THE TIME SERIES APPROACH TO SHORT TERM LOAD FORECASTING

Martin T. Hagan, Member, IEEE
Oklahoma State University

Suzanne M. Behr
Amoco Production Co. Research Center

Abstract - The application of time series analysis methods to load forecasting is reviewed. It is shown than Box and Jenkins time series models, in particular, are well suited to this application. The logical and organized procedures for model development using the autocorrelation function and the partial autocorrelation function make these models particularly attractive.

One of the drawbacks of these models is the inability to accurately represent the nonlinear relationship between load and temperature. A simple procedure for overcoming this difficulty is introduced, and several Box and Jenkins models are compared with a forecasting procedure currently used by a utility company.

I. INTRODUCTION

Load forecasting is an integral part of electric power system operations. Long lead time forecasts of 5 to 20 years ahead are needed for scheduling construction of new generating capacity as well as the determination of prices and regulatory policy. Intermediate term forecasts of a few months to 5 years ahead are needed for maintenance scheduling, coordination of power sharing arrangements and setting of prices, so that demand can be met with fixed capacity. Short term forecasts of a few hours to a few weeks ahead are needed for economic scheduling of generating capacity, scheduling of fuel purchases, security analysis and short term maintenance scheduling. Very short term forecasts of a few minutes to an hour ahead are needed for real-time control and real-time security evaluation. This paper is concerned with the short term load forecasts of one hour to one day ahead.

There has been a wide variety of procedures for short term load forecasting reported in the literature (see [1]-[4], [18] for overviews of the field). Some of these procedures have included: multiple regression [5], spectral decomposition [6], exponential smoothing [7], and state space (Kalman filter) methods [8].

One of the most commonly discussed procedures for load forecasting is time series analysis (or system identification), normally using procedures outlined by Box and Jenkins [9] or Kashyap and Rao [10]. This paper will concentrate on the application of time series analysis methods to short term load forecasting.

Section II of this paper presents the basic time series models and describes the historical evolution of the application of these models to load forecasting.

Section III describes the procedures for developing, checking and updating Box and Jenkins' models. It is the organization and the logic of these procedures which makes the Box and Jenkins models so useful. We feel that this point has been overlooked in some previous work. Section III also compares the forecasting abilities of the various models.

In section IV a procedure which incorporates a nonlinear load-temperature model into the standard time series model is presented. Forecasting results for this model are compared with results from the linear models.

It is, in general, very difficult to compare load forecasting procedures unless they are tested on the same data sets. In order to provide this type of benchmark we have tested our procedures against those currently used by a local utility. Section V describes this material and compares the accuracy of the utility's forecasting methods with our own.

Section VI summarizes our results and presents a few conclusions.

II. TIME SERIES MODELS IN LOAD FORECASTING

A. The Models

The most fundamental time series models are the autoregressive model and the moving average model. In the autoregressive model AR(p) the current value of the process is expressed as a linear combination of p previous values of the process and a random shock.

$$z_t = \phi_1 z_{t-1} + \dots + \phi_p z_{t-p} + a_t \quad (1)$$

In order to write this in a more convenient form the following operators are introduced.

$$B\, z_t = z_{t-1} \qquad B^m\, z_t = z_{t-m}$$

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

So that equation (1) can be written

$$\phi(B)\, z_t = a_t \quad (2)$$

In the moving average model MA(q) the current value of the process is expressed as a linear combination of q previous random shocks.

$$z_t = a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q}$$

$$z_t = \theta(B)\, a_t \quad \theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q \quad (3)$$

The more general mixed autoregressive-moving average model ARMA (p,q) is a combination of (2) and (3).

$$z_t - \phi_1 z_{t-1} - \dots - \phi_p z_{t-p} = a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q} \quad (4)$$

$$\phi(B)\, z_t = \theta(B)\, a_t$$

87 WM 044-1 A paper recommended and approved by the IEEE Power System Engineering Committee of the IEEE Power Engineering Society for presentation at the IEEE/PES 1987 Winter Meeting, New Orleans, Louisiana, February 1 - 6, 1987. Manuscript submitted September 2, 1986; made available for printing November 17, 1986.

0885-8950/87/0800-0785$01.00©1987 IEEE

Equation (4) can be used to model stationary processes with finite variance, and it is assumed that the roots of $\phi(B)$ and $\theta(B)$ lie outside the unit circle. One can model some types of nonstationary processes by differencing the original process, z_t, to obtain a stationary process, w_t.

$$w_t = \nabla^d z_t \quad (\nabla z_t = z_t - z_{t-1};\ \nabla_k z_t = z_t - z_{t-k}) \tag{5}$$

This results in an <u>autoregressive-integrated-moving average model</u> ARIMA (p,d,q).

$$\phi(B)\,\nabla^d z_t = \theta(B)\,a_t \tag{6}$$

Because of the periodic nature of the load curve (eg. the load at 10 A.M. Tuesday is related to the load at 10 A.M. Monday), it is advantageous to use seasonal ARIMA (p,d,q)x(P,D,Q) models.

$$\phi_p(B)\,\Phi_P(B^{24})\,\nabla^d\,\nabla_{24}^D\,z_t = \theta_q(B)\,\Theta_Q(B^{24})\,a_t \tag{7}$$

In some cases it is also useful to recognize the weekly periodicity (Sundays are not like Mondays), and a two period ARIMA $(p,d,q)x(P,D,Q)_{24}x(P',D',Q')_{168}$ model could be used.

$$\phi_o(B)\Phi_P(B^{24})\Phi'_{P'}(B^{168})\nabla^d\nabla_{24}^D\nabla_{168}^{D'}z_t =$$
$$\theta_q(B)\Theta_Q(B^{24})\Theta'_{Q'}(B^{168})a_t \tag{8}$$

The ARIMA model forecasts are essentially extrapolations of previous load history and have problems when there is a sudden change in the weather. The <u>transfer function model</u> allows for the inclusion of some independent variables, such as temperature. The transfer function model TRFU (r,s) is

$$y_t = \frac{\omega(B)}{\delta(B)}\,x_{t-b} + n_t \tag{9}$$

where $\omega(B)$ is a polynomial in B of order s and $\delta(B)$ is a polynomial in B of order r. The disturbance process n_t is not white but can be represented by an ARIMA model.

$$\nabla^d\nabla_{24}^D\nabla_{168}^{D'}y_t = \frac{\omega(B)}{\delta(B)}\nabla^d\nabla_{24}^D\nabla_{168}^{D'}x_{t-b} +$$
$$\frac{\theta(B)\Theta(B^{24})\Theta'(B^{168})}{\phi(B)\Phi(B^{24})\Phi'(B^{168})}\,a_t$$

<u>B. Summary of Time Series Applications to Load Forecasting</u>

Box and Jenkins models were first introduced for intermediate term load forecasts by Vemuri, Balasubramanian and Hill [11], [12] who used an ARIMA $(0,1,1)x(0,1,1)_{12}$ model with a twelve month period to forecast monthly peak loads for lead times of up to 40 months. Uri [13] used the same model (with different parameter values) to forecast monthly average loads for lead times of up to 2 years.

Very short term forecasts were first addressed by Keyhani and El-Abiad [14] using ARMA models. They used an ARMA (1,0) model on 1 minute load data, ARMA (1,1) and (2,1) models on 5 minute data and an ARMA (2,0) model on hourly load data. Later Keyhani and Rad [15] used models which combined AR models with some weather inputs and trigonimetric trend functions to forecast hourly loads up to one week ahead. A typical model is

$$z_t = 0.026+1.36\,z_{t-1}-0.45\,z_{t-2}-0.33z_{t-167}+$$
$$0.0008z_{t-168}+0.239X_{t-4} \tag{10}$$

where x_t is hourly temperature.

Hagan and Klein [16] used Box and Jenkins methods to develop ARIMA models with a daily period to forecast hourly loads with one to four hour lead times. Different models were developed for each season. They later extended the models to include a weekly as well as a daily period and also to include temperature inputs in a transfer function model [17]. Using load and temperature data at three hour intervals, the following was a typical model.

$$\nabla\nabla_{56}z_t = \frac{\omega_0 - \omega_1 B}{1-\delta_1 B-\delta_2 B^2}\,\nabla\nabla_{56}\,x_t + n_t$$
$$n_t = (1-\theta B)(1-\Theta' B^{56})\,a_t \tag{11}$$

They also introduced a method for adaptively updating the parameters in an ARIMA or a TRFU type model [18], [19], so that the load models can adapt continuously to changing seasonal patterns. With this method Box and Jenkins models become well suited to on-line applications.

Meslier [20] later used ARIMA $(1,0,0)x(0,1,1)x_7$ $(0,1,1)_{365}$ models to forecast daily energy consumption one day ahead. Correction factors were added to the model to adjust for the holidays. These corrected models had up to 138 parameters. Meslier also proposed using a transfer function model of the form

$$(1-\delta_1 B)v_t = W_o(1-W_7B^7)(1-W_{365}B^{365})x_t+N_t$$
$$(1-\Phi_{365}B^{365})\nabla\nabla_7 N_t = (1-\theta_1 B)(1-\theta_7 B^7)\,a_t \tag{12}$$

where v_t is consumption which has been corrected to account for holidays, and x_t is temperature.

Uri [21] and Maybee and Uri [22] used periodic ARIMA models to forecast load demand one week ahead and the load duration curve one year ahead.

Abu-El-Magd and Sinha [23], [24] have used multivariate AR models for forecasting load demands of a multinode system. They used an ARI (6,1) model to forecast the load demand of four loading stations at five minute intervals and an AR (2) model with 24 hour differencing to forecast at 1 hour intervals.

Vemuri, Huang and Nelson [25] developed a method for on-line identification of AR models using sequential least squares. They used AR (10) models on 3 hour load data to forecast up to 21 hours ahead.

<u>C. The Contribution of This Paper</u>

One of the disadvantages of the Box and Jenkins transfer function model is that, because it is a linear model, it does not accurately reflect the load/temperature relationship. Hagan and Klein [19] were able to circumvent this problem somewhat by continuously updating the model parameters, which effectively relinearized the model after each measurement.

In this paper a further improvement is gained by subjecting the temperature to a nonlinear transformation before using it in the transfer function model. The forecasting ability of this new procedure is compared with that for the standard transfer function and ARIMA models. In addition, all of these methods are compared with a procedure currently used by a local utility.

III. LINEAR MODEL DEVELOPMENT AND FORECASTING

A. Model Development Procedures

Techniques for preliminary identification of time series models rely on the analysis of the autocorrelation and partial autocorrelation function. These methods are very systematic and are extremely helpful in the determination of model order, in the preliminary estimation of model parameters, and in diagnostic checking and model refinement.

The autocorrelation function (acf) describes inherent correlation between observations of a time series which are separated in time by some lag k.

$$\gamma_k = E[z_t \; z_{t+k}] \qquad \rho_k = \gamma_k/\gamma_o \tag{12}$$

For a white noise process, in which there is no correlation in time, the acf would be as shown in Figure 1.

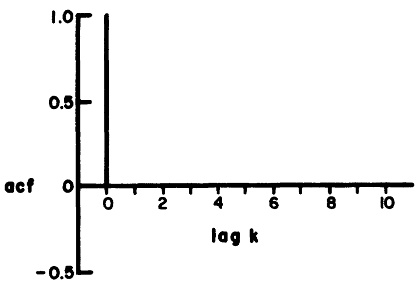

Figure 1. Autocorrelation function of a white noise process.

For an autoregressive process (Eq. (1)) the autocorrelation function satisfies the following equation

$$\rho_k = \phi_1\rho_{k-1} + \dots + \phi_p\rho_{k-p} \tag{13}$$

or

$$\phi(B)\;\rho_k = 0$$

For example, Figure 2 illustrates the autocorrelation function of a first order autoregressive process.

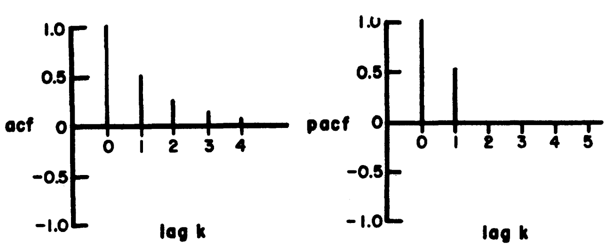

Figure 2. ACF and PACF of $z_t = 0.5\;a_{t-1} + a_t$

The partial autocorrelation function (pacf) is also useful in determining the order of autoregressive processes. It is defined with the use of equation (13). Notice that this equation can be used to solve for $\phi_1, \dots, \phi_p$ if the autocorrelation function is known, and if the order, p, is known. Define the partial autocorrelation at lag j, ϕ_{jj}, to be the solution for ϕ_j if the order (p) is equal to j. It is clear that the pacf will be identically zero for all lags, j, greater than the true order of the process, p. For example, Figure 2 shows the pacf for a first order autoregressive process.

For moving average processes (Equation (3)) it can be shown that the autocorrelation function is identically zero for lags greater than the order of the process, q. Figure 3 illustrates the acf and pacf of a first order moving average process.

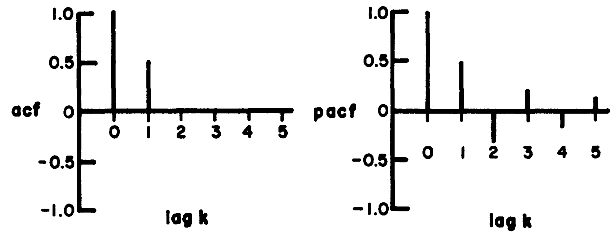

Figure 3. ACF and PACF of $z_t = a_t + 0.8\;a_{t-1}$

Using the acf and pacf it is possible to determine potentially useful model structures. The ACF and PACF are also very useful in determining appropriate model adjustments when diagnostic checks indicate model inadequacy.

Once the model structure is determined, the parameters are estimated using the method of maximum likelihood [9]. Then the residuals (one step ahead forecasting errors), a_t are calculated. The residual sequence should be white. If it is not, the autocorrelation function can be investigated to suggest additions to the model.

These procedures will be illustrated in the following sections.

B. Data Set Description

The preceding model development methods were tested on data provided by a moderately sized southwestern utility with 450,000 customers and a summer peak of approximately 3000 MW. The authors were supplied with hourly net system loads and temperature readings for 1983 and 9 months of 1984. The 1983 data were used to develop ARIMA, TRFU, and nonlinear models for each season of the year. Four weeks of data were used to develop each model and then the models were used to forecast for the following three weeks. For the TRFU models actual temperatures were used in the load forecasts, because of the difficulty of obtaining temperature forecasts from the weather bureau.

Utility load forecasts for the 9 months of 1984 were also provided. The 1983 ARIMA, TRFU and nonlinear models, which were developed on 1983 data, were used for forecasting on the 1984 data in order to provide comparisons with utility forecasts. The following section will present the technique and steps used to develop the models. A later section will discuss the comparisons.

C. Model Development and Forecasting Results

Four weeks of summer data (July 11-August 7, 1983) were used to build the summer models. The first step in developing the model is to examine the autocorrelation function (Figure 4). This oscillatory, nondecaying function indicates a nonstationary process. In order to obtain a stationary process, a number of differencing schemes were tested (Figure 5). The differencing $\nabla_1\nabla_{24}$ was finally chosen. The acf and pacf of the resulting stationary process, $w_t = \nabla_1\nabla_{24}z_t$, were then examined in order to determine model order. The large spikes at k=1 and k=2 in the pacf (Figure 6) suggest a model with a hourly AR(2) component.

To facilitate the identification of the daily (P,Q) order, multiples of 24 are pulled out of the acf and pacf and are inspected separately. Figure 7 suggests adding a daily MA(2) to the model because of the large correlations in the acf at k = 24, 48. Hence, our tentative model is of the form $(2,1,0)_1 x(0,1,2)_{24}$.

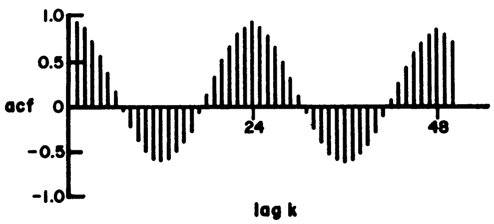

Figure 4. ACF of the Summer Load Series, z_t

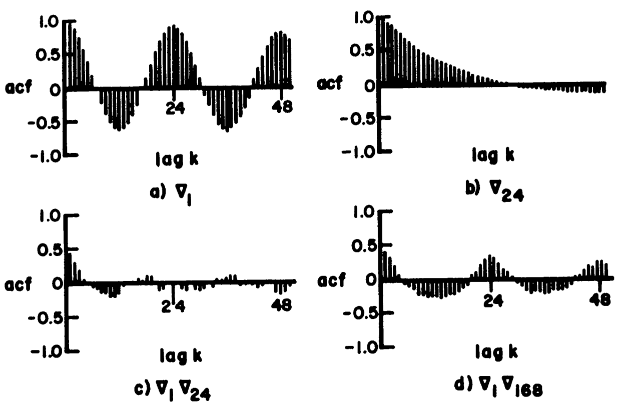

Figure 5. Autocorrelation Functions of the Summer Load Series Differenced wrt. Hours, Days, and Weeks

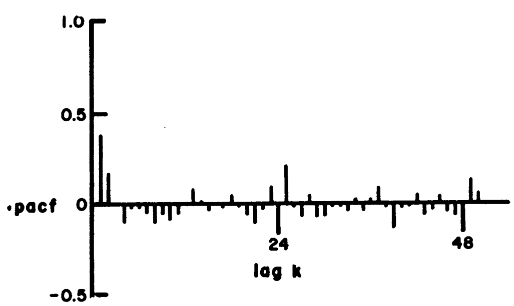

Figure 6. PACF of the Summer Loads Differenced $\nabla_1\nabla_{24}$

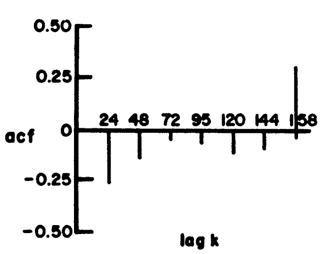

Figure 7. Daily Components of Figure 5c (Enlarged)

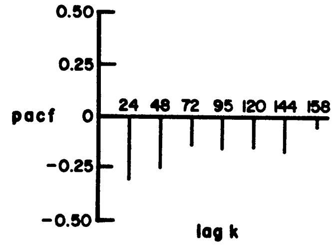

Figure 8. Daily Components of Figure 6 (Enlarged)

The parameters in the initial model were estimated using maximum likelihood, and the model was checked for goodness of fit. An accurate model will produce residuals that are white and will therefore have an acf as in Figure 1. If, however, the model is a poor fit, the residuals will not be white. The residual acf is very useful in revealing information about parameters that were overlooked.

Figure 9 is the residual acf of our tentative model. The large spike at lag 168 represents correlation that was neglected in the original model. This was corrected by adding a weekly AR(1) factor, and the following model was obtained.

$$(1-0.26B-0.18B^2)(1-0.39B^{168})\nabla_1\nabla_{24}z_t = (1-0.73B^{24}-0.09B^{48})a_t \qquad (14)$$

A test for goodness of fit for this model was performed and gave no indication of model inadequacy.

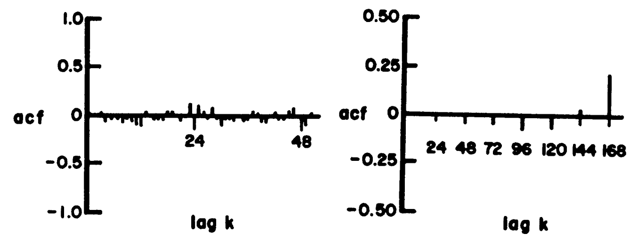

Figure 9. ACF of the Residuals, a_t, in Summer Model $(2\ 1\ 0)_1 \times (0\ 1\ 2)_{24}$

A series of steps similar to those outlined above were employed in building a summer TRFU model. The resulting model was

$$Y_t = \frac{4.5 + 1.5B}{1-0.85B+0.23B^2} X_t + \frac{1-0.70B^{24} -0.11B^{48}}{\nabla_1\nabla_{24}(1-0.14B-0.18B^2)(1-0.47B^{168})} a_t \qquad (15)$$

where Y_t is the power load and X_t is the temperature at hour t.

In all, 4 ARIMA and 4 TRFU models were developed, one for each season of the year. Each model was used to forecast 24 hour load curves every day for a three week period. The average percent errors for those time periods are shown in Table I. From this table it is clear that the TRFU model, with its explicit temperature inputs, does provide a better forecast, on the average, than the ARIMA model.

Table I

Comparison of Mean Absolute Percentage Errors for the ARIMA and Transfer Function Models (1983)

Mean Absolute % Forecasting Error

Season	ARIMA Model	Transfer Function Model
Summer	4.17	3.82
Fall	4.68	4.49
Winter	3.85	3.35
Spring	4.11	4.30

IV. A NONLINEAR EXTENSION

Although the TRFU models do provide better forecasts than the ARIMA models, they do not accurately reflect he nonlinear relationship between temperatures and loads. This causes forecasting errors, particularly in the spring and fall seasons when there is a good deal of temperature variation with small effects on the load.

The goal of this section is to find a simple model for the load/temperature relationship and to use it in combination with the TRFU model for forecasting. If this method provides significant improvement over the linear TRFU model it will indicate that nonlinear model development is a fruitfull area for future research.

The fact that the relationship between temperature and load is nonlinear can be easily seen from the scatter diagram in Figure 10. This is a plot of 1983 peak daily power load readings vs. 1983 peak daily temperature readings for the Tulsa area. To quantify this relationship we fit a third order polynomial to the data [27].

$$Y = 1810.0 + 21.4\,T - 1.04\,T^2 + 0.0093\,T^3 \qquad (16)$$

This curve is shown in Figure 10.

There have been other approaches to fitting the load/temperature curve. The most common is to break the curve into 3 straight line segments [26]: 1) the left negative slope (winter), 2) the middle flat portion (spring and fall), and 3) the right positive slope (summer).

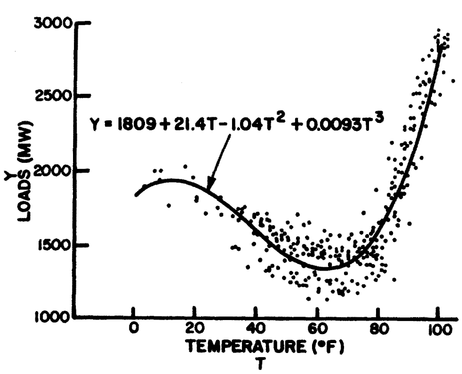

Figure 10. Scatter Diagram of Hourly Loads vs Hourly Temperatures for 1983

To use this nonlinear relationship in load forecasting we first transform the temperatures using Equation (16). We then take the transformed temperatures as input to a TRFU model. Table II compares the results of the nonlinear method with those for the standard TRFU model and for the ARIMA model.

Table II

Comparison of Mean Absolute Percentage Error for the Three Different Time Series Models (1983)

Mean Absolute % Forecasting Error

Season	ARIMA	Standard Transfer Function	Nonlinear
Summer	4.17	3.82	3.55
Fall	4.68	4.49	3.41
Winter	3.85	3.35	2.84
Spring	4.11	4.30	5.16

From Table II it is clear that the nonlinear approach offers some promise for improved load forecasting. Averaged over the four seasons, the ARIMA model had 4.2 average percent error, the TRFU model had 4.0 average percent error, and the nonlinear model had 3.74 average percent error. This is a significant improvement, given that a very simple procedure was used. With further refinements in the nonlinear modeling process we can expect to obtain even better performance.

V. COMPARISON WITH A CONVENTIONAL FORECASTING METHOD

A. Description of the Forecasting Procedure

The time series methods were compared with a conventional utility forecasting procedure. The procedure begins with an historicaly averaged load curve. This curve is obtained by specifying three variables: (1) the season of the year, (2) the day of the week, and (3) the cloud cover (cloudy or sunny) (see Table III). The dispatcher selects these parameters and inputs them into a computer which produces a load curve describing that kind of day. This curve is generated by averaging actual hourly loads from previous years over a predesignated period of time. For example, suppose that tomorrow was forecasted to be a sunny Friday, August 14th. The dispatcher would specify Season #5, Day Type #3, and Cloud Cover #1. The computer averages all the load curves for sunny Fridays in the summer season for the past few years, and generates a representative load curve for tomorrow. The dispatcher may use his/her own discretion and experience to use this curve or to select another one.

After the load curve has been chosen the dispatcher predicts the maximum and minimum loads for tomorrow. These critical points are used to proportionately stretch the shape of the representative load curve to match the high and low values without losing the basic pattern of the curve. Clearly the dispatcher's experience is the key to the success of this method.

B. Comparing Forecasting Results

Time series model forecasts were compared with the conventional forecasts for three 20 day periods in 1984 (winter, spring and summer). Average percent forecasting errors within each season for each type of model are listed in Table IV. All the time series models (which were developed with 1983 data) do very well in predicting 1984 loads when compared to the conventional forecasting method. The nonlinear extension had the lowest percent errors of all models, except in the summer season where it did just as well as the standard transfer function model. Of course, the nonlinear and the standard transfer function model used actual temperature readings, not forecasted ones.

By averaging the three seasonal percent errors for each forecasting method, we obtain a general idea of how each model faired in predicting future loads. The ARIMA model had a total average error of 4.92%, the transfer function error was 4.25%, the nonlinear extension - 3.73%, and the conventional method, 5.75%. Thus, all three types of time series models performed better than the conventional method during those seasons. This translates into improvements of 14%, 26%, and 35%, respectively. Conclusively, the nonlinear extension model is the best of the models and proves itself to be an efficient way of predicting power loads.

Table III

Seasons, Day Types and Cloud Cover Types

	Season	Time Period
1.	Winter	December 1 - February 15
2.	Late Winter-Early Spring	February 16 - DST
3.	Spring	DST - May 31
4.	Late Spring-Early Summer	June 1 - June 30
5.	Summer	July 1 - September 15
6.	Late Summer-Early Fall	September 16 - CST
7.	Fall	CST - November 30

	Day Type	Cloud Cover
1.	Monday	1. Clear-Partly Cloudy
2.	Tuesday-Thursday	2. Party Cloudy-Cloudy
3.	Friday	
4.	Saturday	
5.	Sunday	

Table IV

Mean Absolute % Forecasting Error

1984 Season	ARIMA	Tr. Fu.	Nonlin.	Convent.
Spring	4.92	5.10	4.29	7.03
Summer	5.25	3.93	4.02	5.20
Winter	4.58	3.71	2.87	5.03
Ave. Error	4.92	4.25	3.73	5.75

VI. CONCLUSIONS

Box and Jenkins time series models (ARIMA, Periodic ARIMA and Transfer Function) are very well suited to load forecasting applications. They have been used for long term forecasts of more than a year ahead, as well as for very short term forecasts of less than five minutes.

One of the drawbacks of these models for short term forecasts is their inability to accurately describe the nonlinear relationship between loads and temperatures. This paper has demonstrated that a simple polynomial regression analysis, when combined with a Box and Jenkins transfer function model, can provide more accurate forecasts.

This nonlinear model has been compared with the standard transfer function model, the periodic ARIMA model and with a utility procedure which uses heavy dispatcher input. All of the Box and Jenkins models provide accurate forecasts, but the simple nonlinear extension to the transfer function model provides the best results. These results suggest that continued development of the nonlinear model of the load/temperature relationship should provide further improvements in short term load forecasts.

ACKNOWLEDGMENTS

The authors would like to thank Public Service Company of Oklahoma, and in particular Mr. Jim Pogue, for their support of this project.

BIBLIOGRAPHY

[1] M.S. Sachdeo, R. Billinton, and C.A. Peterson, "Representative Bibliography on Load Forecasting," IEEE Trans. on Power Apparatus and Systems, Vol. PAS-96, No. 2, pp. 697-700, March/April 1977.

[2] IEEE Committee Report, "Load Forecast Bibliography, Phase I," IEEE Trans. Power App. Syst., Vol. PAS-99, No. 1, pp. 53-58, Jan./Feb. 1980.

[3] M.A. Abu-El-Magd and N.K. Sinha, "Short-Term Load Demand Modeling and Forecasting: A Review," IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-12, No. 3, pp. 370-382, May/June 1982.

[4] D.W. Bunn and E.D. Farmer, Eds., Comparitive Models for Electrical Load Forecasting, John Wiley and Sons, New York, 1985.

[5] G.T. Heineman, D.A. Nordman, and E.C. Plant, "The Relationship Between Summer Weather and Summer Loads - A Regression Analysis," IEEE Trans. Power App. Syst., Vol. PAS-85, No. 11, pp. 1144-1154, 1966.

[6] E.D. Farmer and M.J. Potton, "Development of On-Line Load Prediction Techniques with Results from Trials in the Southwest Region of the CEGB," Proc. IEE, Vol. 115, No. 10, October 1968, pp. 1549-1558.

[7] W.R. Christiaanse, "Short Term Load Forecasting Using General Exponential Smoothing," IEEE Trans. Power App. Syst., Vol. PAS-90, No. 2, March/April 1972, pp. 900-910.

[8] J. Toyoda, M. Chen, and Y. Inouye, "An Application of State Estimation to Short-Term Load Forecasting, Part I and Part II," IEEE Trans. Power App. Syst., Vol. PAS-89, No. 7, Sept./Oct. 1970, pp. 1678-1688.

[9] G.E.P. Box and G.M. Jenkins, Time Series Analysis Forecasting and Control, Holden Day, San Francisco, 1970.

[10] R.L. Kashyap and A.R. Rao, Dynamic Stochastic Models from Empirical Data, Academic Press, New York, 1976.

[11] S. Vemuri, E.F. Hill, and R. Balasubramanian, "Load Forecasting using Stochastic Models," Proc. PICA Conf., 1973, paper no. TP1-A, pp. 31-37.

[12] S. Vemuri, E.F. Hill, and R. Balasubramanian, "Load Forecasting using Moving Average Stochastic Models," Ricerche Di Automatica, Vol. 5, Nos. 2-3, December 1974, pp. 103-132.

[13] N.D. Uri, "System Load Forecasts for an Electric Utility," U.S. Department of Labor, Bureau of Labor Statistics, Working Paper 30, November 1974.

[14] A. Keyhani and A. El-Abiad, "One-Step-Ahead Load Forecasting for On-Line Applications," IEEE Winter Power Meeting, Jan. 1975, paper no. C75 027-8.

[15] A. Keyhani and T. Eliassi Rad, "A Simulation Study for Recursive Prediction of Hourly Load Demands," Proc. PICA Conf., 1977, pp. 228-236.

[16] M. Hagan and R. Klein, "Identification Techniques of Box and Jenkins Applied to the Problem of Short Term Load Forecasting," IEEE Summer Power Meeting, July 1977, paper no. A77 618-2.

[17] M. Hagan and R. Klein, "Off-Line and Adaptive Box and Jenkins Models for Load Forecasting," Proc. Lawrence Symp. Syst. and Decision Sci., Berkeley, Calif., Oct. 1977.

[18] M. Hagan, Forecasting Electric Power Loads: A System Identification Approach, Ph.D. Dissertation, Kansas University, Lawrence, Kansas, 1977.

[19] M. Hagan and R. Klein, "On-Line Maximum Likelihood Estimation for Load Forecasting," IEEE Trans. Syst. Man Cybern., Vol. SMC-8, No. 9, 1978, pp. 711-715.

[20] F. Meslier, "New Advances in Short-Term Load Forecasting Using Box and Jenkins Approach," IEEE Winter Power Meeting, New York, 1978, paper no. A78 051-5.

[21] N.D. Uri, "System Load Forecasts for an Electric Utility," Energy Sources, Vol. 3, No. 314, 1978, pp. 313-322.

[22] S. Maybee and N.D. Uri, "Time Series Forecasting of Utility Load Duration Curves," Can. Elec. Eng. J., Vol. 4, No. 1, 1979, pp. 4-8.

[23] M.A. Abu-El-Magd and N.K. Sinha, "Two New Algorithms for On-Line Modeling and Forecasting of the Load Demand of a Multinode Power System," IEEE Trans. Power App. Syst., Vol. PAS-100, No. 7, 1981, pp. 3246-3253.

[24] M.A. Abu-El-Magd and N.K. Sinha, "Univariate and Multivariate Time Series Techniques for Modeling and Forecasting Short-Term Load Demand," IFAC Symp. on Theory and Application of Digital Control, India, Jan., 1982, paper no. 5-4.

[25] S. Vemuri, W.L. Huang, and D.J. Nelson, "On-Line Algorithms for Forecasting Hourly Loads of An Electric Utility," IEEE Trans. Power App. Syst., Vol. PAS-100, No. 8, August, 1981, pp. 3775-3784.

[26] K.N. Stanton, P.C. Gupta, and A.H. El-Abiad, "Long Range Demand Forecasting for the Electric Utility Industry," Proc. PICA Conf., 1969, pp. 565-579.

[27] S. Behr, A Time Series Analysis Approach to Short Term Load Forecasting Models, Master Thesis, University of Tulsa, 1985.

[28] Weather Normalization of Electricity Sales, EPRI Research Report, EA-3134.