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A Hybrid Model of Wavelet and Neural Network for Short Term Load Forecasting

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Abstract

Electric load forecasting is a key to the efficient management of power supply system. Load forecasting, which involves estimation of future load according to the previous load data. This paper presents a pragmatic methodology for short term load forecasting (STLF) using proposed hybrid method of wavelet transform (WT) and artificial neural network (ANN). It is a two stage prediction system which involves wavelet decomposition of input data at the first stage and the decomposed data with other input is trained using separate neural network to forecast the load. The forecasted load is obtained by reconstruction of the decomposed data. The hybrid model has been trained and validated using load data from Australia electricity market.

Keywords: Wavelet transform (WT); short term load forecasting (STLF); resolution level, artificial neural network (ANN); wavelet neural network (WNN).

1. Introduction

With the rise of the competitive energy market, STLF has become one of major areas in electrical engineering in recent years. STLF has a great positive contribution in enhancing electrical network's reliability and its growth and development economically. It is a task of predicting future electricity consumption. Load forecasting is classified as short term, medium term and long term. Short-term load forecasting is needed for control and scheduling of power systems and can also help to estimate load flows. Medium and Long-term forecasts are used to determine the capacity of generation, transmission or distribution system.

Christiaanse [1] used general exponential smoothing for developing an adaptive forecasting system. Park [2] et al. used three layer MLP (multi-layered perceptron) for total load forecasting. Ling [3] et al. realized a STLF by a Neural Fuzzy Network (NFN) and a modified genetic algorithm (GA). The modified GA gives better results than the traditional GA. Bashir [4] et al. used particle swarm optimization (PSO) algorithm to avoid problems of predicting hourly load demand with adaptive artificial neural networks (ANNs). In this proposed paper wavelet transform and artificial neural network are used for STLF. In subsequent sections, wavelet transform and artificial neural network are briefly discussed and proposed method is explained along with results.

2. Techniques Used

2.1 Wavelet Decomposition and Reconstruction

Avelet transforms (WT) is a useful technique which decomposes the time series signal in terms of both time and frequency. Wavelet transform of a function is the improved edition of Fourier transform. WT as the name suggests, uses some small wave like function to analyze a signal and hence called wavelets (mother wavelet function). Mathematically speaking, wavelet transform is the convolution of wavelet function and the signal. The translated and scaling of mother wavelet **Ψ(t)** can be represented as follows in (1).

$$\psi(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

Where, a = Dilation parameter b = Translation parameter

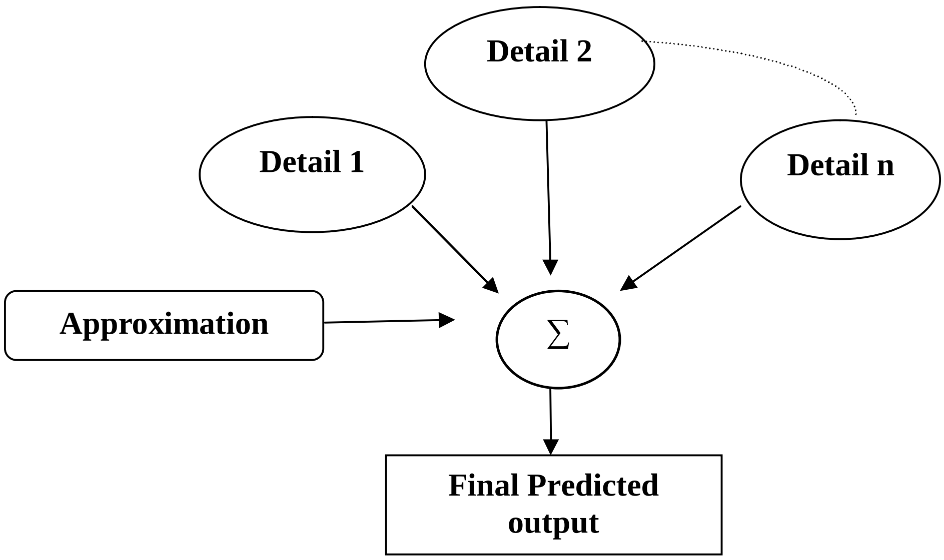

Fig. 1: A three level decomposition (S=A3+D3+D2+D1).

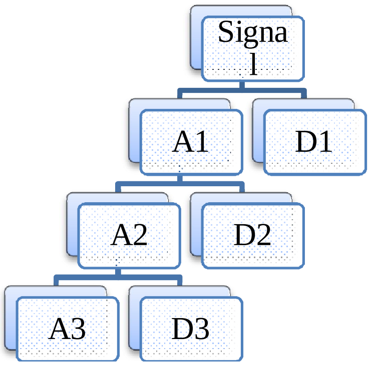

Fig. 2: Wavelet reconstruction process.

The signal is decomposed into approximation coefficient and detail coefficient as shown in Fig.1. Wavelet decomposed components can be assembled back into original signal without loss of information. Reconstruction can be done by combining all the decomposed wavelet coefficients as shown in Fig. 2. In this paper Daubechies4 (db4) is used as the mother wavelet with one level of resolution, hence the respective electricity load data is decomposed into one wavelet detail coefficients and one approximation coefficient[6].

2.2 Artificial Neural Network

It is an information processing model that is inspired by the biological way of processing information as that of brain. One major key feature of ANN is that it can deal with the nonlinear relationships among their input variables and give better performance. The NN parameters are shown in the Table 1. ten input data are given to the NN to forecast the load output accurately shows that Fig. 4

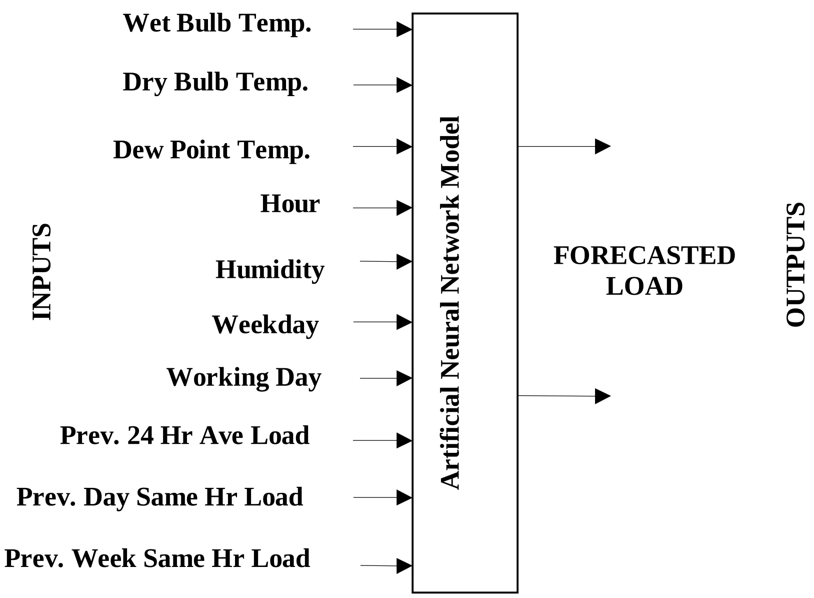

Fig. 4: Proposed Artificial Neural Network model.

Table I: Neural Network Parameter

Training Parameter	Value
Network type	Feed-forward back propagation
Number of input neuron	10
Number of output neuron	1
Number of hidden layer	1
No. of neuron in hidden layer	21
Hidden layer Transfer function	TANSIG
Output layer Transfer function	PURELIN
Training method	TRAINLM
Learning rate	0.7
Momentum coefficient	0.1
Goal	0.0001
Epochs	2000

3. Proposed Work

The key idea of the approach is to predict the load of the year from the month of Jan 2010 to Dec 2010 using historical load data of the year from the month of Jan 2006 to Dec 2009. The hybrid model of WT and ANN is shown in Fig. 5.

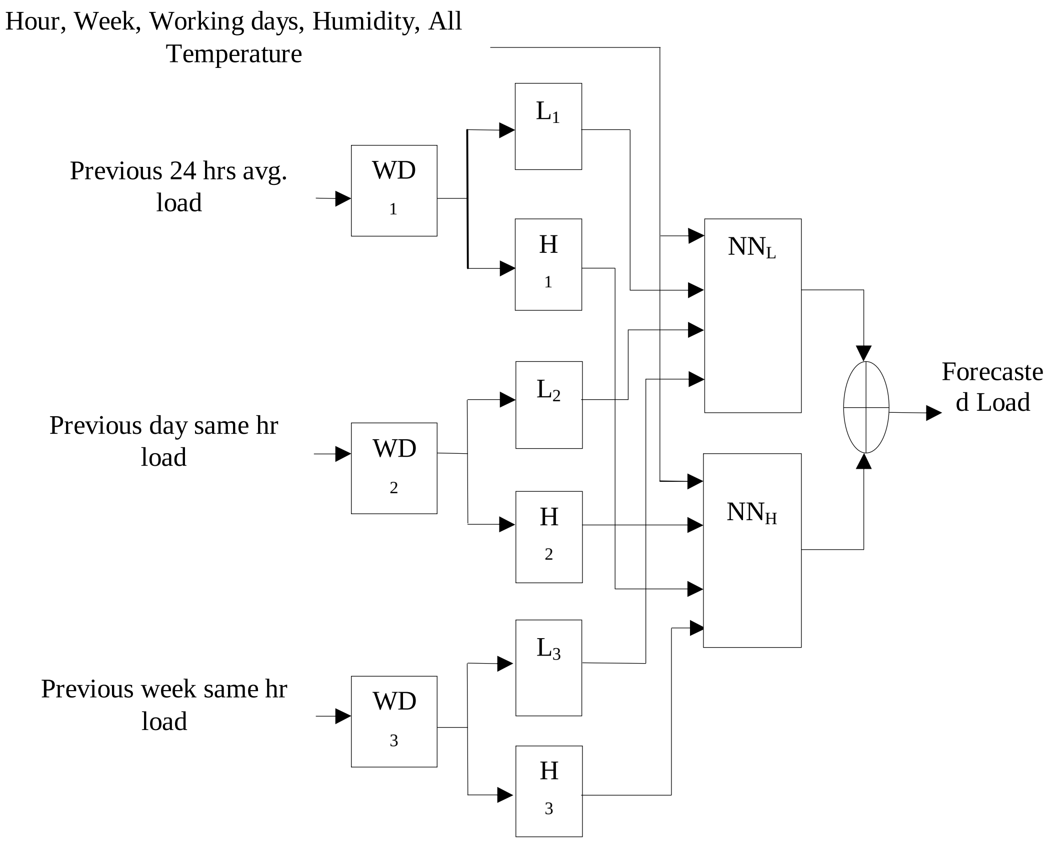

Fig. 5: Structure of proposed wavelet neural network.

1) The three input are decomposed into high and low frequency components via implementing separate wavelet decomposition for each of the load as shown in above figure.
2) Output of each wavelet decomposition is fed into two separate NN, one for high frequency and other for low frequency components along with other input data [7].
3) Reconstruction is done by combining the outputs of each neural network corresponding to higher and lower frequency components to obtain forecasted load.

4. Results and Discussion

All the simulations are performed on MATLAB version R2011b (7.13.0.564) software on PC having 64-bit operating system and Intel core-i5 2.30-GHz processor. We evaluate the predictive performance of proposed approach using five years of Australian electricity data [5].

4.1. Comparison between Actual and ANN Forecasted load.

Fig. 6 show the comparison of actual and ANN forecasted load. It is observed from the results that the forecasted load is almost follow that of actual load curve.

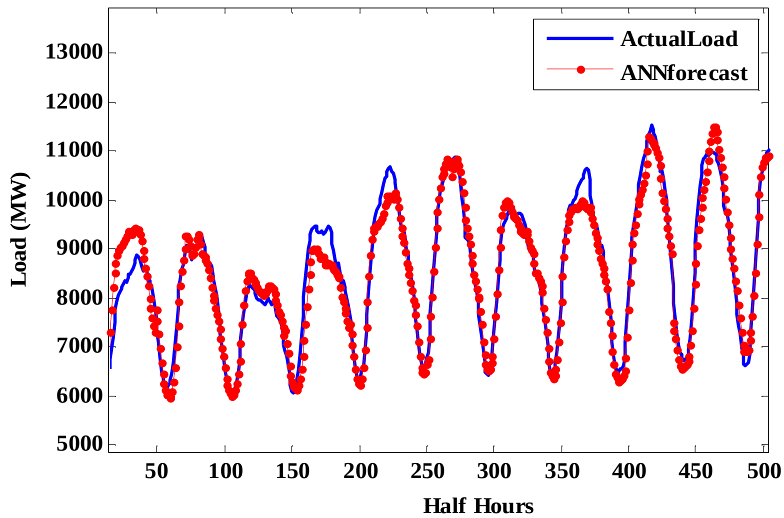

Fig. 6: Contrast of actual load v/s ANN forecasted load.

4.2. Comparison between Actual and WNN Forecasted load.

The Fig. (7-9). show the comparison of actual and WNN forecasted load in decomposed form. It is observed from the results that the forecasted load is almost same as that of actual load.

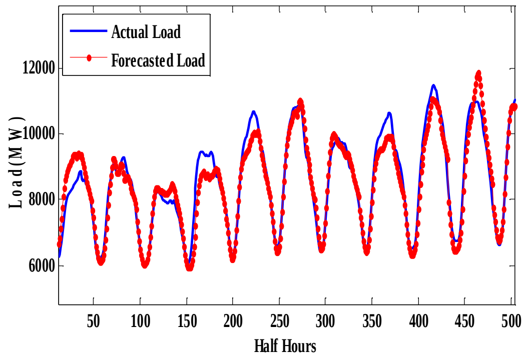

Fig. 7: Actual v/s forecasted load for approximation level.

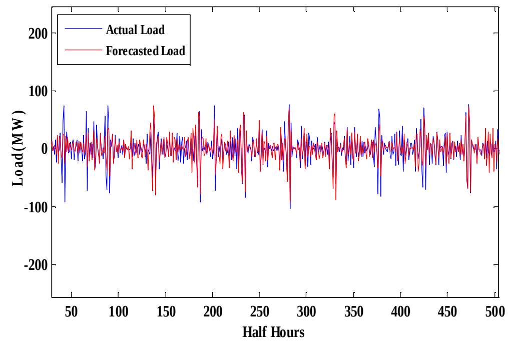

Fig. 8: Actual v/s forecasted load for detail level.

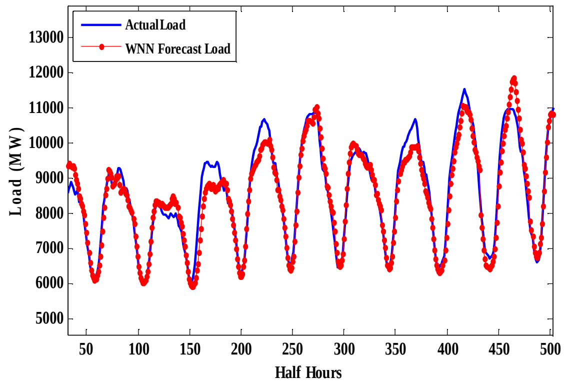

Fig. 9: Contrast of actual load v/s WNN forecasted load.

4.3. Comparison Between Actual, ANN and WNN forecasted load.

Fig. 10 compares the prediction performance of ANN, proposed WNN model and actual load pattern of year 2010. Enlarged view of Fig.10 is shown in Fig. 11.

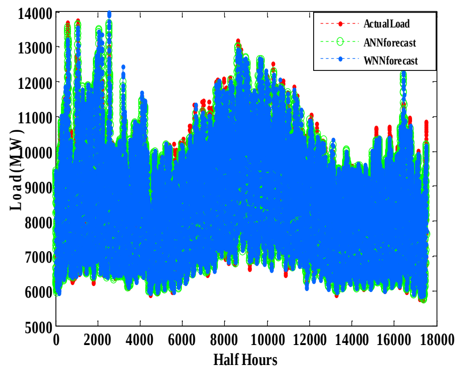

Fig. 10: Forecasting results of different models.

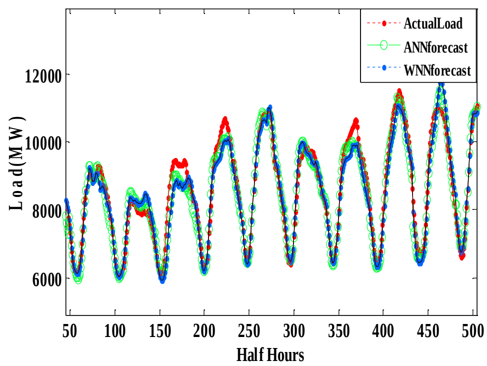

Fig. 11: Enlarged View of figure.10.

4.4. Comparision of MAPE values of ANN and WNN for all weeks of forecasted year

The performance of the models is evaluated by using MAPE (Mean average percentage error) performance index, given by the formula given in (2).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{L_i^{Actual} - L_i^{Forecasted}}{L_i^{Actual}}\right| * 100\% \qquad (2)$$

Table 2: Compares MAPE of Forecasting Based on Proposed WNN Model and ANN for the Year 2010.

S. No.	Months of Year 2010	ANN Forecasted Performance Measure				WNN Forecasted Performance Measure			
		1st week	2nd week	3rd week	4th week	1st week	2nd week	3rd week	4th week
	Jan.	3.20	3.67	3.12	3.23	3.19	3.62	2.86	2.79
	Feb.	2.95	1.96	2.63	2.23	2.70	1.90	2.73	2.26
	March	2.05	2.43	1.40	1.62	1.95	2.60	1.24	1.51
	April	3.70	1.68	1.78	2.85	3.40	1.59	1.77	2.12
	May	1.51	1.25	1.23	1.54	1.43	1.16	1.35	1.35
	June	1.40	2.63	1.57	1.44	1.40	2.37	1.39	1.30
	July	1.90	1.98	1.44	1.82	1.62	1.72	1.31	1.65
	Aug.	1.94	2.24	1.83	1.77	2.02	2.10	1.53	1.60
	Sept.	1.62	1.96	1.54	1.61	1.72	1.82	1.33	1.64
	Oct.	2.38	1.95	1.97	1.74	2.22	1.76	1.88	1.67
	Nov.	2.14	1.54	1.70	1.52	2.00	1.40	1.57	1.54
	Dec.	1.75	1.59	2.09	3.47	1.84	1.70	1.93	3.40

5. Conclusion

The paper presents a novel approach for STLF using WT in combination with ANN. The wavelet is used to decompose data sets to extract useful data and eliminate redundant data. The decomposed output from neural network is reconstructed to obtain the forecasted load for year 2010 using previous 4 years data. It is observed that WNN provides better results as compared to ANN model. It is concluded that the WNN model is capable of producing a reasonable forecasting accuracy. In future work we will increase the resolution level of wavelet transform and also hybrid some other technique with wavelet transform.

References

[1] W.R.Christiaanse, "Short term load forecasting using general exponential smoothing," *IEEE Trans. On Power Apparatus And Systems*, vol. PAS-90, no.2, pp.900-11, Mar./Apr. 1971.

[2] D.C. Park, M.A. EI-Sharkawi, R.J. Marks II, L.E. Atlas and M.J. Damborg, "Electric load forecasting using an artificial neural network," *IEEE Trans. on Power Systems*, vol. 6, no. 2, pp. 442-449, May 1991.

[3] S.H. Ling, H.F. Leung, H.K. Lam and Peter K.S. Tam, "Short-term electric load forecasting based on a neural fuzzy network," *IEEE Trans. On Industrial Electronics*, vol. 50, no. 6, pp. 1305-15, Dec. 2003.

[4] Z. A. Bashir and M. E. El-Hawary, "Applying wavelets to short-term load forecasting using PSO-based neural networks," *IEEE Trans. On Power Systems*, vol. 24, no. 1, pp. 20-27, Feb- 2009.

[5] www.aemo.com.au

[6] Ankita Mohapatra, Manas Kumar Mallick, B K Panigrahi and Zhihua Cui, Samuelson Hong," A Hybrid Approach for Short term Electricity Price and Load Forecasting," *IEEE Conference*, 2011.

[7] Che Guan, Peter B.Luh, Laurent D. Michel, Yuting Wang, and Peter B. Friedland, "Very Short-term load forecasting: wavelet neural networks with data pre-filtering," *IEEE Transactions On Power Systems*, vol. 28, no. 1, pp.30-41, Feb. 2013.