Day-ahead Electricity Price Forecasting Using PSO -Based LLWNN Model

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Abstract - **Price forecasting has become an important activity for market participants in electric power industry for developing their bidding strategies. The work presented in this paper makes use of particle swarm optimization based local linear wavelet neural networks (LLWNN) to find the Market Clearing Price (MCP) for a given period, with a certain confidence level. The results of the new method show significant improvement in the price forecasting process.**

Keywords- Electricity Price, Forecasting, Wavelet Neural Network (WNN), Local Linear Wavelet Neural Network (LLWNN), Particle Swarm Optimization (PSO), Market Clearing Price (MCP), Weekly Mean Absolute Percentage Error (WMAPE)

I. INTRODUCTION

The electric power industry in many countries all around the world is evolving into an era of market economy with deregulation and free competition. The understanding of electric power supply as a public service is being replaced by the notion that a competitive market is a more appropriate mechanism to supply energy to consumers with high reliability and low cost . A key element of the electricity sector restructuring is the establishment of a market-driven price for electricity. The pricing system of electricity plays an important role in a competitive market. In the power market, the electricity price depends on the evolution of balance between the demand for electricity and the available supply. At the same time, many other market factors also influence the electricity price, such as economic growth, weather, the power-plant mix, the prices of fuels and the strategic behavior of large players (usually on the generation side). An active, fully competitive and liquid spot market for wholesale electricity will translate the physical risk of inadequate capacity into a financial risk of high prices and place higher requirements on price forecasting. Producers and consumers rely on price forecasting information to propose their corresponding bidding strategies. If a producer has an accurate forecast of the prices, it can develop a bidding strategy to maximize its profit. On the other hand, a consumer can make a plan to minimize his own electricity cost if an accurate price forecast is available.

Due to the complicated bidding strategies linked with the gaming by market participants and special electric price characteristics [1], such as high frequency, nonstationary behavior, multiple seasonality, calendar effect, high volatility, high percentage of unusual prices, hard nonlinear behavior, etc. and limited information to the market participants, an accurate electricity price forecasting is a challenging task. In the past few years different techniques have been proposed to forecast electricity price. Stationary time series and non-stationary time series models, neural network and its extended models [2-7],support vector machine(SVM) [8-9], and an input/output hidden Markov model(IOHMM) [10], etc. have been applied for electricity price forecasting. Auto regressive integrated moving average (ARIMA) [11], dynamic regression (DR) and transfer function (TF) [12], and generalized auto regressive conditional heteroscedasticity (GARCH) [13] are the most widely used time series models. Although, time series techniques are well established to have good performance, however, due to the use of linear modeling most of them have difficulties in predicting the hard nonlinear behaviors and rapid changes of the price signals. As electricity price is a non-linear function of its input features, the behavior of electricity price signal can not be completely captured by the time series techniques. On the other hand, artificial intelligence (AI) techniques have been extensively used by many researchers for the electricity price forecasting.

A wavelet neural network (WNN)-- , first proposed by Zhang et al. [14] as an alternative to the classical feed- forward neural network (FFNN) for approximating arbitrary nonlinear functions, inspired by both the FFNN and wavelet theory has been emerged as a powerful new type of ANN. A shortcoming of WNN is that for higher dimensional problems many hidden layer units are needed. Curse- of –dimensionality is mainly an unsolved problem in WNN theory which brings some difficulties in applying the WNN to high dimensional problems.

In order to take advantage of the local capacity of the wavelet basis functions while not having too many hidden units, an alternative type of wavelet neural network known as local linear wavelet neural network (LLWNN) has been proposed [15].

The Particle Swarm Optimization (PSO), a population based optimization method first proposed by Kennedy and Eberhart [16] is introduced for training the local linear wavelet neural network. To the best of the authors' knowledge, a PSO based

Local Linear Wavelet Neural Network (LLWNN) has not yet been tested for electricity price forecasting. In this paper an LLWNN model which smoothly bases function of hidden layer neurons according to training data set maps the input-output space by adapting the shape of wavelet is examined for electricity price prediction of the Ontario electricity market. The proposed model does not require external decomposer/composer. So risk of losing high frequency components of electricity price signal is averted. It is found that prediction of electricity price based on LLWNN model gives better performance because of its favorable property of modeling the non-stationary high frequency signals such as electricity price.

The rest of the paper is organized as follows: Section II describes main characteristics of the electricity price series. Electricity price forecasting using LLWNN model is described in section III. Training of LLWNN model by PSO algorithm is described in section IV. Section V describes the statistical measures used to evaluate the forecasting performance. Section VI presents results and discussions on electricity price forecast of Ontario electricity market. Finally, section VII provides concluding remarks.

II. PRICE-DATA ANALYSIS

To develop an appropriate model for price forecasting, we examine the main characteristics of the hourly price series in this section. To illustrate the forecasting procedure the electricity prices for the Ontario power market from 1st June 2004 to 26th Dec., 2004 is used for prediction. An analysis reported in [18], [19], [20] was to find out whose parameters could be used to successfully predict the average Market Clearing Price (MCP). According to the data samples for each hour of the day and each day of the month, it is clear that the price dynamics have multiple seasonal patterns, corresponding to a daily and weekly periodicity, respectively, and are also influenced by a calendar effect, i.e. weekends and holidays. These properties are just the same as those of load. However, in contrast to the load-time series, there are several particular properties of price. The hourly price curve is varied and fluctuates with a high frequency, and there is also a high percentage of an abrupt change or spikes in the price curve (mainly in periods of high demand).

The price presents high volatility and non-constant mean. The abrupt changes and volatility of price can be reflected as a switch in the price series dynamics owing to the discrete behaviors in competitors' strategies. In other words, there exist different regimes in the price–time series, which generally give rise to piece-wise-stationary dynamics. Based on such analysis, we use a hybrid model to classify the non-stationary price-data set to several piecewise stationary data subsets, on which highly accurate learning and prediction can be expected, compared with the conventional approaches.

If price at hour h (Ph) is to be forecasted, the price information of previous hours up to "m" hours i.e. $p_{h-1,} p_{h-2,} \ldots p_{h-m}$ should be taken as a part of the input of short-term price forecasting (STPF) model. The auto co-relation function (ACF) can be used to identify the degree of association between data in the price series separated by different time lags i.e. previous price. Other kind of sensitivity analysis can also be very helpful in determining the variable which has significant influence on the system price. In order to identify the load influence on price, load at hour to be predicted at different lagged hours ($d_{h-1,} d_{h-2,} \ldots d_{h-m}$) is also included as an exogenous variable in the input set of the forecasting models. The historical hourly data of 7 days prior to the day whose price to be predicted have been considered to build the forecasting model. Hence the total data points are equal to 7 x 24 = 168. Since the proposed model uses price data 7 hours ago to predict the price $p_{h,}$ 168-7=161 input vectors are used to develop the forecast model.

III. ELECTRICITY PRICE FORECASTING USING LLWNN

The LLWNN model for the hourly Ontario energy price is developed to forecast for three time periods. The first period comprises two consequent weeks from April 26 to May 9, 2004, which are referred as Week-1, and Week-2 respectively in this paper, the Ontario market presented its lowest spring demand during this period. The second period contains summer peak demand weeks from July 26 to August 8, 2004, which are referred to as Week-3 to Week-4, respectively. The last period includes two high demands winter weeks in 2004, starting on December 13 and ending on December 26, and these weeks are referred as Week-5 and Week-6, respectively. One hour ahead price forecasting using seven hours before price data, twenty-four hours ahead forecasting using seven days before price data have been used in the proposed model. After the one step ahead training, the next hour prediction is evaluated. Multiple steps ahead are reached via recursion i.e. by feeding input variables with model's outputs. The next hour forecasts are performed for every hour of the day. The model is retrained at the end of each day to incorporate the most recent information. The concatenation of 7 days training windows, for a particular day, is shifted one day-ahead and forecasts for the next 24 hours are computed.

According to wavelet transformation theory, wavelet in the following form is a family of functions generated from one single function ψ(x) by the operation of dilation and translation. Ψ(x) which is localized in both time space and the frequency space is called a mother wavelet.

$$\psi = \left\{ \psi_i = |a_i|^{-1/2} \psi\left(\frac{x-b_i}{a_i}\right) : a_i, b_i \in R^n, i \in z \right\}$$
$$x = (x_1, x_2, ..x_n) \tag{1}$$
$$a_i = (a_{i1}, a_{i2}, ...a_{in})$$
$$b_i = (b_{i1}, b_{i2} ....b_{in})$$

The parameters a_i and b_i are the scale and translation parameters, respectively. According to the previous researches, the two parameters can either be predetermined based on wavelet transformation theory or be determined by a training algorithm.

In the standard form of wavelet neural network, the output of a WNN is given by

$$f(x) = \sum_{i=1}^{m} w_i \psi_i(x) = \sum_{i=1}^{m} w_i |a_i|^{-1/2} \psi\left(\frac{x-b_i}{a_i}\right) : a_i, b_i \in R, i \in z \} \tag{2}$$

The above wavelet neural network is a kind of basis function neural network in the sense of that the wavelets consists of the basis function. An intrinsic feature of the basis function networks is the localized activation of the hidden layer units, so that the connection weights associated with the units can be viewed as locally accurate piecewise constant models whose validity for a given input is indicated by the activation functions. Compared to the multilayer perceptron neural network, this local capacity provides some advantages such as the learning efficiency and the structure transparency. However, the problem of basis function networks is also led by it. Due to the crudeness of the local approximation, a large number of basis function units have to be employed to approximate a given system. A shortcoming of the wavelet neural network is that for higher dimensional problems many hidden layer units are needed.

In order to take advantage of the local capacity of the wavelet basis functions while not having too many hidden units, LLWNN has been used as an alternative neural network.

The difference between a local linear wavelet neural network (LLWNN) and a conventional wavelet neural network (WNN) is that the connection weights between the hidden layer and output layer of conventional WNN are replaced by a local linear model. The output of LLWNN is given by

$$Y = \sum_{i=1}^{m} (w_{i0} + w_{i1}x_1 + ...+ w_{in}x_n)\psi_i(x) \tag{3}$$

Where, instead of the straight forward weight w_i (piecewise constant model), a linear model $v_i = w_{i0} + w_{i1}x_1 + ...+ w_{in}x_n$ is introduced.

The activities of the linear models v_i (i=1,2,--------n) are determined by the associated locally active wavelet functions $\psi_i(x)$ (i= 1,2,-------,n), thus v_i is only locally significant.

The architecture of the proposed model is shown in Fig.-1.

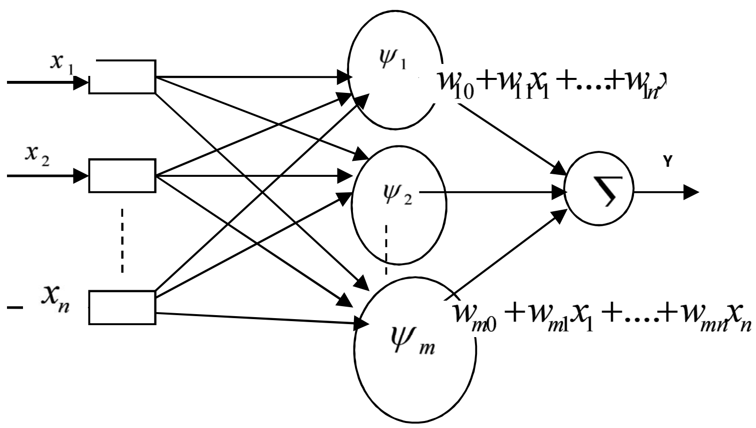

Fig.1 – General structure of a local linear wavelet neural network.

Here m = n is the order of the dynamical system which is predetermined constant.

The mother wavelet is

$$\psi(x) = \frac{-x^2}{2} e^{-x^2/\sigma^2} \tag{4}$$

$$\psi(x) = e^{-\left(\frac{x-c}{\sigma}\right)^2} \tag{5}$$

Where x = $\sqrt{p_1^2 + p_2^2 + \ldots\ldots\ldots\ldots\ldots\ldots + p_n^2}$

IV. LEARNING ALGORITHM

The usually used learning algorithm for LLWNN is gradient decent method to get all the unknown parameters of network i.e. translation and dilation coefficients, weights which are randomly initialized at beginning since the function computed by the LLWNN model is differentiable with respect to all mentioned unknown parameters. But its disadvantages are slow convergence speed and easy stay at local minimum. Hence the proposed model is trained by the PSO algorithm.

Particle swarm optimization is basically developed through simulation of bird flocking in two-dimension space. The position of each agent is represented by XY axis position and also the velocity is expressed by vx and vy. Modification of the agent position is realized by the position and the velocity information.

Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its XY position. Moreover, each agent knows the best value so far in the group (gbest) among pbest. Mainly each agent tries to modify its position using the following information.

(a) The distance between the current position and pbest.

(b) The distance between the current position and gbest.

Velocity of each agent can be modified by the following equation:

$$v \quad v \quad ra\ \ d \quad pbest \quad s \quad ra \quad d \quad best \quad s \tag{6}$$

where, v_i^k is the velocity of agent *i* at iteration *k*, w is called inertia factor, c_1 and c_2 are known as acceleration coefficients, s_i^k is the current position of agent *i* at iteration *k*, $pbest_i$ is the previous best of agent *i* and *gbest* is the global best particle of the group.

Using the above equation, a certain velocity, which gradually gets close to pbest and gbest, can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$S_i^{k+1} = S_i^k + V_i^{k+1} \tag{7}$$

The first term of (6) is the previous velocity of the agent. The second and third terms are used to change the velocity of the agent.

The inertia weight *w* is introduced to improve PSO performance. Suitable selection of inertia weight *w* provides a balance between global and local exploration and exploitation.

The general flow chart of PSO for optimizing a local linear wavelet neural network can be described as follows:

Step.1 Generation of initial condition of each agent Initial searching points (S_i^0) and velocity (V_i^0) of each agent are usually generated randomly within the allowable range. Note that the dimension of search space consists of all the parameters used in the local linear wavelet neural network as shown in Equations (1) and (3). The current searching point is set to pbest for each agent. The best-evaluated value of pbest is set to gbest and the agent number with the best value is stored.

Step.2 Evaluation of searching points of each agent. The objective function value is calculated for each agent. If the value is better than the current pbest of the agent, the pbest value is replaced by the current value. If the best value of pbest is better than the current gbest, gbest is replaced by the best value and the agent number with the best value is stored.

Step.3 Modification of each searching point

The current searching point of each agent is changed using (6) and (7).

Step.4 Checking the exit condition.

The current iteration number reaches the predetermined maximum iteration number, then exits otherwise goes to Step 2.

V. ACCURACY MEASURES

Several errors measures defined in [17] have been used to evaluate the performance of LLWNN based forecasting model. Mean absolute percentage error (MAPE) is used to assess prediction accuracy of the developed models in the paper.

The absolute error (AE) is defined as

$$AE_t = \frac{|Pa,t - P_{f,t}|}{P_{a,t}} \tag{8}$$

The daily mean absolute error (DMAE) can become computed as follows:

$$\text{DMAE} = \frac{1}{24}\sum_{t=1}^{24} AE_t \tag{9}$$

The daily mean absolute percentage error

$$\text{(DMAPE)} = \frac{100}{24}\sum_{t=1}^{24} AE_t \tag{10}$$

The weekly mean absolute error

$$\text{(WMAE)} = \frac{1}{168}\sum_{t=1}^{168} AE_t \tag{11}$$

And

The weekly mean absolute percentage error

$$\text{(WMAPE)} = \frac{100}{168}\sum_{t=1}^{168} AE_t \tag{12}$$

VI. RESULTS & ANALYSIS

The effectiveness of the LLWNN model is demonstrated on SMP prediction in Ontario electricity market for the year 2004. The forecasted price obtained with proposed model during spring test weeks (Week-1, Week-2) are shown in Fig.2 and Fig.4 along with actual price and the corresponding error is shown in Fig. 3. and Fig.5.

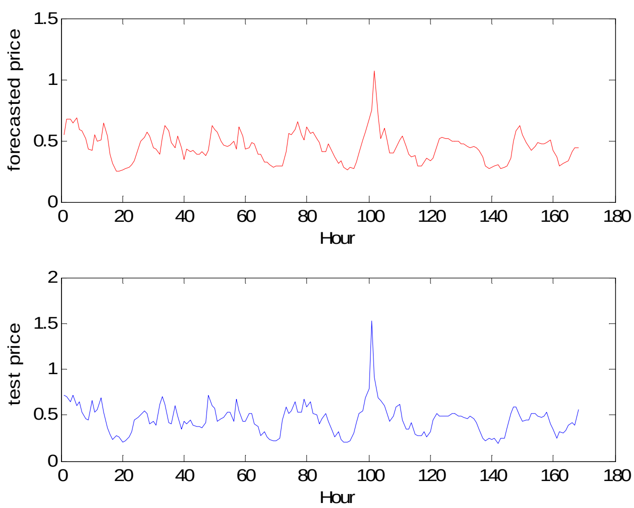

Fig. 2. Dynamic system output and model output for Week-1 data set

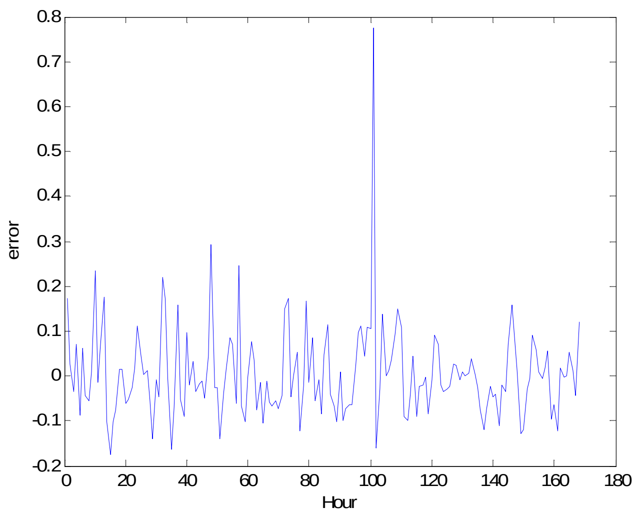

Fig. 3. Hourly error for Week-1 data set

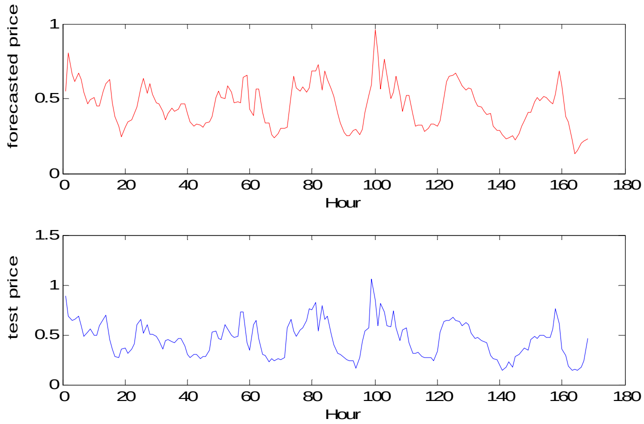

Fig. 4. Dynamic system output and model output for Week-2 data set.

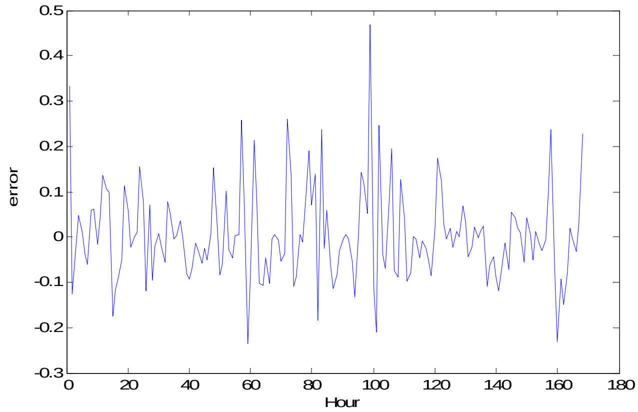

Fig. 5. Hourly error for Week-2 data set.

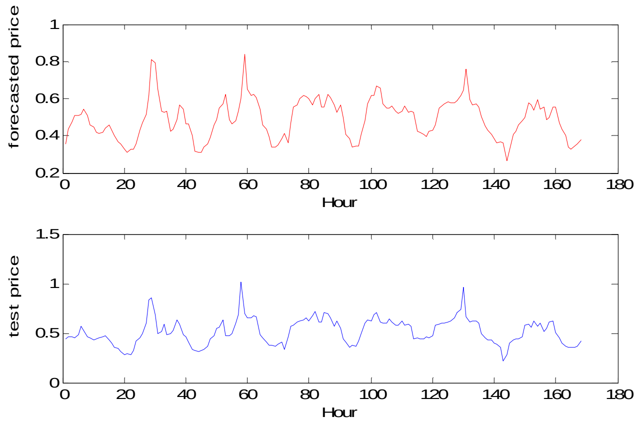

Fig. 6. Dynamic system output and model output for Week-3 data set.

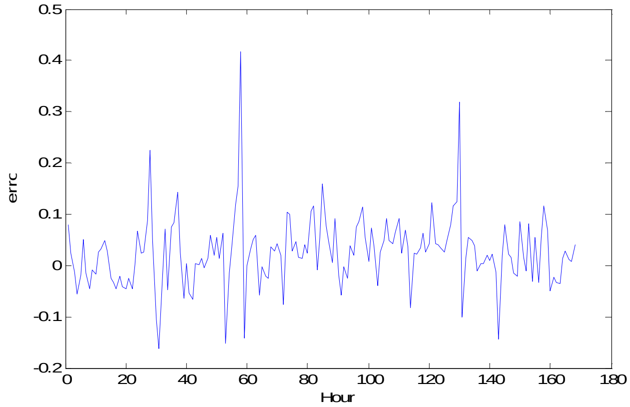

Fig. 7. Hourly error for Week-3 data set

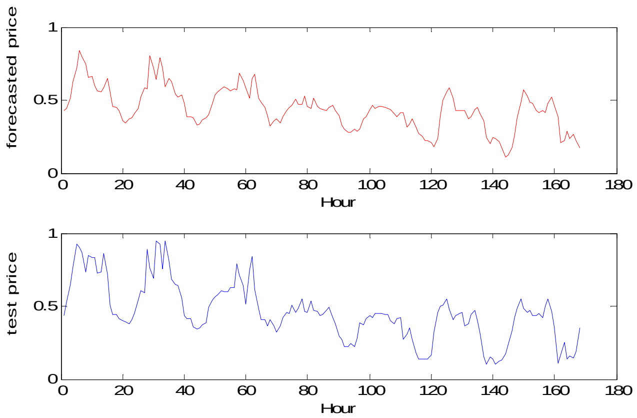

Fig. 8. Dynamic system output and model output for Week-4 data set.

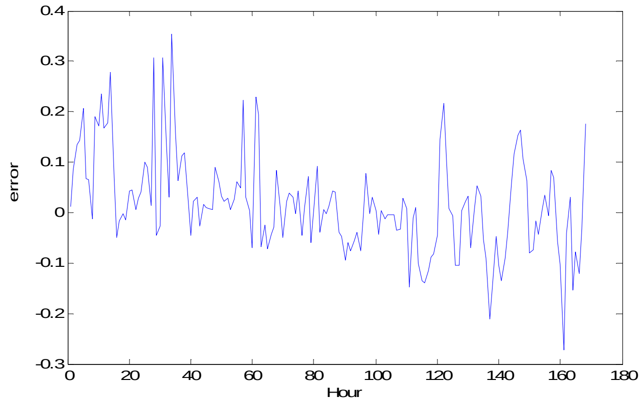

Fig. 9. Hourly error for Week-4 data set.

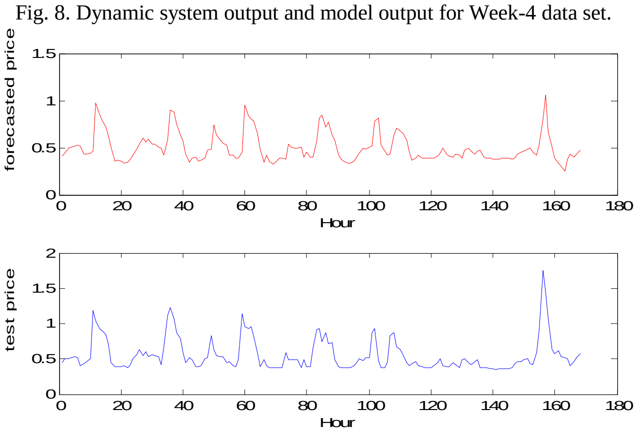

Fig. 10. Dynamic system output and model output for Week-5 data set.

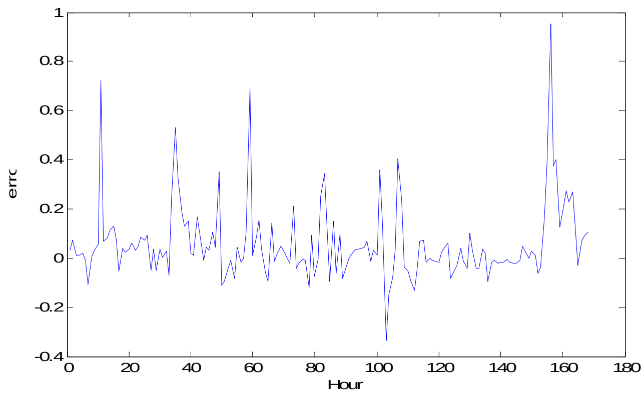

Fig. 11. Hourly error for Week-5 data set.

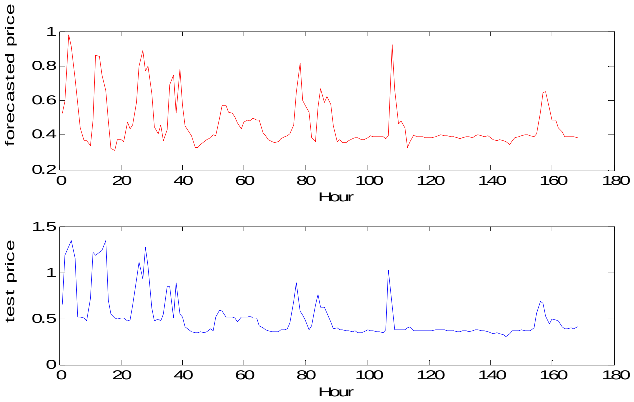

Fig. 12. Dynamic system output and model output for Week-6 data set.

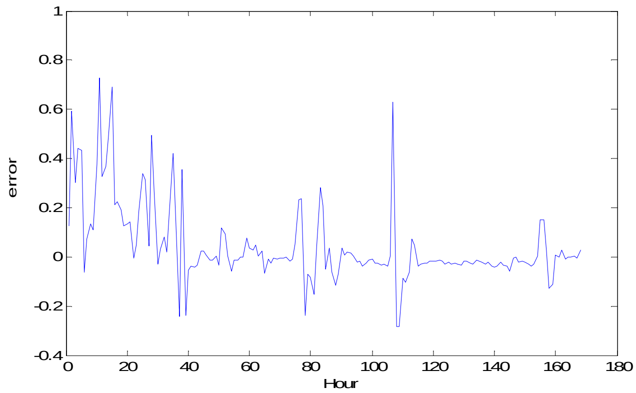

Fig. 13. Hourly error for Week -6 data set

The forecasted price obtained with proposed model during summer test weeks (Week-3, Week-4) are shown in Fig.6 and Fig.8 along with actual price and the corresponding error is shown in Fig. 7 and Fig.9.

The forecasted prices obtained with proposed model during winter test weeks (Week-5, Week-6) are shown in Fig.10 and Fig.12 along with actual price and the corresponding error is shown in Fig. 11 and Fig.13.

It can be seen from figures that the predicated electricity price of the test weeks are quite close to the actual one. The weekly MAPEs of the generated forecasts, using the models developed in this paper for the six weeks under study, are presented in Table I.

For comparison purposes, the weekly MAPEs of the generated forecast, using heuristic method (PM1),independent electricity system operator (IESO) model(PM2), multiple linear regression (MLR) model (PM3), neural network (NN) model (PM4), wavelet NN model (PM5) [18] are also presented in this table.

Accuracy of LLWNN model is better than the other models in Week-2, Week-3, Week-5 and Week-6. Overall, accuracy of LLWNN model is better than the other models The best results were achieved for Week-3, which was one of the high demand weeks of 2004 summer. Despite the high demand, prices on all seven days were in the expected range during this week.

TABLE I WMAPE IN ONTARIO MARKET FOR SIX WEEKS

Test period	**Week no.**	**PM 1**	**PM 2**	**PM 3**	**P M 4**	**PM 5**	**LLWNN**
Apr. 26 to May 2,2004	Week-1	21.70	23.78	16.26	16.56	15.21	15.3413
May 3-9,2004	Week-2	17.80	25.26	19.23	19.34	18.62	17.0082
July 26 to Aug. 1,2004	Week-3	22.92	10.41	17.69	17.45	17.91	9.7870
Aug. 2-8,2004	Week-4	37.77	16.22	20.55	20.27	18.72	19.8554
Dec. 13-19,2004	Week-5	24.60	22.06	16.73	17.03	16.61	14.5401
Dec. 20-26,2004	Week-6	24.55	23.51	18.54	19.69	18.02	14.5834
	Average	24.89	20.21	18.17	18.39	17.51	15.1858

The highest forecast errors occurred during Week-4. In this week, the prices are unusually volatile for the first two days of the week and unusually steady for the rest.

Local Linear Wavelet Neural Network trained by PSO algorithm has been convergent at iteration 380 with average weekly mean absolute percentage error (WMAPE) of 15.1858 for test data set. We believe that these results are reasonably accurate for a study spanning one whole year. Very less training time shows the higher convergence rate of LLWNN model to predict the wind power generation with higher accuracy. A LLWNN performs better than all considered methods, because both smooth global and sharp local variations of electricity price signal can be effectively represented by the wavelet basis activation function for hidden layer neurons without any external decomposer / composer and also not having too many hidden units.

Considering all these points, the performance of the proposed model is satisfactory.

VII. CONCLUSIONS

In this paper, energy price forecasting by using a local linear wavelet neural network (LLWNN) model is used. The characteristic of the network is that the straight forward weight is replaced by a local linear model and thereby it needs only smaller wavelets for a given problem than the common wavelet neural networks. It is also observed that accuracy of LLWNN model is better than other models with high converges and out -performed in the forecasting of the electricity price because of its favorable property for modeling the non-stationary and high frequency signal such as electricity price.

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