Comparison of fuzzy time series, ANN and wavelet techniques for short term load forecasting

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ABSTRACT

The present article presents the load forecasting for a power system (substation) load demands using techniques based on fuzzy time series (FTS), artificial neural network (ANN), and wavelet transform (WT). The mean absolute percentage error (MAPE), integral absolute error (IAE), integral of time multiplied error (ITAE), integral square error (ISE) along with integral time multiplied square error (ITSE) criteria are used for determining the performance indices and minimizing the error. From the investigations of the results obtained in the study, it is inferred that forecasting of electric load based on WT and ANN offers less error as compared to FTS. The suggested integrated model captures the useful properties of artificial neural networks and wavelet transforms in time series and is found to be accurate for real-time data.

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1. INTRODUCTION

Present day power system has a huge and complex structure operating in an interconnected fashion due to various economic and technical reasons. The planning, operation, and control of such systems have become a challenging task for the utilities. To supply affordable quality power to the consumers is an added responsibility for the power engineers/utilities. Thus, load forecasting requires lots of historical data, weather information, and historical events information to run a forecasting model. Figure 1 represents a simplified block diagram of the load forecasting process.

There is a heap of studies available in the literature relating to this topic. In early studies presented so far during the 1940s-1960s were mainly based on classical approaches using interpolation extrapolation of the following trends of available data [1]–[4]. Later, these approaches were found to be inadequate to deal with the processes/systems associated with system dynamic changes along with the operating environment variations. At this stage, the applications of various forms of time series have emerged to circumvent these limitations. For instance, electric load consumed does not have specific pattern trends, it is quite challenging to model accurately. In addition, fuzzy time series is considered to be among the most organized and simple techniques applied to the prospective forecast of the various exciting situation in comparison, if the simple time series method is applied for this purpose [5]. The fuzzy time series forecasting approach was established and used effectively in short-term prediction by [6]. One of the significant aspects of the artificial neural network is to offer efficient modeling for major non-linearity. For that reason, it has attained a very important place in its applications for predicting energy requirements in the power system [7]–[11].

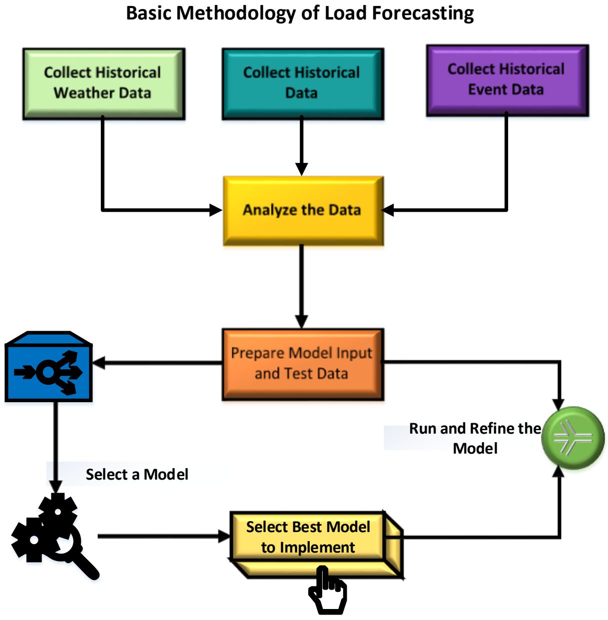

Figure 1. Simplified block diagram of load forecasting process

Over the past few years, it has been proven the use of wavelets transforms to get information in time as well as frequency domain. As a result, researchers have used the characteristics of wavelet transform and suggested some prediction methods. The wavelet transforms combined with an artificial neural network designed for short-term forecasting is effectively realized in [12]. To avoid uncertainty and overtraining [13] the wavelets are utilized differently for ANN building. A hybrid learning method ELM-LM capable of selecting highly informative features of the load is used.

The most of papers identified in the literature [14]–[25] have been found to deal with a wide range of forecasting techniques starting with conventional to most advanced intelligent techniques. The application areas are also varying from small systems to larger and larger systems considering linear and non-linear aspects of their nature. Many applications are visible for load estimation in the power system area also. However, most of the works are lacking in using real-time power utility data for load forecasting. In this paper, real-time data is collected for forecasting from an electric utility in India. A combination of advanced and intelligent techniques like; FT series, ANN, and an integrated technique of WT with ANN are applied. The results achieved are investigated and the superiority of WT has been demonstrated.

2. THE PROPOSED METHODS

There is a vast range of forecasting techniques stretching from conventional to intelligent techniques. However, among them, most advanced and popularly adopted load forecasting techniques for power system utilities for various studies are FTS, ANN and WT. For current study, input data is collected from a distribution company of Noida, U.P. In the course of this forecast has been considered for one hour. Hence hourly data is collected for better accuracy.

2.1. Fuzzy time series

A time series is considered an ordered set of certain variables sequentially in time. It is based on the assumptions that prospective shape of load is connected to its preceding values. Generally, time series technique is applied for forecasting the prospective data for a particular set of previous/past data. The past data must exist for future data prediction. Fuzzy relations, when used to model a time series is called fuzzy time series. In this method, values of fuzzy time series are considered as fuzzy sets and there exists a correlation among the observations in time t and preceding time. The development of fuzzy time series-based model is shown in Figure 2.

For the present research, real time data are collected for a substation in India. The data are so huge; it cannot be presented in the table due to limitation of space. At first stage, to implement the proposed technique described in Figure. 2, the steps to be followed are:

i) Step 1: Assemble the historic data
ii) Step 2: Find the maximum Dmax and the minimum Dmin among all data and define the universe of discourse as: UD = [Dmin, Dmax]

iii) Step 3: Divide the universe of discourse UD into sixteen the same size intervals UDi, i = 1 to 16
iv) Step 4: Conferring to the distribution of the historic data, fuzzy sets which are defined on fuzzy numbers are determined

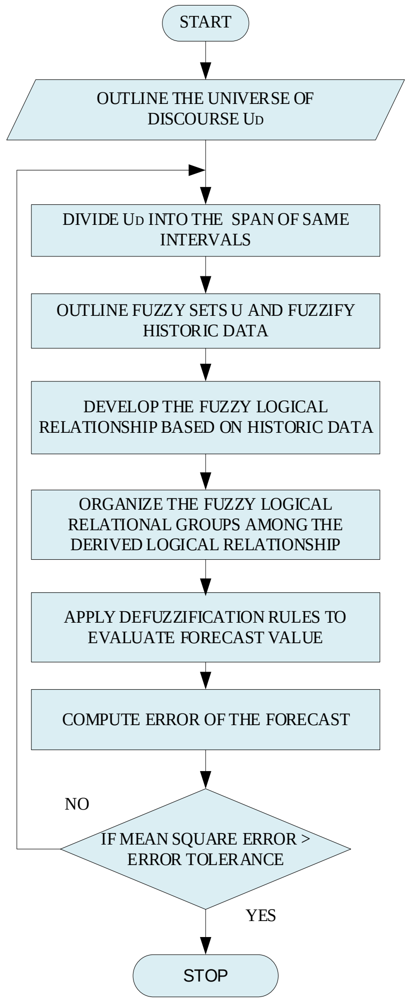

Figure 2. Flowchart showing development of fuzzy time series-based forecasting model

2.1.1. Fuzzy set for each observation

The fuzzy set, based on the universe of discourse U_D are defined by:

- Calculate all the absolute differences between A_{i+1} and A_i (i = 1, 2…, n-1), as the mean values of the differences
- Take one half of the means (in previous step) as the length
- The universe of Discourse for observations, U_D, is defined as [D_{min}, D_{max}] adjusted minimum and maximum value of known historic data
- From the load data, we have selected D_{min} = 3860 and D_{max} = 19000 and hence the universe of discourse is defined as U_D = [3000, 19000]. Average-based length is calculated: The fuzzy set bound is shown in the Table 1.

2.1.2. Establishing fuzzifying rules

Forecasting is done on values for each hour j using any one of the following conditions (1)-(3).

$$F_1 = \frac{1+0.5}{\frac{1}{a_1}+\frac{0.5}{a_2}}, \text{if } j = 1 \quad (1)$$

$$F_n = \frac{0.5+1}{\frac{0.5}{a_{n-1}}+\frac{1}{a_n}}, \text{if } j = n \tag{2}$$

$$F_j = \frac{0.5+1+0.5}{\frac{0.5}{a_{j-1}}+\frac{1}{a_j}+\frac{0.5}{a_{j+1}}}, \text{if } 2 < j < n-2 \tag{3}$$

If only one relationship linguistic variable exists, Fj is mid-point of data taken for forecast. If no relationship of linguistic variables exists in third order, the original data is taken for the forecast. The defuzzied value for each linguistic variable is shown in Table 2.

Table 1. Fuzzy sets with bounds and mid values

Fuzzy sets	Interval	Mid-point of fuzzy interval	Designated mid-point
u_1	[3000,4000]	3500	a_1
u_2	[4000,5000]	4500	a_2
u_3	[5000,6000]	5500	a_3
u_4	[6000,7000]	6500	a_4
u_5	[7000,8000]	7500	a_5
u_6	[8000,9000]	8500	a_6
u_7	[9000,10000]	9500	a_7
u_8	[10000,11000]	10500	a_8
u_9	[11000,12000]	11500	a_9
u_{10}	[12000,13000]	12500	a_{10}
u_{11}	[13000,14000]	13500	a_{11}
u_{12}	[14000,15000]	14500	a_{12}
u_{13}	[15000,16000]	15500	a_{13}
u_{14}	[16000,17000]	16500	a_{14}
u_{15}	[17000,18000]	17500	a_{15}
u_{16}	[18000,19000]	18500	a_{16}

Table 2. Defuzzification

Fuzzy set	Crisp values
A_1	3500
A_2	4790.322581
A_3	5407.56
A_4	6422.15
A_5	7432.74
A_6	8440.77
A_7	9447.08
A_8	10452.16
A_9	11456.36
A_{10}	12459.87
A_{11}	13462.86
A_{12}	14465.43
A_{13}	15467.67
A_{14}	16152.63
A_{15}	16500
A_{16}	18500

2.2. Artificial neural network (ANN)

Artificial neural networks have very wide applications in forecasting problems due to their learning ability. Neural networks, along with neural computing is major component of soft computing. Neural networks are nonlinear modelling techniques that may be applied to resolve the prediction problems. Neural networks do not provide exact inputs output relationship. Rather they learn it with the training. ANN teaches the system for task execution where generation of artificial intelligence system (AI) occurs ANN accurately judges the pattern of the data. Actually, ANN is made up of artificial neurons which are interrelated according to the architecture of the network. The main aim of ANN is to give the appropriate output with the help of given input. The training and learning are an integral and important part of it.

Here ANN is used for forecasting. The training data consist of historic load data from 2011 to 2015, which train the given network to forecast the significant output from input and target data. In this model supervised learning approaches have been applied for the training of ANN to confirm that each input a desired output. The adjustment of weights is performed to get the requisite output, after training.

The development of ANN based forecast model comprises of following steps in sequence;

i) Step 1: Collect the historical data
ii) Step 2: Define the universe of discourse UD as UD= [Dmin, Dmax] where Dmin and Dmax is minimum and maximum among the data
   Import the input data in the workspace as shown in Table 3
   Import the next week data as target data in the workspace as shown in Table 4
iii) Step 3: Construct the model with the specific input and target data
   Training function is taken TRAINM
   Adapting learning Function is LEARNGDM
   Performance function is MSE
   No of Layers is 2
   No of neurons in hidden layers are 10-24
iv) Step 4: Train the network and check the performance using regression and performance plot if it is not suitable then change the maximum no failures to 1000 and continue the training of the network till desired performance is achieved
v) Step 5: Use sample as input and reinitialize and set the weight to simulate the network for forecasting data.
vi) Step 5: Forecasted data is saved in the workspace as shown in Table 5
vii) Step 6: Compute MSE of the forecast

Table 3. Input load (MW) for ANN model

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Mid night	10275.69	8979.966	9771.304	10372.01	10191.16	11658.96	11172.2
01 AM	10087.31	8681.962	9587.908	10177.51	10069.11	11576.05	11076.08
02 AM	9925.078	8559.816	9513.998	10017.53	10056.55	11598.76	11055.63
03 AM	9864.624	8605.673	9507.243	9984.271	10182.77	11776.97	11139.66
04 AM	9947.684	8914.059	9593.574	9998.89	10416.26	12133.98	11496.72
05 AM	10142.57	9608.815	9838.26	9992.47	10862.21	12884.75	12287.76
06 AM	10233.12	10455.79	10135.02	10029.19	11322.88	13664.19	13239.05
07 AM	10170.62	10992.1	10424.15	10139.13	11546.99	13590.77	13367.34
08 AM	10191.59	11257.43	10691.58	10298.34	11793.89	13366.13	13100.38
09 AM	10488.44	11565.08	10899.96	10351.62	11970.43	13131.28	12872.94
10 AM	10706.27	11772.49	11034.4	10183.72	11866.94	12745.05	12551.27
11 AM	10839.91	11751.44	10985.51	9965.072	11685.16	12286.92	12204.82
12 PM	10850.54	11720.89	10829.5	9820.633	11385.38	11879.61	11826.74
01 PM	10781.17	11707.04	10501.13	9583.162	11023.95	11551.69	11533.59
02 PM	10677.87	11588.15	10122.48	9349.382	10711.33	11299.12	11269.21
03 PM	10649.44	11515.68	9795.532	9238.196	10520.23	11245.43	11211.17
04 PM	10812.52	11564.32	9637.174	9337.539	10576.1	11347.46	11486.86
05 PM	11350.43	12041.18	10100.08	10075.1	11420.39	12010.95	12390.22
06 PM	11408.65	12095.66	10807.91	10804.52	12374.7	12754	13202.43
07 PM	11205.3	11903.01	10966.27	10973.55	12725.56	12924.34	13407.91
08 PM	10931.51	11656.87	11089.57	11000.2	12880.55	12931.08	13430.88
09 PM	10625.51	11252.62	11088.05	10950.89	12745.13	12609.53	13049.16
10 PM	10116.16	10722.69	10954.89	10723.68	12351.15	12044.03	12337.44
11 PM	9549.793	10169.88	10680.56	10368.27	11932.7	11511.73	11696.91

Table 4. Sample target load (MW) for ANN model

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Mid night	11424.05	10289.51	10161.25	9506.014	8148.153	8382.572	8940.168
01 AM	11361.26	10036.33	9862.816	9191.916	7949.84	8094.634	8817.103
02 AM	11434.61	9896.517	9689.713	8993.653	7873.245	7918.894	8770.965
03 AM	11622.12	9920.208	9651.646	8837.887	7923.914	7884.312	8899.179
04 AM	12086.35	10232.71	9680.493	8659.052	8126.611	8034.786	9330.707
05 AM	13105.19	11063.85	9885.837	8521.188	8581.424	8557.469	10218.88
06 AM	14344.89	12206.08	10333.35	8585.627	9078.062	9340.249	11427.47
07 AM	14459.73	12483.05	10594.78	8710.264	9320.99	9719.575	11834.6
08 AM	13931.94	12407.18	10830.22	9094.686	9581.55	9890.821	11735.8
09 AM	13557.71	12428.18	11032.85	9452.243	9776.878	10124.69	11636.73
10 AM	13250.48	12501	11142.95	9712.531	9852.607	10376.53	11590.19
11 AM	12922.26	12521.16	11138.15	9865.947	9869.284	10506.99	11556.48
12 PM	12564.15	12467.17	11023.73	9968.272	9915.628	10635.33	11538.3
01 PM	12408.69	12441.15	11051.66	9872.483	9864.792	10631.18	11569.68
02 PM	12210.28	12429.75	11070.14	9785.283	9844.607	10621.56	11501.48
03 PM	12206.8	12453.9	11095.75	9654.717	9777.428	10492.49	11503.91
04 PM	12435.89	12574.49	11120.56	9563.87	9860.972	10472.77	11585.24
05 PM	12970.46	12747.12	11278.06	9687.237	10368.9	10714.52	11952.45
06 PM	13305.93	12837.15	11402.81	9800.397	10489.7	11029.82	12384.19
07 PM	13198.84	12559.28	11224.28	9613.36	10459.54	10993.59	12316.82
08 PM	12998.48	12287.65	11067.2	9478.138	10268.4	10809.04	12124.18
09 PM	12431.3	11881.02	10739.77	9300.773	9965.21	10377.71	11628.7
10 PM	11580.49	11279.06	10379.97	8884.494	9439.62	9794.378	10886.66
11 PM	10765.41	10717.43	9942.914	8488.964	8840.903	9197.507	10220.75

2.3. Wavelet transforms

Wavelet transform is a modern potential technique for analysis of time series. It transforms series of load data into a set of patterns with different frequencies. This new filtered pattern shows an improved behavior than original series and can be forecasted with better accuracy. A Wavelet is considered to be a waveform of limited duration whose average comes out to be zero. If we compare the wavelet with sine wave then sine wave propagates from $+\infty$ to $-\infty$ on time hence infinite time duration. Also, wavelets are irregular and not symmetric whereas sine waves are smooth and periodic. Wavelet transform decomposes a pattern in to shifted and scaled form of parent wavelet. It utilizes time-scale, rather than frequency scale. Therefore, it is suitable for catching trends, irregularity, breaks and similarity.

A fast wavelet transform converts any time series into low and high pass filters. It decomposes the signals into 'approximations' (low frequency components) and 'details' (difference between two consecutive approximations). Approximations consist of trend component of any time series whereas details consist of rapidly occurring components. Any 'n' level decomposition converts the original signal in to 'one' approximation component and 'n' details components. A wavelet function of type Daubechies of order 'm' is known as dbm, which can be utilized as the parent wavelet. Different Daubechies wavelets (db1-db9) are used in the research work). The wavelet decomposition of db3 at level 5 is shown in Figure 3.

The development of wavelet-based forecasting model as shown in Figure 4 consists of the following steps in sequence. The calculations are carried out considering the data which are used in FTS and ANN techniques for load forecasting as:

i) Step 1: Collect the historic data
ii) Step 2: Arrange the data in signal form
iii) Step 3: Select the appropriate number of levels based on the type of the signal to get optimum solution
iv) Step 4: Decompose the signal into different frequency components using wavelet transform, to get valuable information of the signal, called wavelet decomposition
v) Step 5: Train the ANN model for forecasting using these components
vi) Step 6: Reconstruct the signal using these forecasted wavelet components as shown in Table 6
vii) Step 7: Compute the error of the prediction

Table 5. Output data of ANN forecasted model

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Mid night	11546.27	10162.72	9679.192	9379.103	8010.281	8320.566	9032.297
01 AM	11571.97	10122.31	9678.04	9188.469	8019.308	8181.538	9023.008
02 AM	11615.33	10094.42	9678.779	8998.051	8023.175	8121.341	9053.666
03 AM	11720.29	10093.35	9683.262	8857.586	8038.861	8117.329	9119.868
04 AM	12162.8	10201.28	9707.21	8723.847	8122.953	8216.414	9292.558
05 AM	13074.45	11108.06	9885.33	8596.992	8670.834	8494.633	10215.92
06 AM	13946.51	12202.47	10371.57	8657.803	9272.005	9099.532	11403.27
07 AM	13940.7	12390.26	10710.08	8824.007	9524.957	9568.544	11714.73
08 AM	13558.49	12311.12	10764.44	8986.465	9566.392	9708.36	11627.24
09 AM	13387.58	12481.46	10944.42	9365.855	9835.184	10128.77	11735.45
10 AM	13091.21	12591.01	11011.85	9727.714	9971.214	10379.55	11691.24
11 AM	12810.29	12596.45	11050.96	9832.959	10004.4	10545.51	11488.62
12 PM	12528.28	12528.76	11063.33	9856.191	9920.123	10640.14	11372.44
01 PM	12415.47	12470.74	11101.6	9810.139	9918.763	10650.55	11435.96
02 PM	12297.3	12358.37	11069.49	9717.653	9863.533	10556.41	11396.05
03 PM	12277.74	12335.37	10991.46	9604.836	9854.461	10382.5	11366.45
04 PM	12492.35	12478.32	11022.22	9551.368	10008.59	10378.37	11443.46
05 PM	12985.9	12706.49	11213.74	9708.385	10257.27	10728.15	11779.72
06 PM	13443.64	12686.47	11201.3	9743.126	10276.56	10819.87	12020.25
07 PM	13256.33	12546.87	11220.6	9505.247	10294.92	10797.53	12102.21
08 PM	12722.4	12305.08	11223.1	9220	10248.25	10733.01	12091.97
09 PM	12179.32	11860.4	11089.81	9111.939	10100.72	10578.54	11760.09
10 PM	11567.25	11207.23	10432.3	8926.406	9399.264	9548.059	10612.21
11 PM	11110.89	10361	9797.389	8639.425	8339.26	8176.43	9634.727

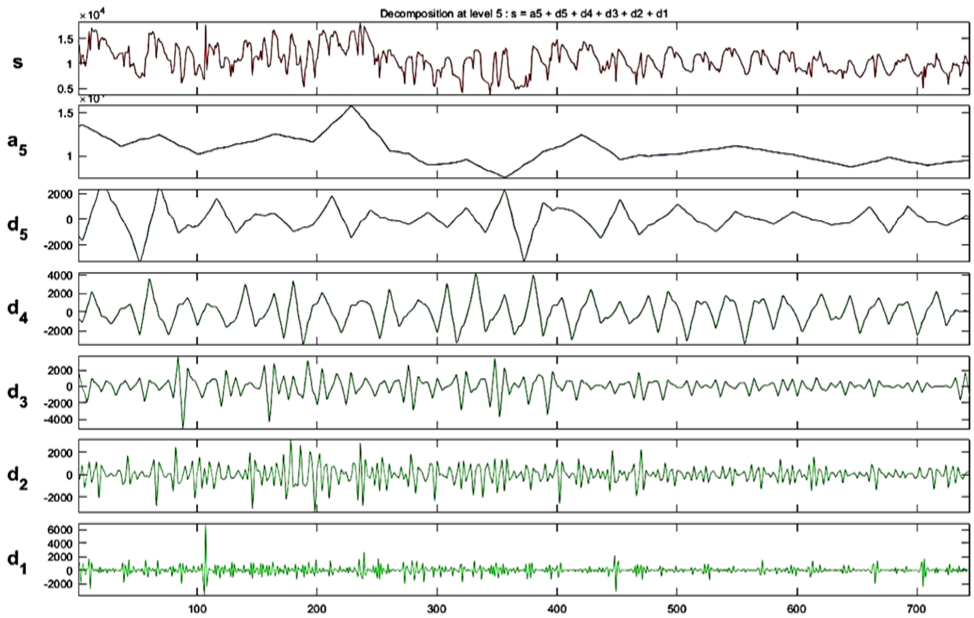

Figure 3. Wavelet decomposition at level 5

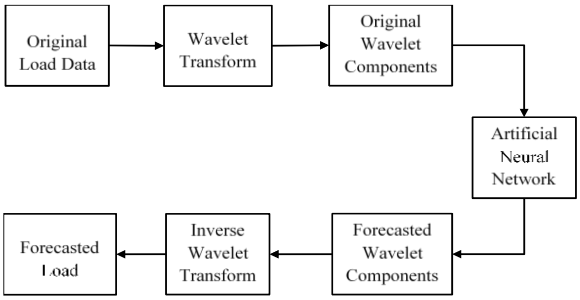

Figure 4. Block diagram of proposed wavelet forecasting model

Table 6. Forecasted load (MW) using the model

Actual load	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9
10275.69	10249.57	10242.74	10231.22	10309.17	10323.05	10325.43	10258.27	10449.42	10465.03
10087.31	10045.57	10038.33	10029.83	10108.26	10121.27	10124.45	10056.65	10249.64	10265.36
9925.078	9872.981	9865.512	9858.924	9937.782	9949.867	9953.864	9885.43	10080.27	10096.1
9864.624	9807.419	9799.689	9796.408	9875.633	9886.744	9891.582	9822.486	10019.19	10035.14
9947.684	9895.775	9887.162	9883.309	9962.285	9975.502	9978.135	9908.226	10103.46	10119.45
10142.57	10106.73	10098.5	10092.4	10169.59	10186.04	10185.34	10114.58	10306.94	10322.93
10233.12	10203.38	10193.53	10190.42	10264.47	10283.81	10280.1	10208.52	10398.15	10414.15
10170.62	10135.56	10126.4	10127.22	10195.18	10217.9	10210.68	10138.27	10324.26	10340.24
10191.59	10165.65	10155.77	10153.56	10214.84	10240.11	10230.2	10157.02	10340.18	10356.16
10488.44	10482.44	10471.81	10464.56	10517.43	10545.11	10532.65	10458.74	10638.98	10654.97
10706.27	10720.58	10710.32	10698.86	10738.58	10769.06	10753.68	10679.02	10855.42	10871.38
10839.91	10868.77	10859.34	10843.23	10865.72	10898.91	10880.72	10805.35	10977.58	10993.5
10850.54	10879.62	10869.9	10855.31	10869.98	10905.01	10884.9	10808.89	10978.15	10994.07
10781.17	10803.19	10793.31	10782.94	10793.52	10830.11	10808.37	10731.76	10898.3	10914.21
10677.87	10691.31	10683.06	10676.4	10680.6	10718.78	10695.43	10618.25	10781.66	10797.57
10649.44	10658.13	10654.45	10654.03	10654.14	10693.73	10668.98	10591.28	10751.63	10767.53
10812.52	10843.99	10831.22	10821.31	10810.87	10852.04	10825.82	10747.63	10904.12	10919.98
11350.43	11420.85	11411.81	11390.11	11366.63	11409.28	11381.79	11303.17	11455.46	11471.27
11408.65	11483.97	11476.41	11456.45	11422.54	11466.42	11437.98	11358.99	11507.25	11523.01
11205.3	11265.2	11268.88	11255.51	11210.45	11255.45	11226.3	11147.02	11291.09	11306.79
10931.51	10970.31	10961.69	10948.05	10950.71	10994.97	10965.49	10885.97	11027.06	11042.75
10625.51	10632.45	10614.93	10614.2	10667.46	10710.24	10680.61	10600.89	10739.43	10755.11
10116.16	10076.87	10059.63	10081	10159.76	10201.15	10171.49	10091.62	10227.37	10243.04
9549.793	9480.404	9473.847	9522.41	9606.756	9646.344	9616.772	9536.804	9669.971	9685.634

3. RESULTS AND DISCUSSION

The proposed models are tested with historical data on hourly basis as collected for a substation in India. The FTS is applied on Microsoft excel toolbox. MATLAB toolboxes have been used for ANN and WT application. The following various error functions are used to evaluate the performance index of the models developed in the study: i) Mean absolute percentage error (MAPE); ii) Integral absolute-error criterion (IAE); iii) Integral of time multiplied error (ITAE); iv) Integral square error (ISE); and v) Integral of time-multiplied square error (ITSE).

As discussed above, the study has been carried out for short term load forecasting considering the real time data collected for a substation. The results obtained using FTS and ANN with these error functions are tabled in Table 7. From the inspection of results of Table 7, it is inferred that ANN offers the better future load prediction as compared to the results obtained with FTS. The time domain plots are obtained to draw investigations for the study carried out. These plots are shown in Figures 5 to 8. The plots of Figures 5 and 6 support the superiority of ANN over fuzzy time series. Finally, Table 8 is prepared to summarize the results of all wavelet dbs corresponding to all levels.

From the inspection of results of Table 8, it is revealed that wavelet db3 at level 3 is identified as the most suitable Daubechies wavelet for load forecasting, which offers the better performance as compared to other Daubechies wavelets for almost all error functions which have been in use to determine the performance index. Also, there is significant variation in peak of actual and forecasted load which is due to error. Although the predictions are not so accurate, still forecasts are almost following actual the actual load series. Moreover, the overall forecasted load is almost on higher side. The error between the actual and forecasted load has been calculated on different parameter indices. An inspection of the plots of Figures 5 to 8 reveal that WT method offers the best results as compared to those obtained with ANN and FTS. Further, ANN offers better load prediction as compared to those provided by FTS.

Table 7. Performance of fuzzy time series and ANN

Method	MAPE	IAE	ITAE	ISE	ITSE
Fuzzy time series	2.5608%	59.22053	729.1478	788.3683	15.88118
ANN	1%	17.00828	203.6755	220.6838	2.1751

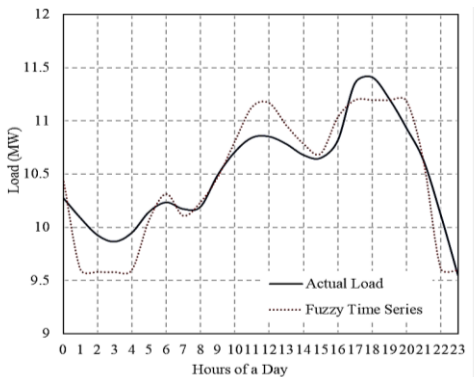

Figure 5. Fuzzy time series forecast

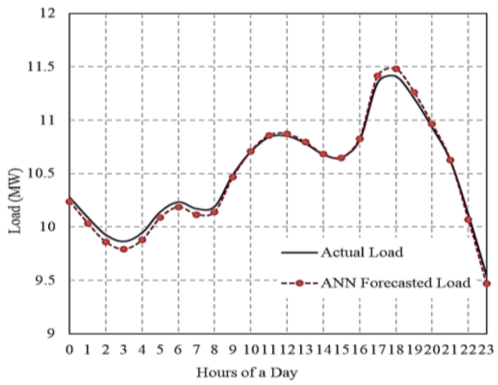

Figure 6. ANN forecast

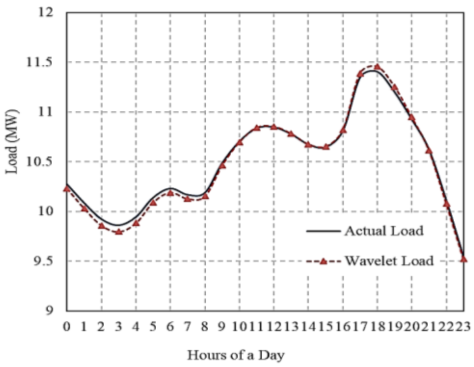

Figure 7. Wavelet based forecast

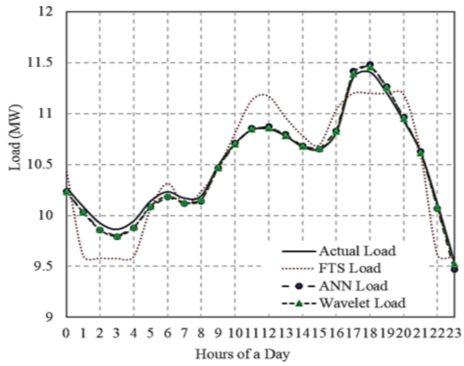

Figure 8. Comparison of fuzzy time series, ANN and wavelet forecast

Table 8. Best performance of wavelets

Wavelet	Level	MAPE	IAE	ITAE	ISE	Wavelet	Level	MAPE	IAE	ITAE	ISE
db1	2	0.78%	17.88508	219.6029	237.488	db6	2	0.74%	16.87423	201.2001	218.0743
db2	1	0.74%	17.18821	209.1389	226.3271	db7	2	0.71%	16.37834	199.8468	216.2252
db3	3	0.70%	15.81069	195.2696	211.0803	db8	2	0.73%	16.93127	206.9848	223.9161
db4	1	0.71%	16.33541	197.4771	213.8125	db9	3	0.72%	16.36085	195.6887	212.0495
db5	1	0.72%	4.89723	56.39988	61.2971						

Many scholars have attempted to predict the electric load in the past, typically using the traditional ANN, time series and other techniques. Researchers used LSTM, Bi-LSTAM and RF-bi-LSTM to forecast the electric load and found that RF-bi-LSTM performed much better based on this statistical mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) [20]. The MAPE examination reveals an error of 127 W, which is around 4.1% to 3.2% of the reported range of peak load encountered in a day and is well within the range of meaningful accuracy. In terms of load forecasting, long-short neural network models [21] demonstrate notable accuracy. To ensure practical implementation in real power plants, where a variation of 4.1 to 3.2% can suggest a difference of the order of 1000s of KWs, additional accuracy is needed.

With an IAE of roughly 15.8 (MAPE of 7%) in our investigation, the WT algorithm accurately predicts the electric load of substation, which compares favorably to the accuracy levels attained by other methods as noted above. The fact that the changes we recommend lead to considerable increases in predicting effectiveness makes the debate irrelevant. When several forecasting efficacy parameters are examined with and without the suggested modifications, this becomes clear.

4. CONCLUSION

The analysis of soft computing methods for predicting electric load is the main goal of this research work. For this study, information for an Indian substation has been collected. To forecast the future load at a substation, the FTS, ANN, and an integrated technique of WT and ANN are used. Wavelet functions from db1 to db9 of all 9 levels are used to decompose the provided electric data. Based on various performance indices, the results are depicted. The results are compared, and it is concluded that wavelet and artificial neural network-based electric load forecasting demonstrate feasibility with lower forecasting errors. The results demonstrate a wavelet db3 at level 3 is identified as the most suitable Daubechies wavelet based intelligent model for the electric load forecasts for real time data. The suggested integrated model captures the useful properties of artificial neural networks and wavelet transforms in time series and found to be accurate for real time data.

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