[International Journal of Instrumentation Control and Automation](https://www.interscience.in/ijica)

Volume 1 | Issue 3 Article 4

October 2011

Short-Term Load Forecasting using PSO Based Local Linear Wavelet Neural Network

Prasanta Kumar Pany
DRIEMS, Cuttack, Orissa, India, Prasantpany@gmail.com

Short-Term Load Forecasting using PSO Based Local Linear Wavelet Neural Network

Prasanta Kumar Pany

DRIEMS, Cuttack, Orissa, India
E-mail : Prasantpany@gmail.com

Abstract **-** Short-term load forecasting (STLF) plays an important role in the operational planning security functions of an energy management system. The short term load forecasting is aimed at predicting electric loads for a period of minutes, hours, days or week for the purpose of providing fundamental load profiles to the system. The work presented in this paper makes use of PSO based local linear wavelet neural networks (LLWNN) to find the electric load for a given period, with a certain confidence level. The results of the new method show significant improvement in the load forecasting process.

Keywords **-** *Electric load, forecast, wavelet neural network (WNN), local linear wavelet neural network (LLWNN), Particle Swarm Optimization ,artificial neural network (ANN), artificial intelligence, ,Weekly mean absolute percentage error (WMAPE).*

I. INTRODUCTION

Electric load forecasting is used by power companies to anticipate the amount of power needed to supply the demand. In the last few years , various techniques for the STLF have been proposed and applied to power systems. Conventional methods based on time series analysis exploit the inherent relationship between the present hour load, weather variables and the past hour load. Auto regressive (AR) and moving average (MA) and mixed Auto regressive moving average(ARMA) models[1] are prominent in the time series approach. The main disadvantage is that these models require complex modeling techniques and heavy computational effort to produce reasonably accurate results [2]. Basically, most of statistical methods are based on linear analysis. Since the electric load is non linear function of its input features, the behavior of electric load signal can not be completely captured by the statistical methods. So statistical methods are not adaptive to rapid load variations. Another difficulty lies in estimating and adjusting the model parameters, which are estimated from historical data that may not reveal short term load pattern change[3].

The emergence of artificial intelligence (AI) techniques has led to their application in STLF as expert system type models. These methods are discrete and logical in nature. By simply learning the historical samples, these methods can map the input-output relations and then can be used for the prediction. Among the AI techniques available, different models of NNs due to flexibility in data modeling have received great deal of attention by the researchers in the area of STLF.

Many type of NN models which are characterized by their topology and learning rules have been successfully for STLF problems [4,5,6,7,8,9,10,11,12,13,14]. A comprehensive review of the literature on the application of NNs to the load forecasting can be found in [9].

Another useful technique for STLF, proposed in the recent years is wavelet based NN method. In this method wavelet is merged with NN and termed as wavelet neural network (WNN). The WNN has been emerged as a powerful new type of ANN. But the major drawback of the WNN is that for higher dimensional problems many hidden layer units are needed. Curse of dimensionality is an unsolved problem in WNN theory which brings some difficulties in applying the WNN to high dimensional problem. So the applications of WNN are usually limited to problems of small input dimensions. The main reason is that they are composed of regularly dilated and translated wavelets. The number of wavelets in the WNN drastically increases with the dimension.

In order to take the advantages of local capacity of the wavelet basic function while not having too many hidden units, the architecture of LLWNN has been used in this paper for STLF.

II. LOAD-DATA ANALYSIS

To develop an appropriate model for load forecasting, we examine the main characteristics of the hourly load series in this Section. To illustrate the forecasting procedure the electric load for the hub of the New England pool from 1 July 2008 to 31 August, 2008 is used for prediction. According to the data samples for each hour of the day and each day of the month, it is clear that the load 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 price.

It is well-known that the temperature is the most dominant weather factor that drives the short term load. The statistical correlation coefficient between temperature and load is found to be 0.7415.

It can be observed that the load series presents multiple periodicities and hence, the past load demand could affect and imply the future load demand. If the load at hour 'h' is to be forecasted , the load information of previous hours up to 'm' hours should be taken as a part of the input of short term load forecasting(STLF) model. The auto correlation function (ACF) can be used to identify the degree of association between data in the load series separated by different time lags i.e. previous load.

The historical hourly load of 7 days prior to day whose load is to be predicted have been considered to build the proposed forecasting model. Hence the total data points are equal to 7*24=168. Since the proposed model uses load data of 7 hours ago to predict the load at hour 'h', 168-7=161 input vectors are used to develop the forecast model.

III. ELECTRIC LOAD FORECASTING USING PSO BASED LLWNN

The structure of LLWNN model is shown in Fig. 1. It comprise of input layer, hidden layer and linear output layer. The input data in input layer of the network are directly transmitted into the wavelet layer. As the hidden layer neurons make use of wavelets as activation functions, these neurons are usually called 'wavelons'. Since load forecasting is used by power companies to anticipate the amount of power needed to supply the demand, accurate load estimates are crucial for producers to maximize their profits and for consumers to maximize their utilities. In stead of using multi layered neural networks and its several variants a LLWNN is used for forecasting the next day and next week electric load in a deregulated environment.

In the proposed model, one hour ahead load forecasting using seven hours before load data and twenty four hours ahead forecasting using seven days i.e. 168 hours before load data have been used.

According to wavelet transformation theory, wavelets in the following form is a family of

$$\psi = \left\{ \psi_i = |a_i|^{-1/2} \psi\left(\frac{x - b_i}{a_i} \right) : a_i, b_i \in R^n, i \in z \right\} \quad (1)$$

$$x = (x_1, x_2, ... x_n)$$

$$a_i = (a_{i1}, a_{i2}, ... a_{in})$$

$$b_i = (b_{i1}, b_{i2} ..... b_{in})$$

functions, generated from one single function ψ(x) by the operation of dilation and translation ψ(x). ψ(x) which is localized in both time space and the frequency space, is called a mother wavelet and the parameters a_i and b_i are the scale and translation parameters, respectively.

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 .Non-linear wavelet basis functions (named wavelets) are localized in both time space and frequency space.

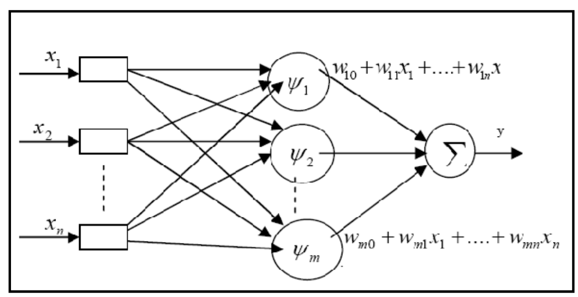

Fig. 1 : General structure of a local linear wavelet neural network.

Here m = n and output (Y) of the proposed model is Calculated as follows:

$$Y = \sum_{i=1}^{M} (w_{i0} + w_{i1}x_1 + -- + w_{in}x_n) \times \psi_i(x) \quad (2)$$

The mother wavelet is

i) $\psi(x) = \dfrac{-x^2}{2} e^{-x^2/\sigma^2}$ (3)

ii) $\psi(x) = e^{-\left(\frac{x-c}{\sigma}\right)^2}$ (4)

where x = $\sqrt{d_1^2 + d_2^2 + ... + d_n^2}$

IV. TRAINING

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 current position and pbest.

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

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

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_1 - s_i^k) + c_2 rand_2 (gbest - s_i^k) \quad (5)$$

where, v_i^k is the velocity of agent i at iteration k, w is weighting function, c_j is weighting factor, s_i^k is the current position of agent I at iteration k, $pbest_i$ is the pbest of agent i and gebst is the gbest 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:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (6)$$

The first term of (5) is the previous velocity of the agent. The second and third terms are used to change the velocity of the agent.

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 is consists of all the parameters used in the local linear wavelet neural network as shown in equation (2). 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 bset 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 (5) and (6).

Step. 4 Checking the exit condition:

The current iteration number reaches the predetermined maximum iteration number, then exit otherwise go to step 2.

V. ACCURACY MEASURES

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

$$AE_t = \frac{|da,t - d_{f,t}|}{d_{a,t}} \quad (7)$$

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

$$\text{DMAE} = \frac{1}{24}\sum_{t=1}^{24} AE_t \quad (8)$$

The daily mean absolute percentage error

$$\text{(DMAPE)} = \frac{100}{24}\sum_{t=1}^{24} AE_t \qquad (9)$$

The weekly mean absolute error

$$\text{(WMAE)} = \frac{1}{168}\sum_{t=1}^{168} AE_t \qquad (10)$$

And,

The weekly mean absolute percentage error

$$\text{(WMAPE)} = \frac{100}{168}\sum_{t=1}^{168} AE_t \qquad (11)$$

VI. RESULTS & ANALYSIS

To illustrate the forecasting procedure, the electric load for the hub of New England Pool from 1st June, 2006 to 31st July, 2006 is used for prediction. The forecasted load obtained with proposed Model is shown in Fig. 2 and the corresponding error is shown in Fig. 3 for training data set. The hourly forecasted load obtained with proposed model by using PSO algorithm as learning algorithm and the actual load are shown in Fig. 4 and Fig-5 shows the error for test data set..

TABLE -1

Results obtained by proposed model for 24 hours of a day.

Test week data set		**Training week data set**	
Predicted hourly load	Hourly Error	Predicted hourly load	Hourly Error
0.6725	0.0111	0.6836	0.0005
0.7514	- 0.0534	0.6980	- 0.0094
0.7210	- 0.0070	0.7140	0.0167
0.7333	-0.0050	0.7284	-0.0124
0.7458	-0.0443	0.7015	-0.0169
0.6976	-0.0004	0.6971	0.0048
0.6653	0.0184	0.6837	0.0464
0.6216	0.0766	0.6981	0.0512
0.6439	0.0998	0.7438	0.0408
0.6918	0.0533	0.7451	0.0158
0.6627	0.0496	0.7123	-0.0379
0.6301	0.0833	0.7134	0.0312
0.6499	0.1116	0.7615	0.0859
0.7115	0.0365	0.7480	-0.0668
Predicted hourly load	Hourly Error	Predicted hourly load	Hourly Error
0.6672	-0.0802	0.5870	-0.1502
0.4612	-0.0421	0.4191	-0.0340
0.3211	-0.0300	0.2911	-0.0106
0.2248	0.0050	0.2299	0.0078
0.1828	0.0178	0.2006	0.0125
0.1404	0.0379	0.1782	0.0525
0.1304	0.0389	0.1694	0.0459
0.2240	0.0091	0.2149	0.0189
0.3401	0.0584	0.3985	0.0624
0.4983	0.1276	0.6259	0.1367

Table I provides the predicted hourly load in terms the maximum load and hourly relative error for 1st 24 hrs. of the training data set and test data set taking d_data as input vectors in proposed model by using PSO algorithm as learning algorithm. Where d_data=(load data-minimum load)/(maximum load-minimum load) for a given period. Local Linear Wavelet Neural Network trained by PSO algorithm was convergent at iteration 2904 with WMAPE 7.56 for training data set and the WMAPE for test data set is 8.63.

It can be seen from Fig. 4 and Table 1 that predicated load of the test week are quite close to the actual load. Very less training time as compared to the other forecasting methods shows the higher convergence rate of PSO based LLWNN model to predict the electric load with higher accuracy. A PSO based LLWNN performs better than all considered methods, because both smooth global and sharp local variations of load 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.

VII. CONCLUSION

In this paper, electric load forecasting by using a PSO based local linear wavelet neural Net work (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. Hence the proposed model requires simple modeling technique and light computational effort to produce reasonably accurate result. Since the proposed model is discrete and logical in nature, by simple learning the historical samples, this method can map the input-output relations and then can be used for the prediction. The highest forecast accuracy is attained by LLWNN model since both smooth global sharp local variation of electric load signal can be effectively represented by the wavelet basis activation function for hidden layer neuron without any decomposer/composer. This method averts the risk of loosing the high frequency components of electric load signals because proposed model for load forecasting is not decomposing load time series data externally. It is also observed that a PSO based LLWNN converges with higher rate and out performed in the forecasting the electric load compared to other models because of its favourable property for modeling the non-stationary and high frequency signal such as electric load.

REFERENCES

[1] S.J.Huang and K.R.Shih,"Short term load forecasting via ARMA model identification including non-Guassian process consideration" IEEE Trans. On power systems, vol 18,no 2, pp 673-679,may 2003..

[2] I.Maghram and S.Rahman: "Analysis and evaluation of five short term load forecasting techniques " IEEE Trans. On power systems, Apr 1989,pp 1484-1491.

[3] S.Rahman, O. Hazim, "Generalized knowledge based short term load forecasting technique", IEEE Trans. On power systems, vol. 8,no 2,pp508-514, May 1993.

[4] C.N.Lu and S.Vemuri, " Neural network based short term load forecasting" IEEE trans. On power systems, vol 8, no.1,pp336-342, Feb 1993.

[5] T.W.S Chow and C.T. Leung, "Non-linear autoregressive integrated neural network model for short term load forecasting", IEE proc. Generation transmission and distribution, vol. 143, no.5, pp500-506, sep 1996..

[6] R.Lamedica,A Prudenzi, M Sforna, M.Caciotta and V.O Cancelli, "Neurar network based technique for short term forecasting of anomalous load periods", IEEE Trans. On power systems, vol 11 no. 4, pp 1749-1756,Nov 1996..

[7] I.Drezga and S.Rahman, "Short term load forecasting with local ANN predictors". IEEE trans. On power systems, vol 14, no. 3, pp 844-850, Aug 1999..

[8] H.Chen, C.Canizare, and A.Singh "ANN based short term load forecasting in electricity markets", proc. IEEE winter meeting, Columbus, Ohio, 2, pp 411-415, Jan 2001..

[9] H.S.Hippert, C.E.Pedreira and R.C. Souza, "Neural network for short term load forecasting, areview andevaluation," IEEE trans. On power systems, vol. 16, no.1, pp 44-55, Feb 2001..

[10] T.Senjya, H. Takara, K.Uezato and T. Funabashi, " One hour ahead load forecasting using neural network,"IEEE trans. On power systems, Vol. 17, no.1, pp 113-118, 2002..

[11] J.W.Taylor and R.Buizza, "Neural network load forecasting with weather ensemble predictors," IEEE Transactions on Power systems, Aug 2002, pp. 626-632..

[12] L.M.Saini and M.K Soni, "Artificial neural network based peak load forecasting using conjugate gradient methods," IEEE Transactions on Power Systems, Aug 2002 vol 12 , no.3, pp. 907-912.

[13] P.Mandal, T. Sanjyu, N.urasaki and T. Funabashi, "A neural. network based several hour ahead electric load forecasting using similar days approach, " Int. Jouranal of electric power and energy system, vol 28, no 6, pp367-373, Jul 2006.

[14] D.Benaouda, F. Murtagh, J.L. Stark and O.Renaud, "Wavelet based non linear multiscale decomposition model for electricity load forecasting," Neuro computing vol 70, pp 139-154,dec 2006.

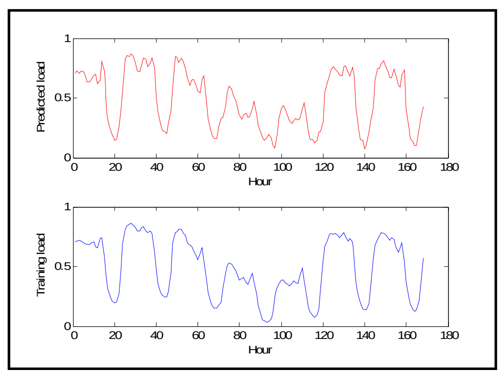

Fig. 2 : Dynamic system output and model output for training week data set

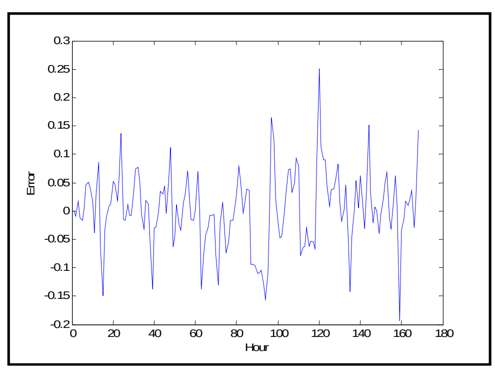

Fig. 3 : Hourly error for training week data set

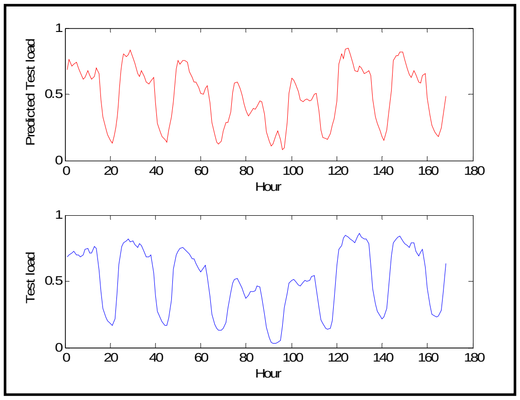

Fig. 4 : Dynamic system output and model output for test week data set

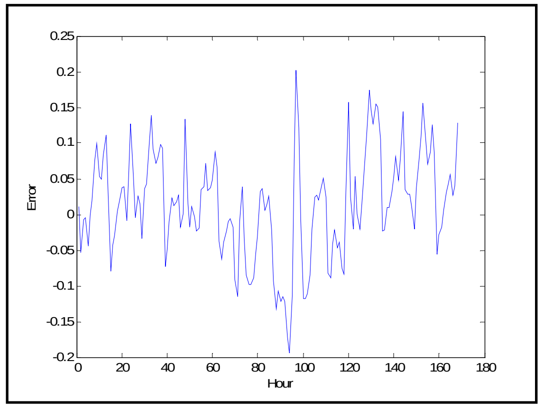

Fig. 5 : Hourly error for test week data

◈◈◈