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FUZZY SHORT-TERM ELECTRIC LOAD MODELING AND FORECASTING

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Abstract

Electrical load forecasting is an essential tool used to ensure that the energy supplied by utilities meets the load and the energy lost in the system. To this end, a staff of trained personnel is needed to carry out this specialized function. Electric load forecasting is always defined as the science or art of predicting the future load of a given system, for a specified period ahead. These predictions may be just for a fraction of an hour ahead for operation purposes or as such as twenty years in the future for planning purposes. Two models are developed in this paper, namely model B and Model C, model B is a harmonic model of the time horizon only, while model C is a hybrid model. The parameters of the two models are assumed fuzzy and are estimated using the fuzzy regression algorithm. Having obtained the fuzzy parameters, the fuzzy load for twenty-four hour ahead is predicted. Results of predication of 24 h load ahead for a utility company are presented. It has been found using such fuzzy model; a reliable operation for the electric power system could be obtained.

Keywords: Fuzzy short term load forecasting, a harmonic Model B, a hybrid model, Model C

1. INRODUCTION

Economic development, throughout the world, depends directly on the state of the availability of electric energy, especially since most industries depend almost entirely on its use. The availability of a source of continuous, cheap and reliable energy is of foremost economic importance. Short term forecasting, is used to predict loads up to a week ahead, so that daily running and dispatching costs can be minimized. In the three categories, an accurate load model is developed to mathematically represent the relationship between the load and influential variables such as time, weather, economic factors etc…

Extrapolating the mathematical relationship to the required lead-time ahead and giving the corresponding values of influential variables to be available or predictable, then forecasts can be made. Since factors such as weather and economic indices are increasingly difficult to be accurately predicted for longer lead times ahead, the greater the lead-time, the less accurate the prediction is likely to be.

The final accuracy of any forecast thus depends on the load model employed, the accuracy of predicted variables and the parameters assigned by the relevant estimation technique. Since different methods of estimation will result in different values of estimated parameters, it follows that the resulting forecasts will differ in prediction accuracy. The most popular models used earlier in the short-term load forecasting are the time series models that relate the load power with the weather factors. The parameters of these loads are estimated using an estimation algorithm such as least error squares, least absolute value algorithm, and may be dynamic estimation algorithm such as Kalman Filter algorithm. An algorithm using a cascaded learning algorithm together with the historical load and weather data is presented in [1] to forecast half-hour load for the next 24 hours. This cascaded neural network algorithm (CANN) includes peak, minimum, and daily energy prediction as additional input data for the final forecast stage. These additional input data are predicted using the first ANN's model.

The use of a weighted least squares procedure when training a neural network to solve the short-term load-forecasting problem is presented in [2]. It is shown that a neural network that implements the weighted least squares procedure outperforms a neural network that implements the least squares procedure during the on-peak period for the two performance criteria specified—mean absolute error and cost—and during the entire period for the cost criterion. This reference shows the potential benefit of using a cost-based weighted least squares training approach.

Reference [3] postulates that the load can be modeled as the output of some dynamic system influenced by a number of weather, time, and other environmental variables. Recurrent neural networks, being members of a class of connectionist models exhibiting inherent dynamic behavior, can thus be used to construct empirical models for this dynamic system. This reference claims that due to the nonlinear dynamic nature of these models, the behavior of the load prediction system can be captured in a compact and robust representation.

Reference [4] presents a self-organizing model of fuzzy autoregressive moving average with exogenous (FARMAX) variables for one-day-ahead hourly load forecasting of power systems. A comparison between the existing and ARAMAX model values shows reduction in error for forecasting results.

An efficient modeling technique based on fuzzy curve notation is presented in reference [5] to generate fuzzy models for short-term load forecasting. The steps in this approach are (a) prediction of the load curve extremes (peak and valley loads) using separate fuzzy models, (b) formulation of the representative day load curve to the forecasted peak values to obtain the predicted day load curves, and (c) transformation of the representative day load curve to fit the forecasted peak and valley loads to obtain the final next days' load curve forecast.

Reference [6] presents an approach to short-time load forecasting by the application of nonparametric regression. The method is derived from a load model in the form of a probability density function of load and load-affecting factors. A load forecast is a conditional expectation of load given the time, weather conditions, and other explanatory variables. This forecast can be calculated directly from historical data as a load average of past observed loads with the size of the local neighborhood and the specific weights on the load defined by a multivariate product kernel. The procedure requires a few parameters that can be easily calculated from historical data by applying the cross-validation technique.

Reference [7] describes a method for input variable selection for artificial neural network–based short-term load forecasting. The method is based on the phase-space embedding of a load-time series. The accuracy of the method is enhanced by the addition of temperature and cycle variables. This reference compares it favorably to the ones reported in the literature, indicating that a more parsimonious set of input variables can be used in STLF without sacrificing the accuracy of the forecast. This allows more compact ANNs, smaller training sets, and easier training.

Reference [8] studies a short-term electric load-forecasting technique using a multilayered feed forward ANN and a fuzzy set-based classification algorithm. The hourly data are subdivided into various classes of weather conditions using the fuzzy set representation of weather variables, and then the ANNs are trained and used to perform the load forecasting accurately up to 120 hours ahead.

Reference [9] presents an architecture that is substantially changed from the earlier neural network techniques. It includes only two ANN forecasters: one predicts the base load, and the other forecasts the change in load. The final forecast is computed by adaptive combinations of these two forecasts. The effects of humidity and wind speed are considered through a linear transformation of temperature. This algorithm significantly improves the accuracy of the holiday forecasts.

Reference [10] presents a method that is suitable for power system operational planning studies. Bayesian estimation is used to predict multiple-step-ahead peak forecasts using peak and average temperature forecasts as explanatory variables. Furthermore, the authors claim that better results can be obtained, with more attention paid to model identification.

Reference [11] describes the application of ANN in forecasting short-term load using a multilayer perception. ANN combines both time-series and regression approaches to predict load demand. A functional relationship between weather variable and electrical load is not needed because ANN can generate the functional relationship in learning and training the data.

A fuzzy modeling method is developed in reference [12] for short-term load forecasting. In this method, identification of the premise part and consequent part is separately accomplished via the orthogonal least squares (OLS) technique. The OLS is first employed to partition the input space and determine the number of fuzzy rules and the premise parameters. In the sequel, a second orthogonal estimator determines the input terms that should be included in the consequent part of each fuzzy rule and calculate its parameters. Different models are developed for each day type in every season.

Reference [13] presents a self-supervised adaptive neural network to perform STLF for a large power system covering a wide service area with several heavy load centers. The self-supervised network is used to extract the correlation features from temperature and load data. The authors' design provides a good adaptability using a rapid, online training mode that is crucial in applications, where the source statistics are non-stationary or where the forecaster is used with different power systems.

The behavior of electric power systems and networks varies considerably due to their characteristics. There does not appear to be one forecasting method that fits all power systems. In fact, the electric load on each system may be forecasted using different techniques to suit different situations. With the appearance of electricity markets, the variation of the price of electricity will influence usage custom of electric energy. This will complicate short-term load forecasting and challenge the existing forecasting methods that are applied to a fixed-price environment. In regard to the influence of real-time electricity prices on short-term load, a model to forecast short term load is established by combining the radial basis function (RBF) neural network with the adaptive neural fuzzy inference system (ANFIS). The model first makes use of the nonlinear approaching capacity of the RBF network to forecast the load on the prediction day with no account of the factor of electricity price, and then, based on the recent changes of the real-time price; it uses the ANFIS system to adjust the results of load forecasting obtained by RBF network. This system integration will improve forecasting accuracy and overcome the defects of the RBF network. As shown in Ref [15] by the results of an example of actual forecasting, the model presented can work effectively.

Ref. [16] addresses the problem of predicting hourly load demand using adaptive artificial neural networks (ANNs). A particle swarm optimization (PSO) algorithm is employed to adjust the network's weights in the training phase of the ANNs. The advantage of using a PSO algorithm over other conventional training algorithms such as the back-propagation (BP) is that potential solutions will be flown through the problem hyperspace with accelerated movement towards the best solution. Thus the training phase should result in obtaining the weights configuration associated with the minimum output error. Data are wavelet transformed during the preprocessing stage and then inserted into the neural network to extract redundant information from the load curve. This results in better load characterization which creates a more reliable forecasting model. The transformed data of historical load and weather information were trained and tested over various periods of time.

The generalized error estimation is done by using the reverse part of the data as a "test" set. The results were compared with traditional BP algorithm and offered a high forecasting precision.

During the last decade, neural networks have emerged as one of the most powerful and accurate nonlinear models for load forecasting. However, using neural networks requires users to have in-depth knowledge to determine the model structure and parameters, which limits their wide application. To overcome this weakness, Ref. [17] proposes an integrated approach which combines a self-organizing fuzzy neural network (SOFNN) learning method with a bi-level optimization method. SOFNNs can automatically determine both the model structure and parameters, while the bi-level optimization method automatically selects the best pre-training parameters to ensure that the best fuzzy neural networks be identified. Therefore, the approach is able to automatically identify the best fuzzy neural network for a given forecasting task and is much easier to use in practice.

In Ref [18], fuzzy inductive reasoning (FIR) is applied to the problem of short-term load forecasting (STLF) in power systems for a day in advance. The FIR model learns both past and future relations from the load and the temperature. The proposed optimization model uses an evolutionary algorithm based on a local random controlled search—simulated rebounding algorithm (SRA)—to choose the inputs to the FIR model. Using an optimization method to determine linear and nonlinear relationships between the variables, a parsimonious set of input variables can be identified improving the accuracy of the forecast. The input variables are updated when a new load pattern is happened or when relative errors are unacceptable. With this update is achieved, a better monitoring of the load trend due to the process is not strictly stationary. The FIR and SRA methodology is applied to the Ecuadorian power system as an application example.

In deregulated electricity markets, short-term load forecasting is important for reliable power system operation, and also significantly affects markets and their participants. Effective forecasting, however, is difficult in view of the complicated effects on load by a variety of factors. Ref. [19] presents a similar day-based wavelet neural network method to forecast tomorrow's load. The idea is to select similar day load as the input load based on correlation analysis, and use wavelet decomposition and separate neural networks to capture the features of load at low and high frequencies. Despite of its "noisy" nature, high frequency load is well predicted by including precipitation and high frequency component of similar day load as inputs. Numerical testing shows that this method provides accurate predictions

2. MULTIPLE FUZZY LINEAR REGRESSION MODEL: CRISP DATA, ($Y_j(t) = m_j(t)$, $j = 1,.., m$; $t = 1, 2,..,..., 24$)

2.1 Fuzzy Load Model B

Fuzzy load model B is a harmonic decomposition model and does not account for weather conditions. It does not account for temperature deviation, wind-cooling factor, or humidity factor. Thus, this model can be used for both winter and summer simulations.

The fuzzy load at any time t, therefore, can be written as:

$$y(t) = A_0 + \sum_{i=1}^{n} \left(A_i \sin i\omega t + B_i \cos i\omega t \right) \tag{1}$$

where

$\underline{Y}(f)$ is the load power at time t and it is assumed to have crisp values;

$\underline{A}_0$, $\underline{A}_i$, and $\underline{B}_i$ are fuzzy parameters having certain middles and spreads and are given as

$A_0 = (p_0, c_0)$, $A_i = (p_i, c_i)$, and $B_i = (\alpha_i, b_i)$

The model described in equation (1) can be rewritten as:

$$y(t) = (p_0, c_0) + \sum_{i=1}^{n} \left[(p_i, c_i) \sin i\omega t + (\alpha_i, b_i) \cos i\omega t \right] \tag{2}$$

Note that the middles and the spreads are constants and are estimated seven times weekly.

The objective is to find the fuzzy parameters that minimize the spread of the load power. Mathematically, this can be written as Minimize

$$J = \left| \sum_{t} \left\{ c_0 + \sum_{j=1}^{m} \sum_{i=1}^{n} \left[c_i x_i(t) + b_i y_i(t) \right] \right\} \right| \tag{3}$$

where

$x_{ij}(t) = (\sin i\ t)_j,\ j = 1,..,m;\ i = 1,..,n;$

$y_{ij}(t) = (\cos i\ t)_j,\ j = 1,..,m;\ i = 1,..,n;$

m, n are the number of observations and harmonics chosen in the model, respectively; $t \in [0, tF]$, tF is the number of days for which data are taken at the hour in question.

Subject to satisfying the inequality constraints given by:

$$y_j(t) \geq [p_0 + p_i \sin i\omega t + \alpha_i \cos i\omega t)]_j - (1 - \lambda)[c_0 + c_i \sin i\omega t + b_i \cos i\omega t)_j \quad (4)$$

$$y_j(t) \leq [p_0 + p_i \sin i\omega t + \alpha_i \cos i\omega t)]_j + (1 - \lambda)[c_0 + c_i \sin i\omega t + b_i \cos i\omega t)_j \quad (5)$$

The optimization problem formulated in equations (3) to (5) is a linear optimization problem and can be solved using the simplex method of linear programming.

Having obtained the fuzzy load parameters, we can then predict the load for the next 24 hours using equation (2).

2.2 Fuzzy Load Model C

Fuzzy load model C is a fuzzy hybrid model that takes into account weather-dependent components. The base load in the model is a time-varying function and takes the form of Fourier's coefficients. This model can be considered as a combination of fuzzy load model A of reference [14] and fuzzy load model B. Here, the weather input is limited only to temperature deviation, and the model is used for both winter and summer load forecast simulations.

The fuzzy load model in this case can be written mathematically as

$$Y_j(t) = \{\underline{A}_0 + \sum_{i=1}^{n} [\underline{A}_i \sin i\omega t + \underline{B}_i \cos i\omega t]\}_j + \{\underline{C}_0 T_j(t) + \underline{C}_1 T_j(t-1) + \underline{C}_2 T_j(t-2) + \underline{C}_3 T_j(t-3)\} \quad (6)$$

where

A0, Ai, and Bi are the weather-independent fuzzy parameters having certain middles and certain spreads;

C0, C1, C2, and C3 are the temperature-dependent fuzzy parameters.

The terms in the first brace in equation (6) can be considered as the base load, which depends only on time, whereas the terms in the second brace are the temperature-dependent load terms.

Equation (6) can be rewritten as

$$Y(t) = (p_0, c_0) + \sum_{i=1}^{n} (p_i, \alpha_i) x_i(t) + (b_i, \beta_i) y_i(t)]_j + [(\gamma_0, s_0) T_j(t) + (\gamma_1, s_1) T_j(t-1) + (\gamma_2, s_2) T_j(t-2) + (\gamma_3, s_3) T_j(t-3)] \quad (7)$$

In equation (7), the first letter in the parameter's brackets indicates the middle of that parameter, and the second letter indicates the spread of this parameter.

In fuzzy regression, the fuzzy model parameters are to be found to minimize the spread of the output. In mathematical form, this can be expressed as

$$J = \left| \sum_{t} \{c_0 + \sum_{j=1}^{m} \sum_{i=1}^{n} [\alpha_i x_{ij}(t) + \beta_i y_{ij}(t)] + \sum_{j=1}^{m} [\, s_0 T_j(t) + s_1 T_j(t-1) + s_2 T_j(t-2) + s_3 T_j(t-3)\,]\} \right| \quad (8)$$

where $t \in [0, tF]$, tF is the number of days for which data are taken at the hour in question.

Subject to satisfying the following two constraints on the output so that the fuzzy regression model could contain all the observed data j, j = 1,…, m in the estimated fuzzy numbers resulting from the model. This can be expressed mathematically as

$$y_j(t) \geq [p_0 + \sum_{i=1}^{n} (p_i x_{ij}(t) + b_i y_{ij}(t)) + \gamma_0 T_j(t) + \gamma_1 T_j(t-1) + \gamma_2 T_j(t-2) + \gamma_3 T_j(t-3)]$$

$$- (1-\lambda)[\, c_0 + \sum_{i=1}^{n} (\alpha_i x_{ij}(t) + \beta_i y_{ij}(t)) + s_0 T_j(t) + s_1 T_j(t-1) + s_2 T_j(t-2) + s_3 T_j(t-3)] \,,\; j = 1,\dots, m \quad (9)$$

$$y_j(t) \leq [p_0 + \sum_{i=1}^{n} (p_i x_{ij}(t) + b_i y_{ij}(t)) + \gamma_0 T_j(t) + \gamma_1 T_j(t-1) + \gamma_2 T_j(t-2) + \gamma_3 T_j(t-3)]$$

$$+ (1-\lambda)[\, c_0 + \sum_{i=1}^{n} (\alpha_i x_{ij}(t) + \beta_i y_{ij}(t)) + s_0 T_j(t) + s_1 T_j(t-1) + s_2 T_j(t-2) + s_3 T_j(t-3)] \,,\; j = 1,\dots, m \quad (10)$$

The problem formulated in equations (8) to (10) is a linear optimization problem and can be solved using linear programming based on the simplex method. Having identified the fuzzy model parameters, we can predict the load for the next 24 hours using equation (7).

3. MULTIPLE FUZZY LINEAR REGRESSION MODEL: FUZZY DATA

In section 2, the load power data are assumed to be non fuzzy, whereas the parameters of the load power are fuzzy. Different linear optimization problems were derived with different load models. In this section, the load data are assumed to be fuzzy power values having a certain middle and certain spread Yj(t) = [mj(t),□j(t)], where mj(t) is the middle of the load power at the time t in question during the observation j, and □j(t) is the spread of the load power at time t and observation

Using this formulation of fuzzy numbers means that a triangular membership function is assumed, as shown in Figures (1).

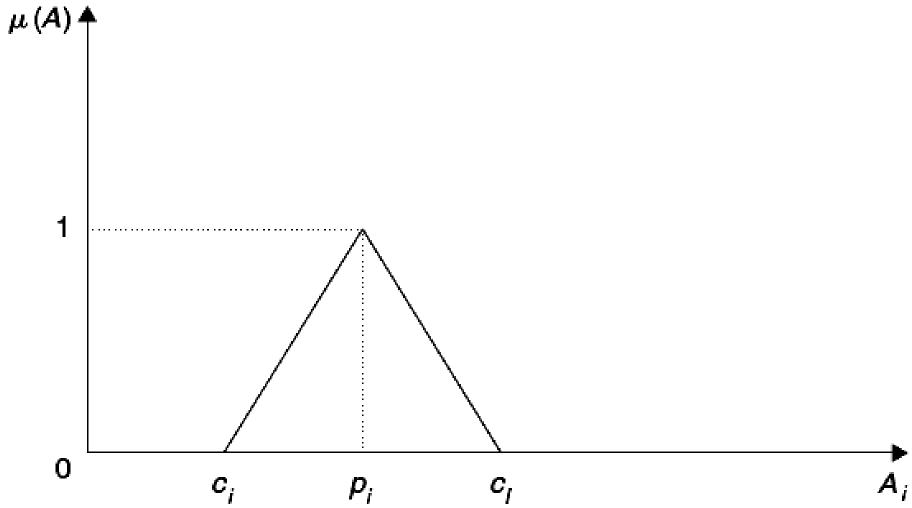


Figure 1 : A triangular membership function $(c_i = m_i)$

3.1 Fuzzy Load Model B

Fuzzy load model B does not account for weather conditions in the load; it can be expressed as

$$Y_j(t) = \left(m_j(t), \alpha j(t)\right) = A_0 + \sum_{i=1}^{n}\left(A_i \sin i\,\omega t + B_i \cos i\,\omega t\right), j = 1,..,m$$

(11)The only difference between equation (1) and (11) is the load power Yj(t) at time t. In (1) the load power is assumed to be a crisp value, whereas in (11) it is assumed to be a fuzzy value having a middle mj(t) and a spread □j(t). Equation (11) can be rewritten as

$$\left(m_j(t), \alpha j(t)\right) = (p_0, c_0) + \sum_{i=1}^{n}\left[(p_i, c_i)\sin i\,\omega t + (\alpha_i, \beta_i)\cos i\,\omega t\right] \quad (12)$$

which can be split into two equalities as:

$$m_j(t) = p_0 + \sum_{i=1}^{n}[p_i \sin i\omega\, t + b_i \cos i\omega\, t]_j, \; j = 1,...,m \quad (13)$$

$$\alpha_j(t) = c_0 + \sum_{i=1}^{n}[c_i \sin i\omega t + \beta_i \cos i\omega t]_j, \; j = 1,...,m \quad (14)$$

The task is to find the fuzzy load parameters that minimize the spread of the fuzzy load power. This can be expressed mathematically as:

$$J = \left| \sum_{t} \left\{ \sum_{j=1}^{m} \left[(mj(t) \text{ - RHS of equation(13))} + (\alpha_j(t) \text{ - RHS of equation (14))} \right] \right\} \right| \quad (15)$$

where $t \in [0, tF]$, and tF is the number of days for which data are taken at the hour in question.

Subject to satisfying the following two constraints as:

$$m_j(t)\text{-}(1 - \lambda)\alpha_j(t) \geq [\text{RHS of equation 13 - RHS of equation 14}];\ j = 1,.., m \quad (16)$$

$$m_j(t)+(1- \lambda)\alpha_j(t) \leq [\text{RHS of equation 13 + RHS of equation 14}];\ j = 1,.., m \quad (17)$$

The problem formulated in equations (15) to (17) is one of linear optimization that can be solved using linear programming. Having identified the middle and the spread of fuzzy parameters, we then can use the harmonic load model described in equation (11) to predict the load at any hour t. Note that the load power obtained in this case is independent of the weather conditions and depends only on the hour in question.

The next model, model C, combines fuzzy load model A and fuzzy load model B. This model takes weather conditions into account.

3.2 Fuzzy Load Model C

Fuzzy load model B is weather insensitive. The fuzzy coefficients of this model depend only on the time in question. The fuzzy load model C is weather sensitive. This fuzzy model is suitable for all weekdays and can be used for both winter and summer load-forecast simulations. Its main disadvantage is the assumption that the relation between load and weather is constant throughout the day.

The fuzzy model for the load in this case can be expressed mathematically as

$$Y_j(t) = (m_j(t), \alpha_j(t)) = \{A_0 + \sum_{i=1}^{n} (A_i \sin i\omega t + B_i \cos i\omega t)\}_j + \{C_0 T_j(t) + C_1 T_j(t-1) + C_2 T_j(t-2) + C_3 T_j(t-3)\}j,\ j = 1,\ldots,m \quad (18)$$

where

$m_j(t)$, $\alpha_j(t)$ is the middle and spread of load power *j, j* = 1,…,*m* at time *t;*

$\underline{A}_0$, $\underline{A}_i$, and $\underline{B}_i$ are the weather-independent fuzzy parameters with certain middles and spreads;

$\underline{C}_0$, $\underline{C}_1$, $\underline{C}_2$, and $\underline{C}_3$ are the temperature-dependent fuzzy parameters with certain middles and spreads.

The left-hand side (LHS) of equation (18) is the fuzzy load power. The terms in the first bracket on the right-hand side (RHS) of equation (18) can be considered as the fuzzy base load, and it depends only on time, whereas the second bracket contains the temperature-dependent fuzzy load terms.

Equation (18) can be rewritten as:

$$(m_j(t),\alpha_j(t)) = \{(p_0, c_0)+\sum_{i=1}^{n}[(p_i,\theta_i)x_i(t)+(b_i,\beta_i)y_i(t)]\}_j+\{(\gamma_0,c'_0)T_j(t)+(\gamma_1,c_1)T_j(t-1)+ (\gamma_2,c_2)T_j(t-2)+(\gamma_3,c_3)T_j(t-3)\}j,\ j=1,...,m \qquad (19)$$

For simplicity, let

$$x_i(t) = \sin i\omega\, t,\ i = 1,...,n \qquad (20a)$$

$$y_i(t) = \cos i\omega\, t,\ i = 1,...,n \qquad (20b)$$

In equation (19), the first letter in all small brackets of the equations indicates the middle of the parameter, and the second letter indicates the spread of that parameter. A triangular membership is used for each parameter.

In the fuzzy model developed in equation (19), the task is to find the fuzzy model parameters to minimize the spread of the output. Mathematically, the fuzzy linear optimization problem can be expressed as

Minimize

$$J = \left|\sum_t \left\{\sum_{j=1}^{m}\begin{array}{l}\left[m_j(t)-\{p_0+\sum_{i=1}^{n}\left[p_i x_i(t)+b_i y_i(t)\right]_j\right]_j ++\gamma_0 T_j(t)+\gamma_1 T_j(t-1)+\gamma_2 T_j(t-2)\\ +\gamma_3 T_j(t-3)\}+\{\alpha_j(t) - [c_0+\sum_{i=1}^{n}\{\theta_i x_i(t)+\beta_i y_i(t)\}_j+\\ c'_0 T_j(t)+ c_1 T_j(t-1)+ c_2 T_j(t-2)+c_3 T_j(t-3)\}]\end{array}\right\}\right| \qquad (21)$$

where $t\in[0, t_F]$, and t_F is the number of days for which data are taken at the hour in question.

Subject to satisfying the following two constraints for each measurement point given as:

$$m_j(t)-(1-\lambda)\alpha_j(t) \geq \left\{p_0+\sum_{i=1}^{n}\left[p_i x_i(t)+b_i y_i(t)\right]_j+\gamma_0 T_j(t)+\gamma_1 T_j(t-1)+\gamma_2 T_j(t-2)+\gamma_3 T_j(t-3)\right\}_j$$

$$-\left\{c_0+\sum_{i=1}^{n}\{\theta_i x_i(t)+\beta_i y_i(t)\}_j+c'_0 T_j(t)+c_1 T_j(t-1)+c_2 T_j(t-2)+c_3 T_j(t-3)\right\}_j,\ j=1,...,m \qquad (22)$$

$$m_j(t)+(1-\lambda)\alpha_j(t) \leq \left\{ p_0+\sum_{i=1}^{n}\left[p_i x_i(t)+b_i y_i(t)\right]_j +\gamma_0 T_j(t)+\gamma_1 T_j\ (t-1)+\gamma_2 T_j\ (t-2)+\gamma_3 T_j\ (t-3)\right\}_j$$

$$+\left\{ c_0+\sum_{i=1}^{n}\{\theta_i x_i(t)+\beta_i y_i(t)\}_j + c'_0 T_j(t)+c_1 T_j(t-1)+c_2 T_j(t-2)+c_3 T_j\ (t-3)\right\}_j,\ j=1,\ldots,m \qquad (22)$$

The problem formulated in equations (21) to (23) is one of linear optimization and can be solved by linear programming. Having obtained the middle and spread of each fuzzy parameter, we can calculate the load power at any hour in question using equation (19)

4. DESCRIPTION OF THE DATA

Nova Scotia Power Inc. supplied the data used in this study for the years 1994 and 1995 hourly load power, while the Atlantic Climate Center of Environment Canada supplied the hourly weather conditions for the same two years that were extracted from Environment Canada's Archives. These data include hourly dry bulb temperatures, the wind speed and the percentage humidity recorded at Shearwater Airport at Halifax. A standard record format has been adopted for climatologically data. Each record consists of station identification number, date (year, month and day) and element number followed by the data repeated 24 times. The element number identifies each data type and implies the units and decimal position. The developed fuzzy models for summer in part one are tested in this section. First, the load power data are assumed crisp values, and the load parameters are fuzzy. Then, the load power data and the load parameters are both assumed to be fuzzy. It is found that ten fuzzy parameters are enough to model this type of load.

5. HARMONICS FUZZY LOAD MODEL, MODEL B

The model developed in Part one of this paper is a harmonic model, and it is not sensitive to the weather parameters, temperature, wind speed, humidity,etc. Nine parameters are chosen for the sine term and nine for the cosine term beside to the base load parameter. The amounts of fuzzy in the load power are simulated by giving the load power some deviation. Here we assume 5, 10 and 20 percent load deviation beside zero deviation, crisp power, to simulate the fuzziness of the load power. Table 1 gives the variation of the fuzzy parameters at percentage load deviations. Examining this table reveals the following:.

- Among the load parameters, only parameters A_o, the base load parameter, and A_5 are fuzzy.

- Parameter A_5 has a zero value at the middle and a different spread value in all cases considered.
- Parameter A_o has a large middle and spread, because A_o represents the base load while the other parameters (either fuzzy or not), are contributing to the excess power variations due to other load factors.
- Both the middle and spread of the base load parameter increase due to the increase in load deviation.
- All load parameters follow the same pattern of variation at each load deviation.

The estimated and predicted loads for a summer day, either weekday or weekend day, are given in Figures (1) to (4) for the ranges zero and 20 % of load deviation and using the estimated fuzzy parameters for each load deviation. Examining these figures reveals the following:

- The harmonics load model developed earlier estimates and predicts the load power at any weekday in any seasons and the actual load does not violate the upper and lower load values.
- As the load deviation increases, the range between the upper and the lower loads increases due to increases in the spread of the fuzzy parameters.

In conclusion, despite the fact that harmonics model does not account for the weather variation, the predicted load does not violate the upper or lower load limits.

6. HYBRID FUZZY LOAD MODEL, MODEL C

The developed hybrid fuzzy model is tested for a summer weekday or weekend days. A summer weekday load data are used to estimate the fuzzy parameters of the model. These parameters are then used to predict the load power one day ahead. The load deviation that creates fuzziness is changed from 0%, 5 % to 20 %, with a degree of fuzziness of 50 %.

Table 1 : Fuzzy parameters for a summer day load, Harmonic Load model, Model B

Parameter	Crisp load		5% load deviation		10% load deviation		20% load deviation	
	Middle	Spread	Middle	Spread	Middle	Spread	Middle	Spread
A_o	874.32	258.7	875.99	299.306	879.498	340.848	886.038	424.722
A_1	1.594	0.0	1.402	0.0	0.0	0.0	0.0	0.0

Parameter	Crisp load		5% load deviation		10% load deviation		20% load deviation	
	Middle	Spread	Middle	Spread	Middle	Spread	Middle	Spread
A_2	28.95	0.0	28.544	0.0	26.8084	0.0	23.770	0.0
A_3	0.0	0.0	0.355	0.0	1.7189	0.0	3.4214	0.0
A_4	45.81	0.0	45.502	0.0	44.6506	0.0	42.304	0.0
A_5	0.0	14.43	0.0	18.5504	0.00.0	19.411	0.00	20.196
A_6	23.40	0.0	23.336	0.0	24.1051	0.0	24.9042	0.0
A_7	13.5	0.0	12.826	0.0	10.7958	0.0	7.3645	0.0
A_8	14.3	0.0	14.083	0.0	12.2520	0.0	11.0160	0.0
A_9	108.9	0.0	104.869	0.0	103.782	0.0	100.678	0.0
B_1	66.22	0.0	65.528	0.0	65.1667	0.0	63.921	0.0
B_2	24.80	0.0	23.676	0.0	22.1530	0.0	18.937	0.0
B_3	9.43	0.0	8.582	0.0	9.42273	0.0	9.601	0.0
B_4	29.16	0.0	28.407	0.0	27.5010	0.0	25.045	0.0
B_5	3.93	0.0	2.192	0.0	1.81461	0.0	2.0200	0.0
B_6	1.02	0.0	0.0	0.0	0.0	0.0	0.0	0.0
B_7	54.67	0.0	51.593	0.0	50.220	0.0	47.1926	0.0
B_8	11.62	0.0	11.832	0.0	11.5480	0.0	12.288	0.0
B_9	2.70	0.0	1.7536	0.0	3.2094	0.0	5.8511	0.0

Table (2) gives the estimated 24 fuzzy parameters, 23 parameters and the base load parameter, at different load deviations. Examining this table reveals the following:

- Most of the load prameters are crisp, since the spreads are zeros. There are three fuzzy parameters, and they are the same parameters in the three cases of the load deviation (A_o, A_4, B_8).
- As the load deviation increases, the spreads of these parameters increase to include the parameter memberships in the solution.
- Large middle and spread values for A_o in the three cases, since A_o is representing the base load.

The estimated parameters are used to predict the load power 24 hours ahead, for either a weekday or weekend day. Figures (5-8) give the estimated and predicted loads at the given load deviations. Examining these figures reveals the following:

- At load deviation equals 5% the actual load is greater than the upper limit for two hours only by about 1.7 % and 4.1 %, which is still an acceptable amount. However, if the load deviation is increased to 10 % the actual load does not violate the upper load.
- The estimated load using the fuzzy parameters for all load deviation does not violate neither the upper nor the lower load.
- Since the load varies between the upper and lower values, the estimated parameters can sufficiently be used to predict the load for any day in the week in any season. The load parameters must be updated from weekday, weekend day and from season to the other.

Table 2 : Fuzzy parameters for a summer day load, Hybrid Model

Parameters	Crisp load		5% load deviation		10% load deviation		20% load deviation	
	Middle	Spread	Middle	Spread	Middle	Spread	Middle	Spread
$\underline{A}_0$	515.54	46.58	520.62	84.5043	520.385	124.141	529.00	205.698
$\underline{A}_1$	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\underline{A}_2$	0.0	0.00	0.408	0.00	2.5126	0.00	3.0646	0.00
$\underline{A}_3$	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\underline{A}_4$	12.14	14.60	17.631	19.00	15.132	12.925	15.346	12.618
$\underline{A}_5$	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\underline{A}_6$	37.0	0.00	36.372	0.00	36.816	0.00	37.101	0.00
$\underline{A}_7$	4.59	0.00	8.1702	0.00	8.097	0.00	5.5347	0.00
$\underline{A}_8$	0.0	0.00	0.00	0.00	0.0182	0.00	3.8353	0.00
$\underline{A}_9$	33.91	0.00	34.568	0.00	33.06	0.00	31.653	0.00
$\underline{B}_1$	31.99	0.00	24.101	0.00	24.0741	0.00	19.783	0.00
$\underline{B}_2$	0.47	0.00	0.614	0.00	0.447	0.00	0.451	0.00
$\underline{B}_3$	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\underline{B}_4$	13.85	0.00	10.476	0.00	9.667	0.00	7.02	0.00
$\underline{B}_5$	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Parameters	Crisp load		5% load deviation		10% load deviation		20% load deviation	
	Middle	Spread	Middle	Spread	Middle	Spread	Middle	Spread
B_6	31.41	0.00	27.631	0.00	25.8138	0.00	21.295	0.00
B_7	52.04	0.00	51.294	0.00	48.9959	0.00	45.185	0.00
B_8	16.86	12.87	16.531	17.918	17.1895	21.881	18.279	21.5500
B_9	20.42	0.00	16.403	0.00	20.160	0.00	23.135	0.00
C_o	16.12	0.00	14.576	0.00	16.620	0.00	15.600	0.00
C_1	0.0	0.00	0.00	0.00	0.000	0.00	0.00	0.00
C_2	1.13	0.00	1.578	0.00	0.2810	0.00	1.955	0.00
C_3	13.39	0.00	12.710	0.00	13.565	0.00	12.066	0.00

Figure (1) Estimated load for a summer

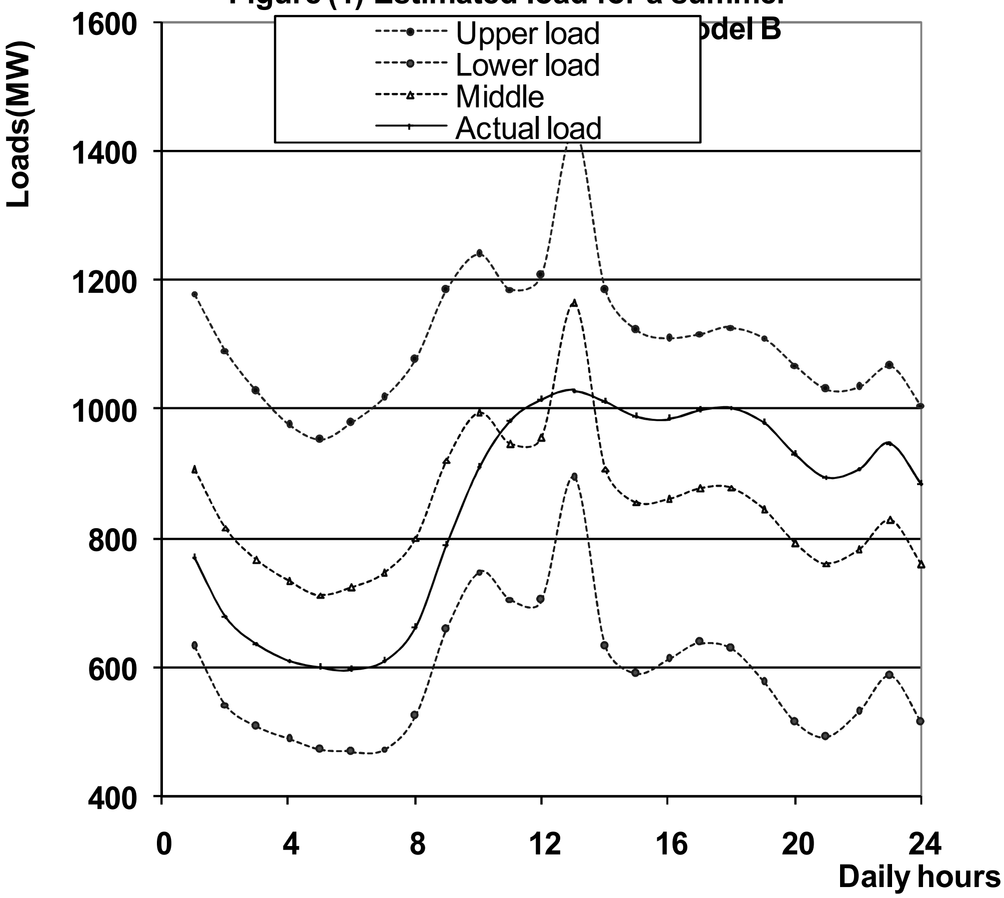


Figure (2) Estimated load for a summer weekday, (20 % load deviation), Model B

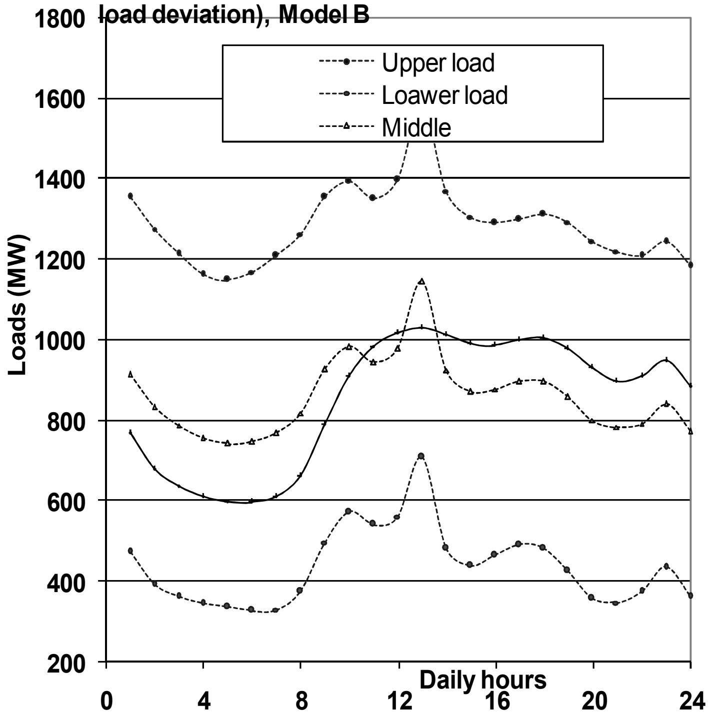
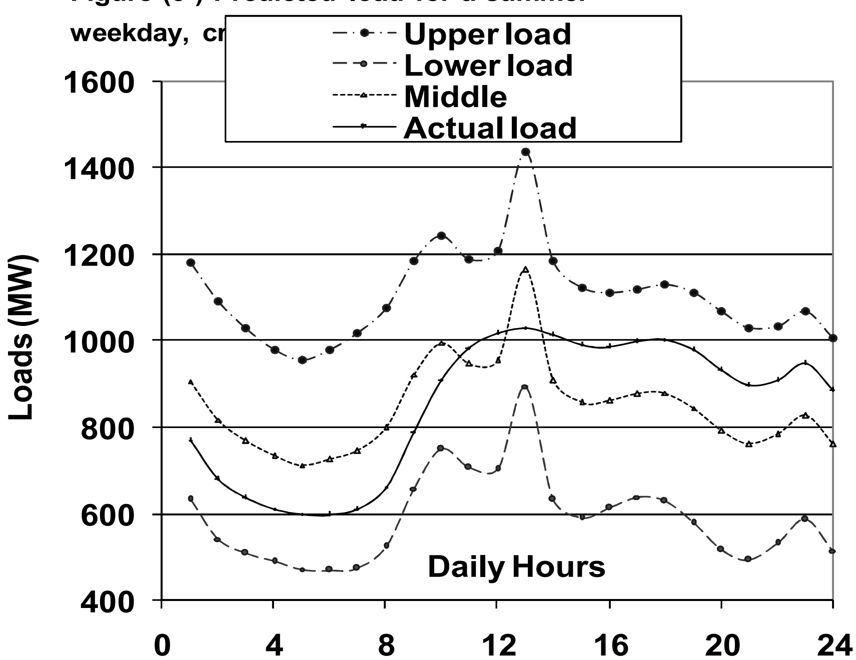


Figure (3) Predicted load for a summer weekday, cr



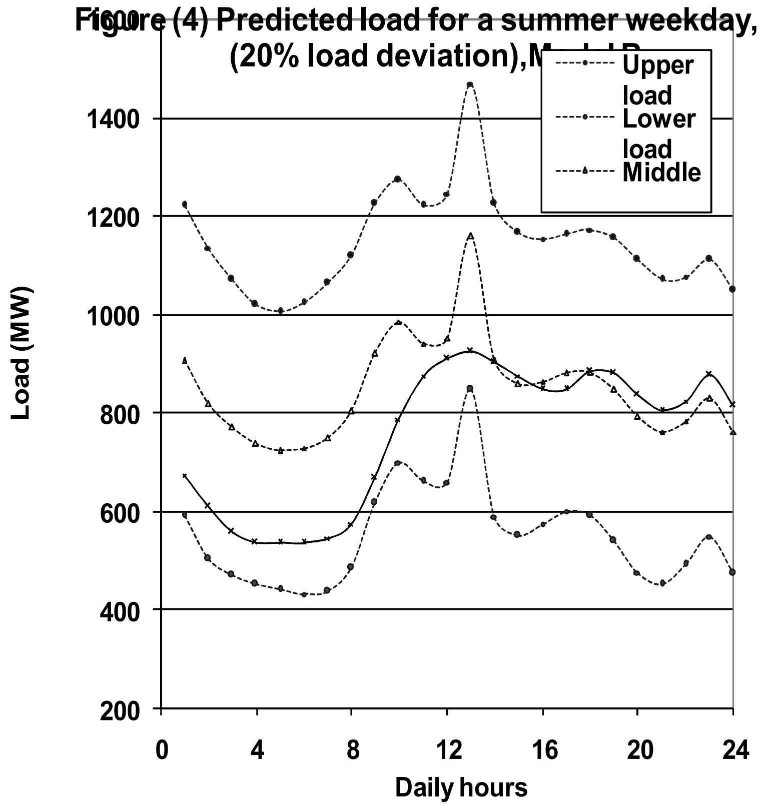


Figure (4) Predicted load for a summer weekday, (20% load deviation),M

CONCLUSION

In this paper, the fuzzy short term load forecasting problem is solved. The two models developed in part one of this paper are implemented to predict the load. The two models are used to estimate the load power at any day in any season, based on fuzzy optimization rules. The predicted load lies between upper and lower limits. It has been shown that the actual load never violates these limits.

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