International Journal of Electrical Engineering.
ISSN 0974-2158 Volume 9, Number 2 (2016), pp. 225-232

http://www.irphouse.com

Wavelet Entropy Based Short Term Load Forecasting

Nikita Mittal* **and Tanuj Manglani**

Department of Electrical Engineering,
Yagyavalkya Institute of Technology, Jaipur-302017, India

Abstract

Modern power network is a complex network with multiple utilities at transmission and distribution end. Distribution system planning consists of load forecasting, loss minimization strategies, smart distribution system and advanced metering infrastructure development. A fair relation is required between system load and generation for successful operation of the power network. With the increase in demands load forecasting is an important aspect of the power system. At energy management centre various decisions are based on the forecasted load. This paper presents a novel method for load forecasting based on wavelet entropy. Historical demand curves are utilized to calculate the entropies of the curves. Four different topologies of neural networks are employed to carry out this forecasting task. Comparison between the conventional and proposed approach is established through different error indices. The proposed approach is promising and can be utilized as an effective tool at energy management centre.

Keywords: Load forecasting, Artificial Neural Network, Layer Recurrent Neural Network, Wavelet Entropy, Mean Square Error (MSE)

1. INTRODUCTION

Because Power system load forecasting is an important task of power system planning and construction [1]. In load forecasting process, different forecasting results appear due to the application of different forecasting algorithms or different data sources. Since, the goal of the power utilities is lower operation cost and higher reliability, accurate load forecasting is essential for optimum scheduling and planning of power system operation [2]. Various approaches have been developed to incorporate

non-linearity and auto-correlation into the modeling process to improve the forecasting accuracy.
To solve the problem of load forecasting, some integrated forecasting models are proposed. To deduce the weight coefficients, the evolutionary programming and fuzzy comprehensive evaluation methods are employed [3] and [4]. In [5], Bayesian multiple models combination method for time series prediction is employed that produces a final prediction which is a weighted prediction of local predictions.

Intelligent approaches like knowledge system [6-7], expert system [8-10] and artificial neural network (ANN)[11-12] are used to solve the problems which are difficult to solve analytically. ANNs are used recently in the area of load forecasting due to the advantage over traditional linear regression methods and its better performance. ANN combines the regression approaches and time-series to find similar previous load patterns and improves the forecasting accuracy. The neural network learns the non-linear relationship between the load and explanatory variables directly from historical data [13].

Entropy was introduced in the information theory by C.E. Shannon, who promoted the development of information theory. Entropy is a measure of uncertainty associated with a random variable in information theory. Entropy serves as a tool to guide the optimization process and is used to solve the problems in power system. Entropy theory is used to analyze the information content of the wavelet decomposed multi-scale data structure. Variants of entropy are wavelet entropy, relative wavelet entropy, log entropy and many more. Entropy based load forecasting introduces the additional parameter which has great impact on the modeling and forecasting accuracy. When entropy is introduced in the forecasting, the ultimate aim is to achieve better understanding of the input and output relationship among variables, with the improved forecasting accuracy in the end [14].

ANN based clustering method on the entropy principle for short-term load forecasting is presented in [15]. Xu at al. [16] used the modified wavelet entropy measure with windows function to differentiate between normal and hypertension state.. Wavelet packet entropy analysis has the ability to resolve neuroelectric waveforms into specific time and frequency components.

Artificial intelligence models such as artificial neural network and support vector machines have achieved a lot of importance in recent days. In this paper four ANN models are constructed, i.e. layer recurrent neural network (LRNN), feed-forward neural network (FFNN), Elman neural network and NARX method, which have the ability of dealing with non-linear problems. Firstly these four models are trained with the data set obtained using the logarithmic wavelet entropy of the demand curves of previous years. Secondly these models are trained with the original data set consisting of historical data, dew points measurements, electricity prices, etc. Results of both approaches are then compared to see if entropy improves the accuracy of forecasting. Entropy method showed satisfactory forecasting results.

The paper is organized as follows. Section 2 proposes the wavelet entropy based approach for load forecasting.. Section 3 presents the proposed methodology. Section 4 presents the results and discussion. Concluding remarks are given in section 5.

2. ENTROPY AND WAVELET ENTROPY THEORY

Let we have n number of observations in a data set, which contains a mixture of data features. Wavelet entropy can be used in estimating the uncertainty and disorder levels in the data. It calculates the entropy value of the probability density function of the energy distribution. If the value of wavelet entropy is small, the data will be more organized and if the value of wavelet entropy is large, data will be disordered and uncertain. The wavelet entropy value size reflects the average level of probability density of the data across different scales. The wavelet entropy value takes into account the structural distribution of randomness across scales and recognizes the preserved data at different scales [17].

The entropy value is measured as the disorder in data, and introduced to analyze the historical data at two levels, i.e., microscope and macro scope. At the macro scope level, the wavelet entropy takes into account the distribution of randomness across different scales to measure the randomness of data. When the wavelet entropy is calculated at the same maximum scale with different wavelet families, the wavelet family with the lowest wavelet entropy value is retained. At the microscale level, the entropy at different scales is calculated for individual coefficients and is used to measure information content at different scales and to compare their randomness directly. The numerical procedure for wavelet entropy based forecasting is as follows.
Firstly we decompose the training data into different sub-data series at different scales up to the maximum scale J, using wavelet algorithm. Wavelet analysis has the capability to conduct multi scale analysis and to project data into time-scale domain [18]. Mathematically, wavelets satisfy admissibility conditions which are continuous functions, as given in (1)

$$C_{\psi} = \int_{0}^{\infty} \frac{|\Psi(f)|}{f} df \langle \infty \leftrightarrow \int_{-\infty}^{\infty} \psi(t) dt = 0 \tag{1}$$

A unit energy condition is given in equation (2):

$$\int_{-\infty}^{\infty} \left| \psi(t)^2 \, dt = 1 \right| \tag{2}$$

Where Ψ is the Fourier transform of ψ. These two equations guarantee that the wavelet functions have zero vanishing moments and improved localization in time scale domain during the analysis. Different families of wavelets are available with their own special characteristics [19]. The Haar wavelet has the characteristic of orthogonality and compact support and it is defined in the equation (3):

$$\psi(t) = \begin{cases} +1 & \text{if} \quad 0 \le t \le 0.5 \\ -1 & \text{if} \quad 0.5 \le t \le 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The wavelets can be translated over time and dilated by scales as given in equation (4):

$$\psi_{u,s} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{4}$$

Wavelets are characterized by two parameters: location u and scale s. Thus, wavelets of different lengths and shapes are formed by adjusting these two parameters.

The original signal can be projected into time scale domain by means of convolving the translated or dilated wavelets to the original signal. Thus the wavelet transform is a function of these two variables as given in equation (5):

$$W(u,s) = \int_{-\infty}^{\infty} x(t)\psi_{u,s}(t)dt \tag{5}$$

The inverse operation can be performed using equation (6):

$$x(t) = \frac{1}{C_\psi}\int_{0}^{\infty}\int_{-\infty}^{\infty} W(u,s)\psi_{u,s}(t)du\frac{ds}{s^2} \tag{6}$$

3. PROPOSED METHODOLOGY

This section explains the methodology adopted in the paper. Normally the demand trends of previous years are boonful for forecasting studies. To investigate the effectiveness of the data analysis of demand curves through wave entropy method is the primary motivation to carry this research work.

A flow of supervised learning model is shown in figure to explain the data training testing and validation process.

a. A data set of 1500 observations is taken from the Australian Electricity market on day basis. The time interval chosen for this analysis is (2006-2010). To forecast the load, neural network features are taken as historical load data, electricity prices, different measurement conditions and weather conditions. This approach is a conventional approach.
b. Log entropies of the demand curves (historical 2006-2009) are obtained and the values of those entropies are incorporated as input features to the neural network in the proposed approach. Predicted load is at output.
c. Normalization of the data is processed between 0.1 to 0.9 for better matching and regression. Out of the data set 70% data are considered for training purpose remaining data are used for testing and validation.

d. Comparison of these two approaches is based on the standard error indices presented in following section. To give more insight on the proposed approach average of the error indices for all the four networks are calculated and

4. RESULTS AND SIMULATION

This section presents simulation results of proposed entropy based load forecast. The data for this simulation is taken from the Australian Electricity Market. The system is implemented using MATLAB 2013 and run on a Pentium IV CPU, 2.69 GHz, and 1.84 GB RAM computer.

4.1 Evaluation Metrics

For evaluating the performance of the models for load forecasting, comparison is made between the forecasts and the actual load. We can test the accuracy over time by comparing the forecasted values to the actual values by calculating three different measures:

- The simplest measure to measure the accuracy of forecast is Mean Absolute Error (MAE). It is the mean of absolute errors and the absolute error is the absolute value of difference between the forecast value and actual value. Mathematically MAE can be defined as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left| y_{act}(i) - y_{pre}(i)\right| \tag{13}$$

- We can find the Mean Absolute error in percentage form by calculating Mean Absolute Percentage Error (MAPE). MAPE allows comparing forecast of different series to different scales. Mathematically MAPE can be defined as:

$$MAPE = \frac{1}{N}\left|\frac{[y_{act}(i) - y_{pre}(i)]}{y_{act}(i)}\right| \times 100\% \tag{14}$$

- To calculate the large rare errors, we calculate Root Mean Square Errors (RMSE). RMSE gives more weight to the large infrequent errors. Errors will be more inconsistent if RMSE and MAE has large difference. Mathematically RMSE can be defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{act}(i) - y_{pre}(i)\right)^2} \tag{15}$$

Where N=500 is the number of samples for validation, y_{act} is the observed value of load and y_{pre} is the predicted value of load.

4.2 Discussions

To determine the predictive ability of the proposed models, we perform simulation for LRNN, FFNN, NARX and Elman neural network models with conventional approach and proposed methodology. So eight model are constructed to test the ability and to select the network with best performance. Input variables are selected as the humidity, electricity price, dew point, wet bulb and dry bulb, so input layer has five neurons.

The output layer has only one neuron which represents the predicted half hourly loads. A set of 1500 data points is selected for training and a set of another 500 data point is used for model validation. To verify the predictive ability of proposed models, we perform simulation for entropy based neural network with all the above mentioned models.

There are many techniques available to measure the effectiveness of the forecasting. To evaluate the forecasting accuracy here we have used three criterions RMSE, MAPE and MAE. Values of errors are calculated and comparative results of models are listed in Table 1.

Table 1: Comparison of errors among the proposed models

	MODELS	RMSE	MAE	MAPE
(i) WITH ENTROPY	FFNN	0.1087	0.0848	0.6160
	LRNN	0.1114	0.0864	0.6560
	ELMAN	0.1140	0.0876	0.6879
	NARX	0.1123	0.0878	0.6740
(ii) WITHOUT ENTROPY	FFNN	0.1738	0.1395	1.3960
	LRNN	0.1131	0.0874	0.6980
	ELMAN	0.1167	0.0910	0.7306
	NARX	0.1213	0.0984	0.7079

In the above table, comparative results are obtained among the models trained with entropy method and without entropy method. First part of table shows the RMSE, MAE and MAPE for the models trained with entropy methods. Second part shows the values of errors for the models trained without entropy. It can be observed from the table that models trained with entropy method are more accurate as the errors are lesser in the case.

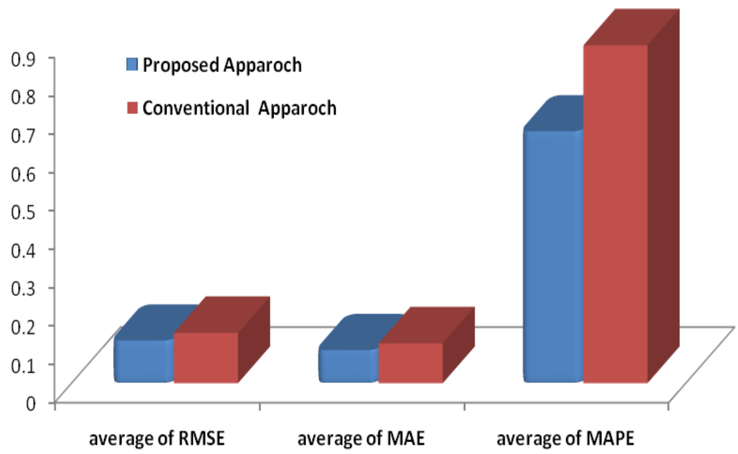

Figure 1: Average of Error indices for conventional and proposed approach

Figure 1 shows the average values of RMSE, MAE and MAPE for all the networks. It is observed that the values of these indices fall in low range when the neural networks are trained through the wave entropy inputs. It is observed that for all four topologies value of RMSE is 0.1116 for proposed method and for conventional method it is 0.1312, similarly in the case of MAE the values are 0.08665 and 0.104075 and for MAPE these are 0.65 and 0.88 respectively. It is concluded that for all neural topologies entropy based method is less erroneous. However, large values of errors appear in prediction in conventional method of forecast. Following section presents the main findings of paper in a conclusive form.

CONCLUSIONS

This paper presents an application of wave entropy (Log) for forecasting the electrical load for a real power system. Load forecasting is an important tool for execution of planning and control of the power network. Following are the main contribution of this paper:

1) Performance of four neural network topologies is observed in this work. On the basis of error indices the performance evaluation is carried out.
2) The choice of features is derived from conventional load forecasting methods and compared with the proposed historical data wave entropy based load forecasting method. It is observed that errors in predictions are very low for the proposed network.
3) At last, the average values of errors are calculated and exhibited for advocating the efficacy of the proposed approach over the conventional one.

REFERENCES

[1] I.Moghram and S.Rahaman, Analysis and evaluation of five short-term load forecasting techniques, IEEE Trans.Power Systems, Vol.4, Oct. 1989, 1484-1494.

[2] W. Charytoniuk, M. S. Chen, Neural Network design for Short-Term Load Forecasting, presented at Proceedings of International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, London, 2000.

[3] G.J. Chen, K.K. Li, T.S. Chung, H.B. Sun, G.Q. Tang. Application of an innovative combined forecasting method in power system load forecasting. Electric Power Systems Research. Vol.59,2001,131–137.

[4] R.C. Bansal, Bibliography on the fuzzy set theory applications to power systems, IEEE Trans. Power Systems, Vol. 18,2003, 12911299.

[5] V.Pedridis, A.Kehagias, L.Petrou, A. Bakirtzis, S. Kiartzis, H. Panagiotou, N. Maslaris.A Bayesian multiple modelscombination method for time series prediction. Journal of Intelligentand Robotic System. Vol.31, 2001, 69-89.

[6] S. Rahman and O. Hazim. A Generalized knowledge based short-term load forecasting technique.IEEE Trans. Power Systems. Vol.8,1993, 508-514.

[7] S. Rahman and I. Moghram. An adaptive knowledge based technique for weekly load forecast. Proceedings of the Power System Computation Conference, Graz, Austria, August 1990.

[8] S.Rahman, R. Bhatnagar, An expert system based algorithm for short term load forecast, IEEE Trans. Power Systems, Vol.3, 1988,392-399.

[9] S. Rahman, Formulation and Analysis of a rule based Short term load forecasting algorithm, proc. of IEEE, Vol.78, 1990,805-815.

[10] R.C. Bansal, Literature survey on expert system applications to power systems, Engineering Intelligent Systems, Vol.11, 2003, 103-112.

[11] R.C. Bansal and J.C. Pandey, Load forecasting using artificial intelligent techniques: a literature survey, Int. Journal of Computer Applications in Technology, Vol.22, 2005. 109-119.

[12] R.C. Bansal, Overview and literature survey of artificial neural networks applications to power systems, Journal of Institution of Engineers- Electrical Engineering, Vol. 86, 2006, 282-296.

[13] W. Sun, J. Lu and Y. He. Information entropy based neural network model for short-term load forecasting. Presented at IEEE Transmission and Distribution Conference and Exhibition, Asia and Pacific, 2005.

[14] Claude E. Shannon: A mathematical theory of communication, Bell System Technical Journal, Vol. 27,1948, 379–423, 623–656.

[15] P. Xu, X. Hu, D. Yao, Improved wavelet entropy calculation with window functions and its preliminary application to study intracranial pressure. Comput. Biol. Med. Vol.43, 2013, 425–433.

[16] H. Mori and A. Yuihara, Deterministic annealing clustering for ANN based short-term load forecasting, IEEE Trans. Power Systems,Vol.16, 2001, 545-551.

[17] Y.F.Sang, Z.G. Wang, Z.L.Li. Discrete wavelet entropy aided detection of abrupt change: a case study in the Haihe river basin, China. Entropy, 2012, 14, 1274–1284.

[18] R. Gencay, F. Selck, B. Whitcher, Multiscale Systematic Risk. J. Int. Money Financ. Vol.24, 2005, 55–70.

[19] R. Gencay, F. Selck, B. Whitcher. An Introduction to Wavelets and Other Filtering Methods in Finance and Economics; Academic Press: San Diego, CA, USA, 2002.