ANALYSIS AND EVALUATION OF FIVE SHORT-TERM LOAD FORECASTING TECHNIQUES

Ibrahim Moghram
Student Member

Saifur Rahman
Senior Member

Energy Systems Research Laboratory
Electrical Engineering Department
Virginia Tech
Blacksburg, VA 24061

ABSTRACT

A review of five widely applied short-term (up to 24 hours) load forecasting techniques is presented. These are: (i) Multiple linear regression, (ii) Stochastic time series, (iii) General exponential smoothing, (iv) State space and Kalman filter, and (v) Knowledge-based approach. A brief discussion of each of these techniques, along with the necessary equations, is presented. Algorithms implementing these forecasting techniques have been programmed and applied to the same database for direct comparison of these different techniques. A comparative summary of the results is presented to give the reader an understanding of the inherent level of difficulty of each of these techniques and their performances.

Keywords: Load forecasting, Multiple regression, Stochastic time series, General exponential smoothing, State space and Kalman filter, Knowledge-based method.

1.0 INTRODUCTION

Load forecast has been a central and an integral process in the planning and operation of electric utilities. Many techniques and approaches have been investigated to tackle this problem in the last two decades. These are often different in nature and apply different engineering considerations and economic analyses.

The IEEE load forecasting working group has published, in two phases, a documentary bibliography on load forecasting. The first bibliography (PHASE I) has covered general philosophies of load forecasting [1]. The second bibliography (PHASE II) has focused on the economic issues of load forecasting [2]. The most recent review is reported by Gross and Galiana [3] in 1987 where the authors have reviewed various short-term load forecasting techniques that have been proposed or in use today. There are additional publications that have reviewed load forecasting. One of these is the work of Bunn [4] which has reviewed the short-term load forecasting procedures in the electricity supply industry. In another work Bunn and Farmer [5] have also reviewed and discussed the forecasting techniques that have been applied in the electric power industry. Another work by Fildes [6] has covered the explorative models for quantitative forecasting. An early review of the techniques for predicting load demands in the electric supply industry was reported by Matthewman and Nicholson [7]. In another paper Abu El-Magd and Sinha [8] have reviewed the short-term load demand modeling and forecasting. Engle and Goodrich [9] have discussed the use of seven different forecasting models to calculate one-month to five years of monthly electricity sales. Even though the targeted application of this report is different from the focus of this paper, which is 24-hour load forecasting, the review of statistical techniques there is useful.

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Different forecasting techniques have been applied to the problem of daily load forecast. Almost all of these techniques fall in the realm of statistical techniques. The exception to this is a recent approach introduced by Rahman and Bhatnagar [10] which is based on applying a knowledge-based algorithm to the short-term load forecasting problem. Another algorithm that has applied the expert system approach is the work of Jobbour et. al. [11].

In this paper a comparative evaluation of five short-term load forecasting techniques is presented. These techniques are:

1. Multiple Linear Regression;
2. Stochastic Time Series;
3. General Exponential Smoothing;
4. State Space Method; and
5. Knowledge-Based Approach.

The authors have applied these algorithms to obtain hourly load forecasts (for up to 24 hours) during the winter and summer peaking seasons. Thus the five forecasting methodologies have been applied to the same database and their performances are directly compared.

It must be mentioned here that the purpose of this paper is to compare the performances of these five forecasting techniques such that the reader can get an understanding of their inherent level of difficulty and the expected results. The value of this paper is in this comparative analysis. For example, a researcher can take any one of these techniques and apply to a specific system and generate some very highly system specific coefficients and rules and possibly obtain a very accurate forecast. In fact one of the motivating factors of this paper is to point the way to the interested reader to go deeper into one of these techniques and produce a highly accurate short-term load forecast.

2.0 MULTIPLE LINEAR REGRESSION (MLR)

In the multiple linear regression (MLR) method, the load is found in terms of explanatory variables such as weather and non-weather variables which influence the electrical load. The load model using this method is expressed in the form as [12]:

$$y(t) = a_0 + a_1x_1(t) + \dots + a_nx_n(t) + a(t) \tag{1}$$

where,

$y(t)$ = electrical load.
$x_1(t), \dots, x_n(t)$ = explanatory variables correlated with y(t).
$a(t)$ = a random variable with zero mean and constant variance.
$a_0, a_1, \dots, a_n$ = regression coefficients.

The explanatory variables of this model are identified on the basis of correlation analysis on each of these (independent) variables with the load (dependent) variable. Experience about the load to be modeled helps an initial identification of the suspected influential variables. The estimation of the regression coefficients is usually found using the least square estimation technique. Statistical tests (such as the F-statistic test) are performed to determine the significance of these regression coefficients. The t-ratios resulting from these tests determine the significance of each of these coefficients, and correspondingly the significance of the associated variables with these coefficients.

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3.0 STOCHASTIC TIME SERIES (STS)

This method appears to be the most popular approach that has been applied and is still being applied to short-term load forecasting in the electric power industry. The theory of stochastic time series is discussed in many text books, and many load forecasting papers using this approach have been published. As a brief review, the load series, y(t), is modeled as the output from a linear filter that has a random series input, a(t), usually called a white noise as shown in Figure 1. This random input has a zero mean and unknown fixed variance $\sigma_a^2(t)$.

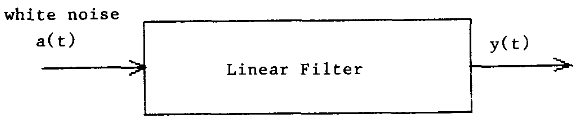

Figure 1. Load Time Series Modeling

Depending on the characteristic of the linear filter, different models can be classified as follows [13]:

3.1 The Autoregressive (AR) Process:

In the autoregressive process, the current value of the time series y(t) is expressed linearly in terms of its previous values (y(t-1), y(t-2), ..) and a random noise a(t). The order of this process depends on the oldest previous value at which y(t) is regressed on. For an autoregressive process of order p (i.e., AR(p)), this model can be written as:

$$y(t) = \phi_1 y(t-1) + \phi_2 y(t-2) + ... + \phi_p y(t-p) + a(t). \quad (2)$$

By introducing the backshift operator B that defines y(t-1) = By(t), and consequently $y(t-m) = B^m y(t)$, equation (2) can be written in the form:

$$\phi(B)y(t) = a(t). \quad (3)$$

where,

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p.$$

3.2 The Moving-Average (MA) Process:

In the moving-average process, the current value of the time series y(t) is expressed linearly in terms of current and previous values of a white noise series a(t), a(t-1), ... This noise series is constructed from the forecast errors or residuals when load observations become available. The order of this process depends on the oldest noise value at which y(t) is regressed on. For a moving average of order q, (i.e., MA(q)), this model can be written as:

$$y(t) = a(t) - \theta_1 a(t-1) - \theta_2 a(t-2) - ... - \theta_q a(t-q). \quad (4)$$

A similar application of the backshift operator on the white noise series would allow equation (4) to be written as:

$$y(t) = \theta(B)a(t). \quad (5)$$

where,

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q.$$

3.3 The Autoregressive Moving-Average (ARMA) Process:

In the autoregressive moving average process, the current value of the time series y(t) is expressed linearly in terms of its values at previous periods (y(t-1),y(t-2),...) and in terms of current and previous values of a white noise (a(t),a(t-1),a(t-2),...). The order of the ARMA process is selected by both the oldest previous value of the series and the oldest white noise value at which y(t) is regressed on. For an autoregressive moving-average process of order p, and q (i.e., ARMA(p,q)), the model is written as:

$$y(t) = \phi_1 y(t-1) + .. + \phi_p y(t-p) + a(t) - \theta_1 a(t-1) - .. - \theta_q a(t-q). (6)$$

By using the backshift operator defined earlier, equation (6) can be written in the following form:

$$\phi(B)y(t) = \theta(B)a(t). \quad (7)$$

where ϕ(B) and θ(B) have been defined earlier.

3.4 The Autoregressive Integrated Moving-Average (ARIMA) Process:

The time series defined previously as an AR, MA, or as an ARMA process is called a stationary process. This means that the mean of the series of any of these processes and the covariances among its observations do not change with time. If the process is non-stationary, transformation of the series to a stationary process has to be performed first. This can be achieved, for the time series that are non-stationary in the mean, by a differencing process. By introducing the ∇ operator, a differenced time series of order 1 can be written as $\nabla y(t) = y(t) - y(t-1) = (1-B)y(t)$ using the definition of the backshift operator, B. Consequently, an order d differenced time series is written as $\nabla^d y(t) = (1-B)^d y(t)$. The differenced stationary series can be modeled as an AR, MA, or an ARMA to yield an ARI, IMA, ARIMA time series processes. For a series that needs to be differenced d times and has orders p and q for the AR and MA components (i.e ARIMA(p,d,q)), the model is written as:

$$\phi(B)\nabla^d y(t) = \theta(B)a(t). \quad (8)$$

where ϕ(B), ∇^d, and θ(B) have been defined earlier.

3.5 Seasonal Processes:

As a result of daily, weekly, yearly or other periodicities, many time series exhibit periodic behaviors in response to one or more of these periodicities. Therefore, a different class of models which have this property is designated as seasonal processes. Seasonal time series could be modeled as an AR, MA, ARMA or an ARIMA seasonal process similar to the nonseasonal time series discussed in the previous sections. It has been shown that the general multiplicative model $(p,d,q)x(P,D,Q)_s$ for a time series model can be written in the form [13]:

$$\phi(B)\Phi(B^s)\nabla^d\nabla_s^D y(t) = \theta(B)\Theta(B^s)a(t) \quad (9)$$

where ∇^d, $\phi(B)$, and $\theta(B)$ have been defined. Similar definitions for ∇_s^D, $\Phi(B^s)$, and $\Theta(B^s)$ are given in the following:

$$\nabla_s^D = (y(t) - y(t-s))^D = (1-B^s)^D y(t),$$

$$\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - ... - \Phi_P B^{Ps}, \text{ and}$$

$$\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - ... - \Theta_Q B^{Qs}.$$

The model presented in equation (9) can obviously be extended to the case where two seasonalities are accounted. The order of the model is $(p,d,q)x(P,D,Q)_s x(P',D',Q')_{s'}$ and is expressed as:

$$\phi(B)\Phi(B^s)\Phi'(B^{s'})\nabla^d\nabla_s^D\nabla_{s'}^{D'} y(t) = \theta(B)\Theta(B^s)\Theta'(B^{s'})a(t) \quad (10)$$

where definitions for $\nabla^{D'}$, $\Phi'(B^{s'})$, and $\Theta'(B^{s'})$ are given using the second seasonal time series terms as:

$$\nabla_{s'}^{D'} = (y(t) - y(t-s'))^{D'} = (1-B^{s'})^{D'} y(t),$$

$$\Phi'(B^{s'}) = 1 - \Phi'_1 B^{s'} - \Phi'_2 B^{2s'} - ... - \Phi'_{P'} B^{P's'}, \text{ and}$$

$$\Theta'(B^{s'}) = 1 - \Theta'_1 B^{s'} - \Theta'_2 B^{2s'} - ... - \Theta'_{Q'} B^{Q's'}.$$

An example demonstrating the seasonal time series modeling is the model for an hourly load data with daily cycle. Such a model can be expressed using the model of equation (9) with s = 24. If this model exhibits a weekly cycle as well, then the model of equation (10) is best suitable where s = 24 and s' = 168.

3.6 Transfer Function (TF) Modeling:

The previous models allow y(t) to be expressed in terms of its history (and a white noise). If other variables are affecting the value of y(t), the effect of these variables can be accounted for using a transfer function model. For the case of one independent variable x(t), such as the temperature, the transfer function model shown by Figure 2 may be written in the form [14]:

$$y(t) = \frac{\omega(B)}{\sigma(B)} X(t-b) + n(t) \quad (11)$$

where,

$$\omega(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - ... - \omega_r B^r$$

$$\sigma(B) = 1 - \sigma_1 B - \sigma_2 B^2 - ... - \sigma_s B^s$$

b = *response lag time*;

$n(t)$ = *a colored (nonwhite) noise series.*

The series n(t) can be modeled in terms of its past values and a white noise using any of the techniques previously discussed in sections 3.1 through 3.5.

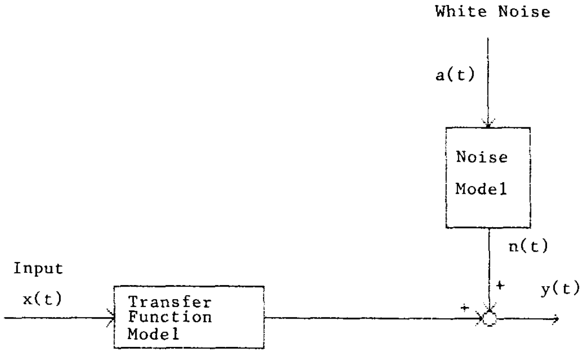

Figure 2. Transfer Function Model

The identification of the time series models is obtained by analyzing the raw load data. This analysis includes the use of the range-mean, autocorrelation function, and partial autocorrelation function plots. The use of these tools leads to initial guesses of the required data transformation and degree of differencing to obtain a stationary process. The degrees of the AR and the MA polynomials are initially determined by means of using the autocorrelation function (ACF) and the partial autocorrelation functions (PACF). For the case of TF (load) time series model, the cross-correlation function (CCF) plot between the load time series, y(t), and the input series, x(t) is also needed for evaluating the response lag time, b, along with the orders r and s of the polynomials $\omega(B)$ and $\sigma(B)$.

The estimation of parameters of the (identified) load forecasting model is usually achieved through the use of an efficient estimation method. For a pure AR model, the application of the Yule-Walker equation solution results in the estimates of the parameters of this process [13]. Other methods such as the maximum likelihood technique are capable of being applied to other processes as well. Along with the estimation of the load forecasting model, estimation of the standard deviation and correlation of the parameters of the model with the variances and covariances of the residuals are established for the analysis.

The load forecast model obtained can be assumed correct (as identified with its parameters as estimated) only if such a model passes the diagnostic checking test. This test is performed simply by checking whether the residual series is a white noise. If not, the inadequacy of the model has to be corrected in view of the ACF and PACF of the residual series.

4.0 GENERAL EXPONENTIAL SMOOTHING (GES)

In this method, the load at time t, y(t), is modeled using a fitting function (equation (20)) and is expressed in the form [12]:

$$y(t) = \beta(t)^T f(t) + \varepsilon(t) \tag{12}$$

where,

- $f(t)$ = fitting function vector for the process
- $\beta(t)$ = coefficient vector
- $\varepsilon(t)$ = a white noise
- T = transpose operator

The estimates of the coefficients are found using weighted or discounted mean square error for the recent N sampled intervals, i.e., to minimize the function

$$\sum_{j=0}^{N-1} w^j [y(N-j) - f^T(-j)\beta]^2 \qquad 0 < w < 1 \tag{13}$$

This minimization gives the estimate vector of the coefficients which has the form:

$$\hat{\beta}(N) = F^{-1}(N)h(N) \tag{14}$$

where,

$$F(N) = \sum_{j=0}^{N-1} w^j f(-j) f^T(-j) \tag{15}$$

$$h(N) = \sum_{j=0}^{N-1} w^j f(-j) y(N-j) \tag{16}$$

The forecast of the series at lead time ℓ is found as:

$$\hat{y}(N+\ell) = f^T(\ell)\hat{\beta}(N) \tag{17}$$

The coefficient estimates and the forecasts can be updated respectively using:

$$\hat{\beta}(N+1) = L^T\hat{\beta}(N) + F^{-1}f(0)[y(N+1) - \hat{y}(N)] \tag{18}$$

$$\hat{y}(N+1+\ell) = f^T(\ell)\hat{\beta}(N+1) \tag{19}$$

where,

$$F = \lim_{N \to \infty} F(N)$$

The L matrix is called the transition matrix and is constructed on the basis that the model will have a fitting function satisfying the relationship:

$$f(t) = Lf(t-1) \tag{20}$$

5.0 STATE SPACE AND KALMAN FILTER (SSKF)

This is a general forecasting approach that can include the previously mentioned methods and more, such as time-varying coefficient models. In this method, the load is modeled as a state variable using state space formulation which is designated by two sets of equations; the system state equations and the measurement equations. These sets are written for load model as:

State Space Equations :

$$X(k+1) = \Phi(k)X(k) + W(k) \tag{21}$$

Measurement Equation :

$$Z(k) = H(k)X(k) + V(k) \tag{22}$$

where,

- $X(k)$ = (n x 1) process state vector at time t_k
- $\Phi(k)$ = (n x n) state transition matrix relating X(k) to X(k + 1) when no forcing function exists
- $W(k)$ = (n x 1) a white noise with a known covariance Q(k)
- $Z(k)$ = (m x 1) vector (load) measurements at time t_k
- $H(k)$ = (m x n) matrix relating X(k) to Z(k) without noise
- $V(k)$ = (m x 1) (load) measurement error which is a white noise with a known covariance R(k)

The covariance matrices for the vectors W(k) and V(k) are given by:

$$E(W(k), W(i)^T) = \begin{bmatrix} Q(k) & i = k \\ 0 & i \neq k \end{bmatrix} \tag{23}$$

$$E(V(k), V(i)^T) = \begin{bmatrix} R(k) & i = k \\ 0 & i \neq k \end{bmatrix} \tag{24}$$

The process noise, W(k), and the measurements noise, V(k), are assumed uncorrelated and accordingly,

$$E(W(k), V(i)^T) = 0 \quad \textit{for all k and i} \tag{25}$$

At any instant t_k there will be an estimate for the process based on knowledge of the process up to t_{k-1}. This estimate is called the apriori estimate and is expressed as $\hat{X}(k/(k-1))$. The associated error between the actual and the previous estimates of the process is given as.

$$e(k/(k-1)) = X(k) - X(k/(k-1)) \tag{26}$$

This error vector has an error covariance matrix expressed by

$$E(e(k/(k-1)), e(k/(k-1))^T) = P(k/(k-1)) \tag{27}$$

The posteriori estimate is obtained as a linear combination from the apriori estimate and the measurement noise as:

$$X(k/k) = X(k/(k-1)) + K(k)[Y(k) - H(k)X(k/(k-1))] \tag{28}$$

where,

X(k/k) = updated estimate
K(k) = blending factor

The error associated with the actual and the posteriori estimate of the process is

$$e(k/k) = X(k) - X(k/k) \tag{29}$$

The covariance matrix of this error vector is expressed by

$$E(e(k/k), e(k/k)^T) = P(k/k) \tag{30}$$

The blending factor K(k) is found such that X(k/k) is optimal in some sense such as the minimum mean-squares error (MSE) criterion. This factor is known as Kalman gain and the procedure for implementing Kalman filter for load prediction is as follows [15]:

1. Find the process apriori estimate X(k/k-1) and the error covariance matrix associated with it, P(k/k-1).
2. Compute the Kalman gain.
$$K(k) = P(k/(k-1))H(k)^T(H(k)P(k/(k-1))H(k)^T - R(k)^{-1}). \tag{31}$$
3. Compute the updated estimate error covariance matrix
$$P(k/k) = [1 - K(k)H(k)]P(k/(k-1)). \tag{32}$$
4. Project ahead the apriori estimate X((k+1)/k) and the error covariance matrix P(k+1/k) associated with it
$$X((k+1)/k) = \Phi(k)X(k/k); \tag{33}$$
$$P((k+1)/k) = \Phi(k)P(k/k)Q(k)^T + Q(k). \tag{34}$$
5. Go to Step 2 moving to the next time step.

It is clear that the state space method is very attractive for on-line prediction as a result of the recursive property of the Kalman filter. The optimal forecast will be based on the assumed model. Therefore, the model has to be known prior to using the Kalman filter. The identification process is the main difficulty of this approach. In particular, the noise covariance matrices Q(k) and R(k) are not easily estimated.

6.0 KNOWLEDGE-BASED EXPERT SYSTEMS (KBES) APPROACH

Expert systems are new techniques that have emerged as a result of advances in the field of artificial intelligence (AI) in the last two decades. In brief, an expert system is a computer program (though not algorithmic) which has the ability to act as an 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 is built using the knowledge about the load forecast domain from an expert in the field. The "Knowledge Engineer" extracts this knowledge from load forecast (domain) expert by what is called the acquisition module component of the expert system. This knowledge is represented as facts and rules by using the first predicate logic to represent the facts and IF-THEN production rules. This representation is built in what is called the knowledge base component of the expert system. The search for solution or reasoning about the conclusion drawn by the expert system is performed by what is known as the "Inference Engine" component of the expert system. For any expert system it has to have the capability to trace its reasoning if asked by the user. This facility is built through an explanatory interface component.

An example demonstrating this approach is the rule-based algorithm (implemented in section 7.5) which is based on the work of Rahman and Baba [16]. This algorithm consists of functions that have been developed for the load forecast model based on the logical and syntactical relationship between the weather and prevailing daily load shapes in the form of rules in a rule-base. The rule-base developed consists of the set of relationships between the changes in the system load and changes in natural and forced condition factors that affect the use of electricity. The extraction of these rules was done off-line, and was dependent on the operator experience and observations by the authors in most cases. Statistical packages were used to support or reject some of the possible relationships that have been observed.

The rule-base consisted of all rules taking the IF-THEN form and mathematical expressions. This rule-base is used daily to generate the forecasts. Some of the rules do not change over time, some change very slowly while others change continuously and hence are to be updated from time to time.

7.0 IMPLEMENTATIONS

The five forecasting techniques that have been discussed in this paper are implemented to predict the hourly load of a southeastern (US) utility. For this purpose a summer peak day and a winter peak day are chosen. Significant assumptions made while implementing these techniques are listed in the Appendix.

7.1 Multiple Linear Regression (MLR)

In the MLR application, the hourly load is modeled as: (i) Base Load Component which is assumed constant for different time intervals of the day and (ii) Weather Sensitive Component which is a function of different weather variables. These weather variables include dry bulb temperature, dew point temperature and wind speed. The relationship between the weather sensitive component and most of the weather variables is not linear, but are rather transformed from current and previous lag time values.

The summer model for the hourly load at each of the considered time intervals has the form:

$$\begin{aligned} y_i(t) = {} & A_i + B_i(T_d(t) - T_{ci}) + C_i(T_d(t) - T_{ci})^2 \\ & + D_i(T_d(t) - T_{ci})^3 + E_i(T_p(t) - T_{pi}) \\ & + F_i(T_{ava} - T_{avb}) + G_i(T_d(t) - T_d(t-1)) \\ & + H_i(T_d(t-1) - T_d(t-2)) \\ & + I_i(T_d(t-2) - T_d(t-3)) \end{aligned} \tag{35}$$

Similarly, the winter model for the hourly load at each of the considered time interval in this season has the form.

$$\begin{aligned} y_i(t) = {} & A_i + B_i(T_{ci} - T_d(t)) + C_i(T_{ci} - T_d(t))^2 \\ & + D_i(T_{ci} - T_d(t))^3 + E_i(T_{pi} - T_p(t)) \\ & + F_i(T_{ava} - T_{avb}) + G_i(T_d(t) - T_d(t-1)) \\ & + H_i(T_d(t-1) - T_d(t-2)) \\ & + I_i(T_d(t-2) - T_d(t-3)) \\ & + J_i(W_c(t)) + K_i(W_c(t-1)) \\ & + L_i(W_c(t-2)) \end{aligned} \tag{36}$$

where, the wind chill factor, [17]

$$W_c(t) = 33 - [10.45 + 10\sqrt{0.477v(t)} - 0.447v(t)]x$$
$$[(33 - 0.556(T_d(t) - 32))/22.04] \tag{37}$$

and where

$y_i(t)$ = load at hour t in the interval i of the day.
A_i = base load component (regression constant coefficient)
B_i through L_i = regression coefficients of weather sensitive component
$T_d(t)$ = dry bulb temperature at time t, deg. F (which will be clamped at the cut off value if necessary)
$T_p(t)$ = dew point temperature at time t, deg. F (which will be clamped at the cut off value if necessary)
T_{ava} = average dry bulb temperature of previous 24 hours to the time t, deg. F
T_{avb} = T_{ava} lagged 3 hours, deg. F
T_{ci} = cut off dry bulb temperature for the interval i in the season, deg. F

T_{pi} = cut off dew point temperature for the interval i in the season, deg. F

v (t) = wind speed at time t, miles/hour

The model parameters have been found for both the summer and the winter weekdays as shown in Table 1 and Table 2 respectively. These parameters have been estimated using 4 weeks of weekday hourly data for each time interval. This was done in order to avoid picking up inter-seasonal variations. It must be noted that the division of the day into six unequal times zones is based on the authors' experience with the characteristics of the load shape of this particular utility.

Table 1. Weekday MLR summer model parameter estimates for different time intervals of the day

	Day Time Interval					
Parameter	12-4AM	5-9AM	10AM-1PM	2-5PM	6-8PM	9-11PM
A_i	2454.75	3733.13	3823.36	3001.17	3180.40	2500.89
B_i	75.28	70.88	-	-	-	-
C_i	-	2.20	6.55	9.16	7.46	8.22
D_i	-	-	-0.09	-0.14	-0.12	-0.15
E_i	48.26	20.40	52.60	42.57	69.03	45.73
F_i	-94.35	-138.60	-556.32	-444.19	-328.45	-320.88
G_i	-109.64	78.41	-55.75	-91.01	-145.43	-143.76
H_i	-88.31	-	-	-63.99	-83.80	-194.78
I_i	-56.50	-	-	-38.83	-	-76.23
T_{ci}	60	60	60	60	60	60
T_{pi}	50	50	50	50	50	50
RMSE	170.94	294.47	225.87	159.86	159.26	305.10
R^2	0.925	0.911	0.943	0.977	0.976	0.908

Table 2. Weekday MLR winter model parameter estimates for different time intervals of the day

	Day Time Interval					
Parameter	12-4AM	5-8AM	9AM-12PM	1-4PM	5-7PM	8-11PM
A_i	2697.67	4771.79	2931.22	3879.89	5502.75	4417.67
B_i	96.35	-	70.15	-	-	-
C_i	-2.84	1.01	-	2.82	1.39	1.00
D_i	0.08	-	0.005	-0.02	-	-
E_i	7.38	-	-	13.50	-7.93	-
F_i	72.74	-	144.14	106.84	-	-
G_i	45.32	-	-	-	-	-
H_i	34.74	-	-	-	-	-
I_i	-	-	-	-	-	-154.12
J_i	6.08	-	4.76	6.53	-	-
K_i	-	-	-	-	-5.19	-
L_i	-	-	4.40	-	-5.02	-
T_{ci}	50.00	70.00	70.00	70.00	70.00	70.00
T_{pi}	40	-	-	60.00	60.00	-
RMSE	84.73	693.38	122.84	135.37	164.67	513.49
R^2	0.982	0.445	0.955	0.934	0.919	0.479

7.2 Stochastic Time Series (STS)

The time series approach has been applied to model the hourly load data for both the summer and the winter seasons. Both seasonal ARIMA and TF models have been developed using 4 weeks of hourly data. The ARIMA model has been identified and its parameters estimated as:

$$(1 - 0.37B - 0.23B^2 + 0.11B^3 + 0.09B^{12} + 0.10B^{14} - 0.10B^{20})$$

$$(1 - 0.12B^{24})(1 - 0.32B^{168})\nabla_1\nabla_{24}y(t) = (1 - 0.91B^{24})a(t) \quad (38)$$

The TF model has been identified and estimated using the same data with the input as the dry bulb temperature and is expressed as:

$$y(t) = (1.94 - 5.25B)\,x(t) +$$

$$\frac{(1 - 0.93B^{24})a(t)}{\nabla_1\nabla_{24}(1 - 0.35B - 0.22B^2 + 0.10B^3 + 0.07B^9 + 0.09B^{12} + 0.11B^{14} - 0.94B^{20})(1 - 0.12B^{24})(1 - 0.33B^{168})} \quad (39)$$

The seasonal ARIMA and TF models are also developed for the winter season using 4 weeks of hourly load data. These are expressed respectively as:

$$(1 - 0.16B - 0.25B^2 + 0.11B^6 + 0.15B^7)\nabla_1\nabla_{168} = (1 - 0.60B^{168})a(t) \quad (40)$$

and

$$y(t) = (-2.847 - 6.554B)x(t) + \frac{(1 - 0.60B^{168})a(t)}{\nabla_1\nabla_{168}(1 - 0.13B - 0.24B^2 + 0.12B^6 + 0.15B^7)} \quad (41)$$

7.3 General Exponential Smoothing (GES)

The general exponential smoothing technique has been applied to model the hourly load for both the summer and winter seasons. Each model has been developed from a constant part, c, and a varying part that is a function of m frequencies with a daily periodicity. These models can be written as:

$$y(t) = c + \sum_{c=1}^{m}(a_i \sin w_i t + b_i \cos w_i t) \quad (42)$$

where

$$W_i = \frac{2\pi}{24} K_i$$

K_i has to a positive integer less than half the daily period (i.e. 12).

The fitting function can be expressed in the form

$$f(t) = \begin{bmatrix} 1 \\ \sin w_1 t \\ \cos w_1 t \\ \cdot \\ \cdot \\ \sin w_m t \\ \cos w_m t \end{bmatrix} \quad (43)$$

An extensive analysis using hourly data for five previous weekdays has been performed to find the best fitting function parameters (m and k) and smoothing constant ($\alpha = 1 - \omega$) of the model. The best suitable parameters for the GES model for both summer and winter are as shown in Table 3.

Table 3. General Exponential Smoothing Summer and Winter Model Estimates

Parameter	Summer Model	Winter Model
m	11	11
K_i	1,2,...,11	1,2,...,11
α	0.025	0.025
RMSE	189.7	168.2

7.4 State Space Approach (SS)

The state space algorithm has been applied to model the hourly load for both summer and winter days. Such an application has been performed on a special state space realization, namely canonical realization using stationary ARMA model. This means the modeled series has to be transformed into stationary series prior to modeling, if required. This transformation has been performed for both the summer and winter models. An hourly and daily differencing has been applied to the summer series and an hourly and weekly differencing has been applied to the winter series. The state space model has been obtained for the summer model as:

$$X(K+1) = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -0.234 & 0.077 & 1.114 \end{bmatrix} X(K) \tag{44}$$

$$+ \begin{bmatrix} 1 \\ 1.307 \\ 1.565 \end{bmatrix} a(t+1)$$

$$Z(K) = [1 \quad 0 \quad 0] \quad X(K) \tag{45}$$

where

$$X(K) = \begin{bmatrix} y(t/t) \\ y((t+1)/t) \\ y((t+2)/t) \end{bmatrix}$$

For the winter model, the state space model has been identified and estimated as:

$$X(K+1) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -0.280 & -0.037 & 0.558 & 0.560 \end{bmatrix} X(K) \tag{46}$$

$$+ \begin{bmatrix} 1 \\ 0.148 \\ 0.263 \\ 0.164 \end{bmatrix} a(t+1)$$

$$Z(K) = [1 \quad 0 \quad 0 \quad 0] \quad X(K) \tag{47}$$

where

$$X(K) = \begin{bmatrix} y(t/t) \\ y((t+1)/t) \\ y((t+2)/t) \\ y((t+3)/t) \end{bmatrix}$$

7.5 Knowledge-Based Expert System (KBES)

Application of the knowledge-based approach is based on the work of Rahman and Baba [16]. In this application, the model of the hourly load using the expert system algorithm is based on selecting a reference day load curve according to a set of rules. This reference day is then reshaped according to other sets of rules as to account for (1) the expected variations in the forecasted day from that of the reference day, and (2) the variations in the impact of weather change on the load from day to the next. The load at hour h of the forecasted day is calculated as:

$$y_h^{FF} = y_h^{F1} + \Delta y_h \tag{48}$$

$$y_h^{F1} = y_h^{Rm} + \Delta y_h^{in} \tag{49}$$

$$\Delta y_h^{in} = (y_{00}^T - y_{00}^R) \times (24 - h)/24 \tag{50}$$

$$\Delta y_h = \pm \Delta t \times F1 \times F2 \times 25\,, \quad \Delta t \leq 10°F \tag{51}$$

$$\Delta y_h = \pm \frac{\Delta t^2}{4} \times F1 \times F2\,, \quad \Delta t > 10°F \tag{52}$$

where,
+ in summer
− in winter
and where,

y_h^{FF} = forecasted load at hour h of the day

Δy_h^{in} = load correction due to inertia at hour h

y_{00}^T = load at hour 00 of the target day

y_{00}^R = load at hour 00 of the reference day

h = hour of the day for which forecast is sought

y_h^{F1} = 1st level forecast of load for hour h

y_h^{Rm} = reference day's load for hour h modified to to account to the day to day variations

Δt = ambient (or effective) temperature difference between hours in forecasted and reference days.

F1 = weighing factor that account for the relative change in temperature between the forecasted and reference days

F2 = weighing factor that account for the different reference day temperatures

The rules governing F2 is changing continuously and therefore a revising mechanism has been developed to update these rules automatically [16].

8.0 COMPARATIVE SUMMARY OF RESULTS

In this section we summarize our results of applying the five load forecasting techniques to a typical southeastern (US) utility. Because of high heating and air conditioning loads this utility experiences high demand in both winter and summer. In order to check how well the implementations of these five forecasting techniques work, the authors have applied them to predict the daily load (up to 24 hours) on winter and summer peak days. The error analyses are provided in Tables 4 and 5 for the winter and summer days respectively. As these results are based on forecasts of two single days, these should be used for comparative purposes only.

Some interesting observations are made about the results presented in Tables 4 and 5. For example, for the peak summer day the transfer function (TF) approach gave the best result, whereas for the peak winter day the TF approach resulted in the next to the worst accuracy. During the peak summer day the temperature profile was typical whereas during the peak winter day the profile was unseasonal. Thus one can see that because of its strong dependency on historical data, the TF approach could not take into account abrupt changes in weather as efficiently as others, like the knowledge based expert system (KBES).

Table 4. Forecast Percent Error for Summer Using the Five Load Forecasting Algorithms

Time	Load	MLR	STS		GES	SS	KBES
			ARIMA	TF			
1	4946.	1.79	.08	.07	1.11	.31	-.33
2	4757.	-.15	.15	.18	1.44	.77	.33
3	4600.	-1.28	-.67	-.53	1.14	.24	.02
4	4586.	-.92	-.93	-.74	1.43	.20	.25
5	4756.	1.91	-.77	-.57	1.34	-.24	-.25
6	5196.	-5.01	.20	.37	1.78	-.05	-.33
7	5809.	1.18	.67	.80	1.88	-.08	-.55
8	6261.	3.14	-.84	-.81	.06	-2.56	-1.26
9	6847.	4.34	.06	-.02	1.49	-1.34	-1.27
10	7106.	.57	-1.16	-1.36	.27	-2.78	-1.69
11	7527.	.20	.13	-.13	1.35	-2.57	-1.52
12	7693.	-1.59	.07	-.28	.77	-3.75	-1.43
13	7698.	-5.80	-1.64	-2.09	-.16	-3.26	-1.43
14	7972.	-4.02	.45	-.05	2.22	.09	-2.30
15	8082.	-.79	.93	.47	3.17	1.57	-1.49
16	8214.	1.41	1.36	.95	4.03	2.96	-2.65
17	8180.	2.46	1.04	.70	4.27	3.36	-2.40
18	7937.	1.85	-.39	-.67	2.93	1.74	-2.75
19	7559.	1.18	-.70	-.95	2.55	1.48	-1.60
20	7467.	4.55	.32	.14	3.44	1.45	-1.93
21	7284.	6.17	.06	-.11	3.53	1.34	-.16
22	6724.	10.02	.23	.10	3.56	1.49	-.11
23	5989.	4.01	.05	-.05	3.38	2.17	1.97
24	5402.	-2.34	.14	.09	3.59	1.97	1.19

Table 5. Forecast Percent Error for Winter Using the Five Load Forecasting Algorithms

Time	Load	MLR	STS		GES	SS	KBES
			ARIMA	TF			
1	4229.	1.75	.77	.62	-.90	.32	-.10
2	4124.	-.31	1.86	1.64	-.24	.43	.10
3	4107.	-2.06	2.77	2.12	-.50	1.12	1.29
4	4182.	-.68	3.95	3.38	.11	2.01	1.61
5	4315.	-.58	4.85	4.49	.02	2.56	2.08
6	4738.	-18.71	4.50	4.31	-.45	2.83	1.30
7	5842.	-1.88	6.19	6.17	.81	5.40	1.22
8	6558.	8.68	6.67	6.75	.54	7.10	2.18
9	6432.	7.47	4.97	5.09	-1.33	4.27	1.58
10	6149.	-2.04	2.34	2.46	-2.99	1.05	.47
11	5879.	-2.40	.83	.47	-4.63	-.16	-2.42
12	5688.	-3.90	.35	-.44	-4.44	-.43	-1.44
13	5463.	-4.98	-.78	-1.84	-4.25	-.85	-.98
14	5303.	-3.17	-.77	-2.09	-4.43	.09	-1.03
15	5219.	-3.03	-.62	-1.75	-3.55	-.15	.09
16	5138.	-3.69	-.50	-1.49	-2.87	.83	.65
17	5364.	-.95	-.50	-1.56	-1.17	1.81	1.25
18	5889.	-3.18	-1.56	-2.78	-.59	1.60	1.74
19	6277.	-.18	-.29	-1.56	-.54	1.46	1.49
20	6156.	-3.80	-.42	-1.72	-.02	.94	.85
21	5921.	3.18	-1.11	-2.33	-1.15	-.36	1.84
22	5597.	-.19	-1.82	-3.11	-1.46	-1.16	1.67
23	5115.	-4.41	-2.16	-3.64	-2.69	-2.50	1.52
24	4628.	-9.07	-1.49	-3.00	-3.26	-1.50	2.10

9.0 CONCLUSIONS and RECOMMENDATIONS

This paper is based on the comparative analysis of five short-term load forecasting techniques. During the implementation of these techniques certain interesting properties of the load and the variables have been observed. For example, for the multiple linear regression (MLR) technique the day was divided into six unequal time zones. This gave a much better fit than not dividing the day, or dividing the day equally. Probably because of this division strong correlations were found between the load, the dry bulb temperature, dew point temperature, and wind speed. On the other hand, when the transfer function (TF) model was built, the authors did not find any significant cross-correlation between the load and these variables, with the exception of the dry bulb temperature. The forecast for the TF approach was based on the historical load and temperature, and the future temperature as forecasted by the temperature model itself. This has a benefit, because of the internally generated temperature forecast the weather prediction error would not contaminate the load forecast. On the other hand if any significant changes in the weather are expected the model cannot use this information unless forced to do so externally. This may cause higher errors. It may be noted that the non-linearity that caused the unequal division of the day for the MLR technique was detected through the authors' experience with the load characteristics. The characterization of such nonlinearities is not an intrinsic property of either the multiple linear regression (MLR) or the transfer function (TF) technique.

Along the same lines, the authors' experience with the knowledge-based technique demonstrate the potential for improvement in the load forecast with greater knowledge about the idiosyncrasies of the system. Therefore, the self-learning aspect of an expert system becomes a very valuable element in the level of accuracy of the forecasting technique.

Based on the observations and the authors' experience in dealing with these five forecasting techniques the following recommendations can be put forward.

1. Devise techniques for automated updating of the model parameters and coefficients.
2. Compare which model perform better under specific conditions and why.
3. Analyze if model performance can be improved by selective use of variables for different times during the day or different days.
4. Study how these techniques can be adapted for weekly instead of daily forecasts.
5. Develop detailed models for holidays and weekend using the MLR and the GES techniques.

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APPENDIX

Significant assumptions in implementing various modeling techniques are summarized in the following. The forecasting techniques to which these assumptions are applied are noted in parenthesis.

- The serial correlation among the load data is negligible (MLR).
- The relationship in each interval between the load and its explanatory variables is linear (MLR).
- The base load in each interval is constant for all weekdays in the period considered (MLR).
- The effect of load inertia can be obtained through a fixed relationship (namely the difference of the average of the previous 24 hours from that lagged by 3 hours) (MLR).
- The effect of the explanatory variables will stay the same during the modeling interval (MLR).
- The considered process is linear (STS, GES, SS).

- The considered process is stationary or can be transformed into stationary process by differencing (STS, SS).
- The noise series (or model error) is of zero mean and constant unknown variance and its observations are uncorrelated with each other (MLR, STS, GES, SS).
- The weekly seasonality is negligible (GES, SS).
- Small order model (up to 3 terms) is sufficient for building the load model (SS).
- The effect of the load control on the load forecast is neglected (MLR, STS, GES, SS, KBES).
- Accurate weather forecasts are available (MLR, KBES).
- The self-learning aspect of the expert system was tested on one year's data (KBES).

Ibrahim S. Moghram (S-83) graduated with a B.E. degree with honors in electrical power and machines in 1980 from Cairo University, Egypt. He worked through 1981 and 1982 in the transmission and distribution departments for the YGEC Corporation (YAR). In 1983, he came to the Electrical and Computer Engineering Department at Arizona State University (ASU) on a scholarship from Sanaa University (YAR). There he obtained his M.S. degree in Electrical Engineering in 1985. At present, he is pursuing his Ph.D. studies in Electrical Engineering at the Virginia Polytechnic Institute and State University where he is a Ph.D. candidate. His areas of interest include Microcomputer Application in Power Systems, Power System Operation and Transmission, and Expert Systems. He has several publications in these areas. He is a member of the Phi Kappa Phi Honor society and the IEEE Power Engineering and Computer Societies.

Saifur Rahman (S-75, M-78, SM-83) graduated from the Bangladesh University of Engineering and Technology in 1973 with a B. Sc. degree in Electrical Engineering. He obtained his M.S. degree in Electrical Sciences from the State University of New York at Stony Brook in 1975. His Ph.D. degree (1978) is in Electrical Engineering from the Virginia Polytechnic Institute and State University.

Saifur Rahman has taught in the Department of Electrical Engineering, at the Bangladesh University of Engineering and Technology, the Texas A&M University and the Virginia Polytechnic Institute and State University where he is a Full Professor. His industrial experience includes work at the Brookhaven National Laboratory, New York and the Carolina Power and Light Company. He is a member of the IEEE Power Engineering, Industry Applications, and Computer Societies. He serves on the System Planning and Demand Side Management subcommittees, and the Load Forecasting and the Photovoltaic working groups of the IEEE Power Engineering Society. His areas of interest are demand side management, power system planning, alternative energy systems and expert systems. He has authored more than 80 technical papers and reports in these areas.