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Forecasting of Rising Demand for Electric Vehicles Based on Artificial Neural Network

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ABSTRACT

These days load forecasting is much more required in order to reduce the wastage of energy. This paper is to implement & develop the idea of short term load forecasting by using Artificial Neural Network, the design of the neural network model, input data selection and Training & Testing by using short term load forecasting will be described in paper. For the EV load forecasting only 2 variables are being used as temperature and humidity to forecast the output as load. This type of designed ANN model will be mapped by using historical data of temperature and humidity (taken from meteorological sites), whereas it is being Trained & Tested by using historical data of loading of EV charging stations (Tech Mahindra) of a particular area as Ontario, Canada to give the desired result. Training & Testing done by using large amount of historical data of weather conditions and loading data (kV). By the help of this model they can predict their daily loads (next day's load) by putting historical data in the acquired algorithm.

Keywords: Artificial Neural network, EV loads forecasting, Training & Testing, Meteorological sites.

1. INTRODUCTION

To Many factors has become influential in electric power generation, demand or load management with the growth of power system networks and the increase in their complexity. Load forecasting is one of the critical factors for economic operation of the power system. Forecasting of future loads also plays a very important role in several fields as infrastructure development and all. However power system load forecasting system is a two dimensional concept:

1. Consumer based forecast and 2. Utility based forecast.

Each forecast could be handled disjointly consumer based in used for reliable use risk management when to use the electricity as in not in peak hours. Where as in off peak hours both utility companies and customer loads. This challenge been in existence since last several decades, thus the variety of the load forecasting technique ranging from classical to intelligent system have been developed to date & highlight in a number of studies and the ultimate distinction can be done on the basis of forecasting accuracy.

In the designing state, utilities need to plan for the future load growth under different possible scenarios. Their decisions and designs can affect the gain or loss of the huge revenue for their companies/utilities as well as customer satisfaction and future economic growth in their area.

There are many things which can be carried out by the load forecasting as the decision on sale purchase, banking of power and generation of electrical energy, load switching and infrastructure development. Precise forecasting has been basis of electric energy trade and spot prize establishment to gain the min electricity purchase cost. Because of high complexity the load forecasting has become a challenge to the electrical engineering scholars. Load forecasting with the historical data or days with the extreme weather conditions has remained a difficulty up to now. To improve the forecasted result one new method came into picture that is the artificial loads are implemented.

- An implementation of neural network based local forecasting model for the EMS (energy management system) This paper gives the idea of development and implementation of an ANN based short term load forecasting for the energy control. It also focuses on the idea how ANN will be helping the companies for the real time operation.
- Neural network based real-time economic dispatch for thermal power plants. This paper describes about the real time optimization generation . It describes how to take the data in the real time operation and train it into the ANN model .

- Short term load forecasting based on weather information. This paper gives the idea of Short term forecasting and next day weather forecasting. In this paper gives the idea of how the system can consider the effect of temperature and relative humidity.

1. **ANNSTLF** – A neural network based electric load forecasting system.

This paper proposes the concept of first generation engine, from this paper got the idea that how to generate the dummy data for temperature and humidity, got the idea that how to model the black box for the ANN dummy data generation .

- Meteorological parameters influence for medium term load forecast. This paper gives the idea that how to apply the meteorological p/m for load forecasting in MLP. This paper gives the idea of correlation study between the parameters deal with the load if the data will be variable in weekdays and weekends in a particular area. Objective of the thesis work

2. NEURAL NETWORK

A. Basic neural network

The basic neural network is an artificial representation of the human brain and it's quite complex, nonlinear and parallel information processing system, here in this work the artificial neural network is being used. In such type of networks there will few nodes by which the information will be processed that are called as neurons to perform certain operational tasks few times faster than the digital computers that are exiting now a days, this will perform the tasks much earlier than the computers can take few days to perform. Eg: the familiar face in a unfamiliar scene the brain take 100-200 ms to recognize whereas tasks of much lesser complexity than this may take days on a conventional computer. A neural network is a machine that is designed to perform a task the way brain does, the network is made up of electronic component that will be simulated in a digital computer or on a software. This network will be massively parallel distributed processor made up of simple processing units which has the natural capacity to store the experimental knowledge and making it available for use, it resembles the brain in two aspects (4)

- Knowledge is acquired from the environment by the network by learning process.
- Interneuron strength is known as synaptic weight which are used to store the acquired knowledge.

For this learning process there is a need to use the learning algorithm called back propagation algorithm the function of this algorithm is to modify the weight in order to attain the desired result.

B. Input variables

3 input neurons along with 5 hidden neurons and 1 output neurons are being used in 1 iteration, so likewise 24 iterations are taking place for 24 outputs for the 24 hours of a day. These 3 inputs in 3 neurons will be of today, yesterday and day before yesterday whereas weather conditions are being taken for the mapping purpose and loading data will be used for training and testing purpose. Performance of different kinds of input variables to get the desired output, so few input variables are listed below:

- Seasonal input load content: weather change and very less load will be changing season to season if we will consider a place as Ontario. It's all about cooling and heating loads over a year period when environmental conditions changes are being considered very less as compare to other tropical countries.

$\sin(2\pi n.\ i/365)$, $\cos(2\pi n.\ i/365)$
where n = (1,2,3)

i: (i = 1,2,-------365) number of days in an year.

Weather condition input: Temperature is most sensitive weather variables which affect the loading in EV cars in the cold weather conditions in the place as Canada. If the data calculation is being varied then weather coefficients for the forecasting will be different than one another because of their geographical and climatic conditions, so there will be somewhat different impact on the loading than the regular impact on the loading. There can be said that there are two types of temperature variables - direct and indirect. So direct temperature variable will work area to area whereas the temperature which affect the loading on the system level can be said as indirect temperature, in the EV level it is the temperature of the motor parts and other devices of the vehicle. So to consider the temperature of the vehicle temperature of all the devices should be taken care (that will also be in hourly basis). In the modeled diagram taking the environmental temperature into consideration there can be seen that how much temperature difference is there in the system. It has been seen that there is a vast effect of temperature in the loading means loading is very much sensitive to the temperature change. nonlinear relationship has been seen between loading and temperature of the EV cars. It has been seen that coolest weather is having more load demand that the hotter weather in the places as Ontario. A certain limit of humid climate increases the temperature and vise versa. Loading inputs are being used of Today, Yesterday and Day before yesterday, the loading data of early past is being used in this variable. Other input variables can also be used (---) for mapping purpose and to give the loading data as input for the training and testing as wind speed, cloud cover, dew point and it has been seen that they have very less effect on EV loading data (Tech Mahindra). So other variables are being neglected to avoid the complexity in forecasting and to acquire an accurate result.

C. Nonlinear modeling criteria and Training and Testing

Nonlinear behavior of the loading has been discussed earlier. Which is being influenced by the temperature and seasonal effects, this model is somewhat different than the earlier published papers because the main focus of the paper is to explain to explain the basic model of ANN based load forecasting system. In the neural network load forecasting model when the output neurons are modeled with the nonlinear combination of the outputs of the hidden neurons.(4).
It can be given as follows:

$$Y_k = w_0 + H_1 w_{11} + H_2 w_{12} + H_3 w_{13} + \text{---------} + H_n w_{1n} \quad (1)$$

where $H_j = H_1, H_2, ---------H_n$ is the output of the j^{th} hidden neuron.
$w_{ij} = w_0, w_{11}, w_{12}$ ------------ w_{in} strength of signal from 1 neuron of a layer to all the neurons of the output layer. w_0 is the threshold output of the neuron k.

From (1) the output of the hidden neuron can be grouped into 3 groups:
Non activated, Linear and Saturated.
In both non activated and saturated neurons output will not very change according to the input change. whereas in the linear state the output will gradually change according to the input change, this is what is happening in the EV case, output will change by the change in the input. So in the linear state this will be seen in the description below:

$$\mathrm{H_j} = \frac{1}{1+e^{\left(-\sum_{i=1}^{n} \mathrm{w_{ij}}\,(\mathrm{n}).\mathrm{X_j}(\mathrm{n})\right)}} \quad (2)$$

where $\mathrm{X_j}(\mathrm{n})$ is the input for the first layer of neuron model (after taking mean of the 3 days data).
$\mathrm{w_{ij}}$ is strength of signal from 1 neuron of a layer to all the neurons of the output layer.

D. Next day's load modeling

So according to the standard modeling 3 days data as today, yesterday & day before yesterday are being taken. In the place of 3 days data, many more days or may be less days than this can be taken as well but for our convenience we are taking 3 days input to forecast the next day's output. So historical loading data of previous day's can be taken into consideration to calculate the forecasted data of the next day.Training & testing will be done by the historical data of the last year because for the comparison purpose actual data of the next day will be needing that is available in the previous year's historical data but the final forecasting data will be calculated of this year, since this year's real time data of forecasted day is not available so we need to acquire it by using mapping phenomenon , calculation is given below :

Let the hourly forecast of the next day is presented by:
[H_j, j = 1, 2, ---------24] and forecasting error [δ_k , k = 1, 2, ---------k ; k<24]

where k is the last hour of the next day with known hourly loads. So hourly load forecast is given by k that is k^{th} hour.
$\delta_k = Y_k - t_k$; k = 1, 2, --------k
t_k is real time loading data of the next day in k^{th} hour.

Let the matrix contains variables i and j. So the function of hourly loads is represented as :

{ *fun* (i, j), where i = 1, 2, ---------24 and j = 1, 2, ---------24

This matrix contains used historical loading data, this data is adjusted once in a year. So now the final forecasting has been done by the following formula :

$Y_k = H_j +$ *fun* (i, j). δ_k
where j = 1--------k, and i = k+1, ---------24

Training and Testing has been done with the real time historical data which substantially improve the ANN algorithm, which helps the dispatchers to send a particular required amount of energy.

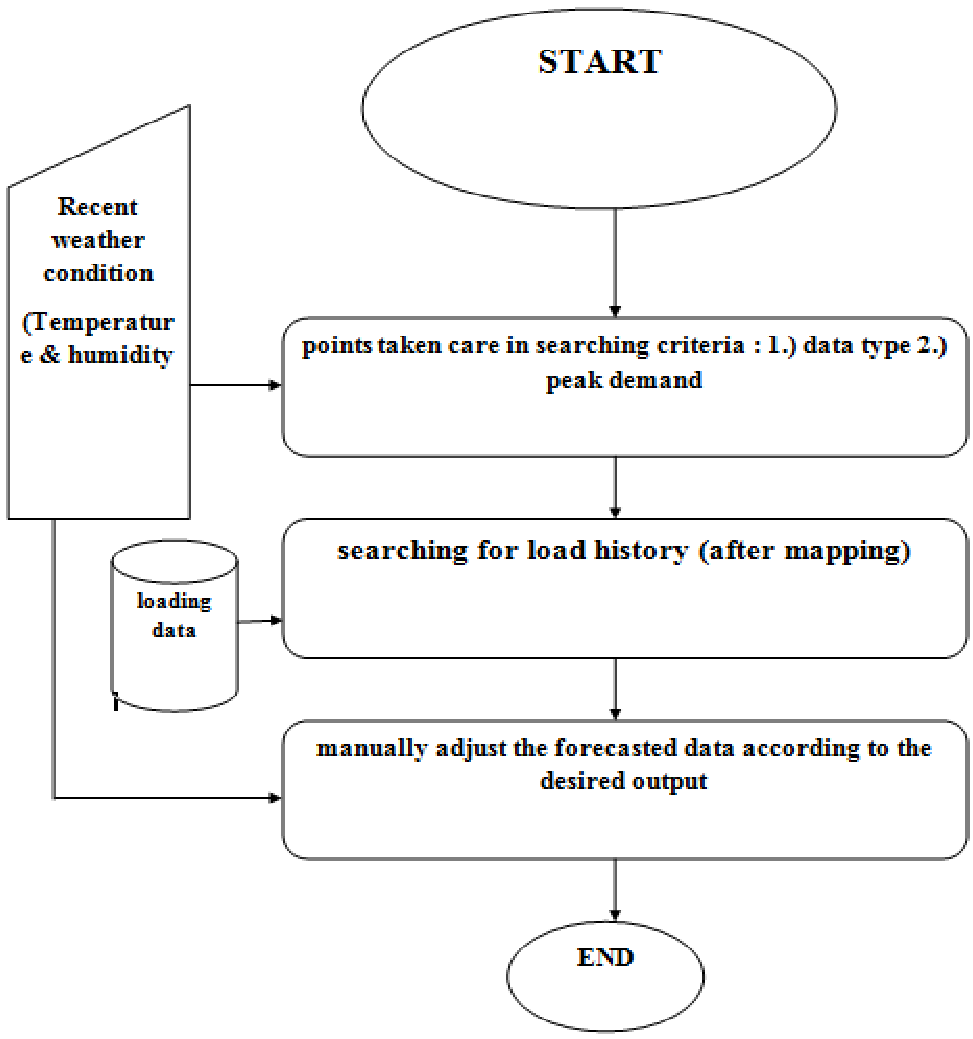

Fig. 1: Equivalent block diagram for short term load forecasting

The following steps are being followed for the data processing:

Mapping

- 15 days data of temperature & humidity of last year of any month (suppose August) and this year has been taken.
- Mapping is done with both years data and tried to acquire the loading data according to that.
- Mapping is done by taking temperature & humidity data for finding the relation between loading data of this year and last year by using the temperature and humidity data of both of the years.
- Since we are working with the neural network so normalization of both set of loading data was needed that is previous year's (15days, same hours data) & this year's (15days, same hours data).

Training & testing

Training and testing from last year's data

- 3days loading data has been taken for Training &Testing.
- Mean of all 3 days loading data in hourly basis is being calculate.
- After calculating mean and reducing the 72 data in 24 data Back propagation Algorithm is being applied.
- Weights are being calculated by used Algorithm and then replaced assumed weight with calculated weight.

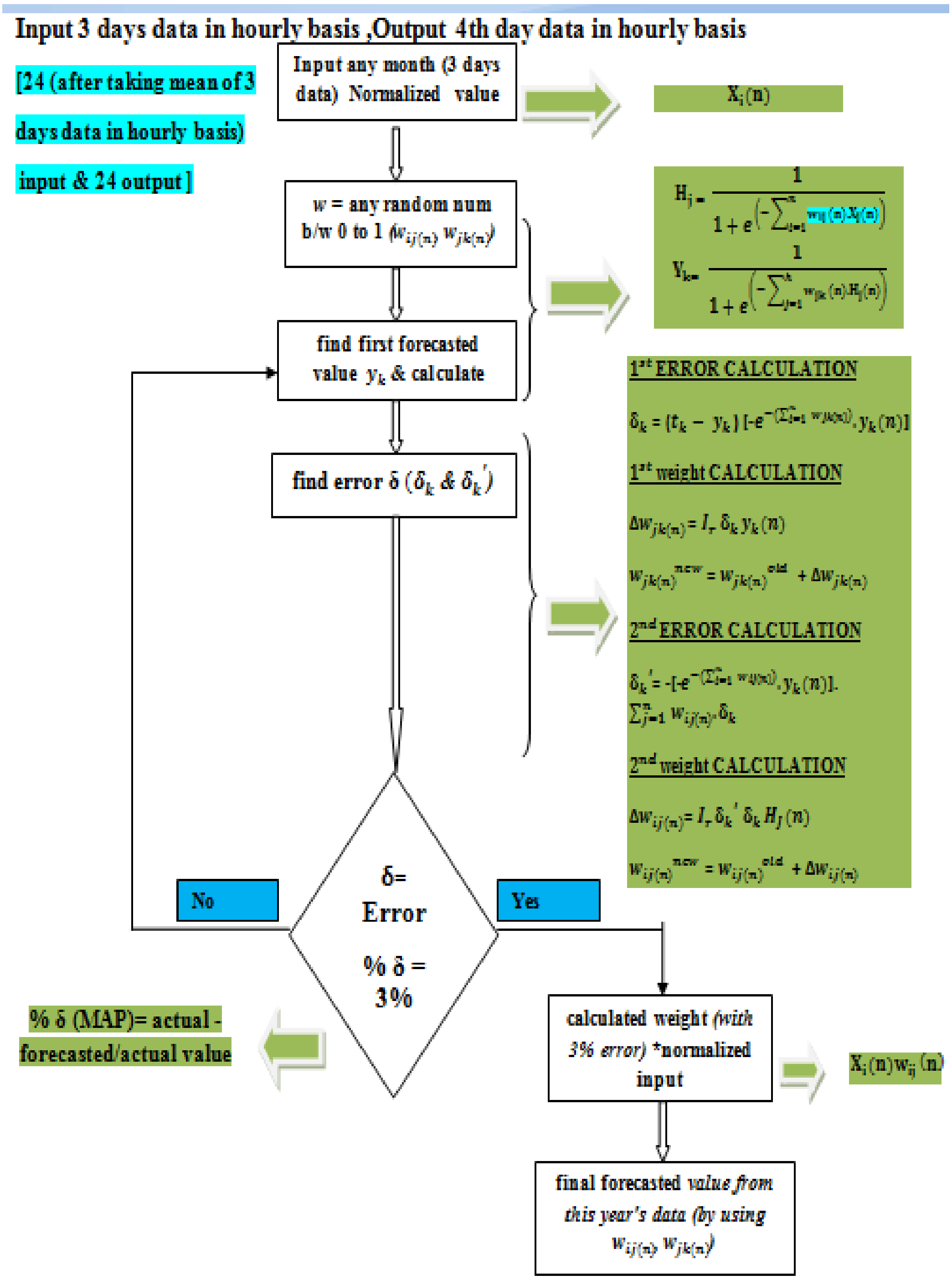

Fig. 2: Algorithm flowchart

Training &testing from last year's data

- For Training & Testing 3days value of mapped normalized loading data are being taken, where as 24inputs and 24outputs will be there in programming.
- This loading data is being trained in a particular model of ANN.
- Intermediate forecasted value has been found of that with assumed weight.
- 1st and 2nd error values and weighting values has been calculated and then by using those weighting values the forecasted data for the next day has been calculated.
- Intermediate forecasted value for next day with the trained weight has been found and then final forecasted value has been found.

3. IMPLEMENTATION AND RESULTS

By taking data from (Tech mahindra) [smart solutions for smart cities, Canada] EV charging stations & implementation has to bare multiple problems, that all the problems has been resolved. Most of the problems were regarding data acquiring and data communication, access the real time data from EV stations, man-man & man-machine interfacing, downloading the data by using man-machine interfacing. Then after the collection of data there was another challenge to put the data in a certain and capable neural network model to give the desired result for the loading to forecast the next day's loading data by using historical loading data. Points to be considered at the time of implementation.

- On line & off line implementation

There will be 2 types of implementations by using neural network, the neural network which is being used for Training & Testing is called off line implementation. In this we are taking historical data (last year's data for input & last year's real time data of forecasted day or next day to match with the last year's forecasted data. Whereas in online implementation we are taking this year's real time data for input & mapped (virtual) data for matching the mapped value. So this kind of implementation with the mapped data can be called as on line implementation. All the data will be Trained & tested by using Back propagation algorithm by taking 3 days values in hourly basis, the online & offline implementation will consist one and one program. Offline implementation with the historical data & online with the real time data.

- Simulation result

This section represent the comparison between on line & offline implementation and the comparison between the real time data of the forecasted day & real forecasted data for both online & offline forecasted implementation which will help the dispatcher unit of Tech mahindra, Canada EV charging station & results were obtained by using Back propagation algorithm.

Table 1: 4th August 2013Data in Training Stage

S N	Comparison between next day's real time data and forecasted data		
	TIME	NEXT DAY'S REAL TIME DATA	RESULT BY TRAINING
1	00:00:00	6.13	6.0926
2	01:00:00	5.24	5.201
3	02:00:00	5.69	5.6468
4	03:00:00	6.03	5.944
5	04:00:00	6.06	5.944
6	05:00:00	6.24	6.2412
7	06:00:00	8.38	8.4702
8	07:00:00	8.53	8.6188
9	08:00:00	9.37	9.5104
10	09:00:00	7.56	7.5786
11	10:00:00	11.07	11.2936
12	11:00:00	12.47	12.631
13	12:00:00	13.04	13.2254
14	13:00:00	14.86	15.1572
15	14:00:00	13.23	13.5226
16	15:00:00	8.1	8.173
17	16:00:00	10.94	11.145
18	17:00:00	9.85	9.956
19	18:00:00	11.48	11.590
20	19:00:00	11.66	11.888
21	20:00:00	10.14	10.253
22	21:00:00	12.35	12.631
23	22:00:00	8.9	8.916
24	23:00:00	7.98	8.024

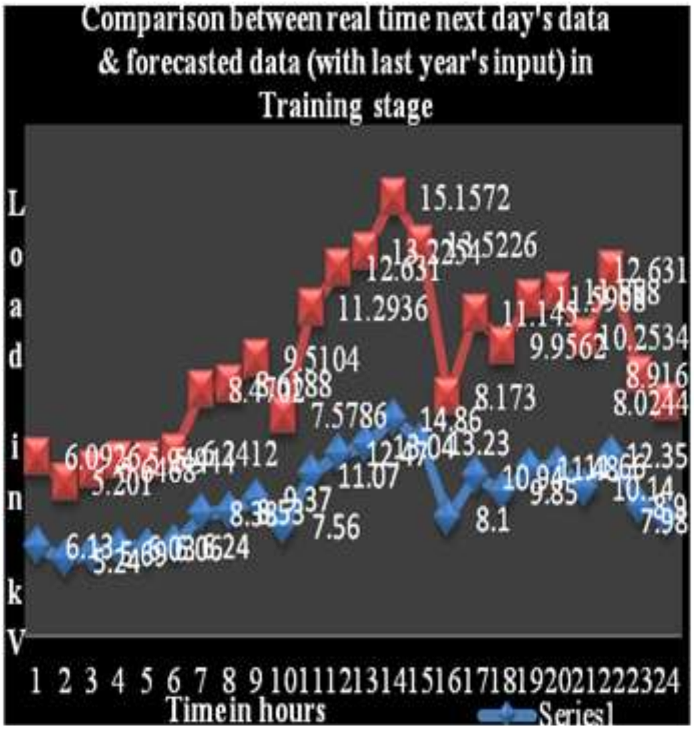

Fig. 3: Training result with real time value of loading (kV) of august 2013 (Red line- Real time data of next day. Blue line- Forecasted data of next day)

Table 2: 4th August 2014 Data in Testing Stage

S N	Comparison between mapped data with this year's input		
	TIME	NEXT DAY'S REAL TIME DATA	NEXT DAY'S MAPPED DATA
1	00:00:00	5.5	5.376
2	01:00:00	5	4.872
3	02:00:00	4.6	4.368
4	03:00:00	4.77	4.536
5	04:00:00	5.5	5.376
6	05:00:00	7.2	7.224
7	06:00:00	10.4	10.416
8	07:00:00	12.4	12.6
9	08:00:00	11.5	11.592
10	09:00:00	8.5	8.568
11	10:00:00	8.8	8.736
12	11:00:00	9	9.072
13	12:00:00	11.5	11.592
14	13:00:00	15	15.288
15	14:00:00	16	16.296
16	15:00:00	14.4	14.614
17	16:00:00	11.5	11.592
18	17:00:00	16.8	17.136
19	18:00:00	15.4	15.792
20	19:00:00	12.4	12.6
21	20:00:00	11	11.088
22	21:00:00	13.5	13.776
23	22:00:00	11	11.088
24	23:00:00	8	8.064

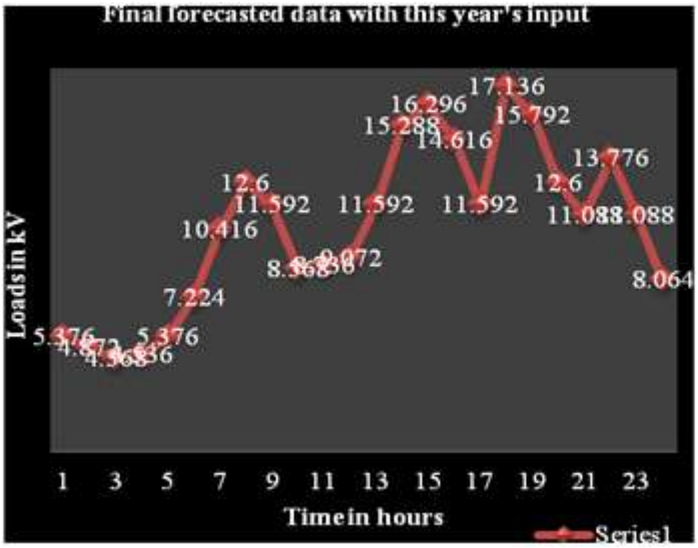

Fig. 4: Final forecasted data with real time value of loading (kV) of august 2014(Red line- Final forecasted data of next day

CONCLUSION

The results of the final forecasting & Training & testing will be almost same, there won't be much difference only the difference will be of data because we are using last year's data for Training & testing & this year's data for final forecasting as input but the models that are being used for both the forecasting will be same that's why there won't be much difference in both the results. The new STLF algorithm will come with the following advances:

The main problem with the stastical model with almost be some experimental error while implementing the result. So to overcome this error and give almost accurately precise result we work with the neural network which will deal with the real time data & give the desired result with less amount of error compared with the other statistical techniques. Neural network is particularly effective in handling outliers, although other methods also can make it done at some extent. The input that is being selected by the mapping process before the final forecasting, since for the final forecasting the real time data is not available of the final forecasted year that's why we need to acquire it by mapping process that is hit & trail method that will be based on previous experiences. (4). Temperature & humidity modeling is being done for the mapping process to get the loading data for the next year so that we can use the data for the matching process for the real forecasted data. Temperature and humidity will give the mapped loading data that will be used for the comparison with the forecasted data of this year so that we can encounter the error of the final forecasted data by seeing the mapped data (mapped data : approximate of the real time data).

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