International Journal of Computational Intelligence Systems, Vol. 4, No. 4 (June, 2011), 476-485

DAY-AHEAD PRICE FORECASTING IN ASIA'S FIRST LIBERALIZED ELECTRICITY MARKET USING ARTIFICIAL NEURAL NETWORKS

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Received 9 December 2010
Accepted 4 April 2011

Abstract

This paper proposes a comparative model for the day-ahead electricity price forecasting that could be realized using multi-layer neural network (MLNN) with levenberg-marquardt (LM) algorithm, generalized regression neural network (GRNN) and cascade-forward neural network (CFNN). In this work applications of various models were applied to national electricity market of Singapore (NEMS), i.e. Asia's first liberalized electricity market. The individual price of year 2006 is very volatile with a very wide range. Therefore, accurate forecasting models are required for Singapore electricity market company (EMC) to maximize their profits and for consumers to maximize their utilities. Hence the year 2006 has been taken for forecasting the uniform Singapore electricity price (USEP). The mean absolute percentage error (MAPE) results show that the proposed CFNN model possess better forecasting abilities than the other models and its performance was least affected by the volatility.

Keywords: Price forecasting, Levenberg-marquardt (LM) algorithm, Generalized regression neural network (GRNN), Cascade-forward neural network (CFNN), National electricity market of singapore (NEMS), Uniform singapore energy price (USEP).

1. Introduction

In a de-regulated electric power industry, the electricity prices play a key role for market participants. The main objective of market participants is to ensure a transparent, professional and cost-effective market. Since the beginning of floating electricity prices, electricity price forecasting has become one of the main endeavors for researchers and practitioners in energy market.[1] The daily load curves have similar load patterns, whereas the electricity price movement shows very great volatility among all commodities.[2] Electricity price can rise to tens of or even hundreds of times its normal values at some periods. Sometimes, it may drop to zero or even to negative values at other periods.[3, 4] A good price forecasting tool in deregulated markets should be able to capture the uncertainty associated with those prices. Some of the key uncertainties are fuel prices, future addition of generation and transmission capacity, regulatory structure and rules, future demand growth, plant operations and climate changes.[5] From these many factors are impacting electricity price, in which some

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factors are more important than others. Besides, the factors, which impact price, they consider are very limited, just including historical price and system load.[6] Therefore, price forecasting tools are essential for all market participants for their survival under new de-regulated environment.[7]

Seeing the importance of the price-forecasting problem several techniques have been tried out in this paper. In general, hard and soft computing techniques could be used to predict electricity prices.[5]

Prediction under hard-computing models, such as auto-regressive integrated moving average (ARIMA) and generalized auto-regressive conditional heteroskedastic (GARCH) are used. This approach can be very accurate, but it requires a lot of information, and the computational cost is very high.[3]

Prediction under soft-computing models, such as artificial neural network (ANN) and other intelligent algorithms are used. In particular, neural networks have been used to solve problems such as load/price predictions, component and system fault diagnosis, security assessment, unit commitment etc. The ANN is a simple, powerful and flexible tool for forecasting, providing better solution to model complex non-linear relationships.[8]

The considered hard computing models are linear predictors,[13] while electricity price is generally a nonlinear. The proposed ANN soft computing approach works on complex nonlinear relationships than the traditional linear models. Moreover, there is no hard computing approach with satisfactory performance in dealing with the spikes.[8] Hence, compared to hard computing, an important advantage of the proposed soft computing approach is, it learns well the nonlinear training pattern. It effectively encounters even large prediction errors in the test phase. The soft computing models are fast in execution. The hard computing models are time consuming.[5] The superiority of the soft computing model is on the robustness, particularly in the easy interpretability of the models.

Some electricity market price forecasting models using a multi-layer neural network (MLNN), training by levenberg-marquardt (LM) algorithm,[5,14,15] and generalized regression neural network (GRNN) with principal component analysis (PCA)[12] have been reported in these literatures.

The price evaluation is different in different markets and therefore large variations exist in price-forecasting accuracy achieved by different models across different electricity markets. No single available model has been applied across data from larger number of markets. There is a need to make more research efforts in other markets as well; this will help in interpreting and understanding the price evolution in different electricity markets in a better perspective.[7]

So, this paper mainly focuses on several half-hour ahead electricity prices using historical data from the Singapore's power system. The Singapore's electricity pool, an Asia's first liberalized electricity market; a new legal and regulatory framework was introduced that formed the basis for a new electricity day-ahead market. The electricity market company (EMC) implemented the wholesale market systems, rules and business that would underpin the new market.

The national electricity market of Singapore (NEMS) opened for trading, placing Singapore's at the forefront of a global movement to liberalize the electricity industry. All of Singapore's electricity is bought and sold through EMC in the NEMS. The EMC is the exchange for wholesale electricity trading, providing a transparent and competitive trading platform and the governance for the market. Generation companies offer every half-hour to sell electricity into the wholesale electricity market. All sales and purchases of electricity through the wholesale market are settled through EMC. Generators and retailers or major users can enter into financial bilateral agreements outside the wholesale market.[9]

In Singapore's electricity market, the price of electricity varies every half-hour, so generators, retailers and consumers require some expectation of future electricity prices to aid them in optimizing their business strategies. Among the different techniques of price forecasting, application of ANN technology has been adopted in this paper because of its ability to learn complex and non-linear relationships that are difficult to model with conventional techniques.[2]

In this study, a comparative electricity price forecasting was realized by using MLNN with LM algorithm, GRNN and proposed cascade-forward neural network (CFNN). The electricity price dataset were prepared by using singapore's daily trading reports, presented on a monthly basis. The CFNN are capable of recasting price efficiently than the other neural network structures, expecting a better mean absolute percentage error (MAPE).

To determine the effect of the proposed CFNN, different ANN models (MLNN with LM algorithm and GRNN) are trained. The remaining neural network models supported by the MATLAB are not able to learn the proposed electricity price dataset. Hence the above three models were taken.

The rest of the paper is organized as follows. The section 2 presents data source and the different neural network structures to forecast electricity price using their dataset. Section 3 presents the numerical results of various neural network structures from a real-world case study based on the electricity market of Singapore. Finally, conclusions are presented in section 4.

2. Methodology

This section describes the data source and different neural network structure for day-ahead price forecasting in Asia's first liberalized electricity market.

2.1. *Data source*

In order to perform the research reported in this paper, the electricity price data taken from Singapore's daily trading reports, presented on a monthly basis was used. The data set which consists of uniform Singapore energy price (USEP) and system demand.[9] As previously mentioned, the inputs of the ANN model is the historical USEP and system demand. The most effective lags (price of the previous half-hours) are selected by correlation analysis.[6] The lags l ε L = {1, 2, 3, 4, 5, 6 47, 48, 49, 50, 95, 96, 97, 98, 143, 144, 145, 146, 191, 192, 193, 194, 239, 240, 241, 242, 287, 288, 289, 290, 335, 336} were selected lags based on this analysis.

All samples have thirty three features. These features are thirty two historical USEP and system demand.

2.2. *Electricity price forecasting using MLNN structure*

In the first stage of the study, the MLNN structure with one hidden layer was used for the electricity price forecasting. This MLNN structure (with one input layer, one hidden layer and one output layer) is shown in Fig. 1. the hidden layer neurons (23 neurons) and the output layer neurons (one neuron) use non-linear hyperbolic-tangent-sigmoid activation functions. In this system, thirty three inputs are featured, and only one output is used for forecast electricity price. Equations used in the MLNN structure with only one hidden layer are shown in (1) and (2).

Outputs of the hidden layer neurons are:

$$\vec{X}^{ih}(n) = 2/(1+\exp(-2*(\mathrm{W}^{\mathrm{ih}}(n)*\vec{f}(n)+\vec{b}^{ih}(n))))-1, \quad (1)$$

Output of the network is:

$$Y(n) = 2/(1+\exp(-2*(\mathrm{W}^{\mathrm{ho}}(n)*\vec{X}^{ih}(n)+b^{ho}(n))))-1, \quad (2)$$

Where $\mathrm{W}^{\mathrm{ih}}(n)$ are the weights from the input to the hidden layer and $\vec{b}^{ih}(n)$ are the biases of the hidden layer, $\mathrm{W}^{\mathrm{ho}}(n)$ are the weights from the hidden layer to the output layer and $b^{ho}(n)$ are the biases of the output layer, $\vec{f}(n)$ values are the input features. $Y(n)$ value is the output for forecast electricity price, and n is training pattern index.

The back-propagation (BP) algorithm (Rumelhart et al., 1986) is widely recognized as a powerful tool for training of the MLNNs. But, since it applies the steepest descent method to update the weights, it suffers from a slow convergence rate and often yields suboptimal solutions (Brent, 1991; Gori & Tesi, 1992). A variety of related algorithms have been introduced to address that problem and a number of researchers have carried out comparative studies of MLNN training algorithms (Hagan & Menhaj, 1994; Hagan, Demuth, & Beale, 1996; Sagiroglu et al., 2000). Levenberg–Marquardt (LM) algorithm (Hagan & Menhaj, 1994) used in this study is one of the fastest types of these algorithms (Gulbag & Temurtas, 2006; Er & Temurtas, 2008). Detailed computational issues about the application of the training algorithms to MLNN structures can be found in references (Er & Temurtas, 2008).

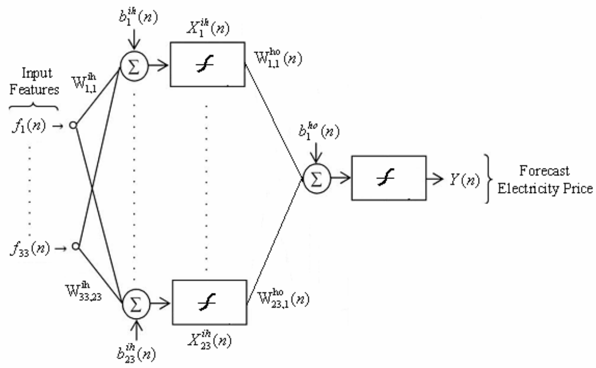

Fig. 1. Implementation of multi-layer neural network for electricity price forecasting.

The MLNN with LM structure employed in the study utilized the newff function implemented in MATLAB. Detailed information about the realization of the MLNN with LM structures can be found in the neural network toolbox part of MATLAB Documentation (MATLAB Documentation, 2007).

2.3. *Electricity price forecasting using GRNN structure*

At the second stage of this study, GRNNs, were devised by Speckt (1990), Speckt (1991). The GRNN structure used in this study has a multilayer structures consisting of an input layer, a single hidden layer (radial basis layer), a layer of regression units, and an output layer as shown in Fig. 2. The regression layer ($S_1(n)$) must have exactly one unit more than the output layer. The regression layer contains linear units. In this system, real valued input vector is feature's vector, and only one output forecast electricity prices. All hidden units simultaneously receive the 33-dimensional real valued input vector. Equations that are used in the neural network model are shown in (3)–(6):

$$X_j = \phi\left(\left\| \vec{f} - \vec{c}_j \right\| * b^{ih} \right), \tag{3}$$

$$\phi(x) = \exp(-x^2), \tag{4}$$

$$b^{ih} = 0.8326 / s, \tag{5}$$

$$Y = \frac{\sum_{j=1}^{h} W_j^{ho} * X_j}{\sum_{j=1}^{h} X_j}, \tag{6}$$

Where j = 1, 2, ..., h (number of hidden neurons), Y is the output, $\vec{f}$ is the 33-dimensional real valued input vector, W^{ho} are the regression layer weights, $\vec{c}_j$ is the center vector of the j^{ih} node, is the real constant known as spread factor, b^{ih} is the biasing term of radial basis layer, and $\phi(\cdot)$ is the non-linear radial basis function (Gaussian).

The GRNN structures employed in the study utilizes the newgrnn function implemented in MATLAB. Detailed information about the realization of the GRNN structures can be found in the neural network toolbox part of MATLAB Documentation (MATLAB Documentation, 2007).

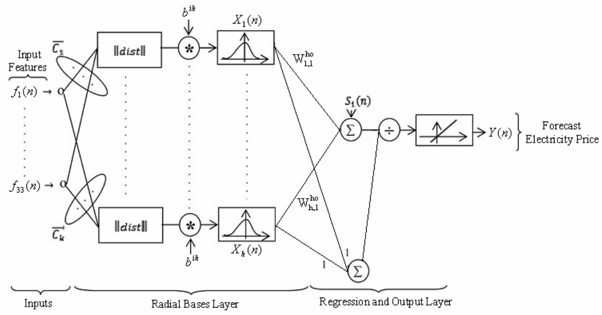

Fig. 2. Implementation of generalized regression neural network for electricity price forecasting.

2.4. *Electricity price forecasting using CFNN structure*

At the third stage of this study, a CFNN was used for the electricity price forecasting. In this CFNN structure (with one input layer, one hidden layer and one output layer), the first layer has connecting weights with the input layer and each subsequent layer has weights coming from the input as well as from all previous layers is shown in Fig. 3. The hidden layer neurons (23 neurons) and the output layer neuron (one neuron) use non-linear hyperbolic-tangent-sigmoid activation functions. In this system, thirty three inputs are featured, and only one output for forecast electricity prices.

Like MLNNs, CFNN uses BP algorithm for updating of weights but the main symptoms of the network is that each neuron is related to all previous layer neurons. In,[10] several neural network topologies were evaluated and it was found that CFNN with BP training provides the best performance in terms of convergence time, optimum network structure and recognition performance. The training of MLNNs normally involves BP training as it provides high degrees of robustness and generalization.[11]

The CFNN structure employed in the study utilizes the newcf function implemented in MATLAB. Detailed information about the realization of the CFNN structures can be found in the neural network toolbox part of MATLAB Documentation (MATLAB Documentation, 2007).

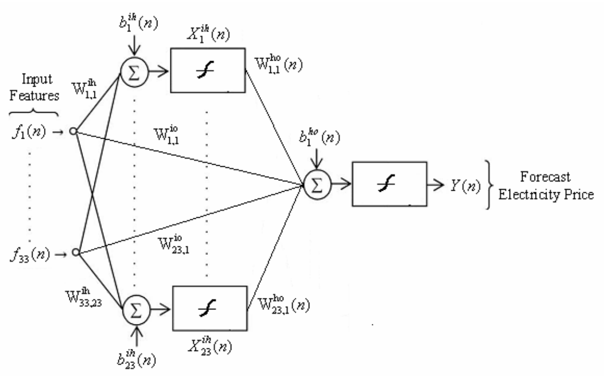

Fig. 3. Implementation of cascade-forward neural network for electricity price forecasting.

3. Numerical Results

This section describes the case study of Singapore's electricity market is forecasted by different neural network structure in the year 2006.

3.1. *Case studies*

The methodology described above has been applied to predict the electricity prices of Singapore's market.

Though there is some high deviation in price in the year 2005, the day-ahead electricity prices were relatively stable compared to 2006, where the prices were highly volatile than the year 2005, 2007 and 2010. A plot of the price variation at different periods of the day for a full year is shown in Figs. 4-7. It shows the electricity prices at half-hourly intervals in each month at every period. It is found that the price at Fig. 4, Fig. 6 and Fig. 7 any one given period of the day remains fairly constant compared to Fig. 5. However the values of the few individual prices only show wide variations in preceding year 2005, succeeding year 2007 and the latest year 2010 compared to year 2006. Therefore, it can be seen from Fig. 5 that the prices vary greatly, the peak prices are close to 4500$/MWh, but the lowest prices are close to zero, which are hard to predict. Hence the proposed model is applied to the year 2006. It can be taken as the bench mark year.

To build the forecasting model for each of the considered weeks, the information available includes half-hourly historical price of the 42 days previous to the day of the week whose prices are to be forecasted. Very large training sets should not be used to avoid overtraining during the learning process.[5]

When we analyzed the years 2005, 2006, 2007 and 2010 of USEP, the year 2006 is very volatile. Hence, we have forecasted the USEP for the year 2006. The proposed model performs well even in the volatile situation. Hence it is understood that it can perform efficiently in other years too which are less volatile.

For the singapore market, the southern summer week is from March 13 to March 19, 2006, the southern winter week is from August 7 to August 13, 2006, the northern summer week is from October 9 to October 15, 2006 and the northern winter week is from December 18 to December 24, 2006; the historical data available includes half-hourly prices from January 30 to March 12, 2006, from June 26 to August 6, 2006, from August 28 to October 8, 2006 and from November 6 to December 17, 2006 are used to forecast the respective week.

In this study, the input features (historical prices and demand) and target output (actual price) are linearly normalized in the range of [-1, 1]. The outputs from the ANN models were de-normalized before being presented in performance evaluation.

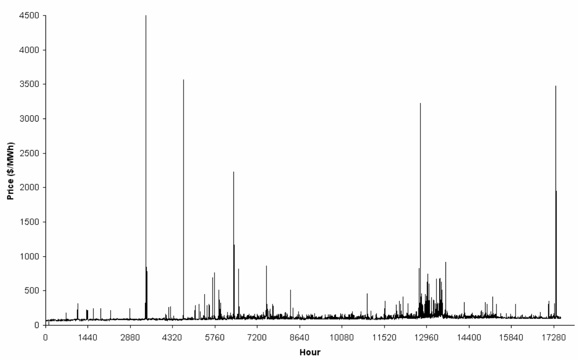

Fig. 4. Daily weighted average of energy price in the electricity market of Singapore at 2005, in SGD$ per MWh.

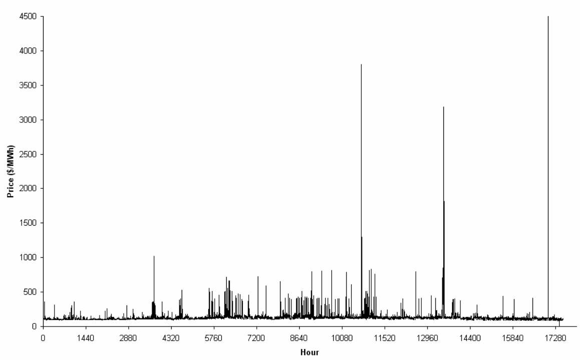

Fig. 5. Daily weighted average of energy price in the electricity market of Singapore at 2006, in SGD$ per MWh.

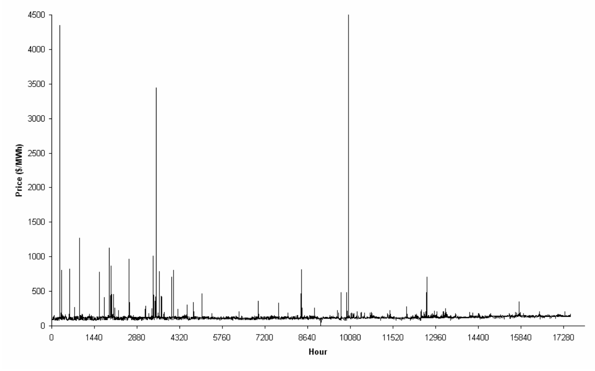

Fig. 6. Daily weighted average of energy price in the electricity market of Singapore at 2007, in SGD$ per MWh.

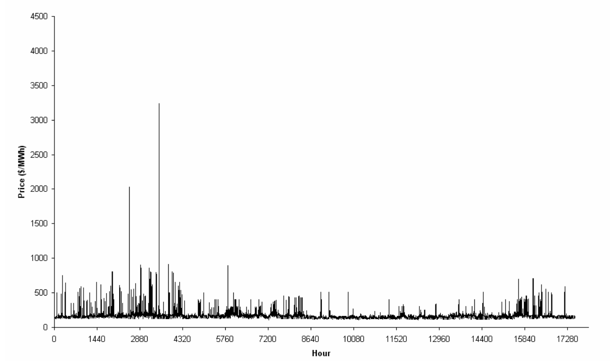

Fig. 7. Daily weighted average of energy price in the electricity market of Singapore at 2010, in SGD$ per MWh.

3.2. *Forecasting with ANN models*

The ANN models are trained in such a way that a particular input leads to a specific target output. There are generally four steps in the training and testing process (1) assemble the training data, (2) create the network, (3) train the network, and (4) compute the network response to new inputs.

In the ANN architecture, training method and spread factor were determined using trial and error approach. Several attempts were made until the proper number of hidden layers, number of neurons in hidden layer and spread factor were reached. The network architecture selected after these attempts produced minimal error in both training and testing.

The performance of the trained network is then evaluated by comparison of the network output with its actual value via statistical evaluation indices. Mean absolute percentage error (MAPE) is used to evaluate the performance of forecasting in electricity prices. The MAPE can be defined as

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| \times 100, \qquad (7)$$

Where A_i and F_i are the actual and forecasted electricity price of i^{th} half-hour, respectively, and N is the number of forecasted half-hours.

The simulations were carried out in AMD processor with 2GHz and 1GB RAM for all Singapore's electricity price forecasting sample templates. This is real world application level simulation. The simulation was conducted in three neural network structures.

3.2.1. *Forecasting with MLNN with LM*

The neural network structure have input layer composed of 33 neurons, hidden layer composed of 23 neurons and output layer with only one neuron. The MLNN is selected as the network type with LM training. The network is implemented by using the MATLAB neural network toolbox. The size of the input vector is 33 (32 historical USEP + demand) × 2016 (42 days training period×48 half-hours), and the size of the target vector is 1 (forecast price) × 2016 in this structure.

The actual and predicted prices values for four weeks using MLNN with LM is shown in Figs. 8-11. Each figure shows the forecasted prices-dashed line, the actual prices-solid line, together with the error-dotted line, the error curve is uniformly close to zero with error peaks due to electricity price volatility.

3.2.2. *Forecasting with GRNN*

The neural network structure have input layer composed of 33 neurons and output layer with only one neuron. The GRNN is selected as the network type with spread factor of 0.06009, 0.285, 0.136 and 0.211 for March, August, October and December weeks for training and forecasting. The network is implemented by using the MATLAB neural network toolbox. The size of the input vector is 33×2016, and the size of the target vector is 1×2016 in this structure.

The actual and predicted prices values for four weeks using GRNN is shown in Figs. 12-15. Each figure shows the forecasted prices-dashed line, the actual prices-solid line, together with the error-dotted line, the error curve is uniformly close to zero with error peaks due to electricity price volatility.

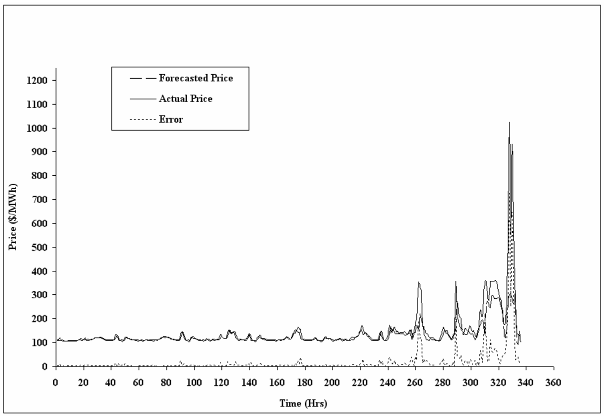

Fig. 8. Southern summer week for the Singapore electricity market: Actual prices (solid), MLNN with LM price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

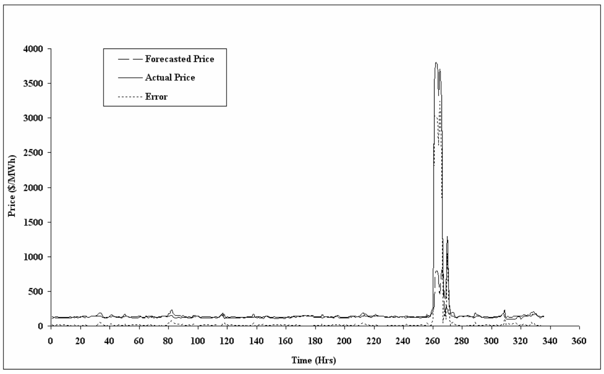

Fig. 9. Southern winter week for the Singapore electricity market: Actual prices (solid), MLNN with LM price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

3.2.3. *Forecasting with CFNN*

The neural network structure have input layer composed of 33 neurons, hidden layer composed of 23 neurons and output layer with only one neuron. The cascade-forward BP neural network is selected as the network type with LM training. The network is implemented using the MATLAB neural network toolbox. The size of the input vector is 33×2016, and the size of the target vector is 1×2016 in this structure. The best performance CFNN cascaded with 33 input neurons plus 23 hidden neurons gives the minimal error.

The actual and predicted prices values for four weeks using CFNN is shown in Figs. 16-19. Each figure shows the forecasted prices-dashed line, the actual prices-solid line, together with the error-dotted line, the error curve is uniformly close to zero with error peaks due to electricity price volatility.

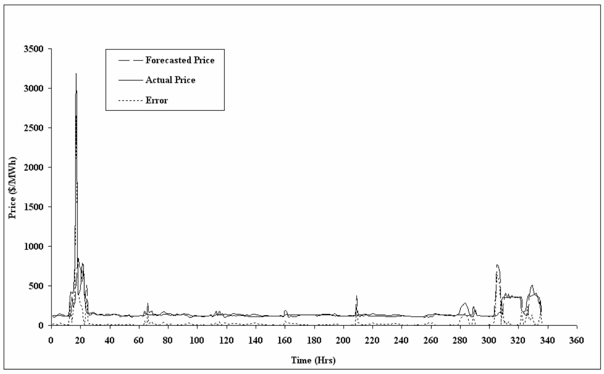

Fig. 10. Northern summer week for the Singapore electricity market: Actual prices (solid), MLNN with LM price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

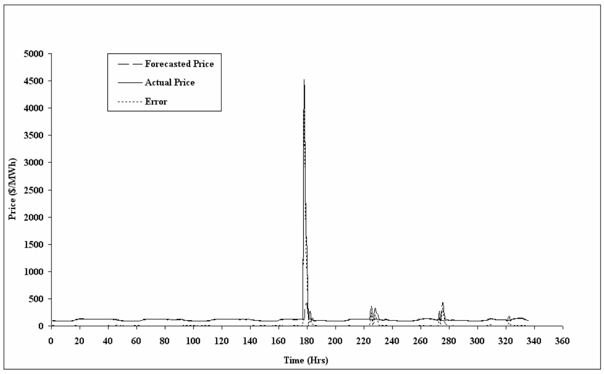

Fig. 11. Northern winter week for the Singapore electricity market: Actual prices (solid), MLNN with LM price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

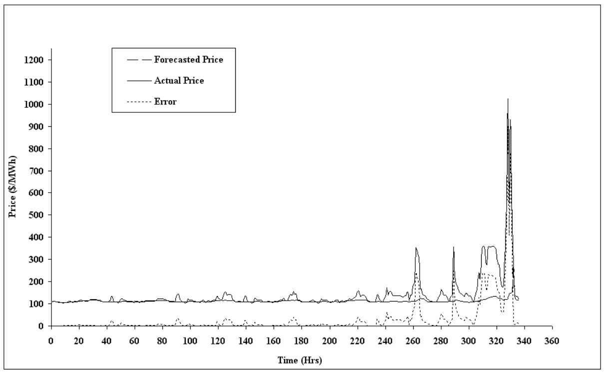

Fig. 12. Southern summer week for the Singapore electricity market: Actual prices (solid), GRNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

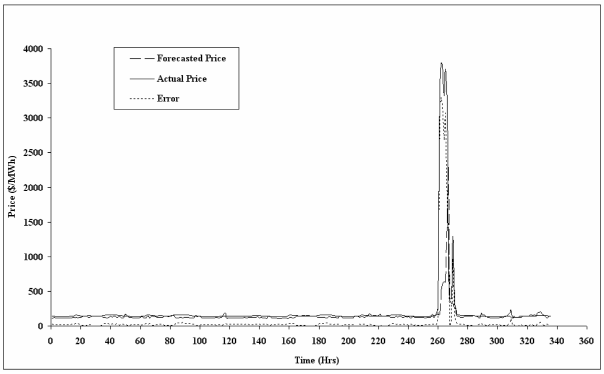

Fig. 13. Southern winter week for the Singapore electricity market: Actual prices (solid), GRNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

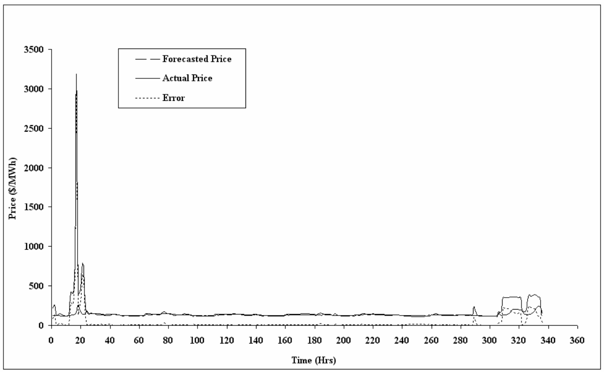

Fig. 14. Northern summer week for the Singapore electricity market: Actual prices (solid), GRNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

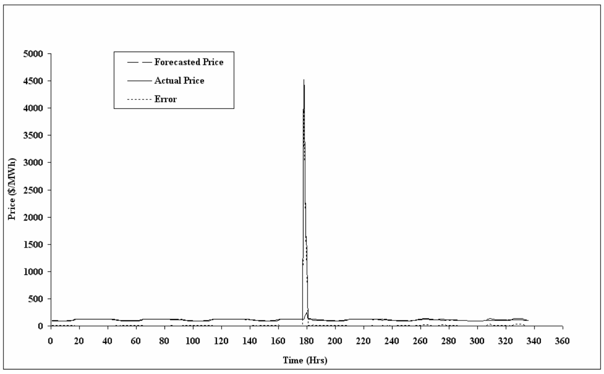

Fig. 15. Northern winter week for the Singapore electricity market: Actual prices (solid), GRNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

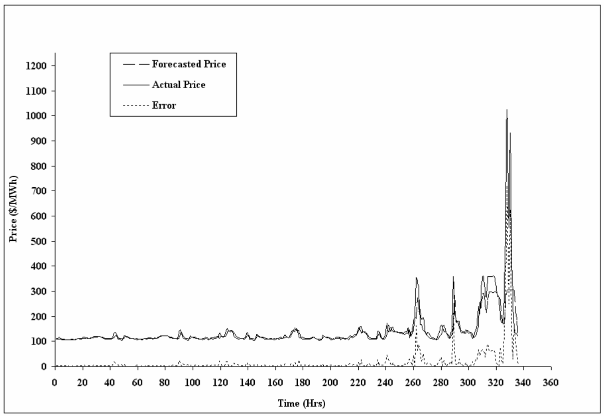

Fig. 16. Southern summer week for the Singapore electricity market: Actual prices (solid), CFNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

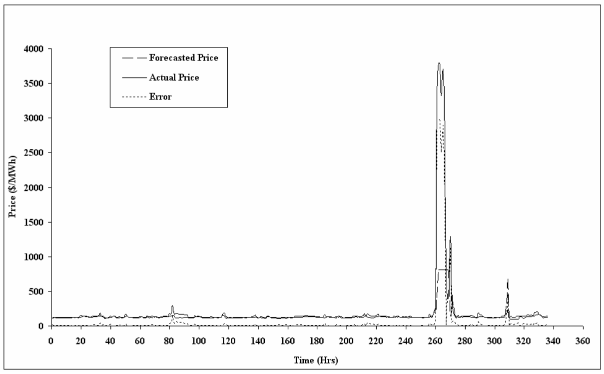

Fig. 17. Southern winter week for the Singapore electricity market: Actual prices (solid), CFNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

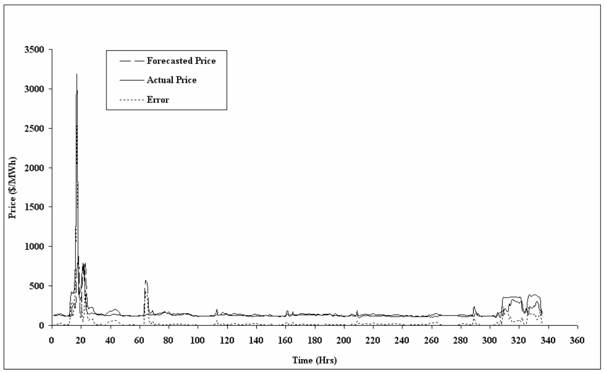

Fig. 18. Northern summer week for the Singapore electricity market: Actual prices (solid), CFNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

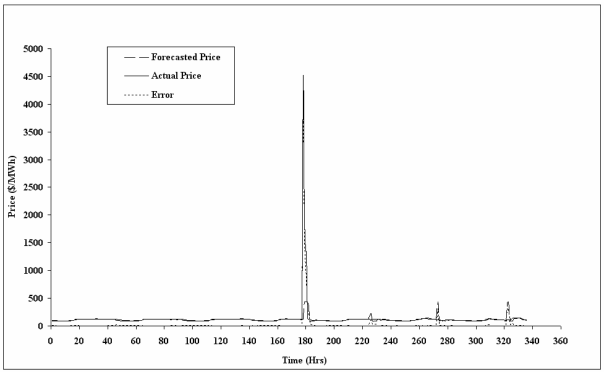

Fig. 19. Northern winter week for the Singapore electricity market: Actual prices (solid), CFNN price forecasts (dashed) and absolute value of forecast errors (dotted, at the bottom), in SGD$ per MWh.

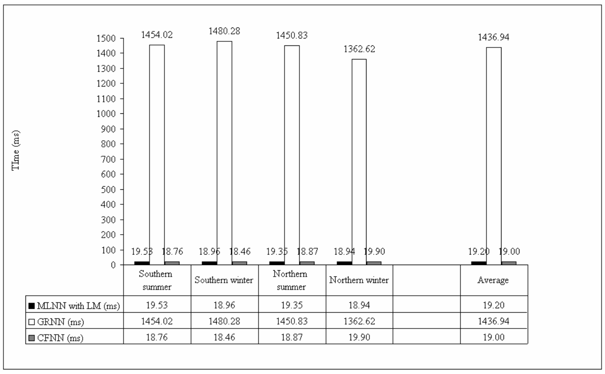

Fig. 20. Comparative computation time results between the neural network approach, MLNN with LM, GRNN and CFNN.

3.3. *The comparison of price forecasting results*

Different neural network structures are tested for NEMS and results of these analyses are compared. Table 1 presents the values to evaluate the accuracy of the neural network models in forecasting electricity prices. The first column indicates the forecast week, the second column indicates MAPE for four weeks using MLNN with LM, the third column indicates MAPE for four weeks using GRNN, and the fourth column indicates MAPE for four weeks using CFNN. The last row indicates the average value of MAPE for MLNN with LM, GRNN and CFNN respectively.

From the same table, the MAPE for the Singapore's electricity market has an average value of 11.22% results obtained using CFNN is better than the results obtained using MLNN with LM and GRNN. So, we can easily say that CFNN model possesses better forecasting abilities that the other models and its performance was least affected by the volatility. Hence, the neural network approach provides a very powerful tool of easy implementation for forecasting electricity prices.

Table 1. Comparative MAPE results between the neural network approach, MLNN with LM, GRNN and CFNN.

Forecast Week	MLNN with LM, MAPE %	GRNN, MAPE %	CFNN, MAPE %
Southern summer	7.55	12.42	7.29
Southern winter	12.36	16.88	12.37
Northern summer	17.99	11.71	15.57
Northern winter	9.23	6.73	9.65
Average, MAPE %	11.78	11.94	11.22

The computation (response) time for four weeks using MLNN with LM, GRNN and CFNN are shown in Fig. 20. In the figure, the black, white and gray bar shows the response time for MLNN with LM, GRNN and CFNN respectively. From the same figure, the computation time for the Singapore's electricity market has an average value of 19 ms. The results obtained using CFNN is better than the results obtained using MLNN with LM and GRNN.

4. Conclusion

This paper presented several ANN models for day-ahead price forecasting in Asia's first liberalized electricity market (NEMS). The important factors impacting electricity price forecasting historical price factors and demand factors are discussed. Past 42 days were trained and the next seven days were forecasted. In the first approach, an MLNN with LM model is used for price forecast. Then, different neural network structures were tested. Network types that have been tested include GRNN and CFNN. All of the neural network structures comprise 33 neurons in the input and one neuron in the output. Prediction results corresponding to the market of Singapore for the four weeks of the year 2006 is reported, yielding an average weekly MAPE which is close to 11.78% for MLNN with LM, 11.94% for GRNN, and 11.22% for CFNN respectively. In this research work, a CFNN has been proposed for price prediction. The simulation results from the comparisons clearly shows that the CFNN model is effective than other forecast models while the average computation time is 19 ms. Results show that the proposed CFNN approach is good in forecasting accuracy and less computation time than other ANN models. The research work is underway in order to develop better feature selection algorithm for different power markets and forecast models.

Acknowledgements

The authors would like to thank the Annamalai University authorities for carrying out this research work in their laboratories.

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