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VERY SHORT-TERM LOAD FORECASTING (STLF) USING HYBRID WAVELET NEURAL NETWORKS

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ABSTRACT
The Hybrid Wavelet Neural Network (HWNN) with based solutions of Short Term Load Forecasting (STLF) has gained great popularity in time-series prediction and classification tasks because of their simplicity and robustness. However, the approach of using HWNN methodology alone is limited which has generated interest to explore hybrid solutions for a better alternative. This paper presents a best solution of the recent work focusing on the STLF solution based on combining HWNN approach. Testing results over MATLAB 2012a demonstrate the effects of data pre-filtering, the accuracy of wavelet neural networks, the effectiveness of hybrid wavelet filters for capturing different features of load components, and the accuracy of derived prediction interval estimates, based on a data set from ISO New England. The Hybrid Wavelet Neural Network based solution of STLF is proposed that provides a better framework for building a more realistic solution.

Index Terms: - Short term load forecasting, Hybrid neural network, power systems, classification etc.

I.INTRODUCTION
Electrical Load Forecasting is the estimation for future load by an industry or utility company.

Load forecasting is vitally important for the electric industry in the deregulated economy. A large variety of mathematical methods have been developed for load forecasting. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. Now a day, development in every sector is a heading at a very rapid pace and in the same pattern, the demand for power is also growing. While speaking about electrical power, it is important to understand that it has three main sectors i.e. generation, transmission and distribution. Electrical power generated by any source is then transmitted through transmission lines at different voltage level and then distributed to different categories of consumers later on. It is not as simple as described in few words but every stage is a complete independent system in itself. Effective load forecasts can help to improve and properly plan these three fields of power systems [1].

A. REQUIREMENTS OF LOAD FORECASTING
In most of Energy Management Systems (EMS) and load dispatch centers there is an STLF module. A good STLF system should fulfill the following requirements:

- **Accuracy**
- **Speed**
- **Detection of bad data**
- **User friendly**
- **Automatic forecasting**

Accuracy

The most important requirement of STLF process is its prediction accuracy. A good accuracy is the basis of economic dispatch, system reliability and trading in electricity markets. The main goal of most STLF of this paper is to make the forecasting result as accurate as possible.

Speed

Employment of the latest historical data and weather forecast data helps to increase the accuracy. The historical data and weather forecast data are employed by the STLF program to reduce the running time of computers and to obtain the forecasted result at the earliest. Therefore the speed of forecasting is a basic requirement of the forecasting program.

Detection of bad data

In the modern power systems, the measurement devices are located over the system and the measured data are transferred to the control center by communication lines. Due to the sporadic failure of measurement or communication, sometimes the load data that arrive in the dispatch centre may be wrong, but they are still recorded in the historical database. In the early days, the STLF systems relied on the power system operators to identify and get rid of bad data manually.

User friendly

The interface of the load forecasting should be easy, convenient and practical. The users can easily define what

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they want to forecast and whether through graphics or tables. The output should also be with the graphical and numerical format, in order that the users can access it easily and record for later use.

Automatic forecasting

To reduce the risk of individual imprecise forecasting, several models are often included in one STLF system. In the past, such a system always needs the operator's interference wherein the operator decides on weight for every model to get the combinative outcome. To be more convenient, the system should generate the final forecasting result according to the forecasting behavior of the historical days.

II.PROBLEM STATEMENT

This section is focuses on electric load forecasting problem in electric distribution networks. The considered prediction problem is detailed next.

Problem 1: For fixed prediction horizon $h > 0$, predict the electric load at time $k+h$ based on the following information:
1. Load observations y up to time k;
2. Active distribution signal ad up to time $k + h$;
3. Temperature observations u up to time k, and predicted temperature $\hat{u}$ from time $k + 1$ to $k + h$.

Problem 1 could be in principle tackled by extending the techniques mentioned in method Section, simply considering AD (active distribution) as an additional input. The important method *box plot* approach, a mathematical relationship of the following type is estimated

Using a batch record of data: $y(k+h) = ((k)) + (k)$, (1) where $z(k)$ is a vector of fixed dimension (called *regression vector*) containing (a subset of) the information available at time k, and $e(k)$ is the error process. Concerning the choice of the mapping $(\cdot)$, it may range from simple linear structures to nonlinear ones (neural networks, kernel methods and support vector machines, etc.). The choice is typically made by considering the mapping that makes the error (k) "small" not only on estimation data, but also on validation data not used for estimation. The "predictor" is then given by: $\hat{y}(k+h|k) = f(z(k))$. (2)

The approach proposed in this paper to solve Problem 1 can be called *grey-box*, since it tries to exploit the characteristics of the variable to be forecasted (the load) and other available knowledge in order to enhance the prediction accuracy, but also to reduce the computational burden of the estimation algorithm, as is typically expected in model estimation when prior knowledge is used.

III. SYSTEM MODEL

The Hybrid wavelet neural network (HWNN) contains three layers: input layer, hidden layer and output layer. All the nodes in each layer are connected to the data of load forecasting in the next layer [6]- [7]. The output layer consists of three objects because of trying to classify three different beat types. Logarithmic sigmoid function was chosen as activation function of the output layer. If the number of output nodes is determined as "one", activation function of output layer should be as "linear".

According to general back-propagation algorithm [14], the training algorithm for a WNN is below:

1. Set all the weights and biases to small real random values
2. Present the input vector $x(1), x(2), \dots, x($ and corresponding desired output $d(1), d(2), \dots, d($, one pair at a time, where is the number of training patterns.
3. Use the (4) to calculate actual outputs of only one output node in forward computation of the WNN.

$$o_m(n) = \varphi(\sum_{j=1}^{N_H} W_{mj} f(\sum_{i=1}^{N_I} W_{ij} x_i(n) \quad (4)$$

Where N a number of hidden data is, $_I$ is a number of input nodes and l is a number of output nodes ($m = 1, 2, \dots, l$). is logarithmic sigmoid activation function, which is used in output layer node. is a mother wavelet function used in hidden layer nodes. In this model, we utilized "Hybrid" and "Mexican hat" wavelet function as activation function of hidden dat. Hybrid wavelet function in the WNN is formulized by (5).

$$f(t) = \cos(1.75t) \times \exp(-t^2/ \quad (5)$$

Mexican hat wavelet function is given in (6).

$$f(t) = (1 - 0.1t^2) \times \exp(-2t \quad (6)$$

After forward computation is employed according to (4), error is computed between desired output and actual output of the WNN as following equation.

$$E(n) = d(n) - o(\quad (7)$$

4. Update W_{mj} and W by using ΔW, and Δv in backward computation of the WNN.

$$\Delta W_{ji}(t+1) = -\mu \frac{\partial E}{\partial W_{ji}} \quad (8)$$

$$\Delta W_{mj}(t+1) = -\mu \frac{\partial E}{\partial W_{mj}} \quad (9)$$

where is learning rate parameter of the WNN. After training period is performed with minimum training error, weights between layers are frozen for test process.

IV. PROPOSED IMPLEMENTATION

Hybridization has been exploited in a variety of ways and solutions have been proposed in the recent years for different applications involving emerging field of intelligent systems using hybrid-symbolic, support vector, and hybrid neural network models [5-8]. The STLF solution has not been exception to this. The synergy of ANN with the intelligent techniques as well as other conventional approaches such as time series and regression techniques etc. have been tried by several researchers to show its promise for a better solution of STLF.

4.1 Hybrid wavelet neural network

The wavelet technique allows decomposing an original signal into several components in multiple scales. In wavelets, a low pass and a high pass filter are applied, extracting the low (approximations) and high (details) frequencies of the signal for the level of decomposition chosen, whose sum is equal to the original series; and which becomes smoother as the level increases.

- The idea when applying hybrid discrete wavelet transforms artificial neural network for time series analysis and forecasting is to decompose the original time series signal into smoother components and then to apply the most appropriate ANN prediction model for each component, individually.
- In this context, the low frequency components contain the general tendencies of the series and can be used to explain the long term trend, while the high frequency components are best to explain near future trends. Time series of monthly municipal water consumption may have a historical pattern of variation that can be separated into long-memory components and short run components.
- Long-memory components are a trend which reflects the year to year effect of slow changes in population, water price, and family income; and seasonality which reflects the cyclic pattern of variation in water use within a year. Short-term components could be autocorrelation which reflects linear dependence of successive water consumption amounts and climate correlation which reflects the effect on water consumption of abnormal climatic events such as no rainfall or a lot of rainfall.
- In the model developed in this research, the one dimensional discrete wavelet transforms were applied, using the Daubechies function of order 1 to 5 with a resolution level of 1 to 5 for each order. The original water consumption data series was initially decomposed on its approximation and details. The components (approximation and details) were then modeled using the traditional MLP neural network as individual time series and then the predictive results obtained for each component were added to build the final results of the

V.RESULT

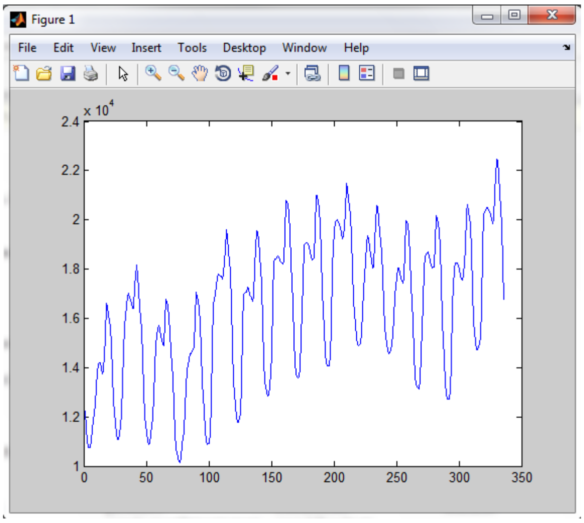

Figure 5.1 Input load energy data

In above figure we had taken input energy data f**or load** forecasting to test the efficiency of dataset.

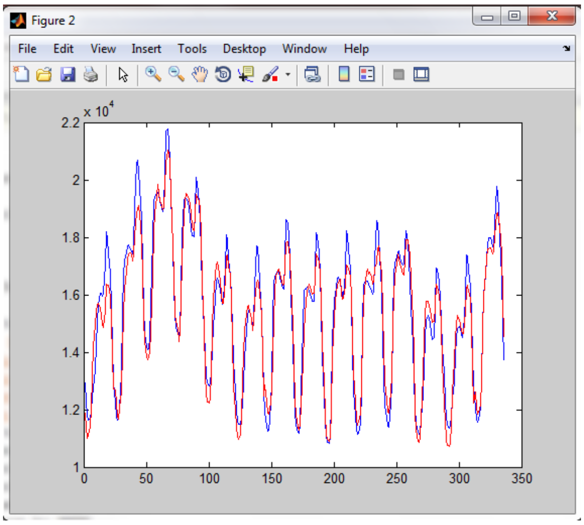

Figure 5.2: Compressed data in red scale before forecasting

In this given figure showing of red scale before compression of data forecasting.

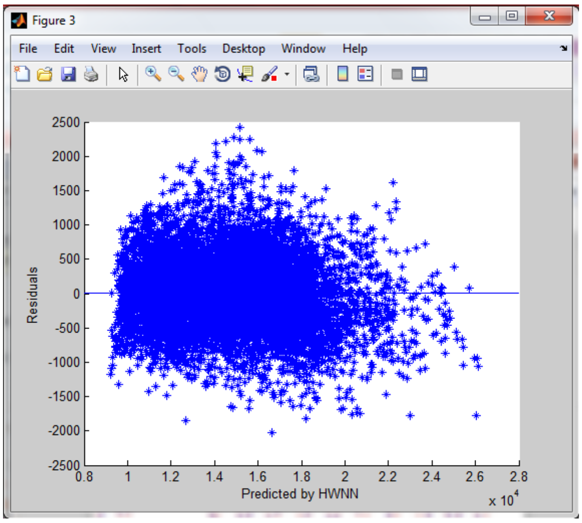

Figure 5.3: compressed cluster data in Load forecasting predicted by HWNN with respect to residuals.

This figure showing that Load forecasting predicted by Hybrid wavelet neural network.

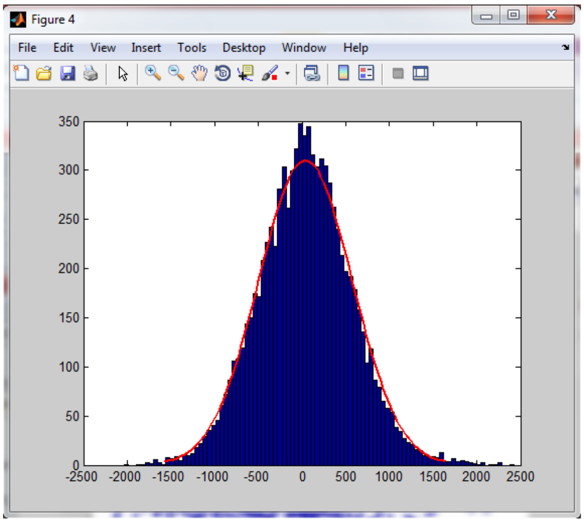

Figure 5.4 Compressed data after hybrid wavelet transform at 2500 values

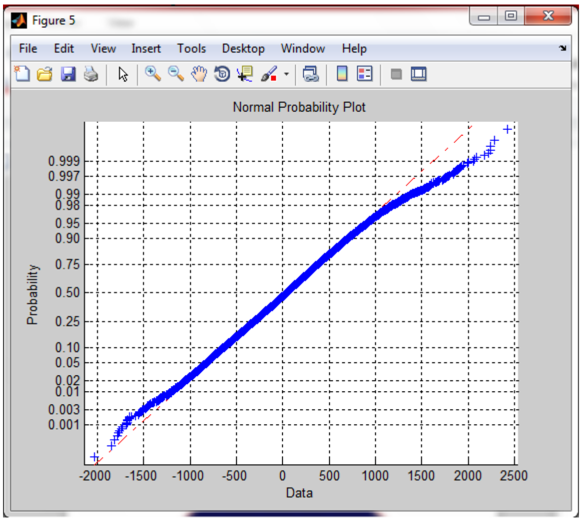

Figure 5.5: Normal probability plot with respect to data and probability

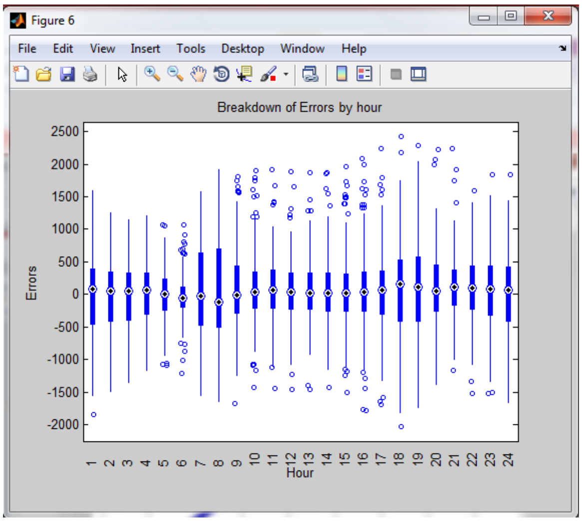

Figure 5.6 Error rate minimization w.r.t to hour

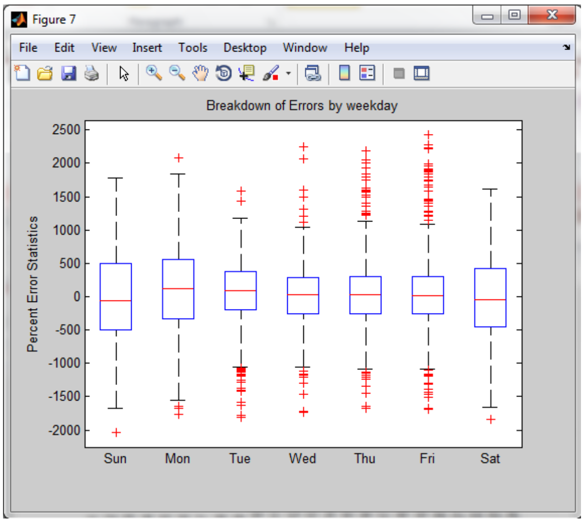

Figure 5.7: Percent error statistics for breakdown weekdays

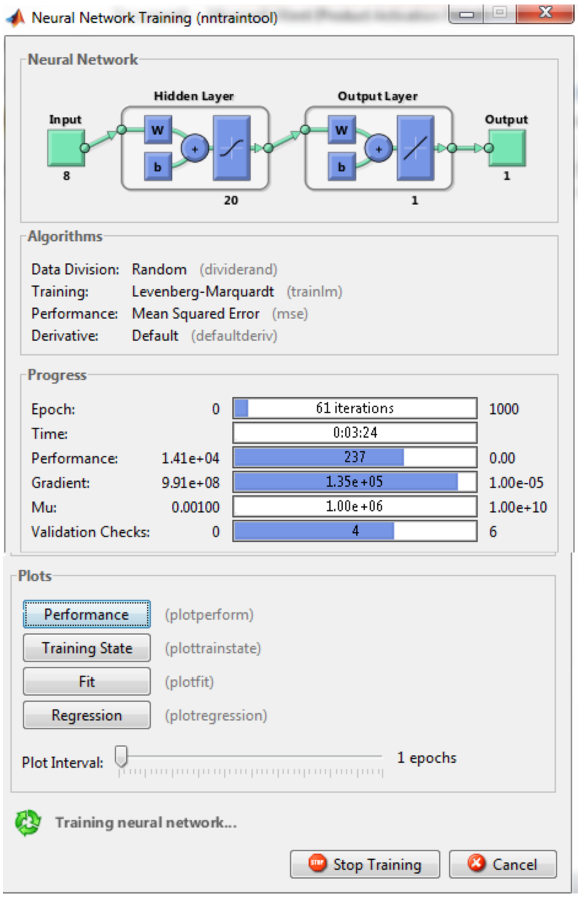

Figure 5.8 Neural network train tool

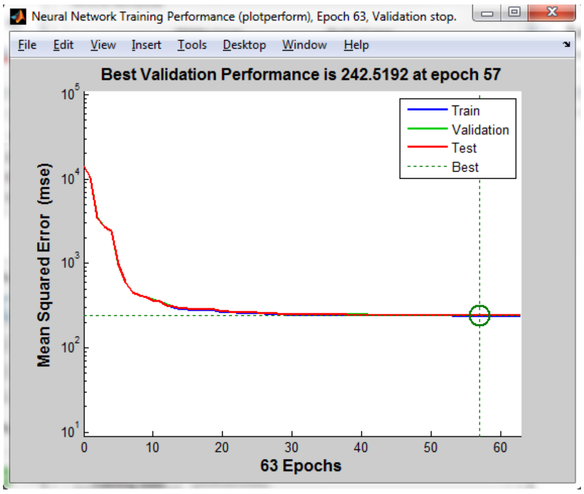

Figure 5.9: NN training performance for Train, validation, Test and Best for 63 epoch in mse

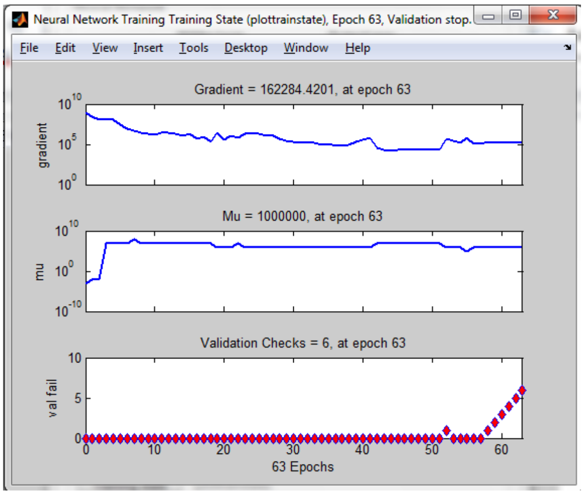

Figure 5.10: Training state of neural network

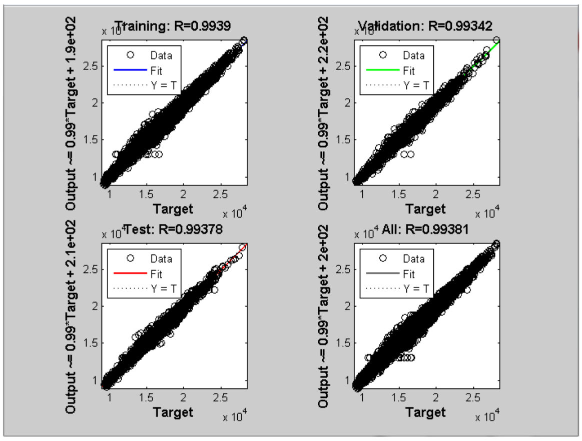

Figure 5.11: Regression epoch validation for load forecasting using neural network

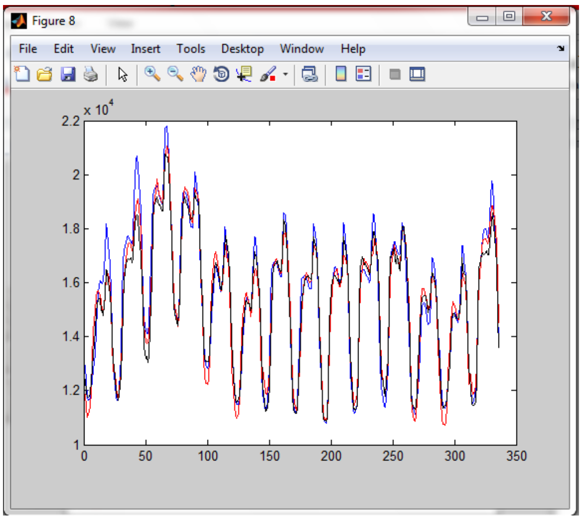

Figure 5.11: After hybrid wavelet Compressed data in red scale forecasting

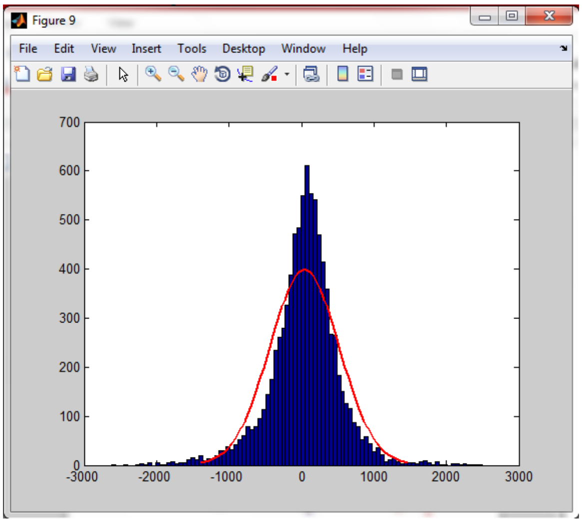

Figure 5.12 Deduction compressed data using hybrid wavelet at 3000 data values

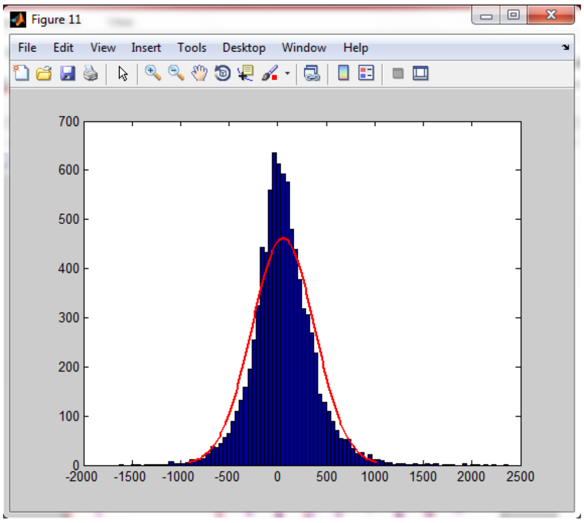

Figure 5.13: Compressed data using singular value based wavelet transform

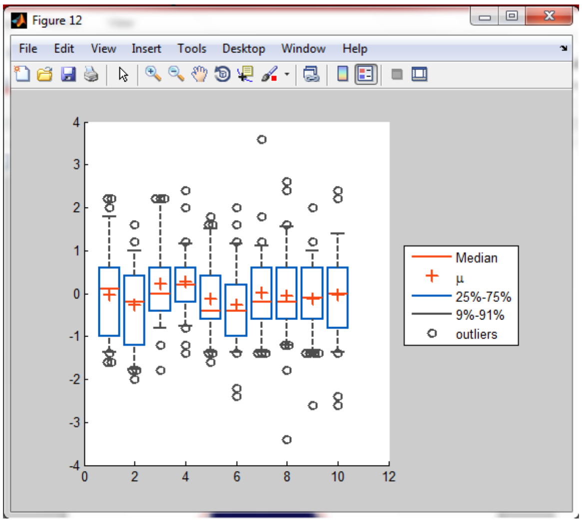

Figure 5.14 Box plots for forecasting errors for 0 to 12 minute outs

VI.CONCLUSION

The model developed in this research for daily and monthly municipal for Electric demand forecasting is a hybrid Wavelet-ANN that combines the discrete wavelet transform (DWT) method with the multilayer perceptron hybrid artificial neural network with SVM classification. The results obtained in this research are highly promising demonstrating the effectiveness of the Wavelet-ANN model in forecasting daily and monthly municipal electric demand. It is quite clear from the results of the developed hybrid Wavelet-ANN time series model that the model provides accurate daily and monthly forecasts as measured using a validation period of 5, 10 and 15 for daily data and 7 days weekly for monthly data.

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