The Journal of CPRI,
Vol. 5, No. 1, March 2009 pp. 37–45

Day-ahead Electricity Price Forecasting in Victoria Electricity Market Using Support Vector Machine-based Model

Sanjeev Kumar Aggarwal*, L M Saini* and Ashwani Kumar**

In this paper, Support Vector Machine (SVM), a new machine learning technique based model to forecast price profile in a single settlement real-time electricity market has been presented. The proposed model has been trained and tested on data from the Victoria Electricity Market (VEM) to forecast the Regional Reference Price (RRP). The selection of input variables has been performed using correlation analysis, and in order to take advantage of the homogeneity of the time series, forty-eight separate SVMs have been used to predict the next-day price profile, with each SVM forecasting price for each trading interval. Forecasting performance of the proposed model has been compared with (i) an heuristic technique, (ii) a naïve technique, (iii) Multiple Linear Regression (MLR) model, and (iv) Neural Network (NN) model. Forecasting results show that the SVM model possesses better forecasting abilities than the other models and can be used by the participants to respond properly as it predicts the price before the closing of the window for submission of initial bids.

Key words: *correlation analysis, learning theory, multiple linear regression, neural network, price forecasting, support vector machine*

1.0 INTRODUCTION

An electricity market is a system for effecting the purchase and sale of electricity using supply and demand to set the price. In an open market, power companies and consumers submit their generation or consumption bids and corresponding prices to the Market Operator (MO), who will then conduct a market-clearing process (Fig. 1), to determine the Market Clearing Price (MCP) for the corresponding time interval [1]. Trading in electricity markets is different from trading in other commodities, because electricity is by nature difficult to store and has to be available on demand. In addition, the laws of physics determine how electricity flows through an electricity network. A consequence of the complexity of a wholesale electricity market, is extremely high price volatility at times of peak demand and supply shortages [2]. Competitive markets have meant that while generation companies can cope with demand uncertainty by the financial techniques of risk management (short-term basis) as well as by the expansion planning (long-term basis), on the other hand customers find an opportunity to safeguard their interests in the form of demand side management and financial hedging [3]. But, the various financial derivatives used to hedge exposure to the often abnormally high and rapidly mean-reverting electricity prices require an understanding

*EED, National Institute of Technology (NIT), Kurukshetra, INDIA
Email: vasusanjeev@yahoo.co.in, lmsaini@rediffmail.com
**Tennessee Technological University (TTU), Cookeville, USA
Email: ashwa_ks@yahoo.co.in

of the pricing process and the ability to accurately estimate future price volatility [4]. If the MCP can be predicted accurately, market participants can reduce their risks and optimise their interests.

Several approaches have been proposed in the recent years for this problem, such as linear time series models like MLR [5], Dynamic Regression and Transfer Function [6], and Autoregressive Integrated Moving Average (ARIMA) [7]. Artificial Intelligence (AI) based models like Artificial Neural Network (ANN) [8-9], and Fuzzy Logic Models (FLM) [10] and hybrid neuro-fuzzy models [11] have been reported. The focus of this paper is the development of a day-ahead price forecasting model in a real-time electricity market using a new machine learning technique for data classification and regression based on recent advances in statistical learning theory [12-13]. Little work has been done in the area of electricity price forecasting using SVM; whereas, the method has already proved its capability for load forecasting [14].

Usually there are two types of electricity markets: day-ahead market and intra-day or real-time market [4]. Real-time electricity markets are highly unpredictable and therefore the proposed model has been applied to real-time single settlement Victoria Electricity Market (VEM). In this work, forty-eight SVMs have been used to fit the training data and predicting the price profile of the next day in VEM. Forecasting performance of the proposed SVM model has been compared with (i) heuristic technique, (ii) naïve technique, (iii) MLR model and (iv) NN model. Comparison of forecasting performance clearly shows that, for the same set of input variables, SVM has the potential to outperform the other models and hence can be utilised as a reliable forecaster by the participants, as the results of its prediction are available before the initial window of the submission of bids gets closed.

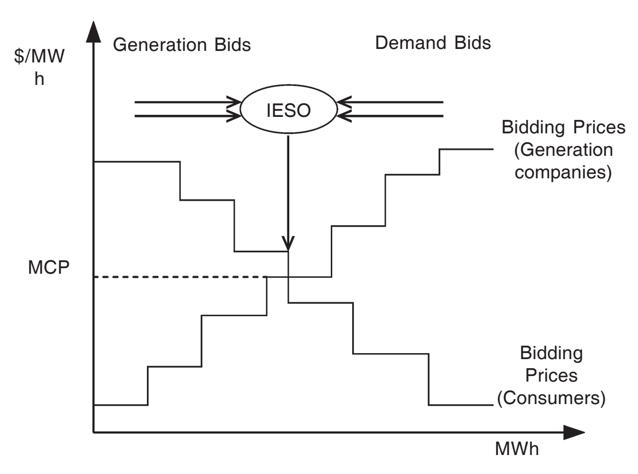

FIG. 1 MARKET CLEARING PROCESS IN AN ELECTRICITY MARKET

2.0 SUPPORT VECTOR MACHINE (SVM)

SVM is a relatively new promising method for learning separating functions in pattern recognition tasks and for performing functional estimation in regression problems and hence is very attractive for many real-world forecasting problems like electricity price forecasting. This learning technique has been introduced in the framework of Structural Risk Minimisation (SRM) and in the theory of VC (Vapnic-Chervonenkis) bounds. More precisely, instead of minimising the absolute value of an error or of an error square, the SVM performs SRM. A detailed account of SVM has been given in [12-15] and a brief introduction of the support vector regression (SVR) method has been presented in this section.

Consider the set of training data $\{(X_i, y_i)\}_{i=1}^{N}$, where X_i is an input vector and y_i is the corresponding output. The support vector regression solves a constrained non-linear optimisation problem of minimising a quadratic cost functional.

$$\min_{\omega,b,\xi,\xi^*} \Phi(\omega, b, \xi, \xi^* \qquad (1)$$

subject to,

$$y_i - (\omega^T \phi(X_i) + b$$
$$(\omega^T \phi(X_i) + b) - y_i$$
$$\xi_i, \xi_i^* \geq 0,\ i = 1, 2, .$$

where, X_i is mapped to a higher dimensional space by the function ϕ. ξ_i and ξ_i^* are called slack variables, ξ_i^* is the upper and ξ_i is the lower training error subject to the ε-insensitivity loss function or tube $\left| y - (\omega^T \phi(X) + b) \right|$. ω is the weight vector and b is the bias. The parameters, which control regression quality, are the cost of error C, the width of the tube ε, and the mapping function ϕ. Mapping function ϕ is used to convert a non-linearly separable problem in input space into a linearly separable problem in feature space.

The constraints of (1) imply that it is attempted to put most of the data X_i in the tube $\left| y - (\omega^T \phi(X) + b) \right|$. If X_i is in the tube, the loss is zero. If X_i is not in the tube, there is an error ξ_i^* or ξ_i which is minimised in the cost functional. SVR avoids underfitting and overfitting the training data by minimising the training error $C\sum_{i=1}^{N}(\xi_i + \xi_i^*)$ as well as the regularisation term $(\frac{1}{2})\omega^T\omega$. This is in accordance with the principle of SRM, where training error (empirical risk) and the regularisation term (VC dimension), both are minimised simultaneously. For traditional least-square regression, ε is always zero and data are not mapped into higher dimensional spaces. Hence, SVR is a more general and flexible treatment of regression problem.

Since ϕ may map X_i to a very high or infinite dimensional space, numerical optimisation in a high dimensional space suffers from the curse of dimensionality. Instead of solving ω for (1) in high dimension, the dual problem of (1) is solved. The dual problem is cast entirely in terms of its training data.

$$\min_{\alpha,\alpha^*} Q(\alpha,\alpha^*) = \tfrac{1}{2}(\quad \varepsilon\sum_{i=1}^{N}(\alpha_i + \alpha_i^*) + \sum_{i=}^{N} \qquad (2)$$

subject to,

$$\sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0,$$

$$0 \le \alpha_i \le C,\ i = 1,2$$

$$0 \le \alpha_i^* \le C,\ i = 1,$$

where, $K_{ij} = \phi(X_i)^T.\phi(X_j)$. However, this inner product may be expensive to compute because $\phi(X)$ has too many elements. Hence, the "kernel trick" is applied to do the mapping implicitly. That is, to employ some special forms which are inner products in higher space, but can be calculated in the original space. Some examples of kernel functions are polynomial kernel $\phi(X_i)^T.\phi(X_j) = (\gamma.X$ and the Radial Basis Function (RBF) kernel function $\phi(X_i)^T.\phi(X_j) =$. These are inner products in very high dimensional space but can be computed efficiently.

3.0 TEST SYSTEM AND PRICE INFLUENCING VARIABLES

The National Electricity Market (NEM) is a wholesale market for electricity supply in the six regions of Australia [16]. Wholesale trading in electricity is conducted as a real-time spot market where demand and supply are instantaneously matched in real-time through a centrally coordinated economic dispatch process. A dispatch price is determined every five minutes, and six dispatch prices are averaged every half-hour to determine the spot price, known as System Marginal Price (SMP). There are 48 trading intervals of half-hour duration in each trading day in the NEM. There is a separate SMP for each trading interval in each of the NEM's six regions known as the Regional Reference Price (RRP). The RRP for Victoria region has been predicted in this study. For each trading day D, participants need to submit their bids on day D-1 before 12:00 pm. Following the definition of historical volatility [6], the daily logarithmic return y_t for all market prices can be calculated as:

$$y_t = \ln(p_t) - \ln(p_{t-} \qquad (3)$$

where, p_t is the price information at time t, and $p_{t\text{-}48}$ is the price information 48 intervals before time t. Historical price volatility (σ) is defined as the standard deviation of y_t over a specified period of time. The yearly volatility of RRP and statistical properties of RRP and Total Market Demand (TMD) has been presented in Table 1.

TABLE 1

YEAR-WISE STATISTICAL PROPERTIES OF RRP AND TMD (VEM)

Statistical Property	RRP ($)			TMD (MW)		
	2002	2003	2004	2002	2003	2004
Mean	33.20	23.10	30.04	5427.2	5560.6	5644.5
Minimum	-228	0.90	-329.9	3760.4	3736	3820.7
Maximum	4906.1	6444.2	3240.9	7581.4	8524.1	7956.7
Skewness	27.8	53.4	29.7	0.11	0.22	0.07
Kurtosis	871.3	3163.2	1144.8	2.28	2.59	2.18
σ	0.46	0.40	0.48	-	-	-

Input variables for the price forecasting model have been selected after performing correlation analysis [17]. The list of price influencing variables have been given in Table 2, which has been used for building the model in this work. The following variables have been considered: (i) historical RRP values (ii) TMD (iii) air temperature (iv) dew point temperature (v) humidity (vi) wind speed and (vii) crude oil prices. When correlation analysis was performed after taking half-hourly series of these variables, no conclusion could be drawn due to the highly volatile nature of RRP. Therefore, a correlation analysis of daily averages was performed and has been presented in Table 2. Some linear correlation between RRP and its past values and TMD can be observed. The correlation coefficient (ρ) between TMD and air temperature has been found to be –0.37. Correlation of RRP with wind speed and crude oil prices is insignificant.

TABLE 2

CORRELATION ANALYSIS OF D-DAY'S PRICE WITH OTHER VARIABLES IN VEM

Sl. No.	Variable	ρ (VEM, 03-01-2002 to 05-31-2002)
1.	RRP (D-n), n = 2, 3, 7, 14	0.49, 0.24, 0.04, 0.18
2.	TMD (D-n), n = 0, 2, 7, 14	0.27, 0.16, 0.15, 0.09
3.	Air temperature (D-2)	-0.37
4.	Dew point temperature (D-2)	-0.17
5.	Humidity (D-2)	0.26
6.	Wind speed (D-2)	-0.035
7.	Crude oil (D-2)	0.045
D - day under consideration, n - number of lagging days		

4.0 PRICE FORECASTING MODELS FOR VEM

The methodologies of price forecasting models compared in this work have been explained as follows:

4.1 Heuristic model (M1)

For price forecasting, heuristic model assumes a strong and linear relationship between price and load, whose trends and levels repeat daily, weekly and seasonally. The expected price predicted by this method can be defined as:

$$RRP_{D,t} = RRP_{D-cc} \tag{4}$$

$RRP_{D,t}$ is the expected price for forecast day D at time t.

$RRP_{D-comp,t}$ is the price at time t of the comparable day of forecast day D.

$DEM_{D,t}$ is the forecast load for day D at time t.

$DEM_{D-comp,t}$ is the load at time t of the comparable day of forecast day D.

Comparable day has been assumed as the corresponding day of the previous week i.e. 7 days before D-day. This has been taken to capture the weekly demand cycle. Load demand, on day D-2, at the corresponding trading interval has been taken as the forecast load $DEM_{D,t}$.

4.2 Naïve method (M2)

For price forecasting, naive method is based on the characteristics of the price curve, following a daily and weekly pattern. So price during a particular half-hour of a trading day ($RRP_{D,t}$) may be assumed to be equal to the last week's price during the same half-hour of the corresponding weekday ($RRP_{D-7,t}$).

$$RRP_{D,t} = RRP_{D-7.} \tag{5}$$

4.3 MLR model (M3)

This model is based on the MLR approach [17]. Since modelling each half-hour of the day separately presents better forecasting properties than the whole time-series [3]; the complete data set has been divided into 48 time-series, each one corresponding to half-hour of the day. Regression coefficients, for each of the 48 time-series for the predicted day (D-day), have been calculated using the data of the past fifteen weeks. The length of data period from fifteen weeks to seven weeks was tried and optimum results were obtained using the data of fifteen weeks. Initially, all input variables given in Table 2 were considered; but the best results were obtained using demand variables and its lags only. The variable set given in Table 3 has been used for final prediction.

4.4 SVM model (M4)

This model has been implemented using MATLAB 7.0. The steps for forecasting procedure are:

Step 1: All variables, as given in Table 4, have been selected as input variables.

Step 2: Complete data set has been divided into 48 separate series, each corresponding to a half-hour of the day. All inputs X_i and output y_i are scaled to be in the range [-1, 1]. For each series, separate SVM models were used for prediction. Overall, 48 SVMs were used for prediction.

TABLE 3

INPUT VARIABLE SET FOR MLR MODEL (M3)

S. No.	Variable	Time lag
1.	Constant	-
2.	TMD	(d-2, t)
3.	TMD	(d-7, t)
4.	Daily Average TMD	(d-2)

Step 3: After model selection and the preparation of data set, SVM model was built for price forecasting. When training an SVM model, there are some parameters to choose as they may influence the performance of an SVM model. These are: (i) cost of error C (ii) the width of the ε-insensitive tube (iii) the mapping function or kernel function ϕ and (iv) number of days of training data for model estimation.

In this work, for each series, the past 105 days, data has been used for SVM model training and estimating the parameters for D-day. For the parameter ε, this was fixed at 0.01 after a few iterations. The Gaussian Radial Basis Function (RBF) kernel was used as a mapping function. The RBF function is of the form:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2.\sigma^2}\right) \tag{6}$$

where, σ is a parameter associated with the RBF function, which has to be tuned. σ and C were set at 17.62 and 65 respectively for training the SVM model and the subsequent prediction.

5.0 RESULT ANALYSIS AND PERFORMANCE EVALUATION

Mean absolute percentage error (MAPE) has been adopted to assess and compare the performance of the models. MAPE can be defined as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_t - X_f}{X_t}\right| \times 100 \tag{7}$$

where, X_t is the actual value of the predicted variable and X_f is the forecasted value. N is the number of observations used for analysis. N = 48 and 1440, for Daily MAPE (DMAPE) and monthly MAPE calculations respectively.

TABLE 4

FINAL VARIABLE SET FOR SVM MODEL (M4)

Variable	Time lag
TMD	D-2
RRP	D-2
Daily average TMD	D-2, D-7, D-14
Daily average RRP	D-2, D-7, D-14
Daily average air temperature	D-2
Daily average dew point temperature	D-2

5.1 Comparison of forecasting performance of the models

The price forecasting has been performed using data from period March 18, 2003 to June 30, 2004. Forecasting test period is from July 1, 2003 to June 30, 2004. Average monthly MAPE comparison along with monthly volatility has been presented in Table 5. It can be observed from the tables that performance of M4 is better than the other three models. Overall MAPE performance of M4 is better than M1, M2 and M3 by 37.36%, 37.67% and 32.05% respectively.

M4 outperforms M1, M2 and M3 during all twelve months. A comparison of DMAPE for 366 days test period has been presented in Table 6, where the count of days having DMAPE below a certain range is given. For 199 days, DMAPE of M4 is below 20%, which is better than the other three models. For only 34 days, DMAPE of M4 is above 50%, which is lowest among all the four models. The maximum DMAPE is also lowest in the case of M4. During the whole test period, volatility was very high. Especially during January and February 2004, volatility was 0.53 and 0.75 respectively. This may be due to complex bidding strategies adopted by the participants. Even then, the performance of M4 is reasonable.

TABLE 5

MONTHLY MAPE COMPARISON IN VEM

Month	M1	M2	M3	M4	Volatility
July, 2003	38.04	40.02	40.55	16.77	0.37
August, 2003	38.13	39.01	40.21	18.25	0.33
September, 2003	**16.88**	**16.02**	**32.52**	**14.79**	**0.27**
October, 2003	31.66	30.86	29.78	20.47	0.34
November, 2003	21.49	17.92	19.49	17.67	0.29
December, 2003	35.78	43.10	32.20	30.66	0.40
January, 2004	55.13	54.75	41.66	36.28	0.53
February, 2004	**113.6**	**115.4**	**59.89**	**48.40**	**0.75**
March, 2004	28.05	26.19	46.01	25.26	0.38
April, 2004	36.46	39.03	37.66	24.99	0.40
May, 2004	28.21	25.69	29.01	20.56	0.36
June, 2004	32.98	30.84	30.19	25.17	0.47
Average	**39.70**	**39.90**	**36.60**	**24.87**	**0.41**

TABLE 6

DMAPE EVALUATION FOR THE TEST PERIOD

DMAPE Range	M1	M2	M3	M4
< 20%	124	146	86	199
< 30%	228	232	203	283
< 40%	277	288	255	312
< 50%	304	303	287	332
> 50%	62	63	79	34
Max. DMAPE	796.28	852.20	193.21	157.43
Min. DMAPE	4.91	4.48	7.93	5.48

5.2 Comparison of forecasting performance M3 with other studies in VEM

A comparison of the forecasting performance of M4 with other studies of price forecasting for VEM was also performed. The other reported works for price forecasting in VEM are based on NN models [8-9]. Authors of [9] have applied NN model for one-time interval (half-hour) ahead price forecasting. In [8], the NN model has been used for one to six-hour ahead RRP forecasting. In [8], a Euclidian norm with weighted factors was used to find days similar to that of the forecasted day. Then, a gradient based NN model was trained with the data of these similar days to predict the price profile using recursive technique. However, the price profile consisted of twenty-four points with each point equal to an average of two half-hourly prices. The MAPE of six-hour ahead price forecasting during September 2003 was 20.03% and during first week of September, 2003 was 25.77%. It is clear from Table 5 that MAPE of M4 during the month of September 2003 was 14.79% for a forecasting horizon of 24-hours. During the first week of September 2003 test period; MAPE of M4 was observed as 6.33%, which is better than results presented in [8]. So model M3 has the potential to outperform other AI based models proposed for VEM. Moreover available models [8-9], can predict RRP after bidding is closed; whereas, the proposed model M3 predicts RRP well before closing of the bids.

5.3 Validation of Model M4

A reasonable forecasting technique can be properly validated if (i) its performance is better than the well-accepted methods; (ii) the comparison is based on the performance of test samples; (iii) the size of the test samples are adequate. In this work, M1, M2 and M3 have been selected as benchmarks and it has been observed that M4 performs better than the other three. Although models M1 and M2 look simple, they have the potential to outperform more complicated models. So these are tough benchmarks to beat in a highly volatile electricity market like VEM. The forecasting accuracy of M4 is better than the available NN models in the literature as well. All comparison has been made on the basis of a 366 days test sample and is sufficient.

In order to understand weaknesses and strengths of the proposed model, the ability of the model M4 to forecast turning points has been shown graphically for one day and four different weeks during four seasons in Figs. 2 to 6. From Fig. 2, it is clear that M4 has the potential to follow the price curve quite closely. During the considered four week period, large daily variations in RRP can be observed. RRP varies from 10$ to 140$ in Fig. 3, 5$ to 70$ in Fig. 4, 10$ to 42$ in Fig. 5 and 3$ to 120$ in Fig. 6. The main strength of the model is that it predicts the trend very well and even predicts the small peaks accurately. This is clearly evident from Figs. 2 to 6. The main limitation of the model M3 is that it cannot predict the large peaks accurately, in fact due to this shortcoming, prediction quality is not very high. But it has been pointed out in [18] that VEM is a highly volatile market and prediction in real-time single settlement electricity markets is very difficult. In this case, the overall performance of M4 is better than M1, M2, M3 and previously reported NN based models. It can be observed from Table 5 that the performance of M3 is least affected by volatility, whereas performance of M1 and M2 suffers the most during the highly volatile periods. The proposed method M4 is easier to implement, it utilises publicly available information only and provides forecasted results before bidding time on D-1 day. Thus it can be utilised by the participants for all practical purposes to respond properly.

6.0 CONCLUSION

In this work, a new approach for price forecasting using SVM has been proposed and implemented on data from VEM, which is a highly volatile electricity market. The problem has been framed as 48 separate half-hourly equations. Correlation analysis of price with its influencing variables has been performed. One of the important contributions of this paper is the case study of VEM by applying SVM for a sufficient forecasting period and comparison with four other techniques. The proposed model (M4) has been compared with heuristic method (M1), naïve method (M2) and MLR model (M3) over a period of one year. Forecasting accuracy has also been compared with the previously reported NN model. Model M4 outperforms M1, M2 and M3 by more than 30%. By analysing the forecasting performance of all the five models, it can be concluded that the proposed SVM based model (M4) provides forecast with better accuracy and can easily find real-world price forecasting application as it predicts price before the submission of bids and utilises publicly available information only.

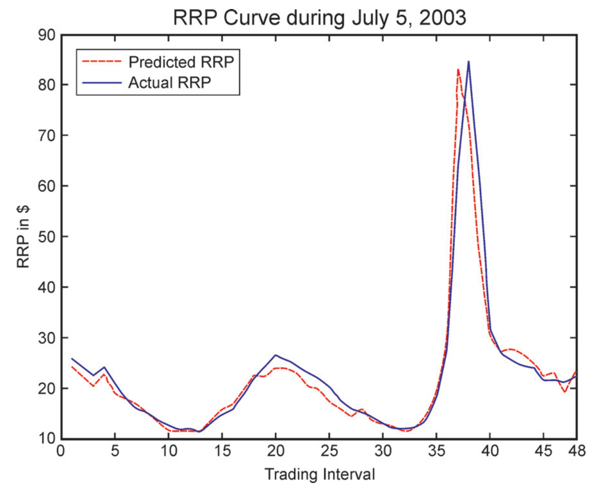

FIG. 2 ACTUAL AND PREDICTED PRICE CURVES FOR JULY 5, 2003

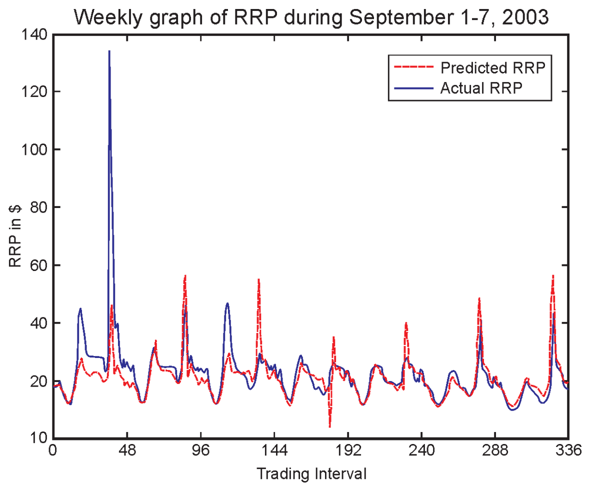

FIG. 3 ACTUAL AND PREDICTED PRICE CURVES DURING SEPTEMBER 1-7, 2003

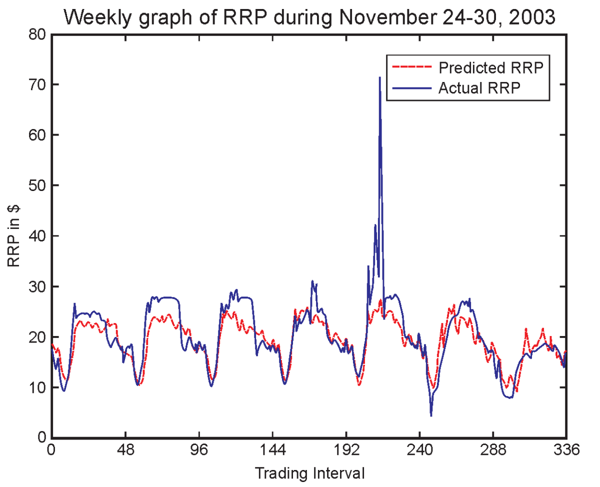

FIG. 4 ACTUAL AND PREDICTED PRICE CURVES DURING NOVEMBER 24-30, 2003

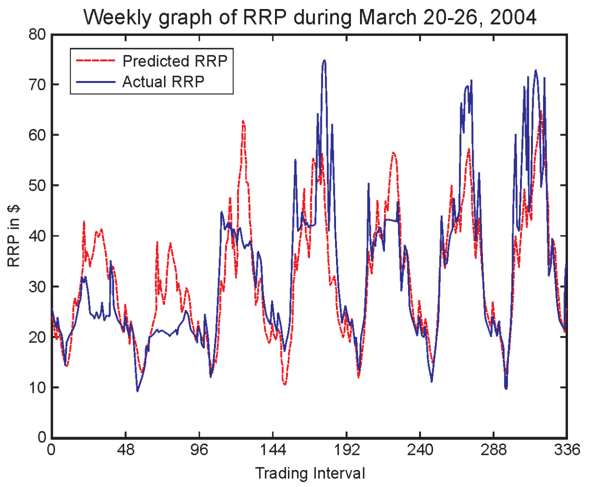

FIG. 5 ACTUAL AND PREDICTED PRICE CURVES DURING MARCH 20-26, 2004

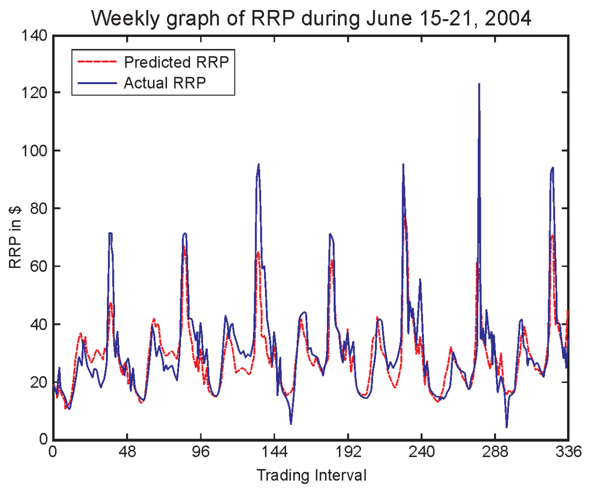

FIG. 6 ACTUAL AND PREDICTED PRICE CURVES DURING JUNE 15-21, 2004

7.0 ACKNOWLEDGEMENT

The authors are thankful to the Bureau of Meteorology, Victoria, Australia, for providing the weather data from their data bank.

REFERENCES

[1] G B Sheble, “Computation Auction Mechanism for Restructured Power Industry Operation”, Norwell, MA: Kluwar Academic Publishers, 1999.

[2] R Deb, R Albert, Lie-Long Hsue and N Brown, “How to Incorporate Volatility and Risk in Electricity Price Forecasting”, The Electricity Journal, May 2000, pp. 1-16.

[3] D W Bunn, “Forecasting Loads and Prices in Competitive Power Markets’, Proceedings of the IEEE, Vol. 88, No. 2, 2000, pp. 163-169.

[4] H Zareipour, K Bhattacharya and C Canizares, “Electricity Market Price Volatility: The Case of Ontario”, Journal of Energy Policy, 2007, doi: 10.1016/ j.enpol. 2007.04.006, pp. 19.

[5] G Li, Chen-Ching Liu, C Mattson, J Lawarree, “Day-ahead Electricity Price Forecasting in a Grid Environment”, IEEE Trans. on Power Systems, Vol. 22, No. 1, February 2007, pp. 266-274.

[6] H Zareipour, C A Canizares and K Bhattacharya, "Application of Public-Domain Market Information to Forecast Ontario's Wholesale Electricity Prices", IEEE Trans. on Power Systems, Vol. 21, No. 4, November 2006, pp. 1707-1717.

[7] C Garcia-Martos, J Rodriguez and M J Sanchez, "Mixed Models for Short-run Forecasting of Electricity Prices: Application for the Spanish Market", IEEE Trans. on Power Systems, Vol. 22, No. 2, May 2007, pp. 544-552.

[8] P Mandal, T Senjyu, T Funabashi, "Neural Networks Approach to Forecast Several Hour Ahead Electricity Prices and Loads in Deregulated Market", Journal of Energy Conversion and Management, 47, 2006, pp. 2128-2142.

[9] B R Szkuta, L A Sanabria, and T S Dillon, "Electricity Price Short-term Forecasting Using Artificial Neural Networks', IEEE Trans. on Power Systems, 1999, Vol. 14, No. 3, 851-857.

[10] T Niimura, T Nakashima, "Deregulated Electricity Market Data Representation by Fuzzy Regression Models", IEEE Trans. on Systems, Man, and Cybernetics – Part C: Applications and Reviews, Vol. 31, No. 3, August 2001, pp. 320-326.

[11] T Niimura, Hee-Sang Ko and K Ozawa, "A Day-ahead Electricity Price Prediction Based on a Fuzzy-neuro Autoregressive Model in a Deregulated Electricity Market", Proc. of the 2002 International Joint Conference on Neural Networks, Vol. 2, No. 12-17, pp. 1362-1366.

[12] V Vapnik, "Statistical Learning Theory", Wiley Interscience, New York, 1998.

[13] V N Vapnik, "An Overview of Statistical Learning Theory", IEEE Trans. on Neural Networks, Vol. 10, No. 5, 1999, pp. 988-999.

[14] Bo-Juen Chen, Ming-Wei Chang and Chih-Jen Lin, "Load Forecasting Using Support Vector Machines: A Study on EUNITE Competition 2001", IEEE Trans. on Power Systems, Vol. 19, No. 4, 2004, pp.1821-1830.

[15] N Christianini and J Shawe-Taylor, Introduction to Support Vector Machines, Cambridge University Press, 2000.

[16] Website of National Electricity Market of Australia: http://www.nemmco.com.au

[17] MATLAB Statistical Toolbox, The Mathworks, Available: http://www.mathworks.com/

[18] Ying Li and Peter C Flynn, "Deregulated Power Prices: Changes Over Time", IEEE Trans. on Power Systems, Vol. 20, No. 2, May 2005, pp. 565-572.

Readers are invited to offer their comments on the article. Please fill in the Reader's Forum.