A Hybrid Short-Term Load Forecasting Method Based on Empirical Mode Decomposition and Feed Forward Back Propagation Neural Network

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***Abstract*— Short term load forecasting is a very important task of a utility company. Short term load forecasting can help to estimate load flow and to make decisions that can prevent overloading, improve reliability and reduce the occurrences of equipment failures and blackouts. In this paper, we use hybrid short-term load forecasting method based on Empirical Mode Decomposition (EMD) technique and artificial neural networks to forecast the load of 24 hours by using the load data of previous three years. By applying the EMD method, the non-linear and non stationary original load series is decomposed into a finite number of stationary intrinsic mode functions (IMFs) and residue. The correlation factor analysis is carried out between the original signal, IMFs and residue. The load is forecasted with the residue only. The forecasted data was then compared with the actual data and error was calculated. The neural network implemented was feed forward back propagation (FFBP). The outcome of basic FFBP neural network and hybrid model were compared and it was found that hybrid model gives the best approximation to the given data pattern.**

Keywords—*Empirical Mode Decomposition (EMD), Intrinsic Mode Function (IMF), Short-Term Load Forecasting (STLF), Feed Forward Back Propagation Neural Network (FFB-NN).*

I. Introduction

Electric Load Forecasting is an important aspect of power system planning and operation for utility companies. Electric load is dependent on many factors such as weather, human work patterns (workdays and weekends), etc. There are different types of load forecasting. Short term load forecasting is done for hours to week. Medium and Long term load forecasting is done for week to year or even for longer period. Short term load forecasting helps the electric utilities to make the decision on buying or selling electricity and load switching during the operation. The STLF methods can be broadly classified into two categories: modern intelligent methods and traditional techniques.

The traditional methods are time series analysis methods based on mathematical statistics, such as regression analysis approach, exponential smoothing, and autoregressive integrated moving average and so on. These methods have the advantage of simple algorithm; they are not suitable for forecasting the non linear and non stationary electric load series. Modern intelligent approaches such as expert system, fuzzy logic based approach and artificial neural networks are now widely used as they increase the performance of load forecasting. Artificial neural network with its ability to derive meaning from complicated and imprecise data and its outstanding performance in data classification and function approximation are now widely used in the field of load forecasting. There is no single best prediction method that can be applied to any specific situation. As a result, many combinations of short-term forecasting methods that uses more than two models are proposed to enhance the performance of existing models. [1] had developed a hybrid model based on wavelet transform and neuro evolutionary algorithm (WTNNEA) for short term load forecasting and used to forecast the load of North American Electric Utility. Similarly, [2] had developed a wavelet transform and grey model improved by practical swarm optimization (WGMIPSO) and used the model to forecast the load of New York City. Empirical Mode Decomposition and Back Propagation Neural Network model has been developed by [3] and Eastern Slovakian Electricity Corporation load had been forecasted by using this model.

In this paper, a hybrid model based on empirical mode decomposition and feed forward back propagation neural network algorithm is used for short term load forecasting. The input load data are decomposed using EMD techniques into the number of intrinsic mode function and the final residue. The noise on the input signal is removed by analyzing the correlation factor between the input data, IMFs and residue. The final forecasted output is obtained by using the residue as the input load data.

II. ANALYZING TECHNIQUES

A) EMD

The EMD is a time domain signal processing method for analyzing non-linear and non-stationary signal in which the signal is decomposed into several simpler forms, called Intrinsic Mode Functions (IMFs). [4] Proposed this process. A number of IMFs can be decomposed from the non linear signal by the process known as sifting. The IMFs have two properties:

(a) The extreme between zero crossings must differ at most by one or equal

(b) Its mean value obtained by averaging upper and lower envelop is zero.

The system load is a random non-stationary process composed of thousands of individual components. The system load behavior is influenced by a number of factors, which can be classified as: economic factors, time, day, season, weather and random effects. Thus, EMD algorithm can be very effective for load demand forecasting. The process of shifting is described as below.

(1) With a given time series signal x (t), create its upper u (t) and lower l (t) envelopes by a cubic-spline interpolation of local maxima and minima.

(2) Find the mean of the envelopes as m (t) = [u (t) + l (t)]/2.

(3) Take the difference between the data and the mean as the proto-IMF, h (t) =x (t) − m (t).

(4) Check the proto-IMF against the definition of IMF and the stoppage criterion to determine if it is an IMF.

(5) If the proto-IMF does not satisfy the definition, repeat step 1 to 5 on *h* (*t*) as many time as needed till it satisfies the definition.

(6) If the proto-IMF does satisfy the definition, assign the proto-IMF as an IMF component, c (t).

(7) Repeat the operation step 1 to 7 on the residue, r (t) = x (t) −c (t), as the data.

(8) The operation ends when the residue contains no more than one extreme.

Finally, the original TS signal is decomposed as:

$$X(t) = \sum_{j=1}^{n} c_j + r_n \qquad (1)$$

Where the number of functions n in the set depends on the original TS signal.

B) FFBP-NN

The FFBP-NN is one of the most widely used artificial neural networks and it has infinite potential in the load forecasting area due to its strong nonlinear processing ability and approaching capability. A typical BPNN is a multilevel hierarchical feedback structure, which is used to adjust the network weights through the back propagation algorithm, including input layer, hidden layer, and output layer. Figure 1 shows the schematic diagram of back propagation model. The working procedure of feed forward back propagation model is described as below.

- Inputs X, flow through the pre-connected path.
- Input is modeled using real weights W. The weights are usually randomly selected.
- Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer.
- Calculate the error in the outputs.
- Error= Actual Output – Desired Output.
- Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased, repeating the process until the desired output is achieved.

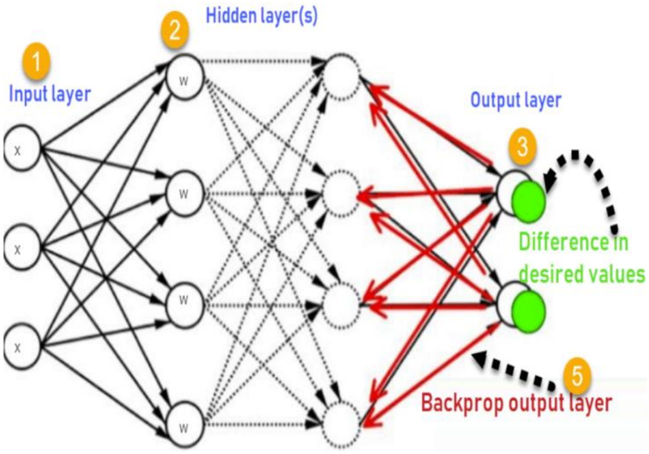

Fig. 1. Flow diagram of feed forward back propagation neural network.

III. A HYBRID STLF MODEL

To reduce the instability of the original load series, EMD is used to decompose the original load series into a finite numbers of IMFs and one residual. Then these components are forecast by FFBP neural network respectively, such that the tendencies of these components can be predicted. Finally, aggregation of the prediction results of all components through NN produces the final forecasting result for the original electric load series, this model can be denoted by EMD–FFBP. Figure 2 shows the algorithm of hybrid ANN model for short term load forecasting. However, all IMFs are not effective for load forecasting. Therefore, in order to select effective IMFs, Correlation Factor Analysis CFA is proposed in [5]. The quantity measures the correlation coefficient between each IMF and the original signal. If the correlation coefficient is too small, then the IMF may be primarily considered to be a redundant or noisy component. The CFA can be formulated as in equation 2.

$$\lambda = \frac{\sum_{n=1}^{N}[x(t)C(t)]}{\sqrt{[\sum_{n=1}^{N} x(t)^2 \sum_{n=1}^{N} c(t)^2]}} \quad (2)$$

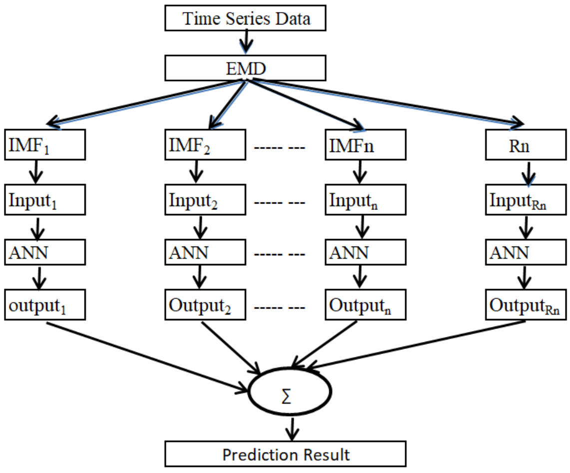

Fig. 2. Flow chart of EMD based Load forecasting

IV. Experimental Setup

A) Statistical Measures of Forecasting Performance

In this study, the following two criteria were used to evaluate the STLF methods. They are the mean absolute percentage error (MAPE) and mean absolute deviation (MAD) which are calculated as:

$$\text{MAD}= \frac{\sum_{i=1}^{n} |A-F|}{n} \quad (3)$$

$$\text{MAPE}= \frac{\sum_{i=1}^{n} (|A-F|)/n}{n} \times 100 \quad (4)$$

Where **A** represent the actual load and **F** represent the forecasted load. Clearly, the above two criteria represent two types of deviation between the actual and forecasted load. Smaller the value better is the forecasting accuracy.

B) Study 1: Examination of Basic FFBP Model

The load data are gathered from the load dispatch centre of Nepal Electricity Authority. The load data include the reading of 1 hour per sampling point. The data used in this study are the data of 2074, 2075 and 2076 B.S for the month of Baishak and the day Sunday only.

The data of Baishak's for the year 2074, 2075 and 2076 B.S are used for training and model fittings and the model is used to forecast the load of Baishak 22, 2076 B.S.

The result of STLF for Baishak 22, 2076 is shown in the Table I. The mean absolute deviation and mean absolute percentage error between the actual and forecasted load are respectively 13.6 MW and 9.02%.

TABLE I. ACTUAL AND FORECASTED LOAD BY BASIC ANN MODEL

Time(Hours)	actual load in MW	forecasted load by basic ANN in MW
1:00	128.34	134.58
2:00	123.84	136
3:00	122.04	171.47
4:00	123.54	178.1
5:00	138.64	195.49
6:00	181.44	218.48
7:00	223.34	233.24
8:00	243.84	239.09
9:00	242.44	240.99
10:00	247.24	241.57
11:00	251.14	241.75
12:00	247.84	241.84
13:00	240.94	241.96
14:00	243.24	242.31
15:00	243.54	243.34
16:00	250.34	246.28
17:00	266.14	253.07
18:00	253.94	252
19:00	311.14	295
20:00	287.29	288.63
21:00	255.74	252.26

22:00	162.64	172.83
23:00	137.54	132
0:00	101.54	116.58

C) *Study 2: Examination of Hybrid Model*

With the same data as in study 1 the load is forecasted for Baishak 22, 2076. In this study the input data points are decomposed into the number of IMFs and residue using EMD technique. The decomposed signals are shown in figure 3. The correlation factor analysis is carried out between the IMFs, residue and the original data. Table II shows the correlation between the input load data, IMFs and residue.

TABLE II. CORRELATION BETWEEN ACTUAL LOAD, IMFS AND RESIDUE

IMFs/Residue	Input
IMF1	0.03
IMF2	0.05
IMF3	0.15
IMF4	0.13
IMF5	0.01
IMF6	-0.16
IMF7	-0.01
IMF8	-0.2
IMF9	-0.35
Residue	0.93

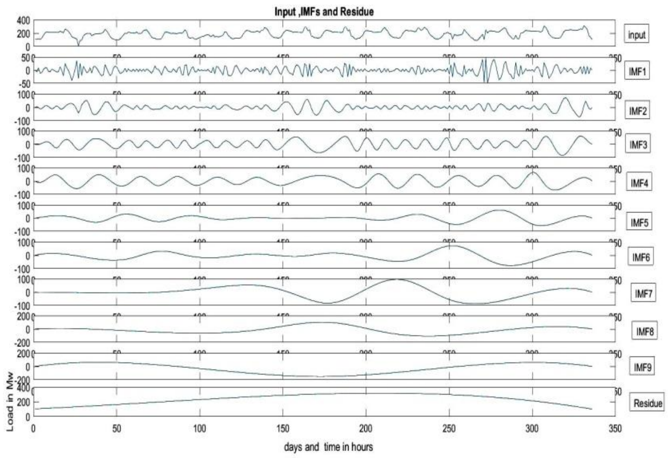

Fig. 3. Input load, its IMF's component and residue.

The total load forecast is obtained by summing up the individual load forecast of IMFs and residue. In this case the MAPE between the actual and forecasted load is found to be 6.2%.

As stated earlier only the strong correlation is found between the residue and the original load data, so using the advantage of EMD technique the load is forecasted by taking residue as the input load data signal. In this case the MAD is found to be 3.27MWand the MAPE is found to be 1.79%.

Table III shows the actual and forecasted load by hybrid model

TABLE III. ACTUAL AND FORECASTED LOAD BY HYBRID ANN MODEL

Time(Hours)	**actual load in MW**	**Forecasted load by hybrid model after CFA analysis in MW**
1:00	128.34	125.83
2:00	123.84	121.11
3:00	122.04	121.2
4:00	123.54	122.31
5:00	138.64	131.49
6:00	181.44	182.59
7:00	223.34	222.64
8:00	243.84	251.73
9:00	242.44	241.91
10:00	247.24	252.03
11:00	251.14	252.08
12:00	247.84	251.16
13:00	240.94	242.29
14:00	243.24	252.38
15:00	243.54	252.42
16:00	250.34	251.51
17:00	266.14	265.61
18:00	253.94	252.66
19:00	311.14	309.69
20:00	287.29	282.75
21:00	255.74	252.86
22:00	162.64	161.91
23:00	137.54	142.91
0:00	101.54	108.86

V. CONCLUSION

We presented in this paper a new approach to short-term load forecasting problem. In particular, the proposed method allows performing a short term load forecasting with hourly time scale and provide a satisfactory solution.

The proposed approach exploits the Empirical Mode Decomposition and artificial neural network for short term estimation of load.EMD allows denoising the original signal which increases the accuracy in forecasting.

The proposed approach has been tested by calculating the MAD and MAPE between the original and forecasted load. The purposed hybrid model decreases the MAD by 10.33 MW and MAPE by 7.23% compared to the general neural network model. The result obtained by EMD and FFBP-NN gives the best approximation in short term load forecasting.

ACKNOWLEDGEMENT

The authors would like to thank Nepal Electricity Authority, Load dispatch centre for providing the necessary data; also we are thankful to Mr. Sristik Pd. kayastha and Mr. Gorakh Raj Joshi for their contribution in programming aspect of this research work.

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