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Short Term Load Forecasting using Neuro-fuzzy-Wavelet Approach

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Abstract

This paper presents a novel approach for short term load forecasting using wavelet in combinations with neuro fuzzy modules. In this paper, an integrated neuro-fuzzy-wavelet approach has been used to forecast the short term electrical load. The wavelet is used to extract the featured coefficients from data and ANFIS is used to predict the trend of these wavelet coefficients, rather then using a simple trained neuro fuzzy system. The results haven been compared with simple neuro-fuzzy approach.

Keywords: Load Forecasting, Soft Computing, Neuro-fuzzy, Wavelet.

I. INTRODUCTION

Load forecasting is an important component of power system to establish economical and reliable operations for power stations and their generating units. An accurate load forecasting approach used to predict load demand is essential part of any energy management system [1-6]. The close tracking of the system load by the system generation at all time is the basic requirement for the reliable operations of power system [7]. An electrical utility faces many economical and technical problems in order to supply high quality electric energy to consumers in a secure and economical manner. In achieving these goals for optimal planning of large scale system, the knowledge of the future electric load is the primary prerequisite. Depending on the forecasting range, broadly we can classify forecasting into four types (Long term forecasting, medium term forecasting, short term forecasting and very short term forecasting) [7]. Various traditional methods like time series method, regression based methods have been used for the prediction of load [8]. The main drawback of this method is the explicit relationship between different variables, requirement of heavy computational time and large amount of memory space. This leads to search for new methods which can solve the above limitations and give better results.

This paper aims to find a solution to short term load forecasting (STLF) using ANFIS an integrated approach of wavelet, neuro fuzzy for forecasting the next 24 hours load. This paper is organized as follows: Section-II discusses various traditional and soft computing based short term load forecasting approaches. Concept of wavelet analysis required for prediction will be discussed in Section-III while elements of neuro fuzzy architecture needed will described in section – IV. A prediction procedure

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using wavelets and neuro fuzzy is discussed in Section – V, while its application to time series of hourly load forecasting consumption is discussed in Section-VI. Section – VII includes discussion and concluding remarks.

II. CONVENTIONAL AND ARTIFICIAL INTELLIGENCE BASED METHODS FOR SHORT TERM LOAD FORECASTING

A. Traditional Approaches

1) Time Series Methods

These methods treat the load pattern as a time series signal with known seasonal, weekly and daily periodicities. These periodicities give a rough prediction of the load at the given season, day of the week and time of the day. The difference between the prediction and the actual load can be considered as a stochastic process (random signal). The techniques used for the analysis of this random signal are

a) Kalman Filters Method
b) Box Jenkins Method
c) Regression Processes and
d) Spectral Expansion Technique

a) Kalman filters method

This requires the estimation of the covariance matrix. Because of the high non stationary load pattern, it is difficult to estimate the covariance matrix accurately *[28]*.

b) Box Jenkins Method

It requires the correlation function for identifying proper Auto Regressive Moving Average (ARMA) models. This can be accomplished by using pattern recognition techniques. A major obstacle here is its slow performance *[29]*.

c) Regression Processes

The regression model is used to describe the stochastic behavior of hourly load pattern on a power system. This model assumes that the load at a particular hour can be estimated by a linear combination of the previous few hours.

Generally, the larger the data set, the better is the result in terms of accuracy. A larger computational time for the parameter identification is required.

d) Spectral Expansion Technique

The spectral expansion technique utilizes the Fourier series. Since load pattern can be approximately considered as a periodic signal, and it can be decomposed into a number of sinusoids with different frequencies. However the load patterns are not perfectly periodic. Abrupt changes of weather cause fast variations of load pattern which result in high frequency components in frequency domain. Therefore, the spectral expansion technique cannot provide accurate frequency for the case of fast weather changes. Generally, these techniques use a large number of complex relationships requires a long computational time.

2) Regression Based Methods

The general procedure for the regression approach is

1. To select the proper and/or available weather variables
2. Assume basic functional elements
3. Find proper coefficients for the linear combination of the assumed basic functional elements.

Since temperature is the most important information of all weather variables, it is used most commonly in the regression approach. However additional variables such as humidity, wind velocity and cloud yields better results.

The functional relationship between load and weather variables however is not stationary but depends on spatiotemporal elements.

B. Intelligent Systems

An intelligent system can be defined as a system that exhibits intelligence in capturing and processing information. Practically speaking, an intelligent system is the one, which employs artificial intelligence techniques to fulfill some or all of its computational requirements.

1) Artificial Neural Networks (ANN)

The ANN is capable to perform non-linear modeling and adaptation. It does not require functional relationship between load and weather variables in advance. The ANN can learn from experience, generalize from previous examples to new ones, abstracts essential characteristics from input containing irrelevant data. The ANN gives more precise forecast as compared to conventional techniques.

2) Rule Based Expert Systems

An expert system is a computer program, which has the ability to act as a knowledge expert. This means this program can reason, explain and have its knowledge base expanded as new information becomes available to it. The load-forecast model can be built using the knowledge about the load forecast domain from an expert in the field. The knowledge engineer extracts this knowledge from the load frequency domain. This knowledge is represented as facts and rules using the first predicate logic to represent the facts and IF-THEN production rules. Some of the rules do not change over time, some changes very slowly; while others change continuously and hence are to be updated from time to time[30].

3) Fuzzy Systems

Fuzzy sets were introduced to represent and manipulate data and information that possesses non-statistical uncertainty. Fuzzy sets are a generalization of conventional set theory that was introduced as a new way to represent vagueness in the data. It introduces vagueness (with the aim of reducing complexity) by eliminating the sharp boundary between the members of the class from nonmembers *[31, 32]*.

These approaches are problem dependent to a large extent and converge slowly and even may diverge in certain cases. In addition to this, the above mentioned approaches use either steady state component or average component or the peak component to predict the load. However, the prediction of the load depends upon the weighted combination of these three components which varies dynamically. In this paper, an attempt is made to predict electrical load that combines the above mentioned features.

III. ELEMENTS OF WAVELET ANALYSIS

Wavelet analysis is a refinement of Fourier analysis [9-15,19-24,27] which has been used for prediction of time series of oil, meteorological pollution, wind speed, rainfall *etc.* [24,27]. In this section some important vaults relevant to our work have been described. The underlying mathematical structure for wavelet bases of a function space is a multi- scale decomposition of a signal, known as multi resolution or multi scale analysis. It is called the heart of wavelet analysis. Let L_2 (R) be the space of all signals with finite energy. A family {Vj} of subspaces of L_2(R) is called a multi resolution analysis of this space if

(i) intersection of all V_j, j = 1, 2, 3, ... be non-empty, that is $\bigcap_j V_j \neq \phi$

(ii)This family is dense in $L_2(R)$, that is, = L_2R

(iii) $f(x) \in V_j$ if and only if $f(2x) \in V_{j+1}$

(iv) $V_1 \subseteq V_2 \subseteq \ldots\ldots V_j \subseteq V_{j+1}$

(v) There is a function preferably with compact support of such that translates $\varphi(x-k)$ $k \in Z$, span a space V_0. A finer space V_j is spanned by the integer translates of the scaled functions for the space V_j and we have scaling equation

$$\phi(x) = a_k \phi(2x-1) \qquad (1)$$

with appropriate coefficient a_k, k ε Z. ϕ is called a scaling function or father wavelet. The mother wavelet ψ is obtained by building linear combinations of ϕ. Further more ϕ and ψ should be orthogonal, that is,

$$<\phi(.-k), \psi(.-l)> = 0,\ l, k \in Z. \qquad (2)$$

These two conditions given by (1) and (2) leads to conditions on coefficients b_k which characterize a mother wavelet as a linear combination of the scaled and dilated father wavelets ϕ :

$$\psi(x) = \sum_{k \in Z} b_k\, \phi(2x-k) \qquad (3)$$

Haar, Daubechies and Coefmann are some well known wavelets.

Haar wavelet (Haar mother wavalet) ψ given below—

$$\psi(x) = \begin{cases} 1, & 0 \le x \le ½ \\ -1, & ½ < x \le 1 \\ 0, & x < 0, x > 1 \end{cases} \qquad (4)$$

Can be obtained from the father wavelet

$$\phi(x) = \begin{cases} 1, & 0 \le x \le 1 \\ 0, & x < 0, x > 1 \end{cases} \qquad (5)$$

In this case coefficients a_k in (1) are $a_0 = a_1 = 1$ and $a_k = 0$ for $k \neq 0, 1$. The Haar wavelets is defined as a linear combination of scaled father wavelets $\psi(x) = \phi(2x) - \phi(2x-1)$ which means that coefficients b_k in (3) are $b_0 = 1$, $b_1 = -1$ and $b_k = 0$ otherwise, Haar wavelets can be interpreted as Daubechie's wavelet of order 1 with two coefficients. In general Daubechies' wavelets of order N are not given analytically but described by 2N coefficients. The higher N, the smoother the corresponding Daubechies' wavelets are (the smoothness is around 0·2 * N for greater N). Daubechies' wavelets are constructed in a way such that they give rise to orthogonal wavelet bases. It may be verified that orthogonality of translates of ϕ and ψ, requires that $\sum_k a_k = 2$ and $\sum_k b_k = 2$. It is quite clear that in the higher case the scaled, translated and normalized versions of ψ are denoted by

$$\psi_{j,k}(t) = 2^{j/2}\, \psi(2^j x - k) \qquad (6)$$

With orthogonal wavelet ψ the set $\{\psi_{j,k} \mid j, k \in Z\}$ is an orthogonal wavelet basis. A function f can be represented as

$$f = \sum_{j \in Z} \sum_{k \in Z} c_{j,k}\, \psi_{j,k}(t) \qquad , c_{j,k} = <f, \psi_{j,k}> \quad (7)$$

The Discrete Wavelet Transform (DWT) corresponds to the mapping $f \longrightarrow c_{j,k}$. DWT provides a mechanism to represent a data or time series f in terms of coefficients that are associated with

particular scales [24,26,27] and therefore is regarded as a family of effective instrument for signal analysis. The decomposition of a given signal f into different scales of resolution is obtained by the application of the DWT to f. In real application, we only use a small number of levels j in our decomposition (for instance $j = 4$ corresponds to a fairly good level wavelet decomposition of f).

The first step of DWT corresponds to the mapping f to its wavelet coefficients and from these coefficients two components are received namely a smooth version, named approximation and a second component that corresponds to the deviations or the so-called details of the signal. A decomposition of f into a low frequency part a, and a high frequency part d, is represented by $f = a_1 + d_1$. The same procedure is performed on a_1 in order to obtain decomposition in finer scales: $a_1 = a_2 + d_2$. A recursive decomposition for the low frequency parts follows the directions that are illustrated in the following diagram.

$$\begin{array}{ccccccccccc} f & \ldots\ldots & a_1 & \ldots\ldots & a_2 & \ldots\ldots & a_3 & \ldots\ldots & a_n & & \\ & \diagdown & & \diagdown & & \diagdown & & \diagdown & & & \\ & & d_1 & & d_2 & & d_3 & & d_4 & \ldots\ldots & d_n \end{array}$$

Fig. 1 Wavelet decomposition in form of coarse and detail coefficients

The resulting low frequency parts a_1, a_2, ... a_N are approximations of f, and the high frequency parts d_1, d_2, ... d_n contain the details of f. This diagram illustrates a wavelet decomposition into N levels and corresponds to

$$f = d_1 + d_2 + d_3 + \ldots\ldots + d_{N-1} + d_N + a_N. \quad (8)$$

In practical applications, such a decomposition is obtained by using a specific wavelet. Several families of wavelets have proven to be especially useful in various applications. They differ with respect to orthogonality, smoothness and other related properties such as vanishing moments or size of the support.

IV. NEURO FUZZY SYSTEM

Theory of ANFIS

The ANFIS architecture [16-18,33] and the learning rule of adaptive network in the previous section is used and is referred as ANFIS standing for Adaptive Neuro-Fuzzy Inference System. The Matlab is used for neuro-fuzzy system training to train the wavelet coefficient.

ANFIS Architecture

According **to** the Takagi and Sugeno type [25,33]. The fuzzy inference system has two inputs x and y and one output z.

Rule 1 : If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$

Rule 2 : If x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

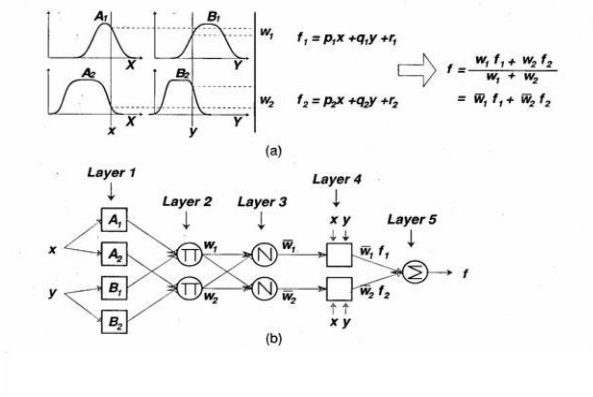


Fig.2. Graphical representation of ANFIS

Layer 1 Every node *i* in this layer is a square node with a node function

$$O_i = \mu A_i(x). \qquad (9)$$

Where x is the input to node i, and A_i is the linguistic label (small, large etc.) associated with this node function. In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i. Usually we choose $\mu A_i(x)$ to be bell-shaped with maximum value equal to 1 and minimum value equal to 0. The generalization bell function is given in equation (10).

$$\mu_A i(x) = \frac{1}{1 + \left[\left(\frac{x - O_i}{a_i}\right)^2\right]^{bi}} \qquad (10)$$

or gaussian function as given in equation (11).

$$\mu_A i(x) = \exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \qquad (11)$$

where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell shaped functions vary accordingly. Thus, exhibiting various forms of membership functions on linguistic label A_i. In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal or triangular-shaped membership functions, are also qualified candidates for node functions in this layer. Parameter in this layer are referred as premise parameter.

Layer 2 Every node in this layer is a circle node labeled Π which multiplies the incoming signals and send the product output as results. For instance

$$W_i = \mu A_i(x) \times \mu B_i(y).\ i = 1, 2. \quad (12)$$

Each node output represents the firing strength of a rule.

Layer 3 Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule's firing strength to sum of all rule's firing strengths

$$\overline{W}_i = \frac{W_i}{W_1 + W_2},\ i = 1, 2. \qquad (13)$$

For convenience, outputs of this layer will be called normalized firing strength.

Layer 4 Every node *i* in this layer is a square node with a node function

$$O_i^4 = \overline{W}_i f_i = \overline{W}_i(p_i x + q_i y + n_i) \quad (14)$$

where $\overline{W_i}$ is the output of layer 3 and (p_i, q_i, n_i) is the parameter set. Parameters in this layer will be referred as consequent parameters.

Layer 5 The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals *i.e.*,

$$O_1^5 = \text{Overall output}$$

$$= \sum_i \overline{W_i} f_i$$

$$= \frac{\Sigma_i W_i f_i}{\Sigma_i W_i} \qquad (15)$$

Thus, we have constructed an adaptive network which is functionally equivalent to a type 3 fuzzy inference system. For type-1 fuzzy inference systems, the extension is quite straight forward and the type-1 ANFIS is shown in fig. 2, where the output of each rule is induced jointly by the output and the firing strength.

V. NEURO-FUZZY-WAVELET APPROACH

The Neuro-Fuzzy Wavelet approach has been used to predit the electrical load. In this approach, Daubechies wavelets Db8 have been applied in the decomposition for the give data pattern. There are four wavelet coefficients are used. All these wavelet coefficients are time dependent (the first three wavelet coefficients from d_1 to d_3 and the coarse approximation a_3. These coefficients are illustrated in the Fig. -3. We observe the substantial difference of variability of the signals at different levels. The higher is the wavelet level, the lower variation of the coefficients and easier prediction of them. Our main idea is to substrate the prediction task of the original time series of high variability by the prediction of its wavelet coefficients on different levels of lower variability's, and then using equation (4) for final prediction of the power load at any time instant *n*. Since most of the wavelet coefficients are of lower variability we expect the increase of the total prediction accuracy.

The wavelet tool available in Matlab is used for the process of wavelet decomposition of the time series representing average of the power load data for 120 hours. This step involves several different families of wavelets and a detailed comparison of their performance. In our case, The Daubechies wavelets of order 8 are performed. Three level wavelet decomposition of the given time series $X_N = f$: is performed

$$f = a_3 + d_3 + d_2 + d_1$$

The smooth part of *f* is stored in a_3, and details on different levels are captured by d_1, d_2, d_3. Consequently a decomposition of the time series in three different scales is obtained. Fig.3 illustrates the decomposition of the original signals.

The basic idea is to use the wavelet transforms and predict the data by neuro fuzzy for individual coefficients of wavelet transform represented by a3, d_1, d_2, d_3. The pseudo code of NF-W is given in fig. 4.

The total predicted power load at an instant (i) is given by

$$F(i) = f1(i) + f2(i) + f3(i) + f4(i) \qquad (16)$$

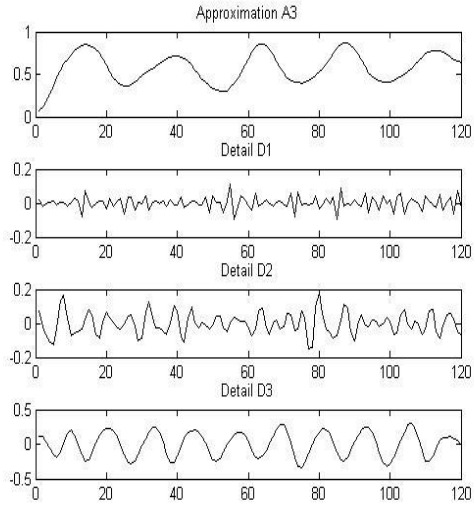
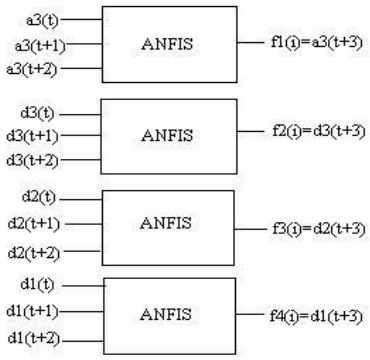


Fig.3. Wavelet decomposition of hour load data into wavelet coefficient




```
Begin NF-W
    Collection of Past data
    Normalization
    Decompose the data using wavelet transform
            for i=1:no. of wavelet components
                Initialize the parameters
                while  mean square error < error tolerance
                        Calculate output using NF-W
                        Modify parameters NF-W
                        Back Propagation Training
                        Calculate error
                end
                Forecast wavelet components
            end
    Reconstruct the forecasted pattern using wavelet components
    Plot the forecasted data
end NF-W
```

Fig.4. Pseudo code of NF-W forecasting.

VI. RESULTS AND DISCUSSIONS

The electric load data have been collected for 120 hr. from Gujarat system and normalize them in the range 0-1. Then those normalize data used for for developing neuro-fuzzy system. The trained neuro-fuzzy system is used for perdition. The results of neuro-fuzzy systems comparing with actual data are shown in Fig. 5 during training phase. Also the error during training is shown in Fig. 6. The trained neuro-fuzzy system is used for testing and the test results are shown in Figs. 7-8. The same normalized data used for prediction using neuro-fuzzy–wavelet approach. The Daubechies wavelet Db8 is used for decomposition and the wavelet coefficients d1-d3 and a3 have been calculated. The trend of coefficients shown in Fig. 9-12 have been used for ANFIS training and predicting the wavelet coefficients for future loads. So wavelet is used to extract the feature coefficients from data and then ANFIS is implemented to predict the trend of the wavelet coefficient. The results of neuro-fuzzy-wavelet and actual load have been compared and shown in Fig. 13.

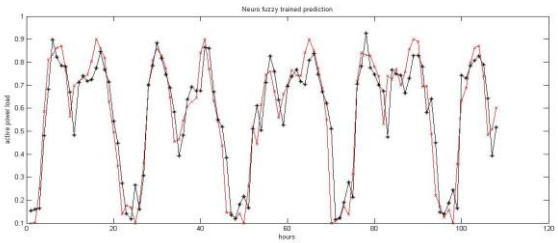


Fig.5. Actual and Predicted data using neuro fuzzy

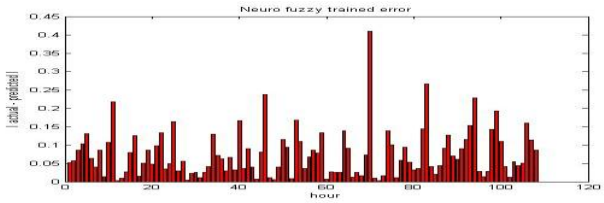


Fig.6. Error for load prediction using Neuro fuzzy

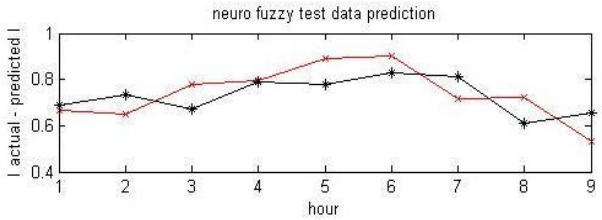


Fig.7. Neuro fuzzy test data prediction

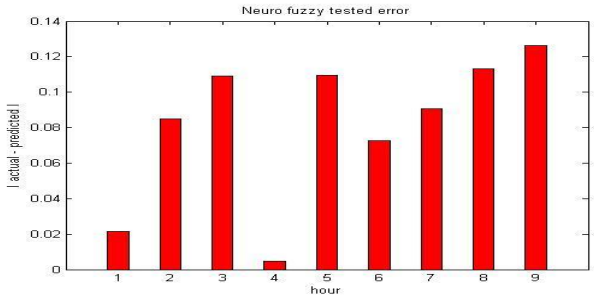


Fig.8. Neuro fuzzy tested error

The wavelet coefficients(a3, d1, d2, d3) are predicted using ANFIS system is represented in Fig.9-12 respectively and compared with actual trend.

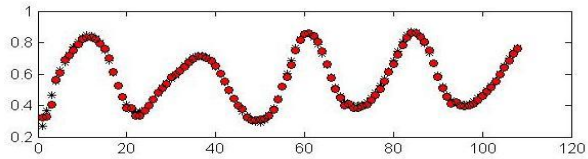


Fig.9. Actual and Predicted Approximate coefficient (A3)

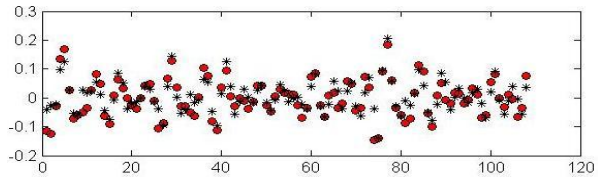


Fig.10. Actual and Predicted detail coefficient (D1).

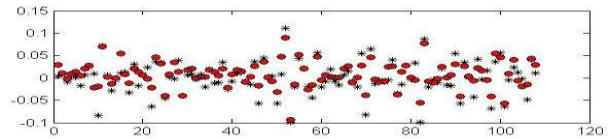


Fig.11. Actual and Predicted detail coefficient (D2).

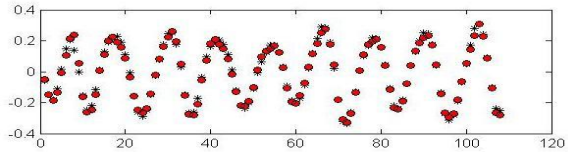


Fig.12. Actual and Predicted detail coefficient (D3).

The trained predicted output is obtained from the decomposed wavelet coefficients by simple summation represented by S(n)

$$S(n) = D_1 + D_2 + D_3 + A_3$$

The actual trained and predicted trained signal is represented in the Fig.13.

The absolute normalized error is given by

$$\epsilon = | d - y |$$

The absolute normalized error obtained the load forecasting which is the difference between actual data (d) and the predicted load forecasting data (y) and is given in the Fig.14. The actual testing coefficients obtained from wavelet decomposition are given to the ANFIS system individually and the predicted the load. Total predicted and the actual testing output, error during training and testing are shown in fig.14. Also the results of Neuro Fuzzy (NF) and Neuro Fuzzy Wavelet (NFW) are compared during training and testing and the results are tabulated in Table 1.

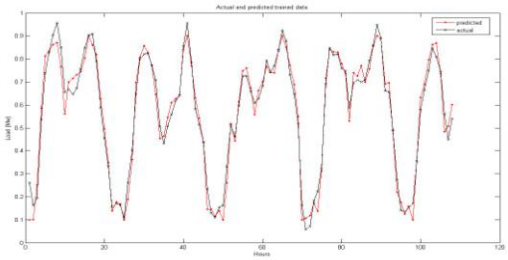
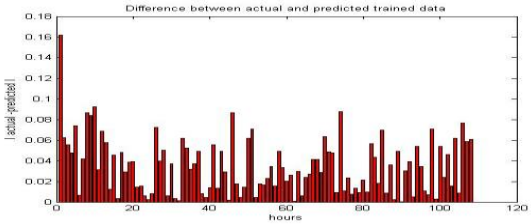
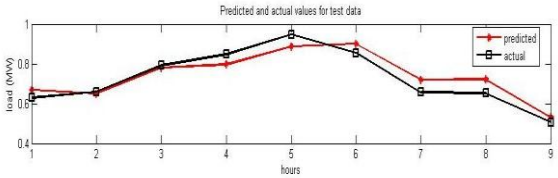


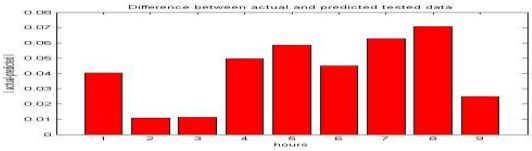
Fig.13. Load forecasting for trained data



(a). Error during trained data



(b) Predicted and Actual values for test data



(c) Error during test data

Fig. 14 Performance of NF-W for short term load forecasting problem

Table 1: Comparison between Neuro fuzzy and Neuro Fuzzy Wavelet technique			
Type	Min. Error (Mw)	Max. Error (Mw)	Average Error (Mw)
NFW (training)	0.000292	0.1621	0.03467

NF (training)	0.003592	0.41	0.0745
NFW (testing)	0.01098	0.07069	0.04161
NF (testing)	0.00456	0.1263	0.08136

VII. CONCLUSIONS

In this work the electric load predicted using integrated approach of neuro-fuzzy-wavelet gives quite encouraging results. The wavelet transform has given the strength of generalization to neural network and specialization to Tagaki Sugeno inference fuzzy logic for training the non stationary data and predicting the output. The absolute normalized percentage error for the past 108 hours for training and next 9 hours for testing is in reasonable limit to predict the future data. The variability of data was unable to be trained by using only neuro fuzzy. Therefore, the wavelet decomposition and coefficient prediction plays a vital role in the analysis of load forecasting.

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