A FINE LOAD FORECASTING USING NEURAL NETWORKS AND FUZZY NEURAL NETWORKS

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ABSTRACT:
        A methodology for short term load forecasting based on artificial neural network and fuzzy logic is presented in this paper. At first this problem is solved using only artificial neural networks with and without temperature effects. Then the proposed method has been implemented by considering the temperature effects on load. The performance of the proposed method is compared with that of pure artificial neural network method.

KEYWORDS: Fuzzy Logic (FL), artificial neural network (ANN), Short Term Load Forecasting (STLF), Gradient Delta Rule (GDR).

1. INTRODUCTION:

A fine short term prediction of future load is helpful in better operation of power systems and its economical utilization. A number of algorithms have been suggested for solving this problem. In this paper presenting a STLF with neural networks and combined Fuzzy Logic, ANN. Above two methods are studied by considering a most effective weather component among all i.e. temperature. Test results were obtained for actual load data obtained from Northern Power Grid, New Delhi, INDIA for 24 hours ahead forecasting with weather information.

2. SHORT TERM LOAD FORECASTING (STLF):

Load forecasting methods can be divided into very short term, long term models according to the time span [1]. In this paper, short term load forecast is presented which is important for online control and security evaluation of a large system. A precise short term load forecasting is essential for monitoring and controlling power system operation.

Short-term load forecasting techniques generally involve physical decomposition of load into components. The load is decomposed into a daily pattern reflecting the difference in activity level during the day. A weekly pattern representing the day of the week effect on the load. A trend component concerning the seasonal growth in load and a weather sensitive component reflecting the deviations in load due to weather fluctuations. The random errors can be statistically analyzed to obtain a stochastic model for error estimation. Thus, the expected hourly load forecast is divided in to five components and can be written as:

Y (i, j). =ADP (j)+AWP (k, j)+WSC (i,j)+TR (i)+
**   SEC (i,j)**   (1)

Where
Y (i, j): Load forecast for j^{th} hour of ith day.
ADP (j): Average daily load pattern at j^{th} hour.
AWP (k,j): Average weekly load pattern at j^{th} hour and k^{th} day of week. (k=1,2...7)
WSC (i, j): Weather sensitive component at j^{th} hour of ith day
SEC (i,j): Stochastic error component which is assumed to be normally distributed.
TR (i): Trend component of load on i^{th} day.
The average daily pattern represents the hour of the day effect. It is an average of the daily load pattern over an optimal number of past days. The average weekly pattern reflects the day of week effect. It is calculated as average of the weekly cycles over a certain number of past weeks.
The weather sensitive components represent the changes in customer requirements according to variations in the weather conditions. Generally temperature is considered as the only weather variable since data banks for other weather variables like wind, humidity etc. are usually not available.
The trend component includes three components: a long-term growth trend, a short-term trend dependent on the economic cycle and a time of the year pattern. The statistical error components represent error in estimate. The standard deviation and variance are usually taken as error parameters.

3. HISTORY:

To tackle this problem, many techniques and approaches have been investigated in the last two decades. Some of the short term load forecasting methods are time of day models multiple regressions, stochastic time series [2], state space [3], knowledge based and expert systems [4], etc.

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4. PROBLEM STATEMENT:

In this paper, ANN and FL-ANN based load- forecasting methods are presented and it is extended this method for better forecasting of electrical load by using different ANN structures and FL-ANN modules.

Here in This paper an algorithm, this combines both time series and regression approaches, has been presented. The algorithm utilizes a layered perceptron artificial neural network (ANN). As is the case with time series approach, the ANN traces previous load patterns and predicts (i.e. extrapolates) a load pattern using recent load data. Algorithm uses weather information for modeling. The ANN is able to perform non-linear modeling and adaptation. It does not require assumption of functional relation between load and weather variables in advance. We can adopt the ANN by exposing it to new data.

Among the ANN based models used for the load forecasting, the static one, implemented as forward neural network, has been used most successfully. This model can be described by the following equation

$$L_{t+k} = f(t, L_t, L_{t-1}, .. L_{t-n}, W_t, W_{t-1}, ... W_{t-r}, \hat{W}_{t+k}) + \varepsilon_{t+k} \qquad (2)$$

Where

   t: time of the day.

   k: time lead of the forecast.

   L_t : load at time t.

   W_t : vector of weather factor observed at time t.

   $\hat{W}_{t+k}$: weather forecast for time t+k.

   ε_{t+k} : random load component.

   The non-linear function 'f 'is approximated by neural network. For STLF, with maximum lead times around 60-90 minutes, variable representing weather conditions can be neglected due to relatively large time constant of the weather relationship. So the model can be simplified as

$$L_{t+k} = f(t, L_t, L_{t-1}, ... L_{t-n}) + \varepsilon_{t+k} \qquad (3)$$

   Using above model (3), load forecast L_{t+1} is calculated directly by the trained neural network based on the time and loads from the recent past. Here, feed forward ANN with back propagation algorithm was used to forecast the data 24 hour ahead.

With STLF within hours and days, is concerned on predicting load as a conditional expectation given the time and expected weather conditions. Only a few first forecasts are significantly affected by the last observed load value. Here, the focus is on predicting relative changes in load based on recent load pattern. Hence, a short term can be formulated as

$$L_{t+k} = L_t (1+\delta_{t+1}) \qquad (4)$$

Where δ_{t+1} is a forecast relative increment in load defined as follows

$$\delta_{t+1} = (L_{t+k} - L_t) / L_t \qquad (5)$$

δ_{t+1} is forecasted by a neural network based on the time and 'n' last relative load increments
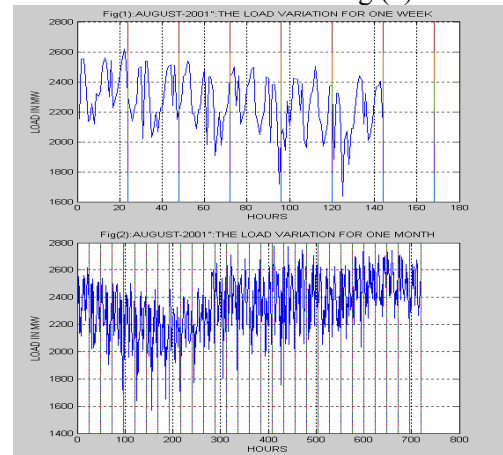
$$\delta_{t+1} = h(t, \delta_t, \delta_{t-1}, ... \delta_{t-n}) \qquad (6)$$

This approach has been implemented in this paper to data obtained from the power plant along with traditional ANN based forecaster, discussed above. This approach allows us to achieve two major improvements as compared to the traditional ANN based forecaster. It ensures a better accuracy and is more reliable. There is a good chance that some values of input variables out of this domain will produce very erroneous forecasts. The sensitivity of this phenomenon depends greatly on the neural network design. Network with too many input variables or too many hidden neurons, providing a good accuracy for typical conditions are more prone to such behavior than the parsimoniously relative load increments which are more repeatable than daily load curves. In other words, two relative increments will remain quite similar. This means that the forecast accuracy represented in the training data. Hence, the second approach leads to an improved reliability as well as to a better accuracy. For the training of network, the generalized delta rule (GDR) [5] is used to a layered perception type ANN.

5. PROPERTIES OF LOAD:

The hourly electric load demand of a Delhi electricity utility is used throughout this work as the test case. The hourly temperature data from the influential district is also available. The data of the months Jan, Feb, Aug and Sept 2001 are available, so the length of the data set is about 4 months. For a more thorough testing, load data of an even longer time period could be preferred.

The monthly load property of the Delhi for August month is shown in Fig (1). The weekly rhythm originates from the working day - weekend rhythm obeyed by most people. On working days social activities are at a higher level than on Saturdays and Sundays, and therefore the load is also higher. The series begins with five quite similar patterns, which are the load curves of Monday-Friday. Then two different patterns for Saturday and Sunday follow. This same weekly pattern is then repeated. This can be shown in the Fig (2).

Fig(1):AUGUST-2001":THE LOAD VARIATION FOR ONE WEEK

Fig(2):AUGUST-2001":THE LOAD VARIATION FOR ONE MONTH

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The daily rhythm on the other hand results from the synchronous behavior of people during the day. Most people sleep at night, and therefore the load is low at night hours. Also during the day, many activities tend to be simultaneous for a majority of people (working time, lunch hour, TV- watching etc.). The daily rhythm changes throughout the year.

6. LOAD FORECASTING WITH ANN:

For the ANN model[6] shown in the Fig below
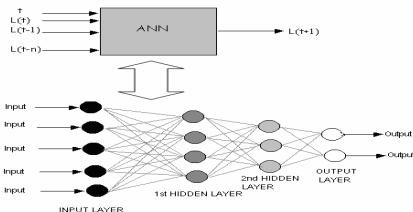
The features that are taken into account as input factors in the load forecast system are as fallows
If 'i' is the forecasted day

- Hourly loads for two days prior to the forecasted day i-2
- Hourly loads for the day prior to the forecasted day i-1
- Forecasted hour of the forecasted day 1,2,3…………24
- Forecasted day of the week i.e Monday-1, Tuesday-2, Wednessday-3, Thursday-4, Friday-5, Saturday-6, and Sun day-7.

Outputs are:

- Load forecast for all 24 hours of the day

Without Temperature Effect:

First, the results of the model using no temperature data are given. For test week, the training data is used. The training with more data gives better results. The performance of the models is illustrated in Fig (3) and Fig (4). They show the actual, forecast loads and percentage error for a test week.

In load figure, it can be seen that the load decreases heavily throughout the week, and the forecasts cannot keep up with that. This is a problematic situation in the view of forecasting. The change during the test week is remarkable. At least for this kind of situations where the temperature changes rapidly, including the temperature in the model is essential.
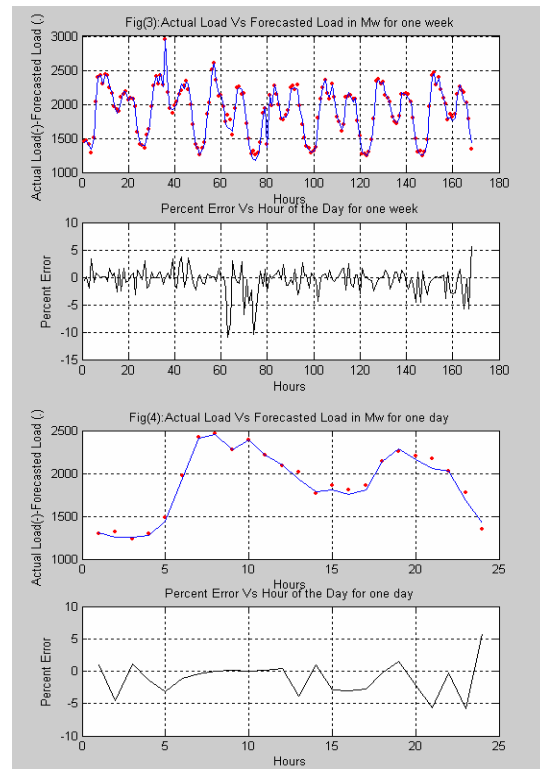
With Temperature Effect:

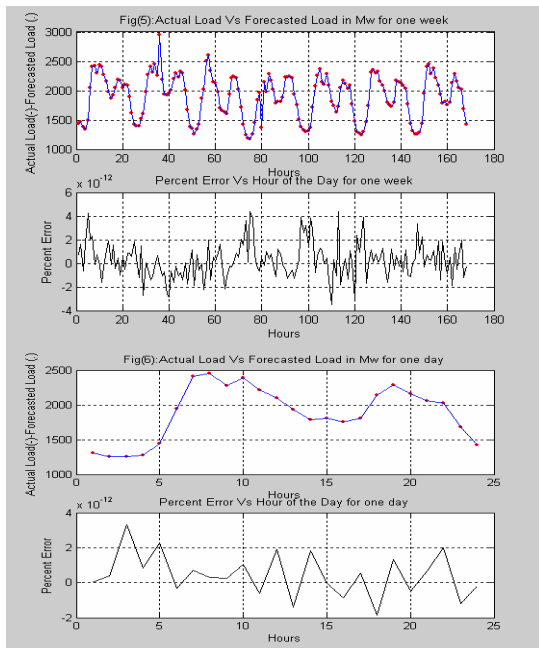The inputs are same as the inputs in above section and

- Hourly Temperatures for two days prior to the forecasted day i-2
- Hourly Temperatures for the day prior to the forecasted day i-1
- Max. Min. temperatures for two days prior to the forecast day
- Max. and Min. temps for the forecast day

Outputs are:

- Load forecast for all 24 hours of the day

On the other hand, with the training sets of the length of two months, including the daily hourly temperatures in the model appears to improve the accuracy. The errors are in general slightly smaller than when forecasting without temperature data. However, on the test week, the errors are still unacceptably large. The training was performed for the model for the period of two months each (Jan, Aug, and Sept 2000-2001). The number of neurons in the hidden layer is determined by the trial and error method using the validation set. This guarantees the proper selection of the number of neurons in the hidden layer. Various neurons have been tested and MSE error on the training, validation and testing has been measured. With 30 neurons in the hidden layer, it produces the lowest error on the validation set.

The actual and forecast loads with the model using temperature, for a test week is shown in Fig (5), Fig (6) and the results are compared at the end for a complete day (Jan 2001). It can be seen that the model can now forecast the decreasing of the load, but still not to the fully satisfying extent.

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Fig(5):Actual Load Vs Forecasted Load in Mw for one week

Percent Error Vs Hour of the Day for one week

Fig(6):Actual Load Vs Forecasted Load in Mw for one day

Percent Error Vs Hour of the Day for one day

7. FUZZY LOGIC AND ARTIF -ICIALNEURAL NETWORKS (FL-ANN):

In the area of fuzzy- neural collaborations, several forms have surfaced, including fuzzy preprocessing of neural network inputs, fuzzy post- processing of neural network outputs, integrated fuzzy-neural networks and parallel fuzzy neural forecasters. Depending on the fuzzy-neural model, the selection of input/output variables and the amount of data used, forecasting errors can be very low range.

Fuzzy logic and neural networks are complementary technologies in the design of intelligent systems. Each method has merits and demerits. Neural networks are essentially low-level computational structures and algorithms that offer good performance in dealing with sensory data. On the other hand, fuzzy logic techniques often deal with issues, such as reasoning, on a higher level than neural networks. However, since fuzzy systems do not have much learning capability, it is difficult for a human operator to tune the fuzzy rules and membership functions from the training data set. Also, because the internal layers of neural networks are always opaque to the user, the mapping rules in the network are not visible and are difficult to understand. Furthermore, the convergence of learning is usually very slow and not guaranteed. Thus, a promising approach for getting the benefits of both the fuzzy systems and neural networks is to merge them in to an integrated system. This collaboration posses the advantage of both neural networks (e.g. learning and optimization abilities) and fuzzy systems (e.g. human like If-Then rules thinking and is of incorporating knowledge).

In light of above discussion the modular network shown in Fig (7) is divided into two components: a FL (Fuzzy logic) module and an ANN (Artificial Neural Network) module. Each of these modules applied to the aspect of the problem for which it is best suited in order to produce better overall forecasting results.
 As shown in the Fig,

- I_1 are the input data to the FL module
- I_2 is the output of the FL module which is used as input to the ANN module
- I_3 (combined with I_2) are input data to the ANN module
- O_F is the forecasted load, O_A is the actual load
- **e** is the error between O_A and O_F.

FL BLOCK:
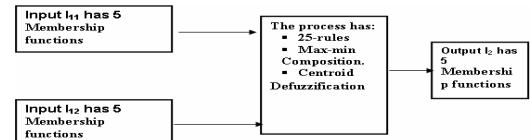
The FL module maps the highly non-linear relationship between the weather parameters and their impact on the daily electric load peak. Fig (8) shows that the FL module has two inputs I_{11} and I_{12} and one output I_2.Several factors such as temperature, wind speed and the humidity have direct impact on the daily electric load peak. In the research it is hypothesized the temperature has the biggest impact.

From the previous hypothesis the inputs are chosen as follows. The first input to the Fuzzy logic module I_{11} represents the maximum temperatures for the day before the forecasted day. I_{11} has five membership functions (MF), as shown in the Fig (9) where vc, co, cf, ho, vh represents the temperature being very cold, cold, comfortable, hot and very hot respectively. These membership functions overlap using triangular and trapezoidal shapes to cover all possible range of temperatures. The shape of membership functions and the degree of overlap were chosen by trial and error. The second input to the FL module I_{12} is identical to the first input I_{11}. In all aspects of shape, overlap, and membership function representation as shown in Fig (10). However this input represents the forecasted maximum temperature for the forecasted day.
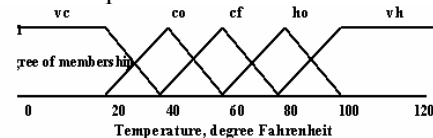

Fig. The first/second input to the FL module I_{ij} ; i =1   j= 1,2.

There are 25 IF-THEN statements shown in the table (1). In the fuzzy rule base that characterize the behavior of the FL module. The choice of the rule, as seen in the Table (1) depended on the experience or knowledge of the problem. In Table (1) NB, NS, ZE, PS, and PB are negative big , negative small , zero equal ,positive small and positive big respectively. This linguistic variable represents the desired out put of the Fl module.

Table (1)

Input I_{11} (The day before)	Input I_{12} (The forecasted day)				
	Very cold (vc) <= 30°F	Cold (co) 10-60° F	Comf (cf) 30-80° F	Hot (ho) 60-90° F	Very hot (vh) >= 70° F
Very cold (vc) ? 30°F	ZE	NS	NB	ZE	PB
Cold (co) 10-60° F	PS	ZE	NS	PS	PB
Comf (cf) 30-80° F	PB	PS	ZE	PS	PB
Hot (ho) 60-90° F	ZE	NS	NS	ZE	PB
Very hot (vh) ? 70° F	NE	NB	NB	NB	ZE

The output of the FL module is a control action that carries a weight between -1 an +1 shown in Fig(11), which represent the expected change in the amount of electric load consumed between the forecasted day, capered to the previous day, and negative value means the exact opposite. The types, shapes and overlaps of the membership functions of the out put, shown below for determine experimentally.

Fig The output of the FL module.
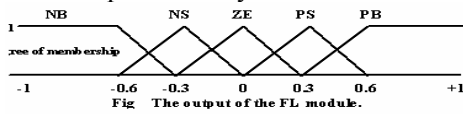
The fuzzy inference that was used to implement the fuzzy rules was the Max-Min composition, and the method that transformed the inference engine rules to one crisp output was Centroid De-fuzzification method (10).

The output of the FL module is used as an input to the ANN module, in order to help provide it with enough scenarios to perform the final forecast.

The ANN module performs the job of learning the highly nonlinear input -output mapping directly from the training data. Furthermore, given enough input-output scenarios along with the correct choice of inputs, the ANN module generalizes the situation in order to interpolate input patterns that are new to the network and fit them into the desired function in order to give a correct output.

Several ANN modules have been investigated. Between the different input combinations and the different ANN structures, unlimited possibilities exist. Due to the highly nonlinear characteristics of the STLF problem, the data had to be divided into parts in order to obtain a more accurate final forecast. The ANN module that was chosen consists of 12 (I have considered here 3 networks due to information availability) networks. Each of these networks performs the final 24-hour and weekly ahead load forecast. This was done due to the difference in the weather load relation-ship over the different months of the year. Each of the 3 neural networks consists of three layers. The first layer, the input layer, has 29 input neurons. The second layer, the hidden layer, has 25 neurons fully connected to the input layer. The third layer, the output layer, has one neuron connected to all hidden neurons. The back propagation technique along with sigmoid activations are used to train all the networks.

The input parameters of each Network:

$I_{3(1)}$: is the forecasted day of the week as follows:
i.e Monday-I, Tuesday-2, Wednessday-3, Thursday-4, Friday-5, Saturday-6, and Sun day-7.

$I_{3(2)}$: is the forecasted hour of the forecasted day (i.e. an integer between 1 and 24).

I_2 : is the output of the FL module.

$I_{3(3)}$ - $I_{3(15)}$: are the actual loads at times (t-24,t-25,t-26,t-48,t-49,t-50,t-72't-73,t-74,t-168,t-169) (i.e. the day before forecasted day, 2 days before, 3 days before).

$I_{3(16)} - I_{3(27)}$: is the actual temperature values at the same time periods as $I_{3(3)}$ -$I_{3(15)}$

$I_{3(28)}$-$I_{3(29)}$:is the maximum and minimum temperature for the day before the forecasted thy, respectively.

The data were used for training the networks was Jan, Feb, Aug, Sept 2001 load and weather data for Delhi area, which was supplied by the POWER GRID CORPORATION OF INDIA Ltd. Different data files were created, each carries one-month data each. Each of the networks are trained separately to perform the final 24-horn ahead and one week forecast of the electric load. The plots for Actual And forecasted Loads with percentage error is shown in the Fig (12) and Fig (13)

8. EVALUATING THE PREDI -CTION PERFORMANCE:

The final step in the design procedure is the assessment of the forecasting performance of the trained networks. Various error metrics (distance measures) between the actual and forecasted load are defined, but the one most commonly adopted by load forecasters, is the absolute percentage error (APE), defined by

$$\epsilon^k_{APE} = \frac{(\text{Actual Load- Forecasted Load})}{\text{Actual Load}} *100 \qquad (7)$$

Where 'k' is the time instant
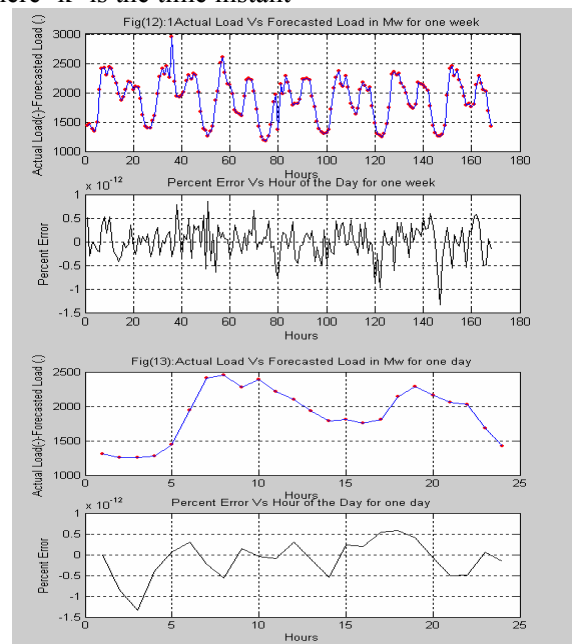
9. TEST RESULTS AND COMPAR -ISONS:

The data were used for testing FL-Ann's was 22-28th of January load weather data for Delhi. Data file were created, each of these carries the one-week data. Each of these data files was tested on the network that was trained for the specific month. The resulting actual vs forecasted loads for January 2001.

Using load and weather data, the model was able to forecast the electric load demand for the next day with relatively low error. The maximum and minimum errors during the summer period were of higher complexity with respect to other weather periods.

In the above, a ANN network model and FL- ANN model utilizing the data of the previous day and week as well as the most recent hours was tested. The forecasting was carried out hour by hour. The model was tested with and without temperature data on a test week. The results were clearer, when daily average temperatures were included.

A FL-ANN model was also tested and compared to the ANN models. The results were better with the FL-ANN model. The percentage errors at lead-times from 1 to 24 hours were sorted out in order to see how efficiently the model could utilize the most recent information. It was found out that the accuracy was clearly better for the next few hours than for longer lead-times. Table (2) presents summary of the forecast error statistics for the FL-ANN model in comparison to the ANN model (with and without temperature affect). It is worth mentioning that two methods did the forecast for the same area, Delhi, utility. In general the FL ANN models, performance is superior to the ANN model.

Table (2)

9. CONCLUSSIONS:

Short term Electric load forecasting using fuzzy neural networks and ANN has been implemented in this paper work. Two approaches have been discussed and results obtained by using these approaches are shown. Table (3)

COMPARISON TABLE FOR ANN AND FL-ANN

METHOD USED FOR STLF	Mean Error for one day
STLF USING ANN WITHOUT TEMPERATURE	-1.1099
STLF USING ANN WITH TEMPERATURE	-4.3369e-013
STLF USING FL-ANN WITH TEMPERATURE	-1.0824e-013

The results show shown in table(3) that the FL-ANN combination is suitable to interpolate among the load and temperature pattern data of training sets to provide the future load pattern. In order to forecast the future load, we need to use the recent load and temperature data in addition to the predicted future temperature. Since the fuzzy-ann simply interpolates among the training data, it will give high error with the test data that is not close enough to any one of the training data.

In general, the networks require training data well spread in the future space in order to provide highly accurate results. The networks typically shows higher error in the days when people have specific start-up activities such as Monday, variant activities such as during holiday seasons. More accurate results, could be obtained by using more sophisticated topology for the networks, which can discriminate start-up days from other days.

In this approach only temperature information among the weather variables has been utilized, as this was the only information available. Use of additional weather variables such as cloud coverage and wind speed could yield even better results.

The results obtained using second approaches are closer to the actual load, as shown in the table. The algorithm of FL-ANN is more robust compared to the ANN.

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