = (B1_j, \ldots, Bl_j)$, $1 = j = N$. The learning process takes place using the following two steps:

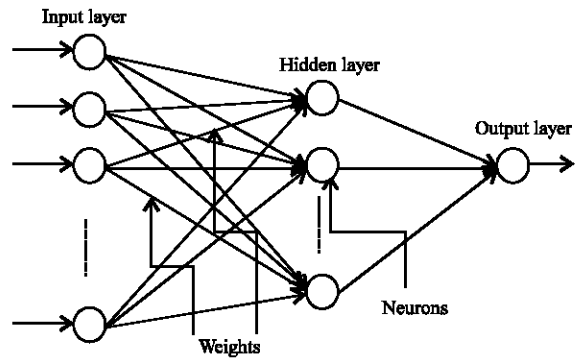

Fig. 1: Forecasting model by ANNs

Forward propagation: The input vector X_j is fed into the input layer and an output vector $O_j = (O1_j, \ldots, Ol_j)$ is generated on the basis of the current weights $W = (W1_1, \ldots, Wn_l)$. The value of B_j is compared with the actual output A_j and the output differences are summed to generate an error function E defined as Eq. 2:

$$E = \frac{1}{2}\sum_{i=1}^{1}\sum_{i=1}^{N}(B_{ij} - O_{ij})^2 \tag{2}$$

Error back propagation: In this step, the error from Eq. 2 is back propagated by performing weights update using gradient descent as follows:

$$\Delta W_{n1} = -\frac{\partial E}{\partial W_{n1}}\eta \tag{3}$$

where, $0<\eta<1$ is a parameter controlling the convergence rate of the algorithm. The process of forward propagation and error back propagation continues until E converges to a predefined small value. ΔW_{nl} is accumulated and updated after a complete run of all the N examples for our research.

Price forecasting by ANNs: With the competition concept introduced into the electricity market, many different factors will influence on the price level. Base on all these influences, the electricity price can't be simply calculating by cost-based engineering calculations. Since the electricity must be produced at the same time that it is consumed, the price is determined on an hourly basis, 24 h a day and 7 days a week. Therefore, for the market participant, the short-term price forecasting is becoming the important challenge. In the past, the price forecasting has been performed with least-cost optimization models. These models computation is based on assumptions of power plant availability, system loads and fuel prices. But they did not include the market price variations related to market strategy and also, the behavior of market participant in the electricity power market. In this study, an Artificial Neural Networks modeling approach was applied and evaluated for forecasting electricity prices. The model estimate and forecast were developed using hourly data from the National Electricity Market Management Company Limited (NEMMCO), has published the historical and real time data of the NEM Regional Reference Price (RRP) through its website (NEMMCO).

Electricity price characteristics: In the deregulated power market, the electricity must obey the market price regulation when it distribute as commodity in the electricity exchange market. The electricity price is determined by a balance between demand and supply. But there are fundamental differences between electricity and most other traded products, some of which are the consequence of the inability to store electricity. The relationship between spot and forward prices is driven by the physical dynamics of generation and by demand and is complex. The Fig. 2 is shows the relationship between electricity spot price and demand of the electricity market of Queensland of Australia. From the Fig. 2, we can see the electricity market price rises with the increase of demand. Sometime when the demand becomes very high suddenly, the spike will result. Electricity spot price exhibit high degrees of daily, weekly and seasonal variability and depending on the particular regional spot market, volatility may exhibit similar variability. In one day, the market price will be periodically rise and decrease with demand.

The Fig. 3 shows the market price and demand fluctuation for 1 week. From the Fig. 3, we understand price changes periodically according to the change of periodically.

Forecast model by ANNs: Through, the analysis of the relation between the demand and the price (Xu and Ken Nagasaka, 2009), we can know the demand is an important factor to impact on the fluctuation of the electricity market price. In this study, we proposed new model to forecast the demand and the price by ANNs.

The forecasting process divided in two phases: in the first phase, an MLP (ANN1) is used to forecast 1 h ahead demand. In the second phase, the demand forecasting that obtained by the first phase be used together others input factors. Another MLP (ANN2) forecast the 1 h ahead price. The flow chart of the forecasting is shown as Fig. 4.

Here we used the Neural Connection software to build the architecture of BP for short-term price forecasting (Fig. 5). Figure 5 shows the architecture of BP used for simulation, which inputs are all those 9 factors described. This is the multiple inputs (9 factors as input) BP architecture which generate us one output (demand or price).The Fig. 6 shows BP dialog box used in this study. This dialog box shows how actually the parameters and centers are chosen for the simulation and obtain a better result by increasing and adjusting the number of centers. Here, the inputs and outputs are normalized and the centers distribution was taken as randomly.

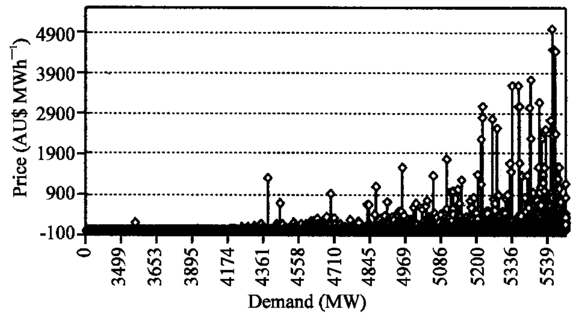

Fig. 2: Demand and price relations in Queensland (2008)

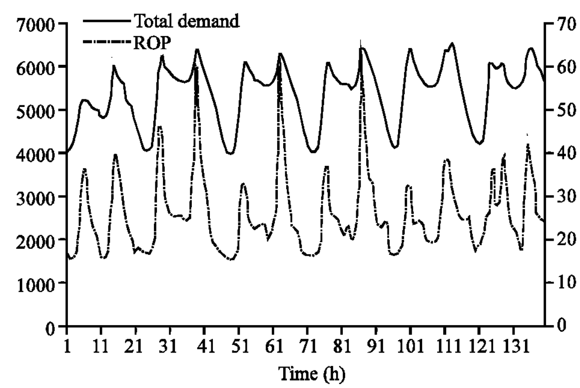

Fig. 3: Demand and price for one week

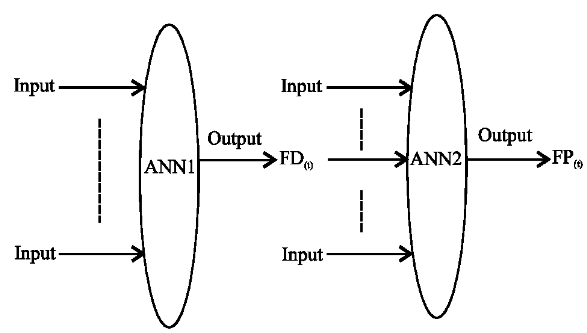

Fig. 4: The flow chart of price forecasting model

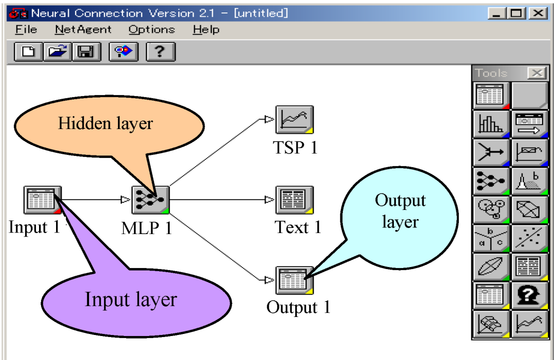

Fig. 5: BP architecture for simulation in this study

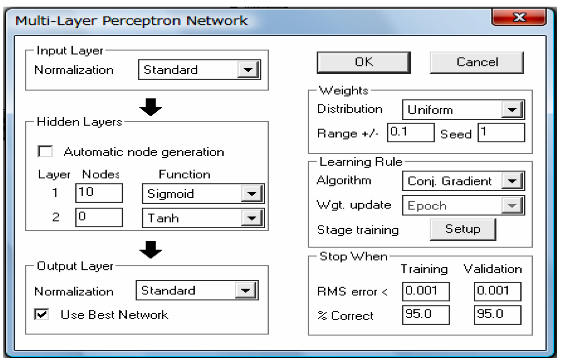

Fig. 6: BP architecture for simulation in this study

Here, ANN1 was used to forecast demand at time t. It was an MLP with 8 neurons in the input layers, 4 neurons hidden layers and 1 neuron in the output layer. ANN 2 was used to forecast price at time t. It was an MLP with 9 neurons in the input layers, 5 neurons hidden layers and 1 neuron in the output layer.

Input data selector: In a deregulated electricity market, electricity price was influenced by many factors: historical demand; historical price; generation outage; operating reserves; temperature and weather effect. The input factors included in this research were:

For the demand forecasting by ANN1 (Fig. 7), the input factors were:

P (t-1) = The electricity price at one hour ahead of time t
D (t-1) = The demand at 1 h ahead of time t
D (t-24) = The demand at 1 day before time t
S (t-1) = The supply at 1 h ahead of time t
G (t-1) = The generation at 1 h ahead of time t
DSI (t-1) = The relation of the Demand (D) and the Supply (S) at time t

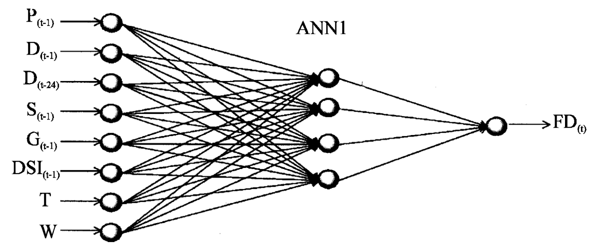

Fig. 7: BP price forecasting model by ANN1

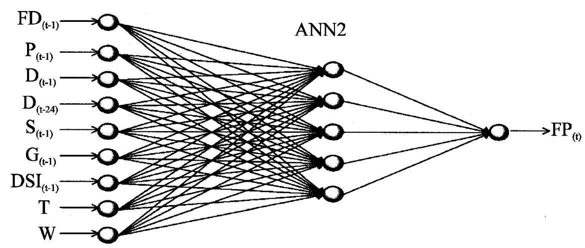

Fig. 8: BP price forecasting model by ANN2

DSI is defined as Eq. 4:

$$\mathrm{DSI}(t-1) = \frac{\text{Demand}}{\text{Supply}} \tag{4}$$

Where:

T = The time t
W = The week. The output of ANN1 was:
FP (t) = The forecasting demand at time equal to t

On the other hand, the input factors used in ANN2 (Fig. 8) model were mostly the same as in ANN1 by including one more factor which the result of forecasting demand obtained from ANN1 model. The input factors for the price forecasting by ANN2 summarized as following:

FD (t-1) = The forecasting demand at time equal t
P (t-1) = The price at 1 h ahead of time t
D (t-1) = The demand at 1 h ahead of time t
D (t-24) = The demand at 1 day before time t
S (t-1) = The supply at 1 h ahead of time t
G (t-1) = The generation at one hour ahead of time t
DSI (t-1) = The relation of the Demand (D) and the Supply (S) at time t

Since, the price forecasting in this research was one hour ahead forecasting, therefore the influence by the temperature and weather condition are not relevance to the forecasting result. Therefore, this is the why these two input factors were not been including in this part of the simulation.

Forecasting evaluation methods: To measure the forecast accuracy of the proposed models, different evaluation statistical measures have been applied in this research. In this study, we examined the accuracy on demand and price forecasting by calculating three different types of evaluation statistics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), these evaluation statistics defined in the following Eq. 5-7:

$$E_{RMSE} = \sqrt{\sum_{i=1}^{n} (F_i - A_i)^2 / n} \quad (5)$$

$$E_{MAE} = \frac{1}{n} \sum_{i=1}^{n} |F_i - A_i| \quad (6)$$

$$E_{MAPE} = \sum_{i=1}^{n} |(F_i - A_i)/A_i| \times 100\% \quad (7)$$

In here, F_i and A_i are the i the forecasted and actual values and n is the total number of forecasting.

RESULTS AND DISCUSSION

In this research, we constructed a new forecasting model by including two parts. In the first part, the demand at 1 h ahead was forecasting by ANN1. In the second part, the result obtained from first part been used as the input factor for ANN2. Two different scenario cases been studied in this research. Under the case A scenario, common technique for price forecasting (without including the demand forecasting in the input factor) been analysis. On other hand, the case B was the price forecasting by using the forecast model that proposed in this research. In this research, we compared the forecast result under the case A and case B scenario, respectively. Forecasting by neural network approach usually contain two steps: training and testing part of the forecast model. Hourly data we selected for training and testing in this research came from Queensland electricity market in Australia.

Demand forecasting result: At the first step, we forecasted the demand at time t by ANN1. The input factors were including P (t-1), D (t-1), D (t-24), S (t-1), G (t-1), DSI (t-1), T and W and the output was FD(t). The training and testing data are using historical hourly data of year 2008 for the Queensland electricity market of Australia. Figure 9-12 indicated the result of demand forecasting in one ahead for a given week in every season. The forecasting demand was in dashed line and actual demand in solid line. Table 1 presented the result on error evaluation of demand forecasting by neural

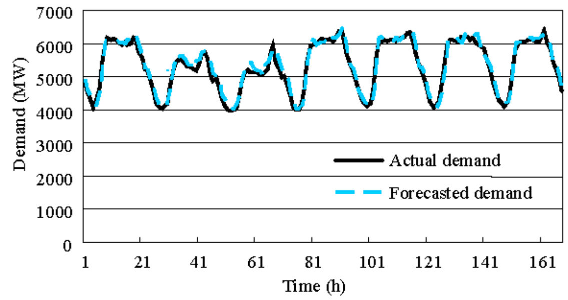

Fig. 9: One hour ahead demand forecasting for 1 week in Spring

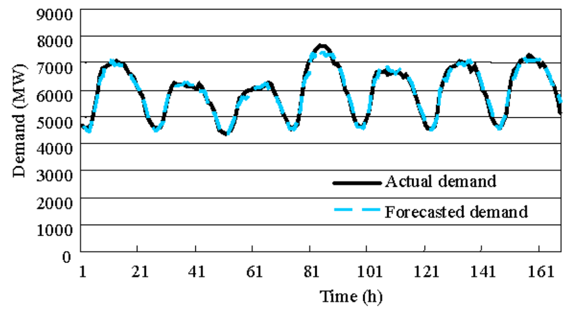

Fig. 10: One hour ahead demand forecasting for 1 week in Summer

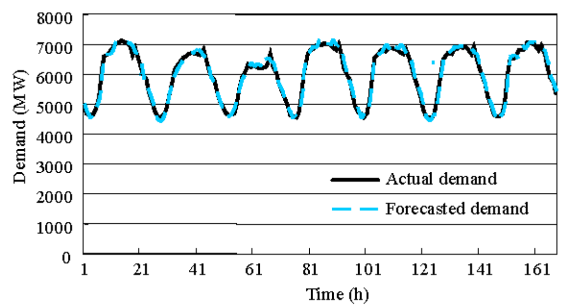

Fig. 11: One hour ahead demand forecasting for 1 week in Autumn

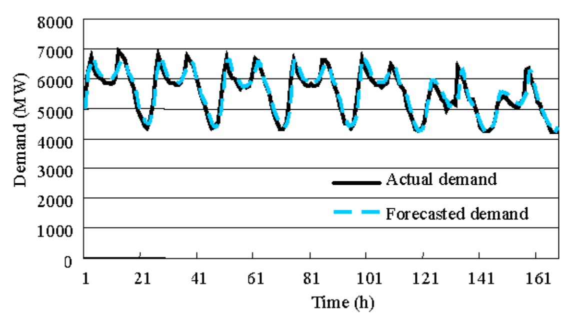

Fig. 12: One hour ahead demand forecasting for 1 week in Winter

Table 1: Demand forecasting error evaluation

Seasons	RMSE (MW)	MAE (MW)	MAPE (%)
Spring	108.20	84.8	2.74
Summer	144.80	116.4	3.25
Autumn	109.20	88.2	2.48
Winter	171.59	116.8	3.47

network approach. The first column in this table indicated the season, the second column was RMSE, the third column presents the MAE and the fourth column presented the MAPE. On the other hand, the maximum forecasting error from the simulation was 345.2 MW in spring, 485.7 MW in summer, 282.57 MW in autumn and 1081.64 MW in winter, the minimum forecasting error from the simulation is 1.95 MW in spring, 1.41 MW in summer, 0.54 MW in autumn and 2.35 MW in winter.

Price forecasting result: At the second step, we forecasted the electricity price at time t by ANN2 model. In the ANN2 model, the result of forecasted demand at time t obtained by ANN1entered as the one of the input element. The other input factors were including FD (t), P (t-1), D (t-1), D (t-24), S (t-1), G (t-1), DSI (t-1), T and W and the output of ANN2 was given in FP (t). The 2008 hourly data from Queensland electricity market been used as the learning and testing data for ANN2 forecasting model. Figure 13-16 presented the forecasting result for 1 h ahead in a given week at every season. Each figure indicated the forecasting price with dashed line and the actual demand with solid line.

Table 2 presented the result on error evaluation of price forecasting by neural network approach. The first column in this table indicated the season, the second column was RMSE, the third column was MAE and the fourth column was MAPE. From the result, the maximum forecasting error was 16.4 AU$ MWh^{-1} in spring, 20.3 AU$ MWh^{-1} in summer, 11.3 MW in autumn and 31.2 AU$ MWh^{-1} in winter.

On the other hand, the minimum forecasting error was 0.05 AU$ MWh^{-1} in spring, 0.12 AU$ MWh^{-1} in summer, 0.03 AU$ MWh^{-1} in autumn and 0.38 AU$ MWh^{-1} in winter. From the result it indicated the intensity changed on electricity demand during the summer and winter time leading the forecasted result had poorer accuracy compared to the result forecasting in spring and autumn period.

Compare two study cases: For analysis the new forecasting model proposed in this research, we compared the forecast result on electricity price for two different study cases (A and B). In case A, we conducted the common forecasting model by ANN (without demand forecasting as the input layer) for price forecasting. On the other hand, the new forecasting model had been built

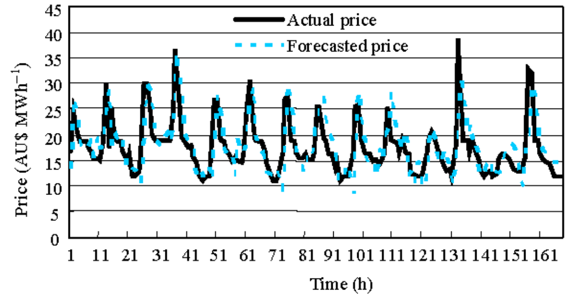

Fig. 13: One hour ahead price forecasting for 1 week in Spring

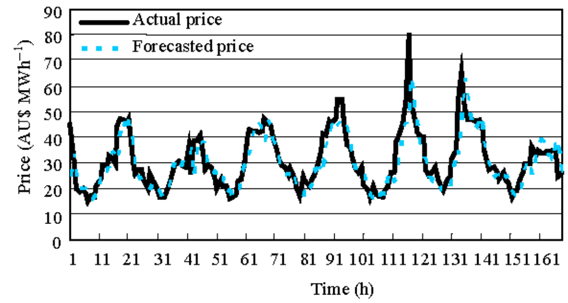

Fig. 14: One hour ahead price forecasting for 1 week in Summer

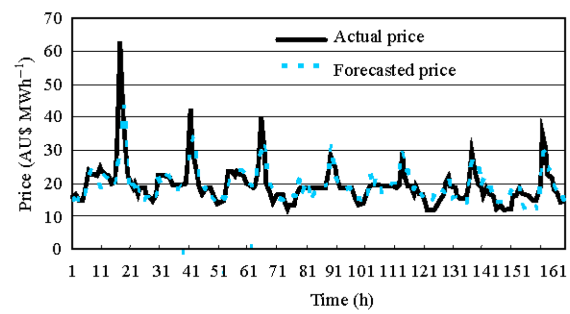

Fig. 15: One hour ahead price forecasting for 1 week in Autumn

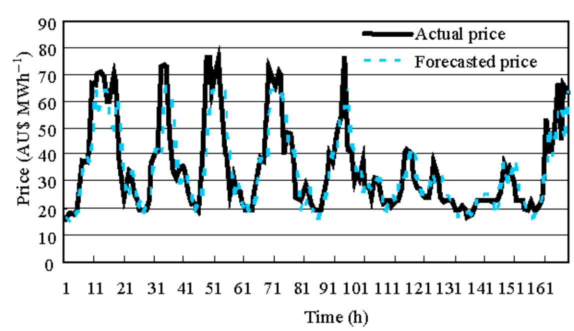

Fig. 16: One hour ahead price forecasting for 1 week in Winter

Table 2: The price forecasting error evaluation

Seasons	RMSE (AU$ MWh^{-1})	MAE (AU$ MWh^{-1})	MAPE (%)
Spring	2.35	1.82	11.02
summer	2.30	1.80	11.60
Autumn	1.97	1.57	9.55
Winter	3.20	2.14	12.50

Table 3: Price forecasting error evaluation

Factors	RMS (AU$ MWh^{-1})	MAE (AU$ MWh^{-1})	MAPE (%)
Training	2.65	1.98	10.23
Test	3.86	2.72	12.96

Table 4: Demand forecast error evaluation

Factors	RMS (MW)	MAE (MW)	MAPE (%)
Training	78.32	65.40	1.21
Test	98.75	85.58	1.50

in the case B. In the case B, we forecasted the demand at time t by ANN1 before forecasted electricity price at time t by ANN2 model.

Case A: Under case A, we forecasted the one hour-ahead price by one phase. The input factors in this case were including P (t-1), D (t-1), D (t-24), S (t-1), G (t-1), DSI (t-1), T and W without FD (t). The output of case A was FP (t) and given in Fig. 17. And the forecasted error evaluation presented in Table 3.

From the Fig. 17, it indicated the forecasting result was good under this case. The forecast error was large when the time at 8, 9, 18 and 19, since the demand was high at this time. Table 3 indicated the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). In case A, for the training part, the Root Mean Squared Error was 2.65 AU$ MWh^{-1}, the Mean Absolute Error was 1.98 AU$ MWh^{-1} and the Mean Absolute Percentage Error was 10.23%. For the testing part, the Root Mean Squared Error was 3.86 AU$ MWh^{-1}, the Mean Absolute Error was 2.72 AU$/MWh and the Mean Absolute Percentage Error was 12.96%.

Case B: In case B, we applied the forecasting model by ANN1 and ANN2. At first, we forecasted the demand at time t by ANN1, the input factors included P (t-1), D (t-1), D (t-24), S (t-1), G (t-1), DSI (t-1), T and W and the output was FD (t). The forecasting result was shown in Fig. 18. The forecasting error evaluation presented in Table 4.

Table 4 represented the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) for the demand forecasting in case B. From the result of simulation, the Root Mean Squared Error was 78.32 MW, the Mean Absolute Error was 65.4 MW and the Mean Absolute Percentage Error was 1.21% for the demand forecasting error in the training section. On the other hand, the Root

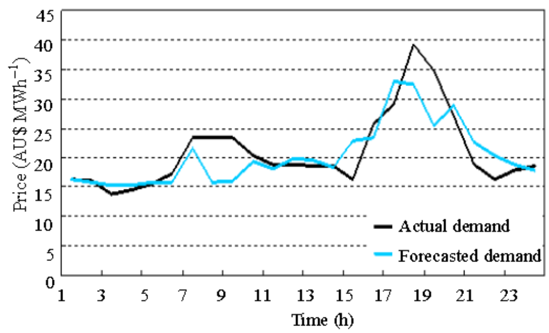

Fig. 17: One hour ahead price forecasting

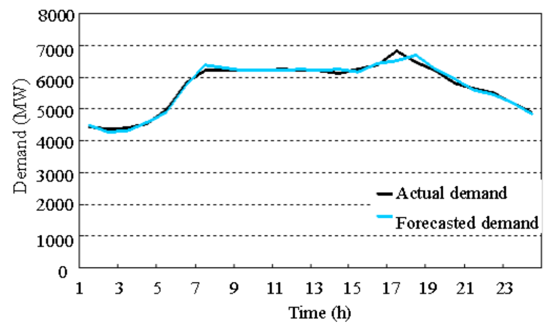

Fig. 18: One hour ahead demand forecasting by ANN1

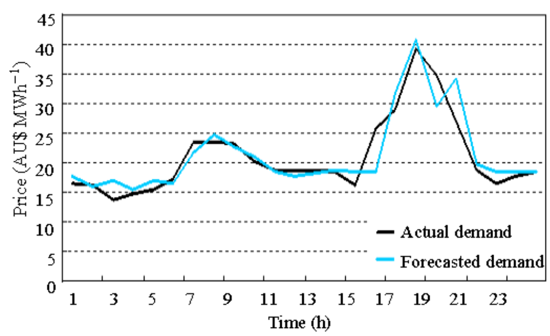

Fig. 19: One hour ahead price forecasting by ANN2

Mean Squared Error was 98.75 MW, the Mean Absolute Error was 85.58 MW and the Mean Absolute Percentage Error was 1.5% in the testing section. By ANN1 the forecasting demand at time t will be obtained. Then, the forecasting demand was used as the input factor with others input factors to forecast the price at time t by ANN2. The input factors included FD (t), P (t-1), D (t-1), D (t-24), S (t-1), G (t-1), DSI (t-1), T and W. The output was given in FP (t). The forecasted result was shown as Fig. 19 and the forecasting error evaluation indicated in Table 5. From the Fig. 19, we could see the accuracy on forecasting had been improved.

Table 5: Price forecast error evaluation

Factors	RMS (AU$ MWh^{-1})	MAE (AU$ MWh^{-1})	MAPE (%)
Training	2.3	1.56	7.95
Test	2.7	1.82	8.68

In case A, the large forecasting error resulted at time 8, 9, 18 and 19. On the other hand, the error was small at 8, 9, 18. For time 19, the forecasting error was higher In conclusion, the forecasting accuracy in case B was higher than in the case A. than at time 18, but it was smaller compared in case A.

Table 5 was given the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) for the price forecasting by ANN2. From the result of the simulation, the Root Mean Squared Error was 2.3 AU$ MWh^{-1}; the Mean Absolute Error was 1.56 AU$ MWh^{-1} and the Mean Absolute Percentage Error was 7.95% for the price forecasting in training section. On the other hand, the Root Mean Squared Error was 2.7 AU$ MWh^{-1}, the Mean Absolute Error was 1.82 AU$ MWh^{-1}, the Mean Absolute Percentage Error was 8.68% in the testing section. Using the new forecast model the MAPE reduced from 12.96-8.68%.

CONCLUSION

This study forecasted 1 h ahead electricity price in the Queensland electricity market of Australia by using neural network approach. From this research, we learned the demand was an important factor which could affect on the electricity price level. This was the reason, why the demand forecasting been included as an input factor for price forecasting model proposed in this research. In this study, we forecasted one hour ahead demand and electricity price for 1 week interval in every season. From the result of simulation, it indicated the forecasting error was smaller in spring and autumn. And for inspecting the new forecasting model, we compared the forecast result on electricity price for two different study cases (A and B). In case A, we conducted the common forecasting model by ANN (without demand forecasting as the input layer) for price forecasting. On the other hand, the new forecasting model had been built in the case B. In the case B, we forecasted the demand at time t by ANN1 before forecasted electricity price at time t by ANN2 model. The forecasting result evaluated by the Mean Absolute Percentage Error (MAPE) in this research.

From the result, it indicated the forecasting error reduced from 12.96-8.68% by using the new forecast model proposed in Case B. The result of this research presented great value for forecasting the short-term electricity under the deregulated electricity market.

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