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A Research on Spike Jump of Electricity Price in the Deregulated Power Markets

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Abstract: In the deregulated power markets, the electricity market price forecasting is very important for the market participants, managers GenCo, DisCo, retailers, etc. Although, most of researches has achieved good results on the electricity market price forecasting, however, these techniques mostly focus on normal price forecasting and not considering price spikes in the electricity market. In this study, we propose a price interval identification model using neural network, which can generate forecasted price interval, level of spike and associated forecast confidence. The model is tested with the Queensland electricity market data of Australia and promising results are been obtained.

Key words: Electricity power market, price forecasting, price spikes, Artificial Neural Networks (ANNs)

INTRODUCTION

In the deregulated power system, the electricity as a commodity, is traded in the market. Electricity price is strongly related to physical characteristics of a power system such as loads, meteorological conditions, fuel prices, unit operating characteristics, emission allowances and transmission capability (Mohammad and Alomoush, 2001). Therefore, electricity market clearing price becomes important at the entire electricity market. Since, the fluctuation of the market price influences the resource distribution and flowing in the competitive market, price forecasting becomes one of the most important information to all market participants including market managers, GenCo, DisCo and the retailer, etc. The market price forecasting is also necessary for negotiation skills and developing bidding strategies. Have many methods was proposed to forecast the electricity market price and obtained good results. Contreras *et al*. (2003) and Conejo *et al*. (2005), they used ARIMA methods to forecast the next day electricity prices and in (Niimura and Ko, 2002), they used fuzzy-neural autoregressive to forecast the price and in Szkuta *et al*. (1999), Guo and Luh (2003) and Xu *et al*. (2004), the artificial neural networks was used to forecast the price by trained historical price data. However, most of these forecasting models are only effective for normal price and not for the price signals including the price spikes. Electricity has a distinct characteristic since it cannot be stored. Transmission congestion may prevent free exchange of electricity among control areas, thus, electricity price shows the greatest volatility among various commodities. Here, it is necessary to make a forecasting model, which can forecast not only the normal price but also the price spikes. This is important for any markets type electricity, because the price spikes could be rise to 100s or 1000s times higher than the normal price, which brings a high risk for the market participants. If someone can forecast these spikes before their occurrence, they may consider risk hedging ways such as option, etc. In this study, first we analyze the relationship between the market price and the electricity demand. By this analysis, we can know about the rise of the demand and price. When the unbalance of the supply and the demand is generated, the price spikes may be caused. The price spikes incidence is higher when the demands became higher and with weather conditions effect. Also, the electricity demand immediately rise in summer and in winter, so in winter and in summer, the probability of price spikes is higher than that in spring and autumn. In this study, we propose a price interval identification model using Artificial Neural Network (ANNs), which can projects price interval, level of spike and spike occurrence probability. The proposed model is tested with the Queensland electricity market data of Australia.

RELATIONSHIP BETWEEN MARKET PRICE AND ELECTRICITY DEMAND

In this study, we used the data of Queensland of Australia from 1999-2004. The data from the National Electricity Market Management Company Limited

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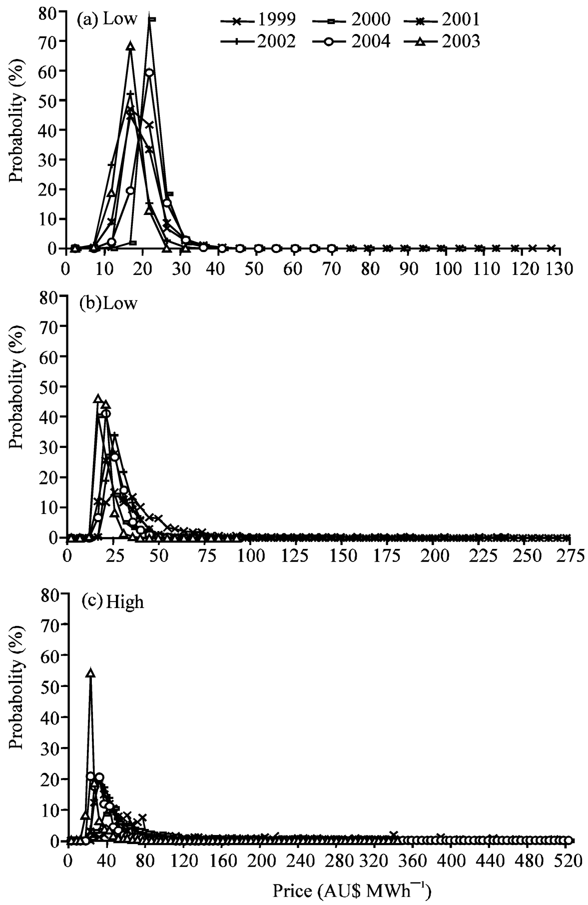

Fig. 1: Probability of the price in low demand level

(NEMMCO), has published the historical and real time data of the NEM Regional Reference Price (RRP) in their website (www.nemmco.com.au).

In this study, electricity demands are categorized into three levels, demands lower than 4500 MW, is considered as level I (low demand level), demands between the 4500 and 5500 MW is considered as level II (medium demand level) and the demands higher than 5500 MW is considered as level III (high demand level). The probability of price at different demand levels and the probability of price spikes at different demand levels are determined in this study. Figure 1a, b and c are the probability of the price in the low, medium and high demand levels.

From the probability analysis of the prices in 3 different demand levels, we can observe that, in low demand level, the price fluctuates from 13-28 AU$, in medium demand level, it fluctuates from 22-46 AU$ and in high demand level, it fluctuates from 38-60 AU$.

However, when the price is higher than 400 AU$ or 500 AU$, the price spikes appear. Therefore, we can

Table 1: Probability of price spikes at different demand levels

	Probability of price spikes (%)		
	High	Medium	Low
1999	87.42	31.35	0
2000	62.86	18.48	0
2001	28.48	5.95	0
2002	19.45	4.10	0
2003	4.00	0.14	0
2004	13.44	0.94	0

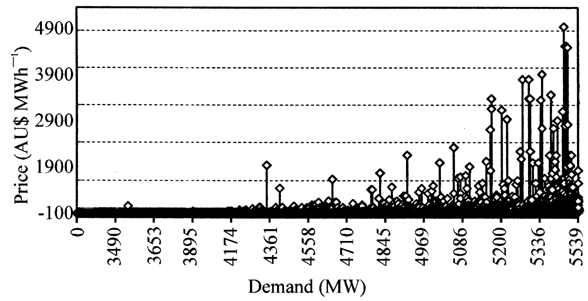

Fig. 2: Price and demand relations in Queensland (1999)

know that, at different demand levels, the probability distributions of price are different. As conclusion, when the demand rise the price increase and the price spike appears. Table 1 shows the probability of price spikes at different demand levels from 1999-2004.

From the Table 1, we can know that, at high demand level, the probability of the price spikes is higher than others levels. Also, the probability of price spikes significantly increases with high level demand.

From Fig. 2, the price spikes occurred with the demand rise and when the demand become high enough, probability of the price spikes became more frequent.

Figure 2 shows the price and demand of Queensland in Australia of 1999.

PRICE SPIKES IN THE ELECTRICITY MARKETS

Definition of price spike jump: The price spike in the electricity market is an abnormal market clearing price at a time point t and is significantly, different from the price at previous time point t-1. These abnormal prices can be classified into 3 categories (Xin *et al*., 2005):

Abnormal high price: A price that is much higher than the normal price.

Abnormal jump price: The different between 2 neighbouring price is larger than a threshold.

Negative prices: The prices which are lower than zero. In this study, forecasting problem of the abnormal high

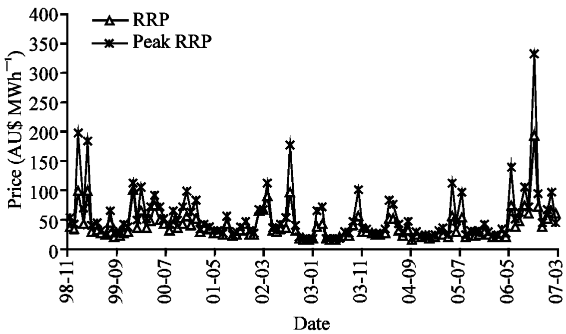

Fig. 3: Average monthly RRP and Peak RRP of Queensland electricity market from November 1998-2007

prices is dealt with. The price spike can be determined by a statistical method based on historical data (Eq. 1):

$$p_v = \mu \pm 2\sigma \quad (1)$$

where:

μ = The mean of the historical market prices.
σ = The standard deviation of the prices.

Figure 3 shows the average monthly price (RRP) and its peak from November 1998-2007. In this study, the prices higher than 75 AU$ MWh^{-1} is considered to be spikes.

The cause of electricity market price spike: In the deregulated electricity market, the price spikes are highly randomized events, it can be caused by market power and can be caused by unexpected incidents, such as transmission contingencies, transmission congestion and generation contingencies.

The price spikes can be influenced by many complex factors including physical characteristics of the system, supply, demand, fuel prices, plant operating costs and weather conditions. The most theoretically is significant factor is the balance between overall system supply and demand.

So, when the demand lager than the supply, or the supply lower than the demand, the price spikes happened. Figure 4 is the supply and price of Queensland electricity market in Australia.

From Fig. 4, we can know when the supply large enough, the price distribute at a low range and no price spikes occurrence. But when the supply reduced to certain extent, the price spikes occurred.

The price forecasting also effect the probability of the price spikes. In the past some ANNs forecast models, with inputs, that has direct relation with the price was selected. The inputs were historical price, demand, time,

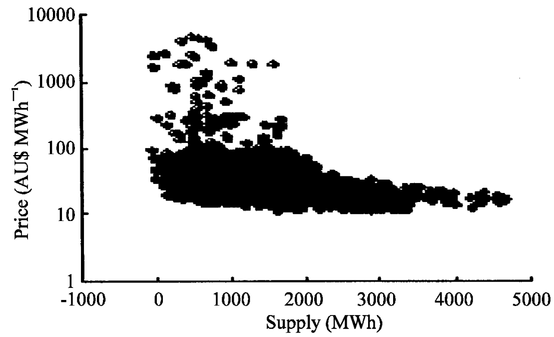

Fig. 4: The supply and the price of Queensland electricity market

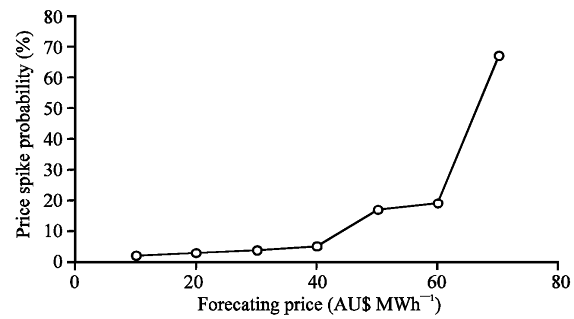

Fig. 5: The probability of spike vs forecasting price

Table 2: Probability of the price spikes at each season

Probability of price spikes (%)	Spring	Summer	Autumn	Winter
1999	7.42	25.26	16.96	10.74
2000	18.37	13.30	19.51	26.10
2001	5.17	25.35	15.98	5.07
2002	6.60	8.29	6.30	14.40
2003	0.18	8.56	0.38	3.35
2004	14.72	7.42	5.53	2.67

fuel price and weather condition etc. However they did not consider other upexpected incidents and some artificial elements. These factors will affect the price forecasting which result a high forecasting error. Figure 5 is the probability of spike and forecasting price of Queensland electricity market.

The probability of price spikes varies in different seasons. For example, in winter and summer, because the weather become cold and hot, the air-conditioning is used more than others season, therefore the electricity demand become higher. In winter and summer, the probability of price spikes become higher than in spring and autumn. Table 2 is the probability of price spikes at each season.

From the Table 2, through calculate the probability of price spikes at each season from 1999-2004, it can be seen that the probability of price spikes is higher in summer and winter than in spring and autumn, the high prices are more likely to happen during peak times.

PRICE SPIKES FORECASTING MODEL

Recognition model of spike jump by ANN: Many price forecasting techniques, such as ARIMA, fuzzy logic and Artificial Neural Networks (ANN), have been developed recently, showing encouraging results. Among them, ANN (s) methods are particularly attractive. Different types 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 this study, a three-layer Back-Propagation (BP) model is used to forecast the price interval. BP consists of three layers: the input layer, hidden layer and output layer. The nodes within each layer are fully connected to the previous layer, a tangent sigmoid function is chosen as the transfer function as showed in Eq. 2:

$$f\,(u) = \frac{1}{1+e^{-u}} \tag{2}$$

Here,

u = The net input to the neurons.
f (u) = The output of that neuron.

Figure 6 is the proposed network of the forecasting spikes. The input factors are as follows:

FP (d, t): Forecasted price.

TD (d, t): The total demand of system at the particular date (d) and time (t).

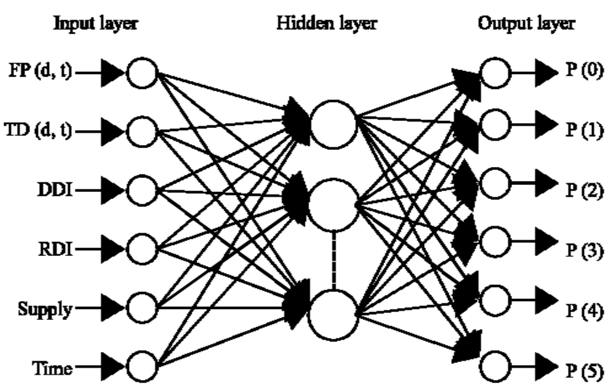

Fig. 6: Structure of proposed neural network model for spike forecasting

Table 3: Output distribution of proposed model

Output level	Level A	Level B	Level C
Price range (AU$/MWh)	(75-100)	(100-150)	(150-250)
	Level D	Level E	Level F
Price range (AU$/MWh)	(250-500)	(500-2000)	(>2000)

DDI: The relative demand index, which refers to the relative degrees of current time demand with the initial demand of the trading day. DDI is defined as Eq. 3:

$$DDI = \frac{D(d,t)}{D(d,1)} \tag{3}$$

RDI: the relation of the reserve (R) and demand (D). RDI is defined as Eq. 4:

$$RDI = \frac{R(d,t)}{R(d,1)} \tag{4}$$

The output P (x) is the probability of spike jump occurrence at each interval level. Table 3 shows the range of prices which are classified from level A-F.

FORECASTING SIMULATION AND RESULTS

In this study, selection of network structures, hidden neurons, data representation is discussed. Then the results, which were obtained from the above-mentioned network is introduced.

Architecture of BP used for simulation: Here we used the Neural Connection Simulator to build the architecture of BP for price spikes forecasting simulation (Fig. 7).

Inputs include FP (d, t), TD (d, t), DDI, RDI, supply and time. These input factors are presented at the last section of this study.

Figure 8 shows the 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 is randomly taken.

The forecasting results: The data from Queensland electricity market from July 2004-2005 was used. The

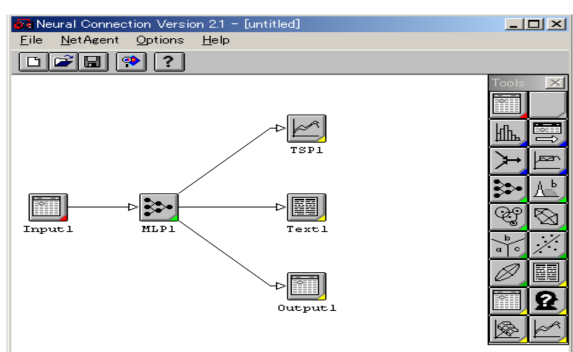

Fig. 7: Architecture of BP for price spikes forecasting

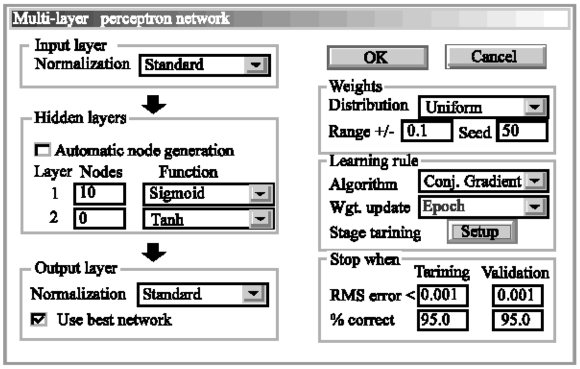

Fig. 8: Selection of BP parameters and centers for simulation

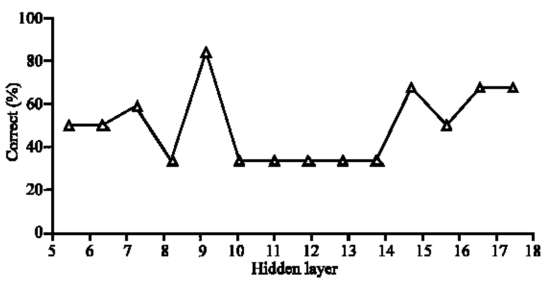

Fig. 9: The percentage correct at different hidden layer

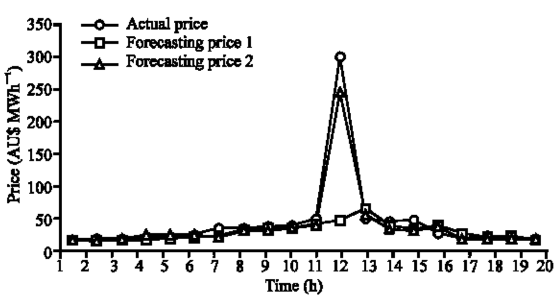

Fig. 10: the percentage correct at different hidden layer

forecast price, total demand, supply, time, DDI and RDI are used to establish the training data sample sets. Twelve data that the price is >75 AU$ MWh^{-1} are used as test data. Number of hidden layer neurons are selected from trial and error shown in Fig. 9. Here, 9 neurons is selected which has about 83.3% correct forecasting result.

The output that shows the probability of spike jump occurrence at each interval level forecast error is shown in Table 4. Here, Root Mean Squared Error (RMS), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) used to evaluate the results. Here RMS is defined as Eq. 5:

Table 4: Forecasting error estimation

Output	RMS error (AU$ MWh^{-1})	Mean absolute error (AU$ MWh^{-1})	Output mean absolute error (%)
A	0.18	0.13	16.18
B	0.19	0.14	16.35
C	0.34	0.30	36.96
D	0.35	0.31	37.87
E	0.38	0.26	32.37
F	0.17	0.10	13.06

Table 5: Price forcasting error

Date	Time	Level Interval	Level Forcasted	AU$ MWh RRP	AU$ MWh Forcastedrrp	Forcasted error (%)
7/17/2004	18:30	A	A	83.31	83.83	0.60
8/13/2004	23:30	A	A	75.05	124.48	64.50
10/13/2004	10:30	B	A	134.11	129.83	3.10
10/13/2004	11:30	C	C	179.00	175.84	1.70
11/11/2004	16:30	C	C	204.73	206.86	1.04
11/11/2004	17:30	B	C	149.36	148.08	0.85
1/12/2004	14:30	E	E	1039.65	1040.62	0.09
2/8/2005	15:00	D	D	300.59	298.18	0.80
2/8/2005	16:00	F	F	4041.39	4031.01	0.25
2/8/2005	16:30	F	F	7312.25	5805.62	20.60
2/8/2005	15:00	D	D	256.40	250.88	2.10
2/8/2005	15:30	E	E	1280.53	1269.77	0.84

$$E_{RMS} = \frac{1}{pk}\sqrt{\sum_{p=1}^{p}\sum_{k=1}^{k}(d_{pk} - O_{pk})^2} \tag{5}$$

and MAPE is defined as Eq. 6:

$$E_{MAPE} = \frac{1}{pk}\left|\sum_{p=1}^{p}\sum_{k=1}^{k}\left(\frac{d_{pk} - o_{pk}}{o_{pk}}\right)\right| \times 100\% \tag{6}$$

where:

P = Study pattern.
k = Number of the output neurons.
d = Actual value.
O = Forecasting value.

From Table 4, F interval level showed the smallest forecasting error.

So, the price interval level was selected as an input factor to forecast the price. Forecasted results for the test data is shown in Table 5.

When the price interval level was used as an input, the average forecasting error reduced to 10.6%, the forecasting results accuracy has remarkable improve.

In order to demonstrate the effectiveness of our proposed model, we selected one day including the spikes. The result is shown in Fig. 10, The forecasting price 1 is ordinarily forecasting price and the forecasting price 2 is the one used we proposed forecasting model to forecast the price. From the Fig. 10, it can be clearly seen that our proposed model has successfully forecasted the price spikes and the result are very close to the actual price spikes.

CONCLUSION

In this study, we analyzed the relationship between the electricity demand and the market price and discuss of the reason of price spikes occurrence. By the analysis, we can know that the price will be rise as the demand rising. When the unbalance happened between the demand and supply, the price spike will be occurred. In this study, we proposed a forecasting model used ANN (s) to predict the price spike at different price level. With our proposed model, we obtained the most suitable parameters. The forecast result enunciated that forecasting results have been significantly improved by our proposed method. The new approach can be useful for the electricity market participants and it is useful to hedge the risk for the market participants.

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